New hybrid quantum annealing algorithms for solving Vehicle Routing Problem

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Abstract. We introduce new hybrid algorithms, DBSCAN Solver and Solution Partinioning Solver, which use quantum annealing for solving Vehicle Routing Problem (VRP) and its practical variant: Capacitated Vehicle Routing Problem (CVRP). Both algorithms contain important classical components, but we also present two other algorithms, Full QUBO Solver and Average Partitioning Solver, which can be run only on a quantum processing unit (without CPU) and were prototypes which helped us develop better hybrid approaches. In order to validate our methods, we run comprehensive tests using D-Wave's Leap framework on well-established benchmark test cases as well as on our own test scenarios built based on realistic road networks. We also compared our new quantum and hybrid methods with classical algorithms - well-known metaheuristics for solving VRP and CVRP. The experiments indicate that our hybrid methods give promising results and are able to find solutions of similar or even better quality than the tested classical algorithms.

Keywords: VRP, Vehicle Routing Problem, quantum annealing.

1 Introduction

Vehicle Routing Problem (VRP) is an important combinatorial optimization problem in which the goal is to find the optimal setting of routes for a fleet of vehicles which should deliver some goods from a given origin (depot) to a given set of destinations (customers) [1]. It is a generalization of the Travelling Salesman Problem (TSP) (introduced first as the Truck Dispatching Problem [1]) in which one vehicle has to visit some number of destinations in the optimal way [2]. Both problems are proven to be NP-hard [3]. There exist the exact algorithms able to find optimal solutions in a reasonable time for relatively small instances, but generally, those problems are computationally difficult and the state-of-the-art approaches applied in practice are based on heuristics (constructive, improvement and composite) and metaheuristics [4, 5].

Recently, we can observe a noticeable progress in the development of quantum computing algorithms and it turned out that they may be particularly successful in solving

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combinatorial optimization problems, such as TSP and VRP [6]. The first quantum algorithms for TSP and VRP already exist and in the scientific literature we can find algorithms which can be run on gate-based quantum computers [7–17] as well as quantum annealing algorithms which can be run on adiabatic quantum computers [18–24].

In this paper, we present new methods for solving VRP and its more practical variant, CVRP (Capacitated Vehicle Routing Problem), in which all vehicles have a limited capacity. The algorithms introduced in this paper are based on quantum annealing, because due to the number of available qubits, those algorithms have currently a greater chance to give any practical improvement over classical algorithms.

We developed and present four algorithms: Full QUBO Solver (FQS), Average Partition Solver (AVS), DBSCAN Solver (DBSS) and Solution Partitioning Solver (SPS). The first and second one are designed only for solving VRP, DBSCAN solver can also solve CVRP if capacities of all vehicles are equal, SPS is able to solve CVRP with arbitrary capacities. It is also important to add that the last two methods are hybrid algorithms and they contain important components which should be run on classical processors.

In order to evaluate different algorithms for solving VRP using quantum annealing, we carried out series of experiments using D-Wave's Leap framework [25] which contains implementations of built-in solvers and allows to implement new solvers. We used QBSolv [26] run on quantum processing unit (QPU) and simulating quantum annealing on classical processors (CPU), as well as hybrid solver [27] run on both, QPU and CPU.

Beside quantum algorithms, we also wanted to test and compare several well-known classical algorithms which gave good results in previous studies. Based on a comprehensive literature review [5] and further analysis, we selected 4 metaheuristics: based on simulated annealing [28], bee algorithm [29], evolutionary annealing [30] and recursive DBSCAN with simulated annealing [31], respectively.

In order to reliably compare different algorithms, we conducted experiments on well-established benchmark datasets [32], [33], as well as on datasets created by us, with realistic road networks (taken from the OpenStreetMap service) and artificially generated orders.

The rest of the paper is organized as follows: in Section 2, we describe in details all the quantum annealing solvers which we used in our experiments. Sections 3 and 4 present the design and results of our experiments, respectively. Section 5 outlines possible future research directions and concludes the paper.

2 CVRP solvers based on quantum annealing

In this section, we describe QUBO formulations and solvers which we developed for different variants of VRP: general VRP, CVRP with equal capacities and CVRP with arbitrary capacities. Before that, we introduce our notation and assumptions.

