Adaptive Charging Network

Research Portal

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Caltech

powerflex
EDF renewables

NREL AEG Workshop August 2020

Acknowledgement

powerflex
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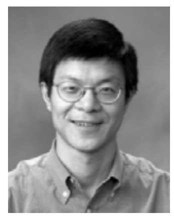
S. Low


Z. Lee


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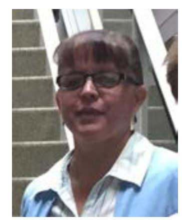
C. Ortega


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Z. Low, Cornell


K. Erliksson, Lund


D. Johansson, Lund

and many others …

Agenda

Motivation: workplace charging

Caltech adaptive charging network (ACN)

- Testbed to commercial deployment

ACN Research Portal

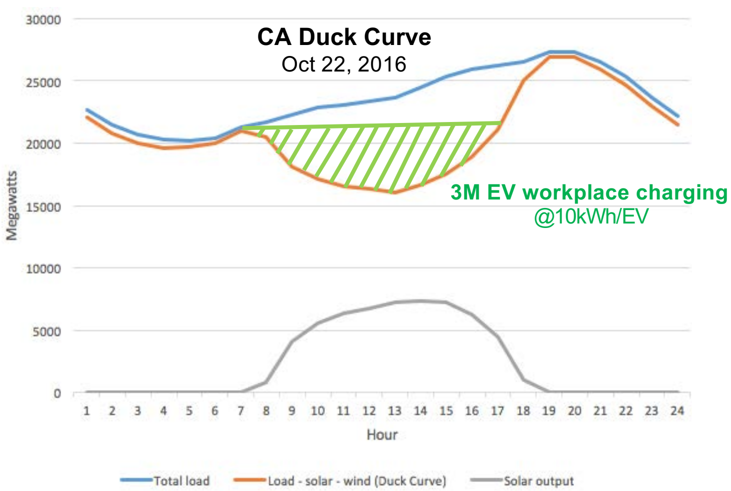
- ACN – Data, Sim, Live
- Example applications

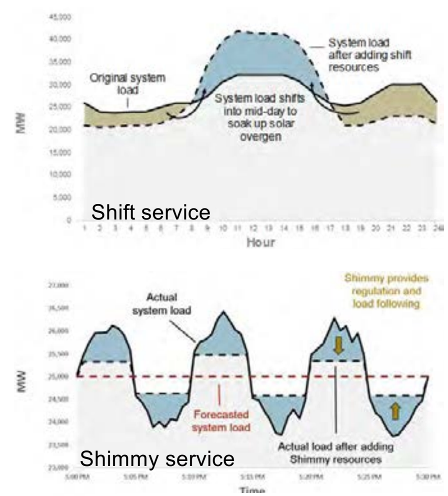
Pricing demand charge

100% clean electricity

CA commitment

- 50% renewables by 2030, 100% by 2045
- 1.5M ZEV by 2025, 5M by 2030





Source: 2025 CA DR Potential Study (LBNL 2017)

	Annual DR value
Shift service	\$190 / EV
Shimmy service	\$150 / EV
@1.5M EV	\$50B

Assumptions: DR value from 2025 CA DR Potential Study (LBNL 2017); each EV drives 12K miles/year, needs 11kWh/day, workplace charging; 10% provide DR

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

(EDF Renewables survey Feb 2018)

100% clean electricity

CA commitment

- 50% renewables by 2030, 100% by 2045
- 1.5M ZEV by 2025, 5M by 2030

How much EVs are enough for 100% renewables?

V2G

2018 CA in-state generation: 195 TWh

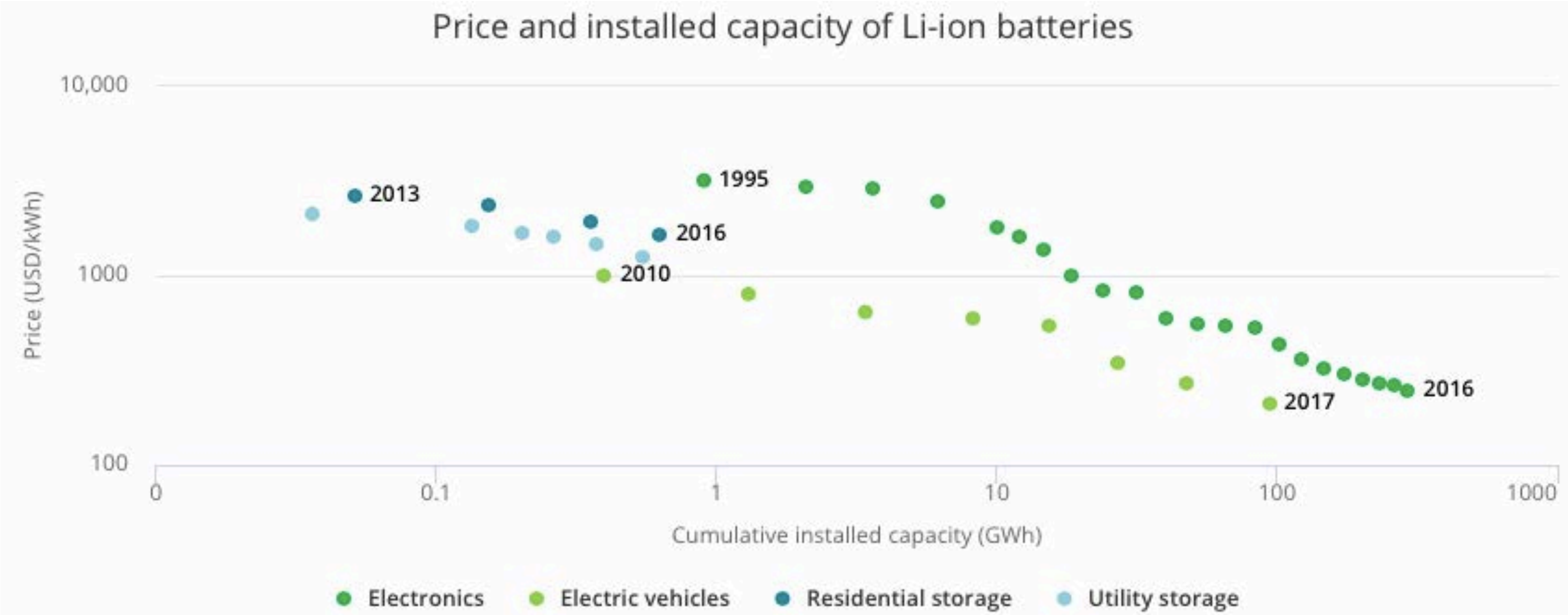
- Daily generation: 534 GWh

Scenario

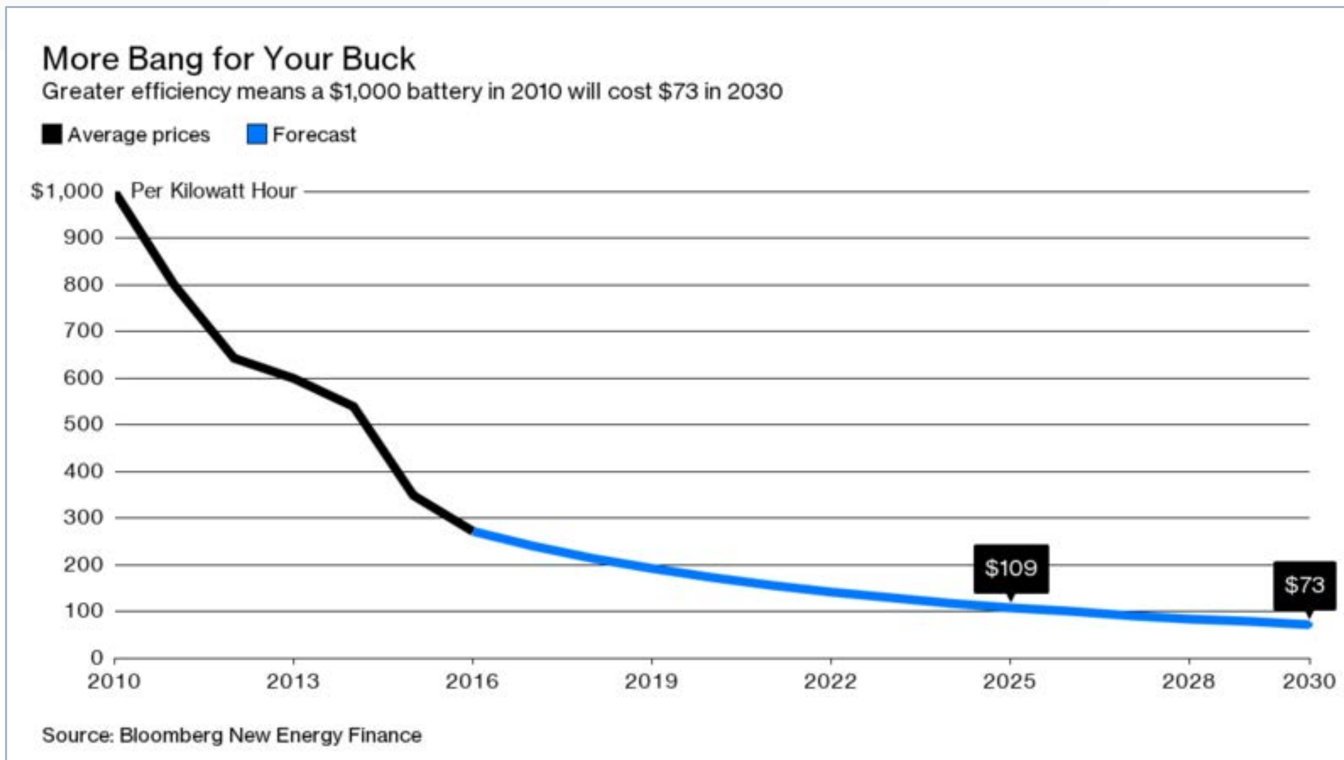
- Wind + solar : 50% generation (~20 days in 2018)
- Energy shortfall: 267 GWh

Storage need seems within reach

- Battery capacity of 300-mile EV: 100 kWh (Tesla 2020)
- 267 GWh = 2.67 million EVs (18% of CA cars)
- CA mandate: 5 million ZEVs in 2030
- … all depends on aggregate flexibility



Source: https://www.iea.org/gevo2018/



At $73 / kWh, 300 GWh only costs $22B

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ACN testbed

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

2018 SmartGridComm Conference:

Large-Scale Adaptive Electric Vehicle Charging

Zachary J. Lee*, Daniel Chang*, Cheng Jin†, George S. Lee†, Rand Lee*, Ted Lee†, Steven H. Low*†
*Division of Engineering & Applied Science, Caltech, Pasadena, CA
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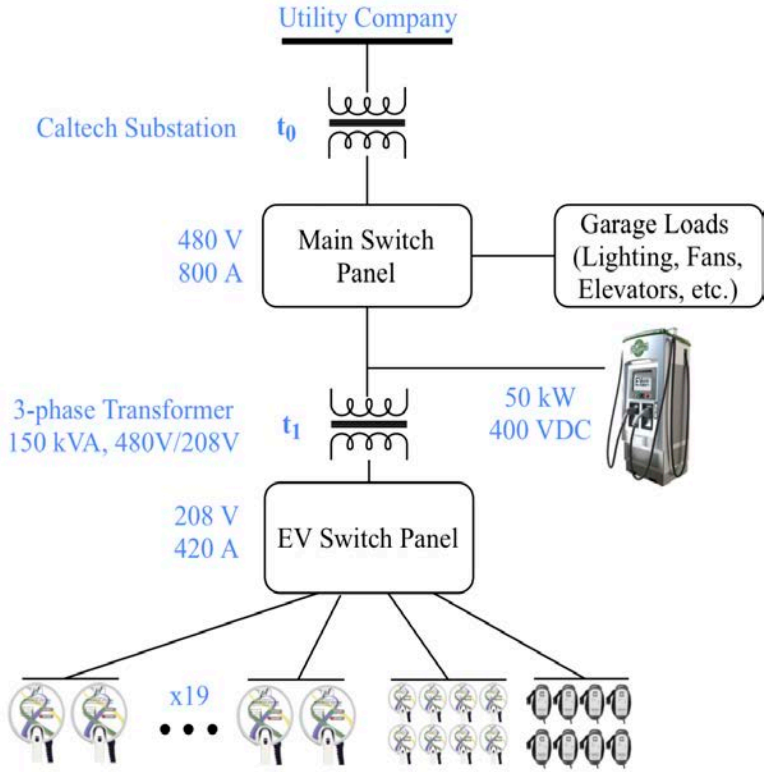
Physical system



