Adaptive Charging Network
for electric vehicles

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POWERFLEX SYSTEMS

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Caltech

March 2017

ACN testbed


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RESNICKINSTITUTE
science + energy + sustainability

POWERFLEX SYSTEMS

ACN theory

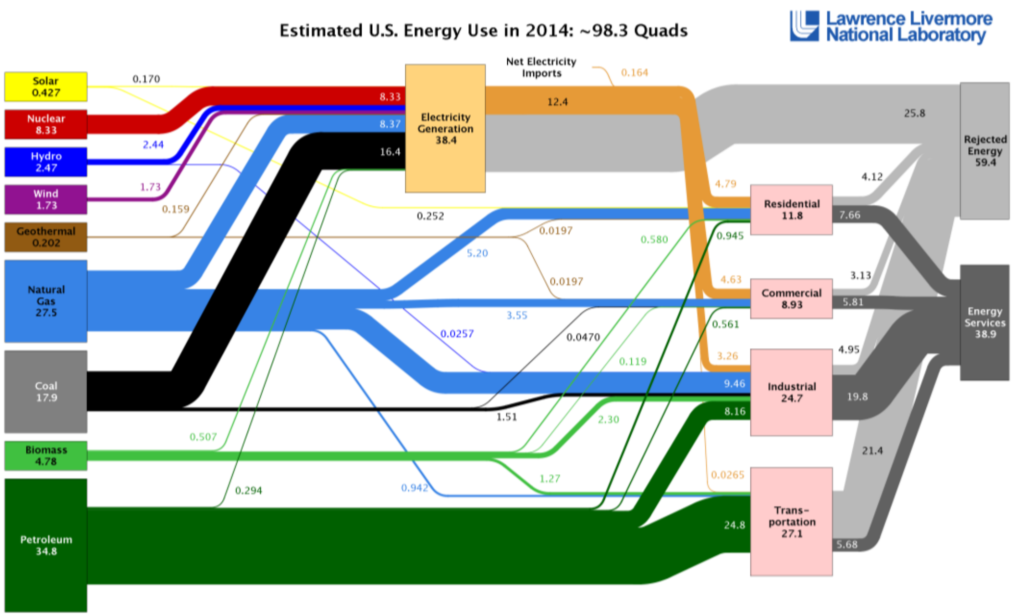
L. Chen, Colorado

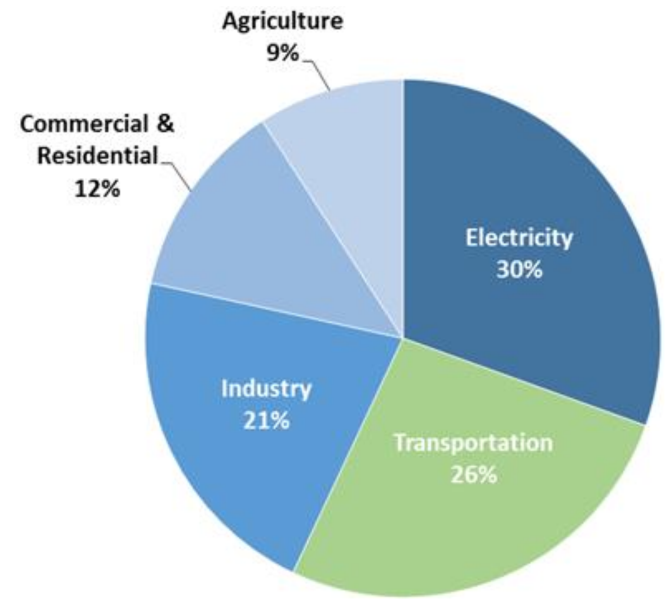
L. Chen, CIT

D. Guo, CIT

Y. Nakhira, CIT

Electricity gen & transportation





They consume the most energy

- Consumer 2/3 of all energy in US

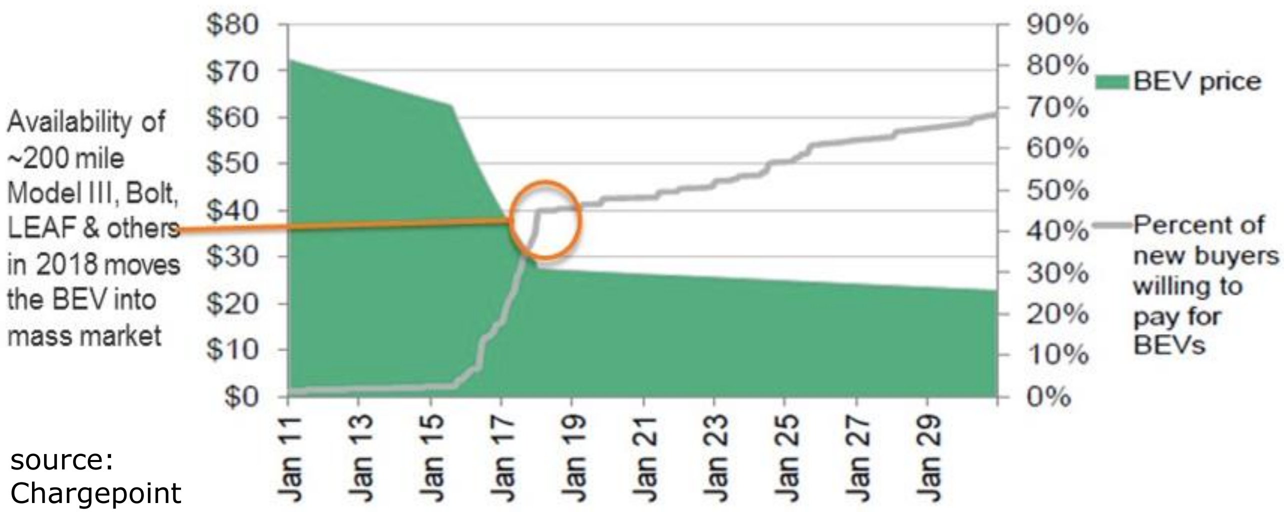
They emit the most greenhouse gases

- Emit >1/2 of all greenhouse gases in US

To drastically reduce greenhouse gases

- Increase renewable generations
- Electrify transportation

EV & charging



source: Chargepoint

Tesla Model 3 (4/2016)

1st week reservation: 325K, $14B

CA 2025 goal

- 1.5 million zero emission cars

Accelerating growth

- 2011-2013: EVs have grown by 8x in US
- 2011-2013: #Public charging stations grown by 7x in US

Painpoints

- Overcrowding, EV shuffling

Publications

- Adaptive Charging Network for Electric Vehicles. Dec 2016
  George Lee, Ted Lee, Zhi Low, Steven H. Low and Christine Ortega, IEEE GlobalSIP, Washington, DC
- Smoothed Least-laxity-first Algorithm for EV Charging. May 2017.
  Y. Nakahira, N. Chen, L. Chen and S. H. Low.
  Proc ACM e-Energy Conference, Hong Kong
- Optimal Online Adaptive Electric Vehicle Charging. July 2017
  Linqi Guo, Karl F. Erliksson and Steven H. Low.
  Proc. IEEE PES General Meeting, Chicago, IL

- The National Electric Transportation Infrastructure Working Council (IWC) Meeting, San Francisco, CA, November 2016

