

Moment Relaxations of Optimal Power Flow Problems: Beyond the Convex Hull

Daniel Molzahn

Argonne National Laboratory

Cédric Josz

*LAAS, French National
Scientific Research Center*

Ian Hiskens

University of Michigan

GlobalSIP

December 8, 2016

Optimal Power Flow (OPF) Problem

- Optimization used to determine system operation
 - Minimize generation cost while satisfying **physical laws** and **engineering constraints**
 - Yields generator dispatches, line flows, etc.
- Many related problems:
 - State estimation, unit commitment, transmission switching, contingency analysis, voltage stability margins, etc.

“Today, 50 years after the problem was formulated, **we still do not have a fast, robust solution technique** for the full ACOPF.”

R.P. O’Neill, Chief Economic Advisor, US Federal Energy Regulatory Commission, 2013.

Classical OPF Problem

$$\min_{V_d, V_q} \sum_{k \in \mathcal{G}} (c_{2k} P_{Gk}^2 + c_{1k} P_{Gk} + c_{0k})$$

Generation Cost

subject to $P_{Gk}^{\min} \leq P_{Gk} \leq P_{Gk}^{\max}$

Engineering Constraints

$$Q_{Gk}^{\min} \leq Q_{Gk} \leq Q_{Gk}^{\max}$$

$$(V_k^{\min})^2 \leq V_{dk}^2 + V_{qk}^2 \leq (V_k^{\max})^2$$

$$|S_{lm}| \leq S_{lm}^{\max}$$

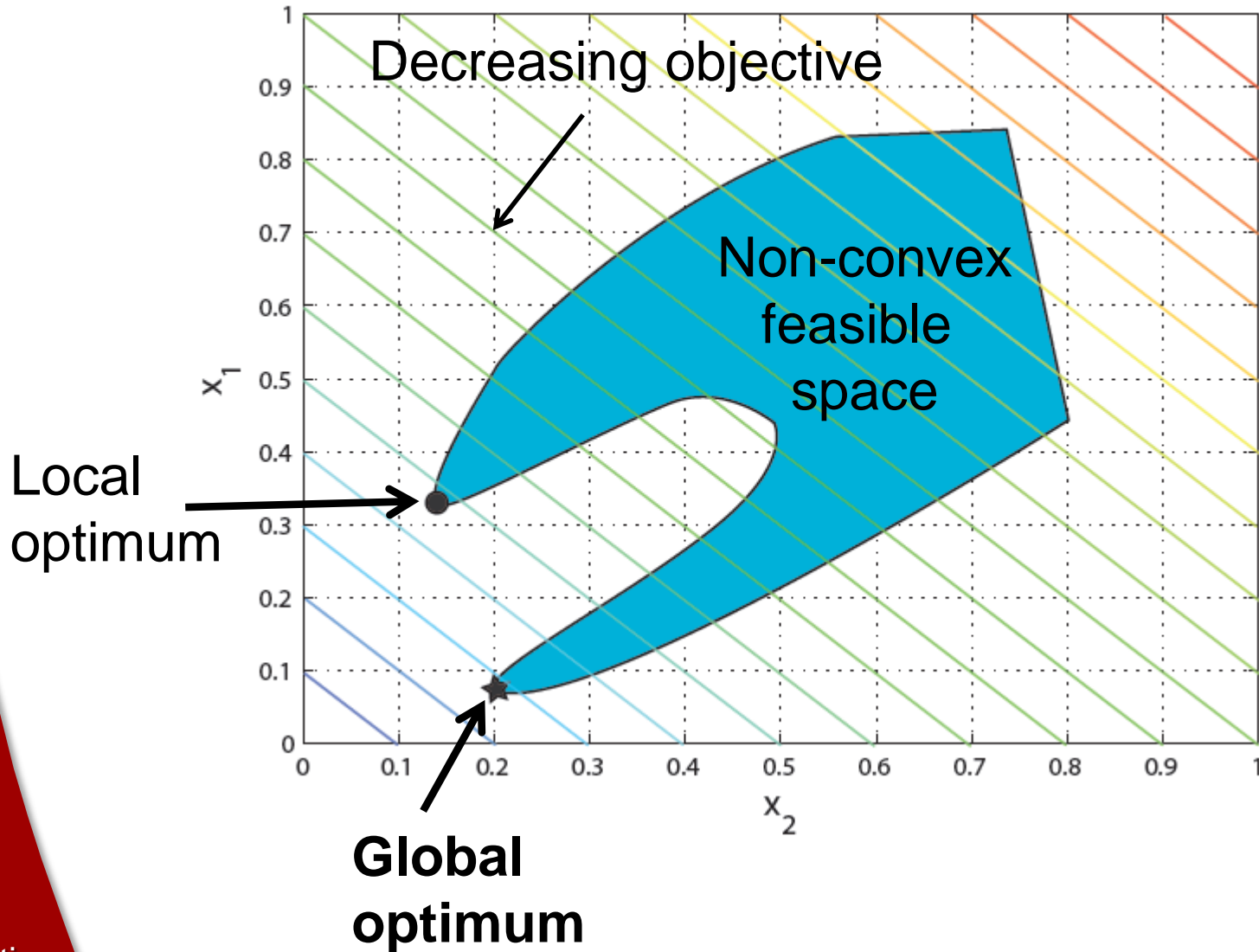
Physical Laws

$$P_{Gk} - P_{Dk} = V_{dk} \sum_{i=1}^n (G_{ik} V_{di} - B_{ik} V_{qi}) + V_{qk} \sum_{i=1}^n (B_{ik} V_{di} + G_{ik} V_{qi})$$

