The System Benefits of Managing Demand Flexibility and Storage Efficiently

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- Pramod Khargonekar (U. of Florida)
- Kameshwar Poolla (U.C. Berkeley)

This Talk

Broad Goals: develop mathematical theory and computational tools to assist market planners and players in the optimal sizing, placement, and operation of energy storage to accommodate variability in renewable supply.

Talk Outline:

1. Renewable Energy Integration Challenges
2. Quantifying the Marginal Value of Storage
   - The Renewable Energy Supplier's Perspective
   - The System Operator's Perspective
3. Closing Remarks

Renewable Energy Integration

Renewables: Drivers and Targets

- Increased interest and investment in renewable energy sources
- Drivers:
  - Environmental concerns, carbon emission
  - Energy security, geopolitical concerns
  - Nuclear power safety after Fukushima
- Ambitious targets:
  - CA: RPS 33% energy penetration by 2020
  - US: 20% wind penetration by 2030
  - Denmark: 50% wind penetration by 2025

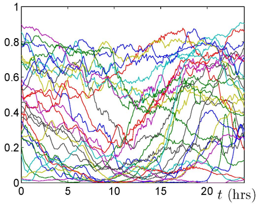
How will we economically meet these aggressive targets?

The Variability Challenge

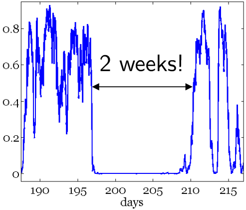
Wind and solar are variable sources of energy:

- Non-dispatchable - cannot be controlled on demand
- Intermittent - exhibit large fluctuations
- Uncertain - hard to forecast

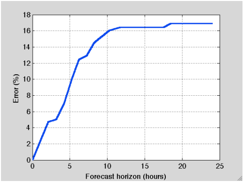
Huge variance in daily patterns



Non-stationary process



Large forecast error

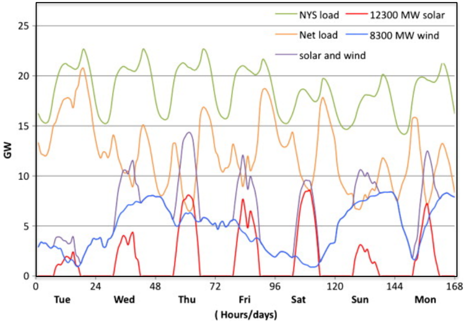


Variability poses serious operational challenges for the electric grid

Impact of Variability Under Current Operating Paradigm

Modus operandi

- All renewable power taken; treated as negative load
- System operator must balance net-load



Source: T. Nikolakakis et al., Energy Policy 39.11 (2011): 6972-6980.

- NY total load and net-load including renewables (simulated)
- Increased Ramping Need
  - Larger magnitude (+/-)
  - Variable timing
  - Higher frequency
- Increased Reserve Capacity
- Lose cheap base-load gen. (10 GW)

Excess reserves costly and defeat carbon benefits

The Role and Value of Storage

Sound bite: storage can absorb variability in supply.

Challenge: there are many avenues through which to deploy storage.

Basic question: what is the value of storage in each setting?

Supplier's perspective

- Next generation markets will penalize renewable energy for imbalances...
- How to leverage on storage to mitigate quantity risk?
- How much to install?

System operator's (SO) perspective

- SO has a network of interconnected storage devices
- How to optimally dispatch networked storage under uncertainty?
- What is locational marginal value of storage capacity in networks?

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The Supplier's Perspective

Selling Random Energy (with storage)

Outline (Supplier's Perspective)

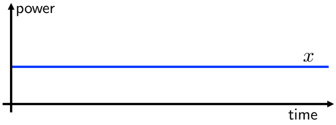
1. Basic Setting
2. Models: *Supply*, *Storage*, and *Market*
3. Marginal Value Results

Setting: Two-Settlement Market

Setting: Generators traditionally sell power in a two-settlement market system

Ex ante (day-ahead)

1. Supplier offers a constant power contract x. Paid at a fixed price.



Ex post (real-time)

- The supply profile ξ reveals itself.
- The realized deviation profile $|x - \xi|$ is penalized.

In the absence of storage...

x^* = newsvendor quantile maximizes supplier expected profit

Bitar et al. Bringing wind energy to market. IEEE Trans. on Power Sys., 2012.

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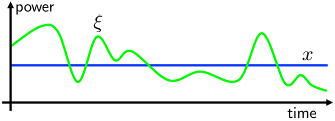

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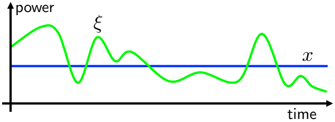

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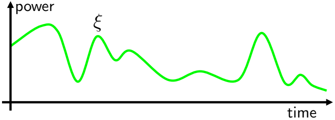
Intermittent Supply Model

The intermittent supply from wind is modeled as a real-valued, discrete time stochastic process defined on a complete probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

$$\boldsymbol{\xi} = (\xi_0, \xi_1, \ldots, \xi_{N-1}), \qquad \xi_k \in \Xi = [0, 1] \quad \text{for all} \quad k$$



The marginal cumulative distribution functions (CDF) are assumed known and defined as

$$\Phi_k(x) = \mathbb{P}\{\xi_k \leq x\}, \quad k = 0, 1, \ldots$$

Denote by $F(\cdot)$ the time-averaged CDF

$$F(x) = \frac{1}{N} \sum_{k=0}^{N-1} \Phi_k(x)$$

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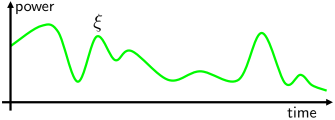

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Storage Model

Consider as a model of a perfectly efficient energy storage device, the scalar linear difference equation

$$z_{k+1} = z_k + u_k, \qquad k = 0, 1, \cdots \qquad (z_0 = 0)$$

- (state) $z_k \in \mathbb{R}_+$ denotes the total energy store just preceding period k
- (input) $u_k \in \mathbb{R}$ denotes the energy extracted ($u_k < 0$) or injected ($u_k \geq 0$)

We impose the following state and input constraints

$$\begin{aligned} 0 \leq \quad & z_k \quad \leq b \qquad \text{(energy capacity)} \\ -r \leq \quad & u_k \quad \leq r \qquad \text{(power capacity)} \end{aligned}$$

Note: Can generalize model to include storage inefficiencies

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Note: Can generalize model to include storage inefficiencies

Admissible Control Policies, $\pi \in \Pi(b)$

Feasible state space, $\mathcal{Z} = \{z \in \mathbb{R}_+ \ : \ z \in [0, b]\}$

Feasible input space, $\mathcal{U}(z) \ = \ \{u \in \mathbb{R} \ : \quad |u| \leq r \quad \text{and} \quad z + u \in [0, b]\}$

Restrict our attention to policies with Markovian information structure,

$$u_k = \mu_k(z_k, \xi_k), \qquad k = 0, 1, \ldots$$

Definition (Admissible policies)

A control policy $\pi = (\mu_0, \ldots, \mu_{N-1})$ is deemed admissible if

$$\mu_k(z, \xi) \in \mathcal{U}(z) \qquad \text{for all} \quad (z, \xi) \in \mathcal{Z} \times \Xi \quad \text{and} \quad k = 0, \ldots, N-1.$$

We denote by $\Pi(b, r)$ the space of all admissible control policies π.

Two-Settlement Market Model

Supplier Decisions

1. Ex ante (x): offer a forward contract $x \in \mathbb{R}_+$

   $p \in \mathbb{R}_+$: forward market clearing price

2. Ex post (π): dispatch storage (π) to minimize imbalance cost over N periods

   $\sigma \in \mathbb{R}_+$: shortfall imbalance price

   $\lambda \in \mathbb{R}_+$: surplus imbalance price

Assumptions

- Supplier is small $\implies$ treat as price taker
- Imbalance prices (σ, λ) not known ex ante

$$m_\sigma = \mathbb{E}[\sigma] \quad \text{and} \quad m_\lambda = \mathbb{E}[\lambda], \qquad (m_\sigma \geq p)$$

Treated as time-invariant, random, and independent of ξ

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Treated as time-invariant, random, and independent of $\boldsymbol{\xi}$

Cost Structure

The expected profit $J^{\pi}(x)$ derived under a forward contract x and policy π is

$$J^{\pi}(x) = \underbrace{pN \cdot x}_{revenue} - \underbrace{\mathbb{E}[\, Q^{\pi}(x, \boldsymbol{\xi})]}_{expected\ \ imbalance\ \ cost}$$

where Q denotes the recourse cost realized under (x, π) and $\boldsymbol{\xi}$.

$$Q^{\pi}(x, \boldsymbol{\xi}) = \sum_{k=0}^{N-1} \sigma\,(x - \xi_k + u_k^{\pi})^{+} + \lambda\,(\xi_k - u_k^{\pi} - x)^{+}$$

Definition (Optimality)

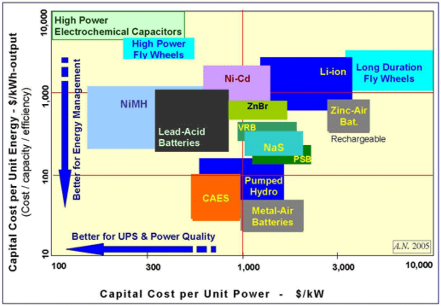
An admissible policy-contract pair (π^*, x^*) is optimal if

$$J^{\pi^*}(x^*) \geq J^{\pi}(x) \quad \text{for all} \quad (\pi, x) \in \Pi(b, r) \times \mathbb{R}_+$$

Denote $J^*(b, r) = J^{\pi^*}(x^*)$ given storage parameters (b, r).

