A Scalable Decomposition Algorithm for Solving Stochastic Transmission and Generation Investment Planning Problems

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Talk Goals

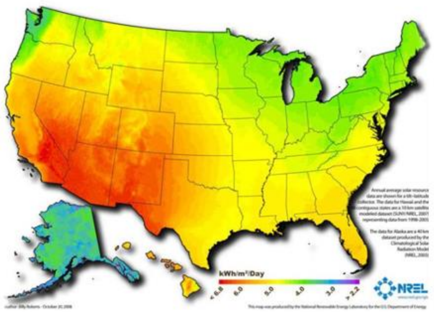
1. Summarize some of the challenges of large-scale transmission and generation planning.

2. Overview practical (industrial) and theoretical (academic) approaches to investment planning.

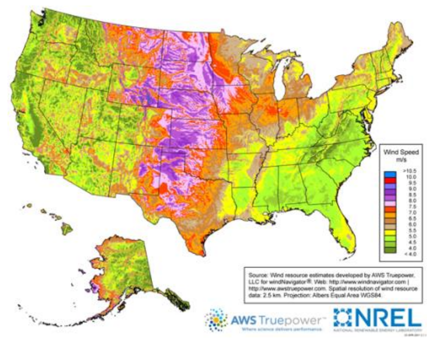
1. Describe and illustrate the performance of the Progressive Hedging decomposition algorithm applied to the WECC 240-bus test case.

Introduction

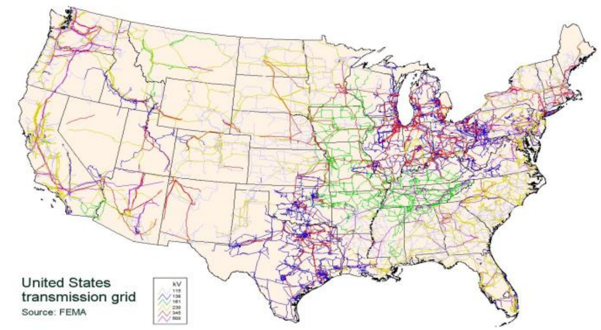
Solar Resources (NREL)



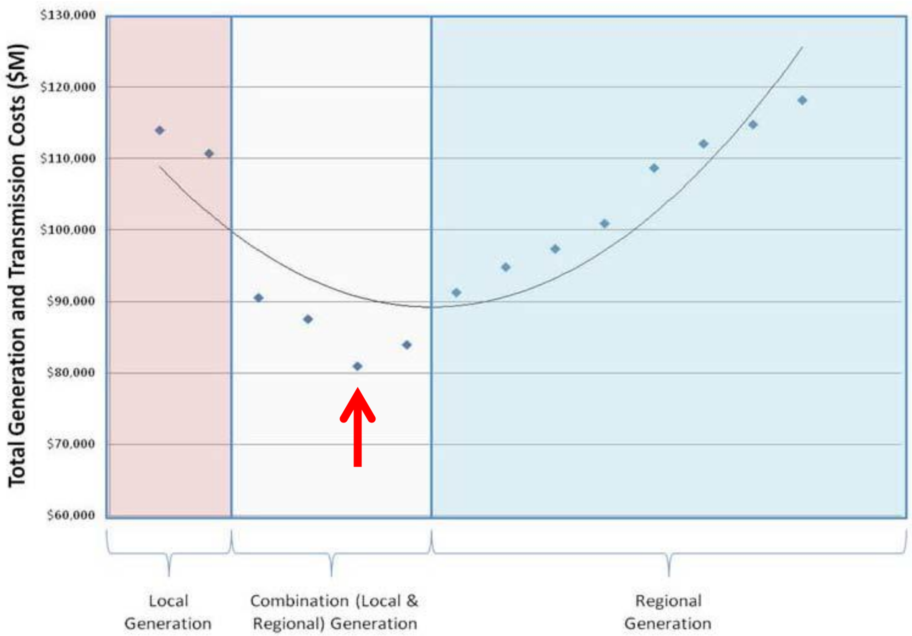
Wind Resources (NREL)



U.S. Transmission System (FEMA)



Zone Scenario Generation and Transmission Cost (MISO, 2010)



Goal:

Identify most cost effective combination of transmission and generation investments to meet:

1) Forecasted demand
2) Renewable and environmental goals

Approaches in industry

Commercial software used for transmission planning

- Simulation packages
  - SIEMENS PSS-E
  - ABB GridView
  - Ventyx PROMOD

  Dispatch simulation, not investment optimization (O'Neill et al, 2012)

- Optimization packages
  - PSR NXT/NetPlan

    Only transmission, not generation

  - PLEXOS LT

    Transportation network (ignores loop-flow effects)

Treatment of uncertainty and hedging strategies

"The "least regrets" approach can be summarized as evaluating a range of plausible scenarios made up of different generation portfolios, and identifying the transmission reinforcements found to be necessary in a reasonable number of those scenarios." (CAISO, 2012)

Potential regret with respect to true stochastic approach: **5-50% of total system cost** (Munoz et al, 2013)

…and from academia

Modeling approaches

- Co-Optimization Models : e.g., Weijde and Hobbs (2012) and Munoz et al (2013)
- Stochastic Models : e.g., Roh et al (2009) and Akbari et al (2011)

Solution approaches

- Tight MILP formulations : e.g., Bahiense et al (2001)
- Benders decomposition : e.g., Munoz et al (2014)
- Heuristics : e.g., Oliveira et al (1995)
- Progressive Hedging : e.g., Reis et al (2005)

In general, *limited by scale*:

- Often applied to **small test cases**
- Usually consider only a **few scenarios** (often just one)
- Exception: Munoz et al (2014) solved WECC 240-bus system using Benders decomposition. Considered 8,736 scenarios, **87 hours to attain a 2.4% optimality gap**.

Stochastic Planning Model

Objective: minimize present worth of capital plus operation costs

Decision variables

- Transmission investments (<u>binary</u>)
- Generation investments (<u>continuous</u>)
- Generation dispatch
- Power flows
- Phase angles
- Load curtailment

Deterministic constraints

- Transmission build limits (max number of circuits per corridor)
- Generation build limits (max capacity per bus, renewable resource potentials)
- Installed reserves (min firm capacity per region, ELCC for renewables)
- RPS constraint (min generation from renewables, <u>based on average capacity factors</u>)

Scenario-dependent constraints (DC OPF)

- Supply = Demand (KCLs)
- Loop-flow constraints for existing lines (KVLs)
- Loop-flow constraints for candidate lines (disjunctive KVLs)
- Thermal limits
- Max generation limits (use hourly capacity factors from historical data for renewables)

Solution Algorithm: Progressive Hedging

Progressive Hedging (Rockafellar and Wets, 1991)

Sub-problem 1	Sub-problem 2		Sub-problem N
Investments Scenario 1	Investments Scenario 2		Investments Scenario N
Operations Scenario 1	Operations Scenario 2	…	Operations Scenario N

→ Used to enforce non-anticipativity constraints on transmission and generation investment variables

https://software.sandia.gov/trac/coopr

Features

- Available in the PySP (Watson et al, 2012) package of Pyomo (Hart et al, 2012)
- Converges if problem is linear, good heuristic for mixed-integer problems
- Several known techniques to accelerate convergence (Watson and Woodruff, 2011)
- New: Lower bounds to assess solution quality from Gade et al (2013) or Munoz et al (2014)

Experience from large-scale stochastic unit commitment problems (ARPA-E)

- ISO NE and 100 scenarios:

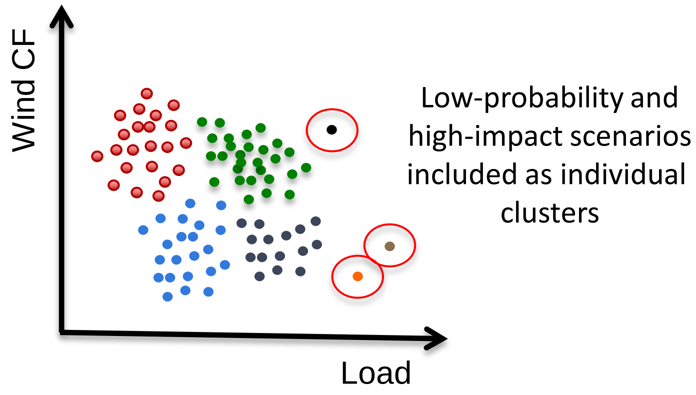
Extensive form on CPLEX → No feasible solution after 1 day of CPU time

