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# Efficient Online Scheduling of Electric Vehicle Charging Using a Service-Price Menu

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***Abstract*—Along with high penetration of Electric Vehicles (EVs), charging stations are required to service a large amount of charging requests while accounting for constraints on the station's peak electricity consumption. To this end, a charging station needs to make online charging scheduling decisions often under limited future information. An important challenge relates to the prioritization of EVs that have unknown valuations for different levels of charging services. In this paper, we take into consideration the inability of EV users to express these valuations explicitly. We consider a paradigm where a menu of possible charging schedules and corresponding prices is generated online. By letting the EV users pick their most preferable menu option, the proposed algorithm commits on each EV's charging completion time upon its arrival, achieves a near optimal total weighted charging completion time, and prevents the users from strategically misreporting their preferences, while offering a practical and implementable solution to the problem of EVs - charging station interaction.**

***Index Terms*—Electric Vehicles, Charging Scheduling, Prompt Scheduling, Online Algorithms, Truthfulness**

## I. Introduction

### A. Motivation and Background

The electrification of urban transportation poses new challenges towards accommodating the charging requirements of Electric Vehicles (EVs). This has motivated the development of Charging Stations (CSs), which are envisaged as facilities that offer charging services to EVs. An EV features certain flexibility regarding its charging profile, e.g., an EV user can choose to charge at a later time, in exchange for a smaller payment. The CS can utilize this flexibility by scheduling the charging of different EVs to achieve various objectives and satisfy certain CS-level constraints. Such constraints relate to the limited capacity of the CS's transformer [1], the requirement to satisfy an upper bound on the CS's electricity consumption, posed by the distribution system operator [2], etc. Since this kind of constraints refer to the EVs' aggregated consumption, they are of the form of *resource* constraints.

The problem of EV-charging scheduling under resource constraints bears a resemblance to the classical problem of scheduling jobs (i.e., EVs' charging requests) to machines (i.e., charging slots). To achieve an efficient scheduling, the CS needs to account for three important requirements: (1) acquire certain characteristics of EV charging tasks (e.g., amount of energy, power consumption, urgency), (2) incentivize the EV users to reveal these characteristics truthfully and (3) process the information as it (gradually) becomes available, i.e., in an online fashion and without breaking the service commitments of past decisions.

### B. Relevant Literature

A significant volume of previous work on EV charging has focused on maximizing either the total number of EVs charged or the total amount of energy allocated, given the energy available per timeslot and the EVs' deadlines (see e.g., [3] and the references therein). In [4], the authors consider a scheduling algorithm that helps the CS to minimize its infrastructure cost while guaranteeing a certain quality of service. In [5], the authors propose a max-min fair allocation of charging services under a resource constraint. The authors in [6] propose a scheduling algorithm that motivates users to select the required energy amount between a guaranteed energy component and a low-priced non-guaranteed part produced by renewable sources. Fewer studies (e.g. [7]) consider the online scheduling problem of the CS, under limited information of future EV arrivals.

Towards acquiring the charging characteristics and preferences of EV users, the majority of relevant studies typically make two fundamental assumptions: (1) the EV user is assumed to truthfully report his/her preferences, which facilitates the scheduling algorithm to optimize the scheduling and (2) the EV user is assumed to be able to express his/her preferences in a closed-form utility function.

Under these two assumptions, decomposition algorithms can solve the scheduling problem to optimality if, additionally, the utility functions are convex. The first assumption can be relaxed by considering users that can act strategically (and selfishly), trying to manipulate the charging schedule in their favour (so that they either get more energy at a lower price or finish earlier, e.g. [3], [8]). When selfish EV users are involved, the charging schedule should incentivize them to act according to their true charging characteristics. Motivated by such considerations, [9] proposes a scheduling algorithm where the user is incentivized to behave truthfully by leveraging techniques from algorithmic mechanism design. The algorithm in [9] can also accommodate non-convex utility functions. [8] proposed a scheduling algorithm and a pricing scheme, which offers discounted electricity prices to users willing to delay

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their consumption. Similarly, [3] presents an online scheduling algorithm which commits, upon arrival of each EV, on the amount of energy that the EV will receive up to its specified deadline. They consider a direct revelation mechanism, where each EV user reports their charging characteristics to the CS.

