USING AN ACTIVITY-BASED MODEL TO EXPLORE POSSIBLE IMPACTS OF AUTOMATED VEHICLES

Suzanne Childress
(Corresponding Author)
Senior Modeler
Puget Sound Regional Council
1011 Western Ave., Suite #500
206-464-7090
schildress@psrc.org

Brice Nichols
Associate Modeler
Puget Sound Regional Council
1011 Western Ave., Suite #500
206-464-7090
bnichols@psrc.org

Billy Charlton
Program Manager
Puget Sound Regional Council
1011 Western Ave., Suite #500
206-464-7090
bcharlton@psrc.org

Stefan Coe
Senior GIS Analyst
Puget Sound Regional Council
1011 Western Ave., Suite #500
206-464-7090
scoe@psrc.org

August 1, 2014

Submitted for presentation at the Transportation Research Board 2015 Annual Meeting, Washington, D.C.

ABSTRACT

Automated vehicles (AV) may enter the consumer market with various stages of automation in ten years or even sooner. Meanwhile, regional planning agencies are envisioning plans for time horizons out to 2040 and beyond. To help decision-makers understand the impact of this technology on regional plans, modeling tools should anticipate automated vehicles' effect on transportation networks and traveler choices. This research uses the Seattle region's activity-based travel model to test a range of travel behavior impacts from AV technology development. The existing model was not originally designed with automated vehicles in mind, so some modifications to the model assumptions are described in areas of roadway capacity, user values of time, and parking costs. Larger structural model changes are not yet considered. Results of four scenario tests show that improvements in roadway capacity and in the quality of the driving trip may lead to large increases in vehicle-miles traveled, while a shift to per-mile usage charges may counteract that trend. Travel models will need to have major improvements in the coming years, especially with regard to shared-ride, taxi modes, and the effect of multitasking opportunities, to better anticipate the arrival of this technology.

INTRODUCTION

Automated vehicles (AVs) are under development by major car manufacturers and technology firms, and may enter the consumer market with various stages of automation in ten years or even sooner (KPMG and CAR 2014). Meanwhile, regional planning agencies are envisioning plans for time horizons out to 2040 and beyond. Within the time horizon of the plans, AVs may significantly alter transportation choices, impacting regions' planning goals. To understand future travel patterns, modeling tools should anticipate automated vehicles' impact on transportation networks and traveler choices.

In the latest long-range regional plan, the Puget Sound Regional Council (PSRC) (2010) established goals to guide the region toward healthy growth, including:

- improving safety and mobility,
- reducing greenhouse gas emissions and congestion,
- focusing growth in already urbanized areas to create walkable, transit oriented communities,
- preventing urbanization of rural and resource lands, and
- helping people live happier and more active lives.

These goals reflect statewide legislation from Washington State's Growth Management Act as well as federal aims outlined in Moving Ahead for Progress in the 21st Century Act (MAP-21). Self-driving cars could impact all these focus areas, so anticipating their adoption is imperative to maintaining timely and informed regional plans.

This paper considers modeling techniques to measure the impacts of self-driving cars using an activity-based model, and explores how modeling capabilities must be improved to better answer questions related to this new technology. Since there is so much uncertainty around the future of AVs, several model scenarios are created to consider broad impacts of self-driving vehicle adoption in the Puget Sound region of Washington State. These scenarios clearly stretch current model capabilities, and depend on highly uncertain inputs. However, it is still useful to test the existing models in order to start a conversation with planners and decision-makers, as well as to highlight shortcomings in our existing methods to modelers. The aim of this paper is not to accurately predict the future impacts of automated vehicles, but rather to develop appropriate ways of evaluating a range of potential impacts on regional transportation.

BACKGROUND

Automated vehicles could drastically change traffic flow, up-ending long-held assumptions about maximum roadway capacity and volume-delay functions. Vehicle-to-vehicle coordination systems allow cars to travel with much shorter headways, enabling higher volumes at high speeds. If AVs also reduce collision rates, non-recurrent congestion would decrease as well. FHWA (2013) estimates that 60% of all congestion is attributed to non-recurring sources such as crashes and other vehicle-roadway mishaps, suggesting that a safer, more coordinated fleet could reduce delay and support more consistent travel times. Even partially-autonomous vehicle capabilities may increase roadway capacity. Tientrakool et al.(2011) estimate that highway capacity could be increased by 43% using vehicle sensors and up to 273% with vehicle-to-vehicle communications. Shladover et al. (2013) estimate that vehicle-to-vehicle coordination of adaptive cruise control could increase capacity by 21% with 50% of all vehicles using the technology, or up to 80% capacity increase with a 100% coordinated vehicle fleet, based on empirical testing. Fernandes and Nunes (2012) estimate that capacity could increase as much as five-fold for platoons traveling around 45 miles per hour. More efficient fleets could be represented as additional roadway capacity, which can be represented very easily in existing travel models.

To date, few regional-scale modeling efforts have addressed potential impacts of AVs. Gucwa (2014) tested some capacity-altering assumptions on regional VMT in the San Francisco Bay Area using the Metropolitan Transportation Commission's activity-based travel model. Gucwa's results suggest that doubling capacity only increases region-wide VMT by around 1%, but does significantly reduce peak congestion. Gucwa found that changing users' values of time had much more impact on VMT than capacity changes, and estimated the Bay Area's VMT would increase between 8% and 24%, depending on how automated vehicles users' time values changed.