The Role of Storage

Sound bite: energy storage can absorb variability in supply



Source: Electricity Storage Association

Storage is expensive!

- energy capacity (b)
  50 K - 10 Mil/MWh
- power capacity (r)
  \$ 100 K - 10 Mil/MW

Some basic questions:

1. Optimal storage sizing?
2. Interplay between variability in supply and value of storage?

The Marginal Value of Energy Storage

Denote by $J^*(b, r)$ the optimal expected profit given parameters (b, r).

Lemma

The optimal expected profit $J^*(b, r)$ *is*

1. *concave in* (b, r)
2. *monotone non-decreasing in* (b, r)

Two implications:

1. Optimal storage sizing amounts to a convex optimization problem
2. Largest marginal benefit derived for 'small' storage

Would like to have the following sensitivity

$$\left. \frac{\partial J^*(b, r)}{\partial b} \right|_{b=0} = ? \quad \text{Marginal Value of Storage}$$

Related Work

Koeppel, Gaudenz, and Magnus Korpas. *Improving the network infeed accuracy of non-dispatchable generators with energy storage devices*. Electric Power Systems Research, 2008.

- Consider certainty equivalent forward contracts
- Marginal value analysis is purely empirical

Kim, Jae Ho, and Warren B. Powell. *Optimal energy commitments with storage and intermittent supply*. Operations Research, 2011.

- Derive marginal value under uniformity assumption on intermittent supply

We provide explicit formulae for marginal value under arbitrary distributions

Related Work

Kefayati, Mahdi, and Ross Baldick. *On Optimal Operation of Storage Devices under Stochastic Market Prices*. ACC 2013.

Qin, Junjie, Raffi Sevlian, David Varodayan, and Ram Rajagopal. *Optimal electric energy storage operation*. PES General Meeting, 2012.

- Assume Gauss-Markov price processes

Faghih, Ali, Mardavij Roozbehani, and Munther A. Dahleh. *On the economic value and price-responsiveness of ramp-constrained storage*. Energy Conversion and Management, Vol. 76, pp. 472-482. 2013.

- Assume price process independent across time
- Derive and upperbound on the value of ramp-constrained storage.
- Show that "value of storage is a non-decreasing function of price volatility"

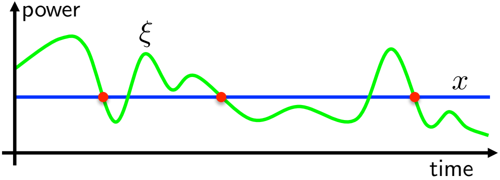
Contract Level Crossings

Definition (Strict Level Down-Crossings)

Let $\Lambda_{\boldsymbol{\xi}}(x) \in \mathbb{N}_0$ denote the # of strict down-crossings of the level $x \in \mathbb{R}_+$ by the random process $\boldsymbol{\xi}$.

$$\Lambda_{\boldsymbol{\xi}}(x) \;=\; \sum_{k=0}^{N-2} \mathbf{1}_{\{\xi_k > x\}} \cdot \mathbf{1}_{\{\xi_{k+1} < x\}}$$

where $\mathbf{1}_{\{\cdot\}}$ is the indicator function.



The Marginal Value of Energy Capacity (b)

Theorem

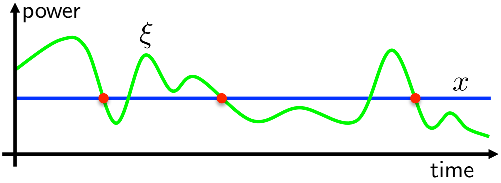
The marginal value of energy capacity at the origin ($b = 0$) is given by

$$\left.\frac{\partial J^*(b,r)}{\partial b}\right|_{b=0} = (m_\sigma + m_\lambda) \cdot \mathbb{E}[\ \Lambda_{\boldsymbol{\xi}}(x^*)\ ] \quad + \quad m_\lambda \cdot \mathbb{P}\{\xi_{N-1} > x^*\}$$

where $x^* = F^{-1}(\gamma)$.

⇒ Marginal value easily computed from time series data!

Just count the number of empirical γ-quantile crossings.



IID Supply Process ($\boldsymbol{\xi}$)

Corollary

Assume that $\boldsymbol{\xi}$ is an iid process. It follows that

$$\mathbb{E}[\ \Lambda_{\boldsymbol{\xi}}(x^*)\ ]\ =\ (1-\gamma)\cdot\gamma\cdot(N-1), \qquad \gamma = \frac{p+m_\lambda}{m_\sigma+m_\lambda},$$

where $x^* = F^{-1}(\gamma)$.

Interesting features:

- Expected # of down-crossings of $x^* = F^{-1}(\gamma)$ invariant under choice of distribution!
- Marginal value depends only on prices

IID Supply Process (ξ)

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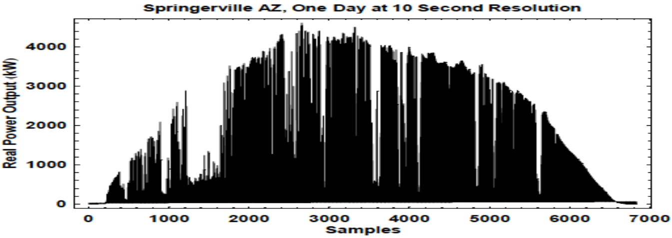
where $x^* = F^{-1}(\gamma)$.

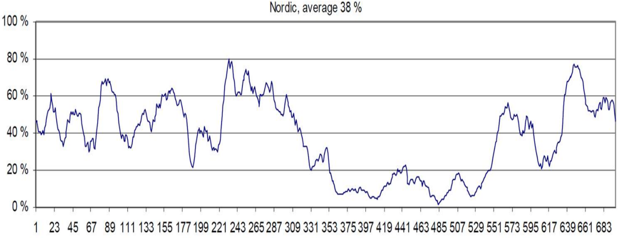
Interpretation:

$$\mathbb{E}[\ \Lambda_{\xi}(x^*)\ ] \ = \ (N-1)\cdot \mathbf{Var}\,(\theta)$$

where $\theta \sim \mathbf{Ber}(\gamma)$.

Spectral Properties of Wind vs. Solar



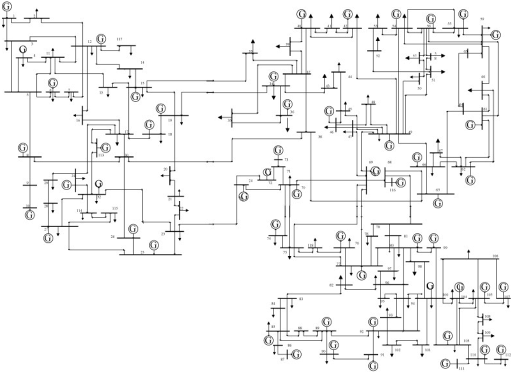


Solar Power data – 1 day, 10 second data [Apt et al., CMU, 2009]

Wind power data – 1 month, 1 hour data from Nordic grid [P. Norgard et al.,2004]

The System Operator's Perspective

Real-Time Economic Dispatch

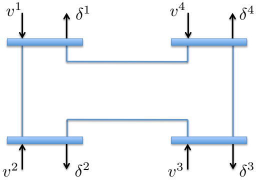


Outline (System Operator's Perspective)

1. Setting
2. Models: *Power Network*, *Net-Demand*, *Storage*, and *RTED*
3. Characterizing the Locational Marginal Value of Storage

Real-Time Economic Dispatch (RTED)

Setting: The system operator (SO) must procure minimum cost generation from available units to balance the realized net-demand profile over N periods.



Essential Features of RTED

1. *(Uncertainty).* The net-demand profile is a random process $\boldsymbol{\delta} = \{\boldsymbol{\delta}_k\}$ $(\in \mathbb{R}^m)$

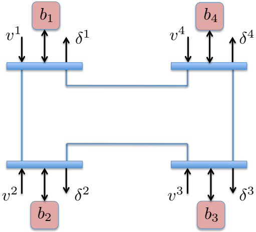
2. *(Network Constraints).* At each period k, the SO buys gen. $\mathbf{v}_k \in \mathbb{R}^m$ to
   - Balance the realized demand profile $\boldsymbol{\delta}_k$
   - Respect network constraints

Dispatch cost heavily dependent on variability in net-demand $\boldsymbol{\delta} = \boldsymbol{\delta}_0, \boldsymbol{\delta}_1, \ldots$

Consider a transmission network with distributed energy storage capacity

$$\mathbf{b} \; = \; (b^1, \ldots, b^m) \in \mathbb{R}_+^m$$

Distributed storage enables spatio-temporal arbitrage of imbalances



Critical Questions

- (Dispatch). Optimal dispatch policy given distributed storage?
- (Sizing). How much storage to install and where?

$$\mathbf{b} \; = \; (b^1, \ldots, b^m)$$

- What is the Locational Marginal Value of storage?

