Adaptive Charging Network

Steven Low

CMS, EE

Caltech

June 2022

EEE Melbourne University

Acknowledgement

powerflex
EDF renewables

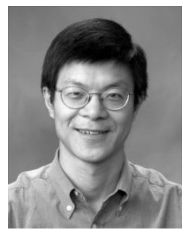
G. Lee

C. Jin

T. Lee

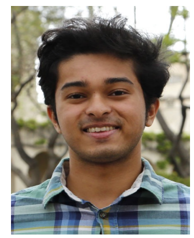
D. Lee

Caltech



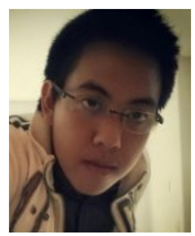
S. Low

Z. Lee

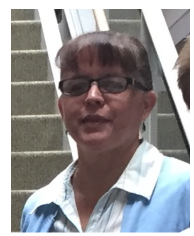


S. Sharma

D. Chang

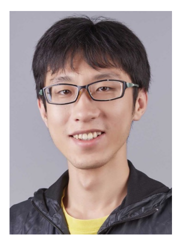


R. Lee



C. Ortega

D. Guo



T. Li

J. Pang

Z. Low, Cornell

K. Erliksson, Lund

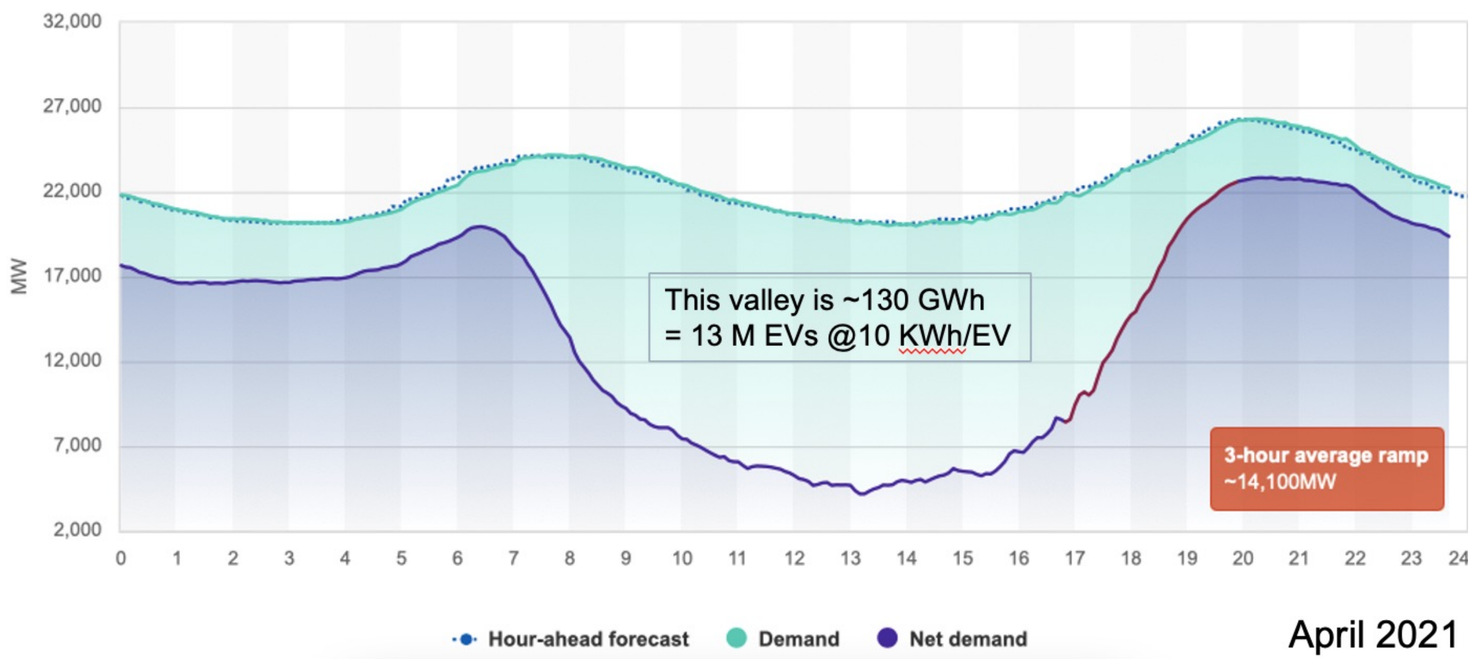
D. Johansson, Lund

and many others …

Workplace charging

CA commitment

- ~~50%~~ 60% renewables by 2030, 100% by 2045
- 1.5M ZEV by 2025, 5M by 2030 (CA has ~15M cars)



Drivers <u>twice as likely</u> to get EV when workplace charging is available

(EDF Renewables survey Feb 2018)

Agenda

Caltech adaptive charging network (ACN)

- Testbed to commercial deployment

ACN Research Portal

- ACN – Data, Sim, Live

Pricing demand charge

- Monthly billing at workplaces

ACN testbed

IEEE TRANSACTIONS ON SMART GRID, VOL. 12, NO. 5, SEPTEMBER 2021 4339

Adaptive Charging Networks: A Framework for Smart Electric Vehicle Charging

Zachary J. Lee, *Graduate Student Member, IEEE*, George Lee, Ted Lee, Cheng Jin, Rand Lee, Zhi Low, Daniel Chang, Christine Ortega, and Steven H. Low, *Fellow, IEEE*

2016 GlobalSIP Conference:

Adaptive Charging Network for Electric Vehicles

George Lee[1,2], Ted Lee[2], Zhi Low[3], Steven H. Low[2], and Christine Ortega[2]

[1]PowerFlex Systems
[2]Division of Engineering & Applied Science, Caltech
[3]Math Department, Cornell

ACN Research Portal

2019 ACM e-Energy:

ACN-Data: Analysis and Applications of an Open EV Charging Dataset

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IEEE TRANSACTIONS ON SMART GRID, VOL. 12, NO. 6, NOVEMBER 2021 5113

ACN-Sim: An Open-Source Simulator for Data-Driven Electric Vehicle Charging Research

Zachary J. Lee, Sunash Sharma, Daniel Johansson, and Steven H. Low, *Fellow, IEEE*

ACN Pricing

ELSEVIER

Electric Power Systems Research

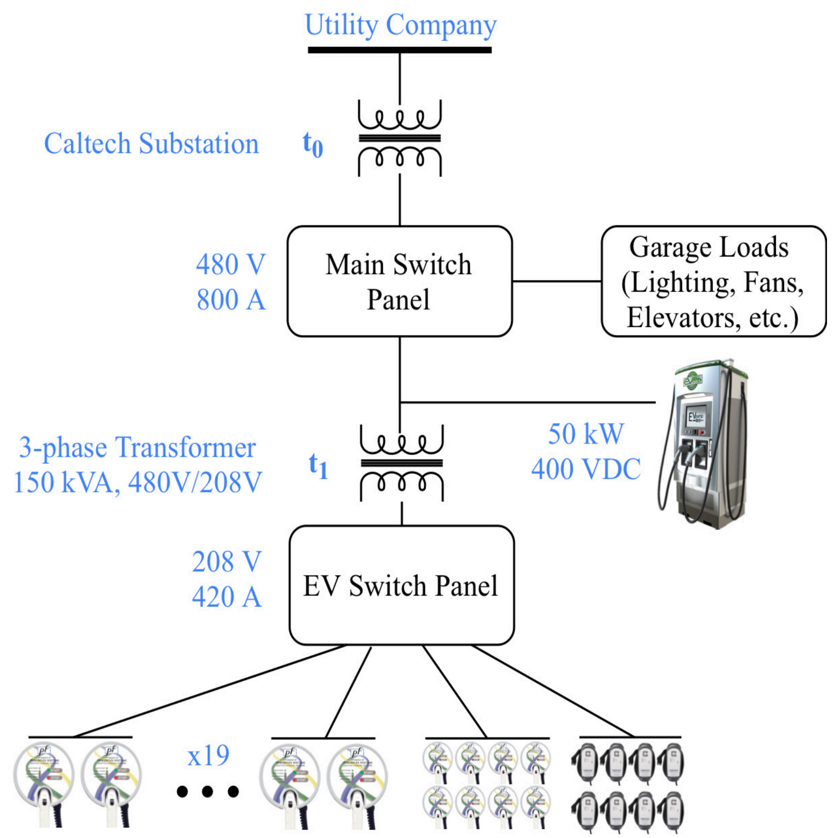
Volume 189, December 2020, 106694

Pricing EV charging service with demand charge ☆

Zachary J. Lee [a], John Z.F. Pang [b], Steven H. Low [a, b]

PSCC 2020

Physical system



Cyber system

Model predictive control: QCQP

$$
\begin{aligned}
\min_{r \geq 0} \quad & C(r) \\
\text{subject to} \quad & r_i(t) \leq \overline{r}_i(t) \qquad \forall i,\ \forall t \\
& \sum_t r_i(t)\,\delta = e_i \qquad \forall i \\
& \sum_i r_i(t) \leq P(t) \qquad \forall t
\end{aligned}
$$

Highly customizable QCQP

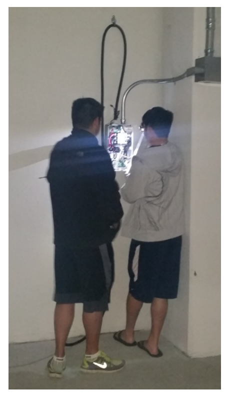
- objectives: cost, PV, asap, regularizatn
- constraints: energy, deadlines, capacities
- determine charging rates for all EVs

First deployment Feb 19, 2016

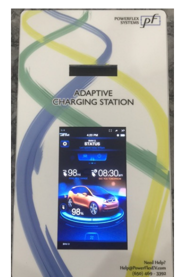
Online optimization of electric vehicle charging

- Enables mass deployment at lower capital & operating costs
- First pilot @Caltech: 54 adaptive programmable chargers
- 2x 150kVA transformers, breakers, grid sensors, etc

debugging

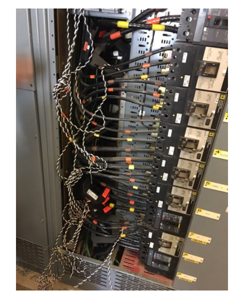


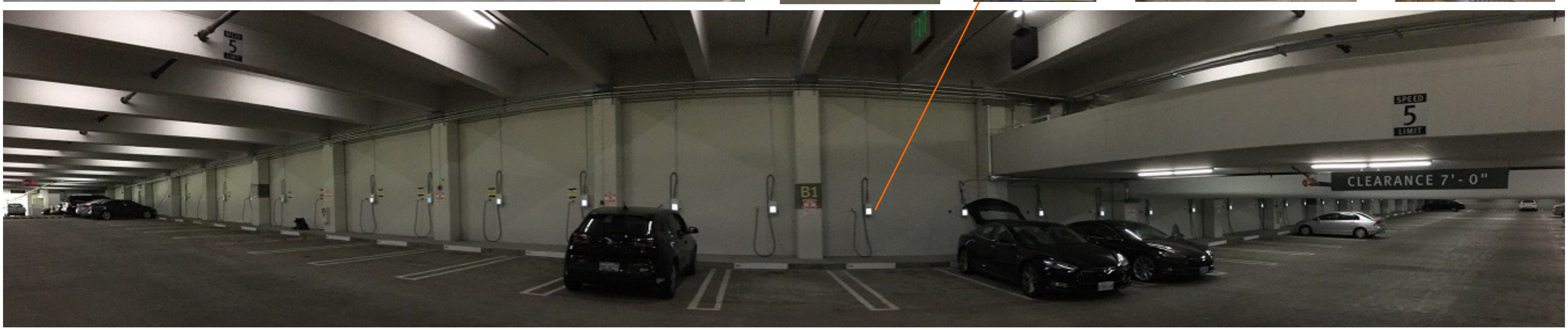
charger



transformer & subpanels

main panel





2020

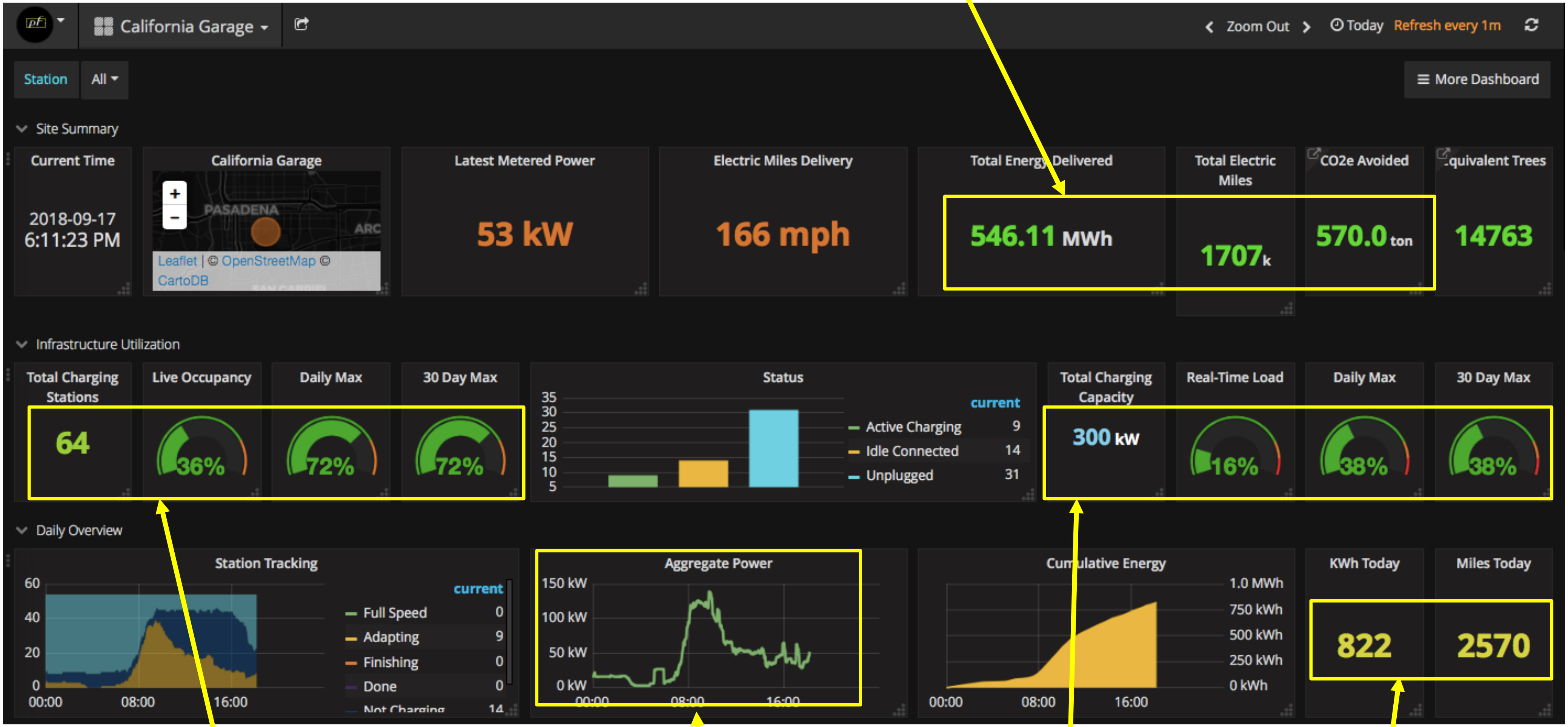
Figure 1. Photos of the N_Wilson_Garage_01 ACN, which is one of the charging sites used to collect data.

