A MORE EFFICIENT REFORMULATION OF COMPLEX SDP AS REAL SDP*

JIE WANG†

Abstract. This note proposes a novel reformulation of complex semidefinite programs (SDPs) as real SDPs. As an application, we present an economical reformulation of complex SDP relaxations of complex polynomial optimization problems as real SDPs and derive some further reductions by exploiting structure of the complex SDP relaxations. Various numerical examples demonstrate that our new reformulation runs several times (one magnitude in some cases) faster than the usual popular reformulation.

Key words. complex semidefinite programming, complex polynomial optimization, semidefinite programming, the complex moment-HSOS hierarchy, quantum information

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1. Introduction. Complex semidefinite programs (SDPs) arise from a diverse set of areas, such as combinatorial optimization [7], optimal power flow [8, 10], quantum information theory [2, 4, 14], signal processing [9, 12]. In particular, they appear as convex relaxations of complex polynomial optimization problems (CPOPs), giving rise to the complex moment-Hermitian-sum-of-squares (moment-HSOS) hierarchy [8, 13]. However, most modern SDP solvers deal with only real SDPs[1]. In order to handle complex SDPs, it is then mandatory to reformulate complex SDPs as equivalent real SDPs. A popular way to do so is to use the equivalent condition

$$H \succeq 0 \quad \Longleftrightarrow \quad Y = \begin{bmatrix} H_R & -H_I \\ H_I & H_R \end{bmatrix} \succeq 0 \tag{1.1}$$

for an Hermitian matrix $H = H_R + H_I\mathbf{i} \in \mathbb{C}^{n\times n}$ with H_R and H_I being its real and imaginary parts respectively. Note that the right-hand-side constraint in (1.1) entails certain structure and to feed it to an SDP solver, we need to impose extra affine constraints to the positive semidefinite (PSD) constraint $Y \succeq 0$:

$$Y_{i,j} = Y_{i+n,j+n}, Y_{i,j+n} + Y_{j,i+n} = 0, \quad i = 1,\dots,n, j = i,\dots,n. \tag{1.2}$$

This conversion is quite simple but could be inefficient when n is large. In this note, we take a dual point of view and propose a novel reformulation of complex SDPs as real SDPs. The benefit of the new reformulation is that there is no need to add extra affine constraints and hence it owns a lower complexity. In the same manner, we can obtain a new reformulation of complex SDP relaxations of CPOPs as real SDPs. Furthermore, by exploiting structure of the complex SDP relaxations, we are able to remove a bunch of redundant affine constraints, which leads to an even more economical real reformulation of the complex SDP relaxations. Various numerical experiments (on randomly generated CPOPs and the AC-OPF problem) confirm our theoretical finding and demonstrate that the new reformulation is indeed more efficient than the usual popular one.

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†Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing, China (wangjie212@amss.ac.cn, https://wangjie212.github.io/jiewang/)

[1] As far as the author knows, `SeDuMi` [11] and `Hypatia` [6] are the only solvers that can handle complex SDPs directly.

Notation. $\mathbb{N}$ denotes the set of nonnegative integers. For $n \in \mathbb{N} \setminus \{0\}$, let $[n] \coloneqq \{1, 2, \ldots, n\}$. We use $|A|$ to stand for the cardinality of a set A. Let $\mathbf{i}$ be the imaginary unit, satisfying $\mathbf{i}^2 = -1$. For $d \in \mathbb{N}$, let $\mathbb{N}^n_d \coloneqq \{(\alpha_i)_i \in \mathbb{N}^n \mid \sum_{i=1}^n \alpha_i \le d\}$ and let $\omega_{n,d} \coloneqq \binom{n+d}{d}$ be the cardinality of $\mathbb{N}^n_d$. For $\boldsymbol{\alpha} = (\alpha_i)_i \in \mathbb{N}^n_d$, let $\mathbf{z}^{\boldsymbol{\alpha}} \coloneqq z_1^{\alpha_1} \cdots z_n^{\alpha_n}$. $\overline{a}$ (resp. $\mathcal{R}(a), \mathcal{I}(a)$) denotes the conjugate (resp. real part, imaginary part) of a complex number a and $v^\star$ denotes the conjugate transpose of a complex vector v. For a positive integer n, the set of $n \times n$ Hermitian matrices is denoted by $\mathbf{H}^n$. We use $A \succeq 0$ to indicate that the matrix A is PSD. For $A, B \in \mathbb{C}^{n \times n}$, we denote by $\langle A, B \rangle$ the trace inner-product, defined by $\langle A, B \rangle = \mathrm{Tr}(A^\intercal B)$.

2. Main results. Let us consider the following complex SDP:

$$\text{(PSDP-}\mathbb{C}\text{)} \qquad \begin{cases} \sup\limits_{H \in \mathbf{H}^n} & \langle C, H \rangle \\ \text{s.t.} & \mathscr{A}(H) = b, \\ & H \succeq 0, \end{cases}$$

where $\mathscr{A}$ is a linear operator given by $\mathscr{A}(H) \coloneqq (\langle A_i, H \rangle)_{i=1}^m \in \mathbb{C}^m$ and $C \in \mathbf{H}^n, b \in \mathbb{C}^m$. By writing $\mathscr{A} = \mathscr{A}_R + \mathscr{A}_I \mathbf{i}, H = H_R + H_I \mathbf{i}, C = C_R + C_I \mathbf{i}, b = b_R + b_I \mathbf{i}$ with $\mathscr{A}_R, \mathscr{A}_I$ being the real linear operators associated to $\mathscr{A}$, $H_R, H_I, C_R, C_I \in \mathbb{R}^{n \times n}$, $b_R, b_I \in \mathbb{R}^m$, we can reformulate (PSDP-$\mathbb{C}$) as a real SDP:

$$\text{(PSDP-}\mathbb{R}\text{)} \qquad \begin{cases} \sup\limits_{Y \in \mathbf{S}^{2n}} & \langle C_R, H_R \rangle - \langle C_I, H_I \rangle \\ \text{s.t.} & \mathscr{A}_R(H_R) - \mathscr{A}_I(H_I) = b_R, \\ & \mathscr{A}_R(H_I) + \mathscr{A}_I(H_R) = b_I, \\ & Y = \begin{bmatrix} H_R & -H_I \\ H_I & H_R \end{bmatrix} \succeq 0. \end{cases}$$