Cyber system

Model predictive control: QCQP

$$
\begin{array}{lll}
\min\limits_{r \geq 0} & C(r) & \\
\text{subject to} & r_i(t) \ \leq \overline{r}_i(t) & \forall i, \ \forall t \\
& \sum\limits_{t} r_i(t)\,\delta \ = \ e_i & \forall i \\
& \sum\limits_{i} r_i(t) \ \leq \ P(t) & \forall t
\end{array}
$$

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

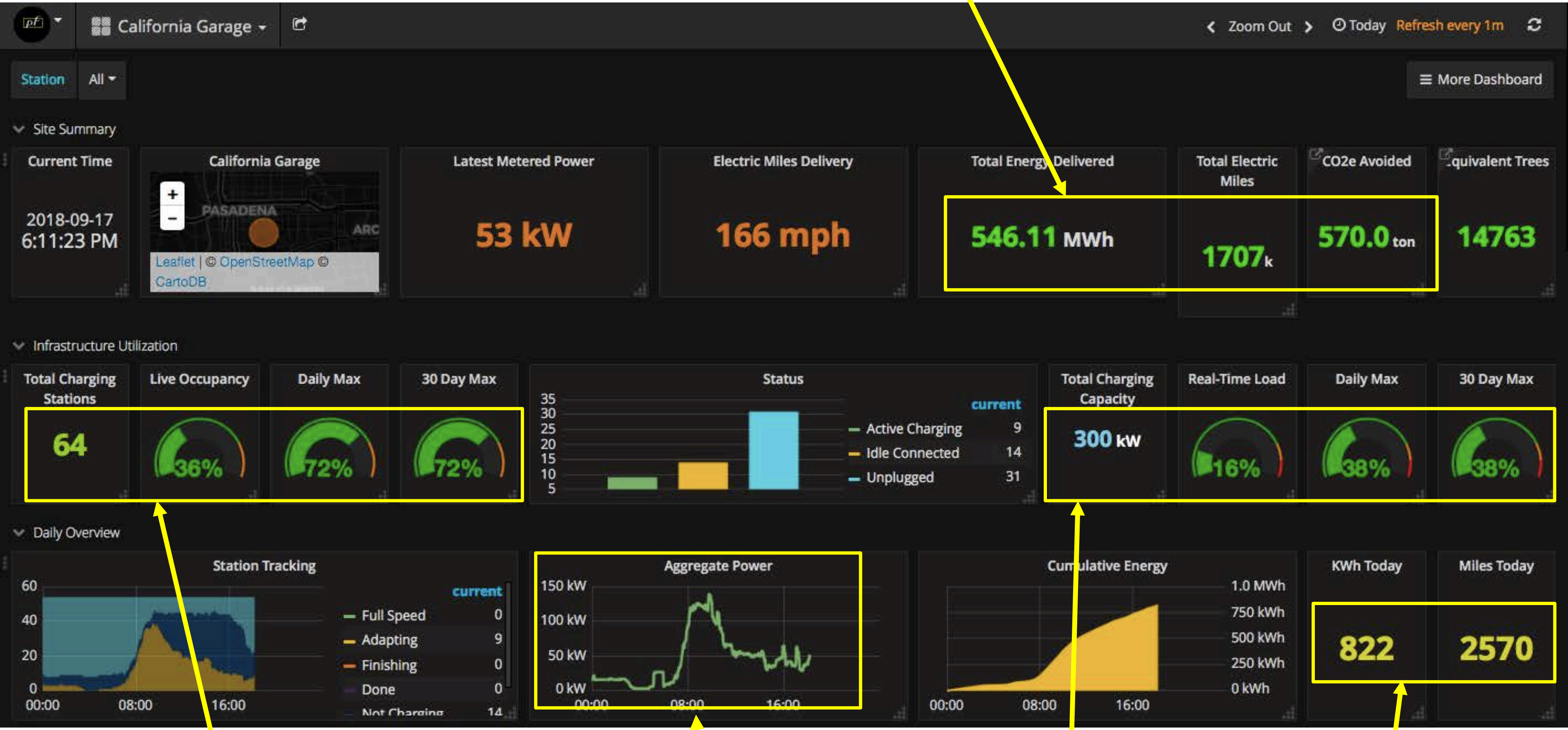
charger

transformer
& subpanels

main
panel

Caltech ACN

energy delivered & impact to date



charging station utilization

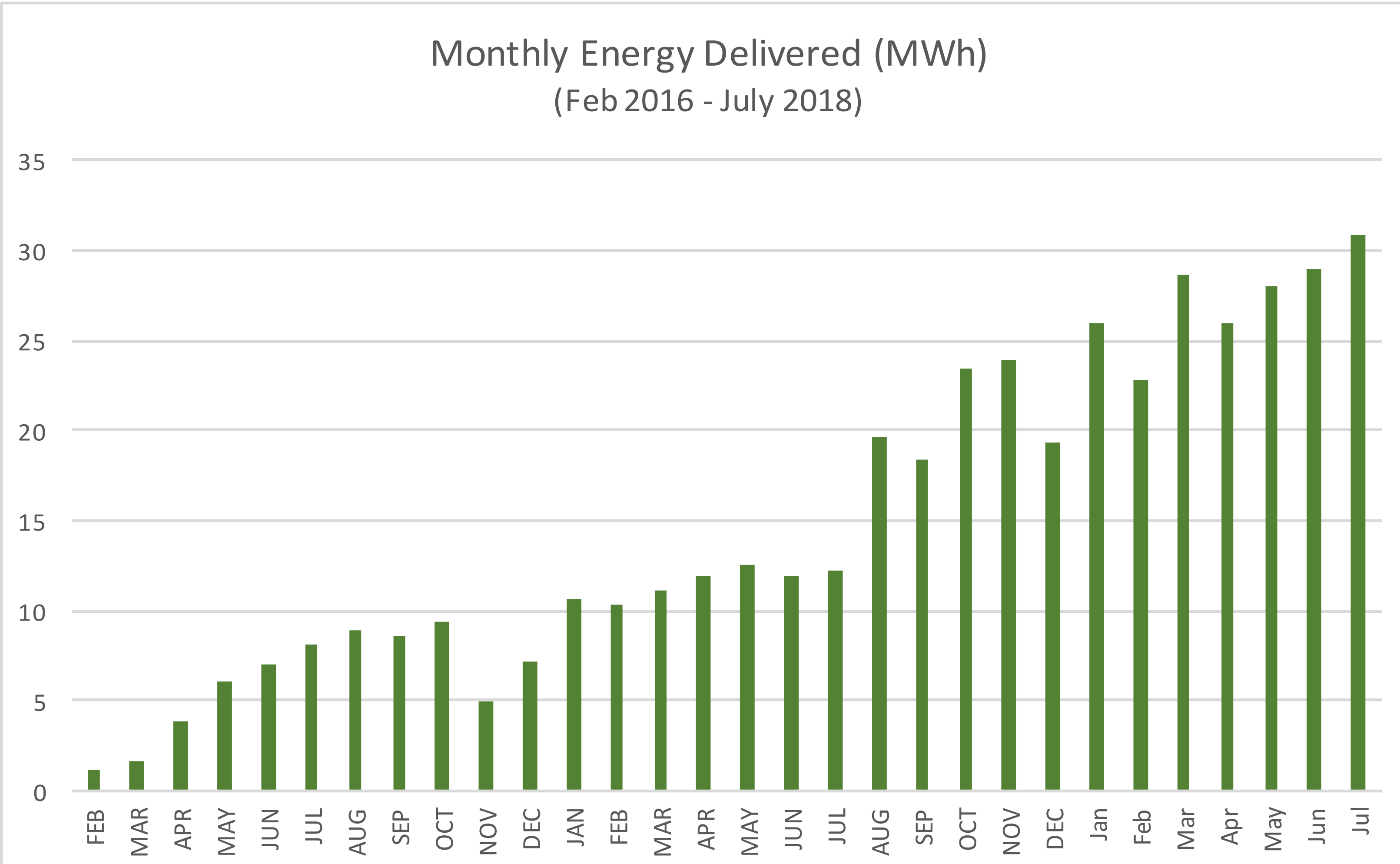
peak power

power utilization

today's energy delivered

Caltech ACN snapshot Sept 17, 2018

Caltech ACN

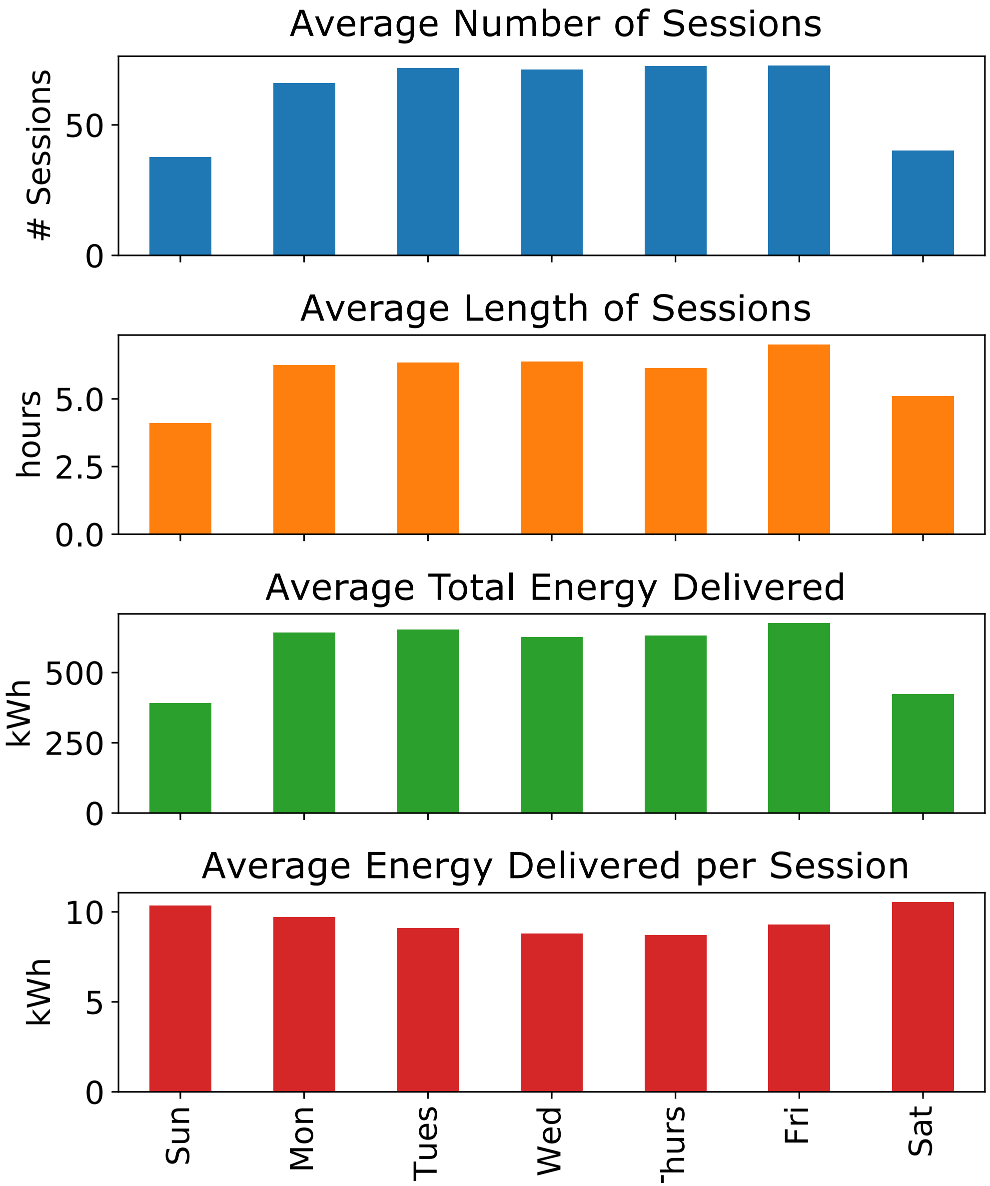


2016: 67 MWh

2017: 186 MWh

2018: 191 MWh

Caltech ACN



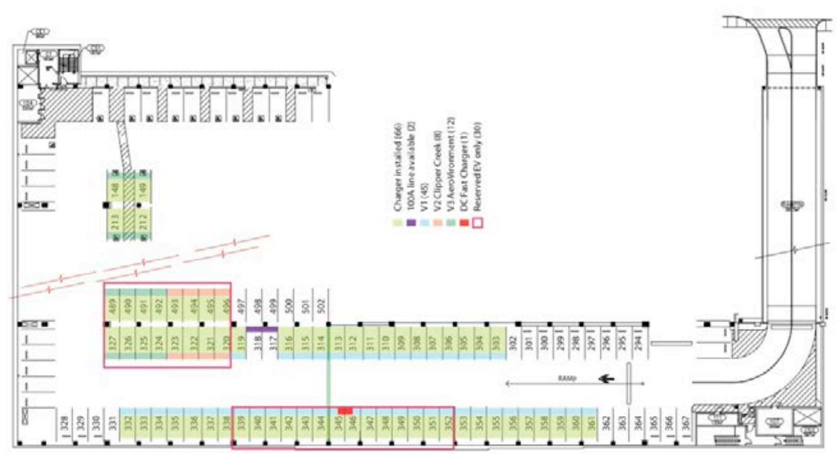
predictable
daily behavior

Caltech ACN
April 15 – Sept 18, 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

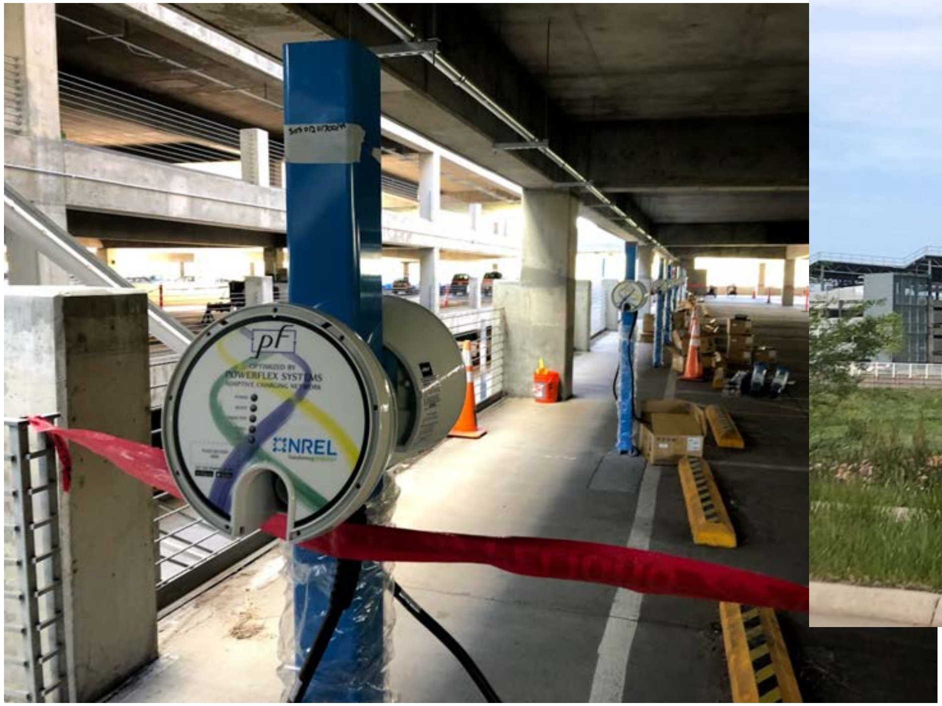
- Operational since 2016
- Delivered 1 GWh (by July 2020, CA)
- Equivalent to 3.2M miles, 1,000 tons of avoided CO_2e

