Scheduling Online EV Charging Demand Response via V2V Auctions and Local Generation

Yulan Yuan, Lei Jiao, Konglin Zhu, Lin Zhang

***Abstract*—Due to the enormous energy consumption and the wide geographic distribution, Electrical Vehicle (EV) charging stations are believed to have great potential in Emergency Demand Response (EDR) participation. However, EDR limits the electricity drawn from the power grid by the charging station, and can pose threats to satisfying EVs' charging demand. In this paper, in order to complement the charging station's energy supply to meet the dynamic EV charging demand, we formulate an online EV charging scheduling problem under EDR as a non-linear mixed-integer program, and propose a novel polynomial-time online algorithm and auction mechanism to jointly incentivize EVs with energy to sell their energy and utilize the charging station's local generator to produce energy. Our approach conducts an auction in each single round based on a primal-dual method and ties these auctions over time to optimize the system's long-term social cost, while accommodating the local generator' on/off-state control, each EV bidder's cumulative energy budget constraint, and the power grid's EDR energy cap. Our approach achieves the economic properties of truthfulness, individual rationality, and computational efficiency simultaneously for each auction, and a parameterized-constant competitive ratio for the long-term social cost. By rigorous theoretical analysis and trace-driven experimental studies, the results exhibit that our approach outperforms multiple alternative algorithms regarding the social cost, attains the economic properties, and also executes efficiently in practice.**

***Index Terms*—EV charging, online scheduling, demand response, vehicle to vehicle, auction.**

I. Introduction

The adoption of the Electric Vehicles (EVs) has been increasing significantly nowadays, making EV charging stations among the most energy-hungry entities [1], [2]. Due to the enormous energy consumption and the wide geographic distribution, EV charging stations are believed well-situated for participating in the Emergency Demand Response (EDR) programs. In a typical EDR program, the charging stations receive signals from the electricity grid during certain time periods and reduce their energy consumption until below a required cap in order to relieve the high load experienced by the grid and protect the availability and the reliability of the grid [3]; in return, the charging stations will receive remuneration from the grid [4].

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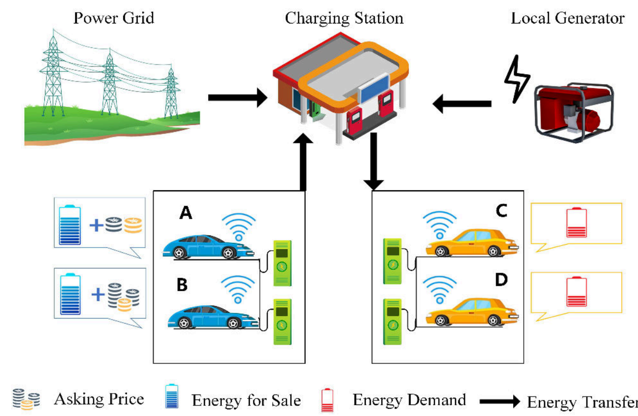

Fig. 1: System scenario

However, restricting the energy drawn from the electricity grid during EDR periods poses threats to satisfying EVs' charging demand, and it is important for the charging stations to use alternative energy sources to complement the energy supply. Among several options, two approaches seem promising and could be considered: one is using the charging stations' local electricity generator [5], [6], and the other is recruiting energy from EVs that have abundant energy. The latter is possible because EVs themselves can be regarded as a flexible energy storage, especially with today's development of rechargeable batteries and their ever-increasing capacity (e.g., 60 kWh or higher [7]). Using Vehicle-to-Vehicle (V2V) and related technologies [8], [9], EVs can now transfer their energy to the charging stations and afterwards to other EVs through dedicated devices and interfaces. Fig. 1 shows the EV charging scenario considered in this paper. The energy to charge the EVs C and D comes from multiple sources including the power grid, the local generator, and the EVs A and B.

To motivate EVs with energy to contribute to the energy supply, an appropriate incentive mechanism needs to be set up. A straightforward approach may be letting EVs price and sell their energy directly. However, it is often difficult for such direct pricing to achieve the maximal profit and market efficiency, due to the highly dynamic and uncertain demand and supply during the EDR periods. The risk of overpricing and underpricing makes this approach less ideal. In stark contrast, in the approach of auction, the charging station can act as the auctioneer, and solicit and buy bids from EVs with energy in order to charge EVs in need of energy. This approach captures the real-time demand-supply, reduces the chance of mispricing, and optimizes the market welfare. In this paper, we focus on auction-based mechanisms.

It is yet non-trivial for charging stations to jointly operate the auctions and the local generator to charge EVs during the EDR periods, which is characterized by several fundamental and critical challenges as follows. First, this is intrinsically an online problem where all the inputs (e.g., charging demand, energy bids, electricity price, energy cap of EDR) are time-varying and unpredictable, and the auctions need to be conducted and the generator needs to be controlled repetitively on the fly. Pursuing the long-term total cost optimization in such a dynamic environment is not straightforward. Second, the difficulty with generator control lies in the time-coupled on/off decisions. Keeping the local generator always on may draw too much fuel cost and maintenance cost resulting in higher social cost, whereas keeping the local generator off may make the system fail to meet the charging demand, especially in EDR periods. Additionally, switching the local generator on and off will cause additional cost such as the long-term wear-and-tear and damage. Therefore, it requires to strike the balance of local generator on/off state over time [10], [11]. Third, the difficulty with V2V auctions is the need to attain the desired economic properties such as truthfulness (i.e., a bid maximizes its utility only by not cheating in the bidding price) and individual rationality (i.e., a bid always achieves non-negative utility), while determining the winning bids and the corresponding payment in each single auction. One also needs to ensure not to consume the bids too early, depleting the bidder's available energy and disabling the bidder's future participation, given the unknown future demand. All these challenges only escalate when they appear simultaneously, intertwined with one another, as in our problem.

Despite many efforts have been devoted to EV charging scheduling, they have limitations and fall insufficient for the scenario targeted in this paper. Some do not consider the multi-source EV charging and the incentives of EVs and charging stations [12], [13]; others lack or neglect the time-varying, online environment, and only focus on offline EV charging scheduling algorithms [14]–[16]. A substantial body of research has focused on auctions or online auctions, but they do not typically account for the decision-switching cost over time (i.e., generator state control as in our problem) [17], [18]. Existing mechanisms such as Vickrey-Clarke-Groves (VCG) auctions [19]–[21] can guarantee the desired economic properties, but requires to solve the social cost problem optimally, which is computationally prohibitive in our case.

In this paper, we investigate and formulate our problem as a nonlinear mixed-integer program. Our problem minimizes the cumulative long-term social cost which includes different types of costs from the power grid, the EV bidders, and the local generator, while meeting the varying charging demand and respecting the EDR's dynamic energy cap, the local generator's capacity, and each EV bidder's cumulative energy budget. The problem is NP hard even in an offline setting, besides all the inputs are arbitrary dynamics. Therefore, it calls for a polynomial-time online approximation algorithms.

We propose EVCDR, a novel online algorithm and auction mechanism to solve our problem. EVCDR solves each single-round problem as an auction and ties these auctions over time while accommodating the generator's on/off state and each bidder's cumulative energy budget, which works as follows.

For each single round, given the specific generator state, we design a primal-dual-based algorithm to overcome the NP-hardness via linear programming relaxation and "flow-cover" constraint strengthening [22], in order to select winning bids and draw energy from the grid and the generator, respectively. We address the long-term capacity constraint of EV batteries [7] via auxiliary variables for each bid to combine its cost and residual capacity. Moreover, we determine the payments following Myerson's characterization [23] for each winning bid, and prove that the properties of truthfulness, individual rationality, and computational efficiency are attained altogether.

For the long term, we design an online control algorithm and focus on determining the generator state that is fed to our aforementioned single-round algorithm. Given that the future inputs remain unknown, we greedily calculate the best state of the local generator for each current time slot, and then determine whether to maintain this state and postpone the on/off state-switching to avoid excessive wear-and-tear by comparing the accumulative cost so far to the harm of the state-switching operation [4]. We prove that our online algorithm produces a parameterized-constant approximation ratio for each single time slot and also a corresponding competitive ratio for the long-term cumulative social cost.

We finally conduct extensive numerical evaluations using real-world data traces. We use the dynamic EV charging records from the adaptive charging networks of California [24] as the charging demand. We also take the corresponding wholesale hourly electricity price [25], the grid load (for EDR) [26], and realistic generator parameters [4] as inputs. Through 168 hours and under the large-scale and small-scale settings, we observe the following results: (1) EVCDR only incurs no more than 1.9 and 1.4 times the total cost of the offline optimal approach in the large-scale and small-scale settings, respectively; (2) EVCDR also saves up to 80% and 62% total cost compared to using no auction and no accommodation of the generator switching cost in these two cases, respectively, validating that EVCDR can achieve even better performance with proper state-switching control and using energy from the EV auctions; (3) EVCDR successfully achieves truthfulness and individual rationality; (4) EVCDR executes fast and finishes within 3.5 ms on average for each single auction, scaling well as the number of bids increases even in a large-scale setting.

II. Model And Problem Formulation

In this section, we present our system model, the social cost optimization problem formulation, the algorithmic challenges and the overview of our online scheme and the performance analysis. For the ease of reference, we summarize all the notations in Table I.

A. System Modeling

Charging Station, EVs, Generator, and Grid: We consider an EV-charging system that consists of a charging station and a group of EVs. Besides the typical charging interfaces to connect and charge the EVs, the charging station is equipped with the following components: (1) the connection to the

TABLE I: NOTATIONS

Inputs	Meaning
$\mathcal{M}$	Set of bidders (or bids)
$\mathcal{T}$	Set of time slots
$W^{(t)}$	Total energy demand at time t
Ca_m	Cumulative energy budget of EVm's for auctions during $\mathcal{T}$
α	Fuel cost for producing one unit local energy
β	Sunk cost of maintaining local generator active
ζ	Start-up cost of turning on local generator
V	Total capacity of local generator
$E^{(t)}$	Cap of energy from grid at time t
$e^{(t)}$	Price of energy from grid at time t
$c_m^{(t)}$	Cost of bid m at time t
$g_m^{(t)}$	Amount of energy bid m at time t sells
$P_m^{(t)}$	Payment to bid m
Variables	**Meaning**
$x_m^{(t)}$	Whether bid m wins or not at time t
$y^{(t)}$	Whether local generator are on or off at time t
$u^{(t)}$	Amount of energy produced locally at time t
$z^{(t)}$	Amount of energy drawn from grid at time t

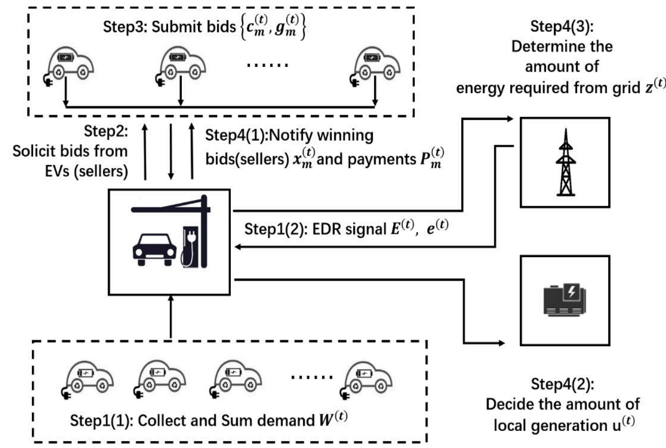

Fig. 2: Illustration of our auction model in a single time slot

electricity grid which can draw energy to charge the EVs; (2) the local energy generator that is collectively managed to produce energy, if needed, for charging the EVs; and (3) the local facilities that enable V2V energy transfer, i.e., to transfer energy from the EVs that are willing to sell energy from their batteries to those that want to charge energy. We highlight that V2V technologies allow vehicles to transfer energy to or get energy from a storage point such as a smart home or a charging station via dedicated devices or interfaces, and then coordinate EVs' energy distribution through a controller [27], [28]. These energy sources working together can be regarded as a local "microgrid" that fulfills the time-varying charging demand of EVs. The charging station also joins the EDR program of an external electricity grid, and when receiving an EDR signal, it is mandatory for the charging station to keep its energy consumption from the electricity grid within a required cap.

