Joint Order Pricing, Partitioning, and Routing for Hybrid Courier Fleets on Crowdsourced Delivery Platforms

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1 INTRODUCTION AND MOTIVATION

Last-mile delivery has been marked by sustained and rapid growth in the last decade. Consumer participation in, and reliance on, E-commerce is a predominant driver for this increase in delivery demand. This trend has accelerated during the COVID-19 pandemic, exemplified by demand surges in food, grocery, and package delivery. Due to cascading effects of the pandemic, many delivery platforms face driver supply shortages, so maximizing a delivery platform's operating efficiency becomes an essential competitive advantage.

At the same time, the emergence of the gig economy has brought with it a new type of courier, one which we refer to as an *ad-hoc courier*. Whereas a traditional courier, referred to as a *committed courier*, is employed by the delivery platform and can be dispatched to execute delivery plans, an ad-hoc courier is a non-employee courier (an independent contractor) who chooses his own work schedule and selects delivery tasks to perform in order to maximize his personal utility. Recently founded delivery platforms like Convoy (freight trucking), Roadie (last mile delivery), and Instacart (grocery delivery) utilize ad-hoc couriers to serve demand.

In this paper, we consider a crowdsourced delivery platform that employs both committed and ad-hoc couriers. The benefit of utilizing both courier types goes beyond increasing delivery capacity. Each courier type has its own advantage: ad-hoc couriers are more flexible and committed couriers are more reliable. We show that by intelligently designing an integrated system using order partitioning, dynamic pricing (for ad-hoc couriers), and routing (for committed couriers), the delivery platform can exploit the benefits of each courier base to improve customer service and minimize total costs.

2 PROBLEM STATEMENT

We consider a dynamic pickup and delivery problem on a bounded service region from the perspective of a delivery platform. Let $\mathcal{T} = [0, T]$ be the operating period in which N customer orders arrive according to a Poisson process with rate λ. Each order has a placement time, pickup location (origin), ready time, delivery location (destination) and a deadline. We define the *distance* (d) of an order to be the Euclidean distance from the pickup to delivery location rounded to the nearest integer and the *relative lead time* (τ) to be the remaining time until the latest possible pickup time for the order to be delivered on time.

In order to serve these dynamically arriving orders, a crowdsourced delivery platform employs two types of couriers: *committed* and *ad-hoc*. In general, M committed couriers are hired prior to $\mathcal{T}$ (and paid a fixed wage w) and are assigned routes, i.e., sequences of delivery tasks, by the crowdsourced delivery platform. Ad-hoc couriers, on the other hand, arrive (at a random location) according to a Poisson process with rate μ. Upon arriving, ad-hoc couriers select an order (or no order) from a *bulletin board* of the current open orders according to a multinomial logit (MNL) choice model. After selecting an order, ad-hoc couriers receive a payout $p_{\tau d}$ which is a function of the relative lead time and O-D distance of the order. We refer to the problem of minimizing the total cost over $\mathcal{T}$ as the Dynamic Hybrid Capacity Management Problem (DHCMP). The delivery platform then has to decide:

1. The number of committed couriers to hire at the start of the time horizon, M;
2. An order allocation policy that splits arriving orders between the two types of courier systems;
3. The (dynamic) prices posted on the bulletin board for delivery tasks for ad-hoc couriers denoted by $\mathbf{P} = \{p_{\tau d} : \forall \tau = 1, ..., B; s = 1, ..., S\}$; and
4. A policy that manages the delivery routes of committed couriers.

3 ANALYSIS

3.1 FLUID MODEL

To analyze the system in a tractable way, we propose a fluid (deterministic) model to approximate the original stochastic system. In the fluid model, the states of all open orders at a specific time are represented by a matrix, depicted in Figure 1, where L is the maximum relative lead time and $d_{\max}$ is the maximum possible distance between origin and destination. The row of the matrix

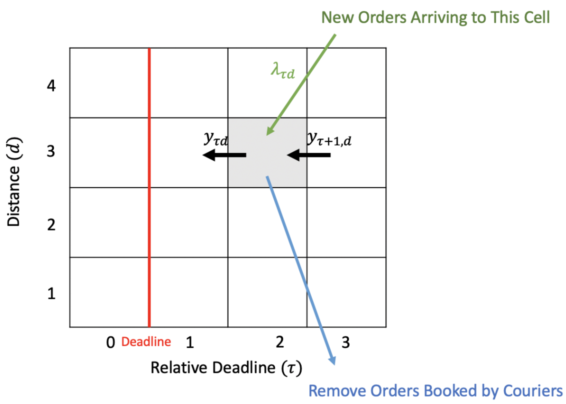

Figure 1 – *An order status matrix illustrating how the states of all open orders are characterized and the flow dynamics for a given state ($L = 3$ and $d_{\max} = 4$.)*

represents orders' relative lead time, and the column represent orders' service time. Parameter $\lambda_{\tau d}$ is the rate at which orders with a specific relative lead time and distance arrive the system and $X_{\tau d}$ represents how many open orders have distance d and relative lead time τ. As time passes, the relative lead time decreases, and for each unit of time that passes, the values in the matrix shift one column to the left. For simplicity, we define the decision variable $y_{\tau d}$ to be the rate at which orders transition to the subsequent cell. The fluid model approximates the system in steady state, where each entry of the order status matrix reaches a flow balance, allowing us to model the system as a deterministic optimization problem.

