HOW WILL SELF-DRIVING VEHICLES AFFECT U.S. MEGAREGION TRAFFIC? THE CASE OF THE TEXAS TRIANGLE

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Research in Transportation Economics 101003 (2020).

ABSTRACT

The Texas Triangle megaregion contains Texas' largest cities and metropolitan areas, and thereby most of the state's economic and social activities. This paper anticipates the impacts of self-driving, full automated or "autonomous" vehicles (AVs), shared AVs (SAVs), and "autonomous" trucks (Atrucks) on travel across this important megaregion using year 2040 land use (and network) forecasts. Various Statewide Analysis Model (SAM) data are leveraged to anticipate the impacts of AVs', SAVs' and Atrucks' impacts on destination and mode choices. A travel demand model with feedback is implemented to forecast changes in vehicle-miles traveled (VMT), congestion, and travel patterns across the megaregion. Results suggest that people will shift to more distant destinations, on average (evidenced by the increase in the megaregion's average travel distance: from 14 miles to 16 miles). Air travel will fall by more than 82%, with these long-distance travelers shifting to ground transport options. Without travel demand management (like credit-based congestion pricing and mandated tight headways between AVs), congestion issues will grow, thanks to an average VMT increase of 47%, which is more evident in the region's major cities: Houston, Dallas-Fort Worth, San Antonio and Austin. Almost 9.6% of the megaregion's link flows will suddenly exceed capacity, relative to a no-AV case has 4.6% exceed capacity. Automobile travel will rise across all trip distance categories, with jumps most evident between suburban and urban zones. Six of the 15 commodity groups simulated are expected to see a >5% increase in their associated truck trips, due to the introduction of Atrucks, with rising truck trade largely between Houston and other major Texas employment centers.

Keywords: Self-driving vehicle, passenger and freight travel, Texas Triangle megaregion, Statewide Analysis Model

BACKGROUND

Fully-automated vehicles (AVs) and trucks (Atrucks), along with shared AVs (SAVs), may dramatically shift passenger and freight travel patterns across cities and regions over time. As the driving burden and heavy fixed costs of vehicle ownership disappear, more distant locations and ground-based travel become relatively more attractive. Atrucks not only free paid operators from the driving task, but allow them to work longer hours, resting en route. They will shift or eliminate driver responsibilities and should improve safety. Truck platooning through vehicle-to-vehicle communication also improves trucking efficiency. Atrucks may be equipped with other automated functions, like freight drop-offs and pick-ups.

The Texas Triangle megaregion makes an interesting case study for such shifts. It is one of the nation's 11 megaregions (America 2050 Project, 2014), and contains 18.2 million of Texas' 25.1 million residents - or 6% of the U.S. population. Its businesses and workers, inside cities like Houston, San Antonio, Austin, Dallas, and Fort Worth, generated 7% of U.S. GDP in 2010 (Todorovich, 2007). Its 66 counties (out of Texas' 254 counties) cover 58,400 square-miles. This region's future traffic patterns are analyzed here, using travel demand models.

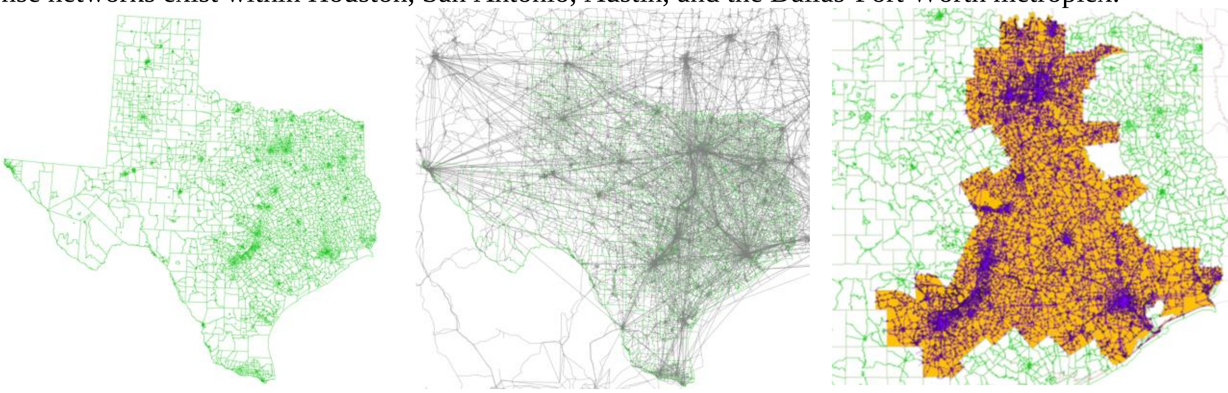
The current research is not only about the mode choice shift due to the AVs (Yong and Kockelman, 2018; Perrine at al., 2018; LaMondia et al., 2016), but also about the impacts on SAV fleet size, volume of travel and parking requirements through SAV simulation (Liu et al., 2017; International Transport Forum, 2015). The shared electric autonomous vehicles are also considered to investigate the environmental impact (Loeb and Kockelman, 2017; Loeb et al., 2018). Yong and Kockelman (2018) apply conventional four-step travel demand model to test the impact of connected AVs (CAVs) and SAVs on the network of Austin, Texas in year 2020. They found that 20% or more vehicle-kilometers traveled will be added to the roadway network, assuming operating costs of conventional vehicle, CAV, and SAV to be \$0.12, \$0.25, \$0.62/km respectively. Moreover, a relatively low values of travel time (VOTT) for AV passengers and competitive pricing assumptions of SAV use result in longer distance travel and reduced transit system use. Liu et al. (2017) simulate conventional vehicles and SAVs in the Austin network using different possible fare levels of SAV, with an agent-based MATSim toolkit. SAV is shown to be not only preferred by longer distance travelers to conventional vehicles, but preferable for trips less than 10 miles by households without a conventional vehicle. Assuming that an SAV could serve 17-20 person-trips per day, a higher rate of SAV results in a greater vehicle replacement, ranging from 5.6 to 7.7 per SAV. Further, The International Transport Forum (2015) report the agent-based simulation results of the potential change in urban mobility in the city of Lisbon, due to the implementation of a shared and fully autonomous vehicle fleet. They anticipate that SAVs could deliver the same mobility with 10% of the fleet but result in a 6% increase in VKT, and the reduced parking needs would free significant public and private places.

This paper is organized as follows: Texas' Statewide Analysis Model (SAM) data are described first, since they provide key inputs, validation values, and several parameters for application of a four-step travel demand model. Model calibration is performed to establish a reasonable base case scenario, before introducing the scenarios offering the new passenger and freight modes. Model results and various sensitivity analyses are described, before providing the paper's conclusions.

DATA SET

The basis of this study is a travel demand modeling process using TransCAD software. The megaregion's 66 counties' come from the regional boundary used by Zhang et al. (2007), and associated network and traffic analysis zone (TAZ) files were obtained from the Texas SAM. The megaregion contains 2,160 of the state's 4,667 TAZs, as shown in Figures 1(a) and 1(c). The entire state transportation situation was simulated, with megaregion results pulled out afterwards, to avoid boundary effects (e.g., missing external-zone travel) at the edges of the region.

The SAM network covers all of North America, with greater detail in and near Texas. Figure 1(b) shows the state's highway, railway and airline networks, which contain 200,445 links and 168,507 nodes. Just 19,549 nodes and 27,976 of the SAM's network lie partially or entirely within the megaregion, including 26,556 roadway links. Some megaregion trips (with both origin and destination zones within the Texas Triangle) can lead to travel outside the region, especially with very heavy traffic conditions, so this paper's extended-network and state-zone analysis allows for this kind of behavior. Figure 1(c) highlights the megaregion TAZs and the road links (in purple) and nodes that lie within it. As illustrated, dense networks exist within Houston, San Antonio, Austin, and the Dallas-Fort Worth metroplex.



a. SAM TAZs b. SAM Networks c. Roadway Network

FIGURE 1 Geographic data of SAM model.

