Pricing EV Charging Service with Demand Charge

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***Abstract*—Pricing electric vehicle (EV) charging services is difficult when the electricity tariff includes both time-of-use energy cost and demand charge based on peak power draw. In this paper, we propose a pricing scheme that assigns a session-specific energy price to each charging session at the end of the billing period. The session price precisely captures the costs of energy, demand charge, and infrastructure congestion for which that session is responsible in that month while optimizing the trade-off between inexpensive time-of-use pricing and peak power draw. While our pricing scheme is calculated offline at the end of the billing period, we propose an online scheduling algorithm based on model predictive control to determine charging rates for each EV in real-time. We provide theoretical justification for our proposal and support it with simulations using real data collected from charging facilities at Caltech and JPL. Our simulation results suggest that the online algorithm can approximate the offline optimal reasonably well, e.g., the cost paid by the operator in the online setting is higher than the offline optimal cost by 9.2% and 6.5% at Caltech and JPL respectively. In the case of JPL, congestion rents are enough to cover this increase in costs, while at Caltech, this results in a negligible average loss of $18 per month.**

***Index Terms*—demand charge, EV charging, pricing, smart charging, online scheduling**

I. Introduction

It is expected that 120 million electric vehicles (EVs) will be on the road by 2030. These EVs will consume 271 billion kWh of electricity annually and require nearly $50 billion in charging infrastructure investments [1]. To reduce capital and operating costs in large-scale facilities, charging must be carefully managed, e.g., [2]. These facilities are generally subject to commercial electricity tariffs, which include both time-varying energy costs ($/kWh) and demand charge ($/kW). Time-of-use (TOU) energy costs incentivize shifting energy use to off-peak periods. Demand charges, which are assessed on the peak power draw of the user over a billing period, incentivize consumers to smooth their demand profile, reducing infrastructure costs. These demand charges can make up a significant portion of a charging facility's total electricity bill, e.g., up to 90% in the case of DC fast charging [3]. In Section II we show that demand charge can be up to 75% of the total electricity cost of uncontrolled level-2 charging and up to 49% even when EVs are scheduled optimally to reduce costs. Currently, most workplace and public-use charging facilities are either free or charge a flat rate based on time or energy delivered. As EV adoption grows, the current practice cannot sustain. An emerging question for operators of large-scale charging facilities is how to fairly allocate the total cost of providing charging services to users of the system.

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In this paper we propose a novel method to price charging services which attributes the operator's total cost to each user based on her contribution to the social cost. Our method is based on three ideas. First, the primary objective of the system operator is to meet EVs' energy requests by their departure times without overloading the charging infrastructure and at minimal cost (energy cost plus demand charge). Second, since users do not directly control when their EV is charged in a managed charging environment, the price the user pays should be based on the lowest cost charging schedule the operator could have used, rather than the actual charging schedule used. This gives systems operators flexibility, by decoupling charging decisions from pricing decisions while holding them accountable to provide low cost charging to their users. It also rewards users for providing useful flexibility even if the operator chose not to utilize that flexibility. Third, in order to properly assign prices to cover costs, billing should take place at the end of the utility company's billing period, when demand charges and the full impacts of congestion are known.

Offline pricing. In Section III we design our pricing scheme. This scheme takes the following form: At the end of each month (billing period), we compute a session-specific energy price α_i^* for every charging session i in that month. Let e_i be the energy delivered in session i and $\mathcal{S}_j$ be the set of all sessions belonging to user j. Then user j's total bill at the end of the month is $\sum_{i\in\mathcal{S}_j} \alpha_i^* e_i$, i.e., user j pays the session energy price for all her sessions. Unlike pricing schemes that use the same fixed or time-varying prices for all users regardless of the burden they place on the system, our prices α_i^* capture in a precise sense the costs of energy, infrastructure congestion, and demand charge for which session i is responsible in that month.

Online scheduling. While the prices are computed with perfect information at the end of each month based on users' collective behavior, charging decisions must be made online with limited information. In Section IV, we propose an online scheduling algorithm, based on model predictive control, that approximates the offline minimum-cost solution with only information available at that time. While many online algorithms have been proposed to minimize the cost

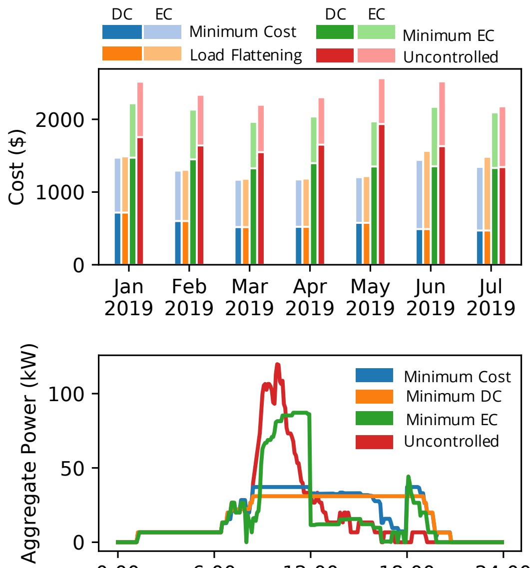

Fig. 1. (top) Total electricity costs, broken down by demand charge (DC) and energy cost (EC), for the Caltech ACN when using SCE's TOU-EV-4 tariff schedule for various scheduling strategies. Note that all schedules here are calculated offline with perfect future information. All algorithms, except uncontrolled, respect the infrastructure constraints of the Caltech ACN described in [10]. (bottom) Example of aggregate power draw for each approach for May 1, 2019.

of EV charging for ToU tariffs [4], [5], [6], [7], these works do not consider demand charge. Many algorithms for load variance minimization have also been proposed [8], [9]. These algorithms tend to minimize demand charge, but neglect the tradeoff between minimizing energy cost and demand charge. Our algorithm, on the other hand, explicitly optimizes this tradeoff.

