Data-Driven Order Assignment for Last Mile Delivery

As ecommerce booms and customers expect faster delivery, food shopping has recently been shaped to a case in point. Fast-growing online platforms enable convenient food ordering and delivery services for customers. In food delivery service provided by platforms such as Grubhub and UberEATS, food is prepared and packaged by restaurants and the platform is only responsible for food pickup and delivery. By contrast, food service providers such as SpoonRocket and Domino’s Pizza prepare and deliver their own food boxes. A key challenge faced by both types of service providers is how to assign prepared orders to available carriers or drivers for fast and efficient delivery.

In this paper, we consider the order assignment problem motivated by a food service provider that prepares and delivers food to its customers in Shanghai, China. The provider operates a central kitchen, which is referred to as “the depot” thereafter, and serves customers within a certain radius from the depot. Customers place orders before each cutoff time, e.g., 10:30 am, are promised to receive the orders within a time window, e.g., by 11:45 am. However, the provider found that delays seemed to be inevitable if the orders were not well allocated to drivers, as a delay at one location will propagate to subsequent visits by the same driver.

The order assignment problem faced by food service providers is complicated, due to the following practical challenges. First, the complex road condition and practical constraints make it difficult for drivers to follow suggested routes or delivery sequences. For example, the considered provider allows drivers to have freedom in deciding their own routes to deliver the assigned orders. It is thus common to see drivers – riding electric bikes in Chinese cities – flexibly adjust their routes
based on their experience and realtime road conditions. Consequently, the actual delivery routes usually deviate from the recommended routes and an accurate estimation of actual delivery tour for serving a set of customer locations is difficult. Second, the time a driver spends at a customer location, which we term as the “service time”, is highly uncertain. As the customer locations are often high rise buildings in metropolitans, drivers usually need to find parking spaces, navigate to the right floor and meet customers in person. The service time varies and depends on the customer location and the order size, which are also random from day to day. Generally, it takes longer service time to navigate in a taller building and to deliver larger orders at one location. Compared to the service time, the travel time on road has much less uncertainty, as indicated by the service provider for reasons, including that the drivers riding electric bikes can take bicycle lanes to avoid traffic congestion. Therefore, the travel time is more predictable by the delivery tour distance and estimated travel speed.

To tackle the challenges described above, in this paper, we propose a data-driven framework to model the delivery performance and optimize order assignment decisions. We use data analytics to develop a delivery tour prediction function from delivery operational data, to incorporate driver’s routing behavior in the subsequent order assignment optimization models. The resulting data analytics also highlight the importance of dealing with service time uncertainty, in meeting the target of on-time delivery. Using historical delivery data in the scheme of sample average approximation (SAA), we propose a data-driven order assignment (DOA) model as a mixed-integer linear program (MILP) that assigns orders to available drivers to minimize the expected total delay of all routes. To deal with the inadequacy of observations at several locations, we further develop a DOA model as a mixed-integer second order conic program (MISOCP), using distributionally robust optimization (DRO) framework, where limited distributional information can be obtained from the data. We then develop a branch-and-price algorithm for both DOA models, aiming to improve the computational performance for real applications.

In the case study using an operational data set of food delivery, we employ a data-driven approach
to evaluate the out-of-sample performance of the proposed DOA models with delivery tour prediction function, in benchmark with the models based on classical vehicle routing problem (VRP). We also discuss several practical and managerial issues, such as the impact of sample size for SAA model and the provider’s staffing considerations. We summarize our contributions as follows.

1. **Data-driven modeling:** We decompose the uncertainty of total delivery time into the uncertainty service time at the customer locations and a more predictable travel time on road. That is, from a graph perspective, we aggregate all uncertainties to the nodes and leaving the edges predictable. Such treatment allows us to model the travel time and integrate uncertainties in the optimization models. Our delivery tour prediction function learned from real data reveals higher prediction accuracy in the practical application compared to the solution from classical traveling salesman problem. Besides, it predicts the tour length without explicit optimization on the delivery sequence and renders computational tractability in the subsequent order assignment optimization.

2. **Data-driven optimization:** We employ the SAA and DRO frameworks to utilize real data for both abundant-data and limited-information contexts. Utilizing the independence in service time, which is verified from data analytics, we overcome the difficulty in solving the robust problem exactly under piecewise linear objective and derive a MISOCP formulation, which is computationally tractable and scalable. Furthermore, by exploiting the problem structure, the branch-and-price algorithm delivers superior performance in both solution time and solution quality, compared to solving the MILP and MISOCP formulations directly using commercial solvers, e.g., Gurobi.

3. **Managerial insights:** From out-of-sample evaluation in the case study, we find that the DOA models significantly outperform the VRP-based models, which ignore driver’s routing behavior. The results numerically quantify the benefit of data-driven modeling. We also observe that the performance of the DOA model using SAA improves with larger sample size, at the cost of longer computational time. However, the VRP-based model using SAA does not necessarily benefit from larger sample size, due to its bias in delivery tour estimation. Moreover, applying the VRP-based model may lead to unnecessary overstaffing to target on-time performance. Finally, the performance gap between the DOA and VRP-based models is higher under more stringent delivery requirements — with less drivers and tighter delivery time window.