

Stochastic Unit Commitment by Progressive Hedging in Parallel with Dynamic Reserves

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Outline

- Background and Motivation
- Progressive Hedging (PH)
- Dynamic Reserves
- PH with Dynamic Reserves: Model Development
- Results
- Conclusions
- Future Work



Background and Motivation



Background

- Existing reserve requirements (**contingency / spinning and non-spinning reserve**) are imposed inside of day-ahead unit commitment to ensure sufficient backup capacity
 - Do not guarantee N-1 because **congestion** may prevent reserves from being deliverable
- Ensuring sufficient and **deliverable** reserves (**quantity + location**) will be increasingly more difficult with renewables
- Potential solutions:
 - Implement stochastic programming Computational challenge
 - Use existing reserve requirements/increase reserve quantity Costly
- **Best solution: a balanced approach** that combines advanced reserve policies with stochastic programming algorithms



Motivation

- Create generalized algorithms that mimic existing (and effective) reserve policies
- Embed dynamic reserve policies within stochastic programming frameworks
- Improve scalability and convergence by attacking the low hanging fruit
- Minimize the uncertainty needed to be captured by stochastic programming



Progressive Hedging



Progressive Hedging

- Horizontal decomposition approach, trivially parallel
 - Treat scenarios as independent, deterministic problems
 - Non-anticipativity constraints are relaxed
- Does not guarantee optimality for MILPs – a heuristic
- Asymptotic linear convergence rate for LP

$$\bullet x_s^{(k)} = \underset{x, y_s}{\operatorname{argmin}} \left(c^T x + w_s^{(k-1)T} x + \frac{\rho}{2} \|x - \dot{x}^{(k-1)}\|^2 + f_s^T y_s \right)$$

$$\bullet \dot{x}^{(k)} = \sum_s P(s) x_s^{(k)}$$

$$\bullet w_s^{(k)} = w_s^{(k-1)} + \rho \left(x_s^{(k)} - \dot{x}^{(k)} \right)$$



Progressive Hedging Tuning

- Penalty factor (ρ)
 - Strong impact on solution quality, convergence
 - Dynamic and logical for best results (future work)
- Bundling scenarios to break degeneracy
- Variable fixing for extensive form
- Declining relative mipgap termination criteria

[1] J.-P. Watson and D. L. Woodruff, “Progressive hedging innovations for a class of stochastic mixed-integer resource allocation problems,” *Computational Management Science*, vol. 8, pp. 355–370, November 2011.



