Applying High Performance Computing to Multi-Area Stochastic Unit Commitment

IBM Research

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Motivation and Research Objective

- Increased computational burden in power systems operations due to:
  - renewable penetration and
  - demand response integration
- Potential applications of distributed computation:
  - Stochastic optimization
  - Robust optimization
  - Topology control, system expansion planning
  - Optimization of storage (deferrable loads/demand response, hydro-thermal scheduling)
- Want to quantify sensitivity of:
  - unit commitment policy
  - duality gaps
  - cost performance

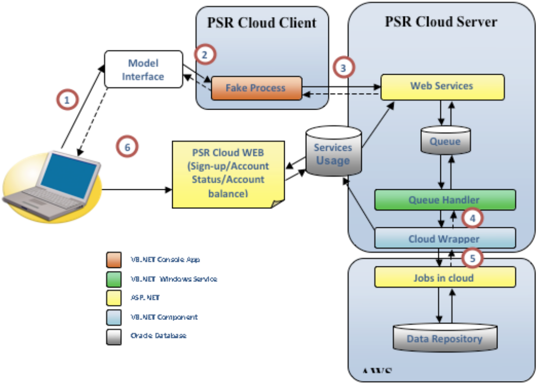
  on number of scenarios.

Parallel Computing Literature in Power Systems

- Monticelli et al. (1987): Benders decomposition algorithm for SCOPF
- Pereira et al. (1990): Various applications of parallelization including SCOPF, composite (generator, transmission line) reliability, hydrothermal scheduling
- Falcao (1997): Survey of HPC applications in power systems
- Kim, Baldick (1997): Distributed OPF
- Bakirtzis, Biskas (2003) and Biskas et al. (2005): Distributed OPF

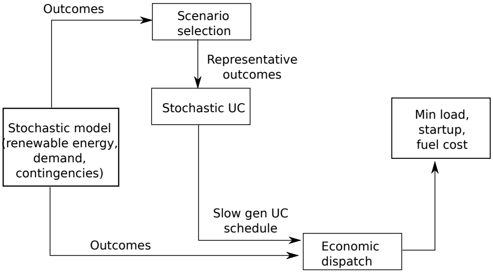
PSR Cloud

Industry practice for hydrothermal scheduling



Full Model

- Application: stochastic unit commitment for large-scale renewable energy integration
- Two-stage model representing DA market (first stage) followed by RT market (second stage)



Unit Commitment Model

- Domain $\mathcal{D}$ represents min up/down times, ramping rates, thermal limits of lines, reserve requirements
- Generator set partitioned between fast (G_f) and slow (G_s) generators

$$(UC): \min \sum_{g \in G} \sum_{t \in T} (K_g u_{gt} + S_g v_{gt} + C_g p_{gt})$$

$$s.t. \sum_{g \in G_n} p_{gt} = D_{nt}$$

$$P_g^- u_{gt} \leq p_{gt} \leq P_g^+ u_{gt}$$

$$e_{lt} = B_l(\theta_{nt} - \theta_{mt})$$

$$(\mathbf{p}, \mathbf{e}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}$$

Stochastic Unit Commitment Model

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

$$s.t. \sum_{g \in G_n} p_{gst} = D_{nst},$$

$$P^-_{gs} u_{gst} \leq p_{gst} \leq P^+_{gs} u_{gst}$$

$$e_{lst} = B_{ls}(\theta_{nst} - \theta_{mst})$$

$$(\mathbf{p}, \mathbf{e}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}_s$$

$$u_{gst} = w_{gt}, v_{gst} = z_{gt}, g \in G_s$$

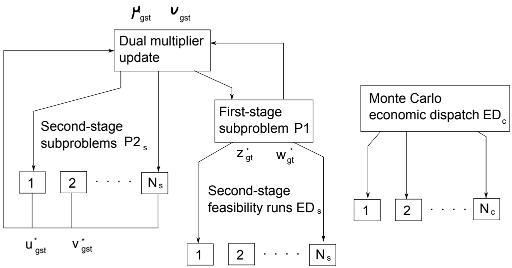
Lagrangian Decomposition Algorithm

- Past work: (Takriti et al., 1996), (Carpentier et al., 1996), (Nowak and Römisch, 2000), (Shiina and Birge, 2004)
- Key idea: relax non-anticipativity constraints on both unit commitment and startup variables
  1. Balance size of subproblems
  2. Obtain lower and upper bounds 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

