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IMPACTS OF SHARED AUTONOMOUS TAXIS IN A METROPOLITAN AREA

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ABSTRACT

The purpose of this paper is to provide an analysis of potential benefits of a fleet of shared autonomous taxis “aTaxis”, in this paper referred to as Shared Autonomous Vehicles (SAV)) when replacing private car commuter trips in a metropolitan area. We develop a framework for dynamic allocation of SAVs to passenger trips, empty-vehicle routing and multi-criteria evaluation with regard to passenger waiting time, trip times and fleet size. Using a dynamic representation of current private vehicle demand for the Stockholm metropolitan area and a detailed network representation, different scenarios (varying levels of accepted passenger waiting time at origin and accepted % increase in travel time) are compared with respect to passenger travel time, number of vehicles needed and vehicle mileage. The results indicate that an SAV-based personal transport system has the potential to provide an on-demand door-to-door transport with a high level of service, using 5 % of today's private cars and parking places. In order to provide an environmental benefit and to reduce total mileage, an SAV-based personal transport system requires users to accept ride-sharing, allowing a maximum 30% increase of their travel time (13% on average) and a start time window of 10 minutes.

Keywords: Shared Autonomous Vehicle, aTaxi, ride-sharing, Stockholm
INTRODUCTION

Today, cars are grossly inefficient and because of our strong emphasis on individual car ownership, cars are utilized less than 5% of their lifetime, wasting precious natural resources and space when not in use. In Sweden, based on the average mileage for private cars of 12,000 km per year (1), the car usage is 3.5% of the time assuming 40 km/h average trip speed. This means that over 96% of the time the cars are parked, occupying space. This is in line with the values reported elsewhere. Bates and Leibling (2) state that in the UK “The average car spends about 80% of the time parked at home, is parked elsewhere for about 16% of the time, and is thus only actually in use (i.e. moving) for the remaining 3–4% of the time”.

Regarding safety, it is commonly acknowledged that human failure is the dominant cause of car accidents, and according to Forward (3) deliberate violations of traffic rules are the main contributor to road crashes.

In order to assist drivers, various car safety devices have been introduced such as anti-lock braking system (ABS), electronic stability control system (ESC) and adaptive cruise control with lane-keeping assistance. However, with the driver still in charge, these innovations are insufficient in preventing human error. In this context robotics may drastically enhance safety by letting a machine using multiple sensors take the wheel (4). Many car manufacturers actively develop such systems and the horizon for availability of such vehicles is expected to be 2020-2030 (5) (6), with Google leading the field with about 20 self-driving cars, which have logged more than 500,000 miles on public roads and highways (7). In Sweden the Volvo Car Group together with Trafikverket, Transportstyrelsen, Lindholmen Science Park and Göteborg City started the project Drive Me, aiming at testing self-driving cars on public roads in Göteborg (8).

Self-driving / autonomous cars are promising safer, more comfortable travel, lower insurance costs and better fuel-efficiency than current private car transport (9) and are expected to solve the congestion issue in urban areas (10). They will increase resource utilization by enabling entirely new ride-sharing and car-sharing models (4) and dramatically cut travel costs (11). They may be considered a crossover between current car-sharing programs (such as ZipCar (12) or Car2Go (13)), a taxi service and public transportation.

In combination with an efficient public transport system and increased biking and walking, they could be the building blocks of tomorrow’s sustainable transport system, i.e. “a vehicle that improves transportation security and reduces resource depletion and emissions” (14).

Several authors have investigated Personal Rapid Transit systems (PRT) as an on-demand public transport mode on a dedicated network. Strategies for ride-sharing have been verified to reduce fleet requirements without reducing passenger service level (15). In this paper we apply strategies developed for large PRT systems to a large fleet of autonomous taxis.

