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AC Optimal Power Flow: a Conic Programming relaxation and an iterative MILP scheme for Global Optimization

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Abstract
We address the issue of computing a global minimizer of the AC Optimal Power Flow problem. We introduce valid inequalities to strengthen the Semidefinite Programming relaxation, yielding a novel Conic Programming relaxation. Leveraging these Conic Programming constraints, we dynamically generate Mixed-Integer Linear Programming (MILP) relaxations, whose solutions asymptotically converge to global minimizers of the AC Optimal Power Flow problem. We apply this iterative MILP scheme on the IEEE PES PGLib [2] benchmark and compare the results with two recent Global Optimization approaches.

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Keywords ACOPF, Global Optimization, Semidefinite Programming, Mixed-Integer Linear Programming.

1 Introduction
1.1 Motivation and related works
The Alternating-Current Optimal Power Flow (ACOPF) is a seminal optimization problem related to the dispatching of electricity in a power network. The authorship of this problem is attributed to Carpentier [6], who introduced it in 1962 as “Economic Dispatch”. Since then, this problem has not only interested the Power Systems research community, but also the community of Operations Research and Mathematical Programming [5, 28]. Indeed, ACOPF was identified as a challenging and fruitful application of Nonlinear Programming (NLP) and Global Optimization methods. Thanks to Interior-Point algorithms, developed since the 1990s, the computation of ACOPF feasible solutions and local minimizers is accessible, even for instances of several thousand nodes [33]. To bound the optimality gap of feasible solutions found by such NLP algorithms, several convex relaxations have been introduced during the past decade. A review of the numerous relaxation techniques for the ACOPF problem is available in [28]. Leveraging NLP algorithms and convex relaxations techniques, several approaches emerged to solve the ACOPF problem to global optimality. We gather these works in four different categories.

- **Relaxation Strengthening and Bound Tightening.** Strengthening the classical convex relaxations [28] such as the rank relaxation helps improving the corresponding lower bounds. This strengthening is possible through additional valid inequalities coming from the polar formulation of the ACOPF problem [10, 19, 20] or derived from the Reformulation-Linearization Technique (RLT) [31]. Feasibility-Based Bound Tightening (FBBT) and Optimization-Based Bound Tightening (OBBT) techniques [3], the latter being based on the value of a known feasible solution, are also known to be particularly efficient for the ACOPF problem [9, 32]. Even if these methods do not have a guarantee of convergence towards a global solution, the aforementioned articles report that they significantly reduce the optimality gap and even close the gap for some instances.

- **Moment-Sum-of-Squares hierarchy.** The celebrated Moment-Sum-of-Squares hierarchy of relaxations for polynomial optimization problems [23] has been applied to the ACOPF problem in several works [14, 13, 27, 29]. The convergence of the relaxations’ values towards the optimal value of the ACOPF problem is proven, at the price of the rapidly increasing size and computational cost of the resulting convex relaxations. In practice, only the first and second order relaxations are solvable for medium-scale ACOPF instances, using the sparse variant of the Moment-Sum-of-Squares hierarchy [24].
A power grid is a network of buses interconnected by lines. We give an arbitrary orientation to each line, so as to distinguish its two extremities. Hence, the grid is modelled as a directed graph $(G, \ell)$ where $(G, \ell)$ is s.t. $G \cap G^R = \emptyset$, where $G^R$ is the set of all generators is $G = \bigcup_{b \in B} G_b$, whose cardinality is $m = |G|$. The parameters of the ACOPF problem are described in Table 1.

| Parameters | Index set | Description |
|------------|-----------|-------------|
| $c_{1g}$, $c_{2g}$ ∈ $\mathbb{R}$ | $g \in G$ | Cost parameters |
| $g$, $\tau_g$ ∈ $\mathbb{C}$ | $g \in G$ | Power injection bounds |
| $g_a$, $\tau_b$ ∈ $[0, 2]$ | $b \in B$ | Normalized voltage bounds |
| $S_b^d$ ∈ $\mathbb{C}$ | $b \in B$ | Power demand |
| $Y_b^s$ ∈ $\mathbb{C}$ | $b \in B$ | Shunt admittance |
| $Y_{ba}^{ff}$, $Y_{ba}^{on}$, $Y_{ba}^{on}$, $Y_{ba}^{tt}$ ∈ $\mathbb{C}$ | $(b, a) \in \ell$ | Line impedance coefficients |
| $\theta_{ba}, \theta_{ba}$ ∈ $[-\pi, \pi]$ | $(b, a) \in \ell \cup \ell^R$ | Angle difference limits |
The objective function is the sum of the generation costs

\[ \sum_{g \in G} (c_{1g} \text{Re}(S_g) + c_{2g} \text{Re}(S_g)^2) , \]  

to be minimized. The decision variables are subject to different types of constraints:

- **Injection Limits for Generators.** For each \( g \in G \), we have

\[ 2g \leq S_g \leq \bar{s}_g. \]  

These inequalities between complex numbers designate the respective real inequalities for the real and for the imaginary parts.

- **Voltage Magnitude Limits.** For each \( b \in B \), the voltage at \( b \) satisfies

\[ g_b \leq |V_b| \leq \bar{v}_b. \]  

The ACOPF instances in the literature are scaled so that each bus has a nominal voltage normalized to 1. The lower and upper bounds respectively correspond to deviations of at most 50% around this nominal value. Introducing \( \Delta_v = \bar{v}_b - g_b \), we assume, thus, that \( g_b, \bar{v}_b \in [0, 2] \) and \( \Delta_v \leq 1 \).

- **Power Flow Equations.** For each bus \( b \in B \), we define the complex matrix

\[ M_b = Y_b^* E_{bb} + \sum_{a: (b,a) \in L} (Y_{ba}^* E_{bb} + Y_{ba}^* E_{ba}) + \sum_{a: (b,a) \in L^R} (Y_{ab}^* E_{bb} + Y_{ab}^* E_{ba}). \]  

With this notation, we write the Power Flow conservation at bus \( b \in B \) as

\[ \sum_{g \in G_b} S_g - S_b^d = \langle M_b, VV^H \rangle. \]  

Constraint (4) describes the equality between the net injection of power at \( b \) and the power transfer towards the adjacent buses.

- **Thermal Limits for Lines.** For each line \((b,a) \in L \), the operational limit in terms of apparent power is

\[ |(Y_{ba}^*)|^2 + |(Y_{ab}^*)|^2 \leq \bar{s}_{ba} \].  

For \((b,a) \in L^R \), this reads

\[ |(Y_{ba}^*)|^2 + |(Y_{ab}^*)|^2 \leq \bar{s}_{ba} \].  

- **Line Phase Angle Difference Limits.** For any \((b,a) \in L \cup L^R \),

\[ \theta_{ba} \leq \Delta V_b - \Delta V_a \leq \bar{\theta}_{ba} \].

In summary, the ACOPF problem is the following Nonconvex Optimization problem

\[
\begin{align*}
\text{ACOPF} \quad \min_{S \in C^m, V \in C^n} & \left( \sum_{g \in G} (c_{1g} \text{Re}(S_g) + c_{2g} \text{Re}(S_g)^2) \right) \\
\text{s.t.} & \forall g \in G \quad 2g \leq S_g \leq \bar{s}_g \\
& \forall b \in B \quad g_b \leq |V_b| \leq \bar{v}_b \\
& \forall b \in B \quad \sum_{g \in G_b} S_g - S_b^d = \langle M_b, VV^H \rangle \\
& \forall (b,a) \in L \\
& \quad |(Y_{ba}^*)|^2 + |(Y_{ab}^*)|^2 \leq \bar{s}_{ba} \\
& \forall (b,a) \in L^R \\
& \quad |(Y_{ba}^*)|^2 + |(Y_{ab}^*)|^2 \leq \bar{s}_{ba} \\
& \forall (b,a) \in L \cup L^R \quad \theta_{ba} \leq \Delta V_b - \Delta V_a \leq \bar{\theta}_{ba}.
\end{align*}
\]
2.2 ACOPF reformulation

**Definition 1.** A tree decomposition $\mathcal{T}$ of the graph $\mathcal{N} = (\mathcal{B}, \mathcal{L})$ is a tree where each node $k \in \mathcal{T}$ is associated with a set $\mathcal{B}_k \subset \mathcal{B}$, and satisfying the following properties:

- The union of the subsets $\mathcal{B}_k$ equals the set $\mathcal{B}$: $\bigcup_{k \in \mathcal{T}} \mathcal{B}_k = \mathcal{B}$.
- For every $(b, a) \in \mathcal{L}$, there exists $k \in \mathcal{T}$ s.t. $(b, a) \subset \mathcal{B}_k$.
- If $b \in \mathcal{B}_k \cap \mathcal{B}_\ell$ for any $k, \ell \in \mathcal{T}$, then $b \in \mathcal{B}_j$ for all nodes $j$ of the tree $\mathcal{T}$ in the unique path between $k$ and $\ell$.

We consider a given tree decomposition $\mathcal{T}$ of the graph $\mathcal{N}$, and we introduce the symmetric set $\mathcal{E} \subset \mathcal{B} \times \mathcal{B}$ of arcs defined as $\mathcal{E} = \bigcup_{k \in \mathcal{T}} \mathcal{B}_k \times \mathcal{B}_k$. As a matter of fact, the sets $\mathcal{B}_k$ are cliques of the undirected graph induced by $(\mathcal{B}, \mathcal{E})$. In this respect, the sets $\mathcal{B}_k$ are called cliques. We denote by $\mathbb{H}_n(\mathcal{E})$ the set of partially defined matrices $W$, seen as vectors indexed by $\mathcal{E}$, and for all $b, a \in \mathcal{E}$. For any $k \in \mathcal{T}$, we denote by $W_{\mathcal{B}_k \mathcal{B}_k}$ the matrix $(W_{ba})_{(b,a) \in \mathcal{E}_k}$. With this notation, we reformulate (ACOPF) as

$\text{ACOPF}_W \left\{ \begin{array}{l}
\min_{S \in \mathbb{C}^n, W \in \mathbb{H}_n(\mathcal{E})} \sum_{g \in \mathcal{G}} \left( c_{2g} \text{Re} (S_g) + c_{e2g} \text{Re} (S_g^2) \right) \\
\text{subject to} \quad \forall g \in \mathcal{G}, \quad 2g \leq S_g \leq 2g \\
\forall b \in \mathcal{B}, \quad \mathcal{G}_b \leq W_{bb} \leq \mathcal{G}_b \\
\forall (b, a) \in \mathcal{L}, \quad |(Y_{bb}^a)^* W_{bb} + (Y_{ab}^a)^* W_{ba}| \leq \mathcal{F}_{ba} \\
\forall (b, a) \in \mathcal{L}, \quad |(Y_{bb}^a)^* W_{bb} + (Y_{ab}^a)^* W_{ba}| \leq \mathcal{F}_{ba} \\
\forall (b, a) \in \mathcal{E}, \quad |W_{ba}|^2 = W_{bb} W_{aa} \\
\forall k \in \mathcal{T}, \quad W_{\mathcal{B}_k \mathcal{B}_k} \succeq 0.
\end{array} \right.$

While the clique-based SDP relaxation is well known, this clique-based reformulation of the ACOPF problem itself is not properly stated in the literature, as far as we know. Yet, we acknowledge that the proof of Theorem 2 is closely related to the developments presented in [7].

**Theorem 2.** A pair $(S, W)$ is feasible (resp. optimal) in (ACOPF$_W$) if and only if there exists $V \in \mathbb{C}^n$ s.t. $(S, V)$ is feasible (resp. optimal) in (ACOPF) and $W_{ba} = V_b V_a^*$ for all $(b, a) \in \mathcal{E}$.

**Proof.** We prove the equivalence for the feasibility, which also proves the equivalence for the optimality since both problems share the same objective value. We take $(S, V)$ a feasible solution in (ACOPF) and we define $W \in \mathbb{H}_n(\mathcal{E})$ as $W_{ba} = V_b V_a^*$ for any $(b, a) \in \mathcal{E}$. For any $b \in \mathcal{B}$, we make the following observations:

- Since $v_b \leq |V_b| \leq \bar{v}_b$, the inequalities $\mathcal{G}_b \leq |V_b|^2 \leq \bar{v}_b^2$ and $\mathcal{G}_b \leq W_{bb} \leq \bar{v}_b^2$ hold.
- Since $\sum_{g \in \mathcal{G}_b} S_g - S_b^2 = (S_b, V_{bb})$ and since $M_b \in \mathbb{H}_n(\mathcal{E})$, we deduce by substitution that $\sum_{g \in \mathcal{G}_b} S_g - S_b^2 \leq (M_b, W)$.

Similarly by direct substitution, we deduce that $|(Y_{bb}^a)^* W_{bb} + (Y_{ab}^a)^* W_{ba}| \leq \mathcal{F}_{ba}$ for all $(b, a) \in \mathcal{L}$ and $|(Y_{bb}^a)^* W_{bb} + (Y_{ab}^a)^* W_{ba}| \leq \mathcal{F}_{ba}$ for all $(b, a) \in \mathcal{L}$.

For any $(b, a) \in \mathcal{L} \cup \mathcal{L}^R$, since $\mathcal{L} W_{bb} = \mathcal{L} V_b V_a^* = \mathcal{L} V_a = \mathcal{L} V_a$, we have $\bar{v}_b \leq \mathcal{L} W_{bb} \leq \bar{v}_b$. Using that $\bar{v}_{ba} \leq \bar{v}_b$, we deduce that $\Re(W_{ba}) \leq \Im(W_{ba}) \leq \Im(W_{ba}) \leq \mathcal{F}_{ba}$.

To conclude about the feasibility of $(S, W)$ in (ACOPF$_W$), we state that $W_{\mathcal{B}_k \mathcal{B}_k} = (V_b V_a^*)_{(b,a) \in \mathcal{B}_k} \succeq 0$ for all $k \in \mathcal{T}$, and that $|W_{ba}|^2 = |V_b|^2 |V_a|^2 = W_{bb} W_{aa}$ for all $(b, a) \in \mathcal{E}$.

