A Stochastic Programming Framework for the Large-Scale Integration of Renewable Energy in Power Systems

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Joint work with
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December 11th, 2013

Renewables Making Headlines

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30 May 2011 Last updated at 12:25 GMT

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COMMENTS (542)

Germany saw mass anti-nuclear protests in the wake of the Fukushima disaster

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BY METTE FRAENDE

COPENHAGEN | Fri Nov 25, 2011 11:49am EST

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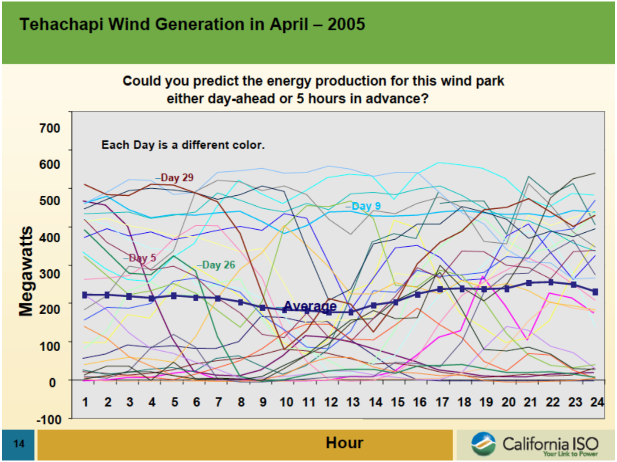
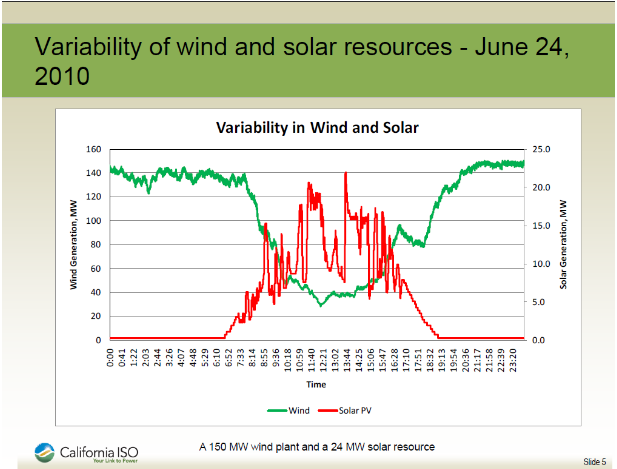
California to nearly double wind, solar energy output by 2020 -regulator

Thu Nov 14, 2013 1:30pm EST

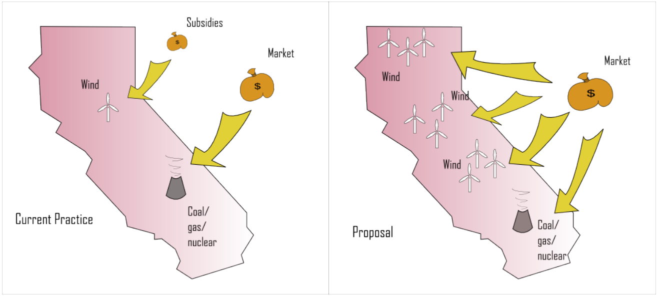
Uncertainty



Variability



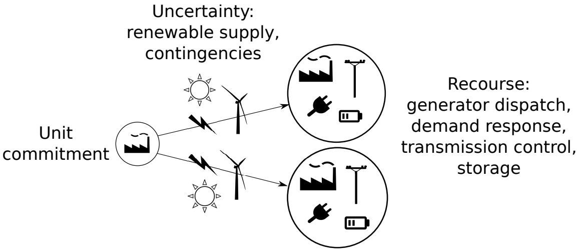
A Vision for Renewable Energy



Stochastic unit commitment appropriate for quantifying:

- Renewable energy utilization
- Cost of unit commitment and economic dispatch
- Capital investment in generation capacity

A Ubiquitous Problem: Unit Commitment under Uncertainty



Appropriate for modeling various balancing options:

- Demand (deferrable, price responsive, wholesale)
- Storage (pumped / run-of-river hydro, batteries)
- Transmission control (FACTS, smart wires, switching)

A Ubiquitous Solution: Parallel Computing

Lawrence Livermore National Laboratory

SEQUOIA

- Optimization under uncertainty (stochastic / robust / probabilistically constrained) can be tackled by distributed algorithms: dual / primal-dual / proximal point / cutting plane methods
- Shift of computation towards parallelization (cloud, multi-core) is impending
- Competitive positioning due to access in LLNL HPC cluster (3rd largest supercomputer worldwide)

