The Capacitated Vehicle Routing Problem with Three-Dimensional Loading Constraints and Split Delivery—A Case Study

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Abstract The capacitated vehicle routing problem with three-dimensional loading constraints (3L-CVRP) combines vehicle routing and three-dimensional loading with additional packing constraints concerning, for example, the stability of packed goods. We consider a logistics company that repeatedly has to pick up goods at different sites. Often, the load of one site exceeds the volume capacity of a vehicle. Therefore, we focus on the 3L-CVRP with split delivery and propose a hybrid algorithm for this problem. It consists of a tabu search procedure for routing and some packing heuristics with different tasks. One packing heuristic generates packing plans for shuttle tours involving special sites with large-volume sets of goods. Another heuristic cares for packing plans for tours with numerous sites. The hybrid algorithm is tested with a set of instances which differs from often used 3L-CVRP test instances and comes from real industrial data, with up to 46 sites and 1549 boxes to be transported. The algorithm yields good results within short computing times of less than 1 min.

1 Introduction

The capacitated vehicle routing problem with three-dimensional (3D) loading constraints (3L-CVRP) generalizes the vehicle routing problem and the container loading problem which are traditionally separately handled combinatorial optimization problems. Real-world settings can be modelled in greater detail by packing constraints which ensure the integrity of sensitive items, stability of packing arrangements and efficient unloading of delivered boxes.

Since the 3L-CVRP was introduced in [1], many effective algorithms proposed in literature are mostly hybrid metaheuristics. A nested tabu search algorithm is

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developed by [1] and an ant colony algorithm is designed in [2]. Further effective hybrid algorithms are proposed in [3–6]. The literature on VRP with 3D loading constraints is surveyed in [7, 8].

In the 3L-CVRP, it is required that each customer is visited just once. However, in practice it is possible that a customer has a demand that does not fit into a single vehicle for reasons of weight or volume. In this case, the demand has to be split and be delivered by two or more vehicles. In the research dedicated to the classical VRP a large body of literature deals with VRP with split delivery (see [9]). But to our best knowledge, only the papers [10, 11] considered the possibility of splitting the customers' demands in a routing-packing problem context. However, these papers did not handle the situation where customer demands are larger than vehicle capacity. To fill this gap, our study addresses the 3L-CVRP with split delivery (3L-SDCVRP) in a milk-run operation of a Shanghai automotive logistics company.

The rest of the paper is organized as follows: the 3L-SDCVRP is formulated and related real-world instances are described in Sect. 2. Our solving approach to the 3L-SDCVRP is outlined in Sect. 3. Results are provided and discussed in Sect. 4. Conclusions are drawn in Sect. 5.

2 Problem Formulation and Shanghai Dataset

Our problem comes from the milk-run operations in and around Shanghai area that are carried out by a Shanghai automotive logistics company, which serves many car makers in metropolitan Shanghai and whole China. It can be formulated similarly to the 3L-CVRP (see [1, 10]).

Let be given a complete network with n nodes, one depot and symmetric distances. There is a fleet of homogeneous vehicles that are rear loaded and have identical 3D rectangular loading spaces. Each node has a pickup demand given by a set of 3D rectangular items. Our task is to determine a set of routes, starting and ending at the depot, and a packing plan for each route. The packing plan should stow all boxes, which are to be picked up at the nodes of the related route, in a feasible way (no overlapping items, each item must lie completely in the loading space, orthogonal packing). The pickup demands of all nodes have to be satisfied and the routes should be chosen so that the total travel distance is minimized and, as second objective criterion, the number of routes (or used vehicles) is as small as possible.

Moreover, some packing constraints have to be observed: (C1) *Loading sequence constraints*. Loading the items of a node must be possible by pure movements of these items in length direction of the vehicle. (C2) *Orientation constraints*. The spatial orientation of all items is fixed with regard to height while horizontal 90° rotations are permitted. (C3) *Support constraints*. A certain percentage a of the base area of all items must be supported by other items. We chose $a = 75\%$ in the experiments. (C4) *Fragility constraints*. Here, if a box type has three dimensions less or equal 100 cm and there is only one item of this type, the item may be classified as fragile. Fragile items can only bear other fragile items. A weight constraint is ignored here since all packed goods are of low density.

Table 1 Summary of the Shanghai dataset

Instance	Nodes (n)	Box types	Items (m)	Vehicle type	Minimum no. of vehicles (v_{LB})	No. of big nodes
Sha01	5	26	261	M	2	0
Sha02	8	50	167	S	6	2
Sha03	10	17	73	S	3	0
Sha04	12	33	204	B	3	1
Sha05	12	59	228	M	4	1
Sha06	15	56	228	M	4	1
Sha07	16	79	439	B	7	2
Sha08	18	51	303	M	6	1
Sha09	27	98	734	C	8	1
Sha10	31	134	590	B	9	1
Sha11	46	185	1549	C	16	4

The eleven problem instances are generated from the automotive logistics company, thus they are called here Shanghai dataset. Most instances include some nodes, called *big nodes*, whose demand exceeds the volume capacity of a vehicle so that (at least) for these nodes two or more routes are indispensable. Our instances have numbers of nodes (n) ranging from 5 to 46 and the numbers of items to be loaded (m) range from 73 to 1549, details are summarized in Table 1.

Although there are four vehicle types, only one type is chosen per instance. The lower bound v_{LB} for the number of vehicles (routes) is calculated as rounded quotient of the total items volume and the vehicles volume capacity.

