A Deployable Online Optimization Framework for EV Smart Charging with Real-World Test Cases

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Motivation

- In the U.S., if federal zero-emission vehicle sales targets are met, there could be more than 48 million electric vehicles (EVs) on the road in 2030 [1]
  - In order to provide charge to this growing EV population, it is estimated that over 1.2 million public EV chargers need to be installed at on-the-go locations and at destinations where EVs are parked for long periods [1]
  - Furthermore, the estimated cost for hardware, planning, and installation of this future public charging infrastructure exceeds $35 billion (U.S.D.) [1]

[1] **P. Kampshoff, A. Kumar, S. Peloquin, and S. Sahdev, "Building the Electric Vehicle Charging Infrastructure America Needs," Mckinsey and Company, https://www.mckinsey.com, April 18, 2022.**

Motivation

- Increasing EV numbers
- Large investment cost of EV charging infrastructure
- Desire to utilize cheap and clean energy

- Clearly, smart charging strategies are required to schedule the power delivery to EVs to maximize the benefits of both the EVs and the infrastructure

Motivation

- Many academic papers in previous years attempting to address this opportunity
- However, many of the implementable solutions
  - Require user input
    - Energy request amounts
    - Departure time estimates
    - Requires 2-way communication capabilities
    - Accuracy of user input data is poor
      - ~20% error on departure time and energy request input [8],[9]
  - Are often facility/infrastructure specific
  - Ignore critical infrastructure constraints

[8] **Z. J. Lee, T. Li, and S. H. Low, "Acn-data: Analysis and applications of an open ev charging dataset," in Proceedings of the Tenth ACM International Conference on Future Energy Systems, 2019, pp. 139–149.**

[9] **Z. J. Lee, S. Sharma, and S. H. Low, "Research tools for smart electric vehicle charging: An introduction to the adaptive charging network research portal," IEEE Electrification Magazine, 2021.**

Key Challenges

- Real-time operation
  - Minimal knowledge of future EV arrivals
  - Adapt the scheduled power delivery as more info is revealed
- Limited or Zero information from the users
  - Common J1772 Standard chargers do not support 2-way communication
  - No knowledge of SOC, departure time, energy request
- Coupled power delivery schedules
  - All chargers in a facility are coupled due to infrastructure constraints (line limits, local transformer, etc.)

Main Contributions

- The smart charging framework is readily deployable and customizable
  - Accommodates a wide range of facilities, infrastructure, objectives, constraints
- The online optimization framework can be easily modified to operate with or without user input
  - Case-by-case 2-way communication chargers or 1-way
- The real-time smart charging strategy outperforms other real-time strategies
  - First-Come-First-Serve, Least-Laxity-First, Earliest-Deadline-First, etc.
- Showcase the performance of our algorithm with charging session data from SLAC and Google campuses in California [17],[18]

[17] N. Tucker, G. Cezar, and M. Alizadeh, "Real-time electric vehicle smart charging at workplaces: A real-world case study," arXiv preprint arXiv:2203.06847, 2022.

[18] A. Moradipari, N. Tucker, T. Zhang, G. Cezar, and M. Alizadeh, "Mobility-aware smart charging of electric bus fleets," in 2020 IEEE Power Energy Society General Meeting (PESGM), 2020, pp. 1–5.

Problem Description - Basics

- Time horizon $t = 1,\ldots,T$
- EV arrivals $i = 1,\ldots,I$
- Energy scheduled for EV i at time t: $e_i(t)$
  - $T \times 1$ vector
- Arrival time of EV i: t_i^a
- Departure time of EV i: t_i^d (potentially unknown)
- Energy demand of EV i: d_i (potentially unknown)

Problem Description – Main Objective Function

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

- f = 1,…,F : multiple objectives in main objective function
- w_f : weight/importance of objective f

Problem Description – Objectives

$$u_{OU}(e) = \sum_i \log(\sum_t e_i(t) + 1)$$

- EV Owner Utility

$$u_{QC}(e) = \sum_t \frac{T - t + 1}{T} \sum_i e_i(t)$$

- Quick Charging

$$u_{PM}(e) = \sum_t q(t) \sum_i e_i(t) - \sum_t p(t)\Big(\sum_i e_i(t) + z(t)\Big)$$

- Profit Maximization

Problem Description – Objectives

$$u_{DC}(e) = -\hat{p} \cdot \max_t \Big(\sum_i e_i(t) + z(t) \Big)$$

- Demand Charges

$$u_{DC}(e) = -\hat{p} \cdot \hat{e}_{inc}$$

where

$$\hat{e}_{inc} = \max_t \left\{ \sum_i \big(e_i(t) + z(t)\big) - \hat{e}_{old}, 0 \right\}$$

