Investigation of Advanced Stochastic Unit Commitment Solution for Optimal Management of Uncertainty

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Motivation

With increasing participation of variable and uncertain resources on both sides of the power system, operational decisions require stochastic methods. Challenges:

- Characterizing uncertainty, scenario selection
- Computational tractability, large networks
- Flexibility,
  - for different types of uncertainty (wind, solar, responsive demand)
  - for integration with complementary tools

Objective

For 2015, we proposed to continue development of a reliable, scalable, and flexible implementation of the SCUC solution, including:

- Tractability for large networks
- Flexiblity for various types of uncertainty and tools
    - Renewables, demand response,
    - Integration with Matpower$^{\mathrm{TM}}$, MOPS$^{\mathrm{TM}}$
- Adjustable levels of risk-aversion

Presentation Overview

To this end, we will summarize progress on:

1. Chance-constrained UC formulation, and scalability
2. Test implementation with AC-OPF
3. Comparative testing with robust and hybrid formulations

Chance-Constrained Unit Commitment

The chance constrained model differs from the stochastic UC model in that we require power balance, spinning, and non-spinning reserve constraints to be probabilistic.

- User-defined reliability levels are used to compute probabilistic trajectories of the uncertain generation
- Power balance of the system is determined with an appropriate netload (representing a user-defined probability level to operate the system)
- System reserves are then allocated with probabilistic guarantees

Stochastic Unit Commitment Formulation

Stochastic two-stage model

Given a set of realization: $\omega \in \Omega$

$$
\begin{aligned}
\min \quad & C_1(u_g, v_g) + \mathbb{E}[C_2(p_g)] \\
& (p_g(\omega), u_g, v_g) \in \mathcal{C}^{\text{gen}}_{\text{dyn}} \cap \mathcal{C}^{\text{gen}}_{\text{stat}}, \\
& \textstyle\sum_{n \in \mathcal{N}_k} p^t_{g_n}(\omega) + \mathbf{p}^t_{r_k}(\omega) + {p_{\text{ij}}}^t_k(\omega) = \mathbf{L}^t_k, k \in \mathcal{K}, \\
& |{p_{\text{ij}}}_l(\omega)| \leq F_l, l \in \mathcal{B}, \\
& \textstyle\sum_{n \in \mathcal{N}} sp^t_n(\omega) = Sr^t, \\
& \textstyle\sum_{n \in \mathcal{N}} sp^t_n(\omega) + np^t_n(\omega) = Sn^t
\end{aligned}
$$

u_g, v_g is the (risk-neutral) commitment that minimizes the expected dispatch cost $\mathbb{E}[C_2(p_g)]$

Chance-Constrained Formulation

Scenarios $\omega \in \Omega$

Risk-averse UC and probabilistic reserve levels:

$$\begin{aligned} \min \quad & C(u_g, v_g, p_g) \\ & (p_g, sp, np, u_g, v_g) \in \mathcal{C}^{\text{gen}}_{\text{dyn}} \cap \mathcal{C}^{\text{gen}}_{\text{stat}}, \\ & \mathbb{P}\big[\textstyle\sum_{n \in \mathcal{N}_k} p^t_{g_n} + {p_{\text{ij}}}^t_k = \mathbf{L}^t_k - \mathbf{p}^t_{r_k}, k \in \mathcal{K}\big] \geq \pi, \\ & |{p_{\text{ij}}}_l| \leq F_l, l \in \mathcal{B}, \\ & \mathbb{P}\big[\textstyle\sum_{n \in \mathcal{N}} sp^t_n = Sr^t + \alpha \mathbf{p}^t_r\big] \geq \rho, \\ & \mathbb{P}[\textstyle\sum_{n \in \mathcal{N}} sp^t_n + np^t_n = Sn^t + \beta \mathbf{p}^t_r\big] \geq \rho \end{aligned}$$

(u_g, v_g, p_g) schedule determined by a risk-averse net-load operating level: $[L - p_r]_\pi$

(sp, np) system reserves allocated with a risk-averse renewable level: $[p_r]_\rho$

