Mobile Storage for Demand Charge Reduction

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***Abstract*—Electric vehicles (EVs) are at the intersection of transportation systems and energy systems. The batteries in EVs, an increasingly prominent type of energy resource, are largely underutilized. In this paper, we propose a new business model that monetizes underutilized EV batteries to significantly reduce the demand charge portion of many commercial and industrial electricity users' electricity bills. This business requires minimal hardware to enable discharging the batteries of electric vehicles and a sharing platform that matches EVs to commercial electricity users in real time. In a case study using real meter data, we show that a large number of users can be served by a small number of EVs in the proposed business model. Cost-revenue analysis based on a real electric tariff suggests that the demand charge saving covers the capital costs of needed hardware and the compensation for EV drivers to provide the service.**

***Index Terms*—Sharing economy, V2G, mobile storage**

I. Introduction

The high cost of electric vehicles (EVs) and the limited access to EV charging facilities are hurdles in the path to transportation electrification [1]. Although the cost of EV batteries is trending down [2], the break-even point between the unsubsidized upfront costs of EVs and gasoline-powered vehicles may not come until 2025 [3]. Moreover, the low penetration of *public* EV charging facilities precludes consumers who cannot install home charging systems from adopting EVs. Even for consumers with access to home charging, limited public charging access coupled with range anxiety leads to the perception that EVs are incapable of long-distance travel and therefore may be inferior substitutes to gasoline-powered vehicles. *Sharing* provides a potential resolution to both challenges: sharing an EV across many uses possibly by many users can increase the value of the EV and thus justify its higher cost; sharing a *private* charging port by many users and possibly for different uses can increase the utilization of the charging hardware and thereby lead to a higher return on investment in charging facilities.

On the grid side, increasing EV charging loads puts more stress on power distribution networks. Accommodating the resulting higher peak loads may require upgrades to distribution network assets such as transformers. In the U.S., utility companies pass part of these costs to large electricity users through *demand charges* that bill users based on their maximum power consumption (kW) during each month in addition to the volumetric charge based on total energy consumption (kWh). Meanwhile, the trend to integrate renewable and distributed energy resources (DERs), such as roof-top solar panels, has encouraged adoption of time-varying retail electricity tariffs such as time-of-use rates and critical-peak pricing. These trends in electricity tariffs encourage commercial and industrial electricity users to procure and operate behind-the-meter DERs including stationary energy storage and vehicle-to-grid (V2G) technologies to reduce their electricity bills.

The conventional wisdom of V2G involves charging and discharging the battery of an EV that is usually parked for a long period of time (e.g. during the evening for an EV parked at home or during the daytime for an EV parked at a workplace) according to grid signals such as prices. The economic viability of V2G hinges on the comparison of the value provided by the EV battery to the grid and various costs, including the capital cost of V2G-enabling equipment and costs associated with degradation of the EV battery from additional cycles performed for V2G purposes [4]. However, individual EV owners can hardly assess the degradation costs to their EV batteries because (a) the time periods for which the EV is providing grid services are usually long, (b) the charging/discharging operations during such long periods are not known a priori, and (c) estimating the impact of any given charging/discharging operations on battery's life is a complex task [5], [6]. On the other hand, the owner of a V2G charging facility has difficulty in predicting the return on investment of such equipment as it depends on stochastic arrivals and departures of EVs and EV owners' willingness to participate in V2G services [7]. As a result market adoption of V2G technologies has been limited [8].

In this paper, we propose the model of a novel business based on sharing *on demand* V2G-compatible electric vehicles. The business builds upon a platform that matches EVs to commercial and industrial electricity users. For each match, in order to reduce the user's demand charge, the EV is dispatched to discharge its battery for a short time period (e.g. 15 minutes for many states in the U.S.) through a behind-the-meter V2G charging port that is connected to the user. We assess the viability of the business by a cost benefit analysis using real meter data, real electricity tariffs, and realistic capital cost numbers for V2G EV chargers. A key finding of the analysis is that different users tend to have different peak (and sub-peak) times and as a result *a small number of EVs can serve a large number of users*. Further, when users make multiple requests per month, the value created by the proposed business model not only covers the costs of the V2G chargers but also leaves a surplus that can be shared between users and EV drivers. These findings suggest that the proposed business (a) can become a successful sharing economy example for the smart grid even in today's institutional and regulatory environment, (b) provides a use case with a strong value proposition for behind-the-meter DER adoption , and (c) initiates a novel approach to V2G that reduces or circumvents concerns with the conventional V2G approach.

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A. Related work

Motivated by recent successes of the sharing economy in the transportation and housing markets and the fact that there are underutilized DERs that can be monetized, a line of research addresses the problem of sharing these DERs through a platform. Kalathil et al. [9] formulate the problem of energy storage sharing among a collection of firms, characterizes the equilibrium prices and analyzes the storage investment game. By establishing that the Nash equilibrium supports social welfare, the authors show that sharing improves welfare and utilization of storage assets. A similar setup for energy storage sharing is studied by Chakraborty et al. [10] where a coalitional game approach is taken. Tusher et al. [11] design an auction scheme to enable residential energy storage owners to share a portion of their storage capacities to certain shared facility controllers. Lombardi and Schwabe [12] evaluate the potential of sharing energy storage with different storage technologies and different use cases. Common to these papers is the use of the electric power network to enable a DER to be shared by users at different locations. However, as the power network is usually owned and operated by an electric utility company, large scale implementation of these proposed sharing businesses requires the permission of utility companies. Our proposed business model, by contrast, uses EVs to enable sharing of DERs (i.e., mobile energy storage) and interacts with the users through behind-the-meter connection points that are beyond the jurisdiction of the utility companies.

V2G has been an active topic of research for the past decade (see e.g. [13], [14] and references therein). Various use cases have been proposed and demonstrated, including peak shaving [15], price arbitrage [16], frequency regulation [17], and distribution constraint management [18]. See [5] for a summary of 50 major V2G demonstration projects around the world. To date wide market adoption has not yet happened because, as discussed before, battery degradation concerns of EV owners and difficulties in predicting EV arrival and departures for businesses providing the V2G facilities. We address these challenges by proposing the novel concept of *on-demand V2G* that provides EV owners monetary benefits in exchange for discharging their batteries for a short period of time.

