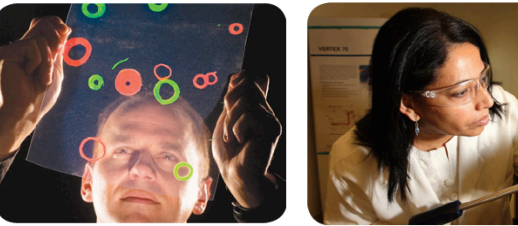


# Solving the Mixed Integer Non-linear Programming Problem of Unit Commitment on AC Power Systems



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# Overview

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- Today's Practice
- Contributions
  - Overview
  - Local Solution Method
  - Global Solution Method
  - UC+ACOPF Results
- Ongoing Work

# TODAY'S PRACTICE

- Operational Challenges
  - Committing Least Cost + Maintaining Reliability
  - Out-of-Merit Reliability Commitments
  - Improving convergence between day-ahead and real-time prices
  
- Algorithmic Challenges
  - Accounting for reliability needs in dispatch and pricing optimization
  - Better physical representation of the generating units and underlying network



# Unit Commitment in the Day-Ahead Market

## Current Practices

### UC/Security-Constrained UC

- Copper-plate (no network/single node)
- Ignores congestion; requires cutsets to proxy capacity limits on network
- Most tractable

### SCUC DCOPF

- Real power flows only (proportional to current)
- $B\theta$  (full) or PTDF (compact) approach

#### Extensions:

- Accounts for losses
- Nomograms/cutsets to proxy reliability requirements

## Proposed Approach

### SCUC ACOPF

- Co-optimizes real and reactive power dispatch
- Accounts for commitments needed for blackstart service, reactive support, voltage support, and interface control
- Nonlinear, nonconvex on meshed networks

# The link between physics and prices

- Locational marginal pricing (LMP) is the spot price of electricity
- Dual variable/Lagrange multiplier ( $\lambda_n$ ) to real power balancing at all buses

$$p_n - p_n^d + p_n^g = 0 \quad (\lambda_n)$$

ACOPF

$$p_n = |v_n| \sum_{m \in \mathcal{N}} |v_m| (G_{nm} \cos \theta_{nm} + B_{nm} \sin \theta_{nm})$$

DCOPF

$$p_n = \sum_{m \in \mathcal{N}} (B_{nm} \theta_{nm}) \approx |\tilde{v}_n| \sum_{m \in \mathcal{N}} |\tilde{v}_m| (B_{nm} \theta_{nm})$$

DCOPF with losses

$$p_n = \sum_{m \in \mathcal{N}} \left( G_{nm} (\theta_{nm})^2 / 2 + B_{nm} \theta_{nm} \right)$$

The LMP incorporates the marginal cost of supplying the next MW of load for a given location in time; includes

1. marginal unit cost,
2. cost of network congestion (due to thermal line limits), and
3. cost of real power losses on the network

# CONTRIBUTIONS

# CONTRIBUTIONS OVERVIEW

**Min Production Costs + Startup Costs + No-Load Costs**

**subject to**

**AC Network Limits**

**Real power balancing**

**Reactive power balancing**

**Voltage magnitude bounds**

**Thermal line limits**

**Spinning reserves**

**System Data**

Nodal voltage limits

Reserve requirements

Real/reactive power load

Transformer tap ratio and phase-shifters

Thermal line limits and line R/X/B

Shunts

**Apparent Power Production Limits §**

**Max/min real/reactive power generation**

**Ramp up/down rates on real power**

**Minimum up/down time**

**Generator Data**

Synchronous condensers

T0 state and startup lags

Minimum up/down time

Ramp up/down limits

Startup/shutdown ramp limits

Min/max real/reactive power limits

# Nodal Power Balancing is Nonconvex

## ■ Polar Power-Voltage Power Flow Formulation (**PSV**)

$$|v_{n,t}| \sum_{m \in \mathcal{N}} |v_{m,t}| (G_{nm} \cos \theta_{nm,t} + B_{nm} \sin \theta_{nm,t}) - p_{n,t}^+ + p_{n,t}^- = 0, \quad \forall n \in \mathcal{N}$$

$$|v_{n,t}| \sum_{m \in \mathcal{N}} |v_{m,t}| (G_{nm} \sin \theta_{nm,t} - B_{nm} \cos \theta_{nm,t}) - q_{n,t}^+ + q_{n,t}^- = 0, \quad \forall n \in \mathcal{N}$$

