

# Assignment 2 – AC-OPF with convex relaxations (SDP-OPF)

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#### **Outline**



- Semidefinite Relaxation of AC-OPF
- Notes on the Implementation
- Assignment 2: AC-OPF with convex relaxations (SDP-OPF)

#### Mathematical Reformulation of AC-OPF



We introduce the variable transformation of complex bus voltages V:

$$X := [\Re\{V\}\Im\{V\}]^T$$

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Then, we can write the bus power injections  $P_{inj_k}$  for bus k as:

Nodal power injections 
$$P_{\mathsf{inj}_k} = \mathsf{Tr}\{X^T\mathbf{Y}_kX\}$$

Multiplicity property of trace operator  $= \mathsf{Tr}\{\mathbf{Y}_k \underline{X} \underline{X}^T\}$ 

Introduce matrix variable  $W = \mathsf{Tr}\{\mathbf{Y}_k \underline{X} \underline{X}^T\}$ 

The term  $Tr\{A\}$  denotes the trace operator which is the summation of the diagonal elements of matrix A. The matrix  $\mathbf{Y}_k$  is an auxiliary variable resulting from the admittance matrix Y of the power grid.

#### Mathematical Reformulation of AC-OPF



The  $2n_{\rm bus}$  - dimensional vector X is transformed to a  $2n_{\rm bus} \times 2n_{\rm bus}$  - dimensional matrix W

$$W = \begin{bmatrix} V_1^r V_1^r & V_1^r V_2^r & \cdots & V_1^r V_n^r \\ V_2^r V_1^r & V_2^r V_2^r & \cdots & V_2^r V_n^r \\ \vdots & & \ddots & \vdots & & \vdots & & \ddots & \vdots \\ V_n^r V_1^r & \cdots & \cdots & V_n^r V_n^r & V_n^r V_1^i & \cdots & \cdots & V_n^r V_n^i \\ V_1^i V_1^r & V_1^i V_2^r & \cdots & V_1^i V_n^r & V_1^i V_1^i & \cdots & \cdots & V_1^r V_n^i \\ V_2^i V_1^r & V_2^i V_2^r & \cdots & V_2^i V_n^r & V_1^i V_1^i & V_1^i V_2^i & \cdots & V_1^i V_n^i \\ V_2^i V_1^r & V_2^i V_2^r & \cdots & V_2^i V_n^r & V_2^i V_1^i & V_2^i V_2^i & \cdots & V_2^i V_n^i \\ \vdots & & & \ddots & \vdots & & \ddots & \vdots \\ V_n^i V_1^r & \cdots & \cdots & V_n^i V_n^r & V_n^i V_1^i & \cdots & \cdots & V_n^i V_n^i \end{bmatrix}$$

#### Convex Relaxation of AC-OPF



 $\dots$  for each node k and line lm:





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$$\begin{array}{ll} \text{Minimize Generation Cost} & \sum_{k \in \mathcal{G}} \{c_{k2} ( \mathrm{Tr} \{ \mathbf{Y}_k W \} + P_{D_k} )^2 + \\ & c_{k1} ( \mathrm{Tr} \{ \mathbf{Y}_k W \} + P_{D_k} ) + c_{k0} \} \end{array}$$

#### Convex Relaxation of AC-OPF



 $\dots$  for each node k and line lm:

$$\begin{split} & \underset{k \in \mathcal{G}}{\text{Minimize Generation Cost}} & \sum_{k \in \mathcal{G}} \{c_{k2} (\operatorname{Tr}\{\mathbf{Y}_k W\} + P_{D_k})^2 + \\ & c_{k1} (\operatorname{Tr}\{\mathbf{Y}_k W\} + P_{D_k}) + c_{k0} \} \end{split}$$
 s. t. Active Power Balance 
$$P_k^{\min} \leq \operatorname{Tr}\{\mathbf{Y}_k W\} \leq P_k^{\max}$$
 Reactive Power Balance 
$$Q_k^{\min} \leq \operatorname{Tr}\{\bar{\mathbf{Y}}_k W\} \leq Q_k^{\max}$$
 Bus Voltages 
$$(V_k^{\min})^2 \leq \operatorname{Tr}\{M_k W\} \leq (V_k^{\max})^2$$
 Active Branch Flow 
$$-P_{lm}^{\max} \leq \operatorname{Tr}\{\mathbf{Y}_{lm} W\} \leq P_{lm}^{\max}$$
 Apparent Branch Flow 
$$\operatorname{Tr}\{\mathbf{Y}_{lm} W\}^2 + \operatorname{Tr}\{\bar{\mathbf{Y}}_{lm} W\}^2 \leq (S_{lm}^{\max})^2$$

#### Convex Relaxation of AC-OPF



... for each node k and line lm:

$$\begin{split} & \underset{k \in \mathcal{G}}{\operatorname{Minimize Generation Cost}} & \sum_{k \in \mathcal{G}} \{c_{k2}(\operatorname{Tr}\{\mathbf{Y}_k W\} + P_{D_k})^2 + \\ & c_{k1}(\operatorname{Tr}\{\mathbf{Y}_k W\} + P_{D_k}) + c_{k0}\} \end{split}$$
 s. t. Active Power Balance 
$$P_k^{\min} \leq \operatorname{Tr}\{\mathbf{Y}_k W\} \leq P_k^{\max} \\ & \text{Reactive Power Balance} & Q_k^{\min} \leq \operatorname{Tr}\{\bar{\mathbf{Y}}_k W\} \leq Q_k^{\max} \\ & \text{Bus Voltages} & (V_k^{\min})^2 \leq \operatorname{Tr}\{M_k W\} \leq (V_k^{\max})^2 \\ & \text{Active Branch Flow} & -P_{lm}^{\max} \leq \operatorname{Tr}\{\mathbf{Y}_{lm} W\} \leq P_{lm}^{\max} \\ & \text{Apparent Branch Flow} & \operatorname{Tr}\{\mathbf{Y}_{lm} W\}^2 + \operatorname{Tr}\{\bar{\mathbf{Y}}_{lm} W\}^2 \leq (S_{lm}^{\max})^2 \\ & \text{Decomposition} & W = \underbrace{[\Re\{V\}\Im\{V\}]^T}_{V}\underbrace{[\Re\{V\}\Im\{V\}]}^T \underbrace{[\Re\{V\}\Im\{V\}]}_{VT} \end{split}$$





 $\dots$  for each node k and line lm:

$$\begin{split} & \underset{k \in \mathcal{G}}{\operatorname{Minimize Generation Cost}} & \sum_{k \in \mathcal{G}} \{c_{k2}(\operatorname{Tr}\{\mathbf{Y}_k W\} + P_{D_k})^2 + \\ & c_{k1}(\operatorname{Tr}\{\mathbf{Y}_k W\} + P_{D_k}) + c_{k0}\} \end{split}$$
 s. t. Active Power Balance 
$$P_k^{\min} \leq \operatorname{Tr}\{\mathbf{Y}_k W\} \leq P_k^{\max} \\ & \text{Reactive Power Balance} & Q_k^{\min} \leq \operatorname{Tr}\{\bar{\mathbf{Y}}_k W\} \leq Q_k^{\max} \\ & \text{Bus Voltages} & (V_k^{\min})^2 \leq \operatorname{Tr}\{M_k W\} \leq (V_k^{\max})^2 \\ & \text{Active Branch Flow} & -P_{lm}^{\max} \leq \operatorname{Tr}\{\mathbf{Y}_{lm} W\} \leq P_{lm}^{\max} \\ & \text{Apparent Branch Flow} & \operatorname{Tr}\{\mathbf{Y}_{lm} W\}^2 + \operatorname{Tr}\{\bar{\mathbf{Y}}_{lm} W\}^2 \leq (S_{lm}^{\max})^2 \\ & \text{Semi-Definiteness of } W & \succeq 0 \\ & \operatorname{Rank Constraint} & \operatorname{rank}(W) = 1 \end{split}$$

