Metaheuristics for the Waste Collection Vehicle Routing Problem with Time Windows

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Abstract

In this problem there is a set of customers which waste is collected by vehicles. Vehicles can visit waste disposal facilities during their working day to empty collected waste and hence continue to collect from customers. The vehicles start and end their routes at a single depot empty. We take into consideration time windows associated with customers, disposal facilities and the depot. Here, we also have a driver rest period. The problem is solved using a number of metaheuristic algorithms namely tabu search (TS) and variable neighbourhood search (VNS). Moreover, we also present a combined metaheuristic algorithm based on variable neighbourhood tabu search (VNTS), where the variable neighbourhood is searched via tabu search. Computational experiments on ten publicly available waste collection benchmark problems involving up to 2092 customers and 19 waste disposal facilities indicates that the proposed algorithms are able to find better quality solutions than previous work presented in literature within reasonable computation times.

Keywords: Vehicle routing, Waste collection, Tabu search, Variable neighbourhood search, Variable neighbourhood tabu search

1. Introduction

This paper considers a vehicle routing problem that arises in commercial waste collection. It is a single period node routing problem where we can reasonably identify our set of customers at which waste must be collected. In this problem we have an unlimited number of homogeneous vehicles with a certain capacity based at a single depot, a set of commercial customers (e.g. retail outlets) and a set of disposal facilities. In addition, each vehicle has a driver rest period (associated with a lunch break during the working day), and a maximum amount of work it can do during the day (both in terms of the total amount of waste collected and the total number of customers dealt with).

Essentially in this problem vehicles start from the depot and collect waste from the customers until they are full. Once full a vehicle needs to go to one of the available disposal facilities to unload the waste. After being emptied, the vehicles repeat the process (collecting and unloading) and so the vehicles can make multiple visits to the disposal facilities per day. Finally, the vehicles return to the depot empty at the end of the working day. The complication here is that a vehicle need not wait until it is completely full to visit a disposal facility. It can, if it is convenient, visit a disposal facility at any time irrespective of the amount of waste it has collected. Besides, by considering multiple disposal facilities makes the selection of the best disposal facility quite challenging.

This paper proposes metaheuristic algorithms to construct a set of good quality feasible routes to minimize the total distance travelled by the vehicles, as well as the number of vehicles needed to serve all the customers within practical computation times. Therefore in order to be feasible, several constraints have to be satisfied:

a) The vehicles could arrive at each stop (i.e. customer, disposal facility) before the time window but they have to wait until it is open.
b) The total waste collected before visiting a disposal facility cannot exceed the maximum capacity of the vehicle.
c) Each customer is served only once.
d) Each vehicle begins and ends its route at the depot with zero waste.
e) Each vehicle driver must take a fixed length rest break in a given time window.

2. Literature survey

In this section we survey a number of papers in the literature focusing on the collection of waste from commercial customers, and is dealt with as a node routing problem. In a node routing problem, there is a problem known as a rollon-rolloff problem which deals with the collection of containers/skips such as are commonly used for construction site waste. Here the vehicle is involved in collection of full skips from customers (that have to be taken to the waste disposal facilities), and delivery of empty skips to customers. The distinguishing feature of problems of this type is that the vehicle can typically only carry one or two skips at a time, hence the number of customers that can be visited before the vehicle has to go to a disposal facility is similarly limited. Example of past papers dealing with this type of collection are De Meulemeester et al (1997), Bodin et al (2000), Archetti and Speranza (2004), Baldacci et al (2006) and Le Blanc et al (2006).

However in this paper we are dealing with the non-skip collection of waste, where the vehicle can visit many customers before it has to go to a waste disposal facility. Most of the past papers focusing on this problem solved real life waste collection problems. For example, Tung and Pinnoi (2000) proposed a heuristic procedure to solve a waste collection problem in Hanoi, Vietnam. Angelelli and Speranza (2002) proposed a model based on tabu search that fits three different waste collection systems to estimate operational costs for two case studies: Val Trompia, Italy and Antwerp, Belgium. Nuortio et al (2006) considered a problem based on waste collection in two regions of Eastern Finland. Alagöz and Kocasoy (2008) considered health waste collection in Istanbul. Repoussis et al (2009) considered waste oil collection and recycling in Greece.

