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R&M Project 2A:
Evaluating the Effects of Managing Controllable Demand and Distributed Energy Resources Locally on System Performance and Costs

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OUTLINE OF THE PRESENTATION

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PART I: Stochastic Inputs

- Simulating Wind Power and Load
- The Effects on System Costs

PART II: Deferrable Demand (DD)

- Model Specifications
- DD Controlled by an ISO
- Cost Effects for Customers
- Sensitivity to Wind and Ramping
- DD Controlled by Aggregators

PART III: Publications

PART I: Stochastic Inputs
a) Simulating Wind Power and Load

North Eastern Test Network (NYNE)

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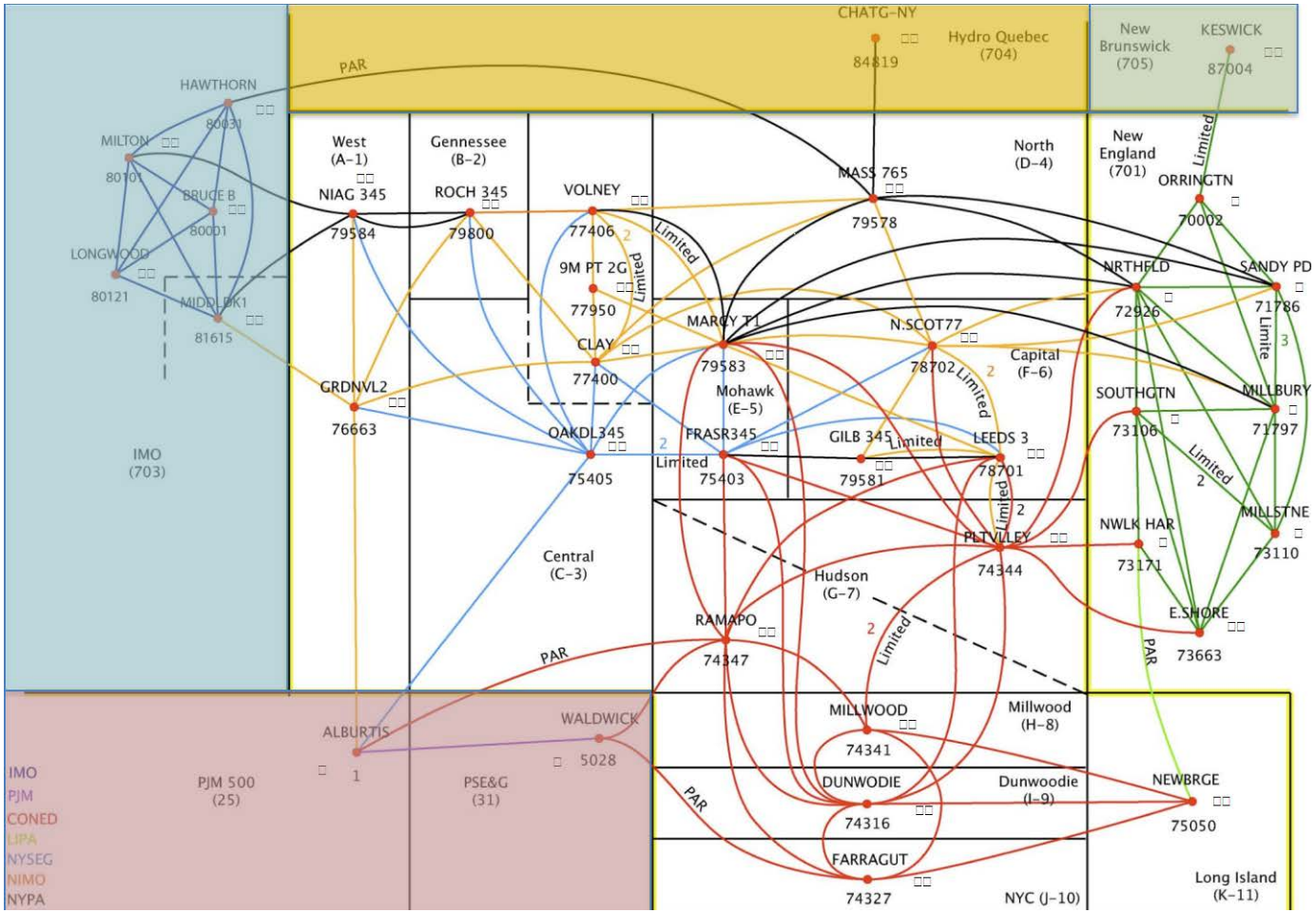
Reduced NPCC System (Allen, Lang and Ilic (2008))



16 Wind Site Clusters
(Derived from the EWITS data from NREL)

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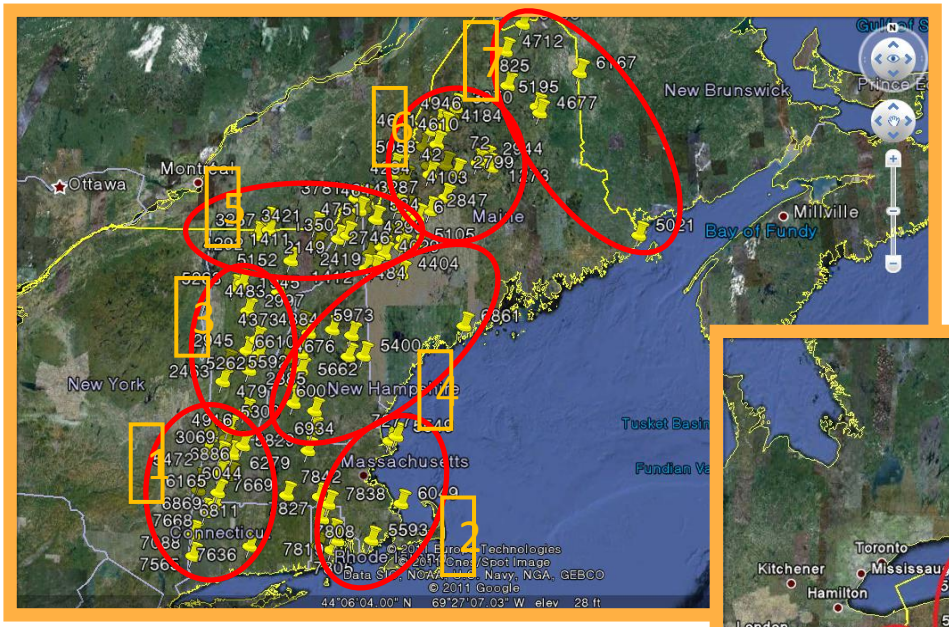
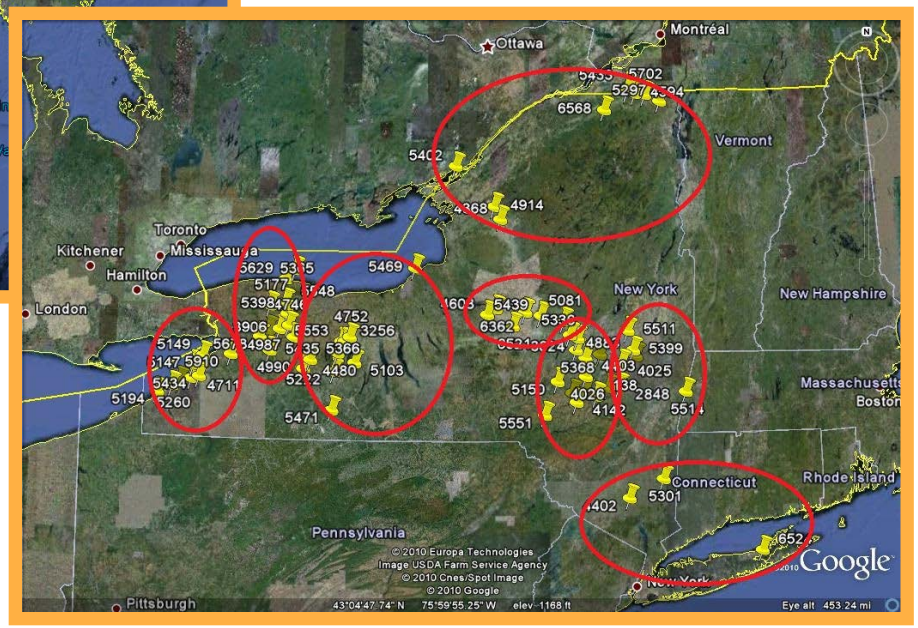
New England



New York State



Each cluster was determined by a principal components analysis and used to define a wind farm at a node on the NYNE network

Correlations among the 16 Wind and 7 Load Sites

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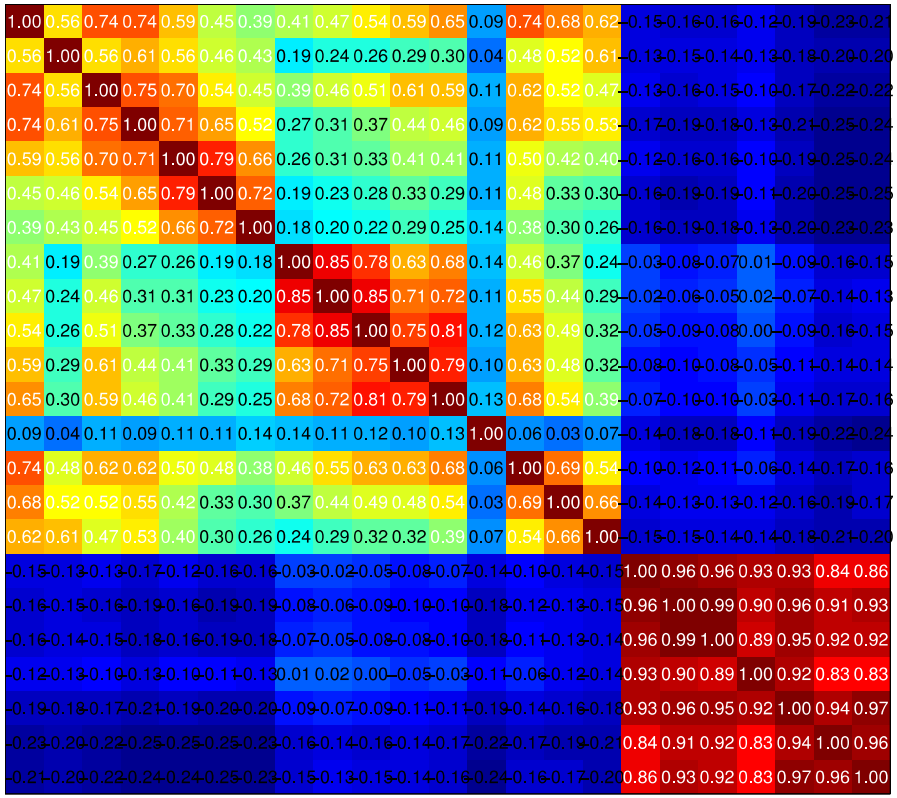

Order of Sites:

1-7	NE Wind
8-16	NY Wind
17-19	NE Load
20-23	NY Load

1. High positive correlations among all seven load sites,
2. Small negative correlations between all load and wind sites,
3. Mixed positive correlations among the wind sites, generally higher in-state.

Uncertainty of Load and Wind Speed

(New York City as an example)

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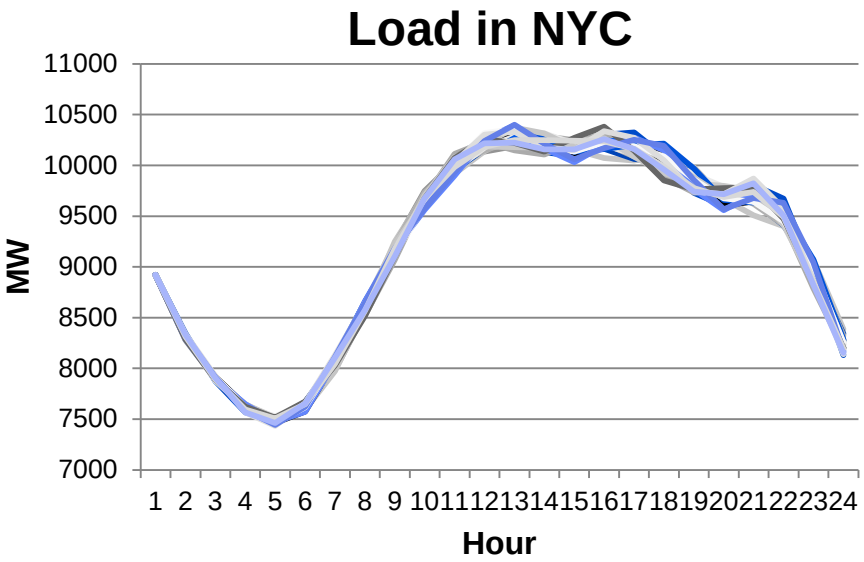
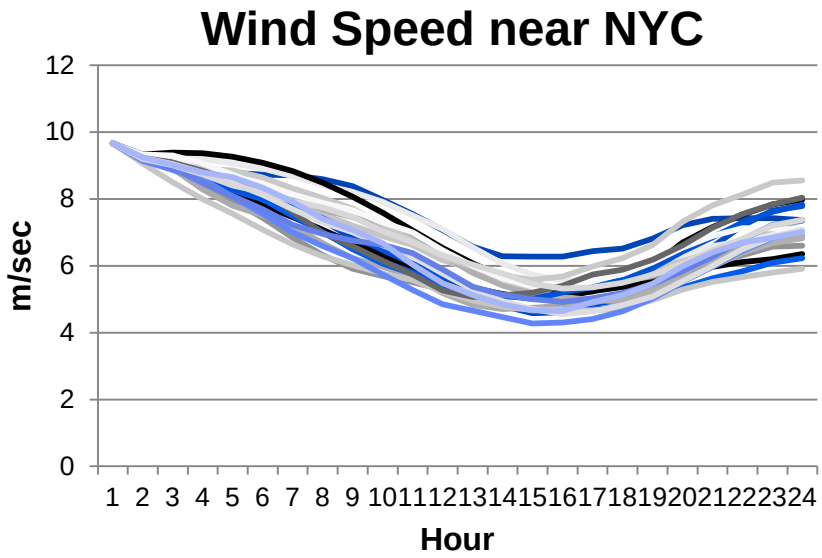
16 ARMAX models estimated for hourly Temperature = f(Seasonal Cycles)
16 ARMAX models estimated for hourly Log[Wind Speed + 1] = f(Temperature, Seasonal Cycles)
7 ARMAX models estimated for hourly Log[Load] = f(CDD, HDD, Seasonal Cycles)
→ Load model estimates Temperature-Sensitive Load and Non Temperature-Sensitive Load
→ Simulate hourly profiles of Wind Speed and Load for any specified day given a forecast of Temperature





