Managing Wind Uncertainty with Self-Reserves and Responsive Demand

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Acknowledgements

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Overview

- Motivation and Objectives
- Wind Self-Reserves
- Framework and Data Development
  - Test system development
  - Test system data and uncertainty inputs
  - OPF *plus* MCS
- Simulation Results
- Conclusions and Outlook

Project Objective

- Develop operational strategies to improve
  - Wind power participation in markets
  - Integration of wind power with current infrastructure
- Potential strategies:
  - Demand Response at various time scales
  - Wind 'self-reserves'
  - Ramping capabilities and markets
  - Storage

Project Overview

Objective: Assess the efficacy of self reserves and demand response in wind power integration

Method: Empirical studies with an integrated system model designed to capture the effects of uncertainty (wind, load, FOR).

Results: Assessment of system performance metrics* under combinations of strategies, with increasing wind penetration

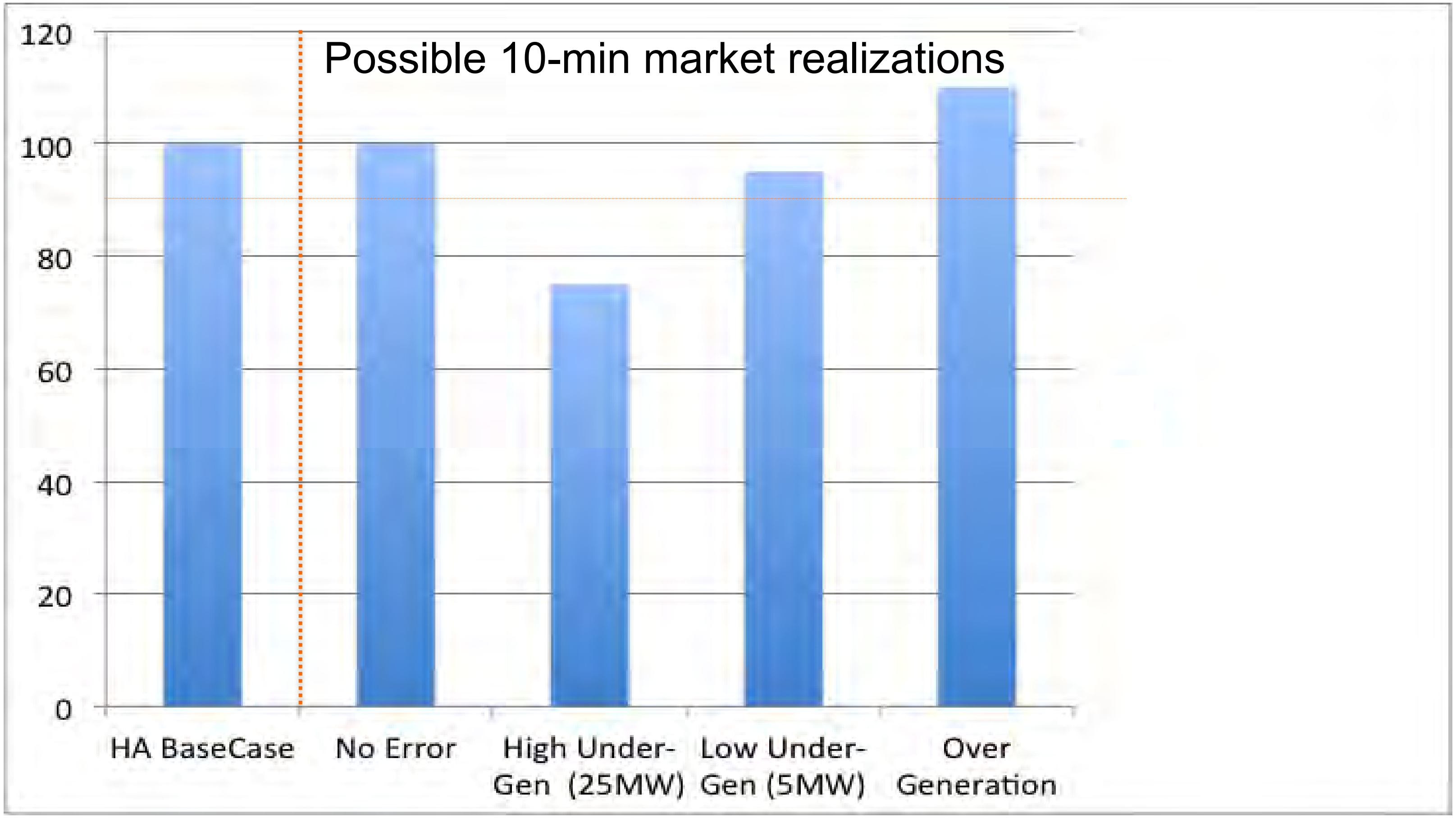
*(price, variability, cost, losses, CO_2...).

What are "Self-Reserves"?

- Wind generators "under schedule" in the hour ahead energy market, to hold some expected output for reserves
- Excess expected wind is available for mitigating forecast errors and other system uncertainty

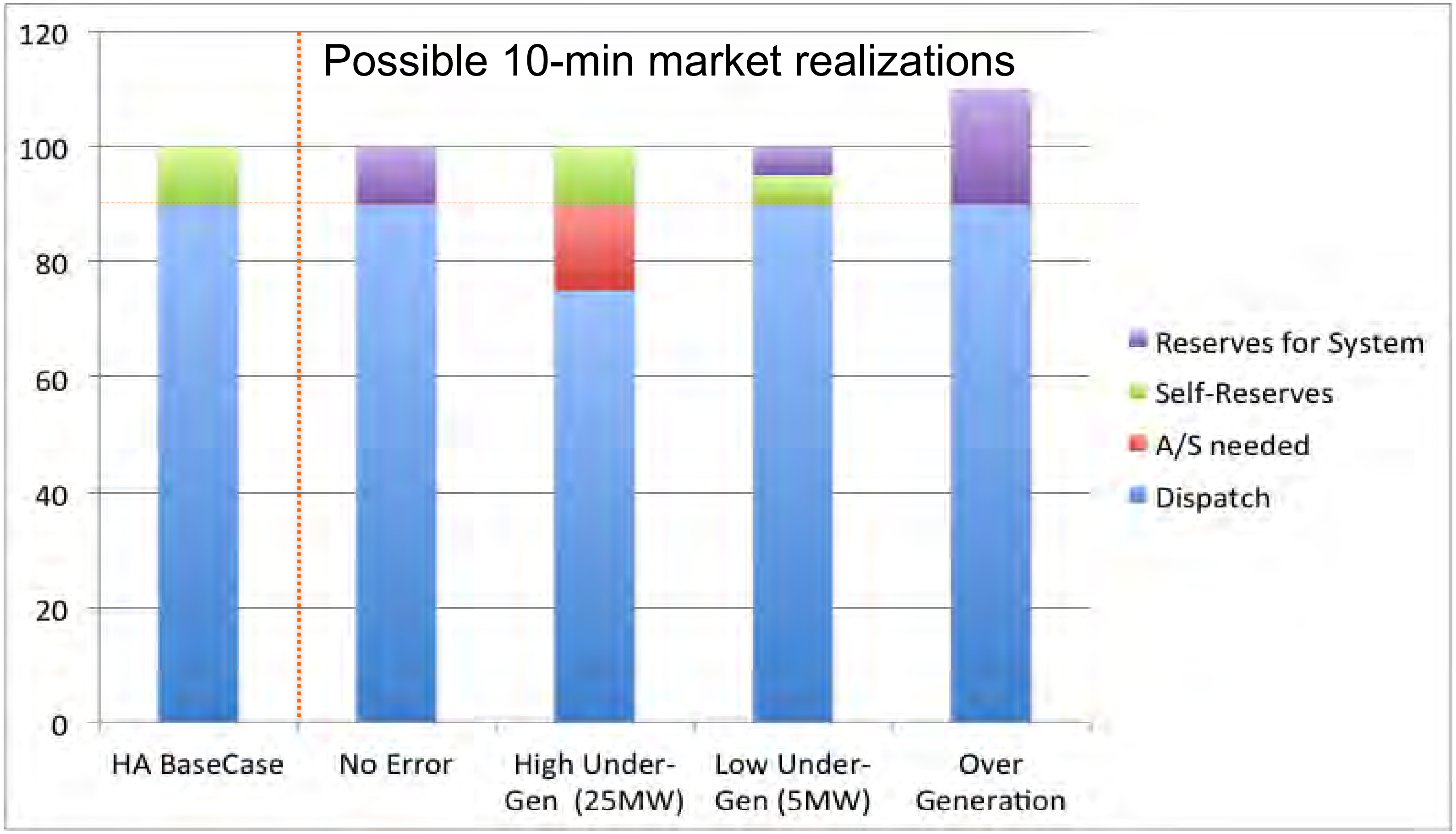
Wind Self-Reserves

- To model wind providing self-reserves
- First examine possible wind output scenarios



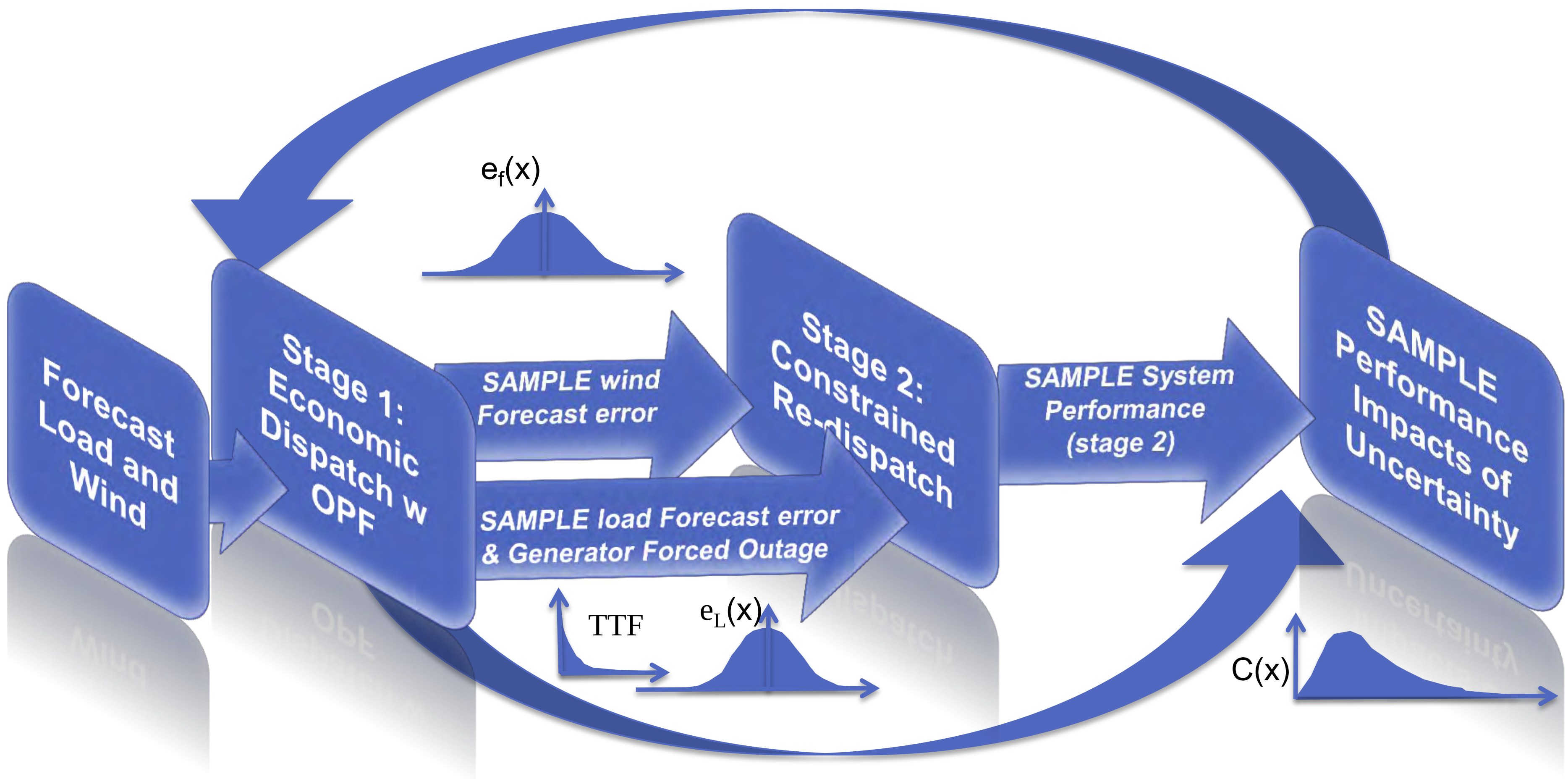
Wind Self-Reserves

- To provide self-reserves, the wind generators are scheduled below the expected output at hour ahead
- 10-minute market operational scenarios:



Core Model Framework

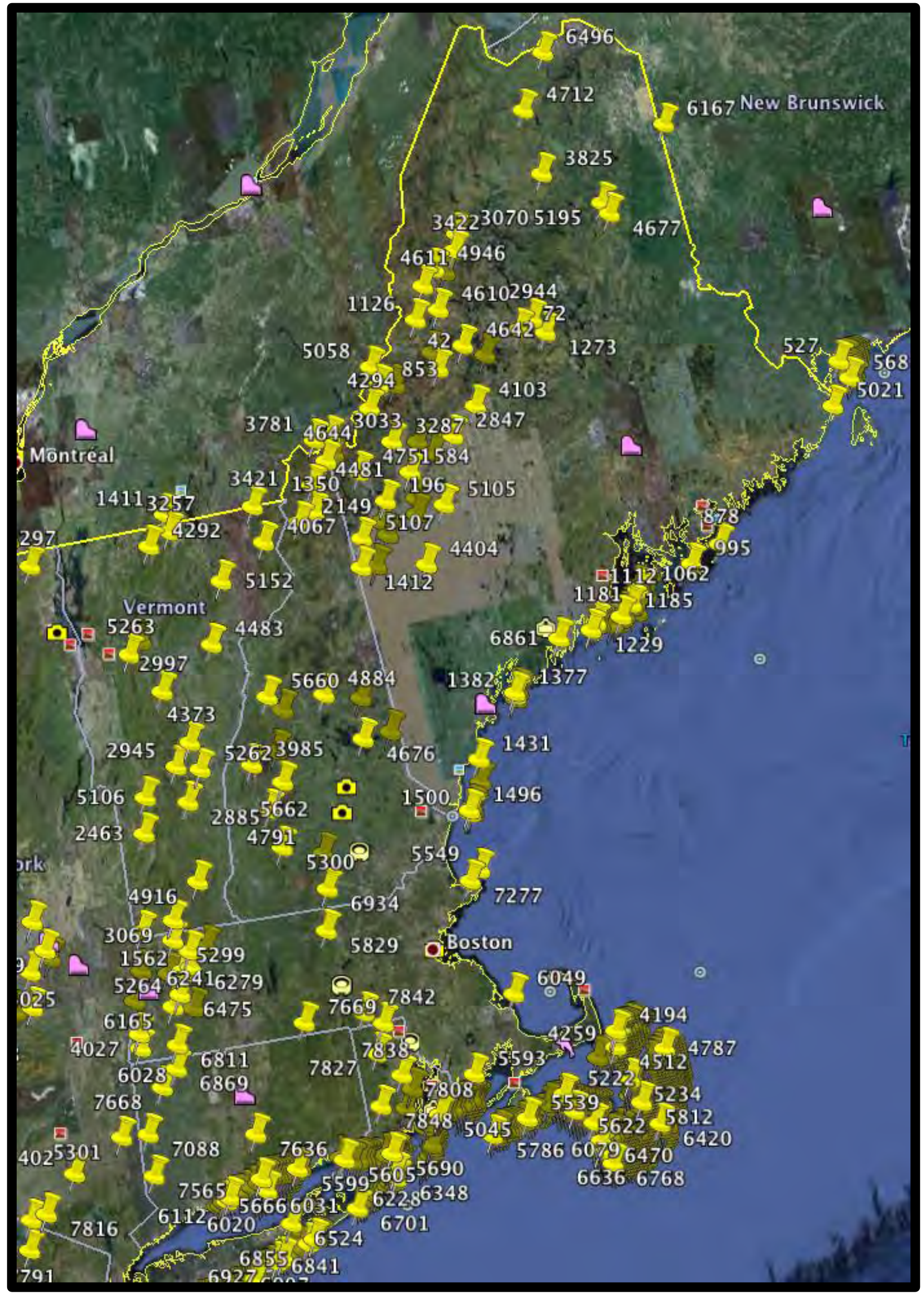
Dispatch/Market Clearing Monte Carlo Framework



Framework and Data Development

1. Model geographic diversity for wind power generation.
2. Model wind generation forecast error.
3. Test system input data – cost curves, ramp rates and costs, EFOR
4. Mitigate wind forecast error with time differentiated demand response (DR)
5. Model redispatch costs of wind power uncertainty using Monte Carlo simulation and the 39-bus test system.