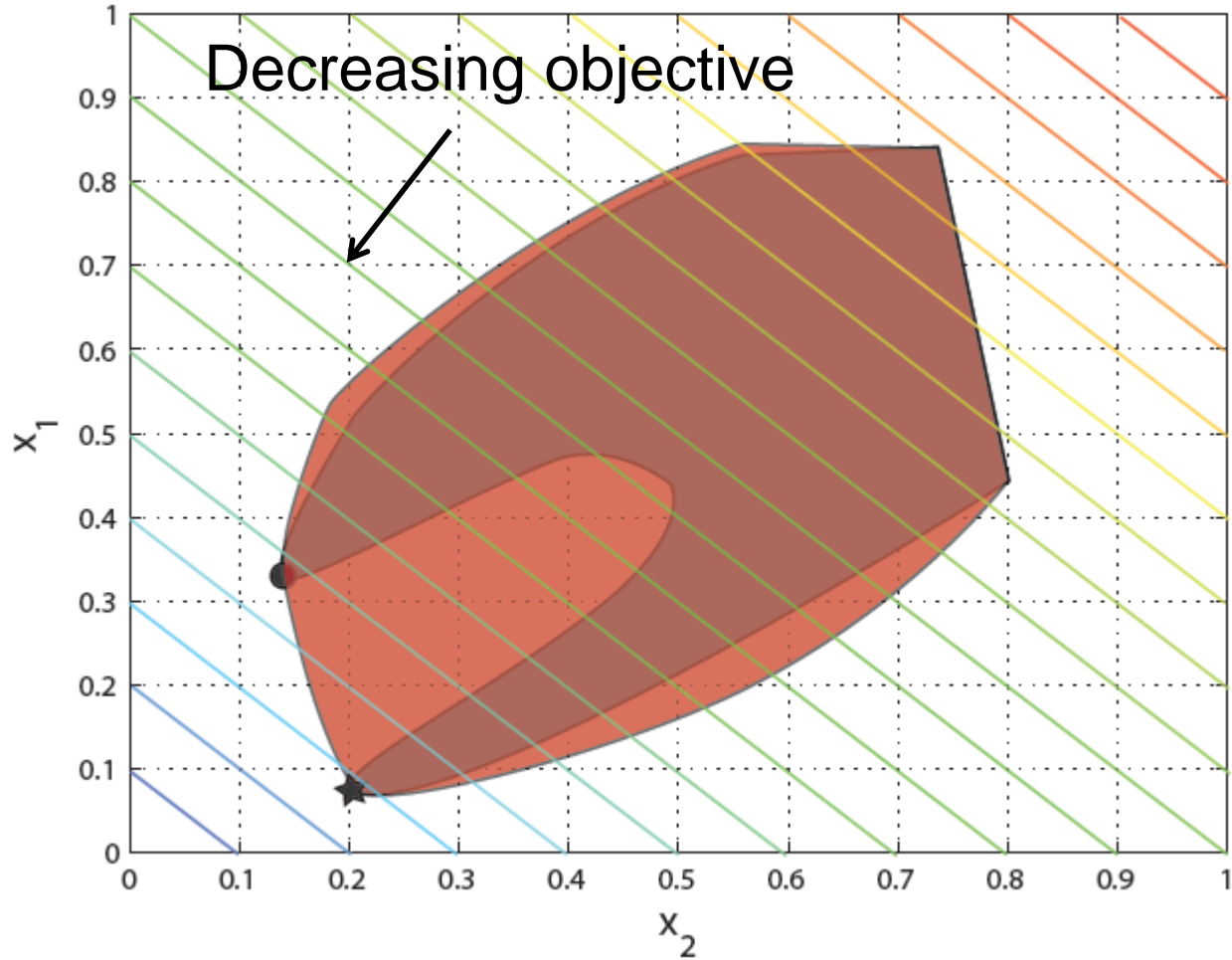
$$Q_{Gk} - Q_{Dk} = V_{dk} \sum_{i=1}^n (-B_{ik} V_{di} - G_{ik} V_{qi}) + V_{qk} \sum_{i=1}^n (G_{ik} V_{di} - B_{ik} V_{qi})$$

Rectangular voltage coordinates: $V = V_d + jV_q$, $V_d, V_q \in \mathbb{R}^n$

Convex Relaxation

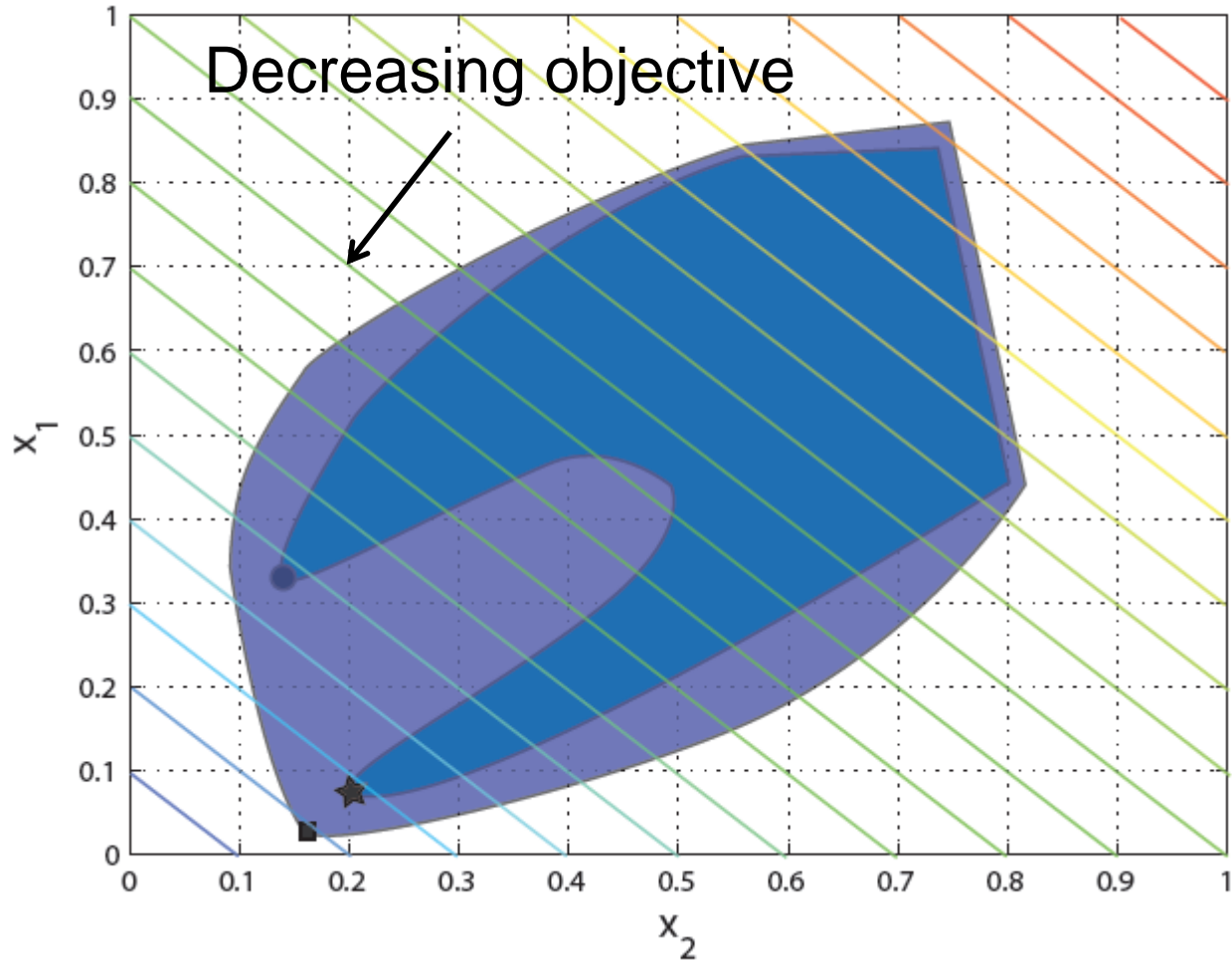


Convex Relaxation



Relaxation finds global optimum

Convex Relaxation



Relaxation does not find global optimum

Semidefinite Programming

- Convex optimization
- Interior point methods solve for the **global optimum** in polynomial time

$$\min_{\mathbf{W}} \text{trace}(\mathbf{B}\mathbf{W})$$

subject to

$$\text{trace}(\mathbf{A}_i \mathbf{W}) = c_i$$

$$\mathbf{W} \succeq 0$$

where \mathbf{B} and \mathbf{A}_i are specified symmetric matrices

$$\text{Recall: } \text{trace}(\mathbf{A}^T \mathbf{W}) = \mathbf{A}_{11} \mathbf{W}_{11} + \mathbf{A}_{12} \mathbf{W}_{12} + \dots + \mathbf{A}_{nn} \mathbf{W}_{nn}$$

$$\mathbf{W} \succeq 0 \text{ if and only if } \text{eig}(\mathbf{W}) \geq 0$$

Moment Relaxations

Preliminaries

- Exploit moment-based semidefinite relaxations for **polynomial optimization problems** [Lasserre '01]

$$\begin{array}{l} \min_x f(x) \quad \text{subject to} \\ g_i(x) \geq 0 \end{array}$$

where $f(x)$ and $g_i(x)$ are **polynomial** functions of $x = [V_{d1} \ V_{d2} \ \dots \ V_{dn} \ V_{q1} \ V_{q2} \ \dots \ V_{qn}]^T$

