Contents

1 Lagrangian relaxation

Consider the following newsvendor-like problem

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

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:

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

It is easy to verify the equivalence of the deterministic version, i.e., without the expectation operator, to the problem above. This problem widely appears in applications of device maintenance, inventory management, crew scheduling and so on.

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

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

We assume the resulting two subproblems for δ, ϵ and y are easy. Denote $f^\star, \phi^\star$ be the optimal objective for primal and dual problem, respectively.

1.1 Affine case

The case for repair problem

Let $f = p^\mathsf{T}\delta + h^\mathsf{T}\epsilon$, 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 $\lambda \in \Lambda$

1.2 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 1.1. *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 1.2. *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 1.2.1. *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 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:

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

Note the direction d_k computed by

$$d_k = \bar{y}_k - b \tag{2.3}$$

where $\bar{y}_k$ is the convex combination of previous iterations $\{y_i\}_{i=1,\dots k}$ and each y_i solves $\phi_i = \phi(\lambda_i)$:

$$\bar{y}_k = \sum_k^i \alpha_k^i y_i, \quad \sum_k^i \alpha_k^i = 1, \alpha_k^i \geq 0 \tag{2.4}$$

Alternatively, one can express the convexity in a recursive manner:

$$\bar{y}_k = (1 - \alpha_k) \cdot \bar{y}_{k-1} + \alpha_k \cdot y_k \tag{2.5}$$

For we simplicity take $g_k = y_k - b$, then g_k is a subgradient of ϕ at λ_k:

$$g_k \in \partial \phi_k \tag{2.6}$$

The direction can be rewritten as the combination of the subgradient and previous directions:

$$d_k = (1 - \alpha_k) \cdot d_{k-1} + \alpha_k \cdot g_k \tag{2.7}$$

The dual subgradient algorithm can be summarized as follows. $\varepsilon, \varepsilon_s$ are the tolerance parameter for objective gap and stepsize, respectively. $\varepsilon > 0, \varepsilon_s > 0$.

Algorithm 1: The Subgradient Algorithm

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

while $\bar{z}_k - \phi_k \geq \varepsilon$ ***and*** $s_k \geq \varepsilon_s$ **do**

Let current iteration be k

Update the multipliers by

$$\lambda_k = \mathbf{P}(\lambda_{k-1} + s_{k-1} d_{k-1})$$

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

Compute γ_k, α_k properly.

Compute current direction by (2.3) or (2.7)

Update $\epsilon_k, \delta_k, \bar{\epsilon}_k, \bar{\delta}_k, z_k, \bar{z}_k$ by the Recovery Algorithm 2

Stepsize is updated by (2.2)

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.

3 Convergence

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. 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 $\hat{\lambda}_k$ instead of λ_k from the best dual bound $\hat{\phi}_k = \max_{i=1,\dots,k} \phi(\lambda_i)$:

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

There is no existing proof of convergence for the volume algorithm.

(Remark / Difference for our method)

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 have analyze the quality of the heuristic, 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).

3.1 Analysis outline

- we've showed zero duality gap $\phi^\star = f^\star = z^\star$
- 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 3.1. *ϵ-subgradient.*

$$\begin{aligned} g_k^\top(\lambda_k - \lambda) \le \phi_k - \phi(\lambda) \\ d_k^\top(\lambda_k - \lambda) \le \phi_k - \phi(\lambda) + \epsilon_k \end{aligned} \tag{3.1}$$

where

$$\epsilon_k = \sum_k^i \alpha_k^i \cdot [g_i^\top(\lambda_k - \lambda_i) + \phi_i - \phi_k] \tag{3.2}$$

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

$$\epsilon_k = \sum_k^i \alpha_k^i \cdot (g_i^\top \lambda_k - \phi_k) \tag{3.3}$$

Lemma 3.2. *Dual convergence, Brännlund (1995). The subgradient method is convergent if ϵ_k satisfies:*

$$\frac{1}{2}(2 - \gamma_k)(\phi_k - \phi^\star) + \epsilon_k \le 0 \tag{3.4}$$

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

$$\|\lambda_{k+1} - \lambda^\star\|^2 \le ||\lambda_k - \lambda^\star||^2 + 2 \cdot \gamma_k \frac{(\phi^\star - \phi_k)}{\|d_k\|^2} d_k^\top(\lambda_k - \lambda^\star) + (\gamma_k)^2 \frac{(\phi^\star - \phi_k)^2}{\|d_k\|^2} \tag{3.5}$$

