Probabilistic Wind Power Forecasting in Electricity Market Operations: a Case Study of Illinois

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Project website: http://www.dis.anl.gov/projects/windpowerforecasting.html

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Outline

- **Background and Motivation**

- **Wind power forecasting**
  - Probabilistic density forecasting
  - Scenario generation reduction

- **System operation with wind power uncertainty**
  - Two-settlement market
  - Stochastic unit commitment

- **Test Case**
  - IL Power System
  - System operation analysis

- **Conclusion and future work**

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Project Overview:
Wind Power Forecasting and Electricity Markets

Goal: To contribute to efficient large-scale integration of wind power by developing improved wind forecasting methods and better integration of advanced wind power forecasts into system and plant operations.

Collaborators: Institute for Systems and Computer Engineering of Porto (INESC Porto), Portugal

Industry Partners: Horizon Wind Energy and Midwest ISO (MISO)

Sponsor: U.S. Dept. of Energy (Wind and Water Power Program)

The project consists of two main parts:

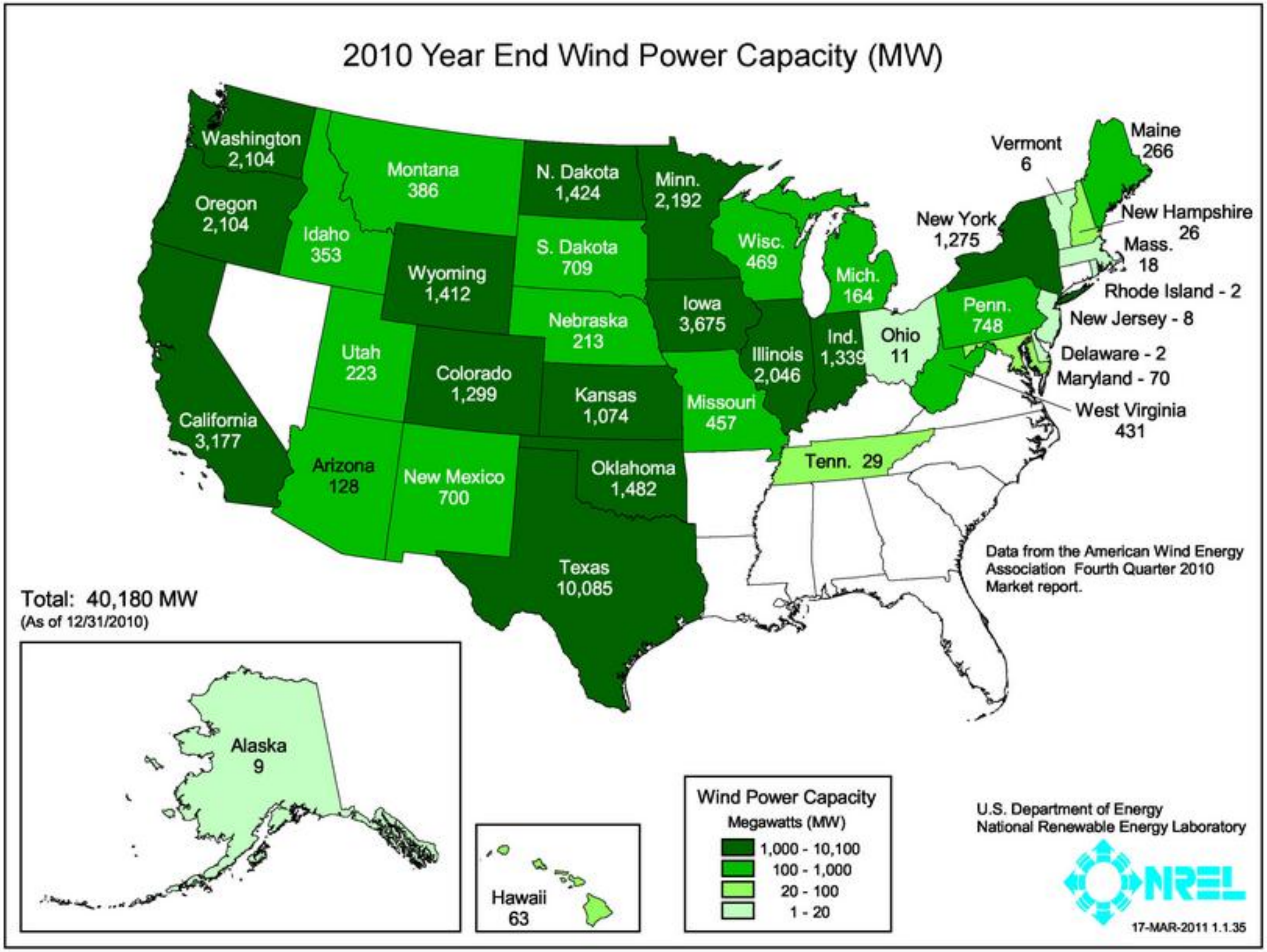
- Wind power forecasting
  - Review and assess existing methodologies
  - Develop and test new and improved algorithms

- Integration of forecasts into operations (power system and wind power plants)
  - Review and assess current practices
  - Propose and test new and improved approaches, methods and criteria

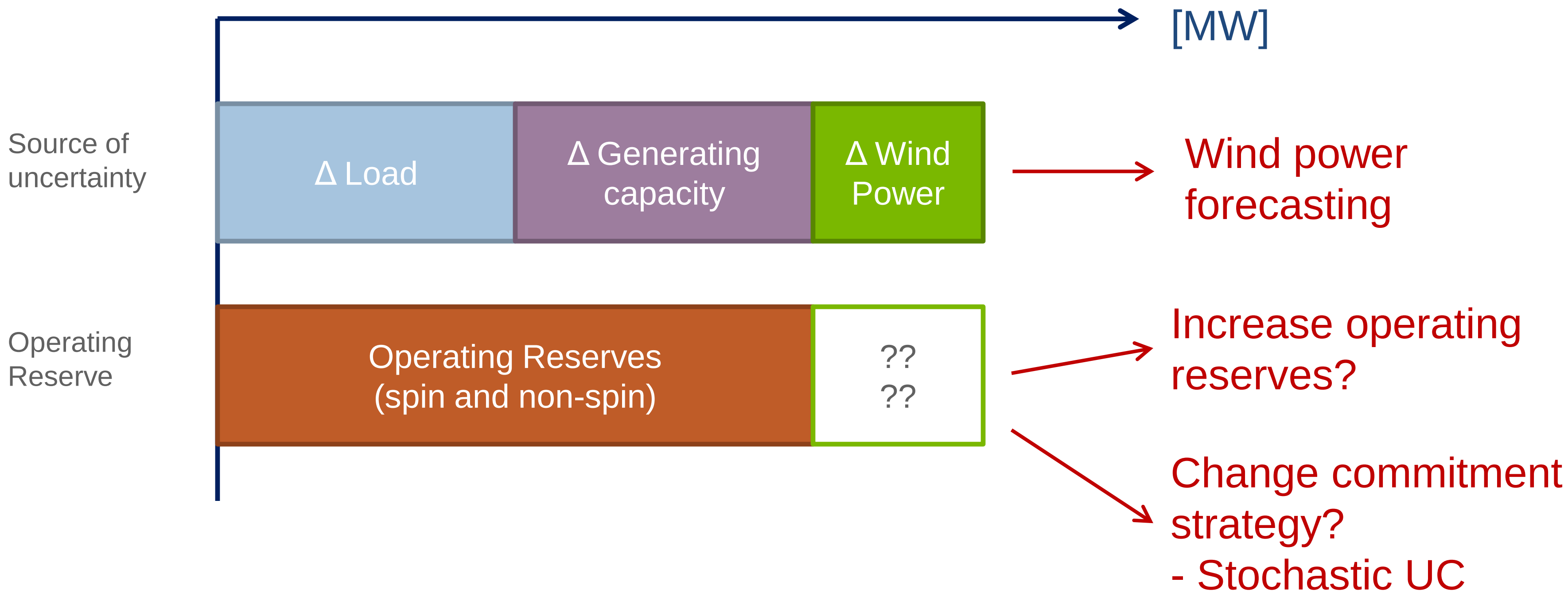
http://www.dis.anl.gov/projects/windpowerforecasting.html