Compared to the 3L-CVRP benchmark instances by [1, 4], our dataset has some important application-oriented attributes. The numbers of box types are quite large. The cargo of a node is often composed by large groups of items of same dimensions. The distance matrix is gained from the real-time road travel distances by Baidu e-map.

From the occurrence of big nodes in the Shanghai problems we can conclude that these problems are instances of 3L-SDCVRP. We assume in this paper that splits are only allowed when necessary, i.e. when the boxes of a node cannot be packed in one loading space. Note that we use the term 3L-CVRP with *split delivery* (instead of *split pickup*) since from a structural perspective there is no difference between these problem variants.

One could raise the question whether a big node cannot be replaced by two or more artificial nodes that have the same coordinates as the big node and the same total demand. In this case and if only inevitable splits are allowed, one could try to reduce the 3L-SDCVRP to the 3L-CVRP.

However, this procedure would require a split of the demand of each big node within the problem formulation. These anticipated splits would often be worse (in terms of solution quality) than splits generated by means of a packing algorithm. Hence, the 3L-SDCVRP seems to be an independent problem even if only inevitable splits are permitted.

3 Solving Approach for 3L-CVRP with Split Pickup

Our approach consists of two main steps and is based on two earlier published papers. In the first step, routes with only one or two nodes and related packing plans are constructed. This step is intended mainly for those nodes whose load almost reaches or exceeds the volume capacity of one vehicle. In the second step, the residual problem is solved by constructing routes with multiple nodes and related packing plans. The steps are described below with some details.

First main step: Packing plans for each node are generated by a genetic algorithm (GA) for the container loading problem that is proposed in [12]. Each packing plan consists of vertical layers that follow each other in length direction. The crossover operator generates an offspring by combining high quality layers from both parents and adding some newly constructed layers.

For each node the GA constructs at least one packing plan (one filled loading space) and two or more if necessary. Then pairs of packing plans of two nearby nodes will be merged to save some loading space. Finally, all packing plans are accepted that satisfy one of the following criteria: (i) the filling rate of the loading space reaches a given limit (e.g. 60%); (ii) the packing plan belongs to a series of at least two packing plans of the same node and does not have the worst filling rate of that series. An accepted packing plan is completed by a route (with one or two nodes) and the packed items and, if necessary, their nodes are removed from the problem instance.

Second main step: The remaining 3L-CVRP instance is solved by means of the hybrid algorithm developed in [3]. A tabu search algorithm serves for routing and performs swap as well as shift moves that include either one or two routes of a given solution. A tree search algorithm is responsible for packing checks. A packing plan for a route is built box by box in a backtracking manner and at each stage a small number of possible placements is examined. Much computational effort is saved by means of special coupling mechanisms between routing and packing, e.g., a cache which includes already tested routes.

However, the original tree search algorithm is only able to cope with small numbers of items and has been modified. Now, vertical layers, which fill the length or width of the loading space, can be integrated in packing plans yielded by the tree search algorithm; these layers are also produced by the above GA in step 1. In the end the best solutions of both steps are assembled.

4 Results and Discussion

Our hybrid algorithm has been implemented in C++ and tested on the above introduced dataset on a PC with an Intel processor (3.30 GHz). Detailed results are shown in Table 2; z stands for the total travel distance.

The reached mean filling rate per instance is given by the quotient (in %) of the total item volume and the total volume of the used loading spaces and is mainly responsible for the number of routes v. The mean filling rates are satisfactory with respect to the required constraints. Similar filling rates were achieved in, e.g. [1, 2]. Note that primarily the loading sequence constraint (C1) makes it difficult to reach larger filling rates in the 3L-(SD)CVRP (see [10], p. 1147). In our total 200 nodes of 11 instances, there are 14 big nodes in 9 instances. The number of nodes with split pickup exceeds the number of big nodes (see Table 1) only for three instances and by at most two nodes. This meets the practical requirement of "less splits, less management cost on sorting and counting".

To what extent nodes that are not "big" are also split, depends on the quality of the used packing algorithm. Thus, the small number of four additional splits in our results also indicates a good solution quality. By the way, the occurrence of additional splits shows again that the 3L-SDCVRP cannot be reduced to the 3L-CVRP even if only necessary splits are allowed.

All in all, we have reached good quality results and our solutions were provided in short running times of less than 1 min while in [10] (p. 1146) running times of nearly 3 h are reported.

Table 2 Summary of results

Instance	z	v	v_{LB}	Mean filling rate (%)	Number of nodes split	Running time (s)
Sha01	582.2	3	2	55.1	0	2
Sha02	2907.0	10	6	52.9	3	13
Sha03	369.2	4	3	53.6	1	42
Sha04	372.0	4	3	61.2	1	13
Sha05	1493.9	6	4	57.6	1	10
Sha06	620.0	7	4	55.7	1	19
Sha07	1701.4	11	7	60.9	2	28
Sha08	387.7	9	6	57.3	1	11
Sha09	1063.8	15	8	48.0	1	17
Sha10	1946.2	15	9	57.6	1	53
Sha11	581.8	29	16	53.0	6	33

5 Conclusions

We have considered the Shanghai dataset, a set of instances of the CVRP with three-dimensional loading constraints and split delivery that comes from the Shanghai automotive industry. We solved the problem under the assumption that only inevitable splits are allowed and showed that the 3L-SDCVRP under this assumption cannot be reduced to the 3L-CVRP and represents an independent problem. Our proposed hybrid algorithm effectively solves the Shanghai dataset in short running times.

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