The EV charging system is intrinsically dynamic. We consider the operation of the system over a series of time slots $\mathcal{T} = \{1, 2, ..., T\}$. We denote the total energy demand from the EVs that want to charge energy as $W^{(t)}$, which is obtained by collecting and then accumulating all the individual charging demands at time slot $t \in \mathcal{T}$, and then denote the set of the EVs that can provide energy to others as $\mathcal{M} = \{1, ..., M\}$, which can represent the set of EVs in the community where the charging station is located. Each EV m has its cumulative energy budget Ca_m for the auctions during the entire $\mathcal{T}$, where we assume that Ca_m is a fixed value and decided empirically by the EV m. That is, the cumulative energy budget for an EV is determined at the beginning of time $\mathcal{T}$, while it is not limited by the EV's battery capability, as Ca_m is estimated by accumulating the charging or discharging energy amount during the whole process.

For the local generator, we use α to represent the fuel cost to produce one unit energy, β to represent the cost needed to maintain the generator active, ζ to represent the start-up or transition cost when turning on the generator, and V to represent the capacity or the maximal amount of energy that can be output by the generator. We note that the local generator in such a microgrid environment is usually equipped with a relatively small capacity, powered by a diesel engine with fast-responding performance, which can implement the on/off state transitions within a minimum time period [29]. For the EDR signal at time slot t, we adopt $E^{(t)}$ to refer to the cap of the energy available from grid, and $e^{(t)}$ to refer to the price of such energy within the cap. We also allow arbitrary dynamics and make no assumption about how $W^{(t)}$, $E^{(t)}$ and $e^{(t)}$ may vary with time.

Auction Model: To incentivize the EVs with surplus energy to sell their energy for charging those in need of energy, we propose an online auction mechanism that executes as follows, where the charging station is the auctioneer and the EVs selling energy are the bidders. An auction is conducted in each time slot of the time horizon $\mathcal{T}$ under consideration. In each time slot $t \in \mathcal{T}$, the charging station firstly receives the total energy demand $W^{(t)}$ which is obtained by accumulating the demand of all individual vehicles, and also the EDR signal, if any, from the power grid, which consists of the cap $E^{(t)}$ and the price $e^{(t)}$. Then, with such information, plus the generator information that is known in prior, the charging station will initiate an auction by soliciting bids from the EV sellers (i.e., bidders). Next, each bidder m can submit a bid $(c_m^{(t)}, g_m^{(t)})$, where $g_m^{(t)}$ is the amount of energy on sale for the time slot t. It is determined by EV mâĂŹs discharging rate and the current remaining energy budget and $c_m^{(t)}$ is the corresponding remuneration requested by this bid. Each EV m can give up participating in the auction at any time t, which can cause the number of bids to vary as time goes. To capture such dynamics by a fixed set $\mathcal{M}$, we can let our system generate a virtual bid, where $c_m^{(t)}$ is set to $+\infty$ (or a very large value in reality), to represent that EV m does not join the auction at t, and this bid will automatically lose in the auction as the social cost is being minimized. Finally, receiving all the bids, the charging station will determine the values of the following variables: (1) whether each bid m wins, denoted by $x_m^{(t)} \in \{1, 0\}$ ($x_m^{(t)} = 1$ for winning and $x_m^{(t)} = 0$ for losing in the auction), with the payment $P_m^{(t)}$ for each bid ($P_m^{(t)} > 0$ for the winner and $P_m^{(t)} = 0$ for the unsuccessful bidder); (2) whether to use the local generator, denoted by $y^{(t)} \in \{1, 0\}$ ($y^{(t)} = 1$ for using and $y^{(t)} = 0$ for not using the generator), and the amount of the energy $u^{(t)} \geq 0$ which needs to be drawn from the local generator; and (3) the amount of the energy $z^{(t)} \geq 0$ which needs to be drawn from the power grid. The charging station will perform the EV charging operations according to these decisions. Fig. 2 visualizes our auction model as mentioned above in a single time slot.

Cost of Charging Station: The total cost of the charging station consists of multiple components. First, the charging station, as the auctioneer, makes payments to the bidders:

$$\sum_t \sum_m P_m^{(t)}.$$

Second, the fuel cost of the energy that charging station consumes via the local generator [30]:

$$\sum_t \alpha u^{(t)}.$$

Note that the fuel cost is conventionally expressed as a quadratic function: $ap^2 + bp + c$ [31], where p is the amount of electricity produced by the generator and a, b and c are the constants depending on the generator. As the order of magnitude of the coefficient a is usually much smaller than that of b, which makes the linear term bp much larger than the quadratic term ap^2 and makes ap^2 negligible especially for the small-capacity generator in the microgrid [32], we thus only consider the linear term in our model, i.e., $\alpha u^{(t)}$. Third, to retrieve energy from the local generator, the charging station incurs the cost of operating the local generator, which includes the maintenance cost and the switching cost [32]–[34]:

$$\sum_t \beta y^{(t)} + \sum_t \zeta [y^{(t)} - y^{(t-1)}]^+.$$

We use $\beta y^{(t)}$ to denote the labor management cost of maintaining the local generator in their active state, and use $\zeta[y^{(t)} - y^{(t-1)}]^+ = \zeta \max\left\{y^{(t)} - y^{(t-1)}, 0\right\}$ to denote the switching cost, which involves the device wear-and-tear and any additional cost caused by each start-up [35]. Fourth, the charging station draws energy from the electricity grid:

$$\sum_t e^{(t)} z^{(t)}.$$

Summarizing all the components, the total cost of the charging station is

$$\sum_t \sum_m P_m^{(t)} + \sum_t \Big(\alpha u^{(t)} + \beta y^{(t)} + \zeta[y^{(t)} - y^{(t-1)}]^+ + e^{(t)} z^{(t)}\Big). \tag{1}$$

Cost of EVs: The total cost of the EVs consists of the total cost of the bids, plus the total payments received from the charging station (treated as negative cost). Therefore, it is represented as

$$\sum_t \sum_m \left(c_m^{(t)} x_m^{(t)} - P_m^{(t)}\right). \tag{2}$$

B. Problem Formulation and Algorithmic Challenges

Social Cost Minimization Problem: The "social" cost refers to the total cost of the entire system. Thus, the social cost is the sum of (1) and (2), where the payments will be canceled (note that we will still determine the payments later, as required by the auction mechanism). We formulate the problem of social cost minimization as follows, which is a mixed integer non-linear program (assuming "truthfulness", which will be defined and proved later):

$$\begin{aligned}
\text{Min} \quad & \sum_t \sum_m c_m^{(t)} x_m^{(t)} + \sum_t \alpha u^{(t)} + \sum_t e^{(t)} z^{(t)} \\
& + \sum_t \beta y^{(t)} + \sum_t \zeta [y^{(t)} - y^{(t-1)}]^+ && (3)\\
\text{s.t.} \quad & \sum_m g_m^{(t)} x_m^{(t)} + u^{(t)} + z^{(t)} \geq W^{(t)}, \forall t, && (3a)\\
& \sum_t g_m^{(t)} x_m^{(t)} \leq Ca_m, \forall m, && (3b)\\
& 0 \leq u^{(t)} \leq V \cdot y^{(t)}, \forall t, && (3c)\\
& 0 \leq z^{(t)} \leq E^{(t)}, \forall t, && (3d)\\
& x_m^{(t)} \in \{0,1\}, y^{(t)} \in \{0,1\}, \forall m, \forall t. && (3e)
\end{aligned}$$

The objective (3) minimizes the social cost. Constraint (3a) ensures that the total demand of EVs to be charged are satisfied by the energy from the bidders, the local generator, and the power grid. Constraint (3b) ensures that the energy sold by a bidder does not exceed the bidder's cumulative energy budget. Constraint (3c) guarantees that energy consumed from the local generator does not exceed the generator's capacity. Constraint (3d) guarantees that the energy obtained from the grid does not exceed the energy cap required by the demand response program. Constraint (3e) specifies the binary domains of some decision variables.

Theorem 1. *The long-term social cost minimization problem (3) is an NP-hard problem.*

Proof. The core idea is to demonstrate that our problem contains an existing NP-hard problem as a special case. That is, any algorithm that can solve our problem can also solve that existing NP-hard problem; in other words, if that existing NP-hard problem cannot be solved in deterministic polynomial time (unless $P = NP$), then our problem also cannot be solved in deterministic polynomial time. Here, we choose to show that our problem contains the "minimum-cost knapsack problem" which is well known to be NP-hard. In fact, in our problem, if α, $e^{(t)}$, β, ζ are all zeros and if Ca_m is large, then our problem can be indeed reduced to the minimum-cost knapsack problem. One version of the minimum-cost knapsack problem can be described as follows. Given a fixed number of items, where each item i has the weight w_i and the value v_i, and given a minimum value requirement C, the optimization objective is minimizing the total weight of the items that are selected $\sum_i w_i x_i$, while satisfying the minimum value requirement $\sum_i v_i x_i \geq C$, where $x_i \in \{1, 0\}$ is a decision variable indicating whether to select the item i or not. Now, note that, $\forall t$, the symbols w_i, v_i, C, and x_i correspond to $c_m^{(t)}$, $g_m^{(t)}$, $W^{(t)}$, and $x_m^{(t)}$ in our problem, respectively; and the constraint $\sum_i v_i x_i \geq C$ corresponds to (3a) in our problem. Consequently, our problem (3) contains the minimum-cost knapsack problem as a special case. □

Algorithmic Challenges: We highlight that solving the social cost minimization problem in an online manner and determining the payments with guaranteed provable performance faces four fundamental challenges.

First, the switching cost $\sum_t \zeta[y^{(t)} - y^{(t-1)}]^+$ couples every time slot $t-1$ and its next time slot t, and without knowing

$y^{(t)}$, which is the decision that will be made at t, it is non-trivial to make the decision of $y^{(t-1)}$ at $t-1$ for minimizing the long-term cost, because any decision of $y^{(t-1)}$ will potentially impact the switching cost between $t-1$ and t. Directly solving each single-round problem to its optimum can incur excessive switching cost in the long run.

Second, the long-term capacity constraint of (3b) must be respected, which makes it difficult to make good decisions in each single time slot. Blind to the unpredictable future power demands and other inputs, putting more energy on sale for the EV sellers may drain the energy too fast and disable future auction participation; in contrast, putting less energy on sale may not help reduce the social cost. Yet, dynamically striking an appropriate balance is not straightforward.

Third, our problem is NP-hard even in the offline setting, not to mention we aim to solve it in an online setting. Note that if we ignore all the terms related to $y^{(t)}$, $u^{(t)}$, and $z^{(t)}$, then our problem becomes a classic minimum 0-1 knapsack problem, which is known to be NP-hard [22]. Our problem thus contains an NP-hard problem as a special case, and desires polynomial-time online approximation algorithms.

Fourth, from the perspective of calculating the payment with truthfulness and individual rationality (both of which will be defined and discussed later), we are also motivated to strive for novel approaches. The standard Vickrey-Clark-Groves (VCG) approach for payment is inapplicable to our problem, as it requires the social cost minimization in each time slot to be optimally solved. Otherwise, truthfulness cannot be guaranteed [36]. However, due to NP-hardness of the problem and an approximation algorithm is applied, which prevents us from doing so. Even without NP-hardness, using VCG in each time slot is still prohibited due to the switching cost and the long-term capacity constraint.

C. Algorithm Design and Performance Analysis Overview

To overcome the aforementioned challenges and to solve the social cost minimization problem in an online manner, we design a novel online scheme consisting of two components: Algorithm for Single-Round Auction (Sec. III) and Algorithms for Long-Term Cost Optimization (Sec. IV), as illustrated in Fig. 3.