Progressive Hedging → 30 iterations / 20 min to attain 2% optimality gap

Scenario Reduction Framework

Constrained k-means clustering

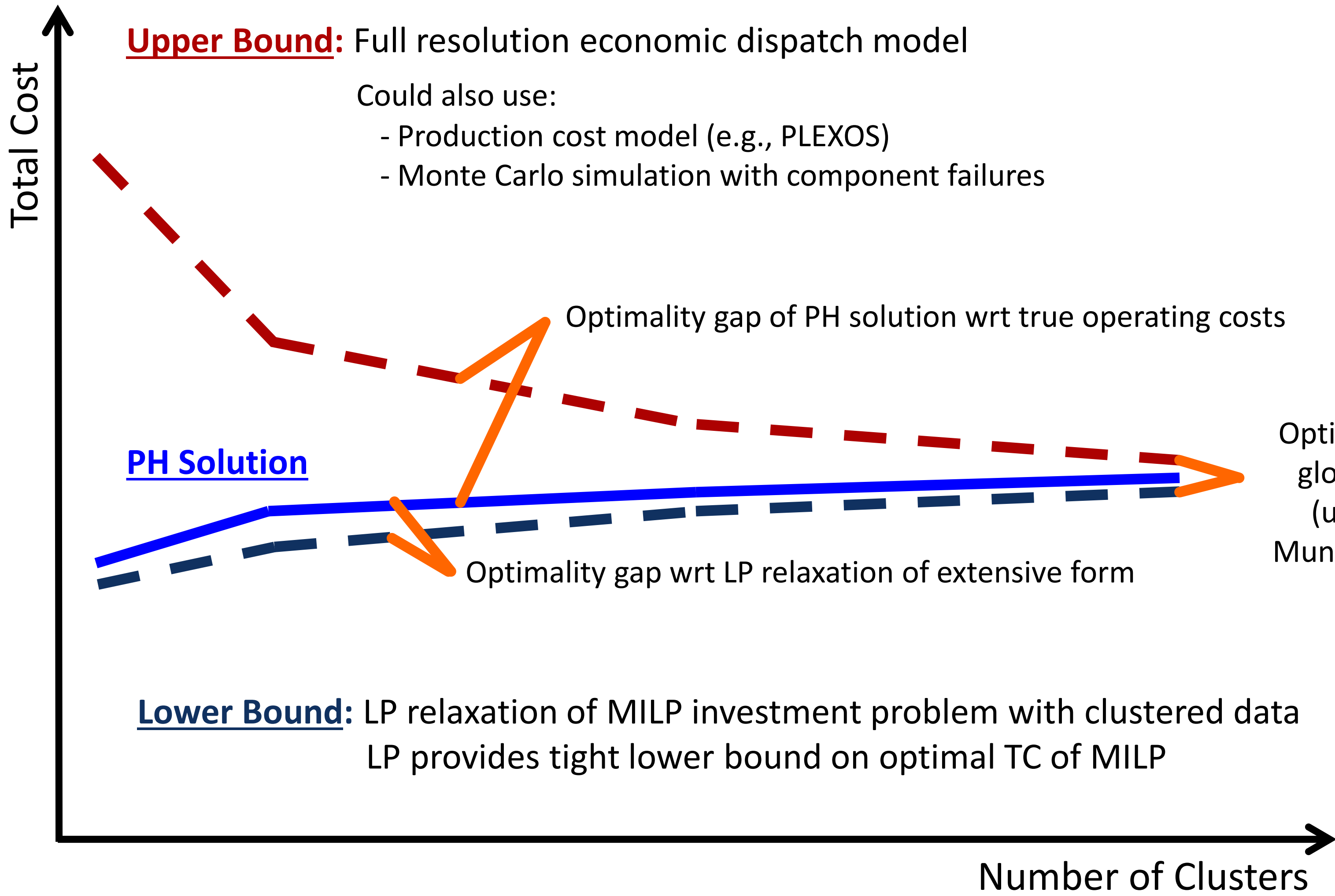
- Group similar hours with similar loads, wind, solar, and hydro levels
- Isolate hours that have high impact on investment decisions
- Reduced problem provides a lower bound on optima total system cost (Munoz et al, 2014). The more clusters, the tighter the lower bound.