Departing from previous work, we seek to optimize the overall quality of service, naturally formalized by the objective of minimizing the total weighted completion time (and consequently, the average completion time and the average number of users in the system, for the case of equal weights). From an algorithmic viewpoint, scheduling a set of jobs to minimize their weighted completion time has been extensively studied. Under the classical multiprocessor environment, completion time minimization is NP-hard [10], while weighted completion time minimization is NP-hard, even on a single machine [11]. For a single machine and unit weights, the *Shortest Remaining Processing Time* (SRPT) rule results in a preemptive schedule of minimum completion time [12]. On multiple identical machines, SRPT results in a 2-approximate preemptive schedule for weighted completion time minimization [10]. [13] provides an excellent survey of scheduling algorithms with the objective to minimize (weighted) completion time.

Completion time minimization becomes even harder, if selfish tasks are involved. [14] proposed a truthful $\frac{3}{2}$-approximate algorithm, when the tasks arrive simultaneously and only their duration is private. In an orthogonal setting, [15] proposed a truthful $4.83$-approximation algorithm for weighted completion time minimization, when only the task weights are private.

Most of the previous work on online scheduling to minimize (weighted) completion time may keep postponing the execution of a task, if shorter tasks arrive, or even may migrate it to a different machine, in case of preemptive algorithms (see e.g., [16] and the references therein). Eden et al. [17] were the first to propose a prompt and online truthful scheduling algorithm, based on a menu of possible scheduling intervals. The algorithm commits on the completion time of each task upon arrival and achieves a logarithmic competitive ratio.

The idea of menu-based scheduling can be naturally applied to the EV charging setting, since EV users can neither express their preferences in closed-form utility functions, nor report their charging preferences to facilitate a truthful scheduling. In contrast, they can make an intuitive choice when provided with a menu of available options. A relevant approach is taken in [18], although in a different setting, where the EV users have a hard energy and deadline constraint and are asked to pick their preferred CS from a set of nearby ones, trading-off CS distance with CS requested payment. An online menu-based pricing scheme is also proposed in [19], where the users select a charging contract to maximize the station's profit without considering the scheduling aspect.

### C. Contributions and Organization

To the best of our knowledge, this is the first time that an efficient truthful online algorithm, operating through a price-service menu, is proposed for EV charging scheduling to minimize the sum of weighted completion times. Our contributions can be summarized as follows:

- We provide a formal model for EV charging scheduling based on weighted completion time minimization.
- We extent the framework of [17] and present an online truthful scheduling algorithm, which interacts with the EV users through a service-price menu. Thus, EV users select their most preferable option, without resorting to direct revelation. Moreover, upon an EV's arrival, the CS commits to the quality of service in its chosen option.
- We prove that our algorithm achieves a reasonable (and essentially best possible) competitive ratio against adversarial EV arrivals. Our experimental evaluation further shows that our algorithm is very efficient in practice.
- We simplify the analysis of [17] and show an improved (though still logarithmic) competitive ratio.

Overall, our online algorithm is prompt, i.e. it guarantees the exact time that the vehicle will be scheduled. Therefore, the user will know as to when the charging will start and finish. Moreover, since some information may be intrinsic to the users, such as their urgency weight, the idea of a service-price menu exempts them from quantifying and reporting their preferences.

## II. System Model and Problem Formulation

We consider a CS responsible for serving a set of EVs $N = \{1, 2, \dots, |N|\}$ in a time horizon $T = \{1, 2, \dots, |T|\}$, where each EV $n \in N$ is characterized by lower/upper bounds $\underline{\mathrm{x}}_n, \overline{\mathrm{x}}_n$ on its power consumption, an arrival time $\mathrm{a}_n$, an energy requirement $\mathrm{E}_n$ and an urgency parameter $\mathrm{w}_n \in [0, 1]$. The CS needs to make a decision, towards the charging schedule of each EV. Let binary variable $y_{n,t}$ denote whether $n$ charges at timeslot $t$, and continuous variable $x_{n,t}$ denote the corresponding charging power. It is

$$y_{n,t} \cdot \underline{\mathrm{x}}_n \le x_{n,t} \le y_{n,t} \cdot \overline{\mathrm{x}}_n, \quad \forall t \in T, n \in N. \qquad (1)$$

