A Scalable Solution Framework for Stochastic Transmission and Generation Planning Problems

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Sandia National Laboratories

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NNSA National Nuclear Security Administration

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Talk Goals

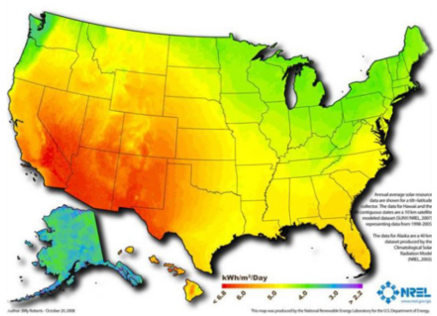
1. Summarize some of the challenges of large-scale transmission and generation planning.

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

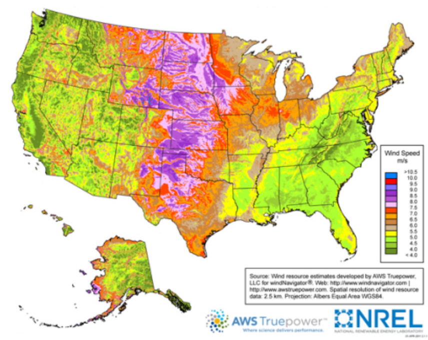
3. Describe and illustrate the performance of the Progressive Hedging decomposition algorithm applied to the WECC 240-bus test case.

Introduction

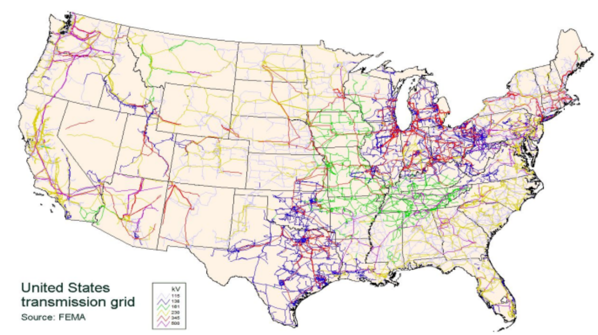
Solar Resources (NREL)



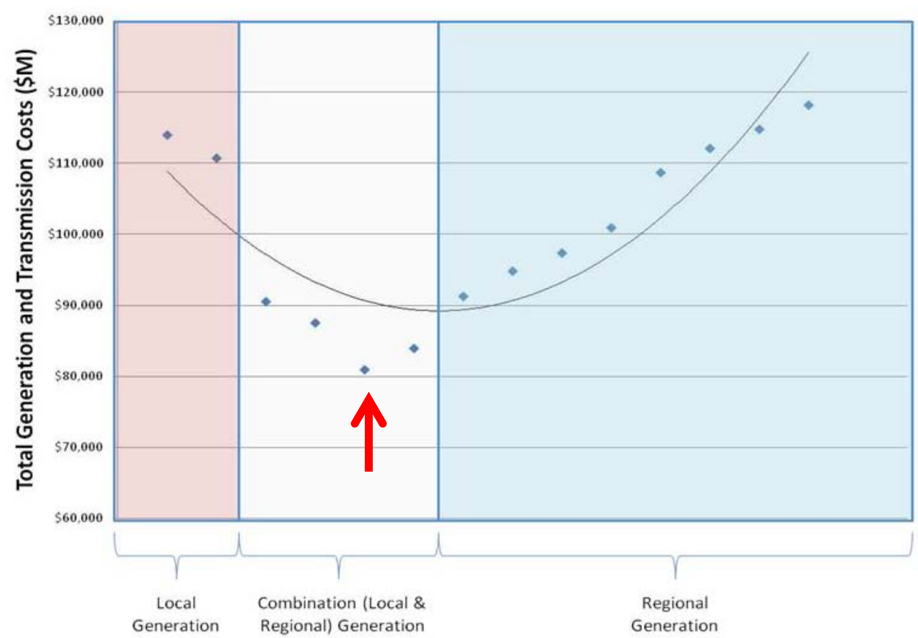
Wind Resources (NREL)



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

The evolution of analytical tools

Operations planning:

Industry standard

Early 1990s
Economic dispatch, linear programming

Late 1990s and early 2000s
Unit commitment, heuristics and Lagrangian relaxation

Late 2000s
Unit commitment, mixed-integer programming

Near future
Stochastic unit commitment

Savings of $250M/year

Transmission planning:

Industry standard

Early 1990s
Engineering judgment, economic dispatch

Late 1990s and early 2000s
Engineering judgment, production cost and reliability simulations

Late 2000s
Optimal transmission planning, mixed-integer programming

Near future
Stochastic transmission planning

Approaches used in industry

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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)

Stochastic Planning Model

Objective: minimize present worth of capital plus operation costs

Decision variables

- Transmission investments (binary)
- Generation investments (continuous)
- 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, dualized, treated as soft constraint)

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 <u>non-anticipativity constraints</u> 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:

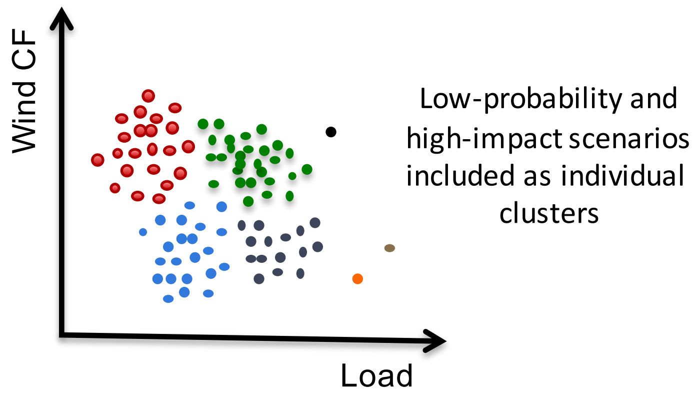
Extensive form on CPLEX → No feasible solution after 1 day of CPU time

