Who's in Charge Here? Scheduling EV Charging on Dynamic Grids via Online Auctions with Soft Deadlines

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ABSTRACT

The electrification of transport is a crucial step towards decarbonizing energy use and meeting climate goals. However, the increased penetration of electric vehicles also drives substantial additional load on the electricity grid; failure to manage this load can result in higher costs and reduced reliability of electricity. In this study, we present a novel online, auction-based technique to manage the charging of electric vehicles. Our technique draws insight from the cloud computing literature, making use of the concept of soft deadlines to ensure high satisfaction among users, reduced costs for charging infrastructure providers, and maximum flexibility for the electricity system. We evaluate our technique with a range of dynamics possible on typical electricity grids, including variable electricity tariffs and deployment of solar photovoltaic generation. Additionally, we consider vehicle-to-vehicle charging, an emerging paradigm for peer-to-peer energy transfer. Compared to uncontrolled charging and two typically deployed algorithms, our results show improved cost and performance in every scenario, with a reduction in costs of 3.5% to 12% compared to the baseline controlled approaches.

CCS CONCEPTS

• **Theory of computation** → **Scheduling algorithms**; *Online algorithms*; • **Hardware** → *Smart grid*;

KEYWORDS

Electric vehicles, online algorithms, auction, smart grids

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1 INTRODUCTION

The electrification of the transportation sector brings together two massive segments of the primary energy budget. In parallel with the decarbonization of the electric power sector, this transformation towards increasing penetration of electric vehicles (EVs) will have profound impacts on the built environment, most notably on electricity grids. According to the Global EV Outlook [1], more than 2.1 million electric vehicles were sold in 2019 with a year-on-year sales growth above 30% since 2016. Moreover, the infrastructure for EV charging is expanding at a rapid pace. In 2019, the number of publicly-accessible slow and fast chargers increased by 60% in comparison to 2018 and globally the total number of chargers is around 7.3 million, surpassing the stock of EVs. This increased load on electric grids from EVs leads to strain on transformers [28] in the short-term and perhaps even bulk supply as penetration continues to increase.

Improved control of EV charging activities is crucial to manage this strain, enabling existing infrastructure to last longer, future infrastructure to be planned more efficiently, and society to increase overall sustainability. Such control aims primarily to charge the vehicles during periods of low electricity demand and take advantage of the renewable generation available. However, there is a range of technologies with different degrees of complexity that can be used not only to reduce this excessive demand on the grid but also to enable energy sharing between vehicles due to the flexibility inherent to the storage capacity of EVs based on real-time information. These dynamics are also present beyond energy systems. For example, in cloud management [26, 34] and data center optimization [18, 20], it has become fundamental to use online optimization techniques to allocate resources in response to real-time "cost" signals and changes in these uncertain environments.

In this paper, we present a technique for efficient online scheduling of EV charging jobs on dynamic electricity grids using empirical data [16] on EV arrivals. We draw inspiration for our technique from the cloud computing community, where providers receive multiple computing jobs with a variety of infrastructure requirements and job durations and must efficiently schedule those jobs to run on their data centers despite error-prone predictions of job characteristics. In particular, we build upon previous work [37] that handles the scheduling of computing jobs under the impact of Demand Response (DR) signals [3] and operating costs, but instead we apply this formulation to the domain of EV charging. Similarly, as in [37], our goal is to present an online auction mechanism to maximize social welfare of both the facility that provides the EV charging service as well as the EV user.

EV charge scheduling is an active area of research – we present a discussion of related work in Section 2. In particular, deadlines for EV charging jobs are often either predicted by algorithms based on historical data or actively solicited from users, both often presented as hard deadlines with substantial penalties for failure; we recognize weaknesses in each of these approaches. Our solution differs in

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that it uses *soft deadlines*, which provide guidance to our algorithm but enable increased flexibility that is valuable to meet constraints presented by the electricity supply, enabling both improved social welfare and reduced costs.

Further, by harnessing an online approach in addition to soft deadlines, our algorithm can allow the charging infrastructure to take the optimal decision one time window at the time. Increased adoption of fluctuating renewable energy sources and the increased deployment of variable electricity pricing schemes further call for online algorithms that adapt to changing constraints. Others have indeed addressed the charging problem under real-time pricing [32], where neither accurate predictions nor distribution of future real-time prices are available to users when making online decisions; however, these pricing scenarios are not prevalent in practice. Our work considers a range of dynamics on electricity systems that are common, including variable penetration of renewable sources of energy as well as the presence of demand response (DR) services. For DR, electric utilities commonly use rate increases, bill credits, or other incentives to control demand on the grid during periods when load generation imbalances threaten the reliability of the electricity supply.

Specifically, this work proposes a novel mathematical formulation for scheduling of EV charging jobs with soft deadlines as a foundation (Section 3). We present an online, auction-based technique for efficiently selecting jobs at each time step (Section 4).

In our evaluation (Section 5), we explore the impact of a range of electricity supply dynamics, including i) EV charging tariffs; ii) levels of integration with renewable sources; iii) demand response services for the central grid; and iv) integration of vehicle-to-vehicle charging techniques. We show that our auction-based technique results in lower user costs than commonly-used algorithms in all cases considered. Last, we conclude by discussing future directions for this work.

2 RELATED WORK

More widespread adoption of EVs certainly causes higher demand on central grids, however, previous work, e.g. [22], have already shown that while charging EVs will indeed further stress the current central grid, there is plenty of flexibility when deciding when and at which power rate to charge the EVs.

In sight of such flexibility, there is vast literature aimed at optimization and scheduling strategies for charging EVs (e.g. [8, 21, 31, 35] to name a few) and more recently Schlund et al. [23] explored the implications for large scale EV fleets. In terms of online design mechanisms there is significant literature with applications in EV but with less emphasis on improving social welfare [24, 30, 36] than in total valuation of served jobs [2, 4, 6, 19, 25, 27].