TRAVEL DEMAND MODEL METHODS

A four-step travel demand modelling process with feedback loop is used here to model traffic patterns across the entire state of Texas (before pulling out megaregion results), including trip generation, trip distribution, mode choice and traffic assignment. For passenger travel's four-step model, the traditional trip distribution procedure was replaced here by a destination choice model, and the PA matrix was then converted into an OD matrix. The model uses just one time of day to recognize that many trips, especially freight trips, are long in distance, spanning many times of day, and many different congestion settings. Computation time is another concern to limit one time of day simulation. For the freight model, a doubly-constrained trip distribution procedure was used, based on the SAM's Year 2040 freight-trip generation parameters. A mode choice model was then applied, reflecting Truck, Rail and Intermodal Transport (IM) alternatives. A base case scenario - without AV, SAV and Atruck modes – was run first, to compare against the self-driving scenarios. Various parameter settings were also tested, using sensitivity analysis, to provide a sense of prediction variability. As noted earlier, the megaregion was modeled within the U.S. network, and recognizing all Texas TAZs, so the results for just the megaregion's links and zones were pulled out from of the results of the statewide analysis.

Trip Generation

Trip generation data were obtained from the SAM Year 2040 scenario results, based on underlying population and jobs forecasts by zone (Alliance Transportation Group, 2018), using 2009 National Household Travel Survey (NHTS) data. Standard trip types include home-based work, home-based other, home-based school, non-home based other, and non-home-based visitor. Long-distance, inter-city trips include infrequent business trips and other long-distance trips. Table 1's 15 commodity groups are based on U.S. Standard Transportation Commodity Codes, and SAM freight transport attraction and production levels exist for for all Texas counties and non-Texas US states.

This work assumes a 15% increase in Year 2040 trip generation rates (productions and attractions) due to AV technologies enabling new trip-making. This assumption is based largley on Harper et al.'s (2016) estimating a 14% increase in U.S. VMT due to non-driving Americans, elderly Americans, and people with travel-restrictive medical conditions being able to make regular use of AVs. More just-in-time freight deliveries, directly to customers, especially on local roads, within cities, may also emerge.

Trip Distribution

For the nested logit modeling of destination and mode choices in passenger travel, each destination TAZs attraction depends on a logsum across mode options (also called a mode accessibility term) and destination's population. Essentially, the systematic utility for trips going from zone *i* to zone *j* was specified as follows:

$$V_{ij}=\gamma \times \ln(pop_i)+\lambda \times \log\left(\sum_m \exp\left(V_{ij}^m\right)\right) + \alpha \times \sqrt{L_{ij}} + \beta \times log(D_{ij})$$

where V_{ij}^m is the utility of travel from zone *i* to zone *j* using mode *m*, and D_{ij} is travel distance from zone *i* to zone *j*. Table 1's model parameter values come from Zhao and Kockelman (2017) and Outwater et al. (2015).

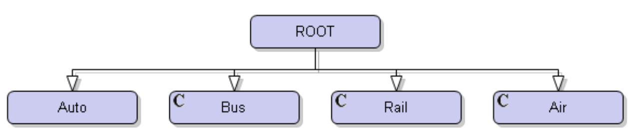
Freight trips are distributed by tons of each commodity, using a doubly-constrained gravity model, to keep values in strong alignment with current freight production and consumption levels across the state of Texas and beyond. The associated utility function is as follows:

$$V_{ijc}=\exp\left(-1/\left(D_c * D_{ij}\right)+\delta \times \ln(pop_i)+\tau \times \log\left(\sum_m \exp\left(V_{ij}^m\right)\right)\right)$$

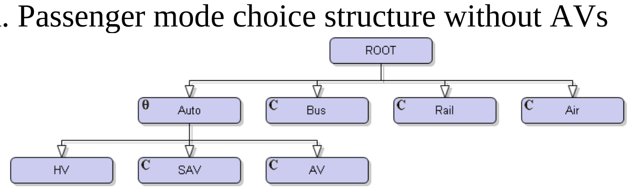
where D_c is the average travel distance for commodity group c and D_{ij} is the distance from zone *i* to zone *j*.

Mode Choice

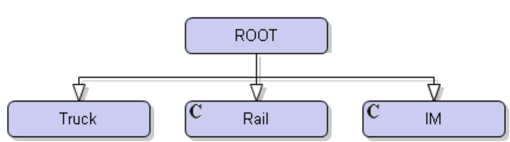
Four passenger modes exit in the base-case (Year 2040) scenario: conventional automobile –labeled as "HV" for human-driven vehicle below, bus, rail and air. Three freight modes exist: Truck, Rail, and Intermodal (IM). These choice models were expanded to accommodate AV, SAV and Atruck modes, as shown in Figure 2. Trips costs, fares, and in-vehicle travel times of bus, rail and air all come from SAM model outputs. Rail's values are the average of all of SAM's rail modes for each OD pair (including urban rail, intercity rail, and high-speed rail alternatives in many OD cases). When AVs and SAVs are added to the set of alternatives, HVs, AVs and SAVs are nested under the Auto mode (Figure 2(b)). There is no parking cost for SAV use (much like a taxi), and privately-owned AVs are assumed to face the same parking cost that HVs pay (since AVs are not expected to be allowed to drive empty, creating additional congestion for cities and regions).



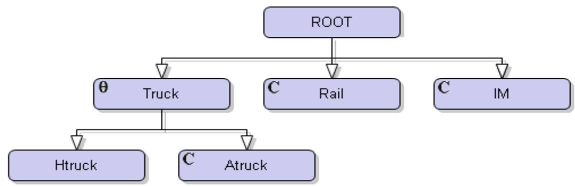
a. Passenger mode choice structure without AVs



b. Passenger mode choice structure with AVs



c. Freight mode choice structure without Atrucks



d. Freight mode choice structure with Atrucks

FIGURE 2 Mode choice structures, for passenger and freight transport, before and after AVs

Operating costs of bus, rail and air modes come directly from SAM model outputs, while several assumptions are used for Auto costs. Litman (2018) anticipates AV operating costs to be $0.80-$1.20 per mile in early years of AV availability, before declining to $0.60-$1.00 per mile, compared to $0.40-$0.60 per mile for Human-driven vehicles (HVs). Johnston and Walker (2017) expect SAVs to debut in some cities in year 2018 at $0.86 per mile, or $0.84 per mile for Shared Autonomous Electric Vehicles (SAEVs), compared to personal HVs costing $0.4 per mile. They expect traditional Transportation Network Company (TNC) vehicles (like today's Lyft and Uber rides) to cost $2.04 per mile, and SAEV fees to fall to $0.51 per mile in 2025, $0.36 in 2030, and $0.33 in 2035. Bösch et al. (2017) predict that SAVs may cost $0.44 per mile to cover operating costs and deliver a very healthy 30% profit margin, while a dynamic ride-sharing (en route carpooling) service may cost between $0.20 and $0.30 per passenger mile. They also suggest that purpose-built SAVs for use as pooled taxis may lower fares to just $0.16 per mile, long-term.

Perrine et al.'s (2018) model of long-distance U.S. travel assumed AV costs to range from $0.10 to $1.65 per mile and VOTT to be $3.00- $9.00 per hour for AV occupants, with the base case scenario of $0.2 per mile operating cost and VOTT of $6.00 across 6 distinct scenarios. Fagnant and Kockelman (2016) estimated that SAV pricing at $1.00 per mile could generate a 19% annual return on investment if each AV's purchase price is $70,000. This return varied from 12.3% to 38.8% for operating costs of $0.50 and $0.25 per mile, respectively. Arbib and Seba (2017) envision internal-combustion SAVs to cost roughly $0.38 per mile, while SAEVs may be much cheaper, at $0.16 per mile in 2021 and $0.10 per mile in 2030. They posit that government subsidies or advertising may one day make SAEVs free to most or all riders.

Based on all these estimates, this work assumes that both AVs and HVs carry operating costs of $0.60 per mile, and SAVs cost either $1.50, $1, or $0.50 per mile (across scenarios). Combined with parameter assumptions from Zhao and Kockelman (2017), mode choice parameters used here are shown in Table 1, with several of these varied later in the paper, during sensitivity analyses. The ASCs (alternative specific constants) for AVs and SAVs are set to be negative, at -0.05 and -0.2, respectively, to reflect some consumer hesitation. This is based on surveys and other work by Casley et al. (2013), Schoettle and Sivak (2014) and Bansal and Kockelman (2016), suggesting that AVs and SAVs will improve travelers' safety and mobility, but may generate some acquisition cost, privacy and controllability concerns (especially when the vehicle is not privately owned).

TABLE 1. Passenger and Freight Model Parameters.

