Modeling Autonomous Vehicles - Challenges and Results Research Brief

Prepared For

Transportation Research Board Conference 2016

By

30 March 2016

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1 Objectives and Motivations

Autonomous vehicles (AV) are an emerging technology that is likely to cause major changes to transport systems in coming decades. Obviously there are still aspects of the driver-less car that still need to be refined, and there are many legal, liability, technical and social problems that must be overcome. However it now seems reasonable to consider AV in future planning, as they are likely to have significant impacts on travel behavior and road network operations. This paper will look at what the introduction of AVs could mean for the future of transport and includes some initial modeling of autonomous vehicle impacts in South East Queensland (Australia), using TransPosition's 4S Model.

If they fulfill their promise, AVs will improve safety on roads as they more closely observe their surroundings using technologies such as radar, lidar, GPS, and computer vision; these will be more reliable than the human eye and the system will not be subject to slow human reaction times. As a result, these driver-less cars will be able to travel closer together and operate at higher speeds, thus increasing capacity on roads. However, the improved comfort; ability to better use the time while traveling; and reduced complexity of parking will make road-based travel more attractive. This is likely to increase trip making and increase average trip lengths. The extra demand pressures could be exacerbated by the use of cars to auto-chauffeur people, reducing parking requirements but increasing counter peak traffic flows. The relative attractiveness of public transport will also be altered; on the one hand the improvements to car travel will make PT relatively less attractive; on the other hand autonomous vehicles could make PT more responsive and affordable. All of these effects are explored in the TransPosition model, and the overall impact on traffic assessed.

As far as we can see, there has been little work done at modeling the specific impacts of autonomous vehicles with reference to a full transport model for a particular city (earlier work by the authors can be found in Davidson and Spinoulas 2015). Part of the reason for this is the nature of most transport models, which are calibrated with aggregate behavioral factors that are not easily amenable to fundamental changes. As described in the methodology section, the 4S model is particularly well suited to investigating changes such as AV, because it is based on a first-principals utility formulation where all parameters can be easily changed.

2 Methodology

2.1 TransPosition's 4S Model

The analysis of the impact of Autonomous Vehicles has been done using TransPosition's 4S model (see Davidson 2011). This is a relatively new modeling approach developed by TransPosition, that includes a very high level of spatial and behavioral detail, and is sensitive to a much wider range of system changes. Unlike other strategic models, the 4S model has a well-defined micro-economic basis and a relatively small number of parameters that are more regionally and temporally stable; this makes it particularly suitable for addressing system-wide change, such as that associated with the introduction of AV. This is done by modifying key behavioral variables, such as the perceived value of time, and vehicle operating costs, to reflect the AV scenarios. The model then works through the consequences of these through the modified behavior of all travelers in the city.

2.2 Description

The TransPosition 4S model has been developed over the last 7 years. The model is structured differently from the usual four-step-model; it is based on a micro-economic utility framework and has strong capabilities in modeling multi-modal systems, freight, pricing and regional analysis.

The Segmented Stochastic Slice Simulation (4S) model is named for the following features:

- Segmented: Uses a comprehensive breakdown of different travel markets, and allows all behavioral parameters to vary by market segment (value of time, tolls, destination utilities etc.)
- Stochastic: Uses Monte Carlo methods to draw values from probability distributions. Every parameter can be a random variable
- Slice: Takes very efficient slices (samples) of the travel market across the whole model area and through the distributions
- Simulation: Uses a traveler/vehicle state-machine with very flexible transition rules to effectively simulate all aspects of travel choice

It differs in many ways from the traditional Four Step Model, and has many compelling advantages over many of the newer models as well.

- It has an elegant, theoretically sound basis that allows for realistic modeling of a very wide range of issues. This includes active transport, mode choice, toll modeling, behavior change, induced demand and time-of-day analysis.
- Models can be prepared with much less effort and arbitrary coding - by eliminating zones, centroids, and centroid connectors the manual effort in putting networks together is vastly reduced.

- It is very computationally efficient - a full integrated, multi-modal choice model for South East Queensland (with 155,000 road links, 82,500 transit links, and 2,500 walk/cycle paths) can be run in around 45 minutes.
- Its simple core allows it to be extended to include time choice models, tour-based models, activity models, links to micro-simulation, latent class models and land-use/transport interaction.

2.3 High level assumptions

There are a number of key, high level assumptions that the model makes about travel behavior.

