

Recent Advances in Solving AC OPF & Robust UC

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PSERC Webinar

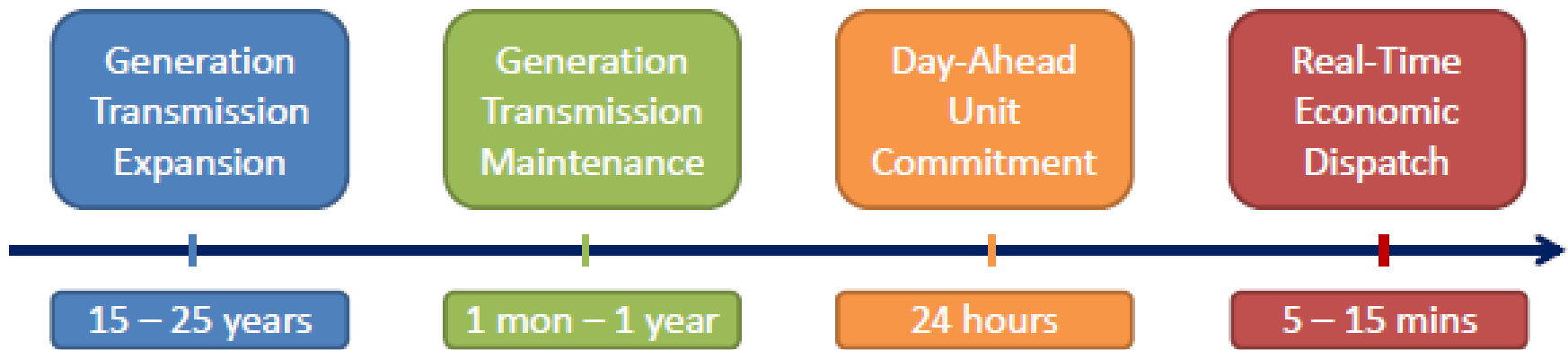
Oct 17, 2017

Major Challenges

- **Non-convexity:**
 - **Discrete decisions:**
 - On/off operational/maintenance decisions
 - Network expansion/topology change decisions
 - **Continuous non-convex constraints:**
 - Non-convex quadratic constraints
 - Differential equation constraints
- **Uncertainty:**
 - Data-driven uncertainty modeling
 - Solving huge multistage robust/stochastic programming

Electric Power Systems Problems

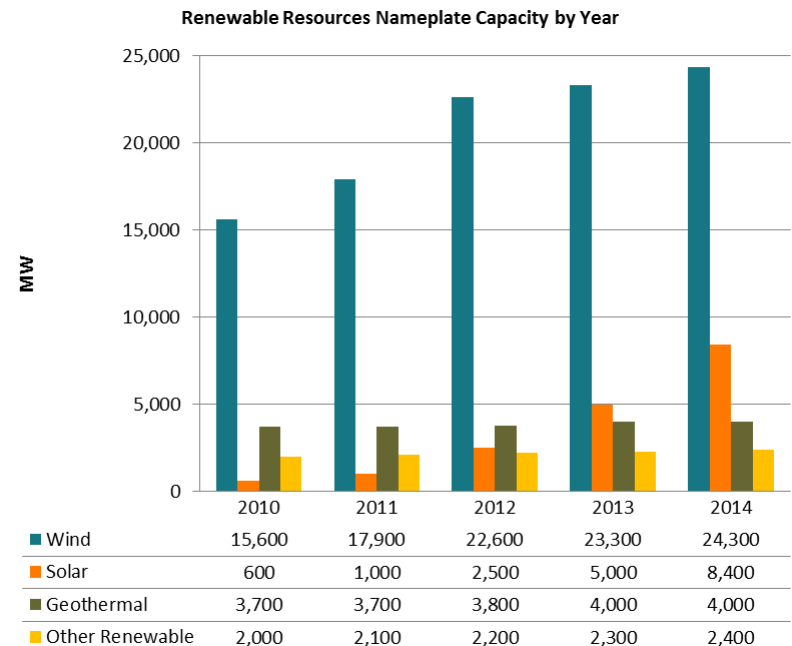
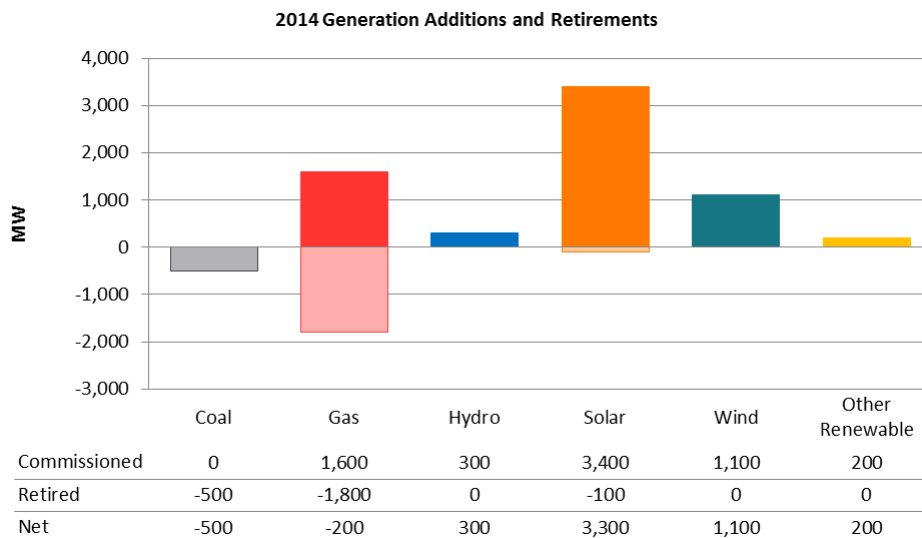
- Key Optimization Problems in power system operations from System perspective:



- Real-Time Economic Dispatch:
 - Hourly bidding and ISO 5, 15 min dispatch
- Day-Ahead Unit Commitment:
 - A day prior to operation to determine unit commitment
- Yearly generation/transmission maintenance:
- Long-term generation/transmission expansion:

Challenge: Renewable Integration

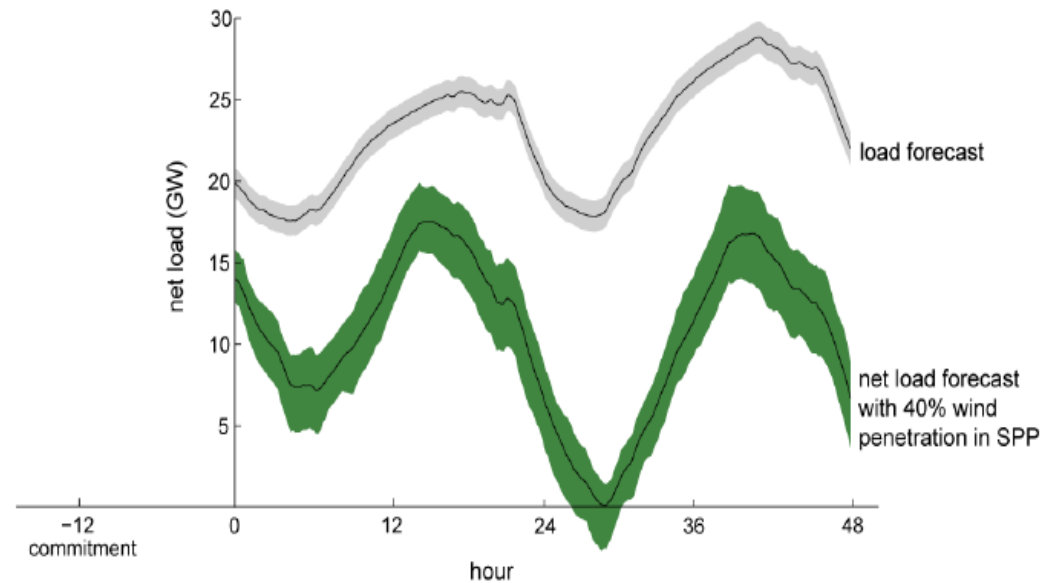
- Renewable Energy Integration in Western Interconnection



- WECC's Largest generation addition in 2014: **3,400 MW utility-scale solar**
- Behind-the-meter solar** at least 3,200 MW
- Since 2010, nearly **10,000 MW wind** and **8,000 MW solar** added