Demand charge reduction using *stationary* storage has been investigated in several papers [19], [20] and has been a major selling point of several energy storage companies in the U.S. [21]. However, with unshared stationary batteries, the demand charge savings are reduced by the high capital and installation costs of on-site battery systems. On the other hand, as will be evident from our analysis, significant demand charge reduction can be achieved with *sparse* manipulations of the electricity consumption profiles, i.e., reducing the electricity consumption in a small number of peak (or sub-peak) metering intervals. Furthermore, if such metering intervals for different users are temporally dispersed, then using a small number of shared EV-based mobile storage can achieve a demand charge reduction comparable to using stationary batteries but with a significantly lower cost.

B. Organization

The rest of the paper is organized as follows. Section II introduces our system and business model. We then describe the approach used to evaluate the potential value that can be created by our business model in Section III. Such a value proposition is supported by certain upfront capital investment and can only be realized if the platform has access to enough number of EVs. We therefore analyze the cost and EV requirements of the proposed business model in Section IV. In Section V, we conduct a case study with real meter data and a real electricity tariff. Section VI concludes the paper.

II. System and business model

We propose to consider an Uber-like matching platform and a two-sided market organized by it. The demand side of the market consists of C&I electricity users. Each user is equipped with a bi-directional EV charger and wishes to reduce its demand charge. The supply side of the market consists of EV drivers who are willing to drive to users' locations to discharge their EV batteries through a bi-directional EV charger. The platform matches the user requests with available EV drivers. Individual components of the business are detailed in the following subsections. A nomenclature is provided in Appendix A.

A. User energy consumption

We consider a setting with I commercial and industrial electricity users. For user i, the *power* consumption (unit: kW) over a month is a continuous time process $\{p_{i,t} : t \in \mathcal{T}\}$, where $\mathcal{T} = [0, T]$ and T is the length of the month in minutes. Typical utility meters only measure and collect *energy* consumption (unit: kWh) data at regular subintervals of $\mathcal{T}$ with length denoted by Δ. These subintervals are referred to as *metering intervals*. For instance, Δ is 15 minutes for many U.S. utilities. For $s = 1, \dots, S$ with $S = T/\Delta$, denote the sth subinterval by $\mathcal{T}_s = [(s-1)\Delta, s\Delta]$. Thus the sequence of discrete time energy consumption measurements collected by the utility company is $\{e_{i,s} : s \in \mathcal{S}\}$, where

$$e_{i,s} = \int_{t \in \mathcal{T}_s} p_{i,t} \, \mathrm{d}\, t, \quad s \in \mathcal{S} = \{1, \dots, S\}.$$

For convenience, we denote the *reversed order statistics* of the energy consumption time series by $\{e_{i,(k)} : k \in \mathcal{S}\}$ so that $e_{i,(1)} \geq e_{i,(2)} \geq \cdots \geq e_{i,(S)}$. We refer to $e_{i,(1)}$ as the peak, and $e_{i,(k)}$ as the kth sub-peak of the time series. We also denote the index of metering interval corresponding to the kth sub-peak by $s_{i,(k)}$, $k \in \mathcal{S}$.

B. Electricity tariff

The monthly electricity bill of user i is calculated based on the sequence $\{e_{i,s} : s \in \mathcal{S}\}$. The most commonly known component of the electricity bill is the *energy charge*, computed based on how much energy is used during the month. When the energy price for different time of the day is constant, energy charge is also referred to as the volumetric charge as it depends on the energy consumption process $\{e_{i,s} : s \in \mathcal{S}\}$ only through $\sum_{s \in \mathcal{S}} e_{i,s}$. It is increasingly common for commercial and industrial users to face a time-of-use tariff in which a weighted sum of $\{e_{i,s} : s \in \mathcal{S}\}$ is used to calculate the energy charge.

In addition to the energy charge, a majority of commercial and industrial electricity users in the U.S. also face *demand charges* [22] that often account for 50% of their monthly electricity bills [23], [24]. For each user i, the demand charge component is usually calculated by multiplying the user's *demand* by some demand charge rate, where the demand is defined to be the user's maximum power consumption (kW) over the month approximated by

$$d_i = \frac{1}{\Delta} \max_{s \in \mathcal{S}} e_{i,s} = \frac{e_{i,(1)}}{\Delta}.$$

The demand charge is then computed by multiplying this demand with a demand rate denoted by π_{d}.

C. V2G charger

We consider the setup where each user is connected to a behind-the-meter V2G charger. The charger can be either an AC level 2 charger (up to 19.2 kW) or a DC fast charging charger (up to 36 kW, 90kW, and 240 kW for DC level 1,2 and 3, respectively) [25], depending mostly on the user's need for charging EVs rather than discharging EVs for demand charge reduction purposes[1]. We denote the maximum discharging rate (kW) by U, taking into account both the charger's power capacity and the power capacity of the user's local circuit[2]. The monthly amortized capital cost of each V2G charger is denoted by C.

D. On demand electric vehicles

There are J EVs available for the service. Each EV is assumed to be compatible with the V2G chargers so that the EV and any V2G charger can be properly connected, and the EV's onboard hardware and software support the V2G charger[3]. Between each EV driver and the platform, there is an active communication link through for example a mobile application. When an EV is requested for service, it is given an address where the driver can find a V2G charger to connect to and a time when the EV starts to discharge its EV battery at the maximum rate[4] U for a period of length Δ. An EV should hold at least ΔU (kWh) amount of energy prior to arriving at the user's location.

E. Matching platform

A sophisticated matching platform may be designed to connect EV drivers to commercial and industrial electricity users in order to reduce users' demand charges while minimizing the costs of providing such services. However, in this paper, we consider a very simple matching design for the purpose of estimating the potential of the proposed business. Better platform designs will of course increase this potential.

