Online Edge Computing Demand Response via Deadline-Aware V2G Discharging Auctions

Fei Wang, Lei Jiao, Konglin Zhu, Lin Zhang

Abstract—Distributed edge computing systems that participate in Emergency Demand Response (EDR) programs can adjust workload across heterogenous edges to reduce total energy consumption. Unfortunately, this approach may not always reduce sufficient energy as required by EDR. In this paper, we propose to leverage Electrical Vehicles (EVs) and Vehicle-to-Grid (V2G) techniques to provide energy to the edge system, and design an auction mechanism to incentivize EVs to discharge energy for the edges. Yet, we face critical challenges, such as the uncertainty of EV bid arrivals, the restriction of discharging deadlines, and the desire to achieve required economic efficiency. To overcome such challenges, we design a novel online approach, E^3DR, of multiple algorithms that decompose our original NP-hard social cost minimization problem into two subproblems, solve the first subproblem via reformulation, the primal-dual optimization theory, and a careful payment design, and solve the second subproblem via standard solvers. We have rigorously proved that our approach finishes in polynomial time, achieves truthfulness and individual rationality economically, and leads to a parameterized competitive ratio for the long-term social cost. Through extensive evaluations using real-world data traces, we have validated the superior practical performance of our approach compared to existing algorithms.

Index Terms—Demand response, edge computing, EV, V2G, auction, online optimization.

1 Introduction

Edge computing has micro data centers or servers, referred to as "edges", located at metro centers, enterprise premises, cellular base stations, or WiFi access points [1], [2], providing low latency, high bandwidth, and data locality to end users, and is well-situated for Emergency Demand Response (EDR) programs. This is due to the massive number of edges, consuming significant energy from the electricity grid, and the wide distribution and the vast heterogeneity of edges, flexible in managing computing workloads. In a typical EDR program, during peak hours when the electricity grid is under stress, it sends energy reduction goals to the distributed edge system; in response, to help maintain the availability, stability, security of the electricity grid [3], [4], the edge system moves its workload, if not dropping any, across heterogeneous edges to save the total energy consumption [5], [6] and receives (monetary) rewards from the grid. However, due to intrinsic physical limitations of edges, only moving workload around may not be able to reduce sufficient energy to meet the EDR goals.

One solution to address this issue is to supply the edge system with additional power from third-party sources during EDR, so that the edges can further reduce electricity consumption from the grid. Thanks to Electrical Vehicles (EVs) and Vehicle-to-Grid (V2G) techniques [7], [8], EVs can transfer energy to the edges, often via a local microgrid. That is, EVs discharge their batteries through dedicated devices and interfaces in charging stations, for example, and such energy flows to the microgrid which further connects to the distributed edge computing system. Therefore, the edges take energy from both the electricity grid and the EVs. Fig. 1 illustrates this scenario, where the edge system receives energy from the EVs E, F and H and migrates workload from the edge A to the edges B and C to reduce the total energy need from the electricity grid during EDR.

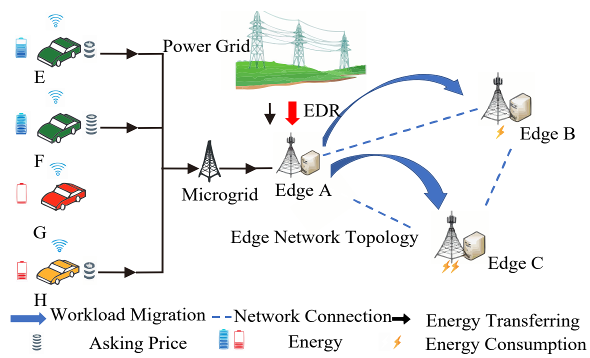


Fig. 1: System scenario

Even though feasible, the problem here is actually how to incentivize EVs to discharge energy for the edges. One may just let EVs sell energy at some price. Due to dynamic and uncertain edge energy demand and EV supply during EDR, it is often tricky and hard for such a direct pricing strategy to achieve the overall market efficiency; it is less ideal also due to possible overpricing and underpricing. In this paper, we

- *This work was partially supported by Beijing Advanced Innovation Center for Future Blockchain and Privacy Computing, in part by the Beijing Natural Science Foundation (4222033), in part by the Hunan Province Science and Technology Project Funds (2018TP1036), in part by the Key Laboratory of Modern Measurement and Control Technology, Ministry of Education (KF20211123202), and in part by the U.S. National Science Foundation under Grant CNS-2047719. (Corresponding authors: Lei Jiao; Konglin Zhu.)*
- *F. Wang, K. Zhu, and L. Zhang are with the School of Artificial Intelligence, Beijing University of Posts and Telecommunications, Beijing 100876, China (e-mail: {feiwang, klzhu, zhanglin}@bupt.edu.cn).*
- *L. Jiao is with the Department of Computer and Information Science, University of Oregon, Eugene, OR, USA (e-mail: jiao@cs.uoregon.edu).*

take a different angle—auctions, where the edge system acts as the auctioneer and purchases energy from the EVs which act as bidders. Auctions enable market agility based on real-time demand-supply, reduce the chance of mispricing, and match bids to buyers that value them most.

However, we confront critical challenges when designing auction mechanisms for this scenario. First, this is intrinsically an online problem where EV bid arrivals and the edge computing workload are unpredictable as time goes. Although the energy reduction goals for future time slots can be observed beforehand as in a typical EDR program, making joint control decisions of buying bids and adjusting workload across edges irrevocably on the fly to minimize and balance the cost of bids and the system overhead (e.g., inter-edge delay) in the long run is not easy. Second, each EV bid can be often characterized by a deadline as EV energy needs to be discharged before the EV leaves. While accommodating the deadline of each EV, one also needs to determine how much energy should be discharged for each time slot, which is not straightforward as it will impact the energy provisioning and thus the decision of buying future EV bids before those bids actually arrive. Third, for an auction, we need to achieve the desired economic properties of truthfulness (i.e., every bid maximizes its utility only if not cheating on its bidding price) and individual rationality (i.e., every bid achieves a non-negative utility), where utility is defined as the difference between the payment received from the auctioneer and the true bidding price. This requires to carefully design the payment (unnecessarily equal to the bidding price), especially for our scenario where the utility also depends on when discharging is scheduled.

Existing research have limitations and are insufficient compared to our work in this paper. None of those on edge computing demand response have considered utilizing EVs as energy sources [9], [10], [11], [12]. Those on EVs have considered EV charging scheduling or the interactions between EVs and the electriciy grid, but have not studied edge computing in this context [13], [14], [15], [16], [17]; and to the best of our knowledge, their solution approaches never consider deadlines or deadline violations when designing dynamic auctions with provable performance guarantees.

In this paper, we firstly formulate the social cost minimization problem as a non-convex mixed-integer program spanning the time horizon. Our optimization objective captures the cost of the EV bids and the performance overhead of edge workload migration; to reflect the deadline of each bid, we also add a penalty term in the form of an arbitrary non-decreasing function if the deadline is violated, which is general and can capture both hard and soft deadlines. Our problem also consists of constraints of respecting charging station and bid energy capacity, preserving edge computing workload, and meeting EDR energy reduction goals. Our problem is NP-hard even in an offline setting, not to mention that we aim to solve it online in polynomial time.

Afterwards, we design a novel online algorithmic approach E^3DR. Our approach decomposes the original problem into a subproblem of bid selection and EV discharging and a subproblem of edge workload migration, respectively. For the former subproblem, we reformulate it as a schedule selection problem, where a bid corresponds to a set of schedules and each schedule corresponds to a concrete arrangement of discharging the bid's energy across time slots. For this reformulated problem, we design a primal-dual-based online algorithm to overcome the intractability, in which we carefully maintain feasible dual solutions, make tight the dual constraints, and set the corresponding primal solutions to satisfy the optimality conditions, all in an online manner in response to each bid arrival. Despite we may have an exponential number of variables for the schedule selection problem, we show a dual oracle that can identify a polynomial number of dual constraints to take into account and calculate the payment using the dual solutions in polynomial time. For the latter subproblem, due to the decomposition, we are able to just apply standard convex optimization solvers to solve it in each individual time slot taking the outputs of the former subproblem as inputs. We highlight that we have also formally proved multiple performance guarantees for our algorithms, including polynomial-time complexity, correctness, competitive ratio, truthfulness, and individual rationality, which are non-trivial.

Finally, we conduct extensive evaluations using real-world data to simulate edge distribution [18], edge heterogeneity [9], [19], EDR events [20], EV energy [14], [21], etc., with a varying number of EV bids dynamically arriving in a one-week period. We observe multiple results, among which are the following: (1) E^3DR saves up to 50% social cost compared to approaches that use no auctions, and up to 40% social cost compared to approaches that randomly or greedily select bids in terms of EV energy price or discharging deadlines, and up to 30% social cost compared to other scheduling approaches; (2) E^3DR achieves truthfulness and individual rationality as desired; (3) E^3DR's social cost is empirically less than 2 times the offline optimal social cost at hindsight; (4) E^3DR executes fast and finishes within 25 seconds as the total number of bids reaches 350 in one week.

2 System Model And Problem Formulation

In this section, we present our system model and formulate the social cost minimization problem. For the quick reference, we summarize all our major notations in Table 1.

2.1 System Modeling

Edge System: We consider an edge computing system that consists of a set $[K] = \{1, ..., K\}$ of distributed and heterogeneous "edges" (e.g., micro data centers or servers) of different energy efficiencies. All such edges are connected to one another via wireline backhaul networks. We consider consecutive time slots $[T] = \{1, ..., T\}$. For $k, j \in [K]$ and $t \in [T]$, we use r_{kj} to represent the propagation or network delay from edge k to edge j, use h_{kj} to represent the amount of energy that can be saved by migrating a single-unit workload from edge k to edge j, use W_{jt} to represent the capacity of edge j at time slot t in terms of the maximum amount of workload permitted, and use V_{kt} to represent the actual amount of workload on edge k at time slot t.

As the EDR signal comes, the edge system must reduce its consumption of the power-grid energy by a certain amount, denoted by $R_t, \forall t$ as required. The edge system can achieve this by (1) migrating or consolidating workload to the edges of better energy efficiency and/or (2) consuming energy that is discharged from the EVs for compensation.

TABLE 1: Notations

Inputs	Descriptions
$[I]$	Set of bids
$[T]$	Set of time slots
$[K]$	Set of edges
b_i	Cost of bid i
R_t	Energy reduction demand from the grid at time t
g_i	Penalty function for bid i
H	Maximal number of simultaneous discharging sessions allowed in the discharging facility
t_i	Bid i' arrival time
h_{kj}	Energy reduction by migrating workload from edge k to edge j
r_{kj}	Propagation delay of migrating workload from edge k to edge j
C_i	Amount of energy the bid i can sell or discharge
s_i	Bid i's discharging rate
d_i	Bid i's deadline for discharging
W_{jt}	Maximum workload allowed at edge j at time t
V_{kt}	Workload of edge k at time t
Decisions	Descriptions
x_i	Whether bid i wins or not
y_{it}	Whether bid i discharges or not at the time slot t
τ_i	Maximum number of time slots that pass bid i's soft deadline
o_{kjt}	Amount of workload migrated from edge k to edge j at time t
p_i	Payment to bid i

EV Discharging: We consider a charging facility where EVs can charge/discharge energy, and a set $[I] = \{1, ..., I\}$ of EVs. We assume that the facility has the following components: (1) the electrical connections and interfaces that allow EVs to be discharged; (2) the local power lines that can transfer energy from the EVs to the edge system through the discharging facility. We denote by H the capacity of the facility in terms of the maximum number of EVs that are allowed to discharge simultaneously at any time. The EVs that want to discharge and sell energy (through auctions which will be described next) to the edge system arrive at the discharging facility dynamically over time.

