# Volume 2: Model Impacts of Connected and Autonomous/Automated Vehicles (CAVs) and Ride-Hailing with an Activity-Based Model (ABM) and Dynamic Traffic Assignment (DTA)—An Experiment

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**16. Abstract**

This report describes the experiment on how to model impacts of connected and autonomous/automated vehicles (CAVs) and ride-hailing with an Activity-Based Model (ABM) and Dynamic Traffic Assignment (DTA) in the context of Exploratory Modeling and Analysis (EMA). EMA is a systematic approach to perform sensitivity analyses using models when users cannot assert many of the model inputs with confidence. The example EMA described integrates the DaySim activity-based travel demand model with the TransModeler dynamic traffic simulation model for the Jacksonville, Florida, region. The approach adapts the travel demand model to simulate households' decisions whether to purchase CAVs instead of conventional vehicles and to simulate travelers' decisions whether to use CAV-based carsharing and ride-hailing services. The dynamic network model simulates operating characteristics of CAVs—depending on network vehicle mix—and simulates the performance of CAV-only infrastructure under different demand scenarios. The integrated model system simulates dozens of different scenario combinations to demonstrate the potential of exploring possible outcomes and finding critical input assumptions while identifying future policy directions that are likely to be the most robust in the face of "deep uncertainty."

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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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| km | kilometers | 0.621 | miles | mi |
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| $m^2$ | square meters | 10.764 | square feet | $ft^2$ |
| $m^2$ | square meters | 1.195 | square yards | $yd^2$ |
| ha | hectares | 2.47 | acres | ac |
| $km^2$ | square kilometers | 0.386 | square miles | $mi^2$ |
| | | **VOLUME** | | |
| mL | milliliters | 0.034 | fluid ounces | fl oz |
| L | liters | 0.264 | gallons | gal |
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**April 2018**

**Federal Highway Administration**

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# List of Abbreviations

| | |
|---|---|
| ABM | activity-based model |
| AV | autonomous/automated vehicle |
| CACC | cooperative adaptive cruise control |
| CAV | connected and autonomous/automated vehicle |
| CV | connected vehicle |
| DTA | dynamic traffic assignment |
| DVE | driver-vehicle entity |
| EMA | Exploratory Modeling and Analysis |
| BB | EMA CAV scenario |
| FHWA | Federal Highway Administration |
| MM | EMA CAV scenario |
| HH | EMA CAV scenario |
| HHAC | EMA CAV scenario |
| HHIC | EMA CAV scenario |
| HHLC | EMA CAV scenario |
| HL | EMA CAV scenario |
| HOV | high-occupancy vehicle |
| IC | EMA CAV Scenario |
| LC | EMA CAV Scenario |
| LH | EMA CAV Scenario |
| LOS | level-of-service |
| MM | EMA CAV scenario |
| NFTPO | North Florida Transportation Planning Organization |
| OD | origin-destination |
| SAE | Society of Automotive Engineers |
| SHRP | Strategic Highway Research Program |
| SOV | single-occupancy vehicle |
| TAZ | traffic analysis zone |
| TNC | transportation network company |
| V2I | vehicle-to-infrastructure |
| V2V | vehicle-to-vehicle |
| V2X | vehicle-to-everything |
| VHD | vehicle hours of delay |
| VHT | vehicle hours traveled |
| VMT | vehicle miles traveled |
| VOT | value of time |
| VPHPL | vehicles per hour per lane |

# 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 *Acknowledgments*

FHWA would like to acknowledge the assistance of the North Florida Transportation Planning Organization (NFTPO) who generously agreed to share their models for this work.

## 1.3 *Introduction and Approach*

This report describes the experiment performed using Exploratory Modeling and Analysis (EMA) with detailed simulation models to help transportation planning agencies understand the impacts of connected vehicle (CV), autonomous/automated vehicle (AV), and ride-hailing technologies.

Connected and autonomous/automated vehicle (CAV), which combines CV and AV capabilities, is an increasingly common term. CAV encompasses both CVs with vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), or vehicle-to-everything (V2X) communication technologies with AV technologies. Exploratory modeling may focus more on either the connected capabilities or the autonomous capabilities of vehicles. For example, a city or state may want to grow/support V2I technologies through capital commitments, while modelers (as in the example exercise described here) may be more interested in analyzing consumer adoption rates of AVs. Importantly, a CV may not be autonomous, and an AV may not be connected.

Ride-hailing, also known as real-time ridesharing, matches a car and driver with the requestor to make a one-time trip in the immediate future. Ride-hailing has been popularized by transportation network companies (TNCs) like Uber and Lyft. At the time of this writing, nearly all ride-hailing services available to the public require a human driver for the vehicle. In the future, TNCs may shift to a fleet of CAVs, or auto manufacturers may deploy fleets for drivers to rent/share while doing ride-hailing work.

The instructions and accompanying example exercise described here integrate the DaySim activity-based model (ABM) with the TransModeler dynamic traffic assignment (DTA) model for the Jacksonville, Florida, region. The integrated model system simulates 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.” The approach adapts the travel demand model to simulate households’ decisions whether to purchase CAVs instead of conventional vehicles and to simulate travelers’ decisions whether to use CAV-based carsharing and ride-hailing services. The dynamic assignment model simulates operating characteristics of CAVs and the performance of CAV-only infrastructure under different demand scenarios.

The organization of this report is as follows:

- **Introduction to Exploratory Modeling and Analysis**.
- **Review of ABM and DTA Models and Approach to Integration**.
- **Revisions to the ABM for CAVs**.
- **Revisions to the DTA Models for CAVs**.
- **Example Exploratory Model Runs and Analysis**.
- **Conclusions and Future Areas of Research**.

The primary objective of this work is to demonstrate and assess the reasonableness of EMA with an integrated ABM-DTA model for understanding the impacts of CAVs and ride-hailing in the long-range planning context. The existing ABM and DTA models were extended/adapted in a reasonable manner to incorporate an understanding of CAVs and ride-hailing. Like most modeling exercises, in practice, the limitations of existing frameworks shape the current approach. However, even while working largely within the existing model frameworks, the two core modeling tools serve as an excellent starting point for this exercise and, as modified, represent the most successful integration of ABM and DTA to date.

For more detail about the initial research-oriented phase of this effort, see Volume 1: *Integrated ABM DTA Methods to Model Impacts of Disruptive Technology on the Regional Surface Transportation System – A Feasibility Study*.

# 2.0 Overview of Exploratory Modeling and Analysis

EMA is a systematic approach to perform sensitivity analyses using models when users cannot assert many of the model inputs with confidence. This helps simultaneously test several different input assumptions. The objective is to find patterns in the results to guide robust decision-making (Lempert, et al., 2003). In brief, the core components of EMA are as follows:

- Define the scope of the system analysis.
- Define the key system relationships and sources of uncertainty.
- Define a method for modeling the system (interactions and inputs).
- Define a method for simultaneously varying the input assumptions to cover a wide range of future scenarios along the defined dimensions of uncertainty.
- Define a method for investigating and communicating the results of applying the model(s) across the wide range of scenarios.

## 2.1 *Uncertainty in Travel Demand Forecasting*

As described by Dewar and Wachs (2008), travel demand forecasting is especially appropriate for EMA since:

> *"Travel demand forecasting as widely practiced today deals inadequately with uncertainty…The current transportation modeling process is demanding in the sense that it employs a great deal of data to a large number of interconnected models having many parameters. The complexity of the modeling process, however, does not extend to the accurate representation of complex economic and social phenomena, and point estimates of many quantities are used that make it difficult to analyze or even to represent the uncertainty that characterizes transportation systems and traveler decision making."*

As suggested above and described in Table 1, travel demand models typically allow for variations in a few key inputs such as the spatial allocation of households and employment and the current transportation options. However, foundational changes, such as new modes of travel or new relationships between the economic and social components of travel, require making many uncertain assumptions for modeling. These uncertain assumptions are best understood in the context of EMA.

**Table 1. Typical travel model input variation across scenarios.**

| Yes | No | Comments |
|---|---|---|
| Spatial allocation of households and employment | Total regional population, employment, demographic shifts | Sometimes scenarios allow for structural shifts in the region/economy |
| Transportation infrastructure, extent and attractiveness of existing services, and pricing | Basic types of travel modes available (especially for auto) | To model CAVs and the ride-hailing scenarios, the basic types of modes available need to be revised, which requires many uncertain assumptions. As a result, this is not typically done in scenario analysis. |
| Travel demand management (such as parking cost) | Model relationships and parameters (such as parking no longer being needed for a single-occupancy auto trip) | To model CAVs and the ride-hailing scenarios, one must vary the model relationships and parameters, which requires many uncertain assumptions |

## 2.2 *EMA Steps for this Example Exercise*

Even though the word "exploratory" may connote an ad hoc approach, EMA is a structured methodology for investigating future scenarios with diverse sources of uncertainty. This example exercise demonstrates an approach to design and test an analytical framework to support the EMA process. The main steps in the approach for this exercise are as follows:

1. Define and select the key sources of uncertainty for input assumptions and the levels of each. (See Key Sources of Uncertainty)
2. Design the analytical model framework to simulate scenarios and ensure that it can represent each of the selected input assumptions. (See Review of ABM and DTA Models and Approach to Integration and Revisions to the ABM Model for CAVs/Revisions to DTA Models for CAVs)
3. Create an experimental design to efficiently analyze the influence of each level of the various input assumptions on the simulated scenario outcomes without simulating every possible combination of inputs. (See Example Exploratory Model Runs and Analysis)
4. Select the scenario outcomes to evaluate and the metrics and analysis methods to evaluate them. (See Example Exploratory Model Runs and Analysis)
5. Implement and test the analytical 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 Revisions to the ABM Model for CAVs/Revisions to DTA Models for CAVs)
6. Conduct the scenario simulation runs specified in the experimental design. (See Example Exploratory Model Runs and Analysis)

7. Analyze the selected scenario outcomes as a function of the input assumptions and communicate the results to help understand the relative importance of the key sources of uncertainty. This includes regression analysis of the scenario outputs as a function of the input assumptions. (See Example Exploratory Model Runs and Analysis)
8. Evaluate the findings and possible extension or enhancement through further EMA. (See Conclusions and Future Areas of Research)

## 2.3 *Key Sources of Uncertainty*

EMA first requires defining and selecting the key sources of uncertainty for use as input assumptions and the levels of each to test. In the example exercise described here, the project team focused on transportation supply and demand in the Jacksonville, Florida, metropolitan region. This is the same planning region as modeled for the metropolitan planning organization's long-range transportation plan. This region was selected for this example exercise since its existing ABM and DTA models could be adapted for EMA of CAVs.

Next, the project team identified and selected the multiple dimensions of uncertainty related to CAV adoption and use. The selected sources of uncertainty enabled the project team to assess the practicality and effectiveness of using the integrated ABM-DTA model for EMA. While a more comprehensive EMA application might consider many additional sources of uncertainty, the approach and example exercise outlined in this report included the set that the project resources permitted studying.

The key sources of CAV travel demand uncertainty for this example exercise are as follows:

1. The ***market penetration and use of AVs*** is the highest-priority assumption to include in the ABM. Simulating the effect of AVs on the network requires predicting whether each auto trip is made in a conventional vehicle or AV. Hence, it was necessary to adapt DaySim to "decide" which households will choose to own AVs instead of conventional vehicles.

2. The ***disutility of in-vehicle time in AVs*** is another assumption to include in the ABM. Productivity, comfort, and perceived safety can affect this assumption. As described later, different value-of-time (VOT) distributions are assumed to directly or indirectly affect every choice model in the ABM and this informs the DTA.

3. The ***level of use of carsharing and ride-hailing as a substitute for private vehicle use*** is a third critical assumption to include in the ABM.

The project team considered other sources of travel demand uncertainty but did not include these in this example exercise due to the significant level of effort required to adapt the existing ABM framework. These other sources of uncertainty are as follows:

1. ***Parking behavior at the destination for AV trips may change*** to include use of nearby superstacked parking at remote parking locations (e.g., just outside the city center).

2. ***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 arise. Such a change would require significant software revisions to simulate every detail of the behavioral mechanisms of how such a change might manifest between household members.

3. 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. Other types of empty vehicle trips can pertain to autos owned by ride-hailing services searching for and picking up passengers and AV trips to remote parking locations. The ABM estimates trips for individuals and does not explicitly model vehicles.

4. ***Telecommuting and peak-spreading behavior*** could change because of 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 already reflect such changes to some extent without adaptation. However, it is conceivable that mass adoption of AVs and TNCs could result in systemic travel changes and cause other shifts to the timing of trips. 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. This project did not consider this revision since it requires significant updates to the day-pattern models used to build the ABM.

5. ***Latent demand for car travel could generate new trips*** in currently congested areas if congestion levels were reduced considerably using AVs or ride-hailing systems. Since major reductions in congestion are not expected on a region-wide basis, the extent of potential induced travel is uncertain.

The key sources of CAV network supply uncertainty for this example exercise are as follows:

1. ***Different vehicle headway and speed characteristics for CAVs*** since CAVs are expected to achieve higher safe traveling speeds or shorter safe following distances than conventional vehicles.

2. ***Provision of CAV-only lanes*** since CAVs will operate most safely and efficiently when they only interact with other CAVs.

The project team considered other sources of network supply uncertainty but did not include these in this example exercise due to the significant level of effort required to adapt the existing DTA framework. These other sources of uncertainty are as follows:

1. The ***frequency and severity of accidents*** for CAV and conventional vehicles in dedicated and mixed-use lanes was not considered in the initial EMA work but is a good candidate for future work.

2. ***Narrowing of traffic lanes*** made possible by CAV-only traffic and resulting changes in capacity was not considered for inclusion in the DTA since the existing network facilities are expected to remain intact.

3. The ***location and use of parking***, including superstacked or remote parking for self-parking vehicles was not considered in the initial EMA work but is a good candidate for future work.
4. ***Paid ride-hailing operator characteristics***, including fleet size, where vehicles in the fleet are located when the simulation begins, how best to match vehicles with ride requests (by making use of constraints such as the travel time between a vehicle's current location and the location of the traveler requesting a ride), (if and) when vehicles will reposition themselves after dropping off a customer, what to do with requests that cannot be served within reasonable time constraints by the available fleet, etc. The project team designed and implemented a paid ride-hailing (TNC) operator module but was not able to finalize it in time for the EMA exercise.
5. The ***location and use of parking***, including superstacked or remote parking for self-parking vehicles was not considered in the initial EMA work but is a good candidate for future work.

The adaptations to the ABM and DTA to incorporate the key sources of uncertainty are described in the Revisions to the ABM Model for CAVs and Revisions to DTA Models for CAVs sections.

# 3.0 Review of ABM and DTA Models and Approach to Integration

The foundation for the EMA analysis is the DaySim ABM framework and software (Bradley, et al., 2009) and the TransModeler DTA software. DaySim was first applied in the Jacksonville region in 2012 for the Strategic Highway Research Program (SHRP2) C10A project (Strategic Highway Research Program, 2014). The NFTPO subsequently adopted DaySim as the model for project planning in 2016 (NFTPO, 2016). The TransModeler was implemented in the Jacksonville region in 2015 by dynamically assigning the trips output by the existing ABM (Morgan, et al., 2015).

## 3.1 *Existing ABM and DTA Models*

The Jacksonville ABM operates at the individual parcel level for land-use variables and spatial choice models. The auto and transit networks are represented at the zonal level with approximately 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, PM peak, evening, and night).

The DaySim software is open source and is maintained online (RSG, 2018). 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 Windows workstation with 12 cores, DaySim requires approximately 30 minutes to simulate weekday travel for the roughly 2 million residents of the Jacksonville region. Memory required for the Jacksonville region is less than 8 GB of RAM.

The Jacksonville ABM 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 the nonresident market components (i.e., 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 are responsible for a significant share of the runtime for the entire model system.

TransModeler is a commercial software package (Caliper Corporation, 2018). The TransModeler DTA encompasses the whole regional planning network and runs microscopically. Microscopic simulation in TransModeler conveys the following features and advantages:

- Ground truth, accurate road and intersection geometry.
- Lane-level and intersection-area representation.
- Temporal dynamics (as low as 0.1 second).
- Vehicle dynamics (e.g., car-following, lane-changing).
- Realistic route choice models.

- Complex network infrastructure (e.g., traffic signals, variable message signs, sensors).
- Multiple simulation modes, user classes, and vehicle types.

Before this project, the traffic simulation software allowed the user to interactively produce travel time matrices resembling network skim matrices based on simulated trip travel times. However, the ability to fill in cells representing origins, destinations, and time intervals for which no trips were simulated based on time-dependent shortest paths was not a fully developed feature. In addition, the creation of the matrix could not yet be automated in a model script for integration with the ABM. As described later, the project team evolved the skim matrix feature in the DTA software for this example exercise. Integrating the ABM with the DTA (rather than static assignment) leverages the activity-based demand simulation's spatial and temporal detail.

Number of processing cores on the central processing unit (CPU) is probably the single-most important determinant of model runtime. A workstation with a minimum of 12 cores is recommended to run the model. However, CPU clock speed, RAM, and hard disk type (e.g., hard disk drive vs. solid state drive) also have an effect. Runtimes to complete 25 iterations of the 4-hour (5:00 a.m.–9:00 a.m.) peak period DTA and to generate skims on various Windows workstations with 12 cores required ran in as little as 15 hours on some workstation configurations and as many as 36 hours on others. Later iterations in a DTA run in less time than the earlier iterations, in which route choices based on unequilibrated travel times and delays are suboptimal. Hence, a DTA run for 50 iterations would not quite double running times.

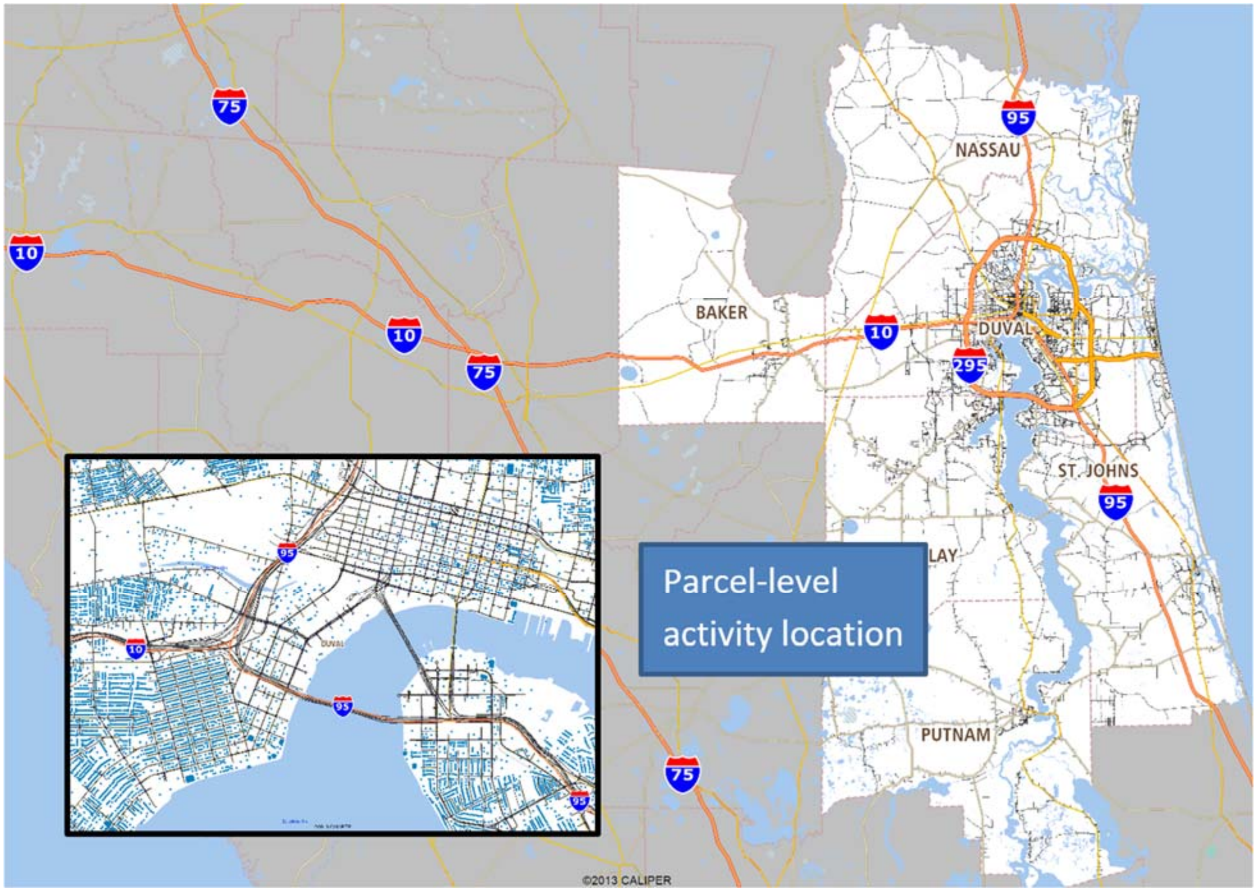


**Figure 1. Regional DTA.**

## 3.2 *Approach to Integration*

DaySim provides the demand (a list of trips) for TransModeler to simulate on the network. TransModeler provides congested travel times back to DaySim to use in simulating demand for the next iteration. The demand simulation and network simulation can run iteratively until an acceptable level of stability is reached in the travel time matrices. This conceptual framework is not fundamentally different from what is currently used for the integration of DaySim with static assignment using Cube or TransCAD. The main differences are that the TransModeler simulation framework is not limited to a specific zone system or to broad time periods for traffic assignment, allowing for flexible customization of the level of spatial and temporal fidelity that best facilitates integration with a given ABM (as discussed below). The traffic simulation can leverage the spatial and temporal detail produced by the demand simulation and model link delays and intersection delays more realistically than is possible in static zone-to-zone assignment methods. All other non-DTA model components (e.g., external trip matrices, transit skims) are borrowed from the existing NFTPO model. A more complete solution would address these integration deficiencies, but this is beyond the scope of this EMA example.

In sum, the example exercise ABM-DTA integration is twofold:

- ABM to DTA:
  - The ABM outputs a list of trips (over 6 million daily trips), parcel-to-parcel, minute-to-minute.
  - The DTA model aggregates the parcel-level trips to traffic analysis zones (TAZs) and then builds several zone connectors to simulate the diversity of real-world loading points.
  - The non-ABM demand for freight, externals, etc. from the existing NFTPO model is also passed to the DTA as aggregate trip matrices. These trips are processed into individual trip lists with more detailed simulated times and locations.
- DTA to ABM:
  - The DTA outputs dynamic TAZ-to-TAZ travel time skims, in 30-minute periods, by user class (e.g., conventional vehicles and AVs).
  - The dynamic travel time skims are created by first running the simulation and then calculating a shortest-path travel time for each origin, destination, and departure time period. The skimmed paths include average simulated turn movement delay.
  - The nonauto network LOS skims (e.g., walk-to-transit) remained fixed from the existing NFTPO model.

Additional information on the integration follows.

## 3.3 *ABM Enhancements for DTA Integration*

The ABM software already outputs trips by minute and by parcel with user VOT. In addition, DaySim can also read TransCAD/TransModeler skim matrices by time period. The only revision made to the ABM software for DTA integration was to modify the chronological consistency of trips generated (See Issues Encountered).

## 3.4 *DTA Enhancements for ABM Integration*

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 PM 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 the NFTPO trip-based model, and numbers of occupants and VOT are supplied by the lists of tours generated by the DaySim ABM.

