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► **To cite this version:**

Aina Rasoldier, Alain Girault, Sophie Quinton, Jacques Combaz, Kevin Marquet. Assessing the Potential of Carpooling for Reducing Vehicle Kilometers Traveled. ICT4S 2023 - 9th International Conference on Information and Communications Technology for Sustainability, Jun 2023, Rennes, France. pp.120-131, 10.1109/ICT4S58814.2023.00021 . hal-04401006

**HAL Id: hal-04401006**

**<https://inria.hal.science/hal-04401006>**

Submitted on 17 Jan 2024

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# Assessing the Potential of Carpooling for Reducing Vehicle Kilometers Traveled

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**Abstract**—The national and local strategies implemented to achieve the French Nationally Determined Contribution (a key element of the Paris Agreement) rely heavily on technological improvements to reach carbon neutrality by 2050, which raises the question of whether these technologies can rise to the challenge, and which social changes are needed to make these technologies reach their full potential. One example of this is the use of digital platforms for developing carpooling. We study the maximum potential of two carpooling schemes for local travel. Our results show that a massive adoption of carpooling would be needed to reach targets set by the national and local strategies, even under maximizing assumptions.

**Index Terms**—carpooling potential assessment, avoided VKT, carpooling platforms, synthetic travel demand, GHG emissions mitigation, decarbonization strategies, local mobility

## I. INTRODUCTION

### A. Context and Motivation

Achieving the objective set by the Paris Agreement of keeping global warming well below two degrees compared to preindustrial levels would require a massive and global reduction of greenhouse gas (GHG) emissions [1]. Nationally Determined Contributions set targets for each country. For France, this has been translated into the *Stratégie Nationale Bas Carbone* (SNBC), the French decarbonization strategy [2]. The SNBC relies heavily on technological improvements to reach carbon neutrality by 2050, which raises two questions. The first one is whether these technologies will be ready on time, and as efficient as expected. Beyond technological aspects, the second question relates to the social changes that are needed in order to make these technologies reach their full potential.

One example of this is the use of digital platforms to develop carpooling for local travel. By carpooling, we mean a form of ridesharing in which people travel together using the personal vehicle of one of them. Ambitious targets have been set regarding carpooling both in the SNBC and at local scales, *e.g.*, in the local transport plan for the Grenoble area called *Plan de déplacements urbains* in French (PDU) [3]. Their objective is in particular to reduce the GHG emissions due to local trips, which are known to be significant. Indeed, in France in 2019, transportation is the sector that emitted the most GHG, equal to 31% of the GHG emissions of the country [4], and local trips represented on average 8,929 km

traveled per person, whereas long trips<sup>1</sup> represented on average 4,198 km traveled per person [5].

In this context, our objective is to study the potential of carpooling for local travel. This will be useful to understand under which conditions carpooling for local travel could fulfill the objectives set by the SNBC or the Grenoble PDU.

### B. Contribution

In this paper, we focus on *prearranged* carpooling, in which travelers decide in advance when and how they are going to travel (typically the day before). This is well suited for (but not restricted to) recurring traveling patterns, *e.g.*, commutes. While our framework is generic, we have implemented two specific prearranged carpooling schemes:

- *identical carpooling*: two people can carpool on a trip if their origin and destination are close enough (typically within a few hundred meters), and if their departure time or arrival time are also compatible.
- *inclusive carpooling*: two people can carpool on a trip if the origin and destination of one (who will be the passenger) are close enough to the route of the other (who will drive).

In practice, passengers may go (*e.g.*, walk) to meet the driver, and/or the latter could make a detour.

Our framework can be configured to allow more than two people to carpool. In addition, it keeps track of people's *activity chains*<sup>2</sup> when determining whether they can carpool, because someone may not be able to carpool as passenger if they need their car later on during the day. Note that our framework does not require a passenger to keep the same driver during the day.

For a given *travel demand*, expressed as a set of trips representative of the traveling patterns of a given population for an average weekday, our analysis proceeds in three steps:

- 1) *Trip filtering*. We filter out trips considered not carpoolable, based on population and trip attributes.
- 2) *Pairwise shareability graph construction*. We build a graph of all the possible trip-specific passenger-driver pairs for the given carpooling scheme.

<sup>1</sup>Plane trips not included.

<sup>2</sup>For example, a person may go shopping on their way back from work.

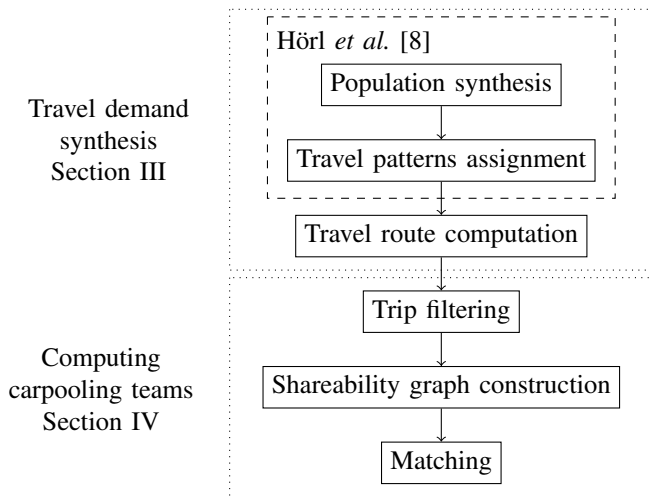


Figure 1. Carpooling potential assessment pipeline

- 3) *Matching*. We compute carpooling teams (*i.e.*, driver and passengers) that are compatible with the graph, vehicle capacities and activity chains.

We do not try to capture precisely the socio-economic factors that could influence travelers’ ability to carpool [6]. Instead, we focus on “structural” obstacles, that is, which part of a travel demand could be met using carpooling with limited adjustments on origin, destination, and timing. In other words, we try to provide an optimistic estimate of the carpooling potential assuming that travel demand (including activity chains) remains constant. This is of course a simplification since people may be willing to adapt their traveling patterns in favor of carpooling, but also because carpooling is subject to rebound effects [7] (*e.g.*, induced demand) that would reduce its benefits. We discuss this in Section VII.

One major challenge of our work is scalability, as we target a synthetic population of roughly one million people. A second difficulty lies in tracking uncertainties in the computed estimates. Finally, a major aspect of our work is the ability to explore and compare different scenarios in order to better understand under which conditions carpooling could have (or not) a significant impact on the GHG emissions of local travel.

The implementation of our framework proceeds in two main stages (see Figure 1): travel demand synthesis using the software of Hörl *et al.* [8], and computation of carpooling teams. We have implemented the identical and inclusive carpooling schemes considering various parameters, *e.g.*, how much slack people have *w.r.t.* their timing. We have experimented with our framework using publicly available data for the Grenoble area<sup>3</sup>. Our results suggest that a massive adoption of carpooling would be needed to reach the targets set by the PDU or the SNBC on occupancy rates, even under maximizing assumptions.

