Integrating a Cyber Infrastructure with Physical Processes

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University of California, Berkeley

Developing Intelligent Food, Energy, and Water Systems (DIFEWS) Workshop
Alumni House, UC Berkeley

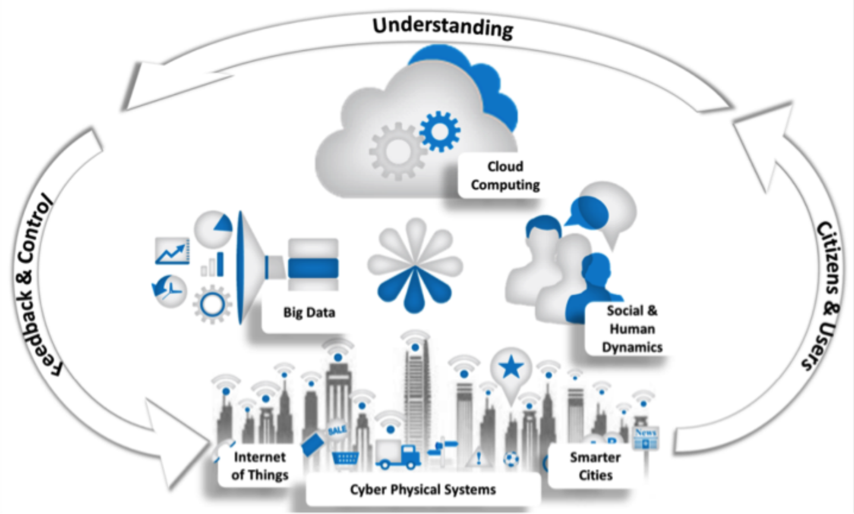
What is a Cyber Physical System (CPS)?

What is a Cyber Physical System (CPS)?

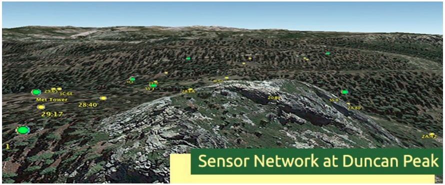
Integration of physical processes with networked computing

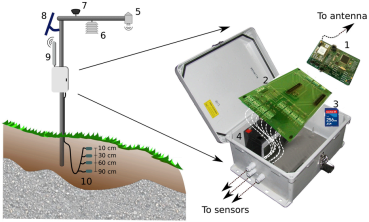
What is a Cyber Physical System (CPS)?

Sensing $\rightarrow$ Understanding $\rightarrow$ Managing



What is a Cyber Physical System (CPS)?





What is a Cyber Physical System (CPS)?

Five Pillars of CPS

1. infrastructure systems;
2. sensing;
3. actuation;
4. connectivity;
5. data analysis;

A History

1949

- Computers Created for Computation

1973

- Real-time computation

1990s

- Hybrid Systems

~2006

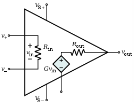
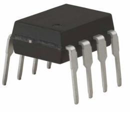
"CPS Instigators": Anstaklis, Krough, Lee, Mitter, Mok, Pappas, Rajkumar, Sastry, Stankovic, Sztipanovits, …

Cyber Physical Systems

The Third Generation of Control Systems

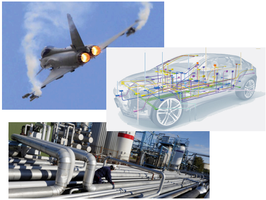
First Generation: Analog Control

- Technology: Feedback amplifiers
- Theory: Frequency domain analysis, Bode, Evans, Nyquist

Second Generation: Digital Control

- Technology: Digital computers
- Theory: State-space design, optimal control, robust/adaptive control



Third Generation: Networked Control

- Technology: Embedded microcontrollers (98%+ of all computers)
- Theory: Communication, Computation, Control, Privacy, Security, Safety/Reliability, Scalability

FUNDAMENTAL CHALLENGES OF CPS

Fundamental Challenges of CPS

a non-exclusive list

1. **Architecture**
2. **Verification & Certification**
3. **Reliability**
4. **Cybersecurity**
5. **Scalability**
6. **Modularity**

Fundamental Challenges of CPS

a non-exclusive list

1. **Architecture**
   - design interconnected control, communication, computation, and physical systems that are efficient & flexible
2. **Verification & Certification**
3. **Reliability**
4. **Cybersecurity**
5. **Scalability**
6. **Modularity**

