Restructuring the Retail Market to Include Load Flexibility

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Objectives

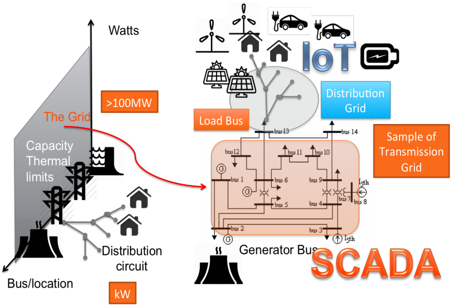
Two threads of research $\rightarrow$ remove and anticipate system level roadblocks for renewables & flexible demand integration

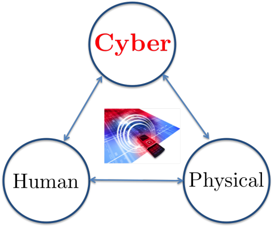
- Model demand response in coupled infrastructures
  - Electrified Transportation networks
- Competitive electric power market for power trajectories
  - Addressing shortage of ramping
  - Understanding how to express degrees of freedom much needed to rebalance net-load

Infrastructures of the future

Into the information age and Internet of Things (IoT):

Large-scale data processing + real-time interactions with humans





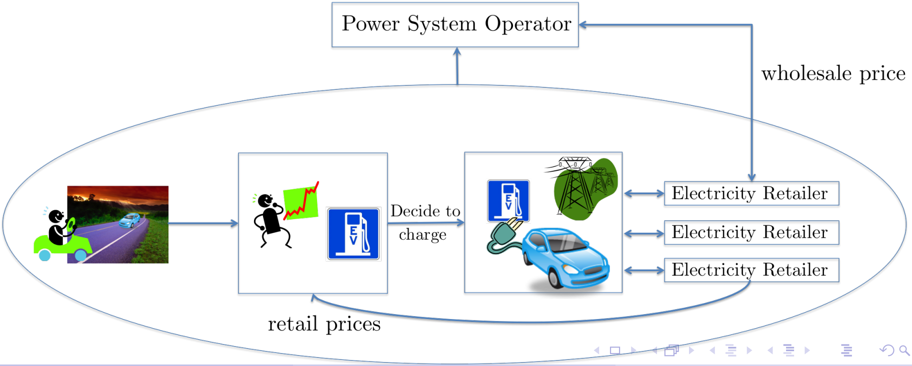
Millions of control knobs for more efficient and sustainable demand, but:

1) We face challenges of dimensionality and stochasticity
2) Humans bring social and and economical issues into control loops

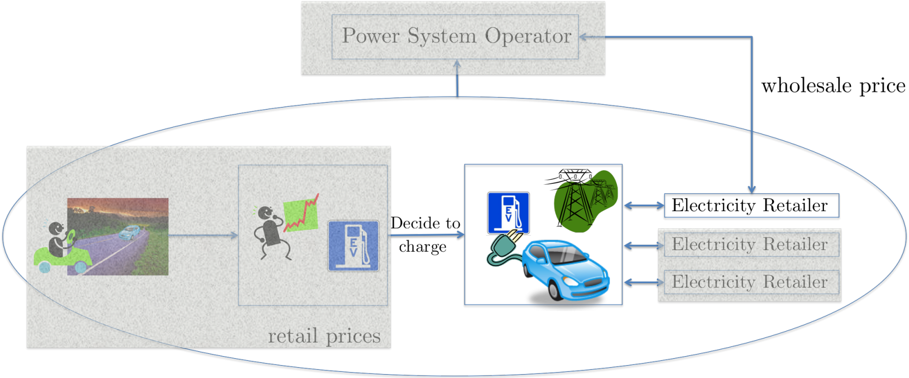
Concrete example: managing Electric Vehicle charge

- Electric Vehicles (EV): the fuel comes from the power grid
  - Forecast → 64-86% of US sales by 2030 [CET, UC Berkeley]

We need: control scheme to incentivize EV drivers to charge their batteries **where and when electricity is abundant and cheap**

