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Evaluating the Effects of Managing Controllable Demand and Distributed Energy Resources Locally on System Performance and Costs

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Consortium for Electric Reliability Technology Solutions

Collaborative Research on the Smart Grid

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OUTLINE

- PART 1 (Wooyoung Jeon)
  - Optimal hourly use of storage to minimize daily system costs
    - Exogenous wind generation
    - No network or reliability standards
- PART II (Alberto Lamadrid)
  - Optimal hourly use of deferrable demand at 5 load centers to minimize the expected daily system costs
  - Optimal hourly use of storage collocated at 16 wind sites to minimize the expected daily system costs
    - Stochastic potential wind generation at 16 sites
    - NE Test Network (36 buses) with contingencies
- PART III (Alejandro Dominguez-Garcia)
  - Manage distributed resources locally in a hierarchical structure to deliver aggregated energy services efficiently
    - Use only information exchange among immediate neighbors

PART I:
Optimize Hourly Storage with Exogenous Wind Generation and No Network

Demand for Electricity in New York City
for a hot summer day (7/16/10)

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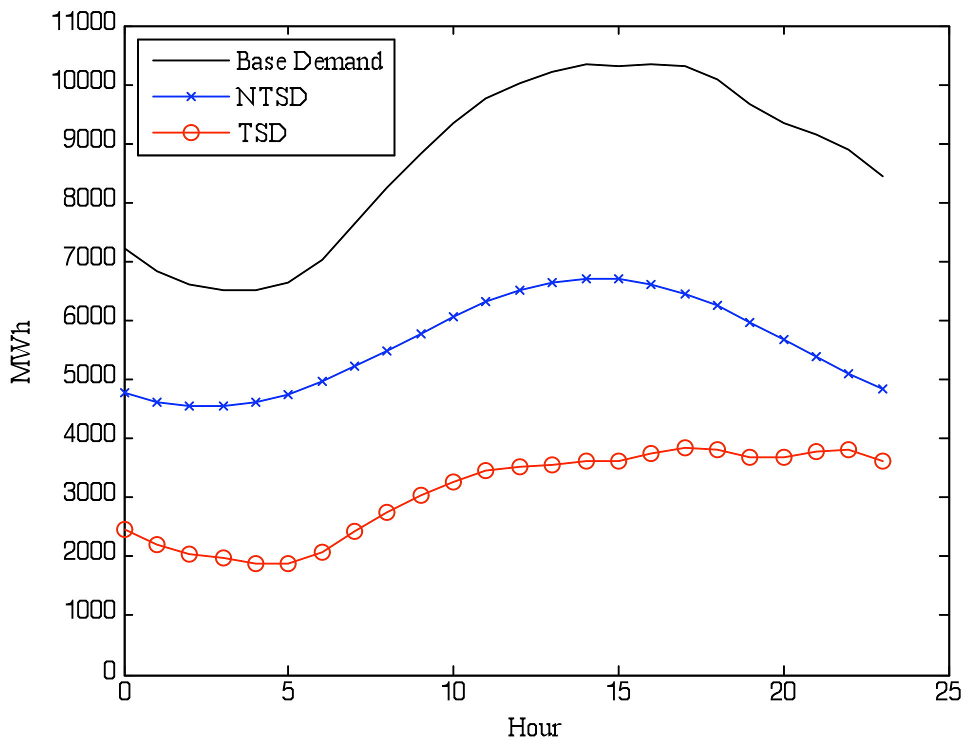


- Cumulative Base Demand over 24 hrs: 208 Gwh
- Cumulative Temperature-Sensitive Demand (TSD): 74 Gwh
- TSD is 35% of the cumulative demand (and 35% of the peak system load)
- Consistent with EIA data (30% of the total electricity demand is used for cooling during the summer)

Use an econometric model to distinguish Temperature-Sensitive Demand (TSD) from Non-Temperature-Sensitive Demand (NTSD)

TSD is a potentially large source of deferrable demand

Simplified Optimization Criterion

$$\underset{Ph_t, Th^+_t, Th^-_t}{Min} \sum_{t=1}^{24} EP_t \cdot CG + RP_t \cdot |\Delta CG| - P_{FEIS} \cdot FEIS$$

$$SCL_{Th} \le \sum_{t=0}^{T'} Th^+_t - \sum_{t=0}^{T'} Th^-_t \le SCU_{Th}, \quad T' = 1, \ldots, 24$$

$$SCL_{Ph,t} \le \sum_{t=0}^{T'} Ph_t \le SCU_{Ph,t}, \quad T' = 1, \ldots, 24$$

$$HCL_{Th^+,t} \le Th^+_t \le HCU_{Th^+,t}, \quad \forall\, t = 1, \ldots, 24$$

$$HCL_{Th^-,t} \le Th^-_t \le HCU_{Th^-,t}, \quad \forall t = 1, \ldots, 24$$

$$HCL_{Ph,t} \le Ph_t \le HCU_{Ph,t}, \quad \forall\, t = 1, \ldots, 24$$

$$0 \le \sum_{t=0}^{T'} Th^+_t - \sum_{t=1}^{T'+1} Th^-_t \qquad \forall t = 1, \ldots, 24$$

$$C_{Th^-} \cdot Th^-_t \le L^C_t, \qquad \forall t = 1, \ldots, 24$$

$$L_t = L^{NC}_t + L^C_t$$

$$L^C_t = C_{Th^-} \cdot Th^-_t + AC_t$$

$$\begin{aligned} CG_t &= L_t - W_t + C_{Th^+} \cdot Th^+_t - C_{Th^-} \cdot Th^-_t + H_{vac} \cdot C_{Th^-} \cdot Th^-_t + DP \cdot C_{Ph} \cdot Ph_t \\ &= L^{NC}_t + L^C_t - C_{Th^-} \cdot Th^-_t - W_t + C_{Th^+} \cdot Th^+_t + H_{vac} \cdot C_{Th^-} \cdot Th^-_t + DP \cdot C_{Ph} \cdot Ph_t \\ &= L^{NC}_t + AC_t - W_t + C_{Th^+} \cdot Th^+_t + H_{vac} \cdot C_{Th^-} \cdot Th^-_t + DP \cdot C_{Ph} \cdot Ph_t \end{aligned}$$

$$EP_t = a + b \cdot CG_t$$

$$RP_t = c \cdot EP_t \cdot |\Delta CG_t|$$

Manage storage capacity to minimize the daily cost of energy and ramping to meet (load – wind generation)

- Linear cost function for energy
- Linear cost function for ramping
- Cooling demand can be met by AC and/or thermal storage (deferrable demand)
- AC can be used to charge storage during off-peak periods at night