Chance-Constrained Unit Commitment

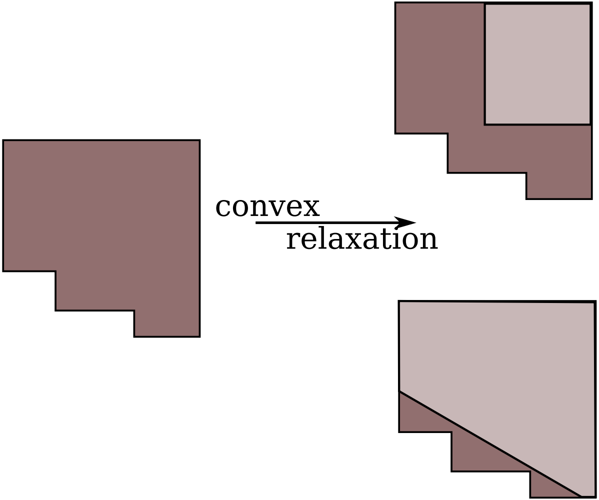
Operating risk-levels

Dual decomposition

Primal-feasible solution

Algorithmic Scheme

Relaxation Approach - Stochastic Subproblems

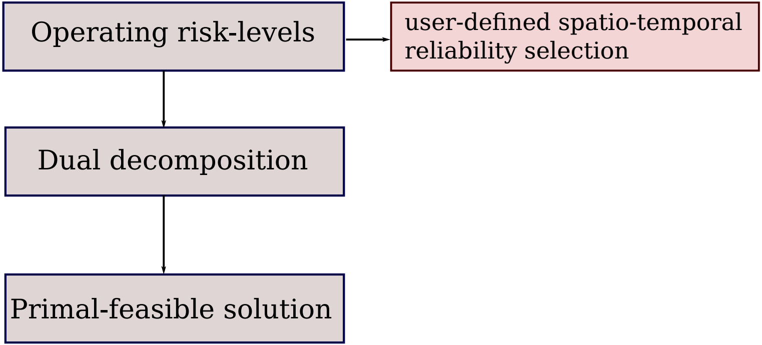


convex relaxation

Robust

Distributed Risk

Chance-Constrained Unit Commitment



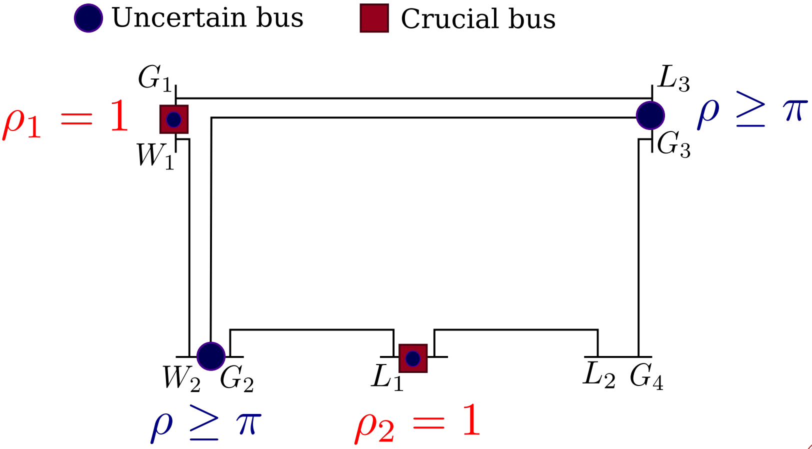
Operating risk-levels

user-defined spatio-temporal reliability selection

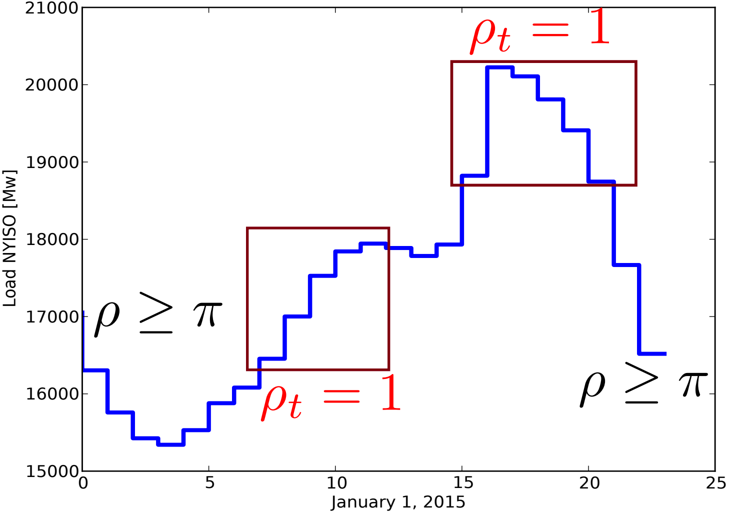