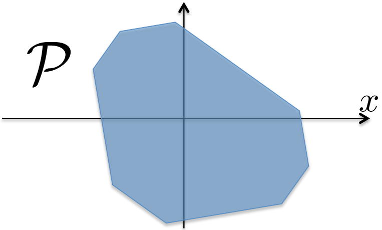
Power Network Model

Network: Consider a connected power network (m nodes, ℓ edges)

- Linear DC power flow approximation
- Feasible injection region $\mathcal{P}$ satisfies

$$\mathcal{P} \; := \; \left\{ x \in \mathbb{R}^m \;\middle|\; -c \leq Hx \leq c, \quad \mathbf{1}^\top x = 0 \right\}$$

- $H \in \mathbb{R}^{\ell \times m}$, shift factor matrix
- $c \in \mathbb{R}^{\ell}_{+}$, vector of transmission line capacities

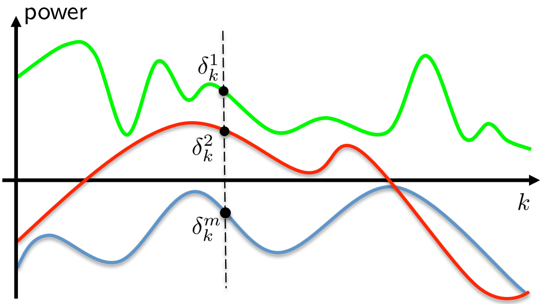


Net-Demand Model

We model the spatio-temporal evolution of the net-demand profile over N periods as a multivariate random process

$$\boldsymbol{\delta}_k \;=\; (\delta_k^1, \ldots, \delta_k^m) \in \mathbb{R}^m \qquad k = 0, \ldots, N-1$$

- $\delta_k^i \leq 0 \implies$ net-energy demand at node i during period k.
- $\delta_k^i > 0 \implies$ net-energy supply at node i during period k.

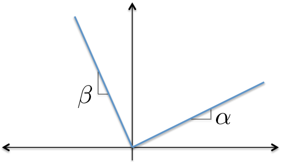


Generation Cost Model

Generation Cost: The cost of generating the profile $\mathbf{v}_k = (v_k^1, \ldots, v_k^m) \in \mathbb{R}^m$ at time k is

$$g(\mathbf{v}_k) \;=\; \sum_{i=1}^{m} \alpha \cdot (v_k^i)^+ \;+\; \beta \cdot (-v_k^i)^+$$

- $\alpha \geq 0$ and $\beta \geq 0$ are given constants
- $v_k^i \in \mathbb{R}$ denote gen. dispatch at node i at time k



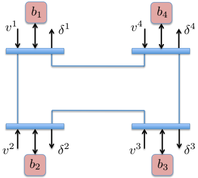
Remark: We have assumed that cost functions are uniform across the network

Storage Model

The collection of energy storage systems evolve according to

$$\mathbf{z}_{k+1} = \mathbf{z}_k + \mathbf{u}_k, \qquad k = 0, 1, \cdots \qquad (\mathbf{z}_0 = 0)$$

- $\mathbf{z}_k \in \mathbb{R}^m_+$ denotes the vector of storage states at stage k
- $\mathbf{u}_k \in \mathbb{R}^m$ denotes the vector of storage dispatches at stage k



Then the collection of energy storage devices are constrained as

$$0 \leq \mathbf{z}_k \leq \mathbf{b}$$

where $\mathbf{b} = (b^1, \ldots, b^m)$ is the installed storage capacity across the network

Admissible Dispatch Policies

We consider causal dispatch policies $\pi = \{\mu_k, \nu_k\}$ of the form

$$\mathbf{u}_k = \mu_k(\mathbf{z}^k, \boldsymbol{\delta}^k) \quad \text{and} \quad \mathbf{v}_k = \nu_k(\mathbf{z}^k, \boldsymbol{\delta}^k) \qquad k = 0, 1, \ldots$$

where $\mathbf{z}^k = (\mathbf{z}_0, \ldots, \mathbf{z}_k)$ and $\boldsymbol{\delta}^k = (\boldsymbol{\delta}_0, \ldots, \boldsymbol{\delta}_k)$.

Definition (Admissible policies)

A dispatch policy π is deemed admissible if

$$\mathbf{v}_k^\pi - \mathbf{u}_k^\pi + \boldsymbol{\delta}_k \in \mathcal{P} \qquad \text{and} \qquad \mathbf{z}_k^\pi \in [0,\ \mathbf{b}] \quad \textit{almost surely} \qquad k = 0, 1, \ldots$$

We denote by $\Pi(\mathbf{b})$ the space of all admissible dispatch policies π.

The Multi-Period Economic Dispatch Problem

Fix a vector $\mathbf{b}$. The expected dispatch cost incurred by policy $\pi \in \Pi(\mathbf{b})$ is

$$J^{\pi} = \mathbb{E}\left[\sum_{k=0}^{N-1} g(\mathbf{v}_k^{\pi}) \right]$$

where expectation take with respect to the net-demand process $\{\boldsymbol{\delta}_k\}$

Definition

An admissible policy $\pi^* \in \Pi(\mathbf{b})$ is optimal if

$$J^{\pi^*} \leq J^{\pi} \qquad \text{for all} \qquad \pi \in \Pi(\mathbf{b})$$

Denote $J^*(\mathbf{b}) := J^{\pi^*}$ to emphasize its dependency on $\mathbf{b}$.

The Multi-Period Economic Dispatch Problem

Fix a vector $\mathbf{b}$. The expected dispatch cost incurred by policy $\pi \in \Pi(\mathbf{b})$ is

$$J^{\pi} = \mathbb{E}\left[\sum_{k=0}^{N-1} g(\mathbf{v}_k^{\pi})\right]$$

where expectation take with respect to the net-demand process $\{\boldsymbol{\delta}_k\}$

Definition

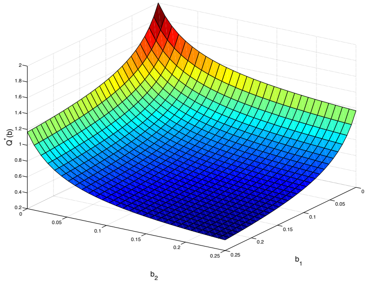
An admissible policy $\pi^* \in \Pi(\mathbf{b})$ is optimal if

$$J^{\pi^*} \leq J^{\pi} \qquad \text{for all} \qquad \pi \in \Pi(\mathbf{b})$$

Denote $J^*(\mathbf{b}) := J^{\pi^*}$ to emphasize its dependency on $\mathbf{b}$.

Locational Marginal Value of Storage

One can show that $J^*(\mathbf{b})$ is convex and non-increasing in $\mathbf{b}$ over $\mathbb{R}^m_+$



Would like to characterize the locational marginal value of storage at $\mathbf{b} = 0$

$$\nabla J^*(0) = \left(\frac{\partial J^*(\mathbf{b})}{\partial b^1}, \cdots, \frac{\partial J^*(\mathbf{b})}{\partial b^m} \right)_{\mathbf{b}=0} = \ ?$$

Main Result: Locational Marginal Value of Storage

Theorem

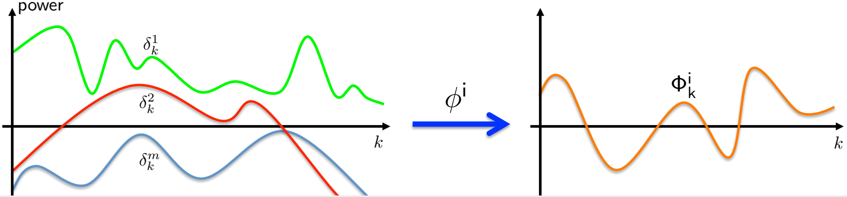
There exists a collection of continuous, piecewise-affine (PWA) mappings

$$\phi^i : \mathbb{R}^m \longrightarrow \mathbb{R} \qquad i = 1, \ldots, m$$

such that under the induced (scalar) random process $\Phi^i_k = \phi^i(\boldsymbol{\delta}_k)$

$$-\frac{\partial J^*(\mathbf{b})}{\partial b^i}\bigg|_{\mathbf{b}=0} = (\alpha + \beta) \cdot \mathbb{E}[\ \Lambda_{\Phi^i}(0)\ ] \quad + \quad \beta \cdot \mathbb{P}\{\Phi^i_{N-1} > 0\}$$

for $i = 1, \ldots, m$.



