# Hidden Convexity in Fundamental Optimization Problems in Power Networks

# Javad Lavaei

# Joint Work with Steven Low

Control and Dynamical Systems California Institute of Technology

### **Power Networks** (TPS 11, IFAC 11, ACC 11, CDC 10, Allerton 10)



**Passivity simplifies optimization for practical power networks** 

Generalizable to many problems in smart grids

Javad Lavaei, California Institute of Technology

# **Power Networks: Optimal Power Flow (OPF)**





□ Stability...

### Importance:

□ Solved every 5-15 mins for market and operation planning.

Javad Lavaei, California Institute of Technology

# **Power Networks: Needs for New Algorithms**

#### **Previous Attempts Since 1962:**

Linear programming
 Interior point method
 Nonlinear programming
 Dynamic programming
 Lagrangian relaxation
 Genetic algorithms....

#### Findings by OR and Power People:

Multiple local solutions
 Disconnected region
 Convexification for trees

#### **Existing algorithms lack:**

- Robustness
- Performance guarantee
- Global optimality guarantee

#### **Challenges for smart grid:**

- □ Scalability issue (100X)
- □ Time-varying renewable
- Pricing mechanism (LMP)

### **Power Networks: Summary of Results**

- **Goal:** Find a global solution in polynomial time
- □ Idea: Physical structure on OPF
- **First result**: A sufficient condition to solve OPF
- **Surprising result:** Condition holds on IEEE benchmark systems
- □ Important result: Condition holds widely in practice due to passivity
- **Promising result:** Generalization to many optimizations in smart grids

## **Power Networks: Summary of Results**

### **Other results:**

- Certificate for global optimality
- Shape of feasibility region
- Multiple solutions to power flow
- Existence of competitive equilibrium points
- Mechanism design

# **Power Networks: OPF Formulation**



### **Power Networks: Weak Duality**



### **Power Networks: Strong Duality**



**Important Constraint in Dual OPF:** 

$$A := \sum_{k \in \mathcal{N}} \left\{ \lambda_k Y_k + \gamma_k \bar{Y}_k + \mu_k M_k \right\} + \sum_{(I,m) \in \mathcal{L}} \left\{ \left( r_{Im} + \lambda_{Im} \right) Y_{Im} + \bar{r}_{Im} \bar{Y}_{Im} \right\} \succeq 0$$

**Theorem:** Zero duality gap if rank A at optimality is at least 2*n*-2.

### **Power Networks: Zero Duality Gap**

Recall the constraint

$$A := \sum_{k \in \mathcal{N}} \left\{ \lambda_k Y_k + \gamma_k \bar{Y}_k + \mu_k M_k \right\} + \sum_{(I,m) \in \mathcal{L}} \left\{ \left( r_{Im} + \lambda_{Im} \right) Y_{Im} + \bar{r}_{Im} \bar{Y}_{Im} \right\} \succeq 0$$

 $\Box$  We trade power based on  $\lambda_1^{\text{opt}}, ..., \lambda_n^{\text{opt}}$ 

**D** Normal condition: Non-negativity of  $\lambda_1^{\text{opt}}, ..., \lambda_n^{\text{opt}}$  (rigorous proof)

Theorem (real case): Zero duality gap under normal condition.

**Sketch of proof:** Use passivity and Perron-Frobenius Theorem.

$$A^{\text{opt}} = \begin{bmatrix} T^{\text{opt}} & 0 \\ 0 & T^{\text{opt}} \end{bmatrix} \succeq 0$$

$$T^{\circ}$$

$$\mathcal{T}^{\text{opt}} = \begin{bmatrix} ? & - & - & - \\ - & ? & - & - \\ - & - & ? & - \\ - & - & - & ? \end{bmatrix}$$

### **Power Networks: Zero Duality Gap**

**Lumped Model:** Transmission lines, transformers and FACTS Devices are resistive + inductive.

□ Story of "normal condition" is much more complicated.

$$P_{L_k} - P_{D_k} = P_{L_l} - P_{D_l} = \tau \times \operatorname{Re}\{y_{kl}\}$$
$$Q_{L_k} - Q_{D_k} = Q_{L_l} - Q_{D_l} = \tau \times \operatorname{Im}\{-y_{kl}\}$$
$$\max\{P_{lm}, P_{ml}\} \le P_{lm}^{\max} - \tau \times \operatorname{Re}\{y_{kl}\}$$

□ Another challenge:

$$A^{\text{opt}} = \begin{bmatrix} T^{\text{opt}} & 0\\ 0 & T^{\text{opt}} \end{bmatrix} \qquad \blacksquare \qquad A^{\text{opt}} = \begin{bmatrix} T^{\text{opt}} & \overline{T}^{\text{opt}}\\ -\overline{T}^{\text{opt}} & T^{\text{opt}} \end{bmatrix}$$

Local Theorem: Zero duality gap for a small power loss.

**Global Theorem:** Given *Re(Y)*, zero duality gap **independent of loads** if *Im(Y)* belongs to an unbounded region.

### **Power Networks: More Advanced Problems**



$$\begin{split} \min_{\mathbf{X}^{(0)},...,\mathbf{X}^{(c)},\mathbf{U}^{(0)},...,\mathbf{U}^{(c)}} f\left(\mathbf{X}^{(0)},\mathbf{U}^{(0)}\right) \\ g_t\left(\mathbf{X}^{(t)},\mathbf{U}^{(t)}\right) &= 0, \quad t = 0,...,c \\ h_t\left(\mathbf{X}^{(t)},\mathbf{U}^{(t)}\right) &\geq 0, \quad t = 0,...,c \\ \left|\mathbf{U}^{(r)}-\mathbf{U}^{(0)}\right| &\leq \Delta \mathbf{U}^{(r)}_{\max}, \quad r = 1,...,c \end{split}$$

OPF with variable shunt elements

- OPF with variable transformer ratios
- Dynamic OPF
- □ Security-constrained OPF
- □ Scheduling for renewable resources ...

**Theorem:** Zero duality gap for OPF implies zero duality gap for all these problems.

### **Proof:**

Good modeling:





Bus 2

### **Power Networks: Impacts**

□ Fundamental study of optimizations in power networks

Potential to change optimization algorithms for grids

**Example 1:** Global solution 15% better than local solution for modified IEEE 57-bus system

### Example 2:

One generator and one load

Multiple solutions

□ Able to find them all by changing the cost function

□ Various feasibility regions:

 $S_v$ = Feasibility region of OPF

 $S_p$ = Projection of  $S_v$  onto the space of active powers

 $S_p$ = Feasibility region of economic dispatch

Economic Dispatch:

$$\min_{(p_1,\ldots,p_k)\in S_p}\sum_{i=1}^k f_i(P_i)$$

# **Mechanism Design**



**D** Existence of CEP:



**Laws of physics introduce nonlinearity.** 

• OPF is NP-hard and has been studied for 50 years.

□ A large class of OPF problems can be convexified.

□ The main reason is the physical properties of the network.

□ This idea is useful to study many other related problems.