As part of the DTA model's development prior to this example exercise, 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. The project team enhanced both the TransModeler software and the tools previously developed to link the DTA model to the regional model to support tighter integration between the DTA model and the DaySim-Cube travel demand model:

1. The project team extended the TransModeler software to manage the simulation of DaySim tours as interdependent, rather than independent, sequences of trips. The project team also modified the tools that transfer the trip data between the DTA model and the NFTPO regional model to maintain the relationships between trips in a tour.
2. The project team wrote modeling software and scripts to make it simpler to run DTAs programmatically and to automate the production of dynamic travel time skims for consumption by the DaySim model. The example exercise produced skimming tools accessible as functions belonging to TransModeler's GIS Developer's Kit, a scripting environment enabling customization of the software. For example, to produce dynamic skims once a DTA is completed, run the following commands:

```
self.SetSimulationRunMode("Simulation")
self.SetDynamic Skims("True")
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 (such as AVs), and "User B" is a designation of trips (such as non-AVs).

## 3.5 *Integrated Setup*

Once the integration of the model components is functioning, the next step is to finalize a model system that is practical for the many model runs that comprise the EMA approach. Due to the long runtimes associated with DTA, the project team decided to only run the example exercise DTA for the AM period. As a result, only the dynamic skims (in 30-minute time intervals) for the conventional and CAV travel times for the AM period and for the PM period (after the AM skims are transposed) are fed back to the demand model. The example integrated ABM-DTA model is run through a DOS BAT file that calls the ABM and DTA programs iteratively and manages the input and output files accordingly (i.e., trip lists and dynamic travel time skims by iteration).

## 3.6 *Verification*

Before applying the integrated model system for EMA, it is important to verify the system produces reasonable results. A good starting point for verifying the model system is to review the dynamic travel time skims, the demand model trip lengths and mode shares, and the DTA simulation results. The key new output of the ABM-DTA integrated system is the dynamic travel time skims.

Comparing the dynamic skims to the static skims and to expected travel times from a third-party source such as Google Maps is recommended.

From the example exercise, the mean DTA travel time skim value was approximately 10 minutes greater than the mean static model travel time skim value (Table 2). The maximum origin-destination (OD) travel time is also significantly greater in the DTA model. These patterns are true for all dynamic time periods.

**Table 2. Descriptive statistics of AM period skims.**

| DS\Mode | SOV Static | HOV2 Static | HOV3 Static | 5:30–6:00 Dynamic | 6:00–6:30 Dynamic | 6:30–7:00 Dynamic | 7:00–7:30 Dynamic | 7:30–8:00 Dynamic | 8:00–8:30 Dynamic | 8:30–9:00 Dynamic |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 41.2 | 41.2 | 41.2 | 49.8 | 50.9 | 52.1 | 52.8 | 52.9 | 52.2 | 51.8 |
| Median | 38.3 | 38.3 | 38.3 | 44.7 | 45.4 | 47.4 | 48.2 | 48.0 | 47.0 | 46.4 |
| Std. Dev. | 26.8 | 26.8 | 26.8 | 33.1 | 33.5 | 33.7 | 33.3 | 33.5 | 33.5 | 33.6 |
| Minimum | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 |
| Maximum | 140.1 | 140.1 | 140.1 | 208.4 | 209.9 | 210.2 | 210.7 | 210.7 | 210.7 | 210.8 |

To better understand the differences, the project team randomly chose 10 OD pairs and compared the static and dynamic skims to the Google travel times. Figure 2 shows the Google Maps path and Table 3 compares skims from the example exercise.

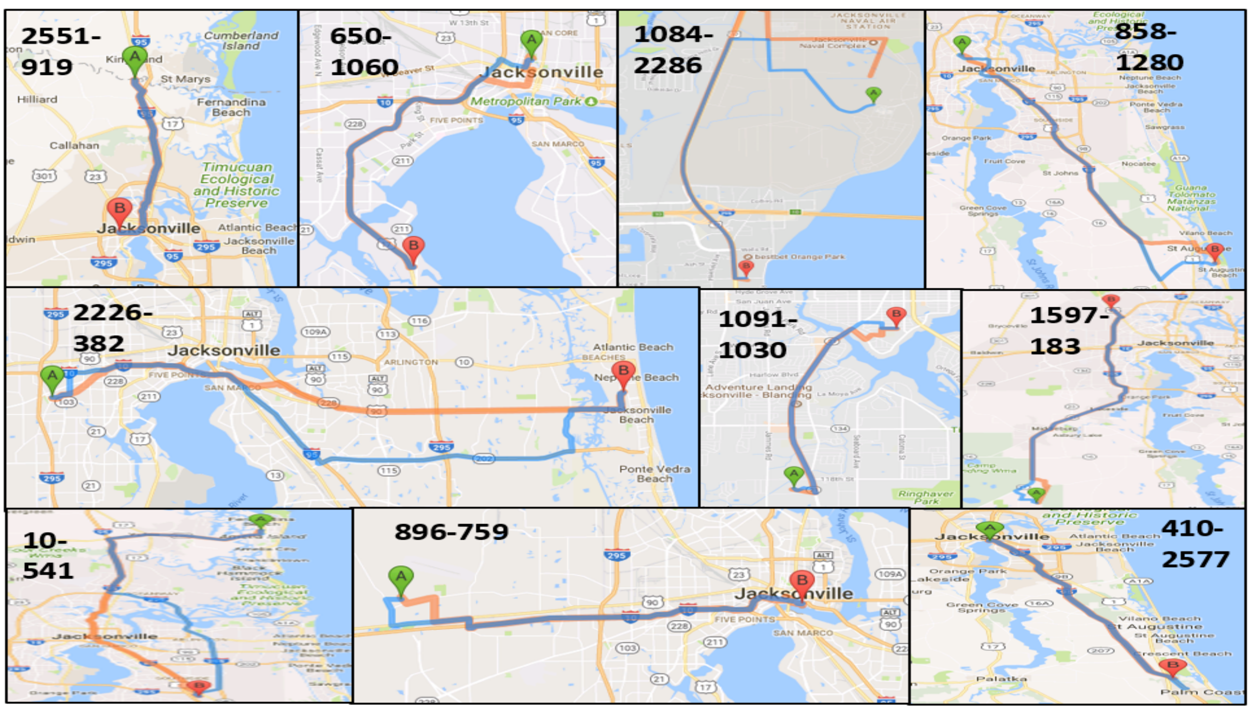


**Figure 2. Google Maps path.**

Source: Google Maps (Map data ©2018 Google)

The project team found the dynamic travel times match well with the Google Maps travel times. The static model travel times appear lower, at least in comparison to Google Maps. Overall, the travel times for the selected OD pairs appear reasonable

**Table 3. Comparison of skims with Google Maps.**

| OD Pair | | Static | | | Dynamic (AM) | | | | | | | Google Maps (AM) (Monday April 2, 2018) | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Origin | Destination | SOV | HOV2 | HOV3 | 5:30–6:00 | 6:00–6:30 | 6:30–7:00 | 7:00–7:30 | 7:30–8:00 | 8:00–8:30 | 8:30–9:00 | 5:30–6:00 | 6:00–6:30 | 6:30–7:00 | 7:00–7:30 | 7:30–8:00 | 8:00–8:30 | 8:30–9:00 |
| 10 | 541 | 50 | 50 | 50 | 54 | 55 | 59 | 60 | 59 | 55 | 55 | 50–70 | 50–75 | 55–90 | 55–85 | 55–80 | 55–75 | 55–75 |
| 410 | 2577 | 53 | 53 | 53 | 52 | 52 | 52 | 52 | 53 | 52 | 52 | 50–65 | 50–65 | 50–65 | 50–65 | 50–70 | 50–70 | 50–65 |
| 650 | 1060 | 9 | 9 | 9 | 12 | 13 | 13 | 14 | 15 | 15 | 14 | 12–16 | 12–18 | 12–18 | 12–20 | 12–20 | 12–22 | 12–22 |
| 858 | 1280 | 49 | 49 | 49 | 54 | 55 | 55 | 56 | 56 | 55 | 55 | 55–70 | 55–75 | 55–75 | 55–85 | 55–85 | 55–80 | 55–80 |
| 896 | 759 | 18 | 18 | 18 | 22 | 24 | 25 | 25 | 25 | 24 | 24 | 22–28 | 24–35 | 26–45 | 28–50 | 28–45 | 26–40 | 24–35 |
| 1084 | 2286 | 5 | 5 | 5 | 6 | 7 | 7 | 7 | 7 | 7 | 7 | 5–7 | 5–8 | 5–9 | 5–9 | 5–9 | 5–9 | 5–9 |
| 1091 | 1030 | 5 | 5 | 5 | 7 | 7 | 7 | 8 | 8 | 8 | 7 | 9–14 | 9–14 | 10–14 | 10–16 | 10–14 | 10–14 | 10–16 |
| 1597 | 183 | 49 | 49 | 49 | 53 | 57 | 62 | 62 | 61 | 60 | 59 | 60–80 | 60–80 | 60–80 | 60–80 | 60–80 | 60–80 | 60–80 |
| 2226 | 382 | 28 | 28 | 28 | 32 | 34 | 35 | 37 | 36 | 35 | 34 | 35–45 | 35–55 | 35–60 | 40–70 | 40–65 | 40–60 | 35–55 |
| 2551 | 919 | 33 | 33 | 33 | 34 | 34 | 37 | 37 | 38 | 35 | 34 | 30–40 | 30–40 | 30–40 | 30–45 | 30–40 | 30–40 | 30–40 |

The project team then investigated the correlation between the static and dynamic skims. In the example exercise, the project team drew a series of scatterplots with static skims on the x-axis and the dynamic skims of various time intervals on the y-axis, as shown in Figure 3. The results show a strong correlation between the static and dynamic skims, with the dynamic travel times higher on average. The plots also revealed a cluster of outliers parallel to and above the regression line. Further investigation by the project team revealed that nearly all these points are related to one zone, the external zone 2558, which contained a network coding error the project team subsequently corrected. Such errors are a routine consequence of any model's development. Scrutiny of model results is critical to identifying them in the development stages of the EMA.

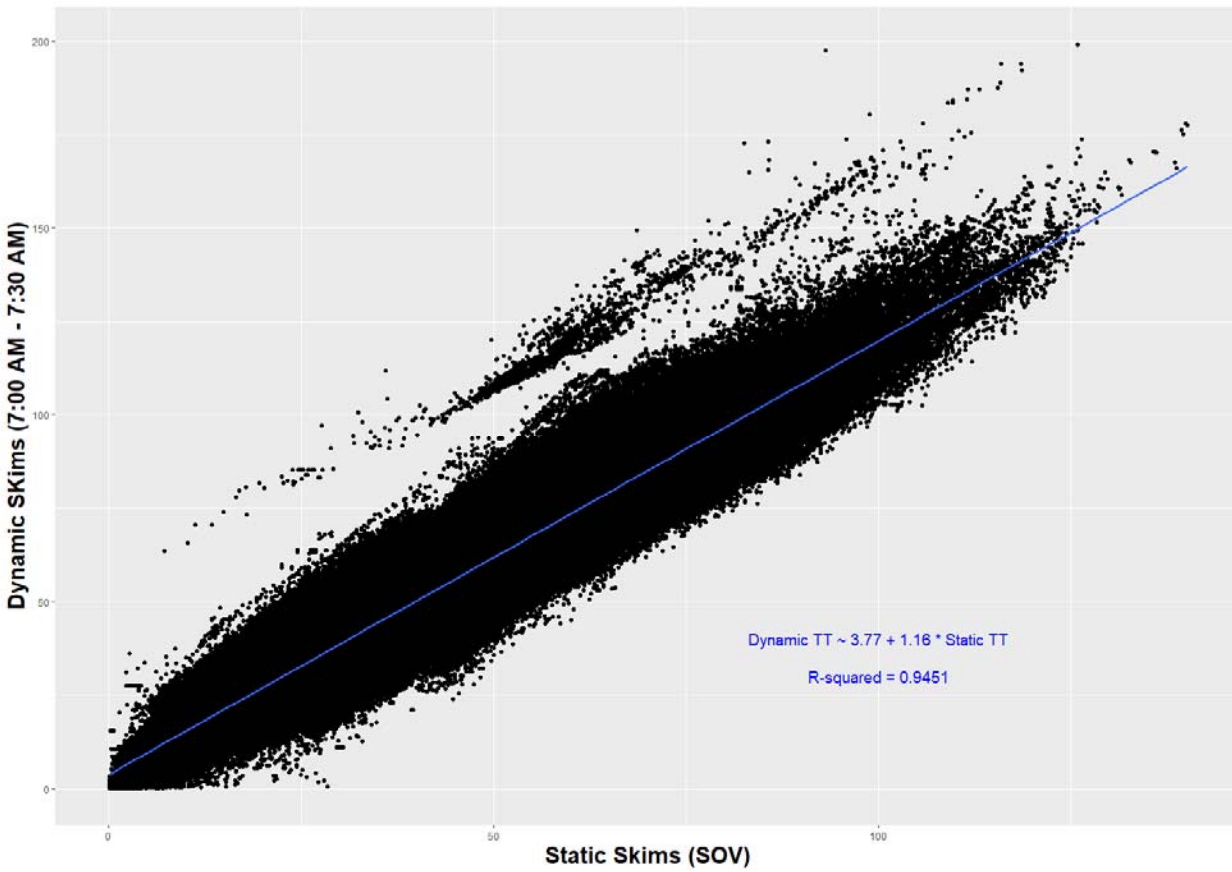


**Figure 3. Scatterplot of static vs. dynamic (7:00 a.m.–7:30 a.m.).**

Since the ABM is calibrated to the static skims, it is important to understand how the dynamic skims differ from the static skims and how these differences impact the model system. The project team compared the DaySim demand model results with the dynamic skims to the previous results with the static skims. In the example exercise, 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 (Figure 4). Shorter trips, in terms of distance, have the largest discrepancies in travel times between the static and dynamic skims because differences in network loading between these two methods is exaggerated for shorter trips, where a higher percentage of the overall trip is made on network connectors. The project team addressed this issue by improving the DTA connector loading methods, but the exercise highlighted the importance of the verification process so crucial to the integration of two complex model systems. Errors in one system (e.g., network coding issues) can propagate to the other system and undermine the efficacy of the model framework for EMA.

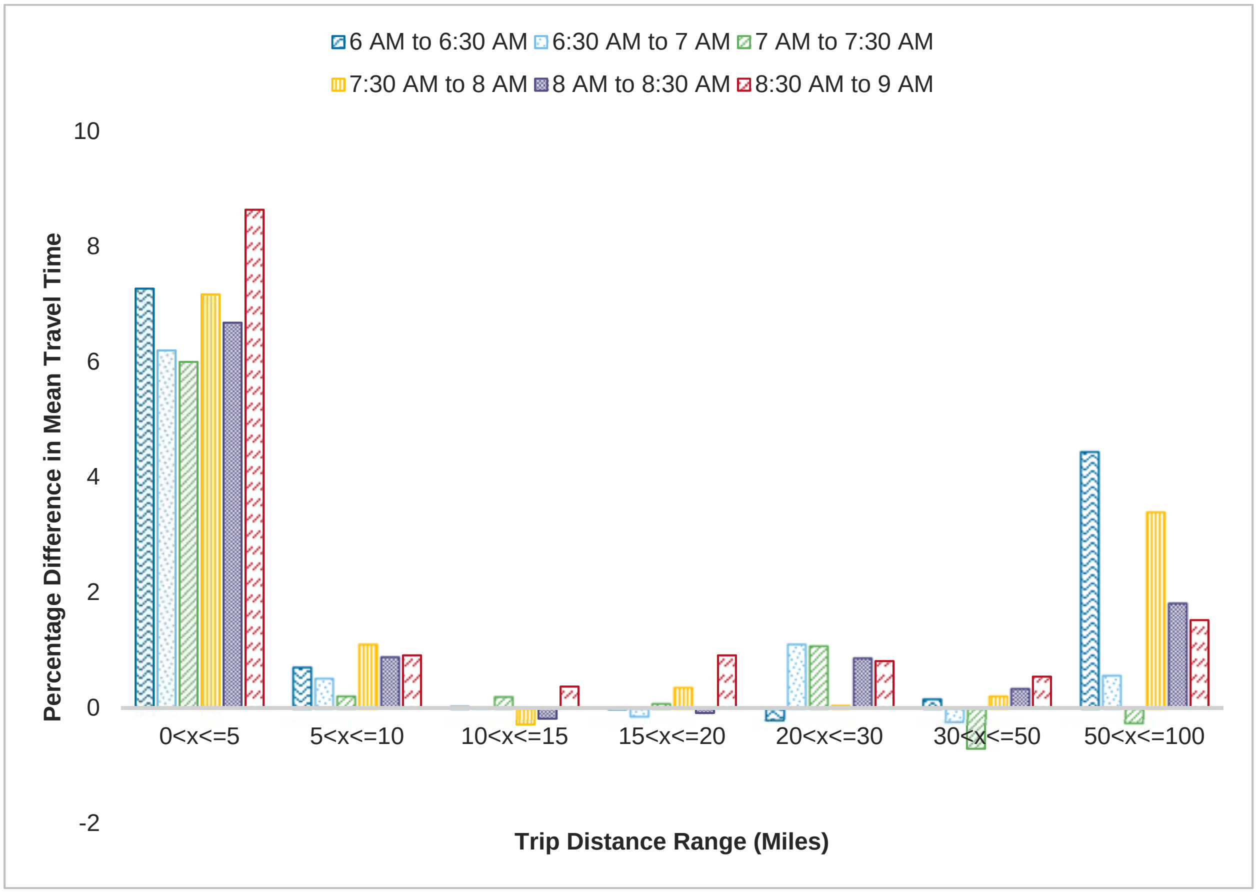


**Figure 4. Percentage difference of mean travel time with trip distance.**

As shown in Table 4, because of the longer auto travel times in the example exercise, auto mode share was reduced by 1.3%. This increased the mode share for the other modes, especially walk and bike, since the dynamic skims are longer for short-distance trips, which makes nonauto modes more attractive.

**Table 4. Percentage difference in mode share (static vs. dynamic).**

| Mode Type | Static Frequency | Dynamic Frequency | % Difference |
|---|---|---|---|
| Bike | 95,565 | 103,387 | 8.19 |
| HOV2 | 1,606,159 | 1,573,810 | -2.01 |
| HOV3+ | 1,108,358 | 1,073,491 | -3.15 |
| School Bus | 127,710 | 119,100 | -6.74 |
| **SOV** | **2,673,029** | **2,637,680** | **-1.32** |
| Transit | 42,010 | 43,616 | 3.82 |
| Walk | 469,337 | 550,681 | 17.33 |

In addition to the dynamic skim reasonability checks, it is important to verify the DTA model functions properly and converges. To do this, look 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 location.

In the example exercise, the results were generally reasonable for exploratory modeling analysis, although some issues remain for follow-up work (discussed in detail below).

## 3.7 *Issues Encountered*

During the development of the integrated model system, the project team discovered and addressed or investigated several issues and challenges requiring resolution. Key issues 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 additional model components (e.g., auxiliary demand, transit skims).

- By far, the most significant issue encountered with respect to EMA is that the AM period DTA simulation and dynamic skim generation takes at least 15 hours depending on the computer configuration and because of the number of iterations required to achieve convergence. Because it is practically inefficient to complete the multiple model runs required for EMA with these runtimes, the project team simplified the demand model's understanding of travel time (i.e., just using AM skims). In addition, a limited number of overall model feedback loops were done—typically between three and five—because of the long model system runtime.
- The ABM outputs trips at the parcel level, which are aggregated to the TAZ level in the DTA model trip importer. The DTA model then builds several zone connectors to simulate the diversity of real-world loading points (Figure 5). 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. Additionally, some of the shortest travel time OD pairs are also a product of connector placement and choice, sometimes in combination with large zone size. An example of the differences for a relatively short-distance OD pair is shown in Figure 6. As a result, the project team considered two revisions to the setup:
    - The first revision was to switch to parcel-to-parcel DTA network loading instead of TAZ-to-TAZ to produce better estimated network travel times. However, this approach produced longer DTA runtimes and some unresolved questions about efficient software implementation and how to collapse the skimmed information to the TAZ level for input to the demand model.

- o To make a detailed approach like parcel-to-parcel more manageable in the example exercise, the project team experimented with using microzones, which can be thought of as superparcels. In the example exercise, microzones produced a satisfactory compromise between TAZs and parcels for DTA integration.


**Figure 5. Connectors to approximate parcel loading.**

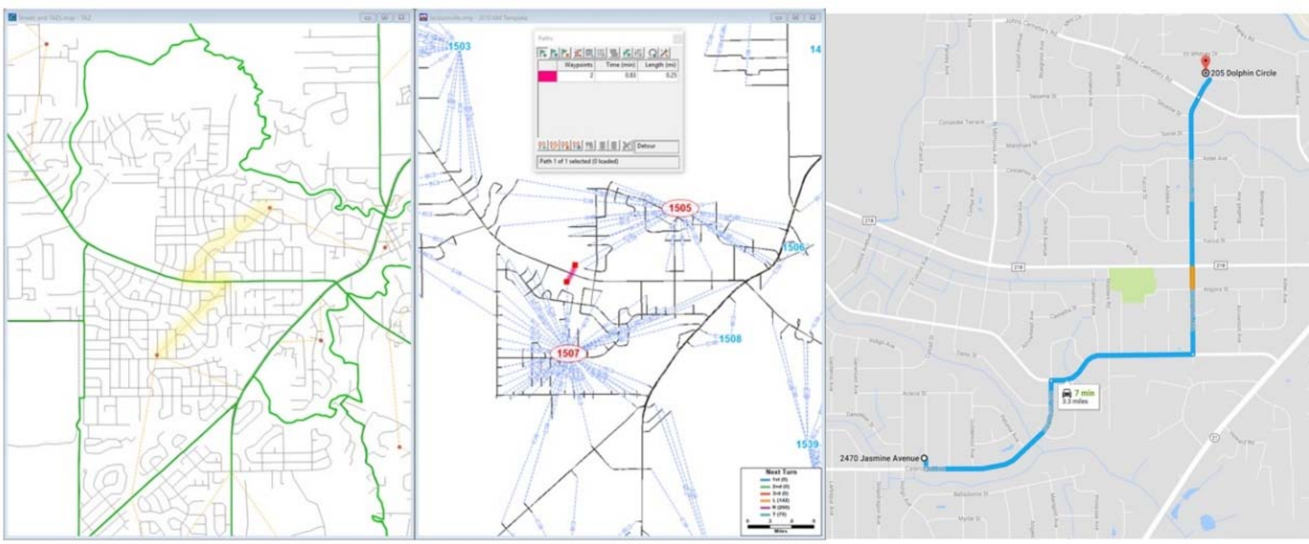


**Figure 6. Path trace from 1507 to 1505 in the static and DTA models and Google Maps.**

Source: Google Maps

- As noted, DaySim tours in the example exercise were in priority order for a person-day and not in chronological order; temporal consistency across tours was not guaranteed. As shown in Figure 7, the same person has two different tours in the example exercise, 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 7. Tour and trip chronological consistency.

Review the trips to ensure the results are typically consistent. Since the DTA is modeling every trip in the simulation model 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 simulation. For the example exercise, chronological consistency within the tour was assumed, but the project team independently simulated different home-based tours within a person-day.

- A process was scripted in TransModeler to generate dynamic skims in 30-minute trip start time periods by querying the simulated travel times for trips in the OD pair in each 30-minute interval. If there are no simulated trips traveling between the OD pair in the time interval, then a shortest-path travel time is calculated. Because the automated calculation of dynamic skim matrices—blending times from simulated trips with calculated dynamic shortest-path times—was a new development adapted for the EMA, numerous trials and close inspection of the resulting skims were required before the skimming step was operational and robust. In addition, the differences between the weighted average travel times across estimated paths versus the minimum shortest-path travel time when no paths were available in the example exercise created significant inconsistencies in travel times across OD pairs. As a result, the project team used the simulation to load the network and then used the shortest-path travel time from the loaded network for all OD pairs. In the example exercise, this reduced the diversity in the experienced travel times in skims, but it also ensured consistency in travel time costs fed back to the demand model. Certainly, further work in this area of the ABM-DTA integration is required.