Potential extensions for other types of uncertainties

- Long-term policy and economic uncertainties (capital costs, fuel prices, and renewable targets). These stochastic parameters are not in the right-hand-side of constraints
- Use a combination of constrained k-means with importance sampling:
  - Constrained k-means : selection of representative load, wind, solar, and hydro states
  - Importance sampling : selection of long-term policy and economic scenarios with high impact on total system cost (e.g., Papavasiliou and Oren, 2012)

Assessing Solution Quality



Test Case: WECC 240-bus System

WECC 240-bus system:
(Price & Goodin, 2011)

- 140 Generators (200 GW)
- 448 Transmission elements
- 21 Demand regions
- 28 Flowgates

Renewables data (Time series, GIS)
(NREL, WREZ, RETI)

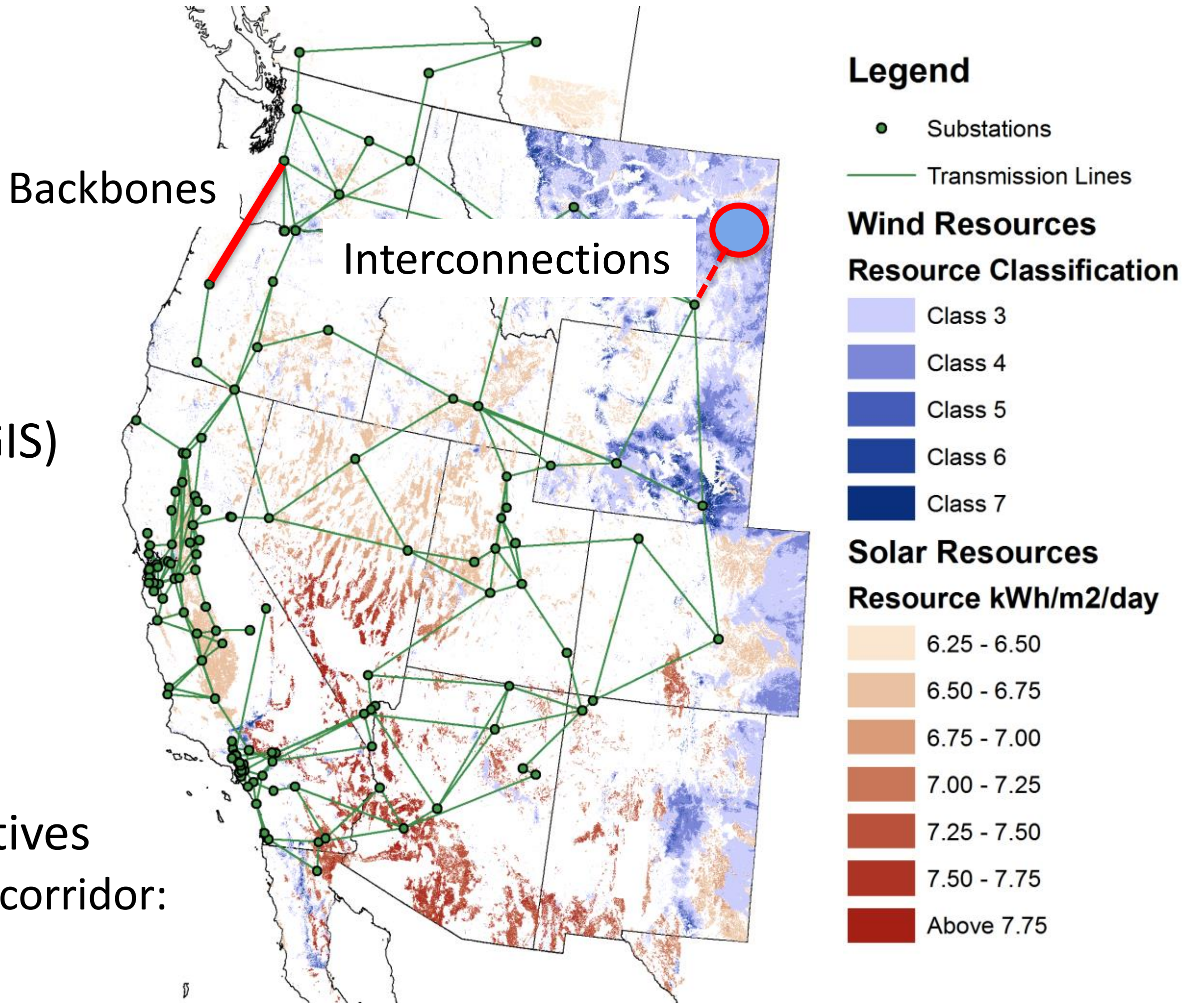
- 54 Wind profiles
- 29 Solar profiles
- 31 Renewable Hubs (WREZ)

