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Solving Quadratic Programs to High Precision using Scaled Iterative Refinement

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Abstract Quadratic optimization problems (QPs) are ubiquitous, and solution algorithms have matured to a reliable technology. However, the precision of solutions is usually limited due to the underlying floating-point operations. This may cause inconveniences when solutions are used for rigorous reasoning. We contribute on three levels to overcome this issue.

First, we present a novel refinement algorithm to solve QPs to arbitrary precision. It iteratively solves refined QPs, assuming a floating-point QP solver oracle. We prove linear convergence of residuals and primal errors. Second, we provide an efficient implementation, based on `SoPlex` and `qpOASES` that is publicly available in source code. Third, we give precise reference solutions for the Maros and Mészáros benchmark library.

Keywords Quadratic Programming · Iterative Refinement · Active Set · Rational Calculations

Mathematics Subject Classification 90C20 · 90-08 · 90C55

1 Introduction

Quadratic optimization problems (QPs) are optimization problems with a quadratic objective function and linear constraints. They are of interest directly, e.g., in portfolio optimization or support vector machines [1]. They also occur as subproblems in sequential quadratic programming, mixed-integer quadratic programming, and nonlinear model predictive control. Efficient algorithms are usually of active set, interior point, or parametric type. Examples of QP solvers are BQP [5], CPLEX [2], Gurobi [12], `qp_solve` [10], `qpOASES` [4], and QPOPT [7]. These QP solvers have matured to reliable tools and can solve convex problems with many thousands, sometimes millions of variables. However, they calculate and check the solution of a QP in floating-point arithmetic. Thus, the claimed precision may be violated and in extreme cases optimal solutions might not be found. This may cause inconveniences, especially when solutions are used for rigorous reasoning.

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One possible approach is the application of interval arithmetic. It allows to include uncertainties as lower and upper bounds on the modeling level, see [13] for a survey for the case of linear optimization. As a drawback, all internal calculations have to be performed with interval arithmetic. Hence standard solvers can not be used any more, the computation times increase, and solutions may be very conservative.

We are only aware of one advanced algorithm that solves QPs exactly over the rational numbers. It is designed to tackle problems from computational geometry with a small number of constraints or variables, [6]. Based on the classical QP simplex method [16], it replaces critical calculations inside the QP solver by their rational counterparts. Heuristic decisions that do not affect the correctness of the algorithm are performed in fast floating-point arithmetic.

In this paper we propose a novel algorithm that can use efficient floating-point QP solvers as a black box. Our method is inspired by iterative refinement, a standard procedure to improve the accuracy of an approximate solution for a system of linear equalities, [15]: The residual of the approximate solution is calculated, the linear system is solved again with the residual as a right-hand side, and the new solution is used to refine the old solution, thus improving its accuracy. A generalization of this idea to the solution of optimization problems needs to address several difficulties: most importantly, the presence of inequality constraints; the handling of optimality conditions; and the numerical tolerances that floating-point solvers can return in practice.

For LPs this has first been developed in [9]. The approach refines primal-dual solutions of the Karush-Kuhn-Tucker (KKT) conditions and comprehends scaling and calculations in rational arithmetic. We generalize further and discuss the specific issues due to the presence of a quadratic objective function. The fact that the general approach carries over from LP to QP was remarked in [8]. Here we provide the details, provide a general lemma showing how the residuals bound the primal and dual iterates, and analyze the computational behavior of the algorithm based on an efficient implementation that is made publicly available in source code and can be used freely for research purposes.

The paper is organized as follows. In Section 2 we define and discuss QPs and their refined and scaled counterparts. We give one illustrating and motivating example for scaling and refinement. In Section 3 we formulate an algorithm and prove its convergence properties. In Section 4 we consider performance issues and describe how our implementation based on `SoPlex` and `qpDASES` can be used to calculate solutions for QPs with arbitrary precision. In Section 5 we discuss run times and provide solutions for the Maros and Mészáros benchmark library, [14]. We conclude in Section 6 with a discussion of the results and give directions for future research and applications of the algorithm.

In the following we will use $\|\cdot\|$ for the maximum norm $\|\cdot\|_\infty$. The maximal entry of a vector $\max_i\{v_i\}$ is written as $\max\{v\}$. Inequalities $a \leq b$ for $a, b \in \mathbb{Q}^n$ hold componentwise.

2 Refinement and Scaling of Quadratic Programs

In this section we collect some basic definitions and results that will be of use later on. We consider convex optimization problems of the following form.

Definition 1 (Quadratic optimization problem (QP)). *Let a symmetric matrix $Q \in \mathbb{Q}^{n \times n}$, a matrix $A \in \mathbb{Q}^{m \times n}$, and vectors $c \in \mathbb{Q}^n, b \in \mathbb{Q}^m, l \in \mathbb{Q}^n$ be given. We consider the quadratic optimization problem (QP)*

$$\begin{aligned} \min_x \quad & \frac{1}{2}x^T Qx + c^T x \\ \text{s.t.} \quad & Ax = b \\ & x \geq l \end{aligned} \tag{P}$$

assuming that (P) is feasible and bounded, and Q is positive semi-definite on the feasible set. The rounded version of this convex rational data QP will be denoted as (\tilde{P}) .

A point $x^* \in \mathbb{Q}^n$ is a global optimum of (P) if and only if it satisfies the Karush-Kuhn-Tucker (KKT) conditions, [3], i.e., if multipliers $y^* \in \mathbb{Q}^m$ exist such that

$$Ax^* = b \quad (1a)$$

$$x^* \geq l \quad (1b)$$

$$A^T y^* \leq Qx^* + c \quad (1c)$$

$$(Qx^* + c - A^T y^*)^T (x^* - l) = 0. \quad (1d)$$

The pair (x^*, y^*) is then called KKT pair of (P) . Primal feasibility is given by (1a–1b), dual feasibility by (1c), and complementary slackness by (1d). Refinement of this system of linear (in-)equalities is equivalent to the refinement of (P) .

Definition 2 (Refined QP). *Let the QP (P) , scaling factors $\Delta_P, \Delta_D \in \mathbb{Q}_+$ and vectors $x^* \in \mathbb{Q}^n, y^* \in \mathbb{Q}^m$ be given. We define the refined QP as*

$$\begin{aligned} \min_x \quad & \frac{1}{2} x^T \frac{\Delta_D}{\Delta_P} Qx + (\Delta_D \hat{c})^T x \\ \text{s.t.} \quad & Ax = \Delta_P \hat{b} \\ & x \geq \Delta_P \hat{l}, \end{aligned} \quad (P^\Delta)$$

where $\hat{c} = Qx^* + c - A^T y^*$, $\hat{b} = b - Ax^*$, and $\hat{l} = l - x^*$. The rounded version of this refined and scaled rational data QP will be denoted as (\tilde{P}^Δ) .

The following theorem is the basis for our theoretical and algorithmic approaches. It is a generalization of iterative refinement for LP and was formulated and proven in [8, Theorem 5.2]. Again, primal feasibility refers to (1a–1b), dual feasibility to (1c), and complementary slackness to (1d).

Theorem 3 (QP Refinement). *Let the QP (P) , scaling factors $\Delta_P, \Delta_D \in \mathbb{Q}_+$, vectors $x^* \in \mathbb{Q}^n, y^* \in \mathbb{Q}^m$, and the refined QP (P^Δ) be given. Then for any $\hat{x} \in \mathbb{R}^n, \hat{y} \in \mathbb{R}^m$ and tolerances $\epsilon_P, \epsilon_D, \epsilon_S \geq 0$:*

1. \hat{x} is primal feasible for (P^Δ) within an absolute tolerance ϵ_P if and only if $x^* + \frac{\hat{x}}{\Delta_P}$ is primal feasible for (P) within ϵ_P/Δ_P .
2. \hat{y} is dual feasible for (P^Δ) within an absolute tolerance ϵ_D if and only if $y^* + \frac{\hat{y}}{\Delta_D}$ is dual feasible for (P) within ϵ_D/Δ_D .
3. \hat{x}, \hat{y} satisfy complementary slackness for (P^Δ) within an absolute tolerance ϵ_S if and only if $y^* + \frac{\hat{y}}{\Delta_D}, x^* + \frac{\hat{x}}{\Delta_P}$ satisfy complementary slackness for (P) within $\epsilon_S/(\Delta_P \Delta_D)$.

For illustration, we investigate the following example.

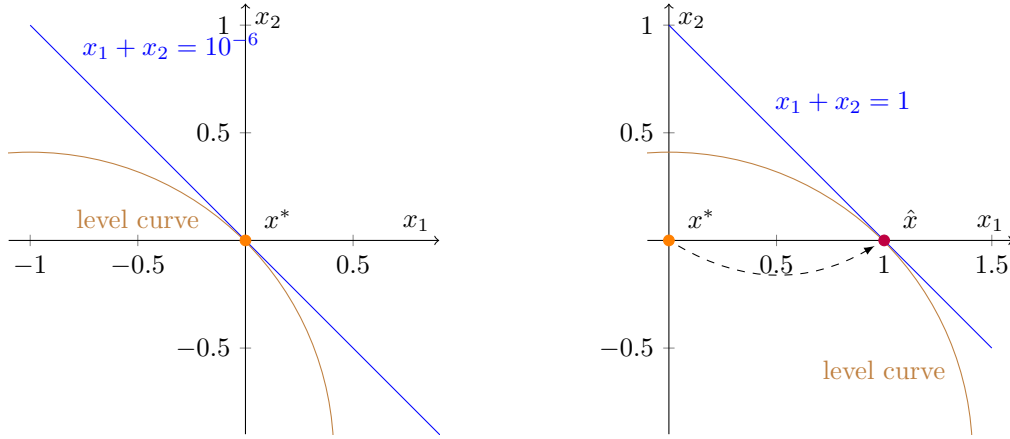
Example 4 (QP Refinement). Consider the QP with two variables

$$\begin{aligned} \min_x \quad & \frac{1}{2}(x_1^2 + x_2^2) + x_1 + (1 + 10^{-6})x_2 \\ \text{s.t.} \quad & x_1 + x_2 = 10^{-6} \\ & x_1, x_2 \geq 0. \end{aligned}$$

An approximate solution to a tolerance of 10^{-6} is $x_1^* = x_2^* = 0$ with dual multiplier $y^* = 1$. This solution is slightly primal and dual infeasible, but the solver can not recognize this on this scale. The situation is depicted in Figure 1 on the left.

