Dual optimization for Newsvendor-like problem

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January 28, 2021

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1 Introduction

This paper is concerned with minimizing a newsvendor-like objective $f : \mathbb{R}^n \to \mathbb{R}$,

$$
\begin{aligned}
& \min f(\delta, \epsilon) \\
\textbf{s.t.} & \\
& y + \delta - \epsilon = b \\
& y \in \Omega_y \subseteq \mathbb{R}^n, \delta \in \mathbb{R}^n_+, \epsilon \in \mathbb{R}^n_+
\end{aligned}
\tag{1.1}
$$

where f is a convex function of δ, ϵ. The right-hand-side on the binding constraints is in the positive orthant: $b \in \mathbb{R}^n_+$. In the basic settings, let y be the ordering quantity quantities in a multi-item multi-period newsvendor problem, one minimizes the total expected cost:

$$\min_{y \in \mathbb{R}_+} \mathbf{E}\left(h \cdot e^{\mathsf{T}} \max\{y-b, 0\} + p \cdot e^{\mathsf{T}} \max\{b-y, 0\}\right)$$

Once the expectation operator is dropped, it is easy to verify the equivalence of such deterministic version to the problem (1.1) above. This problem is motivated from applications in device maintenance, inventory management, crew scheduling and so on.

Let $\lambda \in \mathbb{R}^n$ be the Lagrangian multiplier, we have the Lagrangian dual function,

$$\begin{aligned}\phi(\lambda) = & \min_{\delta,\epsilon} f(\delta, \epsilon) + \lambda^{\mathsf{T}}\delta - \lambda^{\mathsf{T}}\epsilon + \min_y \lambda^{\mathsf{T}} y - \lambda^{\mathsf{T}} b \\ & \mathbf{s.t.} \\ & \quad y \in \Omega_y \\ & \quad \delta \in \mathbb{R}^n_+, \epsilon \in \mathbb{R}^n_+\end{aligned} \tag{1.2}$$

with two independent subproblems. For δ, ϵ we have a convex optimization problem in the positive orthant. We also assume minimizing the linear objective under $y \in \Omega_y$ can be well-solved. In later sections we show some special cases where Ω_y may be further decomposed into smaller problems.

Denote $f^\star, \phi^\star$ be the optimal objective for primal and dual problem, respectively.

1.1 Affine case

Let $f = p^{\mathsf{T}}\delta + h^{\mathsf{T}}\epsilon, p, h \in \mathbb{R}^n_+$, we have

$$\phi(\lambda) = \min_{\delta,\epsilon} (p+\lambda)^{\mathsf{T}}\delta + (h-\lambda)^{\mathsf{T}}\epsilon + \min_y \lambda^{\mathsf{T}} y - \lambda^{\mathsf{T}} b$$

Then ϕ is unbounded unless $\lambda \in \Lambda$ where $\Lambda = \{\lambda : \lambda \in [-p, h]\}$, in which case

$$\phi(\lambda) = \min_{y \in \Omega_y} \lambda^{\mathsf{T}} y - \lambda^{\mathsf{T}} b,\ \lambda \in \Lambda$$

and $\delta^\star(\lambda), \epsilon^\star(\lambda) = 0$ are corresponding optimizers for any $\lambda \in \Lambda$

2 Dual Optimization

2.1 Conditions for strong duality

It's well known that strong duality does not hold in general. We review some of the cases here. The Lagrangian duality theory can be found in any standard text.

Theorem 2.1. *if Ω_y is convex then the strong duality holds ..., i.e. $\phi^\star = f^\star$*

add justifications here (slater, ...)

A more interesting result is devoted to mixed integer problems. We know Lagrangian relaxation produces a bound up to linear relaxation of a problem with the "easy" constraints and the convex hull of relaxed constraints.

(Review Here).

Lemma 2.2. *if $\Omega_y = \{y \in \mathbb{R}^n : y \in \Omega, y \in \mathbb{Z}^n\}$. Then we have the following relation for dual function,*

$$\phi^\star = \min_{\delta,\epsilon} f(\delta,\epsilon) \quad \textbf{\textit{s.t.}}\ y + \delta - \epsilon = b,\ y \in conv(\Omega_y)$$

This immediately allows us to have strong duality by definition of perfect formulation, in which case the linear relaxation solves the original problem.