New England Wind Speed Data: NREL Wind Sites



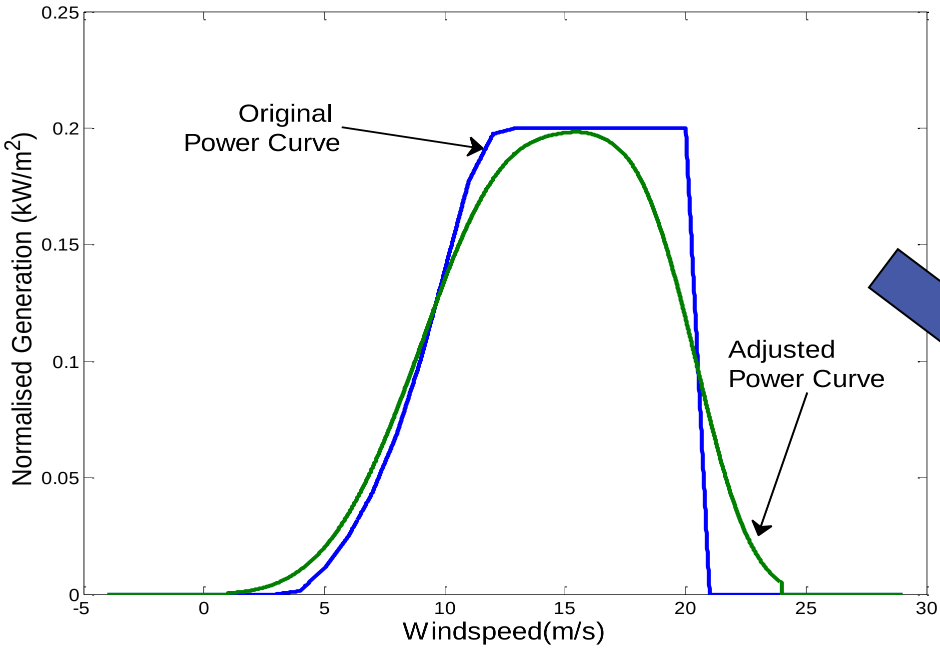
Convert to Wind Farm Power Output

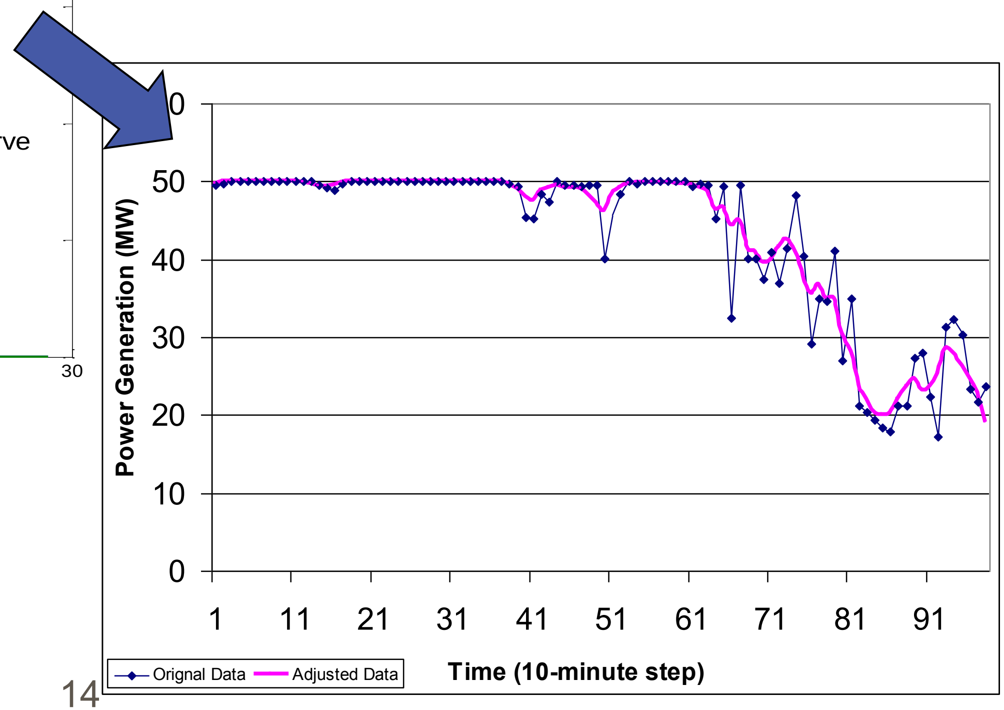
I. Wind Turbine Selection by Site
   - On-shore vs. off-shore turbines

II. Account for geographic diversity
   - Decreased variability of effective wind resource
   - Within a single wind farm
   - Across multiple wind farms

II. Geographic Diversity – Power Curve

- Power curve adjusted for a large windfarm
  - ~200 MW, 200 km long windfarm(s)





Adapted from Norgaard & Holtinnen (2004)

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Geographic Diversity – Multiple Wind Farms

- Geographic diversity modeled explicitly for individual, small wind farms
- Geographic diversity of multiple wind farms modeled implicitly through locating each wind farm at a specific bus, allowing for transmission constraints

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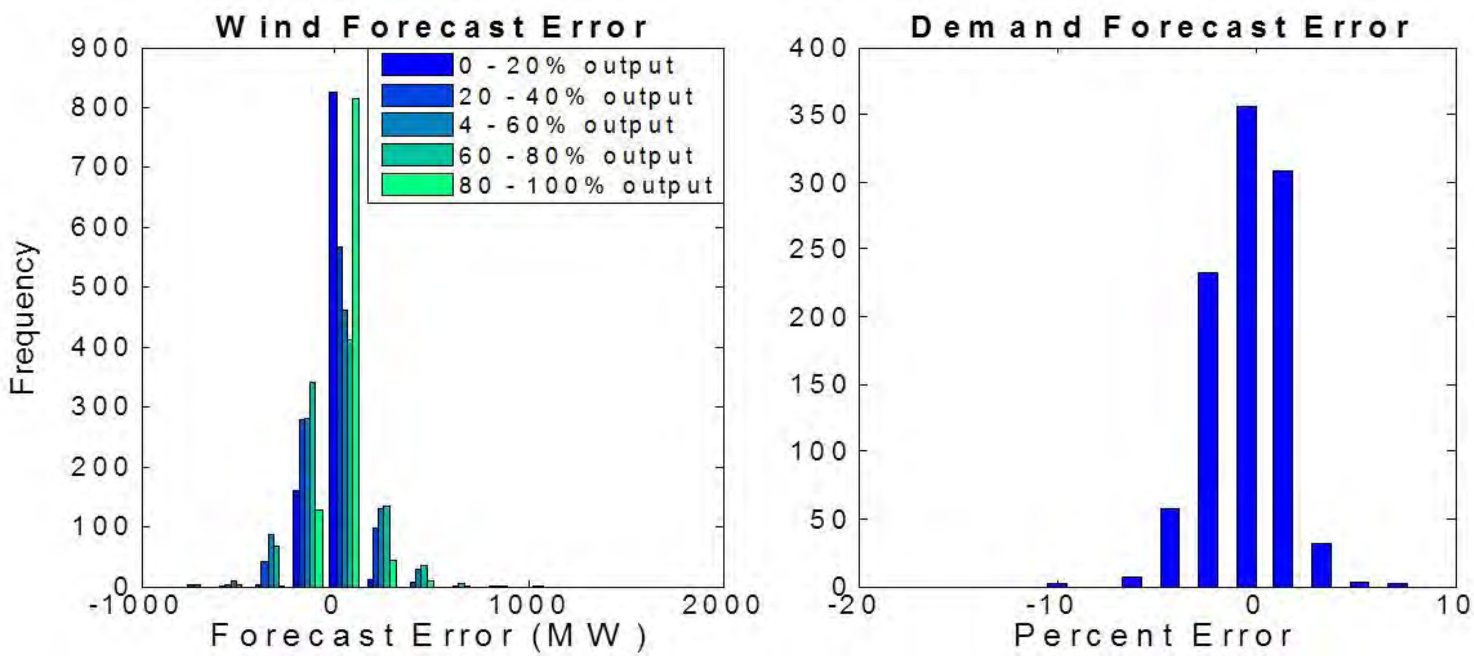
Forecast Uncertainties

- Wind generation: conditional forecast-error probability distributions created from simulated forecasts
- Demand: Single bin (ANN forecast, 2010 NAPS paper)



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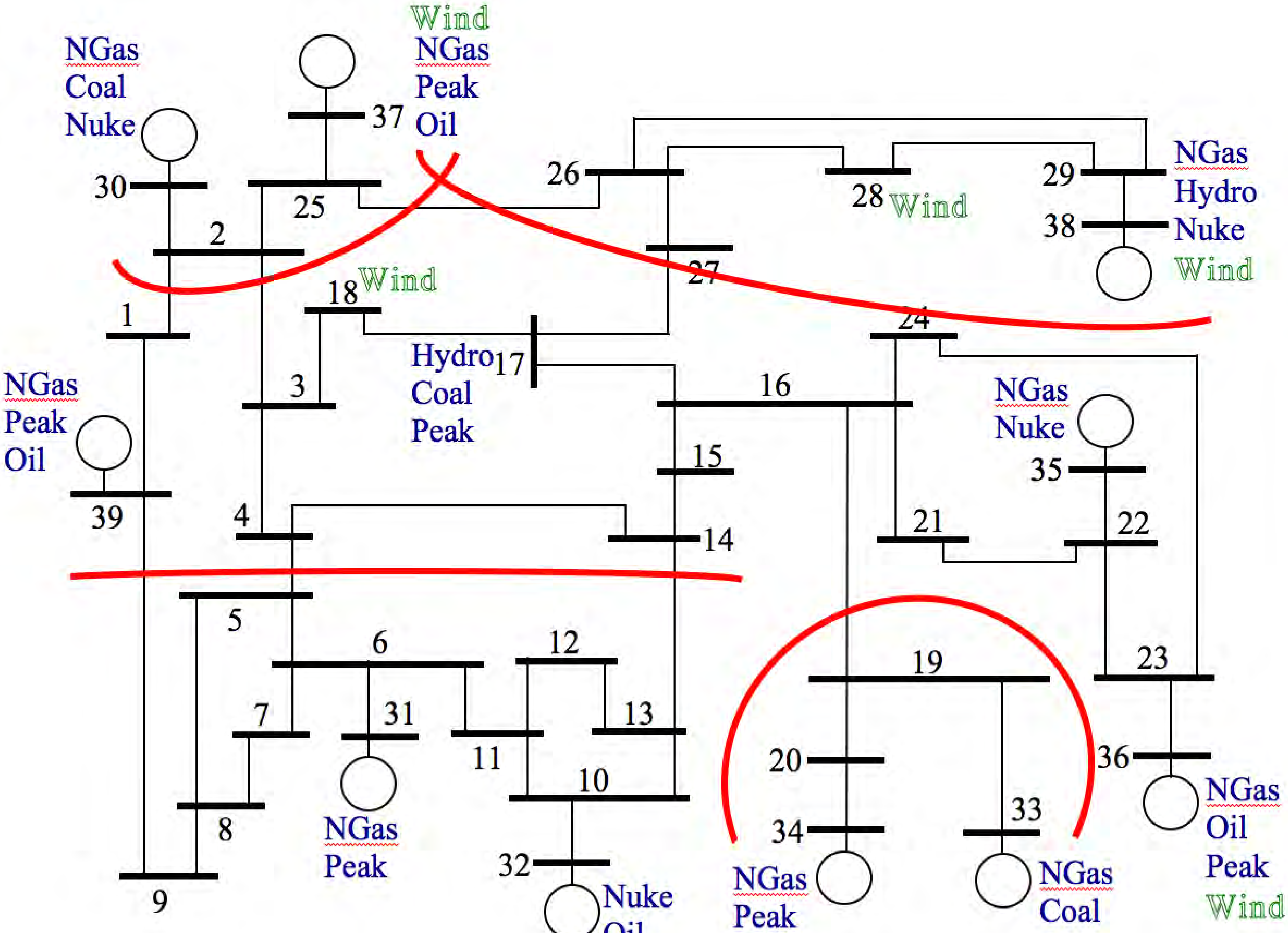

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Coal

Conventional Generating Capacity

- Test system has ~14% actual NE load
- North = ME, NH, VT
- South = CT, RI

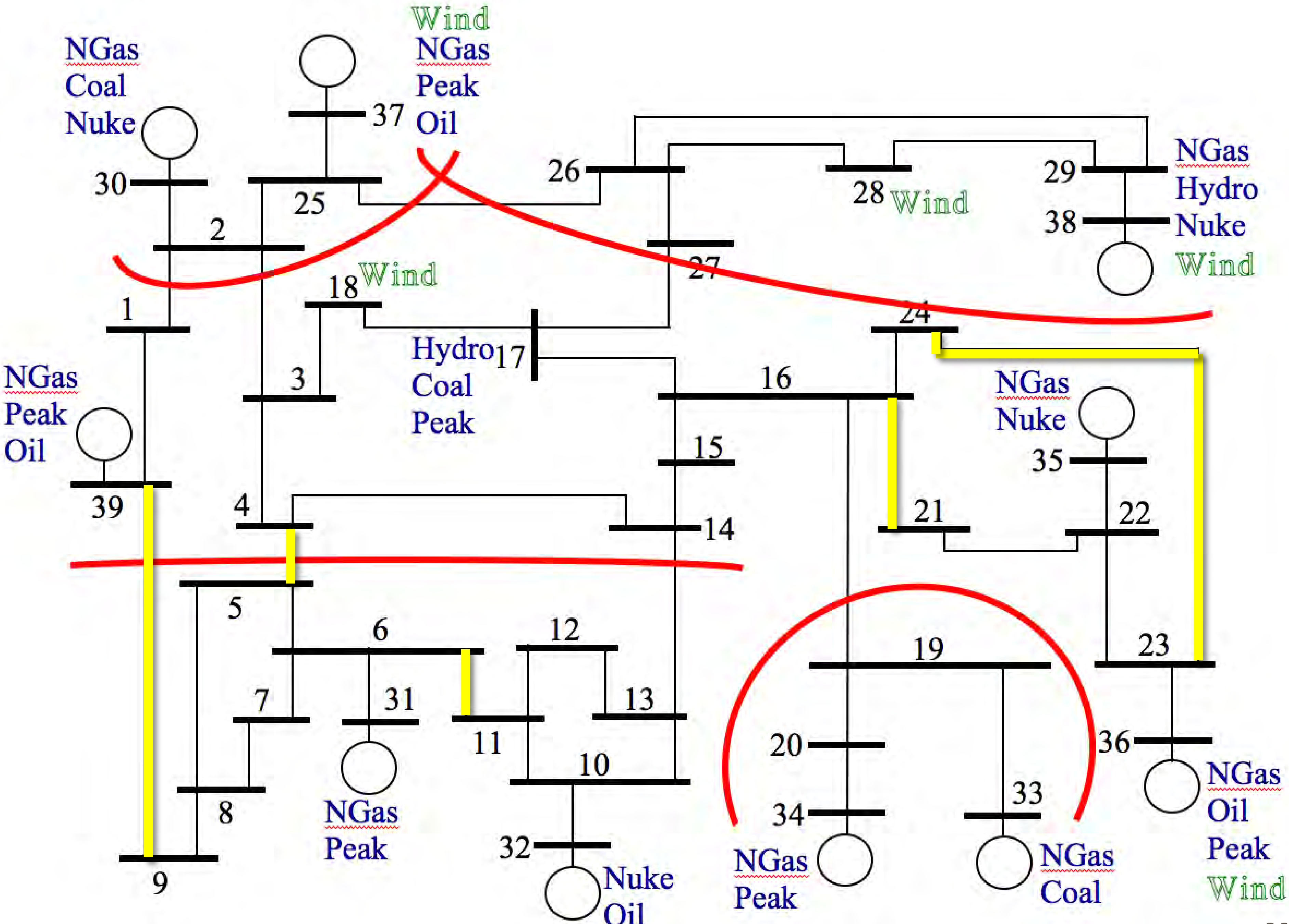
	Coal	Fuel Oil	Peaker	N Gas	Nuke	Hydro
North	80	205	125	890	390	135
Mass	245	600	215	1600	575	250
South	90	410	280	910	370	

Generator Ramping

Tech.	Minimum (%/min)	Maximum (%/min)	Time sustained
Coal	0.6 → 1.2	2.4 → 2.7	
CC	0.8	3.0	5.4 min.
CT	7.0	(30.0)	
Hydro	30.0	50.0 → 100.0	0.9 → 1.9 min.
Nuclear	Not used for	ramping	

Mean Time to Failure

Generator Type	MTTF (hours)
Coal	2940
Hydro	1960
Natural Gas	1980
Nuclear	1104
Oil	480
Peaker	480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Framework and Data Development

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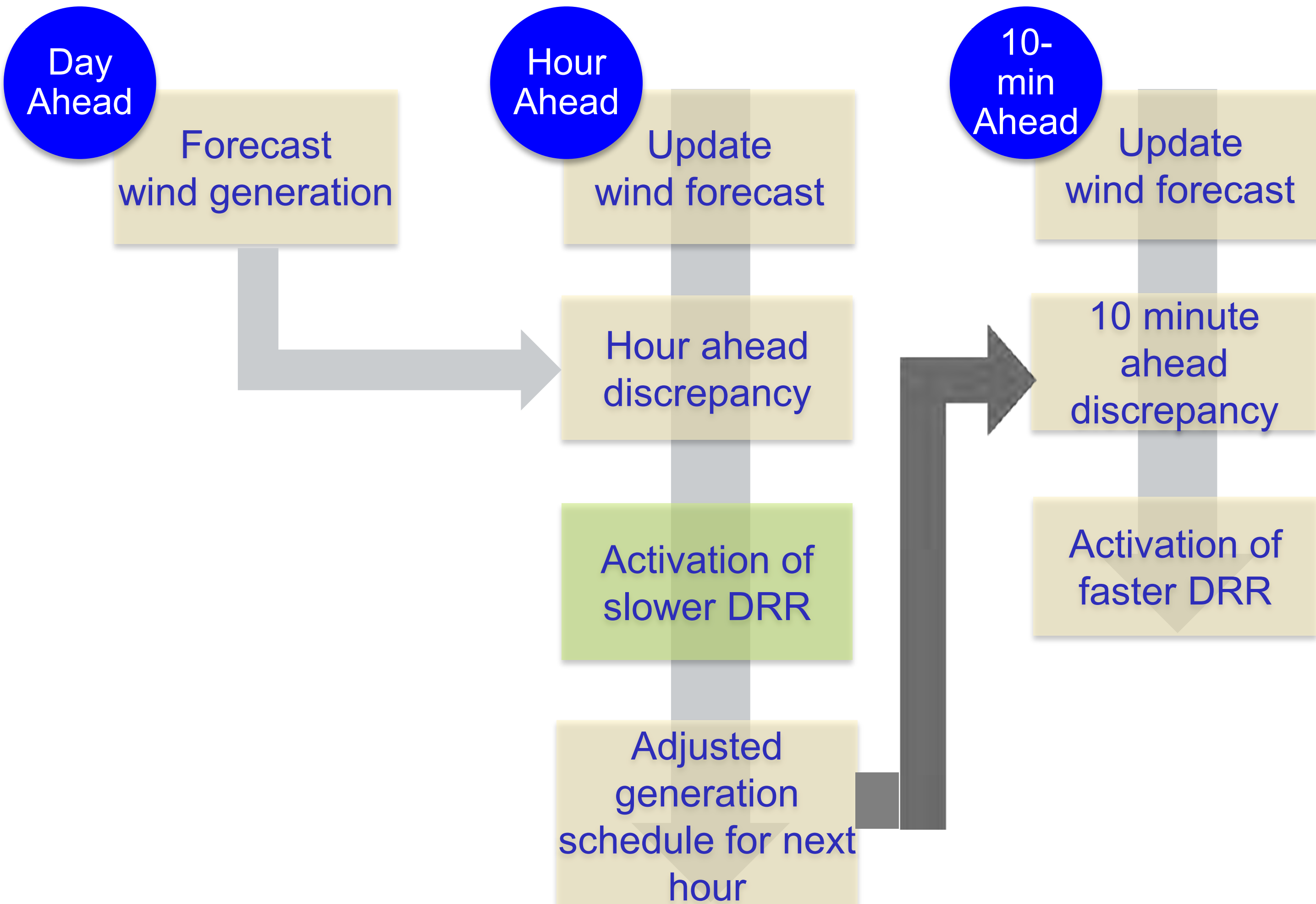
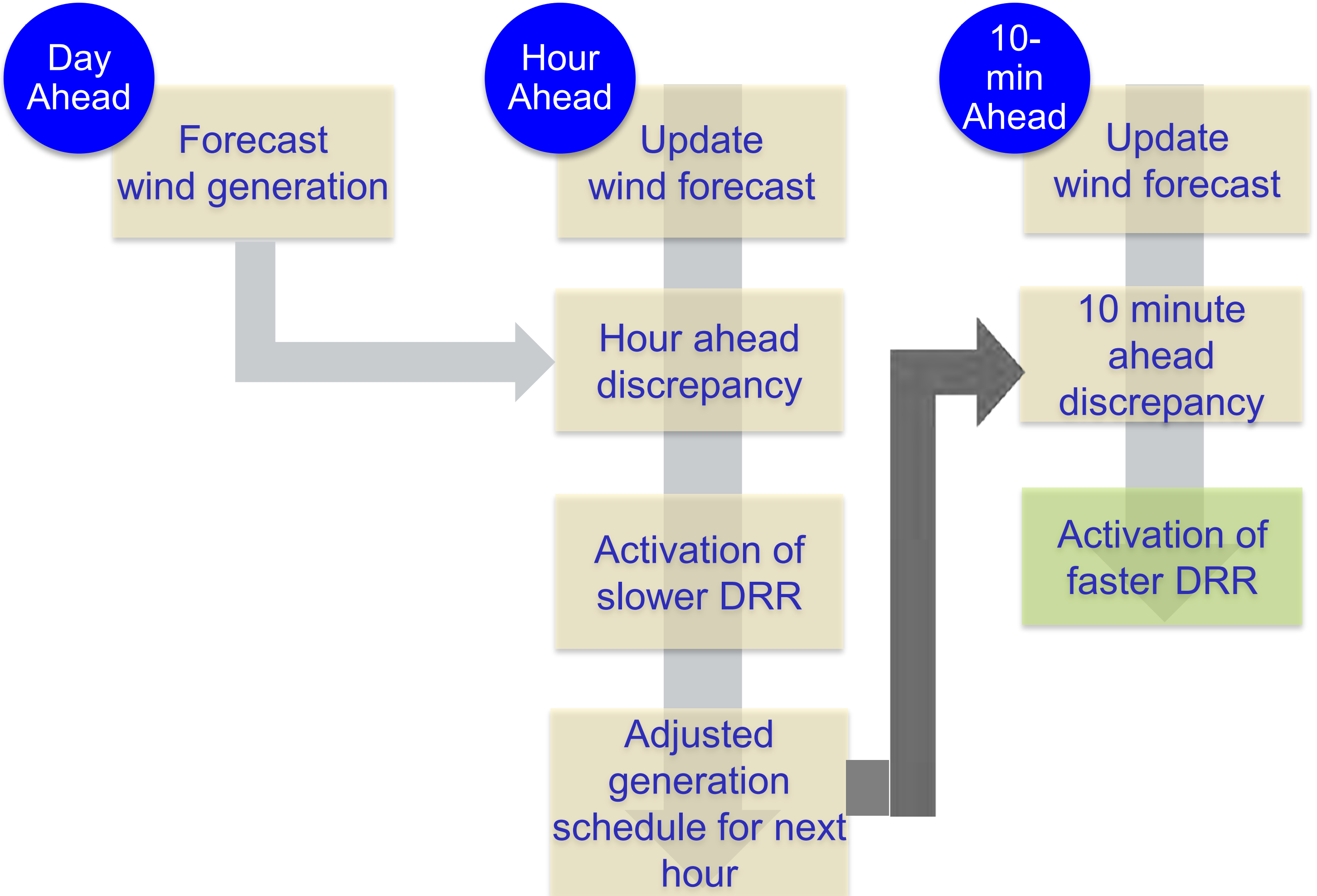
Temporally Differentiated DRR: Proposal



