Applying High Performance Computing to Multi-Area Stochastic Unit Commitment for Renewable Integration

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Outline

Motivation

Increased computational burden in power systems operations due to:

- renewable penetration and
- demand response integration

Potential applications:

- stochastic optimization
- robust optimization
- topology control

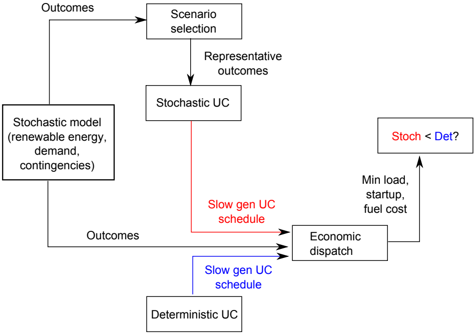
Research Objective

Want to quantify sensitivity of:

- unit commitment policy
- duality gaps
- cost performance

on number of scenarios.

Validation Process



Unit Commitment Model

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

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

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

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

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

Stochastic Unit Commitment Model

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

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

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

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

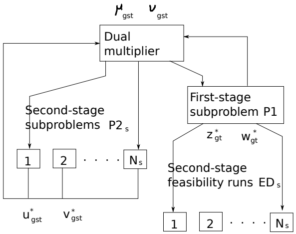
$$(\mathbf{p}, \mathbf{e}, \mathbf{u}, \mathbf{v}) \in \mathcal{D}_s$$

$$u_{gst} = w_{gt}, v_{gst} = z_{gt}$$

Lagrangian Decomposition Algorithm

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

$$+ \sum_{g \in G_s} \sum_{t \in T} (\mu_{gst}(u_{gst} - w_{gt}) + \nu_{gst}(v_{gst} - z_{gt})) \Big)$$



Scenario Selection

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 Production Model

- Relevant literature: (Brown et al, 1984), (Torres et al., 2005), (Morales et al, 2010)
- Calibration steps
  1. Remove systematic effects:

$$y_{kt}^{S} = \frac{y_{kt} - \hat{\mu}_{kmt}}{\hat{\sigma}_{kmt}}.$$

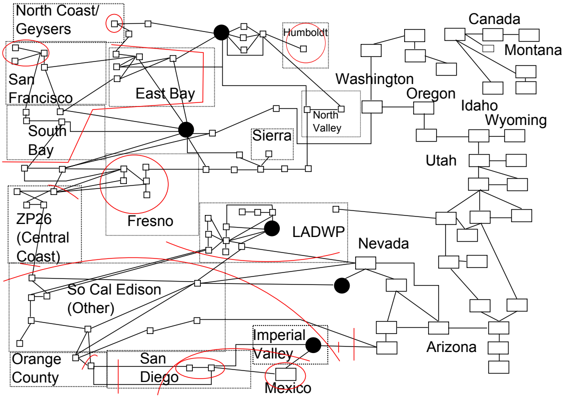
  2. Transform data to obtain a Gaussian distribution:

$$y_{kt}^{GS} = N^{-1}(\hat{F}_k(y_{kt}^{S})).$$

  3. Estimate the autoregressive parameters $\hat{\phi}_{kj}$ and covariance matrix $\hat{\Sigma}$ using Yule-Walker equations.

WECC Model

- 124 units (82 fast, 42 slow), 225 buses, 375 transmission lines



Unit Characteristics

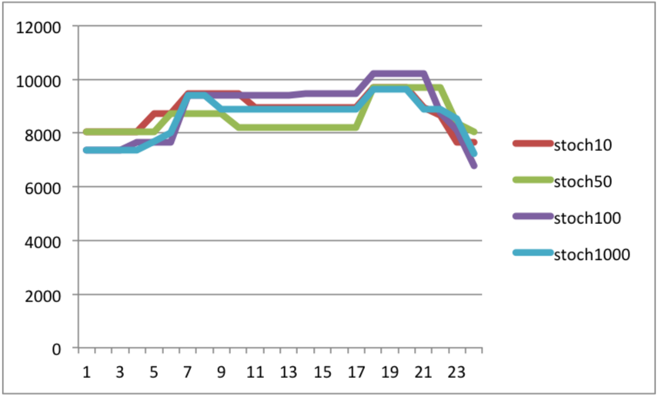
Type	No. of units	Capacity (MW)
Nuclear	2	4,499
Gas	88	18,745.6
Coal	6	285.9
Oil	5	252
Dual fuel	23	4,599
Import	22	12,691
Hydro	6	10,842
Biomass	3	558
Geothermal	2	1,193
Wind (deep)	10	14,143
Fast thermal	82	9,156.1
Slow thermal	42	19,225.4