- As noted, the DTA only outputs dynamic travel time information for auto. It does not produce walk, bike, or transit network LOS indicators (i.e., skims). Running the DTA adds to, but does not replace, the network model component of the model system.

# 4.0 Revisions to the ABM Model for CAVs

To complete the EMA, users must adapt the models to incorporate sensitivities to the uncertain inputs. In the example exercise, the project team implemented the following ABM adaptations.

## 4.1 *Market Penetration of AVs*

The project team adapted the auto ownership model in DaySim in the following ways:

1. In addition to predicting the number of vehicles owned by a household (0, 1, 2, 3, 4+), the model predicts the type of vehicles owned—conventional or autonomous. This is based on two simplifying assumptions:
    - Only two types of vehicles are specified: "conventional," which may have some new connectivity safety features but will require a human operator, and "autonomous," which will not require a human operator. (See Section 5.1 for a complete description of the levels of automation and levels simulated.)
    - 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. The time required for this exceeds the value derived from this level of detail.
2. The utility functions include new variables and coefficients. 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 emphasis on the following:
    - Household income level.
    - Age of head of household.
    - Household size and presence of children.
    - Household workers.
    - The commuting time disutility by car to the usual workplaces of all workers in an AV as compared to a conventional vehicle.
3. The project team asserted the coefficients on the new variables and then calibrated these to reflect three levels of AV ownership:
    - **Low**: For example, 10% AV penetration, on average.
    - **Medium**: For example, 50% AV penetration, on average.
    - **High**: For example, 90% AV penetration, on average.

In the example exercise, 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 was more speculative, although those with children may be more attracted by the presumed 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. EMA typically includes assertions such as these, which require thoughtful development and testing.

## 4.2 *Disutility of In-Vehicle Time in AVs*

The ABM uses the auto travel time coefficient recommended in the SHRP2 C04 project. The coefficient is a function of the following:

- Tour purpose, with a somewhat higher base coefficient for work tours than nonwork tours (i.e. work travel is more important than non-work travel).
- A random component, which, if specified by the user, is drawn from a 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. In the example exercise, the project team proposed using a modified travel time disutility if a household owns AVs, 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.

The project team assumed that the average auto time disutility would never go to zero or be positive, as there is often a more productive or enjoyable way to spend one's time. (Current models do not assume that car passengers have a much lower disutility of time than car drivers, even though passengers in a conventional vehicle could conceivably do the same things as passengers 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 written to the individual trip records for the DTA.

## 4.3 *Level of Use of Carsharing and Ride-Hailing as a Substitute for Private Vehicle Use*

To reflect the level of use of carsharing and ride-hailing as a substitute for private vehicle use, the project team added a "paid ride hail" mode to the tour- and trip-level mode choice models. (These models then generate mode choice logsums that are inputs to other choice models in the ABM.) Several types of paid ride-hailing services could exist and vary in terms of their price structure and flexibility in duration and distance of using the vehicle, among other attributes. As a result, the project team proposed to include a single generic paid ride-hail mode that captures the salient differences from using one's own vehicle.

The paid ride-hail mode is available to all travelers for all persons. The variables in the utility function are as follows:

- The auto travel time to the destination.
- The cost, which is based on auto travel distance plus a user-specified and fixed per-trip cost.
- The access and egress walk plus wait time, which is a function of land-use density at the trip origin, with lower availability and longer wait times 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 age groups.
- A density variable that serves as a proxy for the availability and wait time for paid ride-hail 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 ride-hail mode.
- Effects of the ride-hailing on vehicle ownership. It is expected that a decrease in private vehicle ownership would accompany a large shift toward using shared vehicles. The model specifies the effect of ride-hailing on levels of car ownership, with the probability of owning zero vehicles due to the shared economy also a function of buffer density.

The model can incorporate different paid ride-hail alternatives for different numbers of persons in the travel party. However, DaySim does not explicitly predict vehicle occupancy, so this does not enhance model accuracy. Rather, the model adjusts the cost per passenger as a function of the tour purpose, as average auto occupancies vary by purpose.

For purposes of scenario testing, assumed shifts in auto ownership levels should be behaviorally consistent with the assumed use of paid ride-hailing modes. The variables related to auto ownership in the paid ride-hail mode utility ensure some consistency, but calibration is still necessary. Thus, the project team calibrated the auto ownership and mode choice models in the example exercise to reflect three different assumed levels of disaggregate demand across the entire synthetic population:

- **Low**: 3% of trips by paid ride-hail mode; no corresponding effect on auto ownership.
- **Medium**: 30% of trips by paid ride-hail mode; 15% reduction in auto ownership.
- **High**: 60% of trips by paid ride-hail mode; 30% reduction in auto ownership.

For all levels, the project team made the simplifying assumption that paid ride-hail services will be the earliest adopters of AVs, so all paid ride-hail trips in the model 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 passes separate skims for AVs and conventional vehicles back to the ABM, so it affects the travel time in the paid ride-hail mode utility.

## 4.4 *Changes in Parking Behavior at the Destination for AV Trips*

In addition to the adaptations described above, the project team also experimented with a trip destination parking location choice model that considers a separate parking location zone from the trip destination zone. Due to project schedule constraints, this adaption was tested but not included in the example exercise.

The destination parking location choice model is like how transit park-and-ride lot choice is often modeled. To reduce runtimes, the model is only applied in parking-constrained locations like the city center. The choice set for the parking location choice model includes nearby superstacked parking locations, which were more difficult to define than expected. The project team identified the following important criteria for siting good locations for AV mass-parking locations for downtown trips:

- Near the edge of the downtown area, where there is space (or existing parking) available (not too far from downtown).
- On a major arterial where the flow is fairly one-sided (i.e., many vehicles are coming into downtown in the AM peak, but not many people are leaving downtown in the AM peak). In theory, many empty AV trips would park there, making travel in a direction counter to peak flow optimal to avoid adding to congestion. (The same would be true in the reverse direction in the PM peak when the cars come back to pick up their owners, although the example model does not explicitly simulate the PM peak.)

Figure 8 shows the modeled locations for superstacked AV parking. The final section discusses the results of the parking location choice model.

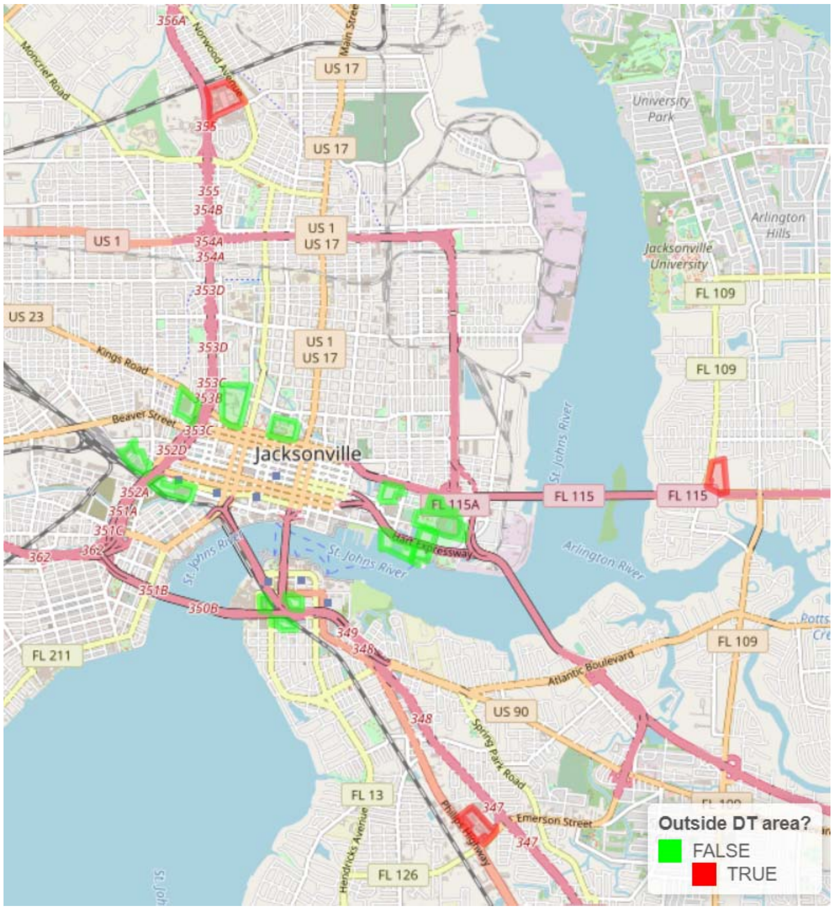


**Figure 8. Potential superstacked parking locations.**

Source: OpenStreetMap

## 4.5 *Changes in the ABM Skim Reader and Output Files*

To input a separate set of network LOS skims for AVs, the project team updated the DaySim skim reader (called the PathType model) to support a new mode, AV, just like it does for the SOV, HOV2, and HOV3 modes. This allows the user to specify skims for travel time, distance, and toll.

In the household-level output file, each output household record has one of the following values if auto type choice is included in the auto ownership model: 0 = household owns conventional vehicles and 1 = household owns AVs.

In the trip-level output file, the project team updated the driver or passenger field to include two new codes (3 and 4) to identify AV trips, as opposed to codes 1 and 2 for non-AV trips. An additional code (5) was added to identify AV trips with no driver or passenger for the case of AV parking location choice. The mode field was also updated to include paid ride-hail (9).

## 4.6 *Verification*

To start, verify any ABM revisions. In the example exercise, the project team verified the ABM revisions to support the CAVs EMA by running the software through several of the EMA scenarios. See Example Exploratory Model Runs and Analysis for more detail.

# 5.0 Revisions to DTA Models for CAVs

The DTA model simulates driver behaviors, including acceleration and lane-changing decision-making, in 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 tested the impacts of AV and related technologies via the example exercise. To that end, the project team enhanced TransModeler 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 allowed 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. The project team updated the software to designate whether individual lanes allow AVs to operate autonomously. This augmentation of the supply-side representation facilitates exploration of scenarios in which certain lanes or facilities may exist exclusively for AVs.
- The representation of simulated drivers and vehicles was extended to allow the levels (L) of automation devised by the Society of Automotive Engineers (SAE) International and adopted by the U.S. Department of Transportation (L0 through L5 described below)—which include automation of acceleration, steering, and other aspects of driving—applied to a user-defined vehicle class.
- The project team identified and selected an acceleration model from the research literature (Wang and Rajamani, 2004) and implemented it to represent a mode of cooperation between CVs, referred to as cooperative adaptive cruise control (CACC).

## 5.1 *Adaptation of the DTA for Simulating AVs*

The project team enhanced TransModeler to support the simulation of AVs. With this enhancement, the modeler can create new vehicle classes and assign to each vehicle class one of the following levels of automation (Figure 9):

- **Level 0—No Automation.**
- **Level 1—Driver Assistance**: The onboard driver assistance system can perform steering (modifying direction) or acceleration/deceleration tasks by using information about the driving environment; the driver performs all other driving tasks.
- **Level 2—Partial Automation**: The onboard driver assistance system performs both steering (modifying direction) and acceleration/deceleration by 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 onboard driving system operates all aspects of driving; the driver responds only to requests to intervene.

- **Level 4—High Automation**: An onboard 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 (e.g., only within a geofence).
- **Level 5—Full Automation**: An onboard driving system operates all aspects of driving under all roadway and environmental conditions, negating any need for driver intervention.

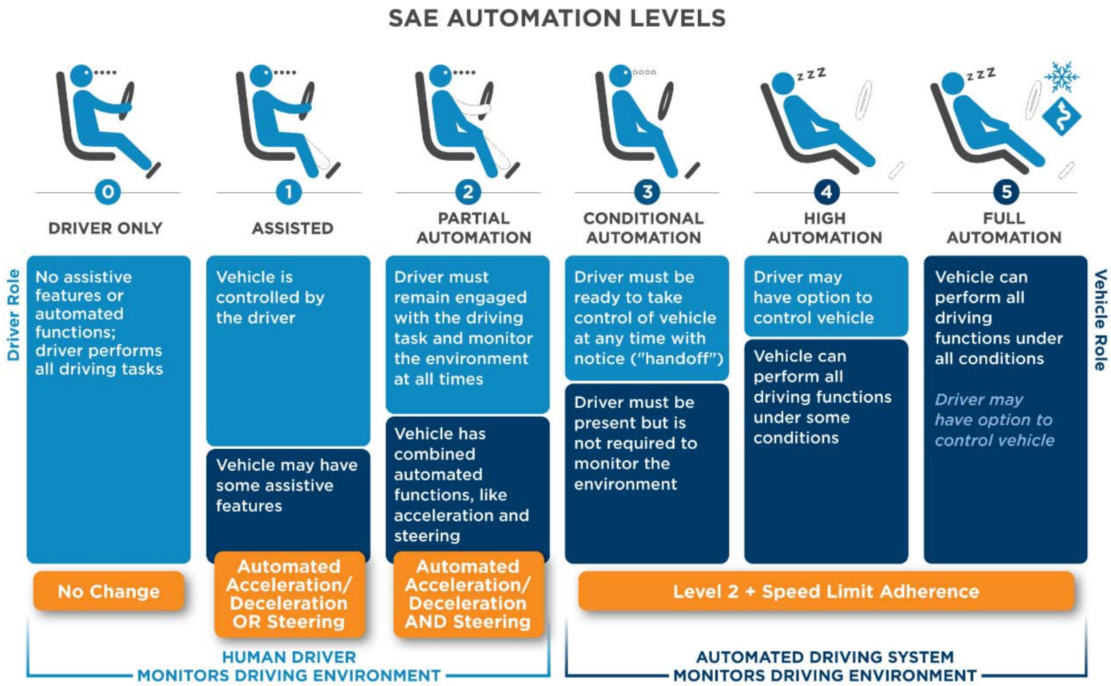


**Figure 9. SAE automation levels.**

Source: US DOT