Gucwa's findings suggest that changes in user behavior may have large effects on regional travel as vehicle fleets become more automated. Gucwa, and many others, assume that being driven by a robotic vehicle will eventually be less stressful than piloting one's self through concentration-demanding and chaotic congestion, thus making travelers less averse to in-vehicle time. Rather than focusing on complicated navigation skills, travelers could spend time relaxing or working, perhaps reducing the disutility placed on travel time. Since AVs are a new technology, the exact influence of such attributes relative to travel time in these vehicles is unknown. However, these factors are similar in nature to non-traditional transit attributes that often contribute to both mode choice and route choice (Outwater et al. 2013). These attributes, such as comfort, reliability and amenities like Wi-Fi, have proven difficult to explicitly represent in travel models. Instead, through empirical methods, travel models can represent the utility associated with these attributes through adjustments in travel time. Similarly, we can attempt to model the behavioral changes that may arise from AVs by making assumptions about the equivalent perceived travel time reductions that may result from ancillary factors.

Many other aspects of AV technology may affect traveler behavior as well, including costs, vehicle availability and ownership, and parking price and location. Since more technical infrastructure will be required to operate and manage self-driving cars, usage could more easily be tracked per mile, making VMT-based taxes and pay-as-you-drive insurance policies more realistic policy tools for personal vehicles. This pricing strategy could reduce overall VMT, as frequently-forgotten fixed costs such as insurance, licensing, and registration fees are replaced with more transparent marginal costs for every trip (Parry and Small 2005, Nichols and Kockelman 2014). Shared autonomous vehicles would likely offer per-mile rates as well, echoing existing business models from hired rideshare services like Uber and Lyft. Shared AVs may become a popular service, since on-demand automated pickups would reduce the need to own and thus store a personal vehicle. Depending on the technology's development, many could find owning a personal driverless vehicle too costly, relying on occasional pickups by shared automated vehicles.

AVs may reduce the need for close-by parking as vehicles could conceivably self-park in cheaper, more distance parking locations (Fagnant and Kockelman 2013). This behavior could alter fixed costs at trip ends, reducing driving costs that lead to mode shifts or more automobile travel to areas with high parking cost. Aside from altering destination choices and mode choice, this behavior may also increase VMT as empty vehicles are sent for pickup and parking by owners or users in a shared system. Some of these impacts can be easily modeled by simply reducing parking costs in all zones, but accounting for increased VMT requires more knowledge on parking cost, location, and trip tour timing.

VMT will likely increase as new users and more (perhaps longer) trips are induced from more efficiently-operated roadways. Baseline demand consistently increases after congestion is reduced with capacity expansion or operational improvements (see Cervero 2001 and Litman 2014b for meta-analyses of induced travel studies). Additionally, as in-vehicle time is less stressful, travelers may be willing to tolerate slower travel times and longer travel distances, adding more congestion still.

Fully autonomous vehicles may provide new mobility opportunities to those unable or unwilling to drive a vehicle themselves, especially unlicensed young people, the physically impaired, and some senior citizens. These user groups may be able to make more trips, access more destinations, and rely on modes other than shared rides, public transit, and taxi. The amount of additional mobility provided by AVs depends on mode shifts for non-drivers. Affordable, competitive trips provided by a personal or shared AV would likely improve the opportunities a non-driver could access, especially in more suburban, automobile-oriented contexts. Recognizing how different groups are affected by AV developments is important to understanding regional mobility and accessibility to jobs and resources.

Altogether, impacts of autonomous vehicles are highly speculative. Future impacts depend on technological development, market reactions, and regulatory actions, making it challenging to confidently predict impacts to regional transportation systems. With so many unknown and potential effects of AVs, it is challenging to anticipate long-term effects with certainty. However, some of these impacts should be considered early on, to understand model sensitivity and develop feasible analysis boundaries. With these analyses, agencies can prepare more dynamic long-range plans, by defining and evaluating some rational futures and exploring most likely scenarios as technologies appear and mature.

MODEL SCENARIOS

To model potential impacts from automated vehicles in the Puget Sound region, four scenarios are considered. The following sections explore ways to model some of the impacts mentioned above and to provide guidance for other regions interested in planning for automated vehicle futures.

PSRC’s activity-based travel model, called SoundCast, was applied to test the possible impacts of automated vehicles. SoundCast includes a travel demand component written in the Daysim software. SoundCast simulates individual travel choices across a typical day (PSRC 2014). These choices include long-term choices like work location and auto-ownership, as well as shorter-term choices like mode choice and route choice. Inputs to the model include parcel-based locations of households and jobs, and highway and transit networks.

The scenarios have all been modeled using the base year of 2010, to avoid forecasting market penetration scenarios or speculation on business models or technology development over time. Using the most recent base year also helps focus the analysis directly on AVs, and avoids uncertainties in future growth and changes to the transportation system. This isolation is useful to understand some model behaviors and helps develop basic guidelines for evaluating automated vehicles. As these analyses mature, future years should be evaluated for more comprehensive case studies.

These scenarios explore how driverless cars can influence demand through changes in capacity, perceived travel time, parking cost, and operating cost. They are described separately below.

