Towards sustainable ride-pooling algorithms for autonomous cars: a comparative study of passenger satisfaction, taxi fleet usage and emission metrics

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SHORT SUMMARY

Reducing traffic-related CO2 emissions is one of the major factors in achieving city-level carbon neutrality. In this work, we study the problem of sustainable ride-pooling of autonomous cars with SUMO traffic simulation software as an environment for testing ride-pooling strategies and explicit emission modelling. We compare the scenarios without ride-pooling (baseline) and with ride-pooling for varying levels of demand, maximum occupancy of cars and penetration rates of autonomous taxis using three groups of metrics, namely, metrics of passenger satisfaction, taxi fleet usage and total emissions. The experimental study showed that simple heuristics (minimizing detours or maximizing the occupancy of the cars) may reduce emissions up to 15% compared to baseline but do not provide the balanced solution for multiple metrics. To overcome this problem, the future work will contain development of simulation-based multi-objective reinforcement learning algorithm for sustainable ride-pooling.

Keywords: electrification and decarbonization of transport, shared mobility, ride-pooling, SUMO, traffic simulation.

1. INTRODUCTION

Transportation is a key factor contributing to urban carbon emissions, and road traffic accounts for up to 80% of emissions of all transportation modes (Lei et. al., 2023; CBO, 2022). In Finland, total annual emissions from domestic road transport are estimated at 10.4 million tonnes in 2020, with 6.5 million tonnes from passenger transport (AT, 2020). Road traffic emissions may be reduced by a number of measures such as promoting eco-friendly transportations modes, introducing financial incentives and developing novel algorithms for vehicle fleet control. As approximately half of the emissions from cars are attributable to short, local journeys (AT, 2020), reducing the emissions from city-wide passenger transportation remains an important problem. One of the ways to lower traffic emissions, especially in urban areas, is shared mobility, which can be defined as the simultaneous use of a vehicle by multiple passengers (Tikoudis et. al., 2021).

In this work, we investigate the environmental impact of shared mobility in the context of ride-sharing (and, more specifically, ride-pooling). Following (Qin et. al., 2022), we define ride-sharing as a service which matches passengers with drivers using mobile apps, and ride-pooling as a special case of ride-sharing when multiple passengers with different trip requests may share the same vehicle. Ride-sharing allows for on-demand vehicle ordering, which reduces the use of private cars. Ride-pooling, in turn, combines trips with similar origins and/or destinations, which improves vehicle fleet usage. With modern ride-pooling algorithms, this improvement can be significant, see e.g. (Alonso-Mora et. al., 2017) which reports that for the New York taxi trip dataset

(Donovan and Work, 2014) 99% of the requests may be satisfied with using only 25% of taxi fleet if ride-pooling is applied.

The research on the environmental impact of ride-pooling can be categorized into two strands. Studies of the first group estimate emissions using observational data, for example, (Li et. al., 2022; Zhu and Mo, 2022; Caulfield, 2009; Tikoudis et. al., 2021). In (Zhu and Mo, 2022), the main studied factor is vehicle kilometer travelled (VKT), and CO_2 emissions are assumed to be linearly dependent on the amount of fuel consumed. (Tikoudis et. al., 2021) estimate the impact of ride-pooling on carbon footprint for different cities by simulating the aggregated travel demand and the choice of transportation mode. Emissions per vehicle kilometer traveled are set at constants for a triple (city, year, transportation mode). The other common choice for emission estimation is COPERT model which accounts for different fuel, vehicle class and engine technology. In (Caulfield, 2009), census data including mode splits, distance traveled and journey time are used as an input for COPERT, while in (Li et. al., 2022), GPS trajectories of DiDi ride-pooling provider serve for this purpose.

The other strand of research focuses on the development of novel ride-pooling algorithms with different target functions. The survey of (Mourad et. al., 2019) enlists the following objectives for optimizing shared mobility: travel distance, travel time, number of participants, operational cost, vehicle emissions, system reliability, occupancy rate, number of used vehicles. However, direct optimization of emissions is rarely considered, e.g. among 35 ride-pooling algorithms which were reviewed in (Mourad et. al., 2019), there is only one paper (Atahran et. al., 2014) considering multi-criteria dial-a-ride problem with reducing emissions as one of the objectives.

Summarizing, the impact of ride-pooling on urban transportation is mostly studied in the context of the reductions in VKT, traffic congestion, fleet size and travel time (Li et. al., 2022). The environmental sustainability aspect is usually considered in an implicit way using the assumption that emissions are correlated with a fuel consumed or a distance travelled. However, there are studies showing that optimization of trip-related measures does not definitely result in the optimal solution in terms of its environmental sustainability, see e.g. (Bektaş and Laporte, 2011). Indeed, emissions depend not only on distance but also on speed profiles of vehicles which are influenced e.g. by congestion level and traffic lights operating schemes. This leads to the necessity of explicit emission modelling while developing and evaluating sustainable ride-pooling algorithms.