1. **Utility maximization** – People make decisions to maximize their overall net utility - that is the utility of the activity they can undertake at a destination minus the cost of travel to that destination.
2. **Random utility theory** – People make different assessments of utility, so utility can be described by a random variable. In practice, this means that variables like walking speeds, wages, preferred arrival time, and perceptions of different destinations are all described with random variables.
3. **Generalized cost** – People assess costs by adding up all of the components of their travel, including the weighted value of time spent traveling, vehicle operating costs, tolls, fares and parking charges.
4. **Behavioral factors constant over time** – The determination of the key parameters that describe behavior is done using current and historical surveys, and calibration against observed travel. In preparing forecasts, we change only those variables that are known to change (such as population, employment and network characteristics). The behavioral parameters are assumed to carry forward into the future. This assumption can be relaxed in scenarios, but is implicit in the use of a current model to make predictions.
5. **Demand determined by land use** – The main locational factor that determines travel demand is classified population and employment.
6. **Individual demand** – A practical assumption made in the model is that demand is determined at the individual, rather than the household level. Some models put significant effort into analyzing the interaction between household members - an example is the activity based modeling (ABM) approach. Our analysis has shown that most of the variation in household trip making can be explained by looking at the individuals within the household (taking account of their role within the household). By calibrating the model to observed household travel we implicitly include many factors associated with intra-household interaction. However we are considering methods to incorporate some of the findings of ABM into the 4S model.

2.4 Model parameters

In addition to these high level assumptions, there are a large number of model specific assumptions; covering the form of utility functions and the probability distributions that describe each random variable. A full discussion of the detail of the model and its calibration is beyond the scope of this paper, but some of the most important random variables are described below.

2.4.1 Value of time

Many of the choices and trade-offs made in travel decisions are about comparing times, distances and costs (fares, tolls etc). In order to allow these comparisons to be made, all elements are converted to dollar costs. For time components, this is done by multiplying the hours spent traveling by the value of time, in dollars per hour.

The value of time is influenced by three main factors:

- Wages - people with higher incomes generally have higher willingness to pay for time savings. Wages are modeled with a log-normal distribution
- Person type - students, workers, working age dependents, retirees and commercial drivers (further segmented by vehicle type)
- Time weights - the model uses a range of time weights, which vary by mode, purpose and network characteristic.

2.4.2 Attraction utility and net utility

Transport is a derived demand; people generally travel not for its own sake, but because they want to undertake activities at other locations. If new options become available, or lower transport costs make more desirable destinations more attainable, then people can travel longer, further and with higher cost. These extra costs are not bad, because they must be associated with even greater benefits enjoyed by travelers; if the benefits did not outweigh the extra costs then the travel would not have occurred.

The model is based on explicitly identifying the net utility of travel. **Net Utility** is calculated for each trip as the dollar value of the benefits of traveling to the selected destination, minus the cost of getting there. Since individuals will have different perspectives on the benefits of travel, and different assessments of the costs, there will be a range of net utility values. These will reflect variations in preferences as well as variations in circumstance.

The model uses an extreme valued gamma distribution for the destination utility based on the size of each destination, with parameters reflecting the average utility, the variability in utility, and the scaling with size. These parameters have been calibrated using data from the South East Queensland household travel survey (SEQHTS), ensuring that estimated trip length frequency distributions match those observed in the survey.

Note that the net utility values output by the model should be used as a basis for comparison, but not as a meaningful absolute benefit; the size of the difference between values is significant but the values themselves are not.

2.4.3 Land use variables

The model uses a range of land use variables, mostly related to population and employment. The land use data is used for two reasons; it gives the sizes of the various travel markets; and it is used for determining the attraction utility for destinations. Each travel market is defined in terms of two key land use variables - the production market size, and the attraction size.

The selection of land use variables is limited by what is readily available, both for the base year and for forecasting. The key source of land use data are those prepared by the state government. This gives population classified by age (0-4, 5-17, 18-64, 65+) and main activity (students, blue collar worker etc.) and employment classified by industry (Retail and trade, Transport and storage etc.) and high level occupation(Blue Collar/white collar). Employment is broken down by 19 industry classifications based on the ANZSIC 2006 Divisions ("Australian and New Zealand Standard Industrial Classification (ANZSIC), 2006 (Revision 2.0)" 2006).