Glossary for the Optimization

EP_t : Energy Price at t

RP_t : Ramping Price at t

L_t : Base Load at t

W_t : Wind Load at t

Th_t : Load stored or discharged by THERMAL Storage at t

Ph_t : Load stored or discharged by PHEV Storage at t

C_{Th} : Charging Efficiency of THERMAL Storage

C_{Ph} : Charging Efficiency of PHEV Storage

AC_t : Air Conditioning Load at t

$L^{NC}{}_t$: Load for Non-Cooling at t

$L^{C}{}_t$: Load for Cooling at t

FEIS : Final Energy In Storage

DP : Driving Profile

SCL:Storage Capacity Lower bound

SCU:Storage Capacity Upper bound

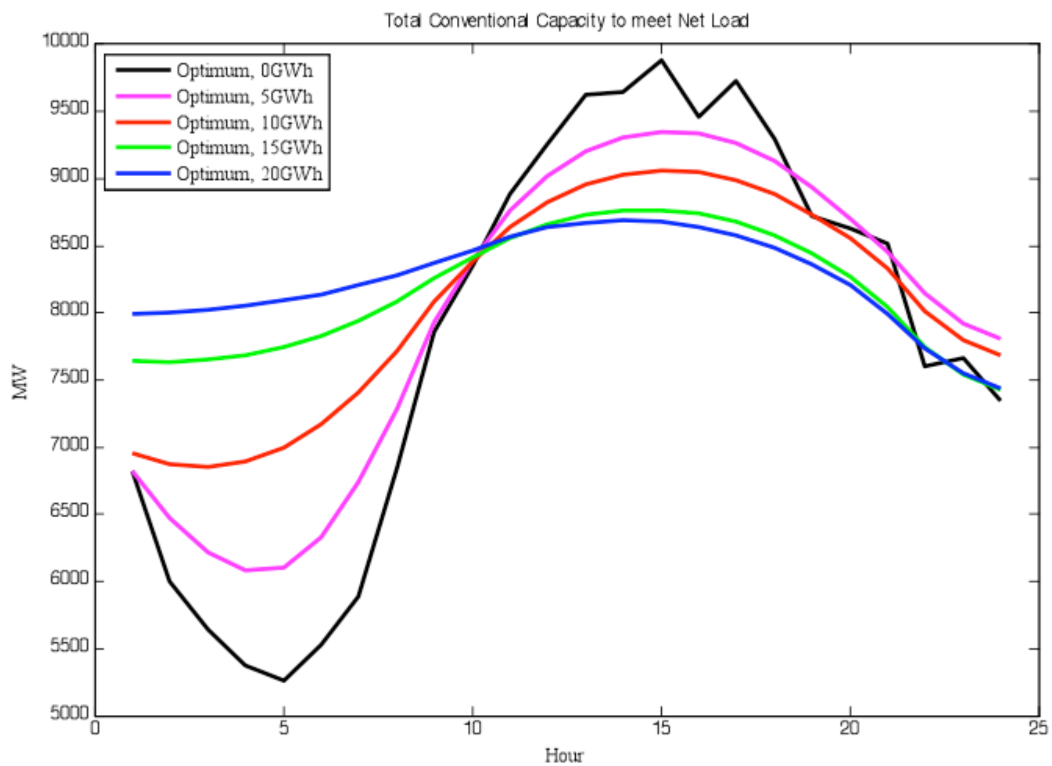
HCL:Hourly Charging Lower bound

HCU:Hourly Charging Upper bound

a,b:estimated from market data

c:Scaling parameter for Ramping Price, $\frac{1}{100}$

The Effect of Adding Storage Capacity on Total Conventional Generation



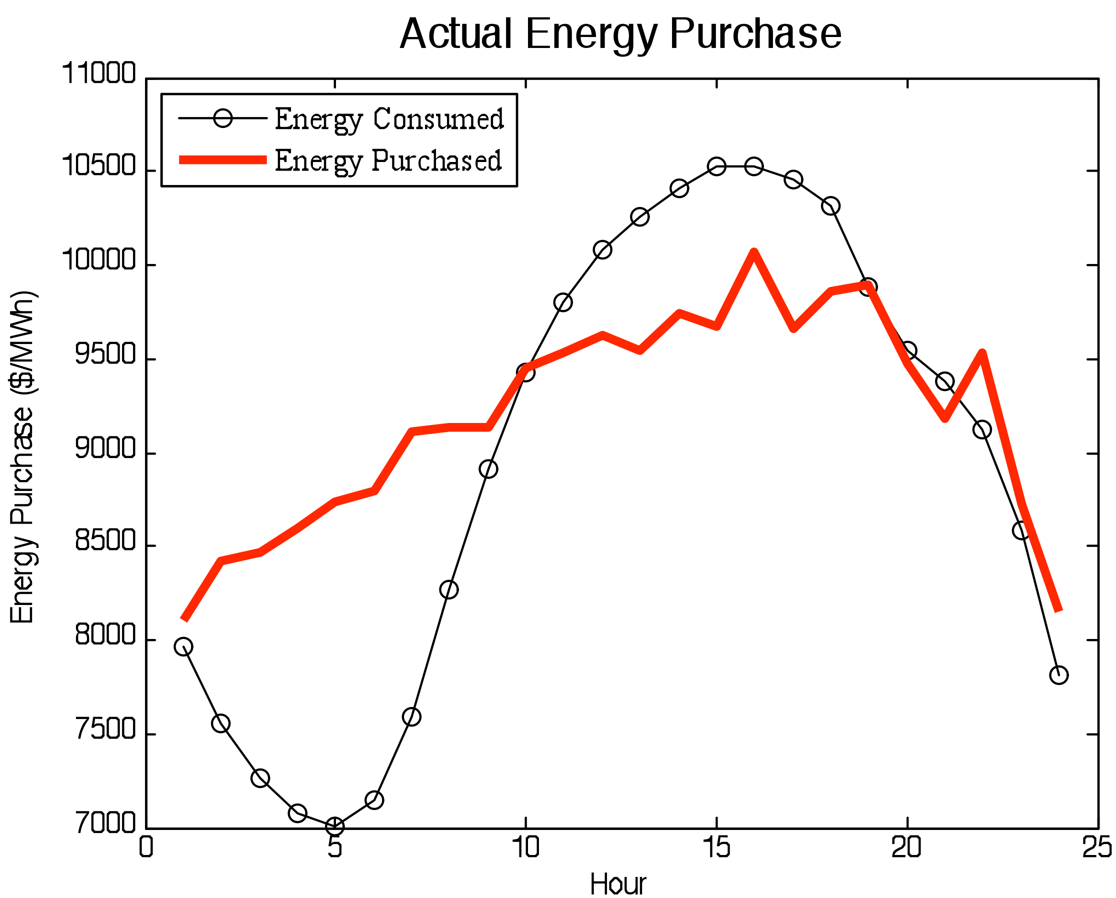
INPUT ASSUMPTIONS

- Daily demand for a typical summer day in New York City
- Total Conventional Generation
  = Load – Wind Generation
  = Net Load
- Wind data are from NREL → hourly variability of generation and less wind during the on-peak period in the daytime
- Wind capacity is 2GW (20% of the Peak System Load that provides 12% of the total daily generated energy)

