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Abstract

In ridesharing, commuters with similar itineraries share a vehicle for their trip. Despite its clear benefits in terms of reduced congestion, ridesharing is not yet widely accepted. We propose a specific ridesharing variant, where drivers are completely inflexible. This variant can form a competitive alternative against private transportation, due to the limited efforts that need to be made by drivers. However, due to this inflexibility, matching of drivers and riders can be substantially more complicated, compared to the situation where drivers can deviate.

In this work, we identify the effect of such a ridesharing scheme on the congestion in a real network of the Île-de-France area for the morning commute. We use a dynamic mesoscopic traffic simulator, Metropolis, which computes departure-time choices and route choices for each commuter. The matching is solved heuristically outside the simulation framework, before departures occur. We show that even with inflexible drivers, ridesharing can alleviate congestion. By slightly increasing flexibility, the performance of the ridesharing scheme can be further improved. Furthermore, we show that ridesharing can lead to fuel savings, CO_2 emission reductions and travel time savings on a network level, even with a low participation rate.

Keywords: Ridesharing; Carpooling; Matching; Dynamic Congestion

JEL: R41, R48

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1. Introduction

Ridesharing, also known as carpooling, is a non-profit shared ride service where a car owner shares his/her vehicle with another person heading in the same direction to share expenses. It aims to solve one key problem of urban congestion: low vehicle occupancy, especially for commuting trips. In the Paris region, there are 1.05 persons per vehicle on average for commuting trips (Enquête Globale Transport, 2010). This rate has been decreasing since 1976 (Cornut, 2017). In urban areas, congestion also has severe implications with regards to air pollution. Ridesharing offers the opportunity to raise average vehicle occupancy and to address public health and climate change issues.

In this work, we propose a ridesharing scheme quite similar to conventional hitchhiking. Drivers do not deviate from their predetermined itinerary, meaning they determine their optimal departure time and exact route without considering a potential rider. The rider than adapts to the itinerary of the matched driver. This implies that the rider may need to walk to reach the driver and to reach his/her final destination after being dropped off by the driver. However, similar to hitchhiking, the trip is assumed to be completely free of charge for the rider.

In a more elaborate version, to come, subscribers will be able to travel the various segments of their trip on the most appropriate transport mode. For example, a trip might include a walk to a meeting point, a ride as a passenger in a personal vehicle, a public transport segment, and another ride as a passenger in a personal vehicle to the final destination.[3] Here we limit our investigation to three-leg trips: a walk to a meeting point, a ride as a passenger in a personal vehicle, and another walk to the final destination. Our key hypothesis is that the segment of the rider's trip spent in a personal vehicle, will be offered by a driver who has already planned to travel that segment on his/her own trip. This is the key feature of our system: drivers are inflexible as for hitchhiking. This hypothesis is explained by the observation that one of the setbacks in the development of the ridesharing process is that the driver is reluctant to change his/her route or his/her scheduling. One cannot avoid the *a priori* inconvenience to have another person in the car; later on, one can think of some certification systems to reduce the uncertainty to have somebody else (unknown) in his/her own car. Of course, such certification (of the car, of the insurance status of the driving license) should preserve anonymity and should not be incompatible with privacy rules.

The 2017 global market size for on-demand transportation was valued at \$75 billion and it is expected to grow at a 20 % annual rate from 2018 to 2025.[4] The impact of COVID-19 increases the attractiveness of private transportation, as was observed in many cities worldwide.

The emergence of ride-sharing services such as UberPool, Lyft Line, and Blablacar Daily (not to be confused with the ride hailing services provided by Uber and Lyft) has been a major competitor to the

[3] In order to be successful, the system also expects to successfully negotiate with transport providers, whether they are public administrations or private entities, to operate on the public right-of-way, to exploit existing on-demand transport networks (such as Uber and Lyft), and to access existing public transport services. But again, this discussion has to be postponed for later.

[4] `https://www.marketsandmarkets.com/Market-Reports/mobility-on-demand-market-198699113.html`

practice of ridesharing (Shaheen and Cohen, 2019). Ridesharing consists of people with similar travel needs traveling together, whereas ride hailing consists of car owners offering paid lifts to gain money. The social benefits of ridesharing are manifold: less traffic congestion (Xu et al., 2015; Cici et al., 2014), less CO_2 and NOx emissions leading to better air quality (Bruck et al., 2017), and better transit accessibility in suburban areas (Teubner and Flath, 2015; Li et al., 2016; Kong et al., 2020). Moreover, ridesharing brings about travel cost sharing for riders and drivers (Malichová et al., 2020). However, the popularity of ridesharing remains low for commuting trips.

Many forms of ridesharing have been studied over the years to increase the mode's convenience and maximise the societal gains it provides in terms of traffic congestion as well as of emissions reduction. Nonetheless, each of them presents certain drawbacks. For instance, multi-hop ridesharing explores the possibility for a rider to use multiple cars to complete his/her trip at the cost of a transfer penalty and waiting time. As for detours created by door-to-door ridesharing services, they increase the driver's travel distance and time, all the more in the case of multiple passengers. Some ridesharing companies have stopped door-to-door service and now ask riders to walk in order to reduce the extent of the detours (Schaller, 2021; Lo and Morseman, 2018).

This research proposes a ridesharing scheme where the driver makes no detour at all and no concession on his/her schedule. The rider may therefore need to walk to reach the vehicle and to adapt his/her arrival time to the schedule of the driver (this will not be the case for the on-line reservation system). The only difference in the driver's generalised cost is the inconvenience associated with taking someone in his/her car. In order to make ridesharing as attractive as possible, the ride is free of charge for the user and the inconvenience of the driver is completely compensated by state subsidies (later on, a monthly/annual public transport pass could be required). This study aims to assess the potential of this ridesharing scheme and its impact on congestion reduction by testing it with the mesoscopic dynamic traffic simulator Metropolis on the Île-de-France network. The simulator uses data from the 2001 Paris travel survey for the morning trip (especially commuting) (Direction Régionale de l'Équipement d'Ile-de-France, 2004; Saifuzzaman et al., 2012).

We wish to contribute to the existing literature on the benefits of ridesharing by analysing its congestion reduction potential, whilst considering dynamic congestion (i.e. congestion depends on the time of the day). We also propose a new policy framework to promote ridesharing in large urban areas.

The remainder of this paper is structured as follows. Section 2 reviews the ridesharing literature and the ways it is modelled. Section 3 details the proposed ridesharing scheme, the dynamic traffic simulator, and the proposed driver-rider matching methodology. Section 4 presents the case study results for Île-de-France (Paris area) under three maximum walking time scenarios, and for various penetration rates. Section 5 concludes with the key results and explores further research steps needed to explore the feasibility of a real operational-system.

2. Literature Review

Sharing mobility is part of the global trend towards a sharing economy (Standing et al., 2019). Shaheen and Cohen (2019) provide an overview of the different shared-ride services. Ridesharing, also known as carpooling, and ridehailing, also known as ridesourcing, are two of the main shared-ride services. Whereas the former is associated with many societal benefits, the latter is an on-demand transportation service similar to taxi service with privately owned vehicles. Ridehailing is often associated with an increased traffic congestion (Schaller, 2021). Ridesharing is inherently a non-profit mode that brings together people with similar trip itineraries to share their trip. The body of literature on this topic has significantly increased in the last decade as it has become more convenient to plan, book, and pay for a ride (Shaheen and Cohen, 2019). Indeed, Transportation Network Companies (TNCs) such as Uber and Lyft offer online ridesharing services (UberPool and Lyft Line) in addition to their standard ridehailing services.

The matching problem between the rider and the driver has been extensively studied. Matching problems can be either static (Liu et al., 2020; Herbawi and Weber, 2012; Yan and Chen, 2011; Ma et al., 2019a; Lu et al., 2020) or dynamic (Agatz et al., 2011; Kleiner et al., 2011; Di Febbraro et al., 2013). In static matching problems, all drivers and riders are known in advance and are matched at the same time. Dynamic matching problems consider that drivers and riders arrive gradually. In this case, partial matchings can be performed with a subset of the drivers and riders. This work uses static ridesharing under dynamic congestion.