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

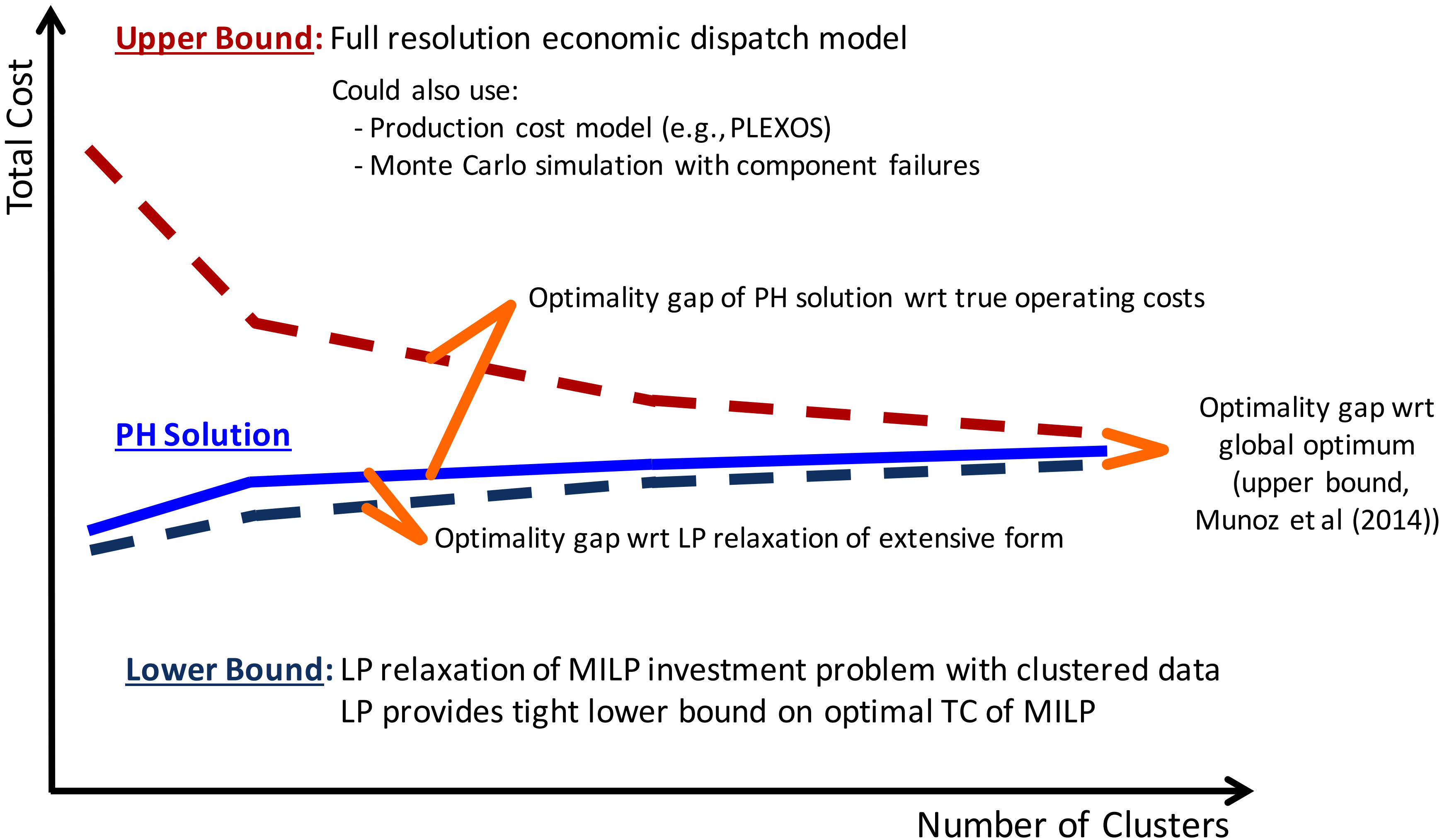
Scenario Reduction Framework

k-means clustering

- Group similar hours with similar loads, wind, solar, and hydro levels.
- Reduced problem provides a lower bound on optima total system cost since all stochastic parameters are on RHS of constraints (Munoz et al, 2014). The more clusters, the tighter the lower bound.



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)

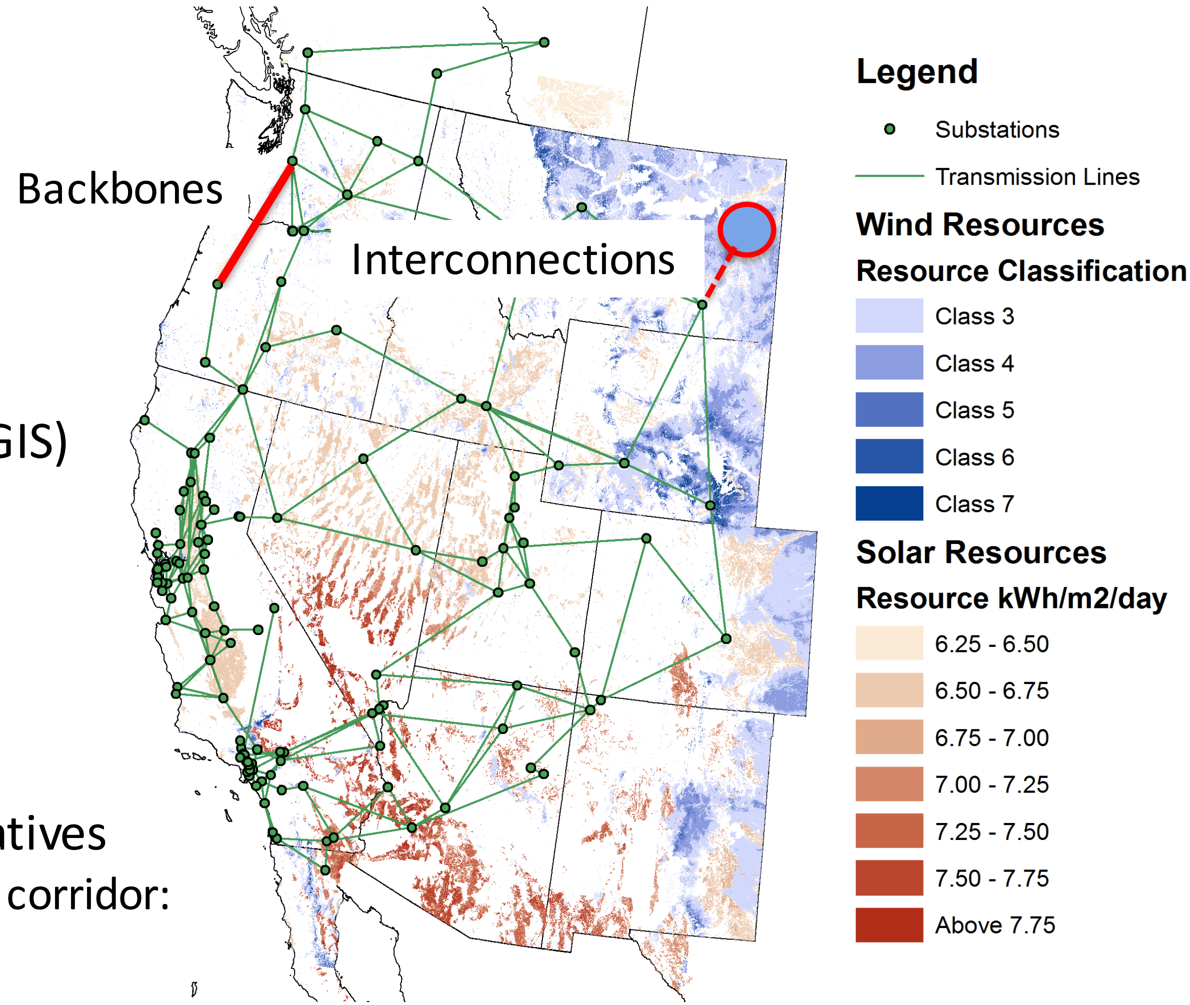
- 54 Wind profiles
- 29 Solar profiles
- 31 Renewable Hubs (WREZ)