CONCLUSIONS - Adding storage (deferrable demand)

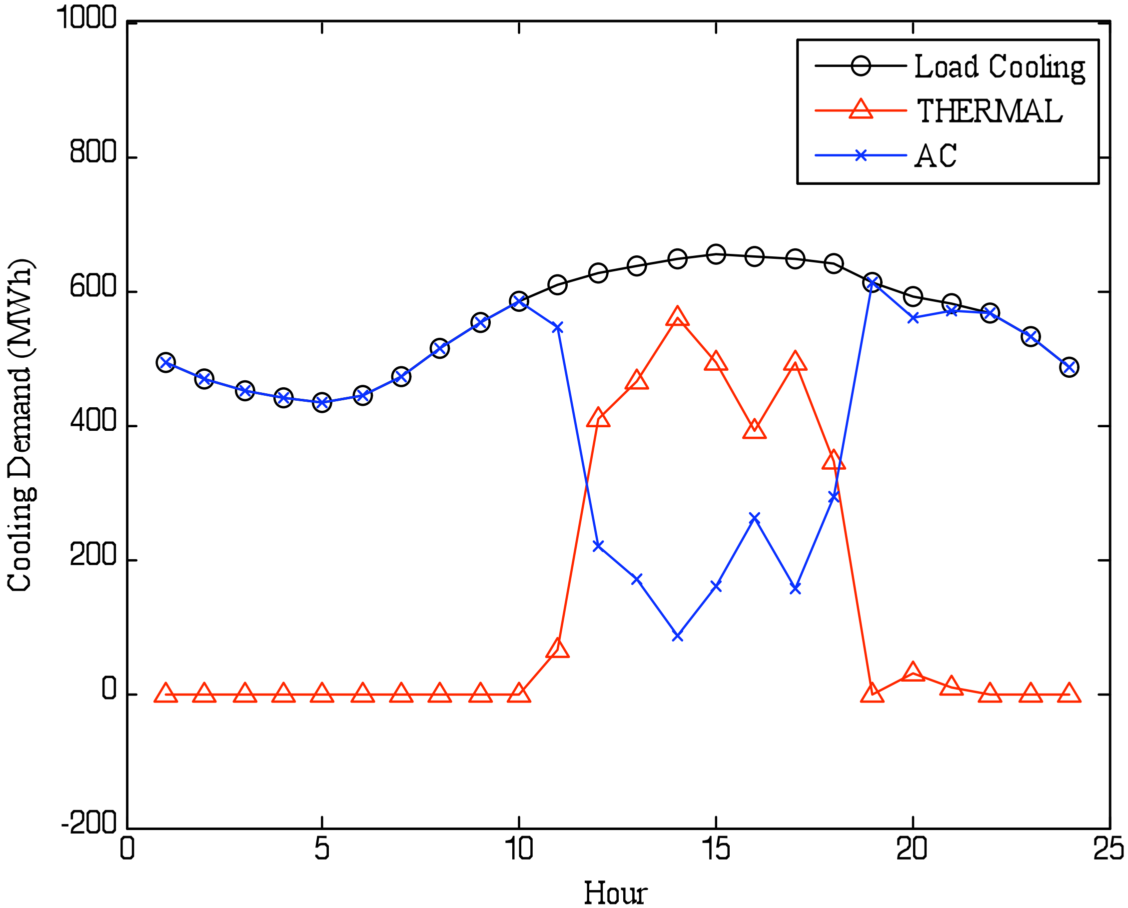
1) flattens the daily pattern of conventional generation → lower peak load
2) mitigates the variability of wind generation → less ramping by conventional sources
3) reduces the day/night price arbitrage → need other economic incentives

Hourly Energy Purchased and Consumed
(10GWh of Storage)



- The energy consumed by customers does not change with deferrable demand
- The energy purchased = generation from wind + conventional sources
- Deferrable demand →
  1) More energy is purchased off-peak at night and the peak load is lower
  2) Provides ramping services to mitigate the variability of wind generation

Composition of the Cooling Demand
Direct (AC) v Stored (THERMAL)



- Deferrable Cooling Demand = 6.2% of TSD
- AC delivers all cooling needed at night (and charges the thermal storage)
- Mix of AC and thermal storage deliver cooling during the day AND reduce the ramping by conventional generators

Pay for services used and get paid for services provided → What happens?

	Ramping Payment ($1000)	Energy Payment ($1000)	Total Payment ($1000)	Total Energy (MWh)	Average Payment ($/MWh)
1) CD	2,120	18,920	21,041	214,911	98
2) WG	1,735	-2,154	-419	27,070	-15
3) CG	-1,125	-17,236	-18,361	196,822	-93
4) DD	-2,730	470	-2,261	12,296	-184
Buyers	(1)+(2) = 3,855	(1)+(4) = 19,390			
Suppliers	(3)+(4) = -3,855	(2)+(3) = -19,390			

- Positive (Negative) payments indicate Paying (Being Paid) for a service
- CD, Conventional Demand and DD, Deferrable Demand
- WG, Wind Generation and CG, Conventional Generation
- The System Cost of ramping is caused by ramping CG
- WG accounts for 11% of Energy Supply and 45% of Ramping Demand
- DD accounts for 2% of Energy Demand and 71% of Ramping Supply

PART II:
Optimize Hourly Storage with Stochastic Wind Generation and the NE Test Network Using the Multi-Period SuperOPF

North Eastern Test Network (NETNet)

