Incorporating Autonomous Vehicles in the Traditional Four-Step Model

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ABSTRACT

Automated vehicles (AVs) are a concrete possibility in the near future. Since AVs may shift transportation paradigms, transportation agencies are eager to update their models to consider them in planning. In this context, the use of advanced models may be challenging, given the uncertainty in the use and deployment of AVs. In this paper, we present a general framework to extend the four-step model to include AVs, and test our extension on NCTCOG's model. Our approach introduces a module for AV ownership and exogenous parameters into an existing four-step model to account for changes in travel decisions for AV owners, and for the impacts of AVs on network performance. The latter is modeled using the concept of passenger-car-equivalent to avoid imposing network-wide assumptions on AVs' capacity consumption. We analyze five scenarios, representing different assumptions on the impacts of AVs, and include references to inform the selection of modeling parameters. We compute aggregate metrics that suggest that the model is sensitive to the proposed parameters, with the passenger-car-equivalent assumptions having the largest impact on model outcomes. Results suggest that, even when we assume that AVs can better use network capacity and that trip making rates do not drastically increase, AVs may lead to an increase of about 2.8 percent in VHT while also improving speeds by about 1.8 percent. If AVs introduce additional friction on traffic, the system performance may deteriorate. The analyses presented here suggest that existing modeling tools may be adjusted to support analyses of a future with AVs.

KEY WORDS
Autonomous vehicles, AVs, self-driving vehicles, demand model, four-step model.

1   INTRODUCTION

Recent technological advances make self-driving automated vehicles (AVs) a concrete possibility in the near future. AVs and connected AVs (those that that can send/receive data to/from each other) are likely to lead to a shift in existing transportation paradigms. As a result, transportation agencies must review and update their models to more accurately analyze future scenarios and plan accordingly, allowing them to accommodate these new developments within their long-term plans (e.g., allocating funds to infrastructure projects).

Advanced transportation models, such as activity-based models (1), dynamic traffic assignment models (2), and agent-based simulations (3), are likely to have the flexibility to capture the impacts of AVs (4). However, the use of these models for long-term planning applications require making detailed assumptions regarding their inputs. Agencies, however, might simply not be ready to make and stand by all of the assumptions needed for such models. For example, in most dynamic traffic applications, some of the model's main inputs are the signal timings for all intersections in the network. However, if an agency is attempting to forecast traffic flow patterns of 20, 30 or 40 years in the future, it can be quite challenging to, *a priori*, provide detailed signal timings data for all of the network's intersections.

This is why MPOs rely so heavily on the four-step model: its assumptions are typically less constraining than those of the advanced models built to substitute its integrating parts, such as dynamic traffic assignment, built to substitute static traffic assignment, or activity-based models, conceived to substitute trip generation (when MPOs generate trips using activity-based models, they typically allocate them to the transportation network through traditional static traffic assignment procedures). Thus, appropriately estimating and calibrating a four-step model is considerably easier than calibrating more advanced models. Furthermore, the four-step model is less prone to reacting poorly to slight inaccuracies in its calibration stage, input parameters or its intermediate outputs. For example, the fact that static assignment does not truly enforce link capacities makes it significantly less sensitive to potential travel demand overestimations.

Even though the basic structure of the four-step model has remained fundamentally the same since its conception, it has also continued to see academic development, with researchers creating faster and more efficient sub-models (5). The enduring application of the four-step model's structure speaks not only to its flexibility, but also to its transparency in terms of its assumptions of how demand and supply interact, and its comparative ease of use. Regardless of its limitations, the four-step model continues to be extensively used by transportation agencies and is still considered the de facto modeling standard in many circles.

In this paper, we present a general framework to extend the traditional four-step model to include AVs, and test our extension on the North Central Texas Council of Governments' (NCTCOG's) four-step model. Our proposed changes, which are implemented through exogenous parameters, include segmenting the household population into AV households and non-AV households, as well as changing each step of the four-step process. Because there is still significant uncertainty concerning how AVs will be used in the future, the investigation of adequate values for each of the parameters is still ongoing. Regardless of what the actual values of these parameters may be, planners may use the exogenous parameters as "levers" that can be easily adjusted to generate future scenarios. In order to assess the performance and sensitivity of our proposed extension to the NCTCOG model, we run several different scenarios with slight changes in the main exogenous parameters, and analyze variations in aggregate results. The latter includes the

total number of trips, total vehicle-miles traveled (VMTs), and total vehicle-hours traveled (VHTs). The model responded according to our expectations in all scenarios, and proved to be a potentially valuable tool capable of answering important practical questions that practitioners might have, such as "What would happen if, instead of capacity gains, the mixing of AVs among non-autonomous vehicles actually reduced capacity?"

Most transportation agencies and Metropolitan Planning Organizations (MPOs) already have a four-step model they use to evaluate infrastructure projects. Thus, we believe that our proposed framework to consider an AV future can be of great interest to many practitioners, given that the extensions we propose in this paper may be incorporated in most planning models. Further, the simplicity of the four-step process allows users to clearly track the impacts of their modeling assumptions (regarding AVs) on network performance. The extensions we developed also have clearly stated assumptions, each of which is characterized by its own exogenous control parameters and informed by literature.

2   AVS IN PLANNING: RESEARCH AND PRACTICE

Transportation planning typically relies on an iterative modeling process that considers the inter-dependencies of travel demand and the performance of multi-modal transportation networks on which travel occurs. The traditional planning approach used by most MPOs relies on a four-step process that consists of multiple models that estimate trip generation, trip distribution, mode choice, and route assignment. Planning models are typically used to study the impact of transportation-related decisions fifteen to thirty years into the future, such as whether or not to fund a new infrastructure project. There is considerable uncertainty regarding how transportation systems will operate in a future that involves autonomous and connected vehicle technologies. Accounting for the impact of such technologies requires revisiting every step in the four-step process.