powerflex EDF renewables Feb 2020

2,000+
EV CHARGING STATIONS DEPLOYED

10,000,000+
ELECTRIC MILES DELIVERED SAFELY

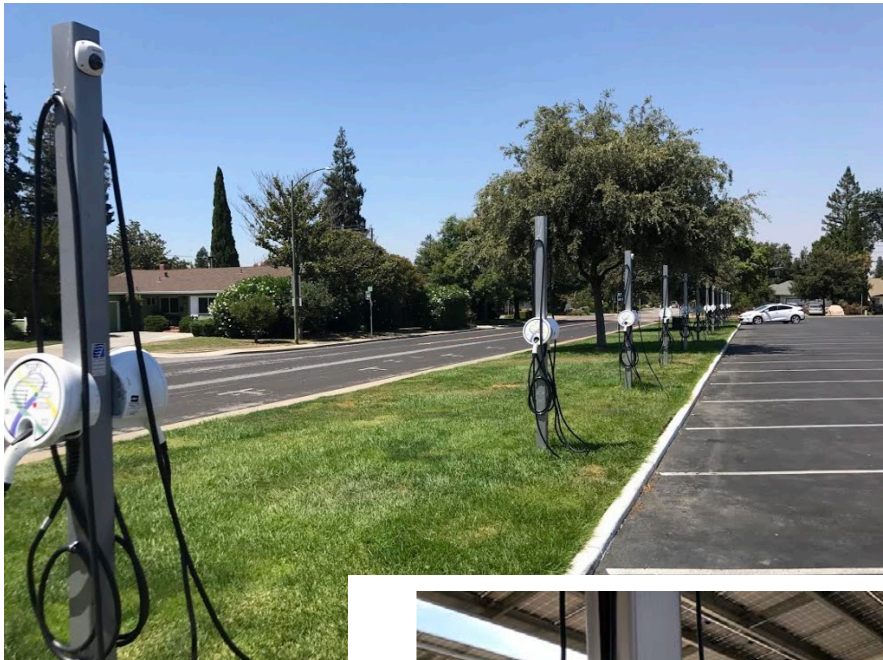
NREL, Golden CO



120 EVSEs

Source: PowerFlex, June 2019

Bay Area high schools

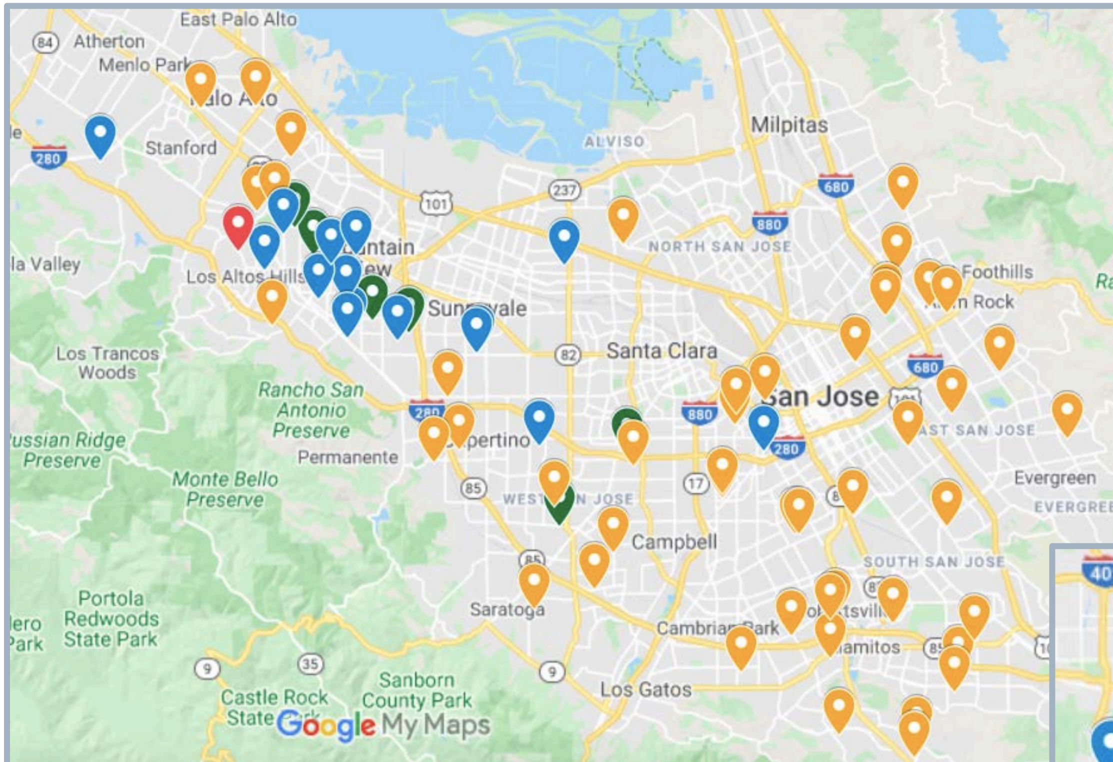


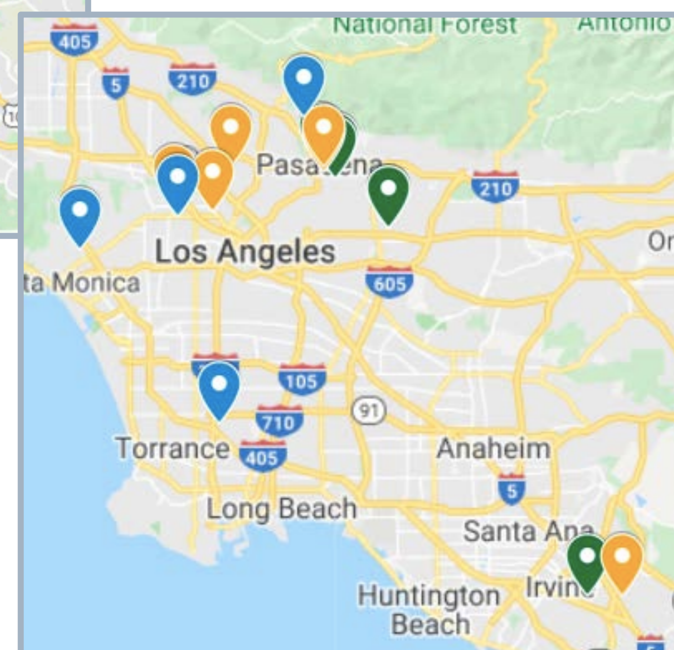
DCFC

Onsite PV

Source: PowerFlex, June 2019

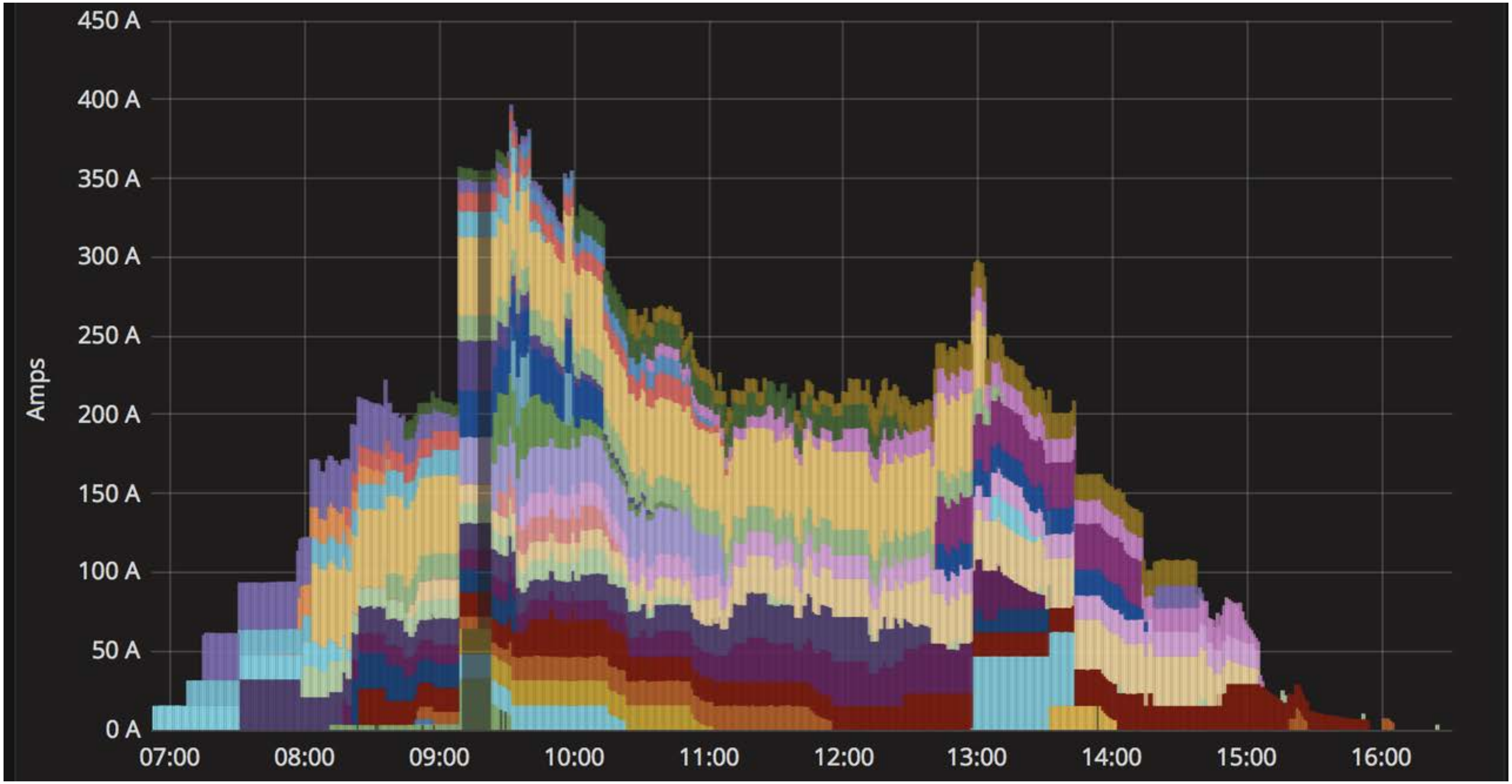
Deployment in CA



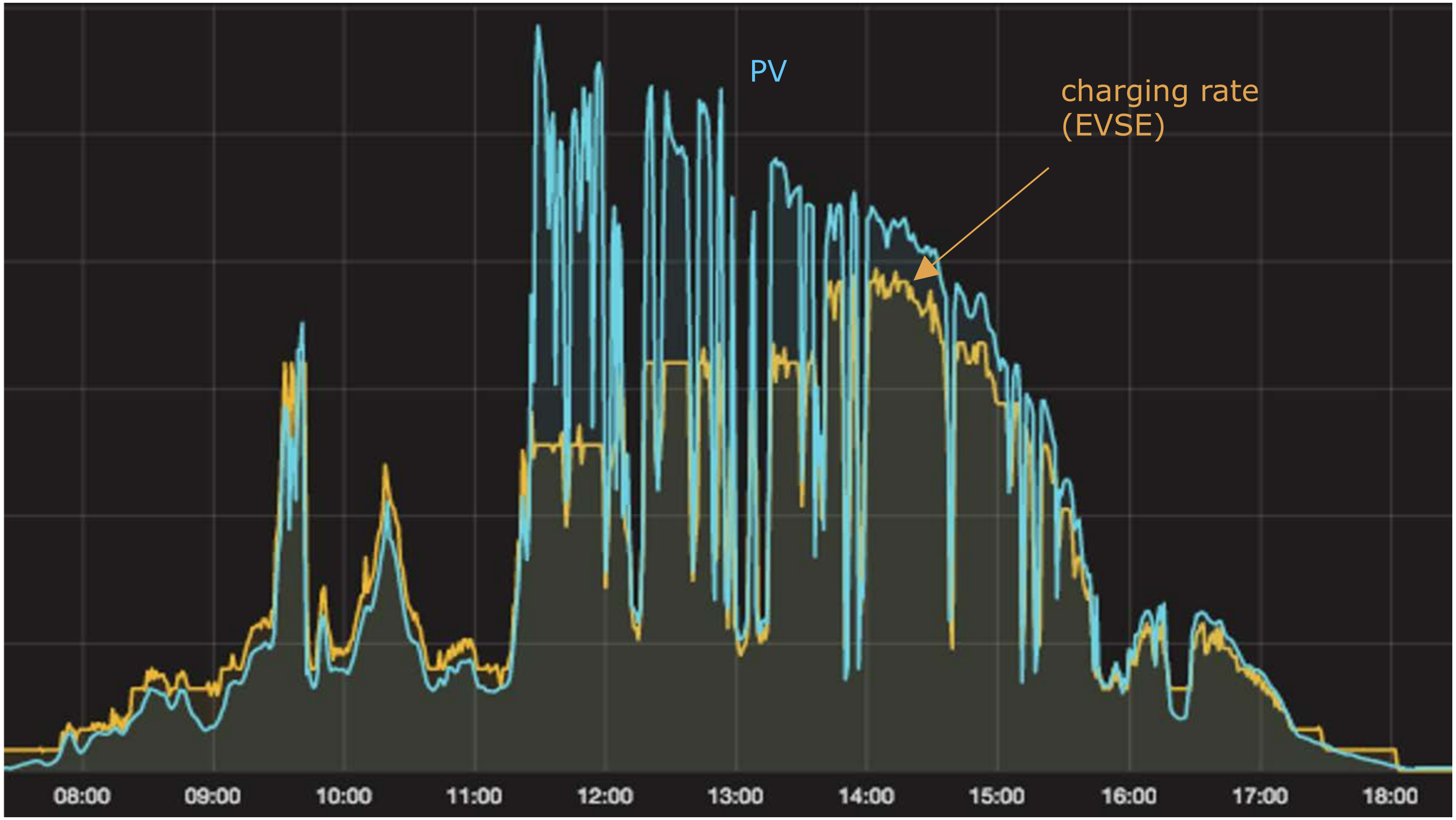


PowerFlex deployment, Sept 2018

Adaptive charging

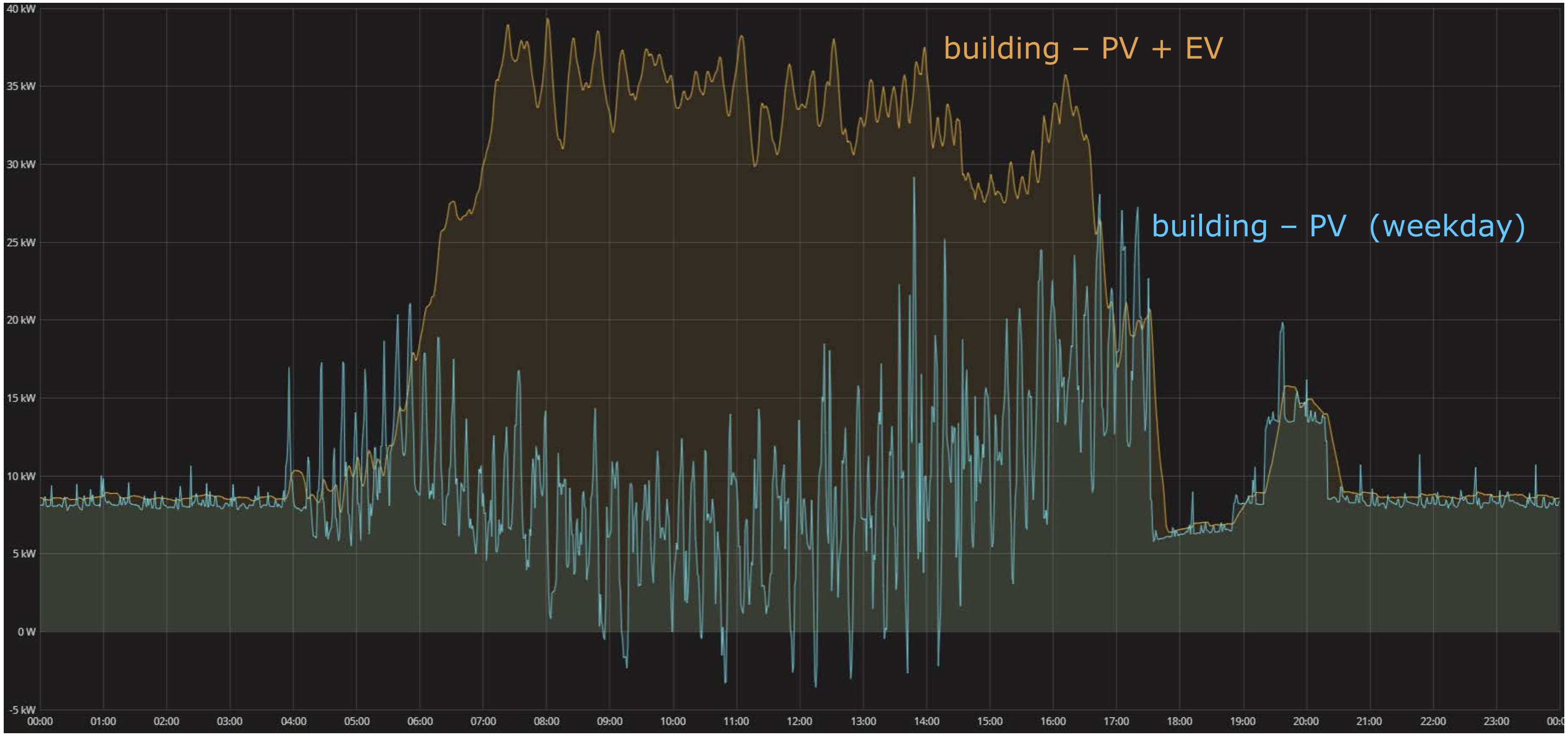


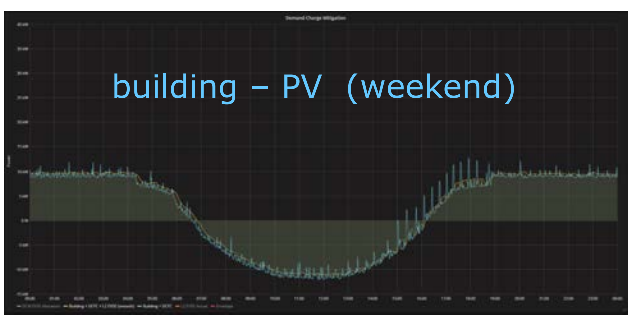
