Simulation of autonomous taxis in a multi-modal traffic scenario with dynamic demand

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Sebastian Hörl, Corresponding Author
IVT, ETH Zürich
CH-8093 Zürich, Switzerland
+41 44 633 38 01
sebastian.hoerl@ivt.baug.ethz.ch

Alexander Erath
Singapore ETH Centre (SEC)
1 CREATE Way, 06-01 CREATE Tower, 138602 Singapore
alexander.erath@ivt.baug.ethz.ch

Kay W. Axhausen
IVT, ETH Zürich
CH-8093 Zürich, Switzerland
+41 44 633 31 05
axhausen@ivt.baug.ethz.ch

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ABSTRACT

Given the rapid technological advances in developing autonomous vehicles (AV), the key question appears not so much anymore how, but when AVs would be ready to be commercially introduced. Therefore, it is very timely to explore how the new way of travelling will shape the traffic environment in the future. Questions regarding the environmental impact, changes in infrastructure and policy measures are widely discussed. Most likely, the introduction of AVs will not only add an option to the traveller’s choice of means of transport, but also shape how people interact with the traffic environment. From a transport planning point of view, key questions concerning the introduction of AVs as a new means of transport are how it will influence travel behaviour, how supply and demand for AV will balance, how it impacts the viability of existing public transport services and how AVs will impact congestion and demand for parking.

In this report, a new simulation framework based on MATSim is presented, allowing for the simulation of AVs in an integrated, network- and population-based traffic environment. The demand evolves dynamically from the traffic situation rather than being a static constraint as in numerous previous studies. This allows for the testing of various scenarios and concepts around the introduction of AVs while taking into account their feedback on the travellers’ choices and perceptions.

Using a realistic test scenario, it is shown that even under conservative pricing a large share of travellers is attracted by autonomous vehicles, though it is highly dependend on the provided fleet size. For sufficiently large supplies it has been found that for the autonomous single-passenger taxis in this report the vehicle miles travelled increase up to 60%.
INTRODUCTION

Recently, the technological development in the area of self-driving cars has reached a point, where extensive tests in open extra-urban traffic are possible and conducted with great public interest (1–3). Experts expect Autonomous Vehicles (AVs) with intra-urban driving capabilities to get widely available by the year 2030 (4). These developments raise questions about their societal, economical and regulatory impact, beyond a bare technological perspective on AVs (5, 6).

One central question that needs to be answered is how self-driving cars would affect the current traffic situation. So far, a number of studies have been performed to assess the fleet size needed to effectively convert a certain fraction of trips performed by private cars to AVs, mainly taking into account acceptable waiting times as a measure of acceptance. It has been found that AVs might reduce the total vehicle fleet in Singapore by 60% (7). In the Zurich region, AVs could replace up to 90% of private cars (8), the same result has been found for Berlin (9). Also in (10) it has been reported that one AV has the potential to replace nine private cars in a study on Austin, Texas. However, the actual number of trips taken by AVs is expected to be lower if actual mode choices by travellers are taken into account. These, in turn, are highly dependent on factors such as the pricing structure and the availability of AVs (11).

The fact that AVs are able to reduce the number of vehicles on the road gives rise to the assumption that congestion can be reduced, less parking space is needed and new opportunities for land use are created. In contrast to those claims stands that people might be inclined to take more trips by vehicle (12, 13) or generate additional unmanned trips for repositioning of AVs and for the transportation of goods. This would effectively increase the total number of trips. It exemplifies that the introduction of AVs not only adds a new transportation mode to a traveller’s options, but that AVs themselves are likely to change the way people use the traffic network. Such feedback effects have not been taken into account in any simulation study so far.

In this report, a simulation framework is introduced, which makes it possible to simulate AVs in traffic scenarios with high spatial detail and dynamic demand. By altering travel plans on a day-by-day basis the aim is to observe shifts in mode choices and departure times, dependent on the availability of AVs and congestion. For an artificial test network, we also test how the number of AVs influence service levels and mode choice. An analysis of the resulting traffic conditions is performed.

The next section will give an overview of the newly developed simulation framework, describing its principal components, while the third section will explain how a suitable simulation scenario is set up. Finally, results will be presented in Section 4, leading to the final conclusions in the last part.

