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

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Talk Goals

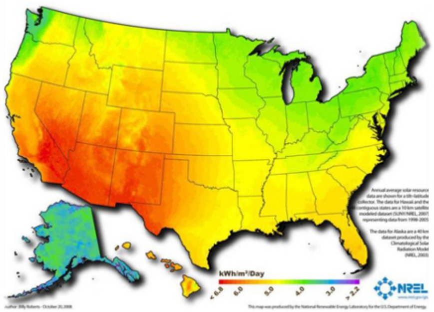
1. Summarize some of the challenges of large-scale transmission and generation planning.

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

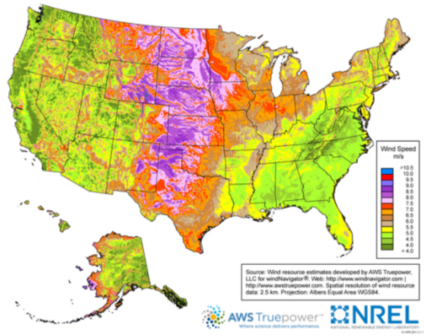
3. Describe and illustrate the performance of the Progressive Hedging decomposition algorithm on the WECC 240-bus test case.

Introduction

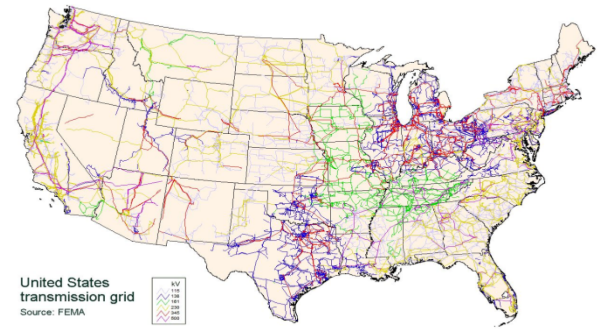
Solar Resources (NREL)



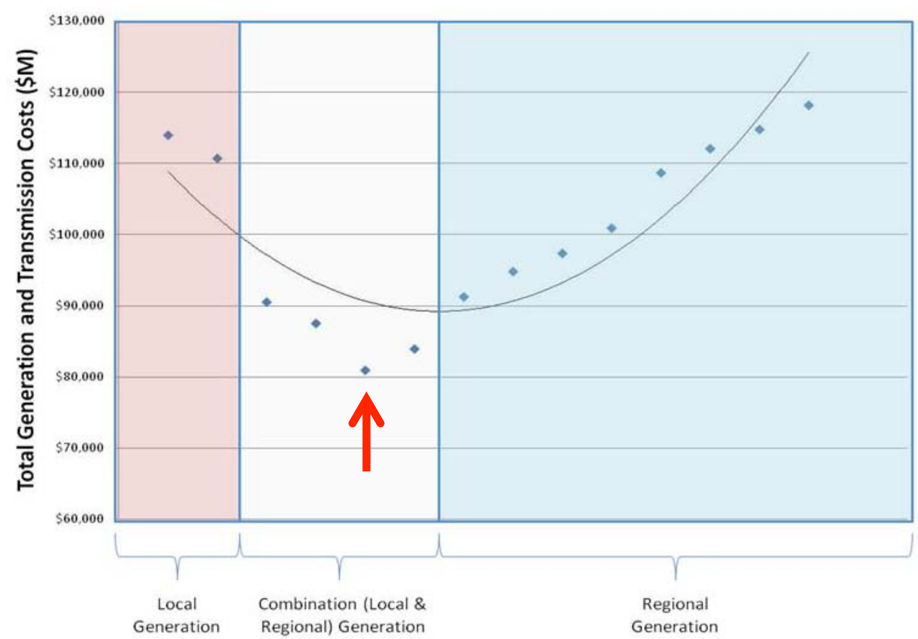
Wind Resources (NREL)



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 (ignoring 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

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Modeling approaches

- Co-Optimization Models : Weijde and Hobbs (2012), Munoz et al (2013)
- Stochastic Models :

Solution approaches

- Tight MILP formulations :
- Benders decomposition : Munoz et al (2014)
- Heuristics :
- Progressive Hedging :

