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Estimating the Benefits of Electric Vehicle Smart Charging at Non-Residential Locations: A Data-Driven Approach

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Abstract

In this paper, we use data collected from over 2000 non-residential electric vehicle supply equipments (EVSEs) located in Northern California for the year of 2013 to estimate the potential benefits of smart electric vehicle (EV) charging. We develop a smart charging framework to identify the benefits of non-residential EV charging to the load aggregators and the distribution grid. Using this extensive dataset, we aim to improve upon past studies focusing on the benefits of smart EV charging by relaxing the assumptions made in these studies regarding: (i) driving patterns, driver behavior and driver types; (ii) the scalability of a limited number of simulated vehicles to represent different load aggregation points in the power system with different customer characteristics; and (iii) the charging profile of EVs. First, we study the benefits of EV aggregations behind-the-meter, where a time-of-use pricing schema is used to understand the benefits to the owner when EV aggregations shift load from high cost periods to lower cost periods. For the year of 2013, we show a reduction of up to 24.8% in the monthly bill is possible. Then, following a similar aggregation strategy, we show that EV aggregations decrease their contribution to the

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system peak load by approximately 37% (median) when charging is controlled within arrival and departure times. Our results also show that it could be expected to shift approximately 0.25kWh ($\sim 2.8\%$) of energy per non-residential EV charging session from peak periods (12PM-6PM) to off-peak periods (after 6PM) in Northern California for the year of 2013.

Keywords: electric vehicles, demand response, non-residential loads, data analysis

1 1. Introduction

2 A recent analysis identifying the infrastructure and technology needs to meet
3 California's greenhouse gas (GHG) reduction goals for 2050 shows that the elec-
4 trification of the transportation system plays a significant role in reaching these
5 goals. In order to achieve the 80% reduction target in electrification, most of
6 the direct fuel uses in buildings, transportation and industrial processes must
7 be electrified. Among these, electrification of transportation yields the largest
8 share of GHG reduction, where 70% of the vehicle miles traveled should be by
9 electrically powered vehicles [1]. A study by the Electric Power Research In-
10 stitute (EPRI) [2] also suggests that electric vehicles will constitute a rather
11 significant 35% of the total vehicles in the US by 2020.

12

13 This rapid growth in the electrification of transportation presents significant
14 challenges as well as opportunities to the operation of today's power system.
15 When considered as inflexible loads, EVs will increase the current peak elec-
16 tricity demand significantly, intensifying the stress on the electric power system
17 and pushing it closer to its limits [3, 4, 5]. However, when considered as flexible
18 resources, where EV charging is controlled by direct or indirect strategies, EVs
19 promote the reliable operation of the power grid [6, 7, 8], while also provid-
20 ing additional revenue streams that can be used towards the electrification of
21 transportation [3, 7, 9]. This is particularly important considering the expected
22 increase of renewable generation sources in the generation portfolio of many

23 states in the U.S., as smart EV charging may provide the means to balance the
24 intermittency of these resources.

25

26 A number of recent studies aim to understand the adaptation needs of the ex-
27 isting operational control mechanisms to realize smart charging, and often pro-
28 pose novel planning and control approaches. These approaches can be grouped
29 into *direct* and *indirect* control approaches [7]. In direct control approaches, the
30 control actions are realized without the vehicle owner in the control loop. Often,
31 load aggregations are created to increase the size of the resource so it can offer
32 economic benefits to the aggregator [8, 10]. In [11], for example, the authors
33 propose a direct load control strategy to provide vehicle-to-grid services for 3
34 different predefined mobility patterns. In [12], the authors conduct a simulation
35 study for 3000 EVs parked at a municipal parking lot and evaluate the real-time
36 performance of a direct control approach, which maximizes the expected state
37 of charge of the EV aggregation in the next time step subject to mobility con-
38 straints. In [13], the authors develop an optimal direct control scheme based on
39 global charging costs. The authors compare the proposed direct control scheme
40 to the local scheduler in a simulation environment including 100-400 EVs. The
41 arrival times of the EVs, the charging periods, and the initial energies of EVs
42 are assumed to have a uniform distribution.

43

44 In indirect control approaches, the control authority is managed by the elec-
45 tric vehicle owner through a decentralized strategy. These strategies often make
46 use of a broadcasted exogenous price signal. The cost of energy is minimized at
47 each electric vehicle charging station considering the local mobility and charging
48 constraints. An iterative cost minimal charging frame(p.1 l.1) work based on
49 game theory is presented in [14] and a similar strategy is given in [15]. How-
50 ever, these approaches do not include the impacts or additional costs that can
51 be induced on the distribution network due to increased demand during low
52 cost periods and often assume that the supply and non-EV demand is known.

53

54 Many researchers have investigated the benefits of EV charging and differ-
 55 ent grid-level services that can be provided by an aggregation of EV population
 56 using different control approaches. The authors of [10] discuss various services
 57 that can be provided by electric vehicles, including peak shaving, regulation,
 58 voltage control, and reserves, and many studies have quantified the benefits of
 59 smart charging from various stakeholder perspectives [16, 17, 18]. In [10], the
 60 authors demonstrate a proof of concept regulation case study. In [16], the au-
 61 thors estimate that smart charging will reduce the daily electricity costs of a
 62 plug-in hybrid EV by \$0.23. They also identify daily profits for the individual
 63 driver when the charging of the vehicles can be regulated. The economic benefits
 64 of fleets that participate in specific markets have also been extensively studied.
 65 For example, in [17], 352 vehicles are used to estimate the economic potential
 66 of fleets when providing regulation up and down services using historical prices
 67 obtained from California Independent System Operator (ISO). In [19], the au-
 68 thors use historical market data and charging data collected from an EV located
 69 in a residential household to investigate financial savings and peak demand re-
 70 duction. The authors conclude that the peak EV demand can be reduced by up
 71 to 56%.

