Volume 1: Integrated ABM-DTA Methods to Model Impacts of Disruptive Technology on the Regional Surface Transportation System – A Feasibility Study

DECEMBER 2017

U.S. Department of Transportation
Federal Highway Administration

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This report investigates using detailed simulation models to help regional and state agencies plan for the effects of connected vehicle (CV) and autonomous vehicle (AV) technologies in long-range planning. The research integrates the DaySim activity-based travel demand model with the TransModeler dynamic traffic simulation model for Jacksonville, Florida, for Exploratory Modeling and Analysis (EMA). The work adapts travel demand models to simulate households' decisions whether to purchase autonomous vehicles instead of conventional vehicles, and to simulate travelers' decisions whether to use CAV-based car-sharing and ride-sharing services. The dynamic network models simulate operating characteristics of CAVs—depending on network vehicle mix—and simulate the performance of CAV-only infrastructure under different demand scenarios. The models simulate dozens of different scenario combinations to explore potential outcomes and find critical input assumptions while identifying future policy directions that are likely to be the most robust in the face of "deep uncertainty."</td></tr>
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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

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m	meters	1.09	yards	yd
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m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
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L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
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g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
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cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
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(Revised March 2003)

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List of Abbreviations and Symbols

Abbreviations

ABM	activity-based model
CACC	cooperative adaptive cruise control
CAV	connected and autonomous vehicle
CPU	central processing unit
CSV	comma-separated values
CV	connected vehicles
DORP	driver or passenger
DTA	dynamic traffic assignment
DVE	driver-vehicle entity
EMA	Exploratory Modeling and Analysis
FBB	EMA C/AV Scenario
FHWA	Federal Highway Administration
FMM	EMA C/AV Scenario
GISDK	Geographic Information System Developer's Kit
HH	household
HHAC	EMA C/AV Scenario
HHIC	EMA C/AV Scenario
HOV	high-occupancy vehicles
LH	EMA C/AV Scenario
LOS	level-of-service
MM	EMA C/AV Scenario
MOE	measures of effectiveness
MPO	metropolitan planning organization
NERPM	Northeast Regional Planning Model
NFTPO	North Florida Transportation Planning Organization
NHTS	National Household Travel Survey
NT	nighttime
OD	origin-destination
PAV	private autonomous vehicle
PCV	private conventional vehicle
QRA	quantitative risk analysis
SAV	shared autonomous vehicle
SH	AV paid rideSHhare
TAZ	traffic analysis zone
TMIP	Travel Model Improvement Program
TNC	transportation network company
V2I	vehicle-to-infrastructure
VHT	vehicle hours traveled
VMT	vehicle miles traveled
VOT	value of time

1.0 Introduction

1.1 Disclaimer

The views expressed in this document do not represent the opinions of FHWA and do not constitute an endorsement, recommendation or specification by FHWA.

1.2 Introduction

The purpose of this project was to demonstrate the concepts of Exploratory Modeling and Analysis (EMA) in the context of the transition to connected vehicle (CV) and autonomous vehicle (AV) technology. The proposed methodology was to integrate an activity-based model (ABM) with dynamic traffic assignment (DTA) in the Jacksonville, FL region, introducing new features in the models to reflect specific assumptions regarding the demand and network supply for CV/AV. Phase 1 of the research was designed to demonstrate the feasibility and usefulness of the approach, while Phase 2 will extend the research to a more complete exploratory scenario analysis. The tasks for Phase 1 were to:

- ***Set up and test the integration of the ABM and DTA model systems for the base scenario.***
- ***Adapt the ABM and DTA models to accommodate key selected dimensions of uncertainty in the context of AVs.***
- ***Perform the Phase 1 exploratory runs and report the results.***
- ***Prepare a work plan for the Phase 2 EMA.***

It is important to keep in mind that the main objective of Phase 1 was to assess the reasonableness of an integrated ABM-DTA approach for EMA applications, particularly in scenario planning to support transportation planning decision-making.

1.3 Steps in the Exploratory Modeling and Analysis Approach

Even though the word “exploratory” may connote an ad-hoc type of approach, EMA is a structured methodology for investigating future scenarios in which there are many different sources of uncertainty. The main steps in the approach are:

1. Define and select the key sources of uncertainty that will be used as input assumption, and the levels of each to be tested. (See Setup and Test the Integration of the ABM and DTA Model Systems for the Base Scenario)
2. Design the analytic model framework that will be used to simulate scenarios, ensuring that it can represent each of the selected input assumptions. (See Setup and Test the Integration of the ABM and DTA Model Systems for the Base Scenario and Adaptation of the ABM and DTA Models to Accommodate Key Dimensions of Uncertainty in the Context of)
3. Create an experimental design so that the influence of each level of the various input assumptions on the simulated scenario outcomes can be analyzed efficiently, without

simulating every possible combination of inputs. (See Perform the Phase 1 Exploratory Runs and Report the Results)

4. Select the scenario outcomes to be evaluated, and what metrics and analysis methods will be used to evaluate them. (See Perform the Phase 1 Exploratory Runs and Report the Results)
5. Implement and test the analytic model framework, testing the reasonableness in terms of reproducing the current situation and representing key types of sensitivities, including the sensitivities to the selected sources of uncertainty. (See Setup and Test the Integration of the ABM and DTA Model Systems for the Base Scenario and Adaptation of the ABM and DTA Models to Accommodate Key Dimensions of Uncertainty in the Context of)
6. Carry out the scenario simulation runs specified in the experimental design. (See Perform the Phase 1 Exploratory Runs and Report the Results)
7. Analyze the selected scenario outcomes as a function of the input assumptions, and communicate the results to aid in understanding the relative importance of the key sources of uncertainty. (See Perform the Phase 1 Exploratory Runs and Report the Results)
8. Evaluate the findings and how they could be extended or enhanced through further EMA. (See Summary of Phase 1 Approach and Phase 2 Priorities)

2.0 Setup and Test the Integration of the ABM and DTA Model Systems for the Base Scenario

This section describes the work completed under Task 3 of the work plan. Task 3 involved setting up and running the DaySim ABM with the TransModeler DTA, in an integrated fashion, for the base scenario. Three subsections describe the integrated model setup and the analysis of the results and a discussion of the issues, challenges, and next steps. Before describing each section in detail, a summary introduction is provided below.

2.1 Background

The DaySim ABM framework and software were first developed for the Sacramento Council of Governments (Bradley, et al., 2009), extending the model framework that had been applied previously in Portland and San Francisco. The DaySim model was first applied in the Jacksonville region in 2012 for the Strategic Highway Research Program SHRP2 C10A project (Strategic Highway Research Program, 2014) to demonstrate the integration of ABMs with DTA. In that project, DaySim was integrated with the TRANSIMS network assignment model.[1]

Shortly after the SHRP2 C10A project was completed, a project was funded by Florida Department of Transportation to use DaySim as the regional planning model in both the Jacksonville and Tampa regions. In these two implementations, DaySim is integrated with Cube, and, to conform to the current state of the practice, static traffic assignment is used rather than DTA. In Jacksonville, the North Florida Transportation Planning Organization (NFTPO) has adopted DaySim as the model for project planning (NFTPO, 2016).

The Jacksonville ABM operates at the individual parcel level for land-use variables and spatial choice models, while the auto and transit networks are represented at the zonal level, with roughly 2,500 zones in the region. The DaySim models use 30-minute time periods for simulation and interpolate to predict the starting and ending time for each activity down to the minute. The highway and transit assignments and skims, however, only treat five different periods of day (AM peak, midday, p.m. peak, evening, and night). Using DTA rather than static assignment leverages the spatial and temporal detail that can be provided by the activity-based demand simulation.

The DaySim software is open source and is maintained in a GitHub repository.[2] It includes a regression-testing system that coordinates across changes made for several different client agencies, ensuring that a change made for one user does not introduce unanticipated changes for other users. DaySim is written in C# for the Windows .NET platform, and supports multithreading. Currently, on a standard workstation with four cores, DaySim requires around 60 minutes to simulate weekday travel for the roughly two million residents of the Jacksonville region. Memory required for the Jacksonville region is less than 8 GB of RAM.

As mentioned above, the model is currently integrated with Cube, which performs auto and transit network assignment and skimming of zone-to-zone time and cost matrices. The scripts for running

[1] Strategic Highway Research Program, Transportation Research Board, Dynamic, Integrated Model System: Jacksonville-Area Application

[2] GitHub, RSGInc/DaySim Activity-Based Model

the nonresident market components (freight, external trips, visitors, and airport travel) are also implemented in Cube using a zonal trip-based framework. These models and traffic assignment are run for three or four global iterations with the DaySim resident demand simulation. The Cube-based model components require a significant fraction of the run time for the entire model system.

The TransModeler DTA software was implemented in the Jacksonville region, dynamically assigning the trips output by the existing NFTPO ABM (Morgan, et al., 2015). The TransModeler DTA encompasses the whole regional planning network and runs microscopically.[3] It could also be run in a mesoscopic mode for speed improvements and possibly as an alternative means of generating travel time skims.

2.2 Integrating DaySim with TransModeler: The Conceptual Design

The conceptual design behind integrating DaySim with TransModeler in Jacksonville is that DaySim provides the demand (a list of trips) for TransModeler to simulate on the network, and TransModeler provides congested travel times back to DaySim to use in simulating demand for the next iteration. The demand simulation and network simulation run iteratively until an acceptable level of stability is reached. This conceptual framework is not fundamentally different from what is currently used for the integration of DaySim with static assignment using Cube or TransCAD.[4] The main differences are that the TransModeler simulation framework is not limited to a specific zone system or broad time periods for traffic assignment, so this opens more options for integration (as discussed below). The traffic simulation can take advantage of the spatial and temporal detail produced by the demand simulation and can also model link delays and intersection delays much more realistically than is possible in static zone-to-zone assignment methods.

2.2.1 Specific Integration Issues

The following integration issues were considered under Phase 1:

1. **The level of spatial detail used in the ABM**: The default here is to use the existing NFTPO zone system, with roughly 2,500 zones. Underlying the zone system is parcel geography, which is used for the location choice models. The travel time and cost for intrazonal trips and other short-distance trips are also adjusted based on the shortest distance path between parcels on an all-streets network. With this short-distance adjustment it may not be necessary to use a more detailed zone system to get the benefit of using DTA-based travel times. However, it would be possible to use a more detailed zone system if it integrated effectively with the DTA.

2. **The level of temporal detail used in the ABM**: The ABM currently uses 30-minute time periods as the choice alternatives in the tour and trip scheduling models. When each trip is simulated, a specific departure minute is selected at random from the available time window within the chosen 30-minute period. This means that the trip timing could be

[3] TransModeler Dynamic Traffic Assignment Model for NERPM ABM

[4] Caliper, 2016. Technical Notes on the TransCAD Conversion of Jacksonville CUBE Travel Demand Model, Jacksonville Model Conversion.

adjusted somewhat within the DTA without becoming inconsistent with the simulated choices from the ABM. If one wishes to maintain consistency across trips in a tour, however, adjusting the timing of one trip on a tour may necessitate retiming other trips on the tour as well. (See further discussion below.) It is easy to change the length of the time periods used as choice alternatives used in DaySim, so it would be possible to use 15-minute periods rather than 30-minute periods, for example. There would be little benefit in doing so, however, unless the travel time information passed back from the DTA is also more detailed than 30 minutes. (See further discussion below.)

3. **The level of spatial detail used in the DTA**: The spatial detail in the TransModeler simulation is at the parcel level to match the level of spatial detail in the DaySim model output. The TransModeler simulation could be made to work with larger spatial units with some additional effort, but there is no advantage in doing so for this application.

4. **The level of temporal detail used in the DTA**: The TransModeler simulation updates each vehicle every 0.1 seconds but uses 15-minute intervals for the route choices for trips. This is a reasonable temporal granularity for regional DTA nd matches well with the level of temporal detail in the ABM.

5. **The method of passing travel time information from the DTA back to the ABM**: This is the main aspect of integrating DaySim and TransModeler that remained to be implemented for this project. The DaySim software is designed to use zone-to-zone skims for its choice models. Dynamic skims could be created in several different ways. One approach, which may be best for the base-year calibration, is to use observed travel times from HERE, INRIX, or Google data to create accurate base-year origin-destination (OD) travel time matrices. These OD skims could subsequently be updated using simulation results. Dynamic shortest path calculations in both TransCAD and TransModeler are fully multithreaded and can be done quickly on a suitable computer. It is possible to store best path sets for each OD pair and use them to accelerate the computation of skims.

   This project focused on testing ABM-DTA integration for scenario analysis rather than on developing completely new methods for integration. As a result, the project used the fastest and most straightforward method that produces reasonably accurate reflections of the simulated travel times in the DTA. The proposed method was to first create base-year OD travel time matrices based on observed data to use in the initial calibration and reasonableness tests, and then run tests to determine the best method for creating dynamic skims in TransModeler to feed back to DaySim.

6. **The time periods used to run the DTA and create travel time skims**: In Jacksonville, there is little congestion in the evening and night hours. Thus, for the purposes of this project, TransModeler was to be run for the AM peak, midday, and p.m. peak periods. If travel time skims are created for each 30-minute period, then this requires writing and reading matrices for 26 different time periods. A free-flow, uncongested travel time skim can be used to represent the remaining periods from 7:00 p.m. to 6:00 a.m. (DaySim also uses auto distance and toll cost matrices. Because those variables are much less congestion-sensitive than travel time, and less important in terms of choice utilities, it is

not worth the added memory requirements to produce auto distance and toll skims for every 30-minute time period, so fewer periods can be used for those skim matrices.)

7. **The different user classes for skim matrices, and the treatment of nonresident travel**: In addition to creating different travel time skims by time-of-day, it is also important to segment by user class. A typical segmentation uses separate skims for single-occupancy vehicles (SOVs), high-occupancy vehicles (HOVs), and one or more classes of commercial vehicles. If tolls are present in the region, separate skims by value-of-time (VOT) class can also be useful. Because the focus is on simulating scenarios related to AVs, rather than forecasting travel for all markets, the project used the following approach:
    a. For the nonresident and special generator markets (commercial vehicles, external trips, visitor trips, and airport trips), the base-year trip matrices are unchanged. To simplify and streamline the integration process, these trips are assumed to be fixed across global iterations, so the external models will not need to be rerun, and no travel time skims for these user classes need to be generated. This leaves the focus of the work on the resident travel demand that is simulated in the ABM.
    b. Rather than using VOT as a user class criterion, the project team proposed to use vehicle type and occupancy. The following classes were proposed:
        i. Conventional vehicle—Single occupant.
        ii. Conventional vehicle—Multiple occupants.
        iii. AV—Single occupant.
        iv. AV—Multiple occupants.
        v. AV—Zero occupants.

    Because the infrastructure that is available for autonomous versus conventional vehicles may be an important component of the different scenarios, the travel times may be quite different for each of these types, so it is important to provide separate travel time skims to the ABM. Producing separate skims for single-occupant and multioccupant vehicles is mainly necessary if there are HOV or high-occupancy toll lanes in the region, which is not currently the case in Jacksonville. The "zero occupant" trips are a new type of trip made possible by AVs and could also be treated differently in the networks under specific scenario assumptions. (The ABM writes out trip records that indicate the type of vehicle, number of occupants, and VOT, which can be used in the DTA to the desired level of detail. The user types above are only used for preparing skim matrices to inform the ABM.)

8. **Treating linkages between trips in a tour and possible trip retiming in the DTA:** The ABM produces a list of trips, and each trip record indicates the trip's position in a tour (home-based trip chain), as well as the trip departure, the arrival time at the destination, and the time spent at the destination before the next trip is scheduled to depart. The trip duration on the trip record is based on the travel time skims from the DTA in the prior global iteration, but the simulated travel time for that trip in the current iteration could be substantially different. If the new simulated travel time is much longer than what was used in DaySim to generate the trip, for example, then that could have a "knock-on" effect on

the rest of the tour—to shorten the activity at the destination or delay the departure time from the destination for the next trip. If the traveler could plan for the longer trip duration in advance, he or she might also choose to start the trip earlier.

Several options exist for how trip linkages can be treated in the DTA:

1. Simulate each trip in a tour independently, ignoring any "knock-on" effects.
2. Ignore any "knock-on" effects for the most part, but do not allow any activity durations to go below some minimum threshold. A trip would only be retimed if the simulated arrival time for the previous trip made the subsequent trip physically impossible. (A vehicle cannot be making two trips at the same time.)
3. Use some simple heuristics to manually retime some trips for the next DTA iteration. As previously mentioned, the DaySim time-of-day choice models use 30-minute periods, and further temporal detail is added in a mostly random way, so some amount of trip retiming could be done while remaining consistent with the ABM scheduling models. The heuristics would be specified based on the trip sequence in the tour and the activity purpose and duration at the trip destination. If a trip on the way to work takes longer in the DTA than expected in the ABM, for example, then the DTA can move the departure time earlier to try to maintain the same arrival time at work. (This adjustment would need to be done in the next DTA internal iteration, as the traffic simulation steps through time so trips cannot be moved earlier in time during the current iteration.) If the trip were leaving work, on the other hand, the departure time would be maintained, and the trip would arrive at the destination later than the trip record indicated. If there are subsequent trips in the tour on the way home, the heuristics would then indicate whether/how to retime the next trip.
4. Use a more detailed, optimization-based retiming algorithm that operates as an intermediate step between the DTA and ABM, such as is being done in the Columbus and Atlanta Travel Works projects. (The project team considers such a method to be in the development stages and beyond the scope of this project.)

In theory, if one iterates between the ABM and DTA and passes the resulting trips and congested travel times back and forth, then the two simulation models will eventually converge to a consistent outcome, even if no trip linkages or retiming are considered in the DTA. The main advantage to implementing a simple heuristic retiming approach as mentioned above could be to let the DTA "anticipate" the type of retiming that would be simulated in the next ABM iteration, and thus perhaps reduce the number of global iterations needed to reach a consistent outcome.

The project team initially proposed to use the simplest approach (first approach) in Phase 1, using no trip linkages or retiming. During the project, however, The second approach was implemented, which is an improvement on the first approach. The project team could consider implementing additional retiming heuristics (third approach) in Phase 2 if it appears promising to obtain a reasonable outcome within a smaller number of iterations. However, this is not a priority for the main purpose of the research, which is investigating AV scenarios.

2.2.2 Hardware Configuration

This project sought to run the full integrated ABM-DTA system on hardware at two separate sites and to be able to run several scenarios simultaneously. The DaySim software is multithreaded and scalable, currently simulating about 250,000 person-days per core/thread per hour. So, with an eight-core workstation with 8 GB RAM, the entire NFTPO region population can be simulated in about 1 hour. Because the DTA needs to run multiple iterations within each global iteration and produce skim matrices for the ABM, the project team expected the run time for TransModeler to be a key consideration.

For initial testing and debugging of the ABM-DTA integration, several approaches could reduce runtime and enable quicker progress toward finding any initial errors in the model setups or data. Although the project team proposed to limit the study region to the City of Jacksonville, the spatial reduction toward "subareas" was not done since it requires amending various input files for networks, land use, and populations. For initial testing, it was efficient to run the DTA for just one time period (e.g., AM peak hours) if any debugging that is relevant to the AM peak networks and configuration was also relevant to the other times of day. Thus, once the integration is completed and debugged for the AM peak period, it is straightforward to run the midday and p.m. peak hours in the DTA.

Another method that is typically used to reduce run times when testing the ABM models is to sample households from the synthetic population (e.g., simulating 1 out of every 10 households and assigning an expansion factor of 10 to each resulting trip). This procedure, however, can cause "lumpiness" of the results at the OD level, particularly as the number of possible zone pairs is already large compared to the number of simulated trips. Thus, sampling was useful for the initial testing but was no longer used once the project team reached the stage where a realistic spatial distribution of the trips was important for evaluating the results. (Also, the run time of the ABM is already short compared to the run time of the DTA.) It was critical that the integrated hardware and software environment created during this task be adaptable in later tasks. This involved using the existing version control and distribution systems for both TransModeler and DaySim to make project-specific software updates available to team members to use in testing and application.

2.2.3 Testing the Reasonableness and Sensitivity of Results

This research sought to establish the soundness of the integrated model system in terms of producing reasonable and robust results for exploratory modeling of scenarios. Thus, the plan for testing the integrated model system is *not* aimed at rigorous calibration and validation toward traffic counts and speeds. It is aimed at higher-level calibration and sensitivity testing with some more detailed sensitivity analysis for a few key points in the network.

A first level of testing is on the convergence of the system model components. Is the DTA reaching an acceptable level of convergence? Are the DTA and ABM reaching a stable outcome in terms of the changes in model predictions between global iterations? Convergence of the DTA was measured with multiple metrics. In a recent review of metrics in use (Caliper, 2015), there is no single agreed upon measure of effectiveness. The fixity of travel times and the consistency of the utilized travel times with those output is sought. This condition is also appealing for the integrated ABM-DTA model. Detailed analyses of convergence measures are an important research focus for other studies, but these analyses are beyond the scope of this project. The objective in this project is to ensure that the convergence has progressed to the point to where the results are meaningful and the sensitivity of the results is reasonable.

A second level of testing was on the outcomes of the ABM and DTA versus available data. The reasonableness of the results depends on the quality and goodness of fit of both the ABM and the DTA. If the ABM does not fit the real world then the DTA will not either. Similarly, if the DTA is not a good model of traffic and travel speeds, then the activity schedules will be distorted. The ABM for Jacksonville was originally calibrated against travel survey data from an add-on sample to the 2009 National Household Travel Survey (NHTS). Data from the ongoing 2017 regional household travel survey is not yet available; as a result, the NHTS data were used again. Automated scripts were used to compare the DaySim outputs against weighted survey data, including the following measures:

- The number of tours per day, by activity purpose and person type.
- The trip length distribution, by activity purpose and mode.
- Trip mode shares, by activity purpose and auto ownership.
- The trip time-of-day distribution, by activity purpose.
- The activity duration distribution, by activity purpose.
- The district-to-district OD pattern of tours, by purpose.

The TransModeler microsimulation is well-calibrated to ground counts and the calibration could be further improved by some recalibration of the DaySim model, specifically with respect to time-of-day of travel issues.

Because the NHTS data are not a perfect, unbiased source of data, further calibration of the ABM may be required after assigning the traffic in DTA. For example, the project team expected that further recalibration of the time-of-day scheduling models would be required to obtain a more accurate distribution of traffic across the various half-hour periods of the day. Compared to static traffic assignment for broad time periods, DTA is much more sensitive to the relative demand in each half-hour period, so the DaySim scheduling model calibration would need to be more detailed than in past applications. For the DTA, the key data for calibration are observed traffic speeds and travel times (i.e., from the same INRIX, HERE, or Google data used to generate base-year travel time skims for the ABM). Comparison against data for volumes and movements at a few key intersections helps to gauge the reasonableness of results.

The third level of testing is sensitivity testing, which is done by varying key model inputs. To the extent possible, these tests should anticipate the types of changes that will be made in the AV-related scenarios to help ensure that the model system will generate reasonable outcomes. The tests gauge the reasonableness of the response in traffic patterns and the relative sensitivity of changes in route choice, time-of-day choice, mode choice, destination choice, and tour generation. For example, one of the key changes anticipated by the project team for AVs was a lower disutility of auto in-vehicle time as the occupant can use his or her travel time more productively or enjoyably than while driving. Accordingly, tests were done to lower the disutility coefficients for auto in-vehicle time by X%. (In this simple initial test, the change could be made for all vehicles, while in the AV-related scenarios, the value of in-vehicle time will vary by vehicle type.)

Another anticipated effect of introducing AV-only facilities is that it will increase the effective capacity of existing infrastructure. The sensitivity to added capacity was tested in the initial task by adding a new lane to specific key freeway links in the region. (Again, this capacity was available to *all* vehicles in the initial test runs, while in the AV-related scenarios, it was selectively available depending on vehicle type.) It is also anticipated by the project team that the future will see less private auto ownership and more use of carsharing, ridesharing, or ride-hailing systems—the future versions of Uber, Lyft, and car2go. An interesting sensitivity tests would be to change the constants in the ABM Auto Ownership Model to reflect a future in which private auto ownership is less attractive. To simulate this more realistically, however, the Rideshare/Carshare mode needs to be added into the ABM mode choice models. This was one of the first subtasks proposed for Task 4, so the project team proposed that this sensitivity test be conducted as part of Task 4.

2.3 TransModeler DTA Enhancements

The DTA model simulates trips having individual and independent departure times and route choice behaviors and includes scenarios that represent periods of the day spanning multiple hours, including AM and p.m. peak periods and a midday (MD) period in between. Trips have individual driver and vehicle characteristics, and those characteristics can assume the user type and vehicle class properties of the models from which they are derived. For instance, medium and heavy truck trips are generated from freight trips produced by a trip-based model, and numbers of occupants and values of time are supplied by lists of tours generated by a DaySim ABM.

As part of the DTA model's development prior to this project, custom tools were developed to read matrices of external and freight trips in Cube format from trip-based elements of the regional model and lists of internal trips in DaySim format from activity-based elements of the regional model. Both the TransModeler software and the tools previously developed to link the DTA model to the regional model were enhanced to support tighter integration between the DTA model and the DaySim-Cube travel demand model:

1. The TransModeler software was extended to manage the simulation of DaySim tours as interdependent, rather than independent, sequences of trips, and the tools that transfer the trip data between the DTA model and the NFTPO regional model were modified to maintain the relationships between trips in a tour.
2. As described in the next section, model scripts were written to make it simpler to run DTAs programmatically and to automate the production of dynamic travel time skims for consumption by the DaySim model. In this framework, an integrated ABM-DTA feedback model can retain temporal fidelity and preserve disaggregate traveler decision-making between the demand and supply models.

These changes to the DTA software and model support the exploratory runs, and analysis of various scenarios estimated the potential impacts of AVs on a metropolitan scale.

2.3.1 ABM-DTA Integration: Simulating Trips on Tours

TransModeler was enhanced to simulate the interactions between trips made by the same traveler as part of a tour. Prior to the enhancement, the trips imported from the NFTPO's DaySim model were treated as independent trips, allowing for the potential that trips in a tour may depart before prior trips and activities were completed. The enhanced implementation does not permit trips to depart on schedule if prior trips were not completed with enough time remaining to satisfy a desired activity duration at the prior first trip's destination (and the second trip's origin). In the table of trips that are to be simulated, fields are now included that may reference the ID and desired activity duration of a preceding trip. When a trip refers to a preceding trip, the software will look up the prior trip's arrival time and, depending on the scheduled activity duration, approve or delay the trip's departure. This enhancement will preserve the integrity of, and consistency with, tours as interdependent trips in accordance with the regional model and provide a more behaviorally sensitive modeling framework for evaluating AV impacts. In the tools that import DaySim trips for input to the DTA, a separate table is now maintained that contains the tour ID, household number, and person number corresponding with each trip. This table can be joined to the trip table after simulation to determine whether travelers were able to meet their scheduled activities and to derive tour-specific performance measures.

2.3.2 ABM-DTA Integration: Generating Dynamic Skims

To integrate an ABM and a DTA is to leverage the DTA's ability to represent how costs (e.g., congested travel times) vary in short time intervals (e.g., between 5 and 30 minutes) over the course of a peak period or day in the decisions that travelers make in the ABM. As travel times change across periods of peak congestion, so too may the decisions travelers make. For example, travelers may change when to depart, when or whether to make discretionary trips and how they to chain them together with other trips, and whether to drive alone, carpool, or use public transportation.

When static traffic assignments are used, differences in travel costs over time, which can be pronounced even within a morning or evening peak period, are lost. This produces both an inaccurate estimation of costs and aggregation bias. These effects undercut the principal advantage of the ABM, which seeks to capture the impacts of transportation improvements and policies on the way individuals behave, because the temporal aggregation of costs make the ABM insensitive to the ways in which improvements and policies may affect the travel experience at the disaggregate, individual level.

To capture the effects of AVs and CVs and supply side strategies relating to AVs and CVs, tools were developed to produce dynamic skims for different classes of travelers and modes. The dynamic skims are generated separately for AV and non-AV trips because their experiences of the network may differ, particularly if supply side strategies involve reserving certain lanes or facilities for the exclusive access of AVs.

The skimming tools are accessed as methods, or functions, belonging to an object called the *Run Manager* in TransModeler's GIS Developer's Kit, a scripting environment enabling customization of the software. Access to the Run Manager is achieved by issuing a single command:

RunMgr = CreateObject("TSM.RunManager")

A simple script for running a DTA programmatically is shown below:

RunMgr.SetSimulationRunMode("Dynamic Traffic Assignment")

RunMgr.RunSimulation()

To produce dynamic skims once a DTA is completed, the following commands can be run:

```
self.SetSimulationRunMode("Simulation")
self.SetDynamic Skims("True")
self.MinimizeSimulationWindows()
self.RunSimulation()
runs = self.GetDynamicSkimRuns()
self.CreateDynamicSkimMatrix({
      {"Run", runs.length }, {"Variable", "Travel Time" }, {"Matrix
      Type", "Dynamic" }, {"Interval", 30 }, {"Vehicle Category",
      {"User A", "User B"}}
})
```

where “Interval” is the desired time interval size into which congested travel times are aggregated and is the interval size that the NFTPO DaySim model expects, “User A” is a designation of trips identified as AVs, and “User B” is a designation of trips, including all other trips generated by DaySim that are not AVs.

2.4 Integrated Setup

As noted, the Task 3 work builds on the existing efforts to build the DaySim ABM and TransModeler DTA models. The TransModeler DTA model development project was principally focused on developing the DTA network model since it did not include feedback of network level-of-service indicators (i.e., skims) to the demand model. However, the project did create a DaySim microsimulated trip list and auxiliary demand import routine, which was modified as part of this work.

Under Task 3, the TransModeler DTA model was updated to produce dynamic skims and the DaySim ABM was updated to make use of the new dynamic skims. TransModeler was run for the AM period only to minimize runtime and then the dynamic skims (in 30-minute time slices) were used in DaySim for the SOV and HOV travel times for the AM period and for the PM period (after being transposed). In addition, both models added an AV mode and the importing of DaySim’s microsimulated trips into TransModeler was revised to understand AV trips.

With the revised model system in place, Task 3 then compared the dynamic skims to the static skims and to expected travel times from Google Maps. The dynamic travel time skims generally match the static skim times, but are, on average, approximately 5 to 10 minutes longer. In addition, some major discrepancies exist as explained later. Finally, the DaySim demand model results with dynamic skims were compared to the previous results with the static skims. Since the ABM was calibrated to the static skims, it is important to understand how the dynamic skims differ from the static skims and the impact on the model system. DaySim trip lengths with the static skims versus the dynamic skims were similar, whereas trip travel times increased due to the longer travel times in the dynamic skims. Because of the longer auto travel times, auto mode share was reduced by over 3%. This increased the mode share for the other modes, especially walk and bike, since the dynamic skims are especially long for short-distance trips, which makes nonauto modes more attractive. Overall, the dynamic skims are generally reasonable for exploratory modeling analysis, although some issues remain to be addressed in follow-up work.

During the development of the integrated model system, several issues and challenges were discovered, addressed, or required further investigation to be reasonably resolved. Key issued included long runtimes, loading of demand into the network, chronological inconsistency of trips, generating dynamic skim values when no simulated trips exist, and integration of the additional model components (e.g., auxiliary demand, transit).

- The AM period DTA simulation and dynamic skim generation takes approximately 36 hours. Because it is practically inefficient to complete the large number of model runs required for this project with these runtimes, some simplifications were made to the demand model's understanding of travel time.
- DaySim outputs trips at the parcel level in the Northeast Regional Planning Model (NERPM) ABM. The TransModeler DTA model aggregates those trips to the traffic analysis zone (TAZ) level and then builds several zone connectors to simulate the diversity of real-world loading points. However, the analysis of the skims revealed that some of the extremely long travel time OD pairs were due not to network travel time differences but to poor connector choice. Phase 2 can address this by using aggregations of parcel-to-parcel travel times rather than centroid-to-centroid, and also by splitting large zones where that is most needed (creating less variance in the travel times aggregated for any zone pair).
- Chronological consistency of the trips generated by the DaySim demand model was also an issue. Isolated cases exist where travel and activity times in the DaySim simulation can overlap, and this consistency issue will be addressed in Phase 2.
- TransModeler generates dynamic skims in 30-minute time periods (for this study) by querying the simulated travel times for trips in the OD pair. If there are no trips in the time slice, then a shortest path travel time is generated for the dynamic skims. Initially this did not work in all instances.
- As currently implemented, the DTA only outputs dynamic travel time information for auto. It does not produce walk, bike, or transit network level-of-service indicators (i.e., skims). Running the DTA adds to, but does not replace, the network model component of the model system.

Further improvements in the integrated model setup are to finalize the connector loading improvements, review the decision to load trips at the TAZ rather than the parcel level, to split large zones, and to improve chronological consistency across tours. Beyond these relatively well-understood improvements, the project team will investigate potential runtime improvements, since this remains the major roadblock for the adoption of this integrated model system in practice.

2.4.1 Detailed Setup

This section describes the model setup for the base scenario. The basic integrated model setup is shown in Figure 1.

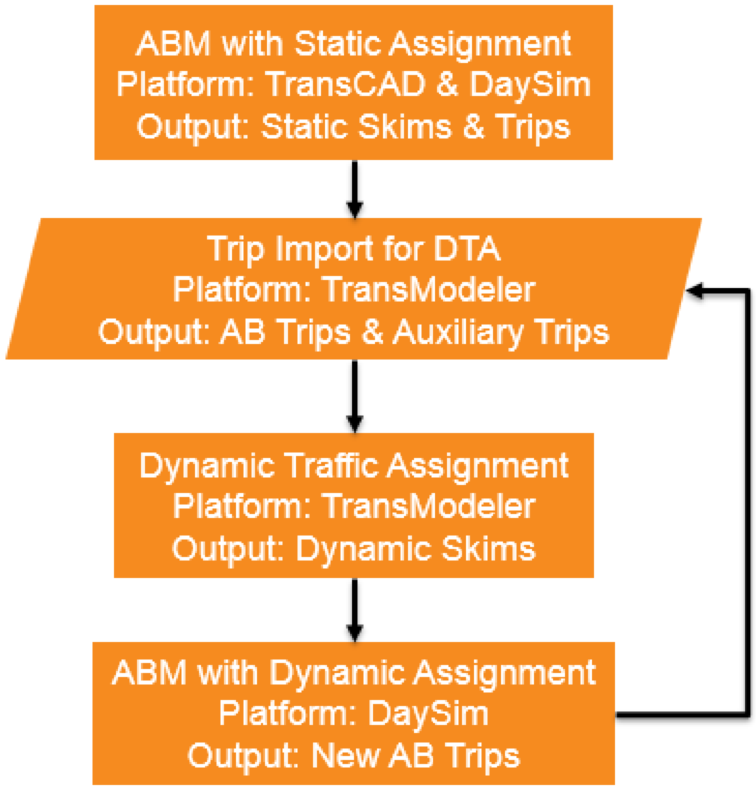


Figure 1. Basic integrated model setup.

The existing ABM with static skims and trips was run to produce the necessary inputs to seed the DTA model. Next, the DaySim trips and the auxiliary trips were imported into TransModeler. The DTA simulation was run and dynamic skims produced. These dynamic skims were then read by DaySim, and DaySim produced a new set of trips using the dynamic (and other static) skims. The new DaySim trips can be fed back to TransModeler to generate new dynamic skims, if desired.

2.4.2 Machine Requirements

The model system required a 64-bit Windows operating system, x64-based processor, a minimum of 32 GB of RAM, powerful processors, and 30 GB of hard drive space for a complete TransCAD and TransModeler run. The machine used for Task 3 is was an Intel® Xeon® CPU with 28 cores @ 2.60 GHz with 256 GB RAM and a 3 TB hard drive. A license is required to run both TransCAD and TransModeler. The file size of trips and skims generated by the model system are approximately 10 GB. Before executing the setup, the project team made sure to change the user profile environment variables %TEMP% and %TMP% folder to a drive with enough memory to avoid running out of temporary hard drive space when building the dynamic skims.

2.4.3 Scenario File and Folder Setup

An example ABM-DTA setup for this project is shown in Figure 2 in the folder FHH AM—AC.

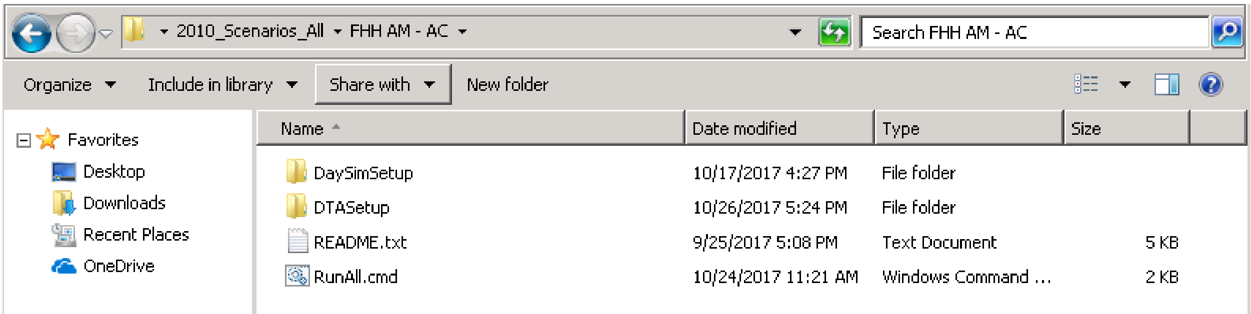


Figure 2. FHH AM—AC folder.

This folder contains the following:

- DaySimSetup folder—required files and folders to run DaySim to generate the trip files.
- DTASetup folder—required files and folders to run the DTA in TransModeler to generate the dynamic skims.
- README—A readme file that explains the steps and instructions to run the entire setup.
- RunAll.cmd—DOS batch file to run the complete integrated DaySim DTA setup.

The subfolder DaySimSetup contains several files and folders as shown in Figure 3.

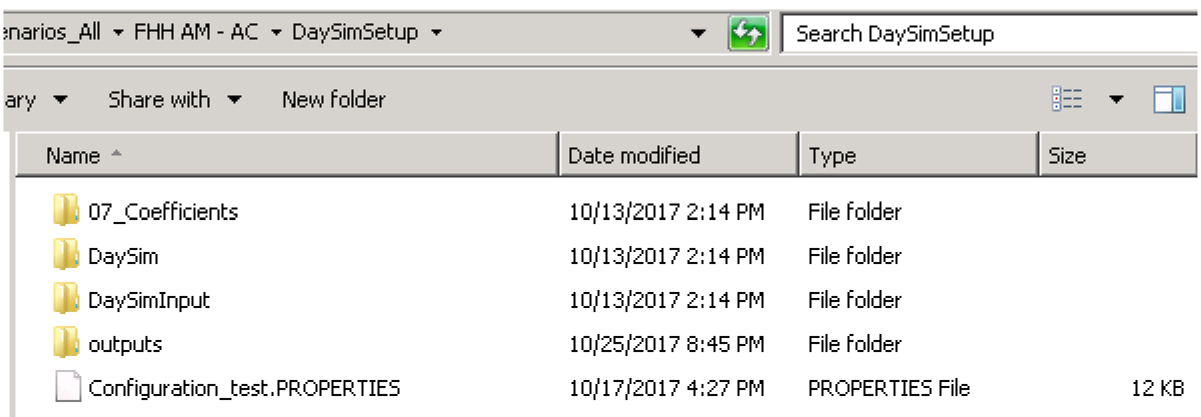


Figure 3. DaySimSetup subfolder.

The key files and folders include the following:

1. 07_Coefficients folder—submodel coefficients, including the new ones for this project.
2. DaySim folder—DaySim program files (e.g., *.exe and *.dll).
3. DaySimInput folder—inputs such as parcels, households, persons, skims, etc.:
    a. 02_parcel—the parcels used in the model, which are the origin and destination of DaySim trips.
    b. 03_household—the synthetic population households.
    c. 04_person—the synthetic population persons.

