Extending AGADE Traffic to Simulate Auctions in Shared Mobility Services

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ABSTRACT

With the number of individual vehicles meeting the capacity limit of urban road infrastructure, the deployment of new mobility services may help to achieve more efficient use of available resources and prevent critical overload. It may be observed that most of the seats in private vehicles remain unused during the journey. Therefore, increasing the number of passengers per vehicle may potentially reduce the overall number of vehicles on the road. For this purpose, ridesharing services can be an effective instrument, if supply and demand for rides are efficiently matched. The use of ridesharing depends on multiple factors, e.g. individual preferences, available infrastructure, alternative mode options (the quality of public transport). Auctions have been established successfully in comparably complex markets in which supply and demand of limited resources have to be matched efficiently. However, finding an appropriate auction design is difficult and can hardly be examined without experimentation that requires appropriate simulation instruments. In this paper, we extend the AGADE Traffic simulator with ridesharing options and implement functionality for simulating and evaluating auctions in shared mobility scenarios. We demonstrate application of the simulator with different auction designs on a ridesharing use case with commuter traffic.

INTRODUCTION

Resource depletion caused by population growth has led to a critical reassessment of ownership and consumption behaviour. This has resulted in the emergence of the *sharing economy* which maximises the use of a resource by sharing it and thus allowing others to gain access when it is typically not in use or when it can be used together (see [1]). For example, private vehicles that are used regularly for commuting spend most of their time parked and thus occupy the already limited space in urban areas. It can be observed that many commuters who travel in private vehicles still have extra room to pick up additional passengers that may have the same destination or a destination that can be reached without significant deviation from the original journey. The rise of shared mobility has challenged the traditional model of vehicle manufacturers (selling parts and vehicles) and encouraged a shift towards selling mobility as a service. Experts estimate that in the long term, mobility will establish itself as a service [2], leading to major investments to advance the deployment of shared mobility services [3]. A specific type of shared mobility is *ridesharing*. Ridesharing is a term for organised carpooling, traditionally arranged among friends and family, but now commercialised as a service to connect individuals that have never met. Such services can help to reduce the number of private cars in use by encouraging individuals to share journeys occupying a single vehicle in place of two or more. The use of commercialised ridesharing depends on the mechanisms through which individuals are brought together, in this paper, such mechanisms are referred to as the *pooling process*. The use of auction-based techniques can improve the optimisation of the pooling process, facilitating better use of the available transportation capacity. Finding an effective auction technique that optimises the sharing of journeys within a ridesharing scheme can be difficult. The use of a simulation tool allows the evaluation of auction mechanisms in silico before deployment into actual rideshare schemes. For this purpose, we extend the AGADE Traffic simulator with functionalities to simulate ridesharing and flexibly "plug in" different auctions mechanisms. We give demonstration by simulating different implementations of ridesharing in commuter traffic.

This paper is organised as follows: The following sections provide a short introduction to the theoretical background of auctions in mobility and then give a discussion on related work. Following this, we present implemented extensions for AGADE Traffic to simulate ridesharing as well as flexible integration of different auction mechanisms for the pooling process. As an example, we perform two simulations for a commuting scenario and look at the changes in simulation output when implementing different auction mechanisms during the pooling process. Finally, summary and conclusions are given as well as indications for future work.

PRELIMINARIES

Auctions are mostly known as a buying or selling process in which individuals place bids to purchase a particular item or service. More formal descriptions have been given in literature where auctions are referred to as *a structured form of negotiation between multiple parties whereby a collective decision about a price, an amount or other attributes is made* [4]; or *a pair of outcome functions which allocate one or more items in exchange for the bidders' fees that depend on their strategies* [5]. The latter definition has a more generic phrasing, indicating that the use of auctions is not exclusively limited to buying and selling processes. Rather, they should be considered as an instrument to organise the access of individuals to the same limited resources. Depending on how auctions are implemented (auction design), strategies of participating individuals may vary and therefore lead to different outcomes [6]. This suggests that a carefully implemented auction design can lead to an outcome favoured by the auction designer which in economics makes this a powerful instrument for guiding self-interested individuals towards social benefit. Relating these ideas to the current challenges in mobility, the application of auctions can help to manage access of individuals to the already available transport capacity e.g. by improving the pooling process in commercialised ridesharing.