Dependent Variable	Temperature	Log[Wind Speed + 1]	Log[Load]
OLS R2	79%	8%	90%
ARMAX Pseudo R2	99%	75%	99%

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Percentage Coefficients of Variation for Load (Region 6) and Wind Power (Area 15) Inputs

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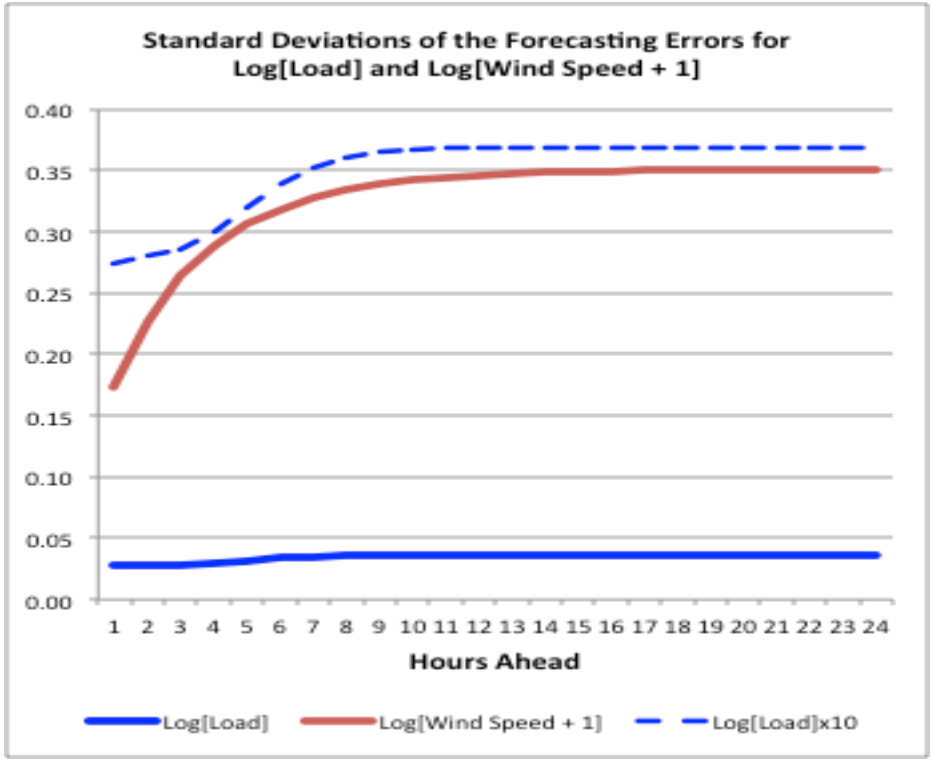
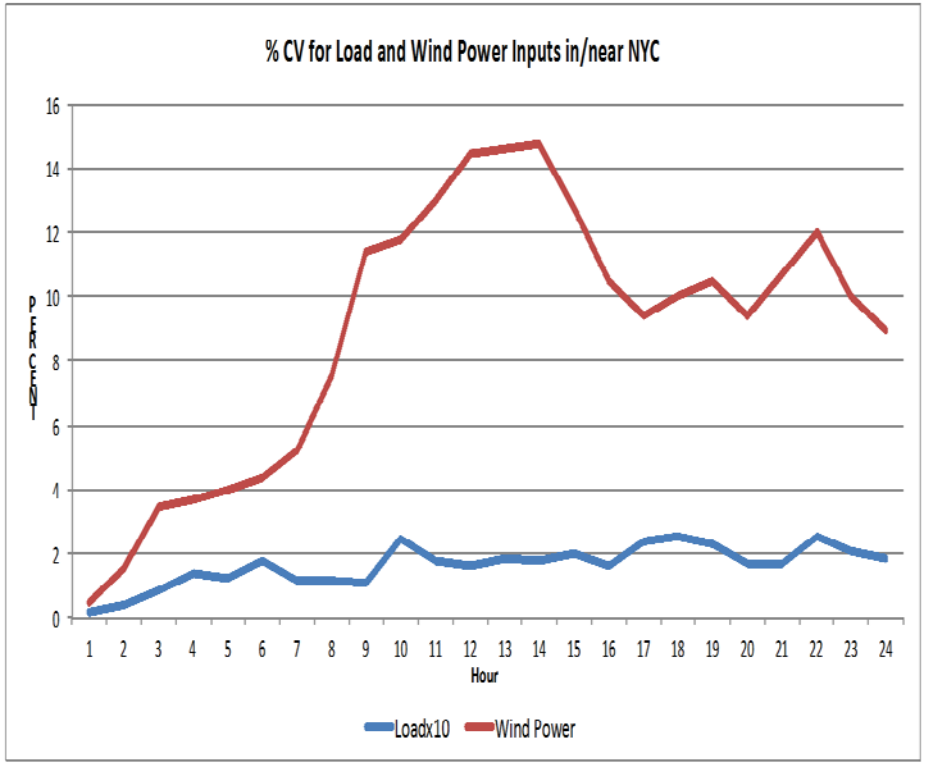
Econometric Models



Simulated Stochastic Inputs



(St. Dev. of Log[Load])x10
≈ St. Dev. of Log[Wind Speed + 1]

%CV = % Coefficient of Variation
= 100xStandard Deviation/Mean

Input Model for the Stochastic Behavior of Potential Wind Generation

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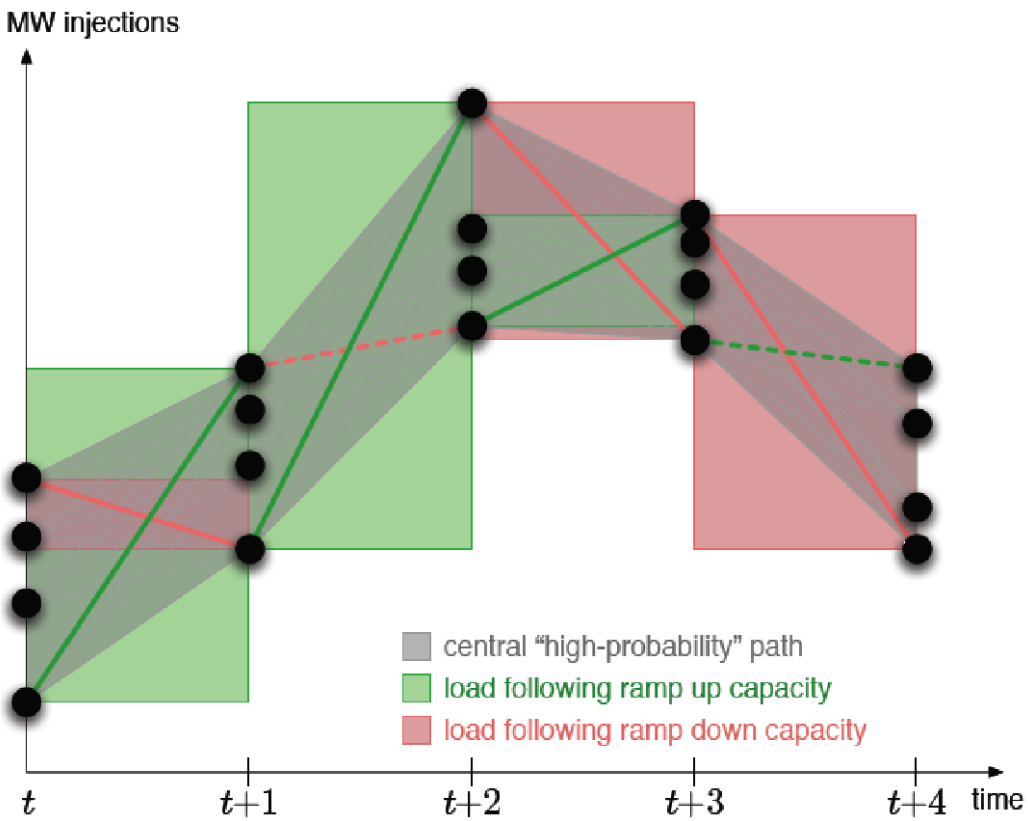
Four discrete intact system states each hour
→ Sixteen transitions from one hour to the next



Steps:

1. Simulate a sample of daily wind speeds for a specified day conditionally on forecasted temperature using the econometric models for 16 sites in New York State and New England.
2. Convert wind speed to potential wind power, rank the system total and assign the sample observations to bins.
3. Use the assigned observations to estimate the transition probabilities from hour t-1 to hour t for t = 1,2,….,24

Capabilities of the MATLAB Functions Used to Simulate Wind Power and Load

- The following MATLAB functions make it possible to:
  - Simulate a sample of hourly realizations of wind speed at 16 sites and load in 7 regions in New York State and New England for any specified day of the year,
  - Transform these simulated values into the stochastic inputs used by the multi-period SuperOPF.
- SimNPCCWindLoad()
  - Generates a time series of hourly realizations of wind speed and load using estimated ARMAX models for 16 wind sites and 7 load regions,
  - The number of daily realizations (sample size), the starting hour, and the number of hours in each daily realization can be customized for any specified day of the year.
- ConvertWindToPower()
  - Converts the simulated hourly wind speeds to the potential wind power from a wind farm at each site using the methodology described in Norgaard (2004).
- CreateScenarios()
  - Generates wind power and load scenarios for each hour using the bin method to cluster the simulated hourly realizations ranked by the total potential wind power for all 16 sites,
  - Calculates the transition probabilities from one hour to the next hour for all scenarios,
  - Applies the same bin allocations to each wind site and load region and computes the mean value for each bin,
  - The number of scenarios and the probability for each scenario bin can be customized.
- SetupWindLoad()
  - Sets up the code that calls the three MATLAB functions described above,
  - Creates the stochastic input files for potential wind power and load in the format used by the SuperOPF,
  - Creates plots of the wind power and load realizations and the scenario profiles (PlotWind.m, PlotLoad.m).

PART I: Stochastic Inputs
b) The Effects on System Costs

2nd Generation Multi-Period SuperOPF

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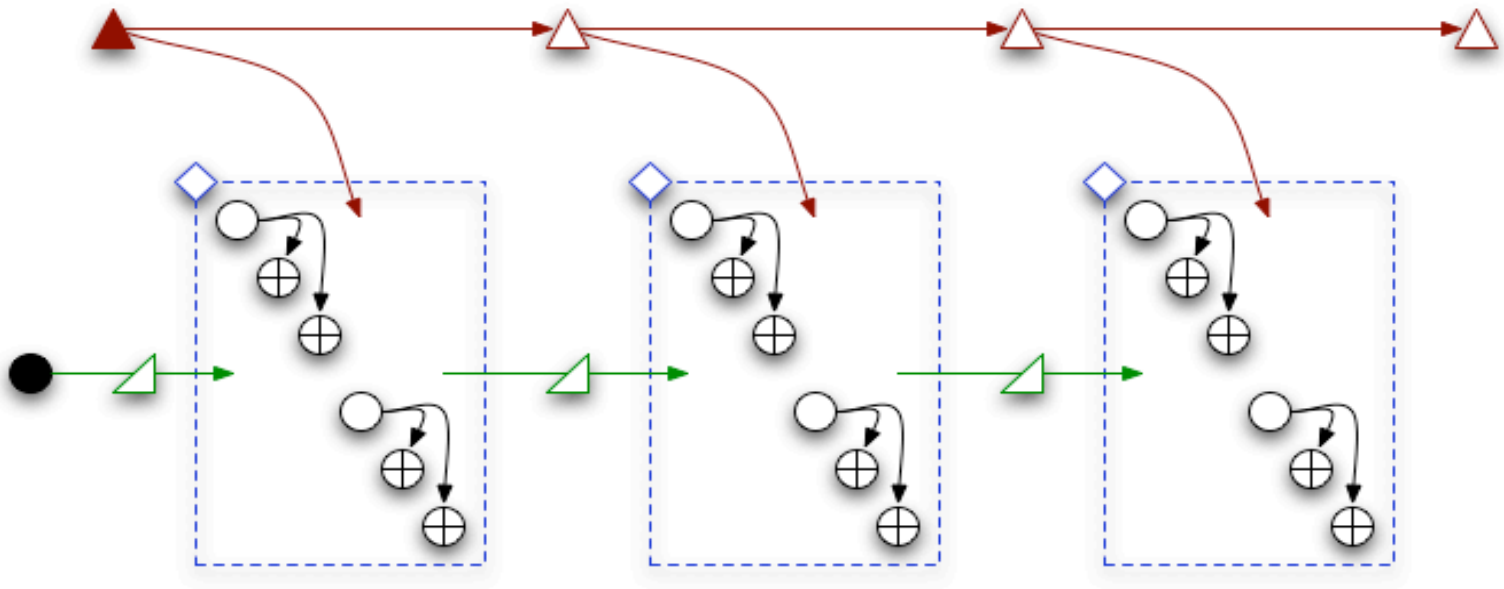

- **Includes:**
  - Multi-Period Optimization
  - Storage Capacity
  - Stochastic Wind Generation
  - Ramping Costs
  - Different Reserves (contingency, load following)

System Characteristics of the NENY Network for a Simulated Hot Summer Day (Cases 1 & 2)

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NYNE GENERATING CAPACITY	
Peaking (GW)	37
Baseload (GW)	26
Fixed Imports (GW)	3
TOTAL (GW)	**66**
New Wind (GW)	16
Storage Capacity (GW)	varying
Storage Energy (GWh)	34
Peak Load (GW)	**62**
Average Load (GW)	**52**

Characteristics of Wind Inputs

Wind/conventional capacity: 24%,
Av. capacity factor of wind: 38%,
E[Potential Wind Generation] (E[PWG]) could supply 12% of the daily energy.

