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Agent-based simulation of autonomous taxi services with dynamic demand responses

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Abstract

An agent-based simulation approach is presented, which makes it possible to capture the dynamic interplay between a supply of autonomous vehicle fleets with distinct operational schemes and a population of artificial persons based on an established multi-agent traffic simulation framework. The simulation is able to show how agents react to the new travel options and make consistent decisions based on a well-defined framework of utility scoring.

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Keywords: autonomous vehicle; taxi; pooling; demand; agent-based simulation

1. Introduction

Today planners and policy makers face an ever more complex traffic system. While they need to ensure smooth traffic flows in the city centres, at the same time an acceptable level of service must be provided in remote areas. Minimisation of energy consumption and a decrease of the environmental impact of the vehicle fleet are desired, while the overall increase in travels asks for a steady growth in system capacity.

Recently, autonomous vehicles have become a reality with autonomous taxi services driving their first miles all around the world.[1,2,3] Future predictions foresee a considerable increase of the effective road capacity through intelligent and interconnected vehicles.[4,5] A fleet of autonomous taxis would drastically reduce the need for parking space in the city and would, therefore, open space for additional lanes to increase the capacity or even make cities are more friendly, greener and liveable place[6]. Individual fleet and vehicle sizes might bridge the gap between remote and high-demand areas. On the flip-side, more vehicles might be observed on the roads if autonomous vehicles [AVs] get so comfortable, cheap and available that aggregated transit forms such as busses or trains become obsolete[7].

Numerous simulation studies exist, which examine the impact of AV taxi or pooling fleets under different assumptions, such as the costs of such a service, expected capacity gains and increases in vehicle kilometres travelled

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(VKT), fleet sizes, and levels of technology acceptance and maturity.[8,9,10,11] Along these lines, assumptions on the travel demand are obtained and simulated, but rarely are feedback dependencies on the generated demand taken into account.[12] To understand these feedbacks, however, is the next step to arrive at relevant results for fleet operators or policy makers. While estimates exist on the necessary fleet sizes for specific levels of demand, there is not a clear quantification what demand one would expect in the first place.

The agent- and activity-based traffic simulation framework MATSim[13] makes it possible to simulate the dynamic interplay between travellers and the supplied means of transport in a traffic scenario. It has already proven to yield consistent results with taxis and AVs[14], but no dynamic feedback effects on the travel demand for these services have been simulated yet. The paper at hand introduces a new extension to the framework which makes such investigations possible.

The simulations in this paper are performed on an artificial test scenario and aim at showing the feasibility and features of the simulation approach. Hints are given on how to transfer the method to a real-world scenario in future work.

2. Methodology

In the following, a short introduction to the simulation framework MATSim[13] shall be given. The core component of the framework is an artificial population of agents, where each of them has a repository of possible travel plans. Those plans incorporate activities that shall be performed throughout a day with their respective locations, durations and arrival times, as well as information on which transport modes the agents plan to use to move between these places. For each iteration of the 24h simulation, the agents try to realise their plans in the traffic simulation. Possibly, they may get stuck in a traffic jam due to congestion, or they might arrive too early at work. The obtained realisation of their daily plan is assigned a score according to the durations and distances covered in specific modes, their arrival times, waiting times, their stay durations at an activity and other dimensions. For the next iteration, the simulation chooses a new plan from the repository with a probability dependent on the associated scores. The selected one can be modified ("re-planned") slightly in any of the choice dimensions mentioned before. For instance, the mode of travel for a leg may be changed at random. This process is performed for a predefined number of iterations until the average scores of the executed plans in the population start only to fluctuate slightly around an equilibrium state.

In that equilibrium state, the travel choices of the agent population can be examined, and aggregate measures can be obtained. This way, it is possible to cover emergent phenomena such as congestion and to observe reactions towards new (or removed/closed) elements in the traffic system.

By default, the framework can simulate walking agents, car travellers on the capacitated road network, as well as public transit lines. This framework has been extended by Bischoff and Maciejewski[15] to incorporate transport services, which can individually react to agent requests. The paper at hand further extends these dynamic services with the scoring and re-planning elements mentioned before. As will be shown here, this way it is possible to simulate travel choices for autonomous vehicles.