The CS draws electricity from the grid through a local transformer, whose capacity imposes an upper bound L on the aggregated electricity consumption at each timeslot:

$$\sum_{n \in N} x_{n,t} \le \mathrm{L}, \qquad \forall t \in T. \qquad (2)$$

We note here that the case of a time varying bound $L(t)$ on the aggregated consumption is also possible under our framework, even though it is not considered in the present paper. Each EV $n$ cannot charge before its arrival time $\mathrm{a}_n$:

$$y_{n,t} = 0, \quad t < \mathrm{a}_n. \qquad (3)$$

The EV departs upon receives its required energy $\mathrm{E}_n$. Let the binary variable $u_{n,t}$ denote whether EV $n$ departs from the station at timeslot $t$. Variable $u_{n,t}$ cannot become 1 before the EV receives its required energy, i.e., it is forced to 0, for as long as the EV's charged energy until $t$ is less than $\mathrm{E}_n$:

$$\sum_{t'=a_n}^{t} x_{n,t'} \ge u_{n,t} \mathrm{E}_n, \quad \forall n \in N, t \in T \qquad (4)$$

Also, the EV can only depart from the station once, i.e.

$$\sum_{t \in T} u_{n,t} = 1, \quad \forall n \in N. \tag{5}$$

If all information was available beforehand, then the optimal charging schedule could be computed by minimizing the sum of the weighted charging completion times, while respecting the transformer's limits, as in:

$$\begin{aligned} \min_{x_{n,t}, u_{n,t}} & \sum_{n \in N} \sum_{t \in T} \mathrm{w}_n \cdot u_{n,t} \cdot t \\ \text{s.t. } & (1) - (5). \end{aligned} \tag{6}$$

Problem (6) can be regarded as a problem of scheduling tasks to machines. However, since EVs arrive at CS over time, we consider an online variant of problem (6), where the decision about which EV starts charging at any time $t$ depends on the set of EVs arriving at or before $t$. The analysis of an online algorithm typically involves comparing its performance to the optimal offline solution. An online algorithm is *c-competitive* if its objective value is at most $c$ times the objective value of the optimal algorithm in-hindsight. Ignoring a factor of 2 in the competitive ratio, we compare the performance of our algorithms to the performance of SRPT.

An additional challenge towards tackling problem (6) is that the parameters $\mathrm{E}_n$ and $\mathrm{w}_n$ are intrinsic to the EV user and not known to the CS (even the users may not know them accurately). In practice, the users can neither conceptualize and report their impatience by providing a number, nor answer iteratively to a series of queries (as inherently assumed by decomposition approaches). Rather, the users are able to intuitively interpret their preferences by choosing among a given finite set of options.

Let $p_n = \mathrm{E}_n / \overline{\mathrm{x}}_n$ be the time that $n$ spent charging, when it charges at its maximum rate (the assumption that EVs always charge at their maximum rate is justified by our objective of minimizing weighted completion time). The time that an EV completes charging is denoted by $c_n$. Note that $c_n \geq \mathrm{a}_n + p_n$. Upon arrival, an EV $n$ is presented with a menu of charging options. A menu entry is of the form $([b, e], \pi)$, with $b \geq \mathrm{a}_n$, which means that the time interval $[b, e]$ is available for $n$'s charging at an urgency payment $\pi$. This urgency payment is in addition to the payment $\lambda \cdot E_n$ for the electricity consumed, assuming a flat price $\lambda$ per unit of electricity. (The case of a time varying electricity price is not considered in the paper to simplify analysis.) Then, the cost of EV $n$ with urgency weight $\mathrm{w}_n$ and charging time $p_n$ for choosing option $([b, e], \pi)$ is an increasing function of $b + p_n$, $\mathrm{w}_n$, and $\pi$. We should highlight that the price $\pi$ just quantifies the externality that $n$ causes to other EVs due to its urgency. Towards facilitating the analysis, we assume a particular utility form:

$$\kappa_n(b) = (b + p_n) \cdot \mathrm{w}_n + \pi \ + \lambda \cdot E_n. \tag{7}$$