RELATED WORK

During the last decade the commercial sector of shared mobility has grown significantly, the same interest can be observed in research on traffic simulation. Previous reviews on traffic simulation, such as [7] demonstrated that there are a number of applications available to conduct such simulations. A number of studies [8], [9], [10] have demonstrated simulation of different problem scenarios related to ridesharing. Many currently available traffic simulation packages do not implement appropriate features to simulate auctions in ridesharing, despite the concepts being established. [11] have proposed an incentive compatible Dynamic Ridesharing (DRS) solution based on auctions whereas the authors of [12] investigated the effects of offering bonuses to get prioritised during the pooling process when vehicles are in shortage. A related study by [13] simulated a ridesharing system in which payments are negotiated through a Vickrey auction. It was noted that experiments described within the current literature, were primarily implemented using custom implementations thus not making use of available traffic simulators even though they offer a lot of potential for reusing common traffic concepts. This shows a need for available traffic simulators to be extended with additional functionality to simulate the application of auctions in shared mobility. Based on this, we focus our work on extending the AGADE Traffic simulator to simulate different auction designs in ridesharing.

METHOD

AGADE Traffic is an agent-based traffic simulator that focuses on modelling individuals and their travel behaviour. The simulator integrates semantic technology to model preferences and knowledge of individual agents. This allows agents to be modelled with a broad knowledge of the world which can be used for implementing decision-making behaviour. The detailed modelling of individuals and their behaviour makes AGADE Traffic particularly suitable for researching the effects of new mobility concepts not only on global system behaviour but also on individuals [14]. For example, the design of the carpooling process in ridesharing services can have a significant impact on whether individuals make use of these services. However, simulating this type of scenario requires the current AGADE Traffic model to be extended. In particular, the travel behaviour of individual agents needs to be extended to allow *ridesharing* to be included in their decisions. Implemented agent behaviour is structured in the two phases *prejourney planning* and *en route replanning*. In this work, relevant modifications primarily affected prejourney planning in which the agent makes a decision about its mode of transport. This decision is based on the highest mode utility which is computed according to the personal preferences of the agent [14]:

$$U_{TT}(a, m, m_c) = \sum_{\tau \in T} u(\tau, m) \cdot a_\tau - c(m_c, m) \qquad (1)$$

Where a is an agent with P_a the set of agent preferences on traffic-related aspects T. T is modelled based on survey data provided by [15] and contains the aspects $flexibility$, *time*, *reliability*, *privacy*, $safety$, *monetary_costs*, *environmental_impact* and *convenience*. Based on this, $u(\tau, m)$ defines the utility of mode m with regard to a specific mode attribute $\tau \in T$ and $a_\tau \in P_a$ the preference value of τ for agent a. Furthermore, there is a cost for modal change which is modelled through the function $c : M \times M \to \mathbb{R}$ with $c(m, m')$ the associated cost for changing from mode m to mode m' with $c(m, m') = 0$ for $m = m'$. M contains an artificial mode m_{null} that represents the start of a journey with $c(m_{null}, m) = 0$ for all $m \in M$.

As an extension, we have added a new mode of transport $M \cup \{m_{ridesharing}\}$ which may be treated as a private vehicle (e.g. car) given that the driver travels alone. The situation changes when an additional passenger joins the vehicle, to share the journey. Thus, values for $u(\tau, m_{ridesharing})$ are based on utilities of $u(\tau, m_{car})$ with deviations depending on the number of additional passengers. Within AGADE Traffic the values of mode utilities are specified by user input as part of the simulation setting. For each additional passenger, mode attributes for $m_{ridesharing}$ need to consider the following deviations as compared to the attributes of m_{car} :