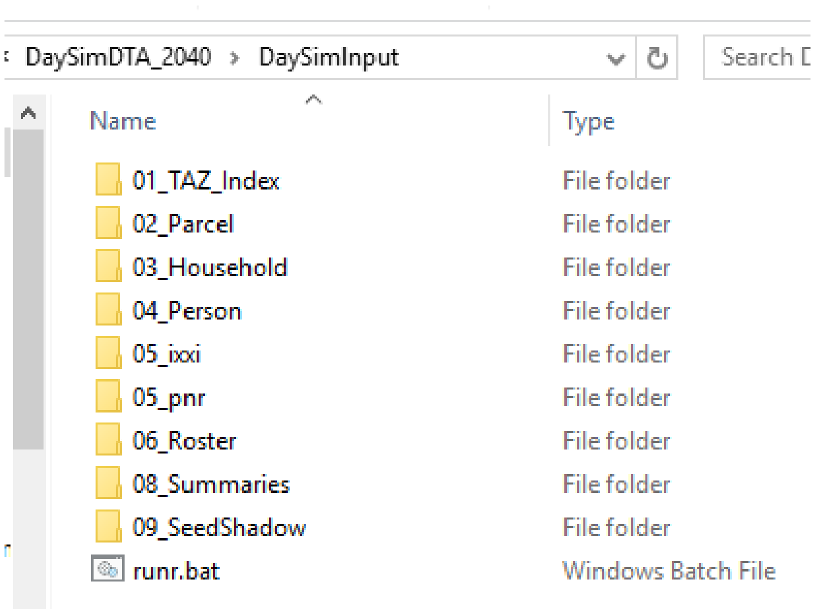


Figure 4. DaySimInput folder.

4. Outputs folder—where DaySim saves outputs. Moreover, it consists of the following:
    a. Skims input to DaySim. The skims can be in various formats, including text format (*.txt) or TransCAD format (*.mtx).
    b. DaySim roster files for understanding which skims correspond to which network level-of-service indicators in DaySim (e.g., which skim contains the AM SOV travel time). Two roster files exist:
        i. roster_av.csv—contains information about what skims file to use for respective modes, indicators, and time periods. This file was revised to connect DaySim to the dynamic skims, as described later.
        ii. roster.combinations_av.csv—combinations file, which includes information regarding the combination of mode choice and network type, such as SOV and full network or SOV and no-toll network. An AV mode was added to this file.
    c. DaySim trip file, _trip.tsv, which is imported into TransModeler as the travel demand.
    d. DaySim also writes household, person, household-day, person-day, and tour files.
5. Configuration_test.properties—The DaySim configuration file, which contains information about file paths and several factors, values, parameters, and settings such as the household sample rate and whether to expect separate skim files for AV versus non-AV. All of the DaySim assumptions varied for the EMA tests are defined and specified in the configuration file.

The subfolder DTASetup contains the following folders and files:

1. Jacksonville.smp—the planning model file that includes all the network and parameter settings and the path to the files and folders necessary to run the desired DTA scenario.
2. DTA folder—consists of all the information pertaining to the delays and turning movements necessary for the dynamic traffic assignment of the network during a time period.
3. Scenarios.RSC macro—This macro performs multiple tasks. It converts the DaySim trip list into TransModeler demand for the desired time period, runs the simulation for the user-specified time period and scenario, and generates the dynamic skims. The macro must be recompiled before running the complete setup since they contain file paths.
4. Trip Tables folder—contains the DaySim auto trip list and the non-DaySim trip list of the auxiliary demand from the existing model.
5. Parameters folder—consists of the parameters of the DTA model.
6. Simulation Database—contains the TransModeler networks of the DTA setup for each supply type.
7. TM folder—contains the "turning movements" of the network.
8. Signal Timings—signal timing files.
9. Output folder—where the dynamic skims files are saved.

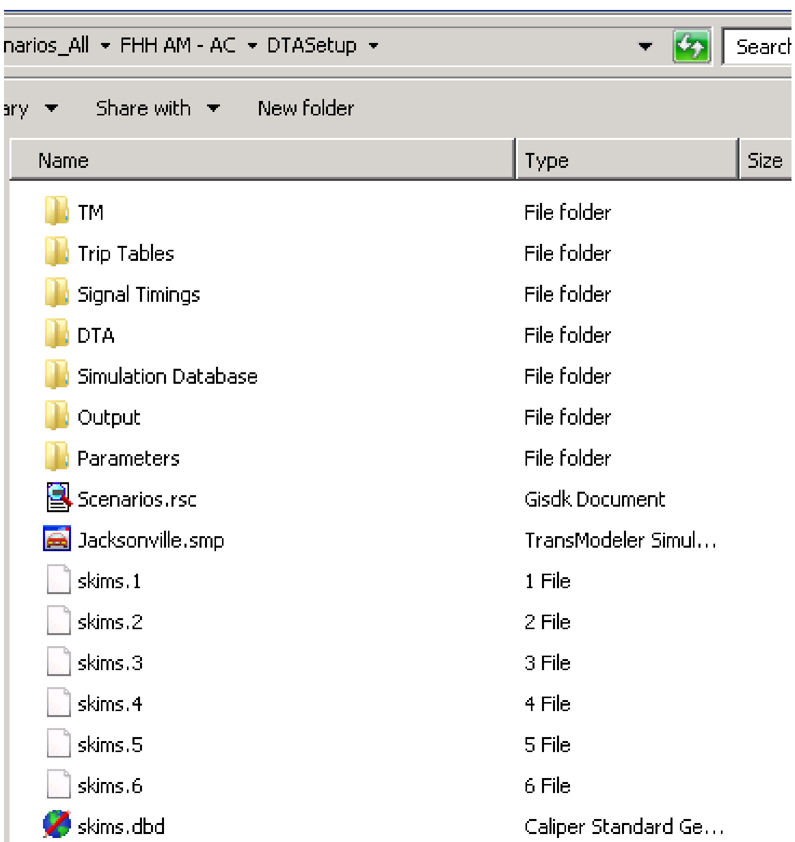


Figure 5. DTASetup subfolder.

The RunAll.cmd file is run in the Windows command prompt to run DaySim DTA integrated setup based on the instructions, scenario, and parameters set by the user. The key output from the DaySimSetup step is the ABM trip list and the key output from DTASetup step is the dynamic skims.

2.4.4 TransCAD and DaySim ABM Setup

The existing TransCAD and DaySim ABM setup was run to obtain the initial DaySim trip list, static skims, and auxiliary demand. For more information on the complete setup, see the earlier documentation. The steps to set up and run the model include the following:

1. Open the Jacksonville.model file in TransCAD (Figure 6).
2. Click on Manage Parameters on the scenario toolbar to review the scenario setup. Set the desired number of model iterations.
3. Click Run Model on the scenario toolbar once all the parameters are set and properly checked.

The key final outputs of the model step include the following as shown in Table 1. The outputs are saved to the Outputs folder. One full run of the model system takes approximately 24 hours to complete, including 4 global iterations between the DaySim and auxiliary demand models and the static network assignment and skimming.

For this project, the full static model system only needs to be run once and does not need to be rerun for each EMA AV scenario. For each of the EMA AV scenarios, the auxiliary trips (freight, externals, and special generators) are kept fixed with the skim matrices for the nonauto modes.

Table 1. Key TransCAD DaySim ABM outputs.

Model Output	Description
_trip.bin	DaySim trip list
_tour.bin	DaySim tour list
autobus.mtx	Auto to bus trip skims for both peak and off-peak hours
Knrbus.mtx	Kiss and ride trip skims for both peak and off-peak hours
Walkbus.mtx	Walk to bus trip skims for both peak and off-peak hours
walkCR.mtx	Walk to commuter rail trip skims for both peak and off-peak hours
Persontrips.mtx	Pedestrian trip skims
Skm_d1.mtx	SOV skims for all four time periods
Skm_s2.mtx	HOV2 skims for all four time periods
Skm_s3.mtx	HOV3+ skims for all four time periods
Skm_nm.mtx	Nonmotorized trip skims
Vehtrips.mtx	Auxiliary vehicle trips for all time periods

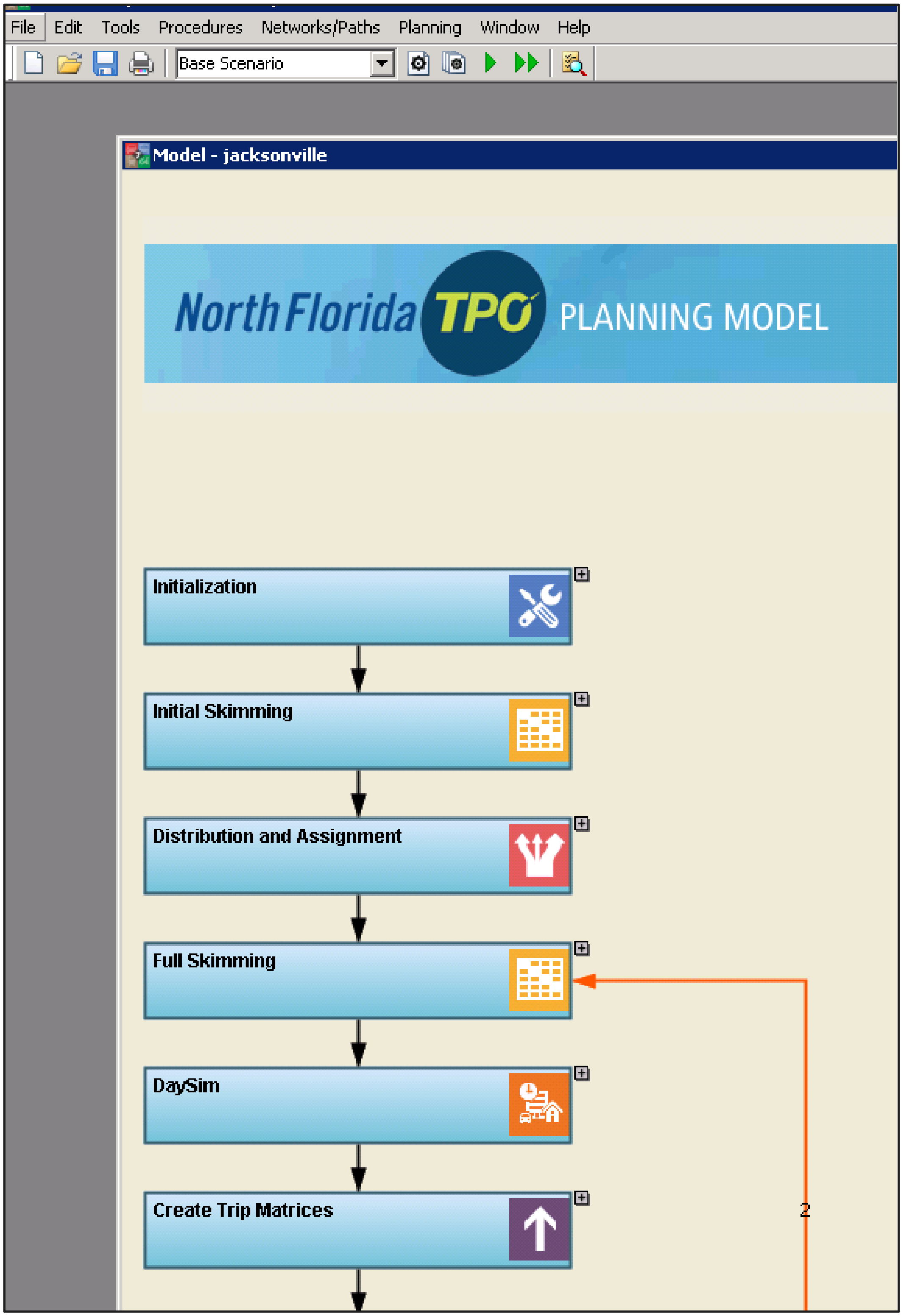


Figure 6. Key TransCAD DaySim ABM outputs folder.

2.4.5 TransModeler DTA Trip Importer

Once the DaySim ABM model is run and a new simulated trip file is generated, the next step is to convert the DaySim text format (tab separated values) trips to TransModeler trip list format for use in the DTA model. The DTA model simulates the parcel-to-parcel vehicle trips estimated by DaySim and the zone-to-zone internal-external, external-internal, external-external, and truck trips generated by the trip-based model in TransCAD. In the current implementation, the DTA model aggregates the DaySim parcel-to-parcel trips to zone-to-zone and creates several connectors to approximate parcel loading, as shown in Figure 7. (The other option is to leave the DaySim trips as parcel-to-parcel and disaggregate the auxiliary trips from zone-to-zone to parcel-to-parcel and run the DTA using parcel-to-parcel detail. That option is being considered for Phase 2.)

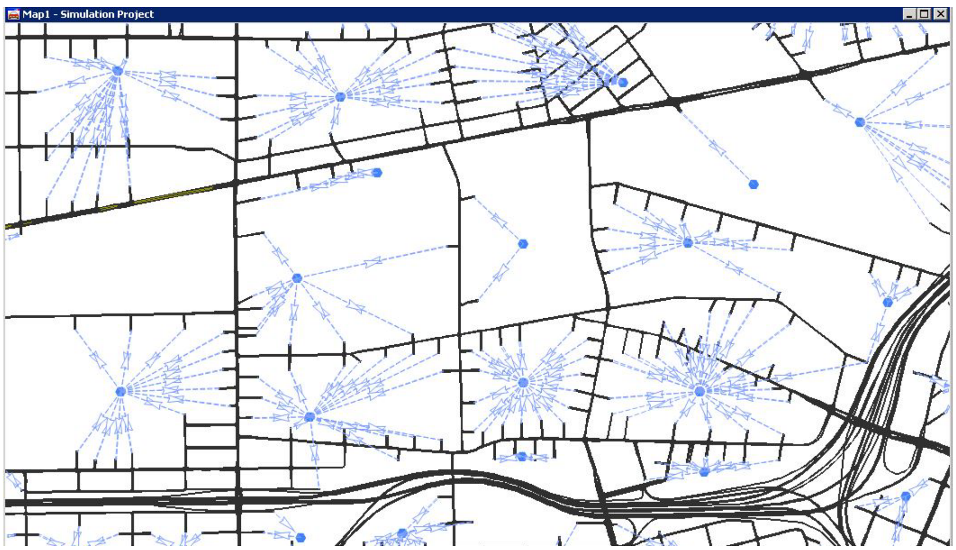


Figure 7. Connectors to approximate parcel loading.

As described in the DTA subfolder, the Scenarios.rsc file contains the TransModeler macro that imports the DaySim and auxiliary demand matrices into TransModeler. The macro will compile for a model assignment time period, such as AM, and import the appropriate trips and matrices. The macro uses the DaySim trip weights to expand the trips to a full population of trips if households were sampled in DaySim. Trip departure times are used to allocate trips into time periods and DaySim's VOTs are also used in TransModeler. As described earlier, the driver or passenger type (DORP) field identifies driver type for AV modeling:

- If 1, driver (or main rideshare passenger) in a conventional vehicle >> assign to network.
- If 2, passenger (or other rideshare passenger) in a conventional vehicle >> do not assign.
- If 3, main passenger in an autonomous vehicle >> assign to network.
- If 4, other passenger in an autonomous vehicle >> do not assign.

The AV trips are set as TransModeler User A and the non-AV trips as User B. The user can use the macro either to run the complete integrated setup or to import the DaySim trips to TransModeler.

Perform the following to run the macro for only importing trips:

1. Open TransModeler and open the DTA project via File + Open TransModeler\Jacksonville.smp.
2. Choose Tools + GIS Developer's Kit + the Geographic Information System Developer's Kit (GISDK) Toolbar. TransModeler will open the GISDK Toolbox.
3. On the GISDK Toolbar, select Compile and Scenarios.RSC.
4. On the GISDK Toolbar, select Test and type NERPM Import DaySim Trips Only.
5. Navigate to the DaySim trip list in ABM\2010\outputs\DaySim and select _trip.tsv that has been obtained from the previous ABM model run.
6. Select the desired time period and the output trip list will be saved in the folder: TransModeler\Trip Tables\DAYSIM\AM DaySim trips.bin.

The DaySim and auxiliary trips will be imported for the scenario and a trip data table in TransModeler tabular, fixed-format binary (*.BIN) format is output along with a TransCAD matrix file (*.MTX) for auxiliary demand. Once the trip tables are imported, they must be added as the input trip tables to the Jacksonville simulation project scenario. The run time for this process is about 8 minutes.

2.4.6 TransModeler DTA Setup

Once the trips have been imported into TransModeler, the DTA will run in TransModeler and the dynamic skims will be created. The DTA can be run either from a cold start, in which drivers assume free-flow conditions in the first iteration, or from a warm start, in which the solution of a previous DTA informs the route choice decisions of drivers in the first iteration. A cold-start DTA must be run for a greater number of iterations. Approximately 50 iterations are generally found to be sufficient for achieving reasonable convergence (i.e., minimization of the user equilibrium relative gap) when the DTA is run from a cold start. However, 25 iterations are generally sufficient when warm starting, which is the configuration for this study. A cold start is advised when significant changes to the network are made (e.g., to simulate the impacts of a managed lanes project). A warm start is advised when modest changes are made to the network or to the input trip data. Key inputs to this step are the trip tables and the warm start files, shown in Figure 8 through Figure 10.

AM DaySim trips Tour ID Lookup.bin	10/25/2017 9:26 PM	BIN File	90,100 KB
AM DaySim trips Tour ID Lookup.BX	10/25/2017 9:25 PM	BX File	6,818 KB
AM DaySim trips Tour ID Lookup.DCB	10/25/2017 9:25 PM	DCB File	2 KB
AM DaySim trips.bin	10/25/2017 9:26 PM	BIN File	59,031 KB
AM DaySim trips.bxl	10/25/2017 9:26 PM	BXL File	2 KB
AM DaySim trips.DCB	10/25/2017 9:26 PM	DCB File	2 KB

Figure 8. DaySim trip list.

HWYTTAB_AM_A10.MTX	10/25/2017 9:27 PM	TransCAD Matrix	41,233 KB
HWYTTAB_AM_A10_AV.MTX	10/25/2017 9:27 PM	TransCAD Matrix	41,233 KB
HWYTTAB_MD_A10.MTX	10/18/2017 4:34 PM	TransCAD Matrix	41,302 KB
HWYTTAB_PM_A10.MTX	10/18/2017 4:34 PM	TransCAD Matrix	41,089 KB

Figure 9. Auxiliary demand.

AM - Historical Travel Times.bin	10/18/2017 4:34 PM	BIN File	7,037 KB
AM - Historical Travel Times.dcb	10/18/2017 4:34 PM	DCB File	4 KB
AM - Turning Delays.bin	10/18/2017 4:34 PM	BIN File	3,121 KB
AM - Turning Delays.dcb	10/18/2017 4:34 PM	DCB File	3 KB

Figure 10. Warm start files.

The RunAll.cmd file calls a complied version of the Scenarios.RSC macro to create the dynamic skims. The following steps compile and run the model:

1. Open TransModeler and choose Tools + GIS Developer's Kit + GISDK Toolbar.
2. On the GISDK Toolbar, select Compile to user interface and select Scenarios.RSC and save to DTASetup\skims.dbd.
3. Open the DTA simulation project Jacksonville.smp.
4. Choose Project-Settings and ensure that the historical travel time and turning delay tables of a prior DTA solution are chosen on the Routing tab.
5. Open a command prompt in the FHH AM—AC setup folder and run RunAll.cmd.

```
RunAll.cmd

E:\Projects\Clients\FHWA_AV\DaySimTransModelerIntegration\2010_Scenarios_All\FHH
 AM - IC>RunAll.cmd
PROJECT: 2010 FHH AM - IC
PROJECTPATH: E:\Projects\Clients\FHWA_AV\DaySimTransModelerIntegration\2010_Scen
arios_All\FHH AM - IC\
TPATH: E:\Projects\Clients\FHWA_AV\DaySimTransModelerIntegration\2010_Scenarios_
All\FHH AM - IC\DTASetup\
MODEL ITERATION 1
Configuration file: DaySimSetup\Configuration_test.PROPERTIES
DaySim...
Initializing...
[Initializing...] Time elapsed: 00:00:02.4234271
[DaySim...] Time elapsed: 00:00:02.4252744
Running raw conversion...
[Running raw conversion...] Time elapsed: 00:00:13.2339257
[DaySim...] Time elapsed: 00:00:15.6596863
Importing Parcel domain models...
[Importing Parcel domain models...] Time elapsed: 00:00:09.5173057
Importing ParkAndRideNode domain models...
[Importing ParkAndRideNode domain models...] Time elapsed: 00:00:00.0009187
Importing Zone domain models...
[Importing Zone domain models...] Time elapsed: 00:00:00.0064254
Importing Household domain models...
[Importing Household domain models...] Time elapsed: 00:00:01.9516111
```

Figure 11. RunAll.cmd output.

6. After completion of DaySim, this will open TransModeler and start the DTA run.

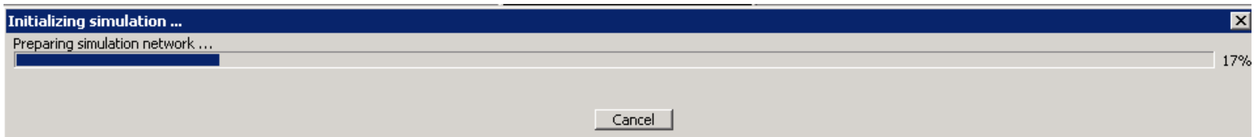


Figure 12. Start of TransModeler DTA run.

7. Once the run is complete, the dynamic skims will be saved in DTASetup\Output\Subarea OD Travel Time (User <A|B>).mtx.

The dynamic skims for user class A are for AV trips, whereas the dynamic skims for user class B are for the non-AV trips. The dynamic skims consist of multiple travel times skims for the analysis period, for example Time_0500, Time_0530, Time_0600, Time_0630, Time_0700, Time_0730, Time_0800, Time_0830. This step runs in about 72 hours for 50 iterations and 36 hours for 25 iterations.

2.4.7 TransModeler DTA DaySim ABM Setup

Once the TransModeler DTA model run is complete and the dynamic skims are ready, then the DaySim ABM model can be rerun in a second global iteration loop to generate a new trip list based on the dynamic skims. The input files for the DaySim ABM with DTA run are the same as before, except for the skim roster file (roster_dta.csv).

The roster file needs to be updated since now the DaySim setup will be run using the newly created dynamic skims files. Since the process is fully automated, the dynamic skims file is copied from the DTASetup\Output folder to DaySimSetup\outputs folder after the completion of the DaySim ABM run to ease file management. For this base scenario, in which TransModeler was run for the AM period, the roster file was revised as follows:

1. Since the new skims are for the AM period, the skims for the p.m. period are set to use the AM skims transposed by setting the “transpose” column in the roster file to TRUE.
2. Additional rows for the more precise AM and p.m. time slices (i.e., the 30-minute skims) were added for the SOV, HOV2, and HOV3 mode.
3. A new mode called AV was added to the roster file as a copy of the SOV roster entries. This allows AV to use a different set of skims.

26	distance	hov3	full-network	medium	360	539	maxzone	Text_IJ	SKM_AM_S3.TXT	4	FALSE	distance	null	null	TRUE
27	ivtime	sov	full-network	medium	540	929	maxzone	Text_IJ	SKM_MD_D1.TXT	3	FALSE	distance	null	null	TRUE
28	distance	sov	full-network	medium	540	929	maxzone	Text_IJ	SKM_MD_D1.TXT	4	FALSE	distance	null	null	TRUE
29	ivtime	hov2	full-network	medium	540	929	maxzone	Text_IJ	SKM_MD_S2.TXT	3	FALSE	distance	null	null	TRUE
30	distance	hov2	full-network	medium	540	929	maxzone	Text_IJ	SKM_MD_S2.TXT	4	FALSE	distance	null	null	TRUE
31	ivtime	hov3	full-network	medium	540	929	maxzone	Text_IJ	SKM_MD_S3.TXT	3	FALSE	distance	null	null	TRUE
32	distance	hov3	full-network	medium	540	929	maxzone	Text_IJ	SKM_MD_S3.TXT	4	FALSE	distance	null	null	TRUE
33	ivtime	sov	full-network	medium	930	959	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	1	TRUE	distance	null	null	TRUE
34	ivtime	sov	full-network	medium	960	989	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	2	TRUE	distance	null	null	TRUE
35	ivtime	sov	full-network	medium	990	1019	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	3	TRUE	distance	null	null	TRUE
36	ivtime	sov	full-network	medium	1020	1049	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	4	TRUE	distance	null	null	TRUE
37	ivtime	sov	full-network	medium	1050	1079	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	5	TRUE	distance	null	null	TRUE
38	ivtime	sov	full-network	medium	1080	1109	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	6	TRUE	distance	null	null	TRUE
39	distance	sov	full-network	medium	930	1109	maxzone	Text_IJ	SKM_PM_D1.TXT	4	FALSE	distance	null	null	TRUE
40	ivtime	hov2	full-network	medium	930	959	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	1	TRUE	distance	null	null	TRUE
41	ivtime	hov2	full-network	medium	960	989	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	2	TRUE	distance	null	null	TRUE
42	ivtime	hov2	full-network	medium	990	1019	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	3	TRUE	distance	null	null	TRUE
43	ivtime	hov2	full-network	medium	1020	1049	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	4	TRUE	distance	null	null	TRUE
44	ivtime	hov2	full-network	medium	1050	1079	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	5	TRUE	distance	null	null	TRUE
45	ivtime	hov2	full-network	medium	1080	1109	maxzone	TransCAD	Subarea OD Travel Time (User B).mtx	6	TRUE	distance	null	null	TRUE
46	distance	hov2	full-network	medium	930	1109	maxzone	Text_IJ	SKM_PM_S2.TXT	4	FALSE	distance	null	null	TRUE

Figure 13. Snippet of the updated roster file.

The combinations roster file was also changed. The updated roster combinations file contains a new mode called "av," which is replaced with other as shown in Figure 14:

#	walk	bike	sov	hov2	hov3	transit	park-and-ride	school-bus	av
full-network	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
no-tolls	FALSE	FALSE	TRUE	TRUE	TRUE	FALSE	FALSE	FALSE	FALSE
local-bus	FALSE	FALSE	FALSE	FALSE	FALSE	TRUE	FALSE	FALSE	FALSE

Figure 14. Updated roster combinations file.

To run the DaySim DTA integrated setup, run the RunAll.cmd batch file. Make sure a TransCAD license is available since it is required to read the TransModeler and TransCAD skims into DaySim. The output trip list will be saved as DaySimSetup\outputs\output_trip.bin (and is a tsv text file). This step takes approximately 50 minutes, which is the same amount of time as running DaySim with the static skims. Once the DaySim run is complete, the trip file will be copied to the DTASetup\Trip Tables\DaySim\2010 folder and the DTA run will continue to create new dynamic skims based on the new DaySim trip list. This process of running DaySim and then TransModeler can be repeated for as many global iterations as required. Each global iteration takes between 18 and 36 hours depending on the number of internal iterations used for the TransModeler assignment.

2.5 Analysis of Dynamic Skims

After TransModeler and DaySim were successfully run with dynamic skims, the next step was to compare the static travel time skims (from the previous TransCAD ABM model run) to the dynamic travel time skims (from TransModeler DTA run). The skims were compared across several measures, including basic descriptive statistics, goodness of fit, trip length distribution, and congested ratio. The travel times and distances for several OD pairs were also manually traced. A total of 10 random OD pairs were chosen to compare the static and dynamic travel time skims with the previous skims and path traces from Google Maps and the Cube-based model.

Before starting the analysis, several unused dummy zones present in the network model needed to be omitted from the analysis. As shown in Figure 15, these "fan" zones total about 690 and are placeholders for future zones.

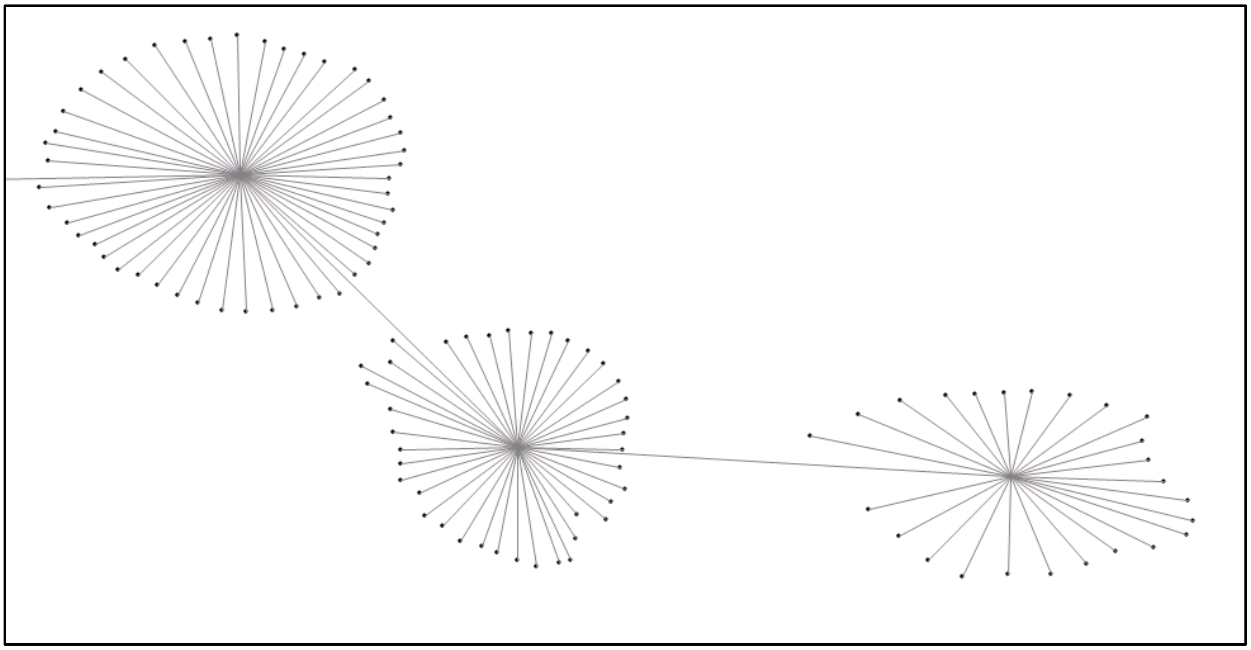


Figure 15. "Fan" dummy zones.

2.5.1 Network Skims

The skim files were first converted to open matrix format[5] and then read into R for analysis. Table 2 shows the descriptive statistics of both the static and dynamic p.m. period skims.

Table 2. Descriptive statistics of p.m. period skims.

DS\Mode	SOV (Static)	HOV2 (Static)	HOV3 (Static)	3:30–4:00 (Dynamic)	4:00–4:30 (Dynamic)	4:30–5:00 (Dynamic)	5:00–5:30 (Dynamic)	5:30–6:00 (Dynamic)	6:00–6:30 (Dynamic)
Mean	36.08	36.08	36.08	46.03	47.62	46.91	45.17	42.74	40.50
Median	31.84	31.84	31.84	41.35	43.23	42.40	40.51	37.88	35.19
Std. Dev	23.05	23.05	23.05	24.82	25.24	25.18	25.04	24.77	24.74
Minimum	0.15	0.15	0.15	0.03	0.02	0.02	0.03	0.02	0.08
Maximum	162.27	162.27	162.27	234.39	506.83	231.82	231.66	231.65	231.65

[5] GitHub osPlanning/omx

From Table 2, the statistics of all three modes (SOV, HOV2, and HOV3) appear similar. However, the mean of the dynamic skims for all time slices are about 5-10 minutes greater than the static skims. Also, the maximum dynamic skim value for the time slice 4:00 p.m. to 4:30 p.m. is about 500, which is likely an error. To better understand the differences, 10 OD pairs were chosen at random and the static and dynamic skims were compared to the Google travel times and the existing static skims. Figure 16 shows the Google Maps path and Table 4 shows the comparison of skims.

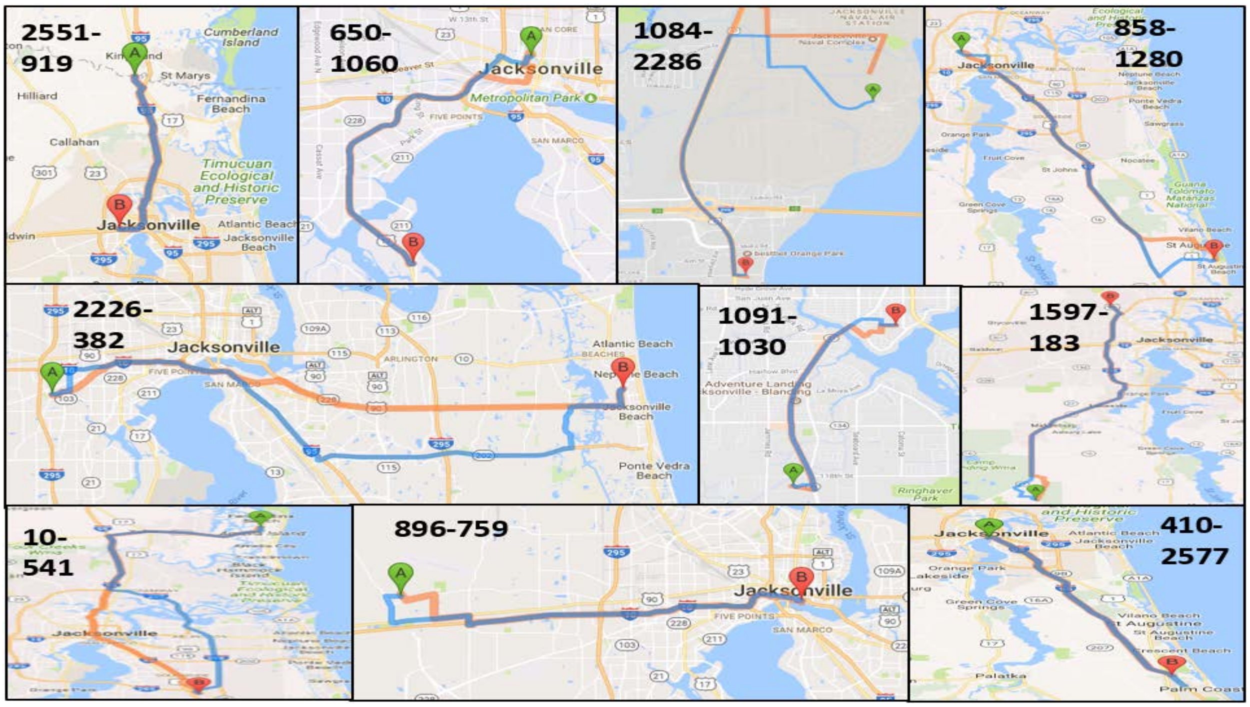


Figure 16. Google Maps path.

Source: Google Map

From Table 3, the dynamic and static travel times are generally similar except for a couple of noted cases. For example, the dynamic skim from 1084 to 2286 for 4:00 p.m. to 4:30 p.m. and the Cube skim from 3:30 p.m. to 4:30 p.m. In the case of the dynamic skim, the issue was poor connector choice. As noted earlier, the model aggregates parcels to zones for DTA, which results in many large zones with many connectors, and TransModeler fails to spread out the loading well enough across connectors, which leads to artificial congestion and long travel times. In the case of the Cube skim, the issue is that the network connectivity was incorrect and a longer indirect route was taken as a result.

Table 3. Comparison of skims with Google Maps.

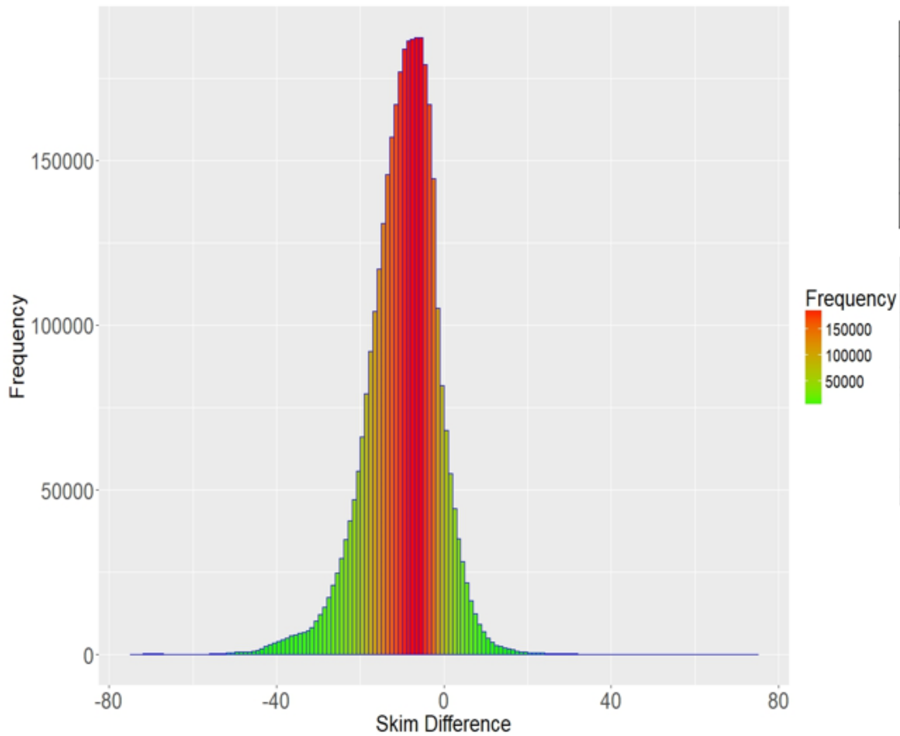
OD Pair		Static			Dynamic						Google Map (Monday Sep 18, 2017)						Cube Skims		
Origin	Dest.	SOV	HOV2	HOV3	3:30 p.m.–4:00 p.m.	4:00 p.m.–4:30 p.m.	4:30 p.m.–5:00 p.m.	5:00 p.m.–5:30 p.m.	5:30 p.m.–6:00 p.m.	6:00 p.m.–6:30 p.m.	3:30 p.m.–4:00 p.m.	4:00 p.m.–4:30 p.m.	4:30 p.m.–5:00 p.m.	5:00 p.m.–5:30 p.m.	5:30 p.m.–6:00 p.m.	6:00 p.m.–6:30 p.m.	3:30 p.m.–4:30 p.m.	4:30 p.m.–5:30 p.m.	5:30 p.m.–6:30 p.m.
2551	919	34.89	34.89	34.89	38.67	39.17	39.41	40.88	39.65	39.21	30-40	30-40	30-45	30-45	30-40	30-40	35.00	35.00	35.00
650	1060	14.18	14.18	14.18	19.47	21.69	21.84	21.15	21.00	20.42	12-22	12-24	14-26	14-30	16-30	14-22	17.22	17.22	17.22
1084	2286	8.89	8.89	8.89	35.78	**506.83**	8.13	18.68	7.60	6.56	10-18	12-22	12-26	12-20	10-20	10-16	**190.02**	190.02	190.02
858	1280	56.19	56.19	56.19	75.58	74.21	67.23	68.75	67.64	63.89	55-80	55-85	60-90	60-100	60-90	55-75	67.05	67.05	67.05
2226	382	41.21	41.21	41.21	42.28	48.54	47.24	46.93	47.11	44.12	35-60	35-65	40-75	40-80	40-75	35-55	42.43	42.43	42.43
1091	1030	8.93	8.93	8.93	22.86	24.31	23.89	20.24	15.92	12.74	10-16	10-18	10-16	10-16	10-16	10-16	7.80	7.80	7.80
1597	183	79.59	79.59	79.59	62.24	61.84	62.57	63.93	63.74	63.38	65-110	65-110	65-110	65-110	60-100	60-100	73.87	73.87	73.87
10	541	57.55	57.55	57.55	78.69	79.73	71.93	68.02	63.75	60.65	55-90	60-100	60-100	65-90	55-80	50-75	60.65	60.65	60.65
896	759	28.15	28.15	28.15	49.17	50.19	41.29	36.26	39.95	30.39	22-35	24-35	24-35	24-35	22-35	22-35	28.14	28.14	28.14
410	2577	49.78	49.78	49.78	64.95	66.94	64.95	62.54	60.42	57.63	50-65	55-70	55-75	55-80	55-80	55-70	59.64	59.64	59.64

Table 4 compares the distance skims for the same trace OD pairs and suggests that the distances across all three sources are all similar. This suggests the route is likely correct and only the times differ.

Table 4. Comparison of distance skims.

