

Optimal Power Flow over Radial Networks

S. Bose, M. Chandy,
M. Farivar, D. Gayme

S. Low

Caltech

C. Clarke

Southern
California Edison

March 2012



Outline

Motivation

Semidefinite relaxation

- Bus injection model

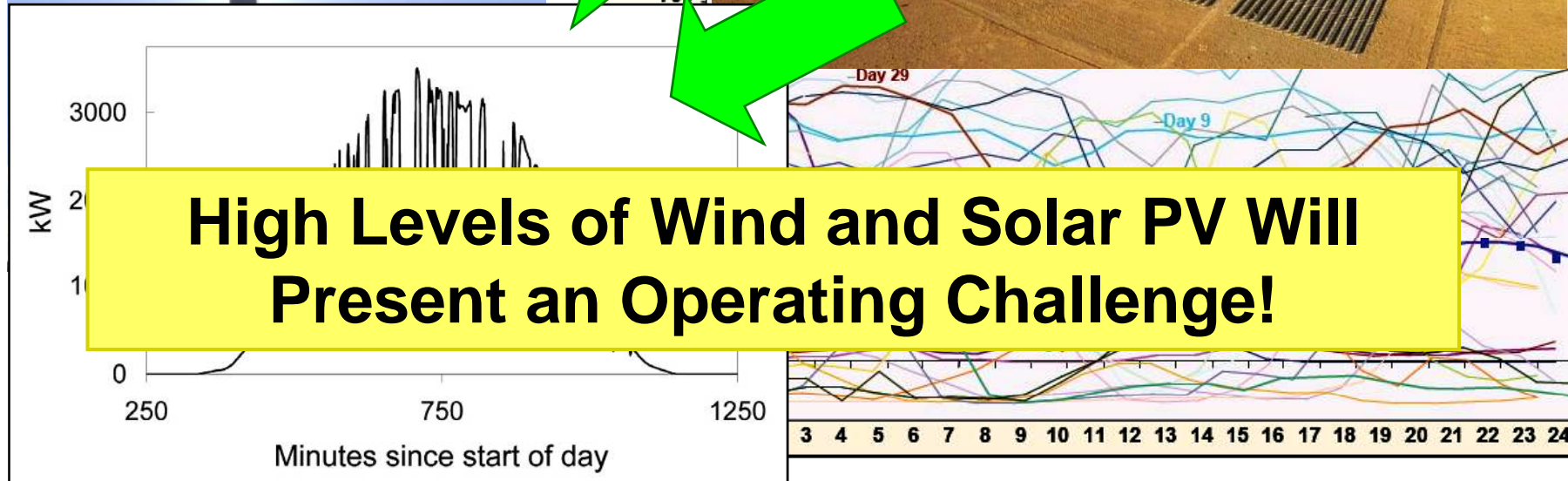
Conic relaxation

- Branch flow model





Challenge: uncertainty mgt



Source: Rosa Yang, EPRI

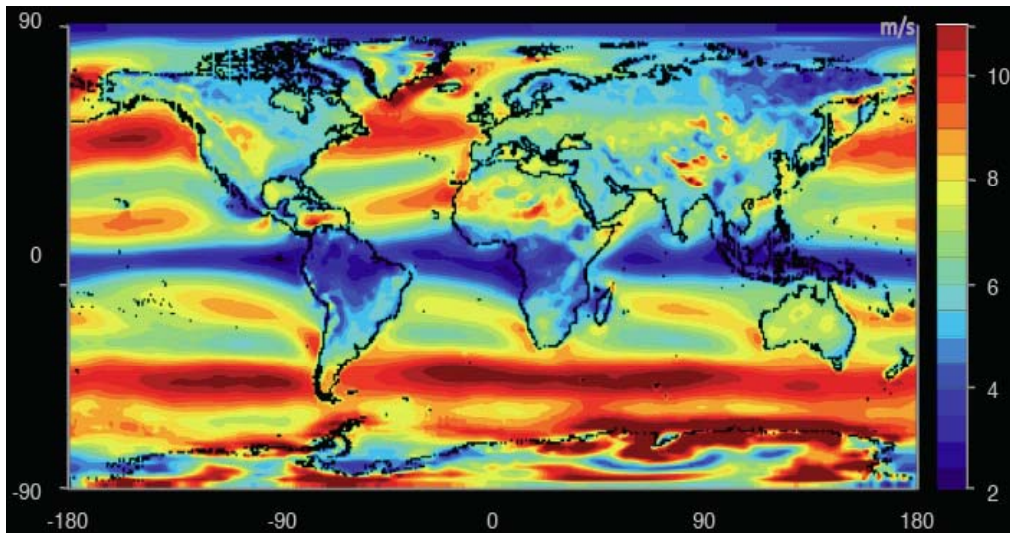


Optimal power flow (OPF)

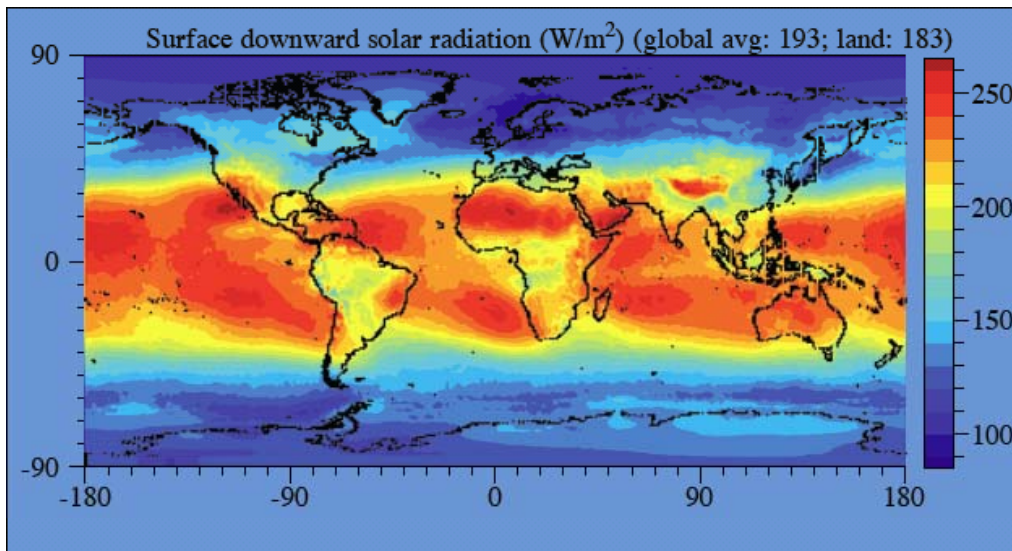
- OPF is solved routinely to determine
 - How much power to generate where
 - Market operation & pricing
 - Parameter setting, e.g. taps, VARs

- Non-convex and hard to solve
 - Huge literature since 1962
 - In practice, operators often solve linearized model and verify using AC power flow model

- Core of many problems
 - OPF, LMP, Volt/VAR, DR, EV, planning ...



**Wind power over land (exc. Antartica)
70 – 170 TW**



**Solar power over land
340 TW**

Worldwide

**energy demand:
16 TW**

**electricity demand:
2.2 TW**

**wind capacity (2009):
159 GW**

**grid-tied PV capacity (2009):
21 GW**

Source: Renewable Energy
Global Status Report, 2010
Source: M. Jacobson, 2011



Implications

Current control paradigm works well today

- Low uncertainty, few active assets to control
- Centralized, open-loop, human-in-loop, worst-case preventive
- Schedule supplies to match loads

Future needs

- **Fast computation** to cope with rapid, random, large fluctuations in supply, demand, voltage, freq
- **Simple algorithms** to scale to large networks of active DER
- **Real-time data** for adaptive control



Implications

Must close the loop

- Real-time feedback control, risk-limiting
- Driven by uncertainty of renewables

Must be scalable

- Distributed & decentralized optimization
- Orders of magnitude more endpoints that can generate, compute, communicate, actuate

Control and optimization framework

- Theoretical foundation for a holistic framework that integrates engineering + economics
- Systematic algorithm design, understandable global behavior
- Clarify ideas, explore structures, suggest direction



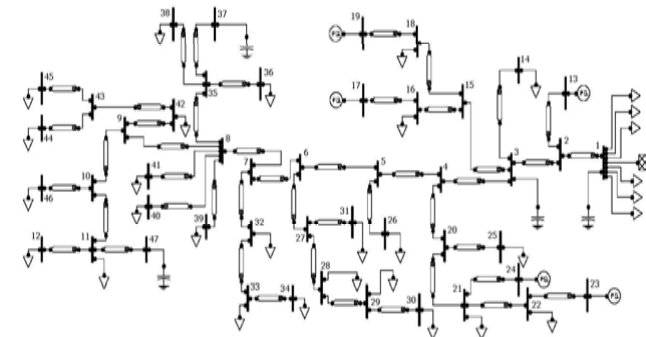
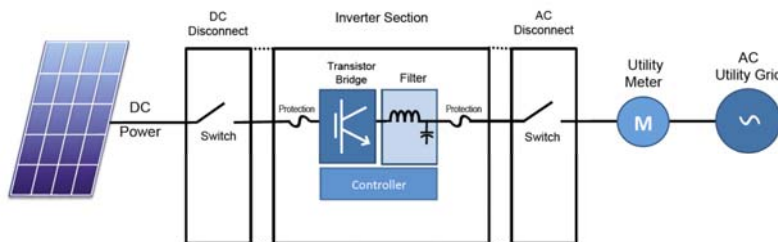
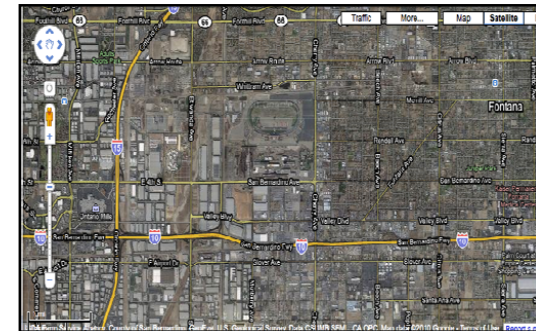
Application: Volt/VAR control