## ■ Rectangular Power-Voltage Power Flow Formulation (**RSV**)

$$v_{n,t}^r \sum_{m \in \mathcal{N}} (G_{nm} v_{m,t}^r - B_{nm} v_{m,t}^j) + v_{n,t}^j \sum_{m \in \mathcal{N}} (G_{nm} v_{m,t}^j + B_{nm} v_{m,t}^r) - p_{n,t}^+ + p_{n,t}^- = 0, \quad \forall n \in \mathcal{N}$$

$$v_{n,t}^j \sum_{m \in \mathcal{N}} (G_{nm} v_{m,t}^r - B_{nm} v_{m,t}^j) - v_{n,t}^r \sum_{m \in \mathcal{N}} (G_{nm} v_{m,t}^j + B_{nm} v_{m,t}^r) - q_{n,t}^+ + q_{n,t}^- = 0, \quad \forall n \in \mathcal{N}$$

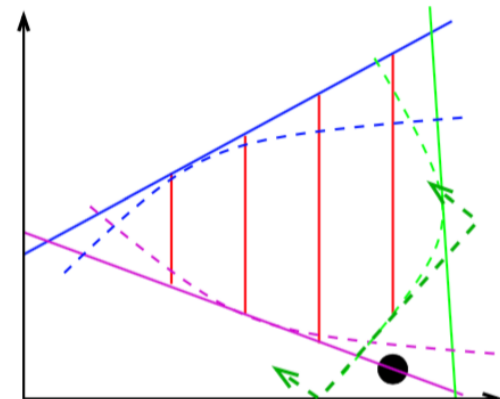
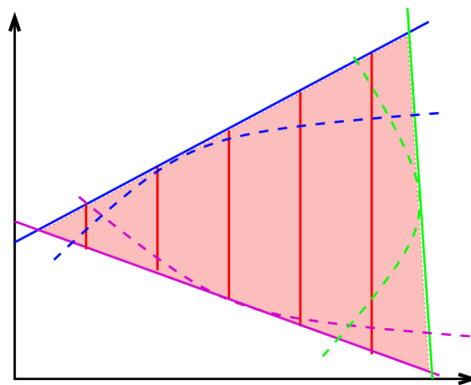
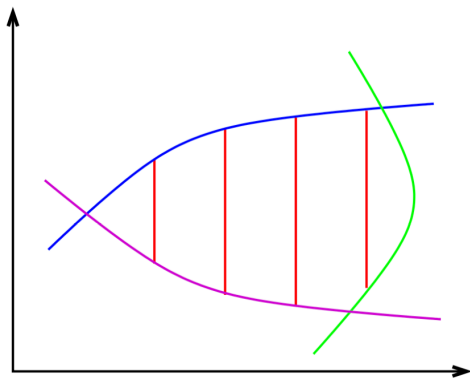
## ■ Rectangular Current Injection Formulation (**RIV**)

$$i_{n,t}^r - \left( \sum_{k(n,\cdot) \in \mathcal{F}} i_{k(n,m),t}^r + G_n^s v_{n,t}^r - B_n^s v_{n,t}^j \right) = 0, \left( v_{n,t}^r i_{n,t}^r + v_{n,t}^j i_{n,t}^j \right) - p_{n,t}^+ + p_{n,t}^- = 0, \quad \forall n \in \mathcal{N}$$

$$i_{n,t}^j - \left( \sum_{k(n,\cdot) \in \mathcal{F}} i_{k(n,m),t}^j + G_n^s v_{n,t}^j + B_n^s v_{n,t}^r \right) = 0, \left( v_{n,t}^j i_{n,t}^r - v_{n,t}^r i_{n,t}^j \right) - q_{n,t}^+ + q_{n,t}^- = 0, \quad \forall n \in \mathcal{N}$$

$$\begin{cases} \text{minimize}_x f(x), \\ \text{subject to } g(x) \leq 0, \\ x \in X, \\ x_i \in \mathbb{Z}, \forall i \in I \end{cases}$$

$f: \mathbb{R}^n \rightarrow \mathbb{R}, g: \mathbb{R}^n \rightarrow \mathbb{R}^m$  are twice continuously differentiable functions,  
 $X \subset \mathbb{R}^n$  is a bounded polyhedral set, and  
 $I \subseteq \{1, \dots, n\}$  is the index set of integer variables



§ Outer Approximation Algorithm (Duran and Grossman, 1986); Graphics (Belotti et al., 2013)

# CONTRIBUTIONS

# LOCAL SOLUTION METHOD



# Successive Linear Programming (SLP) [R1]

**MIN** Piecewise linear cost function with penalty factors

s.t.