Outline

Theory and algorithms

- Algorithm design
- Simulations and analysis

ACN testbed

- System design
- Caltech pilot

Charging model

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

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

EV i: $\left(e_i, a_i, d_i, \overline{r}_i\right)$

energy demand (miles / kWh)

arrival / departure time

peak charging rate (kW)

Charging model

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

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

EV i: $\left(e_i, a_i, d_i, \overline{r}_i\right)$

Power limit: $P(t)$

Compute: charging rates

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

Offline optimal charging

Offline optimal problem is a linear program

$$\min_{r \geq 0} \quad C(r)$$

$$\text{subject to} \quad r_i(t) \leq \overline{r}_i(t) \qquad \forall i, \ \forall t$$

charge only after a_i before d_i
not exceeding peak rate

Offline optimal charging

Offline optimal problem is a linear program

$$\min_{r \geq 0} \quad C(r)$$

$$\text{subject to} \quad r_i(t) \leq \overline{r}_i(t) \quad \forall i, \ \forall t$$

$$\sum_t r_i(t)\,\delta = e_i \quad \forall i$$

meet energy demand

$$\sum_i r_i(t) \leq P(t) \quad \forall t$$

not exceed limit;
can generalize to
linear constraints

Online LP

Offline LP is not implementable

- It needs future EV information

Implement Online LP

- Solve LP with current EVs, assuming no future arrival
- Update remaining energy demand after each online LP iteration
- Model-predictive control

$$
\begin{aligned}
\mathrm{LP}(t): \quad & \min_{r \geq 0} \quad C_t(r) \\
\text{s. t.} \quad & r_i(\tau) \leq \overline{r}_i(\tau), \qquad \tau \geq t \\
& \sum_{\tau=t}^{T-1} r_i(\tau)\delta = e_i(t) \\
& \sum_{\tau=t} r_i(\tau) \leq P(\tau), \qquad \tau \geq t
\end{aligned}
$$

Performance: online LP

Suppose cost coefficients are uniformly monotone

$$C(r) := \sum_t c_t \sum_i r_{it} \quad \text{with } c_t \text{ increasing in } t$$

<u>Theorem</u>

If online LP is feasible, then it attains offline optimal

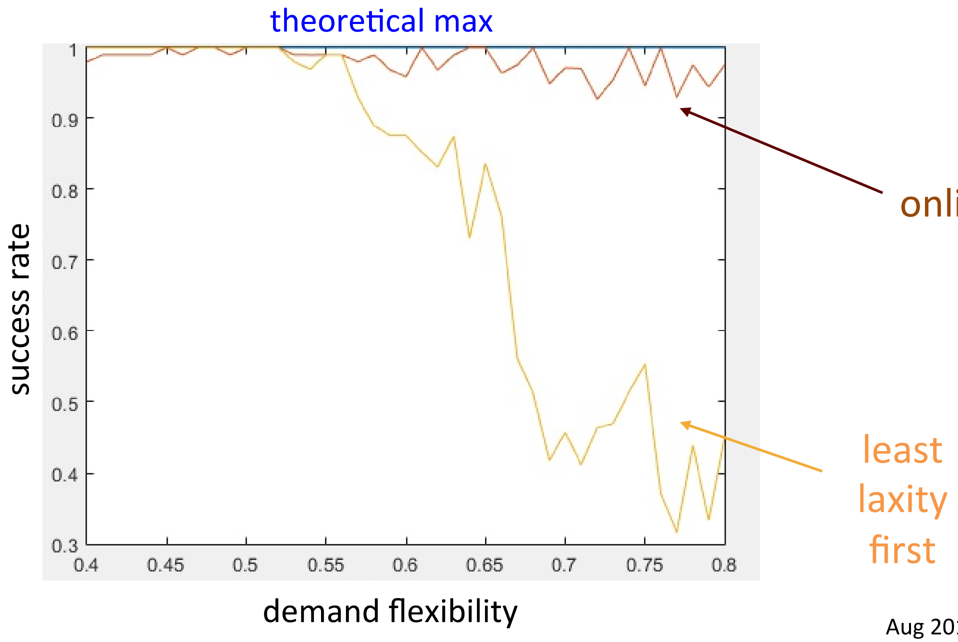
Guo, Erliksson, L. PES GM 2017

Performance: online LP

Theorem

1. competitive ratio can be arbitrarily bad
2. $$\text{competitive ratio } \pounds \ \frac{\max_{i,t} c_{it}}{\min_{i,t} c_{it}} \quad \text{(cost variability)}$$

Performance: online LP



UK EV data
Aug 2010 – Dec 2012

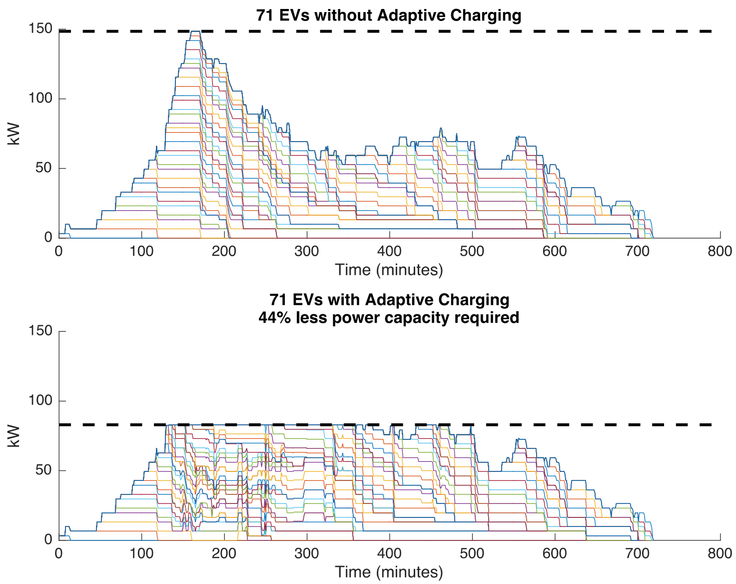
feasibility of online LP
~ feasibility of offline LP

normalized difference (%)		
CA Garage	Mountain View	Sunnyvale
1.24	0.18	0.36

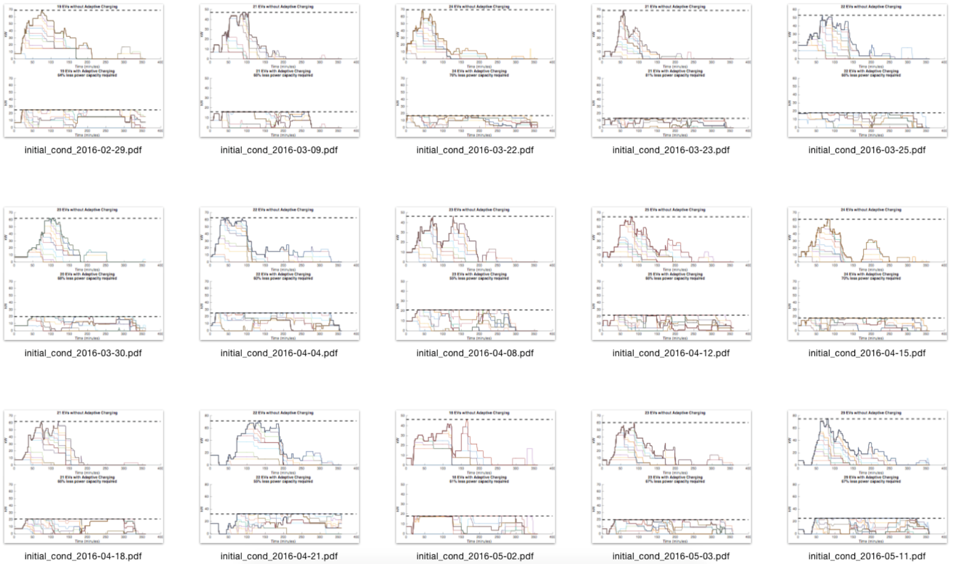
$$\text{normalized difference} = \frac{P_{OLP} - P_{OPT}}{P_{Dumb} - P_{OPT}}$$