The main benefit of ridesharing is that it eases traffic congestion (Xu et al., 2015; Cici et al., 2014). It hence offers a great potential for CO_2 emission reductions (Bruck et al., 2017; Chan and Shaheen, 2012). Furthermore, it offers more accessibility to public transit as a first/last mile solution (Teubner and Flath, 2015; Li et al., 2016; Kong et al., 2020). Ridesharing may, however, increase the driver's trip time through detours to pick up and drop off riders (Diao et al., 2021). Schaller (2021) analyse extensive longitudinal data from TNCs in American cities. They observe that ridesharing services mainly draw people from transit as it is mostly popular in neighbourhoods with low incomes and low car ownership rates. This phenomenon has become even more evident since UberPool and Lyft Line stopped door-to-door services, with the aim to reduce detours. This finding is in line with many other studies concluding that an increase in the modal share of ridesharing does not cause a significant reduction in the modal share of car (Kong et al., 2020; Li et al., 2016; Coulombel et al., 2019; Xu et al., 2015; Shaheen et al., 2016). The ridesharing scheme proposed in this study only allows former drivers to become riders to avoid this rebound effect. Thereby, we consider a ridesharing scheme, that can be a competitive alternative against private transportation.

Despite the many benefits of ridesharing, it is still not widely used as a mode to commute (Liu et al., 2020). Amongst the challenges to have a successful ridesharing system is the large population of drivers necessary to provide high-quality matches in terms of geographic and temporal proximity (Bahat and Bekhor, 2016). Substantial research has been conducted to understand the individual motivations behind ridesharing in order to increase its popularity. Cost savings followed by environmental concerns are the main motivations reported both for the drivers and the riders (Neoh et al., 2017; Pinto et al., 2019; Delhomme and Gheorghiu, 2016; Gheorghiu and Delhomme, 2018). Malichová et al. (2020) observed through a pan-European survey that travelers prefer to adopt ridesharing for work compared to other purposes.

Ridesharing has been modelled alongside transit both as a complement providing a solution to the first/last mile problem (Kumar and Khani, 2020; Reck and Axhausen, 2020; Masoud et al., 2017; Ma et al., 2019b) and as a competitor (Qian and Zhang, 2011; Galland et al., 2014; Friedrich et al., 2018). Qian and Zhang (2011) use a theoretical bottleneck model where the modal choice between car, transit, and ridesharing depends on the generalised travel time. They account for transit perceived-inconvenience depending on transit passenger-flow. Schedule delay is considered for the three modes. de Palma et al. (2020) build on this framework to add dynamic congestion. Coulombel et al. (2019) use a transportation-integrated land use model to consider the impact of ridesharing on car and transit ridership for the Paris region. Finally, Galland et al. (2014) propose an agent-based model for ridesharing to analyse individual mobility behaviour. They test their model on a population of 1000 agents only due to its computational complexity. To predict the route taken by the drivers in a large-scale scenario, this work uses the dynamic traffic-assignment simulator Metropolis (de Palma et al., 1997; de Palma and Marchal, 2002). As Metropolis is a dynamic model, we can also account for the timing of the trips when matching riders with drivers. Metropolis computes, for each individual, the route, departure-time and mode choice, using a nested Logit model. The schedule-delay costs are based on idiosyncratic $\alpha - \beta - \gamma$ preferences (Vickrey, 1969) and congestion is modelled with link-specific bottlenecks.

This work builds on the many ridesharing models present in the literature. The methodology allows to assess the potential of ridesharing in a large urban area under dynamic congestion, whereas previous models were either applied on simple bottleneck models (de Palma et al., 2020; Qian and Zhang, 2011; Yu et al., 2019) or were too sophisticated to provide results for a large urban network (Galland et al., 2014).

3. Methodology

3.1. Ridesharing Scheme

This paper explores a ridesharing scheme where ridesharing drivers make no detour and keep the exact same schedule as when driving alone. Ridesharing drivers simply pick up a passenger at a defined road intersection on their itinerary and drop off their passenger at another intersection on their itinerary. As for the riders, they need to walk from their origin to a pick-up point and from a drop-off point to their destination. They face schedule-delay costs if their arrival time does not match their desired arrival time. However, the trip is free of fare for them.

Figure 1 provides an example of a ridesharing trip under this scheme. The driver itinerary is shown in red whilst the rider itinerary is in orange. The rider is picked up near his / her origin node (O_P) and dropped off near his / her destination node (D_P). In this example, the rider walks approximately for 100 meters between his / her origin and the pick-up point (as shown by the grey line).

Implementing such a ridesharing scheme on a large scale would require some sort of state intervention, in order to convince enough drivers and riders to subscribe to the scheme. We assume in the following

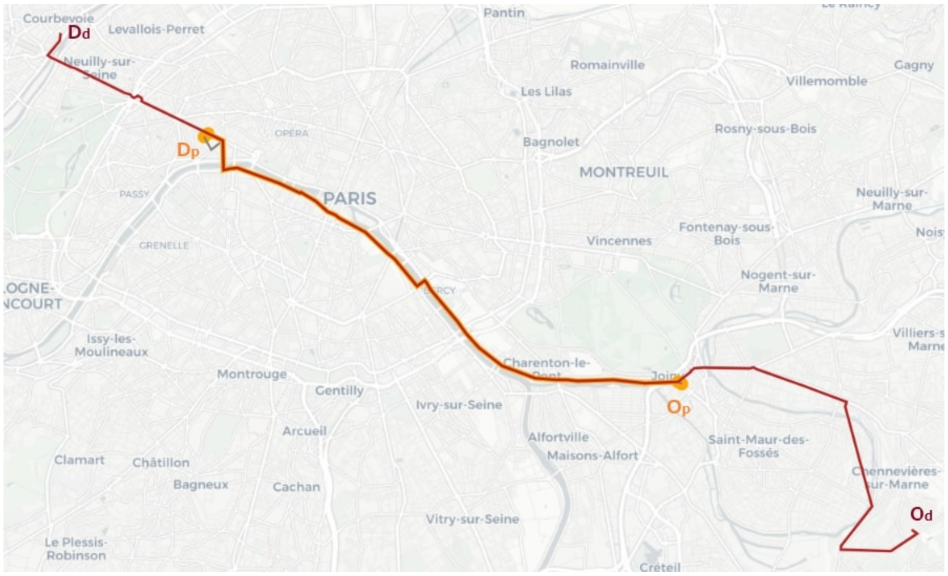


Figure 1: Ridesharing trip example where O_D and D_D are the origin and destination of the driver, O_P and D_P are the origin and destination of the rider, the red line represents the driver's trip, the orange line represents the rider's trip by car and the grey line represents the rider's trip by foot.

that subsidies are proposed to the drivers who agreed to pick up someone in their car. These subsidies are deemed small since drivers keep their itinerary and schedule and thus the only cost incurred by them is the inconvenience of having someone in their car. In practice, the subsidy program could be similar to the one currently implemented in the Île-de-France region (see details in Section 4), where drivers receive a fix amount for engaging into ridesharing and an additional subsidy depending on the shared trip length.[5]

Riders may experience an inconvenience cost, arising from the discomfort of sharing a ride with a stranger (Li et al., 2020). They also have to walk and may incur additional schedule-delay costs. However, the scheme allows them to save money on gas, car wear and tear, parking, and car insurances. Moreover, they do not spent time driving around for a parking slot anymore. Still, if the costs of ridesharing are larger than the benefits, for some individuals, the regulator could propose subsidies to some riders.

An increase in the modal share of ridesharing can greatly reduce the congestion in a city. By increasing the occupancy of vehicles, the number of vehicles on the road decreases. In turn, the externalities associated with congestion (including air pollution, noise pollution and safety) also decrease. Public authorities may therefore be interested in subsidizing ridesharing to reduce congestion and its environmental cost. However, subsidizing ridesharing is only effective if rebound effects (e.g., transit users are getting back to their car) are limited. To prevent the emergence of rebound effects, three criteria are imposed on the potential riders:

1. The scheme only allows riders to use ridesharing for *commuting trips*. This prevent an increase of the travel demand because of subsidized trips.

[5] `https://www.iledefrance.fr/covoiturage-gratuit-lors-des-pics-de-pollution`

2. The scheme only allows *former drivers* to become riders. This prevent transit users from switch to ridesharing.
3. The scheme only allows riders whose free-flow travel-time between origin and destination is greater than a free-flow travel-time threshold ($FFTT_{\text{threshold}}$). The free-flow travel-time is the travel time of a trip when there is no congestion. Switching long car trips to ridesharing saves more vehicle-kilometers traveled (VKT_{saved}) than short trips. Encouraging *long trips* to switch to ridesharing thus provides more benefits in terms of traffic congestion and pollution reduction.

Although these criteria impede transit users from becoming riders, they do not withhold transit users to get back to their car, as drivers (which they may do if congestion decreases). Typically, as congestion decreases, some transit users will tend to drive.

