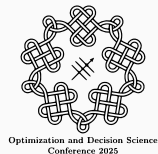




AC Optimal Power Flow problem

A study on Jabr relaxation



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Problem definition

The problem

Let us take a network modeled as a **graph** $(\mathcal{B}, \mathcal{L})$, where \mathcal{B} represents the set of buses and \mathcal{L} represents the set of lines. For every bus k we have a (possibly empty) set of generators $\mathcal{G}(k)$ located at bus k . The problem consists of meeting the energy demand at every bus, and doing so with the lowest possible energy generation cost.

The problem

Let us take a network modeled as a **graph** $(\mathcal{B}, \mathcal{L})$, where \mathcal{B} represents the set of buses and \mathcal{L} represents the set of lines. For every bus k we have a (possibly empty) set of generators $\mathcal{G}(k)$ located at bus k . The problem consists of meeting the energy demand at every bus, and doing so with the lowest possible energy generation cost.

More precisely, we have the following **variables**:

- ▶ for each bus k we have a complex voltage $V_k = |V_k|e^{j\delta_k}$;
- ▶ for each branch km we have two variables S_{km} and S_{mk} , the complex power injected into the branch at k and at m , respectively;
- ▶ for each generator g there is power generation $P_g^G + jQ_g^G$.

These variables are subjected to five classes of **constraints**.

Polar coordinates formulation

$$\inf_{\substack{P_g^G, Q_g^G, \delta_k, \\ |V_k|, S_{km}}} \sum_{g \in \mathcal{G}} F_g(P_g^G, Q_g^G) \quad (1a)$$

s.t.

AC power flow laws:

$$S_{km} = (G_{kk} - jB_{kk})|V_k|^2 + (G_{km} - jB_{km})|V_k||V_m| \cdot (\cos(\theta_{km}) + j \sin(\theta_{km})) \quad \forall km \in \mathcal{L}, \quad (1b)$$

Flow balance constraints:

$$\sum_{km \in \mathcal{L}} S_{km} + P_k^L + jQ_k^L = \sum_{g \in \mathcal{G}(k)} P_g^G + j \sum_{g \in \mathcal{G}(k)} Q_g^G \quad \forall k \in \mathcal{B}, \quad (1c)$$

Branch limits, generator limits, voltage bounds:

$$|S_{km}|^2 \leq U_{km} \quad \forall km \in \mathcal{L}, \quad (1d)$$

$$P_g^{\min} \leq P_g^G \leq P_g^{\max}, \quad Q_g^{\min} \leq Q_g^G \leq Q_g^{\max} \quad \forall g \in \mathcal{G}, \quad (1e)$$

$$V_k^{\min} \leq |V_k| \leq V_k^{\max} \quad \forall k \in \mathcal{B}, \quad (1f)$$

$$\theta_{km}^{\min} \leq \theta_{km} \leq \theta_{km}^{\max} \quad \forall km \in \mathcal{L}. \quad (1g)$$

Variable substitution

One can introduce **auxiliary variables** to tackle the problem of having sine and cosine functions:

$$\begin{aligned}c_{km} &= |V_k| |V_m| \cdot \cos(\theta_{km}) & \forall km \in \mathcal{L}, \\s_{km} &= |V_k| |V_m| \cdot \sin(\theta_{km}) & \forall km \in \mathcal{L}, \\c_{kk} &= |V_k|^2 & \forall k \in \mathcal{B}.\end{aligned}$$

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Substituting such variables in the model without adding their definitions gives us a first relaxed model.

Note that by doing so we manage to remove sine and cosine functions but we also lose **crucial relations** between the new variables.

A first relaxed model

$$\inf_{\substack{P_g^G, Q_g^G, c_{km}, \\ s_{km}, S_{km}, P_{km}, Q_{km}}} F(x) := \sum_{g \in \mathcal{G}} F_g(P_g^G) \quad (2a)$$

$$\text{Subject to: } P_{km} = G_{kk} c_{kk} + G_{km} c_{km} + B_{km} s_{km} \quad \forall km \in \mathcal{L}, \quad (2b)$$

$$Q_{km} = -B_{kk} c_{kk} - B_{km} c_{km} + G_{km} s_{km} \quad \forall km \in \mathcal{L}, \quad (2c)$$

