

HDSDP 1.0: Software for Semidefinite Programming

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Abstract

HDSDP is a numerical software solving the semidefinite programming problems. The main framework of HDSDP resembles the dual-scaling interior point solver DSDP[Benson and Ye, 2008] and several new features, including a dual method based on the simplified homogeneous self-dual embedding, have been implemented. The embedding technique enhances stability of the dual method and several new heuristics and computational techniques are designed to accelerate its convergence. HDSDP aims to show how dual-scaling algorithm benefits from the self-dual embedding and it is developed in parallel to DSDP5.8. Numerical experiments over several classical benchmark datasets exhibit its robustness and efficiency, and particularly its advantages on SDP instances featuring low-rank structure and sparsity. [HDSDP is open-sourced under MIT license and available at https://github.com/COPT-Public/HDSDP](https://github.com/COPT-Public/HDSDP).

1 INTRODUCTION

Semidefinite programming (SDP) is defined by

$$\begin{aligned} \min_{\mathbf{X}} \quad & \langle \mathbf{C}, \mathbf{X} \rangle \\ \text{subject to} \quad & \mathcal{A}\mathbf{X} = \mathbf{b} \\ & \mathbf{X} \in \mathbb{S}_+^n, \end{aligned} \tag{1}$$

where we study linear optimization subject to affine constraints over the cone of positive-semidefinite matrices. Due to its extensive modeling capability, SDP has been broadly adopted by communities including combinatorial optimization [Goemans and Williamson, 1995, Laurent and Rendl, 2005], dynamic systems [Vandenberghe and Boyd, 1996], sums of squares optimization [Laurent, 2009], quantum information [Hayashi, 2016], and distance geometry [Biswas and Ye, 2004, So and Ye, 2007]. We refer the interested readers to [Wolkowicz, 2005] for a more comprehensive review.

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While SDP proves useful in practice, a fundamental issue is to numerically solve it. Theoretically, SDP is a convex conic problem admitting polynomial-time algorithms, and for general SDPs, the interior point method (IPM) is known as a robust and efficient approach. Since the 1990s, high-performance SDP softwares based on the IPM have been developed, including DSDP [Benson and Ye, 2008], COPT [Ge et al., 2022], Mosek [ApS, 2019], Sedumi [Polik et al., 2007], SDPT3 [Toh et al., 2012], CSDP [Borchers, 2006], SDPA [Yamashita et al., 2012] and so forth. While most SDP codes are IPM-based, there are also successful attempts using other methods (for example, [Kocvara et al., 2006, Kwasniewicz and Glineur, 2021, Yang et al., 2015]) and a list of these softwares is reviewed by Majumdar et al. [2020].

SDP solvers based on IPM variants exhibit competitive convergence behavior both theoretically and practically. Most softwares implement primal-dual path-following approaches using either infeasible start [Potra and Sheng, 1998b] or the embedding technique [Potra and Sheng, 1998a], with DSDP being an exception: DSDP adopts a dual IPM method based on the potential reduction framework developed by Benson et al. [1999]. Since its initial release [Benson et al., 2000], DSDP has gone through several major updates and evolved into a popular SDP software [Benson and Ye, 2008]. To further improve DSDP, we make an important extension by incorporating the homogeneous self-dual embedding technique into the dual algorithm. This new implementation, named HSDP, is presented in this manuscript. The manuscript is organized as follows. **Section 2** describes the formulation of interest and some basic notations; **Section 3** reviews the dual-scaling algorithm and describes how embedding technique can be applied. In **Section 4** and **5**, we introduce the practical aspects for HSDP, including software design and algorithm configuration. Last we present comprehensive numerical results on SDP problems.

2 FORMULATION AND NOTATIONS

HSDP solves both primal and dual SDPs in standard form

$$\begin{aligned}
 (P) \quad & \min_{\mathbf{X}} \quad \langle \mathbf{C}, \mathbf{X} \rangle \\
 & \text{subject to} \quad \langle \mathbf{A}_i, \mathbf{X} \rangle = \mathbf{b}, \quad i = 1, \dots, m \\
 & \quad \quad \quad \mathbf{X} \in \mathbb{S}_+^n \\
 (D) \quad & \max_{\mathbf{y}, \mathbf{S}} \quad \mathbf{b}^\top \mathbf{y} \\
 & \text{subject to} \quad \sum_{i=1}^m \mathbf{A}_i y_i + \mathbf{S} = \mathbf{C} \\
 & \quad \quad \quad \mathbf{S} \in \mathbb{S}_+^n,
 \end{aligned}$$

where the problem data $\{\mathbf{A}_i\}, \mathbf{C}$ are $n \times n$ symmetric matrices (\mathbb{S}^n) and $\mathbf{b} \in \mathbb{R}^m$ is a real vector. Matrix inner product $\langle \cdot, \cdot \rangle$ is defined by $\langle \mathbf{A}, \mathbf{X} \rangle := \sum_{i,j} c_{ij} x_{ij}$ and \mathbb{S}_+^n denotes the cone of positive semidefinite matrices. For brevity we use $\mathbf{X} \geq \mathbf{0}$ to denote the relation $\mathbf{X} \in \mathbb{S}_+^n$, and the linear map $\mathcal{A} : \mathbb{S}^n \rightarrow \mathbb{R}^m$ together with its adjoint $\mathcal{A}^* : \mathbb{R}^m \rightarrow \mathbb{S}^n$ is defined by $\mathcal{A}\mathbf{X} := (\langle \mathbf{A}, \mathbf{X}_1 \rangle, \dots, \langle \mathbf{A}, \mathbf{X}_m \rangle)^\top$ and $\mathcal{A}^* \mathbf{y} := \sum_{i=1}^m \mathbf{A}_i y_i$. $\|\mathbf{A}\|_F := \sqrt{\sum_{i,j} a_{ij}^2}$ denotes the matrix Frobenius norm. With the above notations, we rewrite the primal and dual problems by

$$\begin{aligned}
 (P) \quad & \min_{\mathbf{X}} \quad \langle \mathbf{C}, \mathbf{X} \rangle \\
 & \text{subject to} \quad \mathcal{A}\mathbf{X} = \mathbf{b}, \\
 & \quad \quad \quad \mathbf{X} \geq \mathbf{0} \\
 (D) \quad & \max_{\mathbf{y}, \mathbf{S}} \quad \mathbf{b}^\top \mathbf{y} \\
 & \text{subject to} \quad \mathcal{A}^* \mathbf{y} + \mathbf{S} = \mathbf{C} \\
 & \quad \quad \quad \mathbf{S} \geq \mathbf{0}.
 \end{aligned}$$

and primal and dual feasible regions are

$$\mathcal{F}(P) := \{\mathbf{X} : \mathcal{A}\mathbf{X} = \mathbf{b}, \mathbf{X} \geq \mathbf{0}\} \quad \mathcal{F}(D) := \{(\mathbf{y}, \mathbf{S}) : \mathcal{A}^* \mathbf{y} + \mathbf{S} = \mathbf{C}, \mathbf{S} \geq \mathbf{0}\}.$$

$\mathbf{X} \in \mathcal{F}(P)$ is primal feasible and $(\mathbf{y}, \mathbf{S}) \in \mathcal{F}(D)$ is dual feasible. The interior of these regions are denoted by $\mathcal{F}^0(P), \mathcal{F}^0(D)$ and a solution in \mathcal{F}^0 is an interior point solution. HSDP implements a dual method solving (P) and (D) through the self-dual embedding technique.

3 DUAL AND HOMOGENEOUS DUAL SCALING ALGORITHM

In this section, we briefly review the dual-scaling algorithm in DSDP, and give its interpretation through Newton's method on the KKT system. Then we show how it naturally generalizes to the embedding.

3.1 Dual-scaling Algorithm

Dual-scaling method [Benson et al., 1999] works under three conditions. **1)** the data $\{A_i\}$ are linearly independent. **2)** Both (P) and (D) admit an interior point solution. **3)** an interior dual feasible solution $(y^0, S^0) \in \mathcal{F}^0(D)$ is known. The first two conditions imply strong duality and the existence of an optimal primal-dual solution pair (X^*, y^*, S^*) satisfying complementarity $\langle X^*, S^* \rangle = 0$. Also, the central path $C(\mu) := \{(X, y, S) \in \mathcal{F}^0(P) \times \mathcal{F}^0(D) : XS = \mu I\}$, which serves as a foundation of path-following approaches, is well-defined. Given a centrality parameter μ , dual method starts from $(y, S) \in \mathcal{F}^0(D)$ and takes Newton's step towards the solution of the perturbed KKT system $\mathcal{A}X = b, \mathcal{A}^*y + S = C$ and $XS = \mu I$

$$\begin{aligned} \mathcal{A}(X + \Delta X) &= b \\ \mathcal{A}^* \Delta y + \Delta S &= 0 \\ \mu S^{-1} \Delta S S^{-1} + \Delta X &= \mu S^{-1} - X, \end{aligned} \tag{2}$$

where the last relation linearizes $X = \mu S^{-1}$ instead of $XS = \mu I$ and S^{-1} is known as a scaling matrix. By geometrically driving μ to 0, dual-scaling eliminates (primal) infeasibility, approaches optimality, and finally solves the problem to some ε -optimal solution $(y_\varepsilon, S_\varepsilon) \in \mathcal{F}^0(D)$ such that $\langle b, y_\varepsilon \rangle \geq \langle b, y^* \rangle - \varepsilon$. Theory of dual potential reduction shows an ε -optimal solution can be obtained in $O(\log(1/\varepsilon))$ iterations ignoring dimension dependent constants.

An important feature of dual-scaling is that X and ΔX vanish in the Schur complement of (2)

$$\begin{pmatrix} \langle A_1, S^{-1} A_1 S^{-1} \rangle & \cdots & \langle A_1, S^{-1} A_m S^{-1} \rangle \\ \vdots & \ddots & \vdots \\ \langle A_m, S^{-1} A_1 S^{-1} \rangle & \cdots & \langle A_m, S^{-1} A_m S^{-1} \rangle \end{pmatrix} \Delta y = \frac{1}{\mu} b - \mathcal{A} S^{-1}, \tag{3}$$

and the dual algorithm thereby avoids explicit reference to the primal variable X . For brevity we denote the left-hand side matrix in (3) by M . If $\{A_i\}, C$ are sparse, any feasible dual slack $S = C - \mathcal{A}^*y$ inherits the aggregated sparsity pattern from the data and it is computationally cheaper to iterate in the dual space. Another feature of dual-scaling is the availability of primal solution by solving a projection subproblem at the end of the algorithm [Benson and Ye, 2008]. The aforementioned properties characterize the behavior of the dual-scaling method.

However, the desirable theoretical properties of the dual method is not free. First, an initial dual feasible solution is needed, while obtaining such a solution is often as difficult as solving the original problem. Second, due to a lack of information from primal space, dual-scaling method has to be properly guided to avoid deviating from the central path. To overcome the aforementioned difficulties, DSDP introduces artificial variables with big- M penalty to ensure a nonempty interior and a trivial dual feasible solution. Moreover, a potential function is introduced to guide the dual iterations. This works well in practice and enhance performance of DSDP. We refer the interested readers to [Benson and Ye, 2008, Benson et al., 2000] for more implementation details.

Although DSDP proves efficient in real practice, the big- M method requires prior estimation of the optimal solution to avoid losing optimality. Also, a large penalty often leads to numerical difficulties and mis-classification of infeasible problems when the problem is ill-conditioned. Therefore it is natural to seek better alternatives to the big- M method, and the self-dual embedding is an ideal candidate.

3.2 Dual-scaling Algorithm using Embedding Technique

Given a standard form SDP, its homogeneous self-dual model is a skew symmetric system containing the original problem data, whose non-trivial interior point solution certificates primal-dual feasibility. HSDP adopts the following simplified embedding [Potra and Sheng, 1998a].

$$\begin{aligned} \mathcal{A}X - \mathbf{b}\tau &= \mathbf{0} \\ -\mathcal{A}^*y + C\tau - S &= \mathbf{0} \\ \mathbf{b}^\top y - \langle C, X \rangle - \kappa &= 0 \\ X, S &\geq 0, \kappa, \tau \geq 0, \end{aligned} \tag{4}$$

where κ, τ are homogenizing variables for infeasibility detection. The central path of barrier parameter μ is given by

$$\begin{aligned} \mathcal{A}X - \mathbf{b}\tau &= \mathbf{0} \\ -\mathcal{A}^*y + C\tau - S &= \mathbf{0} \\ \mathbf{b}^\top y - \langle C, X \rangle - \kappa &= 0 \\ XS &= \mu I, \kappa\tau = \mu \\ X, S &\geq 0, \kappa, \tau \geq 0. \end{aligned} \tag{5}$$

Here (y, S, τ) are jointly considered as dual variables. Given an (infeasible) dual point (y, S, τ) such that $-\mathcal{A}^*y + C\tau - S = \mathbf{R}$, HSDP selects a damping factor $\gamma \in [0, 1]$ and takes Newton's step towards

$$\begin{aligned} \mathcal{A}(X + \Delta X) - \mathbf{b}(\tau + \Delta\tau) &= \mathbf{0} \\ -\mathcal{A}^*(y + \Delta y) + C(\tau + \Delta\tau) - (S + \Delta S) &= -\gamma \mathbf{R} \\ \mu S^{-1} \Delta S S^{-1} + \Delta X &= \mu S^{-1} - X, \\ \mu \tau^{-2} \Delta\tau + \Delta\kappa &= \mu \tau^{-1} - \kappa, \end{aligned}$$

where, similar to DSDP, we modify (5) and linearize $X = \mu S^{-1}, \kappa = \mu \tau^{-1}$. We use this damping factor γ and the barrier parameter μ to manage a trade-off between dual infeasibility, centrality and optimality. If we set $\gamma = 0$, then the Newton's direction $(\Delta y, \Delta\tau)$ is computed through the following Schur complement.

$$\begin{pmatrix} \mu M & -\mathbf{b} - \mu \mathcal{A} S^{-1} C S^{-1} \\ -\mathbf{b} + \mu \mathcal{A} S^{-1} C S^{-1} & -\mu(\langle C, S^{-1} C S^{-1} \rangle + \tau^{-2}) \end{pmatrix} \begin{pmatrix} \Delta y \\ \Delta\tau \end{pmatrix} = \begin{pmatrix} \mathbf{b}\tau \\ \mathbf{b}^\top y - \mu \tau^{-1} \end{pmatrix} - \mu \begin{pmatrix} \mathcal{A} S^{-1} \\ \langle C, S^{-1} \rangle \end{pmatrix} + \mu \begin{pmatrix} \mathcal{A} S^{-1} R S^{-1} \\ \langle C, S^{-1} R S^{-1} \rangle \end{pmatrix}$$

In practice, HSDP solves $\Delta y_1 := M^{-1}\mathbf{b}, \Delta y_2 := M^{-1}\mathcal{A}S^{-1}, \Delta y_3 := M^{-1}\mathcal{A}S^{-1}RS^{-1}, \Delta y_4 = M^{-1}\mathcal{A}S^{-1}CS^{-1}$, plugs the solution into $\Delta y = \frac{\tau + \Delta\tau}{\mu} \Delta y_1 - \Delta y_2 + \Delta y_3 + \Delta y_4 \Delta\tau$ to get $\Delta\tau$, and finally assembles Δy .