Background and Motivation – U.S. Wind Power Capacity

- Wind power has been rapidly integrated into the current power systems



Background and Motivation - Handling Uncertainties in System/Market Operation



- *What are the impacts on the system?*
  - *Reliability (curtailment,..)*
  - *Efficiency (system cost, price..)*

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Probabilistic forecasting with kernel density estimation

- Conditional wind power probabilistic forecasting

$$f_P\left(p_{t+k} \mid X = x_{t+k|t}\right) = \frac{f_{P,X}\left(p_{t+k}, x_{t+k|t}\right)}{f_X\left(x_{t+k|t}\right)}$$

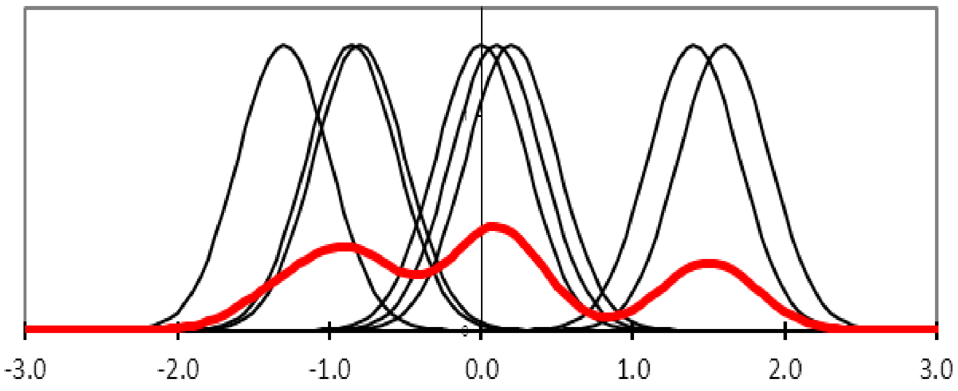
Joint or multivariate density function of *p* and *x*

Marginal density of *x*

- Kernel density estimation (KDE)

$$\hat{f}_X(x) = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{1}{h_i} \cdot K\left(\frac{x - X_i}{h}\right)$$

$$K(x) = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{1}{\sqrt{2\pi}} \cdot e^{-\frac{(x-X_i)^2}{2 \cdot h^2}}$$



Quantile-Copula Estimator for Conditional KDE

Copula Definition

$$F_{XY}(x,y) = C(F_X(x), F_Y(y))$$

multivariate distribution function separated in:
- marginal functions
- dependency structure between the marginal, modeled by the copula

copula density function

$$f(x,y) = \frac{\partial^2}{\partial u \cdot \partial v} \cdot C(u,v) = f_X(x) \cdot f_Y(y) \cdot c(u,v)$$

$$f(y|X=x) = \frac{f_X(x) \cdot f_Y(y) \cdot c(u,v)}{f_X(x)} = f_Y(y) \cdot c(u,v)$$

KDE ESTIMATOR

$$\hat{c}(u,v) = \frac{1}{N}\sum_{i=1}^{N} K\left(\frac{u-U_i}{h_u}\right) \cdot K\left(\frac{v-V_i}{h_v}\right)$$

KDE ESTIMATOR

$$\hat{f}_Y(y) = \frac{1}{N} \cdot \sum_{i=1}^{N} \frac{1}{h_i} \cdot K\left(\frac{y-Y}{h_y}\right)$$

empirical cum. dist.

$U_i = F_X^e(X_i)$ and $V_i = F_Y^e(Y_i)$

$$F^E(t) = \frac{1}{N} \cdot \sum_{i=1}^{N} I(x_i \le t)$$

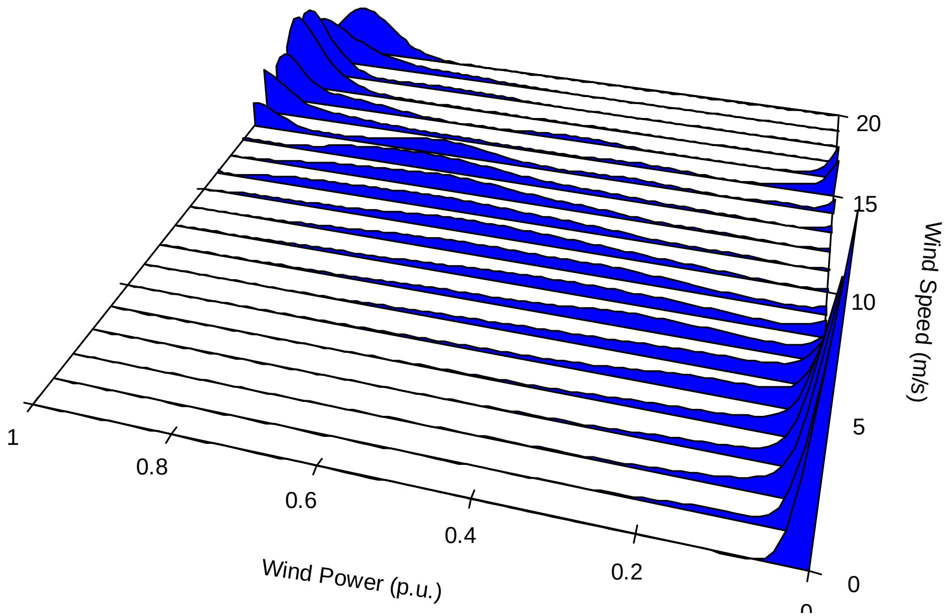
$$\hat{f}(y|X=x) = \frac{1}{N \cdot h_y} \cdot \sum_{i=1}^{N} K_y\left(\frac{y-Y_i}{h_y}\right) \cdot \frac{1}{N} \cdot \sum_{i=1}^{N} K_u\left(\frac{F_X^e(u) - F_X^e(U_i)}{h_u}\right) \cdot K_v\left(\frac{F_X^e(v) - F_X^e(V_i)}{h_v}\right)$$

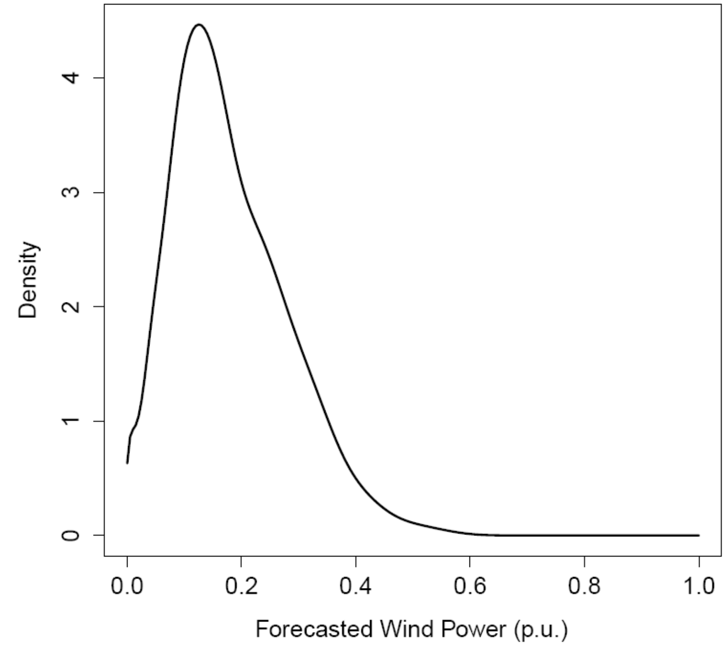
R. Bessa, et. al. “Quantile-copula density forecast for wind power uncertainty modeling,” Proceedings IEEE Trondheim PowerTech 2011, Trondheim Norway, 2011.