In addition there is a paper by Sahoo et al. (2005), which is able to reduce operating costs for a large company involved in waste collection using their own developed system called WasteRoute. The heuristic used for the WasteRoute system of Sahoo et al (2005) is fully described in Kim et al (2006). They extended Solomon's (1987) insertion heuristic using simulated annealing and a local search exchange procedure called CROSS (Taillard et al, 1997). Moreover, they also developed a heuristic based on capacitated clustering that generates clusters based on the estimated number of vehicles required, and then routes customers within each cluster. Computational results were presented for ten problem instances, derived from real-world data, involving up to 2092 customers that the authors make publicly available.

In this paper we consider exactly the same waste collection problem as in Kim et al. (2006) involving multiple disposal facilities, driver rest period and customer/depot/disposal facility time windows. Because Kim et al. (2006) have made their test problems publicly available we can make a direct computational comparison with their work. However some of their insertion heuristic results reported are incorrect and based on Kim (2009) we disregard these results. Therefore in this paper we compare our results only with their clustering heuristic results.

Another paper that uses the test problems of Kim et al (2006) is Ombuki-Berman et al (2007). They presented a multi-objective genetic algorithm using a crossover procedure (Best Cost Route Crossover) from Ombuki et al (2006). However no computation times were given in their paper.

3. Initial solution process

In our methodology, the initial solution process is divided into two parts; route construction and route improvement. In the route construction part we construct an initial solution by attempting to fully utilise a vehicle over the day (thereby aiming to minimise the total number of vehicles used). Once a vehicle cannot be used any more then we start a new vehicle route with a new vehicle. To deal with the vehicle/driver rest period we attempt to schedule it as early as possible consistent with its time window.

Our initial solution procedure adds a customer to the end of the emerging route such that:

- when the vehicle arrives at the customer it will be possible to service the customer as the visit will fall in its time window
- there is time after servicing the customer for the vehicle to visit the nearest (open) disposal facility and then return to the depot before the end of the working day
- if the vehicle has not yet had its rest period there is still time after servicing the customer for the rest period to be started

Moreover there are two issues that we also take into consideration in constructing the initial solution such as:

- if the vehicle is nearly full then we visit a disposal facility if it is closer to the end of the emerging route than a customer that might be added.
- if there are no customers whose time window when the vehicle arrives is open then we consider waiting at a customer for its time window to open.

Next, in the route improvement part we attempt to improve the initial solution by adopting a local search procedure in two different phases:

- Phase 1 : moving customers/disposal facilities elsewhere on the same route, removing unnecessary trips to disposal facilities; also changing disposal facilities
- Phase 2 : interchanging the positions of two customers that are on different routes

In both phases we use a neighbour set for every customer to prevent the number of customer interchanges we have to examine being excessive. Here we consider two main criteria to compose the neighbour set. First, the neighbours of customer i are the closest to customer i. Second, they have compatible time window with the customer i. For example customer j is a neighbour of customer i if it is possible to visit i at some time in its time window, service i and then go directly onto j to service j without waiting for its time window to open. Each customer has K number of neighbours.

Neighbour sets are a key element in our work. This arises for two reasons:

- the nature of our metaheuristics, as will become apparent below, is that we use neighbour sets in seeking to improve a route. As such the larger the value of K the larger the neighbourhood we search.
- by varying K we have a variable neighbourhood. This leads in a natural fashion to applying variable neighbourhood search to the problem.

Computationally we repeat phases 1 and 2 in turn until no further improvement can be achieved. We will then have a locally optimal solution.

4. Vehicle reduction procedure

Based on the examination of preliminary computational results indicated that, for some problems, the number of customers serviced on the last vehicle route constructed was so small that it might well be possible to reduce the number of vehicles used. Therefore, in this procedure we try to reduce the number of vehicles used by moving the customers from the last route to earlier routes. If we manage to move all these customers, then we re-perform phases 1 and 2 to rearrange customers on these earlier routes.

At the end of this procedure, we apply our metaheuristic algorithms, based upon the neighbour sets in a further attempt to improve the solution.

5. Metaheuristic algorithms

In this section we discuss our metaheuristic algorithms for the problem using tabu search (TS), variable neighbourhood search (VNS) and a combined algorithm (VNTS) based on variable neighbourhood search, but where the neighbourhood is searched via tabu search.

5.1 Tabu Search (TS)

In our TS heuristic the move that we consider is an interchange of two customers, who may or may not be on the same route. This move differs from that in phase 2 above since in that phase we only considered customers that were on different route. We do these interchanges however in a tabu search framework (so we allow interchanges that worsen the solution).