With the above relations, $\mathbf{X}(\mu) := \mu \mathbf{S}^{-1}(\mathbf{S} - \mathbf{R} + \mathcal{A}^* \Delta \mathbf{y} - \mathbf{C} \Delta \tau) \mathbf{S}^{-1}$ satisfies $\mathcal{A} \mathbf{X}(\mu) - \mathbf{b}(\tau + \Delta \tau) = \mathbf{0}$ and $\mathbf{X}(\mu) \succeq \mathbf{0}$ if and only if the backward Newton step $-\mathcal{A}^*(\mathbf{y} - \Delta \mathbf{y}) + \mathbf{C}(\tau - \Delta \tau) - \mathbf{R} \succeq \mathbf{0}$. When $-\mathcal{A}^*(\mathbf{y} - \Delta \mathbf{y}) + \mathbf{C}(\tau - \Delta \tau) - \mathbf{R}$ is positive definite, a primal upper-bound follows from simple algebraic manipulation

$$\begin{aligned} \bar{z} &= \langle \mathbf{C} \tau, \mathbf{X}(\mu) \rangle \\ &= \langle \mathbf{R} + \mathbf{S} + \mathcal{A}^* \mathbf{y}, \mu \mathbf{S}^{-1}(\mathbf{S} - \mathbf{R} + \mathcal{A}^* \Delta \mathbf{y} - \mathbf{C} \Delta \tau) \mathbf{S}^{-1} \rangle \\ &= (\tau + \Delta \tau) \mathbf{b}^\top \mathbf{y} + n\mu + (\mathcal{A} \mathbf{S}^{-1} + \mathcal{A} \mathbf{S}^{-1} \mathbf{R} \mathbf{S}^{-1})^\top \Delta \mathbf{y} + \mu(\langle \mathbf{C}, \mathbf{S}^{-1} \rangle + \langle \mathbf{C}, \mathbf{S}^{-1} \mathbf{C} \mathbf{S}^{-1} \rangle) \Delta \tau \end{aligned}$$

and dividing both sides by τ . Alternatively, HDSDP extracts a primal objective bound from the projection problem

$$\min_{\mathbf{X}} \|\mathbf{S}^{1/2} \mathbf{X} \mathbf{S}^{1/2} - \mu \mathbf{I}\|_F^2 \quad \text{subject to} \quad \mathcal{A} \mathbf{X} = \mathbf{b} \tau$$

whose optimal solution is $\mathbf{X}'(\mu) := \mu \mathbf{S}^{-1}(\mathbf{C} \tau - \mathcal{A}^*(\mathbf{y} - \Delta' \mathbf{y}) - \mathbf{R}) \mathbf{S}^{-1}$. Here $\Delta' \mathbf{y} = \frac{\tau}{\mu} \Delta \mathbf{y}_1 - \Delta \mathbf{y}_2$ and

$$\mathbf{z}' = \langle \mathbf{C} \tau, \mathbf{X}'(\mu) \rangle = \mu \{ \langle \mathbf{R}, \mathbf{S}^{-1} \rangle + (\mathcal{A} \mathbf{S}^{-1} \mathbf{R} \mathbf{S}^{-1} + \mathcal{A} \mathbf{S}^{-1})^\top \Delta' \mathbf{y} + n \} + \tau \mathbf{b}^\top \mathbf{y}.$$

Using the Newton's direction $\Delta \mathbf{y}$, HDSDP applies a simple ratio test

$$\alpha = \max \{ \alpha \in [0, 1] : \mathbf{S} + \alpha \Delta \mathbf{S} \succeq \mathbf{0}, \tau + \alpha \Delta \tau \geq 0 \} \quad (6)$$

through a Lanczos procedure [Toh, 2002]. But to determine the aforementioned damping factor γ , we resort to the following adaptive heuristic: assuming that $\mu \rightarrow \infty$, $\tau = 1$ and fixing $\Delta \tau = 0$, the dual update can be decomposed by

$$\begin{aligned} \mathbf{S} + \alpha \Delta \mathbf{S} &= \mathbf{S} + \alpha(\gamma \mathbf{R} - \mathcal{A}^* \Delta \mathbf{y}) \\ &= \mathbf{S} + \alpha(\gamma \mathbf{R} - \mathcal{A}^*(\gamma \Delta \mathbf{y}_3 - \Delta \mathbf{y}_2)) \\ &= \mathbf{S} + \alpha \mathcal{A}^* \Delta \mathbf{y}_2 + \alpha \gamma (\mathbf{R} - \mathcal{A}^* \Delta \mathbf{y}_3), \end{aligned}$$

where the first term $\mathbf{S} + \alpha \mathcal{A}^* \Delta \mathbf{y}_2$ is independent of γ and improves centrality of the iteration. HDSDP conducts a Lanczos line-search to find α_c such that the logarithmic barrier function is improved

$$-\log \det(\mathbf{S} + \alpha_c \Delta \mathbf{S}) - \log \det(\tau + \alpha_c \Delta \tau) \leq -\log \det \mathbf{S} - \log \det \tau.$$

Then given $\alpha = \alpha_c$, by a second Lanczos line-search we find the maximum possible $\gamma \leq 1$ such that $\mathbf{S} + \alpha_c \Delta \mathbf{S} = \mathbf{S} + \alpha_c \mathcal{A}^* \Delta \mathbf{y}_2 + \alpha_c \gamma (\mathbf{R} - \mathcal{A}^* \Delta \mathbf{y}_3) \succeq \mathbf{0}$. Finally, a full Newton's direction is determined by γ and a third Lanczos procedure finally carries out the ratio test (6). The intuition of the above heuristic is to eliminate infeasibility under centrality restrictions, so that the iterations stay away from the boundary of the cone. After the ratio test, HDSDP updates $\mathbf{y} \leftarrow \mathbf{y} + 0.95 \alpha \Delta \mathbf{y}$ and $\tau \leftarrow \tau + 0.95 \alpha \Delta \tau$ to ensure the feasibility of the next iteration. To make further use of the Schur complement \mathbf{M} , the above procedure is repeated several times in an iteration with \mathbf{M} unchanged.

In HDSDP, the barrier parameter μ also significantly affects the algorithm. At the end of each iteration, HDSDP updates the barrier parameter μ by $(z - \mathbf{b}^\top \mathbf{y} + \theta \|\mathbf{R}\|_F) / \rho n$, where z is the best primal bound so far and ρ, θ are pre-defined parameters. By default $\rho = 4$ and $\theta = 10^8$. Heuristics also adjust μ based on α_c and γ . To get the best of both worlds, HDSDP implements the same dual-scaling algorithm as in DSDP5.8. If dual infeasibility satisfies $\|\mathcal{A}^* \mathbf{y} + \mathbf{S} - \mathbf{C}\|_F \leq \epsilon \tau$ and μ is sufficiently small, HDSDP fixes $\tau = 1$, re-starts with $(\mathbf{y}/\tau, \mathbf{S}/\tau)$ and instead applies dual potential function to guide convergence. To sum up, HDSDP implements strategies and computational tricks tailored for the embedding and can switch to DSDP5.8 once a dual feasible solution is available.

4 INITIALIZATION AND FEASIBILITY CERTIFICATE

Internally HSDP deals with the following problem

$$\begin{aligned} \min_{\mathbf{X}} \quad & \langle \mathbf{C}, \mathbf{X} \rangle + \mathbf{u}^\top \mathbf{x}_u + \mathbf{l}^\top \mathbf{x}_l \\ \text{subject to} \quad & \mathcal{A}\mathbf{X} + \mathbf{x}^u - \mathbf{x}^l = \mathbf{b} \\ & \mathbf{X} \geq \mathbf{0}, \mathbf{x}_u \geq \mathbf{0}, \mathbf{x}_l \geq \mathbf{0}. \end{aligned}$$

Together with its dual, the embedding is given by

$$\begin{aligned} \mathcal{A}\mathbf{X} + \mathbf{x}^u - \mathbf{x}^l - \mathbf{b}\tau &= \mathbf{0} \\ -\mathcal{A}^* \mathbf{y} + \mathbf{C}\tau - \mathbf{S} &= \mathbf{0} \\ \mathbf{b}^\top \mathbf{y} - \langle \mathbf{C}, \mathbf{X} \rangle - \mathbf{u}^\top \mathbf{x}_u - \mathbf{l}^\top \mathbf{x}_l - \kappa &= 0 \\ \mathbf{X}, \mathbf{S} \geq \mathbf{0}, \kappa, \tau &\geq 0, \end{aligned}$$

where the primal problem is relaxed by two slack variables with penalty \mathbf{l}, \mathbf{u} to prevent \mathbf{y} going too large. Using the embedding, HSDP needs no big- M initialization in the dual variable and starts from arbitrary $\mathbf{S} > \mathbf{0}, \tau > 0$. By default HSDP starts from $\tau = 1, \mathbf{y} = \mathbf{0}$ and \mathbf{S} is initialized with $\mathbf{C} + 10^p \cdot \|\mathbf{C}\| \mathbf{I}$. One feature of the embedding is its capability to detect infeasibility. Given infeasibility tolerance ε_f , HSDP classifies the problem as primal unbounded, dual infeasible if $\|\mathbf{R}\|_F > \varepsilon_f \tau, \tau/\kappa < \varepsilon_f$ and $\mu/\mu_0 \leq \varepsilon_f^2$. If $\mathbf{b}^\top \mathbf{y} > \varepsilon_f^{-1}$, HSDP starts checking if the Newton's step $(\Delta \mathbf{y}, \Delta \mathbf{S})$ is a dual improving ray. Once a ray is detected, the problem is classified as primal infeasible and dual unbounded.

5 HSDP SOFTWARE

HSDP is written in ANSI C according to the standard of commercial numerical software, and provides a self-contained user interface. While DSDP5.8 serves as a sub-routine library, HSDP is designed to be a stand-alone SDP solver and re-written to accommodate the new computational techniques and third-party packages. After the user inputs the data and invokes the optimization routine, HSDP goes through several modules including input check, pre-solving, two-phase optimization and post-solving. The modules are implemented independently and are sequentially organized in a pipeline. Compared with DSDP, two most important computational improvements of HSDP lie in its conic KKT solver and its abstract linear system interface. To our knowledge, HSDP has one of the most advanced KKT solvers among all the open-source SDP codes.

5.1 Pre-solver

One new feature of HSDP is a special pre-solving module designed for SDPs. It inherits techniques from DSDP5.8 and adds new strategies to work jointly with the optimization module. After the pre-solver is invoked, it first goes through $\{\mathbf{A}_i\}$ two rounds to detect the possible low-rank structure. The first round uses Gaussian elimination for rank-one structure and the second round applies eigenvalue decomposition from Lapack. Two exceptions are when the data matrix is too dense or sparse. Unlike in DSDP5.8 where eigen-decomposition is mandatory, matrices that are too dense to be eigen-decomposed efficiently will be skipped in HSDP; if a matrix has very few entries, then a strategy from DSDP5.8 is applied: 1) a permutation gathers the non-zeros to a much smaller dense block. 2) dense eigen routines from Lapack applies. 3) the inverse permutation recovers the decomposition.

After detecting the hidden low-rank structures, the pre-solver moves on to collecting the sparsity and rank information of the matrices. The information will be kept for the KKT analysis to be described in **Section 5.3**.

Finally, the pre-solver scales down the large objective coefficients by their Frobenius norm and goes on to identify the following seven structures. 1). Implied trace: constraints imply $\text{tr}(\mathbf{X}) = \theta$. 2). Implied dual bound: constraints imply $\mathbf{l} \leq \mathbf{y} \leq \mathbf{u}$. 3). Empty primal interior: constraints imply $\text{tr}(\mathbf{X}\mathbf{a}\mathbf{a}^\top) \approx 0$. 4). Empty dual interior: constraints imply $\mathcal{A}^*\mathbf{y} = \mathbf{C}$. 5). Feasibility problem: $\mathbf{C} = \mathbf{0}$. 6). Dense problem: whether all the constraint matrices are totally dense. 7). Multi-block problem: whether there are many SDP cones. For each of the cases the solver adjusts its internal parameters to enhance its numerical stability and convergence.

5.2 Two-phase Optimization

Underlie the procedure control of HSDP is a two-phase method which integrates the embedding technique (Phase A) and dual-scaling (Phase B). Phase A targets feasibility certificate, while Phase B aims to efficiently drive a dual-feasible solution to optimality.

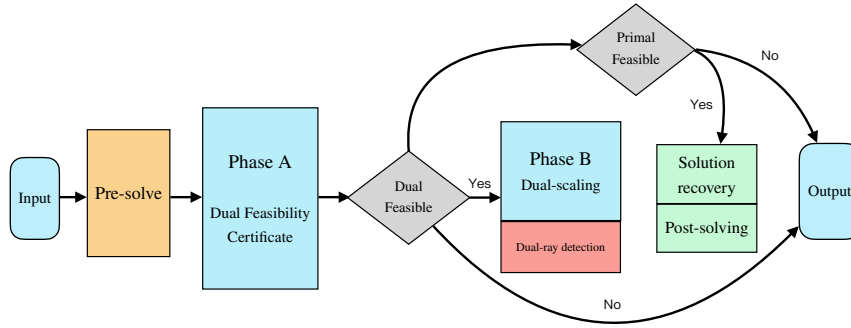


Fig. 1. Pipeline of HSDP

The two phases share the same backend computation routines but are associated with different goals and strategies. HSDP decides which strategy to use based on the behavior of algorithm iterations.

5.3 Conic KKT Solver

The most computationally intensive part in HSDP is in the Schur complement matrix \mathbf{M} . In real-life applications, the SDP objective \mathbf{C} often does not share the same sparsity or low-rank property as $\{\mathbf{A}_i\}$. Therefore, the additional computation from $\mathcal{A}\mathbf{S}^{-1}\mathbf{C}\mathbf{S}^{-1}$ and $\langle \mathbf{C}, \mathbf{S}^{-1}\mathbf{C}\mathbf{S}^{-1} \rangle$ demands more efficient techniques to set up \mathbf{M} .