3 Modeling Autonomous Vehicles in TransPosition's 4S Model

To test the impact of autonomous vehicles, a number of scenarios have been tested using TransPosition's 4S model for South East Queensland. This region contains the three largest cities in Queensland - Brisbane (the state capital), the Sunshine Coast and the Gold Coast, with a combined population of 3.4 million and an annual growth rate exceeding 10%. By focusing on a particular region, the interaction between the multiple changing elements can be considered. In particular, because the 4S model is multi-modal, it can investigate the interaction between car demand and other modes. The 4S model also allows for variable demand, and includes an implicit induced demand component, so changes to transport costs can lead to changes in the overall demand for travel. Although the work has been done in Australian cities, many overall conclusions should be transferable to other cities.

3.1 Autonomous vehicle market share

There is no consensus on how quickly the market will adopt Autonomous Vehicles, but there are some natural constraints. To begin with, AVs will likely cost significantly more than similarly sized non-AV. This will limit the proportion of the market that will be willing to buy them. While the rapid rise of smart phones has shown that people are willing to spend reasonably large amounts of money on things that they previously spent much less on, the high cost of early AV will be impossible for most people to afford.

The best understanding of how much people are willing to pay for vehicles comes from looking at what people are currently spending on vehicles. Looking at the quantity of new vehicle sales also gives a good indication on how quickly the fleet turns over - a critical issue when determining how quickly AV technology will spread through the fleet.

Note that the issue of differential update of AV is complex - it is likely that it will be related to income (increased uptake with income), but also to age (perhaps reduced uptake by age). For this analysis we simply assume uniform adoption rate across the region.

The AV market share model began with data on new vehicle sales, broken down by 28 categories as shown in the table below. For each vehicle type, we assume that the proportion of new vehicles that would be AV will remain at zero until a critical year - the year in which an AV can be built to that price point. The proportion of new AV vehicles will then grow linearly until it reaches 100% at another nominated year. Three cases were considered - conservative, moderate and aggressive. The start and end years for each vehicle class have been estimated for each case, and these assumptions are shown in the table below.

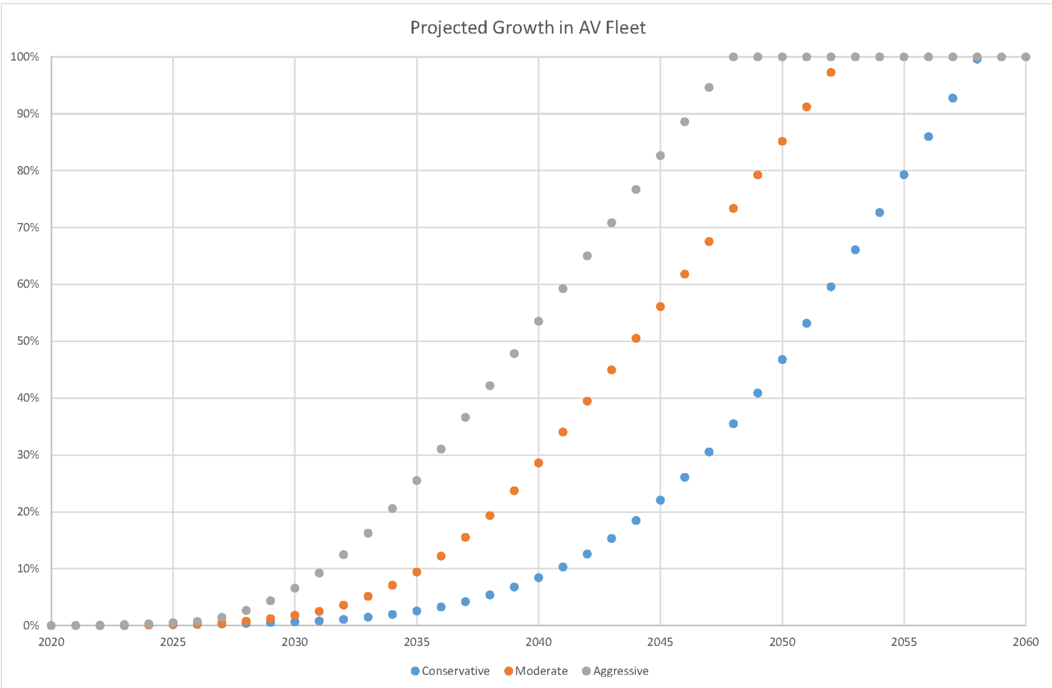
Table 3.1 ***New vehicle sales, first year to market and full adoption year by vehicle type***