(averaged over all locations and all days for each dataset)

Performance



data: g2016mtv2000

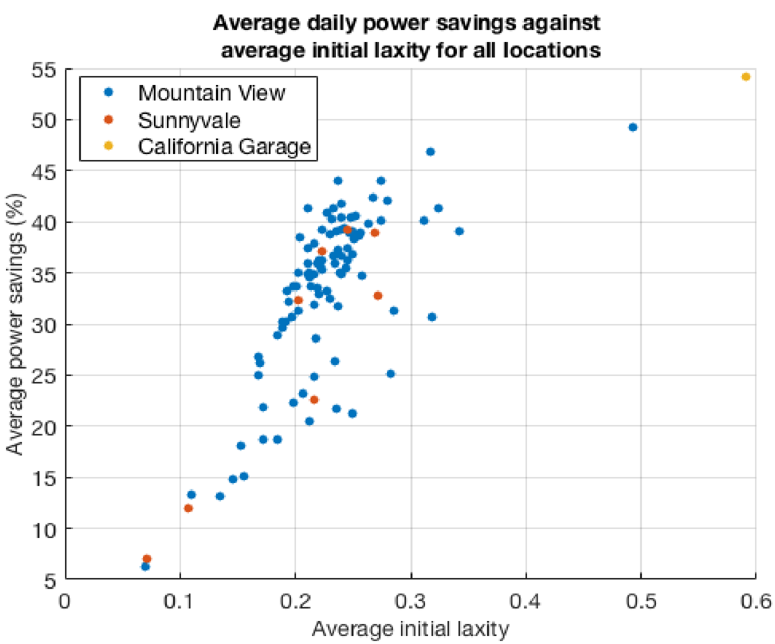


data: CAgarage2016

Adaptive charging network

Daily peak power	Uncontrolled charging	ACN	Power savings
Caltech	85.3 kW	33.8 kW	60%
Mountain View	46.2 kW	28.4 kW	34%
Sunnyvale	94.0 kW	56.2 kW	29%

savings = infrastructure, demand charge



Conclusions

- savings increase in initial laxity
- significant savings even at low laxity

Karl Erliksson 2016 SURF

Table 1: Cleaning statistics for the Mountain View data set.

Description	Quantity	Percentage (%)
EVs before cleaning	46404	100
Total EVs removed	1817	3.9
Energy demand <1 kWh	1673	3.6
Parking time <10 min	501	1.1
Parking time >12 hrs	0	0
Peak charging rate <2 kW	0	0
Peak charging rate >20 kW	0	0
Negative initial laxity	195	0.4

Table 2: Cleaning statistics for the Sunnyvale data set.

Description	Quantity	Percentage (%)
EVs before cleaning	6614	100
Total EVs removed	148	2.2
Energy demand <1 kWh	126	1.9
Parking time <10 min	30	0.5
Parking time >12 hrs	0	0
Peak charging rate <2 kW	0	0
Peak charging rate >20 kW	0	0
Negative initial laxity	32	0.5

Remaining #EVs (charging sessions)

- Mountain View: 44,587
- Sunnyvale: 6,466
- CA Garage: 1,309

Total: 52,362 sessions, in 2016 (over a few months)

104 locations
>4,000 charging days

Table 3: Cleaning statistics for the California Garage data

Description	Quantity	Percentage
EVs before cleaning	1384	100
Total EVs removed	75	5.4
Energy demand <1 kWh	64	4.6
Parking time <10 min	21	1.5
Parking time >12 hrs	0	0
Peak charging rate <2 kW	2	0.1
Peak charging rate >20 kW	0	0
Negative initial laxity	11	0.8

Smoothed Least laxity first (sLLF)

$$\boxed{\text{EV } i: \quad (e_i, a_i, d_i, \overline{r}_i), \; i = 1, \ldots, N}$$

energy demand (miles / kWh)

arrival / departure time

peak charging rate (kW)

State at time t: remaining energy demand

$$e(t) := (e_i(t), \; i = 1, \ldots, N)$$

Compute: charging rates at each time t:

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

no look-ahead

Smoothed Least laxity first (sLLF)

$$\boxed{\text{EV } i: \quad (e_i, a_i, d_i, \overline{r}_i), \; i = 1, \ldots, N}$$

energy demand (miles / kWh)

arrival / departure time

peak charging rate (kW)

$$\text{laxity} \quad l_i(t) := (d_i - t) - \frac{e_i(t)}{\overline{r}_i}$$

remaining time

minimum required

Smoothed Least laxity first (sLLF)

$$\boxed{\text{EV } i: \quad \left(e_i, a_i, d_i, \overline{r}_i\right), \; i = 1, \ldots, N}$$

$$\text{laxity} \quad l_i(t) := (d_i - t) - \frac{e_i(t)}{\overline{r}_i}$$

$$l_i(t+1) = l_i(t) - 1 + \frac{r_i(t)}{\overline{r}_i}$$

Algorithm: max min laxity $l_i(t+1)$ at **next** time

Nakahira, et al, e-Energy 2017

Smoothed Least laxity first (sLLF)

Theorem

sLLF rates $r := (r_i(t),\ i = 1, \ldots, N)$ solves

$$\max_{r(t)} \sum_i -\bar{r}_i \log l_i(t+1)$$

$$\text{s. t.} \quad 0 \le r_i(t) \le \bar{r}_i$$

$$\sum_i r_i(t) \le P(t)$$

➔ water-filling algorithm

Nakahira, et al, e-Energy 2017

Smoothed Least laxity first (sLLF)

