Automated Vehicle Impacts on the Transportation System

Using system dynamics to assess regional impacts

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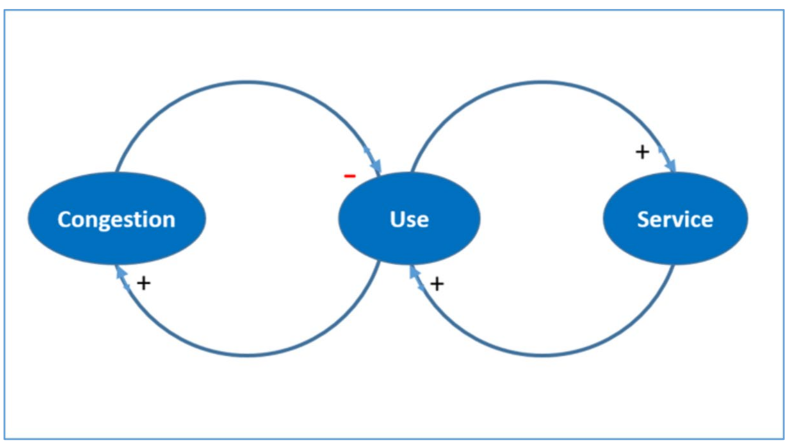
Final Report – March 31, 2021
FHWA-JPO-21-849



U.S. Department of Transportation

Produced by Volpe National Transportation Systems Center
U.S. Department of Transportation
Office of the Assistant Secretary for Research and Technology

Notice

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA-JPO-21-849		

4. Title and Subtitle	5. Report Date
Automated Vehicle Impacts on the Transportation System: Using system dynamics to assess regional impacts	March 2021
	6. Performing Organization Code V336
7. Author(s) Scott Smith ORCID 0000-0003-1476-0361 Ian Berg ORCID 0000-0001-7121-0265 Andrew Eilbert ORCID 0000-0003-4742-1147 Hannah Rakoff ORCID 0000-0003-2008-7900 Jingsi Shaw ORCID 0000-0002-3974-5304 Joe Stanford ORCID 0000-0002-1724-3274	8. Performing Organization Report No. DOT-VNTSC-FHWA-21-05
9. Performing Organization Name and Address John A. Volpe National Transportation Systems Center U.S. Department of Transportation 55 Broadway Cambridge, MA 02142	10. Work Unit No. (TRAIS) 11. Contract or Grant No. Intra-Agency Agreement 693JJ319N300064, HW9EA619
12. Sponsoring Agency Name and Address Intelligent Transportation Systems Joint Program Office U.S. Department of Transportation 1200 New Jersey Ave, SE Washington, DC 20590	13. Type of Report and Period Covered Final Report March 2020 – March 2021 14. Sponsoring Agency Code

15. Supplementary Notes

ITS JPO project manager is Kevin Dopart.

16. Abstract

Many of today's transportation planning tools break down under conditions of deep uncertainty. One example of such an uncertainty is how and when automated vehicles might be adopted in the surface transportation system, their performance capabilities, and user response. System dynamics (SD) techniques focus on causal relationships, and are ideal for gaining insight into the impacts of large changes in the transportation system.

In 2020, the Volpe Center worked with two groups of public-sector organizations, including several Metropolitan Planning Organizations (MPO) and one State Department of Transportation (DOT), to see how SD techniques may be applied to problems of interest to them. Outputs of this effort included causal-loop diagrams (CLDs) and the resulting insights. The MPO partners found the CLDs useful as a discussion tool, to bring planners and modelers together. The SD models also helped to reveal data and modeling gaps in current travel demand models.

17. Keywords	18. Distribution Statement
Automated vehicles, scenarios, mobility benefits, equity, accessibility, transportation planning, system dynamics. metropolitan planning organization	

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	44	

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

Acknowledgements

This project was funded by the Intelligent Transportation Systems Joint Program Office (ITS JPO). We thank Kevin Dopart from ITS JPO for continuing to sponsor research on the impact of automated vehicles.