While some transportation agencies have already started considering the impacts of AVs on their long-range regional transportation plans, Guerra (6) explores the extent to which MPOs have actually engaged in these efforts, and explains that most MPOs have not considered AVs in their current plans. His work highlights three MPOs that have attempted to quantify the impacts of AVs: the Atlanta Regional Commission (ARC) in Atlanta, GA; the Metropolitan Transportation Commission (MTC) in San Francisco, CA; and the Puget Sound Regional Council (PSRC) in Seattle, WA. The approach used in these three cases was to alter some parameters in existing activity-based models. More recently, Freemark et al. (7) surveyed multiple planning officials from 120 cities in the U.S., and inspected municipal planning documents of the twenty-five largest U.S. cities. Their results showed that 36 percent of the largest cities mention AV-related policies, revealing that some local governments have begun planning for a future with AVs. However, the cities that mention AV-related policies usually avoid engaging in concrete strategies, instead focusing on the prioritization of "innovation" and "flexibility." As part of a project funded by the North Central Texas Council of Governments (NCTCOG), we also contacted the New York Metropolitan Transportation Council (NYMTC) to inquire whether and how they have accounted for the potential impacts of AVs in their travel forecasts, and found that they are currently not incorporating these effects into their model because AVs are not yet legal in the state, making their future uncertain.

While the consideration of AVs in practice is limited, there have been some research-based studies using trip-based modeling, including refining the traditional gravity model to enable lower

sensitivity to travel time in the trip distribution step and considering AVs as a distinct mode in the mode choice stage. Some very recent examples include (8), (9), (10), and (11), who implement small refinements on a trip-based framework at the statewide and metropolitan scales in Texas, Toronto (Canada), Michigan, Illinois, Virginia, Indiana, South Carolina, and Ontario (Canada). However, these studies typically take a simplified approach when modeling the capacity consumption of AVs, often using a single network-wide factor to adjust link-level capacities or simply occasionally ignoring capacity impacts altogether.

Other research efforts investigate the direct impacts of AVs on capacity, including (12) and (4). These approaches usually involve developing custom simulation tools to analyze either small highway sections (such as one road link or one intersection) or small cut-outs of larger networks.

In an attempt to more broadly facilitate transportation agencies' development of a system capable of evaluating the impact of AVs, Mahmassani et al. (13) worked with the U.S. Department of Transportation on a generalized conceptual framework for an analysis, modeling, and simulation system. The framework they propose, which can be seen in Figure 1, is divided into four main components: supply changes, demand changes, operational performance, and network integration. The authors also developed a prototype of their framework, applying it to a small testbed: the microsimulation of a 3.5-mile section of Interstate 290 in Chicago. Their proposed framework is very broad and is designed to capture all potential changes brought forth by AVs, while maintaining consistency across multiple sub-models. The framework is intended to take advantage of a number of advanced modeling tools, including agent-based simulations, dynamic traffic assignment, and microscopic flow simulations.

The literature overview suggests that transportation agencies and MPOs are interested in incorporating new AV-related transportation elements in their long-term plans, but are finding it challenging to do so in the context of their current planning methods. While there are several earlier studies that focus on modeling specific elements of time-use and activity-related impacts of AVs, these studies need to make multiple behavioral assumptions and have to use large-scale resource-intensive agent-based simulation approaches. While such activity-based models may provide more accurate forecasts, the uncertainty associated with the model assumptions and the resulting forecasts are at a level where resorting to simpler trip-based models with fewer assumptions, even if less accurate, may be an alternative prudent approach. This approach also has the appeal that it can be readily "wrapped" around the simpler trip-based modeling approach still used by most MPOs in the country.
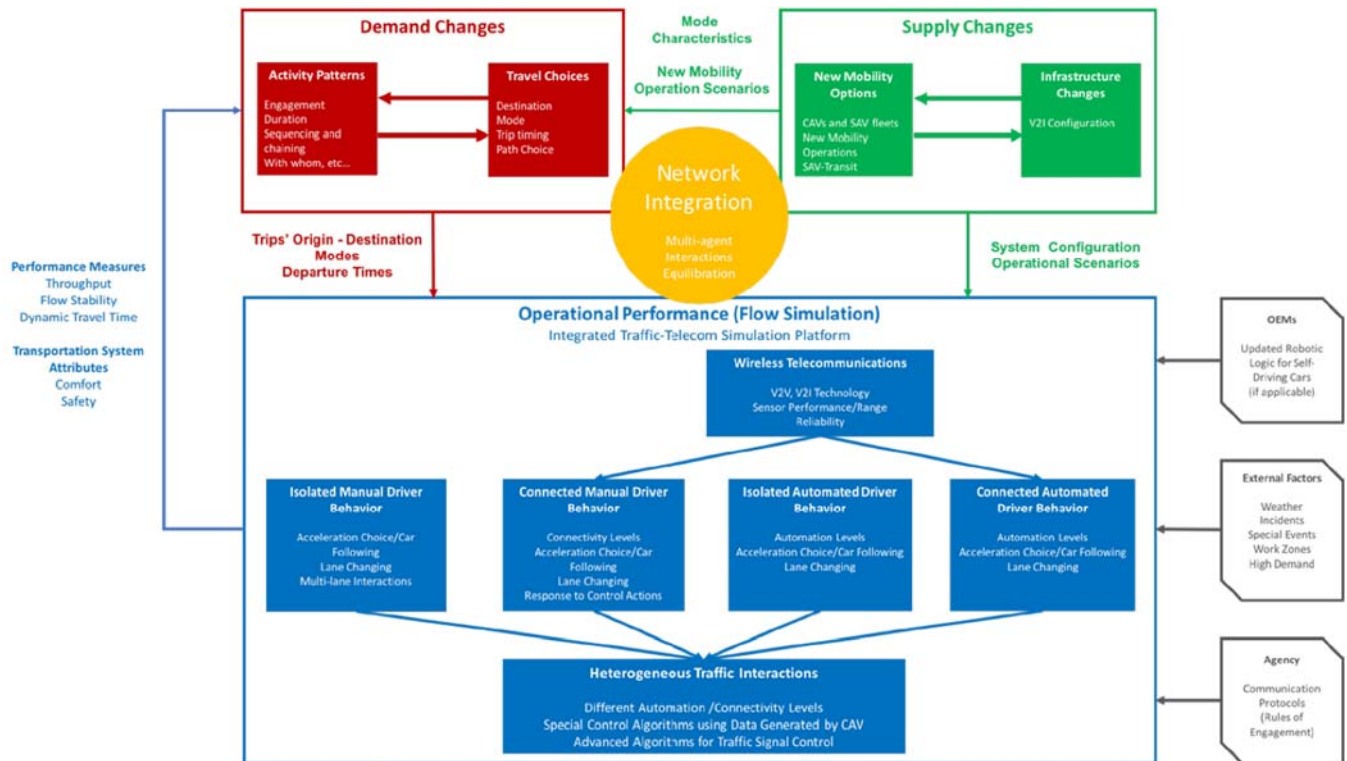
Figure 1 Methodological framework proposed by Mahmassani et al. (13)

3   EXPECTED IMPACTS OF AVS ON THE TRANSPORTATION SYSTEM

In this section we use the main components of the four-step model to summarize the impacts of AVs that are commonly discussed in the transportation literature.