Theorem

sLLF rates $r := (r_i(t),\ i = 1, \ldots, N)$ are

1. Proportionally fair

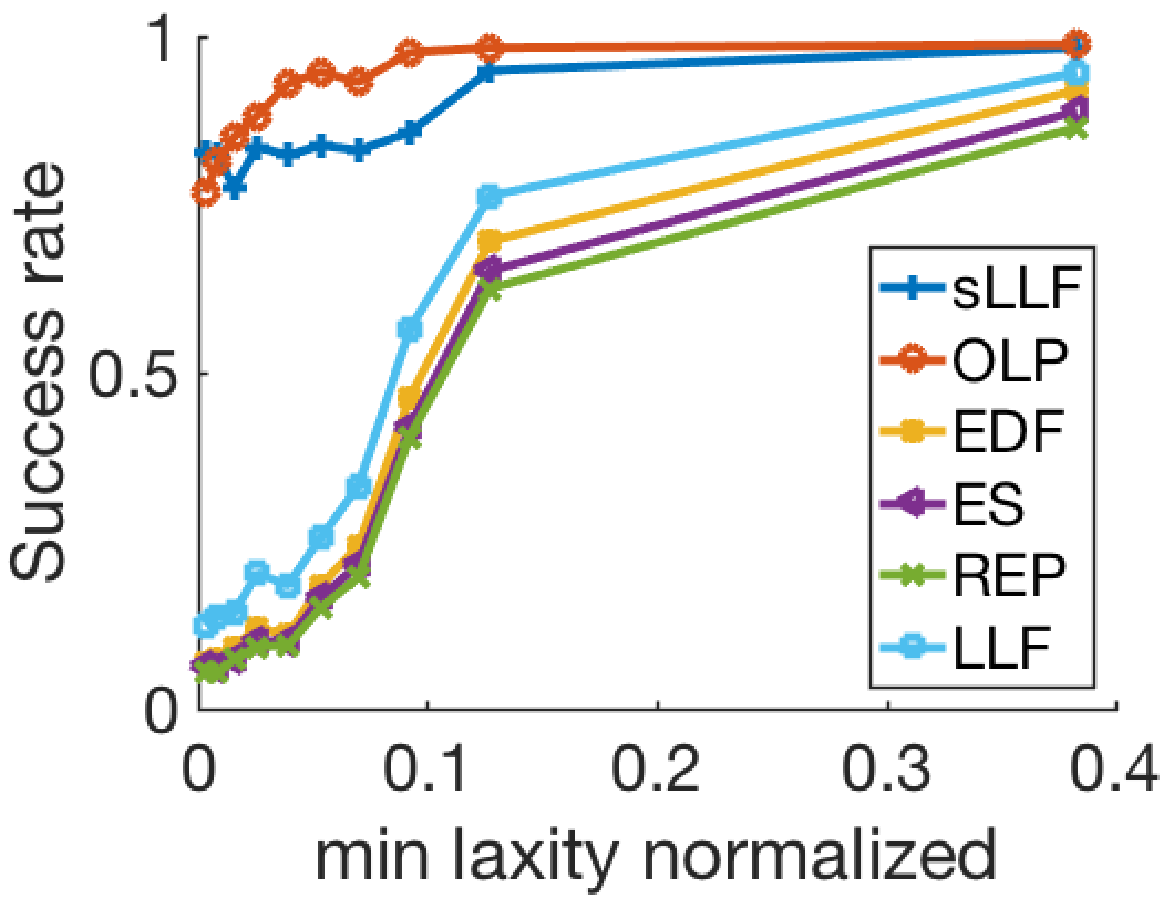
$$\sum_i \frac{l_i'(t+1) - l_i(t+1)}{l_i(t+1)} \le 0$$

2. Maxmin fair

$$\min_i \ l_i'(t+1) \text{ is maximized}$$

Nakahira, et al, e-Energy 2017

Smoothed Least laxity first (sLLF)



Nakahira, et al, e-Energy 2017

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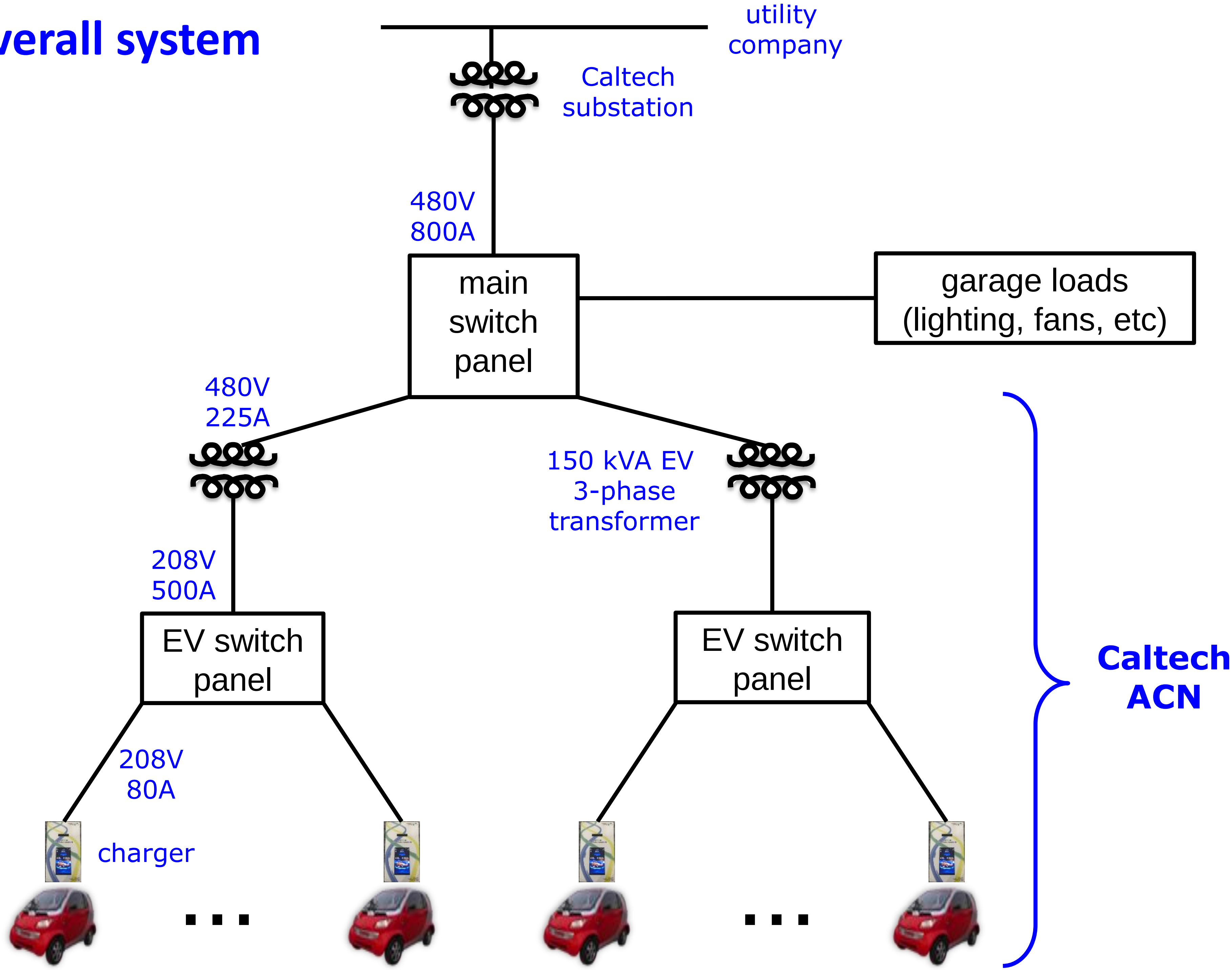
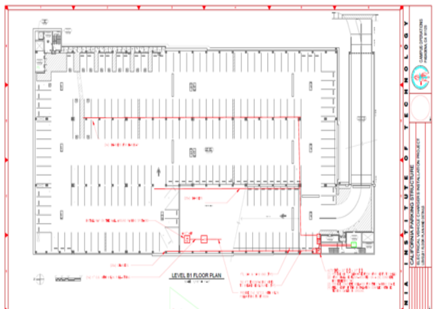
Overall system