<table>
<tr><th colspan="6">(a) Passenger Model</th></tr>
<tr><td rowspan="2">Destination Choice</td><td>Mode Choice Logsum</td><td>Log of Dist.</td><td colspan="2">Square root of Dist.</td><td>Log of Population</td></tr>
<tr><td>1.855</td><td>β = -1.25</td><td colspan="2">α = 0.01</td><td>γ = 0.8</td></tr>
<tr><td rowspan="2">Mode Choice</td><td>Base Case</td><td>Automobile</td><td>Bus</td><td>Rail</td><td>Air</td></tr>
<tr><td>Constant</td><td>0</td><td>-2.8</td><td>-2.8</td><td>-2.8</td></tr>
</table>

	Operating Cost Coefficient	-0.072			-0.14	-0.14	-0.14
	In-vehicle Time Coefficient	-0.019			-0.019	-0.019	-0.019
	Operating Cost ($/mile)	0.6			N/A	N/A	N/A
	Parking Cost	✓			N/A	N/A	N/A
	VOTT	15.83			8.14	8.14	8.14
	AV Case	HV	AV	SAV	Bus	Rail	Air
	Nesting Coefficient	λ = 0.6*			N/A	N/A	N/A
	Constant	0	-0.05	-0.2	-2.8	-2.8	-2.8
	Operating Cost Coefficient	-0.072	-0.072	-0.072	-0.14	-0.14	-0.14
	In-vehicle Time Coefficient	-0.019	-0.015*	-0.015*	-0.019	-0.019	-0.019
	Operating Cost ($/mile)	0.6	0.8*	1*	N/A	N/A	N/A
	Parking cost	✓	✓	×	N/A	N/A	N/A
	VOTT ($/hr)	15.83	11.08*	11.08*	8.14	8.14	8.14

(b) **Freight Model** (Adapted from Texas SAM)					
Trip Distribution	Mode Choice Logsum			Log of Population	
	τ = 0.5			δ = 0.1	
Mode Choice	Rail Constant	IM constant	Cost Coefficient	Time Coefficient	Average Travel Distance (mi.)
Agriculture	-1.343	-5.224	-0.018	-	1539
Mining	-2.291	-6.111	-0.033	-	888
Coal	3.316	-	-0.007	-	1175
Nonmetallic Minerals	-1.441	-8.469	-0.031	-	670
Food	-2.237	-6.430	-0.016	-	1715
Consumer Manufacturing	-6.742	-4.233	-0.012	-	2174
Non-Durable Manufacturing	-5.941	-5.345	-0.019	-	1837
Lumber	-2.253	-6.053	-0.029	-0.021	1437
Durable Manufacturing	2.407	-2.771	-0.008	-0.064	1828
Paper	-1.772	-4.420	-0.013	-	1463
Chemicals	-0.874	-6.644	-0.011	-	1322
Petroleum	-2.529	-8.443	-0.030	-	935
Clay, Concrete, Glass	-2.668	-6.520	-0.019	-	1414
Primary Metal	-0.609	-7.263	-0.010	-	1661
Secondary & Misc. Mixed	-4.143	-4.457	-0.016	-	1902

*Note: Numbers marked with * are modified during sensitivity analysis.*

As shown in Figures 2(c) and 2(d), the Htruck and Atruck alternatives are nested under the truck mode, after AVs are introduced to the market. The Air and Water modes are ignored here, since they are considered fixed in the SAM model. (In reality, some air-freight and water-born freight trips will probably be replaced by Atruck trips, due to its convenience, cost and speed.) An Atruck is assumed to cost 1.5 times that of an Htruck at a per mile basis because of the cost of automation equipment and training expense for the drivers who attend the truck, but assumed to save some connecting (uploading or downloading) times at origins and destinations. The nesting coefficient is set to 0.7, recognizing that Htrucks and Atrucks have more relative substitutability as their costs and times are similar. Travel time and travel cost of IM (intermodal rail) mode are obtained from SAM (Alliance Transportation Group, 2018). Travel cost from SAM considers fixed cost and variable cost, based on Surface Transportation Board 2003 rates and travel time is assumed to be determined intermodal rail time of 24 hours plus 2 hours intermodal dray and travel time for rail at a speed of 24.75 miles per hour (Alliance Transportation Group, 2018).

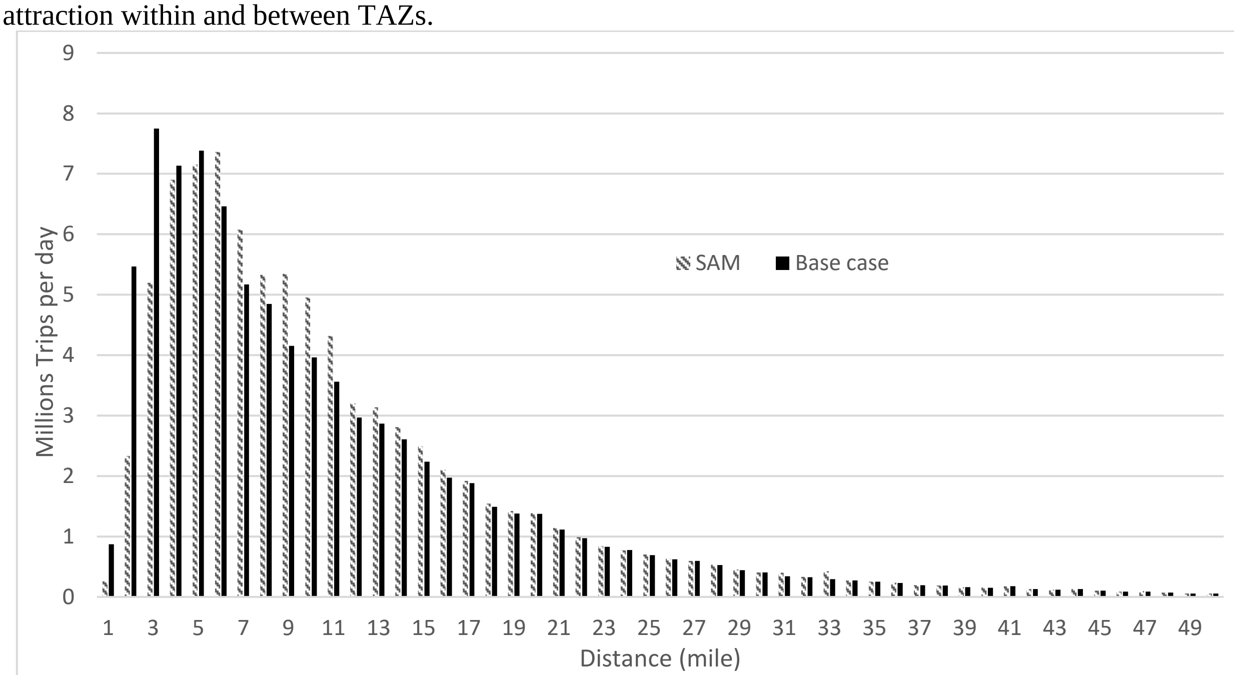
Traffic Assignment and Feedback Loop

Mode and destination choice results are transformed into trip tables or OD matrices, and round-trip tours are split in two for the final traffic assignment. Based on 2009 NHTS data (Santos et al., 2011), HV, AV and SAV occupancies are set to 1.5 persons. The freight trip table (in tons by commodity) are converted to trucks and rail cars, based on SAM weights. Feedback loops are performed to provide consistent results between travel time and cost skims and network assignment flows, feeding congested travel times back for subsequent iterations, using the method of successive averages.