Illustration of Kernel Density Forecast

Forecast the wind power pdf at time step t for each look-ahead time step t+k of a given time-horizon knowing a set of explanatory variables (NWP forecasts, wind power measured values, hour of the day)

$$\hat{f}_P\left(p_{t+k} \middle| X = x_{t+k|t}\right) = \frac{f_{P,X}\left(p_{t+k}, x_{t+k|t}\right)}{f_X\left(x_{t+k|t}\right)}$$





Scenario Generation and Reduction

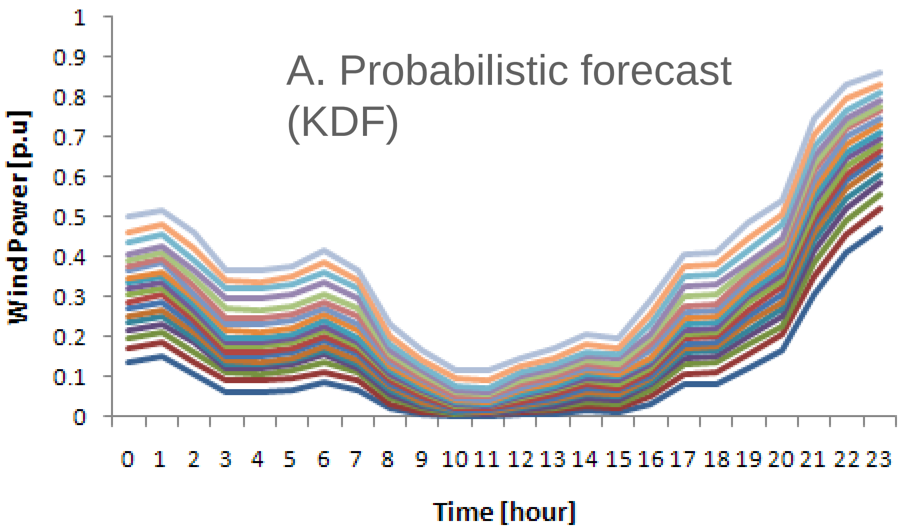
- Kernel Density Forecast (KDF) methods (e.g. Quantile-copula in the IL case study) produce *pdf* forecasts of the wind power generation

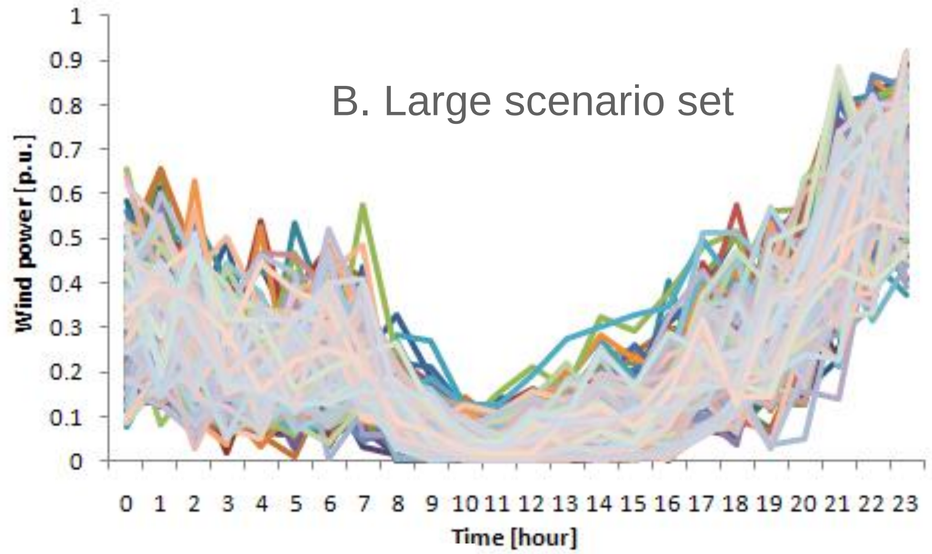
- Stochastic unit commitment model requires scenario representation of wind power forecast → **account for the temporal correlation of forecast errors**

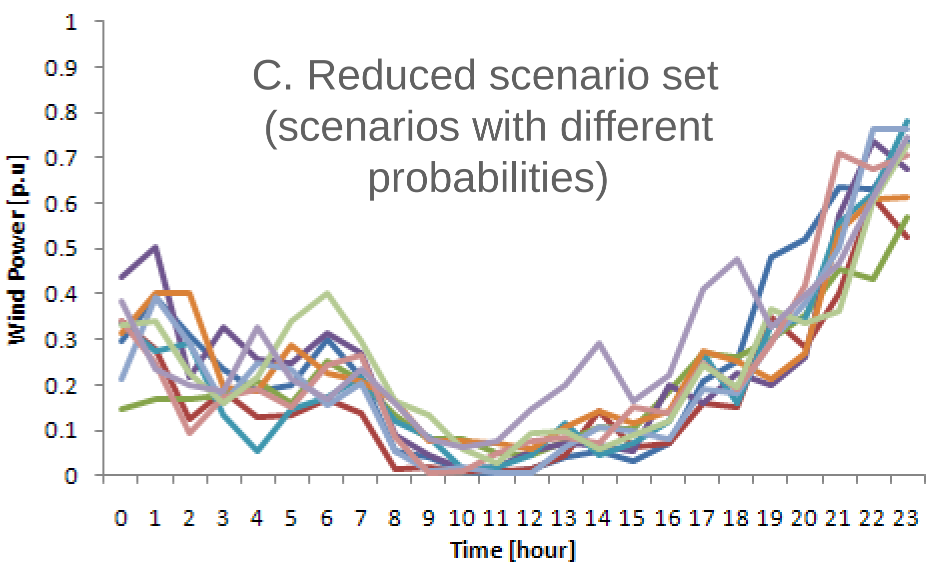
- A large number of scenarios generated with Monte-Carlo simulation based on quantile distribution (multivariate Gaussian error variable, covariance matrix) [Pinson et al. 09]

- Three scenario reduction methods
  - Random selection
  - Scenario reduction method in GAMS [Gröwe-Kuska, Heitsch, et. al, 2003] (used in the IL case study)
  - Scenario clustering approach [Sumaili et al. 2011]