Evaluation using real data. In Section V, we simulate the proposed offline pricing and online scheduling algorithms using large-scale EV charging data from the field. Our design, especially decoupling pricing and charging decisions, and payment at the end of a billing period instead of a charging session, is in stark contrast to the current practice. Our goal is to carefully lay out a theoretical justification and support it with realistic simulations.

II. Demand Charge

For many commercial customers, demand charge can be a significant portion of their electricity bill. This is especially true for large-scale charging systems at sites where demand tends to be synchronized, such as workplaces. With uncontrolled charging, this would lead to large peaks in demand followed by long periods of low utilization, which leads to extremely high demand charges relative to the amount of energy delivered. This can be seen in Fig 1. High demand charges from uncontrolled charging must be passed on to drivers in the form of higher per-unit prices. These higher prices could dissuade customer adoption of EVs.

Managed charging can help reduce demand charges. However, there is an inherent trade-off between minimizing demand charge and minimizing time-of-use energy costs. This trade-off occurs because demand charge is minimized when load is flat across the day, while energy cost is minimized when load is concentrated in low-cost periods. To see this, consider three possible schedules for EV charging, each with its own objective: 1) minimize energy cost only, 2) minimize demand charge only (load flattening), 3) minimize total cost. To find each schedule, we solve an offline convex optimization problem with the appropriate objective as well as constraints and data collected from a real large-scale charging facility at Caltech [10]. We consider the Southern California Edison EV TOU-4 tariff described in Table I. The total cost, broken down by energy cost and demand charge, of each optimal schedule as well as uncontrolled charging, is shown in Fig 1.

The results exhibit two distinctive features. First, uncontrolled charging and energy-cost minimization result in much higher peaks than demand-charge minimization and total-cost minimization. As a consequence, uncontrolled charging (energy-cost minimization) results in up to 335% (258%) increase in demand charge relative to the minimum cost schedule.[1] Second, even in the cases where we minimize the total cost or flatten load, the resulting demand charge is still between 31-49% of the total cost. These results suggest:

- Because demand charges are significant, charging system operators cannot ignore them and must pass these costs on to their users. However, because demand charges are assessed over the whole month, care must be taken to properly attribute these costs to individual charging sessions in a fair and principled way.
- Since managed charging offers the potential to reduce overall costs significantly; the pricing scheme should reward drivers who provide flexibility to the system if that flexibility can be used to reduce overall costs.

Our goal is to design a pricing scheme and an online scheduling algorithm with these properties.

III. Pricing Rule

In this section, we present the basic design of our pricing method. While we calculate prices offline with perfect information such as would be available at the end of a billing period, we explain in Section IV how to combine this pricing scheme with online scheduling algorithms so that it can be used in practice.

A. Basic pricing design

Consider the problem of pricing EV charging service over an entire month in an offline setting. We divide the month into T control periods indexed by $t = 1, \ldots, T$. For our experiments we will consider periods of length 5 minutes. Suppose there are N EVs requiring charging service throughout the month. We will abuse notation and use T and N also to denote

[1] Note that uncontrolled charging has a higher peak as it is not subject electrical infrastructure constraints.

the sets $T := \{1, \ldots, T\}$ and $N := \{1, \ldots, N\}$ respectively. Let

- EV $i = 1, \ldots, N$ be specified by $(a_i, d_i, e_i, \bar{r}_i(t))$ where $a_i \in T$: is its arrival time, $d_i \in T$ is its departure time, e_i is its energy request. For simplicity we express energy in kWp defined as the energy delivered by charging at 1 kW for 1 period, i.e. 1/12 kWh for 5 min period. $\bar{r}_i(t)$ is a possibly time-varying upper bound on the charging rate (in A). Here $\bar{r}_i(t)$ is assumed known and in practice can be a limit imposed by the charger (EVSE) serving EV i, the car's battery management system, some other algorithm, or a combination of these.
- p_t be the possibly time-varying electricity prices (in \$/kWh) at time $t \in T$ that the operator pays the local utility company for energy. For simplicity we will implicitly convert p_t into \$/kWp.
- P be the demand charge defined by the utility (\$/kW).
- c_{lt} be the possibly time-varying capacities of bottlenecks $l = 1, \ldots, L$, at time t.
- A_{li} be the coefficient which relates the charging rate of EV i to the aggregate current which is bound by bottleneck l. In the simplest case this can be 1 if EV i is constrained by bottleneck l, 0 otherwise. In more complex three-phase systems this could be the linearized constraints proposed in [10]. For simulations in this paper we use the latter.

We assume $e_i > 0$, $\bar{r}_i(t) > 0$, $p_t > 0$, $P > 0$, $A_{li} \geq 0$, $c_{lt} > 0$. Given these parameters, the operator will determine the charging rates $r := (r_i(t),\, i \in N, t \in T)$ for every EV i at time t.

To provide the EV charging service, the operator needs to pay for both energy and demand charge (among other expenses). These costs are a function of the charging rates r:

$$C(r) \;\; := \;\; \sum_t p_t \sum_i r_i(t) \; + \; P \max_t \sum_i r_i(t) \qquad (1a)$$

Hence the operator is interested in solving the following minimum-cost charging problem:

$$\begin{aligned} C^{\min} \;\; := \;\; \min_{r_i \in R_i} \quad & C(r) \\ \text{s. t.} \quad & \sum_t r_i(t) \;=\; e_i, & \forall i \qquad (1b) \\ & \sum_i A_{li}\, r_i(t) \;\leq\; c_{lt}, & \forall l,\ \forall t \; (1c) \\ & r_i(t) \leq \bar{r}_i(t), & \forall i,\ \forall t \, (1d) \end{aligned}$$

where

$$R_i \; := \; \{r_i \in \mathbb{R}^T : r_i(t) \geq 0; r_i(t) = 0 \text{ for } t < a_i \text{ or } t > d_i\}$$

Here (1b) ensures every EV's energy request e_i is met before its departure time d_i, (1c), (1d) ensures that the capacity limits of the network c_{lt} and charger $\bar{r}_i(t)$ are respected. We assume problem (1) is feasible. An optimal solution specifies a schedule that meets all EV energy demands safely and at minimum cost to the operator.

