Ways to Consider Driverless Vehicles in Virginia Long Range Travel Demand Models

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ABSTRACT

Regional travel demand models are an institutionalized element of the transportation planning process, requiring a multiyear investment from collaborating agencies that rely on model outputs to assist with project prioritization and community visioning. The purpose of this research is to identify ways in which Virginia might (1) alter existing travel demand models in order to consider the impacts of driverless vehicles and (2) use such models to inform questions of interest to regional planners. Because the behavioral impacts of DVs are not known, the paper examined how five sets of alternative futures regarding DVs could be incorporated into the regional model, using the Charlottesville-Albemarle travel demand model as a case study for both (1) potential model modifications and (2) alternative futures, and by extension, related policy questions that might arise.

An outreach exercise conducted with attendees at the Annual Meeting of the Virginia Association of MPOs suggested five particular alternative futures of interest. DVs may (1) alter capacity (reducing it based on operator comfort or later increasing it as platoons result); (2) increase privately owned zero-occupant vehicle (ZOV) trips as commuters seek to avoid parking fees; (3) alter transit's mode share (decreasing it because DVs make auto travel more appealing by comparison or, alternatively, increasing transit's mode share through shared DVs which reduce transit's waiting time); (4) increase ZOV trips through non-familial sharing of DVs; and (5) increase travel by age groups with traditionally lower vehicle access. The regional model incorporated these impacts through altering the Charlottesville and Albemarle travel demand model as a case study, based on ranges of potential impacts of DVs as reported in the literature. (For example, because two sources had reported DVs might increase capacity by amounts of 30% and 100%, and because a third source had reported DVs might reduce capacity by 32%, scenarios were developed based on each of these values.) For each scenario, the impact on vehicle miles traveled (VMT) and vehicle hours traveled (VHT) was recorded as shown in table 11-17(the relative change rates were also recorded as shown in table 18-23), as well as performance measures of interest for each particular scenario. Examples of such measures include transit's mode share (given stakeholders' interest in transit) and impacts on oxides of nitrogen (NO_x), a precursor to ground level ozone (given stakeholders' interest in air quality).

For comparisons *within* a scenario, the results suggest that concerns about the alternative futures do not carry equal weight. For example, in Scenario 1, a capacity reduction attributed to DVs having lowered acceleration rates increases total travel time (vehicle hours traveled) by 46%. By contrast, a capacity increase attributed to DVs potentially having shorter headways of course reduces travel time—but only by 8%. As another example, within Scenario 3, DVs have the potential to increase transit's mode share from about 0.26% to 3.36% of commute trips if they fully eliminate transit waiting time and render easier the ability to travel from the origin and destination to the transit line. (By contrast, if DVs can make auto travel more appealing, the changes in absolute shares were modest: drive alone, carpool 2, and carpool 3+ increased their mode share from 93.86% to 94.14 %.) Interestingly, the greatest impact for this latter portion of

Scenario 3 was on nonmotorized modes: whereas transit trips decreased by about 5%, bicycle trips decreased by about 6%.

For comparisons *across* scenarios, the results can inform various policy initiatives. For example, the number of zero occupant vehicle trips may increase through a privately-owned DV self-parking (e.g., the owner sends the vehicle back home or to a lower cost parking area) or a shared DV traveling from one person's destination to another person's origin. Scenarios 2 and 4, respectively, suggest that while both situations may increase VMT, the former could increase VMT much more than the latter. (For the former, Scenario 2 increased commute-based VMT by 12% and NO_x by 10.8%; for the latter, Scenario 4 increased VMT by between 2.3% and 7.3%, depending on the degree of geographical and temporal matching between a leading trip's destination and a following trip's origin, and these changes corresponded to NO_x increases of 2.08% and 6.65%.) Such figures potentially inform a policy initiatives public support for sharing DVs (relative to individual ownership of DVs) if NO_x reduction is a priority.

The ability to incorporate alternative futures into legacy regional planning models can help address some, but not all, questions of interest to MPOs. For example, for this region in particular:

- Planners in this region wanted to know about potential development impacts if parking was no longer needed. A sub-scenario within Scenario 2 examined how conversion of parking lots in the Central Business District to other land uses could affect travel conditions. The results indicate a 2% increase in VHT overall, and speed decreases of no more than 5 mph in the downtown area—and the GIS-based analysis showed substantial land development potential in the downtown areas.

- Concerns about the transition period during which DVs might result in a reduction in capacity are justified if one is concerned about VHT, which increases by 46% if capacity drops. However, the impact on emissions, if one is concerned about NO_x, is actually positive—e.g., the reduction in speeds may be associated with a reduction in emissions owing to the parabolic relationship between emissions rates and speeds.

- Generally, induced travel will increase emissions, but not all types of induced travel are of equal concern. For example, an increase in travel by persons who presently do not have access to a vehicle increases NO_x by 1.51%. If empty DVs were sent back to their origin rather than parked for all commuters; in that case, NOx increases by 10.8%--more if this behavior applies to other trip purposes. Finally, if longer trips become more feasible due to DVs offering increased comfort, then NO_x increases by 21.65%. Thus, changes in behavior due to additional vehicle access increase NO_x slightly (by less than two percentage points) by 1.51%—but longer term behavioral changes are much more problematic, with NO_x increases that are more than ten times that amount. (A similar phenomenon is noted with VMT: additional travel by persons without access to a vehicle increases VMT by 1.7%; additional travel due to increased comfort increases VMT by 25.6%).

One caveat to these results: the sensitivity of the model to changes in travel impedance (such as capacity changes in scenario 1 or transit attractiveness in scenario 3) is influenced by whether the trip distribution step uses a singly or doubly constrained gravity model. The original Charlottesville/Albemarle travel demand model is doubly constrained such that forecast attractions and computed attractions are equal; this is not normally the case for a singly constrained gravity model. Assuming that one requires forecast productions to be equal to given productions after executing the trip distribution step, selection of the doubly or singly constrained version depends on the extent to which one has greater confidence in forecast attractions or transportation impedance. Both models were tested in this study and generally yielded similar trends; for example, in both cases, a complete elimination of waiting time for the local bus could increase transit's mode share by about three percentage points in Scenario 3. There were a few cases, however, where the singly constrained gravity model showed a greater magnitude of change than the doubly constrained version. For example, redevelopment of parking lots in the CBD in Scenario 2 increased total VHT by 4% (for the singly constrained model) compared to the 2% as reported above for the doubly constrained version.

To place these results in the context of long range regional planning, they are not as important as key socioeconomic parameters that drive the model. For example, if the region's population and employment doubled unexpectedly, VHT would increase by 102% and NOx would increase by 34.8%--easily dwarfing almost all of the other scenarios discussed herein. Further, because the results presented here are specific to the case study region, they are not necessarily generalizable to all other locations. However, the modifications to the travel demand model made here can indeed be replicated elsewhere in Virginia. Given that a sample of 11 regional travel demand models in Virginia shows an average age over eight years, the approaches suggested herein indicate one way that transportation agencies can begin to incorporate potential impacts driverless vehicles into their existing modeling efforts—just as those agencies periodically examine other types of unexpected changes in land development, regional growth, or the transportation network. Because of the uncertainty associated with DVs (e.g., will they cause us to take longer trips), the scenario-based approach used herein is one way to examine potential impacts relatively quickly.

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INTRODUCTION

Regional long range transportation plans are developed with 20 year horizons; the long period allows for careful consideration of infrastructure investments based on expectations of changes in activity (e.g., population, employment, land development, and other factors that generate transportation demand) and infrastructure (e.g., highways, guideways, bus service, operational improvements, and other ways of satisfying this demand). Within metropolitan areas, such long range regional plans are supported by travel demand models, which forecast how various transportation improvements may affect regional measures, such as vehicle hours traveled, as well as more local measures, such as how an improvement at a given location may affect congestion levels. At present, Virginia has a total of 13 such regional models, serving large metropolitan areas (e.g., the Washington, D.C. metropolitan region which includes Northern Virginia and suburban Maryland with a population of 6.3 million) and smaller areas (e.g., the Danville model serves an area of roughly 70,000) (VDOT, 2017a).

The Role of Travel Demand Models in Transportation Planning

Travel demand forecasts from these models may influence project selection, a process that entails both the metropolitan planning organizations (MPO) and the Virginia Department of Transportation. For example, a candidate project that reduces transit headways in an urban area may be forecast to shift a certain percentage of motorists to transit. The resultant reduction in vehicles on certain links will be forecast to have a reduction in crash frequency, and the anticipated growth rate in vehicle volumes will help determine how the candidate project affects person-hours of delay. Virginia’s statewide prioritization process uses the results of regional travel demand models, such as forecasts of vehicle miles traveled (VMT) and vehicle hours traveled (VHT), to help evaluate how candidate projects affect safety, congestion, and modal choices (Commonwealth Transportation Board, 2016). Such models are also used regionally: the long-range transportation plan for the Richmond Region (Richmond Area Metropolitan Planning Organization, 2014) used these forecasts to determine future projects such as improved signals on Midlothian Turnpike (Route 60), the addition of another lane to Route 360, and sidewalk construction to improve school travel in Hanover. Models also inform strategic planning (e.g., determine how rail improvements may support freight) and community visioning (e.g., examine the impact of land use policies on the highway network) (Meyer and Miller, 2013).

Generally, these transportation plans have presumed fairly consistent vehicle characteristics in terms of capacity, ease of use, and appeal to users. For example, in long range transportation plans, factors that typically influence the choice of owning a vehicle are household size, income, and location, with higher rates of auto ownership in rural locations that offer fewer modal choices. Further, when there have been changes to engineering or planning calculations that use vehicle characteristics, such changes have tended to be incremental. Consider the *Highway Capacity Manual* which is periodically updated and whose information can inform the capacities used in long-range transportation plans. The ultimate (Level of Service E) capacity for an idealized interstate highway segment is 2400 passenger cars per hour per lane (Transportation Research Board, 2010); in the same document a quarter century ago, the 1985

Highway Capacity Manual used a maximum value of 2,000 passenger cars per hour per lane (Garber and Hoel, 1988).

Potential Changes in Travel Demand Models Due to a New Vehicle Type

Yet a research need identified by Virginia's Transportation Planning Research Advisory Committee (2016) suggests that contrary to this quarter century of relatively incremental change, that transportation planning might be poised to shift dramatically owing to the arrival of what at the time were described as "connected/autonomous" vehicles. That research need further articulated that although additional information is forthcoming, that planners need to understand when and how to consider such vehicles *now*. That is, stakeholders who participate in the transportation planning process may ask questions now such as what will be the impacts on highway capacity in two decades; will such impacts affect all functional classes of roadways in a roughly similar manner; should behavioral expectations for auto ownership be modified; and would increases in the penetration of such vehicles be expected to reduce demands for new infrastructure (given potential capacity increases) or might such vehicles increase demand for infrastructure (if this mode reduced transportation impedance from what is faced at present)?

While the initial terminology used by Virginia's Transportation Planning Research Advisory Committee (2016) was "connected/autonomous", additional literature illustrates that there is not a single definition for this phrase. The National Highway Traffic Safety Administration has defined five levels of functionality that automated vehicles can achieve (Campbell et al., 2016). Levels 0, 1, and 2 vehicles entail warning systems and very limited automation of a few driver functions: level 0 provides information only (e.g., a warning to the driver when a vehicle is about to move from a lane or hit another vehicle) and level 1 and 2 vehicles automate just a few specific functions (e.g., adaptive cruise control or assistance with staying in the lane or braking in time) that absolutely require driver intervention. Level 3 vehicles automates operation under certain circumstances with capabilities such as interpreting the communication received from a traffic signal and require some supervision for complex situations. Level 4 vehicles were described therein as fully autonomous operation (Campbell et al., 2016). SAE International (2014) provides six levels of automation, differentiating between "high automation" at level 4 and "full automation" at level 5. Breden et al. (2017) use the term "self-driving vehicles" (SDVs); Isaac (2016a) uses the term "driverless" vehicles; in the latter case, the author explicitly points out that such vehicles "are capable of sensing their environment and navigating roads without human input", with such vehicles corresponding to SAE level 5. Rosekind (2016) stated that "nobody understands the lexicon" of such higher levels. Based on Grier (2016), Isaac (2016a), and Rosekind (2016) this report uses the term "driverless vehicle" or "DV."

Substantial literature has been devoted to the area of including such vehicles in transportation plans, recognizing that such vehicles may affect a variety of improvements such as long-term infrastructure leases (e.g., Pascale [2016] notes the almost 60 years lease for the Midtown Tunnel in Hampton Roads). Hedden (2015) in the presentation *5 Things Planners Need to Know about Self-Driving Vehicles* suggested that non-recurring congestion may decrease substantially and that further the shared economy will dramatically alter the extent to which vehicles are owned with fewer capacity expansions being needed. Bertini and Wang (2016) suggested that regional models may need changes in trip routes, vehicle ownership, and work/residence locations. The literature suggests ways to incorporate DVs into regional models. One approach is to make large scale changes; Zhao and Kockelman (2017) combined the trip distribution and trip assignment step in the Austin MPO model, replacing the gravity model with a simplified multinomial logit model and reducing the modes from 20 to 4. A second approach is to replace the more macroscopic travel demand model with the use of microscopic techniques to capture driver behavior better as noted by Campbell et al. (2015). To be clear, therefore, the literature makes the case for new approaches for estimating travel demand, where such new approaches could replace existing travel demand models entirely.

A Case for Modifying Existing Regional Models

There are at least three considerations that may affect the decision to, instead of replacing regional models entirely, modifying such regional models for the purposes of considering these new types of vehicles.

First, such models are typically developed over a multiyear period, a sample of 11 of Virginia's regional models as of February 2018 showed that the year of model development was between 2003-2009 inclusive for seven of the models with the remaining four models being developed during the period 2013-2017 (VDOT, 2017a). Presently two additional models are "in progress", one of which was last updated in 2009. Part of the reason for the long model development time is that such models require a substantial amount of institutional knowledge in order to make modifications. Although such models may use well-known analysis techniques found in standard texts, regional models are the product of many individual choices of the analyst who built the model. Examples are the method for disaggregating zone level socioeconomic data for the purposes of trip generation, the manner in which feedback among model components is established, the selection of the volume delay function, and the parameters used for the utility choice expressions (The Corradino Group, 2009). In order for someone unfamiliar with the development of the model to make modifications, some fairly detailed documentations are institutional knowledge is needed.

Second, the calibrated base case model reflects assumptions that result from the interagency consultation process. For example, agencies may have invested time agreeing on key elements that might affect air quality determination, such as vehicle ownership rates (FHWA, 2015), number of zones, and estimation of VMT on facilities not represented in the network (Michiana Area Council of Governments, 2007). Agencies may also have discussed how they would represent concepts such as differentiation by time of day (e.g., is there a single 24 hour period only, a 24 hour model plus a single peak period, a separate morning or evening peak period, and so forth), the manner in which freight is included (or not included) in the model, the source of auto occupancy rates for the various trip purposes, and the percentage of trips that may occur during various periods (Cambridge Systematics, Inc. et al., 2012). As an illustration of the diversity of choices in the model, Cambridge Systematics, Inc. et al. (2012) examined the value of time for non-work trips that either began or ended at home based on the coefficients for eight mode-choice models. The implied value of an hour ranged from very low values (21 cents or less for three models) to moderately low values (48 or 80 cents for two models), to moderately higher values ($1.40 and $3.69 for two models). While such values will be based on either data collected for the model or borrowed from other sources, they represent the product of interagency coordination.

Third, outside entities may already have processes that rely on the existing regional model, such as a statewide prioritization process (Commonwealth Transportation Board, 2016, 2017). For example, Virginia's Smart Scale explicitly cites regional travel demand models as one potential source for the number of "peak period person hours of delay" for a particular project. Regional models are also cited as a source for two other measures: person throughput (which can include vehicle travel as well as travel on other modes) and safety: regional models provide vehicle miles traveled (VMT) for various scenarios which inform a different measure—the equivalent property damage only crashes, which in part are based on VMT. As a regional example, Region 2000 (2015) awarded points to projects in part based on the ratio of volume to capacity for that project as reflected in the travel demand model (e.g., for a project that could increase capacity, scores of high, medium, or low were established based on whether the volume/capacity ratio fell into three ranges: 1.10 or more, between 0.8 and 1.09 inclusive, and less than 0.8.) While capacity can be measured in a variety of ways, it is clear that in this context what mattered was the impact on the volume/capacity ratio within the regional model.

A Case for Scenario Planning

Regardless of the modeling approach that is chosen, Krechmer et al. (2015) strongly emphasize that it is impossible to know which technologies—or which impacts—should be expected in the future. Instead, planners should consider a variety of potential scenarios and then update these scenarios as new information emerges, leading Krechmer et al. (2015) to state that

> Long-range planning activities may shift to development of "alternative futures" that make different assumptions about technologies, market adoption, and impacts on the transportation system. These assumptions would then be reviewed on a regular basis and the long-range plan modified based on actual developments.

Shogan (2016) also indicates that "scenario planning" can be used to consider the impacts of DVs, where scenarios could consider the factors such as the impacts on capacity (a supply measure, adoption rates (as previously discussed), vehicle occupancy, and, perhaps most challenging of all, how individuals would respond to these new options. Twaddell et al. (2016) explain that scenario planning can incorporate "potentially radical shifts in conditions over which local, regional, and State agencies have little or no control"—an example of which is the introduction of new vehicle technologies and the resultant behavioral shifts in response to those new technologies. One location cited therein that used scenario planning—Baltimore—showed the necessity of considering alternative futures, where, during a scenario planning exercise with stakeholders, two points of view were expressed regarding future vehicle technologies—(1) they might improve congestion or (2) they might lead to "increased 'sprawl'". While these two points are not necessarily contradictory, Baltimore Metropolitan Council (2016) noted that "opinions were divided" on this topic. In their consideration of how "self-driving vehicles" might alter the future, Brenden et al. (2017) considered alternative futures not just based on technology but on public behavior: while one scenario entailed strong public support for sharing of vehicles, another envisioned a future where the desire to own a vehicle increased.

While multiple alternative futures may thus be one important component of scenario planning, FHWA (2017) notes also that scenario planning should have an active public involvement component, where stakeholders both (1) see their value incorporated into the planning process and (2) are informed regarding "growth trends and trade-offs." For example, Krechmer et al. (2015) suggest that regional plans should include "alternative futures and their impacts on land use." A scenario planning exercise would include not only alternative ways which new vehicle technologies might alter capacity, therefore, but it would also include (1) how stakeholders might want to see land develop and (2) how new vehicle technologies might affect land development compared to a baseline case without those technologies. The scenarios, therefore, should be of interest to stakeholders and thus may be refined based on their input (Reed et al., 2011).

PURPOSE AND SCOPE

The *purpose* of this research is to identify ways in which Virginia might (1) alter existing travel demand models in order to consider the impacts of driverless vehicles and (2) use such models to inform questions of interest to regional planners.

The *scope* is limited to adapting regional travel demand models to impacts that are becoming known about driverless vehicles rather than performing original research on such impacts. For example, consider just one potential impact of driverless vehicles: they might lead to an increase in capacity. This report does not attempt to simulate this increase in capacity, but rather draws on studies that have suggested how capacity might change—and then demonstrates how to incorporate such findings into the regional model.

METHODOLOGY

A case study approach was used for this research effort where one region's travel demand model, that for the City of Charlottesville and Albemarle County, was used as a way of testing how driverless vehicles could be incorporated into the model. This particular model was chosen for two reasons: it was not the most recent model (which made it a reasonable test case for developing techniques that could likely be replicated with other models) and it reflected a location near the researchers (which made it easier to interact with local staff in order to examine policies of interest to the MPO). Five tasks guided this case study approach.

1. Conduct a literature review.
2. Review the Charlottesville/Albemarle travel demand model.
3. Identify issues of local interest the regional model can help address.
4. Develop and refine scenario categories
5. Execute the scenarios.

1. *Conduct a literature review regarding ways to consider the impacts of driverless vehicles within the transportation planning process.*

   This literature review was largely performed in two stages. First, the research team initially identified sources based on a search within the Transportation Research in Development (TRID) database, using a variety of terms such as "autonomous vehicles" and "transportation planning." A review of these initial sources showed a range of potential impacts of driverless vehicles on capacity and VMT. For example, Isaac (2016a) mentions that research suggests an increase in lane capacity of "500 percent" could result in cases of platooning of autonomous vehicles, whereas Campbell et al. (2016) noted that an increase of 8% might initially result from truck platoons. Then, after providing the initial results of the literature review to the TRP in November 2016, a more detailed review was conducted focusing on impacts that the researchers believed could be included in the travel demand model. For example, Biersted et al. (2014) noted that driverless vehicles could potentially affect mode share by making the trip from the origin to the transit stop more palatable, with TRP noting that this could be incorporated into the utility component of the travel demand model. Accordingly, literature that examined how driverless vehicles might influence the perception of time was reviewed.

2. *Review and modify as appropriate the Charlottesville Albemarle travel demand model to understand potential ways of incorporating impacts.*

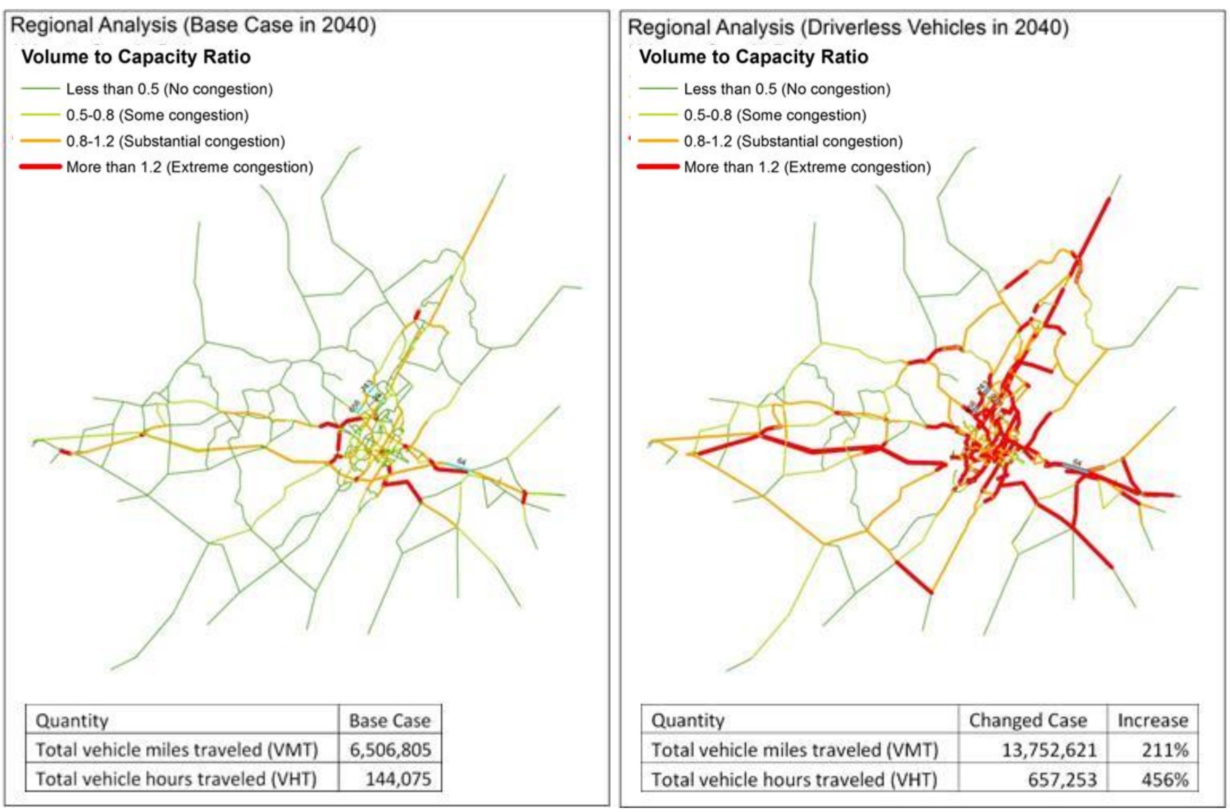
   The model was examined to understand the key assumptions therein. A user's guide provides some documentation of key modeling decisions (The Corradino Group, 2009); however, some details can be learned only from reviewing the model's proprietary scripting language. An effort was made to understand both the computation of outputs and behavioral assumptions. As an example of the former, trip productions and attractions as reported in the user's guide (The Corradino Group, 2009) were compared to trip rates from the model; in this particular case, a modification was made to render the model consistent with the user's guide. As an example of the latter, examination of the scripts for the mode choice step within that particular model showed that free flow speeds are used for nonwork trips whereas congested speeds are used for work trips; this did not require a change, but it explained some of the sensitivity of the model.

3. *Identify issues of local interest the regional model can help address.*

   An outreach exercise was held on June 9, 2017 where 40 members of the Virginia Association of MPOs (VAMPO) were asked questions in person concerning how replacing conventional vehicles with DVs could generate planning-related concerns related to parking. (An earlier March 2017 meeting of the Charlottesville Albemarle MPO model working group attended by the researchers had indicated that the impact of DVs on parking was of interest.) The overall goal of this exercise was to determine the extent to which the regional travel demand model can help address a particular subset of policy concerns related to DVs. Key questions in the exercise included the following:

1. What is the role of the planner as we consider the impacts of driverless vehicles on the parking industry?
2. What are the opportunities or risks if driverless vehicles affect (or do not affect) future demand for parking?
3. For either question 1 or 2, what policy tools (if any) can be considered by decision-makers?
4. Consider the tools noted in question 3. Would any of them be adversely affected if you simply did not worry about driverless vehicles at this point in time?

In advance of the in-person meeting where the questions were posed, attendees were provided with a packet of background information containing the current status of parking (e.g., about 9% of land in the Charlottesville portion of the region serves that purpose), and based on the most current regional model, expected 2040 volumes, speeds, and volume/capacity ratios for two major parking areas (one in the central business district [CBD] near an outdoor pedestrian mall and one in a suburban area near an indoor shopping mall). To stimulate discussion, attendees were also provided with one potential extreme situation where DVs might lead to a doubling of trips (Figure 1). (Staff of the Charlottesville Albemarle MPO had suggested that the researchers include an “extreme” case in the information packet whereby the impacts could be assessed if DVs led to a large change in behavior.)



Quantity	Base Case
Total vehicle miles traveled (VMT)	6,506,805
Total vehicle hours traveled (VHT)	144,075

Quantity	Changed Case	Increase
Total vehicle miles traveled (VMT)	13,752,621	211%
Total vehicle hours traveled (VHT)	657,253	456%

Figure 1. Example of information provided to MPO attendees of the outreach exercise. (Attendees were provided with a total of 14 figures. The figure shows the ratio of volume to capacity, with the left being a business as usual scenario and the right being an extreme scenario where the number of trips doubled.)

At the meeting, a ten-minute presentation was given by five staff from VTRC and the Thomas Jefferson Planning District Commission (TJPDC). Each individual spoke for approximately two minutes. One individual spoke first and last, introducing the exercise and concluding with next steps for attendees to perform. Between the first speaker's presentations, the four remaining staff covered the following topics: the concept of scenario planning and potential capacity impacts of DVs (presenter 1), potential ways in which DVs might affect comfort (presenter 2), how DVs might affect the ability of persons to travel more than is presently the case (presenter 3), and how DVs might affect vehicle sharing and the demand for parking (presenter 4). Then, attendees were divided into five groups of approximately eight persons each, and each group had a facilitator and note-taker. Then, the groups provided responses to the questions during the outreach exercise.

4. *Develop and refine scenario categories reflecting ways to incorporate DV impacts into one region's travel demand model.*

   Based on the literature review, five rough scenarios were initially developed pertaining to changes in capacity, changes in parking behavior (where DVs might self-park in less expensive areas), shifts in mode share (where DVs might increase or decrease transit use), the occurrence of zero-occupant-vehicle (ZOV) trips where DVs might be shared, and the increase in travel that might result from a greater proportion of younger persons (age 10-17) and older persons (age 65+) being able to have access to a vehicle than has historically been the case. In practice, each "scenario" reflects multiple model runs because there are multiple ways to execute each potential impact within the regional model. For example, one may increase the capacity in a regional model by changing the capacity within model's speed lookup table (which would affect, conceptually, both the destination of trips and the route such trips take) or one may alter the volume delay function (which should affect the route but not necessarily the origin or destination). Further, the trip distribution component may also be executed as a singly or doubly constrained model (VDOT, 2014).

   The scenarios were refined based on a meeting with the project technical review panel on March 27 and, as suggested by the TRP, a researcher's attendance at a Charlottesville Model Design Workshop held on March 28 at the Thomas Jefferson Planning District Commission. As an example of input from the former case, it was suggested that a new scenario be added which could result from DVs having a higher margin of safety when they are initially introduced. As an example of input from the latter, when the researcher asked attendees what types of impacts they were most interested in, two impacts rose to the top of the list: deadheading of vehicles (and how that might affect emissions) and the potential for parking in the central business district to be converted to other uses if parking was no longer needed. This caused the researchers to begin to put extra emphasis on these scenarios.

   The scenarios were then further refined based on the results of Task 4 where, in some cases, the researchers identified ways to alter the scenarios to reflect issues of interest to the stakeholders in that task. Although the literature review (Task 1) showed a variety of techniques, the researchers focused on those most relevant to the MPO policy areas of interest. For example, because one concern from Task 3 was that DVs might initially require a greater headway than conventional vehicles, the researchers sought to incorporate a corresponding reduction in capacity into the model within scenario category 1. Because emissions had been mentioned as a result of Task 3, the researchers sought to show how a few scenarios could affect nitrogen oxide emissions, a precursor for ground level ozone which can affect some regions in Virginia.

5. *Execute the scenarios*.