3.1   Trip Generation

AVs are expected to reduce many of the inconveniences associated with driving. For example, the trouble of finding a parking spot may be delegated to the vehicle itself. Such conveniences will likely make AV-related modes more desirable than other existing modes, leading to more vehicle-trips. The repositioning of empty AVs will likely also increase vehicle-trips. AVs might also be used to increase transit ridership by facilitating first mile/last mile connectivity (14, 15, 16, and 17). The number of trips by cars may also increase because of existing latent demand: AVs will allow certain demographics (e.g., older adults, individuals below the age of eighteen, and differently abled citizens) to make more trips (18 and 19). Conversely, access to ICT might reduce the general need for physical travel (20, 21).

3.2   Trip Distribution

It has been speculated that the increased convenience and the possibility of spending time more productively in an autonomous vehicle would make individuals more tolerant of higher in-vehicle travel times (22, 23, 17). To model this fact, it has been suggested in literature to the reduce value of time (VOT) by some factor when computing mode utilities (24, 25). It is also likely that AVs' parking convenience might reduce generalized costs between OD pairs.

6

3.3 Mode Choice

The attractiveness of AVs will likely affect mode splits. If AVs obviate the need for parking, AV's mode share should increase, while the share of transit should decrease (as suggested by 26). Also related to mode choice is the aforementioned reduction in VOT—if time spent inside an AV is perceived as less burdensome than in other modes, it is likely that the share of AVs will increase even further while decreasing that of other modes.

3.4 Trip Assignment

In theory, AVs' low reaction times and better awareness of their surroundings will likely allow them to utilize road space more efficiently than human drivers (27, 28, 29). For example, Automated Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) are autonomous-like features that allow vehicles to follow lead vehicles without any human intervention. Studies have shown that vehicles with ACC and CACC can improve traffic safety, stability, and capacity (30, 31, 32). AVs may also be able to affect network-wide performance by allowing for novel approaches to intersection management (33, 34). However, it has also been shown that platoons of ACC-enabled vehicles may be prone to large speed variations, and that higher headways (which are more likely at lower AV penetration rates) can cause capacity reductions (35, 36).

3.5 Summary

Some forces might push toward increased travel demands (such as induced travel due to increased convenience and lower VOT), while others might push toward reduced travel demands (such as the reduced need for actual person-travel brought forth by internet connectivity and/or virtual reality, and more activity chaining). Given the multitude of possibilities, the new model we developed had to be flexible to account for all cases. The potential AV impacts and the planning step that they may affect are summarized in Table 1.

Table 1 Summary of impacts

Modeling Step	Impacts	References
Trip Generation	• Increased convenience of travel (including increased ease of parking) will likely boost demand • Significant improvement in mobility for certain demographics such as older adults, people with disabilities, and children • Access to ICT may reduce need for physical travel	Mokhtarian and Tal (2013) (21) Kim et al. (2015) (20) Levin and Boyles (2015) (26) Walker (2016) (14) Scheltes and de Almeida Correia (2017) (16) Shen et al. (2017) (15) Truong et al. (2017) (18) Lavieri and Bhat (2019) (19)
Trip Distribution	• Increased travel convenience may cause a drop in VOTs, leading to longer trips • Increased travel convenience (ease of parking) might reduce the generalized cost between OD pairs	Childress et al. (2015) (24) Kröger et al. (2016) (25) Kolarova et al. (2018) (22) Steck et al. (2018) (23) de Almeida Correia et al. (2019) (17)
Mode Choice	• Increased travel convenience may cause a drop in VOTs, increasing the attractiveness for AV modes • The option of parking further for AV users might also affect mode choice	Levin and Boyles (2015) (26) Kolarova et al. (2018) (22) Steck et al. (2018) (23) de Almeida Correia et al. (2019) (17)
Assignment	• AV technologies enable vehicles to maintain lower headways at higher speeds increasing traffic capacity • Communicating with traffic infrastructure such as traffic lights can further boost capacity • Some technologies such as ACC may decrease traffic capacity depending on how they are implemented • At low penetration rates, the mixing of AVs among non-autonomous vehicles might decrease capacity utilization • Increased travel demand may lead to more congestion, lowering network performance	Sheikholeslam and Desoer (1990) (35) Vander Werf et al. (2002) (9) Dresner and Stone (2004, 2005) (33, 34) van Arem et al. (2006) (30) Tientrakool et al. (2011) (28) Okamura et al. (2011) (27) Milanés and Shladover (2014) (31) Delis et al. (2015) (32) Stern et al. (2018) (29)