Introduce the auxiliary variable q that represents the daily peak demand and convert the problem into the equivalent form:

$$\begin{aligned} C^{\min} \;\; := \;\; \min_{r_i \in R_i, s \geq 0} \quad & \sum_t p_t \sum_i r_i(t) \; + \; Pq & (2a) \\ \text{s. t.} \quad & \sum_t r_i(t) \;=\; e_i, \qquad \forall i & (2b) \\ & \sum_i A_{li}\, r_i(t) \;\leq\; c_{lt}, \ \forall l,\ \forall t & (2c) \\ & r_i(t) \leq \bar{r}_i(t), \qquad \forall i,\ \forall t & (2d) \\ & q \;\geq\; \sum_i r_i(t), \qquad \forall t & (2e) \end{aligned}$$

Let $\alpha := (\alpha_i, \forall i)$, $\beta := (\beta_{lt}, \forall l,\ \forall t)$, $\gamma := (\gamma_{it}, \forall i,\ \forall t)$, $\delta := (\delta_t, \forall t)$ be the Lagrange multipliers for (2b), (2c), (2d) (2e) respectively. The dual of the optimization problem (2) is

$$\begin{aligned} \max_{\substack{\alpha, \beta \geq 0 \\ \delta \geq 0, \gamma \geq 0}} \quad & \sum_i e_i \alpha_i - \sum_{t,l} c_{lt} \beta_{lt} - \sum_{t,i} \bar{r}_i(t) \gamma_{it} & (3a) \\ \text{s. t.} \quad & p_t + \sum_l A_{li} \beta_{lt} + \gamma_{it} + \delta_t \;\geq\; \alpha_i \quad \forall i, \forall t & (3b) \\ & P \;\geq\; \sum_t \delta_t & (3c) \end{aligned}$$

Pricing rule. Let (r^*, q^*) and $(\alpha^*, \beta^*, \gamma^*, \delta^*)$ be an optimal primal-dual solution to the minimum-cost charging problem (2), (3). LP duality implies the following observations at optimality.

1) *Network congestion price* β^*_{lt}. We interpret β^*_{lt} as the congestion price at bottleneck l at time t. From (2c), this congestion price is zero, i.e., $\beta^*_{lt} = 0$, if bottleneck l is not congested at time t, i.e., $\sum_i r^*_i(t) < c_{lt}$.
2) *Charger congestion price* γ^*_{it}. We interpret γ^*_{it} as the congestion price at charger i at time t. From (2d), this congestion price is zero, i.e., $\gamma^*_{it} = 0$, if EV i is charged at lower than the peak rate allowed by the charger, i.e., $r^*_i(t) < \bar{r}_i(t)$.
3) *DC price* δ^*_t. We interpret δ^*_t as the demand charge price at time t. From (2e), the price is nonzero, i.e., $\delta^*_t > 0$, only if the total charging rate at time t hits the daily peak (see Theorem 1), i.e., $\sum_i r_i(t) = \max_\tau \sum_i r^*_i(\tau)$.

For each EV i at each time t, define a *composite price* $\pi^*_i(t)$:

$$\pi^*_i(t) \;\; := \;\; \underbrace{p_t}_{\text{energy}} + \underbrace{\sum_l A_{li} \beta^*_{lt}}_{\text{network congestion}} + \underbrace{\gamma^*_{it}}_{\substack{\text{charger} \\ \text{congestion}}} + \underbrace{\delta^*_t}_{\text{demand charge}} \qquad (4)$$

This EV-specific time-varying price $\pi^*_i(t)$ incorporates the energy price p_t that the operator pays the utility, the congestion prices β^*_{lt} at all bottlenecks used by EV i, the congestion price γ^*_{it} at the charger, and the demand-charge price δ^*_t. It captures the social cost that EV i is responsible for at time t. Since $p_t > 0, A_{li} \geq 0$ by assumption, the composite prices $\pi^*_i(t) > 0$ for all i, t.

Given the primal-dual solution pairs, the *pricing rule* is:

- EV i pays $\pi_i^*(t) r_i^*(t)$ at each time $t \in [a_i, d_i]$ it charges.
- Total payment for EV i's session is:

$$\Pi_i^* \quad = \quad \sum_t \pi_i^*(t) r_i^*(t) \tag{5}$$

Clearly the payment $\Pi_i^* > 0$ since $\pi_i^*(t) > 0$. This payment covers energy cost, congestion rents, as well as demand charge for which EV i is responsible. Having defined the above costs and pricing rules, we present Theorem 1 on the consequences of these costs and pricing rules.

Theorem 1. *Suppose EV i charges at the optimal rates $r_i^* := ((r_i^*(t),\ t \in [a_i, d_i])$ and pays Π_i^* given in* (5)*. Then*

1) Decomposition of DC price P. *P is decomposed into DC price δ_t^* at each time t:*

$$P \quad = \quad \sum_t \delta_t^*$$

Moreover the DC price $\delta_t^* > 0$ only if $\sum_i r_i^*(t) = \max_\tau \sum_i r_i^*(\tau)$, i.e., only if the total charging rate at time t hits the daily peak. Thus $Pq^* = \sum_t \delta_t \sum_i r_i^*(t)$.

2) Equivalent session price α_i^*. *EV i's total payment satisfies:*

$$\Pi_i^* \quad := \quad \alpha_i^* \cdot e_i$$

i.e., the total payment of EV i is equivalent to charging i only a time-invariant *price α_i^* per unit of energy. Moreover $\alpha_i^* > 0$.*

3) Nonnegative operator surplus. *The total payment by all EVs exceeds the total electricity cost (energy + demand charge) that the operator pays the utility:*

$$\sum_i \Pi_i^* \quad \geq \quad C^{min}$$

Proof.

1) Since $e_i > 0$ for all i, we must have $q^* = \max_t \sum_i r_i^*(t) > 0$ and hence $P = \sum_t \delta_t^*$ in (3c).

