

# Efficient AC Optimal Power Flow & Global Optimizer Solutions

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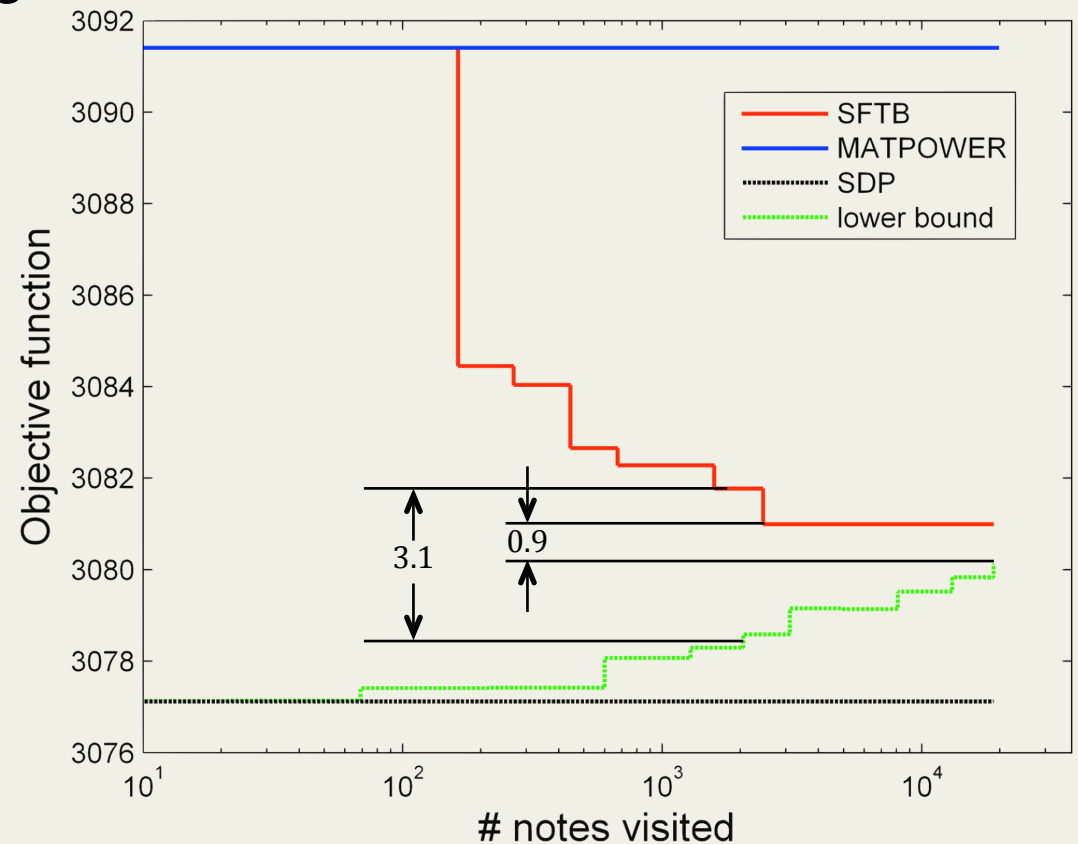


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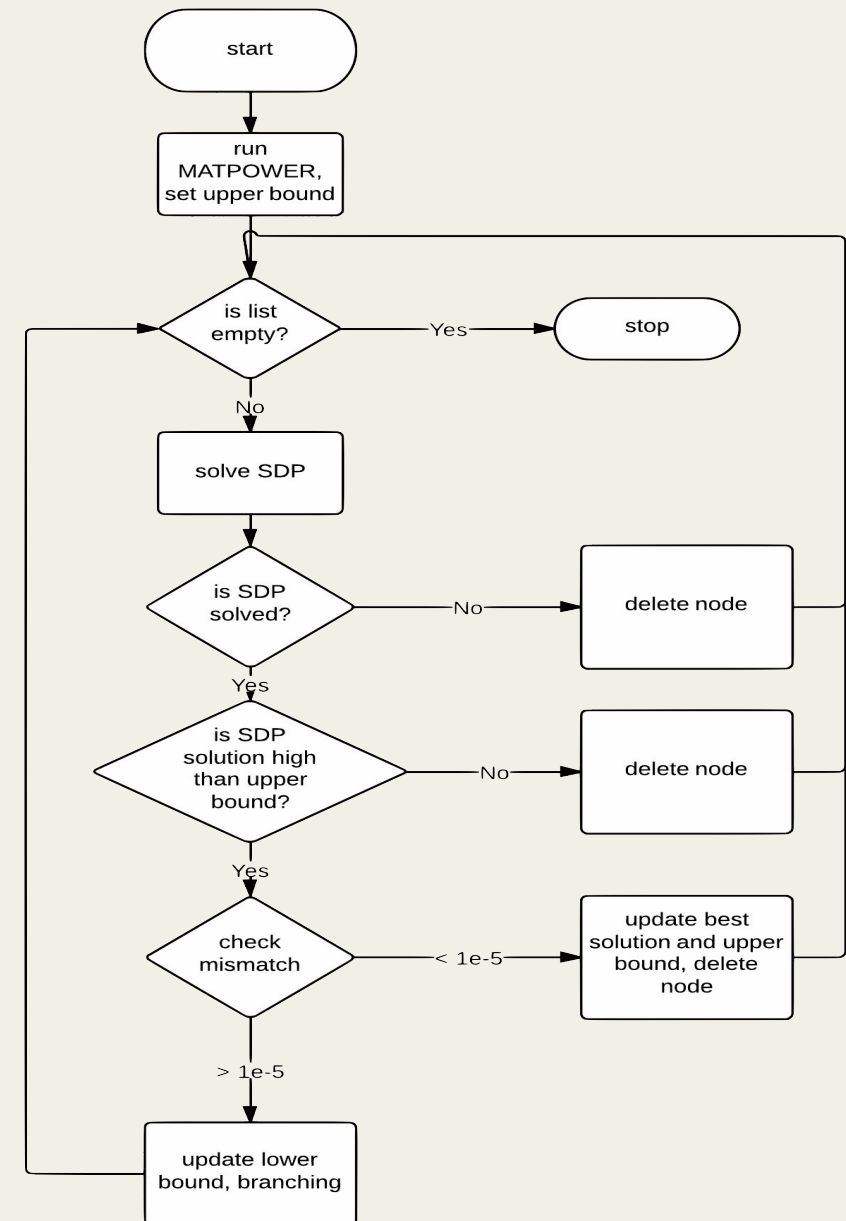
# Presentation at 2014

- Optimal power flow
  - Nonlinear and nonconvex  $\rightarrow$  difficult to solve
    - No guarantee to find a solution
    - Heuristic search aiming for a local solution
- Global solution
  - MATPOWER does not find the global optimizer
  - Divide-and-conquer
  - Visit 20,000 nodes
  - Global optimizer within an epsilon gap  $\rightarrow$
- 2015 research goal
  - Efficient algorithm
  - Parallel computation