Scenario Generation and Reduction - Illustration

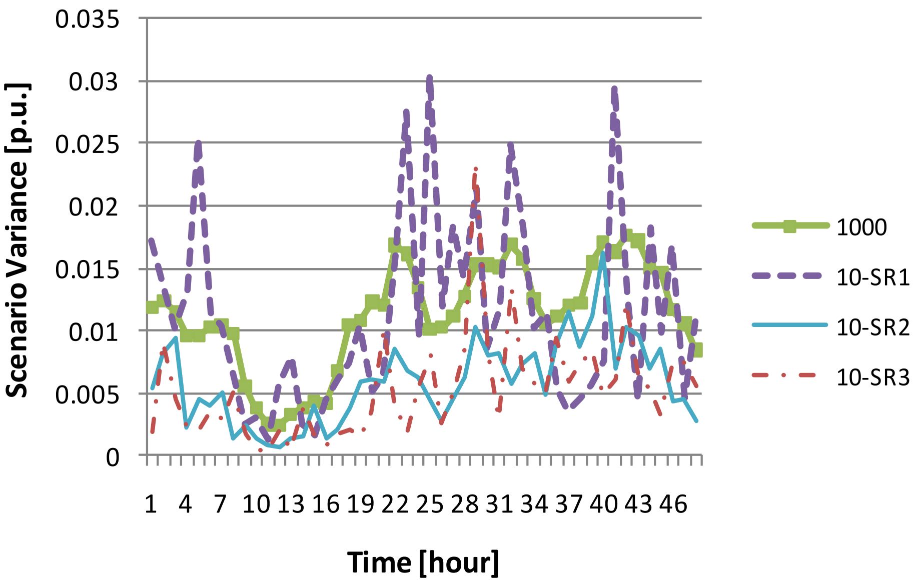




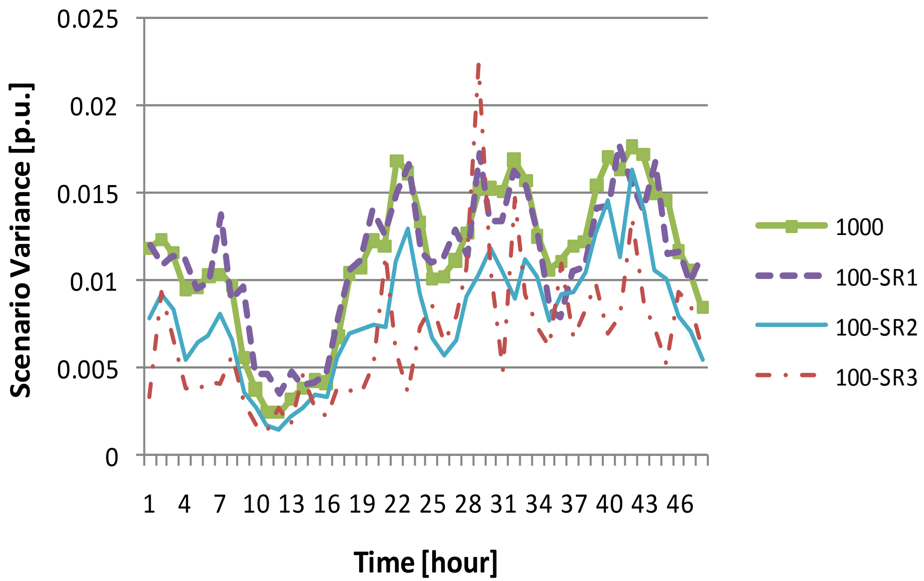


Scenario Reduction Reduces Variance of Scenario Set

10 reduced scenarios:



100 reduced scenarios



SR1 - Random selection
SR2 - ScenRed GAMS
SR3 - Scenario clustering

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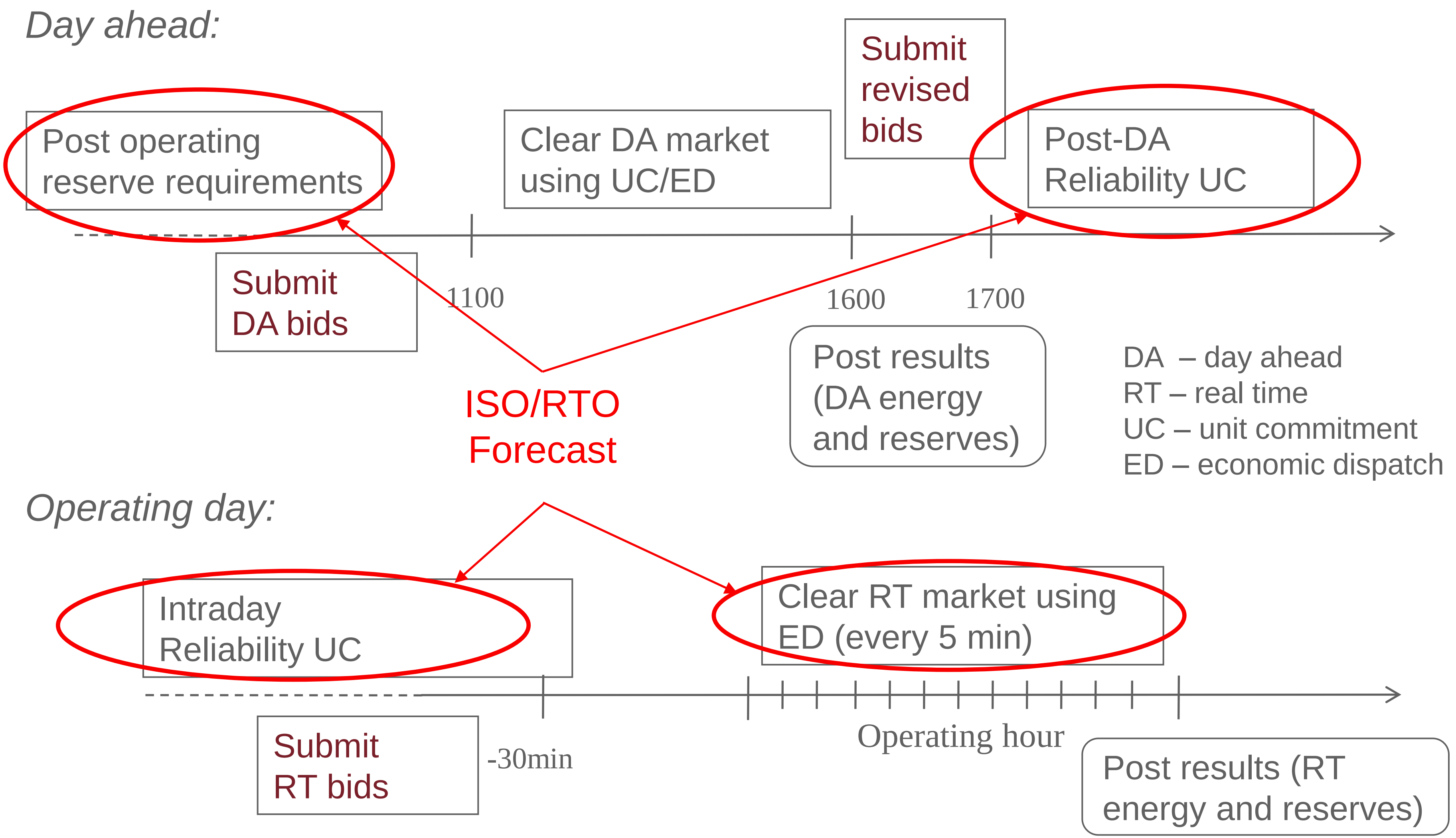
Steps in U.S. Electricity Market Operations
(based on Midwest ISO)



DA – day ahead
RT – real time
UC – unit commitment
ED – economic dispatch

A Stochastic Unit Commitment (UC) Model w/Wind Power Uncertainty

- Formulation using wind power forecast scenarios (s) w/probabilities ($prob_s$):

$$Min \sum_{s} prob_s \cdot \left\{ \sum_{t,i} \left[FC_{t,i}^{s} + C(RNS_t^s) + C(ENS_t^s) \right] \right\} + \sum_{t,i} SC_{t,i}$$

Objective function (min daily expected cost)

$$\sum_i gen_{thermal,i,t}^{s} + gen_{wind,t}^{s} = load_t - ENS_t^s, \quad \forall\, t, s$$

Energy balance (hourly)

$$\sum_{i} sr_{thermal,i,t}^{s} \geq \alpha_{sr} \left(OR_{reg,t} + OR_{wind,t}^{s} \right) - SRNS_t^s, \forall\, t, s$$

Spinning Reserve balance (hourly)

$$\sum_{i} nsr_{thermal,i,t}^{s} \geq (1 - \alpha_{sr}) \left(OR_{reg,t} + OR_{wind,t}^{s} \right) - NSRNS_t^s, \forall\, t, s$$

Non-spinning Reserve balance (hourly)

$$Commitment\ Constraints\ (i, t)$$

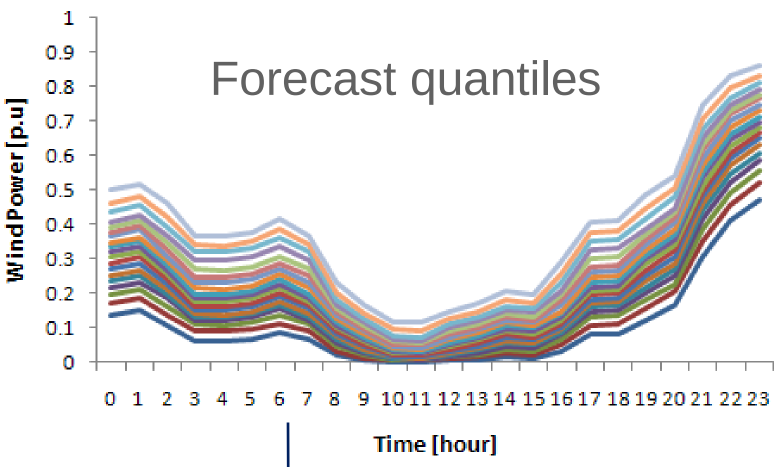
Unit commitment constraints (ramp, min. up/down)

- A two-stage stochastic mixed integer linear programming (MILP) problem
  - First-stage: commitment
  - Second-stage: dispatch

Wang J, Botterud A, Bessa R, Keko H, Carvalho L, Issicaba D, Sumaili J, and Miranda V, Wind power forecasting uncertainty and unit commitment, Applied Energy, in press, 2011.

