



Discrete Optimization

An iterative three-component heuristic for the team orienteering problem with time windows

Qian Hu, Andrew Lim^{*}

Department of Management Sciences, City University of Hong Kong, Tat Chee Ave., Kowloon Tong, Hong Kong

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ABSTRACT

This paper studies the team orienteering problem with time windows, the aim of which is to maximize the total profit collected by visiting a set of customers with a limited number of vehicles. Each customer has a profit, a service time and a time window. A service provided to any customer must begin in his or her time window. We propose an iterative framework incorporating three components to solve this problem. The first two components are a local search procedure and a simulated annealing procedure. They explore the solution space and discover a set of routes. The third component recombines the routes to identify high quality solutions. Our computational results indicate that this heuristic outperforms the existing approaches in the literature in average performance by at least 0.41%. In addition, 35 new best solutions are found.

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1. Introduction

The aim of the team orienteering problem with time windows (TOPTW) is to maximize the total scores collected by visiting a set of locations, each of which has a score, a service time and a time window. The number of routes is limited, and each location can be visited at most once. A route is feasible if no time window for a visited location is violated, and if it begins and ends at the same given location. The TOPTW has numerous real-life applications (Golden, Levy, & Vohra, 1987; Souffriau, Vansteenwegen, Vertommen, Berghe, & Oudheusden, 2008; Tsiligirides, 1984). In this paper, we consider the vehicle routing application in which a shipper sends out a fixed number of vehicles from a depot to serve some of its customers with the aim of maximizing the total profit gained from successful service.

The main contribution of this paper is an iterative three-component heuristic (I3CH) that is straightforward but every effective. The heuristic employs a local search procedure and a simulated annealing procedure as its first two components to explore the solution space. They store the discovered routes into a pool for future use. The third component then recombines these routes by solving a set packing formulation to obtain a high quality feasible solution. Embedded in an iterative structure, these three components cooperate and perform effectively. We conduct computational experiments on the TOPTW test instances in the literature, and find our heuristic to outperform the existing approaches

in terms of average performance. Before these experiments, we classify the test instances with known optimal solutions into an “OPT” category and the remainder into an “INST-M” category. The average performance improvement for the “INST-M” instances is at least 0.49%, and 35 new best solutions are found. For the 66 instances in the “OPT” category, our heuristic found 55 optimal solutions, 16 more than the previous best approach in the literature. In addition, our approach runs efficiently.

The remainder of this paper is organized as follows. Section 2, provides a clear definition of the TOPTW and a brief overview of the research literature addressing it. Section 3 describes the three-component heuristic and its components, and Section 4 extends the heuristic by constructing an iterative framework. Section 5 evaluates the effectiveness of our approach and compares it to the known approaches in the literature. Finally, Section 6 concludes that paper with closing remarks and possible directions for future research. The detailed solution values for each test instance are relegated to the appendix.

2. Problem definition and literature review

The TOPTW examined in this paper is defined as follows. On a given network graph $G = (V, A)$, there are $n + 1$ different locations denoted by the set $V = \{0, 1, 2, \dots, n\}$ and a set of arcs connecting these locations which is denoted as $A = \{(i, j) : i \neq j \in V\}$. The travel time, t_{ij} , from location i to j is equal to the Euclidean distance, d_{ij} , from i to j . Let location 0 be the depot and each of the remaining location corresponds to one customer. The number of available vehicles is fixed at m . Each vehicle must begin and end its route at the depot within the depot's time window $[0_0, C_0]$. Each

^{*} Corresponding author. Tel.: +852 34428248.

E-mail addresses: huqian@cityu.edu.hk (Q. Hu), lim.andrew@cityu.edu.hk (A. Lim).

customer $i = 1, \dots, n$ with a profit p_i , a service time T_i and a time window $[O_i, C_i]$ can be visited at most once. The service delivered to the customer is successful if it begins within his or her time window. In the case of an earlier arrival, the vehicle has to wait until the time window begins. Profit is gained upon successful service. Note that owing to the limited number of vehicles, some customers may not be visited in a feasible solution. The objective of the TOPTW is to identify a feasible routing plan that ensures the maximization of total profit.

The TOPTW is one of many variants of the widely studied Orienteering Problem (OP) (Chao, Golden, & Wasil, 1996a; Fischetti, Salazar Gonzalez, & Toth, 1998; Schilde, Doerner, Hartl, & Kiechle, 2009). Vansteenwegen, Souffriau, and Oudheusden (2011) published an excellent review of the OP and, its applications and variants, including the team orienteering problem (TOP) (Chao, Golden, & Wasil, 1996b; Tang & Miller-Hooks, 2005; Vansteenwegen, Souffriau, & Van Oudheusden, 2009), the OP with time windows (OPTW) (Kantor & Rosenwein, 1992; Righini & Salani, 2009) and the TOPTW. Given a set of locations with a score, OP seeks to determine one path that visits some vertices and maximizes the total score. The TOP extends the OP to identify multiple paths that maximize the total score. The OPTW and TOPTW extend the OP and TOP, respectively, by incorporating time windows constraints. All these problems have many applications (Golden et al., 1987; Souffriau et al., 2008; Tsiligrirides, 1984), and are challenging because of their complexity. As the OP is NP-hard (Golden et al., 1987), the TOPTW must also be NP-hard. Therefore, solving the highly constrained TOPTW optimally in polynomial time is highly unlikely. Recent research shows heuristics and meta-heuristics to be the most popular techniques to solve this problem.