4   MODELING FRAMEWORK

In this section, we document the extensions to the four-step framework proposed to incorporate AVs. The major changes we propose include splitting households into two groups (AV households and non-AV households); setting potentially different trip generation rates for the new AV households; allowing trips generated by AV households to have different perceived values of time in trip distribution, mode choice, and assignment; and, using different passenger-car-equivalent (PCE) values for AV trips to account for the gains (or losses) in capacities brought by AVs. A general illustration of the modifications proposed can be seen in Figure 2. We discuss these changes in more detail below.
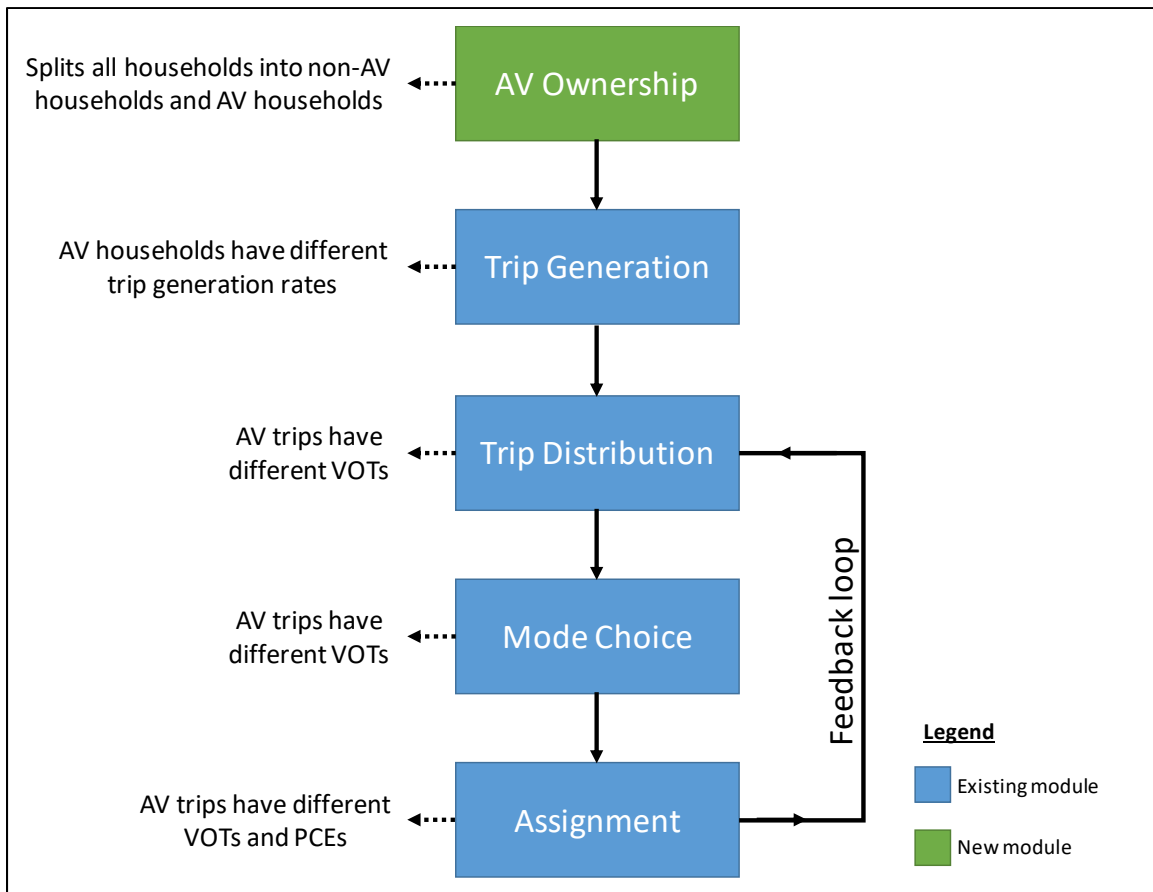

Figure 2 Extension of the four-step framework

4.1 AV Ownership

One of the most common approaches to start the four-step modeling method is to compile traffic analysis zone (TAZ) counts of households by specific segments, such as income, vehicle ownership and size, and pairing the TAZ-level counts with cross-tabulations of average trip generation values per segment. The approach we propose consists of adding another segmentation: whether or not the household is an AV household. This "AV Ownership" module is run before trip generation, and has the objective of splitting all households into two different types: non-AV households and AV households. This is achieved using an exogenous control parameter that we denote by P_{AV}, set by the modeler between 0 and 1. This term represents the overall household-level AV ownership, also known as the "penetration rate" for a desired year or scenario. We acknowledge that, while a deliberate choice of P_{AV} will uncouple the work from any set timeline, as penetration predictions improve in the coming years, this work will be easily matched to any likely timeline of adoption. There have been several attempts at predicting future AV penetration rates (see 37 and 38 for reviews) which could be used to inform the selection of a P_{AV} value.

Once the global P_{AV} value is selected, our implementation uses a method based on survey results to derive varying penetration rates by household segment. We use data from a survey conducted by the research team in the Dallas-Fort Worth area that included a question regarding respondents' willingness to purchase an AV under different cost scenarios. While the adoption rates from the survey might not be suitable for directly predicting AV adoption in future scenarios, the survey did capture individuals' sensitivity to AV technology across income segments. Our method implements a simple binary logit model to explain the adoption of AVs based on individuals' household income. Model results are used in tandem with the number of households in each income segment and TAZ to produce an estimate of the number of AV households per income segment and TAZ by manually calibrating the model's constant to reach the pre-defined overall household-level AV adoption.

It should be noted that there are likely significant differences between owning an AV and having access to AVs through a fleet of shared AVs (39). However, the approach we propose in this paper is agnostic to the distinction between ownership and access to AVs. Even though we mostly use the term "AV ownership" throughout the paper, the outputs of this household AV ownership module could just as well be interpreted as "households who have access to a fleet of shared AVs". Therefore, the distinction between ownership and access is up to the modeler and the suite of assumptions they make. This being said, we recognize that our implementation focused on privately owned AVs. We did not incorporate any specific changes that would make the four-step framework readily appropriate for shared AV fleets, such as repositioning trips for shared AVs (i.e., the trip made by the shared AV after dropping off one passenger and picking up the next passenger).

4.2 Trip Generation

The NCTCOG model uses segment-specific household trip generation rates. In our extended model, the AV ownership module generates estimates of the number of AV households in each of the segments. We use an exogenous parameter, $F_{AV\_TripGen}$, to represent differences in trip-generation rates between AV and non-AV households. As an example, consider that a specific segment of households (characterized by its income level and household size) produces six home-based work trips per household per day in the original model. If we assume that AV households

will generate 5 percent more trips than non-AV households (i.e., $F_{AV\_TripGen}=1.05$), the trip generation rate of an AV-household in that same segment and for that same trip type is $6 \times 1.05 = 6.3$.

In our application to the NCTCOG model, we used $F_{AV\_TripGen}$ values of 1.05 and 1.10 based on (18) and (19).