3.2. The proposed 6-step Procedure

We do not model explicitly the choice between being a rider or not. Instead, we estimate the maximum number of acceptable matches between riders and drivers, where riders are selected as a random sample in the population. A match is *acceptable* if it satisfies some spatial (limited walking time) and temporal (limited schedule delay) constraints. These constraints and the matching process are detailed in Section 3.5. Therefore, we provide a lower bound of expected benefits from carpooling, since better matching processes, based for example on inconvenience costs, can be envisaged.

To find the maximum number of acceptable matches, we run the traffic simulator METROPOLIS and the matching process with different numbers of riders. Since total travel demand is assumed to be inelastic, the number of drivers decreases when the number of riders increases. Therefore, as the number of riders increases, there are less opportunities for good matches and thus the share of riders that can be matched decreases.

To find the maximum number of acceptable matches, we use the following 6-step procedure, illustrated in Figure 2.

1. METROPOLIS *Reference simulation:* The traffic simulator METROPOLIS is run up to a stationary regime, with all the travel demand. It provides the level of congestion in the scenario with no ridesharing. Further explanations about the traffic simulator are presented in Section 3.3.
2. *Identification of potential riders:* Potential riders are randomly chosen among the travelers eligible to the ridesharing scheme (commuters, former drivers and trip duration $\geq FFTT_{\text{threshold}}$).
3. METROPOLIS *Ridesharing simulation:* METROPOLIS is run without the selected riders. The removal of the potential riders creates a new equilibrium with less traffic congestion. The results of the simulation give the itineraries of the potential ridesharing drivers.
4. *Matching:* Potential drivers and riders are matched according to the greedy algorithm described in Section 3.5. Steps 2 to 4 are repeated with different numbers of potential riders to find the highest number of matches.

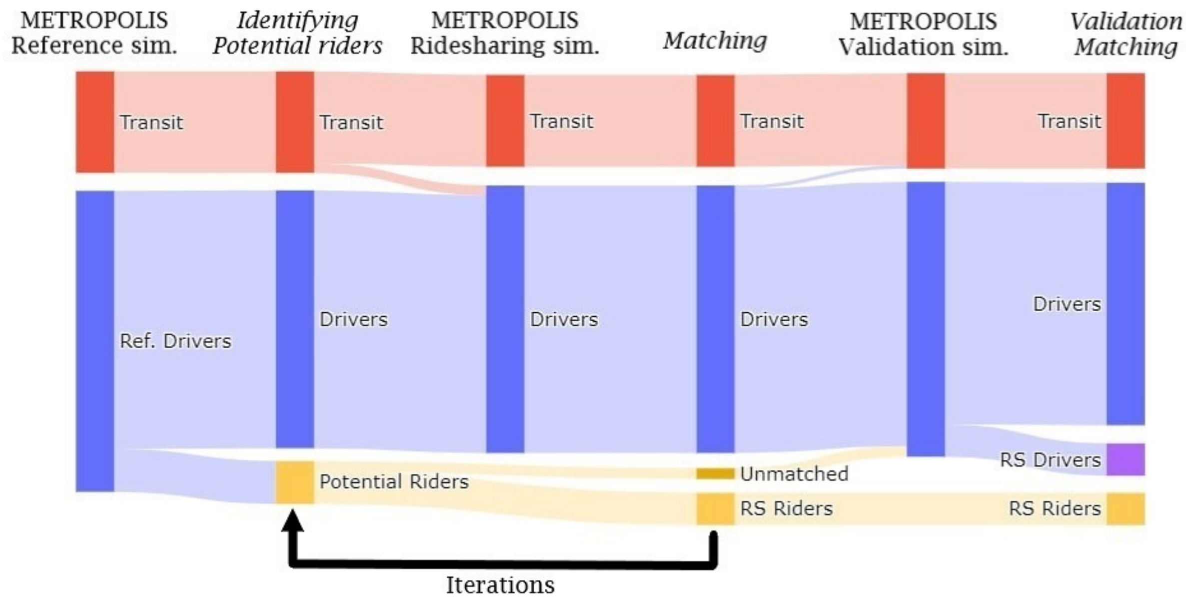


Figure 2: Schematic representation of each step performed to assess the potential of the proposed ridesharing (RS) scheme

5. METROPOLIS *Validation simulation:* For the number of potential riders that maximizes the number of matches, some riders are still unmatched. They are put back into the traffic simulator for a validation simulation, which gives the state of the network when all riders are successfully matched.
6. *Validation matching:* Previously identified riders are matched with the new set of potential drivers. A small portion of riders cannot be re-matched successfully in the validation matching because the itineraries and schedules of the drivers change between the *Ridesharing simulation* and the *Validation simulation*. As it was possible to serve all ridesharing requests in the *Ridesharing simulation*, all requests are deemed matchable. The results from the validation matching are the ones that are presented in the results section below.

3.3. *Traffic Simulator*

To assess how congestion evolves as the number of cars decreases and car occupancy increases, we use METROPOLIS, a mesoscopic dynamic traffic simulator developed by de Palma et al. (1997). Since then, it has mostly been used to estimate various transport policies, including different road pricing schemes (Saifuzzaman et al., 2016; de Palma et al., 2005). METROPOLIS uses a day-to-day iterative procedure. At each iteration, the travelers choose their mode, departure-time and route, given the expected dynamic congestion levels. At the end of each iteration (day), the expected congestion levels are updated using the observed congestion levels, according to a day-to-day adjustment process: the expected congestion for the next iteration is a weighted average of the current expected congestion and the observed congestion. The simulation stops when the two levels are close, i.e., when a stationary equilibrium is reached. The outputs of METROPOLIS include the itineraries of travelers, the travel costs and the schedule delay costs.

The choices made by each traveler in METROPOLIS can be summarised as:

1. Mode choice (between car and transit): The generalised cost for transit is compared with the generalised cost for car. The public transit cost is function of the value of time of transit, the transit travel time, and the transit fare. In the current version, generalized public transport costs are exogeneous. The generalised cost for car is function of the value of time of car, the endogenous travel-time, and the schedule-delay cost. The mode choice is given by a nested logit model.
2. Departure-time choice: The probability of choosing a departure time t is given by a continuous logit model, according to the generalised cost for each possible departure time.
3. Route choice: Each day, at each intersection, travelers observe the congestion on upstream roads and choose a road in order to minimize their generalised cost (closed loop equilibrium).

Note that commuters only choose between car and transit, and ride-sharing is not explicitly modelled as a mode. By assumption, drivers and riders are always fully compensated for ride-sharing inconvenience, which justifies their mode choice for ride-sharing if they are matched.

3.4. Ridesharing Cost

The cost of ridesharing, for a rider, is the sum of walking cost, in-vehicle cost and schedule-delay cost. The walking cost is the cost of walking from the origin to the pickup-point and from the drop-off point to the destination. Let v_{walk} be the walking speed. The duration of the walking trip from the rider's origin to the pick-up point is assumed to be $d_{\text{pick}}/v_{\text{walk}}$, where d_{pick} is the Euclidian distance between the rider's origin and the pick-up point. The duration of the walking trip from the drop-off point to the rider's destination is assumed to be $d_{\text{drop}}/v_{\text{walk}}$, where d_{drop} is the Euclidian distance between the drop-off point and the rider's destination.

The time at which the driver picks up the rider is denoted t_{pick} and the time at which the driver drops off the rider is denoted t_{drop}. Then, the duration of the car trip for the rider is $tt_{\text{iv}} = t_{\text{drop}} - t_{\text{pick}}$ and the arrival time at destination is $t_a = t_{\text{drop}} + d_{\text{drop}}/v_{\text{walk}}$.

Each rider has a specific desired arrival time t^* and a tolerance for lateness or earliness Δ. Riders who reach their destination within the $t^* \pm \Delta$ window experience no schedule-delay penalty. Every minute outside this on-time window generates a schedule delay cost. The schedule delay cost of ridesharing is

$$SD_{\text{RS}} = \beta\big[(t^* - \Delta) - t_a\big]^+ + \gamma\big[t_a - (t^* + \Delta)\big]^+,$$

where $ta = t_{\text{drop}} + d_{\text{drop}}/v_{\text{walk}}$ is the arrival time of the rider at destination, β is the penalty associated to early arrival, γ is the penalty associated to late arrival, and $[x]^+ = \max(0, x)$.

