Stochastic Programming for Improved Electricity Market Operations with Renewable Energy

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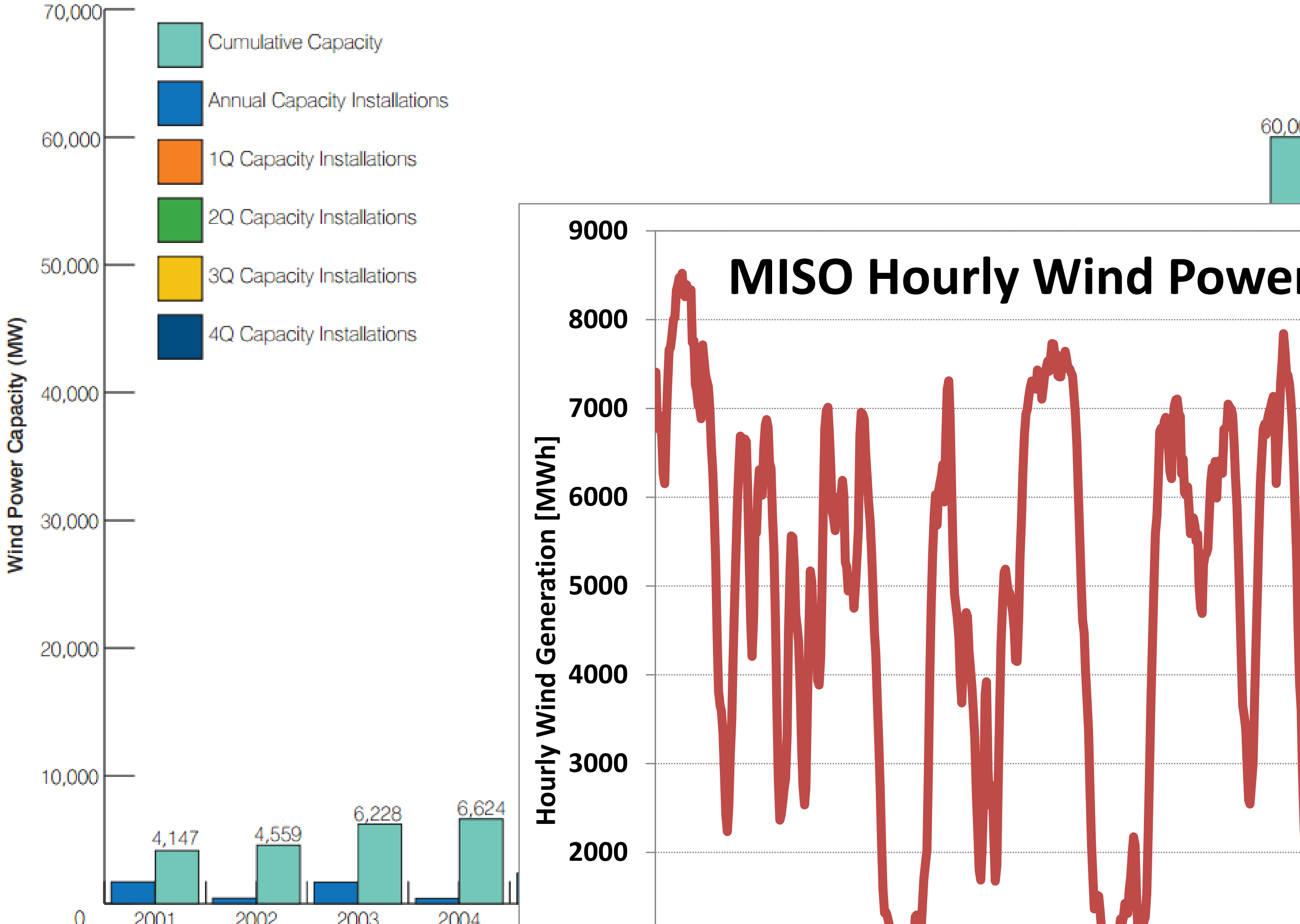
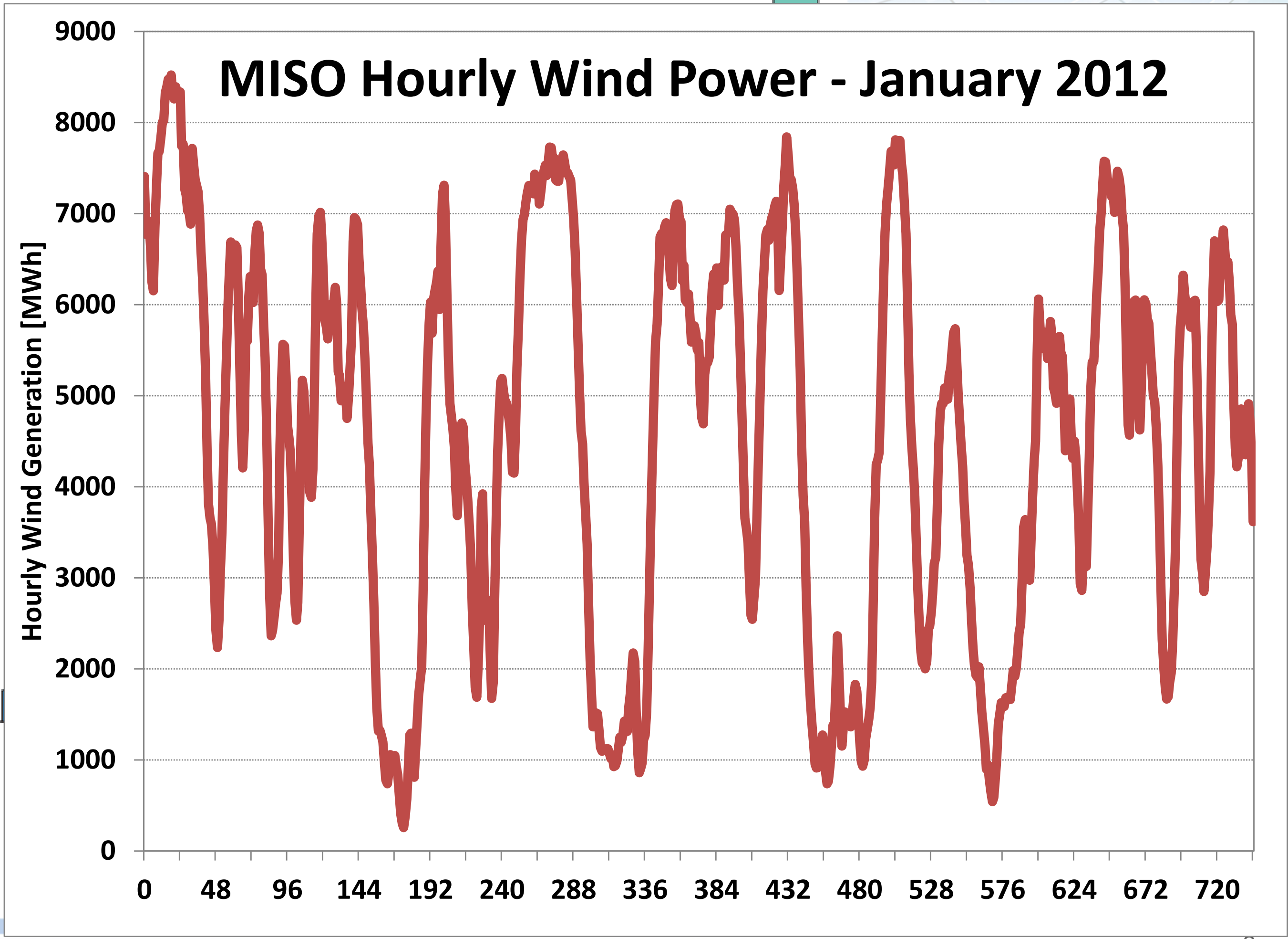
Outline

