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Iterated local search embedded adaptive neighborhood selection approach for the multi-depot vehicle routing problem with simultaneous deliveries and pickups

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ABSTRACT

Although the multi-depot vehicle routing problem with simultaneous deliveries and pickups (MDVRPSDP) is often encountered in real-life scenarios of transportation logistics, it has received little attention so far. Particularly, no papers have ever used metaheuristics to solve it. In this paper a metaheuristic based on iterated local search is developed for MDVRPSDP. In order to strengthen the search, an adaptive neighborhood selection mechanism is embedded into the improvement steps and the perturbation steps of iterated local search, respectively. To diversify the search, new perturbation operators are proposed. Computational results indicate that the proposed approach outperforms the previous methods for MDVRPSDP. Moreover, when applied to VRPSDP benchmarks, the results are better than those obtained by large neighborhood search, particle swarm optimization, and ant colony optimization approach, respectively.

1. Introduction

The vehicle routing problem with simultaneous deliveries and pickups (VRPSDP) is one of the variants of the vehicle routing problem (VRP). In VRPSPD, customers may simultaneously receive and send goods. In addition, all delivered goods must originate from the depot and all pickup goods must be transported back to the same depot. Since it was introduced by Min (1989), VRPSDP has received increasing attention owing to its commercial importance and the high computational complexity. In practice, there are numerous applications. The grocery stores often have both delivery (e.g., fresh food or soft drink) and pickup (e.g., outdated items or empty bottles) demands (Chen & Wu, 2006). Furthermore, pro-environmental practices like recycling of empty packaging and other reusable materials or equipment lead to the necessity of reverse product flows (Dethloff, 2001; Montane & Galvão, 2006; Zachariadis et al., 2010). Additionally, express customers may have both delivery and pick-up demands. In theory, VRPSDP is a NP-Hard problem and the fluctuating carrying load of vehicles increases the difficulty in checking the feasibility (Zachariadis, Tarantilis, & Kiranoudis, 2009).

In this paper, we deal with the extension of VRPSDP called the multi-depot vehicle routing problem with simultaneous deliveries and pickups (MDVRPSDP). Due to the development of communication and information technology, and the increasing pressure of transportation cost, many enterprises select the joint distribution of multiple depots instead of traditional fixed zone service of single depot since the joint distribution of multiple depots can obtain more savings of cost. For example, as is shown in Figs. 1 and 2, customer C is far away from major customers of its zone but close to the major customers of depot B. Obviously, assigning customer C to depot B can save many travel distances. Meanwhile, the response time to customers will be reduced and service level correspondingly be enhanced. MDVRPSDP can be applied to the distribution of chain supermarkets, soft drink and food companies in large cities. For Example, to timely meet the demands of their customers under the heavy traffic conditions, some chain supermarkets usually construct or rent several supply warehouses in the skirts of large cities in China.

From the theoretical point of view, MDVRPSDP is an extension of VRPSDP, therefore, like VRPSDP, MDVRPSDP is also an NP-Hard

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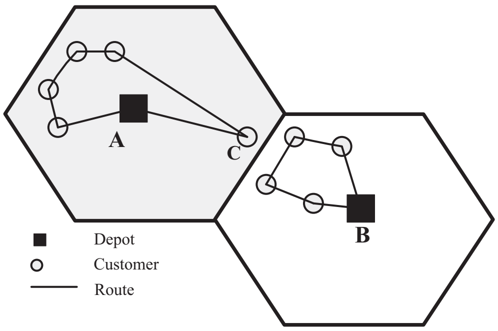

Fig. 1. Vehicle routing under separate distribution of each depot.

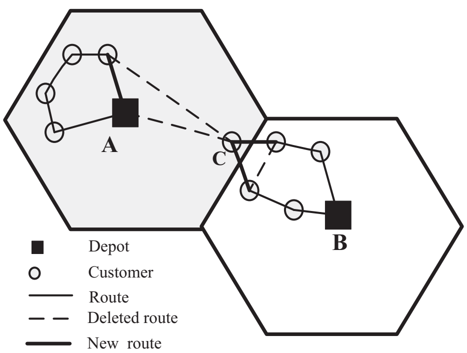

Fig. 2. Vehicle routing under joint distribution of multiple depots.