$$S_{km} = P_{km} + jQ_{km} \quad \forall km \in \mathcal{L}, \quad (2d)$$

$$\sum_{km \in \mathcal{L}} S_{km} + P_k^L + jQ_k^L = \sum_{g \in \mathcal{G}(k)} P_g^G + j \sum_{g \in \mathcal{G}(k)} Q_g^G \quad \forall k \in \mathcal{B}, \quad (2e)$$

$$P_{km}^2 + Q_{km}^2 \leq U_{km} \quad \forall km \in \mathcal{L}, \quad (2f)$$

$$V_k^{\min^2} \leq c_{kk} \leq V_k^{\max^2} \quad \forall k \in \mathcal{B}, \quad (2g)$$

$$P_g^{\min} \leq P_g^G \leq P_g^{\max}, \quad Q_g^{\min} \leq Q_g^G \leq Q_g^{\max} \quad \forall g \in \mathcal{G}, \quad (2h)$$

$$c_{kk} \geq 0 \quad \forall k \in \mathcal{B}, \quad (2i)$$

$$V_k^{\max} V_m^{\max} \geq c_{km} \geq 0 \quad \forall km \in \mathcal{L}, \quad (2j)$$

$$-V_k^{\max} V_m^{\max} \leq s_{km} \leq V_k^{\max} V_m^{\max} \quad \forall km \in \mathcal{L}, \quad (2k)$$

$$c_{km} = c_{mk}, \quad s_{km} = -s_{mk} \quad \forall km \in \mathcal{L}. \quad (2l)$$

Equality

To link the c and s variables we make use of the following equality:

$$c_{km}^2 + s_{mk}^2 = c_{kk}c_{mm} \quad \forall km \in \mathcal{L}. \quad (3)$$

We will denote by **Jabr equality ACOPF relaxation** the model (2) together with constraints (3).

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These **nonconvex** couplings constraints can be relaxed as follows.

Inequality

$$c_{km}^2 + s_{mk}^2 \leq c_{kk}c_{mm} \quad \forall km \in \mathcal{L}. \quad (4)$$

Trees and cycles

Trees

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Lemma 1.

If $(\mathcal{B}, \mathcal{L})$ is a multisource radial network, then the Jabr equality ACOPF relaxation is **exact**¹.

¹Rabih A Jabr. “Radial distribution load flow using conic programming”. In: *IEEE transactions on power systems* 21.3 (2006), pp. 1458–1459

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If $(\mathcal{B}, \mathcal{L})$ is a multisource radial network, then the Jabr equality ACOPF relaxation is **exact**¹.

Why do we need a **tree** structure for the exactness of the model?

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Loop constraints

Definition 1 (Loop constraint).

Given a cycle \mathcal{C} on nodes $\{k_1, \dots, k_n\}$, we define the **loop constraint** on \mathcal{C} as the following

$$\sum_{j=0}^{\lfloor n/2 \rfloor} \sum_{\substack{A \subset [n] \\ |A|=2j}} (-1)^j \prod_{h \in A} s_{k_h k_{h+1}} \prod_{l \in A^c} c_{k_l k_{l+1}} = \prod_{i=1}^n c_{k_i k_i}, \quad (5)$$

with $A^c := [n] \setminus A$.

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with $A^c := [n] \setminus A$.

Lemma 2.

The Jabr equality ACOPF relaxation together with the additional loop constraint (5) written for every cycle of $(\mathcal{B}, \mathcal{L})$ is **exact**².

²Burak Kocuk, Santanu S. Dey, and X. Andy Sun. “Strong SOCP relaxations for the optimal power flow problem”. In: *Operations Research* 64.6 (2016), pp. 1177–1196

Constraint redundancy

Definition 2 (Cycle space).

The (binary) **cycle space** of an undirected graph is the set of its even-degree subgraphs.

Definition 3 (Cycle basis).

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Lemma 3.

It is sufficient to write (5) for every cycle in a **cycle basis** of $(\mathcal{B}, \mathcal{L})$.

Some Linearizations

Multilinear (I)

A first idea is to use cycles of **length three and four** in order to have polynomials of degree 3 and 4, that can be replaced exactly by two bilinear constraints³.

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We instead asked ourself if it was possible to find good linear approximations for multilinear polynomials in general.

