ICASSP, May 22-27, 2011
Prague, Czech Republic

Modeling Nodal Prices in Deregulated Electricity Markets in the USA: Current Practices and Future Needs

Tim Mount
Dyson School of Applied Economics and Management
Cornell University
TDM2@cornell.edu

OUTLINE

- Current Price Behavior in Deregulated Electricity Markets in the USA
  - Modeling Speculative Behavior
    - Adaptive Behavior by Generators
    - Stochastic Regime Switching
  - Modeling Spatial Price Differences
    - Vector Autoregressive Models of Nodal Prices
- Future Price Behavior in a Smart Grid?
  - Responsive Demand and Price Feedback
    - Modifying Daily Patterns of Demand and Price

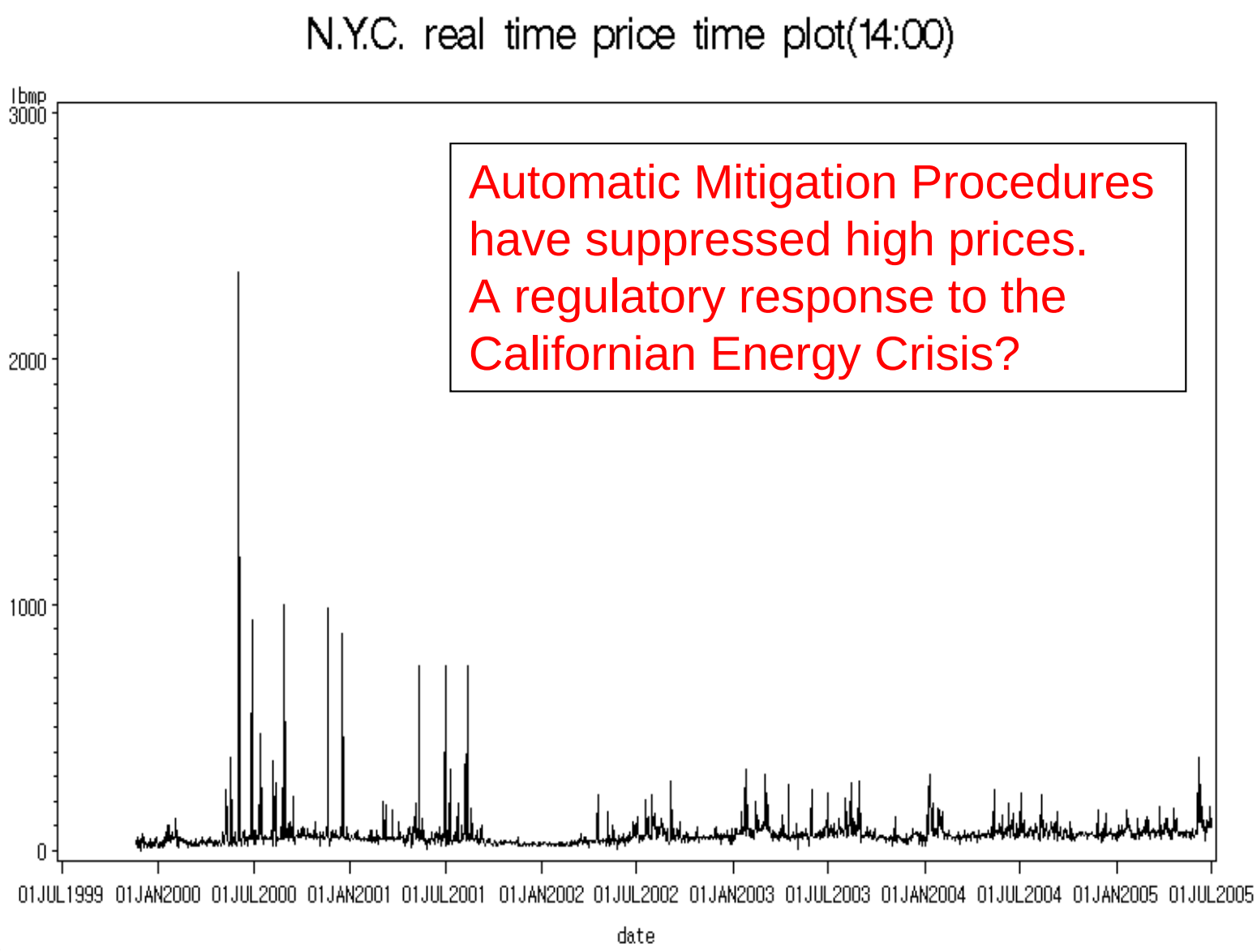
PART I

Modeling Speculative Behavior

Daily Spot Prices in New York City

(1/7/99 - 1/7/05 at 2PM, $/MWh)

Price $/MWh



Automatic Mitigation Procedures have suppressed high prices. A regulatory response to the Californian Energy Crisis?