Vehicle	Price	Sales	Mod Start	Mod Full	Agg Start	Agg Full
Micro	<15	957	2041	2046	2031	2036
Light	<25	8156	2036	2041	2031	2036
Light	>25	380	2031	2041	2026	2036
Small	<40	17160	2036	2041	2031	2036
Small	>40	1422	2031	2041	2026	2036
Medium	<60	4317	2031	2036	2026	2031
Medium	>60	2360	2026	2036	2021	2031
Large	<70	3033	2026	2036	2026	2031
Large	>70	284	2021	2031	2021	2031
Upper Large	<100	179	2031	2041	2021	2031
Upper Large	>100	71	2021	2031	2018	2026
People-movers	<60	908	2031	2036	2031	2036
People-movers	>60	42	2026	2036	2026	2031
Sports	<80	1050	2026	2036	2026	2031
Sports	>80	430	2021	2031	2021	2031
Sports	>200	107	2021	2031	2018	2026
SUV Small	<40	8678	2036	2041	2031	2036
SUV Small	>40	1045	2031	2036	2026	2036
SUV Medium	<60	11344	2031	2036	2026	2031
SUV Medium	>60	1499	2026	2036	2021	2031
SUV Large	<70	9292	2026	2036	2026	2031
SUV Large	>70	1898	2021	2031	2021	2031
SUV Upper Large	<100	867	2026	2036	2021	2031
SUV Upper Large	>100	121	2021	2031	2018	2026
Light Vans	<30	190	2036	2046	2031	2036
Medium Vans	<40	1349	2036	2046	2026	2036
4x2 utes	<50	3291	2031	2041	2026	2036
4x4 utes	<60	10949	2031	2041	2026	2036

The total number of new autonomous vehicles sold each year is estimated by assuming the proportion of new sales by type stays constant in the future; that total sales grow with population; and that the AV proportion follows the linear growth model described above. The size of the fleet in any year can then be determined by combining these new vehicle sales with data on the existing vehicle fleet in Australia, and removing vehicles from the fleet according to a simple vehicle lifetime model.

The AV fleet can now be calculated by adding the new AV sales to the previous year's AV fleet (obviously this is 0 in 2015). In the aggressive case, we estimated a total of 14,598,602 AVs in 2041. Taking the stock of vehicles into account, this means that 58% of the fleet will be autonomous by 2041. This increases further to 87% by 2046. The conservative case estimates only 26% AV fleet in 2046, with 62% in the moderate case. All cases are assumed to reach 100% AV; this is partly an artificial construct of the model formulation, since manually driven cars are likely to remain in small numbers into the foreseeable future, even if they are only allowed limited use on the network. Thus the sharp edges at the top of the fleet proportion curves should almost certainly be rounded, with a residual non-AV fleet. In any case, the model projects a saturation of AVs by 2048 in the aggressive case; 2053 in the moderate case; and 2058 in the conservative case.

Av Fleet Proportion



3.2 Assumptions regarding autonomous vehicles

Autonomous vehicles will differ from current manually driven vehicles in a number of key ways

1. Time spent in an AV will be more easily used for other activities - this will lower the cost of this time
2. The likely linkage between AV technology and plug-in-electric means that AV will likely cost less to run
3. Lower costs and simplified parking will make it more attractive for people to make more trips, and reduced requirements on drivers will eventually open up new travel markets (children, people without licenses etc.)
4. Faster response time, uninterrupted attention, and vehicle-vehicle and vehicle-infrastructure communications will eventually allow AV to travel faster, and at a higher density.
5. When vehicles can operate without a driver, there will be a new type of travel, as vehicles are sent back home, or between family members.
6. If the development of transport-as-a-service becomes popular, then the structure of people paying for transport will change. The cost of owning a vehicle will be included in every trip, rather than paid as once-off and intermittent payments. This will change the marginal cost of each car trip.

To simplify the description of scenarios, we have identified 2 stages of AV adoption. In Stage 1, AVs share the roads with manually driven cars. This limits some of the performance improvements possible from AV technology. In Stage 2 the network is 100% autonomous, allowing increases in speed and capacity.

3.2.1 Value of time

Autonomous vehicles have the potential to improve the driver's experience. This degree to which the experience will be improved will depend on the Autonomous Level (defined by the US National Highway Traffic Safety Administration). Adaptive cruise control and lane following (Level 2) will make long distance driving a bit more pleasant, but the real benefits will come with partial or complete automation (Levels 3 and 4). Once drivers can take their hands off the wheel, and safely turn their attention to their computer or phone, then the experience of driving will be much less onerous. Things will become even better once the vehicle is completely autonomous; in this case the seats could be more comfortable and people may even sleep while they are traveling. For many people it will also be possible to work. These changes will allow this time to be used more effectively, reducing the perceived cost of this time.