The scenarios were executed and for each scenario, the impact on vehicle miles traveled (VMT), vehicle hours traveled (VHT), and mean trip time (MTT) was recorded. In addition, performance measures of interest for each scenario were also obtained. For example, for a scenario that focused on transit, the changes in mode share (e.g., drive alone, carpool, bus, walk, and bike) were examined. For a scenario that focused on capacity, the change in number of facilities that are congested was obtained.

Although it had been the intention to perform these five tasks sequentially, in practice Tasks 2, 3, and 5 were highly iterative. For example, based on Task 2, the original utility function for the local bus included a term for the bus fare; this term was the product of a parameter (-0.005) and the fare itself (75 cents). In discussions with the TRP after an initial transit scenario was developed that modified this utility function in response to driverless vehicles being available (Task 3) and executed (Task 5), it was pointed out that the original utility function should have included a "100" multiplier. Thus the scenario was redone, using the 100 multiplier, and the results between the original scenario and the revised scenario were compared. Table 1 summarizes examples of feedback from the TRP and local stakeholders that influenced this work.

Table 1. Examples of Feedback from the Technical Review Panel, TPRAC Members, or Local Stakeholders that Influenced this Work

Tasks	Description	Dates	Examples of Lessons Learned Based on Feedback
1	Provide initial literature review to the TRP showing potential impacts of DVs and ways to incorporate these impacts into the model.	Nov. 16, 2016	One way to reflect the improved attractiveness of DVs is to modify the out-of-vehicle travel time (OVTT) utility specification associated with transit
1,2	Present project to the Transportation Planning Research Advisory Committee	Nov. 30, 2016	The literature review should distinguish between impacts that can be reflected in existing travel demand models and impacts which cannot be reflected in existing travel demand models.
2,4	Meet with the TRP to discuss proposed scenario categories with the regional model	March 27, 2017	Recognize that contrary to the researchers' initial suggestion; intrazonal trips will not appear on the network, so these must be accounted for separately in the fourth scenario category.
2,4	Meet with Charlottesville, Albemarle model development group to hear areas of interest.	March 28, 2017	Document the types of steps taken so that others can replicate our results; for example, note how deadheading (e.g., ZOV trips are incorporated into the model). The impact on parking should be examined as one of the scenarios.
3	Conduct an outreach exercise with members of VAMPO.	June 9, 2017	Stakeholders are interested in a variety of impacts, some of which can be addressed by modifying the regional model, notably emissions.

Tasks	Description	Dates	Examples of Lessons Learned Based on Feedback
5	Provide initial results for scenario category 1 to the TRP.	July 27, 2017	Although these particular results show that VHT is more sensitive to changes in demand than VMT, the reverse would be the case if the trip distribution step used the distance rather than travel time, in the impedance function.
5	Provide initial results for scenario categories 2,3, and 5 to the TRP.	December 22, 2017 [a]	For Scenario 2d where parking lots are replaced with land development, use percentages for trip purposes based on trips in the Central Business District rather than trips from the entire model.[a]

[a] Based on this feedback, a corrected version of scenarios 2, 3, and 5 was provided to the TRP on February 1, 2018.

RESULTS

Literature Review

The literature review showed that DVs may potentially have a variety of impacts, including a change in capacity, a reduction in urban parking, changes in mode share, longer trips, and increased trip-making by non-drivers. Because these impacts are behavioral in nature, it is not surprising that a review of the literature gives a range of values when one tries to quantify these impacts, leading to an admission of uncertainty noted herein.

Changes in Capacity

Bierstedt et al. (2016) noted that capacity increases of 25% to 35%, and 100% for freeways, are possible, and Childress et al. (2015) in their evaluation of alternatives in Puget Sound noted an increase of 30%. Campbell et al. (2016) suggested that a two- to three-fold capacity increase is possible. Isaac (2016a) cited research suggesting platooning could increase lane capacity by 500%, a percentage also noted by Williams (2013). DVs might also differentially increase capacity by vehicle type (Campbell et al., 2016) and facility type (Zhao and Kockelman, 2017). Farmer (2016) noted that the doubling of freeway capacity may be accompanied by faster travel at capacity (50 mph vs. 40 mph at present). Greater highway capacity owing to DVs being closer to each other has also been noted for the Sarasota/Manatee Florida MPO (2016).

Yet capacity may also drop: Litman (2014) suggested that users may choose to have lower acceleration or deceleration rates, owing in part to passengers tend being more sensitive to acceleration than drivers. Le Vine et al. (2015) suggested that DVs might reduce capacity by 12% to 32%; the authors conducted simulations based on 25% of the traffic stream having driverless vehicles and setting set the rates of longitudinal acceleration equal to those of light rail and high speed rail. When the headway between the leading and following vehicle was increased to ensure passengers in the following vehicle suffered no discomfort due to a sudden change in acceleration by the lead vehicle, capacity was reduced by 12% for the light rail case and 32% for the high speed rail case (Le Vine et al., 2015).

Changes in Parking Needs of Driverless Vehicles

Williams (2013) suggested that DVs' self-parking might reduce the use of parking lots in urban locations, citing previous research that suggested such parking locations could be located further away than is presently the case from the destinations they serve. Grush et al. (2016) noted that the reduction in parking in the CBD could result in a substantial boon for developers who might want to use expensive land for other purposes, noting that the value of all U.S. parking is equal to the value of all U.S. motorized vehicles. Zhao and Kockelman (2017) found that pricing of travel options affects VMT: in an Austin case study, when parking costs were one-half the CBD parking costs, VMT (for self-parking DVs) increased by 4%; when parking costs outside the CBD were nil, VMT increased by 8%. However, Isaac (2016b) suggested that in some highly urban locations, the lack of needing to search for a space could reduce VMT by 30%.

Changes in Mode Share

Polzin (2016) suggested that DVs could either "complement transit in first-mile/last-mile services" (thereby increasing transit use) or lead to transit being used for only "very high volume fixed guideway operations." Based on regional travel demand models (including Atlanta, Los Angeles, Puget Sound, San Francisco, and Washington, D.C.), Rixey (2017) found that transit trips might decrease by 43% or increase by 16%. Elsewhere, the Committee for Review of Innovative Urban Mobility Services (2015) reported that transit can be thwarted or supported by new modes: bike sharing users replaced some transit trips with bicycle trips in one location, but in another transportation network, companies could "complement" public transportation, including providing an alternative during an emergency.

Changes in Comfort

Levin (2015) noted that the increased comfort of DVs may reduce disutility associated with in-vehicle travel time. Childress et al. (2015) suggested that the discomfort of in-vehicle travel time may be reduced by 35% for households having access to a DV. (The 35% estimate came from a finding that light rail travel time was 65% of the disutility of an equivalent amount of local bus travel time, with the difference attributed to comfort levels.) Zhao and Kockelman (2017) used three multipliers—25%, 50%, and 75%—to convert between driverless time and conventional vehicle time. Jaffe (2014) cites research suggesting that commute times may remain relatively fixed should speeds increase—suggesting that trip distances may grow. Isaac (2016a) suggests that if the tendency to be willing to live about half an hour from one's place of employment were to hold, then with higher speeds (e.g., 120 mph on freeways), driverless vehicles could result in increased commuting distances, where more farmland would be converted to residential use and costs of infrastructure to support such distances could increase.

Increased Trips by Non-Drivers

DVs offer a "mobility externality" since persons who currently do not have access to a vehicle or public transportation may be able to take advantage of a DV (Transportation Research Board, 2016). For example, more than one-half (54%) of adults age 75+ without a disability tend not to drive at night (Transportation Research Board, 2016). Truong et al. (2017) found that DVs could increase trip generation by slightly more than 4%, with the largest increase for persons age 76+ (where trip generation increases by 18% relative to the case of DVs not being available). Although not restricted to non-drivers per se, additional trips are a possibility envisioned by one MPO: documentation for one of the regional models used by Florida DOT discusses future plans to modifying the model to accommodate certain elements of DVs including additional trip generation, with "an increase in easy-access one-way trips in urban areas" (Sarasota/Manatee MPO, 2016).

The Uncertainty of Impacts

The aforementioned review shows that while it may be possible to incorporate such impacts into the regional model, the numerical value is uncertain (e.g., should one presume a change in capacity, and if so, should this amount be 25%, 35%, or 100%--or should it be a decrease). It is also possible that the impacts of DVs could be better reflected as changes to the inputs into the regional model, such as population and employment locations. For example, Chase (2016) suggests that highly automated connected vehicles could potentially reduce the costs of housing by 25%, since parking would not be required. Such a behavioral impact would not immediately be captured by a travel demand model (nor a microscopic simulation model) and would require a better understanding of human behavior. However, such a change might thus affect the location and quantity of new housing in a region, which would in turn alter the location of population in the regional model.

A comment by Plosky (2016) implies that the inputs to travel demand models may need to be nonlinear in order to accommodate some behavioral changes. (Plosky [2016] provides an example: some freight stakeholders have suggested that the minimum age for driving a heavy vehicle be reduced from 21 to 18, in order to accommodate an increased need for tractor trailer drivers. However, in theory, with fully automated [driverless] tractor trailers, the need for such drivers would be zero. One can thus envision a travel demand model where, over a relatively long horizon, the need for heavy vehicle drivers would increase [from the point at present] and then, as some point in the future, start to decrease.)

The Charlottesville-Albemarle Travel Demand Model

With the assistance of the technical review panel, the researchers examined the Charlottesville-Albemarle travel demand model to understand assumptions therein. Three initial changes were made to the model structure prior to executing any scenarios. Then, three additional modifications were made incrementally as insights became apparent during the execution of the scenarios. As per discussions with one TRP member, the "S2040_all29" version of the Charlottesville Cube Model was used as that version contained planned projects.

Modification 1. Alter Trip Production Rates

When calculating productions by trip purpose in the trip generation step, the researchers noticed a difference between the rates computed from the model and rates computed by hand for one zone in Albemarle County—but no such error was present in the rates for the City of Charlottesville. The problem appeared to be in a script in the trip generation step showing an "if…else" function indicating that different land use types have different trip generation rates, where area types 1 and 2 correspond to the City of Charlottesville and area type 3 corresponds to Albemarle County (The Corradino Group, 2009). However, the model appeared to incorrectly use area type 3 (the county) in these city rates. Accordingly, as shown in Figure 2, the line "if (zi.2.atype=1-3)" was changed to "if (zi.2.atype=1-2)" (Xiao, 2016).

```
if(zi.2.atype=1-3)

else   ; Calculate Productions for County Zones
```

Figure 2. Script Used in Trip Generation

Modification 2. Add a Script to Obtain the Trip Length Frequency Distribution

Within the model, there was a sequence 13 showing the average trip length in time, however, this trip length reflected free flow conditions. Accordingly, several lines of code were added to show the mean congested travel time and the shape of the trip length frequency distribution as described in Appendix C.

Modification 3. Directly Incorporate Fares into the Mode Choice Step

Initially, when transit fares were altered from a low value of 75 cents to a high value of $5, the initial mode split did not change. As suggested by Xiao (2016), the root problem was that a feedback link needed to be added to the model as shown in Figure 3. (This link connects model sequence 10 (see the output file "Matrix File 1") and model sequence 11 (see the input file "Matrix File 1"); after making this correction, changes to transit fare do affect mode split.

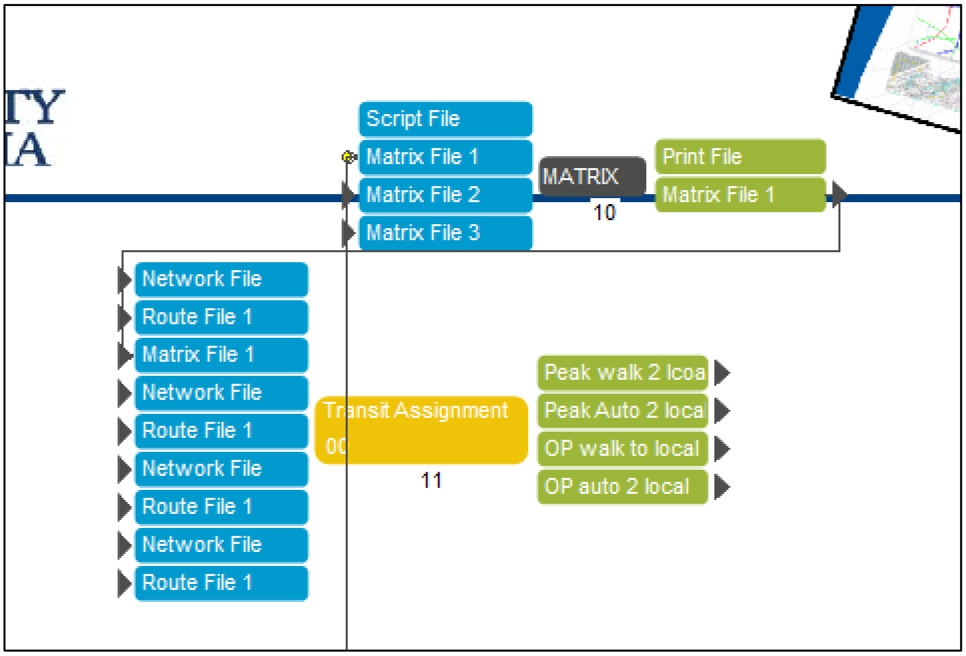


Figure 3. Adding a Link from Sequence 10 to Sequence 11 (Correction provided by Xiao, 2016)

Modification 4. Incorporate both a Singly-Constrained and Doubly-Constrained Gravity Model

Most transportation planning textbooks (e.g., Garber and Hoel, 1988; Meyer and Miller, 2013) use a doubly-constrained gravity model, meaning that within the trip distribution step, that forecast productions are equal to given productions and forecast attractions are equal to given attractions, and the Charlottesville model is also doubly constrained for all trip purposes. By contrast, for a singly constrained model, this equalization is forced only for productions or attractions (usually the former). Assuming that one requires forecast productions to be equal to given productions, the difference between a doubly constrained gravity model and a singly constrained gravity model depends on the extent to which one has greater confidence in forecast attractions (hence the doubly constrained model would be preferred) or the impedance function used in the gravity model (hence the singly constrained gravity model would be preferred). VDOT (2014) points out that while this is acceptable, that there is "no consensus" regarding whether a singly or doubly constrained gravity model is preferred, suggesting that for work trips, a doubly constrained gravity model could be used but that for other trips, the singly constrained gravity model could be used, while also noting that results should be checked for "reasonableness."

Consequently, the researchers implemented both versions when executing the scenarios: a doubly constrained gravity model and a singly constrained gravity model. Implementation of a singly constrained gravity model in Cube does not use friction factors; rather, one uses a function as shown in Equation 1 of the form friction factor = $e^{(c*\text{travel time})}$. Equations 1 and 2 simply obtain the parameters for the singly constrained gravity model, based on the friction factors used for the doubly constrained model via linear regression. For example, Figure 4 shows the resultant fit of the home-based work trips, where a parameter of c = -0.08001 yields a function that matches the friction factors used in the model. (The parameter a is used to scale the function and it may be eliminated from the model [Martin and McGuckin, 1998, Cambridge Systematics, 2012]). As shown in Figure 4, different parameters may be obtained but the general pattern is that travel time offers the greatest impedance for nonhome based trips and a lesser impedance for home-based work trips.

Friction factor (for purpose i and travel time j) = a_j*exp($c_i t_j$) (Eq. 1)

ln (FF_{ij}) = ln(a_j) + $c_i t_j$ (Eq. 2)

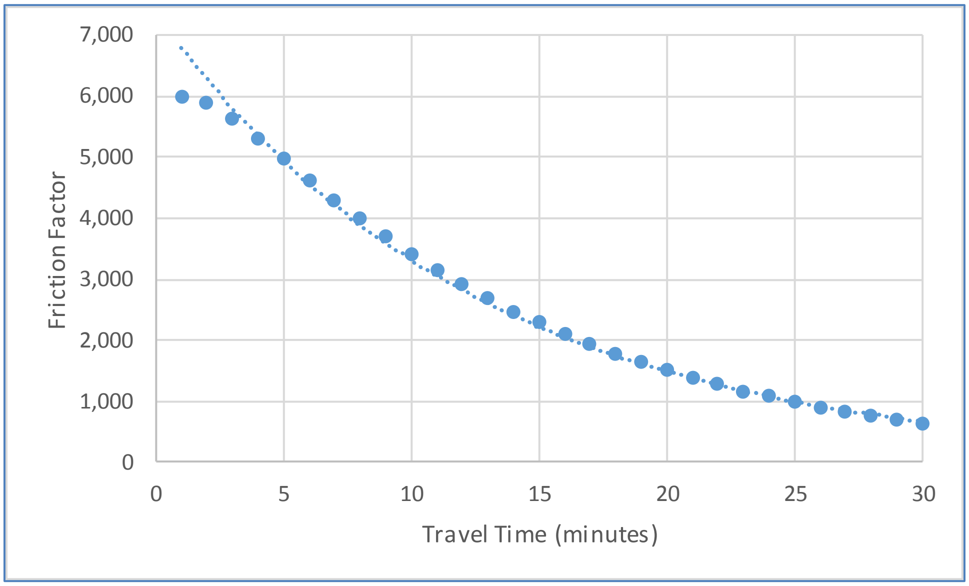


Figure 4. Fit of the Friction Factors for the HBW Trip to Equation A1 (c = -0.08001, a = 7,371)

A more detailed approach for determining the parameters associated with the singly constrained gravity model is available based on Martin and McGuckin (1998), where one performs model runs and updates the parameters based on those runs as well as existing survey data (e.g., American Community Survey Data for Charlottesville/Albemarle was available from the U.S. Census Bureau (undated). The researchers did use this method for the first category of scenarios. However, because the method was considerably more detailed, the simplified approach here may make the use of the singly constrained gravity model feasible in other locations; thus, the simplified approach was used for scenarios 2-5.

Use of different parameters will affect the model results but not substantially, suggesting that the more transferable approach may be preferable. For example, as a test case, consider Scenario 5d, which doubled growth in the area such as population, autos owned, school attendance, households and employment. As doubling of growth relative to the base scenario showed that vehicle miles traveled (VMT) increased by 44%, vehicle hours traveled (VHT) increased by 168%, and mean trip time (MTT) increased by 71%. Both the base scenario and this doubling of growth used the parameters shown the far left column of Table 2. With the simplified approach, the base scenario and Scenario 5d (which doubles growth) used the parameters shown in the middle column of Table 2. Similar values were obtained for Scenario 5d: that is doubling growth leads to an increase of 40% for VMT (rather than 44%), 116% for VHT (rather than 168%), and 71% for MTT (rather than 48%).

Table 2. Parameters for the Exponential Function in the Singly Constrained Gravity Model

Trip Purpose	Calibration with Friction Factors and New Additional Census Data (Scenario 1)	Calibration with Friction Factors Only from the Model (Scenarios 2-5)	Default values from NCHRP 716 (for an MPO under 250,000)[a] (Not Used)
Home-based work	-0.04259	-0.08001	-0.052
Home-based other	-0.09881	-0.18959	-0.126
Non-home based	-0.18995	-0.22559	-0.232
Students living off campus	-0.10779	-0.20830	N/A
Students living on campus	-0.10779	-0.20830	N/A
Internal-external or External-internal trips	-0.10516	-0.20004	N/A

[a] NCHRP 716 (Cambridge Systematics, 2012) provides default values for the Gamma function $F=(time^b)e^{(c*time)}$. These were fit to the exponential function in order to show the values in the rightmost column.

The script for implementing the singly-constrained gravity model is shown in Appendix B.

Modification 5. Adjust the Fare Parameter in the Utility Function in the Mode Choice Step

In the utility, function, the *local bus operating cost*—that is, the fare—was modified to be multiplied by 100 as shown by the line "MW[15]=(mi.3.pkopcostlb*100)*HBWCCST." As suggested by the TRP, this modification was made for the category 3 scenarios, such that the 100 multiplier applies for the operating cost for all three transit modes: walk to local bus, walk to premium transit, and drive to best available.

A justification for changing the multiplier for the local bus is evident from considering the utility function for two modes shown in the model: drive to best available service and walk to local bus, where this fare is multiplied by a cost parameter of -0.005. The product has a multiplier of 100 in the script for the former mode but not the latter. As shown in Table 3, fare has relatively little impact on mode choice. An illustration of these variables is evident from examining data for travel between zone 9 in the CBD and three others zones: zone 20 (near the CBD and which has transit service), zone 113 (further away but which also has transit service) and zone 99 (furthest away and with no transit service). These zones are shown in Figure 5. Table 3 shows the components of the utility for each mode under peak conditions. (The utilities are calculated by multiplying each variable by the appropriate parameter.) Notice that the effort for two elements of the trip—(1) moving between the origin or destination to or from the bus and (2) waiting for the bus—generally account for between 62% and 83% of the utility. For these reasons, the utility functions suggest that for DVs to positively impact transit mode share, the key mechanism would be to reduce the discomfort associated with waiting, traveling to the stop, or traveling from the stop.

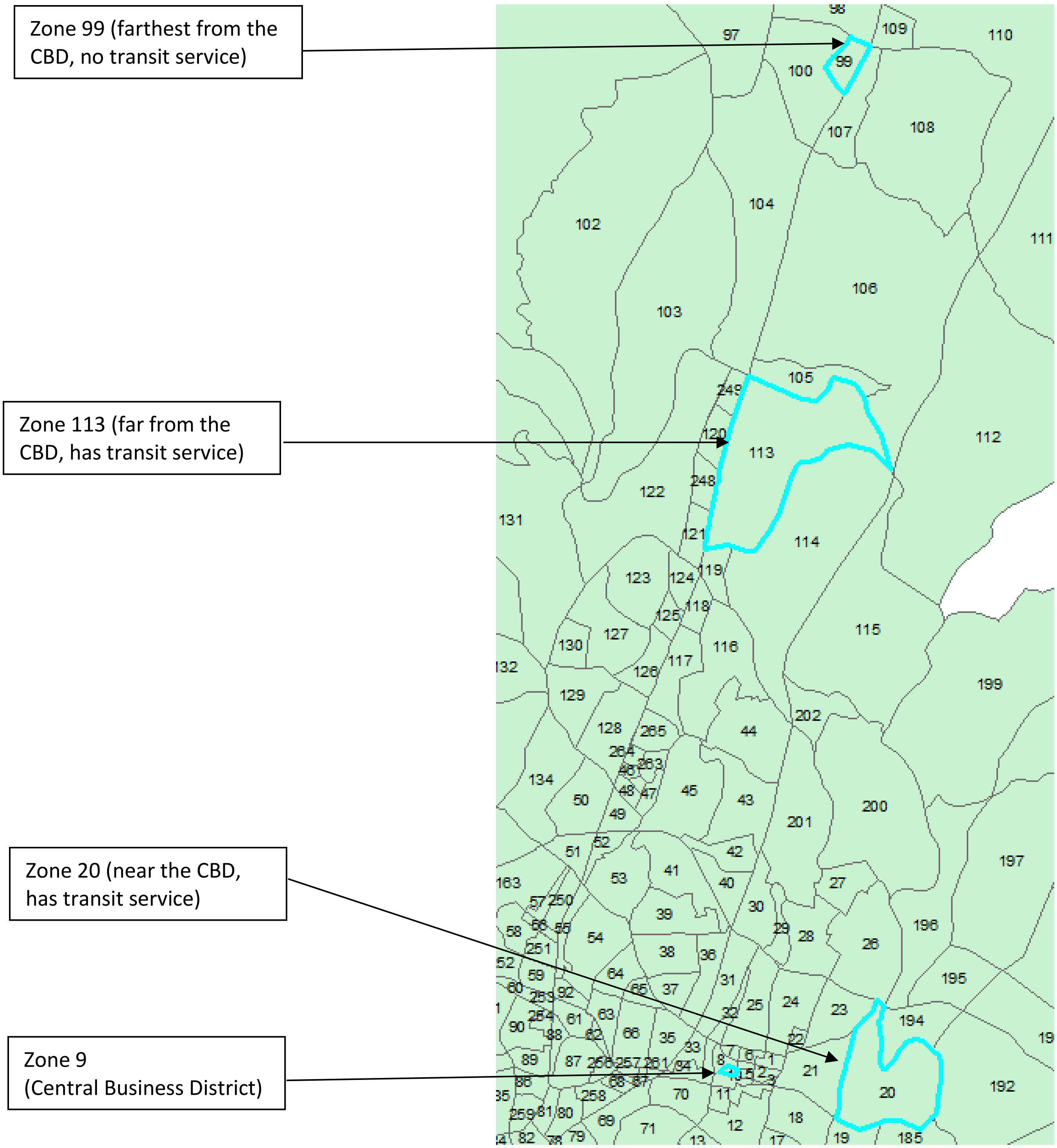


Figure 5. Four Zones of Interest in the Regional Model: Zone 9 (in the CBD), Zone 20 (near the CBD), Zone 113 (further from the CBD), and Zone 99 (No Transit Service Available)

Table 3. Components of Peak Period Utility for the Transit Mode

Zone 20 to Zone 9	Variable		Parameter		Utility	
pkwktimeBA	drive to local bus	17.38	-0.049	HBWCOVT	-0.85162	25%
pkwttimeBA	wait time for local bus	32	-0.049	HBWCOVT	-1.568	46%
pkivtimeBA	bus riding time	25.22	-0.025	HBWCIVT	-0.6305	18%
pkpkcostBA	parking cost	1.8	-0.005	HBWCCST	-0.009	0%
pkopcostBA	operating cost (fare)	0.75	-0.005	HBWCCST	-0.375	11% [a]
				Total	-3.43412	100%
Zone 20 to Zone 113	Variable		Parameter		Utility	
pkwktimeBA	drive to local bus	11.38	-0.049	HBWCOVT	-0.55762	11%
pkwttimeBA	wait time for local bus	51	-0.049	HBWCOVT	-2.499	51%
pkivtimeBA	bus riding time	58.61	-0.025	HBWCIVT	-1.46525	30%
pkpkcostBA	parking cost	6.4	-0.005	HBWCCST	-0.032	1%
pkopcostBA	operating cost (fare)	0.75	-0.005	HBWCCST	-0.375	8% [a]
				Total	-4.92887	100%
Zone 20 to Zone 9	Variable		Parameter		Utility	
pkwktimelb	walk to local bus	17.24	-0.049	HBWCOVT	-0.84476	29%
pkwttimelb	wait time for local bus	32	-0.049	HBWCOVT	-1.568	54%
pkivtimelb	bus riding time	7.98	-0.025	HBWCIVT	-0.1995	7%
pkpkcostlb	parking cost	0	-0.005	HBWCCST	0	0%
pkopcostlb	operating cost (fare)	0.75	-0.005	HBWCCST	-0.00375	0% [a]
SUM[I]	pedestrian environment	10	0.117	HBWPTI	0.2925	10% [b]
				Total	-2.90851	100%
Zone 20 to Zone 113	Variable		Parameter		Utility	
pkwktimelb	walk to local bus	21.35	-0.049	HBWCOVT	-1.04615	22%
pkwttimelb	wait time for local bus	51	-0.049	HBWCOVT	-2.499	52%
pkivtimelb	bus riding time	39.71	-0.025	HBWCIVT	-0.99275	21%
pkpkcostlb	parking cost	0	-0.005	HBWCCST	0	0%
pkopcostlb	operating cost (fare)	0.75	-0.005	HBWCCST	-0.00375	0% [a]
SUM[I]	pedestrian environment	10	0.117	HBWPTI	0.2925	6% [b]
				Total	-4.83415	100%

[a] In the script, a multiplier of 100 is given in the script for pkopcostBA but not for pkopcostlb, which is why the utility for the latter is so low.

[b] Note that the pedestrian environment component of utility, shown as the "HBWPTI" parameter in Table 3, is positive but all other components are negative. Thus, the "total" utility reflects the five negative utilities minus the positive pedestrian environment utility. A multiplier of 0.25 is given in the script, which is why the utility is the product of the parameter*variable*0.25.

Modification 6. Add Geographic Information to the Roadway and Zone Shapefiles

Some scenarios used Census data. Although both Census data (2015a) and the travel demand model are available in a GIS format, it was not possible to immediately overlay these layers because of two distinct problems—what appears to be a relatively minor translation challenge in the travel demand model roadway shapefile and what appears to be a more serious projection challenge in the travel demand model socioeconomic shapefile.

To correct the first challenge, a spatial adjustment procedure suitable for vector layers was performed, where the researchers created "links" between certain locations in the roadway shapefile (such as the intersection of I-64 and U.S. 250 at the western end of the travel demand model) and the same location in real-world coordinates. Then, an affine transformation was performed based on these 15 links as shown in Figure 6 (*left*). While this improved the accuracy of the location of the roadway shapefile, errors were still visible especially in the more urban portion of the model; thus, this process was repeated with an additional 41 links as shown in Figure 6 (*right*). A process similar to that shown in Figure 6 was used for the socioeconomic layer, except the initial projection information was deleted (otherwise the roadway layer would have been placed west of the Gulf of California), then a single affine transformation was performed, and then the projection information was added to the layer.