Temporally Differentiated DRR: Proposal



Temporally Differentiated DRR Findings

- The fraction of expected wind generation shortfall that is mitigated by demand response is not constant across time scales
- Using an optimal amount of demand response at each time stage has a significant impact on overall system cost
- The optimal amount of demand response to activate is location and market specific
- C. L. Anderson & J. B. Cardell (2013) A Decision Framework for Optimal Pairing of Wind and Demand Response Resources. IEEE Systems Journal. *To appear*.

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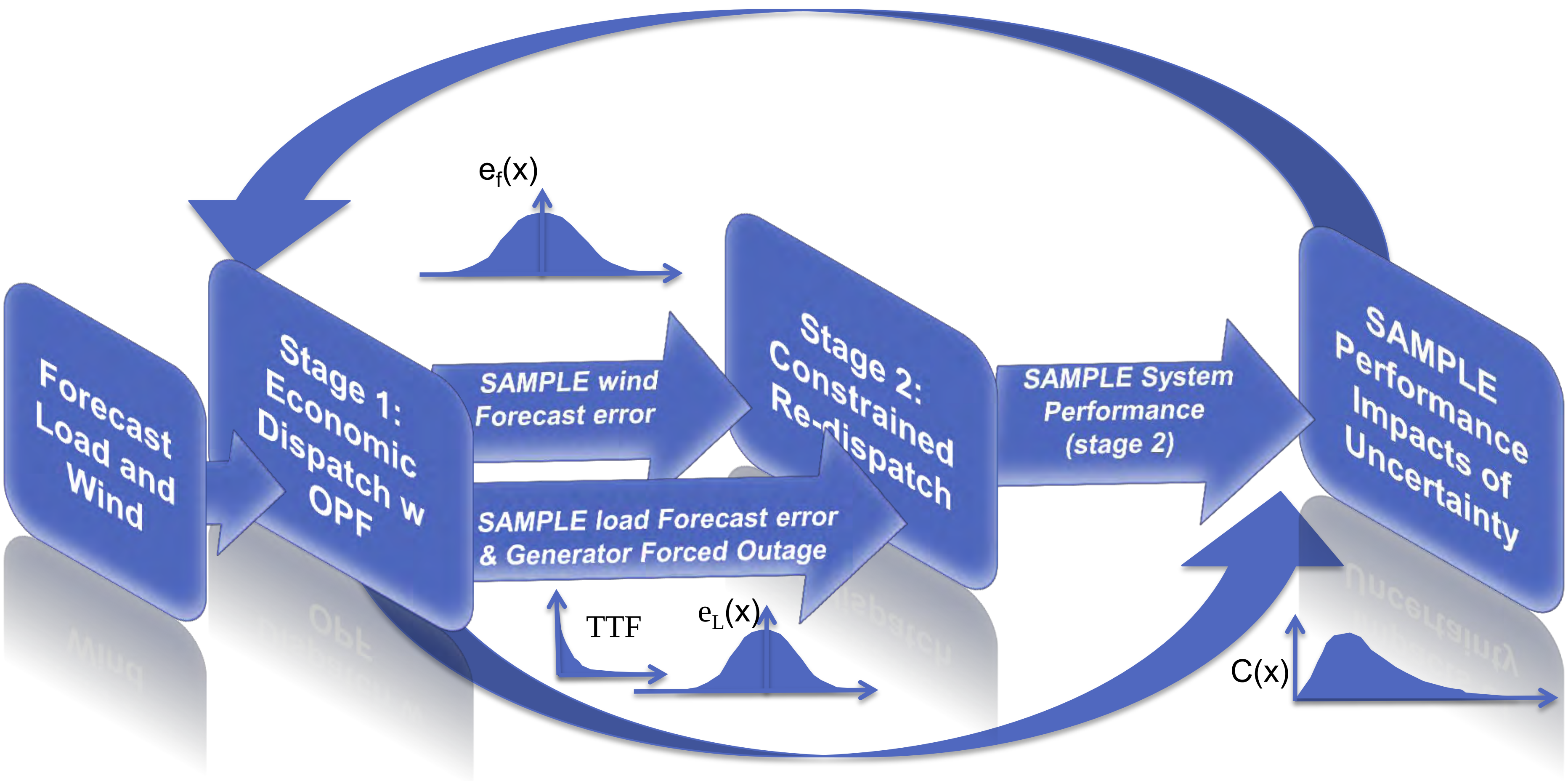
Determining Impact of Uncertainty

- Use MATPower OPF with a Monte Carlo Simulation (MCS) framework to model power system performance.
- Base case scenarios are defined and then MCS is used to identify redispatch impacts from wind and load uncertainty.
- Quantifying the impacts of the uncertainty
  - System lambda and price spikes (variability of λ)
  - Generator dispatch patterns
  - Wind spilled
  - Demand response used
  - Losses, MW and MVAr
  - CO_2 emissions
  - Production cost

Core Model Framework

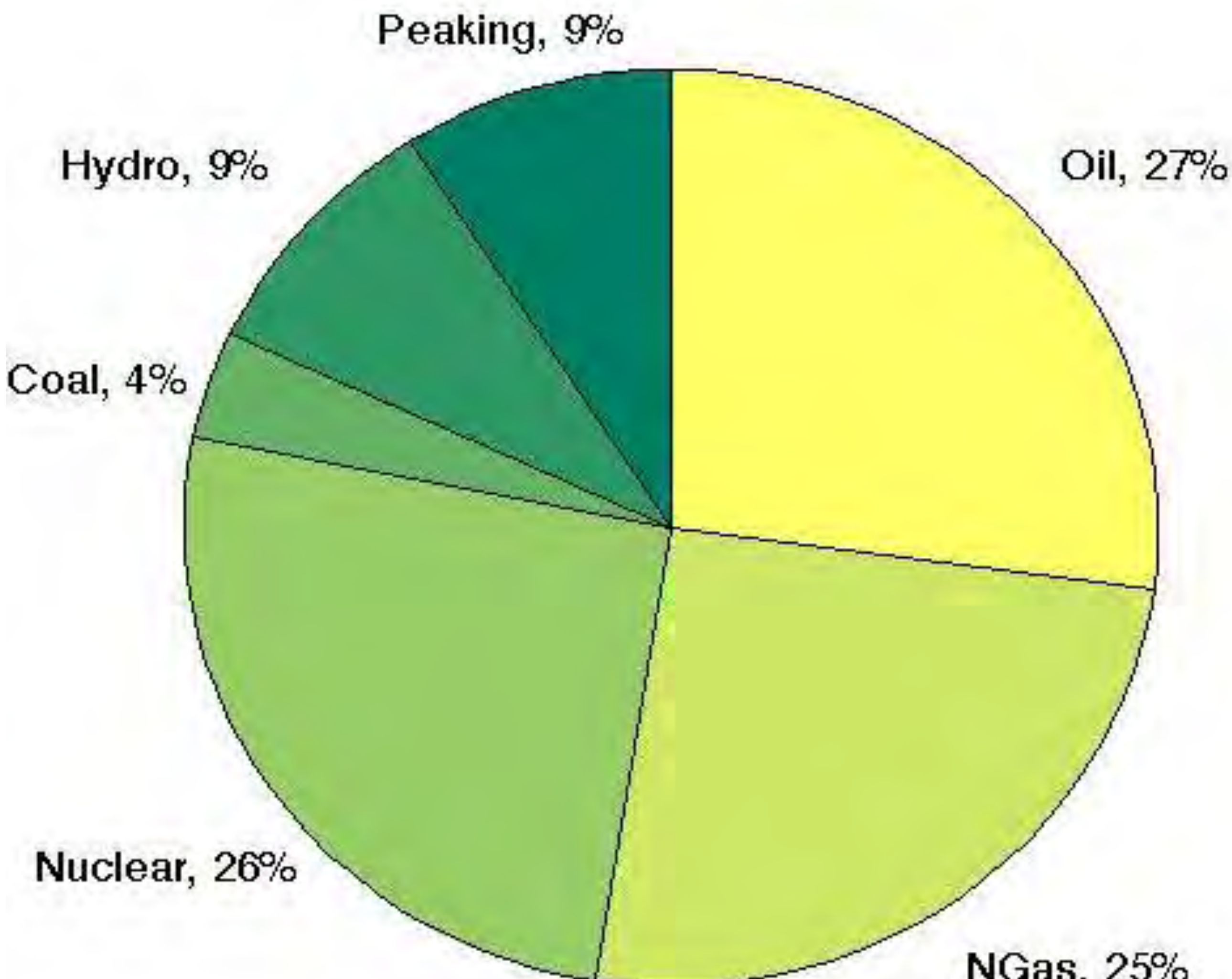
Dispatch/Market Clearing Monte Carlo Framework



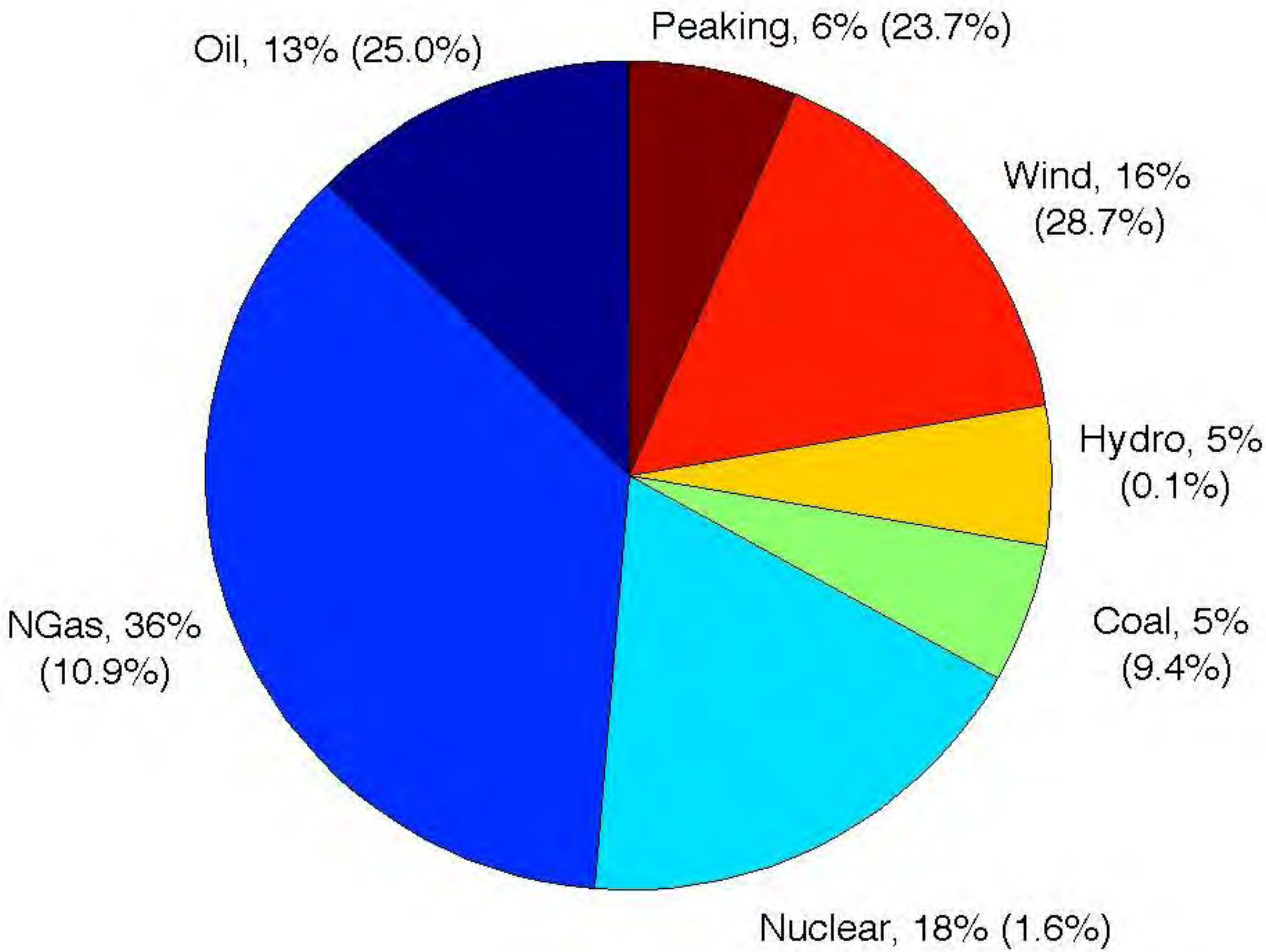
Scenarios

Scenario Options			
Wind Penetration Level	10%	20%	30%
Wind Forecast Level	High (>85%)	Med	Low (<11%)
Reserve Margin (demand)	10%	15%	30%
Demand Response	Yes		No
Self-Reserves	Yes		No
Transmission Constraints	Yes		No