In [30], the authors propose an online auction framework for the park-and-charge scenario in which the goal is to maximize social welfare and user satisfaction; however, this work does not consider grid dynamics such as DR services, EV charging tariffs, or vehicle-to-vehicle energy sharing. In [25], the authors propose an online recommendation system for charging EVs based on a bid-price control policy. The goal is to provide spatial and temporal scheduling for EVs that have freedom to make decisions about charging at a certain facility with a given charging price or reject the offer from the charging network operator and reduce the energy demand or move to a different facility. Even though this work includes changes in tariffs, it does not consider soft deadlines for disconnection given the flexibility that charging jobs may offer.

Most research has tried to create an optimal scheduler by predicting when a user is going to disconnect [16, 29]; however, this typically turns out to be far from accurate, with mean average errors of almost two hours in many scenarios. To put this in perspective, two hours is enough to charge a mid-sized EV between 35% to 50% of its full capacity.

Therefore, given the inaccuracies when predicting disconnection time, many EV charging facilities opted to pass the burden to EV users and directly ask them for how long they estimate their EV will be connected (e.g. [16]). However, users can handle that prerogative as a free card to set deadlines that are ultraconservative in order to guarantee that their EVs will be fully charged before their departure; in fact, average error was nearly worse than the one output by the prediction algorithms, hence increasing even further the operational expenditures from the charging facility operator.

By using soft deadlines, our approach targets a middle ground between the poor satisfaction performance or greediness of deadline prediction techniques and the overuse of charging resources and cumbersome nature of user-entered deadlines. We draw this insight from the cloud computing literature [37], where the authors propose an online auction for dynamic cloud resource provisioning with the presence of emergency demand response programs. The main insight is that similar to datacenters where computing jobs can use a variety of resources to complete a task, EVs can be charged with a dynamic rate and can tolerate soft deadlines given by the idle time after the vehicle has completely charged. In addition, datacenter and EV charging facilities are ideal candidates for DR programs due to their high electricity demand and the elastic nature of their loads; this can enhance the reliability and sustainability of the power grid if the consumption is allocated efficiently.

In this work, we closely follow the formulation presented in [37], with a key difference that we must adapt our scheduling selection algorithm to handle the online variability of charging rates that is present at the beginning of the provisioning. In order to overcome this difference, we modify the schedule selection mechanism using an existing dynamic programming formulation for the Minimum Cost Maximal Knapsack problem [5]. We explain this in detail in the coming sections.

3 MODELS AND FORMULATION

In this section, we describe our system and define our problem formulation and algorithms. We present an adaptation of the problem formulation presented in [37] where the authors develop an online auction mechanism to schedule computing jobs given of Demand Response signals (DR) and the desire to reduce operating costs. Similarly, our goal is to present an online auction mechanism to maximize social welfare among the charging facility and the EV users using a soft deadline to meet the charging demand.

3.1 System Settings and Models

We study the charging scheduling problem in an online fashion with the design of an auction mechanism. We provide the following components for our problem formulation:

Time Horizon. We consider a time-slotted system model of T time slots of equal length κ. We define a prediction window of W in which the electricity prices are available.

Charging Jobs. There are I EV users that arrive dynamically to the charging facility. Upon arrival, each charging job i provides its arrival timestamp t_i, energy demand σ_i, a bidding value b_i if the charging session is completed before the deadline d_i, and a non-decreasing penalty function for passing the deadline with τ_i as the violation:

$$\rho_i(\tau_i) = \begin{cases} \rho_{c_i}(\tau_i), & \text{if } \tau_i \in [0, T - d_i] \\ +\infty, & \text{otherwise} \end{cases} \tag{1}$$

with $\rho_{c_i}(0) = 0$ and τ_i representing the number of time slots after passing the deadline. The completion time is given by $d_i + \tau_i$ and the corresponding bidding price is $b_i - \rho_i(\tau_i)$. The charging job's bid can be expressed as $B_i = \{t_i, \sigma_i, b_i, d_i, \rho_i(\tau_i)\}$.

Charging Stations. Upon arrival, each charging job is associated to one EV supply equipment (EVSE) or charging station that supports J different charging rates. A facility is composed of multiple EVSEs so the maximal number of charging sessions that can be attended at any time is C. Each station can provide a different energy level E_j based on its respective charging rate j.

Operating cost. We model the energy consumption cost as the operating cost for the charging facility. It depends on the power levels used in each EVSE and the electricity price h_t at time t provided by the power utility company. The electricity price is known during the prediction window W before the auction starts. The cost function associated to the charging facility can be defined as:

$$f_t(e_t) = \begin{cases} h_t e_t, & \text{if } e_t \leq \Omega_t \kappa \\ +\infty, & \text{otherwise} \end{cases} \tag{2}$$

where e_t and Ω_t represent the aggregated energy drawn from the grid and the power cap given by a demand response signal respectively.

Decision Variables. This formulation uses $x_i \in \{0, 1\}$ to represent whether to accept the charging job i after the bidding; $y_{it} \in \{0, 1\}$ indicates whether to charge the job i at the time slot t; and $z_{ijt} \in \{0, 1\}$ whether to select the rate j to charge the job i at the time slot t.

In this work, we define the auctioneer and bidders as the charging facility and EV users (charging jobs) i respectively which request σ_i amount of energy with a tolerant deadline d_i. The facility computes the power allocation at each t based on x_i, y_i and z_{ijt}; then, each EV user pays π_i for their charging session based on the auction results. We assume the bidders submit a truthful valuation as a dominant strategy which leads to a truthful auction.