Scenario 1: Increased Capacity

> *"AVs use existing facilities more efficiently."*

The first scenario reflects operational improvements from full or partial vehicle automation. This scenario is modeled by increasing the hourly capacity coded on roadway network links and captures one major impact of AVs on a roadway network. While it's currently unclear what magnitude of capacity increase is likely, based on cited research a 30% increase represents a modest result from AV adoption. All freeway and major arterial capacities are increased by 30%.

Scenario 2: Increased Capacity and Value of Time Changes

> *"Important trips are in AVs."*

Scenario 2 builds upon the first scenario by assuming that, along with capacity improvements from AV use, individuals using the AVs will perceive the time in them less negatively than time spent driving in regular vehicles. The scenario envisions the point in time that AVs have only been partially adopted, and only by higher income households. As with many new technologies, the initial price will most likely only be attractive to higher income households. Considering that the current cost of self-driving GPS technology alone is around $70,000, (KPMG and CAR 2012) adoption may be among high-income households for some time to come. This assumption follows existing adoption patterns of more expensive cutting-edge vehicles such as hybrid and electric vehicles. For example, Hjorthal, (2013) showed that early adopters of electric vehicles were households with high income, owning more than one car, and used mainly to complement a conventional car for commutes. Petersen and Vovsha (2005) found that higher income house-holds tend to utilize newer vehicles, and among household members, the new vehicles are allocated to workers at a higher rate than retirees and school children of driving age. A similar trend might initially occur with AVs adoption. High income households might purchase one of these vehicles, where it would be used for work and other important trips, while regular vehicles would supplement for other, less important uses.

To test this scenario, modeled travel time was changed. In assignment, trip-based VOTs are reduced by 65% for highest-income households, from $24 to $15.60/hour. Then in the demand models, the automobile travel time was directly modified to be 65% of skimmed travel time in the skims for the high value of time trips. In other words, a weight of 0.65 was applied to travel time for auto trips with a high value of time. This travel time reduction reflects empirical results from the Puget Sound, comparing preference for commuter rail lines versus local bus options, where bus trips offer similar or shorter trips times, yet travelers opt for commuter rail, perhaps for a more comfortable ride, consistent scheduling, or some other un-modeled biases. The existing model accurately predicts commuter rail ridership when perceived time on commuter rail is set at 65% of time on public bus. This scenario represents a similar but not equivalent situation, in which travel time is perceived as less onerous between urban driving and sitting in a self-driving vehicle. This behavior, of course, has not been revealed or even stated by drivers and at this point is speculation based on other modes of transport.

Reduction in travel time has implications throughout the modeling chain. Travel time is a variable in the following models: daily activity pattern, mode choice, destination choice, and time of day choice. Because travel times are perceived as shorter, people will be willing to travel further distances to work and school. They will also be willing to travel in more congested conditions at peak hours, and may take more trips to do non-mandatory activities like eating meals and shopping.

Scenario 3: Increased Capacity, Value of Time Changes, and Reduced Parking Costs

"All cars are self-driving, and none are shared."

The third scenario uses assumptions similar to the previous scenario, but takes them a step further to assume that all cars are self-driving. The scenario envisions the progression of the AVs transitioning from high-income early adopters to total market penetration. This progression would be similar to many new technologies like cell phones or the Internet that became affordable through innovation and economies of scale. Since everyone is assumed to use an AV in this scenario, travel time is reduced to 65% of skimmed travel time, for *all* trips, not just high-VOT trips as in Scenario 2. In this scenario, all travelers, for all trip purposes, enjoy the benefits of robot chauffeurs. As in the previous scenarios, freeway and major arterial capacity is increased by 30%.

A third adjustment is also made for this scenario; parking costs are reduced by half to reflect AVs self-parking in cheaper locations or better utilizing existing space (e.g., parking capacity can be increased on existing lots since no room for driver access is required, thus increasing supply of spaces and reducing costs). This change is made only in zonal parking costs and does not capture VMT generated from vehicles seeking distance parking spaces or even roaming the streets waiting for pickup commands. More detailed models could be developed to capture this behavior and could form an independent research topic.

Scenario 4: Per-mile Auto Costs Increased

“"All autos are automated, with all costs of auto use passed onto the user.”

The final scenario considers a counterpoint situation in which AVs have become so common, and shared AVs systems so effective, that personal AV ownership is no longer necessary. Mobility is perhaps treated as a public utility, where all trips are provided by a taxi-like system at a set rate. In this scenario, vehicles and road use are priced by a combination of industry and government to cover infrastructure operation and maintenance costs. The scenario assumes that all costs of driving are passed on to the user. The cost components that would be included under such a scenario are: vehicle parking, vehicle and infrastructure maintenance, accidents, road construction, vehicle cost, and negative externalities like congestion, air pollution, and global warming. It is assumed that the system provides the same service as a personal automobile, but comes at a higher per-mile rate. A rate of $1.65/mile was chosen to reflect total user and system auto per mile costs and current ride-sharing taxi services. Litman (2007) estimated that the cost per auto mile in urban area during the peak period was about $1.51 per mi. Furthermore 2014 per-mile price from Uber (2014) in Seattle was $1.65. The per-mile costs are a large increase from current total costs of around 60 cents/mile (AAA 2013) and much larger than marginal driving costs of 15 cents in PSRC’s model.