Other choices for the function $\kappa_n(b)$ are also possible (e.g., ones involving deadlines set by the users), but the choice made above will lead to the minimization of the weighted sum of the completion times, an important QoS metric. Also, the electricity cost $\lambda \cdot E_n$ under flat pricing will not affect the scheduling of the users and therefore in what follows we will set $\lambda = 0$ wlog. A user is not able to know and report $\mathrm{w}_n$, but can however interpret it by selecting the option $([b, e), \pi)$ that minimizes its cost $\kappa_n(b)$, once provided with a menu.

Next, we present a truthful online algorithm, which builds a menu of possible amounts of energy, completion times and respective prices, from which the user chooses its most preferable option. Truthfulness follows from the fact that the EV users do not reveal anything about their preferences to the algorithm. The next two sections are devoted to the detailed description of the algorithm and its analysis.

## III. Outline of the Approach: Prompt Scheduling with Unit Weights

We first present a solution for the simpler case of unit urgency weights, where we do not need to charge EVs for their urgency. Hence, the option menu for an EV $n$ simply consists of charging intervals $[b, e)$, with $b \geq \mathrm{a}_n$, (7) becomes $\kappa_n(b) = b + p_n$, and EV $n$ simply selects the option with earliest $b$, subject to $e - b \geq p_n$. To facilitate the presentation and the analysis, and without loss of generality, we consider charging intervals $[b, e)$ whose length $l = e - b$ is a power of 2. Note that the actual duration of each timeslot in $T$ can be arbitrarily small (e.g., it could last for just few seconds).

**Setting up a Sequence of Charging Intervals.** Following [17], we generate the charging intervals, from which the menu options are built, by exploiting a carefully structured integer sequence $S$. To formally introduce $S$, we first define the following family of sequences:

$$\begin{aligned} S_0 &= \langle 1 \rangle \\ S_1 &= S_0 || S_0 || \langle 2^1 \rangle = \langle 1, 1, 2 \rangle \\ S_2 &= S_1 || S_1 || \langle 2^2 \rangle = \langle 1, 1, 2, 1, 1, 2, 4 \rangle \\ & \ldots \\ S_k &= S_{k-1} || S_{k-1} || \langle 2^k \rangle \end{aligned}$$

where $||$ denotes concatenation and $k$ is any integer.

By construction, each $S_k$ consists of $2^{k+1} - 1$ integers, all powers of 2. Specifically, for each nonnegative integer $d \leq k$, $2^d$ (and the corresponding subsequence $S_d$) appears $2^{k-d}$ times in $S_k$ . We sometimes let $S_k[i]$ be the $i$-th element of $S_k$. Moreover, we note that all appearances of $2^d$ in $S_k$ sum up to $2^k$, and the sum of all integers appearing in $S_k$ is $(k+1)2^k$. Formally, $\sum_{i: S_k[i] = 2^d} S_k[i] = 2^k$ and $\sum_i S_k[i] = (k+1)2^k$.

We let $p_{\max} = \max_{n \in N} \mathrm{E}_n / \overline{\mathrm{x}}_n$ denote the maximum charging time of EVs, assuming that they charge at their maximum rate. For simplicity of the analysis, we assume that $p_{\max}$ is a power of 2 and let $e_{\max} = \log_2 p_{\max}$. Our basic sequence $S$ is simply $S_{e_{\max}}$:

$$S = S_{e_{\max}} = \langle 1, 1, 2, 1, 1, 2, 4, 1, 1, 2, 1, 1, 2, 4, 8, \ldots, p_{\max} \rangle .$$

Based on $S$, we create a sequence $S^*$, which covers the entire time horizon $|T|$, by concatenating $S$ with itself an appropriate number of times We sometimes index the different copies of $S$

**Algorithm 1** Prompt Online Scheduling with Unit Weights

Given a sequence $S^*$ and its corresponding intervals.
Let EV $n$ arrive at the station at time $\mathrm{a}_n$ .
$\ell = 0$
**repeat**
    Let $[b, e)$ be the earliest feasible interval in $S^*$ with $b \geq \mathrm{a}_n$ and $e - b \geq 2^\ell$.
    Include interval $[b, e)$ in $n$'s menu.
    $\ell = 1 + \log_2(e - b)$
**until** EV chooses interval (i.e., until $p_n \leq e - b$)

as $S^0, S^1, S^2, \ldots$, according to their appearance in $S^*$. Then, $S^* = S^0||S^1||S^2||\cdots||S^q||\cdots$.

