A vehicle routing application for retail delivery with open source tools

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Abstract. This work shows the application of the Capacitated Vehicle Routing Problem with Time Windows (CVRPTW) to collect different cargo-demand in several locations with low time disponibility to attend any vehicle. The objective of the model is to reduce the routing time in a problem with mixed vehicle-fleet. The initial step is the creation of a distance matrix by using the Google Maps API, then cargo capacities for every vehicle and time-windows for every demand point are included in the model. The problem is solved with Google-OR tools using as firt solution aproximated algoritm and as second solution one metaheuristic algorithm for local search.

Keywords: CVRP · Routing · Distribution · Open source tools.

1 Introduction

Colombian Industry presents several routing problems, especially in large cities, problems like significant distribution issues lead to having a higher operational and logistic cost. Many of these problems arise from the poor condition of road infrastructure, distribution centers having incomplete data for demand, ambiguous routing diagrams, among others. Currently, Cargo companies deal with two major sets of problems, the long haul freight transportation problem and the vehicle routing problem[15]. The first one refers to large trucks who have to travel long distances, and this is, in most cases, a problem easy to solve (generally an assignment problem). On the other hand, vehicle routing problems arise in different forms[23,24,26], as improvements over the traveling salesman problem [11]. Frequently, expensive software solutions are used to solve this problem, which has a long time in training and only allow established parameters. We propose to use Open Source Tools to solve huge VRP problems adapting them to the needs of each organization. In this work, we propose the use of Google Optimization Tools to create the distribution plan from 3 deposits to 125 demand points (stores) in a retail organization. First, we create the distance matrix with the Google API; then, we add the load capacities of the vehicles and the demands in each store and use Google OR tools to solve the model. Finally, we present the results and discuss the efficiency of the method.

2 Literature review

As we showed in the previous item, the first application of routing problems was proposed by Flood, years later, Dantzing also proposes an allocation-based model to solve the vehicle routing problem[10]. Later several heuristics rise including savings, proximity, matching, and intra-route inter-route improvement [18,9], exact algorithms were also proposed[7,8,17,12,4]. Modern heuristic development is related to the last years, here we highlight the works in tabu search based algorithms [22,14,25] . According with [18] some algorithms were over-engineered and the best meta-heuristic procedure must have a broad and in-depth search of the solution space and can solve several variants of the problem [20]. From Dantzing to the present, many researchers have proposed interesting solutions to the problem of vehicle routing. A search in Scopus® database shows us the growing interest in this problem: They refer to VRP 11358 documents, 678 of them about CVRP, 12 about MDVRP, 66 about VRPTW, ten documents about VRPB, 14 VRPBTW documents, 70 SDVRP documents, and 23 CVRPTW documents. Improvements have been developed since then. We currently have many variations of the classic VRP formulation; below, we explain the most relevant.

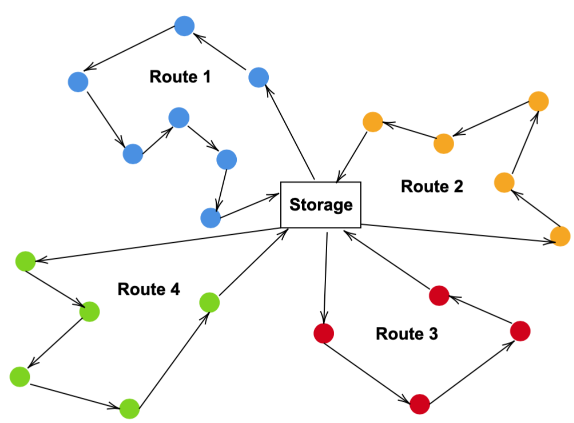

Fig. 1: vehicle routing problem graph

In Colombia, the use of CVRP has been extended to many fields, among which we highlight: distribution of medicines [5] ,collection of food donations [3], also in distribution patterns [6] and school bus routing [13,21]; also there are interesting works applied in other similar countries for pharmaceutical distribution [16].

[19]

3 The CVRPTW Model design

The family of VRP models and his study is extensive. The most study model in their taxonomy is the capacitated vehicle routing problem CVRP; the time windows restrictions form a generalisation of this model named VRPTW. The approximation in this work includes the capacity and time windows constraints simultaneously. Fist, we describe and show the mathematical formulation of the model, later also present the solution algorithms and tools to solve the problem.