4.3 Trip Distribution

The current NCTCOG model uses the gravity model for trip distribution, and its main inputs are travel times between OD pairs. Following the same approach as in the Trip Generation step, we propose an exogenous control parameter, $F_{AV\_TripDistVOT}$, to capture the difference in how users in AVs and non-AVs perceive travel impedances. Since trip distribution is performed separately for each trip type/segment, we obtain the impedances for the AV trips by simply multiplying the non-AV impedances by $F_{AV\_TripDistVOT}$.

In our application to the NCTCOG model, we used $F_{AV\_TripDistVOT}$ values of 0.75, based on the findings of (22), (23), and (17).

4.4 Mode Choice

Since our approach considers that trips generated by AV households are completely separate from the trips generated by non-AV households, we can subject them to different mode-choice frameworks. The NCTCOG model has one mode choice model for each combination of trip type and household segment (e.g., "home-based shopping trips for households with income level = 1, worker count = 2, and vehicle count = 1"). In this planning step, our model extension uses the exogenous parameter $F_{AV\_ModeChoiceVOT}$ to represent the difference in in-vehicle travel time perception between AV households and non-AV households. The procedure consists of simply multiplying the mode choice model's coefficient on in-vehicle travel time by $F_{AV\_ModeChoiceVOT}$. We note here that, in our specific application in the NCTCOG model, we assume that AV households do not own human-driven vehicles, and driving such vehicles is not in their choice set. Analogously, non-AV households do not have "autonomous vehicle" in their choice set, which effectively means that non-AV and AV vehicles are not competing directly in mode choice.

In our application to the NCTCOG model, we assume that $F_{AV\_ModeChoiceVOT}$ is equivalent to the VOT change parameter used in the Trip Distribution stage (i.e., $F_{AV\_ModeChoiceVOT} = F_{AV\_TripDistVOT}$).

4.5 Assignment

In the assignment step, the proposed framework includes extensions to consider the impact of VOT on route choice and the changes in network capacities to consider AVs different driving behavior.

Route selection. The main purpose of the assignment step is to map trips to the transportation network. The assignment of vehicles to paths is typically achieved by assuming that drivers are minimizing their travel cost, which is often a function of travel times and other financial costs related to road use and vehicle maintenance. In this context, the VOT is used to express travel times in monetary units. Following the same approach taken in previous steps, we propose the use of an exogenous parameter, $F_{AV\_AssignmentVOT}$, to describe how individuals in AVs perceive VOT differently than those in non-autonomous vehicles. In our application to the NCTCOG model, we set $F_{AV\_AssignmentVOT}$ to be equal to $F_{AV\_ModeChoiceVOT}$ and $F_{AV\_TripDistVOT}$.

Network link capacity. The use of a static traffic assignment tool imposes some limitations in our ability to reflect the actual effect of AVs on traffic flow, but we propose a simple approach to avoid

setting a fixed network-wide capacity gain/loss. A network-wide capacity adjustment implies that two links with the same capacity and flow but different AV penetrations would experience the same capacity impacts, which is counterintuitive. Therefore, the approach we propose uses the concept of passenger-car-equivalent (PCE) to "scale" benefits/losses as a function of link-specific AV use. The PCE can capture the impact of the potentially smaller headways enabled through automation and can also account for cases where AVs consume more road space than manually-driven vehicles. If we assume that the PCE of a manually driven vehicle to be equal to 1, the PCE of an AV represents the ratio between the road capacity consumed by an AV and the capacity consumed by a manually driven vehicle traveling at the same speed. Once more, we create an exogenous control parameter called F_{AV_PCE}, which directly represents this ratio. To determine a reasonable estimate of F_{AV_PCE}, we consider it to be the ratio of the sum of the length and headway of an AV to that of a standard non-AV as shown below,

$$F_{AV\_PCE} = \frac{l_{AV} + D_{AV}}{l_s + D_s}$$

where, l_{AV} is the length of an AV, l_s is the length of a standard vehicle which consumes a capacity of 1 PCE, D_{AV} is the headway maintained by an AV and D_s is the headway maintained by a vehicle having PCE of 1. The headways D_{AV} and D_S are computed based on the approach proposed by (28) for the case of AVs that do not communicate with each other. The headways are a function of the speed maintained in the link. Varying the speed from 20 mph to 80 mph varied the PCE values from 0.56 to 0.76. Since our model did not allow for speed-dependent PCE values, we selected a constant PCE from this range. Since the calculations above are based on steady traffic flow and do not consider turns and lane changes (i.e., situations that may dampen capacity improvements), we took a conservative approach with respect to AVs' improved use of capacity and used a value of 0.7 for the F_{AV_PCE}.

5 NUMERICAL ANALYSES

5.1 Experimental design

The experimental design for the project was quite simple. We used NCTCOG's 2045 network as well as their 2045 demographic predictions and generated five scenarios:

- **Base scenarios** are used explore the changes in travel patterns and network performance in a possible future scenario with AVs.
    - o "Base – No AV" is NCTCOG's original planning model.
    - o "Base – High AV" is an optimistic AV adoption scenario. The values for the exogenous control parameters, informed by the literature, are combined to represent a future in which a significant portion of households adopt AVs but changes to VOT do not lead to a drastic increase in the number or length of trips. Further, AVs are assumed to have a beneficial impact on network capacity.
- **Sensitivity scenarios** are used to test model sensitivity to assumptions in parameter values, and to understand how future scenarios may differ depending on realized user behaviors and network performance.
    - o "Increased Trip Generation" considers a larger proportion of AV-induced trips.

    o   "No Change in VOT" considers that there is no perceived difference in the values of time between individuals driving non-autonomous vehicles and those in AVs.

    o   "Capacity Decrease" assumes that AVs may consume additional road capacity.

Table 2 presents the values used in each scenario and corresponding source. The scenarios were run in TransCAD 7 using two feedback iterations (0th and 1st iterations) and lenient assignment gaps for each feedback iteration: 0.01 and 0.005. The gaps used during assignment were significantly higher than the standard practice of 10^{-5} mostly because of run times: each scenario had a total run time of approximately thirty-six hours. For comparison, we also ran one scenario with four feedback iterations using the NCTCOG-recommended gaps of 10^{-2}, 10^{-3}, 10^{-4}, and 10^{-5}, respectively. This run took approximately 243 hours and yielded little to no difference in the aggregate measures used in our analysis, which suggests that our parameter selection is adequate for our analysis.