Dynamic Reserves



Dynamic Reserve Policies

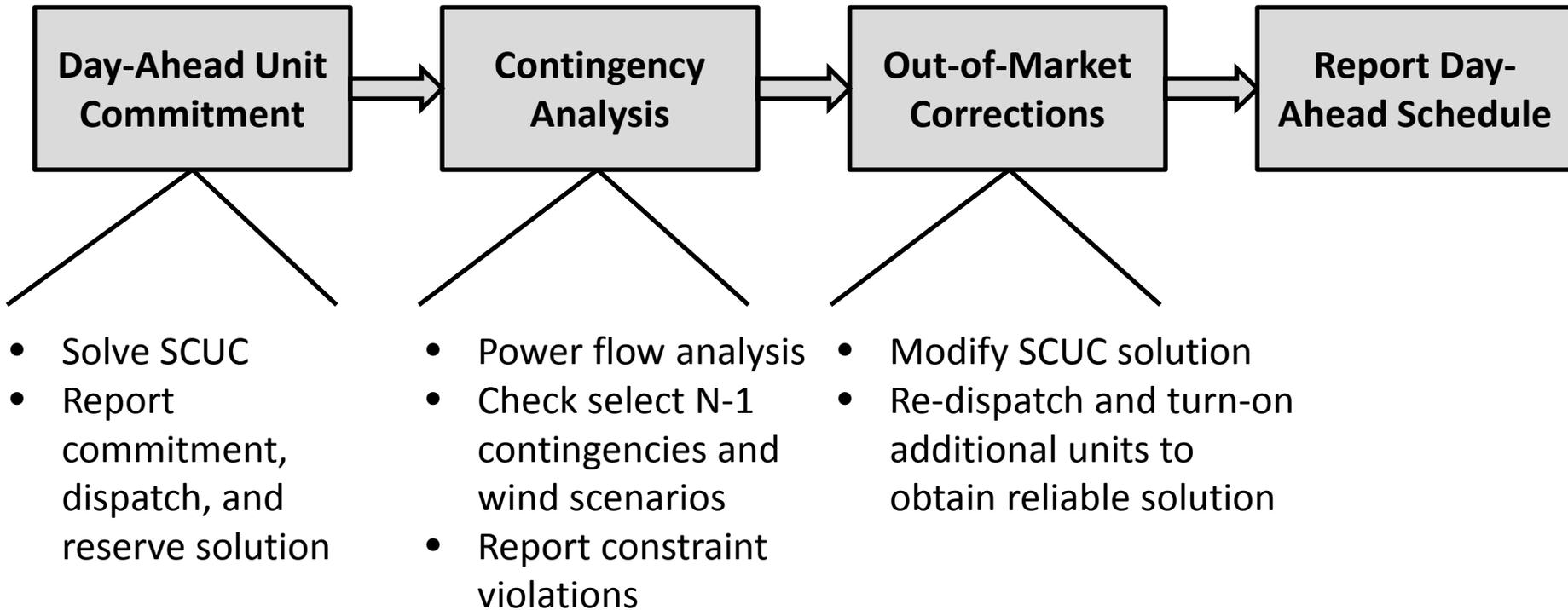
- Existing reserve requirements
 - Quantity of reserve must exceed worst case contingency
 - Impose a quantity requirement but not a *locational* requirement
 - Exception: reserve zones are used to impose regional requirements
 - Exception: stochastic programming determines reserves implicitly
- Dynamic reserve policies:
 - Reserve requirements that reflect operating states
 - Improve *deliverability* of reserves by accounting for congestion
- Dynamic reserve zones:
 - Identify critical bottlenecks and critical regions that require additional reserves
 - Account for impact of renewables
 - Account for post-contingency flows



PH with Dynamic Reserves: Model Development

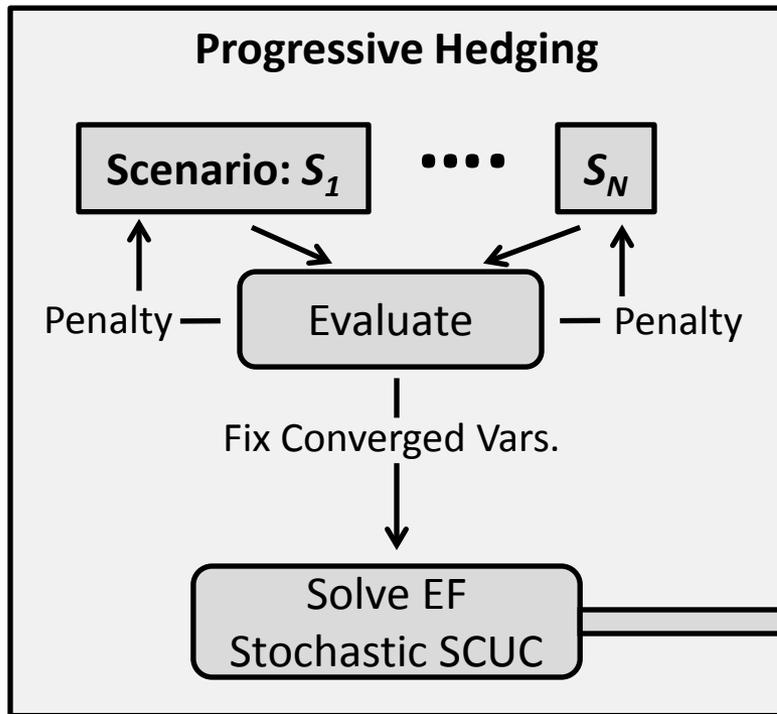
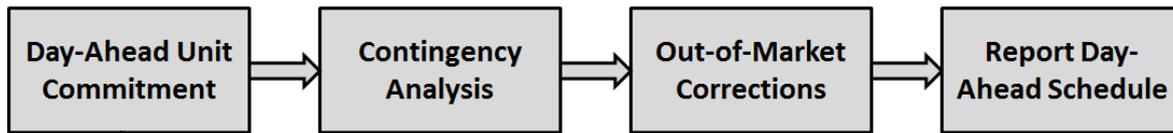