As mentioned in the introduction, to feed the PSD constraint in (PSDP-$\mathbb{R}$) to an SDP solver, we need to include also the extra $n(n+1)$ affine constraints listed in (1.2), which could be inefficient in practice. Below we show that by taking a dual point of view, we can actually get rid of this issue. By the convex duality theory, the dual problem of (PSDP-$\mathbb{C}$) reads as

$$\text{(DSDP-}\mathbb{C}\text{)} \qquad \begin{cases} \inf\limits_{y \in \mathbb{C}^m} & b^\intercal y \\ \text{s.t.} & \mathscr{A}^*(y) \succeq C, \end{cases}$$

where $\mathscr{A}^*(y) \coloneqq \sum_{i=1}^m y_i A_i$ is the adjoint operator of $\mathscr{A}$. By writing $y = y_R + y_I \mathbf{i}$ with $y_R, y_I \in \mathbb{R}^m$, we can reformulate (DSDP-$\mathbb{C}$) as a real SDP:
(DSDP-$\mathbb{R}$)

$$\begin{cases} \inf\limits_{y_R, y_I \in \mathbb{R}^m} & b_R y_R - b_I y_I \\ \text{s.t.} & \begin{bmatrix} \mathscr{A}_R^*(y_R) - \mathscr{A}_I^*(y_I) - C_R & -\mathscr{A}_R^*(y_I) - \mathscr{A}_I^*(y_R) + C_I \\ \mathscr{A}_R^*(y_I) + \mathscr{A}_I^*(y_R) - C_I & \mathscr{A}_R^*(y_R) - \mathscr{A}_I^*(y_I) - C_R \end{bmatrix} \succeq 0. \end{cases}$$

Let $X = \left[\begin{smallmatrix} X_1 & X_3 \\ X_3^\intercal & X_2 \end{smallmatrix}\right]$ be the dual PSD variable of (DSDP-$\mathbb{R}$) with $X_1, X_2, X_3 \in$

$\mathbb{R}^{n\times n}$. Then the Lagrangian associated with (DSDP-$\mathbb{R}$) is

$$
\begin{aligned}
&L(X, y_R, y_I)\\
&= -\left\langle \begin{bmatrix} X_1 & X_3 \\ X_3^\intercal & X_2 \end{bmatrix}, \begin{bmatrix} \mathscr{A}_R^*(y_R) - \mathscr{A}_I^*(y_I) - C_R & -\mathscr{A}_R^*(y_I) - \mathscr{A}_I^*(y_R) + C_I \\ \mathscr{A}_R^*(y_I) + \mathscr{A}_I^*(y_R) - C_I & \mathscr{A}_R^*(y_R) - \mathscr{A}_I^*(y_I) - C_R \end{bmatrix} \right\rangle\\
&\quad + b_R y_R - b_I y_I\\
&= -\langle X_1 + X_2, \mathscr{A}_R^*(y_R) - \mathscr{A}_I^*(y_I) - C_R\rangle + \langle X_3 - X_3^\intercal, \mathscr{A}_R^*(y_I) + \mathscr{A}_I^*(y_R) - C_I\rangle\\
&\quad + b_R y_R - b_I y_I\\
&= \langle C_R, X_1 + X_2\rangle - \langle C_I, X_3 - X_3^\intercal\rangle + \langle b_R - \mathscr{A}_R(X_1 + X_2) + \mathscr{A}_I(X_3 - X_3^\intercal), y_R\rangle\\
&\quad - \langle b_I - \mathscr{A}_R(X_3 - X_3^\intercal) - \mathscr{A}_I(X_1 + X_2), y_I\rangle.
\end{aligned}
$$

Thus the dual problem of (DSDP-$\mathbb{R}$) can be written down as

$$
\text{(PSDP-}\mathbb{R}\text{')}\qquad \begin{cases} \sup\limits_{X\in\mathbf{S}^{2n}} & \langle C_R, X_1 + X_2\rangle - \langle C_I, X_3 - X_3^\intercal\rangle \\ \text{s.t.} & \mathscr{A}_R(X_1 + X_2) - \mathscr{A}_I(X_3 - X_3^\intercal) = b_R, \\ & \mathscr{A}_R(X_3 - X_3^\intercal) + \mathscr{A}_I(X_1 + X_2) = b_I, \\ & X = \begin{bmatrix} X_1 & X_3 \\ X_3^\intercal & X_2 \end{bmatrix} \succeq 0. \end{cases}
$$

The above reasoning leads to the main theorem of this note.

THEOREM 2.1. (PSDP-$\mathbb{R}$') *is equivalent to* (PSDP-$\mathbb{R}$) *(in the sense that they share the same optimum). As a result,* (PSDP-$\mathbb{R}$') *is equivalent to* (PSDP-$\mathbb{C}$)*. In addition, if* $X^\star = \left[\begin{smallmatrix} X_1^\star & X_3^\star \\ (X_3^\star)^\intercal & X_2^\star \end{smallmatrix}\right]$ *is an optimal solution to* (PSDP-$\mathbb{R}$')*, then* $H^\star = (X_1^\star + X_2^\star) + (X_3^\star - (X_3^\star)^\intercal)\mathbf{i}$ *is an optimal solution to* (PSDP-$\mathbb{C}$).

Proof. Let us denote the optima of (PSDP-$\mathbb{R}$) and (PSDP-$\mathbb{R}$') by v and v' respectively. Suppose $Y = \left[\begin{smallmatrix} H_R & -H_I \\ H_I & H_R \end{smallmatrix}\right]$ is a feasible solution to (PSDP-$\mathbb{R}$). Then one can easily check that $X := \left[\begin{smallmatrix} \frac{1}{2}H_R & \frac{1}{2}H_I \\ -\frac{1}{2}H_I & \frac{1}{2}H_R \end{smallmatrix}\right]$ is a feasible solution to (PSDP-$\mathbb{R}$'). Moreover, we have $\langle C_R, X_1 + X_2\rangle - \langle C_I, X_3 - X_3^\intercal\rangle = \langle C_R, H_R\rangle - \langle C_I, H_I\rangle$ and it follows $v \le v'$. On the other hand, suppose $X = \left[\begin{smallmatrix} X_1 & X_3 \\ X_3^\intercal & X_2 \end{smallmatrix}\right]$ is a feasible solution to (PSDP-$\mathbb{R}$'). We then have

$$
\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}^{-1} X \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} X_2 & -X_3^\intercal \\ -X_3 & X_1 \end{bmatrix} \succeq 0,
$$

and thus

$$
\begin{bmatrix} X_1 + X_2 & X_3 - X_3^\intercal \\ X_3^\intercal - X_3 & X_1 + X_2 \end{bmatrix} \succeq 0.
$$

Consequently, we obtain

$$
Y = \begin{bmatrix} H_R & -H_I \\ H_I & H_R \end{bmatrix} := \begin{bmatrix} X_1 + X_2 & X_3^\intercal - X_3 \\ X_3 - X_3^\intercal & X_1 + X_2 \end{bmatrix} \succeq 0.
$$

One can easily see that Y is a feasible solution to (PSDP-$\mathbb{R}$) and in addition, it holds $\langle C_R, H_R\rangle - \langle C_I, H_I\rangle = \langle C_R, X_1 + X_2\rangle - \langle C_I, X_3 - X_3^\intercal\rangle$. Thus $v \ge v'$ which proves the equivalence. The second statement of the theorem is clear from the above arguments. ∎

In contrast to (PSDP-$\mathbb{R}$), the PSD constraint in (PSDP-$\mathbb{R}$') is straightforward, and thus no extra affine constraint is required. This is why the conversion (PSDP-$\mathbb{R}$') is more appealing than (PSDP-$\mathbb{R}$) from the computational perspective.