No capacity increase is assumed in this scenario, to reflect a worst-case scenario in which the AVs provide no additional capacity (perhaps due to regulations preventing close car following, for example). Table 1 summarizes these four scenarios for quick reference.

Table 1. Scenario Definitions.

Scenario 1	Scenario 2	Scenario 3	Scenario 4
"AVs increase network capacity."	*"Important trips are in AVs"*	*"Everyone who owns a car owns an AV."*	*“"All autos are automated, with all costs of auto use passed onto the user.”*
30% capacity increase on freeways, major arterials	30% capacity increase on freeways, major arterials	30% capacity increase on freeways, major arterials	
	Travel time is perceived at 65% of actual travel time for high value of time household trips (>$24/hr.)	Travel time is perceived at 65% of actual travel time for ***all*** trips	
		50% parking cost reduction	
			Cost per mile is $1.65

RESULTS

The model outputs from Scenarios 1-4 are compared to the 2010 baseline to investigate the potential impacts of the new technology. Table 2 shows the scenario results for typical measures output by travel models. All the scenarios with a capacity increase indicate increased vehicle miles travelled (VMT), ranging from around 4 % to 20%. However, only one of the three capacity-increase scenarios showed an increase in vehicle hours traveled (VHT). In the first two scenarios, the additional network capacity offsets the additional vehicle miles by allowing vehicles to travel at a faster speed. In the third scenario, however, the reduction in perceived travel time on all trips to 65% of the actual time, along with reduced parking costs induced so much additional demand that the benefits from increase in capacity was offset.

Table 2. Scenario Results, Base Year 2010, Summaries by Average Travel Day.

Measure	Value	Base	1	2	3	4
VMT	Total Daily	78.7 M	81.5 M	82.6 M	94.1 M	50.8 M
	% Change (Versus Base)	**---**	**3.6%**	**5.0%**	**19.6%**	**-35.4%**
VHT	Total Daily	2.82 M	2.72 M	2.76 M	3.31 M	1.67 M
	% Change	**---**	**-3.9%**	**-2.1%**	**17.3%**	**-40.9%**
Trips	Trips/Person	4.1	4.2	4.2	4.3	4.1
Distance (miles)	Average Trip Length	6.9	7	7.2	7.9	5.8
	Work Trips	12.4	12.9	12.9	20	11.5
	School Trips	5.8	5.8	5.8	6.7	4.7
Delay (1000 hours)	Daily Average	846.0	700.0	727.2	996.1	350.2
	Freeways	288.1	201.2	218.3	338.7	56.4
	Arterials	557.9	498.8	508.9	657.5	293.8
Speed (mph)	Daily Average	27.9	30	29.9	28.4	30.4
	Freeways	40	44.7	44.2	40.8	49.2
	Arterials	22.5	23.2	23.1	22.3	24.3
Mode (%)	SOV Share	43.7	43.7	42.7	44.8	28.7
	Transit Share	2.6	2.7	2.7	2.4	6.2
	Walk Share	8.6	8.6	8.4	6.8	13.1

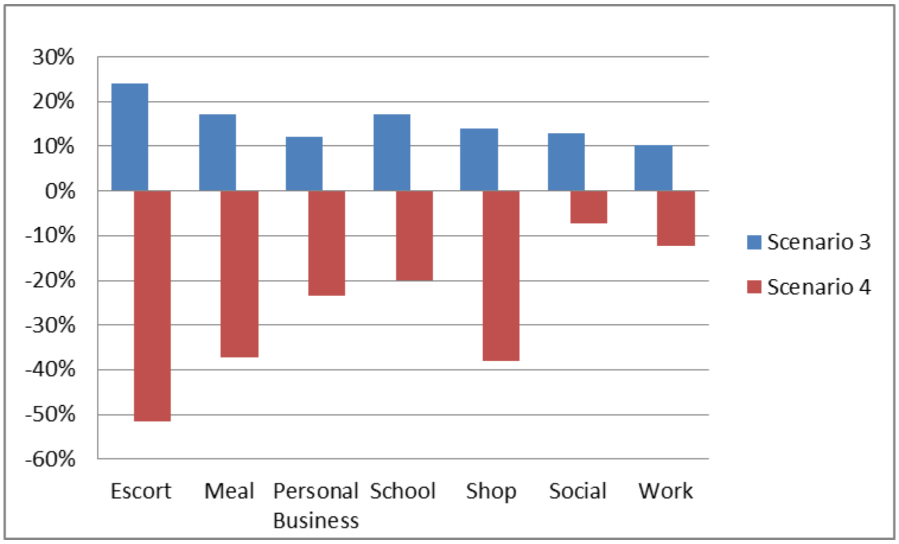
Note that in all three of the capacity-increase scenarios the average network speed is higher than the base scenario by about one or two miles per hour. The vehicle-hours of delay are reduced by about 150,000 vehicle hours in the first scenario and 100,000 vehicle hours in the second scenario, but VHT and delay are both increased in Scenario 3 as VMT increases nearly 20%. This surge in VMT corresponds to about 150,000 hours extra delay and about 17% more vehicle hours. The increase in delay reflects the system-wide assumption of reduced perceived travel time, where people are less averse to delay and thus more willing to tolerate congestion.