Online tracking



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

Duck Curve & DCM



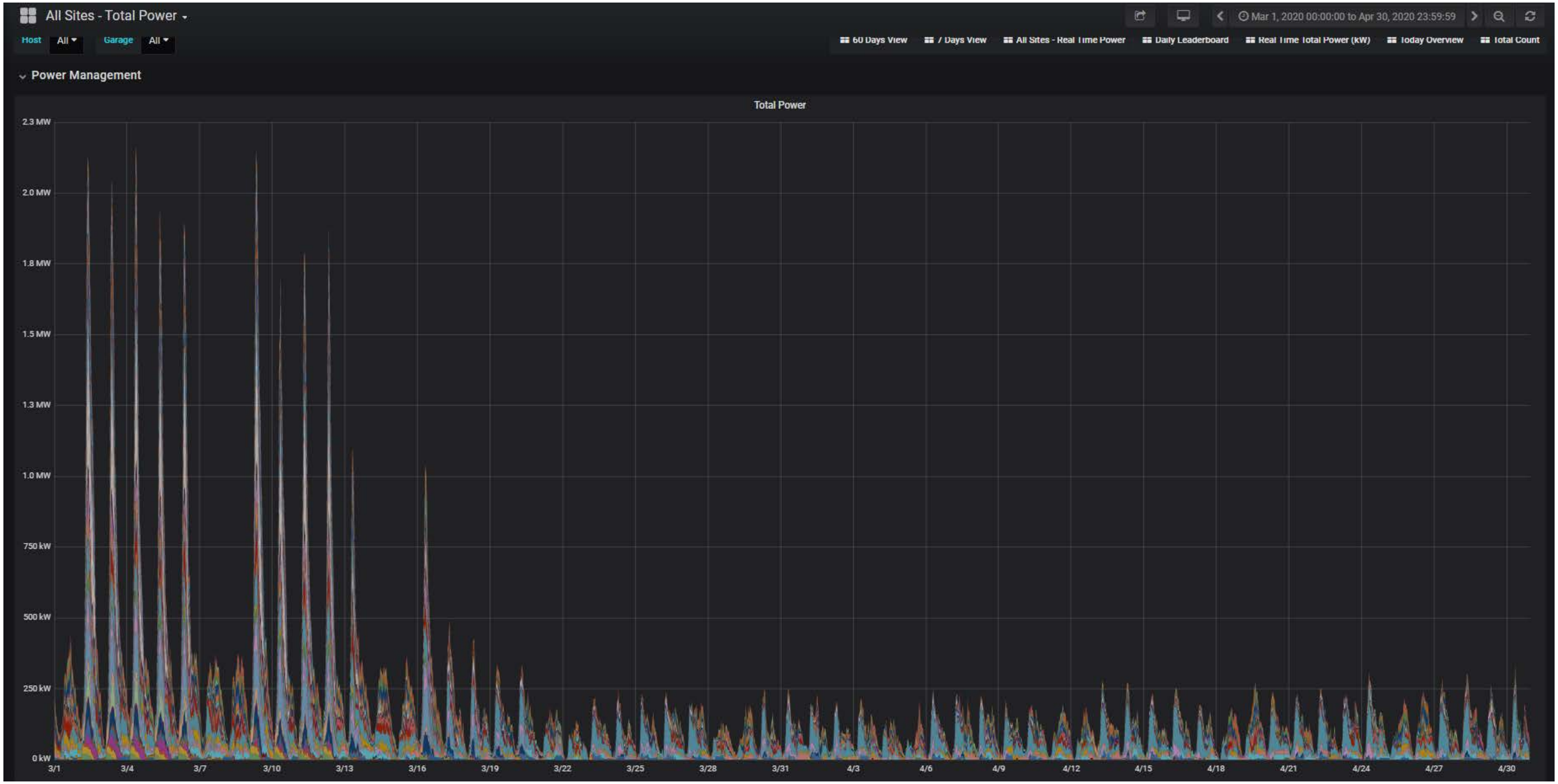


Weekend Duck Curve: building load (10kW) – PV

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 dramatically reduce workplace EV charging

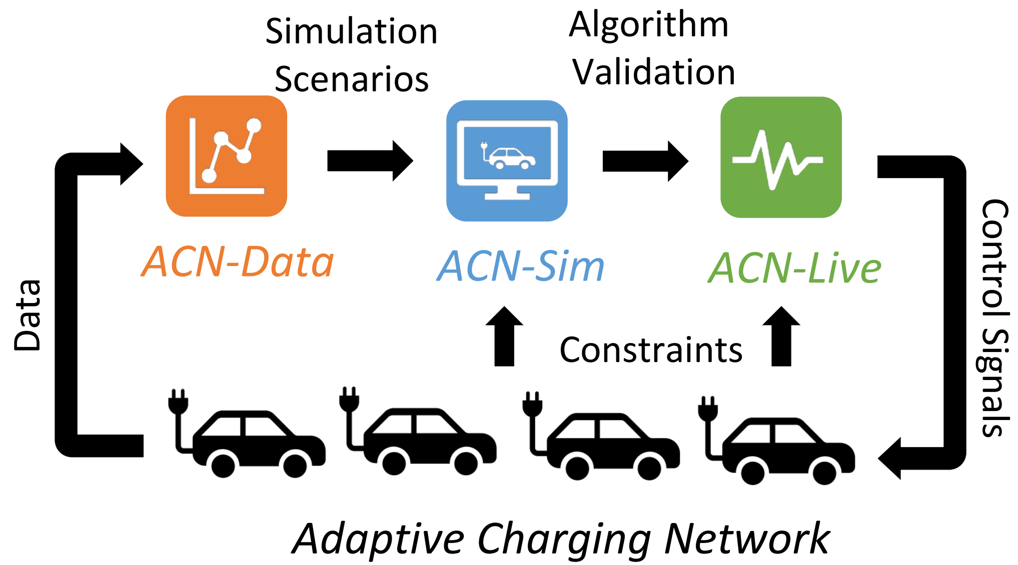


powerflex EDF renewables

April 30, 2020

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

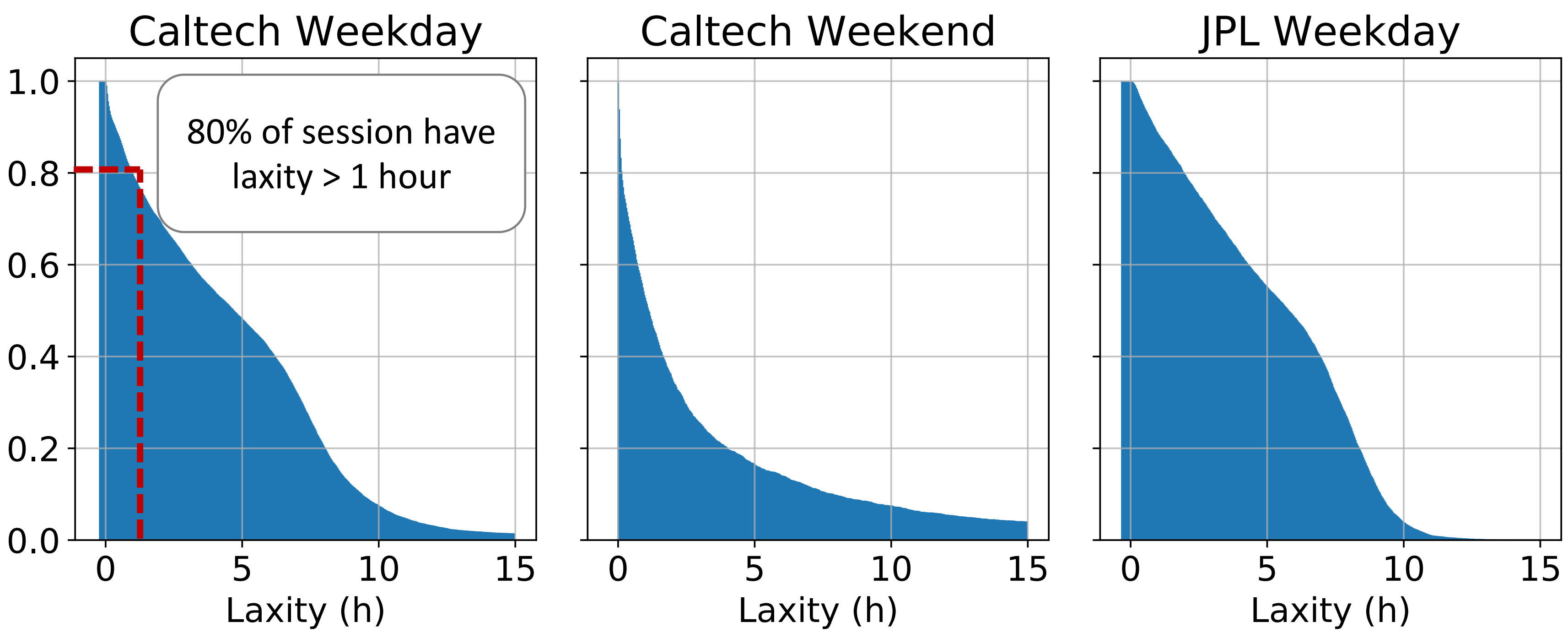
- 35,000+ EV charging sessions (late 2019)
- Publicly available: ev.caltech.edu
- Growing daily 85 sessions / day