Conversely, we consider any $(S, W)$ feasible in (ACOPF$_W$). Since $W_{\mathcal{B}_k \mathcal{B}_k} \succeq 0$ and $|W_{ba}|^2 = W_{bb} W_{aa}$ for all $(b, a) \in \mathcal{B}_k$, we can apply [7, Prop. 6] to state that rank $W_{\mathcal{B}_k \mathcal{B}_k} = 1$ for all $k \in \mathcal{T}$. By induction on the tree decomposition $\mathcal{T}$, we prove that there exists $V \in \mathbb{C}^n$ s.t. $W_{ba} = V_b V_a^*$ for all $(b, a) \in \mathcal{E}$. The case $|\mathcal{T}| = 1$ is trivial, since any rank-one positive semidefinite (PSD) matrix $W$ can be written as $W = V V^H$. We assume now that the induction hypothesis is true for any graph with a tree decomposition with size less or equal than $p \in \mathbb{N}^*$, and we consider a graph $\mathcal{N}$ with a tree decomposition $\mathcal{T}$ with size $p + 1$. We consider a leaf $k$ of $\mathcal{T}$, $\mathcal{B}_k$ the corresponding clique, $\mathcal{B} = \bigcup_{g \in \mathcal{G}_k} \mathcal{B}_g$ the union of the other cliques, and $\mathcal{C}_k = \mathcal{B}_k \setminus \mathcal{B}$. By property of a tree decomposition, since $k$ is a leaf of $\mathcal{T}$, $\mathcal{T} \setminus \{k\}$ is a tree decomposition of the graph $(\mathcal{B}, \mathcal{E})$, where $\mathcal{E}$ denotes the edges in $\mathcal{E}$ that are not adjacent to $\mathcal{C}_k$. Applying the induction hypothesis, since $\mathcal{T} \setminus \{k\}$ has size $p$, there exists a complex vector $V \in \mathbb{C}^{|\mathcal{B}_k|}$ s.t. $W_{ba} = V_b V_a^*$ for all $(b, a) \in \mathcal{E}$. Additionally, since $W_{\mathcal{B}_k \mathcal{C}_k}$ is a rank-one PSD matrix, there exists $U \in \mathbb{C}^{|\mathcal{B}_k|}$ s.t. $W_{ba} = U_b U_a^*$ for all $(b, a) \in \mathcal{B}_k \times \mathcal{B}_k$. For all $b \in \mathcal{B}_k \setminus \mathcal{C}_k$, $|V_b|^2 = W_{bb} = |U_b|^2$, since $b \in \mathcal{B}_k \setminus \mathcal{B}_k$. Hence, $|V_b| = |U_b|$ by nonnegativity of the module. Moreover, for all $(b, a) \in (\mathcal{B}_k \setminus \mathcal{C}_k)^2$, $\mathcal{L} V_b - \mathcal{L} V_a = \mathcal{L} W_{ba} = \mathcal{L} U_b - \mathcal{L} U_a$, and hence, $\mathcal{L} V_b - \mathcal{L} V_a = \mathcal{L} V_a = \mathcal{L} U_a$. Defining $u_a = \mathcal{L} V_a - \mathcal{L} U_a$ for any $b \in \mathcal{B}_k \setminus \mathcal{C}_k$, we define $U_b^* = e^{iu_a} U_b$, which satisfies $U_b^* = V_b$ for all $b \in \mathcal{B}_k \setminus \mathcal{C}_k$. Hence, the vector $V^* = e^{iu_a} V$ defined as $V_b^* = U_b^*$ if $b \in \mathcal{B}_k$ and $V_b^* = V_b$ if $b \in \mathcal{B}$, is well-defined and satisfies $W_{ba} = V_b^* (V_a^*)^*$ for all $(b, a) \in \mathcal{E}$. 
By induction, this proves that there exists a vector $V \in \mathbb{C}^n$ s.t. $W_{ba} = V_b V_a^*$ for all $(b, a) \in \mathcal{E}$. The feasibility of $(S, V)$ in (ACOPF) follows by substituting $W_{ba}$ by $V_b V_a^*$ in the constraints of (ACOPF$_W$).

## 3 Strengthening the SDP relaxation

In formulation (ACOPF$_W$), Constraints (⋆) are the only nonconvex constraints. Removing them leads to the clique-based SDP relaxation [28, 30]. Instead of merely deleting Constraints (⋆), we add valid inequalities based on Voltage Magnitude and Phase Angle Difference bounds.

### 3.1 Conic Programming Outer-Approximation of Constraints (⋆)

For all $b \in \mathcal{B}$, we introduce a variable $L_b \in [\bar{v}_b, \bar{v}_b]$ that represents the Voltage Magnitude $|V_b|$. For all $(b, a) \in \mathcal{E}$, we introduce a variable $R_{ba} \in [\bar{v}_b, \bar{v}_b]$ that stands for $|V_b||V_a|$ and is subject to

\begin{align}
R_{ba} & \geq \bar{v}_b L_a + \bar{v}_a L_b - \bar{v}_b L_a - \bar{v}_a L_b - \bar{v}_a \bar{v}_b \tag{8} \\
R_{ba} & \leq \bar{v}_b L_a + \bar{v}_a L_b - \bar{v}_a \bar{v}_b \tag{9}
\end{align}

For all $b \in \mathcal{B}$, we also define the following constraints

\begin{align}
L_b^2 & \leq R_{bb} \tag{10} \\
R_{bb} + \bar{v}_b \delta_a & \leq (\bar{v}_b + \bar{v}_a) L_b. \tag{11}
\end{align}

Whereas Constraints (8)–(11) approximate the equality $R_{ba}^2 = W_{ba} W_{aa}$, we also need to approximate $|W_{ba}| = R_{ba}$.

For this purpose, we impose for all $(b, a) \in \mathcal{E}$,

\begin{equation}
|W_{ba}| \leq R_{ba}. \tag{12}
\end{equation}

For all $(b, a) \in \mathcal{E} \setminus (\mathcal{L} \cup \mathcal{L}^R)$, we define $\tilde{\theta}_{ba} = -2\pi$ and $\tilde{\delta}_{ba} = 2\pi$. In fact, we present in Section 3.3.3 how these Phase Angle Difference bounds may be tightened based on a Shortest Path algorithm. Then, we can define the angles $\phi_{ba} = \frac{\theta_{ba} + \tilde{\theta}_{ba}}{2}$ and $\delta_{ba} = \frac{\delta_{ba} + \tilde{\delta}_{ba}}{2}$ for any $(b, a) \in \mathcal{E}$. With this notation, the following constraints are valid for any $(b, a) \in \mathcal{E}$ s.t. $\delta_{ba} \leq \frac{\pi}{2}$:

\begin{equation}
\cos(\phi_{ba}) \Re(W_{ba}) + \sin(\phi_{ba}) \Im(W_{ba}) \geq R_{ba} \cos(\delta_{ba}). \tag{13}
\end{equation}

Finally, for every $k \in \mathcal{T}$, we require that

\begin{equation}
R_{B_k} \triangleq (R_{B_k B_k})^H \begin{pmatrix} 1 & L_{B_k}
R_{B_k B_k}^H
\end{pmatrix} \succeq 0, \tag{14}
\end{equation}

where $R_{B_k}$ denotes the matrix $(R_{ba})_{(b,a) \in \mathcal{E}_k}$ and $L_{B_k}$ denotes the vector $(L_{ba})_{b,a \in \mathcal{B}_k}$. Adding the decision vectors $L \in \mathbb{R}^n$ and $R \in \mathbb{R}^\mathcal{E}$ to the optimization problem (ACOPF$_W$) and replacing Constraints (⋆) by Constraints (8)–(14), we obtain a Conic Programming problem, that we denote (R).

\textbf{Proposition 3.} The Conic Programming problem (R) is a relaxation of (ACOPF$_W$).

\textbf{Proof.} We prove the validity of the Constraints (8)–(14). More specifically, we prove that for any couple $(S, W) \in \mathbb{C}_m \times \mathbb{H}_n(\mathcal{E})$ feasible in (ACOPF$_W$), the quadruplet $(S, W, L, R)$ is feasible in (R), where $L$ and $R$ are defined as $L_b = \sqrt{W_{bb}}$ and $R_{ba} = |W_{ba}|$ for all $(b, a) \in \mathcal{E}$. Since the objective function is the same in (R) and (ACOPF$_W$), this will prove that (R) is a relaxation of (ACOPF$_W$). Since $R_{ba} = L_b L_a$ and $(L_b, L_a) \in [\bar{v}_b, \bar{v}_b] \times [\bar{v}_a, \bar{v}_a]$, the triplet $(R_{ba}, L_b, L_a)$ satisfies the McCormick inequalities [26] with respect to (w.r.t.) these bounds, i.e., Constraints (8)–(9). Constraint (10) is satisfied since $W_{bb} \in \mathbb{R}$, as $(S, W)$ is feasible in (ACOPF$_W$), yielding $R_{bb} = |W_{bb}| = W_{bb} = L_b^2$. Constraint (11) also being a McCormick constraint (for $b = a$), it is satisfied by $(R_{bb}, L_b)$, as $R_{bb} = L_b^2$. Constraint (12) just follows from the definition of $R_{ba} = |W_{ba}|$. For any $(b, a) \in \mathcal{E}$, we define $\theta_{ba} = \angle W_{ba}$; considering the definition of $\phi_{ba}$ and $\delta_{ba}$, we notice that $|\theta_{ba} - \phi_{ba}| < \delta_{ba}$. For this reason, if $\delta_{ba} < \frac{\pi}{2}$, we obtain $\cos(|\theta_{ba} - \phi_{ba}|) \geq \cos(\delta_{ba})$, as $\cos$ is decreasing over $[0, \frac{\pi}{2}]$. Using the parity of $\cos$, and multiplying by $R_{ba} \geq 0$, we obtain $R_{ba} \cos(\theta_{ba} - \phi_{ba}) \geq R_{ba} \cos(\delta_{ba})$. Moreover, $R_{ba} \cos(\theta_{ba} - \phi_{ba}) = |W_{ba}|(\cos(\phi_{ba}) \cos(\theta_{ba}) + \sin(\phi_{ba}) \sin(\theta_{ba})) = \cos(\phi_{ba}) \Re(W_{ba}) + \sin(\phi_{ba}) \Im(W_{ba})$, explaining that $(R_{ba}, W_{ba})$ satisfies Constraint (13), whenever $\delta$. Finally, Constraint (14) just follows from the equalities $R_{ba} = |W_{ba}| = |W_{ab}| = R_{ab}$ and \[ \begin{pmatrix} \frac{L_{B_k}}{R_{B_k B_k}} & L_{B_k}
\end{pmatrix} \begin{pmatrix} 1 \\
R_{B_k}
\end{pmatrix} \succeq 0. \]
By construction, the relaxation (R) is tighter than the clique-based SDP relaxation, the value of which equals the value of the standard SDP relaxation [15], also known as rank relaxation. The following theorem shows how Constraints (8)–(13) help having \(|W_{ba}|^2 \approx W_{bb}W_{aa}\) when the Voltage Magnitude and Phase Angle Difference intervals are small. We recall the notation \(\Delta_b = \pi_b - \pi_a\) and that we assume \(\Delta_b \leq 1\) throughout the paper.

**Theorem 4.** For any \((b, a) \in \mathcal{E}\), the following statements hold:

- Under Constraints (8)–(9), we have \(|R_{ba}^2 - L_b^2 L_a^2| \leq 9\Delta_b \Delta_a\).
- Under Constraints (10)–(11), we have \(|W_{bb}W_{aa} - L_b^2 L_a^2| \leq (\Delta_b + \Delta_a)^2\).
- Under Constraints (12)–(13), if \(\delta_{ba} \leq \frac{\pi}{2}\), we have \(|W_{ba}|^2 - R_{ba}^2| \leq 16\delta_{ba}^2\).

Therefore, if Constraints (8)–(13) are satisfied and \(\delta_{ba} \leq \frac{\pi}{2}\), then \(|W_{ba}|^2 - W_{bb}W_{aa}| \leq 9\Delta_b \Delta_a + (\Delta_b + \Delta_a)^2 + 16\delta_{ba}^2\).