OD Pair (Origin)	OD Pair (Destination)	TransCAD	Google Map	Cube Skims
2551	919	33.50	33.59	33.32
650	1060	9.50	8.91	8.95
1084	2286	5.20	4.66	5.18
858	1280	49.20	54.34	52.17
2226	382	23.80	28.5	27.75
1091	1030	4.30	4.32	4.78
1597	183	48.70	50.06	51.71
10	541	49.20	50.32	49.62
896	759	17.30	17.56	18.16
410	2577	53.70	61.64	53.39

To further understand the differences in static and dynamic skims, a histogram of the difference was plotted. Figure 17 shows the skim difference has an even distribution with mild skewness on both sides. The green shaded region of the histogram shows the large differences. The difference was calculated as the dynamic skim subtracted from the static skim and Figure 17 was plotted for the time slice of 3:30 p.m.–4:00 p.m. Around 25% of the OD pairs have a negative skim difference of 15 minutes or above, which means that for these OD pairs, the dynamic skims were higher than the static skims. Around 9% of the OD pairs have a positive skim difference of 10 minutes or higher.



DS	Difference
Mean	-9.92
Median	-9.14
Std. Dev	8.94
Minimum	-178.95
Maximum	75.64

Negative Skim difference	
Range (minutes)	Percent
0 > x >= -1	2.53
-1 > x >= -2	3.26
-2 > x >= -5	15.19
-5 > x >= -10	28.83
-10 > x >= -15	24.06
-15 > x >= -30	23.44
-30 > x	2.69

Positive Skim difference	
Range (minutes)	Percent
1 > x >= 0	20.74
5 > x >= 1	49.62
10 > x >= 5	20.38
15 > x >= 10	5.07
x >= 15	4.18

Figure 17. Differences in static and dynamic skims.

Trips involving external zones are often longer than internal trips and the skim values also tend to be larger. To understand if the external zones have any effect on the increase in skims, the mean travel time skim values were calculated for all the OD pairs across difference movements. Table 5 shows the static and dynamic mean skims for the different movements. The mean dynamic skims are significantly higher than the mean static skims across all zone formats. Moreover, the mean skim for the external zones (IE, EI, EE) are higher than the internal zone (II), which is intuitive.

Table 5. Mean travel time skim, by zone.

Zone	SOV (Static)	HOV2 (Static)	HOV3 (Static)	3:30 p.m.–4:00 p.m. (Dynamic)	4:00 p.m.–4:30 p.m. (Dynamic)	4:30 p.m.–5:00 p.m. (Dynamic)	5:00 p.m.–5:30 p.m. (Dynamic)	5:30 p.m.–6:00 p.m. (Dynamic)	6:00 p.m.–6:30 p.m. (Dynamic)
Internal-Internal	35.03	35.03	35.03	44.81	46.39	45.66	43.88	41.42	39.16
Internal-External	69.47	69.47	69.47	88.33	90.37	90.09	88.39	85.81	83.09
External-Internal	72.19	72.19	72.19	83.42	84.93	86.07	86.38	86.02	85.75
External-External	84.16	84.16	84.16	103.07	104.39	105.44	105.61	105.41	105.08

The OD pairs with the maximum difference are shown below. Table 6 through Table 7 show the OD pair with maximum static and dynamic skim difference, respectively. Figure 18 and Figure 19 show the OD pairs in Google Maps with the maximum static and dynamic difference, respectively.

Table 6. OD pairs with maximum static skim difference.

Time period	Origin (Pair)	Destination (Pair)	Static Skim	Dynamic Skim	Difference value
3:30 p.m.–4:00 p.m.	1376	2477	98.59	22.95	75.64
4:00 p.m.–4:30 p.m.	1372	2477	88.54	13.28	75.25
4:30 p.m.–5:00 p.m.	1372	2477	88.54	13.34	75.19
5:00 p.m.–5:30 p.m.	1376	2477	98.59	22.75	75.85
5:30 p.m.–6:00 p.m.	1376	2477	98.59	22.47	76.12
6:00 p.m.–6:30 p.m.	1376	2477	98.59	21.40	77.19

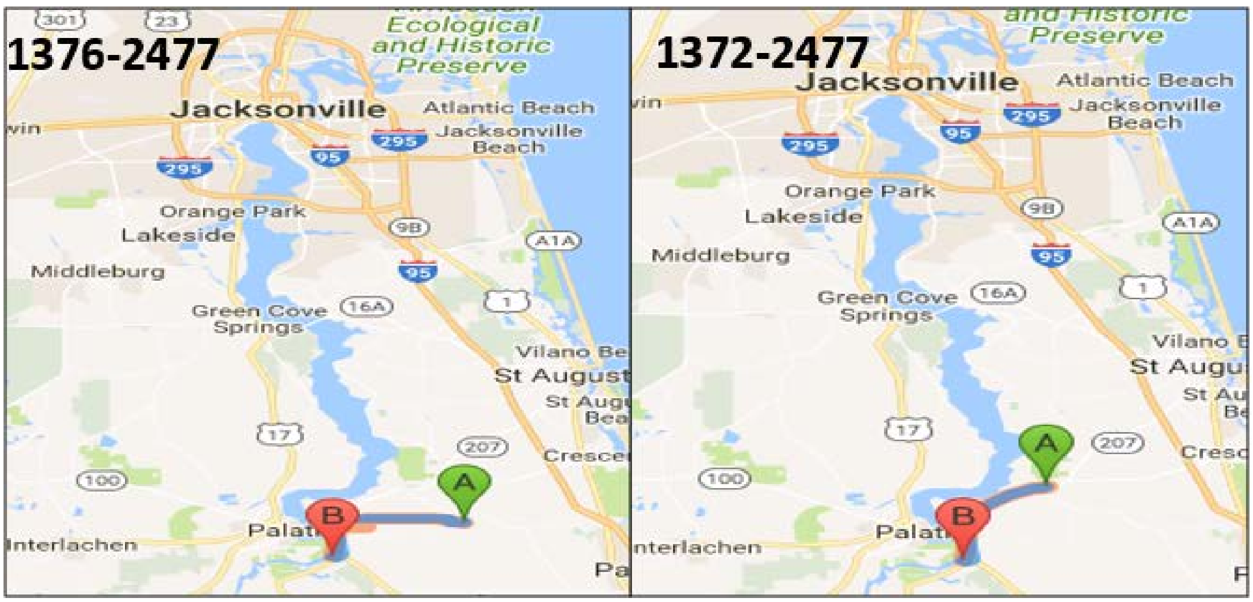


Figure 18. Google Maps trace of OD pairs with maximum static skim difference.

Source: Google Maps

The OD pairs 1376-2477 and 1372-2477 appear multiple times for static and OD pairs 1412-1452 and 1314-1289 appear twice in the dynamic skim difference. Further investigation revealed that the static skims issues were due to errors in the network, whereas the dynamic skim issues were the result of the connector loading issue described earlier.

Table 7. OD pairs with maximum dynamic skim difference.

Difference	Origin (Pair)	Destination (Pair)	Last Slice Skim (6:00–6:30 p.m.)	Difference Skim	Difference value
Last—First (3:30–4:00 p.m.)	1412	1452	77.06	10.74	66.32
Last—Second (4:00–4:30 p.m.)	1966	229	65.32	3.58	61.74
Last—Third (4:30–5:00 p.m.)	1314	1289	75.96	7.02	68.94
Last—Fourth (5:00–5:30 p.m.)	1412	1452	77.06	7.90	69.16
Last—Fifth (5:30–6:00 p.m.)	1314	1289	75.96	3.00	72.96

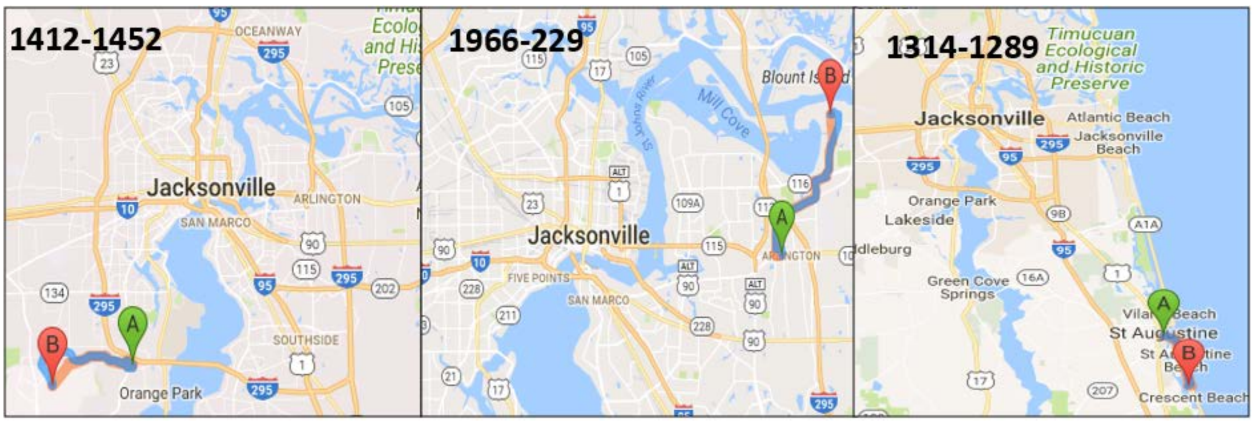


Figure 19. Google Maps trace of OD pairs with maximum dynamic skim difference.

Source: Google Maps

Next, the correlation between the static and dynamic skims was plotted. A series of scatterplots with static skims in the x-axis and the dynamic skims of various time slices in the y-axis are drawn in Figure 21 through Figure 25. The correlation significantly improves with each time period (as seen from the R-square value) with the highest correlation (R-square = 0.94) during 6:00 p.m.–6:30 p.m. This may suggest that the static skim is most representative of the later time slices, although additional research is required to verify this hypothesis. A cluster of points at the bottom of every scatterplot shows that those OD pairs have higher static skims compared to their respective dynamic skims. (Further investigation revealed that these are often for adjacent large zones that have long travel times in the static skims, whereas the actual trips across the zone borders will tend to be shorter, since people travel more often to nearby destinations. Splitting of large zones would address this issue and will be considered for Phase 2.)

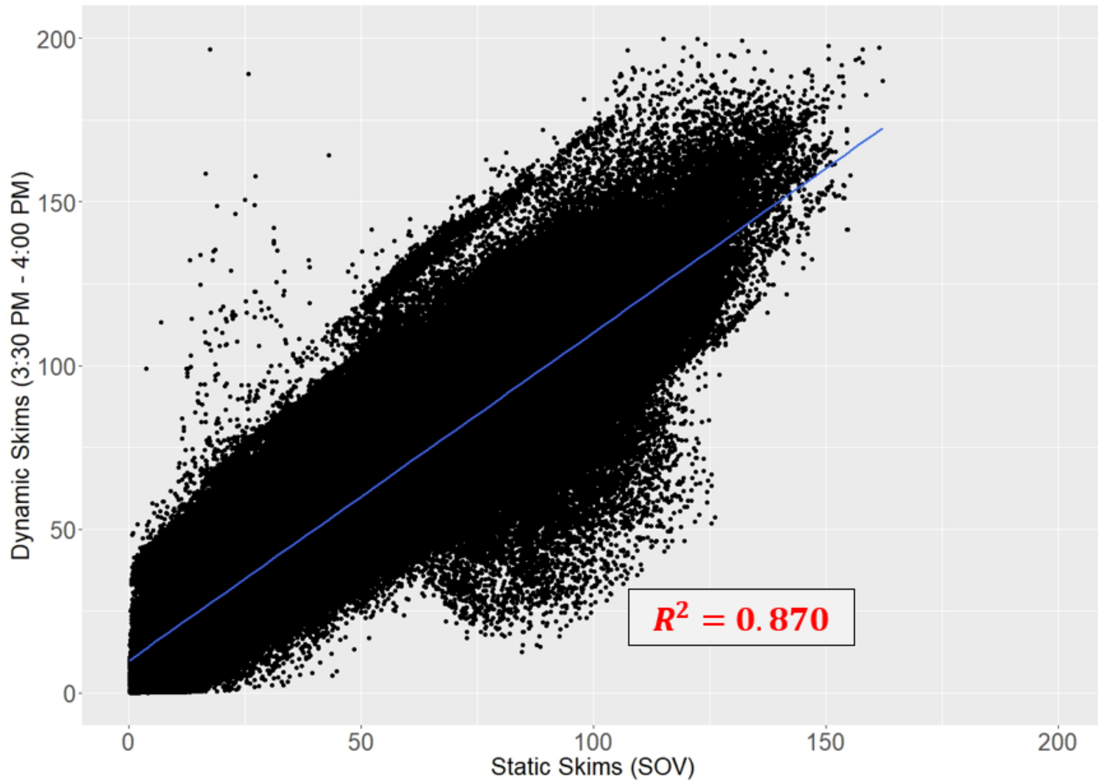


Figure 20. Scatterplot of static vs. dynamic (3:30 p.m.–4:00 p.m.).

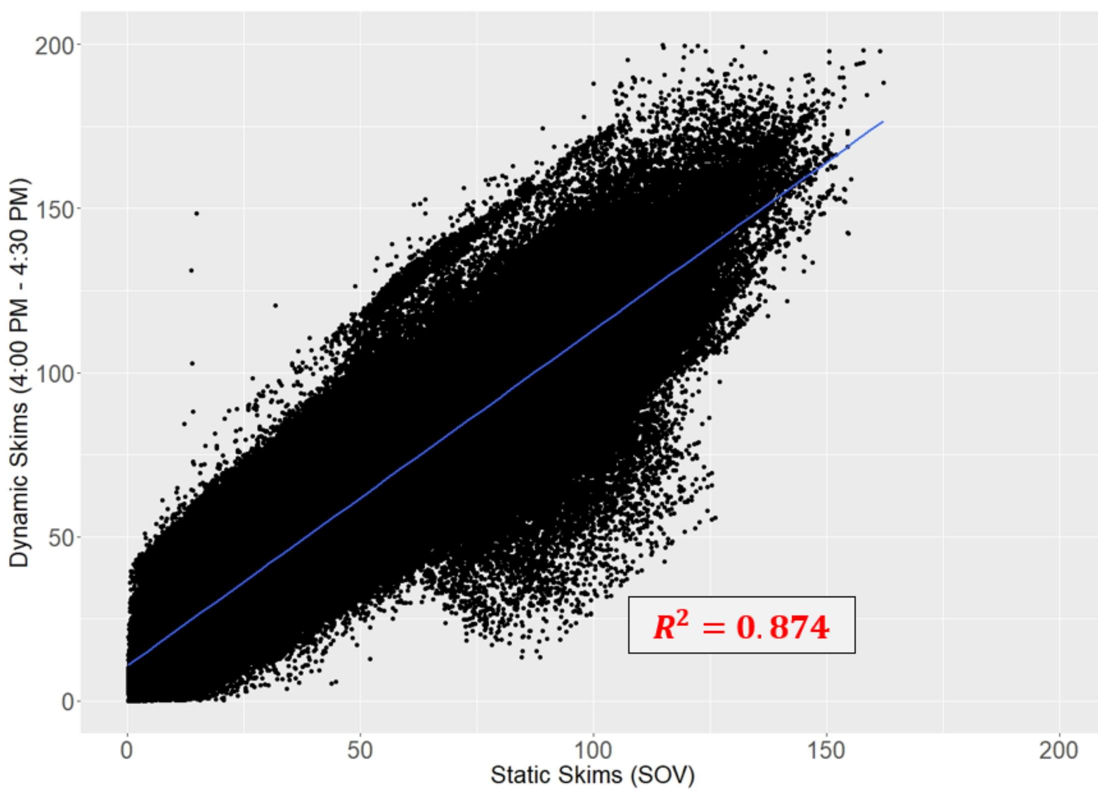


Figure 21. Scatterplot of static vs. dynamic (4:00 p.m.–4:30 p.m.).

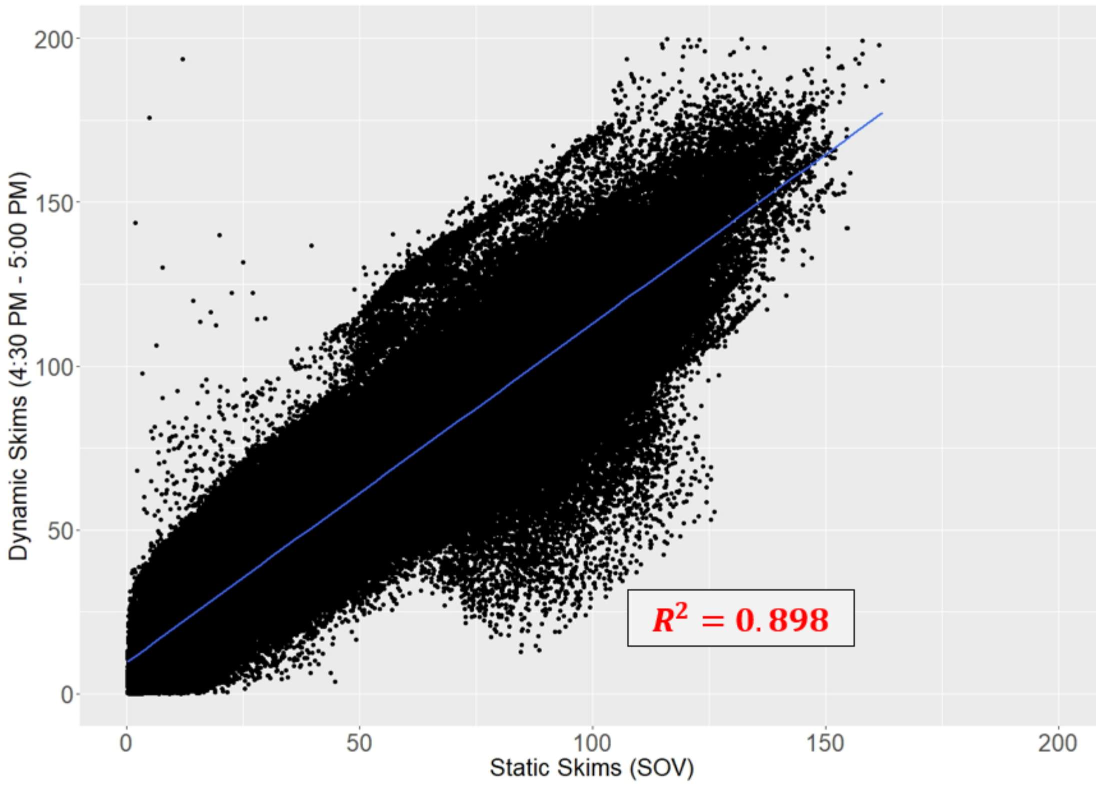


Figure 22. Scatterplot of static vs. dynamic (4:30 p.m.–5:00 p.m.).

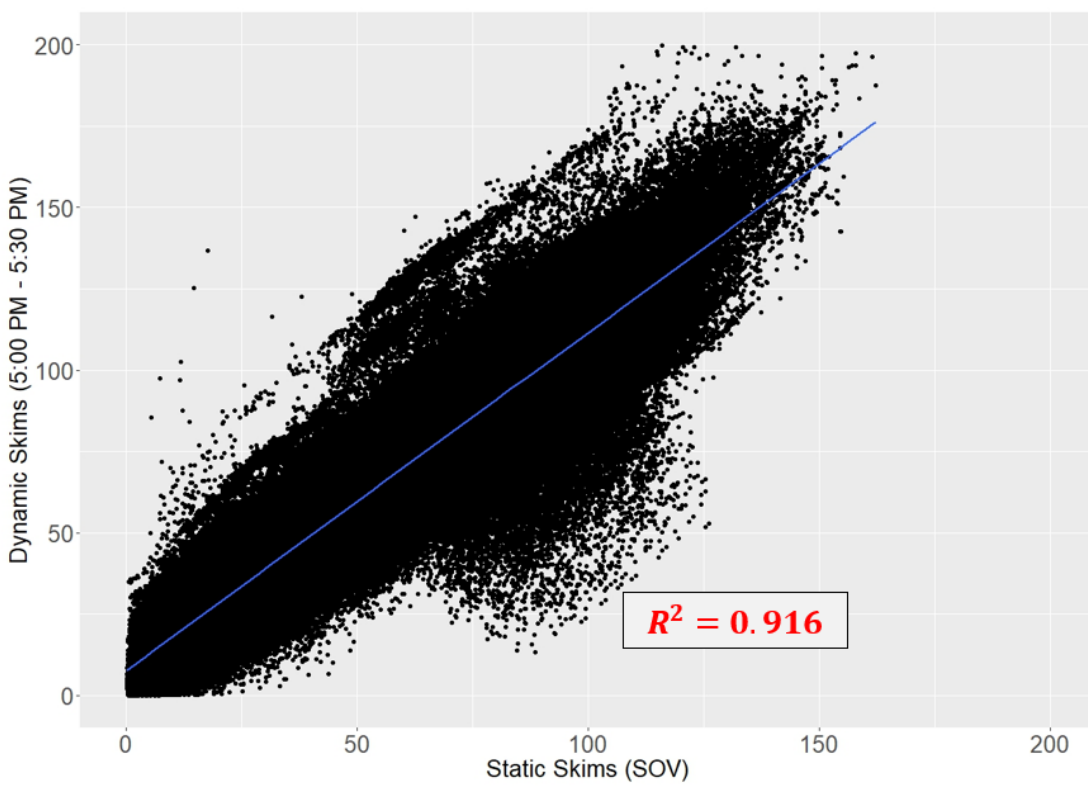


Figure 23. Scatterplot of static vs. dynamic (5:00 p.m.–5:30 p.m.).

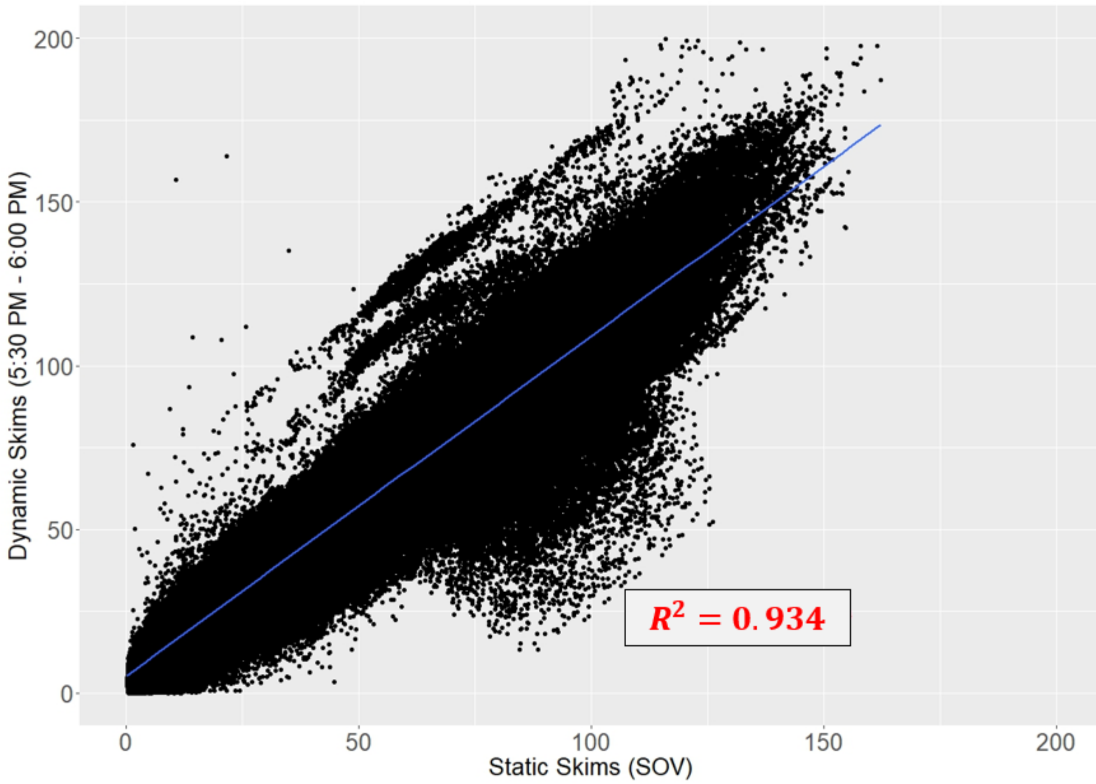


Figure 24. Scatterplot of static vs. dynamic (5:30 p.m.–6:00 p.m.).

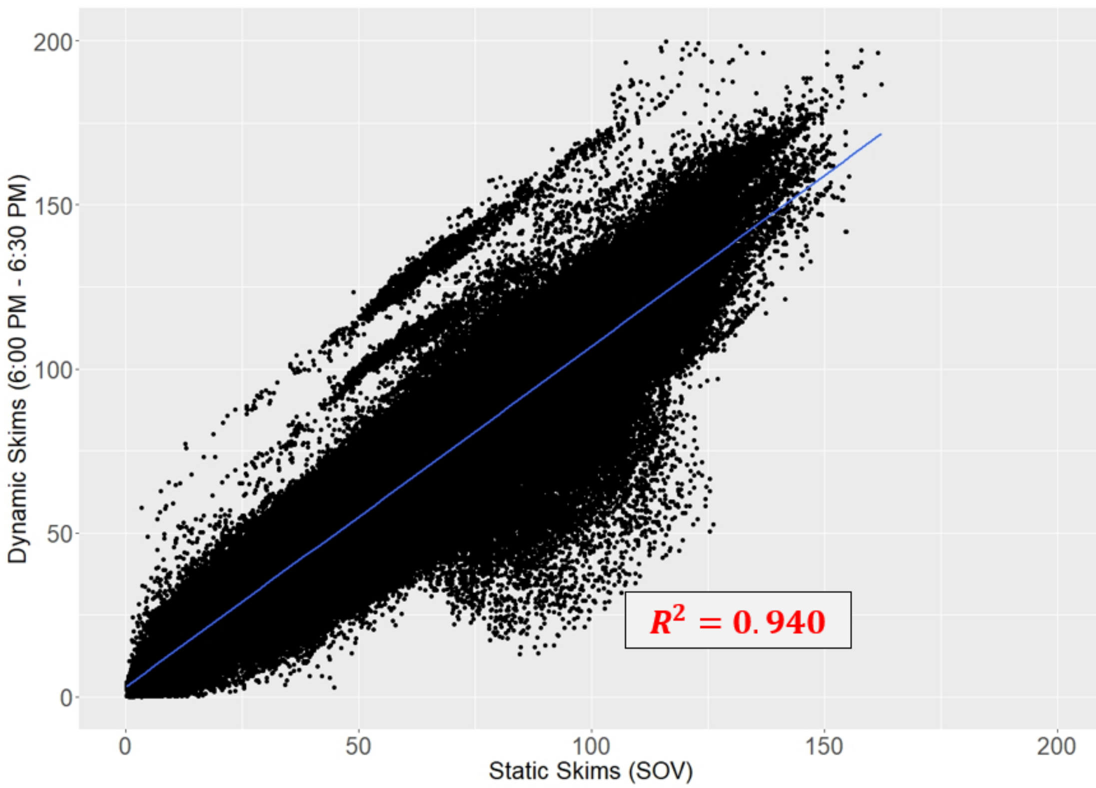


Figure 25. Scatterplot of static vs. dynamic (5:00 p.m.–6:30 p.m.).

Figure 26 shows the change of mean dynamic travel time skim over the six time periods. Initially, the dynamic skim increase from 3:30 p.m., and after 4:30 p.m. the mean reduces. The horizontal red line shows the mean static skim. Figure 26 also shows that the dynamic travel times are higher than the static travel time, which suggests the static time period skims best represent the later dynamic time-slice skims.

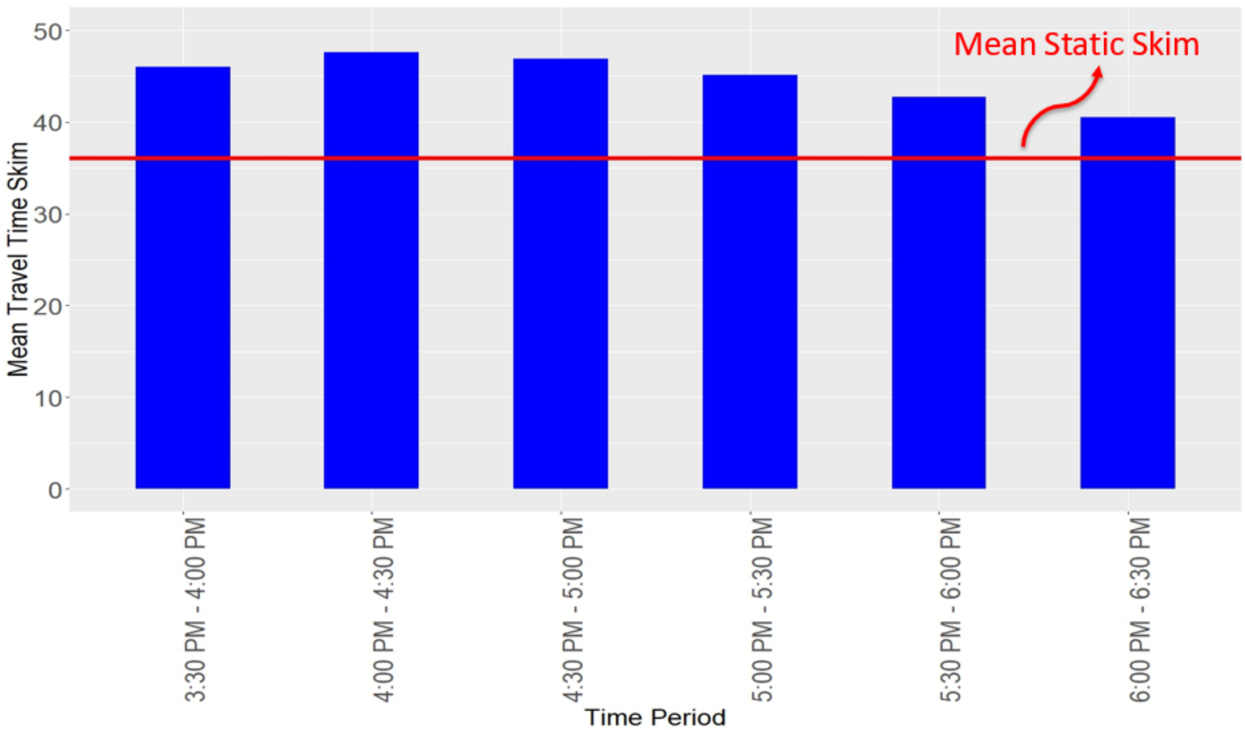


Figure 26. Change of mean dynamic skim over time.

2.5.2 Congestion Ratio

The next summary investigates whether the longer travel times in the dynamic skims are related to congestion. To test this hypothesis, the ratio of congested travel time (p.m. time period) to the free-flow travel time (night [NT] time period) was calculated. The congestion ratio was binned and then the mean travel time for each bin was calculated. Figure 27 shows the histogram of congestion ratio bins and Figure 28 shows the mean travel time for the static and dynamic skims. The second figure does not show a significant difference in the mean static versus dynamic travel times by congestion ratio bin (i.e., congestion does not appear to be the explanation for the differences).

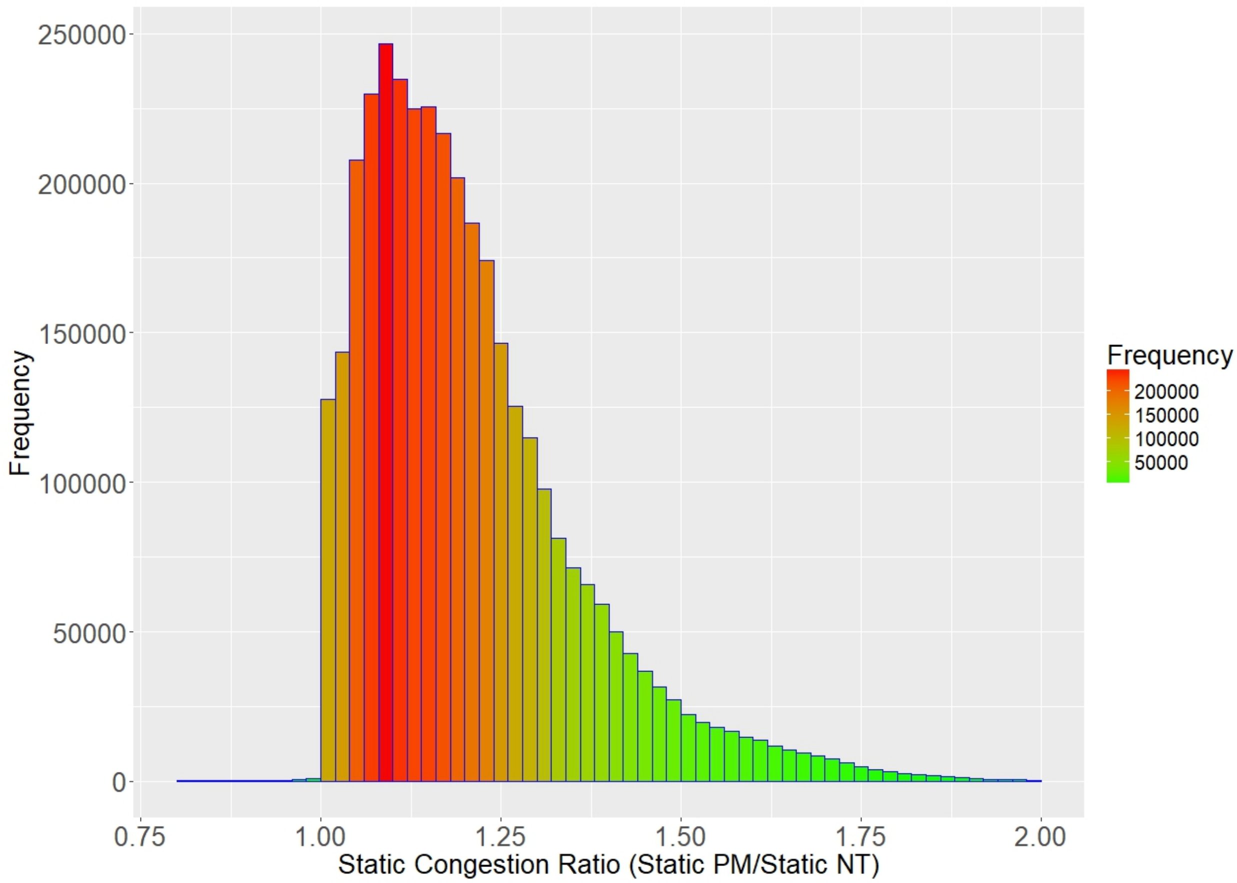


Figure 27. Histogram of static congestion ratio.

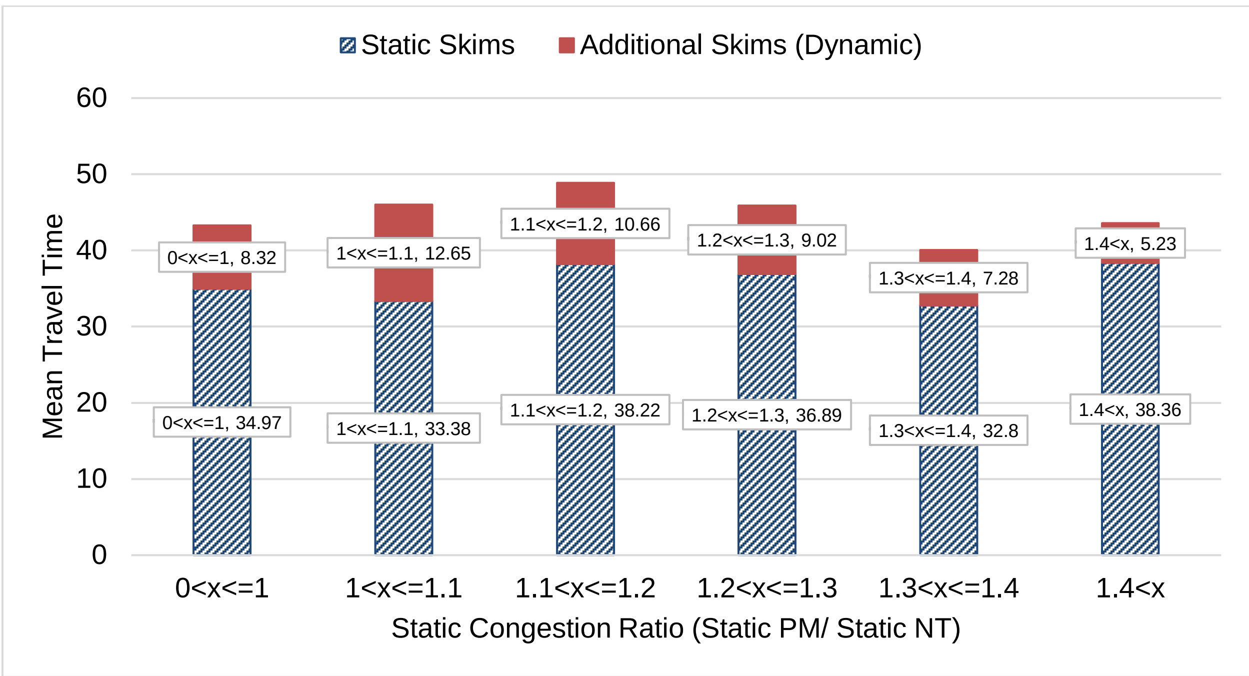


Figure 28. Change in mean travel time with static congestion ratio.

2.5.3 Trip Lengths

The next summary compares the static and dynamic travel times by trip length bin. Figure 29 summarizes trips by length and Figure 30 summarizes mean travel time by trip length bin. Figure 30 shows that both the mean static and dynamic travel times increase with an increase in trip distance. Figure 31 and Figure 32 show that the absolute and percent difference of mean static and dynamic travel times is also significantly different with trip distance bin. The percent difference between the dynamic and static skims is significantly greater for shorter trips.

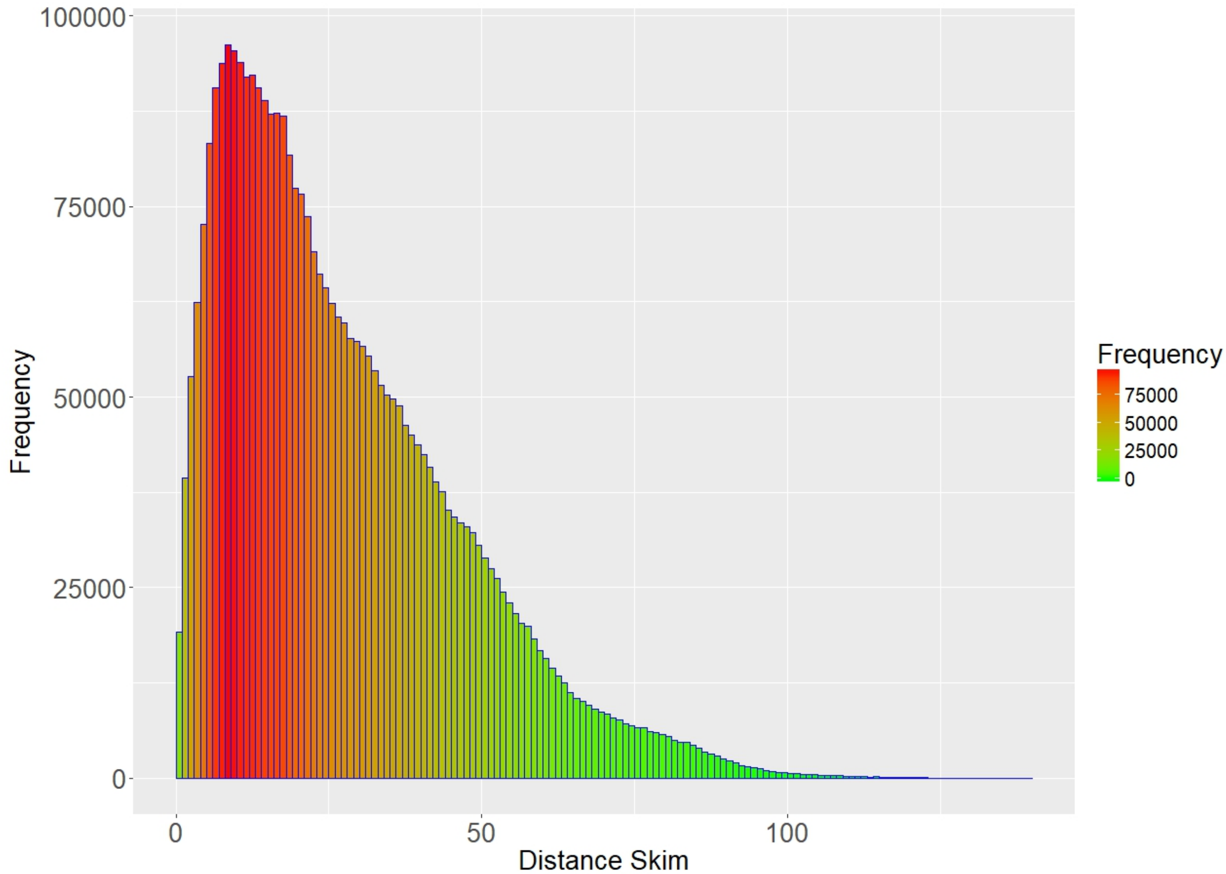


Figure 29. Histogram of distance skim.

