Transportation Research Part E 115 (2018) 246–266

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

A real-time adjustment strategy for the operational level stochastic orienteering problem: A simulation-aided optimization approach

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ARTICLE INFO

Keywords:
Stochastic orienteering problem
Vehicle routing
Routing adjustment
Monte Carlo simulation
Multiple plan approach

ABSTRACT

This paper focuses on operational level stochastic orienteering problem, in which travel time and service time are stochastic and the vehicle can adjust its routing plan. A real-time adjustment strategy, called Simulation-Aided Multiple Plan Approach (SMPA), is proposed to optimize the real-time vehicle routing plan. We embed a "myopia prevention" strategy into SMPA to improve solution quality. The numerical experiment compares the performance of our proposed algorithm with a strategic level algorithm and another commonly used operational level algorithm called re-optimization algorithm. The results show that our algorithm outperforms previous methods in both solution quality and computing time.

1. Introduction

The orienteering problem (OP) is an extension of the classic traveling salesman problem (TSP). It is also known as the traveling salesman problem with profit (Feillet et al., 2005; Bérubé et al., 2009; Jozefowiez et al., 2008), the selective traveling salesman problem (Laporte and Martello, 1990; Gendreau et al., 1998a,b, Thomadsen and Stidsen, 2003) or the maximum collection problem (Kataoka and Morito, 1988; Butt and Cavalier, 1994; Butt and Ryan, 1999). The orienteering problem has a wide array of transportation and logistics applications, such as fuel delivery (Golden et al., 1987), single-ring design when building telecommunication networks (Thomadsen and Stidsen, 2003), tourist trip design (Vansteenwegen et al., 2007; Wörndl et al., 2017), mobile-crowd-sourcing (Liao and Hsu, 2013; Chen et al., 2014), and unmanned aircraft and submarine surveillance activities (Wang et al., 2008; Evers et al., 2014a).

The OP can be defined as follows. A set of customers is given with a corresponding set of rewards. The terms "customer" and "reward" have different meanings in different applications. For example, in the Tourist Trip Design Problem (TTDP), "customers" is defined as a set of attractions to be visited in a city and the "reward" represents the interest level of an attraction. In unmanned aircraft activities, "customers" is a set of sites that are worth being surveilled and the "reward" is the value obtained if a site is surveilled. One vehicle should visit some customers selectively and determine a route with the objective of maximizing the total collected reward. The vehicle has a time budget, within which the vehicle must arrive at the pre-planned destination (Tsiligirides, 1984).

In practice, some elements of the orienteering problem are uncertain. For example, a truck's travel time on a link varies based on traffic conditions. Unmanned aircraft vehicles' travel time is influenced by wind, altitude and blocks. In addition, the service time for customers is not necessarily constant. Therefore, researchers proposed stochastic orienteering problems (SOP) for practical applications (Campbell et al., 2011; Tang and Miller-Hooks, 2005; Papapanagiotou et al., 2013, 2014, 2015a,b, 2016). This paper studies

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https://doi.org/10.1016/j.tre.2018.05.004
Received 1 October 2017; Received in revised form 6 April 2018; Accepted 11 May 2018
Available online 26 May 2018
1366-5545/

the **orienteering problem with stochastic travel and service time**. The objective of the stochastic orienteering problem is to maximize total reward while ensuring that the vehicle can arrive at the planned destination within the time budget for a probability greater than or equal to a required threshold (Varakantham et al., 2017).