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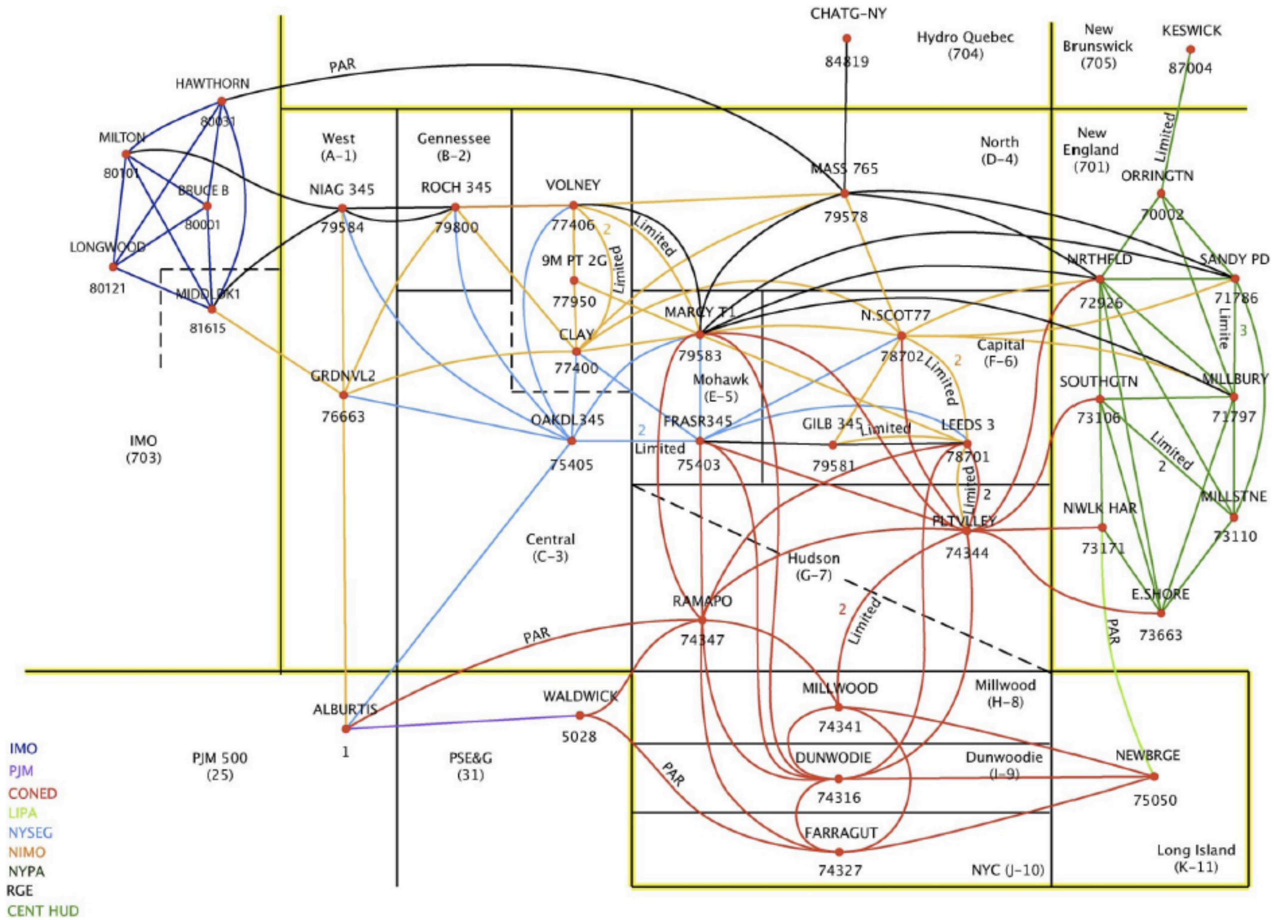
Reduced NPCC System (Allen, Lang and Ilic (2008))



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NREL Wind Site Clusters (EWITS)

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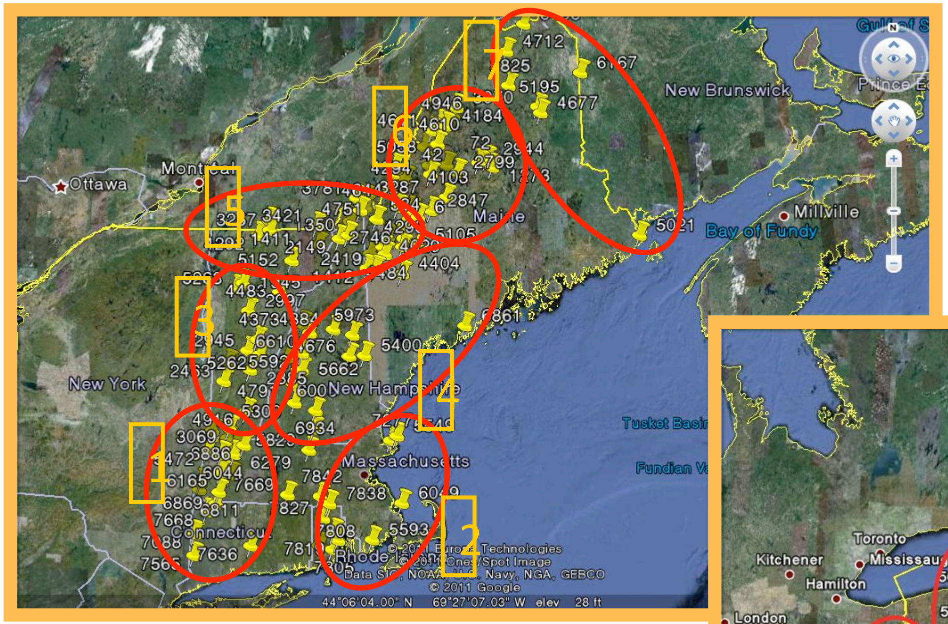
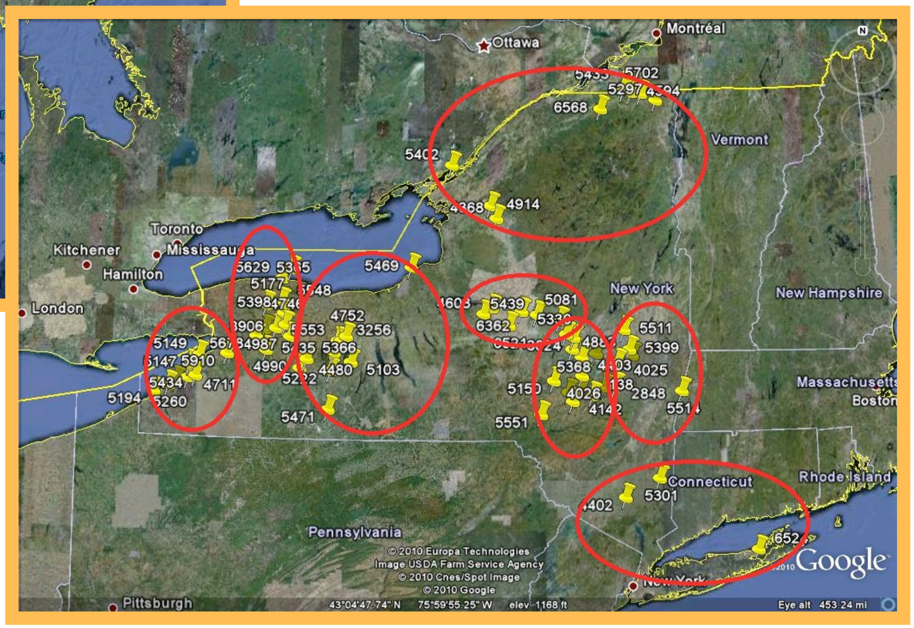
New England



