Online Optimization and Learning for Sustainable Cyber-Human-Physical Systems

Nathaniel Tucker, Ph.D.

Monday, June 27, 2022

Global Energy Transition

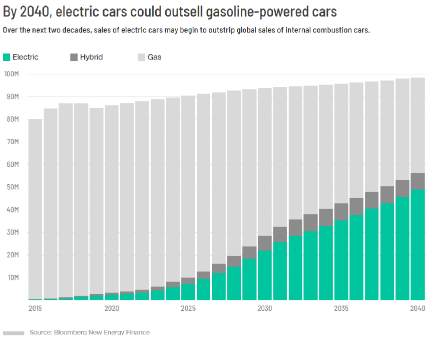
Two Major Components

Global Energy Transition

Two Major Components

Global Energy Transition

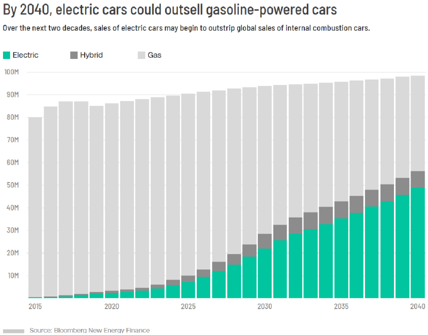
Two Major Components



Transportation Electrification

Global Energy Transition

Two Major Components

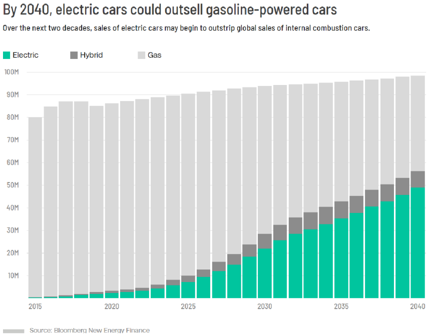


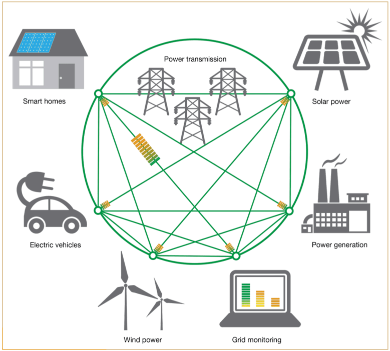
Transportation Electrification

- Infrastructure management
- Effects on the grid

Global Energy Transition

Two Major Components





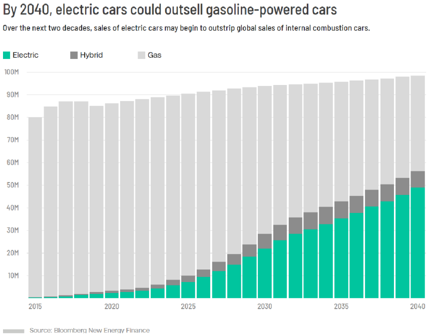
Transportation Electrification

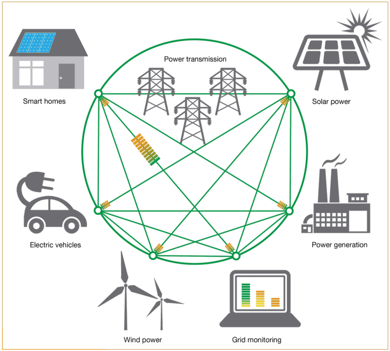
- Infrastructure management
- Effects on the grid

Grid Modernization

Global Energy Transition

Two Major Components





Transportation Electrification

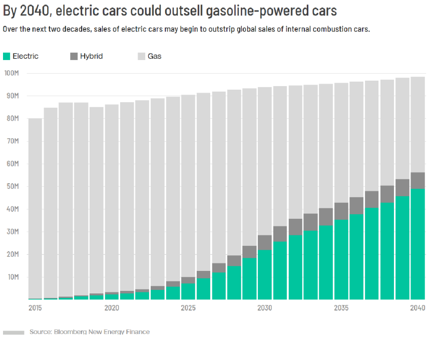
- Infrastructure management
- Effects on the grid

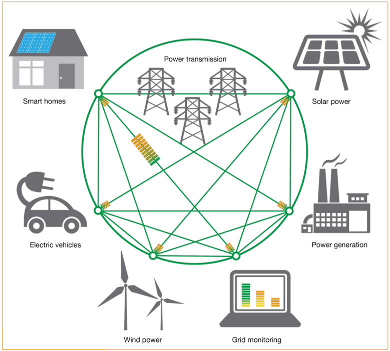
Grid Modernization

- New flexible loads
- Increased renewables

Global Energy Transition

Two Major Components





Transportation Electrification

- Infrastructure management
- Effects on the grid

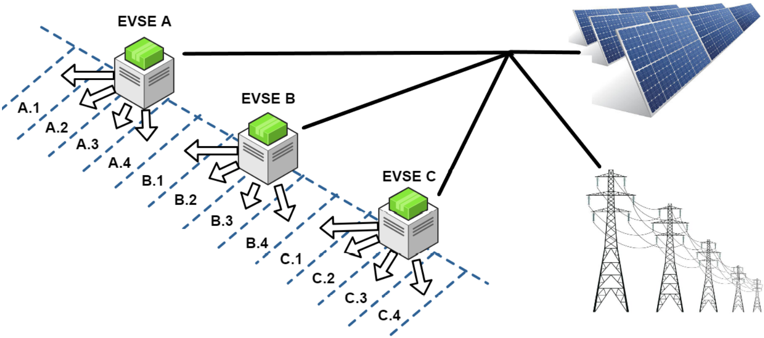
Grid Modernization

- New flexible loads
- Increased renewables

Both can benefit from optimization and learning mechanisms

Recap - Candidacy Part 1

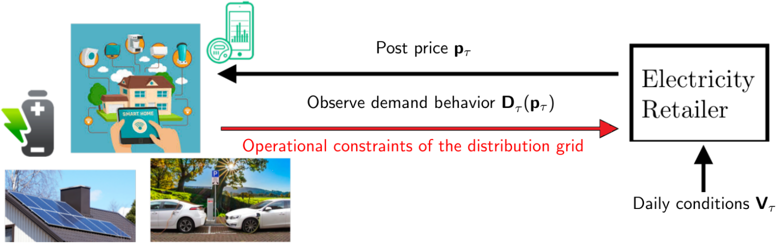
Recap - Candidacy Part 1



[Tucker, Alizadeh, IEEE TSG, '19] An Online Admission Control Mechanism for EVs at Public Parking Infrastructures

Recap - Candidacy Part 2

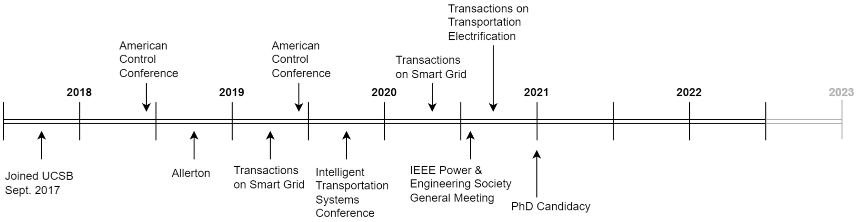
Recap - Candidacy Part 2



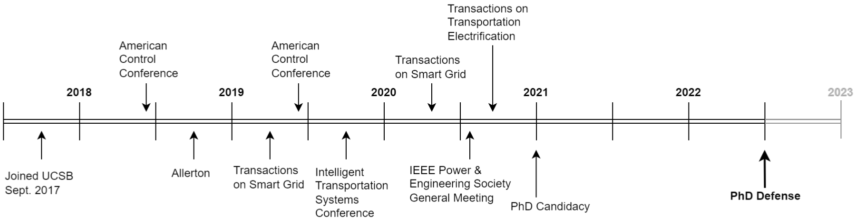
Objective: minimize expected cost $\mathbb{E}\left[f\left(\mathbf{D}_\tau(\mathbf{p}_\tau), \mathbf{V}_\tau\right)\right]$
Subject to: operational constraints of the grid

[Tucker, Moradipari, Alizadeh, IEEE TSG, '20] Constrained Thompson Sampling for Real-Time Electricity Pricing with Grid Reliability Constraints

Timeline

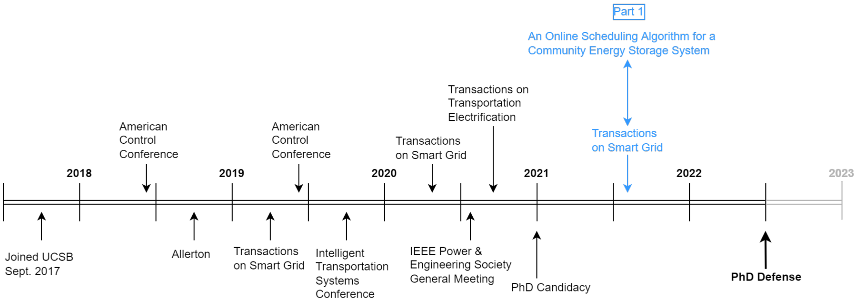

Transactions on
Transportation
Electrification
American
Control
Conference
American
Control
Conference
Transactions
on Smart Grid
2018
2019
2020
2021
2022
2023
Joined UCSB
Sept. 2017
Allerton
Transactions
on Smart Grid
Intelligent
Transportation
Systems
Conference
IEEE Power &
Engineering Society
General Meeting
PhD Candidacy

Timeline



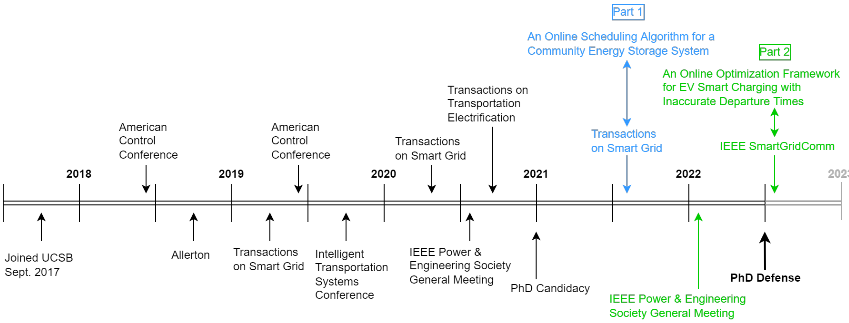
Transactions on Transportation Electrification
American Control Conference
American Control Conference
Transactions on Smart Grid
2018
2019
2020
2021
2022
2023
Joined UCSB Sept. 2017
Allerton
Transactions on Smart Grid
Intelligent Transportation Systems Conference
IEEE Power & Engineering Society General Meeting
PhD Candidacy
PhD Defense