First, removing temporarily the switching cost related to the generator's on/off state $y^{(t)}$ by assuming $y^{(t)}$ is given, we split and solve the long-term problem as a series of single-round auctions (including selecting winners and making payments). Then, we dynamically determine the generator's state and thus tie the individual auctions together by weighing the switching cost versus the non-switching cost on the fly towards the total cost minimization.

For the single-round auction at each individual time slot, we design Algorithm 1:

(i) **Problem Transformation:** Assuming the generator states $\{y^{(t)}, \forall t\}$ are all given, we tentatively ignore the switching cost $\sum_t C_{SC}^{(t)} = \sum_t \zeta[y^{(t)} - y^{(t-1)}]^+$, and only focus on the non-switching cost $\sum_t C_{-SC}^{(t)} = \sum_t \sum_m c_m^{(t)} x_m^{(t)} + \sum_t \alpha u^{(t)} + \sum_t e^{(t)} z^{(t)} + \sum_t \beta y^{(t)}$. We remove the long-term energy capacity constraint (3b) based on a Lagrange multiplier, and thus the non-linear mixed integer programming problem (3) can be decomposed into several one-round problems over time. We also introduce the "flow-cover" type of inequalities [22] to transform the single-round problem for facilitating our primal-dual algorithm design next.

(ii) **Single-Round Auction:** We then design Algorithm 1 to approximately solve the single-round problem (6), which is a mixed integer linear program, through the primal-dual paradigm. We relax the primal problem, derive its Lagrange dual problem, and then control the dual variables to assign appropriate values to the primal variables, i.e., selecting the winning bids. We also carefully calculate the payment for each winning bid in this process.

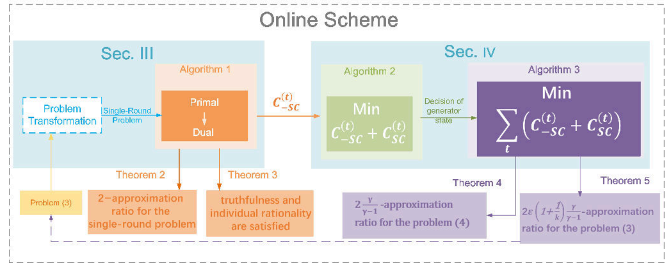

Fig. 3: Structure of the proposed online scheme

For the cumulative social cost optimization in the long run, we design Algorithms 2 and 3:

(iii) **Long-Term Optimization:** We focus on determining the generator states $\{y^{(t)}, \forall t\}$. We design Algorithm 2 to find a temporary generator state that results in the minimum social cost $C_{-SC}^{(t)} + C_{SC}^{(t)}$ at each t from a single-round perspective, where $C_{-SC}^{(t)}$ is obtained by invoking Algorithm 1. We then design Algorithm 3 to determine the final generator state by properly postponing switching on the generator to avoid excessive switching cost, which aims to minimize the cumulative social cost $\sum_t (C_{-SC}^{(t)} + C_{SC}^{(t)})$ from a long-term perspective.

We conduct rigorous formal analysis of the performance of our algorithms. We exhibit that Algorithm 1 guarantees an approximation ratio of 2 for the single-round problem (6) (i.e., Theorem 2), while producing payments that satisfy the desired economic properties of truthfulness and individual rationality (i.e., Theorem 3). We also demonstrate that long-term optimization algorithms (i.e., Algorithms 2 and 3) guarantee an approximation ratio of $2\frac{\gamma}{\gamma-1}$ for the long-term social cost as in the problem (4) (i.e., Theorem 4), and a bounded parameterized-constant approximation ratio (i.e., competitive ratio) of $2\epsilon\left(1+\frac{1}{k}\right)\frac{\gamma}{\gamma-1}$ (i.e., Theorem 5) for the long-term social cost as in our original problem (3).

III. Algorithm for Single-Round Auction

In this section, we first transform problem (3) into a series of time-independent solvable subproblems. Then we will design a primal-dual-based polynomial-time algorithm for single-round auction to determine the winning bids, with the electricity drawn from the local generator and the grid, while addressing the long-term budget constraint and calculating the payment.

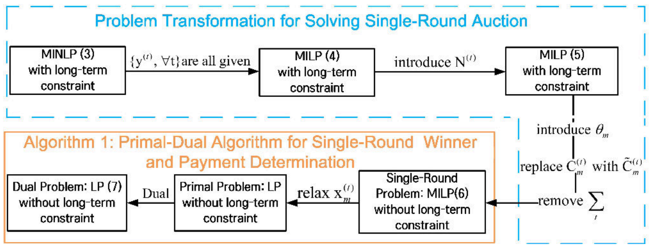

Fig. 4: Roadmap of our algorithm for each single-round auction

We will also rigorously prove the guaranteed approximation performance and the economic properties of our algorithm. The roadmap of this section is shown in Fig. 4.

A. Problem Transformation

For solving the single-round auction at each t, we transform our problem (3), assuming the status of the generator $y^{(t)}$ is given, i.e., the switching cost $C_{SC}^{(t)}$ and the term $\beta y^{(t)}$ are known. Therefore, we only solve $\sum_m c_m^{(t)} x_m^{(t)} + \alpha u^{(t)} + e^{(t)} z^{(t)}$. Our original long-term social cost minimization problem becomes the following:

$$\begin{array}{ll} \text{Min} & \sum_t \sum_m c_m^{(t)} x_m^{(t)} + \sum_t \alpha u^{(t)} + \sum_t e^{(t)} z^{(t)} \qquad (4) \\ \text{s.t.} & \text{(3a), (3b), (3c), (3d), (3e).} \end{array}$$

To solve this problem, we consider a subset $\mathrm{N}^{(t)} = \{m_1, m_2, \ldots\}$ such that $\sum_{m \in N^{(t)}} g_m^{(t)} < W^{(t)}$ [22]. So, $\Delta\left(N^{(t)}\right) = W^{(t)} - \sum_{m \in N^{(t)}} g_m^{(t)}$ represents the residual energy which needs to be met on top of the bids in $N^{(t)}$. We define $g_m\left(N^{(t)}\right) = \min\left\{g_m^{(t)}, \Delta\left(N^{(t)}\right)\right\}$. Then, the problem (4) can be transformed into the following form:

$$\text{Min} \ \sum_t \sum_m c_m^{(t)} x_m^{(t)} + \alpha u^{(t)} + e^{(t)} z^{(t)} \qquad (5)$$

Subject to:

$$\sum_{m \in \mathcal{M} \setminus N^{(t)}} g_m^{(t)}(N^{(t)}) x_m^{(t)} + u^{(t)} + z^{(t)} \geq \Delta(N^{(t)}), \qquad (5a)$$
$$\forall N^{(t)} \subseteq \mathcal{M}, \forall t,$$
$$\sum_t g_m^{(t)} x_m^{(t)} \leq Ca_m, \forall m, \qquad (5b)$$
$$0 \leq u^{(t)} \leq V \cdot y^{(t)}, \forall t, \qquad (5c)$$
$$0 \leq z^{(t)} \leq E^{(t)}, \forall t, \qquad (5d)$$
$$x_m^{(t)} \in \{0, 1\}, \forall m, \forall t. \qquad (5e)$$

To address the long-term budget constraint (5b) in order to split the above problem to a series of one-shot problems over $\mathcal{T}$, each corresponding to a single time slot, we introduce $c_m^{\sim(t)} \triangleq c_m^{(t)} + \theta_m g_m^{(t)}, \forall m, t$, where $\theta_m, \forall m$ is the Lagrange dual variable for (5b). We use $c_m^{\sim(t)}$ to replace $c_m^{(t)}$ in the objective and then remove (5b). This is the key to addressing the long-term budget constraint. $\{\theta_m, \forall m\}$, in addition to $\{y^{(t)}, \forall t\}$, will be addressed in details in Section IV.

B. Primal-Dual Algorithm for Winner and Payment Determination

Based on the above, we can have the single-round problem at t:

$$\text{Min} \ \sum_{m \in \mathcal{M}} c_m^{\sim(t)} x_m^{(t)} + \alpha u^{(t)} + e^{(t)} z^{(t)} \qquad (6)$$

Subject to:

$$\sum_{m \in \mathcal{M} \setminus N^{(t)}} g_m^{(t)}(N^{(t)}) x_m^{(t)} + u^{(t)} + z^{(t)} \geq \Delta(N^{(t)}), \qquad (6a)$$
$$\forall N^{(t)} \subseteq \mathcal{M},$$
$$0 \leq u^{(t)} \leq V \cdot y^{(t)}, \qquad (6b)$$
$$0 \leq z^{(t)} \leq E^{(t)}, \qquad (6c)$$
$$x_m^{(t)} \in \{0, 1\}, \forall m \in \mathcal{M}. \qquad (6d)$$

Primal Problem: We relax the binary variables $x_m^{(t)}, \forall m$ to the continuous domains, which transforms the mixed integer linear program (6) into its linear program relaxation, which is our primal problem:

$$\begin{array}{ll} \text{Min} & \sum_{m \in \mathcal{M}} c_m^{\sim(t)} x_m^{(t)} + \alpha u^{(t)} + e^{(t)} z^{(t)} \\ \text{Subject to:} & \text{(6a)-(6c)}, x_m^{(t)} \geq 0, \forall m \in \mathcal{M}. \end{array}$$

Dual Problem: Our next step is to derive the Lagrange dual problem [37]. By introducing the dual variables $Z(N^{(t)})$, $\rho^{(t)}$, $\phi^{(t)}$ for the corresponding constraints, respectively, we can actually have the following formulation, which is our dual problem:

$$\begin{aligned} \text{Max} \ & \sum_{N^{(t)} \subseteq \mathcal{M}} Z\left(N^{(t)}\right) \Delta\left(N^{(t)}\right) \\ & - \rho^{(t)} V y^{(t)} - \phi^{(t)} E^{(t)} \end{aligned} \qquad (7)$$

Subject to:

$$\sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z\left(N^{(t)}\right) g_m\left(N^{(t)}\right) \leq c_m^{\sim(t)}, \forall m \in \mathcal{M}, \qquad (7a)$$
$$\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq \alpha + \rho^{(t)}, \qquad (7b)$$
$$\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq e^{(t)} + \phi^{(t)}, \qquad (7c)$$
$$Z\left(N^{(t)}\right), \rho^{(t)}, \phi^{(t)} \geq 0, \forall N^{(t)} \subseteq \mathcal{M}. \qquad (7d)$$

Primal-Dual Algorithm: We design Algorithm 1 for the winner and payment determination. Since our problem is NP-hard and the standard VCG approach is no longer applicable, we give an algorithm based on primal-dual optimization, which calculates the payment and constructs a mixed integer solution for problem (6) by solving the primal problem via working with the dual problem (7) simultaneously.

The basic idea is to ensure the dual variable $Z(N^{(t)})$ increases continuously until the dual constraint (7a), (7b) or (7c) becomes tight (a constraint $ax \leq b$ is tight if $ax = b$), and then the corresponding primal variable can be set as a non-zero value. The iteration will not terminate until the constraint (6a) is satisfied (i.e., the energy purchased from the suppliers can cover the whole demand).