Some Intuition

Imagine you have a small ($\varepsilon > 0$) amount of storage installed at node i

- $\phi^i(\boldsymbol{\delta}_k) > 0 \implies$ feas. transfer of network surplus to node $i \implies$ save $\beta\varepsilon$
- $\phi^i(\boldsymbol{\delta}_k) < 0 \implies$ feas. transfer from node i to network shortfall $\implies$ save $\alpha\varepsilon$

Total savings $\approx \varepsilon(\alpha+\beta)\cdot$ (# of times $\phi^i(\boldsymbol{\delta}_k)$ crosses 0 from above)

On can think of $\phi^i(\cdot)$ as a network mixing function. Two extremes are:

$$\phi^i(\boldsymbol{\delta}_k) = \begin{cases} \sum_{j=1}^m \delta_k^j & \text{perfect mixing} \\ \delta_k^i & \text{no mixing} \end{cases}$$

Some Intuition

Imagine you have a small ($\varepsilon > 0$) amount of storage installed at node i

- $\phi^i(\boldsymbol{\delta}_k) > 0 \implies$ feas. transfer of network surplus to node $i \implies$ save $\beta\varepsilon$
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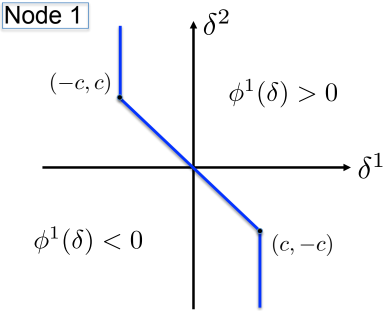
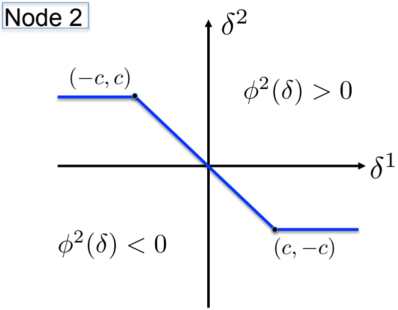
Two-Node Example

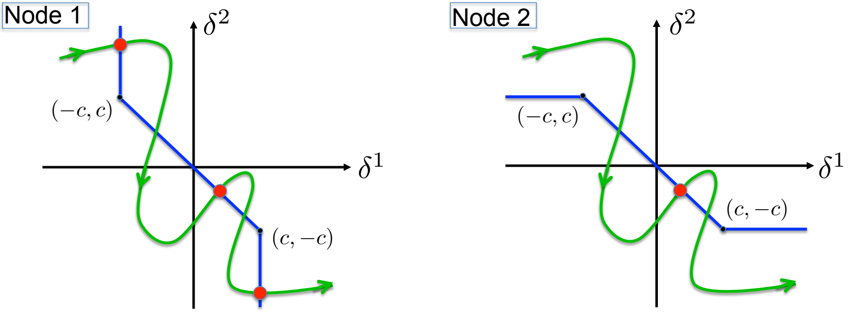
Consider a network consisting of 2 nodes and a transmission capacity $c \geq 0$





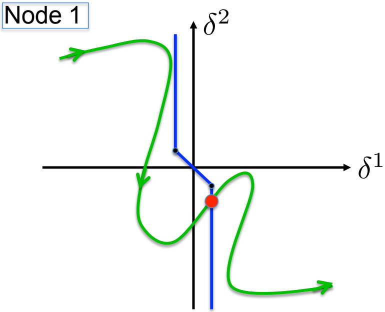
Some Intuition

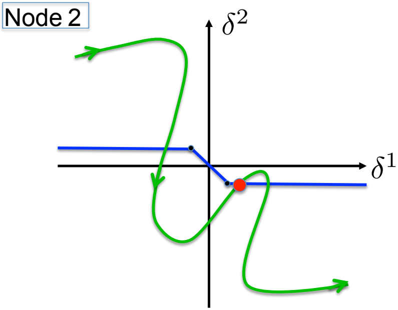
Consider a network consisting of 2 nodes and a transmission capacity $c \geq 0$



Some Intuition

Consider a network consisting of 2 nodes and a transmission capacity $c \geq 0$





Conclusions

Key insights

- Strict level crossings are essential feature of storage marginal value
- Marginal value formulae hold for arbitrary distributions on supply
  - e.g. non-gaussian, non-stationary, etc.
- Can be easily computed from time-series data without requiring the explicit solution of an optimization problem.

Generalizations

- More general (convex) cost structures
- Incorporation of additional constraints on dispatch (e.g. ramping)

Who commands the storage?

- Turning storage capacity into a market product
- Efficiency implications

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5. E. Bitar et al. The role of co-located storage for wind power producers in conventional electricity markets. Proc. of the IEEE American Control Conf., 2011.

An Application to Demonstrate the Mismatch between the System Benefits of Deferrable Demand* and Typical Rate Structures

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Dyson School of Applied Economics and Management, Cornell University

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Department of Economics, Lehigh University

* Deferrable Demand implies that the purchase of energy from the grid can be decoupled from the delivery of an energy service to customers.

PSERC Research on the SuperOPF

PSERC Researchers at Cornell

Engineers

- Lindsay Anderson
- Eilyan Bitar
- Hsiao-Dong Chiang
- Bob Thomas
- Lang Tong
- Max Zhang
- Ray Zimmerman

+

- Judy Cardell, Smith College
- Carlos Murillo-Sanchez, Universidad Nacional de Colombia

Economists

- Wooyoung Jeon*
- Hao Lu*
- Tim Mount
- Dick Schuler
- Bill Schulze

+

- Alberto Lamadrid, Lehigh
- Jung Youn Mo, KIET
- Dan Shawhan, RPI

* Graduate Student

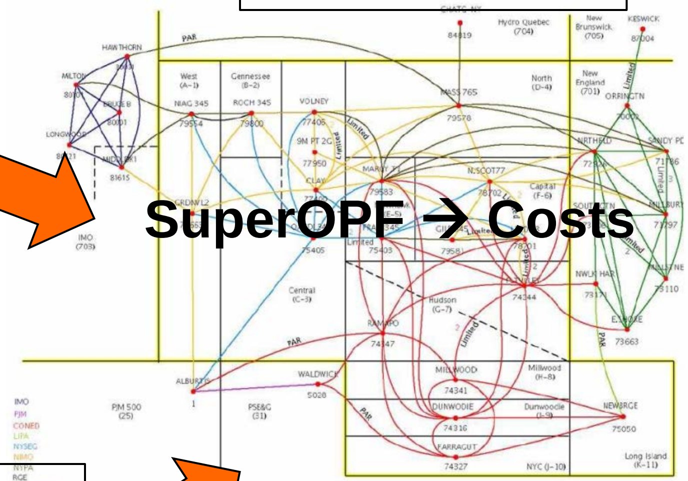
PART I: Description of the Multi-Period SuperOPF

Overview of this Research:

An Integrated Multi-Scale Framework Using the SuperOPF

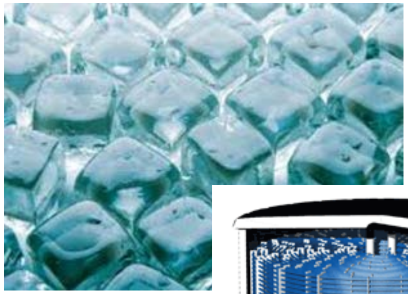
PEV charger capacities → Commuting Patterns → Nodal Capabilities