3.2 Problem Formulation

Social welfare. Each EV user aims to maximize its own utility and it is assumed that they are selfish and rational. Using the true valuation v_i and penalty $\rho'_i(\tau_i)$ for job i's bid, the utility for each i is given by $u_i(b_i - \rho_i(\tau_i)) = v_i x_i - \rho'_i(\tau_i) - \pi_i$. Similarly, the charging facility's utility is defined as the difference between the aggregated EV user's payments and the electricity cost function: $\sum_{i \in [I]} \pi_i - \sum_{t \in T} f_t(e_t)$. Assuming truthful bidding, the social welfare is defined as the aggregated utility of the EV users and the charging facility. Since the aggregated payments from EVs and the facility π_i cancel themselves, summing them up cancels the payment, and leads to social welfare as follows: $\sum_{i \in [I]}(v_i x_i - \rho'_i(\tau_i)) - \sum_{t \in T} f_t(e_t)$.

Having the above, we formulate an optimization problem as follows:

$$\max \quad \sum_{i \in [I]} \Big(b_i x_i - \rho_i(\tau_i) \Big) - \sum_{t \in [T]} f_t(e_t) \tag{3}$$

$$\text{s.t.} \quad y_{it} t \leq d_i + \tau_i, \forall t \in [T], \forall i \in [I] \colon t \geq t_i, \tag{3a}$$

$$\sigma_i x_i \leq \sum_{t \in [T] \colon t \geq t_i} \sum_{j \in [J]} z_{ijt} E_j, \forall i \in [I], \tag{3b}$$

$$z_{ijt} \leq y_{it}, \forall i \in [I], \forall j \in [J], \forall t \in [T], \tag{3c}$$

$$\sum_{i \in [I] \colon t \geq t_i} y_{it} \leq C, \forall t \in [T], \tag{3d}$$

$$\sum_{i \in [I] \colon t \geq t_i} \sum_{j \in [J]} z_{ijt} E_j \leq e_t, \forall t \in [T], \tag{3e}$$

$$\sum_{j \in [J]} z_{ijt} \leq 1, \forall i \in [I], \forall t \in [T], \tag{3f}$$

$$x_i \in \{0, 1\}, y_{it} \in \{0, 1\}, z_{ijt} \in \{0, 1\}, \tau_i \in \{0, 1, 2, \ldots, W\},$$
$$e_t \geq 0, \forall i \in [I], \forall j \in [J], \forall t \in [T], \tag{3g}$$

The objective is to maximize social welfare in the EV charging ecosystem where constraint (3a) ensures that a charging job is scheduled to run upon arrival. Constraint (3b) guarantees that the energy requirement from job i can be met during the time horizon and with the energy levels selected. Constraint (3c) records the nature of the decision variables. Constraint (3d) restricts the number of jobs allocated at any given time to the maximal number of charging sessions allowed in the facility. Constraint (3e) records the total energy consumption into e_t. Constraint (3f) ensures that only one set point is selected for each charging job at any given t.

Challenges. Solving the above problem is non-trivial and we confront fundamental challenges. We are in an "online" setting where job arrivals and each job's information is unknown to us. (1) Any charging job i arrives dynamically at t_i. Its information of $(t_i, d_i, b_i, \sigma_i, \rho(\cdot))$ cannot be known *a priori*, and can only be known as it arrives. (2) For the job i, at t_i, the power prices in $[t_i, d_i + W]$ are accurately predicted; the power prices beyond $d_i + W$ remain unknown. That is, at t_i, $f_t(\cdot)$, $\forall t \in [t_i, d_i + W]$ is known, and is not known beyond. (3) As soon as the job i arrives, its decision of $(x_i, y_{it}, z_{ijt}, \tau_i, e_t)$, $\forall j, \forall t \in [t_i, d_i + W]$ is made. In particular, we do not re-calculate y_{it} and e_t as time goes; rather, we determine y_{it} and e_t, $\forall t \in [t_i, d_i + W]$ at once at t_i. (4) The following inputs are all known beforehand: κ, W, C, and E_j, $\forall j \in [J]$. However, $[T]$ does not have to be known beforehand.

Equivalent Reformulation. In order to overcome the aforementioned challenges and following the approach in [37], we use the primal-dual algorithm design technique. However, it is not possible to apply this technique directly to the formulation in (3) since it involves unconventional constraints to model the EV charging soft-deadline [37]. In addition, we can leverage the key insight that the electricity price is often available within a prediction window that often occurs when commercial and industrial consumers sign an agreement with a power utility to have variable electricity tariffs but not necessarily in real time. Consequently, we reformulate our approach as an online charging schedule selection problem to handle the presence of the penalty function for the soft deadlines in (3).

Let θ_i be the set of feasible time schedules and energy levels for job i to accomplish the energy demand and l one entry of θ_i that contains the decision variables for each time and the deadline violation of that specific schedule $l : (\{x_i\}, \{y_{it}\}_{\forall t\in[T]}, \{z_{ijt}\}_{\forall t\in[T],\forall j\in[J]}, \tau_i)$ that satisfies constraints (3a) and (3b). This leads to the decision variable x_{il} that indicates whether the charging job is accepted and attended according to the selected schedule $l \in \theta_i$ and b_{il} is the bid price based on schedule l. $T(l)$ and $J(l)$ represent the set of time slots that dictate when the charging job is attended and what set point is used in schedule l. The new formulation is as follows:

$$\max \quad \sum_{i\in[I]} \sum_{l\in\theta_i} b_{il}x_{il} - \sum_{t\in T} f_t(e_t) \tag{4}$$

$$\text{s.t.} \quad \sum_{l\in\theta_i} x_{il} \leq 1, \forall i \in [I] \tag{4a}$$

$$\sum_{i\in[I]} \textstyle\sum_{l:t\in T(l)} x_{il} \leq C, \forall t \in [T] \tag{4b}$$

$$\sum_{i\in[I]} \sum_{l:t\in T(l)} \sum_{j:j\in J(l)} x_{il}\cdot E_j \leq e_t, \forall t \in [T] \tag{4c}$$

$$x_{il} \in \{0,1\}, e_t \geq 0, \forall l \in \theta_i, \forall t \in [T], \forall i \in [I] \tag{4d}$$

Constraint (4a) ensures that at most one schedule is selected for the charging session, and constraints (4b) (4c) are equivalent to (3d) and (3e) respectively.