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Let $F = \sum_{I \in \mathcal{I}} \prod_{v \in I} x_v$ be a multilinear polynomial and let us focus on a single monomial $f = \prod_{v \in I} x_v$, with $x_v \in [l_v, u_v]$. Define the cuboid $\mathfrak{C} := \prod_{v \in I} [l_v, u_v]$. We are looking for **valid linear inequalities**, that is, hyperplanes π such that either $\pi(x) \geq f(x)$ for all $x \in \mathfrak{C}$ or $\pi(x) \leq f(x)$ for all $x \in \mathfrak{C}$.

³Burak Kocuk, Santanu S. Dey, and X. Andy Sun. “Strong SOCP relaxations for the optimal power flow problem”. In: *Operations Research* 64.6 (2016), pp. 1177–1196

Multilinear (II)

In addition, we are looking for “good” hyperplanes, that is, we would like $\pi(x^i) = f(x^i)$ for some $x^i \in \mathfrak{C}$.

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Lemma 4.

The hyperplane $\pi_a(x) := \prod_{v \in I} a_v + \sum_{v \in I} C_v(x_v - a_v)$, where $C_v := \prod_{v' \in I \setminus \{v\}} a_{v'}$, is the only hyperplane such that $\pi(a) = f(a)$ and $\pi(y) = \prod_{v \in I} y_v$ for all vertices y in \mathfrak{C} , adjacent to a .

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Not all of these hyperplanes are separating hyperplanes. We proved the following results that completely characterize them.

Multilinear (III)

Theorem 1.

The hyperplane $\pi := \pi_a$ is a separating hyperplane if and only if either for all $J \subset I$, $J = \{j_1, \dots, j_s\}$, $k = 1, \dots, s-1$ and $J_k := \{j_1, \dots, j_k\}$, defining $x^{J_k} := a + \sum_{v \in J_k} d_v$, the following holds:

$$\sum_{k=2}^s \left(\prod_{\substack{v \in I \\ v \neq j_k}} a_v - \prod_{\substack{v \in I \\ v \neq j_k}} x_v^{J_k} \right) (a_{j_k}^{op} - a_{j_k}) \geq 0 \quad (6)$$

or for all $J \subset I$, $J = \{j_1, \dots, j_s\}$:

$$\sum_{k=2}^s \left(\prod_{\substack{v \in I \\ v \neq j_k}} a_v - \prod_{\substack{v \in I \\ v \neq j_k}} x_v^{J_k} \right) (a_{j_k}^{op} - a_{j_k}) \leq 0. \quad (7)$$

Angle variables (I)

However, the number of variables introduced by this approach grows **exponentially** with respect to the number of edges in the chosen cycle basis of the graph.

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For this reason, we explore a different approach: we reintroduce the variables corresponding to the phase angles θ_{km} and link them to the variable c_{km} through a **convex relaxation** of the constraints

$$c_{km} = |V_k| |V_m| \cdot \cos(\theta_{km}),$$

$$s_{km} = |V_k| |V_m| \cdot \sin(\theta_{km}).$$

Angle variables (II)

A natural question arises: is there a **tighter** convex relaxation of the multilinear right-hand side of the ACOPF constraint

$$P_k^G - P_k^L - G_{kk}|V_k|^2 = |V_k| \sum_m |V_m| (G_{km} \cos(\theta_{km}) - B_{km} \sin(\theta_{km}))$$

than the one obtained by taking the convex hull of each monomial and summing the resulting relaxations?

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By generalizing a result from the literature⁴, we showed that the **answer** to this question is **negative**.

⁴Cheng Guo, Harsha Nagarajan, and Merve Bodur. "Tightening quadratic convex relaxations for the alternating current optimal transmission switching problem". In: *INFORMS Journal on Computing* (2025)

Conclusions & future works

Conclusions

- ▶ Some models and relaxations for the OPF problem.
- ▶ The study of the exactness of the relaxation with respect to the network structure.
- ▶ Some multilinear approaches and theoretical results.

Future works

Spatial branching using the convex relaxation of sine and cosine ◀
(under development).

Optimization-Based Bound Tightening for the trilinear terms in ◀
order to get better approximations (under development).

Compare not only new lower bounds but also have a numerical and ◀
theoretical study on constraints violation.

Fine.