



Economic Dispatch with Sub-hourly Simulation

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FERC Technical Conference: Increasing Real-time and Day-Ahead Market Efficiency Through Improved Software. June 26, 2013

The Agenda

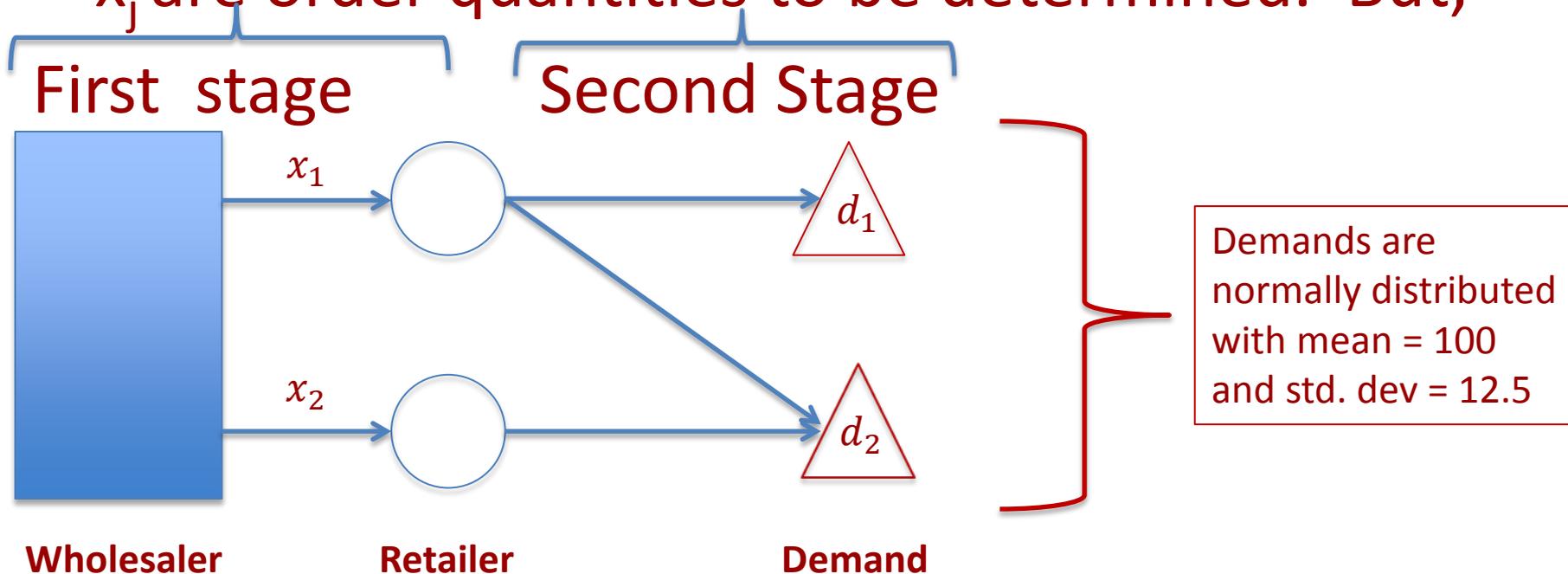


- **Stochastic Programming Technology**
 - Uncertainty Quantification (UQ) for Operations
 - Quick Demo
 - UQ Engines (SAA and SD)
- **Economic Dispatch with Simulation**
 - Economic Dispatch Model
 - Wind Simulation
 - Stochastic Decomposition and Economic Dispatch Setting
- **Results with Hourly and Sub-hourly Simulation**
 - Illinois Network Data
 - Hourly v Sub-hourly Ramping
 - UQ using SAA (Extensive Formulation) and SD
- **Conclusions**
 - Main Take Away
 - Other On-Going Work

UQ for Operations



- Two products serve two types of demands:
- x_j are order quantities to be determined. But,

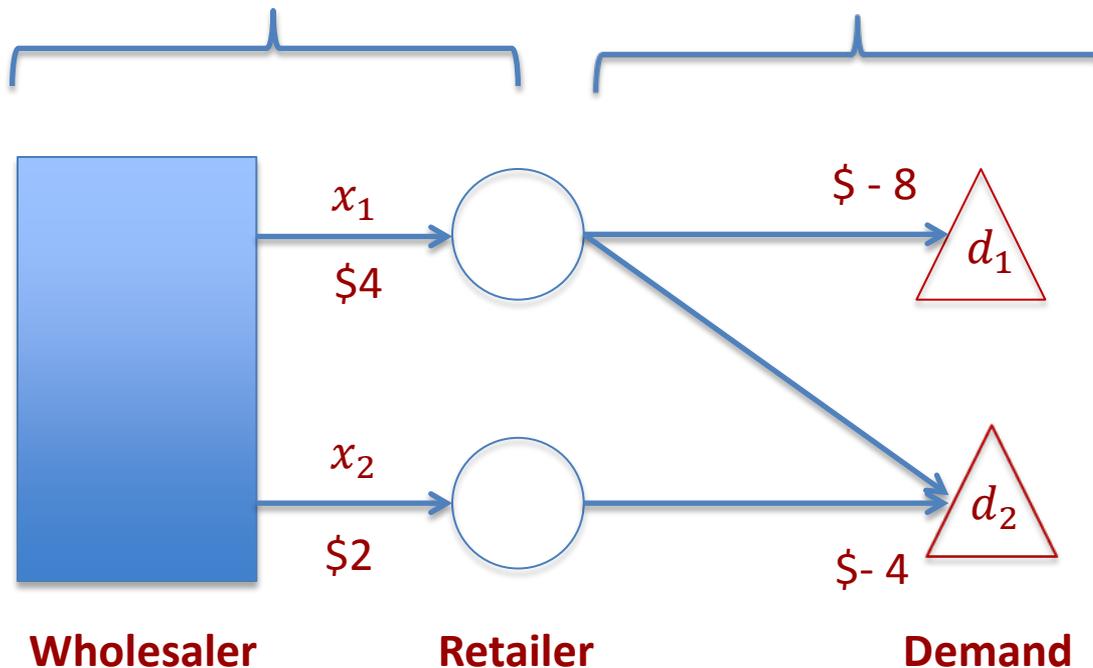


UQ for Operations



First stage

Second Stage



Selling Price 1: \$8
Selling Price 2: \$4
Backorder Cost: \$10
Holding Cost: \$0.20