Efficiency of setting up \mathbf{M} depends mainly on two aspects: 1). the structure of the cones participating in forming the Schur complement, and 2) the structure of the coefficients inside each cone. To exploit both structures, KKT solver in HSDP implements two abstract interfaces, one from conic coefficient to conic operations, the other from cone to \mathbf{M} .

The first interface allows HSDP to set up \mathbf{M} faster, while the second allows the extension of dual-scaling to arbitrary cones. These two interfaces already appeared in DSDP5.8, but unifying them in a conic KKT solver makes the algorithm implementation more compact. Till the date when this manuscript is written, four cones and five types SDP coefficients have been implemented by HSDP.

The interface from SDP coefficients to conic operations is directly relevant to the set up of \mathbf{M} . Using rank and sparsity information from the pre-solver, HSDP analyzes the Schur system and generates a permutation $\sigma(m)$ of the rows of \mathbf{M} . The idea is to permute the most computationally-expensive matrices to the left-most position, and this is a direct extension of [Fujisawa et al., 1997].

$$\begin{pmatrix} \langle \mathbf{A}_{\sigma(1)}, \mathbf{S}^{-1} \mathbf{A}_{\sigma(1)} \mathbf{S}^{-1} \rangle & \cdots & \langle \mathbf{A}_{\sigma(1)}, \mathbf{S}^{-1} \mathbf{A}_{\sigma(m)} \mathbf{S}^{-1} \rangle \\ & \ddots & \vdots \\ & & \langle \mathbf{A}_{\sigma(m)}, \mathbf{S}^{-1} \mathbf{A}_{\sigma(m)} \mathbf{S}^{-1} \rangle \end{pmatrix}$$

After deciding the permutation, for each row of the permuted system, HSDP chooses one out of a pool of five candidate techniques. We denote them by **M1** to **M5**, and they are efficient under different coefficient structures: Technique **M1** and **M2** are inherited from DSDP. They exploit the low-rank structure of the coefficient data and an eigen-decomposition of the data $\mathbf{A}_i = \sum_{r=1}^{\text{rank}(\mathbf{A}_i)} \lambda_{i,r} \mathbf{a}_{i,r} \mathbf{a}_{i,r}^\top$ needs to be computed at the beginning of the algorithm; Technique **M3**, **M4** and **M5** exploit sparsity and need evaluation of \mathbf{S}^{-1} [Fujisawa et al., 1997] every iteration.

KKT Technique M1

- (1) **Setup** $\mathbf{B}_{\sigma(i)} = \sum_{r=1}^{\text{rank}(\mathbf{A}_{\sigma(i)})} \lambda_r (\mathbf{S}^{-1} \mathbf{a}_{\sigma(i),r}) (\mathbf{S}^{-1} \mathbf{a}_{\sigma(i),r})^\top$
- (2) **Compute** $M_{\sigma(i)\sigma(j)} = \langle \mathbf{B}_{\sigma(i)}, \mathbf{A}_{\sigma(j)} \rangle$, for all $j \geq i$

KKT Technique M2

- (1) **Setup** $\mathbf{S}^{-1} \mathbf{a}_{\sigma(i),r}, r = 1, \dots, r_{\sigma(i)}$
- (2) **Compute** $M_{\sigma(i)\sigma(j)} = \sum_{r=1}^{\text{rank}(\mathbf{A}_{\sigma(i)})} \lambda_r (\mathbf{S}^{-1} \mathbf{a}_{\sigma(i),r})^\top \mathbf{A}_{\sigma(j)} (\mathbf{S}^{-1} \mathbf{a}_{\sigma(i),r})$

KKT Technique M3

- (1) **Setup** $\mathbf{B}_{\sigma(i)} = \mathbf{S}^{-1} \mathbf{A}_{\sigma(i)} \mathbf{S}^{-1}$
- (2) **Compute** $M_{\sigma(i)\sigma(j)} = \langle \mathbf{B}_{\sigma(i)}, \mathbf{A}_{\sigma(j)} \rangle$, for all $j \geq i$

KKT Technique M4

- (1) **Setup** $\mathbf{B}_{\sigma(i)} = \mathbf{S}^{-1} \mathbf{A}_{\sigma(i)}$
- (2) **Compute** $M_{\sigma(i)\sigma(j)} = \langle \mathbf{B}_{\sigma(i)} \mathbf{S}^{-1}, \mathbf{A}_{\sigma(j)} \rangle$, for all $j \geq i$

KKT Technique M5

- (1) **Compute** $M_{\sigma(i)\sigma(j)} = \langle \mathbf{S}^{-1} \mathbf{A}_{\sigma(i)} \mathbf{S}^{-1}, \mathbf{A}_{\sigma(j)} \rangle$, for all $j \geq i$ directly

Table 1. Approximate flops for each strategy. f_i is the number of nonzeros of \mathbf{A}_i ; r_i is rank of \mathbf{A}_i , κ is the slow down ratio of discontinuous memory access

KKT Technique	Floating point operations	Extra cost
M1	$r_{\sigma(i)}(n^2 + 2n^2) + \kappa \sum_{j \geq i} f_{\sigma(j)}$	0
M2	$r_{\sigma(i)}(n^2 + \kappa \sum_{j \geq i} f_{\sigma(j)})$	0
M3	$n\kappa f_{\sigma(i)} + n^3 + \sum_{j \geq i} \kappa f_{\sigma(j)}$	n^3
M4	$n\kappa f_{\sigma(i)} + \sum_{j \geq i} \kappa(n+1)f_{\sigma(j)}$	n^3
M5	$\kappa(2\kappa f_{\sigma(i)} + 1) \sum_{j \geq i} f_{\sigma(j)}$	n^3

This newly developed KKT solver improves the speed of HSDP on a broad set of instances. And to our knowledge HSDP is the first SDP software that simultaneously incorporates all the commonly-used Schur complement strategies.

5.4 Linear System Interface and Parallel Computation

Linear system solving is the core of any interior point software, and most of the linear system solvers nowadays provide support for multi-threading. In HSDP, matrix decomposition is required for both the dual matrix S and the Schur complement M , both of which would need different decomposition routines based on matrix data structure and numerical conditioning. To meet this requirement, HSDP adopts a plug-in type abstract linear system interface which allows users to adopt any linear system routine. **Table 2** summarizes the routines supported by HSDP, and by default the multi-threaded Intel MKL routines are used and threading is controlled by a user-specified parameter.

Table 2. Linear systems in HSDP

Linear system type	Implementation	Parallel	Available in Public
Dense Restarted PCG	HSDP	Yes	Yes
Positive definite sparse direct	(MKL) Pardiso [Wang et al., 2014]	Yes	No
Quasi-definite sparse direct	COPT [Ge et al., 2022]	Yes	No
Positive-definite dense direct	COPT [Ge et al., 2022]	Yes	No
Positive definite sparse direct	SuiteSparse [Davis, 2006]	No	Yes
Positive definite dense direct	(MKL) Lapack [Wang et al., 2014]	Yes	Yes
Symmetric indefinite dense direct	(MKL) Lapack [Wang et al., 2014]	Yes	Yes

Aside from the third-party routines, HSDP itself implements a pre-conditioned conjugate gradient (CG) method with restart to solve the Schur complement system. The maximum number of iterations is chosen around $50/m$ and is heuristically adjusted. Either the diagonal of M or its Cholesky decomposition is chosen as pre-conditioner and after a Cholesky pre-conditioner is computed, HSDP reuses it for the consecutive solves till a heuristic determines that the current pre-conditioner is outdated. When the algorithm approaches optimality, M might become ill-conditioned and HSDP switches to LDL decomposition in case Cholesky fails.

6 COMPUTATIONAL RESULTS

The efficiency of DSDP5.8 has been proven through years of computational experience, and HSDP aims to achieve further improvement on instances where dual method has advantage over the primal-dual method. In this section, we introduce several types of SDPs suitable for the dual method and we compare the performance of HSDP, DSDP5.8 and COPT 6.5 (fastest solver on Mittelmann’s benchmark) on several benchmark datasets to verify the performance improvement of HSDP.

6.1 Experiment Setup

We configure the experiment as follows

- (1) (Testing platform). The tests are run on an intel i11700K PC with 128GB memory and 12 threads. We choose HSDP, DSDP5.8 and COPT6.5 are selected as benchmark softwares.
- (2) (Compiler and third-party dependency). Both HSDP and DSDP5.8 are compiled using `icc` with `-O2` optimization and linked with threaded version intel MKL. Executable of COPT is directly obtained from its official website.
- (3) (Threading). We set the number of MKL threads to be 12 for DSDP5.8; the `Threads` parameter of COPT is also set to 12. To enhance reproducibility HSDP uses 8 threads.

- (4) (Dataset). Datasets are chosen from three sources: 1). SDP benchmark datasets from Hans Mittelmann’s website [Mittelmann, 2003]; 2). SDP benchmark datasets from SDPLIB [Borchers, 1999]. 3). Optimal diagonal preconditioner SDPs generated according to [Qu et al., 2020].
- (5) (Algorithm). Default methods in HSDP, DSDP5.8, and the primal-dual interior point method implemented in COPT are compared.
- (6) (Tolerance). All the feasibility and optimality tolerances are set to 5×10^{-6} .
- (7) (Solution status). We adopt the broadly accepted DIMACS error to determine if a solution is qualified. According to Mittelmann [2003], if any of the DIMACS errors exceeds 10^{-2} , the solution is considered invalid.
- (8) (Performance Metric). We use shifted geometric mean to compare the overall speed between different solvers.

6.2 Maximum Cut

The SDP relaxation of the max-cut problem is represented by

$$\begin{aligned} \min_{\mathbf{X}} \quad & \langle \mathbf{C}, \mathbf{X} \rangle \\ \text{subject to} \quad & \text{diag}(\mathbf{X}) = \mathbf{1} \\ & \mathbf{X} \succeq \mathbf{0}. \end{aligned}$$

Let \mathbf{e}_i be the i -th column of the identity matrix and the constraint $\text{diag}(\mathbf{X}) = \mathbf{e}$ is decomposed into $\langle \mathbf{X}, \mathbf{e}_i \mathbf{e}_i^\top \rangle = 1, i = 1, \dots, n$. Note that $\mathbf{e}_i \mathbf{e}_i^\top$ is rank-one and has only one non-zero entry, **M2** and **M5** can greatly reduce the computation of the Schur matrix.

Table 3. Max-cut problems

Instance	HSDP	DSDP5.8	COPT v6.5	Instance	HSDP	DSDP5.8	COPT v6.5
mcp100	0.03	0.02	0.11	maxG51	1.45	2.52	14.40
mcp124-1	0.04	0.02	0.17	maxG55	38.21	273.60	1096.02
mcp124-2	0.04	0.02	0.17	maxG60	87.59	535.20	2926.11
mcp124-3	0.05	0.02	0.16	G40_mb	15.77	8.77	98.97
mcp124-4	0.06	0.05	0.17	G40_mc	6.53	18.68	80.45
mcp250-1	0.09	0.08	0.70	G48_mb	17.83	12.48	183.95
mcp250-2	0.08	0.09	0.72	G48mc	5.09	8.43	118.79
mcp250-3	0.09	0.12	0.65	G55mc	38.06	168.1	1026.10
mcp250-4	0.19	0.16	0.71	G59mc	48.73	302.3	1131.24
mcp500-1	0.26	0.21	2.78	G60_mb	211.22	213.4	5188.11
mcp500-2	0.25	0.32	2.82	G60mc	208.96	218.8	5189.29
mcp500-3	0.30	0.50	2.59	torusg3-8	0.50	0.77	1.04
mcp500-4	0.39	0.86	2.86	torusg3-15	15.30	178.8	137.60
maxG11	0.60	0.46	7.15	toruspm3-8-50	0.41	0.40	2.65
maxG32	4.68	3.66	68.32	toruspm3-15-50	13.32	43.67	309.25

Computational experience suggests that on large-scale sparse max-cut instances, HSDP is more than 5 times faster than DSDP5.8. Two exceptions are G60mc and G60_mb, where the aggregated sparsity pattern of the dual matrix is lost due to the dense objective coefficient, and thereby the dense MKL routines take up most of the computation.

6.3 Graph Partitioning

The SDP relaxation of the graph partitioning problem is given by

$$\begin{aligned}
 & \min_{\mathbf{X}} && \langle \mathbf{C}, \mathbf{X} \rangle \\
 & \text{subject to} && \text{diag}(\mathbf{X}) = \mathbf{1} \\
 & && \langle \mathbf{1}\mathbf{1}^\top, \mathbf{X} \rangle = \beta \\
 & && k\mathbf{X} - \mathbf{1}\mathbf{1}^\top \geq \mathbf{0} \\
 & && \mathbf{X} \geq \mathbf{0},
 \end{aligned}$$

where $\mathbf{1}$ denotes the all-one vector and k, β are the problem parameters. Although the dual \mathbf{S} no longer enjoys sparsity, the low-rank structure is still available to accelerate convergence.

Table 4. Graph partitioning problems

Instance	HSDP	DSDP5.8	COPT v6.5	Instance	HSDP	DSDP5.8	COPT v6.5
gpp100	0.05	0.05	0.19	gpp250-4	0.15	0.14	1.52
gpp124-1	0.07	0.07	0.33	gpp500-1	0.89	0.44	5.52
gpp124-2	0.06	Failed	0.30	gpp500-2	0.80	0.43	5.43
gpp124-3	0.06	0.06	0.31	gpp500-3	0.65	0.36	5.54
gpp124-4	0.06	0.06	0.29	gpp500-4	0.68	0.38	5.40
gpp250-1	0.20	Failed	1.65	bm1	2.28	1.18	18.45
gpp250-2	0.17	0.14	1.21	biomedP	171.64	Failed	Failed
gpp250-3	0.17	0.13	1.41				

On graph partitioning instances, we see that HSDP has comparable performance to DSDP but is more robust on some of the problems.

6.4 Optimal Diagonal Pre-conditioning

The optimal diagonal pre-conditioning problem originates from [Qu et al., 2020], where given a matrix $\mathbf{B} > \mathbf{0}$, finding a diagonal matrix \mathbf{D} to minimize the condition number $\kappa(\mathbf{D}^{-1/2}\mathbf{B}\mathbf{D}^{-1/2})$ can be modeled as an SDP. The formulation for optimal diagonal pre-conditioning is given by

$$\begin{aligned}
 & \max_{\tau, \mathbf{D}} && \tau \\
 & \text{subject to} && \mathbf{D} \leq \mathbf{B} \\
 & && \tau\mathbf{B} - \mathbf{D} \leq \mathbf{0}.
 \end{aligned}$$

Expressing $\mathbf{D} = \sum_i \mathbf{e}_i \mathbf{e}_i^\top d_i$, the problem is exactly in the SDP dual form. If \mathbf{B} is also sparse, the problem can be efficiently solved using the dual method.