problem. Furthermore, the MDVRPSDP is more complicated than the VRPSDP considering that it needs to tackle customers' assignment and the VRPSDP problem simultaneously. Because the practical large-scale MDVRPSPD instances are difficult to be tackled efficiently by exact solution approaches, the purpose of the paper is to propose an effective metaheuristic for MDVRPSDP. To the best of our knowledge, this is the first metaheuristic developed for it. To make the implementation simpler, we employ the iterated local search (ILS) as the algorithm framework. Different structural neighborhood methods are used in the improving and perturbation steps of ILS to broaden the exploration of the search space. Meanwhile, an adaptive neighborhood selection mechanism (ANS) is incorporated into the framework of ILS, denoted by ILS_ANS, to manage the neighborhood methods effectively in improvement and perturbation steps of ILS, respectively. The main idea of ANS is that a neighborhood method is selected according to a probability depending on its success (Ropke & Pisinger, 2006a). In addition to integrating ANS into the framework of ILS, the second contribution of our work is the development of new perturbation neighborhood methods. The effectiveness of the algorithm is tested through 50 benchmarks instances for MDVRPSDP and its variant, VRPSDP.

The remainder of this paper is structured as follows: Section 2 is problem description and formulation. Section 3 is a review of the related literature. The overall structure and the details of the proposed approach are shown in Section 4. Computational results are provided in Section 5. Section 6 is conclusions and some suggestions for future work.

2. Problem description and formulation

MDVRPSDP is defined as follows: Let $G = (V, E)$ be a graph where V is the vertex set and E is the edge set. The vertex set V is partitioned into two subsets $V_c = \{v_1, \dots, v_n\}$ and $V_d = \{v_{n+1}, \dots, v_{n+p}\}$, which represent the set of customers and the set of depots, respectively. Among other things, n is the number of customers and p is the number of depots. Each vertex $v_i \in V_c$ has several nonnegative weights associated to it, namely, a non-negative pickup demand p_i and delivery demand d_i and a service time s_i. Furthermore, in the depot vertex $v_i \in V_d$, there are no demands and service times, i.e. $p_i = d_i = s_i = 0$. Associated with E are a distance matrix (d_{ij}) and a travel time matrix (t_{ij}), and $d_{ij} = t_{ij}$ for all $i, j \in V$. The distance matrix is symmetric and satisfies the triangle inequality, that is, $d_{ij} = d_{ji}$, and $t_{ij} = t_{ji}$. A fleet of m_d identical vehicles of capacity Q is available at each depot $v_{n+d} \in V_d$. The sum of vehicles of all the depots is m. In MDVRPSDP, the following constraints must be met:

(1) Each route starts and ends at the same depot.
(2) Each customer is only visited once by a vehicle or a route.
(3) The maximum load of each route does not exceed the vehicle capacity at each point of the route.
(4) The total duration of each route (including travel and service time) does not exceed a preset limit.
(5) All the vehicles are homogeneous.

2.1. Notations

Sets:

V_d: the depot set.
V_c: the customer set.
V: the vertex set, $V = V_c \cup V_d$.
K: the vehicle set.

Parameters:

d_i: the delivery demand of customer i.
p_i: the pick-up demand of customer i.
s_i: the service time of customer i.
d_{ij}: the distance between customer i and j.
Q_k: the capacity of vehicle k.
T_k: the maximum duration of vehicle k.
m_d : the number of vehicles at depot d.

Decision variables:

x_{kij} is the 0–1 decision variable. If vehicle k travels directly from node i to node j, then $x_{kij} = 1$, otherwise, $x_{kij} = 0$.
t_{kij} denotes the load on arc (i,j) of route k.

2.2. Mixed-integer linear programming formulation

The objective of MDVRPSDP is to determine the optimal routes by minimizing the weighted sum of the fixed cost related to the number of vehicles and the total travel cost of all the vehicles, where α and β are coefficients. The formulation for MDVRPSDP is given as follows:

$$\min \ \alpha \sum_{k \in K} \sum_{d \in V_d} \sum_{j \in V_c} x_{kdj} + \beta \sum_{k \in K} \sum_{i \in V} \sum_{j \in V} d_{ij} x_{kij} \tag{1}$$

subject to

$$\sum_{k \in K} \sum_{j \in V_c} x_{kdj} \leqslant m_d, \quad \forall d \in V_d \tag{2}$$

$$\sum_{k \in K} \sum_{j \in V} x_{kij} = \sum_{k \in K} \sum_{j \in V} x_{kji} = 1, \quad \forall i \in V_c \tag{3}$$

$$\sum_{j \in V_c} x_{kdj} = \sum_{i \in V_c} x_{kid} \leqslant 1, \quad \forall k \in K, \ d \in V_d \tag{4}$$