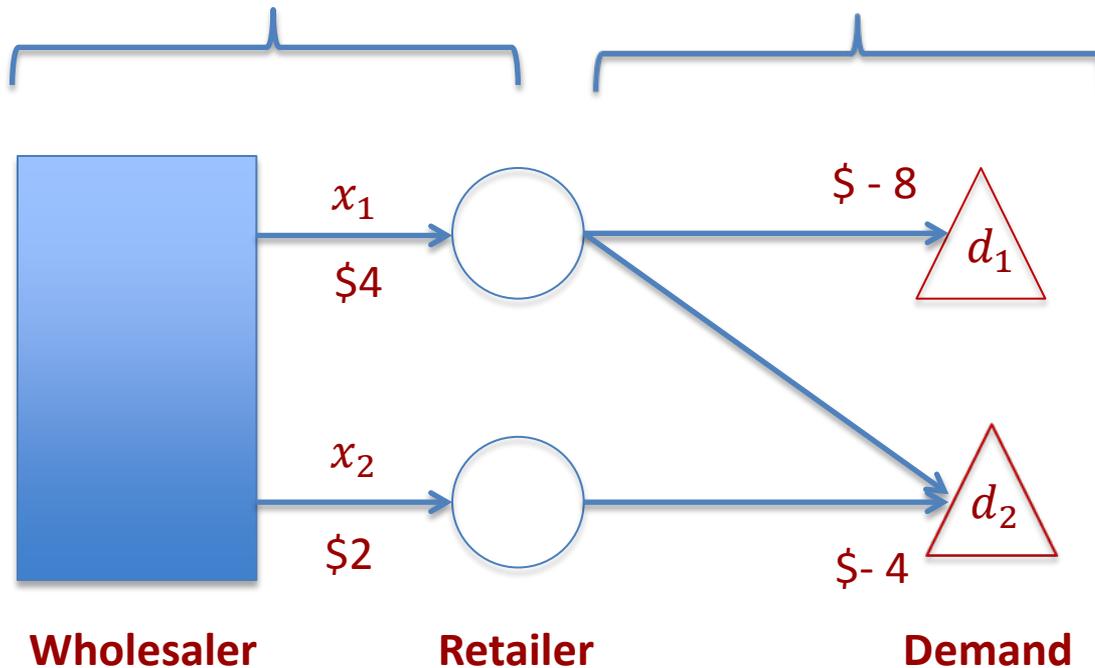
Demands are normally distributed with mean = 100 and std. dev = 12.5

SP for Operations



First stage

Second Stage



Selling Price 1: \$8
 Selling Price 2: \$4
 Backorder Cost: \$10
 Holding Cost: \$0.20