**Line Current Flows**

$$i_{k(n,m)}^r = \text{Re}\left(Y_{1,1}^k v_n + Y_{1,2}^k v_m\right), i_{k(m,n)}^r = \text{Re}\left(Y_{2,1}^k v_n + Y_{2,2}^k v_m\right) \quad \forall k \in K$$

$$i_{k(n,m)}^j = \text{Im}\left(Y_{1,1}^k v_n + Y_{1,2}^k v_m\right), i_{k(m,n)}^j = \text{Im}\left(Y_{2,1}^k v_n + Y_{2,2}^k v_m\right) \quad \forall k \in K$$

**Network Current Balancing**

$$i_n^r - \left( \sum_{k(n, \cdot)} i_{k(n,m)}^r + G_n^{sh} v_n^r - B_n^{sh} v_n^j \right) = 0 \quad \forall n \in N$$

$$i_n^j - \left( \sum_{k(n, \cdot)} i_{k(n,m)}^j + G_n^{sh} v_n^j + B_n^{sh} v_n^r \right) = 0 \quad \forall n \in N$$

**Nodal Power Injections**

First-order Taylor series

**Generator Limits**

Inequality constraints with  
slack variables

**Nodal Voltage Magnitude Limits**

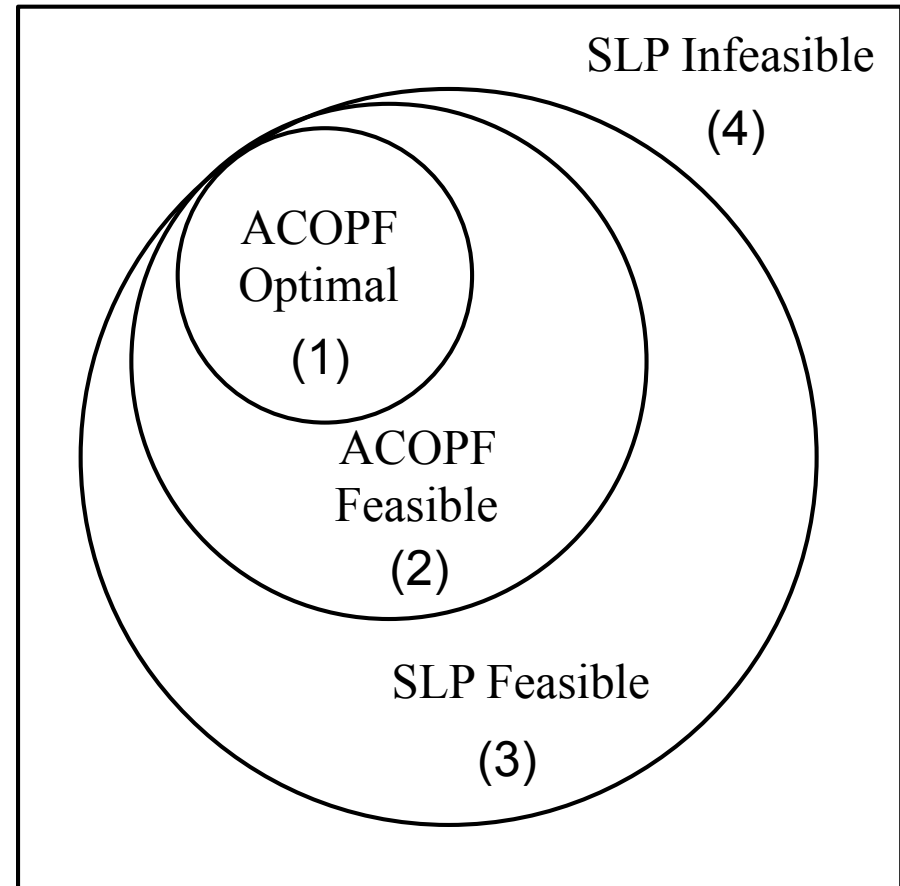
Outer approximation,  
First-order Taylor series,  
Step-size bounds,  
Tangential cutting planes, &  
Inequality constraints with  
slack variables

**Thermal Line (Flowgate) Limits**

Set reduction, Outer approximation,  
First-order Taylor series,  
Tangential cutting planes, &  
Inequality constraints with  
slack variables

# SLP Convergence Properties §

- (1) A KKT point to the ACOPF is found
- (2) The SLP optimal solution is ACOPF feasible but not optimal
  - Still a useful solution; may be better than a DCOPF with AC feasibility or decoupled OPF solution
- (3) The SLP optimal solution is ACOPF infeasible
  - Active penalties present
  - Solution may be useful depending upon whether the violated limits are “soft” or “hard”
- (4) The SLP is infeasible
  - The ACOPF may have no solution
  - The SLP requires a better initialization