To sum up, the generalised cost of ridesharing is

$$Cost_{\text{RS}} = \underbrace{\alpha_{\text{RS}} \cdot tt_{\text{iv}}}_{\text{In-vehicle cost}} + \underbrace{\alpha_{\text{walk}} \cdot \left[\frac{d_{\text{pick}} + d_{\text{drop}}}{v_{\text{walk}}}\right]}_{\text{Walking cost}} + \underbrace{SD_{\text{RS}}}_{\text{Schedule-delay cost}},$$

where α_{RS} is the value of time of riders during the ride and α_{walk} is the value of time of walking. Note that the waiting time of the rider at the pick-up point is neglected.

3.5. Matching

The off-line matching of riders with drivers is assumed to be managed by a single operator who is assumed to be fully informed with regards to trips, costs, and user preferences. It is assumed to take place before any departure.

To simplify, we assume that each driver picks up at most one rider in his/her car. We also impose that all matches satisfy a spatial and temporal constraint. The spatial constraint ensures that the walking distance from origin and to destination is not larger than $d_{\max}$, i.e., we only consider potential matches for which $d_{\text{pick}} \leq d_{\max}$ and $d_{\text{drop}} \leq d_{\max}$. The temporal constraint ensures that the rider does not arrive too early or too late at his / her destination, i.e., we only consider potential matches for which the arrival time at the drop-off point is such that $t_{\text{drop}} \in [\, t^*_{\text{rider}} - \delta_e \,, t^*_{\text{rider}} + \delta_l \,]$.

Not all drivers are willing to share a ride, even if they receive compensation for it. The reason might be that they are driving their kids to school or that their car is full of shopping items. To represent these drivers, we remove a fixed percentage of vehicles from the matching process.

We use a greedy heuristic method aimed at minimising the total ridesharing generalised cost. The matching between the set of potential drivers and the set of potential riders is a two-step process:

1. For each rider request, potential matches that follow the spatial and temporal constraints are identified and the generalised cost of each match is computed. If a vehicle offers multiple trip alternatives to a rider (i.e., multiple pick-up/drop-off points satisfy the constraints), the trip with the smallest cost is kept for the following step. An example of the result of this step is presented in Table 1a.
2. All the potential matches are sorted by the sum of the walking and schedule delay cost (denoted as *Cost* in Table 1). The in-vehicle cost is excluded as it would result in matching short trips first. Riders and drivers are then matched following a greedy algorithm. Tables 1b, 1c and 1d display an example of greedy matching for three riders. The match with the lowest cost at each step is identified and added to a list of confirmed matches. Once a vehicle is matched, all potential trips associated with this vehicle are removed from the list of potential trips. In addition, once a rider's request is served, all other trips proposed to this rider are removed from the list of potential trips.

Note that, if the spatial and temporal constraints are too restrictive, some riders might not be matched to any driver. In this case, the unmatched rider is unable to participate in the ridesharing program and therefore uses an alternative mode of transport.

Rider ID	Driver ID	Cost
1	12	0
1	13	0.2
1	14	0.5
2	12	0.4
2	15	1.1
2	16	1.3
3	13	0.7
3	15	2.4

(a) All possible trips

Rider ID	Driver ID	Cost
1	12	0
1	13	0.2
2	12	0.4
1	14	0.5
3	13	0.7
2	15	1.1
2	16	1.3
3	15	2.4

(b) Match 1

Rider ID	Driver ID	Cost
1	12	0
3	13	0.7
2	15	1.1
2	16	1.3
3	15	2.4

(c) Match 2

Rider ID	Driver ID	Cost
1	12	0
3	13	0.7
2	15	1.1
2	16	1.3

(d) Match 3

Table 1: Matching process between the drivers and the riders

Note. The green rows represent the confirmed matches. The gray rows represent the matches no longer available because either the rider or the driver is already matched.

4. Case Study: Ridesharing in Île-de-France

The Paris area, as many other large cities, experiences frequent heavy pollution episodes partly due to car emissions (Kumar et al., 2021; Degraeuwe et al., 2017). The regional government of Île-de-France created subsidy programs in 2017 to promote ridesharing and address this issue. The programs include, inter alia, direct subsidies for ridesharing drivers, the funding of ridesharing companies so that they offer lower fares to riders, and two monthly free rides to frequent transit users. Drivers receive from the government 1.50 € per passenger plus 0.10 €/km up until a maximum of 3 € per trip. Moreover, the regional government has made ridesharing completely free for riders during peak pollution episodes and during transit strikes.[6] [7]

The ridesharing scheme proposed in this research is tested on the Île-de-France region. Île-de-France accounts for nearly a fifth of France's population with its 12 175 000 inhabitants in 2017. The region, mainly consisting of Paris and its suburbs, has a density of 1013 inhabitants per squared kilometer. Regionwide, there are 43 million trips daily amongst which 42 % are made by foot or bicycle, 22 % by public transit, and 36 % by car. There are however wide disparities between the city of Paris, the inner and the outer suburbs (Île-de-France Mobilités, 2019).

4.1. Network Modelling

We use the calibration of Metropolis for Île-de-France from Saifuzzaman et al. (2012), which is based on demand data from the 2001 Paris origin-destination survey. The road network consists of 43 857 links, 18 584 intersections, and 1360 zones. Each link is unidirectional and represents a bottleneck with a link-specific capacity. The origin and destination of travelers is set to the centroid of their origin / destination zone. The centroids are connected to the road network with uncongested links. Figure 3 is a visual representation of the network. Compared to the original calibration by Saifuzzaman et al. (2012), we enable mode choice, which requires recalibrating the road capacities.

There is no public transit network *per se*, but rather exogenous travel times for each origin and destination pair of Île-de-France. The public-transit generalized costs are taken from the DRIEAT (*Direction régionale et interdépartementale de l'environnement, de l'aménagement et des transports d'Île-de-France*).

The computed walking distance is the euclidean distance between the centroid of the zones and the intersections. Note that, some centroids are too far from the road network to allow the rider to walk under the spatial constraint, i.e., they can only take drivers who have the same origin or destination. For instance, 21 % of the 1360 zones are at more than 500 meters of any road intersection, and 10 % are at more than 1000 meters.

[6] `https://www.iledefrance.fr/la-prime-au-covoiturage-prolongee-et-etendue`
[7] `https://www.iledefrance.fr/covoiturage-jusqua-150-euros-par-mois-pour-les-conducteurs`

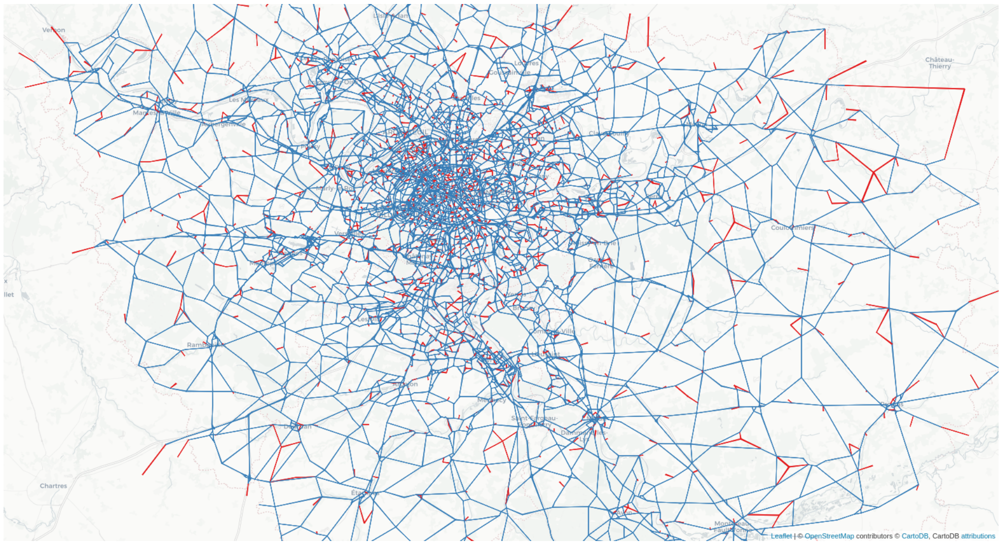


Figure 3: Île-de-France road network

Note. Red lines are uncongested roads connecting the centroids of the zones to the road network (in blue).

4.2. Travel Demand

We simulate the morning commute, which is the most congested period of the day in Île-de-France. The simulation starts at 6AM and ends at 12PM. Travel demand is represented in METROPOLIS as an origin-destination matrix for different traveler groups. All demand data are taken from the calibration of METROPOLIS for Île-de-France (Saifuzzaman et al., 2012). Travel demand for the morning commute is divided in four traveler groups: workers going towards Paris, workers leaving Paris, and two groups of non-workers. Both the demand and the road capacity are scaled-down to reduce computation time. There is a total of 934 042 travelers.