Challenge: Supply/Demand Uncertainty

- Renewable Integration



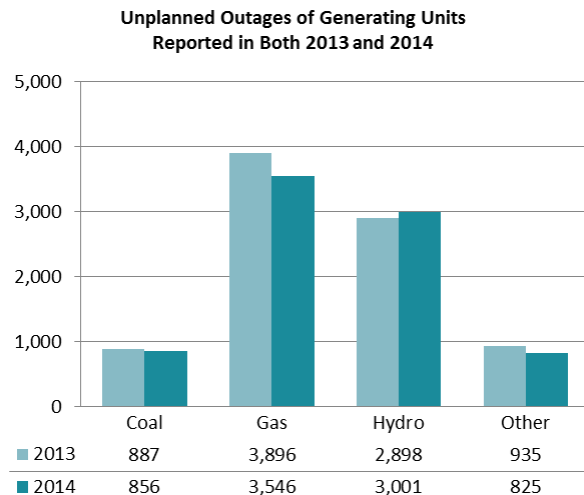
[Ruiz, Philbrick 10]

**Supply Variation:
Wind/Solar Power Penetration
Behind-the-Meter installation**

**Net Load Uncertainty
Can be Huge!**

Challenge: Unplanned Outages

- Unplanned Generator Outages:



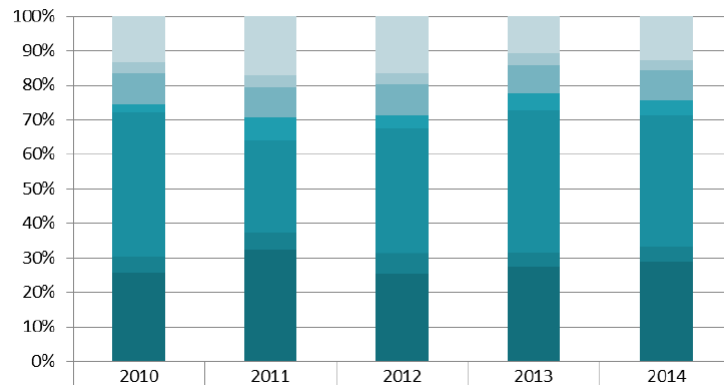
Median Unplanned Outages
Per Unit Per Year, 2013-2014

	2013	2014
Coal	9	9
Gas	5	5
Hydro	3	3

Lack of monitoring
Entails high economic
Cost and threaten
system security

- Unplanned Transmission Outages:

Distribution of Automatic Transmission Outages by Cause, 2010-2014

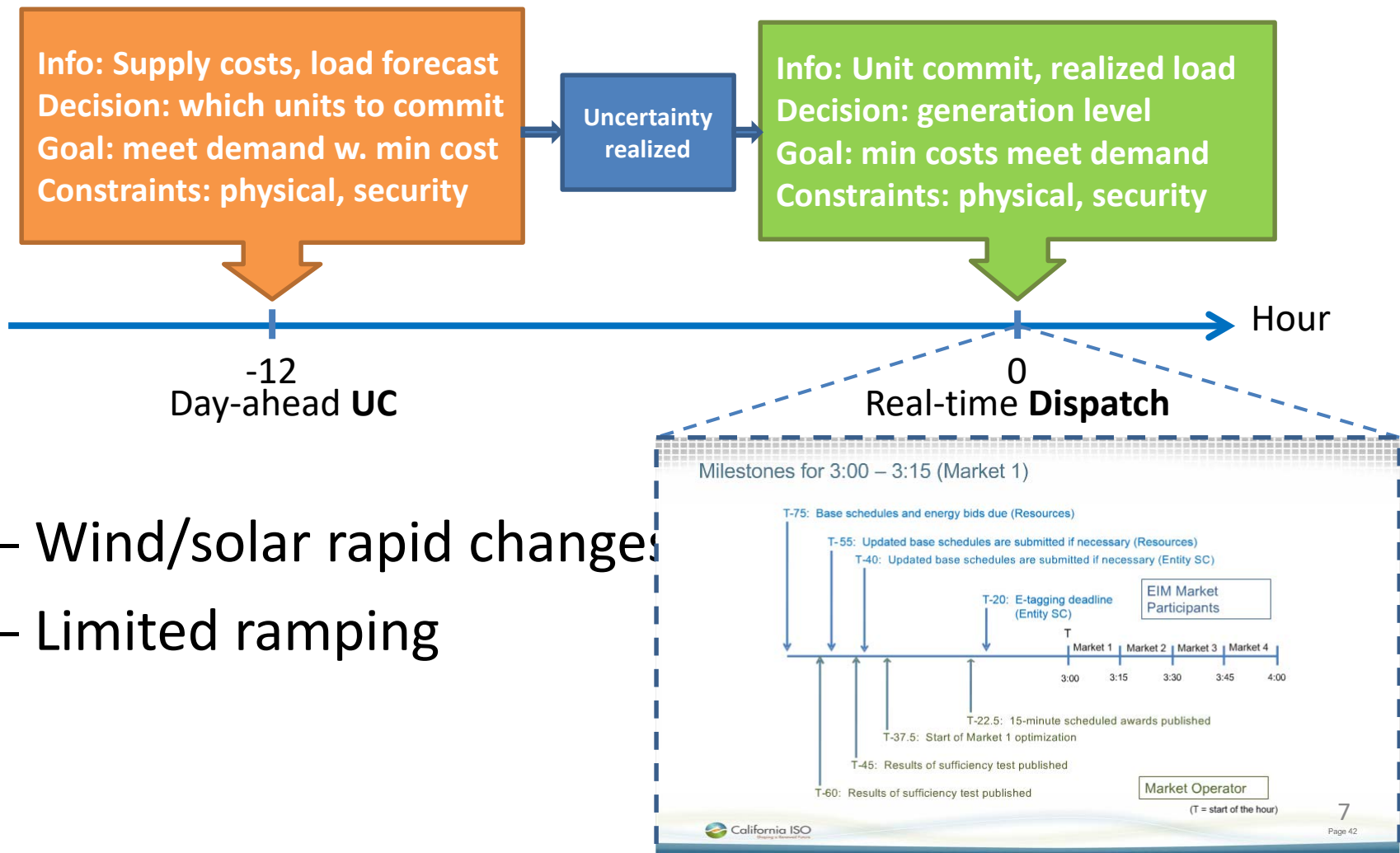


Environmental & Weather: $558/1471=38\%$

Unknown causes: $425/1471 = 29\%$

Challenge: Dynamic Decision Making

- Uncertainty in Dynamic Decision Making



- Wind/solar rapid changes
- Limited ramping

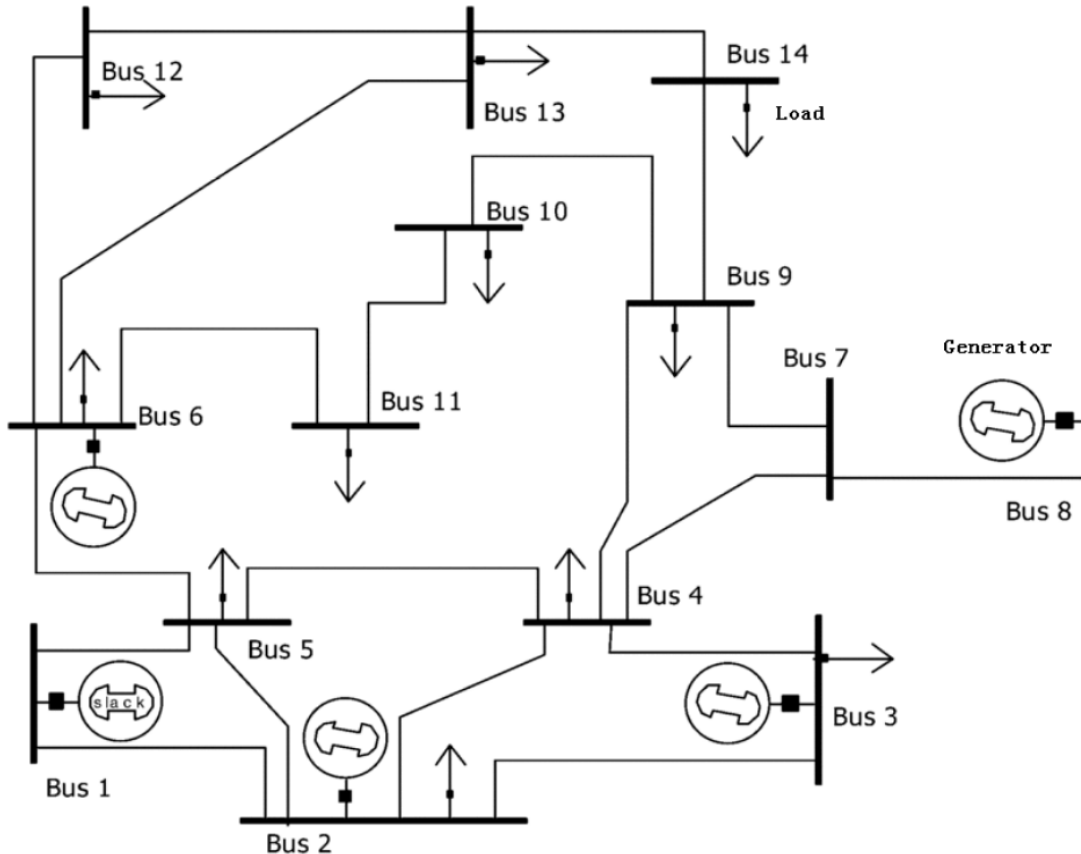
Outline

- Part1: Dealing with **Non-convexity**:
Optimal Power Flow (OPF)
- Part 2: Dealing with **Uncertainty**:
Data-driven Robust Unit Commitment (UC)