We thank the following individuals who took the time to speak with us about planning under uncertainty and applications of SD:

- Bart Benthul; Bryan-College Station MPO
- Alex Bettinardi; Oregon Department of Transportation
- Arun Bhowmick; City of Edmonton, Alberta, Canada
- Joe Castiglione; San Francisco County Transportation Authority
- Kelly Clarke, Lane Council of Governments (Oregon)
- Eric Hill; MetroPlan Orlando
- Raymond Jackson, Mid-Willamette Valley Council of Governments (Oregon)
- Andrew Martin, Lane Transit District (Lane County, Oregon)
- Nick Meltzer, Oregon Cascades West Council of Governments
- Arash Mirzei, Hong Zheng, and Tom Bamonte; North Central Texas Council of Governments (Dallas/Ft. Worth)
- Scott Peterson, Martin Milkovits and Kate White; Central Transportation Planning Staff (Boston)
- Tim Reardon, Alison Felix and Sarah Philbrick; Metropolitan Area Planning Council (Boston)
- Guy Rousseau; Atlanta Regional Commission

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Executive Summary

Many of today's transportation planning tools break down under conditions of deep uncertainty. Deep uncertainty exists "when parties to a decision do not know, or cannot agree on, the system model that relates action to consequences, the probability distributions to place over the inputs to these models, which consequences to consider and their relative importance." (Society for Decision Making Under Deep Uncertainty, 2021). One example of such an uncertainty is how and when automated vehicles might be adopted in the surface transportation system, their performance capabilities, and how they will affect a range of user responses, including new travel behaviors and business models. The appropriate values of modeling parameters for transportation demand models have been topics of debate for as long as the field has existed; we can say that they are uncertain. But automation adds a dimension for which the field has not yet even agreed on the structure of the model that best represents it. That is deep uncertainty.

The Intelligent Transportation Systems Joint Program Office (ITS JPO) and the Federal Highway Administration (FHWA) are leading several programs to understand how scenario planning, robust decision-making, and system dynamics tools can support transportation planning and decision-making in a period of rapid change and uncertainty. Scenario planning involves the imagining of several plausible futures, the driving forces that lead to those futures, and their consequences. Robust decision-making (RDM) is a technique for exploring a large scenario space, to find the near-term decisions that will lead to futures where good outcomes are more likely and bad outcomes less likely. The FHWA Travel Model Improvement Program – Exploratory Modeling and Analysis Tool (TMIP-EMAT) explored the use of robust decision-making in the context of transportation planning. System dynamics provides a simple, user-friendly way to represent complex systems, by breaking them down into the causal relationships and feedback effects among their elements. This approach is especially useful for a system marked by complexity in both technical functioning and in human reactions to it—a complex sociotechnical system.

Scenario planning, robust decision-making, and system dynamics approaches all include elements of stakeholder engagement and are all characterized by the use of fast quantitative models that can explore many scenarios. They complement each other. The ITS JPO project described in this report focuses on the use of system dynamics tools to address current challenges faced by metropolitan planning organizations.

System Dynamics

System dynamics (SD) offers a rigorous approach to dealing with time lags and feedback effects in complex systems and is ideal for gaining insight into the potential impacts of large changes in the transportation system. SD techniques allow modelers to see how causal relationships that produce predictable outcomes in isolation often lead to unexpected results when they interact. SD embraces both qualitative and quantitative modeling, and allows modelers to consider model elements that are normally assumed exogenous. In the context of transportation, such elements may include

- consumer adoption of a new travel mode, via word of mouth or other factors that lead to changes in consumer attitudes,

- business models of providing a new transportation service, and how use of a service may influence the provider to add service, and
- how land use and supporting services (e.g., charging stations) might evolve in response to and/or in support of a new travel mode.

After the causal factors and loops have been identified, these conceptual models can often be converted into rigorous, but fast, simulation models, showing how the sociotechnical system might evolve over time, and what the sensitivities are to input assumptions. These models can then be placed in an RDM framework, to explore the scenario space in a way that considers causality, time lags, and possible tipping points.

As such, system dynamics provides a useful addition to the strategic planning toolbox, one that can effectively deal with the sometimes unexpected dynamics of a transportation / land use system, and how they might evolve over time.

Research in Practice

Following interviews with several metropolitan planning organizations (MPOs) in mid-2020, the Volpe Center then worked with two groups of organizations, including one large MPO, several smaller MPOs and one state department of transportation (DOT), to see how SD techniques may be applied to problems of interest to them. Both groups of agencies were interested in policies that might encourage use of public transportation, such as fare-free transit and transit oriented development. These transit use cases can be viewed as proxy modes for the automation services of the future, because they are affected by service provider business models and land use policies, just as automation services will be. The agencies were interested in environmental and equity impacts. They worked with us to build models of the causal factors of interest (e.g., a lower fare makes service more attractive but reduces revenue per rider), leading to causal loop diagrams and an initial model that can run simple simulations.