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 (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, based on average capacity factors)

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

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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

Features

- Available in the PySP 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 unit commitment problems (ARPA-E)

- WECC-240 and 100 scenarios:

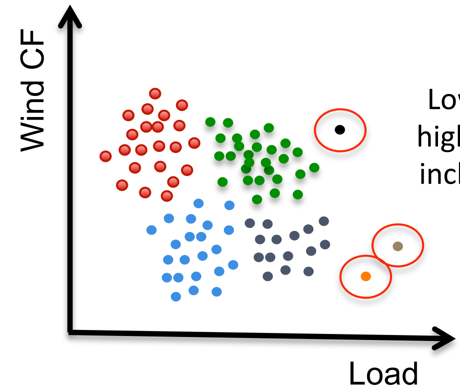
Extensive form on CPLEX → No feasible solution after 1 day of CPU time

Progressive Hedging → 20 iterations / 15 min to attain 1.5% optimality gap

Scenario Reduction Framework

Constrained k-means clustering

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

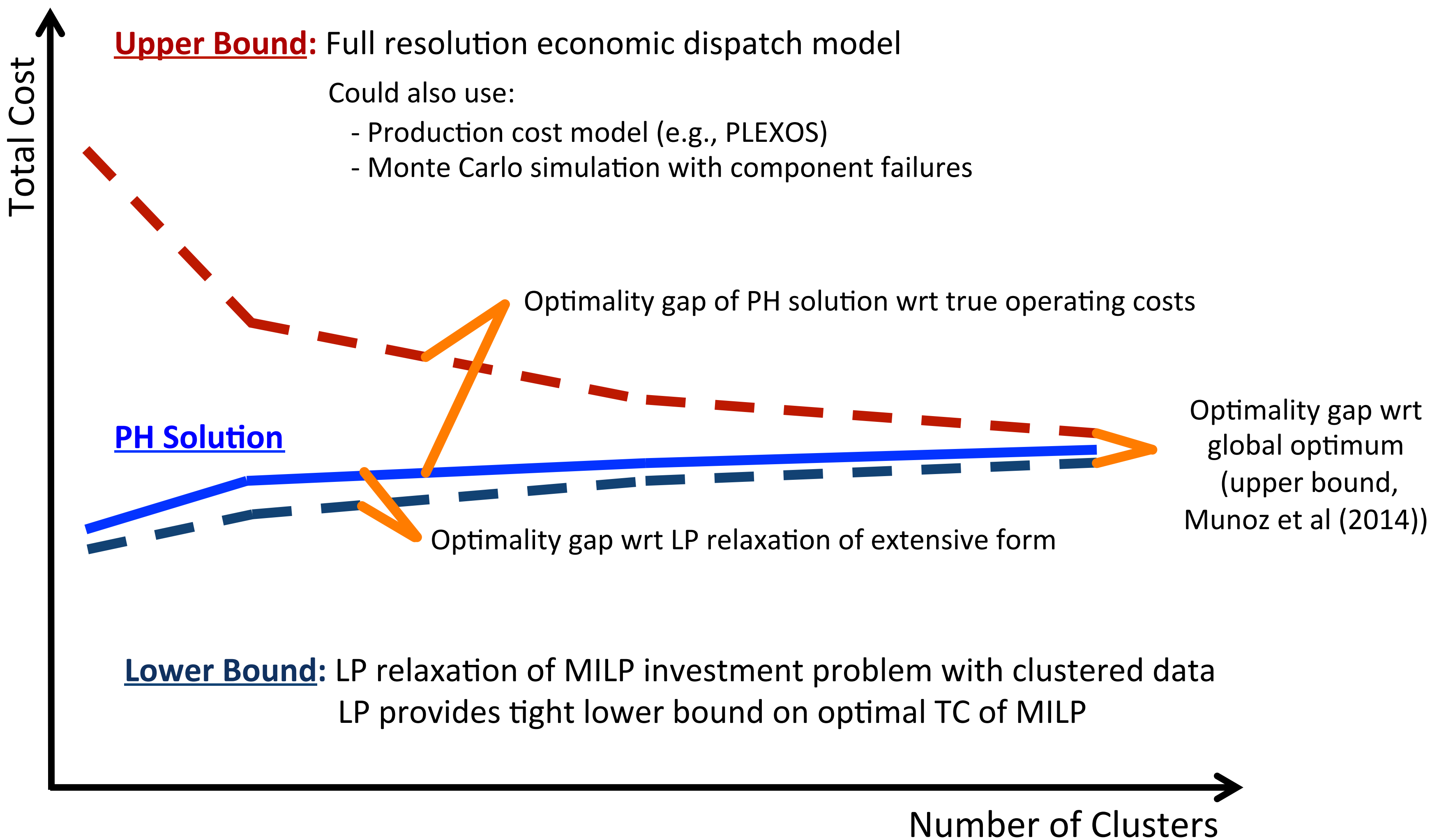


Low-probability and high-impact scenarios included as individual clusters

Potential extensions for other types of uncertainties

- Long-term policy and economic uncertainties (capital costs, fuel prices, and renewable targets). These stochastic parameters are <u>not in the right-hand-side of constraints</u>
- Use a combination of constrained k-means with importance sampling:
  - <u>Constrained k-means</u>: selection of representative load, wind, solar, and hydro states
  - <u>Importance sampling</u>: 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)

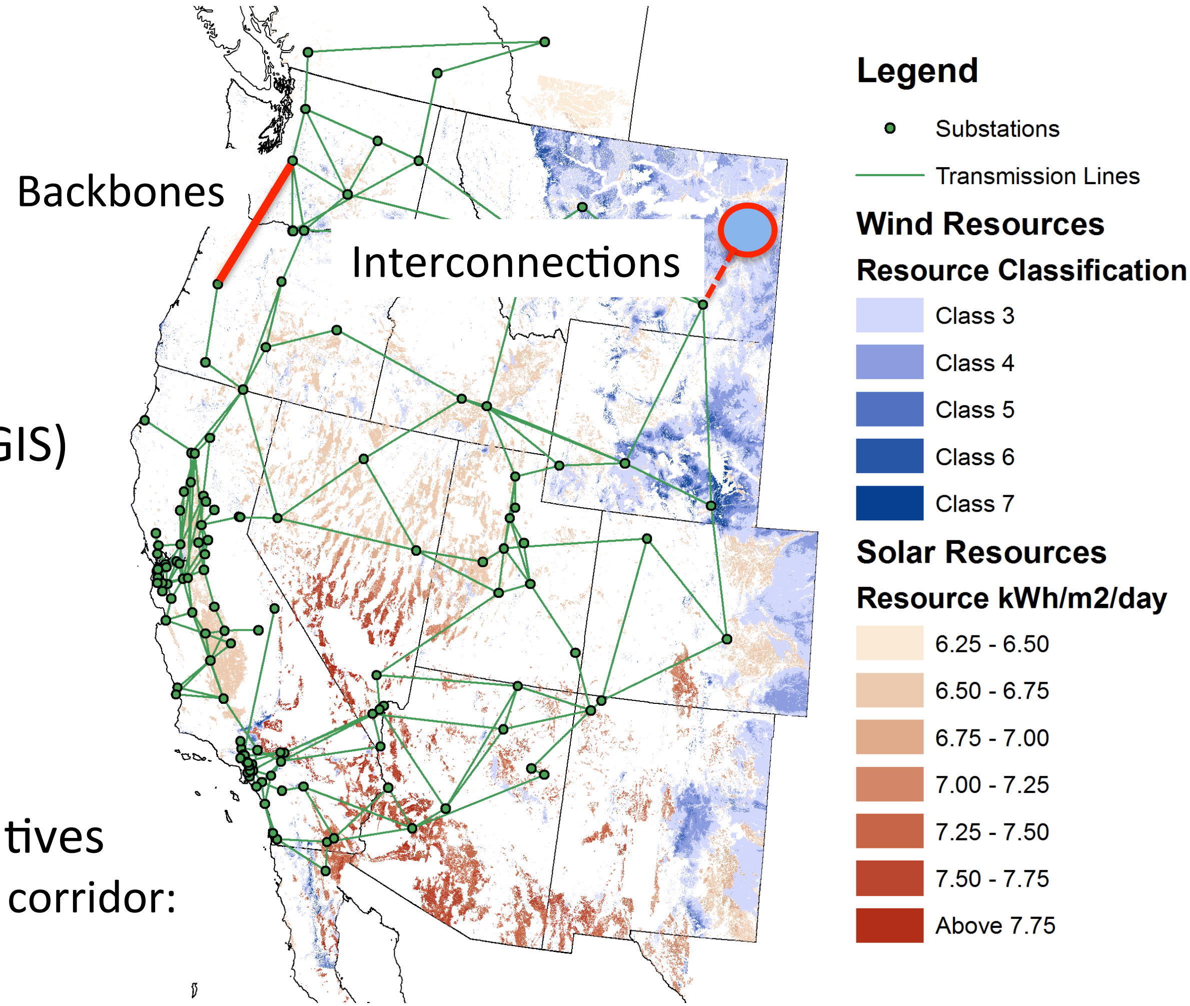
- 54 Wind profiles
- 29 Solar profiles
- 31 Renewable Hubs (WREZ)