METHODOLOGY

The agent- and activity based traffic simulation framework MATSim (14) is based on the simulation of persons in a per-individual, time-step based manner, making it possible to study how phenomena such as congestion arise from the individual daily travel plans of millions of agents. While some elements in their plans, such as the locations of home and work, are fixed, other choice dimensions are updated from iteration to iteration, allowing the agents to make departure time or mode choices using an utility-based scoring framework. Therefore, by adding AVs to the set of options, agents react to the new offer in a dynamic way, which makes MATSim particularly suited for the study and prediction of their rational choice behaviour and
the emerging transport network performance, including travel and waiting times \((15)\).

The co-evolutionary learning approach that MATSim follows can be interpreted as a choice set generator, where each agent holds a set of daily travel plans while only one is executed per iteration. Once the plan has been executed, among other measures, the travel time, travel distance and time spent in activities, is scored. While legs are assigned mode-specific disutilities for waiting time, travel time, travel distance and a per-trip disutility, agents gain utility by performing an activity, such as staying at work within predefined opening hours. At the end of one simulation day, agents evaluate how their daily plan worked out in terms of utility, compare it to previously executed plans and possibly modify some elements to then perform a selection among the available plans for the next simulated day. After simulating a sufficient number of days, all agents will arrive at a set of favorite plans, which worked best and the average score of all agents in the population stabilizes around an equilibrium. This is the point where a stable traffic scenario is reached, that can be used for further analysis.

For the purpose of simulating AVs in MATSim, a new component has been developed \((16)\). In the current version, AVs are residing at certain locations in the network until a customer request is issued. Once this happens, a heuristic dispatcher algorithm \((9)\) determines the best assignment of an AV to the customer request and the AV drives to the pick-up location. Subsequently, it lets the customer get into the vehicle and proceeds to the drop-off location at which the customer can get off the vehicle. Afterwards the AV resides at the current node in the network until a new request is assigned. Please note that only one customer per AV trip is transported in this study. Furthermore, at the beginning of a simulation day, AVs are distributed randomly according to the population density in the scenario.

In order to see how the introduced AV mode changes the traffic situation, a baseline simulation is performed without AVs. Subsequently, simulations with different fleet sizes are done. For each of those cases, the equilibrium traffic environment is examined and the travel statistics are collected from the recorded actions of all agents in the simulation with a time resolution of five minutes.

**SCENARIO SETUP**

In this study an artificial test scenario \((16)\), based on the city of Sioux Falls is used. It features a detailed road network based on current OpenStreetMap data and a population, which has been obtained by a demand generation based on actual data from the city of Sioux Falls \((17)\). In the context of MATSim, this demand describes agents’ daily activities, but does not define specific departure times or travel modes. Those are chosen dynamically by the simulation. The population consists of 84,110 persons, which have home and, dependent on employment status, work or secondary activities assigned at locations out of 24,718 facilities in the network. The scenario, which can be seen in Figure 1, features a bus network consisting of five bus lines with a headway of five minutes.

The utilities for performing an activity or traveling in a specific mode are based on a set of behavioral parameters as used in another study on the impact of AVs on mode choice in the U.S. by \((11)\). There, trips are scored according to per-trip values of travel time (VOTT), which are sampled from two distributions for work and non-work trips with mean $16.40 and $11.98, respectively. In MATSim, a parameter \((\beta_{act})\) for the scoring of time spent at an activity needs to be defined, which has been chosen as the weighted average of those two values, with 20% of trips for work and 80% for other purposes, leading to an utility of $12.86 per hour for performing an activity. Similar parameters have to be defined per mode, though it has to be
FIGURE 1  Map of the test network with the density of facility on a 100x100x resolution.
TABLE 1  Conversion of the utility framework from \(^{(11)}\) to the activity-based utility framework of MATSim.