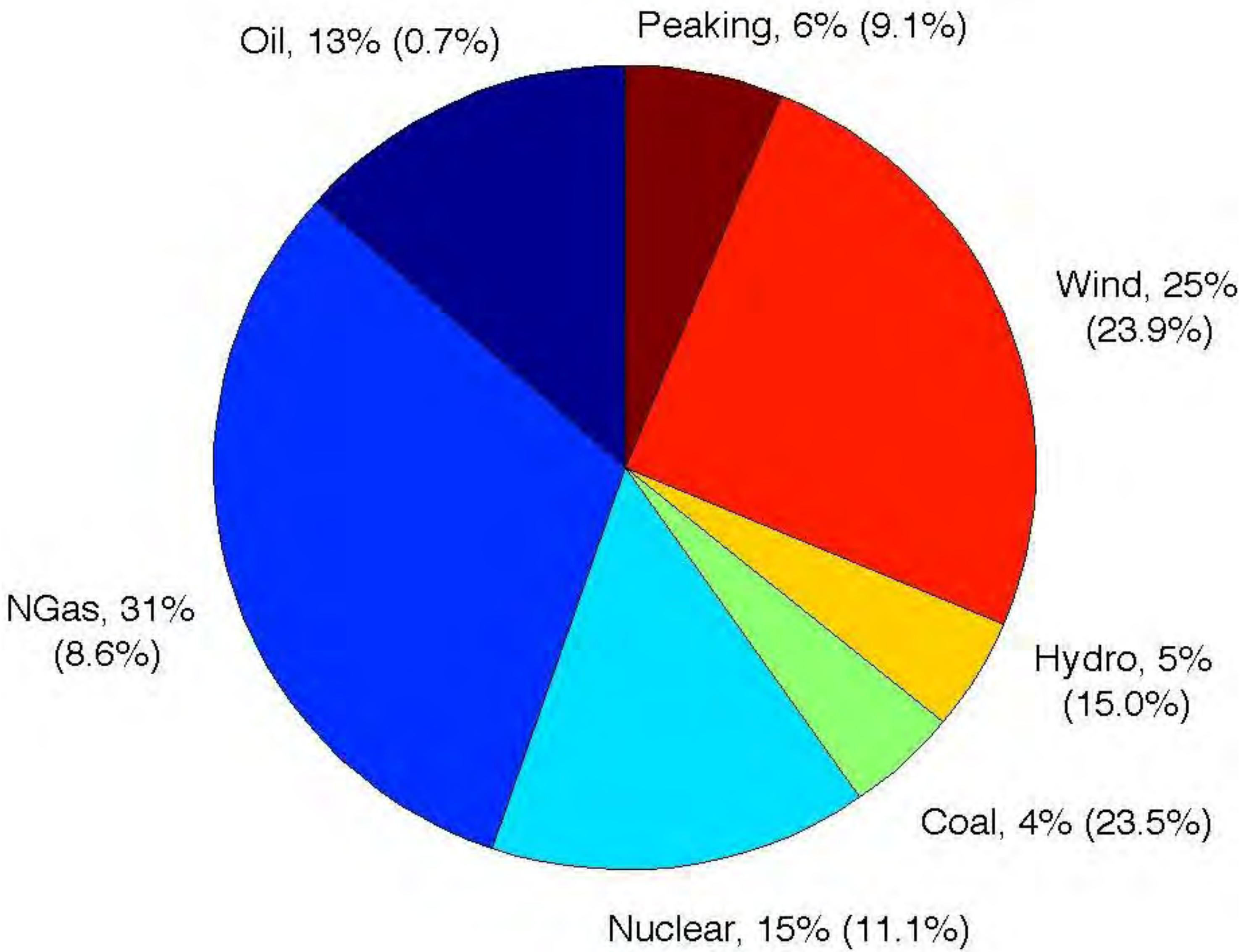
Generator Dispatch – No Wind



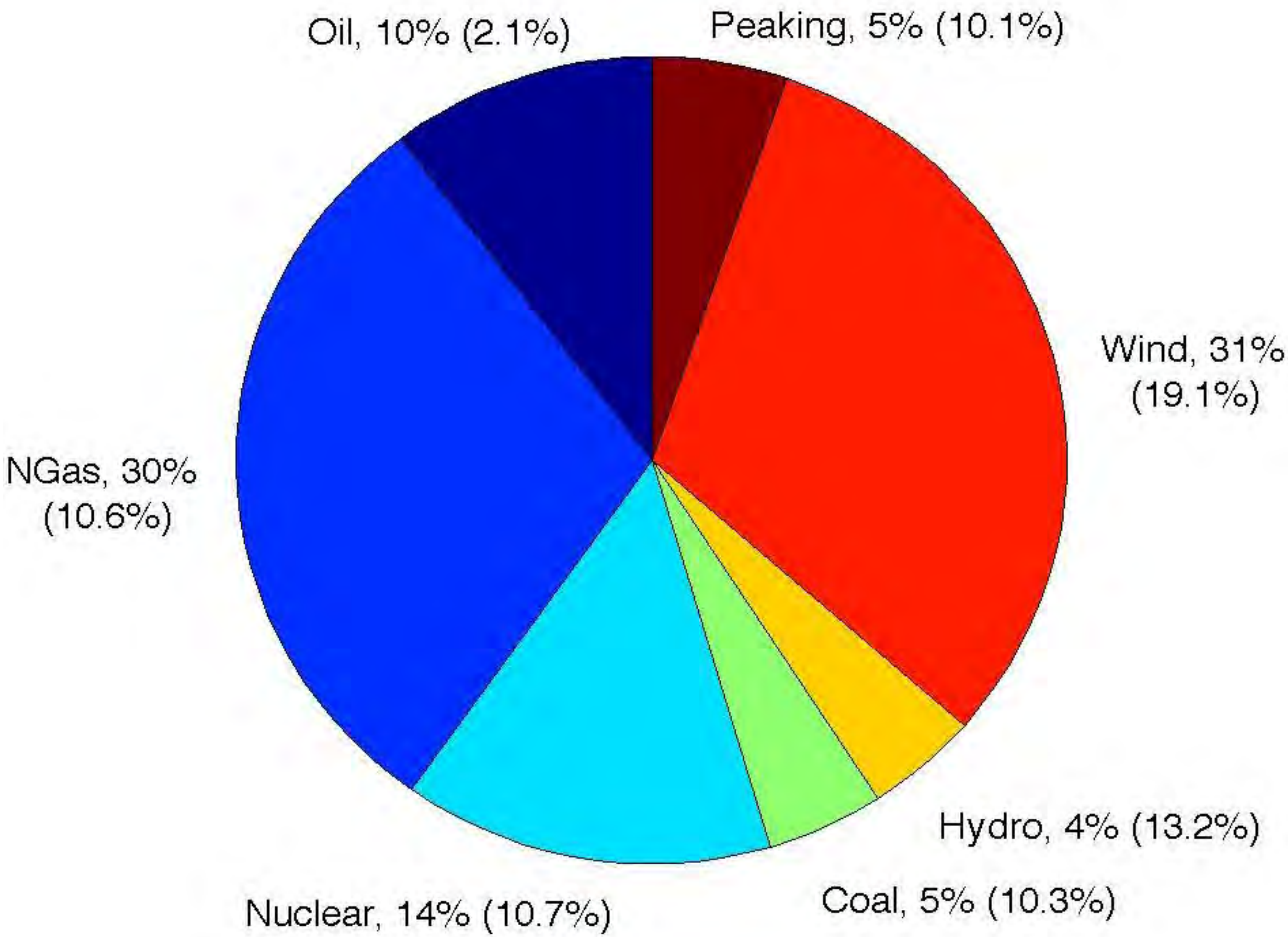
Generator Dispatch – 10% Wind



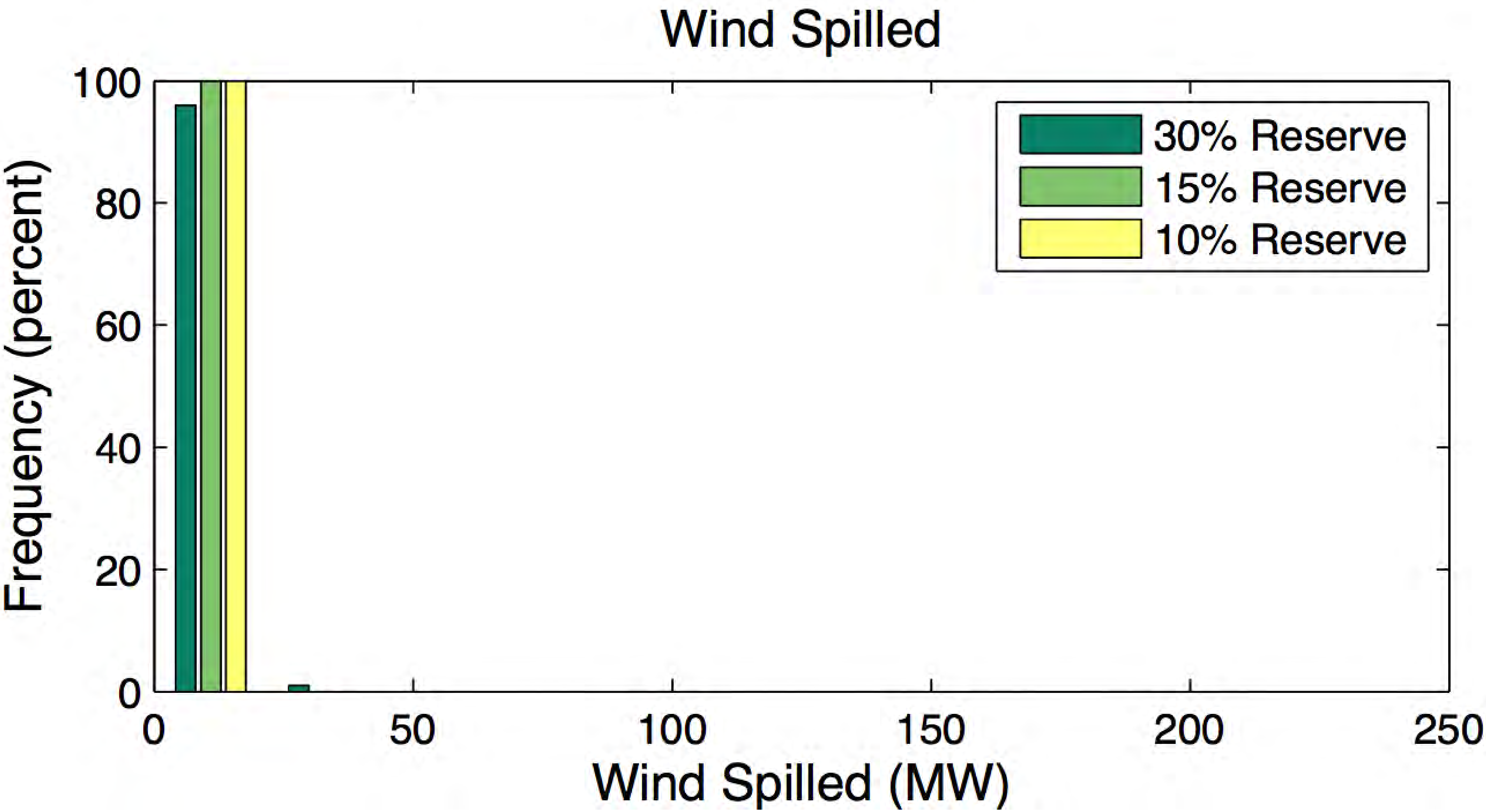
Generator Dispatch – 20% Wind



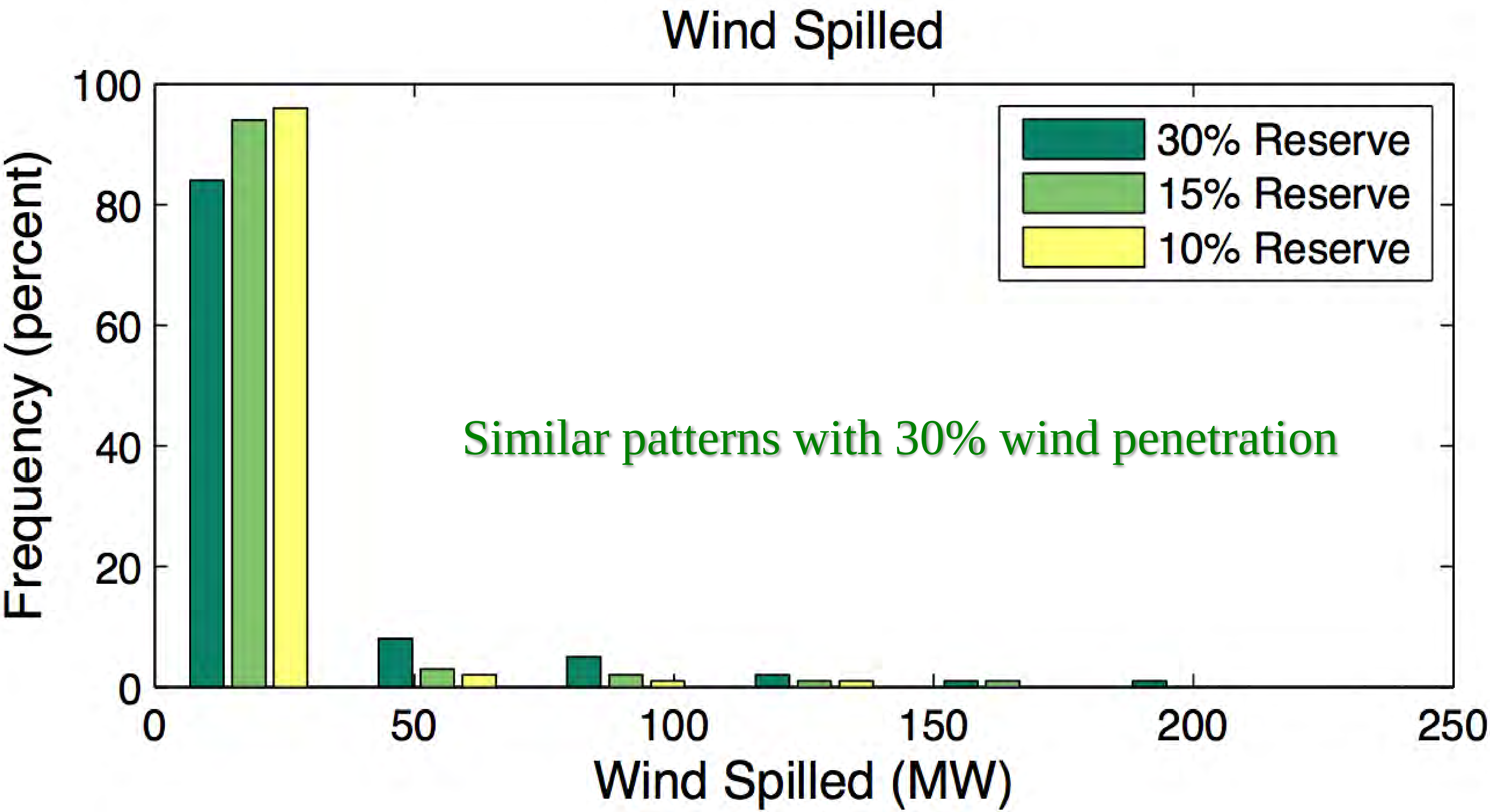
Generator Dispatch – 30% Wind



Example Results: 10% Wind, No Self Reserves



Example Results: 10% Wind With Self Reserves



Results: Mitigating Uncertainty

- We consider the impact of
  - Self Reserves (wind providing its own reserves)
  - Demand Response
  - Combination of both

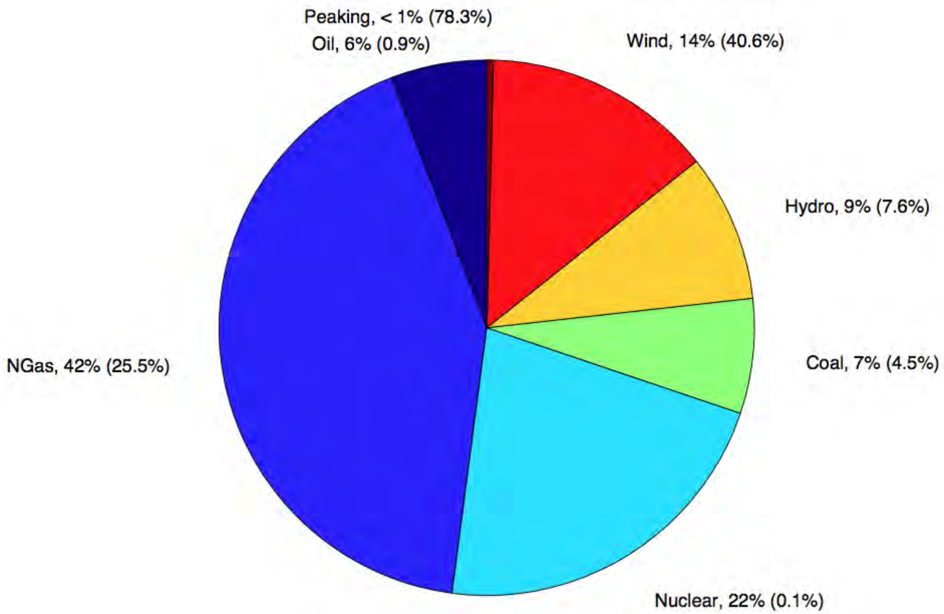
…and assess their impact on LMP, power losses and dispatch variability in the test system

Generator Dispatch Results

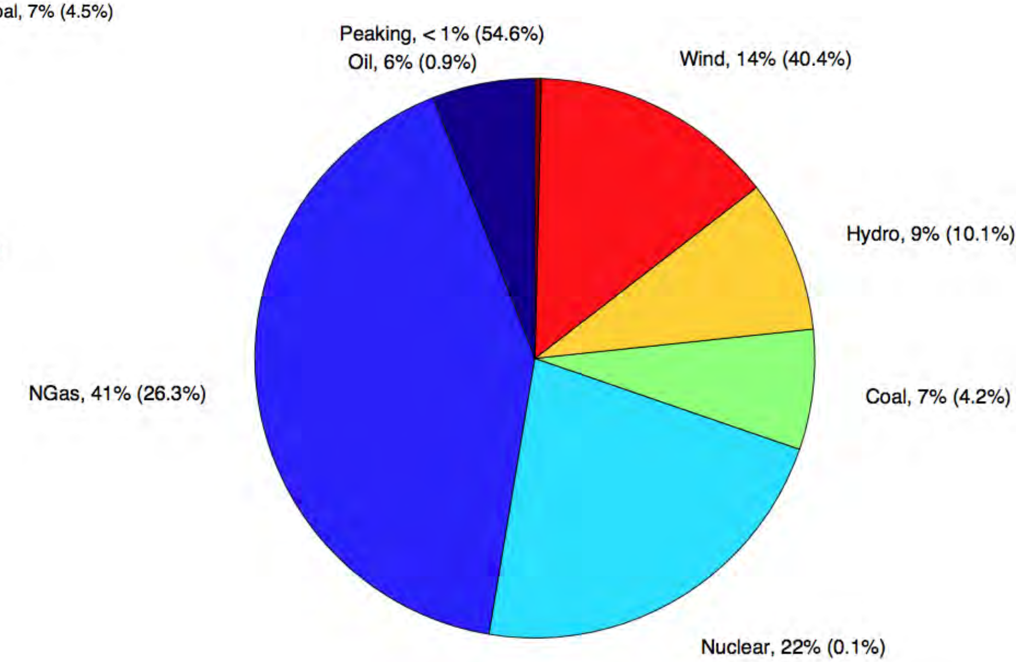
- Pie charts for dispatch of all generator types
  - Aggregated over all load levels
  - Average percent of dispatch, with variability
- Compare
  - 10% and 30% wind penetration
  - With demand response
  - With self-reserves
  - With both