Demands are normally distributed with mean = 100 and std. dev = 12.5

$N = ??$

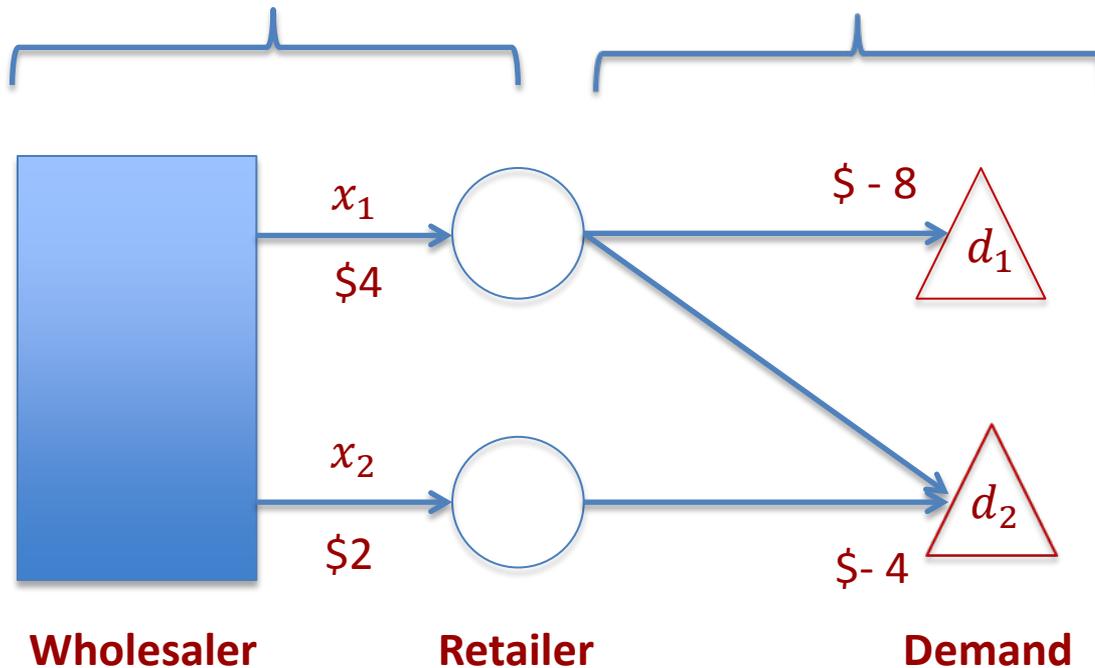


UQ for Operations



First stage

Second Stage

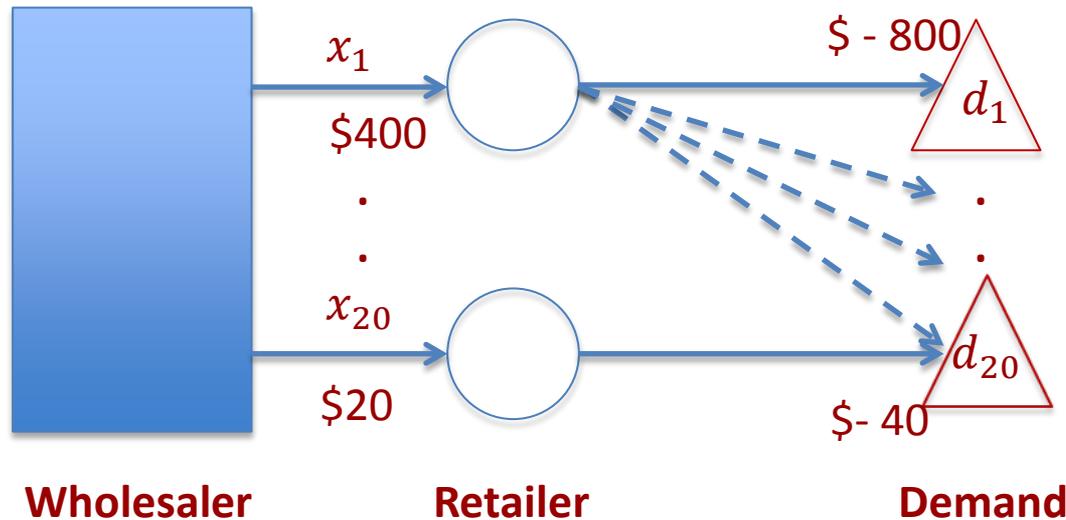


Selling Price 1: \$8
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Backorder Cost: \$10
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Demands are normally distributed with mean = 100 and std. dev = 12.5

UQ Demo

- 20 products, Normally distributed demands



Stochastic Decomposition:
Simultaneously
Optimize + Monte Carlo

Note: We do not commit to a sample size before “seeing” the instance. We try to recognize optimality “on the fly”, thus avoiding unnecessarily large instances.

UQ Engines: SAA and SD



- Sample Average Approximation (Linderoth, Shapiro, Wright; Annals of OR, 2006):
 - **Choose** a sample size;
 - **Optimize** the sampled problem;
 - **Repeat** M times (say $M \sim 7 - 10$)
 - Sampling Strategy: Latin Hypercube Sampling.
 - Computing Platform: Computing Grid (100s of Desktop PCs)
- Stochastic Decomposition (Sen, Encyclopedia of OR/MS (Springer, 2012)):
 - • **Sample** a small number of scenarios (say 1 or more);
 - **Update** a value function approximation;
 - **Optimize** the value function approximation (plus proximal term);
 - ← • **Repeat** until stopping rule is satisfied.
 - **Repeat** M times (say $M = 30$).
 - Sampling Strategy: Uses Common Random Numbers, and find sample size for each replication
 - Computing Platform: Laptop (Mac Book Air)

UQ Comparisons of SAA and SD using SSN



Sample Average Approximation (Linderoth et al 2006)

Sample Size	Lower Bound	Upper Bound	Pessimistic Gap
SAA-100	8.90(+/- 0.36)	10.542 (+/-0.021)	2.023
SAA-500	9.87 (+/-0.22)	10.069(+/- 0.026)	0.445
SAA-1000	9.83(+/- 0.29)	9.996 (+/- 0.025)	0.445
SAA-5000	9.84 (+/- 0.10)	9.913 (+/- 0.022)	0.195

Stochastic Decomposition (Sen 2012, see also Higle and Sen 1994, 1999)

SD Avg. Sample (St.Deviation)	Lower Bound	Upper Bound	Pessimistic Gap
2212.5 (370.3)	9.76 (+/- 0.16)	9.91 (+/- 0.05)	0.36