Unit Commitment

- Objective: min $\sum_{g,t}(K_g u_{gt} + S_g v_{gt} + C_g p_{gt})$
- Load balance: $\sum_{g \in G} p_{gt} = D_t, \forall t$
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The Real Thing

pjm

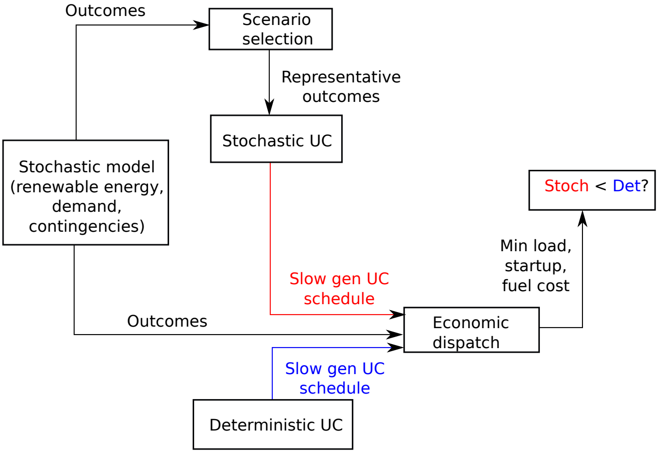
Day-ahead Market – Average Daily Volumes

- 1,210 generators, 3 part offers (startup, no load, 10 segment incremental energy offer curve)
- 10,000 - Demand bids – fixed or price sensitive
- 50,000 - Virtual bids / offers
- 8,700 - eligible bid/offer nodes (pricing nodes)
- 6,125 - monitored transmission elements
- 10,000 - transmission contingencies modeled

Relevant Literature

- Wind integration studies based on stochastic unit commitment: (Bouffard, 2008), (Wang, 2008), (Ruiz, 2009), (Tuohy, 2009), (Morales, 2009), (Constantinescu, 2011)
  - **Contribution:** coupling scenario selection inspired by importance sampling with dual decomposition algorithm
- Integrating demand response with unit commitment: (Sioshansi, 2009), (Sioshansi, 2011)
  - **Contribution:** simultaneous modeling of uncertainty and DR
- Parallel computing in power system operations: (Monticelli, 1987), (Pereira, 1990), (Falcao, 1997), (Kim, 1997), (Bakirtzis, 2003), (Biskas, 2005)
  - **Contribution:** application to sort-term scheduling

Validation Process



Unit Commitment and Economic Dispatch

- Deterministic model (Sioshansi, 2009)
  1. Reserve requirements

$$\sum_{g\in G} s_{gt} + \sum_{g\in G_f} f_{gt} \geq T_t^{\mathrm{req}}, \sum_{g\in G_f} f_{gt} \geq F_t^{\mathrm{req}}, t \in T$$

  2. Import constraints

$$\sum_{l\in IG_j} \gamma_{jl} e_{lt} \leq IC_j, j \in \mathcal{IG}, t \in T$$

- Slow generator schedules are fixed in economic dispatch model: $w_{gt} = w_{gt}^{\star}, g \in G_s$

Two-Stage Stochastic Unit Commitment

1. In the first stage we commit slow generators: $u_{gst} = w_{gt}, v_{gst} = z_{gt}, g \in G_s, s \in S, t \in T$ (corresponds to day-ahead market)
2. Uncertainty is revealed: net demand D_{nst}, line availability B_{ls}, generator availability P^+_{gs}, P^-_{gs}
3. Fast generator commitment and production schedules are second stage decisions: $u_{gst}, g \in G_f$ and $p_{gst}, g \in G_f \cup G_s$ (corresponds to real-time market)
4. Objective:

$$\min \sum_{g \in G} \sum_{s \in S} \sum_{t \in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst})$$

Lagrangian Decomposition Algorithm

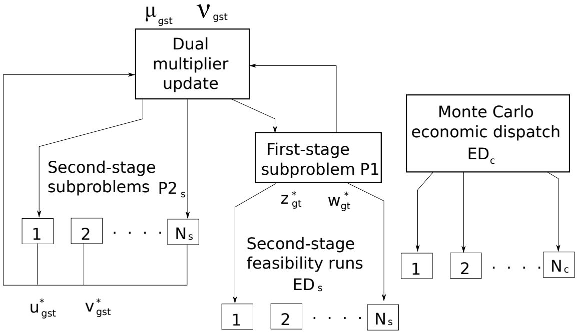
- Decomposition methods: (Nowak, 2000), (Takriti, 1996), (Carpentier, 1996), (Redondo, 1999), (Bertsimas, 2013)
- **Contribution:** relax non-anticipativity constraints on both unit commitment and startup variables
  1. Feasible solution at each iteration
  2. Optimality gap at each iteration