#### Convex Relaxation of AC-OPF



 $\dots$  for each node k and line lm:

$$\begin{array}{ll} \text{Minimize Generation Cost} & \sum_{k \in \mathcal{G}} \{c_{k2}(\operatorname{Tr}\{\mathbf{Y}_kW\} + P_{D_k})^2 + \\ & c_{k1}(\operatorname{Tr}\{\mathbf{Y}_kW\} + P_{D_k}) + c_{k0}\} \\ \text{s. t. Active Power Balance} & P_k^{\min} \leq \operatorname{Tr}\{\mathbf{Y}_kW\} \leq P_k^{\max} \\ \text{Reactive Power Balance} & Q_k^{\min} \leq \operatorname{Tr}\{\bar{\mathbf{Y}}_kW\} \leq Q_k^{\max} \\ & \text{Bus Voltages} & (V_k^{\min})^2 \leq \operatorname{Tr}\{M_kW\} \leq (V_k^{\max})^2 \\ & \text{Active Branch Flow} & -P_{lm}^{\max} \leq \operatorname{Tr}\{\mathbf{Y}_{lm}W\} \leq P_{lm}^{\max} \\ & \text{Apparent Branch Flow} & \operatorname{Tr}\{\mathbf{Y}_{lm}W\}^2 + \operatorname{Tr}\{\bar{\mathbf{Y}}_{lm}W\}^2 \leq (S_{lm}^{\max})^2 \\ & \text{Semi-Definiteness of } W & \succeq 0 \\ & \text{Rank Constraint} & \operatorname{rank}(W) \equiv 1 \Rightarrow \text{Convex Relaxation} \\ \end{array}$$



# **Auxiliary Variables**

A power grid consists of  $\mathcal N$  buses and  $\mathcal L$  lines. The set of generator buses is denoted with  $\mathcal G$ . The following auxiliary variables are introduced for each bus  $k \in \mathcal N$  and line  $(l,m) \in \mathcal L$ :

$$\begin{split} & Y_k := e_k e_k^T Y \\ & Y_{lm} := (\bar{y}_{lm} + y_{lm}) e_l e_l^T - (y_{lm}) e_l e_m^T \\ & \mathbf{Y}_k := \frac{1}{2} \begin{bmatrix} \Re\{Y_k + Y_k^T\} & \Im\{Y_k^T - Y_k\} \\ \Im\{Y_k - Y_k^T\} & \Re\{Y_k + Y_k^T\} \end{bmatrix} \\ & \mathbf{Y}_{lm} := \frac{1}{2} \begin{bmatrix} \Re\{Y_{lm} + Y_{lm}^T\} & \Im\{Y_{lm}^T - Y_{lm}\} \\ \Im\{Y_{lm} - Y_{lm}^T\} & \Re\{Y_{lm} + Y_{lm}^T\} \end{bmatrix} \\ & \bar{\mathbf{Y}}_k := \frac{-1}{2} \begin{bmatrix} \Im\{Y_k + Y_k^T\} & \Re\{Y_k - Y_k^T\} \\ \Re\{Y_k^T - Y_k\} & \Im\{Y_k + Y_k^T\} \end{bmatrix} \\ & M_k := \begin{bmatrix} e_k e_k^T & 0 \\ 0 & e_k e_k^T \end{bmatrix} \end{split}$$

The terms  $\Re\{\cdot\}$  and  $\Im\{\cdot\}$  denote the real and imaginary part. Matrix Y denotes the bus admittance matrix of the power grid,  $e_k$  the k-th basis vector,  $\bar{y}_{lm}$  the shunt admittance of line  $(l,m) \in \mathcal{L}$  and  $y_{lm}$  the series admittance.