The model simulates vehicle classes that are not assigned an automation level, or that are assigned L0, according to the default models of driving behavior in TransModeler. When L1 (driver assistance) is assigned to a vehicle class in TransModeler, the user can choose whether the acceleration/deceleration task or the steering task is automated. Automated driving tasks are assumed to operate mechanically and deterministically by the vehicle, owing to some combination of onboard camera, sensors, computers, and other hardware. Driving tasks that are not automated are assumed to remain under the control of the human driver and exhibit the heterogeneity inherent in human behavior and decision-making. That heterogeneity is captured in a microsimulation environment through random variables that are integral to stochastic, or Monte Carlo, simulation. To approximate the effects of automation, the random variables that are part of the automated task are assumed to have narrow or zero variance, as appropriate.

For instance, when acceleration/deceleration is automated, the car-following model in TransModeler simulates more uniform, deterministic vehicle responses to the speed and proximity of the leading vehicle. This adaptation of the car-following algorithm emulates adaptive cruise control absent the influences of driver attention, reaction time, or other human factors.

Steering in the context of L1 through L3 describes either corrective or otherwise limited assistive actions meant to keep a vehicle centered in its lane and does not necessarily imply the ability to navigate or complete a trip autonomously without driver input or attention. Because TransModeler, like other simulators, assumes that vehicles—with some exceptions, notably motorcycles—do not deviate from the center of the lane, there is little scope for adapting the software to explore the impacts of steering automation in that regard.

However, the software was adapted to assume that a vehicle with automated steering will control steering during the act of changing lanes. Specifically, a vehicle under automated steering will reject short gaps in the target lane that a human driver may accept, requiring a safer gap before commencing the lane-change maneuver. In addition to improving safety, which is not directly measured in the simulation, the automation of steering during lane-changing may contribute to more stable traffic flow by avoiding short gaps that may cause the following vehicle in the target lane to brake and shockwaves to develop as a result. The automation of steering during lane-changing may also reduce disruptive lane-changing events altogether because drivers may forego discretionary lane changes—those that are not necessary to follow one's path—in congested regimes owing to a scarcity of safe gaps.

When L2 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. However, because steering is already idealized to a degree as previously described, there is little practical distinction in the simulation between L1 and L2.

Above L2, the distinctions between levels of automation have less to do with which aspects of driving are automated and more to do with when, or under which circumstances, the driver is prompted or expected to intervene and assume control of the vehicle. However, those events and circumstances are not clearly defined in the literature. Without credible, concrete direction from the literature or from auto manufacturers, it is not known whether those events or circumstances have direct or explicit representation in a simulation model.

That said, a vehicle with L3 automation is one that can monitor the environment and manage most driving tasks. In the adaptation in TransModeler, "most driving tasks" are assumed to include selection of a "desired" speed, or the speed at which drivers travel when uninhibited by other vehicles or traffic control. When L3 is assigned to a vehicle class, the vehicle will select the advisory speed (i.e., the speed limit) as its desired speed, with the assumption that the advisory speed is knowable through geolocation and onboard map data or visual identification of speed limit signs with onboard cameras. Thus, L3 automation can have speed harmonization benefits in the model in addition to the advantages afforded by L2 automation.

In addition to vehicle automation, technologies and strategies exist 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 it can sustain short headways 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., V2I). V2I could, for example, regulate/harmonize speeds upstream of an incident or optimize traffic signal timings in real time.

In a simulation environment like TransModeler, the line between driver and vehicle is not well defined, which makes it somewhat difficult to differentiate between the levels of automation described here. 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 a simulation model might represent driver intervention—which distinguishes L3, L4, and L5. Hence, L3 through L5 are not yet differentiated in any substantive way in the current adaptations.

## 5.2 *Adaptation of the 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. In the example exercise, the project team assumed that vehicles operating in CACC will maintain a desired following time headway. To achieve this, a constant time gap model was implemented (Wang and Rajamani, 2004):

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

**Figure 10. Equation. Constant time gap.**

where $a_i$ is the acceleration 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 ($v_i - v_{i-1}$), $\lambda$ is a parameter, and $\delta_i$ is a deviation from the desired spacing given the desired headway and is calculated as follows:

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

**Figure 11. Equation. Desired headway calculation.**

where $\varepsilon_i$ 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 is 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.

## 5.3 *Changes in the DTA Trip Reader*

As noted, the ABM trip lists for the EMA include new codes for paid ride-hail mode and driver or passenger AV or non-AV trip. If the value of mode is 3 (SOV), 4 (HOV-2), 5 (HOV-3+), or 9 (paid ride-hail), and the value of driver or passenger is 1 to 5, then the following rules apply for assigning trips to the network:

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

2 = passenger (or other ride-hail 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.

5 = no passenger in an AV >> assign to network.

## 5.4 *Changes to Simulate TNC Operations in the DTA*

The project team modified the DTA software platform to accommodate simulation of TNC operations. To accomplish this, a roster of ride-hailing trips, or client trips, is read from the ABM's trip list. A fleet of TNC vehicles is also posited. Vehicles in the TNC fleet are assumed to be in service during various hours of the day. A TNC manager module for the DTA was implemented that accepts, queues, and answers ride requests from client trips and dispatches TNC vehicles to pre- (i.e., pickup) and post-service (i.e., after drop-off) trips.

A preservice trip will have the TNC vehicle's current location as the trip's origin and the origin of the client trip as its destination. A service trip will share the client trip's origin and destination. A TNC vehicle will become immediately available to answer a queued ride request after its service trip is completed, such that its post-service trip may be either the preservice trip for a new client or, in the event no qualifying ride request exists, a repositioning trip to a strategic location (i.e., where a concentration of ride requests is expected). Further, a postservice trip can be interrupted if the vehicle is matched to a qualifying ride request prior to arriving at the postservice trip destination.

A qualifying ride request is one in which the TNC vehicle meets some criteria, including but not limited to a maximum travel time from the vehicle's current location to the client trip's origin. These criteria and other factors, including the size of the TNC fleet and its geographic positioning throughout the day, will determine various level of service variables such as wait times.

For each TNC trip beginning with the first of the day, the nearest TNC vehicle is assigned to the trip. A queue of TNC vehicles is maintained with a first-in-first-out process. This means the first vehicle in the queue satisfying time, distance, and potentially other criteria is dispatched to serve a ride request. Similarly, a ride request queue is also maintained. The principal tasks of the TNC manager module is to match ride requests with qualifying TNC vehicles and dispatch the requisite preservice, service, and postservice trips. The TNC manager subscribes to notifications by the simulator when a trip is completed:

- When a preservice trip is completed, the TNC vehicle will be placed in an in-service pool, and the client trip will be permitted to commence. In this way, the client trip's identity is preserved so that its delay, travel time, and other performance variables can be relayed back to the ABM.
- When a service trip is completed, the TNC manager will remove the TNC vehicle from the in-service pool and search the ride request queue for a qualifying ride request and dispatch the vehicle to service the request if one is found or dispatch the vehicle on a repositioning trip if one is not. If a vehicle is dispatched on a repositioning trip after

service, then it will be placed into the queue of available vehicles. Or, if the vehicle has exceeded a limit of time in service, it may be dispatched back to its home location and removed from the fleet.

- When a repositioning trip is completed, the TNC vehicle will be removed from the network (i.e., assuming it has parked off-street) and remain in the queue of vehicles available to service ride requests.

The implementation summarized above considers several travel behavior and logistical considerations described below:

- **Interaction Between Simulation and Travel Behavior**: TNCs are expected to somewhat cannibalize taxi and transit trips and may also serve trips that would not have otherwise been made due to their hypothetical lower cost and potentially better service. Based on a set of initial assumptions, the ABM will generate TNC trips as a subset of all trips. Assumptions must be made about the number of TNC vehicles available by time of day and where they are initially located. Some of these assumptions should be revisited in future research as part of the equilibration process in the integrated ABM-DTA framework.
- **Pre- and Post-Service Trips**: As previously described, each TNC service trip is likely to be preceded by a preservice trip and is likely to be followed by a repositioning trip or another preservice trip. Each of these trips is modeled with the proviso that the pre-and post-service trips may not be necessary. For instance, a TNC trip serving a client to a destination with high TNC activity (e.g., an airport) may become immediately available for service of a trip originating at the same location.
- **Ride Request Scheduling**: A probability distribution is assumed for how far in advance of desired service trips are scheduled in advance. The mean of this distribution could be 5 or 10 minutes and could possibly vary with location. The ABM assigns departure times to trips without accounting for the waiting time at the origin. Before network simulation, the departure times of TNC trips are made earlier by accounting for a waiting time drawn from a probability distribution. The probability distribution is such that the arrival time of the TNC vehicle at the client trip's origin will generally coincide with the originally desired departure time.
- **Service Availability**: In general, client trips cannot be accepted by a TNC vehicle that is on a preservice or service trip. Hence, client trips are serviced by the nearest vehicle that is not in service. From the ABM, a roster of client trips to be served by TNCs is provided as input to the simulation. Vehicles in the TNC fleet must be attributed some time and origin at which they begin service. Each TNC vehicle has an initial location prior to engaging in service, presumably its home location, and may be assigned a different location for the start of each work shift. Hence, TNC vehicles may initially travel from residential addresses to service locations of reasonable TNC activity (e.g., airports, hotels) at the beginning of the work shift prior to becoming available for service. Such an initial positioning trip may be necessary to place the vehicle within reasonable proximity of client trips.

## 5.5 *Verification*

The project team verified both the CAV and TNC adaptations of the DTA software. To measure the impact of the CAV adaptations, the project team built a small simulation model of an approximately 2.5-mile section of a westbound five-lane freeway with on and off ramps. The project team placed censors in the model 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 verification exercise 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.

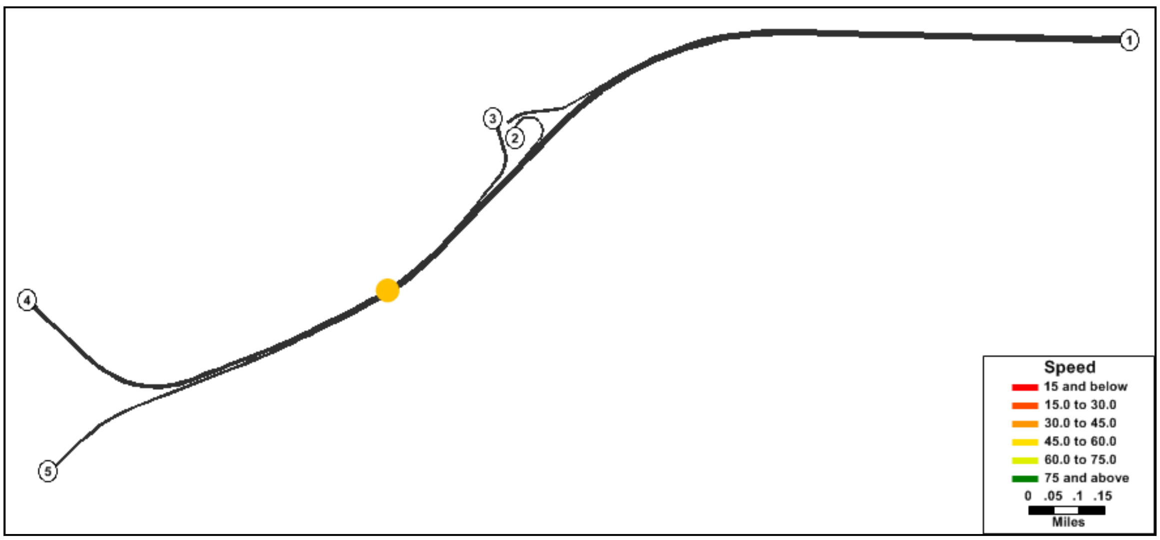