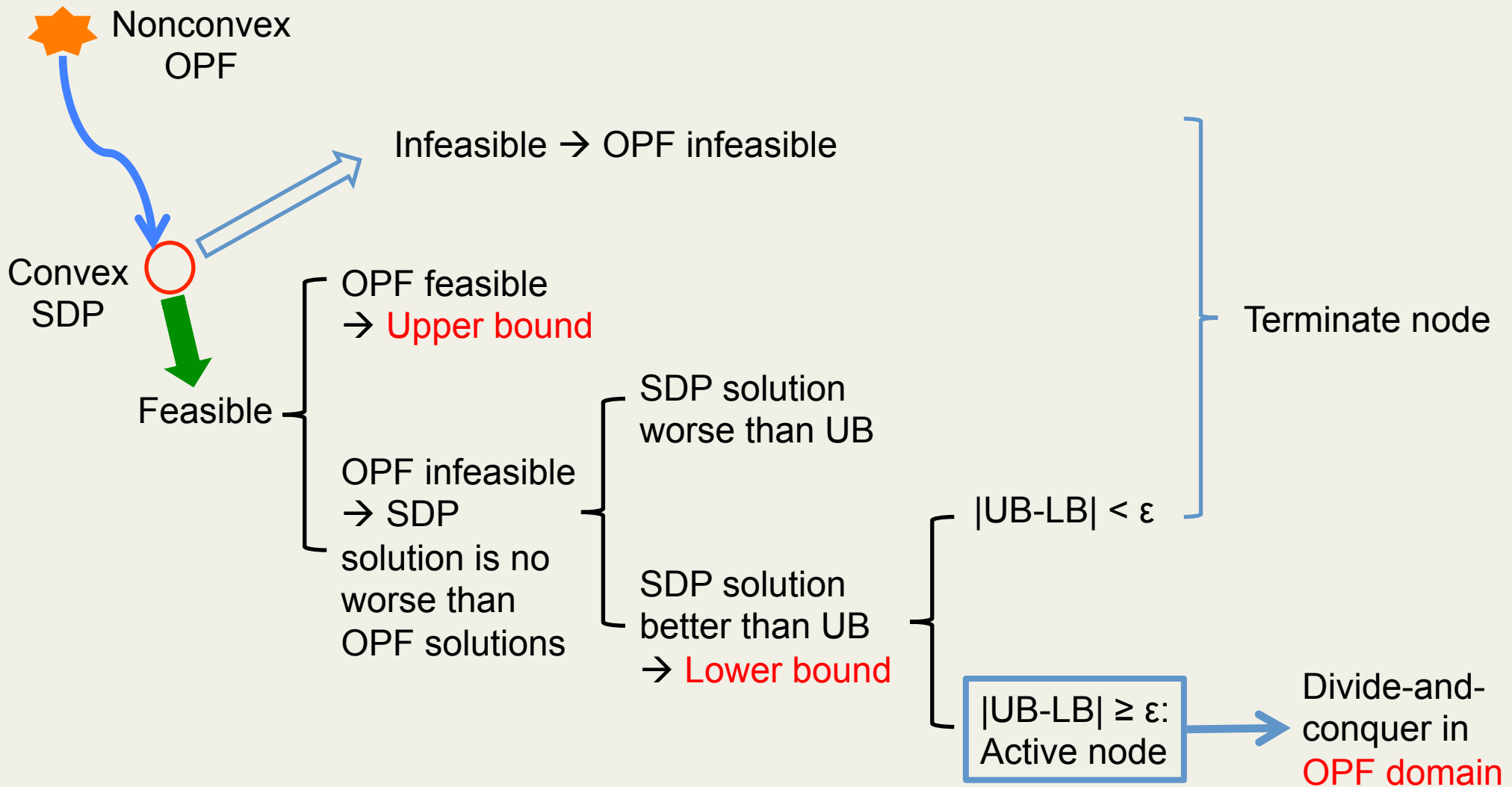


# Algorithm 2014

- Start with MATPOWER
  - Initial lower bound
- Upper bound set by SDP
- Divide-and-conquer
  - Voltage cut
  - Angle cut
- Termination criterion
  - $|UB-LB| < \epsilon$
  - $\epsilon = 3 \times 10^{-4}$



# Divide-and-Conquer Approach

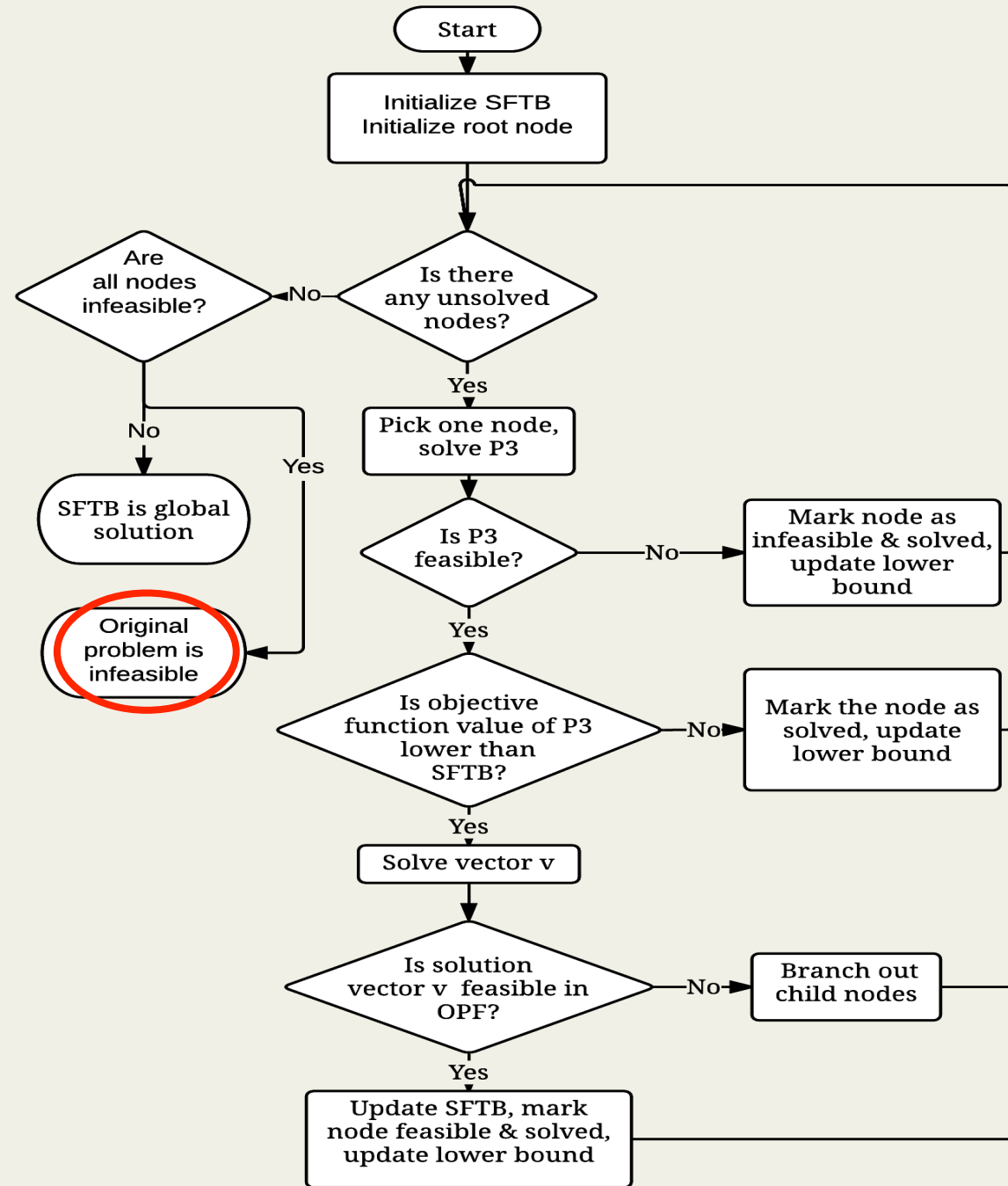


# Two Questions

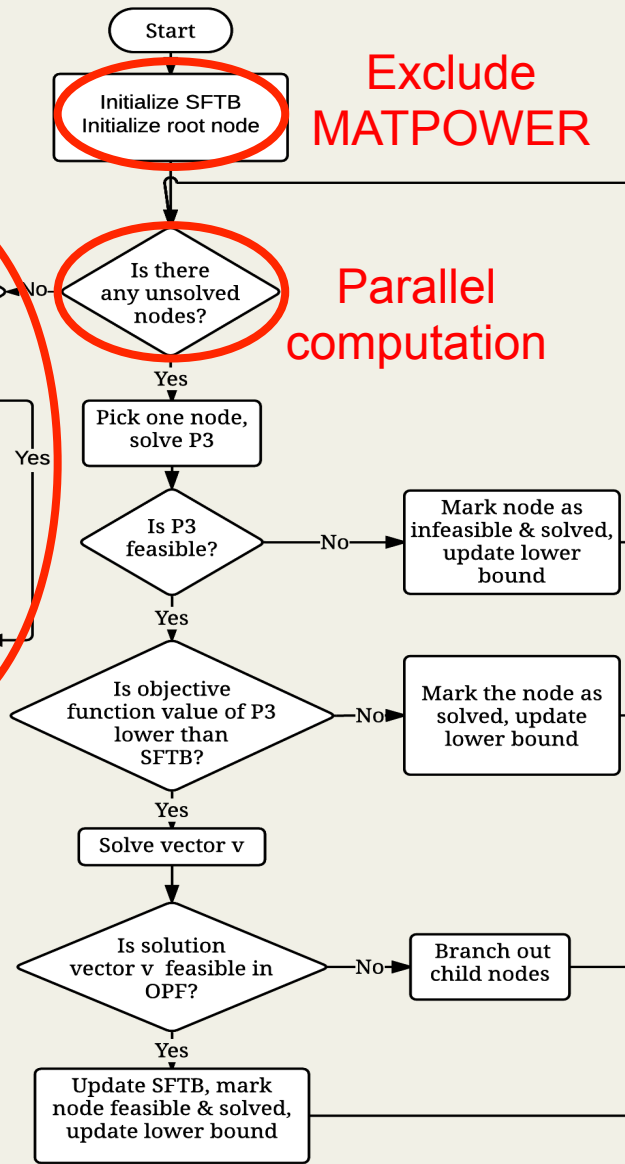
- Global optimizer?
    - A better solution may exist within the epsilon gap
    - Answer: global solution with an epsilon-gap is not uncommon
      - Commercial software such as BARON
      - J. Global Optimization
    - Zero epsilon-gap or an epsilon-gap less than numerical error is computationally expensive
  - What if an NLP solver does not find a solution?
    - NLP fails to find solution  $\neq$  infeasible OPF
    - SDP relaxes/expands the feasible region of OPF
    - Infeasible SDP guarantees the infeasibility of OPF
- Major change in the algorithm