  Lagrangian:

$$\mathcal{L} = \sum_{g \in G} \sum_{s \in S} \sum_{t \in T} \pi_s (K_g u_{gst} + S_g v_{gst} + C_g p_{gst})$$
$$+ \sum_{g \in G_s} \sum_{s \in S} \sum_{t \in T} \pi_s (\mu_{gst}(u_{gst} - w_{gt}) + \nu_{gst}(v_{gst} - z_{gt}))$$

Parallelization

- Lawrence Livermore National Laboratory Hera cluster: 13,824 cores on 864 nodes, 2.3 Ghz, 32 GB/node
- MPI calling on CPLEX Java callable library

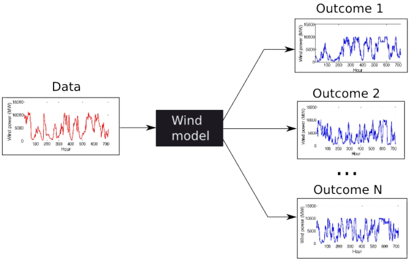


Scenario Selection for Wind Uncertainty and Contingencies

- Past work: (Gröwe-Kuska, 2002), (Dupacova, 2003), (Heitsch, 2003), (Morales, 2009)
- **Contribution:** Scenario selection algorithm inspired by importance sampling
  1. Generate a sample set $\Omega_S \subset \Omega$, where $M = |\Omega_S|$ is adequately large. Calculate the cost $C_D(\omega)$ of each sample $\omega \in \Omega_S$ against the best determinstic unit commitment policy and the average cost $\bar{C} = \sum_{i=1}^{M} \frac{C_D(\omega_i)}{M}$.
  2. Choose N scenarios from Ω_S, where the probability of picking a scenario ω is $C_D(\omega)/\bar{C}$.
  3. Set $\pi_s = C_D(\omega)^{-1}$ for all $\omega^s \in \hat{\Omega}$.

Wind Model Data Source

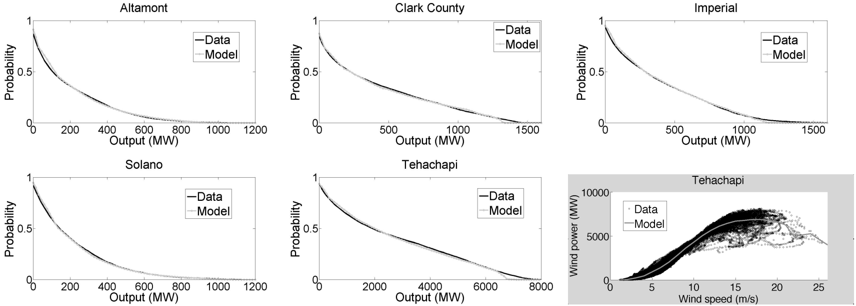
- 2 wind integration cases: moderate (7.1% energy integration, 2012), deep (14% energy integration, 2020)
- California ISO interconnection queue lists locations of planned wind power installations
- NREL Western Wind and Solar Interconnection Study archives wind speed - wind power for Western US



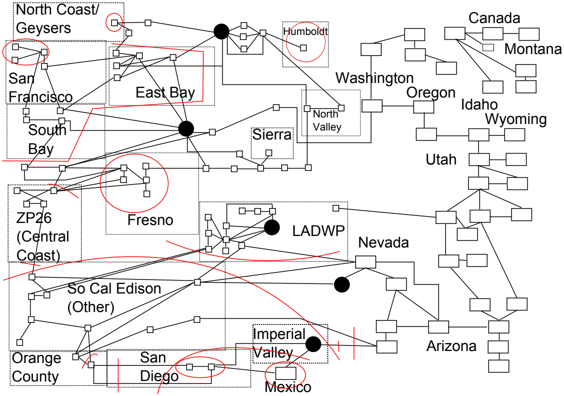
Calibration

- Relevant literature: (Brown, 1984), (Torres, 2005), (Morales, 2010)
- Calibration steps
  1. Remove systematic effects:
  $$y_{kt}^{S} = \frac{y_{kt} - \hat{\mu}_{kmt}}{\hat{\sigma}_{kmt}}.$$
  2. Transform data to obtain a Gaussian distribution:
  $$y_{kt}^{GS} = N^{-1}(\hat{F}_k(y_{kt}^{S})).$$
  3. Estimate the autoregressive parameters $\hat{\phi}_{kj}$ and covariance matrix $\hat{\Sigma}$ using Yule-Walker equations.