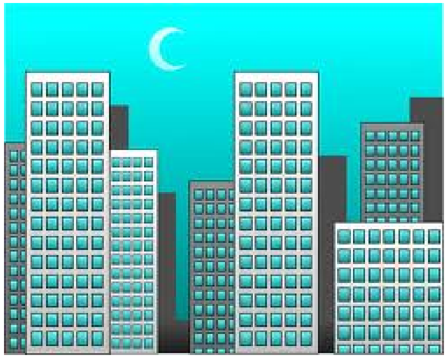
North East Test Network

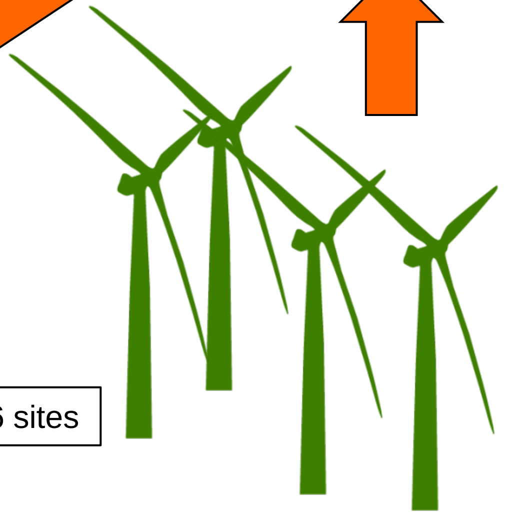


SuperOPF → Costs

Ice storage systems → Buildings → Nodal Capabilities

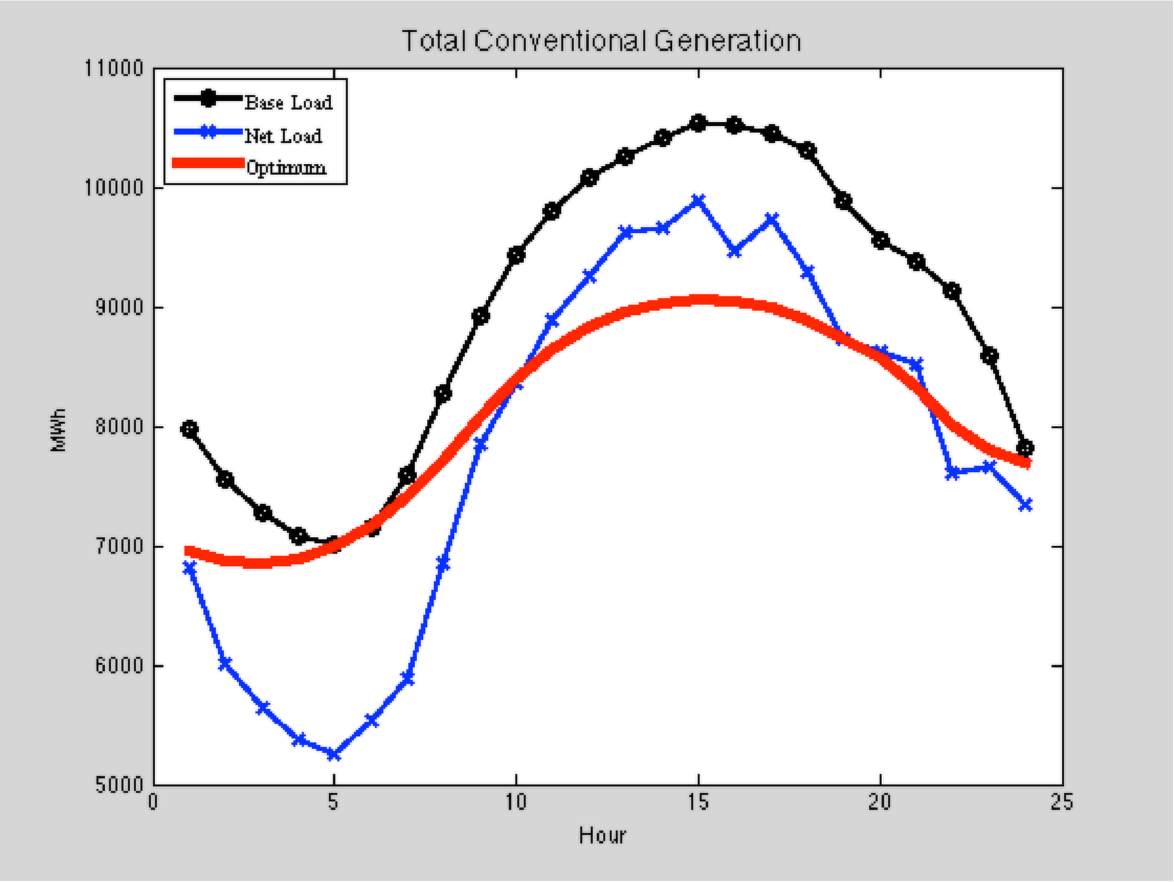






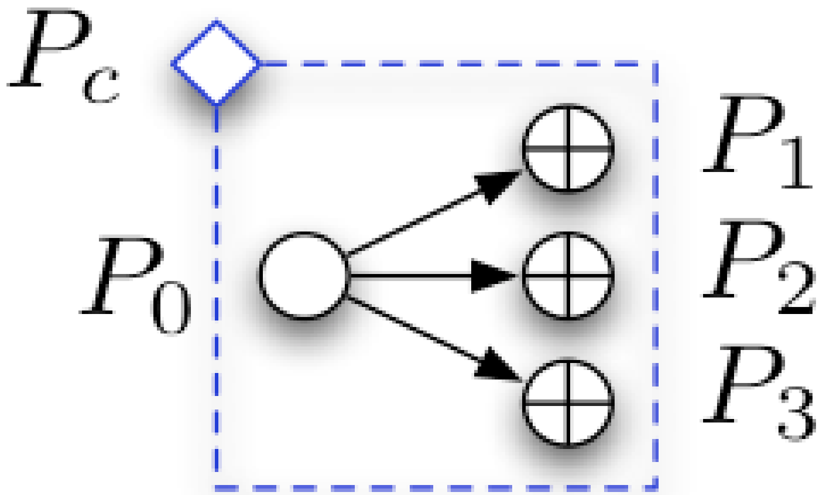
Stochastic wind at 16 sites

Characterizing the Economic Problem of Meeting the Daily Demand for Electricity in NYC



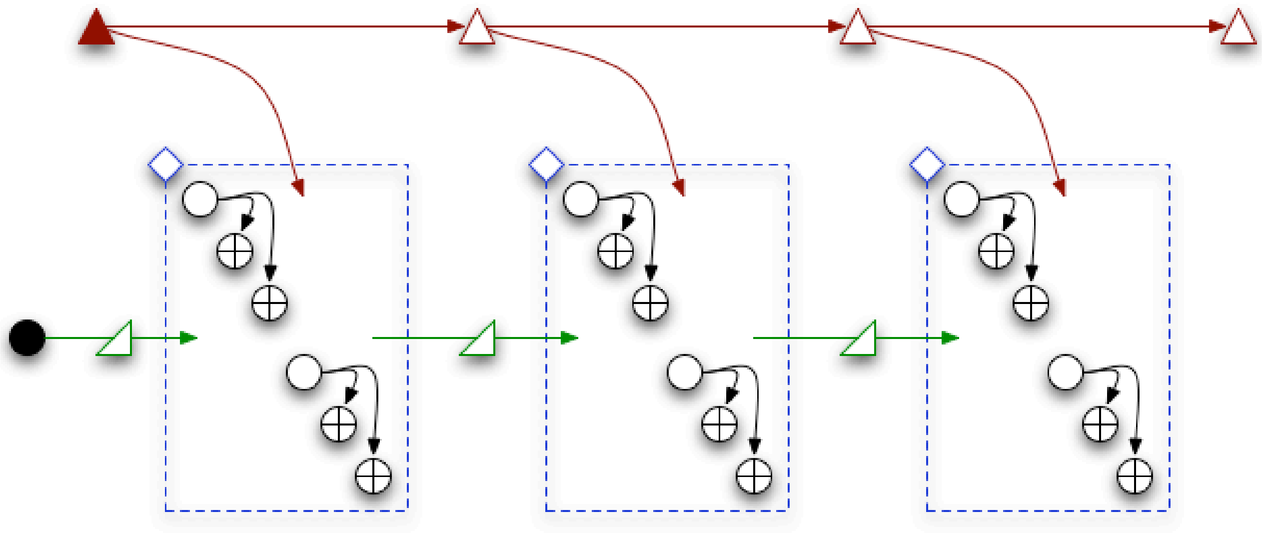
- **Net Load** is defined as Base Load – Wind Generation
- **Optimum** is the least cost dispatch with 5 GWh of PHEV and 5 GWh of thermal storage
- The optimum dispatch is flatter and smoother than Net Load
- **WHAT HAPPENS WHEN A POWER NETWORK IS CONSIDERED?**

Co-optimization Structure for the Single-Period SuperOPF



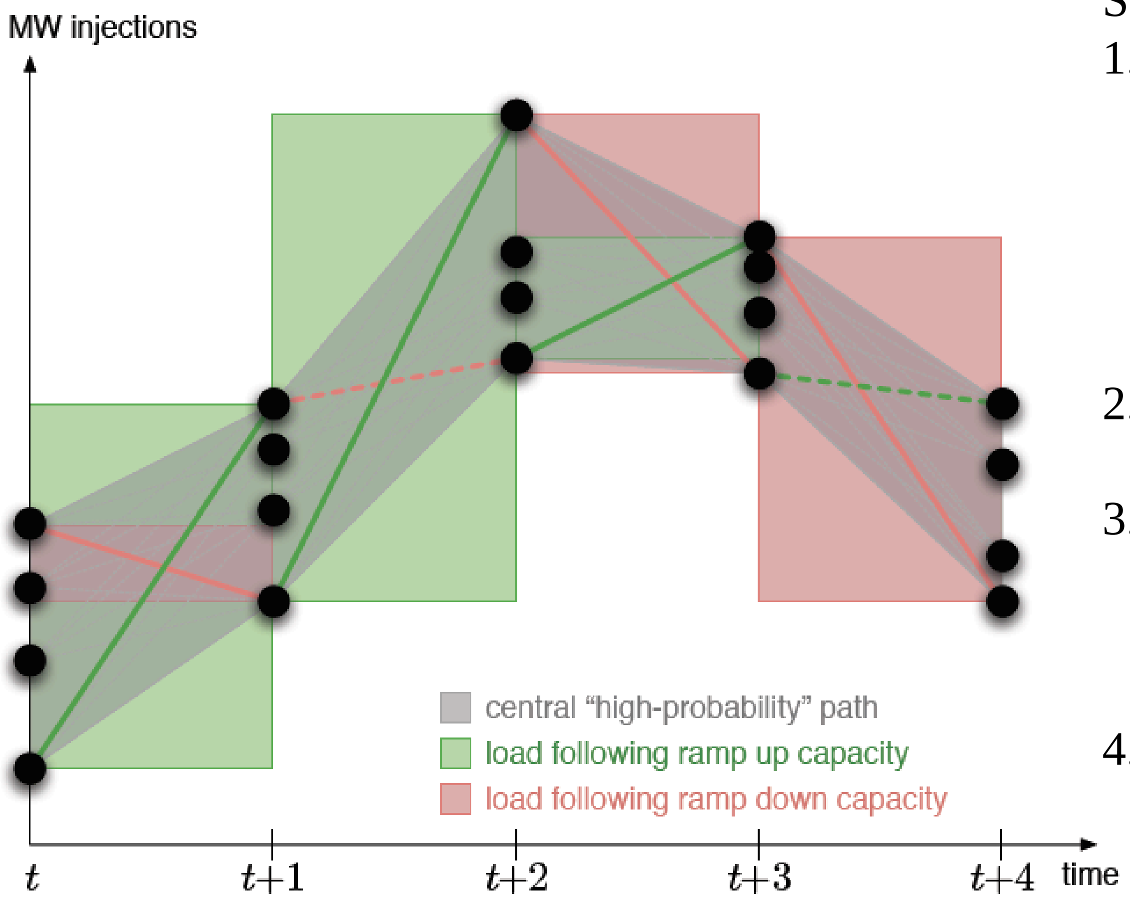
- reference variable set with
  - upward and downward deviation variables
  - deviation limit variables
  - costs on deviations
  - costs and constraints on limits
- e.g. optimal energy contract, incs/decs from the contract, reserves

Co-optimization Structure for the Multi-Period SuperOPF



- **Includes:**
  - Multi-Period Optimization
  - Stochastic Wind Generation
  - Reserve Capacity for Ramping and Contingencies
  - Cost of Ramping Delivered
  - Different Types of Storage

Modeling the Stochastic Behavior of Potential Wind Generation Using Four States (Levels)