<table>
<thead>
<tr>
<th>Utility</th>
<th>Assumption (^{(11)})</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Performing an Activity</td>
<td>Value of Travel Time ((V))</td>
<td>(\beta_{act} = V = $12.86/hr)</td>
</tr>
<tr>
<td><strong>Private Car</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Trip</td>
<td>Parking $2 (compromise between sub-urban and downtown costs)</td>
<td>(C_{car} = -$2)</td>
</tr>
<tr>
<td>Per Hour</td>
<td>Travelling</td>
<td>(\beta_{trav,car} = -V + \beta_{act} = $0/hr)</td>
</tr>
<tr>
<td>Per Kilometer</td>
<td>Costs $0.608 per mile</td>
<td>(\gamma_{car} = -$0.378/km)</td>
</tr>
<tr>
<td><strong>Public Transport</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Trip</td>
<td>Fare $2</td>
<td>(C_{pt} = -$2)</td>
</tr>
<tr>
<td>Per Hour</td>
<td>Travelling</td>
<td>(\beta_{trav,pt} = -V + \beta_{act} = $0/hr)</td>
</tr>
<tr>
<td>Waiting per Hour</td>
<td>Twice the travel disutility</td>
<td>(\beta_{wait,pt} = -2 \cdot V + \beta_{act} = -$12.86/hr)</td>
</tr>
<tr>
<td><strong>Walking</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Hour</td>
<td>Travelling</td>
<td>(\beta_{trav,walk} = -V + \beta_{act} = $0/hr)</td>
</tr>
<tr>
<td><strong>Autonomous Taxi</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Per Hour</td>
<td>Travelling, 35% of private car (V)</td>
<td>(\beta_{trav,av} = -0.35 \cdot V + \beta_{act} = $8.359/hr)</td>
</tr>
<tr>
<td>Per Kilometer</td>
<td>Fixed rate of $0.85 per mile (conservative estimate)</td>
<td>(\gamma_{av} = -$0.528/km)</td>
</tr>
<tr>
<td>Waiting per Hour</td>
<td>Twice the travel disutility</td>
<td>(\beta_{wait,av} = -2 \cdot V + \beta_{act} = -$12.86/hr)</td>
</tr>
</tbody>
</table>

kept in mind that driving a car for instance is penalized implicitly, because no activity is being performed. Therefore the utilities from \(^{(11)}\) have been converted according to Table 1. For comparison, the distance-based pricing from that paper is adopted here.

SIMULATION RESULTS

First, a simulation with 1000 AVs is compared to the baseline scenario, followed by an analysis of the effect of different supply levels on the aggregated measures in the scenario.

Single Supply Case

In this test case, 1000 AVs are introduced into the system and their effect on the aggregated and hourly mode share are examined. Furthermore, the resulting waiting times and service occupancy are investigated.

Table 2 shows the total mode shares on the left-hand side, indicating that the share of private car trips falls from 73.38% to 53.51% after the introduction of AVs, while the share of public transport drops significantly from 13.15% to 3.30%. Also, the share of walk trips decreases roughly by half, leading to the resulting share for autonomous taxi trips of 37.30%.
In order to verify that these changes are not based on random movements, the right-hand side of Table 2 shows the directed migration towards the AV mode. By comparing the daily travel diaries of each agent in the baseline and AV scenario, it is found that 72.41% of private cars users stick to their chosen mode, while 78.03% of public transport trips and 57.23% of walk trips are converted to the AV service. Other choices, e.g. from public transport to private cars are very rare, with only 1.08% of public transport trips being converted.

These changes in mode shares can be observed in more detail on an hourly basis, as depicted in Figure 2: It shows that the number of ongoing trips at each time during the day stays quite the same for private cars, except for off-peak hours, while the number of public transport trips decreases over the whole daily range. In off-peak hours car trips, as well as, public transport trips are almost completely substituted by the AV service.

An interesting effect for the AV mode is, that its peak times are wrapped around the peak hours generated by private car and public transport trips. This can be explained by the unavailability of AVs due to congestion, but also because agents gain more flexibility in avoiding the congestion peak since they are able to perform more directed trips than it is possible with the public transport network.

In order to get insights into how the AV service is performing, Figure 3 shows the customer waiting times for AVs compared to public transport by time of day. Clearly, at peak times the waiting times for AVs at around 10 or 15 minutes, respectively, exceed the ones for public transport, which stay roughly constant over the whole day at around five minutes. This effect is created because of customers waiting for their assigned AVs to pick them up from their current locations. In one time bin, at around 8:30 it can also be seen that AVs have an even faster response time than public transport, due to high congestion on the roads used by the buses.