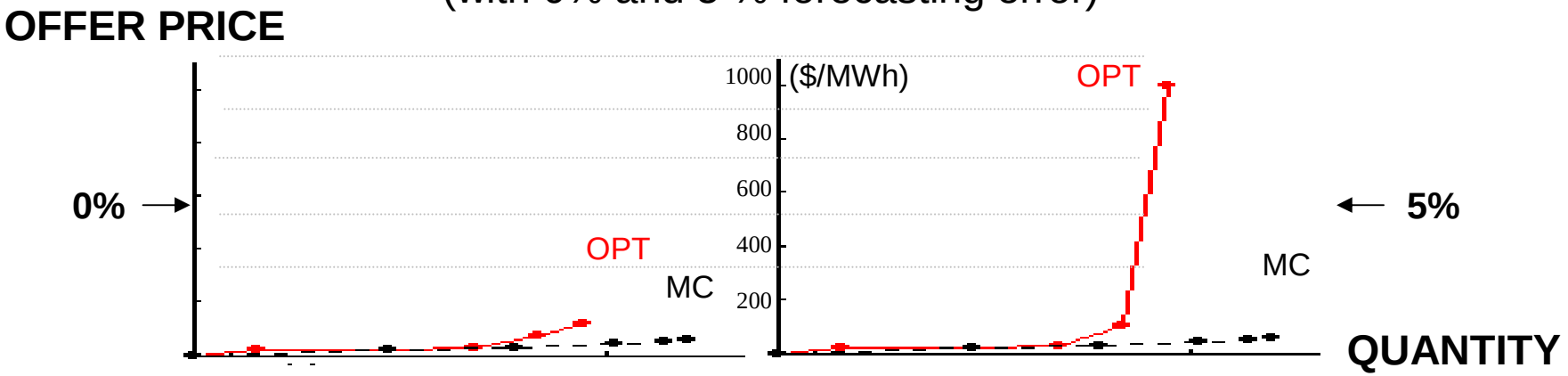
Why do Price spikes occur?

Simulating Speculative Offers by a Generator in a Deregulated Market using Software Agents

A few generators speculate → HOCKEY STICK OFFERS

True Marginal Costs and Optimum Offers

(with 0% and 5 % forecasting error)



Why? The Forecasting Error (or a failure of equipment)

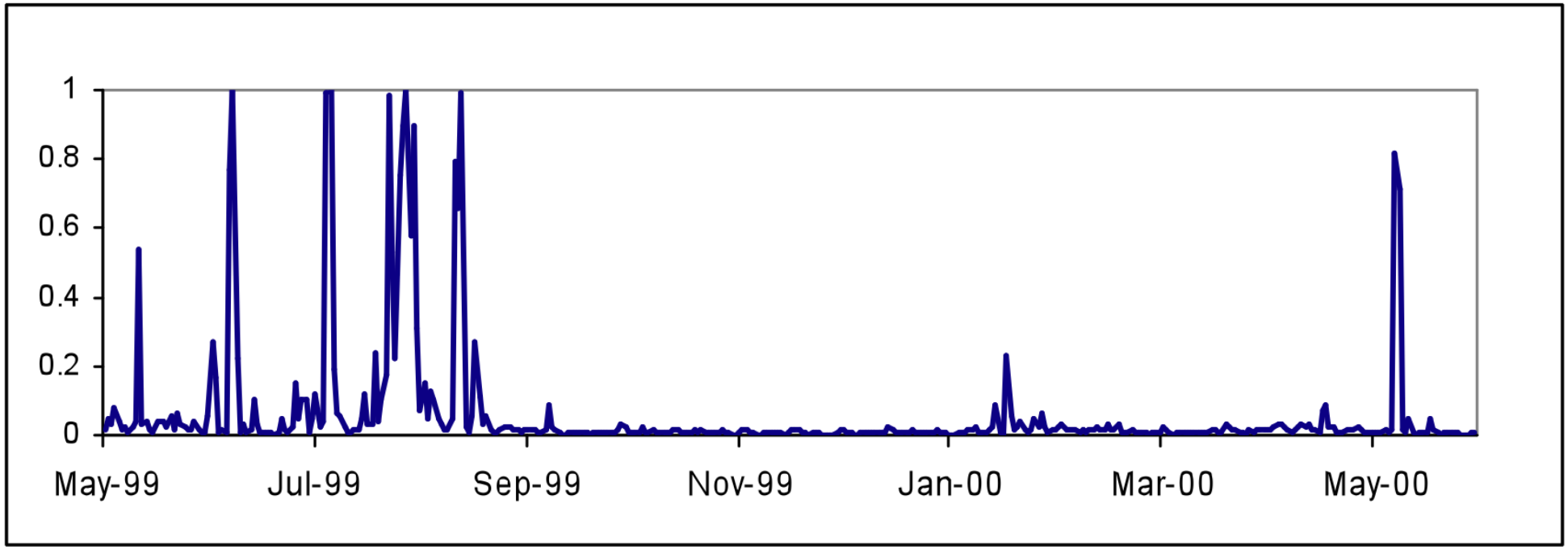
→ Probability of Rejecting a High Offer < 1

→ The generator submits high offer prices and an offer (supply) curve shaped like a hockey stick when there is uncertainty about the actual system load. With this uncertainty, there is a small probability that a speculative offer will set the price if the actual load >> forecasted load.