Steps:

1. Simulate a sample of hourly wind speeds for a specified day using an ARMAX model based on NREL wind speed data (EWITS) for 16 sites in New York State and New England
2. Convert the wind speeds to potential wind generation.
3. For each hour of the day, use the K means++ algorithm to pick K representative levels of potential wind generation (scenarios)
4. Assign the sample days to the nearest mean for hour t and then estimate transition probabilities from hour t-1 to hour t for t = 1,2,….,24

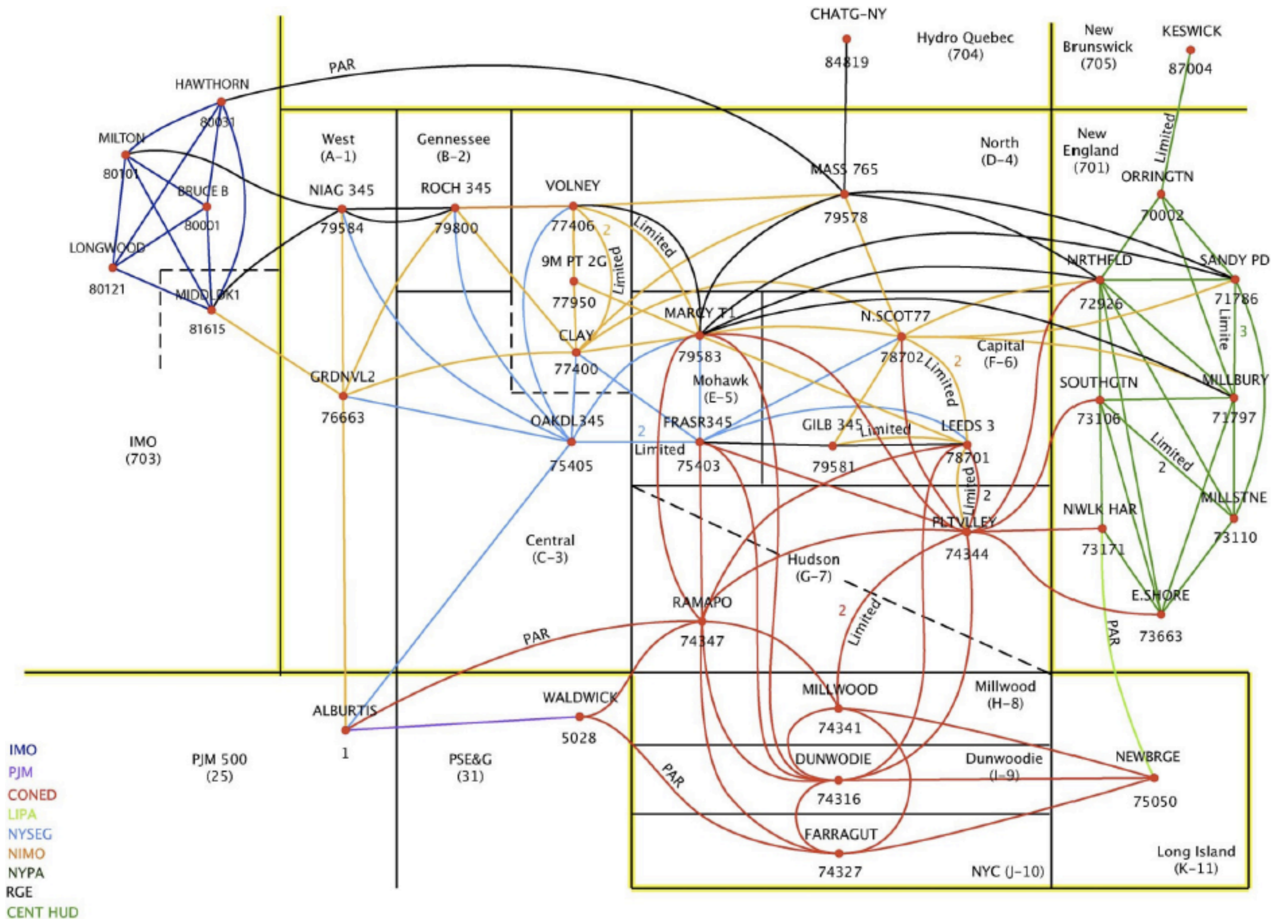
Criterion Used to Determine the Optimum Dispatch in the Multi-Period SuperOPF

Minimize the expected cost of operations over a 24-hour horizon for different wind states and a set of credible contingency states each hour subject to standard network constraints.

- Each hour has 4 wind states and 8 contingency states,
- Acquire reserve capacity to cover the contingencies each hour,
- Acquire up and down ramping capacity to cover the 16 possible transitions to the 4 wind states in the next hour,
- Ramping costs are incurred for actual ramping delivered,
- Spilling potential wind generation and shedding load (at a high VOLL) are allowed.

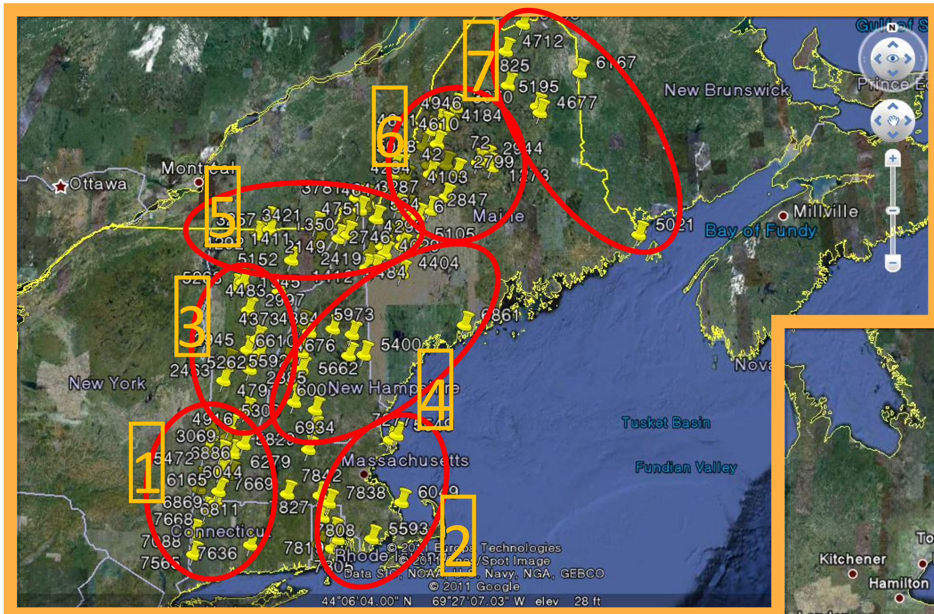
North Eastern Test Network (NETNet)

Reduced NPCC System (Allen, Lang and Ilic (2008))

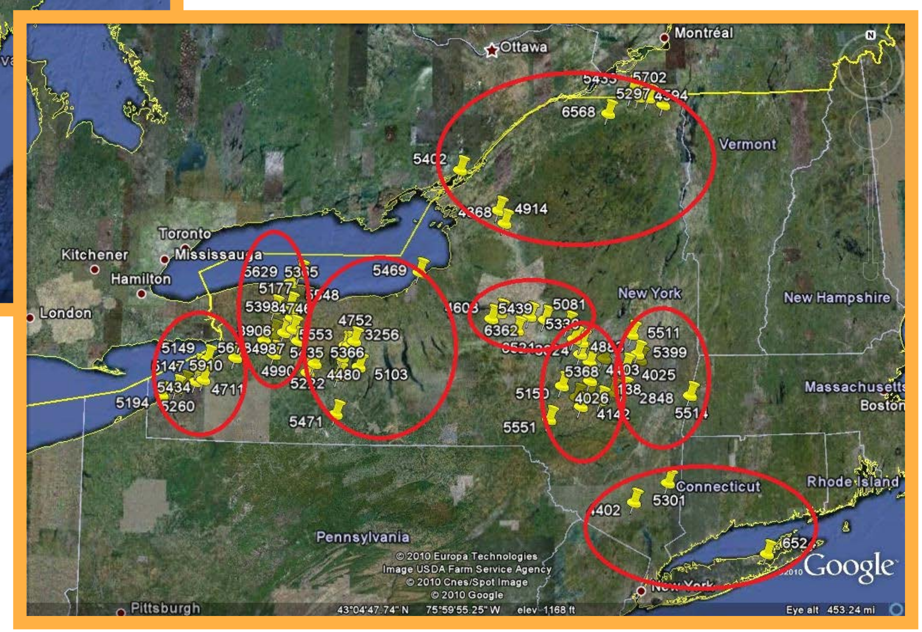


16 Wind Site Clusters Assigned to Specific Nodes (EWITS data from NREL)

New England



New York State



Total Wind Capacity, 32GW,
- Expected potential wind generation could supply 13% of the daily energy.