2.1 Notation and assumptions

We assume that in each instance of VRP (or CVRP) we have a road network represented as a directed connected graph with vertices and edges. We also assume that the depots and destinations to which the orders of customers should be delivered are always located in

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vertices of the road network (in the case of benchmark instances and artificial networks, it may be even assumed that the road network is defined by locations of orders, while in the case of realistic road networks, real locations of orders are usually close enough to vertices determining the road network graph).

Let M be the number of available vehicles and N the number of orders. Let's denote the vehicles as $V = \{v_1, v_2, \ldots, v_M\}$ and the orders as $O = \{o_1, o_2, \ldots, o_N\}$. We assume that there is always a depot located in one of the vertices (we also assume that destinations of orders are not located in the depot - such orders can be just served immediately so are not interesting) and all vehicles are initially located in the depot and should finish all routes back in the depot. Therefore, we have in total $N + 1$ significant vertices and without any loss of generality, we can assume that our graph has exactly $N + 1$ vertices and $N * (N + 1)$ directed edges (we can just consider edges built based on the shortest paths between every pair of vertices in the original graph), destination of the order o_i is located in the vertex i and the depot is located in the vertex $N+1$. We can also denote the cost of the direct travel from the vertex i (destination of the order o_i) to the vertex j (destination of the order o_j) as $C_{i,j}$. We can also define $C_{N+1,i}$ and $C_{i,N+1}$ for $i \in \{1, 2, \ldots, N\}$ as the costs of direct travels from the depot to the destinations of orders and from the destinations of orders to the depot, respectively.

Let's assume that $x_{i,j,k} = 1$ if in a given setting the vehicle number i visits the vertex number j as k-th location on its route (for $j \in \{1, 2, \ldots, N + 1\}$ and $k \in \{0, 1, 2, \ldots, N+1\}$), otherwise $x_{i,j,k} = 0$. We always have $x_{i,N+1,0} = 1$ and $x_{i,j,0} = 0$ for $j < N + 1$ (the depot is always the first location), and if $x_{i,N+1,K} = 1$ for some K then for $k > K$ $x_{i,j,k} = 1$ (each vehicle stays in the depot after reaching it).

2.2 Full QUBO Solver

First, we defined a basic QUBO formulation used for solving VRP instances. The formulation is based on a similar formulation for TSP in [20].

Let's define the binary function

$$A(y_1, y_2, ..., y_n) = \sum_{i=1}^{n} \sum_{j=i+1}^{n} 2y_i y_j - \sum_{i=1}^{n} y_i,$$

where $y_i \in \{0, 1\}$ for $i \in \{1, \ldots, n\}$. It is easy to prove that the minimum value of $A(y_1, y_2, ..., y_n)$ is equal to -1 and this value can be achieved only if exactly one of $y_1, y_2, ..., y_n$ is equal to 1.

By definition of VRP, the problem of minimizing the total cost can be defined as minimizing the function:

$$C = \sum_{m=1}^{M} \sum_{n=1}^{N} x_{m,n,1} C_{N+1,n} + \sum_{m=1}^{M} \sum_{n=1}^{N} x_{m,n,N} C_{n,N+1} + \tag{1}$$

$$+ \sum_{m=1}^{M} \sum_{n=1}^{N-1} \sum_{i=1}^{N+1} \sum_{j=1}^{N+1} x_{m,i,n} x_{m,j,n+1} C_{i,j} \tag{2}$$

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The first component of the sum C is a sum of all costs of travels from the depot - the first section of each cars' route. The second is a cost of the last section of a route (to depot) in a special case when a single car serves all N orders (only in such a case the component can be greater than 0). The last part is the cost all of other sections of routes.

To assure that each delivery is served by exactly one vehicle and exactly once, and that each vehicle is in exactly one place at a given time, the following term (in which all A components are equal to -1 only for such desired cases) should be included in our QUBO formulation:

$$Q = \sum_{k=1}^{N} A(x_{1,k,1}, x_{2,k,1}, \ldots, x_{1,k,2}, \ldots, x_{M,k,N}) + \tag{3}$$

$$+ \sum_{m=1}^{M} \sum_{n=1}^{N} A(x_{m,1,n}, x_{m,2,n}, \ldots, x_{m,N+1,n}) \tag{4}$$

By definition of VRP, QUBO representation of this optimization problem is

$$QUBO_{VRP} = A_1 \cdot C + A_2 \cdot Q, \tag{5}$$

for some constants A_1 and A_2, which should be set to ensure that the solution found by quantum annealer minimizes Q (which should be $-N - NM$) to ensure satisfiability of the aforementioned constraints (after running initial tests we set $A_1 = 1$, $A_2 = 10^7$).