Fundamental Challenges of CPS

a non-exclusive list

1. **Architecture**
2. **Verification & Certification**
   - enable rapid testing and ensure reliable performance, functionality, & safety
3. **Reliability**
4. **Cybersecurity**
5. **Scalability**
6. **Modularity**

Fundamental Challenges of CPS

a non-exclusive list

1. **Architecture**
2. **Verification & Certification**
3. **Reliability**
   - maintain safe operation & functionality in the face of disturbances or faults
4. **Cybersecurity**
5. **Scalability**
6. **Modularity**

Fundamental Challenges of CPS

a non-exclusive list

1. **Architecture**
2. **Verification & Certification**
3. **Reliability**
4. **Cybersecurity**
    - guard against malicious attacks
5. **Scalability**
6. **Modularity**

Fundamental Challenges of CPS

a non-exclusive list

1. **Architecture**
2. **Verification & Certification**
3. **Reliability**
4. **Cybersecurity**
5. **Scalability**
   - capably handle increasing numbers of sensors, actuators, data, nodes, etc.
6. **Modularity**

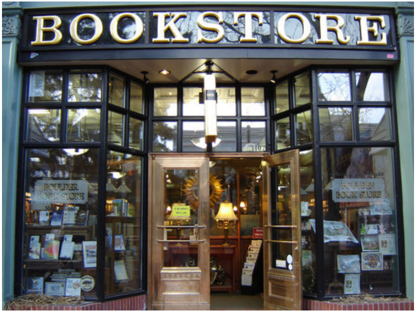
Fundamental Challenges of CPS

a non-exclusive list

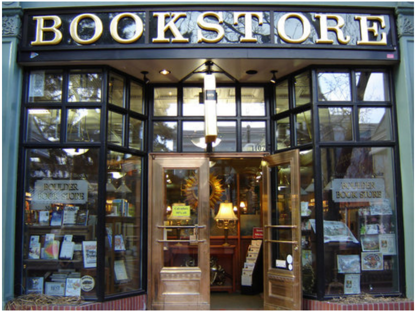
1. **Architecture**
2. **Verification & Certification**
3. **Reliability**
4. **Cybersecurity**
5. **Scalability**
6. **Modularity**
   - enables efficient assembly of CPS from constituent elements

EXAMPLES OF TRANSFORMATIVE INNOVATIONS WHEN ADDING A CYBER LAYER

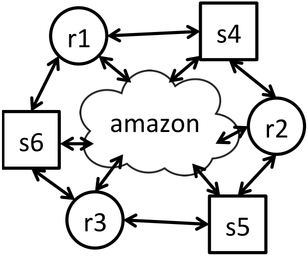
Retail



Retail

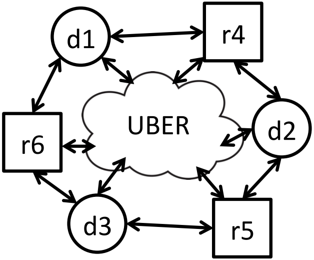

BOOKSTORE
BOULDER BOOK STORE


Cyber
amazon
Physical


r1
s4
amazon
s6
r2
r3
s5

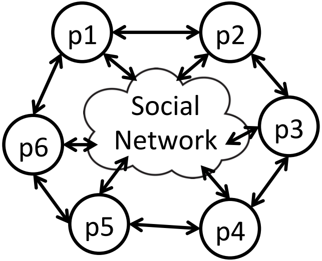
Mobility

Mobility



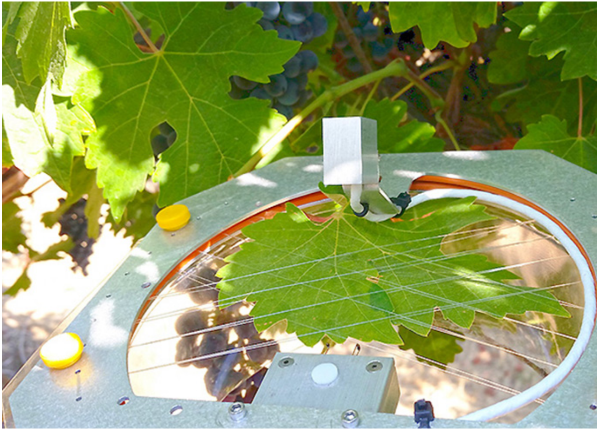
Social Interaction

Social Interaction



CPS CASE STUDIES:

Smart Agriculture Systems

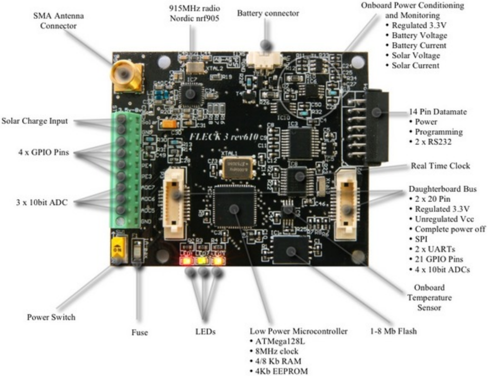


UC Davis Professor Shrini Upadhyaya's sensor to assess plant stress.

Photo credit: Diane Nelson

Sensor Networks for Pasture Monitoring

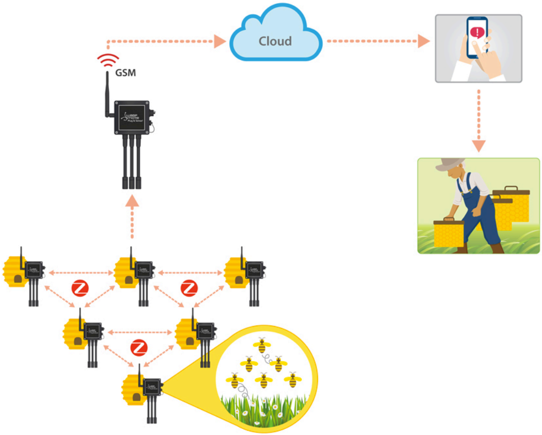
T. Wark, P. Corke, P. Sikka, L. Klingbeil, Y. Guo, C. Crossman, P. Valencia, D. Swain, G. Bishop-Hurley, IEEE Pervasive Computing

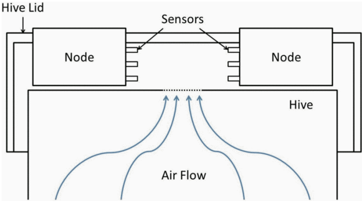


http://www.sensornets.csiro.au/deployments/684

Smart Beehives

F. E. Murphy, E. Popovici, P. Whelan, and Michele Magno,
IEEE Instrumentation and Measurement Technology Conference

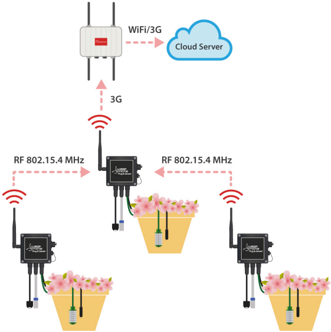




Winners of IBM Students for a Smarter Planet Competition

Greenhouse Monitoring and Irrigation

Flores en la Mesa y Libelium

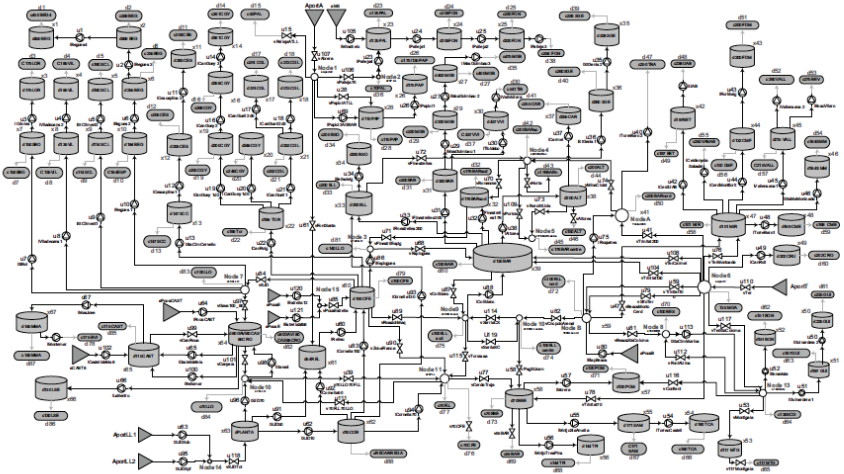


CPS CASE STUDY:

Distributed Control of Barcelona's Water Network

Pavel Trnka, Jaroslav Pekar, Vladimir Havlena, IFAC 2011

Barcelona’s Water Distribution Network



Covers 425 km^2, total length of 4470 km, 237.7 hm^3 of water to 2.8M inhabitants.