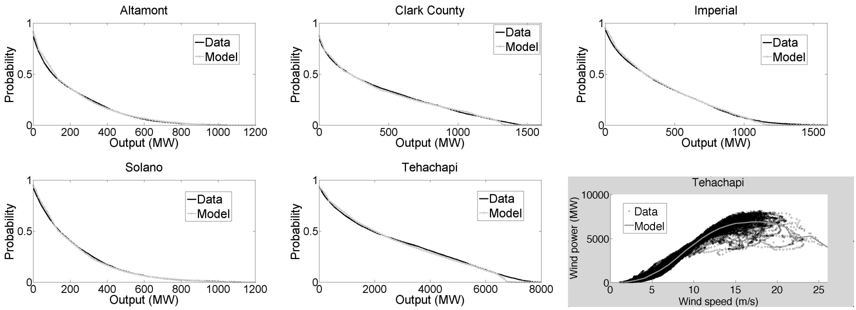
Scenario Selection

- Past work: (Gröwe-Kuska et al., 2002), (Dupacova et al., 2003), (Heitsch and Römisch, 2003), (Morales et al., 2009)
- 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 deterministic 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 $C_D(\omega)/(M\bar{C})$.
  3. Set $\pi_s = C_D(\omega)^{-1}$ for all $\omega^s \in \hat{\Omega}$.

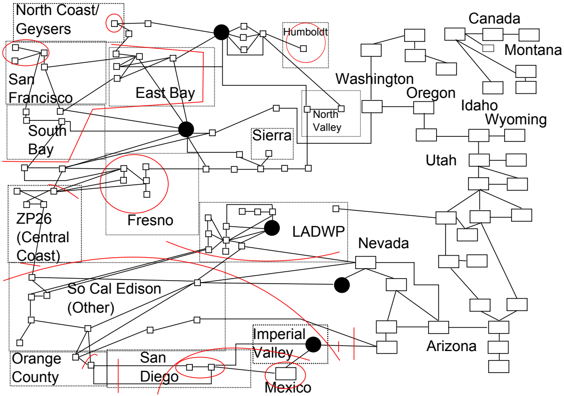
Wind Production Model

- Relevant literature: (Brown et al, 1984), (Torres et al., 2005), (Morales et al, 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
Washington
Oregon
Canada
Montana
Idaho
Wyoming
North
Valley
South
Bay
Sierra
Utah
Fresno
ZP26
(Central
Coast)
LADWP
Nevada
So Cal Edison
(Other)
Imperial
Valley
Arizona
Orange
County
San
Diego
Mexico

Unit Characteristics

Type	No. of units	Capacity (MW)
Nuclear	2	4,499
Gas	94	20,595.6
Coal	6	285.9
Oil	5	252
Dual fuel	23	4,599
Import	22	12,691
Hydro	6	10,842
Biomass	3	558
Geothermal	2	1,193
Wind (deep)	10	14,143
Fast thermal	88	11,006.1
Slow thermal	42	19,225.4

Model Size

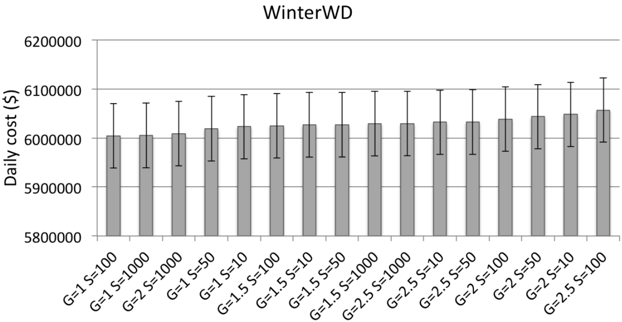
Model	Gens	Buses	Lines	Hours	Scens.
CAISO1000	130	225	375	24	1000
WILMAR	45	N/A	N/A	36	6
PJM	1011	13867	18824	24	1

