Uncertainty Management in Unit Commitment: Stochastic Methods and Reserve requirements

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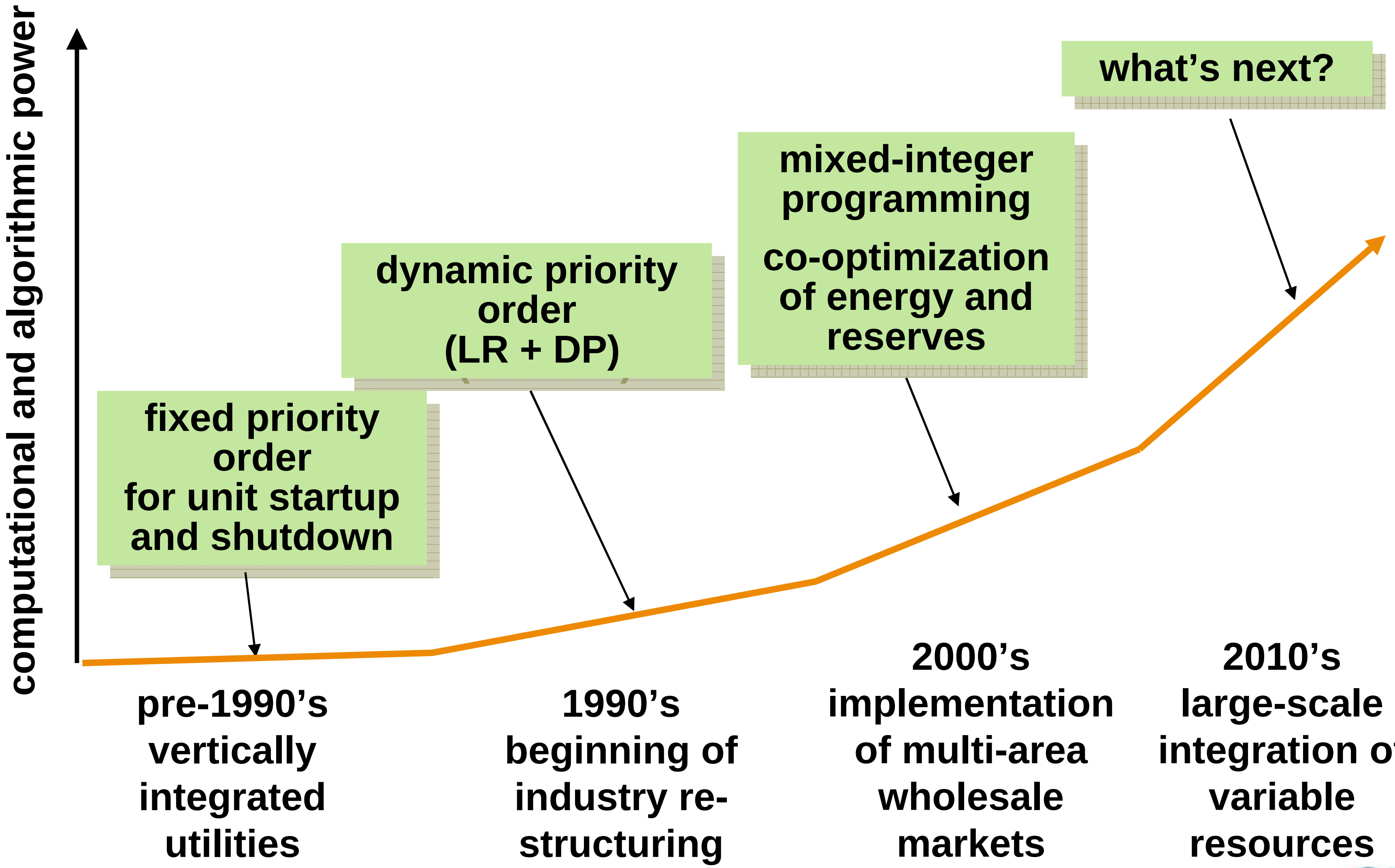
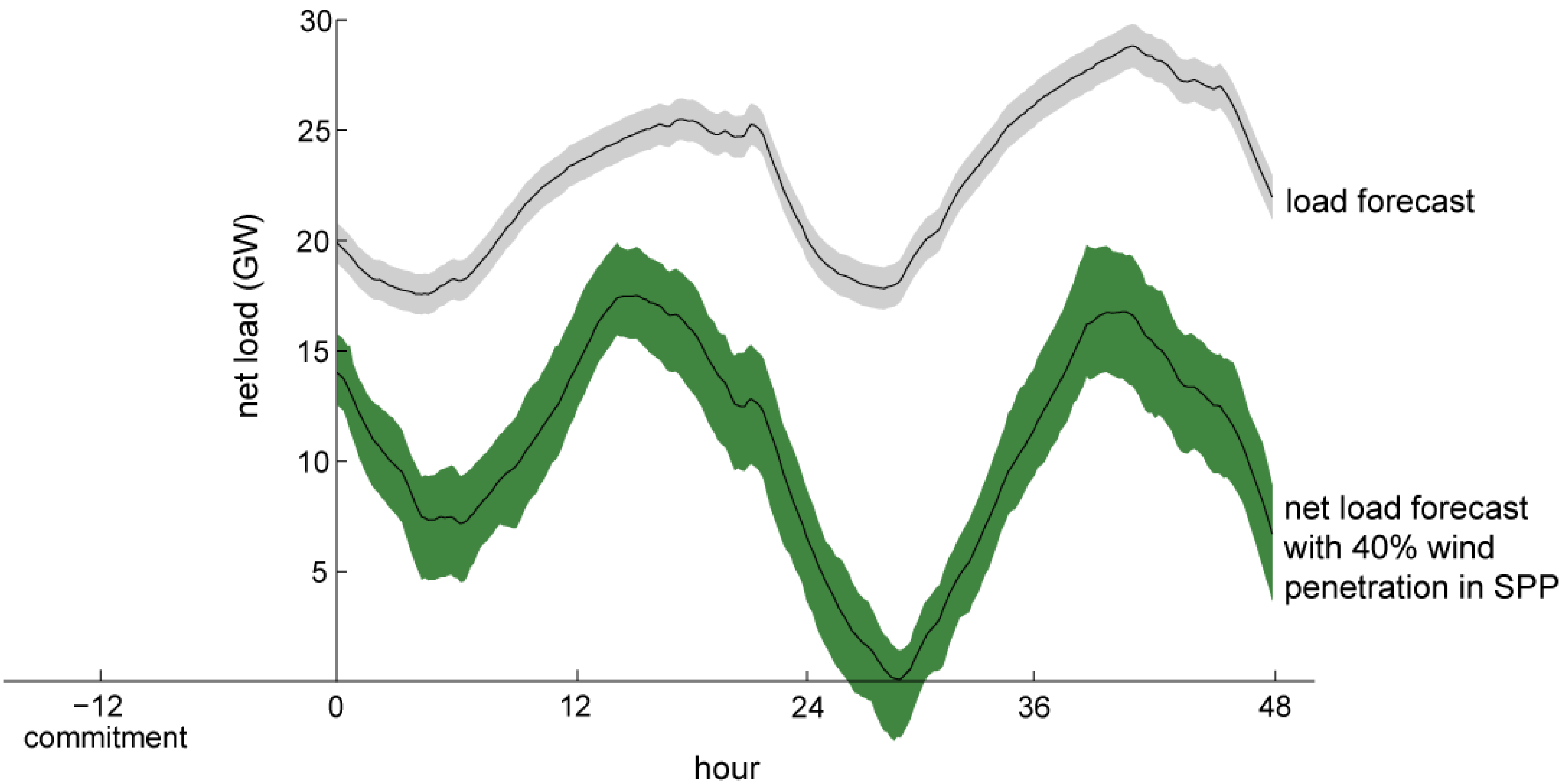
Outline