Candidate Transmission Alternatives

Maximum number of circuits per corridor:

2 for Backbones

4 for Interconnections to Renewable Hubs



Experiments

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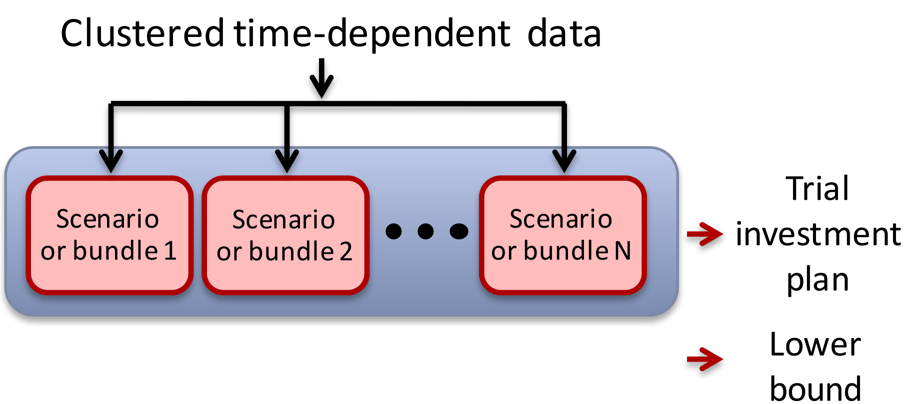
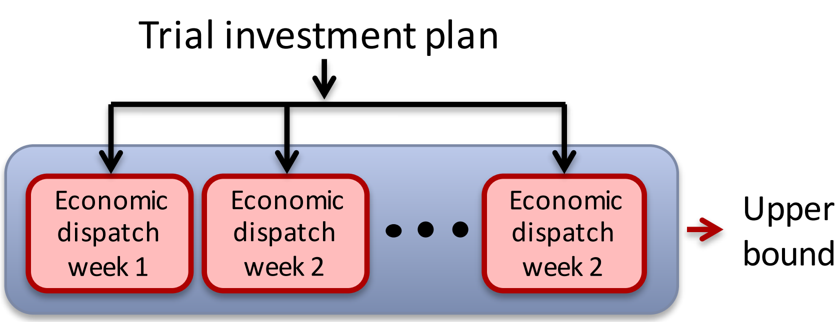
Description

- 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)
- Multi-Core SMP Workstation: 48-core Intel Xeon, 2.3 GHz, 512 GB RAM (~$20K)





Computational Performance

Extensive form, 100 scenarios

- CPLEX, no feasible solution after 1 day on a 48-core workstation

Progressive Hedging, 100 scenarios

- **Red Mesa:** ~15 minutes, 186 iterations until full convergence of investment variables
- **Workstation:** ~31 minutes, 180 iterations until full convergence of investment variables