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

Number of Scenarios Versus Optimality Gap

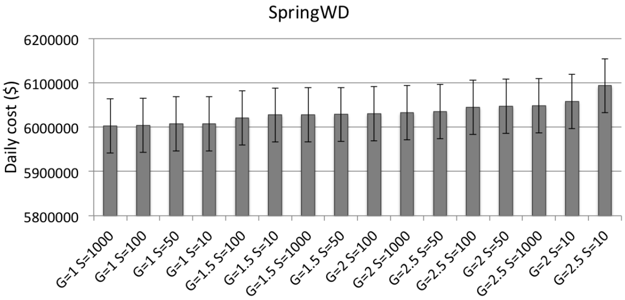
- A large number of scenarios:
  - results in a more accurate representation of uncertainty
  - increases the amount of time required in each iteration of the subgradient algorithm
- A smaller optimality gap implies that the relaxation is ‘closer’ to an optimal solution
- Given a time budget (a few hours at best in day-ahead operations), do we want to solve a more representative problem less accurately or a less representative problem more accurately?

Cost Ranking: Winter Weekdays



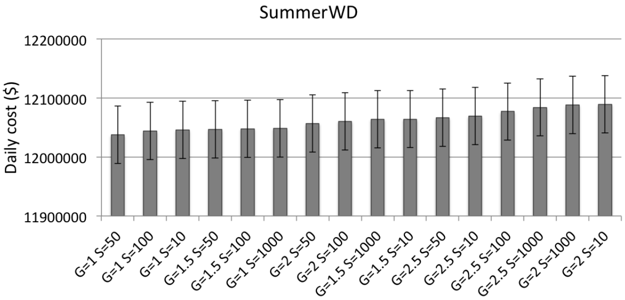
- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

Cost Ranking: Spring Weekdays



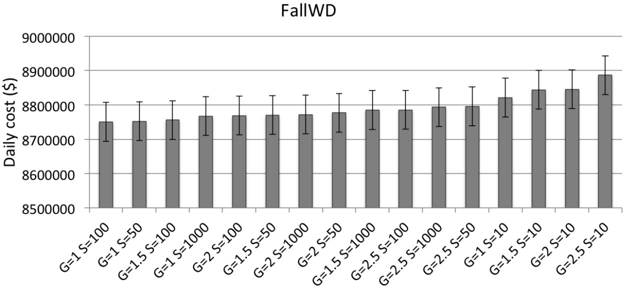
- $S = 1000$ corresponds to Shapiro's SAA algorithm
- Average daily cost and one standard deviation for 1000 Monte Carlo outcomes

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

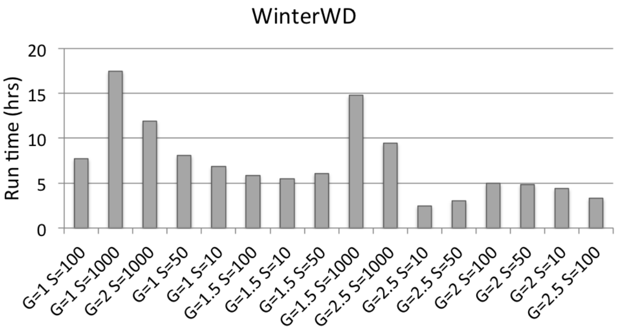
Influence of Duality Gap

- 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

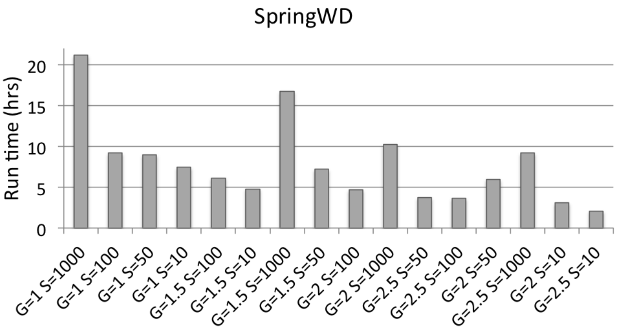
- Top performance for winter, summer and fall is attained by proposed scenario selection algorithm based on importance sampling
- For all day types, the importance sampling algorithm results in a policy that is within the top 2 performers
- Satisfactory performance (within top 3) can be attained by models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