Day-Ahead Scheduling





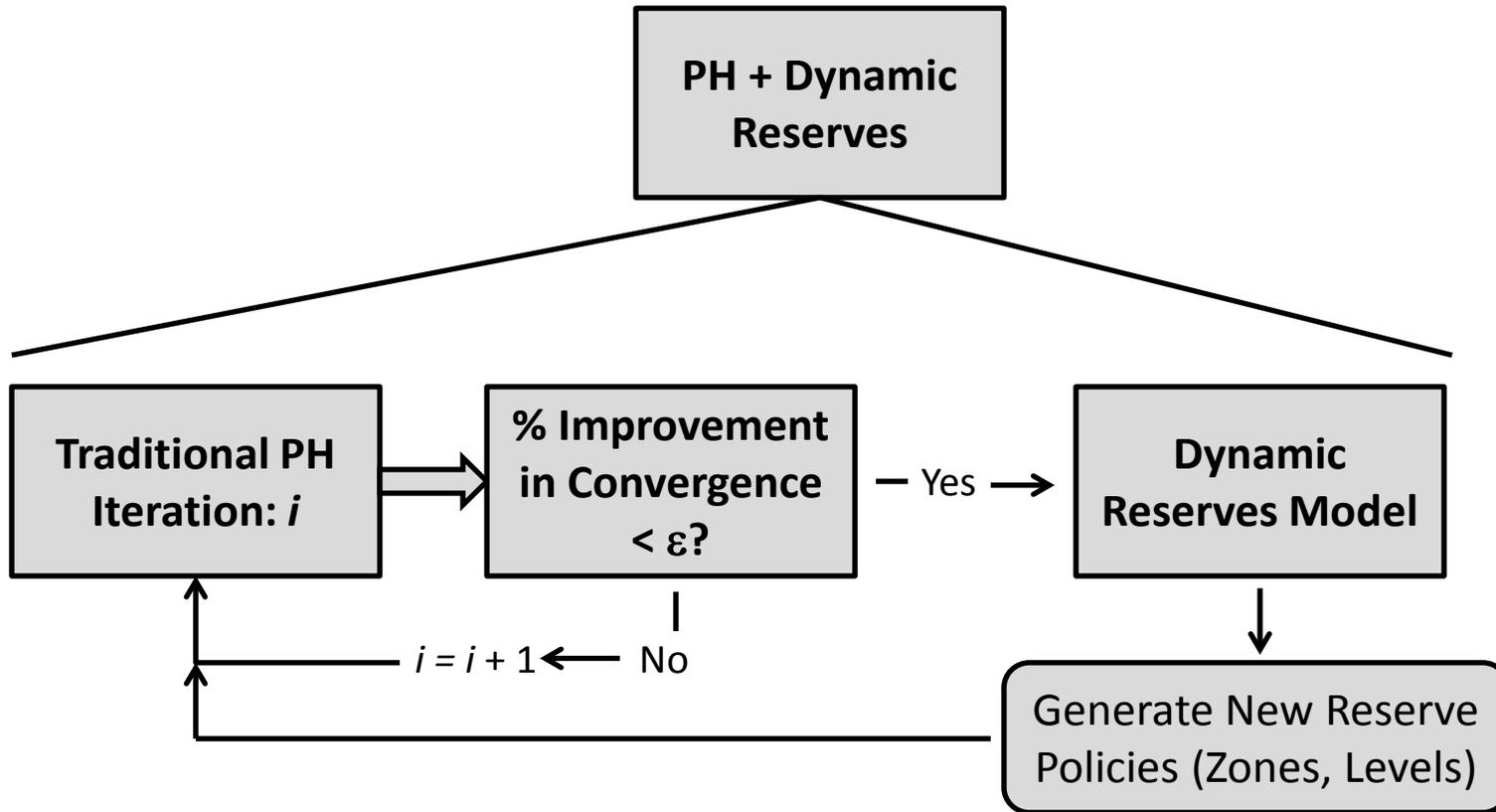
Traditional Progressive Hedging



- Solve N deterministic SCUC in parallel
- Check convergence of solutions
- Apply penalty to each SCUC to encourage convergence
- Stopping criterion: time
 - Fix converged variables; determine status of remaining vars. with EF S-SCUC
- Solve extensive form (EF) stochastic SCUC
 - Send resulting commitment, dispatch, and reserves to contingency analysis