72

73 In this paper, we primarily focus on direct control approaches and we create
 74 two case studies to investigate the potential benefits of smart charging to dif-
 75 ferent stakeholders. To develop these case studies, we use data collected from
 76 over 2000 non-residential electric vehicle supply equipments (EVSEs) located
 77 throughout 190 zip code regions in Northern California spanning one year. To
 78 the best of our knowledge, this is the first study that uses such an extensive
 79 dataset on EV charging. First, we analyze over 580,000 charging sessions to
 80 investigate the trends in load flexibility and infrastructure use in the dataset.
 81 Next, we create virtual aggregation points (VAP) in which a combination of the
 82 EVSEs is assumed to be fed by the same distribution feeder. The VAPs mostly
 83 coincide with Pacific Gas and Electric Company’s (PG&E) sub-load aggregation
 84 points (sub-LAPs). Additional details regarding this relationship is provided in

85 Section 2. We introduce a smart charging framework to estimate the benefits
86 of smart EV charging to various stakeholders in each VAP. As an initial case
87 study, we investigate the potential benefits of EV aggregations operated under
88 a single owner, where a time-of-use pricing scheme is used to estimate economic
89 benefits to the owner via shifting load from high cost periods to lower cost peri-
90 ods. Then, we create a case study where EV aggregations are used to decrease
91 their current contribution to the system-level peak load.

92

93 In this study, our main goal is to understand the potential benefits of smart
94 charging to different stakeholders. Specifically, we aim to estimate an *upper*
95 *bound* for such benefits when the EV charging load is managed preemptively
96 between known EV arrival and departure times to the EVSEs. Previous re-
97 search has developed robust algorithms that can handle randomized arrivals of
98 EVs to an EVSE [20, 13], however, this is beyond the scope of this manuscript.
99 We assume that the arrival and departure times of electric vehicles as well as
100 the energy demand profile of each charging session is known by the controller.
101 These values are obtained from over 580,000 unique charging sessions. This
102 would potentially result in the overestimation of benefits. Furthermore, since
103 we investigate two case studies with focus on aggregators and assume that the
104 aggregators will be responsible of providing grid-level services, we use a central-
105 ized smart charging strategy in both case studies to keep the control authority
106 at the aggregator level. The preemptive EV charging load assumption also re-
107 sults in a mixed-integer-programming problem for the EV aggregation and can
108 be solved with bounded optimality guarantees [21].

109

110 The motivation for this study is threefold: (*i*) Most of the work investigating
111 the potential of smart charging of EVs is based on assumptions made regard-
112 ing trip and customer characteristics. For example, in [22], the authors use a
113 fleet which includes commuter cars, family cars and taxis with predetermined
114 departure and arrival locations randomly selected from a limited number of al-
115 ternatives. In [23], the authors use data from driving surveys that reflect the

116 driving behavior of people using internal combustion engine cars. They assume
 117 that the driving behavior of an EV owner will be similar to that of an internal
 118 combustion engine car owner. The dataset used in this study allows us to ex-
 119 tract trip and customer characteristics, hence no such assumptions are needed
 120 on these characteristics. *(ii)* Often, a limited number of vehicles and mobility
 121 patterns are used in fleet-based studies to capture the most likely driving sce-
 122 narios. For example, in [11], the authors develop a proof of concept strategy
 123 and show cost benefits for 50 EVs with 3 different pre-defined mobility patterns.
 124 Although the exact number of EVs are not available in the dataset used in this
 125 study, the number of charging sessions (over 580,000) and the fact that these
 126 charging sessions are spread throughout the year ensure that a representative
 127 population of non-residential charging is studied. *(iii)* The individual charging
 128 profile of an EV is often represented by a typical constant-voltage, constant-
 129 current curve for certain battery chemistries, or more simply by a constant
 130 charging power [7]. For example, in [24], the charging power is assumed to be
 131 fixed at 4.4kW, whereas in [25], the authors use the charging profile of a typical
 132 lithium-ion battery pack obtained from [26]. The dataset used in this study
 133 includes time series of power measurements obtained every 15 minutes for each
 134 charging session. Hence, no assumptions are made on charging profiles of the
 135 vehicles, and individual charging data is available for each charging session.

136

137 The remainder of the paper is organized as follows: Section 2 introduces the
 138 dataset and discusses the load flexibility and infrastructure use trends obtained
 139 from the dataset. Section 3 presents the smart charging strategy used in this
 140 study. Specifically, it discusses the framework and the underlying assumptions
 141 made when estimating the benefits to different stakeholders. Sections 4 and 5
 142 describe the case studies completed in this research. Finally, Sections 6 and 7
 143 discuss the conclusions, limitations and opportunities for future work.

144 2. Dataset

145 The data used in this study is collected from individual EVSEs located in 16
146 different sub-LAPs in PG&E’s territory for the year of 2013. For each charging
147 session (i.e. from plug-in to departure of an EV), the EVSEs report the start and
148 end period of the charging, the plug-in and departure time stamps, the average
149 power, and the maximum power (measured every 15 minutes), as well as the
150 charging port type, the location (zip-code level), and the non-residential build-
151 ing category. In the CAISO region, load aggregations participate in demand
152 response services must be located within the same sub-LAP [27]. To create
153 aggregations of EVs that are within the region fed by the same sub-LAPs, we
154 use a look up table provided by PG&E that matches the zip codes to sub-LAP
155 regions. Since the dataset includes the location information based on zip codes
156 and some zip codes are fed by multiple sub-LAPs, we create virtual aggregation
157 points (VAPs) for the zip codes that are fed by multiple sub-LAPs. This is
158 done by combining the sub-LAPs’ identifiers. Table 1 presents the final list of
159 VAPs in the dataset and total number of zip code regions forming each of these
160 VAPs, the total number of charging sessions, and the average number of daily
161 charging sessions in each VAP. Figure 1 depicts the centroids of the zip code
162 regions forming the considered VAPs.