Motivation

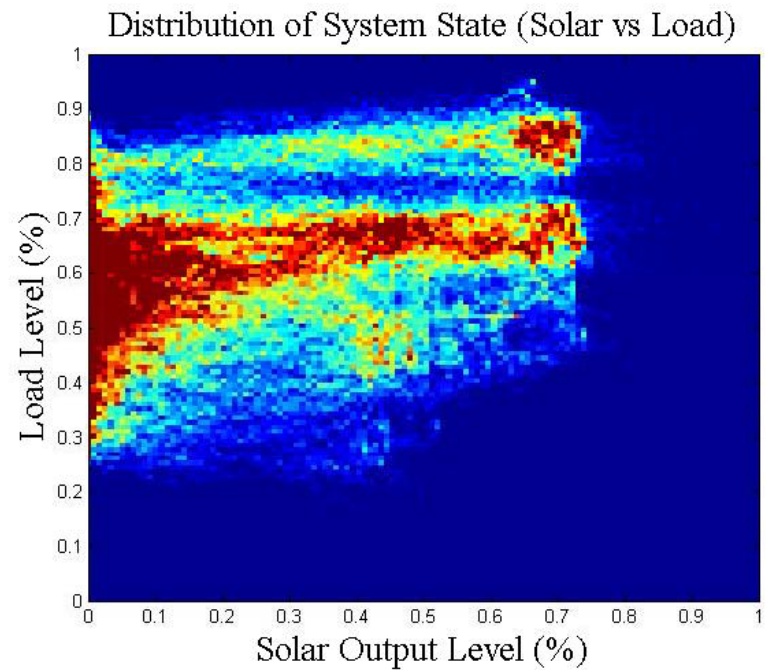
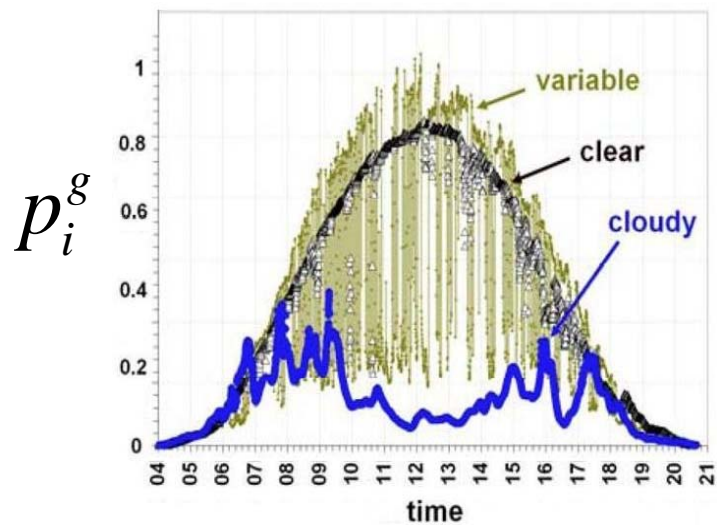
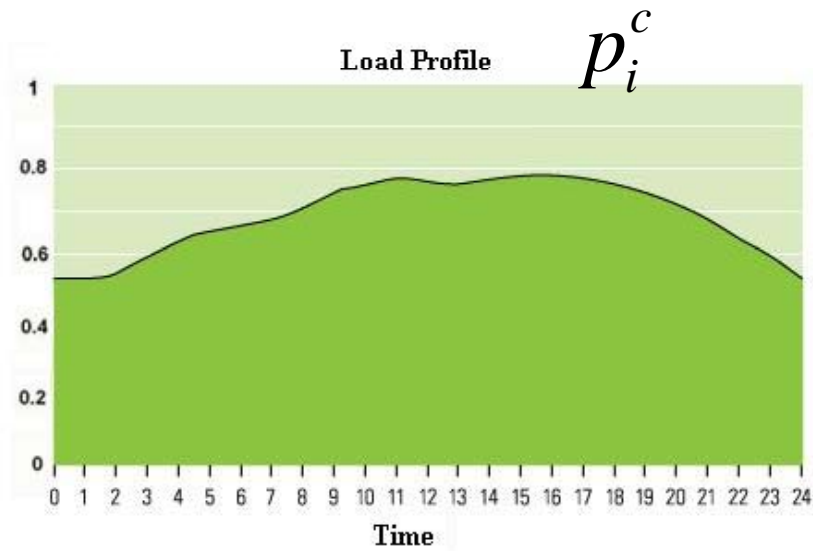
- Static capacitor control cannot cope with rapid random fluctuations of PVs on distr circuits

Inverter control

- Much faster & more frequent
- IEEE 1547 does not optimize VAR currently (unity PF)