Case 1: No Wind: Initial base system

Case 2: Case 1 + 16 GW of wind capacity at 16 locations:

- **a:** **Deterministic** inputs for wind and load
  → **No Uncertainty**,
- **b:** **Stochastic** inputs for wind and load calibrated at the **system** level
  → **Medium Uncertainty,**
- **c:** **Stochastic** inputs for wind and load calibrated at the **site** level
  → **High Uncertainty.**

Changes in Total Operating Costs

Different Levels of Uncertainty for Load and Wind Power

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I : Adding Wind Capacity, (c2a – c1)
II : **No** Uncertainty → **Medium** Uncertainty (c2b – c2a)
III : No Uncertainty → **High** Uncertainty (c2c – c2a)

I **II** **III**

E[$1000/day]

I → Much lower Generation Costs & slightly higher Ramping Costs
II → Slightly Higher Ramping Costs & some PWG spilled (higher Gen. Costs)
III → Even Higher Ramping Costs & more PWG spilled (higher Gen. Costs)

OVERALL EFFECT OF **UNCERTAINTY** ON COST IS **SMALL**

The Timing of the Forecasts Used as Inputs for the Optimization

The conclusions so far:

- **Greater uncertainty** about the future levels of Load and Potential Wind Generation (PWG) has the expected effects on system operations:
  - Increases the reserve capacity needed for ramping,
  - Spills more of the PWG,
- **Greater uncertainty** only leads to a **small increase in the E[Total Daily System Cost]**,
- Although our previous research found a much larger difference in system costs between deterministic PWG and stochastic PWG, the earlier analysis used a sample of **actual summer days instead of econometric forecasts** to represent the level of uncertainty**,**
- The **useful information** from the ARMA models of the autocorrelations in the simulations of Load and PWG **only lasts for 8-10 hours** ahead.

Next step:

- Compare the effects of using forecasts made **SIX hours ahead** (like a Day-Ahead Market) with forecasts made **ONE hour ahead** (like Cases 2a-c) on the **optimal system operations in Hour 1**.

The Optimal Dispatch Patterns in the Five Intact System States for Hour 1 using Different Forecasts

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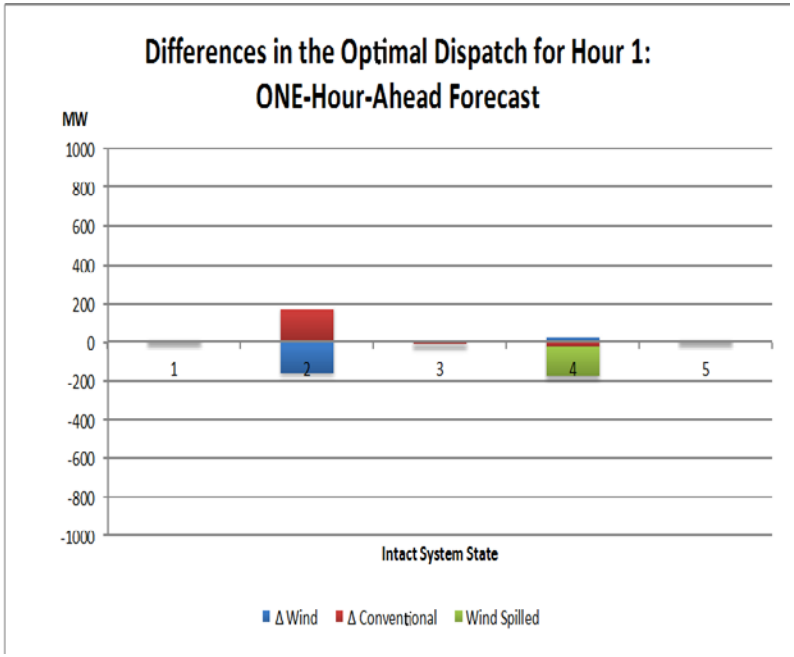

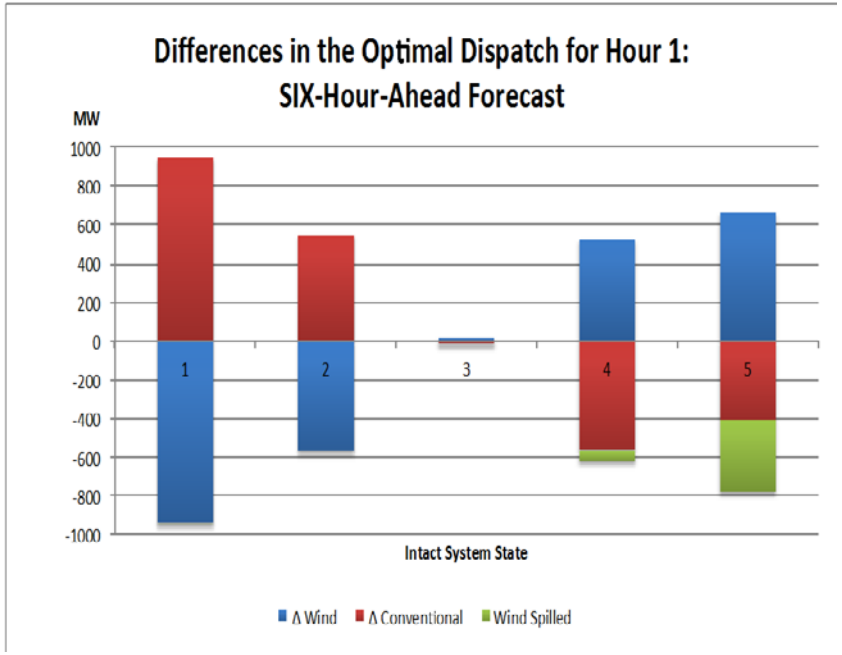

Δ = Deviation around the Mean for Hour 1, (P{States 1 and 5} = 0)
Range of Conventional Generation in Hour 1
= Ramping Capacity Needed = 192 MW

Δ = Deviation around the Mean for Hour 1
Range of Conventional Generation in Hour 1
= Ramping Capacity Needed = 1514 MW

Using the **updated forecasts** made ONE hour ahead requires committing only 192/1514 ≈ **1/8th of the reserve capacity** needed for ramping in Hour 1

→ A potential benefit of using a **rolling horizon** for market operations.

PART II: Deferrable Demand
a) Model Specifications

SPECIFICATIONS FOR DEFERRABLE DEMAND

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- Thermal Storage, Space Conditioning (Total Capacity 17 GWh)
  - Total potentially deferrable demand is 34 GWh on the hottest (coldest) day,
  - Storage capacity is 30 MWh/unit (86% efficient, manufactured by Calmac),
  - Maximum hourly energy delivered for space conditioning is proportional to TSL*.
- Electric Hot Water Heating (Total Capacity 17 GWh)
  - Total potentially deferrable demand is 34 GWh per day,
  - The size of each water tank is 80 gallons with a heating capacity (recovery rate) of 20 GPH (equivalent to 4.5 kW/hour) (91% efficient, manufactured by Rheem),
  - Maximum energy of the hot water used each hour is proportional to N-TSL*.
- Electric Vehicles (Total Capacity 17 GWh)
  - Total deferrable demand is less than 17 GWh per day (the average number of miles driven each day < the maximum electric range) ,
  - Usable battery capacity is 10.8 kWh/vehicle (90% efficient, lithium-ion in GM Volt)
  - Average charging power is 3.31 kW (Level1/Level2 chargers = 70%/30%),
  - Charging is restricted by the Commuter-at-Home Profile (determines the # of vehicles attached to grid each hour) and the Commuter-Driving Profile (determines how much energy is used for transportation each hour).

- Temperature Sensitive Load (TSL) and Non-Temperature Sensitive Load (N-TSL) are derived from the estimated econometric models of demand.

Daily Profiles of (Deferrable) Energy Services Demanded by Customers for Four Seasons*

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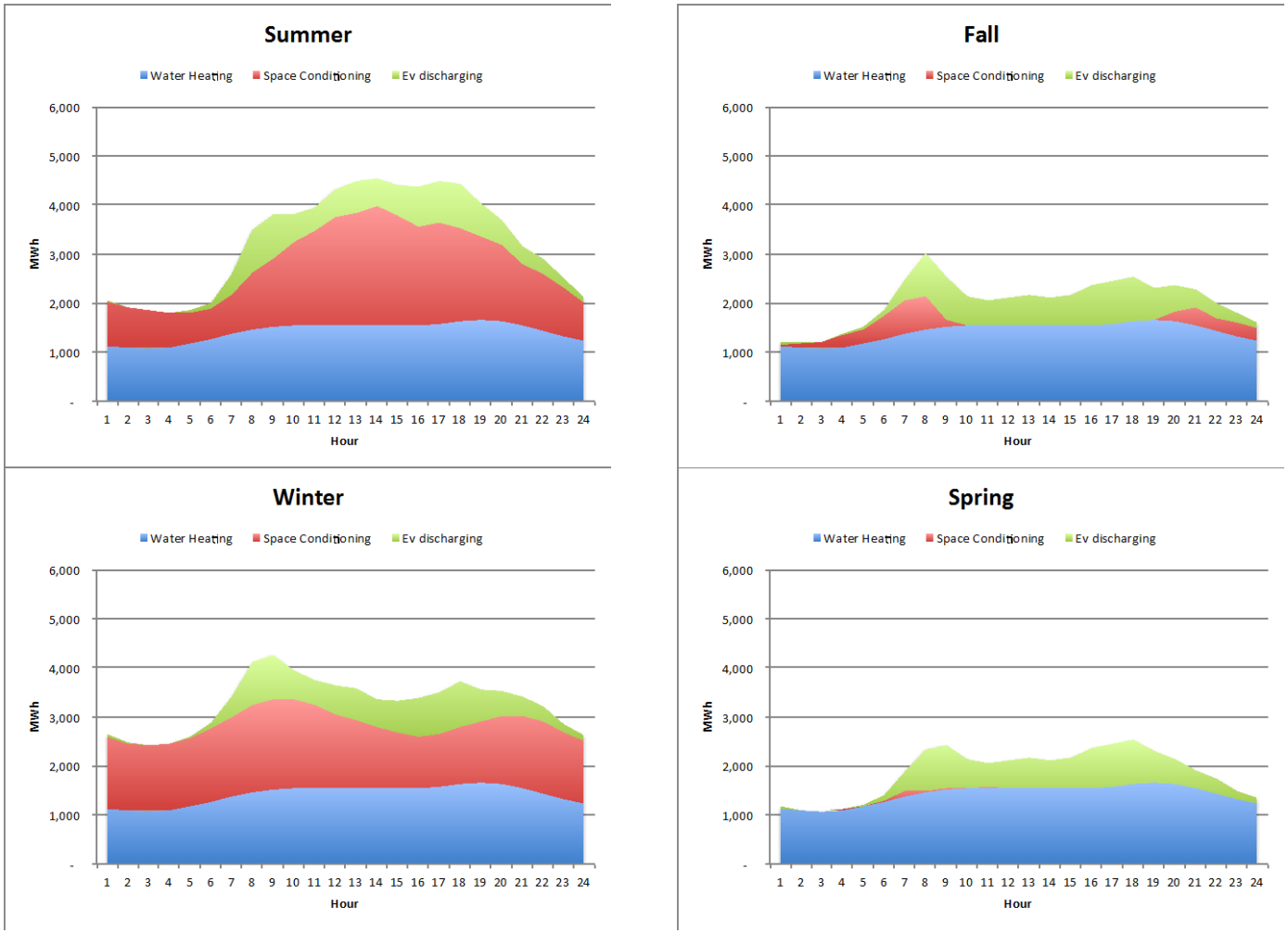