- the utility on $flexibility$ decreases as changes to the

journey have an immediate effect on the other passengers and therefore need to be taken into consideration.
• the utility on *time* decreases as entry and exit of additional passengers as well as potential detours account for extra effort.
• the utility on *reliability* decreases as there are more dependencies to be considered e.g. passengers being late or running into traffic jam due to additional detours.
• the utility on *privacy* decreases as there are more passengers within the vehicle.
• the utility on *safety* decreases due to unpredicted behaviour of passengers e.g. distractions.
• the utility on *environmental_impact* increases as emissions can be split among the driver and the passengers. However, if it wasn't for ridesharing, passengers might have chosen an even more environmentally friendly mode of transport, which is why the effect might be mitigated.
• the utility on *convenience* decreases as there is less room for movement within the vehicle as well as storage space.
• the utility on *monetary_costs* needs to be handled specific to the scenario depending on who is travelling e.g. cost can be evenly split among friends, but is probably paid by the driver when they are driving members of their own family.

In addition to the above a new type of agent is added to the simulation. Within previous versions of AGADE Traffic, the traveller agent selects a mode of transport and then conducts their journey without the option to take additional passengers. The addition of ridesharing to the simulation model will require vehicles and travellers to be modelled as separate agents. Traveller behaviour needs to be extended to model passive passengers while vehicles must be able to contain information about passengers as well as the designated driver. In particular, traffic participants (travellers) hold relevant information about their journey (e.g. origin and destination) as the purpose of travel emerges from the individual. Furthermore, individuals can only use vehicles that are actually at their disposal for example, vehicles that they privately own. Thus, traffic participants need to register vehicle agents to which they have access. Vehicle agents may vary in their passenger capacity depending on their type (e.g. car, truck, van, motorcycle). Based on this, vehicle agents need to record detailed information about which agents are inside the vehicle at any given time during the simulation. Figure 1 gives an overview of the information contained in the different types of agents.

Ridesharing is typically organised either in private settings (among friends or family members) or through the use of commercialised ridesharing services. The former requires implementation of social relations within the agent population. The *Barabási-Albert* algorithm can be used to model social structures and communities (see [16], [17]). The algorithm starts with a user-defined number of agents (σ_0) and iteratively adds new agents, thus creating a social network with eventually n

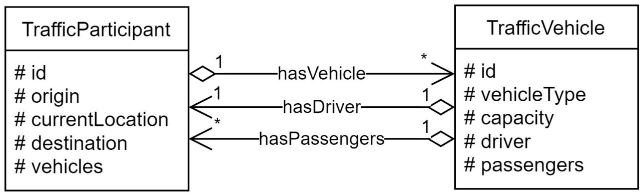

Fig. 1. Separation of traffic participants and vehicle agents.

agents. A new agent is connected to σ existing agents, where σ is a user-specified parameter, with a probability proportional to the number of connections within the existing agent population. As a result, agents with more connections have a higher probability to gain new relations which leads to a social network in which there is a small number of agents with a high number of connections (hub nodes) and the majority of agents with only a small number of connections (satellite nodes). This process is also referred to as *preferential attachment*. However, in the real world new relations among individuals are often established in their immediate surrounding which is typically correlated to the geographic distance of their home location [18]. Consequently, agents in the simulation that are located in the same region should have a higher probability of knowing each other than agents that live farther away. Applying the standard algorithm to the agent population generates a social network that does not reflect this appropriately (see Figure 2). Thus, we modified the Barabási-Albert algorithm into a two-step procedure. We first apply the algorithm to subsets of the agent population based on their home location and clustered by geographic regions. This produces a social network for each of these regions. In the second step, the algorithm is applied to establish transregional relations on the full set of agents. This time the user-specified parameter σ will be chosen to produce fewer connections as the probability for transregional relations should be smaller in comparison to the process of generating connections within the immediate surrounding (see Figure 3).