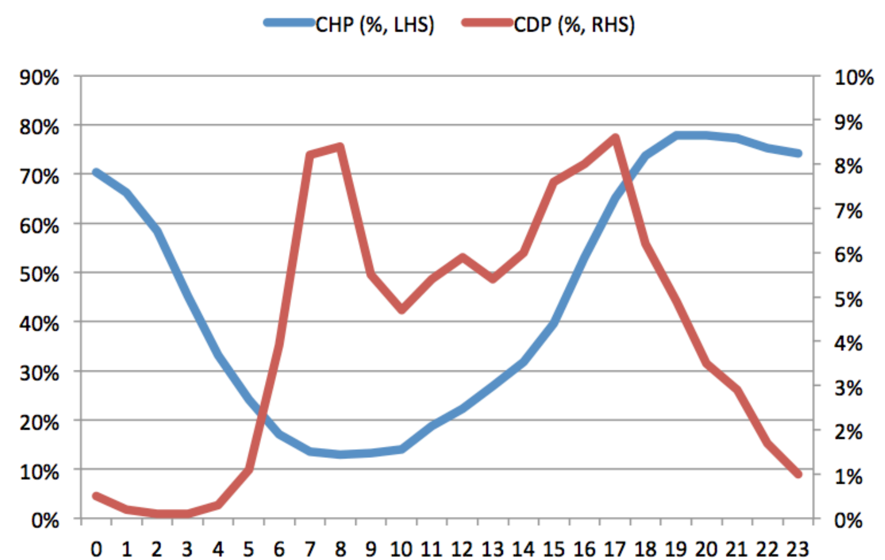
Specifications for the Electric Vehicles

(Valentine, Temple and Zhang (2011), Journal of Power Sources)

- Only G2V is available. (V2G not allowed)
- EVs are connected to grid using smart charger while vehicle is at home
- Technical specification of EV is based on GM Volt 2013

	EV
Target Aggregated EV Capacity	34 GWh
The number of passenger vehicle in NYNE	15,692,624
Total Aggregated EV Capacity	169 Gwh
Penetration Rate (%)	20%
Usable battery capacity per vehicle	10.8 kWh
Charger Level (Level1 / Level2)	70/30
Average Charging Power	3.31 kW
Average Charging Power Rate	31%
Average Driving Distance per kWh	4 mile/kWh
Average Commuting Distance (mile)	27.2(Urban)
Storage Efficiency (%)	90%

- Commuter-at-Home Profile (CHP) is used to compute the number of EVs available for charging at home.
- Commuter Driving Profile (CDP) is used to model hourly energy consumption for commuting

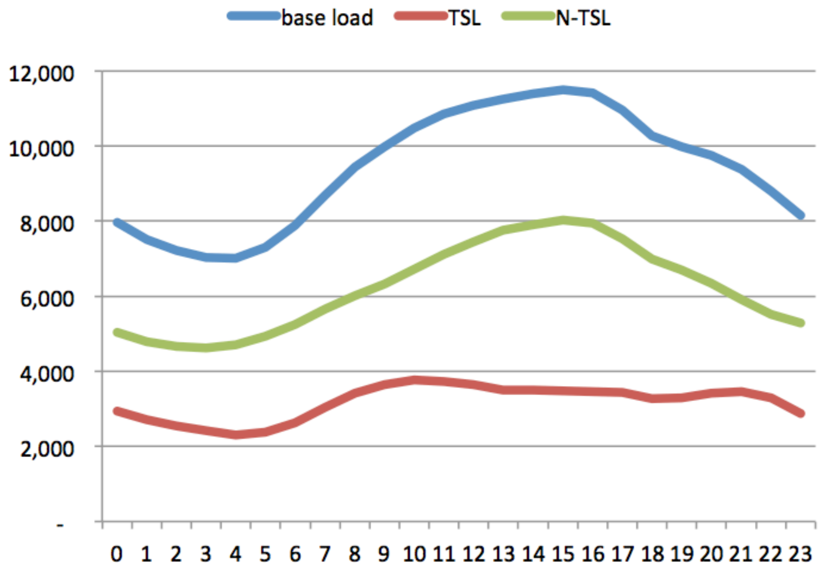


Specifications for Thermal Storage
(Palacio et al., in preparation)

- The same level of aggregate storage capacity of EV is used
- Temperature-Sensitive Load(TSL) is estimated from Base Load. This is a potential limit of cooling load which can be shifted
- Storage capacity of 34 GWh corresponds to 16% penetration based on total daily TSL.
- The Efficiency is computed based on EER of TS, **8.8** and EER of conventional AC, **10.2**

	Thermal Storage
Target Aggregated TS Capacity	34 GWh
Total Aggregated TSD	213 GWh
Penetration Rate	**16%**
TS Capacity of Benchmark Product(Calmac)	30,000 kWh
Ice Building Power (kW)	3,600 kW
Ice Melting Power (kW)	5,000 kW
Ice Building Power Rate (%)	12%
Ice Melting Power Rate (%)	17%
Storage Efficiency	86%

- Ice melting power is limited by hourly TSL
- Ice building power is determined by number of chillers.



PART II: The Effects of Storage on System Level Costs for a Hot Summer Day

System Characteristics of the NE Test Network and the Six Cases

NYNE GENERATING CAPACITY	
Peaking (GW)	37
Baseload (GW)	26
Fixed Imports (GW)	3
TOTAL (GW)	**66**
New Wind (GW)	32
Storage Capacity (GW)	Varies, c. 5GW
Storage Energy (GWh)	34
Peak Load (GW)	**60**
Average Load (GW)	**49**

Characteristics of Wind Input

Wind/conventional capacity: 48%, Capacity factor of wind: 21%, Expected potential wind generation could supply 13% of the daily energy.

Properties of Thermal Storage

For each hour the level of demand (system load) is divided into conventional demand (85%) and cooling demand (15%) that can be covered by ice batteries or by air conditioning.

Case 1: No Wind: Initial base system

Case 2: Wind, 32 GW of wind capacity at 16 locations added.

Case 3a: Case 2 + 34GWh of Thermal Storage (TS) at 5 load centers

Case 3b: Case 2 + 34GWh of Electric Vehicle (EV) at 5 load centers

Case 3c: Case 2 + 34GWh of half TS and half EV at 5 load centers

Case 4: Case 2 + 34GWh of Energy Storage Systems (ESS) collocated at the 16 wind sites

How Does Storage Affect System Operations?

Expected Outcomes (E[MWh]/day)	c1	(c2 - c1)	(c3a - c2)	(c3b - c2)	(c3c - c2)	(c4 - c2)
E[Wind Generation]	-	137,592	12,870	14,731	14,105	27,372
E[Conventional Generation]	1,174,083	-137,591	-8,414	9,210	494	-22,925
Additional Load from EV	-	-	-	21,363	10,682	-
LF Up Reserve	22,199	54,801	-51,748	-14,784	-41,911	-51,238
LF Down Reserve	19,799	51,091	-50,369	-18,146	-43,731	-39,082
Contingency Reserve	21,014	59,039	-68,655	-19,675	-53,455	-57,012
E[Load Shed]	13	-1	-10	0	-6	-9

Column 1: Base Case (c1)

Column 2: Adding Wind (c2 – c1) → **Displaces fossil fuel generation but more (conventional) ramping capacity is needed**

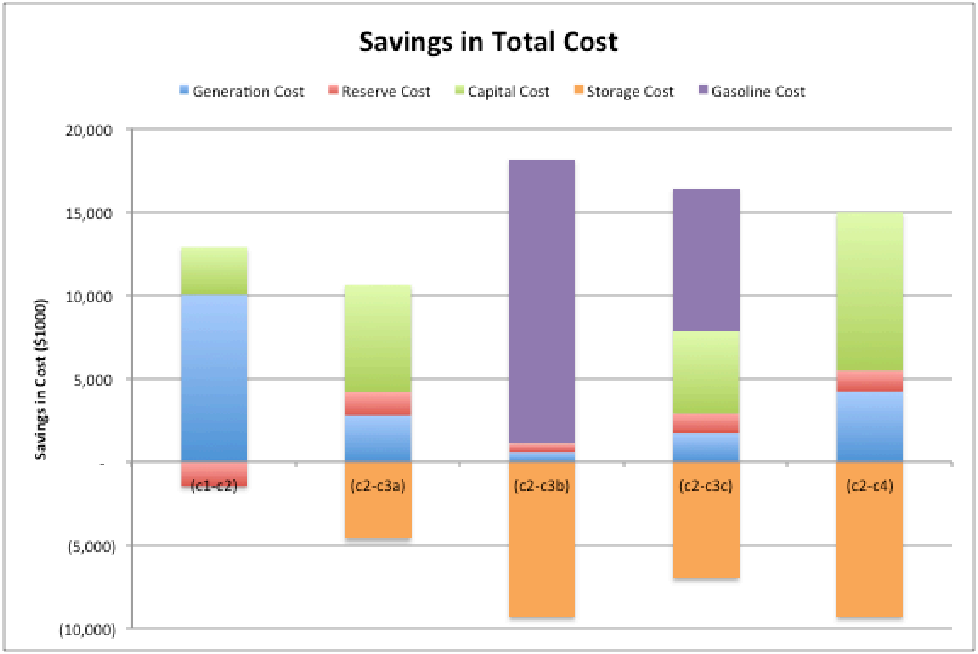
Column 3a: Adding TS (c3a – c2) → **More wind dispatched with much less ramping needed**

Column 3b: Adding EV (c3b – c2) → **More wind and conventional generation with slightly less ramping needed**

Column 3c: Adding TS/2 + EV/2 → **Intermediate between Columns 3a and 3b**

Column 4: Adding ESS (c4 – c2) → **Similar to Column 3a**

Savings in Total Daily Costs for Five Cases



	Net-Saving (k$)
Column 1: Adding Wind (c2 – c1)	11,414
Column 2: Adding TS (c3a –c2)	5,971
Column 3: Adding EV (c3b – c2)	8,837
Column 4: Adding both (c3c – c2)	9,430
Column 5: Adding ESS (c4 – c2)	5,625

COST COMPARISONS
(ignoring the capital cost of storage)

Adding Wind Capacity (c2 – c1)
- Large reduction in Generation Cost (GC),
- Small reduction in Capital Cost (CC),
- Increase in Reserve Cost (RC).