At off-peak times, the AV service is able to provide slightly shorter waiting times than the headway of the public transport network. While it can be seen that both modes perform at around five minutes, one also has to keep in mind that public transport users in this scenario on average need a total of five minutes per trip to walk to and from the stop facilities. Taking this
FIGURE 2 Comparison of the baseline scenario with the case of 1000 available AVs. The upper plot shows the number of private car trips in both scenarios, while the lower one shows public transport, together with the added autonomous taxi service.

into account, the AV service is almost five minutes faster per trip and therefore highly attractive.

From an operator perspective, the off-peak hours are interesting, since only between 500-800 AVs of the available 1000 are active, letting almost 20% to 50% of the fleet stay in idle mode. Looking at the number of AVs, which are actually transporting a passenger, one arrives at a percentage of only 10% to 25%, since half of the AVs are busy driving to a pickup location at any time of the day.

Varying Supply Levels
To see the impact of the supply level on the effects of the AV mode, different fleet sizes are tested.

As can be seen in Figure 4, varying the number of available AVs does significantly affect the share of private car trips. While the share drops considerably until a fleet size of about 1000 AVs, demand for car trips still declines, although at a lower rate if AV fleet sizes are increased further. At 8000 AVs there is still a steady decline, indicating that AVs are attractive enough to replace even more private cars in this model, despite the conservative pricing of $0.85 per mile. In terms of public transport a stable share of around 2-3% is reached after the introduction of
In terms of waiting times, Figure 5 shows that off-peak waiting times decline rapidly with the introduction of more AVs until around 1500 vehicles, after which a response time of less than three minutes can be offered. For peak-hours the waiting times initially increase with the number of AVs, indicating that the small fleet sizes are not able to handle the demand properly. Only after 500 AVs the waiting times start to decrease and the added number of AVs is increasingly better suited to handle the generated demand. These findings resemble results from (8), where it has been claimed that especially for small fleet sizes and low spatial availability covering the demand is difficult.

Comparing Figure 4 and Figure 5, two regimes can be found. With small fleet sizes, the decrease of off-peak waiting time per added AV leads to a quick increase of AV usage, while after around 2000 AVs the increase in shares is explained by a decrease of peak waiting times, on which each added AV has a weaker effect than for the off-peak times.

Another interesting measure is the total distance driven during one simulated day. Figure 6 shows that the total covered distance by travellers increases from around 510,000km to
FIGURE 4  Share of the available travel modes in a percentage of the total number of trips, dependent on the number of available AVs.

590,000km, for high supplies, which is already an increase of 15% from the baseline case. It can be attributed to agents accepting longer travel distances by using the faster AVs instead of walking or public transport. A bigger increase can be seen in travelled distance by vehicle, with a peak of around 740,000km for 1000 AVs, which is a huge increase of 60%. Looking at the respective measures only for AV trips, it can be seen that at 1000 AVs around 100,000km are driven solely for the purpose of picking up passengers, which is around 30% of the total driven distance by AVs and 15% with respect to the total number of vehicle kilometers.

Computation Time

In terms of computation time, measurements have been taken in an isolated environment on a standard current CPU (Intel Core i7-4600U). The baseline scenario performs 500 iterations in around 01:30h, while the scenarios with added AVs need for the same number roughly 04:40h. However, the runtime for the AV simulation is expected to decrease after further optimizations are implemented and possible improvements in parallelization are taken into account. In general, the simulation is sensitive to the actual number of trips performed, not the bare number of additional AV agents. These measurements have been done while simulating 100% scenarios. Scaling down the simulated population and network has the potential to further decrease computation times, though suitable scaling methods for the simulation of AVs are yet to be investigated.
DISCUSSION

Simulation Framework

The results show that the newly developed AV simulation framework for MATSim is able to simulate autonomous vehicles integrated into the overall traffic situation. As expected, agents make rational choices towards the new mode based on the perceived utilities, leading to a new traffic situation. By varying parameters, such as presented here with the supply level, the user is able to get insights into the complex dependencies and interrelations, which are introduced through the new mode. Finally, the simulation allows the user to make predictions of the impact of AVs on today’s traffic, given well-defined assumptions.