In this study, our goal is to develop a method for evaluating the impact of ride-pooling on environmental sustainability, customer satisfaction and resource utilization metrics using simulation-based approach with explicit emissions modeling. In contrast with the existing state-of-the art ride-pooling algorithms, we do not assume that emissions are perfectly correlated with trip-related measures. From the other side, simulation-based approach allows for testing ‘what-if’ scenarios for the cases when data from ride-pooling providers are unavailable. Thus, this paper investigates the sustainability of ride-pooling algorithms while considering the gap between empirically grounded emission measurements and general-purpose ride-pooling solutions. The contributions of the current study are as follows: (i) we present the method and the testbed for evaluating ride-pooling algorithms based on micro-simulation approach with explicit emissions modeling, (ii) we perform a comparative study of the impact of ride-pooling on passenger satisfaction, taxi fleet usage and emissions metrics for a synthetic scenario with different supply and demand levels. The resulting testbed is implemented as a part of simulation environment and further can be used for training reinforcement learning-based ride-pooling algorithms.

2. METHOD

Following (Li et. al., 2022), we estimate the effect of ride-pooling compared to the single rides, that is, to the case when the same demand is served with cars operating in the dedicated mode, with a single passenger per ride. Thus, to evaluate the efficiency of a ride-pooling strategy for a fixed level of demand, we consider two scenarios: (i) baseline – all trips are served by private cars, (ii) ride-pooling – a given percentage of trips is served by ride-pooling service, other trips are still simulated and represent background traffic.

To study different combinations of supply and demand, we vary the following parameters of a ride-pooling scenario: (i) *percPass* – a percentage of trips which are served with the ride-pooling service, (ii) *percTaxi* – percentage of taxis related to the number of passengers (e.g. if *percTaxi*=20%, and the number of passengers is equal to 100, 20 taxis will be available for ride-pooling), (iii) *capacity* – the maximum occupancy of a taxi (the same as the maximum number of passengers sharing the ride).

In this study, we implement ride-pooling environment in SUMO traffic simulation software (Pablo Alvarez Lopez et. al., 2018). We use microscopic simulation approach with default emission model provided by SUMO (HBEFA3 for a gasoline powered Euro norm 4 passenger car). We evaluate two ride-pooling algorithms: (i) *greedyShared* (SUMO built-in strategy) – assigns to each order the closest taxi in terms of travel times and tries to pick up another passenger on the way to the destination, (ii) *maxOccupancy* (proposed) – assigns to each order the closest taxi in terms of pick-up time while maximum capacity of a taxi is not reached. It is worth to mention that *greedyShared* strategy supports maximum capacity of a taxi equal to 2. Thus, *greedyShared* is focused on minimizing detour distance while *maxOccupancy* is oriented to maximizing taxi fleet usage.

The goal of the comparative study is to evaluate the efficiency of ride-pooling according to three groups of metrics: (i) passenger satisfaction measures – waiting time, detour distance, taxi travel time (the sum of the waiting time and the trip time), taxi-private coefficient $tp = \frac{t_{taxi}-t_{car}}{t_{car}} \cdot 100$, where t_{taxi} is a taxi travel time, t_{car} is a private car travel time; (ii) taxi fleet usage measures – average number of customers, occupied / idle time/distance, occupancy rate (average number of passengers per occupied legs of a trip), (iii) emission measures – total emissions of CO_2, CO, HC, NO_x, PM_x, fuel, % of advantage compared to baseline scenario.

The architecture of the resulting experimental testbed is presented in Figure 1. Demand and road network are generated with SUMO built-in *randomTrips* and *netgenerate* tools. *genPassengers* is a Python script which generates all input simulation files according to the given values of *percPass, percTaxi* and *capacity* parameters. For the experiments with a variation of these parameters in the predefined ranges, we also developed shell script *runStat.sh* which allows to run the experiments in a batch mode. The experiment for a baseline scenario is performed once for a fixed demand and road network, while ride-pooling scenario is tested for different combinations of parameters. *maxOccupancy* algorithm was implemented in Python using TraCI programming interface provided by SUMO (*traciLaunch.py)*. The output of SUMO simulation are files with detailed information on the trips (*tripInfo*) and on the resulting emissions (*emissions*). To evaluate the efficiency of ride-pooling, we developed a tool *getStats* which parses SUMO files and calculates the ride-pooling metrics described above. The results of experiments for different parameters are accumulated in *experimentsStats.csv*, which is then used for plotting the metrics for the ranges of the controlled parameters (*statPlots.ipynb*). The code of the developed testbed is available at (Bochenina, 2023).