The AV framework can simulate multiple operators with different characteristics. Each operator consists of:

- A *fleet generator*, which defines where (and how many) AVs are located in the traffic network at the beginning of an iteration. So far, only a generator based on population density is implemented, which is used throughout this paper.
- A *dispatcher*, which defines how to handle requests by agents, who choose to use an AV service. The dispatcher is notified whenever an agent in the simulation wants to depart with the associated operator. The dispatcher has then the task to manage the fleet, i.e. control the movements and pickup/dropoff activities of the dynamic AV agents. A versatile Java interface is provided to integrate new dispatching algorithms in an easy way.
- A *pricing structure*, which can either be implemented individually or can be based on a standard implementation, where one can define monetary costs per time and distance, as well as the billing intervals. Also, it is possible to simulate payments per trip and day (which could be translated to a subscription scheme).

Concerning additional choice dimensions, agents have each leg for the AV mode in their daily travel plans associated with a specific operator. These operators are chosen within the iterative re-planning, where the operator for a leg

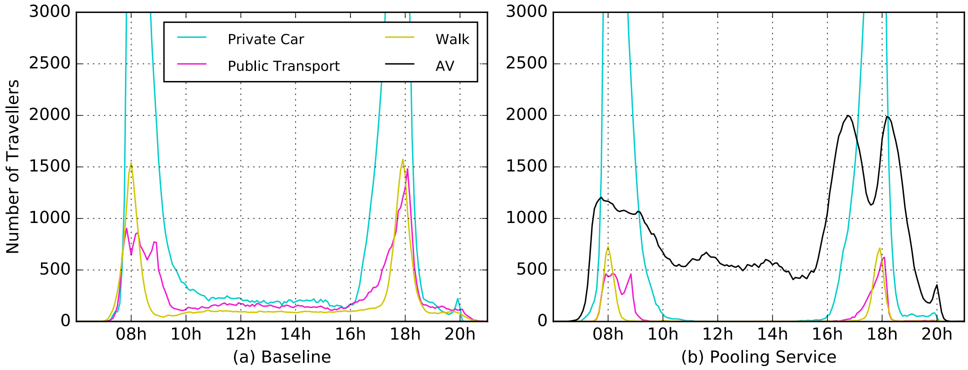

Fig. 1. Share of active travellers (waiting and in-vehicle) by daytime for the baseline scenario (a) and the AV *Pool* service (b).

may be changed in each iteration at random. Since plans with better scores are preferred in the simulation, only the operator that fits best in an agent's plan will be selected in the long run.

3. Scenario Setup

The test scenario that is used in this paper is loosely based on the road network of the city of Sioux Falls. While the population has been generated by Chakirov and Fourie[16], an updated fine-grained road network, which is necessary for the simulation of AVs from Hörl[17] is used. The scenario contains agents that have the options to use a car, use public transport or walk by default and offers five bus lines with several bus stops all over the city. The car ownership in the population is around 88% in the population of around 84,000 people.

A new scoring framework is introduced that is based on average travel choices in Switzerland. It aims at providing a more consistent behaviour of the agents and is used as a test case for future scenarios in this setting, for which a more detailed overview is given in Appendix A.

Additionally, two different AV operators are introduced to the scenario, first separately and then in a combined simulation. The first operator (*Taxi*) uses a heuristic dispatching algorithm[14], which dispatches the closest AV to an incoming request if there is any AV available, but dispatches the latest AV that has gotten free to the nearest customer in the under-supply case, where requests are piling up. The second operator (*Pool*) uses the same algorithm, but tries to aggregate requests. As long as a customer is waiting for an AV to arrive, incoming requests will be attached to his ride if pickup and dropoff locations each match within a radius of 400m. If a trip reaches the maximum number of passengers (4 per AV), aggregation is stopped.

The pricing for the services is based on a cost calculator for autonomous vehicles by Bösch et al.[18], which is consistent with the suggested scoring framework for Switzerland. For the *Taxi* operator, the customers pay 0.48 CHF/km, while the price is only 0.28 CHF/km for the *Pool* service. Please note that the cost calculator is based on assumptions such as the occupancy of the vehicles and the overall fleet size, which would be fixed to 2.6 pax and 1000 vehicles throughout the experiments. Costs are computed on a per-meter basis without flat fares in this simulation to stay consistent with the cost calculator. This issue will be addressed in future scenarios.

