A metaheuretic based on controlled genetic operators to optimize Dynamic Carpooling Service

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1 Introduction

In the face of increasing price of transportation fuel cost and worsening the effects of traffic congestion and environmental pollutions, wise usage of personal automobiles are gaining more attraction. Carpooling is a solution for car travel reduction aiming to bring together travellers with similar itineraries and time schedules...In this paper, we are interested by the carpooling problem in its dynamic context. Our problem differs from traditional carpooling, and is focused on non-recurring trips which does not require long term commitments between people traveling together for a particular purpose. The dynamic carpooling is more reactive because it does not require rigid time schedules or routes over time. The trips are established in real time which means that the users agree to share a ride generated by our system, typically while they are not yet at the same location. The problem is how to assign every new passengers request to one or more vehicles. This assignment must be done in real time. In addition, there is another big handicap, due to the problems high complexity, concerning the way to make the process perform efficiently. To address these gaps, we introduce a novel approach called: Metaheuristic Approach based on Controlled Genetic Operators ($MACGeO$) in order to avoid their blind aspect and it is supported by an original dynamic coding. The generated solution which is an optimal route planning, will be evaluated by an aggregation approach based on the Choquet integral. Finally, the performance of our approach is measured via simulation by using test scenarii which feature various numbers of carpool drivers (vehicles) and riders (passengers).

2 Adopted methodologies

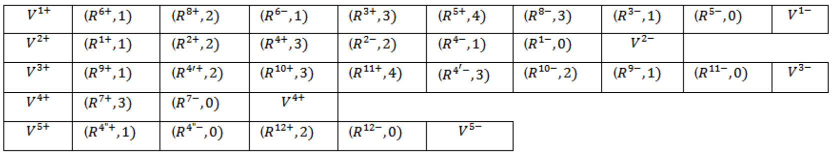
Following a judicious decomposition of the carpooling network and according to geographic coordinates (origins and destinations) of users, our system assigns a set of adequate requests to be served for each vehicle V^k.

$$V^k \leftarrow R_k = \{R_k^1, R_k^2, , R_k^x\}, card(R_k) = x = nbReq_k \tag{1}$$

In cases where a request cannot be served by a single vehicle, our system has to decompose this request into several sub-requests and assigns each one to a corresponded vehicle without taking into account the synchronization between them. The later will be ensured by our $MACGeO$ approach which considerably reduces the time required to match a large number of users in the proposed intelligent carpooling system. Our adaptive metaheuristic searches methods that mimic evolution through natural selection. They work by combining selection, controlled crossover and mutation operators. The selection pressure drives the population toward better solutions while crossover uses genes of selected parents to produce offspring that will form the next generation. Then, mutation is used to escape from local minima in the search space. Following, we discuss the important parts of the algorithm: The chromosome representation, the selection, the crossover and the mutation operators.

2.1 Chromosome representation

A chromosome solution is represented as a schedule of vehicles routes with one route for each vehicle (driver). Each route starts with the origin node of the vehicle followed by a list of pickup and delivery nodes taking into account the dynamic management of the vehicle capacity and ends with the destination node of the vehicle. In addition, if the rider s request could be served through a transit nodes, then the several pairs of pickup and delivery nodes of that request will appear in different routes (Request 4). Figure 1 shows an example of solution representation matching for five vehicles (1-5) and 12 riders' requests (1 - 12). We note that + and - denote the pickup and delivery points of passengers requests and the origins and destinations of the vehicles. The second component of the pickup and delivery pair represents the dynamic capacity of the corresponded vehicle.



V^{1+}	$(R^{6+},1)$	$(R^{8+},2)$	$(R^{6-},1)$	$(R^{3+},3)$	$(R^{5+},4)$	$(R^{8-},3)$	$(R^{3-},1)$	$(R^{5-},0)$	V^{1-}
V^{2+}	$(R^{1+},1)$	$(R^{2+},2)$	$(R^{4+},3)$	$(R^{2-},2)$	$(R^{4-},1)$	$(R^{1-},0)$	V^{2-}		
V^{3+}	$(R^{9+},1)$	$(R^{4'+},2)$	$(R^{10+},3)$	$(R^{11+},4)$	$(R^{4'-},3)$	$(R^{10-},2)$	$(R^{9-},1)$	$(R^{11-},0)$	V^{3-}
V^{4+}	$(R^{7+},3)$	$(R^{7-},0)$	V^{4+}						
V^{5+}	$(R^{4''+},1)$	$(R^{4''-},0)$	$(R^{12+},2)$	$(R^{12-},0)$	V^{5-}				

Fig. 1. Chromosome representation

2.2 Selection Operator

We decided to opt for a stochastic selection operator which is the technique of roulette. We note that the fitness values is obtained thanks to an aggregation criteria process which is determined by applying the Choquet Integral taking into account the weighting, the interaction and the compensation between different criteria: waiting time, route time, delay time, environmental gain and trip's cost. Then, to calculate the partial scores, we apply the fuzzification method in order to make criteria homogeneous and evaluated in the same scale.

2.3 Controlled Crossover Operator

Our crossover method is known as the uniform crossover. The resulting offspring contains a mixture of genes (Vehicles itineraries) from both parents with the help of a crossover mask. We note that the result of our controlled crossover operator guarantees the viability of the new offspring by the respect of the temporal and spatial connectivity constraints.

2.4 Controlled Mutation Operators

Our Controlled Mutation Operator consists in selecting randomly a chromosome, then choosing randomly a vehicle itinerary from this chromosome and a position point (request: R^{+} or R^{-}). If the selected point is R^{+}, we are swapping it with its right adjacent point, so that the pickup constraint is respected in the same route. In order to respect the delivery step, we are swapping the selected point R^{-} with its left adjacent point. Our Controlled Mutation operator does not need a correction process and makes a significant diversity in the population in order to accelerate the convergence of our evolutionary algorithm.

3 Discussion

For the purpose to improve the effectiveness of our approach and to study the merits of optimization for dynamic carpooling, we propose a ridesharing service in the French city of Lille (Nord department) during a transports disturbance. The simulation results shows that the majority of passengers arrived at their destinations with an average waiting time of nine minutes, an average route time which may not exceed ten minutes and sometimes without delay. Moreover, the gain realized by each passenger, if he chooses to carpool, may exceed 2000 g of CO_2 and the travel cost of the carpool matching results generated by the use of the $MACGeO$ algorithms may be less than one euro.

There are many interesting ideas to extend this work. First, we might move to a more realistic scenario. Indeed, we will propose in future works the networks subdivision principle in conjunction with the Multi-Agent concept to highlight the decentralized parallel process