2) The constraint (3b) and complementary slackness imply that, for all $t = 1, \ldots, T$,

$$\pi_i^*(t) \geq \alpha_i^* \quad \text{with} \quad \pi_i^*(t) = \alpha_i^* \ \text{ if } \ r_i^*(t) > 0$$

This implies (using (2b)):

$$\Pi_i^* \quad := \quad \sum_t \pi_i^*(t)\, r_i^*(t) \ = \ \sum_t \alpha_i^* r_i^*(t) \ = \ \alpha_i^* \cdot e_i$$

As noted above $\Pi_i^* > 0$ for all i. Hence $\alpha_i^* > 0$ since $e_i > 0$ by assumption.

3) Assertion 2 implies

$$\begin{aligned}\sum_i \Pi_i^* \quad &= \quad \sum_i e_i\, \alpha_i^* \\ &\geq \quad \sum_i e_i \alpha_i^* - \sum_{t,l} c_{lt} \beta_{lt}^* - \sum_{t,i} \bar{r}_i(t) \gamma_{it}^* \\ &= \quad D(\alpha^*, \beta^*, \gamma^*, \delta^*) \quad = \quad C^{\min}\end{aligned}$$

where $D(\alpha^*, \beta^*, \gamma^*, \delta^*)$ is the optimal dual objective value and the last equality follows from strong duality.

This completes the proof of the theorem. □

Remark 1. 1) *The equivalent session price $\alpha_i^* > 0$ is the Lagrange multiplier associated with the (equality) energy constraint* (2b)*. This EV-specific time-invariant energy price takes into account of energy, congestions, and demand charge. It lower bounds the composite prices at all times, i.e., $\pi_i^*(t) \geq \alpha_i^*$, but it alone determines the total payment $\Pi_i^* = \alpha_i^*\, e_i$. Hence, instead of charging EV i at each time t at the time-varying price $\pi_i^*(t)$, we can instead charge i a session price α_i^* based only on energy e_i delivered. It is in this sense that α_i^* is an equivalent session price for EV i.*

2) *Property* (6) *states that EV i pays a nonzero amount at time t, i.e., $r_i^*(t) > 0$, only if the composite price is at its lower bound, i.e., only if $\pi_i^*(t) = \alpha_i^*$ at time t.*

3) *From assertion 3 of Theorem 1 the* operator surplus

$$\sum_i \Pi_i^* - C^{min} \ = \ \sum_{t,l} c_{lt} \beta_{lt}^* + \sum_{t,i} \bar{r}_i(t) \gamma_{it}^*$$

is a measure of how congested the bottlenecks and the chargers are (congestion rents). The higher the surplus is, the more congested the system is, and the surplus is zero if and only if no bottleneck nor charger is ever congested ($\beta_{lt}^* = 0$ and $\gamma_{it}^* = 0$ for all l, t). The demand charge price δ_t^* does not directly affect the site host surplus.

Separation of pricing and control. Note that under the pricing rule (5), EV i pays an amount $\sum_t \pi_i^*(t)\, r_i^*(t)$ for its service, even if it is *not* charged at rates $r_i^*(t)$ at time t. Indeed charging rates in practice are often determined through other means, e.g., using an online scheduling algorithm that does not have perfect future information or even solving a different optimization problem that has a different objective function and a different set of constraints. However, by using this price structure, operators are incentivized to schedule EVs at as low a cost as possible so that the revenue provided by users is enough to cover their costs. If, however, the operator chooses to determine charging schedules in some other way, the user is indifferent so long as their energy demand is fully met.

B. Pricing with onsite solar

Onsite solar generation can be used to reduce both the environmental footprint and overall cost of an EV charging system. However fairly distributing this savings and incentivizing drivers to provide enough flexibility so that the system can charge their vehicles using solar generation can be challenging. We can easily modify our pricing scheme to account for solar generation by introducing two additional variables $r_i^g(t)$ and $r_i^s(t)$ such that $r_i(t) = r_i^g(t) + r_i^s(t)$. We can interpret $r_i^g(t)$ to the the portion of EV i's charging rate which was delivered from the grid while $r_i^s(t)$ is the portion delivered by onsite solar generation. We can then formulate the optimization as:

$$\min_{\substack{r_i^g\in R_i\\ r_i^s\in R_i\\ s\geq 0}} \quad \sum_t p_t \sum_i r_i^g(t) + \sum_t p_t^s \sum_i r_i^s(t) \; + \; Pq \tag{6a}$$

$$\text{s. t.} \quad \sum_t \left(r_i^g(t) + r_i^s(t)\right) \;=\; e_i, \qquad \forall i \tag{6b}$$

$$\sum_i A_{li}\left(r_i^g(t) + r_i^s(t)\right) \;\leq c_{lt}, \qquad \forall l, \forall t \tag{6c}$$

$$r_i^g(t) + r_i^s(t) \leq \bar{r}_i(t), \qquad \forall i,\; \forall t \tag{6d}$$

$$q \;\geq\; \sum_i r_i^g(t), \qquad \forall t \tag{6e}$$

$$S(t) \;\geq\; \sum_i r_i^s(t), \qquad \forall t \tag{6f}$$

where $S(t)$ is given and specifies the total solar generation available for EV charging at time t. This could be the total production of the PV array or the excess after all other loads are met. Here we assume that energy generated by the onsite solar PV has a price, $p_t^s \geq 0$ (such as from a power purchase agreement). We can then formulate the dual problem, introducing the additional dual variable $\epsilon := (\epsilon_t, \forall t)$ for (6d).