$S^*$ naturally partitions the time horizon into a sequence of charging intervals. For each subsequence $S^q$ of $S^*$, $b(S^q) = q(e_{\max} + 1)2^{e_{\max}}$ denotes the starting time and $e(S^q) = (q+1)(e_{\max}+1)2^{e_{\max}}$ denotes the finishing time of the corresponding interval. Then, thinking of each $S^q$ as covering the time interval $[b(S^q), e(S^q))$, we get a first coarse partitioning of the time horizon with intervals induced by $S^*$. We further partition each time interval $[b(S^q), e(S^q))$ into a sequence of intervals $[b_1^q, e_1^q), \ldots, [b_i^q, e_i^q), \ldots$, where $b_1^q = b(S^q)$, the length of the $i$-th interval is $S_q[i]$, and $i = 1, \ldots, 2^{e_{\max}+1} - 1$. Formally, the starting and finishing times of these intervals are defined inductively as follows: $b_1^q = b(S^q)$, and $e_i^q = b_i^q + S_q[i]$ and $b_{i+1}^q = e_i^q$, for each $i$.

To provide some intuition behind the definition of $S^*$ and the corresponding partitioning of the time horizon, we may think of how SRPT would work in the offline case. With prior knowledge about the input and to avoid delaying of short charging requests, SRPT would schedule the charging request in increasing order of their remaining charging time. However, since this is not possible in the online case, the idea behind $S^*$ is to keep enough short intervals vacant earlier in time, in case some shorter charging requests appear in the future. The definition of $S$ ensures that each different charging time that is a power of 2 gets its fair share in each $[b(S^q), e(S^q))$.

**Building the Menu.** Upon the arrival of EV $n$ at $\mathrm{a}_n$, its charging option menu is generated by sequentially considering the available charging intervals in $S^*$, starting from the first interval $[b, e)$ with $b \geq a_n$. An interval is called *feasible*, if less than $C = \lfloor L/\overline{x} \rfloor$ EVs have been already scheduled to charge in it, where $\overline{\mathrm{x}} = \max_{n \in N}\{\overline{\mathrm{x}}_n\}$ is the maximum charging rate. With this definition of $\overline{\mathrm{x}}$ and $C$, the CS can always serve at least $C$ EVs at any time. The earliest feasible interval $[b, e)$ of each length is included in $n$'s menu and $n$ selects the one with earliest $b$, under the constraint that $p_n \leq e - b$ (see also Fig. 1). Algorithm 1 formalizes the procedure.

By maintaining the earliest feasible interval for each length $2^\ell$, $\ell = 0, \ldots, \log p_{\max}$, Algorithm 1 can be implemented so that an EV's menu can be computed in $O(\log p_{\max})$ time, for each arriving EV $n$, and in $O(m \log p_{\max})$ time, in total, where $m$ is the total number of EVs. Hence, the running time of Algorithm 1 scales almost linearly with the number of EVs.

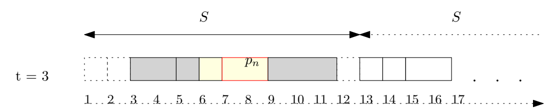


Fig. 1: EV $n$ with $p_n = 2$ arrives at $\mathrm{a}_n = 3$. Let $p_{\max} = 4$. Grey cells represent infeasible intervals. Yellow cells represent the intervals included in EV $n$'s menu. $n$ selects the interval marked red, i.e. the earliest feasible interval of length $\geq p_n$.