Stochastic Switching between High and Low Price Regimes

Probability of switching from a Low Price Regime today to a High Price Regime tomorrow is a Logistic function of tomorrow's forecasted Capacity Margin (Total Offered Capacity – Peak System Load)

Daily Estimated P(Low → High Price Regime) in PJM



PART II

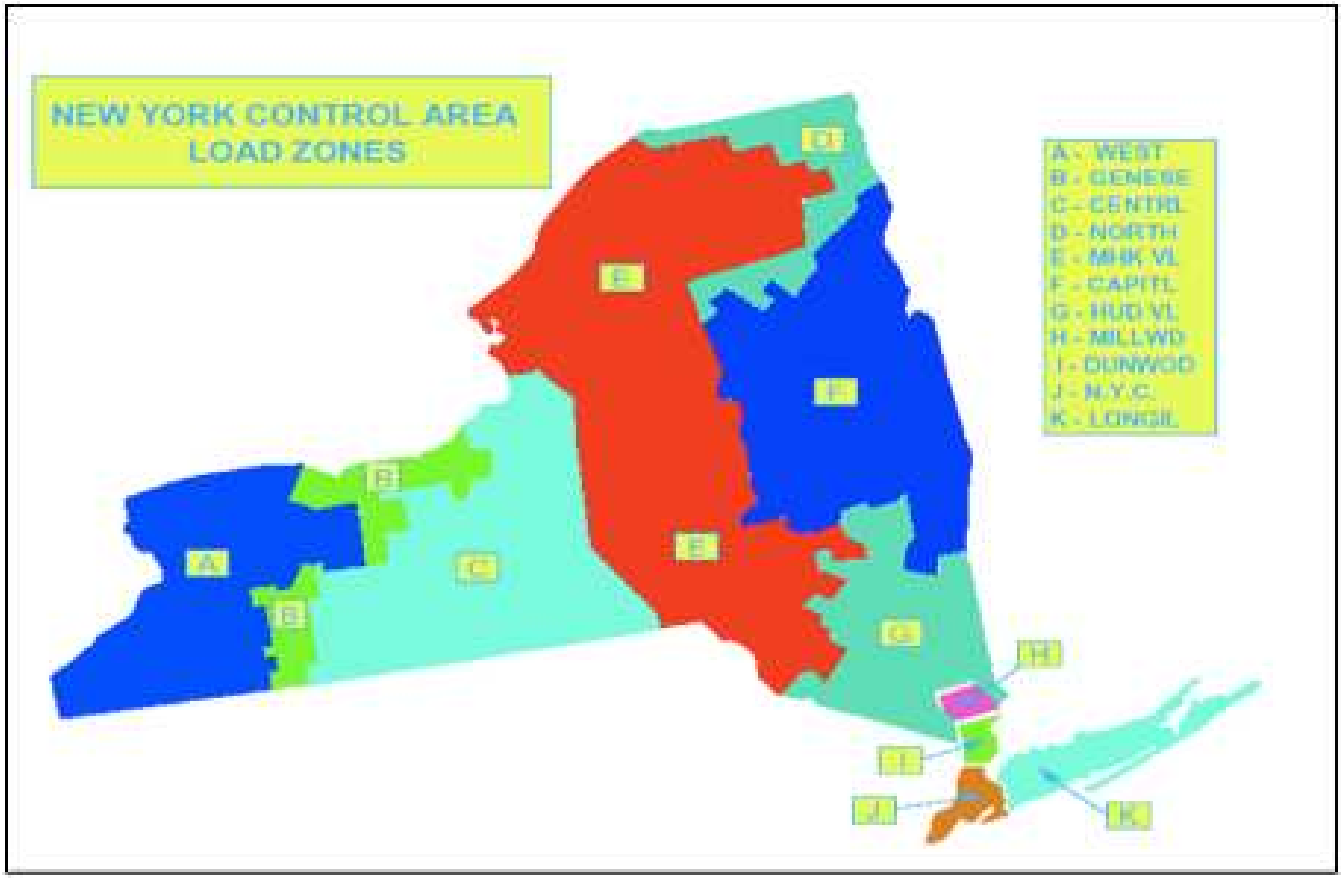
Modeling Spatial Price Differences

Transmission Congestion Credits (TCC)

