Risk-Aware Security-Constrained Unit Commitment: Taming the Curse of Real-Time Volatility and Consumer Exposure

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Two-Stage Wholesale Electricity Market

Day-ahead SCUC Problem $\xrightarrow{\text{Unit commitment decisions}}$ Real-time DCOPF Problem

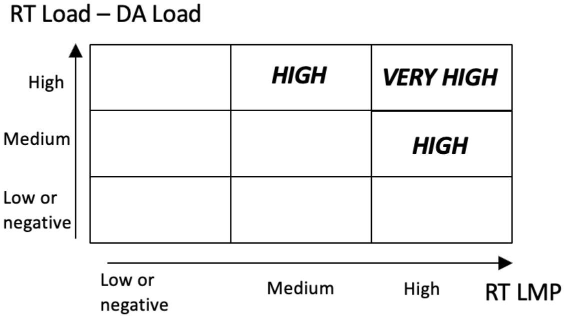
- Day-ahead market: security-constrained unit commitment (SCUC)
  - Currently uses a deterministic model
- Real-time market: DC optimal power flow
- Volatility in real-time market
  - Demand
  - Renewable (wind) production

Prior Work: SCUC and Demand/Renewable Uncertainty

- Two-stage stochastic programming
  - Demand uncertainty: Carpentier et al. [1996], Takriti et al. [1996]
  - Renewable generation: Dvorkin et al. [2014], Morales et al. [2009], Sundar et al. [2016], Wang and Hobbs [2015], Wu et al. [2007]
  - Bottleneck: large number of scenarios. Struggling with 10 scenarios for our data.
- Adaptive robust optimization models for SCUC
  - Polyhedral uncertainty sets: Bertsimas et al. [2012], Jiang et al. [2011]
  - Data-driven uncertainty sets: Velloso et al. [2019], Ning and You [2019]

Our Goal: Protect Consumers from Price Spikes in Real-Time Market

- Consumer payment at bus i:
  - Day-ahead (DA) payment: (DA price at i) $\times$ (DA load at i)
  - Real-time (RT) consumer exposure:
    (RT price at i) $\times$ max{ (RT load at i - DA load at i), 0 }



- Challenge: Very high RT price if there is shortfall in wind

Contributions

- A SCUC model that reduces worst-case consumer exposure
  - Minimal modification; preserves two-stage market structure
  - Real-time uncertainty added as a penalty term in the SCUC ("Mean-variance portfolio optimization")
  - Uncertainty set via principal component analysis (PCA), capturing locational correlation
- Solve the nonconvex model for NYISO case study (1819 buses, 362 generators)
  - Problem-specific logic-based Benders decomposition (LBDD) cuts
  - Grid search
  - Branch-and-cut

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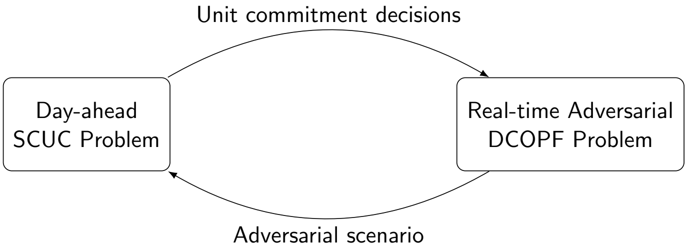
Risk-Aware Security-Constrained Unit Commitment



- A better representation of the impact of RT volatility on system cost

The Model

h_{gt}:	Piecewise linear operating cost
v_{gt}:	Binary start-up decision
w_{gt}:	Binary shut-down decision
p_{it}^{Unmet}:	Unmet load
$\hat{V}(\mathbf{y})$:	Worst-case RT consumer exposure
$\lambda_{it}(\mathbf{y},\boldsymbol{\omega})$:	RT LMP
d_{it}^{RT}:	RT load

$$\min \sum_{t\in\mathcal{T}^{\mathrm{DA}}} \Big(\sum_{g\in\mathcal{G}} \big(h_{gt} + C_g^{\mathrm{Start}} v_{gt} + C_g^{\mathrm{Down}} w_{gt}\big) + \sum_{i\in\mathcal{N}} C^{\mathrm{VOLL}} p_{it}^{\mathrm{Unmet}} \Big) + \rho \hat{V}(\mathbf{y}) \rightarrow \text{DA cost + penalty on worst-case consumer exposure}$$

$$\text{s.t. DA constraints: load, capacity, transmission, ramping} \rightarrow \text{SCUC constraints}$$

$$\hat{V}(\mathbf{y}) = \max_{\omega\in\Omega} \frac{1}{N^{\mathrm{tp}}} \sum_{t\in\mathcal{T}^{\mathrm{RT}}} \sum_{i\in\mathcal{N}} \lambda_{it}(\mathbf{y},\omega)(d_{it}^{\mathrm{RT}} - \bar{D}_{it})^+$$