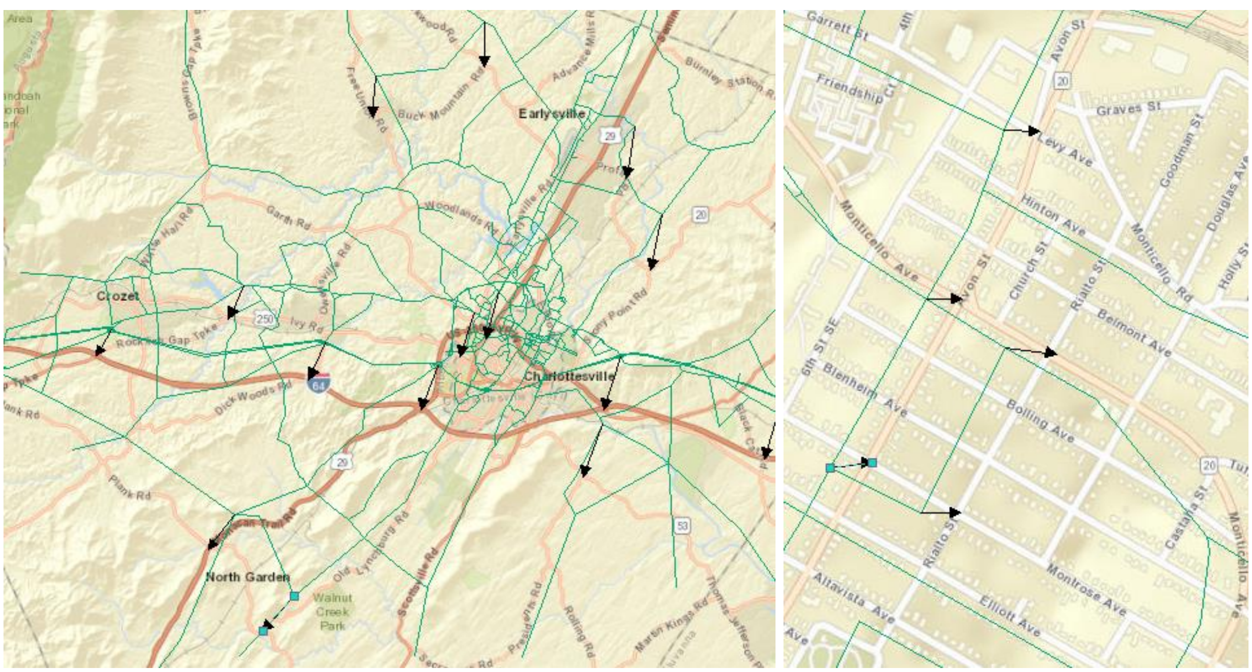


Figure 6. Example of Performing Spatial Adjustments to Correct the Location of the Roadway Layer

Issues of Local Interest the Regional Model can Help Address

Attendees at the annual meeting of the Virginia Association of MPOs, who had been provided outreach information of the type shown in Figure 1 as well as presentations on potential impacts of driverless vehicles, were divided into five groups of approximately eight persons each, and each group had a facilitator and note-taker. Then, the groups provided responses to the questions during the outreach exercise. The complete set of responses is available from the authors, but a summary of findings as they relate to parking concerns is provided here. Table 4 maps related concerns to potential modeling strategies.

Role of the Planner

Planners may have a more active land use role in terms of changing current zoning ordinances, reusing existing parking areas, and discouraging growth outside existing areas. Planners might also have a new traffic engineering role to ensure curbside access at building entrances (e.g., advocacy for pick-up lanes used by DVs while ensuring pedestrian access). Information sharing regarding how pricing (e.g., parking costs in the CBD or per-mile vehicle operating costs) affects behavior was also suggested as a role, as was outreach to the parking industry. Another possibility was for planners not to take a role but rather simply let market decisions dictate any changes to parking wrought by DVs. A comment was made that the answer also depends on whether the planner has a regional versus a local focus.

Opportunities for DVs

DVs could further increase downtown land values, especially as former parking lots are turned into other uses (e.g., housing or public uses)—serving as catalysts for infill development. The advent of more green space (which could reduce the "urban heat density"), reduced noise, and reduced congestion could improve the downtown living areas, the last of which could be enhanced by the parking industry's adoption of new technologies to tell motorists where parking is available. DVs could also enhance transit connections between rural and urban areas, where rural commuters can park autonomous vehicles in a park and ride facility and take a high-capacity mode such as bus rapid transit to the CBD. Finally, as fleet penetration rates approach 100%, the needed roadway infrastructure—parking spaces and travel lanes—could be reduced as the likelihood of human error is reduced. One group of participants had noted that discussions of vehicle automation have occurred at "aging and disabled community service type meetings" which, if DVs were viewed as a way to provide mobility to persons who presently cannot drive, would support a benefit noted in the literature (Transportation Research Board, 2016).

Risks of DVs

DVs are associated with at least four potential risks with respect to parking. First, a lack of needed cooperation between jurisdictions for parking use; an urban city might adjust its parking regulations after considering DVs but an adjacent and more rural county might not be ready to do so, leading to a "shell game" where congestion and parking problems are relocated from one jurisdiction to the next. Second, elimination of parking in the CBD may lead to an increase in VMT attributable in part to the use of ZOVs whose owners choose not to park. (One group noted "increased congestion from zero-occupant vehicles" as a risk and noted the number of trips might double; another group noted the potential emissions impacts of such trips.) This increase in VMT may also alter peaking characteristics, for example, instead of traffic peaks inbound to employment areas in the morning and outbound in the evening, traffic peaks in both directions in both the morning and evening. Third, DVs might lead to is expansion of development into rural area, and hence an increase in VMT, if DVs are more comfortable than regular vehicles. Fourth, during a transition period to DVs, capacity might decrease if DVs initially required a higher margin of safety (e.g., a longer following distance) than conventional vehicles; in fact one group noted "May not get capacity increase" as a potential risk.

Potential Policy Tools

One policy is pricing, where DVs could be charged based on the number of times they enter a congested area to serve passengers; this policy could consider both congestion levels and emissions in setting a fee. Another policy is building DV-specific lanes where efficiency is affected less (than conventional lanes) when riders are picked up or dropped off. An implication is that there could be multiple entrances at some buildings—one reserved for DVs and one reserved for conventional vehicles. Of interest is how the relative attractiveness of DVs compare to transit if reduced emissions or congestion is sought.

The Need (or Lack Thereof) to Consider DVs at Present

Regarding whether it is essential to consider DVs' impacts on parking at this time, opinions were divided.   *One view is that it is not necessary to conduct such long range planning*, given that we are already seeing one impact discussed previously: in some locations, such as multimodal centers, there are already empty parking places. [While empty spaces at present is not attributed to driverless vehicles, an implication is that such an impact does not require a focus on DVs per se.] Another reason for not doing such analysis is the timing of the long range plan: with the transition to DVs being 20 or more years from now [which is at the outer limits of long range planning horizons], there might be future innovations that will change our view of driverless cars. In fact, one planning district commission deliberately chose not to consider driverless vehicles in their long-range plan. Another view is that *it could be productive to consider DVs now in long range planning efforts*. If DVs will tend to be used during the peak hours and not at other times one can begin to better understand how the "rush and lull" will affect traffic performance through the use of simulation modeling. Additionally, implementation of any regulatory approach (such as a fuels tax) requires detailed analysis and probably cannot be implemented in a short time frame without such planning. If, for example, parking behavior changes suddenly (e.g., vehicle trips double due to ZOVs), then without additional regulation or infrastructure, the increase in ZOVs could be detrimental to rural facilities [that are not equipped to handle heavy traffic volumes].

Feasibility of Incorporating Such Concerns into the Regional Model

There are parking-related concerns that are not feasible for examination with the travel demand model. For example, DVs may require detailed management of curbside access, and details such as scheduling arrivals and drop-offs at loading zones require too much geographic detail for inclusion in the regional model. The responses also suggested that regional models could help address some concerns; for example, the risk that DVs may initially require a greater following distance than conventional vehicles can easily be addressed by altering the capacity in the regional model. For the issues that are feasible with the model, the level of difficulty varies by task; for instance, adjusting capacity in the capacity lookup table (which influences the impedance function in trip distribution) is simpler than modifying the script to alter capacity in trip assignment (where just a few lines of code require alteration), which in turn is simpler than representing a new rural transit access mode (where DVs would augment rural park and ride lots by collecting passengers from individual locations in rural areas and enabling them to take higher speed transit to more urban areas).

Throughout the discussion, comments from several groups indicated there are a variety of unknown impacts for DVs. One concerned environmental effects: to what extent would emissions change if DVs are driven more frequently to run errands or to return home to park because parking in commercial areas is expensive? A second concern is "what is the most effective use of resources?" Other unknowns about the technology include cybersecurity, expected rate of fleet turnover, multiple states' inspection requirements, the future of retail if another technology (drones) replaces vehicle-based delivery, and public acceptance; one group drew a connection to the Segway [a new technology that did not revolutionize transportation but which does have some niche applications.]

Table 4 summarizes one way to address the issues of interest identified by attendees. As shown by the right column, there are five issues that modifications to the regional model can potentially address. These are that: (1) DVs may require increased headways [which could potentially reduce capacity], (2) that one can convert existing parking decks to other land uses if parking is no longer needed; (3) that DVs could strengthen the role of transit; (4) that zero occupant vehicles may increase because of self-parking, and (5) that the increased use of DVs may lead to higher emissions. Issues (1), (2), (4), and (5) can be directly covered within the regional model. Issue (3) can be partially covered in that one can examine how DVs affect transit use, without specifically focusing on rural areas. In reviewing these scenarios, the researchers recognized two potential additions:

- For issue 4, that zero occupant vehicles may increase because of self-parking, ZOVs might also increase because of the travel from person 1's destination to person 2's origin. Thus issue 4 could be addressed through two scenarios: a scenario that generates ZOV trips by privately owned DVs (what later became scenario 2) and a scenario that generates ZOV trips by shared DVs (what later became scenario 4)

- For issue 5, that zero occupant vehicles might increase emissions, this could potentially be covered in all scenarios. This issue could be addressed in particular, however, through two scenarios: a scenario that looked at how changes in capacity might affect emissions (what later became scenario 1) and a scenario that looks at how additional travel by persons who do not have a vehicle affects emissions (what later became scenario 5).

Table 4. Ways to Consider Issues of Interest Concerning the Impacts of Driverless Vehicles (DVs) Identified by Attendees at the Virginia Association of MPOs on June 9, 2017

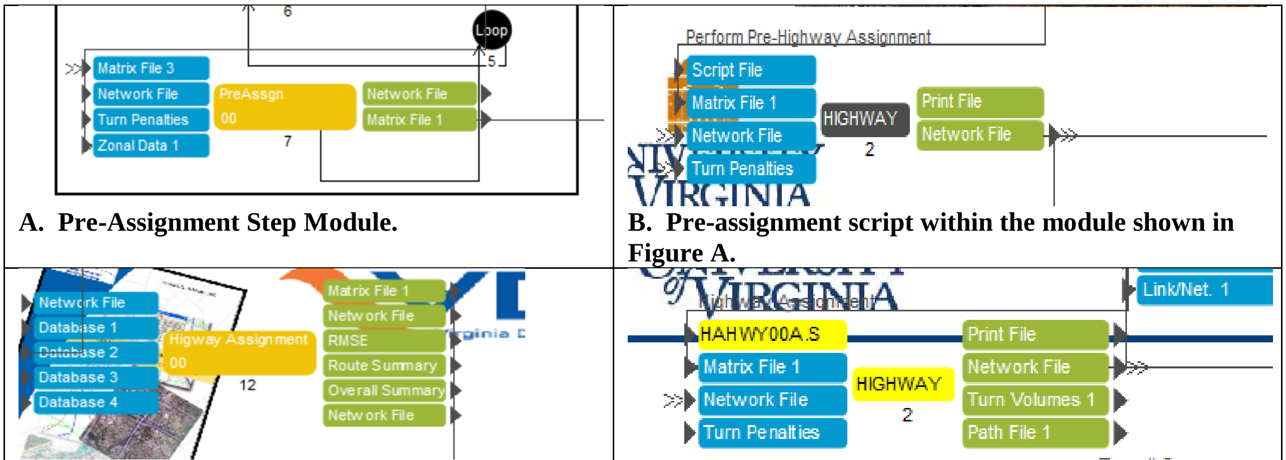
Issue of Interest [Scenario relating to this issue of interest]	Relevant Analytical Approach	Feasibility of Using a Regional Model
Change current zoning ordinances that mandate a minimum number of parking spaces.	Original research on how DVs will influence behavior is needed.	Low: data are not available for the model.
Encourage vehicle sharing rather than ownership of DVs.	If the policy tool is a tax on vehicle ownership, possibly an incremental logit model could be used, but original research on how cost influences decisions is needed.	Probably low: extensive revisions to the regional model would be required.
Convert existing parking decks to other land uses (and increase property values). [Scenario 2]	Within the regional travel demand model, what-if scenarios can be performed that examine how changes in population and employment in certain zones will influence VMT.	Medium: existing models can be used for this analysis, although some modifications to specific zones are required. [a]
Discourage additional growth outside existing areas through higher property taxes.		
Strengthen the role of transit in serving rural park and ride lots. [Scenario 3]	Modify the model to include additional park and ride lots at key nodes and higher capacity transit from such nodes to the central business district. (This can include examining how DVs can serve persons without mobility options. [a])	Medium: extensive model revisions are needed. [a]
Increase enforcement of traffic ordinances regarding curb access for DVs.	With queuing models, how arrivals, departures, and waiting time affect facility performance can be examined.	Low: a regional model is not sufficiently detailed for this analysis.
Advocate for more drop-off and pick-up lanes next to businesses.		
Ensure good access for pedestrians and bicyclists with such lanes.	Modify the queuing models to account for different modes (e.g., bicycle vs. pedestrian).	
Provide information about how parking pricing might influence where DVs are parked.	Within either a regional travel demand model or a stand-alone mode choice model, how the price of parking vs. the price per extra mile traveled influences whether a trip is taken by a zero occupant vehicle can be tested.	Medium: extensive revisions to the mode choice component are needed.
Reduce transit costs by eliminating the need for a driver.	Perform a benefit-cost analysis that compares the costs of purchasing a DV with the reduction in labor costs by eliminating the driver.	Low: a regional model is not appropriate for this purpose.
Quantify the reduced need for infrastructure investments given that DVs may require less right of way than conventional vehicles.		
Zero occupant vehicles may increase because of DVs self-parking. [Scenarios 2,4]	Increase the number of trips in the regional travel demand model to account for such zero occupant vehicles.	High: some modifications can be made to the model. [b]
DVs may require a higher margin of safety initially (such as increased headways). [Scenario 1]	Initially reduce the capacity in the regional travel demand model and examine the impact on VMT and VHT.	High: capacity impacts can be captured in the regional model. [b]
The increased use of DVs may lead to higher emissions. [Scenarios 1,5]	The model by itself will not provide an answer but can provide key inputs (VMT, VHT, and speeds).	Medium: emissions factors can be used in conjunction with outputs from the regional model. [b]

VMT = Vehicle miles traveled; VHT = Vehicle hours traveled
[a] Indicates an issue of interest that is partially addressed in the modeling in Task 5.
[b] Indicates an issue of interest that is directly addressed by the modeling in Task 5.

Develop and Refine Scenario Categories

Scenario 1. Alter Capacity

Capacity changes of 30% (Bierstedt et al., 2014; Childress et al., 2015), 100% (Bierstedt et al., 2014), and -32% (Le Vine et al., 2015) were used in the first category of scenarios in order to obtain a wide range of impacts (although this figure does not include the six-fold possibility noted by Isaac (2016a). Link capacity values are used in three locations in regional model: two are in the volume delay function and a third is shown in the capacity lookup table. The volume delay function equation is used in the pre-assignment step (sequence 7) and the highway assignment step (sequence 12). The pre-assignment and assignment sequences are shown in Figure 7.



A. Pre-Assignment Step Module.

B. Pre-assignment script within the module shown in Figure A.

C. Highway Assignment Step Module

D. Highway Assignment Script within the module shown in C.

Figure 7. Modifying the Travel Demand Model in Order to Accommodate Changes in Capacity

Figure 8 shows that the volume/capacity ratio is represented by a single variable "VC." Accordingly, to represent a change in capacity, the researchers added a new variable VDF computed as VDF = 1/(1+percent increase in capacity). For example, if capacity is doubled (e.g., a 100% increase), the "VC" ratio should be multiplied by 1/(1*(1+100%))=0.5. Therefore, a catalog key named "vdf" was added for every facility type; this key represents the V/C ratio in the model as indicated in Figure 8. Thus if capacity is unchanged, "vdf" is 1, but "vdf" is 0.5 for a capacity increase of 100%. For the changes in capacity of a 32% decrease and a 30% increase, VDF is 1.4706 and 0.769, respectively. Accordingly, the new variable "VDF" represents changes in capacity of -32%, 30% and 100% in the assignment step.

```
; Volume-Delay Relationships
  TC[1] = T0 ;cencons
  TC[2] = T0 * (1 + 0.15 * ({vdf}*VC)^4.0)    ;Freeways
  TC[3] = T0 * (1 + 0.30 * ({vdf}*VC)^6.0)  ;Principal arterials
  TC[4] = T0 * (1 + 0.30 * ({vdf}*VC)^5.5)  ;Minor arterials
  TC[5] = T0 * (1 + 0.30 * ({vdf}*VC)^5.0)    ;Collectors
```

Figure 8. Adding a Catalog Key (vdf) to the Volume/Capacity Ratio

A different way of modifying capacity is to simply change the value in the lookup table, which in the model is stored as the file capacity.dbf. This change does not require modifying the volume delay function.

For Scenario category 1, a total of 14 scenarios were executed: a base doubly constrained gravity model, a base singly constrained gravity model, and then, for each of these gravity model types, changes in capacity of -32%, 30%, and 100%, with each capacity method being deployed in two ways, but only that of Figure 8 (alter the capacity lookup table) was reported since the results are almost identical.

Scenario 2. Reduce Parking Needs

A review of Grush et al. (2016), Isaac (2016a), Williams (2013), and Zhao and Kockelman (2017) suggested that self-parking of DVs could potentially result in up to two behavioral changes. One short-term change, if such vehicles were not shared outside the household, could be that individuals choose to send their vehicles home when they are not needed. For example, a driverless vehicle drops a person off at work, returns home to park, and then makes that same trip again to pick up the worker. Consequently three scenarios model this short term behavior: doubling the number of home-based work (HBW) trips in the trip generation step, doubling the number of home-based other and non-home based trips. Such scenarios provide an upper bound for the increase in VMT.

Scenario 2a presumes that commuters send the DV home; Scenario 2a is implemented by doubling the number of HBW trips. Thus, within the trip generation step, one can change the variable “phbw” to “2*phbw” within the script file “TGGEN00A.S” (Figure 9). This change is done for both the city and the county, so the change is made within two places in the script (Figure 9). Scenario 2a includes a simplification: in theory, one would want to double the number of vehicle trips rather than the number of person trips. That said, the researchers found that doubling person trips increased vehicle trips by a factor of almost 2.0 (the factor was 1.998).

```
if(zi.2.atype=1-2)

phbw=(_rates_city(1,1)* zi.1.h1V0+ _rates_city(1,2)* zi.1.H1V1 + _rates_city(1,3)* zi.1.H1V2 +
     _rates_city(1,4)* zi.1.H2V0 + _rates_city(1,5)* zi.1.H2V1 + _rates_city(1,6)* zi.1.H2V2 +
     _rates_city(1,7)* zi.1.H3V0 + _rates_city(1,8)* zi.1.H3V1 + _rates_city(1,9)* zi.1.H3V2 +
     _rates_city(1,10)* zi.1.H4V0 + _rates_city(1,11)* zi.1.H4V1 + _rates_city(1,12)* zi.1.H4V2)*2
else   ; Calculate Productions for County Zones
  phbw=(_rates_county(1,1)* zi.1.h1V0+ _rates_county(1,2)* zi.1.H1V1 + _rates_county(1,3)* zi.1.H1V2 +
       _rates_county(1,4)* zi.1.H2V0 + _rates_county(1,5)* zi.1.H2V1 + _rates_county(1,6)* zi.1.H2V2 +
       _rates_county(1,7)* zi.1.H3V0 + _rates_county(1,8)* zi.1.H3V1 + _rates_county(1,9)* zi.1.H3V2 +
       _rates_county(1,10)* zi.1.H4V0 + _rates_county(1,11)* zi.1.H4V1 + _rates_county(1,12)* zi.1.H4V2)*2
```

Figure 9. Changes to the Script for Scenario 2a

Scenario 2b is similar to Scenario 2a except this process is performed for HBO and NHB trips. That is, one makes four changes in the script: “phbo” to “2*phbo” (for both the city and the county) and also “pnhb” to “2*pnhb” (for both the city and the county). Scenario 2c is an extreme scenario that combined 2a and 2b which assume all trips will seek to park at home to avoid parking cost.

One long-term change, however, is that parking lots may be converted to other land uses. A fourth approach is thus to convert these parking lots in the central business district to such uses. Scenario 2d sought to account for the fact that in close-in locations, existing parking lots could be converted to other uses, thereby increasing productions and attractions located within certain inner zones. (Scenario 2d thus induces additional residential and commercial development at these former parking lot locations. An alternative approach would be to reduce development at outer locations such that total growth of the region did not change.) To be clear, Scenario 2d provides an order-of-magnitude example of how the conversion of parking lots to new land development may affect travel demand, as the number of parking lots that are converted, as well as the types of land development to which they are converted, will affect the quantity and types of new trips that result.

In Scenario 2d, a portion of the city of Charlottesville—the area near and including the central business district—was treated as the inner location and thus parking lots therein were converted to other land uses (Figure 10). The increase in productions was roughly equal to the increase in attractions, and a mix of land development alternatives were considered based a review of the 9th edition of the ITE *Trip Generation Manual* (2013).

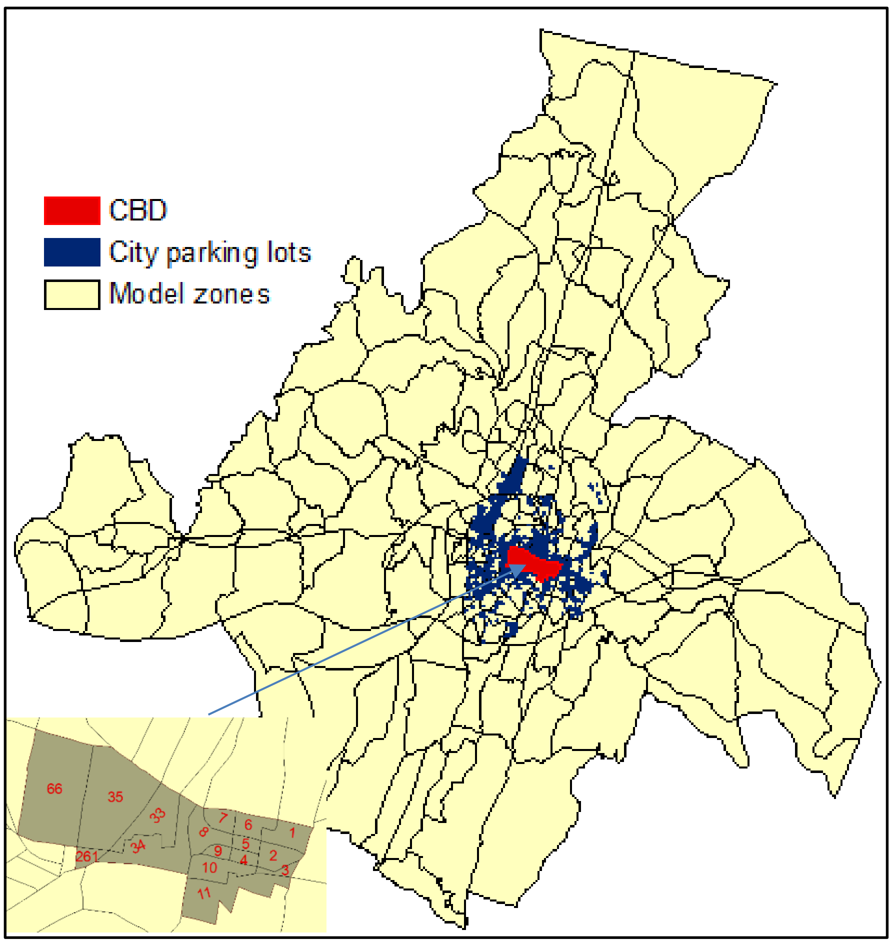


Figure 10. Area of the Charlottesville Business District (Red) Where Parking Areas Could Be Converted to Other Land Uses

Five steps were required to develop this scenario:

- Estimate the new employment that could replace existing parking in Figure A1
- Estimate the trips that such employment could generate
- Adjust the trip estimates to account for multistory parking garages in the CBD
- Convert these trips to productions and attractions by trip purpose
- Modify the trip generation script to accommodate this increase in trips

Estimate the New Employment that could Replace Existing Parking Lots

Because parking data were only available for the City of Charlottesville (rather than the entire region) and for year 2017 (a more recent period than the base year in the model), the researchers used additional data to relate parking to employment. Data from the City of Charlottesville (2017) showed approximately 1,410 parking lots, with these lots having a total area of 2,292,425 m^2. Total employment for the City of Charlottesville from the Bureau of Labor Statistics (2017a) for year 2016 (the last year for which full data are available) was 114,317. The ratio of these two values suggests that there are roughly 20.053 m^2 of parking corresponding to one position of employment. Both the parking data and the employment data have limitations in terms of relating parking area to employment: the parking data do not account for multistory parking garages, on-street parking, and the fact that some parking is likely used for residential rather than employment purposes, and employment data do not include military, proprietor, or household employment (Bureau of Labor Statistics, 2017b).

To allocate the 1,410 parking lots in the city to the roughly 115 transportation analysis zones which contain this parking (see Figure A2), two operations were performed in GIS after reprojecting these data into Albers Equal Area. An identity overlay split parking lots spanning two or more zones into smaller polygons, where the size of each polygon was proportional to the amount of parking lot located in each zone. This operation resulted in 1,694 parking polygons, but the total parking area of 2,292,425 m^2 did not change). Then a dissolve operation was used to determine, for each zone, the sum of the parking areas within each zone.

The results suggest that within the central business district (CBD) shown in Figure 10, there are roughly 2.76 million square feet (256,879 m^2) of parking that could be converted to other uses. This estimate is higher than reality if all such land development is kept to one story, since land development requires a floor area ratio of less than 100% (in fact, a floor area ratio of 40% can be considered relatively high). This estimate is lower than reality if multi-level development (e.g., high rise condominiums or four story shopping complexes) is feasible.

Estimate the Trips that Such Employment Could Generate

In order to create a realistic scenario for the number of new trips that might be generated by additional development, trip generation rates published by the Institute of Transportation Engineers (2012a, 2012b), types of housing that have been built in the Charlottesville area (City of Charlottesville, 2007), and typical square footage of housing types (U.S. Census Bureau, 2017) were consulted. Four iterative steps were then followed:

- First, the researchers assigned a new imaginary employee to one of five commercial land uses cited in ITE (2012a,2012b): general office building, medical-dental office building, discount club, specialty retail center, and furniture store. There are hundreds of different commercial land uses available in ITE (2012a,2012b), and thus other uses could be chosen; these five were selected because they showed a wide range of trip generation rates per employee, they provided trip rates based on number of employees and gross floor area, and they were a manageable number of land uses (five) with which the researchers could experiment.

- The researchers then used three principles in determining the proportion of new employees for each land use. Because the proportion of employment in the region was expected to rise from 20.2% in 2007 to 22.6% in 2035 (The Corradino Group, 2009), the researchers forced retail employment (e.g., discount club, specialty retail center, and furniture store in this case) to be 23.0% of total employment in 2040 (where the 23.0% is an extrapolation of the 2007-2035 trend reported by The Corradino Group [2009]). Because the Bureau of Labor Statistics (2015) forecast at the national level in 2024 that the sum of five service employment categories which the researchers judged to be comparable to office employment (information, financial activities, professional and business services, federal government, and state and local government) would be 3.41 times higher than the category of health care and social assistance, the researchers forced general office building employment to be 3.41 times higher than medical-dental office building employment. Finally, because the number of person-trips per household based on data from the National Household Travel Survey (Santos et al. 2011) was 9.50, the researchers altered the proportions of the three categories of retail employment until this value of 9.50 trips per household was attained.

- For the entire region, socioeconomic data in the 2040 travel demand model—that is, the forecast for year 2040 used to execute the Cube travel demand model—suggested a ratio of roughly 1.29 employees per household, such that each employee "requires" about 0.777 households. Then, based on ITE (2012b), the researchers estimated the number of commercial trip ends per employee as well as the square footage of gross floor area that would be required for each commercial land use. In addition, a weighted average of three types of housing (single family detached dwelling units, condominiums, and apartments) (City of Charlottesville, 2007) along with trip generation rates expected for these housing types (Institute of Transportation Engineers, 2012a) was used by the researchers to estimate the number of residential trip ends per new employee.

- Finally, the number of new employees was increased until all the parking area in the central business district had been used by residential or commercial land uses. The resultant sum of commercial and residential trip ends, when divided in half, gives the net number of new trips in the central business district.

These results are shown in Table 5. For example, Table 5 suggests that the CBD parking lots, if converted to other land uses, might support a total increase in employment of 1,393, which would occupy a total land area of about 2.763 million square feet. About 0.250 million square feet would be general office building, which would generate roughly 2,756 trip ends. The

830 new employees working in this type of land use, along with the other employees who work in the four other types of land development shown (medical-dental office building, discount club, specialty retail center, and furniture store) would live in households that would consume approximately 2.083 million square feet. The results of Table A1 suggest that the combined commercial and residential land uses would generate an additional 20,577 trip ends (e.g., 10,289 trips). Because these trips correspond to 2,763,000 ft^2 (or 257,000 m^2) of parking, Table 5 suggests that each square meter of parking could result in 0.04 additional daily trips.