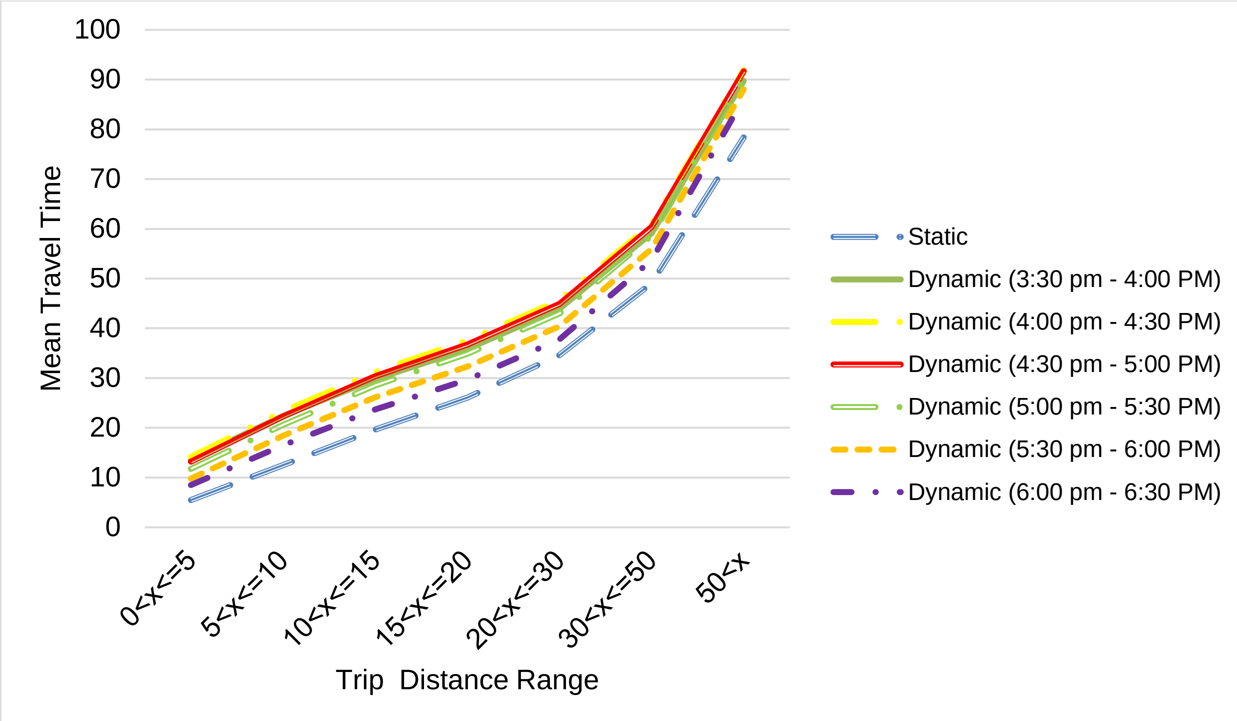


Figure 30. Change in mean travel time with trip distance.

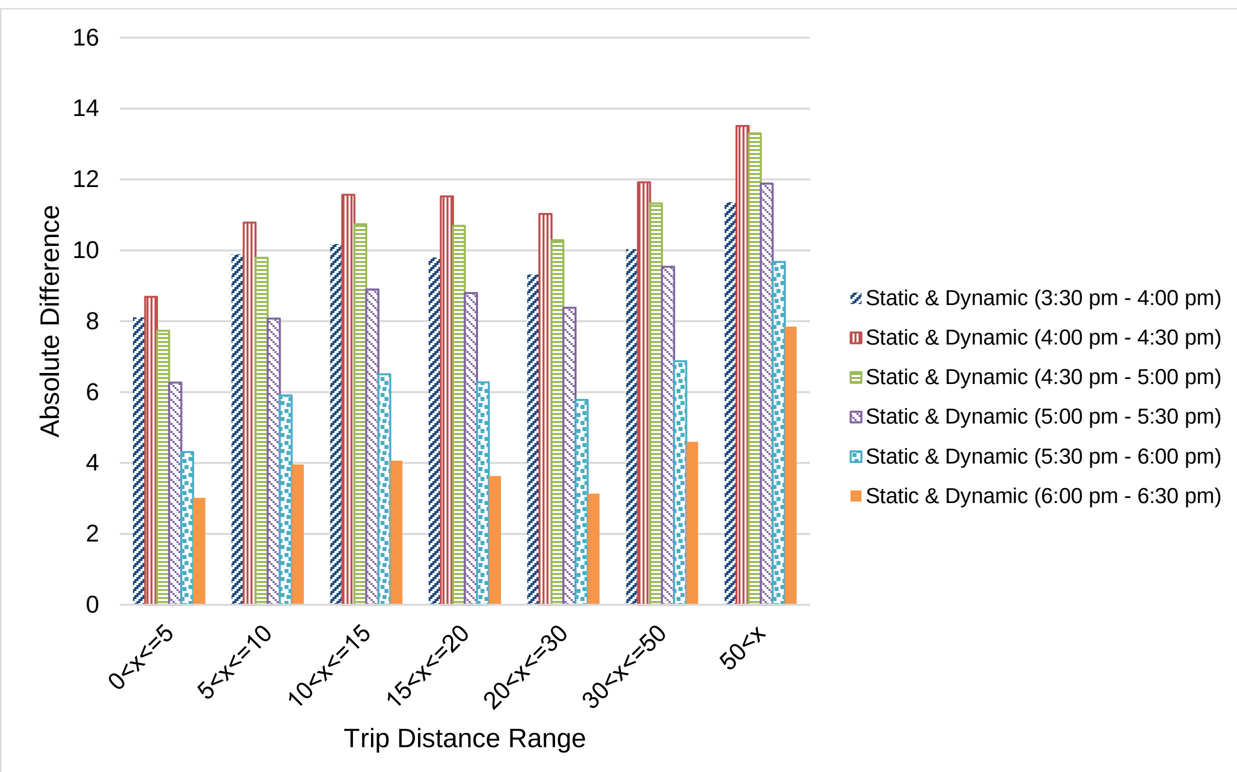


Figure 31. Absolute difference of mean travel time with trip distance.

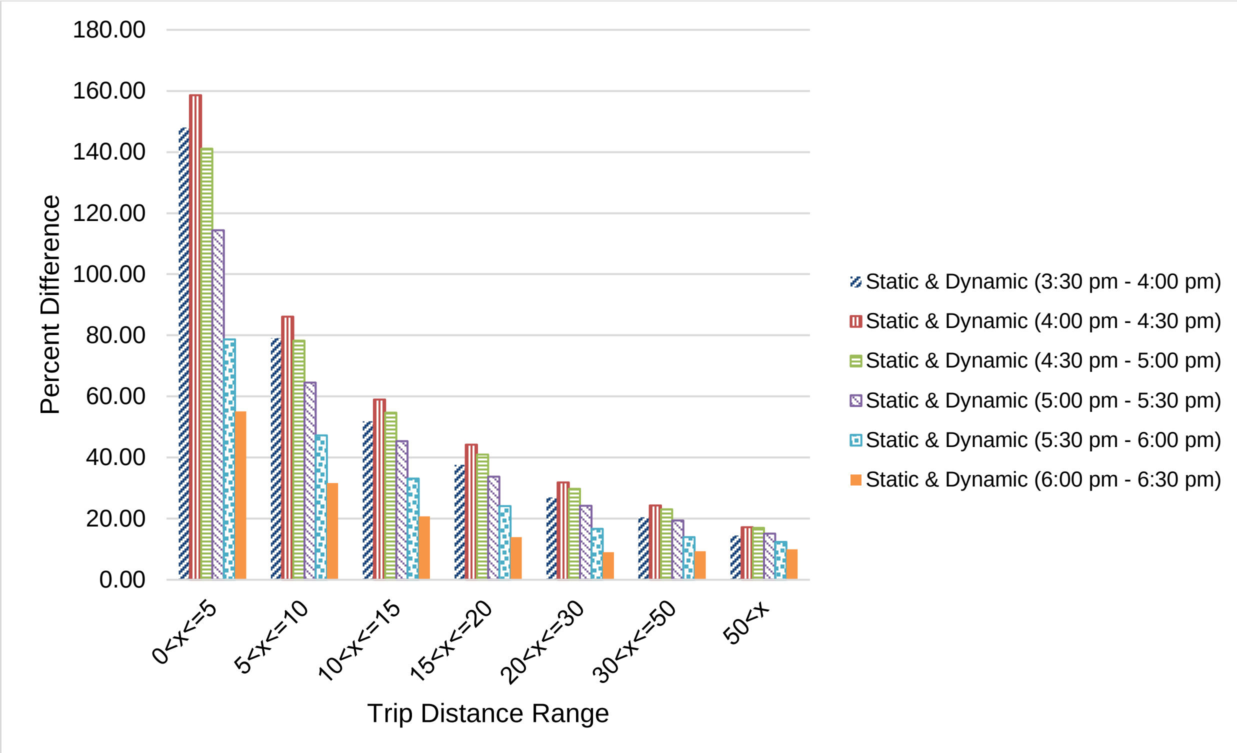


Figure 32. Percentage difference of mean travel time with trip distance.

Figure 33 shows trip length frequencies for static versus dynamic skims. Figure 33 illustrates that the dynamic skims have a higher frequency of shorter trips. The mean static trip length is 6.63 miles, whereas the mean dynamic trip length is 5.95 miles, or about 10% less. This is the result of the demand models predicting shorter trips due to the higher travel times in the dynamic skims.

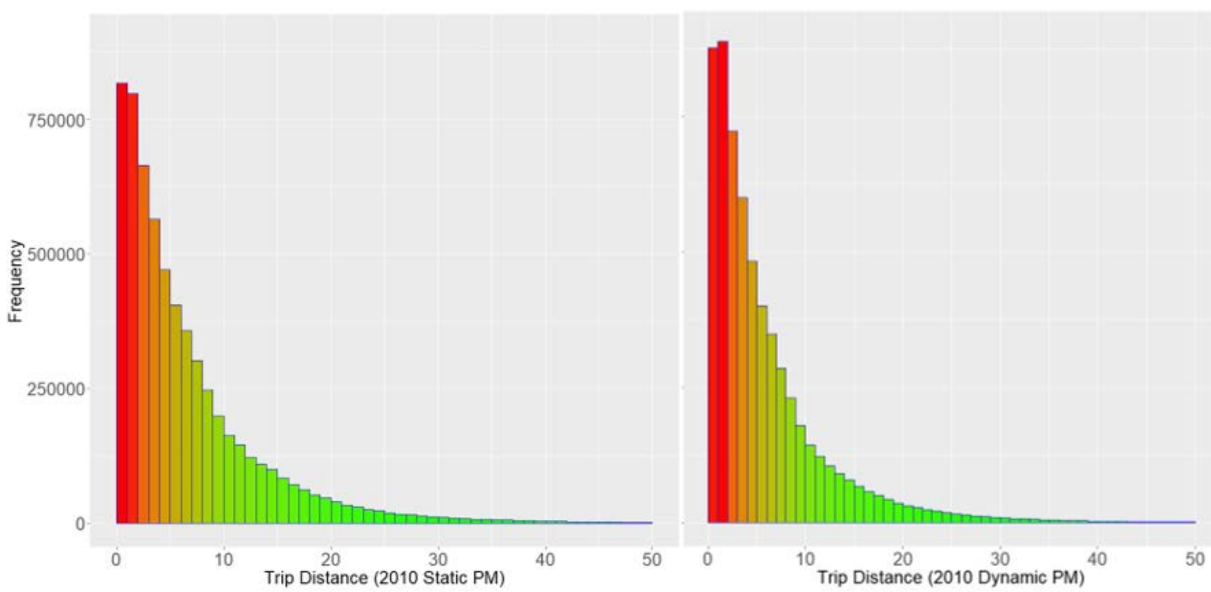


Figure 33. DaySim trip length frequency static vs. dynamic.

Figure 34 shows the frequency of trip travel time for both the static and dynamic skims. In this case, the dynamic travel times have a lower frequency of shorter trips. The mean static trip travel time is 11.08 minutes whereas the mean dynamic trip travel time is 13.07 minutes.

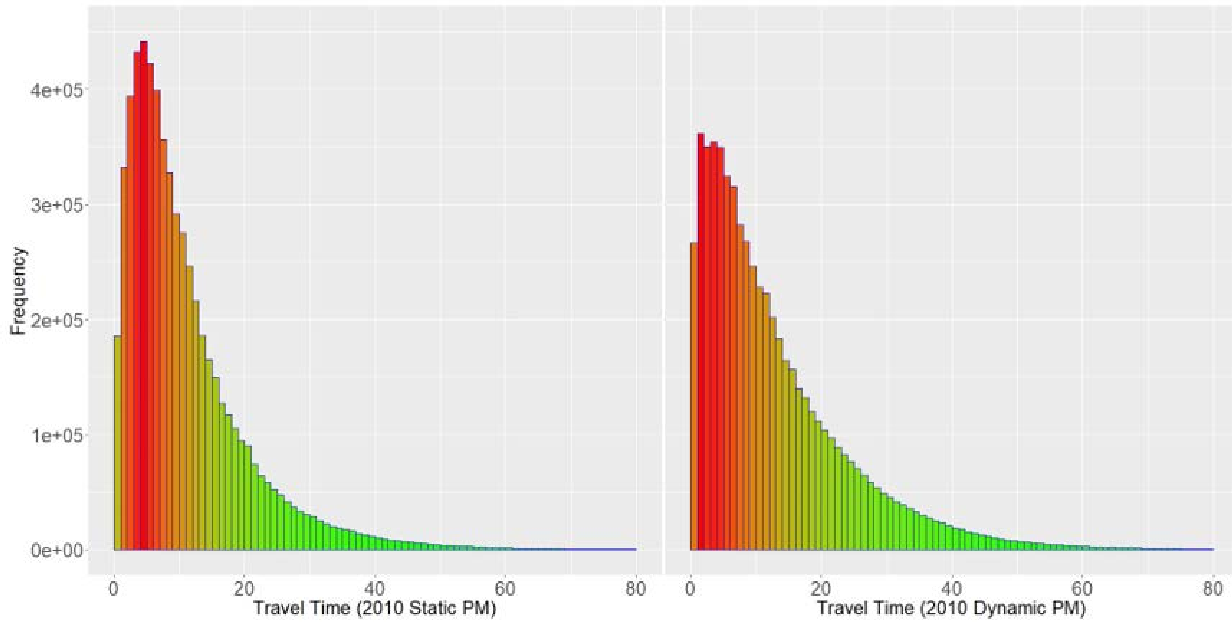


Figure 34. DaySim travel time frequency static vs. dynamic.

1.1 | Mode Shares

The final DaySim summary shows the trip mode share for both the static and dynamic skims DaySim runs. Table 8 shows the percent difference between the trip modes. The number of dynamic bike trips, transit trips, and walk trips are higher than the respective static trips, whereas the auto trips and school bus trips is greater in static than dynamic. This is because the mean dynamic auto trip travel time is higher than the mean static trip travel time. Auto, relative to the other modes, is somewhat less attractive under the dynamic skim scenario.

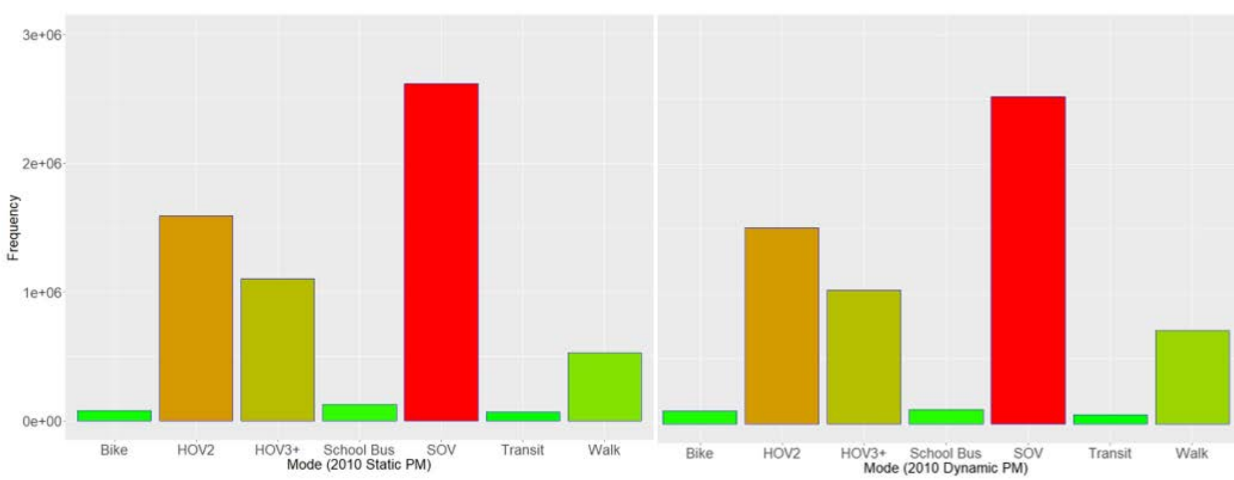


Figure 35. Trip mode share static vs. dynamic.

Table 8. Percentage difference in mode share static vs dynamic.

Mode Type	Static Frequency	Dynamic Frequency	Percent Difference
Bike	78,459	97,964	24.86
HOV2	1,591,339	1,508,563	-5.20
HOV3+	1,101,520	1,029,520	-6.54
School Bus	126,829	112,044	-11.66
SOV	**2,615,740**	**2,521,840**	**-3.59**
Transit	67,910	73,522	8.26
Walk	528,146	720,787	36.47

2.5.4 Summary

In sum, the static and dynamic travel time skims are generally consistent, although a few major differences are present. The dynamic travel times are usually longer (typically between 5 and 10 minutes longer) than the static travel times for all time periods. Moreover, there is an acceptable correlation between the static and dynamic travel time skims, which improves throughout the p.m. period. Because of the longer dynamic travel times, trip travel times are longer in DaySim, trip lengths are a bit shorter, and auto mode share decreases somewhat.

2.6 Issues, Challenges, and Next Steps

The development of the integrated model system brought to light several issues and challenges. The key issues and challenges that were either resolved or require additional investigation were long runtimes, loading of demand into the network, chronological inconsistency of trips, generating dynamic skim values when no simulated trips exist, issues with large zones, and integration of the additional model components (e.g., auxiliary demand, transit).

The P.M. period DTA simulation and dynamic skim generation takes approximately 24 hours depending on the number of iterations used. Because it was not possible to complete large numbers of model runs or global iterations during Phase 1 with these runtimes, running the overall model system to convergence has not yet been done, although the iterative running of the ABM and DTA has been set up and tested.

DaySim outputs trips at the parcel level in the NERPM ABM. The TransModeler DTA model aggregates those trips to the TAZ level and builds many zone connectors to simulate the diversity of real-world loading points. However, the analysis of the skims revealed that some of the extremely long and short travel time OD pairs were due not to network travel time differences, but to poor connector choice, sometimes in combination with large zone size. An example of the differences for a relatively short-distance OD pair is shown in Figure 36.

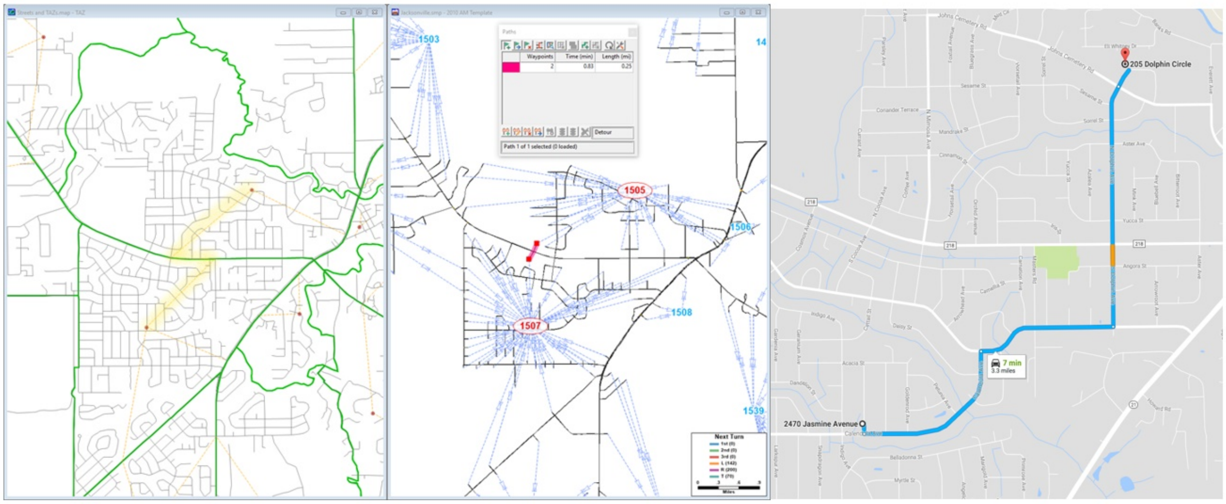


Figure 36. Path trace from 1507 to 1505 in the static and DTA models, and Google Maps.

Some zones were loading all the demand on a few connectors, which created artificial congestion (and travel times). Under Phase 1, the DTA was revised to increase the diversity of the connector loading (i.e., to better distribute the trips across connectors) by randomizing the connection choice. This helped but did not solve the problem. In Phase 2, the project team plans to revisit the idea of parcel-to-parcel loading instead of TAZ-to-TAZ loading. (The initial TransModeler implementation in Jacksonville used parcel-level loading, so that is not an issue. The challenge will be in devising reliable methods for generating zone-to-zone dynamic skims from parcel-to-parcel trips.)

A third issue addressed during the integrated model setup was chronological consistency of the trips generated by the DaySim demand model. DaySim tours are in priority order for a person-day and are not in chronological order; temporal consistency across tours is not guaranteed. As shown in Figure 37, the same person has two different tours, but one starts before the second one finishes (i.e., the end of activity at time 514 occurs after the departure time of the first trip in the following tour at time 511).

A	B	C	D	E	F	G	H	I	J	K	L
id	tour_id	hhno	pno	day	tour	otaz	dtaz	mode	deptm	arrtm	endactt
849534252	8495342	358634	1	1	2	1022	1042	4	484	487	540
849536101	8495361	358634	3	1	1	1024	992	5	435	439	497
849536151	8495361	358634	3	1	1	992	2266	5	497	502	506
849536152	8495361	358634	3	1	1	2266	1024	5	506	509	514
849536252	8495362	358634	3	1	2	2243	1024	4	511	512	812
849536201	8495362	358634	3	1	2	1024	2244	4	514	514	537
849536251	8495362	358634	3	1	2	2244	2243	3	537	538	511

Figure 37. Tour and trip chronological consistency.

A review of the trips shows that the results are typically consistent, but since this is a simulation model, and since the DTA is modeling every trip in a precise spatial and temporal manner, having a trip in a later tour start before the final trip of the previous tour ends can create problems in the DTA. For this phase of the project, chronological consistency within the tour was assumed, but different home-based tours within a person-day were simulated independently.

For this project, TransModeler generates dynamic skims in 30-minute time periods by reporting the simulated travel times for trips in the OD pair. If there are no trips in the time slice, then a shortest path travel time is generated when building the dynamic skims. Initially, this feature of the model system did not work in all instances. After a few iterations of improvements, the dynamic skims no longer contained any zero travel times. Having a set of static skims to compare the dynamic skims to facilitated this discovery.

As currently implemented, the DTA outputs dynamic travel time skims for auto. It does not produce walk, bike, or transit network level-of-service indicators (i.e., skims). Yet, the DaySim ABM requires a complete set of multimodal network level-of-service indicators and requires the existing model system (the NERPM ABM in TransCAD + DaySim). In addition, the auxiliary demand models (e.g., trucks, externals) are implemented in the existing model system, and it was beyond the scope of this effort to reimplement these models to use the new dynamic skims (plus pull in other required inputs from the existing model system). Running the DTA adds to, but does not replace, the network model component of the model system. This would increase runtime, management, and complexity if this model system were used for metropolitan planning organization planning, although this exploratory project can keep the auxiliary trips and nonauto skims constant and focus only on the changes made in the AV scenarios.

The next steps in the integrated model setup are to finalize the connector loading improvements, review the decision to load trips at the TAZ level, consider splitting some large zones, and improve chronological consistency across tours. Beyond these improvements, the project team will investigate potential runtime improvements since this remains the major roadblock for the adoption of this integrated model system in practice

3.0 Adaptation of the ABM and DTA Models to Accommodate Key Dimensions of Uncertainty in the Context of AVs

This project selected multiple dimensions of uncertainty related to CV/AV adoption and use. This selection enabled the project team to assess the practicality and effectiveness of using the integrated ABM/DTA for exploratory modeling and scenario analysis. While a full EMA application might consider many different sources of uncertainty, the prototype approach for Phase 1 included a limited set of scenario assumptions to be varied in the analysis. In this task, the project team accomplished the following:

- Adapted the ABM and DTA software to be able to reflect different levels of the specified scenario variables.
- Tested the sensitivity of the model outputs to each scenario assumption varied in isolation. This initial testing ensured that the variation in the simulation outcomes is reasonable for each input assumption considered by itself.

In the work plan for Phase 1 Task 5, the project team proposed an initial experimental design for varying the scenario input assumptions in combination. Specifying this design up front in the task informed the model adaptations in Phase 1 Task 4 and helped ensured that the work proposed for Phase 1 Task 5 was feasible.

3.1 Adaptation Design

3.1.1 Possible Adaptations to the ABM for Phase 1

Below is a list of possible adaptations to the DaySim ABM software platform to represent the demand for and use of autonomous and shared vehicles. The possible adaptations were prioritized for consideration in this phase of the project. The project team assigned priority based on judgement of how critical each adaptation/assumption is in representing the behavioral effects of AVs and how difficult it is to adapt DaySim to incorporate the particular aspect of AV use. The project team then described the selected, highest-priority adaptations in terms of the specific changes that were planned to be made to the DaySim model specification.

This task considered the following adaptations (listed in prioritized order). (Others may be added later in Phase 2):

1. The **market penetration and use of AVs** is the highest-priority assumption to be incorporated into the ABM. Simulating the effect of AVs on the network requires predicting whether each auto trip is made in a conventional vehicle or AV. So, it is necessary to adapt DaySim to “decide” which households will choose to own AVs instead of conventional vehicles. A simple adaptation could use input assumptions about assumed market penetration rates over time. Alternatively, DaySim could use an explicit auto type choice model that is sensitive to vehicle price and operating characteristics, among other factors. The method for adapting DaySim is described in more detail below.
2. The **disutility of in-vehicle time in AVs** is another assumption to be incorporated into the ABM. This can be affected by productivity, comfort, and perceived safety. As described

below, it is relatively easy to adapt DaySim to represent different VOT distributions depending on type of vehicle owned or used, and it is an assumption that directly or indirectly affects every choice model in DaySim and informs the DTA.

3. The **level of use of carsharing and ridesharing as a substitute for private vehicle use** is a third critical assumption, which can be incorporated into the ABM in a fairly straightforward manner.

4. A fourth assumption that could have a large effect on the simulation outcomes is the way in which **households may change their escorting/chauffeuring** behavior because of owning AVs. The need to give other people rides would clearly diminish with AVs, but it is not obvious what other social and safety considerations will come into play. As described below, it would be a major undertaking to simulate every detail of the behavioral mechanisms of how this might occur between household members, but it may be possible to simulate the emergent effect on generated trips by occupancy, purpose, and time-of-day using a simpler process.

5. Changes in **parking behavior at the destination for AV trips** could include use of nearby super-stacked parking, or empty vehicle trips to remote parking locations. This type of parking behavior for AVs was *not* modeled in Phase 1.

6. The **generation of "empty" vehicle trips** on the network could arise from several types of behavior. One is the case of household-owned AVs being used for driverless pick-up/drop-off trips (assumption four). Other types of empty vehicle trips can be related to autos owned by ridesharing services searching for and picking up passengers and AV trips to remote parking locations. These three types of empty vehicle trips were *not* generated explicitly by the ABM in Phase 1, although their frequency and location can be informed by the ABM trip list (e.g., the trips that use ridesharing vehicles and the trips that use privately owned AVs to go to downtown destinations).

7. Changes could occur **in telecommuting and peak-spreading behavior** resulting from AV ownership and use. The ABM tour generation and scheduling models are sensitive to the disutility of auto trips at different times of day, so the demand models will already reflect such changes to some extent without any adaptations. However, it is conceivable that new types of travel demand model initiatives could be customized to facilitate greater use of AVs or ridesharing. For example, work and school hours could be made more flexible so that the same number of AVs could serve a greater number of trips. The project team did *not* adapt DaySim to reflect such initiatives in Phase 1, though it will be considered in the work plan for Phase 2.

8. If congestion levels were reduced considerably using AVs or ridesharing systems, **new trips could be generated because of latent demand** for car travel in currently congested areas. Such latent demand could cause a "return to the peak" if peak hour speeds and reliability improve considerably. As mentioned under item 7, the ABM tour generation and scheduling models are already sensitive to the disutility of auto trips at different times of day, so the models would generate new trips or reschedule existing trips due to latent demand. (Some travelers would also choose to drive to more distant destinations.) Thus, no changes to the DaySim software were needed to reflect this mechanism, but since

major reductions in congestion have not been observed on a region-wide basis, the extent of induced travel that might be seen is uncertain. In Phase 2, the ABM could be calibrated to produce different levels of induced travel corresponding to different assumed levels of latent demand.

3.1.2 Detailed Adaptations to the ABM in Phase 1

Market Penetration of AVs

The Auto Ownership model in DaySim was adapted in the following ways:

1. In addition to predicting the number of vehicles owned by a household (0, 1, 2, 3, 4+), the model will predict the type of vehicles owned—conventional or autonomous. Two simplifying assumptions were made here in Phase 1:
    a. Only two types of vehicles are specified: "conventional," which may have some new connectivity safety features but will require a human driver, and "autonomous," which will not require a human to be present in the vehicle to operate in traffic. (Some intermediate level of autonomy could be simulated in Phase 2, if it is deemed worthwhile.)
    b. A household is simulated to either own all AVs or all conventional vehicles, but not both. Relaxing this assumption would require a model to allocate the different types of vehicles to different types of trips within a household, which would require a great deal more work. (This may be possible in Phase 2.)
2. New variables and coefficients were added to the utility functions. The probability of owning a specific number of AVs is a function of the same types of variables that affect the level of conventional car ownership in the current model, with particular focus on the following:
    a. Household income level.
    b. Age of head of household.
    c. Household size and presence of children.
    d. Household workers.
    e. The commuting time disutility by car to the usual workplaces of all workers in an AV as compared to a conventional vehicle.
3. The coefficients on the new variables were asserted and then calibrated to reflect three different levels of AV ownership:
    a. Low: For example, 10% AV penetration, on average.
    b. Medium: For example, 50% AV penetration, on average.
    c. High: For example, 90% AV penetration, on average.

Those asserted to be most likely to own AVs are those with higher incomes, lower ages, and longer commuting times. The effects of household size and presence of children on propensity to buy AVs is more speculative, although those with children may be more attracted by the improved safety of owning an AV—particularly at higher overall market penetration levels. The variable related to the commuting time disutility also makes this model sensitive to the assumption about the relative disutility of travel time in AVs versus conventional vehicles, which is discussed next.

Disutility of In-Vehicle Time in AVs

In the current version of the DaySim ABM, the travel time coefficient for auto is specified as recommended in the SHRP2 C04 project report (reference). The coefficient is a function of the following:

- Tour purpose, with a somewhat higher base coefficient for work tours than nonwork tours.
- A random component, which, if specified by the user, is drawn from log-normal distribution for each simulated tour.

VOT is also influenced by the travel cost coefficient, which is a nonlinear decreasing function of both household income and vehicle occupancy. No obvious reason exists why using an AV should affect the travel cost coefficient and only the travel time coefficient was adjusted. It was proposed that if a household owns AVs, a modified travel time disutility be used, which is specified by factoring the conventional vehicle travel time coefficient:

- Low difference: The auto time coefficient for AVs is 10% lower.
- Medium difference: The auto time coefficient for AVs is 40% lower.
- High difference: The auto time coefficient for AVs is 70% lower.

It is assumed that the average auto time disutility would never go to zero or be positive, as there is usually a more productive or enjoyable way that one could choose to spend one's time, even if one can do many things in the car that one could do elsewhere. (Current models do not assume that car passengers have much lower disutilities of time than car drivers, even though nondrivers in a conventional vehicle could conceivably do the same things as nondrivers in an AV.)

In DaySim, the auto travel time coefficient affects every choice model, either directly or indirectly through logsum variables. The models that are affected include the following:

- Tour and trip mode choice.
- Tour and trip departure time choice.
- Tour and trip destination choice.
- Tour and intermediate stop generation (full-day activity pattern choice).
- Work and school location choice.
- Auto ownership.

The relative time and cost sensitivity (VOT) are also written to the individual trip records for use in the DTA.

Level of Use of Carsharing and Ridesharing as a Substitute for Private Vehicle Use

The main change required to DaySim to reflect this assumption was to add a "paid ride share" mode to the tour- and trip-level mode choice models. (These models in turn generate mode choice logsums that are inputs to other choice models in the ABM.) In reality, several different types of paid ridesharing services could exist and vary in terms of their price structure and flexibility in duration and distance of using the vehicle, among other attributes. The project team does not know exactly what such variations will be, and it would not be feasible or useful to model the choice among many different services. As a result, the project team proposed to include a single generic paid ride share mode that captures the essential differences from using one's own vehicle.

The paid ride share mode is available to all travelers for all persons (except, perhaps, for young children going to school). The variables in the utility function are as follows:

- The auto travel time to the destination.
- The cost, which will be based on auto travel distance plus a user-specified fixed per-trip cost.
- The access and egress walk plus wait time, which will be user-specified (and presumably quite low). This could also be made a function of land-use density at the trip origin, with lower availability and longer waits in more rural areas.
- A dummy variable for zero-vehicle households.
- A dummy variable for car competition households (fewer vehicles than drivers).
- Dummy variables for specific age groups. (Currently, younger adults are more frequent users of Lyft and Uber[6], but this may be a cohort-based difference that will dissipate over time.)
- A density variable that serves as a proxy for the availability and waiting time for paid rideshare options. The number of households and jobs within walking distance is already available in DaySim as a distance-decay weighted buffer variable. The higher this buffer density measure near the trip origin, the more likely the person is to use the paid rideshare mode. (In Phase 2, this proxy will be replaced by separate skims for the paid rideshare mode, generated from a transportation network company [TNC] supply model.)
- Effects of the sharing economy on vehicle ownership. It is expected that a large shift toward using shared vehicles would be accompanied by a decrease in private vehicle ownership. The effect of the sharing economy on different levels of car ownership is specified, with the probability of owning zero vehicles due to the shared economy also a function of buffer density (the same variable discussed in the preceding paragraph).

It would be possible to have different paid ride share alternatives for different numbers of persons in the travel party. However, DaySim does not explicitly predict vehicle occupancy, so this would

[6] Pew Research Center. Shared, Collaborative and On Demand: The New Digital Economy

not add a great deal of accuracy to the model. Rather, the cost per passenger will be adjusted as a function of the tour purpose, as average auto occupancies vary by purpose.

For purposes of scenario testing, it is important that assumed shifts in auto ownership levels be behaviorally consistent with the assumed use of paid ridesharing modes. The variables related to auto ownership in the paid rideshare mode utility ensure some consistency, but calibration is also necessary. Thus, the project team proposed to calibrate the auto ownership and mode choice models to reflect three different assumed levels of demand:

1. Low: 3% of trips by paid rideshare mode. No corresponding effect on auto ownership.
2. Medium: 30% of trips by paid rideshare mode. 15% reduction in auto ownership.
3. High: 60% of trips by pair rideshare mode. 30% reduction in auto ownership.

For all levels, the project team made the simplifying assumption that paid rideshare services are the earliest adopters of autonomous vehicles, so all paid rideshare trips are made in AVs. This assumption is mainly needed in the DTA to know how to treat such trips on the network, although the DTA will pass separate skims for AVs and conventional vehicles back to the ABM, so it will affect the travel time in the paid rideshare mode utility.

Changes in Intrahousehold Ridesharing/Chauffeuring Behavior

Compared to the three adaptations to DaySim listed above, this one is much less straightforward to conceptualize and implement. Therefore, the project team had planned to conduct initial analysis of activity patterns to gauge how important these changes might be, but to defer any implementation and testing in the ABM until Phase 2. Below are three examples of ways that adoption of AVs may influence intrahousehold ridesharing trips. (This discussion does not apply to "fully joint tours," in which multiple household members wish to visit the same destination(s). In that case, those people would travel together in an AV just as they would in a conventional vehicle).

1. <u>Current behavior</u>: One household member drives another from home to their destination, drops them off, and drives back home. Or, conversely, one household member drives from home to pick up another and then drives that person back home.

   <u>Adapted behavior</u>: The AV takes the person to their destination and returns home empty. Or, conversely, the AV travels empty to pick the person up and returns home.

   <u>Net effect</u>: This change does not influence the number or OD locations of trips; it replaces a multioccupant vehicle trip with an empty vehicle trip. (It is possible that the person who avoids having to make the trip could use another vehicle to make a trip they would not make otherwise, but that would be relatively rare.)

2. <u>Current behavior</u>: Two people in a household drive from home to different destinations in their own vehicles. The timing and locations are such that they might be able to rideshare, but they prefer the flexibility of having their own vehicle available any time at their destinations.

   <u>Adapted behavior</u>: The two people use the same AV and choose a routing that meets both schedules. If needed, the vehicle will drive empty from one destination to the other. For

example, this would make it possible for the person who is dropped off first to also leave first.

Net effect: This would reduce the number of vehicles used and the vehicle miles on the network, but it could generate empty vehicle trips that offset some of that reduction.

3. Current behavior: Similar to the second item, two people in a household drive to different destinations in their own vehicles. In this case, the timing and locations are different enough that it is not feasible for them to rideshare in the same vehicle.

   Adapted behavior: The two people use the same AV but schedule their trips so that the AV can take the first person from home to their destination, return home, and then take the second person from home to *his or her* destination (and then wait there until a household member needs it somewhere). At least one of the persons is going to need to be picked up by the AV later.

   Net effect: This would decrease the number of vehicles used but *increase* the vehicle miles on the network by generating empty vehicle trips.

A possible adaptation of DaySim would be to wait until the activity patterns are generated for all household members, and then look across household adults and compare patterns to identify current behaviors matching examples 1, 2, or 3 above. For some specified percentage of those matching the examples and owning AV(s), a set of heuristic rules could be used to modify the trip patterns to reflect the corresponding "adapted behavior." In Phase 1, the project team had planned to conduct some analysis of the activity patterns to judge the percentage of households for which these types of behavioral adaptations might be relevant, but this was pushed to Phase 2, along with any eventual implementation revisions in the ABM.

Adaptations to the DTA for Phase 1

For the Phase 1 research, the following three changes were the highest priority for implementation in TransModeler:

1. **Different vehicle headway and speed characteristics for CV/AVs**: It is expected that connected, autonomous vehicles will be able to achieve higher safe traveling speeds or shorter safe following distances than conventional vehicles. This difference was implemented into the TransModeler simulation algorithms as a function of both the vehicle itself and the vehicle(s) it is following, since AV software will presumably treat other AVs differently than vehicles driven by humans.
2. **Provision of AV-only lanes**: Autonomous vehicles will be able to operate most safely and efficiently when they only interact with other autonomous vehicles. The TransModeler networks can be modified to indicate which classes of vehicles can use each link in the network, with AV-only lanes designated in a manner analogous to the way that carpool-only or non-HGV-only lanes are currently simulated. Three different levels for testing may include the following:
   - Low: No AV-only lanes.
   - Medium: Roughly 50% of freeway lanes are AV-only.