Hedge Spatial Price Differences

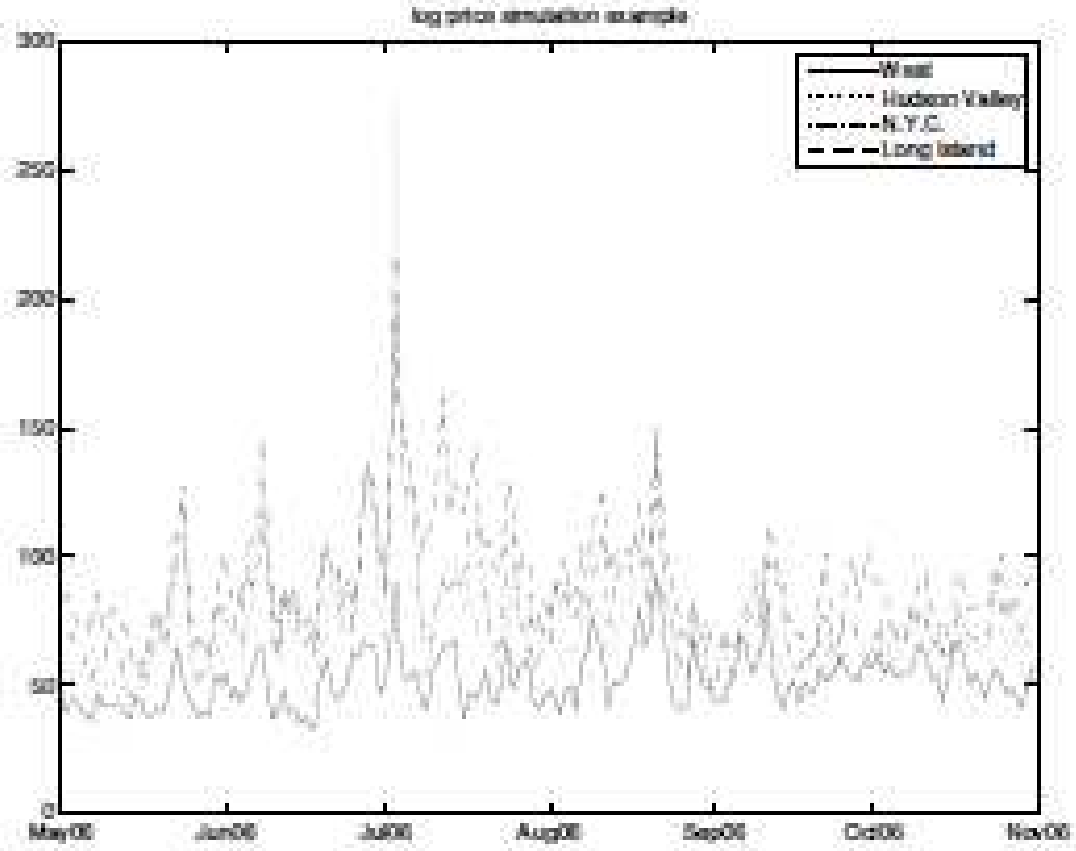
Bid into an Auction to buy a future income stream = Hourly Price Difference between two specified locations over the following summer

Is this market economically efficient?



Simulate daily realizations of Temperature, Load and Price at Different Locations

One realization of the daily prices at four locations in NY for the following summer using information available before the TCC auction is held



VAR models (RECURSIVE)
→ No price feedback on load

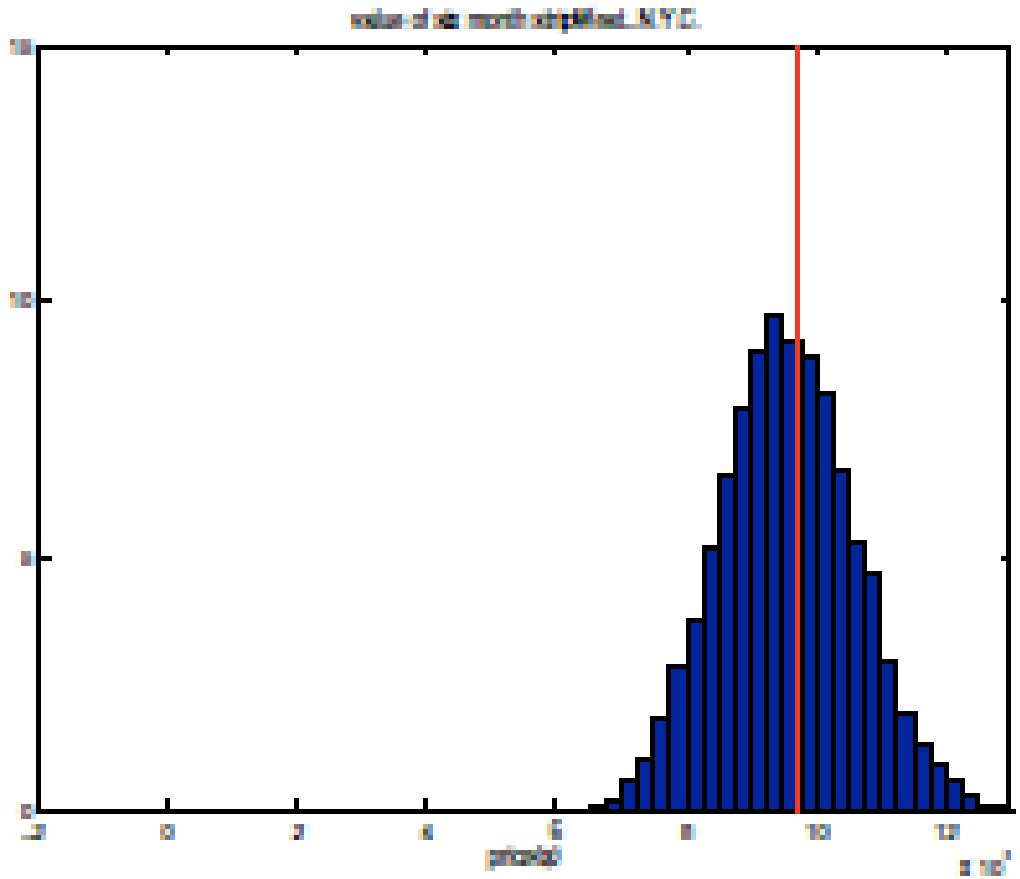
Temperature
= f(daily and seasonal cycles)

Load
= f(temperature, daily, weekly and seasonal cycles)

Price
= f(load, price of natural gas, daily, weekly and seasonal cycles)

