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Solving a Transport Problem with Dynamic Customers and Traffic Factors

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Abstract

Over the years, several variations of the dynamic transport problem have been considered due to its similarities with many real-world applications. In this work, we study a new type of the dynamic transport problem based on the vehicle routing problem with dynamic customers and traffic factors, which takes into account the reception of the new requests, and the variation of the cost between two locations at each period of the day. According to the characteristics of this problem, we use a new strategy based on the hybrid genetic algorithm to solve it. The productivity and the quality of solutions under dynamic conditions are evaluated by the experiment on different test cases of this problem.

Keywords: Transport Problem, Dynamic Customers, Traffic Factors, Hybrid Genetic Algorithm

1 Introduction

The vehicle routing problem (VRP) proposed by Danzig and Ramser in 1959 has become a kind of classic combination and optimization problems in operations research [3]. The purpose of the problem is to achieve the optimization of transport costs through constructing a suitable vehicle schedule from one depot to a set of geographically scattered points. The routes must be designed in such a way that each point is visited only once by exactly one vehicle, all routes start and end at the depot, and the total demands of all points on one particular route must not exceed the capacity of the vehicle. There is a lot of uncertainty existing in VRP, such as the customer needs, the transportation needs, the traffic condition and the vehicle condition, all of the above need the schedule administrator to make a correct response on the updated information in a short time with the scheduling system, and modify to generate a new schedule planning. This kind of VRP is called Dynamic Vehicle Routing Problem (DVRP). It is now possible to solve this problem because we can contact the drivers to change the plan during the execution of the routes, using the development of GPS and new mobile internet applications technologies.

Dynamism in routing can emerge from different aspects of the problem. The most common source of dynamism is the arrival of new customers with a demand for goods (Hvattum et al. [5], Messaoud et al. [9]) or services (Beaudry et al. [1]). Other researchers consider dynamically revealed demands for a set of known customers (Novoa and Storer [11]), dynamic travel times (Tagmouti et al. [12]), vehicle availability (Li et al. [7]), and traffic factors (Mavrovouniotis and Yang [8]).

To be able to solve a dynamic problem, it must simulate a form of dynamicity. Kilby et al. [6] have described a method to do this, which was used also by a lot of authors, we cite as example Montemanni et al. [10] and Messaoud et al. [9]. They proposed to partition the working day into time slices and solve problems incrementally. The notion of a working day of T seconds is introduced, which will be simulated by the algorithm. Not all nodes are available at the beginning. A subset of the nodes has an occurrence time at which it will become available. In this work, we will use this strategy to solve a new kind of DVRP which represents the Vehicle Routing Problem with Dynamic Customers and Traffic Factors VRPDCTF. This new problem takes into consideration both the reception of new requests, and the variation of the cost between two locations (or customers) at each period of the day. This paper is organized as follows. The second section describes our idea of the resolution principle for the VRPDCTF. In the third section, we propose a new hybrid approach to solve this problem based on the genetic algorithm. In the Fourth Section, the results of small and large traffic factors for the VRPDCTF are compared. Finally, the last section summarizes the research and gives the conclusion.

2 Resolution principle of the Vehicle Routing Problem with Dynamic Customers and Traffic Factors VRPDCTF

To solve the VRPDCTF, the working day is decomposed into many time slices. Each time slice represents a partial static VRP, where the vehicles must serve all known customers. The proposed approach runs on each time slice, then from the solutions provided by the algorithm, we decide about commitments within an advanced commitment time, thus we allow a driver to react to new orders prior to the time of processing the order itself.

The first static problem created for the first time slice consists of all orders left over from the previous working day. This means that the optimization starts with customers who would have missed servicing yesterday. The time cut-off parameter controls the time in which new orders may arrive and thus may leave some customers unserved. All the orders received after the time cut-off are interpreted as being customers that were not serviced the day before. This means that the optimization starts with customers who would have missed servicing yesterday because of the time cut-off.

The next static problem will consider all orders received during the previous time slice as well as those which have not been committed to drivers yet. In our simulation, each vehicle starts from the location of the last customer committed to it, with a starting time corresponding to the maximum between the beginning of the next time slice and the end of the serving time for this customer, and with a capacity equal to the remaining capacity after serving all customers previously committed to vehicle.