Table 5. Optimal diagonal pre-conditioning problems

Instance	HSDP	DSDP5.8	COPT v6.5
diag-bench-1000-0.01	37.670	207.500	38.61
diag-bench-2000-0.05	276.960	971.700	161.17
diag-bench-west0989	35.280	Failed	76.900
diag-bench-DK01R	5.010	Failed	Failed
diag-bench-micromass_10NN	20.510	38.45	17.430

6.5 Other Problems

So far HSDP is tested and tuned over a broad set of benchmarks including SDPLIB [Borchers, 1999] and Hans Mittelmann’s sparse SDP benchmark [Mittelmann, 2003]. Using geometric mean as the metric, compared to DSDP5.8, HSDP achieves a speedup of 21% on SDPLIB and around 17% speedup on Hans Mittelmann’s benchmark dataset. Below we list some example benchmark datasets of nice structure for HSDP to exploit.

Table 6. Features of several benchmark problems

Instance	Background	Feature	HSDP	DSDP5.8	COPT v6.5
checker_1.5	unknown	sparse, low-rank	39.55	64.04	868.37
foot	unknown	sparse, low-rank	26.68	13.65	245.41
hand	unknown	low-rank	6.60	2.64	49.39
ice_2.0	unknown	low-rank	284.90	504.70	8561.74
p_auss2_3.0	unknown	sparse, low-rank	528.00	1066.00	1111.72
rend11_2000_1e-6	unknown	low-rank	16.17	14.38	111.43
trto4	topology design	sparse, low-rank	6.25	6.30	27.16
trto5	topology design	sparse, low-rank	67.22	75.20	391.83
sensor_500b	sensor network localization	sparse, low-rank	19.84	35.11	8.97
sensor_1000b	sensor network localization	sparse, low-rank	76.39	98.18	38.96

7 WHEN (NOT) TO USE DSDP/HSDP

While HSDP is designed for general SDPs, it targets the problems more tractable in the dual form than by the primal-dual methods. This is the principle for the techniques implemented by HSDP. Here are some rules in mind when deciding whether to use the dual method (or HSDP).

- (1) Does the problem enjoys nice dual structure?

Many combinatorial problems have formulations friendly to the dual methods. Some typical features include (aggregated) sparsity and low-rank structure. Dual methods effectively exploit these features by iterating in the dual space and using efficient computational tricks. If the problem is dense and most constraints are full-rank, dual method has no advantage over the primal-dual solvers due to **1)** comparable iteration cost to primal-dual methods. **2)** more iterations for convergence.

- (2) Do we need the primal optimal solution or just the optimal value?

For some applications dual method fails to recover a correct primal solution due to numerical difficulties. If the optimal value is sufficient, there is no problem. But if an accurate primal optimal solution is always necessary, it is better to be more careful and to test the recovery procedure in case of failure at the last step.

(3) Do we need to certificate infeasibility strictly?

One weakness of the dual method is the difficulty in infeasibility certificate. Although on the dual side this issue is addressed by HSDP using the embedding, dual methods still suffer from failure to identify primal infeasibility.

(4) Is dual-feasibility hard to attain?

The first phase of HSDP adopts the infeasible Newton’s method and focuses on eliminating the dual infeasibility. This principle works well if the dual constraints are relatively easy to satisfy, but if this condition fails to hold (for example, empty dual interior), experiments suggest the embedding spend a long time deciding feasibility. In this case it is suggested using DSDP5.8 or supply an initial dual solution.

8 CONCLUSIONS

We propose an extension of the dual-scaling algorithm based on the embedding technique. The resultant solver, HSDP, is presented to demonstrate how dual method can be effectively integrated with the embedding. HSDP is developed in parallel to DSDP5.8 and is entailed with several newly added features, especially an advanced conic KKT solver. The solver exhibits promising performance on several benchmark datasets and is under active development. Now HSDP works as one of the candidate SDP methods in the state-of-the-art commercial solver COPT. Users are welcome to try the solver and provide valuable suggestions.

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A SDPLIB BENCHMARK TEST

This section summarizes the benchmark result of HSDP on SDPLIB [Borchers, 1999]. The main setup is consistent with the experiment section. If an instance fails, its solution time is recorded to be 3600 seconds.

A.1 Summary Statistics

Table 7. Summary statistics on SDPLIB benchmark

Solver	Number of solved instances	Shifted geometric mean
HSDP	91	3.58
DSDP5.8	89	4.51
COPT v6.5	92	3.43

A.2 Detailed Solution Statistic

Table 8. Tables of detailed solution statistics

Solver	Table
HSDP	Table 9 and 10
DSDP5.8	Table 11 and 12
COPT v6.5	Table 13 and 14

B MITTELLELMANN'S BENCHMARK TEST

This section summarizes the benchmark result of HDSDP on part of Hans Mittelmann's SDP collection. [Mittelmann, 2003]. The main setup is consistent with the experiment section. If an instance fails, its solution time is recorded to be 40000 seconds.

B.1 Summary Statistics

Table 15. Summary statistics on the benchmark

Solver	Number of solved instances	Shifted geometric mean
HDSDP	67	228.64
DSDP5.8	62	276.96
COPT v6.5	72	100.53

B.2 Detailed Solution Statistics

Table 16. Tables of detailed solution statistics

Solver	Table
HDSDP	Table 17 and 18
DSDP5.8	Table 19 and 20
COPT v6.5	Table 21 and 22

C DIAGONAL PRE-CONDITIONING STATISTICS

This section presents the detailed solution statistics of HDSDP on diagonal pre-conditioning problems. If an instance fails, its solution time is recorded as 3600 seconds.

C.1 Summary Statistics

Table 23. Summary statistics on diagonal pre-conditioning problems

Solver	Number of solved instances	Shifted geometric mean
HDSDP	6	34.78
DSDP5.8	4	396.85
COPT v6.5	5	148.39

C.2 Detailed Solution Statistic

Table 24. Diagonal pre-conditioning problems with HDSDP

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
diag-bench-1000-1.000e-02-L	3.58e-13	0.00e+00	5.41e-10	0.00e+00	2.12e-07	2.85e-07	37.670
diag-bench-2000-5.000e-02-L	1.23e-13	0.00e+00	1.83e-10	0.00e+00	6.39e-07	7.48e-07	276.960
diag-bench-DK01R-L	2.08e-14	0.00e+00	0.00e+00	-0.00e+00	2.87e-03	2.87e-03	5.010
diag-bench-micromass_10NN-L	6.32e-15	0.00e+00	6.11e-10	0.00e+00	3.98e-07	4.53e-07	20.510
diag-bench-west0989-L	1.11e-15	0.00e+00	3.01e-07	0.00e+00	-4.54e-04	2.00e-03	35.280

Table 25. Diagonal pre-conditioning problems with DSDP5.8

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
diag-bench-1000-1.000e-02-L	1.48e-11	0.00e+00	0.00e+00	0.00e+00	3.52e-07	3.53e-07	207.500
diag-bench-2000-5.000e-02-L	6.51e-13	0.00e+00	0.00e+00	0.00e+00	1.91e-07	1.92e-07	971.700
diag-bench-DK01R-L	1.85e+02	0.00e+00	0.00e+00	0.00e+00	9.97e-01	1.58e+00	Failed
diag-bench-micromass_10NN-L	5.98e-11	0.00e+00	0.00e+00	0.00e+00	4.46e-07	4.51e-07	38.450
diag-bench-west0989-L	8.11e-01	0.00e+00	0.00e+00	0.00e+00	6.77e-01	7.07e-01	Failed

Table 26. Diagonal pre-conditioning problems with COPT

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
diag-bench-1000-1.000e-02-L	3.72e-13	0.00e+00	0.00e+00	0.00e+00	1.55e-07	7.02e-06	38.610
diag-bench-2000-5.000e-02-L	5.67e-13	0.00e+00	0.00e+00	0.00e+00	2.47e-08	1.64e-06	161.170
diag-bench-DK01R-L	3.53e-05	0.00e+00	0.00e+00	0.00e+00	1.78e-02	2.35e-03	Failed
diag-bench-micromass_10NN-L	4.30e-10	0.00e+00	0.00e+00	0.00e+00	5.21e-10	7.09e-10	17.430
diag-bench-west0989-L	2.41e-08	0.00e+00	0.00e+00	0.00e+00	1.21e-05	1.83e-06	76.900

Table 9. SDPLIB benchmark HSDP, Part 1

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
arch0	8.82e-13	0.00e+00	0.00e+00	-0.00e+00	4.03e-07	2.21e-07	0.350
arch2	1.20e-12	0.00e+00	0.00e+00	-0.00e+00	2.84e-07	1.54e-07	0.370
arch4	1.37e-13	0.00e+00	0.00e+00	-0.00e+00	2.57e-07	1.39e-07	0.360
arch8	9.48e-12	0.00e+00	0.00e+00	-0.00e+00	4.49e-07	2.76e-07	0.430
control10	1.01e-06	0.00e+00	0.00e+00	-0.00e+00	9.70e-06	9.27e-06	9.720
control11	1.67e-06	0.00e+00	0.00e+00	-0.00e+00	1.43e-05	1.34e-05	15.250
control1	4.65e-07	0.00e+00	0.00e+00	-0.00e+00	4.75e-07	1.45e-07	0.040
control2	6.82e-07	0.00e+00	0.00e+00	-0.00e+00	2.22e-07	1.42e-07	0.070
control3	1.10e-06	0.00e+00	0.00e+00	-0.00e+00	-1.32e-08	2.59e-07	0.110
control4	8.83e-07	0.00e+00	0.00e+00	-0.00e+00	-3.56e-07	5.17e-07	0.260
control5	1.95e-06	0.00e+00	0.00e+00	-0.00e+00	1.22e-06	7.68e-07	0.790
control6	1.97e-08	0.00e+00	0.00e+00	-0.00e+00	1.12e-05	1.12e-05	0.950
control7	3.99e-06	0.00e+00	0.00e+00	-0.00e+00	1.00e-06	4.78e-07	2.070
control8	3.74e-06	0.00e+00	0.00e+00	-0.00e+00	2.65e-04	2.67e-04	6.410
control9	5.40e-06	0.00e+00	0.00e+00	-0.00e+00	7.80e-06	1.04e-05	7.410
equalG11	7.45e-14	0.00e+00	0.00e+00	-0.00e+00	5.34e-07	5.34e-07	5.810
equalG51	1.72e-12	0.00e+00	0.00e+00	-0.00e+00	2.02e-07	2.02e-07	12.110
gpp100	1.36e-07	0.00e+00	0.00e+00	-0.00e+00	-1.77e-07	2.57e-07	0.050
gpp124-1	2.16e-06	0.00e+00	0.00e+00	-0.00e+00	-4.71e-06	2.01e-07	0.070
gpp124-2	3.70e-08	0.00e+00	0.00e+00	-0.00e+00	4.97e-07	5.84e-07	0.060
gpp124-3	2.63e-08	0.00e+00	0.00e+00	-0.00e+00	7.38e-08	1.95e-07	0.060
gpp124-4	1.27e-08	0.00e+00	0.00e+00	-0.00e+00	3.05e-07	2.74e-07	0.060
gpp250-1	2.46e-06	0.00e+00	0.00e+00	-0.00e+00	-1.05e-05	3.35e-07	0.200
gpp250-2	1.34e-07	0.00e+00	0.00e+00	-0.00e+00	-2.20e-07	3.54e-07	0.170
gpp250-3	2.03e-08	0.00e+00	0.00e+00	-0.00e+00	4.67e-07	4.43e-07	0.170
gpp250-4	1.61e-08	0.00e+00	0.00e+00	-0.00e+00	4.76e-07	4.39e-07	0.150
gpp500-1	4.68e-06	0.00e+00	0.00e+00	-0.00e+00	-2.48e-05	2.96e-07	0.890
gpp500-2	2.10e-07	0.00e+00	0.00e+00	-0.00e+00	-3.84e-07	3.25e-07	0.800
gpp500-3	2.18e-07	0.00e+00	0.00e+00	-0.00e+00	1.79e-06	3.05e-07	0.650
gpp500-4	8.53e-09	0.00e+00	0.00e+00	-0.00e+00	2.37e-07	2.01e-07	0.680
hinf10	2.82e-09	0.00e+00	0.00e+00	-0.00e+00	-3.01e-05	2.09e-07	0.050
hinf11	1.68e-09	0.00e+00	0.00e+00	-0.00e+00	-2.88e-05	3.51e-07	0.050
hinf12	3.84e-08	0.00e+00	0.00e+00	-0.00e+00	-2.32e-01	9.18e-04	0.050
hinf13	1.06e-09	0.00e+00	0.00e+00	-0.00e+00	-6.25e-06	4.92e-05	0.070
hinf14	5.06e-08	6.05e-15	0.00e+00	-0.00e+00	-7.15e-08	1.83e-07	0.080
hinf15	1.12e-04	0.00e+00	0.00e+00	-0.00e+00	-2.50e-05	1.04e-05	0.110
hinf1	4.09e-13	0.00e+00	0.00e+00	-0.00e+00	7.17e-08	1.79e-07	0.040
hinf2	3.59e-10	0.00e+00	0.00e+00	-0.00e+00	1.03e-07	1.63e-07	0.050
hinf3	4.55e-11	0.00e+00	0.00e+00	-0.00e+00	1.26e-07	1.75e-07	0.050
hinf4	1.18e-11	0.00e+00	0.00e+00	-0.00e+00	1.68e-07	2.48e-07	0.030
hinf5	1.65e-03	0.00e+00	0.00e+00	-0.00e+00	4.23e-06	2.84e-07	0.050
hinf6	9.60e+01	0.00e+00	7.21e-05	0.00e+00	4.69e-01	3.21e-02	Failed
hinf7	3.93e-06	0.00e+00	0.00e+00	-0.00e+00	1.13e-03	1.39e-03	0.040
hinf8	1.65e-07	0.00e+00	0.00e+00	-0.00e+00	3.63e-07	5.03e-07	0.040
hinf9	1.03e-06	0.00e+00	0.00e+00	-0.00e+00	2.28e-07	2.17e-07	0.050
infd1	1.00e+00	1.00e+00	1.00e+00	1.00e+00	1.00e+00	1.00e+00	0.040