The additional vehicle miles result mostly from an increase in the number of trips and an increase in the length of the trips. SoundCast includes sensitivity to travel time in the daily activity pattern, exact number of tours, and intermediate stop models that predict the number of trips people take. As perceived and actual travel time is reduced, the number of trips people will take will increase because of a negative coefficient on travel time. For trip lengths, the destination choice models have a negative coefficient on travel time, so users will travel farther if the perceived travel time is reduced. In Scenario 3, average distance to work increases dramatically to 20.0 miles, from a base of 12.4 miles. Much of this increase may be due to some curious geographical quirks of our region: with less onerous drive time, some drivers may be choosing to follow a circuitous path around Puget Sound instead of utilizing the shorter car-ferry option across the Sound into downtown Seattle. In this scenario, total vehicle miles also increase as travelers switch modes from transit and walking to single occupancy vehicles; transit shares decrease around 9% and walk shares decline 21%.

Scenario 4 serves as counterpoint to Scenarios 1-3, to explore other ways in which AV could affect regional transportation. This scenario is optimistic towards AV adoption and use; shared AVs make owning a vehicle unnecessary, but travel is priced rather high (up to $1.65 per mile versus 15 cents in the base), such that many trips are suppressed or trip lengths shortened. Pessimism is assumed for operational benefits; AVs are thought to be used so widely in this scenario that operational benefits are saturated, and no capacity increases are realized. If increased per-mile costs were applied to all trips, model results suggest VMT may be reduced as much as 35% versus the base. Vehicle-hours are similarly reduced by over 40%. Though numbers of trips per person are very similar across all scenarios, Scenario 4 indicates travelers will generally opt for shorter trips – average trip lengths are down 15% versus the base and over 25% less than Scenario 3, where average trip lengths are the longest of all scenarios. Scenario 4 results also suggest taxi-like pricing would cut drive-alone mode shares by a third, while transit and walk modes might increase by 140% and 50%, respectively. Though some travel could be suppressed in this scenario, the overall network performs better than the base or any other scenario. Delay is less than half that in the baseline, and freeway speeds are nearly 10 mph faster than the base.

Further analysis of tour lengths was performed. Table 3 shows the percent difference in tour lengths by purpose when comparing Scenario 1 to Scenarios 3 and 4. Escort tours had the greatest sensitivity to the modeled time and cost changes among the scenarios. When comparing average escort tour lengths from the base scenario, Scenario 3 showed a 24% increase and Scenario 4 had a 51% decrease. Because escort tours involve more travelers in the same vehicle, they have a higher value of time than other tours. This higher value of time translates to a greater sensitivity to travel time changes, and thus shorter tour lengths in Scenario 3. Scenario 4's decrease comes from sensitivity to cost per mile of these tours.

Figure 1. Percent Difference in Tour Lengths: Scenario 1 Compared to Scenarios 3 and 4