We further explain how Algorithm 1 works. Lines 1-5 initialize all the variables. Here we highlight that the value

Algorithm 1: Primal-Dual Algorithm for Winner and Payment Determination

Input: $M, y^{(t)}, \alpha, e^{(t)}, W^{(t)}, V, E^{(t)}, \tilde{c}_m^{(t)}$
Output: $\mathcal{I}$, $u^{(t)}, z^{(t)}, P_m^{(t)}$, C_{-SC}

1 $Z\left(N^{(t)}\right) = 0, \forall N^{(t)} \subseteq \mathcal{M}$;
2 $N^{(t)} = \emptyset$;
3 $x_m^{(t)} = 0, \forall m \in \mathcal{M}$;
4 $\tilde{c}_m^{(t)}\star = \tilde{c}_m^{(t)}, \forall m \in \mathcal{M}$;
5 $q(N^{(t)}) = 0$;
6 **while** $\mathcal{M} \neq \emptyset$ ***AND*** $\Delta\left(N^{(t)}\right) > 0$ **do**
7 $\quad \tilde{c}_m^{(t)}\star = \tilde{c}_m^{(t)}\star - Z\left(N^{(t)}\right) g_m\left(N^{(t)}\right)$;
8 $\quad m^* = \arg\min_{m \in \mathcal{M}} \left\{ \frac{\tilde{c}_m^{(t)}\star}{g_m(N^{(t)})} \right\}$;
9 $\quad q(N^{(t)}) = q(N^{(t)}) + g_{m^*}(N^{(t)})$;
10 $\quad m^- = \arg\min_{m \neq m^*} \left\{ \frac{\tilde{c}_m^{(t)}\star}{g_m(N^{(t)})} \right\}$;
11 $\quad Z\left(N_{m^-}\right) = \min_{m \neq m^*} \left\{ \frac{\tilde{c}_m^{(t)}\star}{g_m(N^{(t)})} \right\}$;
12 $\quad Z\left(N^{(t)}\right) = \min_{m \in \mathcal{M}} \left\{ \frac{\tilde{c}_m^{(t)}\star}{g_m(N^{(t)})} \right\}$;
13 $\quad P_{m^*}^{(t)} = \tilde{c}_{m^*}^{(t)} + \left(Z\left(N_{m^-}\right) - Z\left(N^{(t)}\right)\right) g_{m^*}\left(N^{(t)}\right)$,
$\quad N^{(t)} = N^{(t)} \cup m^*$, $x_{m^*}^{(t)} = 1$, $\mathcal{M} = \mathcal{M} \backslash m^*$,
$\quad \Delta\left(N^{(t)}\right) = W^{(t)} - q(N^{(t)})$;
14 $\quad q^{(t)} = \max\left\{0, \min\left\{V y^{(t)} + E^{(t)}, \Delta\left(N^{(t)}\right)\right\}\right\}$;
15 $\quad \Delta\left(N^{(t)}\right) = \Delta\left(N^{(t)}\right) - q^{(t)}$;
16 $\quad$ **if** $q^{(t)} > 0$ **then**
17 $\quad\quad$ **if** $\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq \alpha$ *or* $\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq e^{(t)}$ **then**
18 $\quad\quad\quad$ go to next iteration;
19 $\quad\quad$ **else**
20 $\quad\quad\quad$ find a corresponding new value $\rho^{(t)} \geq 0$, which makes $\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq \alpha + \rho^{(t)}$ tight, and find a corresponding new value $\phi^{(t)} \geq 0$, which makes $\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq e^{(t)} + \phi^{(t)}$ tight; break;
21 $\quad$ **else**
22 $\quad\quad$ break;
23 $\mathcal{I} = N^{(t)}$, $C_{-SC}^{(t)} = \sum_{\mathcal{I}} c_m^{(t)} + \alpha u^{(t)} + e^{(t)} z^{(t)} + \beta y^{(t)}$

$\tilde{c}_m^{(t)}$ in Line 4 is calculated in Algorithm 3 and passed to Algorithm 1 to initialize $\tilde{c}_m^{(t)}\star$. The *while* loop from Line 6 to 22 chooses the winners and decides the payments based on a greedy strategy, and then the primal and dual variables are updated. For each bidder $m \in \mathcal{M}$, the scaled cost $\tilde{c}_m^{(t)}\star$ is constantly updated in decreasing degrees based on the slacks of the dual constraint in Line 7. Line 8 determines the winning bid m^* according to the minimum unit price of energy. Line 10 determines the suboptimal bid m^- when we exclude the winning bid m^* obtained by Line 8. Line 11 records $Z\left(N_{m^-}\right)$ and Line 12 records $Z\left(N_{m^{(t)}}\right)$, which are used to compute the payment. Line 13 computes the payment to the winner m^* according to the critical value rule which ensures a bid will also win if it reports a lower price, and $x_m^{(t)}$ is set to 1 and m^* is removed from $\mathcal{M}$. Line 14 updates the value of $q^{(t)}$, assuming that $q^{(t)} = u^{(t)} + z^{(t)}$. Line 15 updates the remainder of demand. Lines 16-22 update the dual variables and guarantee that the solutions satisfy the constraints (6b) and (6c). Line 23 records the winners set $\mathcal{I}$, and computes the non-switching cost $C_{-SC}^{(t)}$.

C. Approximation and Economic Properties Analysis

We analyze the feasibility and the approximation ratio of Algorithm 1. We also define the economic properties of truthfulness and individual rationality. We prove that they are satisfied by our auction design.

Lemma 1. *Algorithm 1 terminates in polynomial time with a feasible solution for both the single-round problem (6) and the dual problem (7).*

Proof. See Appendix A. □

Theorem 2. *Algorithm 1 is a 2-approximation algorithm, i.e., the cost obtained by Algorithm 1 is at most 2 times the optimal cost in the problem (6).*

Proof. The proof is based on Lemma 1. See Appendix B. □

The above lemma and theorem prove the feasibility and the approximate ratio of Algorithm 1, respectively. Meanwhile, note that we aim to design an auction mechanism that can motivate EVs to participate in the auction while guaranteeing the desired economic properties. We present the following definitions:

Definition 1. *Utility.* The utility of bidder m is

$$u_m\left(b_m^{(t)}, b_{-m}^{(t)}\right) = \begin{cases} P_m^{(t)}\left(b_m^{(t)}, b_{-m}^{(t)}\right) - c_m^{(t)} & \text{if } x_m^{(t)} = 1 \\ 0 & \text{otherwise,} \end{cases}$$

where $b_m^{(t)}$ is the declared cost of supply $g_m^{(t)}$, $b_{-m}^{(t)}$ is the set of bids from bidders except m, and $c_m^{(t)}$ is the true cost of $g_m^{(t)}$, which is only known to bidder m itself. Each bidder is assumed to be rational, with a natural goal of maximizing its own utility. So a bidder may choose to misreport its cost ($b_m^{(t)} \neq c_m^{(t)}$) if doing so leads to a higher utility.

Definition 2. *Truthfulness.* An auction is truthful if for any bidder m, reporting the true valuation always maximizes its utility, i.e., for all $c_m^{(t)} \neq b_m^{(t)}$ ($c_m^{(t)}$ is the true valuation, $b_m^{(t)}$ is the declared cost), $u_m\left(c_m^{(t)}, b_{-m}^{(t)}\right) \geq u_m\left(b_m^{(t)}, b_{-m}^{(t)}\right)$.

Definition 3. *Individual Rationality.* Each bidder is individually rational if it always achieves non-negative utility [38], i.e., for bidder m, the utility $u_m \geq 0$.

Lemma 2. *According to the Myerson's theorem [23], an auction is truthful if and only if*

1) *The result of the auction mechanism is monotone, i.e., $x_m^{(t)}$ output by Algorithm 1 is monotone. That is, for $\forall m_1, m_2 \in \mathcal{M}$, if $\tilde{c}_{m_1}^{(t)} \leq \tilde{c}_{m_2}^{(t)}$ and $g_{m_1}^{(t)} = g_{m_2}^{(t)}$, then $x_{m_2}^{(t)} = 1$ implies $x_{m_1}^{(t)} = 1$;*
2) *The winner is paid with critical payment [4], [39]. That is, if bidder m wins the auction with the bid ($c_{m^\star}^{(t)}$, $g_{m^\star}^{(t)}$),*

it will also win if its asking price satisfies $c_m^{(t)} \le \frac{c_{m^\star}^{(t)} g_m^{(t)}}{g_{m^\star}^{(t)}}$, *and otherwise it will lose in this round.*

Proof. See Appendix C. □

Theorem 3. *Our proposed auction mechanism achieves both truthfulness and individual rationality.*

Proof. The proof is based on Lemma 2. See Appendix D. □

IV. Algorithms for Long-Term Cost Optimization

In this section, we will design an online algorithm to dynamically control the on/off state of the local generator, i.e., to determine $\{y^{(t)}, \forall t\}$, so that the long-term social cost minimization problem can be decoupled into a series of solvable single-round problems (i.e., auctions) using the algorithm presented in the previous section. We will also prove the guaranteed performance of our online algorithms.

A. Online Algorithms for Generator State Control

Online algorithm is designed to overcome two major problems: (1) how to tie each single-round auction together into the long-term social cost minimization; (2) how to determine the state of the local generator for avoiding excessive switching. We present the following algorithms.

Finding temporary generator state: For the one-round auction, we determine the value $y^{(t)}$ which incurs the minimum social cost in Algorithm 2. Here we only regard this value as the temporary value, and we will determine whether to use it as the final state of the local generator later.

Algorithm 2: Algorithm for One-Round Social Cost Minimization

Input: input parameters: $y^{(t-1)}$
1 **for** $\hat{y}^{(t)} = 0, 1$ **do**
2   obtain $\hat{C}_{-SC}(\hat{y}^{(t)})$ by invoking Algorithm 1 and $\hat{C}_{SC}(\hat{y}^{(t)}, y^{(t-1)})$ for every $\hat{y}^{(t)}$;
3 find minimum cost $\hat{C}_{-SC}(\hat{y}^{(t)}) + \hat{C}_{SC}(\hat{y}^{(t)}, y^{(t-1)})$, then determine $y^{(t)} = \hat{y}^{(t)}$, total cost: $\mathbb{C}\left(y^{(t)}\right) = C_{-SC}(y^{(t)}) + C_{SC}(y^{(t)}, y^{(t-1)})$;

The specific steps of Algorithm 2 are as follows: the for loop in Lines 1-2 traverses all possible values of $y^{(t)}$ and obtains switching cost $\hat{C}_{SC}(\hat{y}^{(t)}, y^{(t-1)})$ and the non-switching cost $\hat{C}_{-SC}(\hat{y}^{(t)})$ by invoking Algorithm 1. Line 3 determines the optimal $y^{(t)}$ that can result in the minimum total social cost $\mathbb{C}\left(y^{(t)}\right)$. Thus, the minimum cost output by Algorithm 2 is only for the one-round auction. From a long-term perspective, we still need to judge whether or not the $y^{(t)}$ returned by Algorithm 2 could incur unnecessary cost.

Determining final generator state: Algorithm 1 computes the non-switching cost $C_{-SC}^{(t)}$ when $y^{(t)}$ is given, and Algorithm 2 outputs $y^{(t)}$ which results in minimum social cost. However, if we regard $y^{(t)}$ returned by Algorithm 2 as the final state of the local generator at t directly, the cost may be far from the optimal value due to excessive switching operations. For example, Algorithm 2 suggests keeping the local generator active at $t-1$. At t, Algorithm 2 considers that the local generator should be shut down according to the one-round optimization. Then in the next few time slots, the algorithm may indicate to keep the generator active again. Thus, the cost of turning on and off the equipment over this time period may be higher than the cost of just keeping the equipment always active. For such reasons, we explore dependencies among the states of the local generator in consecutive time slots, and then design a more judicious online algorithm, i.e., Algorithm 3, to achieve social cost minimization in the whole system running span. Our algorithm postpones local generator switching even if the one-round algorithm indicates so, until the cumulative non-switching cost has significantly exceeded the potential switching cost, or until there is no feasible solution, if the state of local generator remains unchanged.