- Need of improved management of uncertainty in unit commitment
- Potential of stochastic unit commitment methods coupled with reserve requirements to address this need
- Simulation results
- Next steps

Evolution of Commercial Unit Commitment Methodology

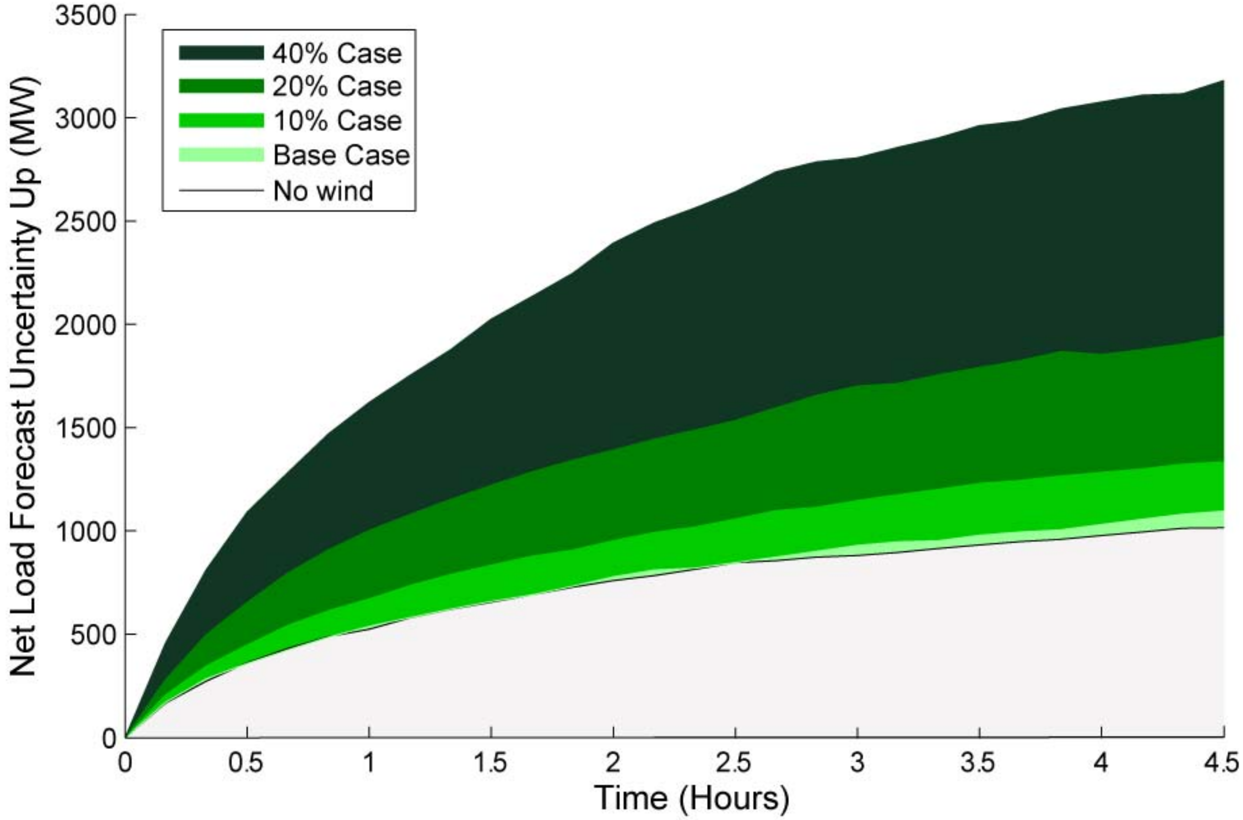


Uncertainty and Variability in Unit Commitment: Day-Ahead Forecast Error