2.3 Average Partition Solver (APS)

APS is a variation of Full QUBO Solver for which we decrease the number of variables for each vehicle by assuming that every vehicle serves approximately the same number of orders. This means, every vehicle can serve up to $A+L$ deliveries, where A is the total number of orders divided by the number of vehicles and L is a parameter (called "limit radius"), which controls the number of orders. The QUBO formulation is the same as in case of Full QUBO Solver but the number of variables $x_{i,j,k}$ is lower ($M(A + L)N$), which simplifies computations.

2.4 DBSCAN Solver (DBSS)

DBSS allows us to use quantum approach combined with a classical algorithm. This particular algorithm is inspired by recursive DBSCAN [31]. DBSS uses recursive DBSCAN as a clustering algorithm with limited size of clusters. Then, TSP is solved for each cluster separately by FQS (just by assuming in the QUBO formulation that the number of vehicles equals 1). If the number of clusters is equal to the number of vehicles, the answer is known immediately. Otherwise, the solver runs recursively considering clusters as deliveries, so that each cluster contains orders which in the final result are served one after another without leaving the cluster. What is more, we concluded that by limit the total sum of weights of deliveries in clusters, this algorithm can solve CVRP if all capacities of vehicles are equal.

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2.5 Solution Partitioning Solver (SPS)

While adding capacity constraints is not simple, we were looking for the solution that can use results generated by DBSS. Therefore, we developed SPS. It is a simple algorithm which divides TSP solution found by another algorithm (e.g., DBSS) into consecutive intervals, which are the solution for CVRP. The idea is as follows:

Let $d_1, d_2, ..., d_N$ be the TSP solution for N orders, let P_v be a capacity of the vehicle v, let $w_{i,j}$ be the sum of weights of orders $d_i, d_{i+1}, d_{i+2}, \ldots, d_j$ (in the order corresponding to TSP solution) and let $cost_{i,j}$ be the total cost of serving only orders $d_i, d_{i+1}, \ldots, d_j$. Also, let $dp_{i,S}$ be the cost of the best solution for orders $d_1, d_2, d_3, ..., d_i$ and for the set of vehicles S. Now, the dynamic programming formula for solving CVRP is given by:

$$dp_{i,S} = \min_{v \in S, 0 \leq j \leq i, w_{j+1,i} \leq P_v} \{dp_{j,S \setminus \{v\}} + cost_{j+1,i}\}, \tag{6}$$

where $cost_{i,j} = 0$ and $w_{i,j} = 0$ for $i > j$. Formula (6) returns a plenty of possible routes, but it also finds the optimal solution. We can speed it up by noticing that if two vehicles have the same capacity, it doesn't matter which one of them we choose, but pessimistically, capacities can be pairwise distinct. We propose the following heuristic to optimize this solution:

1. Instead of set S of vehicles, consider a sequence $v_1, v_2, \ldots, v_M$ of vehicles and assume that we attach them to deliveries in such an order.
2. Now, our dynamic programming formula is given by:

$$dp_{i,v_k} = \min_{0 \leq j \leq i, w_{j+1,i} \leq P_{v_k}} \{dp_{j,\{v_1,\ldots,v_{k-1}\}} + cost_{j+1,i}\} \tag{7}$$

3. To count this dynamic effectively, we can observe that:

$$\forall_{i<j} cost_{i,j} = C_{N+1,i} + C_{j,N+1} + \sum_{k=i}^{j-1} C_{k,k+1} \tag{8}$$

$$\forall_{i<j} cost_{i,j} = cost_{i,j-1} + C_{j-1,j} + C_{j,N+1} - C_{j-1,N+1} \tag{9}$$

$$\forall_{i<j} cost_{i,j} - cost_{i,j-1} = C_{j-1,j} + C_{j,N+1} - C_{j-1,N+1} \tag{10}$$

$$\forall_{i<j, 1 \leq k \leq M} (dp_{i-1,v_k} + cost_{i,j}) - (dp_{i-1,v_k} + cost_{i,j-1}) = C_{j-1,j} + C_{j,N+1} - C_{j-1,N+1} \tag{11}$$

So if we have counted dp for fixed k, then for counting dp for $k+1$ we can store all dp values for k and increase them, one by one (starting from $j = i + 1$), by a right side of equation 10. Using monotonic queue, we can get minimum in $O(1)$ time.