Run Time Ranking: Winter Weekdays



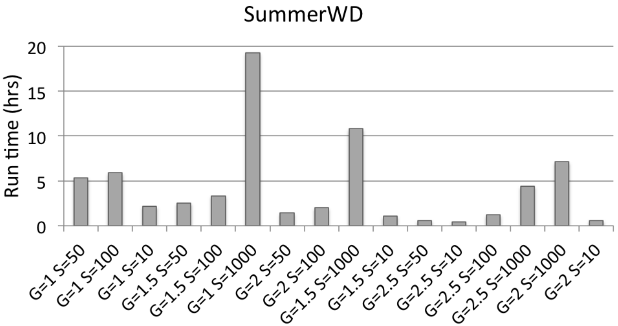
- Best-case running times ($S = P$)

Run Time Ranking: Spring Weekdays



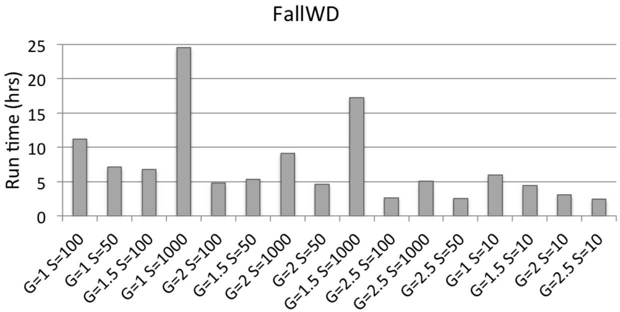
- Best-case running times ($S = P$)

Run Time Ranking: Summer Weekdays



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

Run Time Ranking: Fall Weekdays

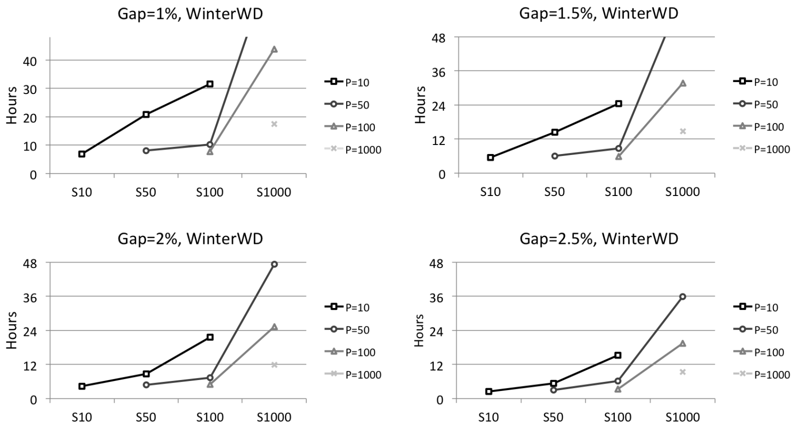


- Best-case running times ($S = P$)

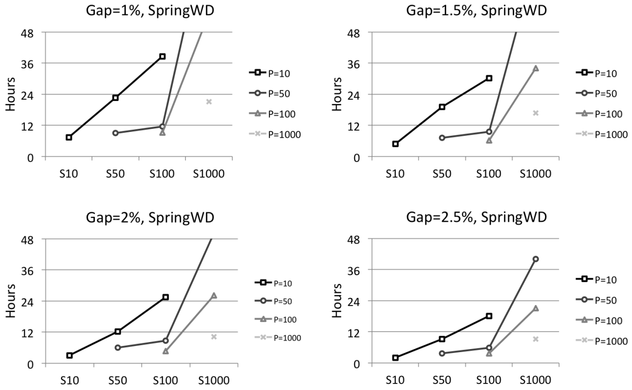
How Many Scenarios?