To take into consideration the traffic factors, we modify at the end of each time slice the distance d_{ij} between customers v_i and v_j as follows:

$$d'_{ij} \leftarrow d_{ij} \times t_{ij} \qquad (1)$$

Where t_{ij} represents the change on the link between nodes v_i and v_j, which is generated as follows:

$$t_{ij} \leftarrow \begin{cases} t_{ij} \leftarrow 1 + r \quad r \in [F_L, F_U] & \textit{If } q \leq m \\ t_{ij} \leftarrow 1 & \textit{Otherwise} \end{cases} \qquad (2)$$

Where r is a random variable uniformly distributed in $[F_L, F_U]$, where F_L and F_U define the lower and upper bounds of the change respectively, q is a random variable uniformly distributed in [0, 1], and m defines the magnitude of change that satisfies $0 < m \leq 1$. For every arc, a different r value is generated to embed real-world characteristics in the constructed VRPDCTF. In this way, links with higher changes are generated when r values are closer to F_U, or links with smaller changes are generated when r values are closer to F_L. For example, traffic jams are not the same for all streets. Similarly, delays are not the same in all the links where packets are sent in communication networks. If t_{ij} is set to 1, it indicates that there is no change between nodes v_i and v_j. Although r may define the degree of a change in a single arc individually, the overall magnitude of change m is defined as the percentage of change for the different arcs.

The frequency of change defines how changes will occur. For the VRPDCTF, a change occurs as defined in Eq. (2) at the end of each time slice.

3 A hybrid genetic algorithm for the Vehicle Routing Problem with Dynamic Customers and Traffic Factor VRPDCTF

For each time slice, the adaptation of our hybrid solver is executed for each problem created at each time slice. The procedure of our hybrid genetic algorithm is given as follows:

1. Set N=1. Generate M solutions to form the first population P_1
2. Evaluate the fitness of solutions in P_1 based its objective function value
3. Apply the crossover operator on two solutions x and y selected from P_N randomly
4. Apply the mutation operator on a solution selected from P_N randomly
5. Evaluate and assign a fitness value to each solution in the population P_N based its objective function value
6. Apply the replacement to select M solutions from P_N based on their fitness and assigned them P_{N+1}
7. Apply the hybridization phase on the best solution of the new population
8. If the stopping criterion is satisfied, terminate the search, else set N=N+1 and go to step 3

a. Encoding the solutions

For every time slice, each solution is composed of the routes of the vehicles, where each vehicle visits the ordered list of customers, starting by the last customer served by this vehicle at the previous time slice, and finishing by the depot.

b. The initial population

To generate the initial population, we apply the following procedure to generate a feasible solution: we generate randomly a partial solution S_p, for 50% of customers selected randomly, via the construction of the routing of available vehicles, beginning with the first one and inserting the requests in its trajectory, until 50% of customers have been served. We insert the remaining customers at the location which minimizes our objective of the partial solution S_p without constraint violations.

c. Fitness function

Once the population is initialized or an offspring population is created, the fitness values of the candidate solutions are evaluated. The fitness function selected for our problem is the inverse of the total cost of transport.

d. Crossover

In the crossover, generally two chromosomes, called parents, are combined together to form new chromosomes, called offspring. In our work, two solutions are selected randomly from the population. A route from each parent is randomly selected and the customers presented between two points selected randomly in each route are removed from both parents and reinserted at the location which minimizes the total cost of transport.

e. Mutation

The mutation operator introduces random changes into characteristics of chromosomes, which could not be supplied by the crossover. The mutation used in our work is to choose two random customers from a randomly selected route and swaps them.

f. Replacement

After the crossover and mutation operators, we will have an intermediate population P_{inter}. This population is composed of the current population P_N and new solutions resulting from the genetic operators: crossover and mutation. The 50% of the new population P_{N+1} will contain the best solutions of P_{inter} and the rest of P_{N+1} will be completed by solutions randomly selected from P_{inter} which have not inserted into $P_{N+1.}$

g. Hybridization phase

At the end of each iteration, we apply the improvement phase on the best solution S of the new population as follows:

- ✓ Select a set of customers randomly
- ✓ Remove the selected customers from S to obtain a partial solution S_1
- ✓ Insert the selected customers, to obtain the complete solution S', into the position that minimizes the insertion cost over all the routes in the solution S_1
- ✓ Accept the new solution S' as the best solution of the new population if the total cost of the new solution decreases

This phase helps our genetic algorithm to give quick and effectively good feasible solutions.

4 Computational Results

To evaluate the effectiveness of our proposed approach, this latter is tested on the benchmark instances proposed by Kilby et al. [6] and extended by Montemanni et al. [10]. The proposed algorithm has been implemented in C++, and the experimental tests were carried out on a MacBook Pro-Core i5/ 2.4 GHz - MacOS X 10.7 Lion. The cut-off time and the advanced commitment time are set to $T/2$ and 0 respectively. The total length of the working day T is simulated by a very short time which corresponds to 200 seconds.