Auction with Deadlines: To incentivize EVs to sell energy to the edge system, we design an online auction model. EVs that sell energy are the bidders, and the edge system that buys energy from EVs is the auctioneer. Upon arrival, the EV i, $\forall i \in [I]$ submits a bid $B_i = \{t_i, C_i, s_i, d_i, b_i, g_i(\cdot)\}$ to the edge system, where t_i is the arrival time slot; C_i is the total amount of energy available for discharging; s_i is the discharging rate, i.e., the amount of energy discharged per single time slot; d_i is the deadline for completing the discharging; and b_i is the bidding price, i.e., the price at which the EV i is willing to discharge energy before or by d_i. In this paper, to maximize the flexibility, we also consider that EVs can tolerate a certain level of delay after the deadline to discharge energy. If any discharging of EV i occurs after d_i, then a penalty is incurred:

$$g_i(\tau_i) = \begin{cases} g_{c_i}(\tau_i), & if\ \tau_i \in [0, T - d_i] \\ +\infty, & otherwise \end{cases} \qquad (1)$$

where τ_i is the number of time slots by which the soft deadline d_i has been passed, and $g_{c_i}(\cdot)$ is a nondecreasing function provided by the EV, with $g_{c_i}(0) = 0$. Then, $d_i + \tau_i$ represents the EV i's time of leaving the facility; and $b_i + g_i(\tau_i)$ represents the corresponding bidding price for discharging energy before or by $\tau_i + d_i$, i.e., the EV i would want to charge more money if the discharging deadline is violated. In this work, we assume one EV issues one bid.

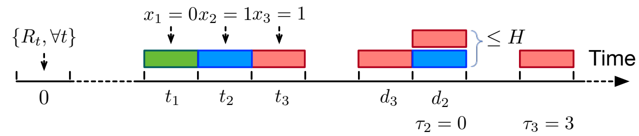


Fig. 2: EV discharging scheduling

Fig. 2 illustrates an example of EV discharging scheduling. Three EVs as the bids arrive at t_1, t_2, and t_3, respectively, and the first EV is rejected while the second and the third EVs are accepted. The second EV is scheduled to discharge energy at t_2 and $t_2 + 4$; the third EV is scheduled to discharge energy t_3, $t_3 + 2$, $t_3 + 3$, and $t_3 + 5$.

Control Decisions: As soon as the edge system receives $B_i, \forall i \in [I]$, it makes the following control decisions in an online manner: (1) whether or not the bid i wins, denoted by $x_i \in \{1, 0\}$, where $x_i = 1$ if the bid i is accepted (i.e., wins) and $x_i = 0$ if it is rejected (i.e., loses); (2) the scheduling of the bid i's energy discharging, denoted by $y_{it} \in \{1, 0\}$, where $y_{it} = 1$ if energy is discharged from EV i at time slot $t \geq t_i$, and $y_{it} = 0$ otherwise; (3) $\tau_i \in \{1, 2, ..., T - d_i\}$, the number of time slots by which the last discharging operation of EV i has passed d_i; (4) the payment $p_i \geq 0$ made to the bid i to buy the bid (note that p_i is not necessarily b_i or $b_i + g_i(\tau_i)$). Also, at each time slot $t \in [T]$, the edge system makes the decision of workload migration online in order to reduce energy, denoted by $o_{kjt} \geq 0$, referring to the amount of workload migrated from edge k to edge j at t.

Cost of EVs: The total cost of EVs consists of two parts, i.e., the cost of the bids with possible penalty, plus the payments (treated as negative cost) received from the edge system. Thus, we have

$$\sum_{i \in [I]} (b_i x_i + g_i(\tau_i) - p_i).$$

Cost of Edges: The total cost of the edge system consists of two parts as well, i.e., the network delay of migrating workload among edges, plus the payments made to the EVs. Thus, we have

$$\sum_{t \in [T]} \sum_{k \in [K]} \sum_{j \in [K]} r_{kj} o_{kjt} + \sum_{i \in [I]} p_i.$$

2.2 Problem Formulation and Algorithmic Challenges

Social Cost Minimization: The "social cost" is the sum of the total cost of the EVs and the total cost of the edge system. The auctioneer makes the control decisions described previously by solving the social cost minimization problem online. We formulate the social cost minimization problem P as follows. Note that the payments are cancelled; but the payments cannot be arbitrary, and in fact, we need to design and calculate the payments carefully in order to satisfy the desired economic properties described later.

$$P: \quad \min \quad \sum_{i \in [I]} (b_i x_i + g_i(\tau_i)) + \sum_{t \in [T]} \sum_{k \in [K]} \sum_{j \in [K]} r_{kj} o_{kjt} \qquad (2)$$

$$\text{s.t.} \quad y_{it} t \le d_i + \tau_i, \forall i \in [I], \forall t \ge t_i \tag{2a}$$

$$\sum_{i \in [I]: t_i \le t} s_i y_{it} + \sum_{k \in [K]} \sum_{j \in [K]} h_{kj} o_{kjt} \ge R_t, \forall t \in [T] \tag{2b}$$

$$\sum_{i \in [I]: t_i \le t} y_{it} \le H, \forall t \in [T] \tag{2c}$$

$$\sum_{t \in [T]: t_i \le t} s_i y_{it} \le x_i C_i, \forall i \in [I] \tag{2d}$$

$$\sum_{k \in [K]} o_{kjt} \le W_{jt}, \forall t \in [T], \forall j \in [K] \tag{2e}$$

$$\sum_{j \in [K]} o_{kjt} \le V_{kt}, \forall t \in [T], \forall k \in [K] \tag{2f}$$

$$x_i \in \{0,1\}, y_{it} \in \{0,1\}, \tau_i \in \{1,2,...,T-d_i\}, \\ o_{kjt} \ge 0, \forall j \in [K], \forall k \in [K], \forall i \in [I], \forall t \in [T] \tag{2g}$$

The optimization objective (2) minimizes the social cost. Constraint (2a) ensures that discharging can only be done after the corresponding EV arrives. Constraint (2b) ensures that the energy discharged from EVs plus the energy saved by migrating workload among edges is no less than the amount of grid energy that is required to be reduced. Constraint (2c) ensures the number of EVs always respects the capacity of the facility. Constraint (2d) ensures that the energy discharged from an EV does not exceed the EV's total energy to sell. Constraint (2e) guarantees that amount of workload migrated to an edge does not exceed that edge's capacity. Constraint (2f) guarantees that amount of workload migrated from an edge does not exceed the total amount of available workload on that edge. Constraint (2g) specify the domains of all the control variables.

Algorithmic Challenges: We highlight that it is non-trivial to solve the social cost minimization problem in an online setting and to calculate the payments with desired economic properties. We face three fundamental challenges.

First, as each EV arrives dynamically with a bid, whether to accept each bid and how to discharge energy from each accepted bid to span future time slots need to be scheduled irrevocably on the fly. High-price bids need to be filtered out to reserve the charging facility's spots for future bids with potentially low prices; energy can be discharged from EVs intermittently and workload can be moved around in the edge system in real time, in order to reduce the grid energy consumption of edges by a desired amount that varies as time goes. These decisions are not straightforward to make.

Second, our problem is in fact NP-hard [22], potentially non-convex, even in an offline setting. The cost of bids plus Constraints (2b) and (2d) (while ignoring everything else) indicates that our problem contains the NP-hard minimum knapsack problem; so, our problem is also NP-hard. Besides, different EVs can have different penalty functions for violating soft deadlines, which can be non-linear and/or non-convex, hard to address in polynomial time. The online setting where the algorithm needs to respond immediately as the inputs are revealed dynamically over time can only escalate the existing hardness for solving this problem.

Third, we need to calculate the payments for each winning bid online and in a way that it can induce "truthfulness" (i.e., if a bidder does not use its true valuation of its bid as its bidding price, then the bidder's "utility", defined as the received payment minus the bidding price, will not be maximized) and "individual rationality" (i.e., the utility of every bidder is non-negative regardless of winning or losing in the auction). Thus, the payment needs to be based on the solution to the social cost minimization problem; while it is not easy to obtain the result of each bid (i.e., winning or losing) online, it is also not easy to design and calculate the payment to ensure such desired economic properties.

Algorithmic Goal: The goal is to design polynomial-time online approximation algorithms to produce control decisions that can lead to a provable competitive ratio $\beta = P/OPT$ and achieve both truthfulness and individual rationality. Here, $\beta \ge 1$; P refers to the value of the objective function of the problem (2) evaluated with the solution produced by our online algorithms; and OPT refers to the value of the objective function of the problem (2) evaluated with the offline optimal solutions to the problem (2), where all the inputs over the entire time horizon are assumed known at once in advance.

3 Online Algorithms Design

In this section, we propose an online approach E^3DR to overcome all the aforementioned challenges while solving the social cost minimization problem and determining the payment to each bid.

3.1 Overview

Our approach E^3DR is composed of three algorithms: an online auction mechanism (Algorithm 1) which invokes the EV discharging scheduling algorithm (Algorithm 2), and the edge workload migration algorithm (Algorithm 3). We decompose our original problem P into the subproblems P_1 and P_2 which are connected by the auxiliary variable c_t, $\forall t$. Based on this, the three algorithms work jointly in an online manner as follows:

- Running Algorithm 1, the edge system invokes Algorithm 2 to solve P_1 upon each EV (or bid) i's arrival, decides whether to accept this bid, discharges the energy from the EV, calculates the payment, finds out c_t for each time slot $t \ge t_i$, and passes the value of c_t as the input to P_2 at t,
- At each time slot t, after receiving the value of c_t, the edge system uses Algorithm 3 to solve the one-shot instance of P_2 at t, and adjusts the workload distribution across the edges.

Note that the algorithms run at different frequencies. Algorithm 1 invokes Algorithm 2 and responds to each EV arrival; they do not run if there are no EV arrivals. Algorithm 3 runs at every single time slot regardless of EV arrivals.

What motivates us to design the decomposition is essentially the fact that EV-related decisions need to only be made in a responsive manner, responding to EV arrivals, while edge workload decisions need to be made in every time slot as time goes. Accordingly, we introduce auxiliary variables and decompose the problem into subproblems P_1 and P_2, respectively. On one hand, P_1 turns out to be an online problem that contains the unconventional constraints

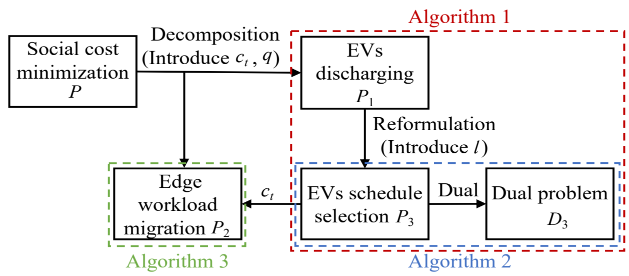


Fig. 3: Structure of E^3DR

of soft deadlines requiring to make EV discharging decisions over consecutive time slots. To overcome this, we firstly reformulate P_1 to an equivalent new problem P_3, where we "expand" the possible discharging decisions and transfer the problem of making discharging decisions into selecting the schedule of existing discharging decisions. To further solve P_3, we derive its dual problem D_3 and design a primal-dual-based algorithm, while also embedding our payment design into it to guarantee the desired economic properties. On the other hand, P_2 can be naturally split into a series of one-shot problems corresponding to individual time slots; moreover, each one-shot problem is a linear program and can be solved via standard optimization solvers.