Relatively few studies exist of SAV-based transport systems. Fagnant et al. (16) use a theoretical grid network with a synthetized demand based on national travel statistics in the US to simulate the travel and environmental implications of SAVs. However the study does not assume ride-sharing. Fagnant shows that the number of vehicles needed is 10% of the current number of private cars and the total mileage increases by 11%. Despite the increase in total mileage (16) shows a reduction in GHG emissions and energy use of 5.6 and 12% respectively. Three reasons are provided to explain the reduction: the use of a single type of car (medium size) for the SAV fleet, replacing less fuel-efficient pickup trucks, SUVs and minivans and representing 47% of all vehicles; the reduction in parking infrastructure; and the reduction in vehicle starts and cold starts. The change in environmental impacts for each of these effects is not reported separately. Another paper by Kornhauser et al. (10) assesses the use of an aTaxi system operating on New Jersey’s roadways, where passengers are loaded and unloaded at dedicated “stations” available within short walking distance (< 5 min). The synthetized demand corresponds to 32+ million trips made by New Jersey’s 9 million inhabitants, where 90% is car traffic. The study includes two ride-sharing schemes: (1) ride-sharing with aTaxi waiting a fixed amount of time for additional passengers destined to any destinations that incur less than a 20% detour for any passenger; (2) ride-sharing where the aTaxi sweeps up a local area to pick-up co-passengers with close-by destination
and about the same start time. The average vehicle occupancy (AVO) is defined as the ratio between the passenger mileage and the vehicle mileage. For ride-sharing scheme 1 with one stop and 5 min waiting time the AVO reaches 2. For scheme 2 with square pick-up and destination areas of 5 km the AVO is 2.16. The fleet size needed to serve the New Jersey demand is 45% of the current private car fleet, as compared to 10% in (16), indicating that the SAVS are not serving as many trips during the day, possibly due to a larger geographic spread of the demand. A third paper (17) provides analytical guidelines for the design of aTaxi mobility systems without ride-sharing, which are applied to the specific case of Singapore to dimension an SAV fleet to serve all ground transport (bus, subway, cars). The trip demand is evaluated from a comprehensive survey gathering information of high-level transportation patterns in Singapore. The trip demand includes nearly 5.6 million trips. The road network is a graph-based representation of Singapore’s road network, and the traffic characteristics (speed and congestion) are estimated using GPS data from about 15 000 taxis (60% of all taxis). The results show that the fleet size needed to keep waiting times below 15 minutes at all times is 300 000 vehicles. This implies that each vehicle is on average serving 20 passenger trips per day.

This paper investigates potential gains of a fleet of shared autonomous vehicles used as taxi (aTaxis) when replacing current private cars for commuting in a metropolitan area, in terms of fleet size, vehicle miles and level of service for passengers. The application focus is the Stockholm metropolitan area, with a dynamic demand representation, ride-sharing and empty-vehicle allocation.

The main research questions addressed in this paper are:

• What is the fleet size needed to serve today's car commuter demand for the Stockholm metropolitan area, while guaranteeing an acceptable level of service to passengers, in terms of waiting and trip time?
• What is an efficient algorithm to assign trips to aTaxi vehicles so that passenger level of service and time efficiency is optimized?
• What is an appropriate algorithm to assign empty trips to match supply with demand at origins?
• What is the impact of such a system in terms of vehicle mileage and fleet size?

The remainder of this paper is structured as follows. First the modeling of SAV systems is described, with focus on the ride-sharing and empty-vehicle routing. Then the modeling framework is applied to the Stockholm metropolitan network and the results of three scenarios are analyzed and put in context with the reported studies. The limitations of this study are discussed and future research directions are discussed in the concluding section.

MODELING SAV SYSTEMS

The trip assignment problem can be modeled as a bi-level optimization problem, where the upper level consists of the assignment of passenger trips to the fleet of SAV vehicles. The assignment of trips is dependent on the travel times on the network, which are output of the lower level of the optimization problem: SAV traffic assignment. The traffic assignment takes the generated trip schedule and generates travel times that are consistent with the resulting traffic on the network. In each iteration the trip schedule is revised and then assigned to the network, which results in updated origin-destination (OD) travel times. In this paper we focus on the upper level of the problem by assuming that OD trip travel times are not affected by the changing trip scheduling. The trip scheduling consists of two main algorithms:

1. An algorithm to assign empty trips to match the asymmetric supply and demand patterns in the network. In the morning peak hour most of the trips start in the periphery and have destinations in the city center, whereas the afternoon period has an inverse pattern.
2. The algorithm to match time-dependent passenger demand for trips to vehicles, whilst respecting certain passenger level of service constraints (wait time, travel time)
FIGURE 1 SAV trip scheduling problem.

Empty trip allocation
The car-sharing algorithm follows the following steps:
1. Take one request for a trip and check which SAVs are free or will be free in time to serve the request.
2. If the number of vehicle candidates is zero then “create” an SAV.
3. If the number of vehicle candidates is more than one then choose the nearest one.