- Introduction
  - Renewable energy in the United States
  - Stochastic Programming
- Scenario generation and reduction
  - Scenarios from probabilistic wind power forecasts
  - Implications for stochastic unit commitment problem
- Stochastic unit commitment experiments
  - Basic model formulation
  - Scenario bundling and non-anticipativity
  - Alternative model formulation with bundles
  - Illustrative examples
- Concluding Remarks

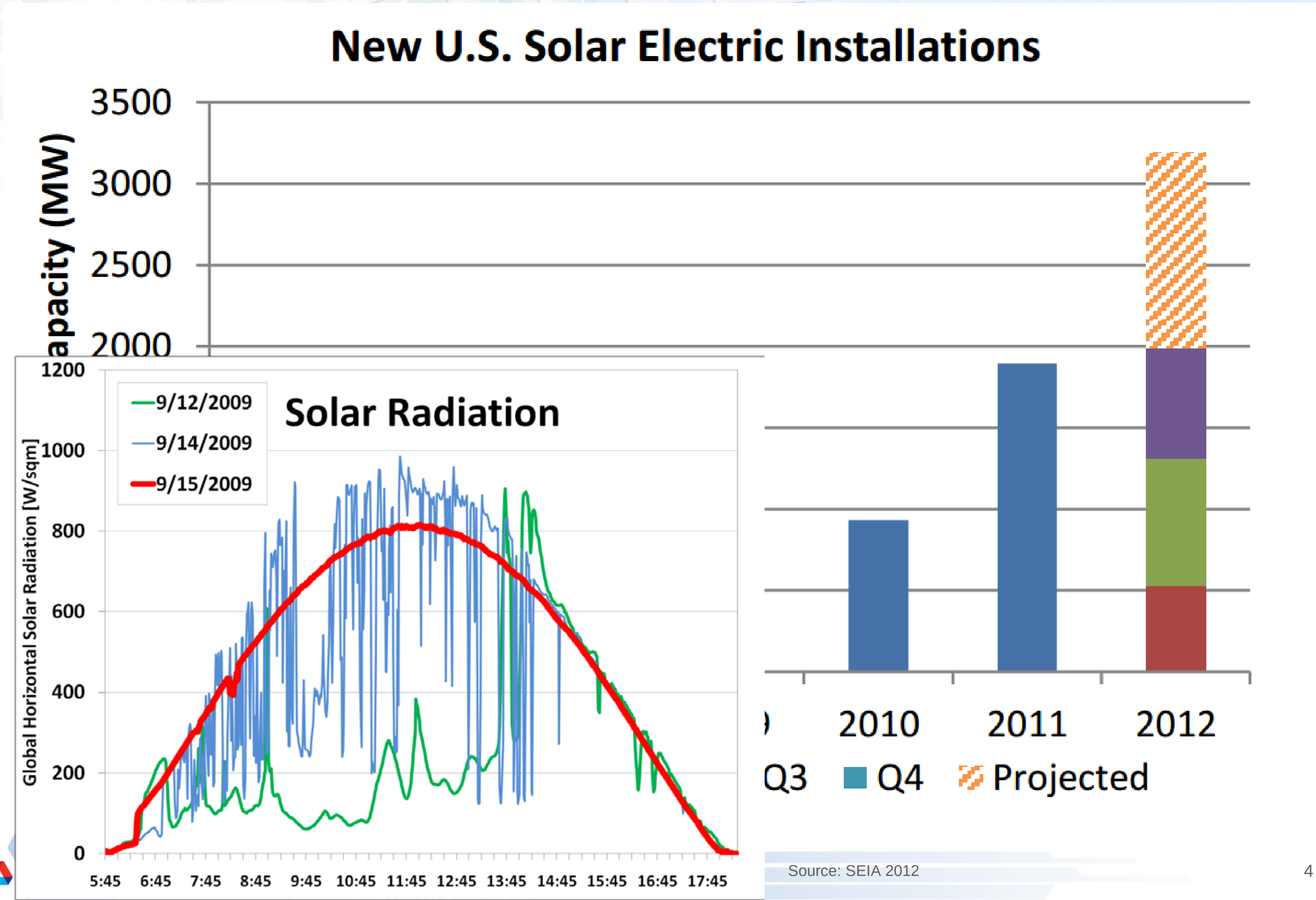
U.S. Wind Power Capacity Reaches 60 GW (282 GW Globally)





Source: AWEA, 2013 MISO 2012

U.S. Solar PV Capacity Reaches 6.4 GW (over 100 GW Globally)



Source: SEIA 2012

Why Stochastic Programming?