Part 1

Optimal Power Flow (OPF): Fast Convexification and
Cutting Plane Method to deal with **non-convexity**

AC Optimal Power Flow



Data:

- Network:

$$\mathcal{N} = (\mathcal{B}, \mathcal{L})$$

- Load at bus i :

$$p_i^d, q_i^d$$

- Generator at bus i :

$$[p_i^{\min}, p_i^{\max}]$$

$$[q_i^{\min}, q_i^{\max}]$$

- Voltage bounds at bus i :

$$[V_i^{\min}, V_i^{\max}]$$

- Network line admittance:

$$(G_{ij}, B_{ij})_{(i,j) \in \mathcal{L}}$$

- Line flow limit:

$$\bar{S}_{ij}$$

AC OPF Formulation: Variables and Objective

Variables:

1. Active and reactive **power** at generator i : (p_i^g, q_i^g)
2. Active and reactive **power flow** on line (i, j) : (p_{ij}, q_{ij})
3. Complex **voltage** at bus i : $V_i = |V_i|(\cos \theta_i + \mathrm{i} \sin \theta_i) = e_i + \mathrm{i} f_i$

Objective:

$$\min \sum_{i \in \mathcal{G}} C_i(p_i^g)$$

Usually a separable increasing function.

AC OPF Formulation: Constraints

$$p_i^g - p_i^d = \sum_{j \in \delta(i)} p_{ij} \quad (\text{active flow balance})$$

$$q_i^g - q_i^d = \sum_{j \in \delta(i)} q_{ij} \quad (\text{reactive flow balance})$$

$$p_{ij}^2 + q_{ij}^2 \leq \overline{S}_{ij}^2 \quad (\text{apparent flow limit})$$

$$p_i^{\min} \leq p_i^g \leq p_i^{\max} \quad (\text{active power limits})$$

$$q_i^{\min} \leq q_i^g \leq q_i^{\max} \quad (\text{reactive power limits})$$

Power flow equations and voltage bounds in **polar coordinates**

$$\begin{cases} p_{ij} = -G_{ij}|V_i|^2 + G_{ij}|V_i||V_j|\cos(\theta_i - \theta_j) + B_{ij}|V_i||V_j|\sin(\theta_i - \theta_j) \\ q_{ij} = B_{ij}|V_i|^2 - B_{ij}|V_i||V_j|\cos(\theta_i - \theta_j) + G_{ij}|V_i||V_j|\sin(\theta_i - \theta_j) \\ \underline{V}_i \leq |V_i| \leq \overline{V}_i \end{cases}$$

Power flow equations and voltage bounds in **rectangular coordinates**

$$\begin{cases} p_{ij} = -G_{ij}(e_i^2 + f_i^2) + G_{ij}(e_i e_j + f_i f_j) - B_{ij}(e_i f_j - e_j f_i) \\ q_{ij} = B_{ij}(e_i^2 + f_i^2) - B_{ij}(e_i e_j + f_i f_j) - G_{ij}(e_i f_j - e_j f_i) \\ \underline{V}_i^2 \leq e_i^2 + f_i^2 \leq \overline{V}_i^2 \end{cases}$$

Recent Literature on OPF

- **Local solvers** by Newton-Raphson and Interior-Point methods
- **Convex relaxations** using **semidefinite programming** (SDP) and Lasserre hierarchy: (Lavaei and Low, 2012; Madani et. al., 2013; Zhang and Tse, 2012; Lavaei et al., 2014, Molzahn et al. 2013, Molzahn and Hiskens, 2014, Chen et al. 2015, Madani et al. 2017)
- **Second order cone program** (SOCP) relaxation: (Jabr 2006, Hijazi et al., 2014)
- **Approximate LPs** with guaranteed bounds for the AC-OPF problem on graphs with bounded tree-width (Bienstock and Munoz, 2015)
- **Global optimal solutions** based on branch-and-bound (Phan, 2012)

AC OPF Reformulation

- Introduce Hermitian matrix $X = (e + if)(e + if)^H$:

$$p_{ij} = -G_{ij}X_{ii} + G_{ij}\mathcal{R}(X_{ij}) + B_{ij}\mathcal{I}(X_{ij})$$

$$q_{ij} = B_{ij}X_{ii} - B_{ij}\mathcal{R}(X_{ij}) + G_{ij}\mathcal{I}(X_{ij})$$

$$\underline{V}_i^2 \leq X_{ii} \leq \overline{V}_i^2$$

X is hermitian

$$X \succeq 0$$

$$\text{rank}(X) = 1$$

- Standard SDP relaxation: Ignore rank constraint
- Our proposal:** A new minor reformulation of rank constraints and use simpler relaxation than SDP

Minor Representation

- **Proposition:** For a nonzero Hermitian matrix X , $X \succcurlyeq 0$ and $\text{rank}(X) = 1$ if and only if all the 2×2 minors of X are 0 and $X_{ii} \geq 0$ for all i .
- AC OPF constraints can be equivalently reformulated as:

$$p_i^g - p_i^d = \sum_{j \in \delta(i)} p_{ij} \quad p_{ij} = -G_{ij}X_{ii} + G_{ij}\mathcal{R}(X_{ij}) + B_{ij}\mathcal{I}(X_{ij})$$

$$q_i^g - q_i^d = \sum_{j \in \delta(i)} q_{ij} \quad q_{ij} = B_{ij}X_{ii} - B_{ij}\mathcal{R}(X_{ij}) + G_{ij}\mathcal{I}(X_{ij})$$

$$p_{ij}^2 + q_{ij}^2 \leq \overline{S}_{ij}^2 \quad \underline{V}_i^2 \leq X_{ii} \leq \overline{V}_i^2$$

$$p_i^{\min} \leq p_i^g \leq p_i^{\max}$$

$$q_i^{\min} \leq q_i^g \leq q_i^{\max}$$

X is hermitian

all 2×2 minors of X are zero

First Type of 2×2 Submatrices

- Type 1: $\begin{bmatrix} X_{ii} & X_{ij} \\ X_{ji} & X_{jj} \end{bmatrix}$

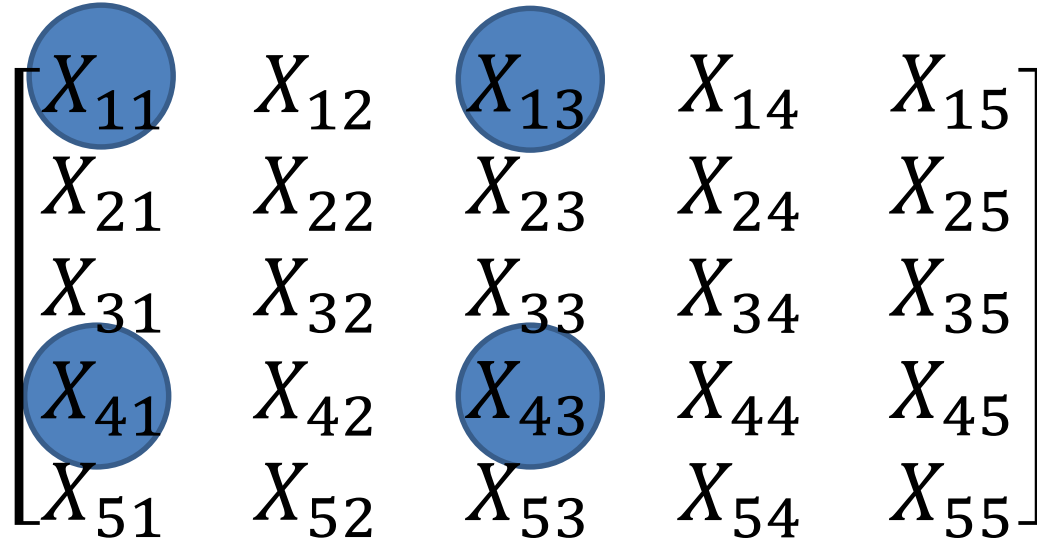
A 5x5 matrix is shown with the following elements:

X_{11}	X_{12}	X_{13}	X_{14}	X_{15}
X_{21}	X_{22}	X_{23}	X_{24}	X_{25}
X_{31}	X_{32}	X_{33}	X_{34}	X_{35}
X_{41}	X_{42}	X_{43}	X_{44}	X_{45}
X_{51}	X_{52}	X_{53}	X_{54}	X_{55}

The submatrices $\begin{bmatrix} X_{11} & X_{12} \\ X_{21} & X_{22} \end{bmatrix}$ and $\begin{bmatrix} X_{32} & X_{33} \\ X_{42} & X_{43} \end{bmatrix}$ are highlighted in blue. The diagonal elements X_{33} , X_{35} , X_{53} , and X_{55} are circled in blue.