Remark 2.2. A similar reformulation to (PSDP-$\mathbb{R}$') but for a restricted class of complex SDP relaxations of multiple-input multiple-output detection has appeared in [9].

3. Application to complex SDP relaxations for CPOPs. In this section, we apply the reformulation (PSDP-$\mathbb{R}$') to complex SDP relaxations arising from the complex moment-HSOS hierarchy for CPOPs. A CPOP is given by

$$\text{(CPOP)}\qquad \begin{cases} \inf\limits_{\mathbf{z}\in\mathbb{C}^s} & f(\mathbf{z},\overline{\mathbf{z}})=\sum_{\boldsymbol{\beta},\boldsymbol{\gamma}} b_{\boldsymbol{\beta},\boldsymbol{\gamma}}\mathbf{z}^{\boldsymbol{\beta}}\overline{\mathbf{z}}^{\boldsymbol{\gamma}}\\ \text{s.t.} & g_i(\mathbf{z},\overline{\mathbf{z}})=\sum_{\boldsymbol{\beta},\boldsymbol{\gamma}} g^i_{\boldsymbol{\beta},\boldsymbol{\gamma}}\mathbf{z}^{\boldsymbol{\beta}}\overline{\mathbf{z}}^{\boldsymbol{\gamma}}\ge 0, \quad i\in[t], \end{cases}$$

where $\overline{\mathbf{z}}\coloneqq(\overline{z}_1,\ldots,\overline{z}_s)$ stands for the conjugate of complex variables $\mathbf{z}\coloneqq(z_1,\ldots,z_s)$. The functions $f,g_1,\ldots,g_t$ are real-valued polynomials and their coefficients satisfy $b_{\boldsymbol{\beta},\boldsymbol{\gamma}}=\overline{b_{\boldsymbol{\gamma},\boldsymbol{\beta}}}$, $g^i_{\boldsymbol{\beta},\boldsymbol{\gamma}}=\overline{g^i_{\boldsymbol{\gamma},\boldsymbol{\beta}}}$. The *support* of f is defined by $\operatorname{supp}(f)\coloneqq\{(\boldsymbol{\beta},\boldsymbol{\gamma})\mid b_{\boldsymbol{\beta},\boldsymbol{\gamma}}\ne 0\}$. For $i\in[t]$, $\operatorname{supp}(g^i)$ is defined in the same way.

Fix $d\in\mathbb{N}$. Let $y=(y_{\boldsymbol{\beta},\boldsymbol{\gamma}})_{(\boldsymbol{\beta},\boldsymbol{\gamma})\in\mathbb{N}^n_d\times\mathbb{N}^n_d}\subseteq\mathbb{C}$ be a sequence indexed by $(\boldsymbol{\beta},\boldsymbol{\gamma})\in\mathbb{N}^n_d\times\mathbb{N}^n_d$ and satisfying $y_{\boldsymbol{\beta},\boldsymbol{\gamma}}=\overline{y_{\boldsymbol{\gamma},\boldsymbol{\beta}}}$. Let L_y be the linear functional defined by

$$f=\sum_{(\boldsymbol{\beta},\boldsymbol{\gamma})} b_{\boldsymbol{\beta},\boldsymbol{\gamma}}\mathbf{z}^{\boldsymbol{\beta}}\overline{\mathbf{z}}^{\boldsymbol{\gamma}}\mapsto L_y(f)=\sum_{(\boldsymbol{\beta},\boldsymbol{\gamma})} b_{\boldsymbol{\beta},\boldsymbol{\gamma}}y_{\boldsymbol{\beta},\boldsymbol{\gamma}}.$$

The *complex moment* matrix $\mathbf{M}_d(y)$ associated with y is the matrix indexed by $\mathbb{N}^s_d$ such that

$$[\mathbf{M}_d(y)]_{\boldsymbol{\beta},\boldsymbol{\gamma}}\coloneqq L_y(\mathbf{z}^{\boldsymbol{\beta}}\overline{\mathbf{z}}^{\boldsymbol{\gamma}})=y_{\boldsymbol{\beta},\boldsymbol{\gamma}},\quad \forall\boldsymbol{\beta},\boldsymbol{\gamma}\in\mathbb{N}^s_d.$$

Suppose that $g=\sum_{(\boldsymbol{\beta}',\boldsymbol{\gamma}')} g_{\boldsymbol{\beta}',\boldsymbol{\gamma}'}\mathbf{z}^{\boldsymbol{\beta}'}\overline{\mathbf{z}}^{\boldsymbol{\gamma}'}$ is a complex polynomial. The *complex localizing* matrix $\mathbf{M}_d(gy)$ associated with g and y is the matrix indexed by $\mathbb{N}^s_d$ such that

$$[\mathbf{M}_d(gy)]_{\boldsymbol{\beta},\boldsymbol{\gamma}}\coloneqq L_y(g\mathbf{z}^{\boldsymbol{\beta}}\overline{\mathbf{z}}^{\boldsymbol{\gamma}})=\sum_{(\boldsymbol{\beta}',\boldsymbol{\gamma}')} g_{\boldsymbol{\beta}',\boldsymbol{\gamma}'}y_{\boldsymbol{\beta}+\boldsymbol{\beta}',\boldsymbol{\gamma}+\boldsymbol{\gamma}'},\quad \forall\boldsymbol{\beta},\boldsymbol{\gamma}\in\mathbb{N}^s_d.$$

For convenience let us set $g_0\coloneqq 1$. Let $d_i\coloneqq\lceil\deg(g_i)/2\rceil$ for $i=0,1,\ldots,t$ and let $d_{\min}\coloneqq\max\{\lceil\deg(f)/2\rceil,d_1,\ldots,d_t\}$. For any $d\ge d_{\min}$, the d-th (d is called the *relaxation order*) complex moment relaxation for (CPOP) is given by

$$\text{(Mom-}\mathbb{C}\text{)}\qquad \begin{cases} \inf\limits_{y} & b^{\intercal}y=L_y(f)\\ \text{s.t.} & \mathbf{M}_d(y)\succeq 0,\\ & \mathbf{M}_{d-d_i}(g_iy)\succeq 0,\quad i\in[t],\\ & y_{\mathbf{0},\mathbf{0}}=1. \end{cases}$$

(Mom-$\mathbb{C}$) and its dual form the complex moment-HSOS hierarchy of (CPOP). For more details on this hierarchy, we refer the reader to [8, 13].