Table 5. Estimated New Trips from the Conversion of Parking Area in the Central Business District

Land use type	**Trip ends per new employee**[a]	**Trip ends per new 1000 ft^2**[a]	**1000 ft^2 per new employee**	**New employees**	**Land area (1,000 ft^2) created from parking lots**	**New trip ends**
General office building	3.32	11.03	0.30	830	250	2,756
Medical-dental office building	8.91	36.13	0.25	243	60	2,169
Discount club	32.21	41.8	0.77	131	101	4,225
Specialty retail center	22.36	44.32	0.50	98	49	2,182
Furniture store	12.19	5.06	2.41	91	220	1,112
Household	5.84	3.90	1.49	1,393[b]	2,083	8,134
Total				1,393[b]	2,763	20,577[c]

[a] Based on data reported by the Institute of Transportation Engineers (2012a, 2012b)
[b] Each employee lives in a household. The sum of employees working in the five commercial land uses equals the sum of employees living in households. These 1,393 employees reside in (0.777)(1393) =1,083 households.
[c] The number of new trips generated is equal to half the trip ends.

These trips were distributed to the CBD zones on the basis of the square meters of parking available in each zone. For example, since zone 66 has 48,259 m^2 of parking, the conversion of parking lots to other land uses could lead to (0.04)(48,259) = 1,933 extra trips.

Adjust the Trip Estimates to Account for Multistory Parking Garages in the CBD

At the regional level, the lack of multistory parking garage data is a relatively small problem compared to the vast amount of surface parking. However, in focusing on the CBD, where parking garages are concentrated, this could be problematic. There are three relatively large garages in the CBD: the Market Street Garage in zone 2 (473 spaces), the Water Street Garage in Zone 10 (1,019 spaces), and the Omni Garage in Zone 8 (400 spaces), based on a draft parking analysis (Nelson\Nygard Consulting Associates Inc., 2015). Based on a planning level analysis from the International Parking Association (Kavanaugh, 2015) of 350 square feet per parking space, these garages would increase the number of trips in zones 2, 8, and 10 in the CBD by approximately 23%. Thus, whereas Table 5 suggested a total of 20,577/2 = 10,288 trips, inclusion of parking garages increased this figure by 23% to 12,752 trips.

Convert these Trips to Productions and Attractions by Trip Purpose

For each of five purposes (HBW, HBO, NHB, internal-external, and off-campus university), the additional trip ends that would result for each zone were summed, giving a total that represents productions and attractions. (The researchers did not perform this operation for a sixth trip purpose—on campus travel—as those trips reflect students living in dormitories.) The total trips ends for each zone were distributed on the basis of the original percentages for each trip purpose: for example, because internal-external productions account for 40% of all trip attractions (excluding external-external trips and dorm-based trips), 40% of the new trip productions were assigned to that purpose (see Table 6). Thus, the conversion of parking lots to other land uses for zone 66 would lead to (1,933)(40%) = 773 internal-external productions for that particular zone.

Table 6. Percentage of Trips that are Productions and Attractions [a]

Purpose	Productions		Attractions	
	Number	Percent	Number	Percent
Home-based work	3,323	5%	14,464	25%
Home-based other	9,691	16%	24,697	42%
Non-home based	19,424	32%	19,424	33%
Internal-External or External-Internal [b]	24,168	40%	0	0%
Off campus university	4,535	7%	0	0%
Total	61,141	100%	58,585	100%

[a] These percentages are based on two files TGEN_HB.dbf and UVAPANDA.dbf. A related file (TGEN_PA.dbf) gives similar percentages, however, that file appears to include multipliers for certain trip purposes. For compatibility with the original script, the researchers believe the percentages shown in Table 6 are more appropriate.
[b] For productions, these are normally internal-external trips (e.g., a traveler living in the region and working outside the region). For attractions, these are normally external-internal trips (e.g., a person living outside the region and working or shopping in the region).

The initial execution of the original scenario 2d showed that the observed number of trips was about two-thirds of the expected number of trips. Examination of total trips produced by purpose showed the researchers had initially inadvertently created a combination of two scenarios: for internal trips (e.g., HBW, HBO, NHB, and HBU and trip purposes that stay within the modeling region), Scenario 2d reflects new development which was the intention of the scenario and which was expected. However, for internal-external trips, the researchers were surprised to learn that productions are balanced to attractions, which meant that while trip ends in the CBD increased, this resulted at the expense of trip ends in other locations.

Martin and McGuckin (1998, p. 55) note that "External station productions are trips whose home base is outside of the region and external station attractions are trips whose home base is within the region." Interestingly, the Charlottesville model appears to be organized a bit differently: a column labeled internal-external productions shows values greater than zero for all CBD zones but equal to zero for all external stations. A different column labeled internal-external attractions shows values of zero for all CBD zones yet greater than zero for all external stations. Examination of the script shows that the internal-external productions appear to be based on both the number of households in the area and the employment, whereas the attractions appear to be based on traffic counts. (Further, the rate for productions is roughly 0.33 trips per household plus 0.724 trips per employee, such that for CBD zones, most of the "IX productions" are based on employment, not households.)

Thus, in order to generate approximately 12,752 trips, the attraction percentages shown in Table 6 had to be modified to account for how productions and attractions are balanced, which will vary by trip purpose: for HBW, HBO, and NHB, productions guide the control total, for HBU no balancing is performed, and for IX, attractions guide the control total. Accordingly, the researchers first increased university attractions from 0% to 7% to equal productions (which appeared reasonable given that the CBD would attract some students from the nearby university), then set NHB attractions equal to NHB productions (which was a slight change from 33% to 32%), and then, recognizing that HBW and HBO attractions would be scaled to equal productions, scaled the attraction percentages for these purposes by the sum of the production percentages for these two categories. (Thus because HBW and HBO productions represent 21% of all productions, HBW attractions become 21%*25%/(25%+42%)) = 8% of all attractions and HBO attractions became 21%*42%/(25%+42%)) = 13%). The script was also modified to increase internal-external attractions by 1.02112 in order to allow an increase in 40% of internal-external productions. Although the nomenclature of the model differed from that in Martin and McGuckin (1998), this change allowed for productions (as defined in the model) to be attracted to internal-external attractions. Table 7 shows that these changes resulted in an increase in total trip ends in the CBD and in the region. (Some experiments showed that increasing the number of HBW attractions in the CBD can be done but, because of scaling to productions, this would result in some trips being taken away from other locations). With the modifications shown, the desired number of trip ends (or total trips) within the CBD was within 3% of the desired amount for this scenario.

Table 7. Trips Generated in Scenario 2d

Trip End	Ps			As			Ps	As	Ps	As	Total	Total	Total
Purpose	HBW	HBO	NHB	HBW	HBO	NHB	IX	IX	HBU	HBU	Ps	As	Trips
Desired	638	2,040	4,081	2,805	4,846	4,081	5,101	0	893	893	12,752	12,624	12,688
Total observed	641	2,040	4,083	650	2,033	4,083	5,106	5,101	893	893	12,763	12,760	12,761
CBD observed	641	2,040	3,954	982	1,492	3,954	9,883	0	893	893	17,411	7,321	12,366

HBW = Home based work, HBO = Home based other, NHB = Nonhome based, IX = Internal External, HBU = Home-based university, Ps = Productions, As = Attractions

Modify the Trip Generation Script to Accommodate this Increase in Trips

Finally, the script was modified to reflect the additional trips that would result from the conversion of parking to some type of employment. The variable ZI.3.ParkPLo is the total number of trip ends resulting from the conversion of parking to another use. This method required modifying a total of 16 lines in two scripts as shown in Appendix A. (There are ten percentages shown in Table 6, but note that the attractions are repeated in the script.) Note that attraction increases were applied to the UVA, CBD, and urban areas while rural areas were unchanged.

For Scenario category 2, a total of 10 scenarios were executed: a base doubly constrained gravity model (which was the same as that used in Scenario 1), a base singly constrained gravity model (which differed from that used in Scenario 1), and then, for each of these gravity model types, four scenarios: replace parking with a zero occupant vehicle trip for work trips only, replace parking with a zero occupant vehicle trip for non-work trips only, replace all parking trips with a zero occupant vehicle trip, and redevelop CBD parking lots with new residential and commercial uses.

Scenario 3. Evaluate Potential Shifts from or to Transit

Because the possibility had been raised that DVs could increase transit use (either reducing the discomfort associated with the portion of the trip prior to boarding or after disembarking from the transit vehicle [Polzin, 2016] or based on execution of travel demand models [Rixey, 2017]) or decrease transit use (also Polzin [2016] and Rixey [2017]) two contrasting scenarios were developed for evaluating the potential of DVs to influence transit use.

Note that in executing these scenarios, within the mode portion of the model, the total number of person trips will differ slightly, by about 0.02%, depending on whether they are extracted from the "InitialTdist.mat" matrix at the beginning of the mode choice step or a file titled "Mode Summary.txt" at the end of the mode choice step. Examination of the mode choice script does not show a clear reason for this modest difference. However, a possibility is that with the several numerical manipulations in the script (e.g., the initial number of person trips is first divided into 0-car, 1+-car, and student households for each zone and then the logit equations for the mode choice step are applied), that there is some rounding that causes the discrepancy. To avoid errors in comparison, we have consistently used the person trip percentages based on the conclusion of the mode choice step—that is, the person trip percentages extracted from the file "Mode Summary.txt".)

Potential Shifts from Other Modes to Transit (Scenario 3a)

Scenario 3a considered how DVs might solve the last-mile problem for transit—that is, lead to an increase in transit use. Part of this increase in comfort may result from shared driverless vehicles performing two activities: (1) eliminating the need to walk to the transit stop and (2) providing greater comfort by removing the driving task (Levin [2015]). The Corradino Group (2009) explains that there are three distinct transit modes in the model: (1) walk to local bus (2) walk to premium service and (3) drive to best available service. This "premium service" does not exist in reality; The Corradino Group (2009) explains that "The premium mode used for transit is a place holder for any future premium service that may be introduced in Charlottesville." Thus, in practice, transit modes 2 and 3 have almost zero values in the base scenario. To examine how DVs could potentially complement transit, the researchers created a new mode that is a hybrid of modes 2 and 3 by performing two changes for the peak hour:

- *Walking to the bus was replaced with taking a shared driverless vehicle*. In the model, walking time was replaced with the driving time, and the cost of *out of vehicle travel time* was replaced with *65% of the cost of in-vehicle travel time* based on a potential change in comfort suggested by Childress et al. (2015). In practice, as shown in Figure 11, two lines in the script were changed: walk time (shown as the variable "pkwktimeex") was replaced with driving time to best available transit ("pkwktimeBA") and the in-vehicle time parameter HBWCIVT was replaced with HBWCIVT*0.65. (Note that the variable "pkwktimeBA" means drive to best available transit, despite the fact that "wk" means walk in other variables.)

- *Waiting for the bus was eliminated*. The wait time was set to zero, which is why the variable "pkwktimeex" is multiplied by zero.

Although the two above bullets represent the change in the mode conceptually, four additional changes were made to the script due to the nature of this particular model. The researchers' understanding of these variables was based on (1) examination of the model documentation (The Corradino Group, 2009), (2) the model script, (3) calculations of the transit utility for three zone interchanges as shown in Appendix B and (4) interactions with the TRP.

- The variable for travel time in premium transit ("pkivtimeex") was replaced with the variable for the travel time in local bus ("pkivtimelb")

- The parking cost variable was set to zero, although the parking cost had been presumed to be zero in the original model.

- The operating cost variable for local bus was used, where the variable "pkopcostex" was replaced with "pkopcostlb."

- For this particular scenario, after discussions with the TRP a new base scenario was developed: *local bus operating cost*—that is, the fare—was modified to be multiplied by 100 as shown by the line "MW[15]=(mi.3.pkopcostlb*100)*HBWCCST." This made the utility function for walk to local bus comparable to the utility functions for walk to premium transit and drive to best available as discussed in Table 3.

```
;   PEAK PERIOD WALK TO PREMIUM TRANSIT ELEMENTS OF UTILITY ARE:
;   WALK TIME
    MW[11]=(mi.3.pkwktimeba)*HBWCIVT*0.65
;   WAIT TIME
    MW[12]=(mi.3.pkwttimeex)*HBWCOVT*0
;   IVTT
    MW[13]=(mi.3.pkivtimelb)*HBWCIVT
    if (mw[13]=0) mw[13]=-9999
;   PARKING COST
    MW[14]=(mi.3.pkpkcostex)*HBWCCST*0
;   OTHER COST - FARE
    MW[15]=(mi.3.pkopcostlb)*HBWCCST
;   PEDESTRIAN ENVIRONMENT
    MW[16]=HBWPTI * ZI.2.SUM[I]*0.25
```

This line was later modified to include a 100 multiplier for the fare.

Figure 11. Initial modifications in order to Implement Scenario 3a. Later, the fare was multiplied by 100 and a revised base scenario, as well as a new version of Scenario 3a, was developed.

Shifts from Transit to Other Modes (Scenario 3b)

Zhao and Kockelman (2017) suggest that by year 2020 for one particular region, connected vehicles may increase VMT by 20%, owing to three factors: (1) "self-parking" of driverless vehicles (e.g., an increase in zero occupant vehicles as discussed in Scenario 2); (2) “door-to-door” service, some of which would result in a shift from existing transit modes [the focus of Scenario 3b which has not yet been performed], and (3) increased comfort for passengers of driverless vehicles. Therefore, within the same mode choice script (file “MCMAT00A.S”), the in-vehicle travel time was multiplied by 0.65 for three modes: drive alone, carpool 2, and carpool 3+ during the peak hour as the figure 12 shows. (As was the case with Scenario 3a, the focus was on the peak hour, so only HBW trips had the utility function modified.

```
; ==================================================================================
; HBW (PEAK) TRIP PURPOSE
; ==================================================================================

  ;   PEAK PERIOD DRIVE ALONE ELEMENTS OF UTILITY ARE:
  ;   WALK TIME
      MW[11]=(MI.5.TERMTIME)*HBWCOVT
  ;   WAIT TIME
      ;MW[12]=(0)*HBWCOVT
  ;   IVTT
      MW[13]=(MI.5.FFTIME)*HBWCIVT*0.65
  ;   PARKING COST - ONLY AT DESTINATION (J), HALF IN EACH DIRECTION
      MW[14]=0.5 * ZI.1.LTERMCST[J] * HBWCCST
  ;   OTHER COST
      MW[15]=MI.5.DISTANCE * {HWYOPCOST} * 100 * HBWCCST
  ;   COMPOSITE UTILITY
      ;MW[021]=(MW[11]+ MW[13]+MW[14]+MW[15]+K1_NC_DA)/NESTMOTOR
      MW[031]=(MW[11]+ MW[13]+MW[14]+MW[15]+K1_WC_DA)/NESTMOTOR
      MW[041]=(MW[11]+ MW[13]+MW[14]+MW[15]+K1_ST_DA)/NESTMOTOR
```

Figure 12. Example of Reducing the Cost of In-Vehicle Travel Time by 35%. (A similar procedure was performed for two-person carpools and 3+ person carpools).

Potential Longer Trips (Scenario 3c)

For the singly constrained gravity model, the friction factors were iteratively adjusted until the congested travel times had increased by 35% based on a review of Childress et al. (2015). Table 8 shows how the travel time changes both for the free flow condition (which is used for the initial measure of impedance in the trip distribution step and applies to each trip purpose separately) and, as given in the last row, the overall congested mean trip time. For the singly constrained gravity model, a multiplier of 0.125 times the friction coefficient yielded a congested travel time (29.81 minutes) that was 35.01% longer than the base model congested time (22.08 minutes). This factor was derived iteratively: previous multipliers included 0.095 (yielding 30.35 minutes, which is a 37.5% trip length increase relative to the base congested time of 22.08 minutes); 0.105 (29.99 minutes, a 35.8% increase); 0.20 (28.95 minutes, a 31% increase), 0.14 (29.56 minutes, a 33.9% increase), and 0.12 (29.97 minutes, a 35.7% increase). For the doubly constrained model, when set all friction factors are equal (e.g., whether that value is 1 or 1,000) the congested mean travel time is 28.23 minutes, which is 35.1% higher than the base congested time of 20.89 minutes.

Table 8. Impact of Adjusted Impedances on Trip length in Minutes

Trip length type	Trip purpose	Doubly Constrained		Singly Constrained	
		Base Model	Revised	Base Model	Revised

			Impedances [b]		Impedances [b]
Uncongested	HBW	17.58	19.02	10.15	11.41
	HBO	15.66	18.99	8.22	10.89
	NHB	14.24	18.2	7.05	10.04
	HBU	11.45	12.07	5.71	8.1
	HDORMU	11.49	11.9	5.11	7.55
	IX	21.93	24.59	16.65	19.94
Congested	All	20.89	28.23	22.08	29.81

[b] Multiplication of the original impedances by 0.125 yielded these trip times. For example, for HBW trips, the original impedance was $e^{-0.08001(\text{travel time})}$. For the revised impedance, this equation became $e^{-0.08001(\text{travel time})*0.125}$. Thus, as shown in Appendix C, the script is modified to read: "mw[21]=MI.2.FFTIME*(-0.08001*0.125)

For Scenario category 3, a total of eight scenarios were executed. With the original utility function, there were four scenarios: Scenario 3a (shift from other modes to transit), Scenario 3b (shift from transit to other modes) [both with the doubly constrained gravity model], and then Scenario 3c (shift from other modes to transit) and Scenario 3d (shift from transit to other modes) [both with the singly constrained gravity model]. Then, these four scenarios were executed again as Scenarios 3a', 3b', 3c', and 3d' with the revised utility function for local bus that included the "100" multiplier.

Scenario 4. Allow Non-Familial Sharing of Driverless Vehicles

Scenario 4 concerns an increase in zero occupant vehicles (ZOV) trips which might result from individuals choosing to share driverless vehicles rather than purchase them outright. Whereas Scenarios 2 and 3 considered a driverless vehicle that was restricted to a single household, it may be possible to either share vehicles within a household or with others who live outside of a household. Williams (2013) suggests DVs may reduce car ownership and facilitate car-sharing, resulting in less time spent parking, more wear-and-tear on the vehicle, and a higher fixed cost; in fact, between 9 and 13 privately owned vehicles could be replaced by a shared DV.

Scenario 4 thus involves consideration of a subscription model, where travelers pay for individual trips to a provider in lieu of owning a vehicle. While such a subscription-based model may differ from a traditional ownership-based model in a number of ways, Scenario 4 considers just one potential difference: how might the increase in deadheading lead to an increase in VMT (and other outputs of interest such as emissions)? For a doubly constrained gravity model, there are a total of eight possible scenarios that may consider this increase in VMT, based on a high or low degree of matching.

A High Degree of Matching

If there is a high degree of matching such that ZOV trips are relatively short (e.g., beginning and terminating within the same zone), then deadheading will generally not occur on the roadway network included in the model. An example is a trip that that starts and stops in the same residential subdivision (e.g., within the same zone). The interpretation of this scenario is that because sharing occurs within each TAZ, the additional VMT is not on the observed roadway network (see Figure 13). Thus, trips B, D, F, H, and J are not on the network.

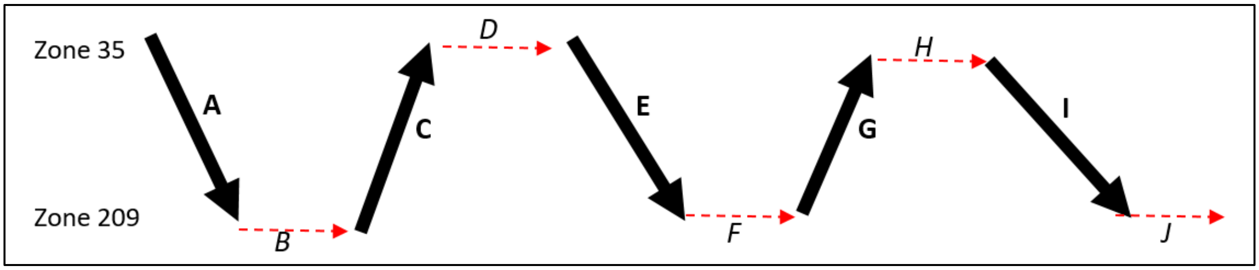


Figure 13. Example of Zero Occupant Vehicle Trips. The occupancies for interzonal Trips **A**, **C**, **E**, **G**, and **I** (in bold) is one person per vehicle. Intrazonal trips *B*, *D*, *F*, *H*, and *J* (italicized) have no occupants in the vehicle.

However, VMT still influences total emissions, as shown in Scenarios 4a-4c. For home-based work trips, Equation 1 makes this trip length a function of individual zone size based on a review of Martin and McGuckin (1999). For example, consider ZOV trips within zones 209 versus those within zone 35. A ZOV trip within zone 209 has a length of 0.5(6.33)^(1/2) = 1.26 miles (since zone 209 is relatively large with an area of 6.33 miles) yet each ZOV trip within zone 35 has a length of 0.5(0.11)^2 = 0.16 miles (since that zone, near the CBD has a much smaller area of 0.11 miles).

0.5(zone area)^0.5 (Number of HBW trips terminating in the zone) (Eq. 1)

To implement this approach, the number of vehicle trips for each zone based on the number of destinations from the origin-destination table may be tabulated. Table 9 illustrates these calculations for the simple two-zone system in Figure 1 where there are five trips between zones 35 and 209 (which occur on the network) and an additional five zero-occupant vehicle trips that occur off the network. The three ZOV trips terminating in zone 35 add roughly 0.49 VMT, by contrast, the two ZOV trips terminating in zone 209 add roughly 2.51 VMT.

Table 9. Example of Tabulating Zero Occupant Vehicle Miles Traveled for Figure 1.

Zone	35	209
On network trips starting in the zone	A, E, I	C, G
Off network trips ending in the zone	B, F, J	D, H
Zone area in miles	0.107	6.322
ZOV trip length in miles	0.163	1.257
Total off-network ZOV VMT	= 3 X 0.163	= 2 X 1.257
Total off-network ZOV VMT	0.49	2.51

For Scenario 4a, the number of home-based work vehicle trips just prior to sequence 7 (trip assignment) was 129,300, although a different answer (112,359) based on the step just prior to trip assignment in sequence 12. For consistency, the number of vehicle trips from the latter process was used, based on the file *modeout.mat*, which meant that the number of vehicle trips for three modes (drive alone, two-person carpool, and carpool 3+) needed to be exported and summed outside CUBE. For Scenario 4b, the process was applied to all vehicle trips, regardless of purpose, except for external-external trips and internal-external or external-internal trips; for this reason, the file CVFINALVEHTRIPS2040.DAT was used with modes of drive alone, two-person carpool, and carpool with more than two people, where again the matrices were exported and summed. Scenario 4c considered the fact that ZOVs might tend to be used to different degrees by persons who drive alone versus carpool and thus examined what might occur if only persons who currently carpool use a driverless vehicle; thus, only the two-person carpool and 3+ carpool matrices were used.

A Medium Degree or Low Degree of Matching

Scenarios 4d and 4e presumed that when one passenger departs the shared driverless vehicle, the vehicle must then make a ZOV trip within a particular region in order to arrive at the origin for the next passenger. Compared to Scenario 4a, Scenario 4d presumes a low degree of matching such that these regions are relatively large: the entire study area is split into 5 regions, consisting of roughly 50 TAZs per region. By contrast, Scenario 4e presumes a greater degree of matching, such that the regions are relatively small, with Scenario 4e splitting the area into 51 regions consisting of roughly 1-13 TAZs per region. As with Scenario 4a, Scenarios 4d and 4e considered only commuting trips (HBW) in order to forecast peak hour transportation system performance.

A GIS analysis was used to develop these regions where the 262 TAZs were converted from a vector format to a raster format. Using five seed zones and the Euclidean allocation tool, a raster consisting of five regions was established (Figure 14, *left*). The resultant raster of five regions was converted to a polygon format and then a spatial join was performed between these five vectorized regions and the 262 TAZs, such that each TAZ now was associated with one of the five regions (Figure 14, right). Then, the number of HBW person trips in file TGEN_PA.dbf 153862.8 that terminated in each region was determined and, based on Equation 1, the trip length for a ZOV trip associated with each HBW trip end was determined.

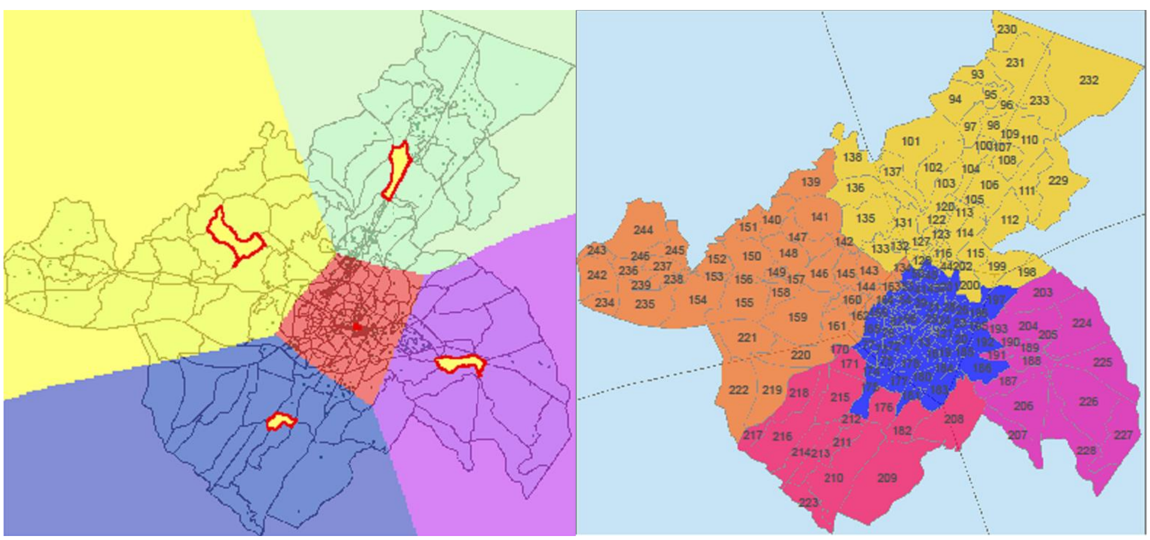


Figure 14. Implementation of Scenario 4d with Five Regions (*left*) and Association of Each TAZ with a Region (*right*)

For example, consider the doubly constrained model and the northwest region in Figure 14. The zones in that region showed a total of 11,098 HBW person trip ends. Because that zone has an area of 153,454,155 square meters (59.24 square miles), Equation 1 suggests that a ZOV trip that stayed within that region would have an average length of 3.849 miles (e.g., $0.5*(59.24)^{1/2} = 3.849$) Thus, ZOV trips for that region generate 29653.4trips*3.849 miles =

114125.8717VMT, and the sum of the additional VMT from all regions yields 496465.6419 VMT as shown in Table 10.

Table 10. Summary of VMT from Zero Occupant Vehicle Trips Based on a Low Degree of Matching for the Doubly Constrained Gravity Model

Region	Area (square meters)	Average ZOV Trip length (miles)	HBW Destination Ends	ZOV VMT
Northwest	153,454,155	3.849	29653.4	114125.8717
Northeast	170,076,017	4.052	50370.6	204088.6948
Southeast	826,59,022	2.825	7863.8	22212.52229
Southwest	86,261,173	2.886	5784.8	16692.3051
Central	55,526,259	2.315	60190.2	139346.248
Total			153862.8 [a]	496465.6419

[a] This number (153862.8person trips) is the total productions used in trip generation. There are a total of 153,863 person trips in the file PDDST00A.PRN which includes HBW productions.

Then, recall that the base case in year 2040 is that the total VMT is 6,829,605.34 for the doubly constrained gravity model. The estimated new VMT is thus 6,829,605.34 + 496465.6419= 7326070.642 VMT. Thus, in the trip generation script (TGGEN00A.S), as shown in Appendix C, a multiplier is used for the NHB trips such that the VMT generated by the model is roughly this amount. The researchers found that multiplying NHB trips by a factor of 1.685 gave a value within approximately 0.0011% of that amount (e.g., 7,325,221.930). A similar process was performed for the singly constrained gravity model: the researchers found that a multiplier of 1.608 yielded a VMT (7,399,473.59) that was within 0.01% of the desired VMT from the GIS analysis (7,399,469.822).

Then, the above steps were repeated for a medium degree of matching, where it was presumed that there are only a few zones per ZOV matching region (Figure 15). As one might expect, with medium matching rather than low matching, the ZOV VMT is less and hence the multiplier for NHB trips is also less, with values of 1.22 and 1.173 for the doubly and singly constrained models, respectively.

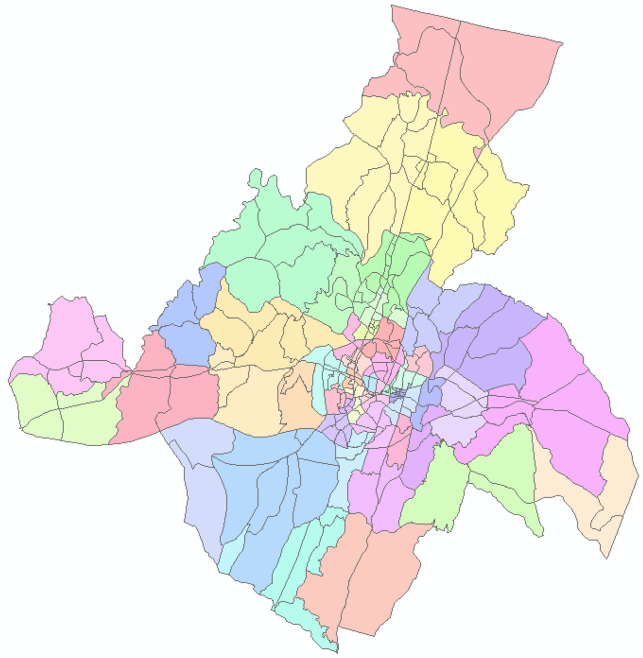


Figure 15. Catchment Area for Scenario 4e Which Presumes a Medium Degree of Matching (Hence 51 smaller regions rather than 5 large regions).