Notice:

$$\begin{aligned} & 2 \cdot d_k^\top(\lambda_k - \lambda^\star) + \gamma_k(\phi^\star - \phi_k) \\ \le & 2(\phi_k - \phi^\star + \epsilon_k) + \gamma_k(\phi^\star - \phi_k) \\ = & (2 - \gamma_k)(\phi_k - \phi^\star) + 2\epsilon_k \le 0 \end{aligned} \tag{3.6}$$

and we have the convergence. □

The next proposition states several convergence-guaranteed choices on parameters for convexity α_k and stepsize γ_k. Part (a) originally appears in Brännlund (1995). Besides, we also consider a slower scheme that is widely used and simple to implement.

Corollary 3.2.1. *Choices of parameters.*

(b) to show the following is convergent?

$$\alpha_k = \frac{1}{k}, \gamma_k = \gamma \in [1, 2]$$

Theorem 3.3. *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)

$$\bar{z}_k \le \sum_{k}^{i} \alpha_k^i z^i$$

(c)

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

Proof. (a) straight-forward. (b) by convexity of $z(\cdot)$. (c) we notice a strong duality pair with fixed d_k at each iteration k.

$$\begin{aligned} (\mathbf{P}) \quad & \min_{\delta,\epsilon} p^\mathsf{T}\delta + h^\mathsf{T}\epsilon \\ \textbf{s.t.} \quad & d_k + \delta - \epsilon = 0 \\ & \delta \in \mathbb{R}_+^n, \epsilon \in \mathbb{R}_+^n \end{aligned} \tag{3.7}$$

and

$$\begin{aligned} (\mathbf{D}) \quad & \max_{\lambda} d_k^\mathsf{T}\lambda \\ \textbf{s.t.} \quad & -p \le \lambda \le h, \lambda \in \mathbb{R}^n \end{aligned} \tag{3.8}$$

by 3.3(a), $(\bar{\epsilon}_k, \bar{\delta}_k)$ minimizes the primal problem. Since **(P)** is well-defined, $\exists\ \mu_k \in [-p, h]$ such that $\mu_k \in \arg\max_\lambda d_k^\mathsf{T}\lambda$.

$$\begin{aligned} d_k^\mathsf{T}\mu_k &= \bar{z}_k = p^\mathsf{T}\bar{\delta}_k + h^\mathsf{T}\bar{\epsilon}_k \\ d_k^\mathsf{T}\mu_k &\ge d_k^\mathsf{T}\lambda_k \end{aligned}$$

□

Now we visit properties for primal solutions.

Theorem 3.4. *Suppose the subgradient is bounded, that is, $\exists L > 0$ such that*

$$\|g_k\| \leq L \tag{3.9}$$

and

$$d_k^\top d_{k+1} \geq 0 \tag{3.10}$$

holds for all iteration k in the subgradient algorithm. 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

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

This immediately follows:

$$\begin{aligned}
& \epsilon_k \leq \frac{1}{2}(2 - \gamma_k)(\phi^\star - \phi_k) \to 0 && (3.11a)\\
\Rightarrow \quad & \epsilon_k = d_k^\top \lambda_k - \phi_k \to 0 && (3.11b)\\
\Rightarrow \quad & d_k^\top \lambda_k \to \phi^\star && (3.11c)
\end{aligned}$$