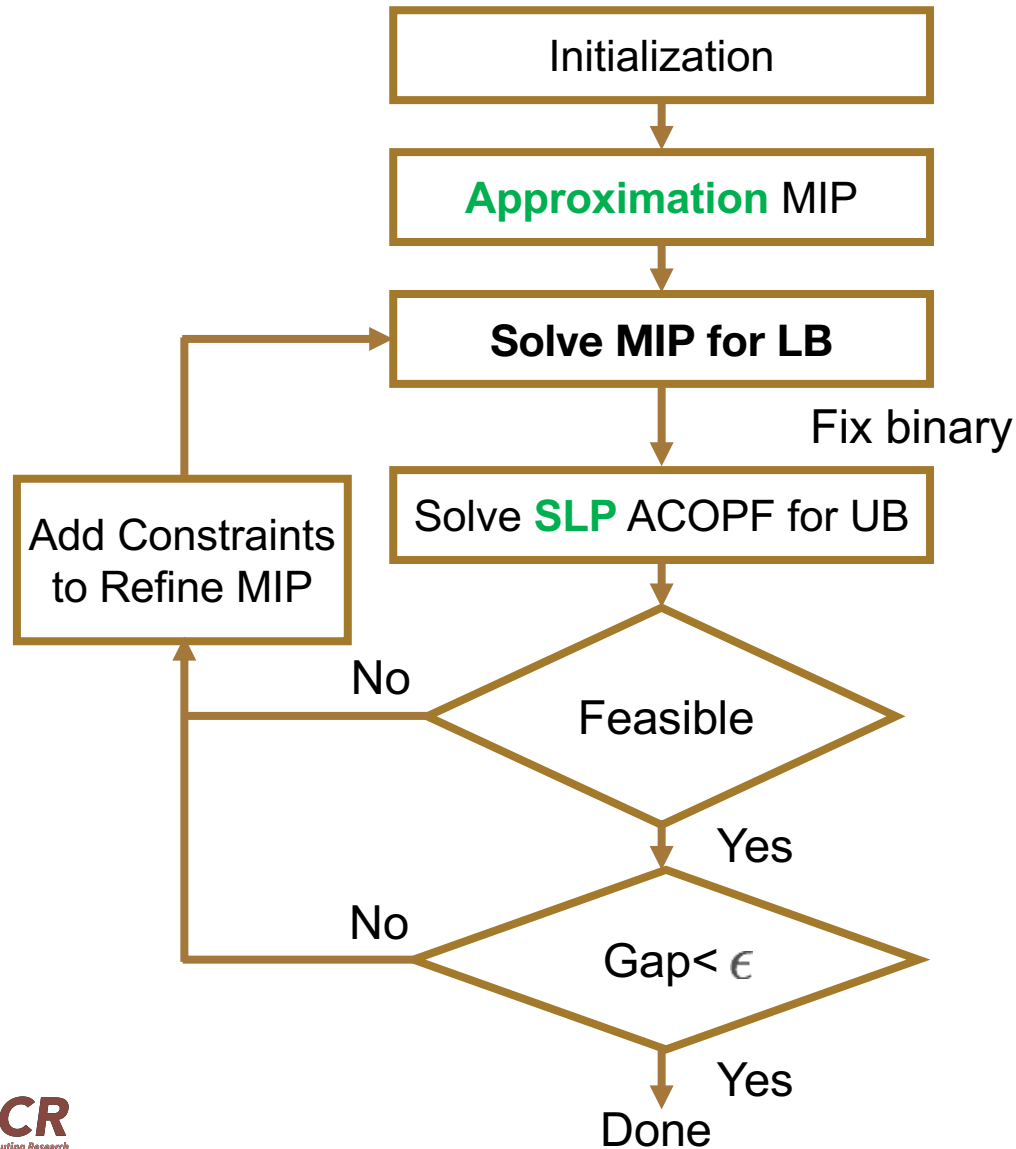
# Time Complexity Performance

$$\Theta(|\mathcal{N}|^p)$$

Baseline	Best-Case Simulations			All Converged Simulations		
	$p$	$R^2$	RMSE (s)	$p$	$R^2$	RMSE (s)
NLP/KNITRO	1.42	0.83	1.46	1.47	0.82	1.40
NLP/IPOPT	1.13	0.95	0.60	1.34	0.97	0.50
SLP/CPLEX	0.97	0.99	0.20	1.01	0.98	0.33
SLP/Gurobi	1.01	0.99	0.21	1.03	0.98	0.33
Thermally Constrained						
NLP/KNITRO	1.39	0.88	1.13	1.39	0.89	1.08
NLP/IPOPT	1.11	0.98	0.36	1.22	0.97	0.50
SLP/CPLEX	0.99	0.99	0.17	1.00	0.98	0.31
SLP/Gurobi	1.06	0.99	0.23	1.05	0.97	0.36