Z. Zhou, A. Botterud, J. Wang, R.J. Bessa, H. Keko, J. Sumaili, V. Miranda, “Application of Probabilistic Wind Power Forecasting in Electricity Markets”, submitted

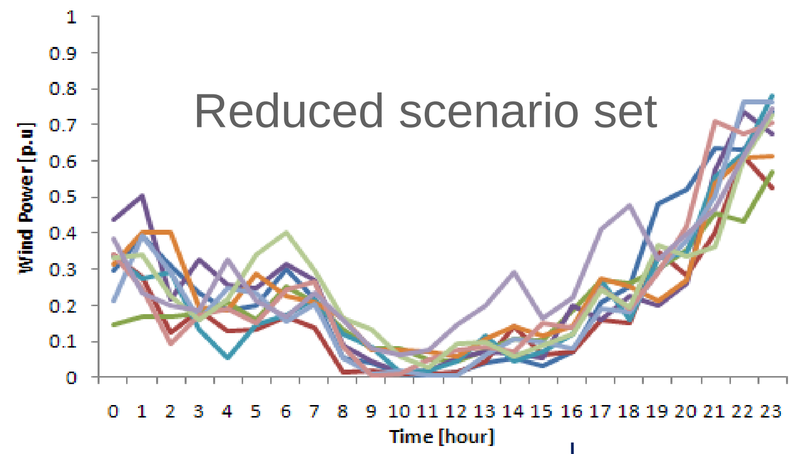
Operating Reserves vs. Stochastic UC



Hourly operating reserve requirement (spinning + non-spinning) + Deterministic UC

Commitment schedule

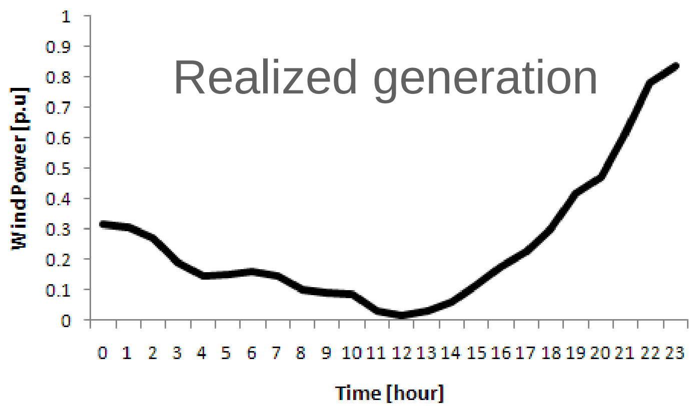
Real-time dispatch



Stochastic UC + scenario set

Commitment schedule

Real-time dispatch



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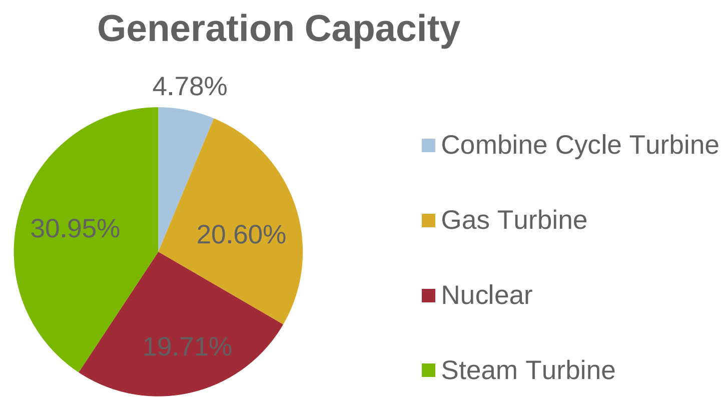
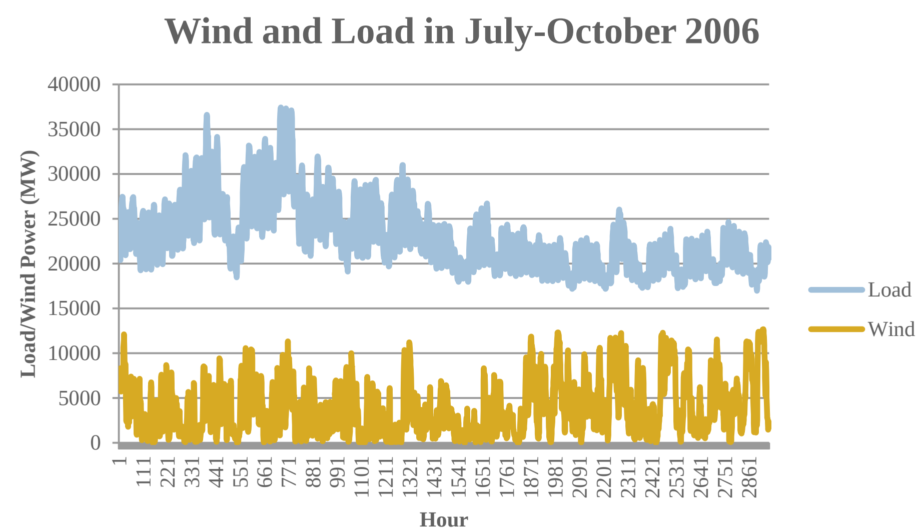
Case Study Assumptions

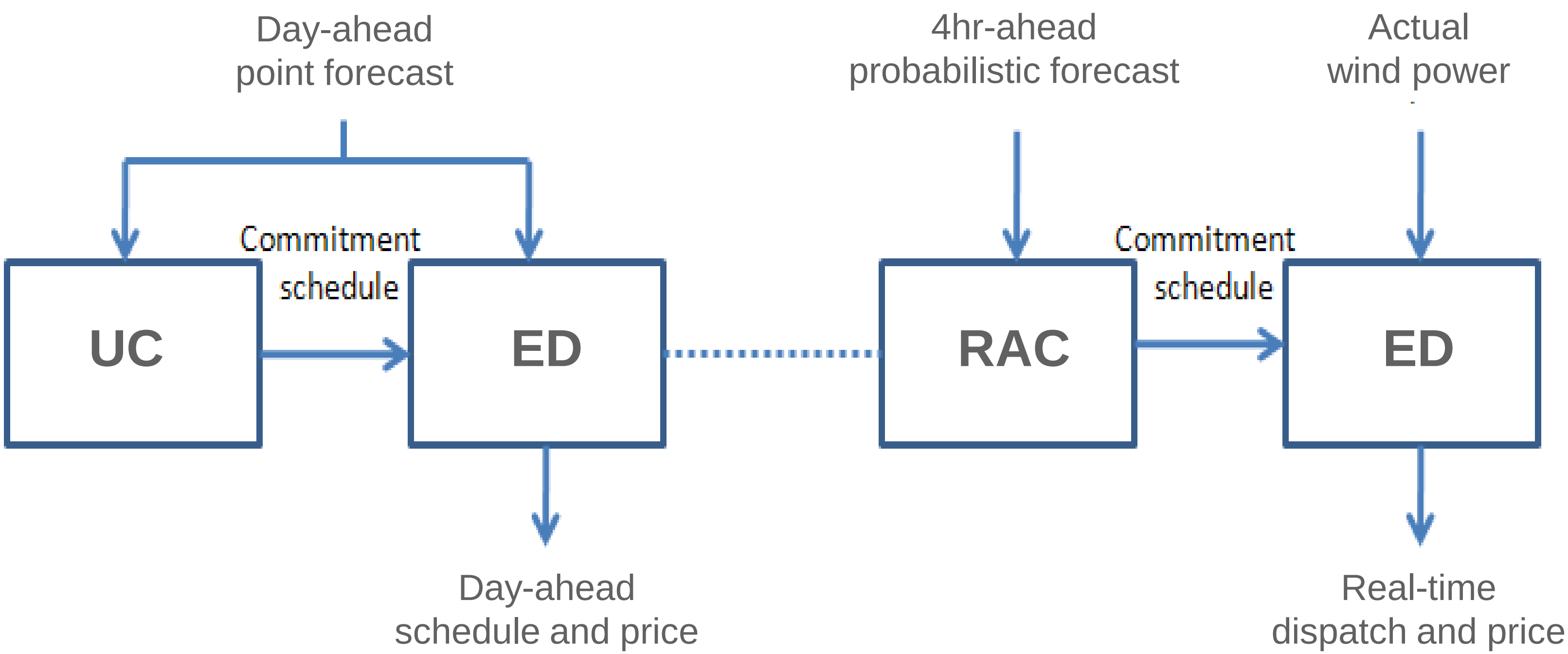
- 210 thermal units: 41,380 MW
  - Base, intermediate, peak units
- Wind power: 14,000 MW
  - 2006 wind series from 15 sites in Illinois (NREL EWITS dataset)
  - 20% of load
- Peak load: 37,419 MW
  - 2006 load series from Illinois
- No transmission network
- 120 days simulation period (July 1st to October 31st, 2006)
  - Day-ahead unit commitment w/wind power point forecast
  - Real-time reliability assessment commitment (RAC) w/ wind power scenarios