163
164 The minimum resource size for an aggregation of loads to participate in DR
165 programs in CAISO [27] and various other ISOs [28] is 100 kW. More than
166 99% of the charging sessions in the dataset are coming from *Level 2* EVSEs
167 (i.e. 4-7kW capacity). Hence, in this study, we use data from VAPs with an
168 average of 20 or more charging sessions per day. This corresponds to approx-
169 imately 96% of the charging sessions (i.e. 530,000 charging sessions in total).
170 These VAPs are indicated in **bold** in Table 1. Figure 2 also shows the total
171 number of charging sessions per month for each VAP used in this study. Over
172 the course of 2013, the total number of charging sessions approximately doubles.

173

Figure 3 shows the combined load profiles of VAPs for the second weeks of January and December. The impact of the growth in charging session is reflected on the daily load profile of the loads. Moreover, the peak non-residential EV load occurs between 9AM and 11AM, and it more than triples from January to December of 2013.

Figure 1: Centroids of zip code regions forming the VAPs

178

179 2.1. Infrastructure Use

To gain further insight into the dataset and to understand the distribution of charging sessions and the use of EVSEs in different regions, we analyze the charging sessions obtained from the VAPs marked in bold Table 1. The infrastructure use, I_{use} , in each VAP is represented by the average number of charging sessions $N_{sessions}$ per EVSE and calculated for every business day of

VAP	Region	# of zip code regions	# of charging sessions	# of charging sessions per day
P2-SB	Peninsula & South Bay	7	207501	568.50
SB	South Bay	21	112250	307.53
SF	San Francisco	30	72996	199.99
P2	Peninsula	17	59252	162.33
EB	East Bay	27	52700	144.38
EB-SB	East Bay & South Bay	6	16902	46.31
NB	North Bay	14	12346	33.82
LP	Los Padres	8	9035	24.75
CC	Central Coast	15	8428	23.09
SA	Sacramento Valley	11	7787	21.33
FG	Geysers	11	7918	21.69
SA-SI	Sacramento V. & Sierra	2	7465	20.45
CC-P2	Central Coast & Peninsula	2	6778	18.57
FG-NB	Geysers & North Bay	4	3845	10.53
F1	Fresno	4	377	1.03
NV	North Valley	1	336	0.92
ST	Stockton	3	244	0.67
FG-NC	Geysers & North Coast	1	246	0.67
SI	Sierra	2	181	0.50
SN	San Joaquin	1	134	0.37
HB	Humboldt	1	101	0.28
P2-SF	Peninsula & San Francisco	1	73	0.20
NC	North Coast	1	15	0.04

Table 1: VAPs used in this study

Figure 2: Number of sessions per month

Figure 3: Load shapes for January and December for all the VAPs

185 2013. Formally:

$$I_{use} = \frac{N_{sessions}}{N_{EVSE}} \quad (1)$$

186 where N_{EVSE} is the number of EVSEs. Figure 4 depicts the box plots of the
187 infrastructure use within 2013 for all of the VAPs. For each month of 2013, a
188 box plot is created to represent the distribution of the I_{use} values calculated
189 for every business day of the month. The median value of infrastructure use is
190 marked with a red line in each box plot, and the boundaries of the box depict
191 the 25th and 75th percentiles. The whiskers correspond to the 99th percentiles
192 assuming the distributions per each month are normal. The median infrastruc-
193 ture use increases in all VAPs from 1.8 to 2.1 sessions per EVSE from January
194 to December. This is due to the fact that the demand has increased faster than
195 the number of EVSEs.

196

197 2.2. Load Flexibility and Arrival and Departure Times

198 In addition to the infrastructure use, we investigate the load flexibility in
199 each VAP. The load flexibility depends on the charging duration d_{charge} and the
200 overall duration of each charging session $d_{session}$. Formally, we define the load
201 flexibility l_{flex} as the ratio of the duration that a car is plugged but not charging
202 to the overall session duration:

$$l_{flex} = \frac{d_{session} - d_{charge}}{d_{session}} \quad (2)$$

203 Figure 5 depicts the load flexibility for all VAPs by month. As observed in
204 Figure 5, the load flexibility decreases slowly as the number of charging sessions
205 per EVSE increases. Also, most of the distributions have a slight positive skew.
206 The size of the box representing the 25th and 75th percentiles is also decreas-
207 ing with time, suggesting an increase in skewness. Identifying the reason behind
208 such behavior requires further assessment of different factors contributing to the
209 load flexibility metric. One such factor contributing to varying flexibility can

210 be the use of auxiliary equipment in electric vehicles (i.e., windshield wipers,
211 air conditioning etc.) and the effects of seasonality. A recent study [29] analyz-
212 ing the impacts of outside temperature to EV battery performance and energy
213 demand shows an approximate 9% change in energy demand between yearly
214 average and the worst day scenarios for San Francisco, California. Hence, fur-
215 ther analysis of the change in flexibility requires considering such factors and is
216 therefore left for future studies. In this study, however, we neglect such impacts
217 on flexibility and overall energy demand.

218 The load flexibility metric shows the charging duration relative to the session
219 duration; however, it does not capture when the charging sessions occur. The
220 start and end times of the charging sessions play a key role when estimating
221 the benefits of EV aggregations to the power system. We show a histogram of
222 arrival (i.e. session start) and departure (i.e. session end) times in Figures 6a
223 and 6b, respectively.

224

225 As can be seen in Figures 6a and 6b, most of the charging sessions start
226 within the 7AM-10AM period and often end within the 5PM-7PM period. Con-
227 sidering these loads are currently uncontrolled (i.e. they immediately start charg-
228 ing when they are plugged in), they coincide with the typical working hours of
229 a non-residential location. These figures suggest that employees or customers
230 arrive in the morning and plug in their vehicles. Some leave around noon and
231 come back, and most leave work between 4PM and 7PM.