A more comprehensive approach to the sensitivity analysis would have been to completely automate the proposed modeling approach and evaluate ranges of input values (as performed in 40). However, such an approach would require extensive additional coding and a significant increase in processing time. Since the focus of this paper is the actual implementation of the extension (and not the sensitivity analysis itself), we decided to engage in a simpler approach. We evaluated the model's sensitivity using just one run for each group of parameters tested. Based on the literature, we chose input parameter values that were not unreasonable and would give us important insights into the intuitive working of the model. We leave more comprehensive sensitivity analyses as avenues for future research.

We used the following metrics to evaluate network performance and travel patterns cross scenarios:

- Number of trips generated
- Total vehicle-miles traveled (VMTs), calculated as:

$$Tot.VMT = \sum_{i=1}^{N} VMT_i = \sum_{i=1}^{N} (link\ flow_i \cdot link\ length_i)$$

- Total vehicle-hours traveled (VHTs), calculated as:

$$Tot.VHT = \sum_{i=1}^{N} VHT_i = \sum_{i=1}^{N} \left(\frac{link\ flow_i \cdot link\ length_i}{link\ speed_i} \right)$$

- Average distance traveled, calculated as: $Avg.\ Dist = \frac{Tot.\ VMT}{Num.\ Trips}$
- Average travel time, calculated as: $Avg.Time = \frac{Tot.\ VHT}{60 \cdot Num.\ Trips}$
- Average link-level speed, calculated as: $Avg.Speed = \frac{1}{N} \sum_{i=1}^{N} \frac{VMT_i}{VHT_i}$
- Average link-level AV penetration, calculated as: $Avg.\ AV\ \% = \frac{1}{N} \sum_{i=1}^{N} \frac{AV\ VMT_i}{VMT_i}$

In the equations above, *i* is the index representing each link in the network, *N* is the total number of links in then network, VMT_i and VHT_i are link-specific VMT and VHT values for link *i*, $link\ flow_i$ is the flow on link *i*, $link\ length_i$ is the length of link *i*, $link\ speed_i$ is the speed on link *i* based on the corresponding BPR function, $AV\ VMT_i$ represents only the VMTs generated by AVs on link *i,* and $Num.\ Trips$ represents the total number of trips in the network.

5.2 Model results

Table 3 and Figure 3 present the main results from each scenario. As expected given the control parameters used in the "Base – High AV" scenario, the introduction of AVs in the network causes an increase in the total number of trips, which in turn contributes to about a 6 percent increase in VMTs. The increase in VMT is accompanied by a 2 percent increase in VHTs. The most likely reason why the increase in VHTs is lower than the increase in VMTs is AVs' improved use of capacity, which generate a 2 percent increase in speeds.

When we analyze the three sensitivity scenarios, we see small but notable changes. Admittedly, the model was less sensitive than we expected. For example, when we assume that AVs' VOTs are identical to non-autonomous vehicle's VOTs in the 'No Change in VOT' scenario, AV users, of course, no longer accept longer distances more so than their non-autonomous counterparts, and the difference in their average travel times and distances are reduced. Differences might still exist simply due to changes regarding where non-AV and AV trips are being generated. Mode-specific results (i.e., non-AV and AV autos) are available online at http://www.caee.utexas.edu/prof/bhat/ABSTRACTS/AVFourStep/AdditionalResults.pdf, and they show that AVs have, in general, longer trips in terms of both distance and time, and that the number of Non-AV and AV trips can be affected by parameters unrelated to trip generation.

Table 2 References and values used in modeling scenarios

Parameter	Reference Literature	Values for each scenario				
		Base – No AV	Base – High AV	Increased Trip Generation	No Change in VOT	Capacity Decrease
Household-level AV Penetration Rate: P_{AV}	Autonomous Vehicles Projections summarized in Kuhr et al. (2017) (37) and Nair et al. (2019) (38)	0%	40%	40%	40%	40%
AV Trip Generation Factor: $F_{AV\_TripGen}$	New travel needs by age and gaps in travel demand to be filled by AVs Truong et al., (2017) (18) and ; Lavieri and Bhat (2019) (19)	NA	1.05	**1.10**	1.05	1.05
AV VOT Factor (Trip Distribution, Mode Choice and Assignment): $F_{AV\_AssignmentVOT}$, $F_{AV\_ModeChoiceVOT}$, $F_{AV\_TripDistVOT}$	Based on Kolarova et al. (2018) (22), Steck et al. (2018) (23), and de Almeida Correia et al. (2019) (17)	NA	0.75	0.75	**1.00**	0.75
AV Passenger-Car-Equivalent: F_{AV_PCE}	Calculations based on Tientrakool et al. (2011) (28)	NA	0.70	0.70	0.70	**1.10**

Note: The bold numbers represent the parameters with changes in the sensitivity scenarios.