In particular, we consider a setting where all users are located in a small urban area (e.g., an area that corresponds to several zip codes) such that from any point to any other point the driving time is bounded by $\alpha\Delta$, and energy needed is bounded by $\beta\Delta U$, where $\alpha, \beta > 0$.

We consider the following mode of operation:

1) At any time, the platform maintains a set of *available EVs*, comprising the EVs not currently serving a user and with state of charge no smaller than $(1+\beta)\Delta U$.
2) At any time τ, any user may make a request for service starting no earlier than $\tau + \alpha\Delta$.
3) Upon receiving a request from user i, the platform matches the user with the available EV closest to the user's location.
4) The matched EV then travels to the user's location, connects to the user's V2G charger, and starts to discharge at the user requested starting time. The EV driver is compensated based on a payment calculation scheme that splits the demand charge reduction with the user and the EV driver.

III. Value Assessment

The major source of value created by this business model is the savings in electricity bills of the users due to the reduced demand charges. We assess the potential total cost saving of the proposed business based on the following two assumptions:

A1 *No uncertainty*: Each user can perfectly forecast its energy consumption time series $\{e_{i,s} : s \in \mathcal{S}\}$, $i = 1, \ldots, I$.

A2 r *requests per month*: Each user makes $r \in \mathbb{Z}_+$ service requests per month, with the value of r to be specified.

Assumption **A**1 is demanding in that it requires the user to foresee its entire time series of energy consumption for all future metering time intervals until the end of the month. Although for many commercial and industrial energy users, short-term energy consumption forecasting with a forecast horizon ranging from 5 minutes to one hour can be done with good accuracy [26], predicting energy consumption many days in advance requires good forecasts about the temperature and other factors such as occupancy. Fortunately, for our purpose it suffices for each user to predict the time intervals when monthly peak and sub-peaks occur. We briefly discuss the case with uncertainty in Section III-A and leave the full problem of requesting the service under uncertainty to future work.

Assumption **A**2 is introduced to simplify the accounting. In the sequel we will vary the value of r and estimate the cost savings as a function of r.

Under these assumptions, each user will request services for time intervals corresponding to the 1st to rth sub-peaks[5]. The resulting *modified* energy consumption time series of user i contain the following entries

$$e_{i,(1)} - \Delta U, \ \ldots, \ e_{i,(r)} - \Delta U, \ e_{i,(r+1)}, \ \ldots, \ e_{i,(S)}.$$

[1]Results in Section V suggests AC level 2 charger has a sufficient power capacity to serve the demand charge reduction requirements of most users.

[2]We do not consider grid-side constraints since our business model only reduces power consumption and does not introduce back-flow into the grid.

[3]An example is Nissan Leaf EVs with CHAdeMO chargers.

[4]The power limit of EV battery is usually much larger than the charger's capacity [4].

[5]We make the mild assumption that $e_{i,(r)} > e_{i,(r+1)}$ for all i so that the rth sub-peak is unique. If this does not hold, we can simply break ties arbitrarily.

For each value r, the modified demand for user i is then

$$\widetilde{d}_i(r) = \frac{\max\left\{e_{i,(1)} - \Delta U,\ e_{i,(r+1)}\right\}}{\Delta},$$

and the corresponding demand reduction is

$$d_i(r) - \widetilde{d}_i(r) = \min\left\{\frac{e_{i,(1)} - e_{i,(r+1)}}{\Delta},\ U\right\}. \qquad (1)$$

Therefore the total demand charge reduction for all users in this month is

$$V(r) = \pi_{\mathrm{d}} \sum_{i=1}^{I} \min\left\{\frac{e_{i,(1)} - e_{i,(r+1)}}{\Delta},\ U\right\}.$$

A. Case with uncertainty

In this section, we relax Assumption **A**1 and discuss the value created by the business model when users cannot accurately forecast their future energy consumption profiles. We do this by considering two scenarios.

a) Information rich scenario: In this case, users have access to data sources that can provide relevant historical and real time data to guide the decision when to request service. Each user i can then form the probability distribution of $e_{i,s}$ for each period s, possibly conditioning on exogenous observations such as prediction of outside temperature. Given the probability distributions, the problem of optimal requesting the service r times over the month can be formulated as a stochastic control problem. As the state variables for the problem are the running maximum (i.e., the maximum modified energy consumption that is observed so far) and the number of remaining requests, which results in a two-dimensional state space, the stochastic control problem can be solved efficiently using standard methods such as discretization (see e.g., [19] for a similar treatment for the problem of using stationary energy storage to reduce demand charge). Further, the problem can be thought of as a variant of the celebrated (multi-choice) *prophet inequality* problem [27]–[29], where the goal of the decision maker is to select top k valued items that are coming up online. Rich structural results have been established for the prophet inequality problem and may be extended to our setting where the payoff for the decision maker depends on the maximum value of the unselected items. We leave the investigation of identifying the exact optimal control policy under uncertainty to future work.

b) Information scarce scenario: At the other extreme, some users may have no information other than the real time energy consumption[6]. To provide a (loose) lower bound for the case with uncertainty relative to the value created in the no uncertainty case, we consider the following *adversarial* uncertainty model.

A3 *Uncertainty model*: Let $\bar{\mathcal{S}} \subseteq \mathcal{S}$ be the subset of metering intervals containing candidate intervals when the energy consumption for the user may peak. An adversary decides a set of $|\bar{\mathcal{S}}|$ energy consumption values. These values are then assigned to the metering intervals in $\bar{\mathcal{S}}$ in an *order* that is picked *uniformly at random*.

In Assumption **A**3, the candidate set $\bar{\mathcal{S}}$ is used to preclude metering intervals that are unlikely to be a peak period based on certain side information. For instance, for a user that does not use any energy during the night, the set $\bar{\mathcal{S}}$ only contains metering intervals during the day. The assumption that the energy consumption levels are determined by an adversary encapsulates the notion that these energy consumption values cannot be predicted due to a lack of information. Meanwhile, the assumption that these energy consumption values are revealed in a random order captures the fact that with no prior information, any metering interval in $\bar{\mathcal{S}}$ is equally likely to be the peak.