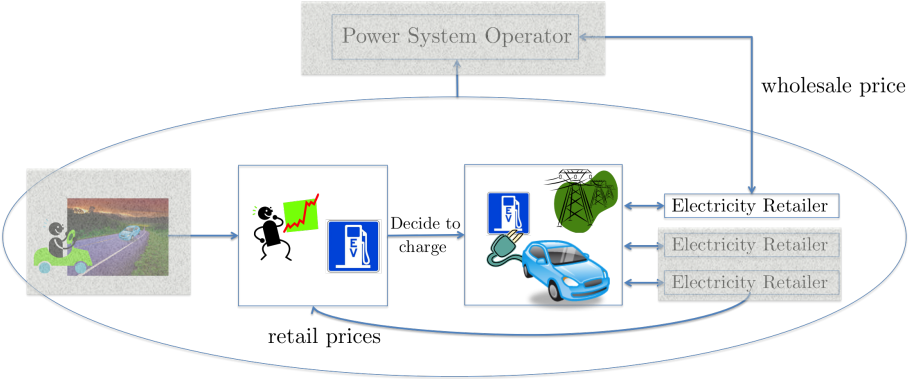


Our previous work



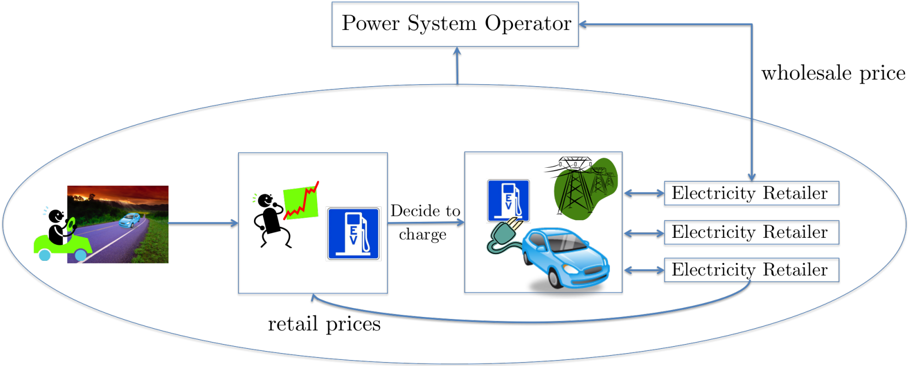
Contribution: enabling large-scale model-predictive scheduling
by systematically reducing model complexity

Our previous work



Contribution: proposing an economic retail mechanism that incentivizes customers to be green

This year



Contribution: designing wholesale prices considering the interconnection between power and transportation systems

Designing wholesale prices in coupled infrastructure

Outline:

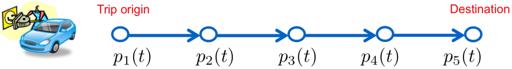
- Mathematical model for how a rational customer charges an EV
- Effect of individual choices on system load
- Design wholesale prices for socially-optimal system-level behavior

The price design challenge: customer choice model

Extensive past research on EV load scheduling

- Study of node-specific control algorithms by local retailers

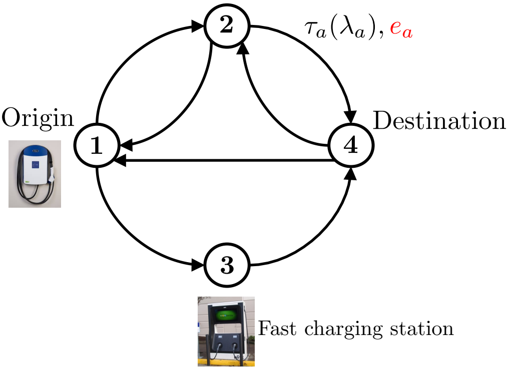
- Aspect not often considered: EVs can move!



Can we safely ignore EV mobility when modeling customers for designing prices?