The structure of our approach E^3DR is shown in Fig. 3.

3.2 Problem Decomposition

We split our original problem P into two subproblems as follows: P_1 for EVs discharging, and P_2 for edge workload migration. To that end, we introduce an auxiliary decision variable c_t, $\forall t \in [T]$, denoting the total amount of energy discharged from EVs at time slot t, and an input q, defined as $q = \min_{k\in[K],j\in[K]} \{\frac{r_{kj}}{h_{kj}}\}$, where r_{kj} and h_{kj} are as described earlier.

$$
\begin{aligned}
P_1: \quad \min \quad & \sum_{i\in[I]} (b_i x_i + g_i(\tau_i)) - \sum_{t\in[T]} q c_t & (3)\\
\text{s.t.} \quad & y_{it} t \le d_i + \tau_i, \forall i \in [I], \forall t \ge t_i & (3a)\\
& \sum_{i\in[I]:t_i\le t} s_i y_{it} \ge c_t, \forall t \in [T] & (3b)\\
& \sum_{i\in[I]:t_i\le t} y_{it} \le H, \forall t \in [T] & (3c)\\
& \sum_{t\in[T]:t_i\le t} s_i y_{it} \le x_i C_i, \forall i \in [I] & (3d)\\
& x_i \in \{0,1\}, y_{it} \in \{0,1\}, \tau_i \in \{1,2,...,T-d_i\}, & \\
& c_t \ge 0, \forall i \in [I], \forall t \in [T] & (3e)
\end{aligned}
$$

$$
\begin{aligned}
P_2: \quad \min \quad & \sum_{t\in[T]} \sum_{k\in[K]} \sum_{j\in[K]} r_{kj} o_{kjt} + \sum_{t\in[T]} q c_t & (4)\\
\text{s.t.} \quad & \sum_{k\in[K]} \sum_{j\in[K]} h_{kj} o_{kjt} + c_t \ge R_t, \forall t \in [T] & (4a)\\
& \sum_{k\in[K]} o_{kjt} \le W_{jt}, \forall j \in [K], \forall t \in [T] & (4b)\\
& \sum_{j\in[K]} o_{kjt} \le V_{kt}, \forall k \in [K], \forall t \in [T] & (4c)\\
& o_{kjt} \ge 0, \forall j \in [K], \forall k \in [K], \forall t \in [T] & (4d)\\
& c_t \ge 0, \forall t \in [T] & (4e)
\end{aligned}
$$

We have split the objective function of P into two components, the objective functions of P_1 and P_2; also, with c_t, we have split (and transformed) Constraints (2a)∼(2g) into Constraints (3a)∼(3e) for P_1 and Constraints (4a)∼(4e) for P_2, respectively.

3.3 Reformulation and Dual Problem

To solve the problem P_1 online, we reformulate it as a "schedule selection" problem, where for each EV i the schedules are defined as $(x_i, \{y_{it}\}_{\forall t\in[T]}, \tau_i)$ and every single schedule corresponds to a group of specific values taken by the decision variables x_i, y_{it}, $\forall t \in [T]$, and τ_i. That is, selecting a schedule means to assign the specific values contained in this schedule to the decision variables. A schedule is a concrete decision on whether to accept a given bid and how to discharge the energy in this bid over time. Thus, solving the reformulated problem corresponds to solving P_1.

The reformulation goes as follows. Let ξ_i be the set of all feasible schedules for EV i, where every feasible schedule satisfies Constraints (3a) and (3d). We use $l \in \xi_i$ to index a schedule. Then, we use b_{il} to represent $b_i + g_i(\tau_i)$ for the schedule l, and use $T(l)$ to represent the set of the time slots when energy is discharged from EV i as specified by the schedule l. Note that our decision variables now become x_{il} and c_t. While c_t has the same definition as described previously, $x_{il} = 1$ indicates we select the schedule l for the EV i and conduct discharging as specified by this schedule and $x_{il} = 0$ indicates we do not choose this schedule. We formulate the schedule selection problem P_3 as follows:

$$
\begin{aligned}
P_3: \quad \max \quad & -\sum_{i\in[I]} \sum_{l\in\xi_i} b_{il} x_{il} + \sum_{t\in[T]} q c_t & (5)\\
\text{s.t.} \quad & \sum_{l\in\xi_i} x_{il} \le 1, \forall i \in [I] & (5a)\\
& \sum_{i\in[I]} \sum_{l\in\xi_i:t\in T(l)} s_i x_{il} \ge c_t, \forall t \in [T] & (5b)\\
& \sum_{i\in[I]} \sum_{l\in\xi_i:t\in T(l)} x_{il} \le H, \forall t \in [T] & (5c)\\
& x_{il} \in \{0,1\}, \forall i \in [I], l \in \xi_i & (5d)\\
& c_t \ge 0, \forall t \in [T] & (5e)
\end{aligned}
$$

The optimization objective (5) is the same as (3). Constraint (5a) ensures that we select up to one schedule for each EV. Constraints (5b) and (5c) correspond to (3b) and (3c), respectively. (5d) and (5e) specify variables' domains.

We derive the formulation of the Lagrange dual problem D_3 of the problem P_3, and this is for designing a primal-dual-based online algorithm, which will be elaborated next. To derive this dual, we introduce the non-negative dual variables μ_i, m_t, and n_t for Constraints (5a), (5b), and (5c), respectively. We also relax $x_{il} \in \{0,1\}$ to $x_{il} \ge 0$. The dual problem of the problem P_3 is as follows:

$$
\begin{aligned}
D_3: \quad \min \quad & \sum_{i\in[I]} \mu_i + \sum_{t\in[T]} n_t H & (6)\\
\text{s.t.} \quad & \mu_i \ge -b_{il} + \sum_{t\in T(l)} m_t s_i - \sum_{t\in T(l)} n_t, &
\end{aligned}
$$

$$\forall i \in [I], \forall l \in \xi_i \tag{6a}$$

$$q \leq m_t, \forall t \in [T] \tag{6b}$$

$$\mu_i \geq 0, m_t \geq 0, n_t \geq 0, \forall t \in [T], \forall i \in [I] \tag{6c}$$

3.4 Online Algorithm for EV Discharging

We design a primal-dual-based approach to solve P_3 and D_3 online simultaneously. That is, in response to each EV or bid arrival, we maintain a carefully-designed, feasible solution for both the primal problem P_3 and the dual problem D_3, respectively, and adapt these solutions continuously as new bids arrive as time goes.

We choose this specific technical path to designing our online algorithms for multiple reasons. First, we can leverage the optimality conditions, i.e., the Karush-Kuhn-Tucker (KKT) conditions, to determine the values of the discrete variables to cope with the NP-hardness. According to the KKT conditions, if we can control the dual variables to make the inequality (6a) become tight, i.e., an equality, then we can set the corresponding primal variable x_{il} to a non-zero value, i.e., 1 in our case. Second, we can exploit the duality, i.e., the dual problem's objective function value is always an upper-bound for the primal problem's optimal objective function value, which essentially leads to our theoretical analysis regarding the bounded gap between the objective value of our online approximate solution and that of the offline optimal solution, as elaborated in the next section. Third, we can also design our payment to ensure the desired economic properties during this process. We will formally define such economic properties and prove how our payment embedded in such a primal-dual approach can indeed achieve these properties in the next section.

To make (6a) tight, since the dual variable μ_i is non-negative, we can set μ_i as follows:

$$\mu_i = \max(0, \max_{l \in \xi_i}(-b_{il} + \sum_{t \in T(l)} m_t s_i - \sum_{t \in T(l)} n_t)). \tag{7}$$

Next, we set the dual variables m_t and n_t as follows:

$$m_t = q = \min_{k \in [K], j \in [J]}\{\frac{r_{kj}}{h_{kj}}\}, \tag{8}$$

$$n_t = L(\frac{U}{L})^{\frac{z_t}{H \max_{i \in [I]}\{s_i\}}}. \tag{9}$$

In n_t, we have introduced some new notations: z_t, U, and L, which are not variables but inputs or quantities that need to be maintained as follows. z_t represents the total amount of energy discharged from all EVs at the time slot t, as dictated by our algorithms. z_t^i is the value of the variable z_t after processing the bid i. That is, as the bid i arrives, we have $z_t = z_t^{i-1}$; then, we update $z_t = z_t^i$ after generating the scheduling decision for the bid or EV i. Having this, we just use the value of z_t to calculate or update the value of n_t, as specified in the manuscript. We initialize $z_t^0 = 0, \forall t \in [T]$; if the bid i wins, we set $z_t^i = z_t^{i-1} + s_i, \forall t \in T(l)$, where l is the corresponding schedule being selected; otherwise, we set $z_t^i = z_t^{i-1}$, $\forall t \in T$. We also set U and L to be the maximum and the minimum value of n_t: $U = \frac{\min_{i \in [I]}\{b_i\} \min_{i \in [I]}\{s_i\}}{H \max_{i \in [I]}\{C_i\}}$ and $L = \frac{\min_{i \in [I]}\{b_i\}}{HT}$. Here, we highlight we are not setting m_t and n_t arbitrarily; instead, we are setting them this way in order to serve our theoretical analysis as elaborated later.

Algorithm 1 Online Auction Mechanism

Input: $\{b_i\}$, $\{C_i\}$, $\{s_i\}$, $\{d_i\}$, $\{R_t\}$, H

Compute m_t, $\forall t \in [T]$ based on (8);
Initialize $x_i = 0$, $p_i = 0$, $y_{it} = 0$, $x_{il} = 0$, $z_t = 0$, $\mu_i = 0$, $n_t = 0$, $c_t = 0$, $\psi_t = 0$, $q = m_t$, $\forall i \in [I]$, $\forall l \in \xi_i$, $\forall t \in [T]$;
for $i = 1, 2, ..., I$ **do**
  Invoke **Algorithm 2** to obtain x_i, $\{y_{it}\}$, p_i, $\{n_t\}$, $\{z_t\}$, $\{\psi_t\}$, $\{c_t\}$;
  if $x_i == 1$ **then**
    Accept bid i;
    Discharge EV i following $\{y_{it}\}_{t \geq t_i}$;
    Pay p_i to EV i;
  else
    Reject bid i;
  end if
end for

We then design our Algorithms 1 and 2. Algorithm 1 exhibits the overall auction process, which invokes Algorithm 2 to handle each EV or bid as it arrives. In Algorithm 2, we firstly find out the set $\pounds$ of the feasible time slots for discharging in Lines 1-6, where ψ_t is the total number of EVs that have so far been decided to discharge energy at the time slot t in the facility. In Lines 7-13, we construct our first schedule l_0, whose discharging completion time is t_{w_i}. Here, Lines 9-13 correspond to Equation (7), where Lines 10-12 consider the case of passing the deadline. Then, in Lines 14-28, we iteratively construct the schedules l_1, l_2, l_3, ..., and these schedules are the best schedules whose discharging completion time are the $(w_i + 1)$-th time slot in $\pounds$, the $(w_i + 2)$-th time slot in $\pounds$, the $(w_i + 3)$-th time slot in $\pounds$, ..., respectively. We always keep the number of time slots of a charging schedule to be w_i. In Lines 21-25, to generate the best schedule whose discharging completion time is t_c, we only need to find out the specific time slot t in $\{t_1, t_2, ..., t_{w_i}\}$ that has the smallest $\varsigma(t)$ value and replace that time slot by t_c. This way, we are able to divide the total $C_{|\pounds|}^{w_i}$ schedules according to different completion times and figure out the best schedule for each different completion time. In Line 29, we obtain the "best of the best" schedule overall. In Lines 30-37, based on the best schedule we find, we set the values of all of our primal and dual variables, determine the payment, and update the status of the facility as we have decided to accept the current bid. We highlight that we only set the primal variables to 1 if the condition in Line 30 is satisfied; this aligns with the primal-dual theory and is also required for our payment calculation in Line 33, which will be useful when we prove the economic properties later.

