Design for Incorporating Autonomous Vehicles in the Regional Strategic Planning Model (RSPM)

Brian Gregor
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Implications of Autonomous Vehicles for Strategic Modeling

Substantial advancements have been made in the development of self-driving cars in just a few years. About twelve years ago (2004) the farthest that a vehicle drove autonomously in DARPA's Grand Challenge was 7 miles. The following year the 150 mile course was navigated successfully by 5 vehicles. Two years later, in DARPA's Urban Challenge, 6 autonomous vehicles traveled through an urban course, sucessfully following the rules of the road and navigating obstacles and traffic (Fagnant 2015). In 2009, Google started working on their self-driving car project. Six years later (May 2016) Google cars had driven over a million and a half miles in autonomous mode (Google 2016a). Google is by no means the only company working on developing self-driving cars, many others including Tesla, GM, Daimler, Volvo, Ford, Jaguar Land Rover, Audi, and BMW are actively working on automated vehicles(Gibbs 2016). The rapid pace of autonomous vehicle research and development has lead some people to predict that self-driving cars will be on the road within a few years: 2 years according to Eldon Musk, the CEO of Tesla Motors, and by 2020 according to the president of GM and the CEO of Nissan Motor Corporation (Yadron 2016). At that pace, most of vehicles on the road could be self-driving within a few decades. Even skeptical analysts think that a majority of vehicle sales and travel could be of autonomous vehicles by the middle of the century (Litman 2015).

Given that self-driving cars could make up a substantial portion of the vehicle fleet within the next 20 to 30+ years, it is important for transportation planners to consider the implications of autonomous vehicles (AVs) and for strategic planning models to be able to assess the implications. However, the RSPM does not currently include these capabilities because, at the time most of the model's components were being designed and estimated, autonomous vehicle research was still in its infancy. Prospects for autonomous vehicles were highly speculative and quantitative analysis of the implications was very limited. This has changed within the past few years and now there is sufficient information to be able to add simple capabilities for modeling autonomous vehicles to the RSPM.

The effect of AVs on the transportation system will depend on the level of autonomy that is achieved. The National Highway Traffic Safety Administration (NHTSA) identified 5 levels of autonomy in its preliminary policy on autonomous vehicles (NHTSA 2013): * Level 0 (No Automation): The driver is in complete and sole control of the primary vehicle controls – brake, steering, throttle, and motive power – at all times. * Level 1 (Function-specific Automation): Automation at this level involves one or more specific control functions. Examples include electronic stability control or pre-charged brakes, where the vehicle automatically assists with braking to enable the driver to regain control of the vehicle or stop faster than possible by acting alone. * Level 2 (Combined Function Automation): This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions. An example of combined functions enabling a Level 2 system is adaptive cruise control in combination with lane centering. * Level 3 (Limited Self-Driving Automation): Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions and in those conditions to rely heavily on the vehicle to monitor for changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control, but with sufficiently comfortable transition time. The Google car is an example of limited self-driving automation. * Level 4 (Full Self-Driving Automation): The vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip. Such a design anticipates that the driver will provide destination or navigation input, but is not expected to be available for control at any time during the trip. This includes both occupied and unoccupied vehicles.

At levels 1 and 2, vehicle automation assists the driver with some driving tasks, but the driver must still maintain control of the vehicle at all times. This automation is already being included in vehicles now being sold: blind-spot warning, lane departure warning, forward collision warning and braking, automated parking, lane keep assist, adaptive cruise control. These features are likely to improve traffic safety by reducing crashes due to driver error (Fagnant 2015). Reducing crashes will have a secondary effect on reducing incident-related delay, but is unlikely to have much effect highway capacity. It is also unlikely to have much effect on travel demand because human drivers must still remain in control of their vehicles.