Adaptive charging network

First pilot @Caltech garage

- 50+ adaptive Level 2 chargers
- 2x 150kVA transformers
- Operational since Feb 2016



main panel

chargers

150kVA transformers

debugging

Caltech ACN

- Provide target charging capacity at much lower infrastructure & operating costs (30% - 60% savings)
- Provide ancillary energy services

$$
\begin{aligned}
\mathrm{LP}(t): \quad & \min_{r \geq 0} \quad C_t(r) \\
\text{s. t.} \quad & r_i(\tau) \leq \overline{r}_i(\tau), \qquad \tau \geq t \\
& \sum_{\tau=t}^{T-1} r_i(\tau)\delta = e_i(t) \\
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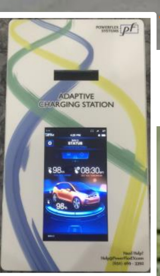
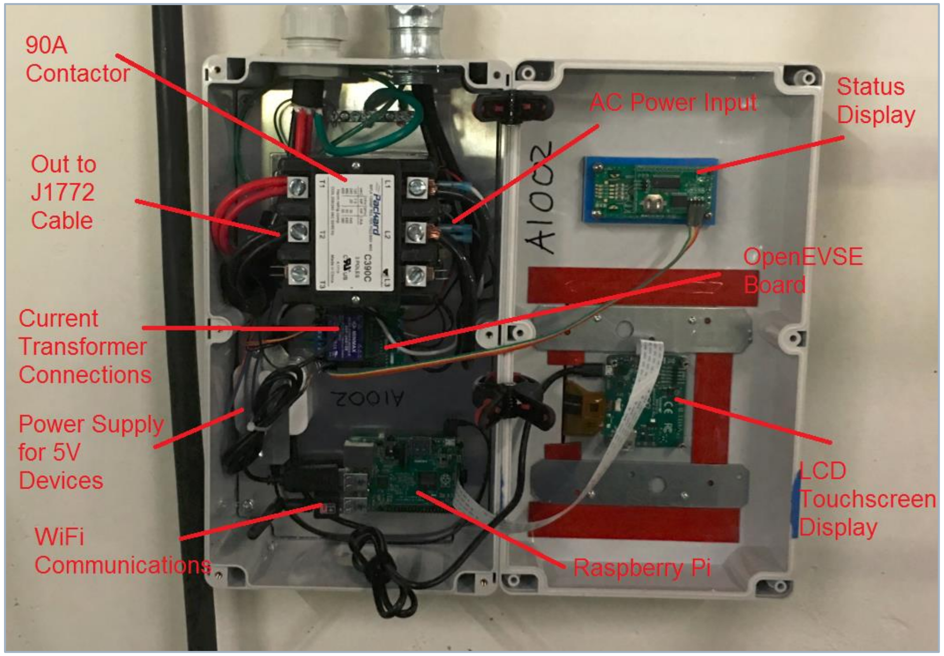
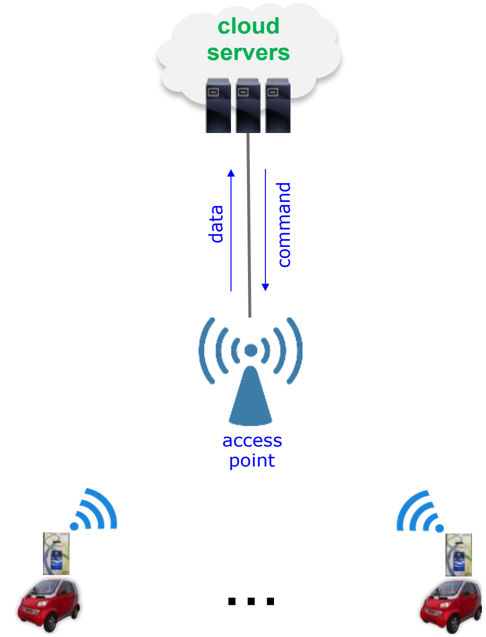
$$

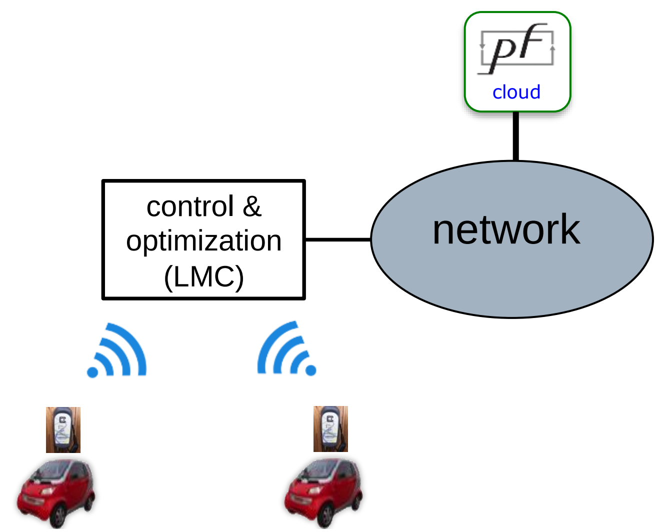


(60 chargers; since 2/2016; 400K+ miles delivered, 140+ tons of GHG avoided; 3/2017)