Data Fit


Altamont
Clark County
Imperial
Solano
Tehachapi
Tehachapi
Probability
Output (MW)
Data
Model
Wind power (MW)
Wind speed (m/s)

WECC Model


North Coast/ Geysers
Humboldt
San Francisco
East Bay
South Bay
North Valley
Sierra
Washington
Oregon
Canada
Montana
Idaho
Wyoming
Utah
Fresno
ZP26 (Central Coast)
LADWP
Nevada
So Cal Edison (Other)
Imperial Valley
Arizona
Orange County
San Diego
Mexico

Model Summary

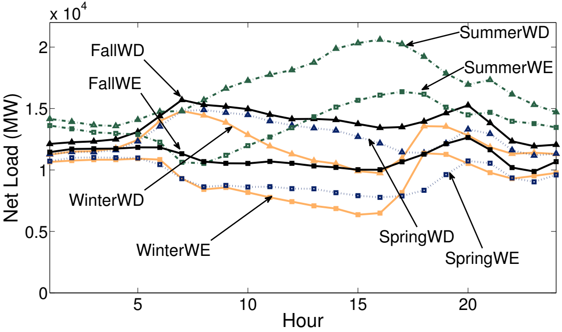
- System characteristics
  - 124 units (82 fast, 42 slow)
  - 53665 MW power plant capacity
  - 225 buses
  - 375 transmission lines
- **Four studies**
  - Deep (14% energy integration) without transmission constraints, contingencies
  - With transmission constraints, contingencies:
    - No wind
    - Moderate (7.1% energy integration, 2012)
    - Deep (14% energy integration, 2020)

Competing Reserve Rules

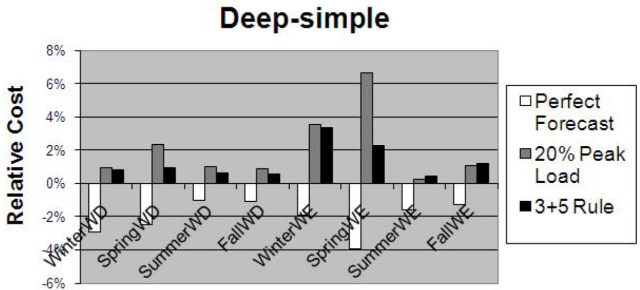
- Perfect foresight: anticipates outcomes in advance
- Percent-Of-Peak-Load rule: commit total reserve T_{req} at least x% of peak load, $F_{\text{req}} = 0.5T_{\text{req}}$
- 3+5 rule: commit fast reserve F_{req} at least 3% of hourly forecast load plus 5% of hourly forecast wind, $T_{\text{req}} = 2F_{\text{req}}$

Day Types

- 8 day types considered, one for each season, one for weekdays/weekends
- Day types weighted according to frequency of occurrence



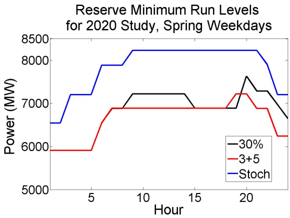
Policy Comparison - Deep Integration, No Transmission, No Contingencies[1]

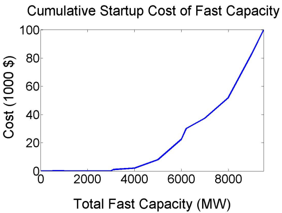


[1] A. Papavasiliou, S. S. Oren, R. P. O'Neill, *Reserve Requirements for Wind Power Integration: A Stochastic Programming Framework*, IEEE Transactions on Power Systems, 26:4, pp. 2197-2206, November 2011.

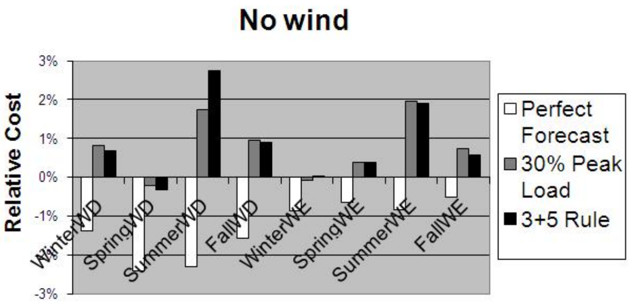
Explanation of SUC Superior Performance

- When reserve constraints are binding, deterministic policy overcommits.
- When reserve constraints are not binding, deterministic policy underestimates value of protecting against adverse wind outcomes.