- Weather-driven renewables are hard to forecast and increase the uncertainty in the electric power grid

- Stochastic programming could serve as a tool to address the increased uncertainty in power system and electricity market operations

- Stochastic programming is a powerful tool in dealing with uncertainty, but it has advantages and disadvantages

  +

  - is based on axioms of foundational decision theory
  - considers uncertainty holistically rather than focusing on worst case scenarios
  - can effectively hedge against randomness

  -

  - requires probabilistic inputs which may be hard to obtain or estimate
  - can be computationally hard to solve stochastic programming models

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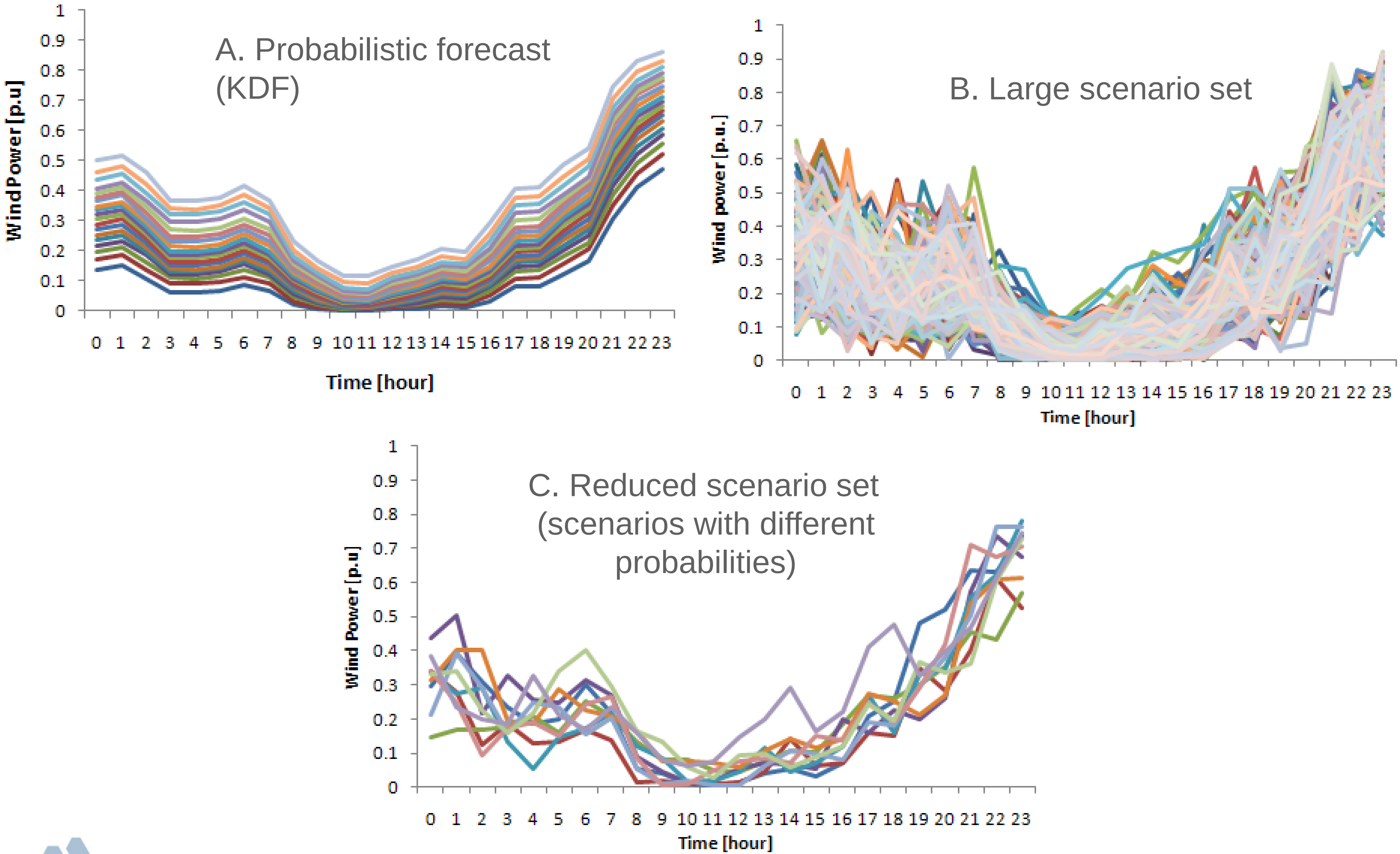
Background: Scenario Generation and Reduction

- We use statistical methods to produce probability density functions for the wind power forecast
  - Kernel Density Forecasting (KDF) [Bessa et al. 2012]

- 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]

