System Dynamics Models of Automated Vehicle Impacts

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Final Report — January 2023
FHWA-JPO-22-985
DOT-VNTSC-FHWA-23-02

U.S. Department of Transportation

Produced by John A. Volpe National Transportation Systems Center
U.S. Department of Transportation
Intelligent Transportation Systems (ITS) Joint Program Office

REPORT DOCUMENTATION PAGE

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1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED	
		START DATE	**END DATE**
31 January 2023	Final Report	March 2021	December 2022

4. TITLE AND SUBTITLE
System Dynamics Models of Automated Vehicle Impacts

5a. CONTRACT NUMBER	5b. GRANT NUMBER	5c. PROGRAM ELEMENT NUMBER
693JJ320N300046		
5d. PROJECT NUMBER	**5e. TASK NUMBER**	**5f. WORK UNIT NUMBER**
HW9EA720		

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8. PERFORMING ORGANIZATION REPORT NUMBER
DOT-VNTSC-FHWA-23-02

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)
U.S. Department of Transportation
Intelligent Transportation Systems Joint Program Office
1200 New Jersey Avenue, SE
Washington, DC 20590

10. SPONSOR/MONITOR'S ACRONYM(S)
HOIT

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
FHWA-JPO-22-985

12. DISTRIBUTION/AVAILABILITY STATEMENT
None

13. SUPPLEMENTARY NOTES
None

14. ABSTRACT
The many potentially transformative changes to the transportation system, such as automated vehicles, electric vehicle adoption, increased telework, and new travel modes, are creating increasing uncertainties for the future. These uncertainties call for fast, flexible models.

System dynamics (SD) is emerging as a research modeling focus area for changes to the transportation system that may have transformative impacts, including those from vehicles using automated driving systems (ADS). System dynamics provides both qualitative methods to bring diverse stakeholders to a common understanding of the problem, and quantitative methods for modeling complex systems that consider feedback effects and changes over time. Qualitative methods include those for representing systems, such as causal loop diagrams, and for collecting information to determine that representation, such as working with stakeholders via group model building techniques. This project developed causal loop diagrams for several "building blocks" (archetypes) that affect how automated vehicles might be used. These building blocks include new product adoption, sustainability of business model, mode choice, scale effects, congestion and residential relocation.

This report then summarizes our use of group model building in several settings and finally presents a quantitative model of a shared mobility service, with initial calibration results and sensitivity results for urban, suburban and rural areas. The results showed that higher trip densities would lead to lower wait times and a greater return on investment. While this result is not surprising, the CLD is a research contribution by demonstrating the causal mechansims that lead to this result, as well as providing a way to test the effects of possible policy levers.

15. SUBJECT TERMS
Automation, automated vehicles, automated driving systems, system dynamics, SD, group model building, shared mobility

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES
a. REPORT	**b. ABSTRACT**	**C. THIS PAGE**	None (UU)	84
Unclassified (U)	Unclassified (U)	Unclassified (U)		

19a. NAME OF RESPONSIBLE PERSON	19b. PHONE NUMBER *(Include area code)*

Table of Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	Term
ADAS	Advanced driver assistance system
ADS	Automated driving system
AV	Automated vehicle
CLD	Causal loop diagram
DOE	Department of Energy
EPA	Environmental Protection Agency
FHWA	Federal Highway Administration
GMB	Group model building
ITS JPO	Intelligent Transportation Systems Joint Program Office
MPO	Metropolitan Planning Organization
NHTS	National Household Travel Survey
SD	System dynamics
TMIP-EMAT	Travel Model Improvement Program – Exploratory Modeling and Analysis Tool
TNC	Transportation network company
TRB	Transportation Research Board
USDOT	U.S. Department of Transportation
VMT	Vehicle miles traveled
VOT	Value of time

Executive Summary

The many potentially transformative changes to the transportation system, such as automation, adoption of electric vehicles, increased telework, and new travel modes, are creating increasing future uncertainties. Current travel demand models, with their definite input assumptions and long run times, may not be up to modeling a wide variety of potential futures.

Accordingly, the planning and modeling community is showing an increasing interest in strategic planning tools, including models like VisionEval and frameworks such as the Travel Model Improvement Program’s Exploratory Modeling and Analysis Tool (TMIP-EMAT), which can quickly explore a wide scenario space. Furthermore, there is an interest in models that can organize complex systems, making sense of the interactions among parts of the system that might produce unexpected outcomes.

System dynamics (SD) methods hold promise in this regard. SD is a methodology with broad applicability, and has been applied in many areas, including business analysis (e.g., adoption of new mobility technologies) (Struben and Sterman 2008), and public health (e.g., spread and containment of pandemics) (Rubin et al. 2021). SD has a qualitative side, including techniques such as group model building, which is useful for establishing a common understanding of the problem among stakeholders. It also has a quantitative side, bringing mathematical rigor to the causal relationships and simulating system behavior under various scenarios. This report explores the use of SD in a transportation context, specifically for understanding the potential impacts of a shared automated mobility service, from perspectives of both the service provider and the household.

On the qualitative side, in the immediately preceding project in this program, the Volpe team and several partners facilitated group model building (GMB) exercises with state and regional agencies (documented in further detail in (Smith et al. 2021)) . In the current project, Volpe shared this work with a broader audience at webinars and the 2021 Transportation Research Board (TRB) Planning Applications conference, as well as conducting a wider GMB workshop that brought staff of several U.S. and European cities and regions into the same virtual room to look at the role of automation in livability of cities (Harrison et al. 2022). These efforts showed that one benefit of system dynamics GMB in the domain of transportation futures is that it speaks a language accessible to both planners and modelers, helping to bridge the gap between those two groups. The resulting causal loop diagrams (CLDs) can be used to develop common mental models of a system, to help surface any miscommunications. Developing CLDs requires participants not only to think about the elements of the system, and how they affect each other, but also to express their thinking on these relationships non-equivocally on paper, thus leading to greater clarity on possible leverage points and differences in perspective.

Several CLDs were developed for this project, covering the following dynamics:

- Reinforcing effects of product adoption, as word-of-mouth from existing users leads to new users

- Balancing effects of the need for a sustainable business model, where it is not sustainable in the long term to have cost exceed revenue
- Reinforcing effects of scale, where in many cases, as a business becomes larger, it is able to more efficiently and consistently match service provision to demand, thus offering shorter wait times
- Balancing effects of congestion, through which mechanism as use of a product (e.g., use of shared mobility trips, space on a transit bus, or space on a road) increases, its use becomes less attractive (e.g., increased wait times for shared mobility trips, standees on a bus, or congestion on a road)

On the quantitative side, the Volpe team constructed and tested a model of a shared automated mobility service, from both the traveler and service operator perspectives. The baseline model was constructed using transportation network company (TNC) data from Massachusetts and Chicago, and then tested on several automation scenarios. This analysis found that:

- Given the higher density of trips in urban areas, all of the services were more attractive to both travelers and operators in urban areas (consistent with the spatial distribution of TNC use today)
- There is an increase in vehicle-miles traveled (VMT), primarily driven by induced travel and affected by value of time
- There is potential for high quality (i.e., low wait time) services in rural areas, except at the lowest population densities

Proposed future work includes using SD to explore vehicle ownership, and the integration of SD techniques with existing strategic models for transportation.

1 Introduction

A clearer understanding of impacts of automated driving system (ADS), and how adoption of ADS[1] will affect the public interest, is of great importance to federal, state, and local policymaking. As the impacts of automation are far-reaching, complex, and uncertain, it is critical to have a systems-level framework for evaluating the potential implications of these new technologies on the transportation system.

System dynamics (SD) has emerged as a research modeling focus area for changes to the transportation system which may have transformative impacts, including those from ADS. System dynamics provides both qualitative methods for bringing diverse stakeholders to a common understanding of the problem, and quantitative methods for modeling complex systems that consider feedback effects and changes over time.

SD models support managing uncertain futures in performance-based planning and programming, with a focus on moving the models towards common usage at metropolitan planning organizations (MPOs), state DOTs, and cities as appropriate.

This report includes three sections: past work, qualitative modeling, and quantitative modeling.

The section on past work briefly describes the impact assessment framework for automated driving systems published and tested in 2015-2018 ((Smith et al. 2015; 2017; 2018; Innamaa et al. 2018), analysis of specific automation applications, (Yanagisawa, Najm, and Rau 2017; A. Eilbert et al. 2018; A. Eilbert, Berg, and Smith 2019) and the motivation for using system dynamics.

The qualitative modeling section discusses the techniques, such as group model building and causal loop diagrams, for bringing diverse stakeholders to a common understanding of the issues. It reports on our use of these techniques, both in a large webinar setting and also in more focused sessions with state and regional governmental organizations in the U.S., as well as engagement with cities in Europe. It presents several causal loop diagrams (CLDs) illustrating major outcomes of policy interest (e.g., mode choice and land use) associated with widespread adoption of ADS.

The quantitative modeling section reviews several existing quantitative SD models, and then focuses on addressing a major gap in current models: that of the business model for shared mobility services. The report presents a quantitative model for such a service, integrating both the business side (financial sustainability) and the user side (a service attractive enough to be used). Our several hundred model runs show the significantly different outcomes in urban, suburban, and rural areas, as well as the importance of induced travel. This section concludes with a discussion of how a quantitative SD model

[1] ADS refers to SAE Level 3 to 5 automation (SAE International 2021). It is a more specific term than "automated vehicle". The potential impacts of ADS are the primary focus of this report.

can be integrated with existing models, such as the VisionEval strategic planning model from FHWA, and the POLARIS agent-based model from Argonne National Laboratory (U.S. Department of Energy).

2 Past Work

This section provides a short summary of the earlier phases of this program. Since 2015, the ITS JPO has sponsored work by the U.S. DOT Volpe Center to investigate the impacts of ADS on the transportation system. In close collaboration with international partners, our early research centered on developing a framework (Figure 2-1) for evaluating the impacts of ADS on safety, emissions, network efficiency, and travel behavior. Investigators also considered impacts beyond the transportation sector, such as land-use patterns and public health.

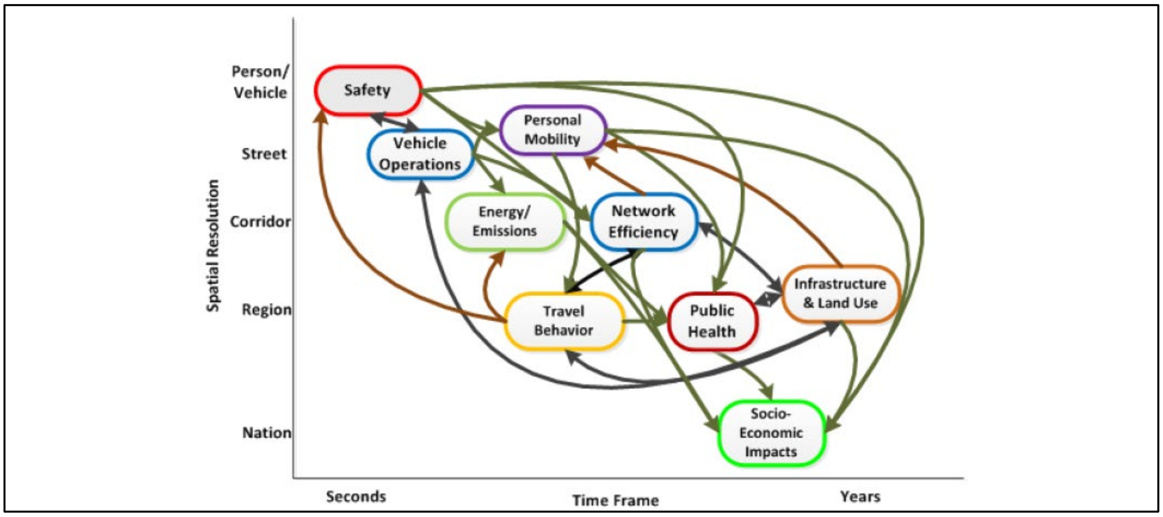


Figure 2-1 Impact assessment framework

(Source: Volpe (Smith et al. 2018))

Subsequent research efforts included detailed modeling and socializing the results at industry meetings like the 2017 Automated Vehicles Symposium (Smith et al. 2017).

As it became clear that most existing transportation planning and operations models were not designed to capture the potentially transformative impacts of ADS, the Volpe team moved from 2017 towards using system dynamics (Berg et al. 2020; Rakoff et al. 2020; Smith et al. 2021; Keith et al. 2022). System dynamics (SD) allows one to take simple causal interactions within a complex system and build a model that can demonstrate not-so-evident dynamic behavior. SD enables one to identify potential tipping points that could indicate a major change in how the transportation system might be used. System dynamics lends itself to both qualitative modeling (e.g., a group model building exercise among a variety of stakeholders to identify the causal relationships) and quantitative modeling (e.g., a model of how the system might evolve over time, starting from today's situation and testing various scenarios). System dynamics models are often useful even without representing great levels of system detail; therefore, they often run much faster than large four-step or activity-based models and are thus a useful addition to the scenario planning and strategic modeling toolboxes.

Meta-analyses (Figure 2-2) also refined the impacts framework, especially as regards the network efficiency and energy/emissions areas. In Figure 2-2, each dot represents the results of a study. The larger black dots are the mean, with the whiskers representing one standard deviation.

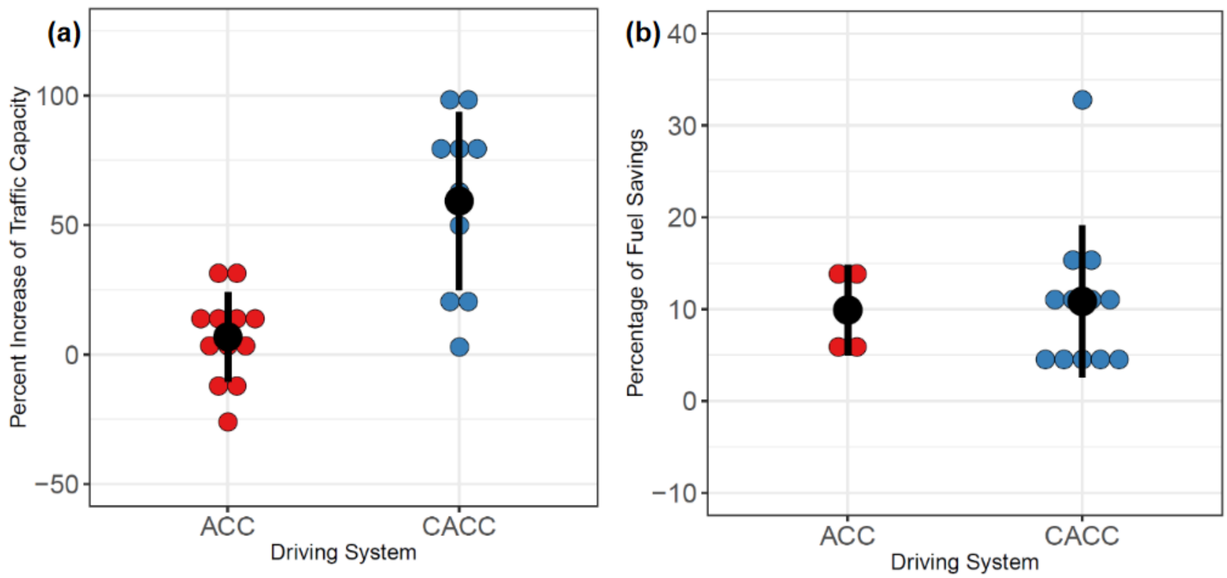


Figure 2-2 Meta-analysis of adaptive and cooperative adaptive cruise control applications

(Source: Volpe (A. Eilbert, Berg, and Smith 2019))

Previous studies through this program have explicitly considered the environmental impacts of automated vehicles, and the differences between cooperative and adaptive cruise control systems in particular. These studies showed that cooperative adaptive cruise control (CACC) can effectively smooth driving by curbing excessive acceleration and braking events, more so than adaptive cruise control (ACC) alone. Smoother CACC driving results in less traffic congestion and delays but also in fuel savings and emission reductions over naturalistic driving. While we were able to confirm the operational benefits of connectivity and automation through instrumented vehicle testing through the CARMA Program, the environmental benefits were much more apparent in the traffic microsimulations.

In these simulations, the Volpe team implemented the well-known MIXIC model for CACC and the Intelligent Driver Model (IDM) for ACC. Volpe then developed emission estimates using the US Environmental Protection Agency's latest regulatory model for highway vehicles, Motor Vehicle Emission Simulator (MOVES3).

There may be a tradeoff between vehicle controllers; some optimize for environmental benefits and while others optimize for traffic capacity. In order to promote energy and emission reductions, the controller must allow for greater following distances and time gaps (A. Eilbert et al. 2018; A. Eilbert et al. 2020).

2.1 Publications

Publications describing work completed during earlier phases of the program are listed below, in chronological order:

Smith, S., Bellone, J., Bransfield, S., Ingles, A., Noel, G., Reed, E., & Yanagisawa, M. (2015). Benefits Estimation Framework for Automated Vehicle Operations. Department of Transportation. https://rosap.ntl.bts.gov/view/dot/4298/dot_4298_DS1.pdf

Yanagisawa, M., Najm, W., & Rau, P. (2017, June). Preliminary Estimates of Target Crash Populations for Concept Automated Vehicle Functions. 25th International Technical Conference on the Enhanced Safety of Vehicles, Detroit. https://www-esv.nhtsa.dot.gov/Proceedings/25/25ESV-000266.pdf

Smith, S., Innamaa, S., Barnard, Y., Gellerman, H., Horiguchi, R., & Rakoff, H. (2017, July 19). Where will Automated Vehicles take us? A Framework for Impact Assessment [Poster]. Automated Vehicles Symposium, San Francisco. https://higherlogicdownload.s3.amazonaws.com/AUVSI/14c12c18-fde1-4c1d-8548-035ad166c766/UploadedImages/2017/PDFs/Proceedings/Posters/Wednesday_Poster%202.pdf

Smith, S., Koopmann, J., Rakoff, H., Peirce, S., Noel, G., Eilbert, A., & Yanagisawa, M. (2018). Benefits Estimation Model for Automated Vehicle Operations: Phase 2 Final Report. https://rosap.ntl.bts.gov/view/dot/34458

Eilbert, A., Noel, G., Jackson, L., Sherriff, I., & Smith, S. B. (2018). A Framework for Evaluating Energy and Emission Impacts of Connected and Automated Vehicles through Traffic Microsimulations. Presentation at 2018 TRB Annual Meeting https://rosap.ntl.bts.gov/view/dot/43934 (Eilbert et al. 2018a)

Eilbert, A. C., Chouinard, A.-M., Berthaume, A., Noel, G., & Smith, S. B. (2018, July). Finding the tipping point: A sensitivity analysis of network performance and environmental benefits of cooperative adaptive cruise control in freeway driving. Automated Vehicles Symposium, San Francisco. http://auvsilink.org/AVS2018/Posters/Scott%20Smith_Finding%20the%20Tipping%20Point%20A%20Sensitivity%20Analysis%20of%20Network%20Performance%20and%20Environmental%20Benefits%20of%20Cooperative%20Adaptive%20Cruise%20Control%20in%20Freeway%20D.pdf (Eilbert et al. 2018b)

Innamaa, S., & Kuisma, S. (2018). Key performance indicators for assessing the impacts of automation in road transportation: Results of the Trilateral key performance indicator survey. https://www.vtt.fi/inf/julkaisut/muut/2018/VTT-R-01054-18.pdf

Eilbert, A., Berg, I., & Smith, S. B. (2019). Meta-Analysis of Adaptive Cruise Control Applications: Operational and Environmental Benefits. John A. Volpe National Transportation Systems Center. https://rosap.ntl.bts.gov/view/dot/41929 (Eilbert et al. 2019a)

Eilbert, A., Berg, I., & Smith, S. B. (2019). Systematic Review and Meta-Analysis of Adaptive Cruise Control Applications: Operational and Environmental Benefits. 19–04981, 2019 TRB Annual Meeting https://rosap.ntl.bts.gov/view/dot/39013 (Eilbert et al. 2019b)

Berg, I., Rakoff, H., Shaw, J., & Smith, S. (2020). System Dynamics Perspective for Automated Vehicle Impact Assessment. https://rosap.ntl.bts.gov/view/dot/49813

Eilbert, A. C., Chouinard, A.-M., Tiernan, T. A., & Smith, S. B. (2020). Performance Comparisons of Cooperative and Adaptive Cruise Control Testing, Air & Waste Management Association conference, 2020. https://rosap.ntl.bts.gov/view/dot/49812

Rakoff, H. E., Smith, S., Innamaa, S., Barnard, Y., Harrison, G., & Shaw, J. (2020). Building feedback into modelling impacts of automated vehicles: Developing a consensus model and quantitative tool. Accepted at Transport Research Arena conference April 2020 (cancelled), Helsinki, Finland. https://rosap.ntl.bts.gov/view/dot/48969

Smith, S., Eilbert, A., (2020) Energy and Environmental Impacts of Automated Vehicles: Framework and Preliminary Results, https://rosap.ntl.bts.gov/view/dot/55246

Smith, S., Berg, I., Eilbert, A., Rakoff, H., Shaw, J., & Stanford, J. M. (2021). Automated Vehicle Impacts on the Transportation System: Using system dynamics to assess regional impacts. https://rosap.ntl.bts.gov/view/dot/55247

Keith, D.R., Naumov, S., Rakoff, H.E., Meyer Sanches, L., Singh, A. (2022) "The effect of increasing vehicle utilization on the automotive industry." *European Journal of Operational Research,* ISSN 0377-2217. http://doi.org/10.1016/j.ejor.2022.10.030.

3 Qualitative Modeling

System dynamics (SD) is a methodology with broad applicability. Before effort is expended developing a quantitative SD model, it is helpful to engage with stakeholders in a structured process to define the problem and important causal relationships as well as the relevant scope of system to be considered.

Group model building (GMB) is a stakeholder engagement method designed to surface the important variables and major causal relationships in a complex system, identifying feedback loops. GMB also helps to bring stakeholders with a variety of perspectives to a common understanding of the system in play and the challenge or problem at hand.

The stakeholder engagement eventually yields a qualitative model, often represented as a causal loop diagram (CLD). The resulting qualitative model, along with available data, forms the basis for building a quantitative model. Section 3.1 introduces CLDs, section 3.2 describes the CLDs developed for this project, and section 3.3 describes several examples of stakeholder engagement.

3.1 Introduction to Causal Loop Diagrams

One important output of a group model building exercise is a CLD, which concisely represents the causal relationships in the system. CLDs are discussed in (Berg et al. 2020). Key points from that discussion are repeated here.

CLDs are constructed using only a few elements: variables, parameters, and causal links. Variables or parameters are indicated just by their names, and causal links are indicated by arrows, with the arrow pointing from the independent variable to the dependent variable in the causal relationship. Every causal link has a positive or negative polarity to indicate the nature of the relationship, shown in Figure 3-1.[2]

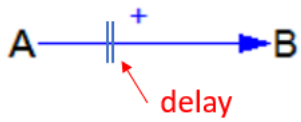
Source: Volpe Center

Figure 3-1 Causal links with positive (left) and negative (right) polarities.