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Adversarial Real-time Problem

$$\begin{aligned} \text{DCOPF-A}(\mathbf{y}^*) := \max_{\boldsymbol{\omega}\in\Omega} \quad & \frac{1}{N^{\mathrm{tp}}} \sum_{t\in\mathcal{T}^{\mathrm{RT}}} \sum_{i\in\mathcal{N}} \lambda_{it}(\mathbf{y}^*,\boldsymbol{\omega})(d_{it}^{\mathrm{RT}} - \bar{D}_{it})^+ \\ \text{s.t.} \quad & \lambda_{it}(\mathbf{y}^*,\boldsymbol{\omega}) \text{ is an optimal solution of DCOPF-D}(\mathbf{y}^*,\boldsymbol{\omega}). \end{aligned}$$

- $\lambda_{it}(\mathbf{y}^*,\boldsymbol{\omega})$: RT market equilibrium price
- Uncertainty set Ω: using PCA to capture covariance of loads and renewable outputs

Data-Driven Uncertainty Set

- PCA
  - Covariance matrix of data for recent past, one per time period
  - K largest leading modes

$$
\begin{aligned}
& d_{it}^{\mathrm{RT}} = \bar{D}_{it} + \sum_{k=1}^{K} Q_{kit}^{d} \alpha_{kt}^{d} && \forall i \in \mathcal{N}, t \in \mathcal{T}^{\mathrm{RT}} \rightarrow \text{RT load} \\
& p_{gt}^{\max,\mathrm{RT}} = \bar{P}_{gt}^{\max} + \sum_{k=1}^{K} Q_{kgt}^{w} \alpha_{kt}^{w} && \forall g \in \mathcal{G}^{\mathrm{Wind}}, t \in \mathcal{T}^{\mathrm{RT}} \rightarrow \text{RT wind output} \\
& \Big|\sum_{k=1}^{K} \alpha_{kt}^{ind}\Big| \leq \Sigma^{ind} && \forall t \in \mathcal{T}^{\mathrm{RT}}, ind \in \{d, w\} \rightarrow \text{Bound on stressors} \\
& |\alpha_{kt}^{ind}| \leq R^{ind} && \forall k = 1, \ldots, K; t \in \mathcal{T}^{\mathrm{RT}}, ind \in \{d, w\} \rightarrow \text{Bound on stressors} \\
& d_{it}^{\mathrm{RT}} \geq 0 && \forall i \in \mathcal{N}, t \in \mathcal{T}^{\mathrm{RT}} \\
& p_{gt}^{\max,\mathrm{RT}} \geq 0 && \forall g \in \mathcal{G}^{\mathrm{Wind}}, t \in \mathcal{T}^{\mathrm{RT}}.
\end{aligned}
$$

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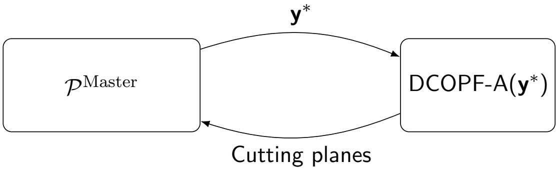
The Decomposition Algorithm

- A mixed-integer nonconvex optimization model
  - $\mathbf{y}$
  - KKT conditions



- $\mathcal{P}^{\text{Master}}$: Relax the constraint $\hat{V}(\mathbf{y}) = \max_{\boldsymbol{\omega}\in\Omega} \frac{1}{N^{\text{tp}}} \sum_{t\in\mathcal{T}^{\text{RT}}} \sum_{i\in\mathcal{N}} \lambda_{it}(\mathbf{y},\boldsymbol{\omega})(d_{it}^{\text{RT}} - \bar{D}_{it})^+$
- Add under-estimators of $\hat{V}(\mathbf{y})$ via cutting planes
  - But DCOPF-A($\mathbf{y}^*$) is nonconvex...