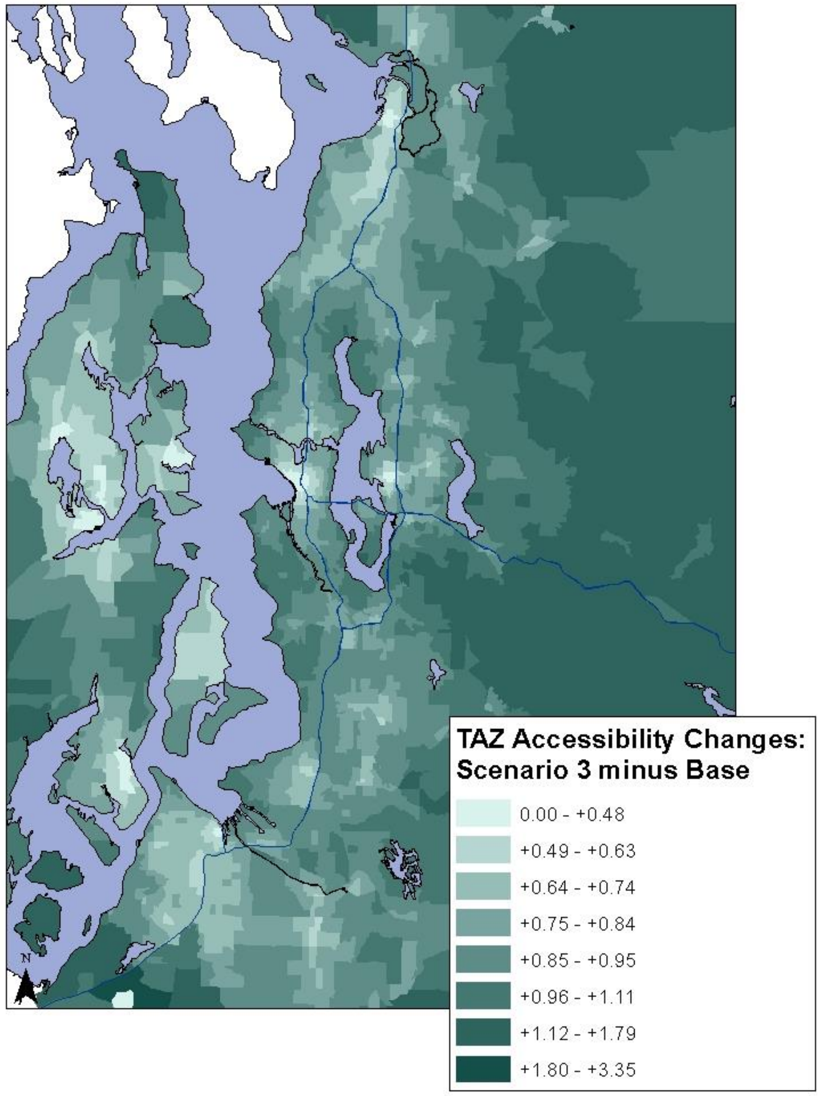


Geographic Distribution of Results

Aside from aggregate system performance, model results were used to provide insight into the spatial distribution of possible effects from AV. Figure 2 visualizes geographic distribution results of the most "aggressive" automated car future, Scenario 3. In this analysis, an accessibility metric called "aggregate tour mode-destination logsums," or simply "aggregate logsums," is used. Aggregate logsums are household-based measures of accessibility, calculated as the sum of the expectation across all possible locations, across all modes (Bowman and Bradley, 2006). The aggregate logsums are calculated separately for households grouped by income, vehicle availability, and transit accessibility, and separately by purpose. A fairly typical household type was selected for analyses in Figures 2: a medium-income household located within ¼ - ½ mile of transit, owning some vehicles, but fewer vehicles than adults. Aggregate logsums are an index measure, and do not have much meaning by themselves, but can be used to compare the differences between two scenarios.

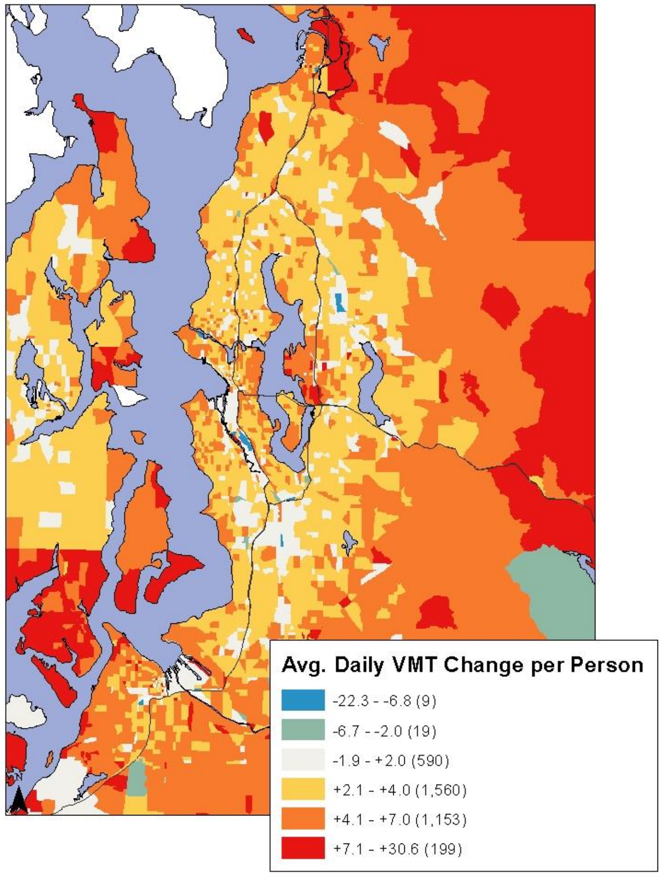
Figure 2 shows that with capacity increases and a reduction in the perception of travel time as in Scenario 3, perceived accessibility would be higher for most households, but especially higher for more remote, rural households. Note that perceived accessibility increases for *all* households, but especially for households in less urban areas. Two groups were selected to analyze how different income groups would be impacted: one low income group and one high income group. For the low income group, the percent change in aggregate logsums was 8.5% between the base scenario and Scenario 3. For the high income group, the percent change in aggregate logsums was about the same at 8.9% between the base scenario and scenario 3. The modest difference between the low and high income groups difference in logsums indicates that with the scenario as designed, low income populations experience nearly the same increase in accessibility as higher income groups.

Figure 2. Accessibility Increase: Scenario 3 minus Base.



This result suggests that AVs, as modeled with assumptions in Scenario 3, would not reduce access for any specific group and would actively increase accessibility in regions away from the typically highly-accessible urban core. Scenario 3 assumes that driving is easier (increased capacity), cheaper (lower parking costs), and more enjoyable (perceived travel time decreases) for all users, leading to a jump in accessibility benefits directly through personal vehicle trips. Though many Puget Sound residents would enjoy higher accessibility in this scenario, total VMT climbs nearly 20%, possibly compromising the region's goals of reducing greenhouse gas emissions and containing growth into existing urban areas. Figure 3 shows how these VMT increases are dispersed across the region.

Figure 3. Scenario 3, Estimated Changes in Average Daily VMT per Person over base



This result indicates that average VMT per person in nearly all zones would increase, with the most extreme increases occurring in outlying areas, and even in some core zones of central Seattle and Bellevue. Zones decreasing in VMT are generally sparsely-populated with few samples to properly estimate. Improving regional mobility is one of PSRC's goals, but such improvements made through increased personal vehicle trips may be conflicting with environmental and land-use targets.