In our approach we apply tabu status only to customers. So if a customer is tabu it cannot be considered for any possible move. Our tabu search algorithm includes:

- aspiration (so we allow a tabu move if it leads to an improvement in the best solution found so far)
- a diversification factor such that any non-improving move we make must move us away from the current solution by at least this factor

Our TS heuristic terminates if sufficient iterations have been performed without improving the best solution we currently have. Limited computational experience indicated that five iterations are enough in our work.

5.2 Variable Neighbourhood Search (VNS)

In our VNS heuristic we consider the same move as in our TS heuristic above. However whilst that heuristic operates with a fixed value of K, the number of neighbours a customer has, in our VNS heuristic we vary K. Thus K^*={set of values of K we consider} is defined in this heuristic.

As for TS we start from the locally optimal solution as derived in the previous section above. In terms of neighbourhood search (for a specified value of K) we use the same neighbourhood as in our TS heuristic. However, unlike our TS heuristic now we only accept moves that improve the best solution.

Our VNS heuristic terminates when we have a solution that cannot be improved by any move associated with any of the K values in K^*.

5.3 Variable Neighbourhood Tabu Search (VNTS)

In our VNTS heuristic we adopt the same variable neighbourhood as in our VNS heuristic above. However whilst our VNS heuristic searches each neighbourhood for improved solutions in VNTS we allow non-improving moves, i. e. we search each neighbourhood in a TS fashion.

This heuristic terminates when we have a solution that cannot be improved by TS associated with any of the K values in K^*.

6. Computational results

The metaheuristics presented in this paper were coded in C++ and run on a 3.16GHz pc (Intel Core2 Duo) with 3.23Gb memory. The performance of these metaheuristics are

tested using ten waste collection vehicle routing problem with time windows benchmark problems, as publicly available at:
http://www.postech.ac.kr/lab/ie/logistics/WCVRPTW_Problem/benchmark.html.

Table 1 shows the number of customers and disposal facilities for each problem. It also shows the results from Kim et al (2006) for their clustering heuristic (using simulated annealing) as well as our metaheuristics results, in terms of the number of vehicles used, total distance travelled and computation time. The solution obtained from the route construction part and the solution after phases 1 and 2 are denoted in Table 1 by IS and ISP1P2 respectively. The results for TS, VNS and VNTS used K=50 and K^*={5,10,25,50}. The last column in Table 1 gives the percentage improvement in distance when compared to the result of Kim et al, namely 100(Kim et al solution distance – our solution distance)/(Kim et al solution distance).

Problem	Number of customers	Number of disposal facilities	Algorithm	Number of vehicles used	Total distance	Total computation time (seconds)	% improvement in distance over Kim et al
102	99	2	Kim et al	3	205.1	3	
			IS	3	206.8	1	-0.83
			ISP1P2	3	183.5	2	10.53
			TS	3	183.5	4	10.53
			VNS	3	183.5	3	10.53
			VNTS	3	183.5	3	10.53
277	275	1	Kim et al	3	527.3	10	
			IS	3	473.8	1	10.15
			ISP1P2	3	466.0	5	11.63
			TS 3		464.5 13		11.91
			VNS	3	464.4	8	11.93
			VNTS	3	464.4	8	11.93
335	330	4	Kim et al	6	205.0	11	
			IS	6	213.3	2	-4.05
			ISP1P2	6	205.7	6	-0.34
			TS 6		203.8 16		0.59
			VNS	6	203.7	10	0.63
			VNTS	6	203.7	12	0.63
444	442	1	Kim et al	11	87.0	16	
			IS 11		92.9	3	-6.78
			ISP1P2	11	89.1	14	-2.41
			TS	11	88.8	31	-2.07
			VNS	11	88.8	22	-2.07
			VNTS	11	88.8	30	-2.07
804	784	19	Kim et al	5	769.5	92	
			IS	6	863.3	8	-12.19
			ISP1P2	6	754.8	48	1.91
			TS 6		754.1 86		2.00
			VNS	6	754.1	70	2.00
			VNTS	6	754.1	85	2.00
1051	1048	2	Kim et al	18	2370.4	329	
			IS 17		2645.1	13	-11.59
			ISP1P2	17	2255.9	54	4.83
			TS	17	2242.7	154	5.39
			VNS	17	2243.6	124	5.35
			VNTS	17	2242.7	188	5.39
1351	1347	3	Kim et al	7	1039.7	95	
			IS	8	984.3	20	5.33