There are 67 tanks, 10 water sources, 111 valves / pumps, 88 points of water consumption and 15 complex nodes. [Trnka, Pekar, Havlena, IFAC2011]

Problem Statement

Objective

Manage water flow between supply and demand to minimize pumping costs, in the face of changes to network topology (ruptures), typical daily/weekly profiles, as well as major shifts in supply/demand.

Physical System: Water distribution network, comprised of sources, tanks, consumption points, valves & pumps.

Sensors: Smart water meters, tank levels, metrological forecasts.

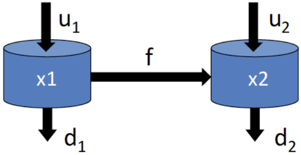
Actuators: Valves & pumps.

Data Analysis: Map demand, & supply to valve positions & pumping rates.

Distributed Optimization

Centralized Problem:

$$\begin{aligned} \min_{u_1,u_2,f} \quad & J(u_1,u_2,f) \\ \text{s. to:} \quad & u_i \in \mathcal{U}_i, \; f \in \mathcal{F} \end{aligned}$$



Separable Objective:

$$\begin{aligned} \min_{u_1,u_2,f} \quad & J(u_1,{\color{red}f}) + J(u_2,{\color{red}f}) \\ \text{s. to:} \quad & u_i \in \mathcal{U}_i, \; f \in \mathcal{F} \end{aligned}$$

d_1, d_2 : demand
u_1, u_2 : pumped supply
x_1, x_2 : tank water level
f : pumping between tanks

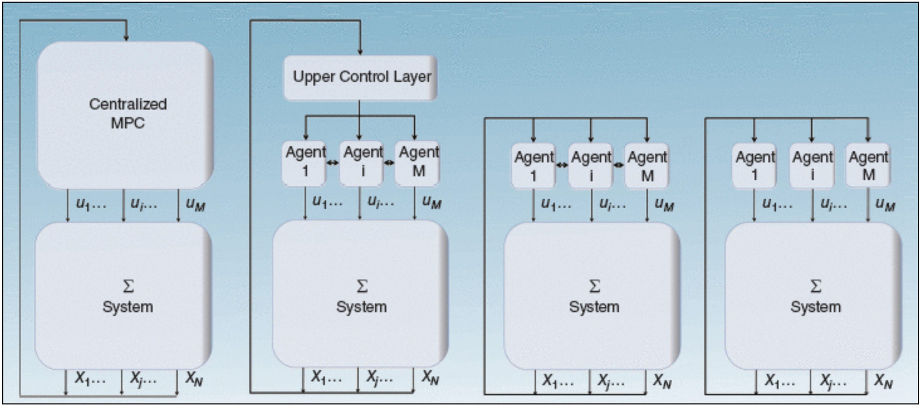
Create a Consensus Variable:

$$\begin{array}{ll|ll} \min_{u_1,f_1} & J(u_1,{\color{red}f_1}) & \min_{u_2,f_2} & J(u_2,{\color{red}f_2}) \\ \text{s. to:} & {\color{red}f_1 = f_2,} & \text{s. to:} & {\color{red}f_1 = f_2,} \\ & u_1 \in \mathcal{U}_1, \; f_1 \in \mathcal{F} & & u_2 \in \mathcal{U}_2, \; f_2 \in \mathcal{F} \end{array}$$

Voilá! Each node optimizes her own cost, while seeking consensus on shared variable f.