Ride-sharing schemes
An important part of the SAV trip scheduling algorithm is the ride sharing. Sharing a ride is promoted as a way to utilize the empty seats in most passenger cars to lower fuel usage, congestion and transport costs. In this context an SAV-based transport solution can provide an efficient and effortless real-time ride-sharing service.
The resulting optimization problem is known as the Dial-A-Ride Problem (DARP) involving choice of vehicle, and choice of route with constraints on time windows, detours, number of stops and capacity. In a real implementation, the ride-sharing optimization would need to be solved based on the real time demand. One can envisage that many trips will be pre-ordered meaning that a significant part of the demand will be known sufficiently in advance to plan for ride-sharing. In this study, we assume an ideal case where the whole demand is pre-ordered, in other words, we assume a perfect knowledge of the demand over time.
The number of ride-sharing combinations grows very fast with the number of trips. For a given trip from A to B and 4 seats per vehicle, i.e. potentially 3 co-passengers, the number of combinations assuming N candidates for ride-sharing is: \(4 \left(\frac{N!}{(N-3)!}\right)^2\). In order to reduce the number of combinations to be evaluated, we chose to apply the following matching heuristics for ride-sharing divided in three schemes, which are implied sequentially.

Ride-sharing scheme 1: Co-passenger(s) with the same origin and destination
1. Take first passenger in the demand with origin in zone A and destination in zone B and allocate passenger to SAV(n).
2. Find list of candidates from zone A to zone B fulfilling the conditions for start time and travel time.
3. If list of candidates is empty go to ride-sharing scheme 2. If not continue.
4. Among the candidates select the candidate with the earliest start time.
5. Allocate selected passenger to SAV(n).
6. If vehicle is not full, repeat procedure from step 2. to find other potential co-passengers.
The possible SAV trip itineraries are: A-B, AA-BB, AAA-BBB and AAAA-BBBB.
Ride-sharing scheme 2: Co-passenger(s) with same origin but different destinations
1. Find list of candidates from zone A to any zone different from B, let’s call it D, fulfilling the conditions for start time and travel time.
2. If list of candidates is empty then go to ride-sharing scheme 3. If not continue.
3. Evaluate itineraries AA-BD and AA-DB for all candidates and select the itinerary with the shortest travel time for the SAV(n).
4. If the selected itinerary has several candidates then select the candidate with the earliest start time.
5. Allocate selected passenger to SAV(n).
6. If vehicle is not full, repeat the procedure with BD/DB as an unbreakable itinerary. This means that we will evaluate itineraries AAA-DBF or AAA-FDB if itinerary AA-DB was selected or AAA-BDF or AAA-FBD if itinerary AA-BD was selected.
The possible SAV itineraries are: AA-BD, DB, AAA-BDF, FBD, DBF, FDB, DBB, BBD, and AAAA-GBDF, BDFG, GFBD, FDBG, GFDB, GDBF, DBFG, GFDB, FDBG, GDBF, DBBG, GDBD, BBDG, DDBB, BBBD.

Ride-sharing scheme 3: Co-passenger(s) with different origin but same destination
1. Find list of candidates from any zone different from A, let’s call it C, to zone B fulfilling the conditions for start time and travel time. Only itinerary AC-BB is possible since A must be before C.
2. If list of candidates is empty then stop. If not continue.
3. If the itinerary AC-BB has several candidates then select the candidate with the earliest start time.
4. Allocate selected passenger to SAV(n).
5. If vehicle is not full, repeat procedure but now evaluating itineraries ACE-BBB.
The possible SAV itineraries are: AC-BB, ACE-BBB, ACEG-BBBB.

Whereas scheme 1 is trivial, the complexity of ordering pick-ups and drop-offs increases rapidly with schemes 2 and 3. Figure 2 illustrates three possible ride-sharing itineraries with full vehicles: two in the case of scheme 2 and one in case of scheme 3.

FIGURE 2 Example of ride-sharing itineraries: (a) applying scheme 2, (b) applying scheme 3.

The following general rules apply to the ride-sharing scheme implemented in this study.
- Within a destination zone, unloading passengers is done in the same order as they were loaded.
- If several itineraries are possible, i.e. the SAV has different co-passenger alternatives implying different routes/itineraries, then the itinerary with the shortest drive time is chosen.
- If several co-passengers are possible for a given itinerary then the one with the closest start time is chosen.
Assumptions

This section deals with the description of the simulation of ride-sharing to be applied to internal traffic in greater Stockholm.

- The maximum number of passengers in one car. We assume a value of 4 for all scenarios.
- The start time window that a passenger is accepting for being picked-up. We consider 5, 10 and 15 min windows.
- The relative increase in travel time that a passenger is accepting. The increase in travel time is used to allow for detours and for loading and unloading co-passengers in the ride-sharing scheme.
- The time for the passenger to board after arriving at the pick-up location is assumed to be 2 minutes.
- The time for each passenger to get out of the car after arriving at the destination is assumed to be 1 minute.
- The intra-zone travel time at origin and destination zones is modeled based on the area of the zone:

\[
\text{Intra-zone drive time} = \frac{\sqrt{A}}{2v_{ref}}
\]

where A is the area for the zone and \(v_{ref}\) is a reference speed in the zone. The reference speed was assumed to be identical in all zones and equal to 20 km/h.