A causal link with positive polarity from variable A to variable B means that *an increase in A will cause B to be larger than it would otherwise be*, and *a decrease in A will cause B to be smaller than it otherwise would be*. It is important to note that this does not mean that *an increase in A will cause an increase in B.* B can still decrease but will decrease less than it otherwise would have. Similarly, a negative polarity means that *an increase in variable A will cause variable B to be smaller than it would be all else equal*, and *a decrease in variable A will cause variable B to be larger than it otherwise would be*. Marks can also

[2] In addition to marking links with “plus” or “minus” signs, this report uses an additional distinction of color, with blue for a positive link and red for a negative one.

be added to causal links to indicate delayed causality (see Figure 3-2). Delay can have a powerful effect on the resulting dynamics.



Source: Volpe Center

Figure 3-2 Causal link with delay.

Once these causal links are assembled, "loops" will arise when the causal links from one variable connect back to that variable, after connecting to one or more additional variables. These loops play a central role in the behavior of the system, so it is important to identify them. Indeed, highlighting causal relationships, as well as feedback loops, and how this system structure influences its behavior, is the key tenet of SD. Loops are labeled to indicate: (a) the dynamic behavior that the loop illustrates – a simple name to refer to that loop and (b) whether the overall effect is ***reinforcing*** (where the net effect of all the links in the loop reinforces a change in any variable in the loop) or ***balancing*** (where the effect of all the links in the loop opposes a change to any variable in the loop). In an isolated reinforcing loop, the variables will either increase exponentially[3], or decay to zero. In a balancing loop, they will tend to resist displacement from initial values, although oscillating behavior can ensue. As will be seen later, the dynamics become more complex when reinforcing and balancing loops are combined.

An example of a CLD on the provision of transit service (adapted from (Rakoff and Bettinardi 2021)), is shown in Figure 3-3. Note that the concepts in Figure 3-3 are applicable to any shared vehicle service (such as a shared automated vehicle service), where a balance must be found between financial sustainability for the service provider and an attractive service for the traveler.

[3]Isolated reinforcing loops can also exhibit exponential decreases, in the case of a non-physical variable which can take on an exponentially large negative value.

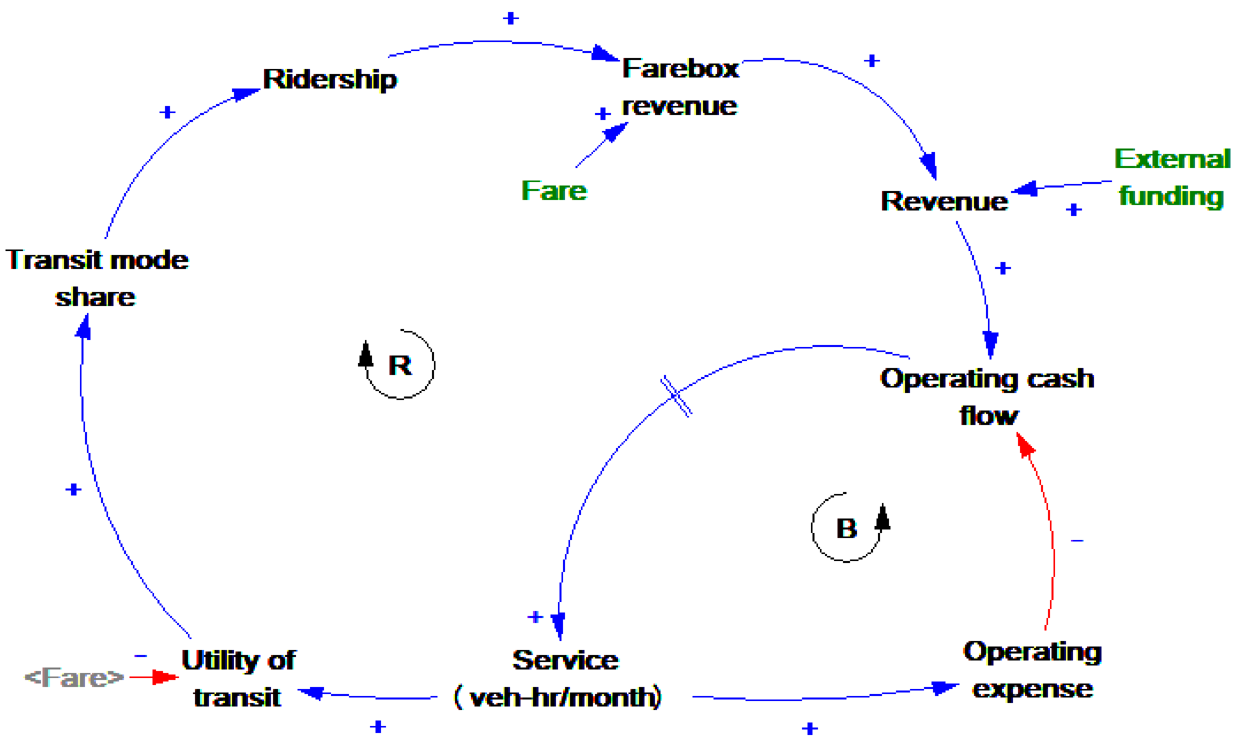


Figure 3-3 CLD of transit use, demonstrating an archetypal behavior applicable to shared mobility (human-driven or automated) as well

(Source: Volpe)

There are two loops in this diagram. First is the transit service and revenue reinforcing loop. All else equal, more ridership leads to more farebox revenue for the transit agency. This, in turn, increases operating cash flow, which enables more service, albeit after a delay. With more service, transit becomes more attractive, leading to greater mode choice for transit. More travelers choosing transit leads to greater ridership, thus closing the loop. This loop could also be a "death spiral", with reduced ridership, revenue, etc.

Second is the balancing loop of cash flow, service, and operating expense. More cash flow enables more service (after some delay), which increases the operating expense, which ***reduces*** the cash flow, thus limiting the ability to add yet more service.

To summarize, building a qualitative model is an essential first step to engage with stakeholders and can even be built in concert with them. It allows stakeholders (and the project team) to reach a common understanding of the problem being addressed. By building out the loops in one or a set of CLDs, a stakeholder can see how simple-looking problems can lead to possibly unexpected system behaviors as the interactions are built out. This, by itself, has value (Smith et al. 2021).

The next section presents the building blocks of a qualitative SD model for a transportation system, as developed during this project. Section 3.3 then presents several examples of stakeholder engagement, in 2020 – 2022, with qualitative modeling of different aspects of the automated vehicle ecosystem.

3.2 Causal Loop Diagrams for Automated Transportation

Causal loop diagrams represent the important causal links and feedback loops in a system. The system boundary needs to be large enough to capture all significant effects (Sterman 2000). For macro-scale impacts of ADS, that means the CLD needs to address transportation supply and demand as well as business models and infrastructure.

This section presents some of the building blocks developed by this project in 2020-2021. They include technology adoption, business models, competition, scale effects (where more use leads to better service), congestion, and the long-term dynamics of vehicle ownership and land use (residential relocation). While conceived of in the context of modeling automated driving, these building blocks will have applicability to nearly any transportation innovation.

Later, in Chapter 4, the report will present a detailed quantitative example for one possible business model of automation, that of a shared mobility service.

3.2.1 Technology adoption

Consumer adoption of an innovation, via word-of-mouth and other influencing factors, is a reinforcing loop, eventually limited by market saturation. A technological innovation enables an innovative service to be launched. For example, in the case of transportation network companies, the enabling innovations included GPS and wide availability of smart phones. Early adopters try the service, like it, and tell their friends. Many of their friends then try the service, like it, and tell *their* friends, and so on (Figure 3-4).

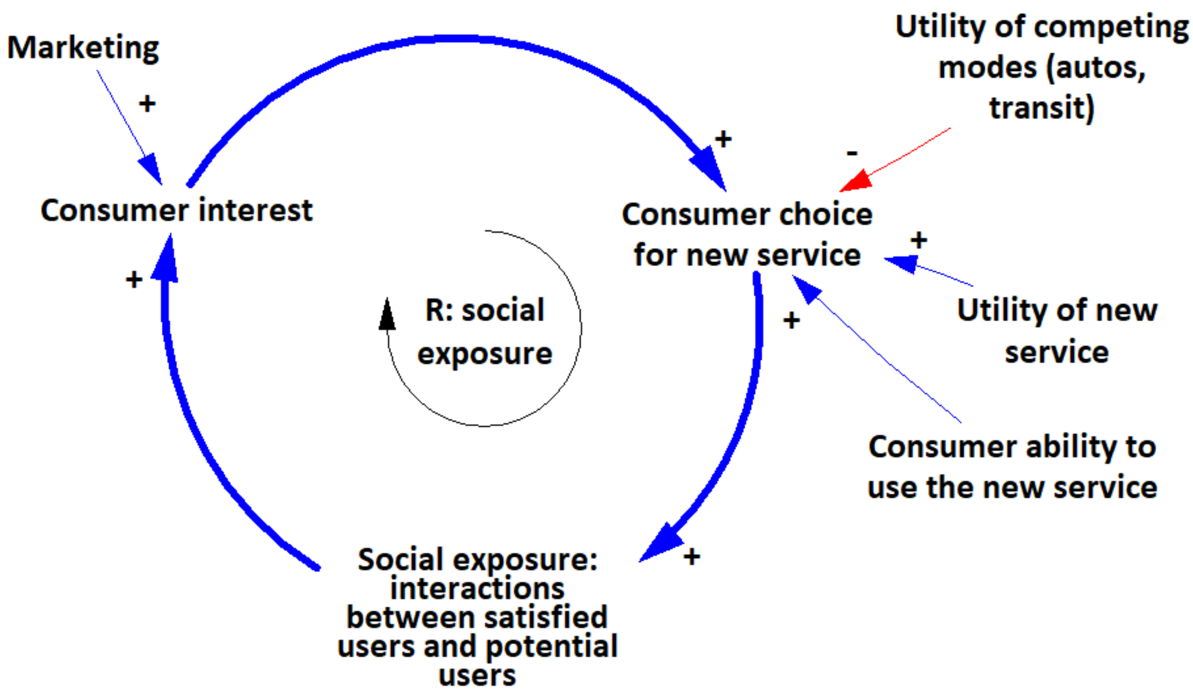


Figure 3-4 CLD for social network effects on product adoption

(Source: Volpe)

One published example of the reinforcing effects of technology adoption comes from (Struben and Sterman 2008). They first point to the historical transition, about a century ago, from horses to cars, and from steam/electric to internal combustion engines. They then develop a model of electric vehicle adoption, which considers social exposure and the installed bases of services supporting internal combustion engines (e.g., gas stations) as significant influencing factors.

Note that the loop holds equally well for a service that people try and *don't* like, or a decrease in service quality perceived by consumers. Utility of the service is lower; fewer people like it; they tell their friends that the service is not good, or is less good than it was; and, all else equal, consumer interest decreases.

It is also worth noting that, in a full model, this reinforcing loop would always be tempered by a balancing loop of a declining stock of people who have not yet adopted a service. This leads to the familiar S-curve of adoption of a new technology: at first, there are few users, so contacts between users and non-users are few and far between. As more people adopt the technology, the exponential growth takes off. At some point, however, rate of adoption slows as again there are few contacts between users and non-users, not because there are few users, but because few non-users remain.

3.2.2 Economically sustainable business models

A transportation service provider, whether it is trucking company, a transit agency, a taxi company, a TNC, or even a bike share provider, needs to have sufficient utilization of their assets so that revenues can, in the long term, exceed costs.

Figure 3-5 shows the fundamental CLD. The key balancing loop is that an increase in service leads to an increase in overall operating cost, which (all else equal) reduces the operating cash flow, making a further increase in service unsustainable (absent some external factor, such as a large amount of external revenue). Figure 3-5 is the generalization of Figure 3-3 to modes other than transit.

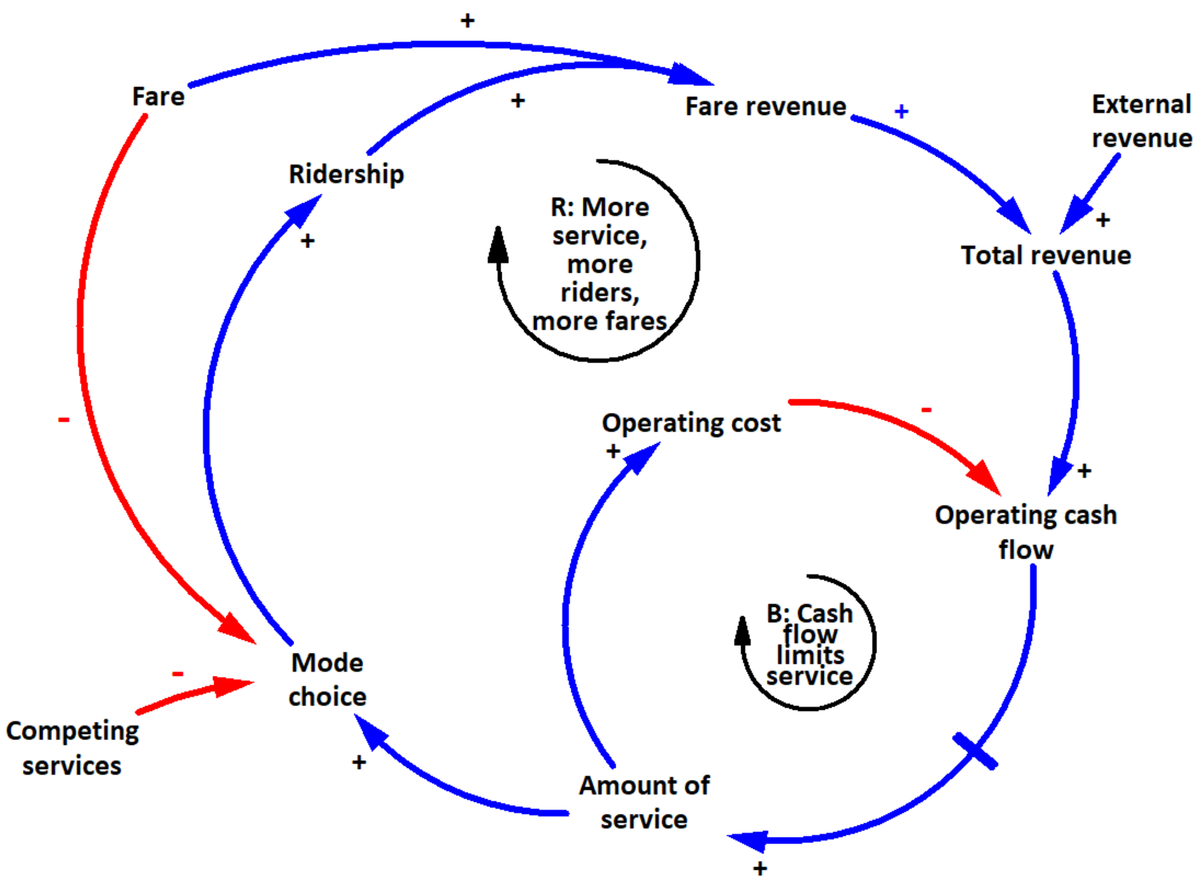


Figure 3-5 Business model CLD

(Source: Volpe)

The balancing loop in Figure 3-5, labeled "Cash flow limits service," runs from amount of service, which increases operating cost. Increase operating cost **reduces** operating cash flow. After some lag, if operating cash flow is reduced, then the amount of service must be adjusted downwards, to reduce costs.

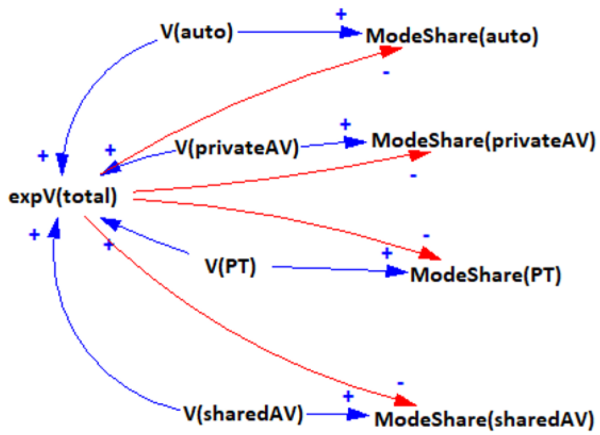
Of course, there is also a reinforcing loop in Figure 3-5: greater service increases mode choice and ridership, thus increasing revenue and allowing, all else equal, greater service provision. This loops is labeled “More service, more riders, more fares.” This figure thus shows in a microcosm how SD can highlight tipping points between scenario spaces. The results of competition between balancing and reinforcing loops in a model (known as loop dominance in SD analysis) often depend on the precise values of the parameters. In this case, for example, what is the ideal level of service which maximizes ridership? What is the ideal fare to maximize cash flow and thus continued ability to provide a good service?

3.2.3 Competition among modes

Automation is not being introduced in a vacuum. Automated driving systems and shared ADS services will be competing with existing modes, including human driven vehicles, public transit, existing taxi / TNC services and non-motorized modes. Mode choice models, described in (NCHRP 2012) and elsewhere, have been part of transportation planning practice for many years. Attributes of the choice typically include:

- Out-of-pocket cost
- Wait and access (walk) time
- In-vehicle time
- Comfort (Am I seated? Do I feel safe?)
- Characteristics of the traveler (e.g., income, automobile access)
- Traveler’s value of time (VOT)

The deterministic component of the utility of a mode, V(mode), is the appropriately weighted sum of these attributes. Figure 3-6 illustrates mode choices in the language of causal links. It includes the multinomial logit equations.



$$ModeShare(auto) = \frac{exp(V(auto))}{expV(total)}$$

$$ModeShare(privateAV) = \frac{exp(V(privateAV))}{expV(total)}$$

$$ModeShare(PT) = \frac{exp(V(PT))}{expV(total)}$$

$$ModeShare(sharedAV) = \frac{exp(V(sharedAV))}{expV(total)}$$

$$expV(total) = \exp\big(V(auto)\big) + \exp\big(V(privateAV)\big) + \exp\big(V(PT)\big) + \exp(V(sharedAV))$$

Figure 3-6 Mode choice as a causal model

(Source: Volpe)

The factors influencing the share of a particular mode include

- The utility of that mode, as experienced by the consumer. Higher utility leads to an increase in mode share.
- The combined utility of all the modes, including competing modes. Here, a higher utility for competing modes leads to a decrease in mode share for the mode of interest.

Note that, strictly speaking, Figure 3-6 is not a CLD as it does not contain any feedback loops. Once the mode competition building block is assembled with other building blocks of the transportation system, the causal links in this figure will slot into loops. For example, a loop can link the utility of a service in Figure 3-6 to the mode choice for that service (reinforcing loop in Figure 3-5), to the financial sustainability of offering a good service for that mode (balancing loop in Figure 3-5), to the attributes of mode choice, described in this sub-section.

3.2.4 Scale effects (more use leads to better service)

These are the reinforcing effects of services and users, where greater usage of a service justifies adding more service and/or higher quality service. In the long term, it may lead to more justification for infrastructure that supports the service.

In fixed route transit service, higher ridership may justify more frequent service, with shorter wait times. For a shared mobility service, higher usage may enable a higher density of vehicles, thus leading to lower empty repositioning times and wait times.

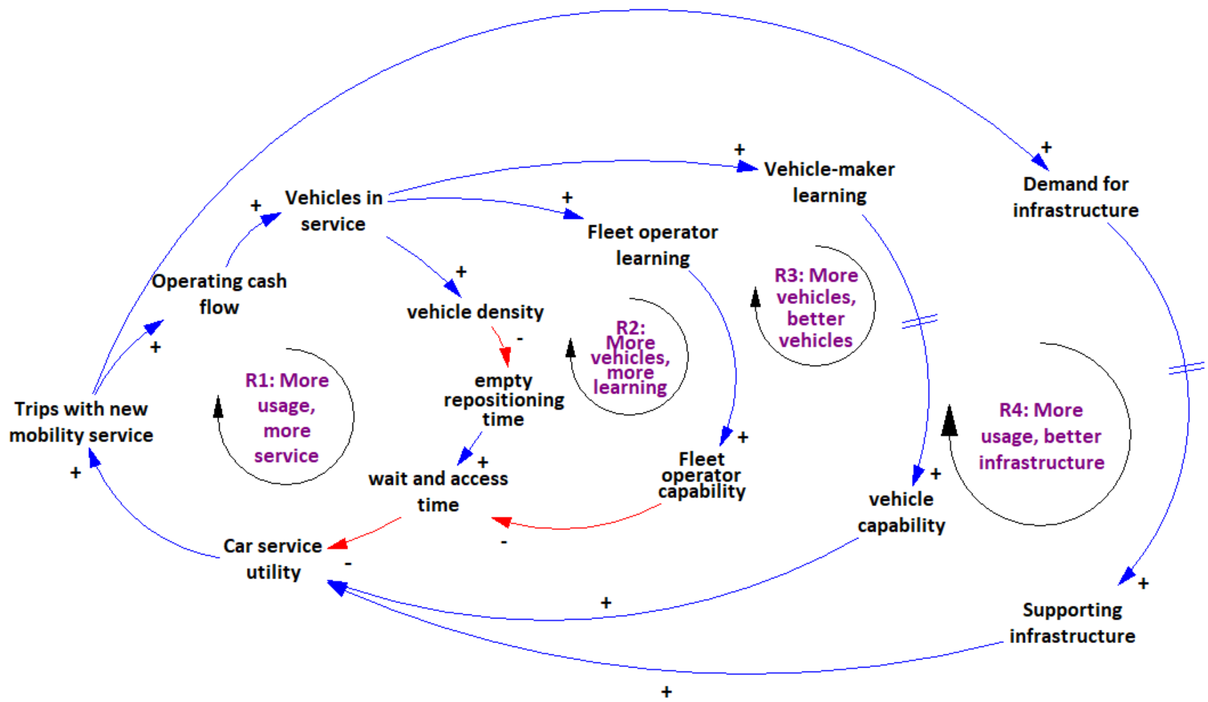


Figure 3-7 CLD for scale effects

(Source: Volpe)

Figure 3-7 has four reinforcing loops. The first two apply to shared mobility services. The last two would also apply to privately owned automated vehicles:

R1, More usage enables more service. With an increased number of trips with the new mobility service, operating cash flow increases. This enables more vehicles to be in service. With more vehicles in service, vehicle density increases, leading a shorter empty repositioning distances and times. (In fixed-route transit, more vehicles may lead to reduced headways or new routes closer to the traveler, a similar effect). With the shorter empty repositioning times, wait and access time is reduced, thus increasing the car service utility for the traveler. The increased car service utility leads to more trips with the new mobility service, thus closing the loop.

R2, More vehicles in service enhances fleet operator capabilities. With more vehicles in service, the fleet operator has more of an opportunity to learn how to run a more efficient service. This will increase fleet operator capabilities (e.g., for matching vehicles and trips), thus leading to a further reduction in wait and access times.

R3, More vehicles in service leads to more suitable vehicles. With more vehicles in service, the vehicle makers have an incentive to provide vehicles that are more suited to the service (for example, more automated vehicles that can serve the operational design domain required, or more vehicles that are accessible to allow persons with disabilities to use the system more easily). It will take time to develop and commercialize better vehicles, so there is a delay mark on this loop. Increased vehicle capability (e.g., better accessibility and traveler amenities) may further increase the utility of the service.