For the purposes of modeling, we have assumed that the autonomous portion of the traveling fleet will enjoy some improvement in their perceived time-cost of traveling, implemented by a reduced weight for time spent in cars. We have assumed that this reduction in VOT will not apply to everyone - the model assumes that the reduction in weighting is uniformly distributed with an upper limit of 1, meaning no change. For all scenarios we have adopted a range of values, with lower limits and upper limits as given in the scenario section below.

3.2.2 Increased trip rates

The widespread use of autonomous vehicles will increase the number of trips for a few reasons

1. They have lower costs (both real and perceived), and so some trips that have marginal net benefits at the moment will become more attractive.
2. Parking will become easier, due to autonomous parking at nearby parking stations or autonomous chauffeuring
3. It will become easier for a vehicle to be shared amongst family members, making it possible to make some trips that are currently impossible, or forced onto other modes.
4. People will be able to drive at times that they currently cannot - for example, when they are drinking or too tired to drive. Some of these trips will change over from taxis, but the high cost and limited availability of taxis at peak times means that some of these trips will be new
5. There will be new travel by people who currently cannot drive, including children; the elderly; people without licenses; and those with disabilities that preclude driving.

We have assumed that all of these factors combined will increase overall trip rates by 10% in Stage 1 and 15% in Stage 2.

3.2.3 Reduced operating costs for AV

Autonomous vehicle technology and plug-in-electric technology are natural allies; they are coming to market at similar times and each one supports the other. AV needs a range of electrically powered sensors and actuators, and the system is more easily controlled with electric motors. Plug-in-electric vehicles need smarter controls, and a better understanding of travel patterns, due to their relatively smaller energy capacity and longer recharge times. The fact that AV is coming to market at the same time that the world is trying to decarbonize only makes the case more compelling.

Electric vehicles should have a much lower vehicle operating cost than standard internal combustion engine vehicles, particularly in traffic. Electric vehicles currently cost more, but costs are likely to reduce over time as technology improves and economies of scale kick in.

It is difficult to predict the relative cost of electrical energy vs fuel energy in the future, but based on 2014 prices, electric vehicles cost around 50% of the energy costs compared with an internal combustion engine (ICE) (see Guterres 2014 for some discussion of the cost differences).

We have again assumed a range for this impact - we have assumed a reduction to 50%-75% of the current vehicle operating costs under Stage 1, and a fixed 50% reduction in Stage 2. Note that we have also included a scenario that makes the unlikely assumption that all AV remain as ICE - this is to test the impact of the change in operating costs. Even under this scenario we have assumed some drop in costs due to increased driving efficiency of an autonomous ICE vehicle, with a cost range of 90%-100% of current costs.

3.2.4 Unoccupied vehicles

Once autonomous vehicles can travel without a driver, there will be scope for a whole new class of travel - maneuvering of unoccupied vehicles. Rather than paying for parking, people may drive into work and then send their vehicle home for the day. When it's time to go home, the vehicle will have returned ready for the homeward trip. If they are running late at work they may send their vehicle back to pick up their children from school, and then return back to work to bring them home. In the extreme case, people may decide to have their vehicle drive around the city streets for an hour while they do their shopping.

Modeling this behavior is very complex, and has not been done at this stage. Furthermore, there would be good reasons to introduce regulations to limit at least the most egregious cases. This could be done using additional charges for specific behavior, or by a more general road pricing approach.

3.2.5 Shared AV

Another more socially beneficial option that becomes available once AV can travel without a driver is shared AV. In this option people would make serial use of a shared autonomous vehicle under a transport-as-a-service arrangement. In the simplest case these would still be single passenger vehicles (like an autonomous taxi), but a more efficient network could also have multi-occupant shared vehicles.

Note that this option could be an early adopter of autonomous technology - the shared use would mean a much higher utilization than privately owned vehicles, making the high capital cost of AV technology much easier to sustain.

The modeling of shared AV is very complex, since it will depend on many aspects of the system that are completely unknown at this point. For example, the usability of the system and the amount of maneuvering traffic will depend on the market penetration of the system; how far ahead people will need to book; where and how many depots will exist; what pricing model the operators will adopt; whether they have increased fees at peak times; how well integrated the AV system is with public transport; and what the vehicle charging/down time/duty cycle will be.