232 3. Smart Charging Strategy

233 In this section, we introduce the proposed smart charging methodology. In
234 particular, we describe the general optimization strategy used to obtain the
235 charging schedules for each charging session.

236

237 The goal of the proposed smart charging framework is to reschedule the
238 power time series measured in discrete time slots $[1, \dots, K]$ for any charging

Figure 4: Average number of sessions per unique EVSE per day

Figure 5: The variation in load flexibility

Figure 6: Arrival and departure time characteristics

239 session in a population of EVs, $[P_1, P_2, \dots, P_K]$ such that an objective function
 240 is optimized. The objective function should capture the desired benefits from a
 241 stakeholder's perspective. While rescheduling the charging, we would like to en-
 242 sure that the order of the measurements in this time series is preserved. This is
 243 because the power that EVSEs draw is dependent on the state of charge (SOC)
 244 of the EV that is being charged, and keeping the order of the measurements
 245 accounts for this dependency. In addition, we assume that the charging is pre-
 246 emptive; that is, the charging tasks are interruptible without any decrease in
 247 the SOC of the EV.

248

249 In a typical charging session, an EV starts charging when it is plugged in,
 250 and often the charging is complete before the vehicle departs. The smart charg-
 251 ing framework proposed in this study is designed to move some of the charging
 252 to the slack time slots (i.e. the time slots where the vehicle is plugged in but
 253 the charging is completed).

254

255 For the purposes of this paper, we discretize a day into 15-minute intervals.
 256 We define the time period for the optimization within a day as the time between
 257 the start time slot t_{start} and the end time slot t_{end} . In this period, each charging
 258 session i has an arrival time slot denoted by $t_a^{(i)}$ and a departure time slot
 259 $t_d^{(i)}$. For each charging session, a column vector including the charging power
 260 time series can be created using the power measurements for every time slot in
 261 $[t_a^{(i)}, t_d^{(i)}]$. If necessary, the time series is zero-padded to match the size of the
 262 optimization time period $[t_{start}, t_{end}]$. Hence, for each EV i , the power time
 263 series is given as follows:

$$\mathbf{P}^{(i)} = [P_1^{(i)}, P_2^{(i)}, \dots, P_K^{(i)}]^T \quad (3)$$

264 where K is the total number of time slots in $[t_{start}, t_{end}]$. Next, for each charging
 265 session i , we identify $\mathbf{Q}^{(i)}$ whose elements $Q_j^{(i)}$ correspond to the j^{th} non-zero
 266 element of $\mathbf{P}^{(i)}$. The goal is to reschedule the time slots $t_j^{(i)}$ in $[t_a^{(i)}, t_d^{(i)}]$ cor-

267 responding to $Q_j^{(i)}$ without changing their order. We define $M^{(i)}$ as the total
 268 number of non-zero power measurements in charging session i (i.e. total number
 269 of elements in $\mathbf{Q}^{(i)}$).

270

271 To capture the precedence and the session duration constraints we proposed
 272 above, the following formal constraints are introduced:

$$\left. \begin{aligned} t_j^{(i)} &\geq t_{start} \\ t_j^{(i)} &\leq t_{end} \\ t_j^{(i)} &\geq t_a^{(i)} \\ t_j^{(i)} &\leq t_d^{(i)} \\ t_j^{(i)} &< t_{j+1}^{(i)} \end{aligned} \right\} \begin{aligned} &\forall i \in [1, N], \\ &\forall j \in [1, M^{(i)}] \end{aligned} \quad (4)$$

273 The proposed constraints are constructed using a binary decision matrix to rep-
 274 resent charging or non-charging time slots within the optimization duration. In
 275 particular, for each element $Q_j^{(i)}$ in $\mathbf{Q}^{(i)}$, we create a binary vector $x^{(i,j)}$ that
 276 includes K binary decision variables. Each element in this vector represents a
 277 candidate time slot at which $Q_j^{(i)}$ could be positioned. Hence, we define row
 278 vectors $x^{(i,j)} \forall i \in [1, N]$ and $\forall j \in [1, M^{(i)}]$. The elements in these vectors are
 279 $x_k^{(i,j)} \in \{0, 1\}$ that are defined $\forall k \in [1, K]$.

280

281 From these binary vectors $x^{(i,j)}$, we form a binary decision matrix $\mathbf{X}^{(i)}$ for
 282 each charging session $i \in [1, N]$. In particular, the individual decision variables
 283 $x_k^{(i,j)}$ form the elements of the binary decision matrix $\mathbf{X}^{(i)}$ as follows:

$$\mathbf{X}^{(i)} = \begin{bmatrix} x_1^{(i,1)} & \dots & x_K^{(i,1)} \\ \vdots & \ddots & \vdots \\ x_1^{(i,M^{(i)})} & \dots & x_K^{(i,M^{(i)})} \end{bmatrix} \quad (5)$$

284 Finally, we write the variables in the constraints given in (4) using the binary

285 decision variable as follows:

$$t^{(i)} = \mathbf{X}^{(i)}O, \text{ where } O = \begin{bmatrix} 1 \\ 2 \\ \vdots \\ K \end{bmatrix} \quad (6)$$

286 The aggregate power vector for the VAP $AP^{(d)} = \sum_{i=0}^N(\mathbf{P}^{(i)})$ for the day d is
 287 given as follows:

$$AP^{(d)} = \begin{bmatrix} \mathbf{Q}^{(1)} \\ \mathbf{Q}^{(2)} \\ \vdots \\ \mathbf{Q}^{(N)} \end{bmatrix}^T \begin{bmatrix} \mathbf{X}^{(1)} \\ \mathbf{X}^{(2)} \\ \vdots \\ \mathbf{X}^{(N)} \end{bmatrix} \quad (7)$$

288 For each case study proposed in this paper, we build on the general opti-
 289 mization framework described above, identify the objective functions to cap-
 290 ture the benefits from each stakeholder's perspective and introduce additional
 291 constraints when necessary. We use the Gurobi optimizer [21] to solve the op-
 292 timization problems formulated for each case study. Due to the size of the
 293 optimization problem for certain VAPs and the number of times the optimiza-
 294 tion problem is solved to obtain values to estimate benefits for the year of 2013,
 295 a proved optimal solution is expected to be hard to reach within a reasonable
 296 time frame. For these reasons, we alter the optimality criteria by controlling the
 297 relative gap between a feasible integer solution and the general optimal solution.
 298 We set this optimality criteria to 5% and allow early termination once a feasible
 299 solution is found.