We can now select some random permutations of vehicles and perform dynamic programming for each of them. The number of permutations can be regulated by additional parameter. With optimization of dynamic programming, the complexity of this algorithm is $O(NMR)$, where R is the number of permutations.

The greatest limitation of SPS is that it considers only one TSP solution. Nonetheless, we observed that DBSS for more than one vehicle works in a similar way.

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3 Design of experiments

The goal of our experiments was to test and compare different formulations of QUBO (solving different variants of VRP) on different datasets and with different solvers and settings (number of qubits and quota of time on quantum processor). We ran them using D-Wave's Leap platform [25] and its 2 solvers: qbsolv [26] and hybrid solver [27]. To run comprehensive and comparable experiments, we prepared several datasets:

- Christofides1979 - a standard benchmark dataset for CVRP, well-known and frequently investigated by the scientific community [32, 33],
- A dataset built by us based on a realistic road network of Belgium, acquired from the OpenStreetMap service.

Christofides1979 consists of 14 tests, where each test instance is described by three files. The first one provides the number of vehicles and their capacity (the same for all vehicles). The second file describes the orders, i.e. their coordinates in $2-$dimensional plane and the demand. The last file reports the time matrix (times of travel between various vertices in a graph). For a purpose of running our experiments and compare the results, we selected only 9 out of 14 tests because in case of other tests some hybrid or classical algorithms were not able to find any good solutions. All the important parameters describing Christofides1979 instances are given in Table 1.

Test name	Nr of vehicles	Capacity	Nr of orders
CMT11	7	200	120
CMT12	10	200	100
CMT13	11	200	120
CMT14	11	200	100
CMT3	8	200	100
CMT6	6	160	50
CMT7	11	140	75
CMT8	9	200	100
CMT9	14	200	150

Table 1. Parameters of instances of Christofides1979 used in our experiments.

In the case of the second dataset, we generated in total 51 tests. Each test was characterized by the number of orders. Table 2 presents a description of this dataset. Basically, it consists of 4 groups of test cases: small test (small number of orders), medium tests (medium number of orders), big tests (large number of order), mixed tests (various number of orders with some additional conditions).

In every experiment, our programs computed the minimal cost of serving all orders. D-Wave's quantum annealing machine is naturally nondeterministic, so are the returned results, so for every algorithm and on every test case we ran 5 experiments. The code of programs used in our experiments is publicly available at [34].

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4 Results of experiments

In this section, we present results of experiments conducted using QBSolv and hybrid solver built-in D-Wave's Leap framework and using algorithms described in Section 3.

4.1 Full QUBO Solver (FQS)

First, we investigated Full QUBO Solver (FQS) on test cases small-0 - small-9. On every test except small-0, we ran experiments for 3 different numbers of vehicles $(1, 2, 3)$ on quantum processor (FQS QPU [26]), its classical simulator (FQS CPU) and using a hybrid solver (FQS Hybrid [27]). On small-0 there were only 2 orders so we tested only $1, 2$ vehicles.

As we can see in Table 3, QBSolv (FQS CPU and FQS QPU) exacerbates final results in test cases with more vehicles. For more vehicles, it can potentially generate the same solution as for less vehicles, because some vehicles can be just ignored. Solutions generated with hybrid solver (FQS Hybrid) confirm that. However, the size of QUBO makes the solutions with more vehicles unavailable for QBSolv. In hybrid solver, we have such a problem in only one case (small-9). However, in only 1 test case (small-3) QBSolv was able to improve the solution returned for smaller number of vehicles. In addition, in most cases QBSolv was not able to find a solution on QPU, the size of the instance and the number of the required variables and qubits was just too large. Also the required time of computations on QPU was worse than in case of CPU or hybrid approach. Therefore, we concluded that it doesn't make sense to run more experiments on QPU for larger test cases (with more cars and more orders) and we conducted next tests only using QBSolv on CPU and using a hybrid solver.