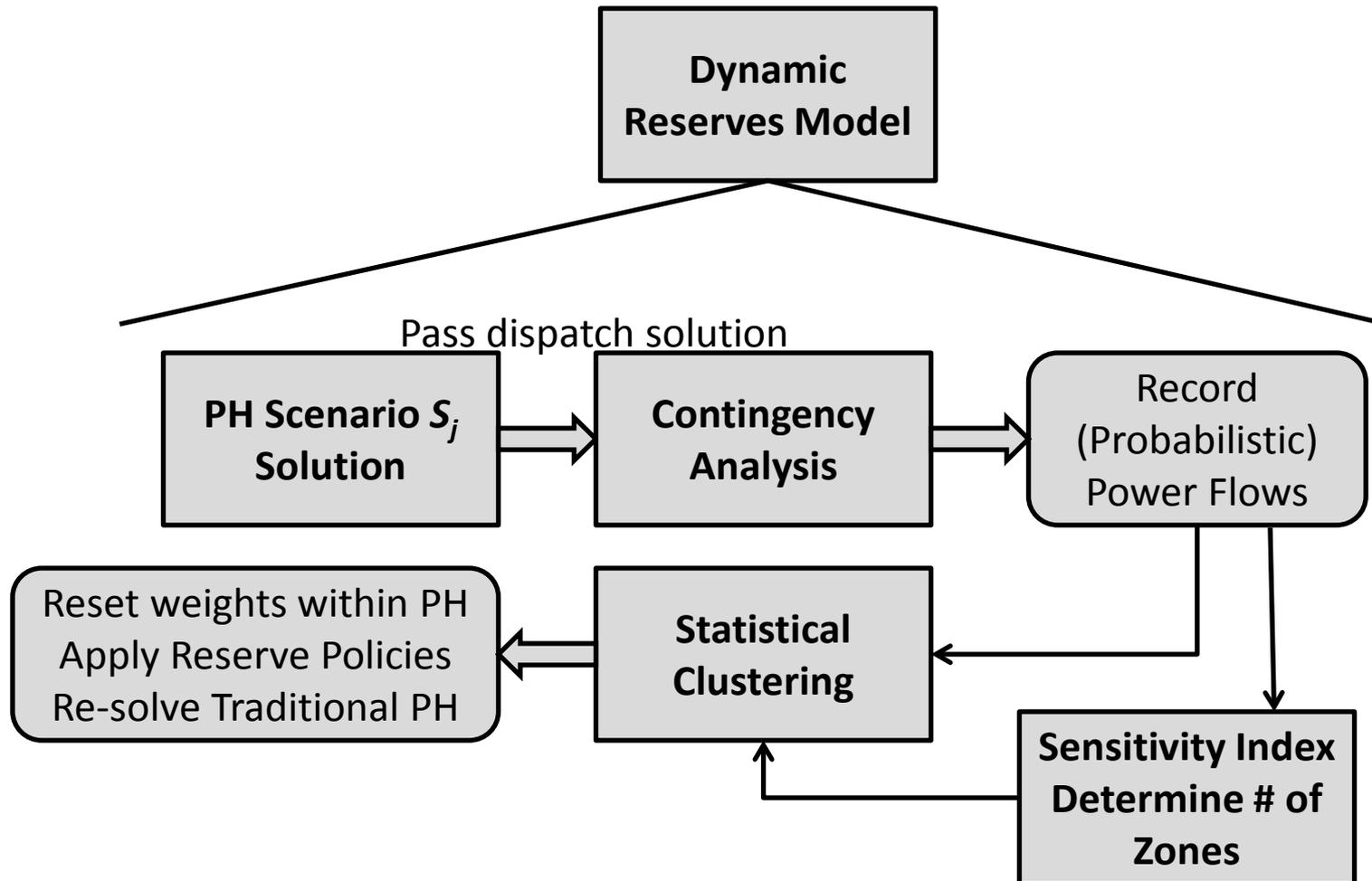


PH with Dynamic Reserves





Dynamic Reserves Model





Statistical Clustering

- Statistical clustering method: *K-means*
- Centrality metric: Weighted PTDF differences
 - Lines with high average loading and variability receive higher weights, [2] [3]
 - Uses a similar metric to the performance index (PI) [4]
- Goal: incorporate variability of renewable resources and post-contingency line flows
- Goal: identify critical lines and generators that have similar impacts on these critical lines
- Goal: improve placement of reserves to encourage convergence

[2] F. Wang and K. W. Hedman, "Reserve zone determination based on statistical clustering," *NAPS* 2012.

[3] F. Wang and K. W. Hedman, "Dynamic reserves for day-ahead unit commitment with renewable resources," *IEEE Trans. Power Syst.*, under review.

[4] A. J. Wood and B. F. Wollenberg, *Power Generation, Operation, and Control*, 2nd Ed. New York, NY: Wiley, 1996.