The ACN Research Portal has three parts:
(1) ACN-Data: a dataset of over 80,000 EV charging sessions (March 2021);
(2) ACN-Sim: an open-source, data-driven simulation environment2, and
(3) ACN-Live: a framework for field testing algorithms on physical hardware.

March 2021: ACN includes a total of 207 level-2 EVSEs and six DC Fast Chargers (DCFC), and covers seven sites at Caltech, NASA's Jet Propulsion Laboratory, a LIGO research facility, and an office building in Northern California.

Caltech ACN

energy delivered & impact to date



charging station utilization

peak power

power utilization

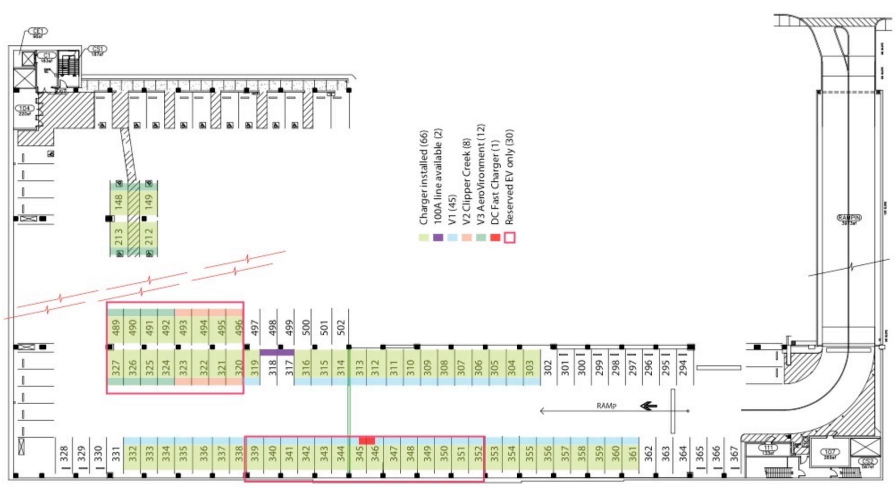
today's energy delivered

Caltech ACN snapshot Sept 17, 2018

Caltech ACN

Spatial utilization snapshot (June 1 – August 31, 2018)

	total	per day	per space	remark
#parking spaces	53			
#days (June 1 – Aug 31, 2018)	92			inc. weekends
#charging sessions	6,103	66	115	>1 session /space/day
occupancy (space-day)	3,374	37	64	69% occupancy
energy delivered (kWh)	54,562	593	1,029	11 kWh /space/day
#hours occupied	28,407	309	536	5.8 hours /space/day



Caltech ACN

- CA Garage operational since 2016
- Delivered 1 GWh (by July 2020, CA)
- Equivalent to 3.2M miles, 1,000 tons of avoided CO_2e

Caltech ACN

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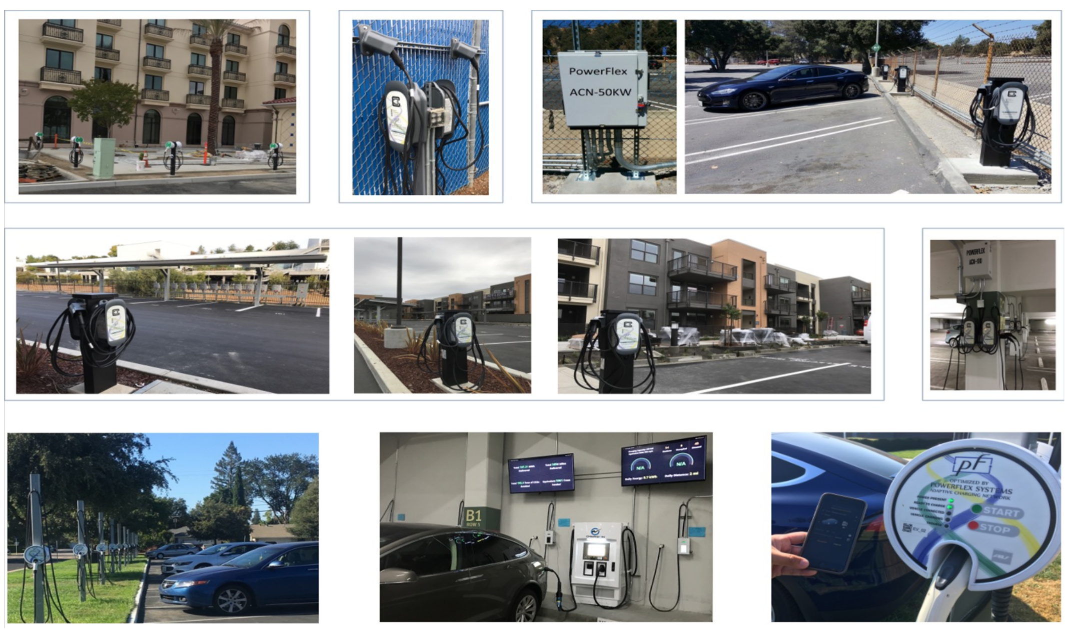
- Equivalent to 3.2M miles, 1,000 tons of avoided CO2e



powerflex EDF renewables Feb 2020

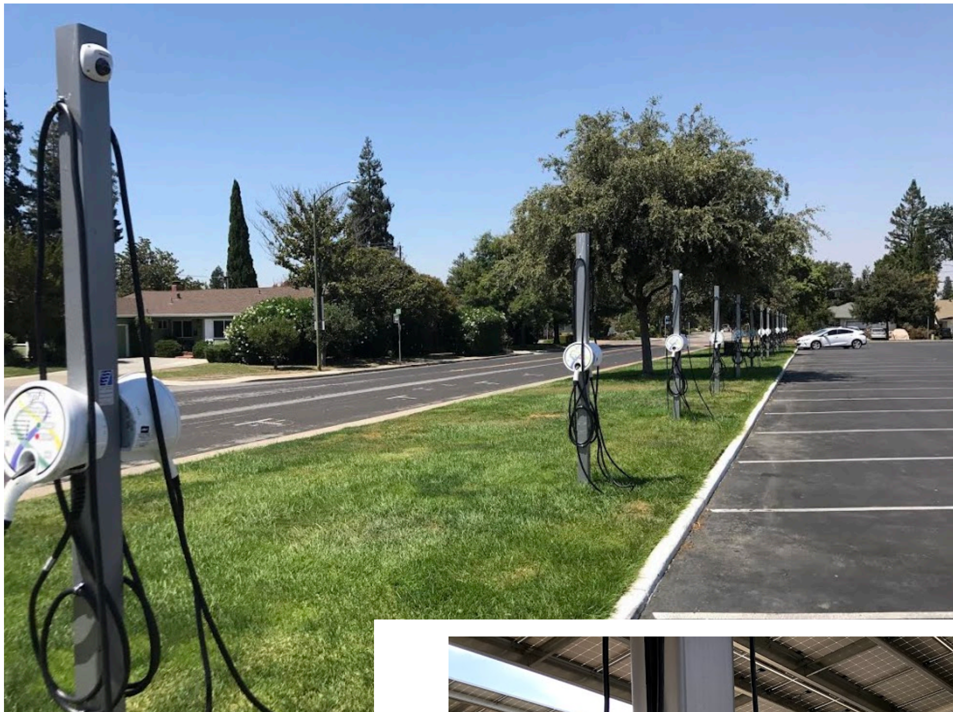
2,000+ EV CHARGING STATIONS DEPLOYED	10,000,000+ ELECTRIC MILES DELIVERED SAFELY

(US wide)