Information on social relations is stored within the agents. Agents can use this information to arrange ridesharing in a private setting. Let A be the set of agents in the social network with $\Delta, P \subseteq A$. Δ is the set of drivers that contains agents that have chosen to travel with an individual vehicle (car) and P is the set of potential passengers containing agents that are looking for ridesharing options. Based on this, we define $\Delta \cap P = \emptyset$. Furthermore, each $a \in A$ has a list of social contacts Λ_a. As we are dealing with ridesharing in a private setting, we assume that agents connected through a social relation are in frequent contact and therefore are informed about the timetables and mobility needs of their friends and family members. Based on this, agents $a_1 \in P$ look in their list of social contacts Λ_{a_1} for potential drivers $\Delta_{a_1} = \Lambda_{a_1} \cap \Delta$, and successively request $a_2 \in \Delta_{a_1}$ sorted by shortest eucledian distance $d(a_1, a_2)$ for whether a_2 would be willing to make a detour and give a_1 a lift. In the event that a_2 still has empty seats in its vehicle, the number of seats

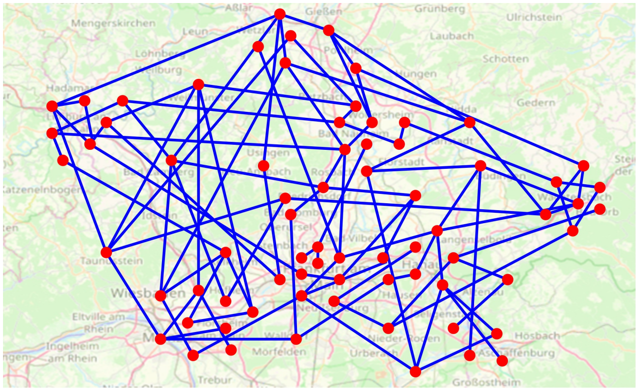

Fig. 2. Example of a social network generated with the standard Barabási-Albert algorithm

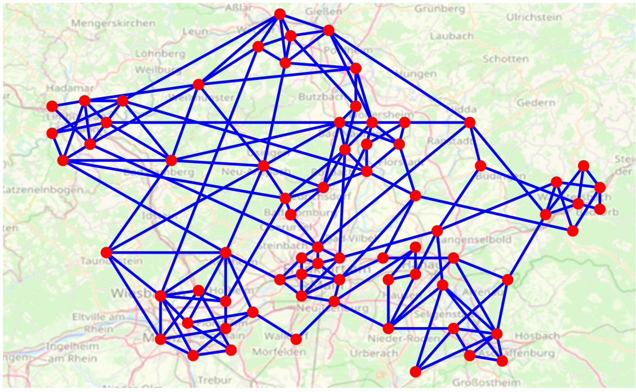

Fig. 3. Example of a social network generated with the modified Barabási-Albert algorithm

already assigned is used to determine the utility U_{TT} of both a_2 and a_1 to take a_1 as an additional passenger. Ridesharing is agreed when U_{TT} determines this to be the best option for both of them. Otherwise, the process continues for a_1 and alternative options are explored (finding another driver or changing to a different mode).

In contrast to this, commercialised ridesharing eventually causes interactions between unrelated individuals i.e. strangers. Agents have therefore been extended with an additional attribute that models their attitude towards travelling with strangers based on survey data provided by [19]. Interaction between these individuals is typically conducted through a digital service platform and thus is managed by the given processes of the platform. Connecting drivers and interested individuals is an essential task of these service platforms which can be implemented using auctions. To simulate the effects of different auction designs, we extended AGADE Traffic with a central interface to flexibly plug in implemented auction algorithms. This interface requires a list of agents participating in the auction and returns the result of the auction i.e. a list of drivers with their assigned passengers. During the auction, agents submit bids according to the implemented mechanism of the auction to request a ride. Before submitting a bid, the agent verifies whether the utility U_{TT} for ridesharing still exceeds all of the alternative mode