In each group, the travelers have the same schedule-delay parameters and values of time but the desired arrival times are normally distributed. Figure 4 represents the desired arrival time distribution for the four groups of travelers. Workers coming from Paris are the ones with the narrowest distribution and the earliest desired arrival time. The workers originating from the suburbs and going towards Paris want to reach their destination, in average, a few minutes later. The desired arrival time of the non-workers is represented by two normal curves with a standard-deviation of 90 minutes. Non-workers have a later desired arrival time than commuters.

In METROPOLIS, the driver's on-time window is centered around the desired arrival time t^*_{driver} and has a length of 2Δ, where Δ represents the acceptable lateness or earliness (i.e., without penalty). It is is fixed at $\Delta = 5$ min and identical for all traveler groups. Although this hypothesis is valid for a mesoscopic analysis, it fails to represent the greater flexibility some individuals, such as office workers, have in their desired arrival time window. A rider-specific delay tolerance is drawn from the lognormal distribution $\Delta \sim \text{Lognormal}(2, 1){+}3$ min to replace the constant value of five minutes for matched riders. This distribution

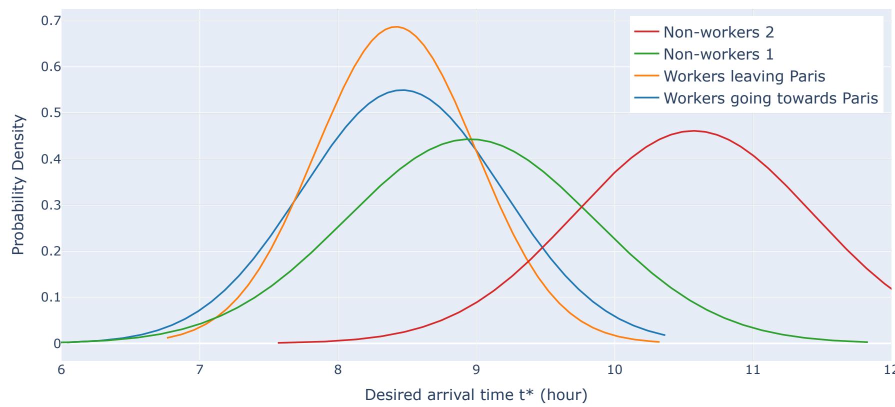


Figure 4: Desired arrival time distribution of the four traveler groups

also reflects the fact that some riders are ready to arrive earlier or later at work in order to find a ridesharing match.

All the preference parameters used in this research are presented in Table 2. The values of time for car and transit as well as the early and late penalties come from the work of Saifuzzaman et al. (2012). The value of time for riders is assumed to be equal to the value of time of car (i.e., $\alpha_{\text{car}} = \alpha_{\text{RS}}$), which means that for riders the savings incurred by ridesharing are completely offset by its inconvenience. Workers starting their journey in Paris are more inflexible in their desired arrival time as shown by their penalty for late arrival being more than twice the one of workers starting their journey in the suburbs. The value of time of walking is assumed to be $\alpha_{\text{walk}} = 1.1 \cdot \alpha_{\text{RS}}$. This hypothesis implies that riders prefer to stay in a car rather than walk (Hensher and Rose, 2007; Wardman, 2001).

<table>
<tr><th>Traveler group</th><th>β</th><th>γ</th><th>α_{car}</th><th>α_{RS}</th><th>α_{PT}</th><th>α_{Walk}</th></tr>
<tr><td>Workers going towards Paris</td><td>6.09</td><td>7.53</td><td rowspan="2">12.96</td><td rowspan="2">12.96</td><td rowspan="2">13.24</td><td rowspan="2">14.26</td></tr>
<tr><td>Workers coming from Paris</td><td>8.36</td><td>17.43</td></tr>
</table>

Table 2: Preference parameters for the two groups of workers, in €/h

The walking speed is set to 4 km/h. We consider three different scenarii, corresponding to three different values of the maximum walking distance parameter d_{max}: a door-to-door service scenario ($d_{\text{max}} = 0$), a maximum walking time of 15 min per leg of the trip ($d_{\text{max}} = 500\,\text{m}$), and a maximum walking time of 30 min per leg of the trip ($d_{\text{max}} = 1000\,\text{m}$). The long trip criterion for the riders' selection is defined as $FFTT_{\text{threshold}} = 10$ min. This threshold keeps 40 % of the commuting trips. The maximum acceptable earliness at the drop-off intersection for the rider is set to $\delta_e = 60\,\text{min}$, whereas the maximum acceptable lateness is set to $\delta_l = 45\,\text{min}$. These parameters are asymmetrical to account for the lower penalty incurred by early arrival compared to late arrival. Any potential match whose drop-off time is outside the time-window $[t^*_{\text{rider}} - 60\text{ min},\ t^*_{\text{rider}} + 45\text{ min}]$ will therefore be ignored. Finally, the share of drivers willing to propose

Scenario	Reference	Door-to-door	15 min walking time	30 min walking time
Congestion	21.7 %	15.1 %	13.9 %	9.29 %
Car VKT (10^6 km)	10.84	9.69	9.50	8.60
Mean travel cost for drivers (€)	3.29	3.02	2.98	2.76
Mean free-flow travel cost for drivers (€)	2.74	2.60	2.60	2.50
Transit modal share	25.2 %	23.6 %	23.3 %	22.1 %
Car modal share	74.8 %	70.4 %	68.9 %	64.8 %
Ridesharing modal share	—	5.9 %	7.8 %	13.1 %
Number of transit users	235 544	221 739	217 591	206 841
Number of drivers	698 499	657 541	643 992	605 093
Number of ridesharing riders	—	54 763	72 460	122 109

Table 3: Comparison of results for the reference scenario and three scenarii with different maximum walking time

their car for ridesharing is set at 90 %. This high proportion is used to assess the maximum potential of the ridesharing scheme. A sensitivity analysis is conducted for this parameter for lower and more realistic values.

4.3. Results

Table 3 presents the results from the Metropolis validation simulation for the reference scenario (with no ridesharing), and the three ridesharing scenarii. The average congestion during the morning commute is given by

$$\frac{1}{|L|} \cdot \sum_{l \in L} \left(\frac{tt_l^{avg} - tt_l^0}{tt_l^0} \right),$$

where L is the set of all links in the network, $|L|$ is its cardinality, tt_l^{avg} is the average travel-time on link l for the recording period and tt_l^0 is the free-flow travel-time of link l. The *Car VKT* indicator represents the total distance (in million of kilometers) travelled by cars during the morning commute.

The number of riders chosen in the three ridesharing scenarii is the maximum number of matches respecting the temporal and spatial constraints, i.e., as the number of riders increase beyond this point, the number of available drivers is so low that not all riders can be matched, under the temporal and spatial constraints.

Under the door-to-door scenario the modal share of ridesharing riders is 5.9 %. In this scenario, the driver and the rider must share the same origin zone and destination zone. It brings road congestion from 21.7 % to 15.1 % with 54 763 ridesharing trips. Schedule delay and travel costs are reduced for all road users as a consequence of lower road congestion. The free-flow travel-cost also improves as less detours are made to avoid congested areas.

By considering that riders can walk from their origin to a pick-up intersection and from a drop-off intersection to their destination, the maximum number of requests that can be matched increases together with the ridesharing modal share and benefits. The main drawback of an increased ridesharing modal share is a larger shift from public transit to car. Yet the shift is contained as only former drivers are eligible to take part in the ridesharing scheme. The modal shift is attributable to the increased attractiveness of car compared to transit under lower congestion. Indeed, by removing vehicles from the road network, congestion decreases and the generalised cost of driving decreases. The generalised cost of transit stays identical since it is exogenous and independent from congestion in METROPOLIS. For the 15-minute maximum walk scenario only 1.9 % of travelers are transit users who shifted to solo driving, while 7.8 % of travelers are riders.

The percentage of drivers willing to participate in the program is the only constraint restraining the set of potential drivers. It is set at 90 % for all results presented. This share assesses a maximum potential. Figure 5 presents the ridesharing share and the level of congestion as a function of the percentage of drivers willing to participate in the ridesharing scheme for the 15-minute maximum walking time scenario. It can be observed that with only 10 % of drivers willing to participate (randomly distributed across the Île-de-France region), the ridesharing share is smaller than 2 % and thus the congestion reduction is insignificant the number of ridesharing matches and hence the congestion reduction is insignificant. With half the drivers willing to engage in the ridesharing scheme, the ridesharing share goes up to about 5.5 %, inducing a congestion level only slightly larger than with 90 % of potential drivers (15.5 % versus 13.9 %). Complete results are presented in Appendix B for 20 % of drivers willing to participate in the program.