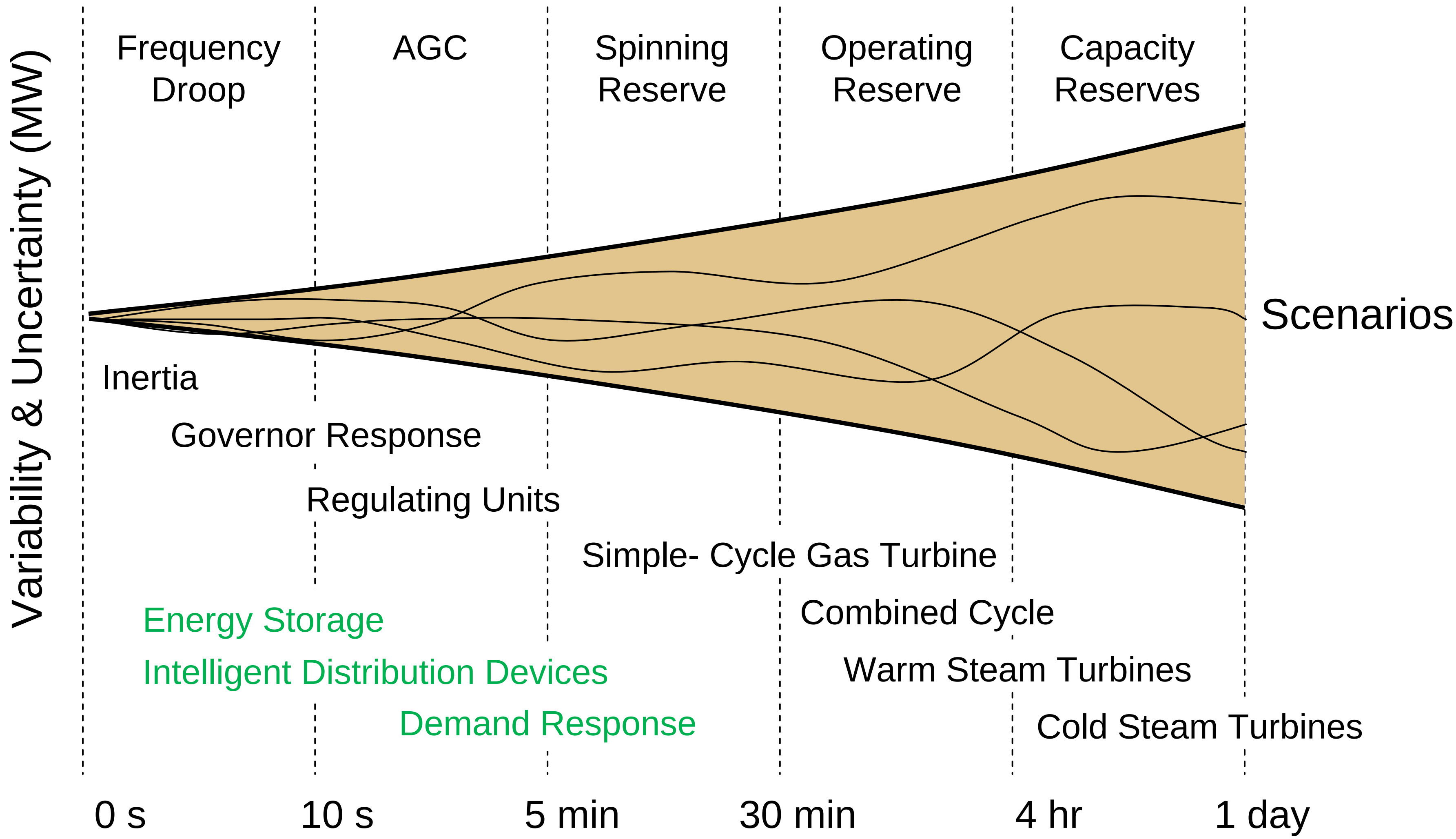
Data from the SPP Wind Integration Study
Error band shows percentiles 16 and 84

Uncertainty and Variability in System Operations: 4-Hour Ahead Forecast



The percentage case refers to the wind penetration level in the SPP system. Uncertainty Up measured using percentile 95. Only Load and wind uncertainty shown. Data from the SPP Wind Integration Study.