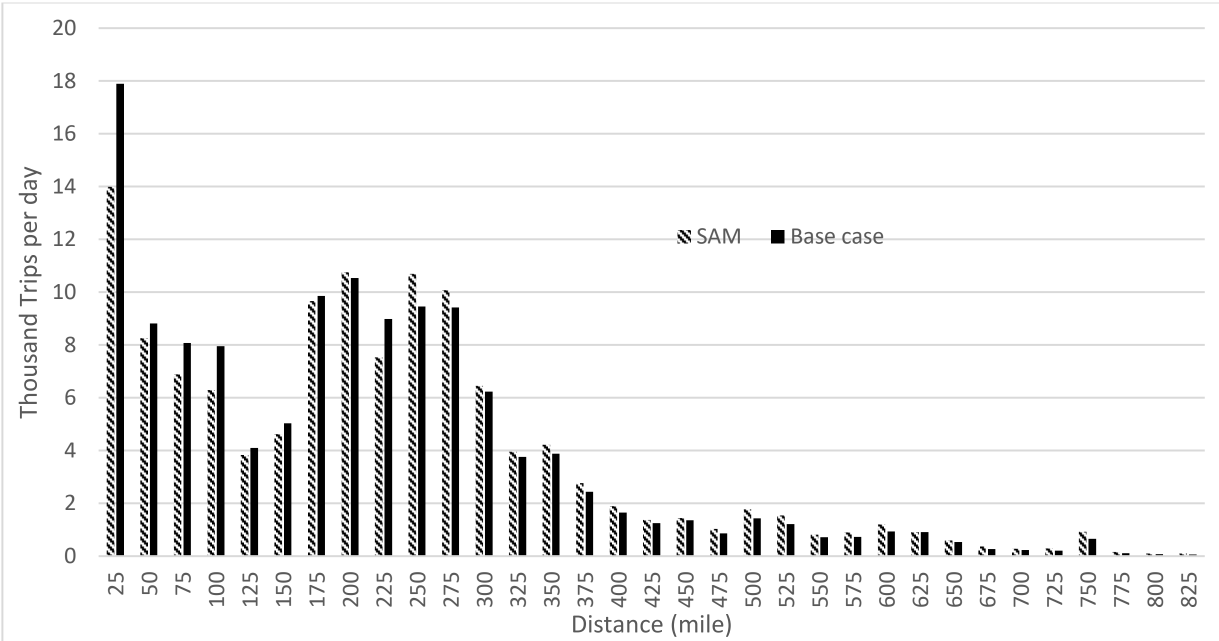
A multi-modal, multi-class assignment was conducted in each scenario, to reflect large differences in VOTT between human-drivers and self-driving vehicles. The feedback loop was set to perform 20 iterations, with a stopping criterion of relative gap below 10^{-4}, to try and achieve a stable, convergent equilibrium.

MODEL CALIBRATION

To appreciate how parameter and model-specification changes affect predictions, the revised model's results (for the before-AVs base case) were compared to the original SAM model's outputs, with histograms of trip distances shown in Figure 3. The base case predictions deliver quite a few more trips under 5 miles and somewhat fewer trips between 6 and 15 miles, but otherwise track the SAM predictions closely (with a correlation coefficient of 0.99 across the binned distances, and 0.82 across flows between all >21M OD pairs). This distinction is probably due to the destination choice model's enabling more attraction within and between TAZs.



a. Passenger Trip Distance Predictions across Texas (< 50 mi.)



b. Freight Trip Distance Predictions across U.S.

FIGURE 3 Comparing Predicted Trip Distance to SAM Model Results

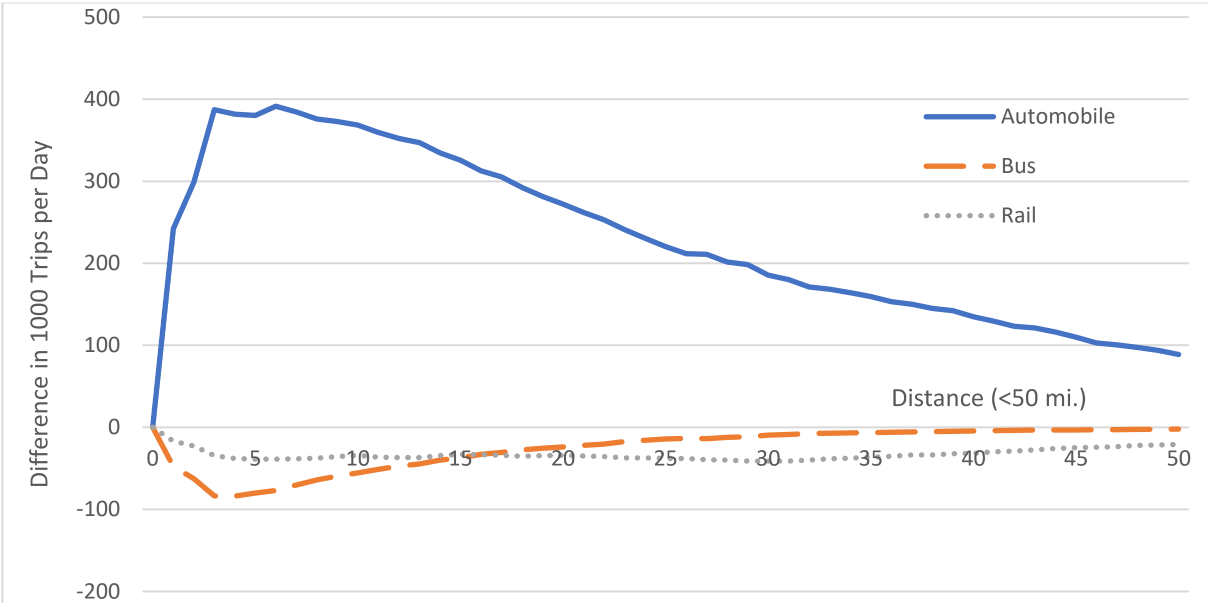
In terms of freight predictions, the correlations are 0.997 for 25-mile distance bins (Figure 3(b)) and 0.81 for trip counts between every all U.S. OD pairs. Truck and Rail volumes exhibit relatively high correlations in each of the 15 commodity classes, while IM results (for intermodal assignments) are relatively uncorrelated. Fortunately, the IM mode accounts for a relatively small amount of Texas trade, so its misprediction is not a serious issue. In reality, freight transport is tricky to predict (since every shipment is unique in various ways), and the SAM model delivers slightly higher mode shares in Rail and IM, while the modified model's base case delivers slightly higher truck shares in most commodity classes.

RESULTS

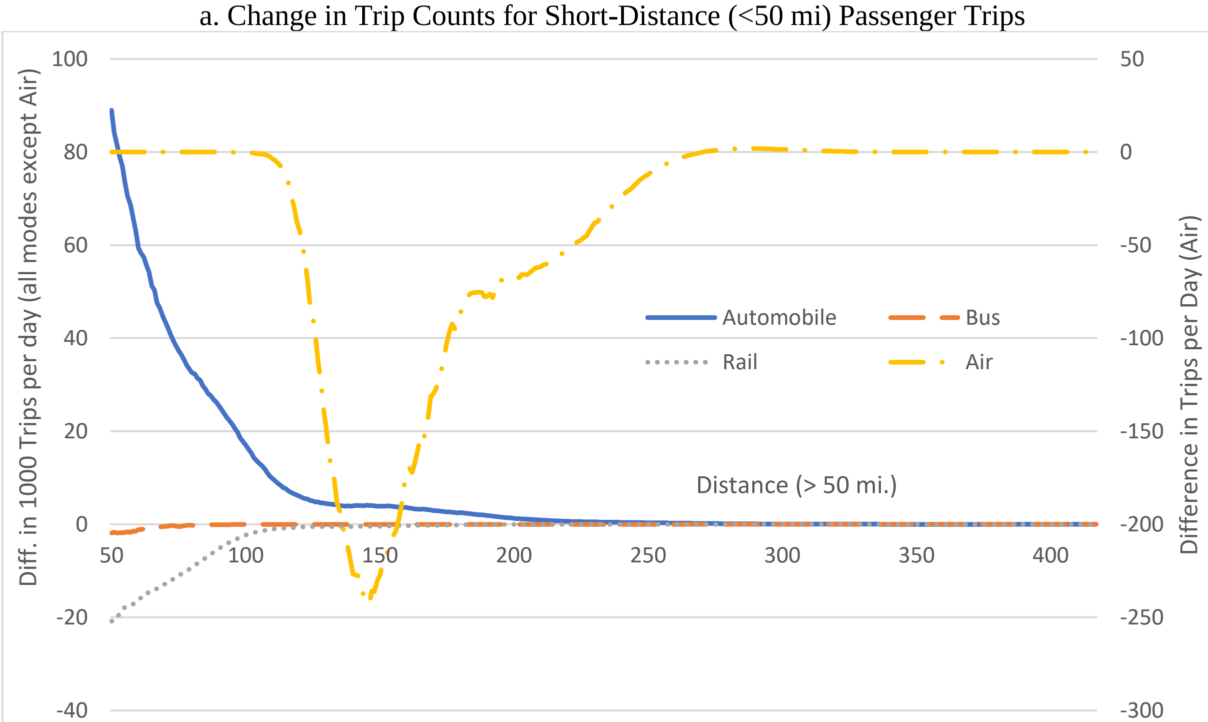
The following discussion looks at mode split shifts before and after AVs are introduced in passenger and freight transport markets across Texas and its megaregion. Trip length distributions and travel patterns across zone pairs are examined, along with VMT values and congestion metrics. Finally, several sensitivity tests provide even better anticipation of the traffic and economic impacts that AVs, SAVs and Atrucks can bring regions and megaregions like the Texas Triangle.