#### Notes on the Convex Relaxation



• In order to obtain zero relaxation gap, i.e. an exact relaxation, include small resistance ( $10^{-4}$  p.u.) to each transformer ⇒ connected resistive graph

<sup>&</sup>lt;sup>1</sup>Javad Lavaei and Steven H Low. "Zero duality gap in optimal power flow problem". In: IEEE Transactions on Power Systems 27.1 (2012), pp. 92–107

#### Notes on the Convex Relaxation



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#### Lavaei and Low<sup>1</sup>show

- rank(W) = 1 or 2 solution to original OPF problem can be recovered
- rank(W) > 3 solution to original OPF problem cannot be recovered

<sup>&</sup>lt;sup>1</sup> Javad Lavaei and Steven H Low. "Zero duality gap in optimal power flow problem". In: IEEE Transactions on Power Systems 27.1 (2012), pp. 92–107

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#### **Notes on the Convex Relaxation**



If rank(W) = 2, then apply eigendecomposition according to Molzahn et al  $^{2}$ .

$$W_{\text{opt}} = \rho_1 E_1 E_1^T + \rho_2 E_2 E_2^T$$
$$X_{\text{opt}} = \sqrt{\rho_1^{\text{opt}}} E_1^{\text{opt}} + \sqrt{\rho_2^{\text{opt}}} E_2^{\text{opt}}$$

The terms  $\rho_1, \rho_2$  denote the first and second largest absolute eigenvalue of W and  $E_1$  and  $E_2$  the corresponding eigenvectors.

<sup>&</sup>lt;sup>2</sup>Daniel K Molzahn et al. "Implementation of a large-scale optimal power flow solver based on semidefinite programming". In: IEEE Transactions on Power Systems 28.4 (2013), pp. 3987-3998

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The objective on generation cost and the constraint on apparent line flow cannot be directly implemented in the SDP.

We can use the so-called Schur's complement to reformulate polynomial equations as semidefinite constraints.



The Schur complement is defined as follows<sup>3</sup>. Given a matrix  $X \in S^n$  which can be partitioned in the sub-matrices A, B and C:

$$X = \begin{bmatrix} A & B \\ B^T & C \end{bmatrix} \tag{1}$$

If det  $A \neq 0$ , the matrix

$$S = C - B^T A^{-1} B \tag{2}$$

is called the Schur complement of A in X. The following statements can be made regarding the positive semi-definiteness of the matrix X:

- $X \succ 0$  if and only if  $A \succ 0$  and  $S \succ 0$
- If  $A \succ 0$ , then  $X \succeq 0$  if and only if  $S \succeq 0$

<sup>&</sup>lt;sup>3</sup>Stephen Boyd and Lieven Vandenberghe. *Convex Optimization*. Cambridge University Press, 2004

<sup>10</sup> DTU Electrical Engineering



To obtain an optimization problem linear in W, the objective function is reformulated using Schur's complement:

$$\begin{split} \min_{W,\,\alpha} \; & \sum_{k \in \mathcal{G}} \alpha_k \\ & \left[ \begin{matrix} c_{k1} \mathsf{Tr}\{\mathbf{Y}_k W\} + a_k & \sqrt{c_{k2}} \mathsf{Tr}\{\mathbf{Y}_k W\} + b_k \\ \sqrt{c_{k2}} \mathsf{Tr}\{\mathbf{Y}_k W\} + b_k & -1 \end{matrix} \right] \preceq 0 \end{split}$$

where  $a_k := -\alpha_k + c_{k0} + c_{k1}P_{D_k}$  and  $b_k := \sqrt{c_{k2}}P_{D_k}$ . The variable  $\alpha$  is introduced as an additional optimization variable. In addition, the apparent branch flow constraint is rewritten:

$$\begin{bmatrix} -(\overline{S}_{lm})^2 & \operatorname{Tr}\{\mathbf{Y}_{lm}W\} & \operatorname{Tr}\{\overline{\mathbf{Y}}_{lm}W\} \\ \operatorname{Tr}\{\mathbf{Y}_{lm}W\} & -1 & 0 \\ \operatorname{Tr}\{\overline{\mathbf{Y}}_{lm}W\} & 0 & -1 \end{bmatrix} \preceq 0$$