# Algorithm

- Infeasible NLP
  - Infeasible SDP
    - Infeasible OPF
  - Feasible SDP
    - Best infeasible solution
      - Lower bound
      - D&C
- SDP finds a feasible OPF solution
  - Best feasible solution → Upper bound



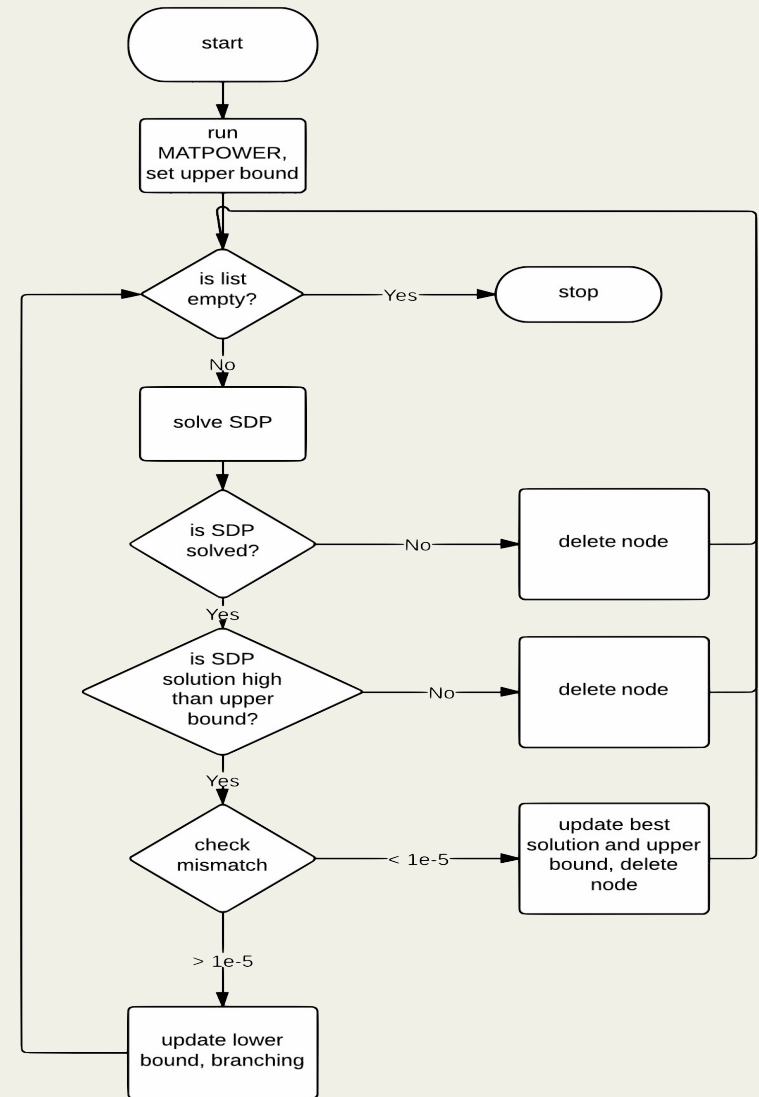
# What's New?



Exclude  
MATPOWER

Parallel  
computation

Capability to  
guarantee  
Infeasibility

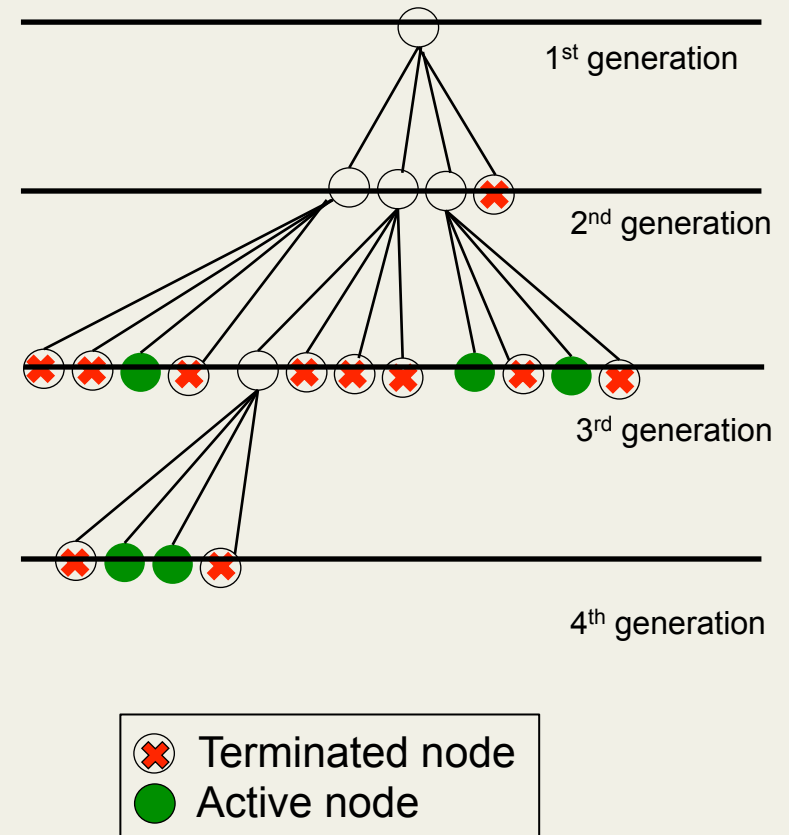




# Selection Criterion to Prune

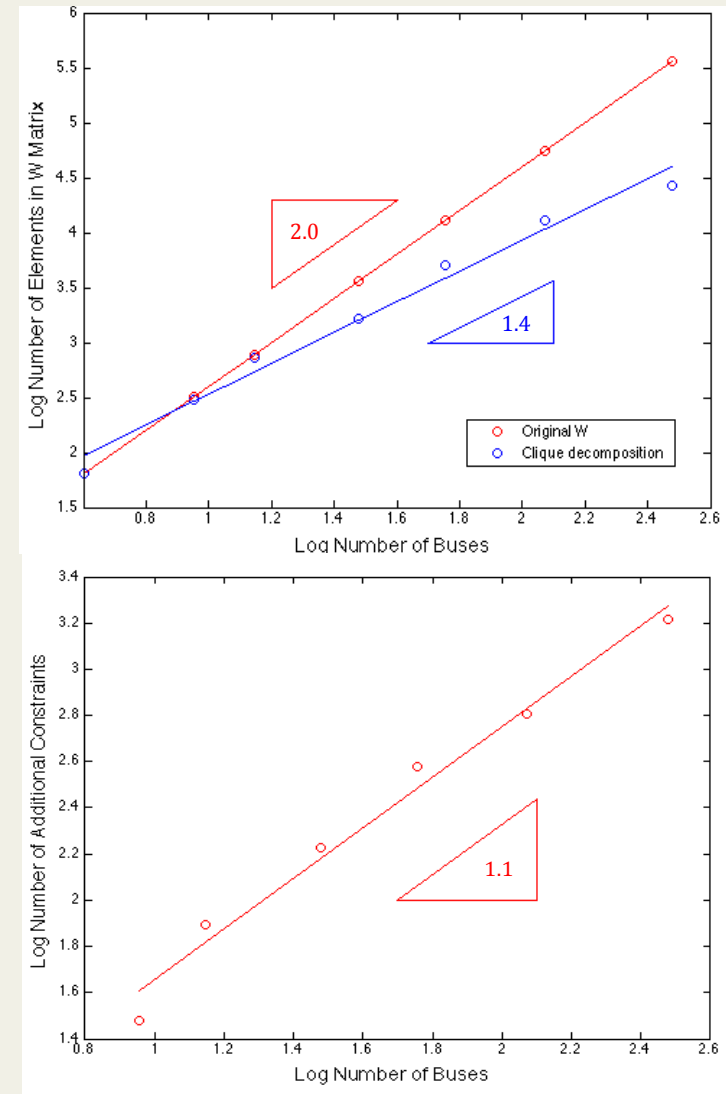
- Best infeasible SDP solution among active nodes set the lower bound
- Upper bound set by the best feasible solution
- How to choose a node to prune
  - SDP finds infeasible but better solution than the upper bound
  - Choose the “best” nodes among active nodes
  - Measure of “good” nodes
    - Close to feasible solution from the eigenvalues of  $W$

$$\arg \max \left[ 1 - \left( \frac{1}{\lambda_{\max}} \right) \sum_{n=2}^N \lambda_n \right]$$