Second Type of 2×2 Submatrices

- Type 2: $\begin{bmatrix} X_{ii} & X_{ij} \\ X_{ki} & X_{kj} \end{bmatrix}$



A 5x5 matrix is shown with elements X_{ij} for $i, j = 1, 2, 3, 4, 5$. The elements X_{11} , X_{13} , X_{41} , and X_{43} are highlighted with blue circles. These four elements form two 2×2 submatrices: one in the top-left corner (rows 1-2, columns 1-3) and one in the bottom-left corner (rows 4-5, columns 1-3).

$$\begin{bmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} \end{bmatrix}$$

Third Type of 2×2 Submatrices

- Type 3: $\begin{bmatrix} X_{ij} & X_{ik} \\ X_{lj} & X_{lk} \end{bmatrix}$

$$\begin{bmatrix} X_{11} & X_{12} & X_{13} & X_{14} & X_{15} \\ X_{21} & X_{22} & X_{23} & X_{24} & X_{25} \\ X_{31} & X_{32} & X_{33} & X_{34} & X_{35} \\ X_{41} & X_{42} & X_{43} & X_{44} & X_{45} \\ X_{51} & X_{52} & X_{53} & X_{54} & X_{55} \end{bmatrix}$$

First Type 2×2 Minors: Edge minor

- Let $c_{ij} = \mathcal{R}(X_{ij})$, $s_{ij} = -\mathcal{I}(X_{ij})$
- Type 1: Edge minor.

- $\begin{vmatrix} X_{ii} & X_{ij} \\ X_{ji} & X_{jj} \end{vmatrix} = 0$

Implies $X_{ii}X_{jj} - X_{ij}X_{ij}^* = 0 \Rightarrow c_{ii}c_{jj} - (c_{ij}^2 + s_{ij}^2) = 0$

- This is the boundary of a rotated Lorentz cone in R^4

– One direction is convex: $c_{ij}^2 + s_{ij}^2 \leq c_{ii}^j c_{jj}^i$

– Other direction is reverse convex:

- $f(c_{ij}, s_{ij}) = \sqrt{c_{ij}^2 + s_{ij}^2} \geq \sqrt{c_{ii}^j c_{jj}^i} = g(c_{ii}^j, c_{jj}^i)$

- f is convex, g is concave

- Overestimate of f and underestimate of g by hyperplanes

Second Type 2×2 Minors: 3-Cycle minor

- Type 2: 3-Cycle minor.

- $\begin{vmatrix} X_{ii} & X_{ij} \\ X_{ki} & X_{kj} \end{vmatrix} = 0$

- $0 = X_{ii}X_{kj} - X_{ij}X_{ki}$

$$= c_{ii}(c_{kj} - is_{kj}) - (c_{ij} - is_{ij})(c_{ki} - is_{ki})$$

$$= (c_{ii}c_{kj} - c_{ij}c_{ki} + s_{ij}s_{ki}) - i(c_{ii}s_{kj} - c_{ij}s_{ki} - s_{ij}c_{ki})$$

- So we have two bilinear constraints:

- $(c_{ii}c_{kj} - c_{ij}c_{ki} + s_{ij}s_{ki}) = 0$

- $(c_{ii}s_{kj} - c_{ij}s_{ki} - s_{ij}c_{ki}) = 0$

Third Type 2×2 Minors: 4-Cycle minor

- Type 3: 4-Cycle minor.

- $\begin{vmatrix} X_{ij} & X_{ik} \\ X_{lj} & X_{lk} \end{vmatrix} = 0$

- $0 = X_{ij}X_{lk} - X_{ik}X_{lj}$
 $= (c_{ij}c_{lk} - s_{ij}s_{lk} - c_{lj}c_{ik} + s_{lj}s_{ik})$
 $\quad -i(s_{ij}c_{lk} - c_{ij}s_{lk} - s_{lj}c_{ik} - c_{lj}s_{ik})$

- So we have two bilinear constraints:

- $(c_{ij}c_{lk} - s_{ij}s_{lk} - c_{lj}c_{ik} + s_{lj}s_{ik}) = 0$

- $(s_{ij}c_{lk} - c_{ij}s_{lk} - s_{lj}c_{ik} - c_{lj}s_{ik}) = 0$

3-, 4-Cycle Minors = Cycle Constraints

For a cycle C , instead of satisfying:

$$\sum_{(i,j) \in C} \arctan \left(\frac{\mathbf{s}_{ij}}{\mathbf{c}_{ij}} \right) = 0,$$

We write “angles sum to zero over the cycle” by the following relaxation:

$$\sum_{(i,j) \in C} \theta_{ij} = 2\pi k, \quad \text{for some } k \in \mathbb{Z}. \quad (1)$$

Condition (1) is equivalent to:

$$\text{Cycle constraint: } \cos \left(\sum_{(i,j) \in C} \theta_{ij} \right) = 1. \quad (2)$$

Cycle constraint (2) can be reformulated as a degree $|C|$ homogeneous polynomial $p_C = 0$ in $\mathbf{s}_{ij}$ and $\mathbf{c}_{ij}$ for $(i, j) \in C$.

3-Cycle, 4-Cycle, and Larger Cycles

- **3-cycle:**

For a 3-cycle: $\cos(\theta_{12} + \theta_{23} + \theta_{31}) = 1$ can be written as

$$\left. \begin{aligned} s_{12}c_{33} + c_{23}s_{31} + s_{23}c_{31} &= 0 \\ c_{12}c_{33} - c_{23}c_{31} + s_{23}s_{31} &= 0. \end{aligned} \right\} \text{Exactly 3-cycle minor} = 0$$

- **4-cycle:**

For a 4-cycle: $\cos(\theta_{12} + \theta_{23} + \theta_{34} + \theta_{41}) = 1$ can be written as

$$\left. \begin{aligned} s_{12}c_{34} + c_{12}s_{34} + s_{23}c_{41} + c_{23}s_{41} &= 0 \\ c_{12}c_{34} - s_{12}s_{34} + c_{23}c_{41} - s_{23}s_{41} &= 0. \end{aligned} \right\} \text{Exactly 4-cycle minor} = 0$$

Our Strategy for Solving AC-OPF

- Workhorse: **SOCP** relaxation for fast computation
- Strengthen **SOCP** relaxation for key non-convexities:
 - **Minor constraints:** Characterize convex hull and linear outer envelopes
 - **Arctangent envelopes + SDP separation:**
 - **Arctangent envelope:** Linear upper/lower approximation
 - **SDP separation:** Lift-and-project

• Results:

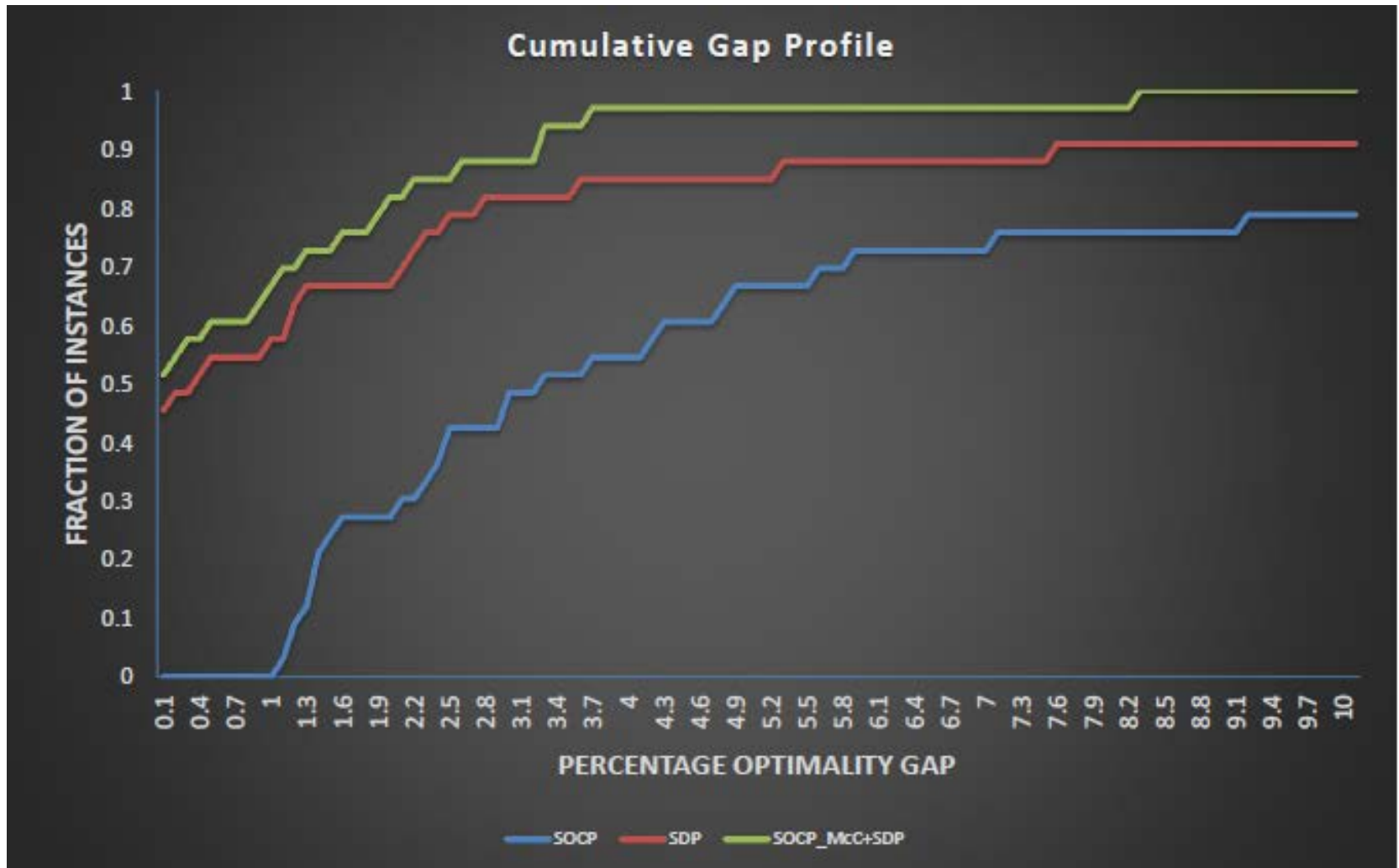
- IEEE instances (Easy):
up to 3375-bus

	%gap	Time (s)
SOCP	0.43	2.62
SOCP_cuts	0.08	207.81
SDP	0.04	380.37

- NESTA (Hard):
up to 3375-bus

	Plain SOCP		SDP		SOCP w. Cuts	
case	%gap	time (s)	%gap	time (s)	%gap	time (s)
Typical	5.14	1.97	0.35	291.20	1.09	54.03
Congested	6.29	0.72	2.91	306.69	1.59	101.27
Small Angle	5.22	1.62	2.30	305.25	1.79	62.34

Cumulative Gap Profile



Part 2

Data-Driven Robust Unit Commitment

Part 2: Data-Driven Robust UC

- **Dynamic Uncertainty Models for Temporal-Spatial Correlations of Wind/Solar/Demand**
- **Respecting Physical Causality Improves Ramping Capabilities of Power System**
- **Computational Results:**
 - **Practical computation time 2718-bus**
 - **Near-optimal performance**
 - **Reduced reserve requirement and increased reliability level**

Recent Works on Robust UC and ED

- Robust Optimization for unit commitment
 - Adaptive two-stage robust SCUC models
 - [Jiang et. al. 2012], [Zhao, Zeng 2012],
 - [Bertsimas, Litvinov, Sun, Zhao, Zheng 2013] (joint w. ISO-NE)
 - RO for security optimization
 - [Street et. al. 2011], [Wang et. al. 2013]
 - Unifying RO with Stochastic UC
 - [Wang et. al. 2013]
 - New types uncertainty set
 - [Guan Wang 2014] [Lorca Sun 2014] [Chen et. al. 2015]
- Robust Optimization for economic dispatch
 - AGC control (two-stage: dispatch + AGC)
 - [Zheng et. al. 2012]
 - Affine policy (dispatch as linear function of total load)
 - [Jabr 2013][Warrington2012,2013]

Dynamic Uncertainty Sets

- In a multi-period problem:

Let ξ_t be the uncertainty vector at time t

Uncertainty set of ξ_t *depends on* the realization of uncertainties before t

$$\Xi_t(\xi_{[1:t-1]}) = \left\{ \xi_t : \exists u_{[t]} \text{ s.t. } f(\xi_{[t]}, u_{[t]}) \leq 0 \right\}$$

- For example: a dynamic interval uncertainty set:

$$\xi_t \in [\underline{\xi}_t(\xi_{[t-1]}), \bar{\xi}_t(\xi_{[t-1]})]$$

- Polyhedral dynamic uncertainty sets:

$$\sum_{\tau=1}^t (A_{\tau} \xi_{\tau} + B_{\tau} u_{\tau}) \leq 0$$

Dynamic Uncertainty Sets for Wind Speed

- A dynamic uncertainty set for wind speed:

$$\mathcal{R}_t(r_{[t-L:t-1]}) = \left\{ r_t : \exists \tilde{r}_{[t-L:t]}, u_t \text{ s.t. } \right.$$

$$r_\tau = g_\tau + \tilde{r}_\tau \quad \forall \tau = t-L, \dots, t$$

Seasonal pattern

$$\tilde{r}_t = \sum_{s=1}^L A_s \tilde{r}_{t-s} + B u_t$$

Linear dynamics:
Temporal & Spatial
correlation

$$\sum_{i \in \mathcal{N}^w} |u_{it}| \leq \Gamma^w \sqrt{N^w}$$

$$|u_{it}| \leq \Gamma^w \quad \forall i \in \mathcal{N}^w$$

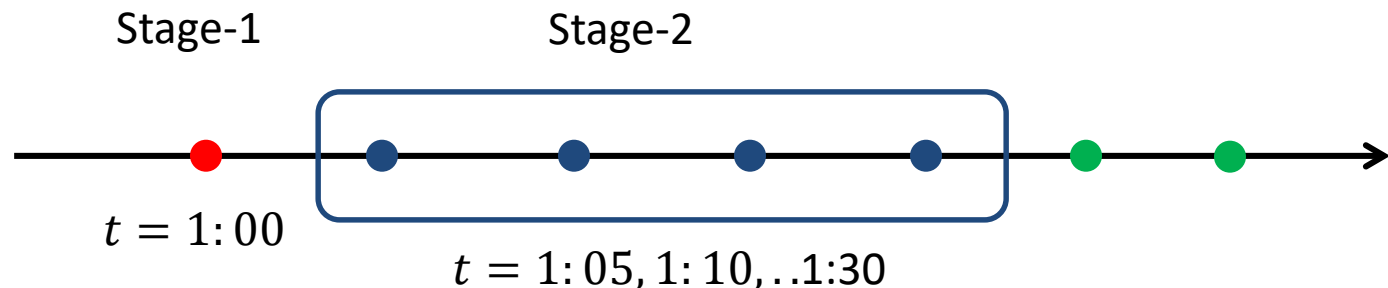
Uncertainty in
Estimation with
Budget Constraints

$$r_t \geq 0 \Big\},$$

Two-Stage Robust ED and Rolling Horizon

- Adaptive robust ED:
 - **Time period 1** is decision to be implemented
 - **Future periods** with dynamic uncertainty sets

$$\min_{x \in \Omega_1^{det}} \left\{ c^\top x + \max_{d \in \mathcal{D}, \bar{p}^w \in \bar{\mathcal{P}}^w} \min_{y \in \Omega(x, d, \bar{p}^w)} b^\top y \right\}$$