**Proof.** First, we take any \((b, a) \in \mathcal{E}\) and we define a tuple \((W, L, R)\) satisfying Constraints (8)–(9). We define \(a_1 = y_b L_a + y_a L_b - y_b y_a\) and we notice that \(L_b L_a - a_1 = (L_b - y_b)(L_a - y_a) \in [0, \Delta_b \Delta_a]\), since \(L_b - y_b \in [0, \Delta_b]\) and \(L_a - y_a \in [0, \Delta_a]\). Hence, \(a_1 \in [L_b L_a - \Delta_b \Delta_a, L_b L_a]\). Similarly, defining \(a_2 = \pi_b L_a + \pi_a L_b - \pi_b \pi_a\), \(a_3 = \pi_b L_a + y_a L_b - \pi_a y_b\), \(a_4 = \pi_a L_b + y_b L_a - \pi_b y_a\), we can prove that \(a_2 \in [L_b L_a - \Delta_b \Delta_a, L_b L_a]\), \(a_3 \in [L_b L_a, L_b L_a + \Delta_b \Delta_a]\) and \(a_4 \in [L_b L_a, L_b L_a + \Delta_b \Delta_a]\). According to Constraints (8)–(9), \(R_{ba} \in [\max(a_1, a_2), \min(a_3, a_4)]\), which proves that \(R_{ba} \in [L_b L_a - \Delta_b \Delta_a, L_b L_a + \Delta_b \Delta_a]\). We square the inequalities \(0 \leq R_{ba} \leq L_b L_a + \Delta_b \Delta_a\) to obtain

\[
R_{ba}^2 \leq L_b^2 L_a^2 + \Delta_b \Delta_a (2L_b L_a + \Delta_b \Delta_a) \leq L_b^2 L_a^2 + 2\Delta_b \Delta_a,
\]

the last inequality following from \(L_b \leq \pi_b \leq 2, L_a \leq \pi_a \leq 2\) and \(0 \leq \Delta_b \Delta_a \leq 1\). Squaring the inequalities \(0 \leq L_b L_a \leq R_{ba} + \Delta_b \Delta_a\), we deduce that \(L_b^2 L_a^2 \leq R_{ba}^2 + \Delta_b \Delta_a (2R_{ba} + \Delta_b \Delta_a) \leq R_{ba}^2 + 9\Delta_b \Delta_a\) since \(R_{ba} \leq \pi_b \pi_a \leq 4\). Consequently,

\[
|R_{ba}^2 - L_b^2 L_a^2| \leq 9\Delta_b \Delta_a.
\]  

Second, we take any tuple \((W, L, R)\) satisfying Constraints (10)–(11) for \(b\) and \(a\). We notice that the maximum of the quadratic form \((y_b + \pi_b) X - X^2 - y_b \pi_b\) is attained for \(X = x_b^2 + \pi_b^2\) with value \(\frac{(x_b + \pi_b)^2}{4} - y_b \pi_b = \frac{\Delta_b^2}{4}\). Hence, \((y_b + \pi_b) L_b - L_b^2 - y_b \pi_b \leq \frac{\Delta_b^2}{4}\) Constraint (11) yielding \(R_{bb} + y_b \pi_b \leq (y_b + \pi_b)L_b\), we deduce that \(R_{bb} - L_b^2 \leq \Delta_b^2/4\). As \(R_{bb} \geq 0\), we have \(0 \leq R_{bb} \leq L_b^2 + \Delta_b^2/4\). Applying the same reasoning for \(a\), we have \(0 \leq R_{aa} \leq L_a^2 + \Delta_a^2/4\). Multiplying both sets of inequalities together, we obtain

\[
0 \leq R_{bb} R_{aa} \leq L_b^2 L_a^2 + L_b^2 \frac{\Delta_b^2}{4} + L_a^2 \frac{\Delta_a^2}{4} + \frac{\Delta_b^2}{4} \frac{\Delta_a^2}{4} \leq L_b^2 L_a^2 + \Delta_b^2 + \Delta_a^2 + 2\Delta_b \Delta_a \leq L_b^2 L_a^2 + (\Delta_b + \Delta_a)^2,
\]

using that \(L_b, L_a \in [0, 2]\) and \(\Delta_b, \Delta_a \in [0, 1]\). As Constraint (10) yields \(L_b^2 \leq R_{bb}\) and \(L_a^2 \leq R_{aa}\), we deduce that \(L_b^2 L_a^2 \leq R_{bb} R_{aa}\) and finally, since \(R_{bb} = W_{bb}\) and \(R_{aa} = W_{aa}\),

\[
|W_{bb}W_{aa} - L_b^2 L_a^2| \leq (\Delta_b + \Delta_a)^2.
\]

Third, we take any tuple \((W, L, R)\) satisfying Constraints (12)–(13). We consider \((b, a) \in \mathcal{E}\) s.t. \(\delta_{ba} \leq \frac{\pi}{2}\). We write \(W_{ba}\) as \(|W_{ba}| e^{i\theta}\) and Constraint (13), which is applicable since \(\delta_{ba} \leq \frac{\pi}{2}\), yields \(|W_{ba}| (\cos(\phi_{ba}) \cos(\theta) + \sin(\phi_{ba}) \sin(\theta)) \geq R_{ba} \cos(\delta_{ba})\). This may be written as \(|W_{ba}| \cos(\phi_{ba} - \theta) \geq R_{ba} \cos(\delta_{ba})\). This implies that \(|W_{ba}| \geq R_{ba} \cos(\delta_{ba})\), and thus \(|W_{ba}|^2 \geq R_{ba}^2 \cos(\delta_{ba})^2\). As \(|W_{ba}|^2 \leq R_{ba}^2\), according to Constraint (12), we have

\[
0 \leq R_{ba}^2 - |W_{ba}|^2 \leq R_{ba}^2(1 - \cos(\delta_{ba})^2) = R_{ba}^2 \sin(\delta_{ba})^2.
\]

Using that \(R_{ba} \leq 4\) and that \(\sin(\delta_{ba})^2 \leq \delta_{ba}^2\), we obtain

\[
|W_{ba}|^2 - R_{ba}^2 \leq 16\delta_{ba}^2.
\]

As a conclusion, for any tuple \((W, L, R)\) satisfying Constraints (8)–(13), we deduce from Equations (15), (17) and (18) that

\[
|W_{ba}|^2 - W_{bb}W_{aa} \leq |W_{ba}|^2 - R_{ba}^2 + |R_{ba}^2 - L_b^2 L_a^2| + |L_b^2 L_a^2 - W_{bb}W_{aa}| \leq 9\Delta_b \Delta_a + (\Delta_b + \Delta_a)^2 + 16\delta_{ba}^2.
\]
3.2 Connections to previous works

Previous works in the Power Systems community proposed valid equalities to strengthen the SDP relaxation of the ACOPF problem [19, 20, 10]. In [10], the authors show that these valid equalities are all dominated by the inequalities [10, (36a), (36b)]. Using the parameter $v_b^d = z_b + \sigma_b$, the inequalities [10, (36a) and (36b)] read, with our notation,

\begin{align*}
  v_b^d v_a^d (\cos(\phi_b) \Re(W_{ba}) + \sin(\phi_b) \Im(W_{ba})) - \sigma_b \cos(\delta_{ba}) v_b^d W_{bb} - \sigma_b \cos(\delta_{ba}) v_a^d W_{aa} & \geq -z_b R_a^\sigma - \sigma_b \tau_a, \quad (i) \\
  v_b^d v_a^d (\cos(\phi_b) \Re(W_{ba}) + \sin(\phi_b) \Im(W_{ba})) - \sigma_a \cos(\delta_{ba}) v_a^d W_{bb} - \sigma_a \cos(\delta_{ba}) v_b^d W_{aa} & \geq -z_a R_b^\sigma - \sigma_a \tau_b. \quad (ii)
\end{align*}

The following Proposition states that Constraints (8)–(13), that we introduce here to strengthen the SDP relaxation, dominate Equations (i)–(iv).

**Proposition 5.** For any $(b, a) \in \mathcal{L} \cup \mathcal{L}^R$, for any quadruplet $(\Re(W_{ba}), \Im(W_{ba}), W_{bb}, W_{aa})$ s.t. there exists $L_b, L_a, R_{ba} \in \mathbb{R}_+$ s.t. Constraints (8)–(13) are satisfied, then the quadruplet $(\Re(W_{ba}), \Im(W_{ba}), W_{bb}, W_{aa})$ satisfies (i)–(iv).

**Proof.** We take any $(b, a) \in \mathcal{L} \cup \mathcal{L}^R$ and any quadruplet $(\Re(W_{ba}), \Im(W_{ba}), W_{bb}, W_{aa})$ s.t. there exists $L_b, L_a, R_{ba} \in \mathbb{R}_+$ s.t. Constraints (8)–(13) are satisfied. Constraints (10)–(11) applied for $b$ and $a$ yields

\begin{align*}
  v_b^d L_b & \geq W_{bb} + z_b \bar{L}_b, \\
  v_a^d L_a & \geq W_{aa} + z_a \bar{L}_a. 
\end{align*}

First, we combine Equations (19)–(20) with $R_{ba} \geq \sigma_a \bar{L}_b + \sigma_b \bar{L}_a - \bar{v}_b R_a$, from Constraint (8), that we multiply by $v_b^d v_a^d \geq 0$, to deduce that $v_b^d v_a^d R_{ba} \geq \sigma_a v_b^d W_{bb} + \sigma_b v_a^d W_{aa} + v_a^d v_b^d \tau_b \bar{L}_b + v_b^d v_a^d \tau_a \bar{L}_a - v_b^d v_a^d \tau_a$, and, thus,

\begin{equation}
  v_b^d v_a^d R_{ba} - \tau_a v_b^d W_{bb} - \tau_b v_a^d W_{aa} \geq \sigma_a v_b^d \bar{v}_b \bar{L}_b + \sigma_b v_a^d \bar{v}_a \bar{L}_a - v_b^d v_a^d \tau_b \bar{L}_b = \bar{v}_b \bar{v}_a (\bar{v}_b \bar{L}_b - \bar{v}_b R_a),
\end{equation}

as $\tau_a v_b^d \bar{v}_b \bar{L}_b + \sigma_b v_a^d \bar{v}_a \bar{L}_a - v_b^d v_a^d \tau_b \bar{L}_b = \bar{v}_b \bar{v}_a (\bar{v}_b \bar{L}_b - \bar{v}_b R_a) = \bar{v}_b \bar{v}_a (\bar{v}_b \bar{L}_b - \bar{v}_a R_a)$. Multiplying Equation (21) by $\cos(\delta_{ba}) \geq 0$, we have

\begin{equation}
  v_b^d v_a^d \cos(\delta_{ba}) R_{ba} - \bar{v}_a v_b^d W_{bb} - \bar{v}_b v_a^d W_{aa} \geq \bar{v}_b \bar{v}_a \cos(\delta_{ba}) (\bar{v}_b \bar{L}_b - \bar{v}_a R_a).
\end{equation}

Multiplying Constraint (13) by $v_b^d v_a^d \geq 0$ yields $v_b^d v_a^d (\cos(\phi_b) \Re(W_{ba}) + \sin(\phi_b) \Im(W_{ba})) \geq v_b^d v_a^d \cos(\delta_{ba}) R_{ba}$; combining this with (22), we deduce Equation (i). We underline that Constraint (13) is indeed applicable since $\delta_{ba} \leq \frac{\pi}{2}$, as $(b, a) \in \mathcal{L} \cap \mathcal{L}^R$ (see Table 1).

Second, we combine the Equations (19)–(20) with $R_{ba} \geq \sigma_a \bar{L}_b + \sigma_b \bar{L}_a - \bar{v}_b R_a$, from Constraint (8), that we multiply by $v_b^d v_a^d \geq 0$, to obtain $v_b^d v_a^d R_{ba} \geq \sigma_a v_b^d W_{bb} + \sigma_b v_a^d W_{aa} + v_a^d v_b^d \tau_b \bar{L}_b + v_b^d v_a^d \tau_a \bar{L}_a - v_b^d v_a^d \tau_a$. As $\tau_a v_b^d \bar{v}_b \bar{L}_b + \sigma_b v_a^d \bar{v}_a \bar{L}_a - v_b^d v_a^d \tau_b \bar{L}_b = \bar{v}_b \bar{v}_a (\bar{v}_b \bar{L}_b + \bar{v}_a \bar{L}_a + \bar{v}_b \bar{L}_a - \bar{v}_a \bar{L}_b - \bar{v}_b \bar{L}_b - \bar{v}_b R_a) = -\bar{v}_b \bar{v}_a (\bar{v}_b \bar{L}_b + \bar{v}_a R_a)$, we deduce that

\begin{equation}
  v_b^d v_a^d R_{ba} - \tau_a v_b^d W_{bb} - \tau_b v_a^d W_{aa} \geq -\bar{v}_b \bar{v}_a (\bar{v}_b \bar{L}_b - \bar{v}_a R_a).
\end{equation}

Multiplying Equation (23) by $\cos(\delta_{ba}) \geq 0$, we obtain

\begin{equation}
  v_b^d v_a^d \cos(\delta_{ba}) R_{ba} - \bar{v}_a v_b^d W_{bb} - \bar{v}_b v_a^d W_{aa} \geq -\bar{v}_b \bar{v}_a \cos(\delta_{ba}) (\bar{v}_b \bar{L}_b - \bar{v}_a R_a).
\end{equation}

Multiplying Constraint (13) by $v_b^d v_a^d \geq 0$ yields $v_b^d v_a^d (\cos(\phi_b) \Re(W_{ba}) + \sin(\phi_b) \Im(W_{ba})) \geq v_b^d v_a^d \cos(\delta_{ba}) R_{ba}$; combining this with (24), we deduce Equation (ii).

The advantage of Constraints (8)–(13) is to enforce a coupling between the convex envelopes of the quadruplets $(\Re(W_{ba}), \Im(W_{ba}), W_{bb}, W_{aa})$ involving a same index $b$. This coupling is realized by the additional decision vectors $L$ and $R$. In Appendix A, we present an illustrative example of two quadruplets $(\Re(W_{ba}), \Im(W_{ba}), W_{bb}, W_{aa})$ and $(\Re(W_{bc}), \Im(W_{bc}), W_{bb}, W_{aa})$ satisfying Equations (i)–(ii) introduced in [10], but for which there is no vector $L$ and $R$ s.t. Constraints (8)–(13) are satisfied. In this respect, we can state that Constraints (8)–(13) strictly dominate Equations (i)–(ii).