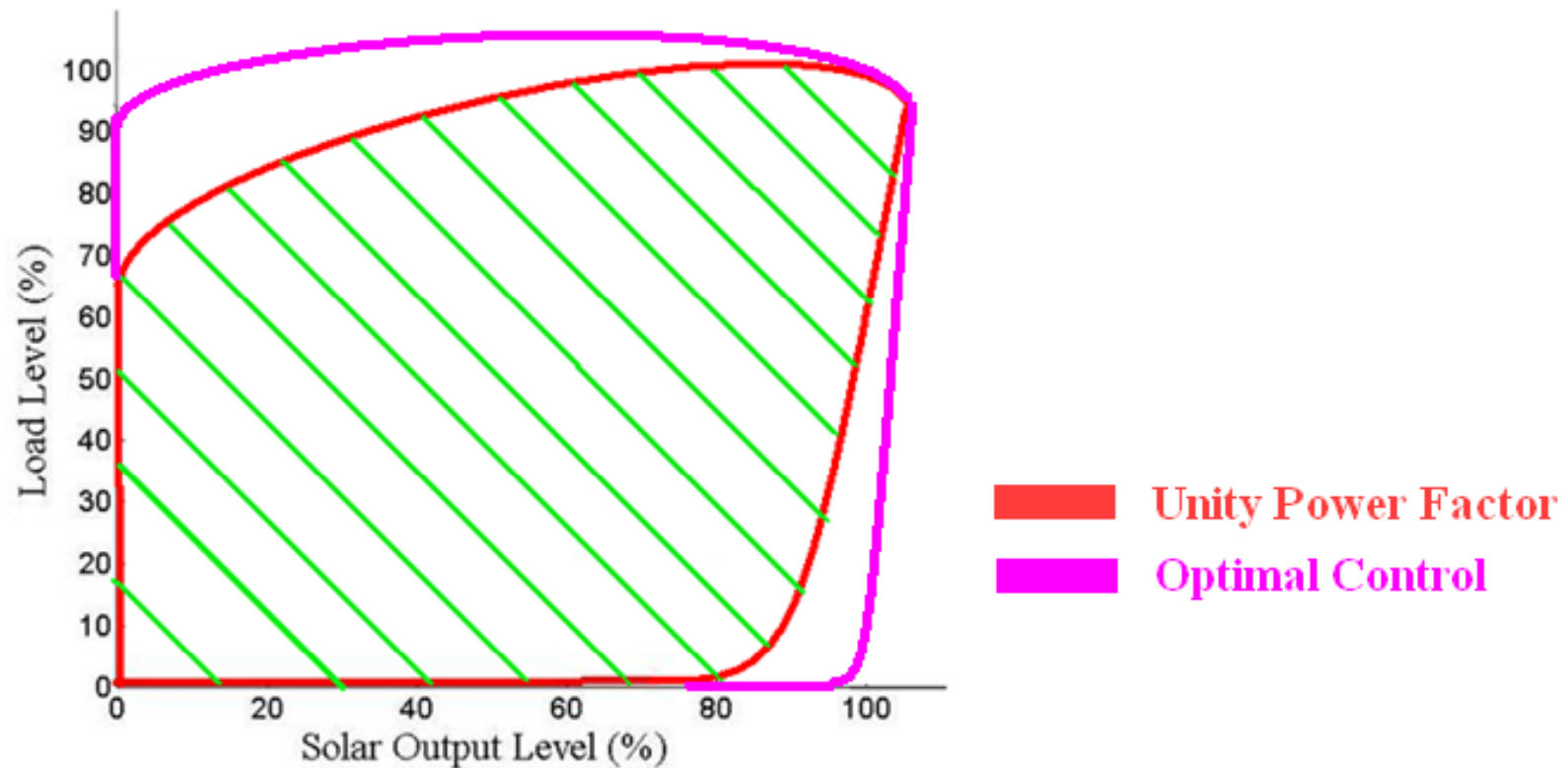
Load and Solar Variation



Empirical distribution
of (load, solar) for Calabash

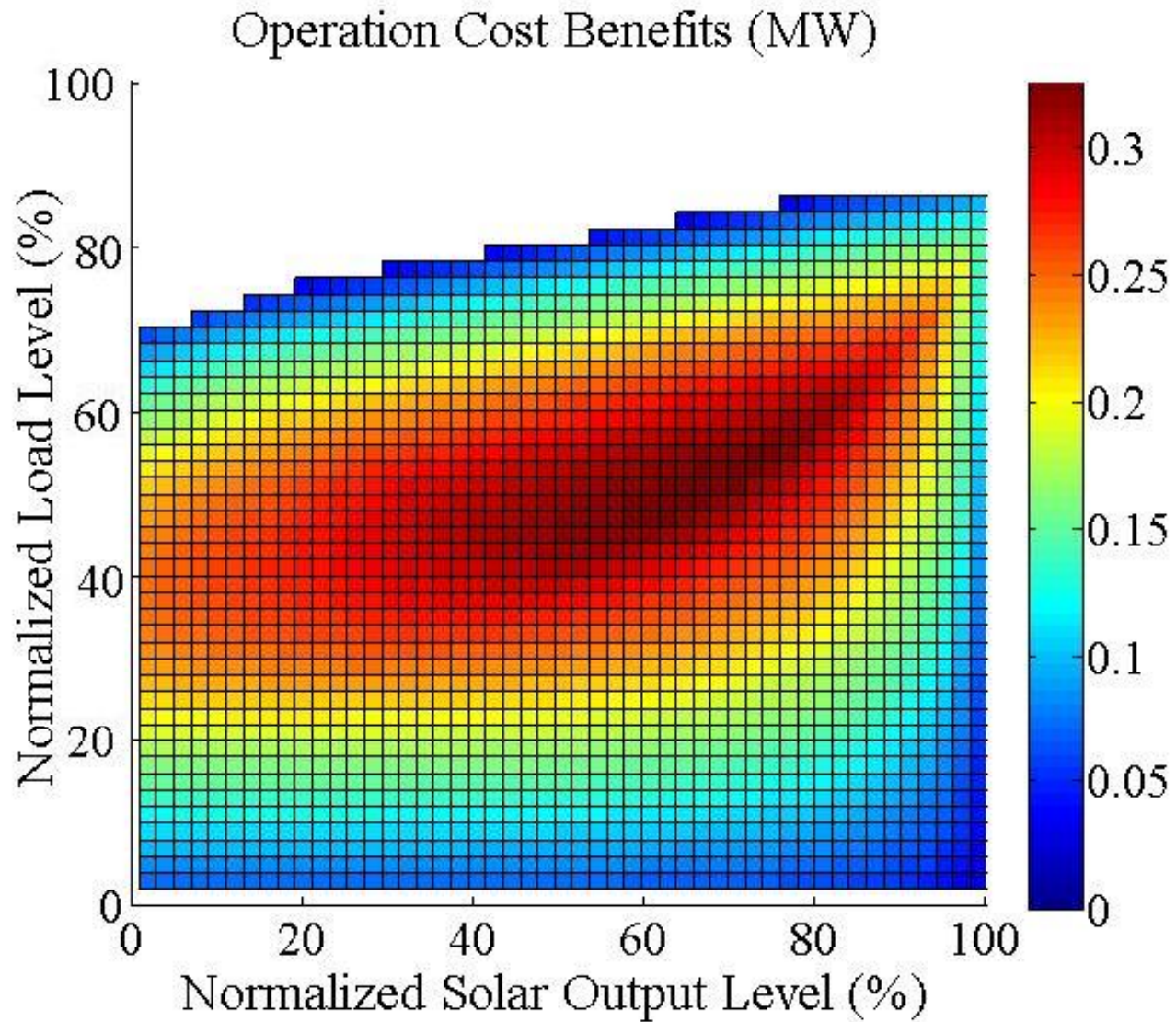
Improved reliability

(p_i^g, p_i^c) for which problem is feasible



Implication: reduced likelihood of violating voltage limits or VAR flow constraints

Energy savings



Summary

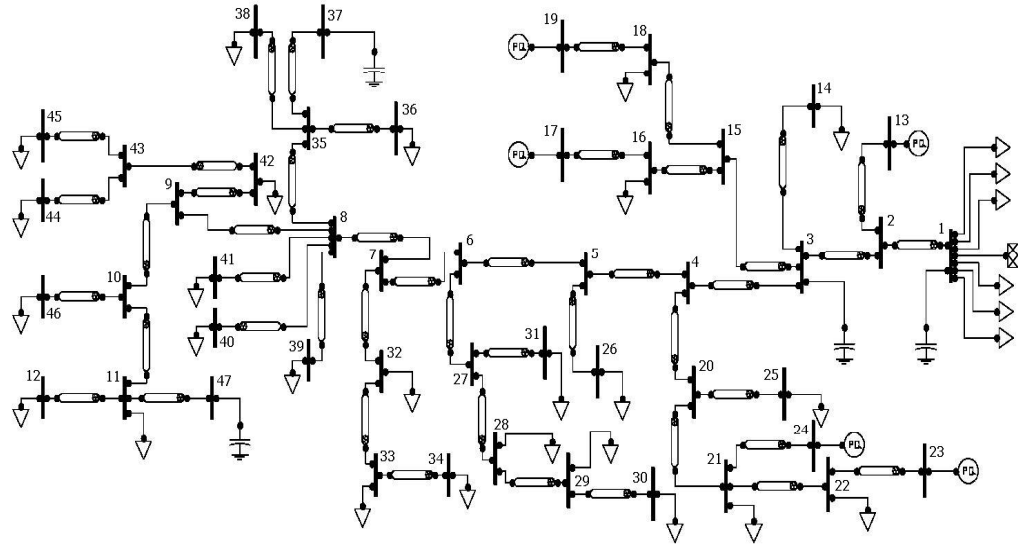
RESULTS FOR SOME VOLTAGE TOLERANCE THRESHOLDS

| Voltage Drop Tolerance(pu) | Annual Hours Saved Spending Outside Feasibility Region | Average Power Saving (%) |
|----------------------------|--|--------------------------|
| 0.03 | 842.9 | 3.93% |
| 0.04 | 160.7 | 3.67% |
| 0.05 | 14.5 | 3.62% |

- More reliable operation
- Energy savings



Key message



Radial networks computationally simple

- Exploit tree graph & convex relaxation
- Real-time scalable control promising



Outline

Motivation

Semidefinite relaxation

- Bus injection model

Conic relaxation

- Branch flow model





Optimal power flow (OPF)

Problem formulation

- Carpentier 1962

Computational techniques:

- Dommel & Tinney 1968
- Surveys: Huneault et al 1991, Momoh et al 2001, Pandya et al 2008

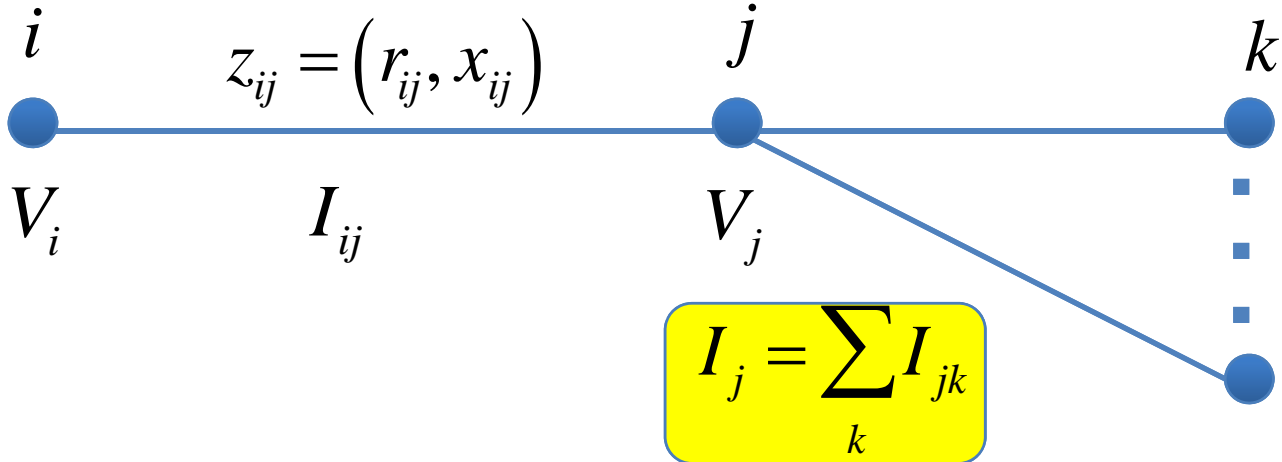
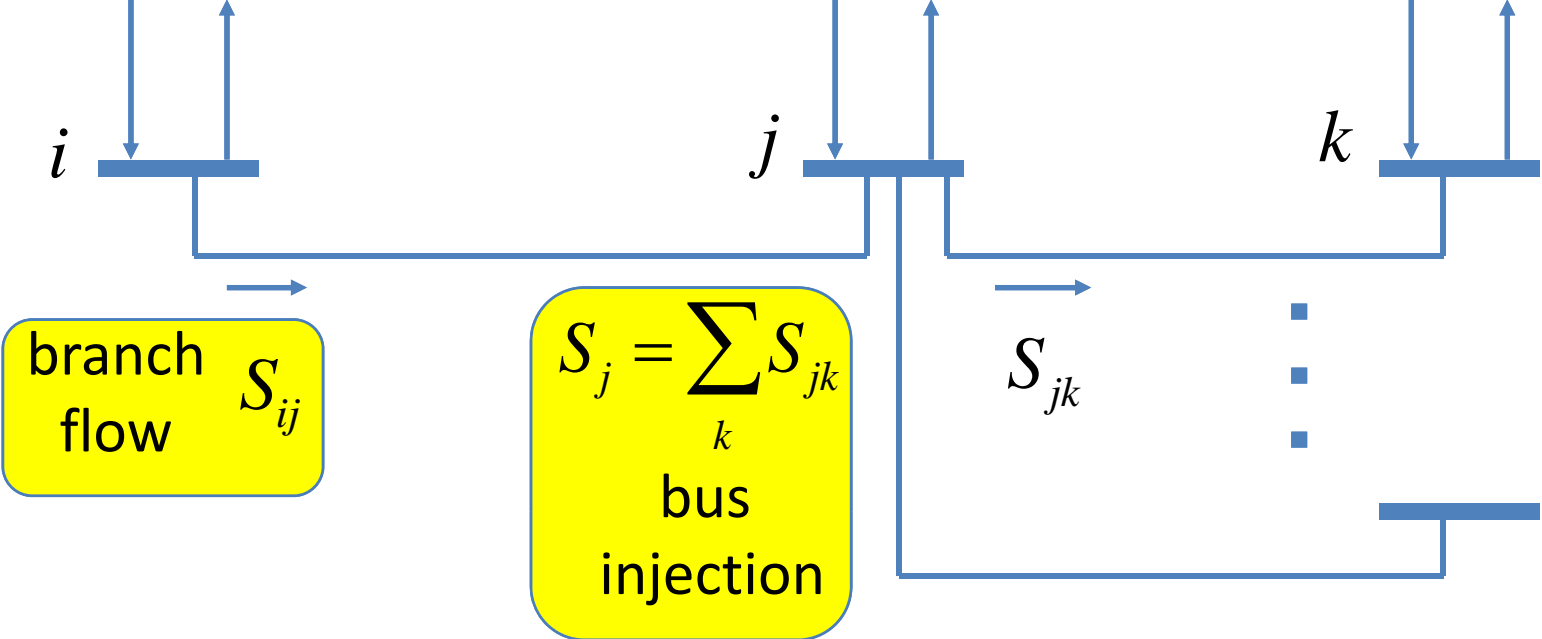
SDP formulation (bus injection model):