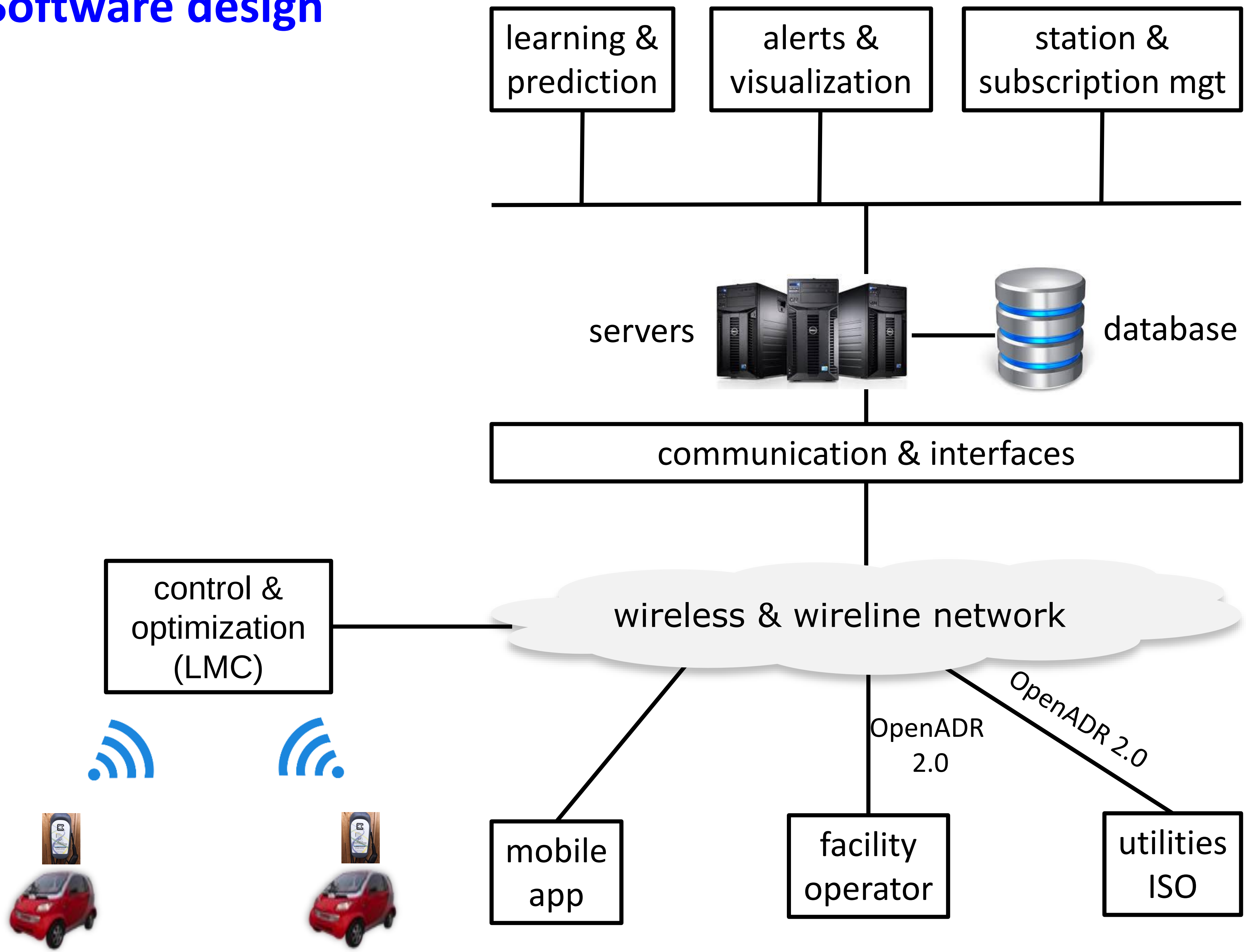
Hardware design



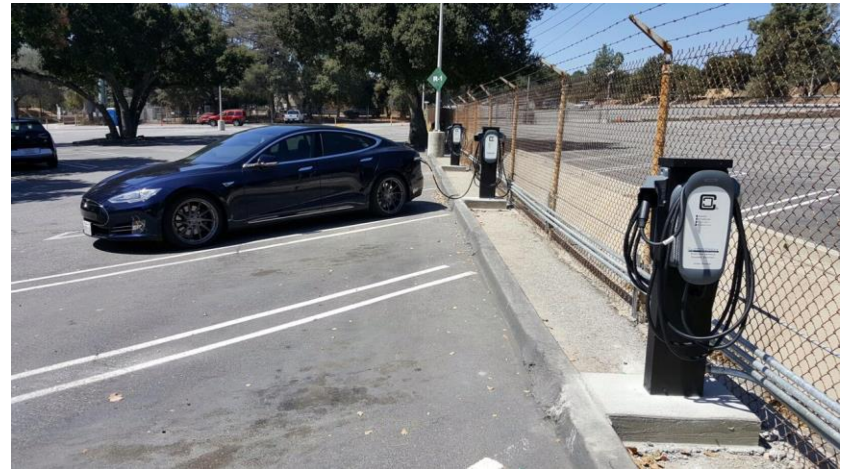




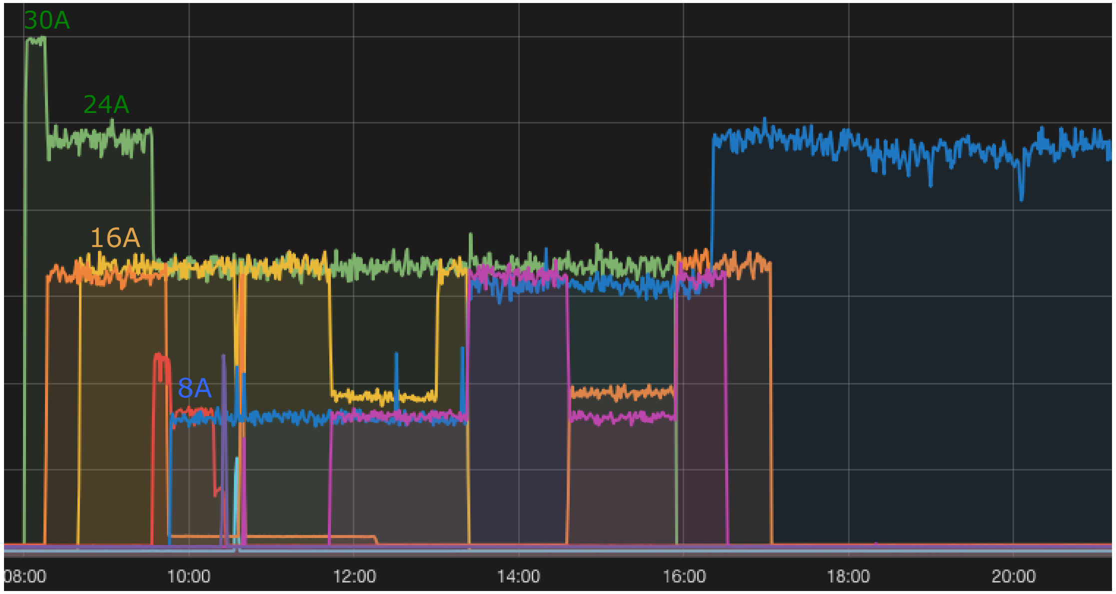
Software design



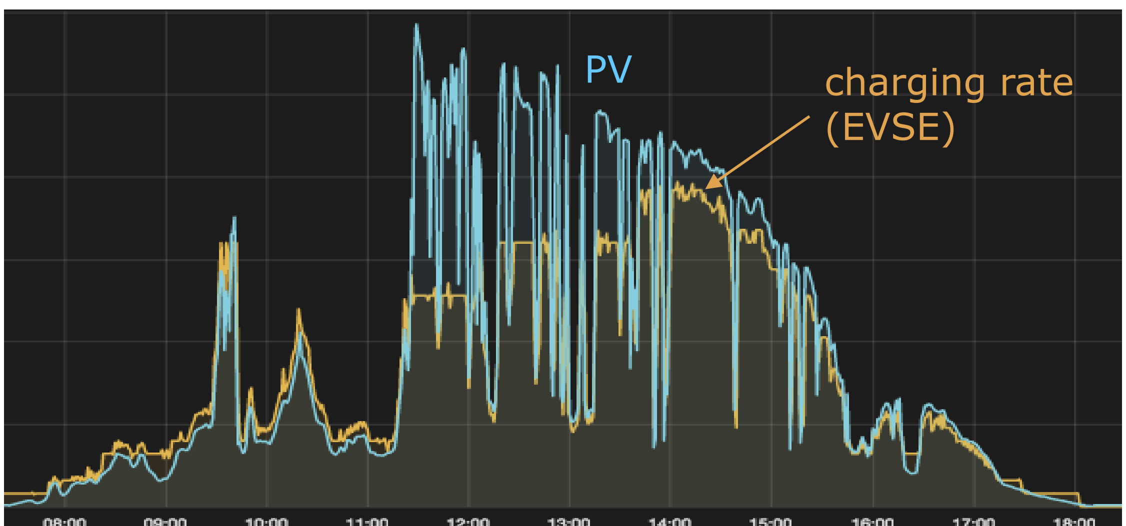
Indoor or outdoor



Adaptation

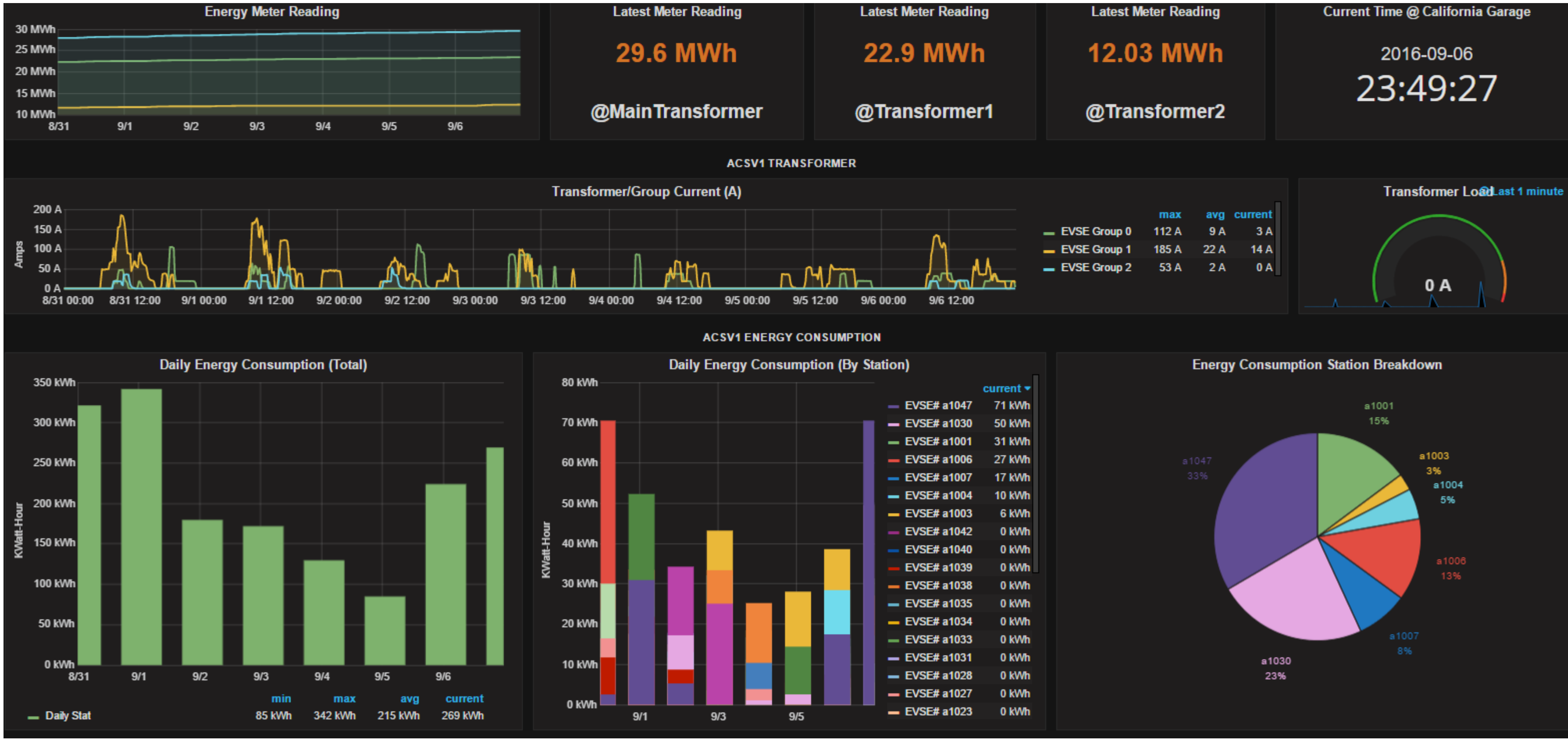


Fair sharing, Aug 2016
- Real-time adaptation