3.5 Online Algorithm for Edge Workload Migration

We solve P_2 at each t by taking the output c_t from Algorithm 2 as the input. This is to decide the amount of workload that needs to be migrated across heterogeneous edges. P_2 at t is only a standard linear program and can be solved optimally by existing optimization solvers in polynomial time [4].

Algorithm 2 EV Discharging Scheduling Algorithm

```
Input: $b_i$, $C_i$, $s_i$ $d_i$, $\{R_t\}$, $\{m_t\}$, $\{n_t\}$, $\{z_t\}$, $\{\psi_t\}$, $q$, $H$
Output: $x_i$, $\{y_{it}\}$, $p_i$, $\{n_t\}$, $\{z_t\}$, $\{\psi_t\}$, $\{c_t\}$
1: £ = ∅, j = 1;
2: for t = t_i, t_i + 1, t_i + 2, ..., T do
3:     if z_t^{i-1} + s_i ≤ R_t and ψ_t ≤ H then
4:         £ = £ ∪ {t};
5:     end if
6: end for
7: w_i = min{C_i/s_i, |£|};
8: Let l_0 be the set of the first w_i slots {t_1, t_2, ..., t_{w_i}} in £;
9: ς(t) = m_t s_i − n_t, ∀t ∈ {t_1, t_2, ..., t_{w_i}};
10: if t_{w_i} > d_i then
11:     ς(t_{w_i}) = ς(t_{w_i}) − g_i(t_{w_i} − d_i);
12: end if
13: P_0 = Σ_{t∈T(l_0)} ς(t);
14: while w_i + j ≤ |£| do
15:     l_j = l_{j−1};
16:     Let t_c be the (w_i + j)-th time slot in £;
17:     ς(t) = m_t s_i − n_t, ∀t ∈ {t_1, t_2, ..., t_{w_i}} ∪ {t_c};
18:     if t_c > d_i then
19:         ς(t_c) = ς(t_c) − g_i(t_c − d_i);
20:     end if
21:     t_m = arg min_{t∈{t_1,...,t_{w_i−1}}} ς(t);
22:     if ς(t_{w_i}) > ς(t_m) then
23:         t_m = t_{w_i};
24:     end if
25:     t_{w_i} = t_c;
26:     P_j = Σ_{t∈T(l_j)} ς(t);
27:     j = j + 1;
28: end while
29: ĵ = arg max_j{P_j}, P̂ = P_ĵ, l̂ = l_ĵ;
30: if −b_i + P̂ > 0 then
31:     x_i = 1, y_it = 1, x_{il̂} = 1, ∀t ∈ T(l̂);
32:     μ_i = −b_i + P̂;
33:     p_i = Σ_{t∈T(l̂)} m_t s_i − Σ_{t∈T(l̂)} n_t;
34:     z_t^i = z_t^{i−1} + s_i, ψ_t = ψ_t + 1, ∀t ∈ T(l̂);
35:     c_t = z_t^i, ∀t ∈ T(l̂);
36:     n_t = L(L/U)^{z_t^i / (H max_{i∈[I]}{s_i})}, ∀t ∈ T(l̂);
37: end if
38: return x_i, {y_it}, p_i, {n_t}, {z_t}, {ψ_t}, {c_t}
```

Algorithm 3 Edge Workload Migration Algorithm

```
Input: {c_t}, {R_t}, {r_kj}, {h_kj}, {W_jt}, {V_kt}, q
Output: {o_kjt}
for t = 1, 2, ..., T do
    Solve the one-shot instance of P_2 at t using a solver
    (e.g., the interior-point method);
end for
return o_kjt
```

4 Theoretical Analysis

In this section, we formally prove that our proposed E^3DR approach terminates in polynomial time, achieves the desired economic properties of truthfulness and individual rationality, and has a gauranteed competitive ratio regarding the long-term social cost.

4.1 Correctness and Polynomial-Time Complexity

Theorem 1. *Algorithm 1 terminates in polynomial time and returns a feasible solution for the problems P_3 and D_3.*

Proof. **Correctness:** In Algorithm 2 invoked by Algorithm 1, Lines 3 and 34 make the solution satisfy (5c). Lines 34-35 ensure that the right-hand side of (5b) equals its left-hand side. For the specific schedule $\hat{l}$ being chosen, Line 31 sets x_{il} to 1, satisfying (5a). (5d)-(5e) are naturally satisfied. Thus, it is feasible for P_3. Also, in Algorithm 2, Lines 32 and 36 set μ_i and n_t according to Equations (7) and (9), respectively, together with Equation (8), make the dual solution satisfy (6a)-(6c), thus feasible for D_3.

Complexity: We first consider the key steps in Algorithm 2. Lines 2-6 take $O(T)$. Line 9 takes $O(T)$. Lines 14-28 have $O(T)$ iterations, where in each iteration Line 17 takes $O(T)$. Thus, overall, Algorithm 2 takes $O(T^2)$. Then, Algorithm 1 invokes Algorithm 2 as each bid arrives for a total number of I bids, and thus takes $O(IT^2)$. □

Theorem 2. *Our approach E^3DR (i.e., Algorithms 1-3) terminates in polynomial time and returns a feasible solution for the problem P.*

Proof. Based on Theorem 1, Algorithm 1 that invokes Algorithm 2 terminates in polynomial time; Algorithm 3 solves a linear program and also terminates in polynomial time.

On feasibility, we have a feasible solution for P_3 based on Theorem 1, and due to the reformulation as stated in Section 3.3, we also have a feasible solution for P_1; given that, we solve P_2 while respecting all of its constraints and thus also have a feasible solution for it. Joining all of these together, we have a feasible solution for the original problem P. □

4.2 Truthfulness and Individual Rationality

We define utility, based on which we further define the economic properties of truthfulness and individual rationality. Then, we prove that our approach in this paper indeed achieves these economic properties. We highlight that the two economic properties are important and desired: truthfulness ensures that there is no motivation for a bidder to lie about its bidding price in an auction, and individual rationality ensures that there is no loss for a bidder regardless of the auction outcome.

Definition 1. *Utility: The utility of the bid i is*

$$u_i = \begin{cases} p_i - (v_i + g_i^{'}(\tau_i)), & if\ x_i = 1 \\ 0, & otherwise \end{cases}$$

where p_i is the payment received; v_i is the true valuation of the bid i by the bidder for the energy of the EV i discharged before the deadline d_i; and $g_i^{'}(\tau_i)$ is the true penalty or additional valuation of the bid i given by the bidder for the energy of the EV i discharged after d_i, as described earlier.

Definition 2. *Truthfulness: Bidding the true valuation maximizes the utility of a bid, i.e., for all b_i and $g_i(\tau_i)$ where $b_i + g_i(\tau_i) \neq v_i + g_i^{'}(\tau_i)$, we have $u_i(v_i + g_i^{'}(\tau_i)) \geq u_i(b_i + g_i(\tau_i))$.*

Definition 3. *Individually Rationality: A bid always has non-negative utility, regardless of the auction outcome [23], i.e., for the bid i, we always have $u_i \geq 0$.*

In the following, we firstly give Lemma 1 and prove that our approach meets the conditions required in this lemma and thus achieves truthfulness. We then present Theorem 3 based on Lemma 1 to further state that our approach also achieves individual rationality.

Lemma 1. *According to the Myerson theorem [24], an auction is truthful if and only if (1) the auction outcome is monotone, i.e., for $\forall i, j$, if $b_{il} \leq b_{jl}$, then $x_j = 1$ implies $x_i = 1$, given all the other inputs do not change; and (2) the winning bid is paid with the critical payment [25], i.e., if the bid i wins the auction with the cost b^*_{il}, and receives the payment p^*_i, then it will also win if it bids $b_{il} < p^*_i$; if it bids $b_{il} \geq p^*_i$, then it will lose in the auction. Our approach satisfies both requirements.*

Proof. **Monotonicity**: Following (7) and Algorithm 1, we have

$$\mu_i = \max(0, \max_{l \in \xi_i}(-b_{il} + \sum_{t \in T(l)} m_t s_i - \sum_{t \in T(l)} n_t)), \forall i.$$

That is, if $b_{il} \leq b_{jl}$ and all the other inputs remain the same, then we have $\mu_i \geq \mu_j$. On the other hand, according to Algorithm 1, if $x_j = 1$, then we have $\mu_j > 0$. Consequently, we have $\mu_i > 0$ and accordingly $x_i = 1$.

Critical Payment: Suppose the bid i wins the auction when bidding b^*_{il}, and the payment is p^*_i. From Lines 30-31 in Algorithm 2, we have the following: if $-b_i + \hat{P} = -b^*_{il} + p^*_i > 0$, then $x_i = 1$; if $-b_i + \hat{P} \leq 0$, then $x_i = 0$. So, if $b_{il} < p^*_i$, then we also have $x_i = 1$. If $b_{il} \geq p^*_i$, then we have $x_i = 0$. □

Theorem 3. *Our approach E^3DR achieves both truthfulness and individual rationality.*

Proof. As our approach satisfies Lemma 1, it is truthful. So, we focus on proving individual rationality.

Based on the definition of utility, if a bid i does not win in the auction, then $u_i = 0$; if a bid i wins in the auction, then we have $x_i = 1$ and

$$\begin{aligned} u_i &= p_i - (v_i + g^{'}_i(\tau_i)) \\ &\geq p_i - (b_i + g_i(\tau_i)) \quad (10) \\ &= \sum_{t \in T(\hat{l})} m_t s_i - \sum_{t \in T(\hat{l})} n_t - g_i(\tau_i) - b_i \quad (11) \\ &= \mu_i \quad (12) \\ &> 0. \end{aligned}$$

We reach (10) due to truthfulness. We further reach (11) due to how we calculate the payment p_i in Line 33 of Algorithm 2. Finally, note that, because $x_i = 1$, we can directly reach (12) from (11), based on (7). As shown, the utility is always non-negative for any bid i. □

4.3 Competitive Ratio

In this part of the analysis, we focus on the "competitive ratio", which is an important performance metric for online algorithms. The competitive ratio of E^3DR for our original problem P is defined as the largest ratio of the social cost (i.e., the value of the objective function of the problem P) incurred by the online approach E^3DR (i.e., Algorithms 1-3) over the offline optimal social cost (i.e., the optimal objective value of P), over all possible inputs for P. We recap that E^3DR does not solve P directly, but solves $P_1 \sim P_3$ and D_3 online to compose the solution for P.