R4, More usage leads to improved infrastructure. With a high number of trips and users invested in the service, infrastructure owner-operators will take notice, especially if a large number of users start demanding improved infrastructure. This could take the form of dedicated curb space for pick-up/drop-off or even dedicated lanes. It usually takes time to change infrastructure, so there is a delay mark on this loop.

3.2.5 Congestion

Congestion leads to several balancing loops (Figure 3-8):

- B1: More people, less space. More use of a shared journey service decreases comfort (e.g., standees on a bus).
- B2: More people, longer wait. More use of a shared vehicle service increases vehicle utilization, which increases wait time for an available vehicle.
- B3: More traffic, slower trip. For vehicles sharing a road, more traffic increases travel time.

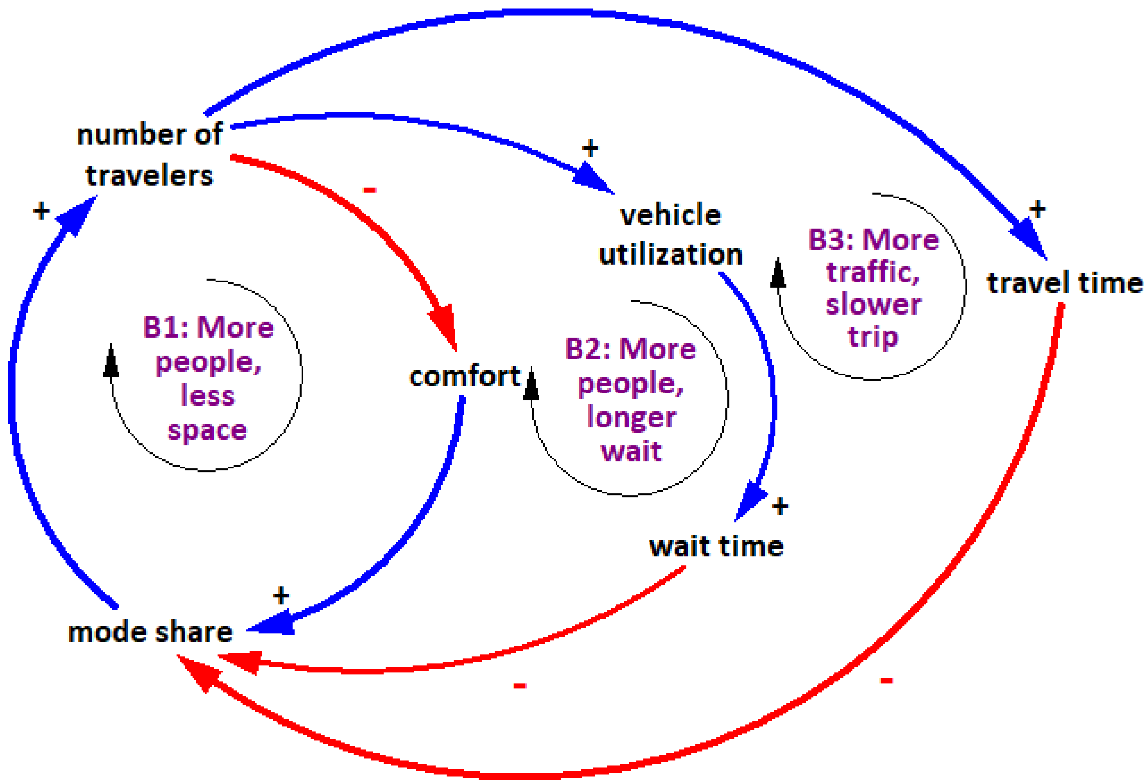


Figure 3-8 CLD for Congestion

(Source: Volpe)

3.2.6 Land use

The last sub-section of this chapter consists of two balancing loops that represent important relationships between travel utility and households' decisions of residential location.

Figure 3-9 shows the causal relationships affecting the desirability of living in an area X, where X might be urban, suburban, rural, or a regional center (a city, that is not the principal city, located in a major metropolitan area). The boxes at the right in the figure represent both the population and housing stock[4] in the region, items that will change over time. Note that both automation and telework frequency may reduce the disutility of the commute: travelers may value time spent traveling less if ADS enables them to be more productive during that time, and telework frequency reduces the disutility by reducing the time spent commuting. The disutility of commuting is affected by telework frequency, automation, travel time and out of pocket cost. The utility of living in a region is affected by the commute, housing space, school quality and housing cost. Housing cost is affected by taxes, the

[4] "Stock" is a concept in system dynamics, explained later in section 4.1.1 of this report.

rent/mortgage and parking cost at home (the latter most notable in urban areas). There is a balancing loop between the population and housing in a region: all else equal, more population/demand for a fixed supply of housing leads to higher housing prices, reducing the utility of living in the region. There is another balancing loop between development and housing price. If more housing is built than is demanded, the housing price might go down, making development less attractive.

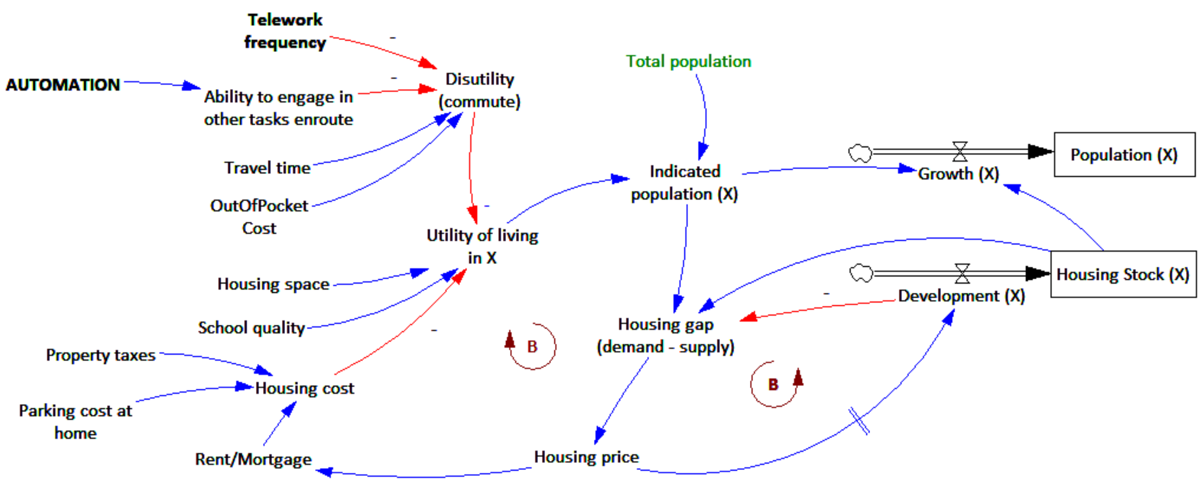


Figure 3-9 Relationships affecting the desirability of living in area X

(Source: Volpe (Shaw and Smith 2022))

3.3 Modeling Exercises, Presentations, and Interim Deliverables

This section sets the work outlined in sub-section 3.2 in the context of the Volpe Center team's work, both in this project and in earlier phases of the program, with collaborators and researchers from other offices and projects. It explains how that collaboration enriched this project's deliverables.

3.3.1 Zephyr webinar (May 2020)

After the 2020 TRB Innovations in Travel Modeling (ITM) conference was cancelled due to COVID-19, the Zephyr Foundation invited the project team to present a webinar, in lieu of the team's accepted presentation at ITM.

In response to this invitation, on May 27, 2020, a Volpe Center team (Hannah Rakoff, Ian Berg, Jingsi Shaw and Scott Smith) and Jeremy Raw of the FHWA Office of Planning presented a 90-minute interactive webinar on using system dynamics for transportation planning.

This webinar kicked off the Zephyr Foundation's spring 2020 series of webinars covering highlights of what would have been presented at the ITM conference. Volpe began with brief presentations on strategic transportation planning and the basics of system dynamics. The team then facilitated an interactive online group model building exercise in using system dynamics to consider the relationship between the COVID-19 pandemic and traffic fatality rates.

The nearly 90 attendees were a diverse and engaged group. Most (80%) were from the U.S., but others came from Canada, Europe, Japan, Australia, and other places around the world. The largest professional affiliations represented were state, MPO and local government in the U.S. (30%), private companies (30%), and academia (27%).

The session recording and slides are available on the Zephyr website: https://zephyrtransport.org/events/2020-05-27-learning-system-dynamics/

3.3.2 Europe – U.S. GMB exercise (February 2021)

The Volpe Center team has built collaborations with European research partners beginning in 2015. These partners research automation impacts, user response, and SD applications in transportation at several European research institutes and universities and Volpe has had a number of joint publications with them over the years. They include:

- Smith, S., Innamaa, S., Barnard, Y., Gellerman, H., Horiguchi, R., & Rakoff, H. (2017, July 19). Where will Automated Vehicles take us? A Framework for Impact Assessment [Poster]. Automated Vehicles Symposium, San Francisco. https://higherlogicdownload.s3.amazonaws.com/AUVSI/14c12c18-fde1-4c1d-8548-035ad166c766/UploadedImages/2017/PDFs/Proceedings/Posters/Wednesday_Poster%202.pdf
- Innamaa, S., & Kuisma, S. (2018). Key performance indicators for assessing the impacts of automation in road transportation: Results of the Trilateral key performance indicator survey. https://www.vtt.fi/inf/julkaisut/muut/2018/VTT-R-01054-18.pdf
- Rakoff, H. E., Smith, S., Innamaa, S., Barnard, Y., Harrison, G., & Shaw, J. (2020). Building feedback into modelling impacts of automated vehicles: Developing a consensus model and quantitative tool. Prepared for Transport Research Arena conference April 2020 (cancelled), Helsinki, Finland. https://rosap.ntl.bts.gov/view/dot/48969

Given the interest in how driving automation will impact the livability of cities, members of the Volpe project team, along with these European partners, organized a group model building exercise that brought several U.S. and European cities and regions into the same virtual room. Volpe and its European partners published the resulting model and analysis in (Harrison et al. 2022). The focus of the workshop was deliberately broad, looking at the potential effects of automation from the perspectives of a variety of city planners, rather than just professionals who work with emerging technology. Quality of life was an important concern for this group, with specific technologies, such as ADS, only being of interest if they can support the goal of improved quality of life. The causal loop diagram that came out of this workshop was complex and included:

- Outcomes including sustainability, public health, community cohesion, and economic vitality
- Competition for road space among various modes
- How the use of public space affects livability in a city
- Equity effects
- City revenues

The group model building workshop broadened the perspective of Volpe's work assessing impacts of automated driving systems, by working with city and regional planning practitioners who are primarily focused on how to improve life in their city via goals such as sustainability, health, community cohesion, and economic vitality, rather than evaluating impacts from the perspective of a particular technology.

3.3.3 Industry Studies and SCAG – teleworking and its impacts on land use (2021-2022)

Existing studies often use proxy modes, such as app-based ride-hailing and bike-sharing systems (Berg et al. 2020), to shed light on the impacts of ADS on the demand and supply of mobility service. The potential impacts include induced trip demand, curbside congestion, equity, system sizing and other questions of local or operational importance. However, they are less useful for understanding automation's long-term consequences on land use. The large-scale adoption of teleworking in 2020 as a response to the COVID-19 pandemic can serve as a living lab for researchers to better understand the implications of ADS on urban form and employment. The research team identified similarities between how ADS and teleworking could influence households' travel decisions and residential location choices, and presented the work at two occasions: the Industry Studies Association (ISA) Annual conference in June 2021 and a meeting of the Southern California Association of Governments (SCAG) modeling task force in January 2022 (Shaw and Smith 2022).

At the ISA annual conference, Hannah Rakoff and Jingsi Shaw presented initial causal loops demonstrating similarities between teleworking and future automated vehicle adoption, as both could lead to less disutility associated with commuting for workers. In addition, Rakoff and Shaw sketched out the potential impacts of teleworking, together with ADS, on the benefits of working in an office setting, spatial clustering of innovation, and urban vitality.

The presentation at the SCAG meeting showed how qualitative system dynamics modeling offers a way to capture the multifaced impacts of disruptive changes, such as teleworking, on transportation and land use. One CLD example illustrates the basic agglomeration effect driven by reinforcing loops between employment and urban amenities (e.g., restaurants) that rely on a high daytime population density. The example further demonstrates how teleworking and traffic congestion play a role in forming several balancing loops, which limit the agglomeration effect and could have negative impacts on economic development in the urban core. Another example shows how teleworking could lead to more households considering moving to less dense areas – population decentralization. This trend could have important implications on land use planning in different types of regions and for how (and whether) mobility services serve suburbs and rural areas, a question that has important links to the business sustainability of ADS for shared mobility services in suburban and rural areas. The study shows that an SD model can provide value to modelers by developing shared mental models and a common language for all stakeholders, facilitating modeling and policymaking, and identifying new directions to explore.

The presentation slides for SCAG meeting can be found at:
https://scag.ca.gov/modeling-task-force

3.4 Summary

In addition to the three exercises summarized above, the project team worked with several state and local planning organizations, work summarized in (Berg et al. 2020). These efforts showed the value of group model building. GMB in the transportation domain speaks a language accessible to both planners and modelers, helping to bridge that gap. The CLDs can be used to develop common mental models of a system, to help surface any miscommunications and to sustain interagency collaborations over a period of months or years. Developing CLDs requires participants to think about the elements of the system, and how they affect each other, thus leading to greater clarity on possible leverage points.

CLDs developed by the core SD modeling team may also provide a useful outreach tool. GMB is also a helpful way to structure engagement with a larger group, as the Zephyr webinar demonstrated.

The engagement with a variety of stakeholders also reveals insights about attitudes towards ADS, and its possible effect on communities. With the city and regional planners in the joint U.S.-Europe workshop, in particular, ADS was viewed as a means to an end, only desirable if it can serve the goal of improved urban livability.

Unlike traffic microsimulation or static planning models, which have a long history and are limited to a few domain areas, system dynamics is a much more general methodology. This has the advantage of potentially revealing new insights, important when a new mode with potentially transformative effects is introduced. For example, SD can easily encompass safety, access to destinations and feelings of social inclusion or exclusion, all in one model (Harrison et al. 2022). To help develop a new SD model, it's useful to keep in mind that certain archetypal behaviors, such as those shown in section 3.2, often apply across modes and even across disciplines. An essential first step is to work with stakeholders to define the problem, via a qualitative model building exercise. Once there is a common understanding of the problem, it becomes possible to build, calibrate and use a quantitative model, which is the topic of the next chapter.

4 Quantitative Modeling

4.1 Introduction to Quantitative SD Modeling

Quantitative SD is a modeling and simulation approach that is well suited for complex systems that evolve over time. It applies ideas from control systems theory to complex technological, social, and economic problems. Key elements[5] include

- Causality: What are the causes and effects in the system? For example, as travel becomes less expensive, people travel more.
- Feedback: How do the effects become causes in their own right, sometimes linking back to their own causes? For example, as people travel more, all else equal, the cost of travel also changes, in this instance becoming more expensive as demand rises.
- Structure of a system: How do these causes and effects influence the system's behavior? It is a key tenet of SD that a system's structure determines its behavior – if one wants to effect change, one must address system structure, such as by changing incentives, rather than insist on the people in the system acting differently within an unchanged system.
- Levels and rates (also known as stocks and flows): What are the attributes of the system that change over time?
- Modeling and simulation: Computer models to show outcomes, often for many scenarios
- Policy design: using the understanding gained to make better decisions

There are many possible business models for ADS. In this chapter, SD is used to address one form of ADS commercialization, that of a shared automated car service. We build a quantitative SD model of the interaction of service provision with demand for that service. The model builds upon concepts of supply and demand with the building blocks presented in section 3.2 to represent the structure of the system and answer the question of how such a system is likely to perform in the various scenarios of travel demand (trip density) that may arise in urban, suburban and rural contexts.

4.1.1 Stocks and flows

In addition to the causal relationships discussed in chapter 3 of this report, an important concept needed to create quantitative models is that of stocks and flows (Figure 4-1). A stock is an accumulation of something. It might be cash on hand, the size of a vehicle fleet, or a stock of information. A stock does not change instantaneously but rather via its flows. A flow is what goes into or out of a stock, with an accompanying rate. In the figure, income represents flow in, and expense represents flow out. Stocks and flows provide a way to rigorously model the key attributes over the system that change over time.

[5] https://systemdynamics.org/what-is-system-dynamics/

Figure 4-1 Stocks and flows

(Source: Volpe)

Table 4-1 shows some examples of stocks and flows.

Table 4-1 Examples of stocks and flows

Stock	Flows increasing the stock	Flows reducing the stock
Cash on hand	• Receiving income • Selling assets • Borrowing	• Paying expenses • Buying assets • Repaying loans
Population in a region	• Births • Immigration	• Deaths • Emigration
Vehicles of a certain type owned by consumers	• Rate of initial sales of vehicles by dealer to consumers	• Vehicles wearing out
Persons familiar with automated driving systems	• Persons becoming familiar via experience with ADS trips or marketing	• Persons forgetting • Persons departing (death, out-migration)
Auto-maker technical knowledge	• Gaining experience from manufacturing, sales, and vehicle maintenance (learning by doing) • Gaining experience via investment to increase technical knowledge via staff recruitment or otherwise	• Knowledge loss through staff departures • Knowledge becoming obsolete

4.2 Review of Relevant Literature on SD for Transportation Modeling

This project's work draws on elements of work from a number of other researchers published over the past 30 years.

(Abbas and Bell 1994) reviewed the strengths and weaknesses of SD with respect to transportation modeling. They found that SD models are more useful for improved understanding and policy analysis, rather than for point predictions. SD, unlike static approaches, has the advantage of directly addressing the dynamic behavior of systems. They conclude that, “The SD methodology can offer a lot in terms of better planning and solving transport related problems. SD should not be thought of as a methodology to replace or substitute for the traditional transport modeling approaches. Rather it should complement and be integrated with the existing approaches, to contribute, in a collective manner, to solving transport problems.”

(Shepherd 2014) reviewed some 50 peer-reviewed papers published since 1994, finding that fields of application include take-up of alternate fuel vehicles, supply change management affecting transport, highway maintenance, airport infrastructure, airline business cycles, and several emerging application areas.

(Struben and Sterman 2008) modeled the transition to alternative fueled vehicles, focusing on the social exposure dynamics that influence adoption. Components of their model include consumers, the automotive industry, automotive services (e.g., repair), energy production/distribution, and other fields relevant to energy development. Important stocks in their model included installed base of vehicles, driver familiarity, and auto-maker production experience. Although this paper is obviously applicable to electric vehicle (EV) adoption, it is also relevant for automated vehicles, as it models industry learning, consumer learning, and vehicle fleet transitions.

(Naumov, Keith, and Sterman 2022) looked at policies to accelerate the replacement of internal combustion engine (ICE) vehicles with EVs, via a cash-for-clunkers (C4C) program. They concluded that simply promoting sales of EVs will not be enough to meet 2050 climate goals. Incentives (such as C4C) will lead to a greater emissions reduction. Major elements of their SD model included the vehicle fleet, total fleet emissions per mile, and market formation (social exposure, learning-by-doing, research & development, and marketing) for EVs.

(Pfaffenbichler, Emberger, and Shepherd 2010) and (Pfaffenbichler 2011) reported on their development of the integrated transportation and land use model MARS. Components of MARS include

1. Scenario input
2. Policy input
3. Transport model, with commuting and other trips
4. Land use model, with housing and workplace development and relocation submodels
5. Fleet composition and emission module
6. Evaluation and assessment module
7. Output representation modules

After initial calibration in Vienna, the MARS model was tested in Leeds, UK and several other cities around the world.

In a conference paper, (Gühnemann et al. 2018) reported testing of several automated vehicle scenarios in the MARS model. Two scenarios integrated AVs with public transport, while the privately owned AV scenario leads to an increase in car mileage traveled.

(Nieuwenhuijsen et al. 2018) simulated the diffusion of AVs in the Netherlands, finding that market penetration would vary greatly depending on assumed scenario and policies. Components of their model for various levels of automation included technology maturity, vehicle purchase price, perceived utility by the end consumer, fleet size/adoption, and the interaction between car-ownership and car sharing.

Building on the model from (Nieuwenhuijsen et al. 2018), (Harrison, Shepherd, and Chen 2021) looked at uptake sensitivities for connected and automated vehicles. Attributes of their scenarios include Internet of Things Quality (the quality of connectivity, which influences comfort and safety), utility (comfort, safety, and acceptance of new technologies), safety value (weighting of safety versus comfort), and car-sharing. They concluded that although car-sharing and safety value had little impact, the utility had a great effect on uptake. Poor quality Internet of Things connectivity could inhibit market uptake.

4.3 Car Service Model

The Volpe team developed a car service model which can apply to any shared fleet, e.g., taxi, transportation network company (TNC), and bike share. It balances the needs of the business (to make money via sufficient vehicle utilization in revenue service) and the user (affordable service with acceptable delay). Figure 4-2 shows a simplified causal loop diagram. As before, the blue links (marked with plus signs) are positive effects, and the red links (with minus signs) are negative effects. Fare is treated as exogenous. There are three feedback loops:

- B1: Net revenue limits service. For the business to be sustainable, the amount of service provided needs to be consistent with the net revenue (revenue minus cost). Providing more service increases the cost. If net revenue becomes negative, then the business is not sustainable. This loop corresponds to the balancing loop in Figure 3-3.
- B2: Tradeoffs between vehicle utilization and service utility. For riders to use the service, the vehicle utilization needs to be consistent with ridership. If there are too many riders for the service provided, the utility of the service decreases (via crowding or long wait times), thus leading to reduced ridership.
- R: Better service, more riders, more revenue, more service. There is a reinforcing loop around the outside of the balancing loops, via which more ridership leads to more revenue, enabling more service, increasing the utility of the service, leading to more ridership. The negative side of this loop is the transit death spiral, with less ridership leading to less revenue, leading to less service, with lower utility. This loop corresponds to the reinforcing loop in Figure 3-3.