Since this work is focused on the behavioral impacts of AV we are more interested in what the system looks like to users than how it might be run by operators. For users, the key question is how much will they be charged for each trip, so we need some way of estimating the likely costs for shared AV.

At its simplest level, the shared AV will look like a taxi, or a ride-sharing service, but with much lower rates due to the lack of a driver and (presumably) minimal licensing costs. So the best approach is to look at the cost structure for existing taxi and ride-sharing services and work from there. This exercise was done using detailed data collected from taxi drivers in Sydney, Australia. The AV service was assumed to run more efficiently than taxi services, due to higher usage and better systems. It was also assumed to have minimal licensing costs, but higher capital costs than taxis. The resulting fare structure for an AV service was estimated as $0.10/min + $0.40/km + $1.20 flag-fall.

It is certainly possible that the fares could be lower once the capital costs of AV are reduced, and as the system operates more efficiently. There is reasons for caution on this though, as the unsupervised vehicles may have higher incidence of vandalism, and people may expect a high standard of cleanliness and amenity before they are happy to depend on the service.

3.2.6 Increased speeds and capacities

Autonomous connected vehicles have the potential to significantly improve the operational efficiency of our roads, with higher speeds and higher capacities. Some microsimulation modeling has indicated that the capacity of roads could double (from 2000 veh/lane/h up to 4000 veh/lane/h) (see Shladover, Su, and Lu 2012 for an example). However these results must be read with some caution, since they can overstate the impact. The aforementioned paper, for example, only considers a single freeway lane in isolation, despite the fact that most delays are due to intersections. It also assumes a much lower inter-vehicle gap than people may be comfortable with - some experimental results show that people are only comfortable using the adaptive cruise control system at gap settings similar to those they choose when driving manually.

There is some research on autonomous intersection management that show significant reductions in intersection delays (more than 50%) due to smart scheduling of intersection space - see Dresner and Stone (2008) and Au, Zhang, and Stone (2014) for examples. However it is likely that there will need to be significant cultural change, and very mature technology, before people will be comfortable with the very efficient autonomous intersections.

Finally, much of the analysis on this issue neglects other road users, such as buses, cyclists and pedestrians. It is difficult to see how these can be incorporated without significantly reducing the theoretical limits.

Given the uncertainty of these issues, we have been somewhat conservative on the speed and capacity improvements. In the transition years, the increased use of connected vehicle technology, and the reduction in the incidence of crashes due to the rising proportion of safer AV vehicles leads to a marginal (5%) increase in roadway capacity (Stage 1). A network with 100% AV allows for significant increases in speed, capacity and intersection operations; the model assumes that roadway capacities are 20% higher; posted speeds are increased by 20%; and intersection delays are reduced by 25% (Stage 2).

4 Scenario analysis

4.1 Description of Scenarios

The scenarios focus on the moderate and aggressive AV cases in 2036 and 2046. The aggressive AV growth profile does not quite reach 100% by 2046, but we were keen to include a set of scenarios with 100% AV, so that the capacity improvements of this case could be considered.

In each of the AV scenarios there are a number of changes; a reduction in the value of time spent in-vehicle; an increase in the rate of trip making; and a reduction in the per-km vehicle operating cost. The size of these effects varies by scenario according to the assumptions in the table below.

Name	AV Stage	AV Share	Value of Time	Trips	Veh op cost	Shared AV
Base11	None	0%	-	-	-	-
Base36	None	0%	-	-	-	-
Av36Mod	Stage1	12%	0.75 - 1.00	10%	0.5 - 0.75	-
Av36High	Stage1	42%	0.75 - 1.00	10%	0.5 - 0.75	-
Base46	None	0%	-	-	-	-
Av46Mod	Stage1	62%	0.60 - 1.00	15%	0.5 - 0.75	-
Av46High	Stage2	100%	0.60 - 1.00	15%	0.5 - 0.5	-
Av46HighShared	Stage2	100%	0.60 - 1.00	10%	0.5 - 0.5	70%
Av46HighIntCom	Stage2	100%	0.60 - 1.00	15%	0.9 - 1.0	-

Note that all AV scenarios assume plug-in-electric vehicles, with the exception of the last one (AV46HighIntCom) which assumes all AVs have internal combustion engines.