- Running time increases linearly with the network size ( $p=1$  corresponds to a linear algorithmic scaling) for the SLP algorithm
- Potentially applicable in the strict time frames of the real-time markets*

# MINLP solved by Outer Approximation (OA)



Local Solution [R2]

# CONTRIBUTIONS

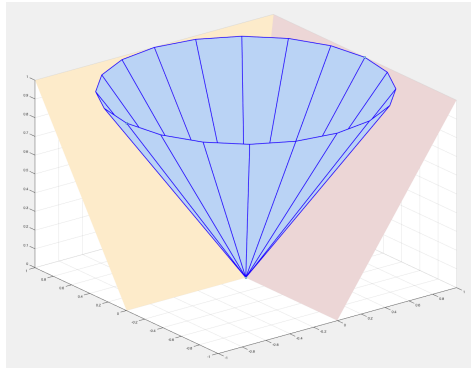
# GLOBAL SOLUTION METHOD

# ACOPF Second-Order Cone Relaxation § (SOCR)

$$c_{b,b} \equiv (v_b^r)^2 + (v_b^j)^2 = v_b^2$$

$$c_{b,k} \equiv v_b^r v_k^r + v_b^j v_k^j = |v_b| |v_k| \cos \theta_{b,k}$$

$$s_{b,k} \equiv v_b^r v_k^j - v_k^r v_b^j = -|v_b| |v_k| \sin \theta_{b,k}$$



$$\min \sum_{g \in \mathcal{G}} [A_g^2 (p_g^G)^2 + A_g^1 p_g^G + A_g^0]$$

$$\text{s.t.} \quad \sum_{l \in \mathcal{L}_b^{in}} p_l^t + \sum_{l \in \mathcal{L}_b^{out}} p_l^f + G_b^{sh} c_{b,b} + P_b^D - \sum_{g \in \mathcal{G}_b} p_g^G = 0 \quad \forall b$$

$$\sum_{l \in \mathcal{L}_b^{in}} q_l^t + \sum_{l \in \mathcal{L}_b^{out}} q_l^f - B_b^{sh} c_{b,b} + Q_b^D - \sum_{g \in \mathcal{G}_b} q_g^G = 0 \quad \forall b$$

$$p_l^f = G_l^{ff} c_{b,b} + G_l^{ft} c_{b,k} - B_l^{ft} s_{b,k} \quad \forall l$$

$$q_l^f = -B_l^{ff} c_{b,b} - B_l^{ft} c_{b,k} - G_l^{ft} s_{b,k} \quad \forall l$$

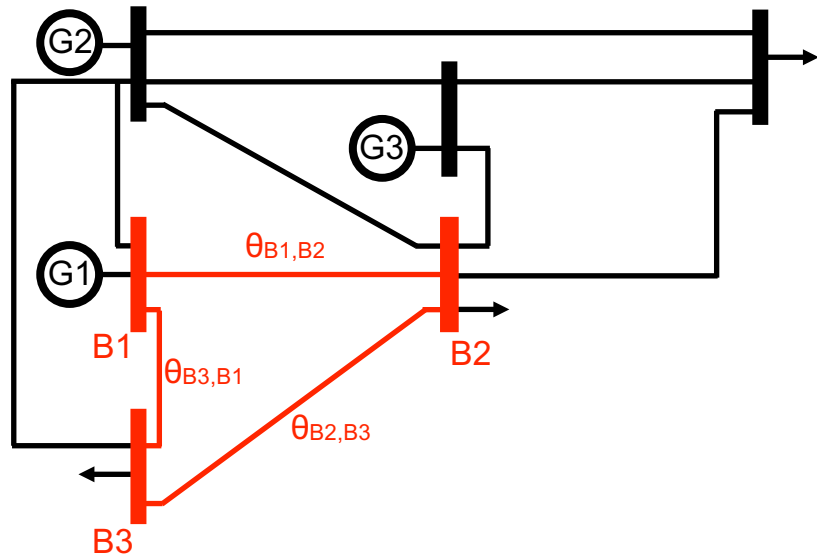
$$p_l^t = G_l^{tt} c_{k,k} + G_l^{tf} c_{k,b} - B_l^{tf} s_{k,b} \quad \forall l$$

$$q_l^t = -B_l^{tt} c_{k,k} - B_l^{tf} c_{k,b} - G_l^{tf} s_{k,b} \quad \forall l$$

$$(p_l^f)^2 + (q_l^f)^2 \leq (S_l^{max})^2, \quad (p_l^t)^2 + (q_l^t)^2 \leq (S_l^{max})^2 \quad \forall l$$

$$(V_b^{min})^2 \leq c_{b,b} \leq (V_b^{max})^2 \quad \forall b$$

$$P_g^{G,min} \leq p_g^G \leq P_g^{G,max}, \quad Q_g^{G,min} \leq q_g^G \leq Q_g^{G,max} \quad \forall g$$