$$\max_{\substack{\alpha\\ \beta\geq 0\\ \delta\geq 0\\ \gamma\geq 0\\ \epsilon\geq 0}} \quad \sum_i e_i\alpha_i - \sum_{t,l} c_{lt}\beta_{lt} - \sum_{t,i} \bar{r}_i(t)\gamma_{it} - \sum_t \epsilon_t S(t) \tag{7a}$$

$$\text{s.t.} \quad p_t + \sum_l A_{li}\beta_{lt} + \gamma_{it} + \delta_t \;\geq\; \alpha_i \qquad \forall i, \forall t \tag{7b}$$

$$p_t^s + \sum_l A_{li}\beta_{lt} + \gamma_{it} + \epsilon_t \;\geq\; \alpha_i \qquad \forall i, \forall t \tag{7c}$$

$$P \;\geq\; \sum_t \delta_t \tag{7d}$$

Let $(r^{g*},\, r^{s*},\, q^*)$ and $(\alpha^*, \beta^*, \gamma^*, \delta^*, \epsilon^*)$ be the optimal primal/dual solution to (6)/(7). The charging rate for each EV is $r_i^*(t) := r^{g*}(t) + r^{s*}(t)$.[2] We define a composite price for each component of the charging current:

$$\pi_i^{g*}(t) := \underbrace{p_t}_{\text{energy}} + \underbrace{\delta_t^*}_{\text{demand charge}} + \underbrace{\sum_l A_{li}\beta_{lt}^*}_{\text{network congestion}} + \underbrace{\gamma_{it}^*}_{\substack{\text{charger}\\ \text{congestion}}} \tag{8}$$

$$\pi_i^{s*}(t) := \underbrace{p_t^s}_{\substack{\text{solar}\\ \text{price}}} + \underbrace{\epsilon_t^*}_{\text{solar congestion}} + \underbrace{\sum_l A_{li}\beta_{lt}^*}_{\text{network congestion}} + \underbrace{\gamma_{it}^*}_{\substack{\text{charger}\\ \text{congestion}}} \tag{9}$$

We then define the total price paid by driver i as

$$\Pi_i^{sol*} \;=\; \sum_t \pi_i^{g*}(t) r_i^{g*}(t) + \pi_i^{s*}(t) r_i^{s*}(t) \tag{10}$$

Theorem 1 and its implications extend directly to the case with onsite solar.

[2]It is important to note that the decomposition into r^{g*}, r^{s*} is purely for accounting purposes, as we cannot control the source of power to each EV.

Theorem 2. *Suppose EV i charges at the optimal rates $r_i^* := r_i^{g*} + r_i^{s*} = ((r_i^*(t),\, t \in [a_i, d_i])$ and pays Π_i^{on*} given in* (10). *Then*

1) Decomposition of DC price P. *Suppose $\exists(i,t)$ s.t. $r_i^{g*}(t) > 0$. P is decomposed into DC price δ_t^* at each time t:*

$$P \;=\; \sum_t \delta_t^*$$

Moreover the DC price $\delta_t^* > 0$ only if $\sum_i r_i^{g*}(t) = \max_\tau \sum_i r_i^{g*}(\tau)$, i.e., only if the total charging rate from the grid at time t hits the peak. Thus $Pq^* = \sum_t \delta_t \sum_i r_i^{g*}(t)$.

2) Equivalent session price α_i^*. *EV i's total payment satisfies:*

$$\Pi_i^{sol*} \;:=\; \alpha_i^* \cdot e_i$$

i.e., the total payment of EV i is equivalent to charging i only a time-invariant *price α_i^* per unit of energy. Moreover $\alpha_i \geq 0$.*

3) Nonnegative operator surplus. *The total payment by all EVs exceeds the total electricity cost (energy + demand charge + solar value) that the operator pays:*

$$\sum_i \Pi_i^{sol*} \;\geq\; C_{sol}^{min}$$

4) Savings with onsite solar. *The total cost to the operator with onsite solar is not greater than the total cost without it.*

$$C^{min} \;\geq\; C_{sol}^{min}$$

Proof.

1) Since by assumption $\exists(i,t)$ s.t. $r_i^{g*}(t) > 0$ we must have $q^* = \max_t \sum_i r_i^{g*}(t) > 0$ and hence $P = \sum_t \delta_t^*$.

2) The constraints (7b) and (7c) and complementary slackness imply:

$$\pi_i^{g*} \geq \alpha_i^* \quad \text{with} \quad \pi_i^{g*} = \alpha_i^* \;\text{ if }\; r_i^{g*}(t) > 0$$
$$\pi_i^{s*} \geq \alpha_i^* \quad \text{with} \quad \pi_i^{s*} = \alpha_i^* \;\text{ if }\; r_i^{s*}(t) > 0$$

This implies (using (6b)):

$$\Pi_i^{sol*} \;:=\; \sum_t \pi_i^{g*}(t)\, r_i^{g*}(t) + \pi_i^{s*}(t)\, r_i^{s*}(t)$$
$$= \sum_t \alpha_i^*(r_i^{g*}(t) + r_i^{s*}(t)) \;=\; \alpha_i^* \cdot e_i$$

3) Assertion 2 implies

$$\sum_i \Pi_i^{sol*} \;=\; \sum_i e_i\,\alpha_i^*$$
$$\geq \sum_i e_i\alpha_i^* - \sum_{t,l} c_{lt}\beta_{lt}^* - \sum_{t,i} \bar{r}_i(t)\gamma_{it}^* - \sum_t \epsilon_t S(t)$$
$$= D_{sol}(\alpha^*, \beta^*, \gamma^*, \delta^*, \epsilon^*) \;=\; C_{sol}^{\min}$$

where $D_{sol}(\alpha^*, \beta^*, \gamma^*, \delta^*)$ is the optimal dual objective value and the last equality follows from strong duality.

4) Let $(r^*,\ q^*)$ be an optimal solution of (2) yielding an optimal value C^{min}. By inspection, $(r_i^g := r_i^*,\ r_i^s := 0, q^*)$ is a feasible point for (6) which achieves C^{min}, implying $C_{sol}^{min} \le C^{min}$.

This completes the proof of the theorem. □

IV. Online scheduling

While the prices are computed in an offline setting with perfect information at the end of each month based on users' collective behavior, charging decisions must be made online with limited information. For example, the operator does not know when future EVs will arrive nor what their energy demands will be. Instead, EVs arrive at random times, but when an EV arrives, it informs the operator, e.g., using a mobile app, its energy demand e_i and departure time $d_i \in T$. We assume in this paper that e_i and d_i provided by the drivers are accurate. In practice, they are not but can be learned from historical data for workplace charging; see [11].