Available Resources Response Times



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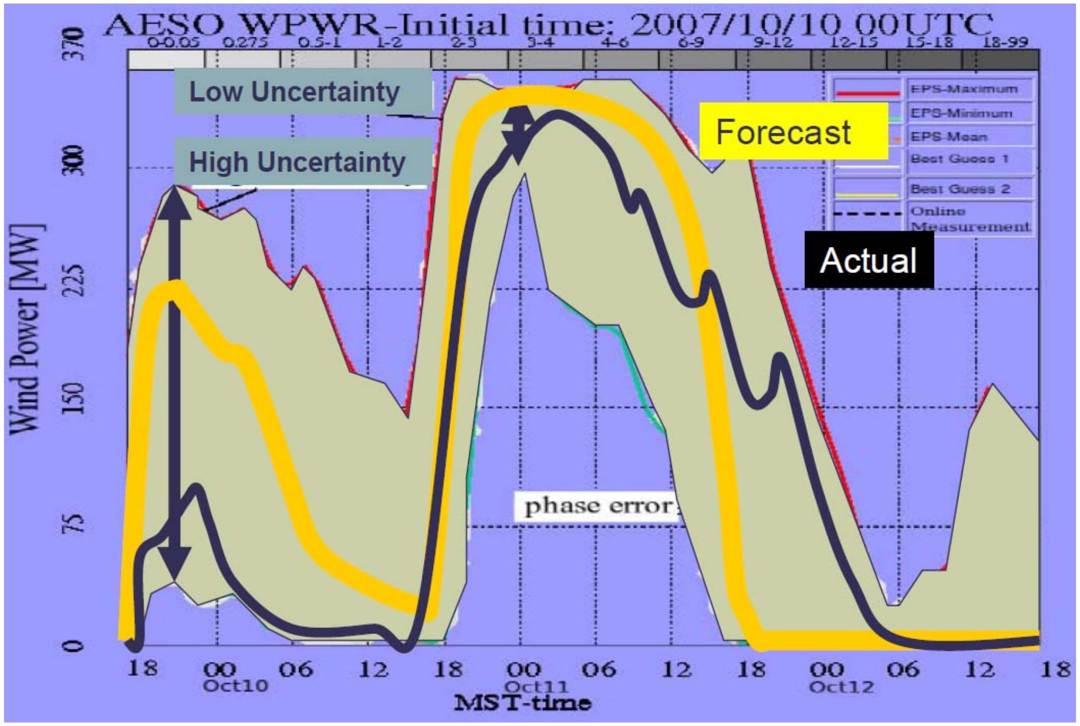
Approaches to Manage Variable Generation

- **Investment in Infrastructure**
  - Transmission, Generation, Storage, Demand
- **Tool Development**
  - Flexible and Robust Commitment
  - Topology control
  - Visualization
- **Market Organization**
  - Balancing Area consolidation
- **Market Design**
  - Intra-day commitment update
  - Frequent economic dispatch decision
- **Information Improvement**
  - Forecasts

Stochastic Methods

Managing Uncertainty in Unit Commitment

- **Forecasts are a best guess; must be prepared for deviations**
  - traditional: procure excess capacity
  - stochastic: consider multiple scenarios



AESO Forecast Uncertainty (c/o John Kehler, UWIG, 10/2/08)

Reserve Requirements

- **To provide for uncertainty, operators schedule units with total capacity in excess of forecasted load**
  – contingency reserve, spinning reserve, regulating reserve, etc.
- **Requirements are chosen to**
  – meet minimum reliability levels,
  – provide a trade-off between operating costs and risks
- **Requirements depend on**
  – load variability and uncertainty,
  – generation unreliability
- **The sources of uncertainty are not explicitly considered**