Generator Dispatch: Impact of DR

10% wind, no DR or SR

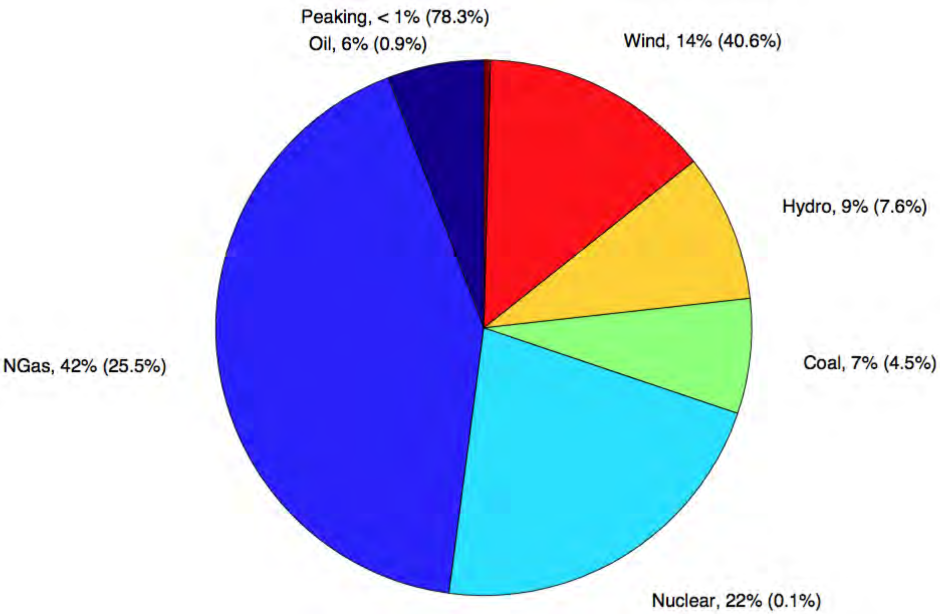


10% wind, DR, no SR

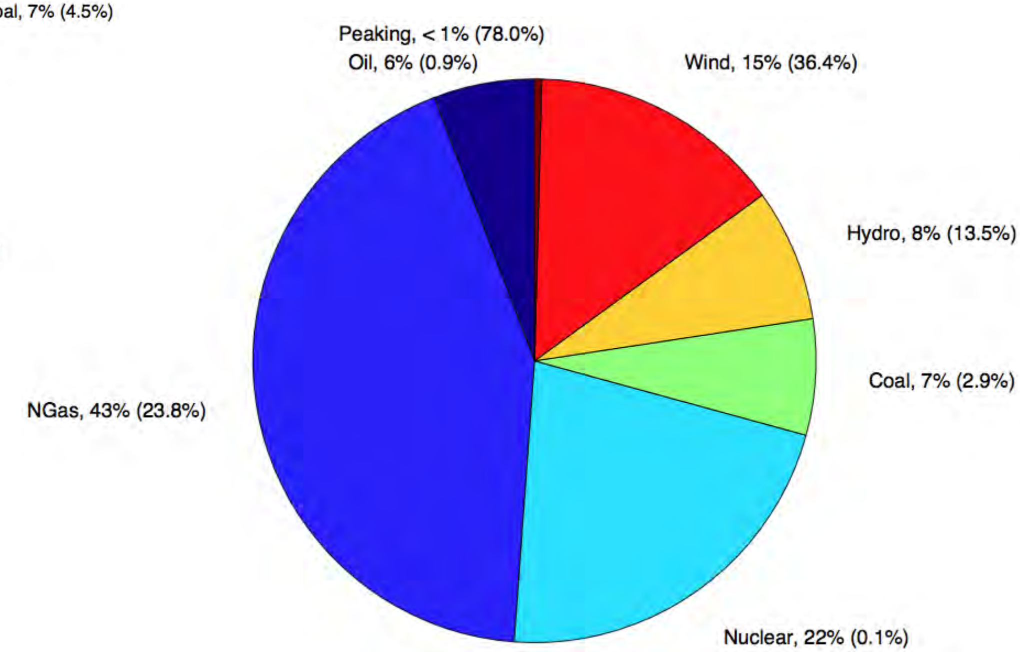


Generator Dispatch: Impact of SR

10% wind, no DR or SR

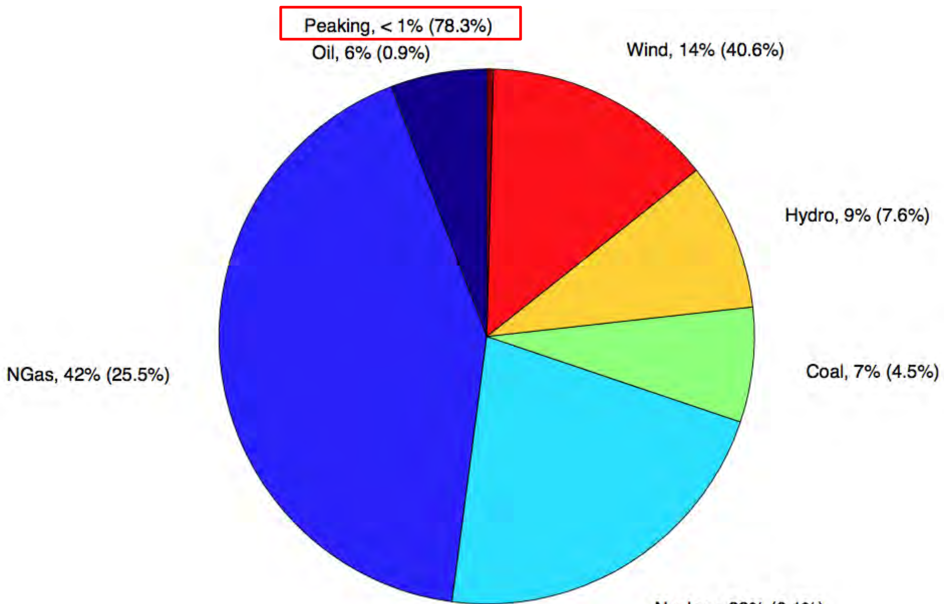


10% wind, no DR, w/SR

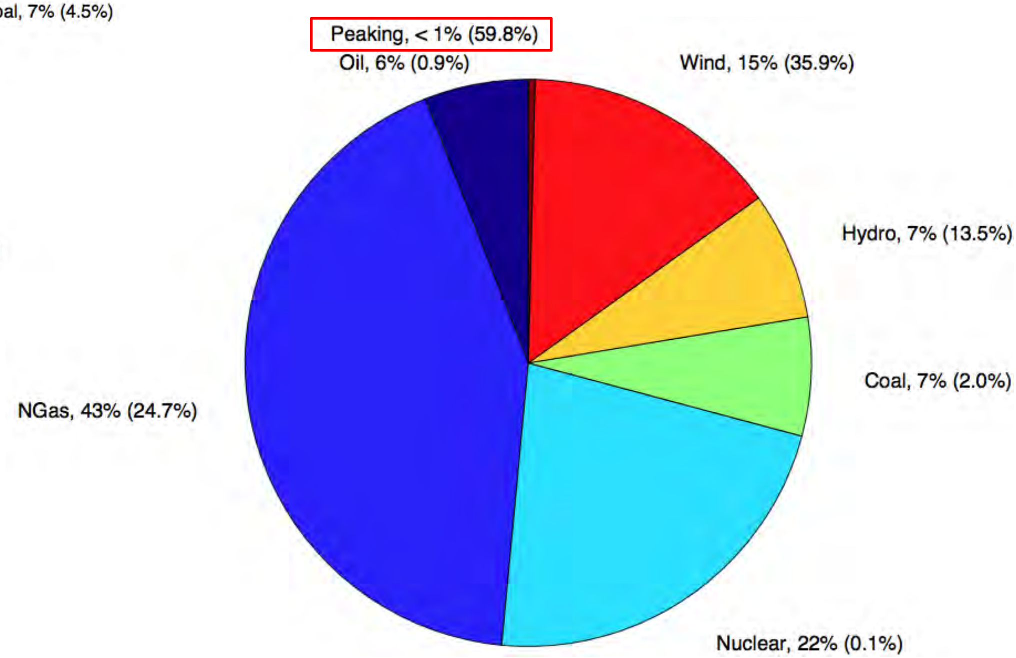


Generator Dispatch: Impact of DR & SR

10% wind, no DR or SR

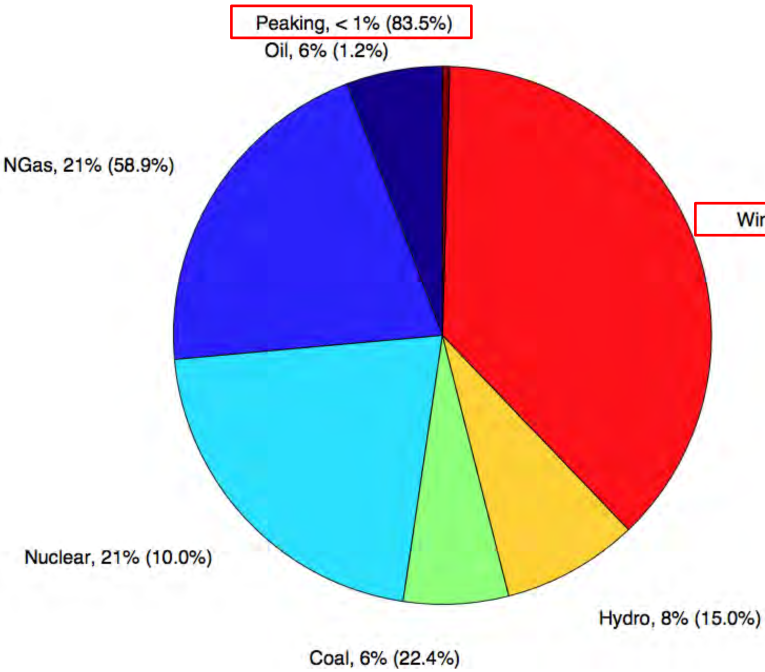


10% wind, DR & SR

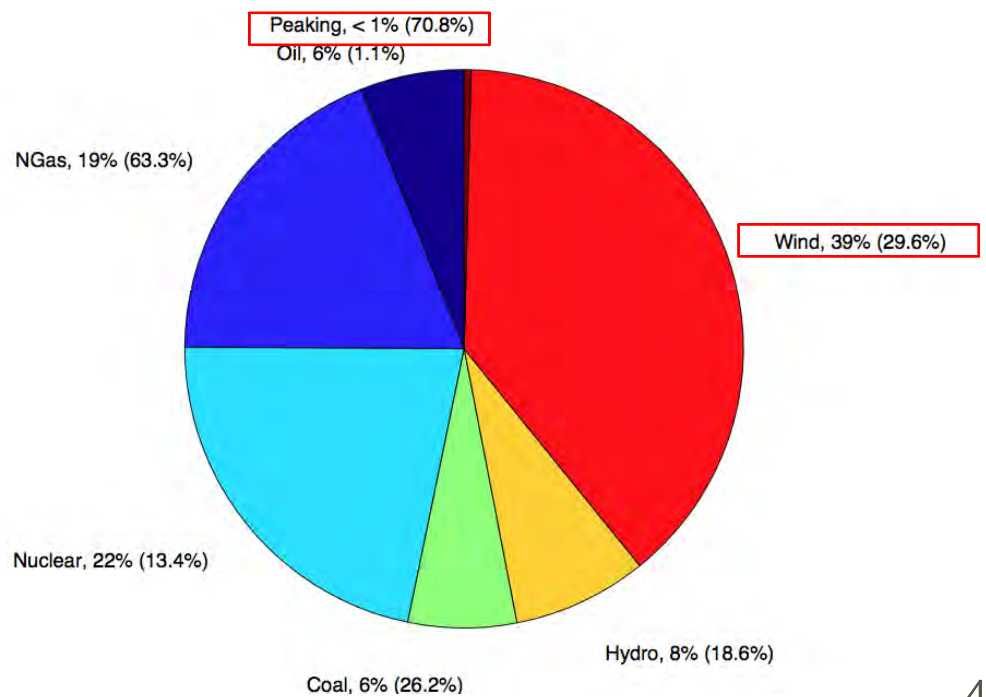


Generator Dispatch: 30% Wind Impact of DR

30% wind, no DR or SR

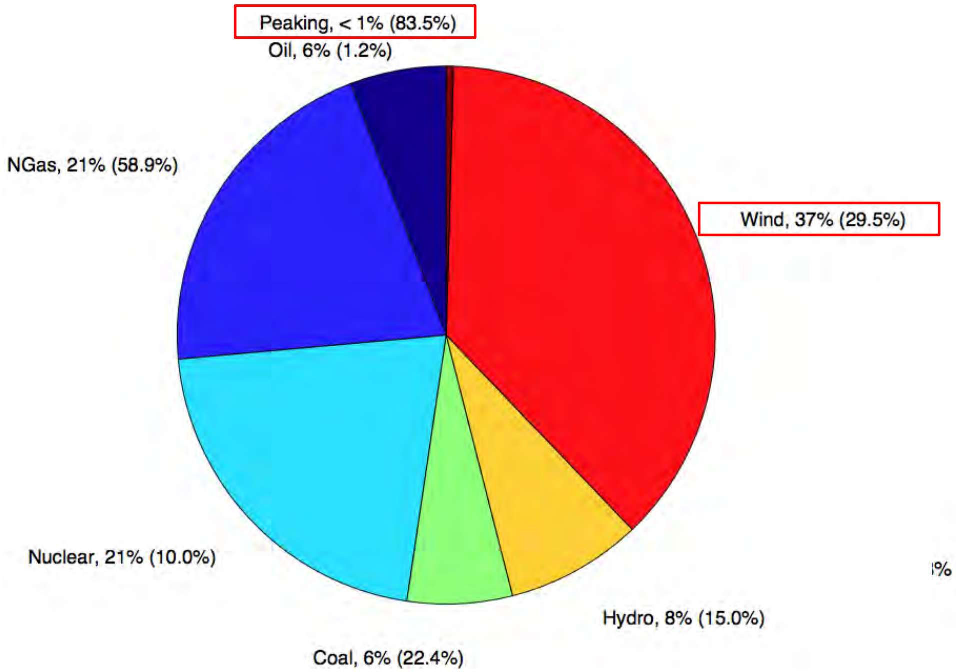


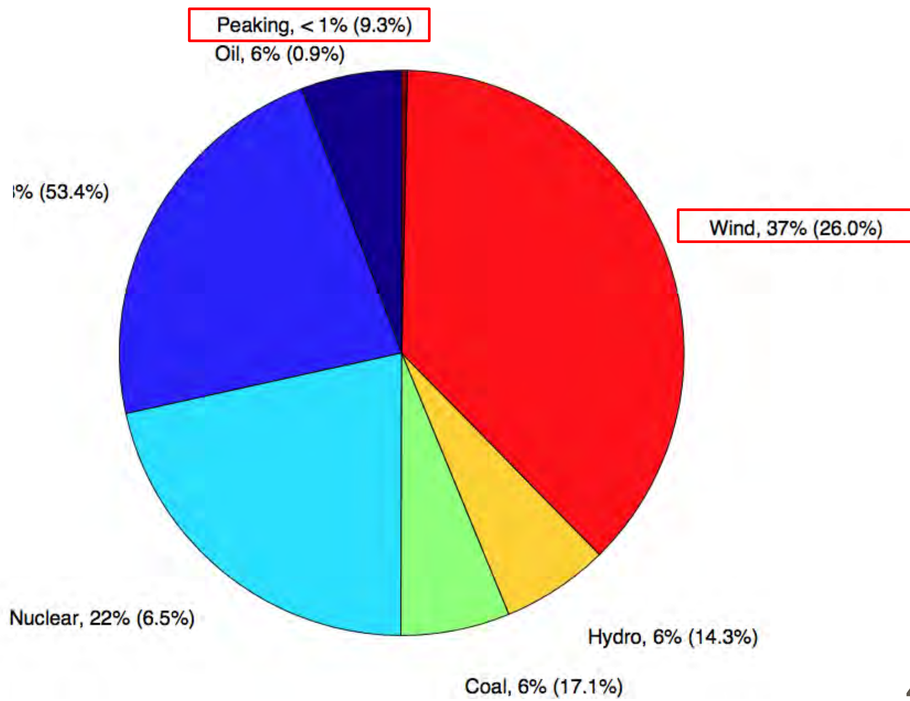
30% wind, with DR



Generator Dispatch: 30% Wind, Impact of SR

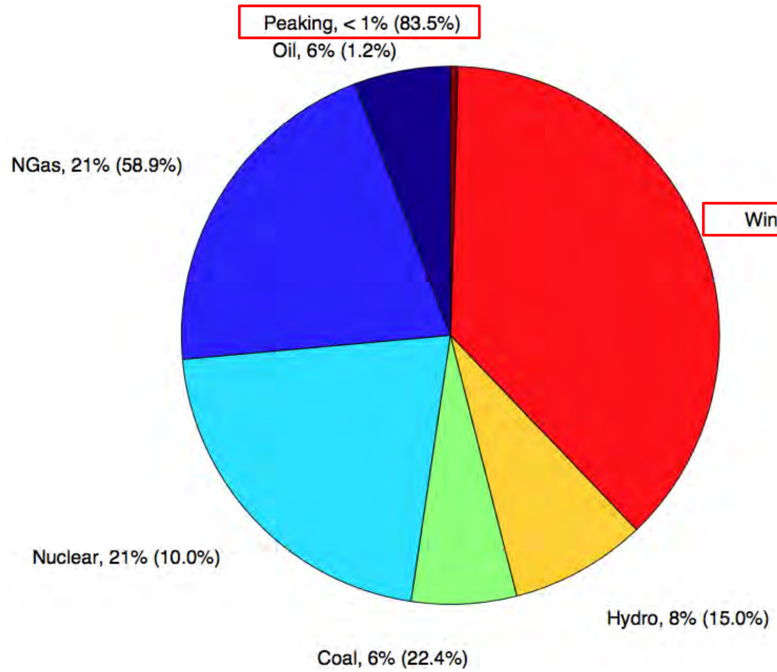
30% wind, no DR or SR

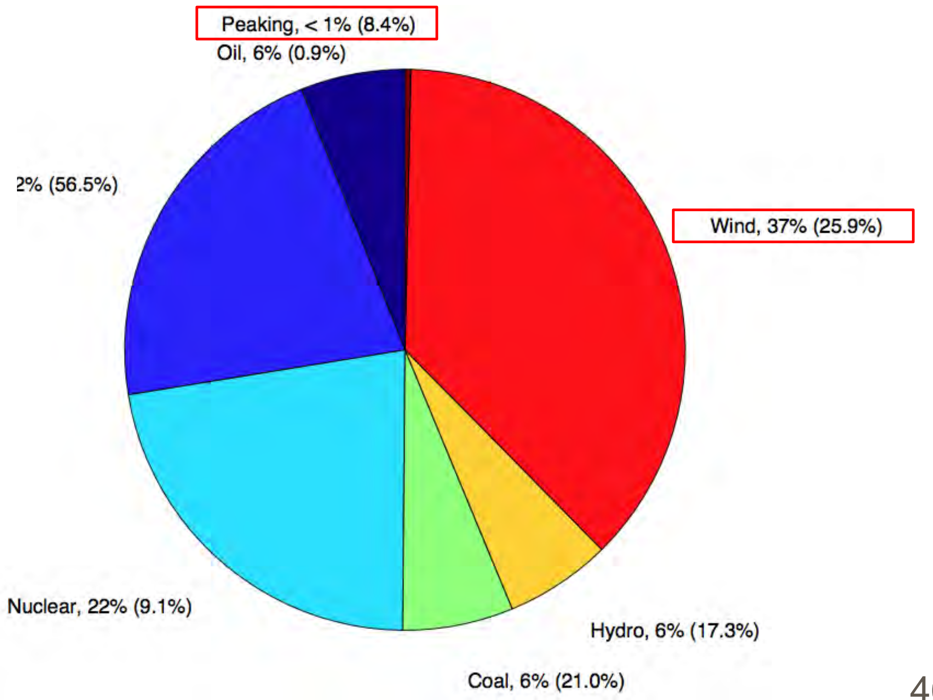




Generator Dispatch: 30% Wind, DR & SR

30% wind, no DR or SR



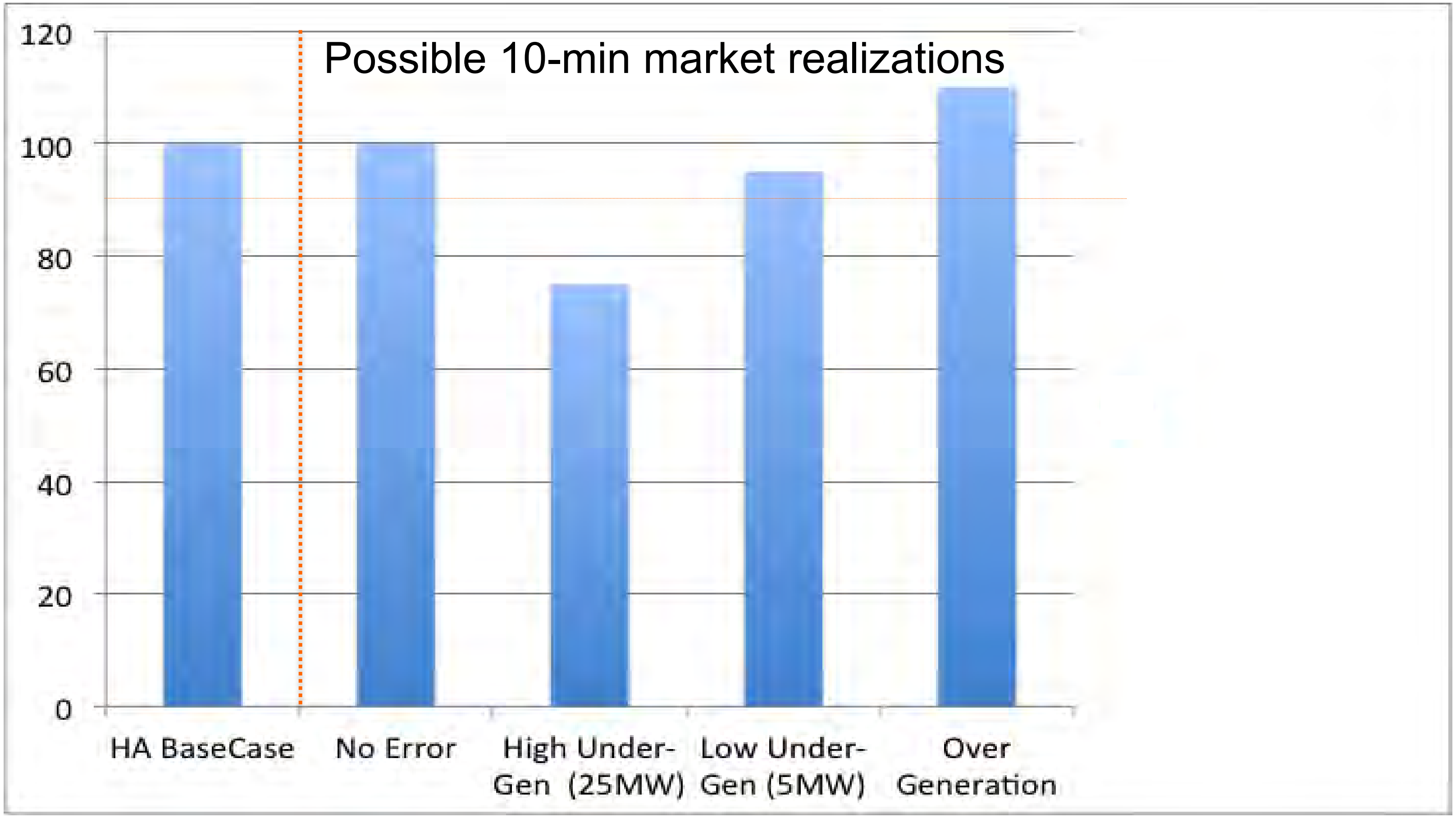


Observations for Dispatch and Variability

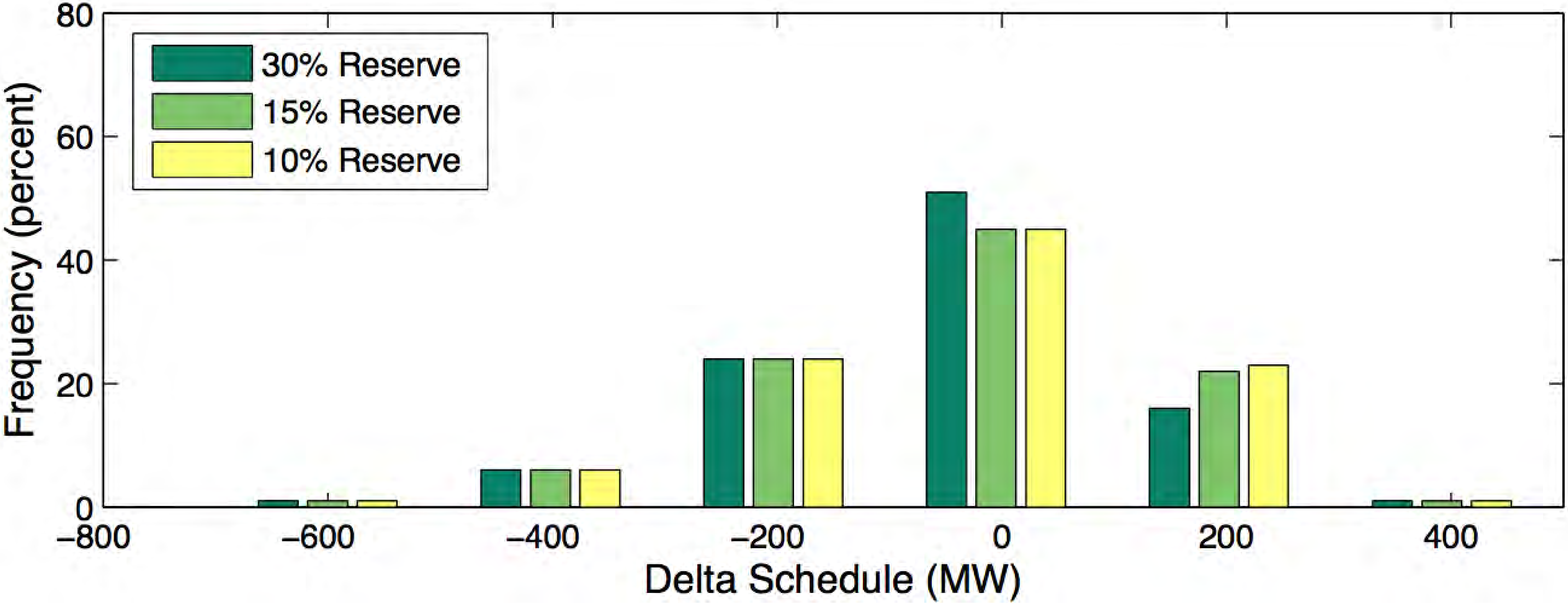
- With 10% wind penetration, there is no significant impact from adding wind self-reserves or demand response