**Figure 12. Model network for testing adaptations.**

The project team performed tests 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 project team tested AV and CACC adaptations in the presence of several complex merge, diverge, and weaving behaviors that are common in the real world and that call on all the aspects of driving that are subject to automation. The project team also set the simulated traffic in the verification exercise 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 that 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.

The project team ran numerous scenarios, 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 L1a (acceleration/deceleration task automated), AV L1b (lane-changing [i.e., modifying direction] task automated), AV L2 (both acceleration/deceleration and lane-changing tasks automated), AV L3 (AV L2 + travel speeds coordinated), and CACC. For each scenario, results from 10 simulation runs were averaged together. This test also assumed 100% AV penetration to analyze the maximum impact a given level of automation or AV technology might have.

To isolate the effects of CACC from those of L3 automation, the project team assumed only the minimum AV level (L1a where the acceleration/deceleration task is automated) in the CACC scenarios. In the scenarios in which CACC was tested, a target following headway of one second was assumed, which falls in the middle of the range of CACC headways considered plausible in the literature.

In the base scenario, as the scaler of the demand increased, flow declined from the maximum observed (1,885 vehicles per lane at a scaling factor of 1.3) because of increased congestion, consistent with the fundamental traffic flow diagram. Figure 13 summarizes the flow rate served in all the scenarios evaluated, and Figure 14 summarizes the increase in flow relative to the base scenario at each demand scale.

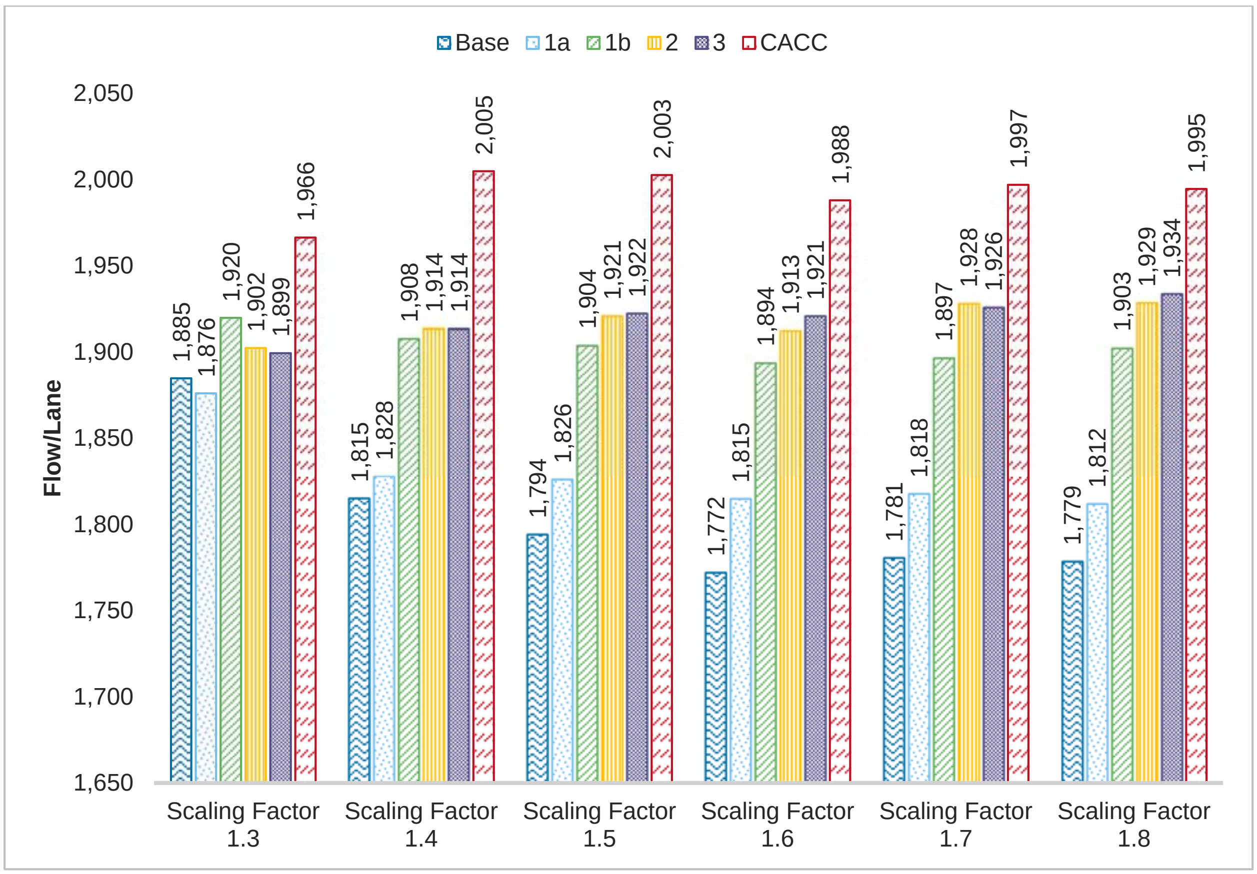


**Figure 13. Simulated flow rate for a range of AV adaptation/demand scale scenarios.**

Figure 13 shows that the flow rate in the base scenario decreased as the demand increased in the verification exercise. This change in the flow rate reflects some combination of the downward trend in flow in the fundamental traffic flow diagram. This occurs as density increases beyond a critical density upstream of the measurement location and demand starvation occurs at the measurement location due to queuing at the upstream merge.

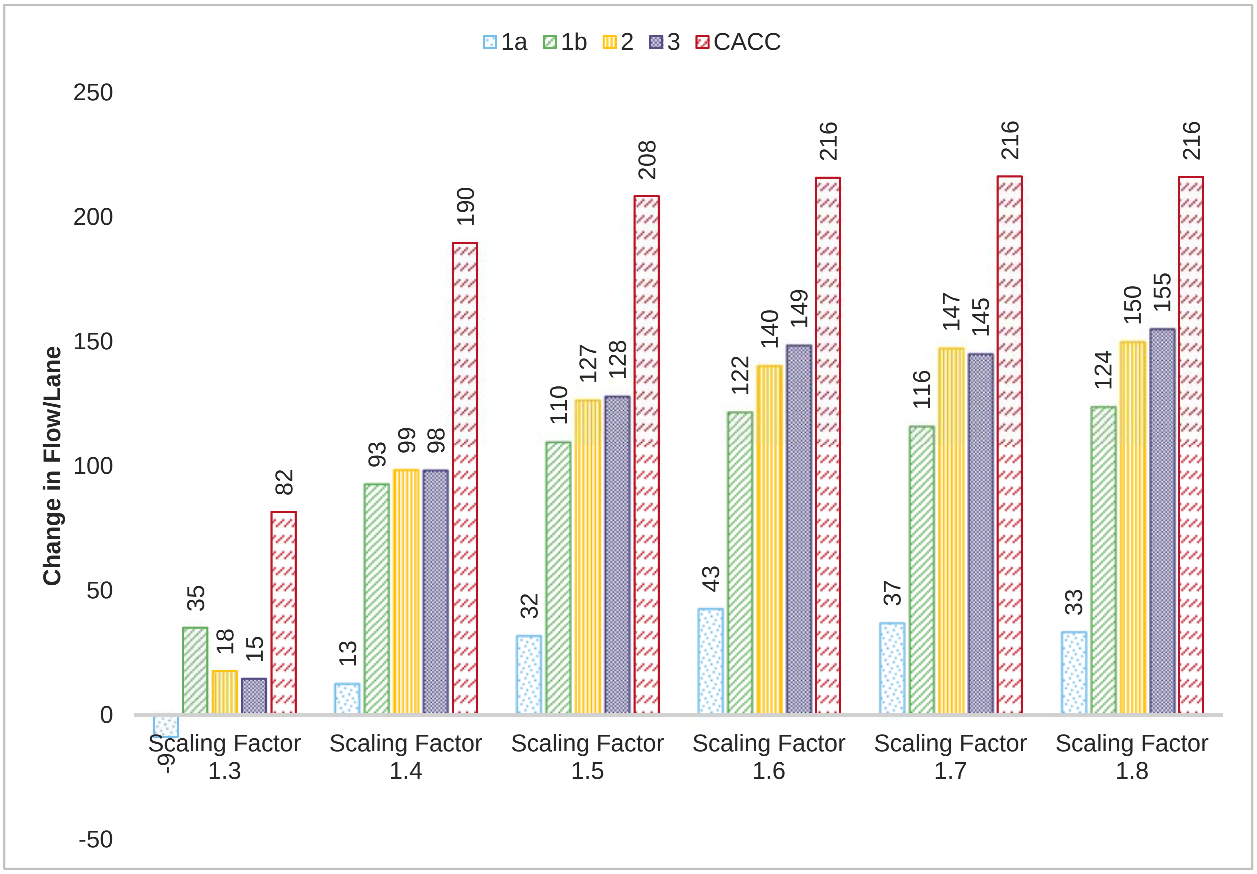


**Figure 14. Change in flow rate for a range of AV adaptation/demand scale scenarios.**

When automation is introduced, only modest or negligible increases in capacity (0–2%) were achieved when only acceleration was automated (1a) in the verification exercise (Figure 14). Traffic operations in heavy merge, diverge, and weaving areas stand 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 L1b, L2, and L3.

Figure 14 also shows that CV technologies, like CACC, may have benefits beyond simple automation. The verification exercise demonstrated that the most significant improvements in capacity occur when CACC is deployed, producing increases in flow as high as 12%. Figure 13 and Figure 14 also show that the benefits increase as demand increases and congestion worsens. Interestingly, 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 CAV operations afford in terms of capacity may be modest or negligible with basic automation of acceleration tasks (i.e., L1a). Rather, the most significant improvements are likely achieved when steering is automated (i.e., unnecessary lane changes minimized) or when another aspect of driving, one that brings about shorter following headways (e.g., CACC), is enabled through these technologies.

To verify the TNC adaptations of the DTA software, the project team performed numerous tests. The verification process established the suitability of the adaptation for EMA, but verification was not completed early enough to incorporate the TNC adaptation into the example exercise. Numerous variables and assumptions are critical to the simulation of TNC operations, which raise a host of questions about the integration of ABM and DTA not already addressed earlier in this document. Additionally, those variables and assumptions open doors to a whole range of EMA scenarios dedicated to TNC alone. To incorporate them into an EMA focused primarily on CAV operations would considerably increase the dimensionality of the analysis.

Before TNC operations can be simulated, basic assumptions must be made regarding the size of the TNC vehicle fleet and where and when those vehicles begin servicing ride requests. TNC trip data were sought by the project team but could not be obtained. Researchers with similar interests in TNC vehicle locations and movements in urban areas have encountered similar difficulty. Lacking any data upon which to base TNC vehicle fleet assumptions, TNC vehicles were distributed throughout the region based on the concentration of TNC trips in the ABM trip lists. In other words, a simplifying assumption was made that TNC vehicles would begin service in areas where ride requests most frequently originate.

A demand scenario with high private AV adoption and low shared AV adoption was used to test the TNC adaptation. Of the 655,000 trips between 5:00 a.m. and 9:00 a.m., about 92,000 are trips requesting a TNC ride. Initially, a fleet of approximately 2,000 vehicles was assumed. However, only about 12,000 of the 92,000 trips were successfully served. The low number of successful TNC trips are a consequence of long trips occupying TNC vehicles. Also, after dropping off riders in remote parts of the region, the repositioning trips were not always successful in positioning TNC vehicles where they could be matched to new customers.

After increasing the size of the TNC fleet to 3,500 vehicles, about 47,000 TNC trips were successfully served. A fleet size of 5,000 successfully served about 58,000 TNC trips. From these results, it is apparent that, without deeper analysis of the TNC fleet assumptions or repositioning behaviors, a larger fleet than is necessary may be required to serve the demand in the simulation.

Figure 15 depicts the status of the 2,000 TNC vehicle fleet initially tested and the clients, who, as of 8:00 a.m., have either requested a ride but have not yet been matched to a vehicle or are waiting for a vehicle that is en route. In Figure 15, the green squares represent idle vehicles in the TNC fleet repositioned and awaiting a rider, and the red squares represent TNC vehicles carrying a rider. The figure further underscores the need for additional testing to refine the fleet size assumptions and decision model underlying the repositioning trip. However, the verification exercise was successful in determining that the basic TNC operations were effective in simulating the core phenomena.

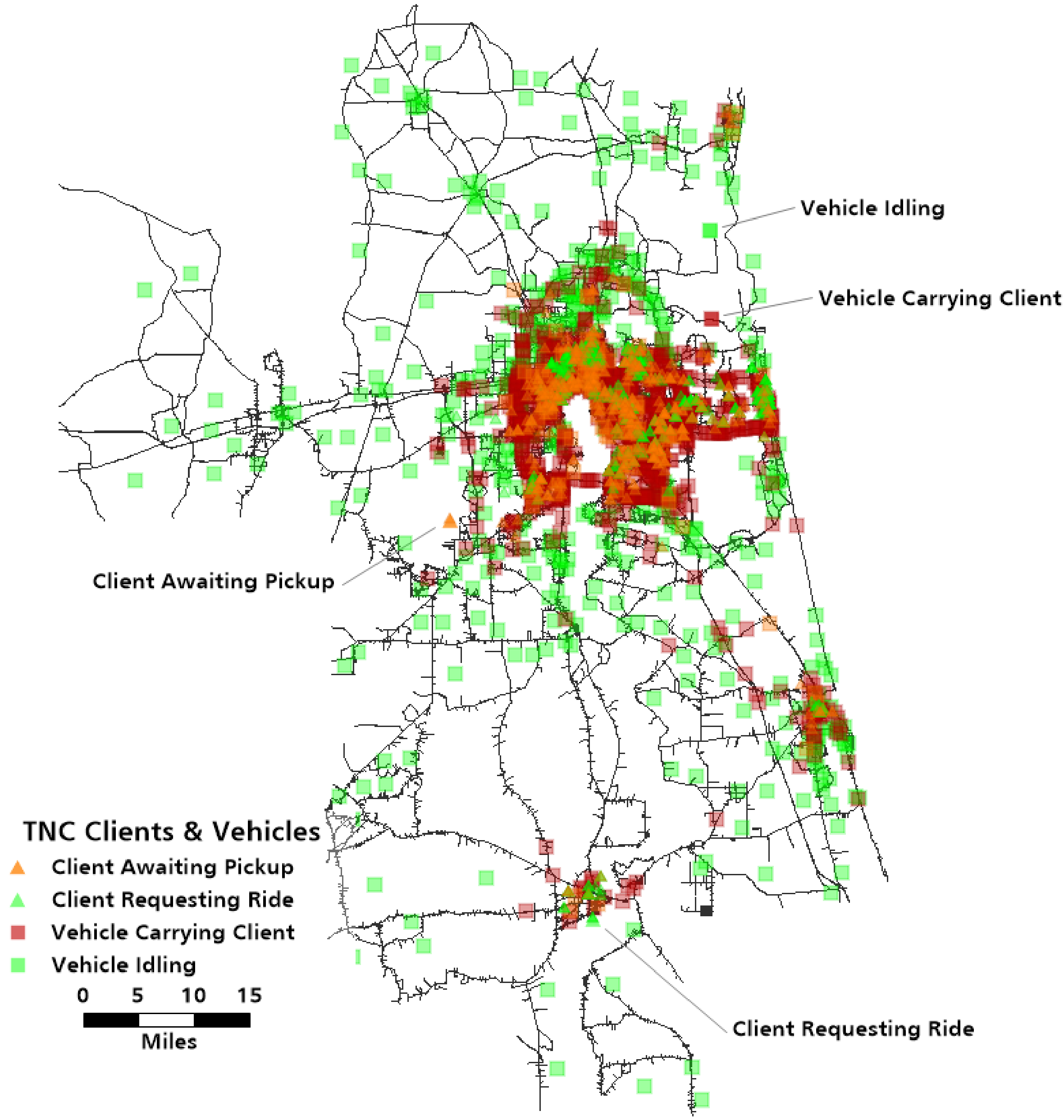


**Figure 15. TNC fleet and client status at 8:00 a.m. in a selected EMA scenario.**

# 6.0 Example Exploratory Model Runs and Analysis

With the improved integrated model in place, the next step in the example exercise represents the core aspect of EMA—designing an experiment, running the experimental scenarios, and analyzing the results.

## 6.1 *Experimental Design*

After the improvements, the project team developed the experimental design. Due to project budget and schedule constraints and the extensive runtime of the model, the project team restricted the input assumptions to be varied to four, testing up to three levels of each. This restricted set of input assumptions was largely a result of the significant runtimes required for DTA. The four input assumptions were as follows:

In the ABM:

- The level of AV ownership among households.
- The level of paid ride-hail 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.

The example EMA also experimented with the level of AV parking at the trip destination, but the project team was unable to fully incorporate this dimension of uncertainty due to complexities noted later.

The project team used a fractional-factorial orthogonal design to allocate the assumption levels to simulation runs, as shown in Table 5. In a fractional-factorial orthogonal design, an adequate subset of the possible combinations of factors is selected for analysis, along with the effects of any one factor balancing out across the effects of the other factors. The design included 16 model runs of which a subset of the most interesting 5 were first run in the earlier testing phases of the project due to long runtimes. In the final analysis, the project team ran and analyzed all 16 scenarios. The coding for Table 5 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 ride-hail 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 Interstate 10, 95, and 295 (L) (only in M and H demand scenarios); and exclusively on interstates within the I-295 beltway and only in the left lanes on interstates on and outside of the beltway (I) (only in H demand scenarios).
- Levels of vehicle automation technology ranging from L0 to L5 and covering the spectrum of degree of automation according to widely accepted definitions (see Section 5.1) and

CV strategies like CACC. These strategies are coded 0-5 and C to represent L3 automation and CACC.

**Table 5. Experimental design for 16 scenario runs.**

| Scenario | Private AV Adoption | Shared AV Adoption | Reserved AV Capacity | Automation Level |
|---|---|---|---|---|
| BB–N0 | None | None | None | None |
| MM–L3 | Medium | Medium | Interstate left lanes | Level 3 |
| MM–AC | Medium | Medium | None | Level 3 + ACC |
| MM–LC | Medium | Medium | Interstate left lanes | Level 3 + ACC |
| MM–IC | Medium | Medium | Interstate all lanes (All interstate lanes only inside the I 295 ring road, otherwise interstate left lanes only) | Level 3 + ACC |
| LH–L3 | Low | High | Interstate left lanes | Level 3 |
| LH–AC | Low | High | None | Level 3 + ACC |
| LH–LC | Low | High | Interstate left lanes | Level 3 + ACC |
| LH–IC | Low | High | Interstate all lanes (All interstate lanes only inside the I 295 ring road, otherwise interstate left lanes only) | Level 3 + ACC |
| HL–L3 | High | Low | Interstate left lanes | Level 3 |
| HL–AC | High | Low | None | Level 3 + ACC |
| HL–LC | High | Low | Interstate left lanes | Level 3 + ACC |
| HL–IC | High | Low | Interstate all lanes (All interstate lanes only inside the I 295 ring road, otherwise interstate left lanes only) | Level 3 + ACC |
| HH–L3 | High | High | Interstate left lanes | Level 3 |
| HH–AC | High | High | None | Level 3 + ACC |
| HH–LC | High | High | Interstate left lanes | Level 3 + ACC |
| HH–IC | High | High | Interstate all lanes (All interstate lanes only inside the I 295 ring road, otherwise interstate left lanes only) | Level 3 + ACC |

The experimental design shown in Table 5 requires 16 runs, which is a design of four demand combinations (LH, MM, HL, and HH) times four supply combinations (L3, AC, LC, and IC). This design helps compare the three AV facility allowance options (A, L, and I) in scenarios that all have the highest levels of automation (C). 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 I-295, so it is about reserving existing capacity for AVs only (Figure 16).

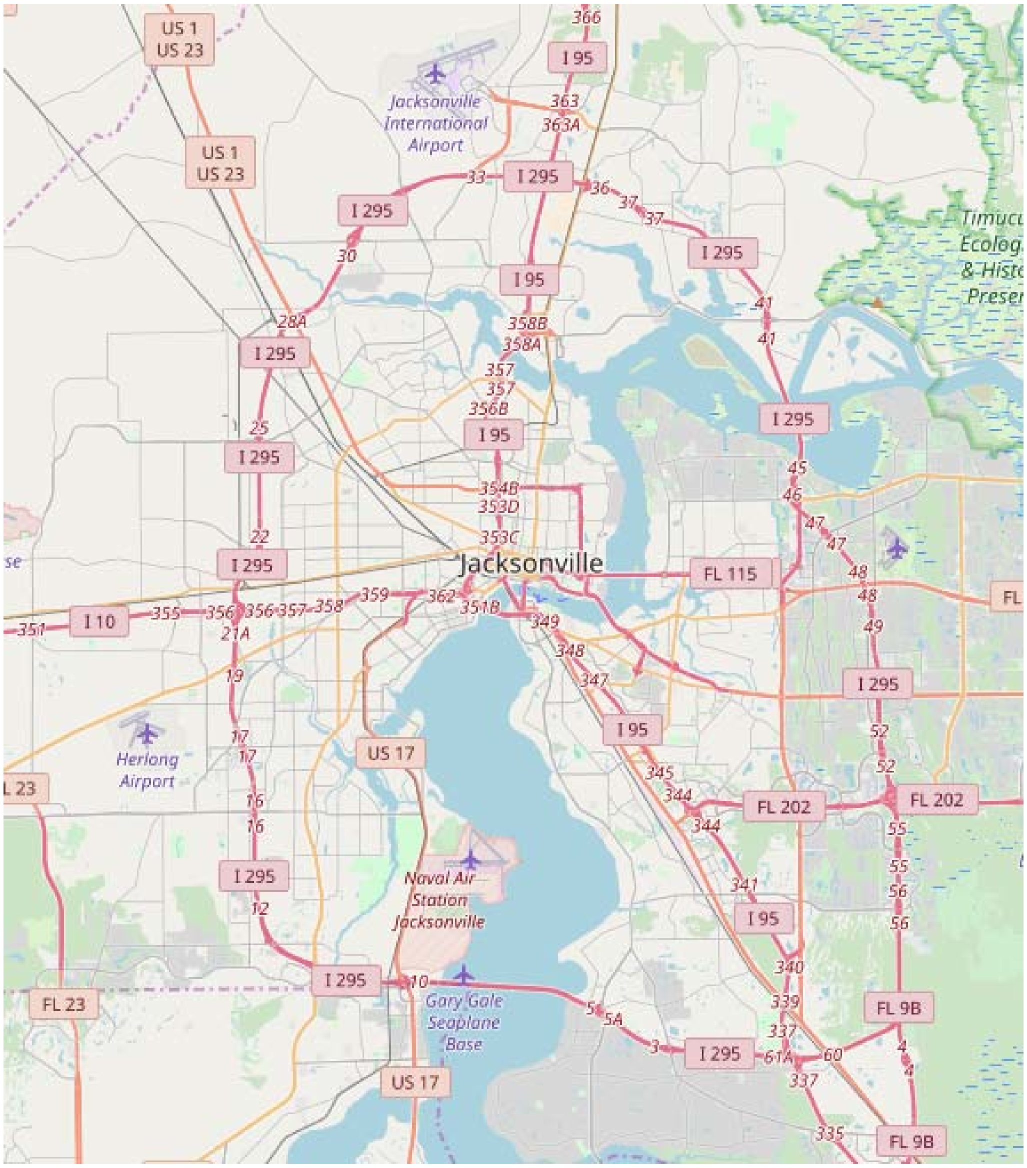


**Figure 16. Interstate highways I-95, I-10, and I-295.**

Source: OpenStreeMap

## 6.2 *Analysis Framework*

In this example, the outcome variables analyzed are similar to the outcome variables used in traditional model calibration and sensitivity testing:

- For the overall system, these include global convergence metrics between subsequent iterations of the integrated ABM-DTA model.

- 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 (VMT).
- On the supply side, the simulation model can produce multiple measures of effectiveness. These range from local measures describing the performance of, for example, an intersection (e.g., queue lengths, signalized delay) to system-wide measures like overall VMT, vehicle hours traveled (VHT), and delay. Because the DTA model spans a region, the project team used the latter category of measures of effectiveness to describe the performance of the network under the various assumptions and modeled scenarios. In this example exercise, the project team used the traditional definition of delay as the difference between experienced travel time and free-flow travel times.
- For the EMA, regression analysis of the scenario outcomes as a function of the input assumptions was also done.

The project team summarized the example exploratory scenarios according to these key metrics:

- Global Convergence:
  - Total numbers of trips, average trip distances, and average trip speeds.
- Demand:
  - Trips by mode and vehicle type.
  - Average trip speeds, distances, and VMT.
- Supply:
  - VMT, VHT, and delay, by facility type.
  - DTA visualizations.
- Regression:
  - Vehicle-trips, average vehicle-trip distances, VMT, and vehicle-trip speed.
  - By vehicle type (conventional vehicle, private AV, shared AV).