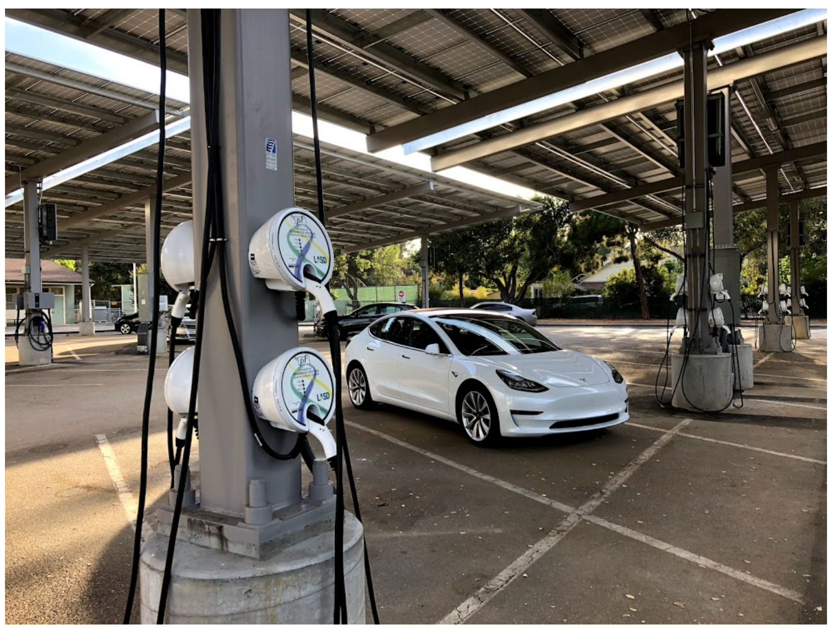
NREL, Golden CO

120 EVSEs

Bay Area high schools

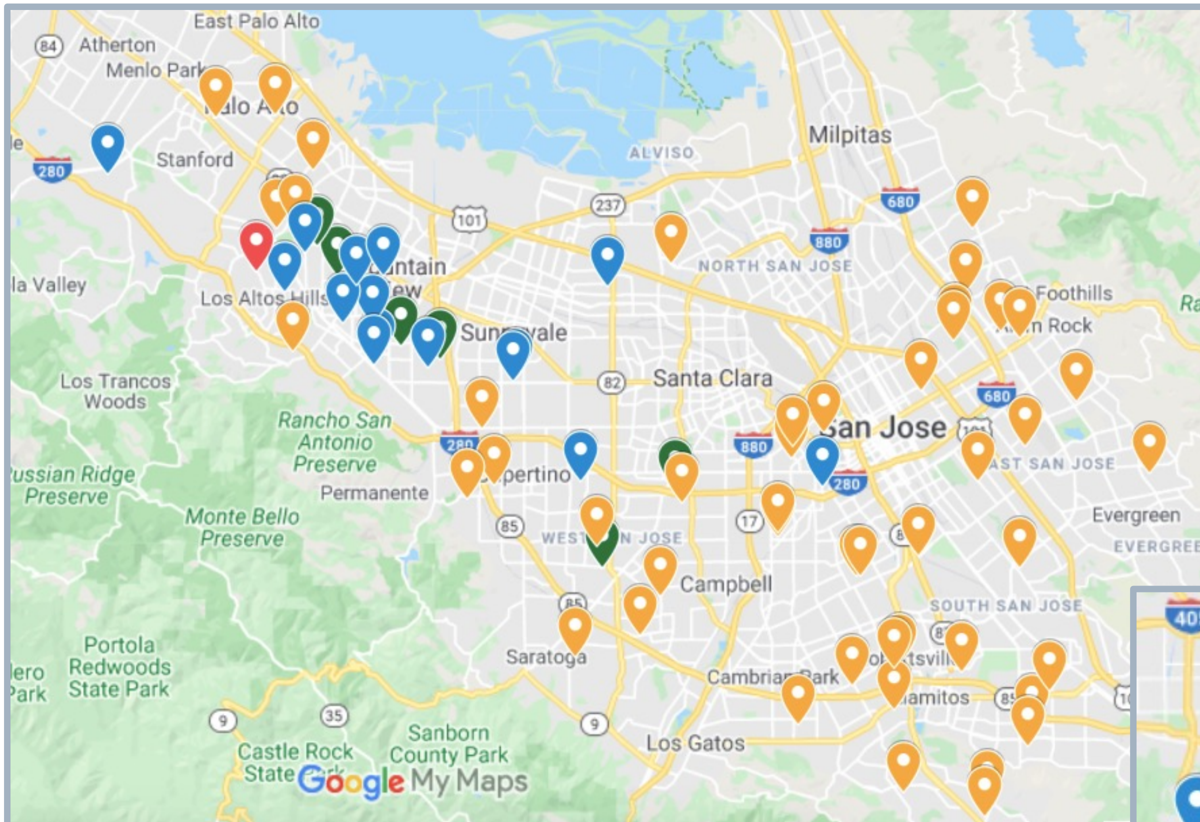


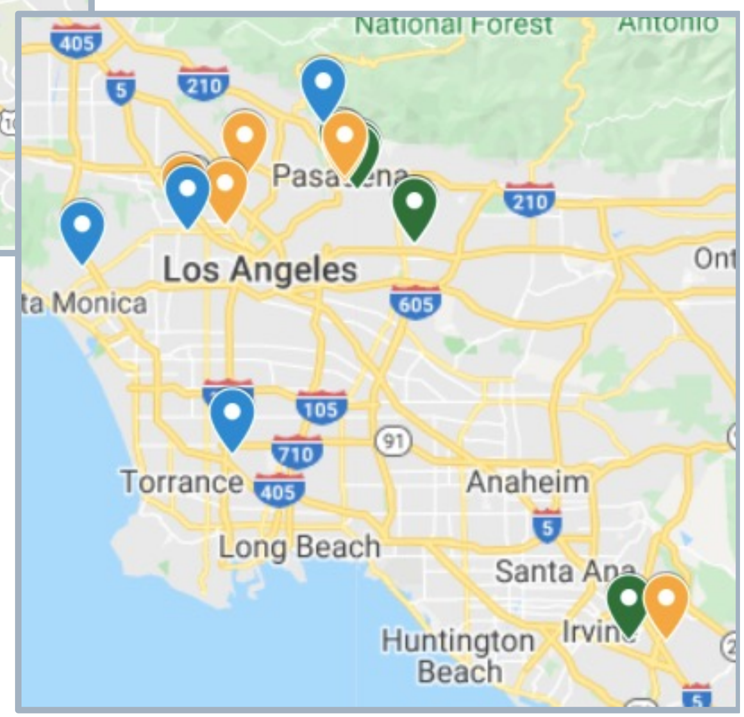
DCFC



Onsite PV

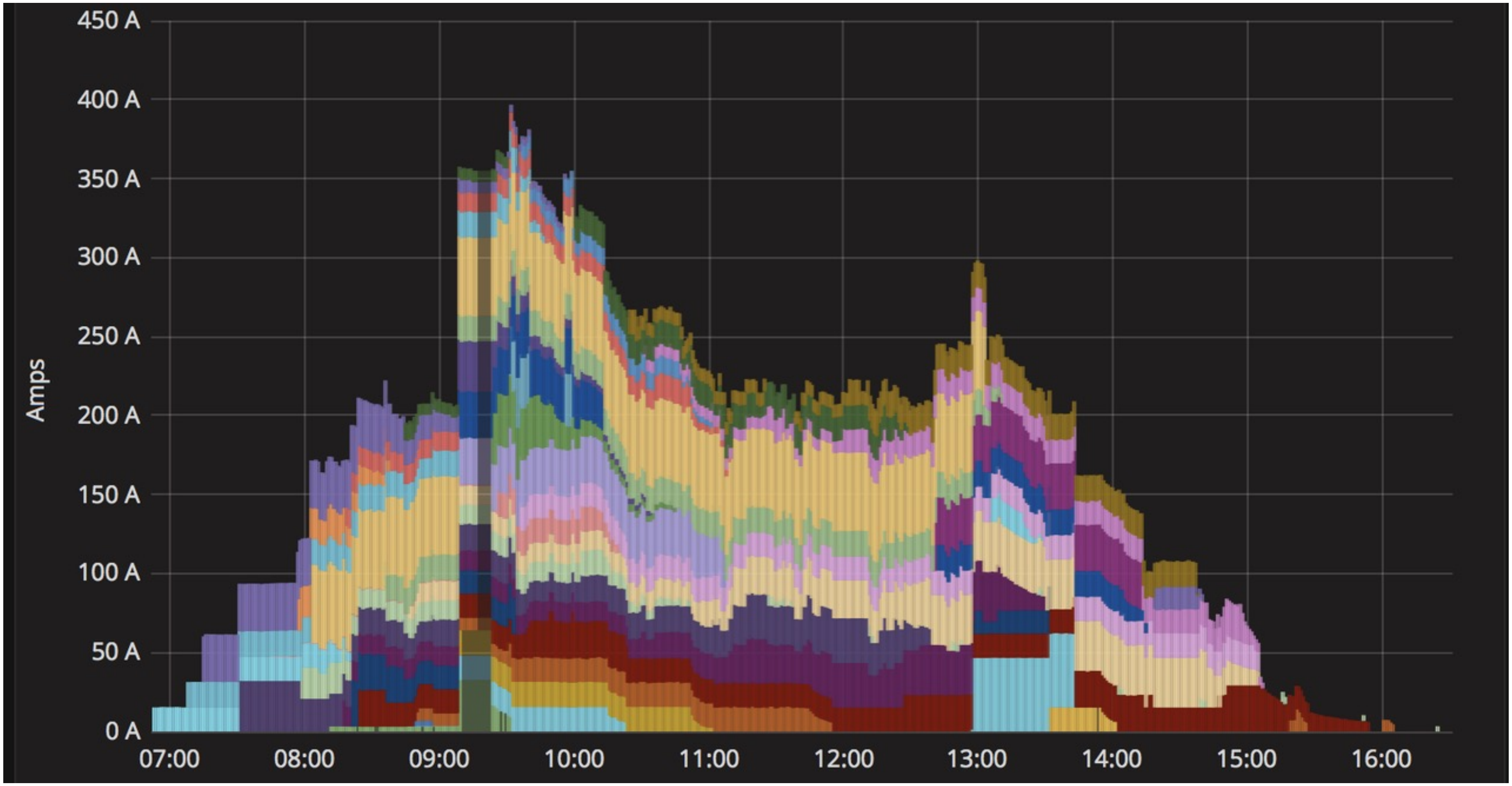
Deployment in CA





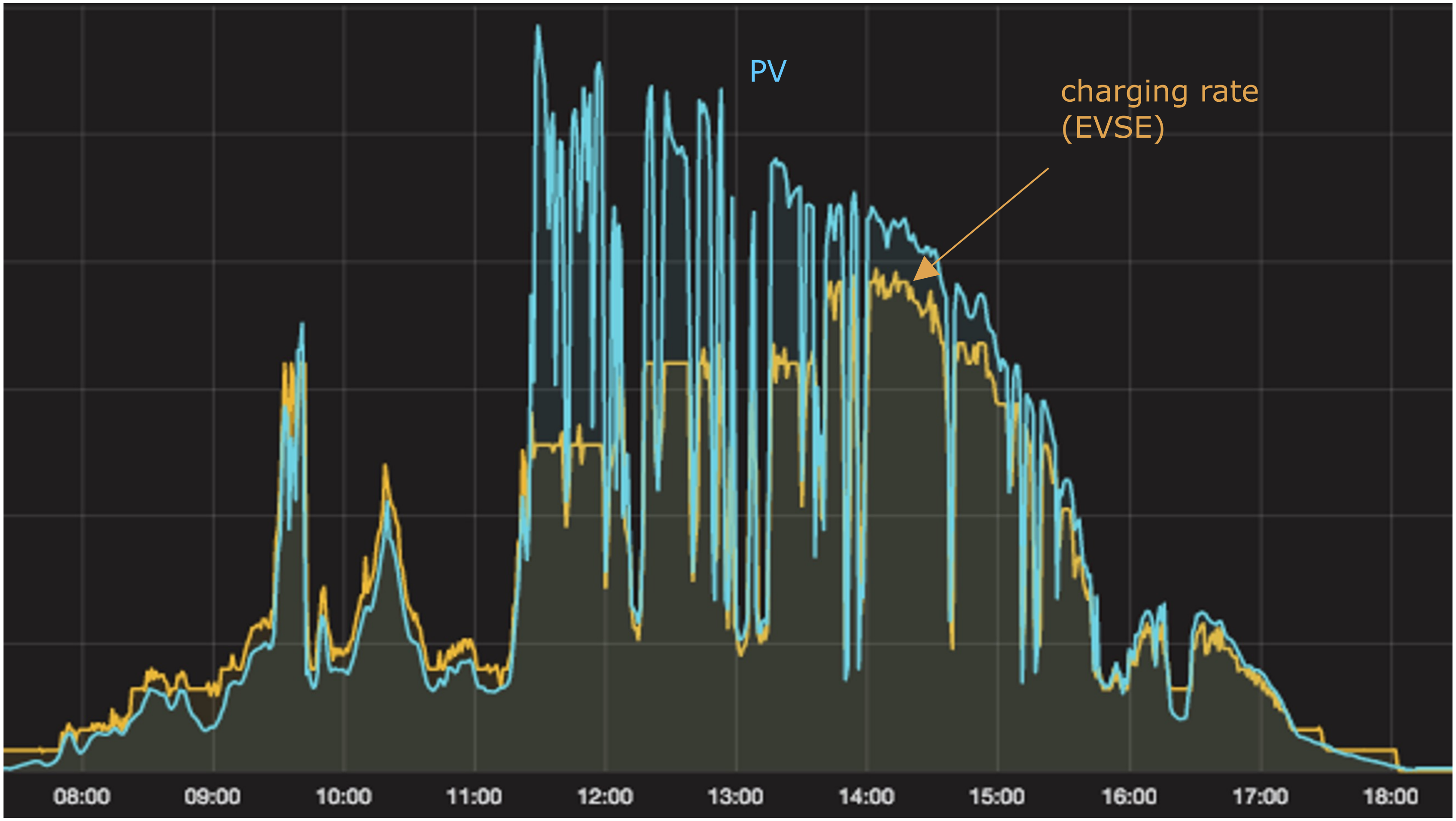
powerflex EDF renewables deployment, Sept 2018

Adaptive charging



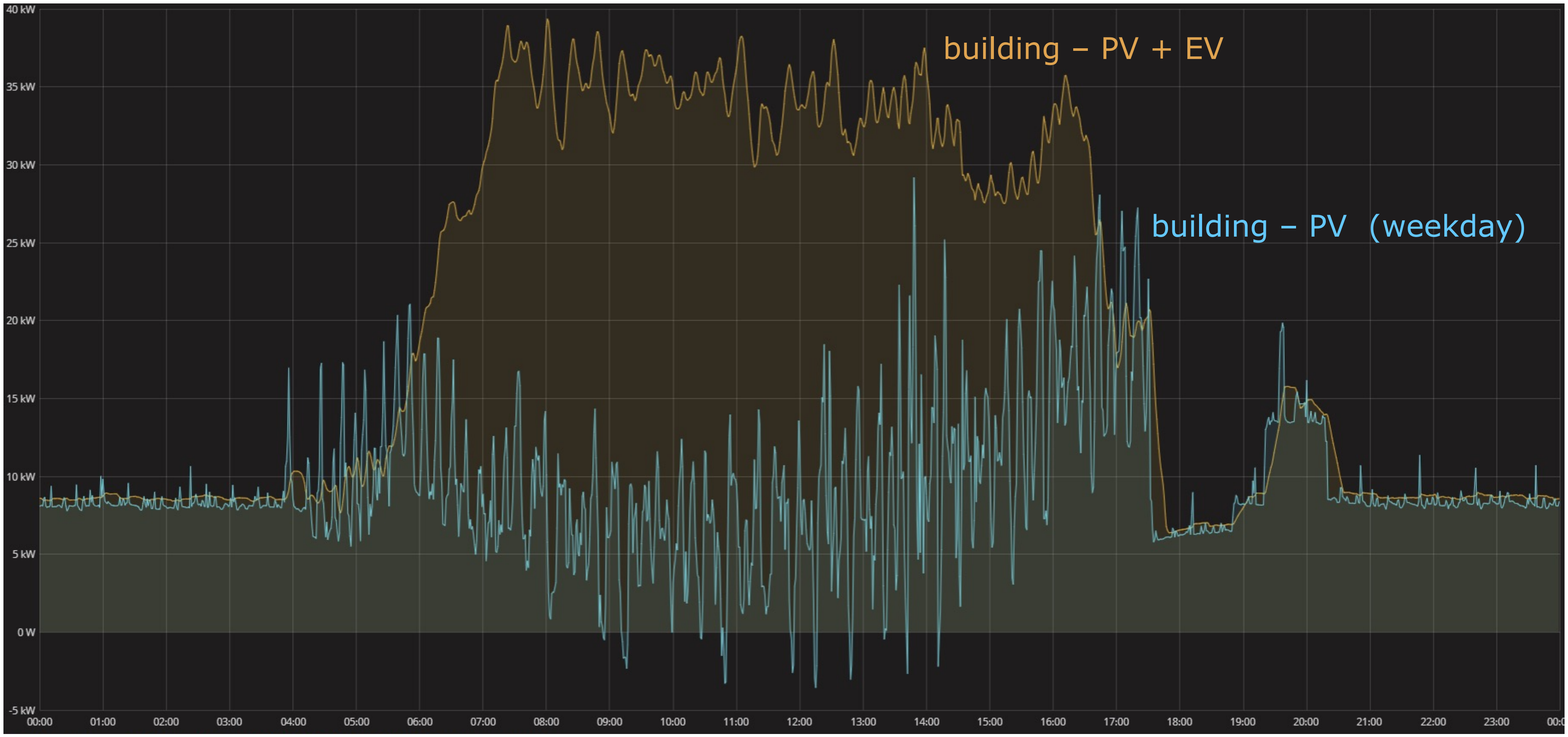
Caltech Jan 2018

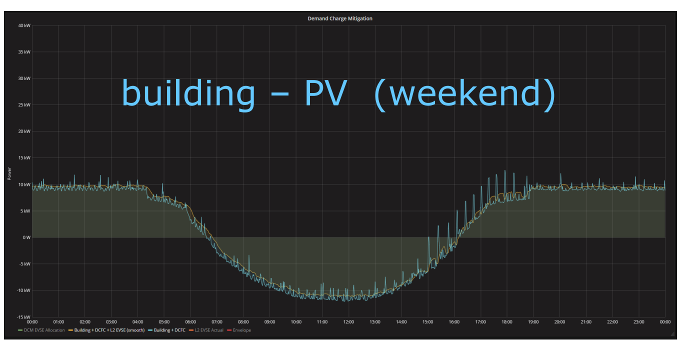
Online tracking



Real-time tracking of PV generation at JPL (10/2016)