To summarize, the main contributions of our paper are: (1) a synthetic travel demand for the Grenoble area, built

<sup>3</sup>Since we use public data, our experiments can be reproduced, and since they are obtained from national databases, this can be done also for other areas in France.

on top of the software of Hörl *et al.* [8], which we slightly improved; (2) a generic method for estimating the potential of prearranged carpooling for a given travel demand, considering activity chains and their implications on car availability; (3) the corresponding open-source framework; (4) experiments for the Grenoble area with two standard forms of prearranged carpooling (identical and inclusive); (5) a discussion of how our framework could be used for exploring and comparing different mitigation scenarios for local mobility, including the limitations of our approach.

### C. Paper Organization

This paper is organized as follows. Section II positions our work in the state of the art. Section III formally describes the travel demand on which our analysis is performed and briefly explains how it is synthesized based on Hörl *et al.* [8]. Section IV presents our analysis of the carpooling potential for a given travel demand. We then show in Section V experimental results for the Grenoble area and discuss in Section VI and Section VII their limitations and their relevance, respectively. Section VIII concludes with future work directions.

## II. RELATED WORK

Few papers focus on assessing the potential of prearranged carpooling to reduce GHG emissions for local travel. There exists, however, an extensive literature on related issues, which we now present to position our work in the state of the art.

### A. Forms of Ridesharing

We consider *peer-to-peer ridesharing* [9] (also called *carpooling*), in which people travel using the personal vehicle of one of them, as opposed to *fleet-based* ridesharing in which vehicles are owned by professional drivers such as taxis [10] or transportation network companies [11] (*e.g.*, Uber and Lyft). Fleet-based ridesharing (and beyond that shared autonomous vehicles services [12]) relies on very different socio-economic assumptions from peer-to-peer ridesharing and the related research problems (*e.g.*, matching trips) are also quite different.

We focus on *prearranged* (also called static, or organized) ridesharing, which supposes that people know in advance their travel needs for the entire day. In contrast, for *dynamic* (or real-time) ridesharing, requests to travel must be treated with much more limited information [13], [14]. Implications of both types of ridesharing are very different, and it would be interesting to compare their potential on the same travel demand.

Finally, there exists a variety of possible matching schemes between drivers and passengers [9], [15]. In some papers, one passenger is matched with one vehicle [13]. Other schemes allow several passengers per vehicle, but passengers do not transfer between vehicles [16]. These two schemes are evaluated in this paper. Finally, in a *multi-hop* scheme, drivers can serve multiple passengers picked up and dropped off along the way, and passengers can transfer from one vehicle to another to reach their destination [17]. We do not address multi-hop ridesharing as the constraints it introduces in a prearranged setting (multiple departures and arrival times)

are hardly compatible with organizational contingency due to traffic and the cohabitation of multiple travelers who can suffer last-minute changes. Neither do we consider *multi-modal transportation*, in which travelers may use ridesharing as well as other means of transportation (e.g., public transport) [18].

The terminology we use for the ridesharing forms we consider is inspired by the *identical* and *inclusive* ridesharing patterns with single and multiple passengers from Furuhata *et al.* [19]. In the identical ridesharing scheme, drivers and passengers can only carpool if their origins (and destinations) are *close*. The inclusive ridesharing scheme is a generalization of the identical ridesharing scheme: passengers can be picked up and dropped off along the driver’s route if the passenger’s origin and destination are *close* to the driver’s route. The difference between our definitions and those of Furuhata *et al.* [19] is that their notion of identical carpooling considers that the origins or destination of the driver and passengers are *the same* and, for inclusive carpooling, that the pick-up and drop-off locations are *precisely on the driver’s route*.

### B. Research Questions

In the large body of work focusing on ridesharing the main focus is often on the efficient implementation of a given ridesharing scheme (see [9] and [20] for a classification of such schemes), in particular in the dynamic case, e.g. [21].

Among the papers that do analyze the potential (or current) impact of ridesharing, the assessment is not necessarily about GHG emissions reduction. Instead, existing studies often use metrics related to traffic (e.g., congestion [22], [23]) or user satisfaction (e.g., based on affinities [24], [25]). Like others (e.g. [26]), we estimate vehicle kilometer traveled (VKT) reduction as a proxy for avoided GHG. Given the high variability of GHG emissions under various driving conditions (traffic, type of vehicle etc.) [27], our work would benefit from a precise calculator for vehicle emissions like COPERT [28].

To the best of our knowledge, this paper is the first to estimate potential VKT reduction for peer-to-peer inclusive ridesharing taking activity chains into account. The papers that are closest to our work are Rodier *et al.* [26] and Jalali *et al.* [29]. Neither supports inclusive ridesharing and [29] cannot handle activity chains either.

### C. Underlying Assessment Methods

One could consider a range of possible methods for assessing the potential of carpooling for local travel, from analyses based on aggregated transport models [raballand:hal-02503684, 7] such as four-step models [30] to estimates obtained using simulations of disaggregated models (typically agent-based models [GALLAND201483]). Our assessment of the carpooling potential strikes a compromise between these extremes, in that it uses a disaggregated (and thus rather precise) travel demand but then performs a simpler, more coarse-grained analysis of it than an agent-based simulation would allow. Our choice of a disaggregated model is justified by our will to take into account travelers’ activity chains.

More specifically, our analysis considers a constant demand. We do not try to account for the expected evolution of travel demand in upcoming years. Furthermore, unlike more fine-grained approaches, our modeling does not account for changes in the demand induced by carpooling, for example changes in route choice or transportation mode due to reduced congestion. This is possible, e.g., with agent-based simulation, at the cost of increased computational complexity. Besides, because we study possible structural limits to carpooling rather than limitations related to social acceptance, we do not need sophisticated modal choice models [31], [32] to determine which trips can be carpooled, and use instead a predefined set of parameters.

In practice, the demand we use is obtained via synthesis using the software of Hörl *et al.* [8], based on current data including public surveys. We could also rely on real-life traces [22], [33] if such traces were publicly available for our local context.

Finally, given a travel demand, we compute the carpooling potential using a matching heuristic. An alternative could be to use exact methods, e.g., relying on ILP techniques [9]. Exploring the different trade-offs between computational complexity and precision of the analysis would be interesting and is left to future work.

## III. TRAVEL DEMAND SYNTHESIS

Our evaluation of the carpooling potential is based on a synthetic *travel demand* computed using the existing software from Hörl *et al.* [8]. Our choice was motivated by the fact that it is open-source and based on publicly available French national data. This is compatible with our will to do open and reproducible science, and it can provide a straightforward retargeting to any subset of departments in France.

In this section, we specify the main parameters of the travel demand used for our evaluation of carpooling, and then shortly describe the synthesis process. Understanding how the travel demand is synthesized is crucial to use it properly.