Stochastic Methods

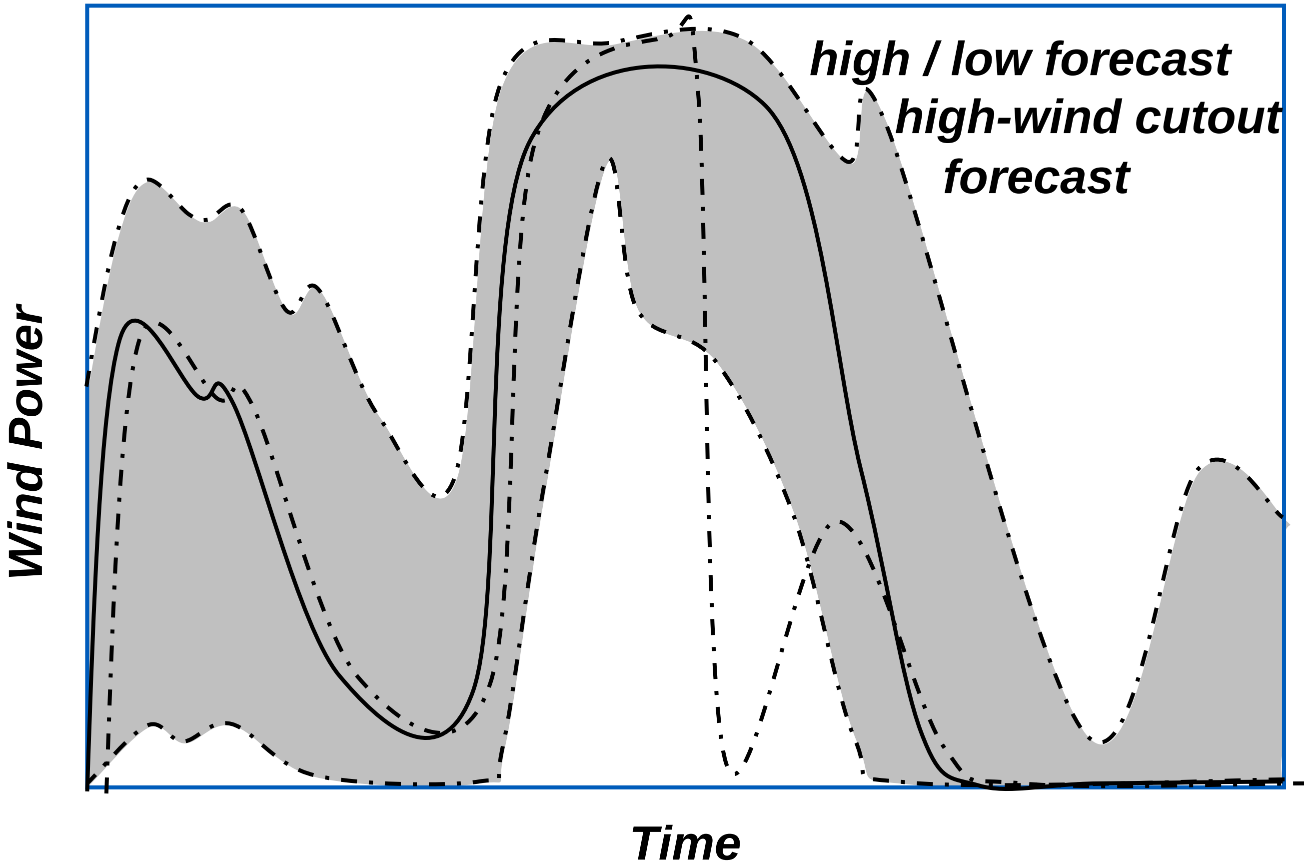
- **Stochastic methods allow the explicit modeling of the sources of uncertainty by considering multiple scenarios**
- **More efficient uncertainty management:**
  - selection of the right amount of capacity at the right time
  - selection of the most cost effective capacity
- **Stochastic methods are not fundamentally different from traditional methods**
  - both procure excess capacity, but stochastic methods rely less on heuristics (e.g., historical experience, operator judgment, etc).

Decisions in the Cloud

- **The goal is to help operators make decisions that:**
  - 1. are robust enough to handle all scenarios
  - 2. are as economically efficient as permitted by #1
- **What scenarios must operators consider? In general, we consider scenarios with:**
  - probability of occurrence above a minimum threshold
  - high impact (e.g., ramp events and high / low net load)
  - significant impact on expected operating costs
- **The "right" scenarios depend on system characteristics and the goals (i.e., reliability and cost).**