Under Assumption **A**3, the following result holds when a user only request one service a month ($r = 1$).

Lemma 1: For $r = 1$, there exists a causal policy resulting in an expected demand charge reduction under uncertainty that is no less than $1/e$ of the demand charge reduction with perfect foresight.

Proof: Under Assumption **A**3, the problem of finding a metering interval in $\bar{\mathcal{S}}$ maximizing the probability that it is the peak period is an instance of the classic *secretary problem*. The policy that does not request a service in the first $|\bar{\mathcal{S}}|/e$ periods and then requests a service in the first period when the energy consumption is the largest observed energy consumption so far is optimal [30]. The probability for this policy to find the peak period is no less than $1/e$. Hence the expected demand charge reduction with this policy is no less than $1/e$ of the demand charge reduction with perfect foresight. ■

IV. Costs and Requirements

In addition to the amortized capital cost of the V2G charger C, there are several other sources of cost for the EVs to provide the service to the users. The first is the cost associated with the energy discharged from the EV batteries. On the users' side, the energy inflow not only reduces their demand charges but also reduces their energy charges. Thus the platform can simply transfer the energy charge savings from the users to the EV drivers to compensate drivers' cost for recharging EV batteries[7]. Other costs include the time and effort of the EV drivers and the potential negative impacts on the lifespan of the EV batteries. These costs are difficult to quantify. Instead of directly model these costs, we will calculate the payments each driver may receive for fulfilling one service request, and compare such payments with the driver earnings for offering services via ride-hailing platforms.

The rest of the section is devoted to the task of estimating the number of EVs required to serve a population of users.

A. Number of EVs needed: the case without inter-service time

To start, we consider the ideal case where there is no inter-service time, that is, after an EV completes a service at an user's location, it is immediately relocated to the next user's

[6]Many users may not have access to real time energy consumption data as it is usually the case that utility companies only provide delayed data access (e.g., after the end of the month with the electricity bill) if any. However, many utility companies indeed provide real time meter data to commercial and business users at a cost (e.g. PG&E's Stream My Data program).

[7]Alternatively, an EV providing service to a user may re-charge the battery at the user's location during an off-peak time.

location (if there is a request for the next period) and always has enough energy to finish the service for the next user. In other words, in this subsection we ignore the time needed for the EV to travel between different user locations and the time needed to recharge the EV battery. We denote by ℓ the inter-service time measured by the number of time periods (so the actual length of the inter-service time is $\Delta\ell$).

In this zero inter-service time case ($\ell = 0$), the number of EVs required to complete the service in time period $s \in \mathcal{S}$, as a function of inter-service time ℓ and the number of request each user makes r, denoted by $\underline{J}_s(\ell, r)$, is the number of concurrent requests in the period:

$$\underline{J}_s(0, r) = \sum_{i=1}^{I} \mathbb{1}\left\{e_{i,s} \geq e_{i,(r)}\right\},$$

and the number of required EVs over all time periods is

$$\underline{J}(0, r) = \max_{s \in \mathcal{S}} \ \underline{J}_s(0, r).$$

B. Number of EVs required: the case with inter-service time

When the inter-service time is nonzero ($\ell > 0$), one estimate of the number of EVs required is simply the number of EV needed in the case without inter-service time multiplying by $\ell + 1$. Indeed, if for example $\ell = 1$, we can serve all requests by a set of $\underline{J}(0, r)$ EVs serving all odd-numbered time periods and a disjoint set of $\underline{J}(0, r)$ EVs serving all even-numbered time periods. This argument easily extends to any number ℓ and therefore we have

$$\underline{J}(\ell, r) = (\ell + 1)\underline{J}(0, r), \quad \ell = 1, 2, \ldots.$$

In our business model, it requires at most $\alpha\Delta$ time for transporting between two locations (see Section II-E) and at most $(1 + \beta)\Delta$ time for recharging the battery assuming availability of an EV charger of capacity U somewhere on the route between each pair of users. Thus after serving a user, an EV is unavailable for at most $\lceil 1 + \alpha + \beta \rceil$ periods of Δ length. It is then straightforward to verify that an upper bound of the number of EVs required for our business model is

$$\underline{J}(r) = (1 + \lceil 1 + \alpha + \beta \rceil)\underline{J}(0, r) = \lceil 2 + \alpha + \beta \rceil \underline{J}(0, r). \quad (2)$$

V. Case study

A. Data description

A dataset containing Irish smart meter data[8] for about 6000 residential and business electricity users for the period from August 2009 to December 2010 [31] is used for our study. The metering interval for this dataset is $\Delta = 30$ minutes. We rank these users according to their peak energy consumption for the entire 17 months and obtain a subset with 100 users that have the largest peak energy consumption values. The peak demand values (kW) for these 100 users are in the range $[45\ \text{kW}, 130\ \text{kW}]$. For the purpose of this case study, we will assume each of these 100 users has a V2G EV charger dedicated for this business and compare the capital costs of the chargers with the revenue generated from demand charge reduction.

We use PG&E A-10 tariff which is a common tariff for small and medium commercial and industrial electricity users (i.e., users with demand less than 500 kW). The summer demand rate under this tariff is $18.28/kW and the winter demand rate is $10.95/kW.

We consider two candidate types of V2G chargers[9]: a low cost AC level-2 charger with capacity $U_{\mathrm{L}} = 15$ kW and amortized cost $C_{\mathrm{L}} = \$230$/year, and a high cost DC fast charging charger with capacity $U_{\mathrm{H}} = 30$ kW and amortized cost $C_{\mathrm{H}} = \$1600$/year.

In this case study, assumptions **A**1 and **A**2 are in force. These results can be extended to the case with uncertainty under **A**3. Under more realistic uncertainty models, how users would optimally request the service is an important direction for future investigation. We also do not treat inter-service time in this case study, because the number of required EVs with non-zero inter-service time can be calculated from that without inter-service time using (2) in a straightforward manner.