Cutting Planes

- Idea: $\hat{V}^*(\mathbf{y}^*) \to$ under-estimator for $\mathbf{y}^*$ and neighboring $\mathbf{y}$'s
- No-good cut: $\hat{V}(\mathbf{y}) \geq \hat{V}^*(\mathbf{y}^*)\left(1 - \sum_{t\in\mathcal{T}^{\mathrm{RT|Hour}}}\left(\sum_{g\in\mathcal{I}_{1t}}(1-y_{gt}) + \sum_{g\in\mathcal{I}_{0t}} y_{gt}\right)\right).$
- Integer L-shaped cut: $\hat{V}(\mathbf{y}) \geq \hat{V}^*(\mathbf{y}^*) + a\sum_{t\in\mathcal{T}^{\mathrm{RT|Hour}}}\left(\sum_{g\in\mathcal{I}_{1t}} y_{gt} - \sum_{g\in\mathcal{I}_{0t}} y_{gt} - |\mathcal{I}_{1t}|\right)$
  - Nontrivial lower bound for 1-neighbors of $\mathbf{y}^*$
  - $a = \max(\hat{V}^* - \hat{V}_1, (\hat{V}^* - \hat{V}_0)/2)$
  - $\hat{V}_1$: the minimum value of $\hat{V}$ when exactly one generator changes its commitment decision
  - $\hat{V}_0$: a lower bound on $\hat{V}$ under a feasible commitment decision
- Logic-based Benders decomposition (LBBD) cut (problem specific):
  $\hat{V}(\mathbf{y}) \geq \sum_{t\in\mathcal{T}^{\mathrm{RT|Hour}}}\left(\hat{V}_t^*(\mathbf{y}^*)\left(1 - \sum_{g\in\mathcal{I}_{0t}} y_{gt}\right)\right)$
  - Nontrivial lower bound when all off-generators remains off

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Validity of the LBBD Cut

Proposition

When there is no congestion in the network and the ramping constraints are not binding in the real-time market:

- *The LBBD cut* $\hat{V}(\mathbf{y}) \geq \sum_{t\in\mathcal{T}^{\mathrm{RT|Hour}}} \left(\hat{V}_t^*(\mathbf{y}^*)\left(1-\sum_{g\in\mathcal{I}_{0t}} y_{gt}\right)\right)$ *provides a correct lower bound for* $\hat{V}(\mathbf{y})$*.*
- *Also, it provides the exact value of* $\hat{V}(\mathbf{y})$ *at the current solution* $\mathbf{y}^*$*.*

- Consider $\mathcal{I}'_{0t}$
- Case 1: $\mathcal{I}'_{0t} \subset \mathcal{I}_{0t}$: open more generators $\rightarrow$ nonpositive RHS
- Case 2: $\mathcal{I}_{0t} \subseteq \mathcal{I}'_{0t}$: turn off generators $\rightarrow$ Less capacity, LMP will not decrease $\rightarrow$ $\hat{V}_t^*(\mathbf{y}^*)$ is a lower bound
- Congestion: Some LMPs may drop in Case 2
- Ramping: LMP depends on the production levels of the previous time period

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Solving DCOPF-A($\mathbf{y}^*$)

- Direct solve with Knitro or Gurobi: not scalable
- McCormick relaxation: not very tight, limited cost reduction
- Grid search
  - Iterate through a set of fixed stressors (i.e, "grids") ($\tilde{\alpha}^d_{kt}, \tilde{\alpha}^w_{kt}$)
  - Solve DCOPF($\mathbf{y}^*, \tilde{\boldsymbol{\omega}}$)

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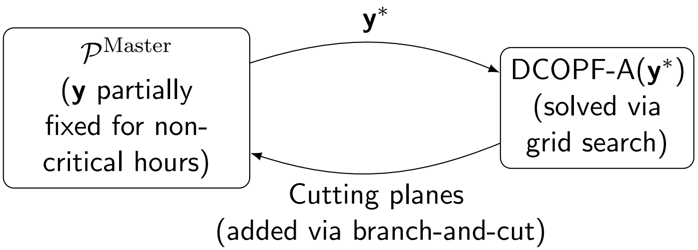
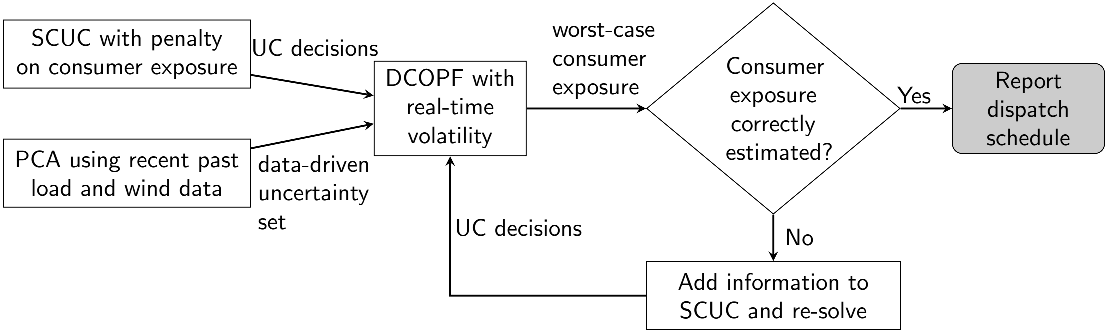
Implementation Details