Individual customer choice model

Each link takes a certain amount of time and energy to travel:



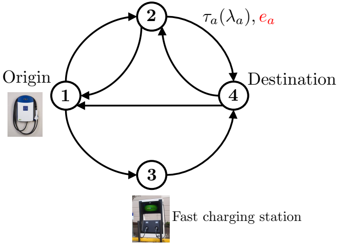
Individual Decision Variables:

- Choice of path: $k \in \mathcal{K}$
- Choice of charge: at nodes visited on path

Individual customer cost

Customer cost affected by the state (demand flows) of the 2 networks

$$\boldsymbol{\lambda}_1 = [\lambda_a]_{a \in \mathcal{A}}, \ \boldsymbol{\lambda}_2 = [\lambda_v]_{v \in \mathcal{B}}, \ \mathbf{p} = [p_v]_{v \in \mathcal{B}}$$



- Inconvenience cost for time en route:

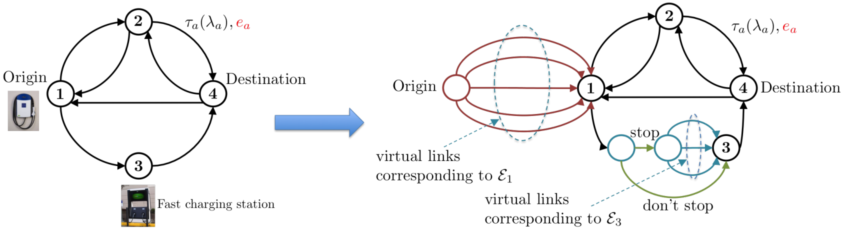
$$s_a(\lambda_a) = \gamma \tau_a(\lambda_a)$$

- Traffic congestion tolls (b_a)
- Electricity costs at node v for charge e_v
  - charging rate $= \rho_v$
  - rate of EVs being plugged in $= \lambda_v$

$$b_v(e_v) = p_v e_v, \qquad s_v(e_v, \lambda_v) = \gamma \left(\frac{e_v}{\rho_v} + \tau_v(\lambda_v) \right).$$

Solution: shortest path on a virtually extended graph

- Charging has the same cost structure as traveling:
  - it takes time
  - it has a cost
  - the battery energy level changes (it increases)
- Consider charging an extra trip
- Adding virtual links to the original transportation graph



Customer choice model: charge and path decision

Find the shortest energy-feasible path on extended graph

Individual customer optimization problem

Set of energy feasible paths

A path is energy feasible iff

$$0 \leq \text{Initial charge} - \sum_{i=1}^{l} i\text{-th link's energy} \leq \text{Battery capacity}, \qquad \forall l$$

Individual problem:

$$\min\{\text{Cost for path } k;\ k \in \text{set of energy feasible paths}\}$$

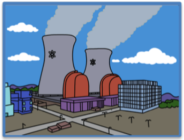
Why did we model the individual? We wanted to design electricity prices

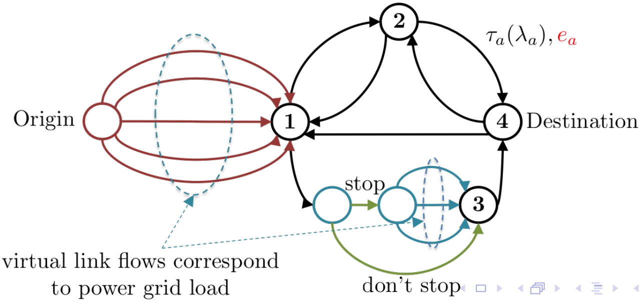
Prices are not designed for individuals! They are designed for aggregates

Aggregate effect of individual decisions

Aggregate behavior affects the state of two infrastructure systems:

1. Traffic congestion (flow on roads and into charging stations)
2. Electric load (flow on virtual links)





Mapping individual choices to network flow

- Cluster customers' travel demand characteristics q (classic step in transportation literature)

$$q \in \mathcal{C} \quad \text{(finite set)}$$

- **Feasible paths on extended graph** for cluster $q \to k \in \mathcal{K}_q$
- $a_q =$ EV arrival rate in cluster q (given)
- $d_q^k =$ rate of EVs in cluster q that take path k (customer decision)

- Travel demand balance:

$$\sum_{k \in \mathcal{K}_q} d_q^k = a_q$$

Path to flow relation in static case

$$\lambda_a = \sum_{q \in \mathcal{C}, k \in \mathcal{K}_q} \delta_a^k d_q^k \quad \left(\sum \text{path rates that include link } a \right)$$