A. Online scheduling algorithm

The goal then of the operator at time τ is to approximate the offline minimum cost solution with only the information available at that time. Since in the online setting we cannot optimize over the entire billing period, we instead employ the model predictive control proposed in [10] where an optimization problem is solved over a receding horizon (12 hrs) assuming no future EV arrivals. To account for the online setting, we make several modifications to (2). First, because the online algorithm could make a decision in one computation period which makes it infeasible to meet all energy demands in a later period, we relax (2b) to

$$\sum_t r_i(t) \le e_i \tag{11}$$

However, doing so would make $r_i(t) = 0,\ \forall i, \forall t$, the optimal solution. To fix this, we also modify the objective (2a) by adding a penalty, ρ, for unmet demand. In addition, there are several equivalent solutions to (2). In the online case we do not have information about future arrivals, thus we wish to select the solution which charges each EV as quickly as possible, while not increasing costs. This frees capacity for future arrivals. Let $\eta(t) < 0$ be a linearly increasing function in t. For a small η, $\sum_{i,t} \eta(t) r_i(t)$ encourages charging quickly while having a negligible effect on the optimal cost. For more information see [10].

$$\begin{aligned} C_{on}(r,s) := \quad & \sum_t p_t \sum_i r_i(t) + Pq \\ & + \rho \sum_i \left(e_i - \sum_t r_i(t) \right) + \sum_{t,t} \eta(t) r_i(t) \end{aligned} \tag{12}$$

When ρ is sufficiently high, and it is feasible to do so, then (11) will be tight and the resulting $\hat{r}^*$ is also a solution to (2).

To account for demand charge in this shortened horizon, we also propose two additional modifications. First, we add a constraint

$$q \ge \max\{q_0,\ q'\} \tag{13}$$

where q_0 is the running peak demand from the beginning of the current billing period up to (but not including) the current time τ, and q' is a prediction of the optimal peak demand based on historical data. With this constraint the optimization is only penalized if q exceeds the maximum of q_0 and q'. Second, we replace P in (12) with a demand charge proxy $\hat{P} \le P$ which can depend on the computation period. The purpose of this proxy is to amortize the total demand charge over each day. The resulting optimization problem is

$$\min_{r_i \in R_i, q \ge 0} \quad C_{on}(r, q) \tag{14a}$$
$$\text{s. t.} \quad \sum_t r_i(t) \ \le\ e_i, \qquad \forall i \tag{14b}$$
$$\sum_i A_{li}\, r_i(t) \ \le\ c_{lt},\ \forall l,\ \forall t \tag{14c}$$
$$r_i(t) \le \bar{r}_i(t), \qquad \forall i,\ \forall t \tag{14d}$$
$$q \ \ge\ \sum_i r_i(t), \qquad \forall t \tag{14e}$$
$$q \ \ge\ \max\{q_0,\ q'\} \tag{14f}$$

The online algorithms is then as follows. For each computation period $k = 1, 2, \ldots$:

1) Construct the modified linear program with the set of EVs that are currently charging (including new arrivals), so the arrival times $a_i = 1$ for all i and $e_i := e_i(k)$ is the *remaining* energy demand in (14).
2) Solve (14) to compute $\hat{r}^*$.
3) Set the charging rate of EV i to $\hat{r}_i^*(1)$.
4) Update the remaining energy demand $e_i(k+1)$ based on the actual energy delivered to EV i.
5) Go to Step 1.

B. Selecting tunable parameters

In (14), ρ, η, q', and $\hat{P}$ are tunable parameters. We let $\eta(t) := 10^{-4} \frac{t-T-1}{T}$. To determine q', we first solve the offline problem (2) on previous month's data to obtain the optimal peak q_{-1}^*. Note this is already done to calculate the prices for each user. One approach would be to set $q' = q_{-1}^*$. While this would be optimal if all months had the same usage pattern, there is some variability in the optimal peak power across months. Instead, we set $q' = 0.75 q^*$. This allows the online algorithm to increase the peak only when necessary to meet demand. Note that the maximum historical variability from month to month in our dataset is 12% (-23%) for Caltech and +13% (-9%) for JPL.

The demand charge proxy $\hat{P}$ controls the trade-off between energy costs and demand charges in the online problem. If $\hat{P}$ is high, i.e., $\hat{P} = P$, the algorithm will only increase its peak when it absolutely must. However, if $\hat{P}$ is too low, e.g., $\hat{P} = 0$, the algorithm will increase its peak significantly if doing so would lead to lower energy costs. We propose the following heuristic, $\hat{P} = P/(D_p - d)$, where D_p be the number of days in the billing period, and d be the index of the current day.

This heuristic is based on a simple amortization. At the beginning of the billing period, any increase in the demand charge can be spread over D_p days. The next day it can only be spread over $D_p - 1$ days, and so on. Thus, this heuristic encourages any increases in demand charge to occur early in the billing period, which allows the algorithm to decrease energy costs in the remainder of the billing period by concentrating charging during low cost times.

C. Prices in the online setting

While scheduling is done online, we still calculate prices offline at the end of the month using (2) and (3) as in Section III. Note that in this case, e_i in (3) is the actual energy delivered which may differ from the user's energy request. This pricing scheme is similar to other services such as electricity, water, and phone bills which are calculated based on usage at the end of the month rather than as the service is used. However, we note that this scheme is more volatile than most other bills faced by consumers owing to the challenges of demand charge. In future work we hope to provide predictions and bounds of the cost faced by consumers when they input their parameters.

V. Simulations

A. ACN Research Portal

To evaluate the pricing scheme proposed in Section III and the online scheduling algorithm proposed in Section IV, we use a large-scale EV charging dataset, called ACN-Data, collected from smart charging facilities, called adaptive charging networks (ACNs), at Caltech and JPL [11]. The Caltech ACN is a large-scale charging facility that has delivered over 998 MWh of energy since it began operation in early 2016 [10], [12]. The facility currently has 54 charging ports, each of which is capable of real-time monitoring and control. Likewise, since beginning operation in October 2018, the JPL ACN has delivered over 358 MWh of energy from 52 charging ports. ACN-Data contains charging data collected from these ACNs. It has recently been released [6] and, to our knowledge, is the only large-scale fine-grained charging data that is publicly available. We use ACN-Data to playback real charging scenarios using ACN-Sim, an open-source simulator, for evaluating our charging algorithms [13].