On the operational level, some uncertain factors will be dynamically revealed after a vehicle visits certain customers, causing the *a priori* routing plan to possibly be no longer optimal for this operational-level stochastic orienteering problem (OSOP). For example, assume that a vehicle is executing its transportation and serving task based on a pre-planned route. After it visits some customers, the vehicle may not have enough time to finish its remaining tasks or the vehicle has redundant time to visit more customers if it continues to travel along the pre-planned route. At this time, the vehicle can adjust its route to ensure a high probability that the vehicle can reach the planned destination within the remaining time budget or to collect more rewards if the vehicle has a sufficient remaining time budget. Thus, this paper proposes a new computationally effective **operational-level adjustment strategy called simulation-aided multiple plan approach (SMPA)** to improve the vehicle routing plan in real time. Since the travel time and service time may not always follow tractable probabilistic distributions (e.g. normal distribution), it is difficult to analytically formulate the probability that the vehicle can reach the planned destination within a given time budget, which is called the "in-time arrival probability" (Varakantham et al., 2017). This paper applies the Monte Carlo simulation (Papapanagiotou et al., 2015b) to estimate the in-time arrival probability of a routing plan. The real-time adjustment strategy is implemented by the Multiple Plan Approach (MPA), which is inspired by a previous study by Bent and Van Hentenryck (2004). The basic idea of the MPA is to generate a solution pool, from which one solution is selected as the future routing plan that will be adopted by the vehicle to execute transportation and serving tasks. The solution pool is generated when the vehicle is traveling or serving a customer, and one solution is selected for future task execution each time the vehicle finishes serving a customer. The MPA can save decision making time when determining the next to-be-visited customer by fully utilizing the computer's leisure time to prepare a solution pool when the vehicle is traveling or serving a customer. However, simply using the MPA to adjust the routing plan in real time may cause the myopia problem, which specifically occurs in the OSOP. For example, simply adopting the optimal routing plan may sometimes cause regret for missing the opportunity to adopt a better routing plan. The myopia problem will be introduced in Section 4 in detail. To improve the quality of the routing plans, we incorporate a "myopia prevention" strategy into the SMPA. The "myopia prevention" strategy aims to minimize the expected regret reward when determining the next to-be-visited customer. Instead of simply adopting the optimal routing plan, the "myopia prevention" strategy preserves the probability to adopt the current routing plan in order not to lose the opportunity to adopt a potential routing plan with higher reward during the upcoming task execution process. Subsequently, a group of numerical examples are designed to test the proposed SMPA. The vehicle routing plan obtained by the real-time adjustment strategy SMPA will be compared with the *a priori* routing plan obtained by a strategic-level algorithm. Then another commonly used real-time adjustment strategy in the dynamic vehicle routing problem called re-optimization algorithm (Pillac et al., 2013) is employed to compare with the proposed SMPA in terms of the solution quality and computing time.

The remainder of the paper is organized as follows: Section 2 reviews existing literature on the orienteering problem. Section 3 introduces the operational-level stochastic orienteering problem. Section 4 proposes the real-time adjustment strategy called the simulation-aided multiple plan approach (SMPA). In section 5, numerical examples are designed and a simulation experiment is conducted to test the performance of the new algorithm compared to selected previous methods. Conclusions are drawn in Section 6 and future work is proposed in Section 7.

2. Literature review

2.1. Existing work

The orienteering problem was first proposed by Tsiligirides (1984) in the form of deterministic and static components. Since then, the problem has received wide attention because of the practical needs of transportation and logistics applications. Researchers have developed various algorithms that attempt to solve the orienteering problem (Leifer and Rosenwein, 1994; Wang et al., 1995; Fischetti et al., 1998; Tasgetiren and Smith, 2000; Schilde et al., 2009; Sevkli and Sevilgen, 2006; Liang et al., 2006; Campos et al., 2014; Chekuri and Kumar, 2004; Kobeaga et al., 2017; Ostrowski et al., 2017).

As attention to this problem has expanded, researchers have proposed some variations of orienteering problems, such as the orienteering problem with times window (OPTW) (Kantor and Rosenwein, 1992; Righini and Salani, 2006, 2009; Tricoire et al., 2010), the team orienteering problem (TOP) (Archetti et al., 2007; Chao, 1996a; Souffriau et al., 2010; Ke et al., 2008), capacitated team orienteering problem (Archetti et al., 2009; Tarantilis et al., 2013), the team orienteering problem with times window (TOPTW) (Vansteenwegen et al., 2009; Labadie et al., 2012; Gunawan et al., 2017), and the multi-objective orienteering problem (MOP) (Jozefowiez et al., 2008; Schilde et al., 2009). Some researchers applied different variants of OP into practice, such as tourist trip design (Baffo et al., 2015; De Falco et al., 2015), mobile-crowdsourcing (Liao and Hsu, 2013; Chen et al., 2014), and unmanned aircraft and submarine surveillance activities (Wang et al., 2008; Evers et al., 2014a). For more variants of the OP, please refer to Gunawan et al. (2016). However, all of these orienteering problems are deterministic and static. In practice, many elements of orienteering are uncertain and dynamic. Thus, more attention has recently been paid to the stochastic and dynamic orienteering problems.

Several researchers have studied stochastic orienteering problems. Ilhan et al. (2008) sought to solve the orienteering problem with *stochastic profits*. Evers et al. (2014b) assumed *stochastic weights* of the rewards collected by the vehicle in the orienteering problem. Zhang et al. (2016) assumed that the *customers' presence* was stochastic (i.e. each customer had a probability of requiring a visit) and optimized both the profit collected and the travel cost. Varakantham and Kumar (2013) and Varakantham et al. (2017)