- High: 100% of freeway lanes and roughly 50% of major arterial lanes are AV-only.

In Phase 2, additional levels could be tested to give empty AVs less priority than AVs carrying passengers.

3. **Provision of "smart intersection controls"**: When most or all vehicles can communicate with intersection traffic controls, then the timing and response of traffic signals can be adjusted dynamically to optimize throughput or to minimize the maximum delay experienced (or some combination of the two). Beginning to introduce this feature into TransModeler was a challenging but important aspect of the Phase 1 work. Since it is possible to change the parameters on intersection delays in the simulation without simulating *exactly* how the dynamic optimization will work, three different levels of optimization could be:

   - Low: No dynamic optimization of signal controls.
   - Medium: Some dynamic improvement of throughput, but still using a conservative "cycling" approach to avoid long delays from any direction.
   - High: Dynamic optimization to maximize throughput.

   "Smart" intersection controls could also be programmed to give AVs priority over conventional vehicles like how buses can currently receive longer green cycles at some traffic signals. This is an additional level of optimization that may be tested in Phase 2.

   Other aspects of network simulation that were not dealt with in Phase 1 but may be interesting for Phase 2 include the following:

   - The frequency and severity of accidents for autonomous and conventional vehicles in dedicated and mixed-use lanes.
   - Narrowing of traffic lanes made possible by AV-only traffic and resulting changes in capacity.
   - The location and use of parking, including super-stacked or remote parking for self-parking vehicles.

3.2 Adaptation of the DaySim Software

The project team modified the DaySim code to reflect demand for AVs and a new "paid rideshare" / "ride-hailing" mode was added, which can also be specified to use AVs. The code was also adapted to use an adjusted disutility of in-vehicle time (VOT) for AV trips. This section documents how to use the new software capabilities and presents results from some example demand scenarios.

3.2.1 Changes in the DaySim configuration settings

Table 9 through Table 13 list new configuration switches and parameters added along with suggested parameter values.

Table 9 shows parameters used in the new "vehicle type choice" model. When the "AV_IncludeAutoTypeChoice" switch is included as True, this model is run. It determines whether each household owns conventional vehicles or AVs. (Currently, it is an "all or nothing" model—no households have a mix of conventional vehicles and AVs, as that would require also adding a vehicle allocation model.)

The other parameters determine the utility function for owning AVs, which includes an auto type constant, effects of low and high household income, effects of younger and older head of household, and an effect of total auto daily commute time for all household commuters.

Two parameters are used in the auto ownership level model that can be specified to make it more likely that households who (would) choose to own AVs also choose to own zero vehicles or one vehicle. (In a sense, the vehicle type choice can be thought of as the propensity to own AVs if one were to own autos, as it is possible for the model to predict that the household [would] own AVs and then predict that the household owns zero autos.)

Table 9. AV parameters.

Parameter	Choice
AV_IncludeAutoTypeChoice	TRUE
AV_AutoTypeConstant	0
AV_HHIncomeUnder50KCoefficient	-1.0
AV_HHIncomeOver100KCoefficient	1.0
AV_HHHeadUnder35Coefficient	0.5
AV_HHHeadOver65Coefficient	-1.0
AV_CoefficientPerHourCommuteTime	0.25
AV_Own0VehiclesCoefficientForAVHouseholds	0
AV_Own1VehicleCoefficientForAVHouseholds	1.0

For these changes to work in DaySim, **a line like the one below must be added** into the AutoOwnershipModel coefficient (F12) file:

200 AVVars T 1.00000

This is a coefficient (#200) constrained to 1 that multiplies the various parameters in the configuration file.

The next set of inputs in Table 10 are for adding the "paid rideshare" mode to the mode choice models. The switch "PaidRideShareModeIsAvailable" makes this mode available for any trips. The other parameters determine the utility of the mode, in terms of a mode-specific constant, an extra cost per mile (in addition to any toll costs), a fixed cost per trip, and effects of the person's age group.

The "PaidRideShare_DensityCoefficient" is applied to the number of jobs and households within the buffer around the trip or tour origin microzone/parcel, and it is a proxy for areas where TNC vehicles are most likely to be available. (In Phase 2 updates, the project team will allow for separate skims for this mode based on a TNC network supply model.)

If "WriteResidentialBufferDensityToOwnOrRent" is set to True, the "OwnOrRent" field in the household output file will be overwritten with the applicable density value for the household's home location to aid in analysis of the outputs.

Table 10. PaidRide parameters.

Parameter	Choice
PaidRideShareModeIsAvailable	TRUE
PaidRideShare_ModeConstant	-5
PPaidRideShare_DensityCoefficient	0.003
PaidRideShare_ExtraCostPerDistanceUnit	1
PaidRideShare_FixedCostPerRide	5
PaidRideShare_Age26to35Coefficient	0.25
PaidRideShare_Age18to25Coefficient	0.5
PaidRideShare_AgeOver65Coefficient	-0.5
WriteResidentialBufferDensityToOwnOrRent	TRUE

For these changes to work in DaySim, **a line like the one below must be added** into the coefficient (F12) files for the TripModeModel, WorkTourModeModel, SchoolTourModeModel, OtherHomeBasedTourModeModel, and WorkBasedSubtourModeModel:

90 PRS-vars T 1.000

This is a coefficient (#90) constrained to 1 that multiplies the various parameters in the configuration file.

The next set of inputs in Table 11 specifies that the paid rideshare mode will use AVs. This is done by setting "AV_PaidRideShareModeUsesAVs" to True, and that only has an effect if "PaidRideShareModeIsAvailable" is also set to True. If this mode uses AVs, the AV-specific settings for the mode-specific constant, extra cost (in dollars) per mile, and fixed cost (in dollars) per ride override the settings in Table 10. An effect from the auto type model is present, "AV_PaidRideShareAVOwnerCoefficient," which says that those in households who have a propensity to own AVs (as opposed to conventional vehicles) also have a greater propensity to use paid rideshare when it uses AVs (as opposed to conventional vehicles).

Table 11. PaidRideShare AV mode parameters.

Parameter	Choice
AV_PaidRideShareModeUsesAVs	TRUE
AV_PaidRideShare_ModeConstant	-5

Parameter	Choice
AV_PaidRideShare_DensityCoefficient	0.003
AV_PaidRideShare_ExtraCostPerDistanceUnit	1.0
AV_PaidRideShare_FixedCostPerRide	5.0
AV_PaidRideShareAVOwnerCoefficient	1

Five additional variables shown in Table 12 in the Auto Ownership Model represent the “sharing economy” under AVs (applicable when AV_PaidRideShareModeUsesAVs is set to TRUE). Making the extra paid rideshare mode available increases the overall mode choice logsum, which can have large indirect effects in other parts of the model system (e.g., induced trips), particularly in the higher-density areas when this mode is more attractive. This effect is counteracted if the “sharing economy” also sees a decrease in private auto ownership. This is included in the Auto Ownership Model via the settings in Table 12. The density-based coefficient makes owning zero vehicles more feasible in higher-density areas where the availability of the TNC mode is higher. The others are additive constants for owning 1, 2, 3, or 4+ vehicles relative to owning zero vehicles, so setting these to negative numbers increases the probability of owning zero vehicles.

Table 12. AV ownership parameters.

Parameter	Choice
AV_SharingEconomy_DensityCoefficientForOwning0Vehicles	0.001
AV_SharingEconomy_ConstantForOwning1Vehicle	-0.5
AV_SharingEconomy_ConstantForOwning2Vehicles	-1
AV_SharingEconomy_ConstantForOwning3Vehicles	-1
AV_SharingEconomy_ConstantForOwning4Vehicles	-1

The final new parameter, in Table 13, is “AV_InVehicleTimeCoefficientDiscountFactor.” This factor reduces the disutility of auto in-vehicle time, either in a privately owned AV or in a paid rideshare AV. When this factor is 0.20, for example, the auto in-vehicle time disutility is reduced by 20% compared to what it would be otherwise. (This is applied multiplicatively after all other systematic and random components that affect the in-vehicle time coefficient have been applied.)

The final new switch, also in Table 13, is “AV_UseSeparateAVSkimMatrices.” If this is set to True, then the roster CSV file should include entries for travel time, distance, and toll matrices for the “av” mode, just like it does for the “sov,” “hov2,” and “hov3” modes.

Table 13. Additional AV parameters

Parameter	Choice
AV_InVehicleTimeCoefficientDiscountFactor	0.5
AV_UseSeparateAVSkimMatrices	FALSE

3.2.2 Changes in the DaySim Output Files

In the household-level output file, the variable ***restype*** is used to indicate the chosen vehicle type. If “AV_IncludeAutoTypeChoice” is set to TRUE, then each output household record will have one of the following values:

0 = household owns conventional vehicles.

1 = household owns AVs.

The variable ***hhvehs*** will still have the number of vehicles owned by the household like before.

In the Trip-level output file, the variable ***dorp*** has two new codes (3 and 4) to identify AV trips, corresponding to codes 1 and 2 for non-AV trips. If the value of ***mode*** is 3 (sov), 4 (hov-2), 5 (hov-3+), or 9 (paid rideshare), then the value of ***dorp*** will be one of the following values:

1 = driver (or main rideshare passenger) in a conventional vehicle >> assign to network.

2 = passenger (or other rideshare passenger) in a conventional vehicle) >> do not assign to network.

3 = main passenger in an AV >> assign to network.

4 = other passenger in an AV >> do not assign to network.

For AV trips, the value of ***vot*** in the trip file also accounts for the “AV_InVehicleTimeCoefficientDiscountFactor.”

3.2.3 Test Runs with Example Scenarios

After running several initial tests and diagnostics, a base scenario plus 10 example scenarios were run for reporting in this document. Table 14 shows the DaySim configuration used for each of the scenarios. The scenarios are as follows:

(1) The Base scenario for comparison purposes. No private AV ownership is simulated, nor is use of the paid rideshare mode.

(2-10) All nine combinations of private AV ownership at Low, Medium, and High levels, and use of AV paid rideshare at Low, Medium, and High levels. These are denoted at combinations of “AV low,” “AV medium,” or “AV high,” and “SH low,” “SH medium,” and “SH high.”

(11) The “AV high/SH high” scenario run again, but with the VOT discount factor set at 75% instead of 25%.

Figure 38 to Figure 53 show results from running DaySim for one iteration through the 2010 Jacksonville region synthetic population of approximately 575,000 households. All runs use the same 2010 base scenario static skim matrices with no feedback from network assignment. (The runs in Task 5 include feedback from the TransModeler dynamic assignment.)

Figure 38 to Figure 47 shows the results in terms of predicted private vehicle ownership patterns. Some results of note include the following:

- The fraction of private vehicles that are AVs rises from 0% in the base scenario to around 10% in the in the AV-low scenarios to about 45% in the AV-medium scenarios, and to over

90% in the AV-high scenarios, providing several private AV ownership scenarios for the exploratory tests.

- Figure 38 shows that AV ownership is slightly higher in the low-density areas in the SH low scenarios, but a little bit higher in the high-density areas in the SH high scenarios. This result illustrates the assumed correlations between private and shared AV use, but the differences are small.
- Figure 39 shows that there is a substantial increase in AV ownership with higher income in the AV-low and AV-medium scenarios, but in the AV-high scenarios, there is high AV market penetration across all income groups.
- Similarly, Figure 40 shows lower AV market penetration for households with heads of household over age 65 in the AV-low and AV-medium scenarios, but in the AV-high scenarios there is high AV penetration in all age groups.
- Figure 41 shows a similar pattern for AV market penetration by total household commute travel time category, although the assumed differences are somewhat smaller than those assumed for income groups and age groups.
- Figure 42 shows that the percent of households owning zero vehicles depends much more on the SH scenario type than on the AV scenario type. In the SH low scenarios, the percent of zero-vehicle households stays close to the Base scenario percentage—less than 10% of all households. In the SH medium scenarios, around 33% of all households own zero vehicles, while in the SH high scenarios, about 50% of households own zero vehicles. The percent of households owning one vehicle is somewhat higher in the AV-high scenarios because of the assumption that households purchasing AVs can use them as “private taxis” in some cases and will need to own fewer vehicles, on average. The percent of zero-vehicle households goes down slightly as AV penetration increases. This is partly because AVs can be used by a wider range of the population, but mainly because the lower disutility of in-vehicle time for AVs makes auto ownership more attractive in DaySim.
- Figure 43 shows that overall vehicle ownership decreases from 1.76 per household in the Base, to between 1.29 to 1.6 in the SH low scenarios, to between 0.91 to 1.11 in the SH medium scenarios, and to between 0.62 to 0.73 in the SH high scenarios. Thus, the SH high scenarios are an extreme shift to the sharing economy, with low vehicle ownership in the denser urban areas.
- The trend in auto ownership with density is illustrated in Figure 44. The most extreme drops in auto ownership are in the denser areas in the SH medium and SH high scenarios.
- Figure 45 shows that the higher-income households maintain higher auto ownership levels in all of the scenarios.
- Figure 46 shows that the variation in auto ownership levels by age group remains similar in all the scenarios (even though the percent of autos owned that are AVs differs substantially by age group—see Figure 40).

- Figure 47 shows that vehicle ownership remains highest in the households with the highest total commute travel time in all scenarios. These are also more likely to be the households living in less dense areas, so the results are consistent with those in Figure 44.
- Although not shown in the figures, reducing the value of in-vehicle time disutility in the AV-high/Shared-high scenario produces only a slight shift toward higher AV ownership. No direct effect of VOT on vehicle type choice in the models exists, so this result arises from an indirect accessibility effect.

Figure 48 to Figure 53 show some key results at the person-trip level. In these figures, the extra AV-high/SH-high/VOT-low scenario is also included since the change in VOT has more substantial effects at the trip level. First, Figure 48 shows trip mode shares for the scenarios. In the Base scenario, about 90% of trips are by private auto, with various occupancy levels (SOV, HOV 2, HOV 3+). When paid rideshare use is low (SH low), the AV-low, AV-medium, and AV-high scenarios do not change the mode share for private auto use much—it remains around 85%, The big shifts are for the paid rideshare use scenarios, with the paid rideshare mode getting about a 10% mode share in the SH low scenarios, a 50% mode share in the SH medium scenarios, and a 70% mode in the SH high scenarios. Paid rideshare is assumed never to reach high mode shares in the more rural areas where availability may be low. The last two bars show that the lower VOT does not affect mode share noticeably since most car trips are by AV in both scenarios and there is little demand for the nonauto modes (walk, bike, transit) for more trips to be attracted from.

As use of paid rideshare increases, the drop in private auto mode share is largest for drive-alone trips and least for shared ride 3+ trips. One reason for this is that the DaySim models do not (yet) have separate occupancy modes for paid rideshare and do not reflect the sharing of cost that occurs when multiple people use paid rideshare together while the choice between drive alone, shared ride 2, and shared ride 3+ *does* reflect such cost-sharing. (This is an issue that could be addressed in Phase 2.) Another reason is that the AV paid rideshare mode is not available in DaySim for trips on Serve Passenger (pick-up/drop-off) tours, assuming that such tours are not compatible with AV use. It would be best to also reduce the generation of such serve passenger tours when they are no longer necessary because the person who was being picked up or dropped off is now using an AV. (This issue will also be addressed in Phase 2 through simulating coordination and adjustment of travel patterns across household members to take advantage of AVs.)

Figure 49 shows the trip shares by “vehicle and passenger type.” As described earlier, just like DaySim designates a driver and (when applicable) passengers for a conventional auto trip, it also needs to designate a “main passenger” and (when applicable) “other passengers” for an AV tour, because only the “main passenger” vehicle trips will be assigned to the network. Currently, the probability of a paid rideshare AV trip being a “main passenger” or “other passenger” is based on base-year auto occupancy rates by purpose in private vehicles, assuming that average party sizes will be similar in private and shared vehicles. Figure 50 shows the percentage of person-trips in AVs in all scenarios. The percentage goes up from 20% in AV low/SH low to 95% in AV high/SH high. The shift to lower in-vehicle time disutility in the last scenario has little effect, raising the AV share from 95% to 96%. Overall, these scenarios will give a broad range of demand conditions to test scenarios with different mixes of conventional vehicles and AVs on the roads, with variations between more urban and more rural areas.

Figure 51 shows the percent of all trips that are by AVs (either private or shared), by traveler residential area density categories. AV use is low in rural areas unless private AV ownership is high. AV use is high in the densest areas in most of the scenarios except those with lowest paid rideshare use. By person age group, AV (Figure 52) use is highest in the 18-24 and 25-34 groups, and lowest in the age 65 plus group. These trends by density and age follow the patterns expected from the way that the auto ownership and mode choice models are specified.

By tour purpose (not shown in the figures), AV use is highest for work tours and lowest for school tours (where school bus remains a major mode). In the SH high scenarios, AV use remains lower for Serve passenger tours for the reasons mentioned above.

Finally, Figure 53 shows average trip distance by mode and scenario. In general, the paid rideshare trips are shorter than the private auto trips (particularly the SOV trips), because they are made in more urban areas and because they have a higher marginal cost per mile. The SOV trips tend to be longest because they are made most often for commute trips, which have the longest average distance. As paid rideshare use goes up in the SH medium and SH high scenarios, the average paid rideshare trip distance goes up as this mode starts to draw more trips away from private auto trips, which are generally longer. Private auto trip average trip length also goes up since it tends to be the shorter private auto trips that shift to paid rideshare (and may also shift to closer destinations at the same time). Interestingly, even though the average trip lengths for private auto trips and paid rideshare trips both go up as paid rideshare use increases, overall trip length (not shown in the figure) goes down somewhat because more trips are made in the mode with the shorter average trip length (paid rideshare).

In Figure 53, the project team observed a substantial effect of reduced in-vehicle time disutility (lower VOT). The main effect is destination-switching, with the average trip length for private car trips increasing by about 20% (from about 10 miles to 12 miles for SOV trips).

In sum, these initial results of running only the demand models demonstrated that the new features added to the DaySim demand models functioned properly to create several plausible scenarios under different sets of input assumptions. In Task 5, some of these scenarios are combined with different supply side scenario inputs to broaden the exploratory runs to include both demand-side and supply side assumptions.

Table 14. Settings used for 11 example scenarios.

	Base (BB)	AV low/SH low (LL)	AV low/SH medium (LM)	AV low/SH high (LH)	AV medium/SH low (ML)	AV medium/SH medium (MM)	AV medium/SH high (MH)	AV high/SH low (HL)	AV high/SH medium (HM)	AV high/SH high (HH)	AV high/SH high/VOT low (HH2)
AV_IncludeAutoTypeChoice	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
AV_AutoTypeConstant		-2.5	-2.5	-2.5	0	0	0	3	3	3	3
AV_HHIncomeUnder50KCoefficient		-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
AV_HHIncomeOver100KCoefficient		1	1	1	1	1	1	1	1	1	1
AV_HHHeadUnder35Coefficient		0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
AV_HHHeadOver65Coefficient		-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
AV_CoefficientPerHourCommuteTime		0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
AV_Own0VehiclesCoefficientForAVHouseholds		1	1	1	1	1	1	1	1	1	1
AV_Own1VehicleCoefficientForAVHouseholds		2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5	2.5
AV_InVehicleTimeCoefficientDiscountFactor		0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.75
PaidRideShareModeIsAvailable	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
PaidRideShare_Age26to35Coefficient		0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
PaidRideShare_Age18to25Coefficient		0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
PaidRideShare_AgeOver65Coefficient		-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5	-0.5
AV_PaidRideShareModeUsesAVs	FALSE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE	TRUE
AV_PaidRideShare_ModeConstant		-2.5	-2.5	-2.5	-2.5	-2.5	-2.5	-2.5	-2.5	-2.5	-2.5
AV_PaidRideShare_DensityCoefficient		0.002	0.006	0.01	0.002	0.006	0.01	0.002	0.006	0.01	0.01
AV_PaidRideShareAVOwnerCoefficient		1	1	1	1	1	1	1	1	1	1
AV_PaidRideShare_ExtraCostPerDistanceUnit		1	0.75	0.5	1	0.75	0.5	1	0.75	0.5	0.5
AV_PaidRideShare_FixedCostPerRide		5	5	5	5	5	5	5	5	5	5
AV_SharingEconomy_DensityCoefficientFor0Vehicles		0	0.001	0.002	0	0.001	0.002	0	0.001	0.002	0.002
AV_SharingEconomy_ConstantFor1Vehicle		0	-0.5	-1	0	-0.5	-1	0	-0.5	-1	-1
AV_SharingEconomy_ConstantFor2Vehicles		0	-1	-2	0	-1	-2	0	-1	-2	-2
AV_SharingEconomy_ConstantFor3Vehicles		0	-1	-2	0	-1	-2	0	-1	-2	-2
AV_SharingEconomy_ConstantFor4Vehicles		0	-1	-2	0	-1	-2	0	-1	-2	-2

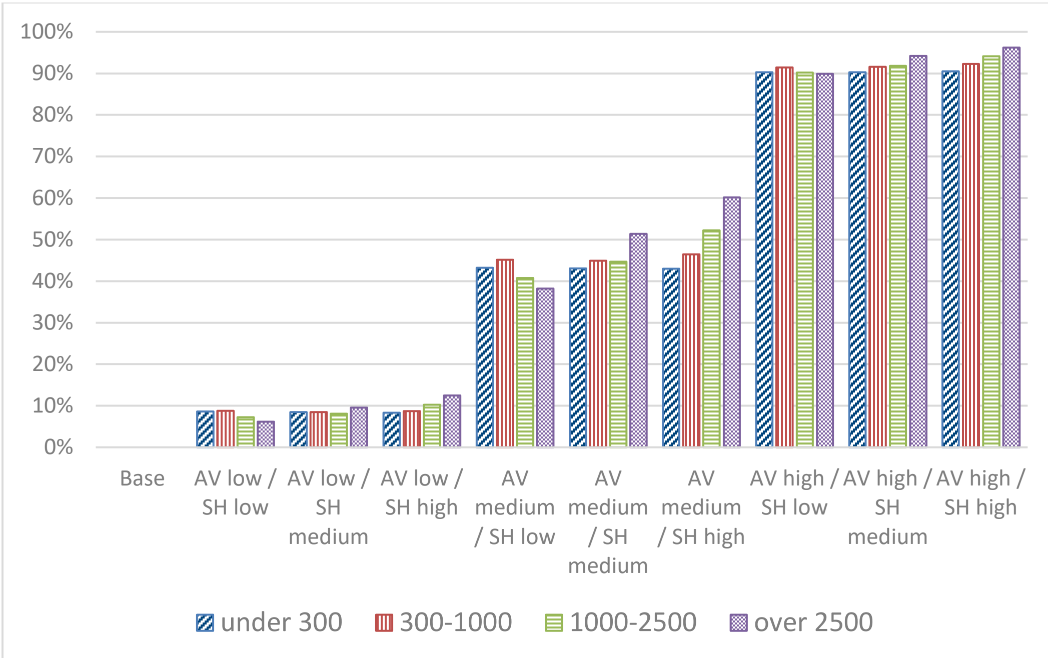


Figure 38. Percentage of private vehicles that are AVs, by land-use density within buffer around residence.

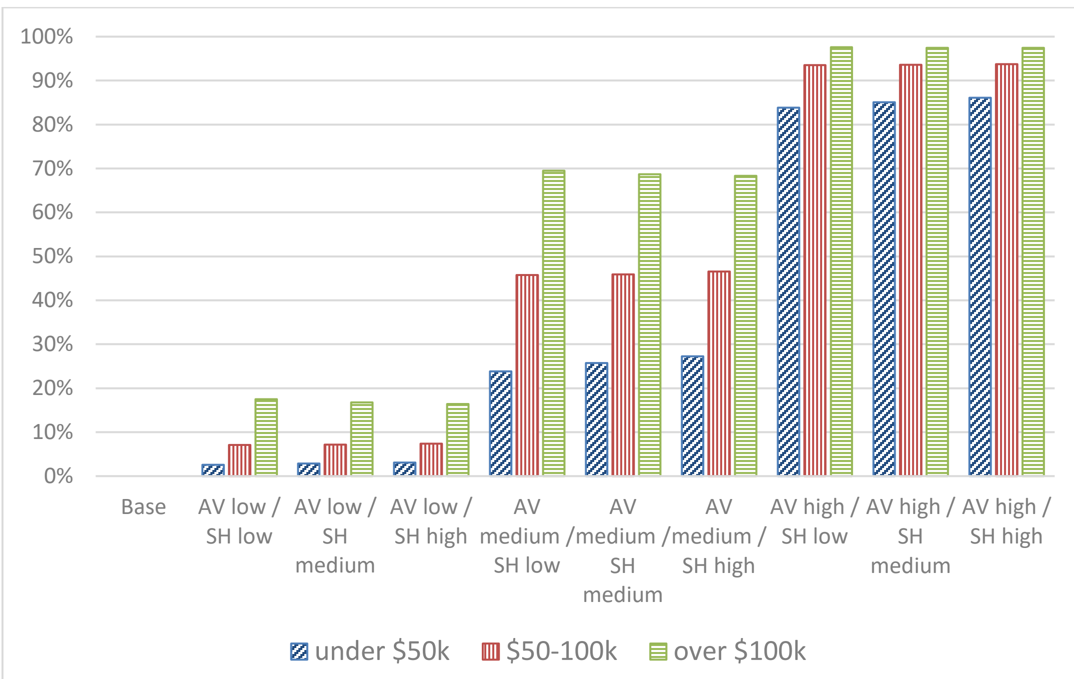


Figure 39. Percentage of private vehicles that are AVs, by household income category.

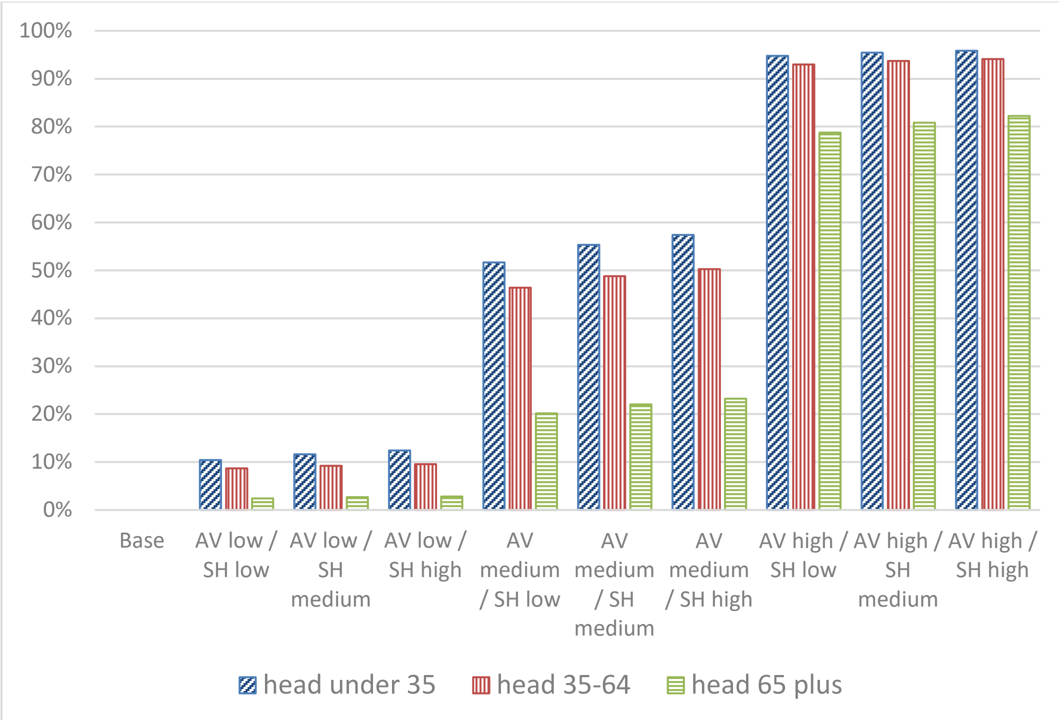


Figure 40. Percentage of private vehicles that are AVs, by household head age category.

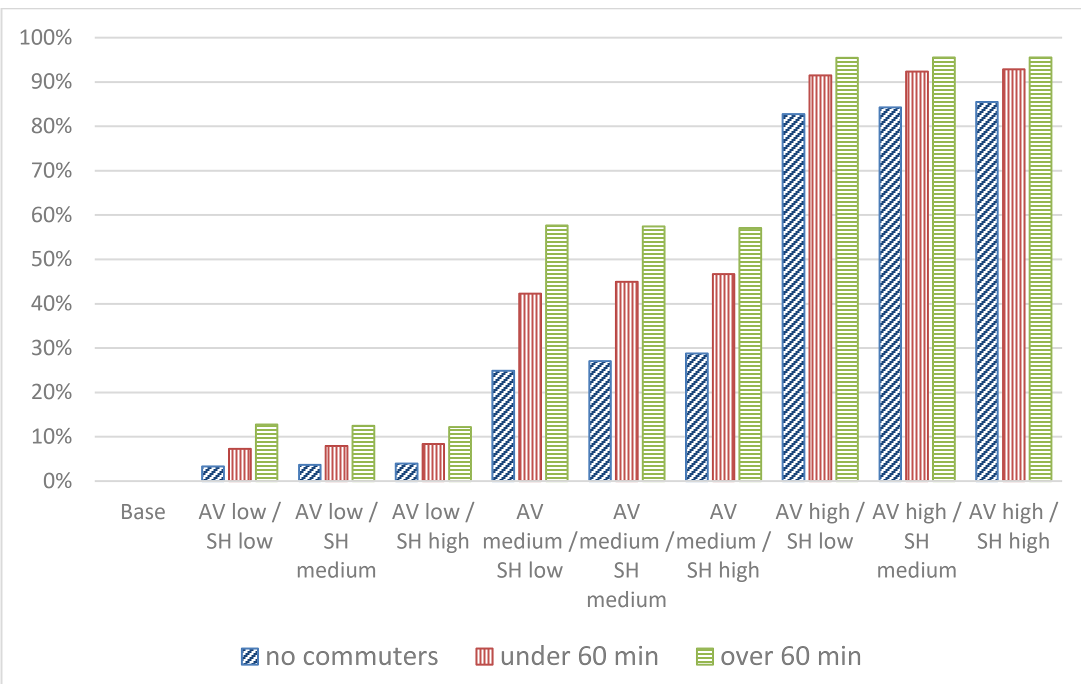


Figure 41. Percentage of private vehicles that are AVs, by household commute travel time category.

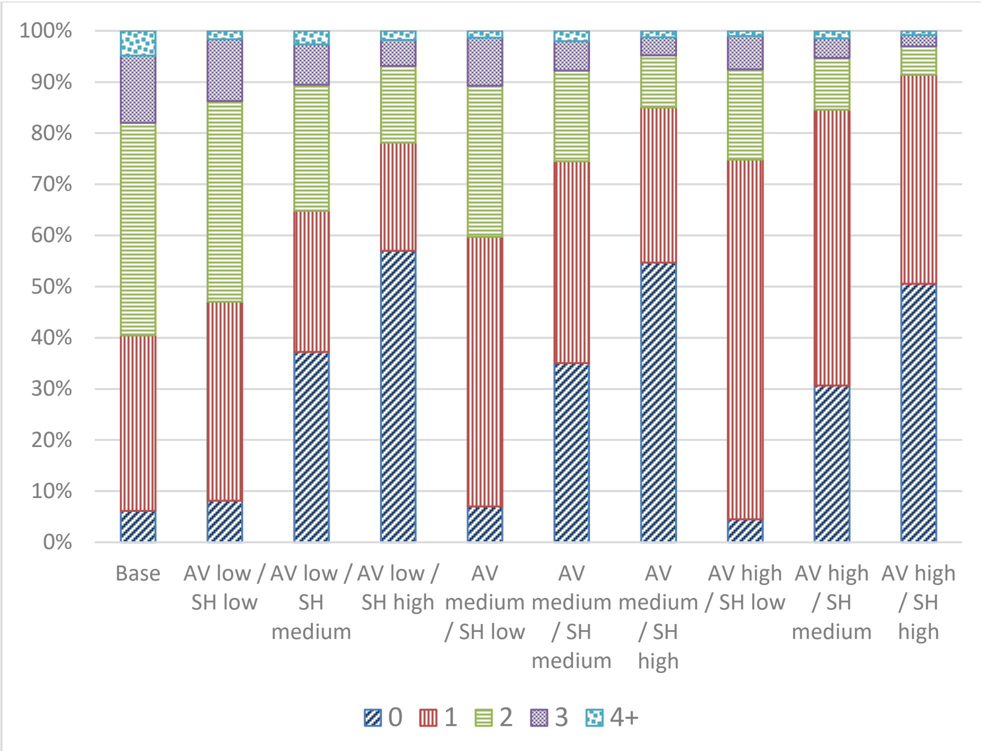


Figure 42. Distribution of number of autos owned, by scenario.

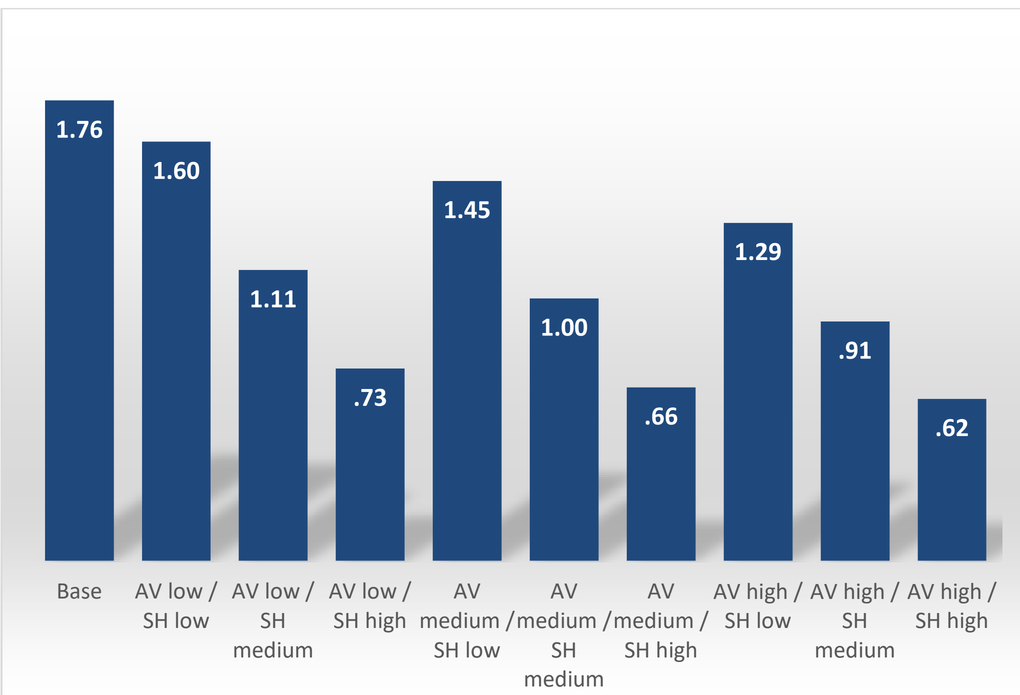


Figure 43. Average number of privately owned vehicles per household, by scenario.

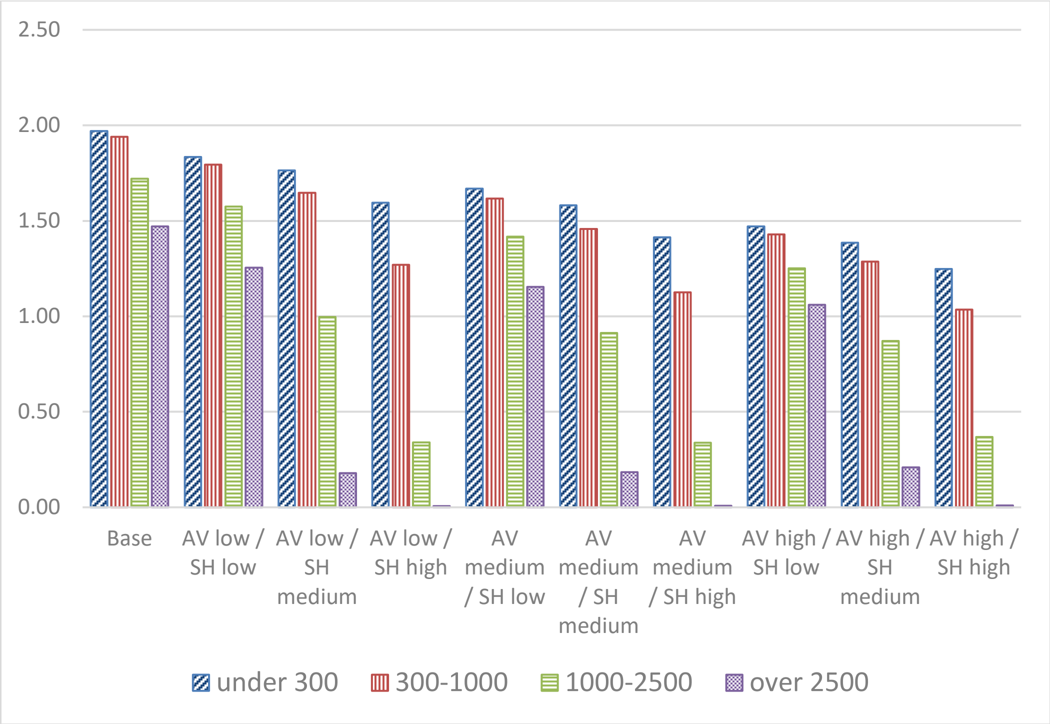


Figure 44. Average vehicles/household, by land-use density in buffer around residence.

Figure 45. Average vehicles/household, by income category.

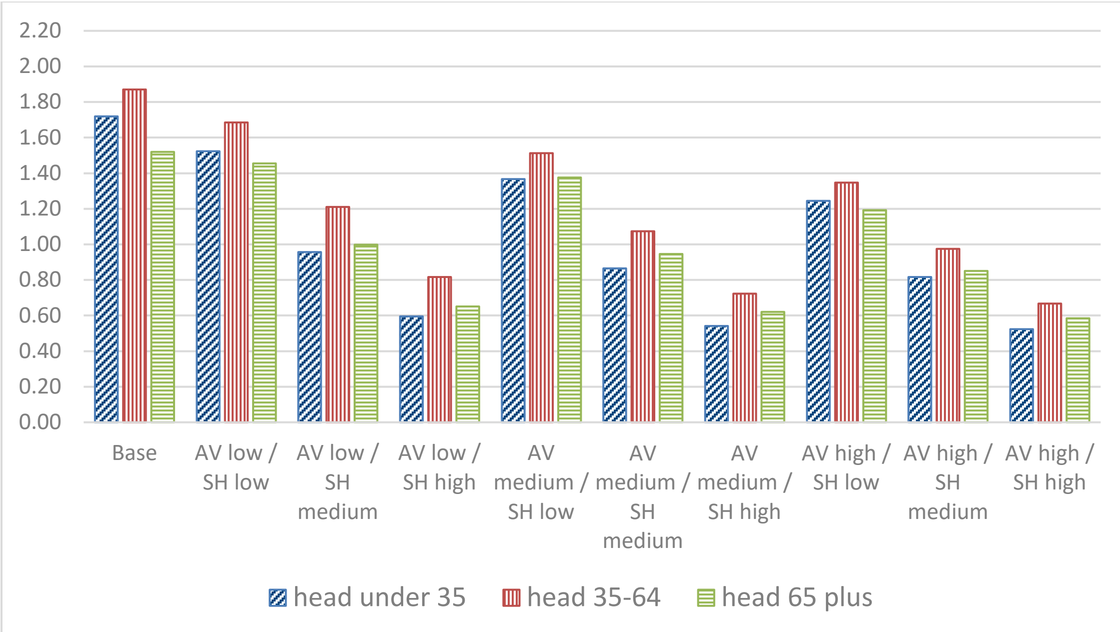


Figure 46. Average vehicles/household, by age group of head of household.