(1) UB from investment cost PH + true operating cost : \$582.7B

(2) Expected cost from PH : \$565.7B

(3) LB from solving extensive form of LP : \$555.4B

Gap UB = 2.9%

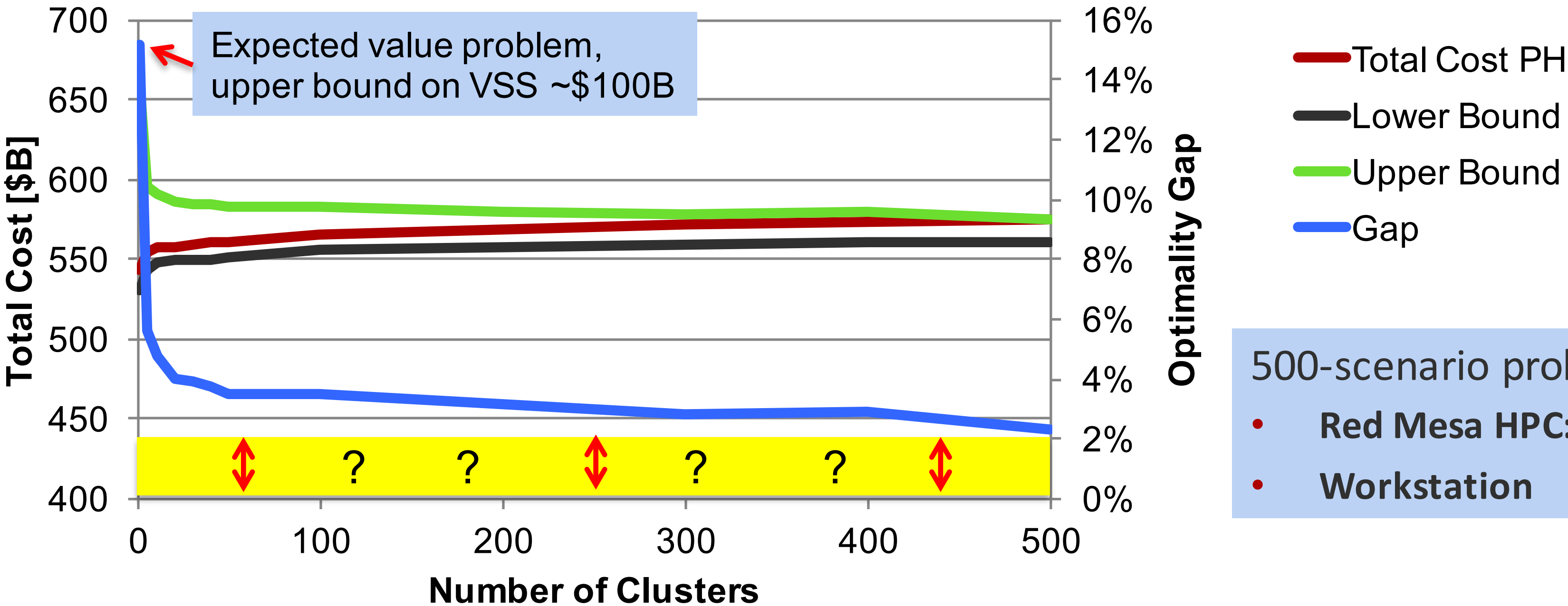
Gap LP = 1.82%

Gap LP => How suboptimal is the solution found using PH w.r.t. LP relaxation (not zero!!)
Gap UB => Difference between operating costs using clustered vs. full dataset

Total Gap => 3.5% (w.r.t. best lower bound)