New York State



Modeling the Inherently Stochastic Behavior of Potential Wind Generation

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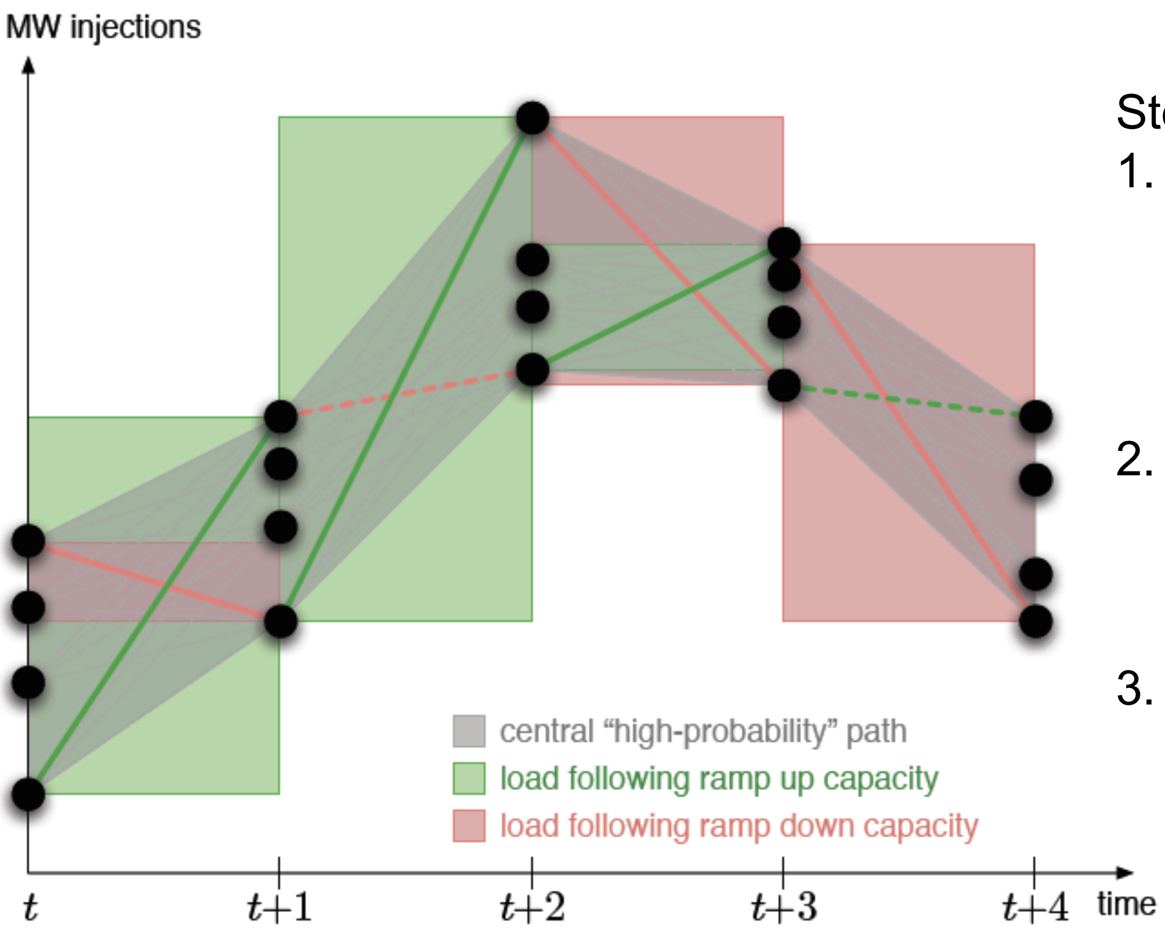

Steps:

1. Select a sample of days (24 hours) using NREL wind speed data (EWITS) for 16 sites in New York State and New England
2. For each hour of the day, use the K means algorithm to pick K representative wind speeds (scenarios)
3. 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

System Characteristics of the NE Test Network

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NYNE GENERATING CAPACITY	
Peaking (GW)	37
Baseload (GW)	26
Fixed Imports (GW)	3
TOTAL (GW)	**66**
New Wind (GW)	32
Storage Capacity (GW)	23
Storage Energy (GWh)	136
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 purchased by customers

Case 1: No Wind: Initial system

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

Case 3: Case 2 + Deferrable Demand (DD) at five load centers with a total capacity of 23GW (136GWh)

Case 4: Case 2 + Energy Storage System (ESS) collocated at the wind sites with a total capacity of 23GW (136GWh)

Summary of the Optimum Results

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	Case 1	Case 2	Case 3	Case 4
E[Wind Generation] MWh	**-**	**137,518**	**147,732**	**153,091**
E[Net System Benefits] (k$/day)	8,885,100	8,896,269	9,112,041	8,998,212
E[Operating Costs] (k$/day)	**50,280**	**41,933**	**41,785**	**40,733**
E[Ramping Costs] (k$/day)	499	1,383	1,104	1,068
E[Gen. Net Revenue] (k$/day)	77,183	52,528	53,804	53,328
E[ISO Surplus] (k$/day)	8,477	8,837	-5,133	8,163
E[Payments by Customers] (k$/day)	**135,940**	**113,430**	**102,829**	**114,823**
Max Conventional Capacity (MW)	**58,550**	**57,004**	**50,919**	**58,310**
Storage Discharge at Peak (MW)	**-**	**-**	**-**	**4,751**

COMPARING THE FOUR WIND, CASES 2-4
- Little difference in E[Operating Costs] and in E[Ramping Costs]
- Little difference in the E[Generator Net Revenue]
- E[ISO Surplus] is lower in Case 3 because there is much less congestion
- E[Payments by Customers] are also lower for Case 3

WHY IS DEFERRABLE DEMAND (CASE 3) THE BEST FOR CUSTOMERS?
- Peak Generating Capacity (conventional MW for System Adequacy)) is lower