Corollary 2.2.1. *We conclude the strong duality holds since $Y = \{(y,\delta,\epsilon) : y + \delta - \epsilon = b,\ y \in \mathsf{conv}(\Omega_y)\}$ is already* a perfect formulation *in the sense that $Y = \mathsf{conv}(Y)$*

show this or add more conditions to justify

2.2 Subgradient Method

To solve the reduced problem for λ, we consider a class of subgradient methods:

$$\lambda_{k+1} = \mathbf{P}(\lambda_k + s_k d_k) \tag{2.1}$$

where $\mathbf{P}$ is the projection onto dual space Λ. d_k is the update direction for current iteration and s_k is the step size using target-based rule:

$$s_k = \gamma_k \frac{\phi^\star - \phi(\lambda_k)}{\|d_k\|^2} \tag{2.2}$$

During the progress on dual problem, we compute an weighted average solution $\bar{y}_k$ from the convex combination of previous iterations: $\{y_i\}_{i=1,\dots k}$ and each y_i solves $\phi_i = \phi(\lambda_i)$.

$$\bar{y}_k = \sum_k^i \alpha_k^i y_i, \quad \sum_k^i \alpha_k^i = 1, \alpha_k^i \geq 0 \tag{2.3}$$

$$= (1 - \alpha_k) \cdot \bar{y}_{k-1} + \alpha_k \cdot y_k \tag{2.4}$$

The second equation (2.4) rephrases the convexity in a recursive manner that may help in programming. By taking $g_k = y_k - b$, then g_k is a subgradient of ϕ at λ_k:

$$g_k \in \partial \phi_k \tag{2.5}$$

The search direction is computed from subgradient. We can use a convex alternative such that $d_k = \bar{y}_k - b$. Similarly, it can be expressed as convex combinations.

$$d_k = (1 - \alpha_k) \cdot d_{k-1} + \alpha_k \cdot g_k \tag{2.6}$$

As a comparison, there is a choice solely involves the subgradient itself,

$$\begin{aligned} \lambda_{k+1} &= \mathbf{P}(\lambda_k + s_k g_k) \\ s_k &= \gamma_k \frac{\phi^\star - \phi(\lambda_k)}{\|g_k\|^2} \end{aligned} \tag{2.7}$$

For simplicity, we refer to the convex choice (2.1) whenever term d_k is used.

The dual subgradient algorithm can be summarized as follows. $\varepsilon, \varepsilon_s$ are the tolerance parameter for objective gap and stepsize, respectively. $\varepsilon > 0, \varepsilon_s > 0$. At each iteration k, let $\gamma_k < 2, \alpha_k = \frac{1}{k}$.

Algorithm 1: The Subgradient Algorithm

Initialization. $\alpha_0 = 1, \lambda_0 = e, \gamma_0 = 1$

while $\phi^\star - \phi_k \geq \varepsilon$ ***and*** $s_k \geq \varepsilon_s$ **do**

  Let current iteration be k

  Update the multipliers by direction and stepsize, either by (2.1), (2.2) or (2.7).

  Solve dual problem ϕ_k by (1.2) and compute subgradient g_k respectively.

end

It is obvious to see the solutions during dual optimization $(y, \epsilon, \delta) = (y_k, 0, 0)$ are feasible if and only if we can find $y_k = d$, which in general will not hold. This motivates the following algorithm based on linear programming theory.

Algorithm 2: Recovery Algorithm

$$\begin{aligned}\epsilon_k &= \max\{y_k - b, 0\}\\ \delta_k &= \max\{b - y_k, 0\}\\ \bar{\epsilon}_k &= \max\{\bar{y}_k - b, 0\}\\ \bar{\delta}_k &= \max\{b - \bar{y}_k, 0\}\end{aligned} \tag{2.8}$$

To simplify our presentation, let z be a function of y such that $z_k = z(y_k) = f(\delta_k, \epsilon_k)$, then z is also convex in y since both function f and $\max\{\cdot, 0\}$ are convex. It's also worth to notice that $\bar{\epsilon}_k$ should not be calculated as running averages: $\bar{\epsilon}_k \neq \sum_k^i \alpha_k^i \epsilon_i$. For such an "averaged" solution, we let $\bar{z}_k = z(\bar{y}_k)$. We later find the recovery algorithm achieves at the optimal objective.