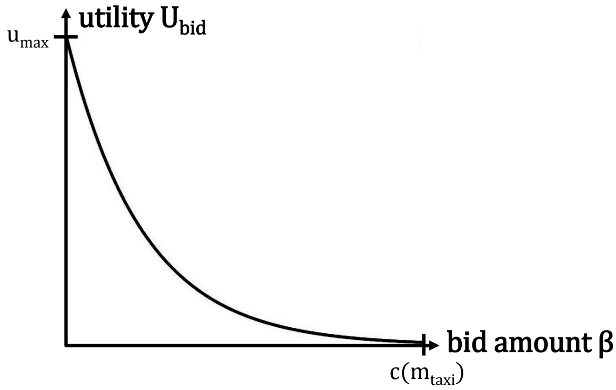

Fig. 4. Function to compute utility of a bid

options based on the *monetary_costs* of the bid. In particular, let β be the amount of the bid to be submitted. β determines *monetary_costs* for the mode $m_{ridesharing}$ and thus has an effect on the mode attribute $u(monetary\_costs, m_{ridesharing})$. However, the computation of $u(monetary\_costs, m_{ridesharing})$ from β differs for every agent as β must be set in relation to the location where the agent wants to be picked up as well as the distance the agent wishes to be transported. For this purpose, we compare β to the costs of local taxi services $c(m_{taxi})$. Local taxi services typically charge a fixum based on the area of the pick-up location and the destination, as well as an additional fee depending on the actual travel time and driven distance. We use estimated $c(m_{taxi})$ as a reference value for which the utility U_{bid} approximates 0 as it would be possible from this point on to simply call a taxi and forget about ridesharing. In addition to this, U_{bid} takes the maximised value on the utility scale $u_{max} = 10$ if a ride turns out to be free of charge. Based on this, we model U_{bid} using the following function (see Figure 4):

$$U_{bid}(\beta, m_{taxi}, u_{max}) = u_{max} * e^{(\beta * \frac{\ln(0.003)}{c(m_{taxi})})} \qquad (2)$$

Furthermore, we define:

$$u(monetary\_cost, m_{ridesharing}) = U_{bid} \qquad (3)$$

Computed utility $u(monetary\_cost, m_{ridesharing})$ is then used to determine U_{TT} for ridesharing. In the event that U_{TT} for ridesharing is expected to fall below the utility of an alternative mode option, the agent exits the auction and thus opts for a different mode of transport. Otherwise, the agent continues in the auction and submits its bid. The final costs of the ride are determined when the auction is completed.

USE CASE

As an example, we look at a scenario situated in the German city of Gießen. Gießen is located within the Rhine-Main region which is part of one of the largest projects for on-demand mobility in Europe [20]. The project involves the launch of a new commercialised

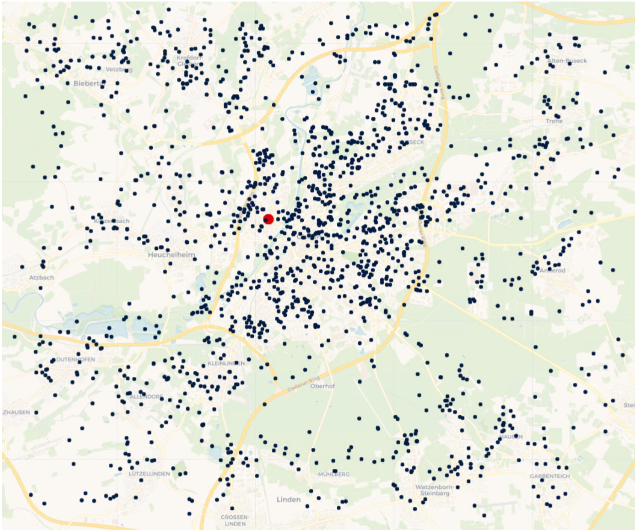

Fig. 5. Agents scattered over the simulated area around Gießen

ridesharing service. Based on this, we simulate different implementations of ridesharing for individuals commuting to a music concert. The music concert takes place at the local event venue *Hessenhallen* which is designed to accommodate 1500 visitors. Assuming that all the tickets for the concert are sold out, we generate an agent population that replicates the empirical distribution of visitors. In particular, census information for persona profiles of the agents is based on survey data provided by [21]. Furthermore, we use a *Poisson* distribution to model the preferred arrival time before the start of the concert. Visitors of the event typically commute from the surrounding area which is why we focus on a map that covers the main residential areas (min. lat: 50.5291; min. lon: 8.5875; max. lat: 50.6257; max. lon: 8.7726). As visitors may come from every direction, we randomly scatter the agents over the map and assume agents to start their journey from their assigned home location (see Figure 5). Details of simulation data as well as source code of the simulation are available at GitHub.[1]

