Multiperiod vehicle loading with stochastic release dates

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1 Context

Production scheduling and transportation planning are well-known processes in operations management. Although these tasks are consecutive in the supply chain, few optimization models simultaneously tackle the associated issues (see Chen [2]). A most common situation is that transportation is disconnected from production planning while it is preferable to set up an integrated production-transportation plan. When such a plan exists many elements can concur to create differences between the provisions of the tactical plan and the actual situation faced daily by transportation managers. As a consequence, operational shipping decisions often rely on deterministic data about items in inventory. The main objective of this paper is to examine whether and how transportation decisions can be improved when information about future releases of items is taken into account. The formulation and the instances are based on an application arising in the steel industry.

2 Formulation

A set of items must be delivered by an unlimited fleet of trucks of equal capacity C to M customers over a discrete (rolling) horizon consisting of T decision periods. The objective of the decisions policy is to minimize the total expected costs per ton shipped. Data relative to the first (current) period $t = 1$ is deterministic. The subsequent periods contain forecasts about the availability of items to be released from production. We represent this information by probabilistic distributions of release dates : $p_{it} \in [0, 1]$ $(i = 1, \dots, N; t = 1, \dots, T)$. We assume that $\sum_{t=1}^{T} p_{it} \leq 1$. Each item i has several deterministic attributes : its weight w_i, a delivery time window $[E_i, L_i]$, a warehouse d_i and a customer c_i locations where the item is un/loaded. It allows us to compute the cost of a truck picking up a given subset of items at their origin and transporting them to their destination according to : the composition of the load and the traveled distance ; the transportation cost per ton ; an inventory cost ; penalties linked to early or late deliveries of items to customers. The decisions to be made are the truckloads to be shipped in $t = 1$. As a general rule, grouping items on a truck is beneficial. Since the horizon is rolling, we solve a sequence of optimization problems P_ℓ, one for each horizon $\{\ell + 1, \ldots, \ell + T\}$, where $\ell = 1, 2, \ldots$

3 Algorithms

Consider a set of items I to be shipped and their release dates, $r(I) = \{r_i \,|\, i \in I\}$. Each pair $(I, r(I))$ is a possible *scenario* (Birge and Louveaux [1]). Given a scenario, optimizing can be expressed as a set covering problem, $SC(I, r(I))$, where each column is a feasible truckload. Several strategies have been developed for the stochastic version of the problem : **First period optimization :** the loading problem $SC(I, r(I))$ is solved with the items available in $t = 1 : I = \{i \,|\, p_{i1} = 1\}$; **Expected release dates :** for each item i, r_i is set to $\sum_{t \in T} t p_{it}$; **Most likely release dates :** here r_i is the modal value of the distribution p_{it} : $r_i = \text{argmax}\{p_{it} \,|\, 1 \le t \le T\}$; **Earliest release dates :** here r_i is the earliest possible release date of item $i : r_i = \min\{t \in T \,|\, p_{it} > 0\}$; **Consensus strategy :** Based on (Van Hentenryck and Bent [3]) a sample of scenarios is generated, then the set covering problems $SC(I, r(I))$ are solved. Finally, items "frequently" selected in period $l = 0, 1, 2...$ are retained in a scenario to compute a new plan ; **Restricted evaluation strategy :** After solving each set covering problem $SC(I, r(I))$ from a sample of scenarios, the quality of each optimal decision $x(I)$ obtained for $t = 1$ is cross-evaluated on the remaining scenarios. The decision $x(I)$ with the smallest overall cost is implemented.

4 Computational results and conclusions

As we are dealing with stochastic optimization problems, attention has been paid : to the estimation of the objective function, to the statistical significance of the comparisons, and to the robustness of the results.

Our main conclusions are as follows :

1. Certain policies, like **First period optimization**, are significantly dominated by others.
2. Policies based on **Earliest release dates** perform surprisingly well and are robust under a variety of assumptions regarding the probability distributions.
3. The expected cost of the best policies is closer to the cost of the optimal plan (perfect information) than to the cost of the worst policies.

Références

[1] J.R. Birge and F. Louveaux, *Introduction to Stochastic Programming*, Springer, Berlin, 1997.

[2] Z.-L. Chen, Integrated production and distribution operations : Taxonomy, models and review in *Handbook of Quantitative Supply Chain Analysis : Modeling in the E-business Era*, Chapter 17, D. Simchi-Levi, S. Wu, and Z.-J. Shen (eds.), Kluwer Academic Publishers, Boston, pp. 711-746, 2004.

[3] P. Van Hentenryck and R. Bent, *Online Stochastic Combinatorial Optimization.* MIT Press, Cambridge, Massachusetts, 2006.