Dual Problem Formulation. Having now the formulation in (4a) we derive the formulation of the dual problem [14] which requires the definition of the non-negative dual variables u_i, α_t and q_t for each constraint (4a), (4b), and (4c). It also requires the relaxation of $x_{il} \in \{0,1\}$ to $x_{il} \geq 0$. The dual formulation is as follows:

$$\min \quad \sum_{i\in[I]} u_i + \sum_{t\in[T]} \alpha_t C + \textstyle\sum_{t\in[T]} sup_{e_t\geq 0}\{q_t e_t - f_t(e_t)\} \tag{5}$$

$$\text{s.t.} \quad u_i \geq b_{il} - \sum_{t\in T(l)} (\alpha_t + q_t \sum_{j\in J(l)} E_j), \forall i \in [I], \forall l \in \theta_i \tag{5a}$$

$$u_i, \alpha_t, q_t \geq 0, \forall t \in [T], \forall i \in [I] \tag{5b}$$

4 ONLINE MECHANISM DESIGN

The goal of this online auction design is to determine if a charging job is accepted and attended during a feasible schedule that maximizes the utility for the charging facility and the EV user. This feasible online scheduler must consider the power constraints derived by the DR signal. If a charging job is accepted ($x_{il} = 1$), y_{it} reflects the time slots in which the EV would be charging and e_t is updated based on the aggregated EV charging consumption. According to our dual formulation presented in the previous section, the auction winner is determined by the value of u_i in constraint (5a). Since u_i is non-negative, it can be the maximum of 0 and the right hand side of the constraint. It also indicates that the charging facility would accept its bid only if $u_i > 0$ and use the schedule that maximizes the right hand side of (5a).

Similarly as in [37], if we interpret u_i, α_t, and q_t as the EV user's utility, unit capital price, and unit electricity price at time t, then the term $\sum_{t\in T(l)}(\alpha_t + q_t \sum_{j\in J(l)} E_j)$ in the right hand side of (5a) represents the total cost of the charging job i using the schedule l; therefore, it assures that i is always accepted and scheduled with the l that maximizes the utility and social welfare as well as guarantees truthfulness.

The design of the dual variables α_t and q_t is as follows:

$$q_t = h_t \tag{6}$$

$$\alpha_t = (L - h_t)\left(\frac{U-h_t}{L-h_t}\right)^{\frac{z_{ijt}E_j}{max(E_j)}} \tag{7}$$

Where $U = \max_{i\in[I]:\sigma_i>0}\left\{\frac{b_i}{\sigma_i}\right\}$ and $L = \min_{i\in[I]:\sigma_i>0}\left\{\frac{b_i-\rho_i(T-d_i)}{\sigma_i}\right\}$, and $L > h_t$. Equation (6) refers to the interpretation of q_t as the unit electricity price. For (7), U and L represent maximum and minimum value per unit of electricity per unit of time so the unit capital price α_t starts at $L - h_t$ when the ratio between the selected energy level and the maximum available level j is small and grows exponentially up to $U - h_t$ when the ratio tends to 1.

Even though the new formulation allows us to use the primal-dual technique, it generates an exponential number of options to obtain an optimal schedule that maximizes social welfare. In order to meet the demand of each charging job i, we can select multiple time slots in T with different energy levels J.

Since we want to minimize the cost of energy levels allocated in different time slots while ensuring the allocated energy levels meet the requested demand σ_i, we define our schedule selection as a minimum-cost maximal knapsack packing problem (MCMKP). We use a dynamic programming (DP) algorithm proposed by [5] which outperforms state-of-the-art mixed-integer programming solvers and runs in $O(n\sigma_i)$ time and $O(n + \sigma_i)$ space. We adapt this algorithm to our problem and present it in algorithm 3. Our MCMKP receives items with the cost of using an energy level at time t, the discrete value of E_j and the capacity of the knapsack in the form of energy demand σ_i. Then it computes the knapsack for a common time window W where tariffs are known, but penalizing more time slots $\in [d_i, W]$. Lines 2-22 compute the MCMKP and lines 23-31 present the backtracking procedure to obtain the optimal items for the knapsack.

Algorithm 3 is embedded in line 4 of the online scheduling algorithm 2 which given the inputs in line 1, generates the input items for the MCMKP algorithm (line 3), determines the cost of charging in the selected time slots $t \in T(l)$(lines 6-7), evaluates if the bid is accepted (line 8) and if so, updates the decision variables, computes the price to be paid by the EV user and updates the e_t(lines 9-11). Finally, it returns the schedule and the aforementioned variables to the online auction algorithm 1. Algorithm 1 receives the bids from the arriving EV charging jobs and initializes dual and primal decision variables in line 4. Upon charging job arrival, computes Algorithm 2(line 5) and if i's bid is accepted, charge the setup the set points and schedule to attend the charging session and requests a payment π_i from the EV user.

Online Algorithm. We present our algorithm as follows.

Algorithm 1: Online Auctions

Input: Bidding language B_i, Ω_t, h_t, C.
Define cost function $f_t(e_t)$;
Define function α_t;
Initialize $x_i = 0, y_{it} = 0, z_{ijt} = 0$, $x_{il} = 0$, $u_i = 0$, $\alpha_t = 0$, $q_t = h_t$, $e_t = 0, \forall i \in [I], \forall l \in \theta_i, \forall t \in [T]$;
As soon as the i**th charging job arrives**
$(x_i, \{y_i t\}, \pi_i, \{\alpha_t\}, \{z_{ijt}\}, \{e_t\}) = A_{sch}(B_i, \{\Omega_t\}, \{\alpha_t\}, \{z_{ijt}\}, \{q_t\}, \{e_t\})$;
if $x_i = 1$ **then**
    Accept job i's bid;
    Charge according to y_{it} and z_{ijt};
    Charge π_i for job i.