In terms of computation time, the test scenario can be simulated in a reasonable time, yet tests need to be done on differently sized scenarios to assess how the framework is scaling and how much more improvement in computation time is necessary.

Simulation Results

The simulation results show that with a conservative pricing of $0.85 per mile, AVs are highly attractive to users of all existant travel modes. While private car owners switch due to the
increased value of travel time, public transport travellers choose AVs to avoid waiting times, as well as walking distances.

The low demand for AVs during off-peak hours introduces a dilemma for the service operator: If a sufficiently large fleet size is used, which serves well at peak hours, a large fraction of AVs is not in use during the day. In addition to the fact that these vehicles are not earning revenue, but are running idle, the question for parking space needs to be answered, or how the AVs can be strategically repositioned during off peak periods. Another alternative could be to provide services such as the transportation of goods during those times. In order to analyse this, the simulation of parking facilities and repositioning strategies needs to be added to the simulation. If only small fleet sizes are used, the number of customers decreases, which is likely to decrease the revenue for the operator. Therefore, a concise financial analysis including the investment and running costs and revenues of the AV operator will be necessary to get further insights into the applicability of different pricing models (11).

Finally, from a policy perspective, the simulation shows that introducing AVs will lead to a substantial increase in the total distance driven on the roads, which can be attributed to three influences. First, the increase in per-person kilometers can be explained by people finding it more attractive to travel by AV, although the distance might be longer compared to the walking distance. Additionally, empty rides are being made for picking up passengers and finally, the biggest share of additional mileage is caused by the actual migration of travelers to single-passenger AV trips. This, however, is partly due to the inability of the simulation to
perform shared trips. The additional mileage has negative impacts on congestion, but also on the environmental impact of the traffic system, especially due to the simultaneous reduction of public transport. Therefore the simulation shows clear downsides of an AV service and underlines the significance of intelligent policy-making regarding the new way of traveling.

SUMMARY AND OUTLOOK

In this report a new framework for the simulation of autonomous taxis in the MATSim environment has been presented. It has been applied to a consistent test scenario, leading the simulated agents to make rational decisions about using the added transport mode or staying with the established choice.

The simulation showed that under a conservative pricing scheme of $0.85 per mile the single-passenger AV mode is highly competitive to the established modes, making around 37% of travelers switch. Reasons for that are an increased value of time spent in the vehicle and reduced waiting times compared to commuting by public transport. It has been shown that an AV fleet of around 1000 AVs can operate with response times of around 7 minutes at peak-hours and 3 minutes at off-peak hours.

For the operator perspective, the dilemma between the investment and running costs for a certain fleet size and the number of customers has been pointed out. A further economic analysis as in (11) has still to be done for the calibrated test case reported here. Equally, further work needs to be done on a high-level welfare analysis, including the impacts on environment and congestion, which is caused by the increase in kilometers driven during one day. It is estimated to be 60%.

The simulations in this report are performed on an test network with assumed utilities. The system of utilities used is consistent in itself, leading to reasonable baseline results. The introduction of AVs into the system, based on the utility framework also provides reasonable levels of AV usage under the given pricing. Nevertheless, it has to be pointed out that the scenario is not calibrated against a real city. Such an investigation has yet to be done.

Furthermore, a couple of components, which are not taken into account in this study, could dramatically change the results: First, the initial distribution of AVs in the network is performed through a random assignment based on population density. Different approaches might be possible, such as taking the number of requests at the beginning of the day as a basis or finding an optimal distribution regarding traveller movements. Second, redistribution during services is not performed in this simulation. Finding an intelligent way of letting AVs move while not serving customers might dramatically increase the performance of the fleet. By providing AVs mainly at those locations where requests are soon to be expected, the response times and empty rides might be reduced substantially. In that regard it will be furthermore interesting to implement preordered trips, which could be used as an input for such a redistribution algorithm. Finally, despite decreases in perceived utility, AVs are expected to be used collectively. Taking this into account might additionally increase the performance of the fleet and yield a more realistic picture. Implementing this feature, along with a component to simulate the needed parking space, will be a significant part of future research on the framework.

REFERENCES