4. Simulation Results

The two operators have been introduced to the simulation separately with fleet sizes of 1000 vehicles. Figure 1 shows how the *Pool* operator is used throughout the day compared to the baseline scenario without any AV service. One can see that a considerable amount of users is opting for the new mode, especially during off-peak hours, where the AV operator substitutes almost any other form of transport. Interestingly, two distinct peaks of AV usage emerge around the afternoon peak. Seemingly, agents try to avoid the high congestion at these times. Since AVs are also heavily substituting the walking mode, a large number of very short trips is to be expected within these peaks. Figure

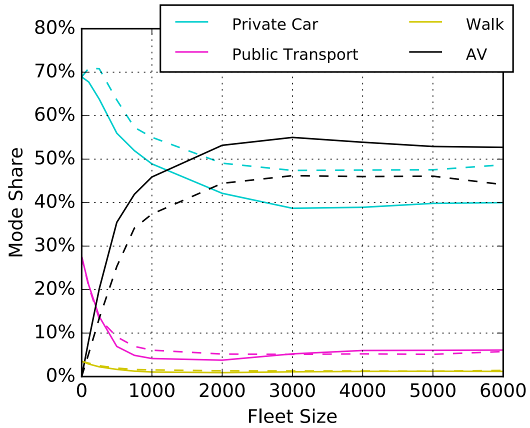

Fig. 2. Mode shares dependent on the AV fleet size for the *Taxi* (*solid*) and *Pool* operator (*dashed*).

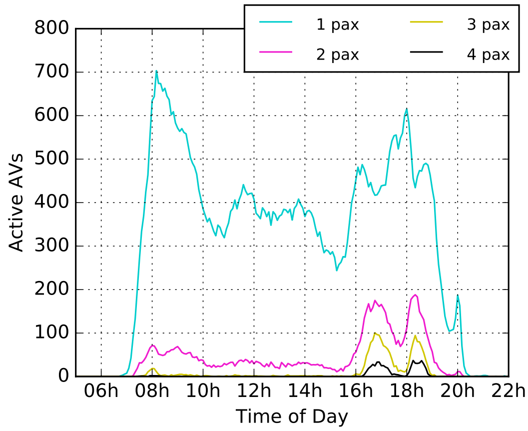

Fig. 3. Travellers per AV for the *Pool* service.

Table 1. Simulation Results with 1000 AVs in each fleet. Peak times from 7am to 10am and 4pm to 6pm.

	Taxi	*Pool*
Mode Share	45.90%	37.37%
Mode Share (Peak)	31.08%	21.13%
Mode Share (Off-Peak)	98.76%	93.74%
Average Travel Time [min]	9.26	10.71
Average Travel Time (Peak) [min]	12.58	15.99
Average Travel Time (Off-Peak) [min]	5.58	6.58
Average Waiting Time [min]	4.56	3.76
Average Waiting Time (Peak) [min]	7.34	6.22
Average Waiting Time (Off-Peak) [min]	1.45	1.83
Average In-Vehicle Time [min]	4.69	6.95
Average In-Vehicle Time (Peak) [min]	5.24	9.77
Average In-Vehicle Time (Off-Peak) [min]	4.07	4.74
Empty Ride Distance	28.01%	30.57%
Average Passenger Trip Distance [km]	4.02	5.61
Fleet Occupancy by Vehicles		
Average (24h)	36.15%	35.65%
Maximum (24h)	99.87%	99.94%
Passengers per Active Vehicle		
Average (24h)	1	1.13
Maximum (24h)	1	1.64

Table 2. Simulation results for the mixed scenario. Peak times from 7am to 10am and 4pm to 6pm.

	Taxi	*Pool*
AV Mode Share	48.63%	
Operator Share	45.23%	54.03%
Operator Share (Peak)	53.77%	46.23%
Operator Share (Off-Peak)	37.05%	62.95%
Average Travel Time [min]	9.51	10.01
Average Travel Time (Peak) [min]	12.01	14.18
Average Travel Time (Off-Peak) [min]	4.79	6.13
Average Passenger Trip Distance [km]	3.71	5.02

2 shows that the fleet size of 1000 AVs does not yet reach saturation in demand for either scheme, but that a supply of twice or thrice the current size would attract an even larger share of customers.

Table 1 summarises selected traffic statistics of the two operator scenarios. The overall mode share for the *Taxi* operator is higher than for the *Pool* operator at peak and off-peak hours. One can see that the *Taxi* service performs better regarding travel times throughout the day. Interestingly, when the travel time is split up into the time from the request until entering the vehicle (waiting time) and in-vehicle time, one observes that agents on average have to wait almost one minute longer for the *Taxi* service than for the *Pool* service at peak times. For the off-peak, the *Taxi* service provides longer waiting times. The in-vehicle time for the *Pool* service is longer at any stage during the day and almost 4:30 min longer than for the *Taxi* service at peak hours.

One has to be careful with the interpretation of these values. While travel times and distances are longer for the *Pool* mode, this is highly influenced by the additional pickup and dropoff elements in the trips. However, it is also possible that slightly different trip characteristics emerge due to the service structure. A more thorough analysis could be done here, which may yield interesting results in a more advanced scenario.