Case study focus is to compare:
-Operating reserves vs. stochastic UC
-Probabilistic forecasting methods

Market Simulation Set-Up

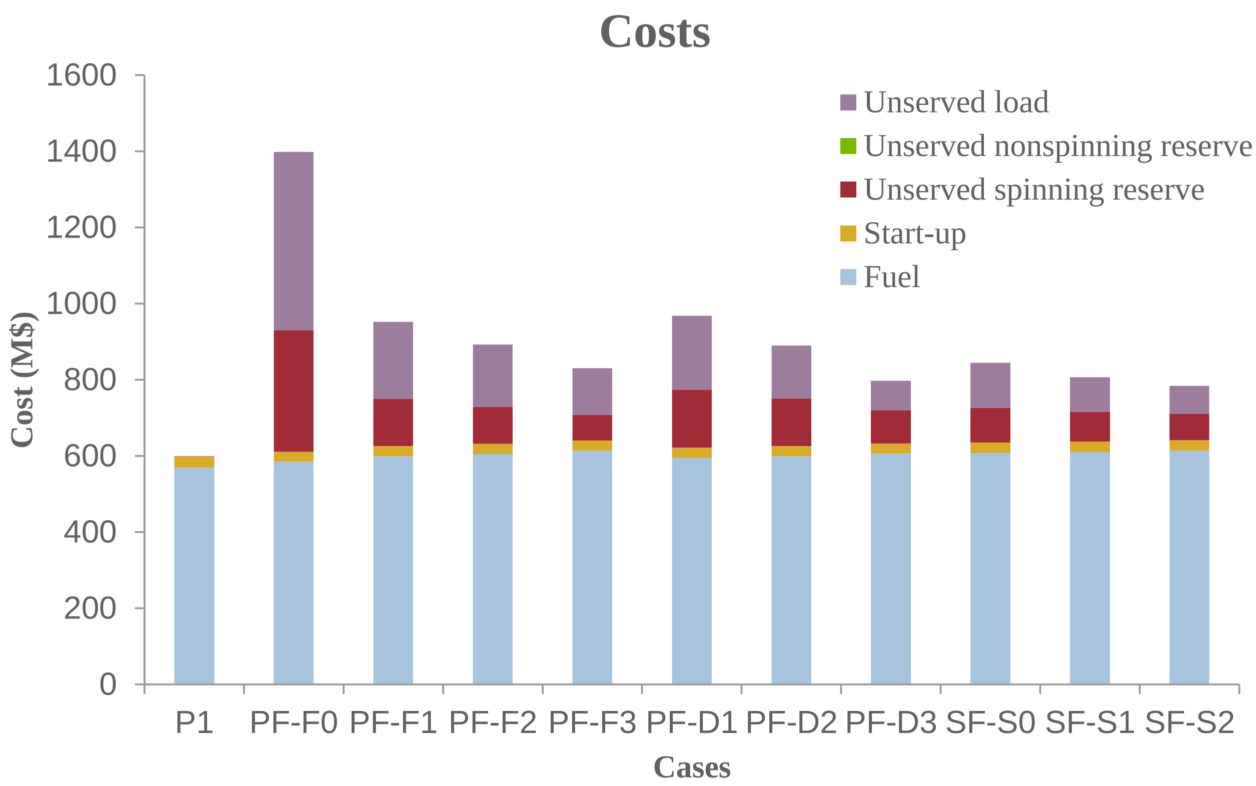


UC Case Study: Deterministic and Stochastic Cases

Case	Add'l Reserve: $OR_{wind,t}$*	Forecast	UC strategy at RAC stage
P1	None	Perfect in both DA and RT	Deterministic
PF-F0	None	50% quantile	Deterministic
PF-F1	Fixed: avg. 50-10% quantile	50% quantile	Deterministic
PF-F2	Fixed: avg. 50-5% quantile	50% quantile	Deterministic
PF-F3	Fixed: avg. 50-1% quantile	50% quantile	Deterministic
PF-D1	Dynamic: 50-10% quantile	50% quantile	Deterministic
PF-D2	Dynamic: 50-5% quantile	50% quantile	Deterministic
PF-D3	Dynamic: 50-1% quantile	50% quantile	Deterministic
SF-S0	None	10 Scenarios	Stochastic
SF-S1	10% of wind scenario	10 Scenarios	Stochastic
SF-S2	20% of wind scenario	10 Scenarios	Stochastic

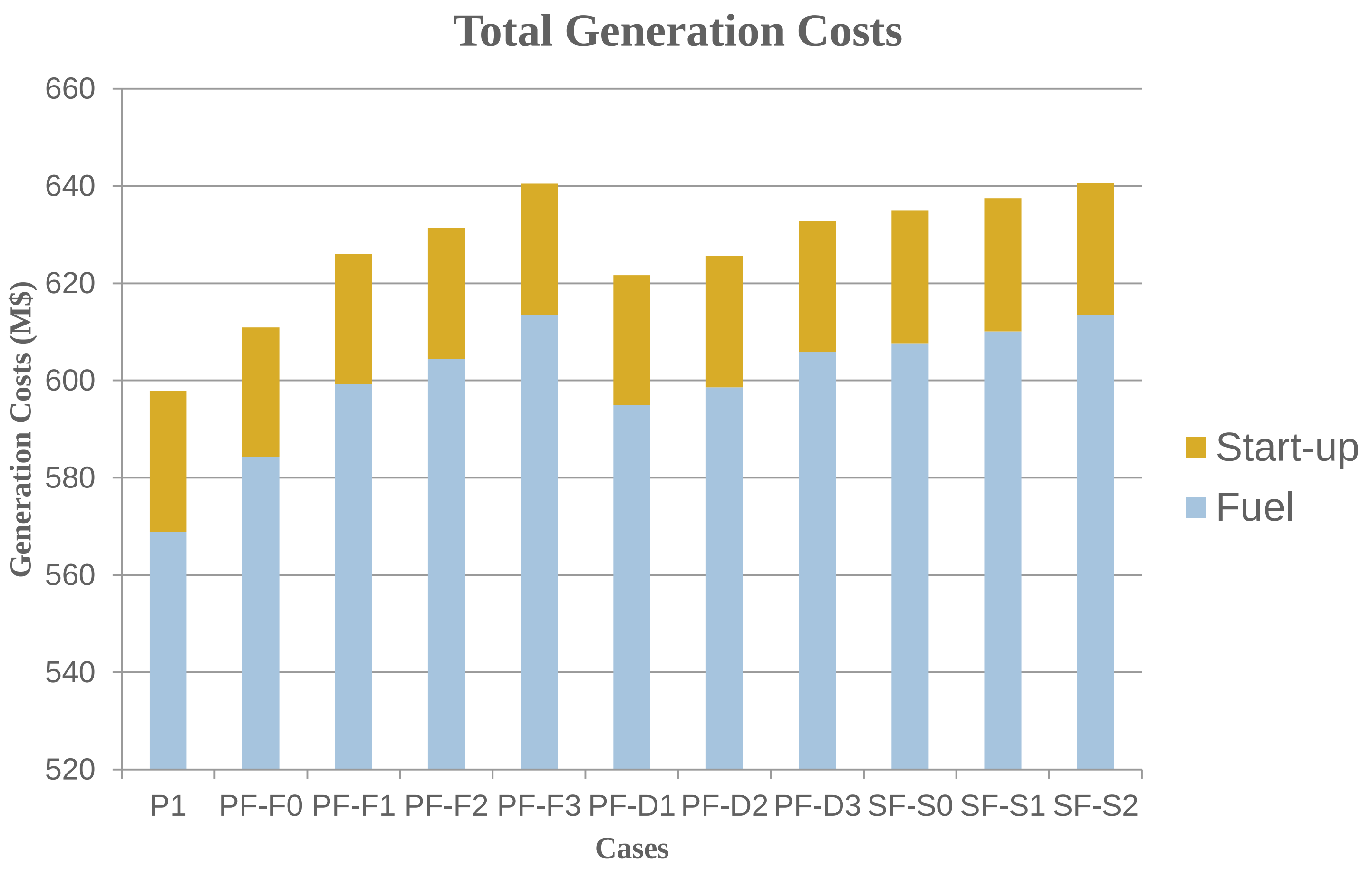
* This additional reserve is applied at the RAC stage only to handle wind power uncertainty. All cases use a regular reserve, $OR_{reg,t}$, equal to the largest contingency (1146 MW).