2.3 Overview

We first review several features for the subgradient method regarding parameters γ_k, α_k and search direction d_k produced from convex combinations.

The target based rule are well-known as the Polyak rule Polyak (1967). The idea of using previous searching directions is introduced to accelerate the subgradient method and provide a better stopping criterion, see Camerini et al. (1975), Brännlund (1995), Barahona and Anbil (2000). Brännlund (1995) showed that with convex combinations the optimal choice of stepsize is equivalent to the Camerini-Fratta-Maffioli modification, it also provides an analysis on its linear convergence rate.

From the primal perspective, our method is close to *primal averaging method.* Nedić and Ozdaglar (2009) gives a line of analysis on convergence and quality of the primal approximation by averaging over all previous solutions with a constant stepsize. They use a simple averaging scheme that can be rephrased into a recursive equation with $\alpha_k = 1/k$ such that:

$$\bar{y}_k = \frac{k-1}{k} \cdot \bar{y}_{k-1} + \frac{1}{k} \cdot y_k$$

then it gives lower and upper bounds for the averaged solution that involve the primal violation, norm of the subgradient, etc. Furthermore, they only analyze the case for constant stepsize $s_k = s, s \geq 0$ and the search direction defined solely by the subgradient. We refer to Kiwiel et al. (2007) for target based stepsizes. The volume algorithm proposed by Barahona and Anbil (2000) is close to the case mentioned in Brännlund (1995) in a dual viewpoint while adopting $\tilde{\lambda}_k$ instead of λ_k from the best dual bound $\tilde{\phi}_k = \max_{i=1,\ldots,k} \phi(\lambda_i)$:

$$\lambda_{k+1} = \mathbf{P}(\tilde{\lambda}_k + s_k d_k)$$

Since the solution is strictly feasible by implementation of the recovery algorithm (2.8), i.e., there is no need to bound for feasibility gap as has been done in most of literature covering the **primal recovery**. Instead, we focus on the quality of the recovery, i.e.:

$$|\bar{z}_k - \phi_k| \text{ or } |\bar{z}_k - z^\star|$$

We found its convergence is closely related to strong duality of the problem. Accounting for performance, we suggest several specific choices of parameters regarding the subgradient method (γ, α, d).

2.4 Convergence Analysis

- we've showed $\phi^\star = f^\star = z^\star$
- we show λ_k converges to $\lambda^\star \in \Lambda^\star$ for our choices of γ_k, α_k
- we show primal solution $\bar{z}_k$ converges to $z^\star$

Lemma 2.3. *ϵ-subgradient.*

$$\begin{aligned} g_k^\mathsf{T}(\lambda_k - \lambda) &\le \phi_k - \phi(\lambda) \\ d_k^\mathsf{T}(\lambda_k - \lambda) &\le \phi_k - \phi(\lambda) + \epsilon_k \end{aligned} \tag{2.9}$$

where

$$\epsilon_k = \sum_k^i \alpha_k^i \cdot [g_i^\mathsf{T}(\lambda_k - \lambda_i) + \phi_i - \phi_k] \tag{2.10}$$

Notice ϵ_k can be further simplified by the definition of ϕ:

$$\epsilon_k = \sum_k^i \alpha_k^i \cdot (g_i^\mathsf{T}\lambda_k - \phi_k) \tag{2.11}$$

Lemma 2.4. *Dual convergence,* **?**. *The subgradient method is convergent if ϵ_k satisfies:*

$$\frac{1}{2}(2 - \gamma_k)(\phi_k - \phi^\star) + \epsilon_k \le 0 \tag{2.12}$$

Proof. The proof can be done by showing the monotonic decrease of $\|\lambda_k - \lambda^\star\|$ via the iterative equations.

$$\|\lambda_{k+1} - \lambda^\star\|^2 \le ||\lambda_k - \lambda^\star||^2 + 2 \cdot \gamma_k \frac{(\phi^\star - \phi_k)}{\|d_k\|^2} d_k^\mathsf{T}(\lambda_k - \lambda^\star) + (\gamma_k)^2 \frac{(\phi^\star - \phi_k)^2}{\|d_k\|^2} \tag{2.13}$$

Notice:

$$\begin{aligned} 2 \cdot d_k^\mathsf{T}(\lambda_k - \lambda^\star) + \gamma_k(\phi^\star - \phi_k) \le &\quad 2(\phi_k - \phi^\star + \epsilon_k) + \gamma_k(\phi^\star - \phi_k) \\ =&(2 - \gamma_k)(\phi_k - \phi^\star) + 2\epsilon_k \le 0 \end{aligned} \tag{2.14}$$

and we have the convergence. □

Now we visit properties for primal solutions.