B. Single request per month: $r = 1$

We start by considering the case when each user requests service only once per month. In this case, the service period for each user will correspond to the metering interval in which the user has the maximum energy consumption, i.e., $s_{i,(1)}$ for $i = 1, \ldots, I$.

Fig. 1 depicts the histograms of the set of metering interval indices $\{s_{i,(1)} : i = 1, \ldots, I\}$ for each of the 17 months, where the number of metering intervals for each month is S. Here the y-axis reveals the number of requests in each interval. By reading the maximum values on the y-axis in each of the histograms, we see that for all but 1 of the 17 months, *peak times for different users are dispersed* and the maximum number of concurrent service requests is 2. Thus $\underline{J}(0, 1) = 2$ for these 16 months and the proposed business model can be implemented with a very small number of EVs if the inter-service time is small. In the other month (July 2010), a similar pattern for the peak time distribution is observed with the maximum number of concurrent requests being 3.

Fig. 2 shows the month-by-month demand reduction (kW) values for the users using box plots[10]. The overall average demand reduction is depicted with the green dashed line, which is slightly less than 2 kW. A high demand reduction can only be realized if the V2G charger has enough power capacity (see (1)). The black dotted line corresponds to the power limit of an AC level-2 charger. Comparing it to the box plots, we find that except for one user in November 2010, the demand charge reduction needs can be well accommodated. In fact, for all months, more than 90% of the requests can be

[8]The meters measure the net load of the users. According to the survey from the dataset, only 2 C&I users in the dataset have behind-the-meter distributed generation (e.g. solar panel).

[9]The amortized annual costs are calculated based on averaging the low estimates and high estimates of total cost numbers reported in [4], [32] with an expected life span of 15 years. No interest adjustment is used in the calculation but including it does not change the qualitative conclusions of the case study.

[10]On each box, the central mark indicates the median, and the bottom and top edges of the box indicate the 25th and 75th percentiles, respectively. The whiskers extend to the most extreme data points not considered outliers, and the outliers are plotted individually using the '+' symbol.

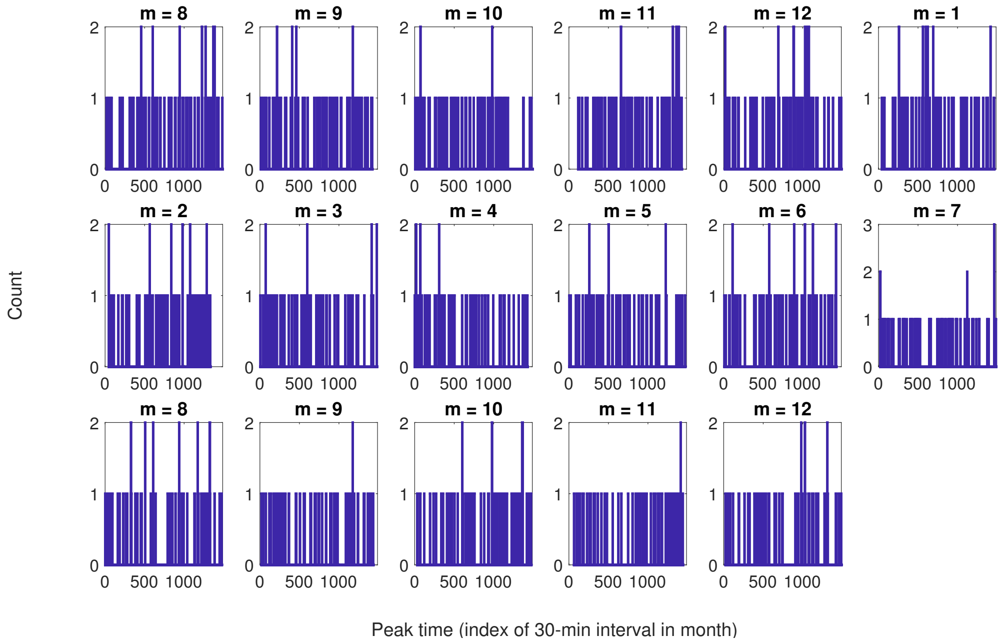

Fig. 1. Histograms of peak times ($r = 1$) for 100 users. The values of m represent the month IDs, which starts with August ($m = 8$) 2009 and ends at December ($m = 12$) 2010.

served with a 6 kW V2G charger if all users only make one request per month.

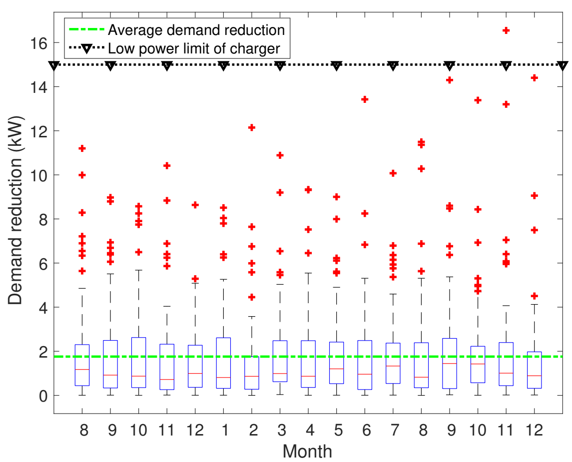

Fig. 2. Month-by-month demand reduction distribution when $r = 1$.

Fig. 3 shows the month-by-month demand charge reduction ($) values for the users using box plots. The overall average demand charge reduction is $28.18 per user per month, which is enough to cover the amortized capital cost of the AC level-2 charger but much less than the amortized capital cost of the DC fast charging charger. Variability over months and users in demand charge reduction is also observed. In some months and for some users, the demand charge reduction by making a single requests can be as high as $200. These correspond to larger users with less regular energy consumption patterns that may be targeted as early customers of the proposed business.