Algorithm 2: Scheduling Algorithm (A_{sch})

Input: $B_i, C, \{\Omega_t\}, \{\alpha_t\}, \{z_{ijt}\}, \{q_t\}, \{e_t\}$.
Output: $x_i, \{y_{it}\}, \pi_i, \{\alpha_t\}, \{z_{ijt}\}, \{e_t\}$.
Add $(z_{ijt}E_j, q_t, t)$ $\forall t \in [t_i, T]$ to set Υ if $\exists\, z_{ijt} : \sum_{i \in [I]} z_{ijt}E_j + e_t \leq \Omega_t \kappa$ and $\sum_{i \in [I]} y_{it} \leq C$;
$\{z_{ijt}E_j\} = MCMKP(\Upsilon, \sigma_i)$;
Let l include the t slots $\in \{z_{ijt}E_j\}$;
$c(t) = \alpha_t + q_t z_{ijt} E_j, \forall t \in T(l)$;
$P = \sum_{t \in T(l)} c(t)$;
if $b_i - P > 0$ **then**
    $x_i = 1$; $y_{it} = 1$; $\forall t \in T(l)$; $x_{il} = 1$;
    $u_i = b_i - P$; $\pi_i = \sum_{t \in T(l)} \alpha_t + q_t z_{ijt} E_j$;
    $e_t = e_t + \sum_{i \in [I]} \sum_{l:t \in T(l)} \sum_{j:j \in J(l)} x_{il} \cdot E_j$;
end
return $x_i, \{y_{it}\}, \pi_i, \{\alpha_t\}, \{z_{ijt} \in T(l)\}, \{e_t\}$

Algorithm 3: The Minimum-Cost Maximal Knapsack Packing Problem (MCMKP)

Input: Set of items with cost m_v and energy level $z_v E_v$ where v is a decreasing index of items sorted by energy level with a corresponding t.
Energy requirement σ_i.
Sums of costs $C_v = \sum_{\alpha < v} m_v$.
Sums of energy levels $Z_v = \sum_{\alpha < v} z_v E_v$.
v_c :Index of the first item that exceeds the energy requirement σ_i.
Output: S^*: The optimal set of $z_v E_v$ with a corresponding t.
Set $M[0] = 0, OPT = \infty$;
Set $A_v[k] = 0, \forall v \in \{v = |\Upsilon|, \ldots, 1\}, \forall k \in \{k = 1, \ldots, \sigma_i\}$;
for k=1,...,σ_i **do**
    Set $M[k] = \infty$;
end
for $v = |\Upsilon|, \ldots, 1$ **do**
    if $v \leq v_c$ **then**
        Set $\overline{\sigma_i} = \max\{0, \sigma_i - Z_v\}$, and $\underline{\sigma_i} = \max\{0, \sigma_i - Z_v - z_v E_v + 1\}$;
        Set $tmp = \min_{\underline{\sigma_i} \leq k \leq \overline{\sigma_i}} \{M[k] + C_v\}$;
        if $tmp < OPT$ **then**
            Set $OPT = tmp, v^* = v$, $\sigma_i^* = argmin_{\underline{\sigma_i} \leq k \leq \overline{\sigma_i}} \{M[k] + C_{v^*}\} + Z_{v^*}$;
        end
    end
    for $k = \sigma_i, \ldots, z_v E_v$ **do**
        Set $M[k] = \min\{M[k], M[k - Z_v] + m_v\}$;
        if $\min\{M[k], M[k - Z_v] + m_v\} = M[k - Z_v] + m_v$ **then**
            $A_v[k] = 1$;
        end
    end
end
$S^* = \{1, \ldots, v^* - 1\}$;
$k = \sigma_i^* - Z_{v^*}$;
for $v = v^*, \ldots, |\Upsilon|$ **do**
    if $A_v[k] = 1$ **then**
        Append $z_v E_v$ to S^* ;
        $k = k - z_v E_v$;
    end
end
return S^*

5 EXPERIMENTAL EVALUATIONS

In order to evaluate our online algorithm, we leverage an existing open source simulator that provides real traces of EV charging sessions and baseline offline algorithms that allow us to compare with our implementation [15]. In addition, we simulate an EV charging facility and implement the presence of PV-solar generation and vehicle-to-vehicle (V2V) charging capabilities. Since those capabilities can be modeled as DR signals, our formulation holds and can be evaluated altogether with different Time-of-Use tariffs. Figure 1 illustrates the set of components that intervene in our simulation where solar generation is usually available during day time and V2V is allocated based on arrival of vehicles willing to perform this function.

5.1 Datasets

EV charging data is extracted from the Caltech Adaptive Charging Network (ACN) dataset [16]. It is composed of over 23 thousand charging sessions that were collected between 2018 and 2019 from 54 EVSEs located at one of Caltech's campus garages. Each charging session includes the following fields: connection and disconnection time, time of the last non-zero current draw recorded, amount of energy delivered, unique identifier of the EVSE, unique identifier of the user, and other inputs provided by the users (e.g., energy requested or expected departure time). Figure 2 illustrates the connection and disconnection distribution throughout the day. These events show a bimodal pattern that is commonly observed in a workplace charging environment where EVs plug-in around 8 am and disconnect at 5 pm.

