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Ensuring service levels in routing problems with time windows and stochastic travel times

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ABSTRACT

In the stochastic variant of the vehicle routing problem with time windows, known as the SVRPTW, travel times are assumed to be stochastic. In our chance-constrained approach to the problem, restrictions are placed on the probability that individual time window constraints are violated, while the objective remains based on traditional routing costs. In this paper, we propose a way to offer this probability, or service level, for all customers. Our approach carefully considers how to compute the start-service time and arrival time distributions for each customer. These distributions are used to create a feasibility check that can be "plugged" into any algorithm for the VRPTW and thus be used to solve large problems fairly quickly. Our computational experiments show how the solutions change for some well-known data sets across different levels of customer service, two travel time distributions, and several parameter settings.

1. Introduction

In times of increasing customer expectations and more customer-oriented business models, the consideration of delivery time windows has become much more common in the creation of delivery routes. For example, in attended home delivery applications, customers and service providers mutually agree on tight delivery time windows. It is not surprising that there have been a considerable number of recent papers on how to solve the vehicle routing problem with time windows (VRPTW), including Baldacci, Mingozzi, and Roberti (2012), Vidal, Crainic, Gendreau, and Prins (2012), and Hashimoto, Yagiura, Imahori, and Ibaraki (2013). The classic VRPTW assumes deterministic travel times between stops on the route. However, in practice, the execution of delivery routes often differs from plans due to a variety of influences such as traffic jams, weather, customer availability, etc. These influences may cost the driver to miss customer time windows, which can create dissatisfaction and loss of future sales.

While the predictability of some of these individual factors is nearly impossible, it is often possible to derive travel time distributions for the travel time between customers based on historical data. This idea is the foundation of a stochastic variant of the VRPTW, known as the SVRPTW, where travel times are assumed to be stochastic. As we will discuss in more detail in Section 2, many papers in this area take a recourse approach to the SVRPTW, putting a penalty in the objective function based on how much the expected arrivals at customers exceed the deadlines. While such an approach considers overall customer service, it does not guarantee a particular level of service at individual customers.

In our chance-constrained approach, restrictions are placed on the probability that individual time window constraints are violated, while the objective remains based on traditional routing costs. Chance-constrained approaches guarantee a given service level for all customers, but are traditionally considered much more difficult to solve due to the use of restrictions. We have seen very little SVRPTW research that addresses how arrival time distributions should properly be propagated throughout a route given the presence of time windows. For example, if an arrival occurs before the opening of a customer's time window, a vehicle must wait, and this impacts the arrival time distribution at future customers.

In this paper, we propose a fairly straightforward way to guarantee a given service level at all customers. Our approach carefully considers how to compute the start-service time and arrival time distributions at each customer on the route, which enables us to verify if the given service level is maintained at individual customers. Our ideas can be "plugged" into any algorithm for the VRPTW and thus be used to solve large problems fairly quickly. In comparison to the limited literature on the SVRPTW that also considers a

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service level requirement, this is a key differentiation point and is a big part of our paper's contribution.

In Section 2, we review the relevant literature, while Section 3 formally defines the problem we solve. In Section 4, we describe how to estimate the mean and variance of the start-service time and arrival time distributions with careful consideration of the impact of time windows. The equations we derive are based on the assumption that travel time between customers follows a normal distribution, but we demonstrate via simulation that these equations work well with instances that have travel times that are not normally distributed. This is an important part of our contribution since travel time distributions are often not normal in practice. In Section 5, we discuss how these equations can be added to any VRPTW algorithm in the form of a feasibility check. Computational experiments in Section 6 show how the solutions change for different levels of customer service across two travel time distributions and several parameter settings.

2. Literature review

In our literature review, we will discuss stochastic routing, then review in more detail the work specifically on the SVRPTW. We will then discuss other recent work that deals with the handling of lateness.

Most stochastic routing literature focuses on stochastic demand rather than travel times. Gendreau, Laporte, and Séguin (1996) review the literature involving the vehicle routing problem with stochastic components and identify several papers that take into account stochastic demands and/or customer realization (i.e., each customer has some probability of realizing demand). The only mention of stochastic travel times is in the context of a traveling salesman problem with a duration constraint. More recent papers involving stochastic customers or stochastic demand include Jabali, Rei, Gendreau, and Laporte (2012) and Taş, Dellaert, van Woensel, and de Kok (2013).