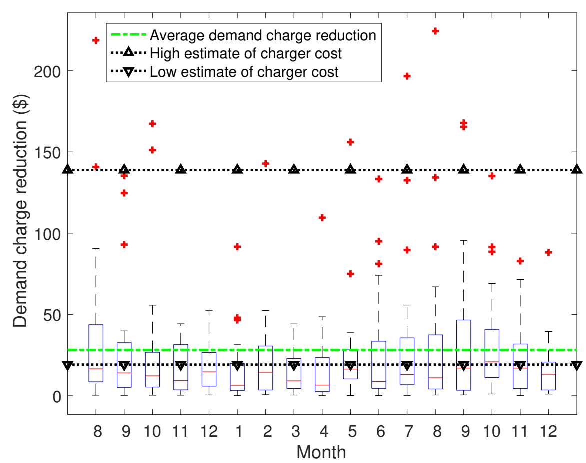

Fig. 3. Month-by-month demand charge reduction distribution when $r = 1$.

C. Multiple requests per month: $r > 1$

When the number of requests per user per month (r) increases, concurrent requests become more likely. However, the increase in r results in a smooth increase in the number of concurrent requests. Therefore, the overall observation that the business model can be sustained with a small number of EVs continues to be true. Indeed, Fig. 4 shows the number of requests in each of the metering intervals in all months as r increases. In particular, for each value of r, Fig. 4 contains a box plot summarizing the distribution of the number of requests in each of the metering intervals[11] in $\mathcal{S}$. From the figure, we can observe that for $r = 1, \ldots, 6$, most

[11]Metering intervals in different months with the same indices are considered different intervals.

metering intervals have 0 requests and the maximum number of concurrent requests $\underline{J}(0, r)$ increases from 3 for $r = 1$ to 8 for $r = 6$. For $r = 7, \ldots, 18$, a certain portion (less than 25%) of the metering intervals start to have 1 requests and the majority of intervals have no more than 2 requests as indicated by the whiskers of the box plots. The maximum number of concurrent requests increases from 8 to 13 in a smooth fashion. For $r = 19, \ldots, 30$, the median number of requests increased from 0 to 1 while the majority of intervals have no more than 5 requests. The maximum number of concurrent requests for $r = 30$ (1 request per day on average) is 21, significantly smaller than the number of users (i.e., 100) and also smaller than r. Overall, Fig. 4 suggests that even when users start to make many requests each month, only a small number of EVs is required to serve a majority of the requests.

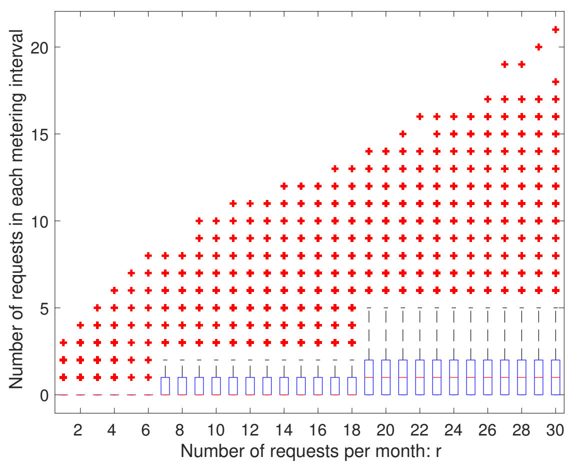

Fig. 4. Distribution of the number of requests in each metering interval as r increases.

On the other hand, increasing the number of requests per month allows each user to reduce their demand to a level corresponding to its $(r+1)$th sub-peak. Thus a larger value of r results in a larger potential in demand reduction and demand charge reduction. Fig. 5 and Fig. 6 demonstrate the demand reduction and demand charge reduction when r increases, respectively, where for each user we have averaged the demand reduction (and demand charge reduction) over the 17 months. As expected, both demand reduction and demand charge reduction increase monotonically as the number of request per month increases. In Fig. 5, we compare the demand reduction with the power capacity of the AC level-2 charger $U_{\mathrm{L}} = 15$ kW and the DC fast charging charger $U_{\mathrm{H}} = 30$ kW. It turns out that the power capacity of the AC level-2 charger covers 75% of the users' need even if the number of requests per month for each user increases to 30. The increased demand reduction results in a higher value of the business, significantly exceeding the amortized capital cost of the AC level-2 charger as evident from Fig. 6. Therefore, when the number of requests per month starts to increase, the value created by this business model not only covers the costs of the V2G charger but also creates surplus that can be shared between the users and the EV drivers.

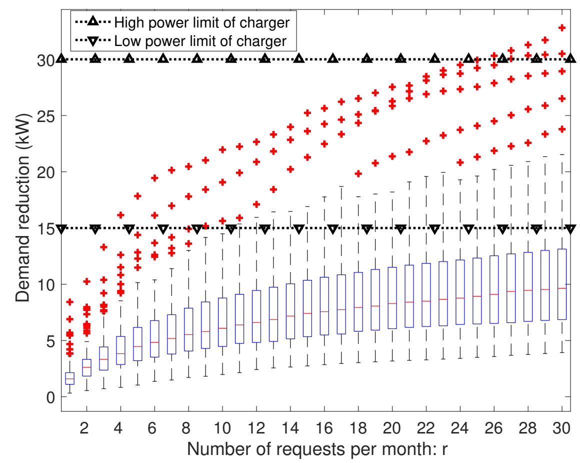

Fig. 5. Demand reduction distribution when r increases.

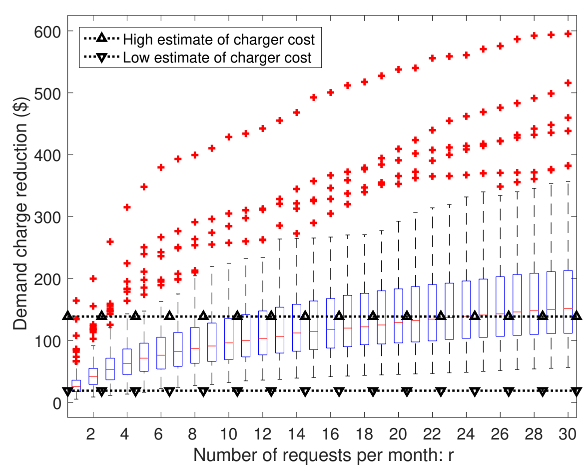

Fig. 6. Demand charge reduction (per month) distribution when r increases.