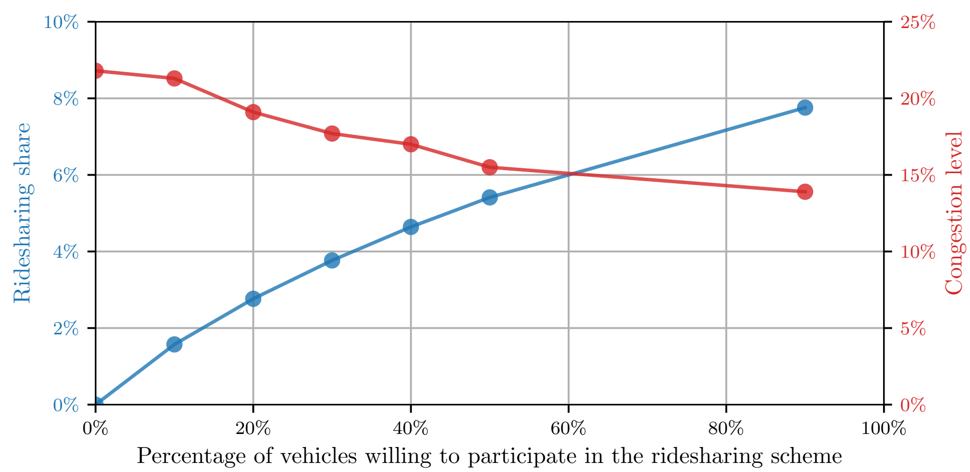


Figure 5: Sensitivity analysis of the percentage of drivers willing to participate in the ridesharing scheme for the 15-minute walking time scenario.

The travel survey used for the Île-de-France model (EGT 2001, Direction Régionale de l'Équipement d'Ile-de-France, 2004) has 2.93 million commuting trips (car + transit) for the morning commute, whereas the OD matrices in METROPOLIS are scaled down to a total of 513 549 commuting trips. Some results, including Car VKT and the number of riders, need to be rescaled to be meaningful. The traffic simulator gives identical results as long as the demand (OD matrices) and the supply (road network) are scaled down in the same proportion. But, more travelers in the matching model means more ridesharing opportunities as the probability of finding multiple vehicles answering a ridesharing request increases. The same request might then be served with less schedule delay and walking time. The rescaled results therefore probably underestimate the potential of ridesharing matches. The rescaled results are presented in Table 4 alongside travel time savings and carbon dioxide equivalent emission savings.

Scenario	**Reference**	**Door-to-door**	**15 min walking time**	**30 min walking time**
Rescaled Car VKT (10^6 km)	61.7	55.2	54.1	49.0
Fuel savings (L)	-	526 000	611 000	1 023 000
CO_{2eq} emission avoided (tons)	-	1270	1474	2467
CO_{2eq} emission avoided (%)	-	10.5 %	12.3 %	20.6 %
Travel-time savings (h)	-	97 900	106 000	160 000
Travel-time savings (%)	-	10.1 %	11.1 %	17.9 %
Number of ridesharing riders	-	311 911	412 707	695 491
Number of drivers	3 981 494	3 747 984	3 670 754	3 449 030
Travel-time savings per road user (min)	-	1.57	1.73	2.78

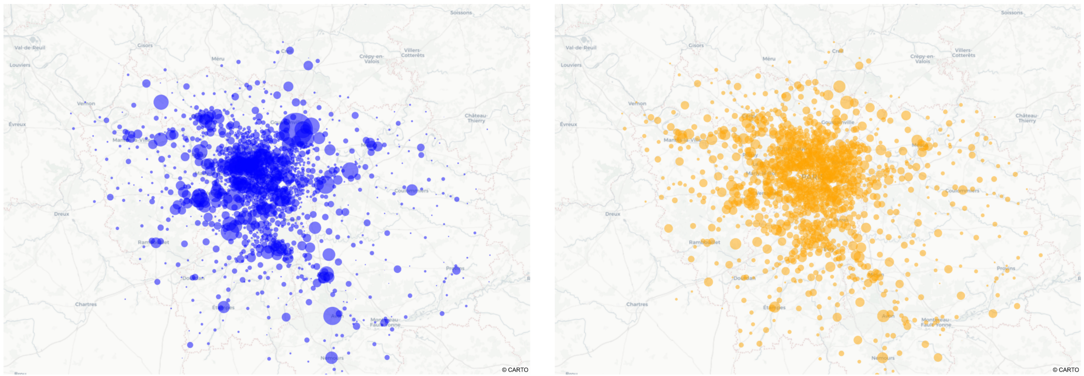
Table 4: Rescaled results and savings for the reference scenario and three scenarii with different maximum walking time

Note. Average fuel consumption: 8 L/100 km (Agence de la transition écologique, 2018). Average car CO_{2eq} emissions: 0.193 kg of CO_{2eq} / km (Agence de la transition écologique, 2021)

With near four million travelers during the morning commute, the benefits of ridesharing are significant. The 30-minute maximum walking time scenario brings a decrease of about 21 % in Car VKT and carbon dioxide equivalent (CO_{2eq}) emissions, compared to the reference scenario. The savings are halved in the door-to-door scenario. At an individual level, road users save on average 1.73 minutes of travel time during the morning commute under the 15-minute scenario. The travel time savings amount to 106 000 hours network-wide under the same scenario. The travel time savings of riders are analysed further in Figure 11.

4.4. Detailed Results for the 15-minute Maximum Walking Time Scenario

The scenario with a maximum walking time of 15 minutes offers a good improvement in road congestion at a relatively low walking cost for the riders. When 90 % of vehicles are willing to engage into the program, ridesharing opportunities arise everywhere in Île-de-France, even in rural areas. Figure 6 presents the origins and destinations of all matched riders. The most frequent origins and destinations are the same as in the overall population. In that respect, the two main destinations are the two largest economic hubs: Paris' CBD (*La Défense*) and Paris Charles-de-Gaulle Airport (*Roissypôle*). In contrast, the origins are scattered across the greater Paris area.



(a) Riders' origins (b) Riders' destinations

Figure 6: Origins and destinations of matched riders in Île-de-France

In this scenario, there are 72 460 ridesharing trips. Figure 7 represents the distribution of the riding times, i.e., the in-vehicle travel time of riders between the pick-up and the drop-off intersections. The mean riding time is 18 minutes. This is higher than the mean driving time of 14 minutes observed amongst ridesharing and non-ridesharing drivers. The discrepancy is explained by the fact that the ridesharing scheme is only accessible to travelers who used to commute by car, with a trip longer than 10 minutes of free-flow travel-time. In fact, if we only consider the ridesharing and non-ridesharing drivers with a free-flow travel-time of 10 minutes, we get an average travel-time of 24 minutes. Observe that, for 10 % of riders, the riding time is smaller than 10 minutes, even though their free-flow travel-time was larger than 10 minutes when driving. The reason is that, as congestion decreases, some vehicles offering a ridesharing trip may take a shorter itinerary than the one that was taken by the rider when he/she was driving.

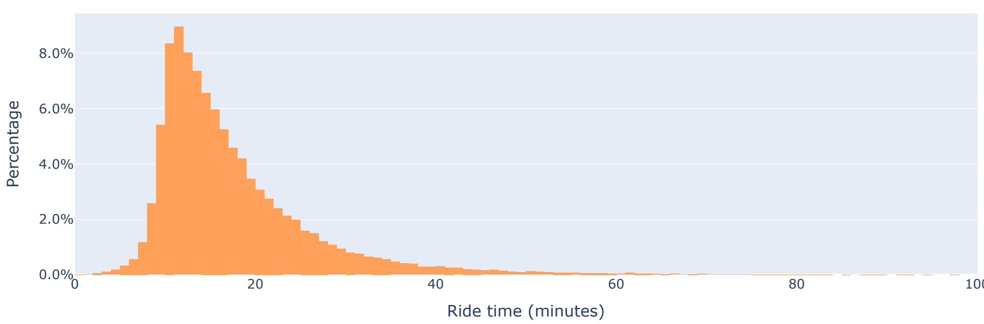


Figure 7: Distribution of riding time for the matched riders

The total walking distance displayed on Figure 8 represents the sum of the euclidean distances between the rider's origin zone and the pick-up intersection (maximum 500 meters) and between the drop-off intersection and the rider's destination zone (maximum 500 meters). The maximum walking distance is therefore 1km in this scenario. There is no walking at all for 56 % of matches, meaning that the rider and the driver have the same OD pair. This data is not displayed on the figure to facilitate its reading. The large gap observed at 500 meters is explained by the fact that most riders walk only at one end of their trip chain. In fact, only 5 % of riders walk at both ends. Even though the maximum walking time for one leg of the trip is 7.5 minutes, only 3 % of riders walk for more than that time for the whole trip. The mean walking distance in this scenario is 141 meters, which corresponds to a mean walking cost of 0.50 €. By allowing a maximum 15-minute walk, the modal share of ridesharing improves by 1.9 % compared to the door-to-door scenario only at the cost of a small walking time for riders.