The load and unload times include all delays associated with picking up and dropping off passengers (getting into or out of possible bays, slowing down, merging into traffic etc.)

CASE STUDY STOCKHOLM METROPOLITAN AREA

In this section we evaluate the SAV trip scheduling algorithms on the Stockholm metropolitan network, (figure 3) using realistic demand for the home-work and work-home commuting.

The Stockholm network consists of 421 demand zones, 11 000 links and covers ca 40 km x 40 km. The network, which is converted from a CONTRAM (18) network, is very detailed and contains link speed limits as well as signal plans for most intersections. Since we consider only the upper level of the SAV trip assignment problem, we assume in this paper that all link speeds are 75 % of their free-flow speeds for the trip assignment. In future work this will be replaced by a dynamic traffic assignment module, which calculates the corresponding link travel times for SAV trip assignments.
The demand was taken from a calibrated regional demand model REGENT (19) and contains the daily vehicle-based home-to-work and work-to-home trips. The total 24h demand consists of 498,732 trips over 132,976 OD pairs. This was then converted to a dynamic demand by fitting morning and afternoon peaks as observed in the toll passage data for central Stockholm from (20). The two demand peaks we fitted assuming Gaussian distribution over time.

**FIGURE 3** The Stockholm metropolitan network.

**FIGURE 4** (a) Number of passages through congestion tolls during a normal working day in Stockholm and Gauss fitting curves. (b) Number of trip starts for H2W and W2H traffic in the synthetized trip demand based on Regent demand.
In order to avoid assumptions for trips with origins or destinations outside the area of study, only internal trips (with both origin and destination within the 40x40km area of study) are considered, leaving nearly 49% of the total traffic (271,868 trips) over 44,015 OD pairs. Table 1 shows the baseline indicators. With current demand, private cars, and assuming no ride-sharing, the total mileage is 2,606,000 km, with an average trip length of 10 km. Total travel time is 66,000 hours, which means 30 min per person (or car). Total parking time is thus 3,196,000 hours, or 23.5 hours per car.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Unit</th>
<th>Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td># person-trips (H2W + W2H)</td>
<td></td>
<td>271,868</td>
</tr>
<tr>
<td># vehicles = private cars</td>
<td></td>
<td>135,934</td>
</tr>
<tr>
<td>Total mileage</td>
<td>km</td>
<td>10</td>
</tr>
<tr>
<td>Average mileage per trip</td>
<td>km</td>
<td>10</td>
</tr>
<tr>
<td>Total travel time</td>
<td>h</td>
<td>66</td>
</tr>
<tr>
<td>Average travel time per person</td>
<td>h</td>
<td>0.5</td>
</tr>
<tr>
<td>Average travel time per private car</td>
<td>h</td>
<td>0.5</td>
</tr>
<tr>
<td>Total parking time</td>
<td>h</td>
<td>23.5</td>
</tr>
<tr>
<td>Average parking time per private car</td>
<td>h</td>
<td>23.5</td>
</tr>
</tbody>
</table>

Three scenarios (out of the 6 studied) are reported here where the allowed maximum increase in travel time and the start time window, are varied as shown in table 2. Case 1 implies no ride-sharing since picking-up co-passengers always implies an increase in travel time.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acceptable travel time increase</td>
<td>0</td>
<td>30%</td>
<td>50%</td>
</tr>
<tr>
<td>Start time window (mins)</td>
<td>0</td>
<td>10</td>
<td>15</td>
</tr>
</tbody>
</table>

Results
In table 3 the results of the SAV fleet performance are reported for the three scenarios. Scenario 1 is the base case without ride-sharing. Scenarios 2 and 3 are designed to minimize vehicle mileage under different acceptance criteria. As expected, the base scenario without ride-sharing, causes the total mileage to increase by 24% over private cars to serve current demand. This is in line with the values reported by (16).
Scenario 2 which includes the most likely acceptable parameters of 10 minute start time window and a 30% allowed increase of travel time to allow for ride-sharing shows that only 5% of the current number of vehicles are needed, with a reduction of total mileage of 11% and 7% reduction of time on the road.
While the allowed increase of travel time was 30%, the average increase is only 13%.
Scenario 3, which increases the time window to 15 minutes and the allowed travel time increase to 50% shows a further reduction in total mileage and drive time, at the cost of a 25% average increase of travel time.
TABLE 3 SAV fleet performance in relation to baseline (private cars)