Outcomes

Staff at MPOs of all sizes were interested in new approaches to modeling, including SD. Many of the problems they are thinking about lend themselves to SD techniques. Models that are created around MPOs' current interests, such as lasting effects of the coronavirus pandemic on travel patterns and mode splits, can be generalized to provide useful insights regarding possible impacts of introduction of automated vehicles (AVs). Furthermore, these models better represent "on-the-ground" conditions than models that begin with assumptions about automation's future state.

Participants from the detailed modeling exercises identified several benefits.

- Articulation of the factors that affect use of a travel mode immediately adds value to the discussion, because it provides a framework for bringing planners and modelers into the same room and helping them speak the same language.
- The factors also enable a qualitative assessment of the effects of uncertainties and policy levers.
- The exercise of developing the causal loops could help to reveal gaps in existing modeling tools and data.

The Volpe team also observed that the process of creating and reviewing a model of a system in close collaboration with those who work day in and day out to analyze, plan for, and manage that system was an efficient way to reveal their decision rules. When the group has to define a precise causal relationship on a shared screen, it is easy for everyone to understand the question in exactly the same way, and provide their perspectives on exactly the same topic, even if those perspectives differ. This points to another benefit of group model building, whether for system dynamics models or as a technique to support other approaches: it is an efficient way to harvest and collate information about a system from several different people with direct knowledge of it. In this way, group model building could be considered within the category of continuous improvement tools that emphasize that the person “in the system” knows it best. Overall, close participation with regional and state transportation agencies has greatly advanced the models of AV impacts that the Volpe Center is developing.

Chapter 1. Introduction

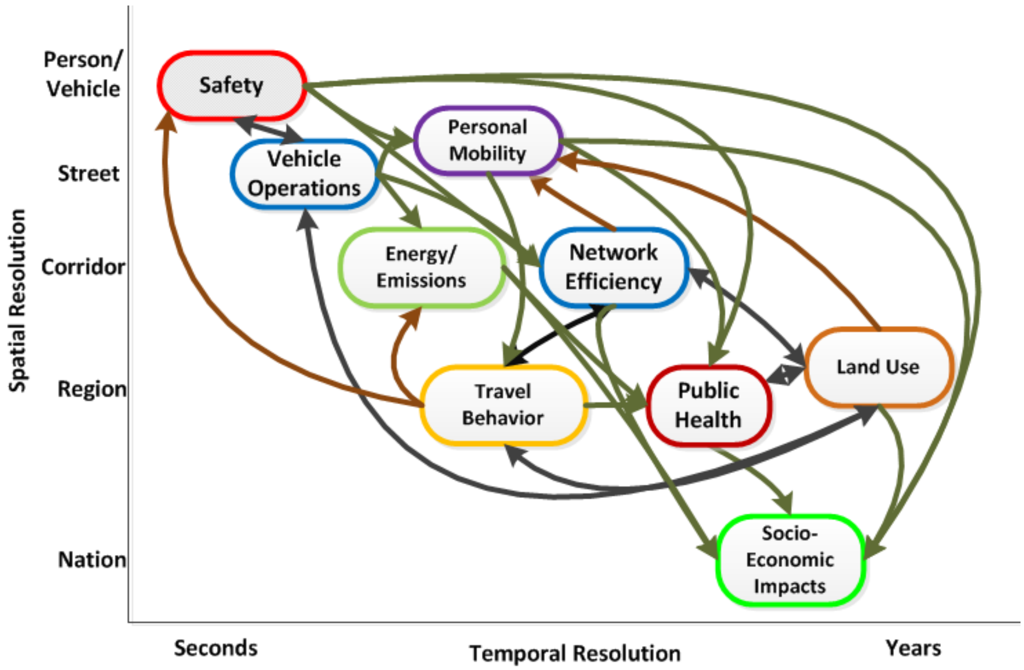
Today's large transportation planning models use a predict-then-act paradigm and make several strong assumptions about future conditions. For example, a 20-year plan might predict future travel on a road, under the explicit assumption that a nearby parcel is developed. Based on this prediction, there might be an action to expand the road, so that its new capacity exceeds the predicted traffic volume. This forecast assumes that the following can be accurately predicted:

- regional changes in land use,
- the number and timing of trips from the parcel, based on characteristics of the parcel,
- the travel modes (e.g., auto, bus, walk) that travelers will choose, based on known characteristics of the modes and the travelers,
- the number of users of the parcel (e.g., homeowners) who will own automobiles, and
- the value-of-time for travelers, which influences the decision of whether to travel and what mode to use.

The classic predict-then-act paradigm breaks down under conditions of deep uncertainty, where there is no agreement on the prediction or its underlying assumptions. The implicit assumptions of current models may not hold up under big changes in transportation and land use.