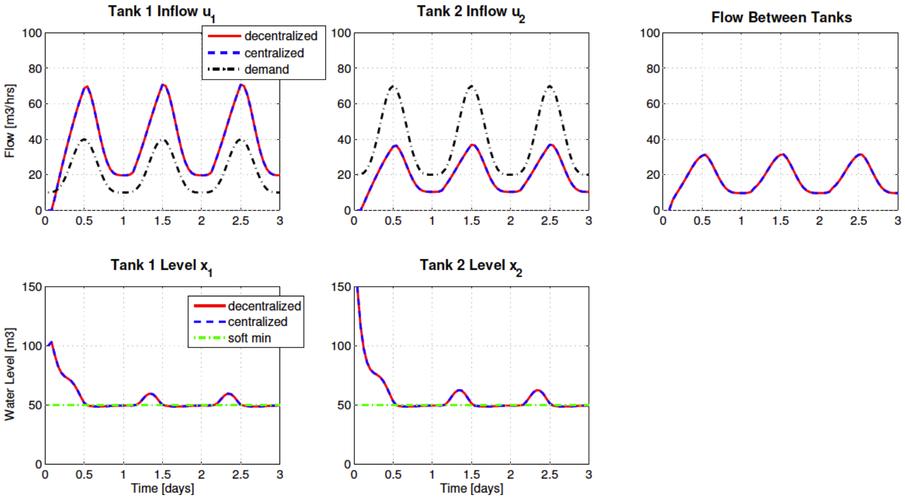
Control Architectures

[Negenborn and Maestre, 2014]