  - Though wind usage increases 1% with SR
  - Peaking variability decreases from 78% to 60%
- With 30% wind penetration there is significant decrease in the *variability* of the dispatch of peaking plants, from 83.5% down to 8.4%
  - Wind self-reserves are available for mitigating the variability of the wind generation
  - Wind self-reserves are also mitigating other uncertainties and variability in the power system (*e.g.*, conventional generation forced outage)

Wind Scheduling Changes from Hour Ahead

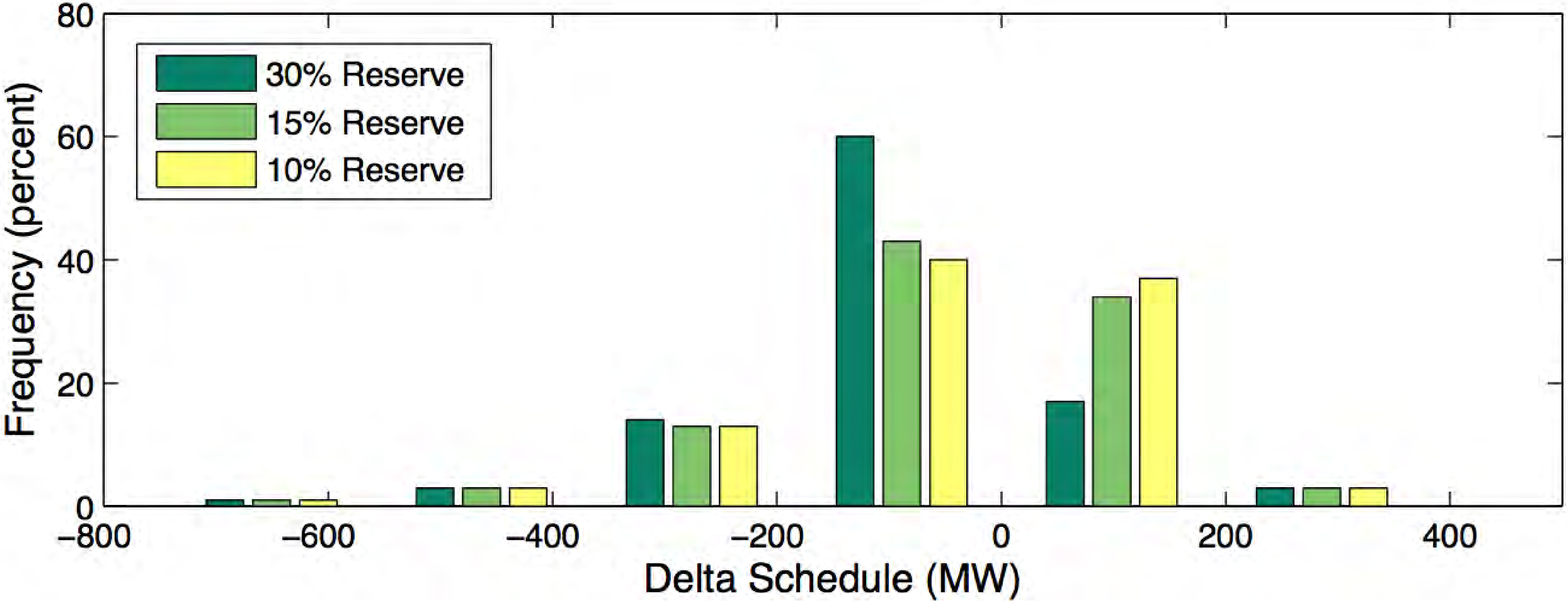
- To model wind providing self-reserves
- First examine possible wind output scenarios



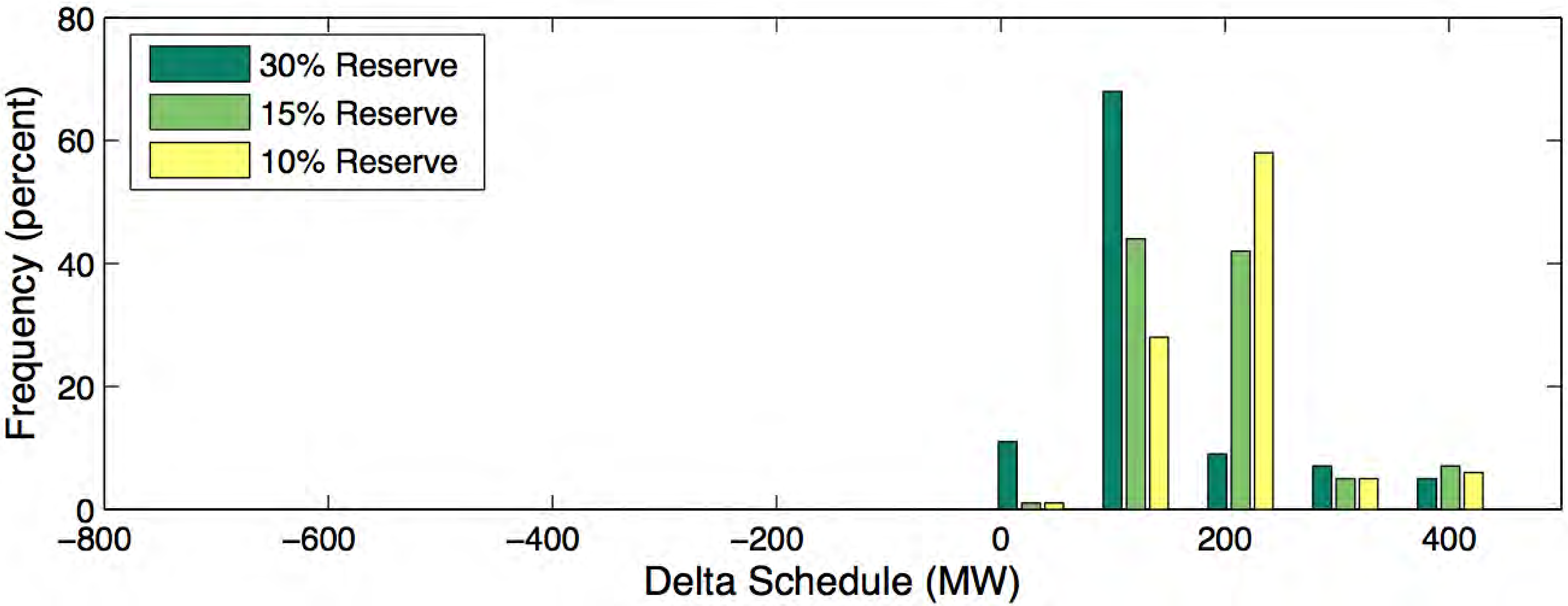
Wind Scheduling Changes from HA: no DR or SR



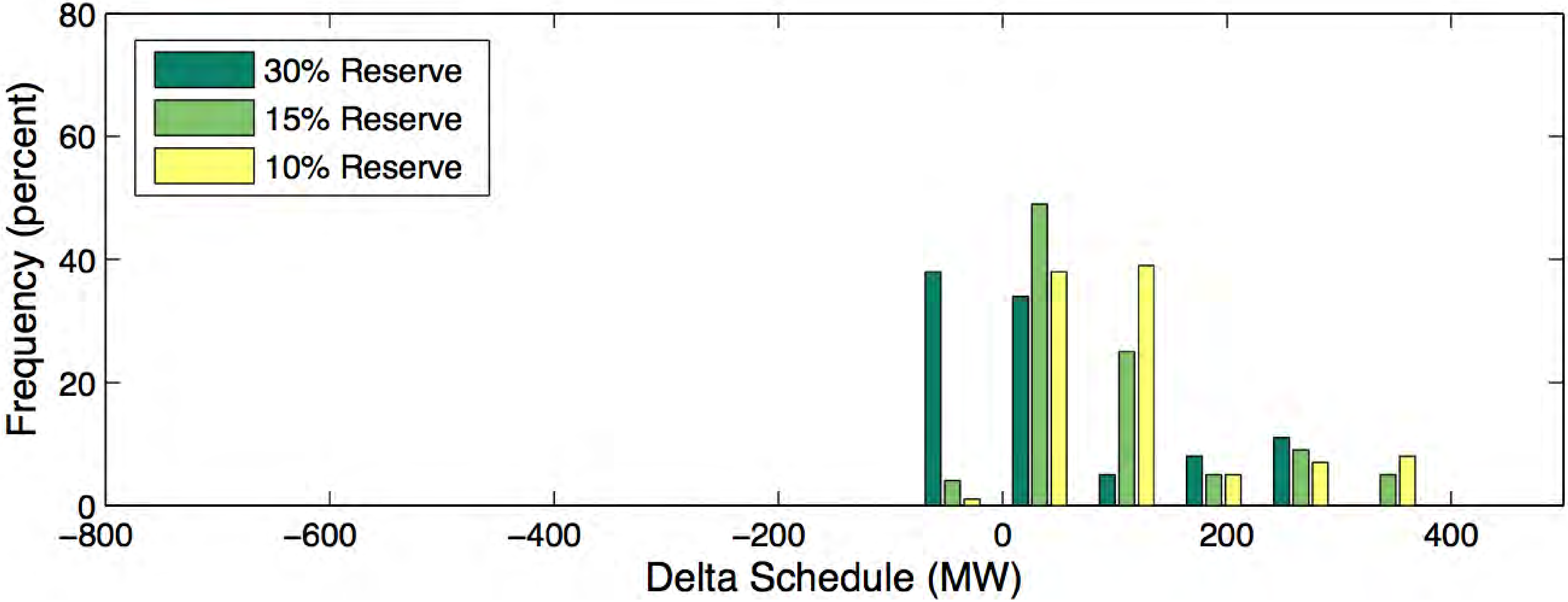
Wind Scheduling Changes from HA: Impact of DR



Wind Scheduling Changes from HA: Impact of SR

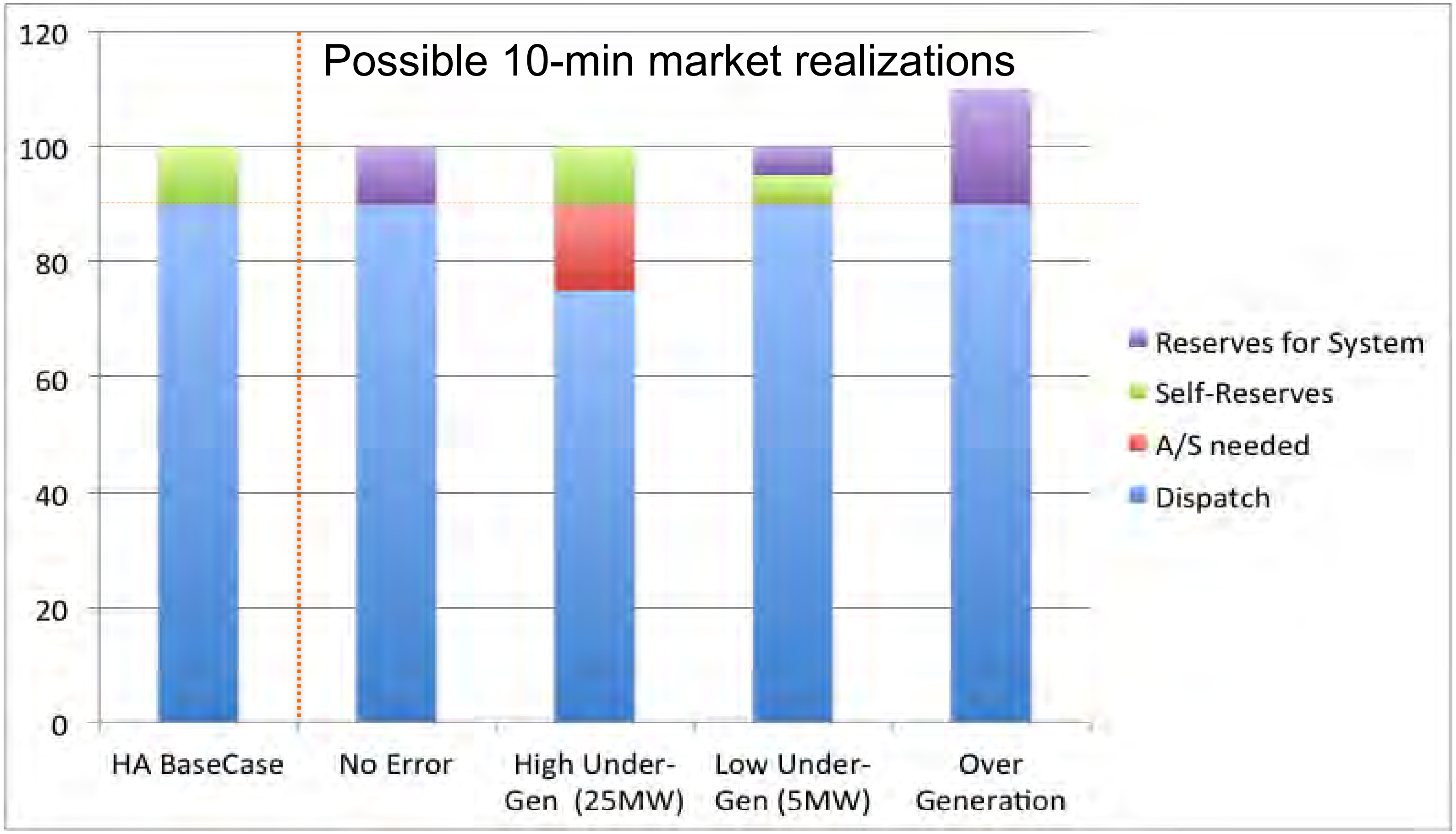


Wind Scheduling Changes from HA: both DR & SR



Wind Scheduling Changes from Hour Ahead

- To provide self-reserves, the wind generators are scheduled below the expected output at hour ahead
- 10-minute market operational scenarios:



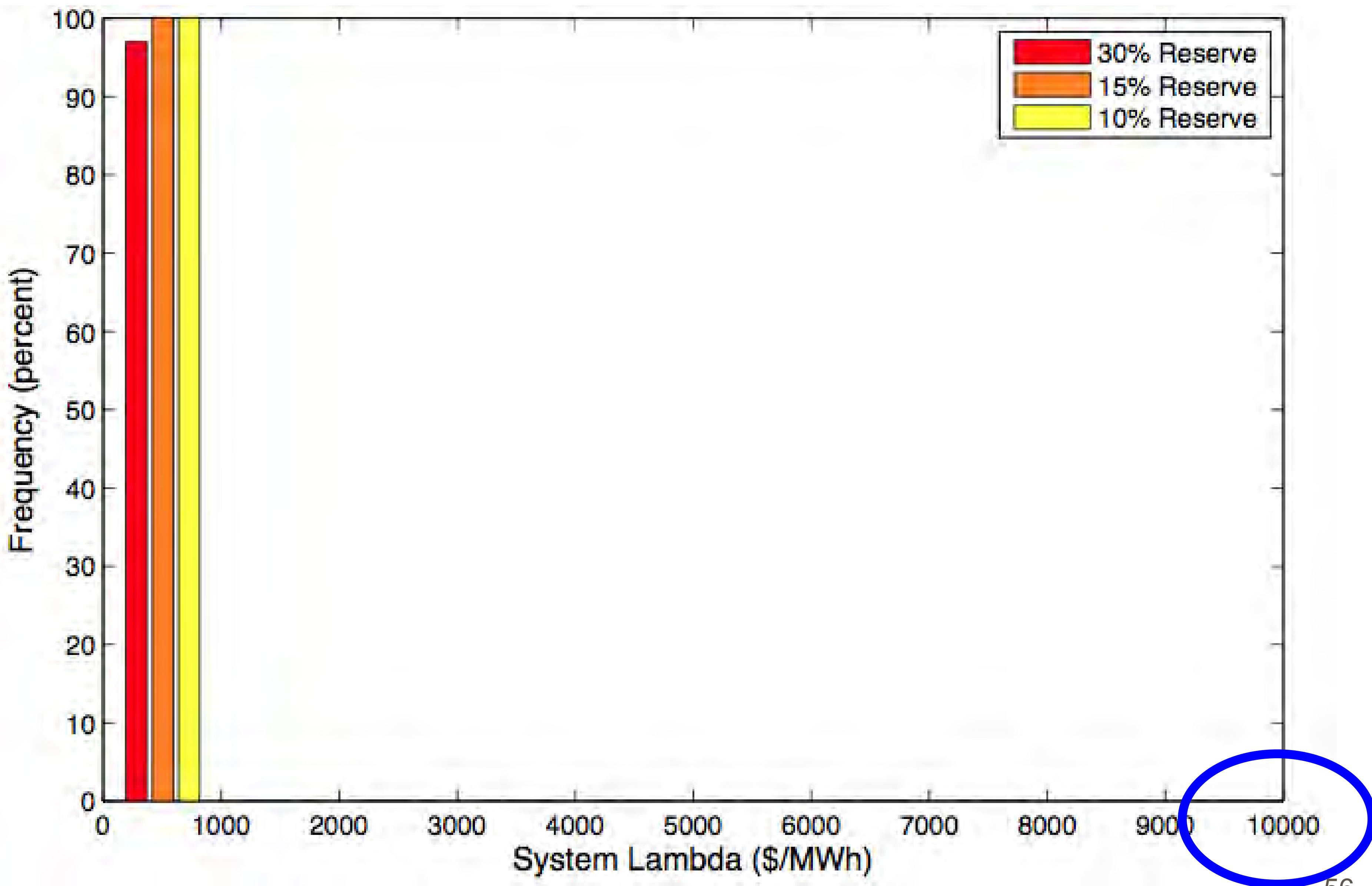
Observations: Changes from HA Schedule

- With neither demand response nor wind self-reserves, wind is as likely to over-generate as under-generate
- As demand response is added to the system dispatch, wind is more likely to over-generate
  - Represented by negative deviations from the HA schedule
- With the incorporation of wind self-reserves,
  - Wind is unlikely to over-generate
  - Positive deviations in from the HA schedule indicate the use of the wind self-reserves by the system

Price Spikes: System Lambda Results

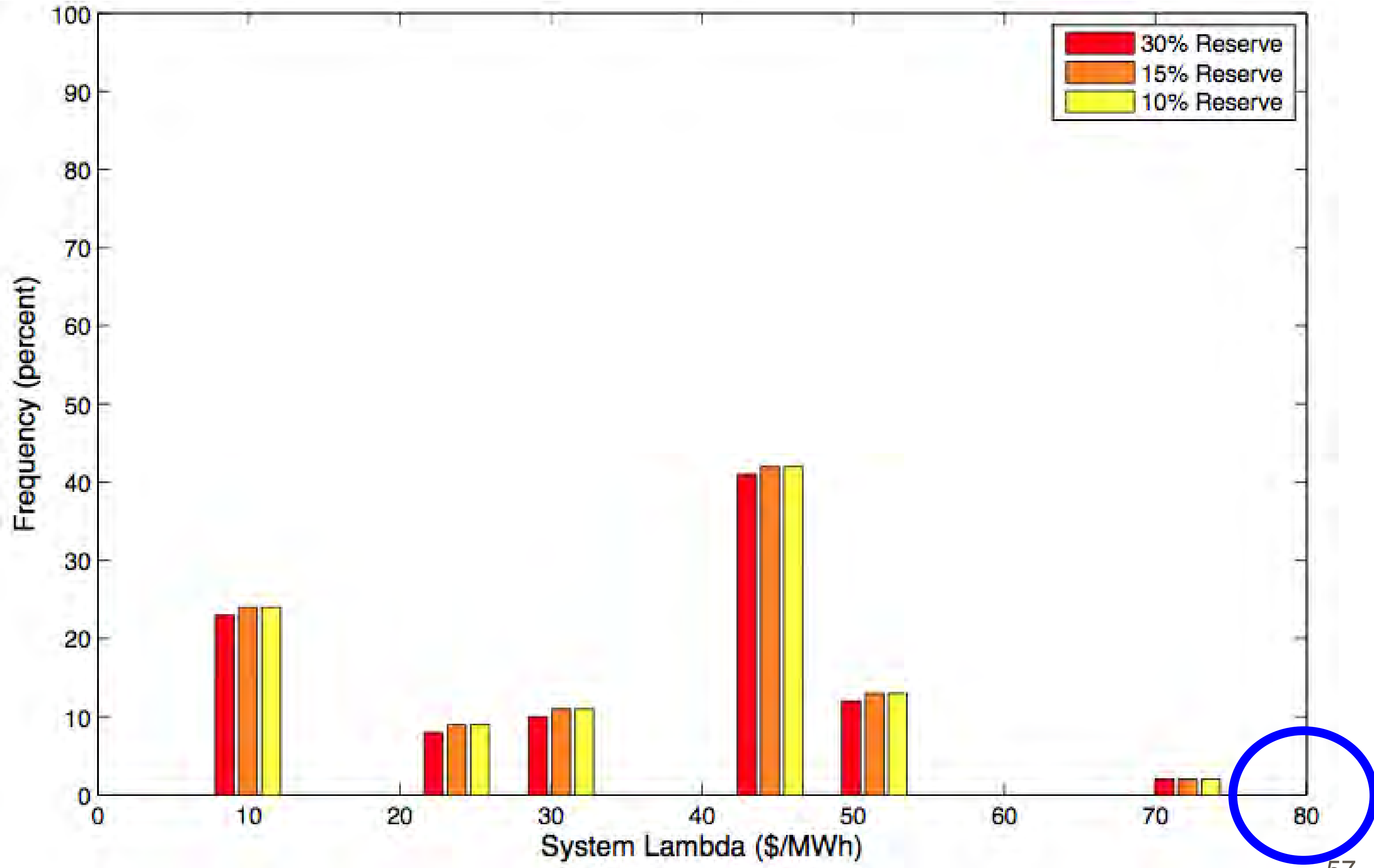
- With high penetrations of wind, and no additional system flexibility, price spikes occur 4.6% of the time
- With the inclusion of demand response, the occurrence of price spikes decreases to 2.4% of the time
- With the inclusion of self-reserves, ***price spikes are eliminated.***