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

$$\begin{aligned}
\bar{z}_{k+1} - \lambda_{k+1}^\top d_{k+1} &= z\left(\alpha g_k + (1-\alpha)d_k\right) - \left(\lambda_k + s_k d_k\right)\left((1-\alpha)d_k + \alpha g_k\right)\\
&\leq \alpha \cdot z(g_k) + (1-\alpha) \cdot z(d_k) - (1-\alpha)\lambda_k^\top d_k - (1-\alpha)s_k\|d_k\|^2 - \alpha\lambda_k^\top g_k - \alpha s_k d_k^\top g_k\\
&= (1-\alpha)(\bar{z}_k - \lambda_k^\top d_k) - s_k d_k\left[\alpha g_k + (1-\alpha)d_k\right]\\
&= (1-\alpha)(\bar{z}_k - \lambda_k^\top d_k) - s_k d_k^\top d_{k+1}\\
&\leq (1-\alpha)(\bar{z}_k - \lambda_k^\top d_k)
\end{aligned} \tag{3.12}$$

We combine (3.12), (3.11a) to $\bar{z}^k \to \phi^\star$ □

Remark

The boundedness of subgradient can be easily verified by (2.3). As for (3.10), Brännlund (1995) suggests the orthogonality $d_k^\top d_{k+1} = 0$ if the optimal stepsize is implemented. Our results show that the angle between two consecutive search directions should be acute to achieve better duality gaps.

3.2 Computational Results

The volume algorithm uses $\hat{\lambda}_k$, instead we useλ_k which actually is better. Figure 3.2 is a typical case of divergence of volume algorithm. `normal_x` means the values are computed from subgradient method by using λ_k. `volume_x` is from the volume algorithm with $\hat{\lambda}_k = \arg\max_k \hat{\phi}_k$

We compare computational results on variants of subgradient method mentioned in our paper.

0. bench: by MILP solver: GUROBI 9.1
1. normal: here we are using $\alpha_k = 1/k$ and a diminishing γ
2. volume: the volume algorithm
3. to-be-added: the α_k choices in Brännlund (1995) **this should be a much quicker choice**

We summarize all 60 test cases randomly generated for the repair model.

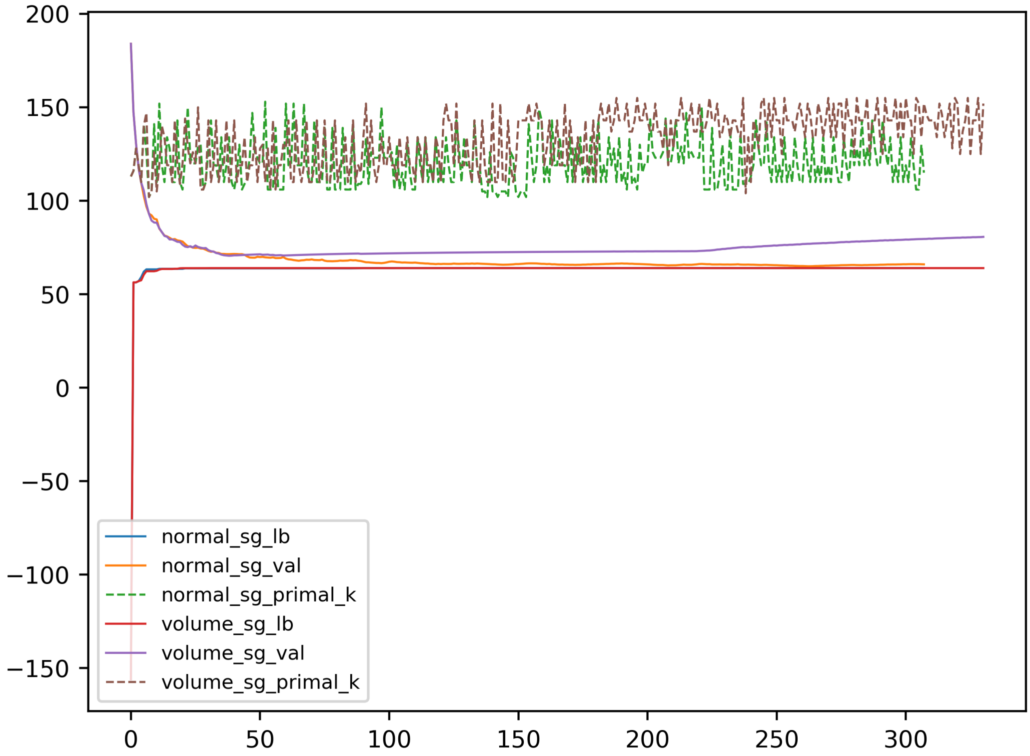
Table 1: Computational results from the repair model