For any $(\boldsymbol{\beta},\boldsymbol{\gamma})\in\mathbb{N}^s_d\times\mathbb{N}^s_d$, we associate it with a matrix $A^0_{\boldsymbol{\beta},\boldsymbol{\gamma}}\in\mathbb{R}^{\omega_{s,d}\times\omega_{s,d}}$ defined by

$$[A^0_{\boldsymbol{\beta},\boldsymbol{\gamma}}]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'}=\begin{cases}1, & \text{if } (\boldsymbol{\beta}',\boldsymbol{\gamma}')=(\boldsymbol{\beta},\boldsymbol{\gamma}),\\ 0, & \text{otherwise.}\end{cases} \tag{3.1}$$

Moreover, for each $i \in [t]$, we associate any $(\boldsymbol{\beta},\boldsymbol{\gamma}) \in \mathbb{N}^s_{d-d_i} \times \mathbb{N}^s_{d-d_i}$ with a matrix $A^i_{\boldsymbol{\beta},\boldsymbol{\gamma}} \in \mathbb{C}^{\omega_{s,d-d_i} \times \omega_{s,d-d_i}}$ defined by

$$[A^i_{\boldsymbol{\beta},\boldsymbol{\gamma}}]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'} = \begin{cases} g^i_{\boldsymbol{\beta}'',\boldsymbol{\gamma}''}, & \text{if } (\boldsymbol{\beta}'+\boldsymbol{\beta}'',\boldsymbol{\gamma}'+\boldsymbol{\gamma}'') = (\boldsymbol{\beta},\boldsymbol{\gamma}), \\ 0, & \text{otherwise.} \end{cases} \tag{3.2}$$

Now for each $i = 0,1,\ldots,t$, we define the linear operator $\mathscr{A}^i$ by

$$\mathscr{A}^i(H) := \left(\langle A^i_{\boldsymbol{\beta},\boldsymbol{\gamma}}, H\rangle\right)_{(\boldsymbol{\beta},\boldsymbol{\gamma})\in\mathbb{N}^s_{d-d_i}\times\mathbb{N}^s_{d-d_i}}, \quad H \in \mathbf{H}^{\omega_{s,d-d_i}}.$$

By construction, it holds

$$\mathbf{M}_{d-d_i}(g_i y) = \sum_{(\boldsymbol{\beta},\boldsymbol{\gamma})\in\mathbb{N}^s_{d-d_i}\times\mathbb{N}^s_{d-d_i}} A^i_{\boldsymbol{\beta},\boldsymbol{\gamma}} y_{\boldsymbol{\beta},\boldsymbol{\gamma}} = (\mathscr{A}^i)^*(y), \quad i = 0,1,\ldots,t.$$

Therefore, we can rewrite (Mom-$\mathbb{C}$) as follows:

$$\text{(Mom-}\mathbb{C}\text{')} \qquad \begin{cases} \inf\limits_{y} & b^\intercal y \\ \text{s.t.} & (\mathscr{A}^i)^*(y) \succeq 0, \quad i = 0,1,\ldots,t, \\ & y_{\mathbf{0},\mathbf{0}} = 1, \end{cases}$$

whose dual reads as

$$\text{(HSOS-}\mathbb{C}\text{)} \qquad \begin{cases} \sup\limits_{\lambda,H^i} & \lambda \\ \text{s.t.} & \sum_{i=0}^t [\mathscr{A}^i(H^i)]_{\boldsymbol{\beta},\boldsymbol{\gamma}} + \delta_{(\boldsymbol{\beta},\boldsymbol{\gamma}),(\mathbf{0},\mathbf{0})}\lambda = b_{\boldsymbol{\beta},\boldsymbol{\gamma}}, \quad (\boldsymbol{\beta},\boldsymbol{\gamma}) \in \mathbb{N}^s_d \times \mathbb{N}^s_d, \\ & H^i \succeq 0, \quad i = 0,1,\ldots,t. \end{cases}$$

Note that we have used the Kronecker delta $\delta_{(\boldsymbol{\beta},\boldsymbol{\gamma}),(\mathbf{0},\mathbf{0})}$ in (HSOS-$\mathbb{C}$).

Let us fix any order "$<$" on $\mathbb{N}^s$.

PROPOSITION 3.1. (HSOS-$\mathbb{C}$) *is equivalent to the following complex SDP:*

$$\text{(HSOS-}\mathbb{C}\text{')} \qquad \begin{cases} \sup\limits_{\lambda,H^i} & \lambda \\ \text{s.t.} & \sum_{i=0}^t [\mathscr{A}^i(H^i)]_{\boldsymbol{\beta},\boldsymbol{\gamma}} + \delta_{(\boldsymbol{\beta},\boldsymbol{\gamma}),(\mathbf{0},\mathbf{0})}\lambda = b_{\boldsymbol{\beta},\boldsymbol{\gamma}}, \\ & \boldsymbol{\beta} \le \boldsymbol{\gamma}, \quad (\boldsymbol{\beta},\boldsymbol{\gamma}) \in \mathbb{N}^s_d \times \mathbb{N}^s_d, \\ & H^i \succeq 0, \quad i = 0,1,\ldots,t. \end{cases}$$