Adding TS (c3a – c2)
- Modest reductions in GC and RC,
- Large reduction in CC.

Adding EV (c3b – c2)
- Trivial changes in GC, CC and RC,
- Large reduction in Gasoline Cost.

Adding TS/2 + EV/2 (c3c – c2)
- Combines effects of TS (c2a) and EV (c2b).

Adding ESS (c4 – c2)
- Similar to TS (c2a) but even more effective

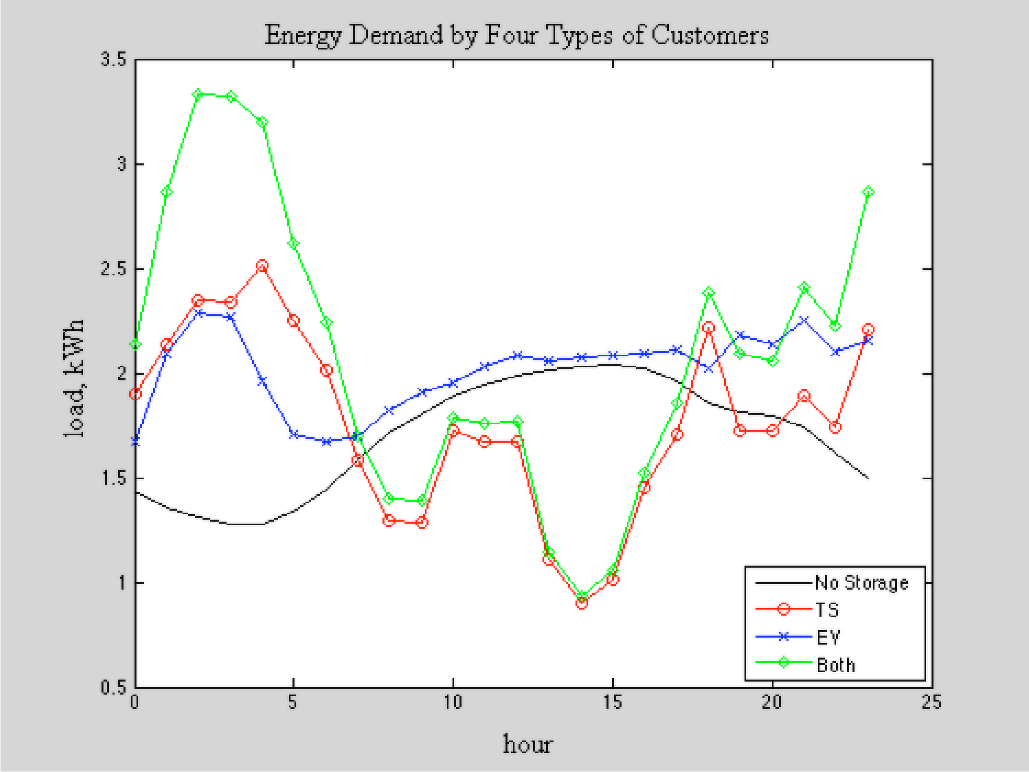
The capital cost of TS is lower than the capital costs of EV and ESS because it represents an augmentation of an existing HVAC system – **costs are shared between providing an energy service and supporting the power grid.**

PART III: Cost Implications for Different Types of Customer

Optimum Hourly Energy Purchases from the Grid by Different Types of Customer

Assume that all customers have identical hourly demand profiles for non-transportation energy services (Case 3c, both TS and EV):

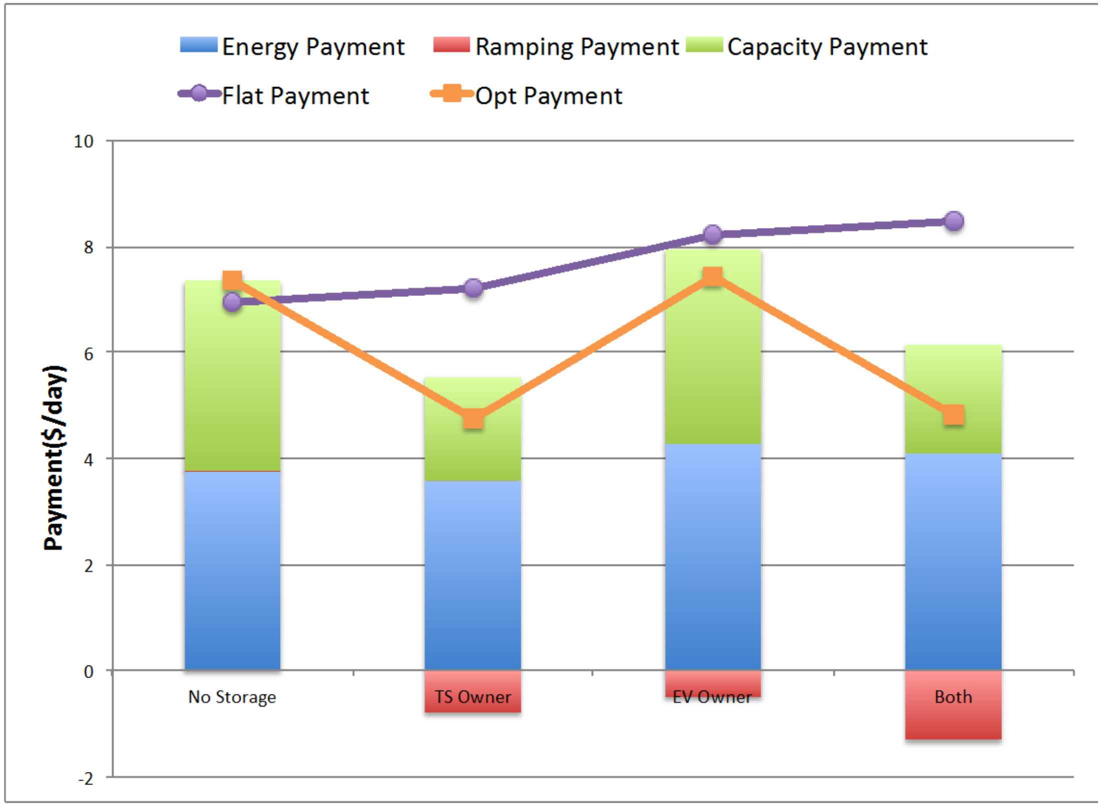
1) 85% of customers have no deferrable demand (storage),
2) 5% have Thermal Storage (TS) only,
3) 5% have an Electric Vehicle (EV) only,
4) 5% have both TS and an EV.



Customers with:

1) No storage (85%)
   - High purchases on-peak
   - Smooth on average
2) TS storage (5%)
   - Higher purchases off-peak
   - Lower demand on-peak
   - Provides ramping services
3) EV storage (5%)
   - Higher purchases off-peak
   - Provides limited ramping
4) Both TS and EV storage (5%)
   - Similar purchases to TS on-peak
   - Lower purchases than TS off-peak

Payments for Electricity by Different Types of Customer (Case 3c, both TS and EV)



Types of customer:

1. No storage (85%)
2. TS only (5%)
3. EV only (5%)
4. Both TS and EV (5%)

Optimum Payments

- Payments for energy are similar using real-time prices
- The main differences are for the cost of capital (level of demand at the Peak System Load)
- Net-payments for ramping are relatively small

Flat Payments for Energy

(Raises the same total revenue)

- Payments by customers with no storage are lower
- Payments for customers with storage are higher, particularly for customers with TS

General Conclusions

- High penetrations of renewable generation lower the cost of energy BUT **increase the cost of ramping** provided by the conventional generators
- Deferrable Demand (DD) is an effective and economically efficient way to **reduce total system costs.** It also **reduces the peak amount of energy delivered** to customers
- **IF** the rates paid by customers are restructured to reflect the true system costs, they should get substantial economic benefits by:
  - Purchasing more energy at less expensive off-peak prices (**pay real-time wholesale prices**)
  - Reducing their demand (capacity) during expensive peak-load periods (**pay "correct" demand charge**)
  - Selling ancillary services (ramping) to mitigate wind variability (**participate in the ramping market by metering DD separately to distinguish between "instructed" and "uninstructed" demand**)

Publications

1. Alberto J. Lamadrid, Timothy D. Mount, Wooyoung Jeon and Hao Lu, “Is Deferrable Demand an Effective Alternative to Upgrading Transmission Capacity?”, forthcoming, Journal of Energy Engineering.
2. Wooyoung Jeon, Jung Youn Mo and Timothy D. Mount, “Developing a Smart Grid that Customers can Afford: The Impact of Deferrable Demand”, Revised and resubmitted to the Journal of Energy Economics.
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7. Lamadrid, A. J., Mount, T. D., Zimmerman, R. D., “Optimal energy storage usage for electricity market operations.” Proceedings of IEEE PowerTech 2013, Grenoble, France, June, 2013.
8. Tim Mount, Alberto Lamadrid, Wooyoung Jeon and Hao Lu, “Evaluating the Effects of Different Flexible Ramping Products on the Total Cost of Supplying Electricity on a Power Grid,” Proceedings of the 26th Annual CRRI Western Conference, Monterey CA, June 19-21, 2013.
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Thank you

Questions?

Suggestions?

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