- Demand Charges Continued

$$u_{LF}(e) = -\sum_t \Big(\sum_i e_i(t) + z(t) \Big)^2$$

- Load Flattening

Problem Description – Objectives

$$u_{ES}(e) = -\sum_{t,i} e_i(t)^2.$$

- Equal Energy Sharing

$$u_{ED}(e) = -\sum_{i} \left(| \sum_{t} e_i(t) - d_i | \right)$$

- Energy Demand

Problem Description – Constraints

$$
\begin{aligned}
&0 \le e_i(t) \le e_{max}, && \forall t, i \\
&e_i(t) = 0, && \forall t \notin [t_i^a, t_i^d] \\
&\sum_t e_i(t) \le d_i, && \forall i \\
&\sum_i e_i(t) \le e_{trans}, && \forall t \\
&\hat{e}_{inc} \ge \sum_i e_i(t) - \hat{e}_{old}, && \forall t \\
&\hat{e}_{inc} \ge 0.
\end{aligned}
$$

- Charger Limit
- Plugged in
- Demand
- Transformer limit
- Peak Demand 1
- Peak Demand 2

Real-Time Optimization

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

subject to:

$$\begin{aligned}
&0 \leq e_k \leq e_{max}, && \forall k = 1, \dots, I+J \\
&{e_i}^T x_{i,n} \leq d_i, && \forall i = 1, \dots, I, \\
& && \forall n = 1, \dots, N, \\
&{e_j}^T x_j \geq d_j^{min}, && \forall j = I+1, \dots, I+J, \\
&\sum_{k=1}^{I+J} e_k(t) \leq e_{trans}, && \forall t = 1, \dots, T, \\
&\hat{e}_{inc} \geq \sum_{k=1}^{I+J} e_k(t) - \hat{e}_{old}, && \forall t = 1, \dots, T.
\end{aligned}$$

- Resolved at each time step t
- Departure time scenario generation
  - N Scenarios for each arrival
- Certainty Equivalent Control
  - Model for future EV arrivals
  - J EVs yet to arrive
- Convex Problem
  - Quickly solved

Real-Time Optimization

Algorithm 1 REAL-TIME SMART CHARGING

for each day **do**
  Update current parking lot state
  for each time interval t **do**
    if new departure from parking lot **then**
      Update parking lot state
    end if
    if new arrival to parking lot **then**
      Generate 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 (13a)
      Add EV i to active constraints (13b)-(13f)
    end for
    for each future EV j in daily model $t_{model} > t$ **do**
      Add EV j to total objective function (13a)
      Add EV j to active constraints (13b)-(13f)
    end for
    Solve optimization (13a)-(13f) **for time** t
    Store planned energy schedule for each EV i
    Set each EVSE's output power for the current time interval
    Update peak load $\hat{e}_{old}$ for demand charge calculation (if a new peak load is observed)
  end for
end for

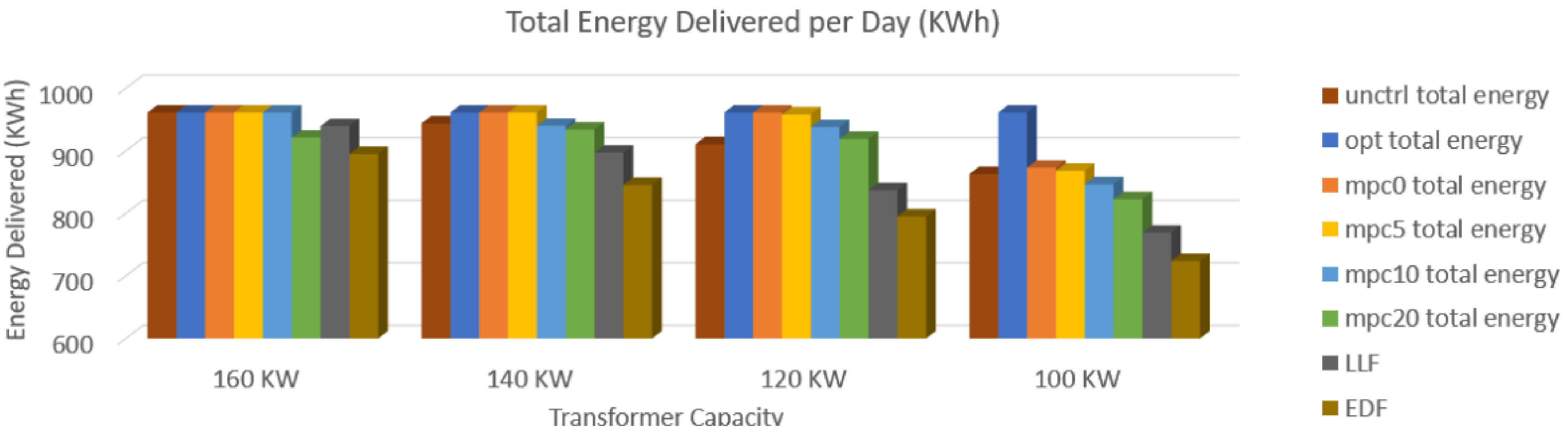
- Update state and generate departure time scenarios
- Construct Optimization for current state
- Solve Optimization and deliver scheduled energy