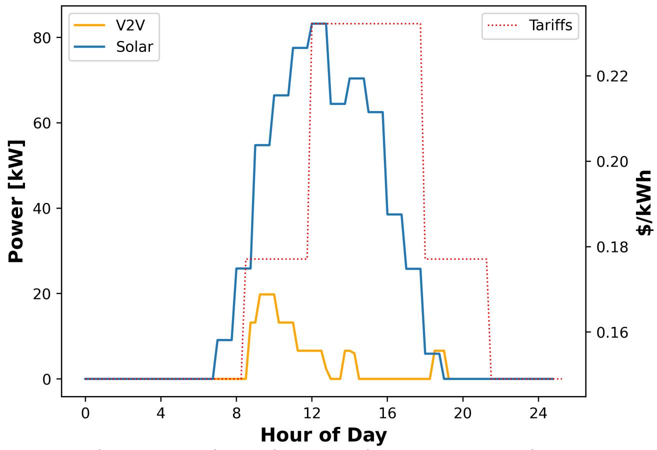

Figure 1: Changes in solar and V2V production power and variations in tariff prices over a 24-hour period.

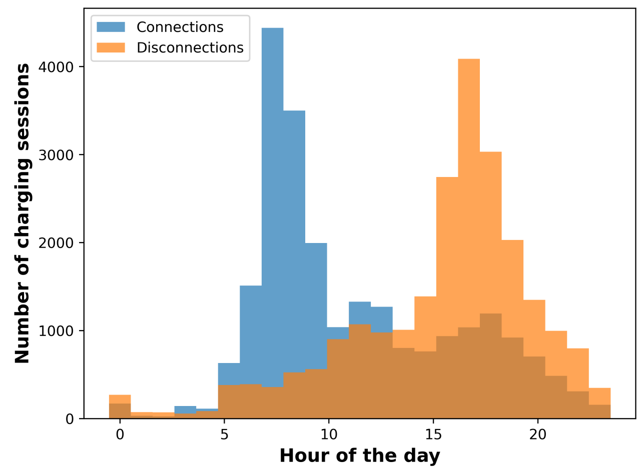

Figure 2: Distribution of hourly arrival and departure times for all EVs in the Caltech ACN dataset.

Another important observation is illustrated in Figure 3, which displays all the Caltech ACN charging events according to its duration and the energy that was transferred. There is a clear line that crosses the origin of the graph with a slope of approximately 7 kW. This corresponds to the rated power of each EVSE installed at the campus garage, which in turn means that all the sessions that are close to (or on) this line have no flexibility. Flexibility in EV charging is understood as the difference between the disconnection time and the time of last non-zero current draw recorded over the total duration of the charging event. The higher the flexibility of a charging event, the greater the potential to schedule charging in a more convenient way. Figure 3 shows that most of the charging sessions are below the 7 kW line, which means that they only drew the rated power for a short duration of time (until the EV battery reached 100% state-of-charge), and finally entered an idle state. This observation shows substantial opportunities to optimize the charging session with a soft deadline approach as the charging session may be tolerant to delays in the completion time – idle time represents a possibility for flexibility, either reducing costs, increasing overall satisfaction, or both.

5.2 Simulation environment

The simulation environment is built around the Caltech ACN-Sim, an open-source, data-driven, simulator [15]. The simulator's object-oriented structure contains a few main objects and classes: a Simulator class, a Charging Network class, EVSE objects, EV objects, Battery objects, and an Event Queue. The environment emulates the real charging infrastructure and power capacities present in the Caltech facility as well as loads the real EV charging traces that were used to evaluate our online algorithm. This environment provides a convenient backbone for the evaluation of EV charging optimization algorithms, which we customized to accommodate our auction-based formulation. Besides our algorithm implementation, a demand response signal, solar compatibility, and vehicle-to-vehicle charge sharing mechanisms were implemented.

In addition, the ACN-Sim platform provides multiple baseline offline algorithms. For our evaluation we compare our online auction

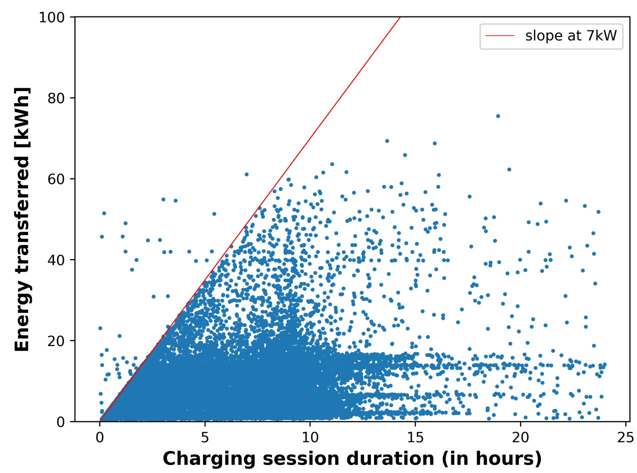

Figure 3: Relation of charging session duration and amount of energy transferred. Energy delivered below the slope at 7kW suggests charging sessions with some amount of idle state (flexibility).

mechanism with uncontrolled charging, an Earliest Deadline First (EDF) policy, and a Least Laxity First (LLF) policy. These represent common methods for charging EVs, and the implementations are all available as part of ACN-Sim.

5.3 Demand Response Signal

While traditional DR programs are often implicit (i.e. time-of-use tariffs), utilities have now begun to tap into other dispatchable sources of generation such as distributed energy resources (DER) or EVs to provide explicit support to the grid. In explicit DR schemes, the aggregated load is traded in electricity markets and consumers receive direct payments to change their consumption upon request. This can be triggered by the activation of balancing services, differences in electricity prices, or a constraint on the grid (typically, on the distribution grid).