### A. Travel Demand Definition

*Definition 1 (Trip):* A trip  $\tau$  is a tuple  $\tau = (p, o, d, t_o, t_d)$  where:

- $p$  identifies the person who needs to travel,
- $o$  is the coordinate of the origin of the trip,
- $d$  is the coordinate of its destination,
- $t_o$  is the departure time,
- $t_d$  is the arrival time.

Trips also have additional *transportation modes* (i.e., car, walk, bike, public transport or car passenger) as well as origin and destination *purposes* (i.e., home, work, education, leisure, shopping or other) attributes that are omitted in the formalization to simplify the presentation.

*Definition 2 (Travel demand):* A population  $\mathcal{P}$  is a set of persons with their sociodemographic attributes. A *travel demand* is a set of trips  $\mathcal{T}$  representative of the traveling patterns of the population  $\mathcal{P}$  for an average weekday.

We denote by  $\mathcal{T}(p) = \tau^1 \rightarrow \tau^2 \rightarrow \dots \rightarrow \tau^n$  the sequence of trips of a person  $p$  during a day. The trips  $\tau^i = (p, o^i, d^i, t_o^i, t_d^i)$  satisfy  $d^i = o^{i+1}$  and  $t_o^i \leq t_d^i \leq t_o^{i+1} \leq t_d^{i+1}$  for all  $1 \leq i < n$ .

## B. Travel Demand Synthesis

Travel demand synthesis is typically part of agent-based transportation modeling but can also be a basis for other types of analysis than traffic forecasting. The idea is to synthesize a population with its sociodemographic attributes, and then attach travel patterns to this population. The synthesis process builds upon various sources of information to match real-life population attributes and mobility behavior, *e.g.*, surveys, census data, origin-destination commuting flows, and geographic databases. In a way, travel demand synthesis boils down to inferring a statistical model of the full travel demand from input data using a combination of statistical techniques such as iterative proportional fitting, iterative proportional updating, sampling, or statistical matching. Hence, synthesis involves randomization to generate travel demand instances. In principle, the synthetic instances match some statistical characteristics of the actual demand, although, in practice, statistical errors and potential bias can limit their quality.

We remind the main steps of the synthesis process and point out some of its limitations (see Hörl *et al.* [8], [34] for a complete description).

1) *Population Synthesis*: Since the sampling rate of the population census is relatively high compared to the possible valuations of sociodemographic attributes (excluding income), the synthetic population is obtained directly by sampling<sup>4</sup> the weighted population census data. In the census, household locations are given by IRIS zones, which subdivide municipalities having more than 10,000 inhabitants. Due to data anonymization, larger areas (*i.e.*, departments or municipalities) are provided instead of IRIS zones when they are sparsely populated. In these cases, IRIS zones are redefined for each person using random sampling inside these larger areas.

The population is then completed with income attributes by sampling municipality income distributions obtained from the tax registry without considering population attributes other than their municipalities of residence.

2) *Travel Patterns Assignment*: Activity chains obtained from household travel surveys are assigned to the population using statistical matching on population attributes. They correspond to sequences of trips with known distances, transportation modes, origin and destination purposes, and departure and arrival times. After this step, trips remain without origin and destination: they are completed depending on trip purposes. Home locations are chosen randomly in household IRIS zones according to a national household address database. Work and education locations are chosen according to enterprise and education facility databases in order to match commute trip distances and known origin-destination flows between municipalities. Leisure, shopping and other locations are chosen according to trip distances and service and facility databases.

3) *Potential Bias*: The sociodemographic attributes that could have a biased distribution in the synthetic population are the income attributes because they are only correctly correlated with household municipalities, and attributes of people living

in sparsely populated IRIS zones due to anonymization in the census data (the number of people in each IRIS zone is still correct).

The number of observations in the household travel survey does not allow for matching activity chains with all population attributes. The statistical matching algorithm proposed by Hörl *et al.* [8] primarily considers age, sex, socio-professional categories, and car ownership attributes for matching activity chains. Household income and location attributes are also included in the statistical matching, but only for a small fraction of the population. Moreover, when locations are included, only the department is considered. As a result, direct correlations between chains and household locations are poorly captured. This can bias trip distribution if the matched sociodemographic attributes are not good predictors of activity chains. For example, we might expect trip distances and transportation modes to depend on locations because of variations in dwelling and job offer densities, as well as on the quality of public transport services. Such dependencies might not be adequately captured in the population synthesis.

Home and education location distributions inside IRIS zones could be biased because (unlike work locations) they are uniformly sampled from the household and education facilities address databases, disregarding their size.

For trips between work, home, and education locations, correlations between trip origins and destinations are respected at the granularity of municipalities by using reliable origin-destination matrices, but not at finer granularity levels. For types of locations other than work, home, and education, only trip distances and service and facility addresses are taken into account. In this case, there is no specific guarantee on the correlations between trip origins and destinations.

## C. Travel Route Computation

To evaluate inclusive carpooling, we also need route information, *i.e.*, the path a person follows to accomplish a given trip. More formally, for a trip  $\tau$ , a *route*  $R$  is a set of intermediate coordinates and times consistent with the origin's and destination's coordinates and times of  $\tau$ .

In agent-based transportation models, routes are obtained by simulation, taking into account the agent's behavior and time-dependent traffic conditions. Instead of relying on simulation, which is very costly and raises serious scalability issues, we propose to use the shortest routes between origins and destinations as estimates of trip routes. They are obtained using *GraphHopper* [35]. The impact of using the shortest routes on the potential of carpooling is discussed in Section VI.

## IV. COMPUTING CARPOOLING TEAMS

To assess the potential of carpooling on a (synthetic) travel demand and associated travel routes, we generate a set of carpooling “teams”, where each team matches one driver with one or more passengers. Our method is parameterized by constraints modeling the specific type of carpooling we assess and additional conditions representing the targeted population and trips, or the adoption rate of carpooling. Our

<sup>4</sup>It corresponds to an upsampling when synthesizing the complete population.

method involves the three following steps, detailed in the next subsections:

- 1) *Trip filtering* selects the subset of carpoolable trips based on population and trip attributes;
- 2) *Pairwise shareability graph construction*, where the pairwise shareability graph, or shareability graph for short, represents all potential passenger-driver pairs considering carpooling constraints that define trip compatibility;
- 3) *Matching* computes carpooling teams from the shareability graph: It produces disjoint subsets of trips such that in each subset, one trip corresponds to the driver, and the others are its passengers, our matching heuristic aiming at maximizing kilometers traveled by passengers.

#### A. Trip Filtering

This step defines carpoolable trips from the travel demand. It can be used for selecting specific types of trips based on transportation modes, origin, destination places or purposes, and people's attributes. For example, we can restrict carpooling to commuting by filtering out trips whose purposes are not home, work, or education. This step can also implement other types of trip subsampling for modeling, *e.g.*, an adoption rate or the fact that a fraction of the trips is not carpoled for various reasons.