Proof. It suffices to show that for $\boldsymbol{\beta} < \boldsymbol{\gamma}$, $\sum_{i=0}^t [\mathscr{A}^i(H^i)]_{\boldsymbol{\gamma},\boldsymbol{\beta}} = b_{\boldsymbol{\gamma},\boldsymbol{\beta}}$ is equivalent to $\sum_{i=0}^t [\mathscr{A}^i(H^i)]_{\boldsymbol{\beta},\boldsymbol{\gamma}} = b_{\boldsymbol{\beta},\boldsymbol{\gamma}}$. Indeed, this equivalence follows from $b_{\boldsymbol{\gamma},\boldsymbol{\beta}} = \overline{b_{\boldsymbol{\beta},\boldsymbol{\gamma}}}$ and

$$\begin{aligned} \sum_{i=0}^t [\mathscr{A}^i(H^i)]_{\boldsymbol{\gamma},\boldsymbol{\beta}} &= \sum_{i=0}^t \langle A^i_{\boldsymbol{\gamma},\boldsymbol{\beta}}, H^i\rangle \\ &= [H^0]_{\boldsymbol{\gamma},\boldsymbol{\beta}} + \sum_{i=1}^t \sum_{\substack{(\boldsymbol{\gamma}',\boldsymbol{\beta}')\in\mathbb{N}^s_{d-d_i}\times\mathbb{N}^s_{d-d_i} \\ (\boldsymbol{\gamma}'',\boldsymbol{\beta}'')\in\text{supp}(g) \\ (\boldsymbol{\gamma}'+\boldsymbol{\gamma}'',\boldsymbol{\beta}'+\boldsymbol{\beta}'')=(\boldsymbol{\gamma},\boldsymbol{\beta})}} g^i_{\boldsymbol{\gamma}'',\boldsymbol{\beta}''} [H^i]_{\boldsymbol{\gamma}',\boldsymbol{\beta}'} \\ &= \sum_{i=0}^t \langle \overline{A^i_{\boldsymbol{\beta},\boldsymbol{\gamma}}}, H^i\rangle = \sum_{i=0}^t \overline{[\mathscr{A}^i(H^i)]_{\boldsymbol{\beta},\boldsymbol{\gamma}}}. \end{aligned}$$ ∎

With $\mathscr{A}^i = \mathscr{A}^i_R + \mathscr{A}^i_I\mathbf{i}, H^i = H^i_R + H^i_I\mathbf{i}, b = b_R + b_I\mathbf{i}$, (HSOS-$\mathbb{C}$') is equivalent to the following real SDP:

(HSOS-$\mathbb{R}$)

$$\begin{cases} \sup\limits_{\lambda,Y^i} & \lambda \\ \text{s.t.} & \sum_{i=0}^t \left([\mathscr{A}^i_R(H^i_R)]_{\boldsymbol{\beta},\boldsymbol{\gamma}} - [\mathscr{A}^i_I(H^i_I)]_{\boldsymbol{\beta},\boldsymbol{\gamma}}\right) + \delta_{(\boldsymbol{\beta},\boldsymbol{\gamma}),(\mathbf{0},\mathbf{0})}\lambda = [b_R]_{\boldsymbol{\beta},\boldsymbol{\gamma}}, \\ & \sum_{i=0}^t \left([\mathscr{A}^i_R(H^i_I)]_{\boldsymbol{\beta},\boldsymbol{\gamma}} + [\mathscr{A}^i_I(H^i_R)]_{\boldsymbol{\beta},\boldsymbol{\gamma}}\right) = [b_I]_{\boldsymbol{\beta},\boldsymbol{\gamma}}, \\ & \boldsymbol{\beta} \le \boldsymbol{\gamma}, \quad (\boldsymbol{\beta},\boldsymbol{\gamma}) \in \mathbb{N}^s_d \times \mathbb{N}^s_d, \\ & Y^i = \begin{bmatrix} H^i_R & -H^i_I \\ H^i_I & H^i_R \end{bmatrix} \succeq 0, \quad i = 0,1,\ldots,t. \end{cases}$$

On the other hand, by invoking Theorem 2.1 to (HSOS-$\mathbb{C}$'), we obtain another equivalent real SDP of (HSOS-$\mathbb{C}$'):

(3.3)

$$\begin{cases} \sup\limits_{\lambda,X^i} & \lambda \\ \text{s.t.} & \sum_{i=0}^t \left([\mathscr{A}^i_R(X^i_1 + X^i_2)]_{\boldsymbol{\beta},\boldsymbol{\gamma}} - [\mathscr{A}^i_I(X^i_3 - (X^i_3)^\intercal)]_{\boldsymbol{\beta},\boldsymbol{\gamma}}\right) + \delta_{(\boldsymbol{\beta},\boldsymbol{\gamma}),(\mathbf{0},\mathbf{0})}\lambda = [b_R]_{\boldsymbol{\beta},\boldsymbol{\gamma}}, \\ & \sum_{i=0}^t \left([\mathscr{A}^i_R(X^i_3 - (X^i_3)^\intercal)]_{\boldsymbol{\beta},\boldsymbol{\gamma}} + [\mathscr{A}^i_I(X^i_1 + X^i_2)]_{\boldsymbol{\beta},\boldsymbol{\gamma}}\right) = [b_I]_{\boldsymbol{\beta},\boldsymbol{\gamma}}, \\ & \boldsymbol{\beta} \le \boldsymbol{\gamma}, \quad (\boldsymbol{\beta},\boldsymbol{\gamma}) \in \mathbb{N}^s_d \times \mathbb{N}^s_d, \\ & X^i = \begin{bmatrix} X^i_1 & X^i_3 \\ (X^i_3)^\intercal & X^i_2 \end{bmatrix} \succeq 0, \quad i = 0,1,\ldots,t. \end{cases}$$

Proposition 3.2. (3.3) *is equivalent to the following real SDP:*

(HSOS-$\mathbb{R}$')

$$\begin{cases} \sup\limits_{\lambda,X^i} & \lambda \\ \text{s.t.} & \sum_{i=0}^t \left([\mathscr{A}^i_R(X^i_1 + X^i_2)]_{\boldsymbol{\beta},\boldsymbol{\gamma}} - [\mathscr{A}^i_I(X^i_3 - (X^i_3)^\intercal)]_{\boldsymbol{\beta},\boldsymbol{\gamma}}\right) + \delta_{(\boldsymbol{\beta},\boldsymbol{\gamma}),(\mathbf{0},\mathbf{0})}\lambda = [b_R]_{\boldsymbol{\beta},\boldsymbol{\gamma}}, \\ & \sum_{i=0}^t \left([\mathscr{A}^i_R(X^i_3 - (X^i_3)^\intercal)]_{\boldsymbol{\beta},\boldsymbol{\gamma}} + [\mathscr{A}^i_I(X^i_1 + X^i_2)]_{\boldsymbol{\beta},\boldsymbol{\gamma}}\right) = [b_I]_{\boldsymbol{\beta},\boldsymbol{\gamma}}, \quad \boldsymbol{\beta} \ne \boldsymbol{\gamma}, \\ & \boldsymbol{\beta} \le \boldsymbol{\gamma}, \quad (\boldsymbol{\beta},\boldsymbol{\gamma}) \in \mathbb{N}^s_d \times \mathbb{N}^s_d, \\ & X^i = \begin{bmatrix} X^i_1 & X^i_3 \\ (X^i_3)^\intercal & X^i_2 \end{bmatrix} \succeq 0, \quad i = 0,1,\ldots,t. \end{cases}$$