Algorithm 3: Online Algorithm for Long-Term Social Cost Minimization

Define: $t = 1$, $\hat{t} = 0$, $\theta_m^{(0)} = 0, \forall m \in \mathcal{M}$, $y^{(0)} = 0$, $\Delta C_{-SC} = 0$;
while $t \le T$ **do**
  $c_m^{\sim(t)} = c_m^{(t)} + g_m^{(t)} \theta_m^{(t-1)}, \forall m \in \mathcal{M}$;
  Obtain $\dot{y}^{(t)}$, $\dot{C}_{SC}^{(t)}(\dot{y}^{(t)}, y^{(\hat{t})})$ and $\dot{C}_{-SC}^{(t)}(\dot{y}^{(t)})$ by invoking Algorithm 2;
  if $k\dot{C}_{SC}^{t}(\dot{y}^{(t)}, y^{(\hat{t})}) \le \Delta C_{-SC}$ *or* $\Delta C_{-SC} = 0$ **then**
    $y^{(t)} = \dot{y}^{(t)}$;
    $C_{-SC}^{(t)} = \dot{C}_{-SC}^{(t)}(\dot{y}^{(t)})$;
    $\Delta C_{-SC} = C_{-SC}^{(t)}$;
    $\hat{t} = t$;
  else
    $y^{(t)} = y^{(\hat{t})}$;
    $C_{-SC}^{(t)} = C_{-SC}^{(t)}(y^{(\hat{t})})$;
    $\Delta C_{-SC} = \Delta C_{-SC} + C_{-SC}^{(t)}$;
  foreach $m \in \mathcal{I}$ **do**
    $\theta_m^{(t)} = \theta_m^{(t-1)}\left(1 + \frac{g_m^{(t)}}{2Ca_m}\right) + \frac{c_m^{(t)} + \alpha u^{(t)} + z^{(t)} e^{(t)}}{2\gamma C a_m}$
  foreach $m \notin \mathcal{I}$ **do**
    $\theta_m^{(t)} = \theta_m^{(t-1)}$
  The auctioneer notifies the winning bids $\mathcal{I}$, payment $P_m^{(t)}$, and sets the amount of energy obtained from local generator and grid according to $u^{(t)}$ and $z^{(t)}$;
  $t = t + 1$;
$\theta_m = \theta_m^{(T)}, \forall m \in \mathcal{M}$

Note that, in Algorithm 3, we replace $c_m^{(t)}$ by $c_m^{\sim(t)}$, where $c_m^{\sim(t)}$ is defined to adjust its cost based on the remaining energy budget for avoiding exhausting EVs' energy prematurely, because selling more energy at early stages could lead to lower probability of participating in future auctions. Once the market encounters a greater imbalance between supply and demand in the future, the cost of crisis relief will be higher. Therefore, a new variable $\theta_m^{(t)}$ is introduced for every bidder $m \in \mathcal{M}$, which increases as the remaining energy decreases. The new cost for each bidder is equal to original cost $c_m^{(t)}$ plus the product of the energy $g_m^{(t)}$ and $\theta_m^{(t)}$. So, the cost of bidders with lower remaining energy will be modified to a higher cost, reducing the probability of successful bidding. In this way, we ensure that more bidders are eligible to participate in future auctions.

We further describe Algorithm 3 in more details. Line 1 initiates $\theta_m^{(0)}$ and $y^{(0)}$. Assume $\hat{t}$ is the time of switching no later than the current time. The *while* loop in Line 2-19 adopts the idea of postponed switching to determine whether to perform the switching operation. Line 3 updates the new cost $c_m^{\sim(t)}$. Line 4 invokes Algorithm 2, and Algorithm 2 further invokes Algorithm 1 (with $c_m^{\sim(t)}$ passed to Algorithm 1 to initialize $c_m^{\sim(t)}\star$) to obtain $\dot{y}^{(t)}$, $\dot{C}_{SC}^{(t)}(\dot{y}^{(t)}, y^{(\hat{t})})$ and $\dot{C}_{-SC}^{(t)}(\dot{y}^{(t)})$. Line 5 checks whether the overall non-switching cost ΔC_{-SC} is at least k times the switching cost $\dot{C}_{SC}^{t}(\dot{y}^{(t)}, y^{(\hat{t})})$, where the value k here represents the "laziness" of switching, determining whether to postpone switching. Then, if so, the state of local generator should be changed, and the non-switching cost and $\hat{t}$ should be updated. If the above conditions are not met, the state of generator remains unchanged as in Line 11-13, which avoids excessive switching. Line 14-15 update $\theta_m^{(t)}$ for each winner $m \in \mathcal{I}$, ensuring that a bid with less remaining energy offered resulting in a larger cost, where $\gamma = \max_{m\in\mathcal{M},t\in\mathcal{T}}\left\{Ca_m/g_m^{(t)}\right\}$. For other bidders $m \notin \mathcal{I}$, the value of $\theta_m^{(t)}$ remains unchanged. Finally, Line 20 sets the dual variable θ_m for constraint (3c) with $\theta_m^{(T)}$. For each round, the adjustment of $\theta_m^{(t)}$ results in the increment of θ_m, which leads to the optimal solution of the dual problem (7).

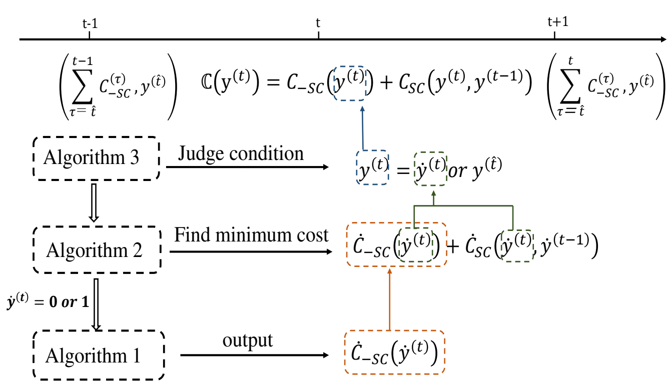

Fig. 5: The procedure of our online algorithm

Fig. 5 illustrates the whole procedure of our online algorithm. The relations among the three algorithms are as follows. At each time slot t, Algorithm 3 invokes Algorithm 2 to obtain switching cost and non-switching cost, then judges whether the $\dot{y}^{(t)}$ value returned by Algorithm 2 meets the condition in Algorithm 3 Line 5. If it is satisfied, then the $y^{(t)}$ value, i.e., the state of the local generator, is determined. Otherwise, the state of the generator is consistent with that of the previous time slot. Algorithm 2 will invoke Algorithm 1. Algorithm 2 traverses the possible values of $y^{(t)}$, and Algorithm 1 returns the non-switching cost to each corresponding $y^{(t)}$. Algorithm 2 finds the $y^{(t)}$ that minimizes the total cost, and returns it to Algorithm 3.

B. Competitiveness Analysis

In this section, we analyze the competitiveness, i.e., the long-term social cost of our online algorithmic framework compared to that of the offline optimal solutions.

Lemma 3. *Algorithm 3 can produce a feasible solution for the problem (5) and the dual LP of the problem (5).*

Proof. See Appendix E. □

Theorem 4. *Algorithm 3 is a $2\frac{\gamma}{\gamma-1}$-approximation algorithm for the problem (4).*

Proof. See Appendix F. □

Theorem 5. *Algorithm 3 is $2\epsilon\left(1+\frac{1}{k}\right)\frac{\gamma}{\gamma-1}$-competitive for the problem (3), where $\epsilon = \max_{\nu\in[1,T]}\frac{\max_{y(\nu)\in\mathcal{Y}} C_{-SC}^{\nu}}{\min_{y(\nu)\in\mathcal{Y}} C_{-SC}^{\nu}}$.*

Proof. The proof is based on Lemma 3 and Theorem 4. See Appendix G. □

V. Experimental Evaluation

In this section, we conduct trace-driven experiments to evaluate EVCDR with multiple alternative approaches, and interpret the results.

A. Experiment Settings

Local Generator: We assume that the charging station's local generator has a total capacity of $V = 1500$ kWh. We adopt the diesel price of $\alpha = 2.24$ cents/kWh [35] for the fuel cost. We set the maintenance cost of the local generator as $\beta = 48$ \$/h, and set the start-up cost as $\zeta = 15$ \$. We associate different weights of 0.5~1.5 to the switching cost to demonstrate a spectrum of evaluation results.

Demand Response: For the demand response signals, we set the energy cap $E^{(t)}$ based on real-world grid load data from September 3, 2019 through September 9, 2019 [26], and to align with this, we treat one hour as one time slot and conduct simulations for a week of $T = 168$ hours. We set the electricity price $e^{(t)}$ based on the hourly real-time pricing data from the wholesale electricity market [25].

EVs' Energy Demand: Our energy demand $W^{(t)}$ is set using the EV charging records from the adaptive charging networks of California [24]. This dataset contains a series of charging records, where each record contains "connectionTime" (i.e., the time when the user plugs in), "disconnectTime" (i.e., the time when the user unplugs), "userID" and "kWhRequested" (i.e., the energy demand).

Due to the limitation of the charging rate, the energy requested by an EV may not be able to be fully charged within a single time slot we set (i.e., an hour). Therefore, we divide the total amount of the energy requested by each EV into several "energy packs", which are random values in 6~8 kWh [40], and each EV only needs to charge one "energy pack" in one time slot and thus finishes charging the requested energy over multiple consecutive time slots. Based on the above, we obtain the input of energy demand for the small-scale charging station setting, and we multiply the energy demand by 100 to simulate a larger-scale test. Fig. 6 depicts the electricity

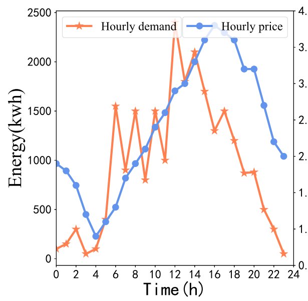

Fig. 6: Electricity price and charging demand

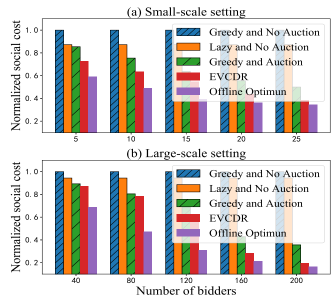

Fig. 7: Social cost with different number of bidders

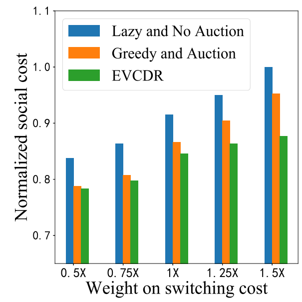

Fig. 8: Social cost with different weights on switching cost

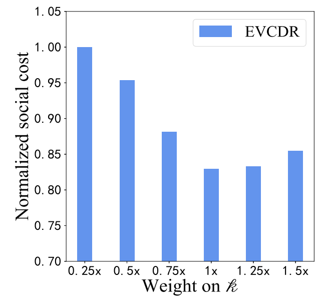

Fig. 9: Social cost with different weights on laziness

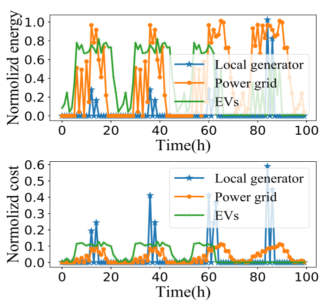

Fig. 10: Energy & Cost

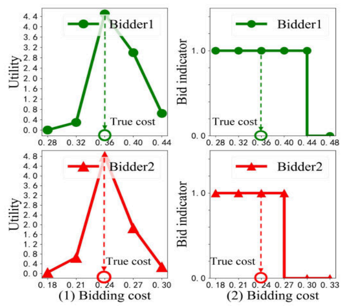

Fig. 11: Truthfulness

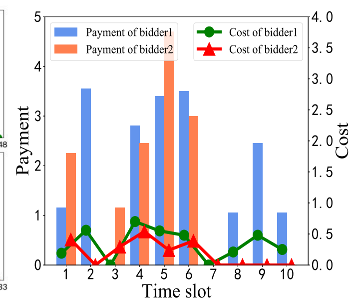

Fig. 12: Cost vs. Payment

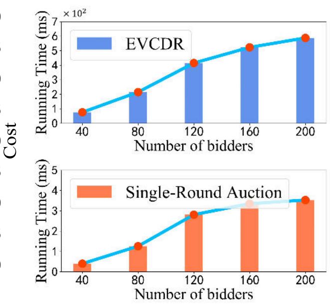

Fig. 13: Running Time

price and the energy demand in a typical day, as used in our evaluations under the setting of a larger-scale test.