At levels 3 and 4, vehicle automation takes full control of vehicle guidance and operation. The difference being that with level 3, the driver has to be prepared to take over control whereas with level 4 the driver does not. These features, at least at level 4, promise to increase highway capacity as well as highway safety because vehicles will be able to communicate with one-another and with infrastructure to increase traffic density and smooth traffic flow while reducing delay (Fagnant 2015). It is likely that full vehicle automation will also affect vehicle travel demand for several reasons. First if the driving task is made less onerous and if people can use the time traveling for other activities, they will be more likely to "drive" and more likely to "drive" farther. Second, if capacity is increased, then travel speed would be higher than it otherwise would be. This also encourage more dispersion of trip origins and destinations and more VMT. Third, it opens up the possibility of a new travel mode, shared autonomous vehicles (SAV), which provides on-demand taxi-like service at costs that are competitive with private vehicle ownership (Burns 2013). This mode will enable many households to have widespread urban mobility without owning a car. It will also increase the mobility of many people who can't drive because of age, physical disability, or income (Levinson 2015).

As was mentioned, vehicles with levels 1 and 2 automation are already on the roadway. These features are likely to decline in price and be available on a wider selection of vehicles in the next few years, acquainting motorists with vehicle automation and increasing demand for even greater automation. Whether or not level 3 is the next step, or whether manufacturers move directly to level 4 is a matter of debate. Google, which has logged over a million miles of level 3 testing has determined that the technology that is provided for public consumption should be level 4 because of the difficulty of keeping drivers as attentive as they need to be to take control of the vehicle when needed. The company has determined that maintaining driver attentiveness will be more difficult than making a vehicle fully automated so that attentiveness is unnecessary (Crothers 2015). Ford is taking the same approach although some other car companies are trying to develop systems that would enable level 3 vehicles to work safely (Davies 2015).

Whether level 4 vehicle automation is deployed through fleets of SAVs or through personally-owned AVs, is also open to debate. Although the use of car-sharing services (e.g. Car-to-Go, Zipcar) has been growing, as have car driving services (e.g. Uber, Lyft), the proportion of trips served by them is still quite low and auto ownership is popular for a number of reasons. This suggests that the main market for AVs will be households. On the other hand, other economic and use considerations provide compelling arguments that SAVs could be the main market. Level 4 AV technology at present is not cheap. The AV technology in Google cars costs about $150,000 (LIDAR is about half the cost) (Google 2016b). Even a ten-fold decrease in cost would still leave a $15,000 price tag. That is large price boost for all but the highest income households to absorb, especially considering that the average household vehicle is only in use about an hour a day (Burns 2013). On the other hand, level 4 AV technology makes economic sense for automated taxi services because it would eliminate the labor cost for driving the vehicle and the added cost would be amortized over a period of almost continuous use. For example, Fagnant and Kockelman estimated that a SAV system serving about 50 thousand daily person trips in the Austin metropolitan area could realize a 19% annual return on investment with AV cars costing $70,000 ($50,000 for the AV technology) at fares of $1.00 per mile (less than a third of the current taxi fare) (Fagnant 2016). It is telling that Uber has gotten into the business of developing self-driving cars (O'Brien 2016) and that GM is investing $500 million in Lyft (Alba 2016).

Whether self-driving cars are purchased more by households or by SAV companies has substantial consequences for the structure of the light-duty vehicle fleet and the rate at which it turns over, and consequently for the rate of new technology adoption. Although a SAV future scenario has the potential for greatly reducing the total number of light-duty vehicles on the road, VMT may not decrease and neither may the number of vehicles purchased each year. Several SAV modeling studies have estimated that each SAV could replace over 10 vehicles (Burns 2013)(Fagnant 2014)(Fagnant 2016). The number of vehicles replaced would not be as high if the SAVs are electric (SAEV)(Chen 2016a). These studies also show that a smaller vehicle fleet will not necessarily translate into less VMT because unlike household vehicles, the SAVs will be in almost continuous use. In fact, VMT may increase as a consequence of SAV travel between dropping off a customer and picking up the next one. This has substantial implications for vehicle turnover and technology advancement. Currently If each SAV replaces 10 vehicles, and if the total VMT driven is the same, then the lifetime of SAVs would be about a tenth of the lifetime of the household vehicles that they replace. This would greatly increase the rate at which newer, more fuel-efficient, vehicles would get on roadways.

Design for Incorporating Autonomous Vehicles into the RSPM

The model will be modified to model level 4 automation scenarios. There are several reasons for this. First, level 1 and 2 automation is likely to have relatively small effects on transportation system operation and use aside from reducing vehicle crashes. A significant objective of strategic planning is to investigate possible disruptive changes. It's level 4 automation that's likely to cause those changes. There is a substantial possibility that level 4 automation will greatly affect roadway capacity, vehicle ownership, vehicle characteristics, and rates of vehicle turnover. Level 3 automation is ignored for the same reasons that Google and Ford are not planning to deploy level 3 automated vehicles.