Sensitivity of Optimal Policy on Number of Scenarios

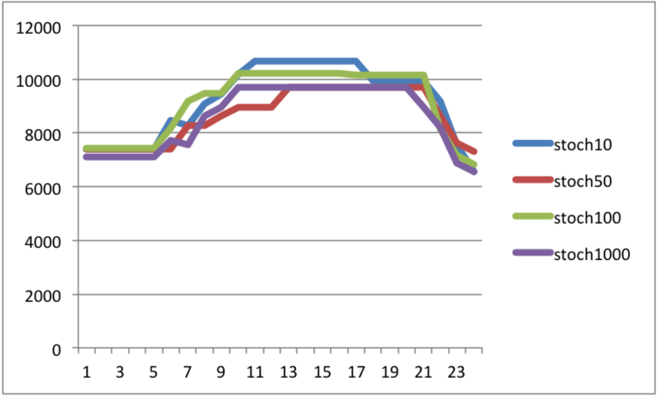
Table: Day-ahead reserve capacity (MW)

	S10	S50	S100	S1000
WinterWD	8846	8575	8885	8600
SpringWD	9173	8639	9077	8572
SummerWD	12185	12327	12261	12497
FallWD	10039	10182	9771	9989
WinterWE	7700	8074	6978	7170
SpringWE	7588	7001	7105	7032
SummerWE	11041	10545	10795	10810
FallWE	9476	8669	8665	8637
Average	9744	9542	9538	9485