3.3 Bound Tightening procedures

We use Bound Tightening procedures to reduce the interval lengths $\Delta_b$ and $\delta_{ba}$ and, thus, reduce the error bound in Theorem 4.
3.3.1 Feasibility-based Bound Tightening (FBBT)

The Power Flow limit for the line $(b,a) \in \mathcal{L}$ implicitly restricts the phase $\angle V_b V_a^*$ and, consequently, can help reduce the length of the interval $[\bar{\theta}_{ba}, \tilde{\theta}_{ba}]$. Dividing the inequality $|\langle Y_{ba} \rangle^T V_b V_a^* + \langle Y_{ab}^T \rangle^T |V_b|| \leq \bar{S}_{ba}$ by $|Y_{ba}| V_a$, we deduce that $|\langle V_b^* \rangle^T V_b - z| \frac{|V_b|}{|V_a|} | \leq R$, where $z = \frac{|\langle Y_{ba} \rangle^T V_b|}{|Y_{ba}|}$ and $R = \frac{\bar{S}_{ba}}{|Y_{ba}| V_a}$. We notice that $u = \frac{|V_b^* V_b|}{|V_b||V_a|}$ is a unit complex number and has a nonnegative real part since $\angle V_b - \angle V_a \in [-\frac{\pi}{2}, \frac{\pi}{2}]$. Representing the ratio $\frac{|V_b^* V_b|}{|V_b||V_a|}$ by a variable $\lambda$, we can formulate the following Convex Optimization problem

$$
\begin{align*}
\max_{u, \lambda} \quad & \text{Im}(u) \\
\text{s.t.} \quad & |u - z\lambda| \leq R \\
& \text{Re}(u) \geq 0 \\
& |u| \leq 1 \\
& u \in \mathbb{C}, \lambda \in \left[ \frac{|V_b^* V_b|}{|V_b||V_a|}, \frac{|V_b||V_a|}{|V_b^* V_b|} \right].
\end{align*}
$$

(25)

Denoting by $\bar{\theta}_{ba}$ its value, we deduce that $\text{arcsin}([\bar{\theta}_{ba}, \tilde{\theta}_{ba}])$ is an upper-bound on $\angle V_b - \angle V_a$. Hence, we can set $\tilde{\theta}_{ba} \leftarrow \min(\bar{\theta}_{ba}, \text{arcsin}(\bar{\theta}_{ba}))$ without changing the value of (ACOPF). If we minimize $\text{Im}(u)$ under the same constraints to get a value $\bar{\theta}_{ba}$, we can set $\bar{\theta}_{ba} \leftarrow \max(\bar{\theta}_{ba}, \text{arcsin}(\bar{\theta}_{ba}))$.

Similarly for any $(b,a) \in \mathcal{L}$, leveraging the inequality $|\langle Y_{ab} \rangle^T V_b V_a^* + |\langle Y_{ba} \rangle^T |V_b|^2| \leq \bar{S}_{ab}$, we use the same procedure with $z = \frac{|\langle Y_{ab} \rangle^T V_b|}{|Y_{ab}|}$ and $R = \frac{\bar{S}_{ab}}{|Y_{ab}|}$ to tighten $\tilde{\theta}_{ab}$ and $\bar{\theta}_{ab}$. This type of Bound Tightening is cheap, since it requires to solve a 2-variable optimization problem for each bound.

3.3.2 Optimization-Based Bound Tightening (OBBT)

We also apply a OBBT procedure to the Conic Programming relaxation (R), as performed in [32] with the QCP relaxation. We use any NLP algorithm to find an ACOPF feasible solution. With the corresponding upper-bound denoted $\bar{b}_{b,a}$, we add the constraint $\sum_{g \in \mathcal{G}} e_{lg} \text{Re}(s_g) + c_{lg} \text{Re}(s_g)^2 \leq \bar{b}_{b,a}$ to Problem (R). We denote by $\mathcal{F}$ the resulting convex feasible set for the tuple $(S, W, L, R)$. Then, we update the following bounds:

- For the Voltage Magnitude at bus $b \in \mathcal{B}$, we set

$$
\bar{v}_b \leftarrow \max_{(S, W, L, R) \in \mathcal{F}} \frac{L_b}{(S, W, L, R)}.
$$

(26)

$$
\bar{v}_b \leftarrow \min_{(S, W, L, R) \in \mathcal{F}} \frac{L_b}{(S, W, L, R)}.
$$

(27)

- For the Phase Angle Difference on line $(b,a) \in \mathcal{L}$, we compute $\bar{\theta}_{ba} = \max_{(S, W, L, R) \in \mathcal{F}} \text{Im}(W_{ba})$ and $\tilde{\theta}_{ba} = \min_{(S, W, L, R) \in \mathcal{F}} \text{Im}(W_{ba})$ and set

$$
\tilde{\theta}_{ba} \leftarrow \min(\bar{\theta}_{ba}, \text{arcsin}(\max\left(\frac{\bar{t}_{ba}}{\bar{t}_{ba}}, \frac{\bar{\theta}_{ba}}{\bar{\theta}_{ba}}\right)))
$$

(28)

$$
\bar{\theta}_{ba} \leftarrow \max(\tilde{\theta}_{ba}, \text{arcsin}(\min\left(\frac{\bar{t}_{ba}}{\bar{t}_{ba}}, \frac{\bar{\theta}_{ba}}{\bar{\theta}_{ba}}\right)).
$$

(29)

3.3.3 Shortest Path algorithm to tighten Phase Angle Difference bounds

Through FBBT and OBBT, we may individually improve the bounds $\tilde{\theta}_{ba}$ and $\bar{\theta}_{ba}$ for any $(b,a) \in \mathcal{E}$. To propagate the reduction of the Phase Angle Difference domains, we apply a Shortest Path algorithm. Indeed we notice that, for any $b_0, b_1, \ldots, b_t$ in the graph $(\mathcal{B}, \mathcal{E})$, for any feasible solution $(S, V) \in (\text{ACOPF})$, we have $\angle V_{b_t} - \angle V_{b_0} = \sum_{t=1}^{t=1} \angle V_{b_{t+1}} - \angle V_{b_t} \leq \sum_{t=0}^{t=0} \tilde{\theta}_{b_{t+1} b_t}$. The Shortest Path between $b_0$ and $b_t$ in the directed weighted graph $(\mathcal{B}, \mathcal{E}, \tilde{\theta})$ helps finding the lowest sum $\sum_{t=0}^{t=1} \tilde{\theta}_{b_{t+1} b_t}$ to update $\tilde{\theta}_{b_t b_0}$. Symmetrically, we have that $\angle V_{b_t} - \angle V_{b_0} \geq \sum_{t=0}^{t=1} \bar{\theta}_{b_{t+1} b_t}$. The Shortest Path between $b_0$ and $b_t$ in the directed weighted graph $(\mathcal{B}, \mathcal{E}, -\bar{\theta})$ helps improving the lower-bound on $\angle V_{b_t} - \angle V_{b_0}$ to update $\bar{\theta}_{b_0 b_t}$. To compute Shortest Paths, we apply the Floyd–Warshall algorithm [11], which fits the context of a weighted directed graph, with weights of unspecified sign. May the Floyd–Warshall algorithm find a cycle with negative weight in the directed weighted graph $(\mathcal{B}, \mathcal{E}, -\bar{\theta})$, it would certify the infeasibility of (ACOPF), since it would give a path $b_0, b_1, \ldots, b_t$ with $b_t = b_0$ and $0 = \angle V_{b_t} - \angle V_{b_0} = \sum_{t=1}^{t=1} \angle V_{b_{t+1}} - \angle V_{b_t} \leq \sum_{t=0}^{t=0} \bar{\theta}_{b_{t+1} b_t} < 0$. Similarly, finding a cycle of negative weight in $(\mathcal{B}, \mathcal{E}, -\bar{\theta})$ certifies the infeasibility of (ACOPF).
4 A MILP-based Global Optimization algorithm

Leveraging the Conic Programming relaxation (R) and its solution, we generate a sequence of MILP problems whose values converge to the ACOPF value.

4.1 Linear Programming Outer-Approximations

The disadvantage of Problem (R) is its computational cost, that is higher, due to SDP constraints, than the cost of a Linear Programming (LP) or a convex QCP relaxation. Hence, it may not be computationally efficient to solve such a relaxation at every node of an exploration tree. The idea of our approach is to solve the relaxation (R) at the root node only, and use it to generate a LP relaxation with the same value. We denote by \( x \in \mathbb{R}^N \) the decision vector \((\text{Re}(S), \text{Im}(S), \text{Re}(W), \text{Im}(W), L, R)\), and we notice that the Problem (R) may also be seen as

\[
\min_{x \in \mathcal{P}} f_0(x) \\
\forall j \in \{1, \ldots, M\} \quad f_j(x) \leq 0,
\]

with \( \mathcal{P} \subset \mathbb{R}^N \) being a polytope and \( f_0(x), f_1(x), \ldots, f_M(x) \) continuous and convex functions. In Appendix B, we detail this polytope, the functions \( f_j(x) \), and show that they share a common structure: for any \( j \in \{0, \ldots, M\} \), there exists an affine application \( \pi_j : \mathbb{R}^N \rightarrow \mathbb{R}^p_j \) and a compact and convex set \( U_j \subset \mathbb{R}^{p_j} \) s.t. for all \( x \in \mathcal{P} \),

\[
f_j(x) = \max_{u \in U_j} u^\top \pi_j(x).
\]

For any finite subset \( \tilde{U}_j \subset U_j \), we define the following polyhedral function \( \tilde{f}_j(x) = \max_{u \in \tilde{U}_j} u^\top \pi_j(x) \). This function, called “cutting-plane model”, is an underestimator of \( f_j \). If we relax the formulation (R) by replacing each function \( f_j(x) \) by its polyhedral underestimator \( \tilde{f}_j(x) \) related to a given finite set \( \tilde{U}_j \), we obtain the LP relaxation

\[
\min_{x \in \mathcal{P}} \tilde{f}_0(x) \\
\forall j \in \{1, \ldots, M\} \quad \tilde{f}_j(x) \leq 0
\]

We show that based on a primal-dual solution of (R), we can compute finite sets \( \tilde{U}_0, \ldots, \tilde{U}_M \) s.t. \( \text{val}(R) = \text{val}(R_L) \).

For \( j \in \{1, \ldots, M\} \) we define \( K_j \) as the convex cone generated by \( U_j \). We define \( K_0 \) as the convex cone generated by \( \{1\} \times U_0 \). We also define \( \lambda \) and \( \bar{\lambda} \) as a priori lower and upper bounds on the value of (R), that may be very rough estimates. We introduce a Lagrangian \( L \) function for the conic program (R), defined for any \((x, \lambda) \in \mathcal{P} \times [\bar{\lambda}, \bar{\lambda}]\), \( \kappa = (\kappa_0, \kappa_1, \ldots, \kappa_M) \in K_0 \times K_1 \times \cdots \times K_M \) as \( L(x, \lambda, \kappa) = \lambda + \kappa_0^\top \left( -\pi_0(x) \right) + \sum_{j=1}^M \kappa_j^\top \pi_j(x) \). With this definition, we see that the conic program (R) is the min-max problem

\[
\inf_{x \in \mathcal{P}, \lambda \in [\bar{\lambda}, \bar{\lambda}]} \sup_{\kappa \in K_0 \times K_1 \times \cdots \times K_M} L(x, \lambda, \kappa).
\]

We define the concave function \( D(\kappa) = \inf_{x \in \mathcal{P}, \lambda \in [\bar{\lambda}, \bar{\lambda}]} L(x, \lambda, \kappa) \in \mathbb{R} \cup \{-\infty\} \), and the dual optimization problem

\[
\sup_{\kappa \in K_0 \times K_1 \times \cdots \times K_M} D(\kappa). \tag{30}
\]

**Proposition 6.** There is no duality gap between Problem (R) and Problem (30), i.e., they share the same value. Moreover, if Problem (30) has an optimal solution \( \kappa^* \in K_0 \times K_1 \times \cdots \times K_M \), written as \( \kappa^* = (\eta_0 v_0^\star, \eta_1 u_1^\star, \ldots, \eta_M u_M^\star) \) with

\[
\eta_j \in \mathbb{R}_+ \text{ for all } j \in \{0, 1, \ldots, M\},
\]

\[
v_0^\star = (1, u_0^\star) \text{ with } u_0^\star \in U_0, \text{ and } u_j^\star \in U_j \text{ for all } j \in \{0, 1, \ldots, M\},
\]

then the definition of the finite sets \( \tilde{U}_j = \{u_j^\star\} \) yields a LP relaxation (R_L) that satisfies \( \text{val}(R_L) = \text{val}(R) \).

**Proof.** The absence of duality gap follows from the Sion min-max theorem [22], since

- The primal optimization set \( \mathcal{P} \times [\bar{\lambda}, \bar{\lambda}] \) is convex and compact,
- The dual optimization set \( K_0 \times K_1 \times \cdots \times K_M \) is convex,
- The Lagrangian \( L \) is continuous and convex w.r.t. \((x, \lambda) \) for any \( \kappa \in K_0 \times K_1 \times \cdots \times K_M \), and,
- The Lagrangian \( L \) is continuous and concave w.r.t. \( \kappa \) for any \((x, \lambda) \in \mathcal{P} \times [\bar{\lambda}, \bar{\lambda}] \).
Then, we assume that Problem (30) has an optimal solution $\kappa^* \in \mathcal{K}_0 \times \mathcal{K}_1 \times \cdots \times \mathcal{K}_M$. Due to the absence of duality gap, we know that $D(\kappa^*) = \text{val}(\mathbf{R})$. Writing $\kappa^* = (\eta_0(1, u_0^1), \eta_1 u_1^1, \ldots, \eta_M u_M^1)$ as indicated above, we define $\bar{U}_j = \{u_j^1\} \subset U_j$ and $\bar{K}_j = \text{cone}(U_j)$, for all $j \in \{0, \ldots, M\}$. With this definition, $(\mathbf{R}_L)$ reads

$$\inf_{x \in \mathcal{P}} \sup_{z \in \bar{K}_i \times \cdots \times \bar{K}_M} L(x, \lambda, \kappa),$$

and its dual problem is $\sup_{\mathbf{x} \in \mathcal{P}} L(\mathbf{R}_L) = \sup_{\mathbf{u} \in \bar{K}_i \times \cdots \times \bar{K}_M} D(\mathbf{u})$. As $\kappa^* \in \bar{K}_i \times \cdots \times \bar{K}_M$, we can write by weak duality that $\text{val}(\mathbf{R}_L) \geq D(\kappa^*) = \text{val}(\mathbf{R})$. As $(\mathbf{R}_L)$ is a relaxation of $(\mathbf{R})$, we conclude that $\text{val}(\mathbf{R}_L) = \text{val}(\mathbf{R})$. 

At the price of finding an optimal primal-dual solution $(\mathbf{x}^*, \mathbf{\lambda}^*, \mathbf{\kappa}^*)$ of $(\mathbf{R})$–(30), we can build an LP relaxation with the same value. In practice, we obtain such a primal-dual solution for every tested instance.