Dual decomposition

Primal-feasible solution

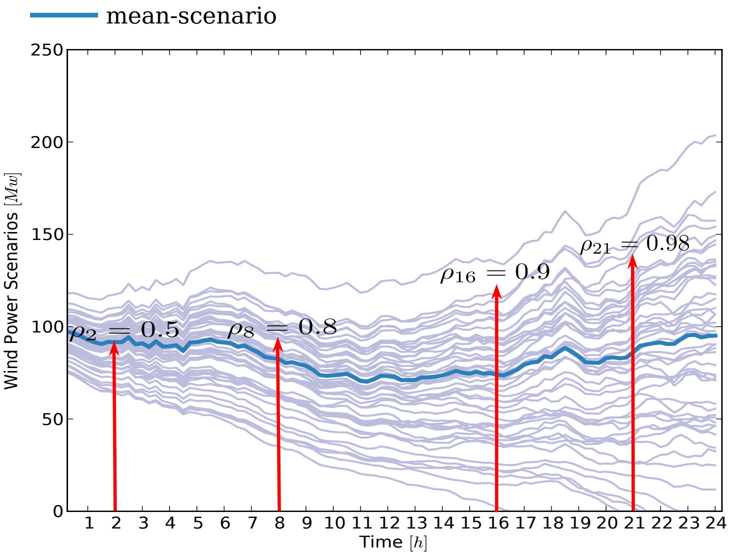
Spatial Distribution of Risk



Temporal Distribution of Risk



Probabilistic System Reserve Levels



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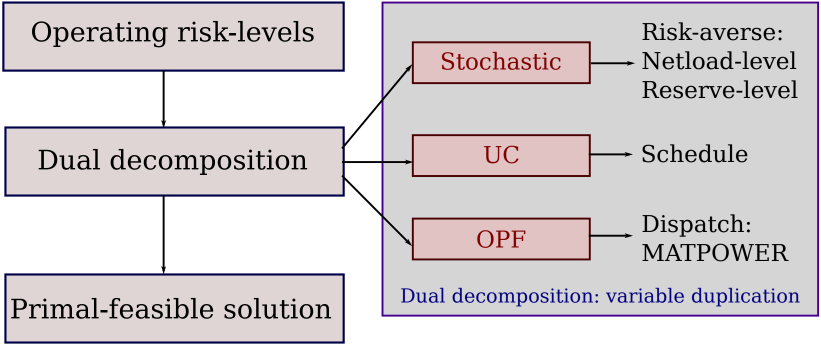
Chance-Constrained Unit Commitment



Operating risk-levels

Dual decomposition

Primal-feasible solution

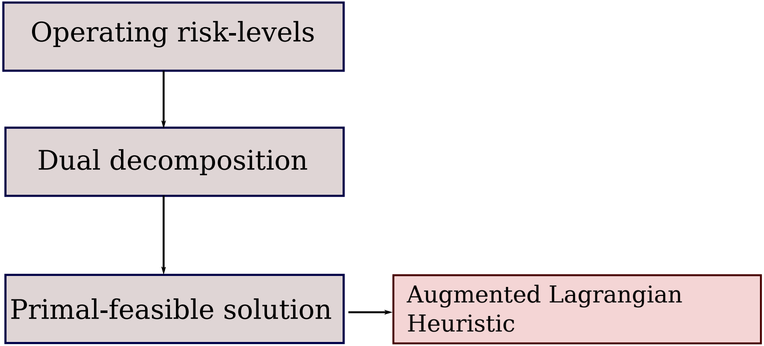
Stochastic → Risk-averse: Netload-level Reserve-level