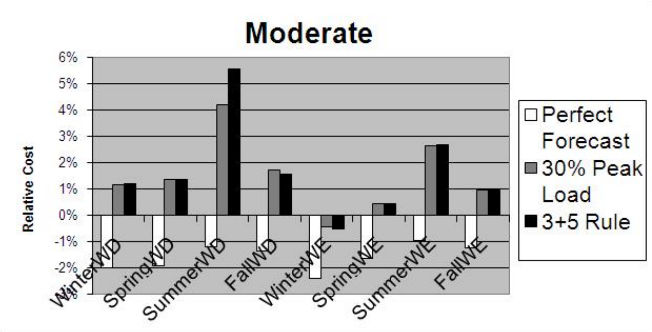




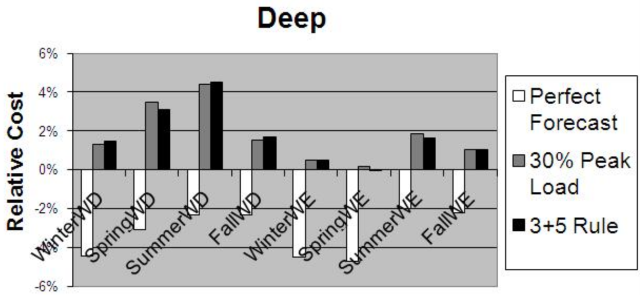
Policy Comparison - No Wind Integration



Policy Comparison - Moderate Integration



Policy Comparison - Deep Integration



Summary[2]

	Deep-S	No Wind	Moderate	Deep
RE daily waste (MWh)	100	0	890	2,186
Cost ($M)	5.012	11.508	9.363	7.481
Capacity (MW)	20,744	26,377	26,068	26,068
Daily savings ($)	38,628	104,321	198,199	188,735
Forecast gains (%)	32.4	35.4	41.9	46.7

[2] A. Papavasiliou, S. S. Oren, *Multi-Area Stochastic Unit Commitment for High Wind Penetration in a Transmission Constrained Network*, Operations Research, vol. 61, no. 3, pp. 578-592, May/June 2013.

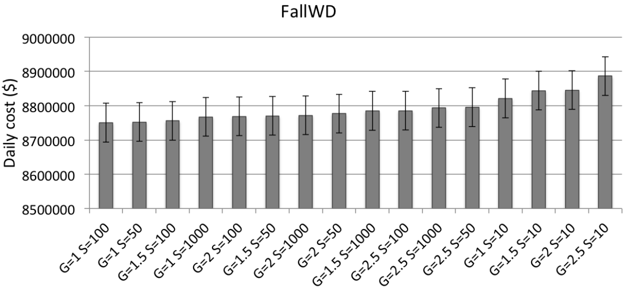
Model Size

How Many Scenarios? Do we want to solve a more representative problem less accurately or a less representative problem more accurately?

Model	Gens	Buses	Lines	Hours	Scens.
CAISO1000	130	225	375	24	1000
WILMAR	45	N/A	N/A	36	6
PJM	1011	13867	18824	24	1

Model	Integer var.	Cont. var.	Constraints
CAISO1000	3,121,800	20,643,120	66,936,000
WILMAR	16,000	151,000	179,000
PJM	24,264	833,112	1,930,776

Gaps Versus Number of Scenarios



A large number of scenarios:

- results in a more accurate representation of uncertainty
- increases the amount of time required in each iteration of the subgradient algorithm

Conclusions

- **Consistent performance of scenario selection:**
  - Stochastic unit commitment yields 32.4%-46.7% of benefits of perfect foresight over various types of uncertainty
  - Favorable performance relative to Sample Average Approximation with 1000 scenarios.
- **Insights from parallel computing[3]:**
  - Reducing the duality gap seems to yield comparable benefits relative to adding more scenarios
  - All problems solved within 24 hours (operationally acceptable), given enough processors.

[3] A. Papavasiliou, S. S. Oren, B. Rountree, *Applying High Performance Computing to Multi-Area Stochastic Unit Commitment for Renewable Penetration*, under review in IEEE Transactions on Power Systems.

Conclusions (II)

- **Transmission constraints and contingencies strongly influence results - need for advanced optimization**
  - Overestimation of capacity credit from 1.2% of installed wind capacity to 39.8% for deep integration
  - Underestimation of daily operating costs from 7.481 \$M to 5.102 \$M for deep integration
- **First steps towards integrating deferrable demand models with renewable supply uncertainty[4]:** Deferrable demand imposes no additional capacity requirements, coupling results in 3.06% - 8.38% operating cost increase

[4] A. Papavasiliou, S. S. Oren, *Large-Scale Integration of Deferrable Electricity and Renewable Energy Sources in Power Systems*, accepted in IEEE Transactions on Power Systems.