Theorem 2.5. *Recovery Algorithm* (2.8)

(a) For fixed $y = y_k$, (ϵ_k, δ_k) is the optimal solution for the restricted primal problem.

$$f(\epsilon_k, \delta_k) \le f(\epsilon, \delta), \quad \forall \delta \ge 0, \epsilon \ge 0, y = y_k$$

(b)

$$\bar{z}_k \ge d_k^\mathsf{T} \lambda_k$$

Proof. We first notice a strong duality pair with *fixed* $t \in \Omega_y$, for example, t may take values in $y_k, \bar{y}_k, k = 1, 2, ...$ in the subgradient iterations.

$$\begin{aligned} (\mathbf{P}) \quad & \min_{\delta,\epsilon} p^\mathsf{T}\delta + h^\mathsf{T}\epsilon \\ \mathbf{s.t.} \quad & t + \delta - \epsilon = 0 \\ & \delta \in \mathbb{R}^n_+, \epsilon \in \mathbb{R}^n_+ \end{aligned} \tag{2.15}$$

and

$$\begin{aligned} (\mathbf{D}) \quad & \max_\lambda t^\mathsf{T}\lambda \\ \mathbf{s.t.} \quad & -p \le \lambda \le h, \lambda \in \mathbb{R}^n \end{aligned} \tag{2.16}$$

Since $\mathbf{P}$ is well-defined. The dual problem $\mathbf{D}$ is straight-forward to solve by comparing t to 0 for each dimension:

$$\mu_j^\star = \begin{cases} h_j & \text{if } t_j > 0 \\ p_j & \text{else} \end{cases} \quad \forall j = 1, ..., n$$

This corresponds to the part (a) and recovery algorithm (2.8) by taking $t = g_k$.

Similarly, take $t = d_k$ we can show part (b).

$$\bar{z}_k = p^\intercal \bar{\delta}_k + h^\intercal \bar{\epsilon}_k \geq d_k^\intercal \lambda_k$$

□

Theorem 2.6. *Suppose the subgradient is bounded, that is, $\exists L > 0$ such that*

$$\|g_k\| \leq L \tag{2.17}$$

and ???

Then the primal-dual bound by the recovery algorithm (2.8) converges to 0, specifically:

$$\bar{z}_k - \phi^\star \to 0$$

Proof. We first notice

$$\phi^\star - \phi_k \leq g_k^\intercal (\lambda^\star - \lambda_k) \leq \|g_k\| \|\lambda^\star - \lambda_k\| \Rightarrow \phi_k \to \phi^\star$$

This immediately follows:

$$\epsilon_k = d_k^\intercal \lambda_k - \phi_k \leq \frac{1}{2}(2 - \gamma_k)(\phi^\star - \phi_k) \to 0 \tag{2.18a}$$

$$\Rightarrow \quad d_k^\intercal \lambda_k \to \phi^\star \tag{2.18b}$$

We now show the convergence from $\bar{z}$ to $\lambda_k^\intercal d_k$?