## Convex Relaxation of *arctan*:

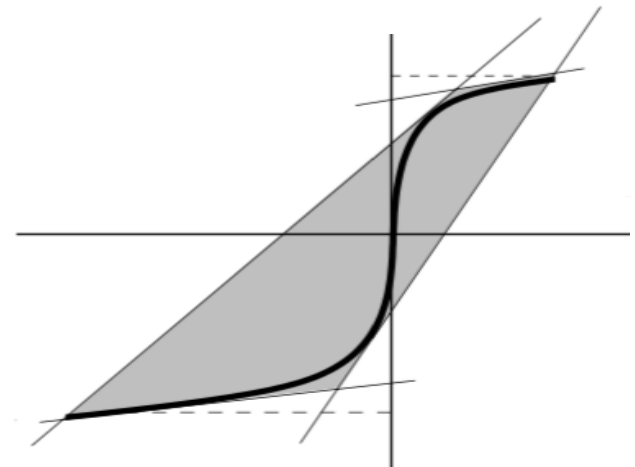
Linear Over- and Under-Estimators  
Optimality-Based Bound Tightening (OBBT)  
Gradually Adding Cycle Constraints

## Cycle Constraints:

the sum of angle differences on each cycle equals to zero

$$\sum_{l \in \mathcal{L}_c} \theta_l = 0 \quad \forall \mathcal{L}_c$$

$$\theta_l \equiv \theta_{b,k} = -\arctan\left(\frac{s_{b,k}}{c_{b,k}}\right) \quad \forall l = (b, k)$$