Simulated Payouts for a Six-Month TCC

Summer months: Niagara Falls → New York City



Red line is the market price for the TCC at the auction

Market price > E[payout]

No indication of an excessively high risk premium in this case

Concluded that there was no evidence of inefficiency in the TCC market

PART III

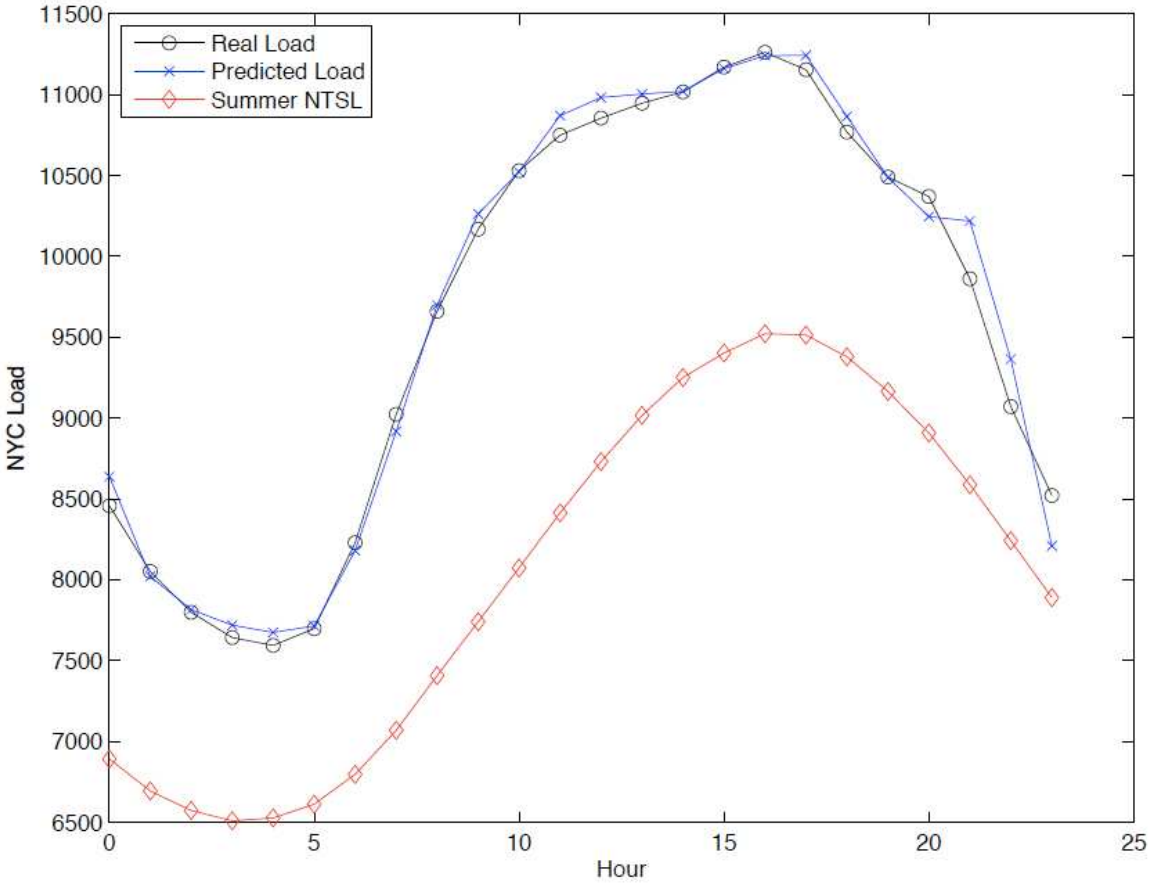
Future Price Behavior in a Smart Grid?

Previous Research

More Wind Generation → Need Storage Capacity

- Lower Wholesale Prices ($/MWh).
- More Missing Money for Financial Adequacy.
- Higher Capacity Prices ($/MW).
- More economic reasons to reduce peak system load.
- Customers are not getting the correct economic incentives/signals to support the network efficiently.
- The financial viability of storage and controllable demand depends on getting paid correctly for different services:
  - Load shifting to reduce energy costs
  - Reducing the Peak System Load (and Capacity Payments)
  - Payments for ramping services