For Scenario category 4, therefore, a total of ten scenarios have been executed: high degree of sharing of home-based work vehicle trips (scenario 4a), high degree of sharing of all vehicle trips (scenario 4b), high degree of sharing of vehicle trips that are carpool only (scenario 4c), low degree of sharing of HBW trips (scenario 4d), and medium degree of sharing of HBW trips (scenario 4e).

Scenario 5. Increase Travel by Age Groups with Traditionally Lower Vehicle Access

The fifth category of scenarios asks "what if persons who do not presently have access to a vehicle because they lack a driver's license could use a DV?" Scenarios 5a and 5b concern persons age 65+ and persons age 13-17, respectively, and focus on non-work trips only. Scenario 5c combines these two scenarios and includes persons age 18-64, and for that age group only, considers both work and non-work trips. Scenario 5d provides a comparison for all scenarios: what if the region's growth doubles the expected value for 2040? The doubling of growth is not attributed to driverless vehicles but rather is an example of an unforeseen shock that might affect the results of the travel demand model—and thus its change can be compared to those of the other scenarios.

Figure 16 shows the percentage of persons by age group who have, or potentially have, a driver's license or access to a driverless vehicle based on roughly current year populations (U.S. Census Bureau [2015b]), forecast year data (Weldon Cooper Center for Public Service, 2012), and rates of licensure by age group available from the literature (e.g., Figure 6 of Miller et al., 2015, Appendix E of Zmud et al., 2016). For example, in year 2015, there were roughly 11,738 persons age 15-19 in the Albemarle Charlottesville area. Because population growth should increase this age cohort from 11,738 to 15,153 by 2040, we would expect the number of licensed drivers to increase from 4,695 to 6,061, based on a 40% rate of licensure for this age group

(Miller et al., 2015). If every person could have access to a vehicle, however (even without a driver's license), then the licensed vehicles in this age group increases from 6,061 to 15,153. Figure 16 shows the impacts of the increase; notice the larger increases are at the upper and lower ends of the age spectrum.

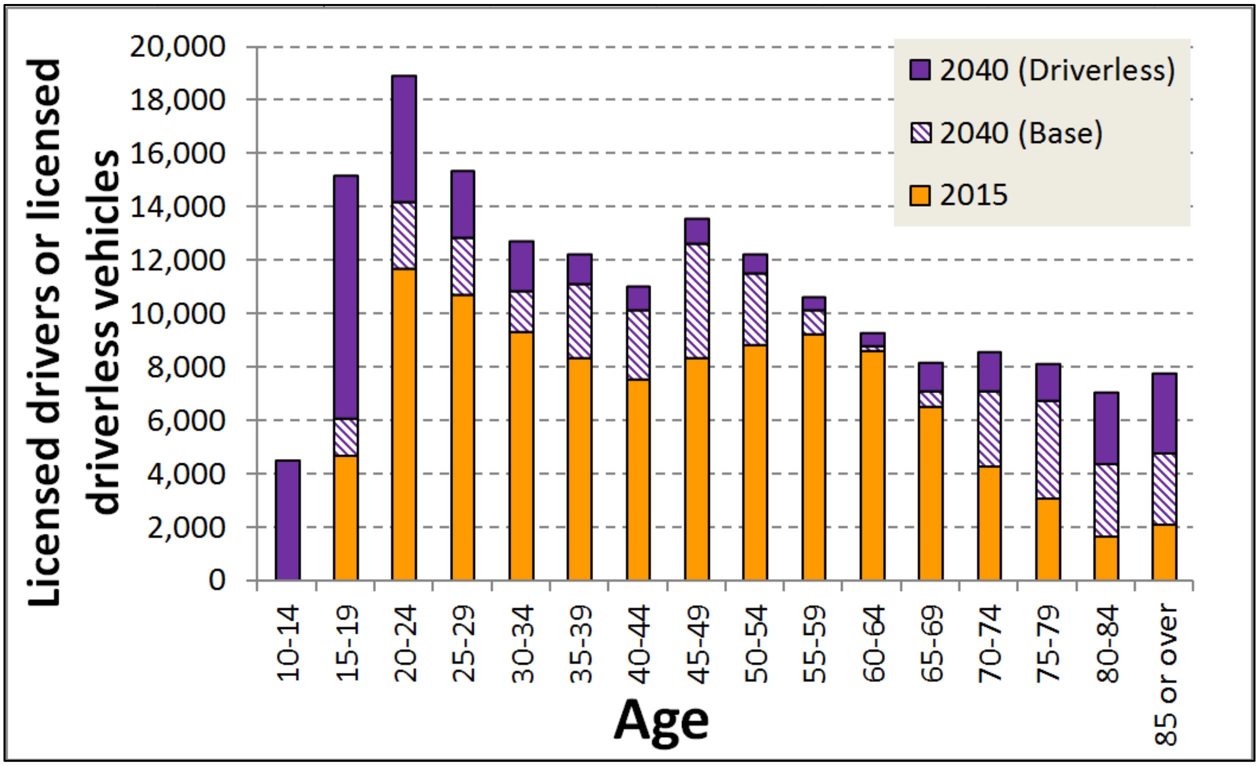


Figure 16. Potential Impacts of Population Growth and Technology on the Number of Licensed Drivers and Licensed Driverless Vehicles in the Charlottesville/Albemarle Area. Drawn based on data from U.S. Census Bureau [2015b], Weldon Cooper Center for Public Service, 2012), Miller et al., 2015, and Zmud et al., 2016)

Concepts for the Scenarios

As reported in Appendix B, the methodology for implementing Scenario 5a consisted of three main steps: obtain current proportions of persons age 65+ in each Census block group, reconcile geospatial errors that resulted when aligning Census geography with travel demand model geography, and finally forecast the 2040 population age 65+ by zone. Those calculations suggest a potential increase of about 15.3% in HBO and NHB trips for persons age 65+.

For Scenario 5b, an approach for estimating the additional trips due to younger individuals (age 13-17) who previously could not travel was also developed, where current populations for persons in that age range were obtained from the U.S. Census Bureau (2016). (Because data were provided in the ranges of ages 10-14 and 15-17, the researchers estimated the number of persons age 13-14 as 40% of the population age 10-14). This method provided an average percentage of persons age 13-17 by Census block group. Then, census block groups and TAZs were aligned after performing an overlay in a GIS environment and checking for errors, yielding a present day percentage of persons age 13-17 by TAZ. While the proportion of persons age 13-17 will change between the present and 2040, the change is not as dramatic as with persons age 65+: this proportion is 6.66% at present (U.S. Census Bureau, 2015b) and will rise to 6.69% in 2040 (Weldon Cooper Center for Public Service, 2012). Accordingly, the percentage population for each zone age 13-17 that were computed based on present-day populations were all increased by the ratio of 6.69%/6.66% = 1.003. Finally, the modified percentages were multiplied by the number of people in each zone in 2040 in order to obtain a forecast of persons age 13-17 in each zone. For example, for transportation zone 161, with 369 people, the percentage of people in that zone forecast to be age 13-17 is 2.93% of 369—about 11 people. Truong (2017) suggests that persons in the age range of 13-17 could see an increase in trips of 11.12%, thus, a multiplier of 1.1112 was used for such persons for HBO and NHB trips. As was the case with Scenario 5a (persons age 65+, HBW trips were not increased.

For Scenario 5c, a similar procedure was considered for persons age 18-64, where approximately 14.8% of Virginians age 18-64 do not have a driver's license (Miller et al., 2015). Data from Truong (2017), when adapted to Albemarle County and the City of Charlottesville data projections for 2040 (Weldon Cooper Center for Public Service, 2012), suggest an additional 3.67% of trips could be realized with the arrival of driverless vehicles; hence a weight of 1.0367 was used for all trip purposes—HBW, HBO, and NHB—and the judgment being that some of these individuals are more likely to be in the work force. These data were combined with those for Scenarios 5a and 5b.

Scenario 5d was implemented by doubling all socioeconomic variables for each zone in the file LandUse_2040A.dbf: population, household, automobiles, total employment, retail employment, school enrollment, university employees, number of on-campus students, dormitory beds, off campus students and classroom seats. No changes were made to acreage and zonal university parking the same. (There is one additional parameter shown in the above file titled "Academic_E." After reviewing the model report and Cube script, the researchers could not determine what this variable means and thus it was not altered.

Implementation of Scenarios

The number of persons age 65+ varies by zone as shown in Figure 17. For example, for zone 230, the total population is 319 with about 18.5% of those persons (59) being age 65+. By contrast, the percent of persons age 65+ in zone 94 is about 24.2% (e.g., 254 persons out of a total of 1,048).   Then, in the trip generation step, the number of HBO and NHB productions is set equal to existing productions multiplied by (1+15.3% * the proportion of people age 65+ in each zone). In zone 93, about 24.2% of the population is expected to see home-based other and non-home based trips increase by 15.3%. Thus, for that zone, which generated 361 HBO trips and 63 NHB trips, Figure 17 shows the calculated increase in the number of HBO trips is 361*(1+(24.2%)*(15.3%)) = about 375 trips and the number of NHB trips is 63*(1+(24.2%)*(15.3%)) = about 65 trips. The script is thus modified as shown in Appendix C (Figure C1).

MODEL_NAME	ZONE	DISTRICT	POP	POP65	PERCENT
CVILLE	230	7	319	59	0.184952978
CVILLE	232	7	1093	206	0.188472095
CVILLE	231	7	2395	450	0.187891441
CVILLE	233	7	603	113	0.187396352
CVILLE	93	7	223	54	0.242152466
CVILLE	94	7	1048	254	0.242366412

Figure 17. New Landuse_2040A.dbf table

A similar procedure was followed for Scenario 5b. For example, for zone 93, about 9% of the population is expected to see home-based other and non-home based trips increase by 11.12%. Thus, for that zone, which generated 361 HBO trips and 63 NHB trips, the increased number of HBO trips is 361*(1+(0.09)*(11.12%)) = about 364.6 trips and the number of NHB trips is 63*(1+(0.09%)*(11.12%)) = about 63.63 trips (see Figure 18).

MODEL_NAME	ZONE	DISTRICT	POP	POPYTEEN	PERCENTTEE
CVILLE	230	7	319	26	0.081504702
CVILLE	232	7	1093	89	0.081427264
CVILLE	231	7	2395	195	0.081419624
CVILLE	233	7	603	49	0.081260365
CVILLE	93	7	223	20	0.089686099
CVILLE	94	7	1048	93	0.088740458

Figure 18. Modification to the Trip Generation Script for Scenario 5b, where HBO and NHB Trips are Increased by 11.12% to Account for Increased Trips by Travelers Age 13-17

Finally, Scenario 5c increases trips for each of these age groups (see Figure C2 in Appendix C). Results were checked by hand and with the model; for example, for HBW, HBO and NHB trips, the model gives 200.2, 386.4 and 67 for Scenario 5c, while, these numbers calculated by hand was 203.26, 386.043 and 67.35.

A Combined Scenario

It was pointed out that this project should include a combined scenario that integrated elements from the previous scenarios. The resultant combined scenario does not seek to provide a worst-case analysis: if one wanted to see a situation where congestion becomes large, for example, one could use Scenario 5d which greatly increases travel time. Rather, the combined scenario entails a situation where driverless vehicles are introduced but are not the dominant mode of transportation. Accordingly, capacity is reduced on some but not all facilities, parking in the CBD is reduced thus allowing some new development in the CBD, and a change in behavior in terms of longer trips as well as additional trips occurs. The environmental impact of two options: DVs being shared versus DVs not being shared, are examined. To execute this scenario, therefore, four key changes were made to the model:

- Capacity was reduced by 32% but only on three types of facilities: interstates, freeways, and major arterials. For all other facilities, capacity was not altered. The rationale is that for high-speed facilities, a greater margin of safety is required but for lower speed facilities, capacity is unchanged. Thus, a modified version of Scenario 1a is used.

- Because DVs may induce some additional travel by persons without access to a license, the number of trips was increased—but not by the same amount shown in Scenario 5c. Rather, to indicate a relatively low percentage of persons who might have a driverless vehicle, a figure of 24.8% was selected based on Bansal and Kockelman (2016) who suggested that percentage for year 2045 if certain events transpire, such as technology decreasing at a cost of about 5% annually. Thus, a modified version of Scenario 5c was used.

- A portion of parking in the CBD area—24.8%--is replaced with development. The idea is that some developers see that greater value can be obtained by converting existing parking lots to parking—but not all. Thus, a modified version of Scenario 2d is used, with the 24.8% figure being selected based on the above bullet.

- Because increased comfort of DVs makes longer trips feasible for some users, impedances were reduced. *For the singly constrained gravity model*, friction factors were increased and for the singly constrained gravity model, the magnitude of the coefficient c for travel time in the expression e^{c*time} was reduced. However, the changes were not as large as those in Scenario 3c. For the singly constrained gravity model, for example, whereas Scenario 3c had reduced impedance by a factor of 0.125 (e.g., changing impedance from $e^{-c*(travel\ time)}$ to $e^{-c*(travel\ time)*0.125}$), this combined scenario only moderately altered the factor, using $e^{-c*(travel\ time)*0.70}$. (The value of 0.70 was chosen because compared to a multiplier of 1.0, it raised VMT from 6,903,004.18 [the singly constrained gravity model base VMT] to 7,466,519.26 for an increase of 8.2 percent, which is roughly a quarter (e.g., roughly 24.8%) of the increase sought in Scenario 3c where DVs increased travel time due to increased comfort. *For the doubly constrained gravity model*, the researchers modified the friction factors to increase VMT by a similar amount using first a linear approximation and later an exponential function. (To start the linear approximation, the friction factor associated with one minute was left unchanged for each of the six trip purposes. These friction factors were 5996 (HBW), 5484 (HBO), 2723 (NHB), 126687 (HBU), 126687 (HDORMU), and 8187 (IX). Then, the friction factors were initially decreased in a linear fashion by the expression *a**time until a trip length was obtained that was about 19% higher than the base trip length. Then, an exponential decay function of the form e^{c*time} was fit to these values for each trip purpose and *c* was adjusted further until the VMT of 7,395,451.47 was obtained, which was 8.3% higher than the base VMT of 6,829,605.34.) Thus a modified version of Scenario 3c was used.

The model was executed based on the above four bullets and became the "base case combined scenario." Then, two policies were contrast, focusing on the peak hour and HBW trips. One policy was to not provide sharing of DVs, where the HBW person trips only were increased by 24.8%. Then, after removing the 24.8% increase in HBW person trips, a second policy was to provide sharing of DVs relative to this new base case combined scenario, where there is a low degree of matching as shown in Scenario 4 (e.g., with five regions). For each HBW vehicle trip from the "base case combined scenario", a ZOV trip was added, where this ZOV trip was the average trip length from Scenario 4e. The NHB VMT was increased until this additional VMT was obtained. The difference in NOx was determined for these two scenarios.

- Step 1. Generate the "New Base Case Combined Scenario" which yields a new VMT of 7,565,546.88.
- Step 2. Increase HBW person trips by 24.8% and run the model. The end of this step yields the results of the not-sharing scenario.
- Step 3. Remove the HBW person trips from Step 2.
- Step 4. Add 24.8% of the induced HBW VMT from Scenario 4e. Recall that Table for Scenario 4e gave 496,466additional VMT from sharing. Thus 24.8%(496466) = 123,123.48is added to obtain a new VMT such that 123,123.48+ 7,565,546.88 = 7,688,670.36.
- Step 5. Use an NHB multiplier to get this new VMT. These multipliers were 1.1 (doubly constrained) and 1.09(singly constrained).

Summary of Base Scenarios

Table 11 shows the key changes in the base scenarios throughout the project: with legacy models, there is a strong possibility that additional information will be learned as one delves more deeply into the model itself, and thus it may not always be realistic to have a single base scenario.

Table 11. Summary of Base Scenarios

Type [a]	Scenario Category	Characteristics	VMT	VHT	MTT
Double	1,2,4,5, and combined	Make three changes that apply to all scenarios: • Adjust trip production rates to match documentation • Incorporate fares into the mode choice step • Add script to obtain mean trip length	6,829,605.34	167,101.64	20.89
Double	3	Include a 100 multiplier for the local bus operating cost	6,828,131.94	167,293.27	20.89

Single	1 only	Develop friction factors for the singly constrained gravity model based on an iterative procedure following Martin and McGuckin (2016)	7,688,831.98	219,496.25	24.57
Single	2,4,5, and combined	Develop friction factors based on a simpler procedure noted in Cambridge Systematics (2012)	6,903,004.18	189,192.57	22.09
Single	3	Develop friction factors based on a simpler procedure noted in Cambridge Systematics (2012) and include a 100 multiplier for the local bus operating cost	6,902,795.22	189,196.84	22.08

[a] Double = Doubly constrained gravity model. Single = Singly constrained gravity model

Summary of Model Results for the Five Categories of Scenarios

Table 12. Results of Scenario 1: Change in Capacity [a]

		Decrease 32%	Base Case	Increase 30%	Increase 100%
Doubly constrained	VMT	7,079,205.500	6,829,605.34	6,747,453.330	6,731,498.390
	VHT	244,207.840	167,101.64	153,157.980	145,056.520
	MTT	26.890	20.89	19.750	19.080
Singly constrained	VMT	8,187,508.82	7,688,831.98	7,543,089.10	7,473,970.15
	VHT	513,664.57	219,496.25	183,405.96	167,491.54
	MTT	47.18	24.57	21.76	20.45

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time
[a] Values reported here are based on changing the capacity in the lookup table

Table 13. Results of Scenario 2: Change in Parking Behavior

		Base Case	Replace HBW parking with ZOV trips	Replace HBO and NHB parking with ZOV trips	Replace HBW, HBO, and NHB parking with ZOV trips	Convert CBD parking lots to other uses
Doubly constrained	VMT	6,829,605.34	7,650,824.51	8,717,886.16	9,665,971.40	6,936,922.85
	VHT	167,101.64	203,327.64	273,749.49	355,343.87	170,977.63
	MTT	20.89	21.76	22.80	25.95	21.00
Singly constrained	VMT	6,903,004.18	7,766,171.68	8,879,039.87	9,854,816.11	7,033,312.45
	VHT	189,192.57	236,682.19	325,566.77	431,957.00	197,080.66
	MTT	22.09	23.79	25.63	29.62	22.45

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time, HBW = Home based work, HBO = Home based other, NHB = Non home based, CBD = Central Business District, ZOV = Zero Occupant Vehicle.

Table 14. Results of Scenario 3: Changes in Comfort Levels

		Base Case	DVs solve the last mile problem for transit	DVs capture transit market share	DVs make longer trips more appealing
Doubly constrained	VMT	6,828,131.94	6,814,366.98	6,826,759.97	8,576,827.18
	VHT	167,293.27	166,670.74	167,312.18	247,556.86
	MTT	20.89	20.91	20.89	28.23
Singly constrained	VMT	6,902,795.22	6,894,671.03	6,907,381.89	8,833,979.39
	VHT	189,196.84	188,745.23	189,195.26	284,238.86
	MTT	22.08	22.11	22.08	29.81

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time

Table 15. Results of Scenario: Shared DVs Increase Zero Occupant Vehicle Trips for HBW Only

	Metric	Base Case	High matching	Medium Matching	Low Matching

			A match is found in the same TAZ	A match is found within nearby TAZs [a]	A match is found but may be several TAZs away [a]
Doubly constrained	VMT	6,829,605.34	No change except off-network VMT increases 33,910	6,988,626.15	7325221.930
	VHT	167,101.64		174,249.01	189867.540
	MTT	20.89		20.83	20.790
Singly constrained	VMT	6,903,004.18	No change except off-network VMT increases 45,460	7,047,368.54	7,399,473.59
	VHT	189,192.57		196,171.89	215029.120
	MTT	22.09		22.16	22.400

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time
[a] Execution of the values herein is based on a multipliers of 1.22 (medium matching, doubly constrained), 1.173 (medium matching, singly constrained), 1.61 (low matching, doubly constrained), and 1.549 (low matching, singly constrained).

Table 16. Results of Scenario 5: Change in Travel Demand

		Base Case	Additional travel by persons age 65+	Additional travel by persons age 13-17	Additional travel by persons of all ages	Double growth in the region
Doubly constrained	VMT	6,829,605.34	6,883,749.25	6,840,372.56	6,946,501.10	9,476,552.78
	VHT	167,101.64	169,602.52	167,697.11	172,561.90	336,840.33
	MTT	20.89	20.88	20.91	20.92	26.99
Singly constrained	VMT	6,903,004.18	6,986,549.27	6,933,309.49	7,049,134.41	9,666,916.34
	VHT	189,192.57	193,210.56	190,194.98	196,484.38	408,361.48
	MTT	22.09	22.28	22.37	22.43	32.64

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time

Table 17. Results of Combined Scenario

		Base Case	New Combined Based Case	Do not share driverless vehicles [a]	Share driverless vehicles (low degree of matching) [b]	Share driverless vehicles (medium degree of matching) [c]
Doubly constrained	VMT	6,829,605.34	7,565,546.88	7,789,345.22	7,687,147.01	7,610,887.48
	VHT	167,101.64	231,041.01	247,546.53	239,630.86	235,742.65
	MTT	20.89	26.05	26.72	26.11	26.19
Singly constrained	VMT	6,903,004.18	7583825.300	7,845,174.08	7,705,895.08	7,623,948.66
	VHT	189,192.57	251680.040	271,217.05	258,676.89	251,829.06
	MTT	22.09	27.020	27.97	27.21	27.08

[a] Reflects new combined base case plus an increase in HBW trips of 24.8%
[b] Execution of the values herein is based on a multipliers of 1.1 (doubly constrained), 1.09 (singly constrained) in NHB trips. This presumes a low degree of matching as per Figure [the figure with 5 regions].
[c] Execution of the values herein is based on a multipliers of 1.05 (doubly constrained), 1.015 (singly constrained) in NHB trips. This presumes a medium degree of matching as per Figure [the figure with 51 regions].

Table 18. Relative Changes for Scenario 1: Change in Capacity [a]

		Decrease 32%	Base Case	Increase 30%	Increase 100%
Doubly constrained	VMT	1.04 [b]	1.00	0.99	0.99
	VHT	1.46	1.00	0.92	0.87
	MTT	1.29	1.00	0.95	0.91
Singly constrained	VMT	1.065	1.00	0.98	0.97
	VHT	2.340	1.00	0.84	0.76

	MTT	1.920	1.00	0.89	0.83

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time
[a] Values reported here are based on changing the capacity in the lookup table
[b] For example, decreasing capacity leads to a 4% increase in VMT

Table 19. Relative Changes for Scenario 2: Change in Parking Behavior

		Base Case	Replace HBW parking with ZOV trips	Replace HBO and NHB parking with ZOV trips	Replace HBW, HBO, and NHB parking with ZOV trips	Convert CBD parking lots to other uses
Doubly constrained	VMT	1.00	1.12	1.28	1.42	1.02
	VHT	1.00	1.22	1.64	2.13	1.02
	MTT	1.00	1.04	1.09	1.24	1.01
Singly constrained	VMT	1.00	1.13	1.29	1.43	1.02
	VHT	1.00	1.25	1.72	2.28	1.04
	MTT	1.00	1.08	1.16	1.34	1.02

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time, HBW = Home based work, HBO = Home based other, NHB = Non home based, CBD = Central Business District, ZOV = Zero Occupant Vehicle

Table 20. Relative Changes for Scenario 3: Changes in Comfort Levels

		Base Case	DVs solve the last mile problem for transit	DVs capture transit market share	DVs make longer trips more appealing
Doubly constrained	VMT	1.00	0.9980	1.000	1.256
	VHT	1.00	0.9963	1.000	1.480
	MTT	1.00	1.0010	1.000	1.351
Singly constrained	VMT	1.00	0.9988	1.001	1.280
	VHT	1.00	0.9976	1.000	1.502
	MTT	1.00	1.0014	1.000	1.350

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time
[a] Reflects the base case where VMT = 6,828,131.94, VHT = 167,293.27, and MTT = 20.89

Table 21. Relative Changes for 4: Shared DVs Increase Zero Occupant Vehicle Trips for HBW Only

		Base Case	A match is found in the same TAZ	A match is found within nearby TAZs	A match is found but may be several TAZs away
Doubly constrained	VMT	6,829,605.34	No change except VMT increases 0.50% a	1.023	1.073
	VHT	167,101.64		1.043	1.136
	MTT	20.89		0.997	0.995
Singly constrained	VMT	6,903,004.18	No change except VMT increases 0.66% a	1.02	1.07
	VHT	189,192.57		1.04	1.14
	MTT	22.09		1.00	1.01

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time
[at] The off-network VMT was calculated by the researchers, and dividing this by the on-network VMT shown for the base case gives these percentages.

Table 22. Relative Changes for Scenario 5: Change in Travel Demand

		Base Case	Additional travel by persons age 65+	Additional travel by persons age 13-17	Additional travel by persons of all ages	Double growth in the region

Doubly constrained	VMT	1.000	1.008	1.002	1.017	1.388
	VHT	1.000	1.015	1.004	1.033	2.016
	MTT	1.000	1.000	1.001	1.001	1.292
Singly constrained	VMT	1.000	1.012	1.004	1.021	1.400
	VHT	1.000	1.021	1.005	1.039	2.158
	MTT	1.000	1.009	1.013	1.015	1.478

VMT = Vehicle miles traveled, VHT = Vehicle hours traveled, MTT = Mean travel time

Table 23. Relative Change for Combined Base Case Scenario

		Base Case	New Combined Based Case	Do not share driverless vehicles	Share driverless vehicles (low degree of matching)	Share driverless vehicles (medium degree of matching)
Doubly constrained	VMT	1.000	1.108	1.141	1.126	1.114
	VHT	1.000	1.383	1.481	1.434	1.411
	MTT	1.000	1.247	1.279	1.250	1.254
Singly constrained	VMT	1.000	1.099	1.136	1.116	1.104
	VHT	1.000	1.330	1.434	1.367	1.331
	MTT	1.000	1.223	1.266	1.232	1.226

DISCUSSION

The results presented in the last twelve tables are interesting but are useful only to the extent that they inform concerns raised by stakeholders—that is, the value of a model derives from its ability to help planners inform stakeholders of the impacts of potential decisions (Meyer and Miller, 2013). Returning to the five local issues of interest cited by VAMPO attendees that are potentially addressed by modifications to the regional model, what information is offered by incorporation of driverless vehicles into the model?

Execution of the model suggests five insights regarding local issues of interest for this particular region:

1. The impact of the transition period where DVs might lead to a decrease in capacity is a significant concern.
2. There is substantial land available for conversion of parking decks, and in this particular location the network appears poised to handle the traffic.
3. DVs can, under the best of conditions, could strengthen the role of transit to some extend (increased by around 13 times). However, there is a significant risk that DVs may reduce the mode share of nonmotorized vehicles.
4. Zero occupant vehicle trips may increase due either to self-parking or unmatched trips, but the former has the potential to be much greater than the latter.
5. If vehicle types do not change, the risk of emissions results from both increased DV use but especially (interestingly) capacity.

Local Issue 1. Impact of a Transition Period where DVs Might Decrease Capacity

The initial concern regarding a capacity decrease during a transition period appears justified. A capacity reduction potentially increases VHT by 46% (if doubly constrained) or 146% (if singly constrained) and is particularly detrimental to some smaller facilities: the proportion of congested major collectors is more than doubled, increasing from 12% to 37% (doubly constrained model) or from 34% to 72% (singly constrained model). Table 18 (for scenario 1) also shows that for this particular region, VHT is more sensitive to changes in demand or capacity than VMT, owing to the nonlinear exponent for volume/capacity in the volume delay function. However, this result is also somewhat specific to the use of the shortest travel time for the impedance function that is used in the gravity model: had the impedance function been based on distance, rather than travel time, then VMT might be more sensitive than VHT (Xiao, 2017).

Note also that one result was counterintuitive at the aggregate level: capacity increases were associated with VMT decreases (although decreases were modest). Table 24 suggests one explanation: 50% of interstate segments and almost 89% of major freeway segments were congested under the base case; thus, it might be the case that such facilities offer more direct routes that because of capacity increases became feasible for more motorists.

Table 24. Impacts of Scenarios on Proportion (%) of Congested Facilities [a]

Trip Distribution Approach	Capacity Change	Interstate	Freeway	Major Arterial	Minor Arterial	Major Collector	Minor Collector	Local Street
Doubly constrained gravity model	32% decrease	88.9[b]	97.5	77.7	71.5	36.9	30.3	15.0
	No change	54.2	73.4	44.2	40.8	12.1	11.2	3.5
	30% increase	0.0	29.1	19.8	24.6	9.4	5.4	0.9
	100% increase	0.0	0.0	7.9	6.0	1.5	0.6	0.0
Singly constrained gravity model	32% decrease	72.2	100.0	90.0	86.0	72.0	61.2	30.2
	No change	50.0	88.6	59.5	58.3	34.2	22.1	6.7
	30% increase	0.0	68.4	37.4	35.4	13.6	5.8	0.5
	100% increase	0.0	2.5	9.8	15.2	4.7	1.3	0.2

HBW = home-based work.
[a] For this region, a segment is defined as congested if its volume/capacity ratio exceeds 0.8.
[b] For example, a 32% decrease in capacity meant that 88.9% of interstate segments had a volume/capacity ratio > 0.8.