Real fine-grained data for

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

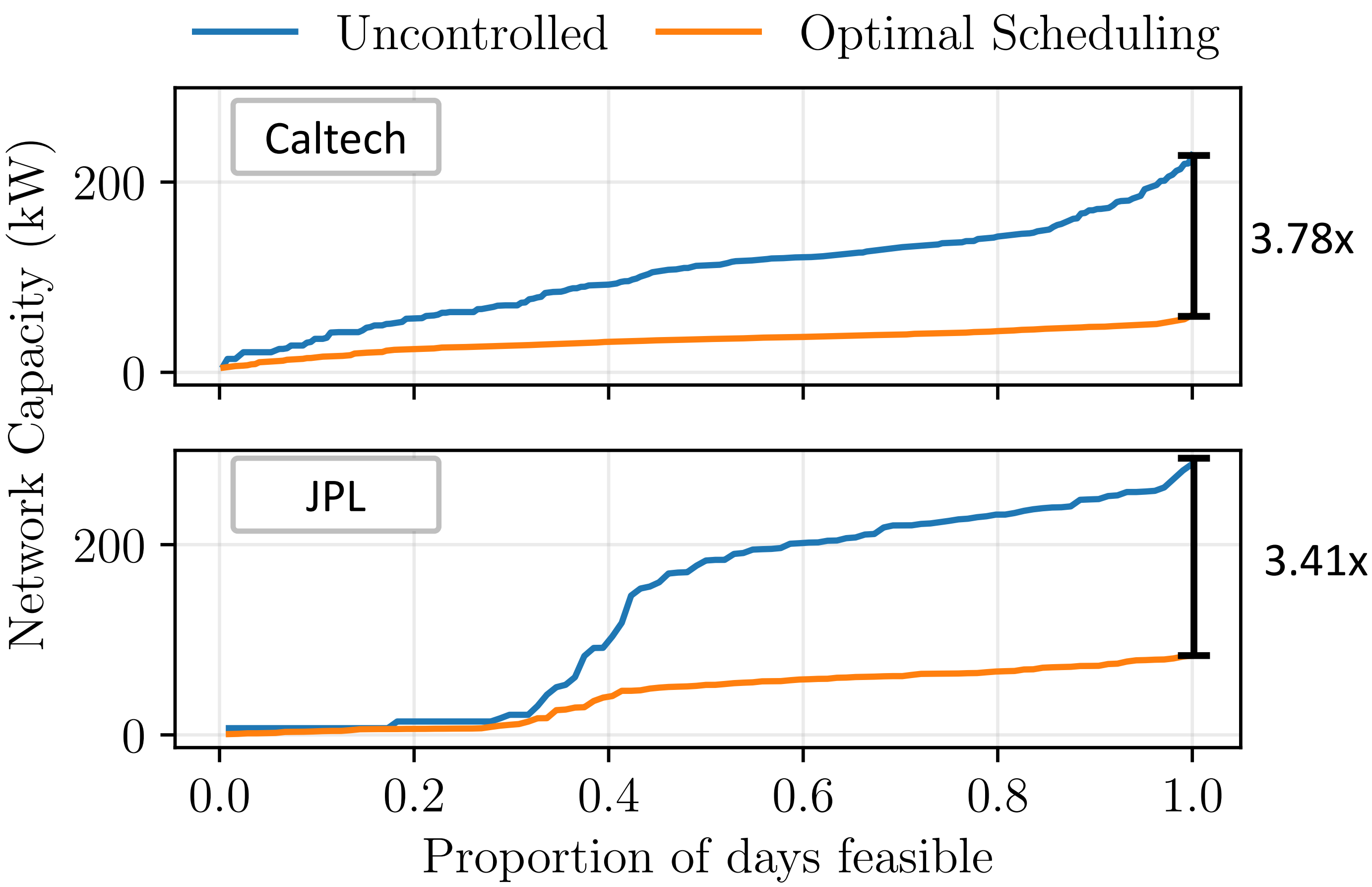
User flexibility

User flexibility



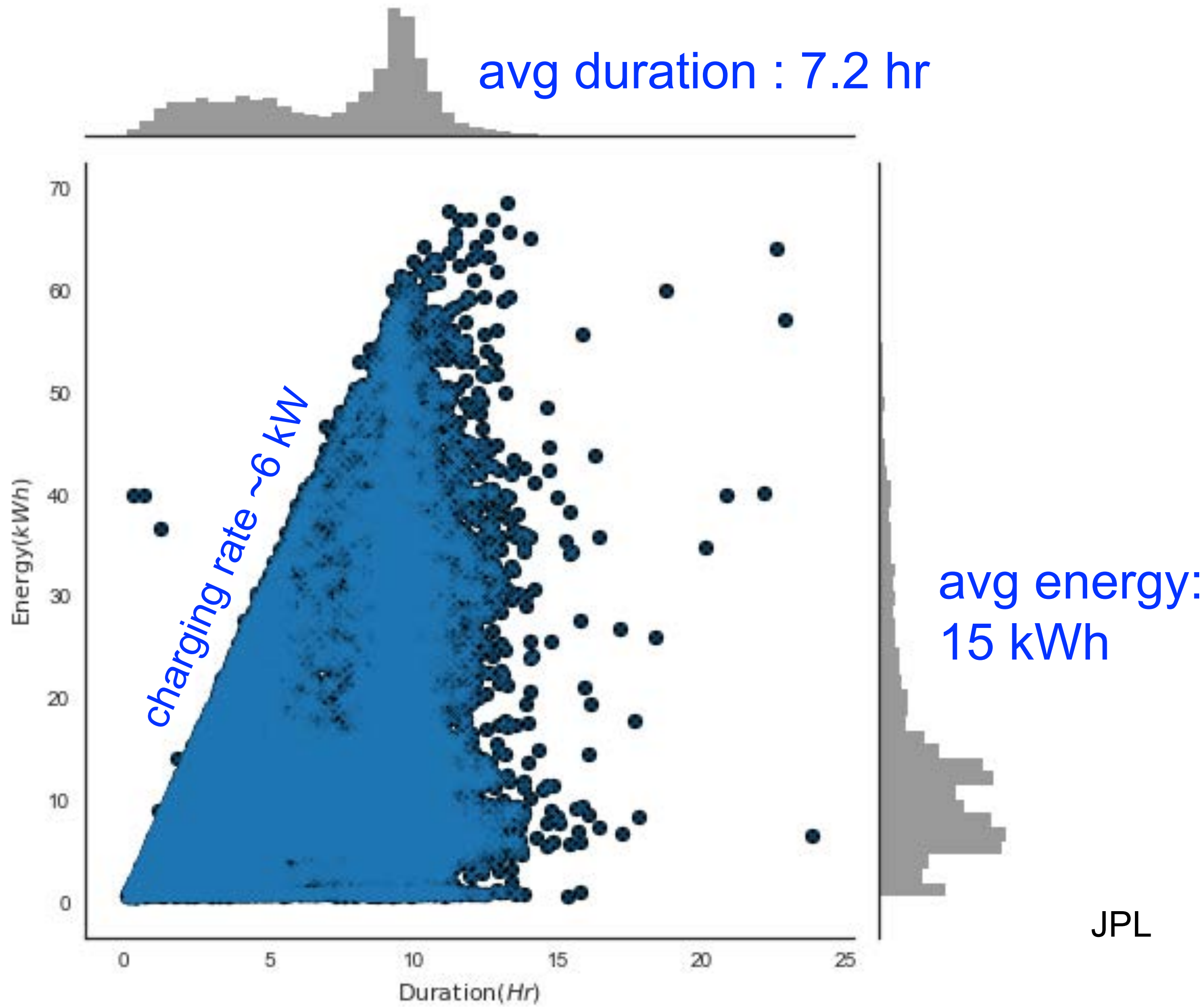
laxity := session duration - min charging time