Laporte, Louveaux, and Mercure (1992) were the first to incorporate stochastic travel times as part of a vehicle routing problem (VRP) model. Because there are no time windows, time windows do not impact how travel times are combined. They present both a chance-constrained model and a recourse model. The chance constraint limits the probability that the duration of the route exceeds a given limit rather than the likelihood of time window violations. They develop a branch-and-cut algorithm to solve problems with up to 20 vehicles and travel times that can take on a value from as many as five discrete states. Lambert, Laporte, and Louveaux (1993) develop a model specific to a particular banking context in which travel time is based on a given probability the route is congested. Kenyon and Morton (2003) consider two models with different objective functions: (i) minimizing the expected time that all vehicles will return to the depot, and (ii) maximizing the probability of completing the routes by a given deadline. They develop a branch-and-cut approach to solve the problem when the cardinality of the sample space is small and embed a sampling-based procedure for larger sample spaces or continuous random parameters. More recently, Mazmanyan and Trietsch (2009) focus on the traveling salesman problem and are concerned with the completion of the route by a given due date. They impose a normal distribution assumption on arrival times. They also assume that travel times are themselves normally distributed or the number of customers is large enough to justify the central limit theorem.

Other papers have considered the reliability of routes. Cook and Russell (1978) evaluate the suitability of deterministically-generated routes on the VRP with stochastic travel times via simulation. Lecluyse, Van Woensel, and Peremans (2009) solve a routing problem with an objective that includes the standard deviation of the travel time. This guides the solution to choose more reliable routes in terms of travel time. Because there are no time windows, the variance of travel time is again added, and they use a lognormal distribution in their experiments. Lee, Lee, and Park (2012) identify robust solutions in which the travel time is represented by an uncertainty set as opposed to a probability distribution. They consider a situation with customer deadlines (i.e., a late time window), so their approach cannot be directly applied to situations with early time windows. Agra et al. (2013) use uncertainty sets to model stochastic travel times in the context of maritime shipping. They present a robust optimization approach to determine routes that are feasible for all values of travel times.

For most problems with stochastic travel times that include time windows, authors use a recourse model. In a recourse model, arrival times before and after the customer time windows are discouraged via penalties in the objective rather than hard constraints. For example, Taniguchi, Thompson, Yamada, and van Duin (2001) examine the vehicle routing and scheduling problem with time windows-probabilistic (VRPTW-P) with an objective consisting of fixed costs, costs of operation, and early arrival and delay penalties. If a vehicle arrives early, it must wait and pay a penalty proportional to the wait time. If the vehicle arrives late, the service provider must pay a penalty proportional to the delay instead of receiving a reward. The authors use a dynamic traffic simulation to calculate the distribution of travel times. Ando and Taniguchi (2006) build on this model to include more information about the variability in travel times. The costs of operation are estimated using average travel times, but delay penalties are computed based on the probability of different arrival times. Different distributions may be used, but the propagation of variance in conjunction with time windows does not appear to be considered in this probability. The authors solve this problem using genetic algorithms and show that considering the uncertainty of travel times can have a big impact on the resulting delay costs. Taş et al. (2013) and Taş, Gendreau, Dellaert, van Woensel, and de Kok (2014) use soft time windows, where service costs are incurred for early and late arrivals. Vehicles do not wait, so the time windows do not impact the propagation of variation. Taş et al. (2013) solve their problem by tabu search and Taş et al. (2014) by column generation. Russell and Urban (2007) also consider stochastic travel times in conjunction with soft time windows where violation of the windows is penalized. They focus on the shifted gamma distribution, as it provides a good representation of realistic travel times. They use a Taguchi loss function to compute penalties and find solutions with a tabu search procedure. Yan, Wang, and Chang (2014) study the SVRPTW in a banking context. They present an integer multiple-commodity network formulation to determine a robust and flexible set of routes. Violations of time windows are again penalized in the objective function.

There are a few papers that consider stochastic travel times, time windows, and a service level constraint. The first we describe is Li, Tian, and Leung (2010). The authors consider both a chance-constrained and a recourse model. In the chance-constrained model, both the duration of the route and the satisfaction of the time windows must be feasible with a certain confidence level. The chance constraints are evaluated via simulation. For example, if the simulation of a route does not show the chance constraints to be satisfied within the confidence level, the route is not acceptable as a solution. Branda (2012) presents a sample approximation technique for mixed-integer stochastic programming problems. The effectiveness of the sampling technique is evaluated based on a limited number of instances of a vehicle routing problem with stochastic travel times and hard time windows.

More closely related work to ours is Jula, Dessouky, and Ioannou (2006). They consider stochastic travel times, time windows, and also try to guarantee a certain level of service. Even though their