Thermal Storage (Ice Batteries) is a Potential Source of Controllable Demand



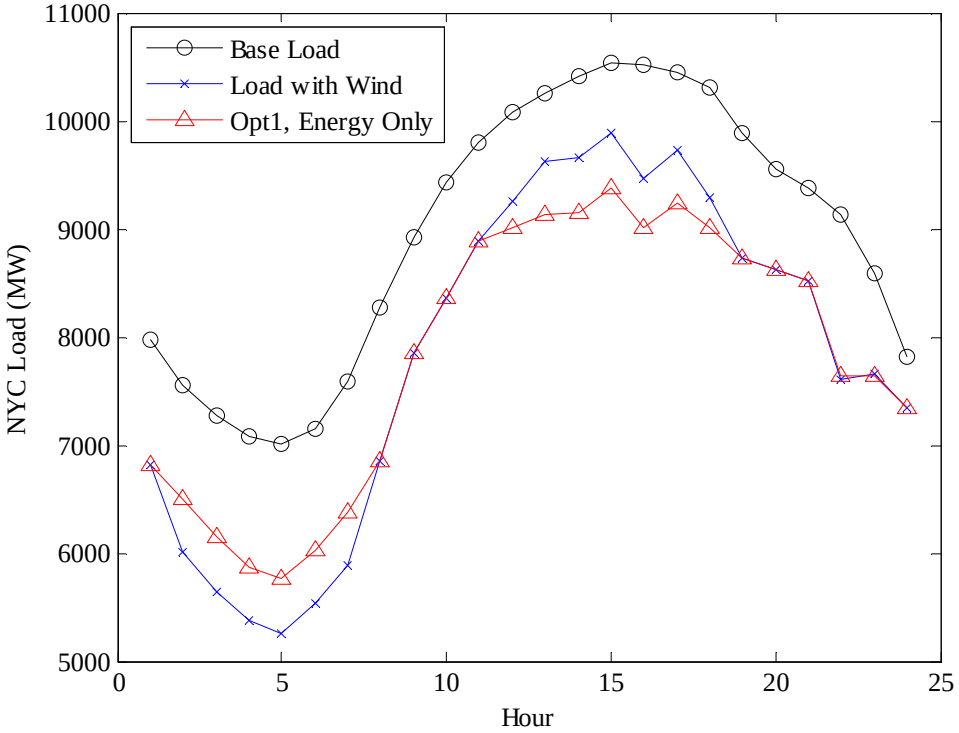
Econometric Analysis of Hourly Demand in New York City: Predictions for a Hot Summer Day

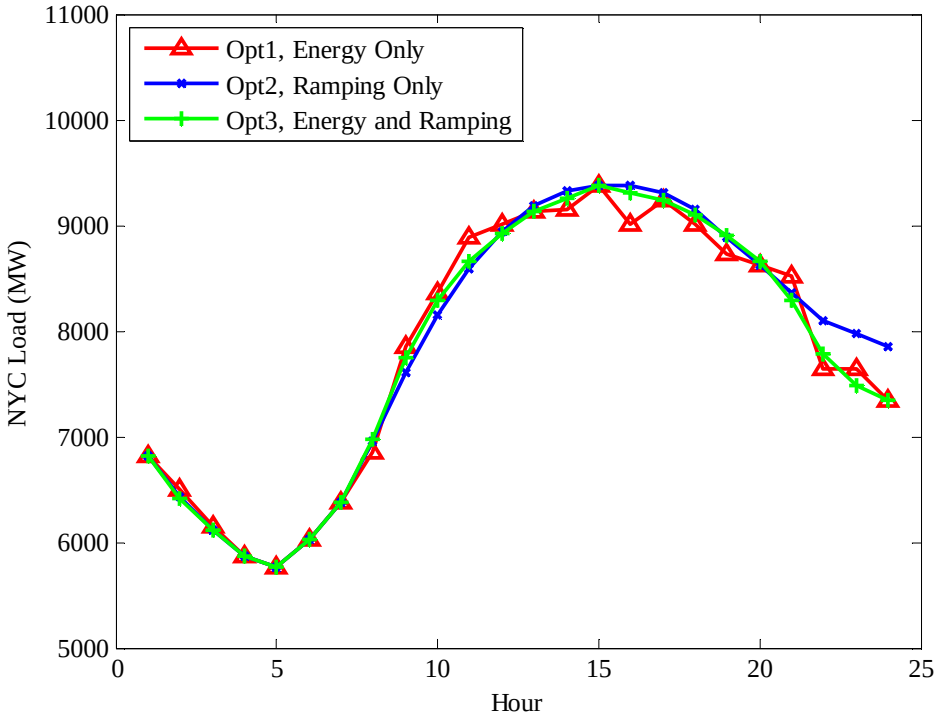
Controllable Demand
- Thermal storage
- Electric vehicles

Separating Temperature–Sensitive Demand from Non-Temperature-Sensitive Demand (NTSL)

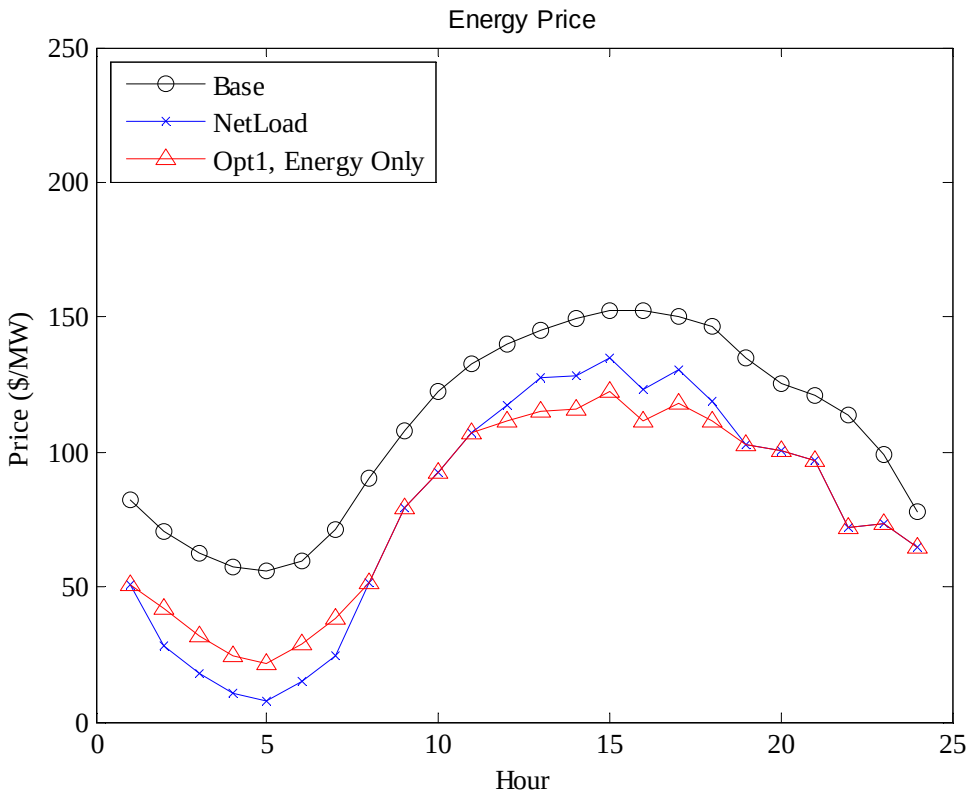
Optimal Dispatch of Conventional Generators for a Hot Day in New York City: Results

