A Blind Insertion Mechanism to Solve the Dynamic Large-Scale Shared Autonomous Dial-A-Ride Problem

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1 Introduction

We study a prospective transportation system where large-capacity Shared Autonomous Vehicles provide dial-a-ride services to fulfill a very large scale of passenger requests (around 300,000). The system operates dynamically, with newly submitted requests needing immediate processing. A crucial aspect of this system's viability in real-time situations is therefore the implementation of an efficient routing algorithm that can deliver high-quality solutions. Studies on similar demand and responsive transportation system are usually based on heuristics ([1, 3]). In this work, we address a dynamic large-scale shared autonomous dial-a-ride problem through a best-fit greedy insertion algorithm. Furthermore, large-scale requests are assumed to be dominated by daily commuting needs, and thus should be similar and repetitive from one day to another. Therefore, there might exist recurring and similar patterns in vehicle trajectories if similar requests can be served in the same manner.

2 Algorithmic Scheme

In order to efficiently manage the online routing process, we propose a *Blind Insertion Mechanism (BIM)* which utilizes a statically and finely resolved historical instance $\bar{\mathcal{R}}$ as a reference to guide dynamic insertions. By learning from high-quality reference solutions $\bar{\Theta}$, the dynamic routing process operates like a blind person guided by a cane, ensuring both efficiency and solution quality.

Given a request $r \in \mathcal{R}$ and the current routes of the SAVs $\Theta = \{\theta^v, v \in \mathcal{V}\}$, where θ^v denotes the current route of vehicle v, we apply the following algorithmic scheme to insert r :

— **Step 1 - Blind Insertion :** We invoke *BIM*. Firstly, we identify several reference requests $\bar{r} \in \bar{\mathcal{R}}$ that are *similar* to the target request r. Then for each reference request, we try to insert r under of guide of the reference insertion information of $\bar{r}$. Specifically, we shall identify from the current SAV fleet a vehicle v which follows a similar travel pattern as $\bar{v}$ where $\bar{r}$ was inserted. Next, within the route θ^v, we identify a couple of insertion positions where the origin and destination of r could be inserted, according to the guidance of how and where r has been inserted in the route of $\bar{v}$. If at least one feasible insertion can be established, we keep the best-fit insertion that minimizes the insertion cost.

— **Step 2 - Filtering Insertion :** As a substitute method in case no feasible insertion for r has been found after BIM, the *filtering system* introduced in [2] is utilized to efficiently select valuable candidate insertion parameters.

— **Step 3 - Activation of a New Vehicle :** Finally, we shall activate a new SAV to serve r if both Step 1 and Step 2 fail.

3 Experimental Results

We consider the network of Clermont-Ferrand with 13839 nodes and 31357 arcs and a service period of 24 hours. SAV capacity is 10, and the fleet size is a-priori unlimited. Due to the lack of resources, pseudo-requests are generated such that commuting dominates other travel intentions during peak hours. Instances with different characteristics (such as different dynamic proportions) are tested.

Compared to the situation where each one-way or round-trip request is served by an individual vehicle, the novel system demonstrates a remarkable 98% reduction in fleet size requirements when servicing all 300k requests. Furthermore, we observe a substantial reduction in energy consumption, particularly during peak hours, thanks to the benefits of ride-sharing.

Thanks to the BIM and the filtering system, all requests at each decision epoch can be processed within the limited execution time. Meanwhile, the quality of the solution to the dynamic problem remains comparable to that of the same problem in the static context.

Detailed experimental results will be presented and discussed during the talk.

4 Conclusion and Perspectives

We provide effective operational management methods and shed light on the dimensions and potential of this novel transportation system. Our on-going and future work focuses on studying viable infrastructure design and better managing active and inactive vehicles so that SAV recharging issues and heterogeneous vehicles can be taken into consideration.

Références

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