- Depends on the amount of available computation time and the number of available computational resources
- No theoretical guarantee that a smaller gap for the same instance will deliver a better result (compare, for example, the case of $G = 2$ with the case of $G = 2.5$ for $S = 10$ for winter weekdays). Nevertheless, it is commonly preferable to decrease the duality gap as much as possible

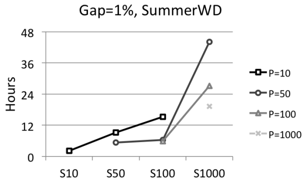
Running Times: Winter Weekdays

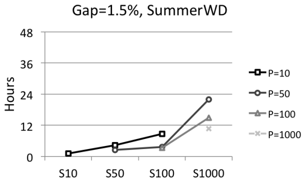


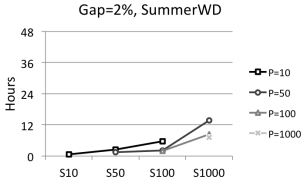
Running Times: Spring Weekdays

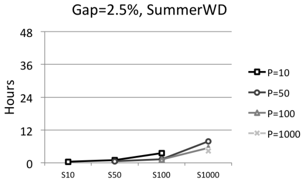


Running Times: Summer Weekdays

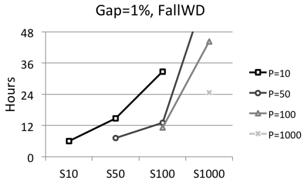


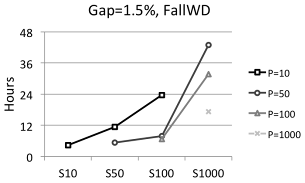


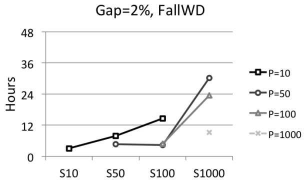


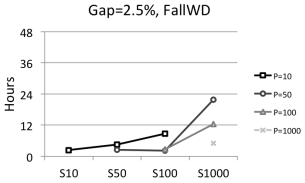


Running Times: Fall Weekdays

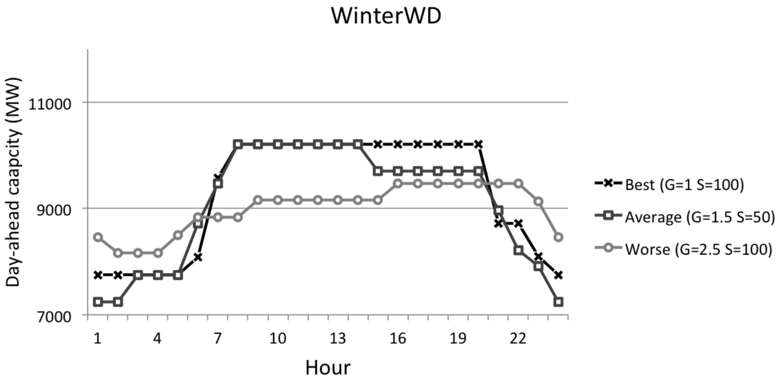




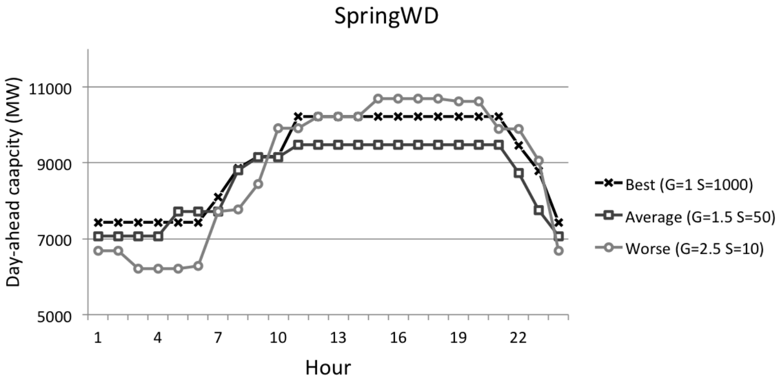




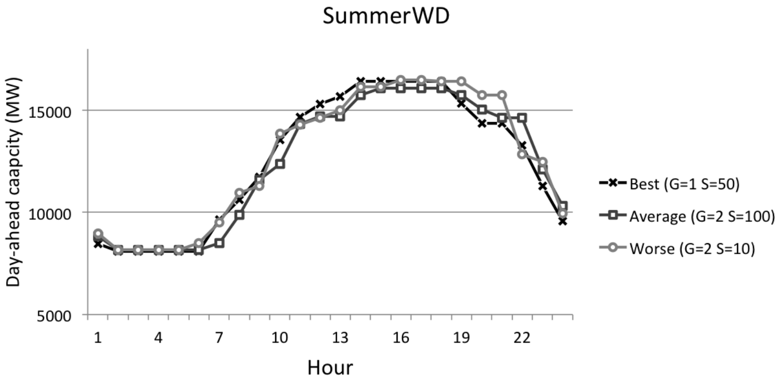