Social costs in terms of individuals' choices

Independent Transportation System Operator

Congestion cost $= s(\text{road flows})$

Independent Power System Operator

Generation cost $= c(\text{virtual link flows})$

$$\text{Congestion cost} = \boldsymbol{\lambda}^T \mathbf{s}(\boldsymbol{\lambda})$$

$$\text{Electricity Cost} = \min_{\mathbf{g}} \mathbf{1}^T \mathbf{c}(\mathbf{g})$$

$$\text{s.t.} \quad \mathbf{g}^{\min} \preceq \mathbf{g} \preceq \mathbf{g}^{\max},$$

$$\mathbf{e} = \mathbf{M}\boldsymbol{\lambda} \rightarrow \ \mathbf{1}^T(\mathbf{e} + \mathbf{u} - \mathbf{g}) = 0,$$

$$\mathbf{H}(\mathbf{e} + \mathbf{u} - \mathbf{g}) \preceq \mathbf{c},$$

Flow as a function of user decisions:

$$\mathbf{d}_q \succeq \mathbf{0}, \quad \mathbf{1}^T \mathbf{d}_q = a_q, \quad \boldsymbol{\lambda} = \sum_{q \in \mathcal{Q}} \boldsymbol{\Delta}_q \mathbf{d}_q$$

If you control the flow $\boldsymbol{\lambda}$, you control traffic and energy costs

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But, $\mathbf{d}_q$ and hence the flow $\boldsymbol{\lambda}$ are the results of individuals decisions

Optimal pricing: results

1) Welfare maximizing price design

A social optimizer can **jointly** calculate:

1. Locational marginal electricity prices;
2. Tolls to be assessed at all roads;
3. Congestion mark-ups for limited charging station capacity;

such that Wardrop equilibrium with cost-minimizing decisions of individual EV drivers will be socially optimal.

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2) Collaboration between power and transportation system operators

Efficient market-clearing prices can be posted through a ex-ante collaboration between the power and transportation system operators following a dual decomposition algorithm.

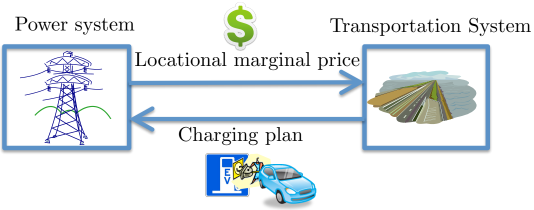
3) The cost of operators not talking!

Reserve generation capacity so power system operators can learn EVs' response.

Pricing without considering EV mobility

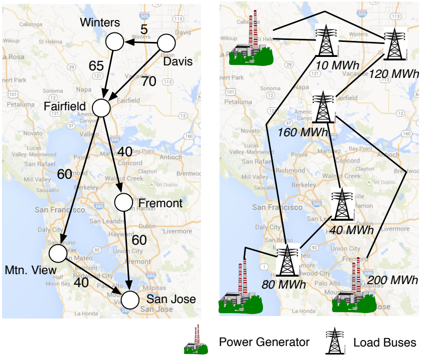
- Power system operator cannot model EV mobility!
- Iterative procedure:

1. Step 1: design electricity prices, taking charge decisions as exogenous
2. Step 2: Find socially optimal travel and charge plan taking electricity prices as exogenous



Numerical experiment - Setting

- Static setting based on IEEE 9 bus test case
- Transportation graph with one O-D pair: (Davis, San Jose)



- All EVs consumes 1 kWh each 25 miles
- Cost of unit time spent en route: $\gamma = 10^{-3}/3$ \$ / 5 min.
- Flow to travel time mapping:

$$\tau_a(\lambda_a) = T_a + \lambda_a/10^4$$

- Rate of travel: 2000, 10000, 10000 EVs, each with initial charge of $2kWh$, $3kWh$ and $4kWh$, respectively