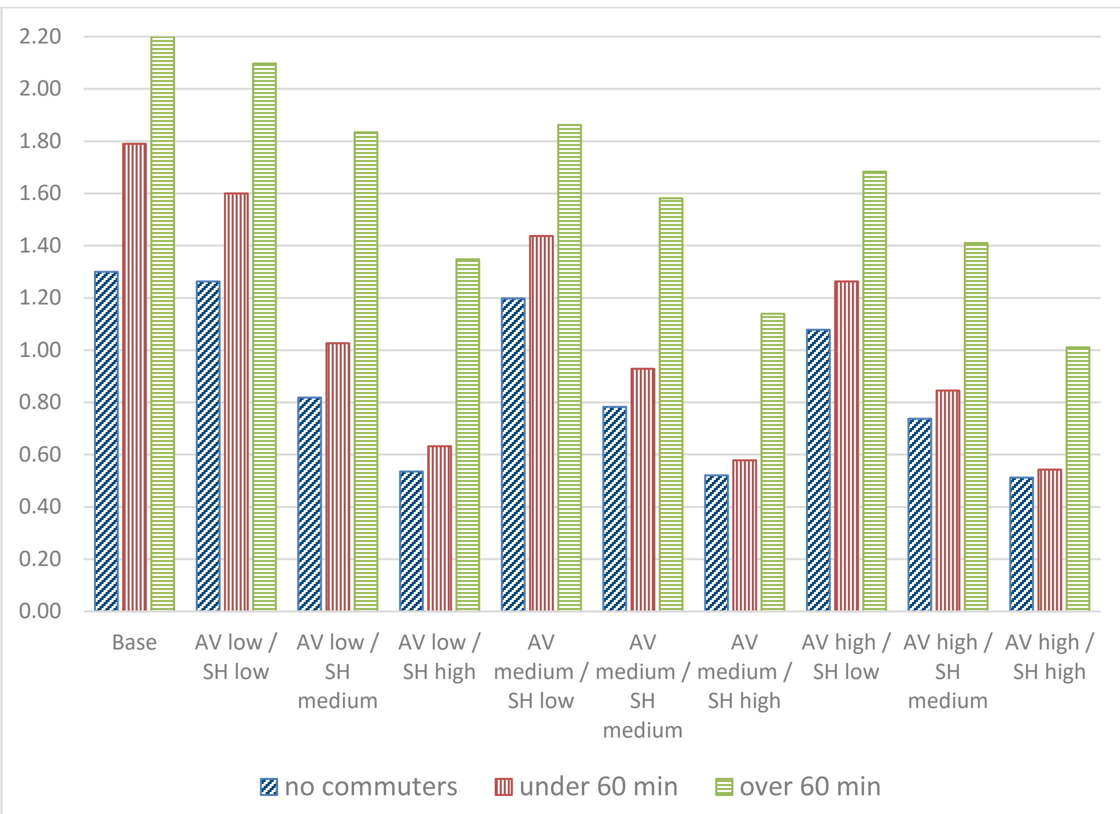


Figure 47. Average vehicles/household, by household commute travel time category.

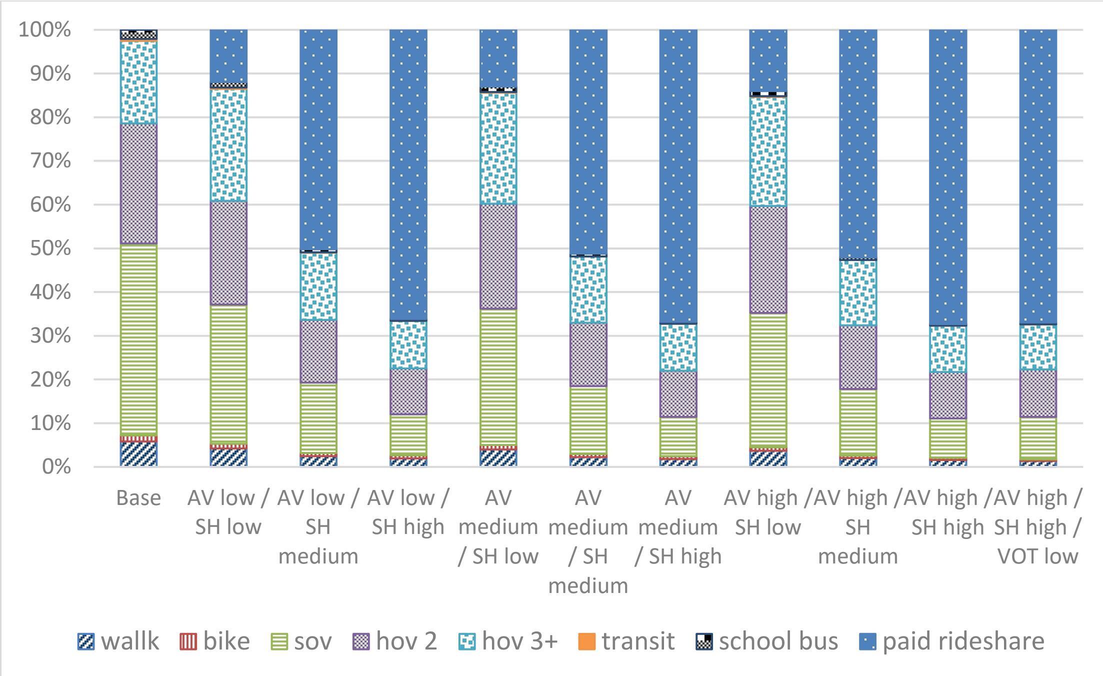


Figure 48. Person-trip mode share, by scenario.

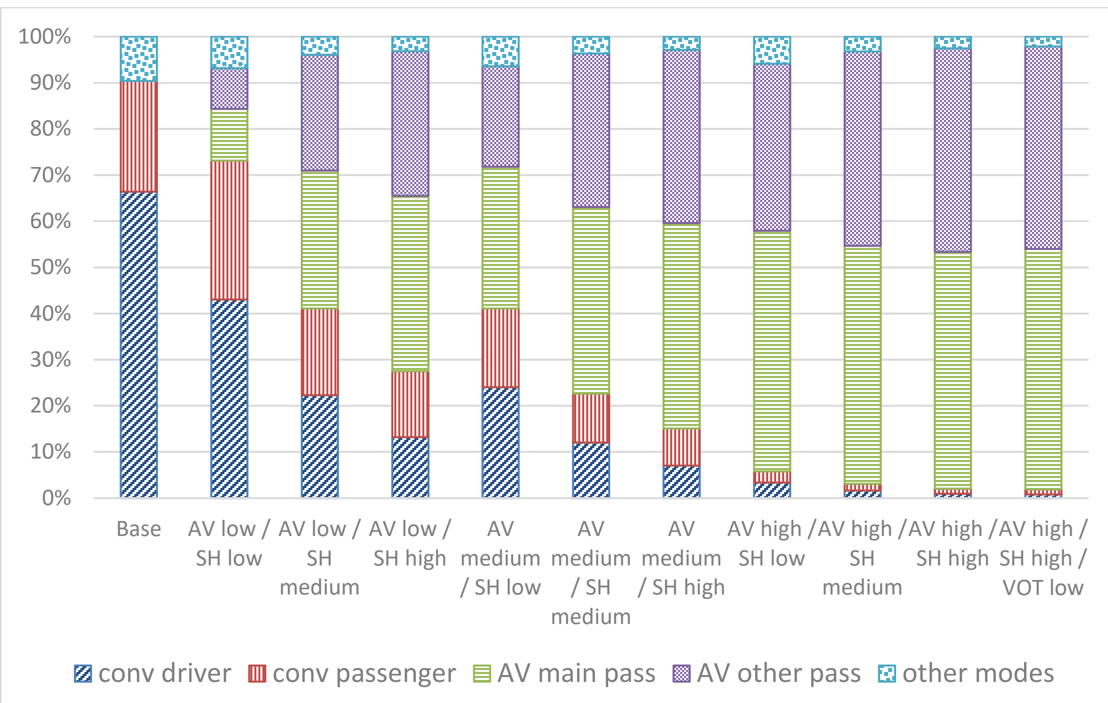


Figure 49. Person-trip vehicle type and driver/passenger type, by scenario.

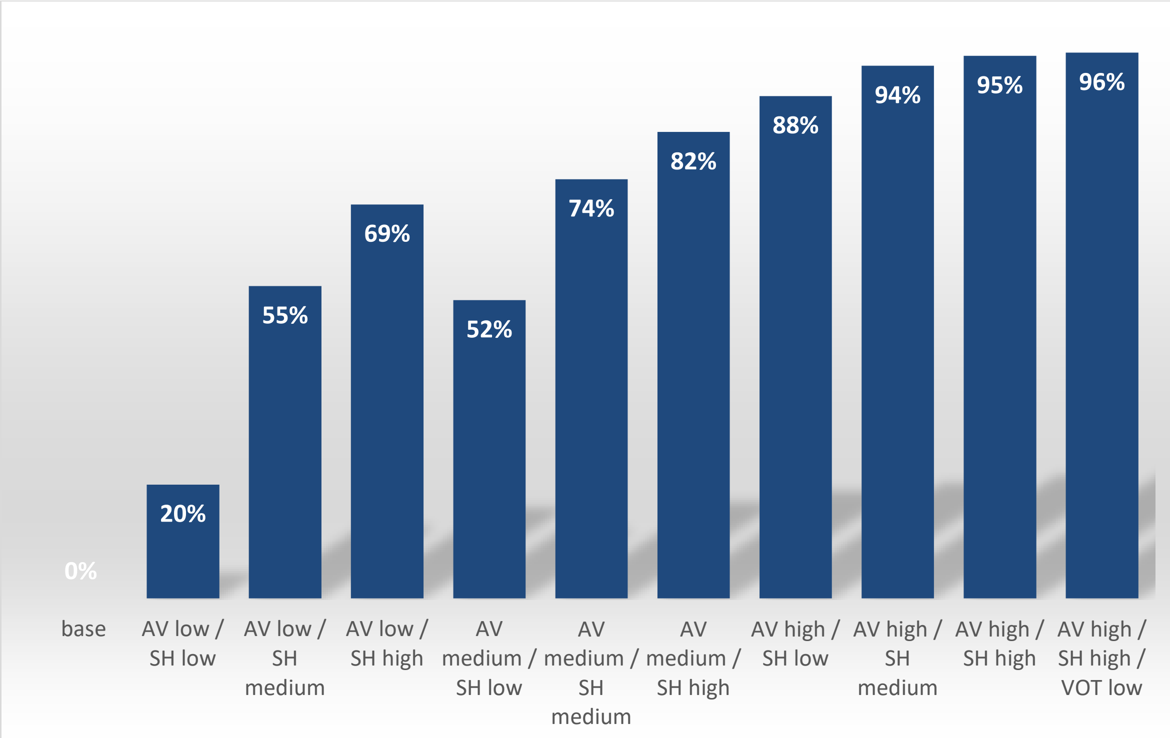


Figure 50. Percentage of person-trips in AVs, by scenario.

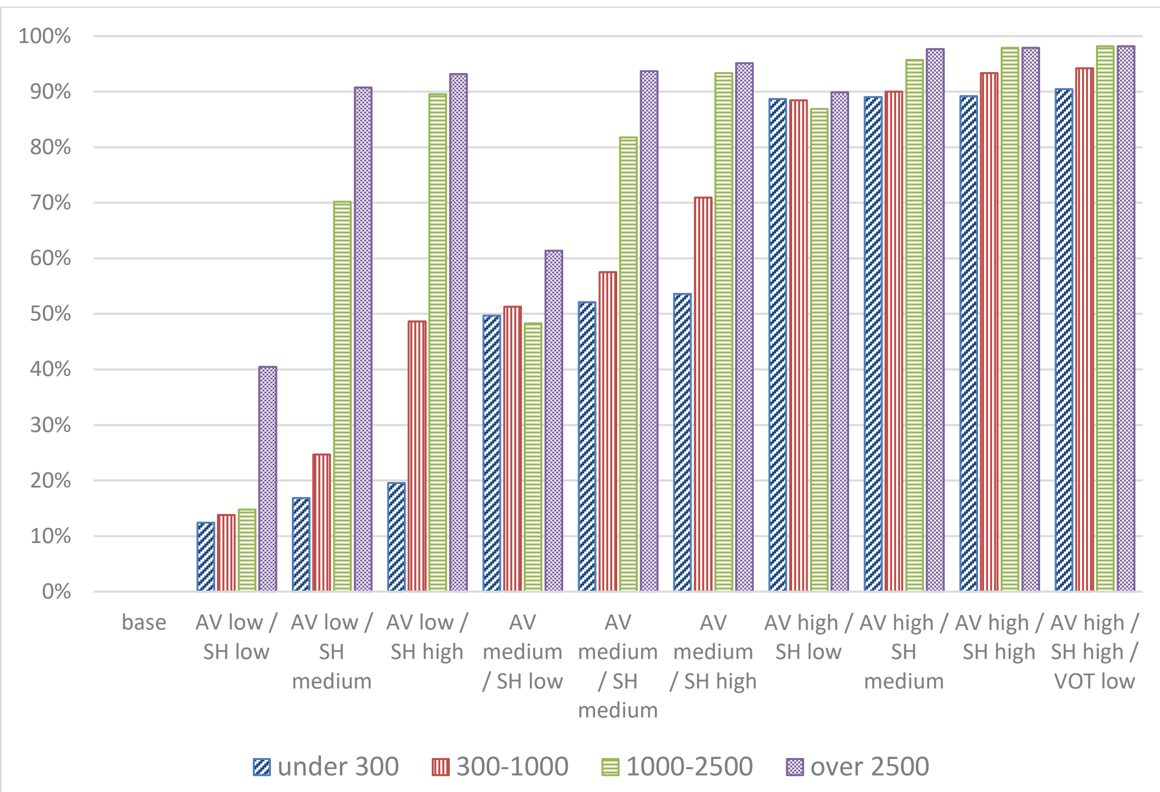


Figure 51. Percentage of person-trips in AVs, by land-use density in buffer around residence.

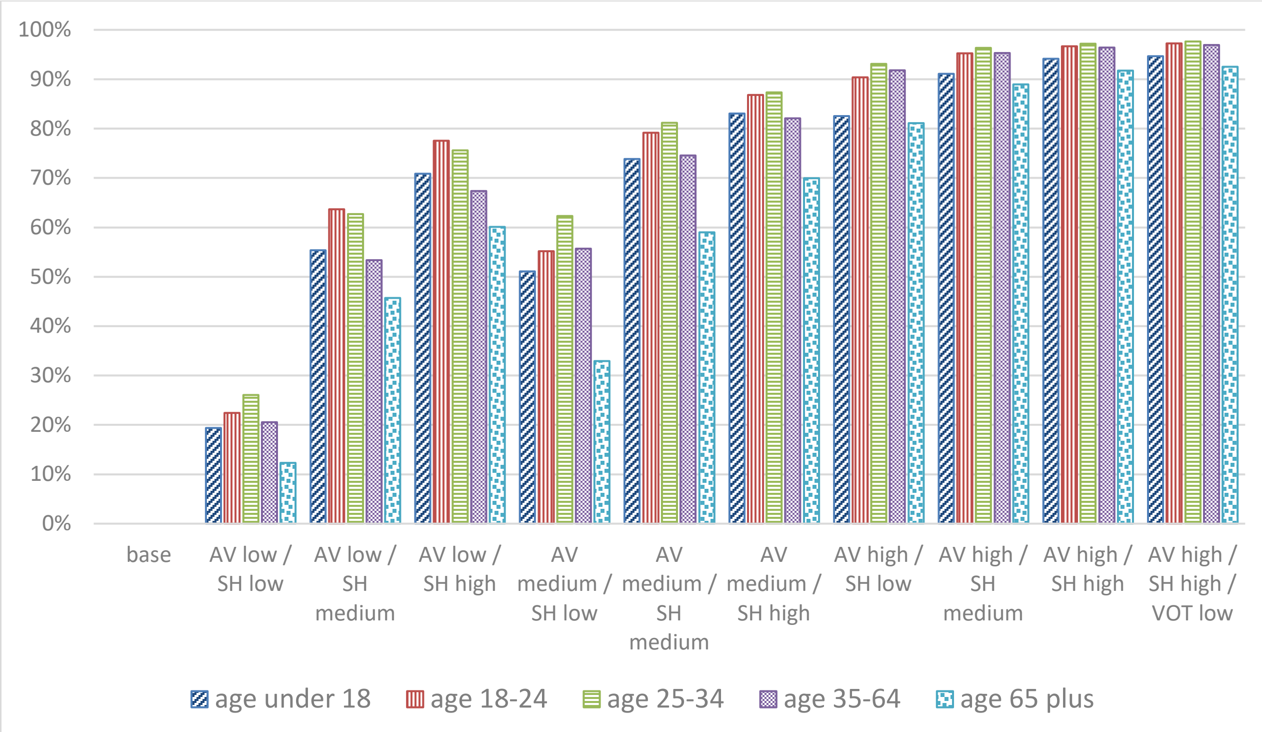


Figure 52. Percentage of person-trips in AVs, by person age group.

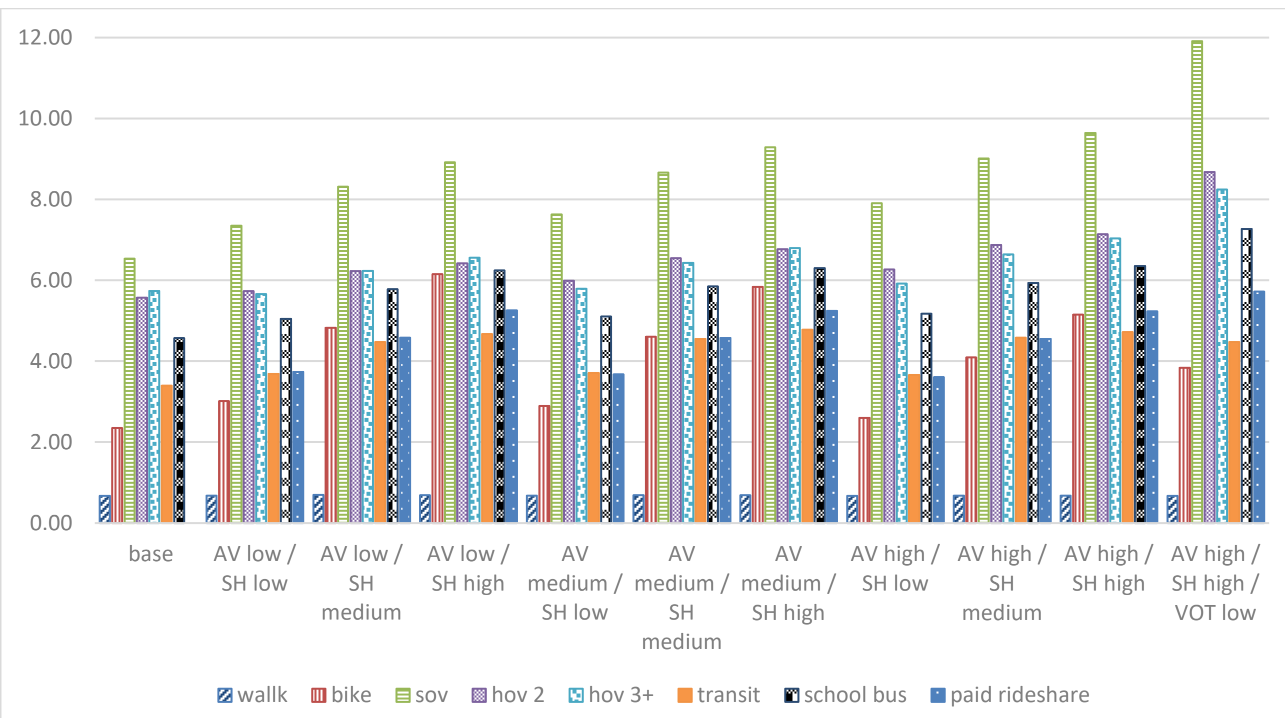


Figure 53. Average trip distance, by mode and scenario.

3.3 Adaptations of the TransModeler DTA software

The DTA model simulates individual trips where each trip is independent from all other trips and tours where the next trip occurs only after the previous trip and the associated activity duration are complete. Each trip, whether it be an individual trip or part of a tour, has independent route choice behaviors, individual driver characteristics, and specific vehicle attributes. The driver and vehicle characteristics of each trip are derived from their source model. For instance, characteristics for medium and heavy truck trips are generated from freight trips produced by a trip-based model, and numbers of occupants and values of time for nonfreight trips are supplied by lists of tours generated by a DaySim ABM.

The DTA model also simulates driver behaviors, including acceleration and lane-changing decision-making, at 0.1-second time steps. By adapting the models of those behaviors to reflect the way an AV, as opposed to a human driver, would operate, the project team can test the impacts of AV and related technologies. To that end, TransModeler was enhanced to support AV analysis in several respects:

- The vehicle characteristics mentioned earlier were extended to include an AV designation. This enhancement of the demand-side representation allows for the analysis of varying degrees of market penetration for AVs and for another model, such as an ABM, to supply a list of trips that explicitly identifies AVs.
- In TransModeler, the simulation network uses an explicit and detailed representation of lanes and lane geometry. This network model was updated to allow lanes to be designated for AV operation. In other words, the analyst may designate in which lanes AVs are permitted to operate under automated control. This augmentation of the supply side representation facilitates exploration of scenarios in which certain lanes or facilities may be reserved exclusively for AVs.
- The representation of simulated drivers and vehicles was extended to allow six commonly recognized levels of vehicle automation (Level 0 through Level 5 described below)—which include automation of acceleration, steering, and other aspects of driving—to be applied to a user-defined vehicle class.
- An acceleration model identified from the research literature was chosen and implemented to represent a mode of cooperation between CVs referred to as cooperative adaptive cruise control (CACC).

3.3.1 Adaptation of a DTA for Simulating AVs

TransModeler was enhanced to support the simulation of AVs. With this enhancement, the modeler can create new vehicle classes and assign to each one of the following Society of Automotive Engineers International-defined and U.S. Department of Transportation-adopted levels of automation:

- **Level 0–No Automation.**
- **Level 1–Driver Assistance**: Steering (modifying direction) and/or acceleration/deceleration can be performed by the on-board driver assistance system using information about the driving environment; the driver performs all other driving tasks.

- **Level 2–Partial Automation**: Both steering (modifying direction) and acceleration/deceleration are performed by the on-board driver assistance system using information about the driving environment; the driver performs all other driving tasks. The driver must be available/alert to take over, if needed.
- **Level 3–Conditional Automation**: An on-board automated driving system operates all aspects of driving; the driver responds only to requests to intervene.
- **Level 4–High Automation**: An on-board automated driving system operates all aspects of driving and continues to do so even if the driver fails to respond to requests to intervene. This level of automation may have situational limitations, for example only within a geofence.
- **Level 5–Full Automation**: An on-board automated driving system operates all aspects of driving under all roadway and environmental conditions, negating any need for driver intervention.

The assumptions described here about the representation of vehicle automation are subject to change pending input from other members of the team and FHWA as the project advances to subsequent tasks.

Vehicle classes that are not assigned an automation level or that are assigned Level 0 are simulated according to the default models of driving behavior in TransModeler. When Level 1 Driver Assistance is assigned to a vehicle class in TransModeler, the user can choose whether the acceleration/deceleration task (e.g., car following or braking for a red light) or the modification of direction task (e.g., lane changing) is operated by the vehicle. When either the acceleration/deceleration or lane-changing tasks are operated by the vehicle, stochastic elements meant to represent driver heterogeneity (e.g., random error terms) are eliminated to remove the human element and reflect more deterministic behavior. When Level 2 is assigned to a vehicle class, both acceleration/deceleration and steering tasks are operated by the vehicle, and the stochastic elements for both tasks are eliminated. While there is no clear dividing line between Levels 2 and 3 in the simulation context, there are other aspects of driving, such as choosing a speed at which to travel, that can be emulated in the software to distinguish Level 3 from Level 2. When Level 3 is assigned to a vehicle class, the vehicle will drive at the advisory speed (i.e., the speed limit) when it is free to travel at an unconstrained, desired speed. Level 3 automation, thus, can have speed harmonization benefits in addition to the advantages afforded by Level 2 automation.

In addition to vehicle automation, there are technologies and strategies that are conditioned on communication and coordination between vehicles (e.g., CVs and CACC). With CACC, a vehicle chooses a headway at which to follow the leading vehicle, and short headways can be sustained because the direct communication allows for rapid responses to changes in the leading vehicle's speed or proximity. Other related technologies considered for inclusion in the simulation include technologies that involve communication and coordination with infrastructure (e.g., vehicle to infrastructure, or V2I). V2I could, for example, regulate/harmonize speeds upstream of an incident or optimize traffic signal timings in real time.

In a simulation environment such as TransModeler, the line between driver and vehicle is not well defined, which makes it somewhat difficult to differentiate between the levels of automation. In much of the traffic simulation literature, in fact, the driver and vehicle are conflated, referred to as the "driver-vehicle entity," or DVE. The same is true in TransModeler. It is unclear how driver intervention, which distinguishes Levels 3, 4, and 5 might be represented in a simulation model. Hence, Levels 3 through Level 5 are not yet differentiated in any substantive way in the current adaptations.

3.3.2 Adaptation of a DTA for Simulating Connected Vehicles

In CACC, vehicles use a feedback loop of measurement (of the position and speed of the vehicle in front) and acceleration (or deceleration) to maintain a safe and consistent following speed and distance or time headway. The project team assumes that vehicles operating in CACC will seek to maintain a desired following time headway. To achieve this, the project team implemented a constant time gap model (Wang and Rajamani, 2004):

$$a_i = -\frac{1}{h}(dv + \lambda\delta_i)$$

Figure 54. Equation. Constant time gap.

where a_i is the acceleration to be applied by the subject vehicle i, h is the desired constant time gap, dv is the difference in speed between the subject vehicle and the vehicle in front of it ($v_i - v_{i-1}$), λ is a parameter, and δ_i is a deviation from the desired spacing given the desired headway and is calculated as:

$$\delta_i = \varepsilon_i + hv_i + L$$

Figure 55. Equation. Desired headway calculation.

where ε_i is the physical gap between the vehicles and L is the desired, or minimum, physical gap between the vehicles at zero speed ($v_i = 0$).

The constant time gap model can be found in numerous articles in the literature such as the paper previously cited as a reasonable approximation of an adaptive cruise control system. In the DTA software, the modeler can choose which classes or groups of vehicles operate with CACC.

3.4 Testing and Validation of Adaptations

To measure the impact of the model adaptations, a small simulation model was built of an approximately 2.5-mile section of a westbound five-lane freeway with on and off ramps. Sensors were placed on the mainline to measure the average flow per lane at several locations, including before vehicles arrived at the ramps and within weaving sections. For simplification, the results presented here focus on the flow located in the map below at the orange circle, where the maximum flow rates in vehicles per hour per lane (vphpl) in the model are observed.

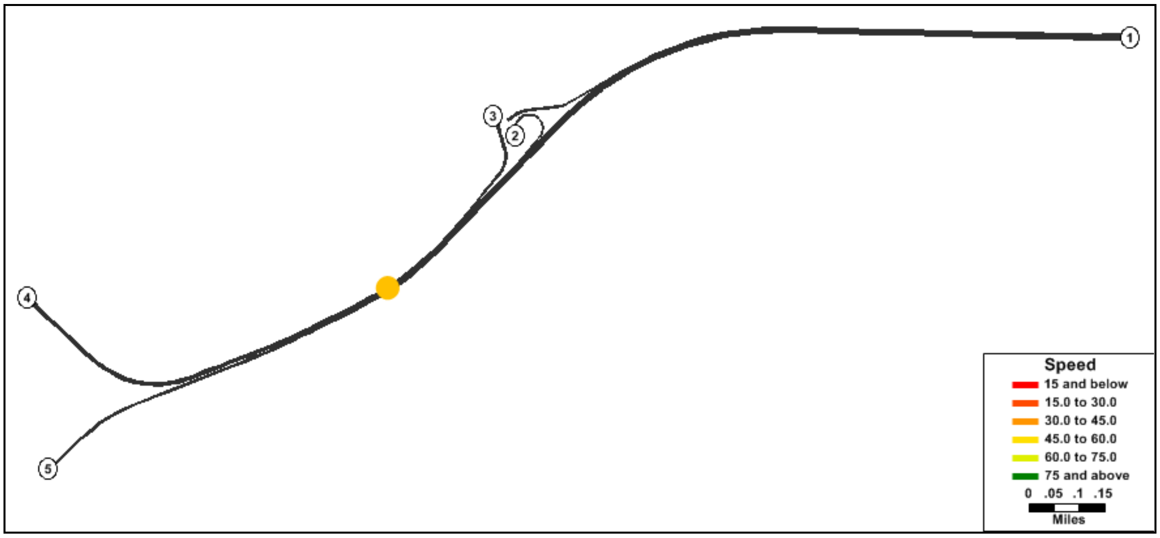


Figure 56. Model network for testing adaptations.

Tests were performed using an OD trip matrix with trips traveling from origins at Nodes 1, 2, or 3 to destinations at Nodes 4 and 5. Hence, the AV and CACC adaptations were tested in the presence of several complex merge, diverge, and weaving behaviors that are commonplace in the real world and that call on all the aspects of driving that are subject to automation. The simulated traffic was also set to have a representative mix of vehicle classes, including passenger cars, single-unit trucks, tractor-trailer trucks, and motorcycles.

In tests, the project team first determined the highest volume of traffic at which traffic flow could be stably sustained without breakdown or notable congestion. Then, the project team increased the volume in increments of 10% to simulate the impacts of the adaptations at different levels of network congestion. For the purposes of these tests, a scaling factor of 1.0 represents an uncongested existing condition. The maximum stable flow condition was observed at scaling factor 1.3, where the maximum flow rate simulated was about 1,885 vphpl. The project team analyzed the impacts of AV and CACC with scaling factors in steps of 0.1 between 1.3 and 1.8.

Numerous scenarios were run, where a scenario is a combination of scaling factor and model adaptation. Scaling factors ranged from 1.3 to 1.8, and the following model adaptations were evaluated: AV Level 1a (acceleration/deceleration task automated), AV Level 1b (lane-changing (i.e. modifying direction) task automated), AV Level 2 (both acceleration/deceleration and lane-changing tasks automated), AV Level 3 (AV Level 2 + travel speeds coordinated), and CACC. For each scenario, results from 10 simulation runs were averaged together. This test also assumed 100% AV penetration to try to understand the maximum impact a given level of automation or AV technology might have.

To isolate the effects of CACC from those of Level 3 automation, the project team assumed only the minimum AV level (Level 1a where the acceleration/deceleration task is automated) in the CACC scenarios. In the scenarios in which CACC was tested, a target following headway h of 1.0 second was assumed, which falls in the middle of the range of CACC headways considered to be plausible in the literature.

An OD matrix of trips was defined where vehicles originate from Nodes 1, 2, or 3 and are destined for Nodes 4 or 5. The matrix was scaled up in increments of 10% to simulate the impacts of the adaptations at different levels of network congestion. For this study, scaling factors of 1.3 to 1.8 were evaluated. Numerous scenarios were run where a scenario is a combination of scaling factor and model adaptation. For each scenario, results from 10 simulation runs were averaged. This test also assumed 100% AV penetration to try to understand the maximum impact a particular adaptation might have.

The maximum flow/lane without any adaptations (i.e., assuming normal driving behaviors with no automation), the Base scenario, was approximately 1,950 vehicles per lane, and occurred when the scaling factor of the OD matrix was scaled with a factor of 1.3. In the Base scenario, as the scaler of the demand increases, flow declines because of increasing congestion, consistent with the fundamental traffic flow diagram. Figure 57 summarizes the flow rate served in all the scenarios evaluated, and Figure 58 summarizes the increase in flow relative the Base scenario at each demand scale.

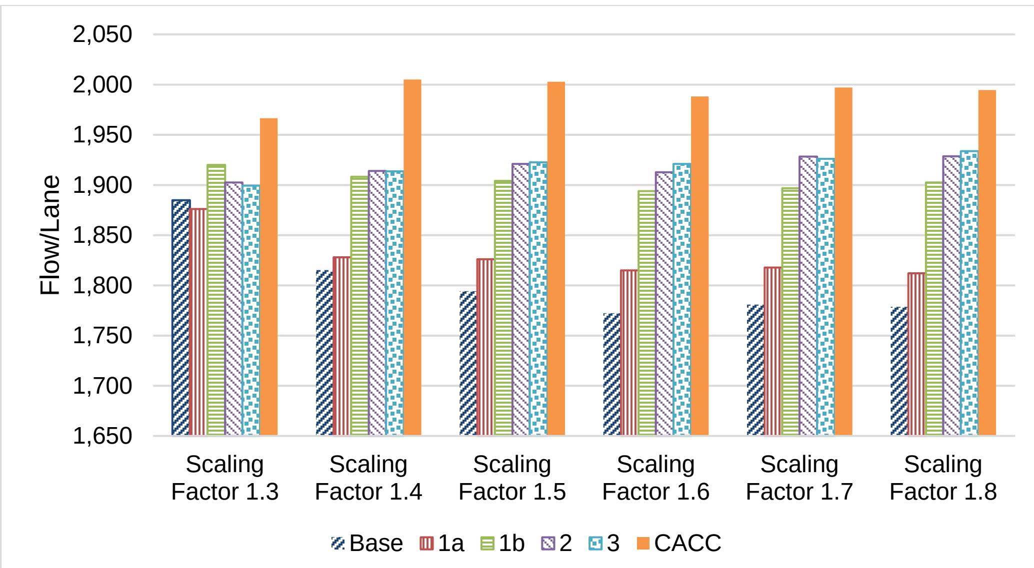


Figure 57. Simulated flow rate for a range of AV adaptation/demand scale scenarios.

Figure 57 shows that the flow rate decreases as the demand increases, which reflects some combination of the downward trend in flow in the fundamental traffic flow diagram as density increases beyond a critical density upstream of the measurement location and demand starvation at the measurement location due to queuing at the upstream merge.

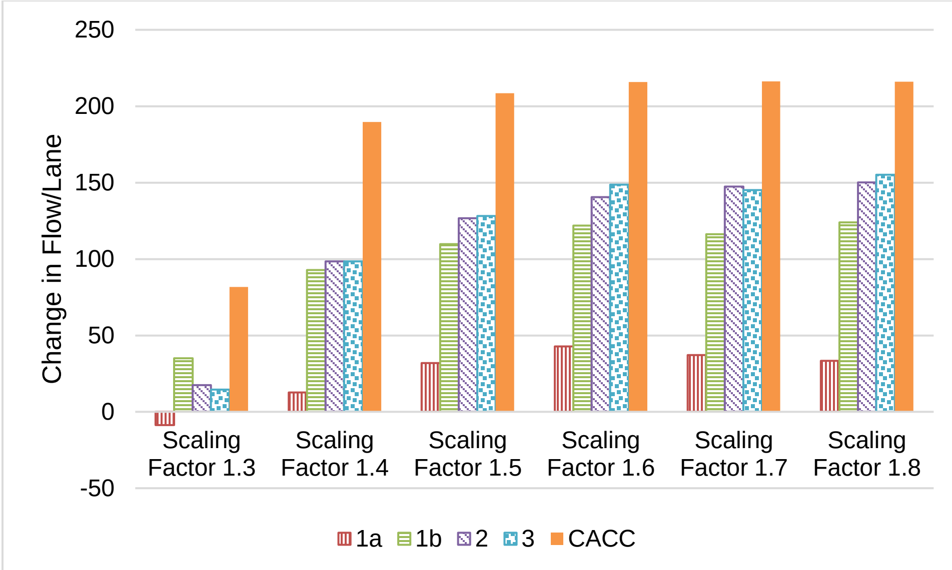


Figure 58. Change in flow rate for a range of AV adaptation/demand scale scenarios.

According to Figure 58, only modest or negligible increases in capacity (0-2%) are achieved when only acceleration is automated (1a). It is likely that traffic operations in heavy merge, diverge, and weaving areas stands to benefit the most from the automation of steering (1b). When steering (i.e. modification of direction) is automated, lane changes that are motivated by human factors and that are not necessary to follow one's path are minimized, which enables the more notable increases in capacity (1-8%) observed at Levels 1b, 2, and 3. Figure 58 also shows that CV technologies, like CACC, may have benefits that go beyond those of simple automation. The most significant improvements in capacity are observed when CACC is deployed, leading to increases in flow as high as 12%. Figure 57 and Figure 58 also show that the benefits increase as demand increases and congestion worsens. Interestingly, the steering automation and CACC have the potential to stem the decline in volume served that is evident in the Base condition.

In sum, safety considerations aside, the benefits that AV/CV operations afford in terms of capacity may be modest or negligible with basic automation of acceleration tasks (i.e., Levels 1a). Rather, the most significant improvements are likely to be achieved when steering is automated or when another aspect of driving, one that brings about shorter following headways (i.e., CACC), is enabled through CV technologies.

4.0 Perform the Phase 1 Exploratory Runs and Report the Results

This section describes the work completed under Task 5, which was to perform the Phase 1 exploratory runs and report the results. Phase 1 sought to demonstrate the suitability of integrated ABM and DTA methods for EMA. A prototype demonstration of the EMA methodology was completed in Task 5 after the reasonableness and sensitivity of the integrated model system was demonstrated in Task 3, and after the methods for simulating various AV-related scenario assumptions were demonstrated and tested individually in Task 4.

4.1 The Experimental Design

Task 5 develop an extensive analysis to meaningfully demonstrate all phases of the EMA approach. Analysis was only constrained by the Phase 1 schedule and resources. For Phase 1, the project team restricted the input assumptions to be varied to four, with up to three levels of each to be tested.

In the ABM:

- The level of **AV ownership** among households.
- The level of **paid rideshare use** and corresponding changes in auto ownership.

In the DTA:

- The level of **allowance for AV operation** (e.g., AV-only lanes).
- The level of **vehicle automation**.

A fractional-factorial orthogonal design was used to allocate the assumption levels to simulation runs, as shown in Table 15. The design includes 16 model runs of which a subset of the most interesting 5 were selected for Phase 1 due to long model runtimes. The project team plans to run all the scenarios in Phase 2 and to possibly extend the plan along additional dimensions if feasible. The coding for Table 15 is as follows:

- AV ownership each ranging from base (B) or zero ownership to low (L), medium (M), and high (H).
- AV sharing (e.g., paid rideshare service utilization) each ranging from base (B) or zero ownership to low (L), medium (M), and high (H).
- Allowance for AV operation: nowhere in the network (N); anywhere in the network (A); exclusively in the left lanes on Interstates 10, 95, and 295 (L) (only in M and H demand scenarios); and exclusively on Interstates (I) (only in H demand scenarios).
- Levels of vehicle automation technology each ranging from 0-5 covering the spectrum of degree of automation according to widely accepted definitions (see previous discussion of adaptation of DTA for AVs performed in Task 4), plus CV strategies such as CACC. These strategies are coded 0-5 and C to represent Level 3 automation and CACC.

Table 15. Experimental design for 16 scenario runs.

#	Ownership	Shared	Allowance	Technology	Comments
0	B	B	N	0	Base 2010
1	L	H	A	2	Run in Phase 1.
2	M	M	L	3	Run in Phase 1.
12	H	L	L	3	Run in Phase 1.
14	H	H	A	C	Run in Phase 1.
4	H	H	I	C	Run in Phase 1.
5	L	H	L	3	L-H demand scenario with the other three supply scenarios besides A-2.
6	L	H	A	C	L-H demand scenario with the other three supply scenarios besides A-2.
7	L	H	I	C	L-H demand scenario with the other three supply scenarios besides A-2.
8	M	M	A	2	These are the M-M demand scenario with the other three supply scenarios besides L-3.
9	M	M	A	C	These are the M-M demand scenario with the other three supply scenarios besides L-3.
10	M	M	I	C	These are the M-M demand scenario with the other three supply scenarios besides L-3.
11	H	L	A	2	These are the H-L demand scenario with the other three supply scenarios besides L-3.
3	H	L	A	C	These are the H-L demand scenario with the other three supply scenarios besides L-3.
13	H	L	I	C	These are the H-L demand scenario with the other three supply scenarios besides L-3.
15	H	H	L	3	These are the H-H demand scenario with two supply scenarios other than A-C and I-C.
16	H	H	L	C	These are the H-H demand scenario with two supply scenarios other than A-C and I-C.

The experimental design in Table 15 requires doing 16 runs, which is a design of four demand combinations (L-H, M-M, H-L, H-H) times four supply combinations (A-2, L-3, A-C, I-C), except that for #16, which is L-C instead of A-2 in combination with H-H. The reason for this is to compare the three AV facility allowance options (A, L, I) in scenarios that all have the highest levels of automation (C) and use (H-H). Under A, L, and I, AVs can operate anywhere on the network. The restrictions are that in L, non-AVs are not allowed to use the left lane of interstates, and in I, non-

AVs are not allowed to use the interstates at all inside the I-295, so it is about reserving existing capacity for AVs only.