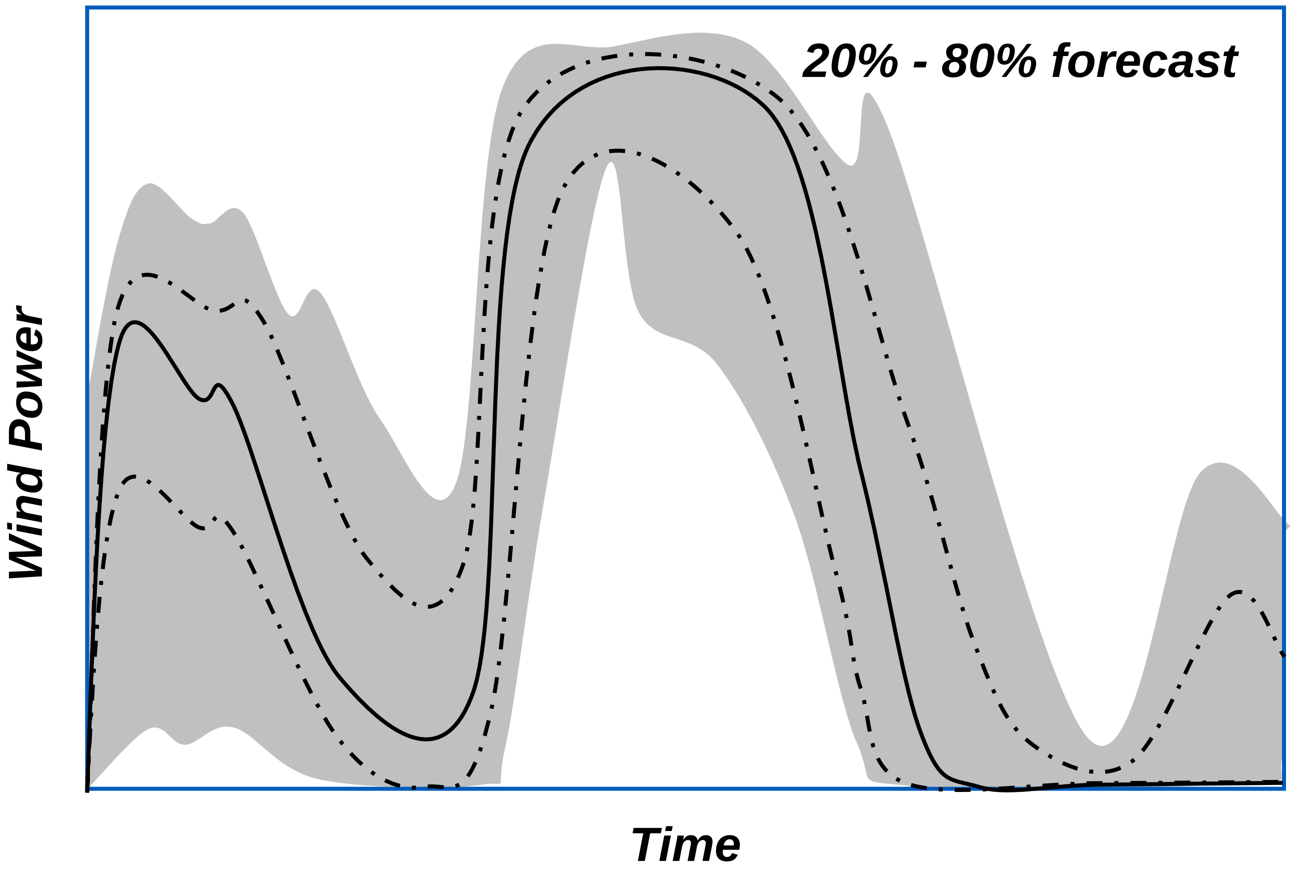
Selection of Scenarios for Reliability

- **Scenarios based on extreme events that impact reliability:**



Selection of Scenarios for Economic Efficiency

- **Scenarios based on likely events that have significant impact on operating costs:**



Stochastic Methods with Reserve Requirements

- **Mixed-integer stochastic programs are computationally expensive**
- **A large number of scenarios is needed to appropriately model all relevant sources of uncertainty**
- **Solution times usually increase with the number of scenarios**
- **Reserve requirements in stochastic formulations:**
  – recognize the limited representation of the uncertainty by scenarios
  – allows a reduction in the number of scenarios needed
  – enables a trade-off between solution performance and solution time

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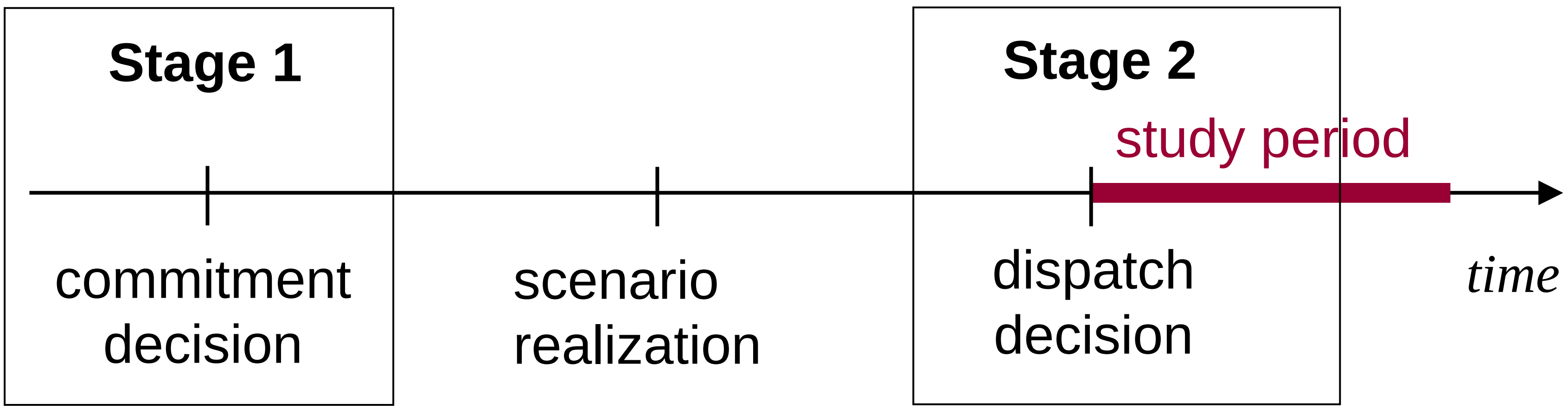
Stochastic Programming Formulation of the UC Problem

- **Two-stage decision:**



- **Reserve requirements are maintained**
- **Feasibility is guaranteed by allowing load shedding at a high cost**

Study Methodology

- **Solve model to identify day-ahead decisions under different policies:**
  - – traditional policy with a range of reserve requirements
  - – stochastic policy with reserves selectively enforced
  - – perfect-foresight with a range of reserve requirements
- **Generate random outcomes using models of wind, load, and outage uncertainty, and evaluate performance of each policy in forward simulations**
- **Perfect-foresight policy gives lower-bound on costs**