The procedure described in the section 2 can convert the Kilby's instances to VRPDCTF benchmark instances, where we take into consideration the instances derived from the conventional available VRP benchmark data, namely Taillard [13] (12 benchmarks instances), Christophides and Beasley [2] (7 benchmarks instances) and Fisher et al. [4] (2 benchmarks instances). More precisely, the magnitude of change was set to $m = 0.25$ and $m = 0.75$, indicating the degree of environmental changes from small to large, respectively. As a result, 42 VRPDCTF benchmark instances (two values of m), with lower and upper bounds $F_L = 0$ and $F_U = 2$ respectively, were generated. The Table 2 shows the results of our approach which correspond to the best value and the average of the total cost for three runs on the different instances of 50 to 199 requests. Each run is guaranteed to be independent of others by starting with different random seeds. The deviations between the best results of our approach in the cases where m=0.25 and m=0.75 are shown by *DEV* in the last column.

Table 1: Numerical results obtained by the proposed approach

	m=0.25		m=0.75		
	Best	Average	Best	Average	*DEV*
tai75a	2132.46	2222.01	2209.83	2290.59	3.63
tai75b	1622.09	1792.10	1810.26	1894.07	11.6
tai75c	1759.26	1788.66	1915.57	2100.48	8.88
tai75d	1592.66	1676.60	1882.3	1976.73	18.19
tai100a	2680.59	2793.81	3271.04	3527.77	22.03
tai100b	2881.13	2964.19	3485.88	3517.1	20.99
tai100c	1753.13	1997.55	2148.34	2201.97	22.54
tai100d	2457.59	2497.76	2500.37	2674.66	1.74
tai150a	4452.88	4670.28	4889.61	4982.79	9.81
tai150b	3996.83	4110.00	4043.71	4148.22	1.17
tai150c	3189.86	3381.5	3511.00	3786.68	10.07
tai150d	3646.09	3797.81	4005.23	4266.18	9.85
c50	664.55	679.9	791.49	838.91	19.10
c75	1115.68	1144.31	1270.53	1301.32	13.88
c100	1123.21	1200.71	1261.41	1344.21	12.30
c100b	1023.74	1113.97	1108.23	1208.14	8.25
c120	1558.11	1646.80	1751.48	1804.49	12.41
c150	1602.65	1647.05	1944.42	1969.60	21.32
c199	2260.99	2281.19	2501.63	2623.14	10.64
f71	336.62	346.32	363.33	396.1	7.93
f134	16818.00	17225.39	17326.52	18189.4	3.02

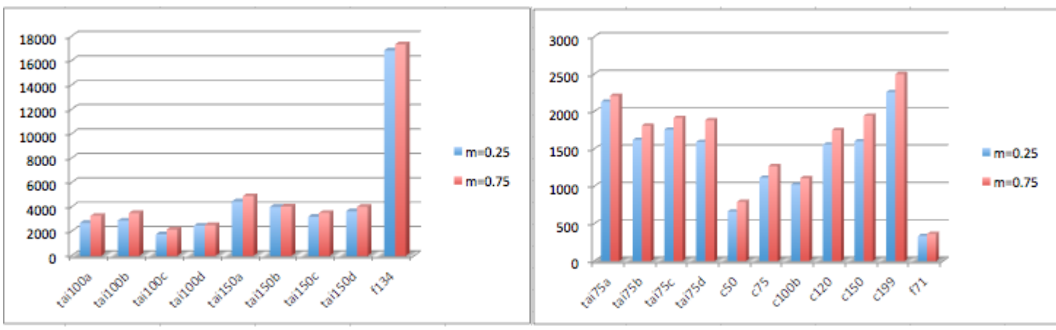

Figure 1: The best results found for *m*=0.25 compared with those for *m*=0.75

A comparison of the solution quality in terms of minimizing travel costs is done between the cases where the degree of environmental changes from small to large. From the table 1 and the figure 1, we can see that, as *m* increases, the maximal and the average of the total cost increase, which can be explained by the traffic jams which lead to increase travel times on certain roads, which implies that the total cost of the solutions increases. Our results show also that the deviations between the best results of our approach in the cases where m=0.25 and m=0.75 are very small for some instances (tai100d, tai150b, tai75a and f134) compared to the others, which can be justified by the geographical positions of the customers in each instance.

The total length of the working day T is simulated by 200 seconds, which implies that our approach gives these results in a very short time, which is very important in the dynamic case where the objective of planning may be looking for a feasible solution as soon as possible. Our results, which took into consideration the reception of the new customers and the traffic factors at the same time, weren't compared with other works of the literature, because in this latter just the dynamic customers or the traffic factors is taken into account.

5 Conclusion

This paper suggested a new kind of the dynamic transport problem based on the vehicle routing problem with dynamic customers and traffic factors. In this work, we proposed our idea of the resolution principle for this type of dynamic problem. Based on this idea, we proposed a new solver using a hybrid genetic algorithm. The computational results show that our strategy is able to solve this transport problem in a simulated dynamic environment with traffic factors in a very short time.

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