300 4. Charging Infrastructure Owner's Perspective

301 In the first case study, our goal is to capture and maximize the benefits of
 302 smart charging from an EV charging service provider's perspective. Currently,

303 each charging meter is independently owned by the building owner, and the con-
 304 sumption is billed to the building owner as part of the building’s monthly bill.
 305 However, in our work, we focus only on the load resulting from EV charging,
 306 i.e. decoupled from other loads, but aggregated over VAPs formed based on sub-
 307 LAPs. This corresponds to the situation in which the charging stations within
 308 each VAP are combined and operated under a single owner or an aggregator and
 309 the owner is charged according to a time of use (TOU) tariff structure, where
 310 shifting load from high cost periods to lower cost periods can offer some benefits
 311 to the owner. Although the current VAPs are created based on sub-LAPs, the
 312 current scale of the charging infrastructure and the number of charging sessions
 313 can easily represent a large parking structure or a campus in the future, where
 314 the EV aggregation is behind a single meter and the non-EV load is relatively
 315 steady.

316

317 4.1. Problem Formulation

318 In a typical TOU rate structure, there are two separate charges forming the
 319 monthly bill: the *energy charges* and the *demand charges*. The energy charges
 320 are calculated based on the amount of energy consumed over given time peri-
 321 ods of the day using the corresponding hourly TOU energy rate. The demand
 322 charges are calculated based on the maximum power demand for specific time
 323 periods of the day over the course of the billing period. At the end of each billing
 324 period, the maximum demand values for the specified periods are multiplied by
 325 the demand charge rates and added to the overall energy charge.

326

327 In order to model a similar rate structure in the proposed smart charging
 328 framework, we define $EC^{(d)}$ as the energy charge for day d of a month with D
 329 days (i.e. $d \in [1, \dots, D]$). Then, we define DC_h as the demand charges for each
 330 time period h of the day of any month. For example, in PG&E’s E-19 TOU rate
 331 structure, for winter billing periods, the demand charges are calculated based
 332 on 2 time periods *part-peak* (i.e. 8:30AM-12:00PM & 6:00PM-09:30PM) and

333 *off-peak* (i.e. 09:30PM-08:30AM) [30]. Formally, the monthly bill for the owner
 334 is therefore given by:

$$f(DC_h, EC^{(d)}) = \sum_{\forall h} DC_h + \sum_{\forall d} EC^{(d)} \quad (8)$$

335 The energy charges $EC^{(d)}$ can easily be incorporated into the proposed daily
 336 optimization routine. Defining ER as a column vector reflecting the price of
 337 energy for each time slot j , $EC^{(d)}$ for any day d in a billing period is given by:

$$EC^{(d)} = AP^{(d)} ER \quad (9)$$

338 For time period h within day d , a subset of the entire daily aggregate power
 339 vector $AP^{(d)}$ is needed and is referred to as $AP_h^{(d)}$.

340

341 In order to minimize the cost function given in (8), the maximum demand
 342 for the daily time periods h must be accurately known beforehand for the entire
 343 month. However, in a real life scenario, this is not a valid assumption. To
 344 incorporate demand charges into the proposed daily smart charging framework,
 345 we therefore propose the following strategy for the owner: for each day d , we
 346 define the peak aggregate power values for each period h as $AP_{peak,h}^{(d)}$. Since the
 347 historic $AP_{peak,h}$ values for each day in $[1, \dots, d-1]$ are available to the main
 348 scheduler, we can define the maximum of the historic $AP_{peak,h}$ values until $d-1$
 349 as follows:

$$AP_{max,h}^{(d-1)} = \max(AP_{peak,h}^{(1)}, \dots, AP_{peak,h}^{(d-1)}) \quad (10)$$

350 Using the above definition, the monthly demand charges can be calculated
 351 at the end of the month based on $AP_{max,h}^{(D)}$ and the demand rates DR_h for each
 352 period as:

$$DC_h = AP_{max,h}^{(D)} DR_h \quad (11)$$

353 As we move from one day to the next, we try to limit the demand charges
 354 based on the maximum daily demands occurred up to the current day. At the

beginning of the billing period, we start with no knowledge of the historical peak values, and we keep track of the maximum historical value up to day d . This strategy can be represented by incorporating the maximum value of the peak values $AP_{max,h}^{(d)}$ for time period h and day d as decision variables into the following optimization problem:

$$\begin{aligned} & \underset{\mathbf{X}^{(i)}, AP_{max,h}^{(d)}}{\text{minimize}} && AP_{max,h}^{(d)} DR_h + EC^{(d)} \end{aligned}$$

subject to (4) and the following additional constraints:

$$\left. \begin{aligned} AP_{max,h}^{(d-1)} &\leq AP_{max,h}^{(d)} \\ AP_h^{(d)} &\leq AP_{max,h}^{(d)} \end{aligned} \right\} \forall h \in [1, TP] \quad (12)$$

Note that with (12), we ensure that the current maximum $AP_{max,h}^{(d)}$ is more than or equal to the maximum historical value $AP_{max,h}^{(d-1)}$ for period h . By definition, this allows for the tracking of the maximum value up to that day. In addition, these maximum values set the day based on which the demand charges will be calculated. If none of the current peak values exceeds the historical maximum values, the demand charges for each period h are not set by the current day d .