Timeline



Part 1
An Online Scheduling Algorithm for a Community Energy Storage System
Transactions on Transportation Electrification
American Control Conference
American Control Conference
Transactions on Smart Grid
Transactions on Smart Grid
2018
2019
2020
2021
2022
2023
Joined UCSB Sept. 2017
Allerton
Transactions on Smart Grid
Intelligent Transportation Systems Conference
IEEE Power & Engineering Society General Meeting
PhD Candidacy
PhD Defense

Timeline


Part 1
An Online Scheduling Algorithm for a Community Energy Storage System
Part 2
An Online Optimization Framework for EV Smart Charging with Inaccurate Departure Times
Transactions on Transportation Electrification
American Control Conference
American Control Conference
Transactions on Smart Grid
Transactions on Smart Grid
IEEE SmartGridComm
2018
2019
2020
2021
2022
2023
Joined UCSB Sept. 2017
Allerton
Transactions on Smart Grid
Intelligent Transportation Systems Conference
IEEE Power & Engineering Society General Meeting
PhD Candidacy
PhD Defense
IEEE Power & Engineering Society General Meeting

Part 1

An Online Scheduling Algorithm for a Community Energy Storage System

Motivation

Individual Consumers/Prosumers

Motivation

Individual Consumers/Prosumers

Motivation

Individual Consumers/Prosumers

Pros:

- Lower electricity bills
- Reduce $CO2$ emissions
- Utilize larger portion of self-generated energy

Motivation

Individual Consumers/Prosumers

Pros:

- Lower electricity bills
- Reduce CO2 emissions
- Utilize larger portion of self-generated energy

Cons:

- Large upfront investment
- Low utilization (single-family home)
- Long period for ROI to breakeven

Motivation

Individual Consumers/Prosumers

Pros:

- Lower electricity bills
- Reduce CO2 emissions
- Utilize larger portion of self-generated energy

Cons:

- Large upfront investment
- Low utilization (single-family home)
- Long period for ROI to breakeven

What can be done to lower costs and increase utilization?

Energy Communities

Energy Communities

- Split investment costs
- Diversify loads
- Utilize excess renewable generation within the community

Energy Communities

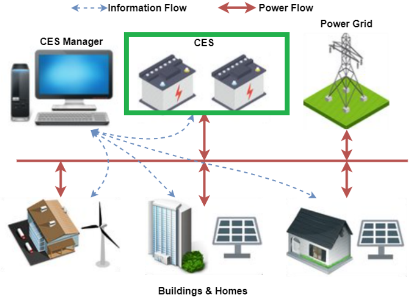
What are the main requirements for an energy community?

Energy Communities

What are the main requirements for an energy community?

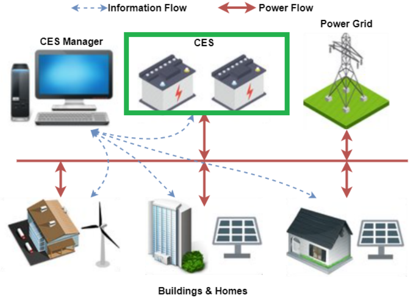
- Connected members (grid and communication)
- Distributed renewable generation
- Community energy storage system (CES)
- CES scheduling strategy

CES Resources



Limited resources:

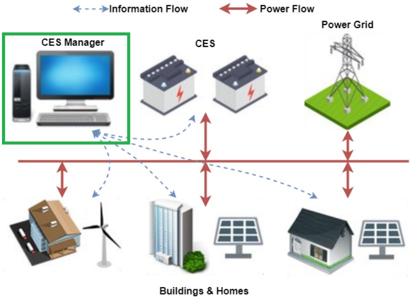
CES Resources



Limited resources:

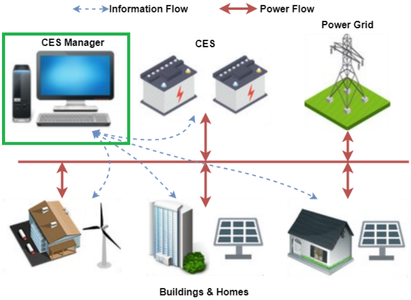
- Energy capacity, up to $\hat{E}$ kWh
- Charging power, up to $\hat{P}_c$ kW
- Discharging power, up to $\hat{P}_d$ kW

CES Objectives



CES Manager's Objectives:

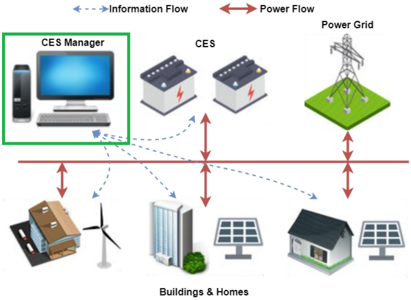
CES Objectives



CES Manager's Objectives:

- Maximize utility for community
- Recover investment cost
- Handle unknown demand, privacy concerns, real-time operation

CES Objectives



CES Manager's Objectives:

- Maximize utility for community
- Recover investment cost
- Handle unknown demand, privacy concerns, real-time operation

Online pricing mechanisms for CES reservations

Related CES Scheduling Works

- [Tushar, et al., '16],[Chen, et al., '17],[Liu, et al., '17]
    - Capacity reservation must be constant for long-term reservations
- [Zhong, et al., '20]
    - Scheduling mechanism can violate CES constraints
- [Zhao, et al., '19]
    - Prices for 'virtual' portions of the CES, but prices remain constant for the whole horizon

Related CES Scheduling Works

- [Tushar, et al., '16],[Chen, et al., '17],[Liu, et al., '17]
  - Capacity reservation must be constant for long-term reservations
- [Zhong, et al., '20]
  - Scheduling mechanism can violate CES constraints
- [Zhao, et al., '19]
  - Prices for 'virtual' portions of the CES, but prices remain constant for the whole horizon

Our Contributions:

Related CES Scheduling Works

- [Tushar, et al., '16],[Chen, et al., '17],[Liu, et al., '17]
  - Capacity reservation must be constant for long-term reservations
- [Zhong, et al., '20]
  - Scheduling mechanism can violate CES constraints
- [Zhao, et al., '19]
  - Prices for 'virtual' portions of the CES, but prices remain constant for the whole horizon

Our Contributions:

- Allow users to modify usage easily
- Uphold CES constraints
- Incentivize diverse usage patterns

Online Solution's Goals

- Design online scheduling strategy for community energy storage systems with shared charging, discharging, and capacity resources to maximize social welfare

Online Solution's Goals

- Design online scheduling strategy for community energy storage systems with shared charging, discharging, and capacity resources to maximize social welfare
- Make irrevocable scheduling decisions in an online fashion

Online Solution's Goals

- Design online scheduling strategy for community energy storage systems with shared charging, discharging, and capacity resources to maximize social welfare
- Make irrevocable scheduling decisions in an online fashion
- Post resource prices, users select to maximize own utility

Online Solution's Goals

- Design online scheduling strategy for community energy storage systems with shared charging, discharging, and capacity resources to maximize social welfare
- Make irrevocable scheduling decisions in an online fashion
- Post resource prices, users select to maximize own utility
- Payment at the time of reservation

Online Solution's Goals

- Design online scheduling strategy for community energy storage systems with shared charging, discharging, and capacity resources to maximize social welfare
- Make irrevocable scheduling decisions in an online fashion
- Post resource prices, users select to maximize own utility
- Payment at the time of reservation
- Handle adversarial request sequences (due to the unpredictable generation and demand)

Online Solution's Goals

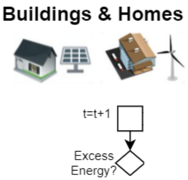
- Design online scheduling strategy for community energy storage systems with shared charging, discharging, and capacity resources to maximize social welfare
- Make irrevocable scheduling decisions in an online fashion
- Post resource prices, users select to maximize own utility
- Payment at the time of reservation
- Handle adversarial request sequences (due to the unpredictable generation and demand)
- Incentivize diverse charging/discharging schedules

Online Solution's Goals

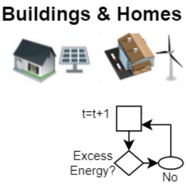
- Design online scheduling strategy for community energy storage systems with shared charging, discharging, and capacity resources to maximize social welfare
- Make irrevocable scheduling decisions in an online fashion
- Post resource prices, users select to maximize own utility
- Payment at the time of reservation
- Handle adversarial request sequences (due to the unpredictable generation and demand)
- Incentivize diverse charging/discharging schedules
- Provide performance guarantees

System Description - Flow Chart

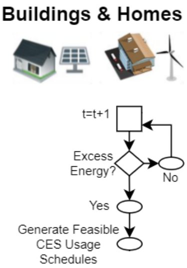
System Description - Flow Chart



System Description - Flow Chart



System Description - Flow Chart



User Characteristics

- Users want to store energy to be used at a later time (from cheap TOU rates or from excess solar generation)
- Potential schedules that benefit user n: $s \in \mathcal{S}_n$

User Characteristics

- Users want to store energy to be used at a later time (from cheap TOU rates or from excess solar generation)
- Potential schedules that benefit user n: $s \in \mathcal{S}_n$
- t_n^-: Start time
- t_{ns}^+: End time
- $i_{nsc}(t)$: Charge/discharge schedule (+ charging, - discharging)
- $i_{nse}(t)$: Energy capacity reservation
- v_{ns}: Valuation

Valuations

Example valuation from free solar generation:
(Value of replacing grid energy with free solar)

$$v_{ns} = -\sum_t p_{\mathrm{grid}}(t) i_{nsc}(t)|_{i_{nsc}(t)<0}$$

Valuations

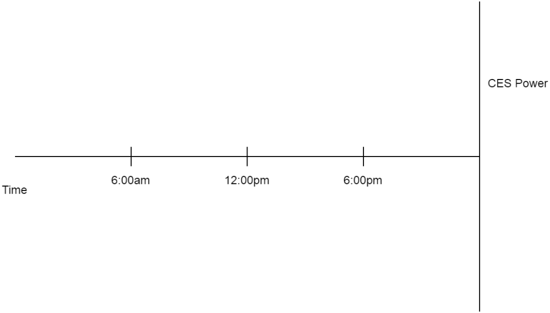
Example valuation from free solar generation:
(Value of replacing grid energy with free solar)

$$v_{ns} = -\sum_t p_{\mathrm{grid}}(t) i_{nsc}(t)|_{i_{nsc}(t)<0}$$

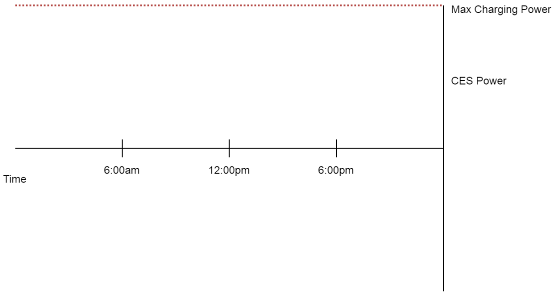
Example valuation from TOU energy arbitrage:
(Value of buying cheap grid energy for later use)

$$\begin{aligned} v_{ns} = &-\sum_t p_{\mathrm{grid}}(t) i_{nsc}(t)|_{i_{nsc}(t)<0} \\ &-\sum_t p_{\mathrm{grid}}(t) i_{nsc}(t)|_{i_{nsc}(t)>0} \end{aligned}$$