- Define linear functional L_y with polynomial argument $h(x)$

$$h(x) = \sum_{\alpha \in \mathbb{N}^{2n}} h_\alpha x^\alpha$$

$$L_y \{h(x)\} = \sum_{\alpha \in \mathbb{N}^{2n}} h_\alpha y_\alpha$$

- Define vector x_d containing all monomials up to order d

$$x_d = \left[1 \ V_{d1} \ \dots \ V_{qn} \ V_{d1}^2 \ V_{d1}V_{d2} \ \dots \ V_{qn}^2 \ V_{d1}^3 \ V_{d1}^2V_{d2} \ \dots \ V_{qn}^d \right]^T$$

Order-d Moment Relaxation

$$\min_x f(x) \quad \text{s.t.} \\ g_i(x) \geq 0$$

↓ Add redundant constraints

$$\min_x f(x) \quad \text{s.t.} \\ g_i(x) x_{d-1} x_{d-1}^\top \succeq 0 \\ x_d x_d^\top \succeq 0$$

↗ Convex relaxation via “lifting”

$$\min_y L_y \{f(x)\} \quad \text{s.t.} \\ L_y \{g_i(x) x_{d-1} x_{d-1}^\top\} \succeq 0 \\ L_y \{x_d x_d^\top\} \succeq 0$$

[Lasserre '01, Parillo '03]

- Increasing d yields a **tighter** relaxation but has a **computational cost**
- Recover global optimum if $\text{rank}(L_y \{x x^\top\}) = 1$



Illustrating the Capabilities of the Moment Relaxations

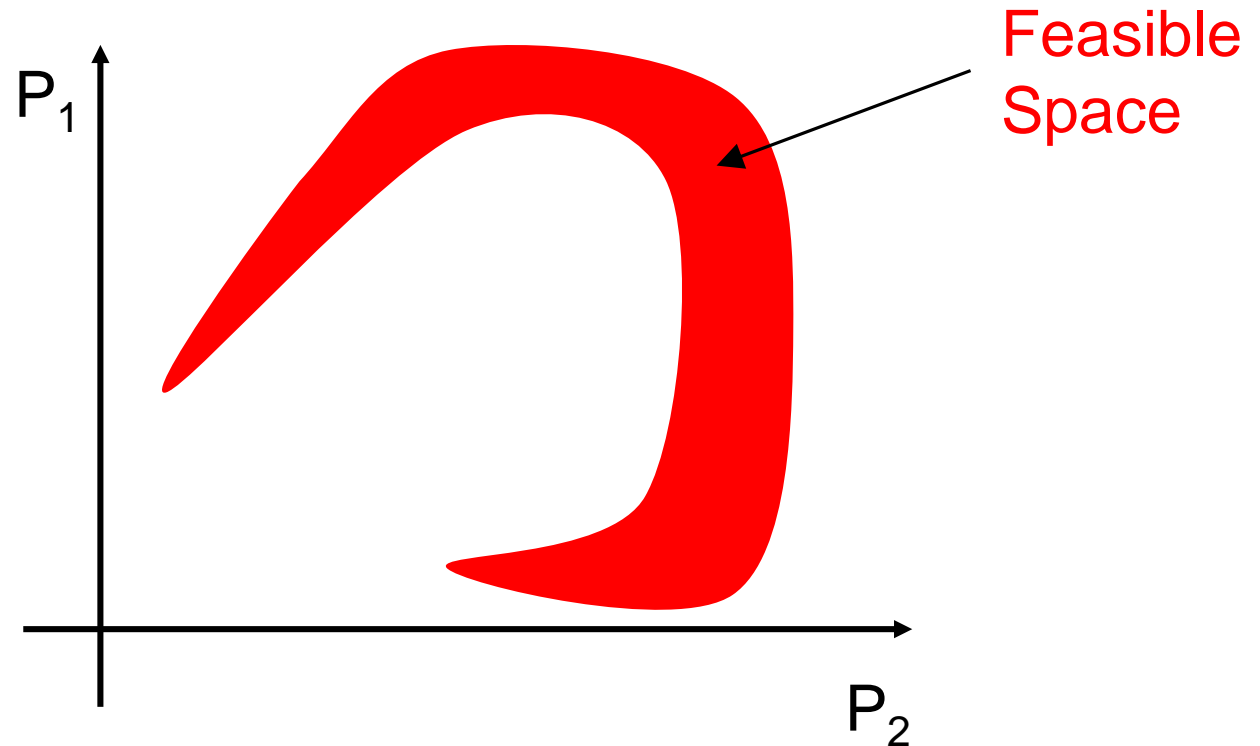
Test Case Results

- Second- and third-order moment-based relaxations globally solve many small OPF problems [M. & Hiskens '14]

Case	Number of Buses	Parameters	Minimum Order
Lesieutre, Molzahn, Borden, & DeMarco '11	3	50 MVA line limit	2
Molzahn, Lesieutre, & DeMarco '14	3	100 MVA line limit	2
Bukhsh, Grothey, McKinnon & Trodden '13	3	$P_{D3} = 17.17$ per unit	2
Lesieutre & Hiskens '05	5		2
Bukhsh, Grothey, McKinnon & Trodden '13	5	$-50 \leq Q_5^{\min} \leq -27.36$ MVAR	2
		$-27.35 \leq Q_5^{\min} \leq -27.04$ MVAR	3
		$-27.03 \leq Q_2^{\min} \leq 0$ MVAR	2
Bukhsh, Grothey, McKinnon & Trodden '13	9		2