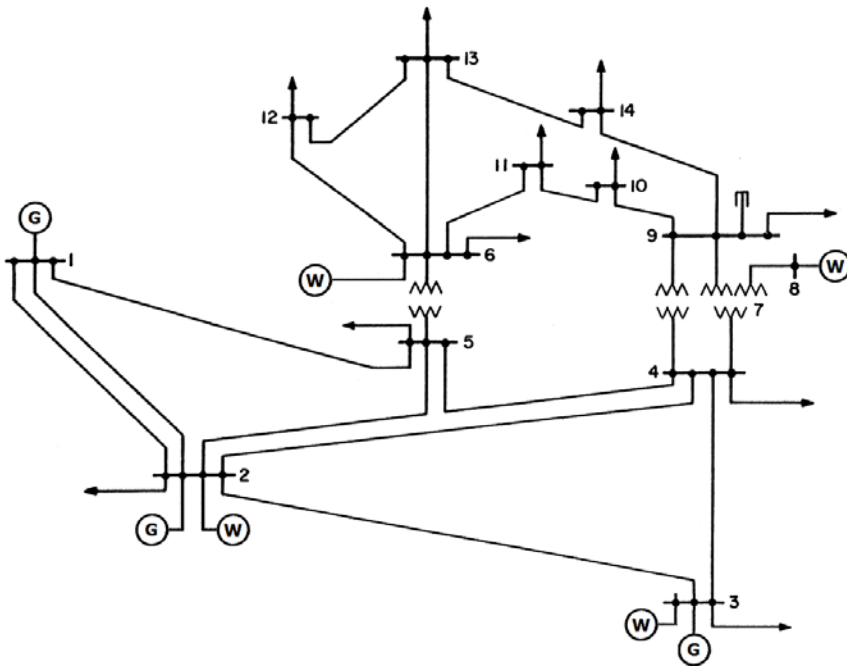


Experiment Setup

- IEEE Test Systems with 14-bus and 118-bus
- 14-bus system: 3 thermal gen, 4 wind farms, 11 loads, 20 transmission lines

THERMAL GENERATORS IN 14-BUS SYSTEM

Gen	Pmax (MW)	Pmin (MW)	Ramp (MW/10min)	Cost (\$/MWh)
1	300	50	5	20
2	100	10	10	40
3	100	10	15	60



Daily system demand:
132.6MW-319.1MW
Avg: 252.5MW

Experiment Setup

- Wind farms:
 - 4 wind farms, each of 75MW (50 GE 1.5MW)
 - Real wind data: 5 min wind speed for a year
 - Exhibit significant temporal/spatial correlations
 - Avg wind speeds: 4.8m/s, 5.6m/s, 5.1m/s, 5.5m/s
 - Avg total available wind power: 104.2MW
 - Equivalent to 34.7% capacity factor
 - Or 32.7% of peak load, 20% of thermal generation
 - Represent significant level of wind penetration

Robust ED Improves Cost and Reliability

- Adaptive robust ED v.s. Determ Look-Ahead ED:

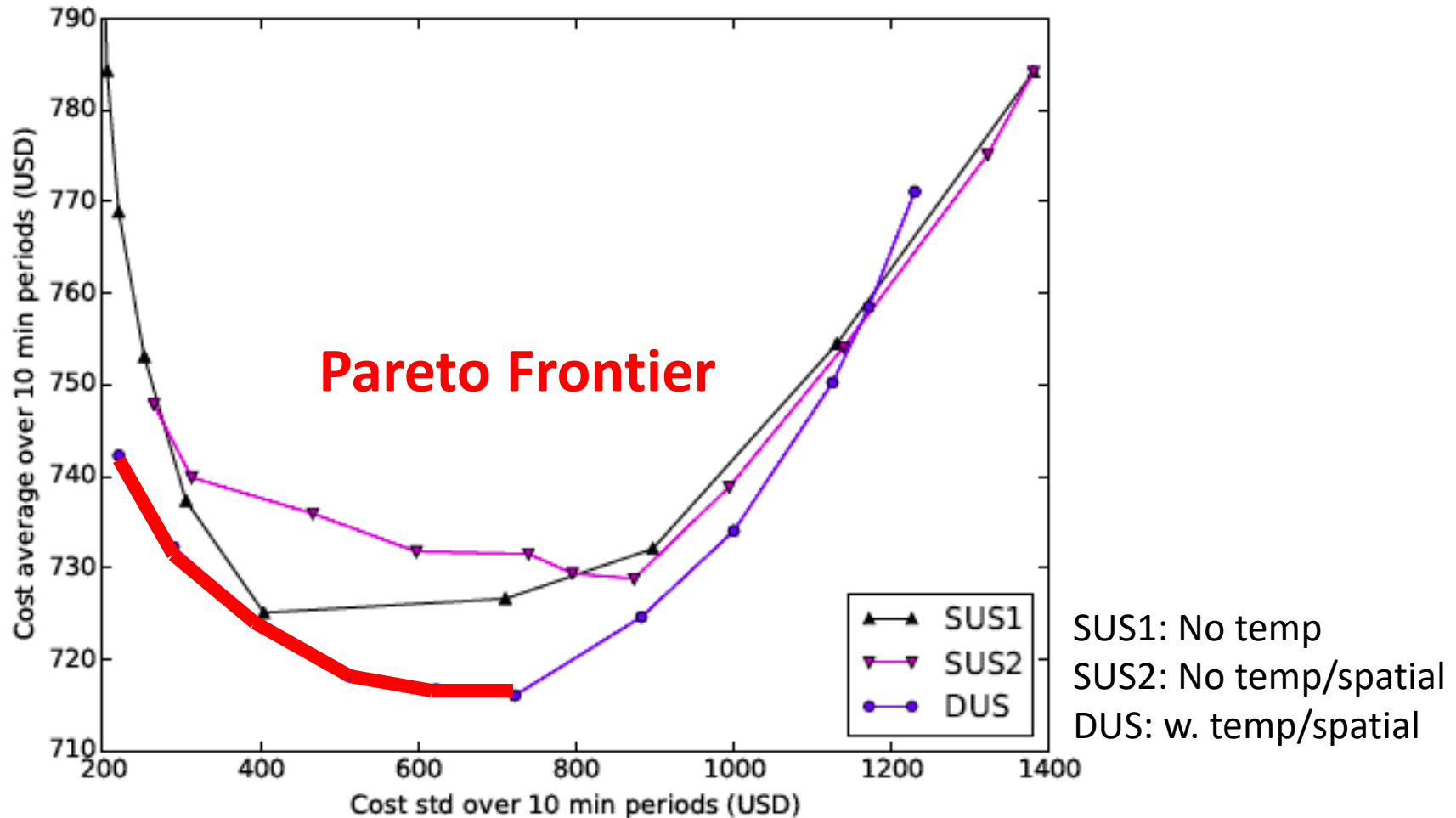
PERFORMANCE OF ROBUST AND DETERMINISTIC ED

	LA-ED	Rob-ED				
Γ^w	0.0	0.1	0.3	0.5	0.7	1.0
Total Cost Avg (\$)	771.1	758.5	734.0	716.0	718.2	742.2
Total Cost Std (\$)	1231	1172	1000	723	513	221
Penalty Avg (\$)	88.2	77.1	54.2	30.6	15.8	2.4
Penalty Freq (%)	1.41	1.21	0.95	0.67	0.46	0.28

- Cost Avg: Rob-ED 7.1% ($\Gamma = 0.5$) lower than LA-ED
- Cost StD: Rob-ED 41.2% lower than LA-ED;
Rob-ED up to 82.0% lower than LA-ED
- Penalty freq: Rob-ED 52.4% lower than LA-ED;
Rob-ED up to 80.1% lower than LA-ED

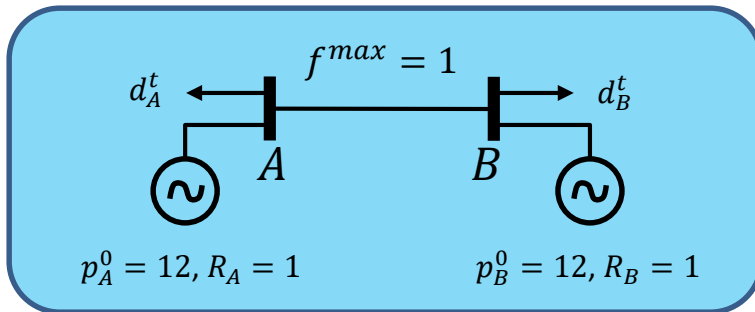
Dynamic U Sets Pareto Dominate

- Dynamic uncertainty sets v.s. Static uncert sets



Issues with Two-Stage Robust UC

- A simple two-bus two-period example:



Demand uncertainty sets:

$$D^1 = \{(12,12)\},$$

$$D^2 = \{(d_A^2, d_B^2): d_A^2 + d_B^2 = 25, d_i^2 \in [10,15]\}$$

- Claim: Two-stage robust UC is feasible**

- UC solution: $(x_A^t, x_B^t) = (1,1)$ for $t = 1,2$
- Feasible dispatch solution:

$$\bullet p_A^1(\mathbf{d}) = 12 + \frac{2}{5}(d_A^2 - 12.5), p_B^1(\mathbf{d}) = 12 - \frac{2}{5}(d_A^2 - 12.5)$$

$$\bullet p_A^2(\mathbf{d}) = 12.5 + \frac{3}{5}(d_A^2 - 12.5), p_B^2(\mathbf{d}) = 12.5 - \frac{3}{5}(d_A^2 - 12.5)$$