Finally, we can calculate the net revenue (demand charge reduction less the amortized capital cost for AC level 2 chargers) that can be shared among the EV drivers. Fig. 7 reports the average net revenue that can be provided to EV drivers per request for various values of r. As the number of request per month r increases, the total demand charge reduction for each user increases but this larger demand charge reduction is realized by requesting the service more times. As such, the average net revenue per request peaks at an intermediate r value ($r = 2$ for this case). If each user requests the service twice a month, the average net revenue that may be paid to the EV driver is \$14.97 per service[12]. Note this payment is in addition to the payment for covering the cost of charging up the EV battery which is derived from the energy charge reduction as discussed in Section IV.

[12]As a comparison, median *hourly* pay with tip for Uber drivers in the U.S. is \$14.73 according to a survey among Uber drivers [33]. Our business only requires the driver to park at a particular location for 15 minutes (for most states in the U.S.) or 30 minutes (for the dataset used in this case study).

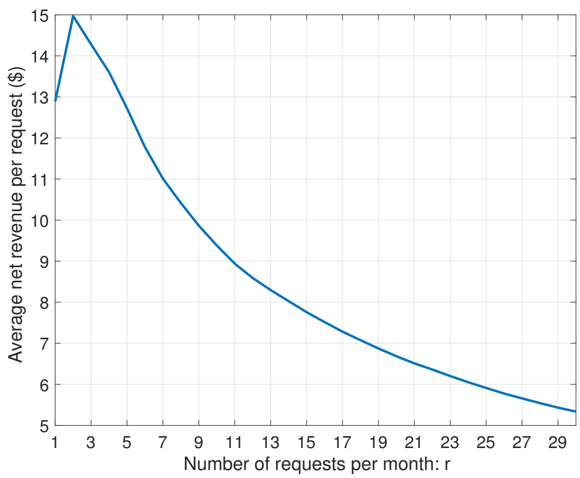

Fig. 7. Average net revenue per request as r increases

D. Comparison to stationary battery

We provide a brief comparison to the setting using stationary batteries for demand charge reduction. The comparison is not comprehensive because we are not accounting for the other values streams created by the stationary batteries and we are not accounting for side values created by V2G chargers and EVs. Nevertheless, it should put the demand reduction and demand charge reduction estimates we obtained for the proposed business model in context.

Parameters for Tesla Powerwall[13] are used for the study. The battery capacity is 13.5 kWh, the power capacity is 5 kW, and the round-trip efficiency is 90%. The capital and installation cost for one Tesla Powerwall is \$7600–\$9600. Given that each Tesla Powerwall comes with a 10-year warranty, the estimated monthly amortized capital and installation cost for one Powerwall is in the range of \$63.3–\$80. For each user, we consider installing 1–6 Powerwall batteries. The optimization solved to determine the battery operation schedules is provided in Appendix B where we made the same no uncertainty assumption as we did for the mobile storage case.

The distribution of demand reduction and demand charge reduction, over the 100 users and averaged across the 17 months, are shown in Fig. 8 and Fig. 9, respectively. In Fig. 8, we see that the median demand reduction is close to the upper bound (5 kW multiplied by the number of batteries) for one and two batteries but becomes considerably lower than the upper bound when each user installs more than 2 batteries. In Fig. 9, the savings from demand charge reduction is compared to low and high estimates of monthly amortized battery capital and installation costs. Unlike the mobile storage case where the savings clearly pay for the cost of an AC level 2 charger, whether the demand charge reduction can cover the costs of the stationary battery system is largely determined by the installation cost as it is the major source of variability in the battery cost estimates. Further, comparing Fig. 6 with Fig. 9, we see that 10 requests per month in the mobile storage case leads to a larger median demand charge reduction than that generated by 1 Tesla Powerwall batteries. This suggests, at least, that sparse manipulation of the load profile using mobile batteries offers a competitive approach to stationary batteries.

[13] The values are retrieved in July 2018 at https://www.tesla.com/powerwall.

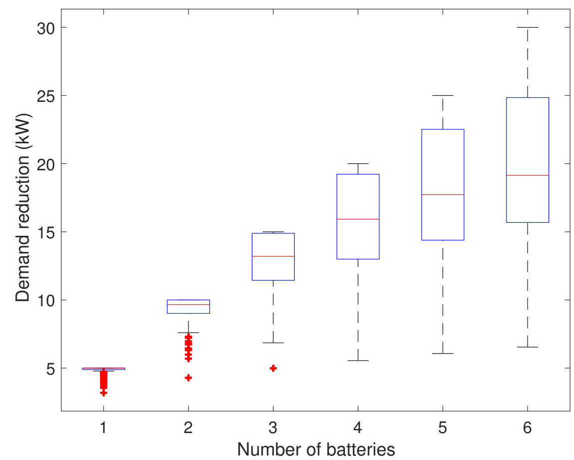

Fig. 8. Demand reduction distribution with an increasing number of batteries

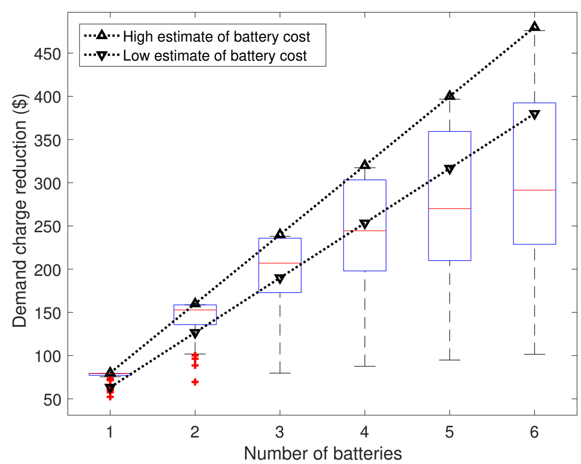

Fig. 9. Demand charge reduction (per month) distribution with an increasing number of batteries

VI. Concluding Remarks

This paper presents a novel business model that reduces commercial and industrial electricity users' demand charges using on demand EVs. We develop a rigorous procedure for estimating the cost and revenue of the proposed business, and through a case study using real electricity usage data we demonstrate that a large number of users can be served by a small number of EVs. Further, when users make multiple requests per month, we show that the value created by the proposed business model not only covers the costs of the V2G chargers but also leaves a surplus that can be shared between users and EV drivers. In particular, we demonstrate that this surplus can support a per service driver compensation that is comparable to Uber's median hourly salary and provide a considerable incentive to encourage EV drivers' participation.