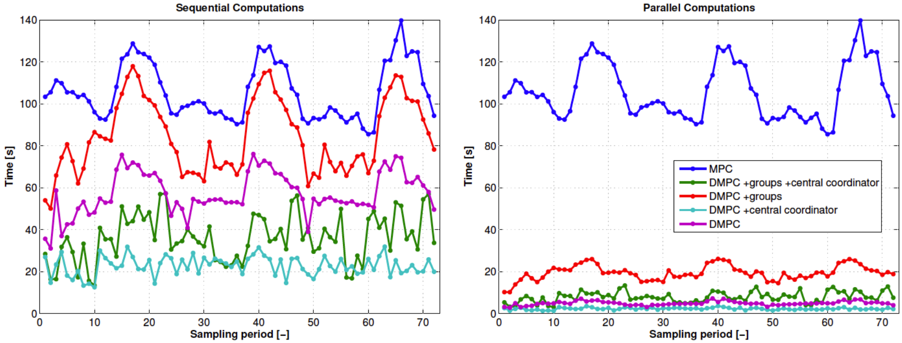


Centralized Hierarchical Distributed Distributed Decentralized

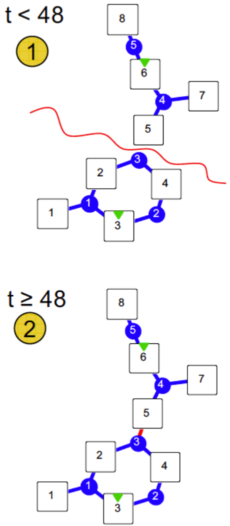
Certified Optimality



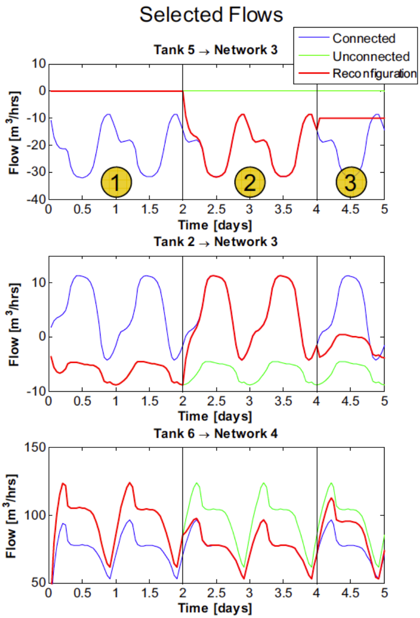
Computational Scalability



Modularity



t < 48
1
8
5
6
7
4
5
3
2
4
1
1
3
2
t ≥ 48
2
8
5
6
7
4
5
3
2
4
1
1
3
2



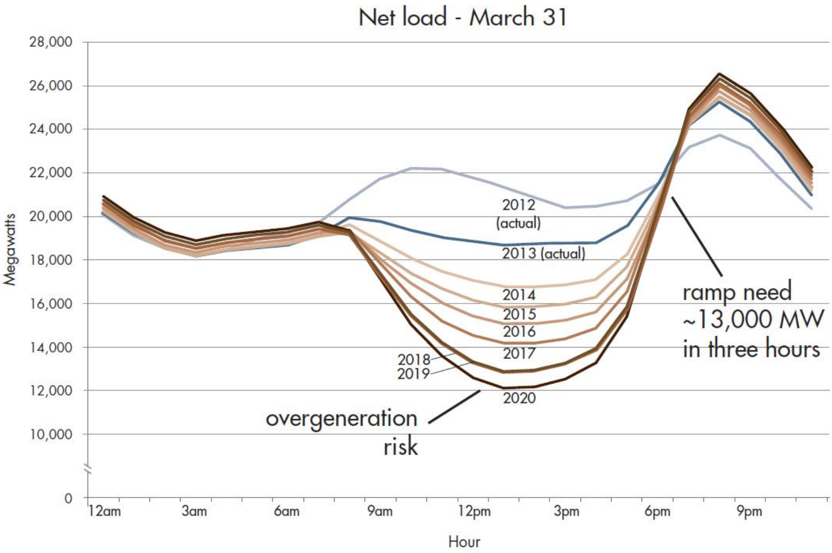
Selected Flows
Connected
Unconnected
Reconfiguration
Tank 5 → Network 3
Flow [m³/hrs]
Time [days]
1
2
3
Tank 2 → Network 3
Flow [m³/hrs]
Time [days]
Tank 6 → Network 4
Flow [m³/hrs]
Time [days]

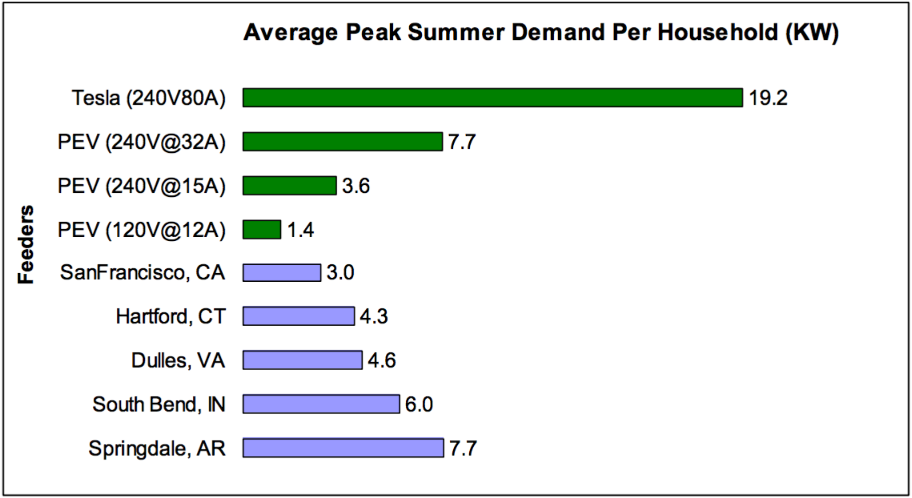
CPS CASE STUDY:

Distributed Optimal Charging of EVs for Load Shaping

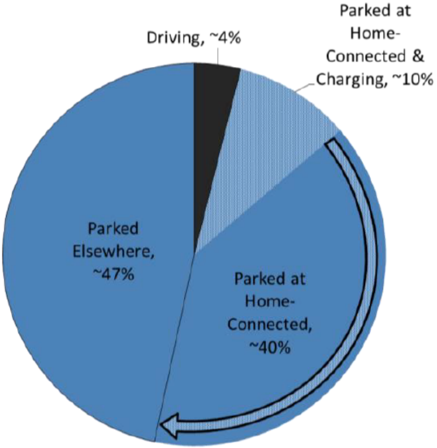
with Caroline Le Floch, Francois Belletti, Samveg Saxena, and Alexandre Bayen

The duck curve shows steep ramping needs and overgeneration risk




Average Peak Summer Demand Per Household (KW)
Feeders
Tesla (240V80A)
19.2
PEV (240V@32A)
7.7
PEV (240V@15A)
3.6
PEV (120V@12A)
1.4
SanFrancisco, CA
3.0
Hartford, CT
4.3
Dulles, VA
4.6
South Bend, IN
6.0
Springdale, AR
7.7

PEV Energy Storage: How much, when, and where?



Estimated percent of time PEVs spend by location and activity.

A. Langton and N. Crisostomo, "Vehicle-grid integration: A vision for zero-emission transportation interconnected throughout Californias electricity system," California Public Utilities Commission, Tech. Rep. R. 13-11-XXX, 2013.