Economic Dispatch



Master Problem

min Generation Cost + Expected recourse value

s.t. Generation ramping limits

Generation capacity limits

$h(\{G\}, \omega) = \min$ Fast Operating reserves/ramping/buying-selling costs

s.t. Network flow balance equations

Line power flow

Line capacity limits

Wind Availability

Storage limits

Bounds on operating reserves/ramping

Recourse Value Function

Economic Dispatch

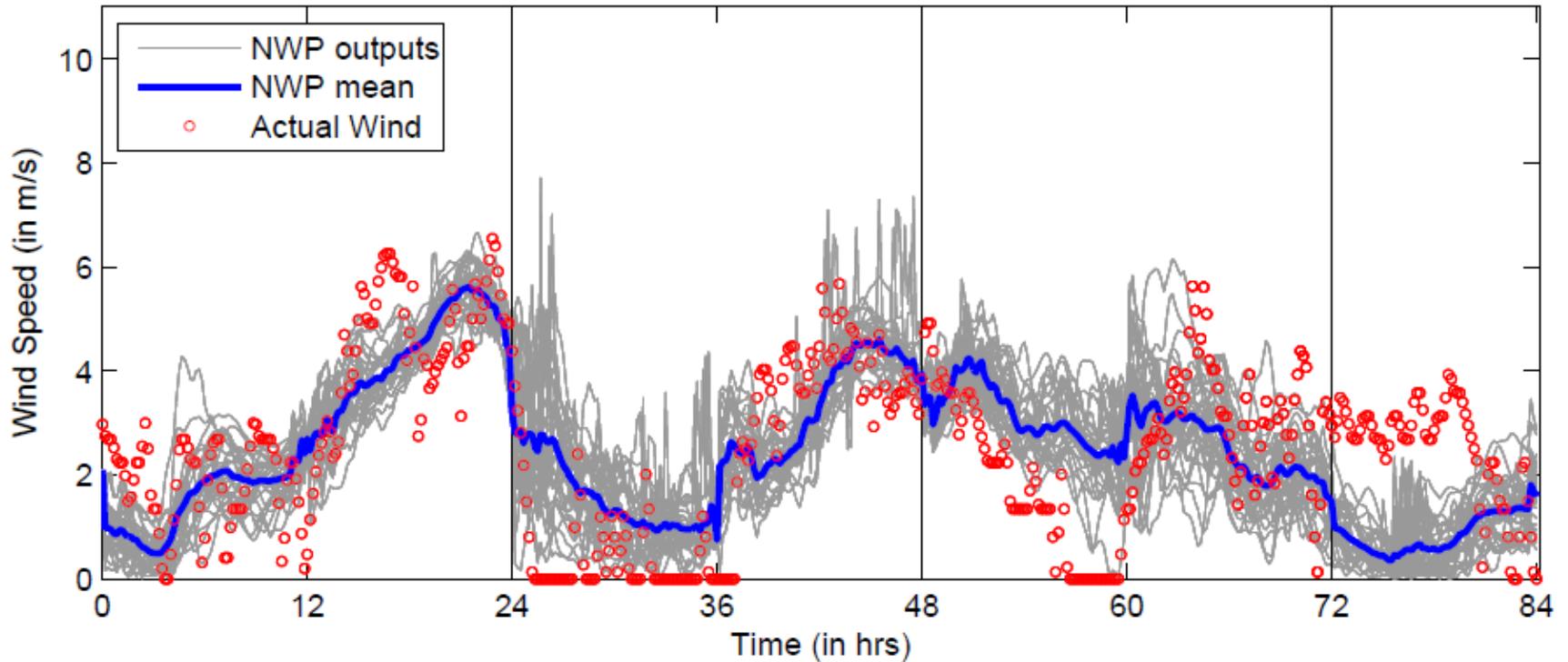


Recurse Value Function Master Problem

$$\begin{aligned} \min \quad & \sum_{i \in \mathcal{G}} c_i G_{hi} + \mathbb{E}\{h(\{G\}, \tilde{\omega})\} \\ \text{s.t.} \quad & \Delta G_i^{\min} \leq G_{hi} - G_{(h-1)i} \leq \Delta G_i^{\max} \quad \forall i \in \mathcal{G} \\ & G_i^{\min} \leq G_{hi} \leq G_i^{\max} \quad \forall i \in \mathcal{G} \end{aligned}$$

$$\begin{aligned} h(\{G\}, \omega) = \min \quad & \sum_{t \in \mathcal{T}} \left(\eta_t^b \sum_{n \in \mathcal{N}} b_{htn} - \eta_t^s \sum_{n \in \mathcal{N}} s_{htn} \right) \\ \text{s.t.} \quad & \sum_{(j,i) \in \mathcal{A}} p_{htji} - \sum_{(i,j) \in \mathcal{A}} p_{htij} + b_{hti} - s_{hti} + \sum_{j \in \mathcal{W}_i} w_{hti} \\ & \quad + \sum_{j \in \mathcal{R}_i} r_{htj} + \sum_{j \in \mathcal{G}_i} G_{hj} = \sum_{j \in \mathcal{D}_i} D_{hj} \quad \forall i \in \mathcal{N} \\ & p_{htij} = V_i V_j (\theta_i - \theta_j) / X_{ij} \quad \forall (i,j) \in \mathcal{A} \\ & p_{ij}^{\min} \leq p_{htij} \leq p_{ij}^{\max} \quad \forall (i,j) \in \mathcal{A} \\ & 0 \leq w_{hti} \leq W_t \quad \forall i \in \mathcal{W} \\ & r_{hti}^{\min} \leq r_{hti} \leq r_{hti}^{\max} \quad \forall i \in \mathcal{R} \\ & b_{hti}, s_{hti} \geq 0 \quad \forall i \in \mathcal{N} \end{aligned}$$

Numerical Wind Prediction



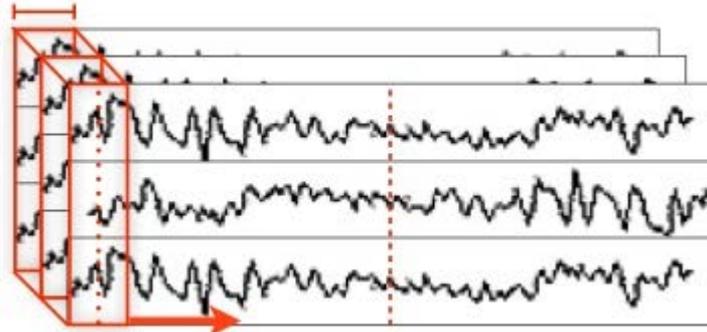


Wind Simulation: Vector Auto-regression

$$VAR(p) : \quad y_t = \boxed{\epsilon_t} + A_1 y_{t-1} + \dots + A_p y_{t-p} + \boxed{\eta_t}$$