4.2. Case Study

For the purposes of this paper, we use the demand and energy rates from PG&E's E-19 TOU rate structure [30]. The E-19 rate structure gives the owner the option to manage their electric costs by shifting load from high cost periods to lower cost periods. Detailed information on E-19 is given in Table 2. The summer period starts with May 1st and ends October 31st, and the winter period includes the remaining months of the year. This rate is for non-residential customers in PG&E's territory with highest demand exceeding 499 kW for three consecutive months.

Demand Charges	\$/kW	Time Period
Max. Peak Demand Summer	\$19.71253	12:00PM-6:00PM
Max. Part-Peak Demand Summer	\$4.07	8:30AM-12:00PM & 6:00PM-09:30PM
Max. Demand Summer	\$12.56	Any time
Max. Part-Peak Demand Winter	\$0.21	8:30AM-09:30PM
Max. Demand Winter	\$12.56	Any time
Energy Charges	\$/kWh	Time Period
Peak Summer	\$0.16253	12:00PM-6:00PM
Part-Peak Summer	\$0.11156	8:30AM-12:00PM & 6:00PM-09:30PM
Off-Peak Summer	\$0.07818	09:30PM-08:30AM
Part-Peak Winter	\$0.10479	08:30AM-09:30PM
Off-Peak Winter	\$0.08200	09:30PM-08:30AM

Table 2: E-19 rate structure [30]

379 To evaluate the benefits of smart charging when the EV aggregation has a
380 single bill calculated on a TOU tariff, we first calculate the current bill under
381 this tariff but without smart charging. Then, we use the proposed optimization
382 strategy to schedule the loads in a way that minimizes the customer’s monthly
383 bills, and we report each monthly bill calculated for each VAP and the contri-
384 butions from energy and demand charges in the bill.

385 Note that, the TOU tariff we use in this paper is devised for loads where the
386 expected system peak is well-aligned with the corresponding peak in the load.
387 For the E-19 tariff, the expected system peak is between 12:00PM and 6:00PM,
388 however the system wide peak of the non-residential EV charging occurs before
389 12:00PM as shown in Figure 3. This suggests that the E-19 tariff might fail to
390 capture the system level objectives that the tariff itself is designed for.

391 *4.3. Results*

392 Figure 7 shows the sum of monthly bills calculated in dollars for all of the
393 VAPs. For each month, the left bar shows the current bill, and the right bar
394 shows the optimized bill for the month. It is obvious that the difference between
395 the summer and winter rates impacts the aggregate monthly bill. The increase
396 within the winter and the summer period is due to the increase in the number
397 of charging sessions over the year.

398

399 Figures 8a and 8b show the total energy and demand charges, respectively,
400 over all LAPs. The cumulative energy charges increase slightly for the summer
401 months when using smart charging, whereas there is a significant drop in the
402 demand charges. This suggests that the peak load of the EVs is shifted from the
403 morning partial-peak period (8:30AM-12:00PM) to the peak-period (12:00PM-
404 6:00PM). This shift is still beneficial because the increase in the energy charges
405 is significantly lower than the decrease in the demand charges.

406

407 The cumulative load shapes given in Figure 3 and the arrival and departure
408 time histograms given in Figures 6a and 6b support these results. These figures

VAP	Period	Bill [dollars]		Reduction [dollars /session]	Reduction [%]		
		Current	Optimized		DC	EC	Total
P2-SB	Summer	63001	50395	0.65	20.86%	-0.85%	20.01%
	Winter	29603	22575	0.46	23.41%	0.33%	23.74%
EB-SB	Summer	4588	3788	0.52	16.96%	0.49%	17.45%
	Winter	2092	1724	0.28	17.23%	0.36%	17.59%
SA-SI	Summer	1645	1413	0.36	13.80%	0.30%	14.10%
	Winter	828	752	0.13	9.06%	0.12%	9.18%
CC	Summer	2365	2178	0.24	7.34%	0.57%	7.91%
	Winter	1037	896	0.22	13.31%	0.29%	13.60%
EB	Summer	12033	10003	0.41	16.44%	0.43%	16.87%
	Winter	5874	4868	0.26	16.66%	0.47%	17.13%
FG	Summer	1803	1568	0.33	11.98%	1.05%	13.03%
	Winter	920	807	0.18	11.82%	0.46%	12.28%
LP	Summer	2370	2135	0.29	9.37%	0.55%	9.92%
	Winter	1141	1002	0.20	11.88%	0.30%	12.18%
NB	Summer	3136	2865	0.23	8.16%	0.49%	8.64%
	Winter	1391	1271	0.13	8.48%	0.22%	8.63%
P2	Summer	16795	14171	0.48	16.13%	-0.51%	15.62%
	Winter	8567	7010	0.34	17.98%	0.20%	18.17%
SA	Summer	2313	1991	0.45	13.88%	0.04%	13.92%
	Winter	1215	914	0.52	24.76%	0.01%	24.77%
SB	Summer	32911	27439	0.53	17.72%	-1.09%	16.63%
	Winter	15645	12602	0.37	19.34%	0.11%	19.45%
SF	Summer	17679	14224	0.51	18.07%	1.47%	19.54%
	Winter	8591	7046	0.28	17.10%	0.88%	17.98%

Table 3: Average results based on summer and winter month rates in E-19

Figure 7: Monthly bills calculated with E-19. The left bar for each month shows the current bill, and the right bar shows the optimized bill.

409 suggest that energy charges increase because a large portion of the EV charging
 410 sessions end (i.e. the charger is unplugged) before the system peak period ends.
 411 Thus, when coupled with the higher part-peak demand rates, the optimization
 412 converges to a result in which the load is shifted from the EV load peak period
 413 (9AM-11AM) to the system peak period (12PM-6PM).