Overview of total cost (4-months period)



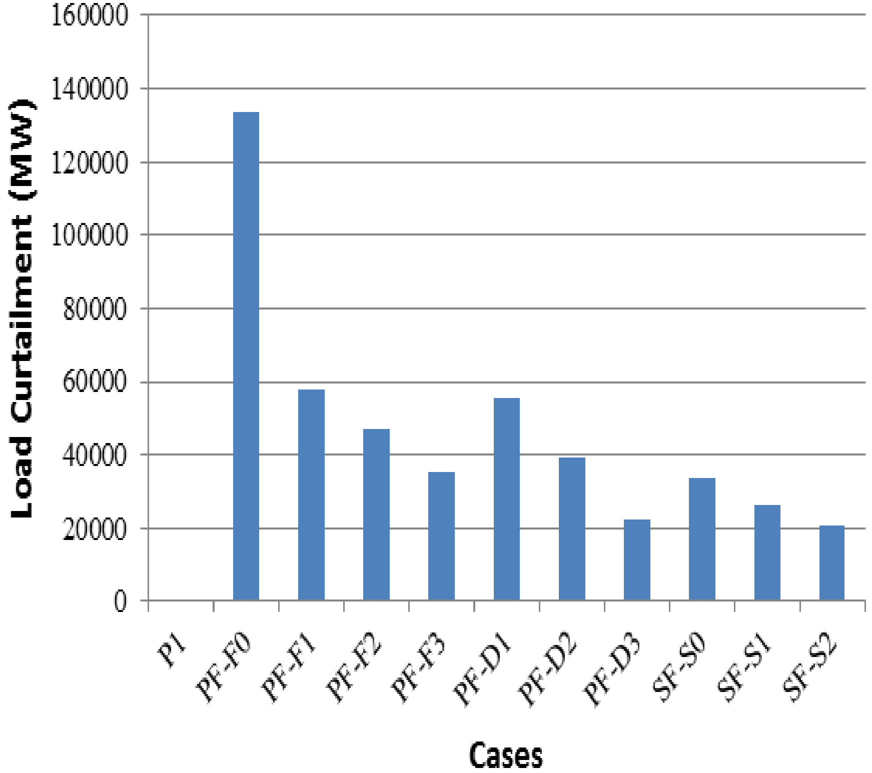
- Point forecast with no additional reserve too risky
- Stochastic unit commitment has the lowest total costs
- Dynamic reserves perform slightly better than fixed reserves
- Overall, more operating reserves lead to lower costs within the same categories

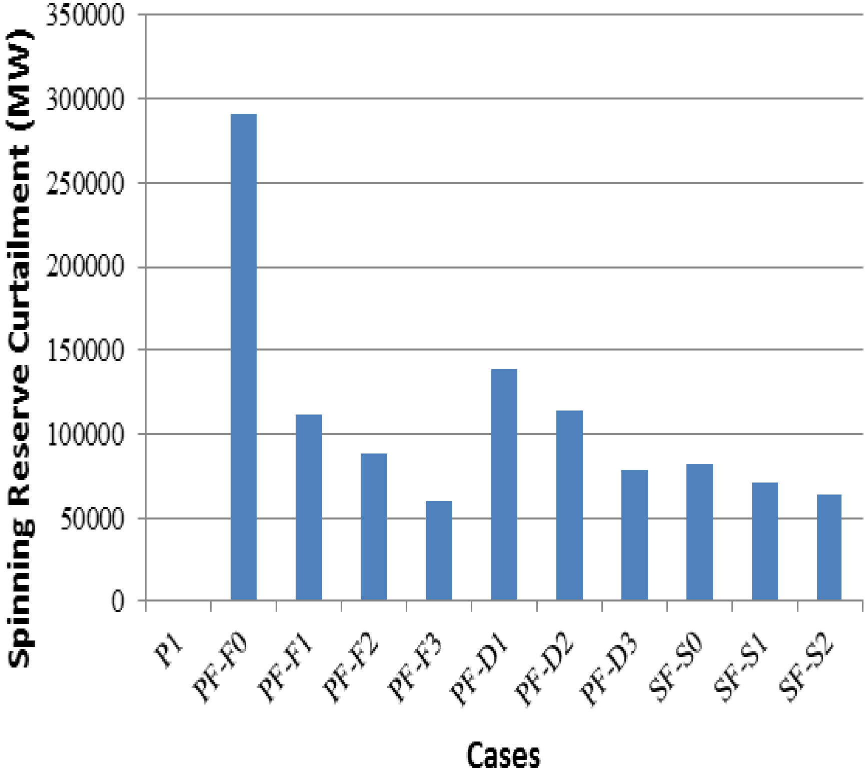
Overview of generation cost (4-months period)



- Stochastic UC model has slightly higher generation costs
- Additional generation costs are more than offset by the reduced curtailment costs

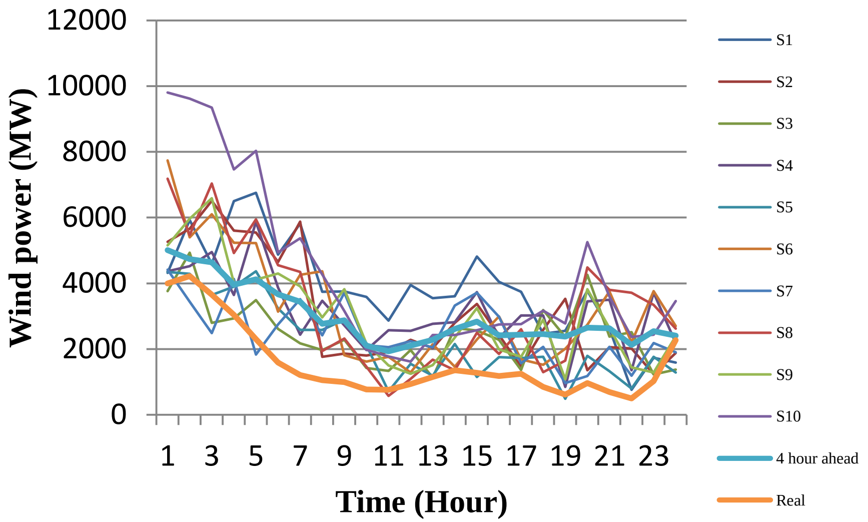
Total curtailment on load and reserve (4-months period)