Table 10. SDPLIB benchmark HSDP, Part 2

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
infd2	1.00e+00	1.00e+00	1.00e+00	1.00e+00	1.00e+00	1.00e+00	0.040
infp1	1.00e+00	1.00e+00	1.00e+00	1.00e+00	1.00e+00	1.00e+00	0.110
infp2	1.00e+00	1.00e+00	1.00e+00	1.00e+00	1.00e+00	1.00e+00	0.110
maxG11	2.23e-14	0.00e+00	0.00e+00	-0.00e+00	2.45e-07	2.45e-07	0.600
maxG32	1.04e-14	0.00e+00	0.00e+00	-0.00e+00	2.25e-07	2.25e-07	4.680
maxG51	2.94e-15	0.00e+00	0.00e+00	-0.00e+00	5.08e-07	5.08e-07	1.450
maxG55	1.58e-15	0.00e+00	0.00e+00	-0.00e+00	4.63e-07	4.63e-07	38.210
maxG60	7.29e-16	0.00e+00	0.00e+00	-0.00e+00	4.29e-07	4.29e-07	87.590
mcp100	4.87e-14	0.00e+00	0.00e+00	-0.00e+00	2.79e-07	2.79e-07	0.040
mcp124-1	8.40e-15	0.00e+00	0.00e+00	-0.00e+00	3.36e-07	3.36e-07	0.040
mcp124-2	4.76e-15	0.00e+00	0.00e+00	-0.00e+00	2.80e-07	2.80e-07	0.050
mcp124-3	1.71e-13	0.00e+00	0.00e+00	-0.00e+00	2.94e-07	2.94e-07	0.050
mcp124-4	3.35e-14	0.00e+00	0.00e+00	-0.00e+00	3.94e-07	3.94e-07	0.060
mcp250-1	7.78e-15	0.00e+00	0.00e+00	-0.00e+00	2.01e-07	2.01e-07	0.090
mcp250-2	3.16e-15	0.00e+00	0.00e+00	-0.00e+00	1.62e-07	1.62e-07	0.080
mcp250-3	1.74e-14	0.00e+00	0.00e+00	-0.00e+00	3.64e-07	3.64e-07	0.090
mcp250-4	6.43e-15	0.00e+00	0.00e+00	-0.00e+00	6.59e-07	6.59e-07	0.110
mcp500-1	2.99e-16	0.00e+00	0.00e+00	-0.00e+00	4.98e-07	4.98e-07	0.260
mcp500-2	1.26e-14	0.00e+00	0.00e+00	-0.00e+00	2.33e-07	2.33e-07	0.250
mcp500-3	2.79e-14	0.00e+00	0.00e+00	-0.00e+00	1.73e-07	1.73e-07	0.300
mcp500-4	2.07e-15	0.00e+00	0.00e+00	-0.00e+00	3.41e-07	3.41e-07	0.390
qap10	2.11e-11	0.00e+00	0.00e+00	-0.00e+00	1.52e-05	2.17e-05	0.640
qap5	9.90e-11	0.00e+00	0.00e+00	-0.00e+00	6.02e-08	9.37e-08	0.040
qap6	2.33e-09	0.00e+00	0.00e+00	-0.00e+00	1.18e-10	8.35e-08	0.070
qap7	2.45e-09	0.00e+00	0.00e+00	-0.00e+00	1.14e-08	5.99e-08	0.090
qap8	2.77e-10	0.00e+00	0.00e+00	-0.00e+00	-3.83e-08	6.13e-08	0.210
qap9	5.55e-13	0.00e+00	0.00e+00	-0.00e+00	7.02e-06	1.66e-05	0.320
qpG11	3.83e-14	0.00e+00	0.00e+00	-0.00e+00	5.15e-07	5.15e-07	2.060
qpG51	1.66e-13	0.00e+00	0.00e+00	-0.00e+00	3.21e-07	3.21e-07	11.840
ss30	2.91e-11	0.00e+00	0.00e+00	-0.00e+00	4.09e-07	2.85e-07	0.560
theta1	9.23e-13	0.00e+00	0.00e+00	-0.00e+00	1.06e-07	1.06e-07	0.050
theta2	7.53e-14	0.00e+00	0.00e+00	-0.00e+00	4.72e-08	4.72e-08	0.130
theta3	1.19e-15	0.00e+00	0.00e+00	-0.00e+00	3.84e-08	3.84e-08	0.440
theta4	1.02e-14	0.00e+00	0.00e+00	-0.00e+00	2.78e-08	2.78e-08	1.400
theta5	8.89e-16	0.00e+00	0.00e+00	-0.00e+00	6.87e-08	6.87e-08	2.850
theta6	3.26e-15	0.00e+00	0.00e+00	-0.00e+00	2.32e-08	2.32e-08	5.990
thetaG11	4.76e-14	0.00e+00	0.00e+00	-0.00e+00	1.29e-07	1.29e-07	13.480
thetaG51	1.90e-10	0.00e+00	0.00e+00	-0.00e+00	6.59e-08	7.17e-08	319.050
truss1	1.88e-13	0.00e+00	0.00e+00	-0.00e+00	5.49e-07	5.48e-07	0.050
truss2	1.14e-11	0.00e+00	5.75e-10	0.00e+00	3.78e-07	3.78e-07	0.390
truss3	6.70e-13	0.00e+00	2.74e-10	0.00e+00	1.35e-07	1.32e-07	0.090
truss4	1.08e-14	0.00e+00	2.12e-10	0.00e+00	3.04e-07	2.93e-07	0.070
truss5	5.16e-12	0.00e+00	0.00e+00	-0.00e+00	8.93e-08	8.92e-08	0.770
truss6	7.31e-09	0.00e+00	0.00e+00	-0.00e+00	4.76e-07	4.75e-07	0.700
truss7	1.39e-08	0.00e+00	0.00e+00	-0.00e+00	3.76e-07	3.75e-07	0.900
truss8	6.82e-12	0.00e+00	1.25e-09	0.00e+00	1.46e-07	1.46e-07	1.740

Table 11. SDPLIB benchmark DSDP5.8, Part 1

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
arch0	2.52e-07	0.00e+00	0.00e+00	0.00e+00	2.75e-07	3.35e-07	0.400
arch2	1.62e-07	0.00e+00	0.00e+00	0.00e+00	3.34e-07	3.59e-07	0.318
arch4	1.38e-07	0.00e+00	0.00e+00	0.00e+00	8.39e-08	1.07e-07	0.375
arch8	7.30e-07	0.00e+00	0.00e+00	0.00e+00	1.23e-07	2.02e-07	0.339
control10	8.77e-07	0.00e+00	0.00e+00	0.00e+00	8.20e-07	3.31e-06	7.343
control11	7.77e-07	0.00e+00	0.00e+00	0.00e+00	2.60e-06	5.70e-06	12.050
control1	4.84e-07	0.00e+00	0.00e+00	0.00e+00	-1.88e-07	3.99e-08	0.032
control2	2.56e-07	0.00e+00	0.00e+00	0.00e+00	-4.63e-08	8.55e-08	0.048
control3	3.25e-07	0.00e+00	0.00e+00	0.00e+00	1.55e-07	2.54e-07	0.087
control4	1.67e-06	0.00e+00	0.00e+00	0.00e+00	2.54e-08	3.29e-06	0.168
control5	5.27e-07	0.00e+00	0.00e+00	0.00e+00	-4.68e-07	5.21e-07	0.487
control6	3.22e-05	0.00e+00	0.00e+00	0.00e+00	-1.75e-07	7.61e-05	0.735
control7	3.99e-06	0.00e+00	0.00e+00	0.00e+00	-4.32e-07	1.28e-05	2.085
control8	7.53e-07	0.00e+00	0.00e+00	0.00e+00	-3.75e-07	1.46e-06	3.734
control9	8.83e-07	0.00e+00	0.00e+00	0.00e+00	-6.64e-07	1.95e-06	4.473
equalG11	7.89e-10	0.00e+00	0.00e+00	0.00e+00	6.50e-08	6.56e-08	1.941
equalG51	9.93e-10	0.00e+00	0.00e+00	0.00e+00	9.23e-08	9.33e-08	2.917
gpp100	1.01e-10	0.00e+00	0.00e+00	0.00e+00	3.51e-08	4.57e-06	0.051
gpp124-1	1.25e-10	0.00e+00	0.00e+00	0.00e+00	1.90e-07	5.51e-05	0.074
gpp124-2	1.38e-05	0.00e+00	0.00e+00	0.00e+00	4.53e-07	8.37e-01	Failed
gpp124-3	1.28e-10	0.00e+00	0.00e+00	0.00e+00	8.71e-08	1.60e-06	0.063
gpp124-4	1.28e-10	0.00e+00	0.00e+00	0.00e+00	1.06e-07	1.35e-06	0.066
gpp250-1	2.78e-05	0.00e+00	0.00e+00	0.00e+00	1.27e-06	9.98e+00	Failed
gpp250-2	2.50e-10	0.00e+00	0.00e+00	0.00e+00	5.21e-08	7.41e-06	0.139
gpp250-3	2.47e-10	0.00e+00	0.00e+00	0.00e+00	4.51e-08	1.45e-06	0.132
gpp250-4	2.48e-10	0.00e+00	0.00e+00	0.00e+00	5.61e-08	5.82e-07	0.137
gpp500-1	4.90e-10	0.00e+00	0.00e+00	0.00e+00	1.57e-06	1.11e-04	0.435
gpp500-2	4.66e-10	0.00e+00	0.00e+00	0.00e+00	5.79e-08	1.72e-05	0.434
gpp500-3	5.19e-10	0.00e+00	0.00e+00	0.00e+00	1.26e-07	2.45e-06	0.355
gpp500-4	5.22e-10	0.00e+00	0.00e+00	0.00e+00	5.39e-08	1.27e-06	0.381
hinf10	1.72e-08	0.00e+00	0.00e+00	0.00e+00	-3.10e-05	5.76e-06	0.029
hinf11	8.25e-10	0.00e+00	0.00e+00	0.00e+00	-3.07e-05	8.35e-07	0.034
hinf12	3.84e-08	0.00e+00	0.00e+00	0.00e+00	-2.32e-01	4.91e-05	0.044
hinf13	3.11e-08	0.00e+00	0.00e+00	0.00e+00	-3.94e-05	2.68e-04	0.041
hinf14	1.13e-09	0.00e+00	0.00e+00	0.00e+00	6.46e-06	2.10e-04	0.047
hinf15	5.30e-09	0.00e+00	0.00e+00	0.00e+00	-8.83e-05	5.37e-04	0.051
hinf1	1.03e-09	0.00e+00	0.00e+00	0.00e+00	1.05e-09	6.17e-05	0.028
hinf2	2.22e-08	0.00e+00	0.00e+00	0.00e+00	-3.61e-08	1.48e-04	0.030
hinf3	5.81e-10	0.00e+00	0.00e+00	0.00e+00	4.29e-10	5.87e-06	0.026
hinf4	1.19e-09	0.00e+00	0.00e+00	0.00e+00	-1.11e-09	5.44e-08	0.030
hinf5	6.41e-07	0.00e+00	0.00e+00	0.00e+00	1.17e-03	3.86e-03	0.024
hinf6	4.01e-07	0.00e+00	0.00e+00	0.00e+00	1.60e-02	2.74e-02	Failed
hinf7	1.61e-05	0.00e+00	0.00e+00	0.00e+00	5.22e-05	9.44e-03	0.030
hinf8	5.62e-08	0.00e+00	0.00e+00	0.00e+00	-1.03e-06	1.51e-03	0.027
hinf9	3.70e-05	0.00e+00	0.00e+00	0.00e+00	-2.55e-07	6.68e-07	0.026
infd1	3.33e-01	0.00e+00	0.00e+00	0.00e+00	-1.00e+00	1.79e-08	0.038

Table 12. SDPLIB benchmark DSDP5.8, Part 2

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
infd2	4.27e-01	0.00e+00	0.00e+00	0.00e+00	-1.00e+00	2.77e-08	0.038
infp1	5.80e-04	3.01e-01	0.00e+00	0.00e+00	-1.00e+00	7.01e-10	0.035
infp2	5.43e-05	2.96e-01	0.00e+00	0.00e+00	-1.00e+00	3.11e-09	0.031
maxG11	1.43e-09	0.00e+00	0.00e+00	0.00e+00	4.83e-08	4.88e-08	0.462
maxG32	2.34e-09	0.00e+00	0.00e+00	0.00e+00	7.10e-08	7.14e-08	3.659
maxG51	1.60e-09	0.00e+00	0.00e+00	0.00e+00	1.16e-07	1.21e-07	2.519
maxG55	3.57e-09	0.00e+00	0.00e+00	0.00e+00	5.86e-07	5.90e-07	273.600
maxG60	4.22e-09	0.00e+00	0.00e+00	0.00e+00	3.60e-07	3.62e-07	535.200
mcp100	5.06e-10	0.00e+00	0.00e+00	0.00e+00	6.03e-08	6.41e-08	0.015
mcp124-1	5.62e-10	0.00e+00	0.00e+00	0.00e+00	1.39e-07	2.16e-07	0.016
mcp124-2	5.63e-10	0.00e+00	0.00e+00	0.00e+00	9.95e-08	1.04e-07	0.018
mcp124-3	5.63e-10	0.00e+00	0.00e+00	0.00e+00	7.73e-08	8.15e-08	0.024
mcp124-4	1.12e-11	0.00e+00	0.00e+00	0.00e+00	1.18e-07	1.23e-07	0.054
mcp250-1	7.98e-10	0.00e+00	0.00e+00	0.00e+00	9.12e-08	9.94e-08	0.084
mcp250-2	7.99e-10	0.00e+00	0.00e+00	0.00e+00	1.05e-07	1.17e-07	0.090
mcp250-3	7.98e-10	0.00e+00	0.00e+00	0.00e+00	9.31e-08	9.78e-08	0.123
mcp250-4	7.98e-10	0.00e+00	0.00e+00	0.00e+00	4.93e-08	5.22e-08	0.160
mcp500-1	1.13e-09	0.00e+00	0.00e+00	0.00e+00	1.06e-07	1.53e-07	0.217
mcp500-2	1.13e-09	0.00e+00	0.00e+00	0.00e+00	7.73e-08	8.12e-08	0.320
mcp500-3	1.13e-09	0.00e+00	0.00e+00	0.00e+00	1.49e-07	1.53e-07	0.496
mcp500-4	1.13e-09	0.00e+00	0.00e+00	0.00e+00	5.69e-08	5.93e-08	0.862
qap10	1.13e-11	0.00e+00	0.00e+00	0.00e+00	4.87e-07	1.06e-06	0.626
qap5	4.70e-10	0.00e+00	0.00e+00	0.00e+00	1.61e-07	8.36e-06	0.049
qap6	6.49e-12	0.00e+00	0.00e+00	0.00e+00	-4.47e-08	1.91e-07	0.065
qap7	4.61e-12	0.00e+00	0.00e+00	0.00e+00	-2.55e-08	1.68e-07	0.113
qap8	9.48e-12	0.00e+00	0.00e+00	0.00e+00	-8.16e-08	1.25e-07	0.207
qap9	6.48e-12	0.00e+00	0.00e+00	0.00e+00	-2.13e-08	7.09e-08	0.364
qpG11	1.44e-09	0.00e+00	0.00e+00	0.00e+00	1.04e-07	1.04e-07	1.446
qpG51	1.61e-09	0.00e+00	0.00e+00	0.00e+00	2.47e-07	2.47e-07	16.050
ss30	4.68e-07	0.00e+00	0.00e+00	0.00e+00	1.18e-07	1.43e-07	0.889
theta1	4.75e-11	0.00e+00	0.00e+00	0.00e+00	4.54e-08	5.24e-08	0.045
theta2	5.05e-11	0.00e+00	0.00e+00	0.00e+00	4.27e-09	5.10e-09	0.105
theta3	7.55e-11	0.00e+00	0.00e+00	0.00e+00	1.78e-08	2.11e-08	0.310
theta4	1.00e-10	0.00e+00	0.00e+00	0.00e+00	5.30e-09	6.37e-09	0.963
theta5	1.25e-10	0.00e+00	0.00e+00	0.00e+00	3.13e-08	3.73e-08	2.190
theta6	1.51e-10	0.00e+00	0.00e+00	0.00e+00	4.59e-08	5.45e-08	4.603
thetaG11	6.22e-09	0.00e+00	0.00e+00	0.00e+00	6.31e-08	6.35e-08	10.860
thetaG51	1.52e-08	0.00e+00	0.00e+00	0.00e+00	3.56e-07	4.20e-07	96.130
truss1	6.52e-12	0.00e+00	0.00e+00	0.00e+00	5.39e-09	6.94e-09	0.026
truss2	2.61e-11	0.00e+00	0.00e+00	0.00e+00	2.03e-08	2.14e-08	0.050
truss3	7.31e-10	0.00e+00	0.00e+00	0.00e+00	2.82e-09	3.01e-09	0.035
truss4	1.77e-11	0.00e+00	0.00e+00	0.00e+00	9.49e-10	1.69e-09	0.026
truss5	3.84e-11	0.00e+00	0.00e+00	0.00e+00	1.34e-08	3.80e-08	0.147
truss6	1.71e-07	0.00e+00	0.00e+00	0.00e+00	1.42e-07	2.76e-07	0.107
truss7	2.68e-06	0.00e+00	0.00e+00	0.00e+00	1.58e-09	2.01e-08	0.070
truss8	4.67e-11	0.00e+00	0.00e+00	0.00e+00	2.50e-08	1.19e-07	0.569