* The Energy Demanded by Customers Each Hour for Specific Energy Services

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The Structure of the SuperOPF

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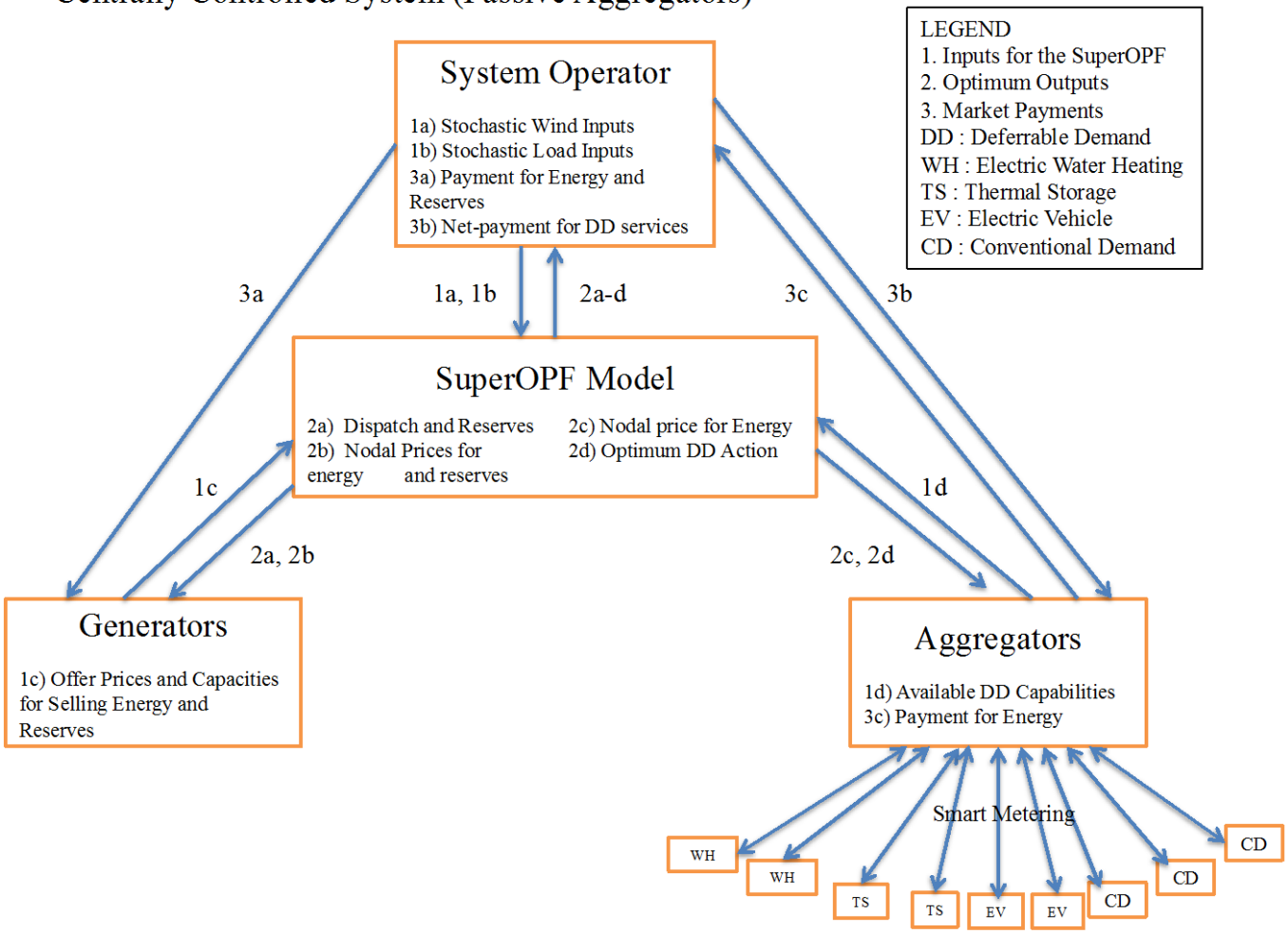
- Centrally Controlled System (Passive Aggregators)



PART II: Deferrable Demand
b) DD Controlled by an ISO

System Characteristics of the NENY Network for Simulated Days in Different Seasons

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NYNE GENERATING CAPACITY	
Peaking (GW)	37
Baseload (GW)	26
Fixed Imports (GW)	3
TOTAL (GW)	**66**
New Wind (GW)	16
Storage Capacity (GWh)	51
Peak Load (GW)	**Varies by Day**
Average Load (GW)	**Varies by Day**

Characteristics of Wind and Load

Same installed wind capacity every day with Potential Wind Generation (PWG) and Load simulated for each specified day.

Properties of Deferrable Demand (DD)

For each hour, the forecasted Load is divided into **conventional demand**, **DD for space conditioning** (cooling or heating), and **DD for hot water**. **DD for transportation** is an additional source of demand.

Case 1: No Wind: Initial base system,

Case 2c: Case 1 + 16 GW of wind capacity at 16 locations,

Case 3a: Case 2c + 51 GWh of DD capacity at 5 load centers:

- 17 GWh of Storage for Space Cooling* or Heating* (Proportional to TSL**)
- 17 GWh of Storage for Hot Water*** (Proportional to N-TSL**)
- 17 GWh of Storage for Electric Vehicles (10% penetration)

* The corresponding amount of potential DD = 2 x energy capacity of storage on the hottest/coldest day

** Temperature Sensitive Load (TSL) and Non-Temperature Sensitive Load (N-TSL)

*** The corresponding amount of potential DD = 2 x energy capacity of storage every day

The Effects of Deferrable Demand on System Costs for the Peak Summer Day → No Surprises

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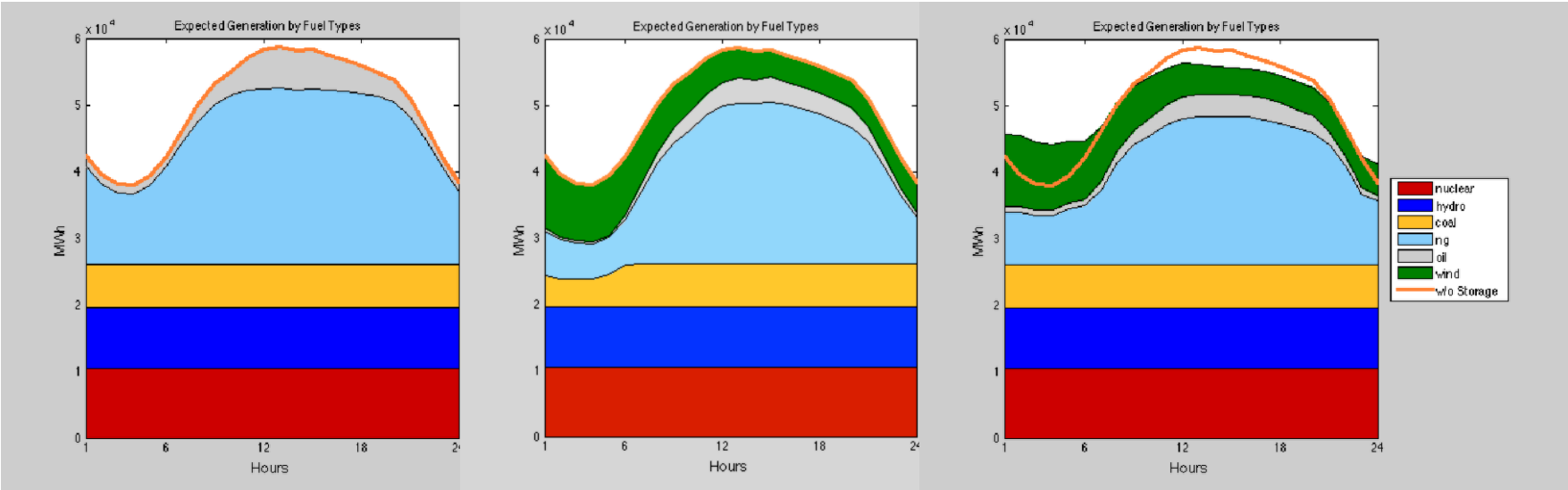
Case 1: No Wind **Case 2c: + Wind** **Case 3a: + DD**



	Case 1: No wind	Case 2c: + Wind	Case 3a: + DD
E[Generationn Cost] ($1000)	55,682	42,791	42,514
E[Ramping Cost] ($1000)	664	976	383
E[Operating Cost] ($1000)	56,346	43,767	42,897
Max Conventional Capacity (MW)	59,904	55,281	51,906
E[Wind Generation] (MWH)	-	144,258	149,909

PART II: Deferrable Demand
c) Cost Effects for Customers

Five Different Types of "Customer"

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1. No DD capacity (No Storage)
2. Water Heating only (WH)
3. Thermal (Hot and Cold) Storage only (TS)
4. Electric Vehicle only (EV)
5. All three types of DD (All DDs)

- Based on Case 3a (Base Case 1 + Wind + DD)
- The total energy capacity for electric vehicles (17 GWh) corresponds to a 10% penetration rate for registered vehicles, and this determines the total number of customers with an EV (1.5 million) and the total number of customers (15 million). Every customer is assumed to have identical daily needs for all non-transportation electric energy services. The customers are assigned to five load centers in proportion to the total daily loads at those locations in the summer, and the hourly patterns of demand for electric energy services vary by location.
- The energy storage capacities for a customer with TS only or with WH only are calibrated to be the same as the maximum useable energy capacity of an EV. This simplifies making comparisons among different types of customer.
- The results presented for different types of customer correspond to the system average for all five locations.

Hourly Patterns of Energy Purchases by Customers in Different Seasons (kWh)

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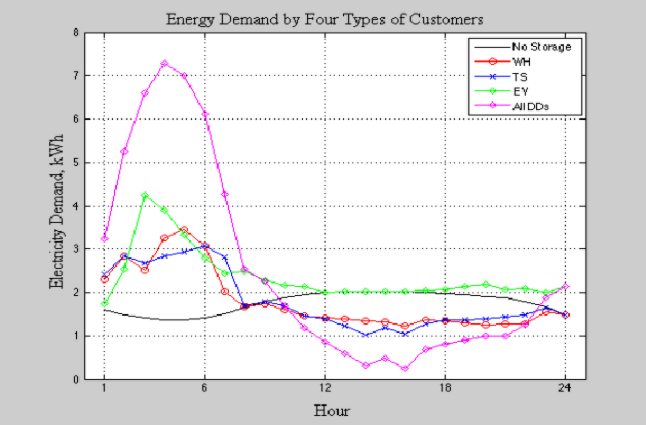
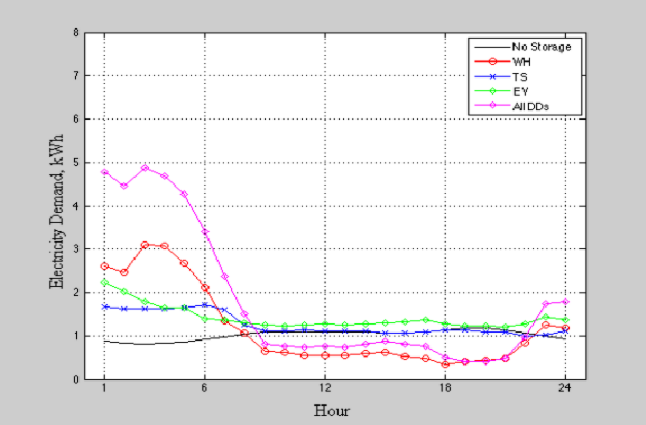
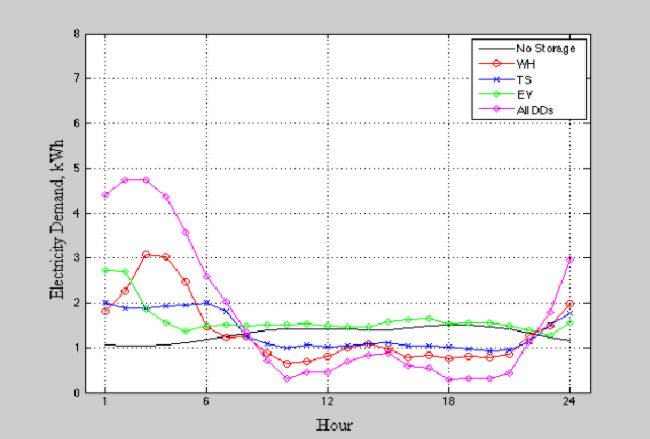
Summer Day (peak)



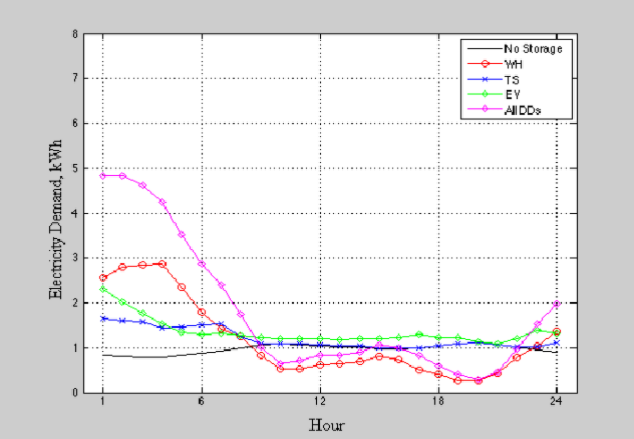
Fall Day



Winter Day



Spring Day



Net Payments by Customers using Efficient Prices versus Flat Energy Prices ($/day)