Candidate Transmission Alternatives

Maximum number of circuits per corridor:

2 for Backbones

4 for Interconnections to Renewable Hubs



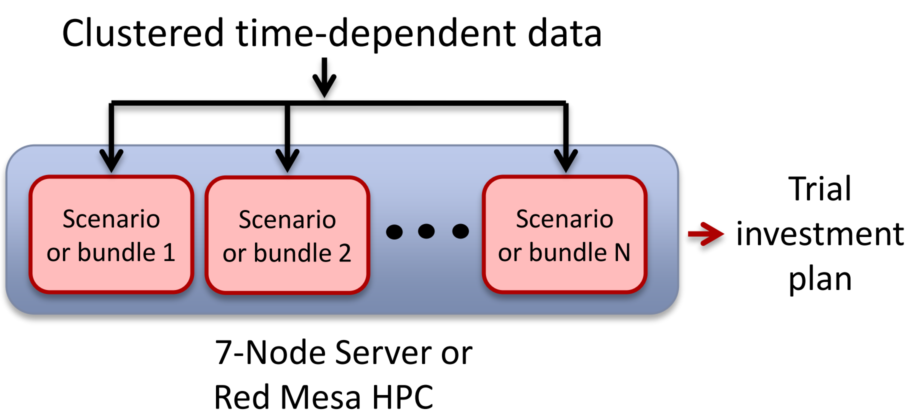
Experiments

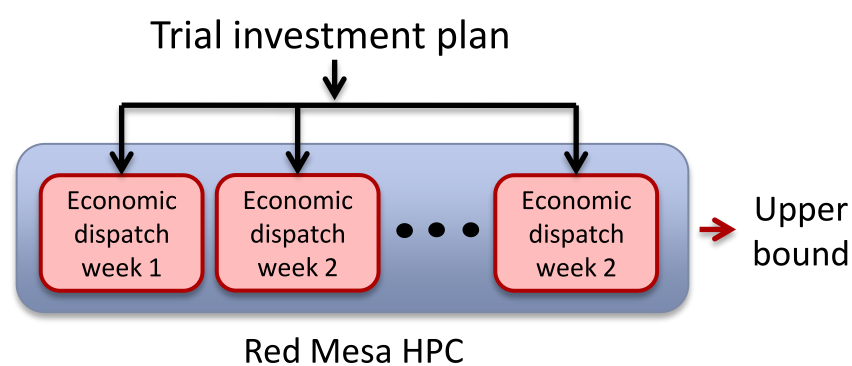
Description

- Dataset of 8,736 historical observations of load, wind, solar, and hydro levels for year 2004
  - Results in ~15M variables and ~35M constraints
- 257 generation investment variables (continuous)
- 339 variables for transmission backbones (binary)
- 31 variables for interconnections to renewable hubs (integer)

Our Hardware Environments

- Red Sky/Red Mesa HPC: 43,440 cores of Intel Xeon series processors, 64TB of RAM (12 GB per node)
- 7-Node Server: 48 cores of Intel Xeon series processors, 48 GB RAM (8 GB per node)
- Multi-Core SMP Workstation: 64-core AMD, 512 GB RAM (~$17K)





Computational Performance

Preliminary Results:

Extensive form, 100 scenarios

- CPLEX, no feasible solution after 1 day on a 32-core workstation (Munoz et al, 2014)

Progressive Hedging, 100 scenarios (34 bundles, 7-Node Server)

- ~53 minutes, 97 iterations until full convergence of investment variables

(1) UB from investment cost PH + true operating cost : \$577.3B

(2) Expected cost from PH : \$561.9B

(3) LB from solving extensive form of LP : \$549.7B

Gap = 2.6%

Gap LP = 2.1%

To do:

- Fine tune PH parameters to accelerate convergence (i.e., rho, variable fixing and/or slamming, etc.).