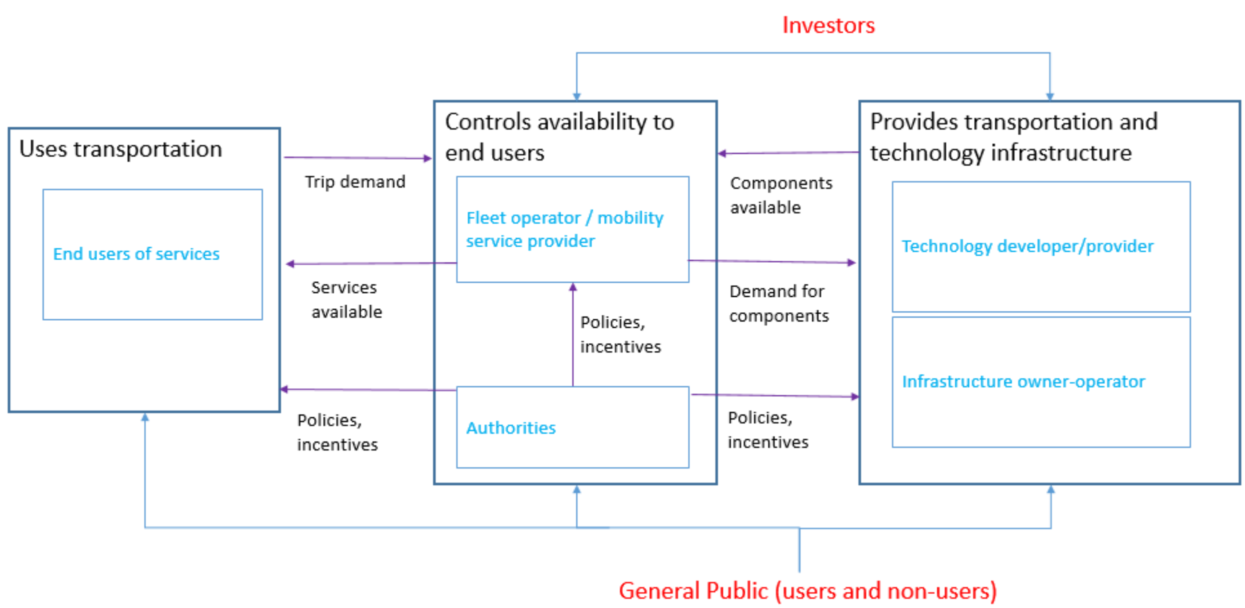
The deployment of automated vehicles (AVs), particularly those operating at SAE Levels 4 and 5 without the need for a human driver (SAE International, 2018), has the potential to be one of those big changes. Prior work under this program has investigated the impact areas that automation will affect (S. Smith, Koopmann, et al., 2018). Figure 1-1 shows the framework describing the different impacts and the scales on which they occur. More recently, we have also developed a framework describing the different roles of agents in a transportation system and their relationships (Rakoff et al., 2020). Figure 1-2 shows the major roles and the levers they have to influence each other. These frameworks provide structured ways to think about and discuss not just the impacts that automation will have, but who can influence the direction and magnitude of those impacts.

To address the uncertainties surrounding automation as well as other potential large changes (such as climate change or lasting impacts of the coronavirus disease 2019 (COVID-19) pandemic), planning agencies need tools that can evaluate many possible future conditions. It is useful to consider these needs through the lens of scenario planning and robust decision making.



Source: (S. Smith, Koopmann, et al., 2018)

Figure 1-1 Automated vehicle benefits framework



Source: (Rakoff et al., 2020)

Figure 1-2 Major transportation system roles and how they influence each other

Scenario planning and robust decision-making

Scenario planning both provides a framework for discussion and can lead to quantitative models of several possible futures. A scenario planning process starts with identifying driving forces (e.g., effects of climate change, advances in vehicle automation, etc.), leading to the several plausible futures and their implications (Bradfield et al., 2005).

Similarly, robust decision-making (RDM) provides a framework for stakeholder engagement and scenario modeling. A key concept is deep uncertainty, where the stakeholders do not know or agree on what the future might bring. Therefore, they should focus on the decisions that can be made today, rather than on a futile effort to agree on a prediction. RDM provides an analytic "XLRM" framework for structuring discussions based on the following elements (Lempert, 2019):

- eXternal factors: the uncertainties (e.g., future sea level, price of energy) that need to be considered
- policy Levers: the decisions that the planner can influence, either now or in the future
- Relationships: the modeled relationships that connect the external factors and policy levers to measureable outcomes
- Metrics: the output performance metrics for each scenario

RDM also lends itself to exploratory modeling, where a fast model is run hundreds to thousands of times to explore the consequences of a decision made today over many future possible scenarios (S. B. Smith, 2019).