Proof. We need to show that the following constraints

$$\sum_{i=0}^t \left([\mathscr{A}^i_R(X^i_3 - (X^i_3)^\intercal)]_{\boldsymbol{\beta},\boldsymbol{\beta}} + [\mathscr{A}^i_I(X^i_1 + X^i_2)]_{\boldsymbol{\beta},\boldsymbol{\beta}}\right) = [b_I]_{\boldsymbol{\beta},\boldsymbol{\beta}} = 0, \quad \boldsymbol{\beta} \in \mathbb{N}^s_d \tag{3.4}$$

in (3.3) are redundant. For each $i = 0,1,\ldots,t$ and $\boldsymbol{\beta} \in \mathbb{N}^s_d$, we have

$$\begin{aligned} &\left\langle (A^i_{\boldsymbol{\beta},\boldsymbol{\beta}})_R, X^i_3 - (X^i_3)^\intercal \right\rangle \\ = &\sum_{\substack{(\boldsymbol{\beta}',\boldsymbol{\gamma}') \in \mathbb{N}^s_{d-d_i} \times \mathbb{N}^s_{d-d_i} \\ (\boldsymbol{\beta}'',\boldsymbol{\gamma}'') \in \mathrm{supp}(g) \\ (\boldsymbol{\beta}'+\boldsymbol{\beta}'',\boldsymbol{\gamma}'+\boldsymbol{\gamma}'')=(\boldsymbol{\beta},\boldsymbol{\beta})}} \mathcal{R}(g^i_{\boldsymbol{\beta}'',\boldsymbol{\gamma}''}) \left([X^i_3]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'} - [(X^i_3)^\intercal]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'}\right) \\ = &\frac{1}{2} \sum_{\substack{(\boldsymbol{\beta}',\boldsymbol{\gamma}') \in \mathbb{N}^s_{d-d_i} \times \mathbb{N}^s_{d-d_i} \\ (\boldsymbol{\beta}'',\boldsymbol{\gamma}'') \in \mathrm{supp}(g) \\ (\boldsymbol{\beta}'+\boldsymbol{\beta}'',\boldsymbol{\gamma}'+\boldsymbol{\gamma}'')=(\boldsymbol{\beta},\boldsymbol{\beta})}} \mathcal{R}(g^i_{\boldsymbol{\beta}'',\boldsymbol{\gamma}''}) \left([X^i_3]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'} + [X^i_3]_{\boldsymbol{\gamma}',\boldsymbol{\beta}'} - [(X^i_3)^\intercal]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'} - [(X^i_3)^\intercal]_{\boldsymbol{\gamma}',\boldsymbol{\beta}'}\right) \\ = &0, \end{aligned}$$

where we have used fact that $[(X_3^i)^\intercal]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'} = [X_3^i]_{\boldsymbol{\gamma}',\boldsymbol{\beta}'}$ and $[(X_3^i)^\intercal]_{\boldsymbol{\gamma}',\boldsymbol{\beta}'} = [X_3^i]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'}$. It follows that $[\mathscr{A}_R^i(X_3^i - (X_3^i)^\intercal)]_{\boldsymbol{\beta},\boldsymbol{\beta}} = \langle (A_{\boldsymbol{\beta},\boldsymbol{\beta}}^i)_R, X_3^i - (X_3^i)^\intercal\rangle = 0$.

In addition, for each $i = 0, 1, \ldots, t$ and $\boldsymbol{\beta} \in \mathbb{N}_d^s$, we have

$$\begin{aligned}
&\left\langle (A_{\boldsymbol{\beta},\boldsymbol{\beta}}^i)_I, X_1^i + X_2^i \right\rangle \\
=& \sum_{\substack{(\boldsymbol{\beta}',\boldsymbol{\gamma}')\in\mathbb{N}_{d-d_i}^s\times\mathbb{N}_{d-d_i}^s\\ (\boldsymbol{\beta}'',\boldsymbol{\gamma}'')\in\text{supp}(g)\\ (\boldsymbol{\beta}'+\boldsymbol{\beta}'',\boldsymbol{\gamma}'+\boldsymbol{\gamma}'')=(\boldsymbol{\beta},\boldsymbol{\beta})}} \mathcal{I}(g_{\boldsymbol{\beta}'',\boldsymbol{\gamma}''}^i)\left([X_1^i]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'} + [X_2^i]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'}\right) \\
=& \frac{1}{2}\sum_{\substack{(\boldsymbol{\beta}',\boldsymbol{\gamma}')\in\mathbb{N}_{d-d_i}^s\times\mathbb{N}_{d-d_i}^s\\ (\boldsymbol{\beta}'',\boldsymbol{\gamma}'')\in\text{supp}(g)\\ (\boldsymbol{\beta}'+\boldsymbol{\beta}'',\boldsymbol{\gamma}'+\boldsymbol{\gamma}'')=(\boldsymbol{\beta},\boldsymbol{\beta})}} \mathcal{I}\left(g_{\boldsymbol{\beta}'',\boldsymbol{\gamma}''}^i + g_{\boldsymbol{\gamma}'',\boldsymbol{\beta}''}^i\right)\left([X_1^i]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'} + [X_2^i]_{\boldsymbol{\beta}',\boldsymbol{\gamma}'}\right) \\
=& \,0,
\end{aligned}$$

where we have used fact that $\mathcal{I}(g_{\boldsymbol{\beta}'',\boldsymbol{\gamma}''}^i + g_{\boldsymbol{\gamma}'',\boldsymbol{\beta}''}^i) = \mathcal{I}(g_{\boldsymbol{\beta}'',\boldsymbol{\gamma}''}^i + \overline{g}_{\boldsymbol{\beta}'',\boldsymbol{\gamma}''}^i) = 0$ and X_1^i, X_2^i are symmetric. It follows that $[\mathscr{A}_I^i(X_1^i + X_2^i)]_{\boldsymbol{\beta},\boldsymbol{\beta}} = \langle (A_{\boldsymbol{\beta},\boldsymbol{\beta}}^i)_I, X_1^i + X_2^i\rangle = 0$.

Putting all above together yields (3.4). ∎

Now we can give the following theorem.