This theorem is used to prove that the semi-definite constraint is equal to the quadratic constraint. The matrix X corresponds to

$$X = \begin{bmatrix} \overline{S}_{lm}^2 & \operatorname{Tr}\{\mathbf{Y}_{lm}W\} & \operatorname{Tr}\{\bar{\mathbf{Y}}_{lm}W\} \\ \operatorname{Tr}\{\bar{\mathbf{Y}}_{lm}W\} & 1 & 0 \\ \operatorname{Tr}\{\bar{\mathbf{Y}}_{lm}W\} & 0 & 1 \end{bmatrix} \succeq 0$$

Applying Schur complement a first time, defining

$$A = \overline{S}_{lm}^2$$
  $B = \begin{bmatrix} \operatorname{Tr}\{\mathbf{Y}_{lm}W\} & \operatorname{Tr}\{\bar{\mathbf{Y}}_{lm}W\} \end{bmatrix}$   $C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ 

yields the following result:



$$\begin{split} S_1 &= C - B^T A^{-1} B \\ &= \begin{bmatrix} 1 - \frac{\text{Tr}\{\mathbf{Y}_{lm}W\}^2}{\overline{S}_{lm}^2} & \frac{\text{Tr}\{\mathbf{Y}_{lm}W\}\text{Tr}\{\bar{\mathbf{Y}}_{lm}W\}}{\overline{S}_{lm}^2} \\ \frac{\text{Tr}\{\mathbf{Y}_{lm}W\}\text{Tr}\{\bar{\mathbf{Y}}_{lm}W\}}{\overline{S}_{lm}^2} & 1 - \frac{\text{Tr}\{\mathbf{Y}_{lm}W\}^2}{\overline{S}_{lm}^2} \end{bmatrix} \succeq 0 \end{split}$$

If Schur complement is applied a second time, the result is the initial quadratic constraint:

$$S_2 = \overline{S}_{lm}^2 - \operatorname{Tr}\{\mathbf{Y}_{lm}W\}^2 - \operatorname{Tr}\{\bar{\mathbf{Y}}_{lm}W\}^2 \ge 0$$

Hence, the proof is completed. In the context of semi-definite programming, Schur complement is a powerful tool, which can be used to transform polynomial constraints into semi-definite constraints.

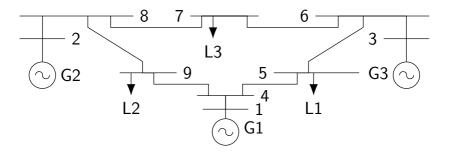
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# Assignment 2: AC-OPF with convex relaxations (SDP-OPF)

- Implement the semidefinite relaxation
- **2** Compare objective value and resulting  $P_{\rm inj}$ ,  $Q_{\rm inj}$  to MATPOWER AC-OPF
- 3 Evaluate exactness of relaxation
- 4 Decompose solution matrix W
- **6** Investigate exactness under varying network parameters for IEEE 9 bus system
- 6 Investigate exactness for 3 bus system
- Bonus: Penalty term on reactive power injections



# Assignment 2: AC-OPF with convex relaxations (SDP-OPF)



IEEE 9-bus system

# Planning of Assignment 2



- Nov. 4: Deadline for Assignment 2
  - 5-10 page report (introduction including literature review, mathematical formulation, answer to the tasks of the assignment, conclusions)
  - Documented code in MATLAB/YALMIP
- Andreas and I will be out of office until end of October
  - We will always be reachable via email
  - We recommend to ask specific questions and not to send your codes.



# Questions?



Feel free to write us an e-mail: {antosat,andven}@elektro.dtu.dk