EVs' Bidding: We vary the number of the EV sellers as $M = 40{\sim}200$. The amount of energy supply $g_m^{(t)}$ of an EV bid varies randomly in the range of $[2, 8]$ kWh; the bidding cost $c_m^{(t)}$ of an EV bid is the product of the amount of energy supply $g_m^{(t)}$ and a random value from the range of $[0.018, 0.078]$ \$/kWh, following the cost of electricity. We assume each EV's cumulative energy budget Ca_m as 40 kWh [41].

Algorithms for Comparison: We compare our proposed approach against the following algorithms: (1) Offline Optimum, the offline Mixed Integer Program (MIP) optimum via the CPLEX solver, where all inputs are the same with online algorithm but known in advance; (2) Lazy and No Auction, the online approach without auctions, where the charging station charges EVs via the power grid and local generator, without EV sellers; and (3) Greedy and Auction, the online greedy approach with auctions, where the charging station directly changes the state of the local generator if the one-shot optimum indicates so, without postponing generator switching; (4) Greedy and No Auction, the online greedy approach without auctions.

B. Evaluation Results

Impact of Number of Bidders: Fig. 7 shows the normalized social costs of different approaches as the number of bidders grows in the small-scale (bidders of $5 \sim 25$) and large-scale (bidders of $40 \sim 200$) settings. The social costs drop significantly as the number of bidders increases in both two cases because the more charging choices (in terms of the number of bids) the charging station has, the cheaper electricity the charging station can obtain to satisfy the demand. As the number of bids increases, EVCDR obtains more cheap energy to lower the total social cost, and thus is always better than the costs of "Greedy and No Auction" and "Lazy and No Auction"; besides, due to accommodating the generator switching cost, EVCDR is more advantageous than "Greedy and Auction" and is also closer to the offline optimum. In this experiment, compared to "Greedy and No Auction", EVCDR saves $13\% \sim 80\%$ and $27\% \sim 62\%$ social cost in the large-scale and small-scale settings, respectively, showing the benefit of jointly accommodating generator switching cost and introducing EVs selling energy via auctions in the system; "Lazy and No Auction" saves 6% and 13% social cost in the large-scale and small-scale settings, respectively, showing the benefit of accommodating generator switching cost; "Greedy and Auction" saves $11\%{\sim}64\%$ and $15\%{\sim}50\%$ social cost in the large-scale and small-scale settings, respectively, showing the benefit of introducing EVs selling energy via auctions.

Impact of Switching Cost: Fig. 8 compares the normalized social costs of different algorithms, as the function of the weight on the switching cost. EVCDR beats "Greedy and Auction" because the latter always pursues one-shot optimum in each time slot and essentially neglects the switching cost. Thus, as the weight grows (i.e., the switching cost becomes more dominating), EVCDR can address the switching cost better. EVCDR also beats "Lazy and No Auction", despite both consider the switching cost. Then, the cost advantage of EVCDR primarily comes from the availability of the more choices (i.e., bids) of energy sources, compared to the latter.

Impact of Generator State-Switching Laziness: Fig. 9 investigates EVCDR with respect to how the "laziness" in our online algorithm affects the social cost. The laziness is captured by the parameter k, which is used to compare the cumulative non-switching cost to the switching cost and then determine whether to postpone changing the state of the local generator. The switching cost is addressed better and the social cost decreases as the weight of k goes up when the weight of k is less than 1, and as the weight of k decreases when the weight of k exceeds 1, respectively. A smaller weight of k may incur frequent switches and a larger weight of k may mean a stricter criterion for the switches, both of which could lead to suboptimal cost. Therefore, k should be carefully tailored empirically in order to prevent postponing necessary switches or causing excessive switches of the generator.

Energy scheduling & Price: Fig. 10 exhibits the varying amount of energy from the power grid, the local generator and the EVs, which is limited by the corresponding energy cap (i.e., the energy cap available from grid, generator and the remaining energy budget of EVs), and their costs, whose sum is defined as the social cost. The periodic changes of EV usersâĂŹ total energy demand reflect a certain diurnal pattern. In peak hours, EVs often become the main energy supplier, especially in the EDR periods when the energy from the power grid is very low. The cost from the local generator is significantly higher than others once the generator is in operation, as its cost includes not only the fuel cost, but also the maintenance cost and the switching cost. It can also be inferred from this figure that the energy provided by the EVs will gradually diminish as the energy that has been sold by the EVs gradually reaches the energy budget, which leads to the increase of the local generator cost as time goes.

Truthfulness: Fig. 11 verifies the truthfulness of our auction mechanism. Fig. 11 (1) picks up two bidders and visualizes how their utilities vary as the bidding costs change. It exhibits that only bidding the true costs, i.e., 0.36 and 0.24, respectively, can make them achieve the highest utilities, and the utilities are always lower when not bidding the true costs. Fig. 11 (2) visualizes how their bid indicators (bid indicator being 1 for the winner and bid indicator being 0 for the unsuccessful bidder) vary as the bidding costs change using the same two bidders. The figure exhibits that bidding lower than the true costs, i.e., 0.36 and 0.24, respectively, will always win the auction and bidding higher may lose, validating the monotonicity allocation which results in truthful auctions.

Individual Rationality: Fig. 12 demonstrates the individual rationality of our auction mechanism. We randomly select two bidders, and record how their bidding costs and corresponding payments change in 10 consecutive slots. We see that the payment is always no less than the cost for each bidder, thus validating the individual rationality.

Execution Time and Scalability: Fig. 13 shows the running time of the single-round auction (i.e., Algorithm 1) and the entire online algorithm (i.e., Algorithm 3). As the number of bidders reaches 200, our approach can finish its execution within 3.5 ms for each single-round auction and 600 ms for the overall social cost optimization. As the number of bidders increases, the growth of the running time gradually slows down, exhibiting the scalability of our approach in practice.

VI. Related Work

EV Charging Scheduling for Demand Response: Yao et. al. [42] propose an online charging scheme which maximizes the number of EV for charging and minimizes the electricity cost based on the real-time electricity tariff. Yi et. al. [12] explore online scheduling algorithms for EV charging under real-time pricing and take into consideration the trade-off between cost-minimization and user dissatisfaction. Tucker et. al. [13] study online charging scheduling strategy for fleets of autonomous-mobility-on-demand electric vehicles and use primal-dual methods to solve the optimization problem. These papers mainly focus on the scheduling of EVs during demand response periods, but none of them consider incentive mechanisms such as auctions.

EV Charging Auction Mechanisms: Zhou et. al. [30] design a randomized auction framework to incentivize the participation of storage devices that aims to minimize the social cost in a demand response. They resort to the art of smoothed polynomial-time algorithm design and guarantee the truthfulness, computational efficiency, and economic efficiency of this auction. Zhong et. al. [43] study an efficient mechanism design for energy trading in a two-layer V2G architecture. However, their algorithms are all based on the offline situation, which cannot address market dynamics.

There are substantial research efforts in adopting online auctions. Zhang et. al. [44] propose an online randomized auction framework, which use fractional VCG and a convex decomposition technique to obtain the results. Xiang et. al. [45] study an online auction framework for park-and-charge operation mode. Zhang et. al. [46] design a novel online continuous progressive second price (OCPSP) based auction scheme. The winner is selected according to the bidding of EV users in the case of limited total power and the total number of charging piles. However, their models don't take V2V charging into consideration. Zhou et. al. [7] propose an online auction mechanism and a primal-dual approximation algorithm is designed. The algorithm is combined with decomposition algorithm to solve the demand response problem in smart grids. These papers do not consider the diversity of charging methods and how to alleviate the power shortage of charging stations during EDR periods, resulting in the inability to meet user demands. Factors such as V2V charging and local generator are not considered and exploited.

Our work in this paper is fundamentally more advantageous than all the aforementioned literature in terms of the following four aspects: (1) we formulate our problem over continuous time slots instead of just one round, which better captures the real-world demand response scenario; (2) we leverage the new V2V charging scheme and introduce local generator as a participant of the energy supply as well, which enriches the diversity and flexibility of the energy source; (3) we focus on the interactions between EV energy sellers and the charging station through auction mechanism, while achieving the desired economic properties; (4) we consider avoiding unnecessary switching costs by carefully controlling the state-switching of the local generator in an online manner with a constant competitive ratio.

VII. Conclusion

In this paper, we address the EV charging scheduling problem under demand response with V2V auctions and local electricity generation. To incentivize EVs to contribute to the energy supply, we propose an online auction mechanism based on the primal-dual approximation algorithm which decomposes the long-term social cost minimization problem into a series of single-round auctions over time. In addition, in order to avoid the cost caused by excessive switching of the local generator, we design an online algorithm based on the idea of postponing switching, which guarantees provable polynomial running time, truthfulness, individual rationality for each auction. Finally, we conduct evaluations using real-world data traces and validate the practical superiority of our approach over multiple existing algorithms.

Appendix

A. Proof of Lemma 1

Firstly, we prove that the solution output by Algorithm 1 is feasible to the single-round problem (6). According to Algorithm 1, $x_m^{(t)}$ is initialized to 0, and set to 1 in Line 13, which satisfies the constraint (6d). $u^{(t)}$ and $z^{(t)}$ are initialized to 0, and updated to no more than $Vy^{(t)}$ and $E^{(t)}$ respectively, which satisfies the constraints (6b) and (6c). The iteration stops when $\Delta(N^{(t)}) \leq 0$ or $\mathcal{M} = \emptyset$. For the former, (6a) holds according to Algorithm 1 Line 14-15, and $\mathcal{M} = \emptyset$ only happens when we cannot find a subset of bidders that meets the energy demand. A solution is feasible for a problem when this solution satisfies all the problemâĂŹs constraints. Thus, the solution given by Algorithm 1 is feasible to the problem (6).

Secondly, for the dual problem (7), we can observe that the constraints (7b) and (7c) will never be violated when $q^{(t)} > 0$, and (7d) holds according to Algorithm 1 Line 12 and Line 20. The dual variable $Z(N^{(t)})$ is initialized to 0 at first, and we can obtain $c_{m^*}^{\sim\tau}\star = g_{m^*}(N^\tau)Z(N^\tau)$ at τ-th iteration, which is guaranteed by Algorithm 1 Line 12. According to Line 7, $c_{m*}^{\sim\tau}\star = Z(N^\tau)g_{m*}(N^\tau) = c_{m*}^{\sim\tau-1}\star - Z(N^{\tau-1})g_{m*}(N^{\tau-1})$, we have $c_{m*}^{\sim 1}\star = Z(N^1)g_{m*}(N^1) + \cdots + Z(N^\tau)g_{m*}(N^\tau)$. $c_{m*}^{\sim 1(t)}\star$ is set to $c_{m*}^{\sim(t)}$ at Line 4, and bid m^* is appended to $N^{(t)}$ at the end of τ-th iteration. Thus we can verity that for all $m \in \mathcal{I}$, $\sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z(N^{(t)})g_m(N^{(t)}) = c_m^{\sim(t)}$. In the case of $m^- \notin \mathcal{I}$, we can obtain $c_{m^-}^{\sim\tau}\star = g_{m^-}(N^\tau)Z(N_{m^-}^\tau) \geq g_{m^-}(N^\tau)Z(N^\tau)$, which is guaranteed by Algorithm 1 Line 11-12. Based on the similar proof as above, we have $\sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z(N^{(t)})g_{m^-}(N^{(t)}) \leq c_{m^-}^{\sim(t)}, \forall m \in \mathcal{M}$. Thus, the constraint (7a) is satisfied.

