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Vehicle routing problem with stochastic travel times including soft time windows and service costs

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ABSTRACT

This paper studies a vehicle routing problem with soft time windows and stochastic travel times. A model is developed that considers both transportation costs (total distance traveled, number of vehicles used and drivers' total expected overtime) and service costs (early and late arrivals). We propose a Tabu Search method to solve this model. An initialization algorithm is developed to construct feasible routes by taking into account the travel time stochasticity. Solutions provided by the Tabu Search algorithm are further improved by a post-optimization method. We conduct our computational experiments for well-known problem instances. Results show that our Tabu Search method performs well by obtaining very good final solutions in a reasonable amount of time.

1. Introduction

Traditionally, the Vehicle Routing Problem with Time Windows (VRPTW) aims to route vehicles such that all customers are served within their respective time windows. Mathematically, this is translated into a deterministic arrival time moment of being in the time window or not. The latter is usually penalized depending on whether the vehicle is early or late. However, solutions of the deterministic routing models deteriorate once applied in real-life problems where (especially) the travel times are stochastic (see [1] for a review). Using stochastic travel times allows for a much richer set of (stochastic) measures to evaluate whether the vehicle arrives in the time windows or not. The definition and incorporation of these stochastic measures in the VRPTW is the subject of this paper.

In practice, carrier companies and their customers have different concerns. From the perspective of the carrier companies, the goal is to deliver the goods to different customers as efficiently as possible. From the customers' point of view, the main concern is to reliably receive the deliveries on-time. In this paper, our routing problem has soft time windows and stochastic travel times, leading to stochastic arrival times. The latter are used to calculate the service costs, defined as the measure of delivery reliability.

The described problem extends the classical Vehicle Routing Problem (VRP) by considering stochastic travel times and soft time windows. The VRP belongs to the class of NP-hard combinatorial optimization problems (see [2] for an explanation). Small-sized instances of such problems are usually handled by exact algorithms. However, metaheuristic algorithms are widely used to solve medium- to large-sized instances. In this paper, we solve the Solomon's problem instances [3] effectively by a solution procedure based on Tabu Search.

The two main contributions of this paper are described below.

1. Our paper proposes the first model that distinguishes between the transportation costs and the service costs. Stochasticity in the travel times plays a role in the calculations of both cost components. The transportation costs are the true costs that the carrier company pays. On the other hand, the intangible service costs are included to provide reliability to the customers by limiting early and late arrivals. The service cost component can be thought of as a surrogate for customer service. Applying the generated model enables us to obtain meaningful combinations of the two cost components, leading to different solution options to the carrier companies to meet their priorities. A comprehensive analysis is performed to examine the behavior and the particular features of the solutions found.
2. We propose a solution approach that comprises three phases. In the first phase, an initial solution is constructed. A number of heuristic methods have been presented by Solomon [3] to build the initial routes for the VRPTW. We extend insertion heuristic I1 by including a criterion related to the penalties resulting from the time window violations. This solution is then improved with respect to the total transportation cost, leading to the initial feasible solution. In the second phase, the given initial solution is improved by a Tabu Search metaheuristic. The algorithm given by Cordeau et al. [4] constitutes the

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base structure of our Tabu Search method. The soft time windows for the deliveries enable us to handle the time window violations either by the objective function or by the constraints. In our model, these violations are taken care of directly in the objective function. Therefore, we have a different cost function from that given in [4] to evaluate the solutions. As another difference from [4], we include a medium-term memory application in our Tabu Search method. This application improves the quality of the solutions by providing intensification in the promising parts of the neighborhood. In the third phase, a post-optimization method is applied to improve the solution obtained by the Tabu Search algorithm. The post-optimization method adjusts the departure time of each allocated vehicle from the depot to reduce the total service cost of the corresponding route.

The remainder of this paper is organized as follows. In Section 2, we present a literature review which deals with the stochastic versions of the VRP and the VRPTW. In Section 3, we describe our model and motivations for the VRPTW with stochastic travel times and soft time windows, and we discuss the issues connected with the model. In Section 4, we explain the methods used in the three phases of our solution approach. In Section 5, we present the results of the Solomon's problem instances solved using the methods developed. Finally, we end the paper with conclusions and with suggestions for future research.