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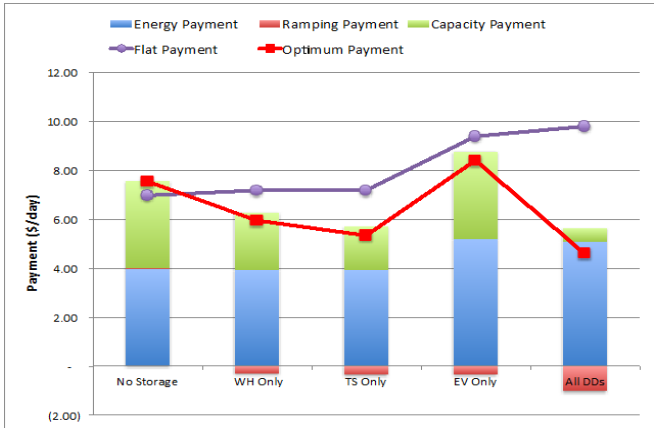
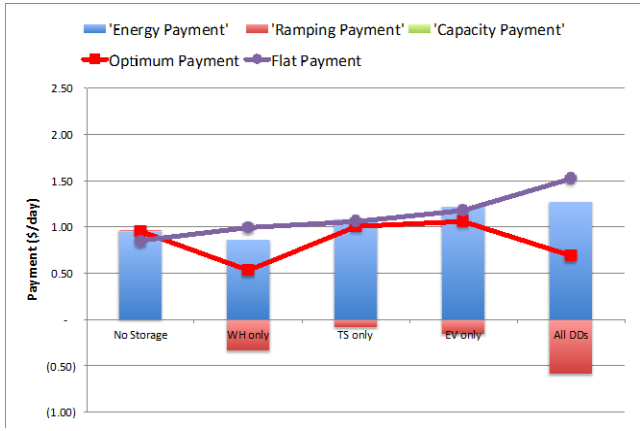
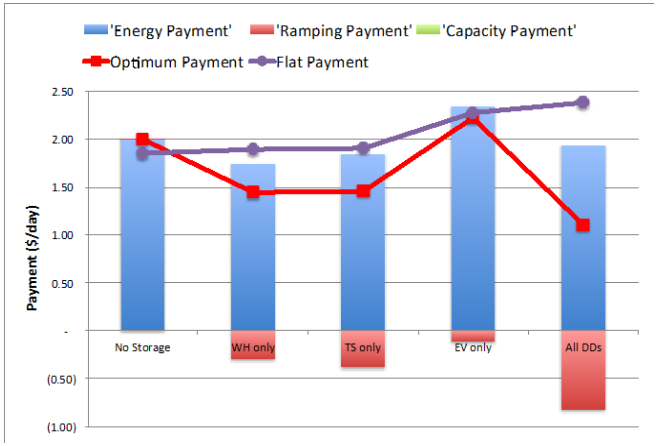
Summer Day (-2 → 12 $/day)



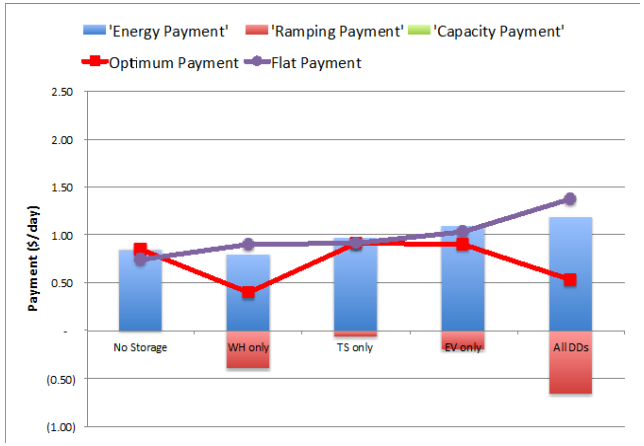
Fall Day (-1 → 2.5 $/day)



Winter Day (-1 → 2.5 $/day)



Spring Day (-1 → 2.5 $/day)



- Capital Payments for Generating Capacity occur only for the Annual System Peak Load when Adequacy Standards are set ($1.76/kW for demand at the peak hour in the Summer Day),

- Summer Payments are by far the highest,

- The total net revenue paid by all customers is the same for the flat rate and the efficient rate,

- Payments are higher for customers with DD using a flat rate structure,

- Savings in the cost of gasoline purchased with an EV are not included.

Annual Payments by Customers

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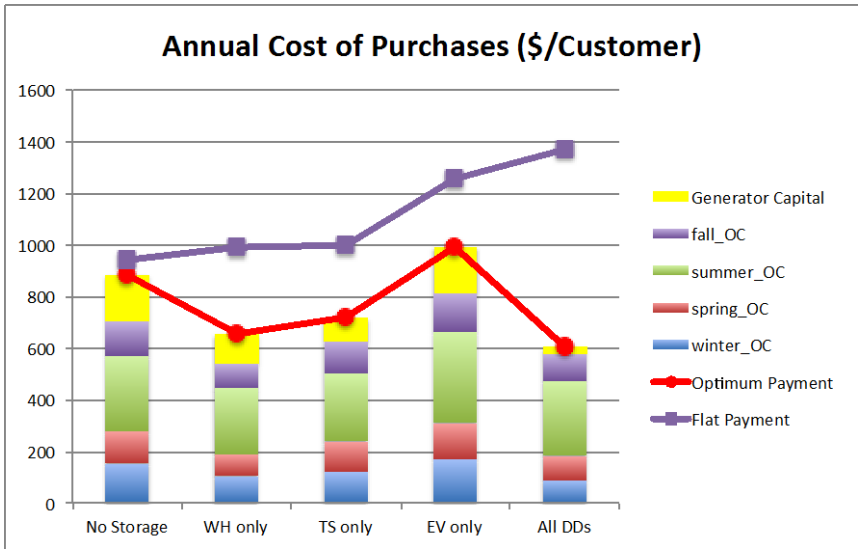
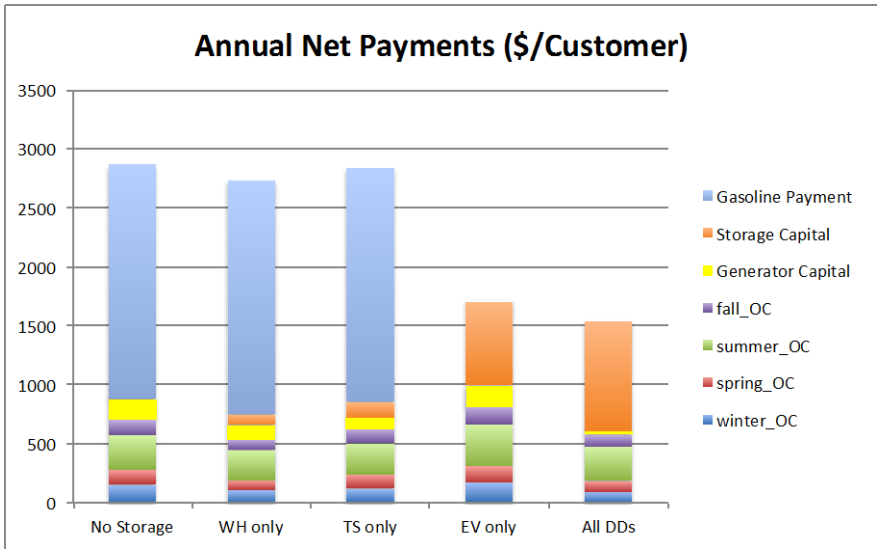




- Customers with DD pay more if a flat rate structure is used,
- Operating costs are highest in the summer,
- EV owners save most from purchasing less gasoline all year,
- WH (all year) lowers costs more than TS (seasonal),
- Annual Net Payments for All DDs is 46% of cost for No Storage.
  - Seasonal costs correspond to 91 day seasons using linear interpolation between the four specified days,
  - The annual capital costs for DD are for specific devices and then scaled to the same energy capacity as a GE Volt,
  - The annual capital cost for:
    - Generator Capital is $88/kW for demand at the summer peak (EIA),
    - EV battery is $65/kWh for a capacity of 10.83 kWh (GM & GE),
    - Thermal Storage is $12.50/kWh for a capacity of 10.83 kWh (MacCraken),
    - Water Heating is $8.52/kWh for a capacity of 10.83 kWh (Rheem),
  - The annual cost of gasoline for a vehicle that travels 27.2 miles/day at 20 miles/gallon and $4/gallon.

PART II: Deferrable Demand
d) Sensitivity to Wind and Ramping

Research Question

Answer 3 fundamental questions

- How to Determine the cost of Ramping as input for the SuperOPF?
- What is the sensitivity to different levels of wind penetrations
- How does compensation for ramping affects the capacity value of wind and the system performance

First Task: Ramping Costs

Ramping costs

- Higher than steady state emissions due to up-ramps [3].
- Cycling costs: Full cycle - [4, 5, 6, 3].

Ramping Cost as a function of Ramp rate

- Ramp rate nonlinear direct relationship for coal fired units - [4].
- Ramping cost $\rightarrow$count the number of minor load following operations - [6].

- Damages to the power plant such as Thermal fatigue and Creep - [2].
  - Creep: Overheating during ramp up can make some components to operate above the design temperature, $\rightarrow$ accumulation or acceleration of creep damage.
  - Thermal fatigue: Changes in temperature results in mechanical failure $\rightarrow$ most prevalent mechanical problem as a result of ramping.
  - Creep-Fatigue interaction: In high temperature, some components may experience both fatigue and creep $\rightarrow$ premature failure. [1]

Simulation Cases

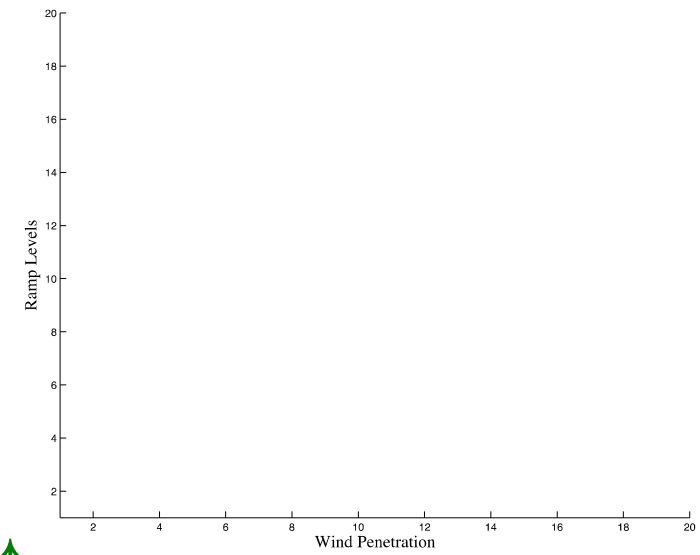
Wind Inputs

- Wind/conventional capacity: 24%
- Capacity factor of wind: 21%
- Potential wind generation could supply 7.5% of daily energy needs

Storage

- Same locations as wind
- Steady state conditions, cyclic constraints
- Two threshold prices, transversality conditions

Results

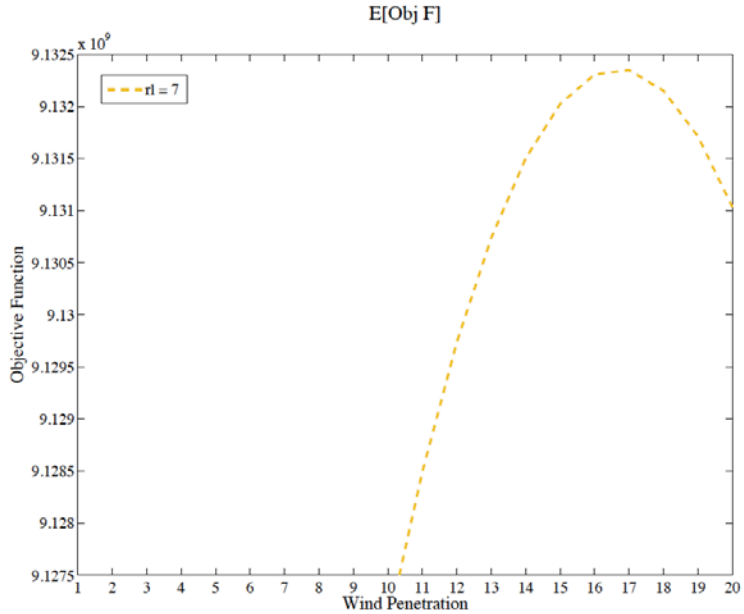


Wind and Ramping Increases

- Increases from 0 to 100% of max wind capacity (from 1 to 20, 20 = 16GW)
- Increases from 1 to 1000× the initial ramping (w-t) costs (from 1 to 20, 1 = baseline ramp) [1]