Duck Curve & DCM



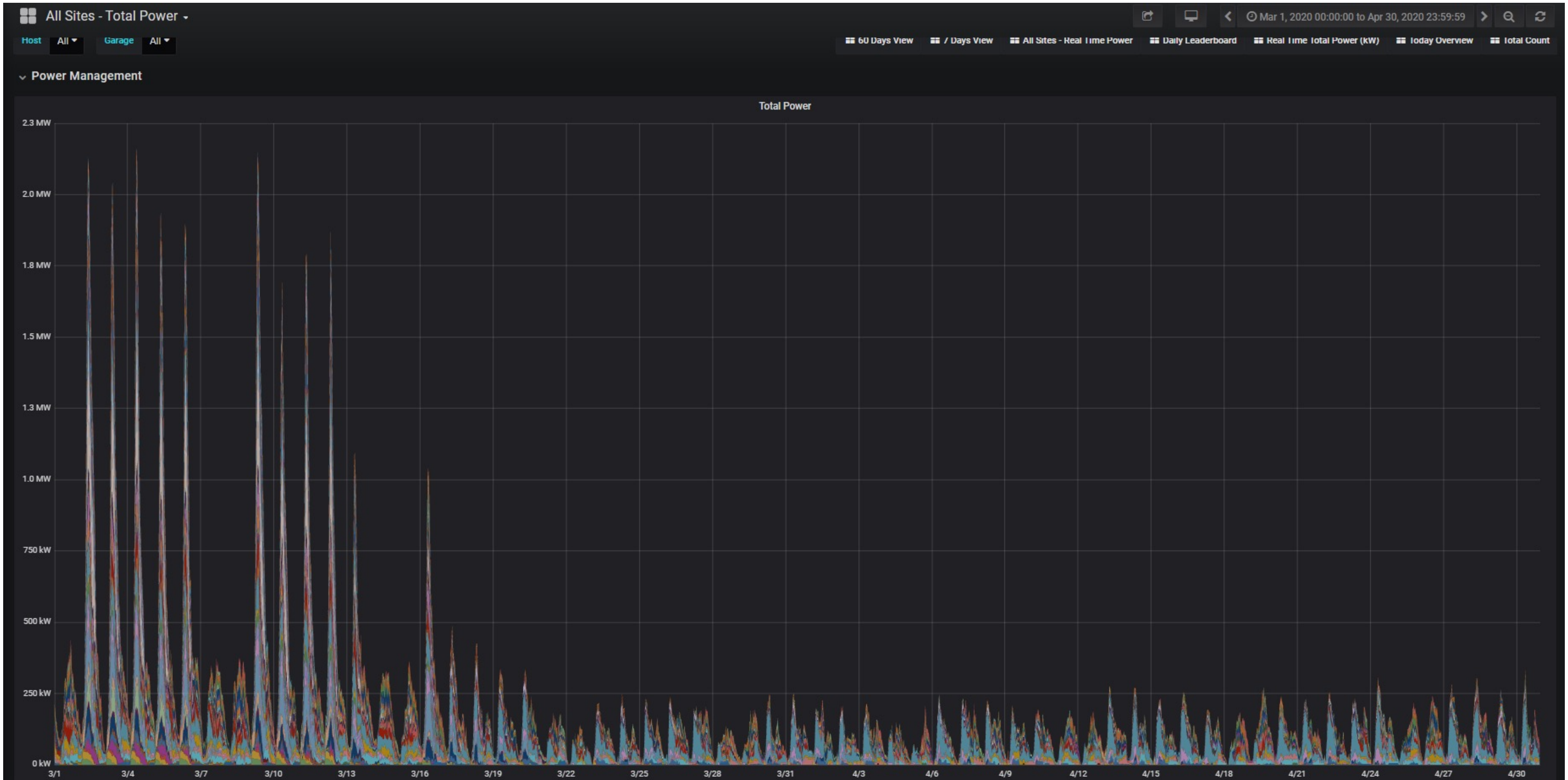


Weekend Duck Curve: building load (10kW) – PV

NREL: demand charge mitigation (Nov 2018)

- Fill Duck Curve valley and maintain net load between 30 kW – 40 kW
- On weekdays: building load is much higher and much more volatile

COVID hit



weekdays

weekdays

powerflex EDF renewables

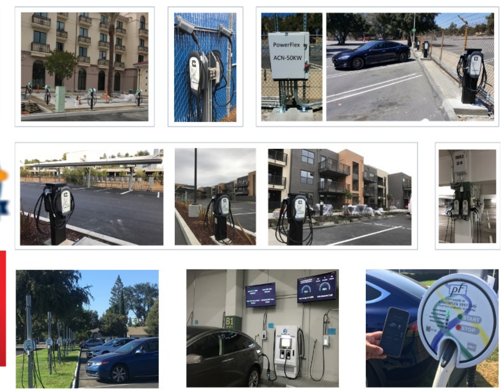
March 16 Monday, 2020

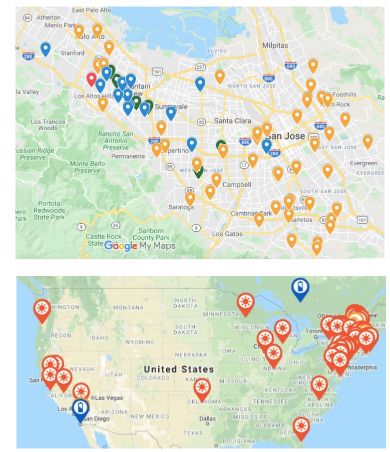
powerflex EDF renewables

Commercialization: timeline

PF: EV + solar + storage

2010 | 2016 | 2017 | 2019 | 2021





Energy mgt **research**

Incubation to **tech transfer**

Scalable **business**

Business case: lower capital cost

Table ES.1: Projections for Statewide PEV Charger Demand

Demand for L2 Destination (Workplace and Public) Chargers (The Default Scenario)			
	Total PEVs	Lower Estimate (Chargers)	Higher Estimate (Chargers)
As of 2017	239,328	21,502	28,701
By 2020	645,093	53,173	70,368
By 2025	1,321,371	99,333	133,270

100,000 Chargers @$15k/ea = $1.5B

$15k/charger is unsustainable

CA CEC & IOU incentive program estimated ~$15k/charger (inc. make ready)

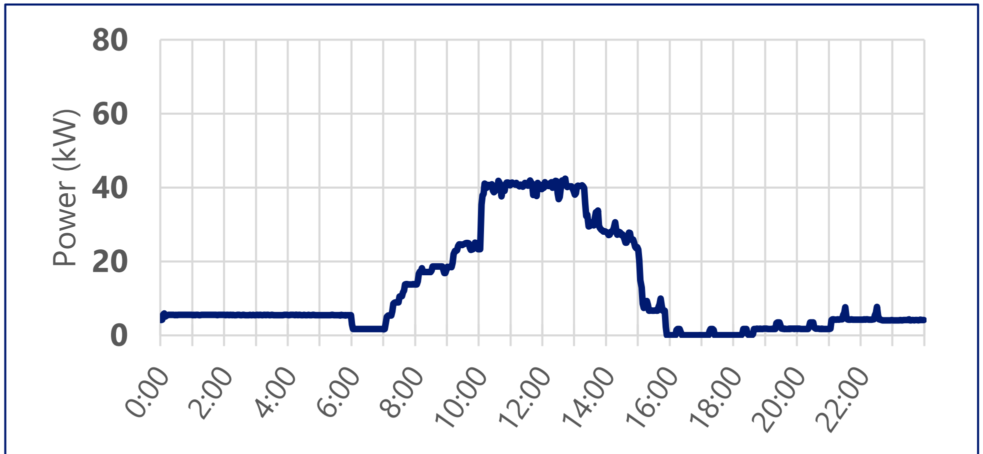
CEC 3/2018 Staff Report

- 168 chargers
  - 118x Universal (J1772) x 6.6kW
  - 50x Tesla x 16kW
- 1.578MW nameplate
  - Connected to 800A/480V panel (max load @80% = 522kW)
  - 3x capacity
  - No Interconnection Upgrade
- Cost: <$3,000/station

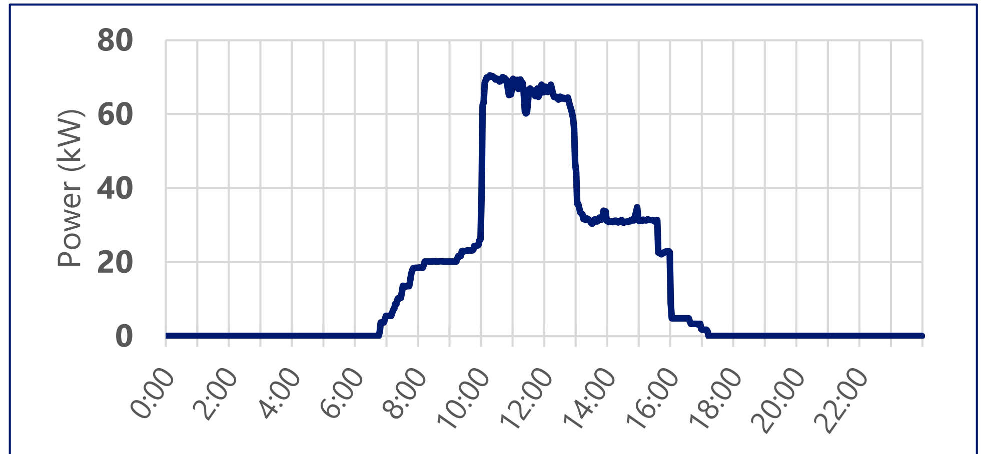
PowerFlex case study: <$3k/charger (inc. make ready)

powerflex EDF renewables 2/2020

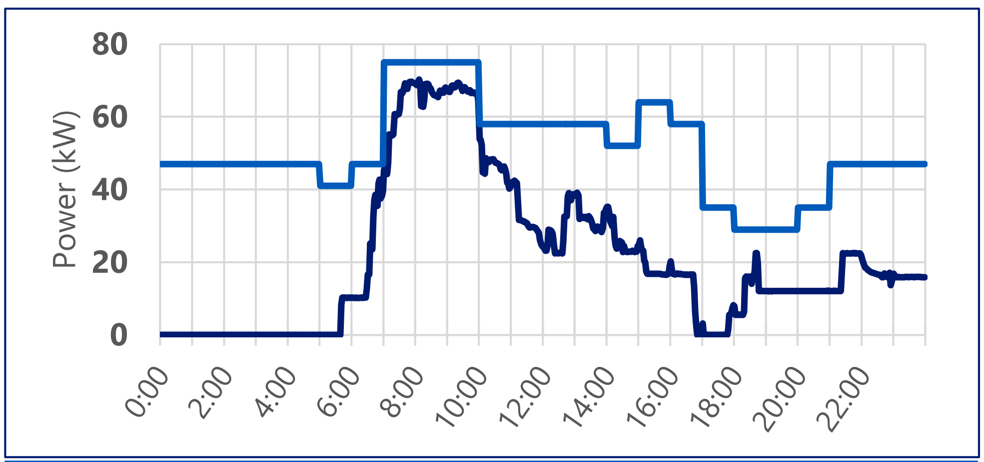
Business case: lower operating cost



Peak Reduction: Reduced Peak by 40% (72kW to 42kW) while still delivering same amount of energy



10am Floodgates: Charging maximized to transformer limits during 10am-2pm to optimize for incentives for consuming surplus solar energy

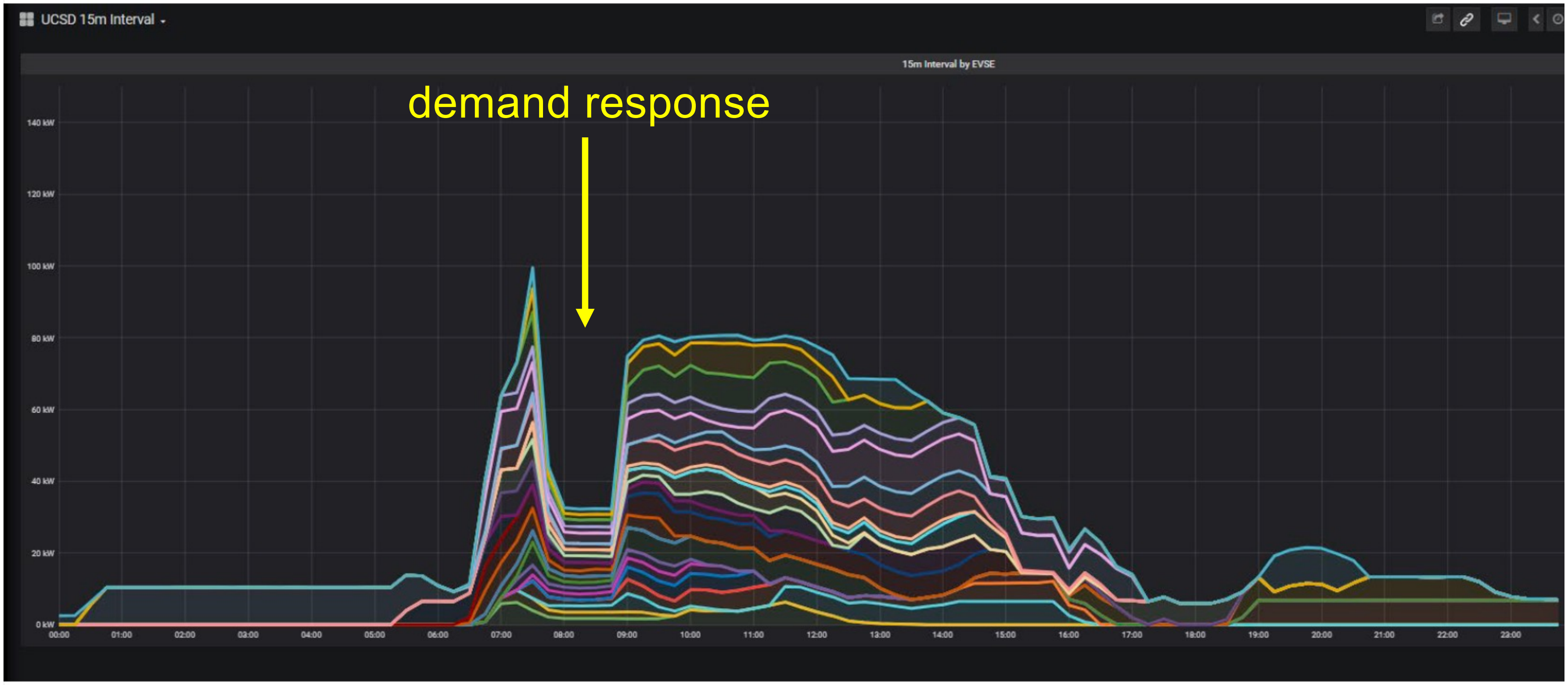


LCFS Curve Following: Charging optimized under LCFS Time-of-Use Value curve

- 3 sample ways to reduce operating cost
- by price arbitrage or increasing LCFS revenue
- EDF – Athena (San Diego, CA)

powerflex EDF renewables 2/2020

Business case: grid services



powerflex EDF renewables 2/2020

Agenda

Caltech adaptive charging network (ACN)