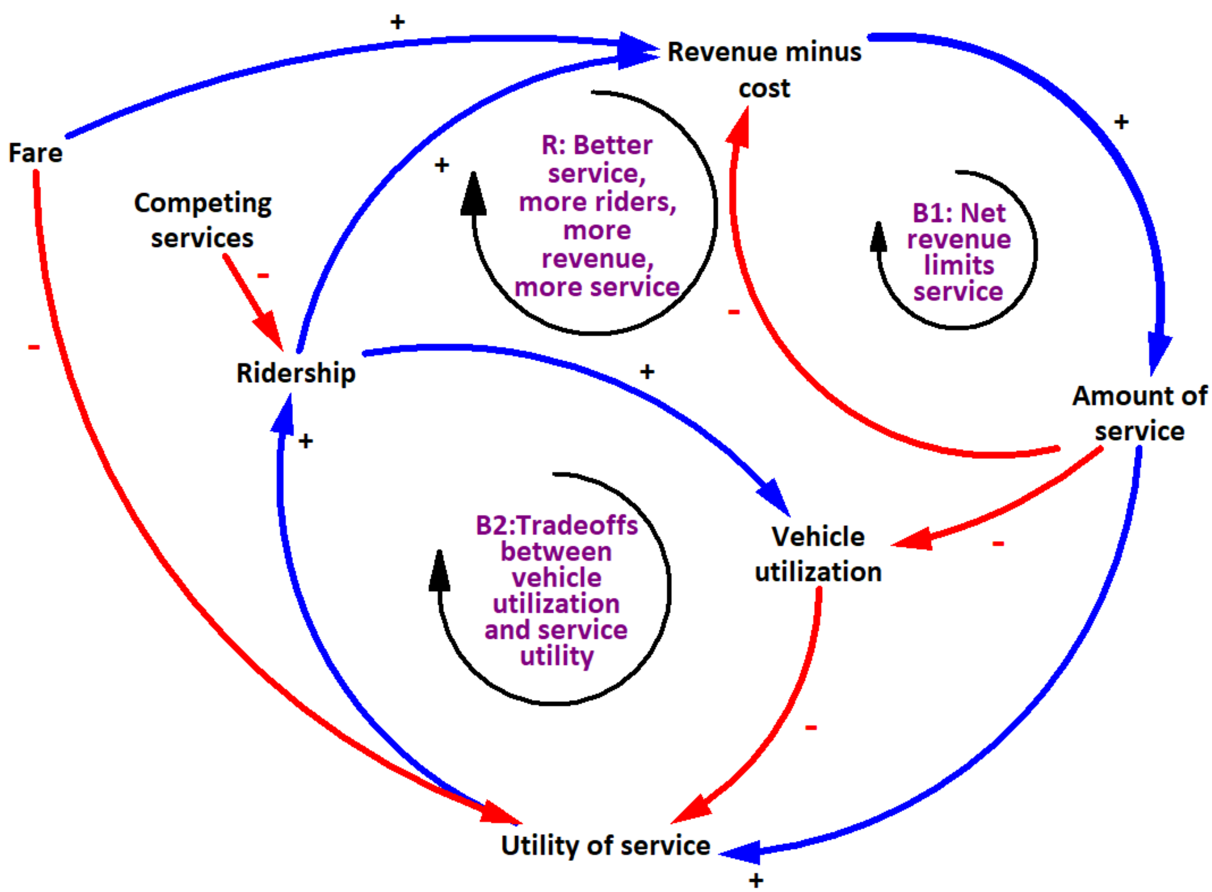


Figure 4-2 Car service model: high level structure

(Source: Volpe)

Figure 4-3 shows the full model. Exogenous input parameters are those with no inputs themselves; they are shown in green in the next several figures for convenience. The other variables are calculated. Appendix 2 contains the text representation (Vensim "mdl" file) of this model.

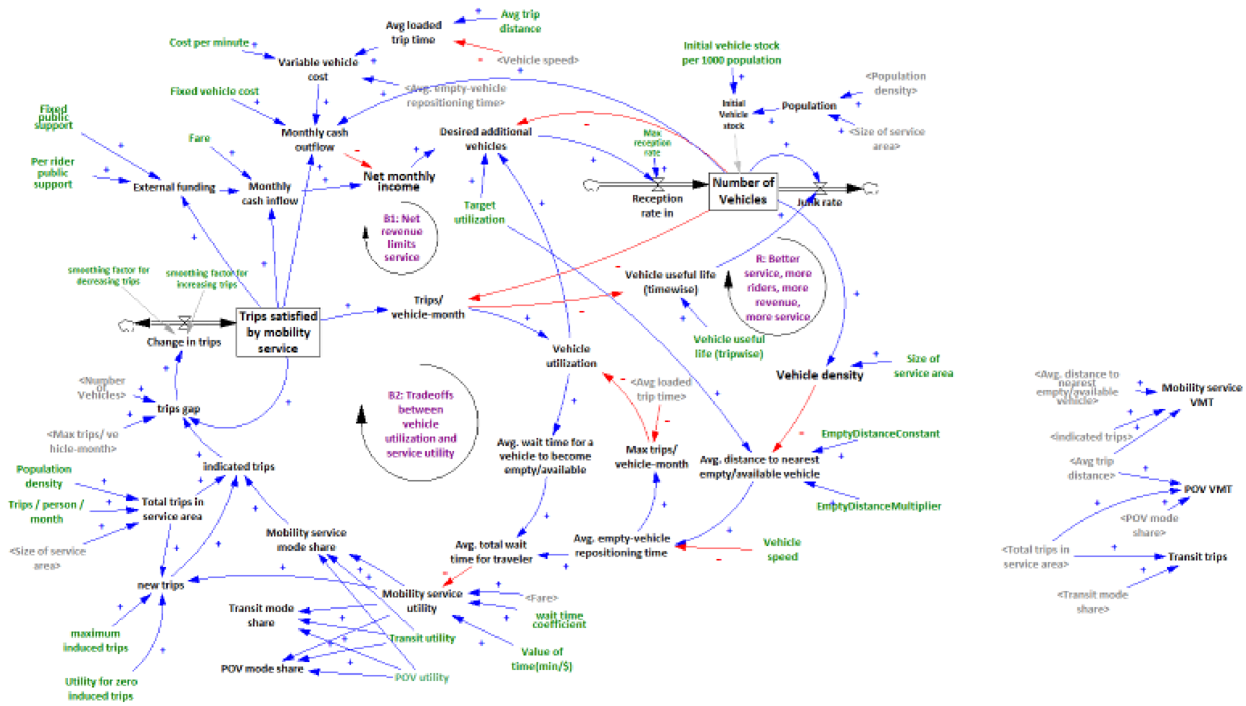


Figure 4-3 Car service model: full model view

(Source: Volpe)

The two balancing and one reinforcing loops depicted in the high level model structure (Figure 4-2) are also labeled on this figure. They are:

- B1: Net revenue limits service. All else equal, a higher number of vehicles decreases the trips/vehicle-month, which also decreases vehicle utilization, decreases the average wait time for a vehicle to become empty and available, and decreases average total wait time for the traveler. This in turn increases mobility service utility, which increases mobility service mode share, increases indicated trips, and increases the trips gap – the gap between indicated trips which are feasible with the number of vehicles in service, and actual trips satisfied by the mobility service. A higher trips gap leads to a greater net increase in trips, the flow to the stock of trips satisfied by the mobility service. In turn, this increases monthly cash outflow, which decreases net monthly income, and then decreases the service provider's desired additional vehicles. That decreases their reception rate in, which is the inflow to the stock of number of vehicles. For a given junk rate (outflow from the number of vehicles), a decrease in the inflow will lead to a decrease in the number of vehicles.
- B2: Tradeoffs between vehicle utilization and service utility. All else equal, the more trips that are satisfied by the mobility service, the higher the trips/vehicle-month and vehicle utilization rises. This increases the average wait time for a vehicle to become empty and available, and increases average total wait time for the traveler. This in turn decreases mobility service utility, which decreases mobility service mode share, decreases indicated trips, and decreases the trips

gap. This reduces the change in trips – the net flow to the stock of trips satisfied by mobility service – so that stock's value decreases.

- R: Better service, more riders, more revenue, more service. Finally, all else equal, a higher number of vehicles increases vehicle density, which decreases the average distance to the nearest empty and available vehicle and in turn decreases average empty-vehicle repositioning time. This then leads to a decrease in average total wait time for the traveler, which means and increase in mobility service utility. That leads to an increase in mobility service mode share, more indicated trips, a higher trips gap, a greater net inflow to the stock of trips satisfied by the mobility service, a higher value for that stock (i.e., more trips), a greater monthly cash inflow, higher net monthly income, more desired additional vehicles on the part of the service provider, and a greater inflow to the stock of number of vehicles, leading to more vehicles.

The model has three major sections:

- Business model of providing the service
- The service as seen by riders
- Rider response

The business model of providing the service is depicted in the top of the stock-flow diagram (Figure 4-3, with close-up view in Figure 4-4). The stock, and key output, of this part of the model is Number of Vehicles. If the net monthly income is positive, and the vehicle utilization is higher than the target utilization, then the service provider increases the number of vehicles. If these conditions do not hold, then the number of vehicles declines as vehicles wear out (Junk Rate). The number of vehicles influences both vehicle density and vehicle utilization, both important causal inputs to the service as seen by riders.

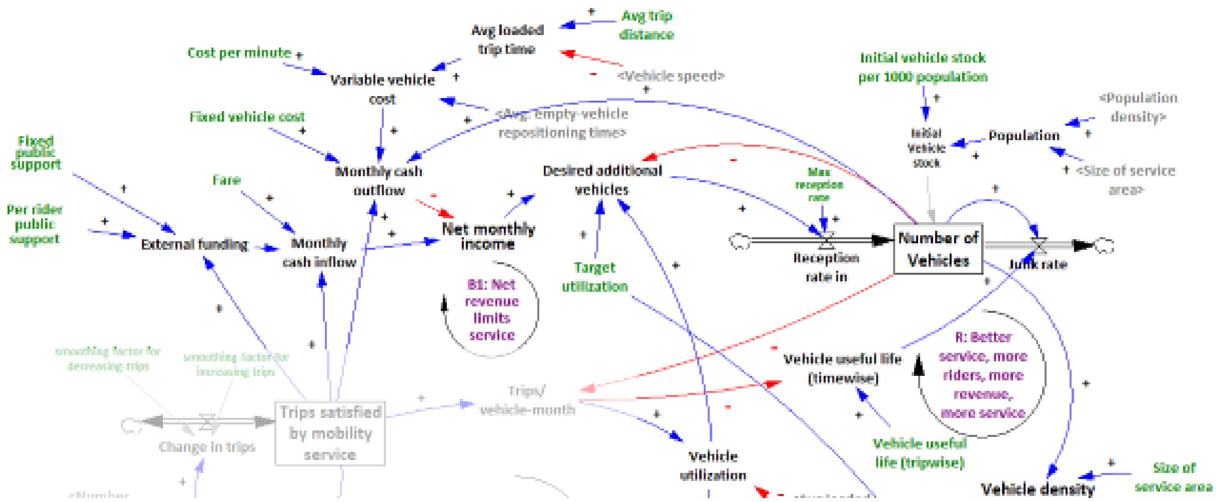


Figure 4-4 Business model section of car service model

(Source: Volpe)

The service as seen by riders is show in the lower right part of Figure 4-3, with close-up view in Figure 4-5. Important inputs to this part of the model include vehicle utilization and vehicle density. The key output of this section of the model is the average total wait time for the traveler, which has two components: the wait for a vehicle to become available, and the amount of time it takes for an empty vehicle to travel to the rider. All else equal, the greater the density of vehicles in the system, the less time a traveler must wait for a vehicle. On the other hand, the higher the utilization of those vehicles, the longer the traveler must wait.

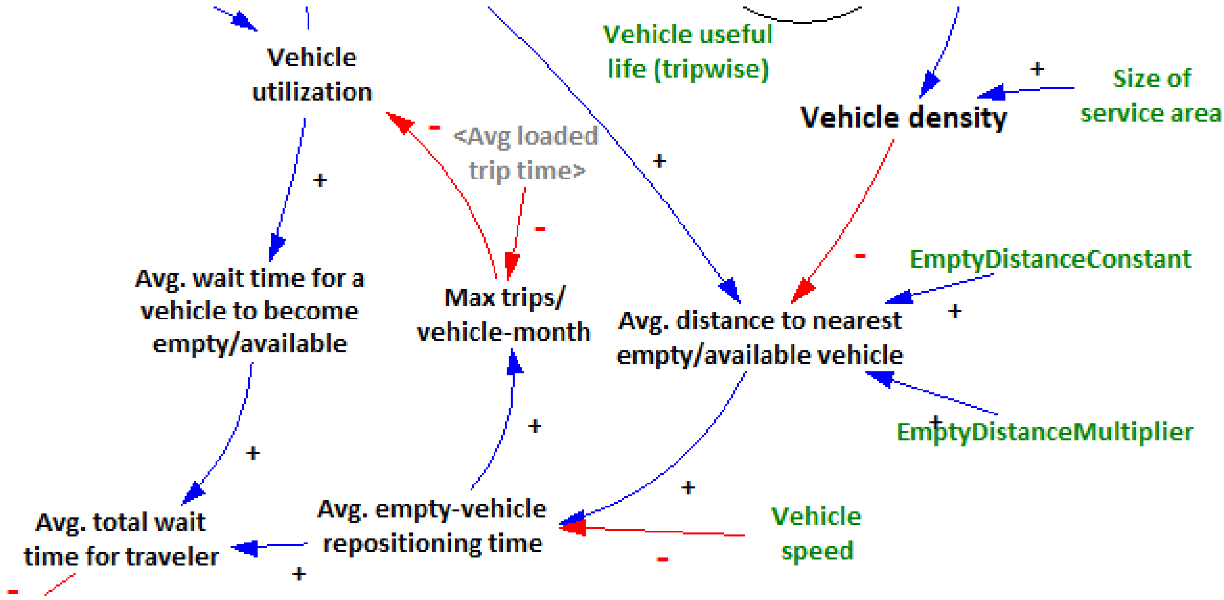


Figure 4-5 Service as seen by riders

(Source: Volpe)

Finally, rider response is shown in the lower left part of the diagram (Figure 4-3, with close-up view in Figure 4-6). There is a three-step process leading to an output of trips satisfied by the mobility service.

The first step is a simple logit model that calculates the utility of the mobility service (see section 4.3.1.6 for the equations) and compares it to the utilities of transit and privately owned vehicle (POV). The transit and POV utilities are set when the initial model is calibrated to current conditions. The mobility service mode share is calculated based on these utilities. The second steps adds induced trips to the new mobility service (see section 4.3.1.7 for the equations). These are trips not being made today, but that will be made if a new mode is offered that is sufficiently attractive in terms of price or wait time. The mobility service mode share, multiplied by current total trips in the service area, plus induced trips (called new trips in the figure), gives the indicated trips on the mobility service. Finally, since travelers won't switch to or abandon a new mode immediately, the actual trips satisfied by the mobility service, is given by a smoothing function that seeks to match indicated trips.

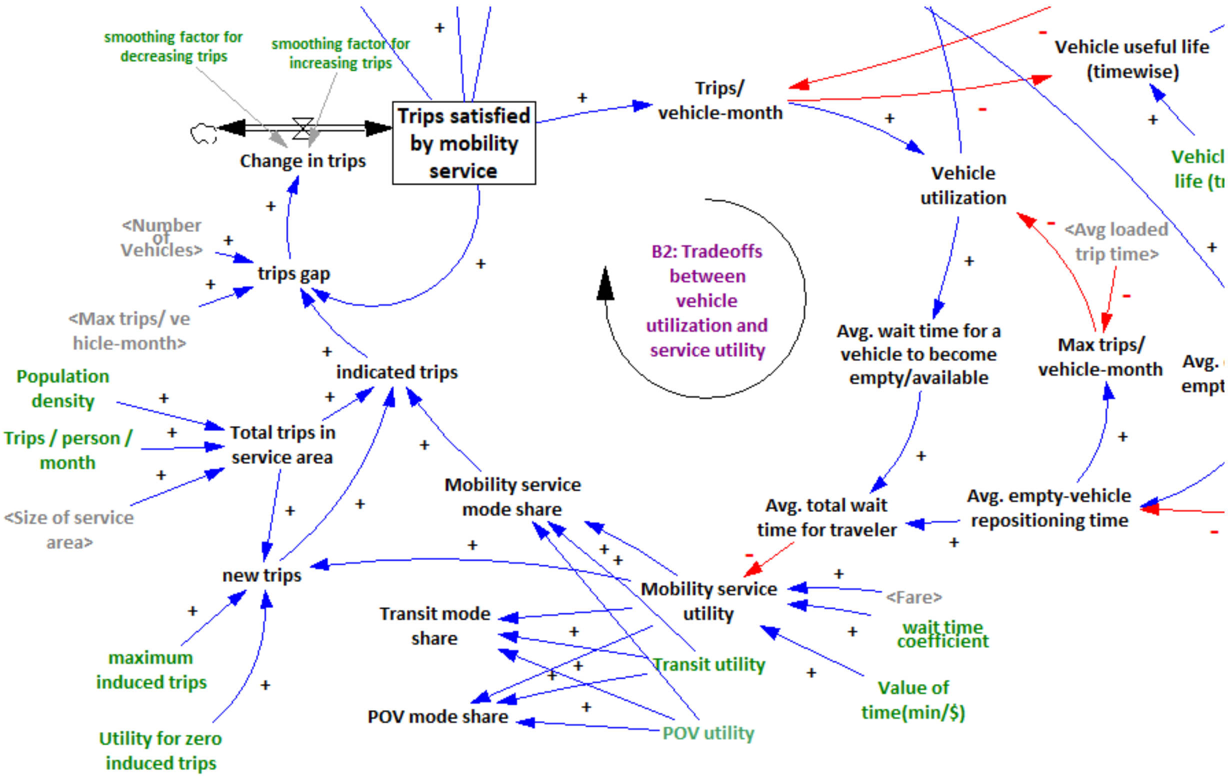


Figure 4-6 Rider response section of car service model

(Source: Volpe)

Table 4-2 summarizes the inputs to the model. These are the exogenous items in the above diagrams, shown in green and with no inputs themselves.

Table 4-2 Inputs to the car service model[6]

Exogenous inputs	Initial Value	Units	Comment
Fixed public support	0	$ / month	asserted; used for sensitivity testing
Per rider public support	0	$/ trip	asserted; used for sensitivity testing

[6] These inputs were developed in 2021. With the recent (May 2022) rapid rise in fuel and other prices, operating costs and fares would be a bit higher today.

Exogenous inputs	Initial Value	Units	Comment
Vehicle operating cost (cost per minute)	0.35 or 0.1[7]	$ / minute	AAA driving costs.[8] FlexCar pricing[9]
Fixed vehicle cost	400	$ / month	AAA driving costs. FlexCar pricing
Fare	10 to 12 or 3 to 4	$ / trip	asserted
Avg trip distance	5	Mile (mi)	Massachusetts TNC data; National Household Travel Survey (NHTS) for all trips with assumption about TNC trip length distribution
Target utilization (rho)	0.6	dimensionless	Asserted. This is the fraction of time a shared vehicle is serving travelers. It includes both the time that vehicles are repositioning themselves, empty, to pick up a traveler, and time with the traveler(s) on-board.
max reception rate (acquiring vehicles)	300	vehicle / month	asserted
Initial vehicle stock per 1000 population	1	vehicle / 1000 persons	The overall initial vehicle stock is then calculated based on - Initial stock per 1000 population (set at 1) - Population For example, a population of 40k would lead to an initial vehicle stock of 40.
vehicle useful life (tripwise)	10000	trips	asserted
Size of service area	varies	mi*mi	Census or community information
vehicle speed	20	mi /hour	Can assert a plausible value or could be an output from a model that considers congestion. For now, asserted
wait time coefficient	-0.05	dimensionless	Obtain from travel demand model. For now, asserted.
value of time	5	minutes / $	Corresponds to $12/hour, which is in the range of values from literature on

[7] The $0.35 per minute includes driver pay. The $0.10 per minute is the vehicle operating cost (without driver)

[8] For a small sedan, AAA estimated operating cost of $0.1567/mile. At 3 minutes / mile, this is $0.05 per minute. Ownership cost was estimated at $4,880 / year, or about $407 / month. https://newsroom.aaa.com/wp-content/uploads/2021/08/2021-YDC-Brochure-Live.pdf .

[9] FlexCar is currently offering short term leases (by the week) for members at $60 / week (~$250 / month) and $0.39 / mile (at 3 minutes / mile, this is about $0.13 / minute). (May 2022)

Exogenous inputs	Initial Value	Units	Comment
			travel demand models. The SD model uses the inverse (minutes / $).
Transit utility	-1	dimensionless	Used to calibrate the model
POV utility	2	dimensionless	Used to calibrate the model
Maximum induced trips	0.2	Percentage of total trips in service area	From the potential increase in trips by transportation disadvantaged populations [10]
Utility for zero induced trips	-3	dimensionless	Matches the utility of human-driven mobility service.
Trips / person / month	varies	trips/(person*month)	NHTS; This model uses values between 90 and 110.
Population density	varies	persons / mi*mi	Census
smoothing factor for increasing trips	6	month	asserted
smoothing factor for decreasing trips	1	month	asserted
Empty distance constant	0	mi	Asserted (could optionally be used to increase empty miles, to account for inefficiency in vehicle assignment or repositioning)
Empty distance multiplier	1	dimensionless	Asserted (could optionally be used to increase empty miles, to account for inefficiency in vehicle assignment or repositioning)

Outputs are listed in Table 4-3.

Table 4-3 Car service model outputs

OUTPUT	Units
Fleet size for shared service	vehicles
Wait time for the traveler	minutes
Net monthly income to the service operator	$ / month
mode share	dimensionless

---

[10] (Stephens et al. 2016) suggest a potential 20-percent increase in overall travel resulting from increased travel by the transportation-disadvantaged. (Harper et al. 2016) reviewed data from the 2009 National Household Travel Survey, comparing overall travel with the amount of travel by the elderly, non-motorists, and those with travel-restrictive conditions. If ADS enables the amount of travel by these populations to increase to the amount of travel (VMT) observed in the remainder of the population, overall annual light-duty VMT would increase by 14 percent.

OUTPUT	Units
trips per month using the service	trips / month
Mobility service VMT	miles / month
POV VMT	miles / month
Transit trips	trips / month

4.3.1 Important relationships in the model

The model includes a number of important relationships:

- net monthly income of the mobility service provider, based on revenue and costs
- desired additional vehicles, based on demand and monthly income of service provider
- vehicle utilization as fraction of trips made over trips possible during service availability time
- average distance to the nearest vehicle that is empty and available
- average total wait time for traveler, based on queuing theory
- mobility service mode share and utility, and
- and induced trips, based on utility of the new service.

4.3.1.1 Net Monthly Income

Determines if the car service can expand, and is equal to

Net Monthly Income = Monthly cash inflow – Monthly cash outflow, where

Monthly cash inflow = (Fare x Trips) + External Funding, and

Monthly cash outflow = (Fixed Cost x Vehicles) + (Variable Cost x Trips)

Variable Cost = Cost per minute x (Loaded trip time + Empty vehicle repositioning time)

4.3.1.2 Desired Additional Vehicles

Drives expansion of the car service and seeks to match vehicle utilization to target utilization. Note that unless new vehicles are acquired, the car service will shrink, due to the vehicle junk rate.

$if\ Net\ Monthly\ Income \leq 0, then\ Desired\ Additional\ Vehicles = 0$, otherwise

$Desired\ Additional\ Vehicles = Number\ of\ Vehicles\ x\ (\max(0, Vehicle\ Utilization - Target\ Utilization))$.

For example, if the system now has 100 vehicles, target utilization = 0.6, and vehicle utilization = 0.8, then Desired Additional Vehicles = 20 = 100 x (0.8-0.6)

4.3.1.3 Vehicle Utilization

$$Vehicle\ Utilization = \frac{Trips\ per\ vehicle\_month}{Max\ Trips\ per\ vehicle\_month}$$

where

$$Max\ Trips\ per\ vehicle\_month = \frac{10\frac{hours}{day}\ x\ 30\frac{days}{month}\ x\ 60\frac{minutes}{hour}}{1 + Avg\ loaded\ trip\ time + Avg\ empty\ vehicle\ repos.time}$$

The denominator is the minutes consumed by each trip, where the "1" is a constant to allow for dispatch time. It is assumed that each vehicle operates 10 hours / day.