In general, one can interpret these travel and wait times as the time that the agents are willing to invest on average to travel with an AV service. Obviously, this is influenced by the price level. What can be seen here is that agents bargain the increased travel and waiting times against considerably lower prices in the *Pool* service.

Furthermore, what Table 1 shows is that the average number of customers in the pooling algorithm is at 1.13 pax and 1.6 pax at most. Especially trips with three or four passengers are rare as is shown in Figure 3. This occupancy does not resemble the assumption of 2.6 pax from the cost calculator and therefore a higher price should be set. This increase, in turn, would lower the share of users and change the customer characteristics of the service. The simulated *Pool* operator has a competitive advantage due to the low price, but realistically this would not be economical. In future work, an iterative process of obtaining fleet measures, generating adjusted prices from the cost calculator and feeding them back into the simulation will give deeper insights into options for the pricing structure of AV services. Nevertheless, this demonstration shows how exogenous assumptions may be used to ensure the validity of the agent-based demand simulation.

Finally, the combined case is examined, where a fleet of 1000 AVs is introduced into the system for each operator simultaneously. Table 2 shows how agents make decisions between the two options. As expected, the overall share of AV usage is higher than in the previous cases due to the increased total supply of AVs. Interesting to see is the AV market share of the operators: While the *Taxi* service is favoured at peak times, the *Pool* service attracts the larger share of customers at off-peak hours. This behaviour can be explained by the low costs of travelling combined with the reduced aggregation at these times.

5. Conclusion

In the experiments, it has been shown that MATSim can produce a consistent demand reaction from the introduction of autonomous vehicles to the traffic system. Based on the collective learning approach, the framework lets agents adapt their travel choices to the new options.

It has been shown that multiple operators can offer their services in parallel in the simulation, which opens possibilities for detailed studies on pricing and fleet management schemes where multiple approaches can compete against each other. As a next step, the proposed dispatching algorithms might be supplemented by intelligent re-balancing strategies for vehicles which are not serving customers at times of the day.

The framework has yet to be tested with real scenarios, such as for the city of Zurich. There, it would be possible to provide meaningful travel time and VKT estimates, that do not only arise from artificial network properties. Interesting will also be to observe spatially distributed choice effects between urban and rural areas. Part of this work will be the iterative integration of the cost calculator, which will make it possible to obtain reasonable operator costs dependent on the demand and realistic price structures including flat fares and subscription schemes. Such an extension will give clearer predictions on the usage of autonomous vehicles in a real-world scenario.

Appendix A. Utility Scoring Framework

Table A.3. Utility framework for the proposed scenario.

	Constant [CHF]	Travel Time [CHF/hr]	Distance [CHF/km]	Waiting Time [CHF/hr]
Car	-2 CHF* - 2.21 CHF*	-23.29 [19]	-0.176 [18,21]	0
Public Transport	0	-14.43 [19]	-0.53 [18]	-24.13 [19]
Walk	0	-33.20 [20]	0	0
AV *Taxi*	0	-14.43*	-0.48 [18]	-24.13 [19]
AV *Pool*	0	-14.43*	-0.28 [18]	-24.13 [19]

* Assumptions explained in the text.

Plans in the MATSim framework are scored according to utility functions. In general, there is one marginal utility for performing an activity (β_{act}) and several other parameters that define the legs. In general, the scoring of a leg can be described as:

$$U = C_m + \beta_{m,trav} \cdot t_{trav} + \beta_{m,dist} \cdot d_{trav} + ... + \beta_{m,wait} \cdot t_{wait} \tag{A.1}$$

It consists of a constant disutility per leg (C_m), a marginal utility of travel time ($\beta_{m,trav}$) and a marginal utility of travel distance. Mode-specific additional terms like a waiting time scoring for public transport or autonomous vehicles may be added.

Table A.3 summarises the scoring framework that is used in this paper. For the constant of the car mode, it is assumed that a disutility of paying 2 CHF (for parking) and 2x2min of walking (to and from the car) is added per leg. The assumption for the valuation of AV travel time is that AVs are as comfortable as public transport (which might be a conservative assumption). To account for fixed costs not being recognised for daily travel choices of private car users, only a fraction of the full costs from the cost calculator is included in the parameter value. Based on information on the average Swiss driver, the relevant non-fixed costs are assumed to be around 40%.[21] To use these parameters in MATSim the recommended utility conversion scheme[22] is applied to the values.