Summary

- Stochastic transmission and generation planning on large-scale systems can be used to:
  a) Capture the true economic value of time-dependent resources
  b) Model different weather scenarios
  c) Explicitly represent long-term policy and economic uncertainties

  → Far easier on paper than in practice!

- Commercially available software does not capture a), b) or c) due to both modeling and algorithmic limitations

- Progressive Hedging coupled with our scenario reduction framework can be used to solve large-scale problems in commodity workstations, not just supercomputers!

- Same algorithm could be applied to multi-stage investment problems to account for optionality (i.e., *here-and-now* vs *wait-and-see* investment solutions)

Relevant References

Akbari, T., Rahimikian, A., and Kazemi A. (2011), “A multi-stage stochastic transmission expansion planning method.” Energy Conversion Management, 52, pp. 2844–2853.

Bahiense, L., Oliveira, G., Pereira, M., and Granville, S. (2001). “A mixed integer disjunctive model for transmission network expansion,” IEEE Transactions on Power Systems, 16 (3), pp. 560–565.

Binato, S., Pereira, M. V. F., and Granville, S. (2001). “A new Benders decomposition approach to solve power transmission network design problems. “ IEEE Transactions on Power Systems, *16*(2), 235-240.

Birge, J. and F. Louveaux (1997). Introduction to Stochastic Programming, Springer.

CAISO, “2011-2012 Transmission Plan,” California ISO, March 2012. http://www.caiso.com

Gade, D., Hackebeil, G., Ryan, S., Watson, J-. P., Wets, R., and Woodruff, D. (2013). “Obtaining Lower Bounds from the Progressive Hedging Algorithm for Stochastic Mixed-Integer Programs.” Under review.

Hart W.E., Watson J.P., Woodruff D.L (2011). “Python optimization modeling objects (Pyomo).” Mathematical Programing Computation **3**, 219–260.

Price, J. E. and Goodin, J. (2011), “Reduced Network Modeling of WECC as a Market Design Prototype, IEEE Power Engineering Society General Meeting, July.

MISO, “Regional Generation Outlet Study,” Midwest ISO, November 2010. http://www.midwestiso.org

Munoz, F. D., Hobbs, B. F., and Watson, J-. P. (2014). “New Bounding and Decomposition Approaches for MILP Investment Problems: Multi-Area Transmission and Generation Planning Under Policy Constraints,” JHU Working Paper (under review).

Park, H. and R. Baldick (2013). "Transmission Planning Under Uncertainties of Wind and Load: Sequential Approximation Approach." IEEE Transactions on Power Systems, **PP**(99): 1-8.

O’Neill, R. P., Krall, E. A., Hedman, K. W., and S. S. Oren (2012), “A model and approach for optimal power systems planning and investment,” Mathematical Programming.

Oliveira, G. C., A. P. C. Costa, and S. Binato (1995). "Large scale transmission network planning using optimization and heuristic techniques." IEEE Transactions on Power Systems, 10 (4), pp. 1828-1834.

Reis, Francisco S., P. M. S. Carvalho, and L. A. F. M. Ferreira (2005). "Reinforcement scheduling convergence in power systems transmission planning." IEEE Transactions on Power Systems, 20 (2), pp. 1151-1157.

Roh, J. H., Shahidehpour, M., and Wu, L. (2009), “Market-based generation and transmission planning with uncertainties.” IEEE Transactions on Power Systems, 24 (3), pp. 1587–1598.

Rockafellar R.T., Wets R.J.-B. (1991). “Scenarios and policy aggregation in optimization under uncertainty.” Math. Oper. Res. **16**(1), 119–147.

Watson J.P. and Woodruff D.L. (2011). “Progressive hedging innovations for a class of stochastic mixed-integer resource allocation problems.” Computational Management Science **8**(4), 355–370.

Watson, Jean-Paul, David L. Woodruff, and William E. Hart (2012). "PySP: modeling and solving stochastic programs in Python." Mathematical Programming Computation 4.2, pp. 109-149.

QUESTIONS

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