The singly constrained gravity model shows greater sensitivity to changes than the doubly constrained model: an increase in capacity of 30% reduces VHT to 92% of its value for the for the doubly constrained case but to 84% of its value for the singly constrained case. This is expected as the singly constrained gravity model relies to a greater extent on travel time, or any other measure of impedance, than does the doubly constrained model (Cambridge Systematics, 2014; VDOT TMPD, 2009)

As noted in the methodology, it is possible to alter capacity not in the lookup table but rather in the volume delay function. If the steps of trip distribution and trip assignment are applied only in sequence, increasing the capacity in a volume delay function that is used in the trip assignment step should affect the route chosen but not the locations of origins and destinations. However, because of multiple feedback loops within the model between trip distribution and trip assignment, changing the capacity in either step yields virtually identical results in terms of VMT, VHT, and MTT. That is, the relative changes in the top row of Table 18 (for the doubly constrained case) are identical except that for the 32% decrease in capacity, modification of the volume delay function yields a 45% increase in VHT (rather than the 46% shown in Table 18) and an increase in MTT of 30% (rather than 29% shown in Table 18). For the singly constrained case, all results are the same except for the drop in capacity, where modification to the volume delay function yields a VHT increase of 130% (rather than 134% in Table 18) or and MTT increase of 92% (rather than 96% shown in Table 18).

Local Issue 2. Impact of Converting CBD Parking Lots to Other Land Uses

For the doubly constrained model, scenario 2d showed a modest increase in VMT (1.57%), VHT(2.32%), and MTT (0.53%) which was not surprising in that the CBD represents a relatively small portion of the regional model. (The singly constrained formulation increases these percentages modestly to 1.89%, 4.17%, and 1.63%, respectively and thus the doubly constrained model remains the focus of the discussion herein). What was surprising was that in the CBD, travel speeds were generally not affected substantially: while the increase in volumes led to speed decreases, these were relatively small and no larger than a drop of 5 mph. Mode splits did not change, which was not surprising given that travel speeds had not changed: no link in the CBD saw speeds decrease by less than 5 mph. (Of the 191 links in the CBD, one had a speed increase of a bit less than 1.5 mph, 36 had speed increases of less than 1 mph, 126 had speed decreases of less than 1 mph, and 16 had speed decreases between 1 and 5 mph).

For this particular case, the model generally suggests that there could be substantial growth in demand as shown by the off-street network. For zones 33, 34, and 35, Figure 19 (that follows) contrasts the relatively few streets that are part of the modeled network with the greater number of local streets that are not part of the modeled network. For example, whereas West Main Street is included in the model network, Hardy Drive is not part of this model network. For zones 33, 34, and 35, the *additional* centroid connector volumes are 2,366, 3,253, and 3,179 respectively (representing both directions), which are percentage increases of 107%, 30%, and 29%, respectively over the base scenario. If these volumes were split evenly over the five north-south and east-west off-network facilities that are represented with dashed lines in Figure 19, this would be an additional 1,760 vehicles per hour on these facilities on a *daily* basis. If one presumes a capacity of 800 vehicles per hour (a value inferred from the capacity for the smallest type of on-network facility, described as "Local Only serves local traffic Local City/Subdivision Streets" [The Corradino Group, 2009], then logically during a peak hour such movements could be accommodated by local streets. For example, with 10% of the volume occurring during the peak hour, the centroid connectors could add, in theory, roughly 176 extra vehicles if these were distributed equally among the five facilities.

That said, the increase in centroid volumes might affect the "livability" of the area: Ben-Joseph (undated) and Spack (2018) suggested that volumes of about roughly 1,000 vehicles per day can adversely affect a community. Further, examination of the volumes reported for the City of Charlottesville (VDOT, 2017c) also suggests these volumes could be relatively large; for example, while most of the streets shown in Figure 19 were not counted, a count is available for a section of Albemarle Street to the north of the area, where that count is 170 vehicles per day. In sum, Scenario 2d does not suggest large regional changes in transportation performance, and frankly it appears that the roadways could support this traffic volume—and the methodology showed ample potential land area that could be converted from parking to other uses. However, it is possible that greater attention may need to be paid to those living near the smaller off-network facilities that would have these local (off-network) trips.

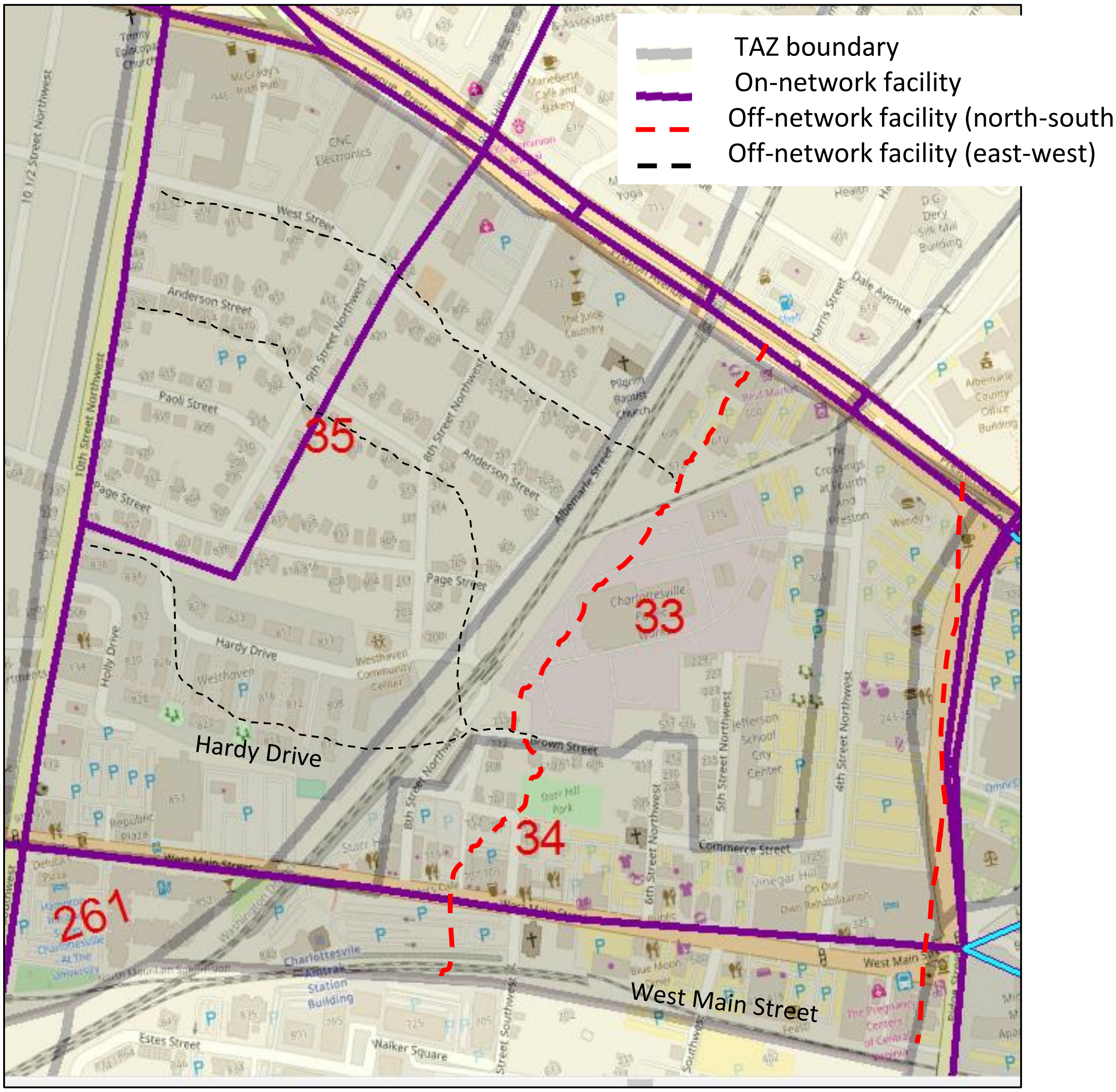


Figure 19. Contrast Between Off-Network and On-Network Facilities Supporting Zones 33, 34, and 35.

Local Issue 3. Impacts of DVs on Transit Mode Share

Table 20 shows that under a scenario where DVs could increase market share by eliminating waiting time, there is almost an imperceptible impact on aggregate performance measures. With the increased mode share for transit, VMT and VHT on the transportation network drop but the amount is negligible: VMT drops by about one fifth of one percent for the doubly constrained model and about one tenth of one percent for the singly constrained model. VHT also drops by relatively small amounts: 0.37% and 0.24% for the doubly and singly constrained cases, respectively. Generally, trips were transferred from drive-alone and carpool to transit, which explains why in the aggregate, VMT and VHT decrease slightly. (Note also that while most of the additional transit trips are from the auto mode, about 9% are transfers from the active modes of bicycling and walking as shown in Table 25). The mean travel time increases by one tenth of one percent for the doubly constrained case and slightly more for the singly constrained case.

In short, if one asks "so if driverless vehicles eliminate waiting time for transit and replace the walk time with a ride in a driverless vehicle, then what is the impact?" then the answer is that DVs can increase mode share for transit by around three percentage points. Some uncertainty include that the utility and condition of current transit system stay the same, which may explain why transit mode share does not see expected big increase. The doubly constrained gravity model suggests a figure of 3.10% (e.g., raising transit mode share from 0.26% to 3.36%, which is about 13 times) and the singly constrained gravity model suggests a figure of 2.71 (e.g., raising mode share from 0.28% to 2.99%). Table 25 also shows that only about half of this increase comes from taking mode share from single occupant vehicles: the next biggest portion of this increase (about a percentage point) comes from carpool shifting to transit, and then about a quarter of a percentage point of the increase is a shift from nonmotorized modes to transit.

Table 25. Impact of Scenario 3a on Transit Mode Share

Gravity Model	Doubly constrained			Singly constrained		
Scenario	Base	Scenario 3a	Difference [a]	Base	Scenario 3a	Difference [a]
Drive Alone	87,553	85,123	-1.58% [a]	87,536	85,435	-1.37%
Carpool 2	38,176	36,856	-0.86%	38,264	37,114	-0.75%
Carpool 3+	18,721	18,121	-0.39%	18,951	18,431	-0.34%
Walk To Local Transit	397	4	-0.26%	424	7	-0.27%
Walk To Premium Transit	0	5,162	3.35%	0	4,589	2.98%
Drive To Best Available Transit	5	4	0.00%	3	3	0.00%
Non-Motorized Walk	4,298	4,051	-0.16%	4,143	3,899	-0.16%
Non-Motorized Bicycle	4,746	4,576	-0.11%	4,580	4,425	-0.10%

[a] Change in absolute mode shares based on the file Mode Summary.txt. For example, under the base scenario, drive alone had 87,553 trips out of a total of 153,896, for a mode share of 56.89%. Under Scenario 3a, this mode share for drive alone dropped to 55.31%. The difference, 55.31% - 56.89% = -1.58%, is reported in Table above.

Scenario 3 had a slightly different utility function than the other scenarios: for Scenario 3, the fare for the mode of "walk to local bus" was modified to be multiplied by 100 for all three transit modes: walk to local bus, walk to premium transit, and drive to best available. In the original model, however, this multiplier of 100 is not present for the fare of walk to local bus. Interestingly, comparable results are obtained: DVs could increase transit's mode share by 2.97% (e.g., raising mode share from 0.39% to 3.36% for the doubly constrained gravity model) or by 2.59% (e.g., raising mode share from 0.40% to 2.99% for the singly constrained gravity model). (Another interpretation of these results is that the utility functions suggest that elimination of the fare alone—without any DV impacts--yields roughly an increase of between 0.12% or 0.13% of transit's mode share for HBW trips.)

As expected, Scenario 3b reduced transit's mode share and increased the auto mode share. The changes in absolute shares were very modest: as shown in Table 26, drive alone, carpool 2, and carpool 3+ increased their mode share from 93.86% to 94.14%. However, examination of the modes in greater detail shows a slight surprise: the greatest impact was on nonmotorized modes—even on a percentage basis relative to such modes, which is interesting in that nonmotorized modes have a larger mode share than transit. That is, more trips were lost to DVs from bike and walk than were lost to transit. For instance, the number of transit trips decreased slightly (an absolute change of 22-23 trips or 5.2%-5.7% in total transit trips). However, the number of nonmotorized trips changed by about 20 times that amount (402-404 trips), with bicycle trips decreasing by 6.3% relative to total bicycle trips.

Table 26. Impact of Scenario 3b on Transit Mode Share

Gravity Model	Doubly constrained			Singly constrained		
Scenario	Base	Scenario 3a	Difference a	Base	Scenario 3a	Difference a
Drive Alone	87,553	87,772	0.14%	87,536	87,760	0.14%
Carpool 2	38,176	38,317	0.09%	38,264	38,403	0.09%
Carpool 3+	18,721	18,786	0.04%	18,951	19,016	0.04%
Walk To Local Transit	397	375	-0.01%	424	402	-0.01%
Walk To Premium Transit	0	0	0.00%	0	0	0.00%
Drive To Best Available Transit	5	4	0.00%	3	3	0.00%
Non-Motorized Walk	4,298	4,195	-0.07%	4,143	4,044	-0.06%
Non-Motorized Bicycle	4,746	4,447	-0.19%	4,580	4,275	-0.20%

[a] Change in absolute mode shares based on the file Mode Summary.txt. For example, drive alone's mode share increased from 56.89% to 57.03% for an increase of 0.14%.

Local Issue 4. Impact of Zero Occupant Vehicles on VMT

The number of zero occupant vehicle trips may increase through DVs either self-parking (if DVs are privately owned and the owner sends the vehicle back home or to a lower cost parking area) or an empty DV traveling from one person's destination to another person's origin (if shared). The results in Table 21 suggest that while both situations may increase VMT, the former could increase VMT much more than the latter.

If all commuters chose to send the DV home, then Scenario 2 showed that VMT would increase by 12% for the doubly constrained model. By contrast, consider the potential increase in VMT due to zero occupant vehicles resulting from DVs being shared. For the doubly constrained model, Table 21 for Scenario 4 suggests that this increase in VMT could range from about 0.50% if DVs could be matched within the same zone (e.g., off network VMT only), 2.3 % if matching occurred within a few zones, to a high of roughly 6.51% if matching occurred across many zones—that is, an almost worst-case matching scenario. The singly constrained gravity model yielded similar results: Scenario 2 (singly constrained) showed a possibility of all commuters sending their vehicles home (thereby increasing VMT by 12.5%) compared to the three cases of a very high degree of matching where all ZOV VMT occurs off the network (increasing VMT by 0.66%), a case of a medium degree of matching (where ZOV VMT increase by 2.1%), and a case of low matching (where ZOV VMT increases by 6.48%). (The doubly constrained model gave similar results: without sharing, VMT increases by 12.0%, while sharing with a medium to low degree of matching increases VMT by 2.33% to 6.51%; a high degree of matching yields an increase of just 0.50% in VMT).

The larger VMT increases have real-world consequences; for example, Scenario 2 showed that the 12-13% increases in VMT for the doubly and singly constrained gravity model could increase VHT by 22%-25%, respectively. Thus, a key question for DVs is the extent to which they will be shared (outside of the household) versus used by multiple members of the household. It is certainly the case that a doubling of all trips is likely a worst-case scenario that would not materialize. However, it is also conceivable that for members of a household who had different departure times and destinations, that some doubling of trips as shown in Table 27 could occur. Note that if the worst-case scenario of non-shared DVs were replicated for non-work trip types (e.g., HBO and NHB), then VMT and VHT would increase by 42% and 113%, respectively.

By contrast, Table 27 below suggests that with a high degree of matching, even for all trips, the VMT wrought by zero occupant vehicles would be about 2.5% of all VMT. This additional VMT is of course smaller if it applies only to work-based trips.

Table 27. Results of Scenario 4: Additional Off-Network VMT Resulting from Zero Occupant Vehicles with a High Degree of Matching

Scenario	Description [a]	Doubly constrained [b]	Singly constrained [c]
4a	All internal vehicle trips, HBW purpose only	33,910	45,460
4b	All internal vehicle trips, all purposes	172,140	170,083
4c	Only carpooling internal vehicle trips, all purposes	51,242	49,237

[a] Internal refers to HBW, HBO, NHB, and HBU trips only and excludes internal-external, external-internal, and external-external trips. There were no HDORMU trips in the model.
[b] For the base scenario where VMT = 6,829,605.34, VHT=167,101.64, MTT = 20.89
[c] For the base scenario where VMT = 6,903,004.18, VHT=189,192.57, MTT = 22.09

Local Issue 5. Impact on Emissions

One area where VAMPO stakeholders had expressed an interest in June was in how DVs might influence emissions. Figure 20 generally shows that as VMT increases, so might NOx (chosen as a focus because it is a contributor to ground level ozone, which has affected other Virginia areas although presently Charlottesville is an attainment area). As table 28 shown, it is not surprising that NOx emissions increased, by 10.8% (for the doubly constrained gravity model), for example, when commuters chose not to share DVs but rather send them home, thereby doubly HBW trips. However, the changes in capacity may have some surprising impacts on emissions, however: emissions increased for the singly constrained model (by 4.9%) but decreased for the doubly constrained model (by 2.5%). Depending on the age and vehicle type, NOx emissions tended to follow a parabolic curve (see Figure that follows); for one set of assumptions, emissions rates were minimized at speeds of around 32 mph and maximized at very low and very high speeds (California Air Resources Board, 2013). (Thus, an increase in speed on a facility might lead to a reduction or an increase in emissions depending on the facility's current speed as shown in Figure that follows.) Examination of speeds by facility type provides an explanation for the case of the reduction in capacity for Scenario 1: for the doubly constrained model only, the reduced speeds on two classes of facilities—freeways and major collectors—on average corresponded to a lower NOx emissions factor than was the case without the capacity reduction. For the singly constrained gravity model, although speeds also decreased for these two classes of facilities, the emissions factor associated with the speed corresponding to a reduction in capacity was lower than for the base scenario. Thus, although the relationship between the number of trips and VMT is fairly constant for these scenarios, the relationship between trips or VMT and emissions rates is not constant. If such capacity reductions were to come to pass, these results could help prioritize the types of facilities that should be improved if a reduction in NOx emissions is a priority.

Table 28. Impact of Certain Scenarios on NOx Emissions

No	Abbreviated Description	Impact on NOx	
		Doubly Constrained Model	Singly Constrained Model
1a	Capacity reduced by 32%	-2.51%	4.87%
2a	Commuters chose not to park	10.80%	11.81%
2b	Non-commuters choose not to park	24.40%	26.84%
2c	All persons choose not to park	37.30%	41.13%
2d	CBD parking lots converted to other uses	1.48%	1.67%
3c	Longer trips	21.65%	25.05%
4d	Sharing with a medium degree of matching	2.08%	1.90%
4e	Sharing with a low degree of matching	6.65%	6.63%
5a	Increase trips for persons age 65+ who do not presently have access to a vehicle or transit	0.70%	0.95%
5b	Increase trips for persons age 13-17 who do not presently have access to a vehicle or transit	0.10%	0.30%
5c	Increase trips for all persons, regardless of age, who do not presently have access to a vehicle or transit	1.50%	1.95%

5d	Double population and employment (all ages)	34.80%	38.32%
	New Combined Base Scenario	2.29%	4.16%
	Combined base case DVs not shared	4.98%	8.07%
	Combined base case DVs shared (low degree of matching)	3.65%	6.13%
	Combined base case DVs shared (medium matching)	2.94%	5.03%

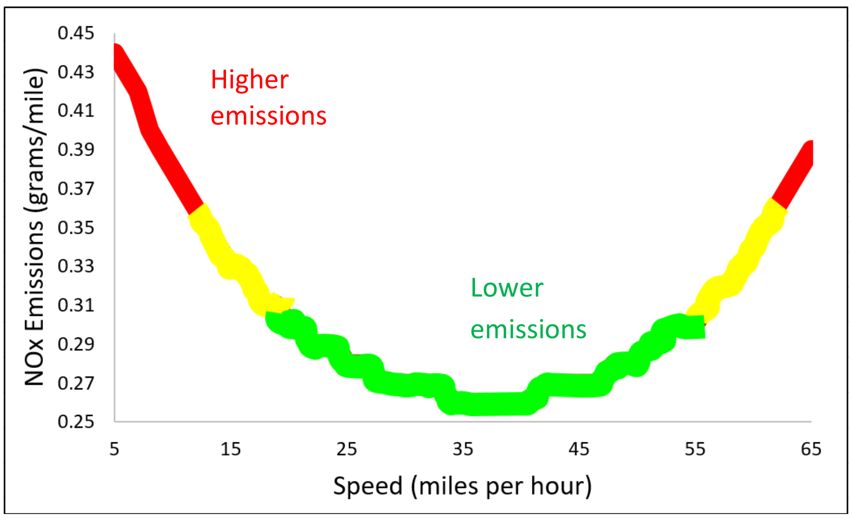


Figure 20. Impact of Speed on Emissions. (Drawn from data provided by: California Air Resources Board. Methods to Find the Cost-Effectiveness of Funding Air Quality Projects for Evaluating Motor Vehicle Registration Fee Projects and Congestion Mitigation and Air Quality Improvement (CMAQ). Sacramento, 2013. https://www.arb.ca.gov/planning/tsaq/eval/evaltables.pdf.)

Table. Relative Change for Combined Base Case Scenario

		Base Case	New Combined Based Case	Do not share driverless vehicles	Share driverless vehicles (low degree of matching)	Share driverless vehicles (medium degree of matching)
Doubly constrained	VMT	1.000	1.108	1.141	1.126	1.114
	VHT	1.000	1.383	1.481	1.434	1.411
	MTT	1.000	1.247	1.279	1.250	1.254
Singly constrained	VMT	1.000	1.099	1.136	1.116	1.104
	VHT	1.000	1.330	1.434	1.367	1.331
	MTT	1.000	1.223	1.266	1.232	1.226

Combine Scenario Results

The combined scenario simulated two possible futures where DVs have many of the elements discussed previously: a potential capacity decrease during the transition period, conversion of the downtown parking lots to other land uses, and additional travel by persons without access to a vehicle. The difference in these two futures was that driverless vehicles were either privately owned or shared. A medium degree of matching for shared driverless vehicles increases VMT by 11.4% (doubly constrained gravity model) and 10.4% (singly constrained gravity model) with respective NO_x emission increases of 2.94% and 5.03%. The results from a low degree of sharing increase NO_x and VMT more; for the doubly constrained gravity model, VMT increases by 12.6% and NO_x increases by 3.65%. Yet both of these futures where DVs are shared yield a lesser environmental impact than if DVs are not shared, where VMT and NO_x increase by 14.1% and 4.98%, respectively. These results are consistent with the results obtained to from the individual scenarios, although the difference between sharing and not sharing herein is not as great as was the difference between Scenario 2a and Scenario 4d. That said, the results suggest a public benefit for shared driverless vehicles.

CONCLUSIONS

1. *For the purposes of discussing DVs, scenario planning can generate useful discussion even if the model inputs are uncertain, and this discussion may proceed in a qualitative or quantitative manner.*

    - *As a qualitative example*, when this work began, MPO staff indicated that they were interested in knowing how DVs might affect parking. Because the parking-related scenario had not been developed at the time the MPO expressed an interest, the research team put together an outreach exercise showing the degree to which parking might be affected if DVs led to a doubling of all trips. Despite this model input (doubling all trips) being different from a later model input (doubling only commute trips), the participants in the outreach exercise were able to provide areas of concern that were later used to refine model scenarios.

    - *As a quantitative example*, uncertainty in the utility function did not seem to affect the results dramatically provided the model was executed in a consistent manner. For example, if one asks "so if driverless vehicles eliminate waiting time for transit and reduce the walk time as well, what is the impact?" then the answers based on the doubly constrained model are either (1) DVs could increase transit's mode share by 3.10% (e.g., raising mode share from 0.26% to 3.36% as shown for Scenario 3a), or, (2) DVs could increase transit's mode share by 2.97% (e.g., raising mode share from 0.39% to 3.36% as shown when the original utility functions were used for Scenario 3). A similar pattern is noted for the singly constrained gravity model: DVs could increase transit's mode share by either 2.59% or 2.71%, depending on whether the utility function includes the "100" multiplier for local bus. In sum, based on the model, it appears that DVs have the potential to raise transit's mode share by about three percentage points under a scenario where the waiting time is eliminated and the access time is replaced by a DV which in turn has a 35% reduction in discomfort compared to driving to the stop in a conventional vehicle.

2. *Some, but not all, policy-related questions can be examined by the regional model, and those that can be examined have varying levels of difficulty*.

   While some issues are not easily addressed with the model (e.g., curbside access management), other macroscopic questions (e.g., the impact of DVs affecting capacity) are feasible within the modeling structure. Then, the effort required to implement the issues that are feasible will vary (meaning that one can start with the simplest changes first.) For example, only a few person-hours were required to modify the capacity in the lookup table, with most of that time being used for conversions between the various database formats. By contrast, knowledge of the proprietary scripting language was necessary in order to increase trips for the population age 65+, and both scripting and calibration procedures were required to develop an appropriate singly constrained gravity model.

3. *The regional model may be used to prioritize areas of concern to local stakeholders*.

   For this region in particular, incorporation of DVs yielded the following observations in response to concerns identified by VAMPO attendees.

   - *The model suggests that if parking is not needed, there is substantial land development opportunity in downtown areas.* Scenario 2d suggests that parking garages and lots in the downtown area, not including street parking, have roughly 3.4 million square feet of redevelopment potential in the downtown area—and the model suggests that the existing transportation network may be able to accommodate this development.

   - *Concerns about the transition period during which DVs might result in a reduction in capacity are justified*. VHT was estimated to increase by 45% for the doubly constrained gravity model. By contrast, the model showed that another potential concern—the impact of additional travel by persons who had not had access to a vehicle—had a far less detrimental impact on performance: VHT was estimated to increase by only about 1%.

   - *The impact on other modes is not substantial*. Under the best of conditions, DVs can modestly increase transit's mode share from a current value of roughly one quarter of one percent to over 3%. With the transit mode share in the model being relatively low, the mode share appeared unlikely to drop substantially, however, a competing scenario where DVs offer increased comfort and hence willingness to travel could reduce nonmotorized mode share by about a quarter of a percentage point.

   - *The impact of DVs being shared versus not shared is substantial*. Considering the commute trip (e.g., HBW purpose) only, if DVs are not shared, then for the doubly constrained gravity model VMT increases by 12.02%, whereas sharing of DVs increases VMT by between 2.33% and 6.51% depending on whether a moderate degree of matching occurs (e.g., the termination of person 1's trip and the origin of person 2's trip is a few TAZs apart) or a low degree of matching occurs (e.g., the driverless vehicle must traverse many zones). A high degree of matching among shared DVs would increase VMT by only one half a percentage point.

- *If vehicle types do not change, emissions may increase but the increases are higher for non-shared DVs than they are for the case of induced travel by persons who do not have access to a vehicle.* The worst-case scenario of a doubling of vehicle trips increases NOx by 37.3%, whereas an increase in persons who do not presently have access to a vehicle increases NOx by 1.5%.

4. *Socioeconomic parameters—population and employment—continue to be of critical importance for the model*.

   Of all the results presented here, the most dramatic change in absolute percentages resulted from a population and employment increase of 100%: Scenario 5d showed that VMT and VHT increased by 39%-40% and 102%-116%, respectively.

5. *The aggregate performance measures may mask important distinctions in more detailed performance measures*.

   The researchers had initially expected to focus on three aggregate measures of performance: VHT, VMT, and MTT. However, for some scenarios, differences in these measures were very slight—yet the scenario demonstrated an impact in other areas. Notably, for example, while the transit-favorable scenario (3a) showed a drop of about 0.20% in VMT or 0.37% in VHT, the mode shift—an increase in transit's mode share from 0.26% to 3.36%--was far more dramatic. Other modal shifts were also of interest: in Scenario 3b, which asked an opposite question of Scenario 3a (what if the increased attractiveness of DVs led them to take market share from transit), while the number of transit trips decreased slightly, the number of nonmotorized trips decreased by about 20 times that amount.

BENEFITS AND IMPLEMENTATION

The direction taken in this report differs from a strict focus on modeling: the goal was not to devise a demand model that captured all elements of DVs but rather one that addressed just a few topics of interest to local decision-makers, which in this case pertained to capacity decreases, parking decisions, greater access for a subset of the population with limited mobility, and resultant impacts on emissions. In that sense, the information in Tables 18-23 (for the five scenarios) suggest that the most productive steps for regions with limited budgets and staff to take in considering DVs might be to identify a few policy concerns and then look at simple changes to the model that can provide insights into those concerns. To implement these steps, the recommendation is to provide guidance in the appropriate modeling guidance document when it is updated as shown in the Recommendations.

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Appendix A. Excerpt of Material Provided to VAMPO Attendees [a]

Get your Hands Dirty: What Do We Do With All that Excess Parking?
Interactive Session: Virginia Association of MPOs Annual Meeting, June 9, 2017

Introduction

Parking is big business, whether at the global scale (a $100 billion industry), the national level ($10 billion annually in revenues in the U.S. alone), or the local scale (the downtown Charlottesville Parking Center just sold for $14 million). Parking is a significant land use component—in the city of Charlottesville alone (population ≈ 45,000), an estimated 567 acres (a bit less than a square mile) is devoted to parking, representing almost nine percent of the land area in the City. In addition to businesses, localities also reap revenue from enforcement—in one year, the City of Charlottesville earned half a million dollars from parking tickets alone (larger cities earned more; for Richmond, the figure was roughly $5 million.)

Yet, this industry is possibly under threat due to the advent of "driverless" vehicles. In fact, such vehicles are expected to potentially have a wide range of impacts. Just a few examples:

- They might increase highway capacity (by amounts ranging from 25% to as much as 500%, depending on whose research you trust); ironically, they might initially reduce our capacity when they are first deployed as we build in a margin of safety, such as extra headway, when they are used.
- Because removal of the driving task may reduce the effort required to travel, driverless vehicles could increase vehicle miles traveled—again, depending on whose research you trust, this increase could be from as little as 5% to as much as 200%.
- Because they can potentially solve the first mile/last mile problem, they might increase transit use (by about 16%)—or, because that first mile is so comfortable, they might decrease transit use (by about 43%).
- Depending on what it costs to own these vs. how easy it is to share them, we might see increased sharing of driverless vehicles—thereby reducing auto ownership (by 43% according to one source).