Test Cases - Basics

- 2 week period from June 17-June 29, 2019
- Google campus parking lot in California
- 57 level 2 ChargePoint Chargers
- 50-100 EV arrivals per day
- Under PG&E's E-19 TOU Rate Structure

Test Case 1 – User Utility Maximization

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



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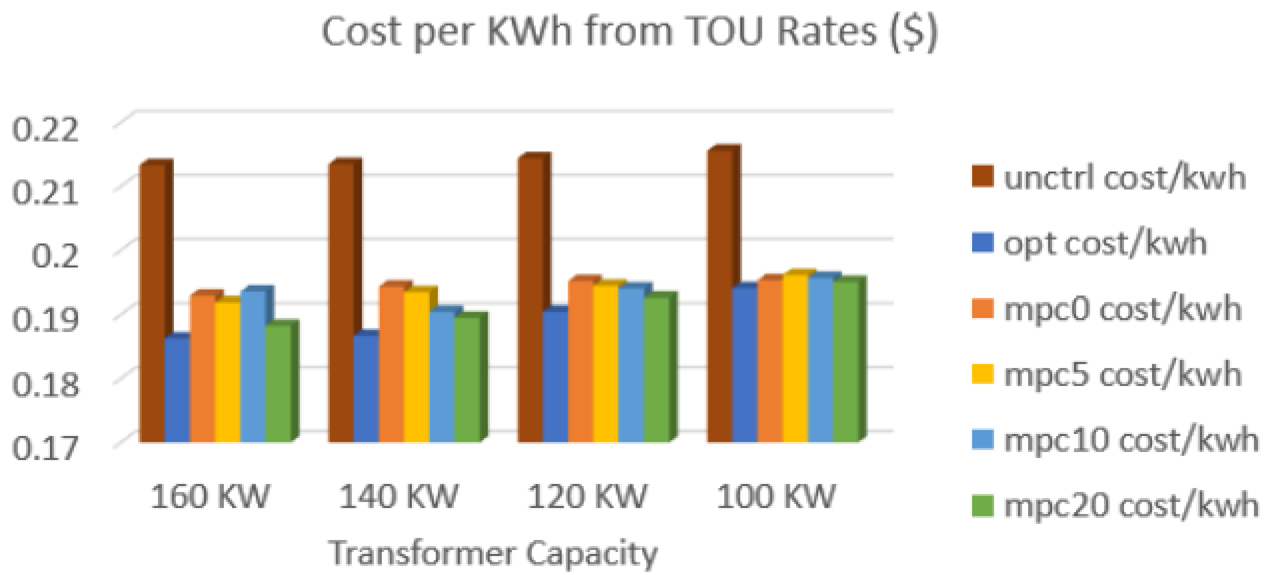