4.2 Confirming the Integration and DTA Model Adaptations

The DTA model has the same geographic scope as that of the NFTPO regional model developed in Cube and DaySim. However, considerable additional local street detail far beyond that of the network used for the static assignments in the regional model had been added to the DTA model prior to this project to reach the parcel-level activity locations that serve as the origins and destinations of trips in the ABM. Even with the parcel-level street detail, the DTA network also retains TAZ centroids and centroid connectors in support of the freight, external, and special generator trips produced in TAZ-TAZ matrices by the trip-based part of the regional model. The coverage area spans four counties: Duval, Clay, Nassau, and St. Johns. The scale of the DTA model is shown in Figure 59.

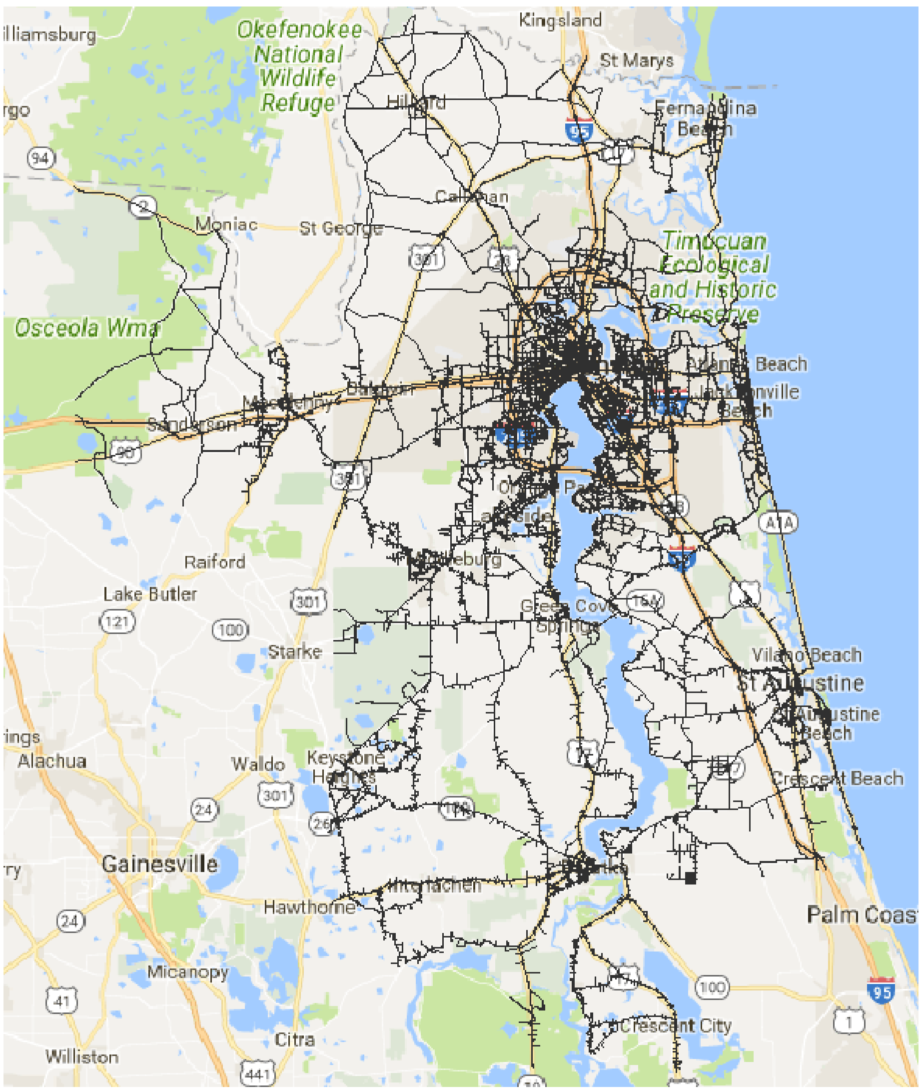


Figure 59. The four county DTA model in North Florida.

Source: Google Maps (Map data ©2018 Google)

To support the integration of the ABM and DTA, the project team modified the TransModeler scripts that automate the import of the tour and trip information produced by the ABM in DaySim to use TAZs rather than parcels as the origins and destinations of trips. This measure simplified the modeling process for the exploratory analysis in Phase 1 of the project; however, this will be revisited and likely revised in Phase 2. The motivation for simulating trips in the DTA from TAZ-to-TAZ rather than from parcel-to-parcel was the ABM-DTA integration objective in Task 3. The ABM implementation expects skims from TAZ-to-TAZ. To compute skims from parcel-to-parcel would come at substantial cost in terms of computational expense. Additionally, the DTA's design is such that it computes skims based only on the origins and destinations of trips, a process that does not lend itself to alteration. That said, the project team could alter the DTA to compute skims based on parcel trip ends and then aggregate those to TAZs prior to feedback to the ABM. This alternative will be attempted in Phase 2 of the project. Figure 60 illustrates the DTA model with TAZ centroids and with parcels in downtown Jacksonville.

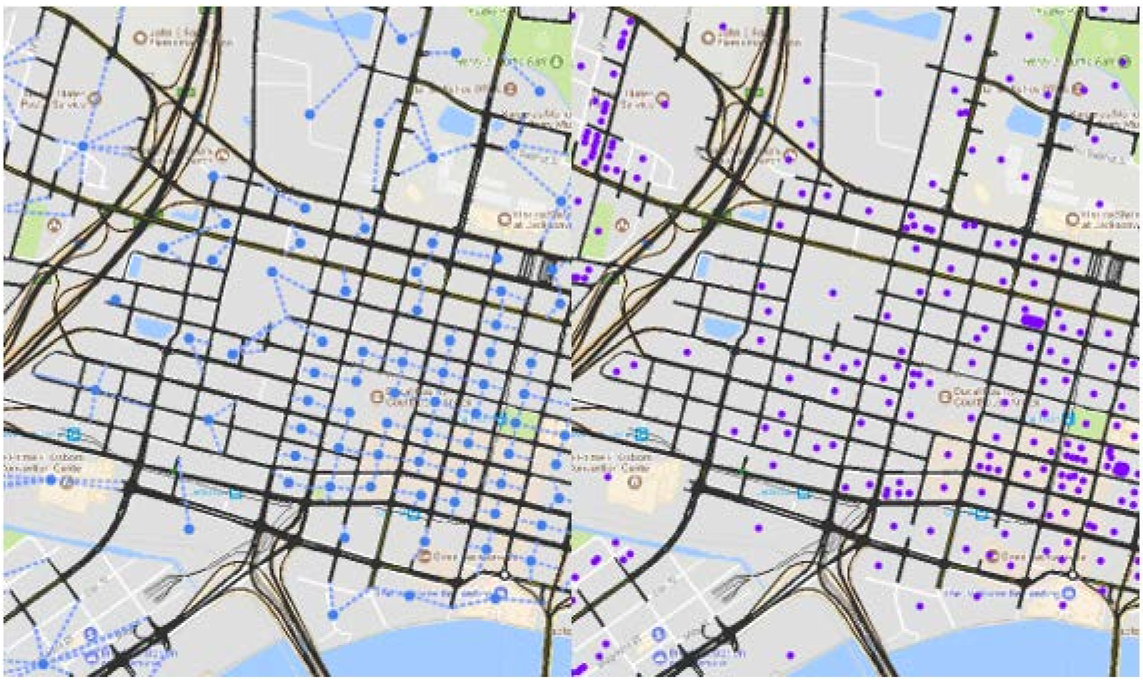


Figure 60. DTA network with centroids & connectors (left) and parcels (right) in Jacksonville.

Google Maps (Map data ©2018 Google)

The project team also verified that the DTA model functional properly and converged. The project team looked for the typical red flags that TransModeler routinely reports as indicators that the DTA network or demand is improperly specified. These red flags include the following:

- Queuing outside the network where links connected to centroid connectors are too fully loaded with traffic to receive new trips attempting to depart.
- Missed turns resulting in trips failing to follow their paths and reach their destinations, which may occur because of network coding errors or capacity insufficient to serve the demand at a particular location.

On reviewing these and other error indicators, the project team determined the DTA model specification to be suitable to proceed with exploratory runs.

4.3 Exploratory Scenario Setup

As described earlier, the exploratory scenarios are a hybrid of existing model components and new ABM-DTA components. To begin, an existing ABM with static skims model run was copied to create a new exploratory scenario. Next, the DaySim resident demand model was run for each scenario to generate a new set of trips, with the possibility of private AV ownership and AV sharing. The AM period trips were then run through TransModeler to produce dynamic skims for a.m. for AV and non-AV trips. The dynamic a.m. skims (and the transpose for p.m.) were then used for AM SOV, HOV, and AV network level-of-service (LOS) in DaySim, and a new set of trips was produced. This final set of trips is summarized in the next section.

For Phase 1, the following base-year population and land-use scenarios were run through the integrated ABM-DTA model:

1. FBB AM-N0: (B)ase (i.e., none) private AV ownership, (B)ase AV vehicle sharing, (N) AVs may not operate anywhere, and (0) level of automation.
1. FHH AM-AC: (H)igh private AV ownership, (H)igh AV vehicle sharing, (A) AVs may operate anywhere, and (C) Level 3 automation + CACC.
2. FHH AM-IC: (H)igh private AV ownership, (H)igh AV vehicle sharing, (I) AVs have exclusive use of some Interstates, and (C) Level 3 automation + CACC.
3. FHL AM-L3: (H)igh private AV ownership, (L)ow AV vehicle sharing, (L) AVs have exclusive use of the left lanes on Interstates, and (3) Level 3 automation.
4. FLH AM-A2: (L)ow private AV ownership, (H)igh AV vehicle sharing, (A) AVs may operate anywhere, and (2) Level 2 automation.
5. FMM AM-L3: (M)edium private AV ownership, (M)edium AV vehicle sharing, (L) AVs have exclusive use of the left lanes on Interstates, and (3) Level 3 automation.

As specified elsewhere, this is a more limited set of scenarios than planned for Phase 1 due to the challenges encountered in the ABM-DTA integration.

4.4 TransModeler DTA Setup

For the demand scenarios, ABM model runs were performed for certain combinations of the B, L, and H demand scenarios, and the output DaySim trip lists were imported into the TransModeler trip data table format for input to the DTA. To simplify the ABM-DTA integration for Phase 1, the project team held the trip-based part of the regional model fixed, relying on an unchanging estimation of the base-year freight, external, and special generator trip matrices. A temporal profile of demand was estimated from 15-minute traffic count data spanning Duval County and applied to the matrices to approximate a rise and fall in demand over the course of the AM peak in a temporal pattern consistent with observed data. The temporal curve is shown in Figure 61.

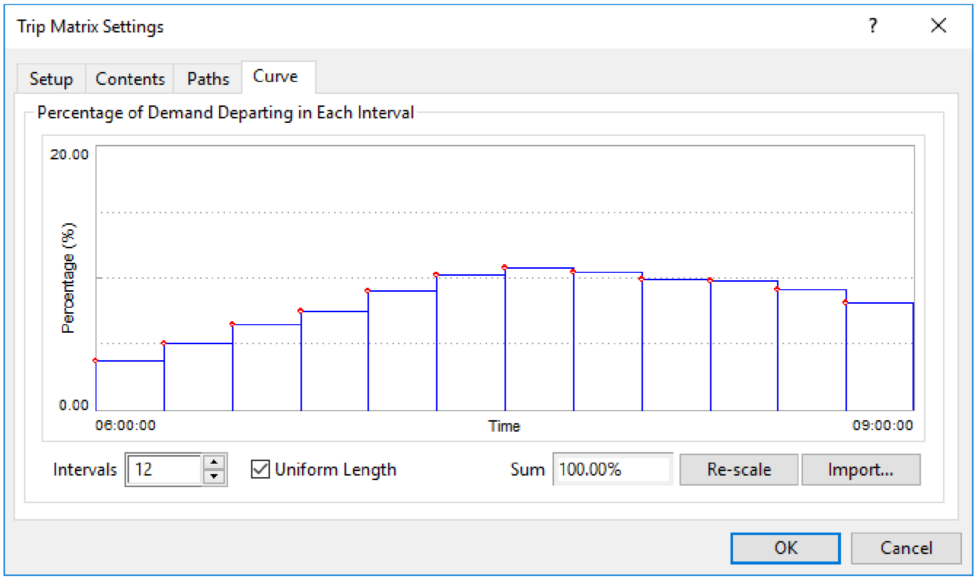


Figure 61. Temporal distribution of trips generated from the trip-based model matrices.

In the supply scenarios L and I, the human driver must control all aspects of driving in AVs when not in the lanes (i.e., left lanes of interstates in supply scenario L) or on the facilities (i.e., on interstates in supply scenario I). These scenarios assume safety-motivated regulatory rules governing the operation of AVs on surface streets where collisions in intersections or conflicts with pedestrians and cyclists are a concern.

Further, to remove a degree of uncertainty from a model of behaviors, systems, and scenarios that is replete with uncertainty, the project team chose to limit the Phase 1 exploratory runs to the a.m. peak hours, from 5:00 a.m. to 9:00 a.m. To simulate the a.m. period eases the burden of defining a critical boundary condition—the presence and pattern of traffic in the network at the beginning of the period to be simulated. A successful simulation of the p.m. peak would hinge on a reasonable loading of the network in the middle of the day, which is considerably more challenging than the more lightly loaded early morning hours. DTA for a 24-hour period is similarly challenging because traffic conditions later in the day hinge on stable, reasonable simulation of the preceding hours. The longer the period to be simulated, the more sensitive the simulation of later hours of the day will be to a reasonable, realistic simulation of the earlier hours, which hinges on a sound estimation of demand and an accurate representation of supply. Because all travel demand model demand requires adjustment or improvement in order to be simulated successfully with operational fidelity, the project team opted to avoid over-adjusting the DTA to the detriment of the focus of the analysis.

4.4.1 Automation of Exploratory Runs

To better facilitate the execution and management of multiple scenarios, the project team developed a script to automate steps performed to complete each run and to produce the desired output. These steps include the following:

1. Copy the simulation network corresponding to the supply scenario over the copy in a working folder.

2. Open the DTA project file and make a copy of a base 2040 scenario, which defines the key inputs, such as the input matrices and time period, to a new, working scenario.
3. Set as input to the working scenario the trip data table corresponding to the demand scenario.
4. Set as input to the working scenario a parameter file defining the automation level and CACC parameters corresponding to the technology scenario.
5. Run a short-term simulation to capture and save a loaded network state to represent traffic already in the network at 5:00 a.m., which is the start of the simulation. Set this initial state as input to the working scenario.
6. Run the DTA for 50 iterations to produce output travel time and delay tables representing congestion patterns to inform route choices in subsequent steps. Set the travel time and delay tables as input to the working scenario.
7. Repeat step five to update the initial state representing 5:00 a.m. such that vehicles in the network at 5:00 a.m. are following routes chosen based on the travel time and delay information produced by the DTA.
8. Set the output settings to produce dynamic skims and run a simulation.
9. Produce the dynamic, 30-minute skim matrices separately for AV and non-AV trips.

In sum, the script automates what would otherwise be a series of steps performed by the user of the DTA software, minimizing model run time and user error.

4.5 Results

An important decision in EMA is which outcome variables to focus on and how to analyze and communicate the results. In this project, the outcome variables analyzed are mostly the same outcome variables used in model calibration and sensitivity testing in the earlier tasks. On the demand side, these include trip rates by person type, income level, purpose, time-of-day, auto ownership/type, mode shares by auto ownership/type, trip travel times and distances, and vehicle miles traveled. On the supply side, the DTA model lends itself to detailed analysis of the ways a strategy or technology might affect the performance of the transportation system and the levels of service that travelers experience. At the center of the DTA is a high-fidelity microsimulation model, which offers a wide range of measures of effectiveness (MOE) that the simulation model can produce, from local measures describing the performance of, for example, an intersection (e.g., queue lengths, signalized delay) to system-wide measures like overall vehicle miles traveled (VMT), vehicle hours traveled (VHT), and delay. Because the DTA model spans a region, the project team used the latter category of MOEs to describe the performance of the network under the various assumptions and scenarios that were modeled. In this analysis, the project team used the traditional definition of delay as the difference between experienced travel time and free-flow travel times.

For Phase 1, the six exploratory scenarios were summarized according to these key metrics:

- Demand:
  - Average skim matrix travel times.
  - Trip and driver type mode shares.
  - Average trip speeds, distances, and household- and person-level VMT.
- Supply:
  - Average skim matrix travel times.
  - VMT, VHT, and delay, by facility type.
  - DTA visualizations.

4.5.1 Trip and Driver Type Mode Shares

Trip mode and driver is a key metric in this EMA. Table 16, Table 17, Table 18, Table 19, Table 20, and Table 21 summarize trips modes for the six scenarios using the static skims and the same six scenarios using the dynamic skims. These results were output by simulating the trips predicted with the static skims (essentially a second global iteration of DaySim). PCV is private conventional vehicle, PAV is private AV, and SAV is shared (TNC) AV. The auto demand and total trip demand increases slightly, which indicates that the travel times in the dynamic skims are lower than in the static skims. This is likely explained by the decision to use the transpose of the a.m. dynamic skims for the p.m. period—the static skims were more congested in the p.m. peak than in the a.m. peak. As shown in Table 18, the largest change in demand is in cells where there are few trips since the mode share does not change by more than 1% in any of the cells. Thus, the difference due to the skims is minor compared to the differences due to the input demand assumptions. This is likely a result of insignificant improvements in effective “capacity” in the network.

Table 16. Trips by mode with static skims, by exploratory scenario.

Trips (Static Skims)	FBB–N0	FLH–A2	FMM–L3	FHL- L3	FHH-AC	FHH-IC
PCV-Driver	4,064,086	1,291,988	996,398	205,379	87,018	87,018
PCV-Passgr	1,466,680	1,509,433	926,903	141,810	117,858	117,858
PAV-"Driver"	--	114,718	1,159,191	2,895,817	1,455,387	1,455,387
PAV-Passgr	--	96,916	836,957	1,768,428	1,382,966	1,382,966
SAV-"Driver"	--	2,424,427	1,543,000	573,945	2,552,686	2,552,686
SAV-Passgr	--	584,192	375,698	142,317	612,821	612,821
Walk	353,416	314,496	329,743	334,219	255,897	255,897
Bike	86,788	77,391	70,617	58,509	54,839	54,839
Transit	22,201	26,261	33,728	22,476	17,940	17,940
School Bus	125,759	54,622	65,278	78,203	45,596	45,596
Total	**6,118,930**	**6,494,444**	**6,337,513**	**6,221,103**	**6,583,008**	**6,583,008**

Table 17. Trips by mode with dynamic skims, by exploratory scenario.

Trips (Dynamic Skims)	FBB–N0	FLH–A2	FMM–L3	FHL–L3	FHH-AC	FHH – IC
PCV-Driver	3,904,254	1,250,584	954,278	196,611	83,031	82,238
PCV-Passgr	1,353,815	1,461,304	892,030	136,390	112,733	112,033
PAV-"Driver"	--	117,877	1,154,198	2,847,766	1,427,823	1,426,896
PAV-Passgr	--	97,440	822,984	1,725,803	1,344,445	1,344,882
SAV-"Driver"	--	2,372,020	1,513,206	561,631	2,493,417	2,491,801
SAV-Passgr	--	568,010	365,919	140,122	594,215	594,176
Walk	558,000	422,388	420,631	410,861	368,369	368,772
Bike	105,305	97,948	88,386	73,339	74,707	74,999
Transit	44,393	26,934	33,834	22,494	18,308	18,245
School Bus	117,568	49,582	59,365	71,657	40,738	40,639
Total	**6,083,335**	**6,464,087**	**6,304,831**	**6,186,674**	**6,557,786**	**6,554,681**

Table 18. Difference in Trips by mode static versus dynamic skims, by exploratory scenario.

Difference	FBB–N0	FLH–A2	FMM–L3	FHL–L3	FHH-AC	FHH A–IC
PCV-Driver	-3.9%	-3.2%	-4.2%	-4.3%	-4.6%	-5.5%
PCV-Passgr	-7.7%	-3.2%	-3.8%	-3.8%	-4.3%	-4.9%
PAV-"Driver"	--	2.8%	-0.4%	-1.7%	-1.9%	-2.0%
PAV-Passgr	--	0.5%	-1.7%	-2.4%	-2.8%	-2.8%
SAV-"Driver"	--	-2.2%	-1.9%	-2.1%	-2.3%	-2.4%
SAV-Passgr	--	-2.8%	-2.6%	-1.5%	-3.0%	-3.0%
Walk	57.9%	34.3%	27.6%	22.9%	44.0%	44.1%
Bike	21.3%	26.6%	25.2%	25.3%	36.2%	36.8%
Transit	100.0%	2.6%	0.3%	0.1%	2.1%	1.7%
School Bus	-6.5%	-9.2%	-9.1%	-8.4%	-10.7%	-10.9%
Total	**-0.6%**	**-0.5%**	**-0.5%**	**-0.6%**	**-0.4%**	**-0.4%**

Table 19. Percentage of Trips by mode static skims, by exploratory scenario.

% of Trips (Static Skims)	FBB–N0	FLH–A2	FMM–L3	FHL–L3	FHH-AC	FHH – IC
PCV-Driver	66.4%	19.9%	15.7%	3.3%	1.3%	1.3%
PCV-Passgr	24.0%	23.2%	14.6%	2.3%	1.8%	1.8%
PAV-"Driver"	--	1.8%	18.3%	46.5%	22.1%	22.1%
PAV-Passgr	--	1.5%	13.2%	28.4%	21.0%	21.0%
SAV-"Driver"	--	37.3%	24.3%	9.2%	38.8%	38.8%
SAV-Passgr	--	9.0%	5.9%	2.3%	9.3%	9.3%
Walk	5.8%	4.8%	5.2%	5.4%	3.9%	3.9%
Bike	1.4%	1.2%	1.1%	0.9%	0.8%	0.8%
Transit	0.4%	0.4%	0.5%	0.4%	0.3%	0.3%
School Bus	2.1%	0.8%	1.0%	1.3%	0.7%	0.7%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Table 20. Percentage of Trips by mode dynamic skims, by exploratory scenario.

% of Trips (Dynamic Skims)	FBB–N0	FLH–A2	FMM–L3	FHL–L3	FHH-AC	FHH-IC
PCV-Driver	64.2%	19.3%	15.1%	3.2%	1.3%	1.3%
PCV-Passgr	22.3%	22.6%	14.1%	2.2%	1.7%	1.7%
PAV-"Driver"	--	1.8%	18.3%	46.0%	21.8%	21.8%
PAV-Passgr	--	1.5%	13.1%	27.9%	20.5%	20.5%
SAV-"Driver"	--	36.7%	24.0%	9.1%	38.0%	38.0%
SAV-Passgr	--	8.8%	5.8%	2.3%	9.1%	9.1%
Walk	9.2%	6.5%	6.7%	6.6%	5.6%	5.6%
Bike	1.7%	1.5%	1.4%	1.2%	1.1%	1.1%
Transit	0.7%	0.4%	0.5%	0.4%	0.3%	0.3%
School Bus	1.9%	0.8%	0.9%	1.2%	0.6%	0.6%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Table 21. Absolute difference in trips, by mode static vs. dynamic skims.

Abs. diff. mode share	Diff. versus static	FBB–N0	FLH–A2	FMM–L3	FHL–L3	FHH-AC
PCV-Driver	-2.2%	-0.5%	-0.6%	-0.1%	-0.1%	-0.1%
PCV-Passgr	-1.7%	-0.6%	-0.5%	-0.1%	-0.1%	-0.1%
PAV-"Driver"	--	0.1%	0.0%	-0.5%	-0.3%	-0.3%
PAV-Passgr	--	0.0%	-0.2%	-0.5%	-0.5%	-0.5%
SAV-"Driver"	--	-0.6%	-0.3%	-0.1%	-0.8%	-0.8%
SAV-Passgr	--	-0.2%	-0.1%	0.0%	-0.2%	-0.2%
Walk	3.4%	1.7%	1.5%	1.3%	1.7%	1.7%
Bike	0.3%	0.3%	0.3%	0.2%	0.3%	0.3%
Transit	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%
School Bus	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%	-0.1%
Total	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**	**0.0%**

4.5.2 Average Trip Speeds, Distances, and VMT

Table 22 through Table 24 show the average trip speed by mode under the various EMA scenarios for both the static and dynamic skims as inputs to DaySim. The average speeds for the trips that are made are about 8% lower with the dynamic skims than with the static skims. They are especially lower for the shared AV trips, which are mainly in the more urbanized part of the area. This suggests that the AV skim speeds are lower than the conventional skim speeds. This could be because the AV trips are in different geographies. Table 25 through Table 29 show the average trip distances by mode under the various EMA scenarios for both the static and dynamic skims as inputs to DaySim. Table 30 through Table 38 summarize VMT across the EMA scenarios.

Overall, compared to the MM scenario, there is a slight increase in total VMT in the scenarios with high private AV ownership and a small decrease in total VMT in the scenarios with large shared AV use. This is because the high mileage-based cost and higher urban availability of the shared AVs means a shorter average trip distance, as noted above, for shared AV trips than for private AV trips. This is also why there is a lower average trips distance across all modes in the LH scenario (private AV low, shared AV high), even though there is a higher average trip distance across each of the vehicle modes separately. Some of the medium distance trips shift from private vehicles to shared AV, which raises the average trip distance for both the shared vehicles and the private vehicles. The relationship goes the other way when there are fewer shared AVs—compared to the MM scenario, the average trip distance for each mode separately goes down, but the overall average trip distance goes up.

Table 22. Average trip speeds, by mode with static skims.

Static Skims	FBBN0	FLHA2	FMML3	FHLL3	FHHAC	FHHIC
PCV-driver	43.3	45.0	44.5	43.9	43.8	43.8
PCV-passgr	41.5	42.9	42.8	42.5	42.7	42.7
PAV-main	--	46.3	46.0	45.6	45.7	45.7
PAV-extra	--	43.6	43.3	43.0	43.4	43.4
SAV-main	--	43.2	42.9	41.8	43.1	43.1
SAV-extra	--	40.7	40.4	39.7	40.4	40.4
Walk	2.5	2.5	2.5	2.5	2.5	2.5
Bike	10.0	10.0	10.0	10.0	10.0	10.0
Transit	6.5	6.4	6.3	6.2	6.4	6.4
School bus	40.8	42.3	42.3	42.2	42.4	42.4
Total	**37.5**	**37.4**	**37.8**	**39.0**	**39.3**	**39.3**

Table 23. Average trip speeds, by mode with dynamic skims.

Dynamic Skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	42.0	42.7	42.2	41.7	42.4	41.6
PCV-passgr	41.2	41.5	41.1	40.8	41.5	40.8
PAV-main	--	42.0	41.5	41.4	41.7	40.8
PAV-extra	--	39.8	39.5	39.5	40.1	39.4
SAV-main	--	39.9	38.8	37.5	39.0	37.9
SAV-extra	--	38.2	37.2	36.2	37.0	36.4
Walk	2.5	2.5	2.5	2.5	2.5	2.5
Bike	10.0	10.0	10.0	10.0	10.0	10.0
Transit	6.4	6.4	6.3	6.2	6.4	6.4
School bus	39.5	40.4	38.6	37.4	37.9	37.1
Total	**33.7**	**34.5**	**34.5**	**35.2**	**35.3**	**34.6**

Table 24. Average trip speeds difference dynamic vs. static skims.

Static Skims	FBBN0	FLHA2	FMML3	FHLL3	FHHAC	FHHIC
PCV-driver	-3.0%	-5.0%	-5.3%	-5.0%	-3.2%	-5.0%
PCV-passgr	-0.6%	-3.4%	-3.8%	-4.0%	-3.0%	-4.4%
PAV-main	--	-9.3%	-9.7%	-9.2%	-8.6%	-10.8%
PAV-extra	--	-8.8%	-8.7%	-8.2%	-7.7%	-9.2%
SAV-main	--	-7.8%	-9.5%	-10.4%	-9.5%	-12.1%
SAV-extra	--	-6.0%	-8.0%	-9.0%	-8.4%	-10.0%
Walk	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Bike	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Transit	-2.8%	0.2%	-0.5%	0.0%	0.2%	0.2%
School bus	-3.1%	-4.6%	-8.6%	-11.4%	-10.8%	-12.5%
Total	**-10.0%**	**-7.8%**	**-8.9%**	**-9.7%**	**-10.1%**	**-12.0%**

Table 25. Average trip distances, by mode with static skims.

Static Skims	FBBN0	FLHA2	FMML3	FHLL3	FHHAC	FHHIC
PCV-driver	6.34	9.39	8.33	7.11	8.38	8.38
PCV-passgr	5.37	6.94	6.47	6.01	6.70	6.70
PAV-main	--	11.19	10.07	8.96	10.41	10.41
PAV-extra	--	7.63	7.01	6.46	7.32	7.32
SAV-main	--	5.10	4.73	4.11	5.01	5.01
SAV-extra	--	3.69	3.49	3.18	3.57	3.57
Walk	0.68	0.89	0.88	0.87	0.87	0.87
Bike	2.35	4.92	4.01	3.00	4.24	4.24
Transit	3.40	5.35	4.99	4.41	5.33	5.33
School bus	4.57	6.60	6.29	5.98	6.98	6.98
Total	**5.67**	**6.21**	**6.56**	**6.99**	**6.48**	**6.48**

Table 26. Average trip distances, by mode with dynamic skims.

Dynamic Skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	7.51	9.51	8.39	7.22	8.56	8.49
PCV-passgr	6.42	7.10	6.61	6.14	6.85	6.83
PAV-main	--	11.51	10.22	9.06	10.61	10.54
PAV-extra	--	7.83	7.24	6.64	7.54	7.51
SAV-main	--	5.21	4.82	4.17	5.12	5.10
SAV-extra	--	3.79	3.56	3.24	3.67	3.66
Walk	0.86	0.84	0.85	0.85	0.82	0.82
Bike	2.74	4.53	3.78	2.97	3.80	3.81
Transit	4.07	5.40	4.99	4.43	5.33	5.34
School bus	5.51	6.96	6.69	6.30	7.42	7.39
Total	**6.51**	**6.22**	**6.58**	**7.02**	**6.51**	**6.48**

Table 27. Average trip distances, by mode difference from FMML3 scenario (static).

Static Skims	FBBN0	FLHA2	FMML3	FHLL3	FHHAC	FHHIC
PCV-driver	-23.9%	12.8%	0.0%	-14.6%	0.6%	0.6%
PCV-passgr	-17.1%	7.3%	0.0%	-7.1%	3.4%	3.4%
PAV-main	--	11.1%	0.0%	-11.0%	3.4%	3.4%
PAV-extra	--	8.8%	0.0%	-7.9%	4.3%	4.3%
SAV-main	--	7.8%	0.0%	-13.1%	5.9%	5.9%
SAV-extra	--	5.9%	0.0%	-8.7%	2.5%	2.5%
Walk	-23.3%	0.5%	0.0%	-1.7%	-1.0%	-1.0%
Bike	-41.5%	22.8%	0.0%	-25.2%	5.6%	5.6%
Transit	-31.9%	7.1%	0.0%	-11.7%	6.7%	6.7%
School bus	-27.3%	5.0%	0.0%	-4.9%	11.0%	11.0%
Total	**-13.6%**	**-5.4%**	**0.0%**	**6.6%**	**-1.3%**	**-1.3%**

Table 28. Average trip distances, by mode difference from FMML3 scenario (dynamic).

Dynamic Skims	FBBN0	FLHA2	FMML3	FHLL3	FHHAC	FHHIC
PCV-driver	-10.4%	13.3%	0.0%	-14.0%	2.1%	1.1%
PCV-passgr	-2.8%	7.5%	0.0%	-7.1%	3.7%	3.3%
PAV-main	--	12.6%	0.0%	-11.3%	3.8%	3.1%
PAV-extra	--	8.1%	0.0%	-8.2%	4.2%	3.7%
SAV-main	--	8.1%	0.0%	-13.4%	6.2%	5.9%
SAV-extra	--	6.7%	0.0%	-8.9%	3.2%	3.1%
Walk	0.9%	-1.0%	0.0%	-0.1%	-3.7%	-3.7%
Bike	-27.6%	20.0%	0.0%	-21.3%	0.6%	1.0%
Transit	-18.4%	8.3%	0.0%	-11.2%	6.7%	7.1%
School bus	-17.6%	4.0%	0.0%	-5.8%	10.9%	10.5%
Total	**-1.0%**	**-5.5%**	**0.0%**	**6.7%**	**-1.1%**	**-1.5%**

Table 29. Average trip distances, by mode difference dynamic minus (static).

Difference	FBBN0	FLHA2	FMML3	FHLL3	FHHAC	FHHIC
PCV-driver	18.6%	1.2%	0.7%	1.5%	2.2%	1.2%
PCV-passgr	19.6%	2.3%	2.1%	2.2%	2.3%	1.9%
PAV-main	--	2.9%	1.5%	1.2%	1.9%	1.2%
PAV-extra	--	2.6%	3.2%	2.9%	3.1%	2.6%
SAV-main	--	2.1%	1.8%	1.4%	2.1%	1.8%
SAV-extra	--	2.8%	2.0%	1.8%	2.6%	2.5%
Walk	27.2%	-4.8%	-3.3%	-1.7%	-6.0%	-6.0%
Bike	16.5%	-8.0%	-5.8%	-0.9%	-10.4%	-10.0%
Transit	19.7%	1.1%	0.0%	0.5%	0.0%	0.3%
School bus	20.6%	5.5%	6.4%	5.4%	6.4%	6.0%
Total	**14.8%**	**0.1%**	**0.3%**	**0.4%**	**0.5%**	**0.0%**

Table 30. VMT with static skims.

Static skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	25,756,129	12,137,078	8,298,843	1,460,738	729,335	729,335
PAV-main	--	1,283,333	11,669,031	25,938,915	15,152,038	15,152,038
SAV-main	--	12,366,071	7,304,004	2,360,363	12,798,425	12,798,425
Total	**25,756,129**	**25,786,482**	**27,271,878**	**29,760,016**	**28,679,798**	**28,679,798**

Table 31. VMT with dynamic skims.

Dynamic skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	29,336,762	11,886,911	8,005,991	1,418,802	710,888	697,803
PAV-main	--	1,356,355	11,793,591	25,803,300	15,143,528	15,038,176
SAV-main	--	12,357,676	7,290,805	2,342,986	12,760,312	12,714,002
Total	**29,336,762**	**25,600,942**	**27,090,387**	**29,565,088**	**28,614,728**	**28,449,981**

Table 32. VMT Difference from the FMM scenario VMT with static skims.

Static skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	210.4%	46.3%	0.0%	-82.4%	-91.2%	-91.2%
PAV-main	-100.0%	-89.0%	0.0%	122.3%	29.8%	29.8%
SAV-main	-100.0%	69.3%	0.0%	-67.7%	75.2%	75.2%
Total	**-5.6%**	**-5.4%**	**0.0%**	**9.1%**	**5.2%**	**5.2%**

Table 33. VMT Difference from the FMM scenario VMT with dynamic skims.

Dynamic skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	266.4%	48.5%	0.0%	-82.3%	-91.1%	-91.3%
PAV-main	-100.0%	-88.5%	0.0%	118.8%	28.4%	27.5%
SAV-main	-100.0%	69.5%	0.0%	-67.9%	75.0%	74.4%
Total	**8.3%**	**-5.5%**	**0.0%**	**9.1%**	**5.6%**	**5.0%**

Table 34. VMT Difference from the static skims.

Dynamic skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	13.9%	-2.1%	-3.5%	-2.9%	-2.5%	-4.3%
PAV-main	--	5.7%	1.1%	-0.5%	-0.1%	-0.8%
SAV-main	--	-0.1%	-0.2%	-0.7%	-0.3%	-0.7%
Total	**13.9%**	**-0.7%**	**-0.7%**	**-0.7%**	**-0.2%**	**-0.8%**

Table 35. VMT per Household Day (static).

Static skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	45.1	21.3	14.5	2.6	1.3	1.3
PAV-main	--	2.2	20.4	45.4	26.5	26.5
SAV-main	--	21.7	12.8	4.1	22.4	22.4
Total	**45.1**	**45.2**	**47.8**	**52.1**	**50.2**	**50.2**

Table 36. VMT per Household Day (dynamic).

Dynamic skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	51.4	20.8	14.0	2.5	1.2	1.2
PAV-main	--	2.4	20.7	45.2	26.5	26.3
SAV-main	--	21.6	12.8	4.1	22.3	22.3
Total	**51.4**	**44.8**	**47.4**	**51.8**	**50.1**	**49.8**

Table 37. VMT per Person-Day (static).

Static skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	18.0	8.5	5.8	1.0	0.5	0.5
PAV-main	0.0	0.9	8.2	18.2	10.6	10.6
SAV-main	0.0	8.7	5.1	1.7	9.0	9.0
Total	**18.0**	**18.1**	**19.1**	**20.9**	**20.1**	**20.1**

Table 38. VMT per Person-Day (dynamic).

Dynamic skims	BBN0	LHA2	MML3	HLL3	HHAC	HHIC
PCV-driver	20.6	8.3	5.6	1.0	0.5	0.5
PAV-main	0.0	1.0	8.3	18.1	10.6	10.5
SAV-main	0.0	8.7	5.1	1.6	8.9	8.9
Total	**20.6**	**17.9**	**19.0**	**20.7**	**20.1**	**19.9**

4.5.3 Average Skim Matrix Travel Times

Table 39 and Table 40 illustrate the mean non-AV and AV a.m. travel times under the different levels of assumed private AV ownership, AV vehicle sharing, AV allowance, and vehicle automation. The mean travel times for the non-AV and VT user classes are similar under each scenario when measures at the regional level. Interestingly, all the AV scenarios result in similar or slightly higher average travel times, with the interstate restrictions for AV resulting in significantly more travel time regionally. These findings suggest AVs do not result in a significant improvement in system performance regardless of the exploratory scenario.

Table 39. Mean dynamic non-AV skim value, by exploratory scenario—Travel Time (8:00 a.m.–8:30 a.m.).

D.S./ Scenario	FBB N0	FLH A2	FMM L3	FHL L3	FHH-AC	FHH-IC	Static Skim
Mean	36.30	36.51	37.28	37.05	36.54	40.46	35.47
Median	31.12	31.33	32.15	31.95	31.41	35.72	31.06
Std. Dev.	23.18	23.30	23.69	23.45	23.29	24.50	22.98
Minimum	0.06	0.06	0.06	1.47	0.07	0.09	0
Maximum	192.41	190.84	193.25	193.01	193.62	194.16	290

Table 40. Mean dynamic AV skim value, by exploratory scenario—Travel Time (8:00 a.m.–8:30 a.m.).

D.S./ Scenario	FBB N0	FLH A2	FMM L3	FHL L3	FHH-AC	FHH-IC	Static Skim
Mean	--	36.55	37.32	37.05	36.58	40.46	35.47
Median	--	31.34	32.17	31.95	31.42	35.72	31.06
Std. Dev.	--	23.26	23.65	23.45	23.25	24.49	22.98
Minimum	--	0.08	0.07	1.47	0.07	0.09	0
Maximum	--	190.84	193.25	193.01	193.62	194.16	290

4.5.4 VMT, VHT, and Delay by Facility Type

Table 41 through Figure 42 summarize VMT, VHT, and vehicle hours of delay, respectively, for various facility types: Interstate, Arterial, and Local. Interstate facilities represent most of the freeway system in the Jacksonville region. Because various supply scenarios restrict access to interstates or to the left lanes of interstate facilities, the VMT, VHT, and delay metrics are examined for interstates independently of arterial and local streets to make sure that any benefits that are observed on interstates are not offset by a deterioration in LOS on arterials or local streets. Because demand varies over time, the metrics are also summarized hourly.

The findings indicate the emergence of AVs may have consequences that offset or outweigh any real benefit in terms of a reduction in VHT or delay. While previous tests demonstrated that different levels of automation and CV technologies may lead to modest increases in operating capacity in congested traffic, the increase in auto trips that accompanies the higher AV adoption scenarios is likely responsible for a far greater shift in LOS in the opposite direction. This shift explains the across-the-board increases in VMT, VHT, and Delay across all AV scenarios relative to the base demand scenario (i.e., BB). Under the most extreme demand assumptions (HH for example) as many as 70,000 additional trips are made relative to the base demand scenario. None of the supply strategies or AV technologies can meaningfully mitigate the increases in vehicle hours of delays most likely brought on by the increase in travel.