Table 3 General network – Aggregate daily results for all scenarios

Result	Base – No AV	Base – High AV	Increased Trip Generation	No Change in VOT	Capacity Decrease
Trips	33,428,247	34,064,090	34,405,630	34,059,693	34,051,584
VMTs	305,224,517	326,382,965	326,795,757	321,748,181	315,395,539
VHTs	9,617,887	9,888,466	9,901,773	9,650,964	10,608,271
Average Distance (miles)	9.13	9.58	9.50	9.45	9.26
Average Time (minutes)	17.26	17.42	17.27	17.00	18.69
Average Link-level Speed	29.3	29.8	29.8	29.9	28.6
Average Link-level AV penetration	0.0%	36.3%	36.8%	35.6%	36.4%
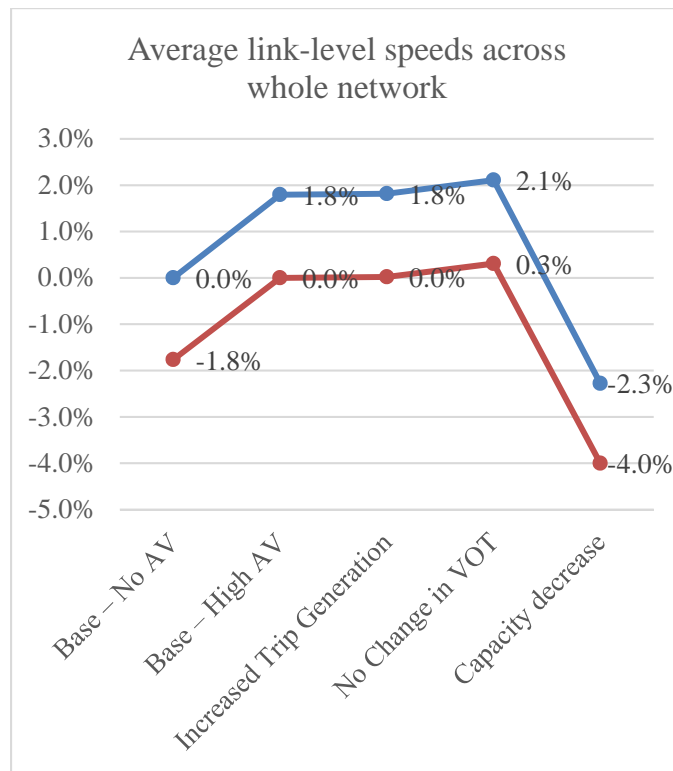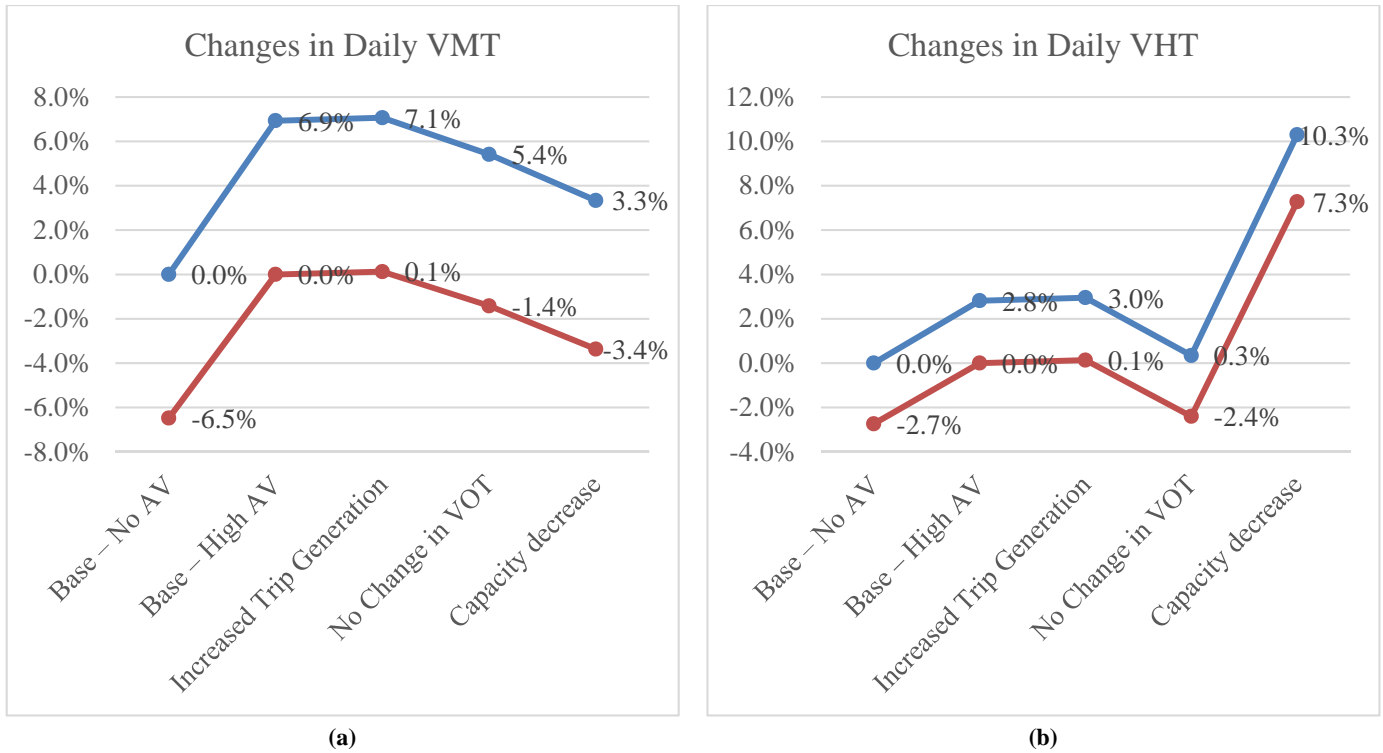
Figure 3 Main simulation results: (a) change in daily VMTs; (b) change in daily VHTs; (c) change in average link-level speeds
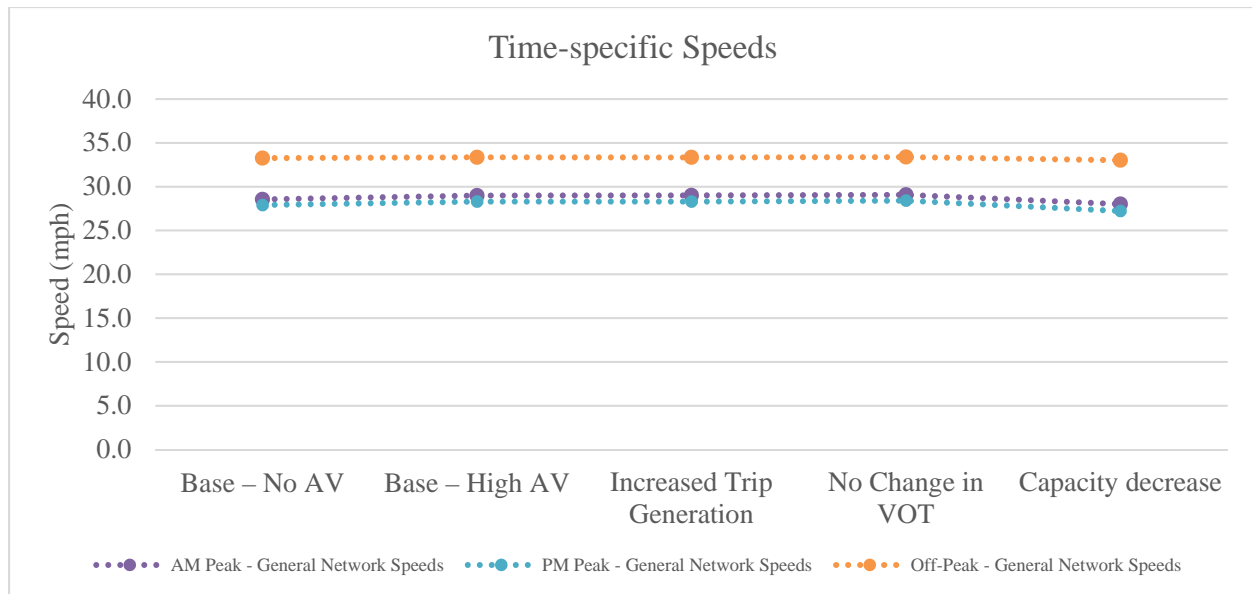
Figure 4 Time-specific speeds on the general network