## 6.3 *Global Convergence*

Table 6 to Table 8 show the percentage changes in predicted total numbers of trips, average trip distances, and average trip speeds encountered between global iteration 2 and iteration 3, for each of the 8 half-hour AM time periods of the DTA simulation in the example. The largest positive changes listed are also shown in green and the largest negative changes shown in red. Changes in all cells are well below 1%, except for the 5:00 a.m. to 5:29 a.m. period, which has greater percentage variation due to a smaller number of trips in the period.

The average speeds show some larger changes toward the later time periods, as the speeds in periods between 7:30 a.m. and 8:30 a.m. are the most affected by simulated congestion. These speeds are reported by the DaySim demand model output and are based on the travel time skims produced by the TransModeler assignment in the previous iteration. Thus, the difference in speeds in the second and third iterations of DaySim reflects changes in the skims resulting from the first and second DTA iterations. The skims from the third DTA would show even smaller changes in experienced travel speeds.

Table 6 to Table 8 reflect all vehicle types. A more detailed tabulation across three separate passenger vehicle types (non-AVs, private AVs, and shared TNC AVs) showed similar percentage changes between iterations 2 and 3 of the model run.

In a production model run for a long-range plan, it would be advisable to run an additional global iteration to ensure that the demand and supply models have converged, even at a fairly detailed spatial level. For the example exploratory analysis, however, the level of convergence indicated in the following tables is adequate to provide confidence that differences in results across the scenarios are due to differences in the scenario inputs and not greatly influenced by random effects of nonconvergence.

**Table 6. Change in predicted vehicle-trips, by time period from iteration 2 to iteration 3.**

| Period | 5:00 a.m.–5:29 a.m. | 5:30 a.m.–5:59 a.m. | 6:00 a.m.–6:29 a.m. | 6:30 a.m.–6:59 a.m. | 7:00 a.m.–7:29 a.m. | 7:30 a.m.–7:59 a.m. | 8:00 a.m.–8:29 a.m. | 8:30 a.m.–8:59 a.m. |
|---|---|---|---|---|---|---|---|---|
| BB–N0 | -0.24% | -0.94% | 0.20% | -0.14% | 0.07% | -0.02% | -0.07% | 0.00% |
| MM–L3 | 0.10% | -0.53% | -0.02% | 0.07% | -0.03% | -0.07% | -0.08% | -0.04% |
| MM–AC | 0.03% | -0.46% | 0.07% | 0.11% | 0.16% | 0.06% | 0.00% | 0.05% |
| MM–IC | 0.77% | 0.45% | -0.15% | 0.05% | 0.01% | 0.04% | -0.08% | 0.03% |
| MM–LC | -0.70% | -0.36% | 0.12% | -0.12% | -0.08% | -0.07% | 0.24% | 0.11% |
| LH–L3 | -0.28% | 0.85% | -0.19% | 0.13% | 0.06% | -0.02% | 0.06% | -0.05% |
| LH–AC | -0.51% | -0.04% | -0.17% | 0.07% | -0.15% | -0.13% | 0.02% | 0.07% |
| LH–IC | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| LH–LC | -0.28% | 0.45% | 0.01% | -0.04% | -0.18% | 0.06% | 0.19% | -0.09% |
| HL–L3 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| HL–AC | 0.21% | -0.53% | -0.02% | -0.11% | 0.16% | 0.12% | 0.07% | 0.00% |
| HL–IC | -0.50% | 0.51% | -0.12% | 0.08% | -0.04% | 0.28% | -0.09% | 0.02% |
| HL–LC | -0.95% | 0.17% | 0.10% | 0.03% | 0.13% | -0.18% | -0.11% | -0.02% |
| HH–L3 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| HH–AC | -0.01% | 0.47% | -0.01% | 0.13% | -0.08% | -0.07% | 0.07% | 0.12% |
| HH–IC | 0.54% | -0.20% | -0.03% | 0.06% | -0.06% | 0.08% | 0.14% | -0.14% |
| HH–LC | 0.54% | 0.30% | 0.05% | -0.05% | 0.02% | 0.03% | 0.23% | -0.04% |

**Table 7. Change in overall predicted average trip distances from iteration 2 to iteration 3.**

| Run | 5:00 a.m.–5:29 a.m. | 5:30 a.m.–5:59 a.m. | 6:00 a.m.–6:29 a.m. | 6:30 a.m.–6:59 a.m. | 7:00 a.m.–7:29 a.m. | 7:30 a.m.–7:59 a.m. | 8:00 a.m.–8:29 a.m. | 8:30 a.m.–8:59 a.m. |
|---|---|---|---|---|---|---|---|---|
| BB–N0 | 0.23% | 0.33% | 0.30% | -0.29% | 0.32% | -0.21% | 0.13% | -0.13% |
| MM–L3 | -0.96% | 0.41% | -0.10% | -0.19% | 0.11% | 0.00% | -0.13% | -0.13% |
| MM–AC | -0.43% | -0.62% | 0.30% | 0.10% | 0.00% | -0.21% | 0.13% | 0.13% |
| MM–IC | 0.43% | -1.03% | 0.10% | 0.00% | 0.22% | 0.00% | 0.13% | -0.26% |
| MM–LC | 0.65% | -0.21% | -0.10% | -0.10% | 0.11% | 0.00% | 0.00% | -0.13% |
| LH–L3 | -0.55% | 0.22% | 0.00% | 0.10% | -0.12% | -0.12% | 0.28% | -0.14% |
| LH–AC | 0.11% | -1.17% | 0.00% | -0.10% | -0.12% | -0.24% | 0.14% | -0.14% |
| LH–IC | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| LH–LC | -0.88% | 0.76% | -0.11% | 0.00% | -0.12% | 0.00% | 0.14% | 0.28% |
| HL–L3 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| HL–AC | -0.31% | 0.40% | 0.19% | 0.09% | 0.10% | 0.10% | 0.12% | 0.12% |
| HL–IC | 1.26% | -0.30% | 0.00% | -0.27% | 0.20% | 0.00% | 0.12% | -0.35% |
| HL–LC | -0.52% | -0.30% | -0.19% | -0.18% | -0.10% | -0.10% | -0.23% | -0.47% |
| HH–L3 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| HH–AC | -1.28% | 0.41% | -0.31% | 0.10% | 0.23% | 0.00% | 0.00% | 0.13% |
| HH–IC | 0.00% | 0.21% | 0.10% | 0.50% | -0.11% | 0.11% | 0.13% | -0.27% |
| HH–LC | 0.21% | -0.51% | 0.10% | 0.10% | 0.00% | -0.11% | -0.13% | 0.00% |

**Table 8. Change in overall predicted average trip speeds from iteration 2 to iteration 3.**

| Run | 5:00 a.m.–5:29 a.m. | 5:30 a.m.–5:59 a.m. | 6:00 a.m.–6:29 a.m. | 6:30 a.m.–6:59 a.m. | 7:00 a.m.–7:29 a.m. | 7:30 a.m.–7:59 a.m. | 8:00 a.m.–8:29 a.m. | 8:30 a.m.–8:59 a.m. |
|---|---|---|---|---|---|---|---|---|
| BB–N0 | 0.13% | -0.13% | 0.09% | 0.23% | 0.16% | 0.00% | 0.24% | 0.29% |
| MM–L3 | -0.07% | 0.17% | -0.31% | -0.16% | -0.25% | -0.11% | -0.70% | -1.17% |
| MM–AC | 0.04% | -0.04% | 0.27% | 0.44% | 0.39% | 0.15% | -0.07% | -0.13% |
| MM–IC | 0.26% | 0.04% | -0.26% | 0.02% | 0.34% | -0.07% | -0.32% | -0.45% |
| MM–LC | 0.15% | -0.11% | 0.33% | 0.33% | 0.45% | 0.49% | 0.47% | 0.67% |
| LH–L3 | -0.11% | -0.11% | 0.12% | 0.16% | 0.06% | 0.73% | 0.34% | 0.13% |
| LH–AC | -0.22% | 0.04% | -0.19% | -0.04% | -0.18% | -0.09% | -0.13% | 0.22% |
| LH–IC | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| LH–LC | -0.17% | 0.07% | 0.27% | 0.14% | 0.10% | 0.64% | 0.70% | 0.58% |
| HL–L3 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| HL–AC | -0.17% | 0.06% | 0.35% | 0.16% | 0.46% | 0.22% | 0.37% | -0.09% |
| HL–IC | 0.17% | 0.04% | -0.28% | -0.08% | 0.13% | 0.18% | -0.23% | -0.46% |
| HL–LC | -0.22% | -0.11% | -0.17% | -0.31% | -0.04% | -0.51% | -0.69% | -1.34% |
| HH–L3 | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% | 0.00% |
| HH–AC | -0.28% | 0.00% | 0.14% | -0.14% | 0.19% | 0.18% | 0.59% | 0.21% |
| HH–IC | 0.15% | 0.00% | -0.12% | -0.08% | 0.04% | 0.04% | 0.09% | -0.26% |
| HH–LC | 0.00% | -0.04% | -0.12% | 0.12% | 0.38% | 0.28% | 0.51% | 0.44% |

## 6.4 *Demand Model Results and Analysis*

Analysis of the demand model results is important. For the example, the project team analyzed trips by mode and vehicle type, distance, speed, and VMT. Figure 17 to Figure 21 summarize the key differences across scenarios for the final iteration. The salient findings are as follows:

- The total number of person-trips and vehicle-trips does not vary much across scenarios. Figure 17 shows that a small percentage of new person-trips are generated because of increased accessibility with the new shared AV mode and lower value of in-vehicle time for AV travel. The most trips are in the HH scenarios with high penetration of both private and shared AVs. Figure 18 shows that the number of vehicle trips is also stable across scenarios and never more than a few percentage points higher than in the base scenario. Private AVs have somewhat higher vehicle occupancy than non-AVs, according to the model assumptions.
- The effects of the scenarios on average trip distance (Figure 19) and total VMT (Figure 20) may seem to contradict each other at first glance. In general, shared TNC AV trips are shorter than private AV trips due to the higher availability in denser urban areas and the higher cost per mile. Compared to the medium-medium (MM) scenarios, the scenarios with high shared AV adoption and low private AV adoption (LH) show higher average trip distances for all vehicle types but lower total VMT overall. This is because more of the medium-distance trips are made by shared AVs, raising the average trip distance for shared AVs. However, those trips were shorter than average for private AVs, so having those trips switch to shared AVs also increases the average trip distance for private AVs. Overall, however, there is a much higher percentage of trips made by shared AVs, and those trips are still shorter on average than private AV trips, so the overall VMT declines. The results for switching to the high private AV, low shared AV (HL) scenarios show opposite trends. Average trip length decreases somewhat for all vehicle types, but the overall VMT is higher because more trips are made by private AV. The HL scenarios are the highest overall in terms of VMT and the LH scenarios are the lowest. Looking at person-miles traveled across all modes (Figure 21), the trends across scenarios are like those for vehicle-miles.
- The simulation does not include zero-occupant AV trips. It is not clear if those will affect VMT more for TNC-based shared AVs or for private AVs, which could use remote parking or serve as households' "private taxis."
- Relative to the variation in trips, average distance, and miles traveled (Figure 17 to Figure 20), less variation exists across scenarios for average vehicle-trip speeds experienced in the network (Figure 21). The speeds for the HL scenarios are a bit lower, and the speeds for the HH scenarios are a bit higher.
- For trips, average distance, and miles traveled, little variation exists for network supply scenarios within each demand scenario. For average trips speeds, however, the network scenarios appear to have a greater effect according to Figure 21. It is difficult to gauge from the raw tables and graphs how systematic and significant these differences are. More insight on the effects of the supply scenarios is obtained from the regression analysis that follows and from more detailed investigation of the network simulation outputs.

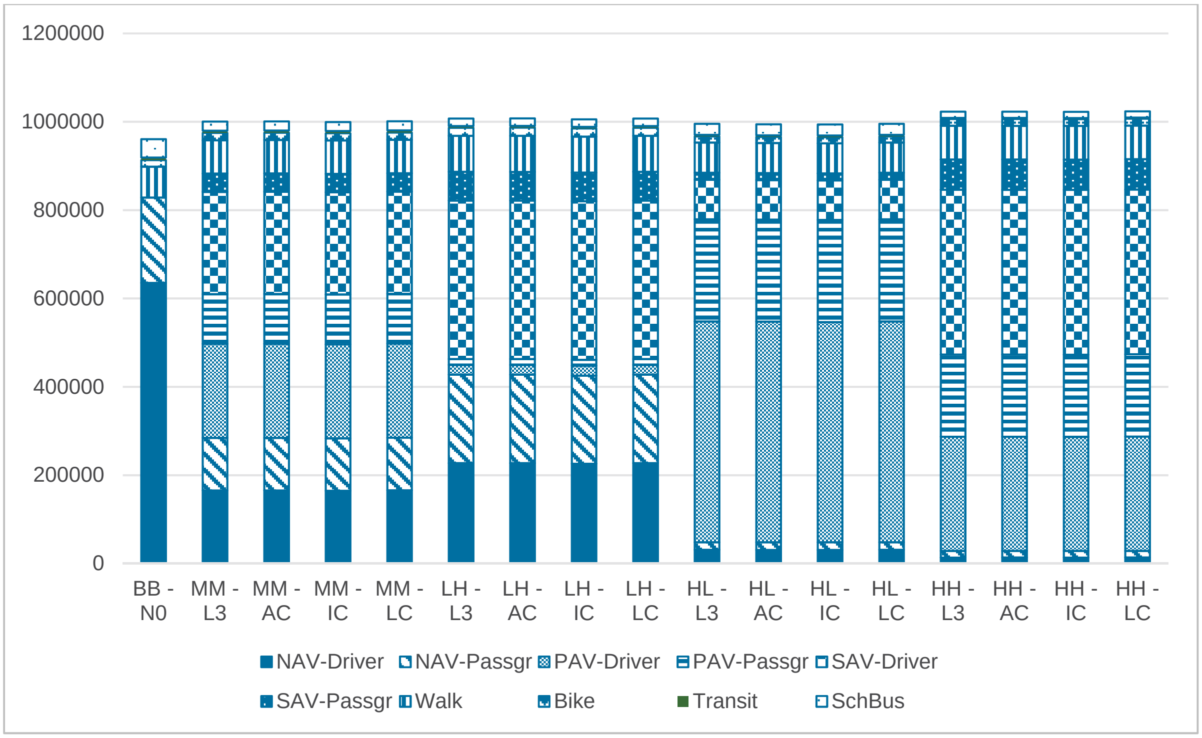


**Figure 17. AM person-trips, by mode/vehicle type and scenario.**

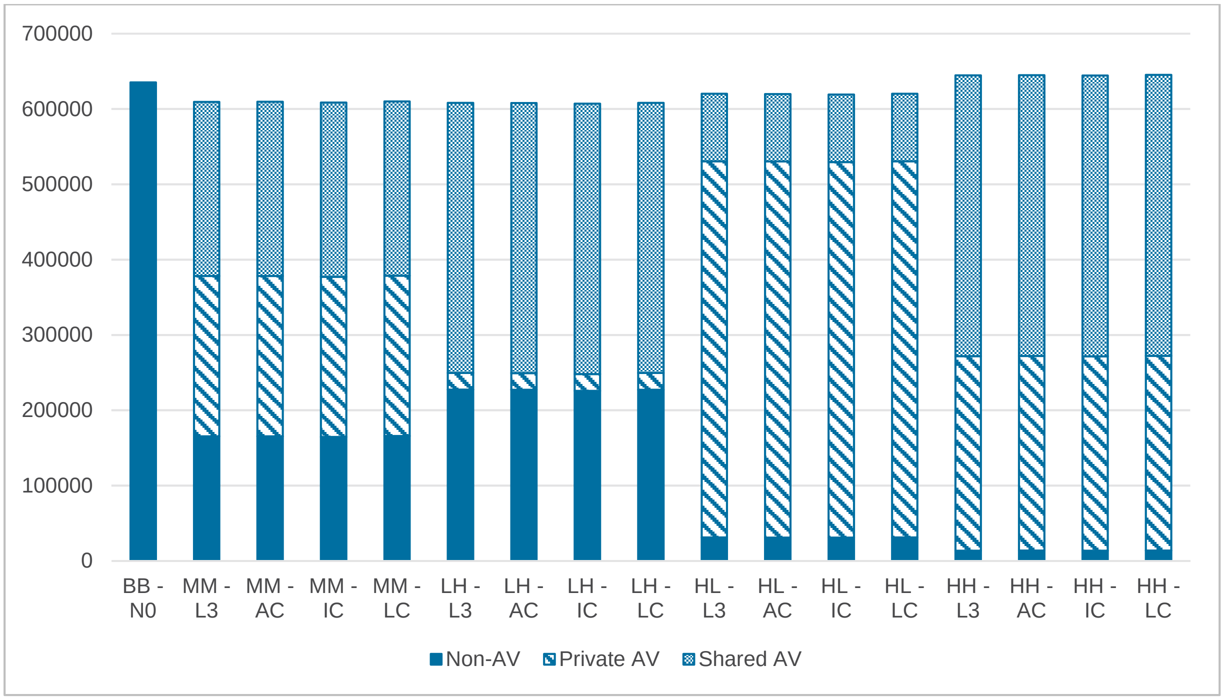


**Figure 18. AM vehicle-trips, by vehicle type and scenario.**

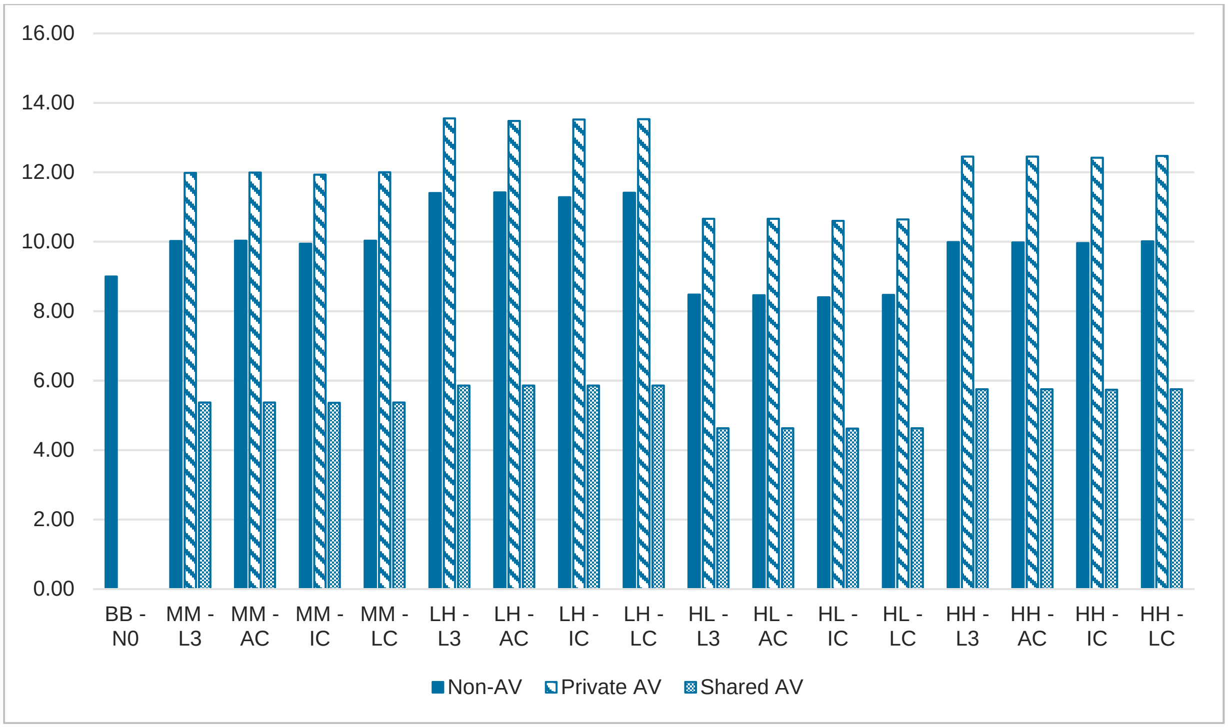


**Figure 19. AM average vehicle-trip distances, by vehicle type and scenario.**

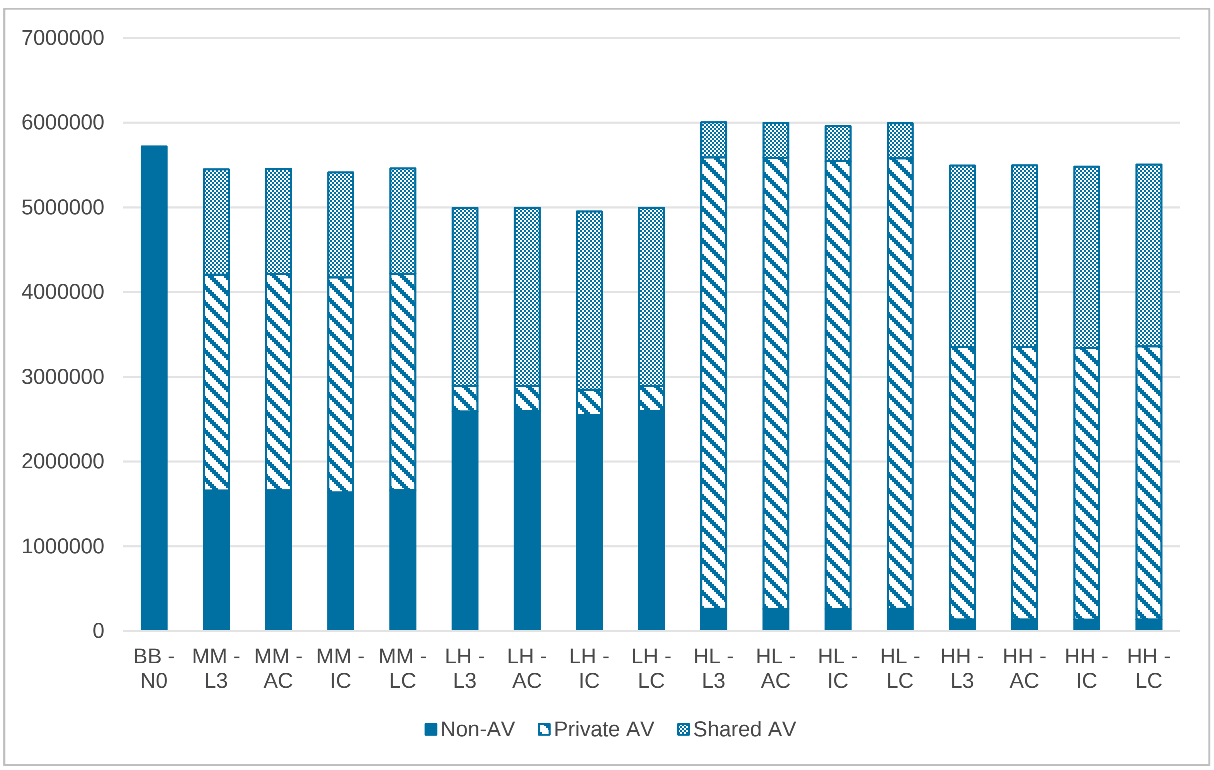


**Figure 20. AM VMT, by vehicle type and scenario.**

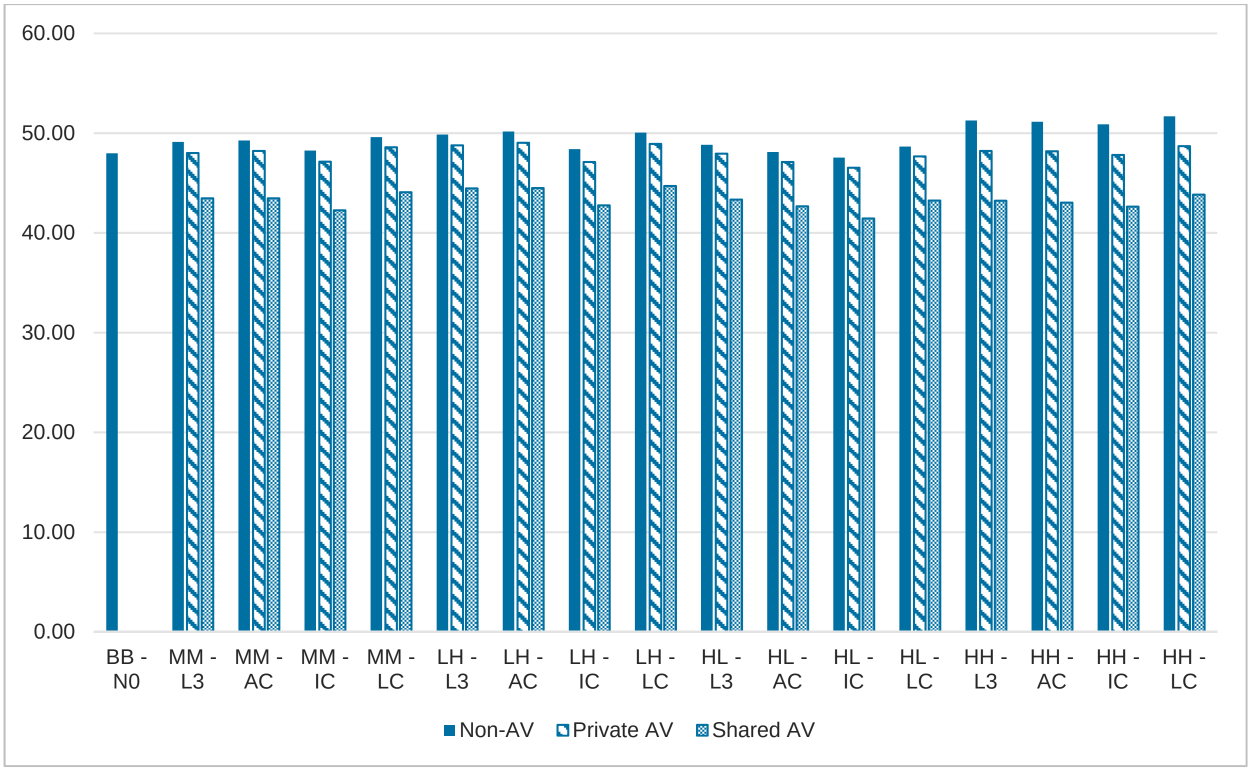


**Figure 21. AM average vehicle-trip speeds, by vehicle type and scenario.**

## 6.5 *Supply Model Results and Analysis*

Figure 22 through Figure 24 summarize VMT, VHT, and vehicle hours of delay (VHD), by scenario. In addition, because various supply scenarios restrict access to interstates or to the left lanes of interstate facilities, the project team also examined the VMT, VHT, and VHD metrics for interstates independently of arterial and local streets to confirm that any benefits that are observed on interstates are not offset by a decline in LOS on arterials or local streets. No such trend was observed. Hence, for simplicity, Figure 22 through Figure 24 summarize the statistics aggregated over all roadway functional classes region-wide.

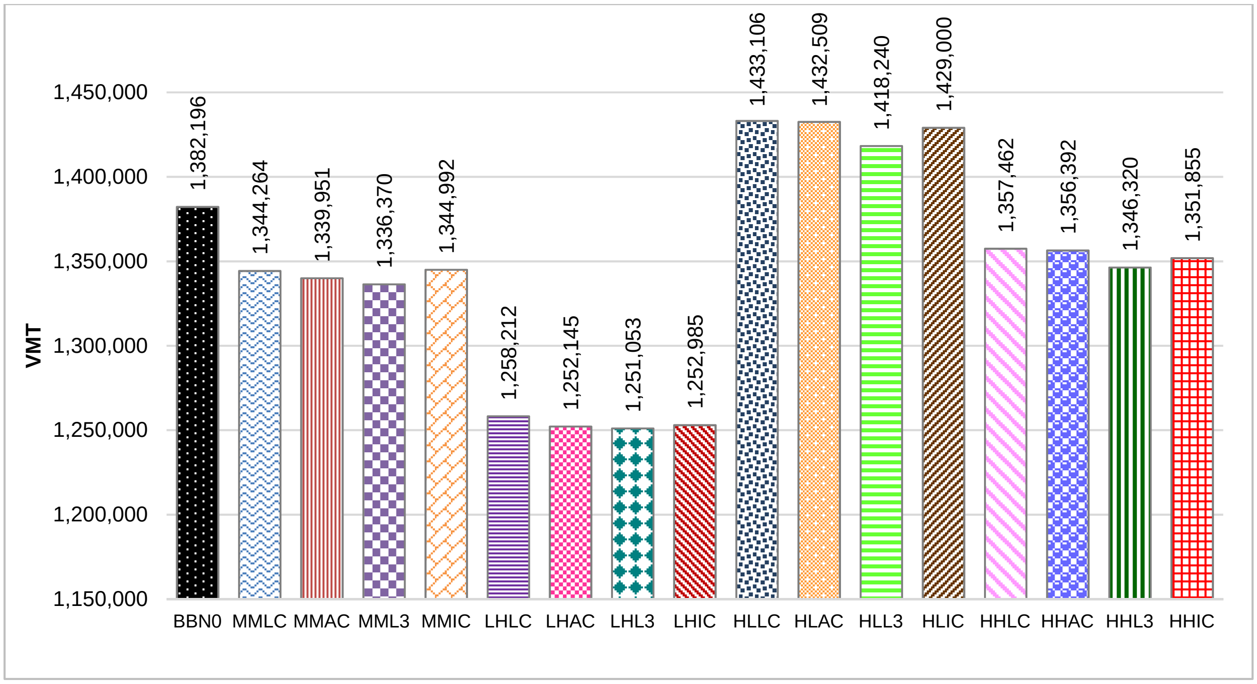


**Figure 22. DTA VMT, by scenario.**

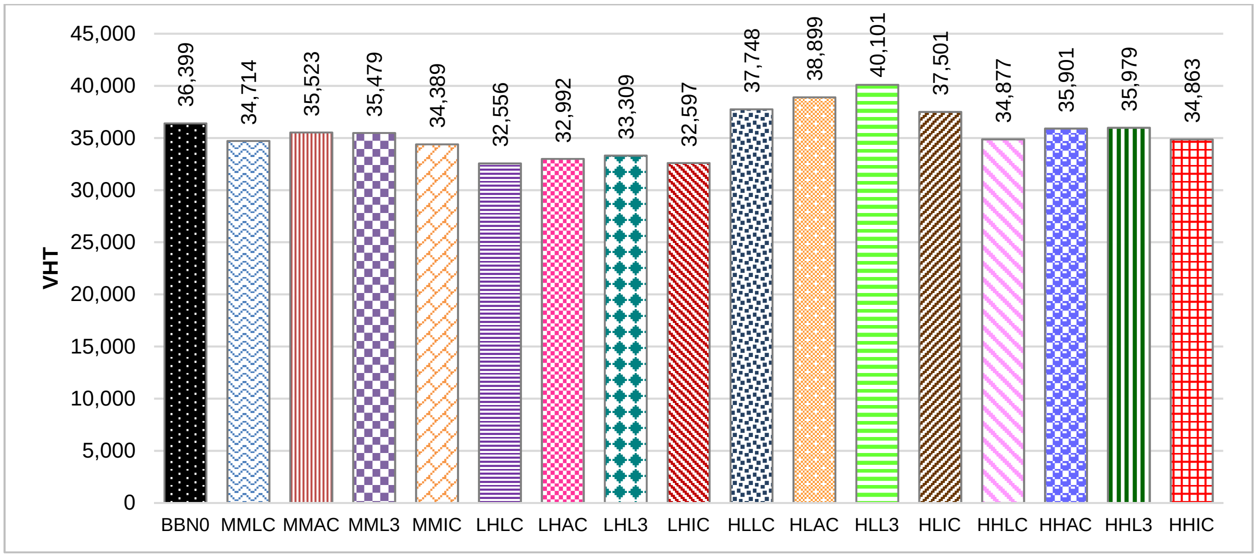


**Figure 23. DTA VHT, by scenario.**

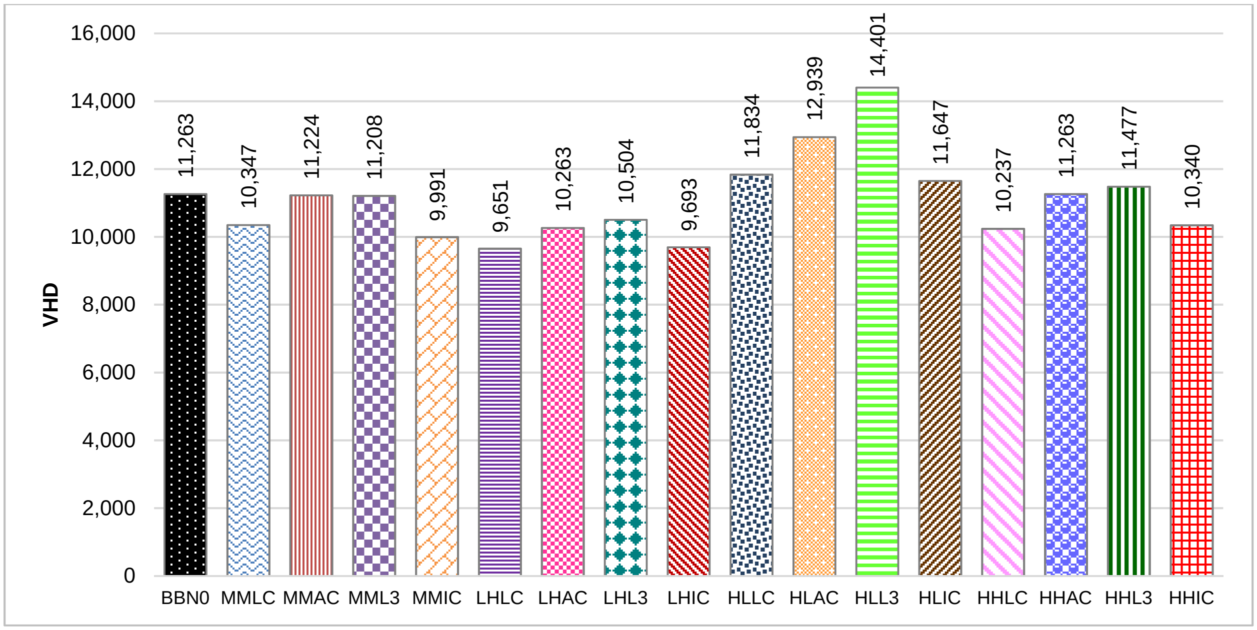


**Figure 24. DTA VHD, by scenario.**

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 increases in VMT, VHT, and VHD across the AV scenarios relative to the baseline demand scenario (i.e., BBN0) in the example exercise. In the scenarios assuming high rates of private auto ownership (e.g., HL and HH), many more trips are made relative to the base demand scenario due to the reduced VOT for AVs (notwithstanding dead-head trips, which were not modeled). None of the supply strategies or AV technologies can meaningfully mitigate the increases in VHD most likely brought on by the increase in travel in those scenarios.

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 promise in other scenarios not identified a priori. Running additional scenarios would better flesh out the relationships between the range of variables and assumptions enumerated in this example exercise analysis.

Nevertheless, of the scenarios that were evaluated, trends are more easily observed when assumptions outside the direct control of policy-makers (e.g., private AV adoption or the success or failure of shared AV services) are held constant and mitigative measures (i.e., supply-side strategies) can vary. To that end, Figure 25, Figure 26, Figure 27, and Figure 28 offer another view of the same example exercise data, summarizing VHD while holding demand assumptions MM, LH, HL, and HH, respectively, constant and varying supply and technology assumptions. Each figure also includes the delay for the baseline scenario, BBN0. The comparisons help identify whether combinations of supply strategies and AV and CV technologies have the potential to reduce delay on the surface transportation system relative to the base scenario in which no supply strategy is applied and no AVs or CVs exist.