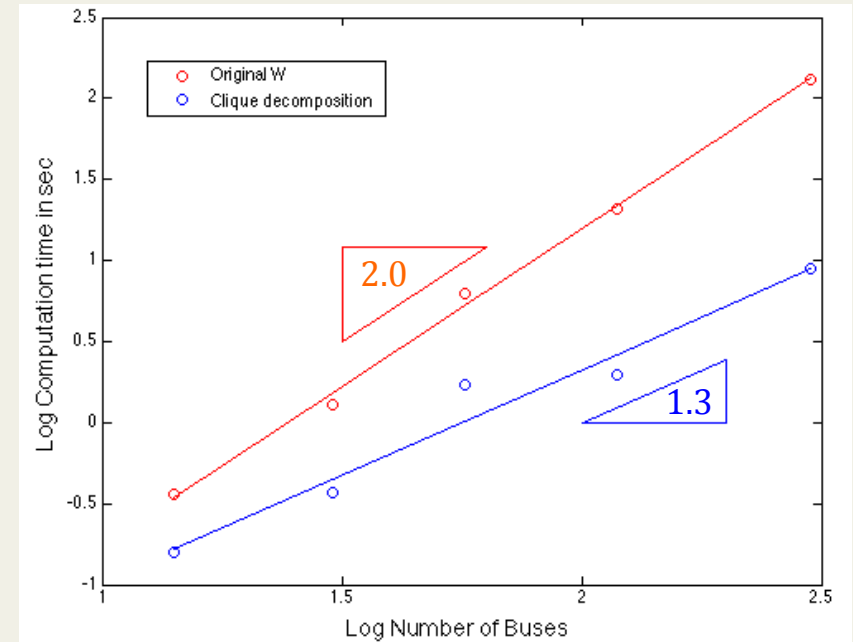
# Clique Decomposition I

- Number of elements in  $W$  is in  $\mathcal{O}(N^2)$ 
  - Computationally inefficient
  - Infeasible to solve a large-scale OPF ( $\geq 30$ -bus case)
- Connectivity in transmission grid is low
  - Sparsity of incidence matrix
  - Decompose into small cliques
  - Large single  $W \rightarrow$  small multiple  $W$ 's
- Number of independent variables in  $W$  decreases (top)
- Number of equality constraints increases to make cliques consistent with  $W$ 's (bottom)



# Clique Decomposition II

- Independent variables in  $W$ 
  - Original  $W$ :  $\mathcal{O}(N_{bus}^2)$
  - Theoretical max with clique decomposition:  $\mathcal{O}(n \times N_{bus})$
  - IEEE model systems:  
 $\mathcal{O}(N_{bus}^{1.3})$
- Computation time decreases  $\rightarrow$
- SDP solvable for large-scaled systems ( $\geq 30$  bus)



# Clique Decomposition III

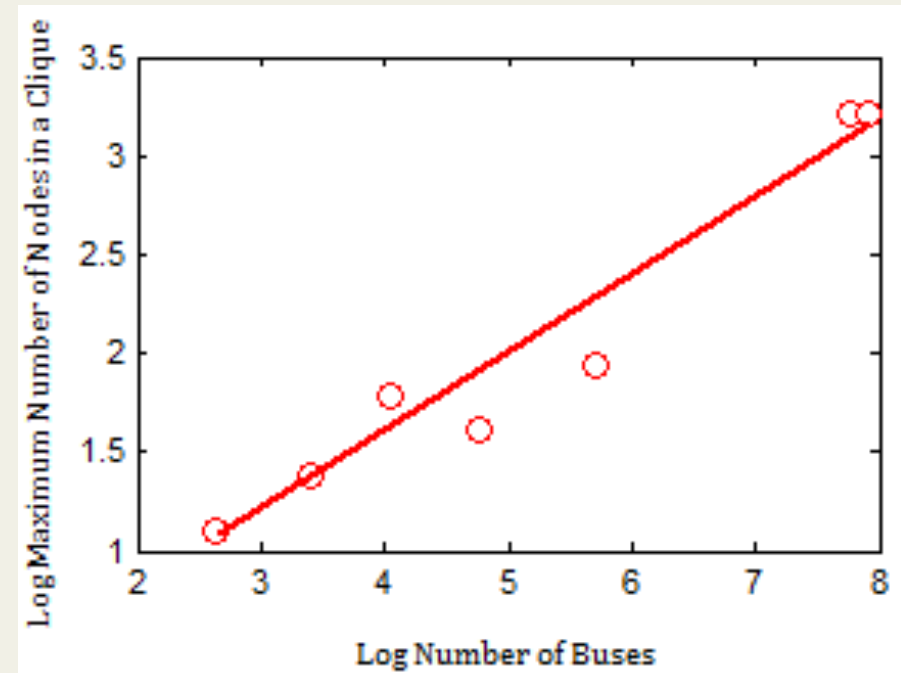
- Clique decomposition tends to create many small cliques
  - Many equality constraints
  - Computational inefficiency may occur
- SDP with clique decomposition reveals **partial** information
  - $\text{Rank}(W) = \max \{\text{Rank}(w_j)\}$  where  $w_j$  is the  $j^{\text{th}}$  clique
  - A low-rank approximation with the rank yields  $v$
  - Many elements in  $W$  are evaluated for a better approximation
- Merging small cliques can increase
  - Computation efficiency
  - Number of elements in  $W$  evaluated

M. Fukuda et. al., "Exploiting Sparsity in Semidefinite Programming via Matrix Completion I: General Framework", *SIAM J. Optim.*, pp. 647-674, 2000

# Merging Cliques I

- Molzahn et. al. suggested merging cliques
  - Sparsity for achieving high computational efficiency
  - No specific control of the individual clique size
- Observation
  - Computation time critically depends on the largest clique size
  - Relation between the largest clique size and the number of busses in IEEE cases
- Merge and create a relatively large matrix for high speed

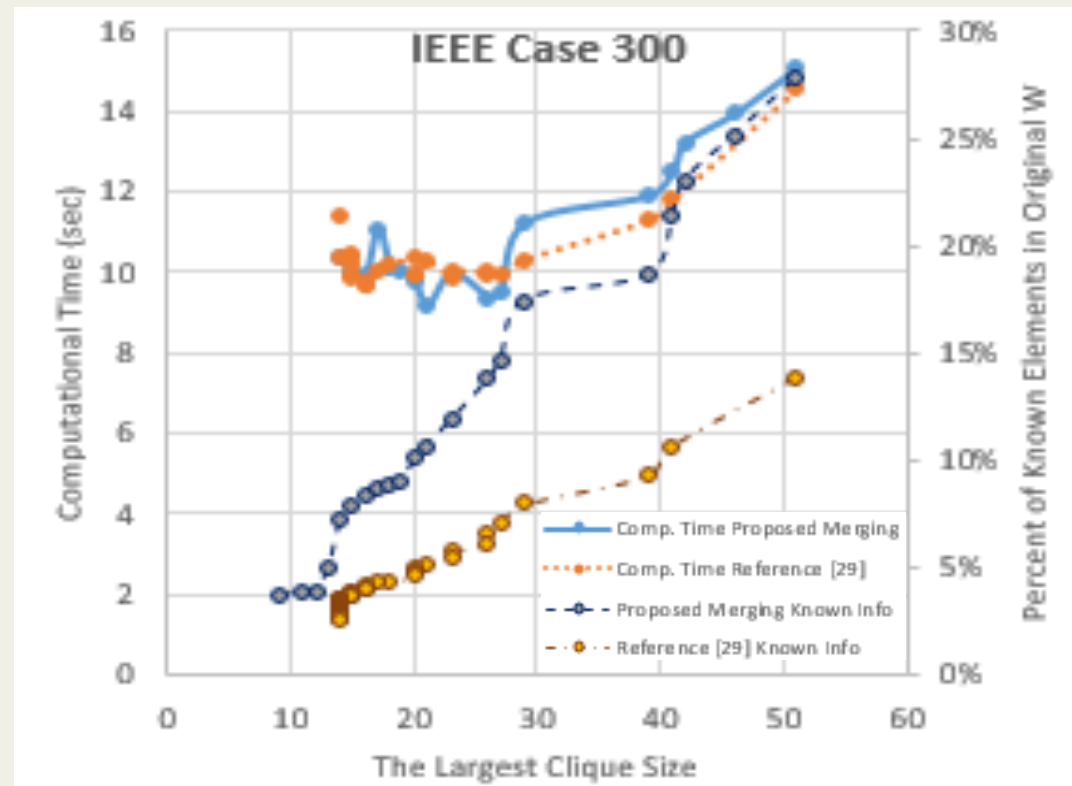
D. K. Molzahn, J. T. Holzer, B. C. Lesieutre, and C. L. DeMarco, "Implementation of a Large-Scale Optimal Power Flow Solver Based on Semidefinite Programming", *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 3987-3998, Apr. 2013



	Case Name - # of Bus						
	14	30	57	118	300	2383	2736
# of Cliques	12	26	52	108	278	2,312	2,652
The largest Clique Size	3	4	6	5	7	25	25
# of Equality Constraints	103	233	758	1,394	3,631	44,729	51,922
# of Independent Variables	241	543	1,477	2,812	7,167	76,498	88,634