- Testbed to commercial deployment

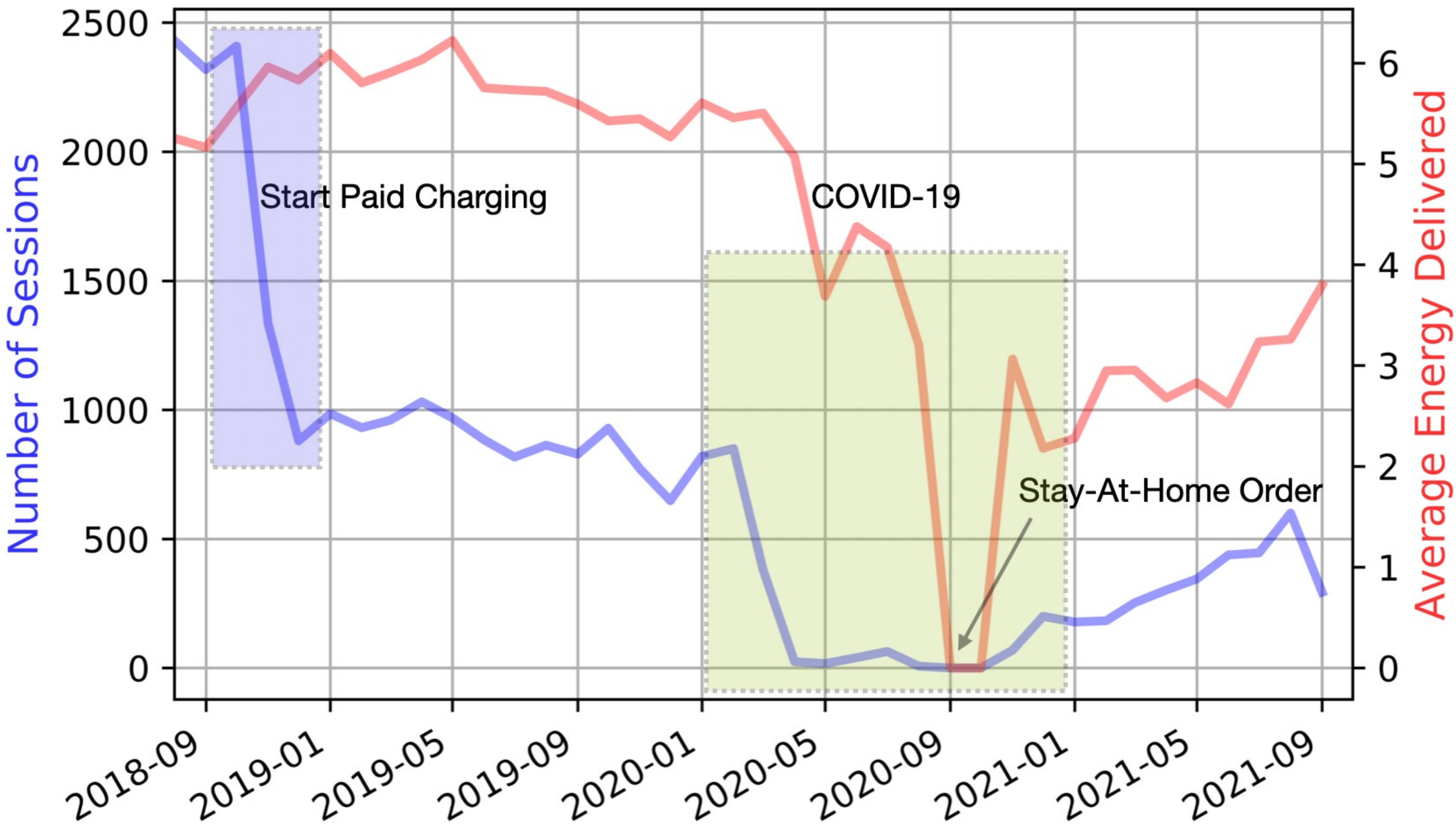
ACN Research Portal

- ACN – Data, Sim, Live

Pricing demand charge

- Monthly billing at workplaces

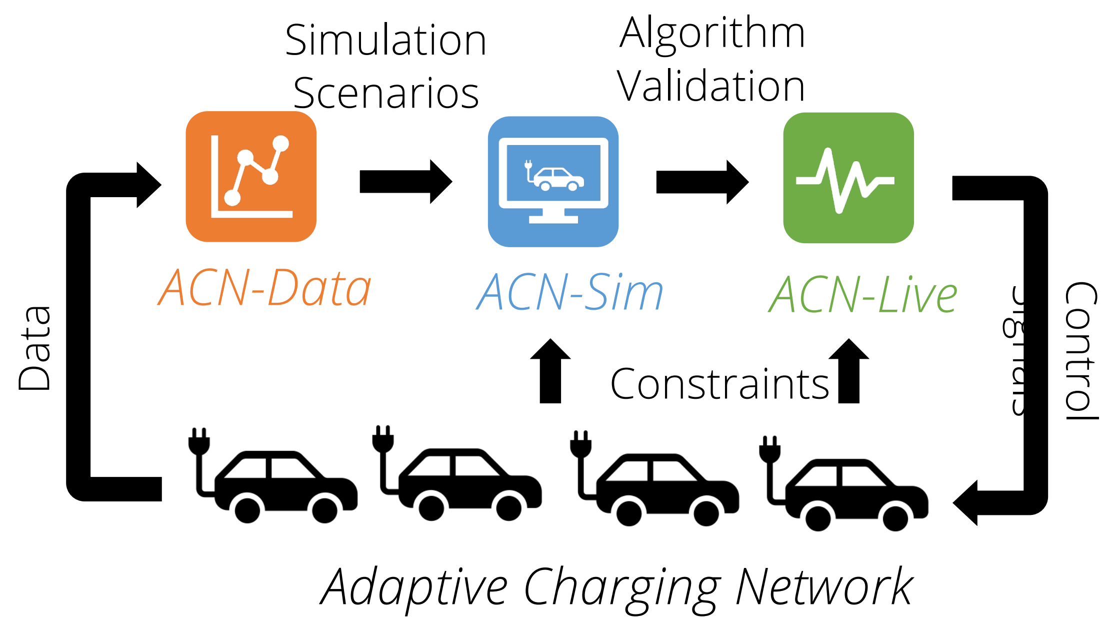
Caltech ACN



Start Paid Charging
COVID-19
Stay-At-Home Order
Number of Sessions
Average Energy Delivered
2500
2000
1500
1000
500
0
6
5
4
3
2
1
0
2018-09
2019-01
2019-05
2019-09
2020-01
2020-05
2020-09
2021-01
2021-05
2021-09

ACN research portal

- ACN-Data
- ACN-Sim
- ACN-Live (HW-in-the-loop)



Lee, Li, Low. ACN-Data: analysis and applications of an open EV charging Dataset
ACM e-Energy, June 2019

Lee, Johansson, Low. ACN-Sim: an open-source simulator for data-driven EV charging research
IEEE SmartGridComm, October 2019

ACN-Data

Caltech, JPL, Bay Area office

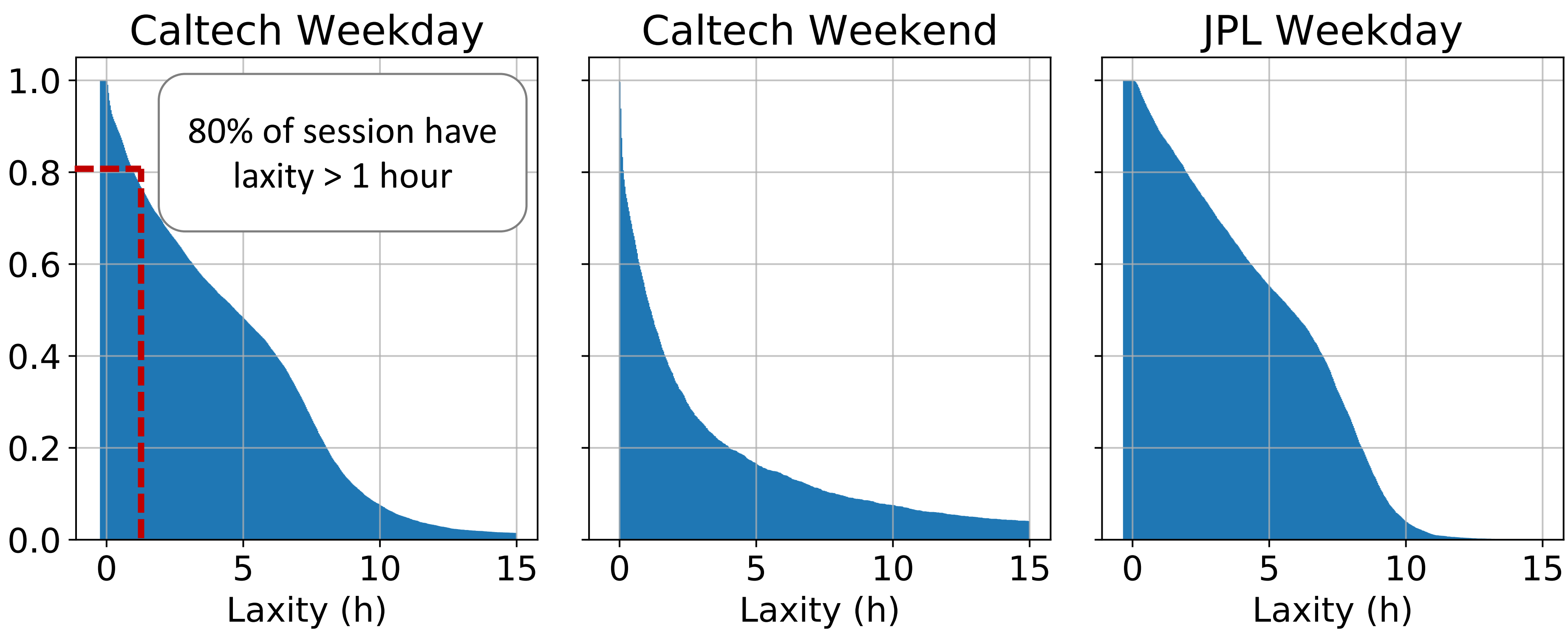
- 53,000+ EV charging sessions (Oct 2020)
- Publicly available: ev.caltech.edu
- Growing daily

Real fine-grained data for

- Modeling user behavior
- Evaluating charging algorithms
- Evaluating charging facilities
- Evaluating grid impacts