**Competitive Ratio.** Next, we analyze the performance of Algorithm 1, by comparing its total completion time to the completion time of the preemptive schedule produced by SRPT, which is a 2-approximation to the optimal total completion time. For the analysis, we assume that all EVs have the same maximum charging rate, i.e. that $\overline{\mathrm{x}}_i = \overline{\mathrm{x}}$, for all $i \in N$. We can remove this assumption by increasing the competitive ratio by a factor of $\max_{n \in N}\{\overline{\mathrm{x}}_n\}/\min_{n \in N}\{\overline{\mathrm{x}}_n\}$.

**Theorem 1.** *Algorithm 1 is $O(\log p_{\max})$-competitive.*

*Proof.* We first state the proof for $C = 1$. At the end, we explain how the analysis can be generalized to any integer $C$. We start with the following technical lemma, which follows from the structure of $S$ and the definition of Algorithm 1.

**Lemma 1.** *Let $\ell \in \{0, \ldots, e_{\max}\}$ and let $S_\ell$ be any subsequence of some $S^q$ in $S^*$ ($S_\ell$ coincides with $S^q$, if $\ell = e_{\max}$). If there is an EV $n$ with $p_n = 2^d \leq 2^\ell$, such that $\mathrm{a}_n \leq b(S_\ell)$ and $c_n > e(S_\ell)$, then the total charging volume of EVs $i$ with $p_i \leq 2^d$ already scheduled in $S_\ell$ by Algorithm 1 is at least $2^\ell$.*

We consider an EV $n$ with $p_n = 2^\ell \leq 2^{e_{\max}}$ arriving at time $\mathrm{a}_n$. Let $c_n$ (resp. $c_n^*$) be $n$'s completion time at the schedule of Algorithm 1 (resp. SRPT). We show that $c_n/c_n^* \leq O(e_{\max})$.

We defer the case where $c_n \leq e(S^0)$ to the full version, and discuss here only the most interesting case where $c_n > e(S^0)$. Then, let $k \geq 0$ and $d \geq 0$, with $k + d \geq 1$, such that:

$$b(S^k) < \mathrm{a}_n + p_n \leq e(S^k)$$
$$b(S^{k+d+1}) < c_n \leq e(S^{k+d+1})$$

I.e., the earliest possible completion time of EV $n$ is after $b(S^k)$, while $n$ completes its charging in the schedule of Algorithm 1 by $(k + d + 1)(e_{\max} + 1)2^{e_{\max}}$. We observe that:

$$c_n^* > k(e_{\max} + 1)2^{e_{\max}} \quad \text{and} \quad c_n^* > d\, 2^{e_{\max}}$$

The first inequality follows from $\mathrm{a}_n + p_n > b(S^k)$. For the second inequality, we apply Lemma 1 to each of the $d$ subsequences $S^{k+1}, \ldots, S^{k+d}$. EV $n$ has arrived before $b(S^{k+1})$ and has not completed its charging in the schedule of Algorithm 1 by $e(S^{k+d})$. Therefore, by Lemma 1, the total charging time of EVs $i$ with $p_i \leq 2^\ell$ that have arrived and scheduled before $n$ by Algorithm 1 in $S^{k+1}, \ldots, S^{k+d}$ is at least $d\, 2^{e_{\max}}$. All these EVs must have completed their charging before $n$ in SRPT's schedule.

Therefore $2c_n^* \geq (k(e_{\max}+1)+d)2^{e_{\max}}$ and

$$c_n/c_n^* \leq \frac{(k+d+1)(e_{\max}+1)}{k(e_{\max}+1)+d}$$
$$= 1 + \frac{(d+1)e_{\max}+1}{k(e_{\max}+1)+d} \leq O(e_{\max})\,.$$

For the generalization to any $C \geq 1$, we observe that our upper bounds on $c_n$ only depend on the interval in which EV $n$ is scheduled by Algorithm 1, while our lower bounds on $c_n^*$ follow from the total charging volume scheduled before $n$ by SRPT (which is multiplied and divided by $C \geq 1$). □