<table>
<thead>
<tr>
<th>Scenario</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle fleet</td>
<td>8%</td>
<td>5%</td>
<td>5%</td>
</tr>
<tr>
<td>Mileage</td>
<td>124%</td>
<td>89%</td>
<td>76%</td>
</tr>
<tr>
<td>Parking time</td>
<td>6%</td>
<td>4%</td>
<td>3%</td>
</tr>
<tr>
<td>Time on road</td>
<td>120%</td>
<td>93%</td>
<td>85%</td>
</tr>
<tr>
<td>Use of time window</td>
<td>0%</td>
<td>60%</td>
<td>56%</td>
</tr>
<tr>
<td>Increased travel time</td>
<td>0%</td>
<td>13%</td>
<td>25%</td>
</tr>
</tbody>
</table>

Figure 5 shows the ride-sharing performance in the two dimensions of a) increase in travel time and b) size of the start time window. In figure 5 a) the start time window is fixed at 10 minutes and the number of SAV trips, mileage per trip and total mileage are shown for increasing sizes of the allowed increase in travel time. As the increase in travel time becomes larger, the mileage per SAV trip increases, at the same time as the total mileage and number of SAV trips decreases. The decrease in total mileage from 40% to 50% allowed increase in travel time seems to flatten out, while mileage per trip is still increasing, indicating that it is unlikely that increasing the allowed detour beyond 50% would provide additional gains.

Figure 5 b) fixes the allowed increase in travel time at 30% and shows the number of SAV trips, mileage per trip and total mileage for increasing sizes of the start time window. The initial increase from 0 to 5 minutes start time window shows the largest gain in terms of reduction of total mileage and number of SAV trips, at the cost of only a small increase in mileage per trip. Increasing the time window beyond 10 min seems to show only marginal improvement in number of SAV trips and mileage per trip.

While ride-sharing reduces the number of SAV trips, the empty vehicle trips add mileage in comparison to the base-case. However, the timing and location of these trips are important to see if these trips contribute to congestion. In order to assess the impact of the scenarios on congestion, figure 6 shows the number of vehicles driving for different times of day, in the case of the baseline (private cars), for the scenarios 1, 2 and 3. It is clear that both scenario 2 and 3 result in fewer vehicles on the road at any time, including the peak periods, and therefore congestion should be reduced. In addition, most of the empty-vehicle trips are in the opposite direction of the main traffic flows (out from the center in the
morning peak and inward during the afternoon peak), which should reduce congestion. Scenario 1, which
excludes ride-sharing, increases the total number of vehicles on the road considerably.
For a full analysis of the effects on congestion, the trip assignment should be performed with a dynamic
traffic assignment model.

![Number of SAV on Road](image)

**FIGURE 6** Number of vehicles per minute on road versus time.

**DISCUSSION**
In this study only the upper level of the ride-sharing problem is studied, whereas a re-assignment loop
with a dynamic traffic assignment (DTA) model would be needed to establish equilibrium travel-times
and SAV (aTaxi) trip assignments. In addition, the likely effects on the supply-side, such as increased
capacity on links due to platoon-driving, smarter anticipating traffic signals etc. can only be studied with
an appropriate DTA model in the loop, which will be the focus of future work.

**CONCLUSIONS**
In this paper we studied potential benefits of a fleet of shared autonomous taxi vehicles (aTaxis) when
replacing private car commuter trips in a metropolitan area. We developed a framework for dynamic
allocation of aTaxis to passenger trips, empty-vehicle routing and multi-criteria evaluation with regard to
passenger waiting time, trip times and fleet size. Using the Stockholm metropolitan area as a case, we
evaluate a number of ride-sharing scenarios, varying the accepted start time window and acceptable travel
time increase with ride-sharing.
Our results show that without ride-sharing, an aTaxi fleet will increase total mileage and drive time,
which is consistent with results reported in the literature. However, when accepting ride-sharing with a
start time window of 10 minutes and a maximum of 30 % longer drive-time (13 % on average), total
mileage is 89 % of the base case, the number of vehicles 5 % and the amount of time vehicles are parked
4 %. Increasing the time window to 15 minutes and accepting a maximum 50 % increase in travel time
due to ride-sharing (25 % on average), the same number of vehicles are needed, but mileage is reduced to
76 % of the base case and vehicles are parked only 3 % of the time.
ACKNOWLEDGEMENTS

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