Hourly Dispatch of Wind and Prices

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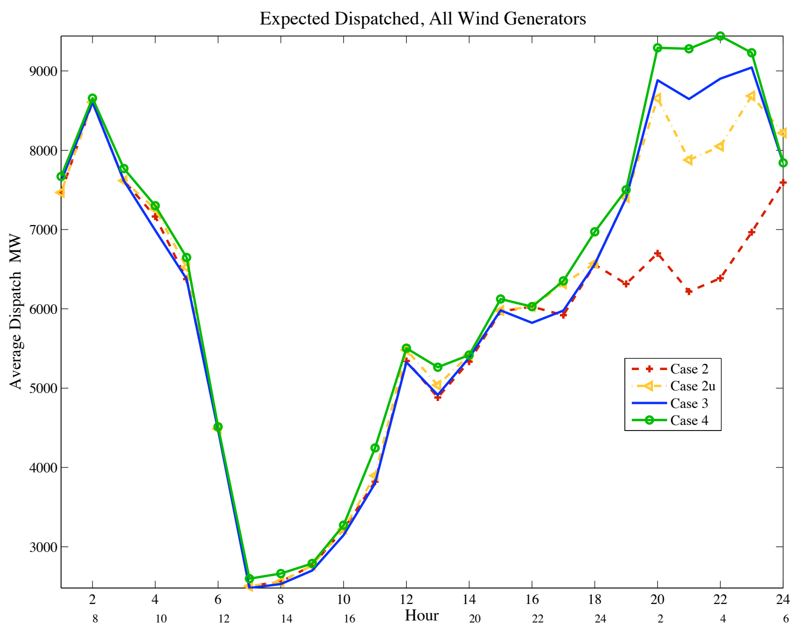
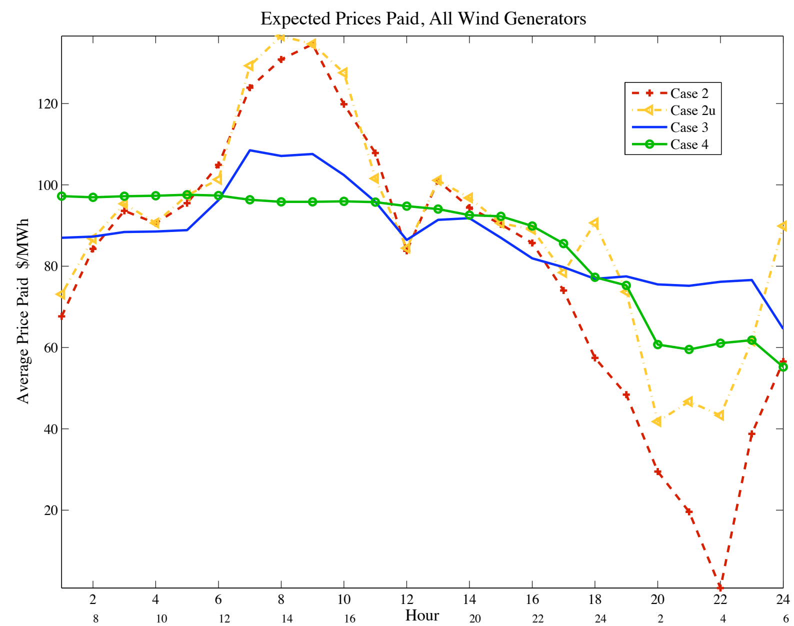
Total Dispatch of Wind Generation, E[MW]



Nodal Prices Paid for Wind, E[$/MWh]



The main differences in dispatch occur from midnight to 5:00AM: Case 2 has the largest amount of wind spilled

Deferrable demand and ESS reduce the range of nodal prices by mitigating wind variability and flattening the load profile

Hourly Payments to Wind Generators

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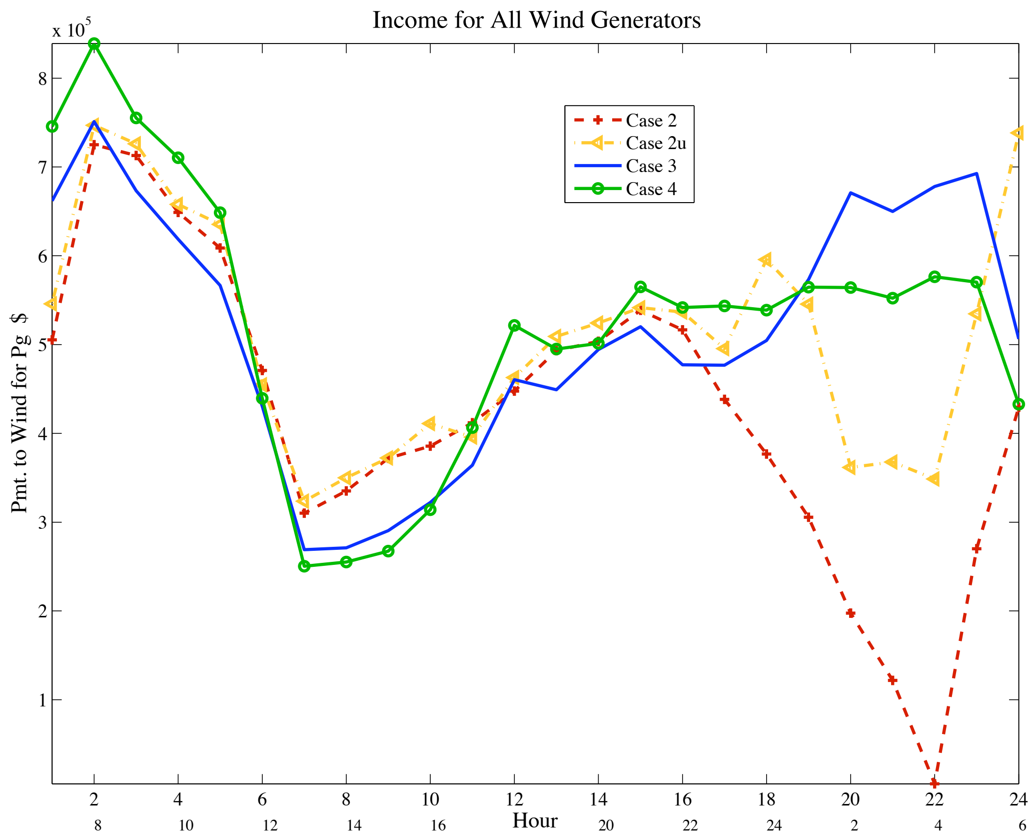
Total Payments, E[$100,000]/hour



Similar revenues during the daytime for Cases 2-4

Case 2

Nodal prices driven down to zero at 4:00AM

Case 2u

Nodal prices higher at night with no congestion

Case 3

Higher system load at night increases the nodal prices

Case 4

Wind generation stored at night does not reduce the nodal prices but still gets paid