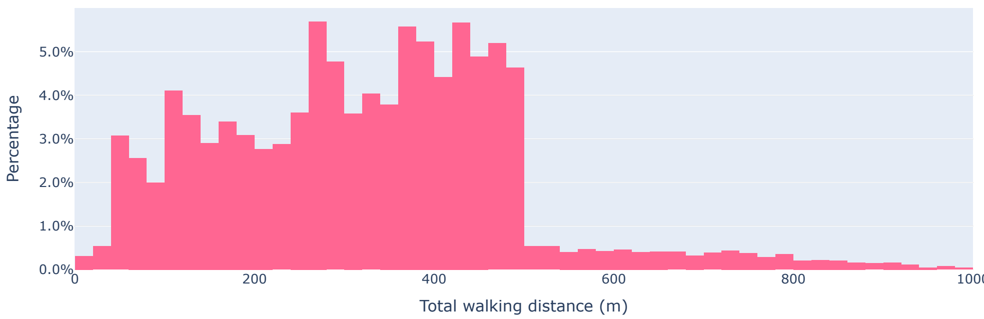


Figure 8: Distribution of walking distance for the matched riders

Note. The 56 % of riders with a null walking distance are excluded from the graph.

Figure 9 presents the schedule delay of riders for the lognormal and constant values of Δ. Schedule delay occurs when a traveler arrives at destination outside the desired arrival time window. The remainder of this analysis only considers the lognormal distribution of delay tolerance. The figure excludes riders whose schedule delay is null (59 % of all riders) to clarify the presentation. The mean delay is 14 minutes for early arrivals and 11 minutes for late arrivals. Together, they represent a mean schedule delay cost of 0.80 €.

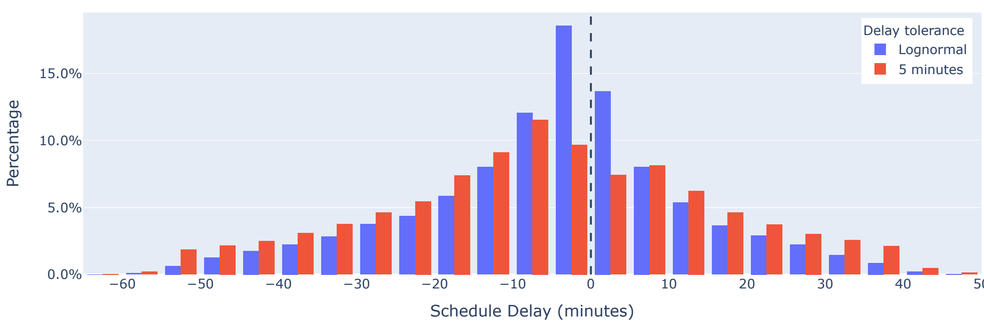


Figure 9: Distribution of schedule delay for the matched riders

Note. The 59 % of riders experiencing no schedule delay are excluded from the graph.

Complete statistics for riding time, walking distance and schedule delay are presented in Appendix A.

Figure 10 presents the distribution of the generalised cost of ridesharing for riders. It is the sum of the schedule delay cost, the walking cost, and the in-vehicle travel cost. An analysis of the ridesharing cost reveals that the main component is the in-vehicle travel cost: the mean cost of 5.09 € can be divided in 16 %

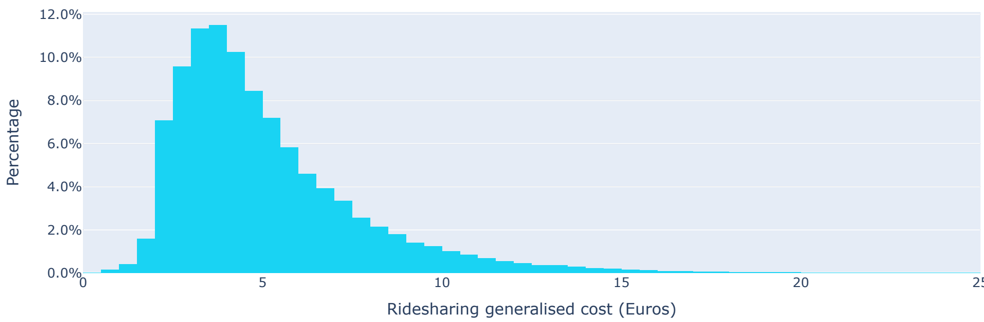
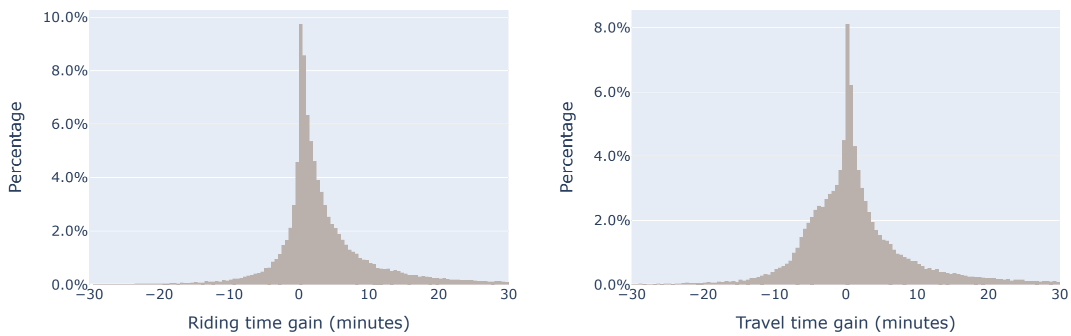


Figure 10: Distribution of the riders' generalised ridesharing cost

of schedule delay cost, 10 % of walking cost, and 74 % of in-vehicle travel cost.



(a) Riding time gain distribution ($tt_{Car} - tt_{RS}$) (b) Travel time gain distribution ($tt_{Car} - tt_{RS} - t_W$)

Figure 11: Riding time and travel time gains of riders, compared to the reference scenario

A comparison of the total travel time and the riding time from an individual point of view allows to better understand the benefits of ridesharing from the user's perspective. Figure 11a presents the distribution of the riding time gain and Figure 11b presents the distribution of the total travel time gain (walking time plus riding time), for riders, compared to the reference scenario where they used their car. Amongst matched riders, some experience a travel time gain due to lower congestion and a smaller riding time, whilst some experience a longer travel time caused by a long walking distance. There is a mean riding time gain of 4 minutes and a median riding time gain of 1.8 minutes mainly attributable to the fact that there are less vehicles on the road network hence making the average travel time 9 % cheaper. However, the travel time gain shrinks because of the walking cost. The mean travel time gain is 2 minutes and the median travel time gain is only 0.4 minutes. In that respect, 43 % of riders will experience a higher travel time when ridesharing instead of driving. As stated before, many other factors may encourage ridesharing behaviours, thus making travelers accept a ridesharing trip with a longer travel time than for car. For example, riders do not need to search for a parking space and to pay parking costs. On top of this, there is the cost of fuel as well as psychological factors that can influence their decisions. Riders whose travel time increase is still too large to be acceptable would receive state subsidies to offset it.

5. Conclusion

Carpooling is a tool with a great potential to reduce pollution and congestion in urban areas. It nevertheless remains unpopular amongst commuters, despite a growing number of carpooling apps (i.e. mobile applications). In this paper, we focus on work commutes because they usually have time-restrictions at the workplace, but there is no need to stick to work related commute in a real-world application. A carpooling app is definitely needed to make such scheme acceptable. Many other technical problems remain to be solved, and in particular the driver should have safe and easy to find meeting points to pick-up their passenger.

This study proposes a state-subsidised carpooling scheme to increase the modal share of carpooling. The potentials of this scheme are tested on the Île-de-France region to evaluate the individual and social benefits. It is based on the dynamic traffic simulator METROPOLIS and a greedy matching procedure. Drivers and riders are matched based on their itineraries. We focus on former car drivers who accept to carpool, but other configuration may be worthwhile exploring: for example, when public transport exists but is of poor quality.