Given a travel demand  $\mathcal{T}$ , trip filtering is implemented by the two unary predicates  $\Pi$  and  $\Delta$  on  $\mathcal{T}$  such that  $\Pi(\tau)$  holds iff  $\tau$  is carpoolable as a passenger and  $\Delta(\tau)$  holds iff  $\tau$  is carpoolable as a driver.

#### B. Pairwise Shareability Graph Construction

Two trips potentially match if they satisfy a set of constraints representing their compatibility for the considered carpooling scheme. In the following, we provide such constraints for the two types of carpooling we study in this paper: identical and inclusive carpooling.

Given a travel demand  $\mathcal{T}$ , carpooling constraints are implemented by the binary predicate  $\Gamma$  over  $\mathcal{T} \times \mathcal{T}$  specifying whether a trip  $\tau_p$  can be realized or not by carpooling as a passenger of a trip  $\tau_d$ . When  $\Gamma(\tau_p, \tau_d)$  is true we say that  $\tau_p$  is a potential passenger of  $\tau_d$  and that  $\tau_d$  is a potential driver for  $\tau_p$ . The shareability graph is then given by the *directed* graph  $G = (V, E)$  such that  $V = \mathcal{T}$  and

$$E = \{(\tau_p, \tau_d) \in \mathcal{T} \times \mathcal{T} : \Pi(\tau_p) \wedge \Delta(\tau_d) \wedge \Gamma(\tau_p, \tau_d)\}.$$

1) *Identical Carpooling*: In the case of identical carpooling, trips are compatible if their origins, destinations, and departure times (or arrival times, depending on trip purposes) are close enough. Given trips  $\tau_p = (p, o, d, t_o, t_d)$  and  $\tau_d = (p', o', d', t'_o, t'_d)$ , the predicate  $\Gamma_{id}(\tau_p, \tau_d)$  corresponding to identical carpooling constraints is:

$$(p \neq p') \wedge (\text{dist}(o, o') \leq \delta^{\text{dist}}) \wedge (\text{dist}(d, d') \leq \delta^{\text{dist}}) \wedge ([\delta_{\min}^t \leq t_o - t'_o \leq \delta_{\max}^t] \vee [\delta_{\min}^t \leq t_d - t'_d \leq \delta_{\max}^t])$$

depending on trip purposes<sup>5</sup>).

<sup>5</sup>We consider, for example, that the constraint is on the arrival time rather than on the departure time when going to work.

2) *Inclusive Carpooling*: In the case of inclusive carpooling, the origins and destinations of the potential passenger should be close enough to the driver's route. We also require that the departure and arrival times of the potential passenger are close enough to the times at which the potential driver could pick up and drop off the passenger.

Let  $\tau_p = (p, o, d, t_o, t_d)$  and  $\tau_d$  be trips and  $R_p$  and  $R_d$  their respective routes. We denote by  $o \rightsquigarrow R_d$  (resp.  $d \rightsquigarrow R_d$ ) the nearest point<sup>6</sup> in  $R_d$  to  $o$  (reps.  $d$ ). We also note  $t_{o \rightsquigarrow R_d}$  (resp.  $t_{d \rightsquigarrow R_d}$ ) the time at which the route  $R_d$  reaches the point  $o \rightsquigarrow R_d$  (resp.  $d \rightsquigarrow R_d$ ).  $\ell(R_p)$  and  $\ell(R_d)$  are the lengths of the routes. The predicate  $\Gamma_{inc}(\tau_p, \tau_d)$  corresponding to inclusive carpooling constraints is:

$$(p \neq p') \wedge (\text{dist}(o, o \rightsquigarrow R_d) \leq \delta^{\text{dist}}) \wedge (\text{dist}(d, d \rightsquigarrow R_d) \leq \delta^{\text{dist}}) \wedge ([\delta_{\min}^t \leq t_o - t_{o \rightsquigarrow R_d} \leq \delta_{\max}^t] \vee [\delta_{\min}^t \leq t_d - t_{d \rightsquigarrow R_d} \leq \delta_{\max}^t])$$

depending on trip purposes<sup>5</sup>).

#### C. Matching

One particularity of our contribution is accounting for activity chains and vehicle locations when matching passengers with drivers. We detail this aspect below.

1) *Tours and Vehicle Location*: Consider a person  $p$  having sequence of car trips  $\tau^1 \rightarrow \tau^2 \rightarrow \dots \rightarrow \tau^n$  starting in  $o^1$ , where  $\tau^i = (p, o^i, d^i, t_o^i, t_d^i)$  for all  $1 \leq i < n$ . If  $\tau^1$  is realized as a passenger of a carpool, then  $\tau^2$  cannot be realized as a driver because after  $\tau^1$ ,  $p$ 's car is not available at  $o^2$  (it has remained in  $o^1$ ); as a consequence,  $\tau^2$  must be carpoled too, assuming that travel demand remains constant except for carpoled trips. Once back in  $o^1$ , further in the sequence of trips,  $p$  can take his own car for the remaining trips. We model such restrictions on car availability by detecting the sequences of trips starting and ending at the same location.

*Definition 3 (Tour)*: A subsequence of trips  $\tau^i \rightarrow \dots \rightarrow \tau^j$  of a person  $p$  is a *tour* if  $o^i = d^j$ , where  $\tau^i = (p, o^i, d^i, t_o^i, t_d^i)$  and  $\tau^j = (p, o^j, d^j, t_o^j, t_d^j)$ . The tour is said *minimal* if in addition for all  $i \leq k < j$  we have  $o^i \neq d^k$ , where  $\tau^k = (p, o^k, d^k, t_o^k, t_d^k)$ . The traveled distance of a tour is simply the sum of the traveled distances of its trips. Note that a trip can be carpoled as a passenger only if it belongs to a tour whose trips can all be carpoled as passengers.

For example, let us consider the following sequence of trips in which the person and the departure and arrival times have been omitted:

$$(H, W) \rightarrow (W, S) \rightarrow (S, H) \rightarrow (H, L) \rightarrow (L, H)$$

This sequence involves only four different locations for origins and destinations, *e.g.*,  $H$  could be a home location,  $W$  a work location,  $S$  a shopping location, and  $L$  a leisure location. The minimal tours for this sequence are  $(H, W) \rightarrow (W, S) \rightarrow (S, H)$  and  $(H, L) \rightarrow (L, H)$ .

<sup>6</sup>If there are several nearest points our implementation based on the *Shapely* Python module picks one among them.

2) *Matching without Considering Tours*: The matching algorithm proposed by Hartman *et al.* [36] (Algorithm 1) computes carpooling teams without considering constraints induced by tours and car locations. The output of this algorithm from the input shareability graph  $G = (V, E)$  is the set  $F$  of pairs  $(\tau_p, \tau_d)$  specifying that  $\tau_p$  is *effectively* a passenger of the driver  $\tau_d$ .