The point x^* seems to be the optimal solution satisfying the equality constraint and the brown circle representing the level curve of the objective function indicates the

Figure 1: Illustration of nominal QP (left) and of refined QP (right) for Example 4. The scaled (and shifted) QP (P^Δ) works like a zoom (and shift) for (P), allowing to correct the solution x^* (orange dot) from $(0, 0)$ to $(10^{-6}, 0)$.



optimality. The corresponding violations are $\hat{l} = (0, 0)^T$, $\hat{b} = 10^{-6}$, and $\hat{c} = (0, 10^{-6})^T$. The refined QP is

$$\begin{aligned} \min_x \quad & \frac{1}{2}(x_1^2 + x_2^2) + x_2 \\ \text{s.t.} \quad & x_1 + x_2 = 1 \\ & x_1, x_2 \geq 0 \end{aligned}$$

with scalings $\Delta_P = \Delta_D = 10^6$. The optimal solution to this problem is $\hat{x}_1 = 1, \hat{x}_2 = 0$ with multiplier $\hat{y} = 1$. This situation is depicted in Figure 1, right. The point x^* is obviously not the optimal solution and the solution to the refined problem is \hat{x} . The refined solution is $x^* + \hat{x}/\Delta_P = (10^{-6}, 0)^T$ and $y^* + \hat{y}/\Delta_D = 1 + 10^{-6}$. These values are primal and dual feasible in the original problem.

3 Iterative Refinement for Quadratic Programming

To solve quadratic programs to arbitrary, *a priori* specified precisions, we apply the refinement idea from the previous section iteratively in Algorithm 1.

Algorithm 1 expects QP data (Q, A, c, b, l) in rational precision, primal and dual termination tolerances (ϵ_P, ϵ_D) , complementary slack termination tolerance (ϵ_S) , scaling limit $\alpha > 1$ and iteration limit k_{max} . First the rounded QP (\tilde{P}) is solved with a floating-point QP solver oracle which returns optimal primal and dual solution vectors (*Line 2*). In *Line 3* the main loop begins. The primal violations for constraints (\hat{b} , *Line 4*) and for bounds (\hat{l} , *Line 5*) are calculated. The maximal primal violation is saved as δ_P in *Line 6*. The reduced cost vector \hat{c} and its maximal violation δ_D are calculated in *Lines 7-8*. In *Line 9* the scaling factor Δ_k is chosen as the maximum of $\alpha\Delta_{k-1}$ and the inverses of the violations δ_P and δ_D . The complementary slack violation δ_S is calculated in *Line 10*. If the primal, dual and complementary slack violations are already below the specified tolerances the loop is stopped (*Lines 11-12*) and the optimal solution is returned (*Line 17*). Else (*Line 13*) the refined, scaled, and rounded QP (\tilde{P}^{Δ_k}) is solved with the floating-point QP oracle in *Line 14*. We save the floating-point optimal primal and dual solution vectors (*Line 15*). We scale and add them to the current iterate (x_k, y_k) to obtain (x_{k+1}, y_{k+1}) , *Line 16*.

Note that all calculations except the expensive solves of the QPs are done in rational precision. Algorithm 1 uses only one scaling factor Δ_k for primal and dual infeasibility

Algorithm 1 Iterative QP Refinement (IQPR)

1: **Input:** (P) in rational precision, termination tolerances ϵ_P and ϵ_D and ϵ_S , scaling limit $\alpha > 1$, iteration limit k_{max}
 2: **Initialization:** $\Delta_0 \leftarrow 1$, solve (\tilde{P}) approximately, save optimal (x_1, y_1)
 3: **for** $k \leftarrow 1, 2, \dots, k_{max}$ **do**
 4: $\hat{b} \leftarrow b - Ax_k$
 5: $\hat{l} \leftarrow l - x_k$
 6: $\delta_P \leftarrow \max \left\{ 0, \|\hat{b}\|, \max\{\hat{l}\} \right\}$
 7: $\hat{c} \leftarrow Qx_k + c - A^T y_k$
 8: $\delta_D \leftarrow \max \{ 0, \max\{-\hat{c}\} \}$
 9: $\Delta_k \leftarrow \min \{ \delta_P^{-1}, \delta_D^{-1}, \alpha \Delta_{k-1} \}$
 10: $\delta_S \leftarrow \sum_i \hat{l}_i \hat{c}_i$
 11: **if** $\delta_P \leq \epsilon_P$ and $\delta_D \leq \epsilon_D$ and $\delta_S \leq \epsilon_S$ **then**
 12: **break**
 13: **else**
 14: solve (\tilde{P}^{Δ_k}) approximately
 15: $(x^*, y^*) \leftarrow$ KKT pair returned as optimal
 16: $(x_{k+1}, y_{k+1}) \leftarrow (x_k, y_k) + \frac{(x^*, y^*)}{\Delta_k}$
 17: **Return:** (x_k, y_k)

to avoid the scaling of the quadratic term of the objective. Keeping this matrix and the constraint matrix A fixed gives QP solvers the possibility to reuse the internal factorization of the basis system between refinements, as the transformation does not change the basis. This allows to use efficient hotstart techniques for all solves after the initial solve.

To investigate the performance of the algorithm we make, in analogy with the LP case [9, Assumption 2.9], the following assumption.

Assumption 5 (QP solver accuracy). *We assume that there exists $\epsilon \in [0, 1)$ and $\sigma \geq 0$ such that the QP solver oracle returns for all rounded QPs (\tilde{P}^{Δ_k}) solutions (\bar{x}, \bar{y}) that satisfy*

$$\begin{aligned}
 \|A\bar{x} - \Delta_k \hat{b}\| &\leq \epsilon \\
 \bar{x} &\geq \Delta_k \hat{l} - \mathbf{1}\epsilon \\
 Q\bar{x} + \Delta_k \hat{c} &\geq A^T \bar{y} - \mathbf{1}\epsilon \\
 |(Q\bar{x} + \Delta_k \hat{c} - A^T \bar{y})^T (\bar{x} - \Delta_k \hat{l})| &\leq \sigma
 \end{aligned}$$

in the rational QPs (P^{Δ_k}).

Note that this ϵ corresponds to a termination tolerance passed to a floating-point solver, while the algorithm uses overall termination tolerances ϵ_P and ϵ_D and a scaling limit $\alpha > 1$ per iteration. We denote $\tilde{\epsilon} = \max\{1/\alpha, \epsilon\}$.

Lemma 6 (Termination and residual convergence). *Algorithm 1 applied to a primal and dual feasible QP (P) and using a QP solver that satisfies Assumption 5 will terminate in at most*

$$k_{max} = \max \{ \log(\epsilon_P)/\log(\tilde{\epsilon}), \log(\epsilon_D)/\log(\tilde{\epsilon}), \log(\epsilon_S/\sigma)/(2\log(\tilde{\epsilon})) + 1 \} \quad (2)$$

iterations. Furthermore, after each iteration $k = 1, 2, \dots$ the primal-dual iterate (x_k, y_k)

and the scaling factor Δ_k satisfy

$$\Delta_k \geq 1/\tilde{\epsilon}^k \quad (3a)$$

$$\|Ax_k - b\| \leq \tilde{\epsilon}^k \quad (3b)$$

$$x_k - l \geq -\mathbb{1}\tilde{\epsilon}^k \quad (3c)$$

$$Qx_k + c - A^T y_k \geq -\mathbb{1}\tilde{\epsilon}^k \quad (3d)$$

$$|(Qx_k + c - A^T y_k)^T (x_k - l)| \leq \sigma \tilde{\epsilon}^{2(k-1)}. \quad (3e)$$

Proof. We prove (3) by induction over k , starting with $k = 1$. As $\tilde{\epsilon} \geq \epsilon$, the claims (3b–3e) follow directly from Assumption 5. Using Lines 6, 4–5, and Assumption 5 we obtain

$$\delta_P = \max \left\{ 0, \|\hat{b}\|, \max\{\hat{l}\} \right\} = \max\{0, \|Ax_1 - b\|, \max\{l - x_1\}\} \leq \epsilon$$

and with Lines 8,7 and Assumption 5

$$\delta_D = \max \{0, \max\{-\hat{c}\}\} = \max \{0, \max\{Qx_1 + c - A^T y_1\}\} \leq \epsilon.$$

Thus from Line 9 we have

$$\Delta_1 = \min \{\delta_P^{-1}, \delta_D^{-1}, \alpha\Delta_0\} \geq \min \{\epsilon^{-1}, \epsilon^{-1}, \alpha\} \geq \tilde{\epsilon}^{-1}$$

and hence claim (3a) for the first iteration.

Assuming (3) holds for k we know that $\delta_{P,k}, \delta_{D,k} \leq \tilde{\epsilon}^k$ and $\Delta_k \geq 1/\tilde{\epsilon}^k$. With the scaling factor Δ_k using $x^* = x_k$ and $y^* = y_k$ we scale the QP (P) as in Theorem 3 and hand it to the QP solver. By Theorem 3 this scaled QP is still primal and dual feasible and by Assumption 5 the solver hands back a solution (\hat{x}, \hat{y}) with tolerance $\epsilon \leq \tilde{\epsilon}$. Therefore using Theorem 3 again the next refined iterate (x_{k+1}, y_{k+1}) has a tolerance in QP (P) of $\tilde{\epsilon}/\Delta_k \leq \tilde{\epsilon}^{k+1}$, which proves (3b–3d).

With the same argument the solution (\hat{x}, \hat{y}) violates complementary slackness by σ in the scaled QP (Assumption 5) and the refined iterate (x_{k+1}, y_{k+1}) violates complementary slackness in QP (P) by $\sigma/\Delta_k^2 \leq \sigma\tilde{\epsilon}^{2k}$ proving (3e).

We have now $\delta_{P,k+1}, \delta_{D,k+1} \leq \tilde{\epsilon}^{k+1}$. Also it holds that $\alpha\Delta_k \geq \alpha/\tilde{\epsilon}^k \geq 1/\tilde{\epsilon}^{k+1}$. Line 9 of Algorithm 1 gives

$$\Delta_{k+1} \geq 1/\tilde{\epsilon}^{k+1},$$

proving (3a).

Then (2) follows by assuming the slowest convergence rate of the primal, dual and complementary violations and by comparing this with the termination condition in Line 11 of Algorithm 1

$$\tilde{\epsilon}^k \leq \epsilon_P, \tilde{\epsilon}^k \leq \epsilon_D, \sigma\tilde{\epsilon}^{2(k-1)} \leq \epsilon_S.$$

This is equivalent to (2). \square

The results show that even though we did not use the violation of the complementary slackness to choose the scaling factor in Algorithm 1, the complementary slackness violation is bounded by the square of $\tilde{\epsilon}$.

Remark 7 (Nonconvex QPs). *Algorithm 1 can also be used to calculate high precision KKT pairs of nonconvex QPs. If the black box QP solver hands back local solutions of the quality specified in Assumption 5 Lemma 6 holds as well for nonconvex QPs and Algorithm 1 returns a high precision local solution.*

However, assuming strict convexity, an even stronger result holds. Inspired by the result for the equality-constrained QP [3, Proposition 2.12] we investigate how this right-hand side convergence of the KKT conditions is related to the primal-dual solution.