# Merging Cliques II – Computed Elements in $W$

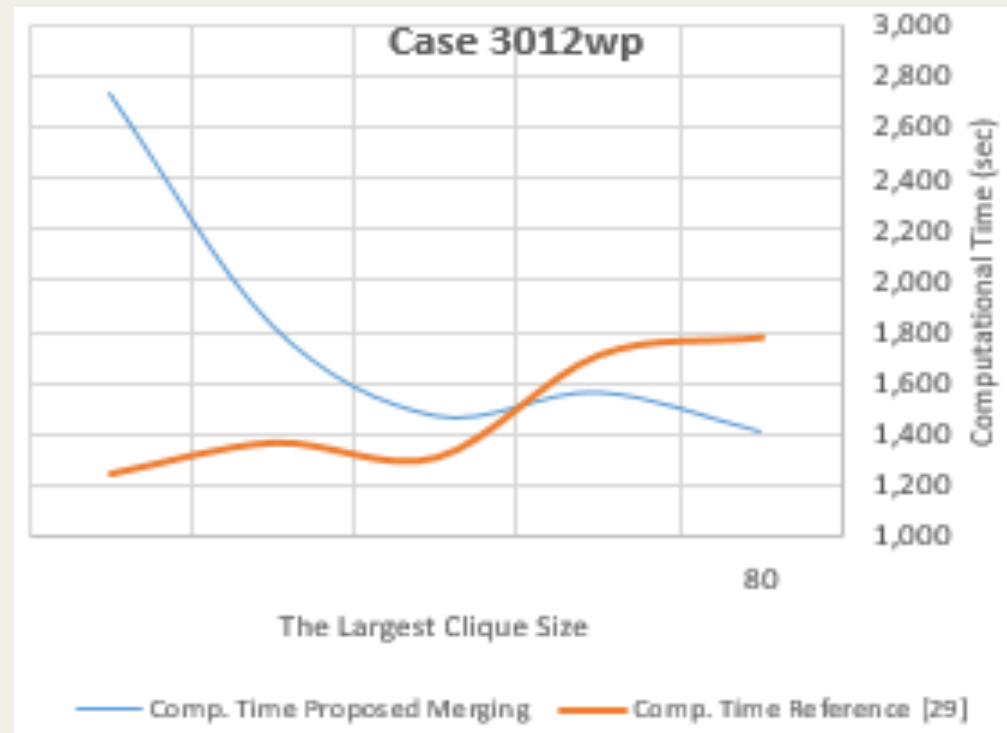
- Molzahn's method (orange)
  - Merging reveals elements in  $W$
  - No specific control of the largest clique
- Our approach (blue)
  - Control the largest clique
  - Same computation time, more elements in  $W$  are evaluated



D. K. Molzahn, J. T. Holzer, B. C. Lesieutre, and C. L. DeMarco, "Implementation of a Large-Scale Optimal Power Flow Solver Based on Semidefinite Programming", *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 3987-3998, Apr. 2013

# Merging Cliques III – Computational Efficiency

- Merging cliques after the clique decomposition
  - Reduce the number of equality constraints
  - Less elements in  $W$  are evaluated
- Proposed method
  - Control the largest clique
  - Different behavior →
  - Direct relation between the largest clique size and the computational time
  - Easier & faster PSD matrix completion
    - Suitable for D&C



D. K. Molzahn, J. T. Holzer, B. C. Lesieutre, and C. L. DeMarco, “Implementation of a Large-Scale Optimal Power Flow Solver Based on Semidefinite Programming”, *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 3987-3998, Apr. 2013

# New Angle Cut

- $f$ : real voltage,  $e$ : imaginary voltage
- Voltage angle in the Cartesian CS:  $\theta_i = \tan^{-1}(f_i/e_i)$
- Angle cut imposes limits of voltage angle:  $e_i \tan \theta_i^{\min} \leq f_i \leq e_i \tan \theta_i^{\max}$
- In the OPF problem, two constraints are combined

$$f_i^2 - \left( \tan \theta_i^{\min} + \tan \theta_i^{\max} \right) f_i e_i + \left( \tan \theta_i^{\min} \tan \theta_i^{\max} \right) e_i^2 \leq 0$$

- In SDP,  $W = vv^T$
- Angle cut is a linear constraint in SDP

$$W_{i,i} - \left( \tan \theta_i^{\min} + \tan \theta_i^{\max} \right) W_{i,N+i} + \left( \tan \theta_i^{\min} \tan \theta_i^{\max} \right) W_{N+i,N+i} \leq 0$$



# Algorithm with the New Angle Cut

- New angle cut is a single linear constraint

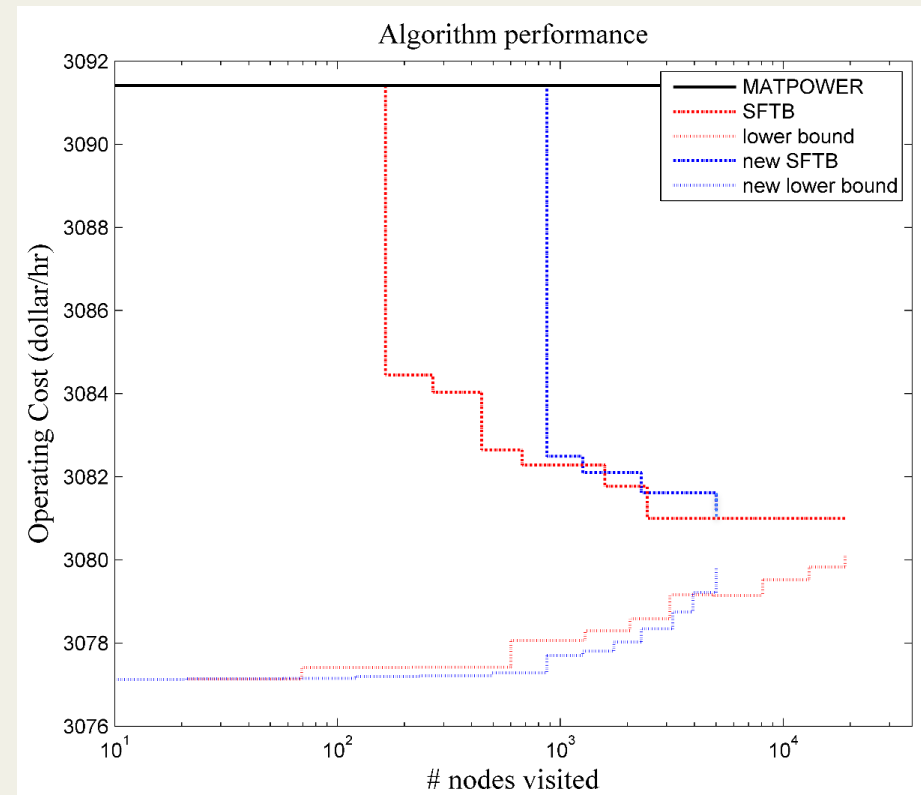
$$W_{i,j} - \left( \tan \theta_i^{\min} + \tan \theta_i^{\max} \right) W_{i,N+i} + \left( \tan \theta_i^{\min} \tan \theta_i^{\max} \right) W_{N+i,N+i} \leq 0$$

- In comparison, old angle cut is from upper and lower constraints

$$\tan \left( \theta_i^{\min} \right) W_{i,j} \leq W_{(i+N),j} \quad \text{and}$$