### 4.2 Binary variables to encode Piecewise Linear constraints

#### 4.2.1 Partitioning Voltage Magnitude intervals

For any $b \in \mathcal{B}$, we may want to split the interval $[\theta_b, \bar{\theta}_b]$ in subintervals. We introduce a tree $\mathcal{J}_b$ and pairs $(\mathbf{y}_b, \mathbf{\bar{y}}_b)$ s.t. $\mathbf{y}_b \leq \bar{\theta}_b$ for all $j \in \mathcal{J}_b$. For $r$ being the root node of $\mathcal{J}_b$, we have $(\mathbf{y}_b, \mathbf{y}_b) = (\theta_b, \bar{\theta}_b)$. Denoting $\mathcal{J}_b^+(i)$ the set of the child nodes of $i$, the partition $[\mathbf{y}_b, \bar{\theta}_b] = \bigcup_{i \in \mathcal{J}_b^+(i)} [\mathbf{y}_b, \bar{\theta}_b]$ holds for any $i \in \mathcal{J}_b$. For any $j \in \mathcal{J}_b$, we introduce a variable $\alpha_{bj} \in \{0, 1\}$. To encode the equivalence $(\alpha_{bj} = 1) \iff (L_b \in [\theta_b, \bar{\theta}_b])$ for any $j \in \mathcal{J}_b$, we impose $\alpha_{b1} = 1$, and for any $j \in \mathcal{J}_b$

$$\sum_{j \in \mathcal{J}_b^+(i)} \alpha_{bj} = \alpha_{b1}.$$  

Moreover we add the following constraint for every $j \in \mathcal{J}_b$,

$$R_{bb} + y_{bj} \bar{\theta}_b \leq (y_{bj} + \bar{\theta}_b)_L + (\bar{\theta}_b^2 + y_{bj} \bar{\theta}_b)(1 - \alpha_{bj}).$$  

For every $j \in \mathcal{J}_b$ and for all $a \in \mathcal{B}$ s.t. $(b, a) \in \mathcal{E}$, we add the inequalities

$$R_{ba} \geq \sum_{j \in \mathcal{J}_b} a_{L} + a_{L} - y_{bj} a_{L} + a_{L} a_{1} (1 - \alpha_{bj}) - 1)$$

$$R_{ba} \leq \sum_{j \in \mathcal{J}_b} a_{L} + a_{L} - y_{bj} a_{L} + a_{L} a_{1} (1 - \alpha_{bj}) - 1)$$

#### 4.2.2 Partitioning Phase Angle Difference intervals

For any $(b, a) \in \mathcal{E}$, we may want to split the interval $[\vartheta_{ba}, \bar{\vartheta}_{ba}]$ in subintervals. We introduce a tree $\mathcal{J}_ba$ and pairs $(\vartheta_{ba}, \bar{\vartheta}_{ba})$ s.t. $\vartheta_{ba} \leq \bar{\vartheta}_{ba}$ for all $j \in \mathcal{J}_ba$. For $r$ being the root node of $\mathcal{J}_ba$, we have $(\vartheta_{ba}, \bar{\vartheta}_{ba}) = (\vartheta_{ba}, \bar{\vartheta}_{ba})$. Denoting $\mathcal{J}_ba^+(i)$ the set of child nodes of $i$, the partition $[\vartheta_{ba}, \bar{\vartheta}_{ba}] = \bigcup_{i \in \mathcal{J}_ba^+(i)} [\vartheta_{ba}, \bar{\vartheta}_{ba}]$ holds for any $i \in \mathcal{J}_ba$. For $j \in \mathcal{J}_ba$, we introduce a variable $\beta_{ba} \in \{0, 1\}$. To encode the equivalence $(\beta_{ba} = 1) \iff (\vartheta_{ba} \in [\vartheta_{ba}, \bar{\vartheta}_{ba}])$, we impose $\beta_{b1} = 1$ and for any $j \in \mathcal{J}_ba$

$$\tan(\vartheta_{ba}) \text{Re}(W_{ba}) + (\beta_{ba} - 1) \bar{\vartheta}_{ba} \leq \text{Im}(W_{ba}) \leq \tan(\vartheta_{ba}) \text{Re}(W_{ba}) + (1 - \beta_{ba}) \bar{\vartheta}_{ba},$$

and for any $i \in \mathcal{J}_ba$ s.t. $\mathcal{J}_ba^+(i) \neq \emptyset$

$$\sum_{j \in \mathcal{J}_ba^+(i)} \beta_{ba} = \beta_{b1}.$$

Moreover, for all $j \in \mathcal{J}_ba$, we define the angles $\phi_{ba} = \frac{\theta_{ba} + \vartheta_{ba}}{2}$ and $\delta_{ba} = \frac{\vartheta_{ba} - \vartheta_{ba}}{2}$, and if $\delta_{ba} \leq \frac{\pi}{2}$, we impose

$$\cos(\phi_{ba}) \text{Re}(W_{ba}) + \sin(\phi_{ba}) \text{Im}(W_{ba}) \geq R_{ba} \cos(\delta_{ba}) + (\beta_{ba} - 1) \bar{\vartheta}_{ba}.$$
4.3 Updating the partitions of the intervals

During the algorithm presented in Section 4.4, the partitions of the intervals $[\theta_a, \theta_b]$ and $[\bar{\theta}_{ba}, \bar{\theta}_{ba}]$ are not static but are made dynamically. The partition trees are all initialized as single-node graphs, and are then updated over the course of the algorithm. We present how these trees are updated, at any iteration $t$ of the algorithm, where the current iterate is $(S^t, W^t, L^t, R^t)$.

For a given bus $b \in \mathcal{B}$, we update the partition tree $\mathcal{F}_b$ by selecting the active leaf $j$, i.e. the only leaf $j$ of $\mathcal{F}_b$ s.t. $L^t_b \in [\theta_{bj}, \bar{\theta}_{bj}]$. We create three new leaves $j_1, j_2, j_3$ in the tree, which are attached to node $j$, and we partition the interval $[\theta_{bj}, \bar{\theta}_{bj}]$ as follows:

- We define $\theta_{bj_1} = \theta_{j_1}$ and $\bar{\theta}_{bj_1} = \bar{\theta}_{j_1}$;
- If $L^t_b < \frac{\theta_{bj_2} + \bar{\theta}_{bj_2}}{2}$, we define $\bar{\theta}_{bj_2} = \bar{\theta}_{j_2}$ and $\bar{\theta}_{bj_2} = \frac{\theta_{bj} + \bar{\theta}_{bj}}{2}$;
- Else, we define $\bar{\theta}_{bj_2} = \frac{\theta_{bj} + \bar{\theta}_{bj}}{2}$ and $\bar{\theta}_{bj_2} = \bar{\theta}_{j_2}$.

For a given pair $(b, a) \in \mathcal{E}$, we update the partition tree $\mathcal{F}_{ba}$ by selecting the active leaf $j$, i.e. the only leaf $j$ of $\mathcal{F}_{ba}$ s.t. $\angle W^t_{ba} \in [\theta_{ba}, \bar{\theta}_{ba}]$. We create three new leaves $j_1, j_2, j_3$ in the tree, which are attached to node $j$, and we partition the interval $[\theta_{ba}, \bar{\theta}_{ba}]$ as follows:

- We define $\theta_{ba_1} = \theta_{ba}, \bar{\theta}_{ba_1} = \bar{\theta}_{ba}$;
- If $\angle W^t_{ba} \leq \frac{\theta_{ba} + \bar{\theta}_{ba}}{2}$, we define $\bar{\theta}_{ba_2} = \bar{\theta}_{ba_1}$ and $\bar{\theta}_{ba_2} = \frac{\theta_{ba} + \bar{\theta}_{ba}}{2}$;
- Else, we define $\bar{\theta}_{ba_2} = \frac{\theta_{ba} + \bar{\theta}_{ba}}{2}$ and $\bar{\theta}_{ba_2} = \bar{\theta}_{ba}$.

The construction procedure of the trees $\mathcal{F}_b$ and $\mathcal{F}_{ba}$ guarantees that (i) $\bar{\theta}_{bj} - \theta_{bj}$, the length of the interval associated with a node $j \in \mathcal{F}_b$ of depth $D(j)$, is less than $\frac{\Delta b}{2^m}$, (ii) the coefficient $\delta_{boj}$ associated with a node $j \in \mathcal{F}_b$ is less than $\frac{\Delta}{2^m}$.

Proposition 7. We assume that the convex Constraints (8)--(13) and the MILP Constraints (31)--(38) are satisfied, but with a tolerance $\rho \in [0, 1]$ for the nonlinear Constraints (10) and (12). Then, for any nodes $j_b \in \mathcal{F}_b$, $j_a \in \mathcal{F}_a$ and $j_{ba} \in \mathcal{F}_{ba}$ that are active, i.e., s.t. $\alpha_{bj} = \alpha_{aj} = \alpha_{boj} = 1$, we have

$$|(R_{ba})^2 - W_{ba}W_{aa}| \leq \frac{9\Delta_a \Delta_b}{2\max(D(j_a), D(j_a))} + \max \left\{ 9\rho, \left( \frac{\Delta_b}{2^m D(j_a)} + \frac{\Delta_a}{2^m D(j_a)} \right)^2 \right\},$$

$$\left( D(j_{ba}) \geq \log_2 \left( \frac{2\Delta_{ba}}{\pi} \right) \right) \implies \left( ||W_{ba}||^2 - (R_{ja})^2 \right) \leq \max \left\{ 9\rho, \frac{16\Delta_{boj}^2}{4^m D(j_{ba})} \right\}. \quad (40)$$

We underline that the implication is still valid if $\Delta_{ba} = 0$ and $\log_2(\frac{2\Delta_{ba}}{\pi}) = -\infty$.

Proof. Since $\alpha_{bj} = 1$, Constraints (34)--(35) yield Constraints (8)--(9), but with $\theta_{bj}$, $\bar{\theta}_{bj}$ and $\Delta_{ba}$ replaced by $\theta_{j_1}$, $\bar{\theta}_{j_1}$, and $\Delta_b$. Similarly, since $\alpha_{aj} = 1$ and since $R_{ba} = R_{ab}$, we also deduce from Constraints (34)--(35) that $|(R_{ja})^2 - L_{ja}^2| \leq 9\frac{\Delta_{ja}}{2^m D(j_a)}$. Hence, we obtain

$$|(R_{ba})^2 - L_{ab}^2 L_{ba}^2| \leq \frac{9\Delta_b \Delta_a}{2\max(D(j_a), D(j_a))}. \quad (41)$$

Since $\alpha_{ja} = 1$ (resp. $\alpha_{boj} = 1$), Constraint (33) yields Constraint (11) for $b$ (resp. $a$) with $\theta_{bj}$, $\bar{\theta}_{bj}$ and $\Delta_{ba}$ replaced by $\theta_{j_2}$, $\bar{\theta}_{j_2}$, and $\Delta_a$ (resp. $\theta_{ba}$, $\bar{\theta}_{ba}$, and $\Delta_b$). Applying Equation (16) in the Proof of Theorem 4, that follows only from Constraint (11), we deduce that $R_{ba} R_{aa} - L_{ba}^2 L_{aa}^2 \leq (\Delta_a + \Delta_b)^2 \leq (\frac{\Delta a}{2^m D(j_a)})^2$. Since Constraint (10) is satisfied with tolerance $\rho \in [0, 1]$, we have that $L_{aa}^2 \leq R_{aa} + \rho$ and $L_{aa}^2 \leq R_{aa} + \rho$. Multiplying both inequalities, we deduce that $L_{ba}^2 L_{aa}^2 \leq R_{ba} R_{aa} + \rho (R_{ba} + R_{aa}) + \rho^2 \leq R_{ba} R_{aa} + 9\rho$, since $R_{ba}, R_{aa} \in [0, 4]$ and $\rho^2 \leq \rho$. Hence, $|W_{ba} W_{aa} - L_{ba}^2 L_{aa}^2| = |R_{ba} R_{aa} - L_{ba}^2 L_{aa}^2| \leq \max(9\rho, \frac{16\Delta_{boj}^2}{4 D(j_{ba})})$. Combining this with Equation (11), we deduce Equation (39) due to the triangle inequality. We assume now that $D(j_{ba}) \geq \log_2(\frac{2\Delta_{ba}}{\pi})$, implying that $\delta_{ba} \leq \frac{\Delta_{ba}}{2 D(j_{ba})} \leq \frac{\pi}{2}$. Since $\alpha_{boj} = 1$, Constraint (38) yields Constraint (13) with $\theta_{boj}$, $\bar{\theta}_{boj}$ replaced by $\theta_{ba}$, $\bar{\theta}_{ba}$. Writing $W_{ba}$ as $|W_{ba}| e^{i\theta}$ we thus have $|W_{ba}| \cos(\phi_{ba} - \theta) \cos(\phi_{boj} - \theta) \sin(\phi_{boj} - \theta) \leq R_{ba} \cos(\phi_{boj} - \theta)$. This also reads $|W_{ba}| \cos(\phi_{boj} - \theta) \geq R_{ba} \cos(\phi_{boj} - \theta)$. This implies that $|W_{ba}| \geq R_{ba} \cos(\phi_{boj} - \theta)$, and thus $|W_{ba}|^2 \geq R_{ba}^2 \cos(\phi_{boj} - \theta)^2$. Noticing that Constraint (12) is satisfied with tolerance $\rho$, we have that $|W_{ba}| \leq R_{ba} + \rho$ and $|W_{ba}|^2 \leq R_{ba}^2 + 2 R_{ba} \rho + \rho^2 \leq R_{ba}^2 + 9 \rho$. In summary, we have $-\rho \leq R_{ba}^2 - |W_{ba}|^2 \leq R_{ba}^2 (1 - \cos(\phi_{boj} - \theta)^2) \leq R_{ba}^2 \sin(\phi_{boj} - \theta)^2 \leq 16 \delta_{boj}^2 \leq 16(\frac{2\Delta_{boj}}{4 D(j_{ba})})^2$. \hfill $\blacksquare$
4.4 The MILP-based iterative scheme

The following Global Optimization algorithm is executed based on (i) a local NLP solver (ii) a Conic Programming solver and (iii) a MILP solver. In this pseudo-code, we use the function $\epsilon (W) = \max_{(a,b) \in E} ||W_{ba}||^2 - W_{bb}W_{aa}$, which denotes the feasibility error in Constraints (*).