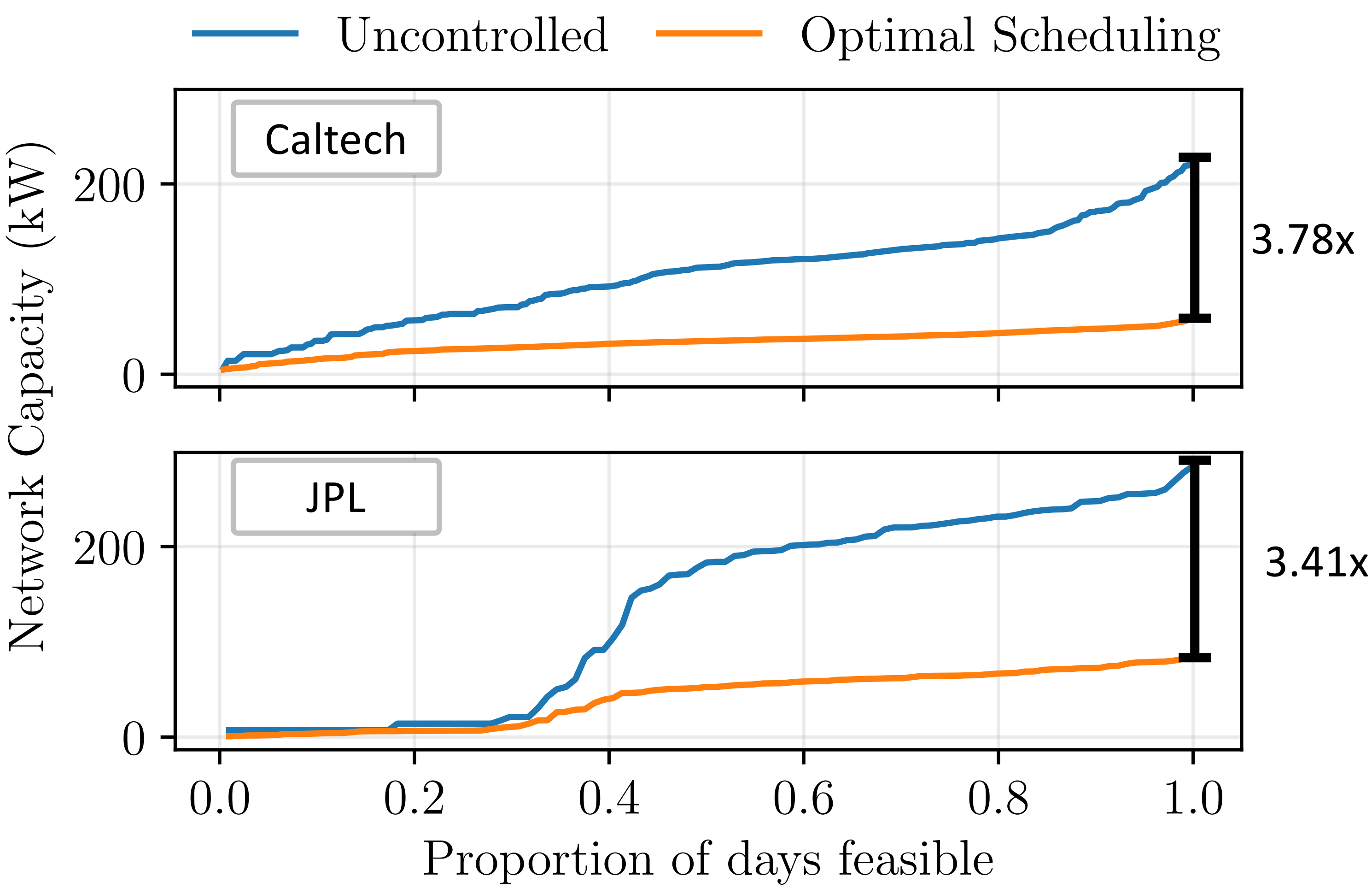
User flexibility

User flexibility



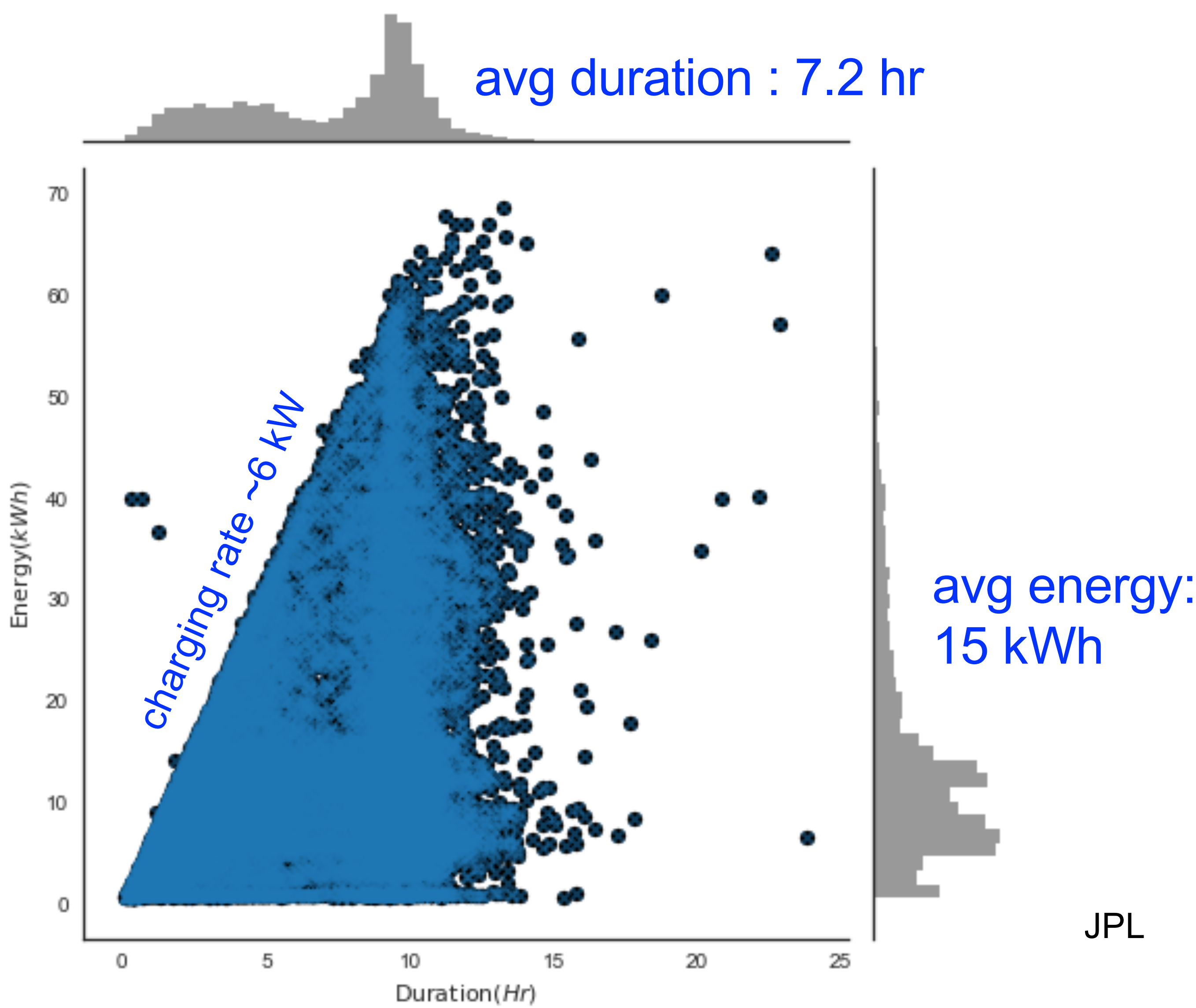
laxity := session duration - min charging time

ACN flexibility



User behavior

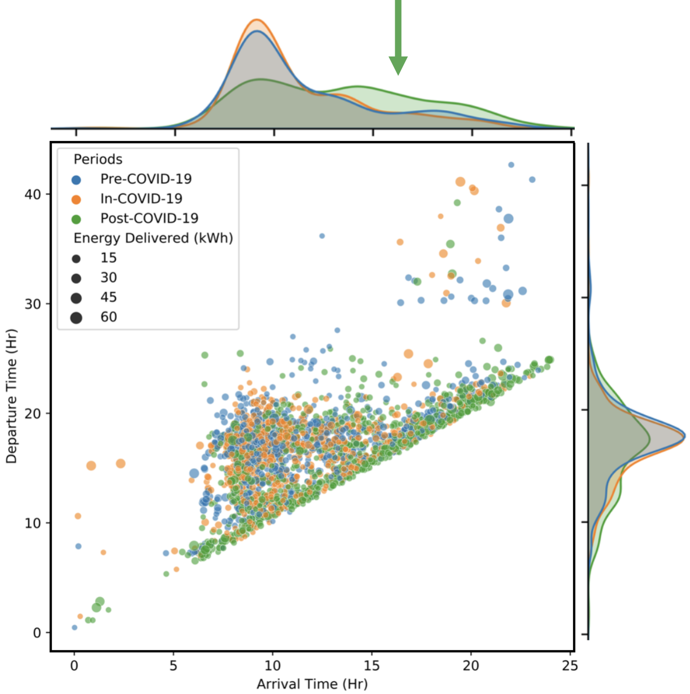
Duration and energy delivered

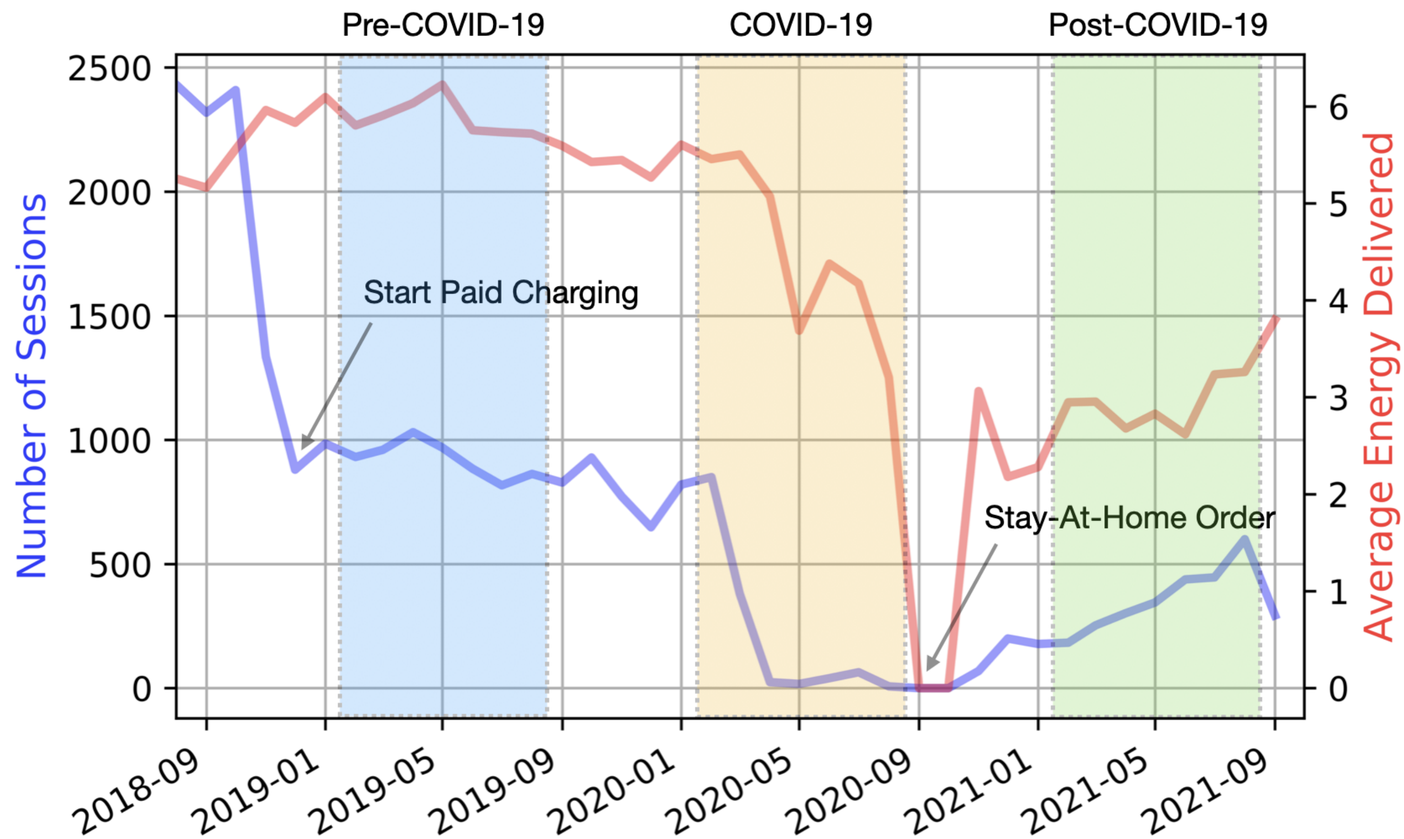


JPL

User behavior

arrival times have larger var post-COVID (more flex hours)