3.1 Mathematical formulation to CVRP

The mathematical formulation for modelling CVRP shows as follows and its described according[23,24,26].

$$Min \sum_{k \in K} \sum_{(i,j) \in A} c_{ij} x_{ijk} \tag{1}$$

subject to

$$\sum_{k \in K} \sum_{j \in \Delta+(i)} x_{ijk} = 1 \qquad \forall\ i \ \in N, \tag{2}$$

$$\sum_{j \in \Delta+(0)} x_{0jk} = 1 \qquad \forall\ k \ \in N, \tag{3}$$

$$\sum_{i \in \Delta+(j)} x_{ijk} - \sum_{i \in \Delta+(j)} x_{jik} = 0 \qquad \forall\ k \ \in N,\ j \ \in N, \tag{4}$$

$$\sum_{i \in \Delta-(n+1)} x_{i,n+1,k} = 1 \quad \forall\ k \ \in K, \tag{5}$$

$$x_{ijk}(w_{ik} + s_i + t_{ij} - w_{jk}) \leq 0 \quad \forall\ k \ \in K, (i,j) \ \in A, \tag{6}$$

$$a_i \sum_{j \in \Delta+(i)} x_{ijk} \leq w_{ik} \leq b_i \sum_{j \in \Delta+(i)} x_{ijk} \quad \forall\ k \ \in K,\ i \in N, \tag{7}$$

$$E \leq w_{ik} \leq L \qquad \forall\ k \in K,\ i \ \in \ \{0, n+1\}, \tag{8}$$

$$\sum_{i \in N} d_i \sum_{j \in \Delta+(i)} x_{ijk} \leq C \qquad \forall\ k \ \in K, \tag{9}$$

$$x_{ijk} \geq 0 \qquad \forall\ k \in K,\ (i,j) \ \in \ A, \tag{10}$$

$$x_{ijk} \in \{0,1\} \qquad \forall\ k \in K,\ (i,j) \ \in \ A. \tag{11}$$

The objective function 1 refers to minimize the total cost expressed like distance units in the distance matrix. Constraints 2 restric the assignment of each client to exactly one vehicle route. In adition, constraints 3-5 characterize the flow on the path to be followed by vehicle k. In addition, constraints 6-8 and 9 guarantee schedule achievability with respect to time concerns and size aspects, correspondingly. Note that for a given k, constraints 7 force $W_{ik}= 0$ whenever client i is not visited by vehicle k. Finally, conditions 11 inflict binary conditions on the flow variables.

3.2 Solution method

– **googleDistance Matrix API:** The CVRPTW is solved using google maps distance matrix API [1], and for solve the algorithm this work use google or-tools [2] for developers.
– **googleORTools:** OR-Tools is open source software for combinatorial optimization, which seeks to find the best solution to a problem out of a very large set of possible solutions.
– **Routing Options:** Time spend in every search of 100 seconds, fist solution strategy cheapest insertion, local search objective tabu search.
– **IDE:** IPython/Jupyter notebooks.

The distance matrix C_{ij} is created by calling google maps distance matrix API, with units as distance in meters using the directions for every client from the Table 1 and represented in the Fig 2.

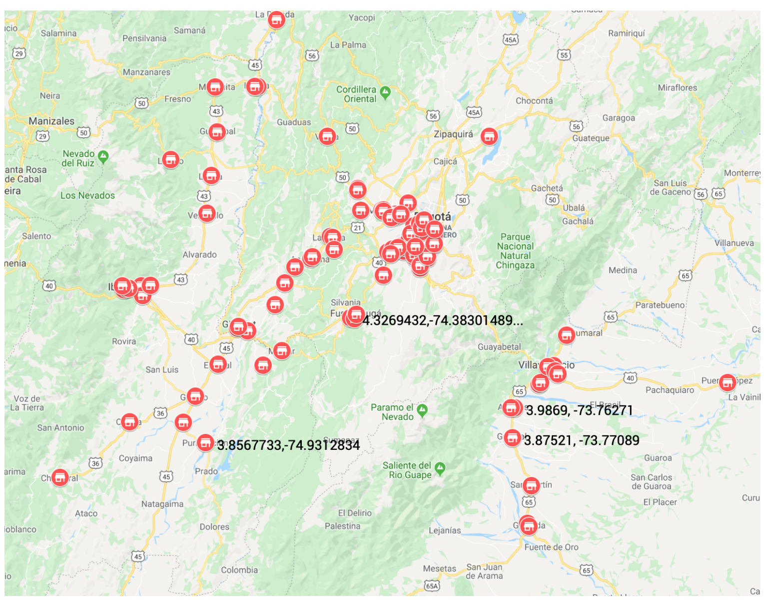

Fig. 2: Clients map - nodes for pick packages

Each client has different demands, the entire fleet is available, but they have different cargo capacity. The first module for the main program developed in python 3.0 is the data creation module, as we say before we use the google distance matrix API, then we add time window constraints with an initial time at 2:00 pm.