Perspectives

- Modeling resources
  - Transmission networks (FACTS, switching, smart wires)
  - Demand response
  - Storage (hydro, batteries)
  - Solar power
- Computational extensions: industrial-scale systems
  - Larger systems: PJM, Germany
  - Better algorithms: proximal point, bundle, cutting plane algorithms
- Model extensions
  - Capacity expansion planning, incentivizing capacity investment
  - European balancing market rules

References

1. A. Papavasiliou, S. S. Oren, R. P. O'Neill, *Reserve Requirements for Wind Power Integration: A Stochastic Programming Framework*, IEEE Transactions on Power Systems, 26:4, pp. 2197-2206, November 2011.
2. A. Papavasiliou, S. S. Oren, *Multi-Area Stochastic Unit Commitment for High Wind Penetration in a Transmission Constrained Network*, Operations Research, vol. 61, no. 3, pp. 578-592, May/June 2013.
3. A. Papavasiliou, S. S. Oren, *Large-Scale Integration of Deferrable Electricity and Renewable Energy Sources in Power Systems*, accepted in IEEE Transactions on Power Systems special section on Electricity Market Operations.

References (II)

4. A. Papavasiliou, S. S. Oren, *Stochastic Modeling of Multi-Area Wind Production*, under review in Resources special section on Spatial and Temporal Variation of the Wind Resource.
5. A. Papavasiliou, S. S. Oren, B. Rountree, *Applying High Performance Computing to Multi-Area Stochastic Unit Commitment for Renewable Penetration*, under review in IEEE Transactions on Power Systems.

Thank you

Questions?

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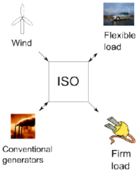
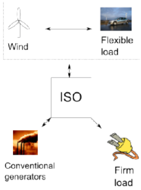
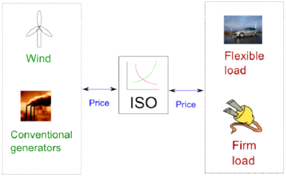
Demand Response Results

	Daily Cost ($)	Daily Load Shed (MWh)
No wind	**9,012,031**	17.301
Centralized Moderate	**8,677,857**	1.705
Bids Moderate	211,010	609.914
Coupled Moderate	265,128	2.217
Centralized Deep	**8,419,322**	10.231
Bids Deep	578,909	1221.492
Coupled Deep	705,497	112.452

Load Flexibility







System operator control

Coupling renewables with deferrable demand

Price-responsive demand

Centralized ⟶ Decentralized

Demand Response Study

	Zero	Moderate	Deep
Wind capacity (MW)	0	6,688	14,143
DR capacity (MW)	0	5,000	10,000
Daily wind energy (MWh)	0	46,485	95,414
Daily DR energy (MWh)	0	40,000	80,000
DR/firm energy (%)	0	6.1	12.2

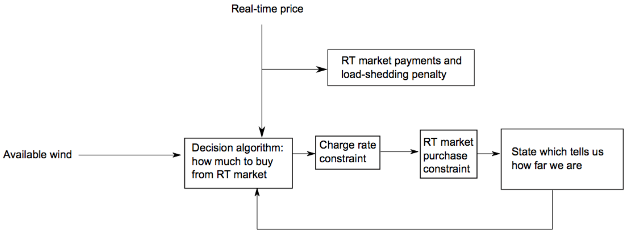
Centralized Load Dispatch

- Stochastic unit commitment with additional constraint:
  $$\sum_{t=1}^{N} p_{gst} = R$$
- Assumptions of centralized load control:
  - Central co-optimization of generation and demand (computationally prohibitive)
  - Perfect monitoring and control of demand
- Centralized load control represents an idealization that can be used for:
  - Quantifying the cost of decentralizing demand response
  - Estimating the capacity savings of deferrable demand

Demand Bids

- Based on retail consumer model of (Borenstein and Holland, 2005), (Joskow and Tirole, 2005), (Joskow and Tirole, 2006)
- State contingent demand functions used in economic dispatch $D_t(\lambda_t; \omega) = a_t(\omega) - \alpha b \lambda^R - (1 - \alpha) b \lambda_t$
- Note that the demand function model has to:
  - Be comparable to the deferrable demand model in terms of total demand R
  - Be consistent with the observed inflexible demand in the system

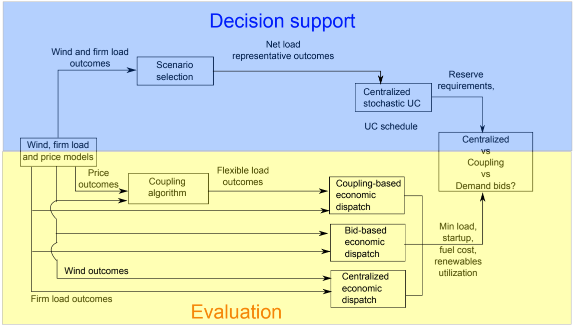
Coupling



$$\min_{\mu_t(x_t)} \mathbb{E}[\sum_{t=1}^{N-1} \lambda_t(\mu_t(x_t) - s_t)^+]\Delta t + \rho r_N]$$