	$\lvert I\rvert$	$\lvert T\rvert$	bench		normal				convex			
			$\hat{\phi}$	$\bar{z}$	$\hat{\phi}$	$\bar{z}$	ϕ_gap	$\bar{z}$_gap	$\hat{\phi}$	$\bar{z}$	ϕ_gap	$\bar{z}$_gap
27	15	10	64.00	64.00	64.00	64.90	-0.00%	1.41%	63.86	65.55	-0.22%	2.43%
13	10	10	30.00	30.00	29.99	32.28	-0.02%	7.61%	30.00	30.41	0.00%	1.36%
45	10	20	72.00	72.00	71.98	72.56	-0.03%	0.78%	72.00	72.78	0.00%	1.09%
11	10	10	36.00	36.00	35.99	36.80	-0.03%	2.22%	36.00	36.36	0.00%	0.99%
26	15	10	30.00	30.00	29.99	32.31	-0.03%	7.70%	29.72	34.07	-0.95%	13.58%
47	10	20	56.00	56.00	55.97	56.94	-0.05%	1.67%	56.00	56.76	0.00%	1.35%
25	15	10	36.00	36.00	35.98	40.26	-0.06%	11.83%	35.58	39.11	-1.16%	8.65%
35	15	15	62.00	62.00	61.96	64.04	-0.06%	3.30%	62.00	63.03	0.00%	1.67%
50	20	20	134.00	134.00	133.90	135.18	-0.07%	0.88%	133.99	137.09	-0.01%	2.31%
15	25	20	176.00	176.00	175.87	178.15	-0.08%	1.22%	176.00	178.33	0.00%	1.32%
58	10	15	26.00	26.00	25.98	27.64	-0.08%	6.30%	25.80	27.92	-0.78%	7.39%
38	15	15	72.00	72.00	71.93	76.07	-0.10%	5.66%	72.00	72.93	0.00%	1.29%
59	10	15	32.00	32.00	31.96	35.03	-0.11%	9.48%	32.00	34.20	0.00%	6.88%
39	15	15	92.00	92.00	91.89	92.60	-0.12%	0.66%	92.00	92.95	0.00%	1.03%
52	20	20	118.00	118.00	117.86	127.39	-0.12%	7.96%	117.98	121.64	-0.02%	3.09%
4	15	25	118.00	118.00	117.82	120.77	-0.15%	2.35%	118.00	119.47	0.00%	1.25%
28	15	10	36.00	36.00	35.94	38.87	-0.16%	7.96%	36.00	37.11	-0.00%	3.08%
23	15	20	80.00	80.00	79.86	86.71	-0.18%	8.39%	80.00	81.20	0.00%	1.50%
22	15	20	58.00	58.00	57.89	59.33	-0.19%	2.30%	58.00	59.17	0.00%	2.01%
44	10	25	40.00	40.00	39.92	41.84	-0.19%	4.59%	39.85	43.54	-0.37%	8.86%
57	10	15	62.00	62.00	61.87	62.42	-0.20%	0.68%	62.00	62.56	0.00%	0.90%
34	25	25	220.00	220.00	219.47	223.67	-0.24%	1.67%	220.00	222.54	0.00%	1.16%
31	25	25	228.00	228.00	227.43	232.15	-0.25%	1.82%	228.00	232.74	0.00%	2.08%
16	25	20	206.00	206.00	205.43	207.41	-0.28%	0.68%	206.00	208.26	0.00%	1.10%
54	20	20	160.00	160.00	159.48	161.15	-0.32%	0.72%	160.00	161.76	0.00%	1.10%

Table 1: (continued)