4.2 Impact on mode share

The model shows that in the absence of AV, the general trend is for more active transport, more public transport and declining car mode share. The introduction of AV changes this; the higher the proportion of AV in the fleet the higher the car mode share. This is because the AV vehicles are more attractive, and generally lower cost, than most other options. If the AV's use internal combustion engines rather than plug in electric, then the trend is slightly reversed - the higher costs of petrol make the AV alternative a little less appealing.

The biggest exception is the shared AV scenario where the relatively high marginal cost of shared AV reduces the attractiveness of cars, increasing share in the other modes.

Table 4.1 ***Mode share results by scenario***

Scenario	Active	PT	Car	Total Trips (m)
Base11	9.9%	7.7%	82.5%	8.49
Base36	10.6%	8.2%	81.3%	13.33
Av36Mod	9.3%	7.0%	83.7%	13.32
Av36High	8.8%	6.6%	84.6%	13.40
Base46	10.8%	8.7%	80.5%	15.31
Av46Mod	8.0%	7.1%	84.8%	15.24
Av46High	7.3%	5.7%	87.0%	15.32
Av46HighIntCom	7.9%	6.6%	85.5%	15.32
Av46HighShared	14.7%	11.5%	73.8%	15.33

Table 4.2 ***System-wide, and per capita costs, times, distances and net utility by scenario***

Scenario	$\sum$Cost	$\sum$Hours	$\sum$Km	$\sum$NetU	Cost	Hours	Km	NetU	Driving Spee
Base11	75.4	3.8	106.2	105.3	22.58	1.13	31.78	31.53	33.8
Base36	120.0	6.2	164.1	176.0	22.33	1.15	30.54	32.76	31.4
Av36Mod	113.4	7.1	201.5	194.4	19.60	1.22	34.81	33.58	32.5
Av36High	114.2	7.1	202.7	195.6	19.73	1.23	35.03	33.79	32.2
Base46	138.6	7.3	185.4	207.8	22.45	1.18	30.03	33.66	30.2
Av46Mod	130.0	8.6	234.8	233.5	19.54	1.30	35.30	35.11	30.2
Av46High	127.9	8.4	269.0	245.4	19.23	1.26	40.44	36.89	35.1
Av46HighIntCom	132.0	7.1	211.9	229.0	19.84	1.07	31.85	34.43	34.0
Av46HighShared	153.9	6.3	146.6	183.0	23.13	0.94	22.04	27.51	31.2

4.3 Impact on costs, time and distances

While preliminary, the modeling in this paper shows that Autonomous Vehicles have the potential to lead to very large increases in both average trip length and in total travel time. The reason for this is that the increased comfort associated with automatic driving make travelers less sensitive to travel times - they will travel more often and will be willing to stay in their vehicles longer. This is compounded further if the shift to electric vehicles leads to big drops in vehicle operating costs - this will reduce travelers sensitivity to travel distances. Both of these effects are important, and their impact on total travel times is similar.

While autonomous vehicles share the road with manually driven cars, and are required to have a licensed driver at all times, they will have a negative effect on congestion, travel times and (probably) total productivity. This could lead to a reinforcing cycle, where those using AVs will increase congestion for everyone but experience the impacts less themselves; they will be more relaxed in their vehicles, and their electric batteries will use little power when idling. The extra congestion will be suffered more acutely by those in traditional vehicles; they will have the frustration of more frequent stop-start conditions, and pay the extra price of running engines on idle while they wait in queues. This could increase the uptake of autonomous vehicles. Nonetheless, the delays will be unavoidable and will also have an impact on commercial, freight and emergency traffic for whom more pleasant driving experiences account for little. These negative impacts will be somewhat offset by the anticipated improvements in road safety.

The effect of increasing AV on average speeds is mixed; the impact of AV is strongest in longer distance trips, and so there is a tendency to differentially increase demand for these trips. Since they involve more travel on higher speed interurban roads they can lead to an increase in average speeds. However more of the road network is congested. Even under cases where the AV adds extra capacity and higher speeds, most of these benefits are more than captured by increased demand on busy roads. The only roads that have improved speeds overall are those that have only limited congestion.

4.4 The impact of shared AV

The final scenario is the most complex, with a fully AV fleet, but with only a minority privately owned. The bulk of the fleet (70%) is assumed to be owned by transport operators, and made available to travelers with a per-trip charge. The extra charge associated with the use of a shared vehicle is added directly to the cost, which is why this scenario has higher per capita costs, and lower per capita net utility than the standard 2046 High AV scenario. This is somewhat misleading, though, since it ignores the savings associated with not having to own a vehicle - these costs are equivalent to per capita costs of $14 - $24/day. If these costs are added to all of the other scenarios, then the shared AV case is much cheaper, with a saving in cost of at least $10/day and an increase in utility of at least $4.60.