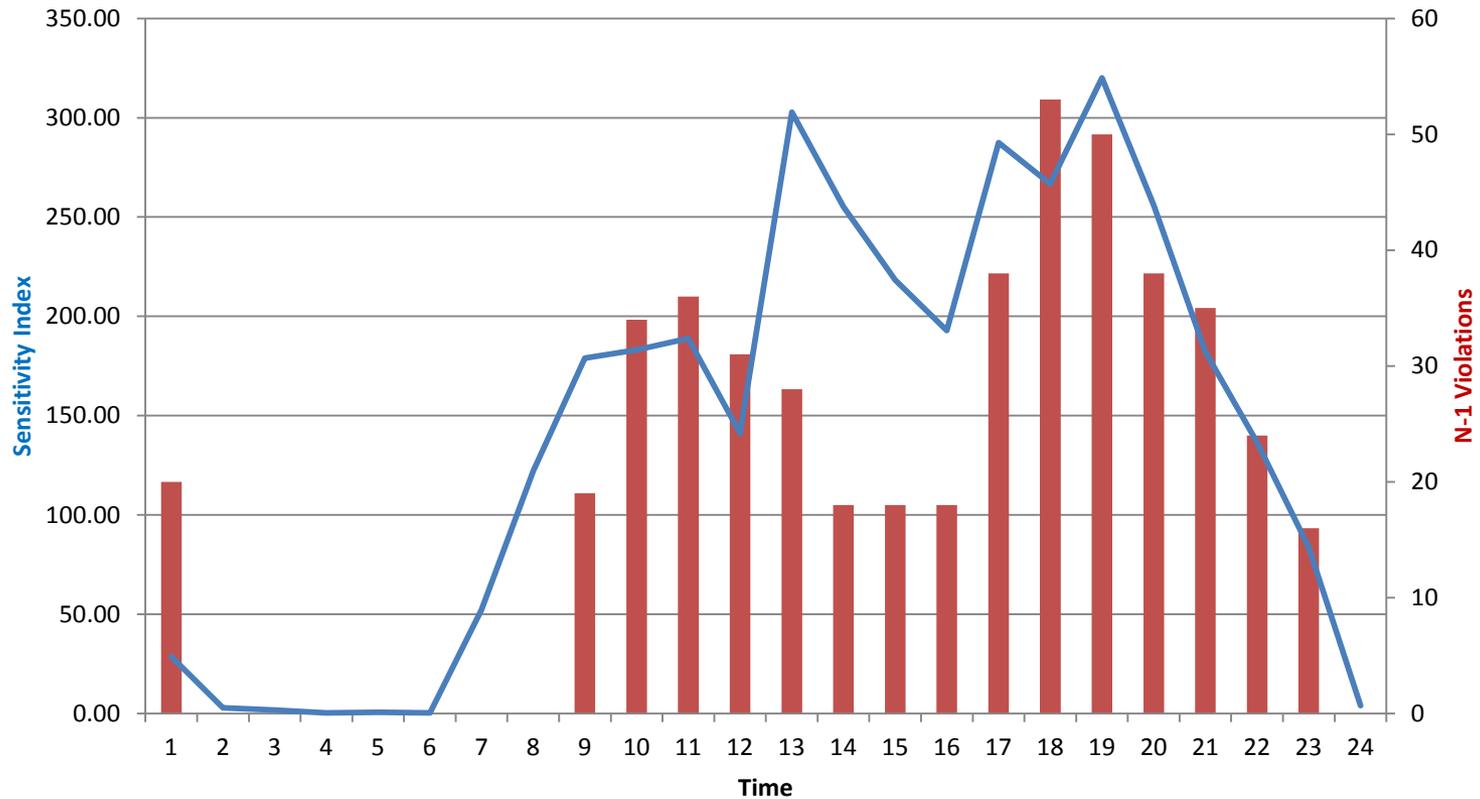
Sensitivity Index

- Custom factors based on OTDF and LODF
- Offline study: loss of 1 MW (generator or line)
- Derivative QP models to minimize sum of squared deviation in line flows
 - Simulation of intelligent re-dispatch for location
- Algorithm from [4] for quick calculation
- Number of zones based on mean and standard deviation of sensitivity index



Sensitivity Index

Sensitivity Index and N-1 Violations





Results



Modeling

- RTS-96 test case: Winter weekday, weekend
- Scenarios developed from the NREL Western Wind Integration Dataset
 - Wind placed at periphery of network
 - 512 scenarios, selection procedure for 64 [5]
- C code for Pyomo in parallel, Gurobi 5.5
- Dual Intel Xeon E5-2687W, 128 GB RAM

[5] J. Dupacová, N. Gröwe-Kuska, and W. Römisich, “Scenario reduction in stochastic programming: An approach using probability metrics,” *Math. Program*, series A, vol. 3, pp. 493–511, 2003.