These figures show that the surface transportation system generally performs better than the baseline condition when supply strategies and AV and CV technologies are introduced in the scenarios with lower rates of private auto adoption (i.e., MM and LH). However, delays are greater than in the baseline condition in the HL and HH scenarios, when supply strategies and AV and CV technologies cannot offset the increased delay likely brought about by the increases in VMT in the other demand scenarios.

Additionally, the comparisons demonstrated in Figure 25 through Figure 28 suggest strongly that the most effective technology in reducing delay given any set of demand assumptions is C, which represents the highest level of automation (L3) with CACC, an outcome that is in keeping with expectations. Less evident a priori, however, are the relative merits of supply-side strategies, which are the system parameters over which transportation system operators have the most leverage. According to the analysis, the most effective supply strategy is I, in which AVs and CVs are granted exclusive use of the left lanes of interstate facilities on and outside of I-295 and of all lanes on interstate facilities within I-295.

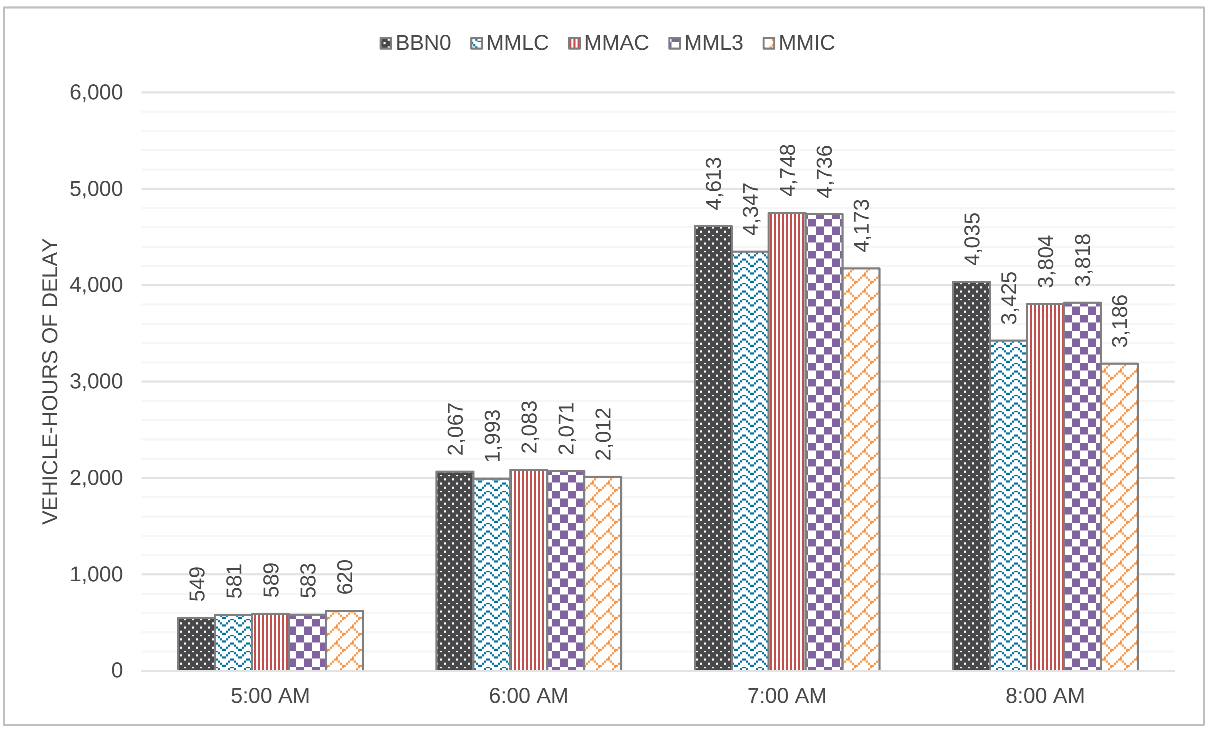


**Figure 25. Total VHD for the MM demand assumption, varying supply and technology.**

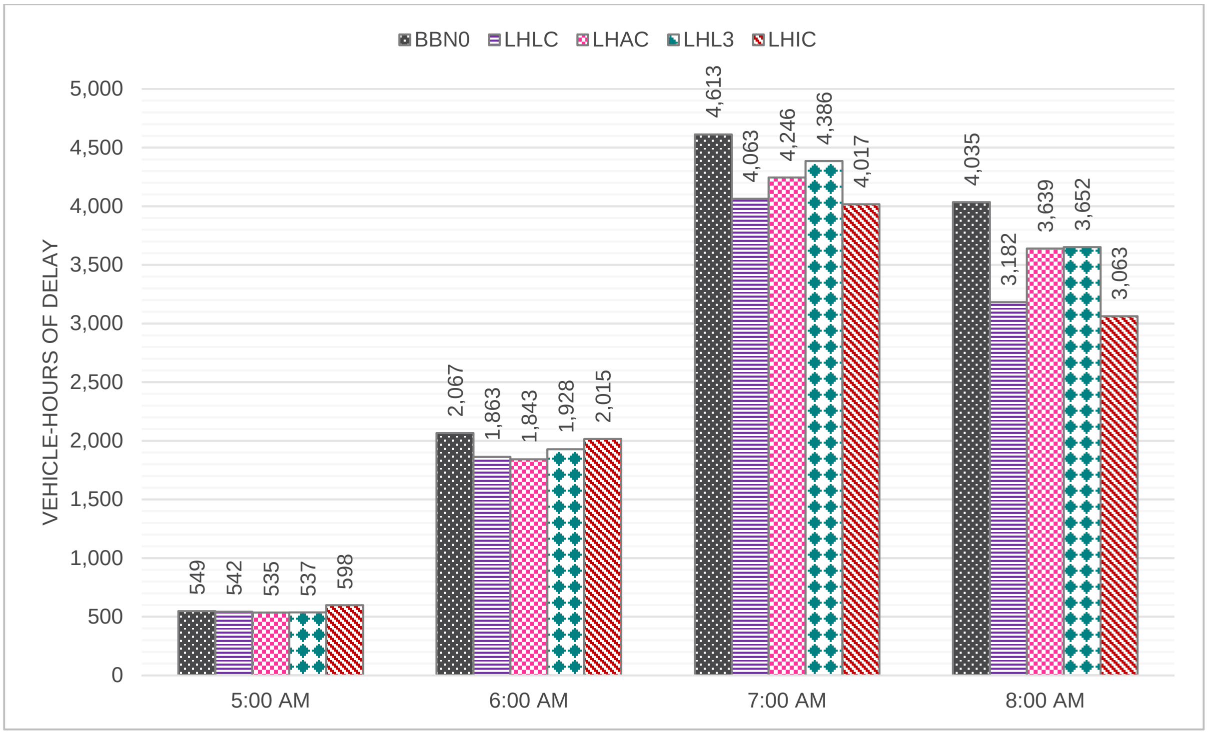


**Figure 26. Total VHD for the LH demand assumption, varying supply and technology.**

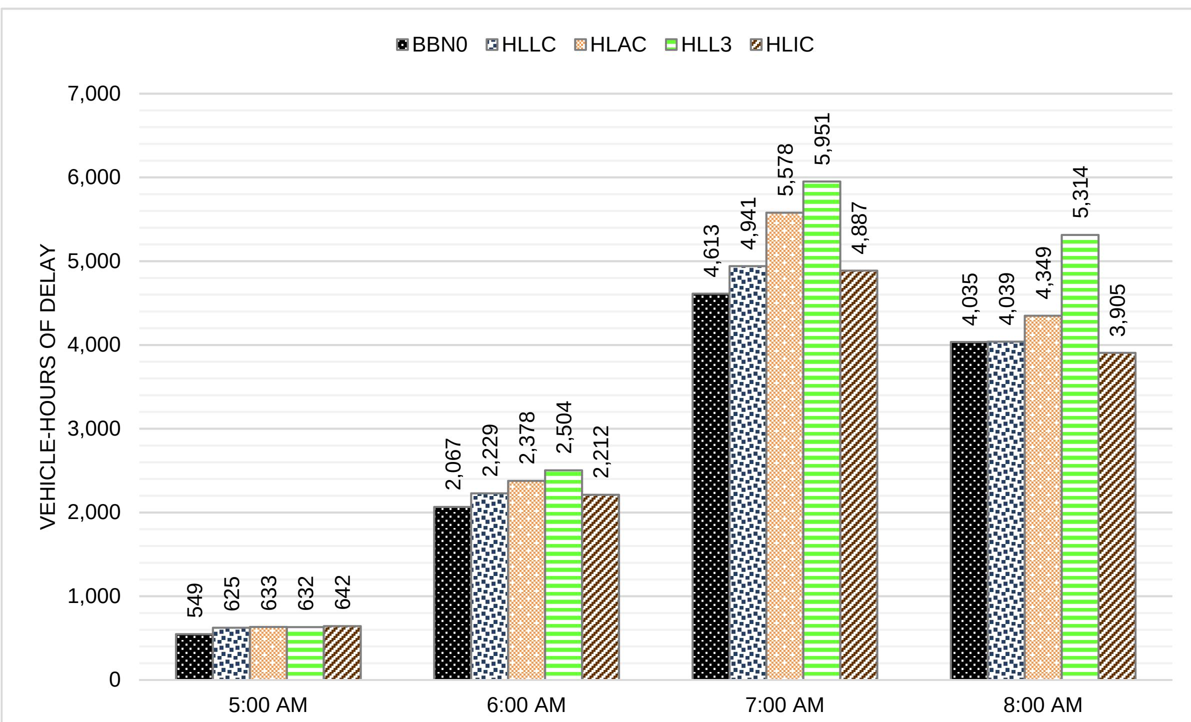


**Figure 27. Total VHD for the HL demand assumption, varying supply and technology.**

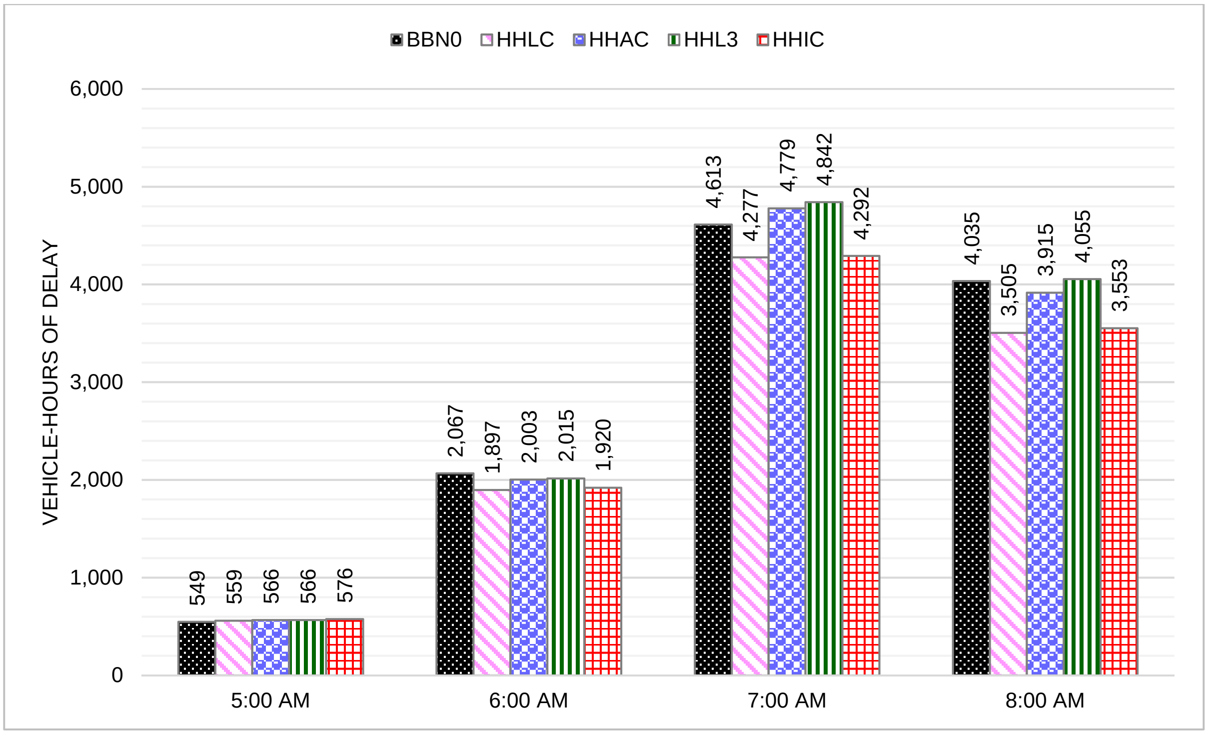


**Figure 28. Total VHD for the HH demand assumption, varying supply and technology.**

The least effective of the strategies appears to be L3, the lone scenario in which the AV or CV technology does not include CACC. Earlier in the experiment, scenarios were included in which L2 automation was assumed. Those scenarios also did not perform well in terms of delay, leading to a narrowing of the final cut of scenarios to L3 and L3 + CACC. Figure 25 through Figure 28 may indicate that any AV or CV technologies lacking the advantages of CACC are unlikely to meaningfully increase capacity. These findings confirm the initial analysis of the DTA adaptations for AV and CV.

Figure 30 through Figure 32 offer another view of the same example exercise data, summarizing delay while holding the supply and technology assumptions—L3, AC, IC, LC—constant and varying demand assumptions. These comparisons support the earlier observation that, whichever supply strategies are considered, and whichever AV and CV technologies are anticipated, surface transportation systems are likely most vulnerable to the convergence of high private AV adoption and low shared AV adoption. This phenomenon is most likely attributable to the aforementioned effects these modes have on average trip lengths.

It is also notable in Figure 30 through Figure 32 that the VHD is consistently and substantively lower than in the baseline scenario, BBN0, only when CACC technology is present *and* a supply strategy—I or L—is applied. Put another way, HL demand scenarios notwithstanding, supply and technology scenarios IC (Figure 31) and LC (Figure 32) are the only scenarios in which the system performs consistently better than the baseline condition irrespective of supply strategy and technology. When AVs do not have CACC (Figure 29) and when AVs, with or without CACC, operate in mixed traffic on all lanes and on all facilities (Figure 30), VHD remains generally on par with, or is worse than, the baseline scenario.

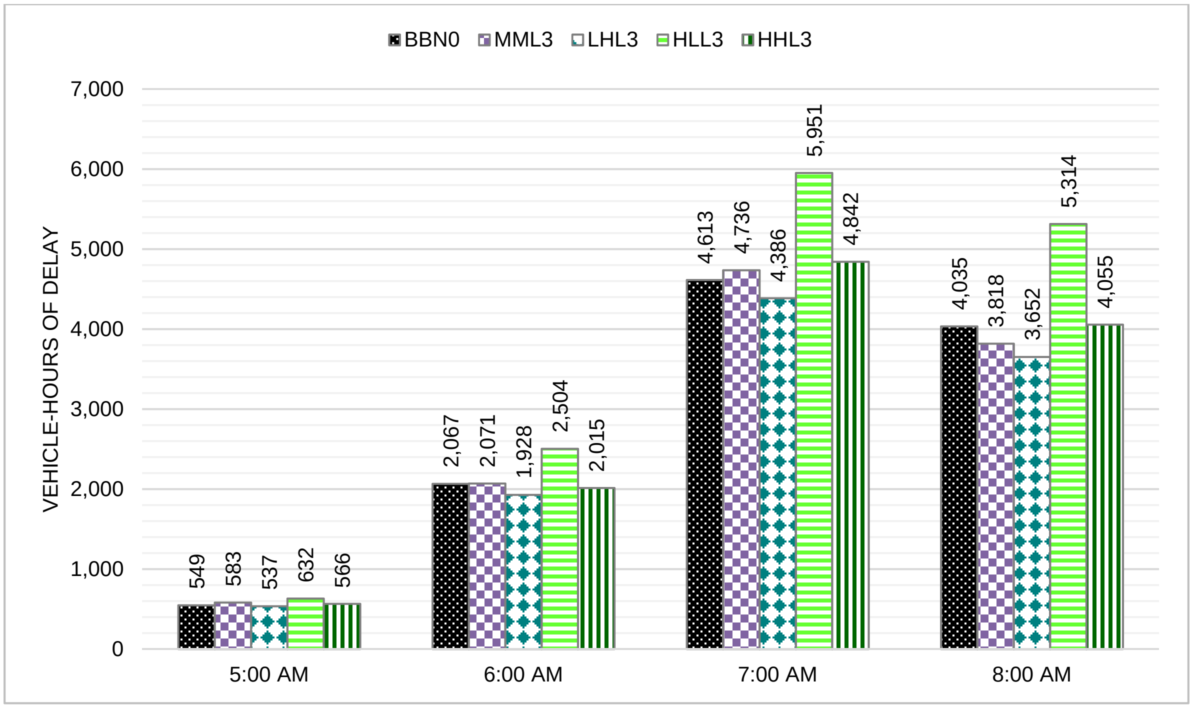


**Figure 29. Total VHD for the L3 supply assumption, varying demand.**

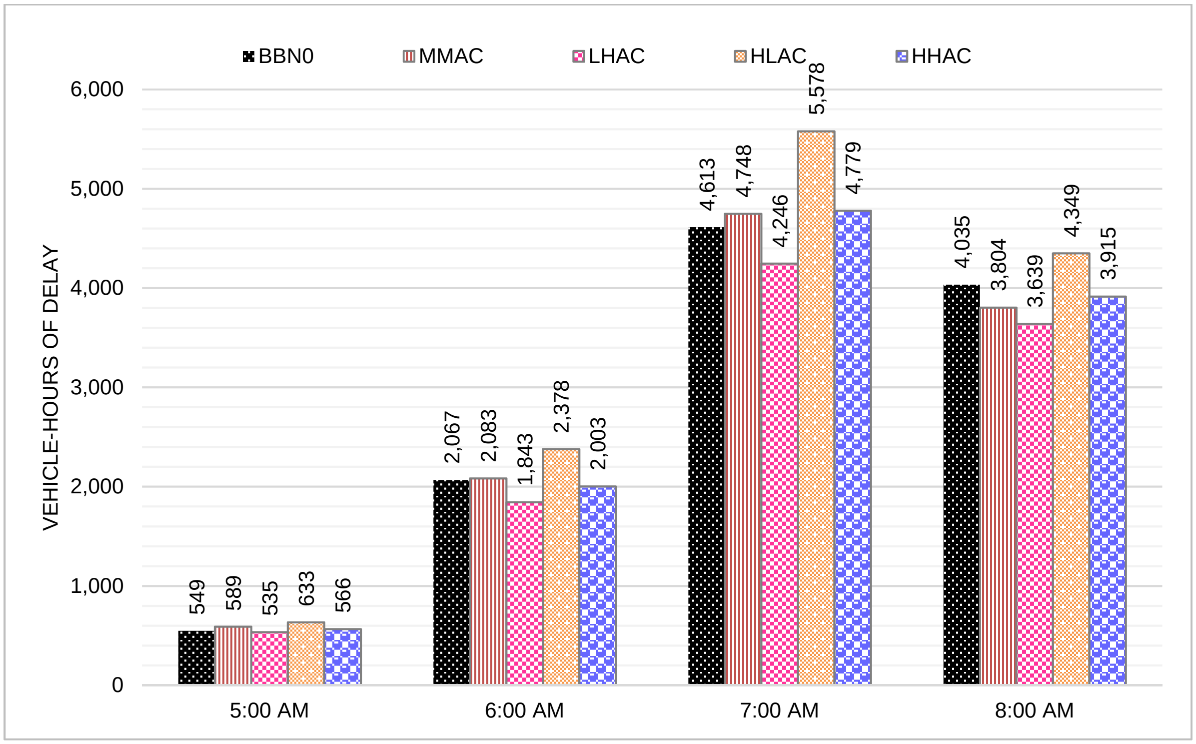


**Figure 30. Total VHD for the AC supply assumption, varying demand.**

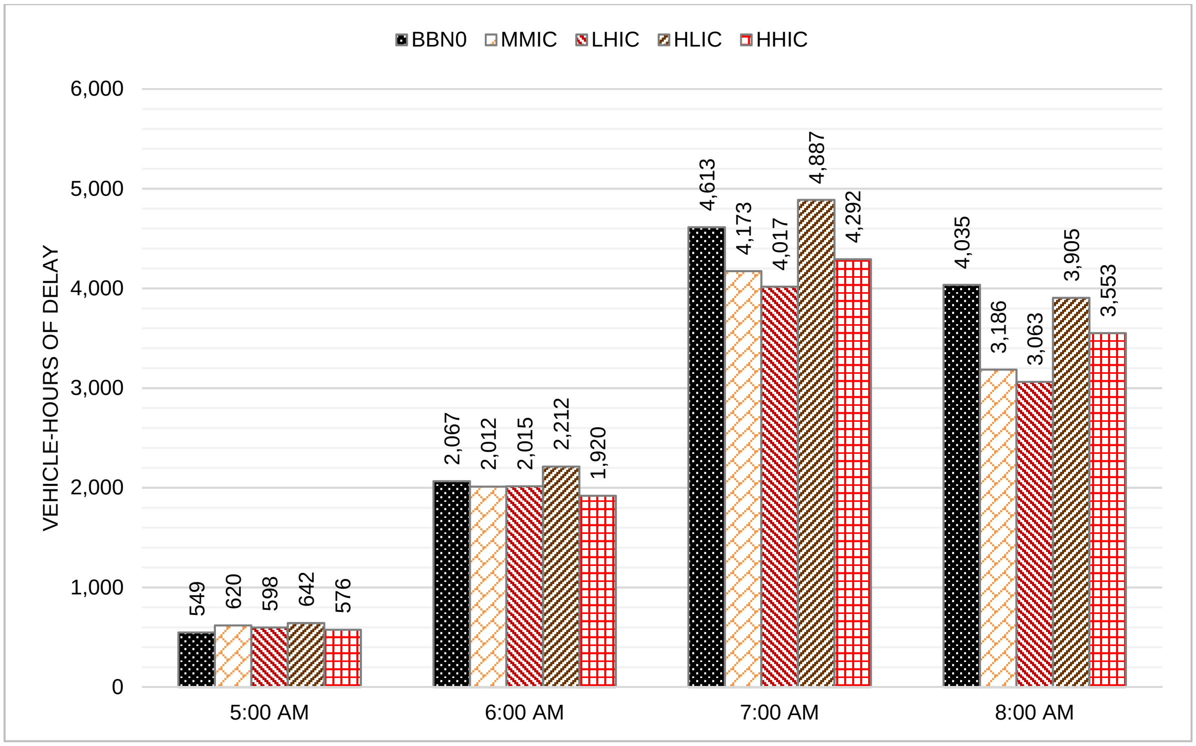


**Figure 31. Total VHD for the IC supply assumption, varying demand.**

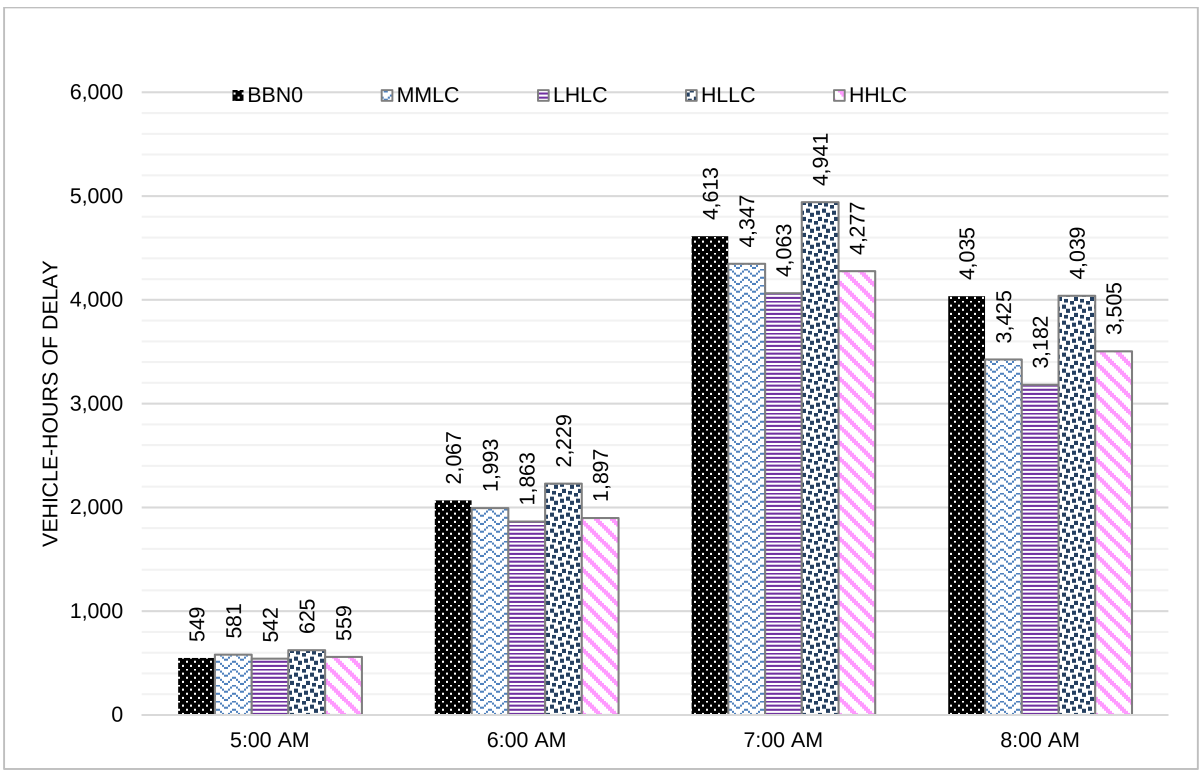


**Figure 32. Total VHD for the LC supply assumption, varying demand.**

Whereas 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 in the example exercise 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 33 through Figure 36 show a congested stretch of I-295 northbound west of downtown Jacksonville at 8:00 a.m. in various AV scenarios from the example exercise. In the images, the conventional vehicles are highlighted with green stars, and the remaining blue vehicles are AVs.

In Figure 33 and Figure 34, one can see in the simulation additional evidence supporting the comparison between the HHIC and HHLC scenarios previously discussed. In the image of the HHIC scenario, the back of the queue of northbound traffic headed for downtown Jacksonville is notably longer than in the HHLC scenario. This visual comparison of queue lengths confirms the previous tables and charts that show the HHIC scenario as having the greater delay of these two scenarios.

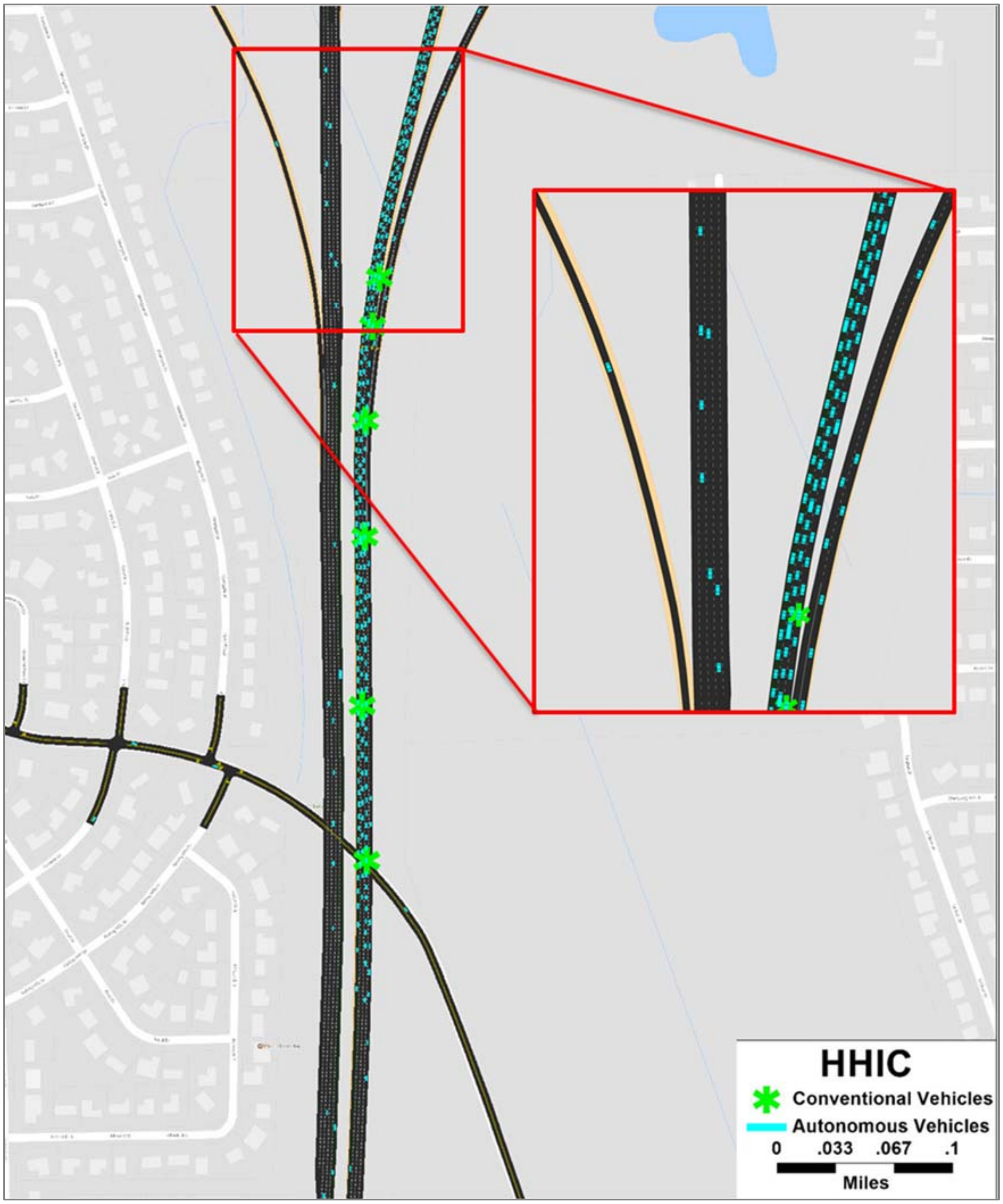


**Figure 33. Visualization of back of I-295 northbound queue in HHIC scenario.**

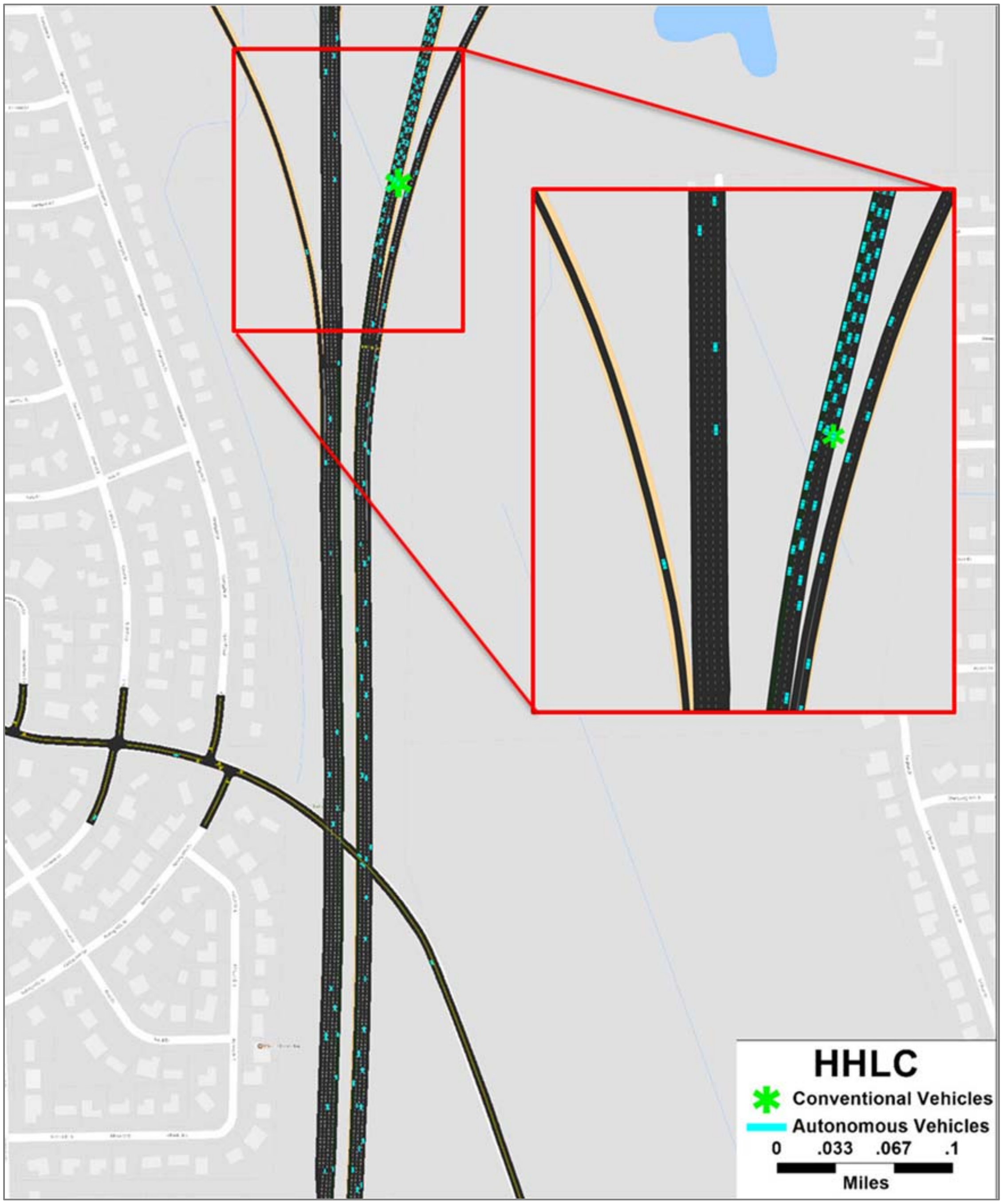


**Figure 34. Visualization of back of I-295 northbound queue in HHLC scenario.**

In the images, the conventional vehicles are highlighted with green stars, and the remaining blue vehicles are AVs. Per Figure 33 and Figure 34, only a few conventional vehicles can be seen in the HH demand scenarios, but in other scenarios, one may observe greater interactions between AVs and conventional vehicles. Figure 35 and Figure 36 show simulations of the HLL3 and MML3 scenarios at the same location on I-295. In the images, the greater number of conventional vehicles is evident.

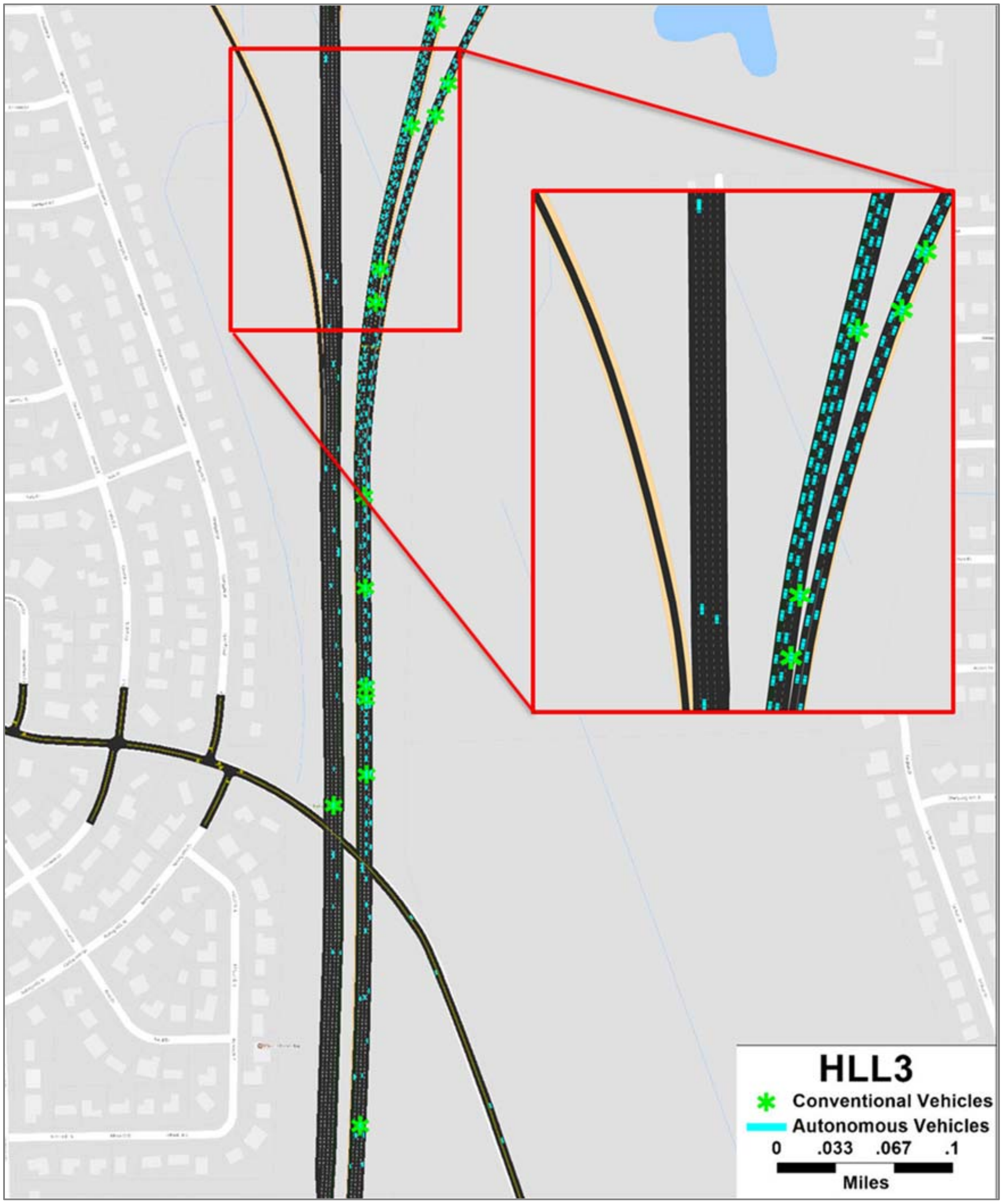


**Figure 35. Visualization of back of I-295 northbound queue in HLL3 scenario.**

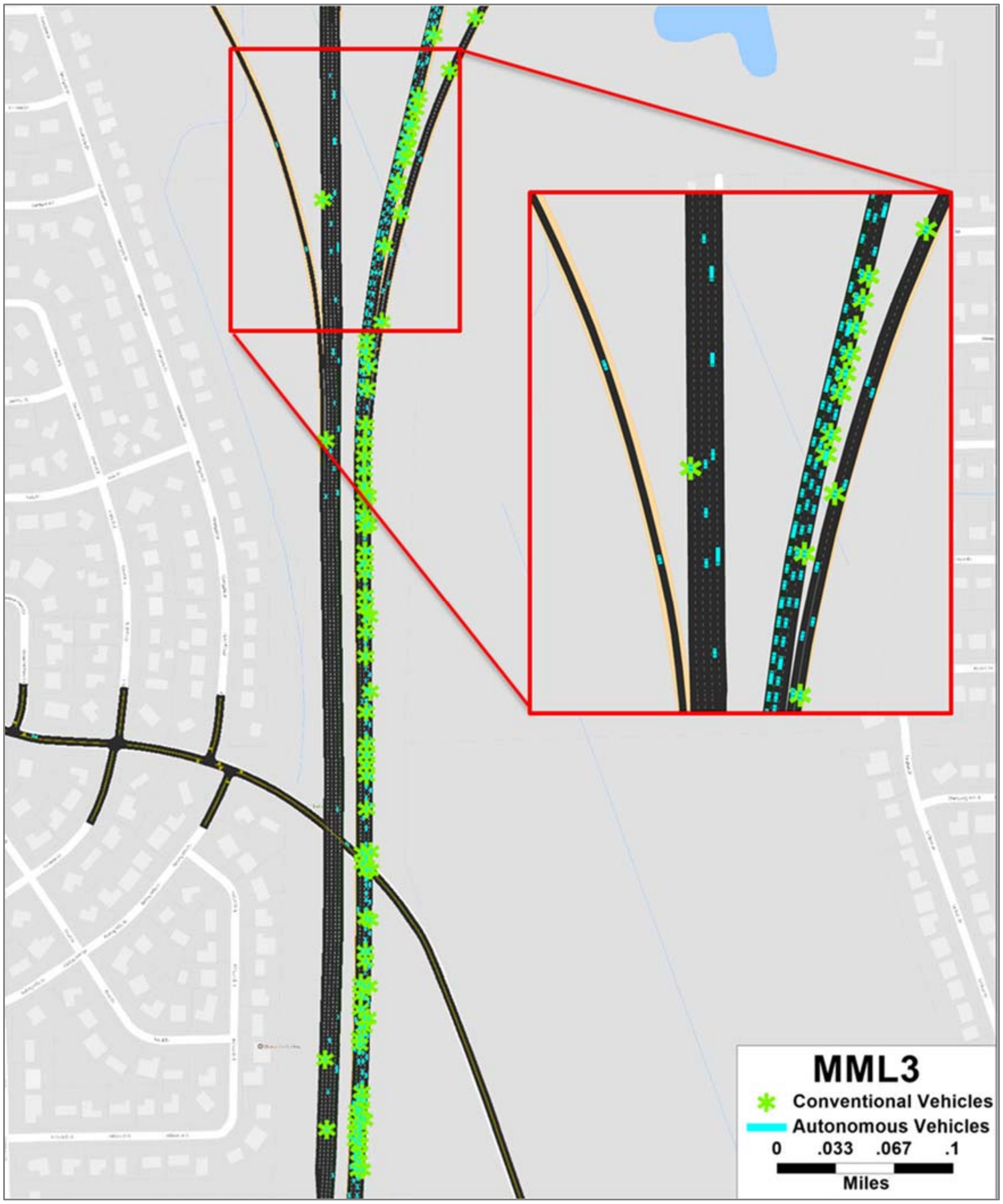


**Figure 36. Visualization of back of I-295 Northbound queue in MML3 scenario.**

## 6.6 *Regression Analysis*

One of the key methodological components of EMA is to use an experimental design in specifying the simulated scenarios. This facilitates independent analysis of the effect of each set of assumptions. This experiment completed the regression analysis of the scenario outcomes as a function of the input assumptions.

Table 9 through Table 16 show the results of regression analysis of the outcomes in terms of vehicle-trips, average vehicle-trip distances, overall VMT, and average vehicle-trip speeds. Each model is estimated separately by vehicle type (non-AV, private AV, and shared TNC AV), and then totaled across all three passenger vehicle types (not including commercial vehicles). The base non-AV scenario is not included in the regressions—only the 16 AV-related scenarios. For each model, there are 16 scenarios times 8 half-hour time periods—or 128 data points as observations.

The overall findings from the regression models, which generally reinforce the findings from the previous section, include the following:

- The model fit, in terms of R-squared is high for all models, indicating that the differences in the outcomes between scenarios are due to the differences in inputs, with relatively negligible effect of random variation or nonconvergence.
- The effects of the demand scenarios on total trips, average distances, and VMT are significant and align with previously articulated findings.
- The effects of time periods show fewer trips during the early AM periods, as one would expect. Also, the trips arriving after 8:00 a.m. tend to be shorter distance.
- For vehicle speeds, the low private AV, high shared AV scenarios have somewhat higher average speeds, with somewhat less congestion due to the lower VMT on the network in these scenarios. Although the difference is statistically significant, it is somewhat less than 1 mph versus an average of around 40 mph, so a difference of approximately 2%. However, an average speed difference of 2% for the entire regional network may translate to large differences in congestion levels and speeds for specific areas, links, and intersections.
- The results for average vehicle speed and arrival time period indicate that average speeds are higher for trips made before 8:00 a.m. This may be because these trips are longer distance on average and spend a smaller proportion of travel time on minor arterials and local streets. Also, traffic congestion often accumulates over time, so the period after 8:00 a.m. has somewhat higher congestion levels.
- The supply scenarios show no significant effects on total trips, average distances, or VMT. For average speeds, however, some significant differences exist. The IC scenarios with all lanes of the interstate inside I-295 converted to AV only have significantly lower average speeds—approximately 2% lower. The effect is not just for non-AVs, but for all vehicle types.

More detailed analysis of the network simulation outputs using the detailed path trajectories rather than the skims, however, shows a different result for the average speeds and delays, with the IC and LC scenarios resulting in fewer delays and slightly higher average speeds. This discrepancy suggests that the ABM trip output files should be used to analyze demand effects (trips, distances, VMT), while the DTA trip output files should be used to analyze network effects (speeds, delays, VHT). It also suggests that additional research is required to fully understand any remaining differences in skimmed travel times versus trajectory travel times.

**Table 9. Regression model for number of trips, by scenario/time period/vehicle type.**

| Vehicle Type | Non-AV | Non-AV | Private AV | Private AV | Shared AV | Shared AV | All Types | All Types |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** |
| Constant | 0.286 | 13.3 | 0.425 | 10.4 | 0.487 | 16.0 | 1.198 | 200.0 |
| Demand—High Private, Low Shared | -0.168 | -10.3 | 0.358 | 11.6 | -0.177 | -7.7 | 0.013 | 2.9 |
| Demand—Low Private, High Shared | 0.077 | 4.7 | -0.238 | -7.7 | 0.159 | 6.9 | -0.002 | -0.4 |
| Demand—High Private, High Shared | -0.190 | -11.6 | 0.057 | 1.8 | 0.177 | 7.7 | 0.044 | 9.8 |
| Supply—Network Scenario AC | 0.000 | 0.0 | 0.000 | 0.0 | 0.000 | 0.0 | 0.000 | 0.0 |
| Supply—Network Scenario IC | -0.001 | -0.1 | 0.000 | 0.0 | 0.000 | 0.0 | -0.001 | -0.2 |
| Supply—Network Scenario LC | 0.000 | 0.0 | 0.000 | 0.0 | 0.000 | 0.0 | 0.000 | 0.1 |
| Arrive Period—5:00 a.m. to 5:29 a.m. | -0.198 | -8.6 | -0.428 | -9.8 | -0.499 | -15.3 | -1.125 | -175.7 |
| Arrive Period—5:30 a.m. to 5:59 a.m. | -0.195 | -8.5 | -0.419 | -9.6 | -0.490 | -15.0 | -1.104 | -172.4 |
| Arrive Period—6:00 a.m. to 6:29 a.m. | -0.091 | -3.9 | -0.173 | -4.0 | -0.250 | -7.7 | -0.513 | -80.2 |
| Arrive Period—6:30 a.m. to 6:59 a.m. | -0.099 | -4.3 | -0.194 | -4.5 | -0.266 | -8.1 | -0.559 | -87.2 |
| Arrive Period—7:00 a.m. to 7:29 a.m. | -0.005 | -0.2 | 0.023 | 0.5 | 0.009 | 0.3 | 0.027 | 4.2 |
| Arrive Period—7:30 a.m. to 7:59 a.m. | -0.028 | -1.2 | -0.037 | -0.8 | -0.042 | -1.3 | -0.107 | -16.8 |
| Arrive Period—8:30 a.m. to 8:59 a.m. | -0.018 | -0.8 | -0.047 | -1.1 | -0.046 | -1.4 | -0.110 | -17.2 |

**Table 10. Number of trips, by scenario/time period/vehicle type model fit.**

| Model Fit | Observations (16 scenarios * 8 time periods) | R-squared |
|---|---|---|
| Non-AV Only | 128 | 0.829 |
| Private AV Only | 128 | 0.844 |
| Shared AV Only | 128 | 0.887 |
| All Three Types | 128 | 0.999 |

**Table 11. Regression model for average trip distance, by scenario/time period/vehicle type.**

| Vehicle Type | Non-AV | Non-AV | Private AV | Private AV | Shared AV | Shared AV | All Types | All Types |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** |
| Constant | 8.689 | 145.5 | 10.745 | 175.1 | 4.627 | 109.0 | 7.794 | 132.3 |
| Demand—High Private, Low Shared | -1.358 | -30.1 | -1.241 | -26.8 | -0.820 | -25.6 | 0.614 | 13.8 |
| Demand—Low Private, High Shared | 1.319 | 29.2 | 1.399 | 30.2 | 0.573 | 17.9 | -0.616 | -13.8 |
| Demand—High Private, High Shared | 0.164 | 3.6 | 0.551 | 11.9 | 0.458 | 14.3 | -0.289 | -6.5 |
| Supply—Network Scenario AC | 0.004 | 0.1 | -0.040 | -0.9 | -0.002 | -0.1 | 0.002 | 0.0 |
| Supply—Network Scenario IC | -0.078 | -1.7 | -0.065 | -1.4 | -0.004 | -0.1 | -0.038 | -0.8 |
| Supply—Network Scenario LC | 0.005 | 0.1 | -0.022 | -0.5 | -0.005 | -0.2 | -0.003 | -0.1 |
| Arrive Period—5:00 a.m. to 5:29 a.m. | 1.348 | 21.1 | 0.468 | 7.1 | 1.451 | 32.0 | 1.641 | 26.1 |
| Arrive Period—5:30 a.m. to 5:59 a.m. | 1.878 | 29.4 | 0.909 | 13.9 | 1.539 | 33.9 | 1.923 | 30.5 |
| Arrive Period—6:00 a.m. to 6:29 a.m. | 2.676 | 41.9 | 2.224 | 33.9 | 1.555 | 34.3 | 2.281 | 36.2 |
| Arrive Period—6:30 a.m. to 6:59 a.m. | 2.859 | 44.8 | 2.593 | 39.5 | 1.758 | 38.7 | 2.544 | 40.4 |
| Arrive Period—7:00 a.m. to 7:29 a.m. | 1.784 | 27.9 | 1.758 | 26.8 | 0.803 | 17.7 | 1.384 | 22.0 |
| Arrive Period—7:30 a.m. to 7:59 a.m. | 1.695 | 26.5 | 1.826 | 27.8 | 0.910 | 20.0 | 1.442 | 22.9 |
| Arrive Period—8:30 a.m. to 8:59 a.m. | -0.063 | -1.0 | -0.022 | -0.3 | 0.091 | 2.0 | 0.020 | 0.3 |