Before the start of the journey, agents determine mode of transport to travel to the event venue. Visitors who have a relatively short commute may be able to walk or cycle to the venue, whereas other visitors will have to rely on public transport or travel by car. This decision depends on the range of transportation modes that is available to the agent which was modelled using data from [19]. Furthermore, mode selection is based on highest utility U_{TT} which is computed based on personal preferences a_τ as well as attributes of the mode $u(\tau, m)$ (see Equation 1). Mode attributes in this scenario are based on assumptions and take utility values from a scale of 1 to 10, with 1 being the lowest and 10 the highest utility (see Table I). In Germany, public transport is typically included in the ticket for the event which in this scenario leads to $u(monetary\_costs, m_{publictransport})$ being maximised. Note that with this publication we do not

[1] see https://github.com/kite-cloud/agade-traffic

TABLE I: Mode utilities $u(\tau, m)$

	Bike	**Walking**	**Public Transport**	**Car**	**Ridesharing for n add'l. passengers**
Flexibility	6	5	6	9	9 - n
Time	5	0	8	10	10 - n
Reliability	10	10	7	7	7
Privacy	9	9	1	10	10 - n
Safety	5	6	10	9	9 - n
Environmental Impact	9	10	8	1	$1 + n$
Monetary Cost	8	10	10	1	tbd from auction
Convenience	1	2	6	10	9 - n

aim at presenting a validated simulation model but to demonstrate how our approach can be used for experimenting with different auction designs in ridesharing.

Individuals that travel by car may offer their friends a lift (private ridesharing). For this purpose, social relations among individuals have been implemented using our modified Barabási-Albert algorithm that uses a two-step procedure to generate (1.) social connections within the region and (2.) transregional relations. We applied *k-means clustering* based on the euclidean distance of their home locations to obtain subsets of the agent population $\Gamma \subseteq A$ according to the 22 residential areas. For each of these subsets Γ we then generated a social network using the Barabási-Albert algorithm with $\sigma_0 = 5$, $\sigma = 5$ and $n = |\Gamma|$. In the second step, transregional relations have been generated within the whole agent population A with $\sigma_0 = 2$, $\sigma = 2$ and $n = |A|$. To reduce the number of individual vehicles, the event organiser encourages visitors that travel by car to not limit ridesharing to their private surrounding but to also consider giving other visitors a ride in exchange for a compensation (commercialised ridesharing). For this purpose, the organiser of the event provides a digital platform that connects drivers and individuals looking for ridesharing options via an auction system. Drivers can indicate their willingness to take additional passengers as well as the number of remaining seats. Interested individuals can submit a monetary bid to request a ride from one of these drivers.

As an artificial use case, we look at *whether different implementations of the pooling process can increase the use of ridesharing* and thus improve the load of passengers in vehicles. This would help to relieve the limited parking space at the venue as well as reduce the environmental impact caused by the event. For this purpose, we performed two simulation runs ($S1$,$S2$) with identical agent population. Note that our current implementation uses stochastic elements only while computing preferences a_τ, thus keeping the subsequent decision processes deterministic. This simplifies analysis of the use case, making comparison of simulations easier. In both simulations, drivers first organise ridesharing in their private surrounding and in the case that a driver is willing to take additional passengers, the agent will participate in the auction process. $S1$ uses an *English auction* for the pooling process while $S2$ implements a *first-price sealed-bid auction*. In the *English* *auction* agents successively submit bids which raises the price until only one agent remains. Agents are allowed to bid multiple times until the highest bid wins. In comparison to this, the *first-price sealed-bid auction* allows agents to only bid once. Bids are submitted independently without any knowledge about their competitors. Same as in the *English auction*, the highest bid wins.

To measure the effects of the different implementations of ridesharing in this scenario, the following performance indicators have been defined. The first indicator looks at the *avg. passenger load in vehicles* which is computed using arithmetic means over the number of agents travelling together in one vehicle. This indicator only considers the two transportation modes m_{car} and $m_{ridesharing}$. Furthermore, we look at indicators that measure the *number of privately organised ridesharing* as well as the *number of commercially organised ridesharing*. We also measure environmental impact using performance indicators on aggregated travelled distances. In particular, *global travel distance* is computed as the sum of the overall distances travelled by the set of all agents. This indicator adds up the travel distance of each agent regardless of whether they were travelling within the same vehicle. In contrast to this, *combustion distance* only considers the two transportation modes m_{car} and $m_{ridesharing}$ as they produce additional exhaust gases. In this case, agents that travel in the same vehicle do not cause additional *combustion distance*. Public transport has been excluded from the calculation of this indicator, as rail and bus services generally operate regardless of the amount of passengers associated with the event.