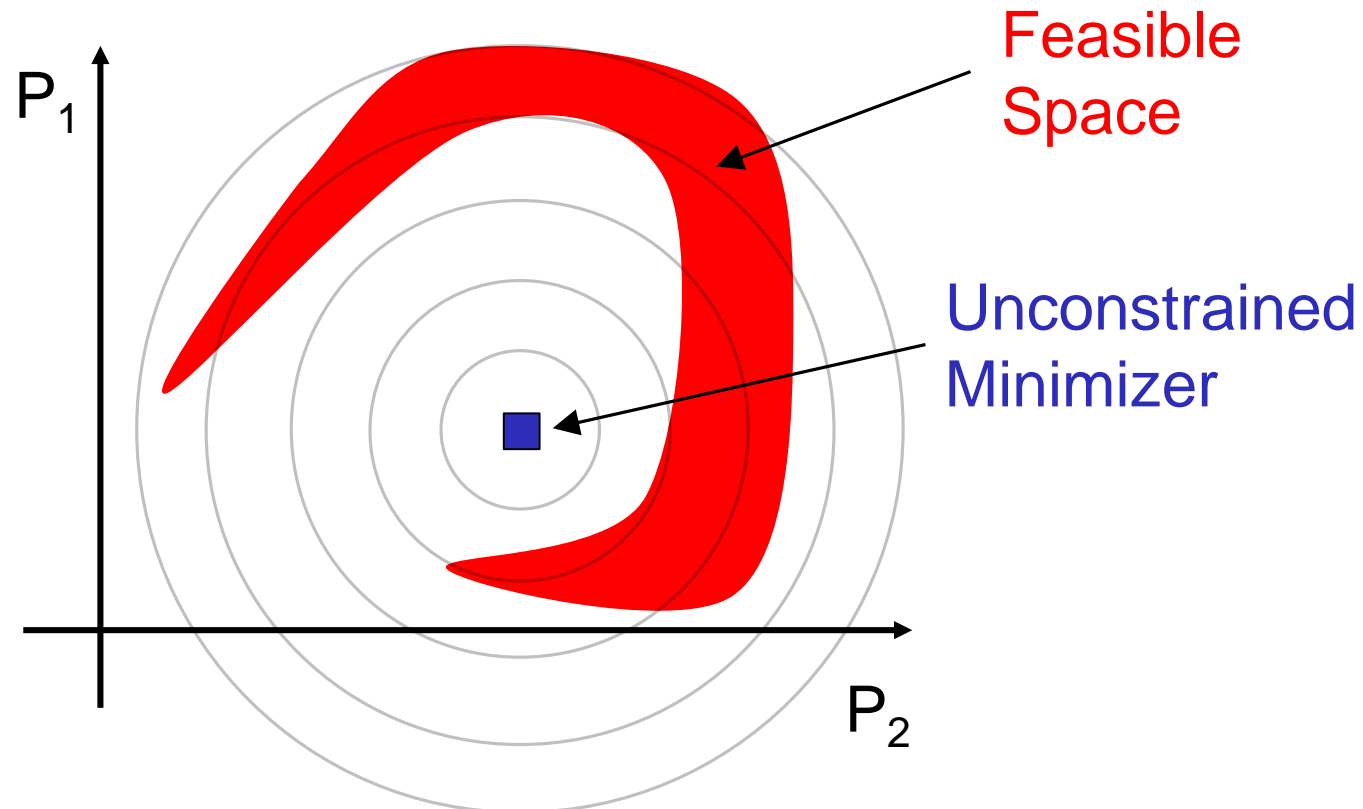
We were perplexed!

- The **unconstrained minimum** could be at an **infeasible point inside the convex hull** of the constraints.
 - How does the second-order relaxation find the global solution?



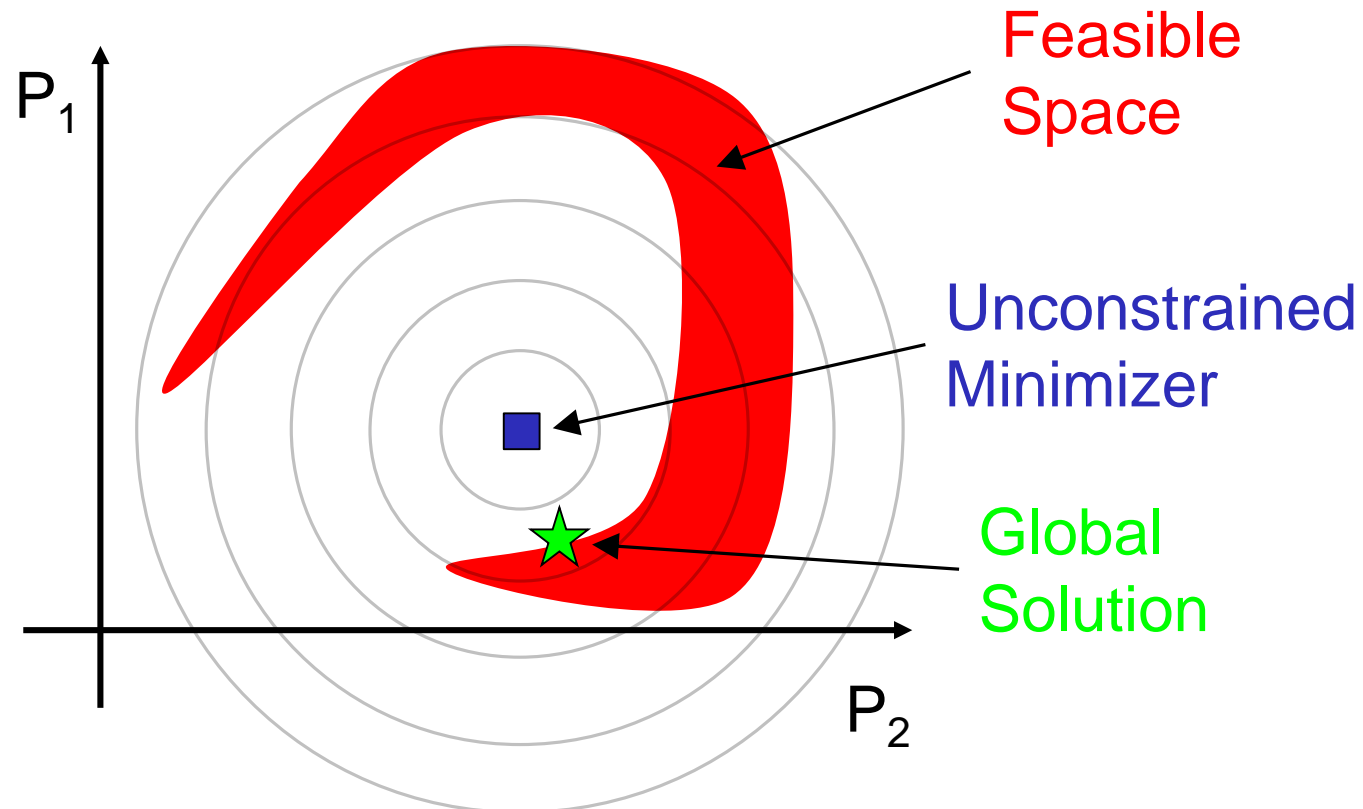
We were perplexed!

- The **unconstrained minimum** could be at an **infeasible point inside the convex hull** of the constraints.
 - How does the second-order relaxation find the global solution?