			ISP1P2	8	915.1	70	11.98
			TS	8	914.5	164	12.04
			VNS	8	914.8	103	12.01
			VNTS	8	914.8	109	12.01
1599	1596	2	Kim et al	13	1459.2	212	
			IS 14		1578.1	28	-8.15
			ISP1P2	14	1419.3	127	2.73
			TS	14	1419.1	226	2.75
			VNS	14	1419.1	161	2.75
			VNTS	14	1419.1	169	2.75
1932	1927	4	Kim et al	17	1395.3	424	
			IS	16	1346.1	41	3.53
			ISP1P2	16	1263.7	146	9.43
			TS	16	1262.0	303	9.55
			VNS	16	1262.0	324	9.55
			VNTS	16	1262.0	492	9.55
2100	2092	7	Kim et al	16	1833.8	408	
			IS	16	1823.6	49	0.56
			ISP1P2	16	1751.6	145	4.48
			TS	16	1748.6	336	4.65
			VNS	16	1748.6	280	4.65
			VNTS	16	1748.6	432	4.65
Average			Kim et al			160	
		IS				16.6	-2.40
			ISP1P2			61.7	5.48
			TS			133.3	5.73
			VNS			110.5	5.73
			VNTS			152.8	5.74

Table 1: Computational results

Examining Table 1 it is clear that our metaheuristic solutions (TS, VNS, VNTS) use less distance than those of Kim et al, on average approximately 5.7% less. With respect to the number of vehicles used our solutions involve (in total) 100 vehicles, those of Kim et al 99 vehicles, so slightly worse. However, results in Table 1 were produced without using our vehicle reduction procedure.

To illustrate the effect of the vehicle reduction procedure we show in Table 2 the results obtained when it is applied to the routes that result from ISP1P2. Table 2 has the same format as Table 1 but for reasons of space we only show in Table 2 those problems where a reduction in the number of vehicles was achieved. For ease of comparison the averages shown at the foot of Table 2 are the averages over all ten problems, computed by combining the results for the three problems explicitly shown in Table 2 with the results shown in Table 1 for the other seven problems. Note here that the average time given at the foot of Table 2 includes the time for applying our vehicle reduction procedure to all problems (whether successful or not).

Problem	Number of customers	Number of disposal facilities	Algorithm	Number of vehicles used	Total distance	Total computation time (seconds)	% improvement in distance over Kim et al
804	784	19	Kim et al	5	769.5	92	
			IS	6	863.3	8	-12.19
			ISP1P2	5	721.9	63	6.19
			TS	5	721.3	100	6.26

			VNS	5	721.3	85	6.26
			VNTS	5	721.1	113	6.29
1351	1347	3	Kim et al	7	1039.7	95	
			IS	8	984.3	20	5.33
			ISP1P2	7	1004.3	150	3.40
			TS	7	1003.1	289	3.52
			VNS	7	1003.1	188	3.52
			VNTS	7	1003.1	212	3.52
1599	1596	2	Kim et al	13	1459.2	212	
			IS	14	1578.1	28	-8.15
			ISP1P2	13	1381.4	218	5.33
			TS	13	1381.3	317	5.34
			VNS	13	1381.3	253	5.34
			VNTS	13	1381.3	260	5.34
Average			Kim et al			160	
			IS			16.6	-2.40
			ISP1P2			80.5	5.31
			TS			156.4	5.57
			VNS			130.3	5.57
			VNTS			174.6	5.58

Table 2: Computational results, vehicle reduction procedure

Considering Tables 1 and 2 then with respect to the number of vehicles used our solutions now involve (in total) 97 vehicles, those of Kim et al 99 vehicles, so slightly better. As before it is clear that our metaheuristic solutions (TS, VNS, VNTS) use less distance than those of Kim et al, on average over these ten problems approximately 5.6% less.

Moreover, it is clear from both tables that our three metaheuristics produce routes of similar quality. On this basis we would be justified in choosing the metaheuristic involving the lowest computation time. From the averages presented at the foot of both tables it is clear that VNS is to be preferred, having a lower average time than either TS or VNTS.

7. Conclusions

This paper presented a number of metaheuristic approaches for a problem concerned with commercial waste collection that involves time windows, driver rest period and multiple disposal sites. Computational results were presented for publicly available waste collection problems involving up to 2092 customers and 19 waste disposal facilities which indicated that our solutions involve less distance than previous approaches presented in the literature. Particularly, variable neighbourhood search was the most effective of these metaheuristics.

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