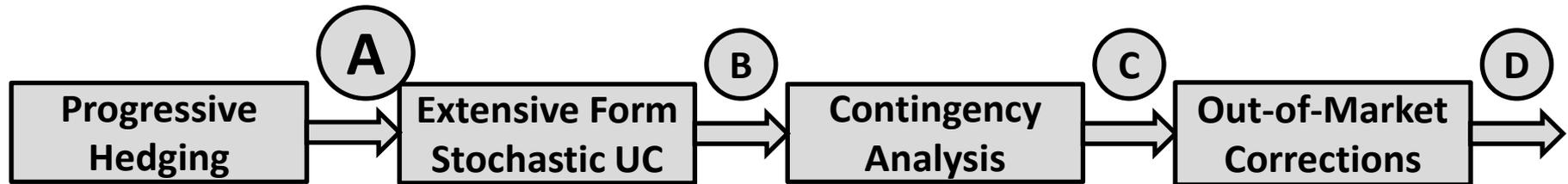


Modeling

- Progressive Hedging
 - Scenario bundling (pairs), declining mipgap
 - Terminates by fixing converged binaries
 - Committed units fixed
 - Uncommitted units fixed only in low sensitivity periods
 - Fast-start units that converged off are never fixed
- Comparison between this form of PH and the expanded algorithm with dynamic reserve zones
 - Reserve zones applied for 3 iterations as hard constraints, then only as PH penalties in augmented objective function



Results: PH

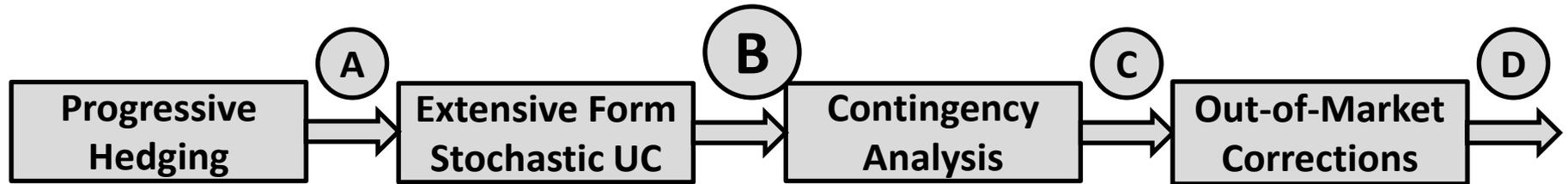


Dec 18 th	New Method Peak Load One Patch	Pure PH Peak Load	New Method Peak Load Three Patches	Pure PH Peak Load
Time	1251s	1255s	3157s	3049s
U norm	0.370446	0.317263	0.186529	0.321895
Binaries	7	13	4	12