THEOREM 3.3. (HSOS-$\mathbb{R}$') *is equivalent to* (HSOS-$\mathbb{C}$).

Before closing the section, we compare complexity of different real SDP reformulations for complex SDP relaxations of (CPOP) in Table 1.

TABLE 1
Comparison of complexity of different real SDP reformulations for complex SDP relaxations of (CPOP). n_{sdp}*: the maximal size of SDP matrix,* m_{sdp}*: the number of affine constraints.*

	(HSOS-$\mathbb{R}$)	(HSOS-$\mathbb{R}$')
n_{sdp}	$2\omega_{s,d}$	$2\omega_{s,d}$
m_{sdp}	$2\omega_{s,d}^2 + 2\omega_{s,d} + \sum_{i=1}^t \omega_{s,d-d_i}$	$\omega_{s,d}^2$

4. Numerical experiments. In this section, we compare the performance of the two formulations for complex SDPs arising from the complex moment-HSOS hierarchy of CPOPs using the software `TSSOS`[2] in which `MOSEK` 10.0 [1] is employed as an SDP solver with default settings. All numerical experiments were performed on a desktop computer with Intel(R) Core(TM) i9-10900 CPU@2.80GHz and 64G RAM. In presenting the results, the column labelled by 'opt' records the optimum and the column labelled by 'time' records running time in seconds. Moreover, the symbol '-' means the SDP solver runs out of memory.

4.1. Minimizing a random complex quartic polynomial over the unit sphere. Our first example is to minimize a complex quartic polynomial over the unit sphere:

$$\text{(4.1)} \qquad \begin{cases} \inf\limits_{\mathbf{z}\in\mathbb{C}^s} & [\mathbf{z}]_2^\star Q[\mathbf{z}]_2 \\ \text{s.t.} & |z_1|^2 + \cdots + |z_s|^2 = 1, \end{cases}$$

[2]`TSSOS` is freely available at https://github.com/wangjie212/TSSOS.

where $[\mathbf{z}]_2$ is the vector of monomials in $\mathbf{z}$ up to degree two and $Q \in \mathbf{H}^{|[\mathbf{z}]_2|}$ is a random Hermitian matrix whose entries are selected with respect to the standard normal distribution.

We approach (4.1) for $s = 5, 7, \dots, 15$ with the second and third HSOS relaxations. The related results are shown in Table 2. From the table, we see that the reformulation (HSOS-ℝ') is several ($2 \sim 7$) times as fast as the reformulation (HSOS-ℝ), and the speedup is more significant as the SDP size grows.

TABLE 2
Minimizing a random complex quartic polynomial over the unit sphere.

s	d	n_{sdp}	(HSOS-ℝ)			(HSOS-ℝ')		
			m_{sdp}	opt	time	m_{sdp}	opt	time
5	2	42	966	-11.2409	0.11	441	-11.2409	0.05
	3	112	6846	-9.47725	8.13	3136	-9.47725	2.00
7	2	72	2736	-14.2314	0.97	1296	-14.2314	0.28
	3	240	30372	-11.0407	389	14400	-11.0407	57.0
9	2	110	6270	-19.0019	5.73	3025	-19.0019	1.62
	3	440	100320	-	-	48400	-15.5614	1944
11	2	156	12480	-22.8630	31.7	6084	-22.8630	6.67
	3	728	271882	-	-	132496	-	-
13	2	210	22470	-25.6352	145	11025	-25.6352	23.5
	3	1120	639450	-	-	313600	-	-
15	2	272	37536	-29.1672	585	18496	-29.1672	86.1
	3	1632	1351976	-	-	665856	-	-

4.2. Minimizing a random complex quartic polynomial with unit-norm variables. The second example is to minimize a random complex quartic polynomial with unit-norm variables:

$$\begin{cases} \inf\limits_{\mathbf{z}\in\mathbb{C}^s} & [\mathbf{z}]_2^\star Q[\mathbf{z}]_2 \\ \text{s.t.} & |z_i|^2 = 1, \quad i = 1, \dots, s, \end{cases} \tag{4.2}$$

where $Q \in \mathbf{H}^{|[\mathbf{z}]_2|}$ is a random Hermitian matrix whose entries are selected with respect to the uniform probability distribution on $[0, 1]$.

We approach (4.2) for $s = 5, 7, \dots, 15$ with the second and third HSOS relaxations. The related results are shown in Table 3. From the table, we see that the reformulation (HSOS-ℝ') is about one magnitude faster than the reformulation (HSOS-ℝ), and the speedup is more significant as the SDP size grows.

4.3. Minimizing a randomly generated sparse complex quartic polynomial over multi-spheres. Given $l \in \mathbb{N}\backslash\{0\}$, we randomly generate a sparse complex quartic polynomial as follows: Let $f = \sum_{i=1}^{l} f_i \in \mathbb{C}[z_1, \dots, z_{5(l+1)}, \overline{z}_1, \dots, \overline{z}_{5(l+1)}]$,[3] where for all $i \in [l]$, $f_i = \overline{f}_i \in \mathbb{C}[z_{5(i-1)+1}, \dots, z_{5(i-1)+10}, \overline{z}_{5(i-1)+1}, \dots, \overline{z}_{5(i-1)+10}]$ is a sparse complex quartic polynomial whose coefficients (real/imaginary parts) are

[3] $\mathbb{C}[\mathbf{z}, \overline{\mathbf{z}}]$ denotes the ring of complex polynomials in variables $\mathbf{z}, \overline{\mathbf{z}}$.

TABLE 3
Minimizing a random complex quartic polynomial with unit-norm variables.

s	d	n_{sdp}	(HSOS-ℝ)			(HSOS-ℝ')		
			m_{sdp}	opt	time	m_{sdp}	opt	time
5	2	42	734	-24.4919	0.10	271	-24.4919	0.03
	3	112	4474	-24.4919	2.34	1281	-24.4919	0.26
7	2	72	2202	-56.5289	0.65	869	-56.5289	0.16
	3	240	21158	-46.7128	132	6637	-46.7128	7.44
9	2	110	5242	-114.342	4.62	2161	-114.342	0.73
	3	440	73312	-	-	24691	-81.2676	184
11	2	156	10718	-202.436	32.1	4555	-202.436	3.86
	3	728	206188	-	-	73327	-	-
13	2	210	19686	-338.041	126	8555	-338.041	12.7
	3	1120	499438	-	-	185277	-	-
15	2	272	33394	-514.226	678	14761	-514.226	55.1
	3	1632	1081514	-	-	414841	-	-

selected with respect to the uniform probability distribution on $[-1, 1]$. Then we consider the following CPOP:

$$\left\{\begin{array}{ll}\inf\limits_{\mathbf{z}\in\mathbb{C}^{5(l+1)}} & f(\mathbf{z},\overline{\mathbf{z}}) \\ \text{s.t.} & \sum_{j=1}^{10} |z_{5(i-1)+j}|^2 = 1, \quad i = 1,\ldots,l.\end{array}\right. \tag{4.3}$$

The sparsity in (4.3) can be exploited to derive a sparsity-adapted complex moment-HSOS hierarchy [13]. We solve the second sparse HSOS relaxation of (4.3) for $l = 40, 80, \ldots, 400$. The results are displayed in Table 4. From the table we see that the reformulation (HSOS-ℝ') is $1.5 \sim 2$ times as fast as the reformulation (HSOS-ℝ).