0. **Input:** A target optimality gap $\text{targetOptGap} \geq 0$, a tolerance $\bar{\epsilon} \geq 0$, integers $N_1, N_2 \in \mathbb{N}^+$ and a sequence $(\rho_t)_{t \in \mathbb{N}}$ with $\rho_1 > 0$.

1. **Initialization:** Compute an ACOPF feasible solution with a NLP solver and denote by $\overline{\partial E}$ its value (if the NLP solver fails, $\overline{\partial E} \leftarrow +\infty$). Solve the Conic Programming relaxation (R). If the gap is greater than $\text{targetOptGap}$, apply FBBT and OBBT to (R). Based on the optimal solution of Problem (R), generate the LP relaxation ($R_L$) with same value as (R) (see Subsect. 4.1). Set $t \leftarrow 0$ and $\overline{\partial E} \leftarrow \text{val} (R)$.

2. **Outer-iterations:** While (i) $\overline{\partial E} - \text{LB}_t > \text{targetOptGap}$ and (ii) $\epsilon (W) > \bar{\epsilon}$, do:
   2.1. For $N_1$ couples $(a,b) \in E$ with largest violation $|R_{ba}^2 - W_{bb}W_{aa}|$, update the partition trees $\mathcal{J}_b$ and $\mathcal{J}_a$ according to Section 4.3 and add the corresponding Constraints (31)–(35) to the MILP relaxation.
   2.2. For $N_2$ couples $(a,b) \in E$ with largest violation $|W_{ba}^2 - R_{ba}^2|$, update the partition tree $\mathcal{J}_b$ according to Section 4.3 and add the corresponding Constraints (36)–(38) to the MILP relaxation.

3. **Inner-iterations:** While $x = (\text{Re}(S), \text{Im}(S), \text{Re}(W), \text{Im}(W), L, R)$ does not satisfy the convex constraints within tolerance $\rho_t$, i.e., while $\max_j f_j(x) - \tilde{f}_j(x) > \rho_t$,
   3.1. Add the corresponding cuts: $\tilde{U}_j \leftarrow \tilde{U}_j \cup \{u\}$, for all $j \in \{0, \ldots, M\}$ and for $u \in \mathcal{U}_j$ s.t. $f_j(x) = u^\top \pi_j(x)$.
   3.2. Solve the resulting MILP problem to global optimality to get $x = (\text{Re}(S), \text{Im}(S), \text{Re}(W), \text{Im}(W), L, R)$.

Theorem 9 states that, if the parameters $\text{targetOptGap}$ and $\bar{\epsilon}$ are set to zero and if $(\rho_t)_{t \in \mathbb{N}}$ vanishes, the algorithm asymptotically recovers global minimizers of (ACOPFw). Before stating this Theorem, we introduce a preliminary Proposition about the finite termination of the inner-loops.

**Proposition 8.** For any outer-iteration index $t \in \mathbb{N}^+$, for any tolerance $\rho_t > 0$, the inner-loop has a finite number of iterations.

**Proof.** During outer-iteration $t \in \mathbb{N}^+$ and the previous iterations, several auxiliary binary variables and associated linear constraints have been added to the relaxation (R). From the perspective of the decision vector $x = (\text{Re}(S), \text{Im}(S), \text{Re}(W), \text{Im}(W), L, R)$, this yields a closed nonconvex set $\mathcal{X}$. We also inherit finite sets $(\tilde{U}_j)_{j \in \{0, \ldots, M\}}$, the subscript 0 denoting the inner-iteration of index $s = 0$. The inner-iteration $s \in \mathbb{N}$ consists in solving

$$\begin{align*}
\min_{x \in \mathcal{P} \cap \mathcal{X}, \lambda \in \mathbb{R}} & \quad \lambda \\
\text{subject to} & \quad u^\top \pi_0(x) \leq \lambda \\
& \quad \forall j \in \{1, \ldots, M\}, \forall u \in \tilde{U}_j, u^\top \pi_j(x) \leq 0,
\end{align*}$$

(42)

to obtain a solution $x_s$, and in defining $\mathcal{U}_j(s+1) = \{u_{js}\} \cup \mathcal{U}_j$s for some $u_{js} \in \text{argmax}_{u \in \mathcal{U}_j} u^\top \pi_j(x_s)$ for all $j \in \{0, \ldots, M\}$. We define the error $e_{js} = f_j(x_s) - \tilde{f}_j(x_s) = f_j(x_s) - \max_{u \in \mathcal{U}_j} u^\top \pi_j(x_s)$. We reason by contrapositive and assume now that the inner-loop is not terminating in finite time, meaning that the generated MILP relaxation is feasible at each inner-iteration and the stopping condition of the inner-loop is never met. This second point means that $\rho_t \leq \max_{j \in \{0, \ldots, M\}} e_{js}$ for all $s \in \mathbb{N}$. We take any $j \in \{0, \ldots, M\}$ and show that $e_{js} \to 0$. Since the sets $\mathcal{P} \cap \mathcal{X}$ and $\mathcal{U}_j$ are compact and since the functions $x \mapsto f_j(x)$ and $(x, u) \mapsto u^\top \pi_j(x)$ are continuous, we deduce that the sequence $(e_{js})_{s \in \mathbb{N}}$ is bounded. We take any limit point $e^* \in$ this sequence, and we take a converging subsequence $(e_{j\psi(s)}) \to e^*$. Without loss of generality, since $\mathcal{P} \cap \mathcal{X}$ and $\mathcal{U}_j$ are compact, we can choose the extraction $\psi(s)$ so that $x_{\psi(s)} \to x^*$ and $u_{j \psi(s)} \to u^*$, for $(x^*, u^*) \in \mathcal{P} \cap \mathcal{X} \times \mathcal{U}_j$. For $s \in \mathbb{N}^+$, we notice that

$$e_{j \psi(s)} = f_j(x_{\psi(s)}) - \max_{u \in \mathcal{U}_j(s)} u^\top \pi_j(x_{\psi(s)}) \leq f_j(x_{\psi(s)}) - u_{j \psi(s-1)}^\top \pi_j(x_{\psi(s)}) \leq u_{j \psi(s-1)}^\top \pi_j(x_{\psi(s)}) - u_{j \psi(s-1)}^\top \pi_j(x_{\psi(s)}) \leq u_{j \psi(s)}^\top \pi_j(x_{\psi(s)}) - u_{j \psi(s-1)}^\top \pi_j(x_{\psi(s)}).$$

Indeed, Equation (44) follows from the fact that $u_{j \psi(s-1)} \in \mathcal{U}_j(s)$ since $\psi(s-1) \leq \psi(s) - 1$, and Equation (45) follows from the definition of $u_{j \psi(s)}$. The limit of the term in Equation (45) is $u^* \pi_j(x^*) - u^* \pi_j(x^*) = 0$. ACOPF: a Conic Programming relaxation and an iterative MILP scheme
Since $0 \leq e_{jw(s)}$, this proves that $(e_{jw(s)}) \to 0$, i.e., $e^* = 0$. This being true for any limit value $e^*$ of the bounded sequence $(e_{jw})$, we deduce that it converges to zero. This implies that $(\max_{j \in \{0, \ldots, M\}} e_{jw}) \to 0$. As $\rho_t \leq \max_{j \in \{0, \ldots, M\}} e_{jw}$, we see that the hypothesis “the inner-loop is not terminating” implies that $\rho_t = 0$. By contrapositive, since $\rho_t > 0$, we deduce that the inner-loop has a finite number of iterations.

**Theorem 9.** If $\text{targetOptGap} = \tau = 0$ and $\rho_t \to 0$, then
- Either the algorithm stops due to the stopping criterion, and yields a global minimizer of $(\text{ACOPF}_W)$.
- Or the algorithm stops due to the infeasibility of a relaxation, certifying the infeasibility of $(\text{ACOPF}_W)$.
- Or the algorithm generates an infinite sequence of iterates $(S^t, W^t, L^t, R^t)$, and
  - The sequence $\text{LB}_t$ monotonously converges to $\text{val}(\text{ACOPF}_W) = \text{val}(\text{ACOPF})$.
  - The limit points of the sequence $(S^t, W^t)_{t \in \mathbb{N}}$ are global minimizers of $(\text{ACOPF}_W)$.

**Proof.** We consider the first case where the algorithm meets the stopping criterion at the beginning of a certain outer-iteration $t$. This means that either (a) $\overline{\text{LB}}_t = \text{LB}_t$, proving that the solution $(S, V)$ found by the NLP solver at step 1. is globally optimal in $(\text{ACOPF})$ and yields $(S, V^{\text{W}})$ globally optimal in $(\text{ACOPF}_W)$, or (b) the solution $(S^t, W^t, L^t, R^t)$ of the current MILP relaxation of $(\text{ACOPF}_W)$ satisfies $\epsilon(W^t) = 0$, i.e., $(S^t, W^t)$ is in fact feasible in $(\text{ACOPF}_W)$ and thus optimal in $(\text{ACOPF}_W)$ since it is the optimal solution of a relaxation.

The second case is trivial: if the relaxation $(\text{R})$ or any MILP relaxation during the iterations is infeasible, this implies that $(\text{ACOPF}_W)$ is also infeasible.

We consider now the third case, where the algorithm does not terminate. We invoke Proposition 8 to claim that for any outer-iteration $t \in \mathbb{N}$, the inner-loop terminates in finite time. Hence, there is an infinite number of outer-iterations and we define the infinite sequence $x_t = (S^t, W^t, L^t, R^t)_{t \in \mathbb{N}}$, where $x_t$ is the solution of the MILP relaxation at the beginning of the outer-iteration $t$. For any $(b, a) \in \mathcal{E}$, we define $\chi_{ba}^{[t]} = |(R_{ba}^{[t]})^2 - W_{ba}^{[t]}W_{ab}^{[t]}|$ and $\xi_{ba}^{[t]} = \max\{x_t \in J^a_b, \chi_{ba}^{[t]}\}$. We let $J_b^a$ (resp. $J_a^b$) denote the state of the tree $J_b$ (resp. $J_a$) at the beginning of iteration $t$, and $\mathcal{J}_b$ (resp. $\mathcal{J}_a$) the (potentially infinite) limit tree $\bigcup J_b^a$ (resp. $\bigcup J_b^a$). We first show that $\chi_{ba}^{[t]} \to 0$ for any $(b, a) \in \mathcal{E}$. For $t \in \mathbb{N}$, we define $(b_t, a_t) \in \mathcal{E}$ s.t. $\chi_{ba}^{[t]} = \max\chi_{ba}^{[t]}$ and we define $j(t) \in J_b^{a_t}$ and $j_a(t) \in J_a^{b_t}$, the active leaves to which three child nodes are attached during step 2.1 since $j(t)$ presents the largest violation. For any $j \in \bigcup \mathcal{J}_b$, we recall that $D(j)$ is the depth of $j$ in the (unique) tree $\mathcal{J}_b$ it belongs to. As $x_t$ is the output of the outer-iteration $t - 1$, it satisfies Constraint (10) and (12) with tolerance $\rho_{t-1}$, and we can apply Proposition 7 with $\rho = \rho_{t-1}$. This yields

$$
\chi_{ba}^{[t]} = |(R_{ba}^{[t]})^2 - W_{ba}^{[t]}W_{ab}^{[t]}| \leq \frac{9\Delta_b \Delta_a}{2 \max(D(j_b(t)), D(j_a(t)))} + \max\left\{9\rho_{t-1}, \frac{\Delta_b}{2 D(j_b(t))}, \frac{\Delta_a}{2 D(j_a(t))}\right\}.
$$

We notice that the sequence $(j(t))_{t \in \mathbb{N}}$ is injective, since each $j(t)$ is a leaf in $J_b^{a_t}$, but not in the trees $J_b^a$ for $s \geq t + 1$. We deduce that $D(j(t)) \to \infty$, otherwise by contrapositive, there would exist $M \in \mathbb{N}$ s.t. an infinite number of nodes of depth less or equal than $M$ are created in the union of ternary trees $\bigcup \mathcal{J}_b$. This is false since the number of nodes with depth less or equal than $M$ is bounded by $n \sum_{s=0}^{M} 3^s$. By the same argument, we have $D(j_b(t)) \to \infty$. Combined with (46), we deduce that $\chi_{ba}^{[t]} \to 0$ since $\rho_t \to 0$ and because $\Delta_b, \Delta_a$ are bounded. For any $t \in \mathbb{N}$ and $(b, a) \in \mathcal{E}$, we have $0 \leq \chi_{ba}^{[t]} \leq \chi_{ba}^{[t]}$ by definition of $(b_t, a_t)$, implying $\chi_{ba}^{[t]} \to 0$.