For larger VRP instances (medium-0 - medium-9), we observed that the transition from one vehicle to two vehicles is difficult. QBSolv usually returns much worse results (there is only 1 exception, test case medium-8). For the hybrid solver, in only one case the result for two vehicles is better (medium-6) but the results are usually still better than in case of QBSolv. We also noticed that the order of deliveries in tests with one vehicle was not optimal for majority of test cases. Only the least instances - with up to 15 orders - seem to be solved optimally. An interesting thing is that differences between results for two vehicles and one vehicle are very discrepant and it is not caused by the number of orders. By analyzing full results, we concluded that for 2 vehicles the solvers divided deliveries evenhandedly and for some tests it is a good way to build the optimal solution. We came up with an idea that since solvers found only these solutions, we can ask them to optimize only that kind of solutions, so we implemented Average Partition Solver, which demands less qubits.

4.2 Average Partition Solver (APS)

We extended Full QUBO Solver with an option of changing the maximum difference between the number of deliveries attached to the vehicles, i.e., a deflection from the average number of deliveries per one vehicle. We found out experimentally that it should be $\frac{1}{10}$ of the number of deliveries, which gives maximum difference in our test cases equal to 5. Having 1 vehicle, APS works exactly the same as Full QUBO Solver, so we

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ran experiments only for more vehicles (but we also included the results for 1 vehicle in Table 3, just for comparison).

In most test cases, the results found using APS were better than results found by FQS. We can also notice that differences between results for 3 vehicles and results for 2 vehicles generated by APS are lower than the differences between results for 2 vehicles and 1 vehicle generated by FQS. However, in case of 3 vehicles, QBSolv on CPU still can't find better solutions with only 2 vehicles. The hybrid solver can find better solutions in cases with 3 vehicles than in cases with only 2 vehicles in 4 (out of 10) test cases.

4.3 DBSCAN Solver (DBSS)

We can see in Table 3 that DBSS usually gives worse results than the APS, but we expected that it may change in case of tests with more orders thanks to utilizing the power of recursive DBSCAN.

Indeed, on big test cases with a larger number of orders, DBSS gives much better results than APS (Table 4). Additionally, DBSS can be run on larger instances and don't need assumption that every vehicle serves approximately the same number of deliveries (as it is in case of APS).

4.4 Solution Partitioning Solver (SPS)

At the beginning, we tested SPS on test cases where all capacities are equal, in order to compare results with DBSS which can solve this problem. The results are presented in Table 5. In some cases, our solvers were not able to find the proper solutions (we mark such cases as "Not valid") but in general, SPS outperformed DBSS.

Based on those experiments, we decided to test further only SPS and compare it with 4 classical algorithms - simulated annealing (SA), bee algorithm (BEE), evolutionary annealing (EA) and recursive DBSCAN with simulated annealing (DBSA). We ran next experiments with even more orders on mixed test cases generated by us (Table 2) and on benchmark datasets Christofides1979 (Table 1). The results are presented in Table 6 and Table 7.

5 Conclusion and future research directions

We introduced new hybrid algorithms for solving VRP and CVRP and ran tests using D-Wave's Leap framework on well-established benchmark test cases and on our own test scenarios built based on realistic road networks. We also compared our new quantum and hybrid methods with classical algorithms - well-known metaheuristics for solving VRP and CVRP. The results indicate that our hybrid methods give promising results and are able to find solutions of a similar quality to the tested classical algorithms.

Our primary future research direction is extending QUBO formulations to solve even more realistic variant of VRP - the Vehicle Routing Problem with Time Windows (VRPTW). Also, we are planning to compare our hybrid algorithms with even more classical algorithms for solving VRP and its variants.

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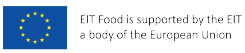

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Test	Number of orders	Description
small-0	2	No further conditions.
small-1	2	
small-2	2	
small-3	1	
small-4	2	
small-5	5	
small-6	6	
small-7	5	
small-8	4	
small-9	6	
medium-0	20	No further conditions.
medium-1	26	
medium-2	27	
medium-3	24	
medium-4	25	
medium-5	25	
medium-6	20	
medium-7	14	
medium-8	17	
medium-9	15	
big-0	52	No further conditions.
big-1	42	
big-2	48	
big-3	48	
big-4	50	
group1-1	42	No further conditions.
group1-2	54	
range-6-1	47	Magazines are at most 6 km from city center.
range-6-2	50	
range-8-12-1	50	Magazines are at least 8km and at most 12 km from city center.
range-8-12-2	50	
range-8-12-3	46	
range-8-12-4	51	
range-8-12-5	50	
range-8-12-6	50	
range-5-1	50	Orders are at most 5 km from city center. Vehicles have capacity greater than total demand.
range-5-1	50	
range-3-1	37	Orders are within 3 km from city center.
range-3-2	29	
range-4-1	9	Orders are within 4 km from city center.
range-4-2	7	
range-4-75-1	75	Orders are within 4 km from city center. We have 75 orders.
range-4-75-2	75	
range-4-100-1	100	Orders are within 4 km from city center. We have 100 orders.
range-4-100-2	100	
range-4-150-1	150	Orders are within 4 km from city center. We have 150 orders.
range-4-150-2	150	
range-4-200-1	200	Magazines and orders are within 4 km from city center. We have 200 orders.
range-4-200-2	200	
clustered1-1	57	In each one of four 1-kilometer circles spread across the map, there is between 6 and 20 orders.
clustered1-2	55	