Our analysis applies the latter approach, similar to Zweistra et al. [38], using variation in the capacity of low-voltage transformers as a method to emulate DR signals. For instance, this signal is

	PG&E	SCE
Peak	$0.2322 / kWh	$0.2666 / kWh
Partial-Peak	$0.1771 / kWh	$0.0925 / kWh
Off-Peak	$0.14903 / kWh	$0.05623 / kWh
Demand Charge	$19.99 / kW / month	$15.51 / kW / month
	LCOS V2V	**Solar**
All-day	$0.12 / kWh	$0.068 / kWh

Table 1: Summary of electricity tariffs

randomly triggered during peak times, for a duration between 2 and 4 hours, and requesting a decrease of up to 40% in the total load from EVs. In our implementation, when a demand response signal is triggered, it only affects the available power capacity from the main grid, allowing the other sources of energy (V2V and Solar) to remain unaffected.

5.4 Electricity Tariffs

The time-of-use (TOU) tariffs considered in our simulation were similar to the ones adopted by the ACN-Data research [16]. In addition to Southern California Edison (SCE) tariff rates, we also utilize Pacific Gas and Electric (PG&E) [11] tariffs to better understand how they would affect the cost reductions over our algorithm during different months. The TOU rates correspond to peak, partial-peak, and off-peak hours from May through October for PG&E and for the whole year for SCE.

In addition, we include different tariffs for V2V and solar generation, which allow us to observe the impact of these resources in the charging facility. For V2V we use the levelized cost of storage (LCOS) provided in [17]. For solar, we adopt tariffs reported in [9]. Table 1 summarizes the tariffs that were used in this evaluation.

5.5 Integration with Solar Charging

The original simulator did not have any renewable energy sources, and assumes the use of power only from the grid. In order to emulate the presence of solar generation in our charging facility, we use PVWatts [13] to estimate the solar generation potential in the location of the charging facility. This model takes into account the effect of system capacity, installation parameters such as tilt and orientation, and weather conditions.

In order to size the system capacity in our charging facility correctly, we perform a daily EV charging simulation for the entire year of 2019 where the only source of power to charge the EVs is the solar installation and estimate the solar capacity that provides the generation to meet a sufficient proportion of the demand in a decent proportion of days in 2019. Figure 4 illustrates the CDF of the proportion of unmet EV charging demand for different solar installation sizes. Based on the results, we choose to use 125kW as a default installation size since it can provide enough energy to supply 80% of the EV charging demand for approximately half of the year. For context, Figure 1 illustrates solar generation during a typical day in California.

5.6 Vehicle-to-Vehicle Charge Sharing

The storage capacity of EVs can also be used for other applications thanks to bidirectional charging. These applications are known as V2X, where X can be the Grid (a concept initially proposed by W. Kempton [10]), a Building, or even other Vehicles. The latter

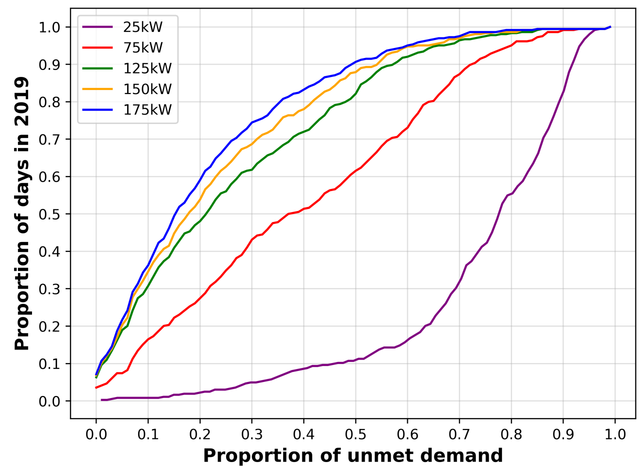

Figure 4: Impact of solar installation capacity in the proportion of unmet demand during 2019. Each line shows different generation sizes.

appears to be of special interest for the current application, as EVs could exchange energy without the need of going through the grid or the facility. A. Koufakis et al. [12] propose an offline and an online charging scheduling algorithm with V2V energy transfer, able to reduce costs by 3.3% and increase onsite renewable energy use by 12%. R. Zhang et al. [33] investigate flexible energy management through active power transfer cooperation between EVs, through different V2V matching algorithms, leading to an improvement of the utilities of the EVs and reducing grid energy consumption.

Implementing V2V with the simulator required a few assumptions to be made. Firstly, we randomly selected 15% of vehicles arriving at the charging site to participate in V2V charge sharing. Secondly, the vehicles chosen were assumed to arrive with an initial battery charge of 80%. Thirdly, we randomly sampled battery capacity sizes from a list of commonly available EV models [7] and assigned the selected capacities to each V2V vehicle. The vehicles then discharged up to 30% of their total battery capacity, until their departure time.

5.7 Results

Cost reduction. First we evaluate the operating cost reduction for the charging facility of our online algorithm. We compare our implementation with baseline algorithms such as uncontrolled charging and EDF and LLF scheduling algorithms. The former two, which in contrast to online algorithms, have information about the future. EDF sorts EVs by departure time in increasing order and charge at the maximum feasible rate in each timestep. EVs that are scheduled first benefit from a higher availability of power capacity. LLF sorts EVs by laxity, which in this case is defined as the difference between the estimated departure time and the time that takes to charge the EVs at the maximum rate. Higher laxity means higher flexibility in satisfying the energy demand.

In addition, we aim to understand the impact of different renewable sources on the EV charging facility. We run simulations with a monthly time-frame and calculate the monthly operating cost for the facilities with each algorithm as well as with the presence or absence of V2V and solar generation.

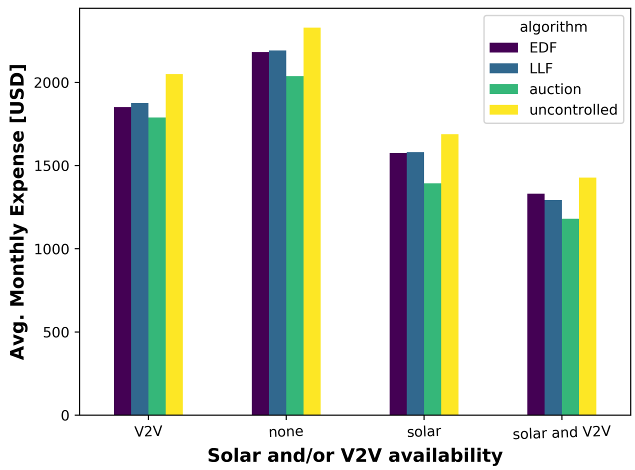

Figure 5: Comparison of the average monthly expense for different offline scheduling algorithms and our auction algorithm.