Lemma 8 (Primal and dual solution accuracy). *Let QP (P) be given and be strictly convex, the minimal and maximal eigenvalues of Q be $\lambda_{\min}(Q)$ and $\lambda_{\max}(Q)$, respectively, and the minimal nonzero singular value of A be $\sigma_{\min}(A)$. Let the KKT conditions (1) hold for (x^*, y^*, z^*) , i.e.,*

$$Ax^* = b \quad (4a)$$

$$A^T y^* + z^* = Qx^* + c \quad (4b)$$

$$z^{*T}(x^* - l) = 0 \quad (4c)$$

$$x^* \geq l \quad (4d)$$

$$z^* \geq 0 \quad (4e)$$

and the disturbed KKT conditions for disturbances $e \in \mathbb{Q}^m$, $g, f, h \in \mathbb{Q}^n$, and $i \in \mathbb{Q}$ hold for (x, y, z) , i.e.,

$$Ax = b + e \quad (5a)$$

$$A^T y + z = Qx + c + g \quad (5b)$$

$$z^T(x - l) = i \quad (5c)$$

$$x \geq l + f \quad (5d)$$

$$z \geq h. \quad (5e)$$

Denote

$$a := \frac{\lambda_{\max}(Q)\|e\|_2}{2\sigma_{\min}(A)} + \lambda_{\max}(Q)\lambda_{\min}(Q)\|g\|_2/2$$

$$d := \lambda_{\max}(Q)\|i - h^T(x^* - l) - z^{*T}f\|_2.$$

Then

$$\|A^T(y - y^*) + (z - z^*)\|_2 \leq a + \sqrt{a^2 + d} \quad (6)$$

and

$$\|x - x^*\|_2 \leq \lambda_{\min}(Q)(a + \sqrt{a^2 + d}) + \lambda_{\min}(Q)\|g\|_2 \quad (7)$$

Proof. By (4a) and (5a) we have that $A(x - x^*) = e$ and taking the Moore-Penrose pseudoinverse A^+ of A we define $\delta = A^+e$ with $A\delta = e$ and $\|\delta\|_2 \leq \sigma_{\min}(A)^{-1}\|e\|_2$. Using this we can start to derive the dual bound by taking the difference of (4b) and (5b)

$$A^T(y - y^*) + (z - z^*) = Q(x - x^*) + g. \quad (8)$$

Multiplying from the left with $Q^{-1}(A^T(y - y^*) + (z - z^*))$ transposed gives

$$\begin{aligned} \|A^T(y - y^*) + (z - z^*)\|_{Q^{-1}}^2 &= (A^T(y - y^*) + (z - z^*))^T((x - x^*) + Q^{-1}g). \\ &= (A^T(y - y^*) + (z - z^*))^T Q^{-1}g + (y - y^*)^T \underbrace{A(x - x^*)}_{A\delta} + (z - z^*)^T(x - x^*). \\ &= (A^T(y - y^*) + (z - z^*))^T(Q^{-1}g + \delta) + (z - z^*)^T(x - x^* - \delta). \end{aligned} \quad (9)$$

The second term of (9) can be expressed as

$$\begin{aligned} (z - z^*)^T(x - l - (x^* - l) - \delta) &= \underbrace{z^T(x - l)}_i + \underbrace{z^{*T}(x^* - l)}_0 - \underbrace{z^T(x^* - l)}_{\geq h^T(x^* - l)} - \underbrace{z^{*T}(x - l)}_{\geq z^{*T}f} \\ (z - z^*)^T(x - l - (x^* - l) - \delta) &\leq i - h^T(x^* - l) - z^{*T}f. \end{aligned}$$

With this and (9) we bound from above the term $\|A^T(y - y^*) + (z - z^*)\|_{Q^{-1}}^2 = *$ giving the inequality

$$* \leq (A^T(y - y^*) + (z - z^*))^T(Q^{-1}g + \delta) + i - h^T(x^* - l) - z^{*T}f.$$

Taking the norm on the right and reordering terms gives

$$\|Q\|_2^{-1}\|A^T(y - y^*) + (z - z^*)\|_2^2 \leq \|A^T(y - y^*) + (z - z^*)\|_2\|Q^{-1}g + \delta\|_2 + \|i - h^T(x^* - l) - z^{*T}f\|_2.$$

This is a quadratic expression in $\|A^T(y - y^*) + (z - z^*)\|_2 = m$

$$m^2 - m\|Q^{-1}g + \delta\|_2\|Q\|_2 - \|i - h^T(x^* - l) - z^{*T}f\|_2\|Q\|_2 \leq 0.$$

It has two roots, but only one is greater than zero and bounds $\|A^T(y - y^*) + (z - z^*)\|_2 (= m)$ from above

$$m \leq \frac{\|Q^{-1}g + \delta\|_2\|Q\|_2/2}{+\sqrt{(\|Q^{-1}g + \delta\|_2\|Q\|_2)^2/4 + \|i - h^T(x^* - l) - z^{*T}f\|_2\|Q\|_2}}. \quad (10)$$

This can be expressed as

$$\|A^T(y - y^*) + (z - z^*)\|_2 \leq a + \sqrt{a^2 + d} \quad (11)$$

where a and d are defined as above. This proves (6). To prove the primal bound we multiply equation (8) from the left with Q^{-1}

$$(x - x^*) = Q^{-1}(A^T(y - y^*) + (z - z^*) - g).$$

Taking norms gives the inequality

$$\|x - x^*\|_2 \leq \|Q^{-1}\|_2\|A^T(y - y^*) + (z - z^*)\|_2 + \|Q^{-1}g\|_2. \quad (12)$$

Combining the dual bound (11) and (12) we get the final primal bound

$$\|x - x^*\|_2 \leq \lambda_{\min}(Q)(a + \sqrt{a^2 + d}) + \lambda_{\min}(Q)\|g\|_2$$

which proves (7). \square

Note that $\lambda_{\max}(Q)\lambda_{\min}(Q)$ is the condition number of Q . The above assumption and lemmas can be summarized to a statement about the convergence of the algorithm for a strictly convex QP.

Theorem 9 (Rate of convergence). *Algorithm 1 with corresponding input and using a QP solver satisfying Assumption 5 solving the QP (P) that is also strictly convex has a linear rate of convergence with a factor of $\tilde{\epsilon}^{1/2}$ for the primal iterates, i.e.*

$$\|x_k - x^*\| \leq \tilde{\epsilon}^{1/2}\|x_{k-1} - x^*\|,$$

with x^* being the unique solution of (P).

Proof. By Assumption 5 and Lemma 6 we know that the right-hand side errors of the KKT conditions are bounded by

$$\|e\| \leq \tilde{\epsilon}^k, \|g\| \leq \tilde{\epsilon}^k, \|f\| \leq \tilde{\epsilon}^k, \|i\| \leq \sigma\tilde{\epsilon}^{2(k-1)}, \|h\| = 0.$$

Here we set the violations h of the inequality KKT multipliers z to zero and count them as additional dual violations g for simplicity. Also note that in Lemma 8 the bound is just depending on the norm of the right-hand side violation vectors, two different

violation vectors with the same norm give the same bound. Therefore we just consider the norms. Combining the above with Lemma 8 we get

$$\|x_k - x^*\| \leq c_1 \tilde{\epsilon}^k + \sqrt{c_2 \tilde{\epsilon}^k + c_3 \tilde{\epsilon}^{2k}}$$

for the primal iterate in iteration k with constants

$$\begin{aligned} c_1 &= \lambda_{\min}(Q)\lambda_{\max}(Q) \left(\left(\frac{1}{\lambda_{\max}(Q)} + \frac{\lambda_{\min}(Q)}{2} \right) + \frac{1}{(2\sigma_{\min}(A))} \right) \\ c_2 &= \lambda_{\max}(Q)\|z^*\| \\ c_3 &= (c_1 - \lambda_{\min}(Q))^2 + \lambda_{\max}(Q)\sigma/\tilde{\epsilon}^2. \end{aligned}$$

Looking at the quotient

$$\frac{\|x_k - x^*\|}{\|x_{k-1} - x^*\|} \leq \frac{c_1 \tilde{\epsilon}^k + \sqrt{c_2 \tilde{\epsilon}^k + c_3 \tilde{\epsilon}^{2k}}}{c_1 \tilde{\epsilon}^{k-1} + \sqrt{c_2 \tilde{\epsilon}^{k-1} + c_3 \tilde{\epsilon}^{2(k-1)}}}$$

and seeing that

$$\frac{\|x_k - x^*\|}{\|x_{k-1} - x^*\|} \leq \frac{\tilde{\epsilon}^{k/2}(c_1 \tilde{\epsilon}^{k/2} + \sqrt{c_2 + c_3 \tilde{\epsilon}^k})}{\tilde{\epsilon}^{(k-1)/2}(c_1 \tilde{\epsilon}^{(k-1)/2} + \sqrt{c_2 + c_3 \tilde{\epsilon}^{k-1}})} = \tilde{\epsilon}^{1/2} \gamma_k$$

with $\gamma_k \leq 1$ proves the result. \square

This theoretical investigation shows us two things. First, we have linear residual convergence with a rate of $\tilde{\epsilon}$. In contrast to usual convergence results our algorithm achieves this rate in practice by the use of rational computations if the floating-point solver delivers solutions of the quality specified in Assumption 5. This is also checked by the rational residual calculation in our algorithm in every iteration. Second, this residual convergence implies primal iterate convergence with a linear rate of $\tilde{\epsilon}^{1/2}$ for strictly convex QPs.

4 Implementation

Following previous work [9] on the LP case we implemented Algorithm 1 in the same framework within the `SoPlex` solver [17], version 2.2.1.2, using the GNU multiple precision library (GMP) [11] for rational computations, version 6.1.0. As underlying QP solver we use the active-set solver `qpOASES` [4] version 3.2. This version of `qpOASES` was originally designed for small to medium QPs (up to 1,000 variables and constraints). Furthermore, we implemented an interface to a pre-release version of `qpOASES` 4.0, which can handle larger, sparse QPs of a size up to 40,000 variables and constraints. Compared to the matured `qpOASES` 3.2, this version is not yet capable of hotstarts and in some cases less robust. Nevertheless, it allows us to study the viability of iterative refinement on larger QPs. The source code of our implementation is available for download in a public repository.¹

In order to treat general QPs with inequalities, our implementation recovers the form (P) by adding one slack variable per inequality constraint. Note that not only lower, but also upper bounds on the variables need to be considered. However, this is a straightforward modification to our algorithm and realized in the implementation.

One advantage of using the active-set QP solver `qpOASES` is the returned basis information. We use the basis in three aspects: first, to calculate dual and complementary slack violations; second, to explicitly set nonbasic variables to their lower bounds after the refinement step in *Line 16* of Algorithm 1; and third, to compute a rational solution

¹<https://github.com/TobiasWeber/QPRefinement>

Table 1: IQPR parameters

parameter set	s1	s2	s3	s4	s5
qpOASES version	3.2	3.2	4.0	4.0	3.2
primal tolerance (ϵ_P)	1e-100	1e-100	1e-100	1e-100	1e-10
dual tolerance (ϵ_D)	1e-100	1e-100	1e-100	1e-100	1e-10
maxscaleincrement (α)	1e12	1e12	1e12	1e12	1e12
sparse	no	no	yes	yes	no
max num backstepping (l_{max})	10	10	10	10	1
refinement limit (k_{max})	300	50	50	50	10
ratfac minstalls	2	0	0	51	30

defined by the corresponding system of linear equations. This is solved by a standard LU factorization in rational arithmetic. If the resulting primal-dual solution is verified to be primal and dual feasible, the algorithm can terminate early with an exact optimal basic solution.