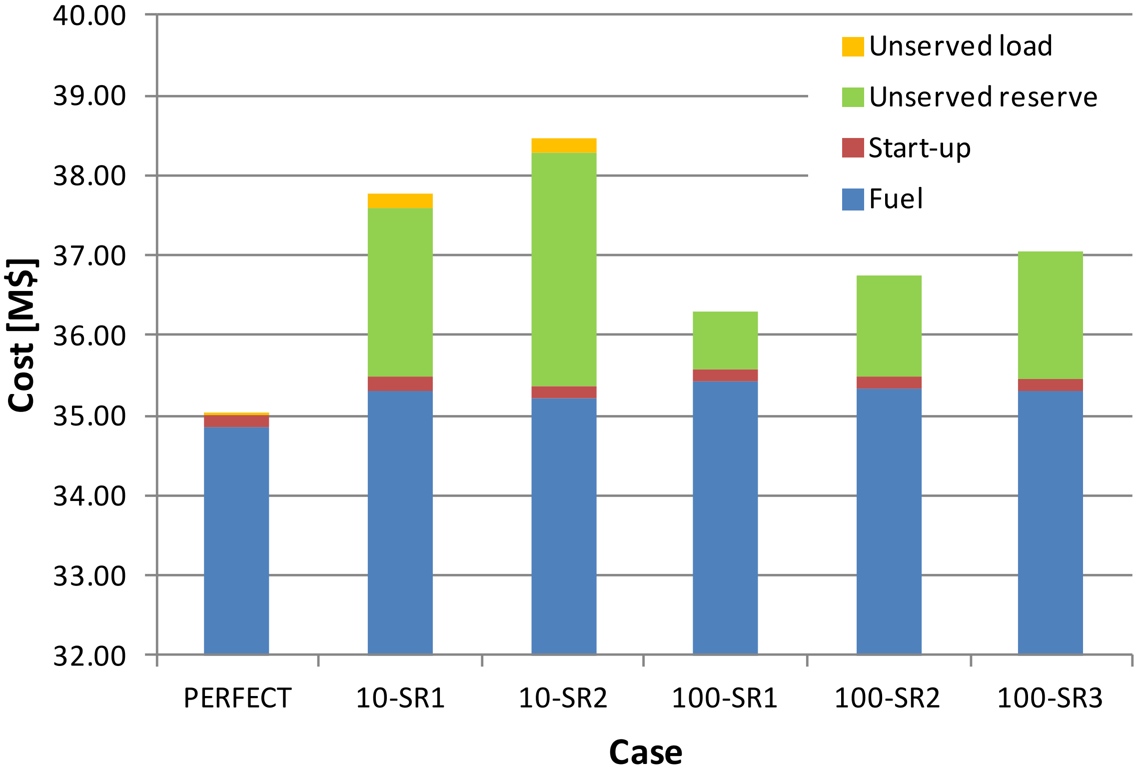
- In previous work, we investigated three scenario reduction methods [Botterud et al. 2011]
  - SR1: Random selection
  - SR2: SCENRED in GAMS [Gröwe-Kuska, Heitsch, et. al, 2003]
  - SR3: Scenario clustering approach [Sumaili et al. 2011]

Scenario Generation and Reduction - Illustration



Scenario Selection is Important for Stochastic UC

Total operating costs from "out-of-sample" simulations:



SR1 - Random selection
SR2 - SCENRED (GAMS)
SR3 - Scenario clustering

- Random scenario selection performs better than both scenario reduction algorithms
  - Scenario reduction reduces scenario variance and level of hedging in UC strategy
- Increasing the number of scenarios improves performance
  - Computational burden also increases, 15-20 times longer run-time with 100 scenarios

[Botterud et al. 2011]

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Basic UC Model Formulation

Probability of scenario s

Start-up cost

Production cost

2-Stage Stoch. Prog.:

$$\min \sum_{s\in S} p_s \sum_{i\in I} \sum_{t=1}^{T} \{g_i(x_{it}^s)u_{it}^s + h_i(u_{i,t-1}^s, u_{it}^s)\}$$

subject to:

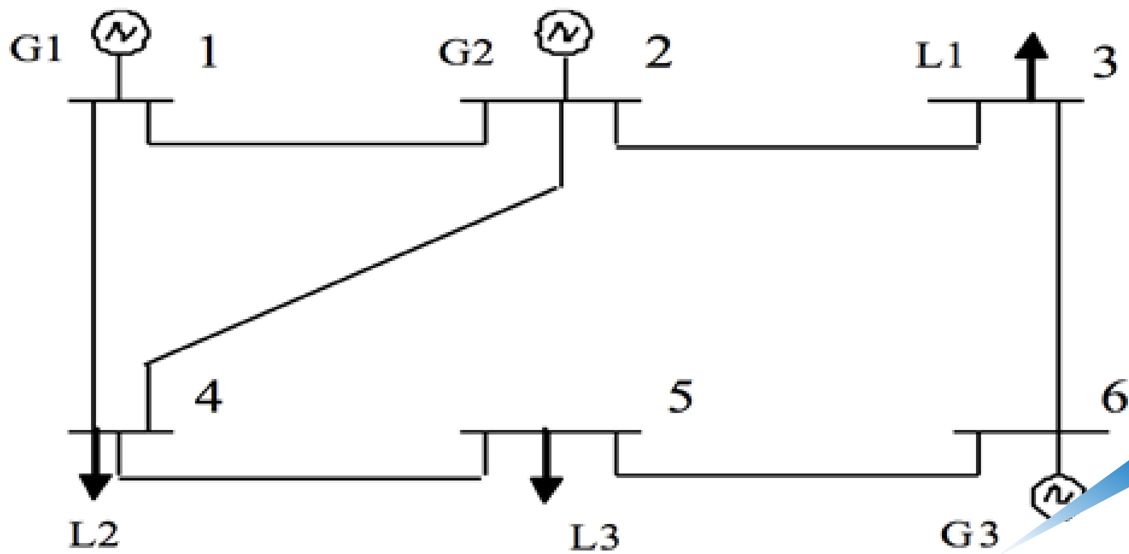
$\sum_{l\in L_n^{in}} f_{lt}^s + \sum_{i\in I_n} x_{it}^s + \sum_{j\in J_n} w_{jt}^s = \sum_{l\in L_n^{out}} f_{lt}^s + D_t$	$\forall t, s$	Load balance
$f_{lt}^s = B_l(\theta_{nt}^s - \theta_{mt}^s)$	$\forall l = (m,n) \in L, t, s$	Flow computation
$-F_l \leq f_{lt}^s \leq F_l$	$\forall l, t, s$	Flow limits
$w_{jt}^s \leq W_{jt}^s$	$\forall j, t, s$	Wind curtailment
$\sum_{i=1}^{I} r_{it}^s \geq R_t$	$\forall t, s$	Spinning reserve requirement
$x_{it}^s + r_{it}^s \leq Q_i u_{it}^{s,b}$	$\forall i, t, s$	Maximum output
$x_{it}^s \leq q_i u_{it}^{s,b}$	$\forall i, t, s$	Minimum output
$x_{it}^s - x_{i,t-1}^s + r_{it}^s \leq u_{i,t-1}^{s,b}\Delta_i + (1 - u_{i,t-1}^{s,b})\Delta_i^{SU}$	$\forall i, t \geq 2, s$	Ramp-up/Start-up
$x_{i,t-1}^s - x_{it}^s \leq u_{it}^{s,b}\Delta_i + (1 - u_{it}^{s,b})\Delta_i^{SD}$	$\forall i, t \geq 2, s$	Ramp-down/Shutdown
$u_{it}^{s,b} - u_{i,t-1}^{s,b} \leq u_{i\tau}^{s,b}$	$\forall t \geq 2, s, \tau = t+1, \dots, \min\{t + L_i - 1, T\}$	Minimum up-time
$u_{i,t-1}^{s,b} - u_{it}^{s,b} \leq 1 - u_{i\tau}^{s,b}$	$\forall t \geq 2, s, \tau = t+1, \dots, \min\{t + l_i - 1, T\}$	Minimum down-time
$u_{it}^s = u_{it}$	$\forall t, i, s$	Non-anticipativity
$x_{it}^s, r_{it}^s \geq 0$	$\forall t, i, s$	Non-negativity
$w_{jt}^s \geq 0$	$\forall t, j, s$	Non-negativity
$u_{it}^s, u_{it} \in \{0,1\}$	$\forall t, i, s$	Integrality

Solution Tool

We use Sandia National Laboratories' optimization tool Coopr, in particular ***PySP (Python-based Stochastic Programming)*** modeling and solver library (Watson et al. 2012). The tool can solve the problem in two ways:

- Extensive form
- Progressive Hedging
  - ***Scenario-based decomposition scheme***
  - ***Relaxation of non-anticipativity constraints***
  - ***Has been used for unit commitment (e.g. Takriti et al. 1996)***

Illustrative 6-Bus System



Replaced with a wind unit

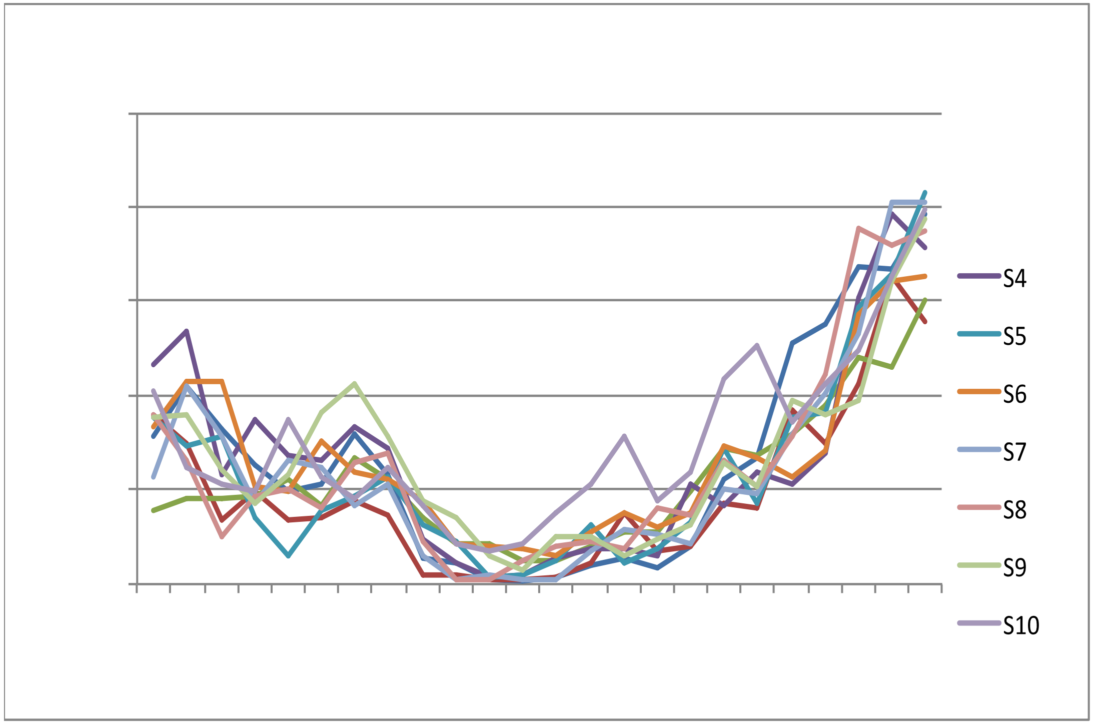
6-Bus system* with

- 2 thermal generators
- 3 loads

	Bus No.	Unit Cost Coefficients			Pmax (MW)	Pmin (MW)	Ini. State (h)	Min Off (h)	Min On (h)	Ramp (MW/h)	Start Up (MBtu)	Fuel Price ($/ MBtu)
		U	b (MBtu/ MW)	c (MBtu/ MW^2)								
G1	1	176.95	13.51	0.0004	220	100	4	4	4	55	10	1
G2	2	129.98	32.63	0.001	100	10	3	3	2	50	200	1