None of these impacts are known with certainty, and in fact, other factors will of course affect these impacts. For example, one study suggested that if parking outside the CBD is half the cost of CBD parking, we'll see VMT increase by 4%--but if parking outside the CBD is free, we'll see VMT increase by 8%. Another disclaimer is that changes in parking-related land use is just one of many potential impacts of DVs. That said, a focus on just one potential impact of these DVs—parking—may illustrate the challenges planners face as we consider what our role is (if any) with respect to DVs possibly (or not) arriving—and when.

Assignment

Prior to the VAMPO Meeting Friday June 9th, review the background maps pages 3-8. It's speculative and incomplete, just as one might expect in any scenario planning exercise. Then, come prepared to debate four questions with respect to how Charlottesville (or any Virginia location) might plan for driverless vehicles with respect to a perennial concern in this town—parking. (And, deciding not to plan is always an option).

Questions for debate:

1. What is the role of the planner as we consider the impacts of driverless vehicles on the parking industry?

2. What are the opportunities or risks if driverless vehicles affect (or do not affect) future demand for parking?

3. For either question 1 or 2, what policy tools (if any) can be considered by decision-makers?

4. Consider the tools noted in question 3. Would any of them be adversely affected if you simply did not worry about driverless vehicles at this point in time?

[a] The alignment of the questions shown to the right as been altered slightly to enhance their readability in this report

Background Information

To help consider these questions on Friday June 2, a few maps have been provided:

- Figure 1 shows the 2040 population per square mile for the Charlottesville/Albemarle region.
- Figure 2 shows the ratio of 2040 jobs to 2040 population for the region.
- Figure 3 zooms to the city of Charlottesville and shows the amount of land occupied by surface parking.
- Figure 4 estimates the proportion of land in each Charlottesville zone used for parking.

There are two very different areas where parking is a concern, and these are shown in Figures 5 and 6.

- Figure 5 shows current use of parking in the downtown area of Charlottesville, near the Downtown Mall.
- Figure 6 shows current use of parking in a suburban location of Charlottesville, near Fashion Square Mall.

One potential behavioral change of driverless vehicles could be an increase in travel, which could result from several factors: travel being easier for existing drivers (due to a reduction of the difficulty of the driving task), persons who previously could not travel now having access to a vehicle, and finally, a decision to have the vehicle return home in order to avoid paying for parking. One tool that has been used in the past to help evaluate potential transportation improvements is the regional travel demand model. The Charlottesville-Albemarle Metropolitan Planning Organization (CAMPO) currently uses the Cube modeling suite with a 2040 forecast year.

The remaining figures are based on the application of that model, where we have doubled the number of trips in 2040 relative to the base case of driverless vehicles not being available. *(This does not mean that driverless vehicles will necessarily increase trips, rather, this is just one of many potential impacts that could result.)*

- Figure 7 shows the change in speeds for the entire region.
- Figure 8 shows the change in volumes for the entire region.

Recall the downtown area where parking was a concern (which was shown in Figure 5).

- Figure 9 shows the change in 2040 speeds for the downtown parking area.
- Figure 10 shows the change in 2040 volumes for the downtown parking area.

Recall the suburban area where parking was a concern (which was shown in Figure 6).

- Figure 11 shows the change in 2040 speeds for the suburban parking area.
- Figure 12 shows the change in 2040 volumes for the suburban parking area.

It may be the case that an increase in travel leads to either no change in travel time for a given road or a substantial change in travel time for a given road.

- Figure 13 shows the ratio of volume to capacity for 2040 assuming no change in trips.
- Figure 14 shows the ratio of volume to capacity for 2040 based on an increase in trips.

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Figures 1-14 are available from the authors. Figures 13-14 are shown as Figure 1 in this report.

Appendix B. Derivation of Socioeconomic Data for Persons Age 65+ (Scenario 5a)

Estimation of Persons Age 65+ By Zone

Zmud et al. (2016) indicate that age is one factor that influences the ability to drive, noting that starting at age 50, the proportion of persons who no longer drive increases as a function of aging. Accordingly, the researchers sought to obtain an estimate of the number of persons age 65+ for each transportation analysis zone (TAZ), where the estimate would be consistent with the projection of total population used in the base 2040 travel demand model. The methodology consisted of three main steps: obtain current proportions of persons age 65+ in each Census block group, align Census geography with travel demand model geography, and finally forecast the 2040 population age 65+ by zone.

Obtain Current Proportion of Persons Age 65+ in Each Census Block Group

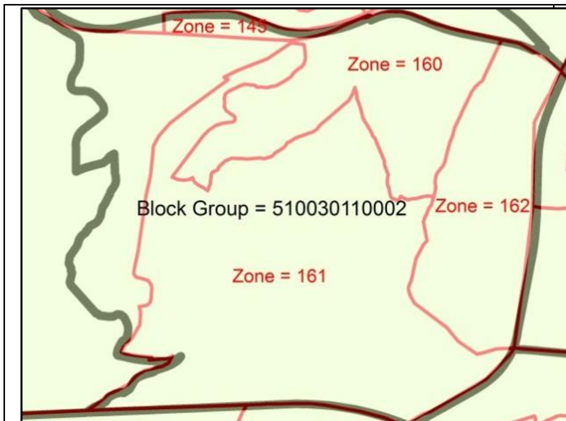
The first step was to obtain current populations over persons age 65+ by census block group from the most recent five year data set available (U.S. Census Bureau, 2016). For each census block group, the percentage of persons age 65+ was determined by summing the male and female persons in the six age categories for age 65+ (e.g., age 65-66, age 67-69, and so forth) and dividing by the total population of the block group. This method provided an average percentage of persons age 65+ by Census block group.

Align Census Geography with Travel Demand Model Geography

Although the effort described in modification 6 (Figure 6) comprised most of the work required to align the zones from the travel demand model and those from the U.S. Census (2015a), some additional processing was also needed in order to overlay the zones from the travel demand model with the Census block groups. The general approach was to use the "Feature to Point" tool in ArcGIS which in this particular case generated a centroid for each transportation analysis zone. Then, the zones were reviewed for errors; for example, in a few cases the centroid might be outside of an irregular shaped zone, and in other cases, there were sliver polygons that had resulted from the geoprocessing. Finally, the centroid of each transportation analysis zone (a point feature) could be easily associated with a census block group (a polygon) such that each zone had a percentage of persons age 65+.

Forecast the 2040 Population Age 65+ by Zone

For the third step, the proportion of persons age 65+ is not expected to remain constant. For Charlottesville and Albemarle as a whole, the number of persons age 65+ based on 2015 data is 22,523 (out of a total population of 152,300)—that is, about 14.8% of the population is age 65+ at present (U.S. Census Bureau, 2015b). For year 2040, this proportion is forecast to rise to 19.5%--that is, with a total population forecast of 203,359, the forecast population age 65+ is 39,656 (Weldon Cooper Center for Public Service, 2012). Accordingly, the percentage population for each zone that were computed based on present-day populations were all increased by the ratio of 19.5%/14.8% = 1.32. Finally, the modified percentages were multiplied by the number of people in each zone in 2040 in order to obtain a forecast of persons age 65+ in each zone. For example, Figure B1 shows how a forecast value of 274 persons age 65+ was obtained for transportation analysis zone 161: the present day percentage is 56% (which should increase by a factor of 1.32 to 74%), and given that the 2040 total population of that zone is 369, one expects the number of persons age 65+ to be 74% of 369 which is 274.



Entity	Quantity	Value
Census block group	Total population 2015	975
	Persons age 65+ (2015)	549
	Percent persons age 65+ (2015)	56%
	Forecast increase in percentage (2040)	132%
Zone 161	Total population (2040)	369
	Percent persons age 65+ (2040)	74%
	Persons age 65+ (2040)	274

Figure B1. Computation of Persons Age 65+ in Transportation Analysis Zone 161, Situated Inside Census Block Group 510030110002

Estimation of Extra Trips by Persons Age 65+

The literature (Truong, 2017; Zmud et al., 2016) suggests that with driverless vehicles, persons who currently cannot drive due to age might take advantage of such vehicles, leading to an increase in trips. Three different approaches using 2040 population forecasts for persons age 65+ in Charlottesville and Albemarle (Weldon Cooper Center for Public Service, 2012) suggest that this increase in trips could be 12.9%, 14.4%, or 18.6%. For this scenario, an average value of 15.3% has been used for two trip purposes—home-based other and non-home based.

Derivation of the Percentages of 14.4% and 18.6%

One approach is to consider how driverless vehicles might affect travel is to compare licensure rates by age group. Calculations specific to Virginia reported in Miller et al. (2015) indicated that as of 2012, approximately 82% of persons age 65+ had a driver's license. If one assumed that the remaining persons age 65+ without a driver's license would use driverless vehicles, and if one further assumed that trip characteristics for such individuals were similar to that of other drivers, then one might expect an 18% increase in trips. A variation in this approach is to consider national (not Virginia specific) rates of licensure for specific age groups reported by Zmud et al. (2016), which are 91.4% (for persons age 60-69), 83.0% (for persons age 70-79), and 61.7% (age 80+). If it is assumed that the rate of licensure for persons age 65-69 is the same as that for persons age 60-64 (e.g., 91.4%), then a weighted average for the Charlottesville-Albemarle region for 2040 would be a 23% increase in trips. (That is, in 2040, among all the persons age 65+, the distribution is expected to be distributed as follows: a proportion of 0.21 is forecast for age 65-69, a proportion of 0.42 is forecast for age 70-79, and a proportion of 0.37 are forecast to be 80+. A weighted average would thus be

91.4%*(0.21)+83.0%*(0.42)+61.7%*(0.37) = 76.8% of such individuals having a driver's license, meaning that 23.2% of such individuals would not have a license.

However, both estimates—the 18% figure and the 23.2% figure—are possibly high given that they presume all persons without a driver's license would like to travel and that persons age 65+ take the same number of trips as younger persons. Data from the 2009 National Household Travel Survey were used by Lynott and Figueiredo (2011) suggest that whereas persons age 16-49 average 4.0 trips per day, persons age 65+ average 3.2 trips per day—a 20% lower figure. Reducing the aforementioned averages by 20% suggests an increase in trips for persons age 65+ of 14.4% and 18.8%, respectively.

Derivation of the Percentage of 12.9%

A lower estimate is available from Truong (2017), who suggested that autonomous vehicles would increase the number of trips by 5.13% (for persons age 65-74) and by 18.48% (by persons age 65+). (As is the case with the aforementioned calculations, Truong et al. [2017] considers age effects on licensure [which is influenced by the presence of disabilities] and trip generation; in addition, Truong et al. [2017] considers modal shifts and auto occupancy rates.) In 2040, the number of persons in these age groups are not expected to be identical; for example, in the Charlottesville/Albemarle region, the number of persons age 65-74 is forecast to be 16,704 (about 42% of the total population age 65+) and the number of persons age 75+ is forecast to be 22,950 (about 58% of the total population age 65+). Accordingly, if the results of Truong (2017) were to be applicable for the Charlottesville/Albemarle region, one would expect the aggregate number of trips by persons age 65+ to increase by a weighted average of 5.13%(0.42) + 18.48%(0.58) or about 12.9%.

Other Potential Percentages Not Used Here

To be clear, these figures are of course variable. It is possible, for example, that one could argue that the 20% difference in trips for persons age 65+ and persons age 16-49 reported by Lynott and Figueiredo (2011) is strikingly similar to the proportion of trips nationally that are usually attributed to the HBW trip purpose of 15% (Cambridge Systematics, Inc., et al., 2012). Accordingly, it might be appropriate to increase the 15.3% figure used in these scenarios by a factor of roughly 15% (e.g., to a value of 17.6%) with the idea that it would only be applicable to the non-work trips (e.g., HBO and NHB). That said, the use of the 15.3% estimate appears to be a reasonable order of magnitude approximation for determining the impact of trips generated by persons age 65+. Accordingly, the 15.3% increase in HBO and NHB trips is used to generate scenarios 5b (doubly constrained) and 5f (singly constrained).

Appendix C. Key Scripts Used in the Scenarios

Script for Implementing a Singly Constrained Gravity Model (all Scenarios)

```
;The researchers that Peng Xiao and Xin Wang for their help with this script!

RUN PGM=MATRIX
PRNFILE="{CATALOG_DIR}\OUTPUT\{SCENARIO_FULLNAME}\Logs\PDDST00A.PRN"

FILEI MATI[2] = "{CATALOG_DIR}\OUTPUT\{SCENARIO_FULLNAME}\FFTIME.MAT"
FILEI ZDATI[1] = "{CATALOG_DIR}\Output\{Scenario_FullName}\TGEN_PA.DBF"
FILEO MATO[1] = "{CATALOG_DIR}\Output\{Scenario_fullname}\InitialTdist.MAT", mo=1-5,
name=HBW,HBO,NHB,HBU,HDORMU
FILEO MATO[2] = "{CATALOG_DIR}\Output\{Scenario_fullname}\EITdist.MAT",
 MO=6, NAME=IX

PARAMETERS
  zones = {Total Zones}
  maxiters ={AITERS}
  ARRAY HBWpersonTrips = ZONES
  ARRAY HBOpersonTrips = ZONES
  ARRAY NHBpersonTrips = ZONES
  ARRAY HBUpersonTrips = ZONES
  ARRAY HDORMUpersonTrips = ZONES
  ARRAY IXpersonTrips=ZONES

JLOOP
    HBWpersonTrips[I]=ZI.1.HBW_P
    HBOpersonTrips[I]=ZI.1.HBO_P
    NHBpersonTrips[I]=zi.1.nhb_p
    HBUpersonTrips[I]=zi.1.HBUP
    HDORMUpersonTrips[I]=zi.1.HDORMUP
    IXpersonTrips[I]=zi.1.IX_P
ENDJLOOP

mw[30]=MI.2.FFTIME
mw[21]=MI.2.FFTIME*(-0.04259)          ;Can replace with -0.08001
mw[22]=MI.2.FFTIME*(-0.09881)          ;Can replace with -0.18959
mw[23]=MI.2.FFTIME*(-0.18995)          ;Can replace with -0.22559
mw[24]=MI.2.FFTIME*(-0.10779)          ;Can replace with -0.20830
mw[25]=MI.2.FFTIME*(-0.10779)          ;Can replace with -0.20830
mw[26]=MI.2.FFTIME*(-0.10516)          ;Can replace with -0.20004

XCHOICE,
ALTERNATIVES=ALL,
DEMAND=HBWpersonTrips[I],
UTILITIESMW=21,
ODEMANDMW=1,
DESTSPLIT=TOTAL All, INCLUDE=1-{Internal Zones},
STARTMW=99
FREQUENCY VALUEMW=1 BASEMW=30, RANGE=0-50

XCHOICE,
ALTERNATIVES=ALL,
DEMAND=HBOpersonTrips[I],
```

```
UTILITIESMW=22,
ODEMANDMW=2,
DESTSPLIT=TOTAL All, INCLUDE=1-{Internal Zones},
STARTMW=99
FREQUENCY VALUEMW=2 BASEMW=30, RANGE=0-50

XCHOICE,
ALTERNATIVES=ALL,
DEMAND=NHBpersonTrips[I],
UTILITIESMW=23,
ODEMANDMW=3,
DESTSPLIT=TOTAL All, INCLUDE=1-{Internal Zones},
STARTMW=99
FREQUENCY VALUEMW=3 BASEMW=30, RANGE=0-50

XCHOICE,
ALTERNATIVES=ALL,
DEMAND=HBUpersonTrips[I],
UTILITIESMW=24,
ODEMANDMW=4,
DESTSPLIT=TOTAL All, INCLUDE=1-{Internal Zones},
STARTMW=99
FREQUENCY VALUEMW=4 BASEMW=30, RANGE=0-50

XCHOICE,
ALTERNATIVES=ALL,
DEMAND=HDORMUpersonTrips[I],
UTILITIESMW=25,
ODEMANDMW=5,
DESTSPLIT=TOTAL All, INCLUDE=1-{Internal Zones},
STARTMW=99
FREQUENCY VALUEMW=5 BASEMW=30, RANGE=0-50

XCHOICE,
ALTERNATIVES=All,
DEMAND=IXpersonTrips[I],
UTILITIESMW=26,
ODEMANDMW=6,
;DESTSPLIT=TOTAL All, INCLUDE=1-{Internal Zones}, EXCLUDE = 1-265,
DESTSPLIT=TOTAL All, EXCLUDE = 1-265,
STARTMW=99
FREQUENCY VALUEMW=6 BASEMW=30, RANGE=0-50


ENDRUN
```

Script for Obtaining a Congested Trip Length Frequency Distribution

The lines shown here yield the average trip length as required by the file CVMAT00A.S in sequence 13.

```
RUN PGM=MATRIX PRNFILE="{CATALOG_DIR}\Output\{Scenario_FullName}\totaltrip length.prn"
MSG='Average trip Length'
```

```
FILEO MATO[1] = "{CATALOG_DIR}\Output\{Scenario_FullName}\Total triplength.MAT", mo=3
name ='total trip length'
FILEI MATI[1] =
"{CATALOG_DIR}\OUTPUT\{SCENARIO_FULLNAME}\FBCONGTIMESOV{Year}.MAT"
mw[1]=mi.1.3
FILEI MATI[2] =
"{CATALOG_DIR}\OUTPUT\{SCENARIO_FULLNAME}\CVFINALVEHTRIPS{Year}.DAT"
mw[2]=mi.2.5
mw[3]=mw[1]*mw[2]
FREQUENCY VALUEMW=2  BASEMW=1,  RANGE=1-100
ENDRUN
```

Script for Implementing Conversion of Parking Lots to Other Uses (Scenario 2d)

;Notice that the file Landuse_2040A.dbf is ZI.2 in the first script but ZI.3 in the second script.

;In the file APPLICATIONS\TGMAT00F.S

```
HBUP = 2.996*ZI.2.OffC_Stu*{HBO-TF}+ZI.2.ParkPLo*0.07; was 0.10
HBUA = 1.375*ZI.2.Total_park*{HBO-TF}+ZI.2.ParkPLo*0.07; was 0.00
```

;In the file APPLICATIONS\TGGEN00A.S

```
pix=0.331*zi.3.HH + 0.724*(zi.3.TOTEMP + zi.3.EMPLOYEE_P)+ZI.3.ParkPLo*0.40
aix=zi.4.COUNT * zi.4.IXPCT+ZI.3.ParkPLo*0
; Balance attractions to productions
 a[4]=aix*1.02112

 if(zi.2.atype=1-2)

 phbw=_rates_city(1,1)* zi.1.h1V0+ _rates_city(1,2)* zi.1.H1V1 + _rates_city(1,3)* zi.1.H1V2 +
     _rates_city(1,4)* zi.1.H2V0 + _rates_city(1,5)* zi.1.H2V1 + _rates_city(1,6)* zi.1.H2V2 +
     _rates_city(1,7)* zi.1.H3V0 + _rates_city(1,8)* zi.1.H3V1 + _rates_city(1,9)* zi.1.H3V2 +
     _rates_city(1,10)* zi.1.H4V0 + _rates_city(1,11)* zi.1.H4V1 + _rates_city(1,12)* zi.1.H4V2
+ZI.3.ParkPLo*0.05

 phbo=_rates_city(2,1)* zi.1.h1V0+ _rates_city(2,2)* zi.1.H1V1 + _rates_city(2,3)* zi.1.H1V2 +
     _rates_city(2,4)* zi.1.H2V0 + _rates_city(2,5)* zi.1.H2V1 + _rates_city(2,6)* zi.1.H2V2 +
     _rates_city(2,7)* zi.1.H3V0 + _rates_city(2,8)* zi.1.H3V1 + _rates_city(2,9)* zi.1.H3V2 +
     _rates_city(2,10)* zi.1.H4V0 + _rates_city(2,11)* zi.1.H4V1 + _rates_city(2,12)* zi.1.H4V2
+ZI.3.ParkPLo*0.16

 pnhb=_rates_city(3,1)* zi.1.h1V0+ _rates_city(3,2)* zi.1.H1V1 + _rates_city(3,3)* zi.1.H1V2 +
     _rates_city(3,4)* zi.1.H2V0 + _rates_city(3,5)* zi.1.H2V1 + _rates_city(3,6)* zi.1.H2V2 +
     _rates_city(3,7)* zi.1.H3V0 + _rates_city(3,8)* zi.1.H3V1 + _rates_city(3,9)* zi.1.H3V2 +
     _rates_city(3,10)* zi.1.H4V0 + _rates_city(3,11)* zi.1.H4V1 + _rates_city(3,12)* zi.1.H4V2
+ZI.3.ParkPLo*0.32

;------------------------------------------------------------------
;
 if(i=55,58-62,68,80-92,163,165-169,251-256,258-260)              ;  Attractions for UVA
   ahbw=ATTRRATES(3,1)*zi.1.temp+ZI.3.ParkPLo*0.08
   ahbo=ATTRRATES(1,5)*zi.1.ret + ATTRRATES(2,5)*nonretail +
ATTRRATES(4,5)*zi.1.hhx+ZI.3.ParkPLo*0.13
```

```
   anhb=ATTRRATES(1,9)*zi.1.ret + ATTRRATES(2,9)*nonretail +
ATTRRATES(4,9)*zi.1.hhx+ZI.3.ParkPLo*0.32
   flag=1
  ;print list=' UVA ',i(6),j(6),ahbw(8.2),zi.1.temp(6),ahbo(9.2),zi.1.ret(6),nonretail(6),zi.1.hhx(6)


  ELSEif(zi.2.atype=1 & flag=0)                    ;  Attractions for CBD
   ahbw=ATTRRATES(3,2)*zi.1.temp+ZI.3.ParkPLo*0.08
   ahbo=ATTRRATES(1,6)*zi.1.ret + ATTRRATES(2,6)*nonretail +
ATTRRATES(4,6)*zi.1.hhx+ZI.3.ParkPLo*0.13
   anhb=ATTRRATES(1,10)*zi.1.ret + ATTRRATES(2,10)*nonretail +
ATTRRATES(4,10)*zi.1.hhx+ZI.3.ParkPLo*0.32


  elseif(zi.2.atype=2-5 & flag=0)                ;  Attractions for Urban
   ahbw=ATTRRATES(3,3)*zi.1.temp+ZI.3.ParkPLo*0.08
   ahbo=ATTRRATES(1,7)*zi.1.ret + ATTRRATES(2,7)*nonretail + ATTRRATES(4,7)*zi.1.hhx +
ATTRRATES(5,7)*zi.1.school+ZI.3.ParkPLo*0.13
   anhb=ATTRRATES(1,11)*zi.1.ret + ATTRRATES(2,11)*nonretail + ATTRRATES(4,11)*zi.1.hhx +
ATTRRATES(5,11)*zi.1.school+ZI.3.ParkPLo*0.32
```

Script for Increasing NHB Trips to Simulate ZOV Trips (Scenarios 4d and 4e)

In the file TGGEN00A.S a multiplier is used to increase NHB trips. For example, for the doubly constrained case with five regions (e.g., Scenario 4d), a multiplier of 1.685 was needed. Thus, the script is modified in two places (one for the city zones and one for the county zones), as shown below.

```
pnhb=(_rates_city(3,1)* zi.1.h1V0+ _rates_city(3,2)* zi.1.H1V1 + _rates_city(3,3)* zi.1.H1V2 +
        _rates_city(3,4)* zi.1.H2V0 + _rates_city(3,5)* zi.1.H2V1 + _rates_city(3,6)* zi.1.H2V2 +
        _rates_city(3,7)* zi.1.H3V0 + _rates_city(3,8)* zi.1.H3V1 + _rates_city(3,9)* zi.1.H3V2 +
        _rates_city(3,10)* zi.1.H4V0 + _rates_city(3,11)* zi.1.H4V1 + _rates_city(3,12)* zi.1.H4V2)*1.685

pnhb=(_rates_county(3,1)* zi.1.h1V0+ _rates_county(3,2)* zi.1.h1V1+ _rates_county(3,3)* zi.1.H1V2 +
        _rates_county(3,4)* zi.1.H2V0 + _rates_county(3,5)* zi.1.H2V1 + _rates_county(3,6)* zi.1.H2V2 +
        _rates_county(3,7)* zi.1.H3V0 + _rates_county(3,8)* zi.1.H3V1 + _rates_county(3,9)* zi.1.H3V2 +
        _rates_county(3,10)* zi.1.H4V0 + _rates_county(3,11)* zi.1.H4V1 +
        _rates_county(3,12)* zi.1.H4V2+ZI.3)*1.685
```

Scripts for Implementing More Trips by Persons Age 65+, 13-17, and 20-64 (Scenario 5)

Figure C1 shows the modification to the script for additional trips by persons age 65+, where for each zone the number of HBO and NHB trips is increased by percentage of persons age 65+ (zi.3.percent) multiplied by 15.3%. Suppose, for example, a zone generated 100 HBO trips and had 50% of its population age 65+. Figure C1 would increase the number of HBO trips by a factor of (0.50*0.153+1) = 1.0765.

```
 if(zi.2.atype=1-2)

 phbw=_rates_city(1,1)* zi.1.h1V0 + _rates_city(1,2)* zi.1.H1V1 + _rates_city(1,3)* zi.1.H1V2 +
      _rates_city(1,4)* zi.1.H2V0 + _rates_city(1,5)* zi.1.H2V1 + _rates_city(1,6)* zi.1.H2V2 +
      _rates_city(1,7)* zi.1.H3V0 + _rates_city(1,8)* zi.1.H3V1 + _rates_city(1,9)* zi.1.H3V2 +
      _rates_city(1,10)* zi.1.H4V0 + _rates_city(1,11)* zi.1.H4V1 + _rates_city(1,12)* zi.1.H4V2

 phbo=(_rates_city(2,1)* zi.1.h1V0 + _rates_city(2,2)* zi.1.H1V1 + _rates_city(2,3)* zi.1.H1V2 +
      _rates_city(2,4)* zi.1.H2V0 + _rates_city(2,5)* zi.1.H2V1 + _rates_city(2,6)* zi.1.H2V2 +
      _rates_city(2,7)* zi.1.H3V0 + _rates_city(2,8)* zi.1.H3V1 + _rates_city(2,9)* zi.1.H3V2 +
      _rates_city(2,10)* zi.1.H4V0 + _rates_city(2,11)* zi.1.H4V1 + _rates_city(2,12)* zi.1.H4V2)*(zi.3
.percent*0.153+1)


 pnhb=(_rates_city(3,1)* zi.1.h1V0 + _rates_city(3,2)* zi.1.H1V1 + _rates_city(3,3)* zi.1.H1V2 +
      _rates_city(3,4)* zi.1.H2V0 + _rates_city(3,5)* zi.1.H2V1 + _rates_city(3,6)* zi.1.H2V2 +
      _rates_city(3,7)* zi.1.H3V0 + _rates_city(3,8)* zi.1.H3V1 + _rates_city(3,9)* zi.1.H3V2 +
      _rates_city(3,10)* zi.1.H4V0 + _rates_city(3,11)* zi.1.H4V1 + _rates_city(3,12)* zi.1.H4V2)*(zi.3
.percent*0.153+1)
else   ; Calculate Productions for County Zones
  phbw=_rates_county(1,1)* zi.1.h1V0+ _rates_county(1,2)* zi.1.H1V1 + _rates_county(1,3)* zi.1.H1V2 +
      _rates_county(1,4)* zi.1.H2V0 + _rates_county(1,5)* zi.1.H2V1 + _rates_county(1,6)* zi.1.H2V2 +
      _rates_county(1,7)* zi.1.H3V0 + _rates_county(1,8)* zi.1.H3V1 + _rates_county(1,9)* zi.1.H3V2 +
      _rates_county(1,10)* zi.1.H4V0 + _rates_county(1,11)* zi.1.H4V1 + _rates_county(1,12)* zi.1.H4V2

  phbo=(_rates_county(2,1)* zi.1.h1V0+ _rates_county(2,2)* zi.1.H1V1 + _rates_county(2,3)* zi.1.H1V2 +
      _rates_county(2,4)* zi.1.H2V0 + _rates_county(2,5)* zi.1.H2V1 + _rates_county(2,6)* zi.1.H2V2 +
      _rates_county(2,7)* zi.1.H3V0 + _rates_county(2,8)* zi.1.H3V1 + _rates_county(2,9)* zi.1.H3V2 +
      _rates_county(2,10)* zi.1.H4V0 + _rates_county(2,11)* zi.1.H4V1 + _rates_county(2,12)* zi.1.H4V2)*(zi.3
.percent*0.153+1)


  pnhb=(_rates_county(3,1)* zi.1.h1V0+ _rates_county(3,2)* zi.1.h1V1+ _rates_county(3,3)* zi.1.H1V2 +
      _rates_county(3,4)* zi.1.H2V0 + _rates_county(3,5)* zi.1.H2V1 + _rates_county(3,6)* zi.1.H2V2 +
      _rates_county(3,7)* zi.1.H3V0 + _rates_county(3,8)* zi.1.H3V1 + _rates_county(3,9)* zi.1.H3V2 +
      _rates_county(3,10)* zi.1.H4V0 + _rates_county(3,11)* zi.1.H4V1 + _rates_county(3,12)* zi.1.H4V2)*(zi.3
.percent*0.153+1)
```

Figure C1. Modification to the Trip Generation Script for Scenario 5a, where HBW and NHB Trips are Increased by 15.3% to Account for Increased Trips by Travelers Age 65+.