Mode Share

Table 2 and Figure 4 shows passenger-mode splits before and after AVs. Figure 4 shows the trip distribution by length (one mile interval) for both short-distance and long-distance trips. The Automobile mode is the sum of HV, AV and SAV trips. With AVs available, Automobile shares rise for short and long-distance trips across the megaregion, shifting markedly away from Texas air travel (with most air travel distances between 100 miles and 280 miles). Existing and future travel between DFW, Houston, San Antonio and Austin is expected to favor AVs and SAVs. Trips by bus less than 50 miles appear to fall, since bus routes are normally no more than 50 miles. Rail trips also fall, for both distances up to 120 miles.



a. Change in Trip Counts for Short-Distance (<50 mi) Passenger Trips



b. Change in Trip Counts for Long-Distance (>50 mi) Passenger Trips

FIGURE 4 Changes in Texas Triangle trip counts by mode (after AVs minus before AVs), versus trip distance

As shown in Table 2, AVs and SAVs see less impact on shorter distances, in which automobile mode increases by 16.1% while bus and rail are reduced by 66.1% and 71.1% respectively. Air trips less than 50 miles are not discussed here because distances less than 50 miles between two airports in Texas is not considered to be a normal trip. However, in distances greater than 50 miles, Automobile and Bus modes show the same trend but with relatively large change. However, Rail was relatively less affected in the longer distances, decreasing by 61.4%. Air remains to be the mode that affected most by the AV and SAV introduction while rail is least affected in long-distance trips. Air travel across Texas decreases by 61.8%

while decreasing by 82.5% across the megaregion. Internal trips starting or ending from airports in the megaregion are shifting to other places instead of staying in the megaregion, while losing to AVs at the same time. San Antonio International Airport, Dallas/Fort Worth International Airport, Love Field Airport, Hobby Airport, Houston International Airport and Austin–Bergstrom International Airport enplanements or deplanements across the U.S. will probably remain after Triangle traffic is lost to AVs.

TABLE 2 Person-Trip Count Changes by Mode for Short and Long-Distance Trips (Internal trips, Thousand Person-Trips per Day)

Mode		Automobile (HVs, AVs, & SAVs)	Bus	Rail	Air
Trips before	< 50 miles (short-distance)	64,678 k/day	1,837 k/day	2,219 k/day	N/A
Trips after		75,088 k/day	623.8 k/day	642.3 k/day	N/A
Change		+16.1%	-66.1%	-71.1%	N/A
Trips before	> 50 miles (long-distance)	2,946 k/day	33.64 k/day	988.2 k/day	14.27 k/day
Trips after		6171 k/day	2.416 k/day	595.7 k/day	2.497 k/day
Change		109.5%	-92.8%	-39.7%	-82.5%
Total change		+20.2%	-66.5%	-61.4%	-82.5%

Based on the SAM's mode choice specification, mode share in freight by different industry sectors can be obtained (Table 3). All modeled 15 industries would witness trips increase in truck and decrease in rail and IM, after Atrucks are introduced. The increase of truck travel varies by mode but most of Rail and IM mode decrease by 30%. Coal commodity truck trips see a massive increase (51.3%), which is mainly shifted from rail models that dominated coal transportation prior to Atruck implementation, followed by chemicals (11.3%), but consumer manufacturing, non-durable manufacturing and secondary and miscellaneous mixed goods have slight increase of less than 1%.

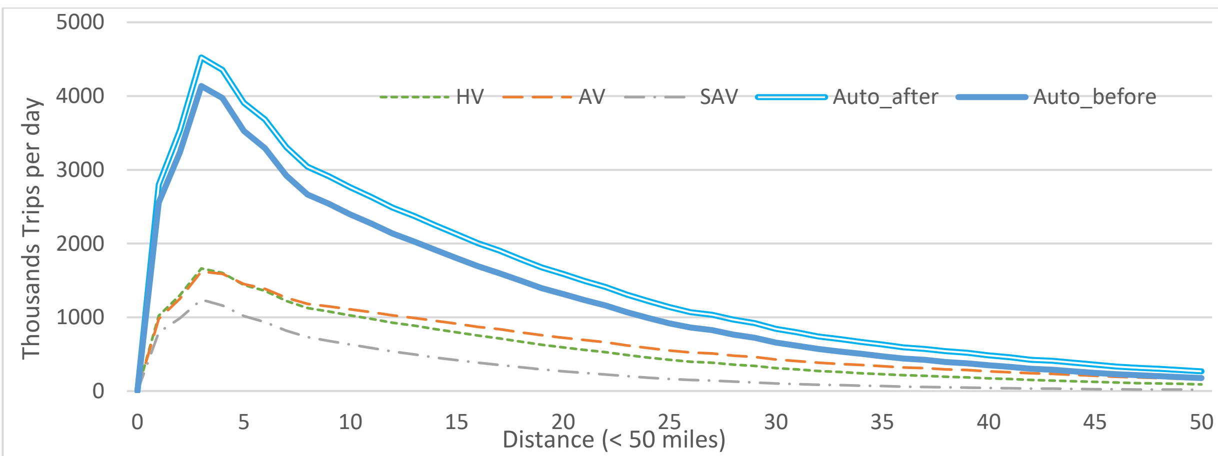
TABLE 3 Mode Splits in Freight Ton-Miles Moved within the Texas Triangle (Internal Trips)

Commodity	Mode Share After Atrucks Introduced					Change from Base Case		
	Atruck	Htruck	Truck	Rail	IM	Truck	Rail	IM
Agriculture	30.4%	52.6%	83.0%	16.9%	0.18%	+7.2%	-25.3%	-25.3%
Mining	37.1%	58.0%	95.1%	4.9%	0.04%	+2.4%	-30.9%	-31.0%
Coal	2.5%	3.5%	6.0%	91.0%	3.08%	+50.0%	-2.0%	-2.0%
Nonmetallic Minerals	26.6%	56.1%	82.7%	17.3%	0.01%	+5.6%	-21.8%	-21.9%
Food	34.5%	58.0%	92.4%	7.5%	0.06%	+3.1%	-28.8%	-28.8%
Consumer Manufacturing	38.6%	60.7%	99.2%	0.1%	0.68%	+1.1%	-31.7%	-31.7%
Non-Durable Manufacturing	35.9%	63.7%	99.6%	0.2%	0.19%	+0.2%	-29.6%	-29.7%
Lumber	36.3%	61.2%	97.5%	2.4%	0.04%	+1.2%	-26.4%	-26.5%
Durable Manufacturing	48.1%	38.4%	86.5%	13.0%	0.53%	+9.6%	-35.1%	-35.1%
Paper	33.8%	54.5%	88.3%	11.2%	0.49%	+5.2%	-28.3%	-28.4%
Chemicals	30.6%	46.6%	77.2%	22.7%	0.05%	+11.1%	-25.6%	-25.6%