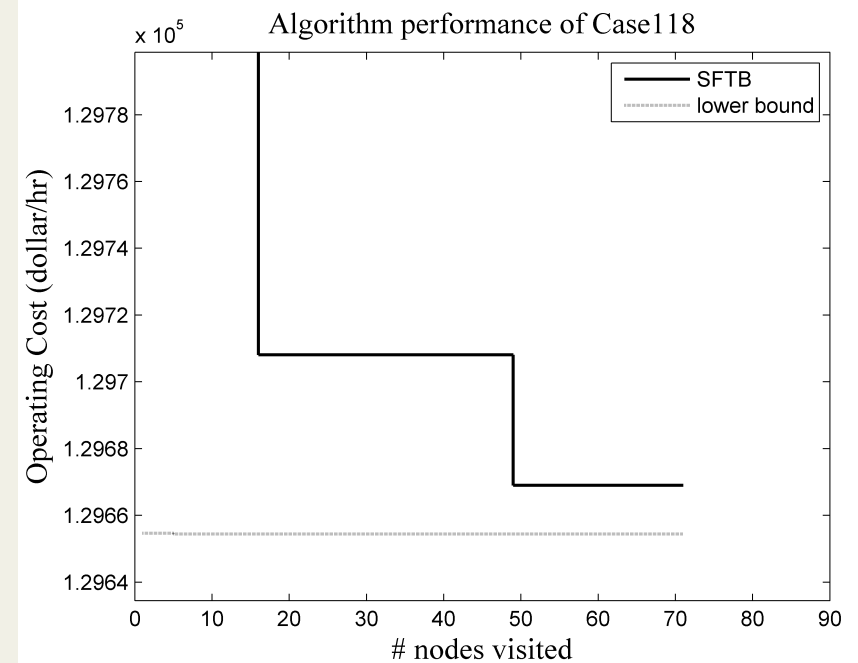
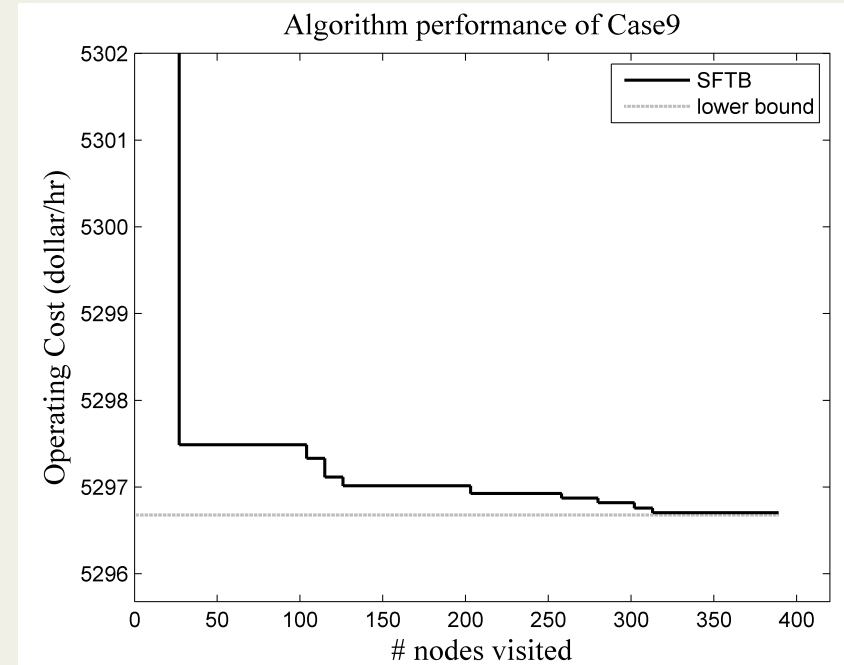
$$W_{(i+N),j} \leq \tan \left( \theta_i^{\max} \right) W_{i,j}$$

- Terminate the process earlier, but find the same solution  
→ more efficient



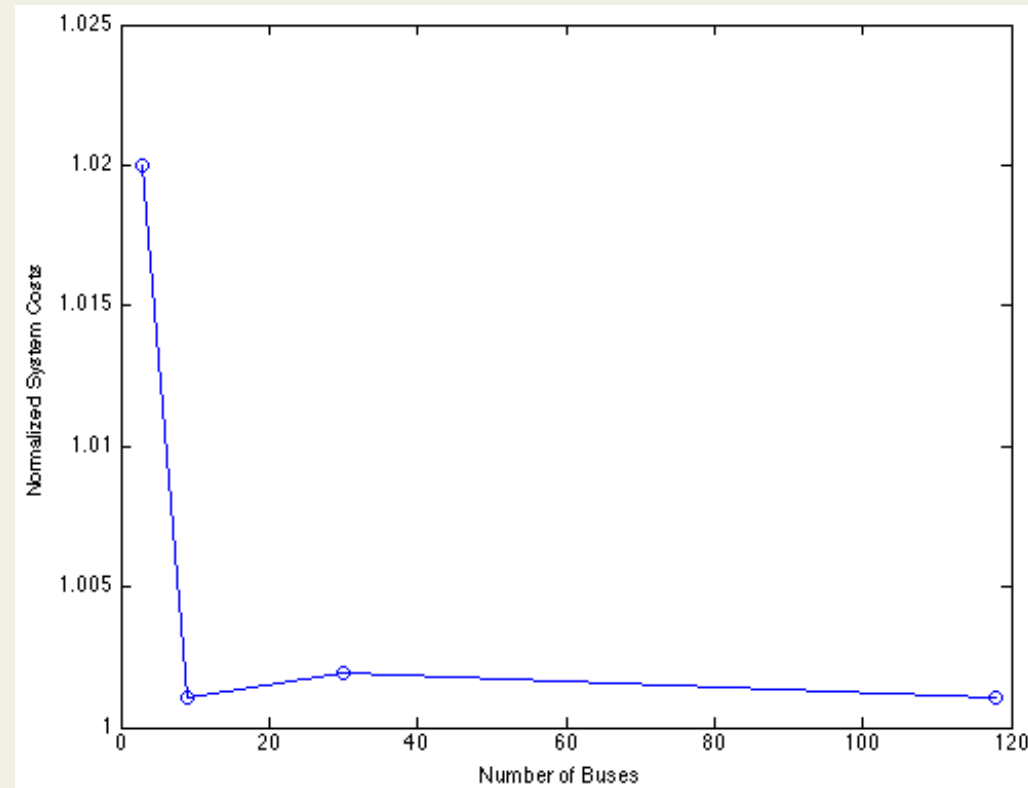
# Results: Global Solutions

- Visit multiple nodes simultaneously
- Server for parallel computation
  - 9 machines
  - 2 processors/machine
  - 6 cores/processor
  - 2.50GHz Intel Xeon processor
- For a same system, depending on the loading conditions, there are changes in
  - Number of nodes visited
  - Computation time
- Epsilon gap  $\leq 10^{-5}$



# Results I – Normalized System Costs

- In comparison to the first feasible solution found →
  - 0.1-2% cost reduction
- 0.1% savings is greater than \$10<sup>9</sup>/year in US [1]
- In comparison to the MATPOWER solutions
  - MATPOWER finds the global solutions
  - Except 14-bus case [2]: 0.3% cheaper solution

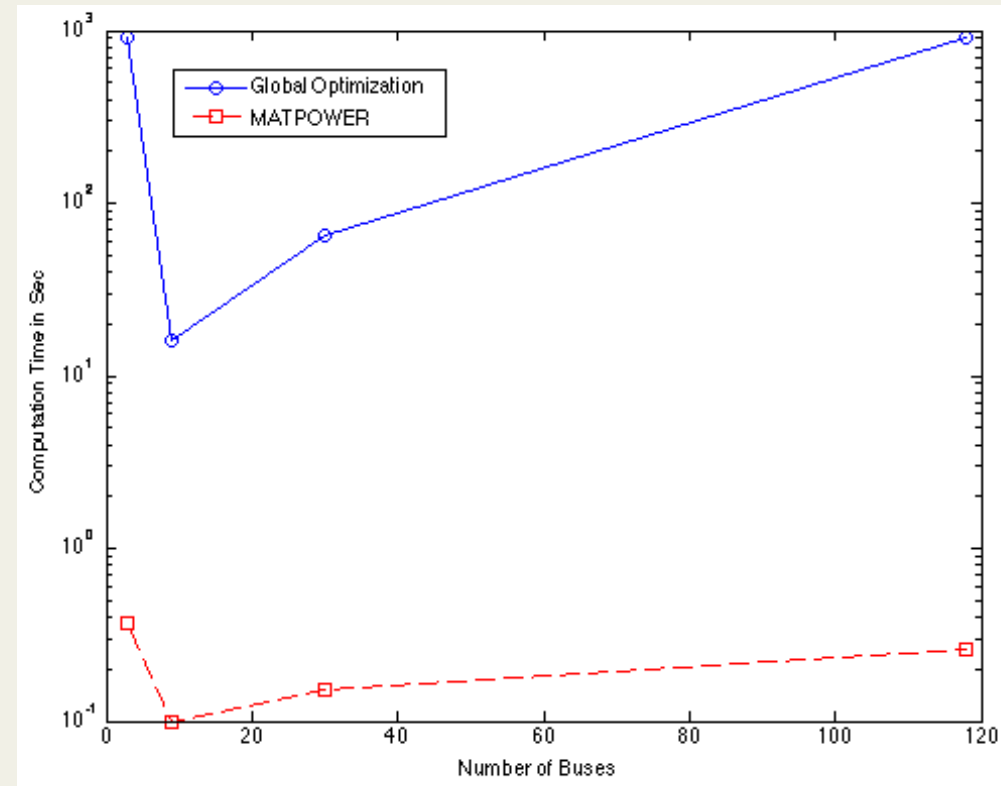


[1] R. O'Neill, "It's Getting Better All the Time (with Mixed Integer Programming)", *Harvard Electricity Policy Group*, Los Angeles, CA, Dec. 2007.

[2] R. Louca, P. Seiler, and E. Bitar. "A Rank Minimization Algorithm to Enhance Semidefinite Relaxations of Optimal Power Flow." *Communication, Control, and Computing (Allerton)*, 2013 51st Annual Allerton Conference on, pp. 1010-1020, 2013.