4.3.1.4 Avg. distance to nearest empty/available vehicle

In a situation where vehicles are randomly and evenly distributed over a region, the expected distance to the nearest empty vehicle is proportional to a constant divided by the square root of the number of vehicles. This is 0.5 / Square root of n (straight line distance), or approximately 0.625 / Square root of n (right angle distance) where n is the number of empty vehicles per square mile (Larson and Odoni 1981, p. 151). However, in reality, the distance traveled will usually be larger, for two reasons: (1) road circuity (actual on-road distance is larger than the straight-line or even right-angle distance) and (2) imbalance of trips. For example, early in the morning, there are typically far more trips to an airport than from the airport, leading to empty distances almost as great as the loaded distances, as vehicles return from the airport to pick up additional passengers. Therefore, Volpe developed two parameters are used to adjust the average empty distance:

EmptyDistanceConstant – a constant added to all empty movements

EmptyDistanceMultiplier – a multiplier applied to empty movements, to account for inefficiency. If the empty movements matched the theoretical value, this multiplier would be 0.5 for straight line movements, and 0.625 for right angle movements.

The equation for Avg. distance to nearest empty/available vehicle is

$$EmptyDistanceConstant + \frac{EmptyDistanceMultiplier}{Square\ Root\ ((1 - Target\ Utilization) * VehicleDensity)}$$

4.3.1.5 Avg. total wait time for traveler

This has two components, the Avg. wait time for a vehicle to become empty/available, and the Avg. empty-vehicle positioning time

$Total\ wait\ time = wait\ for\ empty\ vehicle + empty\ vehicle\ repositioning$, where

the wait for the empty vehicle is proportional to: $\frac{1}{1 - Vehicle\ Utilization}$ (a fundamental result from queuing theory).

In the model, to avoid divide-by-zero issues,

$$wait\ for\ empty\ vehicle = \frac{2}{\max\left(abs(1 - Vehicle\ Utilization), 0.01\right)}$$

The empty vehicle repositioning time is proportional to the average distance to the nearest empty vehicle (see 4.3.1.4).

4.3.1.6 Mobility service mode share and utility

Mode share comes from a simple logit equation, where V(x) is the deterministic component of the utility of x:

$$Mode\ share = \frac{\exp\left(V(mobility\ service)\right)}{\exp\left(V(mobility\ service)\right) + \exp\left(V(transit)\right) + \exp\left(V(POV)\right)}$$

The utility of the mobility service is as follows.

$$V(mobility\ service) = \ WaitTimeCoefficient\ x\ (WaitTime + invValueOfTime\ x\ Fare)$$

In the model, WaitTimeCoefficient = -0.05 and invValueOfTime = 5 minutes / $. For a human-driven service, values of the utility typically range from -2 to -4.

In travel demand modeling, the utility of a traveler using a mode combines the factors that may make use of the mode desirable or undesirable: fare, in-vehicle travel time, wait time, out-of-vehicle travel time, reliability, and intangible factors such as perceived safety and comfort. By itself, the numerical value of utility means very little, except that lower (more negative) values mean that use of a mode is less desirable. It is the difference between utility values for the different modes that is important and is used to calculate the mode share values.

In model calibration, *V(transit)* and *V(POV)* are adjusted so that transit and mobility service mode shares match observed conditions.

4.3.1.7 Induced trips

If the automated mobility service has a lower fare than the taxi/TNC that preceded it, then, all else equal, there will be some induced trips. These are represented via a linear relationship with respect to the mobility service utility (Figure 4-7)

The induced trips fraction is governed by two parameters:

- Maximum induced trip fraction =fraction of total trips that would be induced with a perfect mobility service (free service with zero wait time, leading to a utility of 0). In our model, 0.2 is used, based on the (Stephens et al. 2016) suggestion of a potential 20-percent increase in overall travel resulting from increased travel by the transportation-disadvantaged. Additionally, (Harper et al. 2016) reviewed data from the 2009 National Household Travel Survey, comparing overall travel with the amount of travel by the elderly, non-motorists, and those with travel-restrictive conditions. If ADS-equipped vehicles enable the amount of travel by these populations to increase to the amount of travel (VMT) observed in the remainder of the population, overall annual light-duty VMT could increase by 14 percent.

- Utility for zero induced trips = the baseline (human-driven) mobility service utility, which is a function of fare and wait time. Table 4-4 shows some examples of the utility and induced trips calculation, assuming that the human driven baseline service has a fare of $10 and a wait time of 10 minutes, resulting in a utility of -3.

The utility calculation comes from section 4.3.1.6

$$Utility(mobility\ service) = -0.05\ x\ (WaitTime + 5\frac{minutes}{\$}\ x\ Fare)$$

Induced trip fraction is calculated as

$$InducedTripFraction = MaximumInducedTripFraction\ x\ \frac{UtilityForZeroInducedTrips - Utility(mobility\ service)}{UtilityForZeroInducedTrips}$$

Table 4-4 Utility and induced trip fraction examples

Fare ($)	Wait time (minutes)	Calculated Utility	Calculated Induced trip fraction	Comment
0	0	0	0.2	Theoretical perfect service (0 fare, 0 wait)
0	5	-0.25	0.183333	
0	10	-0.5	0.166667	
3	0	-0.75	0.15	
3	5	-1	0.133333	
3	10	-1.25	0.116667	
10	0	-2.5	0.033333	
10	5	-2.75	0.016667	
10	10	-3	0	Baseline utility for zero induced trips

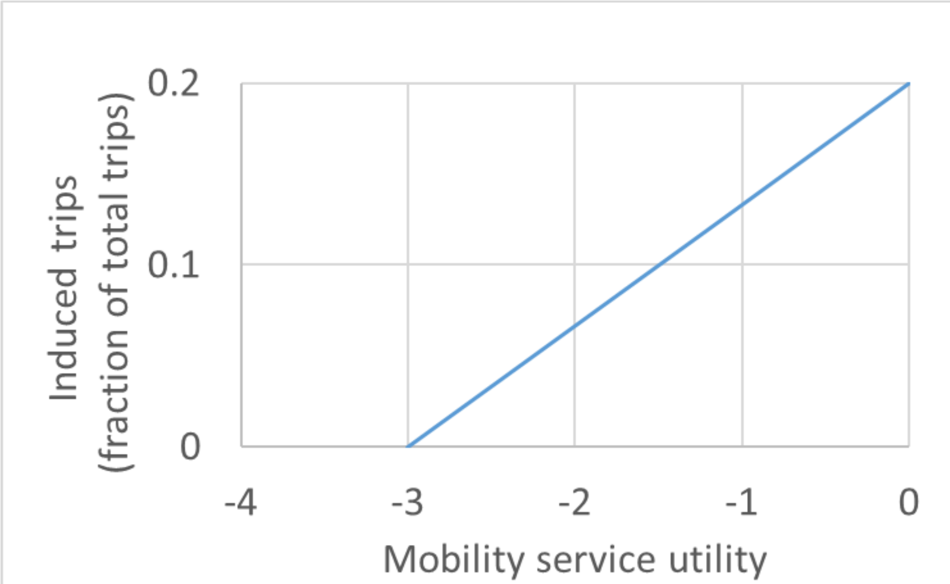


Figure 4-7 Induced trip fraction, assuming a human driven mobility service utility of -3

(Source: Volpe)

4.3.2 Potential sensitivity tests

The model described above is a strategic model: it is an aggregate model that runs in less than one second. It is designed to quickly assess the viability of a shared mobility service from the standpoints of both the service provider and the traveler. Such a fast model lends itself to sensitivity and scenario analysis. Potential sensitivity tests include:

- The effect of public support. A local, state or national government might conclude that providing a mobility service is in the public interest, and may choose to provide either a monthly stipend, or a fixed amount of public support per person-trip, similar to what is done with transit today.
- Changes in vehicle fixed and operating costs. Vehicle costs are modeled as a fixed cost per month, plus an operating cost per minute that the vehicle is running loaded or empty. Automation can reduce the cost of driver labor to reduce the vehicle operating cost.
- Changes in fare, since automation may allow a lower fare.
- Type of region (urban/suburban/rural). This affects several parameters:
    - Trip distance
    - Population density
    - Size of service area
    - Vehicle speed
    - Trips / person / month
    - Transit utility (and mode share)
- Value of time, which affects the sensitivity to fare changes.
- Induced trips. If a low-cost mobility service is introduced, how many new trips will it attract?

- Empty travel per trip. There is a simple mathematical relationship that relates density of available vehicles to the average distance to the nearest vehicle. However, a real service may not be able to achieve the theoretical minimum in empty vehicle miles, due to imbalance of trips (e.g., trips to the airport vs. from the airport in early morning), or other inefficiencies.

The next few sections explore a few of these factors:

- Type of region
- Operating cost and fare for human-driven versus automated
- Value of time
- Whether induced trips are allowed.

4.4 Applications of the Car Service Model

Three sets of applications are presented in this section. First is an application to generic urban, suburban, and rural areas. The second uses TNC data from Chicago. The third is a sensitivity test for a rural mobility service.

4.4.1 Experiments with three types of regions

Initial experiments were conducted using a fairly low value of time (5 minutes per dollar, or 12 dollars per hour). In these initial experiments, target utilization was set at 0.5.

Based on Massachusetts TNC data, Massachusetts employment data for selected communities, and NHTS trip-making data, the Volpe team created parameters for three generic types of communities: urban, suburban, and rural.

Table 4-5 Region-specific SD model inputs and calibration targets

Type of community	Input: Pop Density (persons / sq mi)	Input: Service area (sq M)	Input: Total Trips / resident/month	Target: TNC trips / month	Target: Transit mode share
City	10000	10	110	600000	0.25
Suburb	2000	20	90	20000	0.05
Rural (Exurb)	200	40	90	640	0

The model was calibrated to existing TNC usage, assuming a fare of $10/trip in city and suburb, and $14/trip in rural areas. Vehicle variable operating cost was $0.35 / minute. With the utility of TNC being a function of wait time and fare, calibration was performed by adjusting the utilities for POV and transit to yield the transit mode shares in Table 4-5. In the rural model, the utility of transit was set to be much less than zero, to reflect the absence of transit service. This calibration process yielded initial values for mobility service trips, as well as average traveler wait times for each scenario. Figure 4-8 illustrates the calibration process, and Table 4-6 shows the initial results.

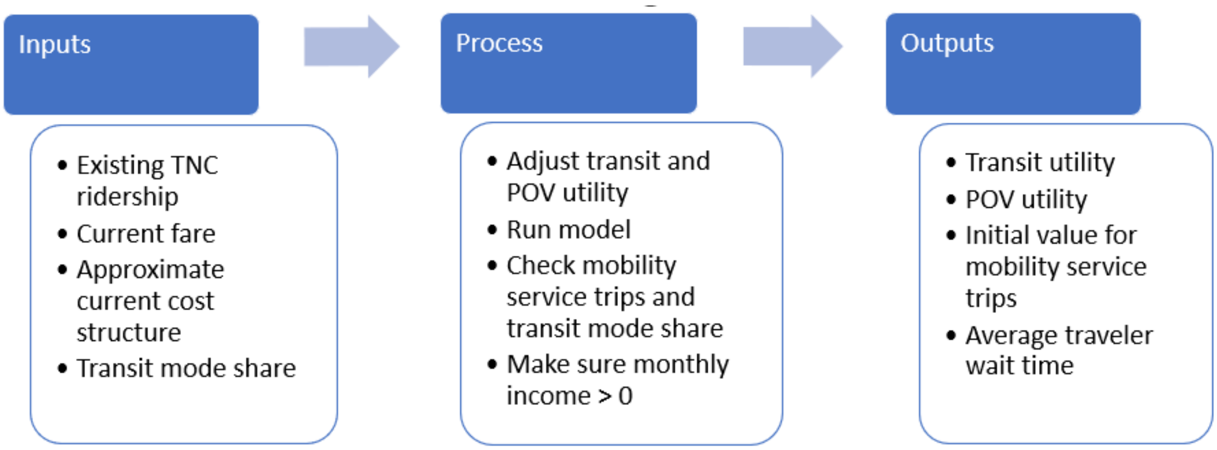


Figure 4-8 Calibration process

(Source: Volpe)

Table 4-6 Initial calibration results

	City TNC	Suburb TNC	Rural TNC
Monthly trips satisfied by the service	623218	19162	670
Transit mode share	0.254	0.049	0
Avg. total wait time (min)	6	8.6	9.6
Vehicles	1012	37	7.9
Net income for the service operator ($ / month)	2463320	55300	1207
Net income per vehicle ($ / month)	2434	1495	153
Mobility service mode share	0.057	0.005	0.001

The cost and fare structure was then changed to reflect a Level 5 automated driving service (ADS). Variable cost was changed from $0.35 / minute to $0.10 / minute. Fare was changed from $10 and $14 for urban/suburban and rural trips to $3 for urban/suburban trips and $4 for rural. Outcomes ***absent*** induced trips are shown in Table 4-7.

Table 4-7 Comparison of ADS and human-driven TNC cases – no induced trips

	City TNC	City ADS	Suburb TNC	Suburb ADS	Rural TNC	Rural ADS
Fare ($/trip)	10	3	10	3	14	4
Monthly trips satisfied by the service (1000s)	623	2827	19	117	0.7	8
New trips (induced travel)	0	0	0	0	0	0
Transit mode share	0.254	0.20	0.049	0.048	0	0
Avg. total wait time (min)	6	5.8	8.6	6.9	9.6	9.8

	City TNC	City ADS	Suburb TNC	Suburb ADS	Rural TNC	Rural ADS
Vehicles	1012	4482	37	202	7.9	16.5
Net monthly income ($1000)	2463	2392	55	79	1.2	9.8
Monthly income per vehicle ($)	2434	534	1495	391	153	596
Mobility service mode share	0.057	0.257	0.005	0.032	0.001	0.011

When induced trips are allowed, the numbers of ADS trips increase significantly.

Table 4-8 Comparison and ADS scenarios without and with induced trips

	City ADS: No Induced Trips	City ADS: Induced Trips	Suburb ADS: No Induced Trips	Suburb ADS: Induced Trips	Rural ADS: No Induced Trips	Rural ADS: Induced Trips
Fare ($)	3	3	3	3	4	4
Total monthly trips satisfied by the service (1000s)	2827	4233	117	580	8	105
New trips (induced travel) (1000s)	0	1382	0	459	0	95
Transit mode share	0.2	0.2	0.048	0.048	0	0
Avg. total wait time (min)	5.8	5.7	6.9	6.2	9.8	6.9
Vehicles	4482	6755	202	955	16.5	181
Net monthly income ($1000)	2392	3578	79	453	9.8	175
Monthly income per vehicle	534	530	391	474	596	969
Mobility service mode share	0.257	0.342	0.032	0.143	0.011	0.128

A low value of time implies that travelers will be comparatively more sensitive to fare changes than to reductions in wait or travel time. As expected, the ADS service (with a fare substantially lower than the TNC fare) attracts a large number of riders. In the urban area, these trips are largely drawn from other modes. In the suburban and rural areas, induced trips are more significant.

4.4.2 Increasing the value of time (VOT)

The previous experiments used a value of time for waiting of $12 / hour. Although this is in the range of values-of-time reported in (NCHRP 2012)[11], the more recent Benefit Cost Analysis Guidance for Discretionary Grant Program (Office of the Secretary 2022) suggests that a higher value should be used. Accordingly, in the next set of experiments, a value of time for waiting of $30 / hour (2 minutes / dollar), was used. The calibration targets (Table 4-5) were the same. The model was again calibrated to existing TNC and transit usage.

[11] See table 4.9 in the report, noting that the value of out-of-vehicle time (e.g., wait time) is typically 2 to 3 times as high as the value of in-vehicle time.

Table 4-9 Initial calibration results – higher VOT

	City TNC	Suburb TNC	Rural TNC
Monthly trips satisfied by the service	615140	19212	654
Transit mode share	0.26	0.047	0
Avg. total wait time (min)	6	8.6	18
Vehicles	1000	37	2
Net monthly Income ($1000s)	2431	56	2
Income per vehicle ($ / month)	2431	1500	1007
Mobility service mode share	0.057	0.005	0.001

Similar to the previous experiment, the cost and fare structure was then changed to reflect a Level 5 ADS. Variable cost was changed from $0.35 / minute to $0.10 / minute. Fare was changed from $10 and $14 for urban/suburban and rural trips to $3 for urban/suburban trips and $4 for rural. Outcomes ***without*** induced trips are shown in Table 4-7. The availability of low-cost ADS leads to an increase in trip-making, but not nearly as much as that shown in the low VOT case represented in Table 4-7.

Table 4-10 Comparison of ADS and human-driven TNC cases – higher VOT, no induced trips

	City TNC	City ADS	Suburb TNC	Suburb ADS	Rural TNC	Rural ADS
Fare ($)	10	3	10	3	14	4
Monthly trips satisfied by the service (1000s)	615	1178	19	40	0.7	2.2
New trips (induced travel)	0	0	0	0	0	0
Transit mode share	0.26	0.25	0.047	0.048	0	0
Avg. total wait time (min)	6	5.9	8.6	7.7	18	13
Vehicles	1000	1899	37	73	2	5.5
Net monthly income ($1000s)	2431	971	56	22	2	1.8
Monthly income per vehicle	2431	511	1500	302	1007	321
Mobility service mode share	0.056	0.107	0.005	0.011	0.001	0.003

When induced trips are allowed, the numbers of ADS trips increase significantly, but not as much as for the low VOT case (Table 4-8).

Table 4-11 Comparison and ADS scenarios without and with induced trips, higher VOT

	City ADS: No Induced Trips	City ADS: Induced Trips	Suburb ADS: No Induced Trips	Suburb ADS: Induced Trips	Rural ADS: No Induced Trips	Rural ADS: Induced Trips
Fare ($)	3	3	3	3	4	4
Total monthly trips satisfied by the service (1000s)	1178	2377	40	423	2.3	92

	City ADS: No Induced Trips	City ADS: Induced Trips	Suburb ADS: No Induced Trips	Suburb ADS: Induced Trips	Rural ADS: No Induced Trips	Rural ADS: Induced Trips
New trips (induced travel) (1000s)	0	1195	0	380	0	89
Transit mode share	0.25	0.25	0.048	0.048	0	0
Avg. total wait time (min)	5.9	5.8	7.7	6.3	13	6.9
Vehicles	1899	3808	73	702	5.5	160
Net monthly income ($1000s)	971	1991	22	324	1.8	153
Monthly income per vehicle	511	523	302	462	321	956
Mobility service mode share	0.107	0.195	0.011	0.106	0.003	0.114

4.4.3 Discussion

All of the models reached equilibrium values after a period of several years where service providers adjusted their services and travelers responded. Models used the reference mode of TNC trips as a starting point, and then adjusted in response to the asserted changed cost and fare structure with ADS. Figure 4-9 shows the evolution of trips for the suburban models.

The factors leading to increased trip making with automation include

- The reduced fare for the consumer leads to a shift away from other modes, to the automated mobility service.
- Increased ridership on the automated mobility service allows (and incites) the service provider to buy more vehicles. This is because the reinforcing loops associated with increases in net monthly income (arising from more rides and lower cost per mile) and increases in vehicle utilization, outweigh balancing loops associated with decrease in fare revenue on a per-ride basis.
- Wait times decrease in the rural scenarios, as the increase in vehicles available outweigh the increase in trip demand (recall that larger systems more efficiently assign vehicles to trips).
- Increased ridership and lower rural wait times lead to new travel, particularly in the rural and suburban scenarios.

Because the higher value of time scenarios imply a reduced sensitivity to fare reductions, the increase in trip making with automation is lower with these higher value of time scenarios.

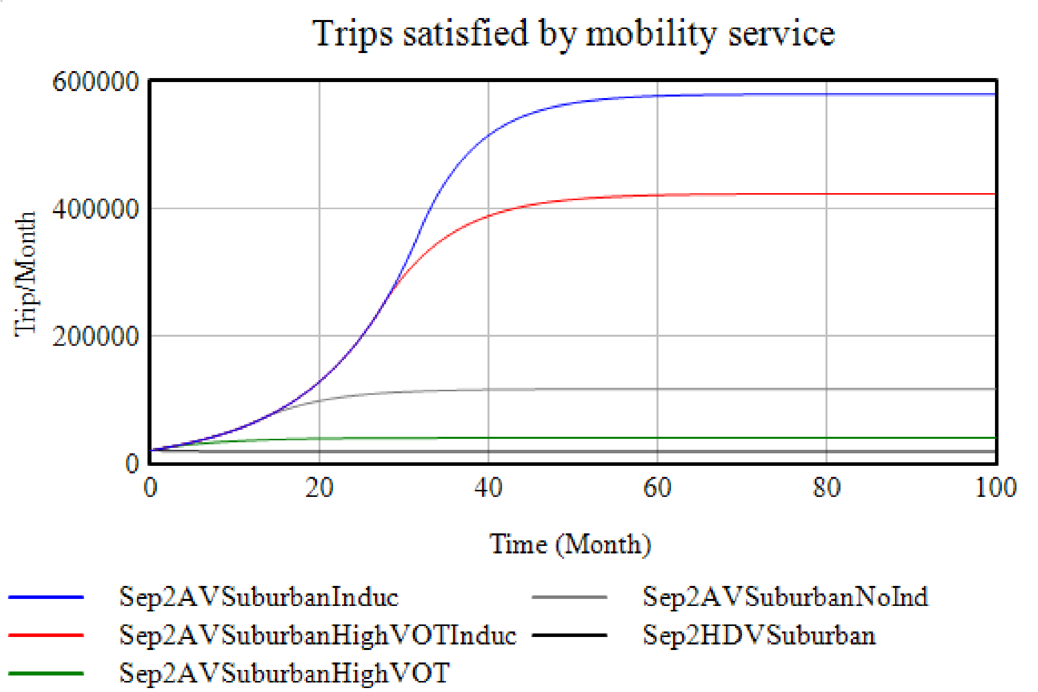


Figure 4-9 Evolution of mobility service trips – suburban models

(Source: Volpe)

The lines in Figure 4-9, working from bottom to top, are as follows:

- Human-driven vehicle (baseline case) – Sep2HDVSuburban
- ADS with high value of time, and no induced trips – Sep2AVSuburbanHighVOT
- ADS with low value of time, and no induced trips – Sep2AVSuburbanNoInd
- ADS with high value of time and induced trips – Sep2SuburbanHighVOTInduc
- ADS with low value of time and induced trips – Sep2AVSuburbanInduc

As demand for the mobility service increases, the service provider responds by acquiring more vehicles (Figure 4-10).