Unit Commitment: Winter Weekdays



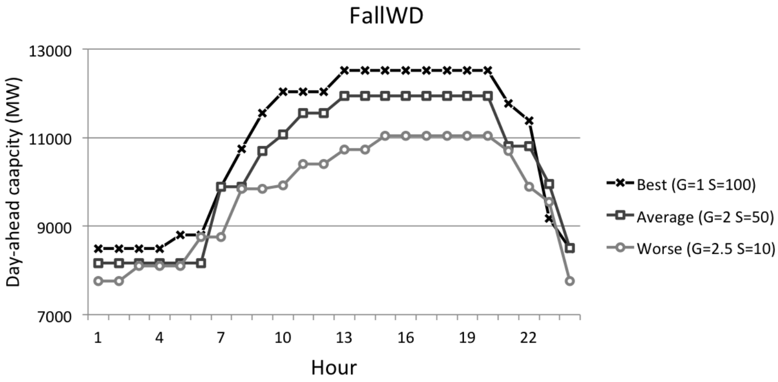
Unit Commitment: Spring Weekdays



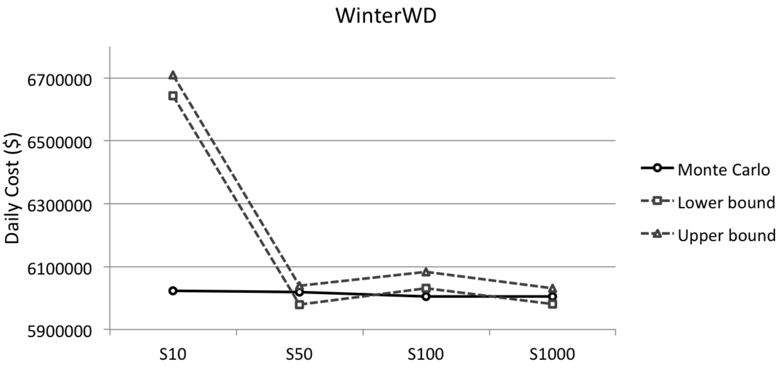
Unit Commitment: Summer Weekdays



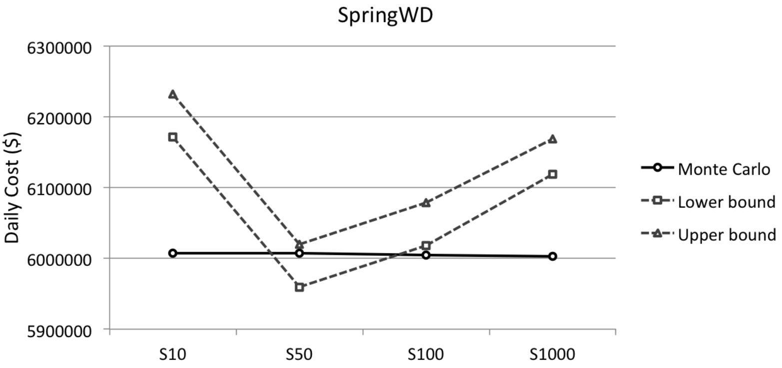
Unit Commitment: Fall Weekdays



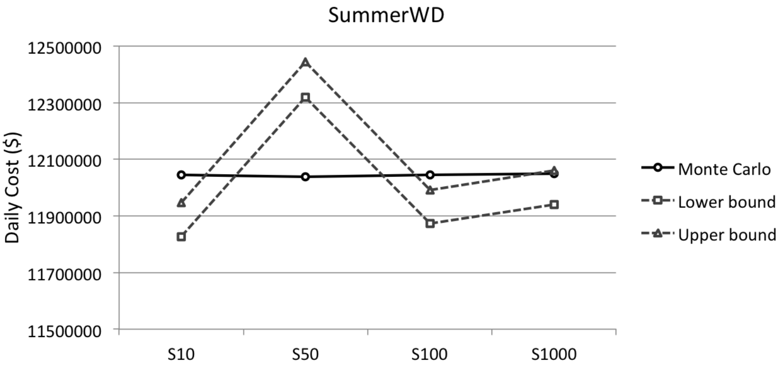
Bounds: Winter Weekdays



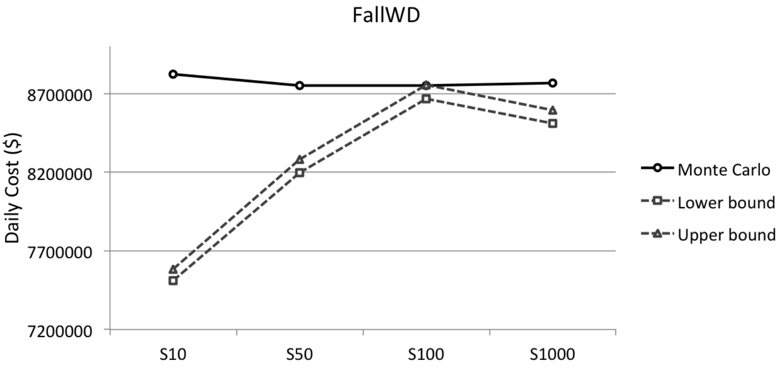
Bounds: Spring Weekdays



Bounds: Summer Weekdays



Bounds: Fall Weekdays



Conclusions

- **Validation of scenario selection algorithm:** The importance sampling scenario selection algorithm performs favorably relative to SAA with 1000 scenarios
- **Decreasing the duality gap versus increasing the number of scenarios:** Reducing the duality gap seems to yield comparable benefits relative to adding more scenarios
- **Efficiency gains:** All problems solved within 24 hours, given enough processors. Parallelization permits the running time of the studied model to run within acceptable time frames from operations standpoint.

Perspectives

- Extensions of present model
  - Bundling methods and asynchronous multiplier updating
  - Analysis of duality gap
  - Comparison of alternative relaxations
- Parallel algorithms for fast topology control (ARPA-E)
- Comparative study of Lagrangian relaxation and Benders decomposition algorithms for stochastic unit commitment and security constrained unit commitment

References

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- A. Papavasiliou, S. S. Oren, R. P. O'Neill, *Reserve Requirements for Wind Power Integration: A Scenario-Based Stochastic Programming Framework, IEEE Transactions on Power Systems*, Vol. 26, No. 4, November 2011.
- A. Papavasiliou, S. S. Oren, B. Rountree, *Applying High Performance Computing to Multi-Area Stochastic Unit Commitment for Renewable Penetration*.

Thank you

Questions?

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http://perso.uclouvain.be/anthony.papavasiliou/public_html/