This report uses system dynamics (SD), informed by RDM and scenario planning, to investigate uncertainties faced by regional modelers. Our prior report (Berg et al., 2020), discusses characteristics of SD models. Chapter 2 of this report places this work in context with the needs of metropolitan planning organizations (MPOs) and the gaps in current travel modeling practice. Chapter 3 provides an overview of causal loop diagramming and describes a general model focused on financial sustainability of a travel mode and the land use ecosystem. Finally, Chapter 4 describes lessons learned from this effort, which can be applied to improve both modeling and planning practice when facing great uncertainty.

Chapter 2. MPO Travel Modeling Context

This chapter provides overall context on the uncertainties of interest to metropolitan planning organizations (MPOs) and state departments of transportation (DOTs), the tools that they have how, and how system dynamics might productively fit in.

Why focus on MPOs?

Every urbanized area with a population over 50,000 has a designated MPO. Among other responsibilities, Federal law[1] requires these MPOs to prepare a long-range transportation plan (LRTP) which guides decisions about investments in a region's transportation system to bring the system from its present state towards the MPO's vision for the system's future. The plan ensures facilities and services required to support the mobility needs of the regional community align with inputs from various stakeholders, including transportation planners, engineers, elected officials and the public.

MPOs engage in a continuous, comprehensive, and cooperative planning process[2] with an eye toward making public participation convenient, inviting, and engaging for everyone. They also rely on models of travel demand and land use changes when developing their plans and evaluating potential projects against their planning goals. MPOs and state DOTs maintain regional/statewide travel demand models, which forecast travel demand in the future. The outputs from these models are used to help prioritize transportation improvement projects.

Transportation planners must plan for the compounding influences of uncertainty and system complexity. Most current travel demand models use land use data and a model of the transportation system (highway and transit) to predict average, aggregate traffic flows. They ignore possible wild card fluctuations in conditions. These models lack consideration of the potential impacts of many emerging factors (like automation and climate change) and their implications. This may suggest that the existing modeling paradigm is no longer adequate, and new approaches to decision-making under uncertainty can contribute to rethinking the current modes of analysis and decision-making models used by MPOs.

Furthermore, some regions have been interested in moving away from expensive capital-expansion projects, instead using their limited funding for small operations-and-management-type projects that support bicycle, pedestrian, and transit improvements, in addition to operational road improvements that avoid major construction. Evaluation of these smaller projects often requires a more detailed spatial and temporal resolution that is typically available in an aggregate travel model.

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[1] 23 U.S. Code § 134

[2] 23 CFR § 450.306 - Scope of the metropolitan transportation planning process, paragraph (b)

MPOs' statutory requirements and their existing use of modeling in developing their plans mean that, practically speaking, focusing on transportation system impacts at the metropolitan scale allows us to build off of their existing efforts, while helping them fill in the gaps not covered by their existing models. This may lead to more robust outcomes from their planning processes, by helping them consider a wider range of scenarios. That is not to say that automation will not cause changes that affect long-distance travel (between metro regions), or rural communities not covered by an MPO. However, focusing on metro-level impacts allows us to leverage and supplement current practices in urban areas, where a majority of Americans live[3]. Furthermore, the findings from this work will also have applicability to rural and long-distance travel.

Looking ahead to the next 30 years, many new factors may play an important role in influencing transportation system performance, such as climate change and emerging technology. However, the direction and magnitude of these effects are unclear. Using emerging technologies as an example, the way in which AVs are introduced may affect system performance differently. Shared AVs could reduce the cost of traveling, but may also induce more people to travel, which could ultimately exacerbate traffic congestion. Because AVs may not be affordable to all travelers, they could also impact transportation equity.

As modeling the interactions between travelers' decisions and these new factors is important, but doing so consumes limited time and funding, modeling tools that allow modelers to map out complicated relationships and sort out the significance of those effects would give them the ability to select critical links to add to their existing modeling tools for long-term transportation strategic planning.

Transportation modelers are showing an increasing interest in strategic transportation planning models, fast models to shed light on specific questions. System dynamics (SD) can help modelers explore complex interactions that arise from simple relationships in different parts of a system. In some cases, SD may provide an opportunity to tackle a long-term problem, which is currently not actively addressed because the appropriate tools are not available to attack it.