We apply the above scheme to prove that $\xi_{ba}^{[t]} \to 0$ for any $(b, a) \in \mathcal{E}$. For $t \in \mathbb{N}$, we define $(b_t, a_t) \in \mathcal{E}$ s.t. $\xi_{ba}^{[t]} = \max\xi_{ba}^{[t]}$ and we define $j(t) \in J_b^{a_t}$ the active leaf to which three child nodes are attached during step 2.2. We also define $\tilde{D}(j(t))$ as the depth of $j(t)$ in $J_b^{a_t}$, which satisfies $\tilde{D}(j(t)) \to \infty$ by injectivity of $(j(t))_{t \in \mathbb{N}}$ and since the number of nodes in the union of ternary trees $\bigcup \mathcal{J}_b$ with depth less or equal than $M$ is bounded by $|\mathcal{E}| \sum_{s=0}^{M} 3^s$. As $\tilde{D}(j(t)) \to \infty$, we know that it exists $t_0 \in \mathbb{N}$ s.t. $\tilde{D}(j(t)) \geq 2$ for all $t \geq t_0$. Hence, for all $t \geq t_0$, $\tilde{D}(j(t)) \geq \log_2(\frac{15}{8}) \geq \log_2(\frac{26h_{ba}}{\pi})$, since $\delta_{ba} \in [0, 2\pi]$. Applying Proposition 7, we know that for any $t \geq t_0$,

$$
\xi_{ba}^{[t]} = \max\{x_t \in J_b^{a_t}, \chi_{ba}^{[t]}\} \leq \max\left\{9\rho_{t-1}, \frac{16\delta_{ba}^2}{4 \tilde{D}(j(t))}\right\} \leq \max\left\{9\rho_{t-1}, \frac{64\pi^2}{4 \tilde{D}(j(t))}\right\}.
$$

Combined with $\rho_t \to 0$ and $0 = D(\tilde{j}(t)) \to \infty$, we deduce that $\xi_{ba}^{[t]} \to 0$. Additionally, since $\xi_{ba}^{[t]} = \max\xi_{ba}^{[t]}$, we have $0 \leq \xi_{ba}^{[t]} \leq \xi_{ba}^{[t]}$ and, thus, $\xi_{ba}^{[t]} \to 0$ for any $(b, a) \in \mathcal{E}$.

We deduce that $\epsilon(W^t) \to 0$, since $\epsilon(W^t) = \max_{(b,a) \in \mathcal{E}} \min\max\{x_t \in J_b^{a_t}, \chi_{ba}^{[t]}\} \leq \sum_{(b,a) \in \mathcal{E}} \chi_{ba}^{[t]} \leq \chi_{ba}^{[t]}$ due to the triangle inequality. Hence, for any limit point $(\overline{S}, \overline{W})$ of $(S^t, W^t)$, we thus have $\epsilon(\overline{W}) = 0$. As $\rho_t \to 0$, this also proves that $(\overline{S}, \overline{W})$ satisfies the nonlinear convex constraints in $(\text{R})$. Hence, $(\overline{S}, \overline{W})$
We conclude that with more than 57 nodes where the MILP scheme is executed, the gap is admittedly not closed within the considered list of instances. For lack of space, we do not detail the computation time of the SOCP and SDP relaxations over the iterations have nonincreasing feasible sets w.r.t. variables \((S, W, L, R)\) and have nondecreasing sequence \(\tilde{f}_0(S)\) as objective functions, the sequence \(\tilde{f}_0(S') = LB_j\) is nondecreasing. It is also bounded above by \(\text{val}(\text{ACOPF}_W)\) and, thus, converges to a value \(v^* \leq \text{val}(\text{ACOPF}_W)\). Since \(\rho_t \to 0\), \(\tilde{f}_0(S') \to f_0(S) = \sum_{g \in G} c_{1g} \text{Re}(S_g) + c_{2g} \text{Re}(S_g)^2\), for any limit point \((\bar{S}, \bar{W})\). By uniqueness of the limit of \(f_0(S')\) and since \((\bar{S}, \bar{W})\) is feasible in \(\text{ACOPF}_W\), we deduce that \(v^* = \sum_{g \in G} (c_{1g} \text{Re}(S_g) + c_{2g} \text{Re}(S_g)^2) \geq \text{val}(\text{ACOPF}_W)\). We conclude that \(v^* = \text{val}(\text{ACOPF}_W) = \text{val}(\text{ACOPF})\) and that \((\bar{S}, \bar{W})\) is optimal in \(\text{ACOPF}\). ◀

5 Experimental evaluation

5.1 Experimental setting

For all experiments, we use a 64-bit Ubuntu computer with 32 Intel(R) Xeon(R) CPU E5-2620 v4 @ 2.10GHz and 64 GB RAM. Along our algorithm, we use the commercial solvers MOSEK [1] and CPLEX [18] called through their Python APIs, as well as the academic solver IPOPT [33] called through the Pyomo interface [16]. We compute the tree decomposition with the approximate minimum degree (AMD) ordering routine of the chompack package. We consider a relative optimality gap of 0.01% for global optimality (GOPT) and use the parameters \((N_1, N_2, \varepsilon) = (4, 4, 10^{-6})\). The FBBT and OBBT procedures are applied for all variables a maximum of 4 times, and with a time limit of 10 hours (TL1). After each pass of FBBT and OBBT, we apply the Floyd–Warshall algorithm and we check whether the gap of the tightened conic relaxation reaches the target optimality gap. If the maximum number of Bound Tightening iterations or time limit is reached, we enter the MILP iterative scheme with a time limit of 5 hours (TL2). Our code is available at github.com/aoustry/SDP-MILP4OPF.

This study focuses on the network instances from the IEEE PES PGLib AC-OPF v21.07 library [2] with less than 500 buses. As shown in Table 2, the instances of this benchmark are split in three categories depending on their characteristics: Typical Operating Condition (TYP) instances correspond to a reference scenario, Congested Operating Condition (API) correspond to situations with greater Power Demands, and Small Angle Condition (SAD) correspond to tighter constraints for the Phase Angle Difference.

We compare our approach with the standard SOCP and SDP relaxations [28], and with two other Global Optimization approaches [13, 32]. We performed these comparative experiments on the same PGLib v21.07 instances, with the same hardware, the same time limit (TL1) as our OBBT algorithm, and the same relative optimality gap tolerance. The concurrent approach from [32] is an OBBT algorithm based on a strengthened QC relaxation. We ran the Julia implementation of this algorithm provided in the PowerModels.jl package [8]. The QC relaxations are solved with IPOPT. The concurrent approach from [13] consists of an OBBT algorithm, based on a Determinant SDP relaxation strengthened with RLT constraints. We ran a C++ implementation of this algorithm, that is based on the Mathematical Modeling Language Gravity [17], and is available at the link indicated in [13]: The corresponding relaxations are also solved with IPOPT. We point out that these competing approaches [13, 32] solely rely on open-source tools, whereas our implementation uses commercial solvers.

5.2 Numerical results

Table 2 presents the optimality gap (in %) and the computational times obtained by the several approaches for the considered list of instances. For lack of space, we do not detail the computation time of the SOCP and SDP relaxations. To give an idea, the computation time of the SOCP relaxation is below 2s for all instances; for the SDP relaxation, the computation time goes from 0.2s for the smallest cases to about 40s for the largest cases. As regards the column “This work”, in the optimality gap section of the table: the entry (GOPT) means that the Bound Tightening procedure based on the Conic Programming relaxation closed the gap; else, the entry a/b represents the gap after the Bound Tightening procedure (a) and the gap after the iterative MILP scheme (b).

This table shows that our algorithm reaches Global Optimality for 35 instances over 51. The optimality gap is below 0.5% for 43 instances over 51. For 4 instances only, the optimality gap at the end of the algorithm is above 2%. As regards the instances with less than 57 buses, they are all solved to Global Optimality in less than 220 seconds. For all these instances with less than 57 buses, except case5_pjm and case30_as_api, the Bound Tightening procedure based on the Conic Programming relaxation (R) manages to close the gap. For the instances case5_pjm and case30_as_api, the gap is closed by the iterative MILP scheme. For all the instances with more than 57 nodes where the MILP scheme is executed, the gap is admittedly not closed within the
time limit, but it is reduced, except for case500_goc_api. For 44 over these 51 instances, our algorithm has the lowest gap; for 14 instances over 51, it has a strictly lower gap than the others approaches. For 5 instances (among those 14 instances), our approach is the only one to reach Global Optimality. Regarding the 7 instances where our approach has not the best gap: for 3 instances, only the QC relaxation-based Bound Tightening algorithm [32] yields a strictly lower gap than our approach; for the 4 other instances, only the Determinant-SDP relaxation-based Bound Tightening algorithm [13] yields a strictly lower gap than our approach.

Table 2 Results for the instances from IEEE PES PGLib AC-OPF v21.07 with less than 500 buses

| Case          | Optimization gap (%) | Time (s) |
|---------------|----------------------|----------|
|               | Benchmark            | This work | Benchmark            | This work |
|               | SOPC [32]            | [13] [R]-BT/MILP | [32] [13] [R]-BT/MILP |
| Typical Operating Condition (TYP) |
| cased_1mbd    | 1.32 0.39 GOPT GOPT GOPT | 1 <1 | 1 0 |
| case5_pgn     | 14.55 5.21 5.76 GOPT 5.01 GOPT | 44 30 | 7 198 |
| case14_ieee   | 0.11 GOPT GOPT GOPT GOPT | 12 <1 | 3 0 |
| case24_ieee_rts | 0.02 GOPT GOPT GOPT GOPT | 41 10 | 7 0 |
| case30_as     | 0.06 GOPT GOPT GOPT GOPT | 107 5 | 10 0 |
| case30_ieee   | 18.84 GOPT GOPT GOPT GOPT | 226 3 | 8 0 |
| case39_epri   | 0.56 GOPT GOPT GOPT GOPT | 272 2 | 9 0 |
| case57_ieee   | 0.16 GOPT GOPT GOPT GOPT | 437 280 | 13 0 |
| case73_ieee_rts | 0.04 GOPT GOPT GOPT GOPT | 399 30 | 21 0 |
| case89_pegasa | 0.75 0.37 0.32 0.08 0.27/0.18 TL1 TL2 TL3 | 10,582 TL2 |
| case18_ieee   | 0.91 0.07 GOPT GOPT GOPT | 8,527 TL2 | 783 |
| case162_ieee_dtc | 0.95 1.78 0.04 1.56 0.59/0.53 TL1 TL2 TL3 | 7,853 TL3 |
| case179_goc   | 0.16 0.07 0.04 0.05 0.04/0.03 TL1 TL2 TL3 | 5,293 TL2 |
| case200_active | 0.01 GOPT GOPT GOPT GOPT | 1,998 1,573 | 54 0 |
| case240_pserc | 2.78 1.43 2.71 1.21 1.02/0.93 TL1 TL2 TL3 | 25,578 TL3 |
| case300_ieee  | 2.63 1.03 2.55 0.05 GOPT TL2 TL3 TL4 | 5,482 0 |
| case500_goc   | 0.25 GOPT 0.19 GOPT GOPT | TL2 10,040 | 139 0 |
| Congested Operating Condition (API) |
| cased_1mbd_api | 9.27 7.10 GOPT GOPT GOPT | 2 3 | 2 0 |
| case5_pgn_api  | 4.09 0.26 GOPT GOPT GOPT | 10 51 | 3 0 |
| case14_ieee_api | 5.13 GOPT GOPT GOPT GOPT | 55 1 | 4 0 |
| case24_ieee_rts_api | 17.9 2.07 GOPT GOPT GOPT | 1,311 67 | 97 0 |
| case30_as_api  | 44.6 10.86 36.1 0.71 0.15 GOPT | 3,331 1,526 | 216 2 |
| case30_ieee_api | 5.46 GOPT GOPT GOPT GOPT | 444 1,673 | 8 0 |
| case39_epri_api | 1.72 0.20 GOPT GOPT GOPT | 622 1,228 | 96 0 |
| case57_ieee_api | 0.08 GOPT GOPT GOPT GOPT | 434 5 | 13 0 |
| case73_ieee_rts_api | 12.9 2.90 0.29 0.23 0.25/0.08 TL1 TL2 TL3 | 2,096 TL2 |
| case89_pegasa_api | 23.1 22.0 18.3 17.6 21.7/19.3 TL1 TL2 TL3 | 16,085 TL2 |
| case181_ieee_api | 0.90 11.7 3.10 1.44 1.86/0.90 TL1 TL2 TL3 | 21,152 TL3 |
| case162_ieee_dtc_api | 4.36 1.44 0.27 1.31 0.29/0.25 TL1 TL2 TL3 | 3,491 TL3 |
| case179_goc_api | 9.88 0.59 0.54 0.39 0.54/0.53 TL1 TL2 TL3 | 5,992 TL2 |
| case200_active_api | 0.03 1.49 GOPT GOPT GOPT | 2,561 1,472 | 55 0 |
| case240_pserc_api | 0.67 0.28 0.62 *1 0.12/0.11 TL1 TL2 | 26,401 TL3 |
| case300_ieee_api | 0.85 0.09 0.81 0.07 GOPT TL1 TL2 TL3 | 7,841 0 |
| case500_goc_api | 3.44 2.36 3.28 2.12 2.19/2.19 TL1 TL2 TL3 | 8,121 0 |

Small Angle Difference (SAD)

| Case          | Optimization gap (%) | Time (s) |
|---------------|----------------------|----------|
|               | Benchmark            | This work | Benchmark            | This work |
|               | SOPC [32]            | [13] [R]-BT/MILP | [32] [13] [R]-BT/MILP |
| case5_pgn_sad | 3.75 1.86 GOPT GOPT GOPT | 1 2 | 1 0 |
| case14_ieee  | 21.53 0.09 GOPT GOPT | 41 367 | 17 0 |
| case24_ieee_rts_sad | 9.55 4.35 GOPT GOPT GOPT | 603 1,050 | 98 0 |
| case30_as_sad | 7.88 0.24 GOPT GOPT GOPT | 168 478 | 71 0 |
| case30_ieee_sad | 9.70 GOPT GOPT GOPT GOPT | 161 5 | 9 0 |
| case39_epri_sad | 0.67 0.02 GOPT GOPT GOPT | 193 1,101 | 90 0 |
| case57_ieee_sad | 0.71 0.05 GOPT GOPT GOPT GOPT | 661 4,925 | 212 0 |
| case73_ieee_rts_sad | 6.73 2.74 GOPT GOPT GOPT | 8,818 TL2 | 1,472 0 |
| case89_pegasa_sad | 0.71 0.37 0.31 0.29 0.25/0.19 TL1 TL2 TL3 | 16,500 TL3 |
| case181_ieee_sad | 8.17 3.25 0.02 0.27 GOPT GOPT TL1 TL2 TL3 | 1,693 0 |
| case162_ieee_dtc_sad | 6.48 2.07 0.02 1.35 0.51/0.48 TL1 TL2 TL3 | 4,144 TL2 |
| case179_goc_sad | 1.12 0.05 0.05 0.93 0.66/0.42 TL1 TL2 TL3 | 4,144 TL2 |
| case200_active_sad | 0.03 GOPT GOPT GOPT GOPT | 2,187 805 | 53 0 |
| case240_pserc_sad | 4.93 3.42 4.34 3.16 2.63/2.61 TL1 TL2 TL3 | 27,875 TL3 |
| case300_ieee_sad | 2.61 0.67 2.34 0.05 GOPT TL1 TL2 TL3 | 5,654 0 |
| case500_goc_sad | 6.67 5.68 5.29 5.57 5.21/5.18 TL1 TL2 TL3 | 27,875 TL3 |

1 IPOPT did not manage to solve the Determinant-SDP relaxation for the instance case240_pserc_api.
6 Conclusion and perspectives

We introduce a Conic Programming relaxation for the AC Optimal Power Flow problem. This relaxation is a tightening of the classical Semidefinite Programming relaxation with additional variables and valid inequalities. These inequalities dominate previously introduced nonlinear cuts, used to strengthen convex relaxations. Our numerical experiments on a reference benchmark illustrate that this Conic Programming relaxation is particularly suitable for a Bound Tightening procedure: it closes the gap in many cases where a Bound Tightening based on a Quadratic Convex relaxation does not. We also introduce an iterative scheme based on Mixed-Integer Linear Programming, that converges asymptotically towards global minimizers of the AC Optimal Power Flow problem. For the instances where the Bound Tightening procedure does not close the gap, this iterative scheme is able to reduce significantly the gap in most of the cases. A future line of research will consist in improving the scalability of the Optimization-Based Bound Tightening: parallelizing this procedure, or targeting the bounds to tighten, based on the graph structure. Another avenue to explore is the possibility of speeding-up the solution of the Mixed-Integer Linear Programming problem at a given iteration, by reusing the Branch-and-Bound trees of the problems solved during the previous iterations.