414

415 The results given in Table 3 provide further insight into the results depicted
 416 in Figures 7, 8a and 8b. Specifically, we reflect on the average monthly bill
 417 before and after optimization for winter and summer months. Then, we report
 418 on average bill reduction per session during these periods. The values range
 419 between 0.13 and 0.65 dollars among all VAPs. Overall, we find that the rate
 420 structure in the summer periods yields to more reductions per session than
 421 the rates in winter months, with the exception of the Sacramento Valley (SA)
 422 VAP. We also report on the total percent bill reduction and we break down this
 423 percentage into contributions from demand charges and energy charges. We
 424 observe that average percent bill reductions range between 8.63% and 24.77%.
 425 Even though the average reduction per session values are mostly higher during
 426 summer months, the relative cost reduction in monthly bills for individual VAPs

(a) Monthly energy charges calculated with E-19

(b) Monthly demand charges calculated with E-19

Figure 8: Decomposition of monthly bills to energy and demand charges. In each figure, the left bar shows the current charges, and the right bar shows the optimized charges for each month.

(a) Demand Charge Reduction in Dollars by Number of Sessions per Month

(b) Demand Charge Reduction Percentage by Number of Sessions per Month

Figure 9: Demand Charge Reduction by Session Size

427 varies less. This is due to high overall costs in the summer months.

428

429 Figures 9a and 9b depict the relationship between the reduction in demand
430 charges and the number of charging sessions in each VAP per month. Specifi-
431 cally, in Figure 9a, we examine the decrease in demand charges in dollars. We
432 observe a linear trend: as the number of sessions per month rises, the reduction
433 in demand charges increases linearly. Given the current load flexibility and ar-
434 rival and departure times, this is expected because most of the EVs contribute
435 to the peak load of the EV aggregation. In Figure 9b, we look at the percent
436 reduction in demand charges. For up to 2000 charging sessions per month (in-
437 dicated by a red dashed line in Figure 9b), there is no clear separation between
438 the winter and summer months and, for a given number of sessions, the demand
439 charge reduction values vary. Beyond this point, we can see a clear separation
440 between the winter and summer months, and the demand charge reduction val-
441 ues show less variance.

442

443 The relative decrease in the summer months is less than the relative de-
444 crease in the winter months. This is due to the time of the peak EV load, the
445 arrival and departure patterns of the EVs and the corresponding rate structure.
446 In particular, the peak EV load coincides with the part-peak rate period, and
447 most of the EVs depart before the system peak period (12PM-6PM) is over.
448 The system peak period has a separate and higher demand rate in the summer
449 months (detailed in Table 2). This limits the smart charging framework’s ability
450 to move the EV loads from part-peak period to system peak period. The winter
451 rates we use in this study do not include a separate demand rate for the system
452 peak period; rather, the part-peak period extends from 8:30AM-09:30PM. This
453 makes it possible to manage the EV peak load in a more effective way.

454

455 5. Distribution System Operator's Perspective

456 Smart charging of an aggregate EV population can offer multiple benefits
 457 to distribution system operators (DSOs). For example, it can help manage the
 458 capacity limits through demand response or can act as a balancing resource to
 459 accommodate distributed energy resources within a distribution system. In this
 460 case study, we investigate the potential of each charging session to decrease its
 461 contribution to the peak system demand via smart charging. We first quantify
 462 the percentage of peak load shed during the system peak load period (12AM-
 463 6PM). We then quantify the amount of energy that is shifted outside the peak
 464 period by the EV load aggregation for each month of 2013. Finally, we report
 465 on the amount of energy that can be expected to be moved outside of the system
 466 peak period per charging session.

467

468 5.1. Problem Formulation

469 To realize peak shaving, we propose to develop a two-stage optimization. In
 470 the first stage, we minimize a bound on the aggregate power consumed by the
 471 EVSEs within a VAP during the pre-defined peak period (12AM-6PM) only.
 472 We simplify refer to the pre-defined peak period as pp , and to simplify the
 473 notation introduced earlier, we refer to the aggregate power vector within the
 474 peak period as $AP_{pp}^{(d)}$. To implement the initial stage optimization, we define
 475 $AP_{bound,pp}^{(d)}$ as a decision variable to represent the proposed bound on the $AP_{pp}^{(d)}$.
 476 Then, in the second stage, using the optimal bound as a constraint, we minimize
 477 the total energy consumed within the peak period. This implicitly ensures that
 478 the energy bill for the customer is decreased or unchanged based on a typical
 479 TOU tariff. The first part of the optimization can be written as:

$$\underset{\mathbf{X}^{(i)}, AP_{bound,pp}^{(d)}}{\text{minimize}} \quad AP_{bound,pp}^{(d)}$$

480 subject to (4) and the following additional constraints:

$$AP_{pp}^{(d)} \leq AP_{bound,pp}^{(d)} \quad (13)$$

481 Then, using the optimal $AP_{bound,pp}^{(d)}$ values obtained in the first stage $AP_{bound,pp}^{*(d)}$,
 482 we can form the second stage as follows:

$$\underset{\mathbf{X}^{(i)}}{\text{minimize}} \quad \sum_{\forall k \subseteq pp} AP_k^{(d)}$$

483 subject to (4) and the following additional constraints:

$$AP_{pp}^{(d)} \leq AP_{bound,pp}^{*(d)} \quad (14)$$

484 5.2. Case Study

485 The motivation behind our second case study is to evaluate the potential
 486 of EV aggregations to decrease their contribution to the system peak load via
 487 smart charging. As the arrival and departure time histograms given in Fig-
 488 ures 6a and 6b suggest, the amount of energy that can be moved outside of
 489 the peak period is expected to be low, mostly because most non-residential EV
 490 sessions end before the system peak period is over. However, there is potential
 491 in using smart charging and exploiting the inherent flexibility in each charging
 492 session to decrease the contribution of EVs to the system peak load.