UC → Schedule

OPF → Dispatch: MATPOWER

Dual decomposition: variable duplication

Chance-Constrained Unit Commitment



Operating risk-levels

Dual decomposition

Primal-feasible solution

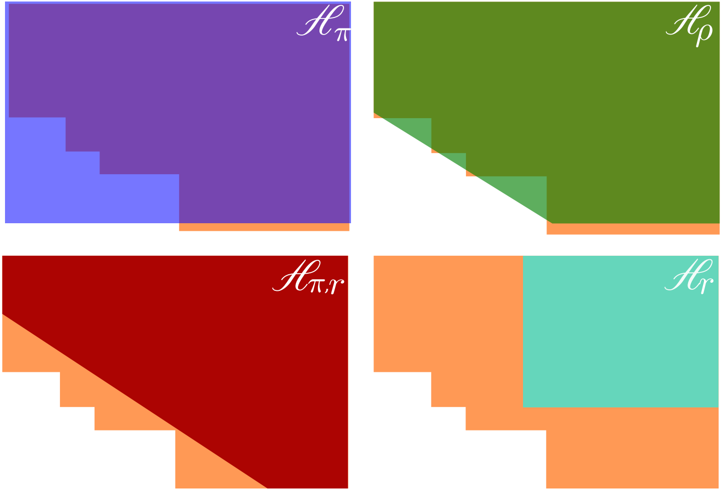
Augmented Lagrangian Heuristic

Results Overview

A sampling of results for various networks:

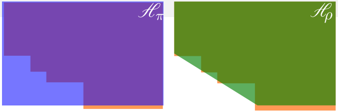
- Out of sample performance for various risk levels
- IEEE 30-bus, 57-bus, and 118-bus
- Polish system 3120 buses, with AC OPF (initial tests)

Data-driven Relaxation $\mathcal{H}_\rho$



Out-of-sample performance for different reliability levels

Out-sample size 10^7



- 🟥 Strongly Infeasible
- 🟧
- 🟩
- 🟦
- 🟦 Feasible

PG_π: risk-level π

M \ π	0.8	0.85	0.9	0.95	0.99	0.999
10^3	0.668	0.757	0.799	0.900	0.960	0.989
10^5	0.699	0.794	0.885	0.910	0.968	0.992
10^6	0.703	0.800	0.888	0.910	0.967	0.992

PG_ρ: risk-levels $\rho \geq \pi$

M \ π	0.8	0.85	0.9	0.95	0.99	0.999
10^3	0.708	0.812	0.814	0.897	0.906	0.994
10^5	0.787	0.823	0.874	0.901	0.932	0.998
10^6	0.796	0.829	0.894	0.901	0.932	0.998

Out-of-sample performance for different reliability levels

Out-sample size 10^7

🟥 Strongly Infeasible
🟧
🟩
🟦
🟦 Feasible

$PG_{\rho,r}$: risk-levels π and 1

M \ π	0.8	0.85	0.9	0.95	0.99	0.999
10^3	0.990	0.992	0.992	0.992	0.994	0.997
10^5	0.992	0.992	0.993	0.993	0.994	0.999
10^6	0.992	0.992	0.993	0.993	0.994	0.999

PG_r: risk-level 1

M \ π	0.8	0.85	0.9	0.95	0.99	0.999
10^3	0.996	0.998	0.998	0.997	0.991	0.999
10^5	0.999	0.999	0.999	0.999	0.999	0.999
10^6	0.999	0.999	0.999	0.999	0.999	0.999

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UC DC Power Flow: Case 57

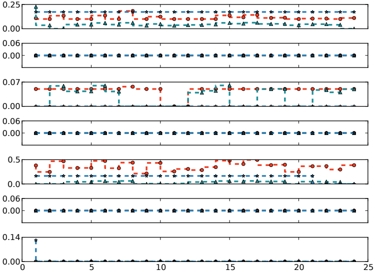
Netload prob. level 0.95. Total reserve prob. level 0.9

wind farms located at nodes 4, 23, 30, 52, 57.