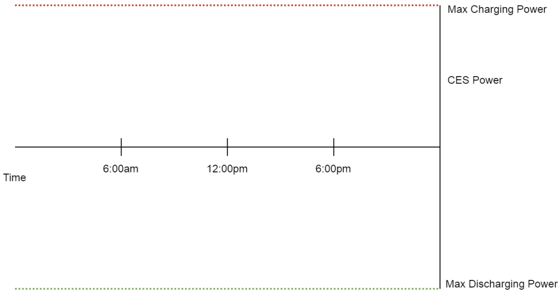
Example



Example

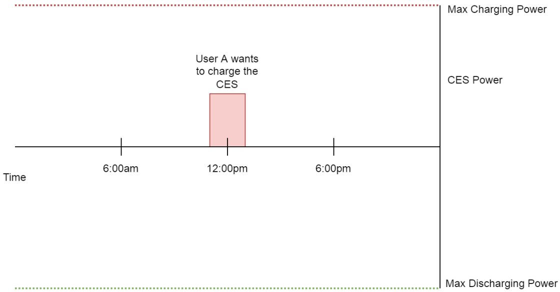


Example

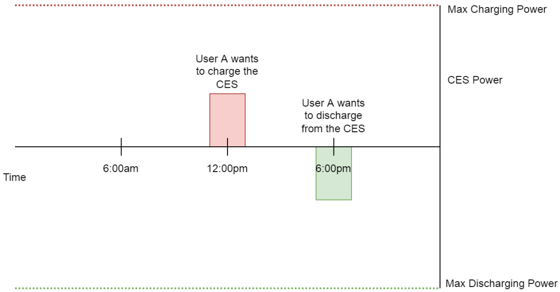


Max Charging Power
CES Power
Time
6:00am
12:00pm
6:00pm
Max Discharging Power

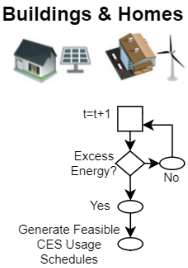
Example


Max Charging Power
User A wants
to charge the
CES
CES Power
6:00am
12:00pm
6:00pm
Time
Max Discharging Power

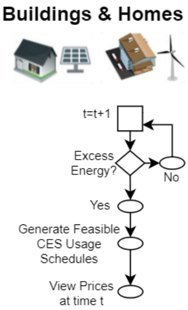
Example


Max Charging Power
User A wants to charge the CES
CES Power
User A wants to discharge from the CES
Time
6:00am
12:00pm
6:00pm
Max Discharging Power

System Description - Flow Chart



System Description - Flow Chart



Proposed Solution: Online Pricing/Remuneration Heuristic

- Determine the prices for the shared resources as requests arrive

Proposed Solution: Online Pricing/Remuneration Heuristic

- Determine the prices for the shared resources as requests arrive
- Proposed Solution: the prices $p_e(t)$, $p_c(t)$, and $p_d(t)$ have heuristic updating functions

Proposed Solution: Online Pricing/Remuneration Heuristic

- Determine the prices for the shared resources as requests arrive
- Proposed Solution: the prices $p_e(t)$, $p_c(t)$, and $p_d(t)$ have heuristic updating functions
- Example payment for schedule s:

$$\widetilde{p}_{ns^\star} = \sum_{\mathcal{T}} \left[i_{nse}(t) p_e(t) + i_{nsc}(t) p_c(t) + i_{nsc}(t) p_d(t) \right]$$

Proposed Solution: Online Pricing/Remuneration Heuristic

- Determine the prices for the shared resources as requests arrive
- Proposed Solution: the prices $p_e(t)$, $p_c(t)$, and $p_d(t)$ have heuristic updating functions
- Example payment for schedule s:

$$\widetilde{p}_{ns^\star} = \sum_{\mathcal{T}} \left[i_{nse}(t) p_e(t) + i_{nsc}(t) p_c(t) + i_{nsc}(t) p_d(t) \right]$$

- We are able to provide performance guarantees for pricing functions of the following form:

Proposed Solution: Online Pricing/Remuneration Heuristic

- Determine the prices for the shared resources as requests arrive
- Proposed Solution: the prices $p_e(t)$, $p_c(t)$, and $p_d(t)$ have heuristic updating functions
- Example payment for schedule s:

$$\widetilde{p}_{ns^\star} = \sum_{\mathcal{T}} \left[i_{nse}(t) p_e(t) + i_{nsc}(t) p_c(t) + i_{nsc}(t) p_d(t) \right]$$

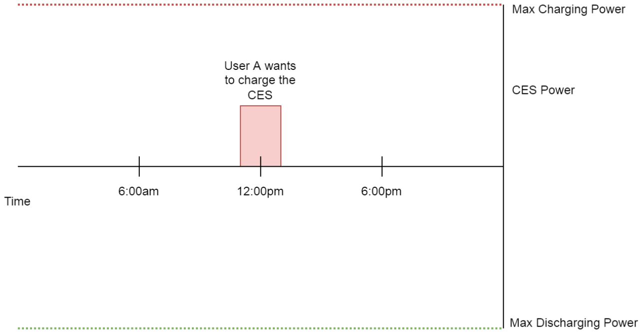
- We are able to provide performance guarantees for pricing functions of the following form:

$$p_e(t) = \left(\frac{L_e}{R}\right)\left(\frac{RU_e}{L_e}\right)^{\frac{y_e(t)}{\hat{E}}}, \qquad y_e(t) \in [0, \hat{E}],$$

$$p_c(t) = \left(\frac{L_c}{R}\right)\left(\frac{RU_c}{L_c}\right)^{\frac{y_c(t)}{\hat{P}_c}}, \qquad y_c(t) \in [-\hat{P}_d, \hat{P}_c],$$

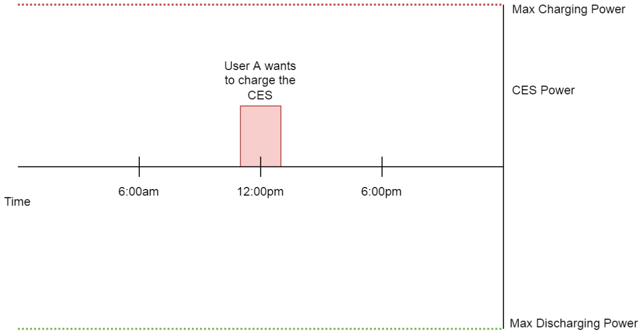
$$p_d(t) = \left(\frac{L_d}{R}\right)\left(\frac{RU_d}{L_d}\right)^{\frac{-y_c(t)}{\hat{P}_d}}, \qquad y_c(t) \in [-\hat{P}_d, \hat{P}_c].$$

Example



User A pays:
$P_c(12:00pm)$

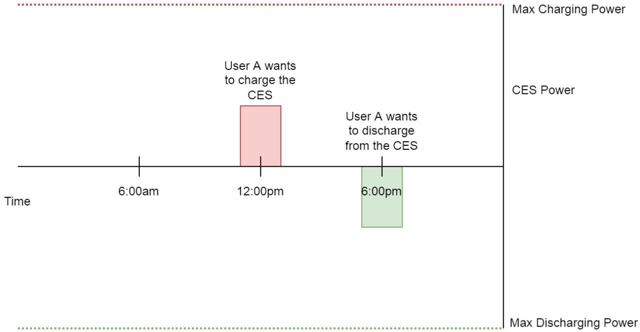
Example



User A pays:

$P_c(12:00pm)$ - $P_d(12:00pm)$

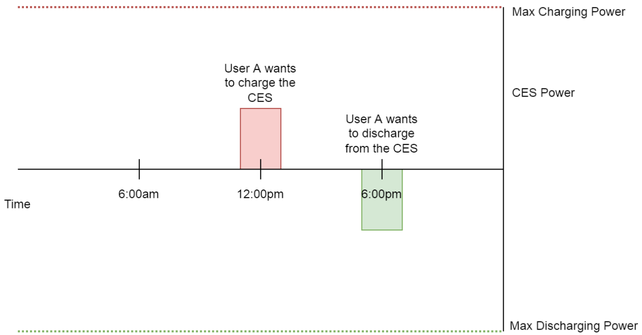
Example



User A pays:

$P_c(12:00pm)$ - $P_d(12:00pm) + P_d(6:00pm)$

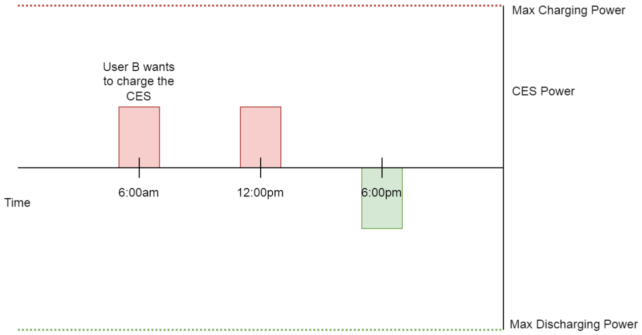
Example



User A pays:

$P_c(12:00pm)$ - $P_d(12:00pm)$ + $P_d(6:00pm)$ - $P_c(6:00pm)$

Example



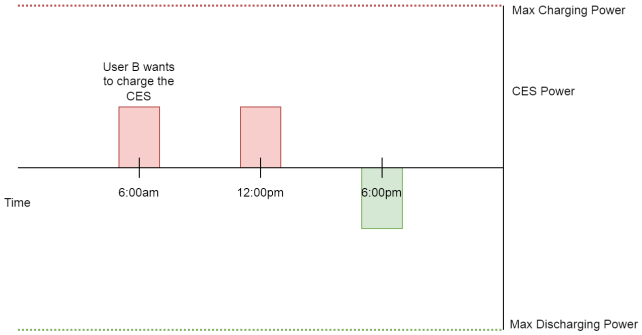
User A pays:

$P_c(12:00pm)$ - $P_d(12:00pm)$ $+$ $P_d(6:00pm)$ - $P_c(6:00pm)$

User B pays:

$P_c(6:00am)$

Example



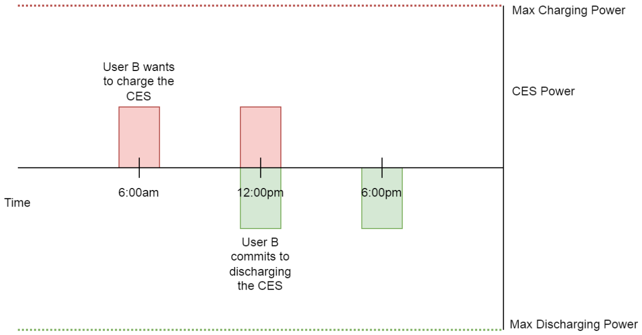
User A pays:

$P_c(12:00pm)$ - $P_d(12:00pm)$ + $P_d(6:00pm)$ - $P_c(6:00pm)$

User B pays:

$P_c(6:00am)$ - $P_d(6:00am)$

Example



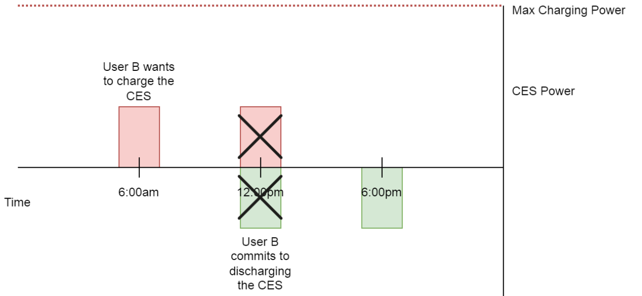
User A pays:

$P_c(12:00pm)$ - $P_d(12:00pm)$ + $P_d(6:00pm)$ - $P_c(6:00pm)$

User B pays:

$P_c(6:00am)$ - $P_d(6:00am)$ + $P_d(12:00pm)$ - $P_c(12:00pm)$

Example



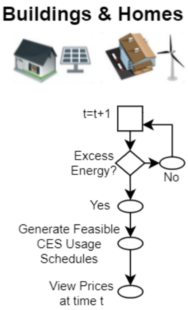
User A pays:

$P_c(12:00pm)$ - $P_d(12:00pm)$ + $P_d(6:00pm)$ - $P_c(6:00pm)$

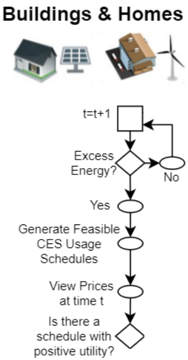
User B pays:

$P_c(6:00am)$ - $P_d(6:00am)$ + $P_d(12:00pm)$ - $P_c(12:00pm)$

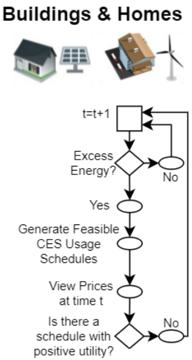
System Description - Flow Chart



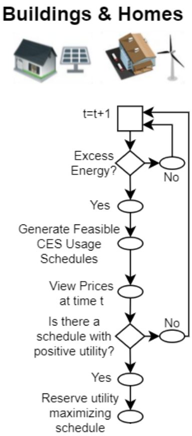
System Description - Flow Chart



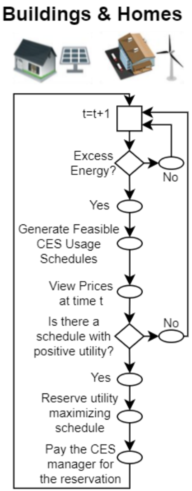
System Description - Flow Chart



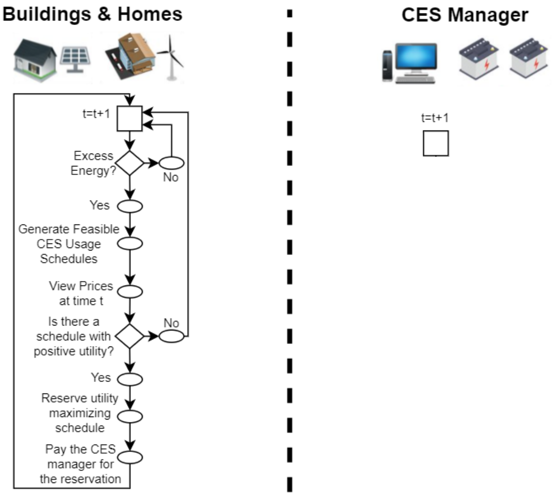
System Description - Flow Chart



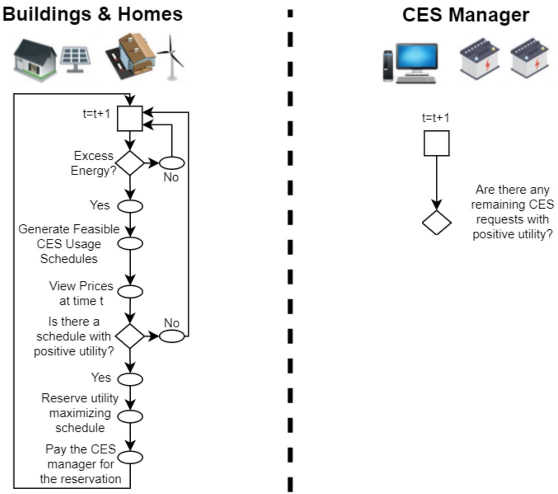
System Description - Flow Chart



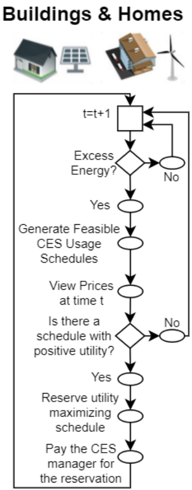
System Description - Flow Chart

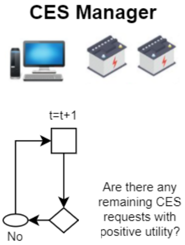


System Description - Flow Chart

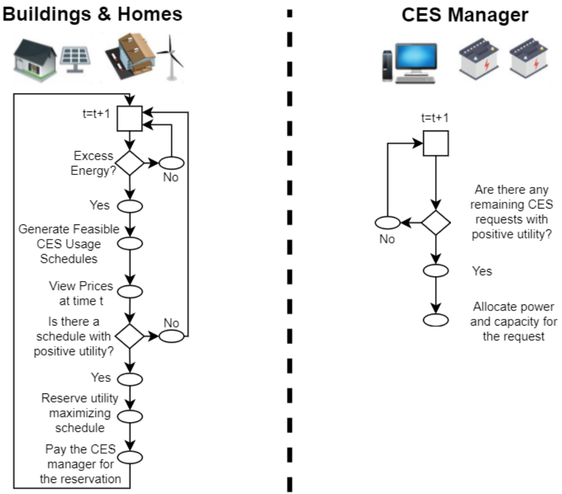


System Description - Flow Chart

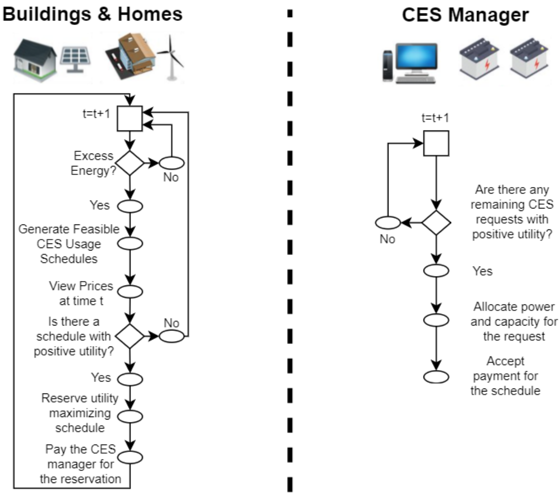




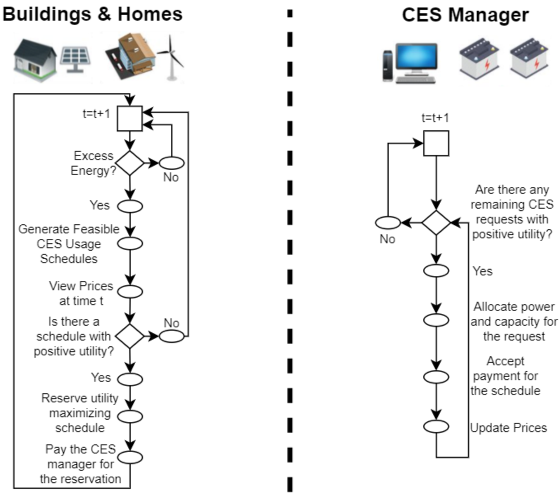
System Description - Flow Chart



System Description - Flow Chart



System Description - Flow Chart



Offline Formulation

$$\max_{x} \sum_{\mathcal{N},\mathcal{S}_n} v_{ns} x_{ns}$$

subject to:

$$x_{ns} \in \{0,1\}, \qquad \forall n \in \mathcal{N}, s \in \mathcal{S}_n$$

$$\sum_{\mathcal{S}_n} x_{ns} \leq 1, \qquad \forall n \in \mathcal{N}$$

$$y_e(t) \leq \hat{E}, \qquad \forall t \in \mathcal{T}$$

$$y_c(t) \leq \hat{P}_c, \qquad \forall t \in \mathcal{T}$$

$$y_c(t) \geq -\hat{P}_d, \qquad \forall t \in \mathcal{T}$$

where:

$$y_e(t) = \sum_{\mathcal{N},\mathcal{S}_n} i_{nse}(t) x_{ns}$$

$$y_c(t) = \sum_{\mathcal{N},\mathcal{S}_n} i_{nsc}(t) x_{ns}$$

Performance Guarantee: Competitive Ratio

- Competitive ratio:

$$\frac{\text{Optimal Offline Solution's Social Welfare}}{\text{Worst Case[Online Mechanism's Social Welfare]}} \geq 1$$

Performance Guarantee: Competitive Ratio

- Competitive ratio:

$$\frac{\text{Optimal Offline Solution's Social Welfare}}{\text{Worst Case[Online Mechanism's Social Welfare]}} \geq 1$$

- An online mechanism is "α-competitive" when:

$$\alpha \geq \frac{\text{Optimal Offline Solution's Social Welfare}}{\text{Worst Case[Online Mechanism's Social Welfare]}} \geq 1$$

Proof Outline

- Ensure that the "social welfare generated" by each CES reservation is above a "threshold value"

Proof Outline

- Ensure that the "social welfare generated" by each CES reservation is above a "threshold value"
- Show the online marginal pricing functions, fenchel conjugates, and facilities' operational cost functions satisfy the following *Differential Allocation-Payment Relationship*:

$$\big(p(t) - f'(y(t))\big)\mathrm{d}y(t) \geq \frac{1}{\alpha(t)} f^{*'}(p(t))\mathrm{d}p(t)$$

Proof Outline

- Ensure that the "social welfare generated" by each CES reservation is above a "threshold value"
- Show the online marginal pricing functions, fenchel conjugates, and facilities' operational cost functions satisfy the following *Differential Allocation-Payment Relationship*:

$$\big(p(t) - f'(y(t))\big)\mathrm{d}y(t) \geq \frac{1}{\alpha(t)} {f^*}'(p(t))\mathrm{d}p(t)$$

"Social welfare generated" $\geq$ "Threshold value"

Proof Outline

- Ensure that the "social welfare generated" by each CES reservation is above a "threshold value"
- Show the online marginal pricing functions, fenchel conjugates, and facilities' operational cost functions satisfy the following *Differential Allocation-Payment Relationship*:

$$\big(p(t) - f'(y(t))\big)\mathrm{d}y(t) \geq \frac{1}{\alpha(t)} f^{*'}(p(t))\mathrm{d}p(t)$$

"Social welfare generated" $\geq$ "Threshold value"

- Resulting competitive ratio is the maximum $\alpha(t)$ over all resources and time.