Increasing Wind Penetration

Fixing the ramping cost in the system

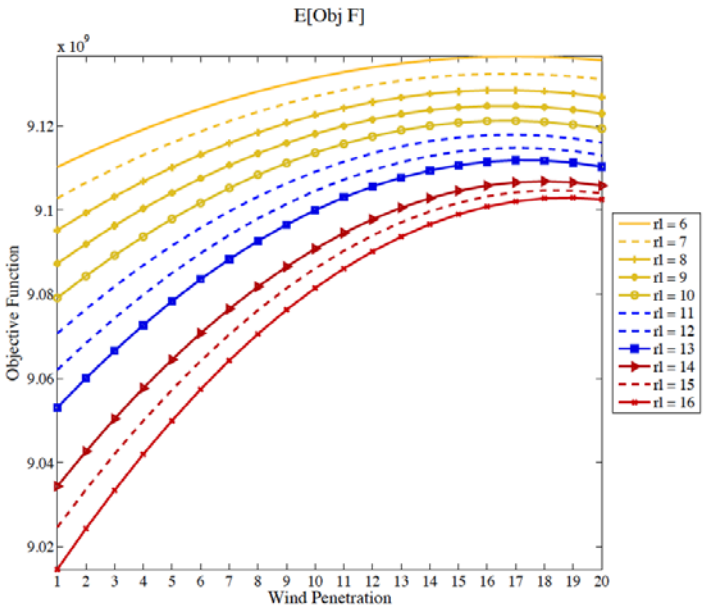


Total Objective Function

Savings in energy cost offset by the increases in other internalized costs (ancillary services, LNS)

Wear-and-tear Cost Levels

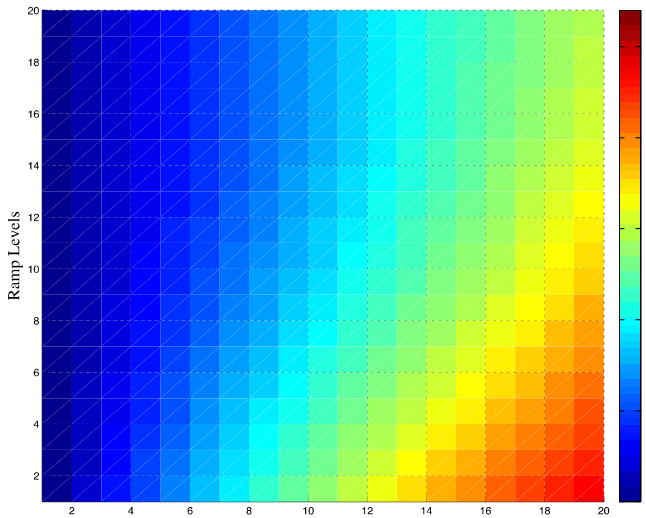
For Several Ramping Cost Levels



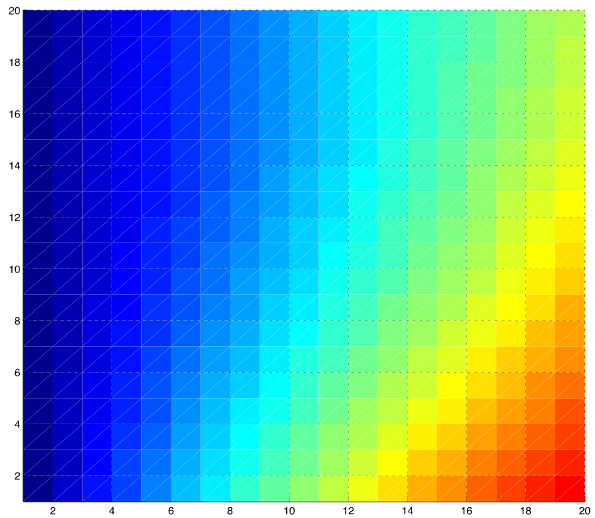
Total Welfare

No Storage available to mitigate impacts of wind

Total Wind Generation, Adding Storage



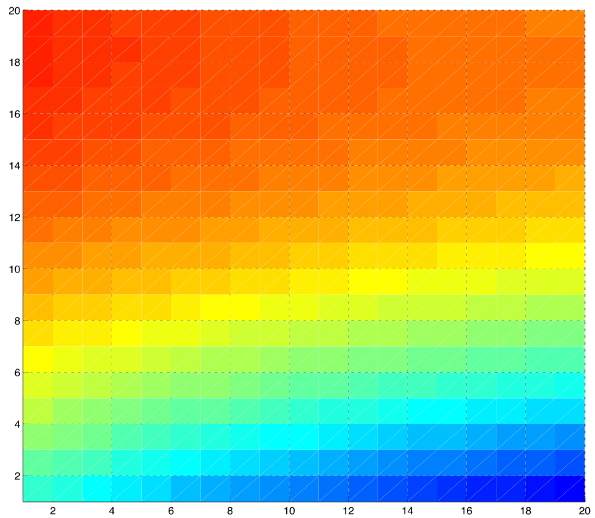
Total Wind Generation, Adding Storage



Storage Effect

14% higher expected wind amounts dispatched (MW/day)

Expected Generation Cost



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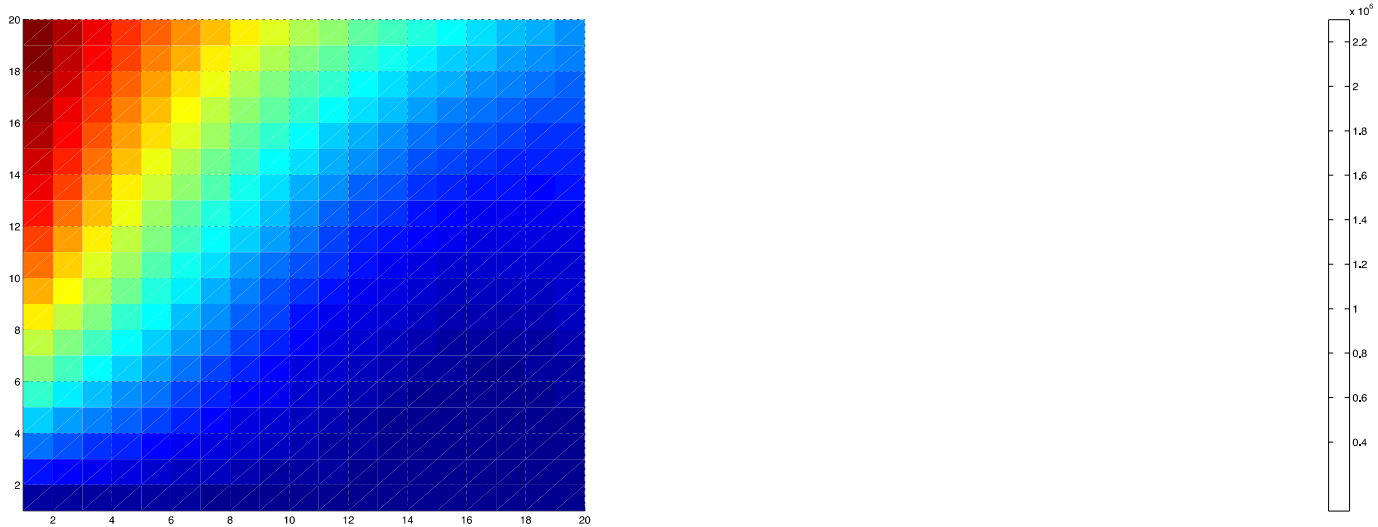
Expensive Energy sources, savings between 9 and 15% ($1000/day)

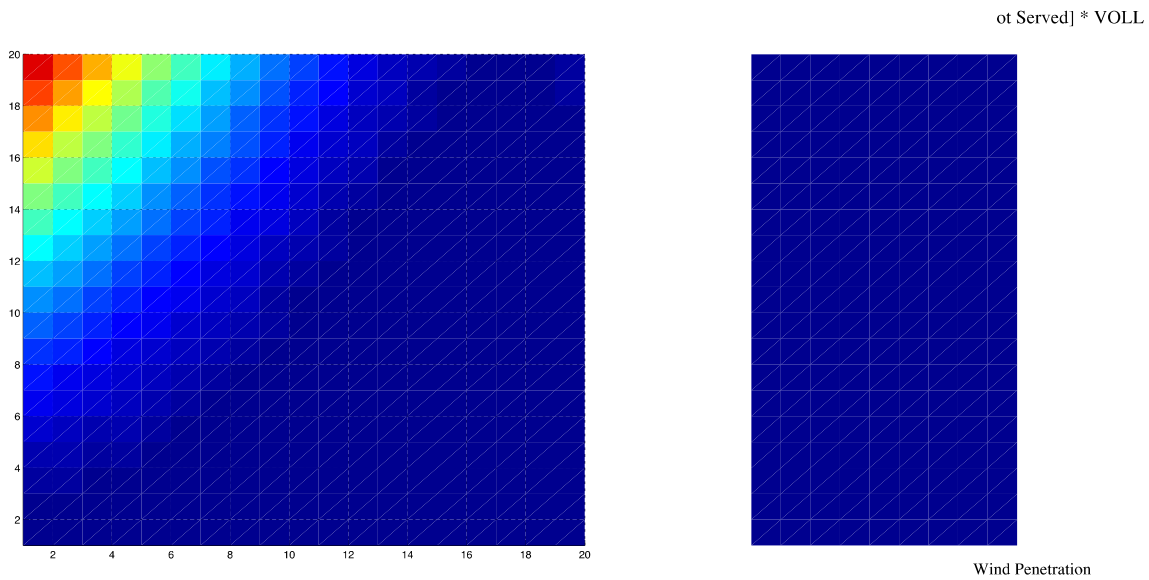
Wholesale Cost, Same Scale



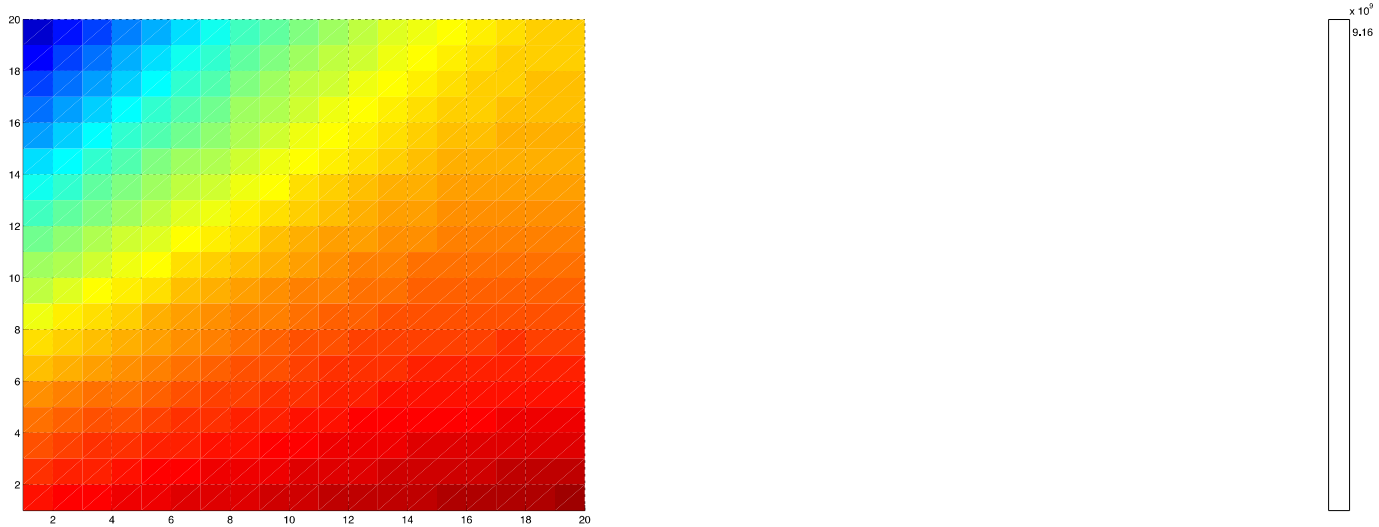
Network Effects

Lower wholesale cost thanks to reduced congestion

LNS × VOLL, same scale



Total Welfare



Storage Effect

Overall higher welfare obtained

Summary

- High penetration of renewable generation lowers the wholesale price of energy
  - **BUT,** increased internalized ramping costs for the conventional generators
  - Additional load following and contingency reserve needed
- Collocated Storage supports the adoption of wind, without the nasty consequences
  - Ramping provided **by** storage units
  - Storage also provides load following and contingency reserve for operational reliability
- Future Work
  - Analyze the capital costs of storage
  - Explore the role of location

PART II: Deferrable Demand
e) DD Controlled by Aggregators

System Characteristics of the NYNE Network for a Simulated Hot Summer Day

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NYNE GENERATING CAPACITY	
Peaking (GW)	37
Baseload (GW)	26
Fixed Imports (GW)	3
TOTAL (GW)	**66**
New Wind (GW)	16
Storage Energy (GWh)	34
Peak Load (GW)	**62**
Average Load (GW)	**52**

Characteristics of Wind Inputs

Wind/conventional capacity: 24%,
Av. capacity factor of wind: 38%,
E[Potential Wind Generation] (E[PWG]) could supply 12% of the daily energy.