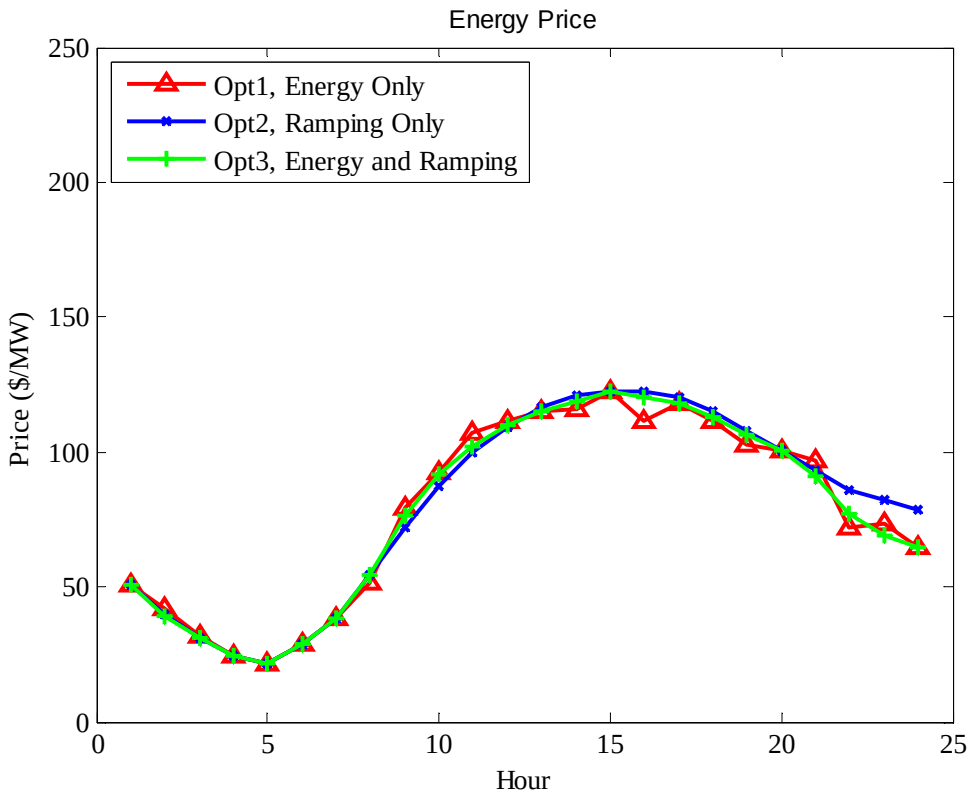
- Case 1 : Optimization for Energy only (Opt1)
- Case 2 : Optimization for Ramping only (Opt2)
- Case 3 : Optimization for Energy & Ramping (Opt3)