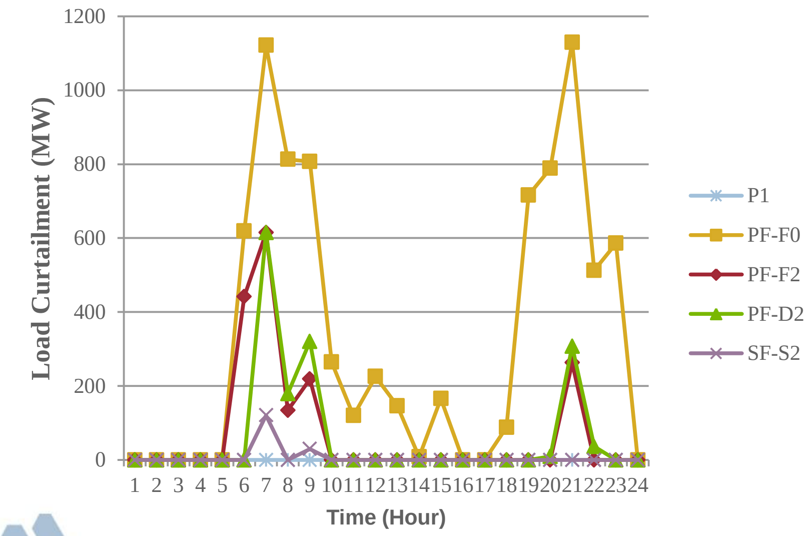


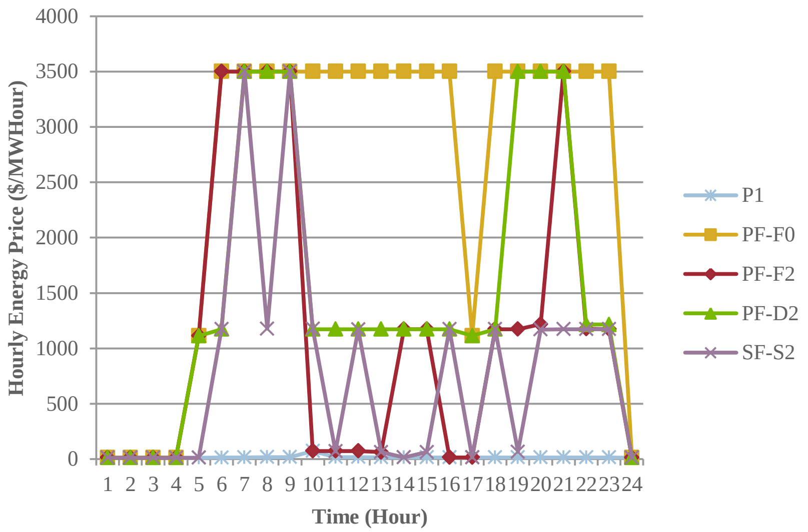
- Same trend on curtailment of load and spinning reserve.
- More load curtailments in cases with fixed reserve strategies
- More spinning reserve curtailment in cases with dynamic reserve strategies
- Least curtailment on both load and spinning reserve in cases with stochastic UC

Selected Over-forecasted Day (October 19th, 2006)

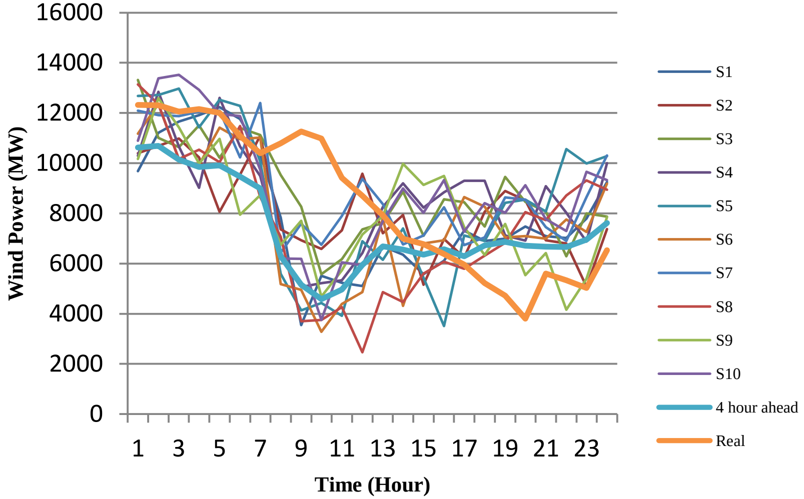


- Efficiency (clearing prices) and reliability (load curtailment)

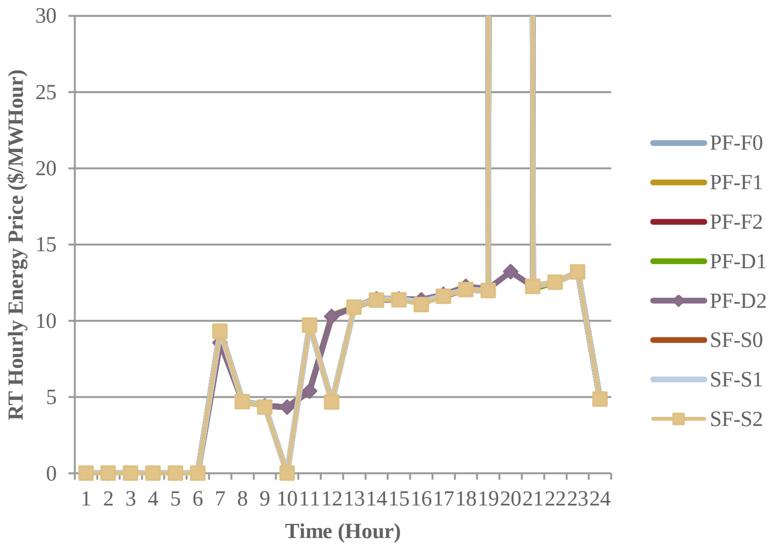


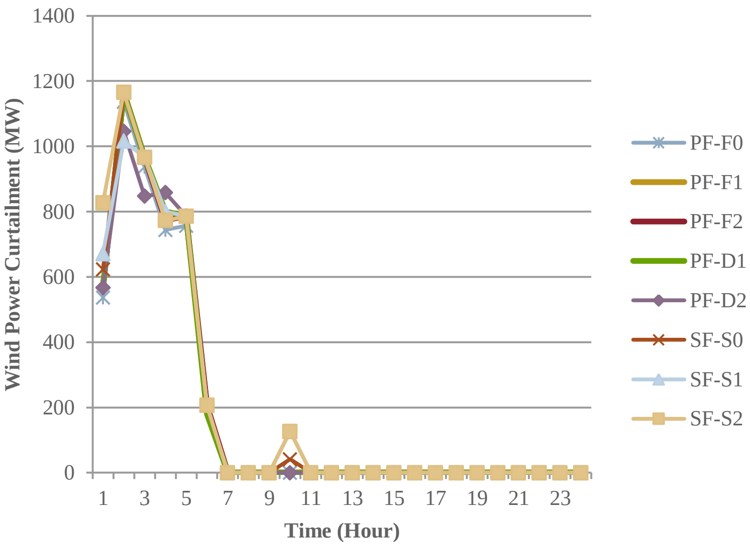


Selected Under-forecasted Day (September 22nd, 2006)



- Efficiency (clearing prices and wind curtailment)





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Conclusions

- ***Probabilistic wind power forecasts*** can contribute to efficiently schedule energy and operating reserves under uncertainty in wind power generation

- ***Dynamic operating reserves*** (derived from forecast quantiles)
  + Well aligned with current operating procedures
  + Lower computational burden
  + Lower cost and increased reliability
  - Does not capture inter-temporal events
  - Uncertainty not represented in objective function

- ***Stochastic unit commitment*** (with forecast scenarios)
  + Captures inter-temporal events through scenarios
  + Explicit representation of uncertainty in objective function
  + Lower cost and increased reliability
  - More radical departure from current operating procedures
  - High computational burden

Conclusions

- ***Others***
  - Dynamic operating reserves and stochastic UC give similar results in the IL Test Case
  - Inaccurate forecasts can lead to large implications for system efficiency and reliability.

Comments and Questions.

Thank You

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