Computational Performance

Convergence of upper and lower bounds

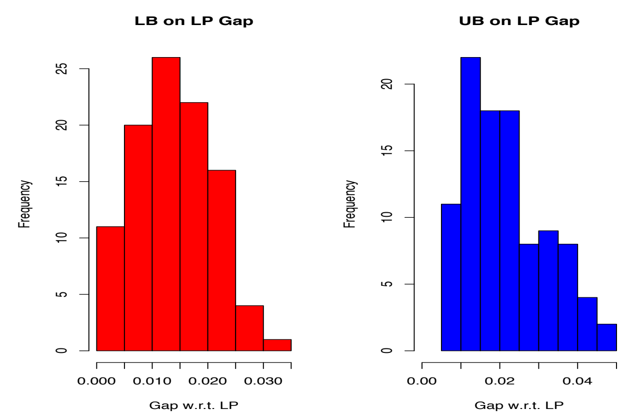


500-scenario problem

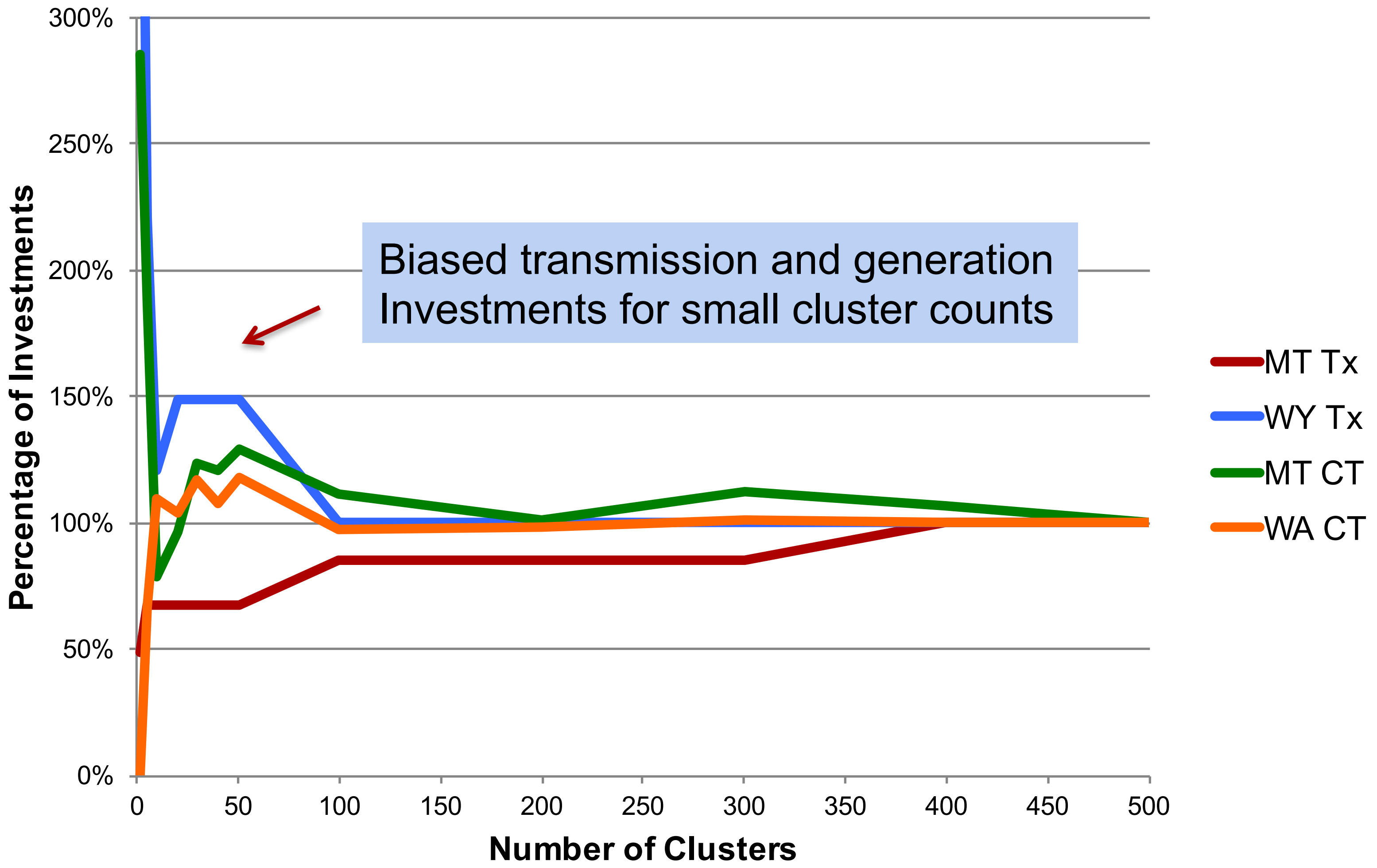
- **Red Mesa HPC:** 1.9 hrs.
- **Workstation** : 8.7 hrs.

LP relaxation vs optimal solution from MILP:

- Solved 100 single-scenario problems, 0.5% gap and 1hr time limit
- MILP lower bound w.r.t. LP relaxation is **1.4%** (average)
- MILP upper bound w.r.t. LP relaxation is **2.2%** (average)



Investments vs. time granularity



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
- 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!

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- O. Ozdemir, F. D. Munoz, J. Ho, and B. F. Hobbs, "Economic Analysis of Transmission with Demand Response and Quadratic Losses: A Successive LP Approach." **IEEE Transactions on Power Systems**, 2015.
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QUESTIONS

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