- Times represent end time of current iteration of PH
- Binaries are the remaining unit commitment variables that have not converged



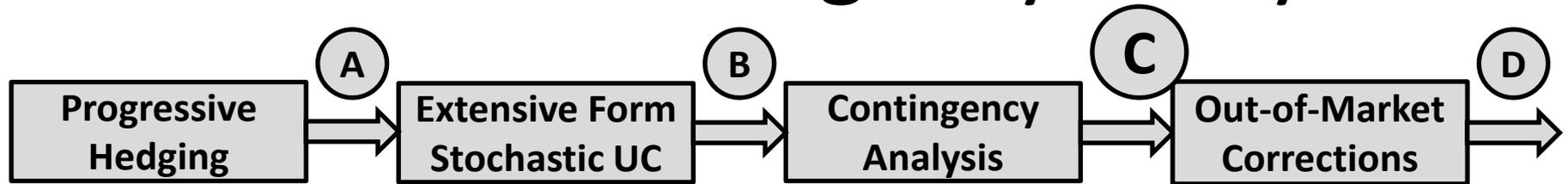
Results: EF Stochastic SCUC



Dec 18 th	New Method Peak Load One Patch	Pure PH Peak Load	New Method Peak Load Three Patches	Pure PH Peak Load
Cost	2736396.05	2736396.05	2727516.72	2736396.05
Time	2422s	2787s	5045s	4454s
Full EF	40189s			
Bound	2638794.33 (to 0.39%)			
Optimality Gap	3.70%	3.70%	3.36%	3.70%



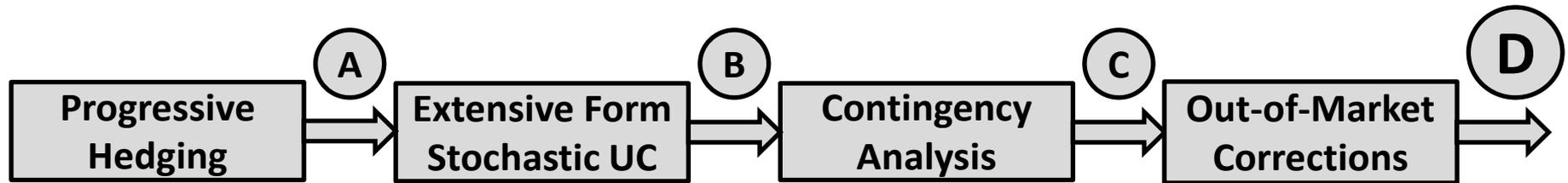
Results: Contingency Analysis



Dec 18 th	New Method Peak Load One Patch	Pure PH Peak Load	New Method Peak Load Three Patches	Pure PH Peak Load
Violations	405	405	389	407
E(LS)/h	0.01893	0.01893	0.01180	0.01894
Diff	0%		-37.66%	
EF E(LS)/h	0.06988			
EF Diff	-72.92%	-72.91%	-83.11%	-72.90%



Results: Out-of-Market Corrections



- Ongoing work
- Developing OMC algorithms [6]
- Developing OMC decision support tool for operators [6]
- Tool can also be used to establish the true cost associated with new day-ahead scheduling procedures and algorithms

[6] Y. Al-Abdullah, M. Abdi-Khorsand, and K. W. Hedman, "Analyzing the impacts of out-of-market corrections," *IREP 2013*, submitted.



Conclusions

- Dynamic reserves can improve both PH convergence rate and solution quality
- Sensitivity metric incorporated within PH algorithm quickly identifies time periods which need stronger reliability policies
- Extensive form termination phase of PH can achieve higher quality solution by not fixing off-converged units in time periods when sensitivity metric is relatively high



Future Work

- Apply it to the FERC PJM 14,000 Bus Test Case
- Utilize out-of-market algorithms to confirm final costs
- Develop embedded nomograms
- Demonstrate scalability



Questions?