Proof Outline

The *Generalized Differential Allocation-Payment Relationship* for the payment and remuneration of two coupled resources (resources *a* and *b*) for a given parameter $\alpha \geq 1$ is:

$$\begin{aligned}&\big[p_a(t) - f_a'(y_a(t))\big]\mathrm{d}y_a(t) + \big[p_b(t) - f_b'(y_b(t))\big]\mathrm{d}y_b(t) \\ &\geq \frac{1}{\alpha(t)}\Big[f_a^{*'}(p_a(t))\mathrm{d}p_a(t) + f_b^{*'}(p_b(t))\mathrm{d}p_b(t)\Big]\end{aligned}$$

Proof Outline

The *Generalized Differential Allocation-Payment Relationship* for the payment and remuneration of two coupled resources (resources *a* and *b*) for a given parameter $\alpha \geq 1$ is:

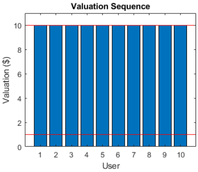
$$\left[p_a(t) - f_a'(y_a(t))\right]\mathrm{d}y_a(t) + \left[p_b(t) - f_b'(y_b(t))\right]\mathrm{d}y_b(t)$$
$$\geq \frac{1}{\alpha(t)}\left[f_a^{*'}(p_a(t))\mathrm{d}p_a(t) + f_b^{*'}(p_b(t))\mathrm{d}p_b(t)\right]$$

Competitive Ratio

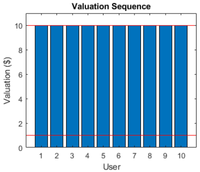
The CES schedules generated by our pricing functions are α-competitive in welfare over N usage requests:

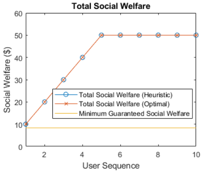
$$\boxed{\alpha = \ln\left(\frac{RU_{c,d}}{L_{c,d}}\right)}$$

Example Input Sequences

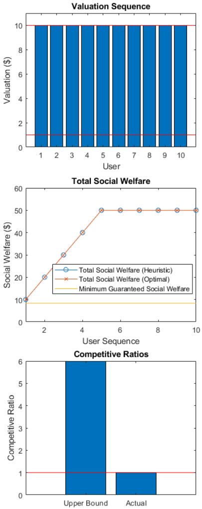


Example Input Sequences

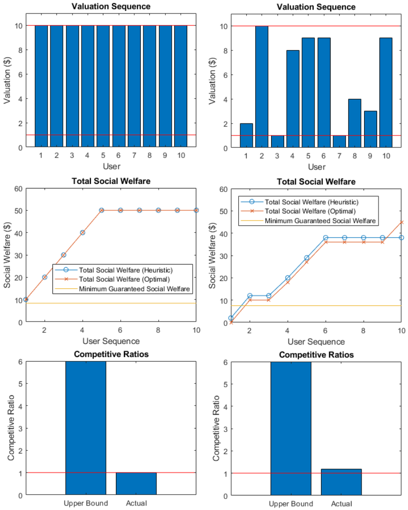




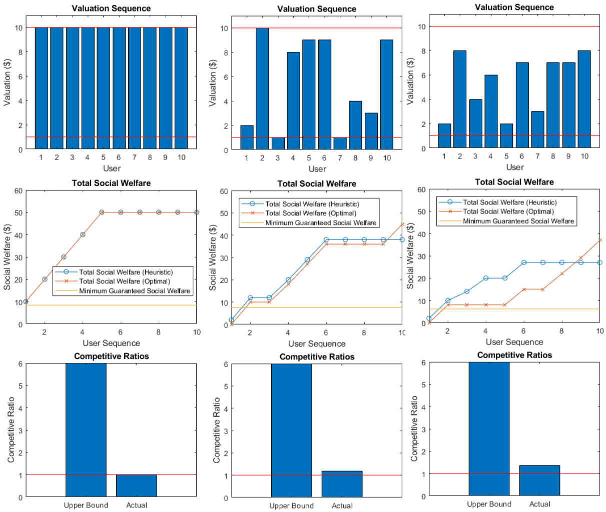
Example Input Sequences



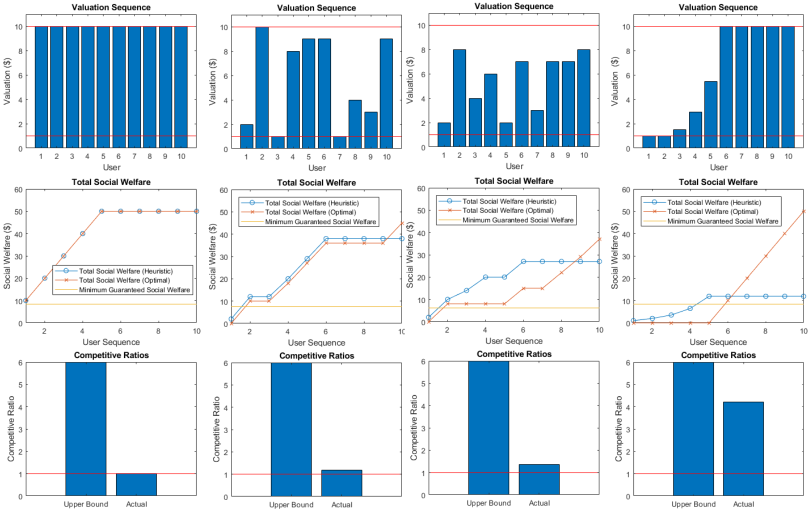
Example Input Sequences



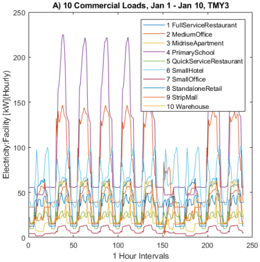
Example Input Sequences



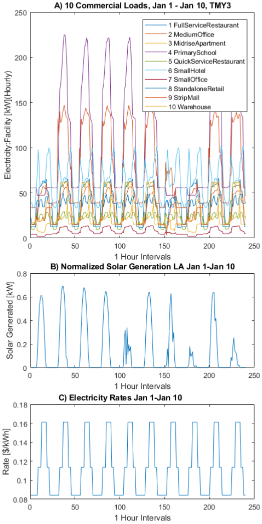
Example Input Sequences



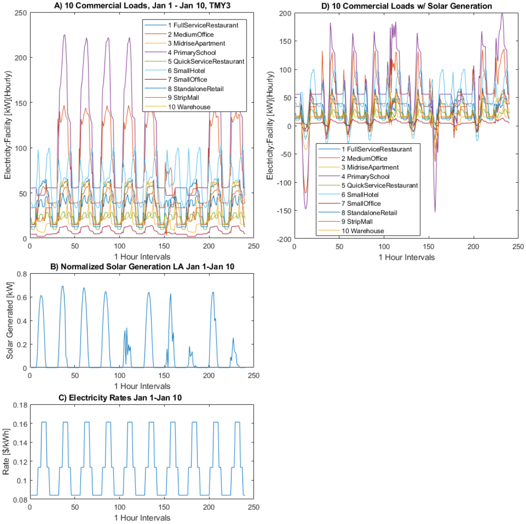
Los Angeles Case Study



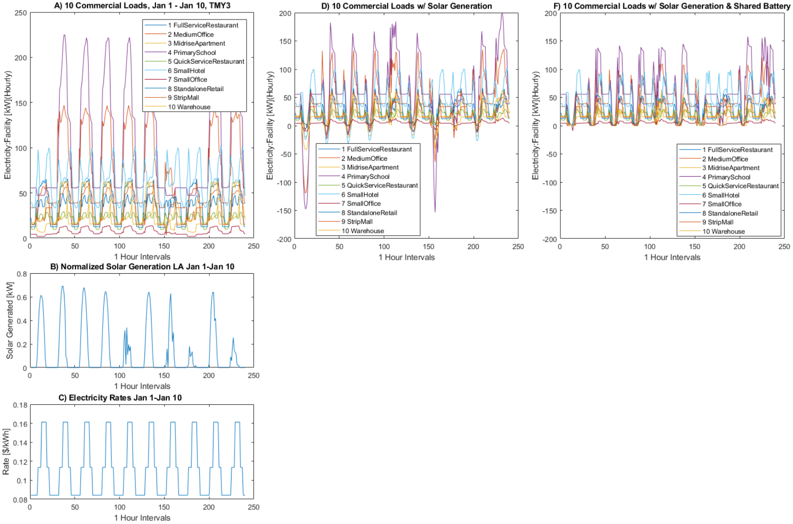
Los Angeles Case Study



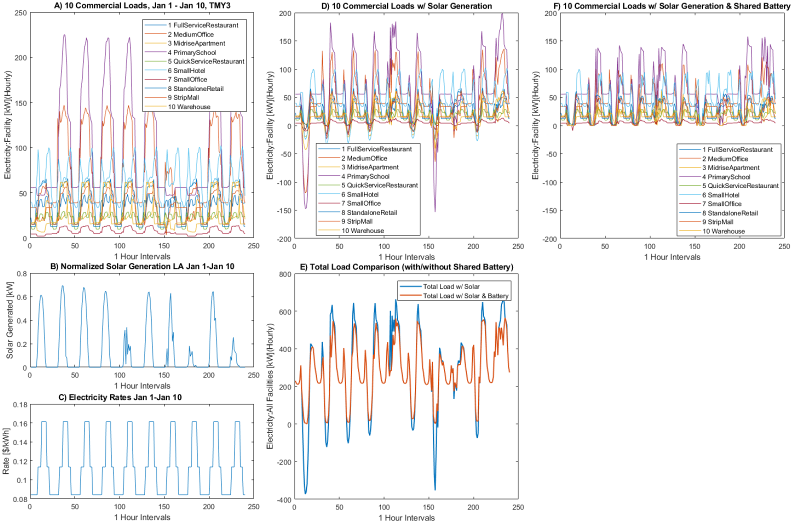
Los Angeles Case Study



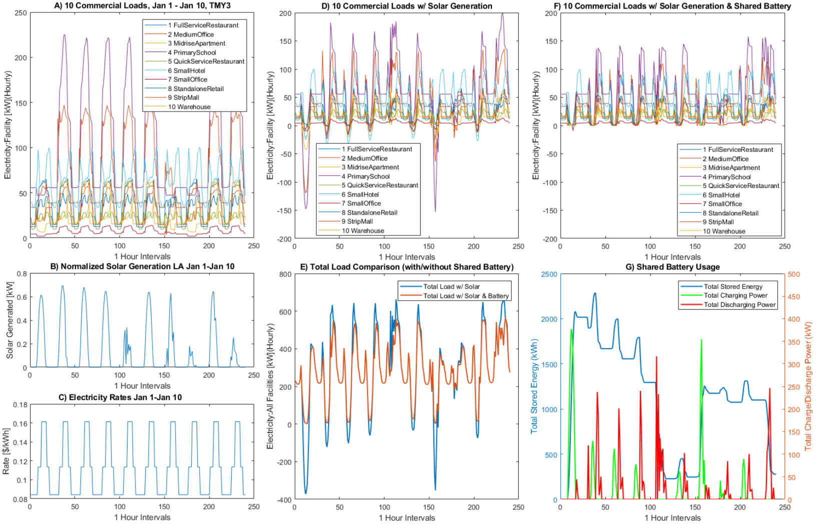
Los Angeles Case Study



Los Angeles Case Study



Los Angeles Case Study



Recap Part 1

Online scheduling strategy for community energy storage systems via heuristic pricing functions in order to maximize social welfare:

Recap Part 1

Online scheduling strategy for community energy storage systems via heuristic pricing functions in order to maximize social welfare:

1. Shared resource manager that optimizes CES usage

Recap Part 1

Online scheduling strategy for community energy storage systems via heuristic pricing functions in order to maximize social welfare:

1. Shared resource manager that optimizes CES usage
2. Promotes diverse charging/discharging patterns

Recap Part 1

Online scheduling strategy for community energy storage systems via heuristic pricing functions in order to maximize social welfare:

1. Shared resource manager that optimizes CES usage
2. Promotes diverse charging/discharging patterns
3. Robust to adversarially chosen request sequences and is α-competitive in social welfare to the optimal offline solution

Part 2

Real-World Implementations

Projects

Collaboration w/ SLAC, Stanford, UCSB, Google, CEC

Projects

Collaboration w/ SLAC, Stanford, UCSB, Google, CEC

- Benefits of coordinated EV charging at workplaces
- SLAC & Google campuses
- PESGM 2022, SGC 2022

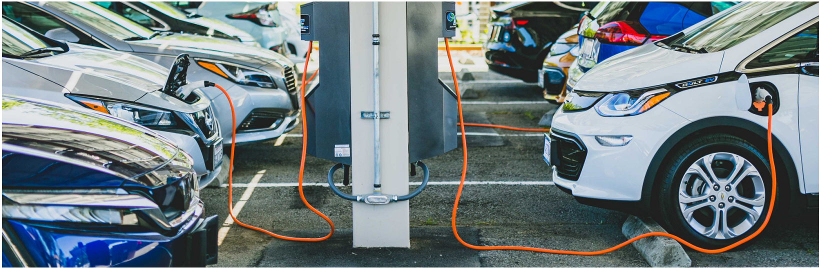
Projects

Collaboration w/ SLAC, Stanford, UCSB, Google, CEC

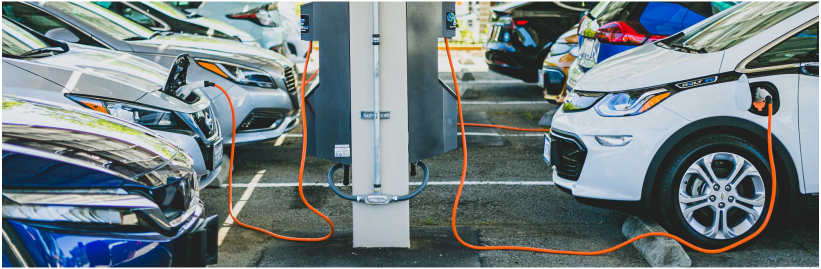
- Benefits of coordinated EV charging at workplaces
- SLAC & Google campuses
- PESGM 2022, SGC 2022

- Optimize charge and routes of an EV bus fleet
- Stanford Marguerite Shuttle
- PESGM 2020

EV Smart Charging at Large-Scale Facilities



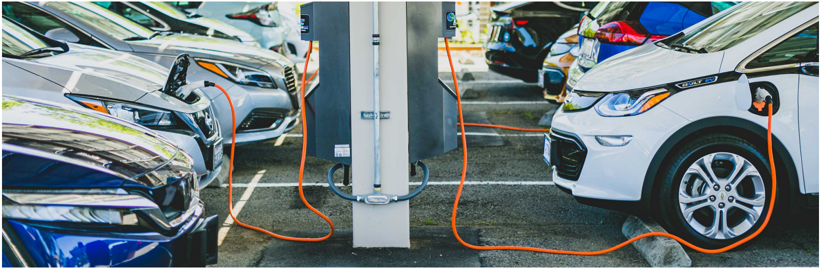
EV Smart Charging at Large-Scale Facilities



- 2012: 120,000 EVs sold

2022 Global EV Outlook, International Energy Agency (IEA)

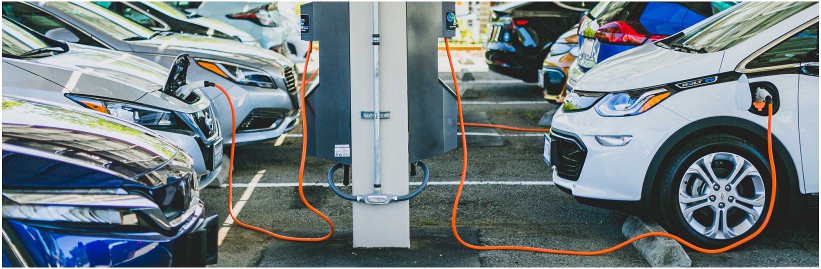
EV Smart Charging at Large-Scale Facilities



- 2012: 120,000 EVs sold
- 2021: 120,000 EVs sold per week

2022 Global EV Outlook, International Energy Agency (IEA)

EV Smart Charging at Large-Scale Facilities



- 2012: 120,000 EVs sold
- 2021: 120,000 EVs sold per week

Smart charging is increasingly critical for large-scale facilities (e.g., workplaces, apartment complexes, shopping centers, airports, fleet depots, etc.)

2022 Global EV Outlook, International Energy Agency (IEA)

SLAC & Google Datasets

Collaboration with the GISMO group at SLAC, have access to a large historical EV charging dataset:

- Workplaces throughout the Bay Area
- Most sessions exhibit typical workplace behavior
- 15-minute interval data for over 10,000 sessions
- Start times, end times, 15 minute avg. power delivered, total energy delivered, etc.

Opportunity to showcase the benefits of various smart charging strategies

Smart Charging Objectives

EV owner utility	$u_{OU}(e) = \sum_i \log(\sum_t e_i(t) + 1)$
Quick charge	$u_{QC}(e) = \sum_t \frac{T-t+1}{T} \sum_i e_i(t)$
Profit	$u_{PM}(e) = q \sum_t \sum_i e_i(t) - \sum_t p(t)\Big(\sum_i e_i(t) + z(t)\Big)$
Demand charges	$u_{DC}(e) = -\hat{p} \cdot \max_t \left(\sum_i e_i(t) + z(t)\right)$
Load flattening	$u_{LF}(e) = -\sum_t \left(\sum_i e_i(t) + z(t)\right)^2$
Equal sharing	$u_{ES}(e) = -\sum_{t,i} e_i(t)^2$
Energy demand	$u_{ED}(e) = -\sum_i \Bigg(\lvert \sum_t e_i(t) - d_i \rvert \Bigg)$

Offline Objective + Constraints

$$\max_e U(e) = \max_e \sum_{f=1}^{F} w_f \, u_f(e)$$

Offline Objective + Constraints

$$\max_e U(e) = \max_e \sum_{f=1}^{F} w_f u_f(e)$$

subject to:

$$
\begin{aligned}
&0 \leq e_i(t) \leq e_{max}, && \forall t, i \\
&e_i(t) = 0, && \forall t \notin [t_i^a, t_i^d] \\
&\sum_t e_i(t) \leq d_i, && \forall i \\
&\sum_i e_i(t) \leq e_{trans}, && \forall t
\end{aligned}
$$

Implementation Challenges

- Real-world systems with human users
- Operate in real-time without knowledge of future
- Adapt as more information is revealed
- Infrastructure constraints coupling all charging profiles
- Limited information from the EV
- Inaccurate information from the EV
  - 18.6% percentage error in user predicted departure times[1]

[1] [Lee, Sharma, Low, '21] Research Tools for Smart EV Charging

Test Case 1: User Utility Maximization with TOU Rates

- Facility manager $\rightarrow$ maximize user utility under TOU electricity rates
- A large company campus who wants to provide free and effective charging for employees

$$U_1(e) = 15u_{OU}(e) + u_{PM}(e) + 10^{-9}\Big(u_{LF}(e) + u_{ES}(e)\Big)$$

Test Case 1: Results

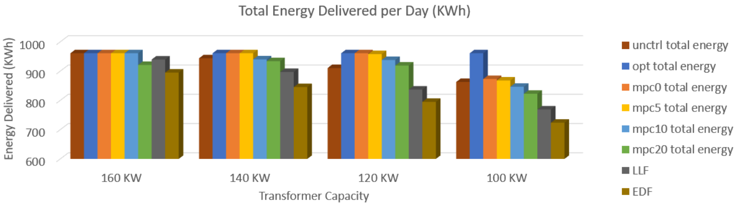


Figure: Total energy delivered for the various cases including Least-Laxity-First and Earliest-Deadline-First (both with perfect departure time knowledge) with varying transformer capacities.