Note that  $(V, F)$  is a subgraph of  $G$  whose weakly connected components correspond to the carpooling teams. It also satisfies that trips have at most one successor (a trip cannot be a passenger of two different drivers) and that trips with a successor have no predecessor (trips cannot be both passenger and driver).

The main heuristic of the algorithm of Hartman *et al.* [36] is trying to match potential passenger trips by descending order of traveled distance. For each trip, we prioritize matching with drivers that already have passengers, *i.e.*, considering the priority order  $\pi : \mathcal{T} \rightarrow \mathbb{N}$  such that  $\pi(\tau_d) = \min(\#P(\tau_d), 1)$ , where  $\#P$  and other operations used in Algorithms 1 and 2 are defined by:

- $\tilde{D}(\tau)$  is the set of potential drivers for  $\tau$ , *i.e.*, the successors of  $\tau$  in the shareability graph  $G = (V, E)$ ,
- $\#D(\tau)$  is the number (0 or 1) of drivers of  $\tau$ , *i.e.*, the out-degree of  $\tau$  in the graph  $(V, F)$ ,
- $\#P(\tau)$  is the number of passengers of  $\tau$ , *i.e.*, the in-degree of  $\tau$  in the graph  $(V, F)$ .

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**Algorithm 1** Basic greedy carpooling algorithm based on Hartman *et al.* [36]

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**input**: a shareability graph  $G = (V, E)$  and vehicle capacities  $c : V \rightarrow \mathbb{N}$

**output**: the set of carpooling passenger-driver pairs  $F$

```

1:  $F \leftarrow \emptyset$ 
2: for all  $\tau_p \in V$  by decreasing traveled distance order do
3:   if  $\#P(\tau_p) = 0$  then
4:      $\triangleright \tau_p$  is not already a driver in a carpooling team  $\triangleleft$ 
5:     choose  $\tau_d \in \tilde{D}(\tau_p)$  s.t.  $\#P(\tau_d) + 1 < c(\tau_d)$  and
6:        $\#D(\tau_d) = 0$  w.r.t. priorities  $\pi$ 
7:     if such  $\tau_d$  exists then
8:        $F \leftarrow F \cup \{(\tau_p, \tau_d)\}$ 
9:        $E \leftarrow E \cap (V \times V \setminus \{\tau_p\})$ 
9: return  $F$ 

```

---

*Quality of the Greedy Algorithm's Solution*: Hartman *et al.* [36] have evaluated the quality of Algorithm 1 with parameter  $\forall \tau, c(\tau) = 1$ . The evaluation compares the results of the aforementioned specialized algorithm with the known optimal solution given by the maximum matching algorithm. Then, they define the quality of a solution as  $\frac{\text{result of the greedy algorithm}}{\text{optimal solution}}$ . We have evaluated the algorithm in the same manner, as it is the only case for which we know the optimal solution in a reasonable time. Our results are similar to what is claimed in Hartman *et al.* [36], *i.e.*, a quality decreasing then stabilizing around 95% when the number of nodes increases.

3) *Matching w.r.t. Tours*: We modified the matching algorithm to account for tours. Trips of a tour cannot be matched

independently of each other: if a trip belonging to a tour is carpoled as a passenger, then all the trips belonging to this tour must also be carpoled as passengers. So rather than iterating on trips, we iterate on tours by decreasing traveled distance. For each tour, we iterate on its trips to build a temporary set of carpooling pairs that partially match the trips with potential drivers. We give priority to potential drivers that already have passengers. Among the drivers that do not have passengers, we prioritize those who do not belong to a tour. This is encoded by the priority order  $\pi_{\mathcal{L}} : \mathcal{T} \rightarrow \mathbb{N}$  such that  $\pi_{\mathcal{L}}(\tau_d) = 2$  if  $\#P(\tau_d) > 0$ ,  $\pi_{\mathcal{L}}(\tau_d) = 1$  if  $\#P(\tau_d) = 0$  and  $\tau_d$  belong to a tour, and  $\pi_{\mathcal{L}}(\tau_d) = 0$  otherwise. We keep the temporary carpooling pairs in the final result only if we have succeeded in matching *all* the trips of the tour.

---

**Algorithm 2** Greedy carpooling algorithm with tours

---

**input**: a shareability graph  $G = (V, E)$ , vehicle capacities  $c : V \rightarrow \mathbb{N}$ , and the set of minimal tours  $\mathcal{L}$

**output**: the set of carpooling passenger-driver pairs  $F$

```

1:  $F \leftarrow \emptyset$ 
2: for all  $\ell \in \mathcal{L}$  by decreasing traveled distance order do
3:    $F_{\text{temp}} \leftarrow \emptyset$ 
4:   for all  $\tau_p \in \ell$  do
5:     if  $\#P(\tau_p) = 0$  and  $\#D(\tau_p) = 0$  then
6:        $\triangleright \tau_p$  is not already in a carpooling team  $\triangleleft$ 
7:       choose  $\tau_d \in \tilde{D}(\tau_p)$  s.t.  $\#P(\tau_d) + 1 < c(\tau_d)$ 
8:         and  $\#D(\tau_d) = 0$  w.r.t. priorities  $\pi_{\mathcal{L}}$ 
9:       if such  $\tau_d$  exists then
10:         $\triangleright$  match temporarily  $\tau_p$  as a passenger
11:         of  $\tau_d$   $\triangleleft$ 
12:         $F_{\text{temp}} \leftarrow F_{\text{temp}} \cup \{(\tau_p, \tau_d)\}$ 
13:   if  $\forall \tau_p \in \ell, \exists \tau_d : (\tau_p, \tau_d) \in F_{\text{temp}}$  then
14:      $\triangleright$  all trips of the tour are matched  $\triangleleft$ 
15:      $F \leftarrow F \cup F_{\text{temp}}$ 
16:      $E \leftarrow E \cap (V \times V \setminus \ell)$ 
15: return  $F$ 

```

---

## V. EXPERIMENTAL EVALUATION

Our case study is the area around Grenoble named Grande Région Grenobloise (GRG) in the French Alps. The GRG is part of the Isère department, which is slightly larger than the GRG. It comprises 281 municipalities and has one million inhabitants unequally distributed over urban, suburban, rural, and mountainous areas totaling 6,000 km<sup>2</sup>.

### A. Implementation

We configured the travel demand synthesis from Hörl *et al.* [8] by loading the census data and address database corresponding to the Isère department. Then, the travel demand of Isère was filtered to keep only people living and having all their trips in the GRG. This filter kept 635,004 out of 972,853 people and 2,623,595 out of 4,034,154 trips.

We completed the travel demand with itineraries for car trips thanks to *GraphHopper* [35]. We considered 1,406,352 car trips in the GRG. *GraphHopper*, with the default parameters,

could not find the itinerary for 4.90% of these trips, which were therefore not considered for carpooling matching because we did not know their traveled distance. The total car VKT found by *GraphHopper* in the GRG was 11,528,185 km.