Since the LU factorization can be computationally expensive, we only perform this step if we believe the basis to be optimal. When the QP solver returns the same basis as “optimal” for several iterations this can be used as a heuristic indicator that the basis might be truly optimal, even if the iteratively corrected numerical solution is not yet exact. Hence, the number of consecutive iterations with the same basis is used to trigger a rational basis system solve. This can be controlled by a threshold parameter called “ratfac minstalls”, see Table 1.

If the floating-point solver fails to compute an approximately optimal solution, we decrease the scaling factor by two orders of magnitude and try to solve the resulting QP again. The scaling factor is reduced either until the maximum number of backstepping rounds is reached or until the next backstepping round would result in a scaling factor lower than in the last refinement iteration ($k - 1$).

Currently, the implementation has no detection mechanism for infeasible or unbounded QPs. Because the testset at hand contains only convex and feasible QPs, this does not affect the numerical experiments. The default parameter set (s1) of our implementation is given in Table 1. The other four parameter sets (s2-s5) are used for our numerical experiments to derive either exact or inexact solutions.

We exploit the different features of the two qpOASES versions. Version 3.2 has hotstart capabilities that allow to reuse the internal basis system factorization of the preceding optimal basis. Therefore we start in the old optimal basis and build on the progress made in the previous iterations instead of solving the QP from scratch at every iteration. Additionally we increase the termination tolerance and relax other parameters that ensure a reliable solve. This speeds up the solving process and is possible because the inaccuracies, introduced by this in the floating-point solution, are detected anyway and handed back to the QP solver in the next iteration for correction. If the QP solver fails we simply change to reliable settings and resolve the same QP from the same starting basis before downscaling. Hence, in Algorithm 1 each ‘solve’ statement means: try fast settings first and if this fails switch to slow and reliable settings of qpOASES 3.2. These two sets of options are given in Table 2.

For the pre-release version 4.0 we use default settings and no resolves. We either factorize after each iteration or not at all (see Table 1).

Table 2: qpOASES options (version 3.2)

Option	Fast	Reliable
Standard settings set	MPC	Reliable
NZCTests	enabled	enabled (default)
DriftCorrection	enabled	enabled (default)
Ramping	enabled	enabled (default)
terminationTolerance	1e-3	1.1105e-9 (default)
numRefinementSteps	0 (default)	10
enableFullLITests	0	0

5 Numerical results

For the numerical experiments the standard testset of Maros and Mészáros [14] is used. It contains 138 convex QPs that feature between two and about 90,000 variables. The number of constraints varies from one to about 180,000 and the number of nonzeros ranges between two and about 550,000.

We perform two different experiments. The goal of the first experiment is to solve as many QPs from the testset as precisely as possible in order to analyze the iterative refinement procedure computationally and to provide exact reference solutions for future research on QP solvers. In the second experiment we want to compare qpOASES (version 3.2, no QP refinement, one solve, default settings) to low accuracy refinement (low tolerance of 1e-10 in Algorithm 1, using also qpOASES 3.2). This allows us to investigate whether refinement could also be beneficial in cases that do not require extremely high accuracy, but a strictly guaranteed solution tolerance in shortest possible runtime.

Experiment 1 We use the three different parameter sets (s2-s4) given in Table 1 to calculate exact solutions. The first set (s2) contains a primal and dual termination tolerance of 1e-100, enables rational factorization in every iteration, and allows for 50 refinements and 10 backsteppings using a dense QP formulation with qpOASES version 3.2. In contrast the other two sets (s3, s4) with qpOASES version 4.0 use a sparse QP formulation, either with factorization in every iteration or without factorization.

Table 3 states for each setting the number of instances which it solved exactly, for which tolerance 1e-100 was reached, and for which it failed to produce a high-precision solution. In total these three strategies could solve 91 out of the 138 QPs in the testset *exactly* and 39 instances within tolerance 1e-100. For eight instances no high-precision solution was computed. These “virtual best” results stated in the fifth column consider for each QP the result of the individual parameter sets that resulted in the smallest violation. It should be emphasized that for each of the three parameter sets there exists at least one instance for which it produced the most accurate solution.

The last column reports the average number of nonzeros of the QPs in the three “virtual best” categories. This suggests that for problems with less nonzeros a higher accuracy was reached. Furthermore, one sees that the entries in the second column (set s2) do not sum to 138 because with the dense QP formulation some of the problems do not return from the cluster due to memory limitations. Hence the set s2 fails in total on 32 instances. For the parameter set s4 without rational factorization we see that one QP is solved by chance exactly while for all others the algorithm terminates with violations greater zero.

In order to solve the 197 (=33+45+118) QPs to high precision the algorithm needed on average 8.84 refinements. This confirms the linear convergence because we bounded the increase of the scaling factor in each iteration by $\alpha = 10^{12}$ and terminate after reaching a tolerance of 10^{-100} . If qpOASES would consistently return solutions with an

Table 3: Results for the three exact parameter sets (s2-s4) over all 138 QPs in the testset: number of instances according to terminal solution accuracy for each setting, for the virtual best setting, and the average number of nonzeros over the instances in the “best” categories.

Accuracy reached	s2	s3	s4	best	avg. nnzs
Exact (no viol.)	73	74	1	91	6.76e+03
High ($\leq 1e-100$)	33	45	118	39	1.45e+04
Fail ($> 1e-100$)	11	18	18	8	9.34e+04

accuracy of 10^{-12} we would expect the algorithm to need 9 iterations ($100/12 \approx 8.33 \dots$ rounded up). We see that `qpOASES` usually delivers solutions of a tolerance below 10^{-12} .

Detailed results can be found in the Appendix in Tables 5, 6, and 7. If an exact solution is found `qpOASES` usually returns the optimal basis in the first three iterations (refinements). Subsequently, the corresponding basis system is solved exactly by a rational LU factorization. For six problems we found that the objective values given in [14] differ from our results by more than $1e-7$: GOULDQP2, HS268, S268, HUESTIS, HUESMOD, and LISWET8. This might be due to the use of a floating-point QP solver with termination tolerance about $1e-7$ when originally computing the values reported. The precise objective value can be found in the online material associated with this paper.

Experiment 2 In the following the iterative refinement algorithm is set to a termination tolerance 10^{-10} and the rational factorization of the basis system is disabled. The refinement limit is set to 10 and the backstepping limit is set to one (parameter set s5). We compare this implementation to `qpOASES 3.2` with the three predefined `qpOASES` settings (MPC, Default, Reliable) that include termination tolerances of $2.2210e-7$, $1.1105e-9$, and $1.1105e-9$, respectively. For these fast solves we select only part of the testset, including the 73 problems that have no more than 1,000 variables and constraints. This corresponds to the problem sizes for which `qpOASES 3.2` was originally designed. In order to allow for a meaningful comparison of runtimes, the evaluation only considers QPs which were solved by all three `qpOASES 3.2` settings and by refinement to “optimality”, where optimality was certified by `qpOASES 3.2` (with its internal floating-point checks) or rational checks in our algorithm, respectively.

An overview over the performance results is given in Table 4. We report runtime, QP solver iterations, and the final tolerance reached, each time as arithmetic and shifted geometric mean. To facilitate a more detailed analysis, we consider the series of subsets “ $> t$ ” of instances, for which at least one algorithm took more than t seconds. Equivalently, we exclude the QPs for which all settings took at most 0.01 s, 0.1 s, 1 s, and 10 s seconds. Defining the exclusion by all instead of one method only avoids a biased definition of these sets of increasing difficulty.

The results show that in no case the mean runtime of the refinement algorithm is larger than the runtime of `qpOASES` with reliable setting. At the same time, the accuracy reached is always significantly higher. Compared to `qpOASES Default`, which results in an even lower level of precision, refinement is faster in arithmetic and slightly slower in shifted geometric mean. The QP solver iterations of the refinement are comparable to the MPC setting. When looking at the different subsets we see that for QPs with larger runtime the refinement approach performs relatively better (smaller runtime, iterations and lower tolerance) than the three `qpOASES 3.2` standard settings. The refinement guarantees the tolerance of $1e-10$ if it does not fail. To achieve this tolerance, for 9 QPs two refinements were necessary, for 21 QPs only one refinement was necessary, and for 35 instances no refinement was necessary at all. The rational computation overhead stated

Table 4: Performance comparison for inexact solves (runtimes are in seconds).

Measure	subset	IQPR s5		qpOASES with standard settings:		
				MPC	Default	Reliable
Time: arith. mean (% rat. time)	all	2.54	(0.16)	1.03	2.77	19.58
	> 0.01	3.25	(0.16)	1.32	3.55	25.08
	> 0.1	4.02	(0.12)	1.64	4.40	31.07
	> 1	5.66	(0.12)	2.31	6.27	44.60
	> 10	7.19	(0.11)	2.77	9.06	69.39
Time: shifted geo. mean, shift=0.01 (% rat. time)	all	0.16	(1.68)	0.08	0.10	0.16
	> 0.01	0.36	(0.98)	0.15	0.20	0.36
	> 0.1	0.60	(0.54)	0.24	0.32	0.64
	> 1	0.94	(0.49)	0.43	0.67	1.66
	> 10	0.54	(1.00)	0.26	0.51	1.51
QP solver iterations: arith. mean	all	283.75		260.53	389.92	386.96
	> 0.01	362.16		332.44	496.91	493.09
	> 0.1	436.67		400.96	591.35	586.96
	> 1	520.91		479.38	765.59	761.56
	> 10	353.00		348.25	837.15	832.75
QP solver iterations: shifted geo. mean, shift=1	all	38.43		36.86	62.08	61.68
	> 0.01	85.18		80.86	113.98	112.72
	> 0.1	108.12		101.95	124.46	123.05
	> 1	105.41		100.22	144.20	142.88
	> 10	36.21		35.23	69.62	69.39
Tolerance: arith. mean	all	1.49e-12		1.29e-08	1.10e-08	2.28e-09
	> 0.01	1.91e-12		1.65e-08	1.40e-08	2.92e-09
	> 0.1	2.10e-12		2.03e-08	1.74e-08	3.62e-09
	> 1	8.89e-13		2.21e-08	2.48e-08	4.98e-09
	> 10	5.29e-14		1.42e-08	3.92e-08	7.32e-09
Tolerance: shifted geo. mean, shift=1e-20	all	1.29e-16		2.14e-12	1.62e-15	4.34e-15
	> 0.01	8.71e-17		1.00e-11	4.91e-15	1.13e-14
	> 0.1	3.57e-17		8.45e-12	6.92e-15	2.10e-14
	> 1	1.94e-17		1.08e-12	2.44e-15	6.02e-15
	> 10	9.36e-19		6.86e-15	3.21e-16	2.45e-16

in brackets after the runtime and is well below 2%. The details are shown in Table 8 in the Appendix. Also note that due to exclusion of fails (which mainly occur with the qpOASES MPC settings) the summarized results have a slight bias towards qpOASES.