Deterministic regressors

White noise

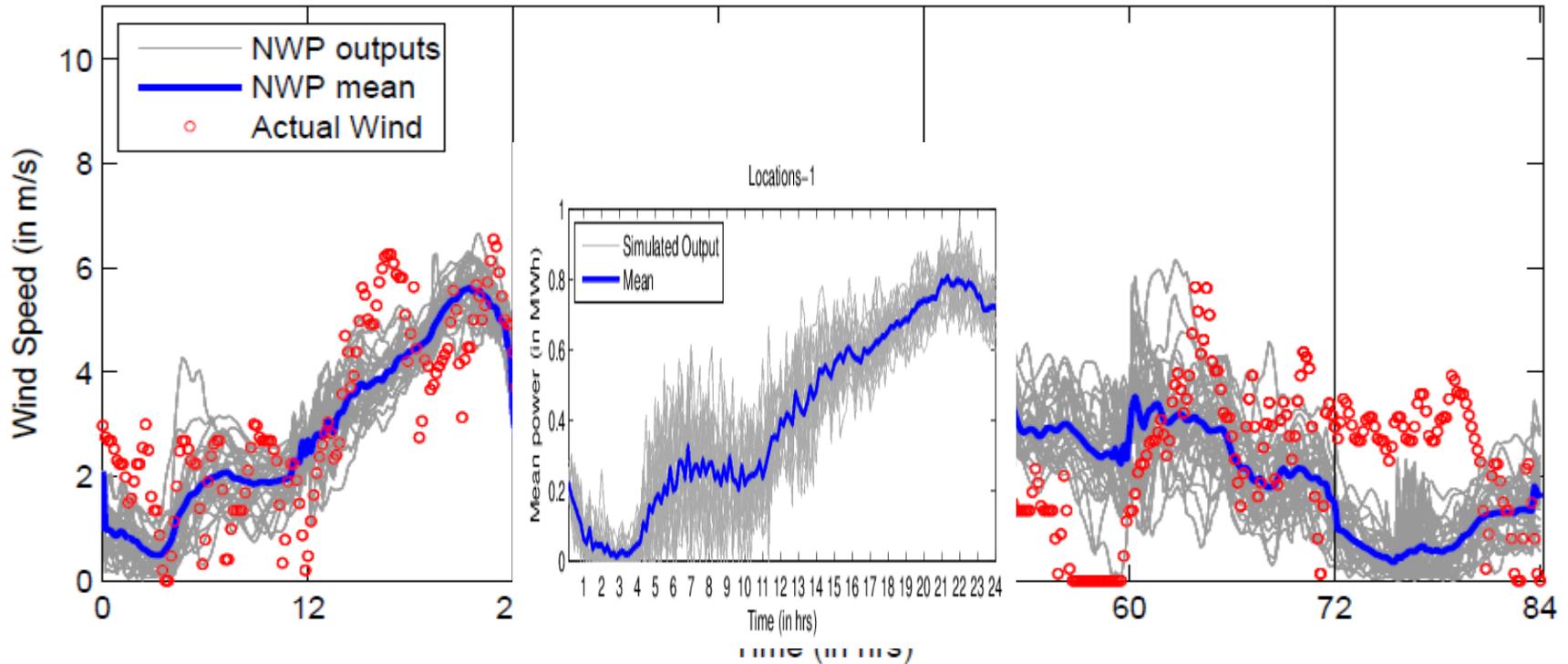


Preprocess

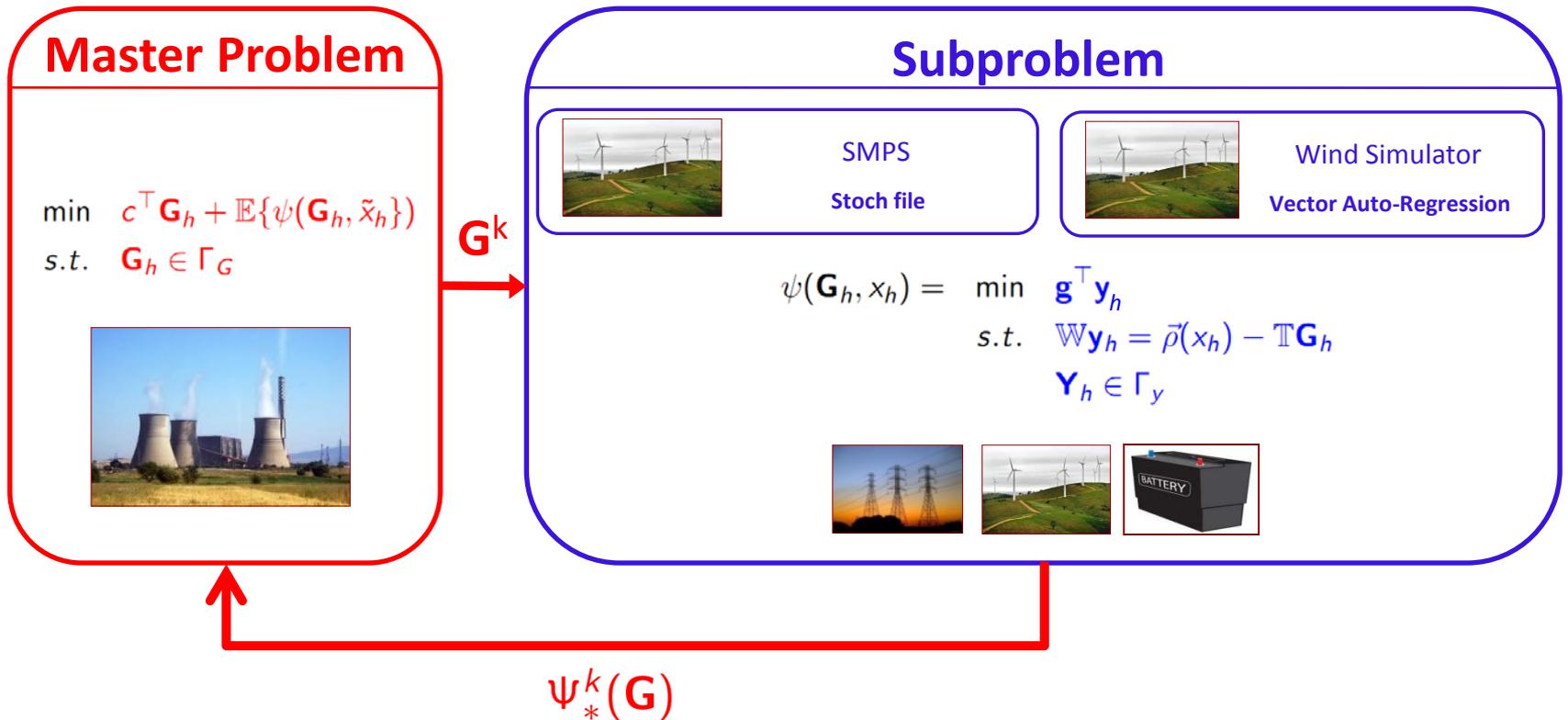
VAR(p)