Table 2. Parameters and descriptions of tests

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Table 3. Results on small and medium datasets

Test	vehicles	FQS CPU	FQS QPU	FQS Hybrid	APS CPU	APS Hybrid	DBSS CPU
small-0	1,2	11286	11286	11286	11286	11286	-
small-1	1	10643	10643	10643	10643	10643	-
	2	10643	10643	10643	12379	12379	-
	3	10643	-	10643	-	-	-
small-2	1	21311	21311	21311	21311	21311	-
	2	21311	-	21311	24508	24508	-
	3	22192	-	21311	-	-	-
small-3	1	18044	18044	18044	18044	18044	-
	2	20819	-	18033	22193	22193	-
	3	22843	-	18033	-	-	-
small-4	1	15424	15424	15424	15424	15424	-
	2	17364	-	15424	19472	19472	-
	3	17364	-	15424	-	-	-
small-5	1	10906	10906	10906	10906	10906	-
	2	11676	-	10906	13480	13480	-
	3	11754	-	10906	-	-	-
small-6	1	20859	20859	20859	20859	20859	-
	2	26735	-	20859	26735	26735	-
	3	27110	-	20859	-	-	-
small-7	1	18117	18117	18117	18117	18117	-
	2	18710	-	18117	23114	23114	-
	3	21666	-	18117	-	-	-
small-8	1	12198	12198	12198	12198	12198	-
	2	12494	-	12198	13282	13282	-
	3	13282	-	12198	-	-	-
small-9	1	19184	19184	19184	19184	19184	-
	2	19848	-	19184	21438	21438	-
	3	21438	-	19848	-	-	-
medium-0	1	20774	-	21775	20774	21775	24583
	2	36966	-	29879	25737	25217	27994
	3				28226	27237	34185
medium-1	1	29868	-	29423	29868	29423	27606
	2	50639	-	39485	30820	31129	31346
	3	-	-	-	33376	32018	32588
medium-2	1	37045	-	35208	37045	35208	29442
	2	55579	-	36511	33235	33163	32947
	3	-	-	-	36600	32569	34480
medium-3	1	30206	-	29422	30206	29422	31092
	2	51787	-	35774	31428	30273	33790
	3	-	-	-	35994	33627	33712
medium-4	1	21257	-	20762	21257	20762	21435
	2	34379	-	25470	22410	22722	22885
	3	-	-	-	23599	22176	25446
medium-5	1	23013	-	21642	23013	21462	21737
	2	36149	-	22041	22775	23076	23403
	3	-	-	-	24899	22386	24336
medium-6	1	23804	-	24664	23804	23804	23926
	2	35826	-	24490	24265	25178	25510
	3	-	-	-	27032	23364	25122
medium-7	1	22847	-	22847	22847	22847	28308
	2	33441	-	26550	24331	24460	30482
	3	-	-	-	27156	27156	34064
medium-8	1	23843	-	14566	23843	14566	15575
	2	20804	-	15931	14256	14808	15829
	3	-	-	-	15815	15466	16930
medium-9	1	12228	-	12395	12228	12395	12842
	2	16606	-	13950	14231	13821	14926
	3	-	-	-	13221	13178	14619

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	vehicles	APS CPU	DBSS CPU
big-0	1	80084	71594
	2	97286	71051
big-1	1	157660	146828
	2	206782	149200
big-2	1	168646	154105
big-3	1	85873	62236
big-4	1	156411	129279

Table 4. Comparison of results for Average Partition Solver and DBSCAN Solver on big test cases.