6 Conclusion

We presented a novel refinement algorithm and proved linear convergence of residuals and errors. Notably, this theoretical convergence result also carries over to our implementation due to the use of exact rational calculations. We provided high-precision solutions for most of the QPs in the Maros and Mészáros testset, correcting inaccuracies in optimal solution values reported in the literature. This is beneficial for future research on QP solvers that are evaluated on this testset.

In a second experiment we saw that iterative refinement provides proven tolerance

solutions with smaller or equal computation times compared to qpOASES with “Reliable” solver settings. It can therefore be used as tool to increase the reliability and speed of standard floating-point QP solvers.

If optimal solutions are needed for rigorous reasoning or to make decisions in the real world the algorithm presented is useful because it is able to fully ensure a specified tolerance. This tolerance then can be adapted to the necessity of the application at hand. At the same time this comes with little overhead in rational computation time, which is important for practical applications.

Regarding algorithmic research and solver development, our framework also provides the possibility to compare different floating-point QP solvers by looking at the number of refinements needed with each solver to detect optimal bases or solutions of a specified tolerance as a measure for solver accuracy. Solver robustness can be checked precisely because violations are computed in rational precision. In the future, the implementation should be extended for the detection of unbounded or infeasible QPs. Also one could try more general variable transformations, e.g. having a different scaling factor for each variable. As a concluding remark, we hope that the idea of checking numerical results of floating-point algorithms in exact or safe arithmetic will become a future trend when applying or analyzing numerical algorithms.

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Appendix

Table 5: Detailed results for exact solve of large QP set with parameter set s2:

Iter.=Iterations, Tol.=Tolerance, Ref.=Refinements,
Back.=Backstepping, Res.=Resolves

QP Name	Status	Time [s]	Iter. [#]	Tol. [-]	Ref. [#]	Back. [#]	Res. [#]
GOULDQP2	inconsistent	6.70e+00	585	00	2	0	0
GOULDQP3	optimal	1.84e+00	176	00	0	0	0
AUG3DCQP	optimal	2.19e+02	540	00	1	0	0
DUALC8	optimal	3.90e-01	13	00	0	0	0
QSCFXM3	optimal	3.20e+02	2510	1.77e-107	10	0	0
QSCFXM2	optimal	8.13e+01	1891	1.25e-108	10	0	0
DUALC1	optimal	1.10e-01	31	00	0	0	0
DUALC2	optimal	7.00e-02	28	00	0	0	0
DUALC5	optimal	7.00e-02	3	00	0	0	0
QPCSTAIR	optimal	2.76e+00	257	00	0	0	0
QPCBOEI2	optimal	2.30e-01	175	00	0	0	0
QPCBOEI1	optimal	3.64e+00	435	00	1	0	0
QSCORPIO	optimal	2.43e+00	233	1.08e-101	7	0	0
QBRANDY	optimal	1.07e+00	450	4.86e-108	8	0	0
CONT-100	timeout	1.08e+04	3	NaN	7	6	0
CONT-101	timeout	1.08e+04	2	NaN	7	6	0
HS268	inconsistent	00	0	00	0	0	0
QETAMACR	optimal	4.75e+00	559	5.17e-102	9	0	0
QSTANDAT	optimal	2.64e+01	1222	00	3	0	0
QBORE3D	optimal	8.70e-01	536	1.97e-111	9	0	0
QAFIRO	optimal	00	30	6.15e-107	7	0	0
ZECEVIC2	optimal	00	3	00	0	0	0
VALUES	optimal	1.00e-01	143	00	2	0	1
QSCAGR7	optimal	1.40e-01	329	00	0	0	0
DUAL3	optimal	1.90e+00	14	00	1	0	0
DUAL2	optimal	1.05e+00	4	00	1	0	0
DUAL1	optimal	2.60e-01	26	00	1	0	0
LASER	optimal	5.93e+02	2838	00	0	0	0
DTOC3	fail	1.91e+04	0	4.40e-15	0	0	0
DUAL4	optimal	2.10e-01	13	00	0	0	0
CONT-050	optimal	4.31e+03	1	00	0	0	0
QSCSD1	optimal	8.78e+00	2054	00	1	0	0
CVXQP2-S	optimal	1.00e-02	62	00	0	0	0
QSCSD6	optimal	1.07e+02	6015	4.11e-101	9	0	0
QBANDM	optimal	2.93e+00	1164	00	0	0	0
CVXQP2-M	optimal	2.60e+01	651	00	0	0	0
AUG3DC	optimal	2.19e+02	0	00	0	0	0
MOSARQP1	optimal	4.45e+02	1528	00	0	0	0
QPCBLEND	optimal	6.00e-02	66	00	1	0	0
HS76	optimal	00	4	00	0	0	0
EXDATA	optimal	8.96e+03	6738	00	1	0	0
CVXQP1-M	optimal	1.68e+01	412	00	0	0	0
KSIP	optimal	3.16e+01	1080	00	1	0	0
HS118	optimal	00	24	00	0	0	0
QSCFXM1	optimal	8.05e+00	801	1.13e-112	11	0	1
QADLITTL	optimal	9.00e-02	232	00	0	0	0
QSHARE2B	optimal	1.90e-01	359	00	1	0	0
STADAT3	timeout	1.83e+04	2144	NaN	0	0	1
STADAT1	optimal	8.01e+03	9995	00	0	0	0
S268	inconsistent	00	0	00	0	0	0
QPTEST	optimal	00	1	00	0	0	0

QSHIP08S	optimal	7.39e+02	3997	1.86e-110	9	0	0
QSHARE1B	optimal	5.10e-01	782	00	1	0	0
QFFFFFF80	error	4.48e+01	1079	NaN	9	3	5
BOYD2	abort	NaN	NaN	NaN	NaN	NaN	NaN
BOYD1	abort	NaN	NaN	NaN	NaN	NaN	NaN
STADAT2	optimal	6.44e+03	6527	00	1	0	0
QPILOTNO	optimal	5.73e+02	7442	1.99e-102	13	0	0
AUG3D	optimal	3.49e+03	0	2.56e-113	8	0	0
QSHIP08L	optimal	3.71e+03	7911	3.68e-102	8	0	0
Q25FV47	optimal	3.73e+02	7362	00	0	0	0
QSCAGR25	optimal	6.17e+00	1076	00	0	0	0
QSCSD8	optimal	1.56e+03	19564	2.22e-104	8	0	0
QSEBA	optimal	2.66e+01	1677	00	0	0	0
CVXQP3.L	timeout	1.08e+04	2990	NaN	1	0	0
CVXQP3.M	optimal	5.95e+00	231	00	1	0	0
CVXQP3.S	optimal	00	22	00	0	0	0
QSHIP04L	optimal	3.98e+02	4847	1.67e-106	8	0	0
STCQP2	optimal	4.20e+02	105	00	0	0	0
STCQP1	optimal	6.04e+02	353	1.05e-103	7	0	0
QISRAEL	optimal	3.80e-01	290	00	0	0	0
QFORPLAN	optimal	2.20e+00	1174	00	0	0	0
HUESTIS	inconsistent	9.78e+03	554	00	0	0	0
QGROW15	optimal	8.11e+00	632	2.54e-105	8	0	0
QSHIP12L	optimal	8.39e+03	9765	4.22e-109	8	0	1
HS35	optimal	00	1	00	0	0	0
YAO	optimal	6.60e+02	2001	00	1	0	0
QSCTAP1	optimal	1.12e+01	1474	2.63e-103	8	0	0
QSCTAP3	optimal	2.16e+03	6964	2.49e-101	8	0	0
QSCTAP2	optimal	8.60e+02	3862	6.58e-113	10	0	0
CVXQP1.S	optimal	4.00e-02	36	00	0	0	0
TAME	optimal	00	0	00	0	0	0
PRIMALC2	optimal	1.70e-01	237	00	0	0	0
CVXQP1.L	fail	1.58e+04	4010	55500	0	0	0
PRIMALC1	optimal	1.10e-01	234	00	0	0	0
PRIMALC5	optimal	2.30e-01	288	00	0	0	0
QSIERRA	error	9.96e+02	6421	NaN	0	0	1
LOTSCHD	optimal	00	5	00	0	0	0
PRIMALC8	optimal	1.86e+00	515	00	0	0	0
QGROW22	optimal	3.29e+01	944	2.86e-109	10	0	0
QGFRDXPN	optimal	2.93e+01	1423	00	0	0	0
MOSARQP2	optimal	2.14e+01	332	00	0	0	0
QSHIP04S	optimal	1.30e+02	2908	2.11e-107	8	0	1
GENHS28	optimal	00	0	00	0	0	0
HS35MOD	optimal	00	0	00	0	0	0
HS21	optimal	00	3	00	0	0	0
PRIMAL2	optimal	2.66e+00	94	00	0	0	0
AUG3DQP	optimal	3.09e+03	324	2.15e-110	8	0	0
QSHIP12S	optimal	1.18e+03	3821	2.30e-109	8	0	0
PRIMAL3	optimal	4.37e+00	117	00	0	0	0
QRECIPE	optimal	7.00e-02	48	9.74e-110	7	0	0
QGROW7	optimal	8.30e-01	298	7.99e-112	8	0	0
PRIMAL1	optimal	5.10e-01	77	00	0	0	0
PRIMAL4	optimal	2.10e+01	88	00	0	0	0
QSHELL	optimal	1.19e+02	3306	7.69e-109	9	0	1
QBEACONF	optimal	9.10e-01	305	8.07e-110	9	0	0
DPKLO1	optimal	2.23e+00	0	00	0	0	0
HS51	optimal	00	0	00	0	0	0

HS52	optimal	00	0	00	0	0	0
HS53	optimal	00	0	00	0	0	0
QSTAIR	optimal	1.34e+01	1136	7.18e-111	9	1	2
QSC205	optimal	7.80e-01	106	1.50e-107	8	0	0
HUES-MOD	inconsistent	9.41e+03	554	00	0	0	0
QSCRS8	optimal	4.92e+01	2016	00	1	0	0
QE226	optimal	4.66e+00	1396	1.71e-101	8	0	0
CONT-300	abort	NaN	NaN	NaN	NaN	NaN	NaN
QCAPRI	optimal	2.95e+00	1051	1.76e-106	8	0	1

Table 6: Detailed results for exact solve of large QP set with parameter set s3:

Iter.=Iterations, Tol.=Tolerance, Ref.=Refinements,
Back.=Backstepping, Res.=Resolves