**Table 12. Average trip distance, by scenario/time period/vehicle type model fit.**

| Model Fit | Observations (16 scenarios * 8 time periods) | R-squared |
|---|---|---|
| Non-AV Only | 128 | 0.985 |
| Private AV Only | 128 | 0.983 |
| Shared AV Only | 128 | 0.980 |
| All Three Types | 128 | 0.972 |

**Table 13. Regression model for VMT, by scenario/time period/vehicle type.**

| Vehicle Type | Non-AV | Non-AV | Private AV | Private AV | Shared AV | Shared AV | All Types | All Types |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** |
| Constant | 0.262 | 11.1 | 0.443 | 10.6 | 0.226 | 12.9 | 0.931 | 117.6 |
| Demand—High Private, Low Shared | -0.174 | -9.8 | 0.346 | 11.0 | -0.103 | -7.8 | 0.068 | 11.4 |
| Demand—Low Private, High Shared | 0.116 | 6.5 | -0.281 | -8.9 | 0.108 | 8.1 | -0.057 | -9.6 |
| Demand—High Private, High Shared | -0.190 | -10.6 | 0.083 | 2.6 | 0.113 | 8.5 | 0.006 | 1.1 |
| Supply—Network Scenario AC | 0.000 | 0.0 | 0.000 | 0.0 | 0.000 | 0.0 | 0.000 | 0.0 |
| Supply—Network Scenario IC | -0.002 | -0.1 | -0.002 | -0.1 | 0.000 | 0.0 | -0.004 | -0.7 |
| Supply—Network Scenario LC | 0.000 | 0.0 | 0.000 | 0.0 | 0.000 | 0.0 | 0.000 | 0.1 |
| Arrive Period—5:00 a.m. to 5:29 a.m. | -0.182 | -7.2 | -0.434 | -9.7 | -0.237 | -12.7 | -0.853 | -100.7 |
| Arrive Period—5:30 a.m. to 5:59 a.m. | -0.177 | -7.0 | -0.422 | -9.5 | -0.231 | -12.3 | -0.830 | -98.1 |
| Arrive Period—6:00 a.m. to 6:29 a.m. | -0.051 | -2.0 | -0.109 | -2.5 | -0.075 | -4.0 | -0.235 | -27.8 |
| Arrive Period—6:30 a.m. to 6:59 a.m. | -0.057 | -2.3 | -0.125 | -2.8 | -0.081 | -4.3 | -0.263 | -31.1 |
| Arrive Period—7:00 a.m. to 7:29 a.m. | 0.035 | 1.4 | 0.107 | 2.4 | 0.051 | 2.7 | 0.192 | 22.7 |
| Arrive Period—7:30 a.m. to 7:59 a.m. | 0.008 | 0.3 | 0.042 | 0.9 | 0.026 | 1.4 | 0.076 | 9.0 |
| Arrive Period—8:30 a.m. to 8:59 a.m. | -0.017 | -0.7 | -0.048 | -1.1 | -0.018 | -1.0 | -0.083 | -9.8 |

**Table 14. VMT, by scenario/time period/vehicle type model fit.**

| Model Fit | Observations (16 scenarios * 8 time periods) | R-squared |
|---|---|---|
| Non-AV Only | 128 | 0.829 |
| Private AV Only | 128 | 0.858 |
| Shared AV Only | 128 | 0.881 |
| All Three Types | 128 | 0.996 |

**Table 15. Regression model for average trip speed, by scenario/time period/vehicle type.**

| Vehicle Type | Non-AV | Non-AV | Private AV | Private AV | Shared AV | Shared AV | All Types | All Types |
|---|---|---|---|---|---|---|---|---|
| **Variables** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** | **Coeff.** | **T-stat** |
| Constant | 47.584 | 195.3 | 45.451 | 289.6 | 40.150 | 240.1 | 44.353 | 286.8 |
| Demand—High Private, Low Shared | -0.583 | -3.2 | -0.526 | -4.4 | -0.768 | -6.1 | -0.050 | -0.4 |
| Demand—Low Private, High Shared | 0.456 | 2.5 | 0.362 | 3.1 | 0.738 | 5.8 | -0.092 | -0.8 |
| Demand—High Private, High Shared | 1.589 | 8.6 | 0.171 | 1.4 | 0.005 | 0.0 | -0.708 | -6.1 |
| Supply—Network Scenario AC | -0.099 | -0.5 | -0.130 | -1.1 | -0.195 | -1.5 | -0.148 | -1.3 |
| Supply—Network Scenario IC | -0.861 | -4.7 | -0.925 | -7.8 | -1.129 | -8.9 | -0.952 | -8.1 |
| Supply—Network Scenario LC | 0.123 | 0.7 | 0.135 | 1.1 | 0.219 | 1.7 | 0.163 | 1.4 |
| Arrive Period—5:00 a.m. to 5:29 a.m. | -2.006 | -7.7 | 1.288 | 7.7 | 4.649 | 26.0 | 2.022 | 12.2 |
| Arrive Period—5:30 a.m. to 5:59 a.m. | -1.618 | -6.2 | 1.570 | 9.4 | 4.791 | 26.8 | 2.279 | 13.8 |
| Arrive Period—6:00 a.m. to 6:29 a.m. | 5.457 | 20.9 | 7.217 | 43.0 | 8.292 | 46.4 | 7.549 | 45.7 |
| Arrive Period—6:30 a.m. to 6:59 a.m. | 4.076 | 15.6 | 5.644 | 33.6 | 7.334 | 41.0 | 6.159 | 37.3 |
| Arrive Period—7:00 a.m. to 7:29 a.m. | 3.039 | 11.7 | 3.986 | 23.8 | 4.809 | 26.9 | 4.223 | 25.5 |
| Arrive Period—7:30 a.m. to 7:59 a.m. | 0.954 | 3.7 | 1.879 | 11.2 | 3.461 | 19.4 | 2.272 | 13.7 |
| Arrive Period—8:30 a.m. to 8:59 a.m. | 0.114 | 0.4 | 0.237 | 1.4 | -0.046 | -0.3 | 0.111 | 0.7 |

**Table 16. Average trip speed, by scenario/time period/vehicle type model fit.**

| Model Fit | Observations (16 scenarios * 8 time periods) | R-squared |
|---|---|---|
| Non-AV Only | 128 | 0.936 |
| Private AV Only | 128 | 0.969 |
| Shared AV Only | 128 | 0.974 |
| All Three Types | 128 | 0.972 |

# 7.0 Conclusions and Future Areas of Research

This report describes the process of integrating an ABM with a DTA for the region of Jacksonville, Florida, to understand the potential impacts of CAVs and ride-hailing. It also outlines an example analysis conducted by the project team. This demonstration is a preliminary investigation leading to the next phase's full EMA process, which is different from typical scenario analysis in that it is designed to handle many uncertain model relationships and inputs. While a standard scenario analysis may vary some 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 CAVs.

## 7.1 *The Project Contribution*

While the example did successfully demonstrate the main components of EMA, this project's key contribution is in ABM-DTA integration. To comprehensively investigate the impacts of CAVs and ride-hailing on the regional transportation system, an integrated ABM-DTA model is required. These disaggregate models are better able to model the complex relationships between individual persons (including drivers and passengers), individual vehicles (CAV or not), and a network that supports vehicle communication (V2V, V2I, V2X). Even though ABM-DTA models require significant resources and runtime, the example exercise helped convince the project team they are a step in the right direction and continue to be a promising area of research. The exercise also demonstrated to the project team that it is essential to vet the integrated system, like what was done for the dynamic skims analysis.

Unlike other attempts at ABM-DTA integration in practice and in the research, this example integrates the ABM with a microscopic simulation-based DTA. Despite the obstacles encountered, it has been one of the most successful integrated models developed in the industry and uses components that were already calibrated and deployed for use at the MPO level. Not only does the microscopic simulation model lend itself to representing CAVs, but it also provides a much more accurate representation of traffic than is possible in a mesoscopic model. Mesoscopic models are a popular choice for ABM-DTA integration, but these models lack lane-level details and represent traffic signals in approximate fashion only. The convergence of DTA models, especially mesoscopic models, has typically also been problematic, so it is noteworthy that it appears that not only does the microscopic DTA in this EMA exercise converge well in Jacksonville, but also that the entire ABM-DTA model seems to be convergent after the requisite computation time.

## 7.2 *Lessons Learned*

The first major effort in this example exercise was to strengthen the integration of the DaySim ABM and the TransModeler DTA, both of which had already been implemented in Jacksonville, Florida. As part of this work, the project team enhanced the feedback between DaySim and TransModeler in several important ways:

- The DaySim trip outputs included a new mode (paid ride-hail) and a new level for the driver or passenger attribute (passenger in an AV or no passenger at all). The project team also updated DaySim to allow for separate skims for AVs since TransModeler models the AVs as a separate “user class.” AV parking at the trip destination was also an area of experimentation.
- Production of dynamic skims. As discussed throughout this report, this was an especially difficult part of the example exercise due to several DTA modeling challenges, including long runtimes, network entrance and exit (i.e., loading point) issues, inconsistency in approaches to generating skimmed travel times, and heavy congestion (i.e., gridlock). Ultimately, the project team produced and verified a solid set of dynamic skims via this exercise.
- Initially, the ABM and DTA both operated at the parcel level. However, to produce skims at the TAZ level, the project team modified the DTA to simulate trips at the TAZ level and to facilitate integration. This inconsistency led to the issues discussed earlier, and as a result, the project team decided to try complete microzone-level integration (i.e., the DTA produces microzone-to-microzone dynamic skims that are also input to the ABM at the microzone-to-microzone level). Although this exercise was not fully completed, it appears to be a promising approach to integration since it is a good balance between spatial detail and computational requirements.

The second major example exercise effort focused on adapting the ABM and DTA models to accommodate key dimensions of uncertainty in the context of CAVs. This work has made possible modeling of the following system input and parameter assumptions:

- The level of AV ownership among households.
- The level of paid ride-hail use and corresponding changes in auto ownership.
- The level of network allowance for AV operation (e.g., AV-only lanes).
- The level of vehicle automation.

The project team developed a fractional-factorial experimental design to allow for the analysis of the independent effect of each level of each assumption. For example, the 4 different assumptions listed above were accommodated using an experimental design with 16 runs.

## 7.3 *Key Findings on the Impacts of CAVs*

The example exercise suggests the transportation system performs best when CAVs are not present because of increases in VMT that appear to be a consequence of CAVs for both the interstate and arterial systems. For the most part, there is currently no differentiation in the transportation system for different types of users in the context of CAVs. The introduction of new types of users like CAVs, which have the potential to use the system more efficiently, only becomes significant once their market saturation exceeds a certain threshold. In addition, repurposing some of the existing system for a minority-share user likely comes at the cost of the majority-share user, which likely also reduces overall system performance. Conversely, many of the purported benefits of CAVs, like in-vehicle passenger productivity (due to not driving), safety, and reliability, are not captured in this model framework.

Nevertheless, the work to date demonstrates the need for a full EMA process to support more comprehensive conclusions. The initial work compared the performance of each scenario to BBN0 as a baseline, but there are enough extra trips in the MM, LH, HH, and other trip tables that it is not possible to tell whether a supply strategy or technology will provide any benefits relative to a BB scenario. If the delay increases, it may simply be a consequence of the change in trip-making. Additional model runs—combining the most interesting demand scenarios with different supply scenarios—may help better understand this issue.

## 7.4 *Recommendations for Future Areas of Research*

A priority area for future research is to improve the integrated ABM-DTA model and improve its ease of use for an EMA process. Long runtimes and artificial congestion due to various ABM-DTA integration and network simulation issues will continue to delay research in this area if not satisfactorily resolved. For the example integrated model, the following issues remain unresolved:

- Fully reconciling the spatial resolution at which trips are loaded in the DTA with the spatial resolution of the skims leveraged in the ABM.
- Cleaning up any remaining network, zone connector abstraction, intersection geometry, and signal timing issues that create artificial congestion.
- Possibly moving to a future-year scenario to experience more congestion, which may result in greater benefits from CAVs. However, this may be difficult as demand forecasts may be unrealistically related to supply, or vice versa.
- Refreshing the calibration of the ABM consistent with the dynamic skims from the DTA and with Google-reported dynamic travel times.

Once the example integrated ABM-DTA model is more reliable and easier-to-use, work can focus on revisions to the key areas of uncertainty with respect to CAVs. These issues include the following:

- Model vehicle-sharing behavior and empty vehicles in more detail and more thoroughly address parking options. On the demand side, these changes could include representing different assumptions regarding the following:
    - Changes in intrahousehold ride-hailing/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 must 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, these changes may include being able to represent different assumptions regarding the following:

- The way in which paid ride-hailing services size their fleet and the way such 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 would influence the typical passenger wait times that are passed to DaySim.
- Different treatment of empty vehicle trips on the network. For example, empty CAVs could be prohibited from using congested facilities during peak periods.
- The location and supply of parking, including superstacked or remote parking for CAVs.

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