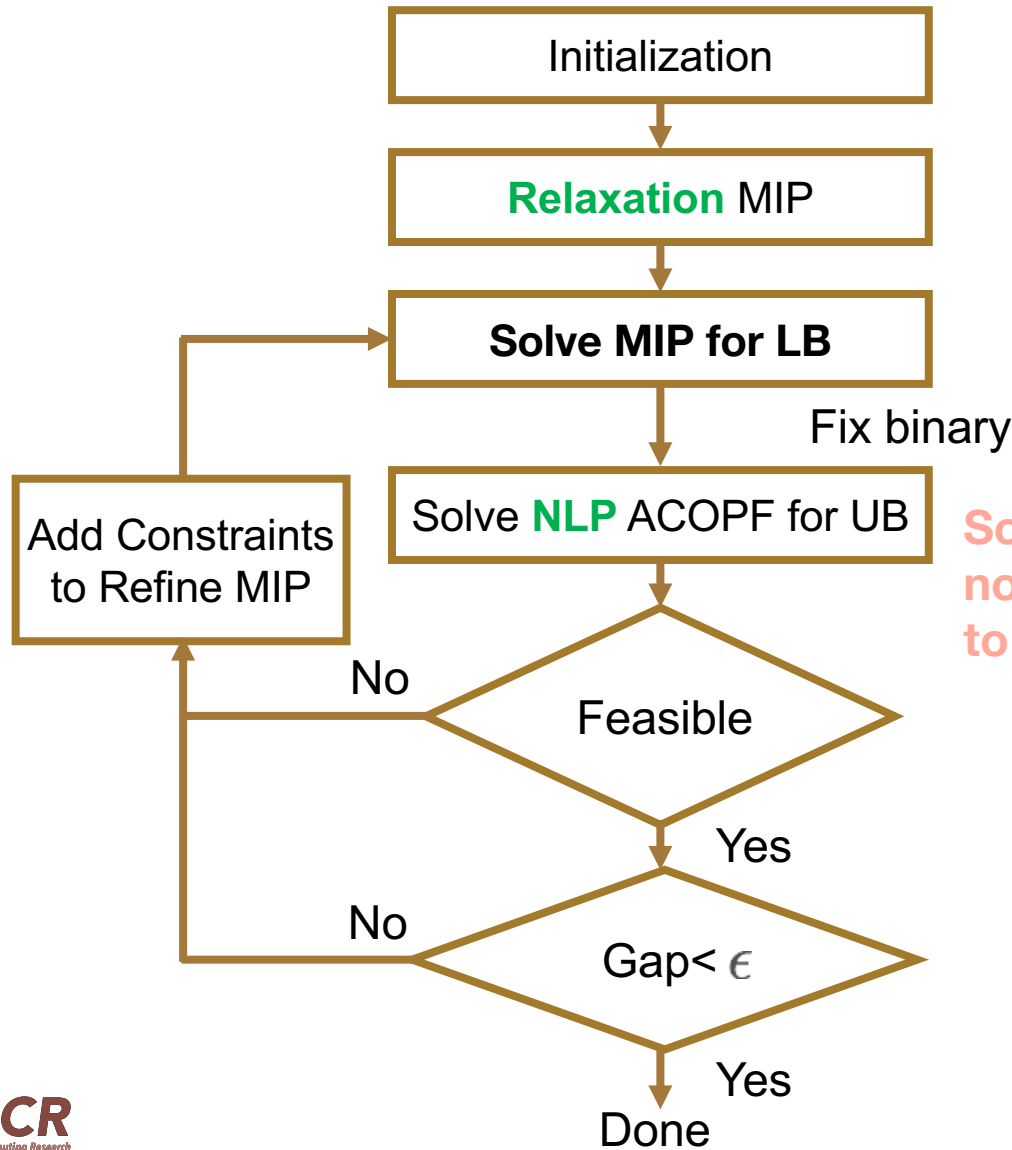


# Global ACOPF Performance

Case Name	Optimal Solution	Optimality Gap (%)	CPU Time (s)	Iteration Number
Case6ww	3126.36	0.008	0.26	4
Case14	8081.52	0.003	0.43	3
Case30	574.52	0.000	0.95	5
Case39	41864.18	0.005	1.21	3
Case57	41737.79	0.006	7.29	12
Case89	5817.60	0.009	46.2	44
Case118	129660.69	0.006	18.5	14
Case300	719725.10	0.009	82.7	49
NESTA Case6ww	3143.97	0.000	0.74	7
NESTA Case14	244.05	0.003	0.22	3
NESTA Case30	204.97	0.000	0.57	4
NESTA Case39	96505.52	0.009	3.00	8
NESTA Case57	1143.27	0.006	9.62	20
NESTA Case89	5819.81	0.009	55.8	57
NESTA Case118	3718.64	0.000	93.7	55
NESTA Case300	16891.28	0.000	138.2	26