QP Name	Status	Time [s]	Iter. [#]	Tol. [-]	Ref. [#]	Back. [#]	Res. [#]
GOULDQP2	inconsistent	2.40e-01	0	1.50e-110	7	0	0
GOULDQP3	optimal	1.10e-01	0	00	0	0	0
LISWET12	optimal	6.32e+01	0	00	0	0	0
LISWET11	optimal	5.43e+01	0	00	0	0	0
LISWET10	optimal	6.45e+02	0	1.60e-105	15	0	0
AUG3DCQP	optimal	1.95e+01	0	00	0	0	0
DUALC8	optimal	1.90e-01	0	00	0	0	0
QSCFXM3	optimal	1.46e+00	0	3.59e-101	8	0	0
QSCFXM2	optimal	7.30e-01	0	5.01e-112	9	0	0
DUALC1	optimal	7.00e-02	0	00	0	0	0
DUALC2	optimal	5.00e-02	0	00	0	0	0
DUALC5	optimal	8.00e-02	0	00	0	0	0
POWELL20	optimal	4.46e+01	0	00	0	0	0
LISWET1	optimal	5.79e+01	0	00	0	0	0
AUG2DCQP	optimal	1.56e+02	0	1.47e-101	8	0	0
QPCBOE1	optimal	5.80e-01	0	5.70e-114	10	0	0
QSCORPIO	optimal	1.60e-01	0	2.31e-101	8	0	0
QBRANDY	optimal	1.80e-01	0	4.04e-106	9	0	0
CONT-100	timeout	1.08e+04	0	NaN	7	6	0
CONT-101	timeout	1.08e+04	0	NaN	7	6	0
HS268	inconsistent	00	0	00	0	0	0
QETAMACR	optimal	1.24e+00	0	3.85e-106	10	0	0
QSTANDAT	optimal	6.00e-02	0	3.62e-107	7	0	0
QBORE3D	inconsistent	1.80e-01	0	NaN	50	0	0
QAFIRO	optimal	00	0	00	0	0	0
QPILOTNO	inconsistent	4.05e+01	0	NaN	50	0	0
ZECEVIC2	optimal	00	0	00	0	0	0
VALUES	optimal	3.00e-02	0	00	0	0	0
QFFFFFF80	optimal	9.90e-01	0	3.05e-114	9	0	0
DUAL3	optimal	7.80e-01	0	00	0	0	0
DUAL2	optimal	5.30e-01	0	00	0	0	0
DUAL1	optimal	1.50e-01	0	00	0	0	0
LASER	optimal	4.15e+01	0	00	0	0	0
DUAL4	optimal	2.00e-01	0	00	0	0	0
CONT-050	optimal	4.22e+03	0	00	0	0	0
QSCSD1	optimal	1.20e-01	0	7.72e-110	7	0	0
CVXQP2.S	optimal	3.00e-02	0	2.25e-110	7	0	0
QSCSD6	optimal	1.80e-01	0	2.69e-111	7	0	0
QBANDM	optimal	2.00e-01	0	1.17e-103	6	0	0
AUG3DC	optimal	1.13e+02	0	00	0	0	0
CVXQP2.M	optimal	1.91e+01	0	00	0	0	0
CVXQP2.L	timeout	1.10e+04	0	NaN	5	4	0
MOSARQP1	optimal	9.60e-01	0	00	0	0	0
QPCBLEND	optimal	3.00e-02	0	00	0	0	0
AUG2DC	timeout	1.08e+04	0	NaN	6	5	0
HS76	optimal	00	0	00	0	0	0
EXDATA	optimal	1.41e+03	0	00	0	0	0
CVXQP1.M	optimal	8.02e+00	0	00	0	0	0
AUG2D	timeout	1.09e+04	0	NaN	1	0	0
KSIP	optimal	2.38e+00	0	00	0	0	0
HS118	optimal	00	0	00	0	0	0

QSCFXM1	optimal	2.00e-01	0	1.79e-112	7	0	0
QADLITTL	optimal	1.00e-02	0	00	0	0	0
QSHARE2B	optimal	4.00e-02	0	00	0	0	0
STADAT3	optimal	4.02e+01	0	00	0	0	0
STADAT1	optimal	9.82e+00	0	00	0	0	0
S268	inconsistent	00	0	00	0	0	0
QPTEST	optimal	00	0	00	0	0	0
QSHIP08S	optimal	1.21e+00	0	2.31e-108	9	0	0
QSHARE1B	optimal	7.00e-02	0	00	0	0	0
QSCAGR7	optimal	2.00e-02	0	3.71e-107	8	0	0
BOYD2	abort	NaN	NaN	NaN	NaN	NaN	NaN
STADAT2	optimal	9.89e+00	0	00	0	0	0
DTOC3	optimal	2.61e+03	0	00	0	0	0
AUG3D	error	7.60e+00	0	NaN	1	0	0
QSHIP08L	optimal	2.14e+00	0	2.31e-110	7	0	0
Q25FV47	optimal	9.14e+00	0	3.75e-114	9	0	0
QSCAGR25	optimal	3.20e-01	0	1.06e-104	7	0	0
QSCSD8	optimal	1.16e+00	0	00	0	0	0
QSEBA	optimal	2.40e-01	0	1.15e-103	9	0	0
UBH1	optimal	1.36e+02	0	00	0	0	0
CVXQP3.L	error	7.59e+03	0	NaN	6	1	0
CVXQP3.M	optimal	2.33e+00	0	00	0	0	0
CVXQP3.S	reached	4.80e-01	0	NaN	50	0	0
QSHIP04L	optimal	6.00e-01	0	7.13e-110	9	0	0
STCQP2	optimal	2.58e+01	0	5.65e-102	9	0	0
STCQP1	optimal	4.71e+01	0	1.91e-107	11	0	0
QISRAEL	optimal	1.10e-01	0	00	0	0	0
QFORPLAN	optimal	2.30e-01	0	1.88e-113	8	0	0
HUESTIS	inconsistent	4.02e+01	0	00	0	0	0
QGROW15	optimal	3.70e-01	0	00	0	0	0
QSHIP12L	optimal	2.78e+00	0	3.71e-113	8	0	0
HS35	optimal	00	0	00	0	0	0
YAO	optimal	1.53e+00	0	00	0	0	0
QPCSTAIR	optimal	9.60e-01	0	1.04e-109	11	0	0
QSCTAP1	optimal	1.80e-01	0	6.15e-106	7	0	0
QSCTAP3	optimal	1.04e+00	0	00	0	0	0
QSCTAP2	optimal	5.50e-01	0	5.86e-111	6	0	0
CVXQP1.S	optimal	2.00e-02	0	00	0	0	0
TAME	optimal	00	0	00	0	0	0
PRIMALC2	optimal	1.00e-02	0	00	0	0	0
CVXQP1.L	optimal	6.64e+03	0	1.90e-101	9	0	0
PRIMALC1	optimal	1.00e-02	0	00	0	0	0
CONT-201	timeout	1.08e+04	0	NaN	7	6	0
CONT-200	timeout	1.08e+04	0	NaN	7	6	0
PRIMALC5	optimal	1.00e-02	0	00	0	0	0
QSIERRA	error	9.50e-01	0	NaN	6	0	0
AUG3DQP	optimal	7.62e+00	0	00	0	0	0
PRIMALC8	optimal	2.00e-02	0	00	0	0	0
QGROW22	optimal	9.00e-01	0	00	0	0	0
QGFRDXPN	optimal	4.50e-01	0	3.34e-104	9	0	0
MOSARQP2	optimal	5.20e-01	0	00	0	0	0
QSHIP04S	optimal	4.30e-01	0	5.88e-109	9	0	0
GENHS28	optimal	00	0	00	0	0	0
HS35MOD	optimal	00	0	00	0	0	0
HS21	optimal	00	0	00	0	0	0
QRECIPE	inconsistent	4.00e-02	0	NaN	50	0	0
LOTSCHD	optimal	00	0	00	0	0	0

QSHIP12S	optimal	03	0	2.82e-104	9	0	0
QGROW7	optimal	2.20e-01	0	00	0	0	0
PRIMAL2	optimal	7.10e-01	0	00	0	0	0
PRIMAL3	optimal	1.45e+00	0	00	0	0	0
PRIMAL1	optimal	2.00e-01	0	00	0	0	0
PRIMAL4	optimal	7.60e-01	0	00	0	0	0
QPCBOEI2	optimal	1.00e-01	0	00	0	0	0
QSHELL	optimal	8.20e-01	0	3.16e-103	9	0	0
QBEACONF	inconsistent	1.60e-01	0	NaN	50	0	0
DPKLO1	optimal	2.26e+00	0	00	0	0	0
HS51	optimal	00	0	3.14e-108	6	0	0
HS52	optimal	00	0	00	0	0	0
HS53	optimal	00	0	00	0	0	0
QSTAIR	optimal	5.80e-01	0	4.32e-101	8	0	0
AUG2DQP	timeout	1.08e+04	0	NaN	6	5	0
QSC205	optimal	3.00e-01	0	1.27e-107	11	0	0
HUES-MOD	inconsistent	2.13e+01	0	00	0	0	0
QSCR8	optimal	3.60e-01	0	1.58e-108	13	0	0
CONT-300	abort	NaN	NaN	NaN	NaN	NaN	NaN
QE226	optimal	1.90e-01	0	4.36e-107	8	0	0
LISWET9	optimal	6.41e+01	0	00	0	0	0
LISWET8	inconsistent	5.70e+01	0	00	0	0	0
LISWET7	optimal	5.49e+01	0	00	0	0	0
LISWET6	optimal	3.25e+02	0	3.68e-102	14	0	0
LISWET5	optimal	3.24e+02	0	4.27e-106	15	0	0
LISWET4	optimal	3.18e+02	0	2.60e-107	15	0	0
LISWET3	optimal	3.06e+02	0	1.20e-101	14	0	0
LISWET2	optimal	7.05e+02	0	4.17e-107	17	0	0
QCAPRI	optimal	1.10e-01	0	00	0	0	0

Table 7: Detailed results for exact solve of large QP set with parameter set s4:

Iter.=Iterations, Tol.=Tolerance, Ref.=Refinements,
Back.=Backstepping, Res.=Resolves