The per capita distances traveled is the lowest of all of the scenarios; even lower than the 2011 base case. This is due to the higher marginal cost of travel; at the moment long car trips are effectively subsidized by annual car ownership. This is because one must buy a car; insure it; register it; and service it; whether or not it is used. This artificially lowers the cost of car travel; since most of the fixed costs have already been paid, the marginal cost is just the fuel cost and perhaps some wear and tear on tires etc. One way of looking at this is to consider that some trips are valuable and others are less so. We buy a car because we need to make the valuable trips; once we own it we may as well use it even for less valuable trips, as long as the benefits are higher than the marginal (fuel) cost. In a sense, the high value trips are cross-subsidizing the lower value trips. Under the shared AV case, these cross subsidies are removed; every trip must pay the full cost of travel, including a pro-rata amount for the ownership of the vehicle. This leads to a focusing of travel; the high value trips will still occur but the lower value ones will not. Similar arguments may be made about mode choice; once people are charged the full cost of car travel the other modes look more attractive.

5 Implications for the science and practice of travel modeling

5.1 Summary of impacts

The initial adoption of autonomous vehicles will increase travel times, increase distances and increase congestion. There will be an increase in car mode share, with reduction in active and PT use. This stage is still associated with a net improvement in perceived costs, however there are many losers (especially those still in manual vehicles).

A 100% AV fleet running on the current model of private ownership will further decrease active and PT share, and increase overall travel. The congestion impacts of this extra demand are mitigated by capacity improvements made possible by eliminating manual vehicles.

Part of the increased demand for car travel comes from the lower operating cost of electric vehicles. AVs based on internal combustion engines would have reduced behavioral impacts due to higher costs, but worse environmental outcomes and lower utility.

Shared AVs change the way that we pay for travel - pay-as-you-go rather than all-you-can-eat. The behavioral impacts for shared AVs are uncertain - we have assumed that people make choices based on the marginal cost of travel. Shared AV will have a lower annual cost than private car ownership, even allowing for high cost vehicles in the shared AV fleet. They will be cheaper for users than even the smallest car - much cheaper if parking is involved. However, the marginal cost of a trip will be much higher - for local trips it may be 3-4 times as high. Therefore, the higher marginal costs felt by users of a shared AV service leads to lower car demand, more PT and active transport and less congestion. Shared AV would have further benefits for congestion management and effectively provides a proxy for road pricing.

5.2 Impact on infrastructure

The results imply that infrastructure requirements will be somewhat reduced in the long term, however there will be significant congestion in the short to medium term. Therefore, we will need to justify infrastructure spending based on much shorter projected benefit streams. The best approach (as usual) would be to implement road pricing - it could take us over the hump associated with the transition.

The results have shown that things will get worse before they get better. If we operate autonomous vehicles as just improved private cars then we will have significant problems with increased demand and increased congestion. The full benefits of autonomy will not be realized until manual vehicles are removed from most roads. Any a privately owned autonomous fleet would be much less efficient than one with a majority of shared vehicles. We need policies that allow us to move as quickly as possible to a fully autonomous fleet and to shared vehicles/transport-as-a-service.

5.3 Implications for modeling

As can be seen from the results, the introduction of autonomous vehicles will have significant impacts on our road networks. Therefore, there is a need to adapt current models to better deal with the modeling of autonomous vehicles as these scenarios should be considered in our transport planning for the future.

As mentioned earlier, traditional models are usually calibrated with aggregate behavioral factors that are not easily amenable to fundamental changes - this is particularly true for models that are highly dependent on detailed survey data, such as matrix estimation or incremental models. This will be problematic when trying to model autonomous vehicles. New methods need to be implemented so that models are more flexible, with deep behavioral sensitivity. TransPosition's 4S model is an example of a model derived from a first principals approach to utility and is very flexible for testing new behavior. This makes it suitable for testing some of the behavioral impacts of AV; we are still working on the best approach to model shared AV.

All modelers need to think about the analytical challenges presented by the new AV technology, and all planners needs to start adjusting their thinking to allow for the most fundamental shift in travel behavior since the introduction of the motor car.

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