Test Case 1: Results

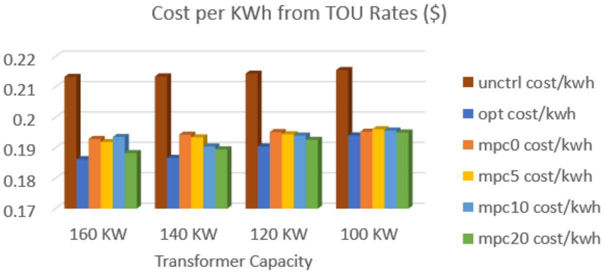


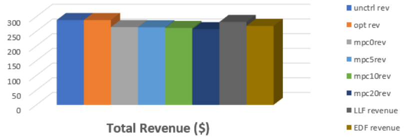
Figure: Cost per KWh from TOU rates for the uncontrolled, offline optimal, and 4 MPC test cases

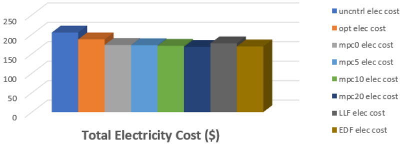
Test Case 2: Profit Maximization with TOU Rates and Demand Charges

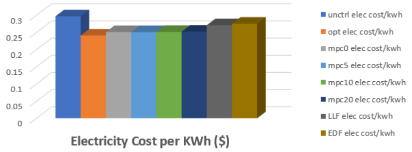
- Facility manager $\rightarrow$ maximize profit while delivering adequate energy to each customer
- For-profit third-party parking structure equipped with chargers and wants to minimize TOU electricity costs and demand charges

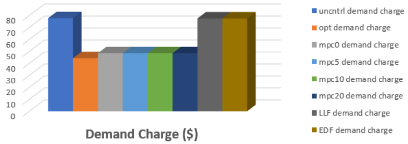
$$U_2(e) = 10\Big(u_{PM}(e) + u_{DC}(e)\Big) + u_{OU}(e) + 10^{-9}\Big(u_{LF}(e) + u_{ES}(e)\Big)$$

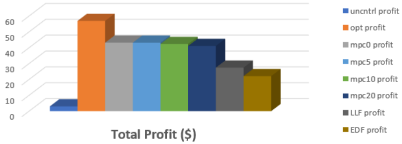
Test Case 2: Results











Test Case 2: Results

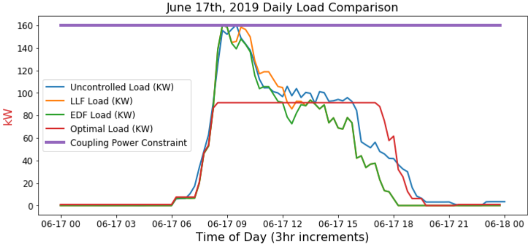


Figure: Daily loads of the charging facility for various charging strategies.

Test Case 2: Results

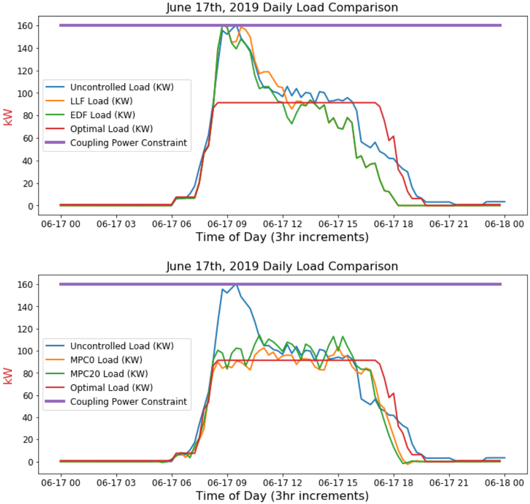


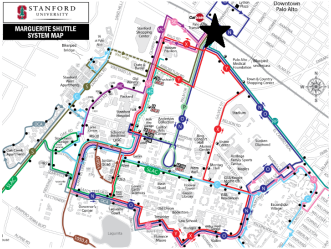
Figure: Daily loads of the charging facility for various charging strategies.

Recap EV Smart Charging

Online optimization framework for workplace EV charging

- Customizable utility functions
- Accounts for infrastructure constraints
- Can be modified based on user data availability/accuracy
- Outperforms FCFS, LLF, EDF in both energy delivery and profit maximization

Stanford Marguerite Shuttle



- 38 BYD Electric Buses
- 23 double port chargers
- 352 unique trips per day
- 1431 miles per day

Minimal Cost Operational Strategy

- Route assignment
- Recharge schedule
- Auxiliary diesel bus usage
- On-site solar sizing
- Operator preferences

Minimal Cost Operational Strategy

- Route assignment
- Recharge schedule
- Auxiliary diesel bus usage
- On-site solar sizing
- Operator preferences

\$715/day $\rightarrow$ \$316/day $\rightarrow$ \$92/day

$$\text{Minimize} \quad \sum_{t \in \mathcal{T}} p(t)V(t) \tag{1a}$$

Subject to:

$$Z^k(t) + \sum_{i \in \mathcal{S}} X_i^k(t) \leq 1, \quad \forall k \in \mathcal{K}, t \in \mathcal{T} \tag{1b}$$

$$\sum_{k \in \mathcal{K}} X_i^k(t) = 1, \quad \forall i \in \mathcal{S}, t \in [a_i, b_i] \tag{1c}$$

$$X_i^k(t+1) = X_i^k(t), \quad \forall i \in \mathcal{S}, k \in \mathcal{K}, t \in [a_i, b_i - 1] \tag{1d}$$

$$\sum_{k \in \mathcal{K}} Y_n^k(t) \leq 1, \quad \forall n \in \mathcal{N}, t \in \mathcal{T} \tag{1e}$$

$$\sum_{n \in \mathcal{N}} Y_n^k(t) = Z^k(t), \quad \forall k \in \mathcal{K}, t \in \mathcal{T} \tag{1f}$$

$$E^k(t) = E^k(t-1) + \sum_{n \in \mathcal{N}} u_n Y_n^k(t) - \sum_{i \in \mathcal{S}} d_i X_i^k(t), \quad \forall k \in \mathcal{K}, t \in \mathcal{T} \tag{1g}$$

$$\sum_{n \in \mathcal{N}} \sum_{k \in \mathcal{K}} Y_n^k(t) u_n = V(t) + S(t), \quad \forall t \in \mathcal{T} \tag{1h}$$

$$E_{min}^k \leq E^k(t) \leq E_{max}^k, \quad \forall k \in \mathcal{K}, t \in \mathcal{T} \tag{1i}$$

$$X_i^k(t) \in \{0, 1\}, \quad \forall i \in \mathcal{S}, k \in \mathcal{K}, t \in \mathcal{T} \tag{1j}$$

$$Y_n^k(t) \in \{0, 1\}, \quad \forall n \in \mathcal{N}, k \in \mathcal{K}, t \in \mathcal{T} \tag{1k}$$

$$Z^k(t) \in \{0, 1\}, \quad \forall k \in \mathcal{K}, t \in \mathcal{T} \tag{1l}$$

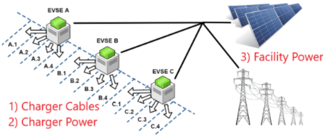
$$0 \leq S(t) \leq g(t), \quad \forall t \in \mathcal{T} \tag{1m}$$

$$E^k(0) = e_0^k, \quad \forall k \in \mathcal{K} \tag{1n}$$

$$E^k(T) = e_0^k, \quad \forall k \in \mathcal{K}. \tag{1o}$$

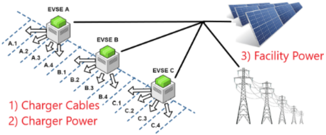
Recap - Online Optimization and Learning for CHPS

Recap - Online Optimization and Learning for CHPS

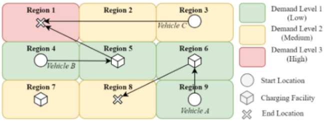


Allerton 2018, ACC 2019, IEEE TSG 2019

Recap - Online Optimization and Learning for CHPS

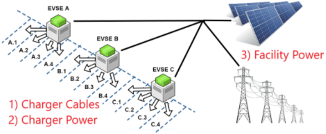


Allerton 2018, ACC 2019, IEEE TSG 2019

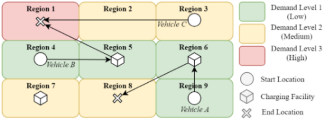


ITSC 2019

Recap - Online Optimization and Learning for CHPS



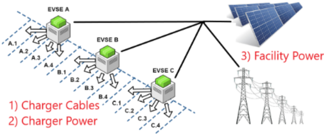
Allerton 2018, ACC 2019, IEEE TSG 2019



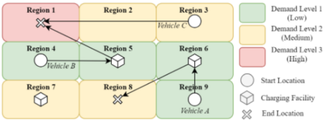
ITSC 2019

IEEE TTE 2020

Recap - Online Optimization and Learning for CHPS

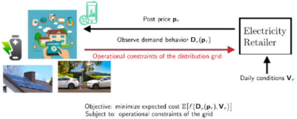


Allerton 2018, ACC 2019, IEEE TSG 2019



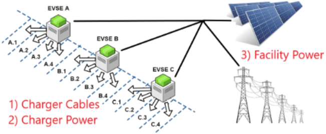
ITSC 2019

IEEE TTE 2020

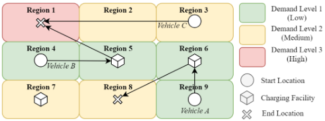


IEEE TSG 2020

Recap - Online Optimization and Learning for CHPS

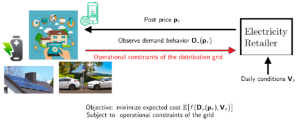


Allerton 2018, ACC 2019, IEEE TSG 2019



ITSC 2019

IEEE TTE 2020

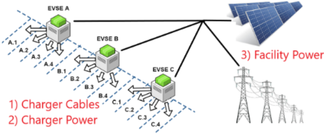


IEEE TSG 2020

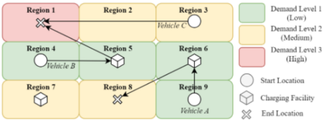
Route Name	Daily Trips	Trip Miles
C Line	33	7.00
C Limited	11	4.60
MC Line (AM/PM)	46	3.00
MC Line (Mid Day)	11	5.10
P Line (AM/PM)	56	2.50
P Line (Mid Day)	11	4.00
Research Park (AM/PM)	24	10.40
X Express (AM)	12	1.20
X Line	44	4.60
X Limited (AM)	10	2.00
X Limited (PM)	10	1.50
Y Express (PM)	20	1.20
Y Line	44	4.60
Y Limited (AM)	10	2.40
Y Limited (PM)	10	2.00
Totals	352 trips/day	1431.50 miles/day

PESGM 2020

Recap - Online Optimization and Learning for CHPS

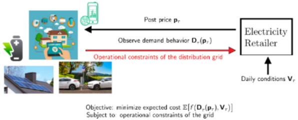


Allerton 2018, ACC 2019, IEEE TSG 2019



ITSC 2019

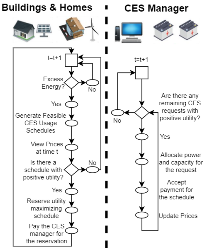
IEEE TTE 2020



IEEE TSG 2020

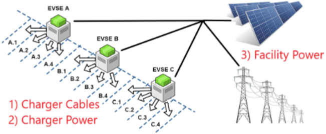
Route Name	Daily Trips	Trip Miles
C Line	33	7.00
C Limited	11	4.60
MC Line (AM/PM)	46	3.00
MC Line (Mid Day)	11	5.10
P Line (AM/PM)	56	2.50
P Line (Mid Day)	11	4.00
Research Park (AM/PM)	24	10.40
X Express (AM)	12	1.20
X Line	44	4.60
X Limited (AM)	10	2.00
X Limited (PM)	10	1.50
Y Express (PM)	20	1.20
Y Line	44	4.60
Y Limited (AM)	10	2.40
Y Limited (PM)	10	2.00
Totals	**352 trips/day**	**1431.50 miles/day**

PESGM 2020

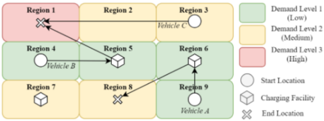


IEEE TSG 2022

Recap - Online Optimization and Learning for CHPS

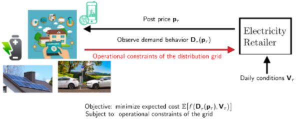


Allerton 2018, ACC 2019, IEEE TSG 2019



ITSC 2019

IEEE TTE 2020

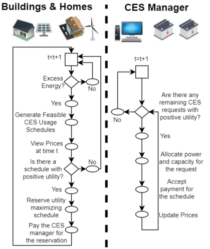


IEEE TSG 2020

Route Name	Daily Trips	Trip Miles
C Line	33	7.00
C Limited	11	4.60
MC Line (AM/PM)	46	3.00
MC Line (Mid Day)	11	5.10
P Line (AM/PM)	56	2.50
P Line (Mid Day)	11	4.00
Research Park (AM/PM)	24	10.40
X Express (AM)	12	1.20
X Line	44	4.60
X Limited (AM)	10	2.00
X Limited (PM)	10	1.50
Y Express (PM)	20	1.20
Y Line	44	4.60
Y Limited (AM)	10	2.40
Y Limited (PM)	10	2.00
Totals	352 trips/day	1431.50 miles/day

PESGM 2020

PESGM 2022, IEEE SmartGridComm 2022



IEEE TSG 2022

What's Next?