B. Summary of simulation results

We use ACN-Data and ACN-Sim to explore several questions about the proposed pricing scheme and online scheduling algorithm. The code and data for these experiments is available at https://github.com/zach401/pricing_ev_charging_service.

- Assuming the pricing scheme proposed in Section III, how much surplus would the operator receive if they were able to schedule charging offline in order to minimize costs (solving (2))?
- How much surplus would the operator receive if they instead schedule according to the online algorithm proposed in Section IV with the same pricing scheme?
- Does the proposed pricing scheme result in reasonable prices on a per session and per user basis?

TABLE I
SCE TOU Rate Schedule for EV Charging

	Summer Rates	Winter Rates
On-Peak	\$0.267 / kWh	\$0.087 / kWh
Mid-Peak	\$0.0925 / kWh	\$0.075 / kWh
Off-Peak	\$0.0562 / kWh	\$0.061 / kWh
Demand Charge	\$15.51 / kW / month	

In summary, our results are:

- On average, when charging vehicles according to the offline optimal charging schedule r^*, the Caltech ACN would receive \$101 in surplus each month, while JPL would receive a surplus of \$324.
- As expected, in the offline case, revenue from energy costs ($\sum_{t,i} p_t r_i^*(t)$) matches the actual energy cost and revenue from demand charges ($\sum_{t,i} \delta_t^* r_i^*(t)$) matches the actual demand charge.
- When using the online algorithm proposed in Section IV, costs for operating the Caltech ACN increase by an average of 9.2%, while costs for JPL increased by 6.5%.
- On average, with the online algorithm, Caltech has a surplus of -\$18 per month, while JPL has a surplus of \$92.
- We find that the basic pricing scheme described in Section III can lead to high prices for some sessions, particularly those involved in setting the peak demand for the month. The maximum price for any one session was \$1.62 / kWh at Caltech and \$1.53 / kWh at JPL out of 12,049 and 15,509 sessions, respectively.

The absolute values of the surpluses being small is a desirable feature since the design objective is not profit maximization. It suggests our pricing design is approximately revenue adequate and sites are sized appropriately.

C. Detailed results

Simulation setup. For each simulation, we used data collected from from Jan. 1, 2019 - Aug. 1, 2019 at the Caltech and JPL ACNs. We adopt the Southern California Edison TOU rate schedule for separately metered EV charging systems between 20-500 kW, which is shown in Table I. Here, Summer runs June 1 - Oct. 1. Weekends are always considered off-peak, while for weekdays, peak periods are 12:00 - 18:00, mid-peak is from 8:00 - 12:00 and 18:00 - 23:00, and all other hours are off-peak [14]. While this rate structure was recently replaced with the TOU-EV-8 structure which temporarily removed demand charges for EV charging, this exception is slated to be removed in 5 years. So it is still relevant to investigate pricing schemes under the old tariff structure.

Operator surplus offline. To investigate the upper bound on the surplus an operator can expect, we solve (2) and (3) for

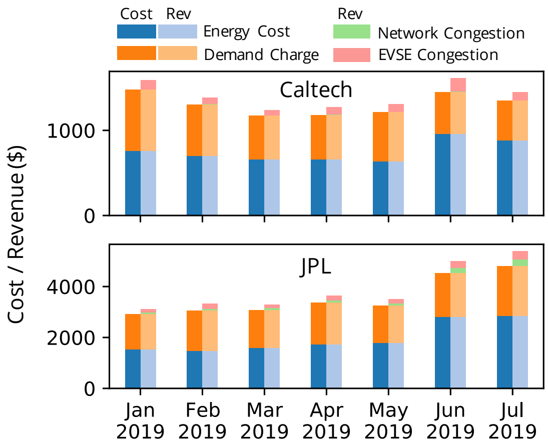

Fig. 2. Comparison of the total cost of providing charging services in the offline case (shown in darker colors to the left) to the total revenue of the operator (in lighter colors to the right).

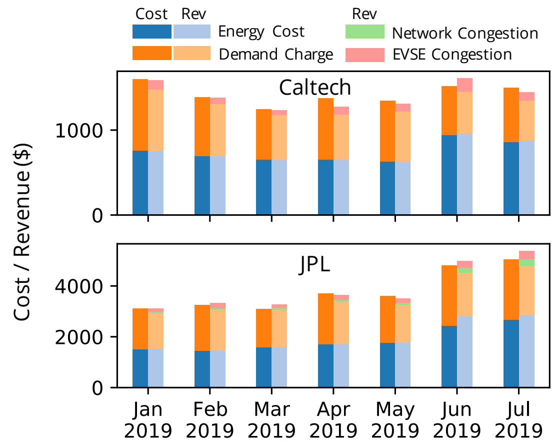

Fig. 3. Comparison of the total cost of providing charging services in the online case (shown in darker colors to the left) to the total revenue of the operator (in lighter colors to the right).

TABLE II
OFFLINE OPERATOR SURPLUS BY MONTH

	Jan	Feb	March	April	May	June	July
Caltech	$114	$82	$64	$93	$95	$165	$99
JPL	$190	$267	$215	$284	$250	$472	$594

TABLE III
ONLINE OPERATOR SURPLUS BY MONTH

	Jan	Feb	March	April	May	June	July
Caltech	-$13	-$3	-$10	-$105	-$38	$94	-$54
JPL	$-7	$68	$194.84	-$56	-$93	$187	$353

TABLE IV
ENERGY SURCHARGES TO ENSURE NON-NEGATIVE SURPLUS ($/KWH)

	Jan	Feb	March	April	May	June	July
Caltech	.0013	.0004	.0011	.012	.0045	-	.0082
JPL	.0003	-	-	.0025	.004	-	-

each month and each site. We then calculate the actual cost of electricity for each scenario as well as the revenue paid to the operator. The results of this experiment are shown in Fig. 2. In each case, we split the total cost and total revenue into its constituent components.