The TOPTW has only recently become popular, and several state-of-the-art papers on the problem can be found in the literature. For example, Montemanni and Gambardella, in 2009, published a paper entitled “The team orienteering problem with time windows” (Montemanni & Gambardella, 2009). They designed an ant colony system (ACO) to solve the problem and achieved the best results on OPTW instances. In addition, they contributed the earliest test instances for this benchmark research. More recently, Montemanni, Weyland, and Gambardella (2011) and Gambardella, Montemanni, and Weyland (2012), extended the ACO and reported new best solutions. Vansteenwegen, Souffriau, Vanden Berghe, and Van Oudheusden (2009) subsequently proposed an iterated local search (ILS) algorithm for the TOPTW, an approach that runs significantly faster than the ACO requiring only a few seconds of computational time to solve an instance while maintaining competitive solution quality. In addition, the authors constructed a new set of test instances with known optimal solutions. Tricoire, Romauch, Doerner, and Hartl (2010) solved an even more complicated problem, the multi-period orienteering problem with multiple time windows, which is a generalization of the TOPTW. They obtained good-quality solutions when they tested their variable neighbor search (VNS) meta-heuristic on the TOPTW instances. Souffriau, Vansteenwegen, Berghe, and Van Oudheusden (2013) studied another generalization, the multi-constraint team orienteering problem with multiple time windows, and found its solution method also to perform well on TOPTW test instances. Concentrating on the TOPTW, Labadi, Melechovský, and Calvo (2011) developed a hybrid meta-heuristic that combines the greedy randomized adaptive search procedure (GRASP) with the evolutionary local search (ELS) approach. This method improved several of the best known results on available benchmark instances at that time. In 2012, Lin and Yu developed two versions of simulated annealing algorithm for the TOPTW (Lin & Yu, 2012). The fast version computes a solution within only several seconds, while the slow version achieves better solutions at the expense of more computational time. Some current best-known solutions are obtained

by the slow version (SSA). Most recently, Labadie, Mansini, Melachovsk, and Calvo (2012) provided new results for the TOPTW. They developed a VNS algorithm that explores granular neighborhoods (GVNS) based on linear programming.

3. Three-component heuristic for the TOPTW

As we have seen, most of the existing approaches are neighborhood search approaches. When a neighborhood search approach solves a TOPTW instance, not only are new solutions explored, but a set of routes is discovered. A feasible solution can be defined as a combination comprising m routes that satisfy route feasibility and the condition that each customer can be served at most once. Given a set of discovered routes, there exists a best combination that is always no worse than the explored solutions. We derive the two following straightforward “no-worse-than” propositions. The proofs are omitted.

Proposition 1. Suppose that a neighborhood search algorithm A solves the TOPTW. It searches N neighbors and obtains a solution S_1 . At the same time, it also discovers a set of mN routes. The best combination S_2 of these routes is no worse than S_1 .

Proposition 2. Suppose that two neighborhood search approaches, A_1 and A_2 , both solve the TOPTW. A_1 discovers a set of routes R_1 and obtains a solution S_1 . A_2 discovers a set of routes R_2 and obtains a solution S_2 . The best combination, S_3 , over $R_1 \cup R_2$ is no worse than S_1 or S_2 .

On the basis of these two propositions, we propose a heuristic that first employs two different neighborhood search approaches to search the solution space, then keeps the discovered routes into a pool, and finally recombines them to obtain the best combination. We call it a three-component heuristic. In our design, the first two components are *local search* and *simulated annealing*. They explore the solution space and store routes. The third component is *route recombination* which recombines the routes to produce the best combination. Fig. 1 illustrates the heuristic's structure.

In the following subsections, we first introduce the representation of a solution, and then the neighborhood operator that will be used in the *local search* and *simulated annealing*. Finally, we demonstrate the three components.

3.1. Solution representation

In the solution encoding, we use m lists to represent the m routes. Each list starts and ends with 0, which is the depot. Denote the

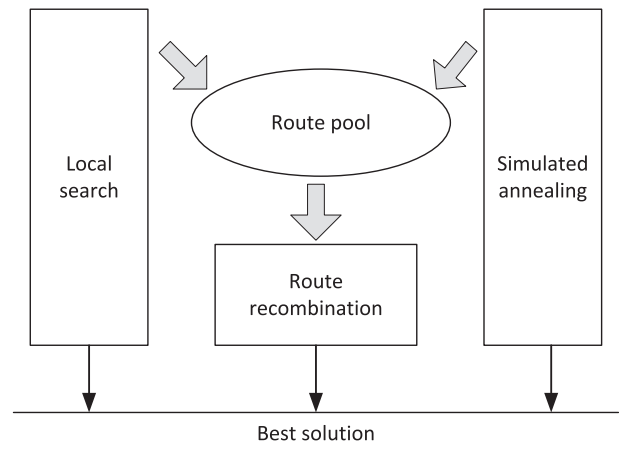


Fig. 1. The structure of the three-component heuristic.

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