The time windows data is a set of pairs with initial time and final time for each time window in every pair into the set.

The vehicle capacities are added as another set of data in the first module of data creation. The second module calculates the distance between directions using the distance matrix created before.

The velocity for every truck is added as a mean velocity for vehicles at the day in Bogota, Colombia (25 km/h). An exciting and useful characteristic of the Google API is the possibility of getting the distance matrix data in real time.

Table 1: First 59 points of 125

Node	**Lat**	**Long**	**Node**	**Lat**	**Long**	**Node**	**Lat**	**Long**
Depot	4.5822314	-74.216822	**T10**	4.71122	-74.22284	**T20**	4.67096	-74.1443
T1	4.59957	-74.16018	**T11**	4.7345481	-74.26601	**T21**	4.57527	-74.24392
T2	4.58815	-74.16602	**T12**	4.62252	-74.08449	**T22**	4.61819	-74.14002
T3	4.58304	-74.10378	**T13**	4.4898	-74.25978	**T23**	4.60872	-74.07171
T4	4.61764	-74.13211	**T14**	4.56999	-74.12444	**T24**	4.55483	-74.13852
T5	4.7178418	-74.2122	**T15**	4.73518	-74.25932	**T25**	4.3269432	-74.383015
T6	4.5785051	-74.182236	**T16**	4.60269	-74.07916	**T26**	4.68172	-74.13387
T7	5.0114959	-74.470696	**T17**	4.643414	-74.067974	**T27**	4.6330803	-74.156796
T8	4.59726	-74.1909	**T18**	4.60343	-74.06713	**T28**	4.45852	-74.63375
T9	4.5731258	-74.225921	**T19**	4.81409	-74.35502	**T29**	4.58155	-74.11814

Node	**Lat**	**Long**	**Node**	**Lat**	**Long**	**Node**	**Lat**	**Long**
T30	4.5822314	-74.216822	**T40**	4.71122	-74.22284	**T50**	4.67096	-74.1443
T31	4.59957	-74.16018	**T41**	4.7345481	-74.26601	**T51**	4.57527	-74.24392
T32	4.58815	-74.16602	**T42**	4.62252	-74.08449	**T52**	4.61819	-74.14002
T33	4.58304	-74.10378	**T43**	4.4898	-74.25978	**T53**	4.60872	-74.07171
T34	4.61764	-74.13211	**T44**	4.56999	-74.12444	**T54**	4.55483	-74.13852
T35	4.7178418	-74.2122	**T45**	4.73518	-74.25932	**T55**	4.3269432	-74.383015
T36	4.5785051	-74.182236	**T46**	4.60269	-74.07916	**T56**	4.68172	-74.13387
T37	5.0114959	-74.470696	**T47**	4.643414	-74.067974	**T57**	4.6330803	-74.156796
T38	4.59726	-74.1909	**T48**	4.60343	-74.06713	**T58**	4.45852	-74.63375
T39	4.5731258	-74.225921	**T49**	4.81409	-74.35502	**T59**	4.58155	-74.11814

All vehicle capacities must be greater than the sum of every demand nodes. Otherwise, the problem has no feasible solution. The use of heuristics helps to find a feasible (but not always the best) solution with faster development in the time of execution for the algorithm previously selected. The imput information for the first module of data creation in our program is Table 1 and vehicle capacities $C_i = \{8500, 5400, 5400, 5400, 5400, 4600, 4200, 4200, 4000, 4000, 4000, 4000, 3500, 8500, 5400, 5400, 5400, 5400, 4600, 4200, 4200, 4000, 4000, 4000, 4000, 3500, 8500, 5400, 5400, 5400, 5400, 4600, 4200, 4200, 4000, 4000, 4000, 4000, 3500, 8500, 5400, 5400, 5400, 5400, 4600, 4200, 4200, 4000, 4000, 4000, 4000, 3500\}$