Table 13. SDPLIB benchmark COPT, Part 1

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
arch0	4.48e-07	0.00e+00	0.00e+00	0.00e+00	-3.52e-09	8.67e-07	0.700
arch2	4.51e-07	0.00e+00	3.56e-07	0.00e+00	-3.11e-09	6.87e-07	0.720
arch4	6.58e-08	0.00e+00	0.00e+00	0.00e+00	-5.78e-10	1.40e-07	0.760
arch8	1.75e-08	0.00e+00	0.00e+00	0.00e+00	-2.48e-10	8.99e-08	0.880
control10	5.36e-09	0.00e+00	6.11e-11	0.00e+00	-3.91e-07	6.54e-05	1.800
control11	5.18e-09	0.00e+00	5.36e-11	0.00e+00	-4.07e-07	7.46e-05	2.640
control1	5.75e-10	0.00e+00	2.63e-10	0.00e+00	-2.25e-09	3.03e-08	0.030
control2	2.67e-10	0.00e+00	2.92e-10	0.00e+00	-2.71e-09	7.20e-08	0.040
control3	1.51e-09	0.00e+00	4.44e-12	0.00e+00	-2.92e-08	1.31e-06	0.050
control4	3.88e-09	0.00e+00	6.33e-10	0.00e+00	-7.48e-08	4.66e-06	0.080
control5	1.71e-09	0.00e+00	7.87e-12	0.00e+00	-2.65e-08	2.13e-06	0.170
control6	5.64e-09	0.00e+00	1.90e-11	0.00e+00	-1.87e-07	1.84e-05	0.320
control7	9.12e-10	0.00e+00	1.78e-11	0.00e+00	-4.96e-08	5.51e-06	0.390
control8	1.14e-09	0.00e+00	1.92e-11	0.00e+00	-5.65e-08	7.30e-06	0.670
control9	3.49e-10	0.00e+00	2.12e-11	0.00e+00	-2.27e-08	3.29e-06	0.940
equalG11	4.17e-09	0.00e+00	0.00e+00	0.00e+00	2.34e-09	1.23e-06	8.820
equalG51	2.12e-08	0.00e+00	0.00e+00	0.00e+00	-4.58e-09	1.21e-06	18.360
gpp100	2.97e-07	0.00e+00	0.00e+00	0.00e+00	2.82e-08	8.89e-07	0.190
gpp124-1	2.20e-08	0.00e+00	0.00e+00	0.00e+00	2.88e-09	7.19e-07	0.330
gpp124-2	2.09e-08	0.00e+00	7.68e-09	0.00e+00	5.65e-09	3.77e-07	0.300
gpp124-3	2.30e-08	0.00e+00	9.30e-09	0.00e+00	7.20e-09	1.69e-07	0.310
gpp124-4	3.17e-08	0.00e+00	5.91e-09	0.00e+00	3.89e-09	2.15e-07	0.290
gpp250-1	1.83e-07	0.00e+00	0.00e+00	0.00e+00	1.12e-08	6.77e-07	1.650
gpp250-2	4.76e-07	0.00e+00	0.00e+00	0.00e+00	3.87e-08	1.10e-06	1.210
gpp250-3	1.09e-07	0.00e+00	0.00e+00	0.00e+00	9.83e-09	2.93e-07	1.410
gpp250-4	3.34e-08	0.00e+00	7.83e-09	0.00e+00	2.78e-09	1.02e-07	1.520
gpp500-1	5.44e-07	0.00e+00	0.00e+00	0.00e+00	1.88e-08	1.16e-06	5.520
gpp500-2	8.13e-08	0.00e+00	0.00e+00	0.00e+00	7.80e-09	3.38e-07	5.430
gpp500-3	1.11e-07	0.00e+00	0.00e+00	0.00e+00	1.05e-08	1.91e-07	5.530
gpp500-4	8.68e-09	0.00e+00	0.00e+00	0.00e+00	2.33e-09	4.27e-08	5.400
hinf10	6.72e-09	0.00e+00	6.16e-09	0.00e+00	-3.79e-08	5.88e-07	0.040
hinf11	3.33e-08	0.00e+00	0.00e+00	0.00e+00	-4.88e-08	1.22e-06	0.050
hinf12	2.32e-16	0.00e+00	0.00e+00	0.00e+00	-3.66e-13	4.29e-12	0.070
hinf13	1.50e-06	0.00e+00	0.00e+00	0.00e+00	-1.49e-04	3.44e-03	0.050
hinf14	1.84e-07	0.00e+00	0.00e+00	0.00e+00	-1.30e-06	4.22e-05	0.060
hinf15	3.01e-05	0.00e+00	0.00e+00	0.00e+00	-8.02e-05	2.90e-03	0.050
hinf1	1.58e-08	0.00e+00	0.00e+00	0.00e+00	-1.54e-06	1.70e-05	0.030
hinf2	4.25e-07	0.00e+00	0.00e+00	0.00e+00	-1.07e-06	1.65e-05	0.030
hinf3	3.17e-07	0.00e+00	0.00e+00	0.00e+00	-1.71e-06	2.56e-05	0.030
hinf4	1.39e-07	0.00e+00	4.09e-13	0.00e+00	-1.97e-07	3.06e-06	0.030
hinf5	1.05e-07	0.00e+00	0.00e+00	0.00e+00	-4.01e-06	6.13e-05	0.030
hinf6	8.33e-06	0.00e+00	0.00e+00	0.00e+00	-6.60e-07	9.27e-06	0.040
hinf7	2.71e-05	0.00e+00	8.00e-11	0.00e+00	-2.25e-07	4.67e-06	0.040
hinf8	5.06e-08	0.00e+00	0.00e+00	0.00e+00	-2.04e-06	3.01e-05	0.030
hinf9	3.12e-05	0.00e+00	0.00e+00	0.00e+00	-3.25e-06	2.13e-04	0.040
infd1	1.87e+00	0.00e+00	0.00e+00	0.00e+00	-6.97e-01	9.10e+00	0.040

Table 14. SDPLIB benchmark COPT, Part 2

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
infd2	1.95e+00	0.00e+00	0.00e+00	0.00e+00	-9.77e-01	1.15e+01	0.030
infp1	7.85e-01	0.00e+00	0.00e+00	0.00e+00	-1.58e-01	2.53e+01	0.030
infp2	1.52e+00	0.00e+00	0.00e+00	0.00e+00	-1.88e-01	2.44e+01	0.030
maxG11	3.45e-12	0.00e+00	0.00e+00	0.00e+00	-1.37e-09	1.09e-07	7.150
maxG32	1.66e-11	0.00e+00	0.00e+00	0.00e+00	-2.42e-10	7.31e-08	68.320
maxG51	2.84e-10	0.00e+00	0.00e+00	0.00e+00	-4.30e-09	2.98e-09	14.400
maxG55	1.07e-10	0.00e+00	0.00e+00	0.00e+00	-1.32e-09	1.83e-09	1096.020
maxG60	5.47e-11	0.00e+00	0.00e+00	0.00e+00	-1.14e-09	1.81e-09	2926.110
mcp100	5.89e-12	0.00e+00	0.00e+00	0.00e+00	-1.72e-09	2.43e-09	0.110
mcp124-1	6.60e-12	0.00e+00	0.00e+00	0.00e+00	-5.65e-10	1.44e-09	0.170
mcp124-2	8.59e-12	0.00e+00	0.00e+00	0.00e+00	-6.00e-10	8.80e-10	0.170
mcp124-3	1.02e-11	0.00e+00	0.00e+00	0.00e+00	-4.61e-09	4.16e-09	0.160
mcp124-4	2.02e-11	0.00e+00	0.00e+00	0.00e+00	-7.56e-10	4.17e-10	0.170
mcp250-1	3.10e-12	0.00e+00	0.00e+00	0.00e+00	-4.52e-09	1.09e-08	0.700
mcp250-2	5.81e-12	0.00e+00	0.00e+00	0.00e+00	-1.26e-09	1.96e-09	0.720
mcp250-3	2.52e-10	0.00e+00	0.00e+00	0.00e+00	-4.78e-09	4.37e-09	0.650
mcp250-4	1.20e-09	0.00e+00	0.00e+00	0.00e+00	-9.63e-10	5.72e-10	0.710
mcp500-1	4.38e-12	0.00e+00	0.00e+00	0.00e+00	-3.84e-09	9.63e-09	2.780
mcp500-2	1.31e-09	0.00e+00	0.00e+00	0.00e+00	-1.03e-09	1.61e-09	2.820
mcp500-3	2.44e-11	0.00e+00	0.00e+00	0.00e+00	-1.88e-09	1.86e-09	2.590
mcp500-4	1.75e-11	0.00e+00	0.00e+00	0.00e+00	-8.25e-10	4.85e-10	2.860
qap10	8.86e-08	0.00e+00	9.13e-13	0.00e+00	-3.19e-08	3.42e-06	0.610
qap5	7.91e-08	0.00e+00	0.00e+00	0.00e+00	1.89e-09	1.10e-07	0.030
qap6	4.72e-08	0.00e+00	8.86e-13	0.00e+00	-1.03e-07	3.72e-06	0.070
qap7	4.17e-08	0.00e+00	5.04e-13	0.00e+00	-6.60e-08	3.35e-06	0.120
qap8	1.12e-07	0.00e+00	6.18e-13	0.00e+00	-8.25e-08	5.96e-06	0.220
qap9	1.02e-07	0.00e+00	5.11e-13	0.00e+00	-2.88e-08	2.60e-06	0.360
qpG11	3.53e-06	0.00e+00	0.00e+00	0.00e+00	-1.23e-10	2.90e-07	34.900
qpG51	8.21e-06	0.00e+00	0.00e+00	0.00e+00	-1.83e-10	5.41e-07	85.440
ss30	2.81e-07	0.00e+00	3.74e-07	0.00e+00	-3.06e-09	4.40e-07	2.190
theta1	2.83e-08	0.00e+00	0.00e+00	0.00e+00	-1.60e-09	4.22e-08	0.050
theta2	7.40e-09	0.00e+00	0.00e+00	0.00e+00	-4.11e-10	1.70e-08	0.150
theta3	2.88e-08	0.00e+00	0.00e+00	0.00e+00	-9.03e-10	5.20e-08	0.380
theta4	1.01e-08	0.00e+00	0.00e+00	0.00e+00	-3.56e-10	1.99e-08	1.130
theta5	7.99e-09	0.00e+00	0.00e+00	0.00e+00	-2.74e-10	1.69e-08	1.700
theta6	7.71e-09	0.00e+00	0.00e+00	0.00e+00	-2.78e-10	2.18e-08	2.890
thetaG11	1.90e-07	0.00e+00	0.00e+00	0.00e+00	-4.65e-09	1.52e-07	7.750
thetaG51	1.08e-07	0.00e+00	0.00e+00	0.00e+00	-1.98e-09	6.69e-08	35.380
truss1	1.90e-08	0.00e+00	0.00e+00	0.00e+00	-3.41e-09	4.60e-08	0.020
truss2	7.82e-08	0.00e+00	0.00e+00	0.00e+00	-2.46e-09	3.64e-07	0.040
truss3	2.05e-08	0.00e+00	0.00e+00	0.00e+00	-1.02e-09	4.66e-08	0.030
truss4	1.93e-08	0.00e+00	0.00e+00	0.00e+00	-2.32e-09	4.46e-08	0.030
truss5	4.30e-08	0.00e+00	0.00e+00	0.00e+00	-4.60e-10	1.68e-07	0.070
truss6	1.24e-07	0.00e+00	0.00e+00	0.00e+00	-3.37e-09	1.74e-06	0.060
truss7	7.24e-08	0.00e+00	0.00e+00	0.00e+00	-3.52e-09	1.23e-06	0.050
truss8	4.21e-07	0.00e+00	0.00e+00	0.00e+00	-2.13e-09	1.50e-06	0.220