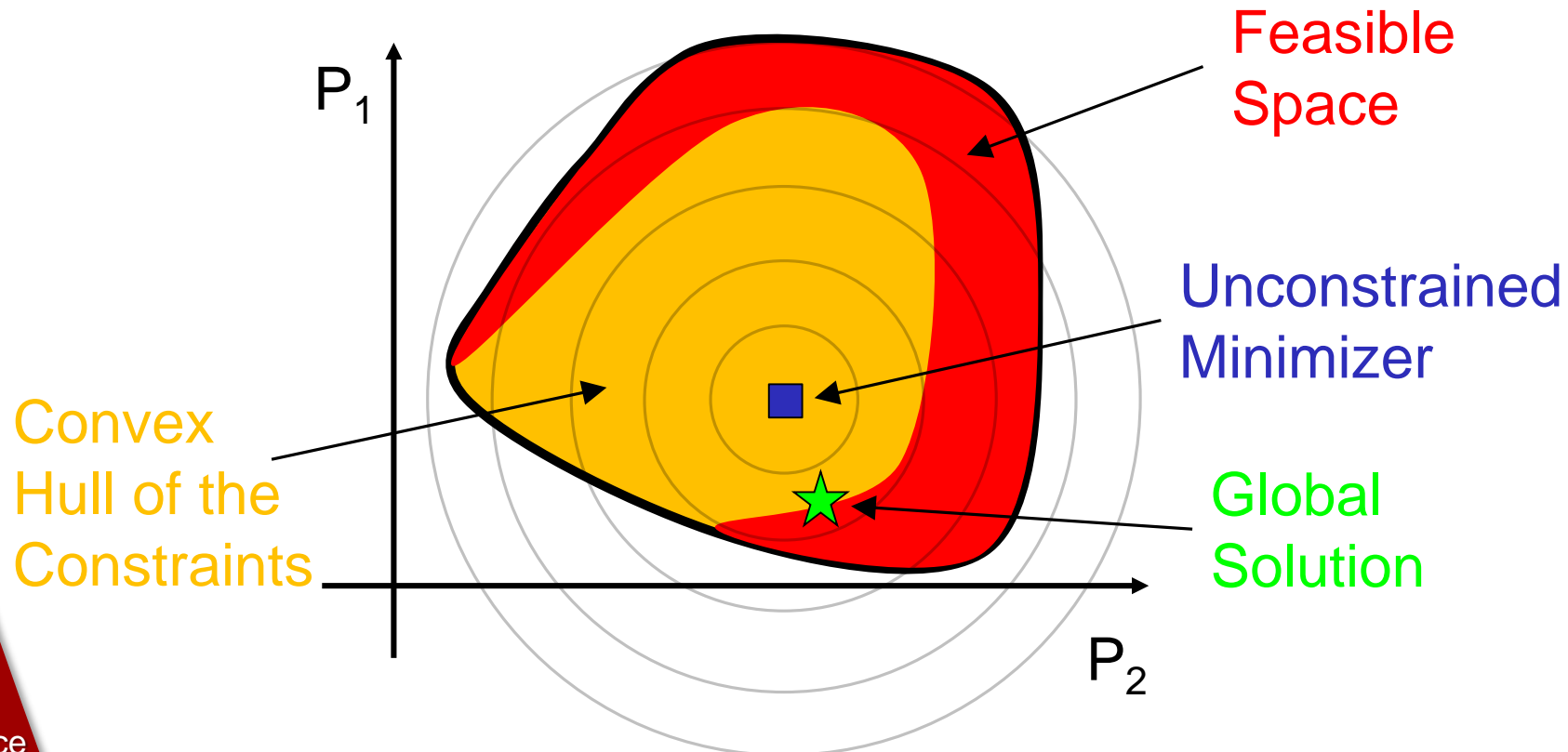
We were perplexed!

- The **unconstrained minimum** could be at an **infeasible point inside the convex hull** of the constraints.
 - How does the second-order relaxation find the global solution?



We were perplexed!

- The **unconstrained minimum** could be at an **infeasible point inside the convex hull** of the constraints.
 - How does the second-order relaxation find the global solution?



Explanation: The Lifted Cost Function

- Quadratic cost of active power generation is **quartic in voltage components**:

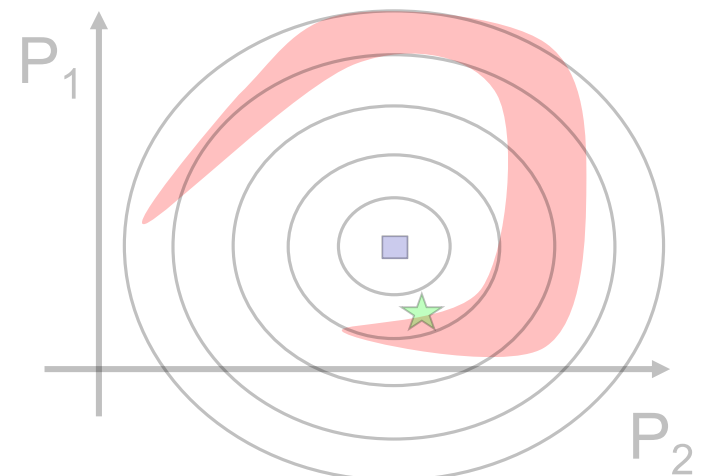
$$\min_y L_y \left\{ \sum_{i \in \mathcal{G}} c_{2,i} (P_{gi}(x))^2 + c_{1,i} P_{gi}(x) + c_{0,i} \right\}$$

$$\text{s.t. } L_y \{g_i(x) x_1 x_1^T\} \succeq 0$$

$$L_y \{x_2 x_2^T\} \succeq 0$$

- Infeasible points** in the non-convex problem have **high-cost** in the relaxation

Non-Convex Problem



Explanation: The Lifted Cost Function

- Quadratic cost of active power generation is **quartic** in voltage components:

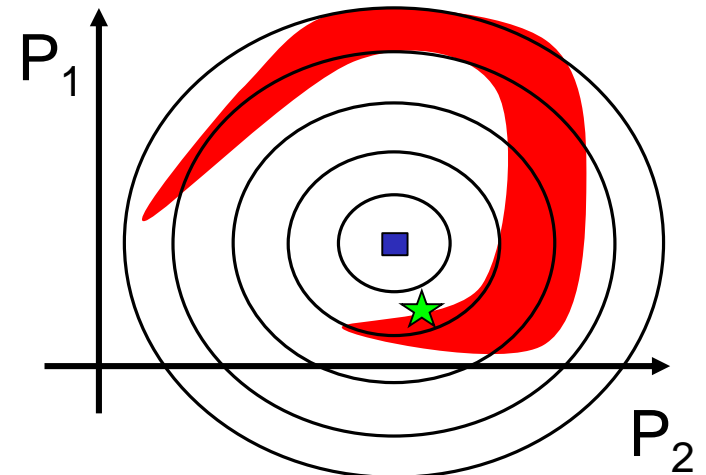
$$\min_y L_y \left\{ \sum_{i \in \mathcal{G}} c_{2,i} (P_{gi}(x))^2 + c_{1,i} P_{gi}(x) + c_{0,i} \right\}$$

$$\text{s.t. } L_y \{g_i(x) x_1 x_1^T\} \succeq 0$$

$$L_y \{x_2 x_2^T\} \succeq 0$$

- Infeasible points** in the non-convex problem have **high-cost** in the relaxation

Non-Convex Problem



Explanation: The Lifted Cost Function

- Quadratic cost of active power generation is **quartic** in voltage components:

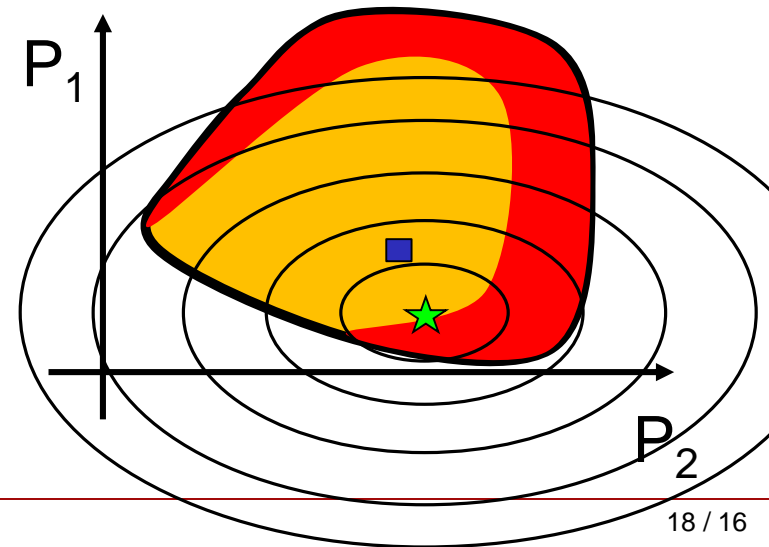
$$\min_y L_y \left\{ \sum_{i \in \mathcal{G}} c_{2,i} (P_{gi}(x))^2 + c_{1,i} P_{gi}(x) + c_{0,i} \right\}$$

$$\text{s.t. } L_y \{g_i(x) x_1 x_1^T\} \succeq 0$$

$$L_y \{x_2 x_2^T\} \succeq 0$$

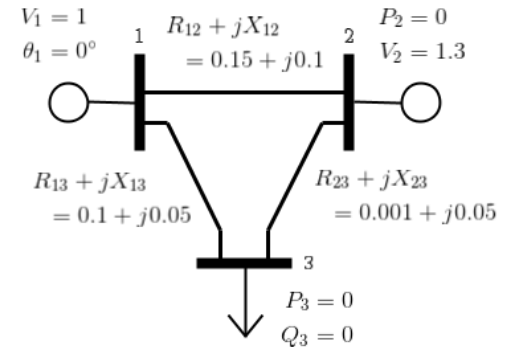
- Infeasible points** in the non-convex problem have **high-cost** in the relaxation