QP Name	Status	Time [s]	Iter. [#]	Tol. [-]	Ref. [#]	Back. [#]	Res. [#]
GOULDQP2	inconsistent	2.20e-01	0	1.50e-110	7	0	0
GOULDQP3	optimal	3.60e-01	0	4.48e-108	11	0	0
LISWET12	optimal	5.75e+02	0	6.47e-106	12	0	0
LISWET11	optimal	5.87e+02	0	4.47e-103	13	0	0
LISWET10	optimal	6.38e+02	0	1.60e-105	15	0	0
AUG3DCQP	optimal	4.73e+00	0	1.52e-102	6	0	0
DUALC8	optimal	2.20e-01	0	7.30e-105	6	0	0
QSCFXM3	optimal	1.50e+00	0	3.59e-101	8	0	0
QSCFXM2	optimal	6.80e-01	0	5.01e-112	9	0	0
DUALC1	optimal	5.00e-02	0	8.05e-106	6	0	0
DUALC2	optimal	7.00e-02	0	1.44e-106	6	0	0
DUALC5	optimal	6.00e-02	0	6.55e-107	6	0	0
POWELL20	optimal	1.28e+02	0	2.82e-110	9	0	0
LISWET1	optimal	7.68e+02	0	1.01e-107	15	0	0
AUG2DCQP	optimal	1.54e+02	0	1.47e-101	8	0	0
QPCBOE1	optimal	5.00e-01	0	5.70e-114	10	0	0
QSCORPIO	optimal	1.60e-01	0	2.31e-101	8	0	0
QBRANDY	optimal	1.80e-01	0	4.04e-106	9	0	0
CONT-100	optimal	1.08e+03	0	2.86e-102	7	0	0
CONT-101	optimal	1.03e+03	0	5.89e-101	7	0	0
HS268	inconsistent	00	0	6.35e-112	9	0	0
QETAMACR	optimal	1.24e+00	0	3.85e-106	10	0	0
QSTANDAT	optimal	1.10e-01	0	3.62e-107	7	0	0
QBORE3D	inconsistent	1.50e-01	0	NaN	50	0	0
QAFIRO	error	1.00e-02	0	NaN	9	0	0
QPILOTNO	inconsistent	4.02e+01	0	NaN	50	0	0
ZECEVIC2	optimal	00	0	2.66e-110	6	0	0
VALUES	inconsistent	8.00e-02	0	NaN	50	0	0
QFFFFFF80	optimal	9.70e-01	0	3.05e-114	9	0	0
DUAL3	optimal	6.00e-02	0	2.48e-103	6	0	0
DUAL2	optimal	6.00e-02	0	1.54e-101	6	0	0
DUAL1	optimal	7.00e-02	0	3.21e-103	10	0	0
LASER	optimal	2.94e+00	0	7.30e-105	12	0	0
DUAL4	optimal	4.00e-02	0	1.37e-104	6	0	0
CONT-050	optimal	5.33e+01	0	2.25e-108	8	0	0
QSCSD1	optimal	9.00e-02	0	7.72e-110	7	0	0
CVXQP2.S	optimal	2.00e-02	0	2.25e-110	7	0	0
QSCSD6	optimal	2.30e-01	0	2.69e-111	7	0	0
QBANDM	optimal	2.40e-01	0	1.17e-103	6	0	0
AUG3DC	optimal	6.38e+00	0	7.59e-108	7	0	0
CVXQP2.M	optimal	9.80e-01	0	1.12e-108	9	0	0
CVXQP2.L	optimal	5.51e+02	0	9.00e-109	9	0	0
MOSARQP1	optimal	2.14e+00	0	2.01e-115	10	0	0
QPCBLEND	optimal	3.00e-02	0	4.29e-114	9	0	0
AUG2DC	optimal	5.68e+01	0	4.76e-109	7	0	0
HS76	optimal	00	0	3.83e-108	6	0	0
EXDATA	error	5.61e+02	0	NaN	5	0	0
CVXQP1.M	optimal	5.74e+00	0	4.34e-107	9	0	0
AUG2D	error	5.51e+01	0	NaN	1	0	0
KSIP	optimal	2.11e+00	0	3.89e-105	6	0	0
HS118	inconsistent	2.00e-02	0	NaN	50	0	0

QSCFXM1	optimal	1.60e-01	0	1.79e-112	7	0	0
QADLITTL	optimal	3.00e-02	0	2.11e-111	7	0	0
QSHARE2B	optimal	5.00e-02	0	1.65e-105	9	0	0
STADAT3	optimal	1.17e+02	0	8.80e-104	12	1	0
STADAT1	optimal	1.57e+01	0	2.28e-107	8	0	0
S268	inconsistent	00	0	6.35e-112	9	0	0
QPTEST	optimal	00	0	2.66e-110	6	0	0
QSHIP08S	optimal	1.18e+00	0	2.31e-108	9	0	0
QSHARE1B	optimal	4.00e-02	0	5.84e-112	7	0	0
QSCAGR7	optimal	2.00e-02	0	3.71e-107	8	0	0
BOYD2	abort	NaN	NaN	NaN	NaN	NaN	NaN
STADAT2	optimal	1.67e+01	0	2.33e-110	11	0	0
DTOC3	optimal	1.12e+02	0	1.48e-114	7	0	0
AUG3D	error	1.54e+00	0	NaN	1	0	0
QSHIP08L	optimal	2.06e+00	0	2.31e-110	7	0	0
Q25FV47	optimal	9.15e+00	0	3.75e-114	9	0	0
QSCAGR25	optimal	3.20e-01	0	1.06e-104	7	0	0
QSCSD8	optimal	8.62e+00	0	2.23e-106	10	1	0
QSEBA	optimal	3.00e-01	0	1.15e-103	9	0	0
UBH1	optimal	2.04e+02	0	3.28e-111	7	0	0
CVXQP3.L	error	7.29e+03	0	NaN	6	1	0
CVXQP3.M	optimal	1.81e+01	0	3.73e-111	9	0	0
CVXQP3.S	reached	4.50e-01	0	NaN	50	0	0
QSHIP04L	optimal	5.80e-01	0	7.13e-110	9	0	0
STCQP2	optimal	2.55e+01	0	5.65e-102	9	0	0
STCQP1	optimal	4.73e+01	0	1.91e-107	11	0	0
QISRAEL	optimal	1.90e-01	0	9.15e-104	9	0	0
QFORPLAN	optimal	2.30e-01	0	1.88e-113	8	0	0
HUESTIS	inconsistent	3.80e+01	0	6.05e-104	7	0	0
QGROW15	optimal	3.20e-01	0	2.68e-107	9	0	0
QSHIP12L	optimal	2.67e+00	0	3.71e-113	8	0	0
HS35	optimal	00	0	9.00e-106	6	0	0
YAO	optimal	2.32e+01	0	1.58e-106	10	0	0
QPCSTAIR	optimal	9.50e-01	0	1.04e-109	11	0	0
QSCTAP1	optimal	1.90e-01	0	6.15e-106	7	0	0
QSCTAP3	optimal	9.20e-01	0	7.96e-110	6	0	0
QSCTAP2	optimal	5.50e-01	0	5.86e-111	6	0	0
CVXQP1.S	optimal	5.00e-02	0	8.55e-102	8	0	0
TAME	optimal	00	0	3.12e-112	6	0	0
PRIMALC2	optimal	1.00e-02	0	8.59e-107	6	0	0
CVXQP1.L	optimal	6.85e+03	0	1.90e-101	9	0	0
PRIMALC1	optimal	4.00e-02	0	1.56e-104	6	0	0
CONT-201	timeout	1.14e+04	0	NaN	3	0	0
CONT-200	timeout	1.35e+04	0	NaN	4	0	0
PRIMALC5	optimal	1.00e-02	0	1.63e-103	6	0	0
QSIERRA	error	9.50e-01	0	NaN	6	0	0
AUG3DQP	optimal	3.31e+00	0	8.00e-103	6	0	0
PRIMALC8	inconsistent	1.50e-01	0	NaN	50	0	0
QGROW22	optimal	5.80e-01	0	1.77e-107	9	0	0
QGFRDXPN	optimal	4.10e-01	0	3.34e-104	9	0	0
MOSARQP2	optimal	8.30e-01	0	1.11e-107	9	0	0
QSHIP04S	optimal	4.30e-01	0	5.88e-109	9	0	0
GENHS28	optimal	00	0	1.25e-110	6	0	0
HS35MOD	optimal	00	0	4.03e-108	6	0	0
HS21	optimal	00	0	00	0	0	0
QRECIPE	inconsistent	2.00e-02	0	NaN	50	0	0
LOTSCHD	optimal	00	0	2.70e-107	6	0	0

QSHIP12S	optimal	2.92e+00	0	2.82e-104	9	0	0
QGROW7	optimal	1.00e-01	0	4.66e-109	9	0	0
PRIMAL2	optimal	2.70e-01	0	2.38e-103	7	0	0
PRIMAL3	optimal	3.90e-01	0	1.38e-102	6	0	0
PRIMAL1	optimal	1.40e-01	0	1.35e-112	7	0	0
PRIMAL4	optimal	7.20e-01	0	1.06e-112	7	0	0
QPCBOEI2	optimal	1.20e-01	0	6.52e-105	9	0	0
QSHELL	optimal	8.00e-01	0	3.16e-103	9	0	0
QBEACONF	inconsistent	2.10e-01	0	NaN	50	0	0
DPKLO1	optimal	9.00e-02	0	8.39e-108	9	0	0
HS51	optimal	00	0	3.14e-108	6	0	0
HS52	optimal	00	0	4.97e-106	6	0	0
HS53	optimal	00	0	2.34e-108	6	0	0
QSTAIR	optimal	6.60e-01	0	4.32e-101	8	0	0
AUG2DQP	optimal	3.21e+02	0	3.10e-107	7	0	0
QSC205	optimal	2.70e-01	0	1.27e-107	11	0	0
HUES-MOD	inconsistent	1.84e+01	0	4.21e-108	7	0	0
QSCRS8	optimal	3.60e-01	0	1.58e-108	13	0	0
CONT-300	abort	NaN	NaN	NaN	NaN	NaN	NaN
QE226	optimal	2.10e-01	0	4.36e-107	8	0	0
LISWET9	optimal	6.71e+02	0	2.04e-104	10	0	0
LISWET8	inconsistent	6.59e+02	0	1.63e-104	15	0	0
LISWET7	optimal	1.19e+03	0	3.11e-108	37	0	0
LISWET6	optimal	3.17e+02	0	3.68e-102	14	0	0
LISWET5	optimal	3.13e+02	0	4.27e-106	15	0	0
LISWET4	optimal	309	0	2.60e-107	15	0	0
LISWET3	optimal	2.99e+02	0	1.20e-101	14	0	0
LISWET2	optimal	6.99e+02	0	4.17e-107	17	0	0
QCAPRI	optimal	2.70e-01	0	8.03e-116	10	0	0

Table 8: Detailed results for inexact and fast solves of medium QP set with parameter set s5 and the three standard qpOASES option sets: Iter.=Iterations, Tol.=Tolerance