## IV. Prompt Scheduling with Urgency Weights

Generalizing the previous approach, we present a prompt online algorithm that deals with urgency weights and operates by computing online a service-price menu for each EV. Towards this end, we let $\mathrm{w}_{\max} = \max_{n\in N} \mathrm{w}_n$, $v_{\max}$ be the smallest power of 2 such that $v_{\max} \geq \mathrm{w}_{\max}$, and $\tau_{\max} = \log_2 v_{\max}$. Our generalized basic sequence $V$ consists of the concatenation of $\tau_{\max}+1$ copies of $S$:

$$V = S^{\tau_{\max}}||S^{\tau_{\max}-1}||\cdots||S^{\tau}||\cdots||S^0\,.$$

Intuitively, we "discretize" urgency weights, using only powers of 2, and have a copy of $S$ for each power of 2 in $v_{\max},\ldots,1$. In the definition of $V$, each $S^\tau$ is associated with value $2^\tau$. As in Section III, we create a sequence $V^*$, which covers the entire time horizon $|T|$, by concatenating $V$ with itself an appropriate number of times. We let $V^* = V^0||V^1||\cdots||V^q||\cdots$. As in Section III, $V^*$ naturally induces a partitioning of the time horizon $T$ into a sequence of charging intervals, where now each interval is associated with an urgency value (inherited by the copy of $S$ in which the interval is included in). Abusing the notation, we identify subsequences of $V^*$ with their corresponding intervals.

To deal with different urgency weights, we basically apply Algorithm 1 for each length $2^\ell$ to the part of $V^*$ consisting of subsequences $S^\tau$ only, for $\tau = 0,\ldots,\tau_{\max}$. Then, the prices are set by considering the time difference of intervals with the same length and different value. More specifically, upon the arrival of an EV $n$ at $\mathrm{a}_n$, the algorithm performs the following steps for each $\ell = 0,\ldots,e_{\max}$:

- The algorithm locates the feasible interval $[b_0^\ell, e_0^\ell)$ with $b_0^\ell \geq \mathrm{a}_n$ and length $e_0^\ell - b_0^\ell \geq 2^\ell$ in any $S^0$ (i.e., the interval $[b_0^\ell, e_0^\ell)$ is associated with value 1). These intervals are included in the menu with price $\pi_0^\ell = 0$.
- For each $\tau = 1,\ldots,\tau_{\max}$, the algorithm locates the feasible interval $[b_\tau^\ell, e_\tau^\ell)$ with $b_\tau^\ell \geq \mathrm{a}_n$ and length $e_\tau^\ell - b_\tau^\ell \geq 2^\ell$ in any $S^\tau$ (i.e., the interval $[b_\tau^\ell, e_\tau^\ell)$ is associated with value $2^\tau$). If $b_{\tau-1}^\ell > b_\tau^\ell$, the interval $[b_\tau^\ell, e_\tau^\ell)$ is included in the menu with price

$$\pi_\tau^\ell = \pi_{\tau-1}^\ell + (b_{\tau-1}^\ell - b_\tau^\ell)\,2^\tau \tag{8}$$

TABLE I: Characteristics of popular EV types

| EV Model | Battery Capacity | Max. Charging Capacity | Charging Time |
|---|---|---|---|
| Tesla Model S 75D | 75 kWh | 11kW - 16kW | 5 h |
| Tesla Model X 75D | 75 kWh | 11kW - 16kW | 5 h |
| Mitsubishi i-MiEV | 16 kWh | 3.7kW | 6 h |
| Kia Soul EV | 27 kWh | 6.6kW | 4.5 h |
| Ford Focus Electric | 23 kWh | 6.6kW | 4 h |
| NISSAN Leaf | 24 kWh | 6.6kW | 4 h |
| BMW i3 | 27.2 kWh | 11 kW | 3 h |
| Mercedes-Benz B-Klasse | 28 kWh | 11kW | 3 h |
| Chevy Spark | 19 kWh | 3.3kW | 6 h |
| Fiat 500e | 24 kWh | 6.6kW | 4 h |

## V. Simulations

In the simulations process we consider the efficient scheduling of the EVs during a 16-hour time horizon. To create the menu, we are interested in the charging times of the vehicles. We use the charging times considering the battery capacity and the maximum charging rates as summarized in [20] for the popular EV models as in [3] (see Table I) and we assume that they are uniformly distributed. We assume that the number of cars arriving per hour follows a Poisson distribution with hourly rates taken from [3].