# MINLP solved by Outer Approximation (OA)

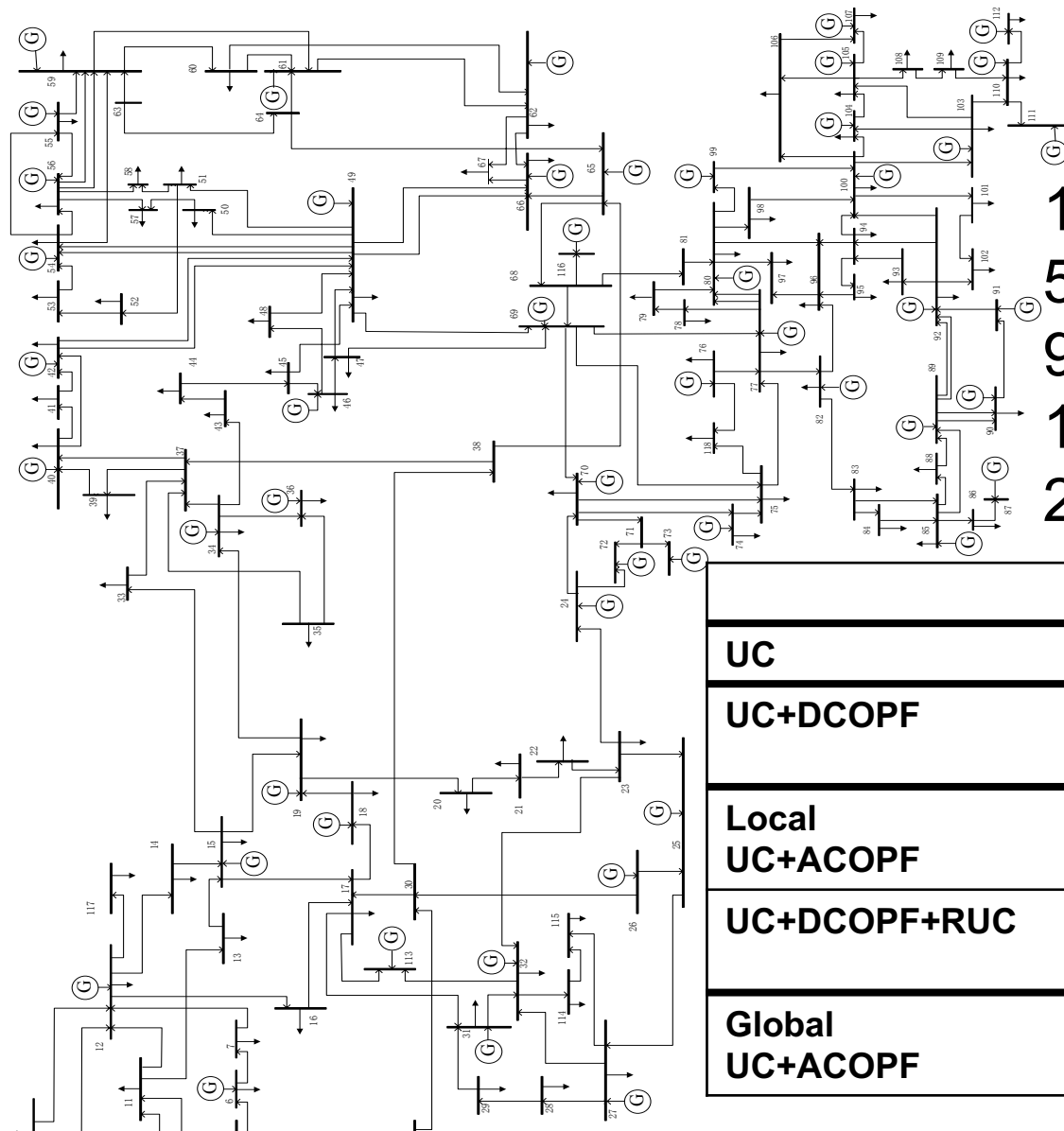


Solving nonlinear,  
non-convex AC OPF  
to global optimality?

Global Solution [R4]

# CONTRIBUTIONS

## UC+ACOPF RESULTS



118 nodes  
54 generators  
91 loads  
186 network elements/lines  
24-hour hourly commitment

	Cost (\$)	AC Feasible?
<b>UC</b>	811,658 (base)	NO
<b>UC+DCOPF</b>	814,715 (+0.4%)	NO
<b>Local UC+ACOPF</b>	843,591 (+3.9%)	YES
<b>UC+DCOPF+RUC</b>	844,922 (+4.1%)	YES
<b>Global UC+ACOPF</b>	835,926 (+3.0%)	YES

- Key Takeaway: Results indicate considerable divergence between the market settlements and stability/reliability requirements

# Computational Results (Local Method)

	UC MILP	UC+DCOPF MILP	UC+ACOPF MILP	SLP	UC+DCOPF+RUC MILP	SLP
Solution Time (s)						
6-Bus	0.13	0.21	0.88(3)	0.07(50)	1.02(1, 1)	0.06(33)
RTS-79	1.86	6.76	88.71(3)	0.75(36)	10.37(1, 2)	0.45(26)
IEEE-118	5.04	21.42	110.17(2)	5.06(46)	57.2(1, 1)	3.71(33)
Cost (\$)						
6-Bus	101, 270	106, 987	101, 763		102, 523	
RTS-79	823, 145	823, 894	895, 281		896, 169	
IEEE-118	811, 658	814, 715	843, 591		844, 922	

- Most of the OA algorithm time spent in the MILP (MIP gap tolerance 0.1%)
- UC+ACOPF: 5x-15x slower than the UC+DCOPF
- UC+DCOPF+RUC: 1.5x-5x slower than the UC+DCOPF

# Local v. Global UC+ACOPF Method

Case	Problem Formulation	Upper Bound	Lower Bound	Relative Gap (%)	CPU Time (s)
6-Bus	Global	101,763	101,655	0.11%	3.6
	Local	101,763	-	0.11%	0.95
RTS-79	Global	895,096	893,967	0.13%	266.4
	Local	895,281	-	0.15%	89.46
IEEE-118	Global	835,926	833,057	0.34%	8480
	Local	843,591	-	1.25%	115.23

- **Note:** Thermal limits different in global solution method (apparent power thermal limit) and local solution method (current thermal limit) so a direct comparison (above) is inexact
- On the largest test case, the approximation method is over 70x faster, at the cost of 0.91% in relative optimality gap change

# ONGOING WORK

- Study of global solution techniques applied to the PSV, RSV and RIV ACOPF formulations
- Implications on market settlements for including AC network constraints in the day-ahead
- Improving the performance of the MIP solution time in the OA algorithm (e.g., hybrid OA + branch-and-bound)
- Comparing the fidelity and computational performance to current market practices on larger scale, more realistic networks (GRIDDATA)

# References

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