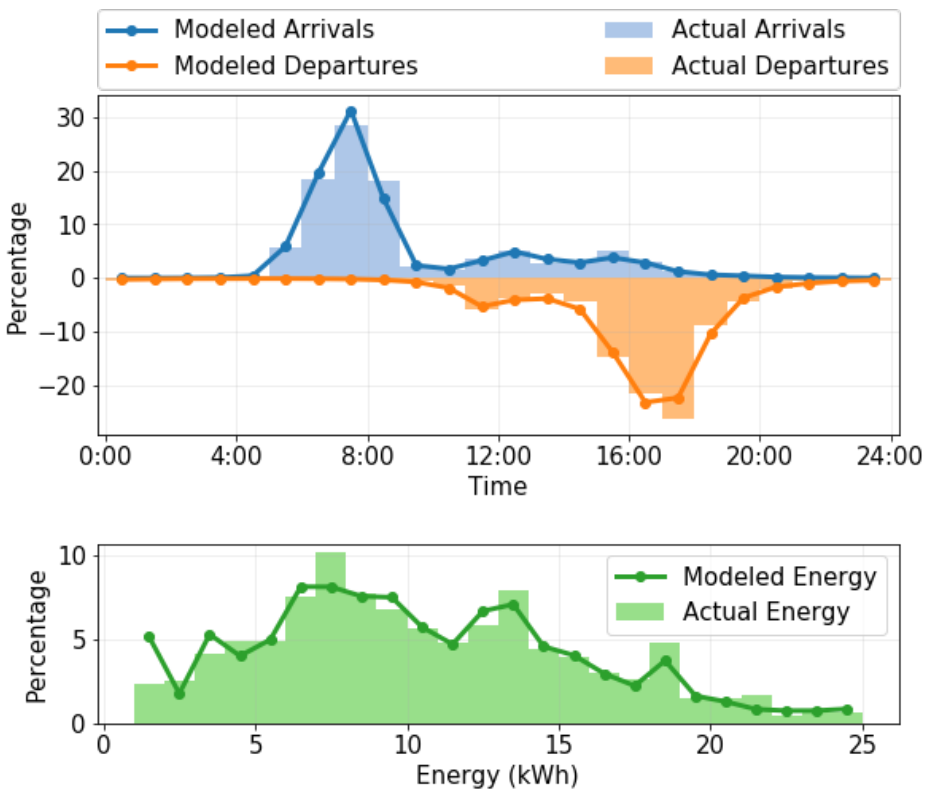
effect of payment & COVID

Caltech

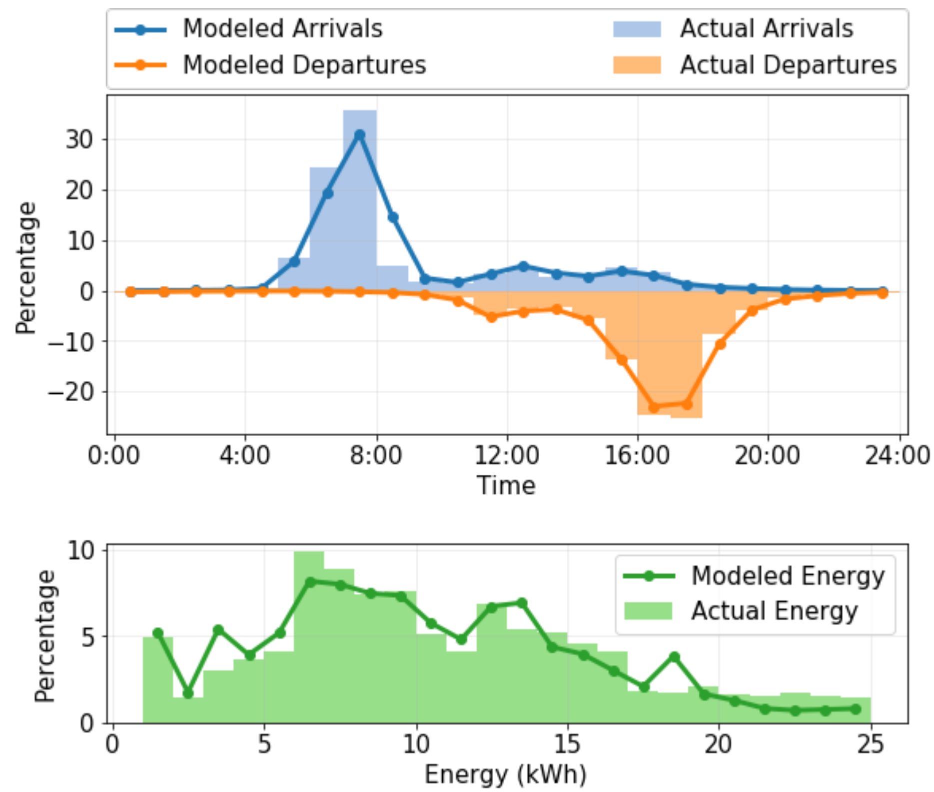
Learning user behavior

Gaussian mixture model

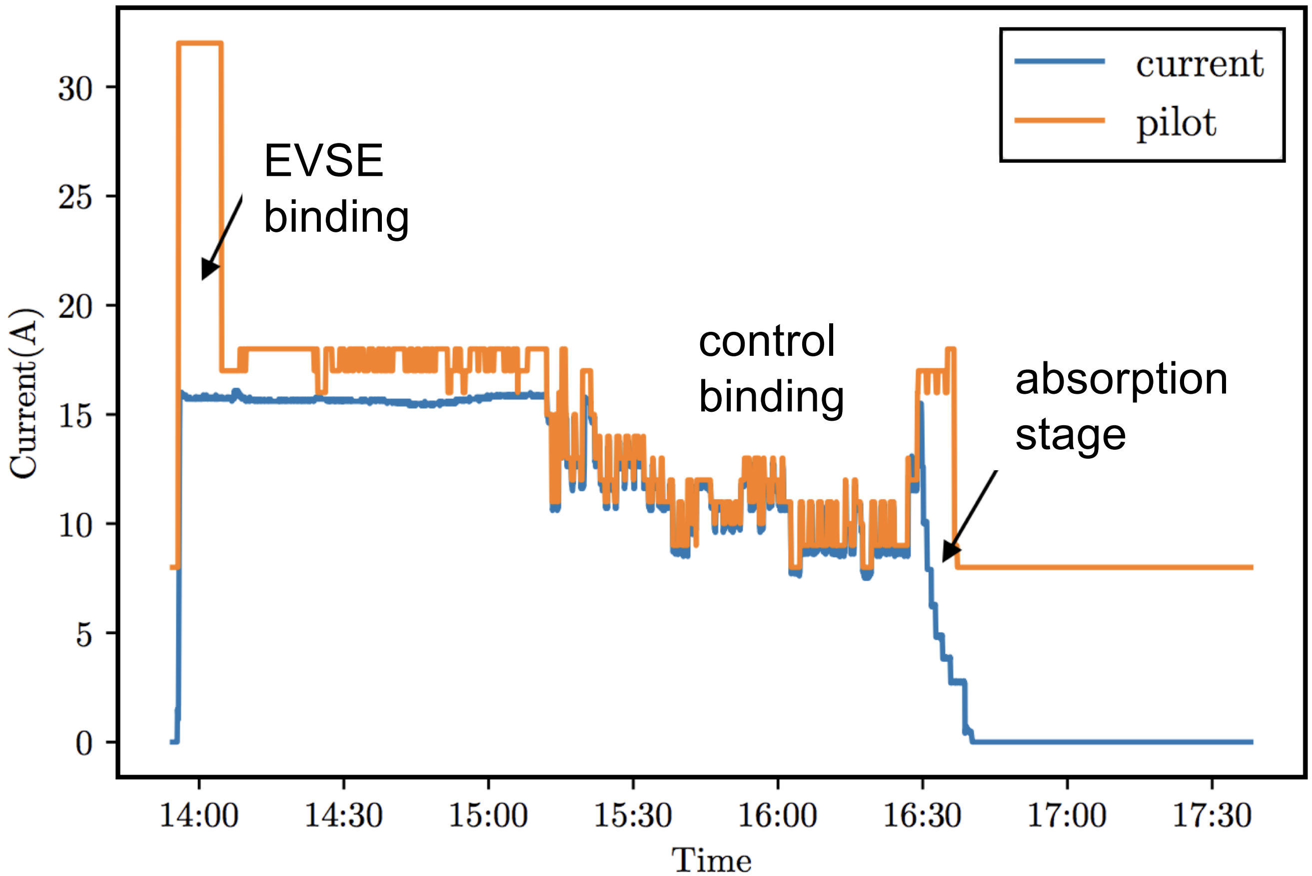
Testing Accuracy (9/1/18 – 11/1/18)



Evaluation Set Accuracy (12/1/18 – 5/1/19)



Charging curves



Caltech Oct 13, 2018

Time series: every 5-10 secs

- pilot signal from controller
- actual current drawn by EV

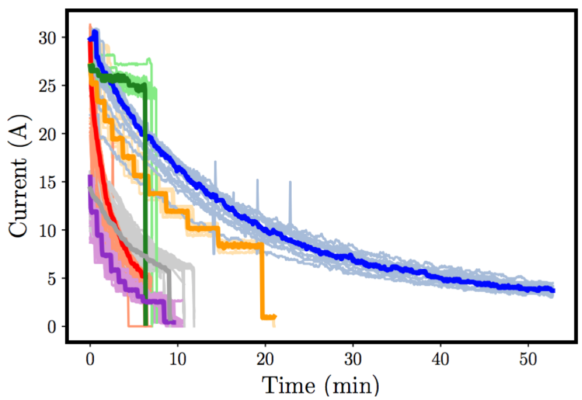
Learning charging curves

Goal: learn representative battery behaviors

- Only small # of batteries used by small # drivers underlying 35,000 charging curves

Challenge: do not know SoC

- Can only characterize tail behavior (absorption stage)
- Charging optimization, BMS actions, missing & noisy data

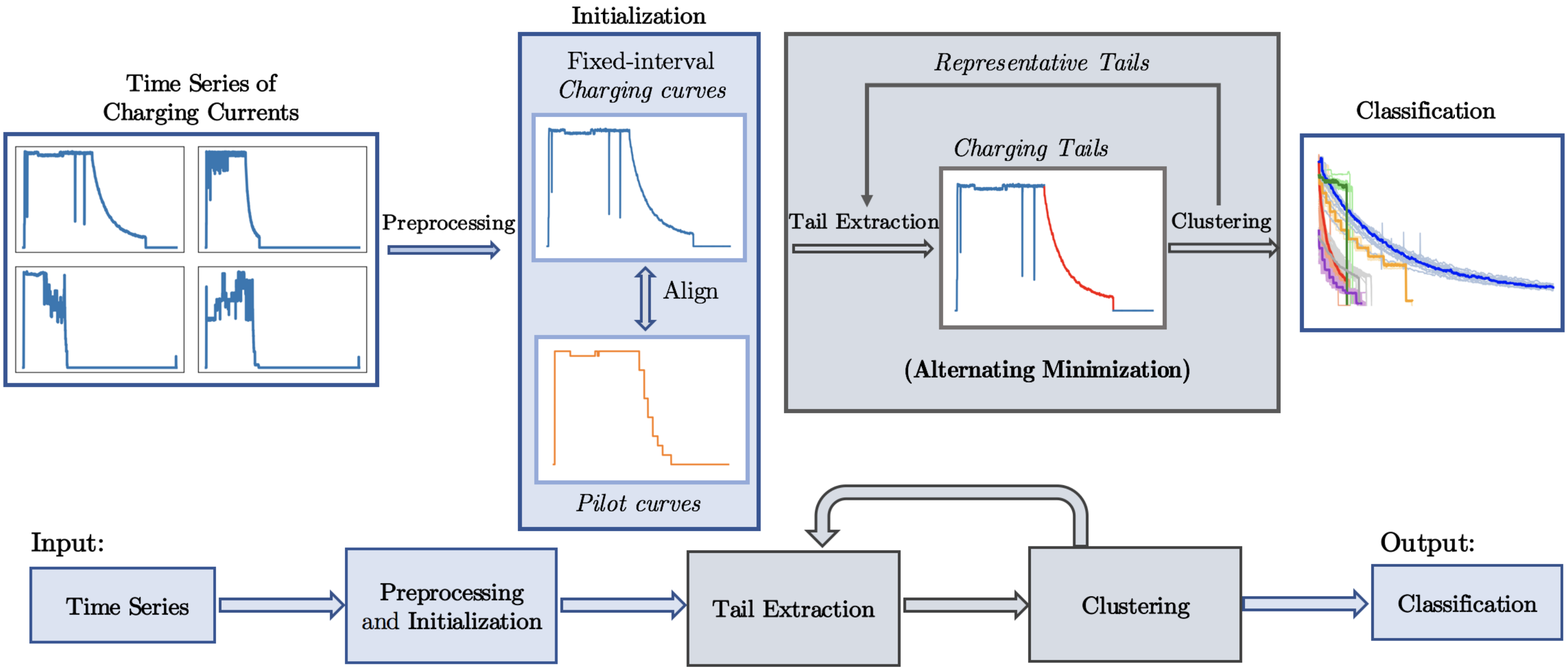


need to

- extract charging tails
- cluster charging tails

Chenxi Sun, Tongxin Li, S. H. Low and Victor Li.
Classification of EV charging time series with selective clustering
PSCC July 2020

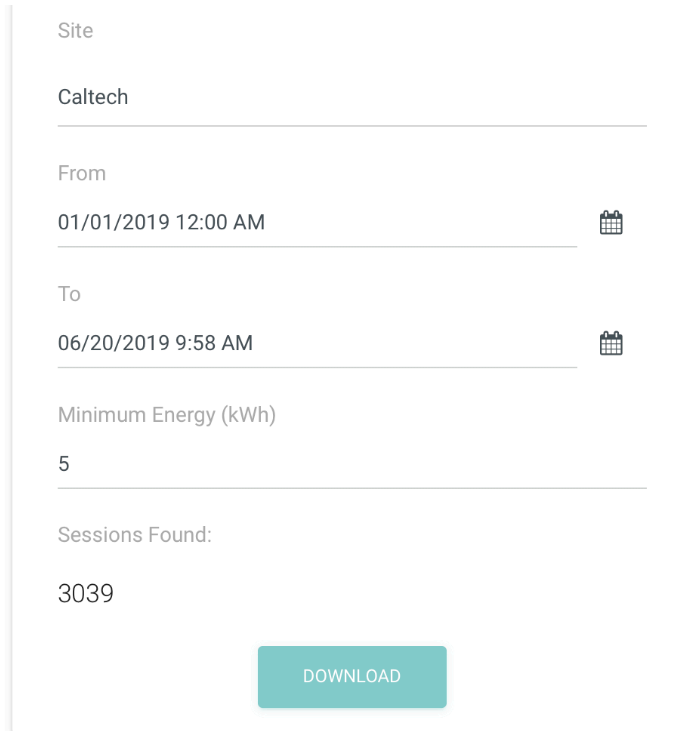
Learning charging curves



Chenxi Sun, Tongxin Li, S. H. Low and Victor Li.
Classification of EV charging time series with selective clustering
PSCC July 2020