We also observed that the overall link-level speeds seem insensitive to most changes apart from the scenario where AVs lead to capacity losses (i.e., the "Capacity Decrease" scenario), in which speeds drop by about 4 percent. This is likely because this speed metric is a link-by-link average across the whole network, which makes it quite robust to changes.

Figure 4 presents the time-specific (AM-peak, PM-peak and off-peak) speeds of the general network. In all scenarios, as expected, speeds are generally higher during the off-peak period. For the "Capacity Decrease" scenario, during the AM-peak and the PM-peak, however, AVs' larger capacity consumption causes a 4 percent decrease in speed (compared to the "Base – High AV" scenario).

Some of the main lessons learned during this endeavor include:

- The parameter that controls the relative capacity consumption of AVs, F_{AV_PCE}, was the exogenous control parameter to which the model showed most sensitivity.
- The aggregate metric that is least sensitive to all exogenous control parameters is the daily average speed on the general network.
- The use of the PCE approach (as opposed to increasing capacities on a link-by-link basis) allowed the impacts of AVs on capacity to be (at least partially) endogenous to our model.
- Model results suggest that, even when we assume that AVs can better use network capacity and that trip making rates do not drastically increase, AVs may lead to an increase of about 2.8 percent in VHT while still improving speeds by about 1.8 percent (when compared to a scenario without AVs).
- Links with large fractions of trips from high-income households will also likely have high AV penetrations.
- When AVs are assumed to have negative impacts on capacity, there is an observable speed drop, causing average travel times to increase. However, AVs are expected to have a negative impact on capacity mostly at lower levels of penetration (Section

3). Our scenario assumes that 40 percent of households own AVs, which leads to more than 90 percent of all used links having AV penetration rates of 20 percent or higher. Such links are unlikely to experience a negative net impact on performance.

- The extended framework can be used to evaluate multiple scenarios. For example, build/no build scenarios for large infrastructure projects, transit expansions, and densification policies.

6 CONCLUSIONS

In this paper, we presented a framework for a simple extension of the traditional four-step model that allows MPOs to capture the impact of autonomous vehicles. We also illustrated how to implement the primary changes in the proposed framework by applying them to the NCTCOG model. Model results were analyzed for five scenarios, for which we computed aggregate metrics of performance consistent with those used by MPOs. Results suggest that the model is sensitive to proposed parameters, in particular to AVs' passenger-car-equivalent. In most modeled scenarios, AVs brought both positive consequences (such as improved speeds) as well as negative consequences (such as increased total system travel times) when compared to a scenario without AVs. These results might not be entirely consistent with much of the prior literature, which primarily focuses on modeling and quantifying the benefits that AVs might bring, and which usually disregard their potential negative consequences on capacity consumption and speeds. Therefore, we believe that our results simply highlight the importance of considering integrated modeling frameworks to comprehensively assess the true impacts of AVs.

It is important to note that any limitation that is associated with the original four-step model will persist even after the model is extended using our proposed framework. For example, the assignment stage in NCTCOG's model assigns transit trips independently from auto-based and truck trips. One important avenue of future research would be the development of new multi-modal assignment algorithms that better accommodate for cross-modal congestion effects. Additional opportunities for model refinement include considering trips made by AVs with no passengers and addressing the fact that the impact of AVs on road capacity may not be exactly linear as assumed by our PCE based approach.

At a more practical level, our implementation of the framework was quite cumbersome and required writing substantial amounts of additional TransCAD GISDK code. The network in the original NCTCOG model has approximately 55,000 links, 35,000 nodes, and 5,300 zones. In our application, the assignment step involved twenty different OD matrices. Given the large network size and the large number of matrices, the run times were very high, totaling around thirty-six hours even when using only two feedback iterations and assignment gaps of 0.01 and 0.005. This, however, was a direct consequence of the already significantly complex nature of NCTCOG's current four-step model.

Despite the many limitations of the traditional four-step model, we still believe it is an invaluable tool for MPOs and planning agencies. We trust that the extension we propose in this paper will prove to be very useful for practitioners given that a) it generates the same type of results that transportation planners and modelers are already accustomed to using on a day-to-day basis; and b) it can be quite easily implemented by almost any MPO that already has a four-step model. Ongoing work is exploring the use of the proposed framework to answer planning questions (e.g., "Will the ranking of infrastructure project be affected by the adoption of AVs?" or "How will AVs affect transit use?"). Researchers will also consider methodological refinements, including

addressing some of the limitations of using the PCE factor to model AVs impact on network capacity, and the consideration of empty AV trips.

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AUTHOR CONTRIBUTION STATEMENT

The authors confirm contribution to the paper as follows: study conception and design: F.F. Dias, G.S. Nair, N.R. Juri, C.R. Bhat, A. Mirzaei; data collection: NCTCOG; analysis and interpretation of results: F.F. Dias, G.S. Nair, N.R. Juri, C.R. Bhat, A. Mirzaei; draft manuscript preparation: F.F. Dias, G.S. Nair, N.R. Juri, C.R. Bhat, A. Mirzaei. All authors reviewed the results and approved the final version of the manuscript.

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