From this plot, we can see that the revenue for energy and demand charge perfectly match their respective costs. Thus in the offline case, the operator passes on these costs to users, as we expected. All surplus comes from congestion rents on the network and EVSEs. Note that for Caltech, there is very little rent for network congestion, as the charging network has been over-provisioned for future growth. On the other-hand, JPL experiences significant network congestion in the summer months. Note that the magnitude of congestion rents are higher in the summer, when there is higher price variability. This reflects how congestion rents allow (3b) to hold with equality despite variability in p_t and δ_t. Table II shows a more detailed breakdown of the surplus for each site. In total, Caltech had a surplus of $711 for these seven months, while JPL had a surplus of $2,270. Since in this context, the surplus is a result of congestion, this indicates that JPL should invest these surpluses in increasing the capacity of bottleneck links.

Operator surplus online. Since in practice operators cannot apply the offline optimal schedule that requires future information, they must instead use an online algorithm like the one proposed in Section IV. For this experiment we let $\rho = 20$, $\eta(t) := 10^{-4}\frac{t-T-1}{T}$, $\hat{P} = P/(D_p - d)$, and $q' = 0.75q^*_{-1}$. We can then compare the cost of this online algorithm with the revenues generated based on the offline pricing scheme, as shown in Fig. 3. We find that this online algorithm results in an average increase of 9.2% and 6.5% in total costs at Caltech and JPL, respectively.

In some cases, such as JPL in July, the surplus is enough to cover this increase in cost. However, in other cases, such as Caltech in July, the costs are higher than the revenue generated, and operator surplus is negative. Table III shows a breakdown of the operator surplus in each month for each site. From this table, we can see that over these seven months, Caltech lost $129 while JPL made $647. This shows that non-negative operator surplus cannot be guaranteed in the online setting with this pricing scheme (even though these surplus and loss are small).

If this possibility of negative surplus is troubling to operators, a simple solution is to distribute any negative surplus as a energy surcharge to be covered by each user in proportion to the energy they consumed.[3] The resulting energy surcharges for each month are shown in Table IV. From this table, we can see that only a modest (<$0.015) surcharge on each kWh delivered is necessary to ensure a non-negative surplus. Note that even with this surcharge, the proposed pricing scheme still communicates price signals which align individuals' incentives with those of the group. This is in contrast to a plan which divides all costs by the total energy delivered and provides a flat price to all users.

[3]This could also be done with surpluses if the operator does not wish to make a profit or reinvest the surpluses in reducing congestion.

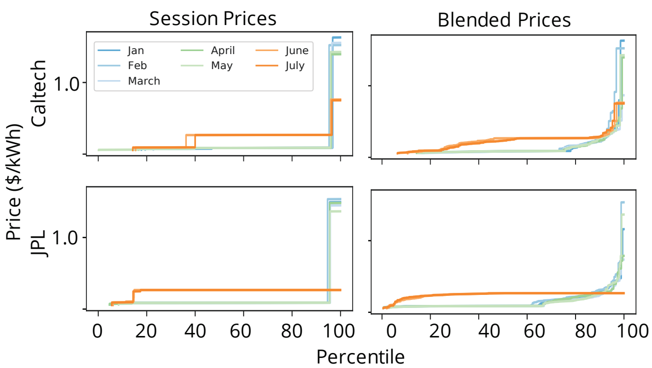

Fig. 4. Distribution of prices per session (left) and blended per user (right) for each month.

Distribution of prices. The left panels of Fig 4 show the distribution of session prices α_i. From the figure, we see that most sessions (>95%) have α_i very near to or below the maximum energy cost for the period ($0.087 for winter months and $0.267 for summer months). We also note that in winter months, a small percentage of the total charging sessions have very high prices. Upon close examination, we find that these sessions all occur on the same day and are responsible for setting the demand charge for the month. In summer months (June and July) we see that this effect is much less pronounced at Caltech and non-existent at JPL. The likely reason for this is that the higher variation in prices during the summer months causes the scheduling algorithms to concentrate charging during low-cost periods. This means that δ_t^* is non-zero in more periods, spreading the demand charge among more charging sessions.

Since the proposed pricing scheme involves charging users at the end of the month, users are more likely to care about their blended price, defined as the total price paid by the user divided by their total energy received, rather than the price paid for any individual session. The distribution of these blended prices is shown in the right panels of Fig 4. From the figure, we see that these blended prices tend to smooth out the price distribution. In addition, we can see that even though some users may experience one or more high-cost sessions throughout the month, for most users these are offset by other lower-cost sessions, lowering their blended price.

VI. Conclusions and Future Work

In this paper, we propose a pricing scheme which assigns a per-session price α_i^* to each charging session that captures the session's effect on energy cost, demand charge, and system congestion. This scheme has several desirable properties, including guaranteed non-negative operator surplus in the offline setting, and an explicit decomposition to prices on each cost component (energy, demand, and congestion).

We also propose an online scheduling algorithm based on model predictive control, which uses historical information and a demand charge proxy in order to manage the trade-off between energy costs and demand charge. Using data collected from large-scale charging facilities at Caltech and JPL, we demonstrate that the proposed online scheduling algorithm approximates the offline optimal reasonably well, e.g., the online optimal cost is higher than the offline optimal cost by 9.2% and 6.5% at Caltech and JPL respectively. In the case of JPL, congestion rents are enough to cover this increase in costs, while at Caltech, this results in a negligible average loss of $18 per month.

While in this work, we consider pricing only at the end of each billing period (1 month), in the future, we hope to build on this scheme to develop online variants. For example, if we can predict session prices when an EV arrives and provide real-time feedback to the driver as they select their energy request and departure time, we can incentivize users to provide more flexibility to the system. Likewise, if final prices can be set when a user leaves, we no longer will need to bill the user at the end of the month. We also plan to address the case where users can provide willingness to pay bids to the system which bound their session price α_i.

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