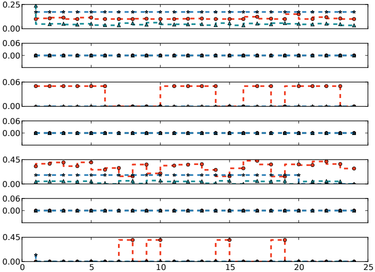
Risk-averse selection of units case 57

IEEE 57 bus, wind farms at nodes 4 23 30 52 57. Prob. reserve level 0.9

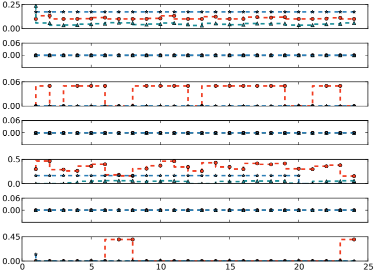
Netload prob. 0.8



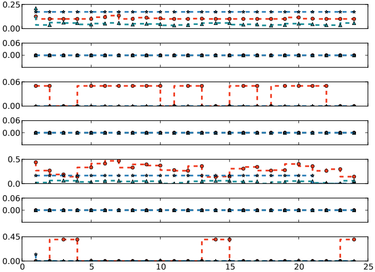
Netload prob. 0.9



Netload prob. 0.95

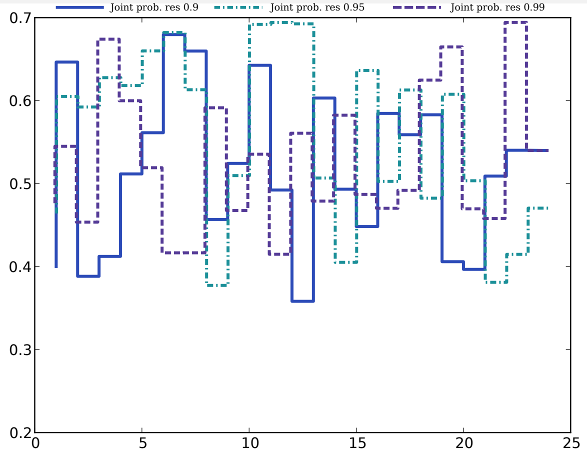


Netload prob. 0.99



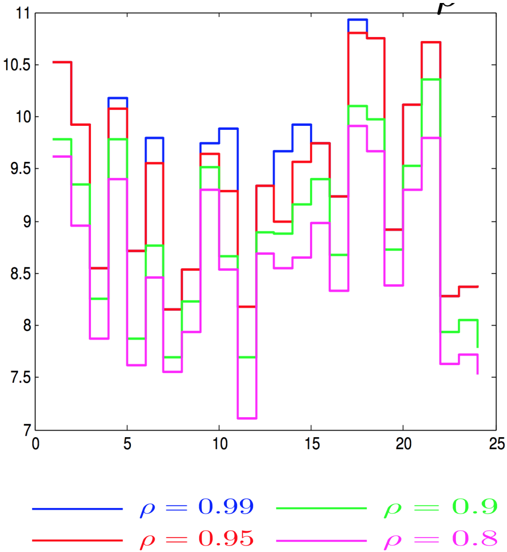
System Reserve Levels

IEEE 57 bus. Netload prob 0.9



Different patterns are caused by selection of joint-probability total wind power trajectories. Probabilistic reserve levels are determined by optimization model (non-trivial).

Example of (time) Marginal Probabilistic Reserves



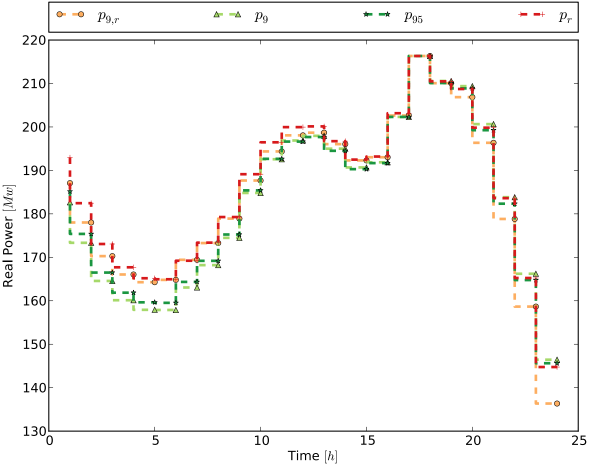
AC Power Flow Testing (Proof of Concept)

- Heuristic is required to ensure feasible solution
- AC dispatch is forward dynamic optimization (myopic)
- No guarantees on global optimality, only know this is a local minimum

UC AC Power Flow: Case 3120sp

Wind power share corresponds to 30 percent

Load pattern NYISO, wind power pattern production ELIA (Belgium)



UC AC power flow: Case 3120sp

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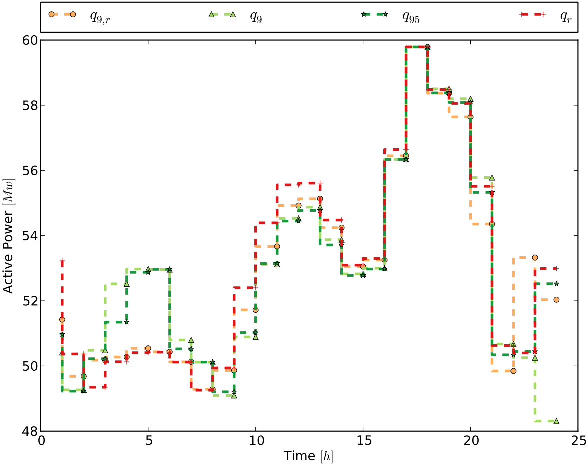