To prove the competitive ratio, we take the following roadmap. We introduce and recap some important notations first. We use the notations P, P_1, P_2, and P_3 to represent both the problems and the corresponding objective values of these problems evaluated with the solutions produced by our proposed algorithmic approach. Analogously, we also use D, D_1, and D_3 to represent the dual problems of the problems P, P_1, and P_3, respectively, and also represent the objective values of these dual problems correspondingly. Therefore, our goal here is to prove $P \leq \beta D$, and then due to $D \leq OPT$, i.e., the weak duality, we will automatically have $P \leq \beta OPT$, where OPT denotes the optimal objective value of the problem P and β will denote the competitive ratio for solving the problem P. To elaborate it, we will show the following:

$$\begin{aligned} P &= P_1 + P_2 \\ &\leq \frac{1}{\alpha} D_1 + \gamma \sum\nolimits_{t \in [T]} m_t R_t \\ &\leq \beta(D_1 + \sum\nolimits_{t \in [T]} m_t R_t) \\ &\leq \beta D \\ &\leq \beta OPT. \end{aligned}$$

First, by Lemmas 2 and 3, and Theorem 4, we point out that Algorithm 2 is α-competitive with regards to the problem P_3 (and thus the problem P_1). That is, we prove $P_3 \geq \frac{1}{\alpha} D_3$ and find out α; this also means $P_1 \leq \frac{1}{\alpha} D_1$, due to $P_3 = -P_1$ and $D_3 = -D_1$. Second, by Lemma 4, we prove $P_2 \leq \gamma \sum_{t \in [T]} m_t R_t$ and find out γ. Finally, by Theorem 5, we exhibit that E^3DR is β-competitive with regards to the problem P. we show $D = -\sum_{i \in [I]} \mu_i - \sum_{t \in [T]} n_t H + \sum_{t \in [T]} m_t R_t - \sum_{j \in K} \sum_{t \in [T]} z_{jt} W_{jt} - \sum_{k \in K} \sum_{t \in [T]} \varphi_{kt} V_{kt}$, $D_1 = -\sum_{i \in [I]} \mu_i - \sum_{t \in [T]} n_t H$. We can then let $m_t = \min_{k \in [K], j \in [J]} \{\frac{r_{kj}}{h_{kj}}\}$, $n_t = L(\frac{U}{L})^{\frac{z_t}{H \max_{i \in [I]}\{s_i\}}}$, $\varphi_{kt} = 0, z_{jt} = 0$. Afterwards, we have $D_1 + \sum_{t \in T} m_t R_t \leq D$, prove $\frac{1}{\alpha} D_1 + \gamma \sum_{t \in [T]} m_t R_t \leq \beta D$, and find out β.

Lemma 2. *If Algorithm 2 guarantees $P^i_3 - P^{i-1}_3 \geq \frac{1}{\alpha}(D^i_3 - D^{i-1}_3)$, $\forall i$, where $\alpha \geq 1$, then Algorithm 2 is α-competitive for P_3.*

Proof. We have

$$P^I_3 = P^I_3 - P^0_3 = \sum_i (P^i_3 - P^{i-1}_3),$$

based on

$$P^i_3 - P^{i-1}_3 \geq \frac{1}{\alpha}(D^i_3 - D^{i-1}_3).$$

Adding up each inequality, we can find

$$\sum_i (P^i_3 - P^{i-1}_3) \geq \frac{1}{\alpha} \sum_i (D^i_3 - D^{i-1}_3) = \frac{1}{\alpha}(D^I_3 - D^0_3) = \frac{1}{\alpha} D^I_3.$$

According to weak duality [26], $D^I_3 \geq OPT_3$; therefore, we have $P^I_3 \geq \frac{1}{\alpha} OPT_3$. Thus, the algorithm is α-competitive. □

Assumption 1. *The Usage-Cost Relation, with $\alpha > 1$, is defined as*

$$n_t^{i-1}(z_t^i - z_t^{i-1}) \geq \frac{1}{\alpha}(H \max_{i\in[I]}\{s_i\})(n_t^i - n_t^{i-1}), \forall i \in [I], \forall t \in T(l).$$

The Differential Usage-Cost Relation, with $\alpha \geq 1$, is defined as

$$n_t dz_t \geq \frac{1}{\alpha}(H \max_{i\in[I]}\{s_i\}) dn_t, \forall i \in [I], \forall t \in T(l).$$

We believe the Differential Usage-Cost Relation can hold reasonably in reality. If we rearrange the terms in the Differential Usage-Cost Relation, we have $\frac{dn_t}{dz_t} \leq \alpha \cdot \frac{n_t}{H \max_{i\in[I]} s_i}$. That is, given $\alpha > 1$, what we essentially assume here is that the derivative of n_t is upper-bounded at any t—a common assumption made in lots of real-world situations. We will prove if the Differential Usage-Cost Relation holds, then the Usage-Cost Relation holds for the same α later.

Lemma 3. *If the Usage-Cost Relation holds, then Algorithm 2 guarantees $P_3^i - P_3^{i-1} \geq \frac{1}{\alpha}(D_3^i - D_3^{i-1})$, $\forall i$.*

Proof. When the bid i is rejected, $P_3^i - P_3^{i-1} = D_3^i - D_3^{i-1} = 0$. Next, we assume the bid i wins, and suppose l is the best schedule for it. After processing this bid i, the increment of the primal objective function (5) is

$$P_3^i - P_3^{i-1} = -b_{il} + \sum_{t\in T(l)} q(c_t^i - c_t^{i-1})$$
$$= \mu_i - \sum_{t\in T(l)} m_t s_i + \sum_{t\in T(l)} n_t^{i-1} + \sum_{t\in T(l)} q(c_t^i - c_t^{i-1}).$$

Since the left-hand side of Constraint (6a) equals the right-hand side when the bid i is accepted with the schedule l, the second equation is valid. Due to $s_i = c_t^i - c_t^{i-1}$, we have

$$P_3^i - P_3^{i-1} = \mu_i + \sum_{t\in T(l)} n_t^{i-1}.$$

The dual objective value increases as

$$D_3^i - D_3^{i-1} = \mu_i + \sum_{t\in T(l)} H(n_t^i - n_t^{i-1}).$$

According to Assumption 1, i.e.,

$$n_t^{i-1}(z_t^i - z_t^{i-1}) \geq \frac{1}{\alpha}(H \max_{i\in[I]}\{s_i\})(n_t^i - n_t^{i-1})$$

and $z_t^i = c_t^i$, then we have

$$n_t^{i-1} s_i \geq \frac{1}{\alpha} H \max_{i\in[I]}\{s_i\}(n_t^i - n_t^{i-1}).$$

Obviously,

$$n_t^{i-1} \geq \frac{1}{\alpha}\frac{H \max_{i\in[I]}\{s_i\}}{s_i}(n_t^i - n_t^{i-1}) \geq \frac{1}{\alpha} H(n_t^i - n_t^{i-1}).$$

In addition, when we add up Usage-Cost Relation over all $t \in T(l)$, we obtain

$$\sum_{t\in T(l)} n_t^{i-1} \geq \sum_{t\in T(l)} \frac{1}{\alpha} H(n_t^i - n_t^{i-1}),$$
$$P_3^i - P_3^{i-1} \geq \mu_i + \frac{1}{\alpha}(D_3^i - D_3^{i-1} - \mu_i).$$

Due to $\mu_i \geq 0$ and $\alpha \geq 1$, we have

$$P_3^i - P_3^{i-1} \geq \frac{1}{\alpha}(D_3^i - D_3^{i-1}).$$

□

Theorem 4. *Algorithm 2 is α-competitive for P_3, with $\alpha = ln\frac{U}{L}$ satisfying the Differential Usage-Cost Relation.*

Proof. The deferential of n_t is

$$dn_t = L(\frac{U}{L})^{\frac{z_t}{H \max_{i\in[I]}\{s_i\}}} ln(\frac{U}{L})\frac{1}{H \max_{i\in[I]}\{s_i\}} dz_t.$$

The Differential Usage-Cost Relation is

$$L(\frac{U}{L})^{\frac{z_t}{H \max_{i\in[I]}\{s_i\}}} dz_t \geq$$
$$\frac{H \max_{i\in[I]}\{s_i\}}{\alpha}(L)(\frac{U}{L})^{\frac{z_t}{H \max_{i\in[I]}\{s_i\}}} ln(\frac{U}{L})\frac{1}{H \max_{i\in[I]}\{s_i\}} dz_t$$

$$\Rightarrow \alpha \geq ln(\frac{U}{L}).$$

As a result, the lemma holds for $\alpha = ln\frac{U}{L}$. □

Lemma 2 points out that if the increment of the primal objective value can be used as an upper bound for a constant times the increment of the dual objective value, then the competitive ratio for P_3 can be found accordingly. Suppose P_3^i and D_3^i denote the objective value of the primal problem P_3 and the dual problem D_3, respectively, after Algorithm 2 has dealt with EV i's bid. We also introduce and define the "Usage-Cost Relation" and the "Differential Usage-Cost Relation", respectively. The latter ensures the former, due to the following. An EV's discharging rate is often much lower than the station capacity in the real world, i.e., $s_i \ll H \max_{i\in[I]} s_i$. Then we have $dz_t = z_t^i - z_t^{i-1} = s_i$. Based on differential calculus, we can further have $dn_t = n_t^{'}(z_t)dz_t = n_t(z_t^i) - n_t(z_t^{i-1}) = n_t^i - n_t^{i-1}$, where n_t^i denotes the equipment cost after processing the EV i's bid, and $n_t = n_t^{i-1}$ when the bid i is submitted.

Lemma 4. *We have $P_2 \leq \gamma \sum_{t\in[T]} m_t R_t$ with $\gamma = \frac{r_{\max} h_{\max}}{r_{\min} h_{\min}}$, where*

$$r_{\max} = \max_{k\in[K],j\in[J]}\{r_{kj}\}, r_{\min} = \min_{k\in[K],j\in[J]}\{r_{kj}\},$$
$$h_{\max} = \max_{k\in[K],j\in[J]}\{h_{kj}\}, h_{\min} = \min_{k\in[K],j\in[J]}\{h_{kj}\}.$$

Proof. We derive the dual problem of the problem P_2:

$$\max \quad \sum_{t\in[T]} m_t R_t - \sum_{j\in K}\sum_{t\in[T]} z_{jt} W_{jt} - \sum_{k\in K}\sum_{t\in[T]} \varphi_{kt} V_{kt} + \sum_{t\in[T]} q_t c_t - \sum_{t\in[T]} m_t c_t \quad (13)$$

$$\text{s.t.} \quad h_{kj} m_t \leq r_{kj} + \varphi_{kt} + z_{jt}, \quad \forall k \in [K], \forall j \in [K], \forall t \in [T] \quad (13a)$$

$$\varphi_{kt} \geq 0, z_{jt} \geq 0, m_t \geq 0, \quad \forall k \in [K], \forall j \in [K], \forall t \in [T]. \quad (13b)$$

We can let $m_t = q = \min_{k\in[K],j\in[J]}\{\frac{r_{kj}}{h_{kj}}\}$, $\varphi_{kt} = 0$, $z_{jt} = 0$. Suppose there is a γ such that

$$\sum_{t\in[T]}\sum_{k\in[K]}\sum_{j\in[K]} r_{kj}o_{kjt} + \sum_{t\in[T]} qc_t \leq \gamma \sum_{t\in[T]} m_t R_t.$$