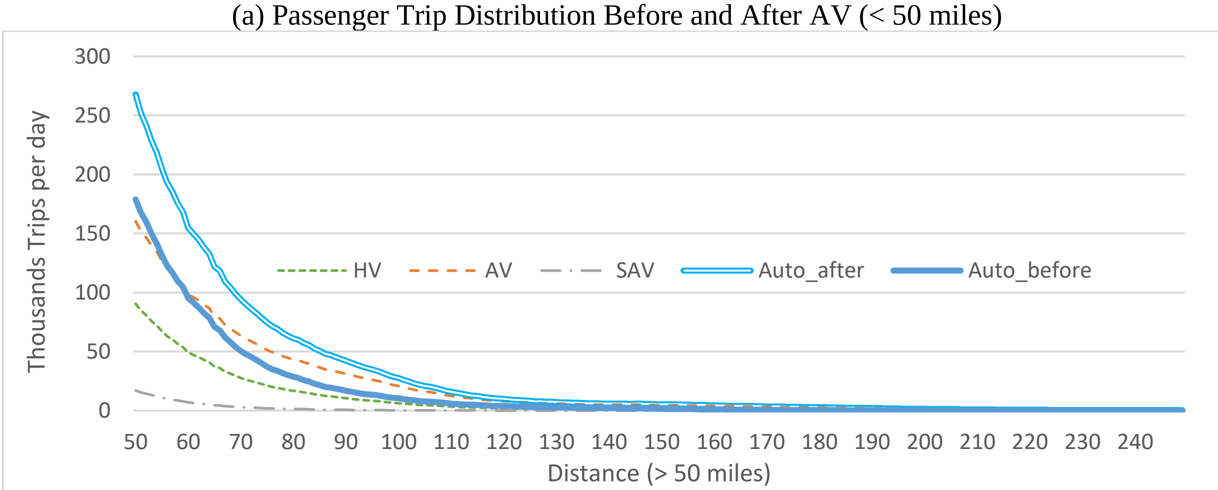
Petroleum	30.6%	62.9%	93.5%	6.5%	0.01%	+2.2%	-24.5%	-24.7%
Clay, Concrete, Glass	34.3%	60.5%	94.8%	5.2%	0.06%	+2.1%	-28.4%	-28.4%
Primary Metal	34.2%	47.7%	81.9%	18.0%	0.02%	+9.0%	-27.8%	-27.8%
Secondary & Misc. Mixed	36.6%	61.7%	98.3%	1.2%	0.49%	+0.5%	-30.5%	-30.6%

Trip Distribution

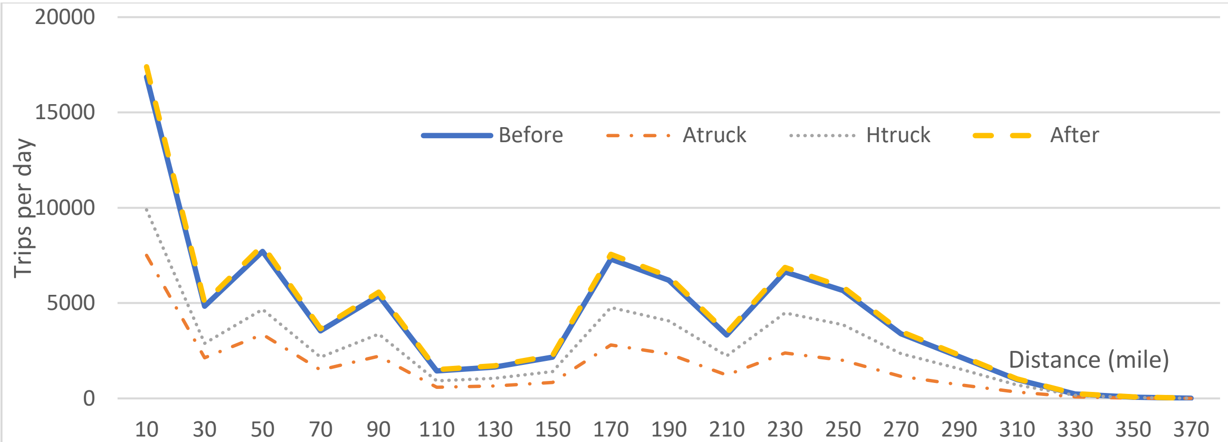
Figure 5 shows the trip distribution of a thousand trips per day by automobile before and after AV introduction. Air and rail travel is assumed to have straight line travel distance, while bus has the same as automobile in the road network. After AVs and SAVs are introduced, trips of all distances increase, while trips between 4 miles to 120 miles see greater increases in trip distances before and after AV introduction, at 14 miles before AVs, compared to 16 miles after the AV scenario. Travelers are shifting to longer distances due to the potential benefits that AVs would bring. As shown in Figure 5(a) and 5(b), AVs have slightly less share than the HV mode less than 6 miles, but there are more trips longer than 6 miles and the share of AV increase when the trip distance increases. SAV shows a similar trend, but few SAV trips greater than 80 miles are observed.



(a) Passenger Trip Distribution Before and After AV (< 50 miles)



(b) Passenger Trip Distribution Before and After AV (> 50 miles)



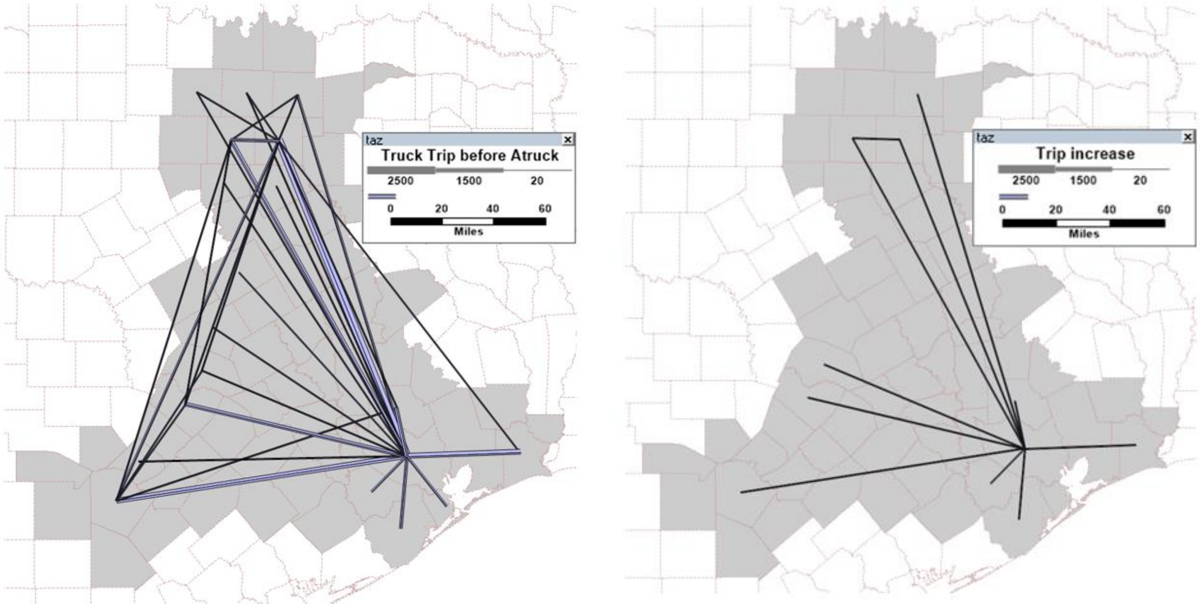
(c) Freight Trip Distribution Before and After AVs

FIGURE 5 Trip distributions before and after AVs (across modes, by distance, for passenger and freight travel)

Figure 5(c) presents the trip distribution of trucks before and after Atrucks become available. Since the freight mode choice is doubly-constrained, truck share after AV shows the same trend as “before” scenario. There is a slight increase in truck trips of all trip distances, with the conventional Htruck retaining a greater share of tons at all distances than the Atruck does in this megaregion, since the Atruck costs more, especially for these intermediate travel times (all under 5 hours). In the future, as the cost of Atrucks decreases, a greater market share of Atrucks would be expected. The jump of 170 miles and 230 miles can be seen as the distance between Dallas-Fort Worth and Houston, and San Antonio to Houston or Austin to Houston. It is evident that Houston is a main freight center in the megaregion.

Freight Spatial Analysis

Figure 6 maps the major commodity movements (and their changes) between OD pairs in the Triangle. It does not show the smallest flow volumes, which sum to the first 10% of tons moved. Therefore, Figure 6(a) shows 90% of the freight movement (in tons) that happens in the megaregion. Trade happens mostly between the megaregion’s four key sub-regions: Houston, Dallas-Fort Worth, San Antonio and Austin, as well as counties near Dallas-Fort Worth and Houston (Texas’ most populous regions). After Atrucks’ introduction, trade rises mostly between Houston and the other three regions.