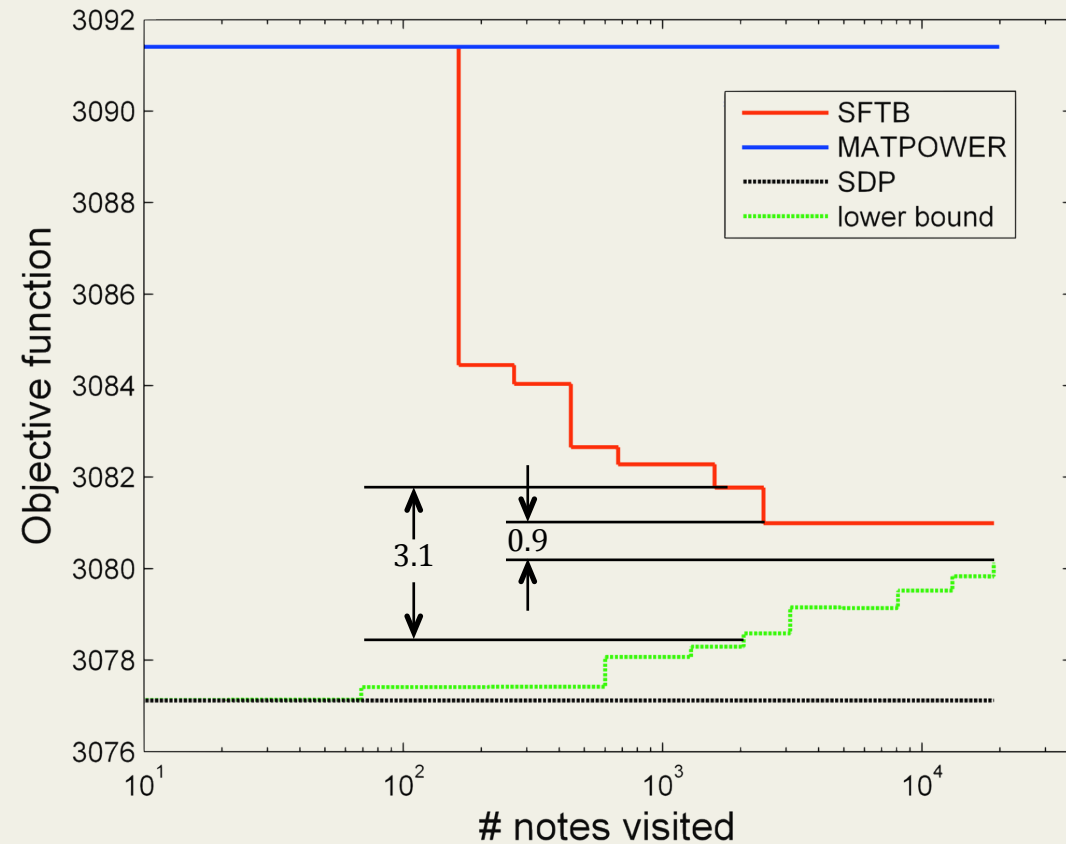
# Results II – Computation Time

- Computation time
  - Typically 50-times faster with parallelization
  - 150~3,000 times slower than an NLP solver
  - BARON: 1.5 days ( $10^5$  sec) for 9-bus case
- Epsilon-gap =  $10^{-5}$ 
  - BARON's default =  $10^{-3}$
  - Numerical error  $\leq 10^{-8}$



# Global Optimizer?

- Non-zero epsilon-gap
  - Zero gap is computationally very expensive to achieve with D&C
- Terminate the process after visiting many nodes
- If there is any way to guarantee the global optimizer, the process can be terminated earlier
- Check if MATPOWER solution is the global optimizer



# Trust Region Method I

- Quadratic objective function  $\min \quad g^T x + 0.5x^T Bx$ 
  - Trust region constraint
  - No other constraints
$$s.t. \quad \|x\| \leq \Delta$$
- If  $\lambda$  and  $p$  satisfies the following conditions,  $p$  is the global solution
  - Equality constraint:  $(B + \lambda I)p = -g$
  - Positive definiteness:  $B + \lambda I \succeq 0$
  - Either if
    - $\lambda = 0$  and  $\Delta \rightarrow \infty$  OR
    - $\lambda > 0$  and  $\|p\| = \Delta$

D. C. Sorensen, "Trust region methods for unconstrained optimization", *SIAM J. Numerical Analysis*, 19 (1982), pp. 409-426.

# Trust Region Method II

- General quadratic optimization
  - Trust region constraint
  - Equality constraints
  - Inequality constraints
- If  $\mu^*$ ,  $\sigma^*$ ,  $\lambda$ , and  $p$  satisfies the following conditions,  $p$  is the global solution inside the trust-region  $\rightarrow$  epsilon gap is **NOT** necessary

$$\begin{aligned} \min \quad & g^T x + 0.5x^T Bx \\ \text{s.t.} \quad & \|x - x_0\| \leq \Delta \\ & h^T x + 0.5x^T Cx = 0; \mu \\ & k^T x + 0.5x^T Dx \leq 0; \sigma \end{aligned}$$

$$(B + \mu^* C + \sigma^* D + \lambda I) p = -g - \mu^* h - \sigma^* k + \lambda x_0$$

$$B + \mu^* C + \sigma^* D + \lambda I \succeq 0$$

$$\{\sigma^* = 0 \ \& \ k^T x + 0.5x^T Dx \leq 0\} \text{ OR } \{\sigma^* > 0 \ \& \ k^T x + 0.5x^T Dx = 0\}$$

$$\{\lambda = 0 \ \& \ \Delta \rightarrow \infty\} \text{ OR } \{\lambda > 0 \ \& \ \|p - x_0\| = \Delta\}$$

Global optimizer

# Trust Region Method for Optimal Power Flow

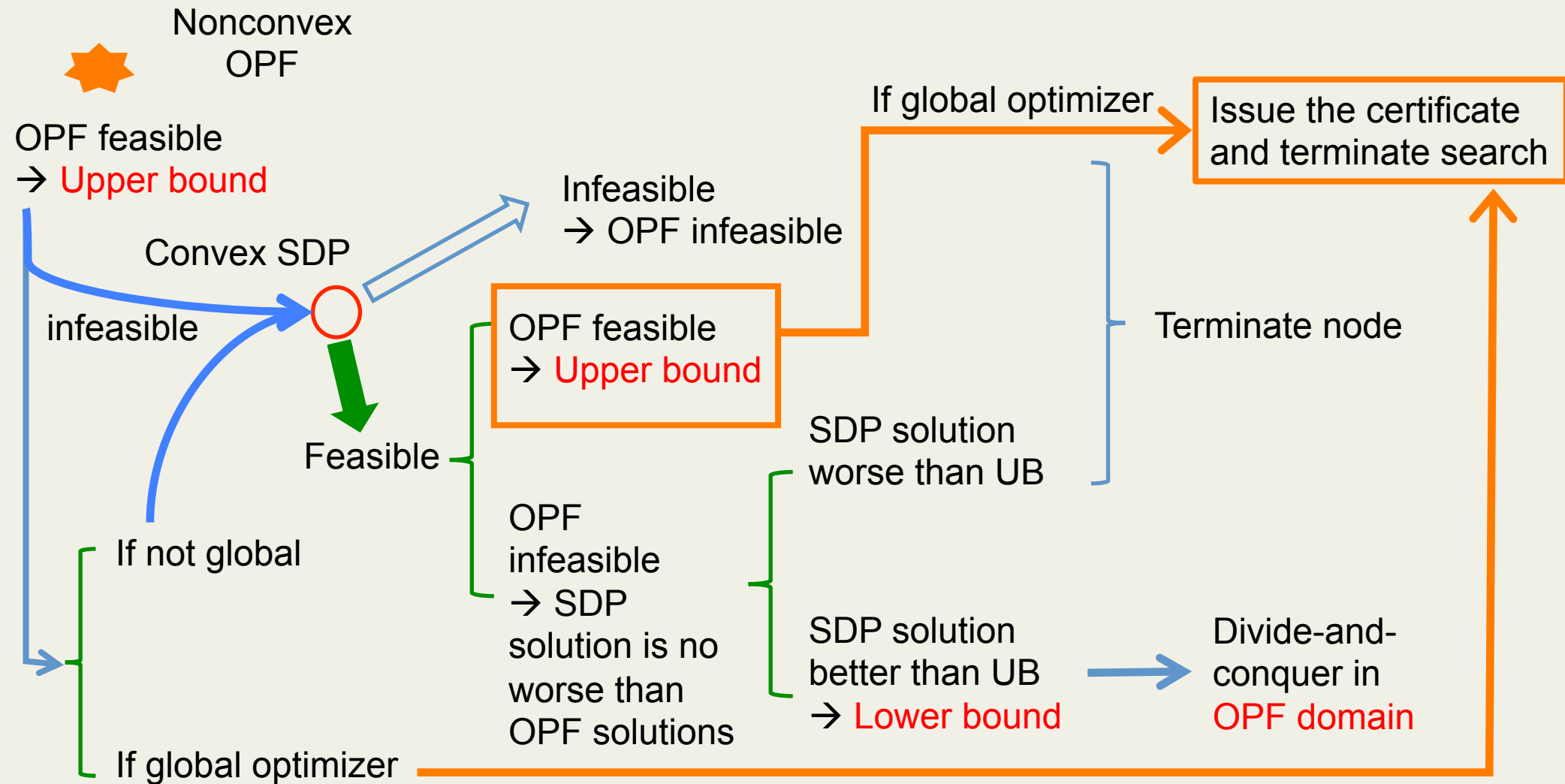
- Rewrite OPF into QCQP
  - Flow constraints are in quartet
  - Introduce real and reactive power injection variable over a line

$$\min \quad 0.5 p^T B p + g^T p$$

$$s.t. \quad \begin{cases} v^T \Phi_j^P v = p_j - p_{d,j}, v^T \Phi_j^Q v = q_j - q_{d,j} \\ v^T \Psi_k^P v = p_k, v^T \Psi_k^Q v = q_k, p_k^2 + q_k^2 \leq c_k^2 \\ v_{\min}^2 \leq v^T M v \leq v_{\max}^2 \\ p_{\min} \leq p \leq p_{\max}, q_{\min} \leq q \leq q_{\max} \end{cases}$$