As shown in 2.5, by (2.15), (2.16), suppose $\exists\ \mu_k \in [-p, h]$ such that $\mu_k \in \arg\max_\lambda d_k^\intercal \lambda$

It's equivalent to show:

$$\mu_k^\top d_k - \lambda_k^\top d_k \to 0 \tag{2.19}$$

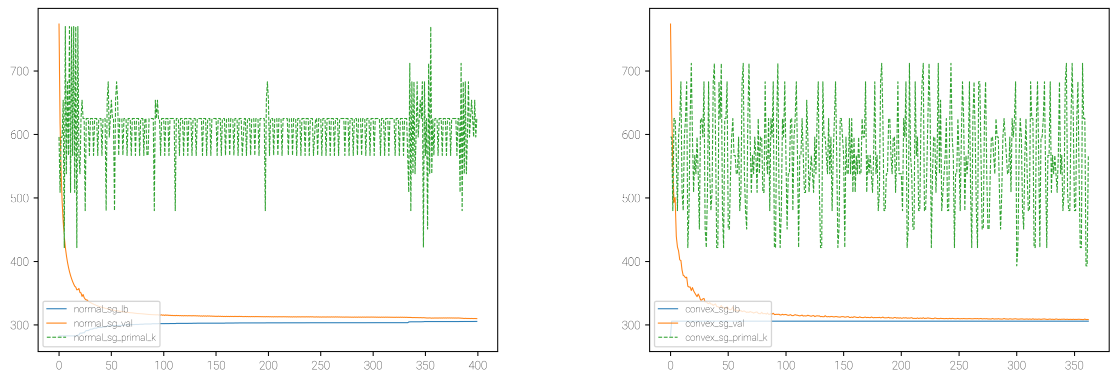
□

2.5 Computational Results

We present our computational results to validate the convergence analysis on subgradient method. The experiments are done on the Fleet Maintenance Problem (see **??**). The baseline is set by MILP modeled in Gurobi 9.1 to provide lower bound and best integral solution. We implement subgradient methods mentioned in our paper in Python 3.7. Specifically, we test on two specific subgradient variants:

1. Normal subgradient, labelled as `normal_sg`. This is the simplest subgradient method using iteration:
$$\lambda_{k+1} = \mathbf{P}(\lambda_k + s_k g_k)$$
2. Convex subgradient, `convex_sg`, using:
$$\lambda_{k+1} = \mathbf{P}(\lambda_k + s_k d_k)$$
where d_k is averaged over past iterations, cf. (**??**)

As shown in Figure 1, our results show that averaged solution by recovery algorithm (2.8) converges to the best lower bound.



(a) Normal subgradient method using g_k **(b)** Convex subgradient method using d_k

Figure 1: An instance illustrating the convergence of the subgradient methods and the recovery algorithm (2.8). `sg_lb` and `sb_val` are lower bound for the subgradient method and averaged primal value from the recovery algorithm, respectively. `primal_k` is the primal value at iteration k without averaging. We find that averaged solution avoids the zig-zag behavior of `primal_k`.

We summarize all test cases in Table 1.