There are a number of limitations of our current analysis. (a) Although we have provided a way to bound the impacts of demand uncertainty and non-zero inter-service time (which includes the time needed to recharge EV batteries), a more detailed model and analysis could lead to a more accurate estimation of these impacts. (b) There are a number of arguably less significant cost and benefit items that are not considered in our analysis. For instance, due to the conversion loss, user-side energy charge savings may not fully cover EV drivers' cost of recharging their EV batteries. However, this difference is relatively small because our service only requires discharging the EV battery for 15 minutes (in the U.S.) and thus only discharges a relatively small amount of energy from the EV battery. On the benefit side, our analysis shows that demand charge reduction can cover the cost of bi-directional AC level 2 chargers needed for the business. However, these charger may be used for other purpose during off-peak hours. Carefully accounting these additional costs and benefits can result in a more realistic analysis of the business case. (c) The quantitative results in the case study depend on the characteristics of the C&I users involved (e.g., size of the users and whether behind-the-meter solar is present). Thus to determine whether the proposed business model is suitable for a particular set of users, one should apply our methodology to the energy consumption data of these users.

Going beyond the basic question "is there indeed a business" for the proposed business model, we can identify the following important future directions. First, developing an efficient and robust matching platform is critical for the proposed business. Addressing practical complexities that arise from both the energy side (e.g., uncertainty in peak times) and the transportation side (e.g., travel time prediction) is the key of scaling up the service in practice. Pricing is a key aspect in the platform design. In practice, it is essential to set the price of the service to grow both sides of the market. On the demand side, the price should incentivize C&I users to install a bi-directional charger and start to use the service. On the supply side, the price should lead to sufficient compensation for the drivers to incentivize driver participation and compliance. The price is also likely to vary across time and locations reflecting the spatial and temporal variation of supply and demand. Second, as the peak demand for the proposed service only occurs in a small fraction of time (see Fig. 1 and Fig. 4), some EVs will be idle when few users are requesting the service. Thus stacking additional revenue streams on top of the proposed service can further increase the utilization of the EVs and the revenue of the matching platform. Such revenue streams include providing additional energy services (e.g., EV roadside rescue services [34]) and transportation services (e.g., ride sharing). Finally, it is interesting to explore and quantify the impacts of the proposed business on both the energy sector (e.g., impacts to utility companies' revenue and to aggregate peak demand at the distribution feeders) and the transportation systems (e.g., impacts on local traffic congestion).

Appendix A
Nomenclature

Variable	Description
I	Total number of C&I users
i	User index
T	Number of minutes in the month
$\mathcal{T}$	Continuous time window for the month
Δ	Number of minutes in a metering interval
S	Number of metering intervals in the month
s	Metering interval index
$\mathcal{T}_s$	Continuous time window for sth metering interval
$p_{i,t}$	Power consumption (kW) of user i at time t
$e_{i,s}$	Energy consumption (kWh) of user i in metering interval s
$e_{i,(k)}$	kth sub-peak in user i's energy consumption process
$s_{i,(k)}$	Metering interval index of user i's kth sub-peak
d_i	User i's demand (kW) in the month
$\widetilde{d}_i$	User i's modified demand (kW) in the month
π_{d}	Demand charge rate ($/kW)
U	Maximum discharging rate of the charger (kW)
C	Amortized capital cost of the charger ($/month)
$\alpha\Delta$	Upper bound of driving time between requests
$\beta\Delta U$	Upper bound of energy needed for driving between requests
r	Number of requests each user makes per month
$V(r)$	Total demand charge reduction
$\ell\Delta$	Inter-service time
$\underline{J}_s(\ell, r)$	Number of EVs required in metering interval s
$\underline{J}(\ell, r)$	Number of EVs required across all time periods

Appendix B
Demand reduction using stationary battery

For the ith user, we denote the battery capacity by B, the power limit by U, round-trip efficiency by μ^{R}, the state of charge in time slot s by $b_{i,s}$, charging in time slot s by $C_{i,s}$, and discharging in time slot s by $D_{i,s}$. The optimization we solve to find the battery operation is

$$\begin{aligned}
\min_{C_i\in\mathbb{R}^S, D_i\in\mathbb{R}^S, b_i\in\mathbb{R}^{S+1}} \quad & \max_{s\in\mathcal{S}} \{e_{i,s} + C_{i,s} - D_{i,s}\} \\
\text{s.t.} \quad & 0 \le C_{i,s} \le U, \quad \forall s, \\
& 0 \le D_{i,s} \le U, \quad \forall s, \\
& b_{i,s+1} = b_{i,s} + \mu^{\mathrm{C}} C_{i,s} - D_{i,s}/\mu^{\mathrm{D}}, \ \forall s, \\
& 0 \le b_{i,s} \le B, \quad \forall s, \\
& b_{i,0} = b_{i,S} = 0,
\end{aligned}$$

where the charging efficiency μ^{C} and discharging efficiency μ^{D} are determined as $\mu^{\mathrm{C}} = \mu^{\mathrm{D}} = \sqrt{\mu^{\mathrm{R}}}$.

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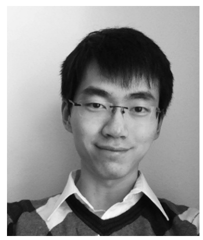

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