DR capability, Oct 2016
- Capability to track PV generation in real time
- JPL demo

Management interface



- Real-time monitoring
- Deployed on ACN cloud server

Key benefits

Provide target charging capacity at 30%-60% lower costs

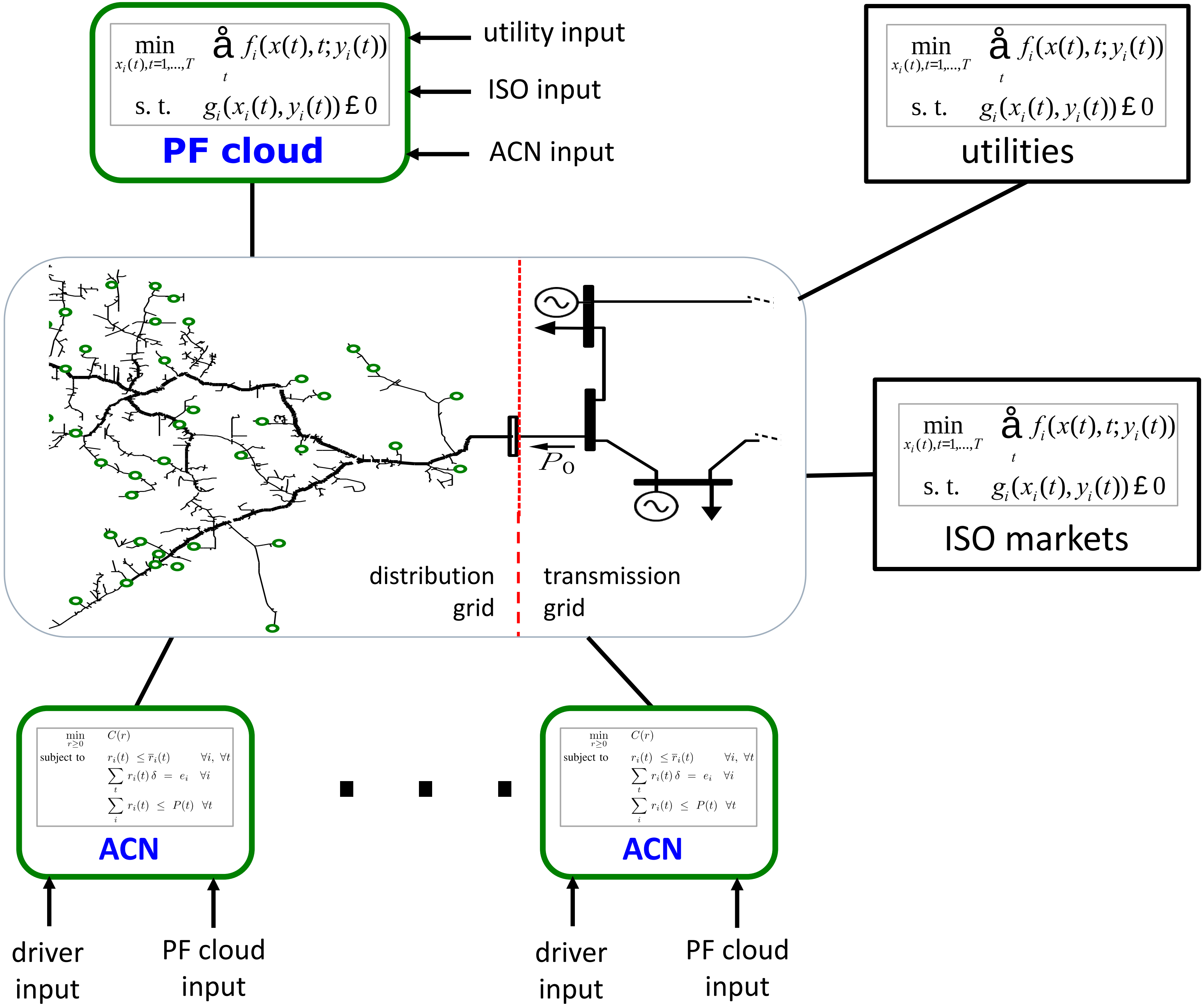
- infrastructure costs
- operating costs (demand charges)