Then, $\gamma = \max \frac{\sum_{t\in[T]}\sum_{k\in[K]}\sum_{j\in[K]} r_{kj}o_{kjt} + \sum_{t\in[T]} qc_t}{\sum_{t\in[T]} m_t R_t}$. Thus, we can do the following:

$$\begin{aligned}
&\frac{\sum_{t\in[T]}\sum_{k\in[K]}\sum_{j\in[K]} r_{kj}o_{kjt} + \sum_{t\in[T]} qc_t}{\sum_{t\in[T]} m_t R_t} \\
\leq & \frac{\sum_{t\in[T]}\sum_{k\in[K]}\sum_{j\in[K]} r_{kj}o_{kjt} + \min_{t\in[T]}\{m_t\}\sum_{t\in[T]} c_t}{\min_{t\in[T]}\{m_t\}\sum_{t\in[T]} R_t} \\
\leq & \frac{\frac{\max_{k\in[K],j\in[K]}\{r_{kj}\}}{\min_{k\in[K],j\in[K]}\{h_{kj}\}}\sum_{t\in[T]}(R_t - c_t) + \min_{t\in[T]}\{m_t\}\sum_{t\in[T]} c_t}{\min_{t\in[T]}\{m_t\}\sum_{t\in[T]} R_t} \\
\leq & \frac{\max_{k\in[K],j\in[K]}\{r_{kj}\}\max_{k\in[K],j\in[K]}\{h_{kj}\}}{\min_{k\in[K],j\in[K]}\{r_{kj}\}\min_{k\in[K],j\in[K]}\{h_{kj}\}},
\end{aligned}$$

where we let $\gamma = \frac{r_{\max}h_{\max}}{r_{\min}h_{\min}}$. □

Theorem 5. *Our approach E^3DR is β-competitive for P, with*

$$\beta = \gamma + \frac{\gamma - \frac{1}{\alpha}}{\varepsilon - 1},$$

where $\varepsilon = \frac{\max_{t\in[T]}\{m_t R_t\}}{\max_{t\in[T]}\{m_t R_t\} - \min_{t\in[T]}\{n_t\}\frac{\min_{t\in[T]}\{R_t\}}{\max_{i\in[I]}\{s_i\}}}$.

Proof. Suppose there is a β such that

$$\begin{aligned}
P &= \sum_{i\in I}\sum_{l\in\xi_i} b_{il}x_{il} + \sum_{t\in[T]}\sum_{k\in[K]}\sum_{j\in[K]} r_{kj}o_{kjt} \\
&= \sum_{i\in I}\sum_{l\in\xi_i} b_{il}x_{il} - \sum_{t\in T} qc_t + \sum_{t\in T} qc_t \\
&+ \sum_{t\in[T]}\sum_{k\in[K]}\sum_{j\in[K]} r_{kj}o_{kjt} \\
&\leq \frac{1}{\alpha}(-\sum_{i\in[I]}\mu_i - \sum_{t\in[T]} n_t H) + \gamma\sum_{t\in T} m_t R_t \\
&\leq \beta(-\sum_{i\in[I]}\mu_i - \sum_{t\in[T]} n_t H + \sum_{t\in T} m_t R_t) \\
&\leq \beta D \leq \beta OPT.
\end{aligned}$$

In contrast to reformulating the problem P_1 as done in our paper, we can now actually reformulate the problem P in a similar fashion as follows:

$$\min \quad \sum_{i\in[I]}\sum_{l\in\xi_i} b_{il}x_{il} + \sum_{t\in[T]}\sum_{k\in[K]}\sum_{j\in[K]} r_{kj}o_{kjt} \tag{14}$$

$$\text{s.t.} \quad \sum_{l\in\xi_i} x_{il} \leq 1, \forall i\in[I] \tag{14a}$$

$$\sum_{i\in[I]}\sum_{l\in\xi_i:t\in T(l)} s_i x_{il} + \sum_{k\in[K]}\sum_{j\in[K]} h_{kj}o_{kjt} \quad \geq R_t, \quad \forall t\in[T] \tag{14b}$$

$$\sum_{i\in[I]}\sum_{l\in\xi_i:t\in T(l)} x_{il} \leq H, \forall t\in[T] \tag{14c}$$

$$\sum_{k\in[K]} o_{kjt} \leq W_{jt}, \forall t\in[T], \forall j\in[K] \tag{14d}$$

$$\sum_{j\in[K]} o_{kjt} \leq V_{kt}, \forall t\in[T], \forall k\in[K] \tag{14e}$$

$$x_{il}\in\{0,1\}, o_{kjt}\geq 0, \tau_i \geq 0, \quad \forall j\in[K], \forall k\in[K], \forall i\in[I], \forall t\in[T] \tag{14f}$$

For the above problem, we can derive the dual problem D, which requires the non-negative dual variables μ_i, m_t, n_t, z_{kt} and φ_{kt} for Constraints (14a), (14b), (14c), (14d) and (14e), respectively. We also relax $x_{il}\in\{0,1\}$ to $x_{il}\geq 0$. The dual problem denoted as D is as follows:

$$\max \quad -\sum_{i\in[I]}\mu_i - \sum_{t\in[T]} n_t H + \sum_{t\in[T]} m_t R_t - \sum_{j\in K}\sum_{t\in[T]} z_{jt}W_{jt} - \sum_{k\in K}\sum_{t\in[T]}\varphi_{kt}V_{kt} \tag{15}$$

$$\text{s.t.} \quad \mu_i \geq -b_{il} + \sum_{t\in T(l)} m(t)s_i - \sum_{t\in T(l)} n_t, \forall i\in[I], \forall l\in\xi_i \tag{15a}$$

$$h_{kj}m_t \leq r_{kj} + \varphi_{kt} + z_{jt} \quad \forall k\in[K], \forall j\in[K], \forall t\in[T] \tag{15b}$$

$$\mu_i\geq 0, m_t\geq 0, n_t\geq 0, \varphi_{kt}\geq 0, z_{jt}\geq 0, \quad \forall k\in[K], \forall j\in[K], \forall t\in[T], \forall t\in[T], \forall i\in[I] \tag{15c}$$

We can let $m_t = \min_{k\in[K],j\in[J]}\{\frac{r_{kj}}{h_{kj}}\}$, $n_t = L(\frac{U}{L})^{\frac{z_t}{H\max_{i\in[I]}\{s_i\}}}$, $\varphi_{kt} = 0, z_{jt} = 0$. Then, we have $0 \leq -\sum_{i\in[I]}\mu_i - \sum_{t\in[T]} n_t H + \sum_{t\in T} m_t R_t \leq D$. So, this theorem holds for

$$\beta = \max\left(\frac{\frac{1}{\alpha}(-\sum_{i\in[I]}\mu_i - \sum_{t\in[T]} n_t H) + \gamma\sum_{t\in T} m_t R_t}{-\sum_{i\in[I]}\mu_i - \sum_{t\in[T]} n_t H + \sum_{t\in T} m_t R_t}\right),$$

where $m_t = \min_{k\in[K],j\in[J]}\{\frac{r_{kj}}{h_{kj}}\}, n_t = L(\frac{U}{L})^{\frac{z_t}{H\max_{i\in[I]}\{s_i\}}}$.

We let $\chi = \frac{\sum_{t\in T} m_t R_t}{\sum_{i\in[I]}\mu_i + \sum_{t\in[T]} n_t H}$,

$$\beta = \max\left(\frac{-\frac{1}{\alpha} + \gamma\chi}{-1+\chi}\right)$$

$$F(z) = \frac{-\frac{1}{\alpha} + \gamma\chi}{-1+\chi} = \gamma + \frac{\gamma - \frac{1}{\alpha}}{\chi - 1}.$$

When χ takes the minimum value, the value of β takes the maximum value.

$$\begin{aligned}
\chi &= \frac{\sum_{t\in T} m_t R_t}{\sum_{i\in[I]}\mu_i + \sum_{t\in[T]} n_t H} \\
&= \frac{\sum_{t\in T} m_t R_t}{\sum_{i\in[\hat{I}]}(-b_{il} + \sum_{t\in[T]} m_t s_i - \sum_{t\in[T]} n_t) + \sum_{t\in[T]} n_t H} \\
&\geq \frac{\sum_{t\in T} m_t R_t}{-\min_{i\in[I]}(b_i) + \sum_{t\in[T]} n_t H + \sum_{i\in[\hat{I}]}\sum_{t\in T}(m_t s_i - n_t)} \\
&\geq \frac{\sum_{t\in T} m_t R_t}{\min_{i\in[I]}\{-b_i\} + \sum_{t\in[T]} n_t H + \sum_{t\in T}(m_t R_t - n_t\frac{\min_{t\in[T]}\{R_t\}}{\max_{i\in[I]}\{s_i\}})}
\end{aligned}$$

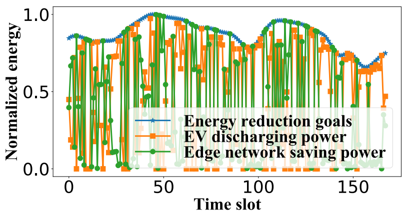


Fig. 4: Energy reduction dissection

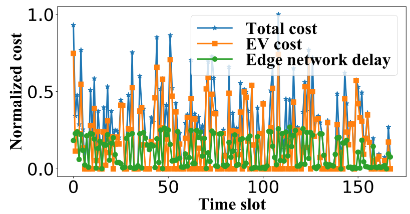


Fig. 5: Social cost dissection

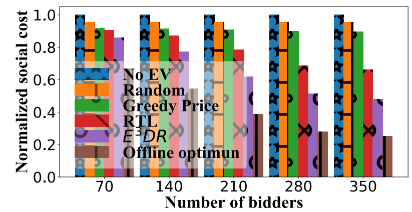


Fig. 6: Social cost comparison

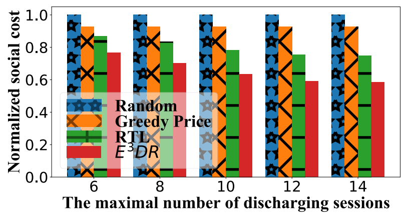


Fig. 7: Social cost vs. facility capacity

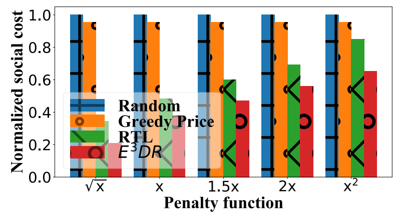


Fig. 8: Social cost vs. penalty function

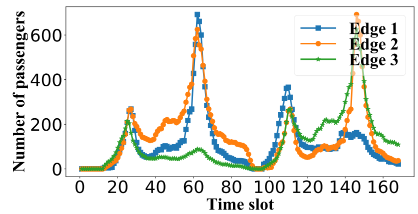


Fig. 9: Passenger counts

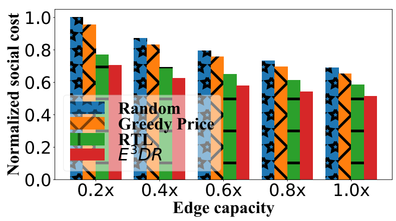


Fig. 10: Social cost vs. edge capacity

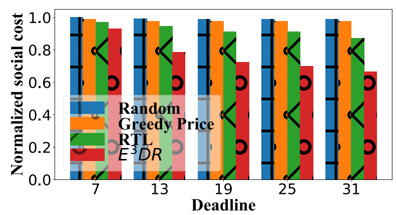


Fig. 11: Social cost vs. deadline

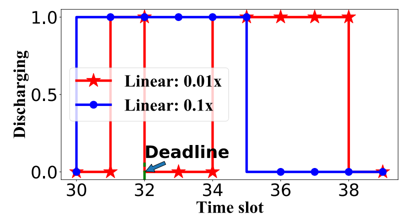


Fig. 12: Discharging dissection

$$\geq \frac{T \max\limits_{t\in[T]}\{m_t R_t\}}{T \max\limits_{t\in[T]}\{m_t R_t\} - T \min\limits_{t\in[T]}\{n_t\} \frac{\min\limits_{t\in[T]}\{R_t\}}{\max\limits_{i\in[I]}\{s_i\}}}$$