The CVPTW presents in each node a time window expressed as the initial time i_t and the final time f_t when a truck can visit a demand node at a time v_t as we show as follows:

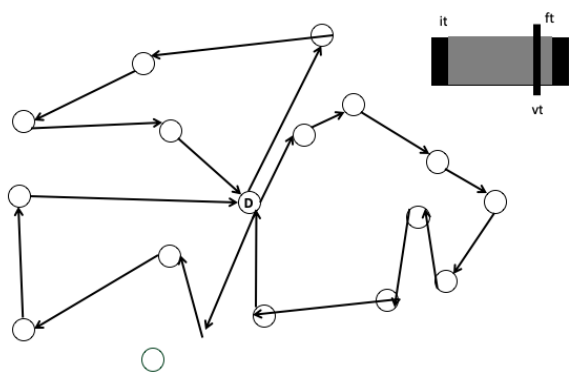

Fig. 3: VRPTW representation of time windows

The vehicle routing problem with time-windows (CVRPTW) refers to As can bee seen in the Fig 3,4 a fleet of shipping cars with equal capacity must attend customers with known demand and opening hours for a particular commodity. At a D depot node, the cars begin and end their routes. Only one car can attend each customer. The purposes are to minimize the fleet units and assign a sequence of customers to each truck minimizing the distance covered so that all customers are served and the total demand attended by each truck does not exceed its limit. The time windows are represented as the time interval vt from it to ft in which each customer can receive deliveries.

4 Results

The solution of the problem was performed using the algorithm of Objective tabu search and includes time window constraints and capacity constraints simultaneously. The performance of the algorithm was measured, given a solution at a time execution of 1.131150484085083 seconds.

The routes for the Trucks contains load in every node, total time and total distance for each. The total distance for every route was 200304 meters, the total

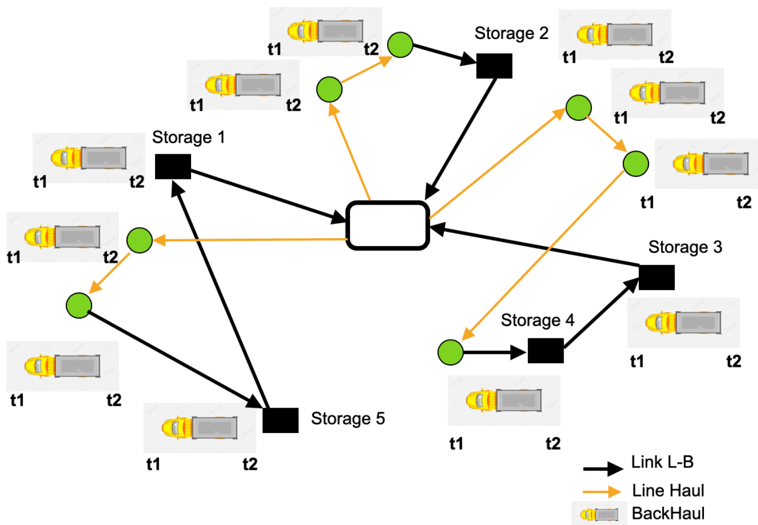

Fig. 4: VRPTW representation of time windows

time of every route was 5986 minutes. Also, we can plot every route, as can see the first two of them as follows:

Table 2: Results for the CVRP

Item	performance results
Total Distance of all routes	200304m
Total Load of all routes	70244
Total Time of all routes	5986min
Algorihtm performace	1.131150484085083 seconds

As can be seen in Tables 3 to 19 it is possible to obtain the routes of each vehicle where the first row shows the route that each vehicle must follow starting from the deposit and returning to it.

The second row shows the load collected at each point, rows 3 and 4 show the total load collected by each vehicle and the total route time.

5 Conclusions

The use of google optimization tools allows to solve optimization and meta-heuristic problems efficiently and also allows its integration with visualization tools such as google maps for a better understanding of the results.