Utilizing this fluid approximation, we formulate multiple optimization problems to study optimal policies for the DHCMP. Firstly, we formulate a pure ad-hoc courier system where the optimal price is derived from the MNL choice model. We characterize the structure of the solution to this formulation, and prove that this implies that the optimal price is non-decreasing in the relative deadline of an order (i.e. more urgent orders will have a higher price.) Secondly, we formulate a pure committed courier system, where the number of couriers to hire, M, is a decision. Unlike an ad-hoc system where the rate at which orders are selected is constrained by the arrival rate of couriers, the hiring decision M controls the maximum rate at which orders can be served. We model this effect in a similar manner to Castillo *et al.* (2017) by introducing a constraint which essentially splits the total number of committed couriers into those that are idle, currently delivering orders, or en-route to a pickup location. Next, we model two versions of a hybrid system, a *pooled* and *dedicated* system. In the pooled system, committed and ad-hoc couriers select from the same pool of orders; in contrast, in the dedicated system, orders are partitioned according to a rule in an irrevocable manner, namely, once an order has been assigned to a courier type it cannot be changed.

3.2 COMPUTATIONAL RESULTS

We present some computational results in Figure 2 that illustrate how our analytical results of the fluid model translate to the original stochastic model in a simulation setting. Several order allocation policies are considered in this simulation. In the *pooled* policy, all open orders are available for selection by ad-hoc or committed couriers. The *random*, *JSQ* and *JSQ-condition* policies are all variants of a dedicated, irrevocable policy. When an order arrives, it is either assigned to the ad-hoc or committed subsystems. For random, the assignment is dictated by probabilities directly from the hybrid formulation (low distance orders have a higher probability of being assigned to the committed subsystem.) For JSQ, the order simply joins the subsystem with the smallest current expected waiting time. Lastly, the JSQ-condition policy is simply the JSQ policy, under the condition that the order must below a fixed distance to join the committed queue. Notice that the random policy does well in heavy traffic (defined by higher demand to

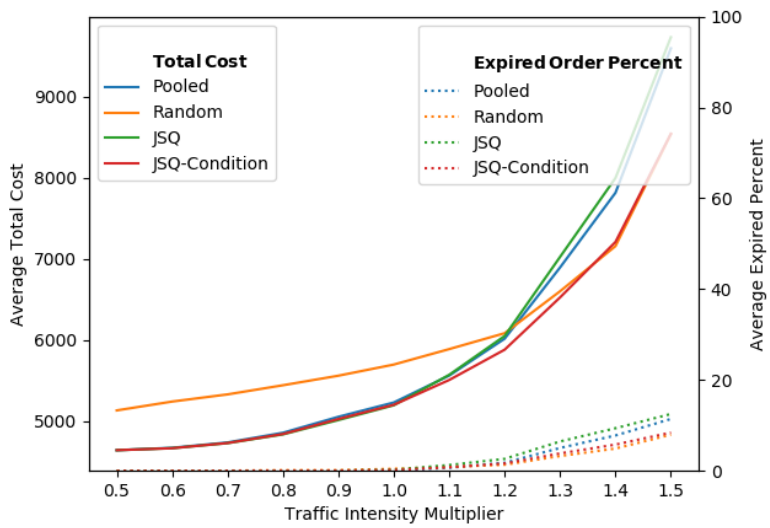

Figure 2 – *Total cost and expired order percentage under varying traffic intensity.*

capacity ratios), as the benefit of utilizing committed couriers becomes more and more important for reducing the number of expired orders (an order expires if it cannot be delivered at or before its deadline). However in low traffic, cost is associated with assigning orders to the bulletin board when they could have been served by committed couriers. While JSQ does not perform as well as pooled or random in heavy traffic, we are able to leverage the benefit of intelligently selecting orders with specific characteristics (orders below a certain O-D distance) to go to the committed subsystem with JSQ-condition. In turn, we can outperform a pooled system in both low and heavy traffic conditions by simply restricting the distances of orders in the committed system. This results serves as motivation for the next section, where we present a method of taking complex routing decisions into account when partitioning orders and show it further improves our solutions.

4 JOINT PARTITIONING AND ROUTING

Using the optimal prices for delivery tasks for ad-hoc couriers derived above, we consider joint order partitioning and committed courier routing decisions in the DHCMP. We present a rolling-horizon approach. At the start of the time horizon, we first solve a single-stage optimization problem for the fluid approximation of the hybrid system for the number of couriers hired M and the price matrix $\mathbf{P}$. Then, at each subsequent decision epoch, we formulate the decision problem as a fixed fleet pickup and delivery problem with order dependent outsourcing costs. Algorithm 1 illustrates the basic implementation of our column generation method to be executed at each decision epoch.

Algorithm 1: A column generation approach to joint routing and order allocation at decision epoch t.

Data: $\mathbf{g}_t$: vector of expected costs of assigning each open order to the ad-hoc subsystem at time t.
$\mathbf{col}_{t-1}$: the columns (feasible routes) found from the last decision epoch.
Result: routingPlan, adhocList
Init: startColumns $\leftarrow$ truncate($\mathbf{col}_{t-1}$);
improvingColumns $\leftarrow$ basis(newOrders);
columns $\leftarrow$ startColumns $\cup$ improvingColumns
while improvingColumns $\neq \emptyset$;
do
improvingColumns $\leftarrow$ dual_directed_search(newOrders, columns, $\mathbf{g}_t$);
columns $\leftarrow$ columns $\cup$ improvingColumns
routingPlan, adhocList = solve_IP(columns, $\mathbf{g}_t$);
return routingPlan, adhocList

5 DISCUSSION

In sum, this work presents an integrated decision problem faced by crowdsourced delivery platforms using a hybrid fleet of committed and ad-hoc couriers, provides theoretical insight by introducing and analyzing fluid formulations, proposes a column generation method for joint order partitioning and routing, and validates the approaches outlined in this work with computational experiments. As such, this work is of interest to those engaged in modern logistics research and industry partners.

References

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