- Bai et al 2008, 2009, [Lavaei et al 2010](#)
- [Bose et al 2011](#), [Sojoudi et al 2011](#), Zhang et al 2011
- Lesieutre et al 2011

Branch flow model

- Baran & Wu 1989, Chiang & Baran 1990, [Farivar et al 2011](#)

Models

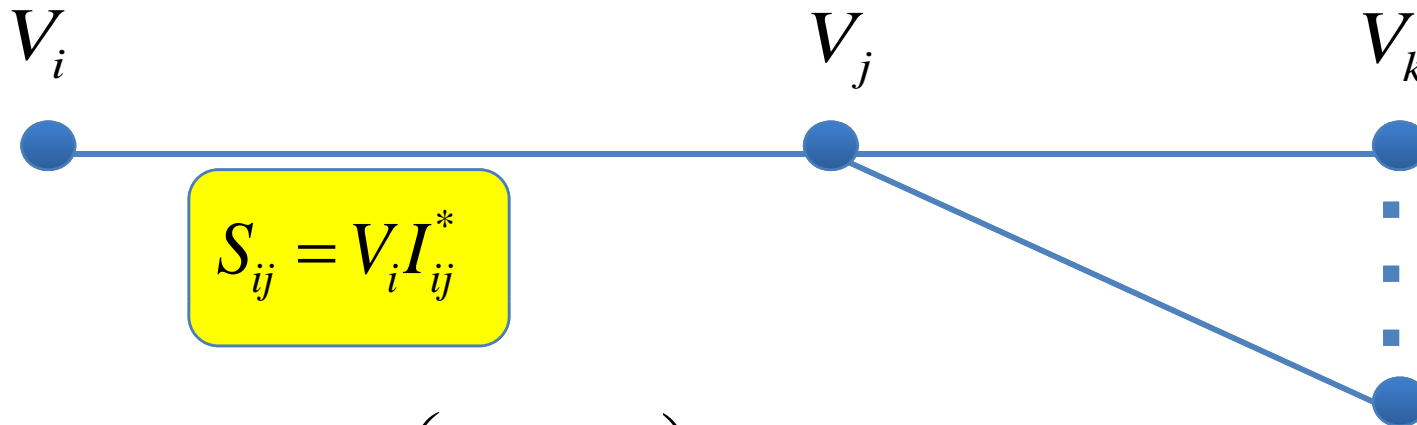


Models: Kirchoff's law

$$S_i = \sum_j S_{ij} = V_i I_i^*$$

linear relation:

$$I = YV$$



$$S_{ij} = V_i \left(\frac{V_i^* - V_j^*}{Z_{ij}^*} \right) = \frac{|V_i|^2}{Z_{ij}^*} - \frac{V_i V_j^*}{Z_{ij}^*}$$



Bus injection model

Nodes i and j are linked with an admittance $y_{ij} = g_{ij} - \mathbf{i}b_{ij}$

$$Y_{ij} = \begin{cases} y_{ii} + \sum_{j \sim i} y_{ij}, & \text{if } i = j \\ -y_{ij}, & \text{if } i \sim j \\ 0 & \text{otherwise} \end{cases}$$

- Kirchhoff's Law: $I = YV$



Classical OPF

$$\min \sum_{k \in G} f_k(P_k^g) \quad \leftarrow \text{Generation cost}$$

$$\text{over } (P_k^g, Q_k^g, V_k)$$

$$\text{subject to } \underline{P}_k^g \leq P_k^g \leq \bar{P}_k^g$$

Generation power constraints

$$\underline{Q}_k^g \leq Q_k^g \leq \bar{Q}_k^g$$

$$\underline{V}_k \leq |V_k| \leq \bar{V}_k$$

Voltage magnitude constraints

KVL/KCL

power balance \leftarrow nonconvexity



Classical OPF

In terms of V :

$$P_k = \text{tr } \Phi_k VV^*$$

$$Q_k = \text{tr } \Psi_k VV^*$$

$$\Phi_k := \begin{pmatrix} \frac{Y_k^* + Y_k}{2} \end{pmatrix}$$

$$\Psi_k := \begin{pmatrix} \frac{Y_k^* - Y_k}{2i} \end{pmatrix}$$

$$\min \sum_{k \in G} \text{tr } M_k VV^*$$

over V

$$\text{s.t. } \underline{P}_k^g - P_k^d \leq \text{tr } \Phi_k VV^* \leq \overline{P}_k^g - P_k^d$$

$$\underline{Q}_k^g - Q_k^d \leq \text{tr } \Psi_k VV^* \leq \overline{Q}_k^g - Q_k^d$$

$$\underline{V}_k^2 \leq \text{tr } J_k VV^* \leq \overline{V}_k^2$$

Key observation [Bai et al 2008]:
OPF = rank constrained SDP



Classical OPF

$$\min \sum_{k \in G} \text{tr } M_k W$$

over W positive semidefinite matrix

$$\text{s.t. } \underline{P}_k \leq \text{tr } \Phi_k W \leq \bar{P}_k$$

$$\underline{Q}_k \leq \text{tr } \Psi_k W \leq \bar{Q}_k$$

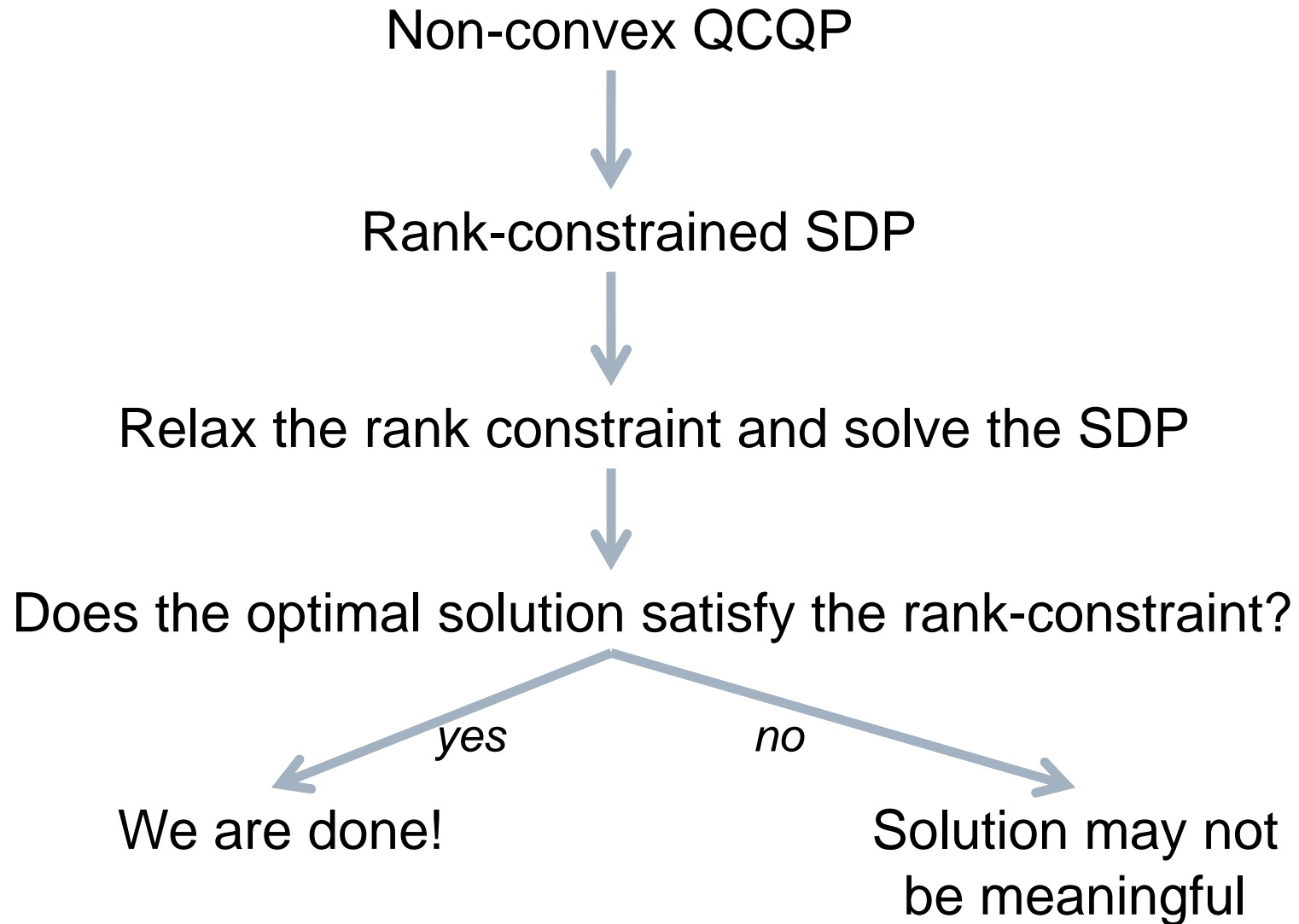
$$\underline{V}_k^2 \leq \text{tr } J_k W \leq \bar{V}_k^2$$

$$W \geq 0, \quad \cancel{\text{rank } W = 1}$$

convex relaxation: SDP



Semi-definite relaxation





SDP relaxation of OPF

$$\min \sum_{k \in G} \text{tr } M_k W$$

over W positive semidefinite matrix

$$\text{s.t. } \underline{P}_k \leq \text{tr } \Phi_k W \leq \bar{P}_k$$

$$\underline{Q}_k \leq \text{tr } \Psi_k W \leq \bar{Q}_k$$

$$\underline{V}_k^2 \leq \text{tr } J_k W \leq \bar{V}_k^2$$

$$W \geq 0$$

$$\underline{\lambda}_k, \bar{\lambda}_k$$

$$\underline{\mu}_k, \bar{\mu}_k$$

$$\underline{\gamma}_k, \bar{\gamma}_k$$

Lagrange
multipliers

$$A(\lambda_k, \mu_k, \gamma_k) := \sum_{k \in G} M_k + \sum_k (\lambda_k \Phi_k + \mu_k \Psi_k + \gamma_k J_k)$$



Sufficient condition

Theorem

If A^{opt} has rank $n-1$ then

- W^{opt} has rank 1, SDP relaxation is exact
- Duality gap is zero
- A globally optimal V^{opt} can be recovered

IEEE test systems (essentially) satisfy the condition!



