SlrpEV: 
**Smart Learning Research Pilot for Electric Vehicle Charging Stations**

Professor Scott Moura  
eCAL Director  
Clare and Hsieh Wen Shen Endowed Distinguished Professor  
University of California, Berkeley

September 19, 2021
Battery Management Systems (#BATT)  
Automated, Connected, & Electric Vehicles (#ACES)  
Power Systems, Grids, Markets (#GRID)

Dynamic Systems & Control

Optimization

Data Science

eCAL Research Areas
Projects I won’t speak about

**ARPA-E NEXTCAR**
Reduce energy consumption by ≥20%
Optimal Eco-Driving thru Signalized Intersections

**Honda Research Institute**
Lane Change in Dense Traffic

**Berkeley University of California**
Model Predictive Control for Urban Adaptive Cruise Control
Outline

1. Background & Motivation
2. Overview of SlrpEV
3. Behavioral Experiments
4. Optimizing Price & Power
5. Summary
The California Example: Duck Curve

The duck curve shows steep ramping needs and overgeneration risk.

Net load - March 31

- Ramp need ~13,000 MW in three hours
- Overgeneration risk
The California Example: Duck Curve

Net load - March 31

Quack!
The Evening Charging Problem

Current challenge, potentially exacerbated by EV penetration:
• Ramp rates increase, as folks return home and charge EVs
• CO$_2$ emissions are typically highest in evening

Opportunity:
• EV charging can be controlled
Flatten the Duck Curve
Minimize Emissions

Scale 1:10,000
2M EVs

Pollution Inequity in United States:
- Non-Hispanic whites experience 17% less PM2.5 air pollution exposure than they cause.
- Blacks and Hispanics bear 56% and 63% more PM2.5 air pollution exposure than they cause.

CW Tessum, JS Apte, AL Goodkind, NZ Muller, KA Mullins, DA Paolella, S Polasky, NP Spring, SK Thakrar, JD Marchall, and JD Hill, "Inequity in consumption of goods and services adds to racial-ethnic disparities in air pollution exposure," Proceedings of the National Academy of Sciences, March 2019.
Are we electrifying transportation where it’s needed most?

[Bar chart showing U.S. household income distribution, 2017. The chart compares all households with households owning battery electric or plug-in hybrid electric vehicles. The data indicates that a higher percentage of households in the higher income brackets own battery electric or plug-in hybrid electric vehicles.]
On average, low-income communities have fewer per capita chargers.
Low-income communities have some of the longest drive times to fast charging.

Source: Tiffany Hoang, Senate Bill 1000 Staff Workshop: Electric Vehicle Charging Infrastructure Deployment Assessment, July 8, 2021.
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SMART LEARNING PILOT FOR
electric vehicle
CHARGING STATIONS
Goal & Objectives

**SlrpEV Goal:** Create next generation of workplace/public EV charging that decreases emissions, increases facility operator revenues, and decreases EV owner costs.

**Research Objective:**
- Optimize price and charging schedule by learning user preferences.
Cyber-Physical & Human System
The Physical

- **UC Berkeley**
  - 8 ports, Level 2 (~6.6 kW)
- **UC San Diego**
  - 8 ports, Level 2 (~6.6 kW)
- **SunPower Silicon Valley (San José)**
  - 10 ports, Level 2 (~6.6 kW)
Cyber-Physical & Human System

The Cyber

- 5min State Update
- Price generation
- Power Schedule

Prices

Power Schedule

Metrology Data

userID, Choice

• eCAL
• KITU SYSTEMS

Deep DAYARAMANI

Akshat JAIN

REGULAR $2.00/hr
Max power for the duration of charging.

SCHEDULED $6.00
30 miles & free parking
$1.50/hr equiv.; $3.00/hr after 1:15am

Departure Time: 1:00 pm
Range: 30 miles
09:00am to 9:00pm
0 miles to 200 miles

Save Charge Settings: 

Confirm Regular
Cyber-Physical & Human System

The Human

REGULAR
- Fixed rate in USD/hr
- Max power until unplug or top-off
- NOTE: charging power is uncontrollable load

SCHEDULED
- User provides departure time & added range
- Total cost fixed a priori
- NOTE: charging power is now controllable

If I want to shift load, then how much should you discount SCHEDULED to acquire flexibility?
Discrete Choice Model – How to model human behaviors

\[ U_j = \beta_j^T z_j + \gamma_j^T w_j + \beta_{0j} + \varepsilon_j \]

where

- \( U_j \): Utility of j-th alternative, \( j \in \{ \text{asap, flex} \} \)
- \( \beta_j \): Parameters of controlled attributes
- \( z_j \): Controlled attributes
- \( \gamma_j \): Parameters of UN-controlled attributes
- \( w_j \): Uncontrolled attributes
- \( \beta_{0j} \): Alternative specific constant
- \( \varepsilon_j \): Undefined errors