The *while* loop iterates at most M times and Line 7-8 and Line 10-12 take M steps respectively. Thus, the time complexity of Algorithm 1 is $O(M^2)$. So Algorithm 1 terminates in polynomial time with a feasible solution for both the single-round problem (6) and the dual problem (7).

B. Proof of Theorem 1

Suppose p_{A1} is objective value for the single-round problem (6) obtained by Algorithm 1, p_{LPR}^* is the optimal objective value for the linear program relaxation of problem (6), i.e., our Primal problem, and p^* is the optimal objective value of the single-round problem (6), our Algorithm 1 guarantees that $p_{A1} \leq 2p_{LPR}^* \leq 2p^*$. We prove it through as follows.

Case 1: According to Algorithm 1 Line 6, the *while* loop stops when $\Delta(N^{(t)}) \leq 0$, which means there is no set $N^{(t)} \subseteq \mathcal{M}$, such that $\Delta(N^{(t)}) > 0$, i.e., any EV bidder' energy supplied can meet the whole demand without purchasing the energy from the local generator or the power grid. Hence the minimum social cost can be obtained by comparing the costs incurred by purchasing energy only from the EV bidders, the power grid or the local generator. Next we will discuss the cases when the number of set $\{N^{(t)} | N^{(t)} \subseteq \mathcal{M}, \Delta(N^{(t)}) > 0\}$ is no less than 1.

Case 2: $q^{(t)}$ in Algorithm 1 means the total energy from the local generator and the grid, i.e., $q^{(t)} = u^{(t)} + e^{(t)}$. So we firstly discuss the case when $q^{(t)} = 0$:

$$
\begin{aligned}
p_{A1} &= \sum_{m \in \mathcal{M}} c_m^{\sim(t)} x_m^{(t)} + \alpha u^{(t)} + z^{(t)} e^{(t)} && \text{(9a)}\\
&= \sum_{m \in \mathcal{I}} c_m^{\sim(t)} && \text{(9b)}\\
&= \sum_{m \in \mathcal{I}} \sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z(N^{(t)}) g_m(N^{(t)}) && \text{(9c)}\\
&= \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \sum_{m \in \mathcal{I} \setminus N^{(t)}} g_m(N^{(t)}) && \text{(9d)}\\
&\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) (\sum_{m \in \mathcal{I} \setminus l} g_m^{(t)} - \sum_{m \in N^{(t)}} g_m^{(t)} + g_l(N^{(t)})) && \text{(9e)}\\
&\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) (W^{(t)} - \sum_{m \in N^{(t)}} g_m^{(t)} + g_l(N^{(t)})) && \text{(9f)}\\
&\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) (\Delta(N^{(t)}) + g_l(N^{(t)})) && \text{(9g)}\\
&\leq \sum_{N^{(t)} \subseteq \mathcal{M}} z(N^{(t)}) (\Delta(N^{(t)}) + \Delta(N^{(t)})) && \text{(9h)}\\
&\leq 2p_{LPR}^* \leq 2p^* && \text{(9i)}
\end{aligned}
$$

Here l denotes the last bid added to the set $\mathcal{I}$. Due to $q^{(t)} = 0$, we can obtain (9b). (9c) follows from (7a). (9e) holds by $g_m(N^{(t)}) = \min\{g_m^{(t)}, \Delta(N^{(t)})\}$, and $\sum_{m \in \mathcal{I} \setminus N^{(t)}} g_m(N^{(t)}) \leq \sum_{m \in \{\mathcal{I} \setminus \{l\}\} \setminus N^{(t)}} g_m^{(t)} + g_l(N^{(t)}) = \sum_{m \in \{\mathcal{I} \setminus l\}} g_m^{(t)} - \sum_{m \in N^{(t)}} g_m^{(t)} + g_l(N^{(t)})$. (9f) follows from $\sum_{m \in \mathcal{I} \setminus l} g_m^{(t)} \leq W^{(t)}$.

Case 3: When $q^{(t)} > 0, \rho^{(t)}, \phi^{(t)} = 0$, it means the constraints (7b) and (7c) go tight and then the iteration stops, i.e., the maximum energy supplied by the grid and the local generator is no less than the remainder demand $\Delta(N^{(t)})$, so we obtain:

$$
p_{A1} = \sum_{m \in \mathcal{I}} c_m^{\sim(t)} + \alpha u^{(t)} + e^{(t)} z^{(t)}
$$

We divide p_{A1} into two parts: $\sum_{m \in \mathcal{I}} c_m^{\sim(t)}$ and $\alpha u^{(t)} + e^{(t)} z^{(t)}$, and we discuss $\alpha u^{(t)} + e^{(t)} z^{(t)}$ at first.

$$
\begin{aligned}
&\alpha u^{(t)} + e^{(t)} z^{(t)} && \text{(10a)}\\
&= \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) u^{(t)} + \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) z^{(t)} && \text{(10b)}\\
&= \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) q^{(t)} && \text{(10c)}
\end{aligned}
$$

$$= \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})\Delta(N^{(t)}) \tag{10d}$$

(10b) follows from (7b) and (7c). (10d) follows from the definition of $q^{(t)}$. Then we focus on $\sum_{m\in\mathcal{I}} c_m^{\sim(t)}$.

$$\sum_{m\in\mathcal{I}} c_m^{\sim(t)} \tag{11a}$$

$$= \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \sum_{m\in\mathcal{I}\setminus N^{(t)}} g_m(N^{(t)}) \tag{11b}$$

$$\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})[\sum_{m\in\mathcal{I}} g_m^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)}] \tag{11c}$$

$$\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(W^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)}) \tag{11d}$$

$$= \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})\Delta(N^{(t)}) \tag{11e}$$

(11b) follows from (7a). (11d) is due to $W^{(t)} = \sum_{m\in\mathcal{I}} g_m^{(t)} + u^{(t)} + z^{(t)}$. (11e) follows from $\Delta(N^{(t)}) = W^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)}$, so we can summarize as follows.

$$\begin{aligned} p_{A1} &= \sum_{m\in\mathcal{I}} c_m^{\sim(t)} + \alpha u^{(t)} + e^{(t)} z^{(t)} \\ &\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(\Delta(N^{(t)}) + \Delta(N^{(t)})) \\ &\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(2\Delta(N^{(t)})) \\ &\leq 2p^*_{LPR} \leq 2p^* \end{aligned}$$

Case 4: when $q^{(t)} > 0, \rho^{(t)}, \phi^{(t)} > 0$, it means that the constraints (7b) and (7c) go tight once while the maximum energy supplied by the grid and the local generation cannot meet the remainder demand $\Delta(N^{(t)})$, i.e., $Vy^{(t)} + E^{(t)} < \Delta(N^{(t)})$.

$$p_{A1} = \sum_{m\in\mathcal{I}} c_m^{\sim(t)} + \alpha u^{(t)} + e^{(t)} z^{(t)} \tag{12a}$$

$$\begin{aligned} &= \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(\sum_{m\in\mathcal{I}\setminus l} g_m^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)} + g_l(N^{(t)}))+ \\ &\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})Vy^{(t)} - \rho^{(t)}Vy^{(t)} + \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})E^{(t)} \\ &- \phi^{(t)}E^{(t)} \end{aligned} \tag{12b}$$

$$\begin{aligned} &= \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(\sum_{m\in\mathcal{I}\setminus l} g_m^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)} + g_l(N^{(t)})+ \\ &Vy^{(t)} + E^{(t)}) - \rho^{(t)}Vy^{(t)} - \phi^{(t)}E^{(t)} \end{aligned} \tag{12c}$$

$$\begin{aligned} &\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(W^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)} + g_l(N^{(t)}))- \\ &\rho^{(t)}Vy^{(t)} - \phi^{(t)}E^{(t)} \end{aligned} \tag{12d}$$

$$\begin{aligned} &\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(2\Delta(N^{(t)}) - Vy^{(t)} - E^{(t)})- \\ &\rho^{(t)}Vy^{(t)} - \phi^{(t)}E^{(t)} \end{aligned} \tag{12e}$$

$$\leq 2(\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})\Delta(N^{(t)}) - Vy^{(t)}\rho^{(t)} - E^{(t)}\phi^{(t)}) \tag{12f}$$

$$= 2p^*_{LPR} \leq 2p^* \tag{12g}$$

(12b) follows from the constraints (7a)-(7c). (12d) is due to $W^{(t)} > \sum_{m\in\mathcal{I}\setminus l} g_m^{(t)} + Vy^{(t)} + E^{(t)}$. (12e) holds by $\Delta N^{(t)} = W^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)}$ and $g_l(N^{(t)}) = W^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)} - E^{(t)} - Vy^{(t)}$. (12f) is due to the fact that the number of set $\{N^{(t)} | N^{(t)} \subseteq \mathcal{M}, \Delta(N^{(t)}) > 0\}$ is no less than 1.

Case 5: when $q^{(t)} > 0, \rho^{(t)} = 0, \phi^{(t)} > 0$, it means that the constraints (7b) and (7c) go tight and $e^{(t)}$ reaches its maximum value $E^{(t)}$.

$$p_{A1} = \sum_{m\in\mathcal{I}} c_m^{\sim(t)} + \alpha u^{(t)} + e^{(t)} z^{(t)} \tag{13a}$$

$$\begin{aligned} &= \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(\sum_{m\in\mathcal{I}\setminus l} g_m^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)} + g_l(N^{(t)}))+ \\ &\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})u^{(t)} + \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})E^{(t)} - \phi^{(t)}E^{(t)} \end{aligned} \tag{13b}$$

$$\begin{aligned} &= \sum_{N^{(t)} \subseteq \mathcal{M}} z(N^{(t)})(\sum_{m\in\mathcal{I}\setminus l} g_m^{(t)} - \sum_{m\in N^{(i)}} g_m^{(t)} + g_l(N^{(t)})+ \\ &u^{(t)} + E^{(t)}) - \phi^{(t)}E^{(t)} \end{aligned} \tag{13c}$$

$$\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(W^{(t)} - \sum_{m\in N^{(t)}} g_m^{(t)} + g_l(N^{(t)})) - \phi^{(t)}E^{(t)} \tag{13d}$$

$$\leq \sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})(2\Delta(N^{(t)}) - E^{(t)}) - \phi^{(t)}E^{(t)} \tag{13e}$$

$$\leq 2(\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) - E^{(t)}\phi^{(t)}) \tag{13f}$$

$$\leq 2p^*_{LPR} \leq 2p^* \tag{13g}$$

Case 6: When $q^{(t)} > 0, \rho^{(t)} > 0, \phi^{(t)} = 0$, the proof process is the same as case 5.

Based on above discussion, we prove that Algorithm 1 is a 2-approximation algorithm.

C. Proof of Lemma 2

Firstly, we prove that the mechanism is monotone. According to Algorithm 1, we have $m^* = arg\min_{m\in\mathcal{M}}\{\frac{c_m^{\sim(t)} - \sum_{N^{(t)}\subseteq\mathcal{M}: m\notin N^{(t)}} Z(N^{(t)}) g_m(N^{(t)})}{g_m(N^{(t)})}\}$. $g_{m_1}^{(t)} = g_{m_2}^{(t)}$ means $g_{m_1}(N^{(t)}) = g_{m_2}(N^{(t)})$. When $c_{m_1}^{\sim(t)} \leq c_{m_2}^{\sim(t)}$, we have

$$\begin{aligned} &\frac{c_{m_1}^{\sim(t)} - \sum_{N^{(t)}\subseteq\mathcal{M}: m_1\notin N^{(t)}} Z(N^{(t)}) g_{m_1}(N^{(t)})}{g_{m_1}(N^{(t)})} \\ \leq &\frac{c_{m_2}^{\sim(t)} - \sum_{N^{(t)}\subseteq\mathcal{M}: m_2\notin N^{(t)}} Z(N^{(t)}) g_{m_2}(N^{(t)})}{g_{m_2}(N^{(t)})}, \end{aligned}$$

so if m_2 is selected at the τ-th iteration, m_1 must be selected.

