Freight consolidation in urban networks with transshipments


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1 Introduction

The demand for goods in urban areas has seen a sharp growth in the past years; this trend is expected to continue in years to come (Benjelloun and Crainic, 2009). As a result, urban areas experience an increase in inflow of trucks, contributing to problems such as congestion, air pollution, and noise hindrance. Often, these trucks carry a relatively small volume of goods for a few destinations within the area. A possible solution to reduce the number of trucks in urban areas is the use of consolidation centers at the edge of these areas, where goods from incoming trucks are transshipped to dedicated urban delivery vehicles. These vehicles can subsequently make efficient tours within the urban area.

We study the dispatching decisions at an urban consolidation center with uncontrolled batch arrivals of Less-than-Truckload goods. The uncontrolled arrivals reflect the delivery of goods by independent carriers. A batch may well contain orders with, e.g., dispersed destinations and various delivery windows. Directly distributing an arriving batch may therefore render poor solutions. Instead, the hub operator could decide to hold some orders and wait for more incoming batches that allow for consolidation within the delivery vehicles. As such, more efficient routes can be taken. Various uncertainties affect the planning, such as the arrival time of new batches and the properties of the orders in a batch (e.g., size, volume, time windows). Based on the available knowledge regarding current and future orders, the operator is able to make informed waiting decisions. This can be accomplished by deploying a waiting policy that provides shipping decisions given the information and beliefs of the operator. For this purpose, we propose an Approximate Dynamic Programming (ADP) approach, aimed at efficiently dispatching urban delivery vehicles. As such, we facilitate the need for operational planning at the urban distribution level, where the arrival process of goods at the consolidation center has a significant impact.

2 Problem description

We formulate the problem as a Stochastic Dynamic Program (SDP), where the hub operator aims to minimize the total costs over a given planning horizon. We define stages as decision moments within this horizon, at which the hub operator can decide to ship orders available at the center. New orders – or knowledge regarding future orders – may arrive at the consolidation center at every stage. Each order is characterized by its arrival time at the center, its destination in the urban area, its size, and its delivery window. We consider the latter as a soft constraint, allowing to violate delivery windows (up to a maximum deviation) in favor of more efficient dispatching. Every combination of attributes represents a unique order type. As delivery tours may take multiple stages, we also consider fleet availability during the planning horizon. The fleet is either owned by the hub operator or rented, resulting in distinct cost structures. We describe the state of the system as the amount of every order type available and the fleet

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availability. The action space is given by all possible combinations of orders to dispatch. The outcome space follows from the transition of inventory and fleet due to the action taken in combination with the new random arrivals. Costs are comprised of two elements. First, transportation costs are incurred according to a cost function based on travel distance and fill rate. Second, the operator incurs a financial penalty in case of violating the delivery windows. The operator aims to minimize total costs, and is therefore required to strike a balance between lateness and efficiency. The key difficulty in finding this balance lies in the uncertainty regarding future arrivals. New arriving batches may allow to combine orders and generate more efficient routes, but the waiting time increases the risk of lateness without the desired orders arriving.

3 Solution approach

The state- and outcome space of the SDP increases in accordance with a binomial coefficient depending on both the number of orders and the number of order types. Also, the action space quickly become very large. The SDP therefore becomes intractable for realistic instances. Following Powell et al. (2012), we develop an ADP approach to (i) solve the decision problem for large instances, and (ii) obtain fitted value function approximations that allow for fast decision making in a practical setting.

To efficiently learn values of states, we define features that partially describe the state of the system, and determine the explanatory values of these features by applying linear regression on a small but representative instance of the corresponding SDP. The features we use are the total volume of (urgent) orders available, the number of distinct destinations, and fleet availability in the current stage. By considering the features instead of the full state description, we drastically reduce the computation effort. We learn the weights corresponding to specific features by simulating random arrivals and learning the expected values of actions. The result of the procedure is a value function, where inputting the batch properties and the corresponding weights directly yields the action to take.

4 Computational study

Inspired by a real-life case of urban distribution, we design a network and infer probability distributions for order types. To assess the quality of the value function approximation, we first make use of toy-sized instances. For these instances, we are able to compare the ADP results with the exact results of the SDP. To obtain insights into the behavior of the algorithm, we subsequently focus on larger instances. We vary several of the real-life characteristics to obtain a broad insight into the behavior of the algorithm. Variables we assess are (i) transportation- and penalty costs, (ii) sources of uncertainty (batch arrival time and/or contents of the batch), (iii) frequency of incoming and departing batches, (iv) flexibility in delivery windows, and (v) sizes of batches and orders (order sizes, capacity of long-haul trucks and delivery trucks). For the large instances, we compare our approach with two benchmark heuristics.

References