	vehicles	capacity	SPS (CPU)	DBSS (CPU)
big-0	2	100	70928	73508
	2	85	72295	73189
	2	80	75150	Not valid
	3	100	71320	76717
	3	70	71251	78012
	3	55	Not valid	76807
	5	100	71740	Not valid
	5	50	78726	91066
	5	40	85976	Not valid
big-1	2	100	150608	158631
	2	80	150608	152946
	2	65	150804	156188
	3	100	151525	153673
	3	60	153190	152854
	3	45	164055	Not valid
	5	100	151930	168789
	5	40	156242	165271
	5	30	174519	176935

Table 5. Comparsion of DBSCAN Solver and Solution Partitioning Solver (SPS) run on CPU on big test cases with various capacities.

Test name	SPS	SA	BEE	EA	DBSA
CMT11	25.54	23.62	36.18	16.52	19.94
CMT12	26.84	53.06	20.24	20.68	21.37
CMT13	25.97	86.72	34.66	35.05	19.44
CMT14	26.83	52.52	20.23	20.23	22.8
CMT3	25.13	48.3	28.38	28.82	-
CMT6	17.58	48.3	15.42	28.82	15.82
CMT7	29.42	41.4	27.89	31.68	23.18
CMT8	26.5	51.16	26.67	28.09	19.4
CMT9	34.14	76.34	44.25	42.81	-

Table 6. Comparison of results achieved by Solution Partitioning Solver (SPS) and classical algorithms (SA - simulate annealing, BEE- Bee algorithm, EA - evolutionary annealing, DBSA - DBSCAN with simulate annealing) on a benchmark dataset Christofides79.

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	type	deliveries	SPS	Simul. Ann.	Bee	Evolution
clustered1-1	average	57	69850	66379	60876	48923
	best	57	69080	52119	56358	48152
clustered1-2	average	55	77173	74341	81438	54719
	best	55	75530	59947	68772	53490
group1-1	average	42	158919	156217	153495	137989
	best	42	155388	146526	142774	135593
group1-2	average	54	171732	145380	145325	137626
	best	54	165043	141065	140947	136307
range-6-1	average	47	71670	68003	67234	59937
	best	47	68459	62312	64404	59827
range-6-2	average	50	80490	84380	83915	73651
	best	50	79640	79574	85917	73051
range-8-12-1	average	50	142008	146553	142835	129069
	best	50	140170	136369	127372	126555
range-8-12-2	average	50	146798	137628	145332	129048
	best	50	143598	135493	136776	128803
range-8-12-3	average	46	105544	105051	98366	92792
	best	46	101577	99004	94423	91921
range-8-12-4	average	51	147993	143309	148900	128316
	best	51	145559	140088	128575	124405
range-8-12-5	average	50	146719	143516	145685	134162
	best	50	143993	139784	139796	133245
range-8-12-6	average	50	146984	148194	150121	136326
	best	50	141467	138781	139400	134692
range-5-1	average	50	81728	68900	69052	67896
	best	50	72527	67984	68022	67691
range-5-2	average	50	81759	69342	68564	67981
	best	50	76868	67958	67780	67716
range-3-1	average	37	39790	37268	36260	29326
	best	50	36851	32877	35650	29180
range-3-2	average	29	34361	39336	34068	30497
	best	50	33548	35340	32908	30466
range-4-1	average	50	21559	21604	21604	21604
	best	50	21317	21604	21604	21604
range-4-2	average	50	18044	18498	18640	18498
	best	50	18044	18498	18497	18498
range-4-100-1	average	100	84916	106625	118550	85346
	best	50	81303	98522	112389	84514
range-4-100-2	average	100	91527	105538	127744	86538
	best	50	88566	97312	111513	84750
range-4-150-1	average	150	90394	98711	119547	101126
	best	50	88040	91972	108442	100195
range-4-150-2	average	150	112539	118351	171620	125444
	best	50	110104	110401	170164	121462
range-4-200-1	average	200	112618	124269	179239	139991
	best	50	111259	120510	171530	137684
range-4-200-2	average	200	135243	158634	223262	202373
	best	50	131349	135931	203352	194707
range-4-75-1	average	75	62439	60423	65381	52701
	best	50	60283	56337	62051	51846
range-4-75-2	average	75	72077	76964	85849	60753
	best	50	70403	71164	84140	60168

Table 7. Results of Solution Partitioning Solver compared with results for classical algorithms run on artificially generated test cases.

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