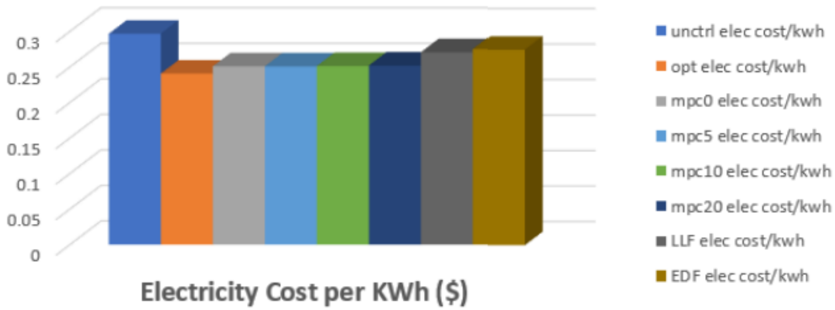
Test Case 1 – User Utility Maximization

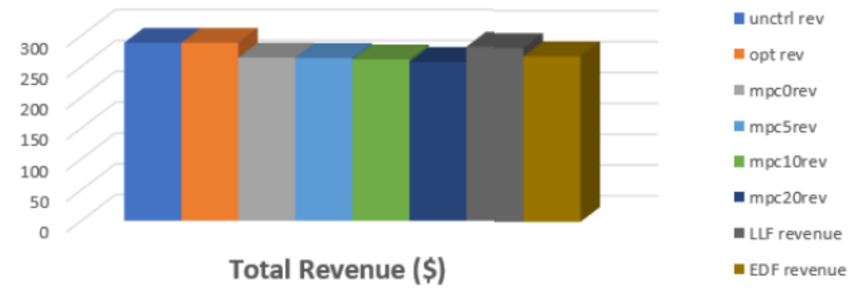
$$U_1(e) = 15u_{OU}(e) + u_{PM}(e) + 10^{-9}\Big(u_{LF}(e) + u_{ES}(e)\Big)$$

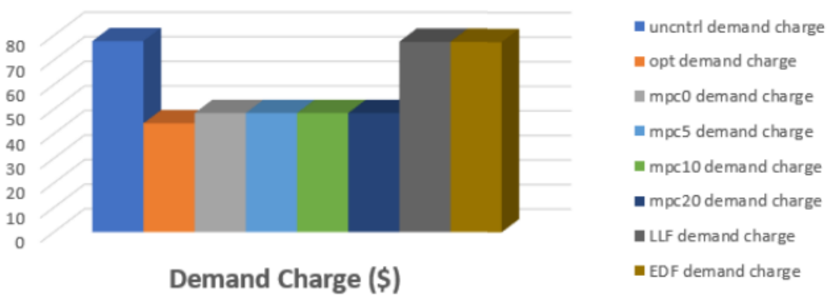
- Key Results:
  - As the coupling constraint becomes more restrictive, many of the charging strategies begin delivering significantly less energy
  - Our RTSC Algorithm w/ inaccurate departure times consistently outperforms EDF and LLF (w/perfect knowledge of departure times)
  - Our RTSC Algorithm purchases the cheapest energy in TOU rates (\$0.195/kWh versus \$0.21/kWh in the uncontrolled case)

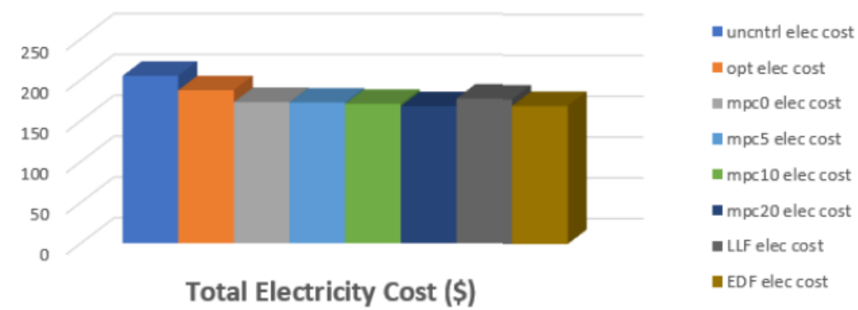
Test Case 2 – Profit Maximization w/ Demand Charges

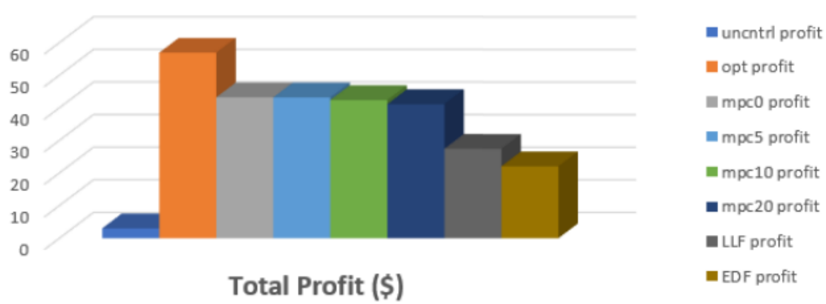
$$U_2(e) = 10\Big(u_{PM}(e) + u_{DC}(e)\Big) + u_{OU}(e) + 10^{-9}\Big(u_{LF}(e) + u_{ES}(e)\Big)$$