Table 17. HSDP: Mittelman's Benchmark Test Part 1

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
1dc.1024	4.16e-14	0.00e+00	0.00e+00	-0.00e+00	5.56e-07	5.56e-07	730.950
1et.1024	2.90e-12	0.00e+00	0.00e+00	-0.00e+00	8.20e-08	8.20e-08	62.870
1tc.1024	2.72e-13	0.00e+00	0.00e+00	-0.00e+00	2.60e-07	2.60e-07	44.270
1zc.1024	2.79e-14	0.00e+00	0.00e+00	-0.00e+00	1.30e-07	1.30e-07	369.410
AlH_1-Sigma+_STO-6GN14r20g1T2_5	2.20e-01	-0.00e+00	0.00e+00	-0.00e+00	-9.95e-01	0.00e+00	Failed
Bex2_1_5	7.15e-10	0.00e+00	9.02e-12	0.00e+00	3.98e-07	1.15e-07	199.260
BH2_2A1_STO-6GN7r14g1T2	1.40e-10	0.00e+00	2.37e-09	0.00e+00	1.36e-07	3.17e-07	282.880
biggs	8.36e-10	2.29e-15	1.87e-12	0.00e+00	2.76e-08	2.95e-08	8.580
broyden25	9.98e-14	0.00e+00	0.00e+00	-0.00e+00	1.92e-08	1.92e-08	1066.460
Bst_jcbpaf2	1.15e-13	0.00e+00	1.66e-10	0.00e+00	1.94e-07	1.52e-07	317.920
buck4	2.27e-11	0.00e+00	0.00e+00	-0.00e+00	3.83e-07	2.07e-07	21.100
buck5	1.39e-07	0.00e+00	0.00e+00	-0.00e+00	6.48e-04	3.36e-04	185.080
butcher	3.03e-07	0.00e+00	3.63e-07	0.00e+00	-9.42e-05	8.56e-09	333.150
cancer_100	2.85e-12	0.00e+00	0.00e+00	-0.00e+00	3.58e-09	1.42e-08	213.620
CH2_1A1_STO-6GN8r14g1T2	2.05e-11	0.00e+00	4.35e-09	0.00e+00	1.53e-07	2.65e-07	271.080
checker_1.5	6.71e-14	0.00e+00	0.00e+00	-0.00e+00	7.17e-07	7.17e-07	39.550
chs_5000	0.00e+00	0.00e+00	0.00e+00	-0.00e+00	3.34e-08	3.34e-08	57.980
cnhil10	3.39e-08	0.00e+00	0.00e+00	-0.00e+00	7.39e-09	1.73e-08	37.520
cphil12	8.00e-15	0.00e+00	0.00e+00	-0.00e+00	1.06e-09	1.06e-09	253.960
diamond_patch	1.00e+00	-0.00e+00	5.25e-05	0.00e+00	1.00e+00	1.00e+00	Failed
e_moment_quadknapp_17_100_0.5_2_2	1.63e-10	0.00e+00	4.92e-09	0.00e+00	-1.71e-06	8.77e-09	118.180
e_moment_stable_17_0.5_2_2	1.05e-12	0.00e+00	3.63e-07	0.00e+00	-1.20e-05	2.76e-08	123.590
foot	9.94e-06	0.00e+00	0.00e+00	-0.00e+00	2.18e-04	1.20e-05	26.680
G40_mb	4.02e-09	0.00e+00	0.00e+00	-0.00e+00	2.66e-07	2.17e-07	15.770
G40mc	7.81e-15	0.00e+00	0.00e+00	-0.00e+00	3.66e-07	3.66e-07	6.530
G48_mb	3.28e-05	0.00e+00	0.00e+00	-0.00e+00	-6.27e-04	4.31e-07	17.830
G48mc	2.38e-14	0.00e+00	0.00e+00	-0.00e+00	2.36e-07	2.36e-07	5.090
G55mc	2.82e-15	0.00e+00	0.00e+00	-0.00e+00	1.67e-07	1.67e-07	38.060
G59mc	1.28e-14	0.00e+00	0.00e+00	-0.00e+00	2.33e-07	2.33e-07	48.730
G60_mb	8.93e-09	0.00e+00	0.00e+00	-0.00e+00	2.46e-07	2.52e-07	211.220
G60mc	8.93e-09	0.00e+00	0.00e+00	-0.00e+00	2.46e-07	2.52e-07	208.960
H3O+_1-A1_STO-6GN10r16g1T2_5	2.09e-12	0.00e+00	6.27e-12	0.00e+00	2.32e-07	2.32e-07	1086.470
hand	1.82e-08	0.00e+00	0.00e+00	-0.00e+00	6.54e-07	3.73e-07	6.600
ice_2.0	1.48e-13	0.00e+00	0.00e+00	-0.00e+00	1.72e-07	1.72e-07	284.900
inc_1200	1.85e-04	0.00e+00	0.00e+00	-0.00e+00	-2.27e-03	2.53e-06	46.420
neosfbr25	8.64e-13	0.00e+00	0.00e+00	-0.00e+00	7.00e-08	7.00e-08	543.240
neosfbr30e8	2.27e-11	0.00e+00	0.00e+00	-0.00e+00	4.15e-08	4.15e-08	2733.590
neu1	1.66e-11	0.00e+00	1.60e-07	0.00e+00	4.85e-06	2.08e-05	86.940
neu1g	1.92e-08	0.00e+00	7.94e-10	0.00e+00	4.09e-08	8.37e-08	65.970
neu2c	5.24e-03	0.00e+00	3.79e-10	0.00e+00	-9.87e-05	9.07e-04	183.370

Table 18. HSDP: Mittelmann's Benchmark Test Part 2

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
neu2	5.44e-01	0.00e+00	6.14e-03	0.00e+00	9.98e-01	1.28e-01	Failed
neu2g	3.76e-10	1.66e-16	7.94e-10	0.00e+00	3.39e-09	2.42e-08	57.240
neu3	1.11e-14	0.00e+00	6.42e-07	0.00e+00	-1.97e-06	2.04e-08	788.670
neu3g	2.76e-14	0.00e+00	0.00e+00	-0.00e+00	7.71e-09	2.04e-08	861.030
NH2-.1A1.STO6G.r14	1.07e-12	0.00e+00	3.37e-09	0.00e+00	2.74e-07	3.25e-07	259.130
NH3_1-A1_STO-6GN10r16g1T2_5	4.14e-12	0.00e+00	6.20e-09	0.00e+00	1.29e-07	2.18e-07	1076.710
NH4+.1A1.STO6GN.r18	6.50e-10	0.00e+00	3.22e-09	0.00e+00	8.83e-06	9.02e-06	3601.580
nonc_500	5.47e-11	0.00e+00	0.00e+00	-0.00e+00	7.58e-08	7.58e-08	6.080
p_auss2_3.0	9.88e-15	0.00e+00	0.00e+00	-0.00e+00	2.37e-07	2.37e-07	311.050
rabmo	1.36e-11	0.00e+00	1.63e-07	0.00e+00	-4.28e-05	1.18e-08	66.380
reimer5	4.65e-02	-0.00e+00	1.15e-07	0.00e+00	9.38e-01	0.00e+00	Failed
rendl1_2000_1e-6	1.74e-11	0.00e+00	0.00e+00	-0.00e+00	3.88e-07	3.87e-07	16.170
ros_2000	4.44e-16	0.00e+00	0.00e+00	-0.00e+00	9.09e-08	9.09e-08	9.110
ros_500	4.52e-11	0.00e+00	0.00e+00	-0.00e+00	1.33e-07	1.34e-07	2.040
rose15	1.13e-08	0.0e+00	1.40e-07	0.00e+00	-9.69e-05	8.37e-09	46.850
sensor_1000	1.06e-11	0.00e+00	0.00e+00	-0.00e+00	3.19e-07	7.21e-08	98.180
sensor_500	3.38e-12	0.00e+00	0.00e+00	-0.00e+00	1.21e-07	2.27e-08	35.110
shmup4	1.83e-09	0.00e+00	0.00e+00	-0.00e+00	6.63e-07	4.67e-07	73.280
shmup5	2.18e-08	0.00e+00	8.54e-11	0.00e+00	-2.91e-06	4.98e-07	663.480
swissroll	9.48e-06	0.00e+00	0.00e+00	-0.00e+00	-7.34e-03	1.19e-07	31.170
taha1a	9.01e-11	0.00e+00	1.84e-07	0.00e+00	-1.41e-07	1.78e-07	135.320
taha1b	2.20e-11	0.00e+00	2.51e-10	0.00e+00	4.90e-08	6.07e-08	391.190
taha1c	1.50e-10	0.00e+00	3.76e-07	0.00e+00	-2.06e-07	1.93e-07	1631.100
theta102	1.89e-14	0.00e+00	0.00e+00	-0.00e+00	6.65e-08	6.65e-08	1196.390
theta12	1.84e-14	0.00e+00	0.00e+00	-0.00e+00	2.89e-08	2.89e-08	167.570
tiger_texture	4.33e-05	0.00e+00	1.05e-09	0.00e+00	6.48e-04	9.81e-04	47.520
trto4	2.88e-09	0.00e+00	0.00e+00	-0.00e+00	2.49e-07	8.11e-08	6.250
trto5	3.26e-08	0.00e+00	0.00e+00	-0.00e+00	-3.72e-07	1.84e-07	67.220
vibra4	1.94e-06	0.00e+00	0.00e+00	-0.00e+00	6.11e-06	3.21e-06	27.360
vibra5	4.31e-07	0.00e+00	1.46e-08	0.00e+00	2.11e-04	1.11e-04	293.290
yalsdp	2.00e-07	0.00e+00	0.00e+00	-0.00e+00	9.83e-07	9.82e-07	118.100

Table 19. DSDP5.8: Mittelmann's Benchmark Test Part 1

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
1dc.1024	2.00e-06	0.00e+00	0.00e+00	0.00e+00	8.26e-01	7.95e+00	Failed
1et.1024	6.22e+01	0.00e+00	0.00e+00	0.00e+00	6.55e-01	1.04e+02	Failed
1tc.1024	5.13e-10	0.00e+00	0.00e+00	0.00e+00	6.34e-08	7.46e-08	44.310
1zc.1024	5.43e-10	0.00e+00	0.00e+00	0.00e+00	5.47e-09	7.61e-09	497.000
AlH_1-Sigma+_STO-6GN14r20g1T2_5	2.27e-10	0.00e+00	0.00e+00	0.00e+00	9.53e-05	1.09e-04	7296.000
Bex2_1_5	1.84e-06	0.00e+00	0.00e+00	0.00e+00	6.79e-07	1.15e-06	47.120
BH2_2A1_STO-6GN7r14g1T2	3.16e-10	0.00e+00	0.00e+00	0.00e+00	1.16e-07	1.18e-07	182.200
biggs	7.21e-09	0.00e+00	0.00e+00	0.00e+00	1.98e-09	4.08e-08	3.729
broyden25	5.14e-11	0.00e+00	0.00e+00	0.00e+00	1.20e-07	1.68e-07	392.900
Bst_jcbpaf2	3.30e-08	0.00e+00	0.00e+00	0.00e+00	8.72e-08	2.12e-07	60.910
buck4	7.06e-06	0.00e+00	0.00e+00	0.00e+00	2.20e-07	3.54e-07	18.760
buck5	2.94e-05	0.00e+00	0.00e+00	0.00e+00	1.21e-06	1.59e-06	421.900
butcher	8.33e-05	4.61e-14	0.00e+00	0.00e+00	3.03e-06	3.21e-06	125.200
cancer_100	1.77e-09	0.00e+00	0.00e+00	0.00e+00	3.60e-08	4.68e-06	137.700
CH2_1A1_STO-6GN8r14g1T2	1.61e-10	0.00e+00	0.00e+00	0.00e+00	1.34e-07	1.35e-07	184.800
checker_1.5	3.19e-09	0.00e+00	0.00e+00	0.00e+00	5.25e-07	5.25e-07	64.040
chs_5000	1.84e-10	0.00e+00	0.00e+00	0.00e+00	2.23e-07	6.53e-07	539.100
cnhil10	7.00e-07	0.00e+00	0.00e+00	0.00e+00	3.46e-06	1.56e-05	11.710
cphil12	1.03e-11	0.00e+00	0.00e+00	0.00e+00	2.05e-06	6.89e-06	85.760
diamond_patch	1.41e-07	0.00e+00	0.00e+00	0.00e+00	5.04e-04	8.43e-02	Failed
e_moment_quadknapp_17_100_0.5_2_2	1.84e-08	2.61e-15	0.00e+00	0.00e+00	3.42e-09	1.20e-07	35.770
e_moment_stable_17_0.5_2_2	1.68e-01	1.41e-16	0.00e+00	0.00e+00	-1.83e-02	6.56e-01	Failed
foot	2.90e-09	0.00e+00	0.00e+00	0.00e+00	1.08e-07	7.66e-08	13.650
G40_mb	2.00e-09	0.00e+00	0.00e+00	0.00e+00	6.49e-08	4.10e-06	8.774
G40mc	2.26e-09	0.00e+00	0.00e+00	0.00e+00	1.10e-07	1.12e-07	18.680
G48_mb	3.05e-09	0.00e+00	0.00e+00	0.00e+00	4.18e-07	5.24e-06	12.480
G48mc	2.77e-09	0.00e+00	0.00e+00	0.00e+00	1.23e-07	1.23e-07	8.434
G55mc	3.57e-09	0.00e+00	0.00e+00	0.00e+00	5.15e-07	5.18e-07	168.100
G59mc	3.57e-09	0.00e+00	0.00e+00	0.00e+00	3.43e-07	3.44e-07	302.300
G60_mb	7.10e-09	0.00e+00	0.00e+00	0.00e+00	2.30e-06	2.35e-05	213.400
G60mc	7.10e-09	0.00e+00	0.00e+00	0.00e+00	2.30e-06	2.35e-05	218.800
H3O+_1-A1_STO-6GN10r16g1T2_5	3.94e-12	0.00e+00	0.00e+00	0.00e+00	1.17e-07	1.20e-07	821.800
hand	1.38e-09	0.00e+00	0.00e+00	0.00e+00	8.10e-08	4.03e-07	2.641
ice_2.0	4.67e-09	0.00e+00	0.00e+00	0.00e+00	5.12e-07	5.12e-07	504.700
inc_1200	1.58e+00	0.00e+00	0.00e+00	0.00e+00	2.24e-01	2.13e-01	Failed
mater-5	5.19e-09	0.00e+00	0.00e+00	0.00e+00	5.66e-07	6.32e-07	20.280
mater-6	1.06e-08	0.00e+00	0.00e+00	0.00e+00	8.67e-07	9.51e-07	68.250
neosfbr25	1.30e-10	0.00e+00	0.00e+00	0.00e+00	1.52e-08	1.91e-08	233.800
neosfbr30e8	1.65e-10	0.00e+00	0.00e+00	0.00e+00	5.42e-09	6.60e-09	1286.000
neu1	7.00e-11	0.00e+00	0.00e+00	0.00e+00	2.35e-04	2.08e-02	Failed
neu1g	8.17e-09	0.00e+00	0.00e+00	0.00e+00	2.25e-07	3.77e-05	38.390
neu2c	1.84e-03	2.70e-15	0.00e+00	0.00e+00	-2.00e-03	1.70e-05	88.330