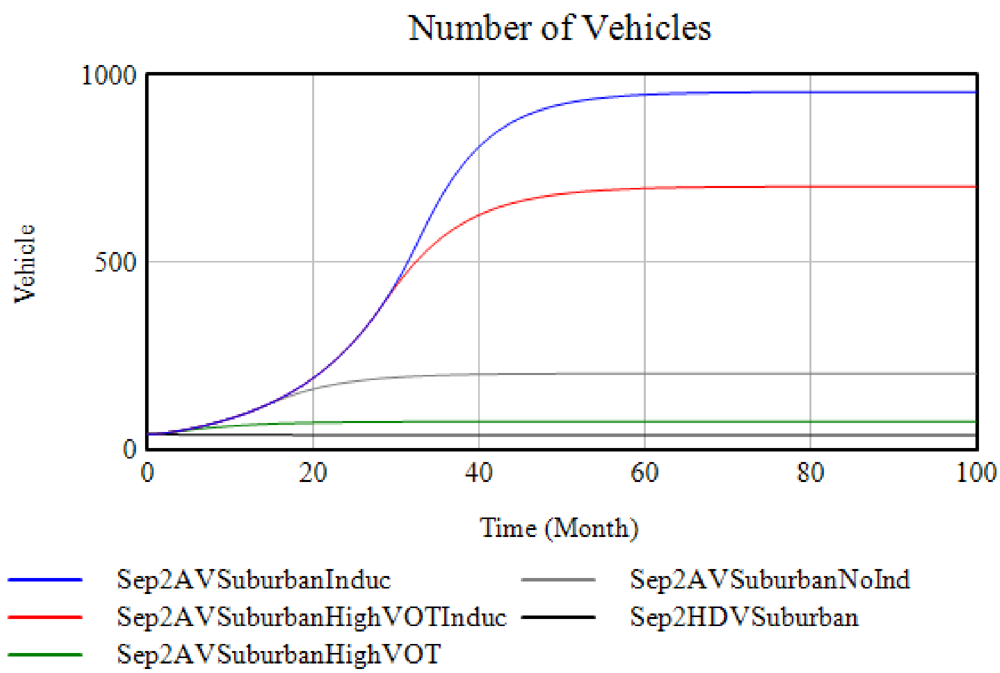


Figure 4-10 Evolution of number of vehicles - suburban models

(Source: Volpe)

4.4.4 Chicago urban and suburban model

As part of an ongoing inter-agency collaboration between U.S. DOT, the U.S. Department of Energy, and the Environmental Protection Agency, the team obtained urban and suburban TNC data from Chicago that was used in the Polaris model of Argonne National Laboratory (ANL). The Volpe car service model was run using these datasets (Table 4-12).

Table 4-12 Chicago model inputs

Input	City	Suburban	Units	Comment
Avg trip distance	4.2	7.7	mi	from ANL
Initial vehicle stock per 1000 population	33	4	vehicle / 1000 persons	from ANL (includes part-time vehicles)
vehicle speed	14.6	26.2	mi /hour	from ANL
Size of service area	236	2380	mi*mi	from ANL
Trips / person / month	93	93		from ANL
Population density	12154	2396	persons / mi*mi	from ANL
Fare	13.6	19.1	$ / trip	from ANL
Calibration target	9000000	1080000	trips / month	From Chicago TNC data and ANL
Transit mode share calibration target	0.12	0.017		From 2019 CTA, METRA, and PACE ridership data

City and suburban models were created using steps similar to those in section 4.4.

Results for baseline TNC, ADS and ADS with induced traffic are shown in Table 4-13.

Table 4-13 Chicago model outputs, low VOT

	City TNC	City ADS	City ADS: Induced	Suburb TNC	Suburb ADS	Suburb ADS: Induced
Fare ($)	13.6	3	3	19.1	5	5
Monthly trips satisfied by the service	9.2M	90.7M	129.3M	1.1M	32.4M	104.7M
New trips (induced travel)	0	0	38.5M	0	0	71.9M
Transit mode share	0.1151	0.079	0.079	0.017	0.016	0.016
Avg. total wait time (min)	6.1	5.7	5.7	7	8.3	8
Vehicles	17480	168213	239150	11834	71032	226265
Monthly income per vehicle	2431	276	279	663	946	976
Mobility service mode share	0.034	0.34	0.341	0.002	0.06	0.062

Figure 4-11 shows the mobility service (MS) trips, normalized to initial total trips, for both the generic urban model (section 4.4, the left three columns) and the Chicago city model (the right three columns).

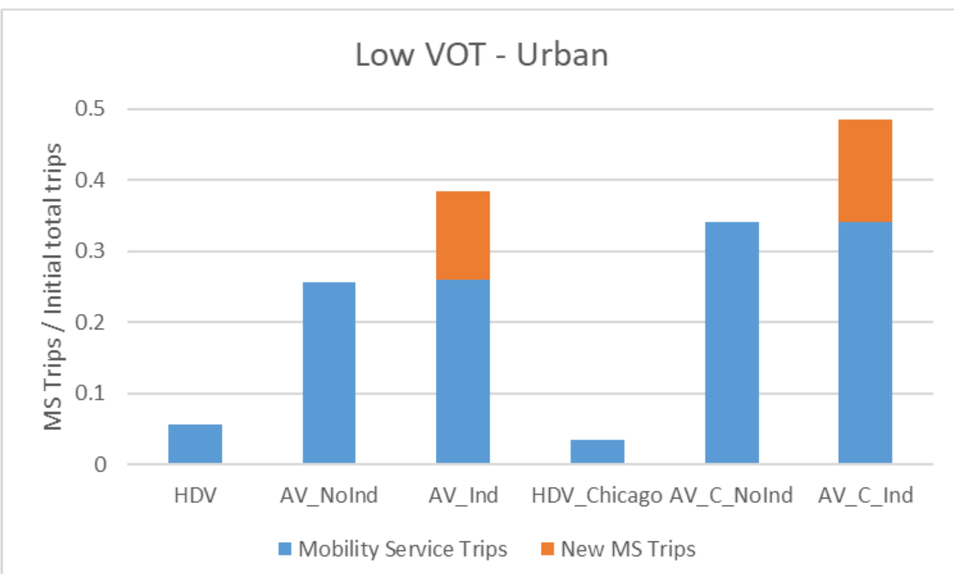


Figure 4-11 Mobility service trips, urban, low VOT

(Source: Volpe)

Figure 4-12 shows the mobility service trips, normalized to initial total trips, for both the generic suburban model (section 4.4) and the Chicago suburban model.

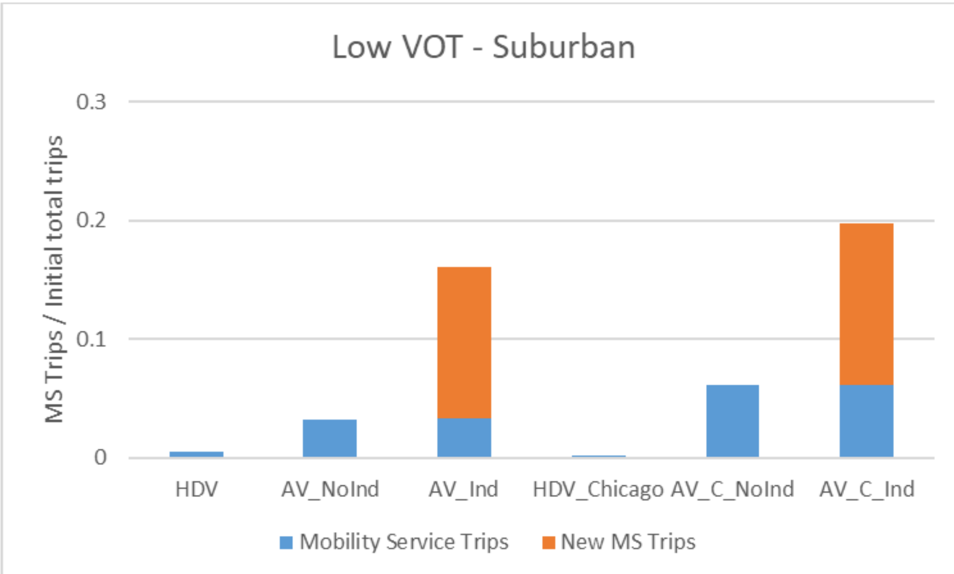


Figure 4-12 Mobility service trips, suburban low VOT

(Source: Volpe)

Again, a low VOT leads to greater increases in trips caused by reduction in fare, as utility of the automated mobility service depends relatively more on cost and less on time.

The next set of experiments changed the value of time from 5 minutes per dollar ($12 / hour) to 2 minutes per dollar ($30 / hour). Results for baseline TNC, ADS and ADS with induced traffic are shown in Table 4-14.

Table 4-14 Chicago model outputs, high VOT

	City TNC	City ADS	City ADS: Induced	Suburb TNC	Suburb ADS	Suburb ADS: Induced
Fare ($)	13.6	3	3	19.1	5	5
Monthly trips satisfied by the service	9.1M	24.9M	59.7M	1.1M	39.8M	67.8M
New trips (induced travel)	0	0	34.6M	0	0	63.6M
Transit mode share	0.115	0.108	0.108	0.018	0.018	0.018
Avg. total wait time (min)	6.1	5.9	5.8	7	9.3	8.2
Vehicles	17313	46768	110939	11698	9192	147174
Monthly income per vehicle	3444	258	271	69	832	97

	City TNC	City ADS	City ADS: Induced	Suburb TNC	Suburb ADS	Suburb ADS: Induced
Mobility service mode share	0.034	0.094	0.094	0.002	0.008	0.008

Figure 4-13 shows the mobility service trips, normalized to initial total trips, for both the generic urban model (section 4.4, the left three columns) and the Chicago city model (the right three columns).

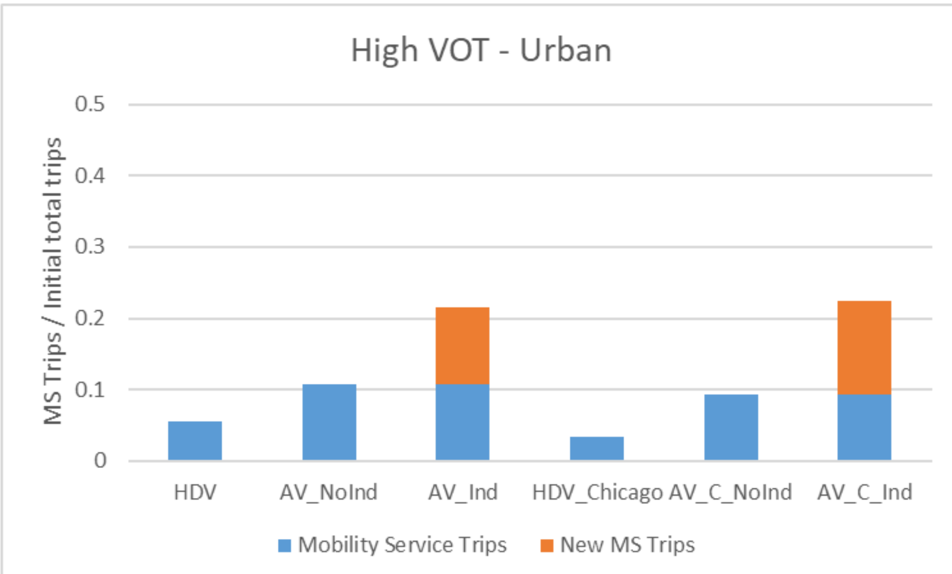


Figure 4-13 Mobility service trips - urban high VOT

(Source: Volpe)

Figure 4-14 shows the mobility service trips, normalized to initial total trips, for both the generic suburban model (section 4.4) and the Chicago suburban model.

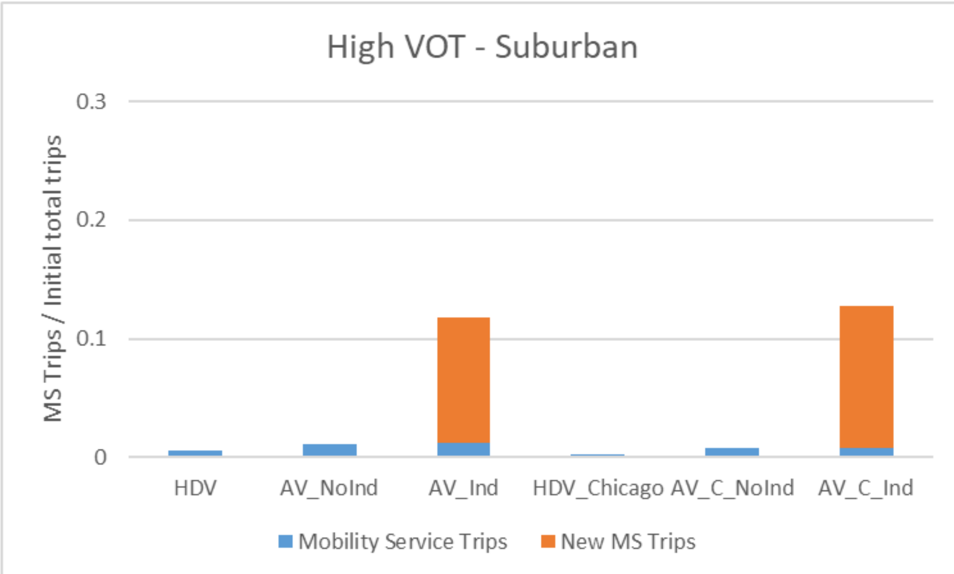


Figure 4-14 Mobility service trips - suburban high VOT

(Source: Volpe)

Because a high value of time means less sensitivity to a lower fare, the number of increased trips is lower with the high VOT model.

Graphs of the evolution of the system for the Chicago model are similar to those for the generic model, with one important difference: the Chicago model started with too many vehicles (presumably many of these registered TNC vehicles in the current human-driven baseline are only used part time), but the model adjusted itself to an equilibrium leading to a lower number of full-time vehicle equivalents in the human-driven baseline case.

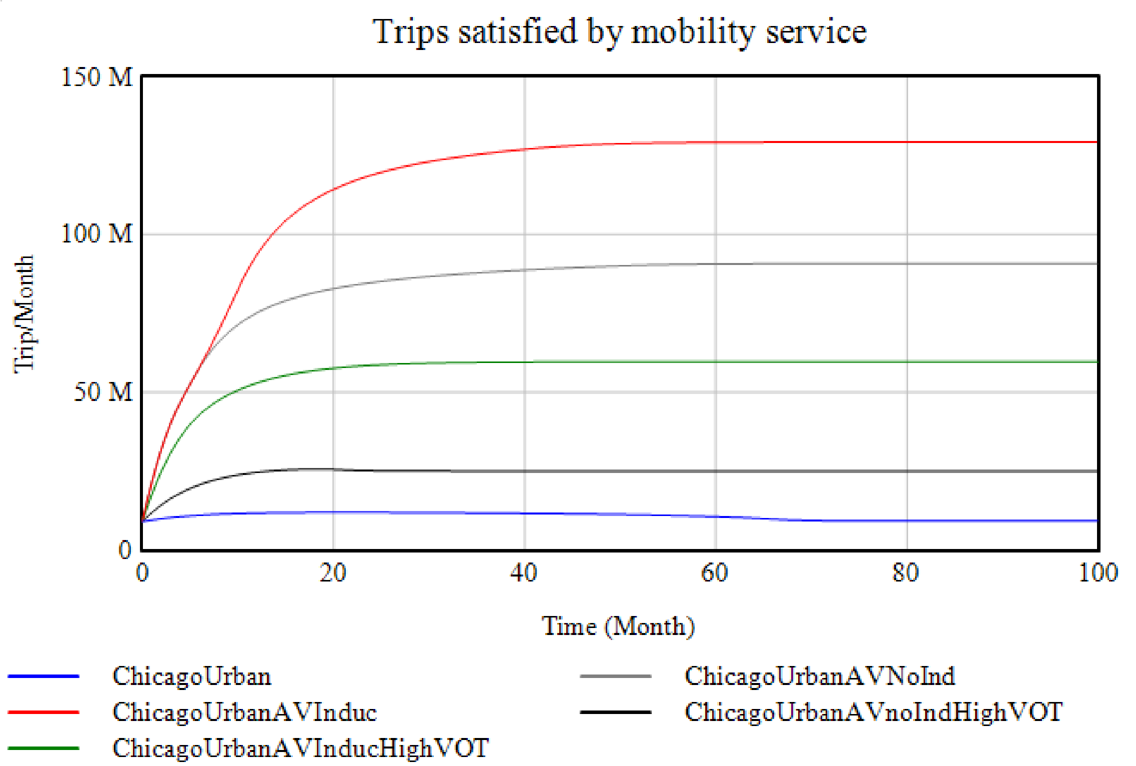


Figure 4-15 Evolution of trips, Chicago Urban

(Source: Volpe)

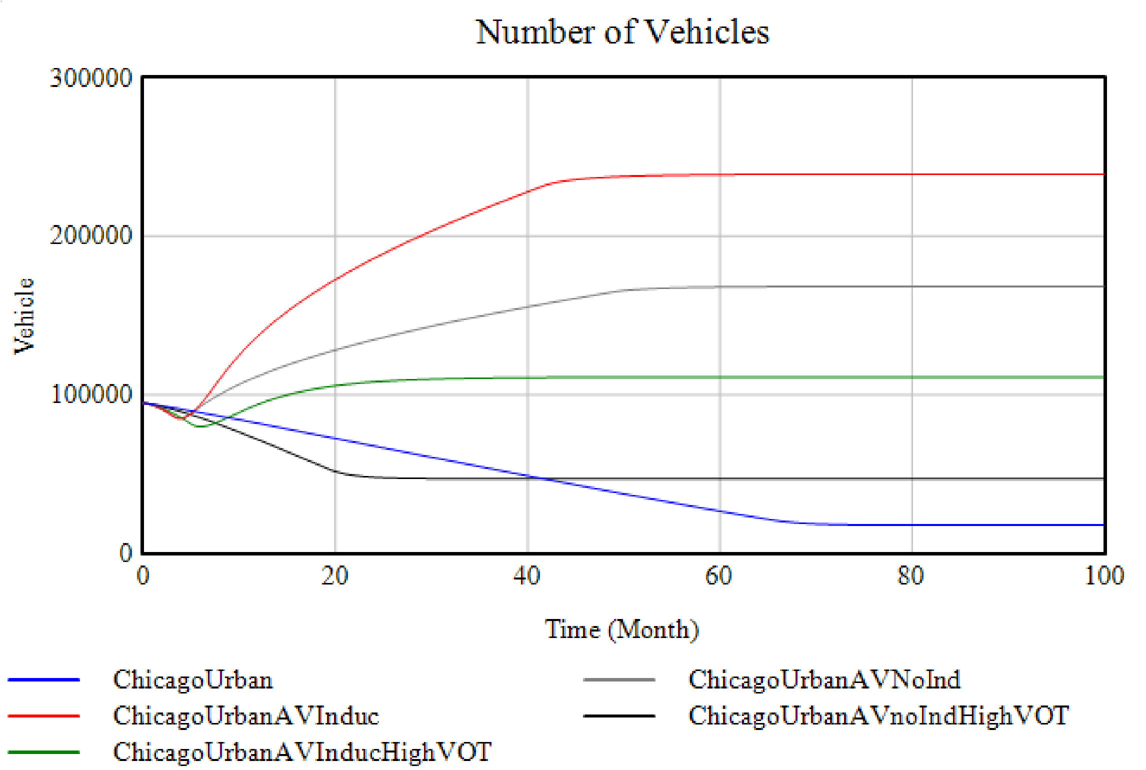


Figure 4-16 Evolution of vehicles, Chicago Urban

(Source: Volpe)

4.4.5 Sensitivity analysis for rural areas

Rural areas often lack travel options other than privately-owned vehicle, with little transit, and TNC services often not being available.[12] The earlier analysis (see Table 4-6) showed a lower income per vehicle in rural areas than in either urban or suburban areas.

The Volpe car service model runs in less than one second, and thus lends itself to sensitivity analysis. This section presents the results of some 600 model runs, for human driven services, automated services without induced travel, and automated services with induced travel, for population densities ranging from 13 to 398 persons per square mile. Average trip distance was set at 10 miles, average speed to 30 mph, and human-driven vehicle fare to $20. The automated mobility service fare was set at $5.

[12] "Transportation experts see Uber and Lyft as the future. But rural communities still don't use them", in vox.com (2019), https://www.vox.com/the-goods/2019/1/11/18179036/uber-lyft-rural-areas-subscription-model

With a service area of 100 square miles, 90 trips per person per month, and a baseline density of 100 persons per square mile, the number of baseline trips was 900,000. The baseline human-driven vehicle run yielded 672 mobility service trips per month, like the rural result in Table 4-10. Key findings were as follows:

- With population densities below approximately 30 persons / square mile, none of the services had positive operating revenue. There is a discontinuity when the density rises above approximately 30 persons / square mile, where all the services shift from being non-viable to viable, with positive net income.
- Given the assumption of a lower fare, usage was much higher for the automated services than for the human-driven services.
- Wait times declined as population densities increased, and were lower for the automated services (with their efficiencies of scale in assigning vehicles to trips)
- With their higher usage, the automated services could support larger fleets.

Figure 4-17 shows the average traveler wait time as a function of rural population density, for a total of 600 model runs:

- The orange circles (labeled HDV_IncPerVeh) are the model runs for idealized full-time human driven vehicles (with $20 fare).
- The blue triangles (labeled AV_IncPerVeh) are for an automated service, with $5 fare and no induced travel.
- The red diamonds (labeled AVInd_IncPerVeh) are for an automated service with induced travel.

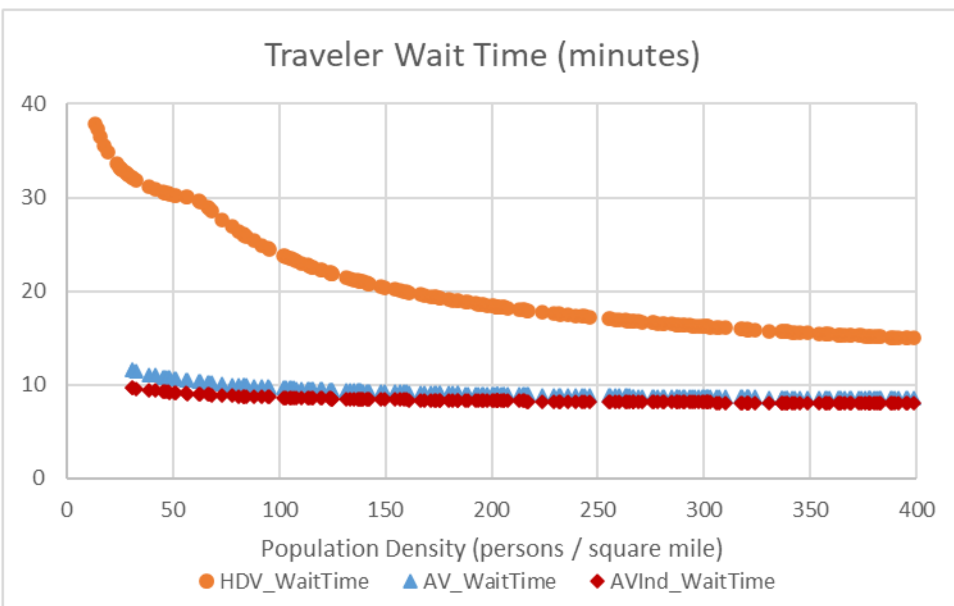


Figure 4-17 Traveler wait time as a function of rural population density

(Source: Volpe)

Below 30 persons per square mile, wait times for the automated services were extremely high (off the chart), indicating a non-viable service, as the model reduced the number of vehicles in an unsuccessful attempt to make the service financially sustainable (similar to a classic transit death spiral).

Figure 4-18 shows the number of vehicles as a function of rural population density, with the same symbols and color coding as in Figure 4-17. The y-axis is on a logarithmic scale in this figure, because the number of vehicles for the automated services is much higher than the number of vehicles for the human-driven service. The discontinuity in the trends for the automated services at about 30 persons/square mile represents the same "death spiral" behavior explained above, showing where the model reduces the vehicles sharply.