42	10	25	58.00	58.00	57.81	60.02	-0.32%	3.49%	58.00	58.97	0.00%	1.67%
6	20	25	160.00	160.00	159.34	163.45	-0.41%	2.16%	160.00	162.25	0.00%	1.40%
5	20	25	162.00	162.00	161.32	163.46	-0.42%	0.90%	162.00	164.13	0.00%	1.32%
49	10	20	68.00	68.00	67.71	68.59	-0.43%	0.87%	68.00	68.79	0.00%	1.16%
41	10	25	36.00	36.00	35.83	39.86	-0.47%	10.72%	35.93	38.92	-0.20%	8.10%
30	25	25	210.00	210.00	208.73	215.32	-0.60%	2.53%	210.00	212.71	0.00%	1.29%
24	15	20	86.00	86.00	85.16	88.24	-0.97%	2.61%	83.51	88.77	-2.90%	3.22%
43	10	25	54.00	54.00	53.46	55.03	-1.00%	1.91%	53.92	55.87	-0.15%	3.47%
37	15	15	42.00	42.00	41.55	46.14	-1.07%	9.86%	41.02	45.19	-2.33%	7.61%
12	10	10	14.00	14.00	13.82	15.83	-1.30%	13.04%	13.94	15.00	-0.44%	7.13%
20	15	20	82.00	82.00	80.88	83.98	-1.37%	2.42%	82.00	83.13	0.00%	1.38%
36	15	15	50.00	50.00	48.98	52.68	-2.04%	5.36%	48.70	54.10	-2.60%	8.20%
10	10	10	22.00	22.00	21.29	23.73	-3.24%	7.86%	22.00	22.42	0.00%	1.92%
14	10	10	22.00	22.00	21.26	25.88	-3.35%	17.63%	22.00	23.34	0.00%	6.09%
56	10	15	46.00	46.00	44.21	47.32	-3.90%	2.86%	44.90	47.19	-2.38%	2.59%
19	25	20	124.86	126.00	125.06	127.52	0.16%	1.21%	126.00	128.16	0.91%	1.72%
8	20	25	184.89	186.00	185.35	187.43	0.25%	0.77%	186.00	188.11	0.60%	1.13%
17	25	20	74.27	76.00	74.67	83.78	0.54%	10.23%	74.40	80.86	0.18%	6.39%
18	25	20	176.57	178.00	177.82	180.60	0.71%	1.46%	178.00	180.16	0.81%	1.21%
51	20	20	120.57	122.00	121.47	123.17	0.75%	0.96%	122.00	123.69	1.19%	1.39%
33	25	25	254.98	258.00	257.04	260.86	0.81%	1.11%	257.88	260.43	1.14%	0.94%
32	25	25	122.61	124.00	123.68	126.85	0.87%	2.30%	124.00	126.79	1.13%	2.25%
2	15	25	108.50	110.00	109.48	112.29	0.90%	2.08%	110.00	111.41	1.38%	1.29%
7	20	25	102.54	104.00	103.55	105.64	0.99%	1.58%	104.00	105.95	1.43%	1.88%
21	15	20	78.75	80.00	79.68	82.36	1.18%	2.95%	80.00	81.27	1.59%	1.59%
3	15	25	100.58	102.00	101.90	103.39	1.31%	1.36%	102.00	104.03	1.41%	1.99%
1	15	25	100.60	102.00	101.95	106.37	1.34%	4.28%	102.00	103.52	1.39%	1.49%
9	20	25	140.65	144.00	142.72	146.27	1.48%	1.58%	143.82	149.00	2.25%	3.47%
53	20	20	112.64	116.00	114.88	118.00	1.98%	1.72%	115.97	119.21	2.95%	2.76%
55	10	15	44.92	46.00	45.87	46.79	2.13%	1.71%	45.98	47.27	2.37%	2.77%
48	10	20	46.62	48.00	47.67	51.61	2.25%	7.52%	47.96	49.25	2.87%	2.60%
46	10	20	41.00	42.00	41.96	42.82	2.35%	1.96%	42.00	43.63	2.44%	3.87%
40	10	25	74.11	76.00	75.96	76.98	2.50%	1.29%	75.98	78.32	2.53%	3.05%
0	15	25	103.65	108.00	107.95	110.64	4.14%	2.45%	108.00	109.25	4.19%	1.16%
29	15	10	24.41	26.00	25.98	30.25	6.47%	16.33%	26.00	27.06	6.54%	4.08%

in 1, $\bar{z}$ is the objective value computed from the averaged primal solution, $\hat{\phi}$ is the best lower bound at termination.



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