10% Wind System Lambda: No DR or SR

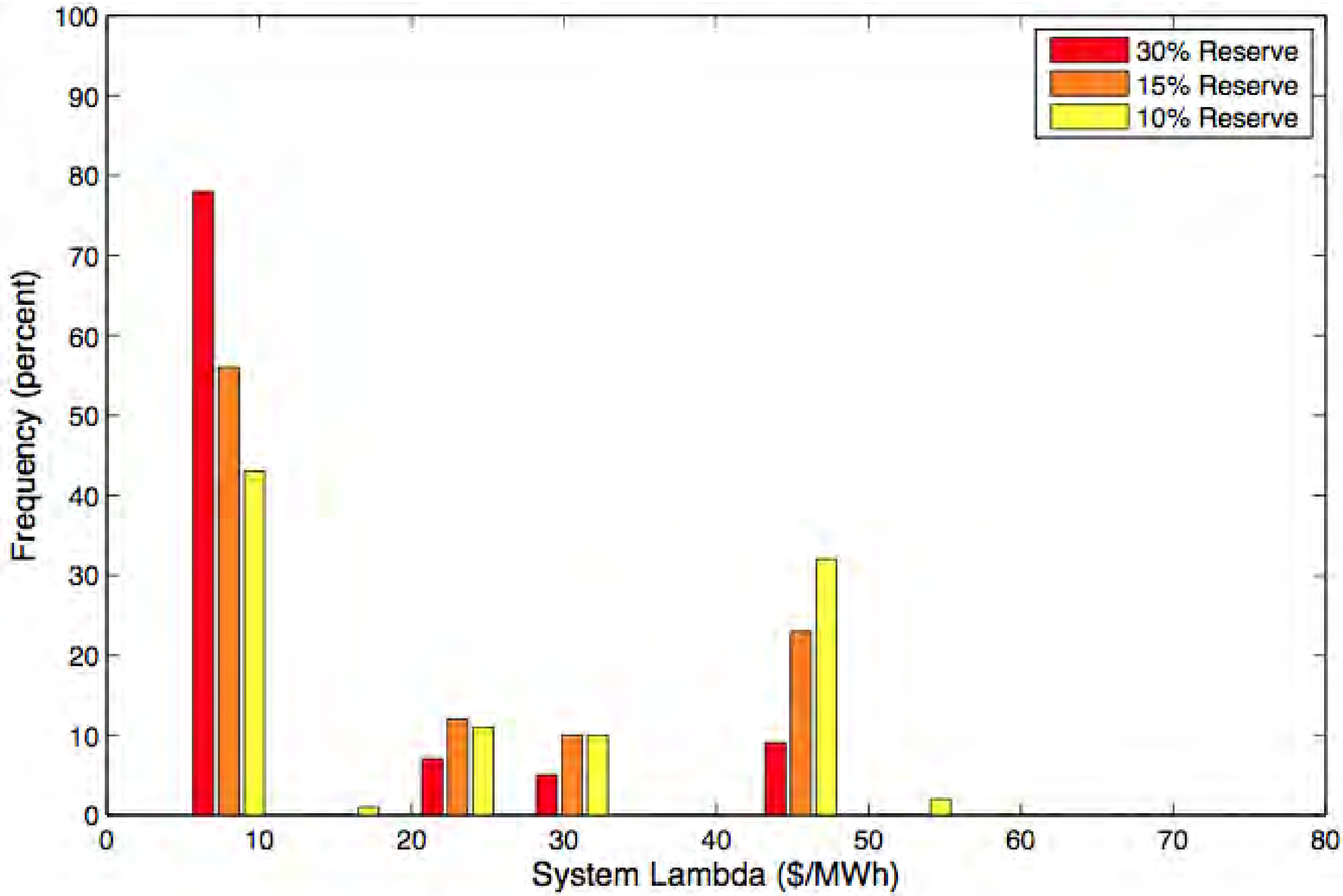


10% Wind System Lambda: No DR or SR

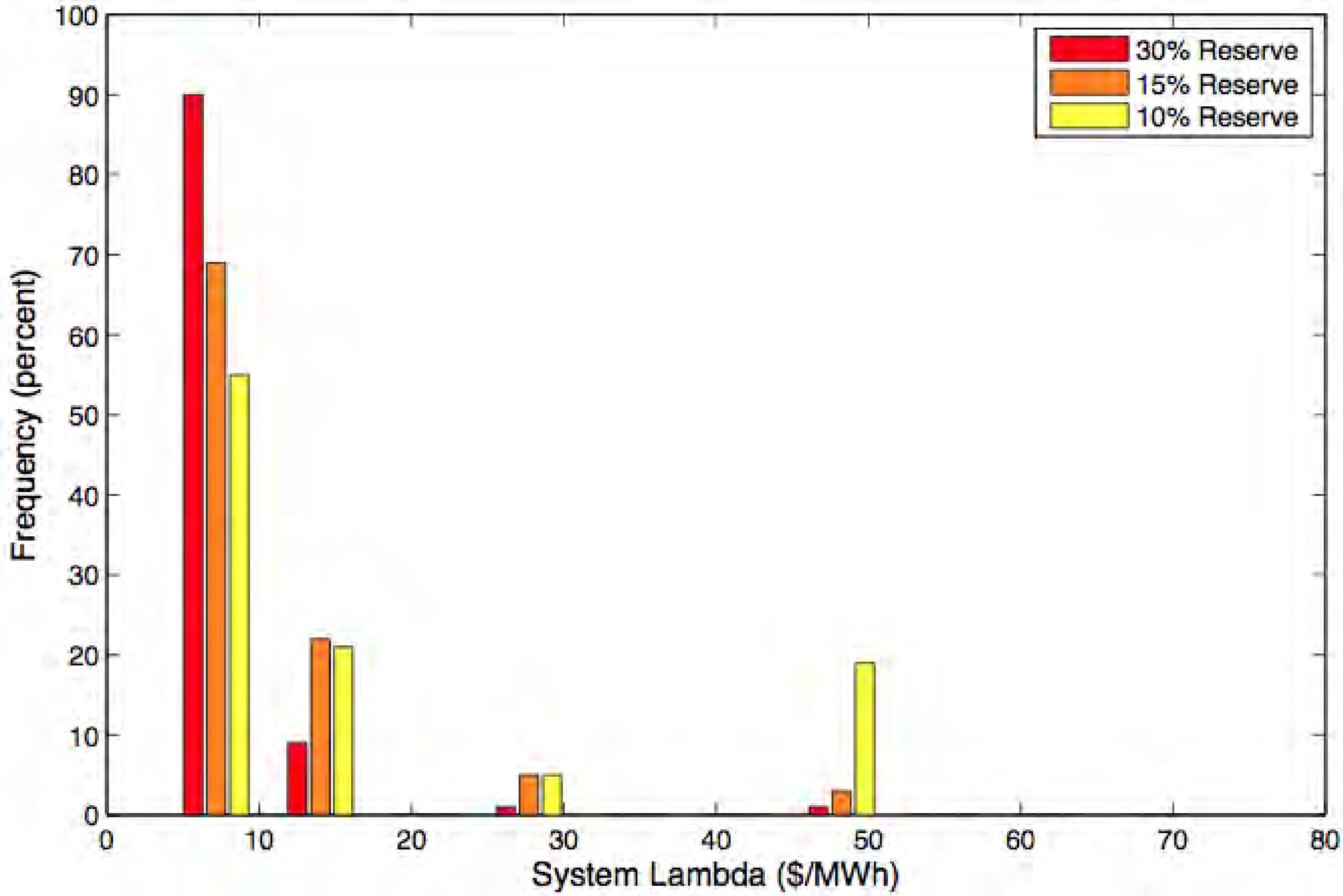
Cropped x-axis



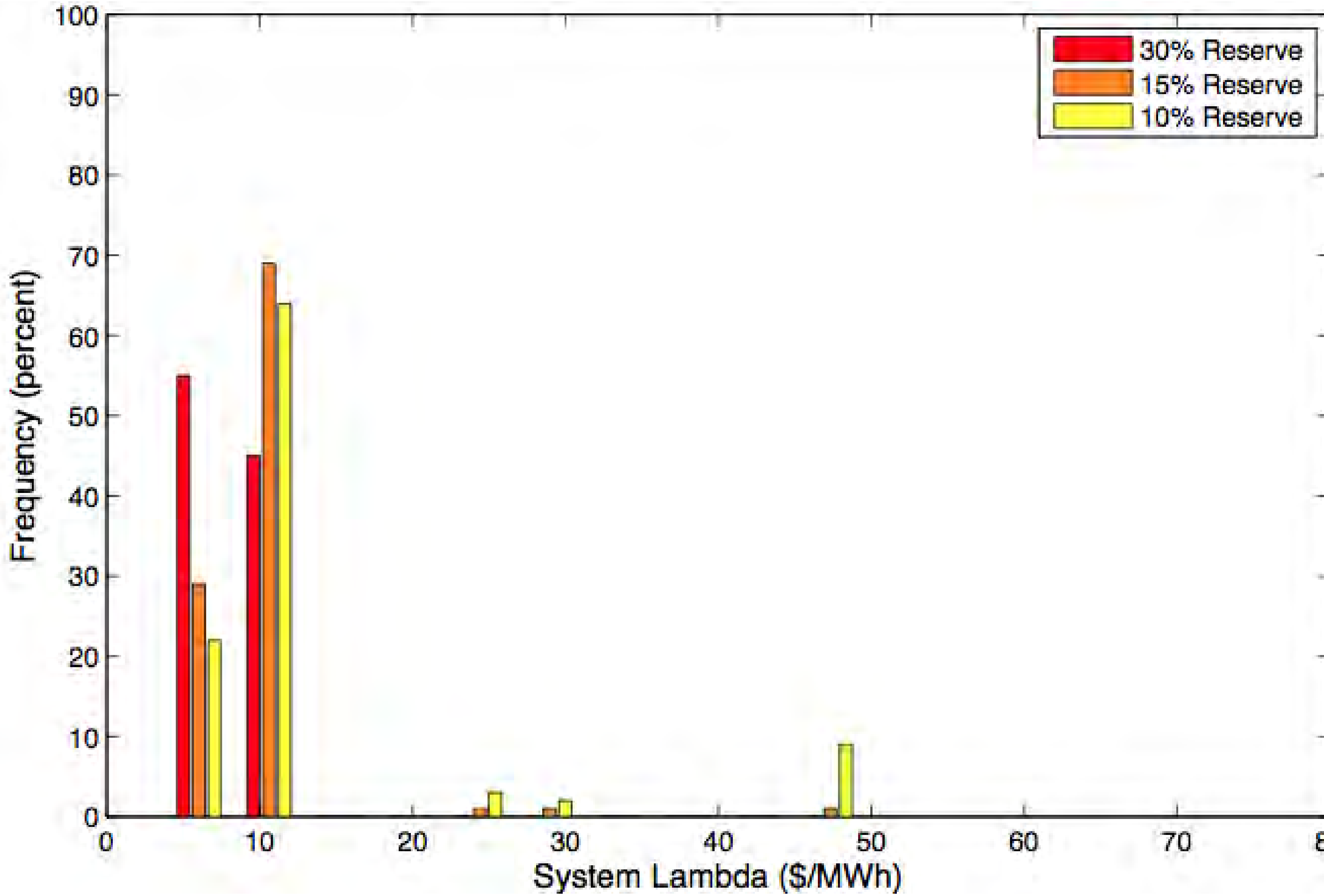
10% Wind System Lambda: Impact of DR



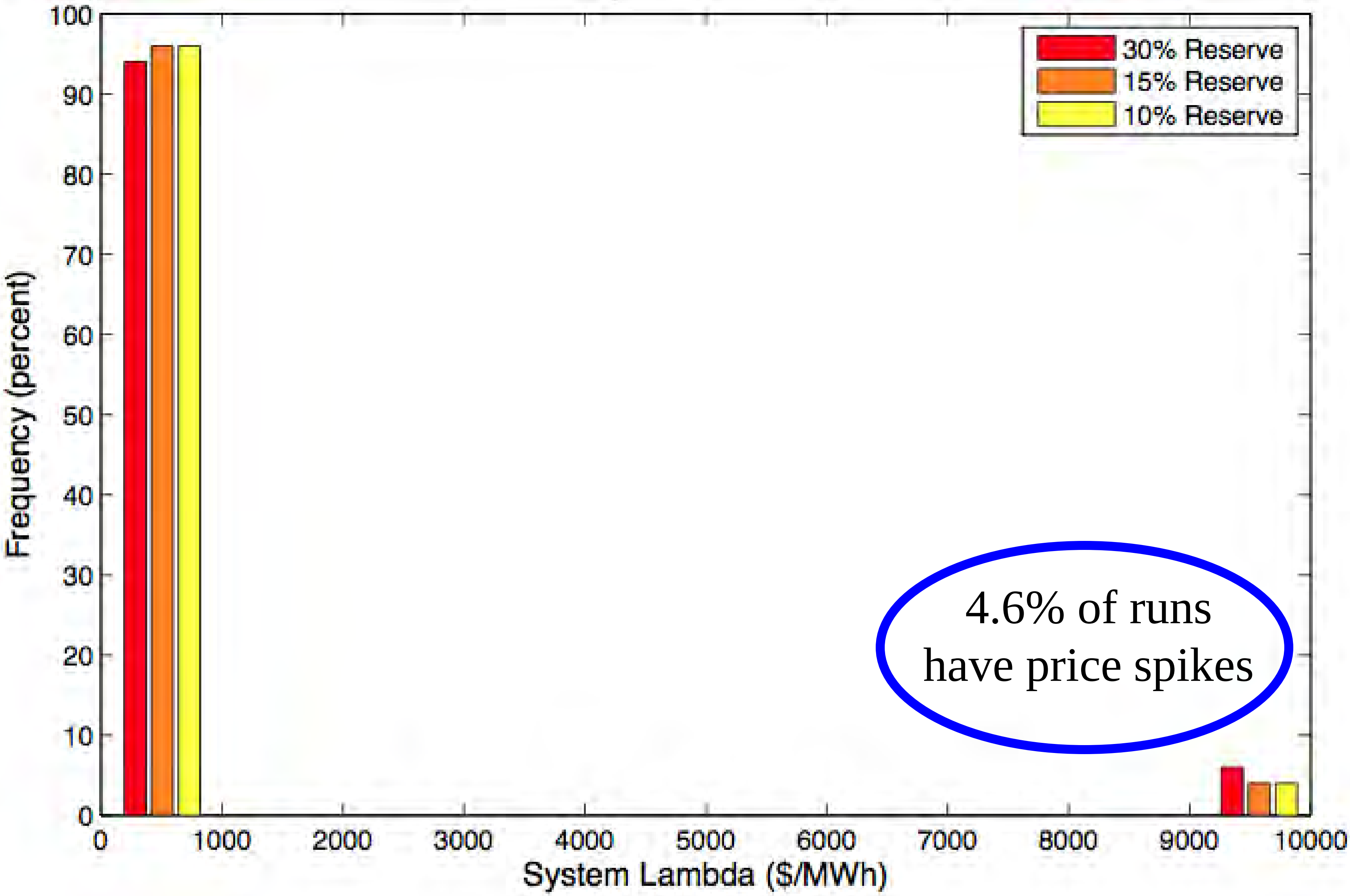
10% Wind System Lambda: Impact of SR



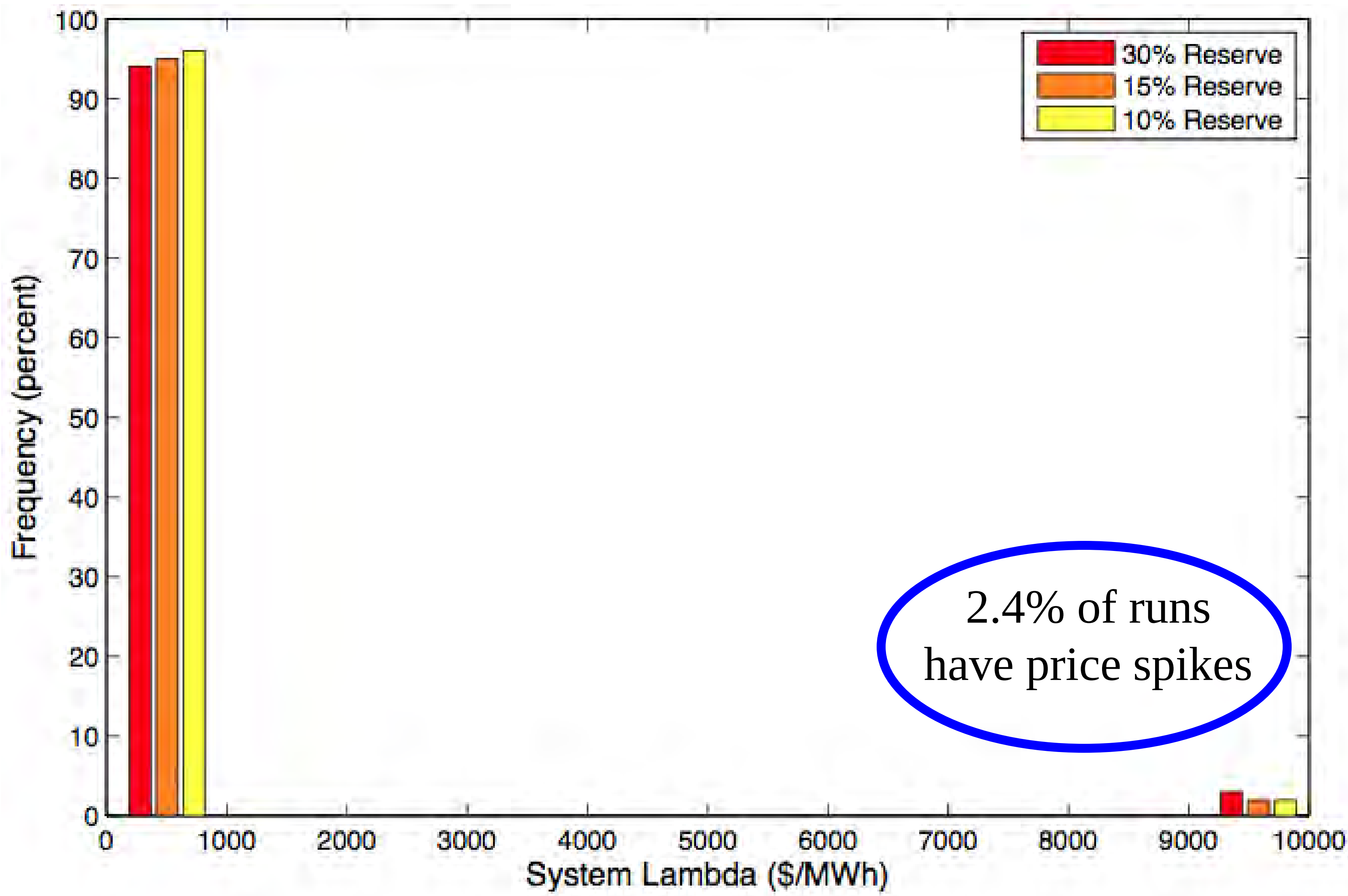
10% Wind System Lambda: Both DR & SR



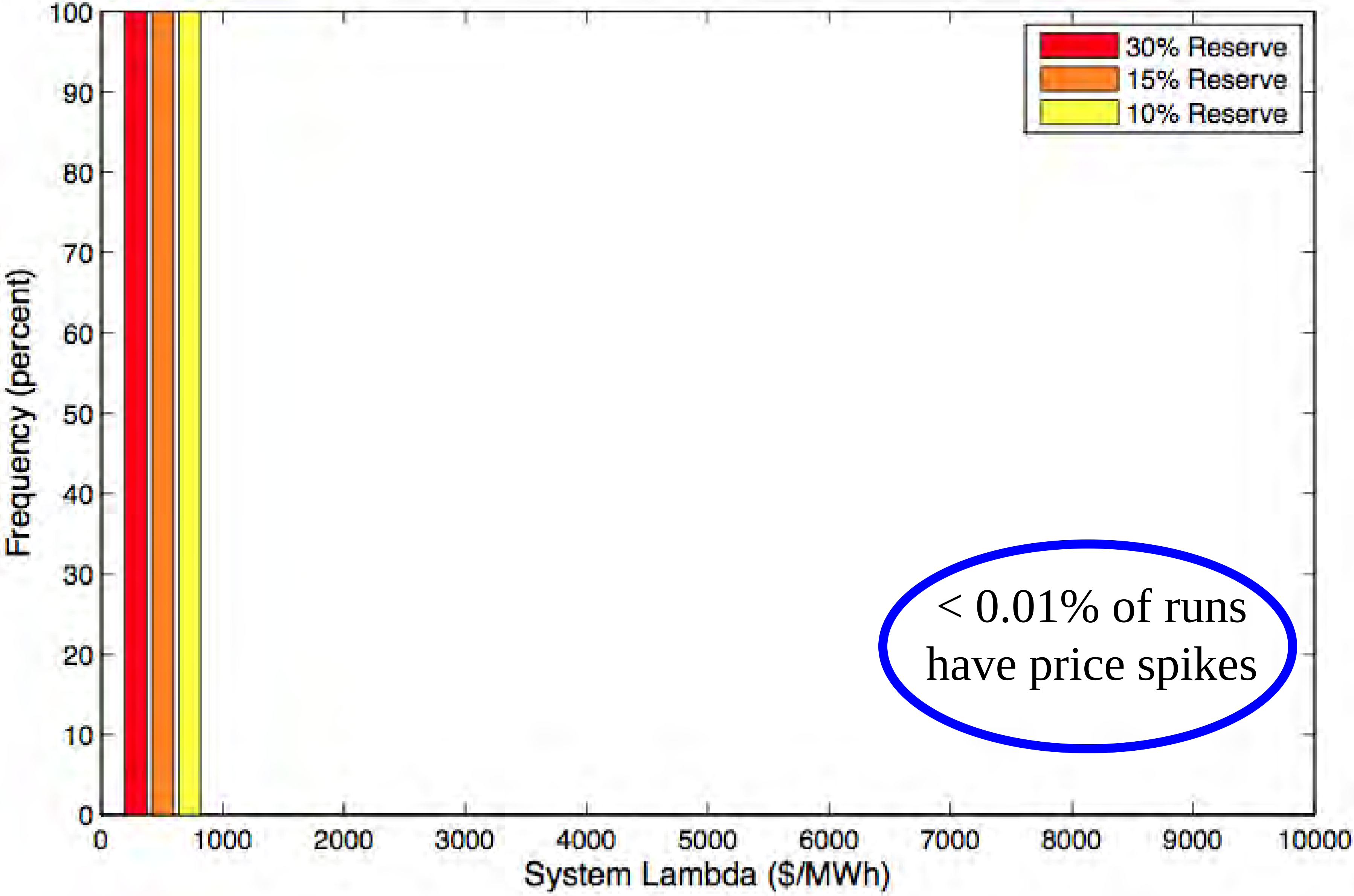
30% Wind System Lambda: No DR or SR



30% Wind System Lambda: Impact of DR



30% Wind System Lambda: Impact of SR



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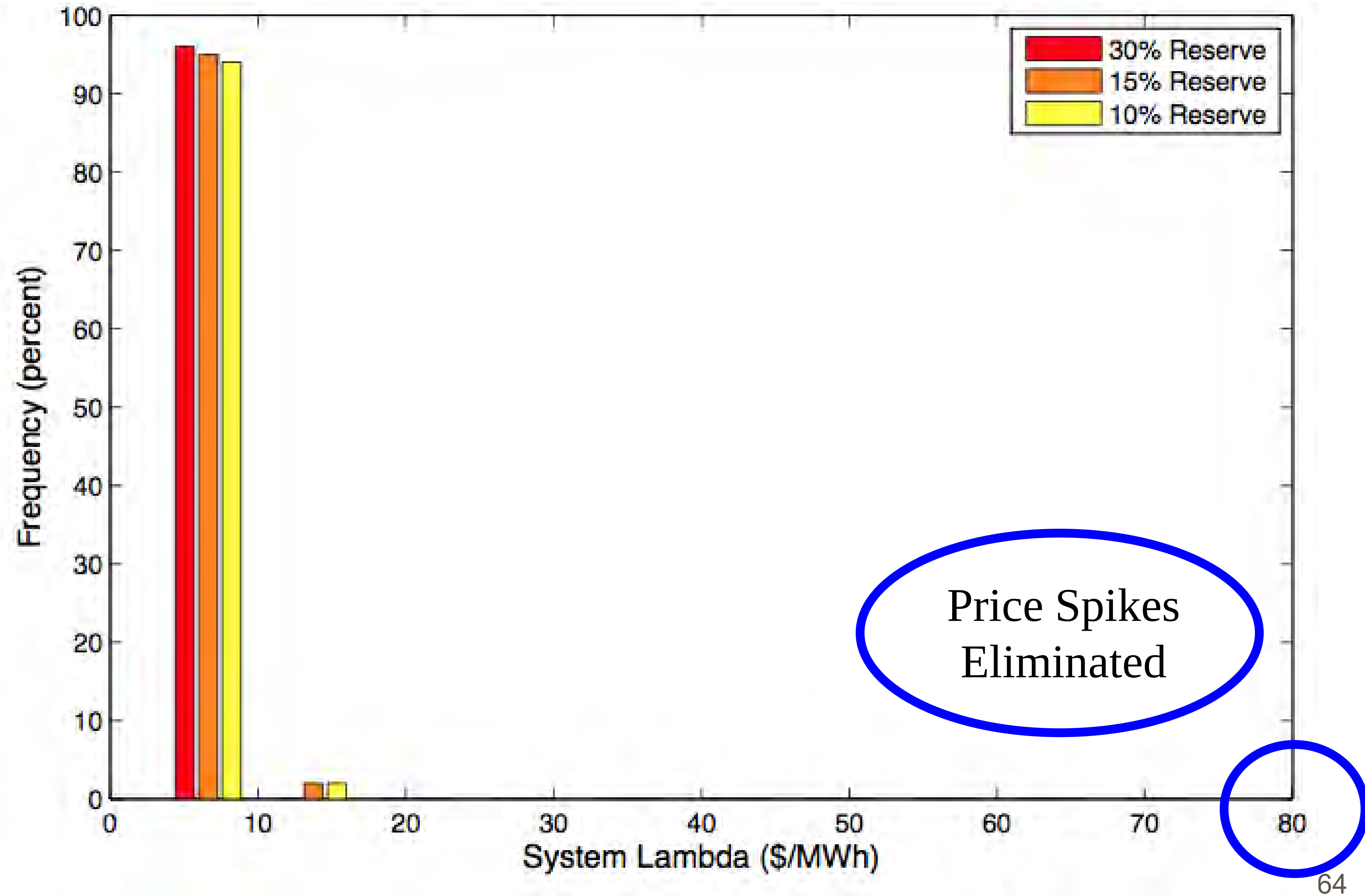

Results: Performance Parameters

	with DR	with SR	with both
LMP	↓	↓	↓
LMP σ (price spikes)	↓	↓	eliminated
Production Cost	↓	↓	↓
Losses: MW & MVAr	↓	↓	↓
Fossil Fuel Generation	↓	–	↓
CO_2 Emissions	↓	–	↓
Deviations from hour ahead schedule	–	↓	↓

Simulation Results Summary

- Increasing wind penetration increases variability of dispatch in ramp-capable generators
- Requiring wind generators to provide self-reserves
  - Significantly reduces other generators' variability in dispatch
  - Dramatically reduces occurrence of price spikes (resulting from load shed)
  - Reduces overall production cost
  - Reduces real power losses in the system
- Provision of demand response resources
  - Has additional positive effects (CO_2 reduction),
  - Eliminates price spikes in conjunction with self-reserves

Ongoing Research

- Develop optimization framework to recommend the *level* of self-reserves that are
  - most effective for the system
  - feasible for wind generators

Additional References

- Selecting optimal demand response levels are various temporal scales:

  C. L. Anderson & J. B. Cardell (2013) A Decision Framework for Optimal Pairing of Wind and Demand Response Resources. IEEE Systems Journal. *To appear*.

- Carbon and cost impacts of increasing penetration of wind generation:

  J.B. Cardell, L. Anderson (2012). The Impact of Wind Energy on Generator Dispatch Profiles and Carbon Dioxide Production. Proceedings of the 45th Hawaii International Conference on System Sciences (HICSS).