For additional information or to provide additional feedback, contact:

Garret LaBove (garret@asu.edu)

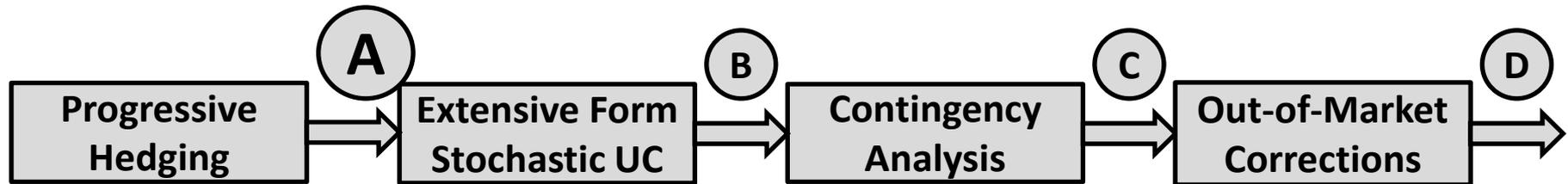
Kory Hedman (Kory.Hedman@asu.edu)



Appendix



Results: PH

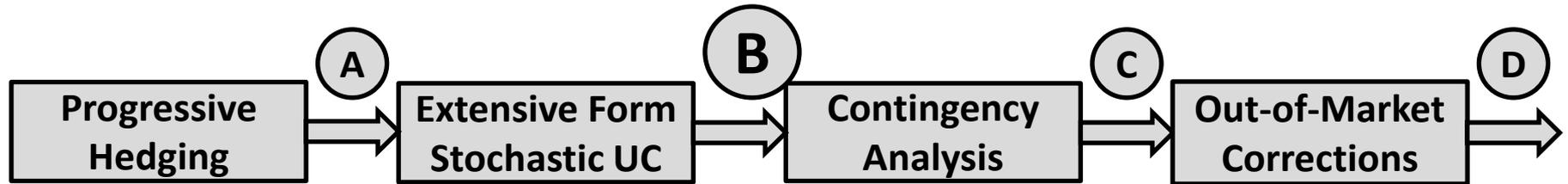


Dec 16 th	New Method Light Load One Patch	Pure PH Light Load
Time	951s	996s
U norm	0.00000	0.085626
Binaries	0	2

- Times represent end time of current iteration of PH
- Binaries are the remaining unit commitment variables that have not converged



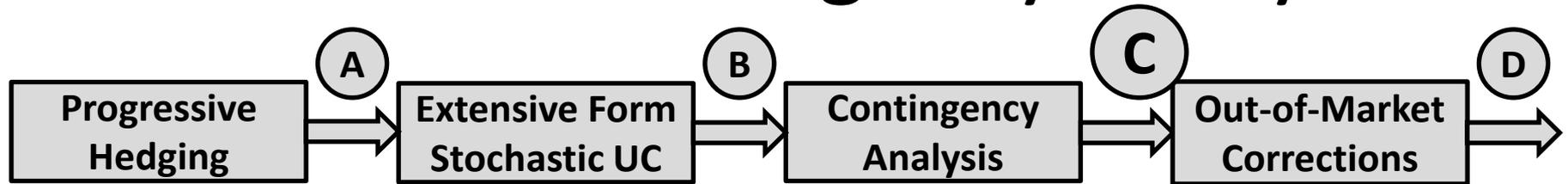
Results: EF Stochastic SCUC



Dec 16 th	New Method Light Load One Patch	Pure PH Light Load
Cost	1101406.32	1078137.01
Time	2679s	3024s
Full EF	30137s	
Bound	1056715.41 (to 0.37%)	
Optimality Gap	4.23%	2.03%



Results: Contingency Analysis



Dec 16 th	New Method Light Load One Patch	Pure PH Light Load
Violations	367	390
E(LS)/h	0.00885	0.00959
Diff	-7.70%	
EF E(LS)/h	0.06303	
EF Diff	-85.96%	-84.79%