Obtaining Risk-Aware Day-ahead Schedule with Our Method



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NYISO Case Study

- Realistic NYISO data set: 1819 buses, 2207 lines, 362 generators and 38 wind farms
- Linux workstation with Intel Xeon processor and 250 GB memory (Palmetto Clusters)
- Gurobi 10.0.1; time limit of 24 hours; all solved under 0.5% optimality gap

Risk-Aware vs. Deterministic Models

- Cost saving for most instances
- Larger savings under higher volatility
- Relatively small increase in DA cost
- Lower $\rho \rightarrow$ less cost savings when volatility is lower/higher $\rightarrow$ more conservative decisions

R^d	R^w	Save (k\$)	Deter. cost (M\$)	Cost red. (%)	DA cost diff (\$)	Consr. exp. (k\$)
0.1	0.2	0.00	5.37	0.00	0.00	8.53
0.1	0.4	0.12	5.37	0.00	116.16	8.53
0.1	0.6	0.00	5.37	0.00	0.00	8.89
0.1	0.8	42.29	5.41	0.78	116.16	8.89
0.1	1.0	42.28	5.41	0.78	123.50	8.89
0.2	0.2	114.71	5.50	2.09	116.16	17.78
0.2	0.4	114.14	5.50	2.08	688.03	17.78
0.2	0.6	115.74	5.50	2.11	1446.22	16.76
0.2	0.8	108.58	5.50	1.98	8130.20	17.78
0.2	1.0	115.64	5.50	2.10	1072.06	17.78

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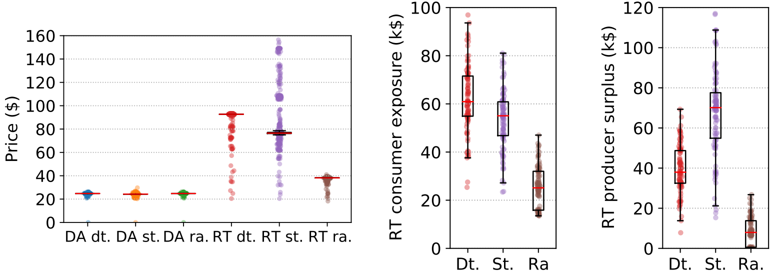
Risk-Aware vs. Stochastic Models

- Two-stage stochastic programming SCUC model
  - Objective: Minimize Expected cost + ρ CVaR
  - 10 scenarios, 48-hour time limit, with warm start
  - L-shaped via branch-and-cut not useful
- Stochastic model: higher DA cost & consumer exposure

R^d	R^w	Opt. gap (%)	Save (k$)	Cost red. (%)	DA cost diff (k$)	Sto consr. exp. (k$)
0.1	0.2	3.69	243.93	4.34	-185.95	66.51
0.1	0.4	2.22	158.57	2.87	-114.88	52.22
0.1	0.6	3.30	234.16	4.18	-176.80	66.25
0.1	0.8	2.55	190.63	3.43	-133.17	66.36
0.1	1.0	2.32	178.97	3.22	-120.88	66.99
0.2	0.2	0.55	136.20	2.47	-20.62	133.36
0.2	0.4	1.00	151.53	2.74	-36.65	133.36
0.2	0.6	3.29	289.53	5.11	-173.80	132.49
0.2	0.8	0.40	121.72	2.21	-5.53	133.97
0.2	1.0	0.72	146.50	2.65	-31.19	134.16

Out-of-Sample Tests

- Perturbed adverse stressors: sample vector $\boldsymbol{\alpha}^{ind} = (\alpha^{ind}_{1t}, \alpha^{ind}_{2t}, \alpha^{ind}_{3t})$ with fixed norm
  - DA LMPs are similar
  - Our model: lowest RT LMPs, consumer exposure, and producer surplus
- Uniformly distributed stressors: sample α^{ind}_{kt} in $[-R^{ind}, R^{ind}]$



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Summary

- Modify SCUC to reduce RT consumer exposure due to load and wind volatilty
- Data-driven PCA-based uncertainty set for correlation of uncertain data
- Algorithmic development for nonconvex optimization problem
- Large-scale NYISO case study
- Cost saving across various levels of variation, without substantial expenses for dispatch
- Published on IEEE Transactions on Energy Markets, Policy and Regulation (2024)