Secondly, we prove that the mechanism can output critical payment. According to the Algorithm 1, if we exclude m^* from the candidates set, m^- would be the first bid to be chosen, so m^- is the threshold bid for m^*. We compute the payment to bidder m^* such that $\frac{c_{m^*}^{\sim(t)}\star}{g_{m^*}(N^{(t)})} = \frac{c_{m^-}^{\sim(t)}\star}{g_{m^-}(N^{(t)})}$, which means at τ-th iteration, $c_{m^*}^{\sim\tau}\star = g_{m^*}(N^{(\tau)})Z(N_{m^-})$. According to the previous proof in Lemma 1, we have $\sum_{N\subseteq\mathcal{M}: m\notin N} Z(N) g_m(N) = c_m^{\sim}, \forall m \in \mathcal{I}$,

$$\begin{aligned} c_{m*}^{\sim} &= Z(N^1) g_{m*}(N^1) + \cdots + Z(N^\tau) g_{m*}(N^\tau) \\ P_{m^*} &= Z(N^1) g_{m*}(N^1) + \cdots + Z(N_{m^-}) g_{m*}(N^\tau) \\ P_{m^*} &= c_{m^*}^{\sim} + (Z(N_{m^-}) - Z(N^\tau)) g_{m^*}(N^\tau) \end{aligned}$$

Thus, we obtain $P_{m^*}^{(t)} = c_{m^*}^{\sim(t)} + (Z(N_{m^-}) - Z(N^{(t)})) g_{m^*}(N^{(t)})$.

D. Proof of Theorem 3

We prove the truthfulness of Algorithm 1 according to Lemma 2. As for individual rationality, due to $P^{(t)}_{m^*} = c^{\sim(t)}_{m^*} + (Z(N_{m^-}) - Z(N^{(t)}))g_{m^*}(N^{(t)})$, and $Z(N_{m^-}) > Z(N^{(t)})$, we have $P^{(t)}_{m^*} \geq c^{\sim(t)}_{m^*}$, utility $u_{m^*} \geq 0$ and payment $P^{(t)}_{m^*} \geq 0$. Finally, we prove that the proposed auction mechanism achieves truthfulness and individual rationality.

E. Proof of Lemma 3

Firstly, Algorithm 1 can provide a feasible solution for the problem (6) according to Lemma 1. Hence, $x^{(t)}_m$ satisfies (5e), and the constraints (5a) (5c) (5d) are also guaranteed. As for the constraint (5b), each bidder cannot offer energy exceeds its remaining energy budget, so this constraint is also guaranteed. Secondly, Algorithm 3 has the time complexity of $O(TM^2)$. Line 1 takes $O(M)$ steps. Line 4 invokes Algorithm 2, and Algorithm 2 takes constant steps to invoke Algorithm 1 which is proved in $O(M^2)$ steps. Line 3, Lines 14 and Line 16 run at most M times, respectively. The *while* loop has T iterations. Thus, the total time complexity is $O(TM^2)$.

Next for the dual LP of problem (5). Based on the primal problem (5), we can derive its dual LP problem as follows by introducing $Z(N^{(t)}), \theta_m, \rho^{(t)}, \phi^{(t)}$ as dual variables for the constraints (5a), (5b), (5c), (5d), respectively:

$$\text{Max} \ \sum\nolimits_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)})\Delta(N^{(t)}) + \sum_{m\in[M]} \theta_m Ca_m - \rho^{(t)} V y^{(t)} - \phi^{(t)} E^{(t)}$$

Subject to:

$$\sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z(N^{(t)}) g_m(N^{(t)}) \leq c^{(t)}_m + \theta_m g^{(t)}_m, \forall m \in \mathcal{M}$$

$$\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq \alpha + \rho^{(t)}$$

$$\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq e^{(t)} + \phi^{(t)}$$

$$Z(N^{(t)}), \rho^{(t)}, \phi^{(t)} \geq 0, \forall N^{(t)} \subseteq \mathcal{M}$$

Due to that Algorithm 1 can provide a feasible solution for the problem (7) which is proved in Lemma 1, the constraints $\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq \alpha + \rho^{(t)}$, $\sum_{N^{(t)} \subseteq \mathcal{M}} Z(N^{(t)}) \leq e^{(t)} + \phi^{(t)}$ and $Z(N^{(t)}), \rho^{(t)}, \phi^{(t)} \geq 0$ can be guaranteed. And then we prove $\sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z(N^{(t)}) g_m(N^{(t)}) \leq c^{(t)}_m + \theta_m g^{(t)}_m$ as follows:

$$\sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z(N^{(t)}) g_m(N^{(t)}) \leq c^{\sim(t)}_m \tag{14a}$$

$$\sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z(N^{(t)}) g_m(N^{(t)}) \leq c^{(t)}_m + g^{(t)}_m \theta^{(t-1)}_m \tag{14b}$$

$$\sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z(N^{(t)}) g_m(N^{(t)}) \leq c^{(t)}_m + \theta^T_m g^{(t)}_m \tag{14c}$$

$$\sum_{N^{(t)} \subseteq \mathcal{M}: m \notin N^{(t)}} Z(N^{(t)}) g_m(N^{(t)}) \leq c^{(t)}_m + \theta_m g^{(t)}_m \tag{14d}$$

(14a) follows from (7a). (14b) holds by $c^{\sim(t)}_m = c^{(t)}_m + g^{(t)}_m \theta^{(t-1)}_m$ in Algorithm 3 Line 3. (14c) holds by the fact that $\theta^{(t)}_m$ is no-decreasing with t. (14d) is due to the last line in Algorithm3, i.e., $\theta_m = \theta^{(T)}_m$. So the constraints of the problem (5) are all satisfied, and Algorithm 3 can output a feasible solution for dual LP of problem (5).

Based on the above, Algorithm 3 produces a feasible solution for the problem (5) and the dual LP of problem (5).

F. Proof of Theorem 4

Suppose $P^{(t)}$ is the objective value of problem (5) returned by Algorithm 3, $\Delta P^{(t)} = P^{(t)} - P^{(t-1)}$, and $\Delta D^{(t)} = D^{(t)} - D^{(t-1)}$ is for its dual LP of problem (5). Then, we can obtain:
$\Delta P^{(t)} = P^{(t)} - P^{(t-1)} = \sum_{m\in\mathcal{I}} c^{(t)}_m + \alpha u^{(t)} + e^{(t)} z^{(t)}$
$\Delta D^{(t)} = D^{(t)} - D^{(t-1)} = d + \sum_{m\in\mathcal{I}} Ca_m(\theta^{(t-1)}_m - \theta^{(t)}_m)$

$$\Delta D^{(t)} = \sum_{m\in\mathcal{I}} Ca_m(\theta^{(t-1)}_m - \theta^{(t)}_m) + d \tag{15a}$$

$$= d - \frac{\sum_{m\in\mathcal{I}} g^{(t)}_m \theta^{(t-1)}_m}{2} - \frac{\sum_{m\in\mathcal{I}} c^{(t)}_m + \alpha u^{(t)} + e^{(t)} z^{(t)}}{2\gamma} \tag{15b}$$

$$\geq \frac{p_{A1}}{2} - \frac{\sum_{m\in\mathcal{I}} g^{(t)}_m \theta^{(t-1)}_m}{2} - \frac{\sum_{m\in\mathcal{I}} c^{(t)}_m + \alpha u^{(t)} + e^{(t)} z^{(t)}}{2\gamma} \tag{15c}$$

$$\geq \frac{\sum_{m\in\mathcal{I}} c^{\sim(t)}_m + \alpha u^{(t)} + e^{(t)} z^{(t)}}{2} - \frac{\sum_{m\in\mathcal{I}} g^{(t)}_m \theta^{(t-1)}_m}{2} - \frac{\sum_{m\in\mathcal{I}} c^{(t)}_m + \alpha u^{(t)} + e^{(t)} z^{(t)}}{2\gamma} \tag{15d}$$

$$= (\frac{1}{2} - \frac{1}{2\gamma})\Delta P^{(t)} \tag{15e}$$

(15b) holds by $\theta^{(t)}_m = \theta^{(t-1)}_m(1 + \frac{g^{(t)}_m}{2Ca_m}) + \frac{c^{(t)}_m + \alpha u^{(t)} + z^{(t)} e^{(t)}}{2\gamma Ca_m}$. (15c) is due to $p_{A1} \leq 2d$ according to Theorem 1. Since $P^{(0)} = 0, D^{(0)} = 0$, and $\Delta P^{(t)} \leq 2\frac{\gamma}{\gamma-1}\Delta D^{(t)}$, we have $\Delta P^{(T)} \leq 2\frac{\gamma}{\gamma-1}\Delta D^{(T)}$. By the validity of the flow-cover inequalities, every feasible solution to problem (5) is a feasible solution to problem (4), so Algorithm 3 is a $2\frac{\gamma}{\gamma-1}$ -approximation algorithm for problem (4).

G. Proof of Theorem 5

According to Algorithm3, we know that the switching cost at time slot t is at most $\frac{1}{k}$ times the non-switching cost within the time frame $[\hat{t}, t-1]$, i.e., $C_{SC} \leq \frac{1}{k}\Delta C_{-SC}$, here $\hat{t}$ is the last time stamp of local generator switch. So we have $\sum_{\nu=1}^{T} C^{\nu}_{SC}(y(\nu), y(\nu-1)) \leq \frac{1}{k}\sum_{\nu=1}^{T} C^{\nu}_{-SC}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))$ in the worst case, i.e., the state of local generator changes in each time slot, and then we obtain:

$$\sum_{\nu=1}^{T} \mathbb{C}^{\nu}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))$$
$$= \sum_{\nu=1}^{T} C^{\nu}_{SC}(y(\nu), y(\nu-1)) + \sum_{\nu=1}^{T} C^{\nu}_{-SC}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))$$
$$\leq (1 + \frac{1}{k}) \sum_{\nu=1}^{T} C^{\nu}_{-SC}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))$$

Because $\epsilon = \max_{\nu\in[1,T]} \frac{\max_{y(\nu)\in\mathcal{Y}} C^{\nu}_{-SC}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))}{\min_{y(\nu)\in\mathcal{Y}} C^{\nu}_{-SC}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))}$, and $C^{(t)}_{-SC}$ given by Algorithm 3 is at most $2\frac{\gamma}{\gamma-1}$ times optimal solution which is verified by Theorem 4, we have:

$$\sum_{\nu=1}^{T} C_{-SC}^{\nu} \leq \sum_{\nu=1}^{T} \max_{y(\nu)\in\mathcal{Y}} C_{-SC}^{\nu}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))$$
$$\leq \epsilon \sum_{\nu=1}^{T} \min_{y(\nu)\in\mathcal{Y}} C_{-SC}^{\nu}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))$$
$$\leq 2\epsilon \frac{\gamma}{\gamma-1} \sum_{\nu=1}^{T} C_{-SC}^{\nu *}$$
$$\leq 2\epsilon \frac{\gamma}{\gamma-1} \sum_{\nu=1}^{T} \mathbb{C}^{*}$$

Based on the above, we can obtain:

$$\sum_{\nu=1}^{T} [C_{SC}^{\nu}(y(\nu), y(\nu-1)) + C_{-SC}^{\nu}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))]$$
$$\leq (1+\frac{1}{k}) \sum_{\nu=1}^{T} C_{-SC}^{\nu}(y(\nu), \boldsymbol{x}(\nu), u(\nu), z(\nu))$$
$$\leq 2\epsilon(1+\frac{1}{k}) \frac{\gamma}{\gamma-1} \sum_{\nu=1}^{T} \mathbb{C}^{*}(\boldsymbol{x}^{*}(\nu), y^{*}(\nu), u^{*}(\nu), z^{*}(\nu))$$

Finally, we prove that Algorithm 3 is a $2\epsilon(1+\frac{1}{k})\frac{\gamma}{\gamma-1}$-competitive algorithm for the problem (3).

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