ACN flexibility



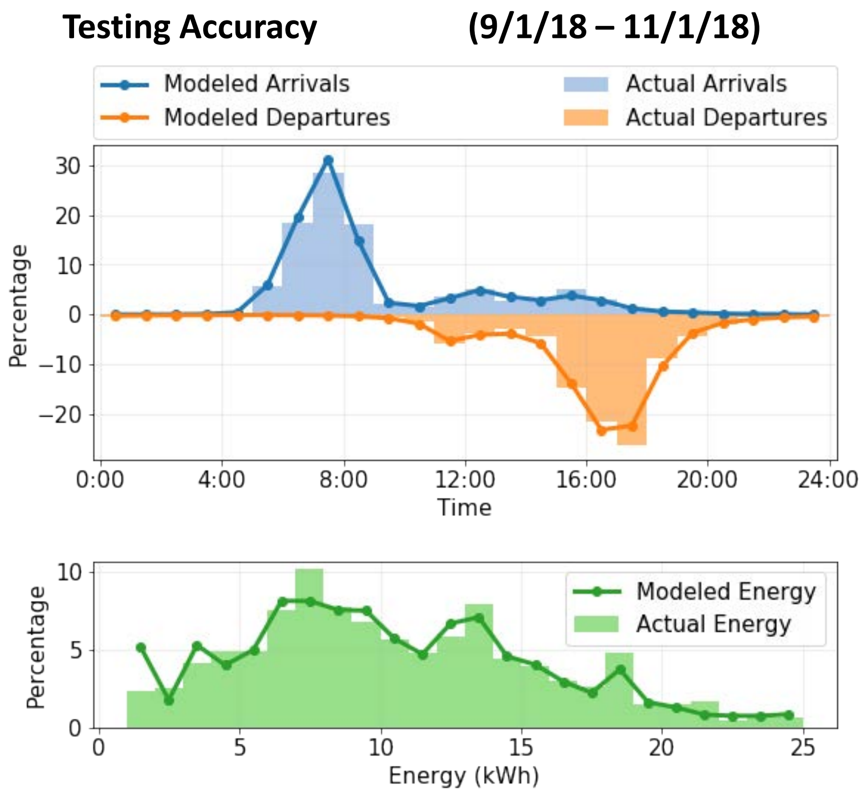
User behavior

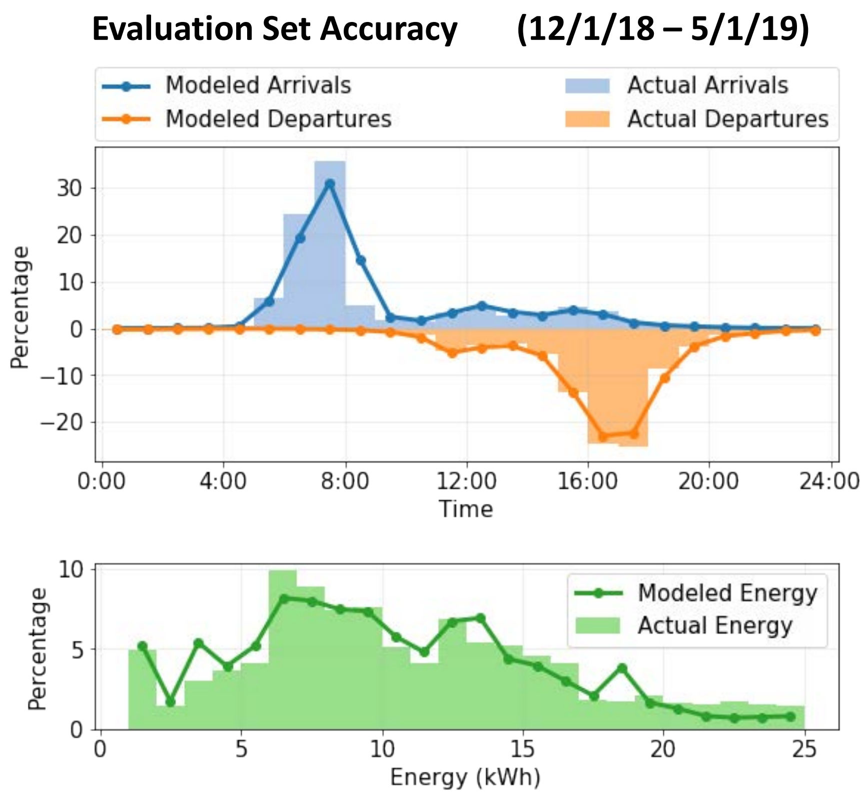
Duration and energy delivered



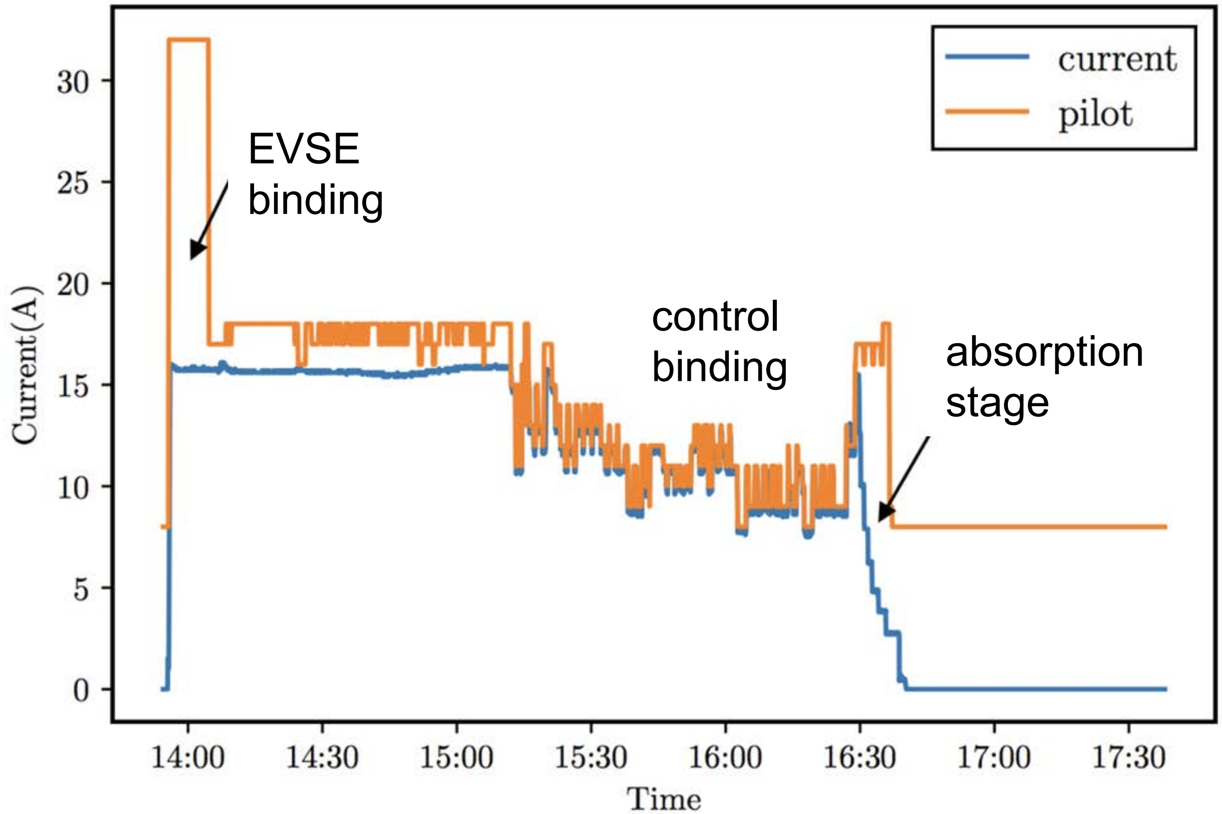
Learning user behavior

Gaussian mixture model





Charging curves



Caltech Oct 13, 2018

Time series: every 5-10 secs

- pilot signal from controller
- actual current drawn by EV

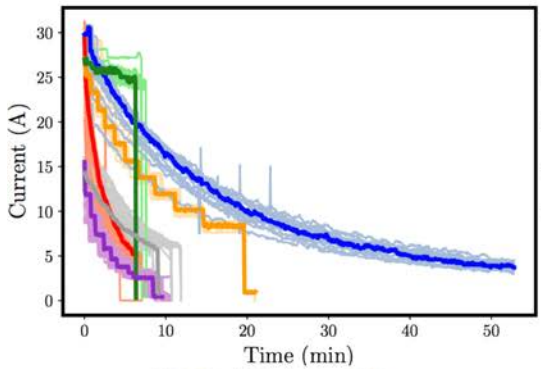
Learning charging curves

Goal: learn representative battery behaviors

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

Challenges: do not know SoC

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

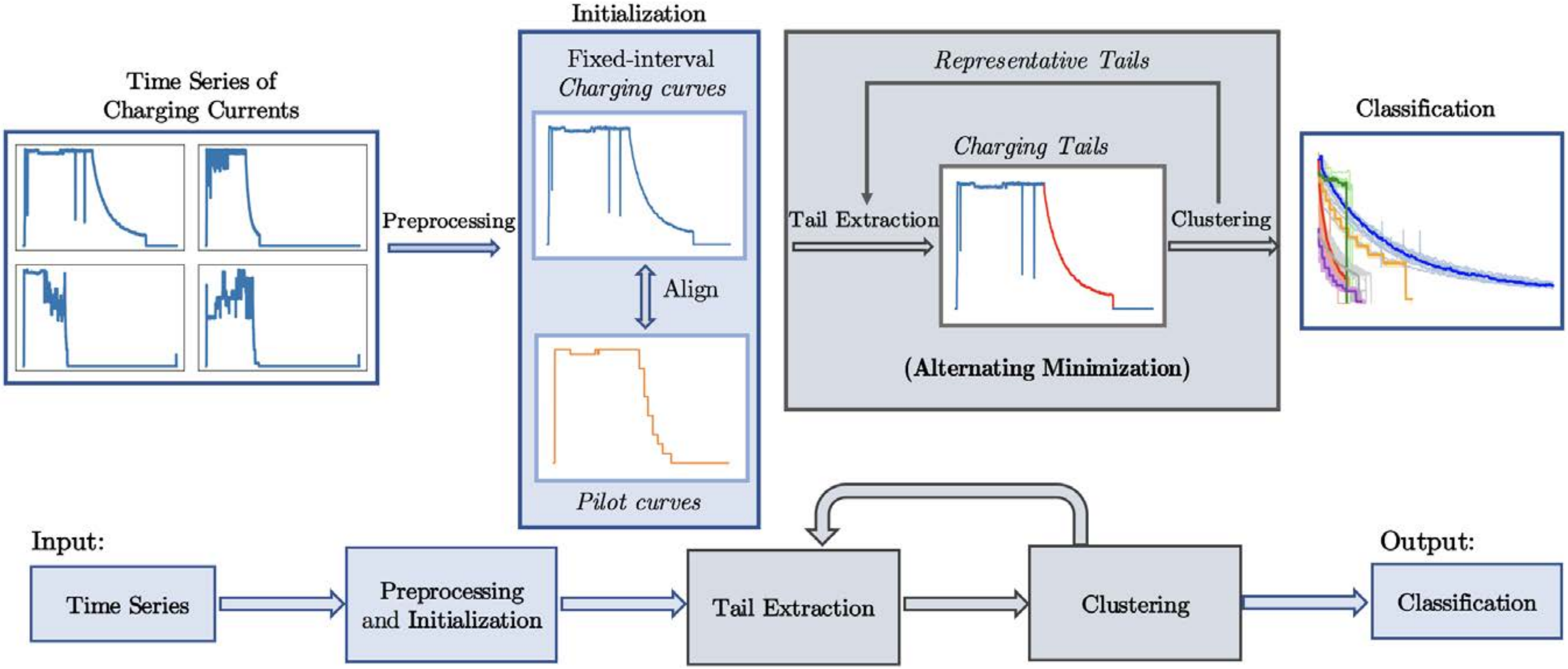


need to

- 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

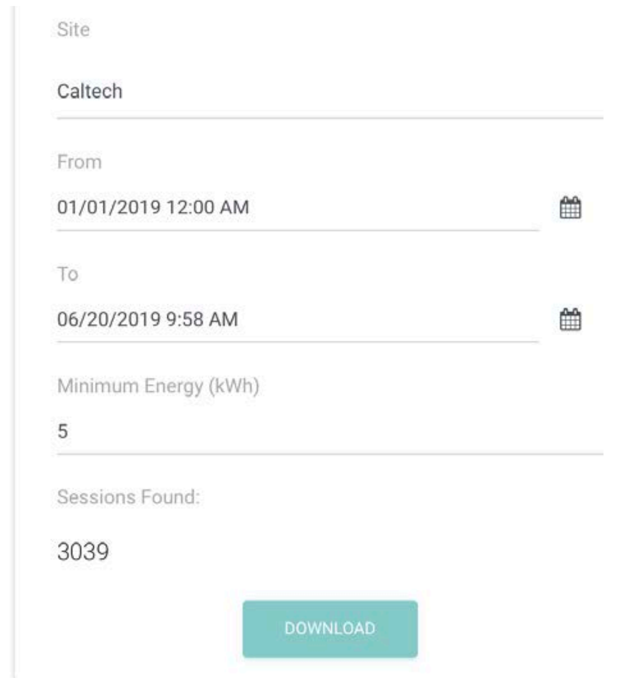
Learning charging curves



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

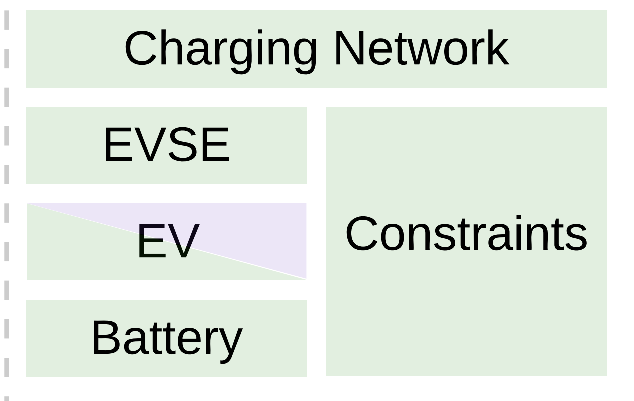


ev.caltech.edu

Caltech

open-source & extensible

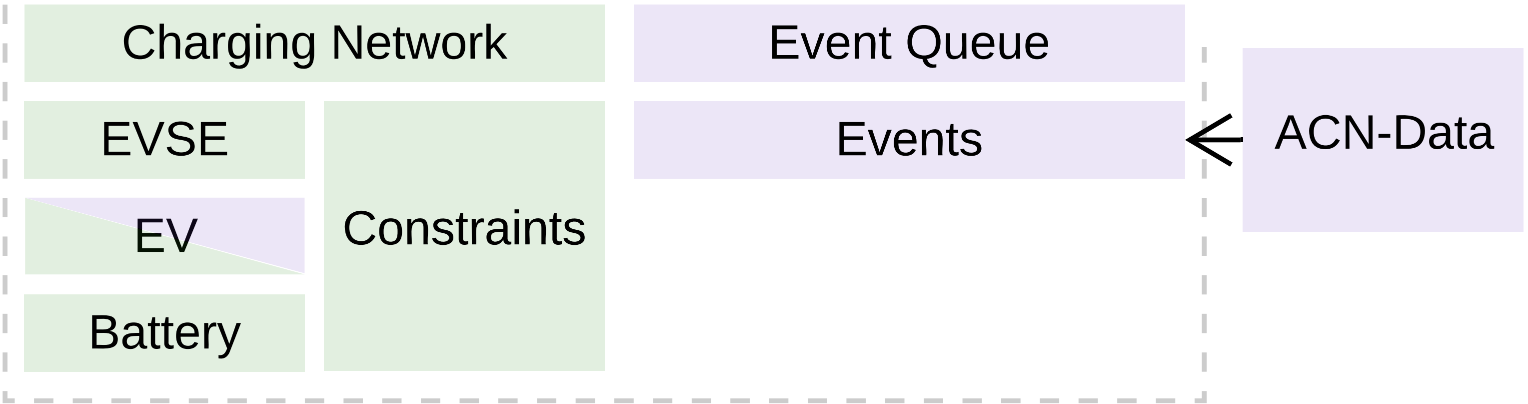
ACN - Sim



physical system /
simulation models

open-source & extensible

ACN - Sim

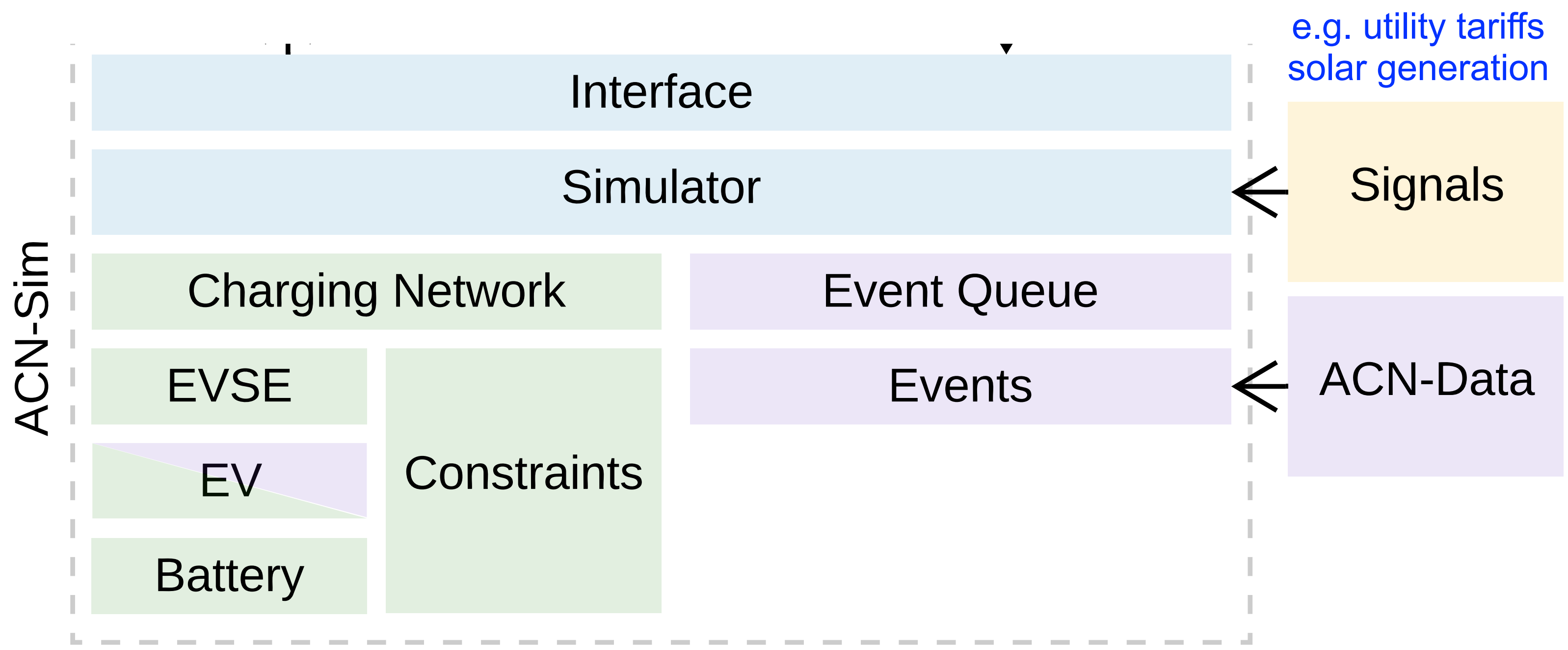


physical system / simulation models

integrated with ACN-Data

open-source & extensible

ACN - Sim

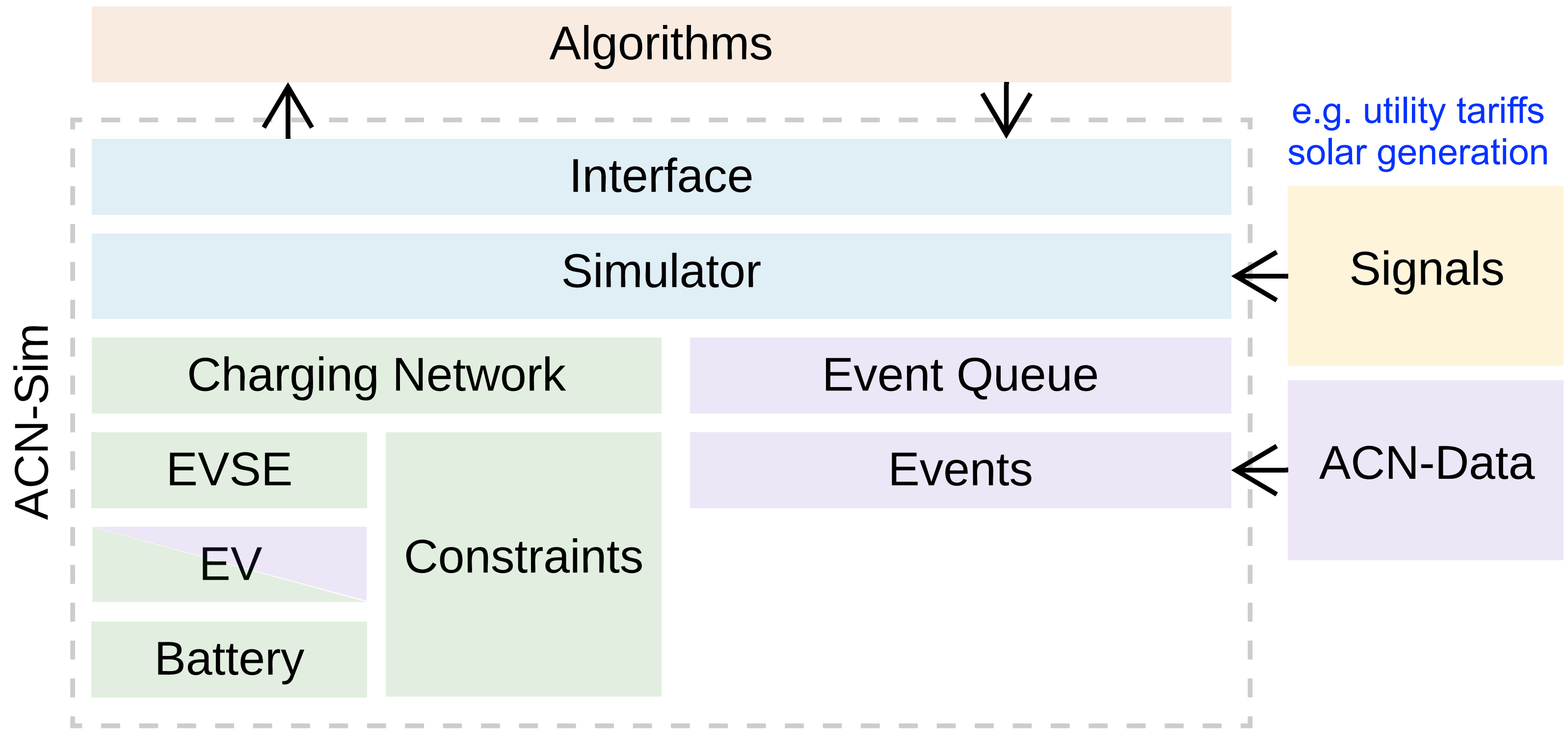


physical system / simulation models

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

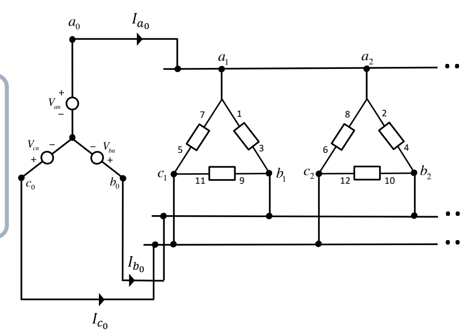
$$\max_r \quad \sum_v \alpha_v u_v(r)$$

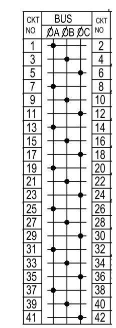
Compute: charging rates

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

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