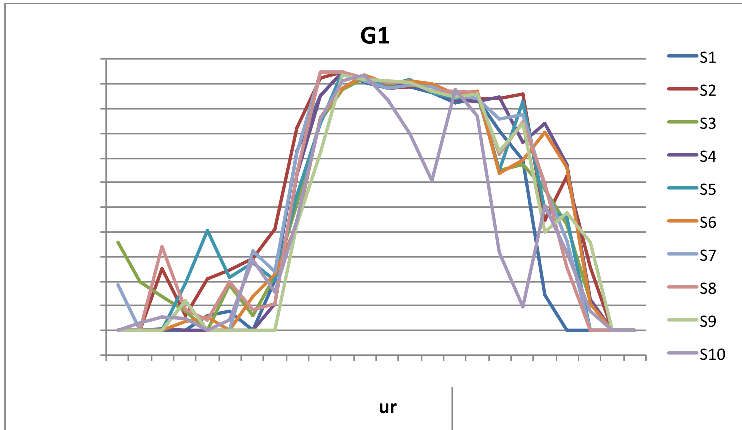
* The details of the system and parameters are available at: http://motor.ece.iit.edu/data/

Wind Power Day-Ahead Forecast Scenarios

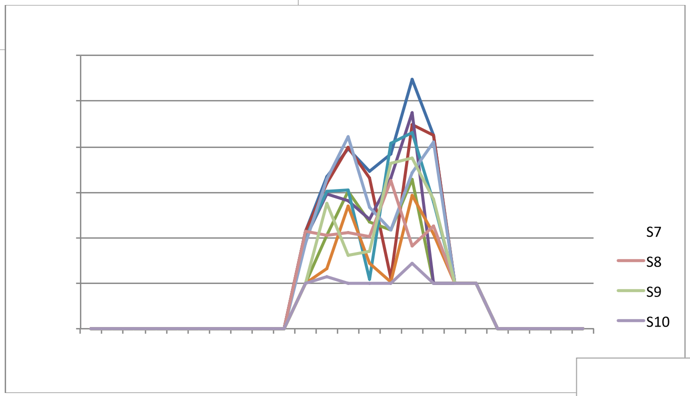


- 10 wind scenarios
- Derived from EWITS data with KDF, MC sampling, and scenario reduction
- Wind unit capacity is set so that it can satisfy 30% of the daily load

Basic UC Model: Dispatch Results

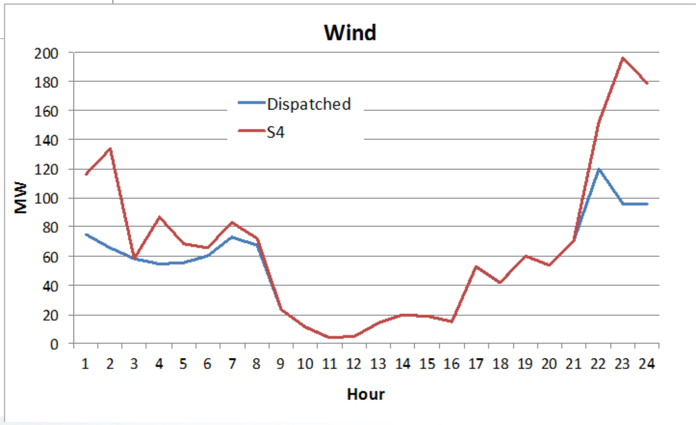


Unit 1 is always on.



Unit 2 is on when the wind generation is low.

Wind is dispatched down (curtailed) early morning and late night.



The Expected Value of Perfect Information (EVPI)

	Probability	Total cost ($)
Scenario 1	0.10	61,306
Scenario 2	0.06	64,503
Scenario 3	0.09	59,321
Scenario 4	0.07	61,067
Scenario 5	0.11	61,996
Scenario 6	0.19	58,074
Scenario 7	0.13	61,944
Scenario 8	0.10	59,577
Scenario 9	0.08	58,850
Scenario 10	0.07	53,268
Perfect information solution		59,913
Stochastic solution		60,427
The expected value of perfect information (EVPI)		***515***

The Value of a Stochastic Solution (VSS)

	Load Curtailment	Total cost ($)
Scenario 1	0.00	61,306
Scenario 2	3.90	77,523
Scenario 3	0.00	59,321
Scenario 4	1.72	66,755
Scenario 5	0.46	62,950
Scenario 6	0.00	58,074
Scenario 7	0.00	61,944
Scenario 8	0.00	59,577
Scenario 9	0.00	58,850
Scenario 10	0.00	53,526
Expected value solution		61,247
Stochastic solution		60,427
The value of stochastic solution (VSS)		***880***

Alternative Approach with Bundling of Scenarios

- Stochastic programming models tend to give better results with more scenarios, capturing the full range of uncertainty.
- Unit commitment is a multi-stage decision problem in electricity market operations (day-ahead, reliability, real-time).
- To solve the problem with a large number of scenarios and to capture the multi-stage decision process we consider bundling. We observe that:
  – the scenarios can be bundled according to their deviation from the average forecast.
  – the bundles might be different across the time horizon.
- The idea is:
  – to enforce the non-anticipativity constraints for the bundles only

Alternative Model Formulation with Bundles

Add bundle indices to the unit commitment decision

$$\min \sum_{s \in S} p_s \sum_{i \in I} \sum_{t=1}^{T} \{ g_i(x_{it}^s) u_{it}^{s,b} + h_i(u_{i,t-1}^{s,b}, u_{it}^{s,b}) \}$$