Problem Statement

Objective

Optimally charge/discharge all PEVs in California to flatten the “Duck Curve,” in the face of varying net demand and personal mobility requirements.

Physical System: Population of PEVs.

Sensors: PEV battery charge levels, and energy requirements for mobility.

Actuators: Electric vehicle charge stations.

Data Analysis: Map net demand & mobility requirements to charging schedules for each PEV.

Optimal PEV Aggregator Problem

$$\begin{aligned} \min_{u} \quad & \sum_{t=1}^{T} \left(D^t + \sum_{n=1}^{N} u_n^t \right)^2 \\ \text{s. to} \quad & (1 - R_n)^T u_n = 0, \qquad \forall n,\ \forall t \\ & \underline{P}_n^t \leq u_n^t \leq \overline{P}_n^t, \qquad \forall n,\ \forall t \\ & \text{[Battery Storage Dynamics]} \end{aligned}$$

A Quadratic Program (QP)

$T \times N$ optimization variables

$T \times N$ linear equality constraints

$4T \times N$ linear inequality constraints

Optimal PEV Aggregator Problem

$$\min_{u} \quad \sum_{t=1}^{T} \left(D^t + \sum_{n=1}^{N} u_n^t \right)^2$$

$$\text{s. to} \quad (1 - R_n)^T u_n = 0, \qquad \forall n, \ \forall t$$

$$\underline{P}_n^t \leq u_n^t \leq \overline{P}_n^t, \qquad \forall n, \ \forall t$$

[Battery Storage Dynamics]

A Quadratic Program (QP)	100K EVs*, 24 hrs
$T \times N$ optimization variables	2.4M
$T \times N$ linear equality constraints	2.4M
$4T \times N$ linear inequality constraints	9.6M

*cumulative PEVs sold in CA by mid-2014

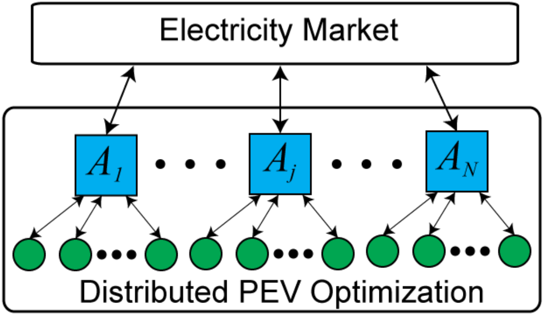
Optimal PEV Aggregator Problem

$$
\begin{aligned}
\min_{u} \quad & \sum_{t=1}^{T} \left(D^t + \sum_{n=1}^{N} u_n^t \right)^2 \\
\text{s. to} \quad & (1 - R_n)^T u_n = 0, \qquad \forall n, \ \forall t \\
& \underline{P}_n^t \leq u_n^t \leq \overline{P}_n^t, \qquad \forall n, \ \forall t \\
& \text{[Battery Storage Dynamics]}
\end{aligned}
$$

A Quadratic Program (QP)	1.5M EVs*, 24 hrs
$T \times N$ optimization variables	32M
$T \times N$ linear equality constraints	32M
$4T \times N$ linear inequality constraints	144M

*Gov. Brown 2025 ZEV Goal

Distributed Optimization via Dual Splitting



$$\max_{\mu} \frac{-\|\mu\|^2}{4} + \mu^T D \quad + \quad \sum_{n}^{N} \min_{u_n} \mu^T u_n + \sigma \|u_n\|^2$$

$$\text{s. to} \quad L_n \leq B u_n \leq M_n$$

$$A_n u_n = 0$$

μ is time-varying price incentive uniformly provided to each PEV owner.