OPF over radial networks

Suppose

- tree (radial) network
- no lower bounds on power injections

Theorem

A^{opt} always has rank $n-1$

- W^{opt} always has rank 1 (exact relaxation)
- OPF always has zero duality gap
- Globally optimal solvable efficiently

S. Bose, D. Gayme, S. H. Low and M. Chandy, OPF over tree networks.
Allerton 2011



OPF over radial networks

Suppose

- tree (radial) network
- no lower bounds on power injections

Theorem

A^{opt} always has rank $n-1$

- W^{opt} always has rank 1 (exact relaxation)
- OPF always has zero duality gap
- Globally optimal solvable efficiently

Also: B. Zhang and D. Tse, Allerton 2011

S. Sojoudi and J. Lavaei, submitted 2011



QCQP over tree

QCQP (C, C_k)

$$\min \quad x^* C x$$

$$\text{over } \quad x \in \mathbf{C}^n$$

$$\text{s.t.} \quad x^* C_k x \leq b_k \quad k \in K$$

graph of QCQP

$$G(C, C_k) \text{ has edge } (i, j) \iff$$

$$C_{ij} \neq 0 \text{ or } [C_k]_{ij} \neq 0 \text{ for some } k$$

QCQP over tree

$$G(C, C_k) \text{ is a tree}$$



QCQP over tree

QCQP (C, C_k)

$$\min \quad x^* C x$$

$$\text{over} \quad x \in \mathbf{C}^n$$

$$\text{s.t.} \quad x^* C_k x \leq b_k \quad k \in K$$

Semidefinite relaxation

$$\min \quad \text{tr} C W$$

$$\text{over} \quad W \geq 0$$

$$\text{s. t.} \quad \text{tr} C_k W \leq b_k \quad k \in K$$



QCQP over tree

QCQP (C, C_k)

$$\min \quad x^* C x$$

$$\text{over } \quad x \in \mathbf{C}^n$$

$$\text{s.t.} \quad x^* C_k x \leq b_k \quad k \in K$$

Key assumption

$$(i, j) \in G(C, C_k): 0 \notin \text{int conv hull} \left(C_{ij}, [C_k]_{ij}, \forall k \right)$$

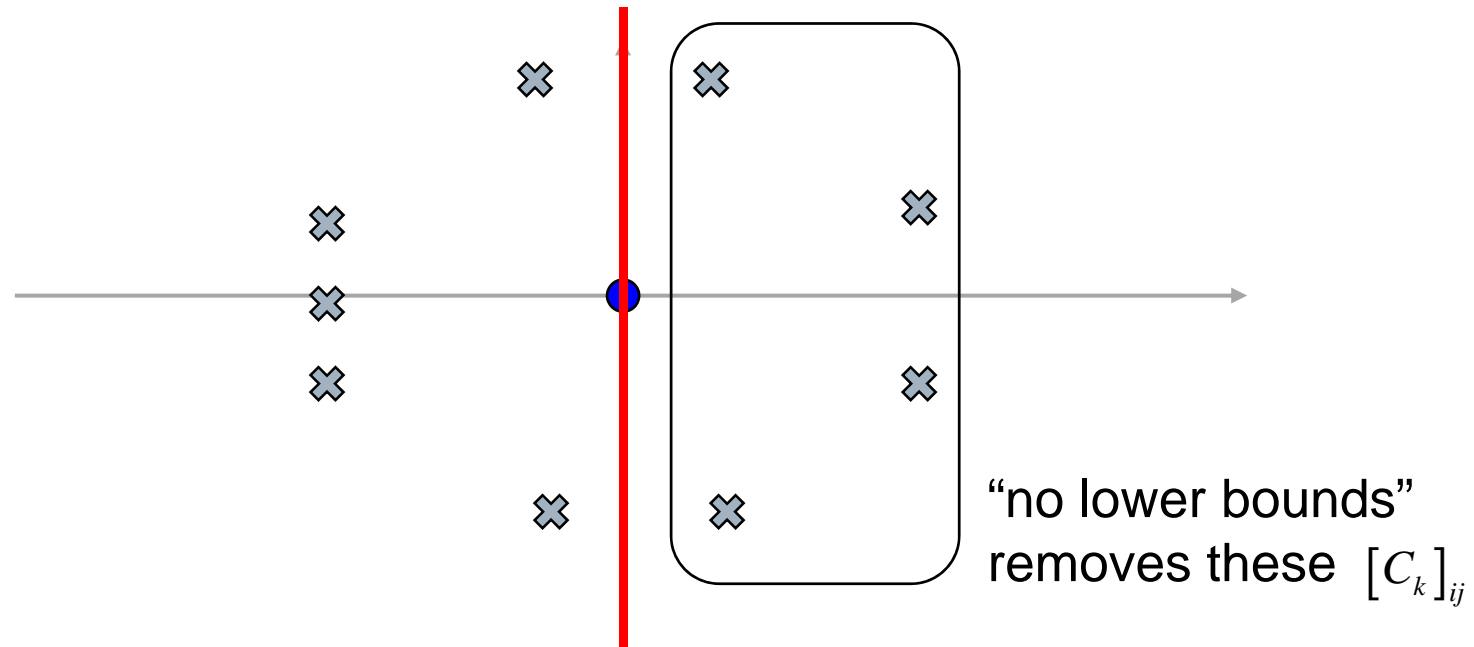
Theorem

Semidefinite relaxation is exact for
QCQP over tree

S. Bose, D. Gayme, S. H. Low and
M. Chandy, submitted March 2012



OPF over radial networks



Theorem

A^{opt} always has rank $n-1$

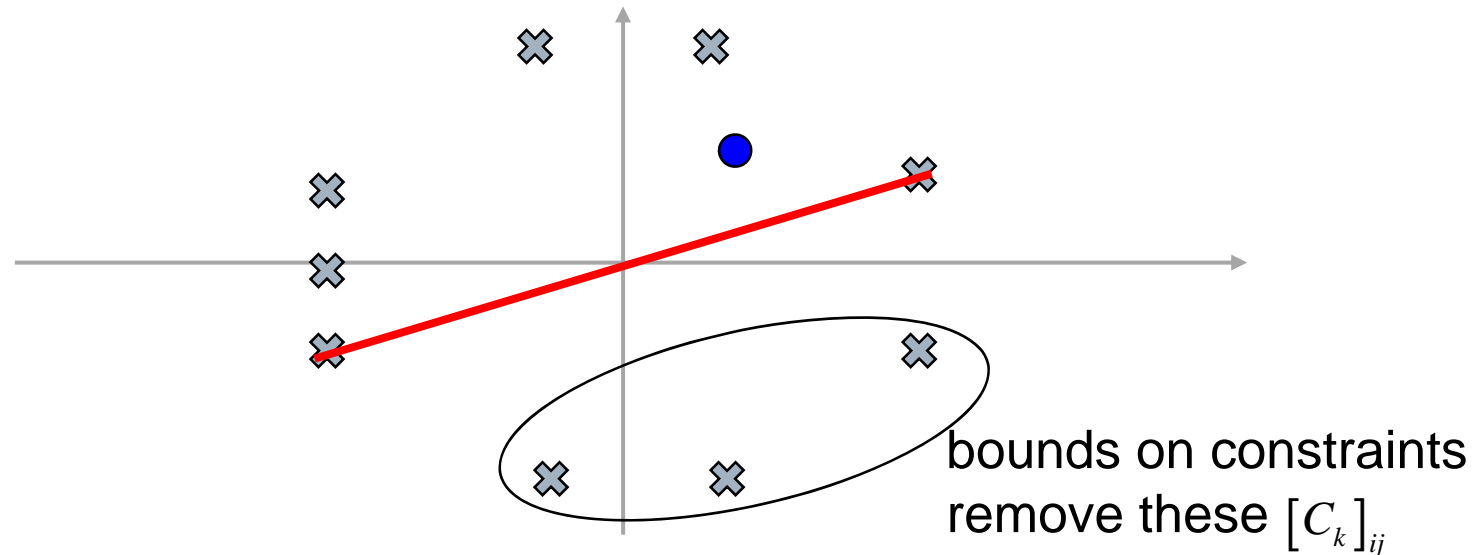
□ W^{opt} always has rank 1 (exact relaxation)

□ OPF always has zero duality gap

□ Globally optimal solvable efficiently



OPF over radial networks



Theorem

A^{opt} always has rank $n-1$

□ W^{opt} always has rank 1 (exact relaxation)