Joint vs. disjoint marginal pricing of power and traffic

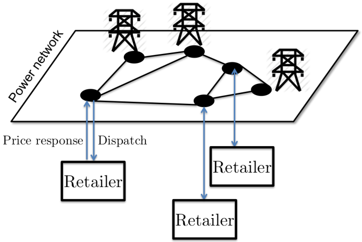
Limit-cycle behavior seen in load values at different iterations

	Joint	DP (iter. odd)	DP (iter. even)
Davis	91.67 MWh @\$53.43/MWh	110.0 MWh @\$54.49/MWh	15.411 MWh @\$66.45/MWh
Winters	35.27 MWh @\$51.76/MWh	4.921 MWh @\$54.49/MWh	46.12 MWh @\$44.50/MWh
Fairfield	18.82 MWh @\$52.09/MWh	15.93 MWh @\$54.49/MWh	84.12 MWh @\$48.84/MWh
Fremont	0.211 MWh @\$52.33/MWh	7.819 MWh @\$54.49/MWh	0.00 MWh @\$51.93/MWh
Mtn. View	0.103 MWh @\$52.85/MWh	7.326 MWh @\$54.49/MWh	0.00 MWh @\$58.85/MWh

Next steps

1. We saw the emergence of coupled infrastructure due to EVs
   - We have shown numerically that ignoring this coupling can be dangerous to the grid
2. We saw how we can control such systems in an ideal world

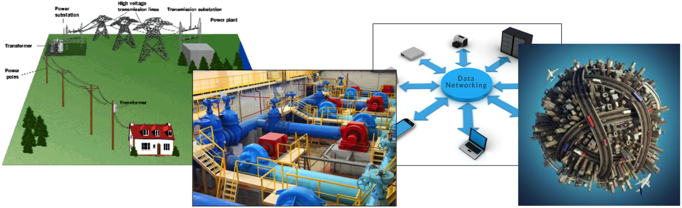
We need to tackle



Temporal dynamics + system not at equilibrium + humans not rational

Need to maintain compositionality → Inter-layer decoupling to prevent formation of highly complex systems

Higher Goal: Sustainable intelligent coupled infrastructure



Resilient interdependent human-cyber-physical systems
e.g., power, water, and data networks in smart cities

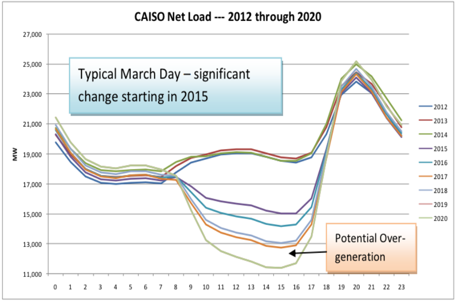
- Significant flexibility in electricity consumption supports the delivery of goods and services by other networked infrastructure
- Solution steps:
  1. Systematic and case-dependent reduced-state modeling + control
  2. Modeling retailer and human behavior in the control loop
  3. Layered solutions that don't need centalized collaboration

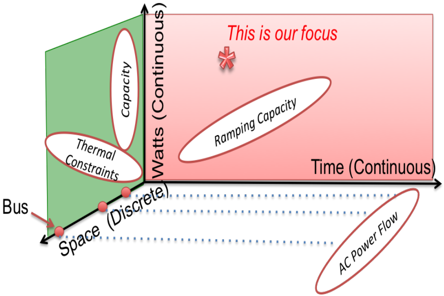
Unit Commitment with Continuous-time Generation and Ramping Trajectory

Outline:

- Why the UC problem poorly schedules for ramp resources
- From Continuous Time UC to a tractable representation for Power Trajectories
- Solution of the Continuous Time UC and advantages