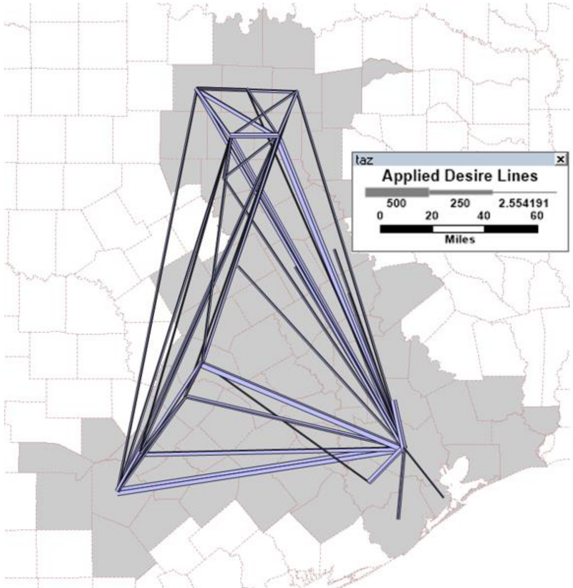


(a) Truck Trip before Atruck (b) Truck Trip Increase After Atruck

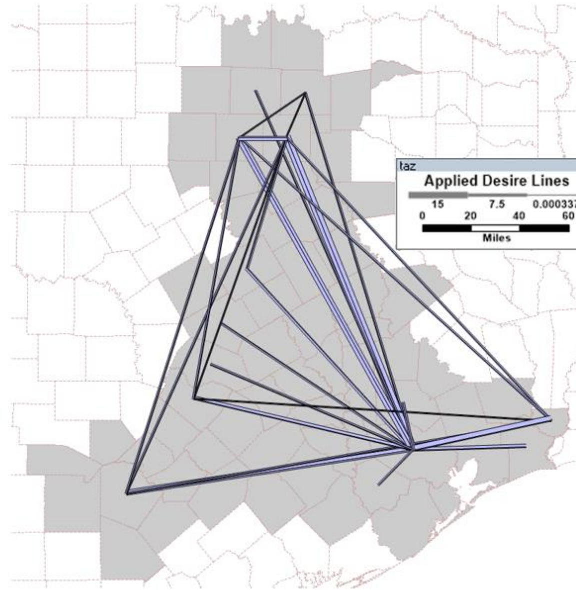
FIGURE 6 Major freight movements across the Texas Triangle.

The spatial increase of the commodities can also be analyzed. Figure 7 shows the commodities that have an increase in truck trips greater than 5%. The lines that show growth less than 10% of the total increase of the corresponding commodity have been hidden. For agriculture, chemical and primary metal, most connections are seen between Houston and Dallas-Fort Worth/San Antonio/Austin. For coal, increased trips happen across central megaregion and the south. For nonmetallic minerals and paper, there is an increased connection between Houston and Dallas-Fort Worth, but also west of the megaregion.

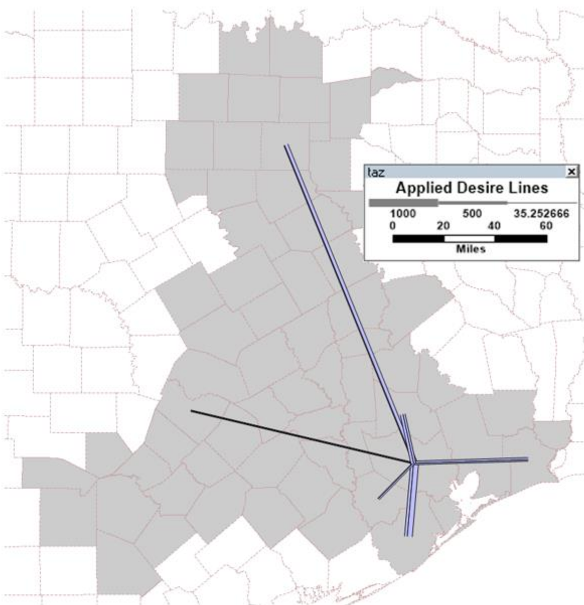
(a) Agriculture (b) Coal



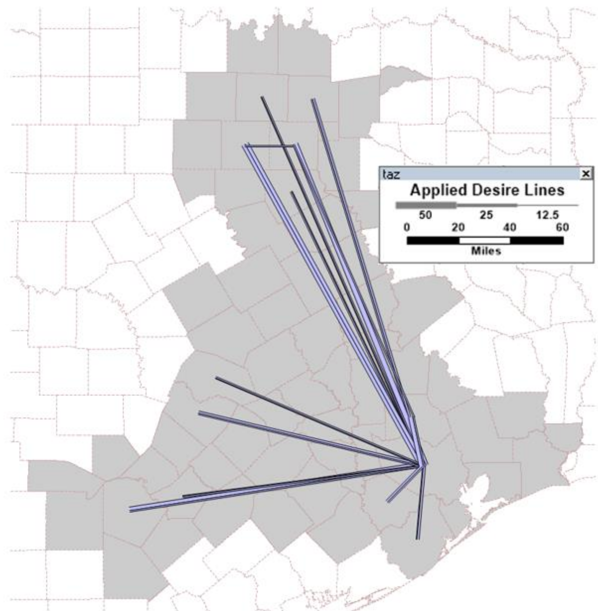
(c) Nonmetallic Minerals



(d) Paper



(e) Chemicals



(f) Primary Metal

FIGURE 7 Top truck trip Increases by commodity (based on Figure 6 flows, if more than a 5% change)

Vehicle-Miles Traveled

Table 4 shows passenger-VMT changes for all passenger modes after introducing AVs. The VMT is approximated for rail, bus and air. Based on the trip distribution results, VMT is obtained by multiplying average trip distances with trip counts for each corresponding distance band. Rail, bus, and air modes show a decrease in VMT, with rail travel decreasing by 77.1%, air travel by 84.6% and bus VMT shrinking by 49.8%. Overall automobile modes show a 46.7% increase in VMT after AVs' introduction. Passenger airline travel is the mode most affected by the arrival of AVs. The 15% of this VMT increase is probably due immediately to the assumption that trip generation and attraction values all rise by 15% in all zones.

TABLE 4 Texas Triangle VMT Changes by Passenger Modes Before and After AVs (for internal trips only)

VMT (1M mi per day)	Automobile	Rail	Bus	Air
Before	955.2M mi/day	19.4M mi/day	114.1M mi/day	2.0M mi/day
After	1400.9	4.5	57.3	0.3
Change	46.7%	-77.1%	-49.8%	-84.6%

Table 5 details the VMT changes in major cities in megaregion area. Dallas-Fort Worth, San Antonio, Houston and Austin all show a VMT increase of almost more than 30%. Houston presents the smallest increase among them at 36.0%, while Austin gains a VMT increase of 56.9%. On average, VMT increases by 47.0% across the megaregion area. The considerable increase in VMT due to the advent of AVs and SAVs could probably raise burden for the infrastructure of the major cities in the megaregion, especially in the Austin area.

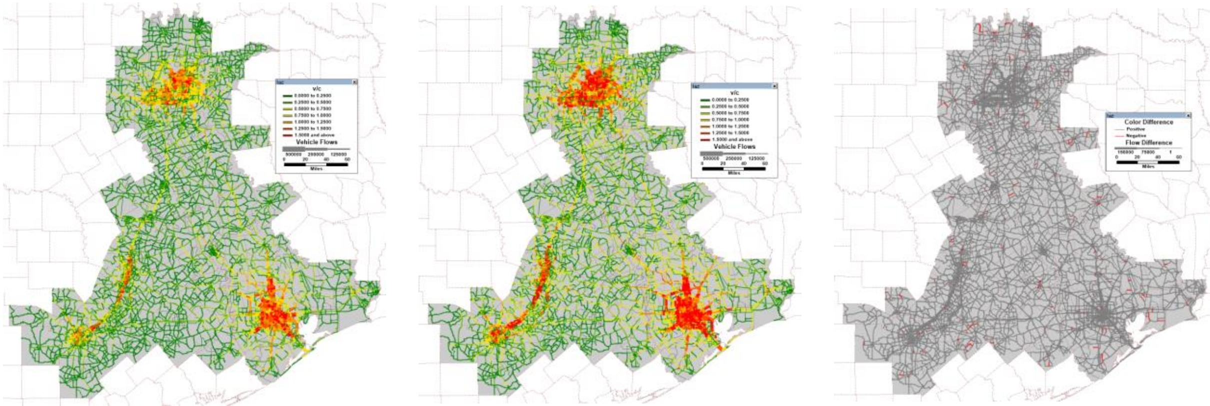
TABLE 5 VMT Changes (for Passenger + Freight) in Texas Triangle's Main Cities Before and After AVs

	VMT before AV (1M per day)	VMT after AV (1M per day)	Change
Dallas-Fort Worth	453M miles	669M miles	+47.7%
San Antonio Region	118	171	+45.8%
Austin Region	119	186	+56.9%
Houston Region	432	587	+36.0%
Total Megaregion	*1,367*	*2012*	*+47.2%*

Note: Dallas-Fort Worth Counties are Denton, Collin, Hunt, Parker, Tarrant, Dallas, Rockwall, Kaufman, Ellis, Johnson, Henderson and Hood; San Antonio Counties are Bexar, Comal, Guadalupe and Wilson; Austin Counties are: Williamson, Travis, Bastrop, Caldwell and Hays; Houston Counties are Harris, Montgomery, Liberty, Chambers, Brazoria, Galveston and Fort Bend.