We implemented the carpooling model in Python 3.11. We used the pipeline framework *Synpp* [37] of the population synthesis to automatically save the execution results of each stage to reduce execution time between parameter sets. We slightly modified *Synpp* to improve performance on big datasets (tens of gigabytes).

We used optimized data structures to implement the steps described in Section IV. For the distance computation and filtering, we use a KD-Tree implemented in SciPy [38]. The trips and geographical data are stored and filtered using *pandas* and *GeoPandas* [39]–[41].

The code of the implementation is available at <https://gitlab.inria.fr/carpooling-potential/carpooling-potential-analyzer>.

### B. Hardware used

We ran all the experiments on the total population on a server with 112 cores and 506 GB of RAM. Depending on the parallelization setup, our usual runtime for the total pipeline, knowing the trips calculation, the graph constructions, and the matching, is less than 24 hours. The peak RAM usage with 100 processes for the inclusive carpooling shareability graph construction is about 400 GB. In general, one graph construction and one matching steps are necessary to plot each point in the Figures 2 and 3. Even with caching the results, depending on the number of points, the total runtime can be longer than 24 hours to generate the entire Figure 2. However, on a personal computer, it is possible to run the model with a reduced runtime provided that we run it on a subsampled population (typically 1% or less).

### C. Set-up of Experiments

We estimated the carpooling potential for 6 scenarios. We obtained 4 of them by considering the two forms of carpooling discussed in Section IV, and a trip filtering that keeps either the complete travel demand or only commute trips (*i.e.*, trips between home and workplaces).

Then, for each carpooling scheme, we added the *no tour* scenario. In these additional unrealistic scenarios, the tours we described in Section IV-C3 are not considered. Instead, the matching step is done using the original algorithm from Hartman *et al.* [36] (Algorithm 1). These scenarios can be seen as equivalent to carpooling services with unlimited and omnipresent shared vehicles.

For each scenario, we set the space parameter  $\delta^{\text{dist}}$ , the time parameters  $\delta_{\min}^t = \delta_{\max}^t$ , and the vehicle capacity  $c$  (*i.e.*, the maximal number of passengers a driver may take), to maximal values 1,000 m, 900 s, and 4 respectively. From these maximal values, we studied the evolution of the avoided VKT when we independently reduce the parameters. We also studied the effect of random subsampling of the population on the avoided VKT (Figure 2). This subsampling represents a situation where not all people can participate in the carpooling service. We

plotted the same graphs for a subsampling of 20% of the population by filtering out people randomly (Figure 3). The role of the subsampling is discussed in Section VII.

### D. Results discussion

For all the scenarios, the avoided VKT increase with space, time, and capacity parameters, according to diminishing returns (concave curves). This suggests that avoided VKT saturate for higher values of these parameters. The sensitivity to the space parameter is more significant than the time parameter.

Conversely, the avoided VKT increase with the subsampling parameter according to increasing returns (convex curves), which we explain as follows. Although the number of selected trips increases linearly with the subsampling rate, the share of potential and actual passengers within the selected trips also increases because of an increasing density.

For the capacity variation, we also plotted a theoretical maximal avoided VKT for a given capacity. The intuition is that if one carpool with one passenger, this carpool team avoids, at most, about 50% of their initial VKT. In the case of 4 passengers, this amount rises to 80%. This maximum is given by  $\text{VKT}_{\max}(c) = \frac{c}{c+1} \text{VKT}_{\text{matched}}$ , with  $\text{VKT}_{\text{matched}}$  being the VKT of the trips in the shareability graph with one neighbor or more. This intuition holds only if the passenger’s traveled distance is around or lower than the driver’s distance, which is the case with the introduced carpooling forms. When considering 100% of the population (Figure 2), the avoided VKT variation closely follows this theoretical maximum for the scenario *All trips, identical and inclusive carpooling (no tour)*.

Not surprisingly, the share of avoided VKT is globally significantly lower at 20% of the subsampling rate than with the entire population (see Figure 3). Still, it is worth noting that at 20% of subsampling, the shapes of the curves are very similar to those at 100%.

## VI. LIMITATIONS

In this section, we discuss the limitations of our approach.

### A. Simplifying Assumptions

In this paper we only aimed at preserving existing people’s activities when assessing carpooling potential, hence we worked *w.r.t.* fixed travel demand. By this, we mean that, besides departure and arrival times, transportation modes, and potential additional trips due to passenger-driver synchronizations, trip sequences are essentially inflexible. Considering a fixed travel demand is simplistic: the potential of carpooling could increase if people engaging in carpooling adapt their daily schedule and activities (*e.g.*, by replanning their week to avoid a shopping stop), or could decrease due to rebound effects such as induced traffic [7]. Moreover, the travel demand in France is expected to change over the next few years [42]. These aspects are left as future work.

Our carpooling constraints could also be completed by activity-specific constraints, such as the need to carry specific equipment or even to use a specific vehicle, or inflexible arrival and departure times. To give a very preliminary and rough idea