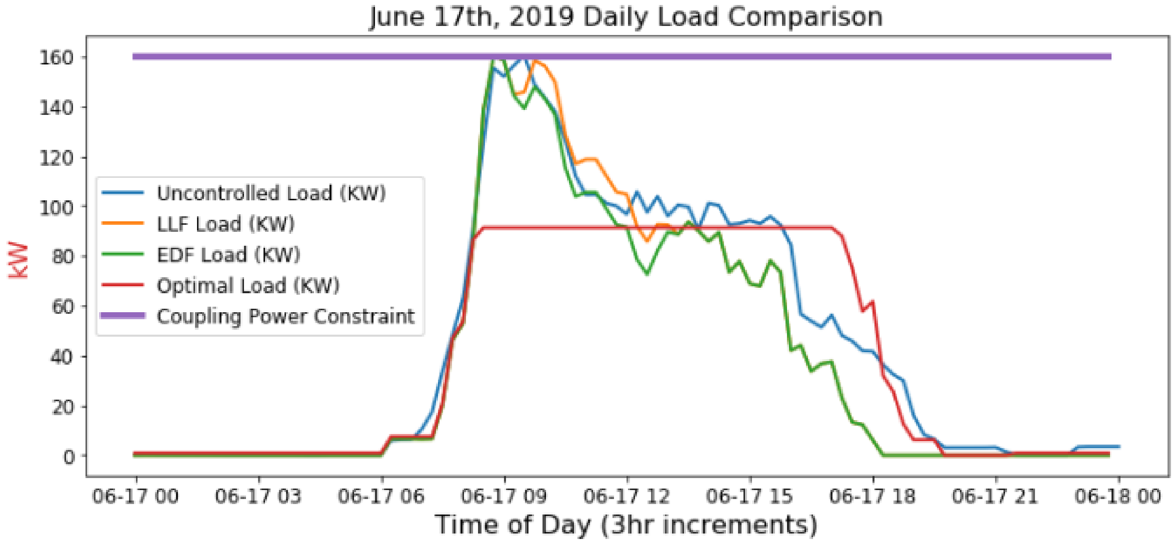


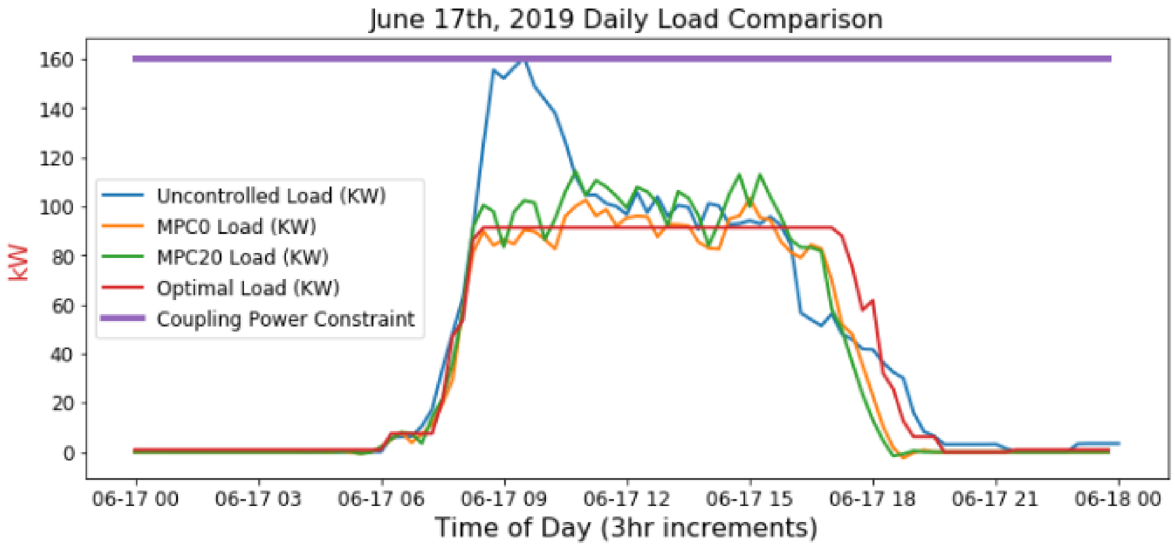
Test Case 2 – Profit Maximization w/ Demand Charges

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

- Key Results:
  - Revenue, electricity cost (from TOU only), and electricity cost per KWh (from TOU only) are similar
  - Demand charges from the offline optimal and our RTSC Algo are significantly lower
  - Net profit of our RTSC Algo significantly outperforms the other real-time approaches

Test Case 2 – Daily Load Profile Comparison





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Conclusion

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- The online optimization framework can be easily modified to operate with or without user input
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- Showcase the performance of our algorithm with charging session data from SLAC and Google campuses in California

Thank You

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