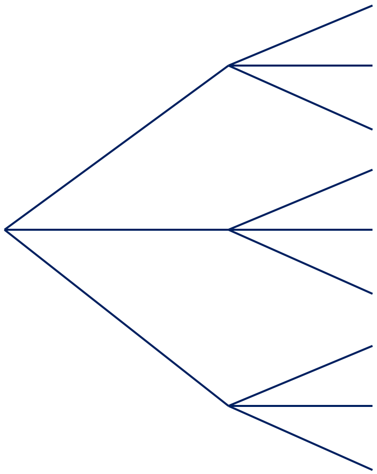
subject to:

$\sum_{l \in L_n^{in}} f_{lt}^s + \sum_{i \in I_n} x_{it}^s + \sum_{j \in J_n} w_{jt}^s = \sum_{l \in L_n^{out}} f_{lt}^s + D_t$	$\forall t, s$	Load balance
$f_{lt}^s = B_l(\theta_{nt}^s - \theta_{mt}^s)$	$\forall l = (m,n) \in L, t, s$	Flow computation
$-F_l \leq f_{lt}^s \leq$		
$w_{jt}^s \leq W_{jt}^s$		
$\sum_{i=1}^{I} r_{it}^s \geq R_t$		
$x_{it}^s + r_{it}^s \leq Q$		
$x_{it}^s \leq q_i u_{it}^{s,b}$		
$x_{it}^s - x_{i,t-1}^s -$		
$x_{i,t-1}^s - x_{it}^s \leq u_{it}^{s,b} \Delta_i + (1 - u_{it}^{s,b}) \Delta_i^{SD}$	$\forall i, t \geq 2, s$	Ramp-down/Shutdown
$u_{it}^{s,b} - u_{i,t-1}^{s,b} \leq u_{i\tau}^{s,b}$	$\forall t \geq 2, s, \tau = t+1, \ldots, \min\{t + L_i - 1, T\}$	Minimum up-time
$u_{i,t-1}^{s,b} - u_{it}^{s,b} \leq 1 - u_{i\tau}^{s,b}$ $\forall t \geq 2, s, \tau = t+1, \ldots, \min\{t + l_i - 1, T\}$		Minimum down-time
$u_{it}^{s,b} = u_{it}^{b}$	$\forall t, i, s$	Non-anticipativity
$x_{it}^s, r_{it}^s \geq 0$	$\forall t, i, s$	Non-negativity
$w_{jt}^s \geq 0$	$\forall t, j, s$	
$u_{it}^s, u_{it} \in \{0,1\}$	$\forall t, i, s$	Integrality

What if we divide the time horizon into time blocks, and enforce the non-anticipativity constraints across bundles only?
→ If the scenarios in the bundles behave similarly, we could get the same solution with LESS non-anticipativity constraints by enforcing them at the end of the blocks only.

Bundling Approach

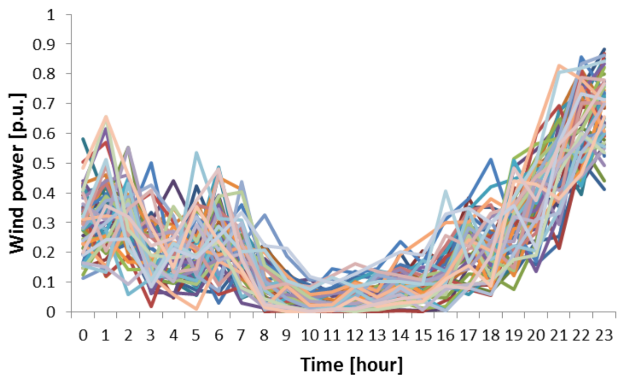
- Tradeoff
  - More variables versus ability to capture uncertainty
- Advantages of bundling
  - Captures multi-stage decision process
    - no need to enforce formal tree structure
  - Reduces the need for scenario reduction
    - can take into account extreme scenarios
  - May reduce computational burden
    - relaxation of traditional 2-stage formulation
- Three approaches
  - Non-anticipativity constraints across scenarios
  - Non-anticipativity constraints across bundles
  - Non-anticipativity constraints across bundles at the end of the blocks

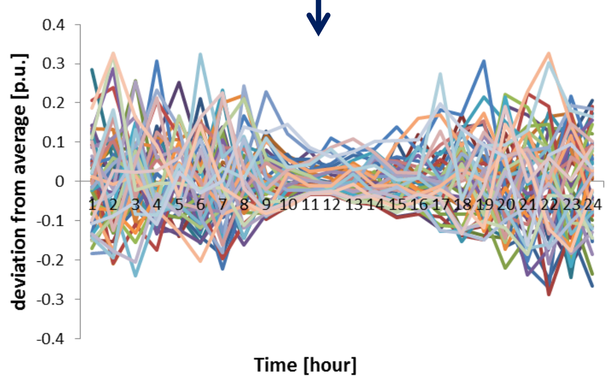


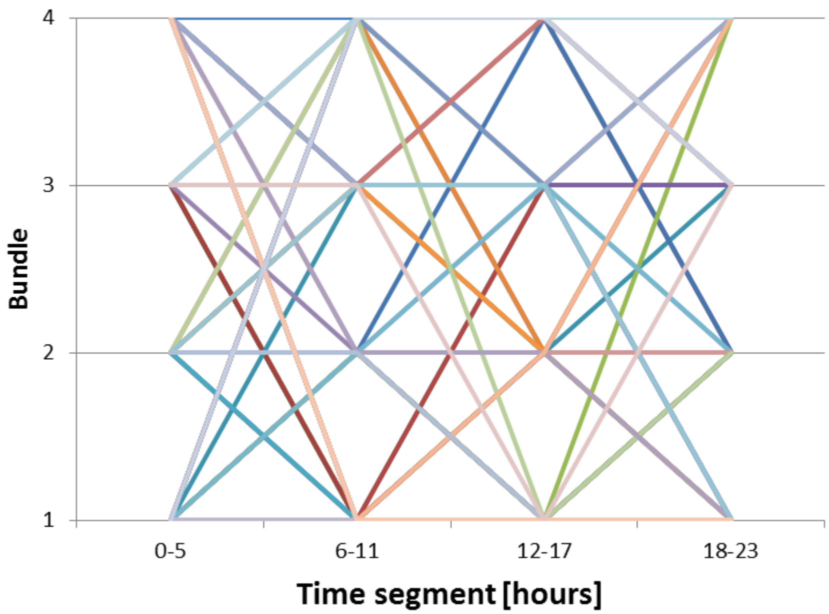
Bundles for 50 Scenarios (Day-Ahead Forecast)