Second-Order
Moment Relaxation

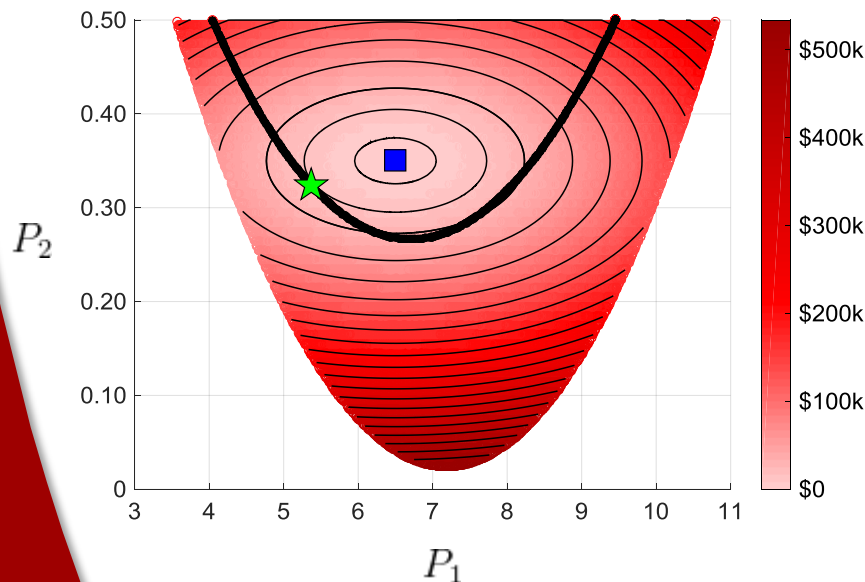


Hole in the Feasible Space

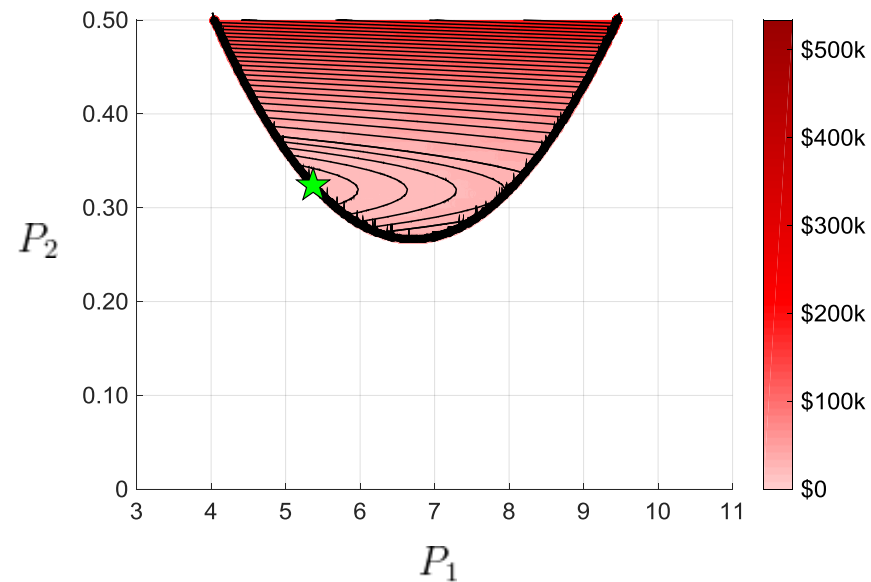
- Three-bus example OPF problem
[Molzahn, Baghsorkhi, & Hiskens '15]



First-Order Relaxation



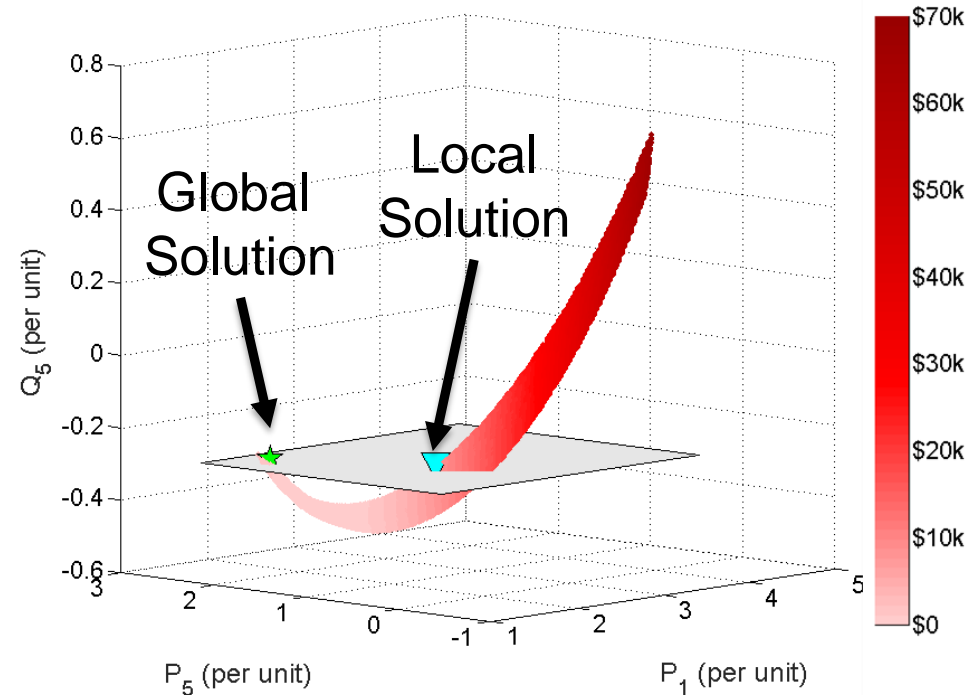
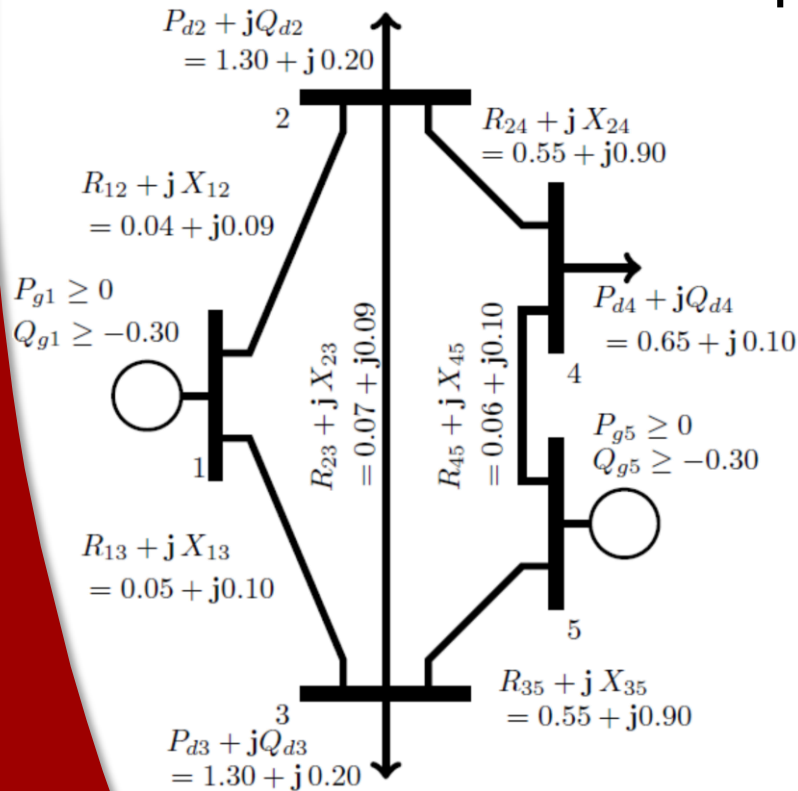
Second-Order Relaxation