Candidate Transmission Alternatives

Maximum number of circuits per corridor:

2 for Backbones

4 for Interconnections to Renewable Hubs



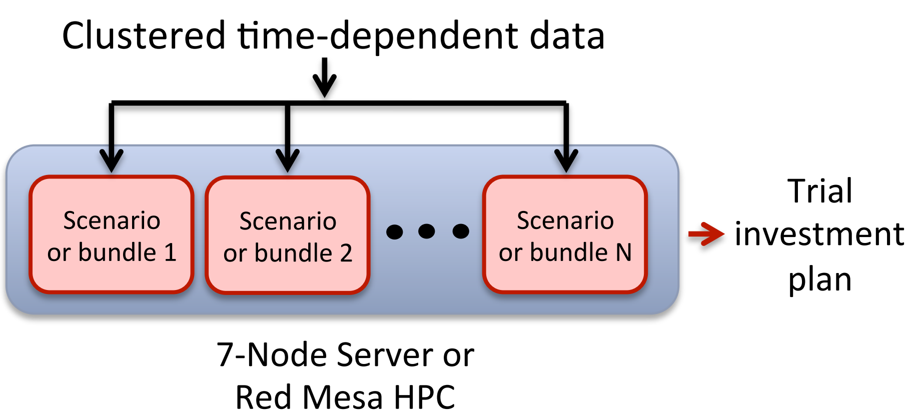
Experiments

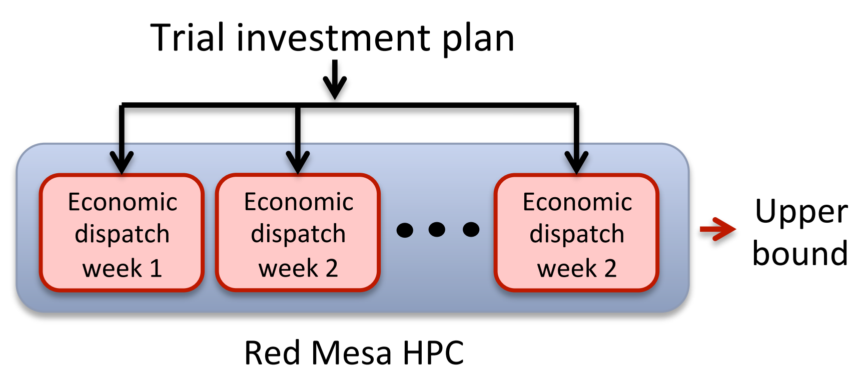
Description

- 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%

Progressive Hedging, 500 scenarios (100 bundles, Red Mesa HPC)

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

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 and in academia than in practice!

- Commercially available software <u>do not capture a), b) or c)</u> due to both modeling and algorithmic limitations

- Progressive Hedging coupled with our scenario reduction framework can be used to solve large-scale problems <u>in commodity workstations</u>, 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)

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QUESTIONS

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