As this is an artificial use case we can only speculate about the results of the simulation. We note that conclusions on behavioural changes require a well-designed research effort with field experiments which is not within the scope of this publication. However, as we aim to present AGADE Traffic as a tool to examine this type of scenario we demonstrate how it can be used to compare simulation output for the artificial use case: Simulation results in AGADE Traffic include information on the modal choices of the agents (see Table II). The comparison of both simulation runs shows that the total amount of ridesharing increases in $S2$. Drivers and passengers that participate in ridesharing can be examined separately. While the amount of ridesharing drivers show a slight decrease, a more significant increase can be observed in the number of ridesharing passengers. Performance indicators in Table III reveal that this increase exclusively applies to *the number of commercially organised rideshares* as *the number of privately organised rideshares* remains the same. Thus, it can be concluded that the increasing use of ridesharing is the result of changes in the auction design. As the English auction in $S1$ allows agents to look into the bids of the others, agents only need to submit bids that are slightly higher than the others. This may lead to the final bid turning out to be lower than the winner would have been willing to pay. In contrast, as agents in $S2$ are limited through the *first-price sealed-bid auction* to only bid once without any knowledge of their competitors, agents are more likely to bid what they are actually willing to pay. As a result, bids in $S2$ tend to be higher than in $S1$ which increases the utility for drivers to accept additional passengers and thus leads to more rideshares. We note that the indicator *average passenger load in vehicles* reflects this appropriately (see Table III). Furthermore, it can be observed that the two indicators on *global travel distance* and *combustion distance* have increased. This shows that promoting the use of ridesharing in this artificial use case does not necessarily improve environmental impact. One reason for this is that picking-up passengers requires a detour which causes additional travel distances. Another reason can be seen in the shift in modal choices when looking at which agents have actually switched to ridesharing (see Table II). In particular, the number of pedestrians, cyclists and individuals that use public transport has decreased. Furthermore, the number of car drivers also decreases as they are counted as *ridesharing drivers* when taking additional passengers or switching to being *ridesharing passengers*. All in all, results show that rather than getting visitors to abandon their private vehicles, ridesharing in this scenario has served as an alternative to more environmentally friendly options which has led to counterproductive effects. This concludes our demonstration of how AGADE Traffic can be used as a tool to simulate different implementations of auctions in ridesharing.

TABLE II: Comparison of modal choices

Modal Choice	**S1**	**S2**
Ridesharing (Driver)	21.53%	21.46%
Ridesharing (Passenger)	27.33%	30.73%
Walking	01.00%	00.86%
Bike	02.13%	01.86%
Public Transport	22.46%	21.53%
Car	25.53%	23.53%

TABLE III: Performance indicators

KPI	**S1**	**S2**
Avg. passenger load in vehicles	1.58	1.68
Number of privately organised rideshares	253	253
Number of commercially organised rideshares	157	208
Global travel distance [km]	10033.60	11028.95
Combustion distance [km]	8656.04	9705.58

CONCLUSIONS AND FUTURE WORK

This paper addressed the issue of developing a tool to allow the evaluation of ridesharing schemes through simulation. Finding an appropriate auction design can be difficult as outcomes may vary depending on the regional infrastructure as well as the range of available mobility services. To meet these difficulties we extended the AGADE Traffic simulator with additional functionality to simulate private and commercial ridesharing schemes. The solution presented implements an interface that allows different auction types in ridesharing to be evaluated. As a use case, we demonstrated the use of AGADE Traffic to simulate different auction methods within a commuting scenario. The next stage of this work is to utilise the tools developed for AGADE Traffic to formally evaluate the effects of auctions in ridesharing within real-world case studies and to evaluate the effectiveness of differing auction types when applied to ridesharing problems.

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