$$\mu_t(x) \leq C, (\mu_t(x) - s_t)^+ \leq M_t, r_{t+1} = r_t - u_t$$

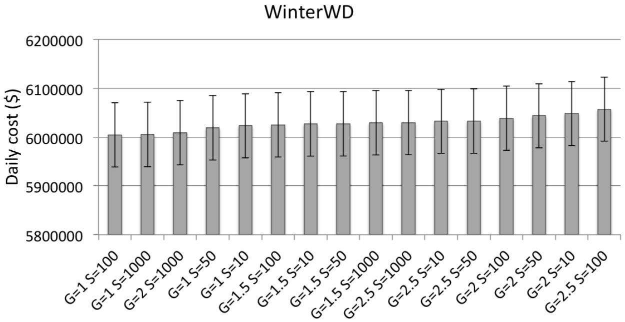
Integrating Demand Response in Stochastic Unit Commitment



Running Times

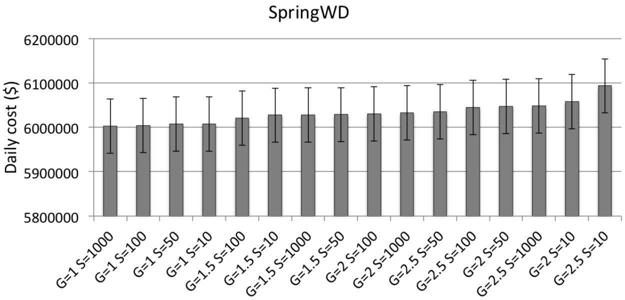
- CPLEX 11.0.0
- DELL Poweredge 1850 servers (Intel Xeon 3.4 GHz, 1GB RAM)
- $(P1), (P2_s)$ run for 120 iterations, (ED_s) run for last 40 iterations
- Average running time of 43776 seconds on single machine
- Average MIP gap of 1.39%

Cost Ranking: Winter Weekdays



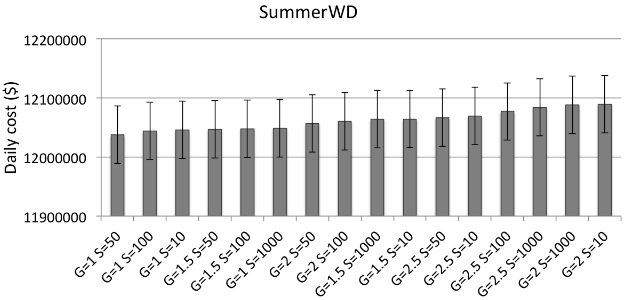
- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

Cost Ranking: Spring Weekdays



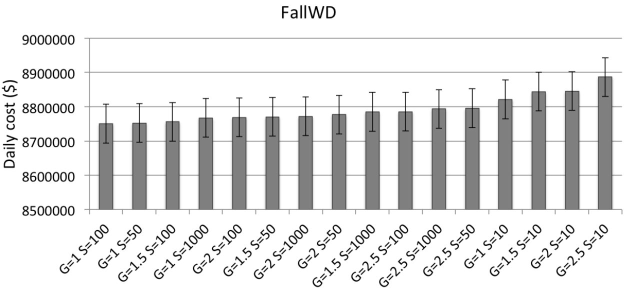
- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

Cost Ranking: Summer Weekdays



- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

Cost Ranking: Fall Weekdays



- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

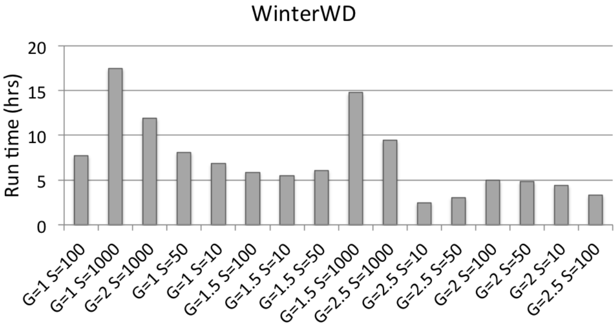
Influence of Duality Gap

- Among three worse policies in summer, $S = 1000$ with G = 2%, 2.5%
- Best policy for all day types has a 1% optimality gap ($S = 1000$ only for spring)
- For all but one day type the worst policy has $G = 2.5\%$
- For spring, best policy is $G = 1$, $S = 1000$
- For spring, summer and fall the worst policy is the one with the fewest scenarios and the greatest gap, namely $G = 2.5$, $S = 10$