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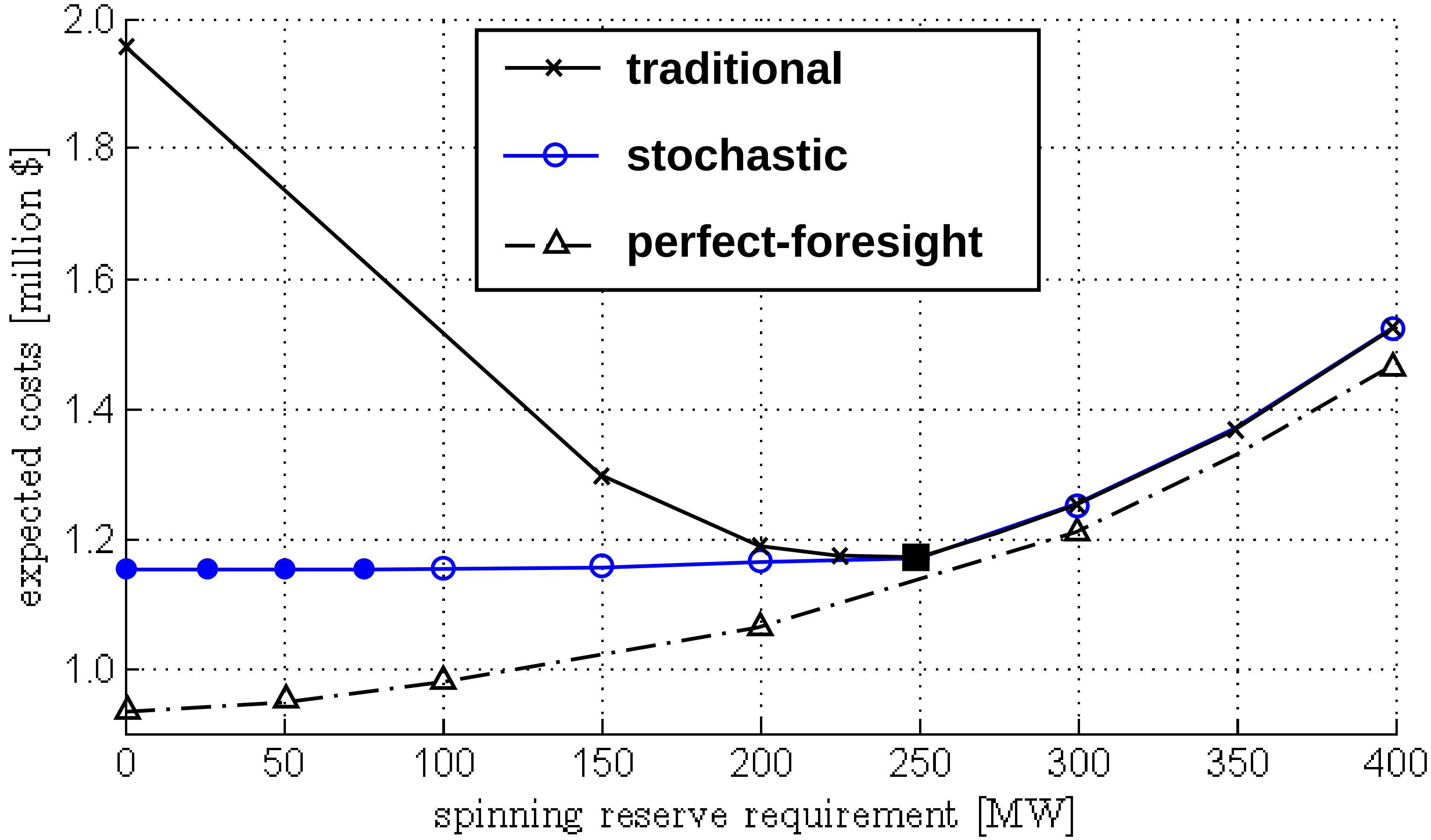
Impacts of Generation Unreliability (IEEE RTS-96)



Generation + Load Uncertainty (IEEE RTS-96)

formulation	traditional (deterministic)	stochastic
number of scenarios	1	12: 4 gen x 3 load
spinning reserve requirement	250 [MW]	10 [MW]
committed spinning reserve	250 [MW]	168 [MW]
expected costs	$1,437,900	$1,418,900
cost standard deviation	$934,000	$717,100
savings w.r.t. deterministic	--	1.32%
expected unserved energy	54 [MWh]	27 [MWh]

Selected Simulation Studies: PSCo Test System

- **Historical PSCo data, January to November of 2004:**
  - day-ahead hourly load forecast
  - hourly load realization
  - day-ahead wind power forecast, every 3 hours
  - wind power realization, every 3 hours
  - fuel costs
  - generation characteristics, maintenance and forced outage sched.
- **Wind power scaled to account for expected expansions**
- **60 generators, amounting to 9390 MW:**
  - 33% coal, 25% CT (11% fast-start), 23% CC, 15% wind, 4% pumped storage
- **6922 MW peak load**

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PSCo Test System Data Limitations

- Wind power scaled to account for expected wind capacity expansions (i.e., no diversity impact)
- Stochastic models developed for wind and load using limited data
- Load-shedding modeled using expensive virtual generator ($2000 / MWh)
- Simplified generator models (e.g., combined-cycle)
- No transmission constraints