- Satisfy $p_A^t(\mathbf{d}) + p_B^t(\mathbf{d}) = d_A^t + d_B^t, f_{AB}(\mathbf{d}) \leq f^{max}, \forall \mathbf{d} \in D$

Respecting Physical Causality is Important

- Can we find a policy $p(\cdot)$ that does not look into the future? i.e. $\mathbf{p}^1(\mathbf{d}^1), \mathbf{p}^2(\mathbf{d}^1, \mathbf{d}^2)$?
 - Because real-time dispatch cannot depend on future
- No feasible **non-anticipative** policy exists!
 - No feasible $\mathbf{p}^1$ s.t. for any $\mathbf{d}^2 \in D^2$ there exists $\mathbf{p}^2$
 - If $p_A^1 \in [11,12]: p_A^2 \leq 13$, impossible to satisfy $\mathbf{d}^2 = (15,10)$
 - If $p_A^1 \in [12,13]: p_B^2 \leq 13$, impossible to satisfy $\mathbf{d}^2 = (10,15)$
- Bottleneck: Ramping constraint

Multistage Robust UC

$$\min_{\mathbf{x}, \mathbf{u}, \mathbf{v}, \mathbf{p}(\cdot)} \left\{ \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}_g} (G_i x_i^t + S_i u_i^t) + \max_{\mathbf{d} \in \mathcal{D}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}_g} C_i p_i^t(\mathbf{d}^{[t]}) \right\}$$

s.t.

constraints for $\mathbf{x}, \mathbf{u}, \mathbf{v}$

$$p_i^{min} x_i^t \leq p_i^t(\mathbf{d}^{[t]}) \leq p_i^{max} x_i^t \quad \forall \mathbf{d} \in \mathcal{D}, i \in \mathcal{N}_g, t \in \mathcal{T}$$

$$-RD_i x_i^t - SD_i v_i^t \leq p_i^t(\mathbf{d}^{[t]}) - p_i^{t-1}(\mathbf{d}^{[t-1]}) \leq RU_i x_i^{t-1} + SU_i u_i^t \quad \forall \mathbf{d} \in \mathcal{D}, i \in \mathcal{N}_g, t \in \mathcal{T}$$

$$-f_l^{max} \leq \alpha_l^\top (B^p \mathbf{p}^t(\mathbf{d}^{[t]}) - B^d \mathbf{d}^t) \leq f_l^{max} \quad \forall \mathbf{d} \in \mathcal{D}, t \in \mathcal{T}, l \in \mathcal{N}_l$$

$$\sum_{i \in \mathcal{N}_g} p_i^t(\mathbf{d}^{[t]}) = \sum_{j \in \mathcal{N}_d} d_j^t \quad \forall \mathbf{d} \in \mathcal{D}, t \in \mathcal{T}$$

Notation: $\mathbf{d}^{[t]} = (d^1, \dots, d^t)$

Affine Multistage Robust UC

- Tractable alternative for $p(\cdot)$:

$$p_i^t(d^1, \dots, d^t) = w_i^t + \sum_{s \in \{1, \dots, t\}} \sum_{j \in \mathcal{N}_d} W_{itjs} d_j^s$$

- Multistage robust UC with affine policy:

$$\min_{x, u, v, w, W} \left\{ \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}_g} (G_i x_i^t + S_i u_i^t) + \max_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} \sum_{i \in \mathcal{N}_g} C_i \left(w_i^t + \sum_{s \in \{1, \dots, t\}} \sum_{j \in \mathcal{N}_d} W_{itjs} d_j^s \right) \right\}$$

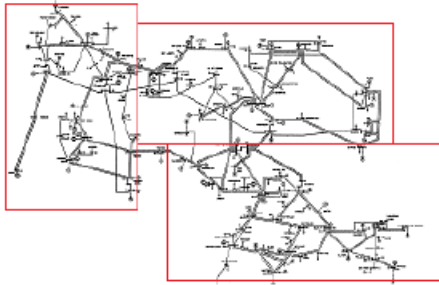
s.t.

constraints for x, u, v

$$p_i^{\min} x_i^t \leq w_i^t + \sum_{s \in \{1, \dots, t\}} \sum_{j \in \mathcal{N}_d} W_{itjs} d_j^s \leq p_i^{\max} x_i^t \quad \forall d \in \mathcal{D}, i \in \mathcal{N}_g, t \in \mathcal{T}$$

...

Simplified Affine Policies



Temporal Aggregation

Spatial Aggregation

General affine policy:
$$p_i^t(d^{[t]}) = w_i^t + \sum_{s \in \{1, \dots, t\}} \sum_{j \in \mathcal{N}_d} W_{itjs} d_j^s$$

Simpler information basis:
$$p_i^t(d^{[t]}) = w_i^t + \sum_{j \in \mathcal{N}_d} W_{itj} d_j^t$$

All loads aggregated:
$$p_i^t(d^{[t]}) = w_i^t + W_{it} \sum_{j \in \mathcal{N}_d} d_j^t$$

Loads and time periods aggregated:
$$p_i^t(d^{[t]}) = w_i^t + W_i \sum_{j \in \mathcal{N}_d} d_j^t$$

Solution Method

- **Dualization** approach does not work:
 - Traditionally, robust constraints are dualized
 - Resulting problem is too large for power systems

- **Constraint generation** makes sense:

$$p_i^{\min} x_i^t \leq w_i^t + W_{it} \sum_{j \in \mathcal{N}_d} d_j^t \leq p_i^{\max} x_i^t \quad \forall d \in \mathcal{D}, i \in \mathcal{N}_g, t \in \mathcal{T}$$

- However, naïve CG also does not work

Solution Method

- **Valid inequalities** for x and specific d 's for ramping, generating limits, and line flow
- **Fixing** binary decisions and finding cuts by CG with an LP master
- **Iteratively improving** policy structure (e.g. $W_i \rightarrow W_{it}$) with approximate warm-start (not solving W_i fully)
- **Exploiting structure** of special policy form: e.g. pre-computing all needed constraints for ramping and generation limit constraints for W_{it} -policy.

Computational Study

- How good is the proposed algorithm?
 - Effectiveness of various algorithmic improvements
- How good is the simplified affine policy?
 - Compared to the “true” multi-stage robust UC
- Why should we use multi-stage formulation?
 - Worst case infeasibility of two-stage robust UC
 - Managing Ramping capability
- How good is affine UC “on average”?
 - Rolling-horizon Monte-Carlo simulation
 - Average performance in cost, std, reliability

How Good is the Algorithm?

Solution time (s) for three test systems using W_{it} policy:

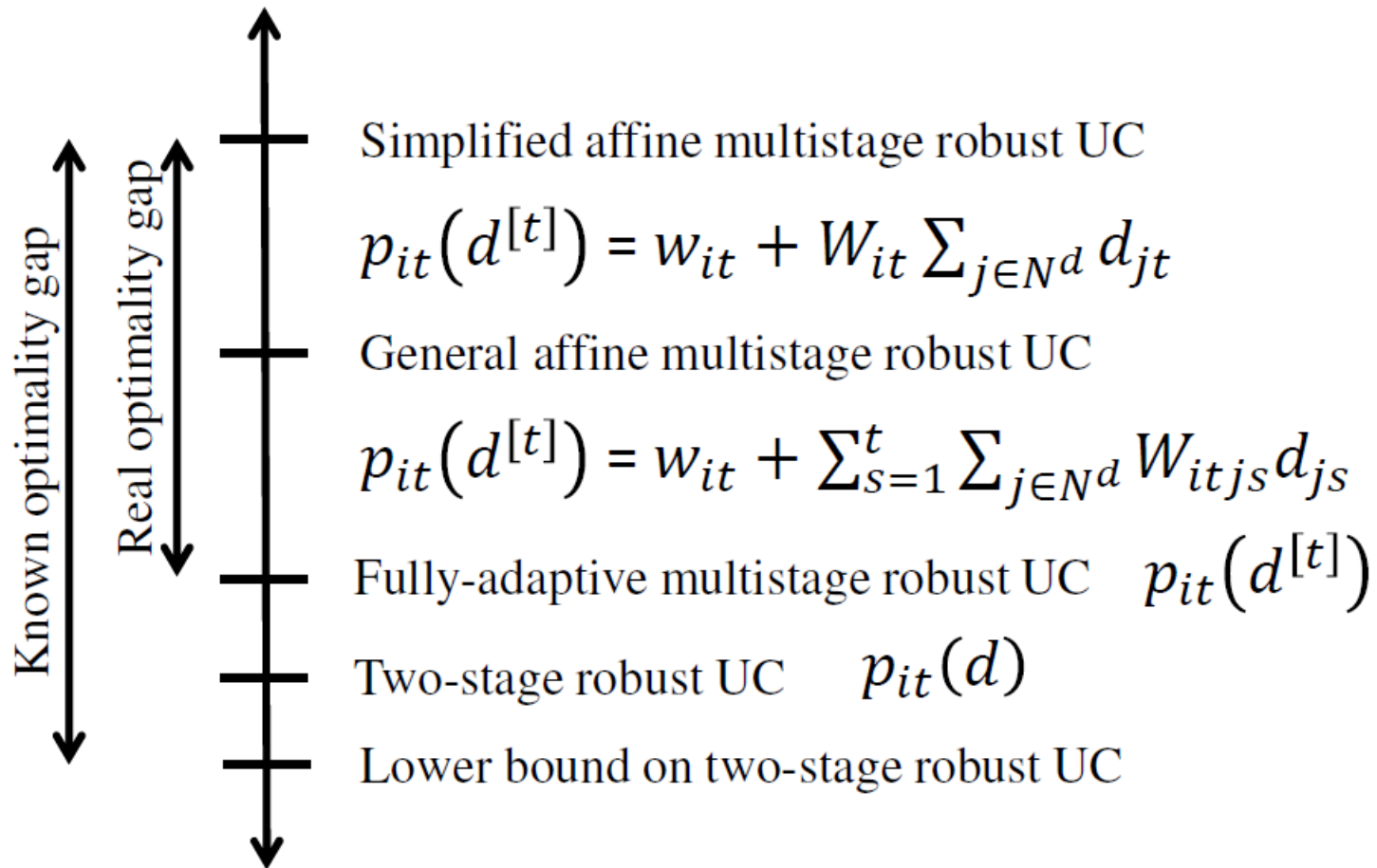
System	$\Gamma = 0.25$	$\Gamma = 0.5$	$\Gamma = 1$	$\Gamma = 2$	$\Gamma = 4$
30 bus	6s	3s	8s	6s	29s (inf)
118 bus	66s	64s	47s	63s	178s
2718 bus	3.6h	3.2h	2.3h	2.0h	0.4h (inf)