Accessing ACN - Data

- Web Interface
- API
- Python Client
- ACN-Sim

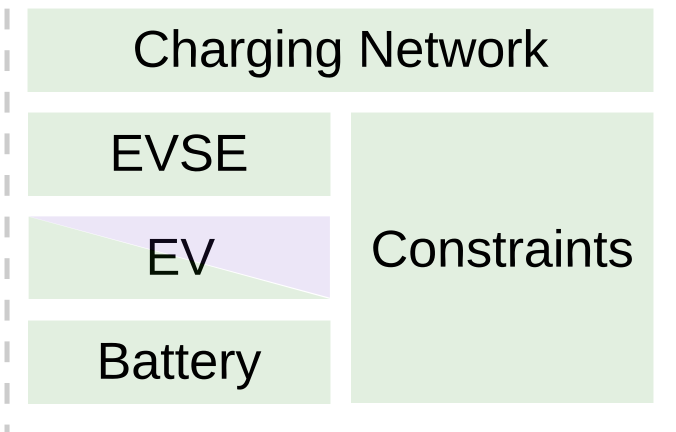


ev.caltech.edu

Caltech

open-source & extensible

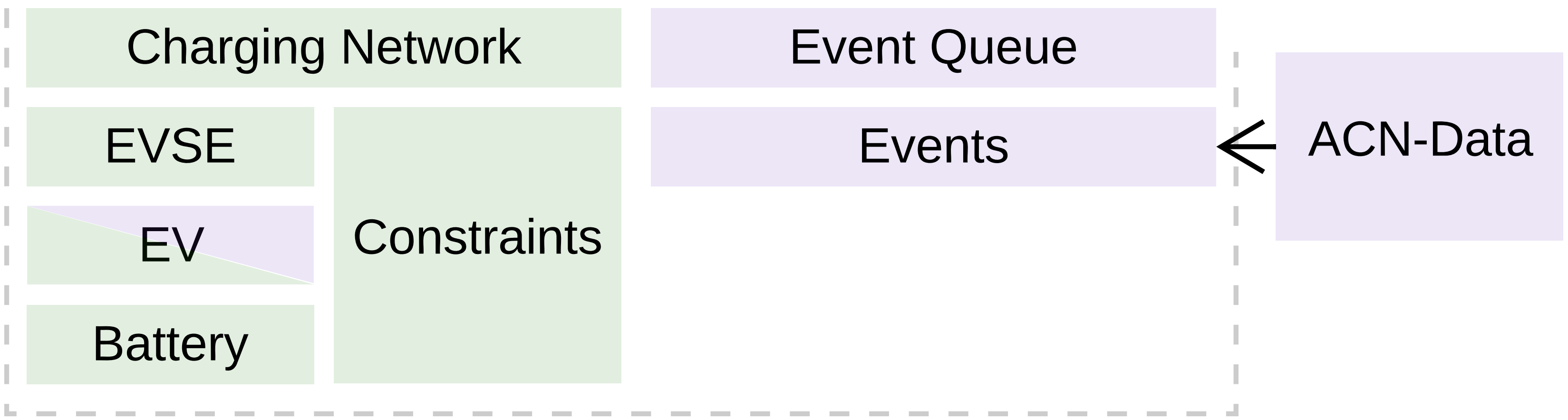
ACN - Sim



physical system /
simulation models

open-source & extensible

ACN - Sim

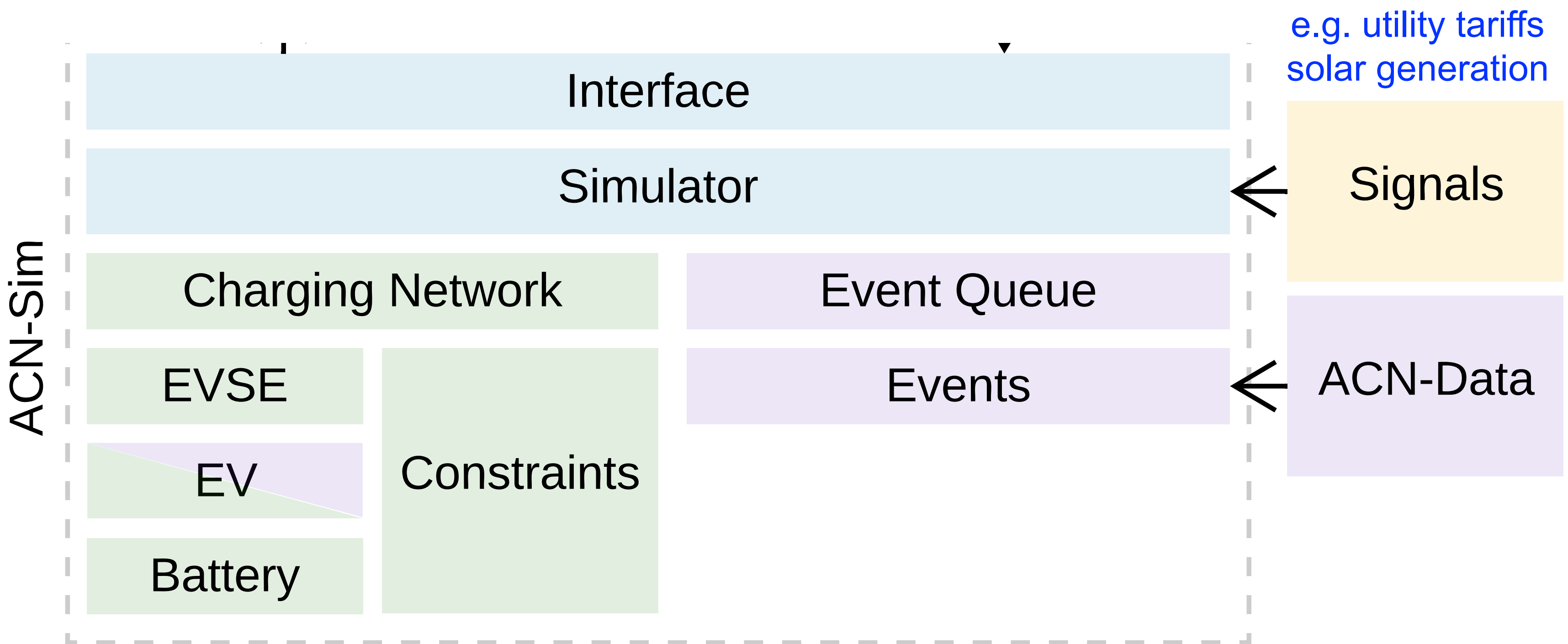


physical system / simulation models

integrated with ACN-Data

open-source & extensible

ACN - Sim

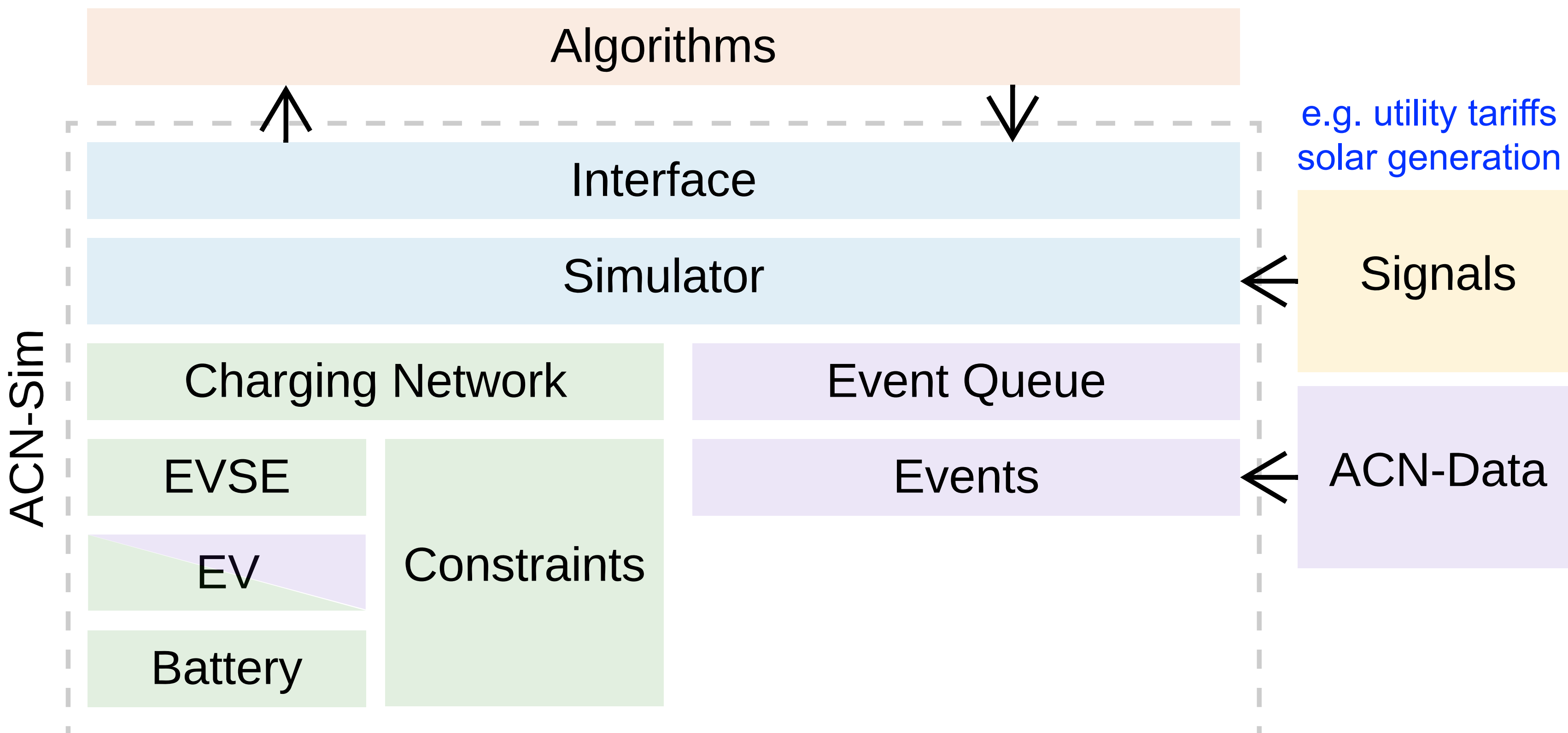


physical system /
simulation models

integrated with
ACN-Data

open-source & extensible

ACN - Sim



physical system /
simulation models

integrated with
ACN-Data

open-source & extensible

Grid impact

How can large-scale EV charging mitigate Duck Curve ?

Charging model

N EVs: $i = 1, \ldots, N$

T control intervals: $t = 1, \ldots, T$

EV i: $(e_i, a_i, d_i, \bar{r}_i)$

energy demand (miles / kWh)

arrival / departure time

peak charging rate (kW)

customizable utility functions

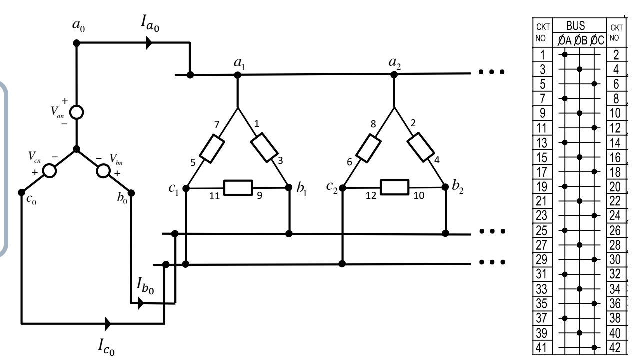
$$\max_r \sum_v \alpha_v u_v(r)$$

Compute: charging rates

$$r := (r_i(t),\ i = 1, \ldots, N,\ t = 1, \ldots, T)$$

$$0 \ \leq \ r_i(t) \ \leq \ \bar{r}_i(t)$$

$$\sum_{t \in \mathcal{T}} r_i(t) \ \leq \ e_i$$



infrastructure constraints

$$\left| \sum_{i \in \mathcal{V}} A_{li} r_i(t) e^{j\phi_i} \right| \ \leq \ c_{lt}(t)$$

SoC constraints, or linear approx.

Grid impact

MPC

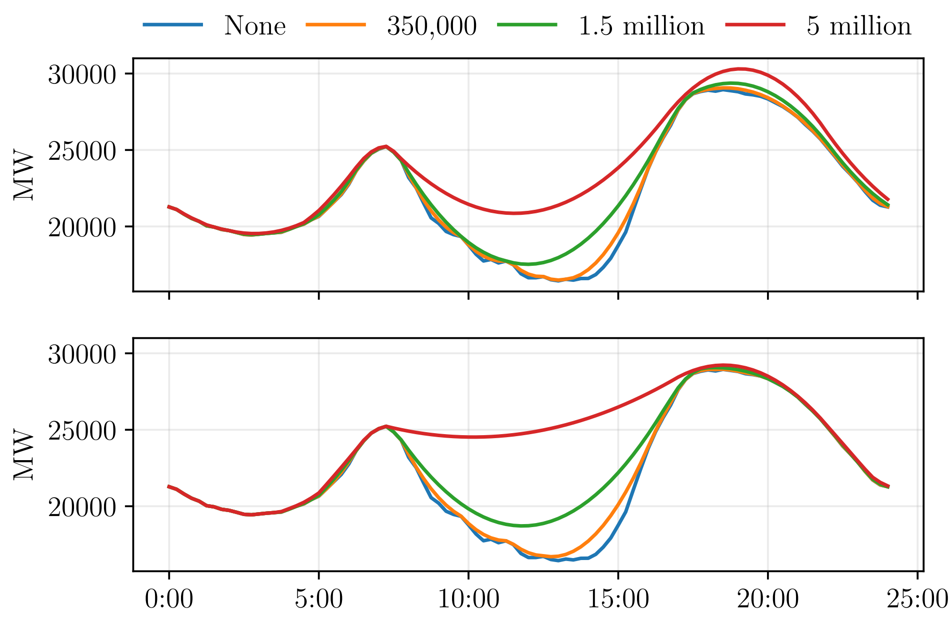
$$\max_{r} \quad \sum_{v} \alpha_v u_v(r)$$

subject to

$$0 \;\le\; r_i(t) \;\le\; \bar{r}_i(t)$$

$$\sum_{t \in \mathcal{T}} r_i(t) \;\le\; e_i$$

$$\left| \sum_{i \in \mathcal{V}} A_{li} r_i(t) e^{j\phi_i} \right| \;\le\; c_{lt}(t)$$



Minimize evening ramp based on real data

- EV data from ACN-Data
- Simulation models from ACN-Sim
- CAISO solar and load data

ACN - Live

Algorithms

Interface

Safety / Reliability Checks

PowerFlex ACN Control System

open-source
& extensible

ACN research portal

Agenda

Caltech adaptive charging network (ACN)

- Testbed to commercial deployment

ACN Research Portal

- ACN – Data, Sim, Live

Pricing demand charge

- Monthly billing at workplaces

Online adaptive charging

Model predictive control:

$$\max_{r} \quad \sum_{v} \alpha_v u_v(r)$$

subject to

$$0 \;\leq\; r_i(t) \;\leq\; \bar{r}_i(t)$$

$$\sum_{t \in \mathcal{T}} r_i(t) \;\leq\; e_i$$

$$\left| \sum_{i \in \mathcal{V}} A_{li} r_i(t) e^{j\phi_i} \right| \;\leq\; c_{lt}(t)$$

Pricing design

Charging design

- Must adapt to system state in real time
- Objectives must be customized for site hosts

Pricing design: recover cost for individual EV's

- Energy
- Externality: system peak (demand charge)
- Externality: infrastructure congestion

Key idea: decouple charging and pricing

- Drivers receive energy in time, at minimum payments
- Charging is socially optimized by MPC
- Site host fully recovers electricity cost

Offline optimal pricing

start with conclusion …

At end of month

- Compute ex post session price α_i^*
- Driver pays: $\sum_i \alpha_i^* e_i$

sum over driver's sessions

energy delivered in session i

No uncertainty nor need for pricing forecasts

Pricing design

$$C(r) \quad := \quad \sum_t \underset{\text{time-varying prices}}{p_t} \sum_i r_i(t) \; + \; \underset{\text{demand charge}}{P} \; \underbrace{\max_t \sum_i r_i(t)}_{\text{peak power}}$$

What is min system electricity cost to meet demand ?

How to fairly allocate system cost to drivers ?

Pricing design

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

Pricing min system cost:

$$
\begin{aligned}
C^{\min} \;:=\; \quad \min \quad & \sum_t p_t \sum_i r_i(t) \;+\; Pq \\
\text{s. t.} \quad & \sum_t r_i(t) \;=\; e_i, && \text{meet demand} && \alpha_i \\
& \sum_i A_{li}\, r_i(t) \;\le\; c_{lt} && \text{infrastructure capacity limit} && \beta_{lt} \\
& r_i(t) \le \bar{r}_i(t), && \text{EVSE limit} && \gamma_{it} \\
& q \;\ge\; \sum_i r_i(t), && \text{system peak} && \delta_t
\end{aligned}
$$

Pricing design

Fairly (incentive compatibly) allocate system cost to EVs

$$\pi_i^*(t) \quad := \quad \underbrace{p_t}_{\text{energy}} +$$

time-varying
prices

Pricing design

Fairly (incentive compatibly) allocate system cost to EVs

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

driver & time dependent

Driver pays for each session i

$$\Pi_i^* \;:= \sum_t \pi_i^*(t)\, r_i^*(t)$$

This achieves pricing goals: recovers

- Energy cost
- Congestion rents
- Demand charge EV i is responsible for

Pricing design

Design principle:

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

$$\Pi_i^* \quad = \quad \sum_t \pi_i^*(t) r_i^*(t)$$

Theorem

1. Demand charge: $P = \sum_t \delta_t^*$ EVs that cause peak will pay

Pricing design

Design principle:

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

$$\Pi_i^* \;=\; \sum_t \pi_i^*(t)\, r_i^*(t)$$

Theorem

1. Demand charge: $P = \sum_t \delta_t^*$ — EVs that cause peak will pay
2. Time-invariant session price α_i^*: $\Pi_i^* = \alpha_i^*\, e_i$

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

EVs pay min cost

Pricing design

Design principle:

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

$$\Pi_i^* \quad = \quad \sum_t \pi_i^*(t) r_i^*(t)$$

Theorem

1. Demand charge: $P = \sum_t \delta_t^*$ EVs that cause peak will pay

2. Time-invariant session price α_i^*: $\Pi_i^* = \alpha_i^* e_i$

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

EVs pay min cost

3. Cost recovery: $\sum_i \Pi_i^* \quad \geq \quad C^{min}$

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

Congestion rents

[Lee, Pang, Low. PSCC 2020]

Offline optimal pricing

At end of month

- Compute ex post session price α_i^*
- Driver pays: $\sum_i \alpha_i^* e_i$

No uncertainty nor need for pricing forecasts

Backup slides