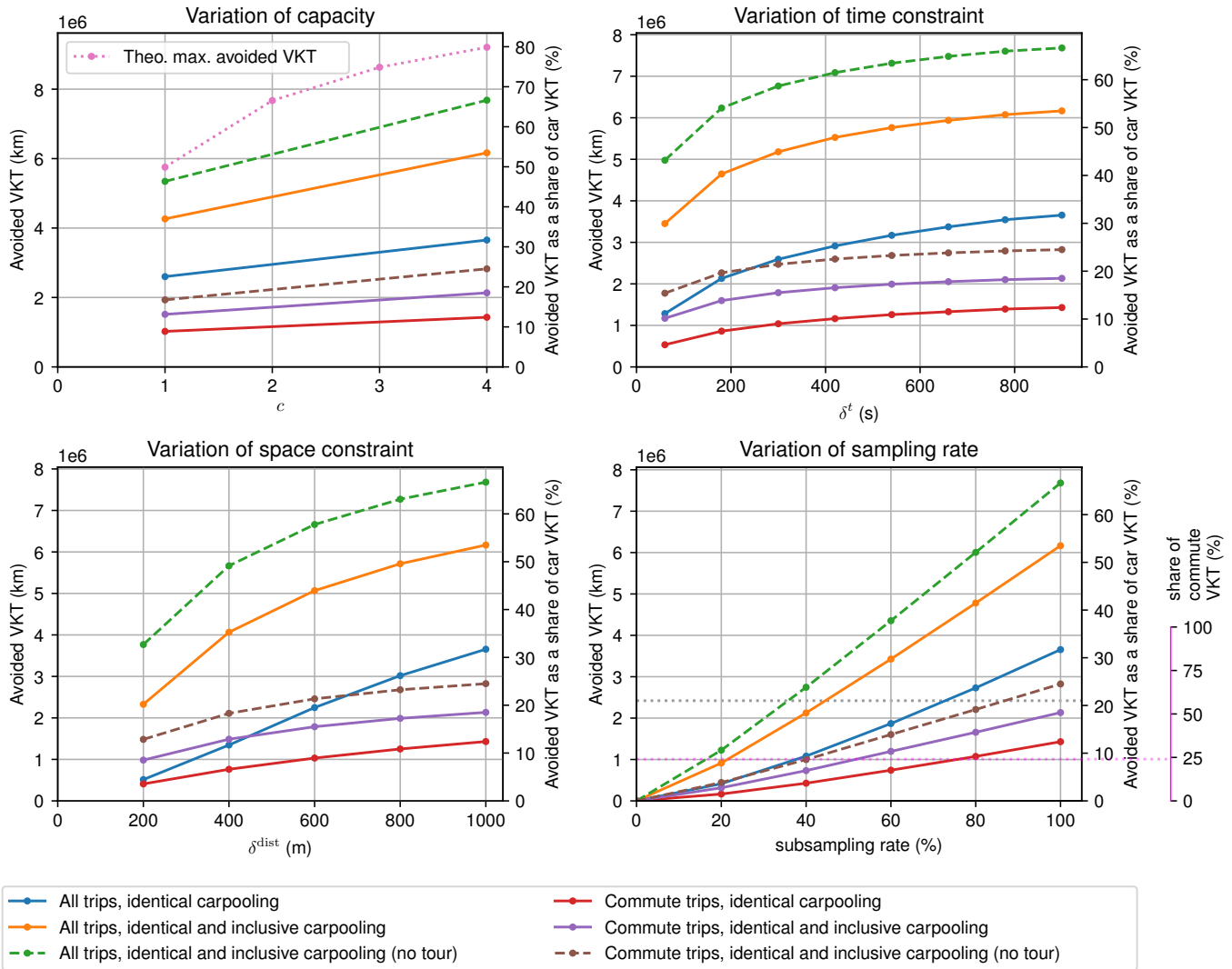


Figure 2. Potential of carpooling to avoid VKT for 100% of the travel demand

of the effect of including additional constraints, we studied the impact of a uniform subsampling of the trips on estimates of avoided VKT. This subsampling could also be used to approximate other forms of limitations to the adoption of carpooling, *e.g.*, related to social and behavioral aspects, even though this paper is not intended to address them directly.

Lastly, we did not specify how carpooling would practically take place under identified constraints. Passengers and drivers need to meet at adequate locations for pick-up and drop-off. This means that besides the flexibility in arrival and departure times required by the carpooling constraints we proposed in Section IV-B, traveling times of passengers and/or drivers are also expected to increase. The exact values of these additional traveling times highly depend on the exact location of meeting points, as well as the transportation mode passengers chose to

reach them<sup>7</sup>. We plan to improve this part by computing lower and upper estimates of these additional travel times.

### B. Uncertainties on VKT Reductions

Sections III and IV already discussed how each computation step may introduce discrepancies in the proposed pipeline. We explain here how this may impact the distribution of avoided VKT over the studied area, which we exploited in experimental results of Section V to estimate potential VKT reduction. In the following, we discuss whether origin-destination pairs  $(o, d)$  of passenger trips  $\tau = (p, o, d, t_o, t_d)$  are correctly distributed geographically and whether VKT reductions are correctly estimated from origin-destination pairs.

<sup>7</sup>For example, we may consider walking and driving. If a parking area is present at a meeting point common to the first and the last trip of a passenger's tour, this passenger could choose between using their personal car or walking to reach and leave this point at the beginning and the end of their tour. Meeting points far from any parking area may be rather reached (at least partially) by walk.

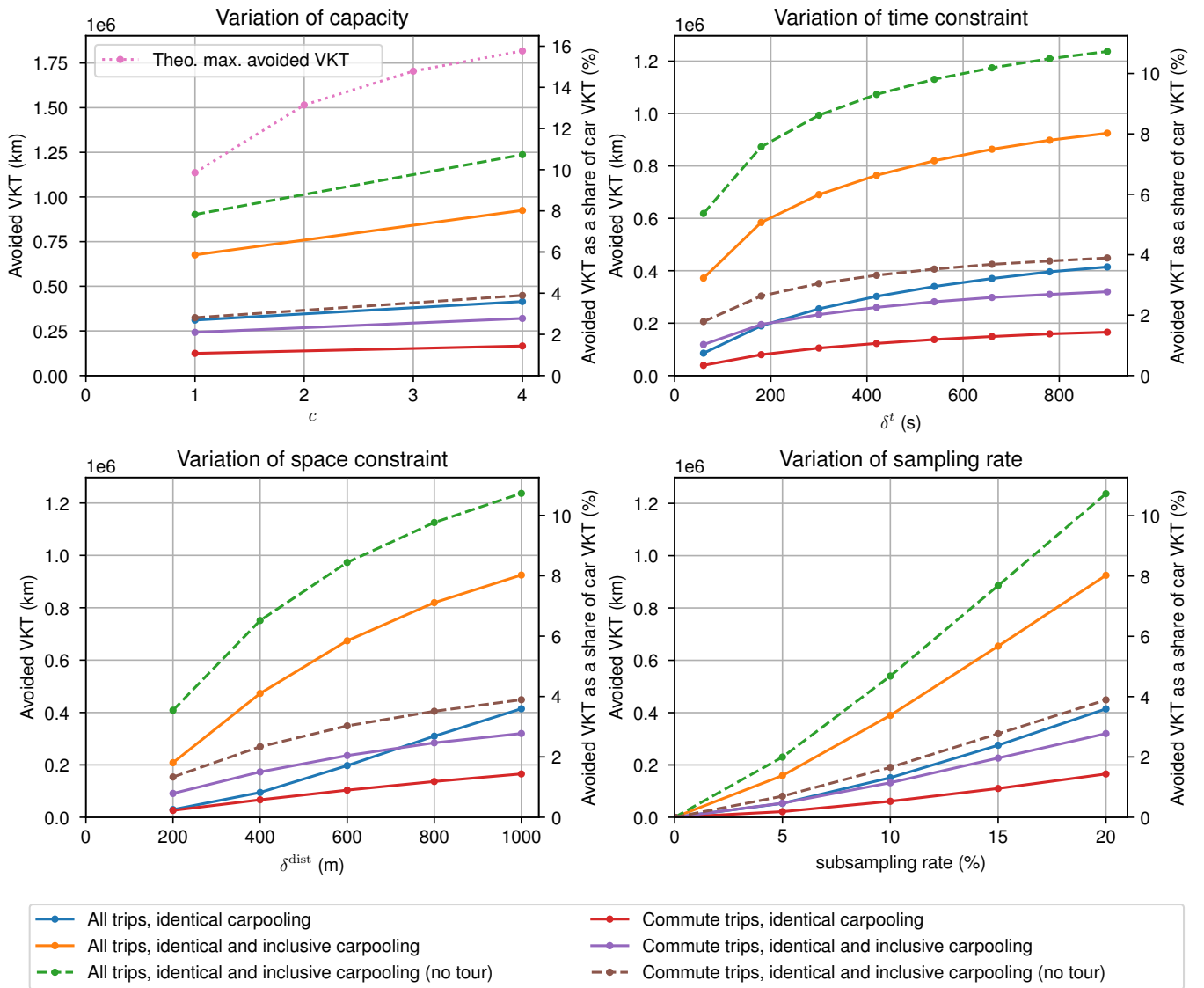


Figure 3. Potential of carpooling to avoid VKT for 20% of the travel demand

### 1) Uncertainties on Origins and Destinations of Passengers:

As mentioned in Section III, our carpooling analysis is based on a travel demand synthesized for a single day that averages actual population travel patterns. We may misevaluate the carpooling potential because of weekly and monthly travel patterns fluctuations. We could improve this by running an analysis for each representative level of travel demand.