Summary

Table: Comparing *Approximate* Computation Time

Network	Scenarios	Solve Time (min)	Comments
5-bus	10^6	< 1	DC, no reserves
57-bus	10^4	1	DC, reserves
118-bus	10^5	5-10	DC, reserves
3120sp	10^3	120	AC, reserves

Summary

- The CCUC model is scalable in reasonable computation time
- Provides customized risk distribution across time and space
- Integrates with AC OPF through Matpower$^{\text{TM}}$, and (likely) subsequently MOPS$^{\text{TM}}$

Comparison of Probabilistic and Robust Approaches[1]

The objective of this analysis was to consider renewables in conjunction with responsive demand, and to compare efficacy of approaches on a simple, and practical case study.

Description of the analysis proceeds as follows:

- Classes of reserves
- Description of three approaches to risk
- Comparative results and summary

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[1] joint work with J.L. Mathieu

The model

This analysis builds on the stochastic OPF model developed in Li & Mathieu (2015) with the addition of the following:

- Addition of significant wind penetration at multiple locations
- Development of model and uncertainty characterization for wind output
- Implementation of ramp limits
- Adaptive risk levels to allow a mixed approach

Reserves Classifications

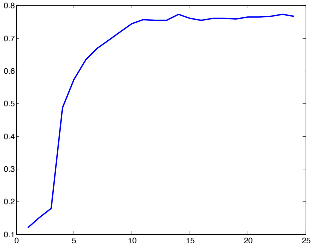
The model uses three types of reserves, defined as follows:

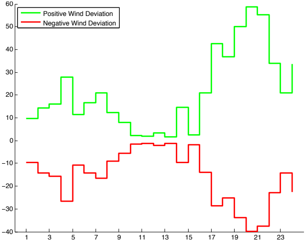
1. reserves from responsive (thermostatically controlled) loads,
2. frequency reserves provided by online generators (AGC), and
3. generator intra-hour re-dispatch reserve, on 15-minute time scale.

Solution Approaches

We use this augmented model to compare the following solution approaches:

- Robust approach: worst case scenarios are considered
- Percentile approach: use of probabilistic levels of wind scenarios
- Mixed approach: percentile approach is used for the first few hours when the wind forecast error is relatively small. Robust approach is used for remaining periods.





Test System

- IEEE 30 Bus System.
- 4 wind farms at bus 1, 10, 20, 30.
- Maximum Share of Wind (WS) is 30%.
- 10% of the each load could provide demand response.
- 90% is used for the percentile approach.

Result: Total System Reserve

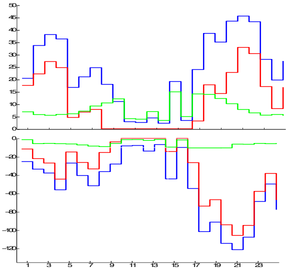


Figure: Robust

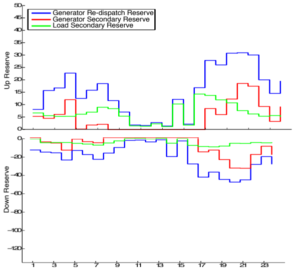


Figure: Percentile

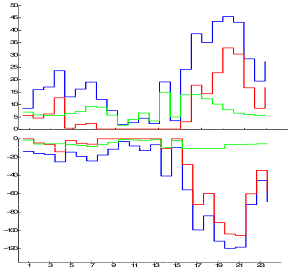


Figure: Mixed

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Result: Generator Total Secondary and Re-dispatch Reserve