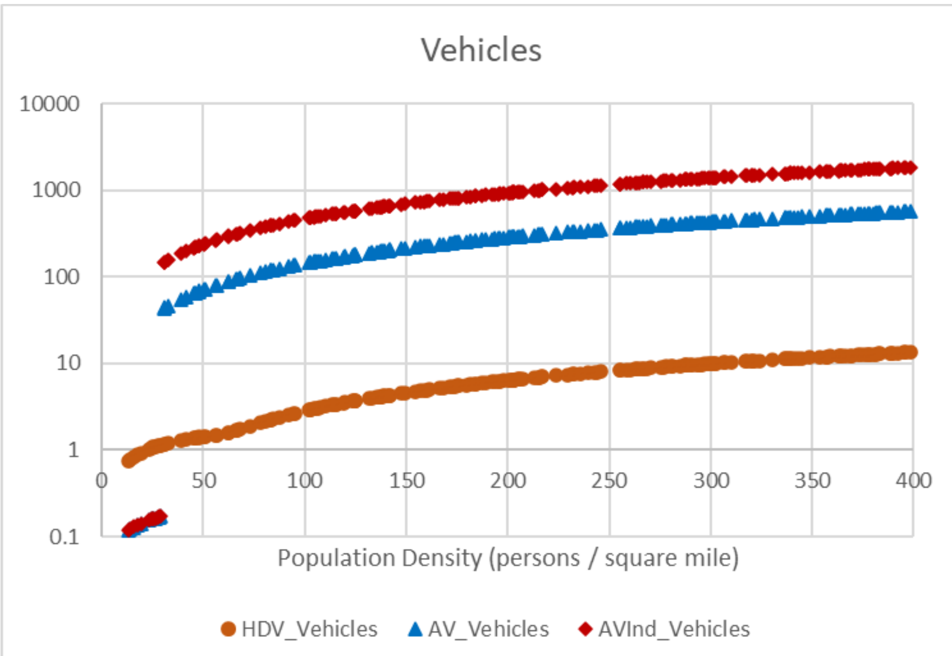


Figure 4-18 Vehicles as a function of rural population density

(Source: Volpe)

4.5 Connections to Existing Models

4.5.1 VisionEval

In 2021-2022, FHWA sponsored a project to add connected and automated vehicle capabilities to VisionEval. The household vehicle model now has level 3 and level 5 automated vehicles, in addition to level 0 human-driven vehicles.[13] Changes include:

- Household drivers, to change the percentage of age cohorts who could now be "drivers" (e.g., travel independently in an automated vehicle)
- Propensity for using car service
- Propensity for using L5 automated vehicles
- Updates to household models for number of vehicles owned (including zero)
- L5 and car service deadhead inputs and calculation
- Capacity factors for automation.

Car service availability is still an asserted input but may now be set by detailed zone (Bzone). This is a gap that the SD model could help fill, by identifying areas where car services are likely to be viable.

4.5.2 Polaris

Polaris is a detailed agent-based transportation model developed by Argonne National Laboratory that has been tested with the UrbanSim land use model in several urban areas. It has been tested using shared mobility services as a mode (the inputs to the Chicago model presented in this report), but the availability of shared mobility service is still asserted, a gap similar to that for VisionEval.

4.6 Lessons Learned

As was stated earlier, system dynamics is a much more general methodology than traffic microsimulation and static planning models. This has the advantage of potentially revealing new insights, important when a new mode with potentially transformative effects is introduced. One can build a model that includes causal effects that cannot be represented by traditional transportation planning models, for example, the service provider view of a shared mobility service.

Another benefit of building an SD model is that one can provide explanations of results in terms of the causal structure of the system. This is very different from, for example, any model that makes predictions based on correlation, so SD models can offer complementary insights to correlation-based models.

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[13] See (SAE International 2021) for definitions of the levels of driving automation.

Conceptually, the steps are similar to that for building a traditional transportation model. One starts with a baseline to demonstrate that the model can replicate existing conditions. Once that first step is complete, future scenarios can be explored. The system dynamics model runs very fast (a set of 200 runs was completed in a few seconds) and can explore a wide variety of questions not well handled by traditional models. Given that the model is a highly aggregate model (though could be disaggregated into multiple instances), it should not be viewed as a substitute for traditional planning models, but rather as a complement, to provide insights into the characteristics of future scenarios that might go into the more detailed traditional models.

5 Conclusion

Many potentially transformative changes to the transportation system, such as automation, electric vehicle adoption, increased telework, and new travel modes, are creating increasing future uncertainties. Accordingly, the planning and modeling community is showing an increasing interest in strategic models that can quickly explore a wide scenario space. Furthermore, there is an interest in models that can organize complex systems, making sense of the interactions among parts of the system that might produce unexpected outcomes.

System dynamics (SD) is a methodology with broad applicability that has seen application in transportation and land use. SD has both a qualitative and quantitative side. The qualitative modeling section of this report showed how techniques, such as group model building and causal loop diagrams, can bring diverse stakeholders, including both planners and modelers, to a common understanding of a complex problem.

The quantitative modeling section reviewed several existing quantitative SD models, and then focuses on a major gap in current models: that of the business model for shared mobility services. It presents our quantitative model for such a service, integrating both the business side (financial sustainability) and the user side (a service attractive enough to be used). Our several hundred model runs showed the significantly different outcomes in urban, suburban, and rural areas, as well as the importance of induced travel. This section concludes with a discussion of how a quantitative SD model can be integrated with existing models, such as the VisionEval strategic planning model from FHWA, and the POLARIS agent-based model from Argonne National Laboratory (DOE).

This report analyzed the short-to-medium term choice for a shared mobility service. A remaining gap is to evaluate the **longer-term impacts** of automation, shared mobility services, and other changes to the transportation / land use system. These changes can lead to significant shifts over time, which affect travelers' choice sets, not only their daily travel choices. How will household behavior evolve over a multi-year time horizon as legacy vehicles wear out? Will new transportation choices, options and tradeoffs change vehicle purchase behavior? The household vehicle ownership decision, already a gap in existing models, will become increasingly important to understand for the transportation system of the future, as more travel choices become available giving more households the option not to own a vehicle.

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Appendix I: Massachusetts TNC Data

The Massachusetts Department of Public Utilities (Massachusetts DPU 2019) requires TNCs to share data, reporting TNC rides for each of the state's 351 cities and towns, ranging in size from Boston to small towns with populations less than 1000. (Note: every location in Massachusetts is part of a city or town. A rural town may comprise a few villages along with a substantial surrounding area).

The 2018 data show that TNC use, measured in annual trips per resident, correlates strongly with population density. TNC use is primarily focused in the Boston metropolitan area, with very low usage in rural communities. Exceptions include resort areas, such as Nantucket, which have significant numbers of non-resident visitors during the summer.

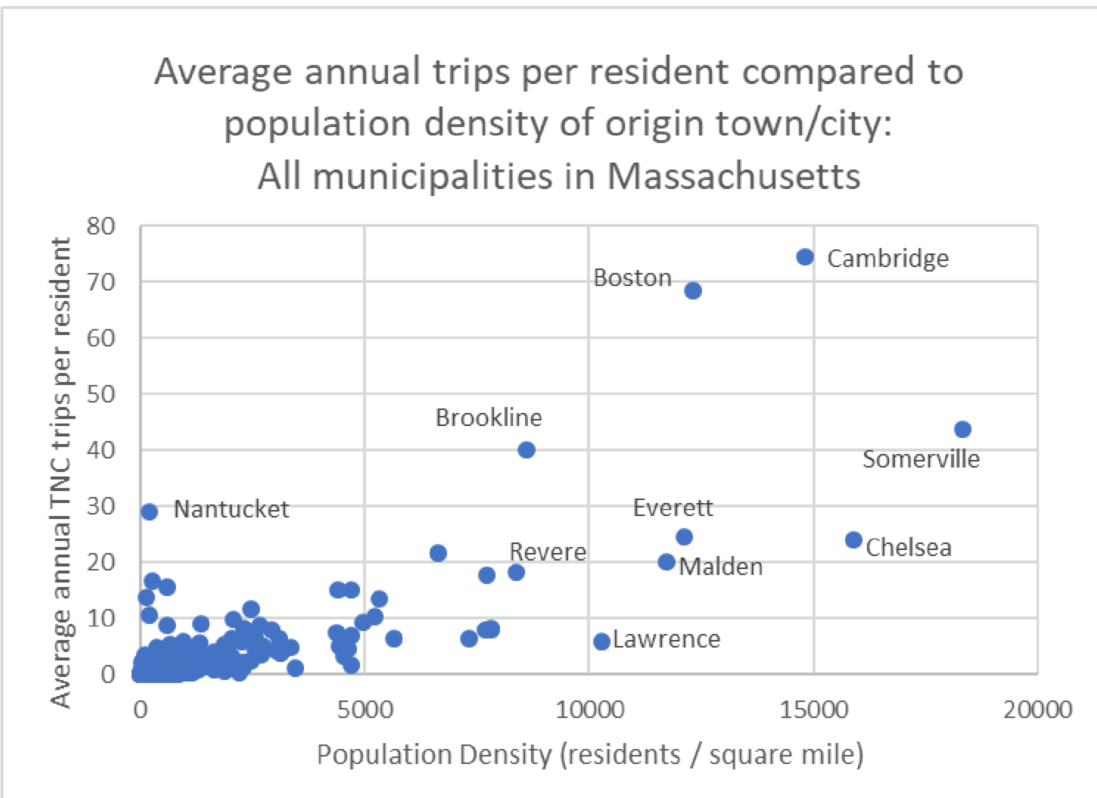

Figure A-1-0-1 Mass. TNC data from 2018 (Source: Derived from Rideshare Data Report from Mass.gov)

Data from 2019 show a similar story. [Rideshare Data Report | Mass.gov]

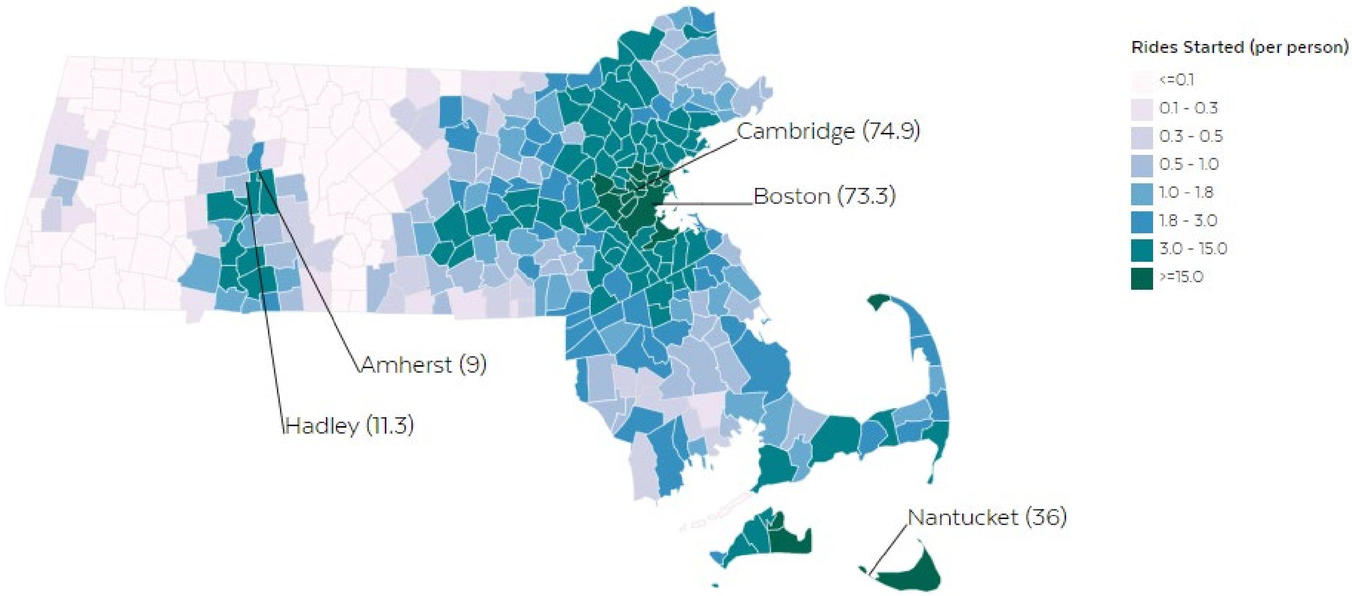

Figure A-1-0-2 Mass TNC map from 2019 (Source: Rideshare Data Report | Mass.gov)

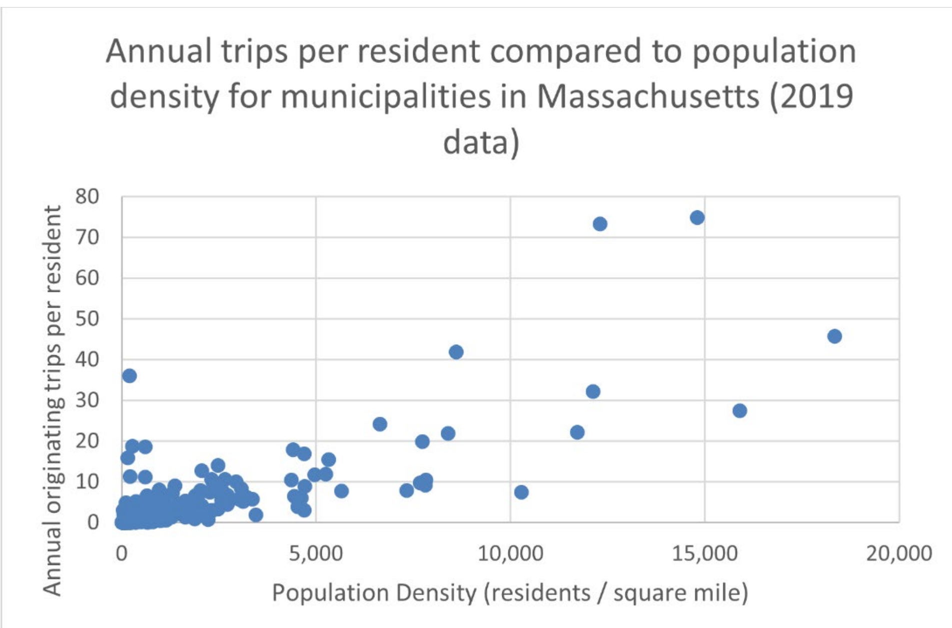

Figure A-1-0-3 Mass TNC 2019 data (Source: Derived from Rideshare Data Report from Mass.gov)

Observations: communities in the Boston metropolitan area have higher TNC usage. Wealthy communities have higher TNC usage.

Figure A-1-0-4 focuses on rural areas.

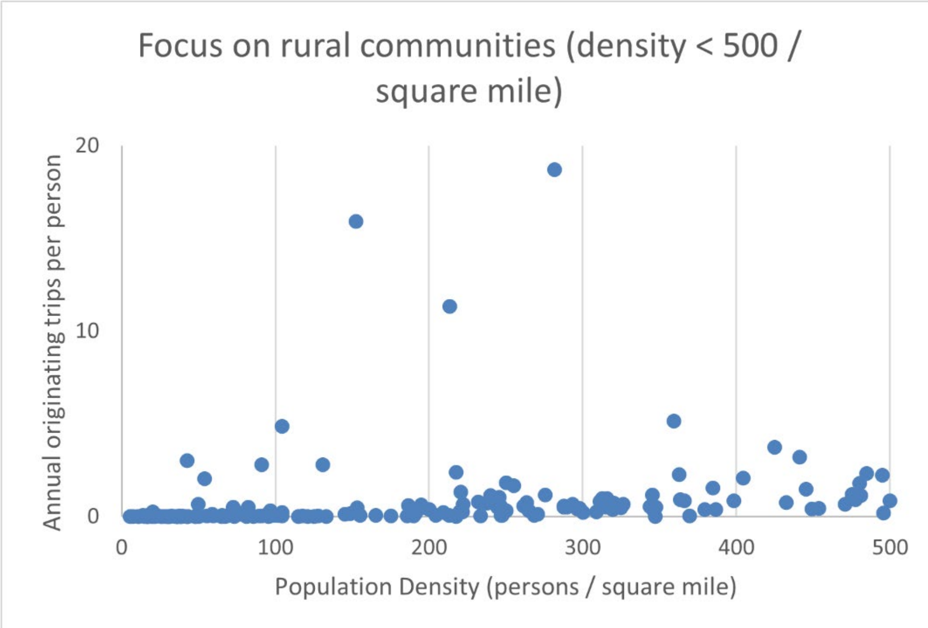

Figure A-1-0-4 Mass TNC 2019 data, focus on rural areas (Source: Derived from Rideshare Data Report from Mass.gov)

The rural areas with high TNC trip making include

- Resort areas (Nantucket, towns on Martha's Vineyard and Cape Cod). These areas have higher summer populations than year-round residents. Two are islands where visitors are discouraged from bringing their own cars by high ferry fares and the need to make vehicle reservations.
- A small community (Hadley) located near a larger college town (Amherst).

To calibrate the car service model, data from six communities were chosen (Table A-1-1).

Table A-1-1 Communities for car service model

TOWN	SQ MI	POP (K)	POP DENSITY	BOSTON METRO	JOBS (K)	AVG WEEKLY WAGE	ANNUAL TNC ORIGIN TRIPS / RESIDENT
CAMBRIDGE	7.11	105	14801	Y	137	2551	74.92
LAWRENCE	7.43	76	10284	N	28	1070	7.40
LEXINGTON	16.64	31	1887	Y	23	2219	6.65
METHUEN	23.00	47	2055	N	16	874	4.17
STOW	18.00	7	366	Y	2	1297	0.85
ASHBURNHAM	40.95	6	148	N	1	943	0.15

The first step is to set the model inputs for TNC-like service in these communities. The total number of trips is calculated based on population, jobs and overall trip-making data from NHTS. The numbers of trips come from the 2017 NHTS (Table 10a, annual person trips per person). Associations with jobs and residents are asserted, with commuting trips split evenly, work-related travel associated with jobs, shopping travel is split, and other travel is associated with residents.

Table A-1-2 Trip making (from NHTS)

Trips per person	To/From work	Work related	Shopping	School	Social	Other
Annual	214	20	473	134	339	50
Monthly	18	2	39	11	28	4
Associated with jobs	0.5	1	0.3	0	0	0
Associated with residents	0.5	0	0.7	1	1	1

Table A-1-3 Community-specific SD model inputs

TOWN	POP DENSITY (PER SQ MI)	SERVICE AREA (SQ MI)	TOTAL TRIPS / PERSON/MONTH[14]	TNC TRIPS / PERSON/MONTH	TNC TRIPS / MONTH[15]
CAMBRIDGE	14801	7.11	109	6.24	656603
LAWRENCE	10284	7.43	88	0.62	47077
LEXINGTON	1887	16.64	97	0.55	17408
METHUEN	2055	23.00	88	0.35	16433
STOW	366	18.00	88	0.07	469
ASHBURNHAM	148	40.95	84	0.01	75

References

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- Employment data
  https://data.bls.gov/cew/apps/table_maker/v4/table_maker.htm#type=2&st=25&year=2019&qtr=A&own=0&ind=10&supp=0
  https://lmi.dua.eol.mass.gov/lmi/EmploymentAndWages#

[14] Based on NHTS (see Table A-1-2

[15] From Massachusetts TNC data

Appendix 2: Vensim Model

```
{UTF-8}
Per rider public support=
	0
	~	Dollar/Trip
	~		|

Fixed public support=
	0
	~	Dollar/Month
	~		|

Fare=
	13.6
	~	
	~		|

Cost per minute=
	0.35
	~	Dollar/minutes
	~		|

Fixed vehicle cost=
	400
	~	Dollar/Month
	~		|

Avg trip distance=
	4.2
	~	mi
	~		|

Target utilization=
	0.5
	~	
	~		|

Initial vehicle stock per 1000 population=
	1
	~	
	~		|

Max reception rate=
	15000
	~	Vehicle/Month
	~		|
```

"Vehicle useful life (tripwise)"=
	10000
	~	Trip/Vehicle
	~	How many trips does an Vehicle last?
	|

Size of service area=
	236
	~	mi*mi
	~		|

EmptyDistanceConstant=
	1
	~	mi
	~		|

EmptyDistanceMultiplier=
	1
	~
	~		|

Vehicle speed=
	14.6
	~	mi/hour
	~		|

wait time coefficient=
	-0.05
	~
	~		|

"Value of time(min/$)"=
	5
	~	minute/Dollar
	~		|

POV utility=
	-0.7
	~
	~		|

Transit utility=
	-2.7
	~
	~		|

Utility for zero induced trips=

```
	-3.9
	~
	~		|

maximum induced trips=
	0.2
	~
	~	Maximum percent of Total Trips that can be added as induced trips
	|

"Trips / person / month"=
	93
	~	Trip/(person*Month)
	~		|

Population density=
	12154
	~	person/(mi*mi)
	~		|

smoothing factor for increasing trips=
	6
	~	Month
	~		|

smoothing factor for decreasing trips=
	1
	~	Month
	~		|

"Avg. distance to nearest empty/available vehicle"=
	EmptyDistanceConstant + EmptyDistanceMultiplier/SQRT((1-Target utilization)*Vehicle density\
		)
	~	mi
	~		|

Mobility service utility=
	wait time coefficient*("Avg. total wait time for traveler"+"Value of time(min/$)"*Fare\
		)
	~
	~		|

Monthly cash inflow=
	Fare*Trips satisfied by mobility service+External funding
	~
	~		|

new trips=
```

```
	Total Trips in Service Area*MAX( 0 , maximum induced trips*((Utility for zero induced trips\
		-Mobility service utility)/Utility for zero induced trips
	))
	~	
	~		|

Initial Vehicle stock=
	Initial vehicle stock per 1000 population*Population/1000
	~	Vehicle
	~		|

Population=
	Population density*Size of service area
	~	
	~		|

Net monthly income=
	Monthly cash inflow-Monthly cash outflow
	~	Dollar/Month
	~	100 = $/vehicle/month, 15 = loaded trip time, 0.10 = cost / vehicle minute
	|

Monthly cash outflow=
	Number of Vehicles*Fixed vehicle cost+Trips satisfied by mobility service*Variable vehicle cost
	~	
	~		|

Desired Additional Vehicles= ACTIVE INITIAL (
	IF THEN ELSE(Net monthly income>0, Number of Vehicles*MAX(Vehicle utilization-Target 
utilization\
		, 0 ) , 0 ),
		0)
	~	Vehicle
	~		|

indicated trips=
	Total Trips in Service Area*Mobility service mode share+new trips
	~	Trip/Month
	~		|


Avg loaded trip time=
	Avg trip distance/(Vehicle speed/60)
	~	minutes
	~		|

Mobility service VMT=
	(Avg trip distance+"Avg. distance to nearest empty/available vehicle")*indicated trips
```

```
	~	mi
	~		|

POV VMT=
	Avg trip distance*(POV mode share*Total Trips in Service Area)
	~	mi
	~		|

Transit trips=
	Total Trips in Service Area*Transit mode share
	~	Trip/Month
	~		|


POV mode share=
	EXP(POV utility) / (EXP(Mobility service utility)+EXP(POV utility)+EXP(Transit utility\
		))
	~	
	~		|


Transit mode share=
	EXP(Transit utility) / (EXP(Mobility service utility)+EXP(POV utility)+EXP(Transit utility\
		))
	~	
	~		|

Mobility service mode share=
	EXP(Mobility service utility) / (EXP(Mobility service utility)+EXP(POV utility)+EXP(\
		Transit utility))
	~	Dmnl
	~		|


Total Trips in Service Area=
	Population density*Size of service area*"Trips / person / month"
	~	Trip/Month
	~		|

trips gap=
	MIN( indicated trips , Number of Vehicles * "Max trips/ vehicle-month" )-Trips satisfied by
mobility service
	~	Trip/Month
	~		|

"Max trips/ vehicle-month"= ACTIVE INITIAL (
	10*30*60 / (1 + Avg loaded trip time + "Avg. empty-vehicle repositioning time"),
		450)
```

```
	~	Trip/(Month*Vehicle)
	~	10*30*60 = available minutes / month,  1 = dispatch,
	|

Variable vehicle cost=
	Cost per minute*(Avg loaded trip time+"Avg. empty-vehicle repositioning time")
	~	Dollar/Trip
	~		|

External funding=
	Fixed public support+ Per rider public support*Trips satisfied by mobility service
	~	Dollar/Month
	~		|

Change in trips=
	IF THEN ELSE(trips gap>=0, trips gap / smoothing factor for increasing trips , trips gap\
		 / smoothing factor for decreasing trips )
	~	Trip/Month/Month
	~		|

Number of Vehicles= INTEG (
	Reception rate in-Junk rate,
		Initial Vehicle stock)
	~	Vehicle
	~		|

Reception rate in=
	MIN(Desired Additional Vehicles, Max reception rate )
	~	Vehicle/Month
	~		|

"Avg. wait time for a vehicle to become empty/available"=
	2/MAX(ABS( 1-Vehicle utilization ), 0.01 )
	~	minutes
	~	The 2 is a queuing parameter
	|

Trips satisfied by mobility service= INTEG (
	Change in trips,
		1.08e+06)
	~	Trip/Month
	~		|

"Trips/ vehicle-month"=
	Trips satisfied by mobility service/Number of Vehicles
	~	Trip/(Vehicle*Month)
	~		|
```