In the settings chosen for experimental results of Section V, the computation of carpooling teams is only based on trip attributes, hence sociodemographic attributes of the population has no (direct) impact on the results. However, we expect the results to be sensitive to the distribution of trip attributes, as explained below.

Trip filtering used in our experiments depends on trip purposes and transportation modes, so it could propagate bias introduced by travel pattern assignment. More specifically, it

may under- or overestimate the share of car trips for certain origins and destinations, leading in the end to locally under- or overestimate the potential of carpooling. In addition, the construction of the shareability graph strongly depends on how spatiotemporal attributes (origin, destination, and departure and arrival time) are distributed.

In the case of identical carpooling and given specific upper bounds for the constraints, the local average degree of nodes in the shareability graph is mainly determined by the presence of correlations<sup>8</sup> between the spatiotemporal attributes of trips. As explained in Section III-B3, the travel pattern assignment proposed by Hörl *et al.* [8] may fail to capture those correlations, leading to an underestimation of the carpooling

<sup>8</sup>By correlations, we mean any type of correlation, not necessarily linear correlations. For example, clustered data leads to a greater average degree in the shareability graph than randomly scattered data.

potential. We plan to improve this by (i) checking the quality of the distributions of activity chains over municipalities or IRIS zones, and by (ii) modifying the statistical matching to improve this quality (e.g., by prioritizing locations in the matching).

In the case of inclusive carpooling, the estimation of potential passengers is based on the shortest routes of potential drivers instead of an accurate traffic model. People may deviate from the shortest route for various reasons: congestion, personal preferences, short stops in multipurpose travel, etc. This may under- or overestimate the number of potential passengers. We might improve this part with a traffic model.

The effect of tours (see Section IV-C1) on the carpooling potential also depends on how activity chains are geographically distributed, for example, whether longer tours are correlated with the local average degree in the shareability graph.

Our matching heuristic also marginally depends on origins and destinations because it orders tours based on trip distances, but we expect the carpooling potential to be moderately impacted. Conversely, being suboptimal, our matching heuristic may underestimate the carpooling potential. Suboptimality is already discussed in Section V.

2) *Uncertainties on Traveling Distances*: The distances of passenger trips may be underestimated because they are also based on the shortest routes. In Section V, we showed relative values that we expect to be less affected, but this has to be confirmed with a traffic model. We use these distances as a proxy for computing the potential of carpooling to reduce VKT. These are optimistic as they do not account for extra kilometers induced by picking up and dropping off passengers: in practice, drivers may make detours, and passengers may reach meeting points by car.

## VII. DISCUSSION

Let us now put our experimental results for the Grenoble area into the general perspective of the role expected from carpooling in decarbonization strategies.

In the local transport plan for the Grenoble area, called *Plan de déplacements urbains* in French (PDU) [3], carpooling is explicitly mentioned as a lever to reduce VKT. The objective for 2030 is expressed as an increase from an average occupancy rate of 1.06 to 1.4 on commutes between the core metropolitan area and the greater Grenoble area. Multiplying that rate (assuming demand is constant) by 1.32 corresponds to dividing the VKT by 1.32, i.e., a 24% reduction for the selected trips. Based on our results, we claim that reaching such a target in the whole area would be possible if

- more than about 50% of randomly chosen commuters participate in the inclusive carpooling scheme with parameters: distance = 1,000 m, time = 900 s, and capacity = 4 (see the purple curve in the bottom-right part of Figure 2); or
- more than about 70% of randomly chosen commuters participate in the identical carpooling scheme with parameters: distance = 1,000 m, time = 900 s, and capacity = 4 (see the red curve in the bottom-right part of Figure 2).

This rough estimate should however be refined because the share of avoided VKT is slightly higher in the area targeted by the PDU than on average.

The French decarbonization strategy, called *Stratégie Nationale Bas Carbone* in French (SNBC) [2], is also counting on carpooling for short-distance trips to increase the occupancy rate from 1.45 (for all trips, in contrast to the PDU which focuses on commutes) in 2015 to 1.75 in 2050. This would mean a 21% VKT reduction, corresponding to

- more than about 40% of all trips participate in the inclusive carpooling scheme (see the orange curve in the bottom-right part of Figure 2); or
- more than about 60% of all trips participate in the identical carpooling scheme (see the orange curve in the bottom-right part of Figure 2).

Note that the target of the SNBC cannot be reached if only commutes are carpoled with either carpooling scheme, even if all parameters are set to high values.

These preliminary analyses of the Grenoble PDU and the SNBC suggest that massive adoption of carpooling would be needed to reach their targets on occupancy rates — again under maximizing assumptions. Bigo [42] lists several scenarios that could be similarly investigated.

## VIII. CONCLUSION

This paper presents a parameterized method and the associated open-source tool to assess the potential of prearranged carpooling for a given local travel demand. We have applied it to the Grenoble area and put our results into the perspective of national and local strategies for GHG emissions mitigation. Our results suggest that such strategies may be optimistic in their targets for carpooling. This conclusion should however be considered with precaution, given the simplifying assumptions of our model and the uncertainties on our VKT reduction estimates. Rather than a “push-button” tool for decision support, we view it as useful for model exploration, to understand the dynamics underlying carpooling and local mobility in general.

There are several directions for future work, which we intend to follow. First, we plan to improve our method and our tool to reduce some of the uncertainties listed in the paper. Second, we want to make our tool easier to use and understand for (expert) local policymakers as well as for the (non-expert) public. We consider it specifically important that restrictions and limitations be highlighted, well-explained, and understandable. In particular, we are working on better result visualization, including representations focusing on specific geographical zones. Finally, in line with Rasoldier *et al.* [43], we need to refine the scenarios underlying our assessment. Two key elements for this are: (1) the expected evolution of travel demand, which has different implications for carpooling and for public transportation or biking; (2) the integration and the comparison with other levers to reduce GHG emissions of local mobility. Preliminary results indicate, e.g., that about 30% of VKT avoided by carpooling in our experiments could be traveled by bike with a time penalty of less than 10 minutes.

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