Logit Model
Assuming “perception” errors \( \varepsilon_j \) have i.i.d. Extreme Value Distribution, the prob. of choosing j-th alternative is

\[
Pr(alt j chosen) = Pr\left( \cap_{j \neq i} (U_j > U_i) \right) = \frac{e^{V_j}}{\sum_{i=1}^{J} e^{V_i}} = sm(V)
\]

where \( V_j = \beta_j^T z_j + \gamma_j^T w_j + \beta_{0j} \)
Quick Stats (5 Nov 2020 – 18 Sep 2021)

- 12.34 MWh Delivered
- 42,500 e-miles Delivered
- 647 Charging Sessions

- 80 unique users
- Choices
  - 294 REGULAR
  - 353 SCHEDULED

- 142 at UC San Diego
- 505 at UC Berkeley

- Stated Pref Survey
  - 227 responses
Vehicle User Distribution is Diverse

Distribution of Vehicles by kWh Delivered
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A Specific Case of Optimal Control for Human-Actuated Dynamic Systems

S. Bae, S. M. Han, S. J. Moura, “Modeling and Control of Human Actuated Systems,” 2nd IFAC Conference on Cyber-Physical & Human-Systems, Miami, FL, USA, 2018. IFAC Young Author Award Finalist. DOI: 10.1016/j.ifacol.2019.01.016
Really? Can you actually shift people’s choices IRL?

<table>
<thead>
<tr>
<th>CHOICE during CONTROL Period</th>
<th>CHOICE during TEST Period</th>
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<tr>
<td>Presented Price (cents/hr) during CONTROL Period</td>
<td>Presented Price (cents/hr) during TEST Period</td>
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<tr>
<td>REGULAR</td>
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<table>
<thead>
<tr>
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<tr>
<td>Avg Session Time</td>
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<td>Avg kWh</td>
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<td>$0.91/hr</td>
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<tr>
<td>Avg. schPerHr</td>
<td>$0.83/hr</td>
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</tbody>
</table>
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Expected Cost Minimization w/ Discrete Choice Model

**Expected Cost Minimization Problem**

\[
\min_{z,u} \sum_j \Pr(J = j|z) \, h_j(z, u)
\]

subject to: linear functions of \((z, u)\)

where \(z\) is incentive control, \(u\) is direct control, and \(h_j(z, u)\) is bi-convex in \((z, u)\).

**Compact Form**

\[
\min_{z,u} v^T h(z, u)
\]

where \(v_j = sm(\Theta_j z)\), \(h = [h_{flex}(z, u) \quad h_{asap}(z, u)]^T\)

Q: How to effectively and efficiently find solutions?
A: Re-formulate into multi-convex problem
Fenchel-Young Inequality

Denote log-sum-exp function as: \( lse(u) = \ln(\sum_{j \in A} \exp(u_j)) \)

The convex conjugate of is \( lse^*(v) = \max_u u^T v - lse(u) \)

Using Fenchel-Young ineq and first-order optimality condition:

\[ lse(u) + lse^*(v) - u^T v \leq 0 \iff v = sm(u) \]
Reformulation to Multi-convex Problem

\[
\min_{z,u,v} v^T h(z, u)
\]
where \( v = sm(\Theta z) \)

subject to:
\[
lse(\Theta z) + lse^*(v) - v^T(\Theta z) \leq 0
\]
where \( lse(x) = \log(\sum_j \exp(x_j)) \)

Multi-convex in \((z, u, v)\)
Apply block coordinate descent
Monte Carlo Sims

Comparison of price & power controller vs. without (first-come/first-serve)

- **41% reduction** in mean overstay time
- **38% increase** in mean net profit
- **32% increase** in mean EVs served

T. Zeng, S. Bae, B. Travacca, S. J. Moura, “Inducing Human Behavior to Maximize Operation Performance at PEV Charging Station,” *IEEE Transactions on Smart Grid*, v12, n4, pp. 3353-3363, July 2021. DOI: [10.1109/TSG.2021.3066998](https://doi.org/10.1109/TSG.2021.3066998)
Prices – encourage SCHEDULED during peak hours

- Peak tariff is 12n-5p
- Significant discount for FLEX relative to ASAP during/just-prior to peak

T. Zeng, S. Bae, B. Travacca, S. J. Moura, “Inducing Human Behavior to Maximize Operation Performance at PEV Charging Station,” *IEEE Transactions on Smart Grid*, v12, n4, pp. 3353-3363, July 2021. DOI: 10.1109/TSG.2021.3066998
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• EV Smart Charging Pilot for *incentivizing* service choice

• Cyber-Physical & *Human* system modeling framework, with *discrete choice models*

• Theoretical reformulation of optimal pricing and scheduling to convert into *multi-convex optimization program*


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California Partners for Advanced Transportation Technology