QP Name	Refinement			qpOASES with standard settings:								
	Tol. 1e-12			MPC			Default			Reliable		
	Time	Iter.(Ref.)	Tol.	Time	Iter.	Tol.	Time	Iter.	Tol.	Time	Iter.	Tol.
[s]	[(#)](Ref.)	[-]	[s]	[(#)]	[-]	[s]	[(#)]	[-]	[s]	[(#)]	[-]	
DUAL3	5.0e-02	14(1)	2.5e-17	3.0e-02	14	1.7e-12	6.0e-02	97	1.0e-15	6.0e-02	97	9.3e-16
DUAL2	4.0e-02	4(1)	6.3e-17	3.0e-02	4	3.0e-11	5.0e-02	92	6.1e-16	5.0e-02	92	7.4e-16
DUAL1	3.0e-02	26(1)	5.1e-17	2.0e-02	28	1.1e-11	4.0e-02	75	8.8e-16	2.0e-02	75	7.1e-16
GOULDQP3	1.7e+00	176(0)	7.5e-15	1.5e+00	176	5.9e-13	3.0e+00	740	8.4e-15	1.8e+01	740	8.2e-15
TAME	0	0(0)	1.1e-16	0	0	1.1e-16	0	2	1.9e-16	0	2	1.9e-16
S268	0	0(1)	1.7e-16	0	0	2.6e-12	0	11	8.6e-07	0	12	7.9e-13
DUAL4	1.0e-02	13(0)	1.0e-15	1.0e-02	13	1.5e-11	3.0e-02	62	1.0e-15	2.0e-02	62	8.0e-16
GENHS28	0	0(0)	3.5e-16	0	0	3.5e-16	0	14	6.8e-16	0	14	5.1e-16
QSCSD1	8.8e+00	2054(1)	3.4e-22	6.5e+00	1075	8.8e-11	6.4e-01	204	4.8e-13	5.7e-01	153	1.4e-10
CVXQP2.S	2.0e-02	62(0)	7.5e-14	2.0e-02	60	1.3e-11	1.0e-02	68	9.9e-14	1.0e-02	68	5.8e-14
QPCBLEND	3.0e-02	66(1)	2.2e-16	1.0e-02	64	8.4e-14	2.0e-02	176	7.6e-16	2.0e-02	176	9.7e-16
HS21	0	3(0)	8.8e-16	0	3	1.3e-17	0	1	5.6e-17	0	1	5.6e-17
CVXQP3.M	4.5e+00	231(2)	8.1e-22	3.9e+00	229	5.4e-09	7.9e+01	3867	3.9e-10	3.1e+02	3869	3.2e-10
QBANDM	2.9e+00	1164(0)	1.5e-13	1.6e+00	870	1.6e-08	5.4e+00	1512	2.2e-13	7.7e+00	1512	9.6e-14
QRECIPE	7.0e-02	48(0)	5.9e-15	2.0e-02	42	1.0e-10	2.0e-02	88	1.6e-14	2.0e-02	88	1.6e-14
CVXQP3.S	2.0e-02	22(0)	7.2e-12	2.0e-02	24	5.3e-11	7.0e-02	189	4.7e-13	5.0e-02	181	2.5e-13
CVXQP2.M	1.0e+01	651(0)	1.0e-12	9.5e+00	663	5.7e-11	6.8e+00	712	1.5e-12	4.5e+01	713	8.4e-13
MOSARQP2	1.8e+01	332(0)	1.2e-15	2.5e+00	332	6.3e-13	9.0e+00	1012	1.8e-15	3.2e+02	1012	1.3e-15
QSCORPIO	8.7e-01	233(0)	5.2e-14	1.2e-01	0	NaN	8.7e-01	470	3.2e-11	1.2e+00	469	1.1e-11
QGROW7	4.5e-01	296(1)	1.6e-19	2.8e-01	266	5.1e-08	4.2e-01	340	1.9e-09	4.5e-01	298	3.2e-09
PRIMAL2	3.5e+00	94(0)	8.2e-16	5.2e-01	96	4.0e-11	3.0e+00	742	1.4e-15	8.6e+01	742	1.7e-15
PRIMAL3	3.0e+00	117(0)	1.2e-15	6.9e-01	101	4.8e-11	4.9e+00	841	1.5e-15	1.3e+02	841	1.8e-16
PRIMAL1	3.8e-01	77(0)	1.9e-16	1.7e-01	75	1.8e-11	5.0e-01	399	2.3e-16	6.1e+00	399	1.1e-15
QSCAGR25	7.4e+00	1077(2)	1.8e-18	3.6e+01	0	NaN	6.1e+00	1327	1.1e-11	8.9e+00	1299	1.4e-11
QSCFXM1	4.2e+00	799(2)	1.2e-15	1.7e+00	988	1.3e-07	1.7e+00	580	9.1e-12	2.7e+00	612	1.5e-11
DUALC8	6.0e-01	13(1)	6.1e-19	2.0e-02	11	9.0e-10	1.0e-02	6	5.2e-11	1.0e-02	0	NaN

GOULDQP2	6.5e+00	585(2)	9.0e-21	3.8e+00	573	7.8e-14	1.5e+01	2409	1.1e-09	2.5e+02	2409	1.1e-09
QSCFXM2	4.3e+01	1890(2)	3.8e-18	1.7e+01	2189	1.6e-07	1.7e+01	1454	6.8e-11	2.6e+01	1370	3.9e-11
QBRANDY	5.6e-01	444(0)	4.7e-12	2.8e-01	414	2.5e-08	8.5e-01	854	2.4e-13	1.2e+00	854	3.1e-13
QADLITTL	5.0e-02	234(1)	1.9e-17	3.0e-02	189	5.9e-09	2.0e-02	132	3.3e-13	2.0e-02	124	1.4e-10
QISRAEL	4.1e-01	290(0)	3.1e-12	1.1e-01	360	4.0e-08	8.0e-02	258	4.8e-12	1.2e-01	258	5.0e-12
QFORPLAN	2.2e+00	1180(1)	7.3e-22	1.5e+00	1930	2.4e+06	1.3e+00	796	8.0e-10	1.8e+00	804	7.1e-10
DUALC1	8.0e-02	31(0)	4.4e-12	1.0e-02	31	2.2e-10	1.0e-02	4	6.2e-13	0	4	6.2e-13
DUALC2	1.4e-01	28(1)	1.9e-21	1.0e-02	30	2.2e-09	0	5	2.3e-13	0	5	2.7e-13
DUALC5	1.0e-01	3(0)	3.3e-13	1.0e-02	3	1.3e-09	1.0e-02	5	2.7e-13	0	5	8.7e-14
HS76	0	4(0)	3.2e-17	0	4	2.8e-16	0	4	6.4e-16	0	4	6.4e-16
PRIMALC1	1.7e-01	234(1)	2.7e-22	1.0e-01	222	2.5e-09	2.0e-02	27	6.5e-13	1.0e-02	27	1.0e-12
KSIP	2.4e+01	1080(1)	1.6e-18	1.5e-01	1088	3.6e-15	2.1e-01	1019	1.9e-16	2.0e-01	1019	3.7e-17
QBEOCONF	4.3e-01	304(2)	1.2e-18	2.4e-01	302	2.4e-08	9.0e-02	133	1.3e-11	9.0e-02	133	1.3e-11
HS35MOD	0	0(0)	1.0e-15	0	0	1.0e-15	0	4	1.7e-16	0	4	1.7e-16
HS118	0	24(0)	4.7e-15	0	24	6.8e-13	0	27	6.9e-15	0	27	5.6e-15
DPKLO1	2.0e-02	0(0)	2.7e-14	2.0e-02	0	2.7e-14	1.4e-01	321	5.7e-15	3.1e-01	321	7.3e-15
QPCBOEI2	3.0e-01	175(0)	6.1e-11	7.0e-02	177	7.4e-10	7.0e-02	224	4.2e-10	1.6e-01	224	3.0e-10
QPCBOEI1	3.2e+00	435(2)	2.1e-13	1.1e+00	441	2.2e-09	1.3e+00	652	2.7e-11	7.7e+00	652	3.2e-11
HS35	0	1(0)	3.6e-16	0	1	2.2e-16	0	4	7.8e-16	0	4	3.1e-16
QPCSTAIR	1.3e+00	257(0)	1.6e-11	5.4e-01	239	9.3e-11	2.3e+00	908	8.8e-12	3.7e+00	908	8.1e-12
HS51	0	0(0)	2.5e-16	0	0	2.5e-16	0	5	8.2e-15	0	5	8.2e-15
HS52	0	0(0)	1.2e-15	0	0	1.2e-15	0	10	2.3e-15	0	10	1.1e-15
HS53	0	0(0)	3.9e-16	0	0	3.9e-16	0	9	1.0e-15	0	9	8.3e-16
QSHARE2B	1.2e-01	359(1)	2.0e-13	2.0e-02	355	5.3e-10	6.0e-02	207	1.3e-12	5.0e-02	196	1.2e-12
QSTAIR	3.2e+00	792(0)	6.4e-12	1.3e+00	784	1.9e-08	1.7e+00	740	4.4e-12	2.7e+00	740	4.4e-12
HS268	0	0(1)	1.7e-16	0	0	2.6e-12	0	11	8.6e-07	0	12	7.9e-13
QSC205	2.9e-01	93(1)	4.2e-18	4.0e-02	43	7.6e-08	8.0e-02	215	3.8e-16	8.0e-02	215	4.4e-16
QETAMACR	4.1e+00	558(2)	6.1e-16	2.1e+00	493	2.1e-09	7.9e+00	1354	2.3e-07	2.3e+01	1354	2.3e-07
QGROW15	4.1e+00	629(1)	8.6e-18	2.7e+00	531	1.0e-07	3.3e+00	600	4.3e-09	4.2e+00	589	6.4e-09
QPTEST	0	1(0)	7.4e-16	0	1	1.2e-15	0	2	3.9e-16	0	2	3.9e-16
QSCTAP1	6.8e+00	1374(1)	7.4e-15	3.0e+01	0	NaN	1	500	9.2e-12	1.4e+00	503	1.5e-08
QBORE3D	7.8e-01	522(1)	5.3e-13	2.5e-01	155	NaN	3.0e-01	221	4.6e-13	3.1e-01	221	2.8e-11
QAFIRO	0	30(0)	5.5e-15	0	29	8.4e-11	0	16	3.5e-15	0	16	3.5e-15
QSHARE1B	5.9e-01	782(2)	1.2e-16	1.8e-01	468	2.5e-08	3.4e-01	517	1.2e-09	5.1e-01	497	3.7e-11

ZECEVIC2	0	3(0)	1.2e-16	0	3	1.1e-12	0	2	2.2e-16	0	2	2.2e-16
CVXQP1_S	2.0e-02	36(0)	2.7e-13	2.0e-02	36	4.0e-12	2.0e-02	139	4.4e-13	6.0e-02	139	3.9e-13
QSCAGR7	1.9e-01	329(0)	3.9e-12	6.0e-02	349	3.2e-10	2.2e-01	418	4.6e-12	2.2e-01	418	5.0e-12
PRIMALC2	1.6e-01	237(1)	1.0e-22	1.1e-01	237	6.0e-13	0	10	8.0e-16	0	10	1.7e-13
CVXQP1_M	9.5e+00	412(1)	8.5e-21	6.9e+00	404	2.2e-10	2.4e+01	1705	2.2e-11	1.7e+02	1705	2.3e-11
VALUES	1.0e-01	142(0)	1.5e-12	4.0e-02	0	NaN	5.0e-02	142	4.3e-16	4.0e-02	142	2.4e-15
QE226	3.2e+00	1393(1)	1.1e-13	9.5e-01	1431	2.6e-08	1.2e+00	825	2.4e-14	2.1e+00	813	3.8e-14
PRIMALC5	2.7e-01	288(1)	7.1e-23	1.7e-01	292	3.1e-10	3.0e-02	23	2.5e-14	2.0e-02	23	2.6e-14
LOTSCHD	0	5(0)	8.8e-15	0	5	5.3e-13	0	18	1.8e-14	0	18	2.3e-14
PRIMALC8	2.8e+00	515(1)	3.9e-17	7.0e-01	519	2.3e-09	7.0e-02	25	1.9e-14	5.0e-02	26	4.1e-12
QGROW22	1.5e+01	934(2)	1.5e-20	7.6e+00	621	1.1e-07	1.1e+01	888	3.7e-07	1.5e+01	881	5.0e-08
QFFFFFF80	1.9e+01	1008(1)	2.3e-13	7.8e+00	1005	9.9e-08	2.1e+01	2293	1.6e-11	7.3e+01	1722	NaN
QCAPRI	2.7e+00	1050(1)	3.6e-19	1.1e+00	1008	9.7e-08	6.4e-01	457	4.8e-10	9.1e-01	457	4.3e-10