DISCUSSION and RECOMMENDATIONS

Planning Implications

These results imply that AVs could both help and hinder PSRC's policy goals. Speed and capacity increases may improve regional mobility, but they also could induce additional demand, leading to more VMT, and hence greater greenhouse gas emissions. If, on the other hand, a greater share of AVs are electric than would have been otherwise, greenhouse gas emissions could possibly fall. Reducing perceived travel time may provide a more enjoyable traveling experience, but could facilitate longer trips and more VMT. The model runs show that improvements in vehicle hours of delay from capacity expansion can easily be offset by the reduction in perceived time. The amount of additional network capacity this technology can provide is unknown, as are behavioral reactions of travelers. These analyses simply show that a range of reasonable assumptions about AV adoption could have quite different impacts on regional transportation. For example, if self-driving cars are priced per mile, both vehicle miles travelled and vehicle hours travelled could be greatly reduced, by as much as 20 and 30%, respectively, with SOV shares declining 40% and transit shares almost doubling. Conversely, model assumptions in the first three scenarios indicate potential for much more VMT and delay, with more people carried in SOVs, generally worse or equivalent network performance, but higher mobility overall.

Self-driving vehicle adoption impacts are addressed in this paper from the perspective of PSRC's long-range plan goals of mobility, accessibility, and congestion impacts, but future research should explore potential safety, emissions, and land use changes. Many simplifying assumptions were used to isolate and test network and behavioral changes potentially associated with automated technology development. However, if AV use does dramatically change regional VMT, trip lengths, and mode shifts, it follows that land uses may shift dramatically as well. Understanding these built environment changes will be very important in planning for future impacts of AV technology.

Modeling Implications

Some improvements to this study's methodology are achievable now, such as testing future-year settings and linking the travel and land use models. These are perhaps the next logical next steps in more detailed AV analyses, since changes in accessibility may be quite large and those accessibility changes would impact land use development patterns.

More importantly, existing tools are demonstrably not sufficient for expressing the full range of possibilities that automated vehicles may present. This study makes oversimplifications, such as using a present-year land use assumptions and assuming broad AV costs and user values of time. The model was estimated and calibrated against data that represents today's network reality, which is far outside of the reality that may exist with wide AV adoption. The challenges faced in modeling AV scenarios highlight limitations of today's tools in addressing this technology. Many modeling improvements are considered below.

The future business model for shared AVs is entirely opaque. At a minimum, this could be represented more directly with a top-tier taxi mode, which SoundCast currently lacks. Most recent travel surveys indicate growing shares for taxi and taxi-like trips from ridesharing services. Including a taxi mode would allow modelers to tweak performance and prices specific to shared AVs. This would go a long way toward preparing our model for outcomes where many of us may have robotic chauffeurs.

In activity-based models, household-owned AVs could be represented as a separate mode from non-automated vehicles with their own modal constants and variables. Representing AVs as a separate mode may be necessary if policy makers would like to consider separated lanes for

AVs. As with high-occupancy vehicles and toll links, AVs may need to be modeled using a separate set of user classes with unique values of time and network link attributes.

The reduction in perceived travel time in AVs would be better modeled by attributing the improvement in experience of travel time to actual measurable variables, as has been researched with transit (Outwater, 2013). In mode and destination choice models, the stages of automation could be a set of zero-one variables for the AV mode; assuming that the AV mode would become more attractive with more automation and that with more automation, travel impedance variables would have lower coefficients.

Currently, modelers lack the evidence to add AV-related alternatives and variables into travel demand models. Because these vehicles do not yet exist but modelers need to incorporate their possible impacts on travel demand, the most straightforward way to understand behavior would be to conduct a stated preference survey.

A stated preference survey about travel behavior using AVs should try to answer some of the following questions:

- How much would different types of people be willing to purchase different levels of automation and for what price?
- Who would prefer to use the AVs as a shared service, and forgo car ownership?
- How will people perceive and value their time differently in AVs?
- Would people anticipate moving farther away from work?
- Would businesses choose to locate farther from the city center?
- What aspects of the AVs would cause people change their behavior most such as ability to work, avoiding congestion, or safety?

Stepping further back and thinking about more than just variables and their coefficients, there are some real shifts in how people perceive travel even today that our models simply don't capture. Multitasking (e.g. reading/emailing on a smartphone while on the bus), the effect of ingrained habits and "lifestyle choices" (e.g., a person who really loves driving their luxury car, or another person who would never consider driving to work even if it had free parking) need to be incorporated in the next generation of models. Those types of high-level differences will be amplified when a disruptive technology like AVs are introduced.

Closing Remarks

For modelers and policymakers alike it's important to remember that, when presented with automated vehicle technology, people are still going to behave based on the options available to them and on the constraints they face in their daily lives. We have tried to lay out reasonable (or at least conceivable) scenarios in this study, but the future may be more different than we've envisioned. That possibility makes it even more critical that we improve our tools now to support the policymakers and planners who will have to grapple with this new technology.

This research is just a starting point. We hope to continue the discussion as we sharpen our predictive tools in the coming years.

REFERENCES

AAA (2013) Your Driving Costs. https://exchange.aaa.com/wp-content/uploads/2013/04/Your-Driving-Costs-2013.pdf

Anderson, J., N. Kalra, K. Stanley, P. Sorensen, C. Samaras, O. Oluwatola (2014) Autonomous Vehicle Technology: A Guide for Policymakers. RAND Institute. http://www.rand.org/content/dam/rand/pubs/research_reports/RR400/RR443-1/RAND_RR443-1.pdf.