Flexibility in implementing operator objectives

- min electricity bill
- min charging time
- max asset utilization
- max system robustness

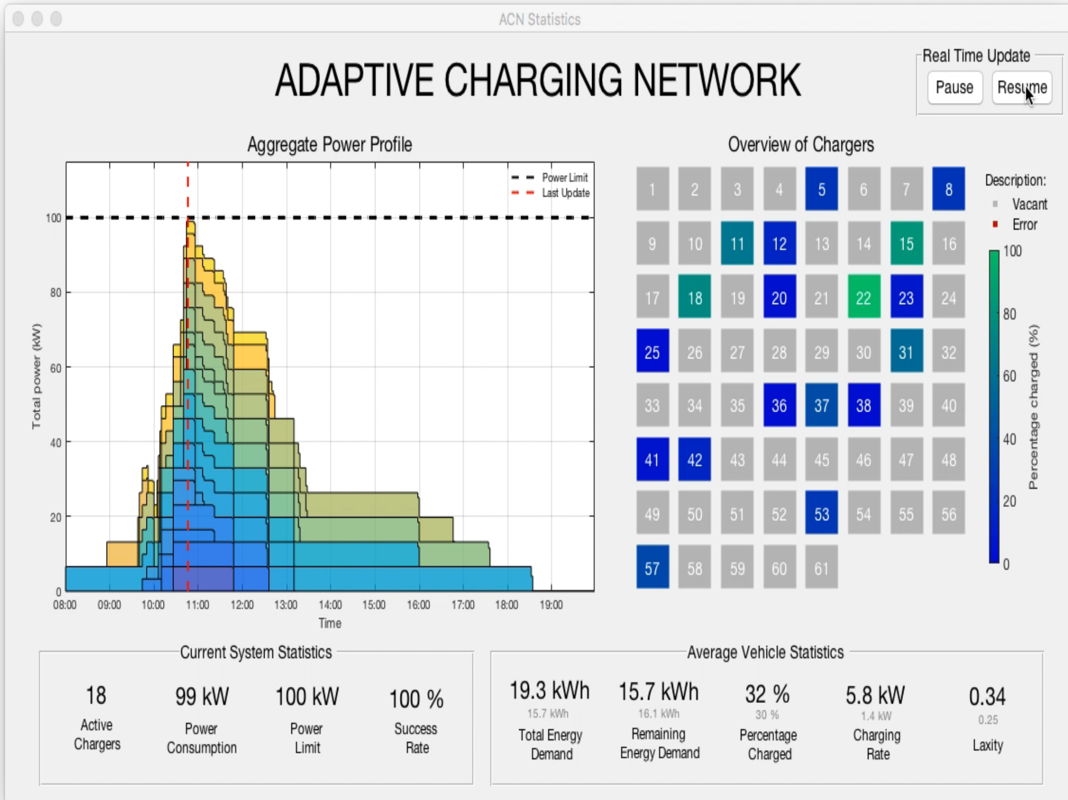
Potential for providing DR/ancillary services

- Help distribution grid operation



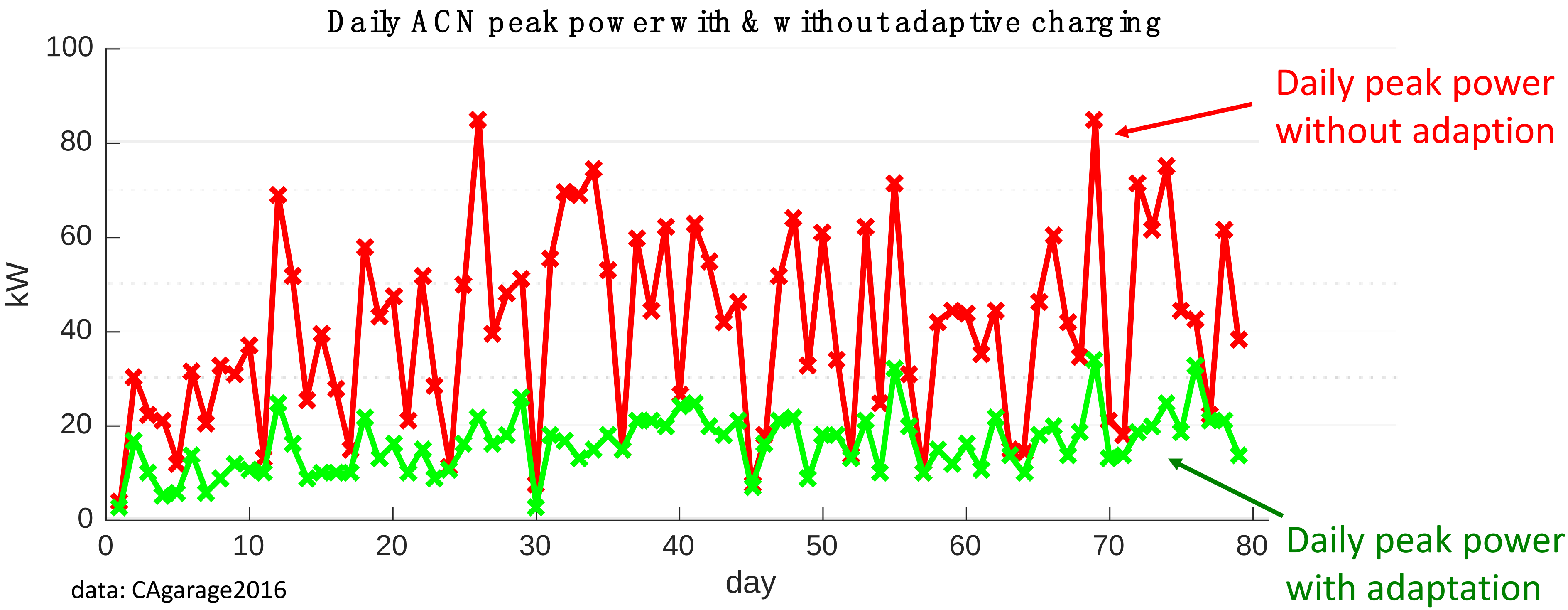
utility input
ISO input
ACN input
PF cloud
utilities
ISO markets
distribution grid
transmission grid
P_0
ACN
ACN
driver input
PF cloud input
driver input
PF cloud input

Simulation tool



Karl Erliksson 2016 SURF

Backup Slides



ACN benefit

Caltech data (Feb – May, 2016)

	Daily ACN peak (peak-rate charging)	Daily ACN peak (offline LP)	Capacity saving
max	85 kW	34 kW	60%
average	41 kW	16 kW	-

savings = infrastructure, demand charge