Bundling

- According to the deviations from the average forecast
  - < 25% quantile -> Bundle 1
  - < 50% quantile -> Bundle 2
  - < 75% quantile -> Bundle 3
  - < 100% quantile -> Bundle 4

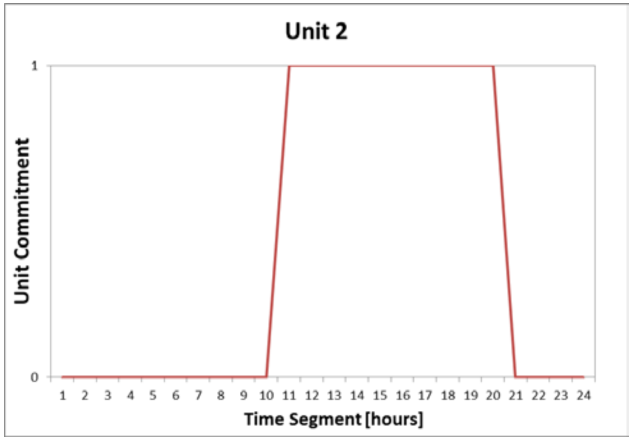




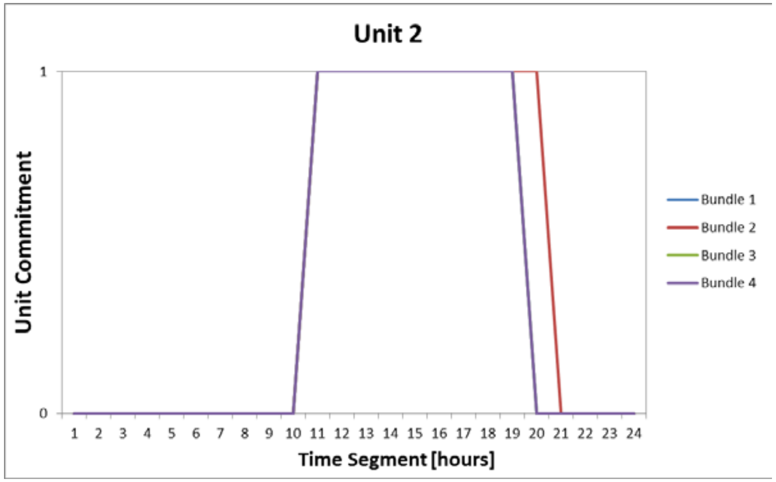


Bundle UC Model: Dispatch Result Comparison

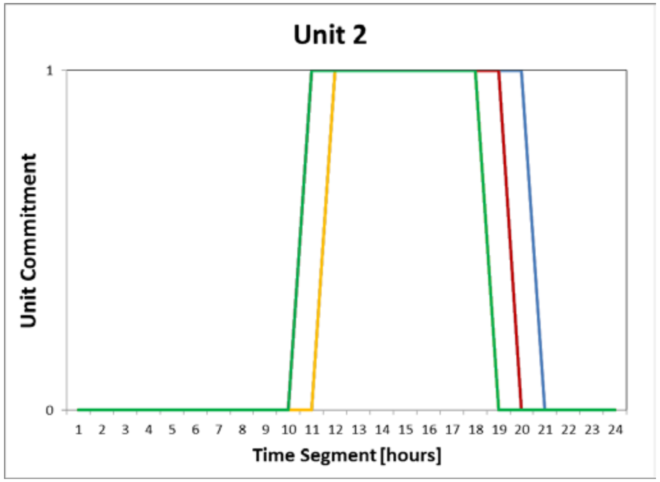
- Unit 1 is always on for the three approaches.
- Unit 2 decision may change depending on the scenario.



“Across all scenarios”



“Across bundles”



“Across bundles at the end of time blocks”

Bundle UC Model: Objective Function and Run-time

Extensive Form	"Across scenarios"	"Across bundles"	"Across bundles at the end of time blocks"
Objective	62,401	62,162	61,860
Execution time (sec)	18.15	23.37	23.29

Progressive Hedging*	"Across scenarios"	"Across bundles"	"Across bundles at the end of time blocks"
Objective	62,401	62,162	61,846
Execution time (sec)	635.29	400.56	399.19
Number of PH iterations	50	26	29

*rho = 200

The bundling approach gives

- Lower expected operating cost
- Improved run-time and fewer iterations (under PH)

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Conclusions and Future Work

- Stochastic programming is a powerful tool in solving problems with uncertainty
  - Has the potential to address uncertainty from renewables in operational decisions
- Computational effort is a challenge
  - We propose addressing this by bundling forecast scenarios and reducing the number of non-anticipativity constraints within a progressive hedging framework
  - The formulation also captures some of the multi-stage nature of the unit commitment problem
- Future work includes
  - Developing methods for more effective bundling of scenarios
  - Solving larger problems with more scenarios and stochastic variables
  - Investigate potential for improved pricing and financial incentives under stochastic scheduling

References and Acknowledgement

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