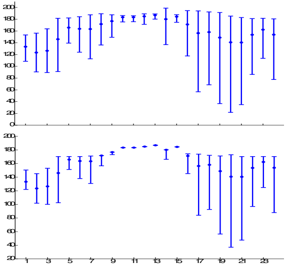


Figure: Robust

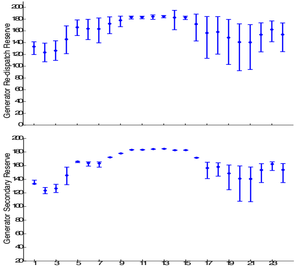


Figure: Percentile

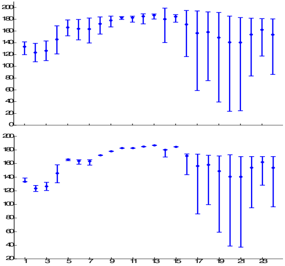


Figure: Mixed

Result: Unit 5 Secondary and Re-dispatch Reserve

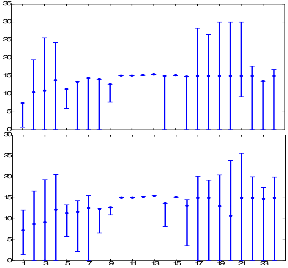


Figure: Robust

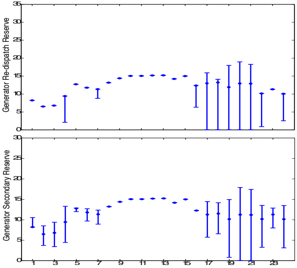


Figure: Percentile

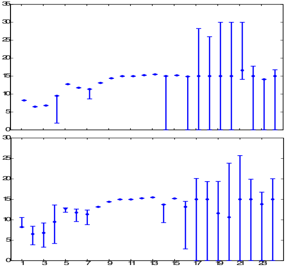


Figure: Mixed

With Ramping

- With ramping, the robust and mixed approach is no longer feasible at high WS.

WS	10%	15%	20%	25%	30%
$Robust$	F	F	I	I	I

Table: Feasibility of Robust Approach at Different WS

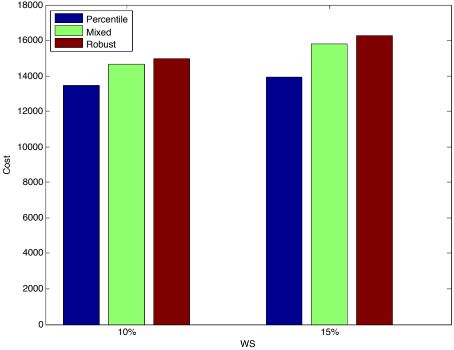
- Wind Curtailment (WC) might be needed at high WS for the percentile and mixed approach.

WS	10%	15%	20%	25%	30%
$Probability$	0	0	≤ 0.01	≤ 0.02	≤ 0.04
$WC(MW)$	0	0	≤ 0.1	≤ 0.24	≤ 0.53

Table: Hourly Probability of Wind Curtailment

Cost Comparison

- Cost of the three approaches for 10% & 15% WS



Summary: Method Comparison

- Robust methods may not allow inclusion of high levels of wind penetration within ramp limits
- A hybrid method can provide highest protection under significant uncertainty, while maintaining feasibility
- Even when feasible, the reserves add to system costs as wind penetration increases

Conclusions

The primary conclusions of recent work are as follows:

- Tests of chance-constrained UC on larger networks show promising computation times for large scenario sets
- Provides a balance of risk and cost between expected value methods and robust methods
- Comparisons indicate that robust solutions may not be practical as uncertainty increases
- Chance-constrained implementation allows complete customization of risk preferences (both time and space)

Future Directions

Ongoing work for this project includes:

- Further work on AC implementation
- Integration with MOPS$^{\text{TM}}$
- Integrate storage through approximate dynamic programming methods (initiated)
- Testing of solution quality impact of scenario selection algorithms (in progress)

Contributions

- Martinez, G., & Anderson, C. L. (2014). Toward a scalable chance-constrained formulation for unit commitment to manage high penetration of variable generation. Allerton Conference on Communication, Control and Computing, 18.
- Martinez, M. G., & Anderson, C. L. (2015) A Risk-averse Optimization Model for Unit Commitment Problems. 48th Hawaii International Conference on System Sciences (HICSS).
- Liu, J., Martinez, M. G., Li, B., Mathieu, J. L., & Anderson, CL. A Comparison of Robust and Probabilistic Reliability for Systems with Renewables and Responsive Demand. Submitted to 2016 49th Hawaii International Conference on System Sciences (HICSS)
- Tupper, Laura L., Matteson, David, S., & Anderson, C. L. Comparing and Clustering Nonstationary Time Series with Applications to Wind Speed Behavior, to be presented at the Joint Statistical Meetings, Seattle, WA. August 8-13, 2015.

Thank you!