References

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Appendix

Table 1: Computational Results of the Fleet Maintenance Problem

	$\|I\|$	$\|T\|$	bench			normal			convex		
			$\hat{\phi}$	$\bar{z}$	time (s)	time (s)	ϕ_gap	$\bar{z}$_gap	time (s)	ϕ_gap	$\bar{z}$_gap
68	12	25	1332.00	1332.00	2.49	62.95	-0.00%	0.50%	58.28	0.00%	0.56%
6	12	15	828.00	828.00	0.64	22.65	-0.02%	0.48%	21.30	0.00%	0.57%
63	16	30	2102.93	2106.00	1.25	139.24	-0.02%	0.53%	124.89	0.15%	0.59%
60	16	30	1650.52	1656.00	1.89	137.05	-0.02%	0.67%	124.76	0.33%	0.74%
16	16	25	2196.00	2196.00	1.25	79.32	-0.05%	0.45%	71.44	0.00%	0.50%
44	12	20	756.00	756.00	16.86	44.41	-0.05%	1.29%	41.69	0.00%	0.77%
5	12	15	774.00	774.00	0.53	21.38	-0.06%	0.50%	20.08	0.00%	0.56%
70	20	15	985.02	990.00	103.11	32.87	-0.06%	1.63%	32.68	0.50%	1.47%
76	20	30	2589.23	2592.00	1.71	155.53	-0.07%	0.52%	129.33	0.11%	0.64%
20	16	15	954.00	954.00	1.10	28.71	-0.07%	0.55%	28.58	-0.00%	1.00%
21	16	15	756.00	756.00	1.50	25.99	-0.08%	1.06%	25.99	-0.00%	1.85%
19	16	25	1890.00	1890.00	1.44	83.96	-0.11%	0.47%	70.26	0.00%	0.56%
1	24	25	2445.43	2448.00	2.55	127.85	-0.11%	0.57%	106.56	0.11%	0.70%
51	24	20	2124.00	2124.00	2.36	81.04	-0.11%	0.72%	68.38	0.00%	0.59%
9	12	15	540.00	540.00	1.60	25.58	-0.11%	1.03%	23.93	0.00%	0.87%
11	20	25	2214.00	2214.00	1.39	93.73	-0.15%	0.49%	77.50	0.00%	0.59%
73	20	15	1278.00	1278.00	0.61	34.89	-0.16%	0.52%	29.43	0.00%	0.62%
35	24	30	3258.00	3258.00	2.01	179.31	-0.17%	0.49%	150.41	0.00%	0.59%
59	16	20	1332.00	1332.00	9.22	57.39	-0.19%	0.53%	47.99	0.00%	0.64%
23	16	15	952.79	954.00	0.72	25.50	-0.20%	1.02%	22.26	0.13%	0.69%
69	12	25	1242.00	1242.00	2.25	74.43	-0.21%	0.55%	67.85	0.00%	0.61%
46	12	30	1422.00	1422.00	1.45	111.73	-0.21%	0.57%	101.88	0.00%	0.64%
36	24	30	2826.00	2826.00	2.89	177.13	-0.23%	0.60%	146.85	0.00%	0.74%
47	12	30	1220.49	1224.00	3.43	93.64	-0.25%	1.13%	94.00	0.20%	2.40%
77	20	30	2340.00	2340.00	1.83	165.61	-0.26%	0.58%	137.36	0.00%	0.70%
56	16	20	1206.00	1206.00	1.12	53.11	-0.29%	0.60%	48.09	0.00%	0.66%
45	12	30	1206.00	1206.00	1.07	98.67	-0.33%	0.66%	89.92	0.00%	0.76%
10	20	25	1638.00	1638.00	1.76	105.16	-0.34%	0.66%	94.73	0.00%	0.72%
40	12	20	1078.94	1080.00	1.51	48.66	-0.44%	1.71%	42.05	0.10%	0.55%
7	12	15	594.00	594.00	0.69	26.63	-0.52%	1.49%	23.49	0.00%	0.74%

Table 1: (continued)