However, supply strategies and AV technologies may provide some congestion-mitigating advantages relative to a scenario with the same demand assumptions but without the supply strategy or AV technology. Such is the virtue of EMA: that exploration of an initial set of scenarios may inspire or indicate another. In Phase 2 of the project, the number of scenarios analyzed will be greatly increased to better flesh out the relationships between the range of variables and assumptions enumerated in this analysis.

Despite there being some limitation on the conclusions that may be drawn from the comparisons between the scenarios, two of the scenarios are based on the same demand assumptions (HH) and therefore present an opportunity to compare the advantages of differing supply and technology assumptions. In the HHAC and HHIC scenarios, the AVs are equipped with CACC technology. In the HHIC scenario, those AVs have exclusive access to the left lanes of the interstates outside of I-295 and on I-295 and have exclusive access to all interstates entirely inside I-295. In the HHAC scenario, the AVs may operate with CACC anywhere in the network but do not have exclusive access to any lanes or facilities. In comparing the HHIC and HHAC scenarios, it can be seen, as expected, that operating conditions on the interstates are characterized by fewer VHT and fewer hours of delay in the HHIC scenario than in the HHAC scenario. These benefits appear to be achieved without a notable or consistent deterioration in LOS on the arterial system.

Table 41. VMT summarized by facility type (interstate).

VMT	BBN0	HHAC	HHIC	HLL3	LHA2	MML3
5:00 a.m.	429,648	474,000	465,090	528,324	444,971	481,602
6:00 a.m.	641,431	861,718	859,192	947,223	802,034	868,836
7:00 a.m.	744,196	1,033,802	1,048,297	1,114,110	967,915	1,048,211
8:00 a.m.	670,142	931,991	926,047	1,001,746	826,956	928,020

Table 42. VMT summarized by facility type (arterial).

VMT	BBN0	HHAC	HHIC	HLL3	LHA2	MML3
5:00 a.m.	322,661	337,216	335,868	369,110	315,765	344,223
6:00 a.m.	576,073	699,925	700,488	752,936	648,878	702,158
7:00 a.m.	704,855	985,262	984,087	1,034,579	894,948	955,000
8:00 a.m.	647,647	914,088	902,597	967,545	803,542	867,393

Table 43. VMT summarized by facility type (local).

VMT	BBN0	HHAC	HHIC	HLL3	LHA2	MML3
5:00 a.m.	3,137	2,602	2,500	2,834	2,509	2,522
6:00 a.m.	6,372	5,548	5,646	6,046	5,298	5,564
7:00 a.m.	8,260	8,670	8,950	8,079	7,618	8,318
8:00 a.m.	7,093	8,233	8,514	8,637	7,219	7,638

Table 44. VHT summarized by facility type (interstate).

VHT	BBN0	HHAC	HHIC	HLL3	LHA2	MML3
5:00 a.m.	7,013	7,733	7,692	8,792	7,309	8,048
6:00 a.m.	10,906	15,378	15,305	17,792	14,437	16,063
7:00 a.m.	13,097	21,298	21,127	24,851	19,513	22,035
8:00 a.m.	11,262	18,053	17,557	21,323	16,132	18,984

Table 45. VHT summarized by facility type (arterial).

VHT	BBN0	HHAC	HHIC	HLL3	LHA2	MML3
5:00 a.m.	8,993	9,137	9,170	10,122	8,571	9,404
6:00 a.m.	17,258	21,126	21,326	23,365	19,678	21,522
7:00 a.m.	22,100	34,831	33,703	38,379	31,789	34,553
8:00 a.m.	19,999	31,972	30,871	35,637	29,783	31,274

Table 46. VHT summarized by facility type (local).

VHT	BBN0	HHAC	HHIC	HLL3	LHA2	MML3
5:00 a.m.	127	101	99	111	96	99
6:00 a.m.	268	231	241	258	219	236
7:00 a.m.	355	381	395	362	344	402
8:00 a.m.	299	363	379	380	328	344

Table 47. Vehicle hours of delay summarized by facility type (interstate).

Delay	BBN0	HHAC	HHIC	HLL3	LHA2	MML3
5:00 a.m.	535	621	714	838	631	795
6:00 a.m.	1,125	2,234	2,197	3,300	2,149	2,749
7:00 a.m.	1,734	5,534	5,136	7,850	4,696	6,029
8:00 a.m.	1,087	3,864	3,470	6,051	3,502	4,828

Table 48. Vehicle hours of delay summarized by facility type (arterial).

Delay	BBN0	HHAC	HHIC	HLL3	LHA2	MML3
5:00 a.m.	2,402	2,263	2,323	2,597	2,135	2,386
6:00 a.m.	5,466	6,819	7,011	7,981	6,420	7,178
7:00 a.m.	7,664	14,631	13,546	17,181	13,453	15,002
8:00 a.m.	6,735	13,232	12,371	15,809	13,322	13,507

Table 49. Vehicle hours of delay summarized by facility type (local).

Delay	BBN0	HHAC	HHIC	HLL3	LHA2	MML3
5:00 a.m.	37	27	27	31	25	27
6:00 a.m.	87	73	80	85	68	77
7:00 a.m.	120	134	140	132	127	165
8:00 a.m.	97	128	136	134	122	126

Figure 62, Figure 63, and Figure 64 offer another view of the same data, summarizing VMT, VHT, and delay, respectively, for interstate facilities by hour and scenario. Figure 65, Figure 66, and Figure 67 summarize VMT, VHT, and delay, respectively, for arterial facilities by hour and scenario. Comparing these figures is helpful in light of the reasonable expectation that the supply assumptions that reserve exclusive access for AVs to some lanes or facilities may have consequences for arterial system that may serve as an alternative for non-AV trips. These figures show that the surface transportation system performs best when AVs are not present given the increases in VMT that appear to be a consequence of AVs for both the interstate and arterial system. Further, the worst-performing scenarios in terms of VHT and delay, HLL3 and MML3, are those that reserve the left lanes on all interstate facilities for AVs, which suggests, pending further exploration, that reserving the left lanes on all interstate facilities is not a good strategy, perhaps under intermediate AV adoption assumptions or under any circumstances.

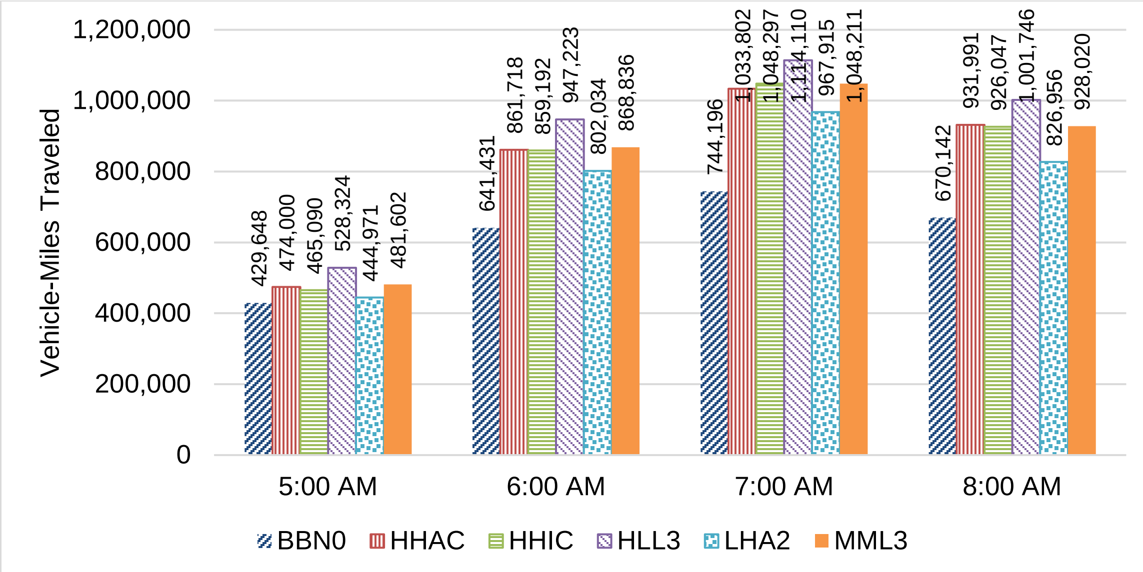


Figure 62. Interstate VMT summarized by hour and scenario.

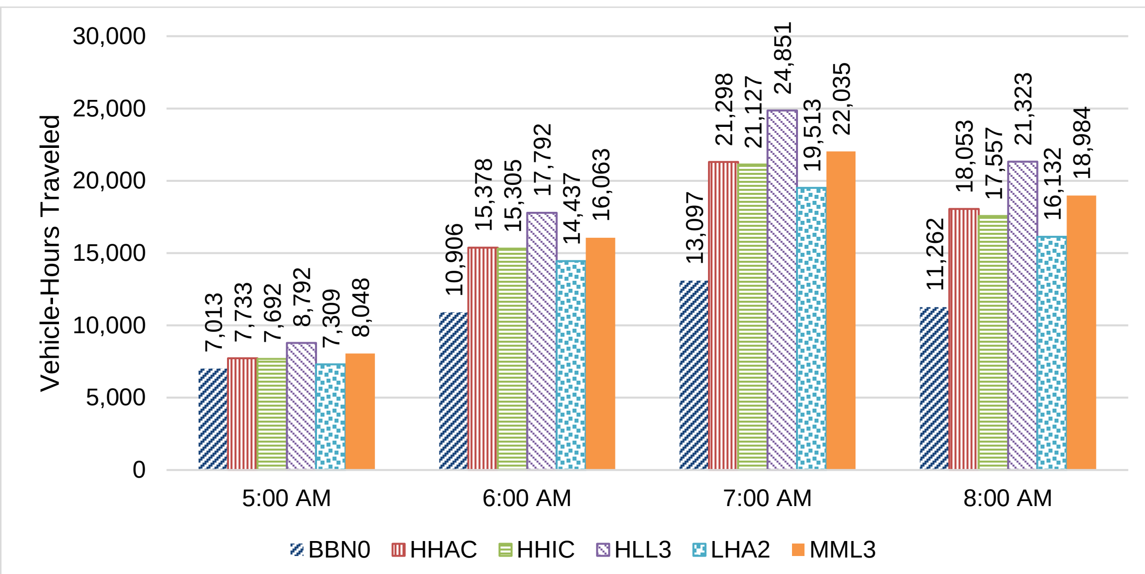


Figure 63. Interstate VHT summarized by hour and scenario.

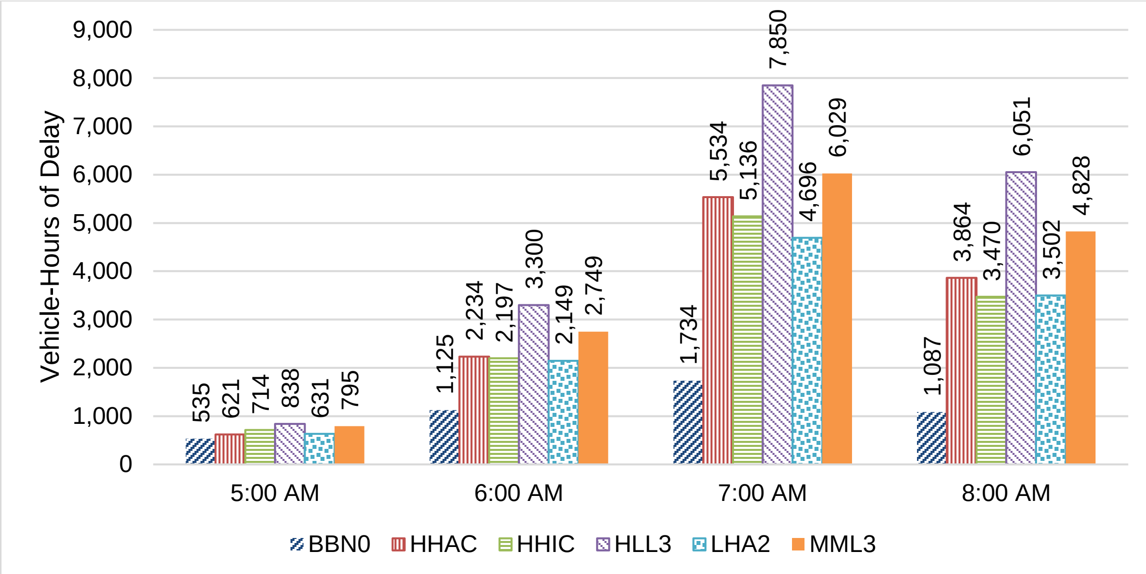


Figure 64. Interstate delay summarized by hour and scenario.

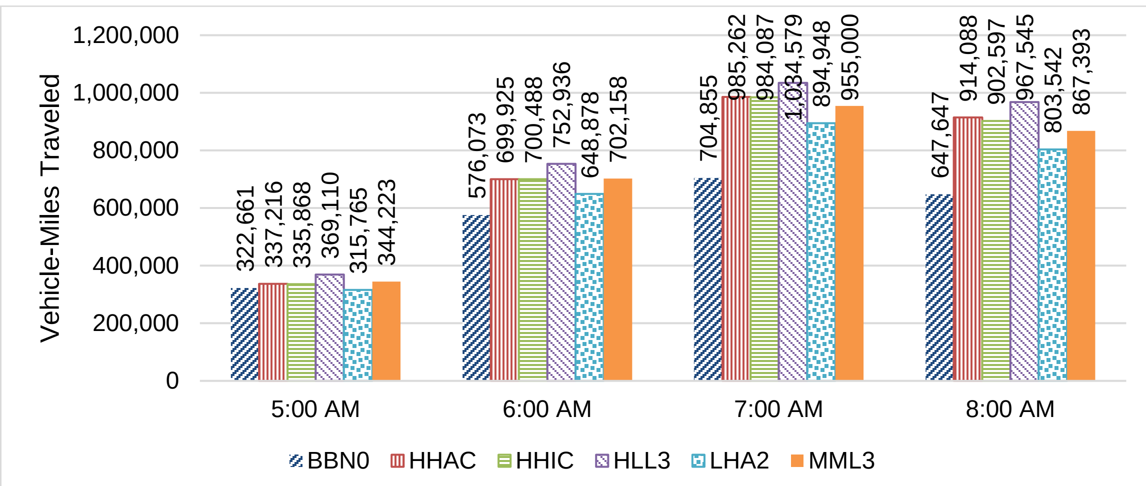


Figure 65. Arterial VMT summarized by hour and scenario.

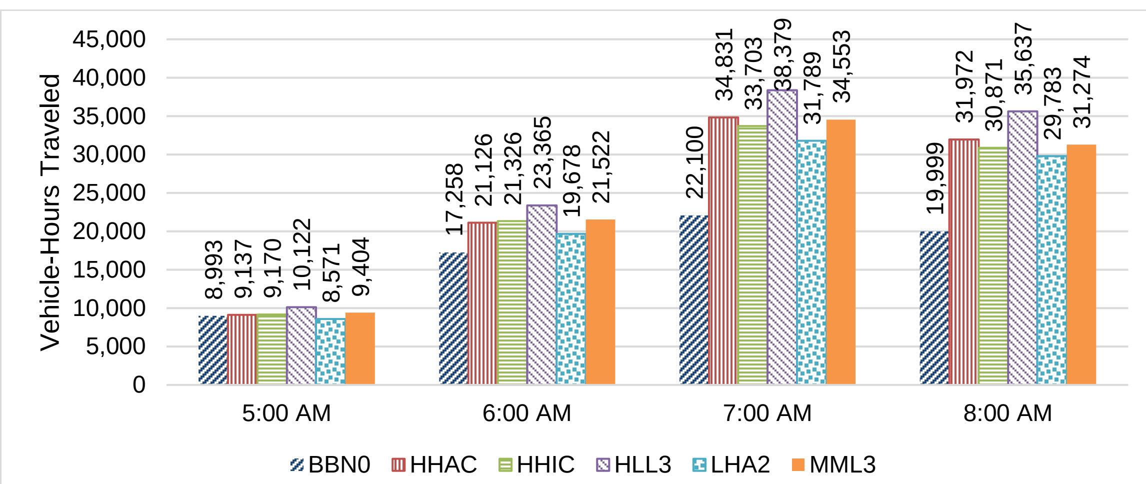


Figure 66. Arterial VHT summarized by hour and scenario.

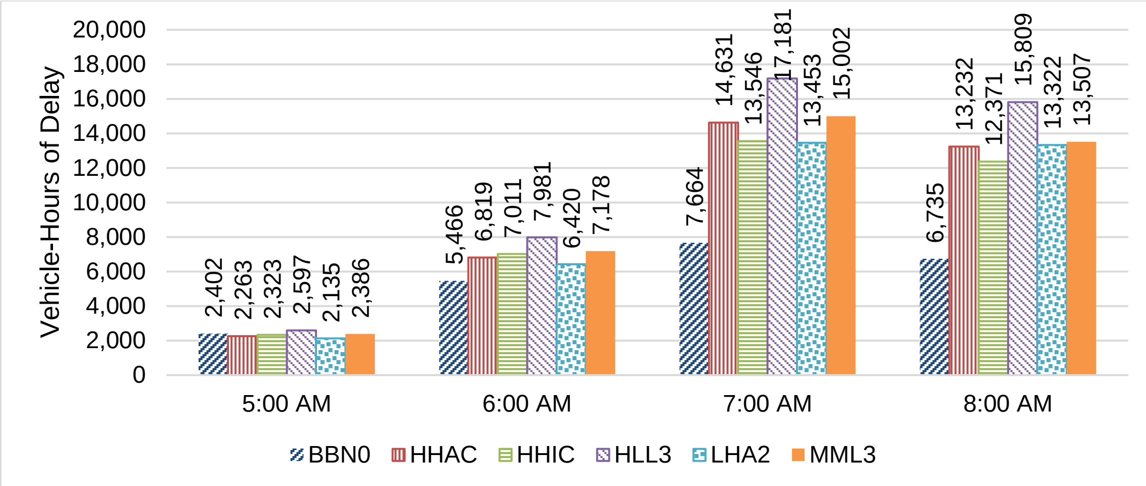


Figure 67. Arterial delay summarized by hour and scenario.

4.5.5 DTA Visualizations

Where tables and charts of model outputs help promote understanding of complex models and processes, simulation as a dynamic modeling tool can help interpret the analysis via animation and visualization. The DTA model that was used to produce the tables and charts previously described is also a time step Monte Carlo simulation in which individual drivers and vehicles are simulated at frequent time steps (i.e., 0.1 to 0.5 seconds). As time steps advance and traffic ebbs and flows, one can observe the animation of the vehicles to better understand traffic congestion patterns and where, how, and why certain bottlenecks form. Figure 69 and Figure 71 show a congested stretch of I-10 Eastbound west of downtown Jacksonville at 8:00 a.m. in the various AV scenarios. In Figure 68 and Figure 69, one can see in the simulation additional evidence supporting the comparison between the HHIC and HHAC scenarios previously discussed. In the image of the HHIC scenario, the back of queue of eastbound traffic headed for downtown Jacksonville can be observed, whereas the back of queue in the image of the HHAC extends considerably farther to the west. This visual comparison of queue lengths confirms the previous tables and charts that suggest the HHAC scenario to have the greater delays of the two scenarios.

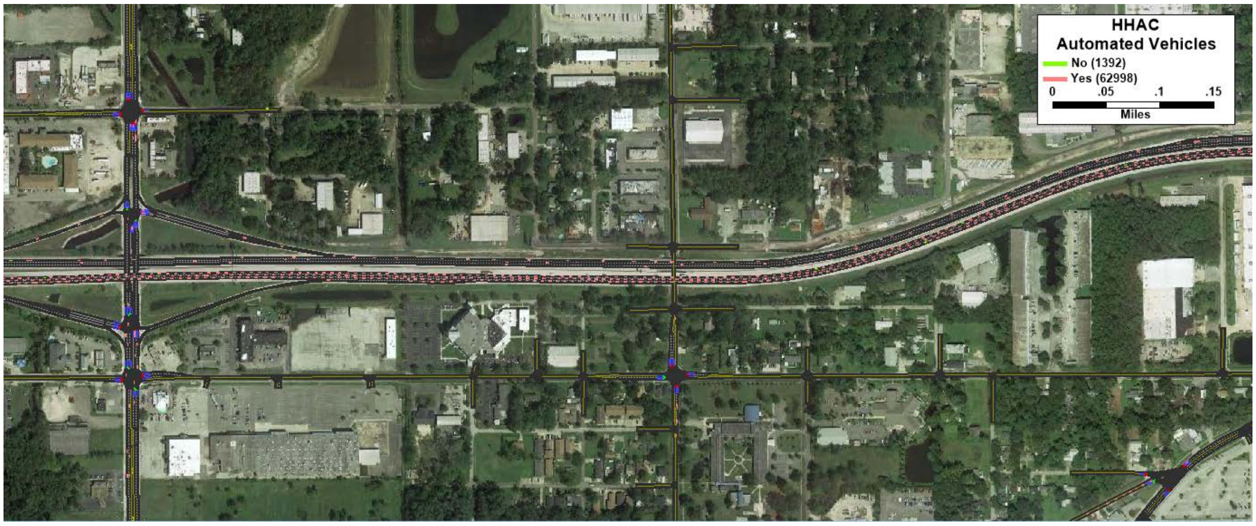


Figure 68. Visualization of back of I-10 Eastbound queue in HHAC scenario.

Source: Image ©2018 Google

Figure 69. Visualization of back of I-10 Eastbound queue in HHIC scenario.

Source: Image ©2018 Google

In the images, the red vehicles are AVs, and the green vehicle are conventional vehicles. Conventional vehicles can scarcely be spotted in the HH demand scenarios, but in other scenarios, one may observe the interactions, for example, between autonomous and conventional vehicles. Figure 70 and Figure 71 show simulations of the HLL3 and MML3 scenarios at same location on I-10. In the images, the greater number of conventional vehicles is evident.

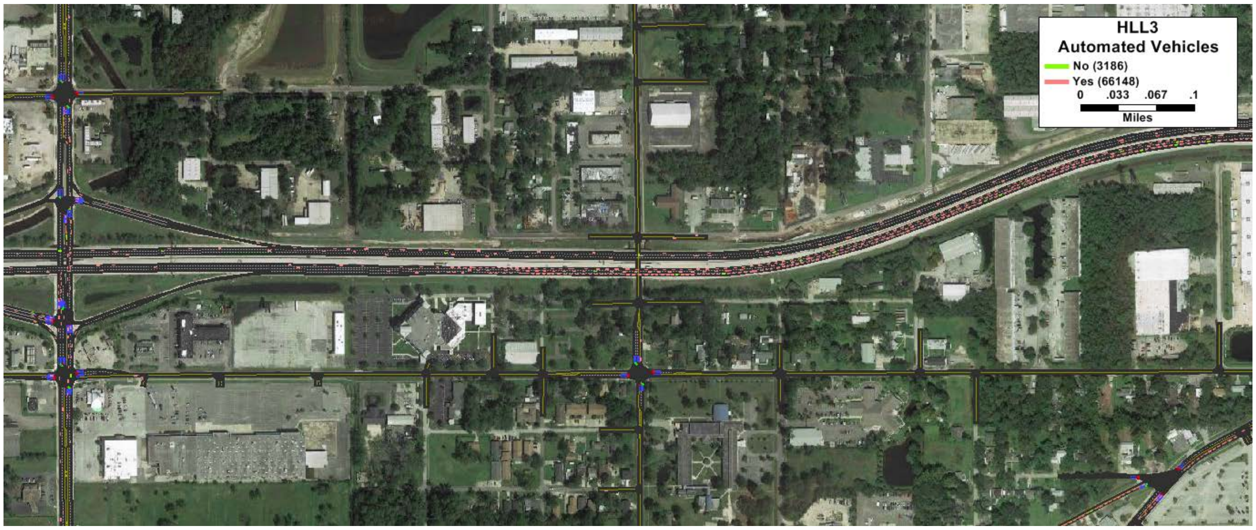


Figure 70. Visualization of back of I-10 Eastbound queue in HLL3 scenario.

Source: Image ©2018 Google

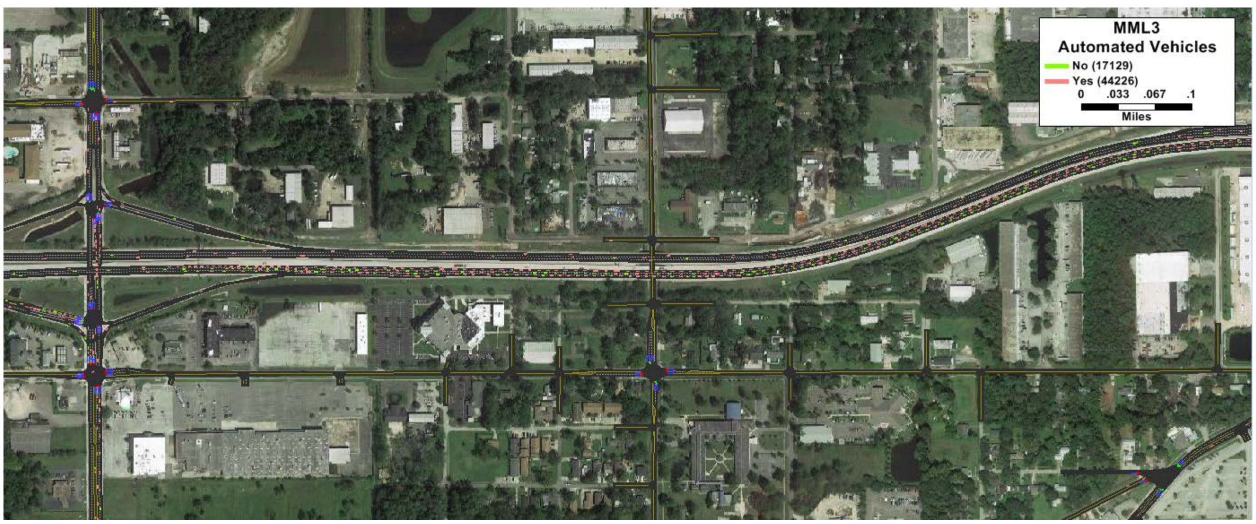


Figure 71. Visualization of back of I-10 Eastbound queue in MML3 scenario.

Source: Image ©2018 Google

5.0 Challenges Encountered

The project team encountered numerous challenges during the exploratory runs. These challenges are described below along with proposed implementations for Phase 2 of the project.

5.1 TAZ-to-TAZ Trip Ends for ABM trips

The decision to simulate the trips from TAZ-to-TAZ rather than from parcel-to-parcel allowed for the production of TAZ-to-TAZ dynamic skims for feedback to the ABM. This was done to avoid more costly revisions that would have been required of either the ABM or DTA to support parcel-to-parcel skims or to transform parcel-to-parcel travel times to TAZ-to-TAZ skims. However, this adversely affected TAZ-to-TAZ travel modeling, which is the effective distribution of trips among loading points (represented by centroid connectors) in a TAZ. Many TAZs in the DTA model are large and have dozens of centroid connectors to streets throughout the zone due to the high level of local street detail. A parcel-level simulation would have set the loading point to the street nearest to the parcel. However, when using centroids and centroid connectors, one must somehow regulate the spread of traffic across loading points via several means, all of which are imperfect, or risk exceeding capacity at loading points, at which point traffic waits outside the network in a virtual queue for an opportunity to enter the network, delaying departures and jeopardizing tour itineraries. The project team used travel costs reflecting the size of the zone to encourage a more diverse selection of loading points in Phase 1, but the mechanism does not prevent loading point overload. In Phase 2, the project team proposes devising a method to simulate the ABM trips parcel-to-parcel and aggregate their travel times to TAZ-to-TAZ matrices prior to feedback to the ABM.

5.2 Model Running Times

As described earlier, the relatively long DTA simulation times makes running many exploratory scenarios somewhat difficult. This issue is compounded by the need to run the ABM and the DTA together, in an iterative fashion, until reasonably converged. The project team will continue to look for ways to improve the DTA simulation times in Phase 2 since this represents the bulk of the overall integrated model runtime.

5.3 Future-Year Demand and Supply Inconsistencies

As is common in planning models, the 2040 forecasts predicted massive growth that is unlikely to be realized. The total forecast demand for 2040, between the ABM and trip-based matrices, is on the order of 1,270,000 trips, representing growth in traffic of almost 50% relative to the approximately 850,000 trips in 2010. This demand exceeds capacity in many parts of the network, leading to long queues by the end of the AM peak. This congestion, in turn, delays arrivals of earlier trips in tours, which delays activities, which delays departures of subsequent trips. At the end of the simulation, large numbers of travelers fail to complete their tours. When observed visually, the route choices and queuing patterns comport with reason and expectation. Surface streets and signalized intersections lack the capacity to serve the demand. The project team proposes to run the scenarios instead with 2010 demand so that the focus may remain on disruption that AVs and CVs may cause and to review the demand estimates to determine where they may be improved.

As a secondary effect of the heavy congestion, considerable resources were spent investigating the causes of queuing outside the network and of failed tours. While investigating, the project team noted shortcomings in the network coding (in terms of representing widening and other capacity projects constructed since 2010 and those that are anticipated for the future but for which no specific plans exist) that were not evident in the earlier DTA tests with 2010 demand. It was also determined that signal timings required significant adjustment to address some queuing problems. Numerous adjustments to the network and signal timings were made based on observations, but those adjustments proved only modestly effectual in resolving the congestion problem. The project team proposes in Phase 2 to gain a fuller understanding of the capital improvement projects that are likely to be built before 2040 or, as previously mentioned, address the issue of high forecast demand in the regional model.

The heavy year 2040 congestion previously described has a tertiary effect of substantially increasing the model running times. Model running times are largely a function not of the size of the network but of the number of vehicles in the network at one time. With the 2040 forecast demand and the heavily congested condition of the network as time advances into the a.m. period, the model running times increased well above the times achieved in the 2010 tests. While some increase in running time will be expected with increased numbers of trips in future years, much of the increase in running times can be attributed to traffic queuing outside the network in large numbers and to large numbers of trips in a tour awaiting the completion of the prior trip and activity. The project team expects the model run times will once again become practicable when the congestion problem is resolved.

6.0 Summary of Phase 1 Approach and Phase 2 Priorities

6.1 Introduction

This project integrated the DaySim ABM with the TransModeler DTA for the region of Jacksonville, Florida, as a basis for EMA. EMA is an approach developed by researchers to deal with "deep uncertainty." The approach is different from typical scenario analysis in that it is designed to deal with many uncertain model relationships and inputs. While more standard scenario analysis might vary a few of the model inputs (e.g., future population growth and income levels), EMA is more appropriate in a future context where even the fundamental relationships or parameters of the model may be in question. Such a context is a "disruptive" technology like AVs and CVs. The EMA approach is similar in concept to the method for "quantitative risk analysis" (QRA) in forecasts described by Adler, et al.[7] and to the method for "ridership and revenue risk analysis" described by Cambridge Systematics.[8]

Table 50 summarizes the key similarities and differences between the QRA approach and the EMA approach. The first three steps—1) selecting output variables to analyze; 2) selecting input assumptions to vary and specific levels of those assumptions to test, and 3) using an experimental design to define a set of runs with different sets of inputs, and carrying out those runs—look similar between the methods. One important difference is that QRA focuses on a few key model outcomes (volume/ridership and revenues), while the EMA approach looks at many model outcomes. Secondly, QRA tends to focus mainly on exogenous input variables, such as sociodemographics while varying only a few key model parameters (e.g., the Cambridge Systematics study varies the alternative-specific constant for high-speed rail and one or two travel time coefficients). The EMA approach focuses more on uncertain model parameters and relationships and less on typical exogenous inputs.

The later phases of the two approaches are quite different. The QRA method produces regression "meta-models" between the selected set of inputs and the key model outcomes and then uses an assumed multidimensional probability distribution of the inputs to carry out Monte Carlo application of the regression model to generate probability distributions of the outcomes. For an EMA context, such as AV futures, there is too much uncertainty to provide meaningful probability distributions on the input assumptions or to generate meaningful quantitative risk assessments on the outputs. Rather, the EMA approach can use several analysis techniques, including graphical surface analysis, regression models, correlation analysis, and other exploratory statistical methods. The objective is to gain a better understanding of the sensitivity of the outputs to each input variable and possibly to interactions of the input variables. EMA is often done iteratively—after learning more about the model responses, one can refine the input assumptions or the model specification and perform additional phases of exploratory analysis.

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[7] Adler, et al. 2014. Methods for Quantitative Risk Analysis for Travel Demand Model Forecasts

[8] Cambridge Systematics, 2016 California High-Speed Rail Business Plan Ridership and Revenue Risk Analysis, Technical Report

Table 50. Comparison of QRA vs. EMA.

QRA of Forecasts	EMA
Select one or two key outputs (e.g., ridership and revenues).	Select a range of outputs to explore.
Select a set of key input assumptions to vary and levels to test. Inputs focus on sociodemographic inputs and a few key model parameters (e.g., toll bias or new mode constants).	Select a set of key input assumptions to vary and levels to test. Inputs cover several model parameters and relationships with less emphasis on sociodemographic inputs.
Use an experimental design to define a set of model runs to test effects of assumptions. Do the model runs and save the outputs.	Use an experimental design to define a set of model runs to test effects of assumptions. Do the model runs and save the outputs.
Use regression analysis to model the key outputs as a function of the input assumption levels.	Use regression analysis, charts, maps, and any other useful presentation methods to explore the various model outputs as a function of the multidimensional variation in the inputs.
Define the joint probability distribution of the input assumption levels.	N/A. Too much uncertainty about the input assumptions to assess probabilities.
Apply the regression model to thousands of sets of input assumptions, drawing each set randomly from the joint probability distribution to create a probability distribution of the key model outputs.	N/A. Too much uncertainty to generate probability distributions of the outputs.

6.2 Summary of the Phase 1 EMA Approach

The first task of Phase 1 was to more tightly integrate the DaySim ABM and the TransModeler DTA, both of which had already been implemented for Jacksonville. As part of this work, the feedback between DaySim and TransModeler was enhanced in important ways. First, the DaySim trip outputs include a new mode (Paid Rideshare) and a new level for the DORP Type attribute (Passenger in an AV). DaySim also uses separate travel time and cost skims for AVs, which means that TransModeler will treat AVs as a separate "user class" and pass back AV-specific skims.

A key challenge being dealt with was the production of dynamic skims—using the TransModeler simulated travel times to update the OD travel time matrices that are fed back to the DaySim demand model. As discussed throughout this report, this was especially challenging due to several DTA modeling challenges, including long runtimes, network entrance and exit (i.e., loading point) issues, and heavy congestion (i.e., gridlock).

The second task focused on adapting the ABM and DTA models to accommodate key dimensions of uncertainty in the context of AVs. The following model input and parameter assumptions can now be modeled and varied because of the Phase 1 work:

- The level of AV ownership among households.
- The level of paid rideshare use and corresponding changes in auto ownership.

- The level of allowance for AV operation (e.g., AV-only lanes).
- The level of vehicle automation.

The project team also proposed using a fractional-factorial experimental design to allow the analysis of the independent effect of each level of each assumption. For example, the four different assumptions listed above can be accommodated using an experiment design with 16 runs. In the end, only six scenarios were run and analyzed due to the issues noted earlier.

6.3 Summary of the Phase 1 EMA Findings

The Phase 1 EMA suggests the transportation system performs best when AVs are not present because of increases in VMT that appear to be a consequence of AVs for both the interstate and arterial systems. However, the work to date also suggests that many more scenarios must be run to draw more comprehensive conclusions. Phase 1 compared the performance of each scenario to FBB–N0 as a baseline, but there are enough extra trips in the FMM, FLH, FHH, and other trip tables that it is not possible to tell whether a supply strategy or technology will provide any benefits relative to a FBB scenario. If the delay increases, it may simply be a consequence of the change in trip-making. Thus, in Phase 2, the project team plans to run the complete set of scenarios—four of the most interesting demand scenarios, each with four different supply scenarios, to analyze what is causing the differences. The project team also plans to address several simulation issues, including the appropriate level of network loading (e.g., TAZs vs. parcels).

6.4 Phase 2 Priorities

The highest-priority work for Phase 2 is to improve the integrated ABM-DTA model so it can more easily be used for the EMA analysis. Long runtimes and heavy congestion due to various network simulation issues will likely continue to plague this project if not satisfactorily resolved. Issues to be resolved include the following:

- Load trips onto the network at the parcel level instead of the TAZ level.
- Clean up the network, intersection geometry, and signal timing.
- Produce dynamic skims that reasonably match observed travel time estimates from sources like Google Maps.
- Possibly move to a future-year scenario in order to experience more congestion, which may result in greater benefits from CAVs. However, this may backfire as demand may be forecasted to be unrealistically related to supply, or vice versa.

Based on interest of FHWA and the project team, the Phase 2 EMA will model vehicle sharing behavior and empty vehicles in more detail and more thoroughly address parking options. On the demand side in DaySim, these changes will include being able to represent different assumptions regarding the following:

- Changes in intrahousehold ridesharing/chauffeuring behavior due to AV ownership (and associated changes in the generation of empty vehicle trips). For example, an AV may drop off a household commuter then return home empty to be available for any nonworkers until it has to pick up the commuter at the end of the work day.

- These household decisions should also reflect parking availability for AVs at the destinations as that may influence the relative attractiveness of returning home.

On the network side in TransModeler, these changes will include being able to represent different assumptions regarding the following:

- The way in which paid ridesharing services route and locate vehicles when empty. While it would be difficult to model an "optimal" system, some reasonably efficient behavior should be possible to simulate. (This could influence the typical passenger wait times that are passed to DaySim.)
- Different treatment of empty vehicle trips on the network. For example, empty vehicles could be prohibited from using congested facilities during peak periods.
- The location and supply of parking, including super-stacked or remote parking for self-parking vehicles. (Only off-street parking will be dealt with explicitly, and, due to schedule constraints in Phase 2, it will likely be necessary to make simplifying assumption about the way that parking supply is represented.)

In addition to the specific model system revisions described here, the project team will address the following questions when developing the Phase 2 work plan:

- Should the sources of uncertainty that were already modeled and analyzed in Phase 1 be modified in any way, including new levels to test or new ways of incorporating them into the ABM and DTA models?
- Should additional sources of uncertainty be added to the analysis? If so, how should those new input assumptions be incorporated into the ABM and DTA models, and what specific levels should be tested in simulation?
- How should the EMA experimental design be modified?
    - Should new input assumptions or levels be added into the analysis?
    - How successful was the Phase 1 experimental design?
    - The phase 1 model run times are quite long. How should the phase 2 experimental design be revised as a result?
- Based on the effectiveness of the methods used in Phase 1 to analyze and communicate the outcomes, how can the analysis and visualization methods be enhanced for Phase 2?
- What are the best visualizations for explaining the EMA results? This is especially importation when presenting results of unknown input distributions.

7.0 References

Bradley, M., Bowman, J., and B. Griesenbeck. (2009). SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution. *Journal of Choice Modeling*, Vol. 3, No. 1, pp. 5-31.

Caliper Corporation (2015). Traffic Assignment and Feedback Research to Support Improved Travel Forecasting. Final Report Prepared for the Federal Transit Administration Office of Planning and Environment. Newton, MA.

Morgan, D., Yang, Q., and H. Slavin. (2015). "Simulation-based Dynamic Traffic Assignment for Planning Applications." Presentation to the North Carolina DOT Model Users' Group. November 19, 2015.

North Florida Transportation Planning Organization. (2016). Northeast Regional Planning Model: Activity-based: Technical Report #4: Calibration and Validation.

Strategic Highway Research Program. (2013). "SHRP 2 Report S2-C04-RW-1: Improving our Understanding of How Highway Congestion and Pricing Affect Travel Demand." Transportation Research Board, Washington, DC.

Strategic Highway Research Program. (2014). "SHRP 2 Report S2-C10A-RW-1: Dynamic, Integrated Model System: Jacksonville Area Application." Transportation Research Board. Washington, DC.

Wang, J., and R. Rajamani. (2004) "Should Adaptive Cruise-Control Systems be Designed to Maintain a Constant Time Gap Between Vehicles?" IEEE Transactions on Vehicular Technology, Vol. 53, No. 5, pp. 1480-1490.

NOTICE

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