- Segment Adaptive VAR
- Captures **spatio-temporal** correlations
- Information criterion (Bayes-Schwartz) based model selection
- Validated from residual whiteness, stability and consistency.

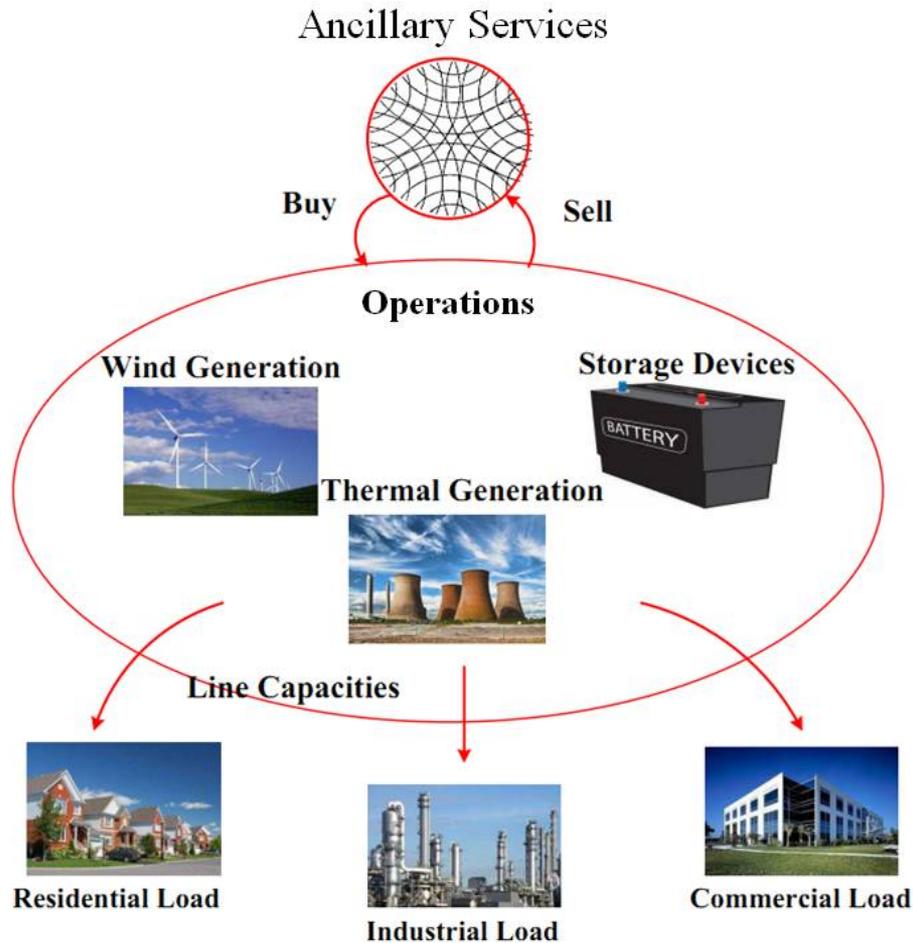
Simulated Wind Model



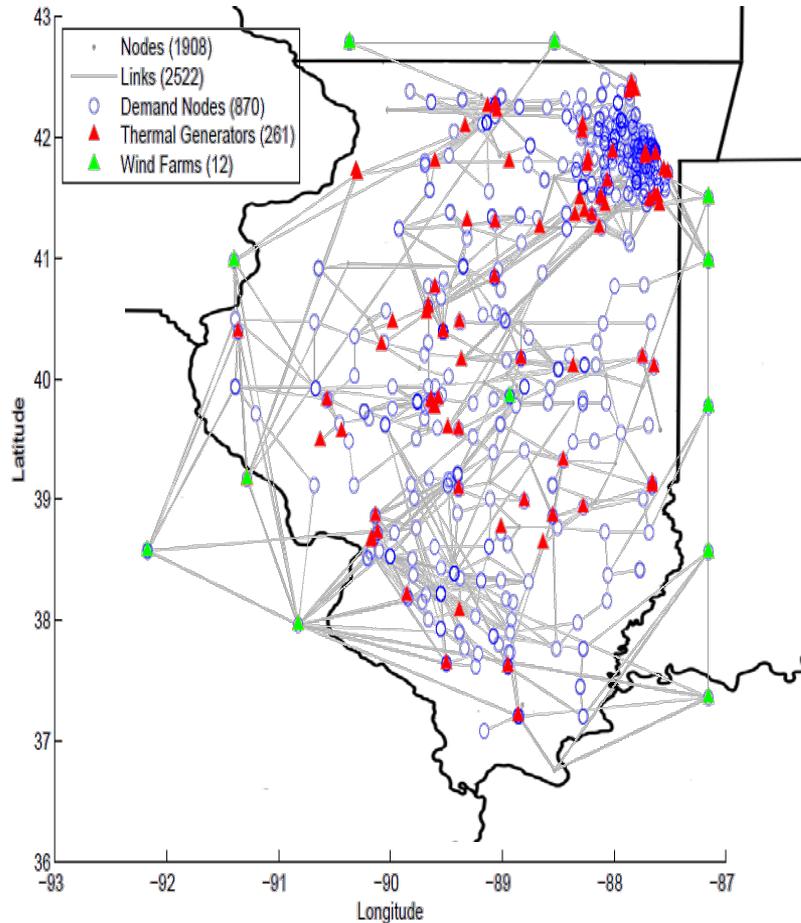
Stochastic Decomposition (Hourly Simulation)