Figure 5 shows the average monthly expense in electricity of the EV charging facility which includes both the electricity cost and demand charge. Each bar represents a different scheduling technique and the groups shows the availability or not of renewables and V2V capabilities in the simulation. We observe that our online auction algorithm outperforms other schedulers showing cost reductions of up to 13.5% with respect to the uncontrolled charging and from 3.5% to almost 12% with respect to EDF and LLF. We also observe that in general the presence of solar generation brings significant benefits to cost reduction of up to 38%. While these specific numbers are a reflection of the differences in tariffs used in this study, the dominant performance of our technique in all scenarios is promising.

Impact of tariffs in the EV user's utility. Since our auction algorithm is truthful and the price that the charging job i pays depends on the energy demand and electricity price, we explore how different tariffs affect the utilityu_i for each charging job i that participates in the auction. We analyze more than 90K auctions results that were generated for simulations of the whole year of 2019. Figure 6 illustrates the CDF of the utility value obtained for the two different electricity tariffs used in the evaluation. However, we do not observe a significant difference between the two rates. In addition, even though our goal is not maximizing the acceptance of bids, we observe that approximately only 2.5% and 4.5% of bids are rejected for SCE and PG&E tariffs respectively which is observed when the EV user's utility are negative.

Running time. Similarly as in the previous evaluation, using the results for each event that triggered our auction algorithm during the whole of 2019, we record the running time to compute the schedules for the number of active EVs participating in the auction at a given time t for a realistic charging facility design in the ACN-sim. Figure 7 shows the resulting average running time for the number of EVs that were found to be active during the whole year. We observe that the mean time is 0.3s across different numbers of EVs without any particular trend as the number of EVs increases. We observe a spike for 31 EVs with a high standard error which might be representative across all the remaining cases. Nonetheless, these running times are well within a reasonable range for an online

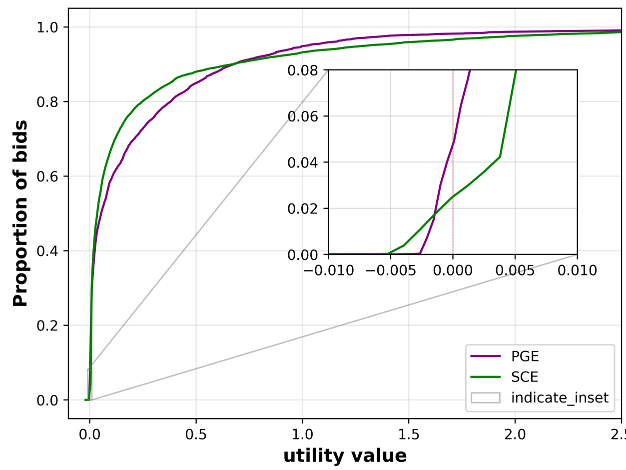

Figure 6: Impact of tariffs in the EV user's utility value.

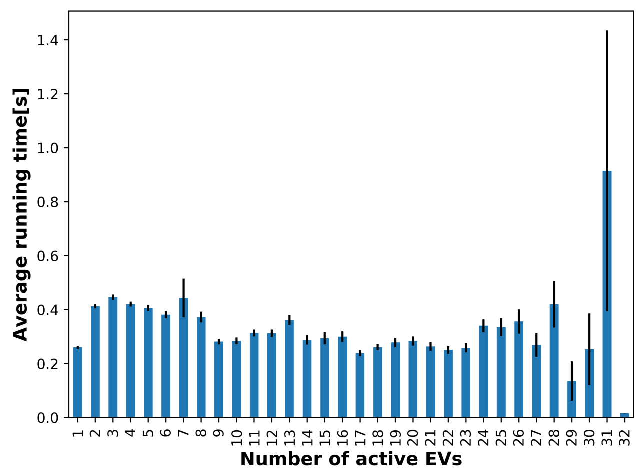

Figure 7: Average running times of our online scheduler for different number active EVs participating in the auction.

algorithm that controls EV charging, providing evidence that our dynamic programming approach is effective.

6 CONCLUSION AND FUTURE WORK

In this work we developed an efficient online auction mechanism to charge electric vehicles using a soft deadline-based user satisfaction technique and under the presence of demand response and time-of-use signals. We leverage existing online algorithms from the cloud computing domain and use an effective dynamic programming approach to obtain feasible charging schedules that maximize social welfare for the charging facility and EV users. We evaluate our algorithm using an open source data-driven simulator that emulates existing EV charging facilities and uses over 23k real traces of charging sessions. In our simulations, to consider further dynamics, we implement vehicle-to-vehicle capabilities and solar generation in the facility running our online algorithm.

Our algorithm outperforms all the baseline algorithms we considered in every scenario, showing significant reductions of up to 13% in the operating cost of the charging facility. Our algorithm also computes schedules in a tractable time (less than 1 second for multiple EVs) and shows consistency under the variation of electricity tariffs for truthful auctions.

Given the increasing penetration of EVs, further exploration of this implementation can enable the creation of global optimal charging algorithms that aim to reduce carbon emissions and encourages the integration with renewable energy sources. As future work, we plan to extend our analysis to datasets from different domains such as residential and public transportation systems and with distributed systems that might have additional components to improve overall social welfare. We also plan to deploy our algorithm in a real setting and evaluate its impact on maximizing social welfare.

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