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





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

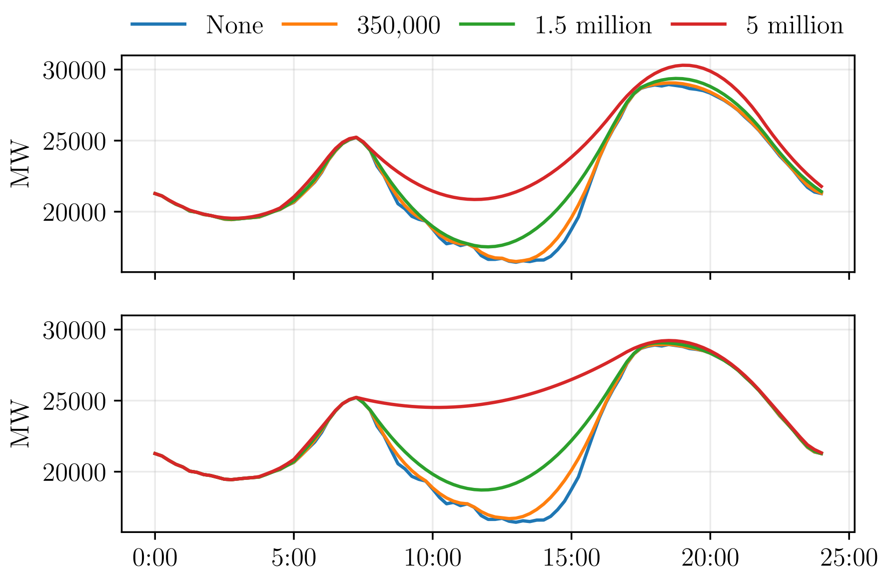
MPC

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

$$\text{subject to} \quad 0 \;\le\; r_i(t) \;\le\; \bar{r}_i(t)$$

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

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



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

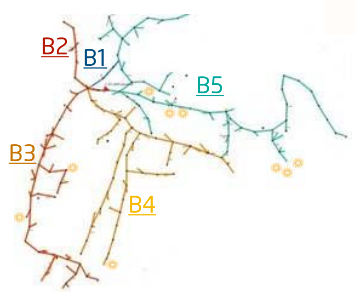
Example applications

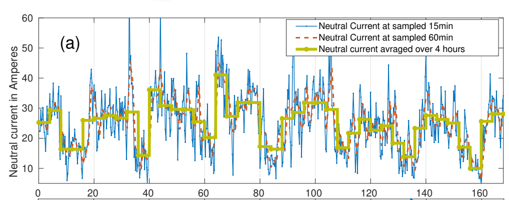
Towards Phase Balancing using Energy Storage

Md Umar Hashmi[1], José Horta[2], Lucas Pereira[3], Zachary Lee[4], Ana Bušić[1], and Daniel Kofman[2]
[1] INRIA and the Computer Science Dept. of Ecole Normale Supérieure, CNRS, PSL Research University, Paris, France
[2] Laboratory of Information, Networking and Communication Sciences, Télécom ParisTech, Paris, France
[3] ITI, LARSyS, Técnico Lisboa and prsma.com, Funchal, Portugal
[4]Electrical Engineering Department, California Institute of Technology, Passdena, CA, USA

arXiv 2020

Use ACN-Data and ACN-Sim, and real substation data in Portugal, to study phase imbalance and mitigation strategy using storage





Example applications

FlexAbility - Modeling and Maximizing the Bidirectional Flexibility Availability of Unidirectional Charging of Large Pools of Electric Vehicles

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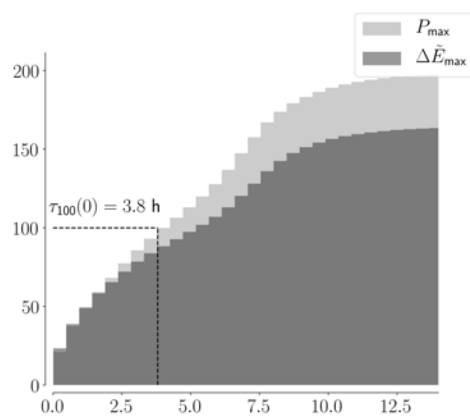
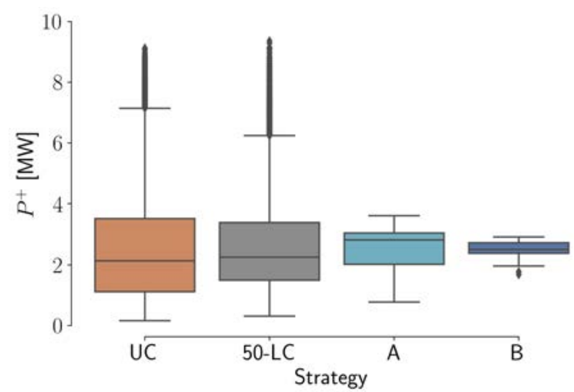
Erlangen, Germany

ACM e-Energy 2020