Composition of the Optimum Daily E[Pattern of Generation] for Cases 1 and 2

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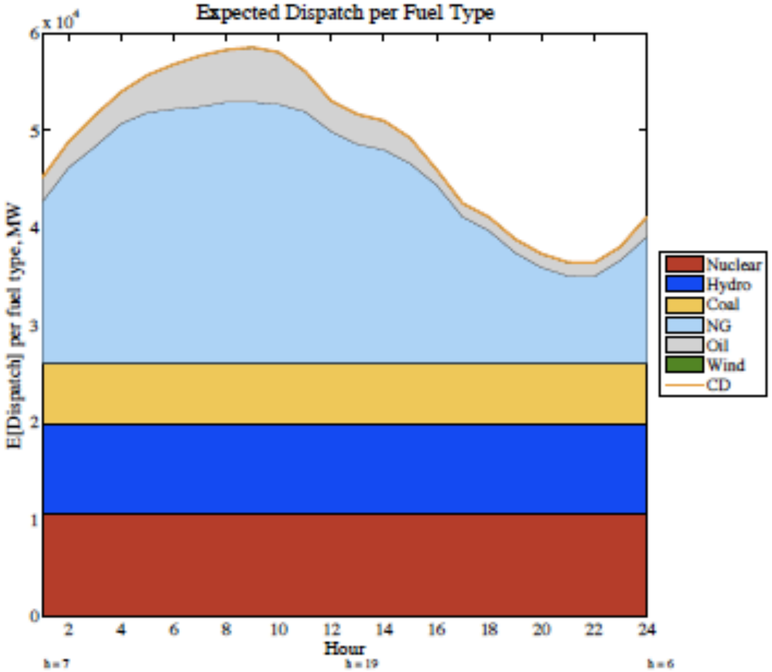
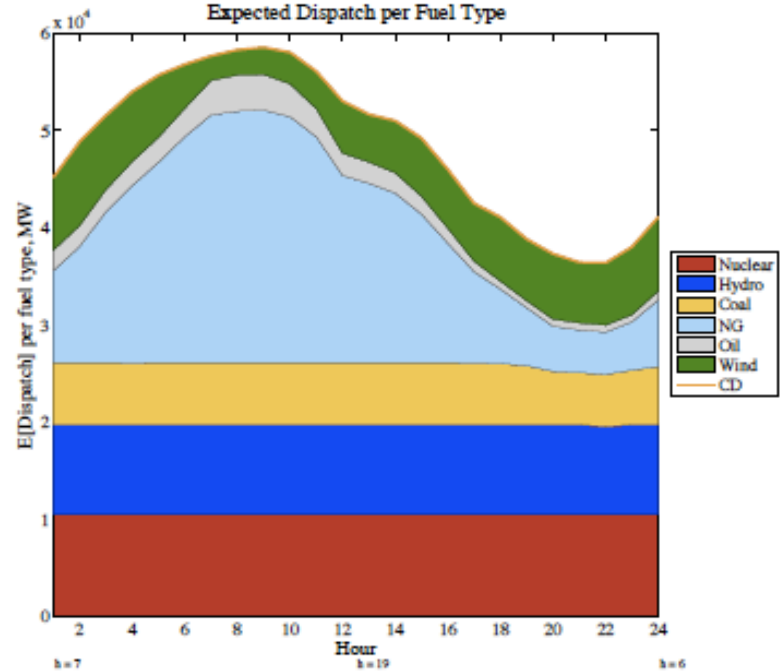
Case 1: Base



Case 2: Base + 32GW Wind



Case 1

Ramping for the daily load profile is provided by oil and natural gas capacity

Case 2

Wind displaces mainly oil and natural gas capacity and this capacity also provides additional ramping services to mitigate wind variability

Composition of the Optimum Daily E[Pattern of Generation] for Cases 3 and 4

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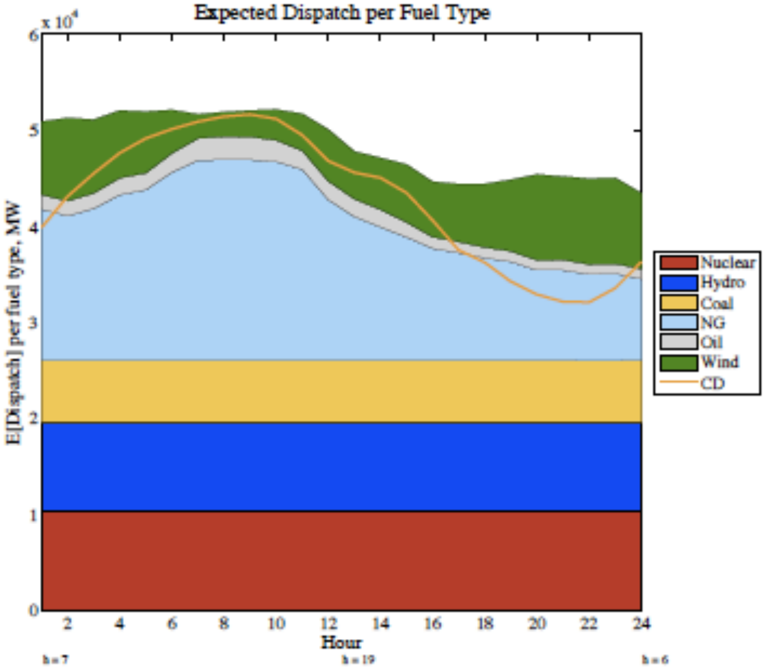
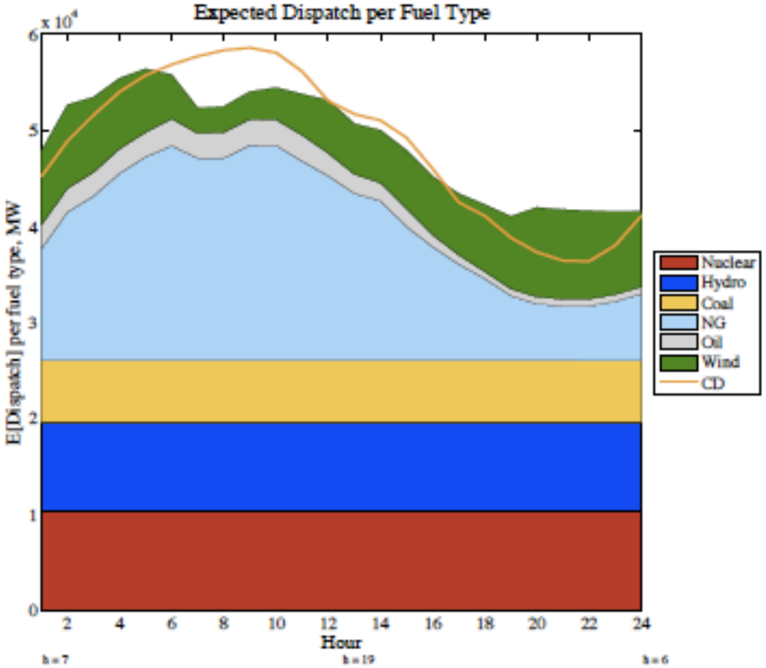
Case 3: Base + 32GW Wind
+ 136GWh Deferrable Demand



Case 4: Base + 32GW Wind
+ 136GWh Collocated Storage



Case 3 v Case 2
More wind is dispatched and the daily load pattern is flatter (lower peak energy)
Case 4 v Case 2
Even more wind is dispatched but the peak energy delivered is unchanged

