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Model-based delivery cost approximation in attended home services

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ABSTRACT

Most commonly, attended home services are designed such that a booking period precedes the actual service period which is subdivided in several predefined time windows. During the booking period, the provider and each of her customers agree upon one of the time windows for service delivery. Providers try to influence the customers' choices by restricting the availability of time slots or asking for time slot dependent fees in order to minimize the resulting delivery costs. Several integrated optimization models which simultaneously consider both periods have been proposed in the literature for the case where delivery costs are mainly due to routing costs of service vehicles. Usually, these models consider decisions in the booking period on a very detailed level, whereas the resulting routing costs in the service period are approximated on a rather rough level. To get better approximations, we propose four new linear mixed-integer programming models which can be combined with the existing approaches for modelling the booking period. The basic idea consists in generating a pool of possible routes, subsets of which are selected using a set-covering approach to get feasible routings. Following this idea, standard solvers can be used for the resulting integrated models, a requirement becoming more common in practice. Computational experiments show that the approximated costs are sufficiently close to the real ones.

1. Introduction

In recent years, prospering businesses have established that deliver goods or services to customers at appointed service time windows. We name these businesses attended home services (AHS). Service time windows (synonymously called service time slots) might be necessary for various reasons, for instance, due to perishable goods (e.g. food or flowers), because goods are physically large (e.g. furniture or kitchen appliances), for security reasons (e.g. expensive technical equipment or pharmaceutical products), or because of service completion (e.g. repairman or service technicians) (Agatz, Fleischmann, & van Nunen, 2008). Moreover, in the competitive market environment of the internet era, the demand of high-quality customer service changes many classical businesses traditionally operating without service time windows. Service providers' so called "self-imposed time windows", during which the customer can expect the service, gain popularity and replace the traditional policy of only communicating the delivery or service day. Examples are parcel delivery, furniture delivery, and internet installation services (Jabali, Leus, van Woensel, & de Kok, 2015). The growing demand for these services can be illustrated by forecasts of growth for the global e-grocery sector. The Boston Consulting Group predicts the compound annual growth rate to exceed 23% from 2013 to 2018, leading to an increase of the expected sales volume from \$36 billion (in 2013) to \$100 billion in the worldwide e-grocery sector (in 2018) (Crawford, 2014).

Compared to "self-imposed time windows", the service experience is clearly improved when the customers are allowed to choose their respective service time window by themselves, which has become common, for instance, in the area of e-grocery. Regarding the temporal sequence, a booking period precedes the actual service period in which delivery will take place. In the example of e-grocery, the service period consists of a certain day of the week which is subdivided in time windows (e.g. six non-overlapping 2-h time windows). The booking period ends at a certain cut-off point (e.g. on the eve of delivery), until when the customers have to place their order and select a time window.

In such a setting, a service provider can use demand management to influence the customers' service time window choices. In order to set appropriate incentives, she might, for instance, price the service time windows differently (e.g. Klein, Neugebauer, Ratkovitch, & Steinhardt, 2015; Yang, Strauss, Currie, & Eglese, 2016), announce discounts (e.g. Campbell & Savelsbergh, 2006), or even close certain service time windows (e.g. Agatz, Campbell, Fleischmann, & Savelsbergh, 2011; Campbell & Savelsbergh,

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2005). All incentives can be set statically or changed dynamically during the booking period. It must be noted that throughout this paper, the provider is referred to as "she" with the sole purpose of distinguishing him or her from the customer, who is correspondingly referred to as "he".

The main motivation for the provider to conduct demand management is to reduce the routing costs for service delivery. Assuming that she is able to exactly forecast the customers-to-come, their demand and location as well as their reaction on certain incentives, a basic idea could be to formulate an integrated optimization model which conceptually consists of two components. The first component controls the setting of the incentives, while the second one determines optimal delivery routings for the resulting distribution of customers over time windows. However, in practice, this is not possible for the following reasons:

- Firstly, customer data cannot be forecasted on a sufficiently detailed level, because orders arrive stochastically during the booking period.
- Secondly, setting up an integrated model would require to introduce the vehicle routing constraints of the Vehicle Routing Problem with Time Windows (VRPTW) into her optimization model. However, since the VRPTW itself is a NP-hard problem (e.g. Solomon & Desrosiers, 1988), this approach does not seem promising when standard software for optimization is to be used, a requirement becoming more important in practice.