Motivation

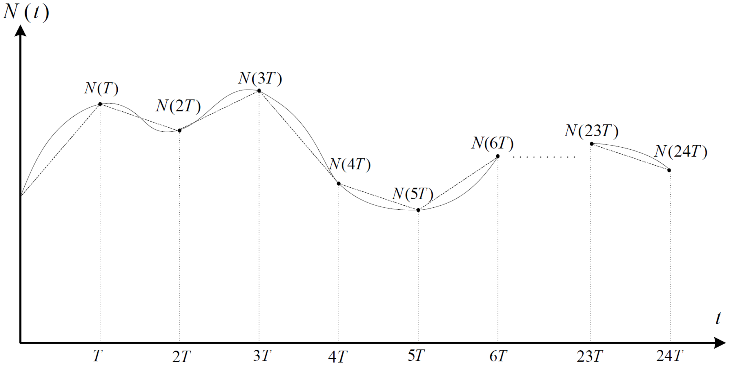




- Problem: Shortage of ramping resources in the real-time operation of power systems → ramping is not appropriately incentivized
- Flexible ramping products in CAISO and MISO: 1) complicate the market; 2) what is the reasonable level of cost allocation?

Interpretation of Current UC practice

1. Current UC practice: schedule of hourly energy by the generating units → piecewise constant generation trajectory
2. Trajectory Interpretation: Hourly ramping constraints → piecewise linear generation trajectory



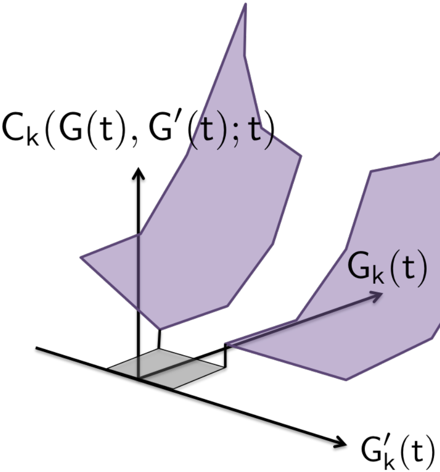
Continuous-time UC Formulation

- A set of K generating units are modeled by:
  Generation Trajectory: $\mathbf{G}(t) = (G_1(t), \ldots, G_K(t))^T$
  Ramping Trajectory: $\mathbf{G}'(t) = (G_1'(t), \ldots, G_K'(t))^T$
  Commitment Status: $\mathbf{I}(t) = (I_1(t), \ldots, I_K(t))^T$
  $$I_k(t) = \sum_{h=1}^{H_k} \left(u(t - t_{k,h}^{(\mathtt{SU})}) - u(t - t_{k,h}^{(\mathtt{SD})}) \right)$$
  Cost Function: $C_k(G_k(t), G_k'(t), I_k'(t); t)$
- Continuous-time UC:

$$\begin{aligned}
\min \quad & \sum_{k=1}^{K} \int_{\mathcal{T}} C_k(G_k(t), G_k'(t), I_k'(t))dt \\
\text{s.t.} \quad & \sum_{k=1}^{K} G_k(t) = N(t) \qquad \forall t \in \mathcal{T} \\
& \underline{G}_k I_k(t) \leq G_k(t) \leq \overline{G}_k I_k(t), \quad \underline{G}_k' I_k(t) \leq G_k'(t) \leq \overline{G}_k' I_k(t) \\
& t_{k,h}^{(\mathtt{SD})} - t_{k,h}^{(\mathtt{SU})} \geq T_k^{(\mathtt{on})}, \quad t_{k,h+1}^{(\mathtt{SU})} - t_{k,h}^{(\mathtt{SD})} \geq T_k^{(\mathtt{off})}, \quad \forall k, h, t \in \mathcal{T}
\end{aligned}$$

Defining cost in the $(G_k(t), G'_k(t))$ plane

- Idea: If we need more ramp in addition to representing better the need for ramp, why not allowing bids that include a cost for ramp?



Generation and Load Trajectories in a Function Space

Assume that in the horizon $\mathcal{T}$, except for a small residual error, $N(t)$ lies on a countable and *finite function space* of dimensionality P, spanned by a set of bases functions $\mathbf{e}(t) = (e_1(t), \ldots, e_P(t))$:

$$N(t) = \sum_{p=1}^{P} N_p e_p(t) + \epsilon_N(t) = \mathbf{e}(t)\mathbf{N} + \epsilon_N(t)$$