Modeling Congestion Effects

There are two approaches that could be taken to modeling the effects of autonomous vehicles on congestion. The first is to adjust freeway lane-miles account for predicted effects of autonomous vehicles on capacity. Doing so affects the proportions of DVMT at different congestion levels and in turn affects the base levels of recurrent and non-recurrent delay. An alternative approach is to specify delay reductions in the 'other_ops.csv' input file. Of the two, the first is preferred for several reasons: 1. It

enables effects on recurring and non-recurring congestion to be separated and easier to model. Estimates of the capacity effects of autonomous vehicles are available as are estimates of the effects on accident rates. Calculating the joint effects on delay would require more off-model computations to produce the inputs.
2. Adjusting freeway lane-miles also accounts for the effect of improved capacity on the amount of VMT due to increases in auto accessibility. Both the auto ownership model and the household VMT model are sensitive to freeway lane-miles. Furthermore since the new alternative mode trip models (walk, bike, transit) are sensitive to household VMT (negative coefficient) those model result will be sensitive to changes in auto accessibility due to automated vehicles.

Regarding how much to change freeway lane-miles, Fagnant and Kockelman report on the estimates by Shladover et al. that cooperative adaptive cruise control (CACC) deployed at the 10%, 50% and 90% levels would increase freeway lane capacities by 1%, 20%, and 80% respectively (Fagnant 2015). CACC enables automated vehicles to travel in closely spaced platoons and would only be possible with level 4 automation. A simple polynomial model can be fitted to these data to estimate lane-mile increases at different levels of level 4 deployment.

As noted above, autonomous vehicle deployment will also affect non-recurring (i.e. incident-related) congestion. As reported by Fagnant and Kockelman, the FHWA estimates that about half of incident-related congestion is caused by crashes (Fagnant 2015). The effects of reduced crashes due to vehicle automation can be addressed in the RSPM congestion by altering the 'OpsDelayReduce_$Incident' table in the GreenSTEP model object. For automated vehicle scenarios, the model table values for percentage reduction in freeway non-recurring congestion will be overwritten with percentage reductions reflecting the level of crash reduction due to automation. For example, in the unlikely event that all crashes are eliminated, freeway non-recurring congestion delay would be reduced by 50%.

Modeling Automated Vehicle Ownership

It is proposed that automated vehicle ownership be modeled in the same way that other vehicle characteristics are modeled. A new input table will be created which specifies the automated vehicle sales proportions by model year and vehicle type (i.e. auto, light truck). The inputs will be developed to take into account projections of automated vehicle costs and industry/expert opinions about market penetration. Because the existing vehicle age model in RSPM allocated newer vehicles preferentially to higher income households, it will skew automated vehicle ownership towards higher income households as it should. The other characteristics of household-owned automated vehicles will be assumed to be the same as non-automated vehicles of the same model year. In essence, household vehicles will have an additional attribute (automated vs. non-automated). That attribute will affect household travel, as explained in the Modeling the Effects on VMT section below.

Modeling Shared Autonomous Vehicle (SAV) Deployment

SAVs will be modeled by modifying the existing RSPM car-sharing models. It will be assumed that households are or are not regular users of SAV services. There will be no capability for modeling occasional SAV use because of the increased challenge of determining how much use a household would have and because it is likely that only regular users would alter the number of vehicles they own as a result of SAV availability. The first model modification will be to simplify the input that quantifies the degree of car-sharing deployment. Currently, the input is expressed as the number of persons per car-share vehicle. This approach follows that used in the "Moving Cooler" study. This has proven to be confusing for model users. The new approach that will be applied to both car-sharing and SAV participation will be to specify the proportion of households that are subscribers/regular users. A new input will be added for specifying the SAV regular users (percentage of households) by forecast year. The model which determines which households are subscribers will be modified to add another factor, whether a household member has to pay for parking at work. Paying for parking is likely to be a significant consideration for households choosing to commute by SAV rather than a vehicle they own because using an SAV to get to work eliminates the cost of parking which can be fairly sizable relative to the estimated cost of SAV travel.