Table 20. DSDP5.8: Mittelmann’s Benchmark Test Part 2

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
neu2	3.42e-13	0.00e+00	0.00e+00	0.00e+00	8.97e-08	1.28e-05	30.270
neu2g	7.84e-08	0.00e+00	0.00e+00	0.00e+00	-1.73e-09	7.55e-06	28.600
neu3	2.23e-09	0.00e+00	0.00e+00	0.00e+00	4.13e-08	5.76e-04	194.300
neu3g	1.22e-08	0.00e+00	0.00e+00	0.00e+00	3.77e-08	4.41e-04	252.100
NH2-.1A1.STO6G.r14	2.56e-01	8.85e-16	0.00e+00	0.00e+00	-5.24e-02	4.50e-02	Failed
NH3_1-A1_STO-6GN10r16g1T2_5	5.71e-12	0.00e+00	0.00e+00	0.00e+00	1.45e-07	1.48e-07	802.500
NH4+.1A1.STO6GN.r18	1.65e-01	9.75e-15	0.00e+00	0.00e+00	-4.93e-02	2.94e-03	Failed
nonc_500	1.40e-09	0.00e+00	0.00e+00	0.00e+00	2.38e-07	5.83e-07	2.225
p_auss2_3.0	4.83e-09	0.00e+00	0.00e+00	0.00e+00	1.96e-07	1.96e-07	528.000
rabmo	6.39e-04	5.41e-16	0.00e+00	0.00e+00	-7.59e-06	4.24e-07	37.470
reimer5	4.95e-08	4.57e-15	0.00e+00	0.00e+00	2.41e-09	1.24e-06	244.200
rendl1_2000_1e-6	1.91e-09	0.00e+00	0.00e+00	0.00e+00	3.53e-08	3.57e-08	14.380
ros_2000	6.88e-11	0.00e+00	0.00e+00	0.00e+00	1.39e-08	6.75e-08	16.620
ros_500	4.22e-11	0.00e+00	0.00e+00	0.00e+00	8.85e-08	3.87e-07	2.039
rose15	6.74e-08	0.00e+00	0.00e+00	0.00e+00	1.34e-02	2.68e-02	Failed
sensor_1000	9.41e-10	0.00e+00	0.00e+00	0.00e+00	3.75e-07	5.58e-07	76.390
sensor_500	7.91e-10	0.00e+00	0.00e+00	0.00e+00	5.06e-07	8.71e-07	19.840
shmup4	5.17e-06	0.00e+00	0.00e+00	0.00e+00	3.63e-07	4.81e-07	93.490
shmup5	2.73e-05	0.00e+00	0.00e+00	0.00e+00	3.64e-07	6.92e-07	668.800
spar060-020-1_LS	1.63e-08	0.00e+00	0.00e+00	0.00e+00	9.06e-08	9.73e-08	109.300
swissroll	1.53e-03	0.00e+00	0.00e+00	0.00e+00	-1.39e-02	7.32e-01	Failed
taha1a	1.04e-01	0.00e+00	0.00e+00	0.00e+00	2.03e-02	1.56e+00	Failed
taha1b	1.64e-11	0.00e+00	0.00e+00	0.00e+00	1.97e-07	4.15e-04	139.700
taha1c	9.63e-01	0.00e+00	0.00e+00	0.00e+00	3.52e-01	1.81e-02	Failed
theta102	2.50e-10	0.00e+00	0.00e+00	0.00e+00	7.40e-09	1.13e-08	705.800
theta12	3.00e-10	0.00e+00	0.00e+00	0.00e+00	6.94e-09	8.56e-09	182.600
tiger_texture	6.12e-08	0.00e+00	0.00e+00	0.00e+00	1.57e-06	1.77e-03	245.300
trto4	1.52e-04	0.00e+00	0.00e+00	0.00e+00	6.81e-08	4.16e-07	6.302
trto5	6.89e-04	0.00e+00	0.00e+00	0.00e+00	3.61e-06	5.38e-06	75.200
vibra4	6.05e-05	0.00e+00	0.00e+00	0.00e+00	2.25e-07	3.59e-07	24.370
vibra5	2.83e-04	0.00e+00	0.00e+00	0.00e+00	1.19e-06	1.54e-06	314.000
yalsdp	1.65e-10	0.00e+00	0.00e+00	0.00e+00	4.84e-07	4.88e-07	93.430

Table 21. COPT: Mittelmann's Benchmark Test Part 1

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
1dc.1024	2.04e-08	0.00e+00	0.00e+00	0.00e+00	-5.73e-10	9.19e-08	196.160
1et.1024	1.50e-09	0.00e+00	0.00e+00	0.00e+00	-3.92e-11	1.04e-08	37.670
1tc.1024	1.87e-08	0.00e+00	0.00e+00	0.00e+00	-5.02e-10	1.38e-07	31.410
1zc.1024	2.98e-08	0.00e+00	0.00e+00	0.00e+00	-1.17e-09	1.64e-07	63.790
AIH_1-Sigma+_STO-6GN14r20g1T2_5	7.34e-10	0.00e+00	0.00e+00	0.00e+00	2.50e-09	4.56e-09	1835.230
Bex2_1_5	2.51e-07	0.00e+00	0.00e+00	0.00e+00	-4.07e-10	2.54e-06	5.630
BH2_2A1_STO-6GN7r14g1T2	8.39e-10	0.00e+00	0.00e+00	0.00e+00	2.54e-09	7.04e-09	30.500
biggs	7.32e-07	0.00e+00	6.03e-09	0.00e+00	-3.51e-09	2.13e-06	1.760
broyden25	3.81e-08	0.00e+00	0.00e+00	0.00e+00	-7.77e-10	1.95e-06	12.460
Bst_jcbpaf2	8.55e-09	0.00e+00	0.00e+00	0.00e+00	1.56e-10	1.13e-07	7.270
buck4	4.17e-06	0.00e+00	0.00e+00	0.00e+00	-2.94e-09	7.70e-06	41.940
buck5	2.16e-05	0.00e+00	0.00e+00	0.00e+00	-6.07e-09	4.48e-05	834.240
butcher	1.28e-03	0.00e+00	0.00e+00	0.00e+00	-1.10e-05	3.39e-01	Failed
cancer_100	4.10e-05	0.00e+00	0.00e+00	0.00e+00	-8.40e-09	2.66e-06	38.400
CH2_1A1_STO-6GN8r14g1T2	9.90e-10	0.00e+00	4.64e-10	0.00e+00	3.68e-09	7.75e-09	27.450
checker_1.5	6.02e-10	0.00e+00	0.00e+00	0.00e+00	2.48e-09	2.57e-09	868.370
chs_5000	1.09e-10	0.00e+00	0.00e+00	0.00e+00	7.40e-11	2.59e-09	39.060
cnhil10	2.20e-06	0.00e+00	0.00e+00	0.00e+00	4.10e-07	2.09e-05	3.430
cphil12	1.58e-11	0.00e+00	0.00e+00	0.00e+00	3.90e-12	6.03e-10	14.960
diamond_patch	7.08e-07	0.00e+00	1.15e-06	0.00e+00	-1.65e-07	7.68e-04	2939.110
e_moment_quadknep_17_100_0.5_2_2	2.78e-07	0.00e+00	0.00e+00	0.00e+00	-2.51e-09	1.57e-05	7.450
e_moment_stable_17_0.5_2_2	7.00e-08	0.00e+00	0.00e+00	0.00e+00	2.64e-09	3.21e-06	5.670
foot	7.32e-06	0.00e+00	0.00e+00	0.00e+00	-7.37e-09	7.76e-06	245.410
G40_mb	8.27e-07	0.00e+00	0.00e+00	0.00e+00	3.45e-09	4.97e-06	98.970
G40mc	5.06e-11	0.00e+00	0.00e+00	0.00e+00	1.72e-10	1.41e-08	80.450
G48_mb	7.27e-11	0.00e+00	0.00e+00	0.00e+00	1.53e-09	5.07e-08	183.950
G48mc	1.12e-12	0.00e+00	0.00e+00	0.00e+00	-4.22e-10	6.32e-10	118.790
G55mc	1.48e-10	0.00e+00	0.00e+00	0.00e+00	-3.67e-09	4.28e-09	1026.100
G59mc	4.67e-10	0.00e+00	0.00e+00	0.00e+00	-3.86e-11	7.64e-09	1131.240
G60_mb	2.09e-07	0.00e+00	0.00e+00	0.00e+00	9.02e-09	4.96e-07	5188.110
G60mc	2.09e-07	0.00e+00	0.00e+00	0.00e+00	9.02e-09	4.96e-07	5189.290
H3O+_1-A1_STO-6GN10r16g1T2_5	7.27e-10	0.00e+00	0.00e+00	0.00e+00	3.49e-09	5.11e-09	93.900
hand	4.68e-07	0.00e+00	0.00e+00	0.00e+00	-2.50e-09	2.34e-07	49.390
ice_2.0	3.03e-10	0.00e+00	0.00e+00	0.00e+00	3.90e-08	4.01e-08	8561.740
inc_1200	1.10e-07	0.00e+00	0.00e+00	0.00e+00	-1.25e-09	4.89e-06	99.020
mater-5	9.00e-07	0.00e+00	0.00e+00	0.00e+00	-9.24e-10	1.60e-05	2.840
mater-6	1.08e-06	0.00e+00	0.00e+00	0.00e+00	-3.08e-10	1.64e-05	7.100
neosfbr25	1.50e-09	0.00e+00	0.00e+00	0.00e+00	8.65e-10	6.25e-09	85.810
neosfbr30e8	9.48e-09	0.00e+00	0.00e+00	0.00e+00	4.62e-09	4.07e-08	438.710
neu1	2.58e-09	0.00e+00	2.91e-09	0.00e+00	-8.26e-09	2.31e-06	3.610
neu1g	7.58e-07	0.00e+00	0.00e+00	0.00e+00	-2.01e-09	9.33e-07	3.000
neu2c	2.81e-07	0.00e+00	1.41e-07	0.00e+00	-7.33e-10	6.68e-07	7.560

Table 22. COPT: Mittelmann's Benchmark Test Part 2

Instance	Error 1	Error 2	Error 3	Error 4	Error 5	Error 6	Time
neu2	7.66e-09	0.00e+00	1.19e-08	0.00e+00	-4.11e-10	8.68e-08	2.980
neu2g	1.65e-07	0.00e+00	3.05e-10	0.00e+00	-1.30e-09	3.31e-07	4.340
neu3	2.15e-08	0.00e+00	0.00e+00	0.00e+00	8.48e-09	7.05e-07	19.410
neu3g	1.44e-08	0.00e+00	0.00e+00	0.00e+00	9.38e-09	2.84e-07	24.360
NH2-.1A1.STO6G.r14	1.77e-09	0.00e+00	0.00e+00	0.00e+00	2.55e-09	7.60e-09	25.890
NH3_1-A1_STO-6GN10r16g1T2_5	5.22e-10	0.00e+00	0.00e+00	0.00e+00	2.98e-09	4.26e-09	94.540
NH4+.1A1.STO6GN.r18	1.48e-08	0.00e+00	0.00e+00	0.00e+00	2.09e-09	9.87e-09	591.090
nonc_500	1.60e-09	0.00e+00	1.65e-10	0.00e+00	3.20e-10	2.60e-09	0.340
p_auss2_3.0	1.47e-08	0.00e+00	2.26e-14	0.00e+00	3.58e-09	3.58e-09	12868.900
rabmo	1.36e-07	0.00e+00	0.00e+00	0.00e+00	-1.63e-09	1.74e-05	5.150
reimer5	1.54e-06	0.00e+00	0.00e+00	0.00e+00	-2.10e-09	3.84e-04	14.440
rendl1_2000_1e-6	9.69e-07	0.00e+00	0.00e+00	0.00e+00	3.37e-09	8.81e-07	111.430
ros_2000	5.85e-10	0.00e+00	5.52e-11	0.00e+00	3.74e-10	2.78e-09	1.460
ros_500	1.80e-09	0.00e+00	5.12e-10	0.00e+00	8.15e-10	1.25e-08	0.280
rose15	1.02e-08	0.00e+00	5.60e-10	0.00e+00	-9.33e-09	9.29e-07	3.180
sensor_1000	9.62e-09	0.00e+00	1.27e-08	0.00e+00	1.40e-10	5.41e-08	38.960
sensor_500	5.85e-08	0.00e+00	0.00e+00	0.00e+00	4.41e-10	1.91e-07	9.570
shmup4	2.70e-07	0.00e+00	0.00e+00	0.00e+00	-4.62e-09	2.36e-05	469.190
shmup5	1.78e-06	0.00e+00	0.00e+00	0.00e+00	-6.45e-09	6.97e-05	7118.160
spar060-020-1_LS	5.90e-07	0.00e+00	0.00e+00	0.00e+00	4.96e-10	2.11e-06	11.910
swissroll	2.95e-03	0.00e+00	0.00e+00	0.00e+00	-2.68e-05	2.37e-02	Failed
taha1a	2.46e-09	0.00e+00	0.00e+00	0.00e+00	6.98e-10	5.31e-08	5.030
taha1b	5.56e-09	0.00e+00	6.74e-10	0.00e+00	1.28e-09	6.38e-08	21.220
taha1c	7.48e-09	0.00e+00	0.00e+00	0.00e+00	1.90e-09	2.37e-07	38.820
theta102	4.25e-09	0.00e+00	0.00e+00	0.00e+00	-4.15e-10	8.05e-09	484.170
theta12	2.87e-09	0.00e+00	0.00e+00	0.00e+00	-1.25e-10	6.44e-09	60.580
tiger_texture	7.48e-07	0.00e+00	1.08e-06	0.00e+00	-6.88e-08	1.14e-04	117.210
trto4	5.40e-05	0.00e+00	0.00e+00	0.00e+00	-1.90e-08	3.83e-05	27.160
trto5	1.95e-04	0.00e+00	0.00e+00	0.00e+00	-2.34e-08	1.52e-04	391.830
vibra4	1.14e-05	0.00e+00	0.00e+00	0.00e+00	-6.30e-08	1.94e-04	64.660
vibra5	5.93e-05	0.00e+00	0.00e+00	0.00e+00	-3.75e-07	3.78e-03	841.620
yalsdp	8.63e-10	0.00e+00	8.86e-11	0.00e+00	-4.99e-10	1.45e-09	9.460