Note: “inf” indicates that the problem is infeasible

MIP optimality gap used for 30, 118, 2718 bus systems: 0.1%, 0.1%, 1%

How Good is the Simplified Affine Policy?

- How good is the simplified affine policy?



How Good is the Simplified Affine Policy?

Table : Opt. gap under different policy structures, for the 118 bus system.

$(n_g, n_{\mathcal{T}}, n_d, L)$	$\Gamma = 0.5$	$\Gamma = 1$	$\Gamma = 2$	$\Gamma = 4$
(10,1,1,0)	0.03%	0.06%	0.11%	0.95%
(21,1,1,0)	0.03%	0.05%	0.11%	0.77%
(31,1,1,0)	0.02%	0.04%	0.10%	0.74%
(54,1,1,0)	0.02%	0.04%	0.10%	0.67%
(54,4,1,0)	0.02%	0.03%	0.10%	0.52%
(54,24,1,0)	0.02%	0.03%	0.07%	0.35%

Table : Opt. gap for the 2718 bus system under the “ W_{it} ” policy.

$(n_g, n_{\mathcal{T}}, n_d, L)$	$\Gamma = 0.25$	$\Gamma = 0.5$	$\Gamma = 1$	$\Gamma = 1.5$	$\Gamma = 2$
(289,1,1,0)	0.09%	0.22%	0.42%	0.55%	1.05%
(289,24,1,0)	0.07%	0.11%	0.25%	0.35%	0.53%

Why Multistage? Worst-Case

- Worst-case (US\$) of multistage robust dispatch under two-stage and Multistage UC solutions for the 2718-bus system.

	$\Gamma = 0.5$	$\Gamma = 1$	$\Gamma = 1.5$	$\Gamma = 2$	$\Gamma = 3$
Affine multistage UC solutions					
Total Cost	9,445,069	9,596,788	9,746,685	9,905,527	10,234,459
Penalty	0	0	0	0	0
Two-stage UC solutions					
Total Cost	9,505,651	9,745,889	10,183,433	10,975,403	12,864,719
Penalty	96,313	224,952	591,661	1,165,324	2,703,522
Rel Diff	0.64%	1.55%	4.49%	10.80%	25.70%

How Good is Affine UC on Average?

- Average performance over independent demand

Affine multistage robust UC with policy-enforcement robust ED						
Γ	0.25	0.5	1	1.5	2	3
Cost Avg (\$)	9,397,528	9,319,396	9,342,754	9,360,359	9,379,464	9,442,858
Cost Std (\$)	113,725	15,970	12,828	12,509	12,363	12,092
Penalty Cost Avg (\$)	93,552	3497	727	61	5	0
Penalty Freq Avg	10.00%	1.47%	0.40%	0.01%	0.00%	0.00%

Two-stage robust UC with look-ahead ED						0.46%
Γ	0.25	0.5	1	1.5	2	3
Cost Avg (\$)	9,398,109	9,456,599	9,408,732	9,383,569	9,407,290	9,362,379
Cost Std (\$)	93,470	195,774	173,884	144,698	162,469	45,584
Penalty Cost Avg (\$)	80,127	152,637	98,113	66,801	82,864	6,103
Penalty Freq Avg	9.93%	12.26%	7.80%	5.11%	5.57%	0.37%

Deterministic UC with reserve and look-ahead ED						0.95%
Reserve	2.5%	5%	10%	15%	20%	30%
Cost Avg (\$)	9,556,549	9,575,446	9,424,678	9,561,024	9,408,173	9,411,741
Cost Std (\$)	261,464	288,777	121,122	196,354	92,268	69,050
Penalty Cost Avg (\$)	254,627	271,672	119,127	248,658	83,938	51,907
Penalty Freq Avg	15.93%	13.37%	14.31%	18.16%	10.03%	7.22%

How Good is Affine UC on Average?

- Average performance over wind power and persistent demand

Affine multistage robust UC with policy-enforcement robust ED

Γ	0.25	0.5	1	1.5	2	3
Cost Avg (\$)	10,996,931	9,459,785	8,502,923	8,581,532	8,646,665	9,415,693
Cost Std (\$)	3,665,301	2,007,317	490,457	466,999	424,801	458,865
Penalty Cost Avg (\$)	2,679,299	1,110,032	101,234	81,834	27,344	218
Penalty Freq Avg	18.84%	14.44%	1.67%	0.47%	0.18%	0.01%

Two-stage robust UC with look-ahead ED

1.23%

Γ	0.25	0.5	1	1.5	2	3
Cost Avg (\$)	10,390,214	11,365,568	8,734,840	8,863,975	8,609,160	8,947,959
Cost Std (\$)	1,831,279	1,059,427	620,301	802,441	522,881	793,447
Penalty Cost Avg (\$)	2,064,045	1,032,109	380,451	490,562	195,681	443,401
Penalty Freq Avg	12.73%	3.68%	7.37%	5.19%	2.07%	2.66%

Deterministic UC with reserve and look-ahead ED

24.52%

Reserve	2.5%	5%	10%	15%	20%	30%
Cost Avg (\$)	13,186,705	14,272,477	13,110,030	13,617,194	11,879,817	11,248,546
Cost Std (\$)	5,557,309	7,023,964	5,596,039	6,082,173	4,095,780	3,113,902
Penalty Cost Avg (\$)	4,905,635	6,003,861	4,827,766	5,334,746	3,578,986	2,912,186
Penalty Freq Avg	30.45%	29.94%	33.00%	32.43%	23.61%	15.03%

References

- A. Lorca, X. A. Sun Adaptive Robust Optimization with Dynamic Uncertainty Sets for Multi-Period Economic Dispatch under Significant Wind, *IEEE Trans Power Syst* 30(4): 1702-1713, 2015
- A. Lorca, X. A. Sun, E. Litvinov, T. Zheng, Multistage Robust Optimization for Unit Commitment Problem, *Operations Research*, 64(1): 32-51, 2016
- A. Lorca, X. A. Sun, Multistage Robust Unit Commitment with Dynamic Uncertainty Sets and Energy Storage, accepted for publication at *IEEE Trans Power Syst*, 2017

Some Concluding Remarks

- Significant challenges:
 - AC Optimal Flow Problem with Discrete Decisions
 - Voltage-stability constrained OPF
 - Robust UC with AC OPF
 - Sensor-driven real-time operation and maintenance scheduling
- Many more challenging computational problems!

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The workshop hopes to attract graduate and senior undergrad students in ECE, IE, and related disciplines both from Georgia Tech and nationwide. It



- Nov 9 – 10, 2017 at Georgia Tech
- Please come to GT and continue our discussion!

Thank you!

Questions?

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