Properties of Deferrable Demand

For each hour the level of demand (system load) is divided into **conventional demand, demand for space cooling and demand for hot water.**

Case 1: No Wind: Initial base system
Case 2: Case 1 + 16 GW of wind capacity at 16 locations.
Case 3 ISO: Case 2 + 34 GWh* of Deferrable Demand (DD)** at 5 load centers
Case 3 AGG: Case 3 ISO with DD controlled by aggregators at 5 load centers

* 17 GWh of Thermal Cooling (Ice Batteries) and 17 GWh of Electric Water Heating **(i.e. no EVs)**
** DD decouples the purchase of electricity from the delivery of an energy service to customers

The System Effects of Deferrable Demand (DD)

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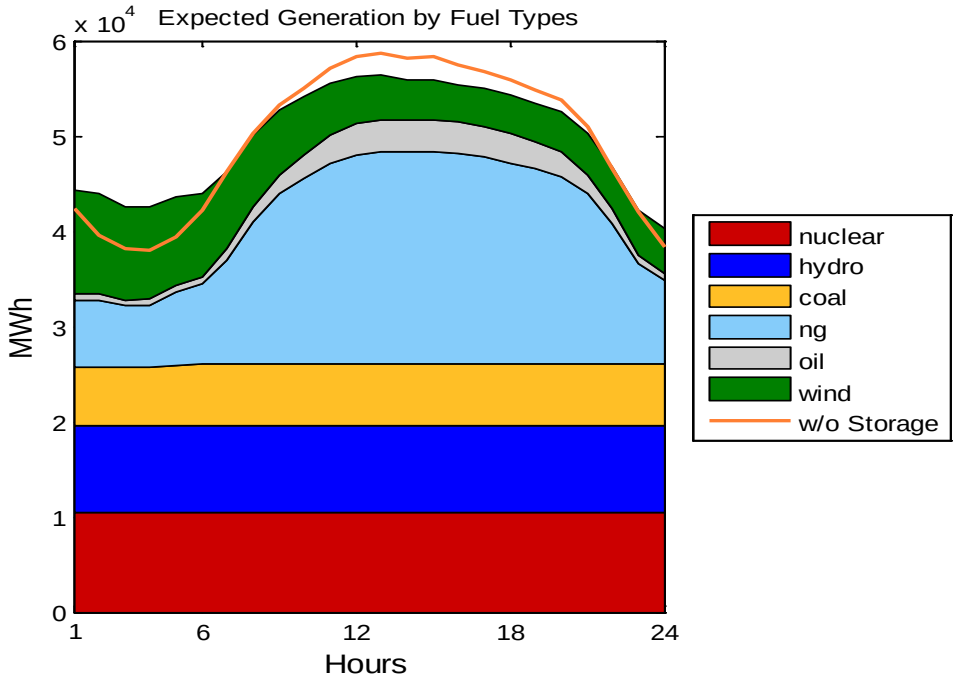
Case 3 ISO: Wind + Centrally Controlled DD



Cost ($1000/day)	No Wind c1	Add Wind c2	Add DD c3 ISO
Generation Cost	54,628	42,021	40,958
Ramping Cost	663	987	464
Total Operating Cost	**55,292**	**43,008**	**41,422**
E[Wind Gen.] (MWh)	-	144,391	150,002
Max Conv. Capacity (MW)	59,538	55,033	51,235

Case 2: Adding Wind Capacity →
- Lower Fuel Costs
- Higher Ramping Costs

Case 3 ISO: Adding DD →
- Slightly Lower Fuel Costs
- Lower Ramping Costs

Can **Aggregators Control DD Locally** in response to price forecasts, submit bids into the wholesale market and make the system perform as well as it does when an **ISO Controls DD Centrally**?

How Should an Aggregator Respond to Forecasts of Energy Prices?

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Objective

Minimize the expected cost of purchasing energy from the grid and deliver the energy services demanded by their customers subject to the capacity constraints of Deferrable Demand (DD) devices.

Deterministic Price Forecasts →

Submit a set of deterministic quantity bids to shift purchases from peak to off-peak periods and benefit from price arbitrage. This strategy does NOT provide ramping services.

Stochastic Price Forecasts →

Submit a set of price/quantity bids to shift purchases from peak to off-peak periods and benefit from price arbitrage. This strategy DOES provide ramping services by:

Discharging DD when the price > High Threshold
Charging DD when the price < Low Threshold

Aggregator's Optimum Bid Strategy

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Expected Cost →

$$\min_{L_t,H_t}\sum_{t=1}^{24}[E(P_t)\cdot D_t + c\cdot E(P_t|P_t \le L_t)\cdot Prob(P_t \le L_t) - \min(D_t,d)\cdot E(P_t|P_t > H_t)\cdot Prob(P_t > H_t)]$$

Max Storage Capacity →

$$\text{subject to } g_i(L_t,H_t) = \sum_{t=1}^{i}[c\cdot Prob(P_t \le L_t)\cdot e - \min(D_t,d)\cdot Prob(P_t > H_t)] - (S_{max} - S_0) \le 0, \forall i = 1,2,\dots,23$$

Min Storage Capacity→

$$h_j(L_t,H_t) = \sum_{t=1}^{j}[\min(D_t,d)\cdot Prob(P_t > H_t) - c\cdot Prob(P_t \le L_t)\cdot e] - S_0 \le 0, \forall j = 1,2,\dots,23$$

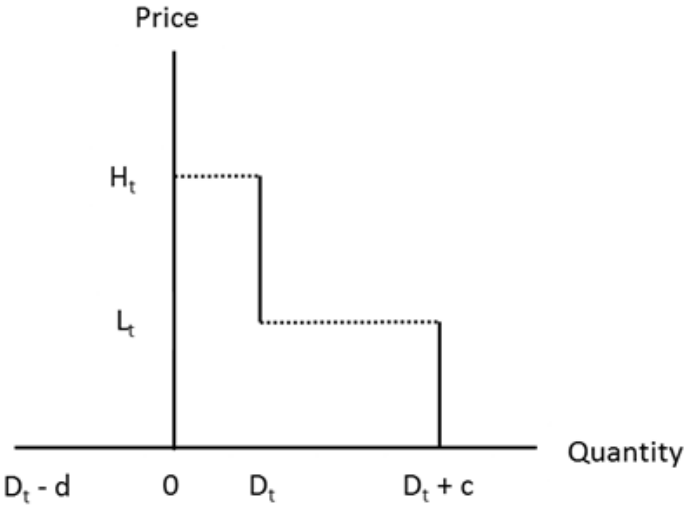
$E[S_{24}] = S_0$ →

$$k(L_t,H_t) = \sum_{t=1}^{24}[\min(D_t,d)\cdot Prob(P_t > H_t) - c\cdot Prob(P_t \le L_t)\cdot e] = 0$$

Given stochastic forecasts of energy prices for the 24 hour planning horizon, the aggregator determines bids to buy energy to minimize the expected cost of purchasing energy from the grid for space cooling and hot water:

→ Low Threshold Price for Charging, L_t

→ High Threshold Price for Discharging, H_t



Optimal Thresholds Analysis

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Kuhn-Tucker Conditions

$$(1a)\ \frac{\partial \mathcal{L}}{\partial L_t} = \frac{\partial f}{\partial L_t} + \sum_{i=t}^{23} \mu_i \frac{\partial g_i}{\partial L_t} + \sum_{j=t}^{23} \lambda_j \frac{\partial h_j}{\partial L_t} + \gamma \frac{\partial k}{\partial L_t} = 0$$

$$(1b)\ \frac{\partial \mathcal{L}}{\partial H_t} = \frac{\partial f}{\partial H_t} + \sum_{i=t}^{23} \mu_i \frac{\partial g_i}{\partial H_t} + \sum_{j=t}^{23} \lambda_j \frac{\partial h_j}{\partial H_t} + \gamma \frac{\partial k}{\partial H_t} = 0$$

$$(2a)\ g_i(L_t, H_t) \le 0, \forall i = 1, 2, \dots, 23$$

$$(2b)\ h_j(L_t, H_t) \le 0, \forall j = 1, 2, \dots, 23$$

$$(2c)\ k(L_t, H_t) = 0$$

$$(3a)\ \mu_i g_i(L_t, H_t) = 0, \mu_i \ge 0, \forall i = 1, 2, \dots, 23$$

$$(3b)\ \lambda_j h_j(L_t, H_t) = 0, \lambda_j \ge 0, \forall j = 1, 2, \dots, 23$$

$$\longrightarrow$$

$$H_t = -\left[\sum_{i=t}^{23} \mu_i - \sum_{j=t}^{23} \lambda_j - \gamma\right]$$

$$L_t = -\,e \cdot \left[\sum_{i=t}^{23} \mu_i - \sum_{j=t}^{23} \lambda_j - \gamma\right] = e \cdot H_t$$

- Optimal low threshold equals optimal high threshold multiplied by efficiency rate of the storage device.
- If energy capacity constraints are never binding, then optimal thresholds will be the same across 24 hours.

E[Dispatch Profiles] for Centralized and Decentralized Control of DD

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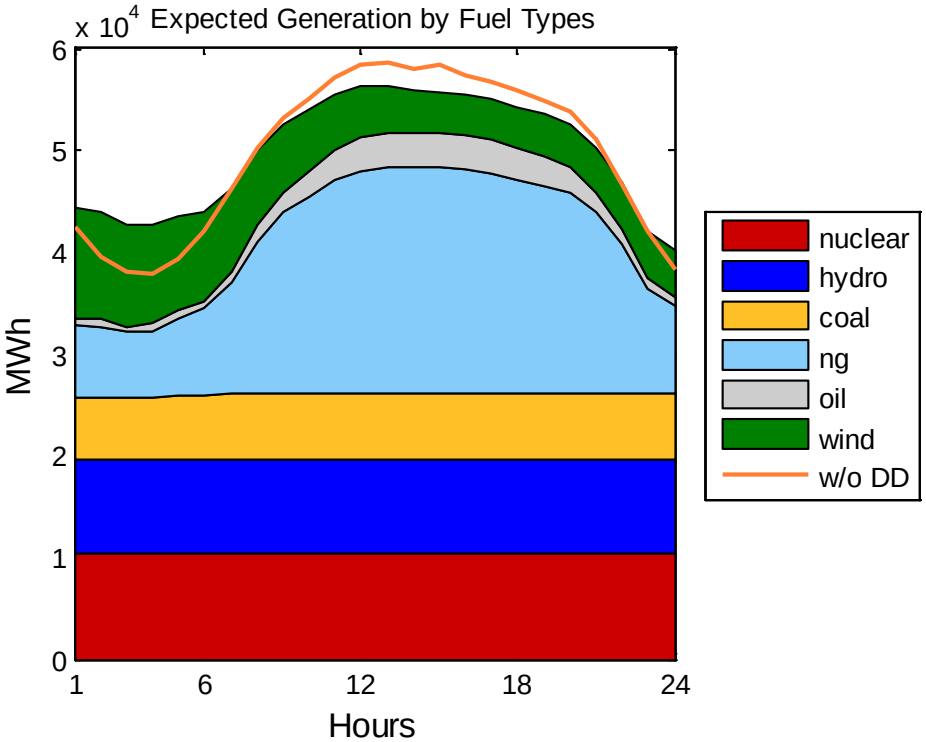
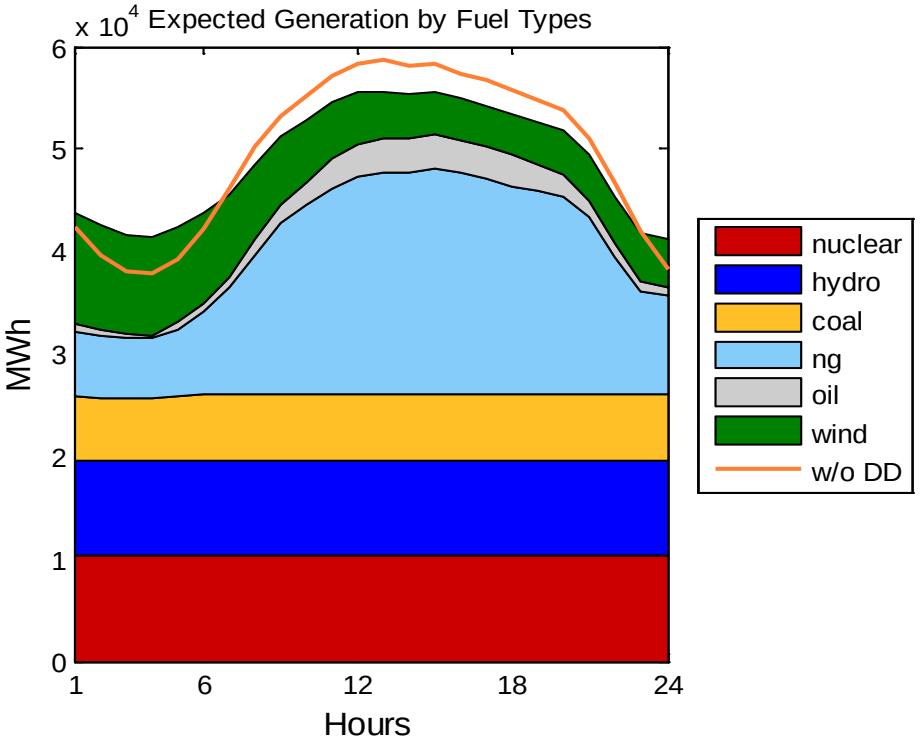
Centralized Control by an ISO (Case 3 ISO)



Decentralized Control by Aggregators (Case 3 AGG)



The E[Dispatch Profiles] and the ramping services provided by DD are very similar for centralized and decentralized control.