$\mathbf{N} = (N_1, \ldots, N_P)^T$ are the *coordinates* of the approximation onto the subspace spanned by $\mathbf{e}(t)$. Also, any generation trajectory has a component is in the same subspace spanned by $\mathbf{e}(t)$ and a component orthogonal to it, i.e.:

$$G_k(t) = \sum_{p=1}^{P} G_{kp} e_p(t) + \epsilon_{G_k}(t) = \mathbf{e}(t)\mathbf{G}_k + \epsilon_{G_k}(t).$$

Spline Representation using Cubic Hermite Polynomials

- Day-ahead scheduling horizon $\mathcal{T}$ is divided into M intervals, edges $0, t_1, t_2, \cdots, t_M$.
- Splines of order > 1 allow to *encode* ramping information explicitly.
- Cubic Hermite basis functions: four polynomials of third order in $t \in [0, 1)$, vector: $\mathbf{H}(t) = (H_{00}(t), H_{01}(t), H_{10}(t), H_{11}(t))$

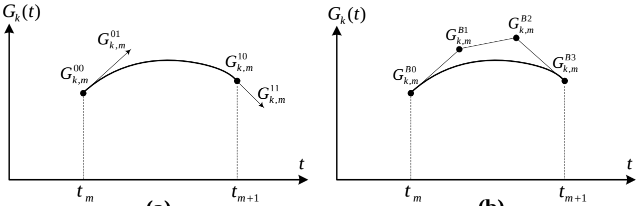
$$H_{ij}(\tau_m) = H_{ij}\left(\frac{t - t_m}{t_{m+1} - t_m}\right) \ , \quad i, j \in \{0, 1\}, \quad t_m \leq t < t_{m+1}$$

- Load and Generation trajectory in cubic Hermite spline function space:

$$\hat{N}(t) = \sum_{m=0}^{M-1} \mathbf{H}(\tau_m)\mathbf{N}_m^H, \qquad G_k(t) = \sum_{m=0}^{M-1} \mathbf{H}(\tau_m)\mathbf{G}_{k,m}^H$$

where $\mathbf{N}_m^H$ and $\mathbf{G}_{k,m}^H$ are the vectors of Hermite coefficients.

Spline Representation using Bernstein Polynomials



- 3rd oder Bernstein polynomials representations:

$$\hat{N}(t) = \sum_{m=0}^{M-1} \mathbf{B}_3(\tau_m)\mathbf{N}_m^B \ , \quad G_k(t) = \sum_{m=0}^{M-1} \mathbf{B}_3(\tau_m)\mathbf{G}_{k,m}^B$$

  where $\mathbf{N}_m^B$ and $\mathbf{G}_{k,m}^B$ are the vectors of Bernstein coefficients.
- The Bernstein and Hermite coefficients are linearly related as $\mathbf{G}_{k,m}^B = \mathbf{W}\mathbf{G}_{k,m}^H$, and $\mathbf{N}_{k,m}^B = \mathbf{W}\mathbf{N}_{k,m}^H$.

Why Bernstein Polynomials?

- The Bernstein coefficients of the generation derivative are linearly related with the Bernstein coefficients of the generation trajectory:

$$G'_k(t) = \sum_{m=0}^{M-1} \mathbf{B}_2(\tau_m)\mathbf{G}'^{B}_{k,m} \;, \quad \mathbf{G}'^{B}_{k,m} = \mathbf{K}^T \mathbf{G}^B_{k,m} = \mathbf{K}^T \mathbf{W}^T \mathbf{G}^H_{k,m}$$

- Convex hull property of the Bernstein polynomials $\rightarrow$ trajectories bounded of the convex hull formed by the four Bernstein points:

$$\min_{t_m \le t \le t_{m+1}} \{\mathbf{B}_3^T(\tau_m)\mathbf{G}^B_{k,m}\} \ge \min\{\mathbf{G}^B_{k,m}\}$$

$$\max_{t_m \le t \le t_{m+1}} \{\mathbf{B}_3^T(\tau_m)\mathbf{G}^B_{k,m}\} \le \max\{\mathbf{G}^B_{k,m}\}$$

$$\min_{t_m \le t \le t_{m+1}} \{\mathbf{B}_2^T(\tau_m)\mathbf{G}'^B_{k,m}\} \ge \min\{\mathbf{G}'^B_{k,m}\}$$

$$\max_{t_m \le t \le t_{m+1}} \{\mathbf{B}_2^T(\tau_m)\mathbf{G}'^B_{k,m}\} \le \max\{\mathbf{G}'^B_{k,m}\}$$

