Workload Balance in Last-Mile Delivery in Mega-Cities

Yang Wang[a*], Lei Zhao[a†], Martin Savelsbergh [b‡], Xue Luo[a§]

[a]Department of Industrial Engineering, Tsinghua University, Beijing, 100084, China

[b]H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, Georgia, 30332

In recent years, the world has witnessed fast pace of urbanization and rapid growth of e-commerce, which jointly post significant challenges in urban delivery. In China, 1.18 million express delivery personnel delivered more than 20 billion packages in 2015. 61.7% of the delivery personnel worked 8-12 hours per day and 24.7% worked over 12 hours per day, with their daily delivery ranging from 10 to 150 packages (Beijing Jiaotong University et al., 2016). In the rest of the paper, we refer to the delivery personnel as "drivers" despite that they typically ride e-tricycles rather than driving vehicles.

In practice, at the beginning of each delivery shift, the delivery station manager needs to perform the package-to-driver assignment (delivery dispatching), while each driver determines the actual routing to deliver the assigned packages to customers. As a driver's income is highly (sometimes solely) dependent on the number of packages delivered, he/she wants to be assigned as many packages as possible, which we refer to as *incentive workload*. On the other hand, the effort (e.g., travel distance, delivery time, etc.) to deliver the assigned packages may vary significantly, depending on the proximity of the delivery addresses, restrictions in accesses to certain delivery addresses, familiarity of the driver to the delivery addresses, etc. For the same amount of delivery packages, a driver wants to be assigned packages that enable him/her to spend as little effort as possible, which we refer to as *effort workload*. Therefore, recognizing and balancing these two types of workload among the drivers is critical in maintaining their morale and ensuring high-quality and sustainable last-mile delivery services to customers.

In the multi-objective routing literature, the objectives include minimizing load or route imbalance and minimizing the total travel distance/duration/cost. A few researchers study routing problems with load balance (corresponding to incentive workload, e.g., Bowerman et al., 1995; Kritikos and Ioannou, 2010), while most focus on routing problems with route balance (corresponding to effort workload). The route (im)balance criteria include: the maximum distance/duration/cost among the routes (Corberán et al., 2002), the range of distances/durations/costs among the routes (Jozefowiez et al., 2009), and other criteria (Halvorsen-Wearea and Savelsbergh, 2016). Baŋos et al. (2013a,b) study routing problems with either load or route balance.

In this paper, we study the impact of the above two types of workload balance in the last-mile delivery dispatching. More specifically, we use the number of delivery packages as the measure of incentive workload and delivery time as the measure of effort workload. We study two (im)balance criteria, namely, maximum and range of the workload. Therefore, we have $MaxI$ and $RangeI$ for the incentive workload and $MaxF$ and $RangeF$ for the effort workload. In practice, a delivery dispatching with "perfect" workload balance may result in unnecessarily longer delivery time, while a dispatching with minimum total delivery time may

*yang-wan15@mails.tsinghua.edu.cn

†lzhao@tsinghua.edu.cn

‡martin.savelsbergh@isye.gatech.edu

§luoxue16@mails.tsinghua.edu.cn

result in serious workload imbalance. Therefore, the problem under study is a bi-objective routing problem with minimizing workload imbalance and minimizing total delivery time as the objectives. We extend the two-index two-commodity flow formulation (Baldacci et al., 2004) to a three-index model to formulate the problem as a bi-objective mixed integer program (MIP). We adopt the balanced box method (BBM, Boland et al., 2015) to obtain the complete set of Pareto solutions.

To properly evaluate the delivery time of a driver with a given set of assigned delivery packages, we assume each driver delivers that packages in an "optimal" way. In reality, it involves many practical aspects such as knowing specific restrictions or conveniences at a certain address around some time of the day. In the model, we simplify the practical details but simply ensure that each driver delivers the packages according to a TSP (Traveling Salesman Problem) tour, which we refer to as the *tour optimality* constraints. When using $MaxI$, $MaxF$, or $RangeI$ as the balance criterion, the tour optimality constraints can be implicitly satisfied. However, when using $RangeF$ as the balance criterion, a routing solution may arbitrarily increase the delivery time of the shortest route in order to reduce $RangeF$, which leads to a non-TSP tour of the corresponding route and thus violates the tour optimality constraints ("artificial Pareto optimality"). However, the tour optimality constraints cannot be explicitly formulated in the MIP model. Therefore, we introduce the Sequence Breaking Inequality (SBI) as the valid inequalities. When detecting a non-TSP tour during the iterations of the BBM, we adaptively add the SBI cuts to cut off the violating solution.

We generate the instances by randomly choosing 10, 12, or 15 customers from the customer set of R and C categories of Solomon instances (Solomon, 1987). Preliminary numerical results suggest that 1) effort workload balance criteria generate more Pareto points than incentive workload balance criteria and range criteria generate more Pareto points than maximum criteria; 2) as a consequence, RangeF criterion generates the most number of Pareto points and demands the most computational time, also due to the effort to handle the artificial Pareto optimality; 3) the dispatching and routing decisions generated by the two types (incentive and effort) of workload balance criteria are significantly different.

Keywords: Last-mile urban delivery; offline dispatching; workload balance; balanced box method; cutting plane algorithm

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