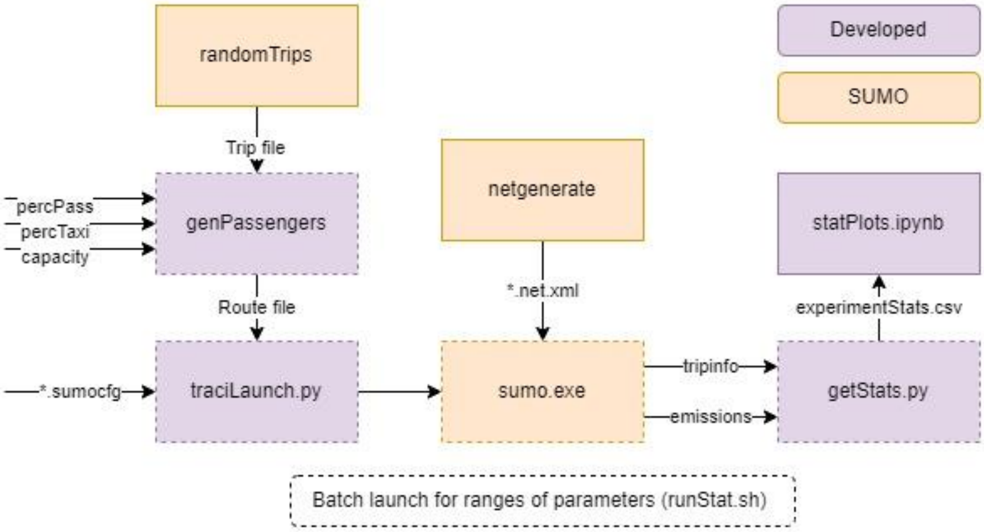

Figure 1 – The architecture of the testbed for evaluating ride-pooling algorithms (yellow rectangles are SUMO packages, purple rectangles are tools developed in frames of this study)

3. RESULTS AND DISCUSSION

The road network for the experimental study was generated with *netgenerate* tool with default parameters and 200 iterations. The demand was generated with *randomTrips* tool with minimum distance equal to 1.5 km, fringe factor equal to 5, starting times between 0 and 900 seconds and uniform distribution within this time period. Ranges of parameters for the ride-pooling scenario are: (i) *percPass*: 40, 80; (iii) *percTaxi*: 10, 20,…70. (iii) *capacity*: 1…7. The example of a single run of ride-pooling algorithm in SUMO-GUI is given in a video (Demo, 2024) (green triangles are taxis, yellow are private cars, blue dots are passengers).

For all series of experiments, *greedyShared* algorithm provided disadvantage in 2-40% of CO2 emissions compared to the baseline. This confirms the conclusions from (Li et. al., 2022) that ride-pooling is not always beneficial in terms of emissions compared to single ride mode. *greedyShared* algorithm has a limitation on maximum occupancy (only two passengers may share the ride), and for the simulated scenario this was insufficient to reduce emissions compared to the private car mode. The other reason for the low performance is that we compare emissions of taxi trips which include non-occupied legs (e.g. from the initial location of a taxi to the first pick-up) with private car mode when the cars are spawned at the origins of the passengers.

The results for different groups of evaluated metrics for *maxOccupancy* algorithm, fixed levels of demand and supply and varied capacity are presented in Figure 2. Increasing the capacity leads to the decrease in the waiting time (Figure 2a), however, increasing the capacity over 4 does not lead to larger reduction of waiting times which can be explained by the nature of the demand in the simulated scenario (a number of passengers which simultaneously wait for the boarding, is restricted).

Detour time and detour distance increase with the increase of the capacity (Figure 2b), because larger number of passengers share the rides. The optimal value of the capacity for the passenger satisfaction measures is equal to 4. In the single-ride mode (capacity equal to 1), large waiting time eliminates the benefits of the absence of detours (Figure 2a, Figure 2b). With capacity equal to 3, detours are already significantly increased while waiting time is still high. For the optimal value of capacity, waiting time already reached the plateau, but detours did not increase compared to capacity equal to 3.

Figure 2c represents taxi fleet usage measures. For single-ride case, there exist gaps between passengers resulting in the high values of idle time/distance while for high capacity values the supply is larger than demand which explains lower taxi usage. The occupancy rate which is calculated as the average number of passengers for the occupied legs, reaches the plateau after capacity equal to 4 because there are no more waiting passengers to pick up.