□ OPF always has zero duality gap

□ Globally optimal solvable efficiently



Outline

Motivation

Semidefinite relaxation

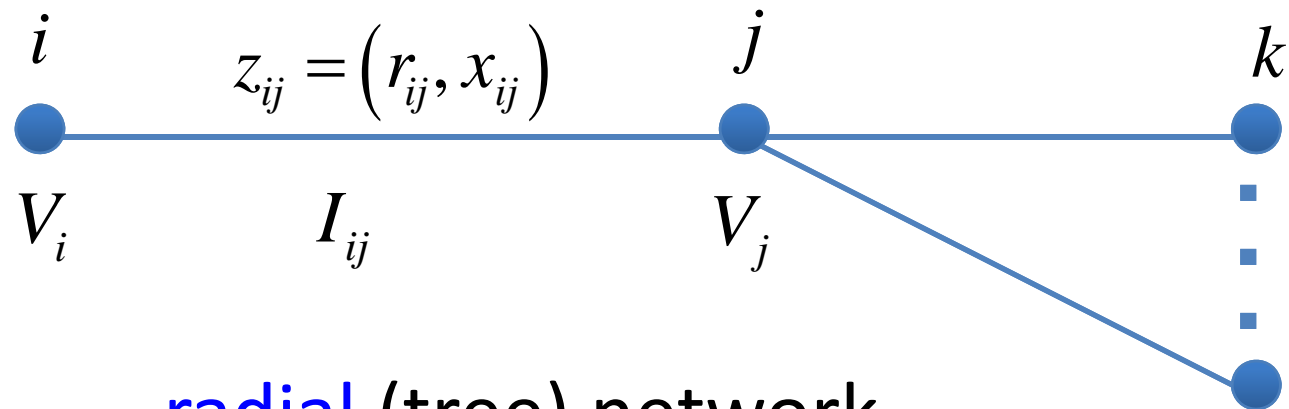
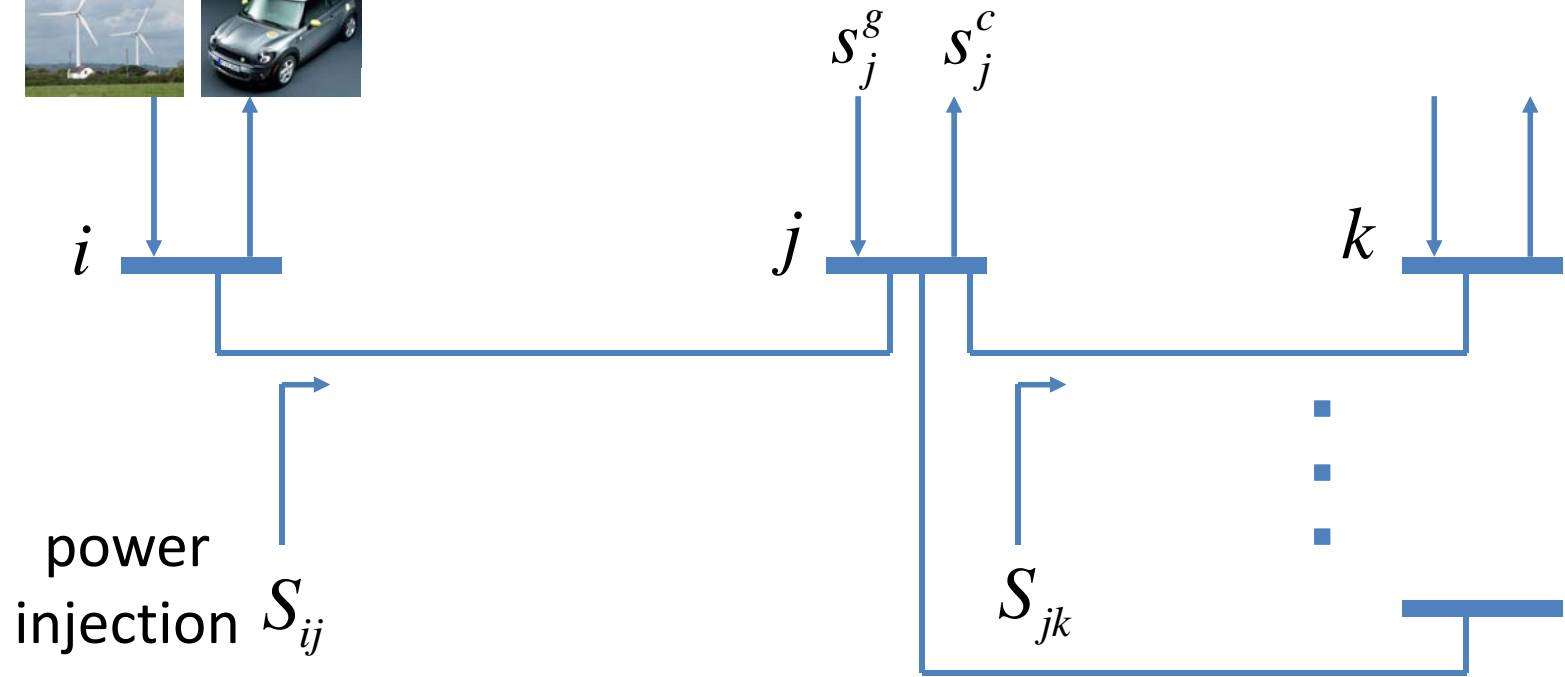
- Bus injection model