1993-2012
2012-2017
2017-2022
UCSB
Washington
Oregon
California
Idaho
Nevada
Montana
Wyoming
Utah
Arizona
Colorado
New Mexico
North Dakota
South Dakota
Nebraska
Kansas
Oklahoma
Texas
Minnesota
Iowa
Missouri
Arkansas
Louisiana
Wisconsin
Illinois
Michigan
Indiana
Ohio
Kentucky
Tennessee
Mississippi
Alabama
Georgia
Florida
South Carolina
North Carolina
Virginia
West Virginia
Pennsylvania
New York
Vermont
Maine
New Hampshire
Massachusetts
Rhode Island
Connecticut
New Jersey
Delaware
Maryland

What's Next?

1993-2012
2012-2017
2017-2022
2022...
UCSB
Washington
Oregon
California
Nevada
Idaho
Montana
Wyoming
Utah
Arizona
Colorado
New Mexico
North Dakota
South Dakota
Nebraska
Kansas
Oklahoma
Texas
Minnesota
Iowa
Missouri
Arkansas
Louisiana
Wisconsin
Illinois
Michigan
Indiana
Ohio
Kentucky
Tennessee
Mississippi
Alabama
Georgia
Florida
South Carolina
North Carolina
Virginia
West Virginia
Pennsylvania
New York
Vermont
Maine
New Hampshire
Massachusetts
Rhode Island
Connecticut
New Jersey
Delaware
Maryland

What's Next?

1993-2012
2012-2017
2017-2022
2022...
2026?
UCSB
Washington
Oregon
California
Nevada
Idaho
Montana
Wyoming
Utah
Arizona
Colorado
New Mexico
North Dakota
South Dakota
Nebraska
Kansas
Oklahoma
Texas
Minnesota
Iowa
Missouri
Arkansas
Louisiana
Wisconsin
Illinois
Michigan
Indiana
Ohio
Kentucky
Tennessee
Mississippi
Alabama
Georgia
Florida
South Carolina
North Carolina
Virginia
West Virginia
Pennsylvania
New York
Vermont
Maine
New Hampshire
Massachusetts
Rhode Island
Connecticut
New Jersey
Delaware
Maryland

Thank you!

- Mahnoosh Alizadeh
- Committee
- Gustavo Cezar, SLAC National Lab
- UCSB Institute for Energy Efficiency (IEE)
- Smart Infrastructure Systems Lab
- UCSB ECE graduate students

References

- [Tucker, Alizadeh, IEEE TSG 2019] An Online Admission Control Mechanism for EVs at Public Parking Infrastructures
- [Tucker, Moradipari, Alizadeh, IEEE TSG 2020] Constrained Thompson Sampling for Real-Time Electricity Pricing with Grid Reliability Constraints
- [Tucker, Alizadeh, IEEE TSG 2022] An Online Scheduling Algorithm for a Community Energy Storage System
- [Tucker, Cezar, Alizadeh, IEEE PESGM 2022] Real-Time Electric Vehicle Smart Charging at Workplaces: A Real-World Case Study
- [Tucker, Alizadeh, IEEE SGC 2022, *In Progress*] An Online Optimization Framework for EV Smart Charging at Workplaces

Online Optimization Framework

- Rolling horizon optimization
- Future model: certainty equivalence
  - Account for future arrivals
  - Utilize an "average day" model
- Scenario generation/pruning for EVs' departure times
  - Users can input multiple departure times
  - Can be generated from population/personal datasets
- Modify utility functions and constraints
  - Demand charge utility function

Online Optimization Framework

$$\max_{e} \sum_{i} \sum_{n} \frac{1}{C_n} \Big[U(e_i, x_{i,n}) \Big] + \sum_{j} \Big[U(e_j, x_j) \Big]$$

subject to:

$$
\begin{aligned}
& 0 \le e_k(t) \le e_{max}, && \forall k = i, j, \forall t \\
& {e_i}^T x_{i,n} \le d_i, && \forall i \\
& {e_j}^T x_j \ge d_j, && \forall j \\
& \sum_{k=i,j} e_k(t) \le e_{trans}, && \forall t \\
& \hat{e}_{inc} \ge \sum_{k=i,j} e_k(t) - \hat{e}_{old}, && \forall t \\
& \hat{e}_{inc} \ge 0
\end{aligned}
$$

Real-Time Smart Charging Algorithm (RTSCA)

Algorithm 1 Real-Time Smart Charging

```
for each day do
    Update current parking lot state
    for each 15 minute interval t do
        if new departure from parking lot then
            Update parking lot state
        end if
        if new arrival to parking lot then
            Generate/solicit N potential departure times for new arrival
            Update Parking lot state
        end if
        Formulate optimization for time t:
        for each EV i plugged in at time t do
            Add EV i to total objective function
            Add EV i to active constraints
        end for
        for each future EV j in daily model t_model > t do
            Add EV j to total objective function
            Add EV j to active constraints
        end for
        Solve optimization for time t
        Store planned energy schedule for each EV i
        Set each EVSE's output power for the current 15 minute interval
        Update peak load ê_old for demand charge calculation (if a new peak load is observed)
    end for
end for
```

Real-Time Smart Charging Algorithm (RTSCA)

Algorithm 1 REAL-TIME SMART CHARGING

```
for each day do
    for each 15 minute interval t do
        if new departure from parking lot then
            Update parking lot state
        end if
        if new arrival to parking lot then
            Generate/solicit N potential departure times for new arrival
            Update Parking lot state
        end if
        Formulate optimization for time t:
        for each EV i plugged in at time t do
            Add EV i to total objective function
            Add EV i to active constraints
        end for
        for each future EV j in daily model t_model > t do
            Add EV j to total objective function
            Add EV j to active constraints
        end for
        Solve optimization for time t
        Store planned energy schedule for each EV i
        Set each EVSE's output power for the current 15 minute interval
        Update peak load ê_old for demand charge calculation (if a new peak load is observed)
    end for
end for
```

Real-Time Smart Charging Algorithm (RTSCA)

Algorithm 1 REAL-TIME SMART CHARGING

for each day **do**
  Update current parking lot state
  for each 15 minute interval t **do**
    if new departure from parking lot **then**
      Update parking lot state
    end if
    if new arrival to parking lot **then**
      Generate/solicit N potential departure times for new arrival
      Update Parking lot state
    end if
    Formulate optimization for time t:
    for each EV i plugged in at time t **do**
      Add EV i to total objective function
      Add EV i to active constraints
    end for
    for each future EV j in daily model $t_{model} > t$ **do**
      Add EV j to total objective function
      Add EV j to active constraints
    end for
    Solve optimization for time t
    Store planned energy schedule for each EV i
    Set each EVSE's output power for the current 15 minute interval
    Update peak load $\hat{e}_{old}$ for demand charge calculation (if a new peak load is observed)
  end for
end for

Real-Time Smart Charging Algorithm (RTSCA)

Algorithm 1 Real-Time Smart Charging

```
for each day do
    Update current parking lot state
    for each 15 minute interval t do
        if new departure from parking lot then
            Update parking lot state
        end if
        if new arrival to parking lot then
            Generate/solicit N potential departure times for new arrival
            Update Parking lot state
        end if
        Formulate optimization for time t:
        for each EV i plugged in at time t do
            Add EV i to total objective function
            Add EV i to active constraints
        end for
        for each future EV j in daily model t_model > t do
            Add EV j to total objective function
            Add EV j to active constraints
        end for
        Solve optimization for time t
        Store planned energy schedule for each EV i
        Set each EVSE's output power for the current 15 minute interval
        Update peak load ê_old for demand charge calculation (if a new peak load is observed)
    end for
end for
```

Real-Time Smart Charging Algorithm (RTSCA)

Algorithm 1 Real-Time Smart Charging

```
for each day do
    Update current parking lot state
    for each 15 minute interval t do
        if new departure from parking lot then
            Update parking lot state
        end if
        if new arrival to parking lot then
            Generate/solicit N potential departure times for new arrival
            Update Parking lot state
        end if
        Formulate optimization for time t:
        for each EV i plugged in at time t do
            Add EV i to total objective function
            Add EV i to active constraints
        end for
        for each future EV j in daily model t_model > t do
            Add EV j to total objective function
            Add EV j to active constraints
        end for
        Solve optimization for time t
        Store planned energy schedule for each EV i
        Set each EVSE's output power for the current 15 minute interval
        Update peak load ê_old for demand charge calculation (if a new peak load is observed)
    end for
end for
```

Real-Time Smart Charging Algorithm (RTSCA)

Algorithm 1 Real-Time Smart Charging

for each day **do**
  Update current parking lot state
  for each 15 minute interval t **do**
    if new departure from parking lot **then**
      Update parking lot state
    end if
    if new arrival to parking lot **then**
      Generate/solicit N potential departure times for new arrival
      Update Parking lot state
    end if
    Formulate optimization for time t:
    for each EV i plugged in at time t **do**
      Add EV i to total objective function
      Add EV i to active constraints
    end for
    for each future EV j in daily model $t_{model} > t$ **do**
      Add EV j to total objective function
      Add EV j to active constraints
    end for
    Solve optimization for time t
    Store planned energy schedule for each EV i
    Set each EVSE's output power for the current 15 minute interval
    Update peak load $\hat{e}_{old}$ for demand charge calculation (if a new peak load is observed)
  end for
end for