2. Literature review

There is a wide range of literature on the VRP as it is a highly relevant, yet complicated problem. We refer to Laporte [2,5] for exact, heuristic and metaheuristic algorithms, and to Baldacci et al. [6] for recent exact algorithms applied to the VRP. A related problem also frequently seen in practice and studied is the VRPTW. In his seminal paper, Solomon [3] extended a number of VRP heuristic methods for the VRPTW. The interested reader is referred to Bräysy and Gendreau [7,8] and Desrosiers et al. [9] for an overview of various solution methods applied to the VRPTW. Most of the models developed for the VRP and the VRPTW in the literature considered deterministic parameters such as deterministic travel times, demands and service times.

A comprehensive survey on the stochastic VRP can be found in Gendreau et al. [1]. The authors argued that uncertainty can be seen in various components of the VRP: stochastic travel times, stochastic demands and/or stochastic customers. In Laporte et al. [10], the VRP with stochastic travel and service times was considered. The authors introduced three distinct formulations based on stochastic programming and developed a branch-and-cut approach. Kenyon and Morton [11] developed a solution procedure by inserting a branch-and-cut algorithm into a Monte Carlo solution approach to solve large-sized problems effectively. Van Woensel et al. [12] studied the VRP with the travel times resulting from a stochastic process due to the traffic congestion. The developed queueing models were solved by means of a Tabu Search metaheuristic. Stewart and Golden [13] studied the stochastic VRP where uncertain customer demands were considered.

Stochastic versions of the VRPTW are introduced more recently. Ando and Taniguchi [14] considered the VRPTW with uncertain travel times. The objective was to minimize the total cost which included the penalty costs due to the early and late arrivals, the operation costs and the fixed cost of vehicles used. A genetic algorithm was proposed to solve the described problem. Russell and Urban [15] also studied the VRPTW where the travel times were random variables with a known probability distribution. The number of vehicles used and the total distance traveled were minimized along with the penalties due to arrivals outside the time windows. The authors developed a Tabu Search method. The VRPTW with stochastic travel and service times was studied by Li et al. [16]. Two formulations based on stochastic programming were proposed. A heuristic algorithm based on Tabu Search was developed to obtain the results effectively. The models in these studies placed emphasis on the customers and considered all cost components together regardless of their relations and differences. Since efficiency plays an important role in operations, we separate out the cost components into transportation costs and service costs. We develop a one-stage model which enables different combinations of these two cost components with respect to the company preferences. Additionally, in our model the time window violations and the overtime of the drivers are handled by the objective function. A technique similar to that applied in Stewart and Golden [13] is used in our study to calculate the penalties incurred for early and late servicing. Our model takes into account penalties proportional to the expected duration of the earliness and lateness derived from the arrival time distributions.

The classical routing problems and their stochastic versions have been widely solved by applying the Tabu Search metaheuristic to obtain good solutions within a reasonable time. The interested reader is referred to Glover [17,18] for the details about this metaheuristic. Gendreau et al. [19,20] implemented the Tabu Search method for the VRP. Rochat and Taillard [21] proposed the adaptive memory, which turned out to be very effective for Tabu Search applications in the VRP. For the VRPTW, some implementations of the Tabu Search method come from Cordeau et al. [4], Garcia et al. [22], and Taillard et al. [23]. Our Tabu Search implementation is based on the algorithm given in [4]. We however apply a different function in the local search algorithm to evaluate the solutions since the violations of the time windows are handled by the objective function. In the process of evaluating the solutions, the stochasticity of the problem is taken into consideration. Furthermore, the Tabu Search algorithm is improved by adding a medium-term memory which focuses the search on the promising solutions in the neighborhood. This intensification mechanism operates by restarting from the best feasible solution, and searching its neighborhood effectively by means of a list which includes the moves previously applied from that solution. This structure makes our medium-term memory application different from the intensification approaches in which solutions are generated by extracting good routes from high-quality solutions on-hand (see [21]).

The interested reader is referred to Cordeau et al. [4], Rochat and Taillard [21], Russell and Urban [15], and Taillard et al. [23] for a post-optimization heuristic applied in the VRPTW. In [4,23], the authors used a heuristic method developed by Gendreau et al. [24] for the traveling salesman problem with time windows by modifying the GENIUS procedure (see [25]). In the post-optimization phase of their heuristic, each node of a route was successively removed and re-inserted to improve the solution on-hand. As a post-optimization method, Rochat and Taillard [21] solved a set partitioning model at the end of the diversification and intensification techniques to improve the solution by using the routes already generated. In Russell and Urban [15], a post-optimization method was applied to optimize the waiting times at each customer by using a generalized reduced gradient method. In this paper, we improve the solution obtained by Tabu Search by applying a post-optimization method which is based on adjusting the departure time of each route from the depot, and is thus different from the post-optimization methods given in the literature. In our approach, we do not change the nodes, but the