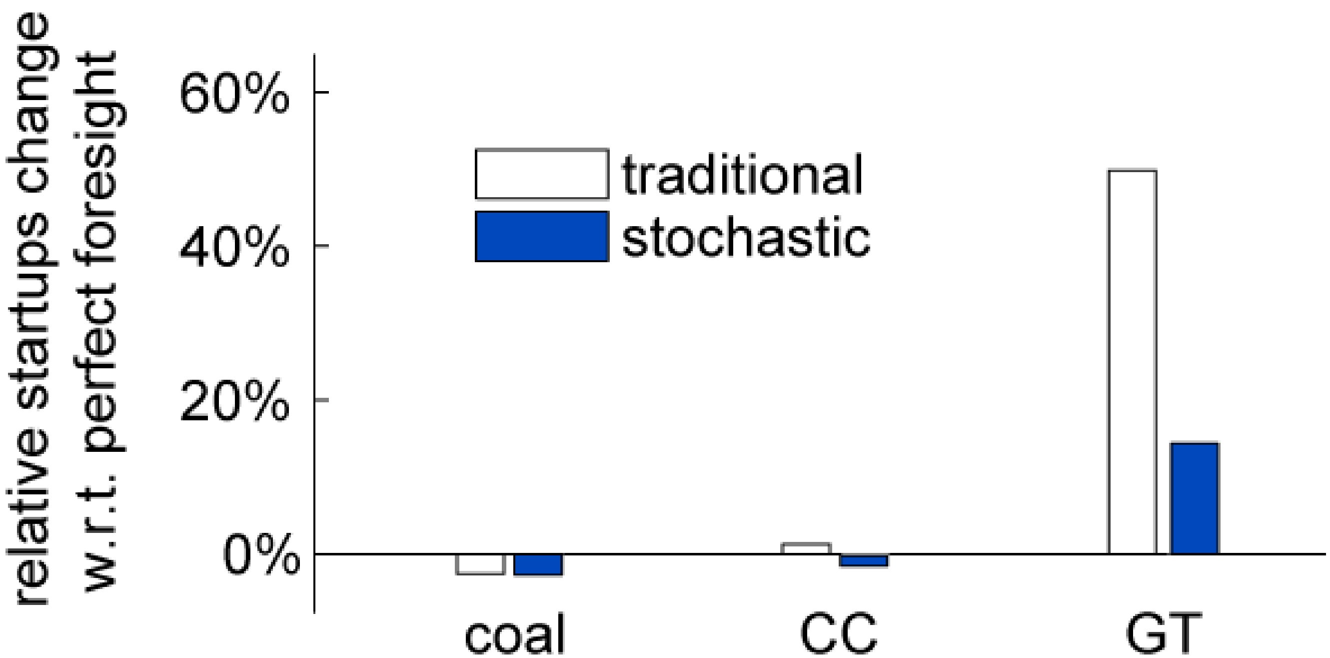
Policies Performance

policy	perfect foresight	traditional (nominal)	traditional (optimal)	stochastic
no. of scenarios	1	1	1	6
spin reserve req [MW]	0	182	145.6	109.2
expected costs [$$10^6$]	641.0	652.3	651.3	650.8
cost std dev [$$10^6$]	4.6	4.7	4.4	4.9
savings w.r.t. trad (n)	1.70%	--	0.15%	0.23%
exp marg cost [$/MWh]	38.4	37.7	38.5	43.9
marg cost std dev [$/MWh]	15.4	36.8	36.2	11.2
exp curt wind [MWh]	3500	7300	1100	41
exp curt wind hours	25 h	58 h	27 h	21 h
computational time [s]	~20*	43*	33*	100†

* with 3.2-GHz Pentium 4 processor

† with 2-GHz Intel Core 2 Duo processor

Policy Impacts: Number of Startups



Stochastic methods make more efficient use of available flexibility

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Observations from Simulation Results

- **Combining scenarios with a proper amount of reserve requirements leads to robust solutions**
- **Solution robustness leads to reduced expected costs, and usually to reduced cost variance and increased reliability**
- **Improvements come from having more flexible commitments**
  - units with higher ramp limits, lower minimum up and down times and lower economic minimum capacity are weighted more favorably with stochastic formulations than with deterministic formulations
- **Stochastic policies are especially effective in systems with high uncertainty and with a limited number of flexible units**

Observations from Simulation Results

- Average marginal costs can be higher with stochastic policies, but their standard deviations are usually lower
- Stochastic policies attain lower wind curtailments than traditional policies or even the perfect foresight policy
- There is a sizable range of parameters that leads to improved solutions over the optimal deterministic policy
- Solution times can be currently reduced to a manageable magnitude for small/medium systems with adequate modeling, solution techniques and computational power

Concluding Remarks

- Improved uncertainty management is required for large-scale integration of variable generation
- Stochastic methods are one of the key tools to manage uncertainty in the unit commitment timeframe
- Stochastic models enable the full use of forecasting and available flexibility in the system
- Stochastic unit commitment solutions can yield flexible, robust and efficient schedules

Next Steps

- **Policy and Economics: development of pricing rules and analysis of impacts of stochastic formulations**
- **Planning: evaluate the impact that stochastic unit commitment has to reduce infrastructure requirement needs and costs**
- **Algorithms and Modeling: research on the selection of reserve requirements in stochastic formulations and reduction of computational times**
- **Implementation: test stochastic unit commitment policies on a detailed model of a real system**

Selected Reports

1. **P. A. Ruiz, C. R. Philbrick, E. Zak, K. W. Cheung, and P. W. Sauer, "*Uncertainty management in the unit commitment problem*," *IEEE Trans. Power Syst*ems, vol. 24, no. 2, May 2009, pp. 642 – 651.**

2. **P. A. Ruiz, C. R. Philbrick and P. W. Sauer, "*Modeling approaches for computational cost reduction in stochastic unit commitment formulations*," *IEEE Trans. Power Syst*ems, vol. 25, no. 1, Feb 2010, pp. 588 – 589.**

3. **P. A. Ruiz, C. R. Philbrick and P. W. Sauer, "*Wind power day-ahead uncertainty management through stochastic unit commitment policies*," *in Proc. 2009 IEEE Power Syst Conf and Expo*, Seattle, WA, March 2009.**

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