We examine two demand scenarios: (a) when the arriving vehicles demand full charging; and (b) when the charging demand varies. The performance is measured wrt. the total completion time of the vehicles charging and is compared against the total completion time of SRPT's schedule.Generally, higher performance is expected when the charging slots are enough to charge all of the arriving EVs. Recall that at most $C = \lfloor L/\overline{x} \rfloor$ EVs can charge in the same interval. Furthermore, prior knowledge on the arrival times as well as the charging times of the arriving vehicles, could optimize the design of the sequence $S$, which in turn could lead to a better performance overall. Therefore, in our simulations we examined these two key elements: (1) the impact of the number of vehicles versus the number of available charging slots and (2) the impact of the sequence design.

To investigate the performance of the proposed solution in denser scenarios, we fluctuate the volume of the cars while maintaining the peak intervals of the arrival rates and we increase the charging slots $C$ from 10 to 50. Furthermore, to observe how the design of the sequence affects the performance of the proposed algorithm, we examine different integer sequences $S$, which have been optimized based on the actual charging times in Table I.

As for the running time, for the setting considered in our simulations, with the number of EVs up to 600 and $p_{\max} = 6$, Algorithm 1 runs in few msecs in a standard laptop.

**Impact of Density.** To investigate the impact of density on the performance of the algorithm, we compare its total completion time, given a sequence design, in different levels of $C$. Comparing, in Fig. 2, the SRPT ratio of the algorithm in full demand instances (left) and when the demand varies (middle), we note that in the latter case the SRPT ratio decreases with $C$. This is because the algorithm performs better in high demand-high density scenarios, as it keeps less vacant intervals. For

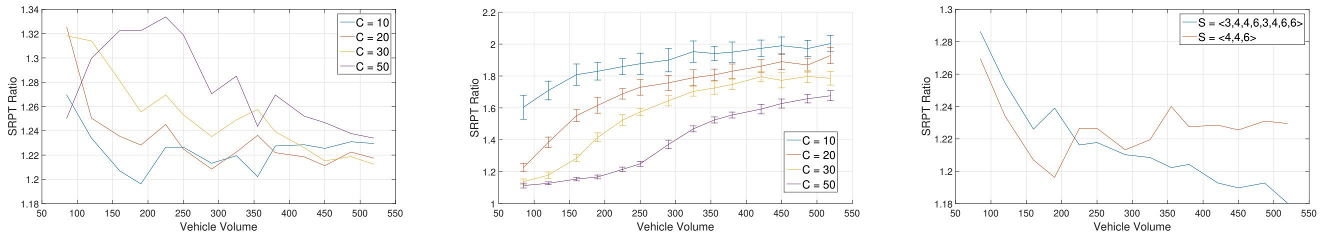


Fig. 2: SRPT ratio on full-time demand when the number of charging slots varies (left), SRPT ratio on variability in demand when the number of charging slots varies (middle) and SRPT ratio comparison of two different sequence designs when charging slots equal 10 for full-time demand (right).

full charging demand, we use the sequence $\langle 4,4,6\rangle$, while for the varying demand, the sequence is $\langle 2,4,6\rangle$.

**Impact of Sequence Design.** In Fig. 2, right chart, we compare two different sequences in the extreme case of $C = 10$. Each line represent the algorithm performance expressed as the total completion time for two different sequence designs. It is clear that the design of the sequence plays a key role to the performance of the algorithm. As expected, in both demand scenarios, when the lengths of the intervals in $S$ are closer to the actual charging times, the SRPT is better.

## VI. Conclusions

We presented an online algorithm for scheduling the charging of EVs in a CS aiming to optimize the weighted completion time. To prevent EVs from acting strategically, and since in practice, they may not be able to accurately report their charging characteristics, we present them with a menu of possible charging options. Thus EVs can intuitively choose their most preferable option. We prove that our algorithm achieves a reasonable competitive ratio. Our simulations further confirm that the algorithm performs well in practice, especially in scenarios where the requested energy and the number of arriving EVs are large. In future work, it would be interesting to consider a time-dependent transformer's capacity bound $\mathrm{L}(t)$ and to include time-varying electricity prices Another interesting research direction would be to use our approach in a network of multiple charging stations and to also consider the economic profits of each individual station.

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