To cope with these difficulties, several simplifications have been proposed in the literature:

- Agatz et al. (2011) and Klein et al. (2015) propose to aggregate potential customers to "customer sets". This can, for instance, be done based on time windows and delivery zones and by identifying segments with a similar choice behavior. Concerning the modelling of the booking period, this allows to derive the total demand for these sets based on incentives chosen. Furthermore, to deal with uncertainty, the expected demand can be considered. With respect to the modelling of the service period, planning is done based on average distances within delivery zones.
- Customers are assumed to have unit demand. This assumption is justified for two reasons: Firstly, in many AHS all customers demand (nearly) the same capacity volume (e.g. a standard-sized transport box in the e-grocery business; see, e.g. Yang et al., 2016), and secondly, it is reasonable to assume the same average demand volume for all future expected customers.

Based on these simplifications, both static and dynamic approaches have been proposed for demand management, i.e., for setting incentives. Agatz et al. (2011) present a time slot management problem, in which they approximate the routing costs using a seed-based scheme introduced by Fisher and Jaikumar (1981). Klein et al. (2015) discuss a time slot pricing problem in the e-grocery business and propose two approximations that adapt and extend the ideas introduced by Fisher and Jaikumar (1981) as well as by Agatz et al. (2011). Both approaches are static, i.e., the incentives are not changed during the booking period and completely rely on solving linear mixed-integer problems using standard software. By the way of contrast, to the best of our knowledge no such model-based approaches for dynamic problems in AHS exist in the literature. To date, most dynamic models, for instance, Campbell and Savelsbergh (2005, 2006), and Ehmke and Campbell (2014), are solved building on insertion heuristics (e.g. Solomon, 1987) and hence, cannot be solved by means of standard optimization software. It must be noted that the models presented in the literature are generally intended to support the service provider's demand management decisions during the booking period. After the booking period's end, the final operative vehicle routes are planned, for instance, by means of professional routing software.

One major challenge to obtain better integrated models, which also can be solved by standard software, is to approximate the routing costs in a more accurate, but still efficient way. Sticking with the prevalent approach of working with "customer sets", a slightly modified version of the Split Delivery Vehicle Routing Problem with Time Windows (SDVRPTW) has to be considered within the second component addressing the service period. It consists in determining least cost sets of routes starting and ending at the depot, such that every customer is served, the vehicle capacity is being respected, and the service of customers is executed within their service time windows (e.g. Gendreau, Dejax, Feillet, & Gueguen, 2006; Ho & Haugland, 2004). The costs are composed by a fixed cost for every chosen route, i.e. every vehicle in use, and variable costs per unit of travel distance. From a modelling perspective, visiting a single customer in the standard SDVRPTW corresponds to visiting a "customer set" in our problem. A split can occur if a "customer set" is served by multiple vehicles. However, a single customer has to be served by a sole vehicle. In general, it is assumed that the service provider has access to a fleet of homogeneous delivery vehicles located at the same depot. It must be noted that there is a vast body of literature on vehicle routing problems in general. Eksioglu, Vural, and Reisman (2009) present a comprehensive taxonomic review.

In this paper, we introduce four linear mixed-integer programming-based approaches for solving the slightly modified version of the SDVRPTW heuristically and which are suited as "plug-ins" for integrated models for AHS. By "plug-in" we mean, for instance, that they could be integrated in the formulations of Agatz et al. (2011) or Klein et al. (2015) by simply replacing their vehicle routing restrictions with our models' restrictions and adapting their objective functions. Furthermore, they are suitable for any practical application (e.g. repairman or e-grocery business), any demand management concept (e.g. time slot pricing or management), and any planning level (i.e. tactical or operative level).

All approaches are based on set-covering vehicle routing formulations. While in classical vehicle routing models the routes are constructed during the models' solution, set-covering formulations require a pool of routes and the choice of the best routes constitutes the solution. The pool of routes consists of a set of feasible routes as input for all approaches. These feasible routes can be generated in various ways. For instance, historical routes utilized in the past, routes proposed by the provider's decision makers in the operations department, and/or routes constructed by some (heuristic) algorithm can fill the pool of routes. As all approaches are intended to solve the same problem, the key differentiator between the models is the extent of decisions made during the models' solution and decisions already fixed in the routes. In general, the simpler the model formulations are, the more information has to be included in the routes. Depending on the model, while constructing the pool of routes, various restrictions might be considered that do not have to be explicitly incorporated in the respective model formulation. For instance, a desired minimum or maximum number of stops might be determined, certain (parts of) routes might be forbidden, or time-dependent travel times might be incorporated. We implement the four model-based approaches using the standard optimization package ILOG CPLEX Optimization Studio. By evaluating over 5000 demand instances, we investigate which model should be utilized in practice and which is the best size for the pools of routes depending on the delivery region size and the provider's ability to influence the customers' service time window choices. Finally, we introduce a heuristic approach as benchmark to assess the approaches' performance.