A K-medoid Algorithm with Adaptive Large Neighborhood Search for the VRPTW

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1 Introduction

In this paper, we propose a new approach which combine the k-medoid with the Adaptive Large Neighborhood Search inorder to find a set of routes, starting and ending in one or more common depots, to serve a set of customers such that the overall of the routes is minimized. In this contrast, we subdivise the group of nodes of the general problem into small sets of customers which represent subproblems using the K-medoid algorithm (We use K-medoid for the clustering algorithm as prototype and it is not restrictive and of course, we can adopt other techniques such K-means or density based spatial clustering of applications with noise, [2]). Then, we apply the Adaptive Large Neighborhood Search algorithm which explores multiple neighborhoods within the same search and defined implicitly the large neighborhood thereby to solve each subproblem. Finally, we gather the obtained solutions to get a final complete solution.

2 Approach to the resolution of the VRPTW

Our approach fits into the algorithms cluster first and route second, and it works as follows :
Phase 1 : The first phase of the algorithm consists in identifying a set of clusters through a $K-$medoids algorithm. The main idea of this iterative clustering algorithm is to divide the input data set into K distinct clusters $C_1,...,C_K$. We first begin by selecting K of the N input data points as the initial medoids. Then, we associate each data point x_i the nearest centroid C_j by computing the a specific spatio-temporal measure between specified instance x_i and cluster center c_j and then we pick the cluster which have a minimum measure. We assign each data to the closest cluster j. The next step is to recompute the position of the centroids from individuals attached to the groups by taking the average of the all data points that belong to each cluster. The new centroid C_j is the mean of all points x_i assigned to cluster j in previous step. We repeat the previous steps until none of the cluster assignments change. We obtain then a partition of the instances in K groups characterized by their centroids.

Phase 2 : The second phase which is the most crucial aims at selecting the different neighborhoods according to some strategy for the effectiveness of the search process. The strategy adopted in this work is to let ALNS solve each subproblem related to each cluster separately. The used ALNS is a metaheuristic proposed by Ropke and Pisinger in 2006 [3]. It is a common technique used to enhance a locally optimal solution. Given an initial solution obtained by a construction method, it is based on the idea of improving the initial solution by applying various destroy and repair operators to generate large neighborhoods through which the search space is explored. Finally, we collect the solutions related to each subproblem and we gather them to obtain a complete solution when the subsolutions will be the routes of the final solution.

3 Computational experiments

The examined approach was tested on a set of small instances based on the reference of Solomon benchmark (1987)[1], and large instances of Gehring & Homberger's benchmark. We computed then the mean absolute percentage deviation (MAPD) which is the absolute difference between the new approach and the ALNS cost function divided by the magnitude of the objective function in the new approach.

Table : Comparison between ALNS and K-medoids + ALNS

Instance	K-medoids + ALNS	ALNS	Average : MAPD
c103	1823	2315	0.26
c104	1636	2385	0.45
c105	1396	1771	0.26
r105	2099	2470	0,17
r106	1883	2376	0,26
r107	2002	2350	0,17
rc205	2691	2951	0,09
rc206	1911	2376	0,24
rc208	2073	2724	0,31

The results show the improvement of the final objective function in the approach which combines the K-medoid with the ALNS compared to the ALNS.

Références

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[3] *S. Ropke, D. Pisinger. An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. Transportation Science*, 455–472, 2006.