Use ACN-Data in its modeling and optimization of aggregate flexibility of distributed loads, showing tradeoff between energy & power flexibility





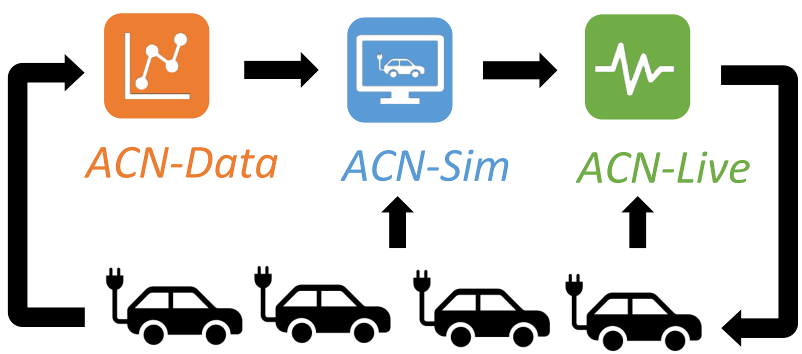
Example applications

Adaptive Control of Plug-in Electric Vehicle Charging with Reinforcement Learning

Authors: Abdullah Al Zishan, Moosa Moghimi Haji, Omid Ardakanian

ACM e-Energy 2020

Use ACN-Sim to study application of reinforcement learning to optimize decentralized EV charging algorithm



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Pricing demand charge

Z. Lee, J. Pang and S. H. Low.
Pricing EV charging service with demand charge, PSCC 2020

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: charging

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

Pricing design: recover individual EV's cost of

- 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

Pricing design

$$C(r) \;:=\; \sum_t p_t \sum_i r_i(t) \;+\; P \underbrace{\max_t \sum_i r_i(t)}_{\text{peak power}}$$

time-varying prices

demand charge

What is min system 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:

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

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

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

this achieves pricing goals

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

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

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

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

[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 forecast

ACN research portal

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