Disconnected Feasible Space

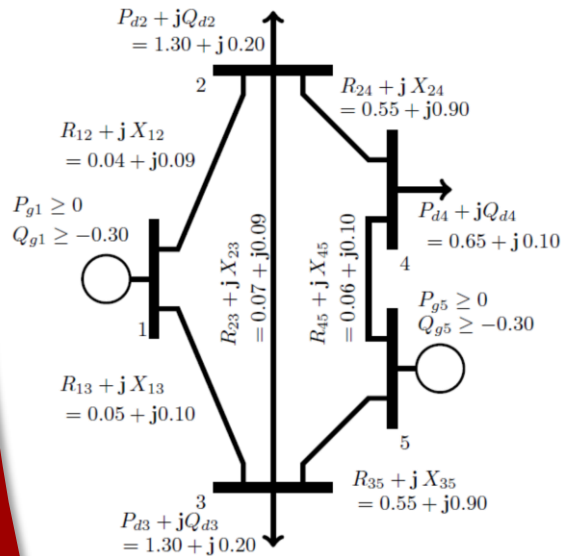
- Five-bus example OPF problem (modified objective)
[Bukhsh et al. '13]

Feasible Space of OPF Problem

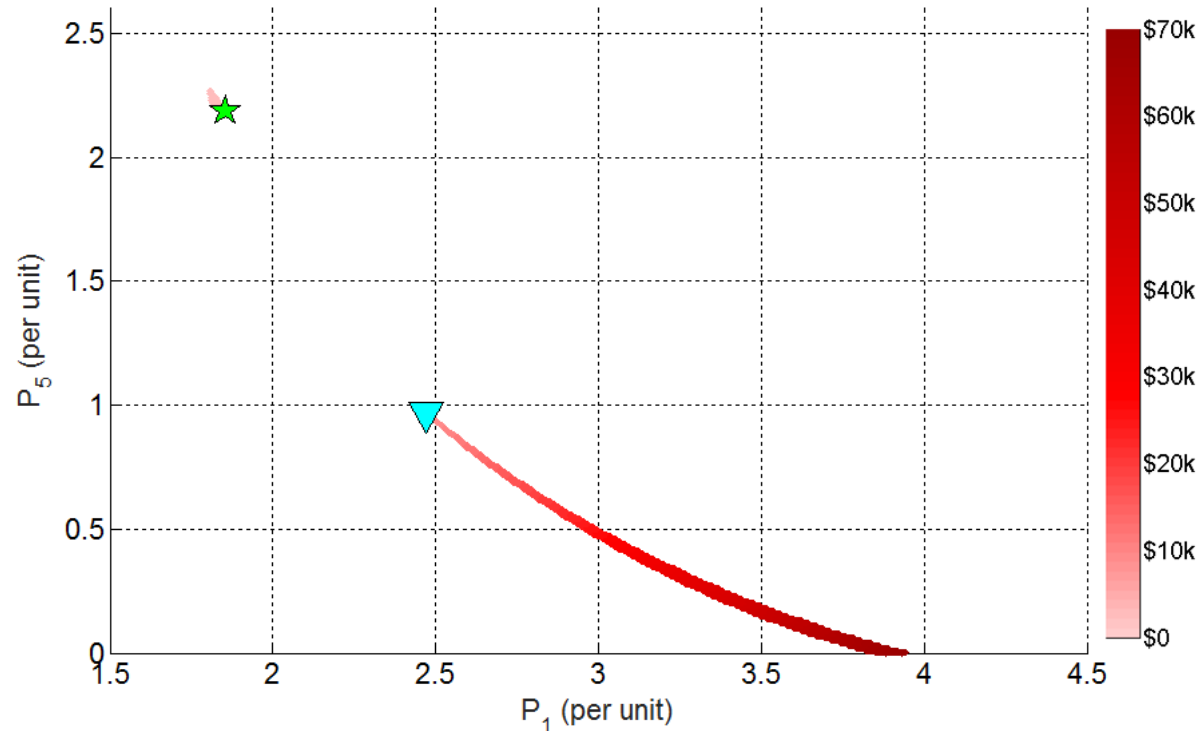


Disconnected Feasible Space

- Five-bus example OPF problem (modified objective)
[Bukhsh et al. '13]