To better understand modelers' needs and interest in new tools, we interviewed representatives from several MPOs and one state DOT, regarding the use of system dynamics for planning under uncertainty. The following section presents the themes from those interviews.

What we heard from them

In July and August 2020, the Volpe Center had conversations with staff at nine agencies which practice transportation or land-use modeling, including five MPOs, to identify problems of interest to regional modelers that lend themselves to SD approaches. Outreach included professional contacts of the Volpe

[3] U.S. Census Urban Area Facts, https://www.census.gov/programs-surveys/geography/guidance/geo-areas/urban-rural/ua-facts.html

team, discussion with staff at the Association of MPOs (AMPO) and the Federal Highway Administration Office of Planning, and follow-up communication to a webinar that Volpe presented in May 2020.[4]

These conversations took place during a public health crisis (the COVID-19 pandemic), which was producing a significant reduction in travel demand (especially for transit), increased unemployment, and increased working from home. Despite these short-term issues, the MPOs still recognized the need to consider long range uncertainties.

Themes

While these conversations were framed in the context of Volpe's work investigating AV impacts, many interviewees noted that AVs were not a primary concern in their recent modeling efforts. Key uncertainties that nearly all metropolitan areas face include the prevalence of teleworking and e-commerce (especially in the context of the COVID-19 pandemic) and questions about the long-term uptake of transportation network companies (TNCs). These sorts of questions, where there is deep uncertainty, are useful to evaluate through the lens of robust decision making, and SD is a useful tool that can provide insight through this lens (Pruyt, 2015). Including SD in the MPO modeling toolbox does not replace classic travel demand modeling (TDM) techniques; rather, it can supplement traditional TDM methods and fill in gaps.

Models created about MPOs' current interests – and, in particular, those uncertainties identified above – can be extended or generalized to investigate AV impacts. For example, some cities have done extensive research into TNC trip patterns and their effects, including congestion, equity, and impacts on transit ridership (Erhardt et al., 2019). Using SD to model interactions between TNC business model choices, like fare structure, and ridership could lead to insights on similar interactions in an AV-based shared mobility system.

Indeed, models based on real data from current challenges would better represent "on-the-ground" conditions than models that begin with assumptions about automation's future state. Interviewees noted, and the literature verifies, that when MPO models have been used in the past to investigate AV impacts, researchers often postulate changes to input factors such as value of time, cost per mile, parking cost, and roadway capacity based on what they envision an AV future could look like, without updating the underlying structure of the model (Childress et al., 2015; Gucwa, 2014; Kim et al., 2015; Zhao & Kockelman, 2017). An SD-based approach might be to instead build a model based in real data on current conditions (a "reference mode") and then consider how automation might change the structure of the system. Rather than simply changing parameter values in a pre-built model, this approach might involve modifying the underlying relationships as well as the numeric values.

For example, one near-term topic of interest discussed by several of the interviewed modelers was the effect of managed lanes. Modeling managed lanes is not simple, since their use is not driven solely by time savings and cost. Branding, habits, and payment methods/structures all affect behavior. One interviewee observed that some drivers' use of these lanes appears to be irrational, under standard assumptions of time and out-of-pocket cost minimization. To replicate this behavior using their current

[4] https://zephyrtransport.org/events/2020-05-27-learning-system-dynamics/

models, one would have to assign a negative value of time to the driver. This unintuitive result suggests that there are other important factors not considered by the existing model.

Given sufficient data on how managed lane users behave, an SD model could be built which aligns with the reference mode, and parameters identified which drive that behavior. This effort could then be extended to automation in one of several ways: on one hand, such a model could inform whether dedicated lanes for AVs is a feasible option for a region. On the other hand, interviewees noted that some factors that lead travelers to choose managed lanes are similar to those that drive technology adoption, and so such a model could inform how MPOs think about how AVs will be adopted in their regions.

On the demand side, in addition to the aforementioned TNC studies, multiple interviewees noted that other new modes of travel (like microtransit, dockless bikes/scooters, and even automated shuttle pilots) have started to show up in their communities, and some of them are collecting data about these novel modes. Questions about choice-set-formation, mode choice, and trip generation with these new modes in play may not easily be answered by plugging adjusted values into existing models. One particular challenge that arises with many of these new modes is their envisioned role as “first-mile/last-mile” services, where a single trip could involve several modes, both established and emerging. The business models of some of these services – where profit generation may take a back seat to attracting investors – also pose new challenges for modeling. Again, thinking about these questions through the lens of SD may not only strengthen how these existing problems are modeled, but also provide hints as to how users will adopt and use forthcoming new modes, like AVs.