33	20	20	1402.16	1404.00	15.10	65.98	0.04%	0.63%	57.33	0.13%	0.72%
31	20	20	1923.43	1926.00	1.49	59.74	0.05%	0.46%	49.63	0.13%	0.56%
4	24	25	2785.33	2790.00	3.12	127.48	0.05%	0.47%	105.67	0.17%	0.57%
3	24	25	2276.87	2286.00	5.05	138.55	0.05%	0.62%	115.09	0.40%	0.77%
25	24	15	1510.24	1512.00	1.35	35.67	0.06%	0.52%	29.54	0.12%	0.60%
30	20	20	1580.59	1584.00	2.58	67.05	0.06%	0.56%	55.52	0.22%	0.70%
39	24	30	2489.16	2502.00	3.44	191.46	0.09%	0.92%	190.77	0.51%	1.36%
28	24	15	1668.00	1674.00	1.56	38.92	0.09%	1.80%	32.62	0.36%	0.61%
0	24	25	2475.97	2484.00	2.02	113.65	0.12%	0.53%	94.05	0.32%	0.66%
66	12	25	968.73	972.00	8.09	78.03	0.14%	1.08%	77.34	0.34%	0.74%
17	16	25	1272.11	1278.00	6.76	98.75	0.15%	1.50%	89.32	0.46%	0.76%
18	16	25	1956.46	1962.00	1.65	89.64	0.18%	0.44%	75.18	0.28%	0.55%
78	20	30	2871.00	2880.00	1.37	145.98	0.18%	0.46%	121.96	0.31%	0.56%
58	16	20	1561.50	1566.00	0.91	54.82	0.20%	0.42%	45.30	0.29%	0.52%
50	24	20	1863.90	1872.00	2.27	78.09	0.20%	0.57%	65.59	0.43%	0.69%
29	24	15	1364.62	1368.00	1.34	33.98	0.22%	0.79%	28.69	0.25%	0.72%
38	24	30	2704.73	2718.00	2.95	190.06	0.23%	0.61%	158.32	0.49%	0.73%
14	20	25	2100.99	2106.00	2.18	98.94	0.23%	0.63%	98.80	0.23%	0.91%
55	16	20	1416.62	1422.00	1.19	54.22	0.24%	0.50%	49.50	0.38%	0.57%
72	20	15	1382.40	1386.00	1.26	30.06	0.25%	0.49%	26.53	0.26%	0.62%
52	24	20	2043.68	2052.00	2.67	71.74	0.25%	0.51%	59.82	0.41%	0.62%
79	20	30	2581.10	2592.00	2.17	175.35	0.25%	0.51%	145.95	0.42%	0.62%
22	16	15	913.85	918.00	1.43	26.61	0.25%	0.59%	22.43	0.45%	0.70%
67	12	25	896.26	900.00	17.62	74.01	0.27%	0.74%	66.90	0.42%	0.82%
41	12	20	861.46	864.00	1.54	40.29	0.28%	0.67%	40.32	0.30%	1.40%
53	24	20	2186.99	2196.00	1.75	74.49	0.29%	0.49%	62.76	0.41%	0.59%
61	16	30	1863.00	1872.00	1.87	151.73	0.30%	0.60%	131.44	0.48%	0.68%
26	24	15	1882.99	1890.00	1.45	35.32	0.31%	0.44%	28.54	0.37%	0.55%
42	12	20	986.91	990.00	1.24	44.64	0.31%	0.54%	39.41	0.31%	0.61%
27	24	15	1307.42	1314.00	1.09	38.37	0.33%	0.59%	32.33	0.50%	0.78%
8	12	15	662.15	666.00	1.72	23.08	0.35%	0.58%	21.10	0.58%	0.66%
12	20	25	2058.75	2070.00	300.02	109.29	0.37%	0.57%	91.62	0.55%	0.68%
24	16	15	1164.18	1170.00	0.53	26.36	0.39%	0.45%	22.16	0.50%	0.55%
54	24	20	2220.91	2232.00	2.16	67.87	0.39%	0.46%	56.28	0.50%	0.56%
34	20	20	1880.52	1890.00	1.80	62.09	0.39%	0.47%	51.36	0.50%	0.59%
2	24	25	2292.19	2304.00	26.96	132.40	0.39%	0.76%	131.94	0.51%	0.63%
64	16	30	2292.23	2304.00	1.14	140.09	0.40%	0.46%	116.67	0.51%	0.55%
15	16	25	1773.58	1782.00	1.65	99.49	0.40%	0.53%	83.24	0.47%	0.65%
74	20	15	1271.49	1278.00	2.52	30.54	0.40%	0.84%	25.28	0.51%	0.62%
37	24	30	2883.32	2898.00	2.88	224.79	0.42%	0.59%	220.62	0.51%	1.26%
32	20	20	1809.64	1818.00	1.06	64.22	0.45%	0.49%	53.86	0.46%	0.61%
75	20	30	2310.74	2322.00	2.69	180.16	0.45%	0.55%	181.30	0.48%	1.96%
13	20	25	2310.22	2322.00	2.46	104.55	0.46%	0.46%	87.16	0.51%	0.55%
48	12	30	1665.18	1674.00	2.51	101.36	0.47%	0.49%	101.66	0.53%	0.86%
43	12	20	1235.38	1242.00	2.84	33.27	0.49%	0.46%	34.40	0.54%	0.50%
57	16	20	1468.37	1476.00	1.21	51.02	0.51%	0.55%	51.03	0.51%	1.04%
49	12	30	1252.32	1260.00	300.02	114.56	0.58%	0.86%	114.81	0.61%	1.73%
62	16	30	1495.06	1512.00	300.02	140.53	0.62%	1.09%	139.62	1.05%	1.87%
71	20	15	1031.76	1044.00	300.01	32.00	1.15%	1.20%	32.43	0.92%	3.13%
65	12	25	1133.18	1152.00	300.03	79.02	1.59%	0.93%	69.02	1.66%	0.63%

$\bar{z}$_gap is the relative gap from averaged primal solution to benchmark solution. $\hat{\phi}$_gap is the gap for best lower bound at termination.