Roadway Network Performance

Figures 8(a) and 8(b) illustrate traffic flows (by line thickness) and congestion levels (volume-to-capacity ratios, by color) on all of the region's road links in before- and after-AV cases. Figure 8(c) illustrates the changes across regional links, with added flows heaviest within the Dallas-Ft Worth and Houston regions, and many V/C ratios suddenly exceeding 1.5 once AVs are introduced, notably along the IH-35 corridor.



(a) Base Case Before AV (b) After AV (c) Changes after AVs

FIGURE 8 Flows and congestion

4.9% of the megaregion’s 27,976 links are simulated to have V/C values above 1 before AVs are introduced (with a maximum ratio of 3.2), and this more than doubles, to 9.9% (with a max value of 4.1), after AVs are widely available to travelers. 92.3% of the links experience higher flows in both directions, 1.6% have decreased flow in both directions, and 2.0% have higher flow in just one direction and lower flow in the other.

TABLE 6 Sensitivity Analysis Results

Scenario	Base	1	2	3*	4	5	6	7*	8	9	10	11*	12	13	14	15
Scenario Settings	AV and SAV VOTT ($/hr)						Operating Cost ($/mile)				Nesting Coefficients					
	N/A	14.25	12.67	11.08	9.50	7.92	AV	AV	AV	AV	0.5	0.6	0.7	0.8	0.9	1
	Reduced VOTT Percentage						0.6	0.8	1	1						
	0	0.1	0.2	0.3	0.4	0.5	SAV	SAV	SAV	SAV						
							0.6	1	1	1.5						
Total VMT (Passenger + Freight) (Billion per day)	1.367	1.997	2.012	2.030	2.051	2.086	2.088	2.012	1.991	1.990	2.152	2.012	1.894	1.793	1.707	1.632
HV VMT (Billion per day)	0.955	0.576	0.509	0.449	0.397	0.340	0.398	0.509	0.505	0.540	0.512	0.509	0.499	0.484	0.466	0.448
AV VMT (Billion per day)	N/A	0.672	0.744	0.810	0.871	0.944	0.576	0.744	0.735	0.777	0.846	0.744	0.667	0.607	0.559	0.520
SAV VMT (Billion per day)	N/A	0.129	0.136	0.142	0.148	0.155	0.458	0.136	0.135	0.057	0.111	0.136	0.157	0.174	0.188	0.198
HV market penetration	93.0%	40.1%	37.6%	35.3%	33.1%	30.45%	31.9%	37.6%	37.7%	40.6%	37.4%	37.6%	37.6%	37.5%	37.3%	37.0%
AV market penetration	N/A	41.4%	43.5%	45.6%	47.5%	49.84%	36.5%	43.5%	43.4%	46.7%	45.5%	43.5%	42.0%	40.8%	39.9%	39.1%
SAV market penetration	N/A	16.2%	16.6%	17.0%	17.4%	17.81%	29.4%	16.6%	16.7%	10.5%	14.4%	16.6%	18.5%	20.1%	21.4%	22.6%
Link Percentage, V/C > 1	4.60%	9.60%	9.78%	9.94%	10.20%	10.60%	10.63%	9.78%	9.56%	9.55%	11.47%	9.78%	8.56%	7.83%	7.19%	6.64%
Maximum V/C	3.215	4.046	4.067	4.072	4.092	4.117	4.126	4.061	4.025	4.036	4.213	4.061	3.883	3.730	3.606	3.491

*Notes: * is the AV scenario discussed in previous section, and the base case is the scenario without AV/SAV; Total VMT is VMT within megaregion area, including trips travel through megaregion; HV, AV and SAV VMT consider inter-megaregion trips only.*

Sensitivity Analysis

Table 6 shows results of sensitivity analysis from varying VOTT, operating costs, and nesting parameters. As the VOTT for those using AVs falls, regional VMT rises, with higher AV and SAV market shares and more congestion. Such behaviors also emerge when VOTT is fixed but AVs and HVs are more correlated, thanks to a lowered nesting coefficient (implying that AVs and HVs are closer substitutes/have more in common). Also as expected, lowered AV and SAV operating costs deliver higher VMT, congestion and AV market share. With the development of the automation technology, AVs and SAVs will become less costly in the further, so it is reasonable to believe AVs and SAVs will be more widely used as time goes by. SAV is also increasingly popular as the market shared of SAV almost double, when the same operating cost of AV and SAV decrease from $1/mile to $0.6/mile, which may probably happen with automation technology becoming mature. The operating cost for AV and SAV may be much lower than an HV in the future. Further, with improved technology of AV, through which people could perform task much more easily like working and sleeping, the VOTT would be smaller and eventually be similar with the value of time working at office or sleeping at home. The nesting coefficient in the future could vary based on the nest structure, for example: SAV could be nested in a public transportation mode instead of the auto mode, and if the HVs are completely replaced by AV, there is no need for a nesting coefficient.

CONCLUSION

This work uses a four-step model structure with nested logit models to reflect future widespread availability of AVs, SAVs, and Atrucks across a statewide area. It starts with Texas' SAM data and relies on TransCAD 7.0 software to equilibrate (with travel time and cost feedbacks) the passenger and freight flow volumes across shortest paths via preferred modes, to preferred destinations. Changes in mode choices, trip distances, and congestion levels across the Texas Triangle region are examined, comparing before vs. after conditions, and assuming that trip generation rates also rise (by those presently unable to drive, for example).

As expected, the average travel distance for passenger travel across the megaregion rises, from 14 to 16 miles. Air travel between Triangle airports is expected to fall dramatically, by over 80%, which could account for roughly 4.3% of all air trips in Texas. Without road pricing or other forms of demand management, VMT is predicted to rise 39.1%, along with many links' V/C ratios, especially in the megaregion's top sub-regions (Houston, Dallas-Fort Worth, San Antonio and Austin). The number of links having demand exceed capacity is predicted to more than double (to nearly 10% of links). In terms of freight transport, movements in 7 of the 15 commodity classes are predicted to rise over 5%, with coal the most (50%), followed by chemicals (11.1%), durable manufacturing (9.6%), primary metal (9.0%), agriculture (7.2%), nonmetallic mineral (5.6%) and paper (5.2%), and such movements increase mostly between Houston and other key population hubs, like Dallas-Fort Worth, San Antonio and Austin. Added travel can easily mean greater energy use and air pollution, human health issues, climate change issues, reductions in active transport, and higher rates of obesity, diabetes, and other issues.

Predictions of much-lowered local air travel and rising demand for highway infrastructure should help state and city departments of transport, planning organizations, manufacturers, transit providers, and airport authorities think about the kinds of policies and practices they should be putting into law and their budgets now. These may be a doubling or tripling of fuel taxes (which have not risen in Texas in 25 years), credit-based congestion pricing (so that everyone "owns" a piece of the limited road network), limits on size and fuel use of privately owned AV (to avoid vehicles getting bigger [to include beds, for example] and less efficient), and very clear limits on empty-AV use (so that SAV fleet managers cannot add more than 15% VMT from empty travel and private AV owners cannot send their vehicles out empty on public roadways [only in private parking lots, for example]).

In terms of modeling improvements, the dynamics of congestion and use of SAVs between drop-offs and pickups are not reflected here. Microsimulation models like MATSim and POLARIS can track vehicles and travelers, while simulating traffic dynamics over 24 hours, but are challenging to learn and apply at such scale. Trips across the Mexico border are also neglected here, as well as the details of dynamic ride-sharing (between strangers using SAVs, saving on trip costs). Of course, SAVs can also serve as first-mile and last-mile modes supporting longer-distance trains, planes, and (self-driving) buses. And only time will tell how quickly (and affordably) manufacturers and fleet operators bring such technologies to market, how quickly businesses and individuals can afford and adopt the new modes, and how thoughtfully regions, states and nations will govern themselves, to pursue healthier and more sustainable futures.

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