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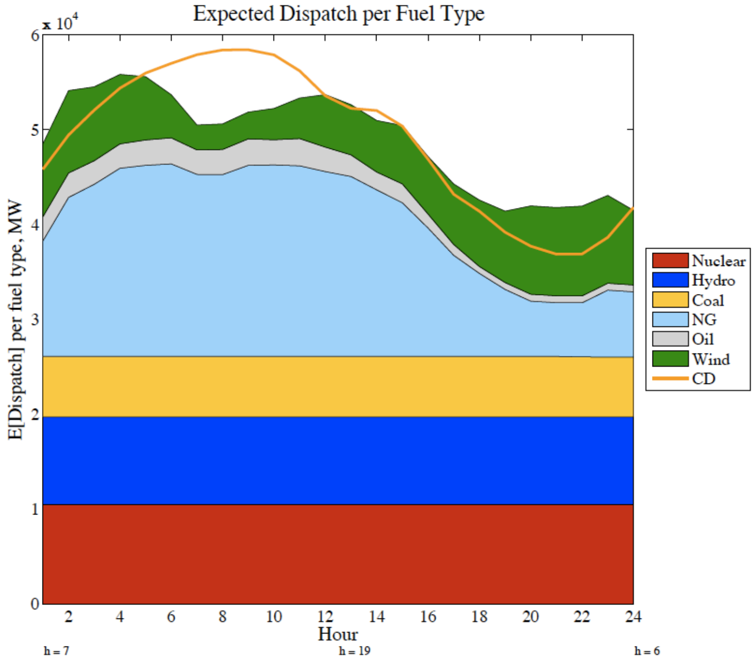
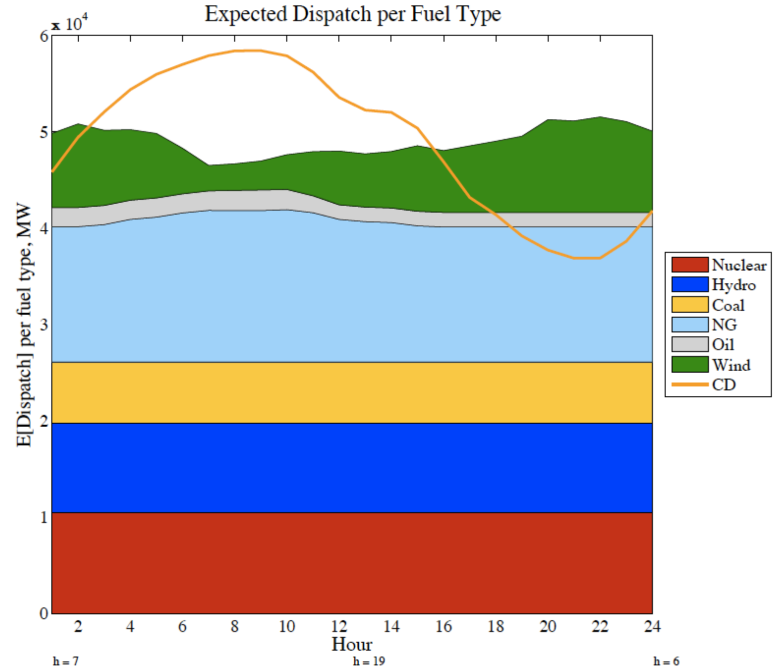
Why isn't Storage used more for Peak Shaving/Valley Filling in Case 4?

Case 4: Base + ESS
with STOCHASTIC WIND



Case 4: Base + ESS
with DETERMINISTIC WIND



With stochastic wind, it is optimum to use storage mainly for ramping
Still true if ramping costs are set to zero → a physical ramping reserve is needed
With deterministic wind, it is now optimum to use storage mainly for peak shaving/valley filling → STOCHASTIC INPUTS MATTER!

Next Steps for Research Using the Multi-period SuperOPF

- Extend the analysis to cover operations for a full year to evaluate the Total Annual System Costs, including capital costs, and the Net Benefits of different cases
- Use a combination of the stochastic characteristics of loads as well as potential wind generation as inputs
- Model the physical characteristics of storage and deferrable demand explicitly to provide more accurate constraints on the aggregate demand for and supply of energy services at nodes
- Model the behavior of Aggregators of Residential Customers (ARC) explicitly to compare the performance of a hierarchical structure of control for Distributed Energy Resources (DER) versus centralized control by a system operator
- Compare the performance of a rolling time horizon with non-binding price projections versus the day-ahead/ real-time market structure currently being modeled

PART III: Manage Distributed Resources Locally to Deliver Aggregated Energy Services Efficiently

Enabling Distribution-level Markets: Interaction between DSOs and DERs

- Study of suitable communication/control architectures that would enable the implementation of the distribution-level portion of an envisioned hierarchical market structure; two potential solutions:
  - Centralized architecture in which each Distributed Energy Resource (DER) is directly controlled by a Distribution System Operator (DSO):
    - Requires a communication network connecting DSO with each DER
    - Requires up-to-date knowledge by the DSO of DER availability on the distribution side
  - Distributed architecture potentially offers several advantages:
    - Easy and affordable deployment (no requirement for communication infrastructure between the DSO and various DERs)
    - Ability for the DSO to handle incomplete knowledge of the available DERs
    - Potential resiliency to faults and/or unpredictable DER behavior

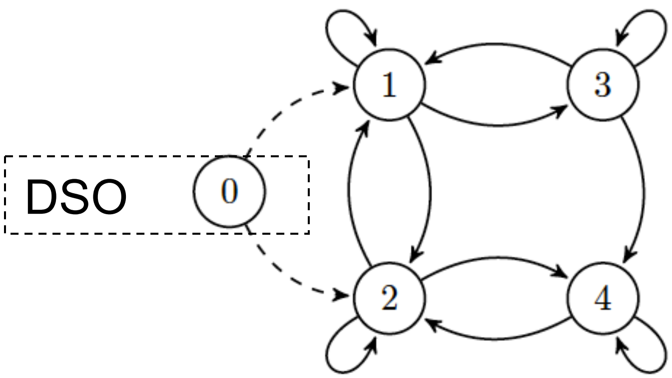
The (Perhaps Naïve) Starting Point: DER Economic Dispatch (ED)

- Consider *n* DERs with constraints on the amount of active (or reactive power) they can provide
- Denote by *X* the total amount of active (or reactive power) they need to collectively provide (i.e. demanded by the DSO)
- Assume the cost of each DER is quadratic. Then, the DER ED problem can be formulated as:

$$
\begin{aligned}
\text{minimize} \quad & \sum_{j=1}^{n} \frac{(x_j - \alpha_j)^2}{2\beta_j} \\
\text{subject to} \quad & \sum_{j=1}^{n} x_j = X \\
& 0 < \underline{x}_j \leq x_j \leq \overline{x}_j, \ \forall j
\end{aligned}
$$

A Distributed Solution to the DER ED Problem [D-G, Cady, Hadjicostis, '12]

- The objective is to solve the DER ED problem without relying on the DSO having access to all the data defining the problem; instead, the computations are distributed as necessary to solve the problem
- To this end, we assume that each DER is equipped with a processor that can perform simple computations, and can exchange information with neighboring DERs.
  - In particular, the information exchange between nodes (DERs) can be described by a directed graph



Exchange of information between the DERs and the DSO

Experimental validation: DER Communication and computation hardware