Distributed Optimization via Dual Splitting

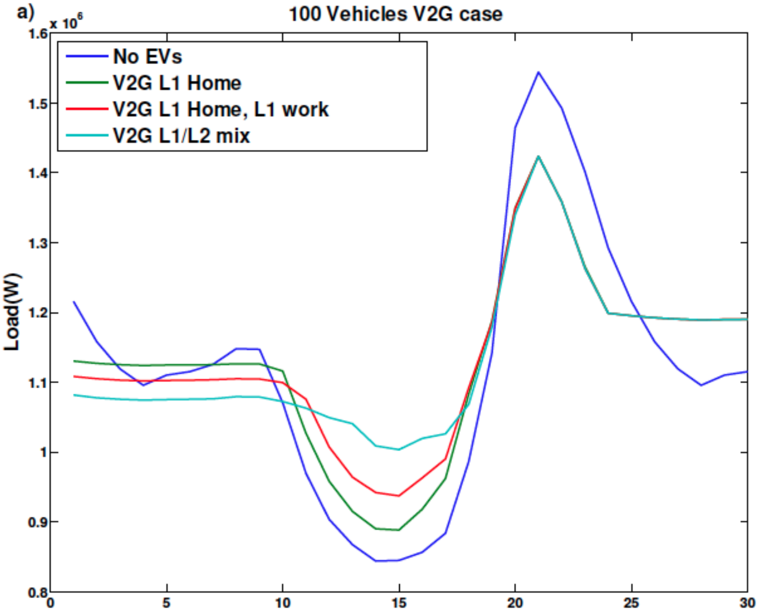
$$\max_{\mu} \frac{-\|\mu\|^2}{4} + \mu^T D \quad + \quad \sum_{n}^{N} \min_{u_n} \mu^T u_n + \sigma \|u_n\|^2$$

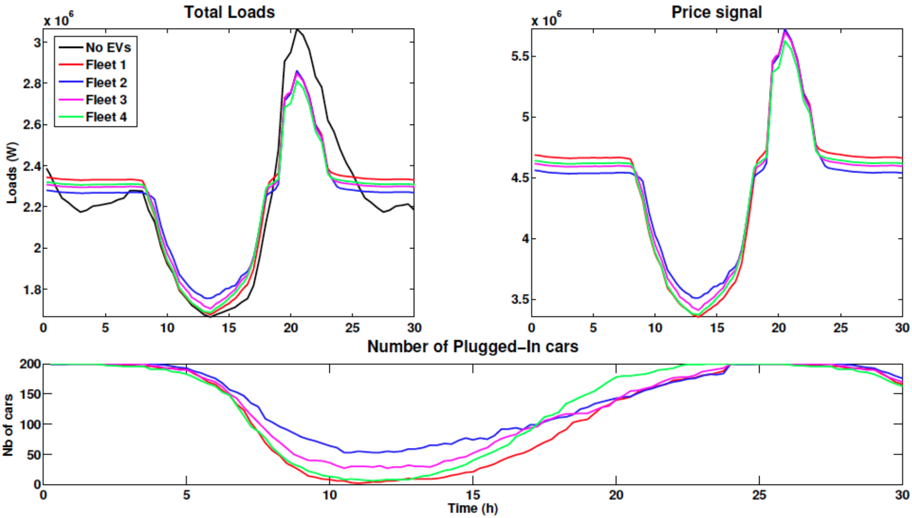
$$\text{s. to} \quad L_n \leq B u_n \leq M_n$$

$$A_n u_n = 0$$

μ is time-varying price incentive uniformly provided to each PEV owner.

Outer (Aggregator) QP	**Inner (PEV) QP (N in parallel)**
T optimization variables	T optimization variables
0 linear equality constraints	T linear equality constraints
0 linear inequality constraints	$4T$ linear inequality constraints


a)
100 Vehicles V2G case
x 10^6
No EVs
V2G L1 Home
V2G L1 Home, L1 work
V2G L1/L2 mix
Load(W)
1.6
1.5
1.4
1.3
1.2
1.1
1
0.9
0.8
0
5
10
15
20
25
30

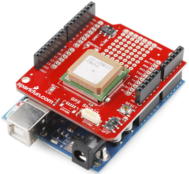


C. Le Floch, F. Belletti, S. Saxena, A. Bayen, S. J. Moura,
"Distributed Optimal Charging of Electric Vehicles for Demand Response and Load Shaping"
2015 Conference on Decision and Control, Osaka, Japan.

Project-based Course

- Fleet of eScooters
- Indoor environmental sensing node
- Smart refrigerator
- Learn to design and prototype CPS
- Berkeley Energy and Climate Lectures Curriculum Innovation Award
- Taught in Jacobs Hall


CYBER-PHYSICAL
CE 186
SYSTEMS



QUESTIONS?

Energy, Controls, and Applications Lab (eCAL)

Pubs available at ecal.berkeley.edu

smoura@berkeley.edu