The Optimal Dispatch Patterns in the Five Intact System States for the Peak Hour

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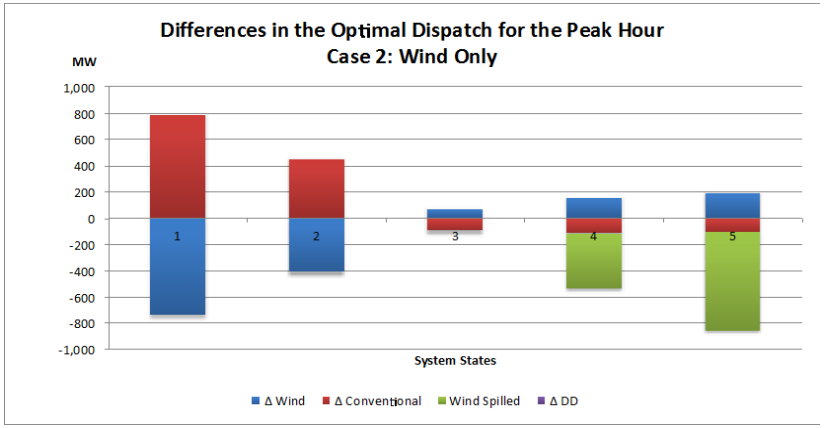
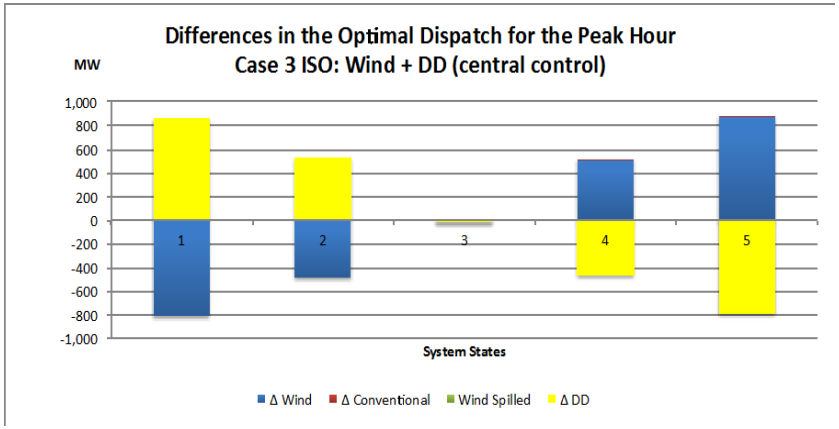
No DD (Case 2)

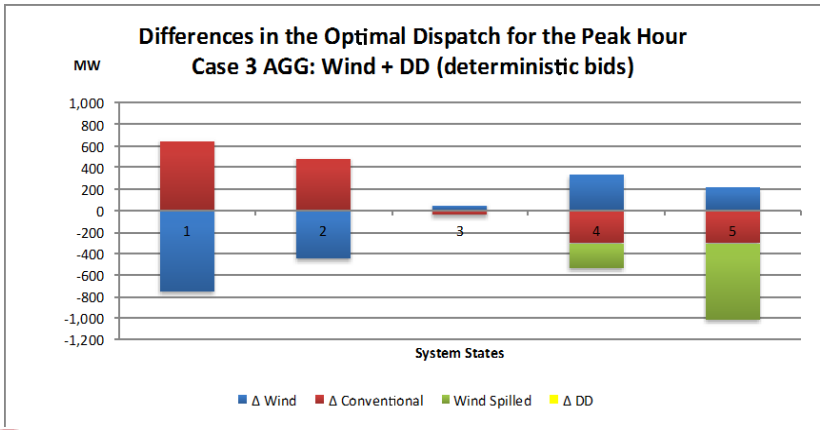


DD controlled by ISO (Case 3 ISO)



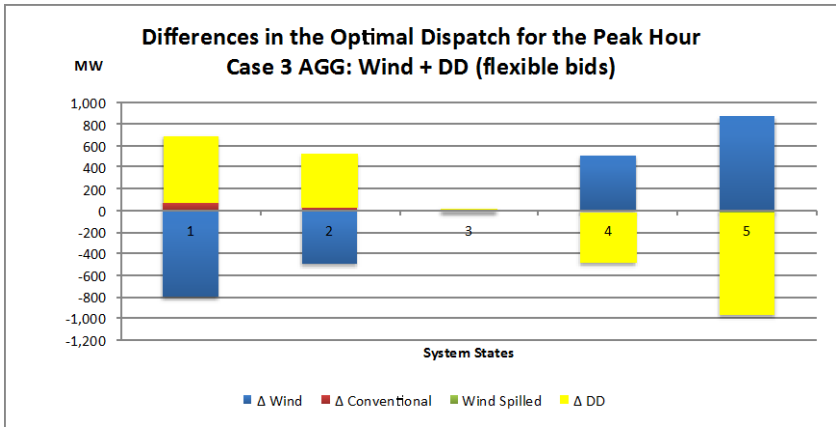
DD controlled by Aggregators I

- Deterministic price forecasts



DD controlled by Aggregators II

- Stochastic price forecasts



E[Stored Energy] Violates Capacity Bounds with Bids Submitted by an Aggregator

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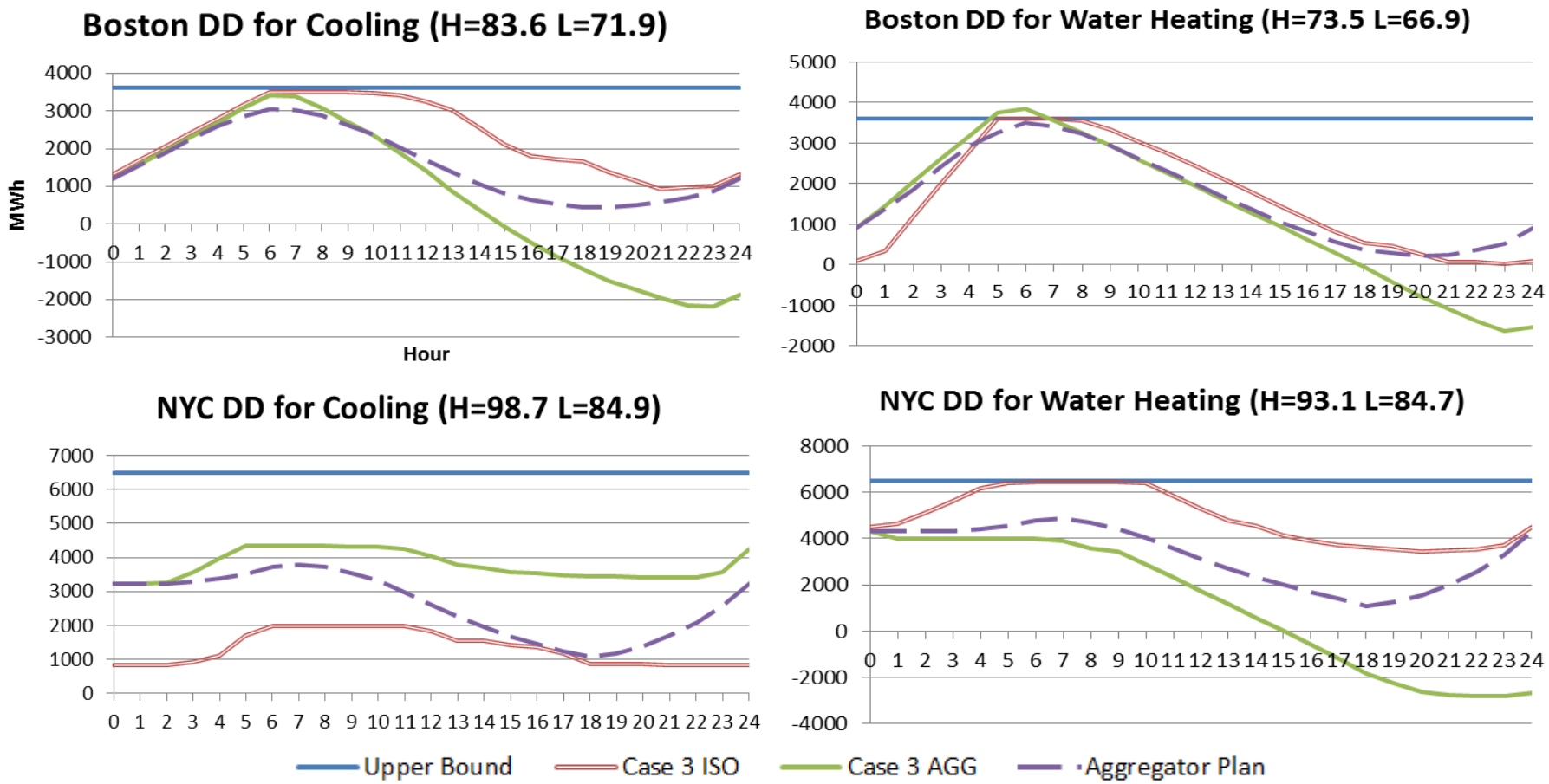

Even though the aggregators plans fall within the capacity bounds, the actual dispatch by the ISO can violate them

Summary

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- Deferrable Demand (DD) controlled locally by aggregators can help the system in the same way as centrally controlled DD, if:
  - Aggregators have access to stochastic forecasts of energy prices,
  - Aggregators minimize E[Cost of Purchasing Energy from the Grid] subject to meeting the delivery of DD services to customers,
  - Aggregators submit elastic demand curves and thus can be modeled as negative generators (rather than as fixed load).
- There is no guarantee that the dispatch of DD by an ISO will respect the energy capacity constraints of DD:
  - **Need accurate forecasts of the price distribution** (normal, triangular, shifted lognormal distributions have been tested),
  - **ISO should use a rolling horizon** so that aggregators can adjust their bids using updated information each hour.

PART III: PUBLICATIONS

Papers and Panels

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Papers

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,* 2014.
2. Wooyoung Jeon, Jung Youn Mo and Timothy D. Mount, “Developing a Smart Grid that Customers can Afford: The Impact of Deferrable Demand”, Forthcoming, *Journal of Energy Economics,* 2014.
3. Alberto J. Lamadrid, Timothy D. Mount, Wooyoung Jeon and Hao Lu, “Barriers to Increasing the Role of Demand Resources in Electricity Markets”, Proceedings of the 47th Annual IEEE HICSS Conference, January 2014.
4. Hao Lu, Wooyoung Jeon, Alberto J. Lamadrid, Timothy D. Mount, and Jung Youn Mo, “Evaluating the Effectiveness of Demand Aggregators in Accommodating the Uncertainty of Wind Generation”, Proceedings of the 33nd Annual CRRI Eastern Conference, May 2014.
5. Wooyoung Jeon, Jung Youn Mo, Alberto J. Lamadrid, Hao Lu, Timothy D. Mount, “Modeling Stochastic Wind Generation and the Implications for System Costs”, Proceedings of the 27th Annual CRRI Western Conference, June 2014.
6. Alberto J. Lamadrid et al. “Stochastically Optimized, Carbon-Reducing Dispatch of Storage, Generation, and Loads". Transactions on Power Systems, revise and resubmit

Panel

1. Alberto J. Lamadrid and Jim Price (California ISO) co-chairs, Panel on “Multistage Optimization and its Impact on Electricity Markets”, 2014 PES General Meeting, Washington DC, July 2014.

Presentations and Working Papers

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Presentations

1. Tim Mount, “Barriers to Increasing the Role of Demand Resources in Electricity Markets”, Invited Lecture at Imperial College, London UK, October, 2013.
2. Alberto Lamadrid, “Energy Storage Systems, Stochastic Optimization and Robust Control”, INFORMS Annual Meeting, Minneapolis MN, October, 2013.
3. Eilyan Bitar and Timothy D. Mount, “The System Benefits of Managing Demand Flexibility and Storage Efficiently.” PSERC Public Webinar, March, 2014.
4. Alberto J. Lamadrid, Timothy D. Mount, Wooyoung Jeon and Hao Lu, “A Squirrel’s Dilemma: The Value of Distributed Storage in the Transition to a Low-Carbon Electric Grid”, 37th Conference of the International Association of Energy Economists, New York, NY, June 2014.
5. Alberto J. Lamadrid and M. Mohsen Moarefdoost, “Mathematical Formulation for Generation, Storage and Dispatch in Electricity Systems with Ramping Constraints”, Proceedings of the 2014 PES General Meeting, Washington DC, July 2014.

Working Papers

1. Lamadrid, A. J., Moarefdoost, M. “Generation and Dispatch in Electricity Systems with Ramping Constraints”, 2014.
2. Lamadrid, A. J., Moarefdoost, M, Luis F. Zuluaga, “Chance Constrained Optimization in Electricity Networks with Ramping Constraints”, 2014.
3. Jeon, W., Lamadrid, A.J., Mount, T. and Lu, H. “On The Value of Deferrable Demand for Customers”, 2014

Thank you
Questions?