493

494 To demonstrate and quantify this potential, we calculated optimal schedules
 495 for each VAP-level aggregation using the optimization strategy described in the
 496 above section, and obtained percentage of peak shed values and the total energy
 497 moved outside of the peak period for every day in each month of 2013.

Figure 10: Distribution of percent peak shed for all the VAPs

5.3. Results

Figure 10 shows the box plots created using daily peak shed values for each month of 2013. The percentage of peak shed for each day d is defined as:

$$\%peakshed^{(d)} = \frac{AP_{bound,pp}^{*(d)}}{\max(AP_{pp}^{(d)})} \quad (15)$$

The red lines denote the median value of the distribution, the box boundaries are the 25th and 75th percentiles and the whiskers denote the 1st and 99th percentiles, assuming the distributions per each month are normal. The outliers outside the whiskers' boundaries are marked with points. As expected, the smart charging significantly reduces the peak EV load during the system peak period. The median values for all of the months range between 30 and 42%. A decrease in the peak shaving potential and a slight decrease in the variation of the distributions over the course of 12 months are also apparent in Figure 10. This can be explained by the increase in the number of charging sessions per EVSE and the related decrease in the variation of available flexibility.

Figure 11 depicts the distribution of the average energy moved outside of the peak period per charging session for all of the VAPs estimated every day of the month. The median value over 2013 is approximately 0.25kWh per charging session, which corresponds to $\sim 2.8\%$ of the average energy put during each

Figure 11: Total energy moved outside of system peak period

charging session.

6. Conclusions

In this paper, we quantify the potential benefits of smart charging to different stakeholders using data collected from over 2000 non-residential electric vehicle supply equipment (EVSEs) located throughout 190 zip code regions in Northern California. We created virtual aggregation points (VAP) in which the aggregate power consumption of a selected population of EVSEs is assumed to be managed via individual charging control at each EVSE. We developed and used a smart charging framework to estimate the benefits of EV smart charging to different stakeholders: a single owner/an aggregator of behind-the-meter EVSEs (i.e. aggregators) and distribution system operators.

In our first case study, we investigated the potential benefits of behind-the-meter EV aggregations. The aggregate load is re-scheduled using a TOU rate structure. Our results suggest that up to 24.8% decrease in the aggregate monthly bill per VAP is possible. In all months, this reduction is due to a corresponding decrease in demand charges in the monthly bill: we observed that decreases in energy charges are contributing by up to 1.5% to the overall decrease, whereas the demand charges contribute up to 24.7%.

535

536 In our second case study, we used the EV aggregations to decrease their con-
537 tribution to the system-level peak load. We have observed median peak shed
538 values around 30%-42% for each month. In addition, we have quantified the
539 amount of energy that can be shifted outside the peak period per charging ses-
540 sion over the course of 2013, and found the median value to be approximately
541 0.25kWh/session ($\sim 2.8\%$ of the average energy put in each session).

542

543 The results from the optimization from the perspective of the EV infrastruc-
544 ture owners includes most, if not all of the optimized charging patterns from
545 the DSO perspective due to the differential cost of electricity between peak and
546 off peak. However, there is a strong additional incentive to reduce the overall
547 peak consumption, which happens immediately before the system peak period,
548 in the infrastructure owners case. Hence, as the results suggest, the deferment
549 of electricity consumption into the system peak to reduce demand charges is
550 greater than the resulting shift of load out of the system peak period.

551 7. Limitations and Future Work

552 In this paper, we assume that the session start and end times of the EVs are
553 available to the controller. However, in a real-life scenario, start and end times
554 must be forecasted. Since the current strategy does not account for potential
555 errors in forecasting, the benefits are overestimated. Furthermore, we assume
556 that there is no modulation of charging power, and that the amount of energy
557 charged by each EV is required by the EV owner. Hence, a constraint is included
558 to ensure that the observed charging energy consumption in each session is con-
559 served through the optimization. In a real-life scenario, the mobility patterns of
560 an EV owner might allow for only partial charging at the EVSE and defer the
561 rest of the charging to a later time. Both of these assumptions might result in
562 an underestimation of the flexibility of charging sessions and the potential ben-
563 efits. The impact of these assumptions will be further elaborated in future work.

564

565 In addition to the assumptions made on the availability of information from
566 different charging sessions, this study is limited to data obtained from non-
567 residential charging loads only. In case similar residential data is available, a
568 broader discussion of the benefits of smart charging could be done that may lead
569 to different results and conclusions. Furthermore, we have selected a commer-
570 cial tariff from PG&E for the first case study. Different tariff structures would
571 significantly impact the savings estimated from the EV aggregations. Lastly,
572 we would like to acknowledge that the study captures the EV charging benefits
573 estimated based on charging patterns obtained in Northern California. Hence,
574 the mobility constraints and the energy demand reflected in the dataset are
575 shaped by the users of EVSEs in Northern California.

576

577 Although the session length and the flexibility play an important role in the
578 estimated benefits for EV aggregations, understanding the contributing factors
579 of these benefits at the charging session level is challenging. Additional charging
580 session characteristics, such as start time and end time, play a significant role in
581 the estimated aggregate benefits. This is because these benefits are impacted by
582 the time of use. For example, two different charging sessions that have identical
583 session lengths and flexibility levels can provide significantly different benefits
584 depending on what time of the day the charging session starts. Hence, we leave
585 the discussion of contributing factors to EV aggregation benefits at the charging
586 session level to future work.

587

588 In the future, we would also like to investigate the impact of different non-
589 residential customer categories (e.g., retail vs. workplace) within each VAP to
590 similar metrics calculated in this study and identify suitable grid services for
591 these customer categories. In addition, we would like to expand the current
592 smart charging framework and develop control algorithms for workplace charg-
593 ing that use variable charging rates. We also would like to study the impacts
594 of smart non-residential EV charging to the overall system load, in particular

595 when the system level solar generation is expected to cause over-generation and
596 ramping problems in the grid.

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