Representation of Cost Function and Balance Constraints

- Piecewise line continuous-time cost function can be written in terms of the spline coefficients of generation trajectory:

$$\int_{\mathcal{T}} C_k(G_k(t), G'_k(t), I'_k(t))dt = C_k(\mathbf{G}_k, \mathbf{G}'_k, \mathbf{I}_k).$$

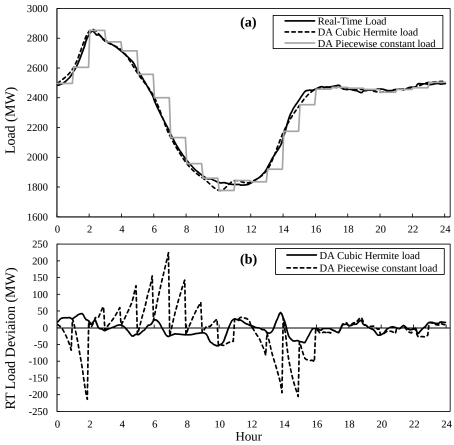
- The continuous-time balance constraint is assured by balancing the four cubic Hermite coefficients for each interval m:

$$\sum_{k=1}^{K} \mathbf{G}^H_{k,m} = \mathbf{N}^H_m \quad \forall m$$

- One can deal with DC power flow nodal constraints similarly

Simulation Results: IEEE-RTS + CAISO Load

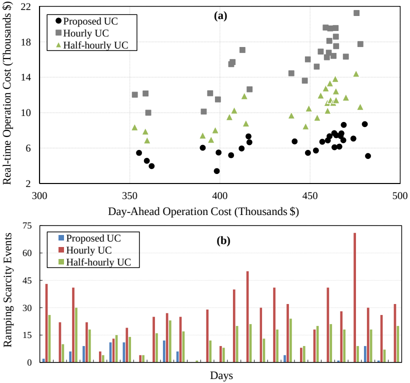
- The data regarding 32 units of the IEEE-RTS and load data from the CAISO are used here.
- Both the day-ahead (DA) and real-time (RT) operations are simulated.
- The five-minute net-load forecast data of CAISO for Feb. 2, 2015 is scaled down to the original IEEE-RTS peak load of 2850MW, and the hourly day-ahead load forecast is generated where the forecast standard deviation is considered to be %1 of the load at the time.

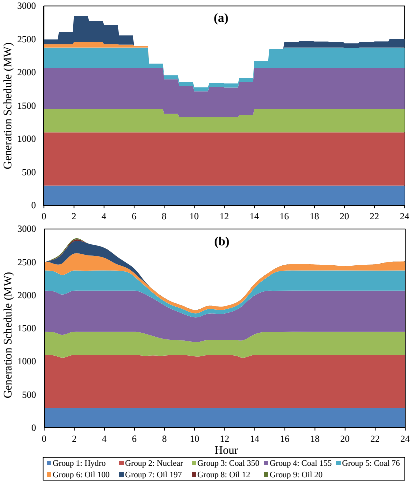


Reduced Operation Cost and Ramping Scarcity Events

- Case 1: Current UC Model
- Case 2: The Proposed UC Model

Case	DA Operation Cost ($)	RT Operation Cost ($)	Total DA and RT Operation Cost ($)	RT Ramping Scarcity Events
Case 1	471,130.7	16,882.9	488,013.6	27
Case 2	476,226.4	6,231.3	482,457.7	0





Next steps

1. How can we calculate the continuous time price?
2. What is the best way of capturing the uncertainty of the net-load? (Stochastic Continuous-Time UC?)
3. Can we also include other inter-temporal constraints (Energy: $\int_{t_0}^{t} G_k(\tau)d\tau$) and allow Demand Response and Storage (with negative generation utility) submit a bid in the Whole Sale market

Thanks for Feedback and Questions...