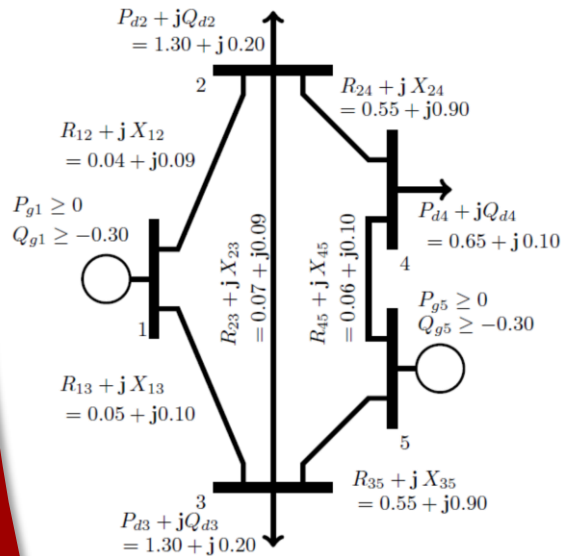


Feasible Space of OPF Problem

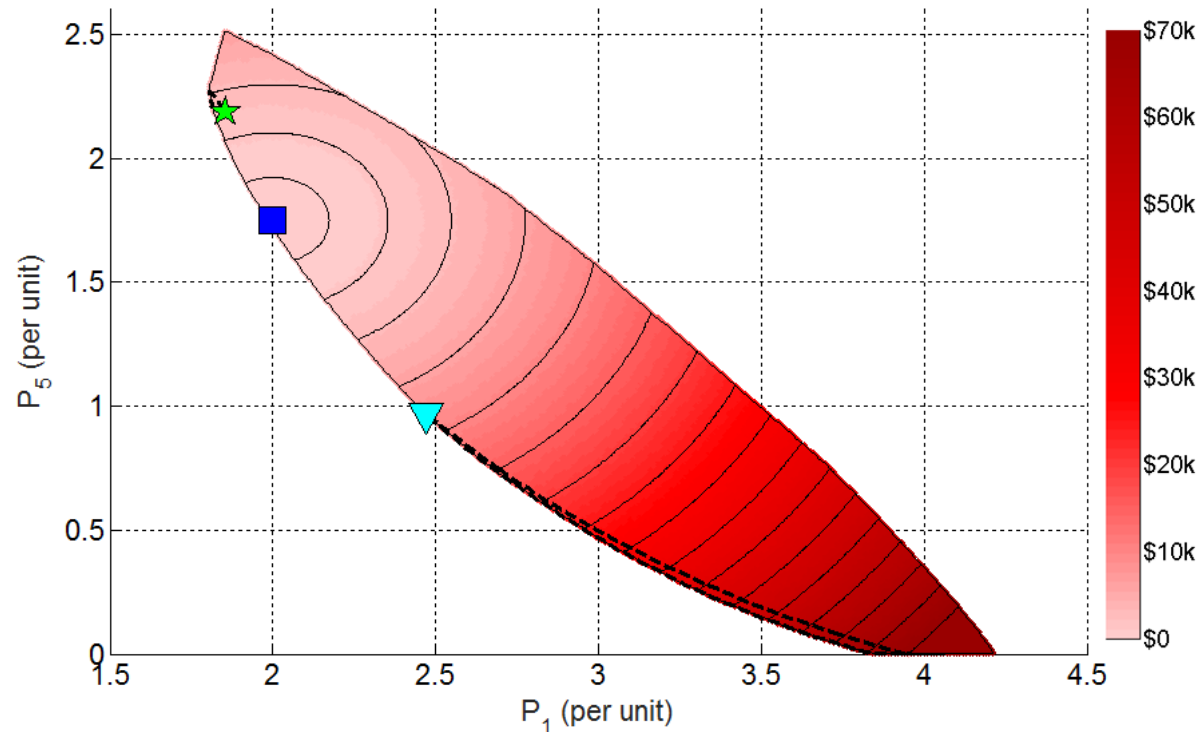


Disconnected Feasible Space

- Five-bus example OPF problem (modified objective)
[Bukhsh et al. '13]

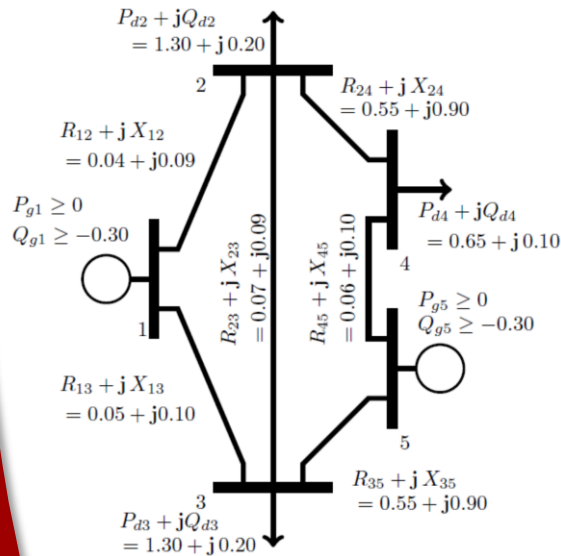


Feasible Space of First-Order Moment Relaxation

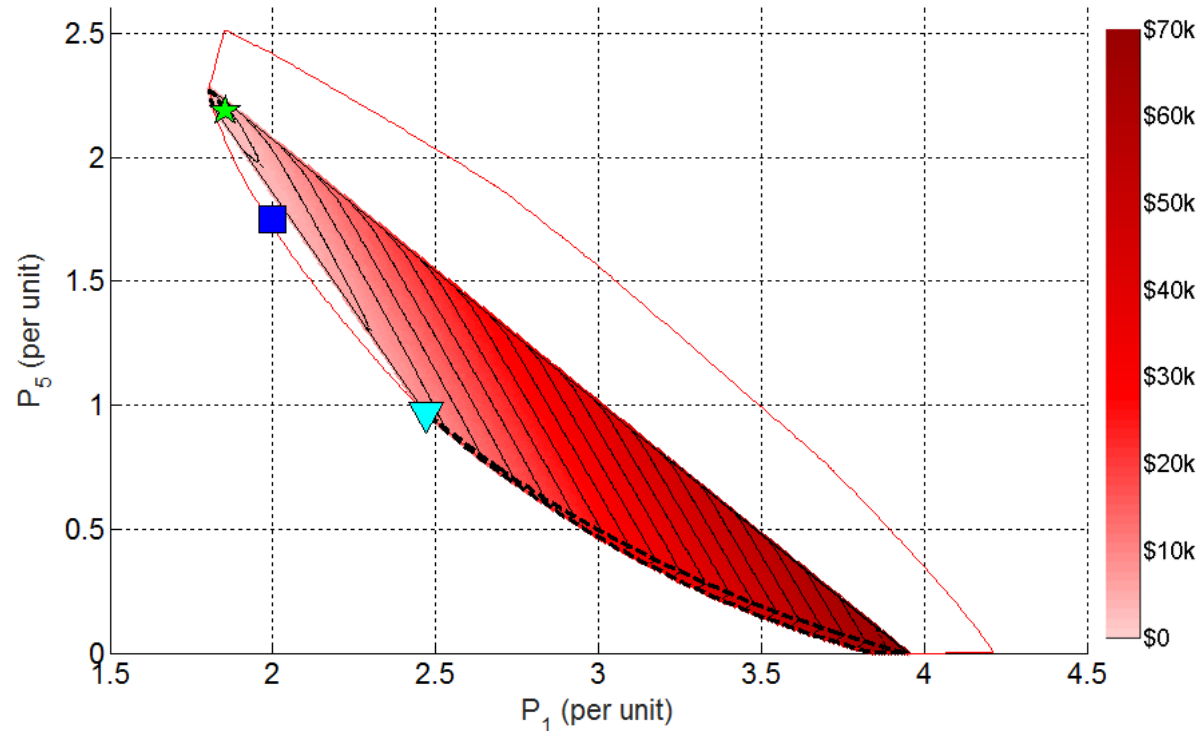


Disconnected Feasible Space

- Five-bus example OPF problem (modified objective)
[Bukhsh et al. '13]



Feasible Space of Second-Order Moment Relaxation



Second-order moment relaxation finds the global solution

Conclusion

Conclusion

- **Moment relaxations** find global solutions to many OPF problems
- **Illustration of the moment relaxations' capabilities** to find global optima despite infeasible points inside the constraints' convex hull

The Cost Function

- First-order relaxation:

$$\min_y L_y \left\{ \sum_{i \in \mathcal{G}} \alpha_i \right\}$$

$$\text{s.t. } \alpha_i \geq L_y \left\{ c_{2,i} (P_{gi}(x))^2 + c_{1,i} P_{gi}(x) + c_{0,i} \right\}$$

$$L_y \{g_i(x)\} \succeq 0$$

$$L_y \{x_1 x_1^T\} \succeq 0$$

Schur Complement
Reformulation as an
SOCP



- Second-order relaxation:

$$\min_y L_y \left\{ \sum_{i \in \mathcal{G}} c_{2,i} (P_{gi}(x))^2 + c_{1,i} P_{gi}(x) + c_{0,i} \right\}$$

$$\text{s.t. } L_y \{g_i(x) x_1 x_1^T\} \succeq 0 \quad L_y \{x_2 x_2^T\} \succeq 0$$