Scenarios 5b and 5c followed a similar approach. For example, in Scenario 5c, HBW trips were increased by a factor of 3.67% mulitiplied by the percentage of persons age 18-64 (variable zi.3.Percent186). Further, Scenario 5c also increased non-work trips (e.g., HBO and NHB), for all three age groups, where the percentage of persons age 65+, age 13-17, and age 18-64 are represented by the variables zi.3.Percent65, zi.3.PercentTee, and zi.3.Percent186, respectively.

```
  if(zi.2.atype=1-2)

  phbw=(_rates_city(1,1)* zi.1.h1V0 + _rates_city(1,2)* zi.1.H1V1 + _rates_city(1,3)* zi.1.H1V2 +
       _rates_city(1,4)* zi.1.H2V0 + _rates_city(1,5)* zi.1.H2V1 + _rates_city(1,6)* zi.1.H2V2 +
       _rates_city(1,7)* zi.1.H3V0 + _rates_city(1,8)* zi.1.H3V1 + _rates_city(1,9)* zi.1.H3V2 +
       _rates_city(1,10)* zi.1.H4V0 + _rates_city(1,11)* zi.1.H4V1 + _rates_city(1,12)* zi.1.H4V2)*(
       zi.3.Percent186*0.0367+1)

  phbo=(_rates_city(2,1)* zi.1.h1V0 + _rates_city(2,2)* zi.1.H1V1 + _rates_city(2,3)* zi.1.H1V2 +
       _rates_city(2,4)* zi.1.H2V0 + _rates_city(2,5)* zi.1.H2V1 + _rates_city(2,6)* zi.1.H2V2 +
       _rates_city(2,7)* zi.1.H3V0 + _rates_city(2,8)* zi.1.H3V1 + _rates_city(2,9)* zi.1.H3V2 +
       _rates_city(2,10)* zi.1.H4V0 + _rates_city(2,11)* zi.1.H4V1 + _rates_city(2,12)* zi.1.H4V2)*
       (zi.3.Percent65*0.153+zi.3.PercentTee*0.1112+zi.3.Percent186*0.0367+1)


  pnhb=(_rates_city(3,1)* zi.1.h1V0 + _rates_city(3,2)* zi.1.H1V1 + _rates_city(3,3)* zi.1.H1V2 +
       _rates_city(3,4)* zi.1.H2V0 + _rates_city(3,5)* zi.1.H2V1 + _rates_city(3,6)* zi.1.H2V2 +
       _rates_city(3,7)* zi.1.H3V0 + _rates_city(3,8)* zi.1.H3V1 + _rates_city(3,9)* zi.1.H3V2 +
       _rates_city(3,10)* zi.1.H4V0 + _rates_city(3,11)* zi.1.H4V1 + _rates_city(3,12)* zi.1.H4V2)*
       (zi.3.Percent65*0.153+zi.3.PercentTee*0.1112+zi.3.Percent186*0.0367+1)

;  print list=i(5),atype(4),_rates_city(1,1)(6.3),zi.1.a0hh1(5),_rates_city(1,10)(6.3),zi.1.H4V0(5),phbw(5)
;  _tst=_rates_city(1,1)
;  print list=i(5),atype(4),_tst(6.3),_rates_city(1,2),_rates_city(1,3),_rates_city(1,4)

else   ; Calculate Productions for County Zones
  phbw=(_rates_county(1,1)* zi.1.h1V0+ _rates_county(1,2)* zi.1.H1V1 + _rates_county(1,3)* zi.1.H1V2 +
       _rates_county(1,4)* zi.1.H2V0 + _rates_county(1,5)* zi.1.H2V1 + _rates_county(1,6)* zi.1.H2V2 +
       _rates_county(1,7)* zi.1.H3V0 + _rates_county(1,8)* zi.1.H3V1 + _rates_county(1,9)* zi.1.H3V2 +
       _rates_county(1,10)* zi.1.H4V0 + _rates_county(1,11)* zi.1.H4V1 + _rates_county(1,12)* zi.1.H4V2)*
       (zi.3.Percent186*0.0367+1)

  phbo=(_rates_county(2,1)* zi.1.h1V0+ _rates_county(2,2)* zi.1.H1V1 + _rates_county(2,3)* zi.1.H1V2 +
       _rates_county(2,4)* zi.1.H2V0 + _rates_county(2,5)* zi.1.H2V1 + _rates_county(2,6)* zi.1.H2V2 +
       _rates_county(2,7)* zi.1.H3V0 + _rates_county(2,8)* zi.1.H3V1 + _rates_county(2,9)* zi.1.H3V2 +
       _rates_county(2,10)* zi.1.H4V0 + _rates_county(2,11)* zi.1.H4V1 + _rates_county(2,12)* zi.1.H4V2)*
       (zi.3.Percent65*0.153+zi.3.PercentTee*0.1112+zi.3.Percent186*0.0367+1)


  pnhb=(_rates_county(3,1)* zi.1.h1V0+ _rates_county(3,2)* zi.1.h1V1+ _rates_county(3,3)* zi.1.H1V2 +
       _rates_county(3,4)* zi.1.H2V0 + _rates_county(3,5)* zi.1.H2V1 + _rates_county(3,6)* zi.1.H2V2 +
       _rates_county(3,7)* zi.1.H3V0 + _rates_county(3,8)* zi.1.H3V1 + _rates_county(3,9)* zi.1.H3V2 +
       _rates_county(3,10)* zi.1.H4V0 + _rates_county(3,11)* zi.1.H4V1 + _rates_county(3,12)* zi.1.H4V2)*
       (zi.3.Percent65*0.153+zi.3.PercentTee*0.1112+zi.3.Percent186*0.0367+1)

endif
```

Figure C2. Modification to the Trip Generation Script for Scenario 5c.

Script for Implementing a Congested Travel Time Increase of 35%

;The multiplier 0.125 leads alters the congested travel time from 22.08 to 29.81, an increase of 35%.

```
mw[21]=MI.2.FFTIME*(-0.08001*0.125)
mw[22]=MI.2.FFTIME*(-0.18959*0.125)
mw[23]=MI.2.FFTIME*(-0.22559*0.125)
mw[24]=MI.2.FFTIME*(-0.2083*0.125)
mw[25]=MI.2.FFTIME*(-0.2083*0.125)
mw[26]=MI.2.FFTIME*(-0.20004*0.125)
```

Script for Implementing the Combined Scenario

This portion of the script converts parking lots in the CBD to other land uses (with the ParkPLo variable) and increases trips for persons without access to a vehicle (hence the variables Percent186,PercentTee, and Percent65) in the TGGEN00A.S file.

```
 if(zi.2.atype=1-2)

  phbw=((_rates_city(1,1)* zi.1.h1V0+ _rates_city(1,2)* zi.1.H1V1 + _rates_city(1,3)* zi.1.H1V2 +
       _rates_city(1,4)* zi.1.H2V0 + _rates_city(1,5)* zi.1.H2V1 + _rates_city(1,6)* zi.1.H2V2 +
       _rates_city(1,7)* zi.1.H3V0 + _rates_city(1,8)* zi.1.H3V1 + _rates_city(1,9)* zi.1.H3V2 +
       _rates_city(1,10)* zi.1.H4V0 + _rates_city(1,11)* zi.1.H4V1 + _rates_city(1,12)*
zi.1.H4V2+ZI.3.ParkPLo*0.05*0.248)*(zi.3.Percent186*0.0367*0.248+1))~~*1.248~~

  phbo=(_rates_city(2,1)* zi.1.h1V0+ _rates_city(2,2)* zi.1.H1V1 + _rates_city(2,3)* zi.1.H1V2 +
       _rates_city(2,4)* zi.1.H2V0 + _rates_city(2,5)* zi.1.H2V1 + _rates_city(2,6)* zi.1.H2V2 +
       _rates_city(2,7)* zi.1.H3V0 + _rates_city(2,8)* zi.1.H3V1 + _rates_city(2,9)* zi.1.H3V2 +
       _rates_city(2,10)* zi.1.H4V0 + _rates_city(2,11)* zi.1.H4V1 +
_rates_city(2,12)*zi.1.H4V2+ZI.3.ParkPLo*0.16*0.248)*(zi.3.Percent65*0.153*0.248+zi.3.PercentTee*0.1112*0.2
48+zi.3.Percent186*0.0367*0.248+1)

  pnhb=(_rates_city(3,1)* zi.1.h1V0+ _rates_city(3,2)* zi.1.H1V1 + _rates_city(3,3)* zi.1.H1V2 +
       _rates_city(3,4)* zi.1.H2V0 + _rates_city(3,5)* zi.1.H2V1 + _rates_city(3,6)* zi.1.H2V2 +
       _rates_city(3,7)* zi.1.H3V0 + _rates_city(3,8)* zi.1.H3V1 + _rates_city(3,9)* zi.1.H3V2 +
       _rates_city(3,10)* zi.1.H4V0 + _rates_city(3,11)* zi.1.H4V1 +
_rates_city(3,12)*zi.1.H4V2+ZI.3.ParkPLo*0.32*0.248)*(zi.3.Percent65*0.153*0.248+zi.3.PercentTee*0.1112*0.2
48+zi.3.Percent186*0.0367*0.248+1)

else   ; Calculate Productions for County Zones
  phbw=((_rates_county(1,1)* zi.1.h1V0+ _rates_county(1,2)* zi.1.H1V1 + _rates_county(1,3)* zi.1.H1V2 +
       _rates_county(1,4)* zi.1.H2V0 + _rates_county(1,5)* zi.1.H2V1 + _rates_county(1,6)* zi.1.H2V2 +
       _rates_county(1,7)* zi.1.H3V0 + _rates_county(1,8)* zi.1.H3V1 + _rates_county(1,9)* zi.1.H3V2 +
       _rates_county(1,10)* zi.1.H4V0 + _rates_county(1,11)* zi.1.H4V1 + _rates_county(1,12)*
zi.1.H4V2)*(zi.3.Percent186*0.0367*0.248+1))~~ *1.248~~

  phbo=(_rates_county(2,1)* zi.1.h1V0+ _rates_county(2,2)* zi.1.H1V1 + _rates_county(2,3)* zi.1.H1V2 +
       _rates_county(2,4)* zi.1.H2V0 + _rates_county(2,5)* zi.1.H2V1 + _rates_county(2,6)* zi.1.H2V2 +
       _rates_county(2,7)* zi.1.H3V0 + _rates_county(2,8)* zi.1.H3V1 + _rates_county(2,9)* zi.1.H3V2 +
       _rates_county(2,10)* zi.1.H4V0 + _rates_county(2,11)* zi.1.H4V1 + _rates_county(2,12)*
zi.1.H4V2)*(zi.3.Percent65*0.153*0.248+zi.3.PercentTee*0.1112*0.248+zi.3.Percent186*0.0367*0.248+1)


  pnhb=(_rates_county(3,1)* zi.1.h1V0+ _rates_county(3,2)* zi.1.h1V1+ _rates_county(3,3)* zi.1.H1V2 +
       _rates_county(3,4)* zi.1.H2V0 + _rates_county(3,5)* zi.1.H2V1 + _rates_county(3,6)* zi.1.H2V2 +
       _rates_county(3,7)* zi.1.H3V0 + _rates_county(3,8)* zi.1.H3V1 + _rates_county(3,9)* zi.1.H3V2 +
       _rates_county(3,10)* zi.1.H4V0 + _rates_county(3,11)* zi.1.H4V1 + _rates_county(3,12)*
zi.1.H4V2)*(zi.3.Percent65*0.153*0.248+zi.3.PercentTee*0.1112*0.248+zi.3.Percent186*0.0367*0.248+1)



;--------------------------------------------------------------------
;
  if(i=55,58-62,68,80-92,163,165-169,251-256,258-260)              ;  Attractions for UVA
    ahbw=ATTRRATES(3,1)*zi.1.temp+ZI.3.ParkPLo*0.08

    ahbo=ATTRRATES(1,5)*zi.1.ret + ATTRRATES(2,5)*nonretail +
ATTRRATES(4,5)*zi.1.hhx+ZI.3.ParkPLo*0.13*0.248
    anhb=ATTRRATES(1,9)*zi.1.ret + ATTRRATES(2,9)*nonretail +
ATTRRATES(4,9)*zi.1.hhx+ZI.3.ParkPLo*0.32*0.248

    flag=1
```

;print list=' UVA ',i(6),j(6),ahbw(8.2),zi.1.temp(6),ahbo(9.2),zi.1.ret(6),nonretail(6),zi.1.hhx(6)

ELSEif(zi.2.atype=1 & flag=0) ; Attractions for CBD
ahbw=ATTRRATES(3,2)*zi.1.temp+ZI.3.ParkPLo*0.08*0.248
ahbo=ATTRRATES(1,6)*zi.1.ret + ATTRRATES(2,6)*nonretail + ATTRRATES(4,6)*zi.1.hhx+ZI.3.ParkPLo*0.13*0.248
anhb=ATTRRATES(1,10)*zi.1.ret + ATTRRATES(2,10)*nonretail + ATTRRATES(4,10)*zi.1.hhx+ZI.3.ParkPLo*0.32*0.248

elseif(zi.2.atype=2-5 & flag=0) ; Attractions for Urban
ahbw=ATTRRATES(3,3)*zi.1.temp+ZI.3.ParkPLo*0.08*0.248
ahbo=ATTRRATES(1,7)*zi.1.ret + ATTRRATES(2,7)*nonretail + ATTRRATES(4,7)*zi.1.hhx + ATTRRATES(5,7)*zi.1.school+ZI.3.ParkPLo*0.13*0.248
anhb=ATTRRATES(1,11)*zi.1.ret + ATTRRATES(2,11)*nonretail + ATTRRATES(4,11)*zi.1.hhx + ATTRRATES(5,11)*zi.1.school+ZI.3.ParkPLo*0.32*0.248

;----------------------------
; Calculate External Trips
;----------------------------
pix=0.331*zi.3.HH + 0.724*(zi.3.TOTEMP + zi.3.EMPLOYEE_P)+ZI.3.ParkPLo*0.40*0.248 ; Production for external trips (internal zone --> external zone)
aix=zi.4.COUNT * zi.4.IXPCT+ZI.3.ParkPLo*0.0000*0.248 ; Attraction for external trips (external zone --> internal zone)

; Balance attractions to productions
p[1]=phbw*1.0
p[2]=phbo*1.0
p[3]=pnhb
p[4]=pix
a[1]=ahbw
a[2]=ahbo
a[3]=anhb
a[4]=aix*(1+0.02112*0.248)

These changes occur in TGMAT00F.S

HBUP = 2.996*ZI.2.OffC_Stu*{HBO-TF}+ZI.2.ParkPLo*0.07*0.248 ; home-based university PRODS from off-campus (students); old production rate = 2.996
HBUA = 1.375*ZI.2.Total_park*{HBO-TF}+ ZI.2.ParkPLo*0.07*0.248 ; home-based university ATTRSS from off-campus(parking spaces); old attraction rate = 1.375

This portion of the script reduces the impedance for the singly constrained gravity model. For the doubly constrained gravity model, no changes are necessary in the script, although new friction factors are used.

mw[30]=MI.2.FFTIME
mw[21]=MI.2.FFTIME*(-0.08001*0.7)
mw[22]=MI.2.FFTIME*(-0.18959*0.7)
mw[23]=MI.2.FFTIME*(-0.22559*0.7)
mw[24]=MI.2.FFTIME*(-0.2083*0.7)

```
mw[25]=MI.2.FFTIME*(-0.2083*0.7)
mw[26]=MI.2.FFTIME*(-0.20004*0.7)
```

This portion of the script is performed only for the case of no-sharing, where the number 1.248 is added in two places in the file TGGEN00A.S.

```
  phbw=((_rates_city(1,1)* zi.1.h1V0+ _rates_city(1,2)* zi.1.H1V1 + _rates_city(1,3)* zi.1.H1V2 +
      _rates_city(1,4)* zi.1.H2V0 + _rates_city(1,5)* zi.1.H2V1 + _rates_city(1,6)* zi.1.H2V2 +
      _rates_city(1,7)* zi.1.H3V0 + _rates_city(1,8)* zi.1.H3V1 + _rates_city(1,9)* zi.1.H3V2 +
      _rates_city(1,10)* zi.1.H4V0 + _rates_city(1,11)* zi.1.H4V1 + _rates_city(1,12)*
zi.1.H4V2+ZI.3.ParkPLo*0.05*0.248)*(zi.3.Percent186*0.0367*0.248+1))*1.248

else   ; Calculate Productions for County Zones
  phbw=((_rates_county(1,1)* zi.1.h1V0+ _rates_county(1,2)* zi.1.H1V1 + _rates_county(1,3)* zi.1.H1V2 +
      _rates_county(1,4)* zi.1.H2V0 + _rates_county(1,5)* zi.1.H2V1 + _rates_county(1,6)* zi.1.H2V2 +
      _rates_county(1,7)* zi.1.H3V0 + _rates_county(1,8)* zi.1.H3V1 + _rates_county(1,9)* zi.1.H3V2 +
      _rates_county(1,10)* zi.1.H4V0 + _rates_county(1,11)* zi.1.H4V1 + _rates_county(1,12)*
zi.1.H4V2)*(zi.3.Percent186*0.0367*0.248+1)) *1.248
```

This portion of the script is performed only for the case of sharing. That is, the number ***1.248*** *shown above in purple is removed. Then, the NHB multiplier is adjusted for low matching doubly combine scenario, as follows in two places in* TGGEN00A.S:

```
  if(zi.2.atype=1-2)

  pnhb=((_rates_city(3,1)* zi.1.h1V0+ _rates_city(3,2)* zi.1.H1V1 + _rates_city(3,3)* zi.1.H1V2 +
      _rates_city(3,4)* zi.1.H2V0 + _rates_city(3,5)* zi.1.H2V1 + _rates_city(3,6)* zi.1.H2V2 +
      _rates_city(3,7)* zi.1.H3V0 + _rates_city(3,8)* zi.1.H3V1 + _rates_city(3,9)* zi.1.H3V2 +
      _rates_city(3,10)* zi.1.H4V0 + _rates_city(3,11)* zi.1.H4V1 +
_rates_city(3,12)*zi.1.H4V2+ZI.3.ParkPLo*0.32*0.248)*(zi.3.Percent65*0.153*0.248+zi.3.PercentTee*0.1112*0.2
48+zi.3.Percent186*0.0367*0.248+1))*1.1


pnhb=((_rates_county(3,1)* zi.1.h1V0+ _rates_county(3,2)* zi.1.h1V1+ _rates_county(3,3)* zi.1.H1V2 +
      _rates_county(3,4)* zi.1.H2V0 + _rates_county(3,5)* zi.1.H2V1 + _rates_county(3,6)* zi.1.H2V2 +
      _rates_county(3,7)* zi.1.H3V0 + _rates_county(3,8)* zi.1.H3V1 + _rates_county(3,9)* zi.1.H3V2 +
      _rates_county(3,10)* zi.1.H4V0 + _rates_county(3,11)* zi.1.H4V1 + _rates_county(3,12)*
zi.1.H4V2)*(zi.3.Percent65*0.153*0.248+zi.3.PercentTee*0.1112*0.248+zi.3.Percent186*0.0367*0.248+1))*1.1
```

Appendix D. Example of Validation

Because they were using a model developed by others (The Corradino Group, 2009), the researchers sought to ensure that they had not inadvertently misunderstood the model results or added errors when developing scenarios. Examples of steps necessary to understand the model and confirm results are shown in this Appendix.

Example of Understanding the Overall Model

For the base scenario, it was possible to confirm that person trips and vehicle trips from the model matched expected values. In sum, Table 1 suggests that there should be approximately 772,132 *vehicle trips* after considering all seven purposes (HBW, HBO, NHB, HBU, HDORMU, IX/XI, and XX). The total volumes on all centroid connectors—including both internal zones and external stations—summed to 1,529,438 vehicle trip ends. As shown in Figure 1, recognizing that a single trip (e.g., from Zone 1 to Zone 50) takes two trip ends, the traffic assignment as shown in the file LoadedNet2040A_BaseValues.net reflects 1,529,438/2 = 764,719 *vehicle trips*. Further, the values were reasonable for individual zones: for example, for zone 1, there are 3,539 productions and 4,557 attractions for zone 1 after balancing as shown in the files TGEN_PA.DBF and (for productions) InitialTdist.MAT. One would expect that conversion of these to an origin-destination table would yield an average of roughly 4,048 person trip origins and destinations. If 77% of such person trips became vehicle trips, one would expect there to be 3,177 vehicle trip origins and destinations. A similar number is shown for zone 1 in the file CVFINALVEHTRIPS2040.DAT (3,280.9 vehicle trip origins and destinations) and in LoadedNet2040A_.net, the number of vehicle trip ends is comparable: the single connector shows 3,285.82 vehicle trip ends entering zone 1 and of course the same number (3,285.82) vehicle trip ends leaving zone 1.

The researchers used Table 1 to confirm that the results they were obtaining for the base case were as expected without gross errors. For example, The Corradino Group (2009) reported that for the base model, after one summed productions for the five internal trip purposes (HBW, HBO, NHB, and students living off campus plus students living in dorms) and then divided by the total number of households, one obtained a trip generation rate of 9.31 trips per household. Performing the same type of exercise with the 2040 base case data shows 772,557 person trips (e.g. the sum of the first five rows of Table 1) divided by the 82,105.68 households yields 9.41 trips per household. It was also possible to replicate the calculations for the conversion of person trips to vehicle trips; for example, the 772,132 vehicle trips (see Vehicles.mat) can be derived for the different trip purposes. Table 1 thus explains a bit of the sensitivity of the model; for example, alterations of behaviors or conditions that only affect the commuting are impacting only 14.9% of all person trips, after one considers those trips that pass through the area.

Table 1 shows that in the aggregate, about 66% of all person trips become vehicle trips (e.g., there are 772,557 person trips and 510,291 vehicle trips). These percentages for converting person-trips to vehicle trips vary by trip purpose: 73% (HBW), 60% (HBO), 85% (NHB), 0% (for on-campus university), and 100% (for internal-external). Such percentages affect the scenarios. For example, for Scenario 2d which focuses on the central business district, there is a relatively high percentage of internal-external and external-internal trips (37%) compared to that trip purpose's percentage for the model overall (23%). In part for that reason, whereas about 66% of all person trips become vehicle trips when focusing on the overall region, this percentage is closer to 77% for Scenario 2d. Such an observation does not mean that the CBD automatically generates more vehicle trips than other areas (as one would expect the reverse in theory) but rather reflects the fact that for this particular model, there are a relatively large portion of internal-external trips.

The researchers also found that execution of some scenarios twice, while increasing effort, was also helpful for understanding model sensitivity. For example, in order to modify the socioconomic data which is stored in a .dbf format, the researchers noted that it was possible for decimals to be truncated (e.g., zone with 37.253 autos could be truncated to 37.0 autos) unless a specific modification to the the .dbf file was made. (That modification was to make zone 66 be the first row in the dataset, as this particular zone had decimal values for all attributes where decimal values were needed.) However, this rounding was not a substantial cause of error for Scenario 2d. An explanation of the sensitivity of the model is that this rounding caused less than 0.01% change in VMT (from 6,829,605.34 to 6,828,949.12) and VHT (from 167,101.64 to 167,085.5), respectively. The rounding also caused a total difference of 108 trips from the HBW, HBO, and NHB categories (which reflects about 0.02% of these productions), with no difference in HBU or HDORMU productions.

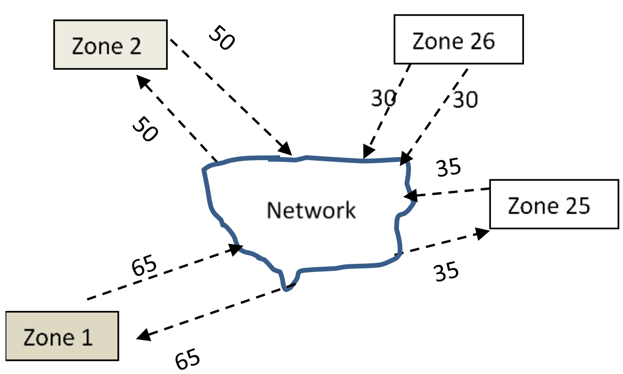
Table D1. Summary of Trips for the Base Case (Doubly Constrained Gravity Model [c]

Quantity	**Purpose**	**Drive alone**	**Carpool (2 persons)**	**Carpool (3+)**	**Walk to bus**	**Drive to bus**	**Walk**	**Bike**	File or derivation
	Abbreviation	DA	CP	CPX	WB	BA	WK	BK	
Person trips	HBW	87,460	38,115	18,694	600	4.3	4,283	4,739	Modeout.mat
	HBO	102,129	143,136	52,802	837	0.3	16,692	2,660	Modeout.mat
	NHB	145,788	42,855	9,198	35	0.0	706	1,174	Modeout.mat
	HBU	35,285	3,970	2,762	12,343	7.3	13,633	1,646	Modeout.mat
	HDORMU				4,878		15,504	10,624	Modeout.mat
	Internal person	772,557							InitialTdist.mat, TGEN_PA.DBF
	XX [d]	20,244							ProcEXT_2040A.MAT
	IX + XI [d]	241,609							IX_OD.MAT [a]
	Total person	1,034,410							Internal person + XX + IX + XI
Vehicle trips	HBW	87,460	19,058	5,842		4.3			Divide person trips by 2 (for CP2). Divide person trips by 3.2 (for CP3) except HBO (use 3.3)
	HBO	102,129	71,568	16,000		0.3			
	NHB	145,788	21,427	2,874		0.0			
	HBU	35,285	1,985	863		7.3			
	HDORMU								No vehicle trips
	Internal vehicle	370,662	114,038	25,580					Vehicles.mat
	XX	20,244							ProcEXT_2040A.MAT
	IX	241,609							IX_OD.MAT [a]
	External vehicle	261,853							Vehicles.mat, ODVehTrips 2040.MAT
	All vehicle	772,132							CVFINALVEHTRIPS2040.DAT
Trips of interest	Peak transit				600	4.3			TRANSIT.MAT
	Off peak transit				18,091	7.6			TRANSIT.MAT
	Transit				18,704				TRANSIT.MAT
	Nonmotorized						50,817	20,843	NONMOTOR.MAT
	Person	632,515	228,076	83,456	18,692	12	50,817	20,843	Sum person trips by mode [b]

[a] The file "EITdist.MAT" reflects IX and XI trips, comes from trip generation, and feeds IX_OD.MAT (with 241,585.46 rips)
[b] The file "InitialTdist.MAT" reflects (772,732) internal person trips and is within 0.02% of the sum of HBW, HBO, NHB, HBU, and HDORMU person trips (772,557) shown in this table, as is the file TGEN_PA.DBF (772,724 person trips).
[c] Base case doubly constrained gravity model with values of 6,829,605.34 (VMT), 167,101.65 (VHT), and 20.89 (MTT).
[d] Abbreviations XX, IX, and XI denote external-external, internal-external, and external-internal trips, respectively

Example of Checking a Specific Scenario

Efforts were made to confirm that the results obtained were not due to errors in coding the model. When examining all zones and external stations for the entire model, it should be the case that the centroid volumes (shown as dashed lines) reflect vehicle *trip ends*, such that dividing the total centroid volume by two yields the number of vehicle *trips*. For example, Figure 1 shows that the 360 trip ends from the centroid volumes correspond with 180 trips. If one only examines centroid connectors within a particular portion of the model, such as the CBD, then the percent of vehicle trips that should be ascribed to the CBD will be between 50% and 100% of the total centroid connector volumes, depending on whether most of the CBD trips remain within the CBD (hence a value of 50%) or leave the CBD (a value closer to 100%). In Figure 1, most CBD trips remain within the CBD, thus, the value is considerably closer to 50%. (That is, the centroid volumes show *230 trip ends*, but since most trips remain within the CBD, a multiplier relatively close to 50% yields 130 *trips*). The logic that underscores Figure 1 is used for the validation of Scenario 2d.



Zone	1 (CBD)	2 (CBD)	25	26	Total
1	0	50	10	5	65
2	50	0	0	0	50
25	10	0	0	25	35
26	5	0	25	0	30
Total	65	50	35	30	180

Sum of centroid volumes: 360
Sum of trips: 180
Sum of CBD centroid volumes: 230
Sum of CBD trips: 130

Figure 1. Origin-Destination Table and Centroid Volumes for a Simple 4 Zone System.

For Scenario 2d, consider the additional 12,752 *person trips* that were anticipated from the conversion of parking lots that resulted from execution of the model for Scenario 2d. Because the researchers were initially surprised that these trips did not increase VMT, VHT, and MTT in the regional model by a substantial amount, the researchers sought to confirm that these trips had been incorporated into the script correctly. For the CBD zones, it was generally the case that 77% of *person trips* became *vehicle trips* (with the other person trips using carpool, transit, and nonmotorized modes). Accordingly, the 12,752 person trips (e.g., 12,752 productions and 12,752 attractions for a total of 25,504 *person trip ends*) produced by the CBD should have yielded, roughly 77% of 25,504 or 19,638 *vehicle trip ends*. For the base scenario, the vehicle trip table CVFINALVEHTRIPS2040DAT showed that roughly 7.1% of vehicle trips remained with the CBD. Because, contrary to Figure 1, only a small percentage of CBD trips remained within the CBD, one would expect the total additional volume on the CBD connectors to be slightly lower than 100% of 19,638 (e.g., perhaps (100%-7.1%)(19,638) = 18,263 *vehicle trips ends*. Accordingly, the CBD centroid connectors in the model were identified (e.g., for zones 1-11, 33-35, 66, and 261) and, for those connectors, the difference in volumes between the base scenario and Scenario 2d was summed. For these connectors that difference was 22,631 *vehicle trip ends* based on the file link.dbf. This suggested that the number of vehicle trip ends was reasonable.