"Avg. total wait time for traveler"=
    1+"Avg. empty-vehicle repositioning time"+"Avg. wait time for a vehicle to become empty/available"
    ~   minutes
    ~   The 1 is a dispatch time constant
    |

Vehicle utilization=
    "Trips/ vehicle-month"/"Max trips/ vehicle-month"
    ~   Dmnl
    ~ |

"Avg. empty-vehicle repositioning time"=
    "Avg. distance to nearest empty/available vehicle"/(Vehicle speed/60)
    ~   minutes
    ~ |

"Vehicle useful life (timewise)"=
    "Vehicle useful life (tripwise)"/"Trips/ vehicle-month"
    ~   Month
    ~   At current trips/Vehicle/mo rate and # of Vehicles, how long will it take \
    for a Vehicle to wear out?
    |

Junk rate=
    Number of Vehicles/"Vehicle useful life (timewise)"
    ~   Vehicle/Month
    ~   "Death rate"
    |

Vehicle density=
    Number of Vehicles/Size of service area
    ~   Vehicle / (mi*mi)
    ~ |

****
    .Control
**~
        Simulation Control Parameters
    |

FINAL TIME = 100
    ~   Month
    ~   The final time for the simulation.
    |

INITIAL TIME = 0
    ~   Month

```
	~	The initial time for the simulation.
	|

SAVEPER  =
        TIME STEP
	~	Month [0,?]
	~	The frequency with which output is stored.
	|

TIME STEP  = 1
	~	Month [0,?]
	~	The time step for the simulation.
	|

\\\---/// Sketch information - do not modify anything except names
V300  Do not put anything below this section - it will be ignored
*View 1
$192-192-192,0,Calibri|12|B|0-0-0|0-0-0|0-0-255|-1--1--1|-1--1--1|96,96,85,0
10,1,Number of Vehicles,979,197,45,25,3,131,0,8,0,0,0,0,-1--1--1,0-0-0,|14||0-0-0,0,0,0,0,0,0
12,2,48,780,189,12,8,0,3,0,0,-1,0,0,0,0,0,0,0,0,0
11,3,48,867,188,8,8,2,3,0,0,1,0,0,0,0,0,0,0,0,0
1,4,3,1,4,0,0,22,0,0,0,-1--1--1,,1|(904,188)|
1,5,3,2,100,0,0,22,0,0,0,-1--1--1,,1|(824,188)|
1,6,8,3,4,0,0,22,0,0,0,-1--1--1,,1|(867,188)|
1,7,8,3,100,0,0,22,0,0,0,-1--1--1,,1|(867,188)|
11,8,48,867,188,8,8,34,3,0,0,1,0,0,0,0,0,0,0,0,0
10,9,Reception rate in,867,215,37,19,40,131,0,0,-1,0,0,0,0,0,0,0,0,0
12,10,48,1124,193,12,8,0,3,0,0,-1,0,0,0,0,0,0,0,0,0
1,11,13,10,4,0,0,22,0,0,0,-1--1--1,,1|(1092,193)|
1,12,13,1,100,0,0,22,0,0,0,-1--1--1,,1|(1037,193)|
11,13,48,1059,193,8,8,34,3,0,0,1,0,0,0,0,0,0,0,0,0
10,14,Junk rate,1059,212,36,11,40,131,0,0,-1,0,0,0,0,0,0,0,0,0
1,15,1,13,1,0,0,0,0,128,0,-1--1--1,,1|(984,165)|
10,16,"Vehicle useful life (timewise)",884,316,63,19,8,131,0,0,0,0,0,0,0,0,0,0,0,0
10,17,Trips satisfied by mobility service,371,381,55,32,3,131,0,8,0,0,0,0,-1--1--1,0-0-0,|14|B|0-0-
0,0,0,0,0,0,0
10,18,Vehicle density,1079,437,59,12,8,131,0,8,0,0,0,0,-1--1--1,0-0-0,|14||0-0-0,0,0,0,0,0,0
1,19,1,18,1,0,0,0,0,128,0,-1--1--1,,1|(1091,333)|
10,20,Size of service area,1215,425,43,21,8,131,0,2,0,0,0,0,-1--1--1,0-0-0,|12|B|0-128-0,0,0,0,0,0,0
1,21,20,18,1,0,0,0,0,128,0,-1--1--1,,1|(1152,421)|
1,22,17,26,1,0,0,0,0,128,0,-1--1--1,,1|(464,357)|
10,23,Mobility service mode share,408,652,63,24,8,131,0,8,0,0,0,0,-1--1--1,0-0-0,|14||0-0-0,0,0,0,0,0,0
1,24,1,26,1,0,45,0,3,128,0,255-0-0,|12||0-0-0,1|(656,332)|
1,25,16,13,1,0,0,0,0,128,0,-1--1--1,,1|(1047,212)|
10,26,"Trips/vehicle-month",567,348,53,19,8,131,0,0,0,0,0,0,0,0,0,0,0,0
10,27,"Vehicle useful life (tripwise)",952,385,57,25,8,131,0,2,0,0,0,0,-1--1--1,0-0-0,|12|B|0-128-
0,0,0,0,0,0,0
1,28,27,16,1,0,0,0,0,128,0,-1--1--1,,1|(908,345)|
```

10,29,Initial Vehicle stock,967,96,24,27,8,131,0,8,0,0,0,0,-1--1--1,0-0-0,|10||0-128-0,0,0,0,0,0,0
1,30,29,1,1,0,0,0,0,128,1,-1--1--1,,1|(968,140)|
10,31,Desired Additional Vehicles,643,128,69,19,8,131,0,0,0,0,0,0,0,0,0,0,0,0
1,32,1,31,1,0,45,0,3,128,0,255-0-0,|12||0-0-0,1|(775,101)|
10,33,"Trips/ vehicle-month",1100,28,53,19,8,2,1,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
1,34,26,16,1,0,45,0,3,128,0,255-0-0,|12||0-0-0,1|(748,345)|
10,35,"Avg. empty-vehicle repositioning time",820,660,69,19,8,131,0,0,0,0,0,0,0,0,0,0,0,0
10,36,"Avg. total wait time for traveler",640,677,80,24,8,3,0,8,0,0,0,0,-1--1--1,0-0-0,|14||0-0-0,0,0,0,0,0,0
1,37,18,40,1,0,45,0,3,128,0,255-0-0,|12||0-0-0,1|(1032,524)|
1,38,35,36,1,0,0,0,0,128,0,-1--1--1,,1|(712,680)|
10,39,Net monthly income,523,185,48,25,8,131,0,8,0,0,0,0,-1--1--1,0-0-0,|14||0-0-0,0,0,0,0,0,0
10,40,"Avg. distance to nearest empty/available vehicle",1000,557,88,19,8,131,0,0,0,0,0,0,0,0,0,0,0,0
10,41,"Avg. wait time for a vehicle to become
empty/available",651,589,71,28,8,131,0,0,0,0,0,0,0,0,0,0,0,0
1,42,40,35,1,0,0,0,0,128,0,-1--1--1,,1|(935,640)|
1,43,41,36,1,0,0,0,0,128,0,-1--1--1,,1|(652,640)|
10,44,Vehicle speed,1031,665,41,24,8,131,0,2,0,0,0,0,-1--1--1,0-0-0,|12|B|0-128-0,0,0,0,0,0,0
1,45,44,35,0,0,45,0,3,128,0,255-0-0,|12||0-0-0,1|(948,663)|
10,46,Max reception rate,864,132,37,20,8,131,0,10,0,0,0,0,-1--1--1,0-0-0,|10||0-128-0,0,0,0,0,0,0
10,47,"Max trips/ vehicle-month",859,544,53,19,8,131,0,0,0,0,0,0,0,0,0,0,0,0
10,48,Vehicle utilization,755,413,40,24,8,131,0,0,0,0,0,0,0,0,0,0,0,0
1,49,26,48,1,0,0,0,0,128,0,-1--1--1,,1|(692,372)|
1,50,47,48,1,0,45,0,3,128,0,255-0-0,|12||0-0-0,1|(812,449)|
1,51,48,41,1,0,0,0,0,128,0,-1--1--1,,1|(723,488)|
1,52,39,31,1,0,0,0,0,128,0,-1--1--1,,1|(555,148)|
1,53,48,31,1,0,0,0,0,128,0,-1--1--1,,1|(704,217)|
10,54,Total Trips in Service Area,232,612,47,19,8,131,0,0,-1,0,0,0,0,0,0,0,0,0
12,55,48,171,373,12,8,0,3,0,0,-1,0,0,0,0,0,0,0,0
1,56,58,17,4,0,0,22,0,0,0,-1--1--1,,1|(285,372)|
1,57,58,55,68,0,0,22,2,0,0,-1--1--1,|12||0-0-0,1|(212,372)|
11,58,48,247,372,8,8,34,3,0,0,1,0,0,0,0,0,0,0,0
10,59,Change in trips,247,397,53,11,40,3,0,0,-1,0,0,0,0,0,0,0,0
10,60,smoothing factor for increasing trips,304,308,44,27,8,131,0,10,0,0,0,0,-1--1--1,0-0-0,|10||0-128-0,0,0,0,0,0,0
10,61,smoothing factor for decreasing trips,223,312,40,25,8,131,0,10,0,0,0,0,-1--1--1,0-0-0,|10||0-128-0,0,0,0,0,0,0
1,62,61,59,0,0,0,0,1,128,0,160-160-160,|12||0-0-0,1|(236,356)|
1,63,60,59,0,0,0,0,1,128,0,160-160-160,|12||0-0-0,1|(276,356)|
10,64,trips gap,240,481,32,11,8,3,0,0,0,0,0,0,0,0,0,0,0,0
10,65,indicated trips,319,557,52,11,8,3,0,0,0,0,0,0,0,0,0,0,0,0
1,66,23,65,1,0,0,0,0,128,0,-1--1--1,,1|(351,601)|
1,67,54,65,0,0,0,0,0,128,0,-1--1--1,,1|(275,584)|
1,68,65,64,1,0,0,0,0,128,0,-1--1--1,,1|(275,529)|
1,69,17,64,1,0,0,0,0,128,0,-1--1--1,,1|(372,465)|
1,70,64,59,1,0,0,0,0,128,0,-1--1--1,,1|(236,429)|
1,71,35,47,1,0,0,0,0,128,0,-1--1--1,,1|(863,601)|

1,72,46,8,0,0,0,0,0,64,0,-1--1--1,,1|(865,159)|
1,73,31,8,1,0,0,0,0,64,0,-1--1--1,,1|(787,141)|
12,74,0,520,484,36,36,4,135,0,27,-1,0,0,0,128-128-0,0-0-0,|24|B|128-128-0,0,0,0,0,0,0
B1
12,75,0,1007,320,31,31,4,135,0,27,-1,0,0,0,128-64-0,0-0-0,|24|B|128-64-0,0,0,0,0,0,0
R1
10,76,"Max trips/ vehicle-month",148,513,53,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
1,77,76,64,0,0,0,0,0,128,0,-1--1--1,,1|(200,496)|
10,78,External funding,235,192,59,11,8,3,0,0,0,0,0,0,0,0,0,0,0,0
1,79,17,78,0,0,0,0,0,128,0,-1--1--1,,1|(299,281)|
10,80,Fixed public support,76,100,40,21,8,131,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
10,81,Per rider public support,75,172,52,24,8,131,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
1,82,80,78,0,0,0,0,0,128,0,-1--1--1,,1|(157,147)|
1,83,81,78,0,0,0,0,0,128,0,-1--1--1,,1|(144,180)|
10,84,Fixed vehicle cost,287,65,60,11,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
10,85,Variable vehicle cost,423,37,57,19,8,3,0,0,0,0,0,0,0,0,0,0,0,0
10,86,Avg loaded trip time,548,-12,52,19,8,3,0,0,0,0,0,0,0,0,0,0,0,0
10,87,"Avg. empty-vehicle repositioning time",560,53,76,25,8,130,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
1,88,86,85,0,0,0,0,0,128,0,-1--1--1,,1|(492,12)|
1,89,87,85,0,0,0,0,0,128,0,-1--1--1,,1|(488,47)|
10,90,Cost per minute,280,1,56,11,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
1,91,90,85,0,0,0,0,0,128,0,-1--1--1,,1|(337,15)|
10,92,Avg loaded trip time,863,456,56,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
1,93,92,47,0,0,45,0,3,128,0,255-0-0,|12||0-0-0,1|(861,493)|
10,94,Number of Vehicles,139,453,41,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
1,95,94,64,0,0,0,0,0,128,0,-1--1--1,,1|(187,468)|
10,96,"Value of time(min/$)",716,808,44,19,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12|B|0-128-0,0,0,0,0,0,0
10,97,Population density,63,569,41,19,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
10,98,"Trips / person / month",67,616,56,19,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
10,99,Size of service area,68,677,55,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
1,100,97,54,0,0,0,0,0,128,0,-1--1--1,,1|(137,587)|
1,101,98,54,0,0,0,0,0,128,0,-1--1--1,,1|(147,616)|
1,102,99,54,0,0,0,0,0,128,0,-1--1--1,,1|(143,648)|
10,103,wait time coefficient,732,757,56,15,8,131,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
12,104,0,535,625,40,20,8,3,0,0,-1,0,0,0,0,0,0,0,0,0
10,105,Transit mode share,349,751,48,19,8,3,0,0,0,0,0,0,0,0,0,0,0,0
10,106,POV mode share,351,821,59,11,8,3,0,0,0,0,0,0,0,0,0,0,0,0
10,107,Mobility service utility,559,732,60,19,8,3,0,0,0,0,0,0,0,0,0,0,0,0
10,108,Transit utility,559,781,48,11,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
10,109,POV utility,559,833,39,11,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||64-160-98,0,0,0,0,0,0
1,110,108,23,0,0,0,0,0,128,0,-1--1--1,,1|(496,727)|
1,111,109,23,0,0,0,0,0,128,0,-1--1--1,,1|(493,756)|
1,112,107,105,0,0,0,0,0,128,0,-1--1--1,,1|(456,740)|
1,113,108,105,0,0,0,0,0,128,0,-1--1--1,,1|(460,767)|

1,114,108,106,0,0,0,0,0,128,0,-1--1--1,,1|(468,800)|
1,115,109,106,0,0,0,0,0,128,0,-1--1--1,,1|(471,827)|
1,116,109,105,0,0,0,0,0,128,0,-1--1--1,,1|(472,800)|
1,117,36,107,0,0,45,0,3,64,0,255-0-0,|12||0-0-0,1|(601,703)|
1,118,96,107,0,0,0,0,0,64,0,-1--1--1,,1|(643,773)|
1,119,103,107,0,0,0,0,0,64,0,-1--1--1,,1|(656,745)|
1,120,107,23,0,0,0,0,0,128,0,-1--1--1,,1|(496,697)|
1,121,107,106,0,0,0,0,0,64,0,-1--1--1,,1|(451,777)|
10,122,Avg trip distance,688,-27,31,19,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
1,123,122,86,0,0,0,0,0,128,0,-1--1--1,,1|(635,-21)|
10,124,Vehicle speed,711,24,57,11,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
1,125,124,86,0,0,45,0,3,128,0,255-0-0,|12||0-0-0,1|(637,7)|
10,126,Mobility service VMT,1500,461,60,19,8,3,0,0,0,0,0,0,0,0,0,0,0,0
10,127,POV VMT,1508,584,36,11,8,3,0,0,0,0,0,0,0,0,0,0,0,0
10,128,Transit trips,1495,673,43,11,8,3,0,0,0,0,0,0,0,0,0,0,0,0
10,129,Avg trip distance,1356,557,35,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-
128,0,0,0,0,0,0
10,130,"Avg. distance to nearest empty/available vehicle",1357,452,76,28,8,2,0,3,-1,0,0,0,128-128-
128,0-0-0,|12||128-128-128,0,0,0,0,0,0
10,131,indicated trips,1356,516,60,11,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
10,132,Total Trips in Service Area,1283,672,52,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-
128,0,0,0,0,0,0
10,133,POV mode share,1356,620,43,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-
128,0,0,0,0,0,0
10,134,Transit mode share,1357,731,52,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-
128,0,0,0,0,0,0
1,135,130,126,0,0,0,0,0,128,0,-1--1--1,,1|(1429,455)|
1,136,131,126,0,0,0,0,0,128,0,-1--1--1,,1|(1412,496)|
1,137,129,126,0,0,0,0,0,128,0,-1--1--1,,1|(1421,512)|
1,138,129,127,0,0,0,0,0,128,0,-1--1--1,,1|(1424,568)|
1,139,133,127,1,0,0,0,0,128,0,-1--1--1,,1|(1412,595)|
1,140,132,127,1,0,0,0,0,128,0,-1--1--1,,1|(1368,612)|
1,141,134,128,0,0,0,0,0,128,0,-1--1--1,,1|(1428,700)|
1,142,132,128,0,0,0,0,0,128,0,-1--1--1,,1|(1388,672)|
10,143,new trips,216,712,36,11,8,3,0,0,0,0,0,0,0,0,0,0,0,0
1,144,54,143,0,0,0,0,0,128,0,-1--1--1,,1|(224,659)|
1,145,143,65,1,0,0,0,0,128,0,-1--1--1,,1|(280,649)|
10,146,maximum induced trips,131,784,48,19,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
1,147,146,143,0,0,0,0,0,128,0,-1--1--1,,1|(172,748)|
10,148,Utility for zero induced trips,131,844,48,19,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-
0,0,0,0,0,0,0
1,149,148,143,1,0,0,0,0,128,0,-1--1--1,,1|(207,789)|
10,150,Target utilization,635,224,37,19,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
1,151,150,31,0,0,0,0,0,128,0,-1--1--1,,1|(637,184)|
1,152,150,40,1,0,0,0,0,128,0,-1--1--1,,1|(847,376)|
10,153,Monthly cash inflow,360,200,41,19,8,131,0,0,0,0,0,0,0,0,0,0,0,0
10,154,Monthly cash outflow,419,129,49,19,8,3,0,0,0,0,0,0,0,0,0,0,0,0
1,155,85,154,0,0,0,0,0,128,0,-1--1--1,,1|(421,76)|

1,156,84,154,0,0,0,0,0,128,0,-1--1--1,,1|(337,89)|
1,157,78,153,0,0,0,0,0,128,0,-1--1--1,,1|(299,195)|
1,158,17,153,0,0,0,0,0,128,0,-1--1--1,,1|(365,292)|
1,159,1,154,1,0,0,0,0,128,0,-1--1--1,,1|(763,60)|
1,160,154,39,0,0,45,0,3,128,0,255-0-0,|12||0-0-0,1|(460,152)|
1,161,153,39,0,0,0,0,0,128,0,-1--1--1,,1|(431,193)|
1,162,17,154,0,0,0,0,0,64,0,-1--1--1,,1|(396,255)|
10,163,Population,1065,84,40,11,8,3,0,0,0,0,0,0,0,0,0,0,0
10,164,Population density,1160,57,45,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
10,165,Size of service area,1167,128,55,19,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
1,166,164,163,0,0,0,0,0,128,0,-1--1--1,,1|(1115,68)|
1,167,165,163,0,0,0,0,0,128,0,-1--1--1,,1|(1112,104)|
1,168,163,29,0,0,0,0,0,128,0,-1--1--1,,1|(1016,89)|
10,169,Initial vehicle stock per 1000 population,964,15,73,19,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12|B|0-128-0,0,0,0,0,0,0
1,170,169,29,0,0,0,0,0,128,0,-1--1--1,,1|(964,44)|
1,171,107,143,1,0,0,0,0,128,0,-1--1--1,,1|(377,700)|
10,172,Fare,267,128,17,11,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
1,173,172,153,0,0,0,0,0,128,0,-1--1--1,,1|(304,155)|
10,174,Fare,716,729,25,11,8,2,0,3,-1,0,0,0,128-128-128,0-0-0,|12||128-128-128,0,0,0,0,0,0
1,175,174,107,0,0,0,0,0,128,0,-1--1--1,,1|(661,729)|
10,176,EmptyDistanceConstant,1145,520,88,9,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
10,177,EmptyDistanceMultiplier,1145,607,92,9,8,3,0,2,0,0,0,0,-1--1--1,0-0-0,|12||0-128-0,0,0,0,0,0,0
1,178,176,40,0,0,0,0,0,128,0,-1--1--1,,1|(1100,531)|
1,179,177,40,0,0,0,0,0,128,0,-1--1--1,,1|(1093,589)|
///---\\\
:L<%^E!@
4:Time
5:"Avg. distance to nearest empty/available vehicle"
9:ChicagoUrbanHDV2_TS1
19:85,0
24:0
25:100
26:100
60:AVRural2SensitivityInduc
61:65001
62:1
63:1
64:0
65:1
66:0
67:0
68:0
69:0
70:1
23:0

18:VehicleUtilization_v7.vsc
20:VehicleUtilization_v7.lst
15:0,0,0,0,0,0
27:0,
34:0,
42:1
72:0
73:0
35:Date
36:YYYY-MM-DD
37:2000
38:1
39:1
40:2
41:0
95:0
96:0
77:1
78:0
93:0
94:0
92:0
91:0
90:0
87:0
75:
43:

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