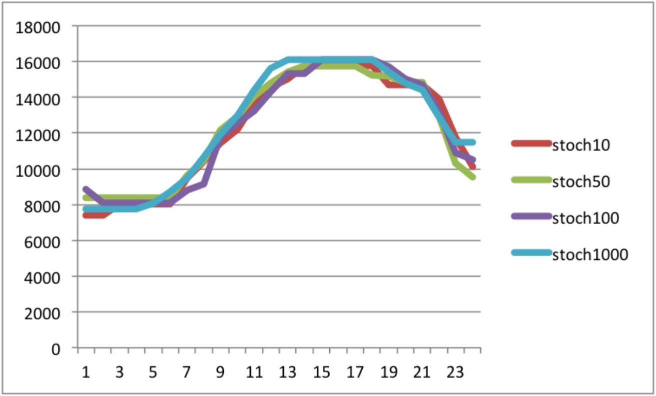
Unit Commitment: Winter Weekdays



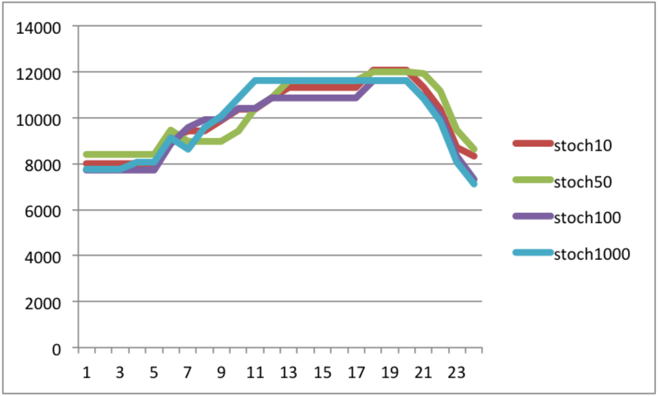
Unit Commitment: Spring Weekdays



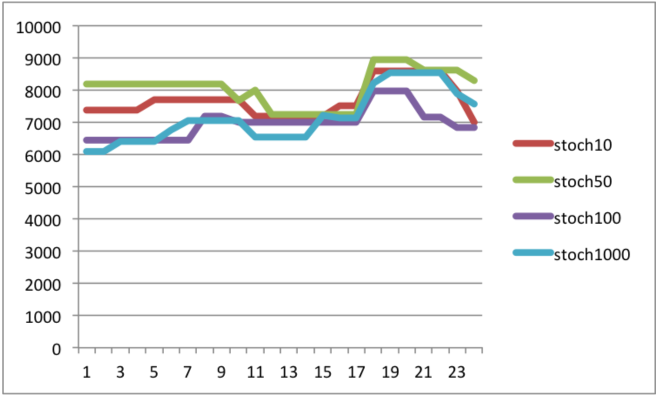
Unit Commitment: Summer Weekdays



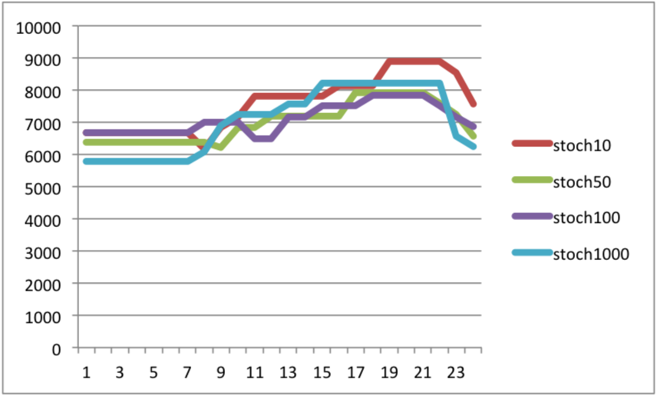
Unit Commitment: Fall Weekdays



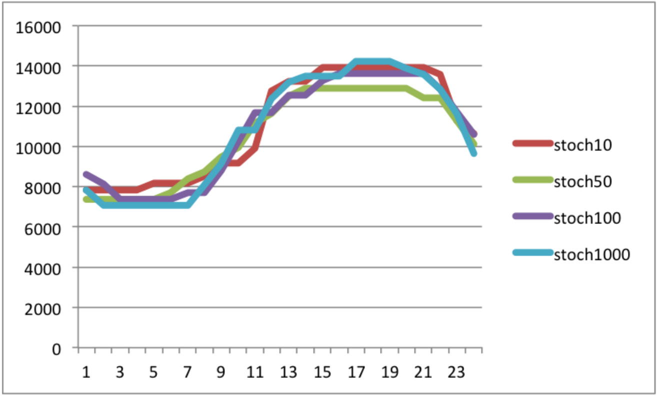
Unit Commitment: Winter Weekends



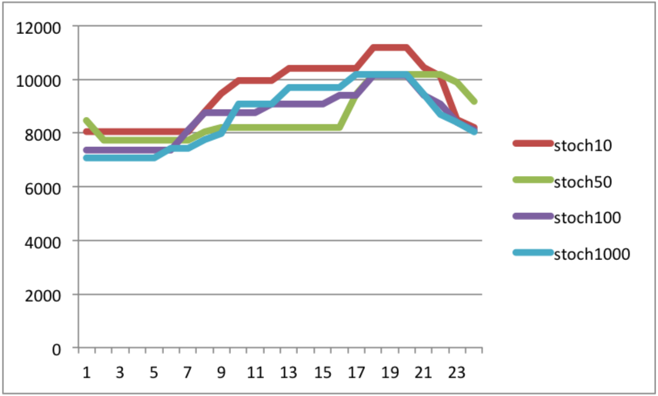
Unit Commitment: Spring Weekends



Unit Commitment: Summer Weekends



Unit Commitment: Fall Weekends



Sensitivity of Bounds on Number of Scenarios

Table: Lower and Upper Bound ($ 1000s)

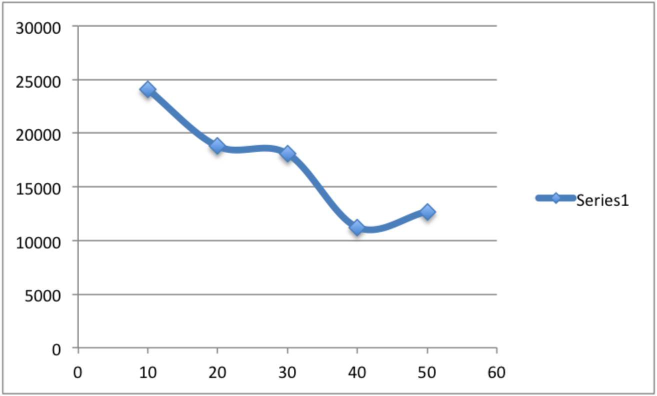
	S10	S50	S100	S1000
WinterWD	(254, 325)	(100, 169)	(-165, -93)	(-180, -105)
SpringWD	(1073, 1123)	(135, 28)	(97, 154)	(115, 164)
SummerWD	(-367, -234)	(48, 87)	(187, 304)	(-76, 62)
FallWD	(-146, -45)	(-292, 397)	(-191, -77)	(-108, 7)
WinterWE	(185, 295)	(-323, 413)	(-504, -411)	(-84, 17)
SpringWE	(668, 783)	(-121, 202)	(-228, -153)	(52, 128)
SummerWE	(-57, 99)	(438, -283)	(-150, 93)	(-108, 50)
FallWE	(810, 913)	(-530, 624)	(-304, -207)	(-92, 7)

Improving the Gap Versus Adding More Scenarios

Table: Performance Improvement as a Function of Gap Improvement

Policy	Gap ($)	Cost ($M)
$S10$	97827	7.303
$S10^{\star}$	70559	7.300
$S50$	92413	7.308
$S50^{\star}$	62190	7.286
$S100$	93711	7.299
$S100^{\star}$	67069	7.289
$S1000$	98485	7.301

Running Times



Conclusions

- **Validation of scenario selection algorithm:** The importance sampling scenario selection algorithm with 10 scenarios performs as well as a stochastic unit commitment model with 1000 scenarios
- **Decreasing the duality gap versus increasing the number of scenarios:** Reducing the duality gap seems to yield superior benefits relative to adding more scenarios
- **Scaling of running times:** The speedup benefits of parallelization seem to be limited beyond 20% of the problem size

Thank you

Questions?

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http://www3.decf.berkeley.edu/∼tonypap/publications.html