The Economic Dispatch Setting



The Data: Illinois Network (12 Wind Farms)



Master:

- Columns - 261
- Rows - 522

Sub-problem:

- Columns - 33510
- Rows - 26658
- Wind farms - 12

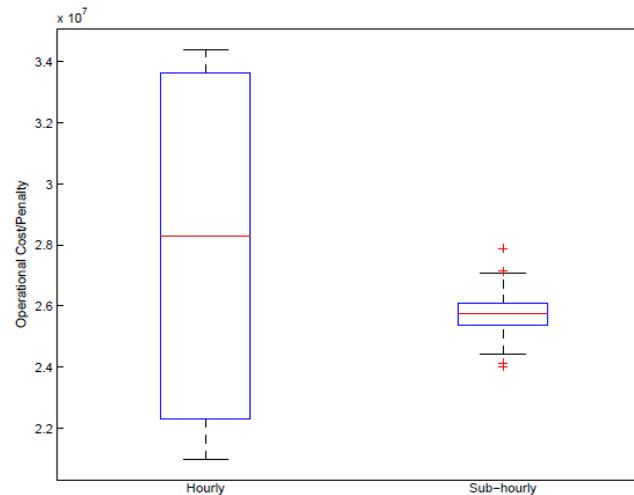
UQ Results: Hourly vs. Sub-hourly



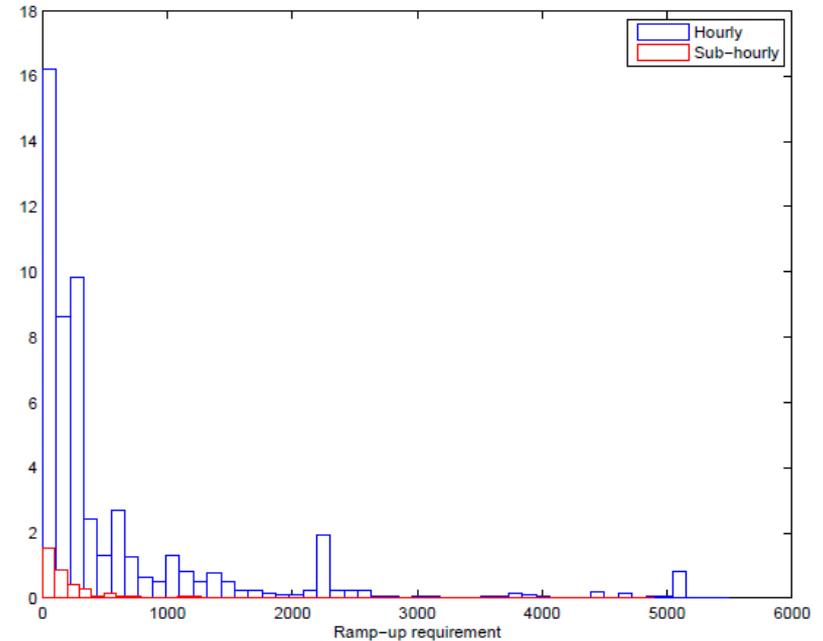
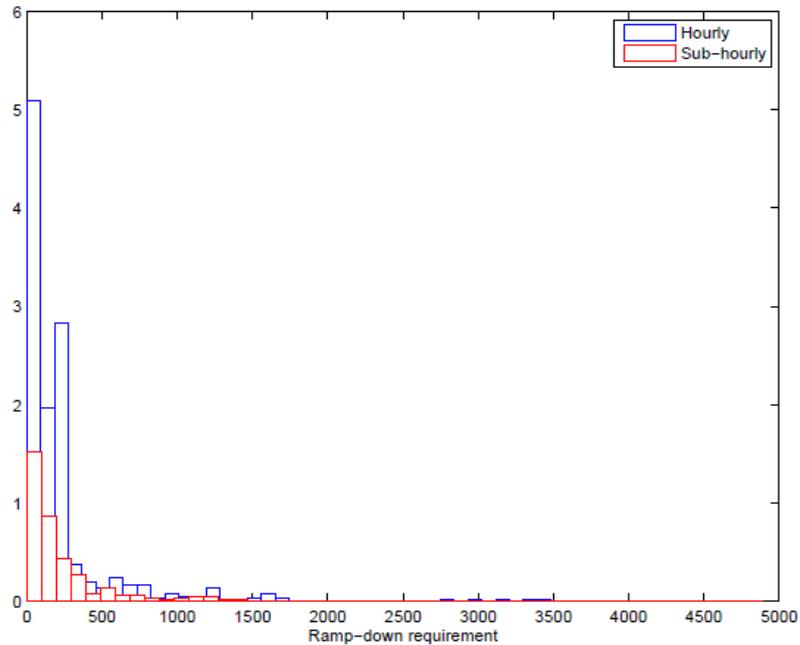
Conventional Generation Planning:

	Hourly Planning	Sub-hourly Planning
Total generation (MWh)	8.8812×10^4	9.2073×10^4
Generation cost (\$)	6.9862×10^6	7.2614×10^6

Operating Costs/penalties:



UQ Results: Hourly vs. Sub-hourly



Histogram of operating reserve requirement under the two plans

UQ performance: Hourly & Sub-hourly



Processor: Inter Core i7-2600 @ 3.4GHz x 8; Platform: Ubuntu 12.04(64 bit)