Validation of Scenario Selection Policy

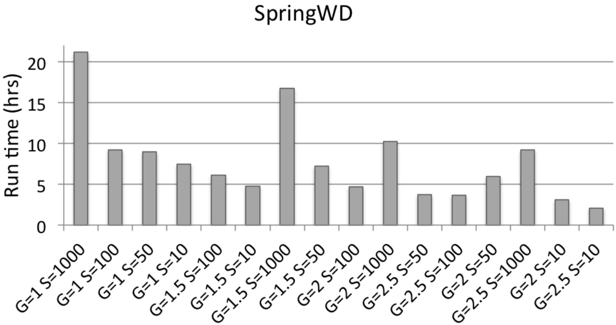
- Top performance for winter, summer and fall is attained by proposed scenario selection algorithm based on importance sampling
- For all day types, the importance sampling algorithm results in a policy that is within the top 2 performers
- Satisfactory performance (within top 3) can be attained by models of moderate scale (S50), provided an appropriate scenario selection policy is utilized

Run Time Ranking: Winter Weekdays



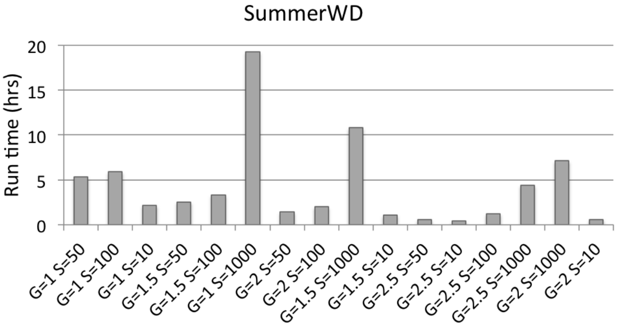
- Best-case running times ($S = P$)

Run Time Ranking: Spring Weekdays



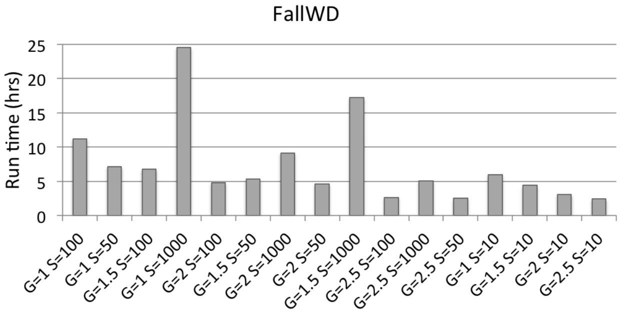
- Best-case running times ($S = P$)

Run Time Ranking: Summer Weekdays



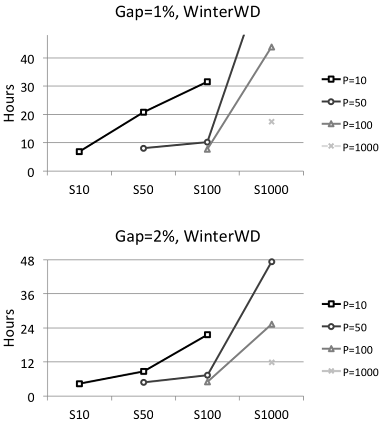
- Best-case running times ($S = P$)

Run Time Ranking: Fall Weekdays

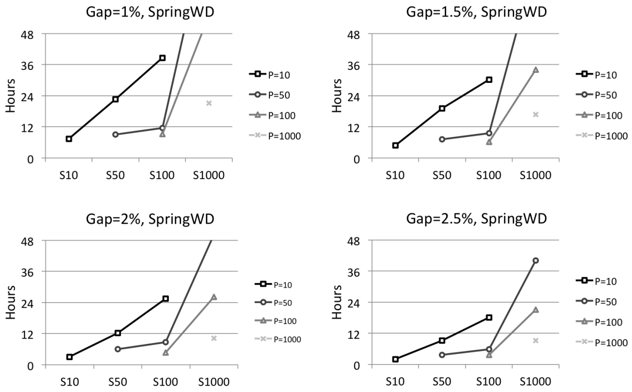


- Best-case running times ($S = P$)

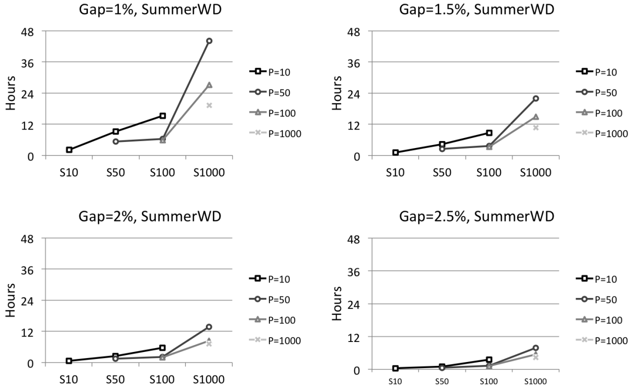
Running Times: Winter Weekdays



Running Times: Spring Weekdays



Running Times: Summer Weekdays



Running Times: Fall Weekdays