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A Strict dominance of Constraints (8)–(13) with respect to Constraints (‡)–(‡)

In Section 3.2, Proposition 5 states that Constraints (8)–(13) dominate Constraints (‡)–(‡). The advantage of Constraints (8)–(13) is to enforce a coupling between the convex envelopes of the quadruplets $(\Re(W_{ba}), \Im(W_{ba}), W_{bb}, W_{aa})$ involving the same index $b$. In this Appendix, we present an illustrative example of two quadruplets $(\Re(W_{ba}), \Im(W_{ba}), W_{bb}, W_{aa})$ and $(\Re(W_{bc}), \Im(W_{bc}), W_{bb}, W_{cc})$ satisfying Constraints (‡)–(‡) introduced in [10], but for which there are no vectors $L$ and $R$ s.t. Constraints (8)–(13) are simultaneously satisfied for $(b, a)$ and $(b, c)$.

We consider any $(b, a, c) \in B^3$ with the following realistic data:

- Voltage Magnitude Bounds: $\bar{v}_b = \bar{v}_a = \bar{v}_c = 0.9$ and $\bar{v}_a = \bar{v}_c = 1.1$.
- Phase Angle Difference Bounds: $\delta_{ba} = -\delta_{ba} = -\delta_{bc} = \arccos(0.99) \approx 8.11^\circ$.

As a consequence, we have $v_b^2 = v_a^2 = v_c^2 = 2$ and $\phi_{ba} = \phi_{bc} = 0$ and $\delta_{ba} = \delta_{bc} = \arccos(0.99)$. We consider the quadruplets

\begin{align*}
(\Re(W_{ba}), \Im(W_{ba}), W_{bb}, W_{aa}) &= (1.1, 0, 1, 1.21) \\
(\Re(W_{bc}), \Im(W_{bc}), W_{bb}, W_{cc}) &= (1.085, 0, 1, 1.21),
\end{align*}

noticing that $W_{bb}$ has indeed the same value in both quadruplets. These quadruplets both satisfy Equations (‡)–(‡).

- First quadruplet: It satisfies (‡), since $v_b^2 v_a^2 (\cos(\phi_{ba}) \Re(W_{ba}) + \sin(\phi_{ba}) \Im(W_{ba})) - v_a \cos(\delta_{ba}) v_b W_{bb} - v_a \cos(\delta_{ba}) v_b W_{aa} = 2 \times 2 \times 1.1 + 0 - 1.1 \times 0.99 \times 2 \times 1.1 - 0.99 \times 2 \times 1.21 = -0.41383$, which is greater than $v_a \cos(\delta_{ba}) v_b (\bar{v}_a - \bar{v}_b \bar{v}_a) = 1.1 \times 1.1 \times 0.99 \times (0.9 \times 0.9 - 1.1 \times 1.1) = -0.47916$. It satisfies (‡), since $v_b^2 v_a^2 (\cos(\phi_{ba}) \Re(W_{ba}) + \sin(\phi_{ba}) \Im(W_{ba})) - v_b \cos(\delta_{ba}) v_a W_{bb} - v_b \cos(\delta_{ba}) v_a W_{aa} = 2 \times 2 \times 1.1 - 0.99 \times 2 \times 1.21 = 0.46178$ is greater than $-v_a v_b \cos(\delta_{ba}) (\bar{v}_a - \bar{v}_b \bar{v}_a) = -0.9 \times 0.9 \times 0.9 \times (0.9 \times 0.9 - 1.1 \times 1.1) = 0.32076$.

- Second quadruplet: It satisfies (‡), since $v_b^2 v_c^2 (\cos(\phi_{bc}) \Re(W_{bc}) + \sin(\phi_{bc}) \Im(W_{bc})) - v_c \cos(\delta_{bc}) v_b W_{bb} - v_c \cos(\delta_{bc}) v_b W_{cc} = 2 \times 2 \times 1.1 + 0 - 1.1 \times 0.99 \times 2 \times 1.1 - 0.99 \times 2 \times 1.21 = -0.47383$, which is greater than $v_b \cos(\delta_{bc}) v_c (\bar{v}_b - \bar{v}_c \bar{v}_b) = 1.1 \times 1.1 \times 0.99 \times (0.9 \times 0.9 - 1.1 \times 1.1) = -0.47916$. It satisfies (‡), since $v_b^2 v_c^2 (\cos(\phi_{bc}) \Re(W_{bc}) + \sin(\phi_{bc}) \Im(W_{bc})) - v_c \cos(\delta_{bc}) v_b W_{bb} - v_c \cos(\delta_{bc}) v_b W_{cc} = 2 \times 2 \times 1.1 - 0.99 \times 2 \times 1.21 = 0.40178$ is greater than $-v_b v_c \cos(\delta_{bc}) (\bar{v}_c - \bar{v}_b \bar{v}_c) = -0.9 \times 0.9 \times 0.9 \times (0.9 \times 0.9 - 1.1 \times 1.1) = 0.32076$.

We assume now that there exists $L_b \in [\bar{v}_b, \bar{v}_b]$, $L_a \in [\bar{v}_a, \bar{v}_a]$, $L_c \in [\bar{v}_c, \bar{v}_c]$, $R_b \in [\bar{v}_b \bar{v}_a, \bar{v}_b \bar{v}_a]$, $R_b \in [\bar{v}_c \bar{v}_c, \bar{v}_b \bar{v}_b]$, s.t. Constraints (8)–(13) are satisfied. Since $W_{ba} = \bar{v}_a^2$, we deduce from Constraint (11) that $\bar{v}_a^2 + \bar{v}_b \bar{v}_a = \cdots$
We recall that the decision vector in relaxation (10) works, to our knowledge, only use cuts associated to an extreme value of \( \cos(\phi_{bc}) \Re(W_{bc}) + \sin(\phi_{bc}) \Im(W_{bc}) \geq R_{bc}(\cos(\delta_{bc}), \sin(\delta_{bc})) \) greater than 1. As \( L_v \leq W_{ba} = 1 \) according to Constraint (10), \( L_v = 1 \). As we did after, we deduce from \( W_{ba} \geq \pi_{ab} \) and Constraint (11) that \( L_v = \pi_{ab} \). We use \( R_{bc} \geq \pi_{ab}L_v + \pi_{ab}L_v - \pi_{ab}L_v \) from Constraint (9) to state that \( R_{bc} \geq \pi_{ab}L_v \). Hence, \( R_{bc} = \pi_{ab}L_v = 1 \). As Constraint (13) imposes \( \cos(\phi_{bc}) \Re(W_{bc}) + \sin(\phi_{bc}) \Im(W_{bc}) \geq \pi_{ab}L_v \), we deduce that \( \Re(W_{bc}) + \sin(\phi_{bc}) \Im(W_{bc}) \geq 1.089 \). This is contradictory with the fact that \( \Re(W_{bc}) + \sin(\phi_{bc}) \Im(W_{bc}) = 1.085 \). As a conclusion, there does not exist \( L_b \in \{ y_v \pi_{ab}, L_v \}, L_c \in \{ y_v \pi_{ab}, L_v \}, R_{bc} \in \{ y_v \pi_{ab}, L_v \}, R_{bc} \in \{ y_v \pi_{ab}, L_v \} \) s.t. Constraints (8)–(13) are satisfied simultaneously for the pairs \((b, a)\) and \((b, c)\). This illustrates the interest of setting the trigonometric cuts (13) with a variable radius \( R_{bac} \), whereas previous works, to our knowledge, only use cuts associated to an extreme value of \( R_{bac} \).

### B Nonlinear but convex objective and constraints in relaxation (R)

We recall that the decision vector in relaxation (R) is \( x = (\Re(S), \Im(S), \Re(R), \Im(R), L, R) \). First, we denote by \( \mathcal{P} \subset \mathbb{R}^N \) the polytope defined by the following box constraints:

- For all \( g \in \mathcal{G} \), \( \Re(S_g) \in [\Re(y_g), \Re(z_g)] \) and \( \Im(S_g) \in [\Im(y_g), \Im(z_g)] \),
- For all \((a, b)\in \mathcal{E} \), \( \Re(W_{ab}) \in [0, \pi_{ab}L_v], \Im(W_{ba}) \in [-\pi_{ab}L_v, \pi_{ab}L_v] \) and \( R_{bc} \in [\pi_{ab}L_v, \pi_{ab}L_v] \),
- For all \( b \in \mathcal{B} \), \( L_b \in [y_v \pi_{ab}, \pi_{ab}] \).

Now, we review the nonlinear terms in the objective and in the constraints of relaxation (R), as functions of \( x \). We show that all these functions have the form \( f(x) = \max_{u \in \mathcal{U}} u^\top \pi(x) \) for all \( x \in \mathcal{P} \), with a given affine application \( \pi : \mathbb{R}^N \to \mathbb{R}^p \) and a compact and convex set \( \mathcal{U} \subset \mathbb{R}^p \).

- **The objective function** is \( \sum_{g \in \mathcal{G}} (c_{1g} \Re(S_g) + \sum_{g \in \mathcal{G}_2} c_{2g} \Re(S_g)^2) \), where \( \mathcal{G}_2 \) is the set of generators \( g \in \mathcal{G} \) s.t. \( c_{2g} > 0 \). This function reads max\
  \[ u \in \mathcal{U} u^\top \pi(x) \] for all \( x \in \mathcal{P} \) with

  - The compact and convex set \( \mathcal{U} = \{1\} \times \prod_{g \in \mathcal{G}_2} [1 + z_g - \pi_{ab}L_v - S_{ba} \leq 0 \}

- **Thermal limits for lines** yield constraints of the form \( |y_{ab}| W_{ab} + |y_{ba}| W_{ba} - S_{ba} \leq 0 \), with (\( y_{ab}, y_{ba} \)) = (\( y_{ab}^\top, y_{ba}^\top \)) if \( (b, a) \in \mathcal{L} \). This constraint is \( (r_1 \Re(W_{ba}) + r_2 \Re(W_{ba}) + h_2\Im(W_{ba}))^2 + (-h_1 \Re(W_{ba}) + r_2 \Im(W_{ba}) - h_2 \Re(W_{ba}))^2 \leq S_{ba} \) with \( S_{ba} \leq 0 \). This is max\
  \[ u \in \mathcal{U} u^\top \pi(x) \] for all \( x \in \mathcal{P} \) with

  - The compact and convex set \( \mathcal{U} = \{(-1, z_1, 2z_2) \in \mathbb{R}^3 : z_1^2 + z_2^2 \leq 1 \}

- **Constraint** (10), i.e., \( L_v^2 - R_{ab} \leq 0 \) for any \( b \in \mathcal{B} \), has the form max\
  \[ u \in \mathcal{U} u^\top \pi(x) \] for all \( x \in \mathcal{P} \) with

  - The compact and convex set \( \mathcal{U} = \{(-1, z_1, -z_2) \in \mathbb{R}^3 : z_1^2 + z_2^2 \leq 2z_2 \}

- **Constraint** (12), i.e., \( |W_{ba}| - R_{ab} \leq 0 \) for any \((b, a)\in \mathcal{E} \), has the form max\
  \[ u \in \mathcal{U} u^\top \pi(x) \] for all \( x \in \mathcal{P} \) with

  - The compact and convex set \( \mathcal{U} = \{(-1, z_1, z_2) \in \mathbb{R}^3 : z_1^2 + z_2^2 \leq 2z_1 \}

- **The relaxation** (R) includes several SDP constraints \( \mathcal{A}(x) \geq 0 \), where \( \mathcal{A} \) is a linear matrix operator. Such a constraint amounts to max\
  \[ u \in \mathcal{U} u^\top \pi(x) \] for all \( x \in \mathcal{P} \) with

  - The compact and convex set \( \mathcal{U} = \{M \in \mathbb{H}_p : (\text{Tr}(M) = 1) \land (M \succeq 0)\} \)

- The linear application \( \pi(x) = -\mathcal{A}(x) \),

  - and seeing \( p \times p \) Hermitian matrices as real vectors of length \( 2p^2 \).

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