Table 3: Route of truck 29

Route 29	**D**	**55**	**99**	**63**	**121**	**53**	**49**	**60**	**D**
Load - Kg	0	0	970	1569	1874	2202	3157	3938	4611
Total Load	4611								
Total Distance-m	25371								
Total Time	380								

Table 4: Route of truck 31

Route 31	**D**	**10**	**5**	**11**	**15**	**95**	**107**	**54**	**48**	**D**
Load - Kg	0	0	208	791	1770	2103	3055	3594	4063	4204
Total Load	4204									
Total Distance-m	20459									
Total Time	363									

Table 5: Route of truck 32

Route 32	**D**	**59**	**61**	**47**	**89**	**115**	**102**	**114**	**D**
Load - Kg	0	0	339	941	1659	2436	2793	3517	4098
Total Load	4098								
Total Distance-m	20053								
Total Time	362								

Table 6: Route of truck 33

Route 33	**D**	**73**	**21**	**124**	**106**	**D**
Load - Kg	0	0	153	1118	1687	2390
Total Load	2390					
Total Distance-m	746					
Total Time	331					

Table 7: Route of truck 34

Route 34	**D**	**81**	**65**	**45**	**31**	**110**	**94**	**96**	**D**
Load - Kg	0	0	297	645	1093	1873	2576	3050	3718
Total Load	3718								
Total Distance-m	17138								
Total Time	363								

Table 8: Route of truck 35

Route 35	D	13	51	25	123	32	52	46	30	D
Load - Kg	0	0	397	512	725	1361	1514	1671	2623	3229
Total Load	3229									
Total Distance-m	13467									
Total Time	355									

Table 9: Route of truck 38

Route 38	D	7	85	91	90	42	D
Load - Kg	0	0	725	1138	2107	2774	3349
Total Load	3349						
Total Distance- m	25030						
Total Time	372						

Table 10: Route of truck 39

Route 39	D	2	3	16	23	109	37	101	103	57	92	62	82	D
Load - Kg	0	0	870	1270	1699	2021	2958	3827	4003	4203	4578	4843	7427	8350
Total Load	8350													
Total Distance- m	18966													
Total Time	372													

Table 11: Route of truck 41

Route 41	D	9	111	43	79	39	83	41	40	28	D
Load - Kg	0	0	893	1025	1680	2477	2918	3767	3995	4254	4900
Total Load	4900										
Total Distance- m	12987										
Total Time	354										

Table 12: Route of truck 42

Route 42	D	4	12	18	17	119	87	35	71	19	88	D
Load - Kg	0	0	594	935	1214	2181	2307	3016	3805	4255	4854	5250
Total Load	5250											
Total Distance- m	16752											
Total Time	356											

Table 13: Route of truck 43

Route 43	D	33	97	75	105	34	72	112	76	D
Load - Kg	0	0	479	1100	1510	2383	3269	3772	4243	5050
Total Load	5050									
Total Distance- m	10640									
Total Time	358									

Table 14: Route of truck 45

Route 45	D	113	20	69	117	116	118	38	D
Load - Kg	0	0	394	703	1606	1891	2693	3039	3957
Total Load	3957								
Total Distance- m	3198								
Total Time	335								

Table 15: Route of truck 46

Route 46	D	27	100	120	68	66	56	D
Load - Kg	0	0	741	1654	2614	2900	3748	4127
Total Load	4127							
Total Distance- m	3751							
Total Time	338							

Table 16: Route of truck 47

Route 47	D	1	58	98	122	50	108	D
Load - Kg	0	0	877	1610	2263	2420	2886	3557
Total Load	3557							
Total Distance- m	2288							
Total Time	333							

Table 17: Add caption

Route 48	D	93	104	78	24	D
Load - Kg	0	0	273	780	1184	2151
Total Load	2151					
Total Distance- m	2306					
Total Time	334					

Table 18: Add caption

Route 49	D	6	14	77	67	29	64	36	D
Load - Kg	0	0	541	1017	1590	2103	2375	2951	3883
Total Load	3883								
Total Distance- m	2059								
Total Time	333								

Table 19: Add caption

Route 51	D	8	70	22	26	86	74	D
Load - Kg	0	0	642	934	1458	1841	2565	3420
Total Load	3420							
Total Distance- m	5093							
Total Time	347							

The routing problem in a real case for a Colombian company is solved by reducing the delivery time and the fleet required to carry out the cargo collections.

The biggest contribution of google tools in this case is the possibility of changing the loading capacity of trucks in a simple way.

The solution time is very efficient, achieving a response in a short time for a complex metaheuristic problem.

The company needs 17trucks; the demand is satisfied with 17 trucks as it was described in the last item. The model provides dynamic planning for delivery routes using a heterogeneous capacity fleet.

Future research can include machine learning algorithms to add human preference behaviour to chose how to accomplish the routes, including perception aspects like security or comfort.

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