TABLE 4
Minimizing a randomly generated sparse complex quartic polynomial over multi-spheres.

l	n_{sdp}	(HSOS-ℝ)			(HSOS-ℝ')		
		m_{sdp}	opt	time	m_{sdp}	opt	time
40	8	23090	-98.9240	3.12	12529	-98.9240	2.06
80	8	46768	-197.577	12.6	25549	-197.577	8.07
120	8	70958	-292.024	30.1	38871	-292.024	19.0
160	8	94278	-389.652	45.9	51563	-389.652	30.7
200	8	117526	-482.684	84.5	64185	-482.684	37.7
240	8	140298	-578.896	130	76389	-578.896	59.5
280	8	162504	-671.047	173	89241	-671.047	65.4
320	8	187528	-766.403	206	102171	-766.403	88.5
360	8	210370	-866.771	291	114589	-866.771	147
400	8	233396	-963.137	297	127173	-963.137	138

4.4. The AC-OPF problem. The alternating current optimal power flow (AC-OPF) is a central problem in power systems, which aims to minimize the generation cost of an alternating current transmission network under physical and operational constraints. Mathematically, it can be formulated as the following CPOP:

$$
\left\{
\begin{array}{ll}
\inf\limits_{V_i, S_k^g} & \sum_{k\in G}\left(\mathbf{c}_{2k}(\mathcal{R}(S_k^g))^2+\mathbf{c}_{1k}\mathcal{R}(S_k^g)+\mathbf{c}_{0k}\right)\\
\text{s.t.} & \angle V_r = 0,\\
& \mathbf{S}_k^{gl}\le S_k^g\le \mathbf{S}_k^{gu},\quad \forall k\in G,\\
& \boldsymbol{v}_i^l\le |V_i|\le \boldsymbol{v}_i^u,\quad \forall i\in N,\\
& \sum_{k\in G_i} S_k^g-\mathbf{S}_i^d-\mathbf{Y}_i^{sh}|V_i|^2=\sum_{(i,j)\in E_i\cup E_i^R} S_{ij},\quad \forall i\in N,\\
& S_{ij}=(\overline{\mathbf{Y}}_{ij}-\mathbf{i}\frac{\mathbf{b}_{ij}^c}{2})\frac{|V_i|^2}{|\mathbf{T}_{ij}|^2}-\overline{\mathbf{Y}}_{ij}\frac{V_i\overline{V}_j}{\mathbf{T}_{ij}},\quad \forall (i,j)\in E,\\
& S_{ji}=(\overline{\mathbf{Y}}_{ij}-\mathbf{i}\frac{\mathbf{b}_{ij}^c}{2})|V_j|^2-\overline{\mathbf{Y}}_{ij}\frac{\overline{V}_iV_j}{\overline{\mathbf{T}}_{ij}},\quad \forall (i,j)\in E,\\
& |S_{ij}|\le \mathbf{s}_{ij}^u,\quad \forall (i,j)\in E\cup E^R,\\
& \boldsymbol{\theta}_{ij}^{\Delta l}\le \angle(V_i\overline{V}_j)\le \boldsymbol{\theta}_{ij}^{\Delta u},\quad \forall (i,j)\in E,
\end{array}
\right.
\tag{4.4}
$$

where V_i is the voltage, S_k^g is the power generation, S_{ij} is the power flow (all are complex variables; $\angle\cdot$ stands for the angle of a complex number) and all symbols in boldface are constants. Notice that G is the collection of generators and N is the collection of buses. For a full description on the AC-OPF problem, we refer the reader to [3] as well as [5].

We select test cases from the AC-OPF library PGLiB-OPF [3]. For each case, we solve the minimal relaxation step of the sparse HSOS hierarchy [13]. The results are displayed in Table 5. From the table, we see that the reformulation (HSOS-ℝ') is several ($1.4\sim 5$) times as fast as the reformulation (HSOS-ℝ).

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TABLE 5
The results for the AC-OPF problem. s: the number of CPOP variables; t: the number of CPOP constraints.

Case	s	t	n_{sdp}	(HSOS-$\mathbb{R}$)			(HSOS-$\mathbb{R}$')		
				m_{sdp}	opt	time	m_{sdp}	opt	time
14_ieee	19	147	14	2346	1.9940e3	0.19	422	1.9940e3	0.10
30_ieee	36	297	12	4828	8.1959e3	0.73	836	8.1960e3	0.37
30_as	36	297	12	4828	5.0371e2	0.55	836	5.0371e2	0.24
39_epri	49	361	14	5270	1.3568e5	0.74	966	1.3579e5	0.54
89_pegase	101	1221	96	57888	9.4098e4	63.6	10262	9.4101e4	15.1
57_ieee	64	563	24	11102	3.6644e4	2.36	2008	3.6644e4	1.06
118_ieee	172	1325	20	25374	9.3216e4	8.27	4471	9.3216e4	2.68
162_ieee_dtc	174	1809	40	64874	1.0492e5	43.4	11327	1.0495e5	13.8
179_goc	208	1827	20	25712	6.0859e5	10.3	4368	6.0860e5	3.57
240_pserc	383	3039	24	52172	2.8153e6	31.9	9243	2.8170e6	10.7
300_ieee	369	2983	22	53946	5.3037e5	40.6	9647	5.3037e5	10.6
500_goc	671	5255	24	90502	3.9697e5	89.8	15918	3.9697e5	25.4
588_sdet	683	5287	16	79362	1.9799e5	91.7	13933	1.9749e5	21.3
793_goc	890	7019	16	104978	1.1194e5	105	18536	1.1222e5	31.5
1888_rte	2178	18257	30	280580	1.2537e6	939	47205	1.2545e6	180
2000_goc	2238	23009	34	455530	9.1876e5	2087	77974	9.1881e5	439

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