Improved Packing and Routing of Vehicles with Compartments

Workshop on *Heuristic Problem Solving*

Sandro Pirkwieser[1], Günther R. Raidl[1], and Jens Gottlieb[2]

[1] Institute of Computer Graphics and Algorithms
Vienna University of Technology, Vienna, Austria
`{pirkwieser,raidl}@ads.tuwien.ac.at`
[2] SAP AG, Walldorf, Germany
`jens.gottlieb@sap.com`

In this work we investigate the *Vehicle Routing Problem with Compartments* (VRPC) which has been tackled in the literature only very recently. We will adhere to the definition of a rather general variant given by Derigs et al. [1]; see this original work for more details. In addition to the classical VRP a vehicle is assumed to have several (at least two) compartments in which the customers' orders have to be placed. As in [1] we will consider the cases of having compartments which are flexible in size/capacity (but bounded by the total vehicle capacity), together with products that only fit in specific compartments, as well as fixed compartment capacities and product groups that might not be placed in the same compartment. The former setting occurs in practice for food retail when delivering frozen and dry goods, whereas the second—and from a computational point of view more challenging and thus interesting—setting occurs when distributing petrol involving different fuel types. In El Fallahi et al. [2] and Muyldermans and Pang [3] a simpler scenario was further considered, comprising of two compartments with fixed capacities and two product groups that are compatible with one compartment each. Contrary to previous work we concentrate here primarily on the packing aspect and introduce additional suitable neighborhoods. Besides trying to minimize the total routing costs, which still is the ultimate goal, we also aim at increasing the *density*, i.e. the efficiency, of the packing. This measure is the average squared loading ratio (load divided by capacity) on a per compartment basis for fixed capacities and on a per route basis otherwise.

Our heuristic solution approach is mainly based on Variable Neighborhood Search (VNS) [4] and includes some of the concepts and methods from [1] which were reported to yield a good performance.

As initial solution for the classical single-trajectory VNS we select the best solution out of several generated with best insertion, the savings algorithm, and two variants of the sweep algorithm. In the shaking phase we utilize different move operations. On the one hand we remove and reinsert orders via choosing them either at random, based on the costs (detour), or on their similarity to a seed order, orders belonging to a certain customer, contained in a route selected at random, having the highest routing costs, or the least density. Similarly, orders might belong to a randomly selected compartment or those with the least load (and most orders). On the other hand we also try to exchange route segments of limited size between two different routes. When packing a single order we apply best-fit and for a set of orders best-fit-decreasing (BFD) strategies. The insertion in a route's sequence is either done in a purely greedy way or using a regret heuristic [5, 1]. For solution improvement w.r.t. travel costs we apply 3-opt and 2-opt*, the packing (density) is tackled via reinserting all orders of a route also based on BFD and iteratively applying several order exchange moves similarly to the heuristic presented in [6].

The algorithm was implemented in C++, compiled with GCC 4.3 and executed on a single core of a 2.53 GHz Intel Xeon E5540 with 24 GB RAM, 3 GB RAM dedicated per core. For testing we used the instances introduced in [1] and available online at `http://www.ccdss.org/vrp/` together with the best known solutions. The termination criterion was a runtime limit of 10 minutes. The instances differ in type (petrol or food), number of customers (10 to 200, either clustered or not) and products (2 or 3), vehicle capacity (600 to 9000), and maximal order demand. We performed 10 runs per instance and setting and state following results: the minimal and average travel cost as well as the average density as percentage gaps to the so far best known solution. The results of the algorithm as described above and denoted by VNS-BFD$^{\mathrm{D=1}}$ are given in Table 1, and for comparison those of a variant applying only necessary packing methods, i.e. using first-fit, no density, none of the new shaking neighborhoods considering the actual packing, and no additional heuristics for improving the packing, denoted by VNS-FF$^{\mathrm{D=0}}$, are given in Table 2. The results are averaged for instances with the same number of customers n and products p. As expected our algorithm benefits more from the additions on the instances of type petrol, but also for the somewhat simpler (in terms of packing) food instances a slight gain can be observed. Altogether, the performance of our algorithmic framework is very encouraging: For 145 out of 200 instances a new best solution could be obtained by VNS-BFD$^{\mathrm{D=1}}$, the same objective value was reached for 32 instances, and only for 23 instances the solution quality is inferior. Remarkably, VNS-FF$^{\mathrm{D=0}}$ performs very similar w.r.t. the new best solutions, but looking at the 10 runs each VNS-BFD$^{\mathrm{D=1}}$ is 43 times significantly better and only 15 times worse; using a Wilcoxon rank sum test with an error level of 5%.

In the future we plan to investigate those cases (moves) more closely where no feasible packing could be obtained. For this we might apply an exact method for checking, and for the larger instances and especially when inserting single orders a heuristic based on swap moves so as to make room for the new order will be tried, similarly to the one used for improving the packing. In addition, it would be interesting to test on further instances exhibiting a more challenging packing component.

References

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Table 1. Average results of $\mathbf{VNS\text{-}BFD^{D=1}}$ compared to so far best solutions obtained by Derigs et al. [1]

n	p	petrol			food		
		%-gap$_{\text{min.cost}}$	%-gap$_{\text{avg.cost}}$	%-gap$_{\text{avg.dens}}$	%-gap$_{\text{min.cost}}$	%-gap$_{\text{avg.cost}}$	%-gap$_{\text{avg.dens}}$
10	2	0.00	0.02	1.98	-0.16	-0.14	6.86
	3	0.00	0.39	0.79	0.00	0.00	0.35
25	2	-0.15	-0.01	0.90	-0.23	-0.04	1.11
	3	-0.45	0.43	-0.30	-0.26	-0.08	0.83
50	2	-0.54	-0.18	1.24	-0.36	-0.12	0.83
	3	-0.77	0.01	0.70	-0.37	-0.11	1.56
100	2	-0.87	-0.26	1.87	-0.24	0.07	0.23
	3	-1.22	-0.27	2.29	-0.75	-0.47	1.27
200	2	-1.47	-0.97	1.77	-0.12	0.28	-0.29
	3	-3.67	-2.32	4.79	-0.24	-0.02	-0.06
		-0.77	-0.16	1.29	-0.34	-0.09	0.93

Table 2. Average results of $\mathbf{VNS\text{-}FF^{D=0}}$ compared to so far best solutions obtained by Derigs et al. [1]

n	p	petrol			food		
		%-gap$_{\text{min.cost}}$	%-gap$_{\text{avg.cost}}$	%-gap$_{\text{avg.dens}}$	%-gap$_{\text{min.cost}}$	%-gap$_{\text{avg.cost}}$	%-gap$_{\text{avg.dens}}$
10	2	0.00	0.08	-0.42	-0.16	0.35	5.85
	3	0.00	0.37	0.04	0.00	0.02	-0.05
25	2	-0.14	0.11	-0.18	-0.18	0.09	0.57
	3	-0.37	0.57	-1.68	-0.10	0.16	0.18
50	2	-0.56	-0.01	0.46	-0.35	-0.13	0.35
	3	-0.70	0.16	0.22	-0.12	0.17	0.65
100	2	-0.56	0.10	0.74	-0.30	-0.04	0.17
	3	-0.90	-0.06	1.98	-0.45	-0.23	0.11
200	2	-0.74	-0.31	-0.62	-0.23	0.43	-0.86
	3	-3.34	-1.63	2.50	-0.30	-0.04	-0.07
		-0.62	0.06	0.26	-0.25	0.03	0.34

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