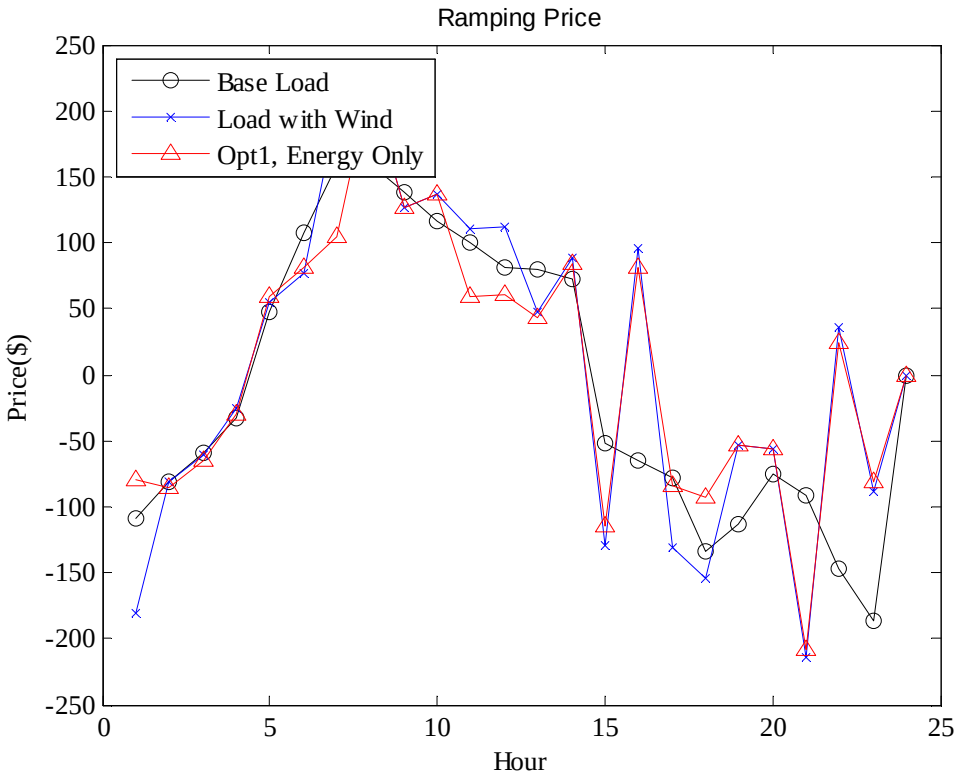
The corresponding Energy Prices

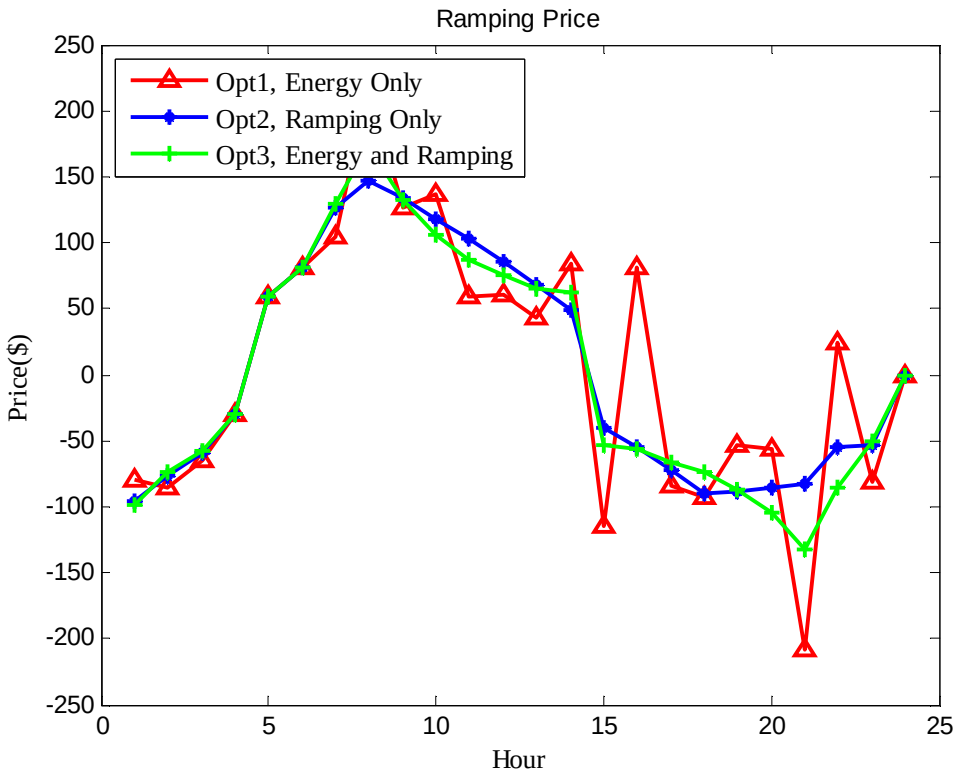




Including ramping costs smoothes the daily patterns of demand and price

The corresponding Ramping Prices





Including ramping costs smoothes the daily pattern of ramping prices

CONCLUSIONS

- High penetrations of wind generation lower the price of energy BUT also increase ramping (variability) for the conventional generators → HIGHER ANCILLARY COSTS
- Storage capacity can shift demand from peak to off-peak periods, cover contingencies AND mitigate the variability of wind generation → PRICE FEEDBACK ON DEMAND
- Customers (aggregated) can lower net payments by having controllable demand and:
  - Purchasing more energy at low prices
  - Mitigating price spikes in Energy-Only markets
  - Reducing their demand during system peak periods
  - Selling ramping services to mitigate wind variability

Acknowledgements

This research was supported jointly by the US Department of Energy through the Consortium for Electric Reliability Technology Solutions (CERTS) and by the Power Systems Engineering Research Center (PSERC).

Researchers at Cornell

Engineers

Lindsay Anderson
Hsiao-Dong Chiang
Andrew Hunter
Bob Thomas
Lang Tong
Max Zhang
Ray Zimmerman
+
Judy Cardell, Smith College
Carlos Murillo-Sanchez, U Autónoma de Manizales, Colombia
Dan Shawhan, RPI

Economists

Wooyoung Jeon**
Alberto Lamadrid**
Jung Youn Mo*
Surin Maneevitjit**
Tim Mount
Dick Schuler
Bill Schulze
Hao Lu*

* Graduate Student, **Supported by PSERC