References

1. Fortune (2016) Uber Debuts Self-Driving Cars in Pittsburgh, `http://fortune.com/2016/09/14/uber-self-driving-cars-pittsburgh/`, Accessed 20 September 2016.
2. Navya (2016) Launch of NAVLY in the confluence district of Lyon, `http://navya.tech/2016/09/launch-of-navly-in-the-confluence-district-of-lyon/?lang=en`, Accessed 10 July 2016.
3. Abdullah, Z. (2016) Grab to partner with nuTonomy for driverless car trial, users can book vehicles for free, `http://www.straitstimes.com/singapore/transport/grab-to-partner-with-nutonomy-for-driverless-car-trial-users-can-book-vehicles`, Accessed 19 December 2016.
4. Tientrakool, P., Y.-C. Ho and N. F. Maxemchuk (2011) Highway capacity benefits from using vehicle-to-vehicle communication and sensors for collision avoidance, paper presented at the IEEE Vehicular Technology Conference, 5.
5. Friedrich, B. (2015) Verkehrliche Wirkung Autonomer Fahrzeuge, in M. Maurer, J. C. Gerdes, B. Lenz and H. Winner (eds.) Autonomes Fahren, chap. 16, 331-350, Springer-Verlag, Berlin.
6. Skinner, R. and N. Bidwell (2015) Making Better Places: Autonomous vehicles and future opportunities, WSP — Parsons Brinckerhoff.
7. Litman, T. (2015) Autonomous Vehicle Implementation Predictions: Implications for Transport Planning, Victoria Transport Policy Institute.
8. Fagnant, D. J., K. M. Kockelman and P. Bansal (2015) Operations of Shared Autonomous Vehicle Fleet for Austin, Texas, Market, Transport Research Record, 2538, 98106
9. LaMondia J. J, D. J. Fagnant, H. Qu, J. Barrett and K. Kockelman (2016) Shifts in Long-Distance Travel Mode Due to Automated Vehicles: Statewide Mode-Shift Simulation Experiment and Travel Survey Analysis, Transportation Research Record, 2566, 1-11.
10. Boesch, P. M., F. Ciari and K. W. Axhausen (2015) Required autonomous vehicle fleet sizes to serve different levels of demand, Transport Research Record, 2542, 111 - 119.
11. Maciejewski, M. and J. Bischoff (2016) Congestion effects of autonomous taxi fleets, Submitted to TRANSPORT
12. Chen, T. D. and K. M. Kockelman (2016) Management of a Shared Autonomous Electric Vehicle Fleet: Implications of Pricing Schemes, Transportation Research Record, 2572, 37-46.
13. Horni, A., K. Nagel and K. W. Axhausen (2015) The Multi-Agent Transport Simulation MATSim, Ubiquity, London.
14. Bischoff, J., M. Maciejewski (2016) Simulation of City-wide Replacement of Private Cars with Autonomous Taxis in Berlin, Procedia Computer Science, 83, 237-244.
15. Maciejewski, M. (2015) Dynamic Transport Services, in A. Horni, K. Nagel and K. W. Axhausen (eds.) The Multi-Agent Transport Simulation MATSim, chap. 23, 145-152, Ubiquity, London.
16. Chakirov, A. and P. J. Fourie (2015) Enriched Sioux Falls Scenario with Dynamic And Disaggregate Demand, Arbeitsberichte Verkehrs- und Raumplanung, 978, IVT, ETH Zurich, Zurich.
17. Hörl, S. (2016) Implementation of an autonomous taxi service in a multi-modal traffic simulation using MATSim, Master Thesis, Chalmers University of Technology, Gothenburg.
18. Bösch, P.M., F. Becker, H. Becker and K.W. Axhausen (2017) Cost-based Analysis of Autonomous Mobility Services, Working paper, 1225, IVT, ETH Zurich, Zurich.
19. Schweizerischer Verband der Strassen- und Verkehrsfachleute VSS (2009) Kosten-Nutzen-Analysen im Strassenverkehr, SN 641 922a, Zurich.
20. Becker, H., F. Ciari and K. W. Axhausen (2017) Empirical analysis of free-floating car-sharing usage patterns in Switzerland, Working Paper, 1226, IVT, ETH Zurich, Zurich.
21. TCS (2016) Kosten eines Musterautos. `https://www.tcs.ch/de/auto-zweirad/auto-kaufen-verkaufen/auto-unterhaltskosten/kosten-eines-musterautos.php`. Accessed 1 December 2016
22. Nagel, K., B. Kickhöfer, A. Horni and D. Charypar (2015) A Closer Look at Scoring, in A. Horni, K. Nagel and K. W. Axhausen (eds.) The Multi-Agent Transport Simulation MATSim, chap. 3, 23-33, Ubiquity, London.