Application of a memetic algorithm to the fleet size and mix vehicle routing problem with electric modular vehicles

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ABSTRACT

Electric vehicles have emerged as a new promising technology guaranteeing sustainable transport activities. To save the environment and avoid our dependence on foreign oil, new laws and regulations concerning the emission of greenhouse gases are made in order to reduce harmful emissions and promote electric vehicles for urban goods distribution. This paper proposes to address the electric Modular Fleet Size and Mix Vehicle Routing Problem with Time Windows, which incorporates electric modules that can be recharged at customer locations. For that purpose, we apply a memetic algorithm that combines a Genetic Algorithm with a Local Search method. Experimental results demonstrate that with the modularity feature, using electric vehicles for freight delivery in cities is interesting economically.

KEYWORDS

Urban logistics, Vehicle Routing Problem, Genetic Algorithm, Evolutionary Computation, Electric Modular Vehicles

1 INTRODUCTION

Urban freight transportation contributes to harm the environment with pollution, noise and congestion. Indeed emissions from the road sector increased by 68% since 1990 and reported approximately three quarters of transport emissions in 2013 [3]. For example, in 2013, transportation activities have caused approximately nearly 23% of greenhouse gas (GHG) emissions in the European Union. Consequently, in E.U., policy makers implement measures to encourage improved vehicle efficiency. In parallel, researchers are developing models highlighting different aspects of green logistics integrating electric vehicles (EVs) into goods distribution problems. For instance, Bruglieri et al. [2] addressed the problem of serving a set of customers, within fixed time windows by using EVs and considering their need to stop at Recharging Stations (RSs) during the trips. Furthermore, Lin et al. [4] have introduced a general Electric Vehicle Routing Problem (EVRP), in which electric commercial vehicles with a limited range may recharge at a charging station during their daily delivery and pick-up tours.

In this paper, we are interested in a variant of the electric Fleet Size and Mix Vehicle Routing Problem which incorporates the possibility of recharging the electric modules at customer locations [1]. The available vehicles differ from the battery ones since the modules are autonomous in terms of consumption and electric charging. This is a completely new class of problems called eM-fleet size and Mix VRPs with Time Windows integrating both the complexity of the original VRP and specific constraints induced by using electric and modular vehicles. The objective is to minimize the acquisition cost, the total distance travelled and the recharging costs. We propose, as a resolution method, a hybrid approach that combines a Genetic Algorithm (GA) with a Local Search (LS) method. In other words, the resulting memetic algorithm is applied to this new type of problem. An extensive experimental study shows the effectiveness of including the modularity feature in electric vehicles for goods distribution.

This paper is organized as follows. In section 2, we provide the presentation of eM-fleet size and Mix VRPs with Time Windows. Section 3, discusses the adaptation of the memetic algorithm to address it. The computational results are presented and discussed in Section 4. Section 5 concludes the paper.

2 PROBLEM PRESENTATION

The originality of the electric modular vehicles is that they are based on a modular and active frame system. This means that payload modules are designed in addition to a cab module (where the driver sits) in order to bring more space and flexibility. This enables the vehicle to drop off modules at respective delivery locations and pick them up later during a run. One of the interests for the vehicle to drop off a module is the possibility to overcome length or weight restrictions for delivery vehicles in certain areas. Releasing a module at a customer location can also help respecting delays for deliveries or permit to recharge the module battery if a charging terminal is available, allowing the vehicle to benefit later from this additional energy. Recharging the modules separately instead of the whole vehicle permits also to save time. The eM-fleet size and Mix VRP with Time Windows can be stated as follows. A fleet

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of heterogeneous vehicles is stationed at the depot. Before leaving, each electric vehicle must be fully charged at the maximum recharge quantity. Each customer located at a node has a positive demand, a service time, a time window and a recharging time. Our model is based on the use of electric vehicles. For this reason, some hypothesis have been set in order to define properly the problem. These assumptions are related basically to the recharging policy [5]. The objective of the problem to minimize the total traveling distance, the acquisition cost and the recharging cost.

3 A MEMETIC ALGORITHM AS A SOLUTION APPROACH

We use a typical memetic algorithm (MA) that combines the genetic algorithm with a local search, an approach that proved to be promising on routing and transportation problems such as the VRPTW with single or multiple depots. Different features need to be carefully considered in order to achieve good results. Among these features, one could consider the initial solution representation, the fitness function and the crossover and mutation operators. As an initial solution, we used a simple representation in which a solution is represented with an array of n customer nodes which are served by the vehicles. Once individuals are created, they are ranked as per their fitness value calculated as the sum of the total distance travelled, acquisition cost and recharging cost. According to the results from the evaluation function, a new population is created after having applied operators such as the Tournament selection one and the Partial Mapping Crossover (PMX). This latter was chosen because it has the advantage of providing best solutions in a short time frame. Finally, the memetic method consists in enhancing the performance of the genetic algorithm by introducing a local search as a mutation operator to intensify the child quality obtained with the crossover operator.

4 PRELIMINARY COMPUTATIONAL RESULTS

Recently, the concept of eM vehicles has been the subject of a first study and a first implementation which yielded to encouraging results, see [5]. Hence, in order to test our new approach, we applied the memetic algorithm to different classes of problems. The benchmark instances have been addressed, each one with 100, 200 or 400 customers stemmed from Solomon benchmarks [6]. The instances are divided into three categories: C-type, R-type and RC-type depending on the geographical distribution of the customers. In Table 1, our results are compared to the Best Known Solutions (BKS) obtained in the literature, see [7]. The table columns refer respectively to: the instance name, the number of customers of the benchmark, the number of vehicles (# Veh) used and the total distance (TD) of a tour for the BKS and our memetic algorithm (MA). The capacity of the electric vehicles is the triple of the one of a module and is equal to the one of an equivalent combustion engine vehicle. For all the tested instances, experimental results presented in Table 1, show that our MA gives excellent results as compared with the Best Known Solutions regarding the decreased numbers of electric modular vehicles needed to perform the tours. This represents an average decrease of 25.47%, without a significant increase of the total distance (3.48% in average). Therefore, although the purchasing cost of an electric vehicle can be higher than the one of a combustion engine one, the decreased number of required electric modular vehicles to perform the tours leads to lower costs.

Table 1: Comparison of Results Obtained with the MA compared to the Best Known Solutions

Benchmark		BKS		MA		
Instance	NbC	#Veh	TD	#Veh	TD	Δ%
C105	100	10	828,7	8	890,27	7,43
C109	100	10	832,7	8	896,40	7,65
RC109	100	13	1381,31	10	1387,34	0,43
C_1_2_1	200	20	3503,84	20	3646,76	4,07
C_1_2_2	200	27	4531,8	21	4561,94	0,66
C_1_2_3	200	23	3902,48	15	4000,57	2,51
C_1_2_5	200	20	3525,93	16	3640,21	3,24
C_1_4_1	400	40	9693,75	27	9733,01	0,40
C_1_4_3	400	49	12127,6	33	12728,92	4,95
Total		212	40328,11	158	41485,42	3,48

5 CONCLUSION AND FUTURE WORKS

This paper proposes to address a brand new logistics scheme for urban delivery involving electric modular vehicles. The solving approach consists of a memetic algorithm which enhances the performances of the so-called genetic algorithm using a local search technique. Our next step is to develop a more enhanced version of our meta-heuristics or other meta-heuristics to solve our problem and find better solutions.

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