$$= \frac{\max\limits_{t\in[T]}\{m_t R_t\}}{\max\limits_{t\in[T]}\{m_t R_t\} - \min\limits_{t\in[T]}\{n_t\} \frac{\min\limits_{t\in[T]}\{R_t\}}{\max_{i\in[I]}\{s_i\}}}$$

$$= \varepsilon$$

where $\hat{I}$ represents the set of winning bids, because of the value of n_t, $-\min\limits_{i\in[I]}\{b_i\} + \sum_{t\in[T]} n_t H < 0$, $\varepsilon > 1$. Therefore this theorem holds for

$$\beta = \gamma + \frac{\gamma - \frac{1}{\alpha}}{\varepsilon - 1}.$$

□

5 Experimental Evaluation

5.1 Experiment Settings

Edge System: We choose 40 underground stations in London and envisage that an edge is located at each of such stations. The geographical distance between two stations is used to approximate the propagation delay between the edges [18]. The dynamic passenger numbers at each station are available, and we use such data to represent the workload of the corresponding edge. The maximum workload allowed at each edge is randomly generated in [400, 500]. The energy reduction by migrating workload across different edges changes randomly in [0, 2] kWh [27].

Demand Response: We consider real-world EDR events of PJM, a regional transmission organization, on Jan. 4, 2014 [20]. The EDR lasted for a total of 168 hours, where we consider one hour as one time slot. In EDR events, it is reported that 25% of the edge system peak IT power consumption is a reasonable reduction, not negatively impacting the participants [19]. The idle and the peak power of an edge could be 8 kWh and 24 kWh, respectively [9]. Therefore, the maximum energy reduction goal is set to 240 kWh and the minimum energy reduction goal is set to 150 kWh based on the real EDR events. The energy reduction goal sent to the edge system from the electricity grid at each time slot is set to be within the range of [150, 240] kWh based on the real EDR events.

EV Bidding: We set $70 \sim 350$ EV bidders [28] [29], each with a single bid. We set the charging facility's capacity as 100, which is the maximum number of simultaneous discharging sessions allowed at any time. We generate the bid arrival sequence randomly over [0, 168]. The electricity that can be discharged from each EV varies randomly within the range of [2, 8] kWh [14] per time slot (but is a fixed value for every given EV). The price of the energy contained in EV bids is set randomly within the range [0.018, 0.078] $/kWh [14]. The battery capacity of each EV is assumed to be 40 kWh, and the amount of discharging energy of each EV is set to be within [0, 40] kWh [21]. Each EV's discharging deadline is randomly generated between its arrival time and the end of the time horizon under consideration. We consider a linear penalty function unless explicitly specified.

Algorithms for Comparison: We implement and compare our approach, E^3DR, against the following approaches: (1) the online approach that uses no EVs or auctions for edge computing demand response; (2) the online random approach which randomly chooses the EV bids; (3) the online greedy approach which chooses the EV bids with the lowest unit energy price; (4) the online algorithm RTL [30], which schedules an EV according to the optimal sum of the deadline violation penalty, the energy cost and the edge network delay, without considering auctions; and (5) the offline optimal approach that solves the problem P via the Gurobi [31] solver, assuming inputs over the entire time horizon are known at once.

5.2 Evaluation Results

Energy Reduction and Social Cost Dissection: Fig. 4 displays the time-varying energy reduction goals from the grid, and how such energy reduction is fulfilled in terms of EV energy discharging and edge computing workload adjustment in each time slot. Introducing EVs helps a lot, while adjusting the edge workload can often achieve limited energy reduction. Fig. 5 shows the social cost in real time, and how much the EV cost and the edge system cost occupies, respectively, in the social cost in each time slot. Upon the arrival of each bid, our algorithms immediately compute the auction outcome and the edge network's workload allocation. Thus, the EV cost increases as the bid wins.

Social Cost of Different Approaches: Fig. 6 demonstrates the social cost of our proposed online approach compared to three different other algorithms as the number of bids increases. This figure shows that our approach E^3DR saves $20\% \sim 50\%$ social cost, performs better than other methods, and is also close to the offline optimum. We also see that the more bids the system has, the less the social cost becomes, because there exists more room for leveraging various bids to optimize the social cost of the entire system.

Impact of Discharging Capacity on Social Cost: Fig. 7 exhibits the social cost of our proposed online approach compared to three other algorithms as the facility capacity (i.e., the allowed maximal number of discharging sessions per time slot) changes. The social cost decreases as the facility capacity increases, because the system can accept more bids simultaneously. We highlight that, as the facility capacity exceeds 12, the social cost sees only minor decrements. This is because the capacity has become 'too large', greater than the number of bids that arrive per time slot; so, continuing to increase the capacity has no significant impact on social cost. This figure also confirms our approach E^3DR performs consistently better than the other methods.

Impact of Penalty Function on Social Cost: Fig. 8 exhibits how the social cost varies when five different penalty functions are applied: $\sqrt{x}$, x, $1.5x$, $2x$ and x^2. As the penalty of the deadline violation becomes more significant, the EV bids are more likely to be rejected by our approach, resulting in the increased social cost. Yet, our approach remains always better than others for different deadline-violation penalty functions.

Impact of Edge Capacity on Social Cost: Fig. 9 displays the number of passengers arriving at each time slot, and Fig. 10 exhibits the social cost of our proposed online approach compared to three other algorithms as edge capacities increase. Because of the larger capacity, the edge system can move more workload around in order to further reduce the social cost.

Impact of Deadline on Social Cost: Fig. 11 exhibits the social cost of our proposed online approach compared to three other algorithms as the deadline of the bids increases. The random and the greedy approaches are not very much impacted by the deadline. As the deadline becomes later, the EV bids are more likely to be accepted by our approach, resulting in the decreased social cost.

Discharging Operations: Fig. 12 exhibits how the discharging operations spread over time slots as dictated by our algorithm for different penalty functions. Here, we pick up one bid randomly, and change the weight of the penalty function for that bid. As shown in the Fig. 13, as the deadline-violation penalty becomes more significant, the EV can only violate the deadline for a fewer number of time slots; also, in this case, the EV can only discharge energy in a more restrictive (and collective) manner across time slots.

Truthfulness: Fig. 14 confirms the truthfulness of our approach. As an example, in this figure, we consider one bid drawn from our EV bids. We can observe that, when bidding the true cost, the utility is maximized. We also see that, the bidding price actually impact the auction outcome, and bidding any price which is lower than the true cost can always win the auction—this actually verifies the monotonicity required in our lemma as described previously.

Individual Rationality: Fig. 15 depicts the EVs' total payment received and their total bidding cost at different time slots. Seventy random bids are selected for 10 consecutive time slots. In fact, for every single bid, we have exactly the same observation—the payment is no less than the bidding cost. Besides, Fig. 14 has also visualized that the utility is indeed non-negative. These phenomena all confirm the individual rationality of our approach.

Impact of Discharging Deadline on Payment: Fig. 16 illustrates how the payment is impacted by the discharging deadline of the bids. Here, we pick up two bids of different bidding cost b_i for this figure. Both bids receive more payments as the deadlines extend; the second bid, which is originally rejected by the auction, even becomes accepted. With deadlines extended, the edge computing system can arrange discharging schedules for EVs more flexibly and thus tend to leverage more bids in the EDR programs.

Empirical Competitive Ratio: Fig. 17 further evaluates the empirical competitive ratio. We see that a smaller value of U/L leads to a better competitive ratio, and the number of bids does not obviously influence the competitive ratio. Here are some explanations: according to Theorem 4, α decreases as U/L decreases, leading to a better competitive ratio; also, α and γ have nothing to do with the number of bids according to Theorems 4 and 5.

Algorithms Execution Time: Fig. 18 shows the running time of our proposed approach on a computer with an Intel(R) Core(TM) i5 CPU of 2.9 GHz and 8 GB memory. Our approach consumes up to about 20 seconds for 350 EVs for the time horizon of 168 hours. Therefore, our approach runs fast and its execution time is acceptable.

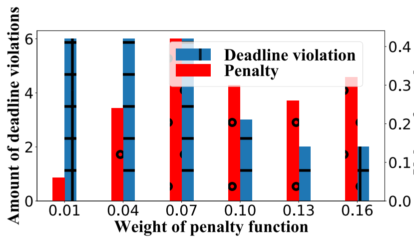


Fig. 13: Deadline violations

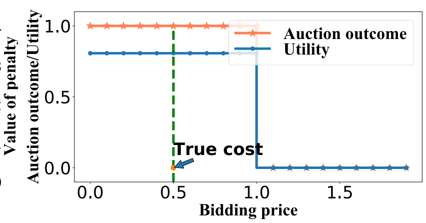


Fig. 14: Truthfulness

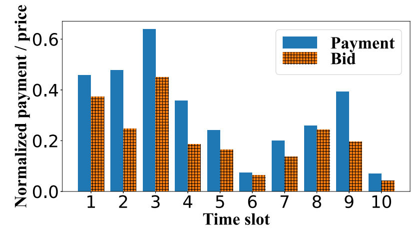


Fig. 15: Individual rationality

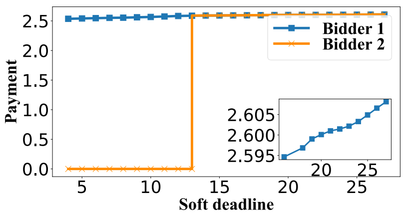


Fig. 16: Payment vs. deadline

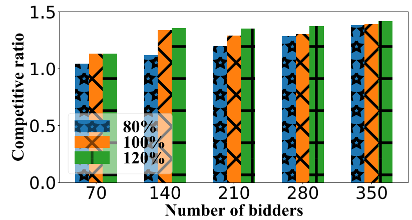


Fig. 17: Empirical competitive ratio

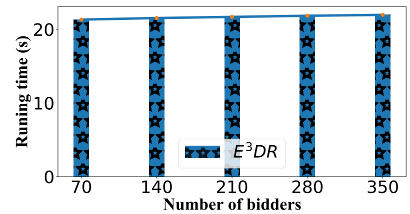


Fig. 18: Algorithms running time

6 Related Work

Demand response for edge computing has gained recent attention. Chen *et al.* [9] propose an online auction mechanism that incentivizes edges to participate in EDR. Song *et al.* [10] design an online task scheduling algorithm selecting clusters to dispatch workload to meet the energy reduction targets. Song *et al.* [32] propose a reverse auction involving local generators to guarantee target EDR power reduction and VCG to ensure truthful auction. Chen *et al.* [11] design an online auction mechanism for performing power EDR and computing EDR altogether for the edge. Cui *et al.* [12] develop a two-phase game-theoretical algorithm to solve the mobile edge computing EDR problem. Zhou *et al.* [33] design efficient online auctions for scheduling cloud computing jobs with completion deadlines. None of these papers have considered leveraging EVs as energy sources, nor deadlines of bids when designing auctions in EDR.