The carpooling scheme we propose considers, since no detour nor extra schedule delays are involved, that the vast majority of drivers would be ready to pick up someone in their car in exchange for a small monetary incentive. This state subsidy then only compensates for the inconvenience cost of sharing a car. Riders need to walk, but benefit from a free ride. Their individual savings are gasoline saving, time and monetary saving related to parking, and wear and tear (beside the reduced congestion). The social saving is a result of less vehicles on the road, which means less travel time and therefore less accidents and pollution.

Three main scenarios were tested for Île-de-France to show the potential benefits of carpooling. The less optimistic one (the one where the rider walks in average 141m, and no more than 15 minutes, the maximum walking time) proves to be also the most interesting one. It saves 7.6 million vehicle-kilometres travelled for the morning commute, reducing CO2 emissions by 1 474 tons, and travel times by 106 000 hours. This represents an average time saving of 1.73 minutes per road user.

In this paper, we consider the morning commute, which has to be seen as an intermediary step for two reasons. First, the evening commute is a not a mirror case of the morning commute in dynamic models (as shown for example by de Palma and Lindsey, 2002). Second, if a user decides not to take his/her car the morning, he/she has to carpool or take public transport in the evening. Moreover, if the schedule preferences of two matched users are similar in the morning, this does not necessarily mean they will be similar in the evening for the same driver/rider couple. So, in general, the same match could not be arranged in the morning and in the evening. As a consequence, the riders are not guaranteed to find another convenient match for their return trip in the evening. Matching for round-trip commuting is a constraint that could be imposed on future research. A mathematical formulation of this problem was proposed by de Palma and Nesterov (2006), in the case of stable-dynamic models.

To keep the analysis simple, this research only considered that riders take one car to complete their trip and that each vehicle can only satisfy one ridesharing request. Allowing for riders to take multiple vehicles to satisfy their ridesharing request and for drivers to serve multiple ridesharing requestions can increase the potential of ridesharing. The success of carpooling depends heavily on how many drivers are willing to participate. This type of ridesharing, referred to as multi-hop ridesharing, has been recently investigated (Herbawi and Weber, 2012; Teubner and Flath, 2015). Even though multi-hop ridesharing generates transfer penalties between cars, it could be interesting for some segments of a network, in particular for OD pairs with low demand. The combinatorial issues (the multiple matching problem) remain widely unexplored in the matching literature in economics (labour market and marriage market, for rather obvious reasons).

However, it remains to be seen if riders and drivers are prepared to be involved in a more complex organization. Empirical research is needed in order to evaluate the acceptance of such an organization. Thereby, a mobile application needs to be developed such that all unnecessary complexity is eliminated. For example, in Uber all the complexity is hidden from drivers and riders.

Another important extension that could be considered is to include an explicit and structural mode choice model at the individual level. Instead of randomly selecting a fixed number of individuals to be riders, as we did, the mode choice model could be augmented with an endogenous choice to be a rider or not. Moreover, adding inconvenience cost to match a specific rider with a specific driver will change the results. The mathematical treatment of this case is rather straightforward, but the empirical required input parameters are delicate. This would increase the quality of the matches, as the individuals choosing to be riders would be the ones who can get the highest quality matches (as far as detour, scheduling and idiosyncratic inconvenience costs). This would also allow to better evaluate the subsidies required to convince more drivers to switch to carpooling.

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Appendix A. Results with 20 % of Drivers Willing to Participate in the Ridesharing Scheme

Table A.5 presents the simulation results for the three maximum walking time scenarii, with 20 % of drivers willing to participate in the ridesharing scheme.

Scenario	Reference	Door-to-door	15min	30min
Congestion	21.7 %	21.6 %	19.1 %	17.9 %
Car VKT (10^6 km)	10.84	10.54	10.40	10.24
Mean travel cost for drivers (€)	3.29	3.32	3.23	3.19
Mean free-flow travel cost for drivers (€)	2.74	2.72	2.70	2.69
Transit modal share	25.2 %	24.8 %	24.5 %	24.2 %
Car modal share	74.8 %	73.4 %	72.7 %	72.0 %
Ridesharing modal share	-	1.7 %	2.8 %	3.8 %
Number of transit users	235 544	232 027	228 720	225 833
Number of drivers	698 499	685 904	679 501	672 509
Number of ridesharing riders	-	16 112	25 821	35 701

Table A.5: Results for the reference scenario and three walking scenarii with 20 % of drivers willing to participate in the program

Table A.6 presents the rescaled results of the same simulation.

Scenario	Reference	Door-to-door	15min	30min
Rescaled Car VKT (10^6 km)	61.7	60.0	59.2	58.4
Fuel savings (L)	-	136 000	200 000	264 000
CO_{2eq} emission avoided (tons)	-	328	483	637
CO_{2eq} emission avoided (%)	-	2.8 %	4.1 %	5.3 %
Travel-time savings (h)	-	11 100	36 800	50 300
Travel-time savings (%)	-	1.1 %	3.7 %	5.1 %
Number of ridesharing riders	-	91 838	147 180	203 496
Number of drivers	3 981 494	3 909 653	3 878 156	3 833 301
Travel-time savings per road user (min)	-	0.17	0.57	0.79

Table A.6: Rescaled results and savings for the reference scenario and three walking scenarii with 20 % of drivers willing to participate in the program

*Average fuel consumption: 8 L/100 km (Agence de la transition écologique, 2018), Average car CO_{2eq} emissions: 0.193 kg of CO_{2eq} / km (Agence de la transition écologique, 2021)

Appendix B. Statistics for the Three Maximum Walking Time Scenarii

Table B.7 presents the statistics of the ridesharing matches for riders for the door-to-door scenario with 90 % of drivers willing to participate in the ridesharing scheme.

	Mean	σ	Min	25^{th} Perc.	Median	75^{th} Perc.	Max
Riding time (min)	20.3	10.9	0.8	12.8	17.1	24.2	120
Schedule delay earliness (min)	18.1	13.8	0.0	6.3	15.0	27.7	56.3
Schedule delay lateness (min)	13.4	10.2	0.0	4.7	11.2	20.7	40.8
Schedule delay cost (€)	1.28	1.99	0.00	0.00	0.02	2.04	11.64
Ride and travel time gain (min)	3.1	10.2	-97.1	-0.3	1.1	4.9	135
Rider generalised cost (€)	5.66	3.18	0.18	3.29	4.84	7.17	31.01

Table B.7: Statistics for the door-to-door scenario for riders

Table B.8 presents the statistics of the ridesharing matches for riders for the 15-minute maximum walking time scenario with 90 % of drivers willing to participate in the ridesharing scheme.

	Mean	σ	Min	25^{th} Perc.	Median	75^{th} Perc.	Max
Riding time (min)	17.6	8.9	0.4	11.7	15.0	20.6	103
Walk distance (m)	141	195	0	0	0	289	996
Schedule delay earliness (min)	14.2	13.0	0.0	3.9	9.9	21.4	61.3
Schedule delay lateness (min)	11.1	10.0	0.0	3.0	8.0	17.1	47.4
Schedule delay cost (€)	0.80	1.59	0.00	0.00	0.00	0.87	13.40
Riding time gain (min)	4.04	9.78	-79.9	0.13	1.77	5.73	153
Travel time gain (min)	1.92	10.1	-80.7	-2.69	0.42	4.03	153
Rider generalised cost (€)	5.09	2.62	0.24	3.29	4.40	6.17	28.90

Table B.8: Statistics for the 15-minute maximum walking time scenario for riders

Table B.9 presents the statistics of the ridesharing matches for riders for the 30-minute maximum walking time scenario with 90 % of drivers willing to participate in the ridesharing scheme.

	Mean	σ	Min	25^{th} Perc.	Median	75^{th} Perc.	Max
Riding time (min)	14.9	6.3	2.1	10.7	13.3	17.2	86.6
Walk distance (m)	857	313	0	651	804	971	1982
Schedule delay earliness (min)	15.2	13.7	0.0	5.1	11.2	20.8	70.1
Schedule delay lateness (min)	14.7	12.4	0.0	4.6	11.2	22.3	55.8
Schedule delay cost (€)	1.27	1.97	0.00	0.00	0.39	1.82	15.76
Riding time gain (min)	5.9	8.6	-57.2	1.6	3.5	7.4	123
Travel time gain (min)	-6.9	9.6	-79.4	-11.6	-8.2	-4.2	112
Rider generalised cost (€)	7.53	2.88	1.75	5.50	6.83	8.86	31.28

Table B.9: Statistics for the 30-minute maximum walking time scenario for riders