Even for automation impacts that are further afield and less readily extrapolated from current conditions – for example, changes to land use patterns (which themselves range in scale from curb space allocation to new development) and the associated impacts on travel – an SD approach can still have value. An SD model need not be operational (that is, be defined as a system of equations and present quantitative results) to provide insights on the gaps in current modeling and the directions of potential impacts. A causal loop diagram (CLD), for instance, could be used to identify important insights and data needs, and to inform scenario development for integration into scenario planning.[5]

Overall, all of the interviewed modelers expressed interest in new approaches to modeling, which was also evidenced by the strong attendance at the May webinar that Volpe hosted with the Zephyr Transport Foundation. In particular, multiple interviewees noted that SD aligned with the way they think about problems in their region, and noted that current planning practices don’t always consider feedback effects as explicitly as SD does. Many of the MPOs interviewed – both small and large – also have active academic partnerships to expand their capabilities and to conduct research related to their goals. Continuing to engage with both practitioners and academia may open the door for further collaboration and increased adoption of SD as a tool to address emerging transportation challenges.

[5] For more background on causal loop diagrams, see Chapter 3.

Challenges that they face

In developing models that inform long-range planning, challenges faced by MPOs include the long-lasting consequences of infrastructure decisions, network effects, and uncertainty about the future.

The impacts of infrastructure decisions are long-lasting. Potential changes can come from new construction decisions, technology adoption, maintenance and reconstruction, and operations. Urban transportation systems includes extensive networks of physical facilities for a variety of modes, such as highways, railways, bridges, tunnels, bike paths, and sidewalks. The coverage, location, and available right-of-way of the current system are among the longest lasting of all the elements of the urban environment.

Infrastructure investment can benefit from network effects. Using a bike lane as an example, the first bike lane built in a community, which may have as few as one origin and destination pair, could be of little value to a cyclist who is not willing to ride in a shared traffic lane. However, as an integrated network expands, bike lanes connect more trip origin and destination combinations at an exponential rate.

Uncertainty about the future

Travel modelers are increasingly interested in scenario planning, knowing that a single point forecast of the future will almost certainly be wrong. Following the language used in decision-making under deep uncertainty, the scenario space is a combination of uncertainties and policy levers (Lempert, 2019). The uncertainties are factors that the decision-maker cannot control, while the policy levers are things that they can control. Note that one decision-maker's uncertainties may be another's policy lever. For example, AV technological development may be an uncertainty for an MPO, but is at least partially a policy lever for a national government that is allocating research funds (recall that several of today's automated vehicle developers have their origins in a series of challenges funded by the Defense Advanced Research Projects Agency in 2004-2007). Furthermore, some of the uncertainties listed below may actually be, to some extent, policy levers for some MPOs.

The uncertainties used in MPO scenario planning may be broadly classified into five areas, with some overlap. They include:

- Environmental, e.g.,
  - Effects of climate change, including sea-level rise, drought, excessive heat
  - Likelihood and intensity of natural disasters
- Economic, e.g.,
  - Price of oil and/or gasoline
  - Population growth
  - Employment growth
  - Types of industry (e.g., manufacturing, services, retail, etc.)
- Land use, e.g.,
  - Geographic distribution of jobs and residential locations
- Political, e.g.,
  - Environmental regulation
  - Tax structure
  - Immigration and trade policy
- Technology (capabilities, availability, cost), e.g.,
  - Cost and technological capability of automation

  - Connected vehicle infrastructure and adoption
  - Fuel economy
  - Electric vehicle availability

On their own, these uncertainties do not drive changes to the transportation system. Rather, reactions and responses to these by people and businesses affect how the system performs. For example, responses to new technologies may include:

- Individual travelers' responses
  - E-commerce share
  - Sensitivity of the amount of driving to the cost of driving
  - Attitudes towards shared trips (e.g., public transit)
  - Attitudes towards driving
  - Attitudes towards use of automated vehicles
- Business responses, including changes to existing business models and the introduction of new ones
  - Telecommute share
  - New uses for road space
  - Expansions of existing uses for automobiles

Table 2-1 lists some uncertainties of particular interest, based on our conversations with MPOs, as well as their potential impacts and data availability for use in modeling.