Meanwhile, there exist many studies on online mechanisms for EVs. Li *et al.* [13] propose a randomized auction framework that adopts the smoothed analysis mechanism to incentivize EVs to participate in EDR. Yuan *et al.* [14] design a novel polynomial-time online algorithm and an auction mechanism to incentivize EVs with remaining energy to sell their energy to satisfy EVs charging demand. Zhong *et al.* [15] propose a mechanism that can stimulate energy interaction between EVs and grids via V2G technologies. Yi *et al.* [16] devise an online mechanism that formulates the EV charging scheduling problem with both the charging cost and the EV's dissatisfaction in consideration. Guo *et al.* [17] present an online linear program to handle the online variability of charging rates in each control period. This branch of works are often not for edge computing, and only consider EV charging or the interaction between EVs and the grid; also, none of them have considered the deadlines.

Our work in this paper differs significantly from previous research in multiple aspects. First, we introduce EVs to power edge computing systems, which enhances the flexibility of energy sources and is environmentally friendly, and incorporate this new energy source in EDR of edge computing. Second, we formulate the auction of dynamic EV discharging over time with arbitrary bid arrivals, deadlines, and penalty of deadline violations, rather than a simple single-round auction, for realistic EDR scenarios. Third, to the best of our knowledge, our proposed algorithmic approach is different from all the aforementioned research, featuring the problem decomposition for responsive scheduling and time-based scheduling, the primal-dual maintenance, the payment calculation, and the various performance guarantees.

7 Conclusion and Future Work

EVs and V2G techniques provide new opportunities for realizing edge computing demand response, but have been largely ignored. In this paper, we propose to utilize EVs to power the distributed edge computing system via V2G when it is requested to reduce its energy consumption from the electricity grid in demand response programs. We model and formulate an online optimization problem, focusing on incentivizing EVs to sell their battery energy to the edges via auctions. We design novel decomposition and primal-dual-based algorithms to solve this problem while addressing unpredictable EV arrivals, energy discharge deadlines, and desired economic efficiency. We have proved multiple theoretical performance guarantees and also conducted extensive evaluations to exhibit the practical effectiveness and superiority of our proposed approach compared to others.

For future work, we plan to further explore edge system operations beyond workload migration combined with EV energy provisioning in the edge demand response scenario. For example, allowing partially dropping workload or dynamically turning on/off the edges can bring new challenges and flexibilities when jointly considered with EVs.

References

[1] Y. Li, H. Yu, B. Song, and J. Chen, "Image encryption based on a single-round dictionary and chaotic sequences in cloud computing," *Concurrency and Computation: Practice and Experience*, vol. 33, no. 7, pp. 1–1, 2021.

[2] M. Satyanarayanan, "The emergence of edge computing," *Computer*, vol. 50, no. 1, pp. 30–39, 2017.

[3] L. Zhang, S. Ren, C. Wu, and Z. Li, "A truthful incentive mechanism for emergency demand response in colocation data centers," in *IEEE INFOCOM*, 2015.

[4] Q. Sun, C. Wu, Z. Li, and S. Ren, "Colocation demand response: Joint online mechanisms for individual utility and social welfare maximization," *IEEE Journal on Selected Areas in Communications*, vol. 34, no. 12, pp. 3978–3992, 2016.

[5] I. Mohiuddin and A. Almogren, "Workload aware vm consolidation method in edge/cloud computing for iot applications - sciencedirect," *Journal of Parallel and Distributed Computing*, vol. 123, pp. 204–214, 2019.

[6] Y. Xiao and M. Krunz, "Distributed optimization for energy-efficient fog computing in the tactile internet," *IEEE Journal on Selected Areas in Communications*, vol. 36, no. 11, pp. 2390–2400, 2018.

[7] E. Bulut, M. C. Kisacikoglu, and K. Akkaya, "Spatio-temporal non-intrusive direct v2v charge sharing coordination," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 10, pp. 9385–9398, 2019.

[8] R. Zhang, C. Xiang, and L. Yang, "Stable matching based cooperative v2v charging mechanism for electric vehicles," in *IEEE VTC-Fall*, 2017.

[9] S. Chen and F. Liu, "An online market mechanism for edge emergency demand response via cloudlet control," in *IEEE INFOCOM*, 2019.

[10] Z. Song, R. Zhou, S. Zhao, S. Qin, and Z. Li, "Edge emergency demand response control via scheduling in cloudlet cluster," in *IEEE INFOCOM WKSHPS*, 2020.

[11] S. Chen, L. Jiao, F. Liu, and L. Wang, "Edgedr: An online mechanism design for demand response in edge clouds," *IEEE Transactions on Parallel and Distributed Systems*, vol. 33, no. 2, pp. 343–358, 2021.

[12] G. Cui, Q. He, X. Xia, F. Chen, T. Gu, H. Jin, and Y. Yang, "Demand response in noma-based mobile edge computing: A two-phase game-theoretical approach," *IEEE Transactions on Mobile Computing*, pp. 1–1, 2021.

[13] R. Zhou, Z. Li, C. Wu, and M. Chen, "Demand response in smart grids: A randomized auction approach," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 12, pp. 2540–2553, 2015.

[14] Y. Yuan, L. Jiao, K. Zhu, and L. Zhang, "Scheduling online ev charging demand response via v2v auctions and local generation," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 8, pp. 11 436–11 452, 2022.

[15] W. Zhong, X. Kan, L. Yi, Y. Chao, and S. Xie, "Efficient auction mechanisms for two-layer vehicle-to-grid energy trading in smart grid," in *IEEE ICC*, 2017.

[16] H. Yi, Q. Lin, and M. Chen, "Balancing cost and dissatisfaction in online ev charging under real-time pricing," in *IEEE INFOCOM*, 2019.

[17] L. Guo, ErlikssonKF, and LowSH, "Optimal online adaptive electric vehicle charging," in *IEEE PESGM*, 2017.

[18] L. Jiao, L. Pu, L. Wang, X. Lin, and J. Li, "Multiple granularity online control of cloudlet networks for edge computing," in *IEEE SECON*, 2018.

[19] G. Ghatikar, V. Ganti, N. Matson, and M. A. Piette, "Demand response opportunities and enabling technologies for data centers: Findings from field studies," lawrence Berkeley National Laboratory, Tech. Rep. LBNL-5763E, 2012. [Online]. Available: http://drrc.lbl.gov/sites/all/files/ LBNL-5763E.pdf

[20] "Demand response activity on january 7-8, 2014." [Online]. Available: http://www.pjm.com

[21] D. Li, Q. Yang, W. Yu, D. An, X. Yang, and W. Zhao, "A strategy-proof privacy-preserving double auction mechanism for electrical vehicles demand response in microgrids," in *IEEE IPCCC*, 2017.

[22] R. Al, "Strengthening integrality gaps for capacitated network design and covering problems," *Proceedings of the Eleventh Annual ACM-SIAM Symposium on Discrete Algorithms (San Francisco, CA, 2000)*, pp. 106–115, 2000.

[23] N. Nisan, T. Roughgarden, E. Tardos, and V. V. Vazirani, "Algorithmic game theory," 2007.

[24] R. B. Myerson, "Optimal auction design," *Discussion Papers*, vol. 6, no. 1, pp. 58–73, 1981.

[25] M. Babaioff, "Truthful mechanisms for one-parameter agents," in *IEEE FOCS*, 2001.

[26] S. Boyd and L. Vandenberghe, *Convex Optimization*. Convex Optimization, 2004.

[27] E. Strubell, A. Ganesh, and A. McCallum, "Energy and policy considerations for deep learning in nlp," *arXiv preprint arXiv:1906.02243*, 2019.

[28] M. Tian, Z. Xin, and Z. Baorong, "Modeling and solving method for supporting 'vehicle-to-anything' ev charging mode," *Applied Sciences*, vol. 8, no. 7, pp. 1048–1048, 2018.

[29] Y. Gu and M. Liu, "Fair and privacy-aware ev discharging strategy using decentralized whale optimization algorithm for minimizing cost of evs and the ev aggregator," *IEEE Systems Journal*, vol. 15, no. 4, pp. 5571–5582, 2021.

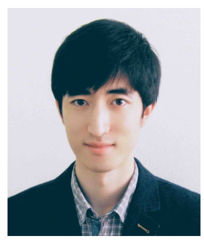
[30] N. Jain, I. Menache, J. Naor, and J. Yaniv, "Near-optimal scheduling mechanisms for deadline-sensitive jobs in large computing clusters," *ACM Transactions on Parallel Computing*, vol. 2, no. 1, pp. 1–29, 2015.

[31] "Gurobi." [Online]. Available: http://www.gurobi.com

[32] Z. Song, R. Zhou, S. Zhao, S. Qin, J. Lui, and Z. Li, "Emergency demand response in edge computing," *EURASIP Journal on Wireless Communications and Networking*, vol. 2020, no. 1, pp. 1–24, 2020.

[33] R. Zhou, Z. Li, C. Wu, and Z. Huang, "An efficient cloud market mechanism for computing jobs with soft deadlines," *IEEE/ACM Transactions on Networking*, vol. 25, no. 2, pp. 793–805, 2017.

Fei Wang received the master's degree in Information and Communication Engineering from Harbin Engineering University, China, in 2021. He is currently working towards the Ph.D. degree in School of Artificial Intelligence in Beijing University of Posts and Telecommunications. His research interests are in the areas of online learning and federated learning.



Lei Jiao received the Ph.D. degree in computer science from the University of Göttingen, Germany. He is currently an assistant professor at the Department of Computer Science, University of Oregon, USA. Previously he worked as a member of technical staff at Nokia Bell Labs in Dublin, Ireland and as a researcher at IBM Research in Beijing, China. He is interested in the mathematics of optimization, control, learning, and economics applied to computer and telecommunication systems, networks, and services. He publishes papers in journals such as JSAC, ToN, TPDS, TMC, and TDSC, and in conferences such as INFOCOM, MOBIHOC, ICNP, ICDCS, SECON, and IPDPS. He is an NSF CAREER awardee. He also received Best Paper Awards of IEEE LANMAN 2013 and IEEE CNS 2019. He was on the program committees of many conferences, including INFOCOM, MOBIHOC, ICDCS, IWQoS, and WWW, and was also the program chair of multiple workshops with INFOCOM and ICDCS.

Konglin Zhu received the master's degree in computer Science from the University of California, Los Angeles, CA, USA, and the Ph.D. degree from the University of Göttingen, Germany, in 2009 and 2014, respectively. He is now an Associate Professor with the Beijing University of Posts and Telecommunications, Beijing, China. His research interests include Internet of Vehicles, Edge Computing and Distributed Learning.

Lin Zhang received the B.S. and the Ph.D. degrees in 1996 and 2001, both from the Beijing University of Posts and Telecommunications, Beijing, China. From 2000 to 2004, he was a Postdoctoral Researcher with Information and Communications University, Daejeon, South Korea, and Nanyang Technological University, Singapore, respectively. He joined Beijing University of Posts and Telecommunications in 2004, where he has been a Professor since 2011. He is also the director of Beijing Big Data Center. His current research interests include mobile cloud computing and Internet of Things.