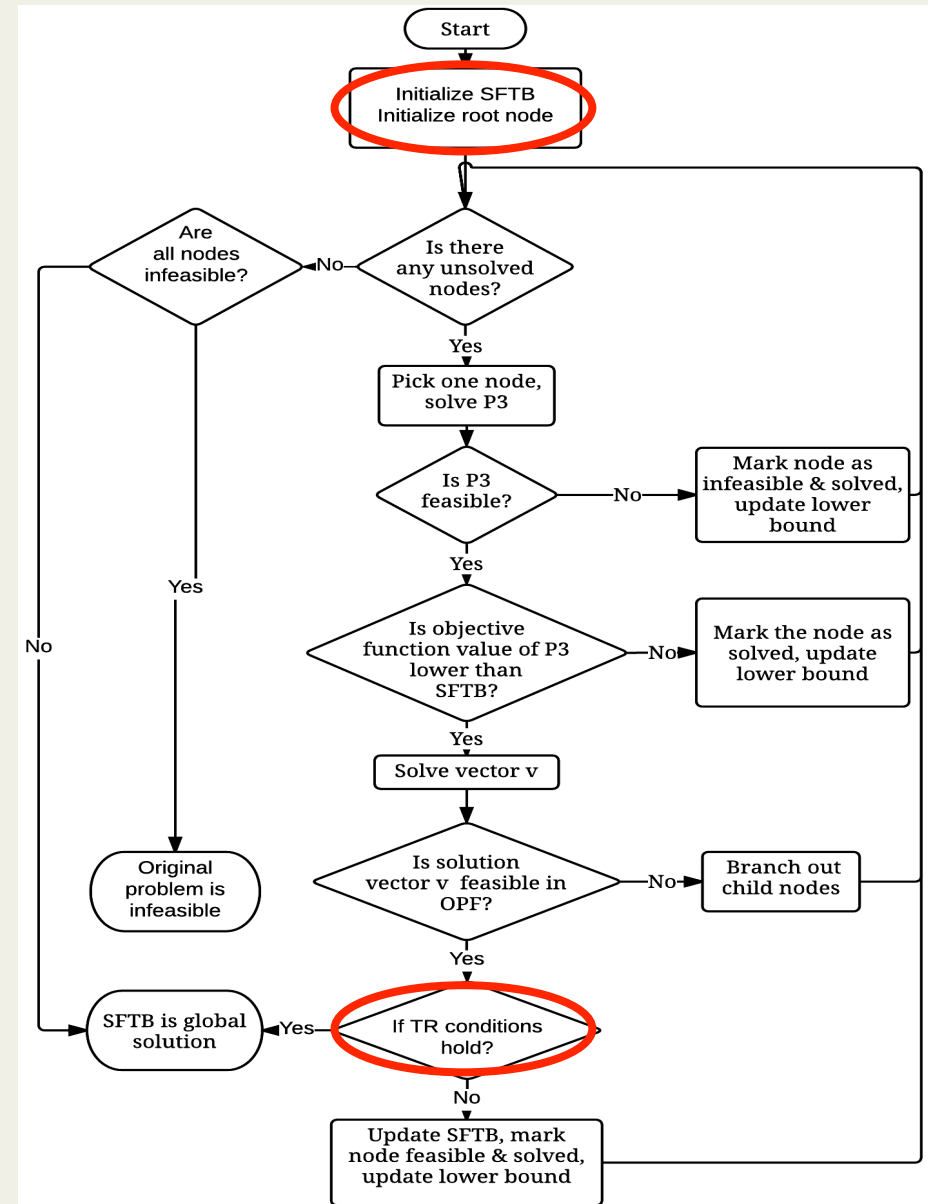


# Revisit to the Divide-and-Conquer Approach



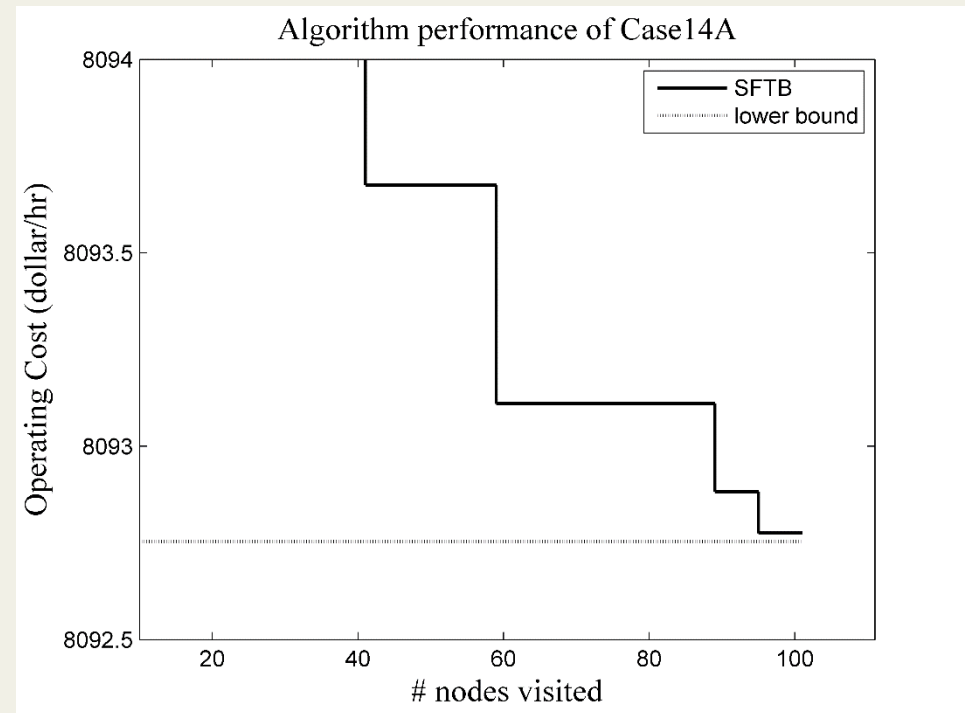
# New Algorithm Incorporating the Certificate

- SDP feasible solution
- OPF local solution
- Issue the certificate to guarantee the global optimizer
- Epsilon-gap is removed from the algorithm
- Process to check  $|UB - LB| \leq \epsilon$  is not necessary



# New Termination Criterion with the TR Certificate

- During the searching process, find local optimizers
- Trust-region global optimality condition
  - Local optimizers do not satisfy
  - Global optimizer does → Terminate the search process
- Performance of D&C with TRC
  - Terminated when gap  $> 10^{-5}$
  - Only 100 nodes visited
  - Tested with Case14A only



# This Approach vs. MATPOWER

- MATPOWER
  - High efficiency to search for an optimizer
  - Based on our experience up to now, MATPOWER finds the global solution except one case (Case14 with modified offers, by 0.2%)
- This approach
  - MATPOWER finds an optimizer
    - Most cases: Global optimizer → Issue the certificate & terminate the search process
    - Some cases: 10 times slower than MATPOWER, but much faster than an algorithm with  $\epsilon$ -gap (150-3,000 times slower)
  - Guarantees
    - Infeasibility of an OPF problem
    - Global solution
  - Finds multiple local optimizers

# Conclusions

- Our D&C finds the global solution in an efficient way by
  - Dividing regions with voltage cut and angle cut
  - Finding the ideal place to prune using the sub-optimization problem
  - Terminating a node efficiently
- Our D&C is modified
  - Added capability to guarantee the infeasibility of OPF
  - New angle cut in a single linear form
  - Clique decomposition & merging
  - Parallel computation to enhance efficiency
  - Early termination with the Trust-Region Certificate