Conic relaxation

- Branch flow model

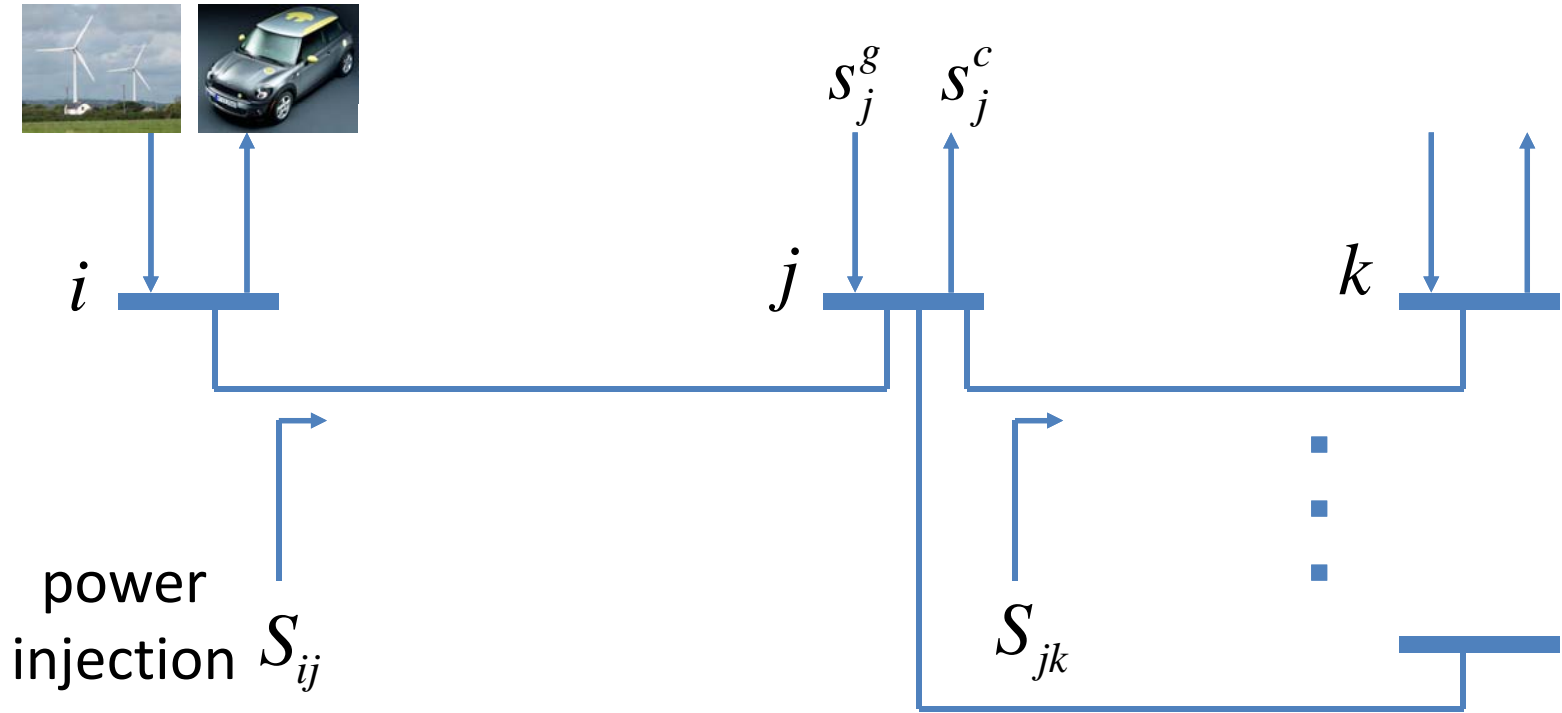


Model



radial (tree) network

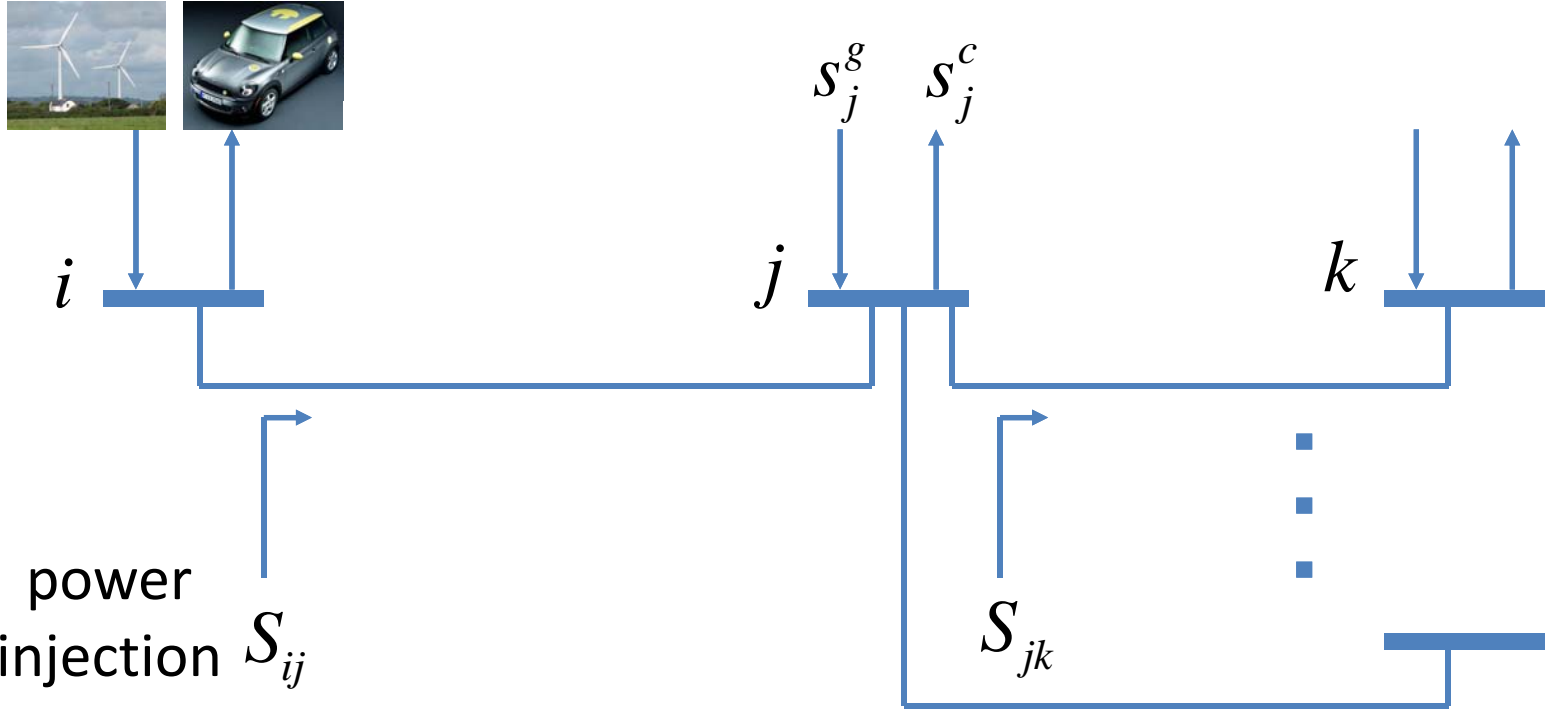
Model



Kirchoff's Law:
$$S_{ij} = \sum_{k:j \sim k} S_{jk} + z_{ij} |I_{ij}|^2 + s_j^c - s_j^g$$

line
load - gen
loss

Model



Kirchoff's Law:
$$S_{ij} = \sum_{k:j \sim k} S_{jk} + z_{ij} |I_{ij}|^2 + s_j^c - s_j^g$$

Ohm's Law:
$$V_j = V_i - z_{ij} I_{ij}$$

$$S_{ij} = V_i I_{ij}^*$$

OPF

$$\min \sum_{i \sim j} r_{ij} l_{ij} + \sum_i \alpha_i v_i$$

real power loss

CVR (conservation
voltage reduction)

$$l_{ij} := |I_{ij}|^2$$
$$v_i := |V_i|^2$$

OPF using branch flow model

$$\min \sum_{i \sim j} r_{ij} l_{ij} + \sum_i \alpha_i v_i$$

$$\text{over } (S, I, V, s^g, s^c)$$

$$\text{s. t. } \underline{s}_i^g \leq s_i^g \leq \bar{s}_i^g \quad \underline{s}_i \leq s_i^c$$

$$\underline{v}_i \leq v_i \leq \bar{v}_i$$

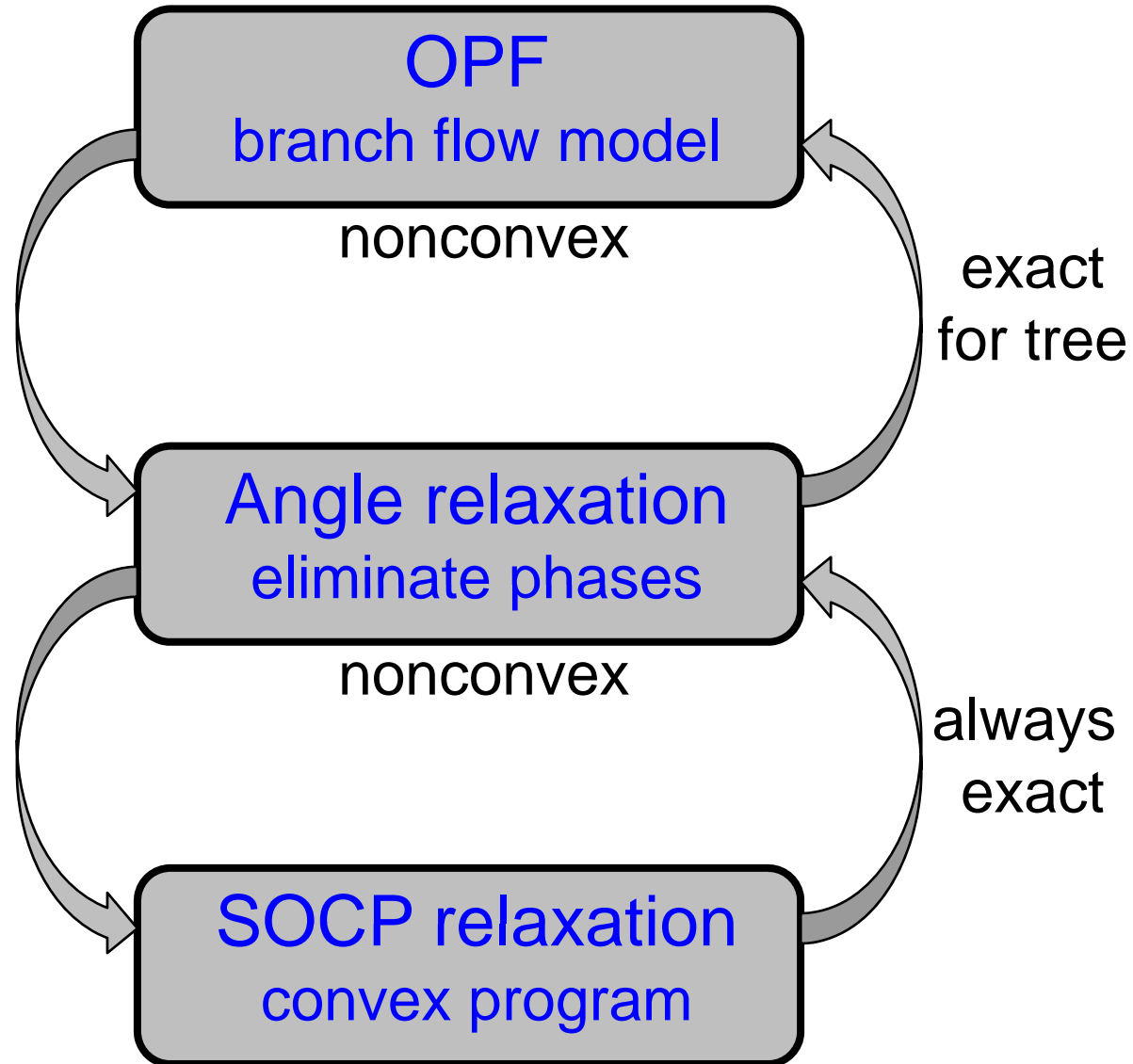
$$\text{Kirchoff's Law: } S_{ij} = \sum_{k:j \sim k} S_{jk} + z_{ij} |I_{ij}|^2 + s_j^c - s_j^g$$

$$\text{Ohm's Law: } V_j = V_i - z_{ij} I_{ij}$$

$$S_{ij} = V_i I_{ij}^*$$



Solution strategy



1. Angle relaxation

Angles of I_i, V_i eliminated !

Points relaxed to circles

demands

$$P_{ij} = \sum_{k:j \sim k} P_{jk} + r_{ij} |I_{ij}|^2 + p_j^c - p_j^g$$

$$Q_{ij} = \sum_{k:j \sim k} Q_{jk} + x_{ij} |I_{ij}|^2 + q_j^c - q_j^g$$

$$|V_i|^2 = |V_j|^2 + 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) - (r_{ij}^2 + x_{ij}^2)|I_{ij}|^2$$

$$|I_{ij}|^2 = \left(\frac{P_{ij}^2 + Q_{ij}^2}{|V_i|^2} \right)$$

Baran and Wu 1989
for radial networks

1. Angle relaxation

Angles of I_i , V_i eliminated !

Points relaxed to circles

$$P_{ij} = \sum_{k:j \sim k} P_{jk} + r_{ij} |I_{ij}|^2 + p_j^c - p_j^g \longleftarrow \text{generation}$$

$$Q_{ij} = \sum_{k:j \sim k} Q_{jk} + x_{ij} |I_{ij}|^2 + q_j^c - q_j^g \longleftarrow \text{VAR control}$$

$$|V_i|^2 = |V_j|^2 + 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) - (r_{ij}^2 + x_{ij}^2)|I_{ij}|^2$$

$$|I_{ij}|^2 = \left(\frac{P_{ij}^2 + Q_{ij}^2}{|V_i|^2} \right) \quad \underline{s}_i^g \leq s_i^g \leq \bar{s}_i^g \quad \underline{s}_i \leq s_i^c$$
$$\underline{v}_i \leq v_i \leq \bar{v}_i$$

1. Angle relaxation

$$l_{ij} := |I_{ij}|^2$$

$$v_i := |V_i|^2$$

- Linear objective
- Linear constraints
- Quadratic equality

$$\min \sum_{i \sim j} r_{ij} l_{ij} + \sum_i \alpha_i v_i$$

$$\text{over } (S, l, v, s^g, s^c)$$

$$\text{s. t. } P_{ij} = \sum_{k:j \sim k} P_{jk} + r_{ij} l_{ij} + p_j^c - p_j^g$$

$$Q_{ij} = \sum_{k:j \sim k} Q_{jk} + x_{ij} l_{ij} + q_j^c - q_j^g$$

$$v_i = v_j + 2(r_{ij} P_{ij} + x_{ij} Q_{ij}) - (r_{ij}^2 + x_{ij}^2) l_{ij}$$

$$l_{ij} = \left(\frac{P_{ij}^2 + Q_{ij}^2}{v_i} \right), \quad \underline{s}_i \leq s_i^g \leq \bar{s}_i$$

$$\underline{v}_i \leq v_i \leq \bar{v}_i, \quad \underline{s}_i \leq \bar{s}_i^c$$