Bowman, John L. and Mark Bradley (2008), Activity-based models: approaches used to acheive integration among trips and tours throughout the day. European Transport Conference, Leeuwenhorst, The Netherlands, October, 2008. http://www.jbowman.net/papers/2008.Bowman_Bradley.Approaches_to_integration_ETC.pdf

Burns, L., W. Jordan, B. Scarborough (2013) Transforming Personal Mobility. The Earth Institute, Columbia University. http://sustainablemobility.ei.columbia.edu/files/2012/12/Transforming-Personal-Mobility-Jan-27-20132.pdf.

Cervero, R. (2001) Induced Demand: An Urban and Metropolitan Perspective. University of California, Berkeley. http://www.uctc.net/papers/648.pdf.

Fagnant, D., K. Kockelman (2013) Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers, and Policy Recommendations for Capitalizing on Self-Driven Vehicles. Eno Center for Transportation. http://www.enotrans.org/wp-content/uploads/wpsc/downloadables/AV-paper.pdf.

Fernandes, P., U. Nunes (2012) Platooning with IVC-Enabled Autonomous Vehicles: Strategies to Mitigate Communication Delays, Improve Safety and Traffic Flow. *IEEE Transactions on Intelligent Transportation Systems* 13(1): 91-106.

FHWA (2013) Traffic Incident Management. U.S. Department of Transportation, Federal Highway Administration. http://ops.fhwa.dot.gov/aboutus/one_pagers/tim.htm.

Gucwa, M. (2014) The Mobility and Energy Impacts of Automated Cars. Dissertation, Stanford University.

Hjorthal, R. (2013) Attitudes, ownership and use of Electric Vehicles - a review of literature. Institute of Transport Economics. Report 1261/2013. 4/2013. https://www.toi.no/getfile.php/Publikasjoner/T%C3%98I%20rapporter/2013/1261-2013/1261-hele%20rapporten%20nett.pdf

Litman, T. (2007) Transportation Cost and Benefit Analysis II Cost Summary and Analysis. Victoria Transport Policy Institute. http://www.vtpi.org/tca/tca06.pdf

Litman, T. (2014) Autonomous Vehicle Implementation Predictions: Implications for Transport Planning. Victoria Transport Policy Institute. http://www.vtpi.org/avip.pdf.

Litman, T. (2014b) Generated Traffic and Induced Travel. Victoria Policy Institute. http://www.vtpi.org/gentraf.pdf.

Lyons, G., J. Jain, D. Holley (2007) The use of travel time by rail passengers in Great Britain. *Transportation Research Part A: Policy and Practice* 41(1): 107-120.

Nichols, B. and K. Kockelman (2014) Pay-As-You-Drive Insurance: It's Impact on Household Driving and Welfare. *Transportation Research Record*.

Outwater, M., B. Sana, N. Ferdous, W. Woodford, C. Bhat, R. Sidharthan, R. Pendyala, S. Hess (2013) Characteristics of Premium Transit Services That Affect Mode Choice: Key Findings and Results. TCRP H-37. Resources Systems Group, University of Texas at Austin, Arizona State University, and University of Leeds.

Parry, I. and K. Small (2005) Does Britain or the United States Have the Right Gasoline Tax? *American Economic Review* 94(4): 1276-1289. http://www.econ.wisc.edu/~scholz/Teaching_742/Parry-Small.pdf.

Pinjari, A., B. Augustin, N. Menon (2013) Highway Capacity Impacts of Autonomous Vehicles: An Assessment. Center for Urban Transportation Research. University of South Florida. http://www.usfav.com/publications/TAVI_8-CapacityPinjari.pdf.

Puget Sound Regional Council (2010) Transportation 2040. http://www.psrc.org/assets/4847/T2040FinalPlan.pdf.

Puget Sound Regional Council (2014) Activity-Based Travel Model. http://www.psrc.org/data/models/abmodel/.

Shladover, S. E. (2009) Cooperative (Rather than Autonomous) Vehicle-Highway Automation Systems (pp. 10–19). Berkeley.

Shladover, S., D. Su, X. Lu (2013) Impacts of Cooperative Adaptive Cruise Control on Freeway Traffic Flow. *Transportation Research Record* 2324 (pp. 63-70). http://trb.metapress.com/content/c7x847k3647888n1/.

Tientrakool, P., Y. Ho, N. F. Maxemchuk (2011) Highway Capacity Benefits from Using Vehicle-to-Vehicle Communication and Sensors for Collision Avoidance. Vehicular Technology Conference , 2011 IEEE. 10.1109/VETECF.2011.6093130.

Van Arem, B., C. van Driel, R.Visser (2006) The Impact of Cooperative Adaptive Cruise Control on Traffic-Flow Characteristics. *IEEE Transactions on Intelligent Transportation Systems* 7(4), December 2006. http://doc.utwente.nl/58157/1/Arem06impact.pdf.

Petersen, E, P. Vovsha (2005) Intra-Household Car Type Choice for Different Travel Needs. Association for European Transport and contributors. http://abstracts.aetransport.org/paper/download/id/2119.

Uber (2014) UberX Rates. https://www.uber.com/cities/seattle.

Wood, S., J. Chang, T. Healy, J. Wood (2012) The Potential Regulatory Challenges of Increasingly Autonomous Motor Vehicles. Santa Clara Law Review 52(4): 9. http://digitalcommons.law.scu.edu/cgi/viewcontent.cgi?article=2734&context=lawreview.