Restructuring the Retail Market to Include Load Flexibility

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August 3, 2015
Objectives

Two threads of research → 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 economical issues into control loops
Concrete example: managing Electric Vehicle charge

- Electric Vehicles (EV): the fuel comes from the power grid
  - Forecast $\rightarrow$ 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:

\[ \tau_a(\lambda_a), e_a \]

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

\[ \lambda_1 = [\lambda_a]_{a \in A}, \quad \lambda_2 = [\lambda_v]_{v \in B}, \quad p = [p_v]_{v \in B} \]

- **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 = \(\lambda_v\)

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

\[ 0 \leq \text{Initial charge} - \sum_{i=1}^{l} \text{ith link's energy} \leq \text{Battery capacity}, \quad \forall l \]

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)
  \[ q \in C \text{ (finite set)} \]

- **Feasible paths on extended graph** for cluster \( q \rightarrow k \in K_q \)

- \( a_q \) = 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:
  \[ \sum_{k \in K_q} d_q^k = a_q \]

**Path to flow relation in static case**

\[ \lambda_a = \sum_{q \in C, k \in K_q} \delta_a^k d_q^k \left( \sum \text{ path rates that include link } a \right) \]
Social costs in terms of individuals’ choices

Congestion cost $= \lambda^T s(\lambda)$

Electricity Cost $= \min_g 1^T c(g)$

s.t. $g^\min \preceq g \preceq g^\max$

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

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

Flow as a function of user decisions:

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

If you control the flow $\lambda$, you control traffic and energy costs
Social costs in terms of individuals’ choices

Congestion cost = $\lambda^T s(\lambda)$

Electricity Cost = $\min_g 1^T c(g)$

s.t.  $g^{\min} \leq g \leq g^{\max}$,
      $e = M\lambda \rightarrow 1^T (e + u - g) = 0$,
      $H(e + u - g) \preceq c$,

Flow as a function of user decisions:

$d_q \succeq 0, \quad 1^T d_q = a_q, \quad \lambda = \sum_{q \in Q} \Delta_q d_q$

But, $d_q$ and hence the flow $\lambda$ 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 an 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: $\gamma = 10^{-3} / 3 \, \text{$/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 2 kWh, 3 kWh and 4 kWh, respectively
Limit-cycle behavior seen in load values at different iterations

<table>
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<th></th>
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<th>DP (iter. odd)</th>
<th>DP (iter. even)</th>
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<td></td>
<td>@$53.43/MWh</td>
<td>@$54.49/MWh</td>
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<tr>
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</table>
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 centralized 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
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 $\rightarrow$ piecewise constant generation trajectory

2. **Trajectory Interpretation**: Hourly ramping constraints $\rightarrow$ 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:** $\mathbf{I}(t) = (I_1(t), \ldots, I_K(t))^T$

  \[
  I_k(t) = \sum_{h=1}^{H_k} \left( u(t - t_{k,h}^{(SU)}) - u(t - t_{k,h}^{(SD)}) \right)
  \]

  **Cost Function:** $C_k(G_k(t), G'_k(t), I'_k(t); t)$

- Continuous-time UC:

  \[
  \begin{align*}
  \min & \quad \sum_{k=1}^{K} \int_{\mathcal{T}} C_k(G_k(t), G'_k(t), I'_k(t)) dt \\
  \text{s.t.} & \quad \sum_{k=1}^{K} G_k(t) = N(t) \quad \forall t \in \mathcal{T} \\
  & \quad G_k I_k(t) \leq G_k(t) \leq G_k I_k(t), \quad G'_k I_k(t) \leq G'_k(t) \leq G'_k I_k(t) \\
  & \quad t_{k,h}^{(SD)} - t_{k,h}^{(SU)} \geq T_{k}^{(on)}, \quad t_{k,h}^{(SU)} - t_{k,h}^{(SD)} \geq T_{k}^{(off)}, \quad \forall k, h, t \in \mathcal{T}
  \end{align*}
  \]
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 \textit{finite function space} of dimensionality $P$, spanned by a set of bases functions $e(t) = (e_1(t), \ldots, e_P(t))$:

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

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

$$G_k(t) = \sum_{p=1}^{P} G_{kp} e_p(t) + \epsilon_{G_k}(t) = e(t)G_k + \epsilon_{G_k}(t).$$
Spline Representation using Cubic Hermite Polynomials

- Day-ahead scheduling horizon $T$ 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**:
  
  \[ \hat{N}(t) = \sum_{m=0}^{M-1} \mathbf{H}(\tau_m) \mathbf{N}_m^H, \quad G_k(t) = \sum_{m=0}^{M-1} \mathbf{H}(\tau_m) \mathbf{G}_{k,m}^H \]

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

- 3rd order Bernstein polynomials representations:

\[
\hat{N}(t) = \sum_{m=0}^{M-1} B_3(\tau_m) N^B_m, \quad G_k(t) = \sum_{m=0}^{M-1} B_3(\tau_m) G^B_{k,m}
\]

where \( N^B_m \) and \( G^B_{k,m} \) are the vectors of Bernstein coefficients.

- The Bernstein and Hermite coefficients are linearly related as 

\[
G^B_{k,m} = W G^H_{k,m}, \quad N^B_{k,m} = W N^H_{k,m}
\]
Why Bernstein Polynomials?

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

\[
G_k'(t) = \sum_{m=0}^{M-1} B_2(\tau_m)G_{k,m}^{IB}, \quad G_{k,m}^{IB} = K^T G_{k,m}^B = K^T W^T G_{k,m}^H
\]

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

\[
\begin{align*}
\min_{t_m \leq t \leq t_{m+1}} \{B_3^T (\tau_m)G_k^B\} & \geq \min \{G_{k,m}^B\} \\
\max_{t_m \leq t \leq t_{m+1}} \{B_3^T (\tau_m)G_k^B\} & \leq \max \{G_{k,m}^B\} \\
\min_{t_m \leq t \leq t_{m+1}} \{B_2^T (\tau_m)G_k^{IB}\} & \geq \min \{G_{k,m}^{IB}\} \\
\max_{t_m \leq t \leq t_{m+1}} \{B_2^T (\tau_m)G_k^{IB}\} & \leq \max \{G_{k,m}^{IB}\}
\end{align*}
\]
Piecewise line continuous-time cost function can be written in terms of the spline coefficients of generation trajectory:

\[ \int_{T} C_k(G_k(t), G'_k(t), l'_k(t)) dt = C_k(G_k, G'_k, l_k). \]

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

\[ \sum_{k=1}^{K} G_{k,m}^H = N_{m}^H \quad \forall m \]

One can deal with DC power flow nodal constraints similarly
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**

<table>
<thead>
<tr>
<th>Case</th>
<th>DA Operation Cost ($)</th>
<th>RT Operation Cost ($)</th>
<th>Total DA and RT Operation Cost ($)</th>
<th>RT Ramping Scarcity Events</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>471,130.7</td>
<td>16,882.9</td>
<td>488,013.6</td>
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<td>Case 2</td>
<td>476,226.4</td>
<td>6,231.3</td>
<td>482,457.7</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Generation Schedule (MW)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Group 1: Hydro</td>
</tr>
<tr>
<td>Group 2: Nuclear</td>
</tr>
<tr>
<td>Group 3: Coal 350</td>
</tr>
<tr>
<td>Group 4: Coal 155</td>
</tr>
<tr>
<td>Group 5: Coal 76</td>
</tr>
<tr>
<td>Group 6: Oil 100</td>
</tr>
<tr>
<td>Group 7: Oil 197</td>
</tr>
<tr>
<td>Group 8: Oil 12</td>
</tr>
<tr>
<td>Group 9: Oil 20</td>
</tr>
</tbody>
</table>

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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...