2. SOCP relaxation

$$\min \sum_{i \sim j} r_{ij} l_{ij} + \sum_i \alpha_i v_i$$

$$\text{over } (S, l, v, s^g, s^c)$$

$$\text{s. t. } P_{ij} = \sum_{k:j \sim k} P_{jk} + r_{ij} l_{ij} + p_j^c - p_j^g$$

$$Q_{ij} = \sum_{k:j \sim k} Q_{jk} + x_{ij} l_{ij} + q_j^c - q_j^g$$

$$v_i = v_j + 2(r_{ij} P_{ij} + x_{ij} Q_{ij}) - (r_{ij}^2 + x_{ij}^2) l_{ij}$$

Quadratic inequality

$$l_{ij} \geq \left(\frac{P_{ij}^2 + Q_{ij}^2}{v_i} \right)$$

$$\underline{s}_i \leq s_i^g \leq \bar{s}_i$$

$$\underline{v}_i \leq v_i \leq \bar{v}_i,$$

$$\underline{s}_i \leq s_i^c$$

OPF over radial networks

Theorem

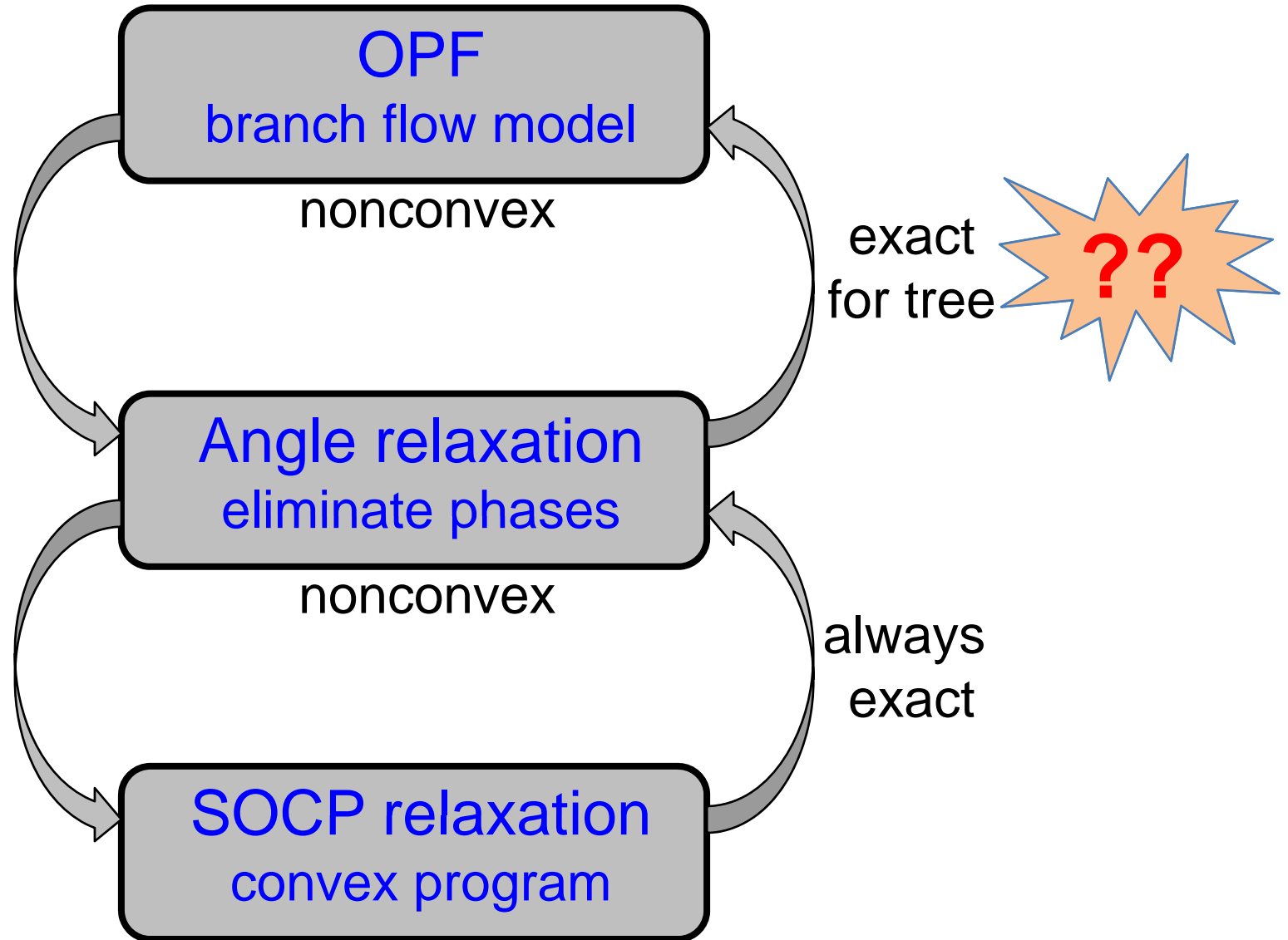
Both relaxation steps are exact

- SOCP relaxation is (convex and) exact
- Phase angles can be uniquely determined

Original OPF problem has zero duality gap

What about mesh networks ??

Solution strategy



OPF using branch flow model

$$\min \sum_{i \sim j} r_{ij} l_{ij} + \sum_i \alpha_i v_i$$

$$\text{over } (S, I, V, s^g, s^c)$$

$$\text{s. t. } \underline{s}_i^g \leq s_i^g \leq \bar{s}_i^g \quad \underline{s}_i \leq s_i^c$$

$$\underline{v}_i \leq v_i \leq \bar{v}_i$$

$$\text{Kirchoff's Law: } S_{ij} = \sum_{k:j \sim k} S_{jk} + z_{ij} |I_{ij}|^2 + s_j^c - s_j^g$$

$$\text{Ohm's Law: } V_j = V_i - z_{ij} I_{ij}$$

$$S_{ij} = V_i I_{ij}^*$$



Convexification of mesh networks

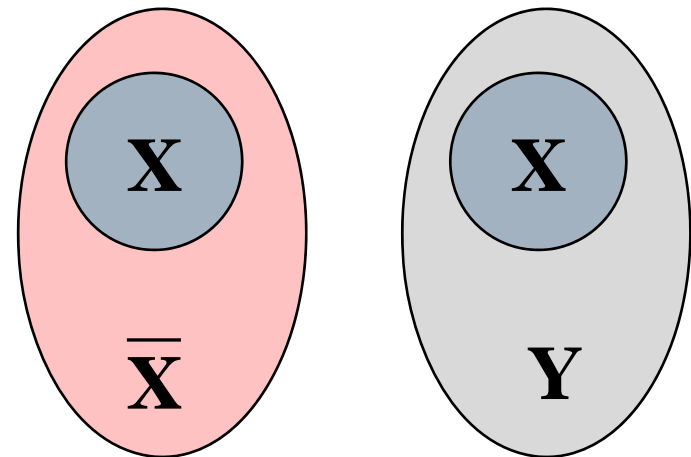
$$\text{OPF} \quad \min_{x,s} f(\hat{h}(x)) \quad \text{s.t.} \quad x \in \mathbf{X}, s \in \mathbf{S}$$

$$\text{OPF-ar} \quad \min_{x,s} f(\hat{h}(x)) \quad \text{s.t.} \quad x \in \mathbf{Y}, s \in \mathbf{S}$$

$$\text{OPF-ps} \quad \min_{x,s,\phi} f(\hat{h}(x)) \quad \text{s.t.} \quad x \in \overline{\mathbf{X}}, s \in \mathbf{S}$$

Theorem

- $\overline{\mathbf{X}} = \mathbf{Y}$
- Need phase shifters only outside spanning tree





Convexification of mesh networks

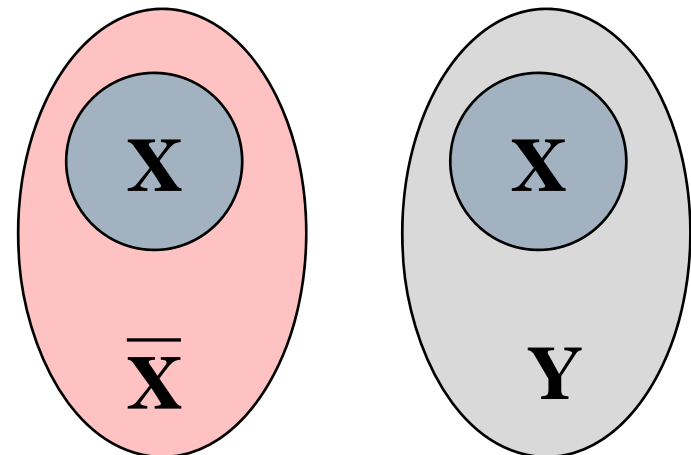
$$\text{OPF} \quad \min_{x,s} f(\hat{h}(x)) \quad \text{s.t.} \quad x \in \mathbf{X}$$

$$\text{OPF-ar} \quad \min_{x,s} f(\hat{h}(x)) \quad \text{s.t.} \quad x \in \mathbf{Y}$$

$$\text{OPF-ps} \quad \min_{x,s,\phi} f(\hat{h}(x)) \quad \text{s.t.} \quad x \in \overline{\mathbf{X}}$$

Theorem

- $\overline{\mathbf{X}} = \mathbf{Y}$
- Need phase shifters only outside spanning tree





Key message

Radial networks computationally simple

- Exploit tree graph & convex relaxation
- Real-time scalable control promising

Mesh networks can be **convexified**

- Design for simplicity
- Need few phase shifters (sparse topology)