The existing model will also be changed with regard to how household vehicle equivalents are calculated for households subscribing to car-sharing or SAV services. The current model assigns 1/20th of a vehicle to a household that subscribes to a car-sharing service. This value was chosen because the methodology used in the "Moving Cooler" study assumes that on average 20 households share one car-share vehicle. This may be reasonable at low levels of car-share deployment, but it is likely to substantially underestimate the effect of SAVs on household travel, especially at high deployment levels. Several simulation studies show that SAVs can provide urban service that rivals private vehicle use and so subscribing to a well-deployed service should be viewed as equivalent to owning a vehicle. {To Do: add some examples of findings from simulation studies.} The new approach will be to add an input where the vehicle equivalence ratio will be specified for households that subscribe to car-share services and for households that are regular users of SAV services. The values in this table will be a function of the level of deployment and can be informed by the results of research by Burns, Fagnant, Kockelman, Chen and others.

Modeling the Effects on VMT

Level 4 automated vehicles are likely to affect VMT in several ways including: 1. Improved automobile accessibility due to increased freeway capacity (and speed) is likely to increase automobile use and distance traveled. 2. Eliminating the need to drive will make traveling by car less onerous and relatively more desirable. 3. Self-driving cars will make it possible for people who can't drive because of age, physical disability, or income to be able to travel by car without being chauffeured by another person. 4. A household owning an autonomous vehicle may send it unaccompanied to destinations to avoid paying for parking or for other purposes. 5. SAV vehicles will need to travel additional miles to get between customers. 6. Travel by SAV will have a higher variable cost than traveling by a household-owned vehicle (which has higher sunk cost and lower variable cost) and will as a result be used less.

The first of these effects will be addressed as explained above by increasing the freeway lane-miles to reflect the effect of autonomous vehicle deployment on capacity.

The second, third, and fourth effects will be addressed by an additional input that multiplies the VMT assigned to household-owned autonomous vehicles to account for this additional travel. This input would largely be a judgement call, but some sense of the second effect might be gained by referring to the paper by Chen and Kockelman (Chen 2016b).

The fifth effect will also be addressed by a multiplier input. Household VMT assigned to SAV travel will be multiplied by this factor to calculate total SAV travel. However, unlike the multiplier for household-owned autonomous vehicle travel, the SAV VMT multiplier will not be applied at the household level. It will be applied at the system level. The results of several SAV simulation studies can be used to establish the value of the multiplier.

The sixth effect will be modeled using the existing RSPM household budget model. Household-owned vehicle VMT will be multiplied by the unit cost calculated in the same was as present. The unit cost for SAV VMT will be calculated in the same way except it will include the estimated costs for SAV depreciation, financing, insurance, overhead, and profit. Values for these quantities will be derived from the papers by Burns, Fagnant, Chen et al.

Doing these things requires that each household's VMT is split between autonomous vehicles, non-autonomous vehicles, and SAV use. This will be done in proportion to the number of vehicles in each category, or the number of equivalent vehicles in the case of SAV. This approach will necessitate eliminating a feature of the current model which reshuffles VMT among household vehicles to minimize fuel consumption. This is a feature that has almost never been used and is unlikely to be missed.

Model Effects on Fuel Consumption and Emissions

The deployment of driverless cars is likely to significantly reduce the rates of fuel consumption (gallons per mile) and emissions (grams per mile) for a couple of reasons: 1. CACC will smooth traffic flows, reducing speed variation and accelerations and decelerations that waste fuel;, 2. SAVs will enable vehicle fleets to be smaller, more fuel efficient, and powered largely by electricity; and, 3. The fleet of SAVs will turn over more rapidly, enabling advanced technology to be incorporated more rapidly.

The first of these effects can be modeled using the existing "speed_smooth_ecodrive.csv" file which enables users to specify the proportion of VMT that is affected by speed smoothing.

The second and third effects will be modeled using new input files that specify the assumed characteristics of the SAV fleet by model year. These files would be much like the commercial service vehicle input files. The average vehicle will be calculated based on the total SAV miles, the number of SAVs deployed, and the useful SAV life (in miles).

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