Space cutting-based approach to optimize vehicle ride-sharing in the city of Lomé

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1 Introduction

Growing urbanization of the population brings its share of challenges, in particular, regarding global climate change. Contemporary cities are plagued by pollution, traffic congestion, lack of parking space and rising travel costs. In this context, ride-sharing emerges as a promising, environmentally friendly, solution. However, its widespread adoption is hampered by often limiting service quality parameters, namely long travel times and waiting times. Thus, the need arises to implement optimization methods for ride-sharing that would minimize these metrics. Several studies have proposed solutions that benefit from the potential of metaheuristics and machine learning, to address different purposes. Some have studied the impact of ride-sharing on cities [3], while others have developed heuristics for optimizing dynamic ride-sharing, using shareability function and clustering algorithms [1], multi-agent simulation-based model [2], etc.

In this study, we devise a solution of the ride-sharing problem based on the division of the area of interest (Lomé, Togo) and then the use of a genetic algorithm to optimize vehicle ride-sharing.

2 Modelling the problem

2.1 Meshing the area of study

The area is divided into 300 m x 300 m square meshes; each mesh is assigned an index. A mesh is used to refer to an origin or a destination of a passenger trip request. So a mesh is represented as: $m_i(i, x, y)$, where i is the index identifying the mesh, and x, y the geographic projected coordinates of the mesh center.

2.2 Problem objectives and constraints

The path $L(v)$ (see Equation 1) of a vehicle v is represented as a suite of k meshes, each mesh being an origin or a destination of a passenger trip. k is not known in advance and a mesh can be present several times in the path $L(v)$.

$$L(v) = (m_1, m_2, ..., m_k), k \in \mathbb{N} \tag{1}$$

Three types of objectives are considered for the vehicle v: 1) minimize overall wait and travel time of passengers $PT(v)$ [1]; 2) minimize total travelled distance $D(v)$ [1]; 3) maximize occupation rate $OR(v)$.

Four constraints are also considered to limit the negative impacts of ride-sharing: 1) The waiting time $WT_i(v)$ of each passenger request i served by the vehicle v must not exceed a threshold $WT_{max}(i)$, which can be defined globally, or per request; 2) The travel time $T_i(v)$ of each passenger request i served by the vehicle v must not exceed a threshold $T_{max}(i)$, which can also be defined globally, or per request; 3) The number of onboard passengers $P_{i,i+1}(v)$ on each section $[m_i, m_{i+1}]$ of vehicle v path must not exceed the vehicle capacity $C(v)$; 4) The number of detours for each passenger request $DC(v,p)$ served by the vehicle v must not exceed a threshold $DC_{max}(p)$, which can also be defined globally, or per request.

These result to the multi-objective optimization problem with constraints of Equation 2. In this equation, $d(m_i, m_{i+1})$ is the real distance between consecutive meshes m_i and m_{i+1}. These values and real travel times between meshes are obtained from openstreemap.org.

$$\begin{cases} min & D(v) & = & \sum_{i=1}^{k-1} d(m_i, m_{i+1}) & v \in V \\ min & PT(v) & = & \sum_{i \in P_v} (WT_i + T_i) & v \in V \\ max & OR(v) & = & \sum_{i=1}^{k-1} \frac{P_{i,i+1}}{C(v)} & v \in V \\ s.t. & WT_i(v) & \leq & WT_{max}(i) & \forall i \in P_v \\ & T_i(v) & \leq & T_{max}(i) & \forall i \in P_v \\ & P_{i,i+1}(v) & \leq & C(v) & v \in V, \forall i \in [1, k[\\ & DC(v,p) & \leq & DC_{max}(p) & \forall p \in P \end{cases} \tag{2}$$

A passenger request can be in 5 states: 1) *Pending* - request sent by the passenger but not yet processed; 2) *Assigned* - request processed and assigned to a vehicle's path; 3) *Onboard* - passenger onboard the vehicle; 4) *Served* - passenger dropped off at destination; 5) *Rejected* - request processed but no vehicle can fulfill it.

2.3 Space cutting

For each mesh, we added the number of passenger requests originating from it, to obtain a weighted mesh $\mu_i(x_i, y_i, \theta_i)$. We then cluster all weighted mesh with the unsupervised algorithm k-means. The optimal number of clusters is determined by the elbow method.

2.4 Solving approach and experiments

We used the NSGA2 algorithm to solve the problem, with the following setting: 1) an individual is a vehicle path, from 2 to 10 meshes; 2) a population of 100 individuals; 3) stop criteria: 3 generations without optimization, 100 maximum generations; 4) a vehicle mainly stays and serves passenger requests originating from its cluster.

We built a dataset by generating plausible mobility data based on data from a urban bus company in the city of Lomé. We conducted experiments with 3253 passenger requests, corresponding to 10 min requests in the dataset, a vehicle capacity of 4 passengers in each cluster, and three thresholds: $WT_{max} = 20min, T_{max} = 1h, DC_{max} = 3$.

References

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