Instance Generation for Computational Experiments

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For our computational experiments, we generated instances of the robust CTSNDP based on the seven instance classes (named R4-R10) of the fixed-charge capacitated multi-commodity network design (CMND) problem available in the literature Ghamlouche et al. (2003). These classes of CMND instances have been utilized in previous studies to generate test instances for various stochastic capacitated fixed charge network design problems (see, for example, Crainic et al. 2011, Sarayloo et al. 2021a,b).

The sizes of the node set $\mathcal{N}$, arc set $\mathcal{A}$, and commodity set $\mathcal{K}$ vary from 10 to 20, from 60 to 120, and from 10 to 50, respectively, among instances belonging to different classes. Each class consists of five networks with varying values for the ratio of fixed cost to variable cost, and for the ratio of the total demand of commodities to the total capacity of the network. These instances are referred to as "untimed" instances, as they do not have any temporal attributes such as travel times of arcs, or earliest available times and due times of commodities.

To obtain "timed" instances for each of the 7 classes of the CMND problem, we followed an approach similar to that presented in Boland et al. (2017) to generate fixed costs and time attributes of the CTSNDP. First, for each arc $(i,j) \in \mathcal{A}$, we set the nominal value of travel time (in minutes) $\overline{\tau}_{ij}$ to be proportional to its fixed cost f_{ij} by setting $\overline{\tau}_{ij} = f_{ij}/0.55$, as in Boland et al. (2017). This is based on the same premise that f_{ij} represents the transportation cost for carriers that spend 0.55 cents per mile, and that their trucks travel at 60 miles per hour.

Next, for each commodity $k \in \mathcal{K}$, we followed a normal distribution to randomly generate the available time e^k. Let $\mathscr{L}_k$ denote the length of the shortest-time path from origin o^k to destination d^k for commodity k in the flat network under the nominal travel times $\overline{\boldsymbol{\tau}}$. We then set the due time l^k of each commodity $k \in \mathcal{K}$ by $l^k = e^k + \mathscr{L}_k + \mathscr{F}_k$. Here, the parameter $\mathscr{F}_k \geq 0$ represents the time flexibility for the delivery of commodity k, which we also set randomly using a normal distribution. We used the same normal distribution to generate the available times e^k for all instances, but used two different normal distributions to generate $\mathscr{F}_k$ for instances of high and low time flexibility, respectively. Consequently, we had two combinations of normal distributions to generate commodities' available times and time flexibility. The detailed settings of these normal distributions are described in Table 0.1, where $\mathscr{L}$ denotes the average of $\mathscr{L}_k$ over all $k \in \mathcal{K}$.

Table 0.1 Detail setting of the normal distributions used for generating "timed" instances.

Normal Distribution	Mean(μ)	Standard Deviation(σ)
For generating e_k	$\mathscr{L}$	$\frac{1}{6}\mathscr{L}$
For generating $\mathscr{F}_k$	$\frac{1}{2}\mathscr{L}$ $\frac{1}{4}\mathscr{L}$	$\frac{1}{6} \cdot \frac{1}{2}\mathscr{L}$ $\frac{1}{6} \cdot \frac{1}{4}\mathscr{L}$

For each "timed" instance obtained, we then generated unit in-storage holding costs and unit delay penalties for the commodities. We set the per-unit-of-demand-and-time in-storage holding cost h^k for each commodity $k \in \mathcal{K}$ to be proportional to its cheapest per-unit-of-time per-unit-of-flow cost, i.e., $h^k = 0.5 \min_{a \in \mathcal{A}} \{(c_a^k + f_a/u_a)/\overline{\tau}_a\}$ where $\overline{\tau}_a$ is the nominal value of the travel time generated. Inspired by Lanza et al. (2021), for each commodity $k \in \mathcal{K}$, we set its penalty g^k per unit of time for the delay to be twice the most expensive per-unit-of-time transportation cost for it to pass through an arc, i.e., $g^k = 2 \cdot \max_{a \in \mathcal{A}} \{(c_a^k \cdot q^k + f_a \lceil q^k/u_a \rceil)/\overline{\tau}_a\}$.

Moreover, to characterize travel time uncertainty, we generated the maximum deviation $\hat{\tau}_{ij}$ of the travel time for each arc $(i,j) \in \mathcal{A}$ by setting $\hat{\tau}_{ij} = \hat{\mu}_{ij}\overline{\tau}_{ij}$. Here, $\overline{\tau}_{ij}$ is the nominal value of the travel time generated, and $\hat{\mu}_{ij}$ is a coefficient randomly selected from 0.1 to 0.5.

For each network in each problem class, we randomly generated 3 instances for each combination of the distributions for commodities' available time and time flexibility. As a result, we obtained $5 \times 2 \times 3 = 30$ test instances for each of the 7 instance classes, and thus obtained $7 \times 30 = 210$ test instances in total.

In our second set of experiments, under different parameters Γ and μ_z, we need to evaluate the worst-case and average total costs of solutions obtained from models RO, RS and SP over randomly generated scenarios for instances in class R7. For each of the 30 instances in class R7, we generated 200 scenarios at random to create the set Π for model SP. To generate each scenario $\boldsymbol{\delta}$, we drew each of the realization of δ_{ijr} for $(i,j) \in \mathcal{A}$ and $r \in \{1, 2, ..., |\mathcal{K}|\}$ uniformly from the set

$\{-1, -(\hat{\tau}_{ij}-1)/\hat{\tau}_{ij}, -(\hat{\tau}_{ij}-2)/\hat{\tau}_{ij}, \cdots, -1/\hat{\tau}_{ij}, 0, 1/\hat{\tau}_{ij}, \cdots, (\hat{\tau}_{ij}-1)/\hat{\tau}_{ij}, 1\}$. Using the same approach, we also generated 1000 random *testing scenarios* for each of the 30 instances in class R7.

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