Scenarios SOLVER	Hourly Planning			Sub-hourly Planning		
	SAA-10 CPLEX (Def)	SAA-25 CPLEX (Def)	SD	SAA-10 CPLEX (Def)	SAA-25 CPLEX (Def)	SD
Rows	52260	130650	522 4443	274410	844275	522 26658
Columns	58460	140150	261 5585	337709	686025	261 33510
RV's	-	-	12	-	-	72
Iterations	54494	256137		455720	682372*	
Time (s)	341.13	5016.05		31237.52	78939.23*	

*Run aborted

UQ performance: Hourly & Sub-hourly



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	Hourly Planning			Sub-hourly Planning		
	CPLEX (Def) 10 Scenarios	CPLEX(Def) 25 Scenarios	SD	CPLEX(Def) 10 Scenarios	CPLEX(Def) 25 Scenarios	SD
Rows	52260	130650	522 4443	274410	844275	522 26658
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RV's (Sample)	-	-	12 (913)	-	-	72
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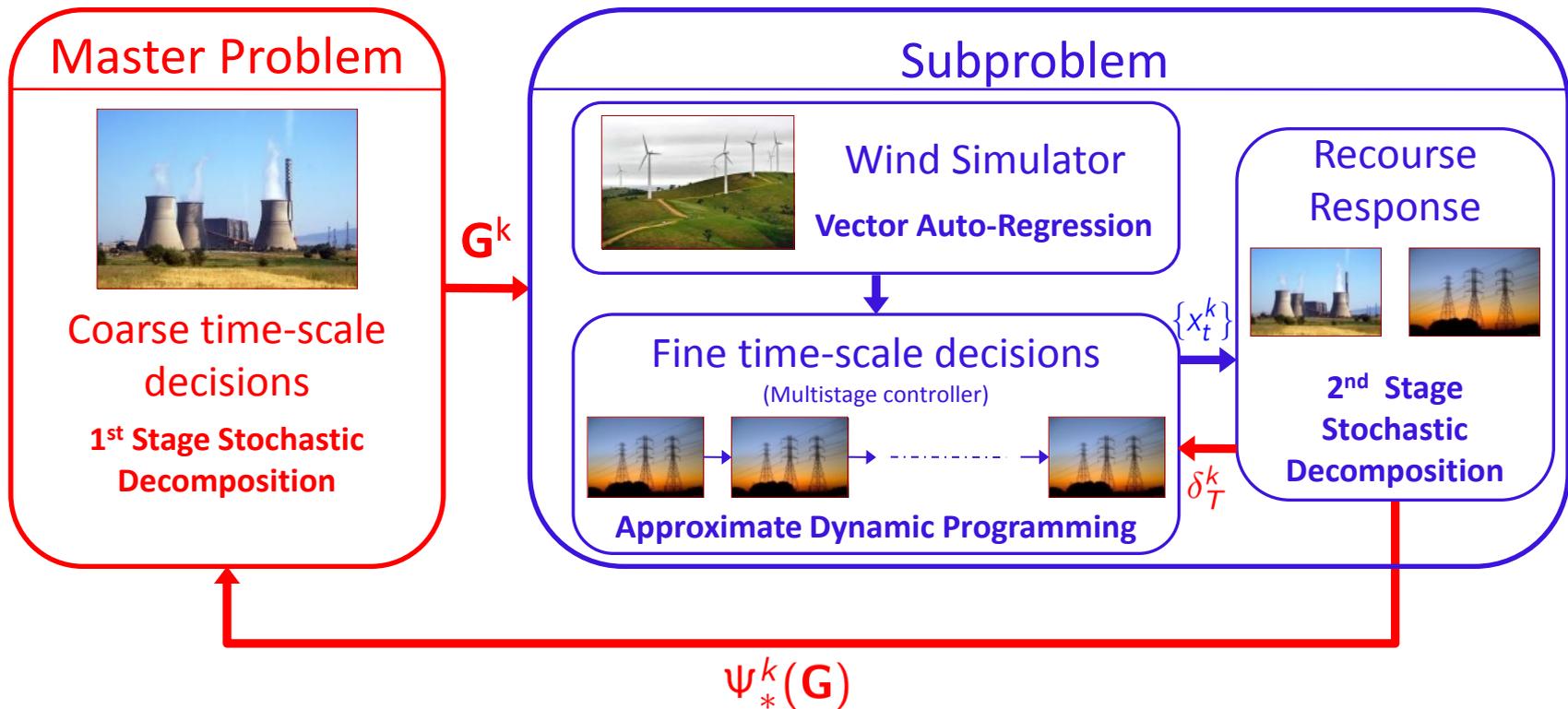
*Run aborted

Main Take Away



- Can SP Technology Provide Realistic Decision Support for Hourly Dispatch with Hourly Wind Simulation?
 - Yes, absolutely!
- Can SP Technology Provide Realistic Decision Support for Hourly Dispatch with Sub-hourly Wind Simulation?
 - Yes, with a bit of tuning! (e.g. Upper and Lower Bounds are within 0.1% of each other. Do we need that? NO!)
- Increased Computing Power =>
Time to Combine Optimization + Statistics
 - (Not to Abandon it!)

Combining SP and Optimal Control



Acknowledgment: NSF Grant CMMI 0900070 and AFOSR FA 9550-13-1-0015

Stochastic UC as Two-stage SMIP



- **Binary First Stage (Start-up, ramping ...)**
- **Continuous Second-Stage (LPs)**

- **Algorithm (Uses General Stochastic MIP Method)**
 - Use UQ with Stochastic Decomposition for Two-stage **SLP**
 - Correct Fractional Solutions Using Strong Relaxations for **First-stage SIP**