Finally, Figure 2d illustrates sustainability metrics. One can see that there is a minimum value of taxi capacity after which ride-pooling provides emission benefits (up to 15% for CO_2). This is related to the fact that for small average occupancy values the reduction in the overall number of cars does not compensate for increasing detours (Figure 2b). Summarizing, the experiments confirm that the ride-pooling is not always beneficial compared to single-ride trips, and one needs to determine the optimal value of capacity for the combination of ride-pooling algorithm and the level of demand in the studied scenario. As Figure 2 shows, this problem is multi-objective as optimal values of the capacity differ for passenger satisfaction, taxi fleet and sustainability measures. Thus, the future research may include the development of meta-algorithm which selects the parameters of ride-pooling to maximize the joint objective. As the testbed that we present in this study can be used as an external simulation environment, the reinforcement learning approach would be applicable for this purpose.

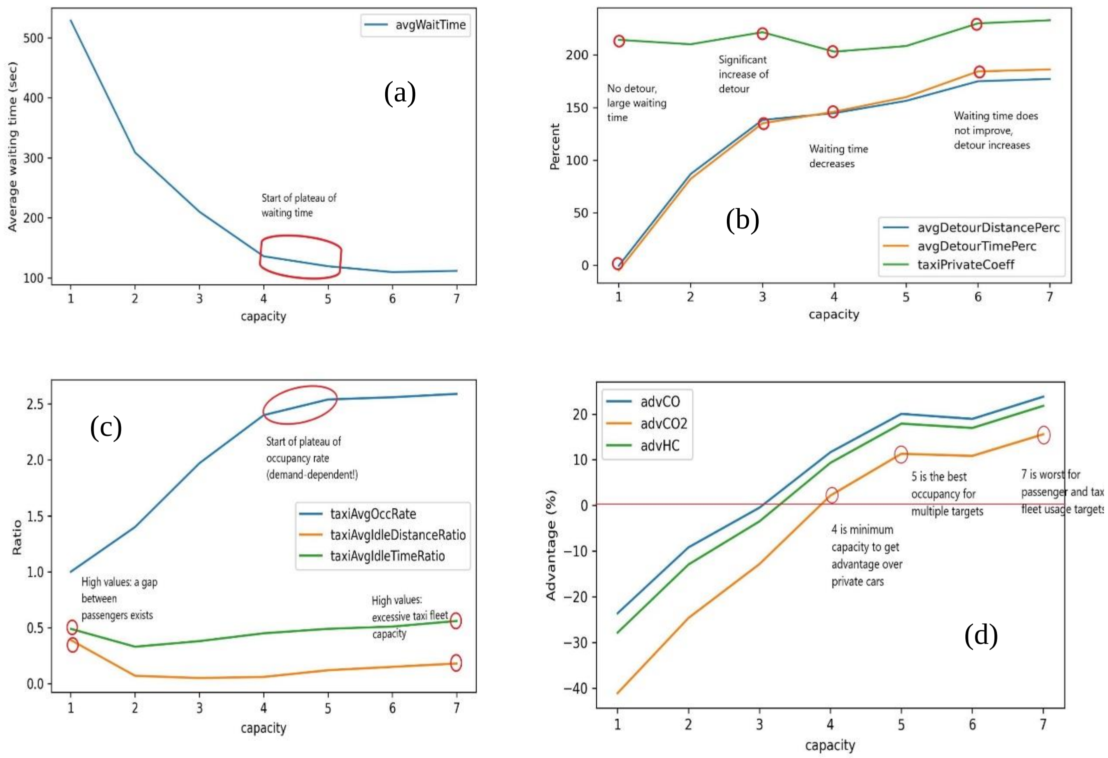

Figure 2 – Evaluated metrics for varying taxi capacity for percPass=80, percTaxi =20, maxOccupancy algorithm: (a) Average passenger waiting time, (b) Passenger satisfaction measures, (c) Taxi fleet usage measures, (d) Emissions measures

4. CONCLUSIONS

In this study, we present a method and the testbed for evaluating ride-pooling algorithms for different groups of metrics, namely, passenger satisfaction, taxi fleet usage and sustainability metrics, with explicit modelling of emissions using micro-simulation approach with SUMO traffic simulation platform. The experimental study is performed for two ride-pooling algorithms (optimizing detour times and taxi fleet usage, respectively) and for a variety of simulated scenarios with different levels of supply, demand and taxi capacity. Our main findings are as follows: (i) explicit modelling of emissions is necessary for the development of sustainable ride-pooling algorithms, (ii) heuristic ride-pooling strategies may not always be beneficial in terms of emissions compared to dedicated cars, (iii) three groups of metrics (passenger satisfaction, taxi fleet usage, emission metrics) needs to be accounted in a target function. Thus, the future work may be focused on the development of multi-objective reinforcement learning algorithms for sustainable ride-pooling with explicit emissions modelling.

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