Table 2-1 Example uncertainties faced by transportation modelers

Events with Uncertainties	**Data**	**Effects on transportation infrastructure**	**Effects on decision makers**
Climate change	**Very challenging** (Individual weather events more extreme than we have ever seen)	**Long-lasting** (Some could be local and temporary, and some other could be long-lasting. The time for the next event to happen is unknown, which makes prediction very challenging)	**Significant** (Unclear in short term and could be significant in long term)
Automation	**Very challenging** (A new mode that no one have ever experienced)	**Long-lasting** (Some infrastructure need to be changed and the time horizon is unclear but more manageable)	**Significant** (Have similar effects as TNCs in the short term and could have a significant impact on land use in long term)
Pandemic (e.g., COVID-19)	**Less challenging** (Data can be collected, some behavior changes are useful to understand (e.g. telework, etc.))	**Not much** (Could have long-lasting effect on existing modes, especially for shared mobility services (e.g., transit, TNCs))	**Somewhat** (Changes types of trips, travel time, mode choices, etc.)

To summarize, transportation planning decision-makers need to make decisions today about investing in the transportation systems of the future. These decisions will have consequences that last many decades. Investments may take several forms, such as adding capacity via a new highway lane or transit line, making improvements aimed at safety, or making resilience investments (e.g., designing a road or bridge to withstand an earthquake or flood).

The classic paradigm for transportation planning is to first, predict what will happen in the future (e.g., trips in a region will increase 20%), and then act on that prediction (e.g., add transportation capacity). This paradigm breaks down when the future is highly uncertain. Under these conditions, the prediction of a single future is likely to be incorrect, and the resulting decisions may be sub-optimal. The next section discusses the current state of MPO travel models, as well as some tools and approaches that have the potential to address these challenges.

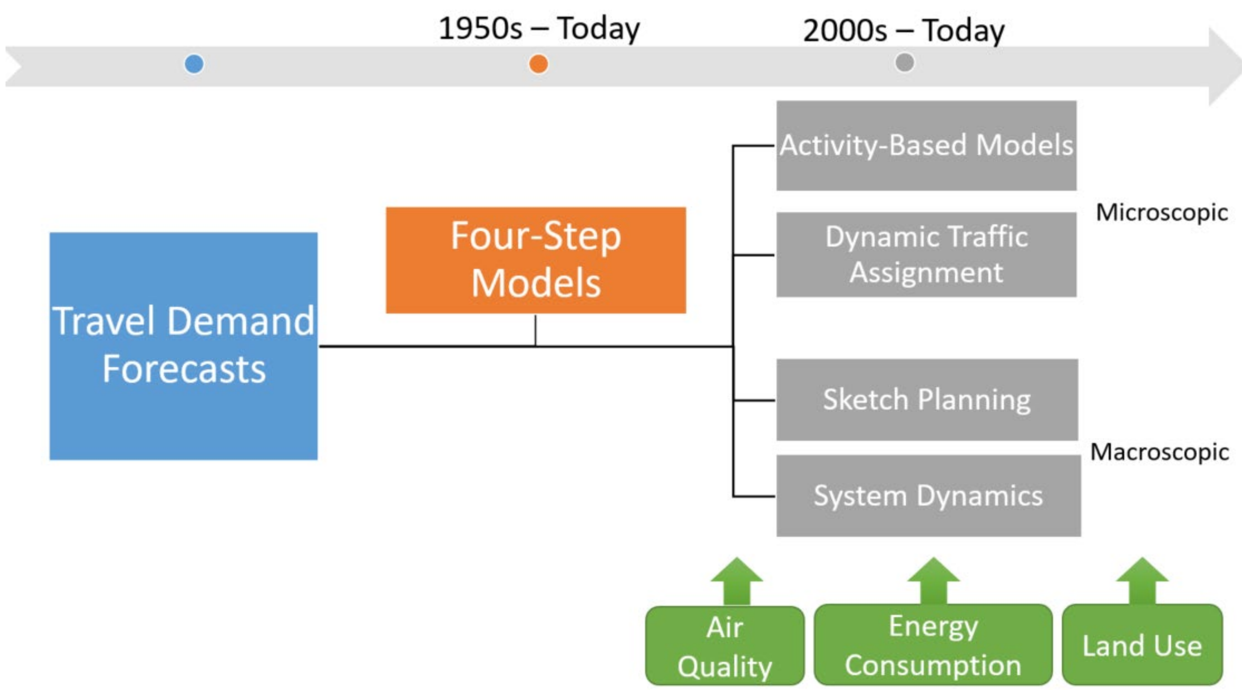
Current state of travel modeling – and potential new approaches

Federal law requires transportation planning agencies to develop a long-range regional transportation plan that looks ahead twenty to thirty years and specifies objectives that will be used to make spending decisions over that time period. In general, population, economic growth and changes, and land use patterns are forecasted first. The travel demand model takes those predictions (future population, economic activity and the location patterns of households and firms) as given and predicts the trips made by various modes, such as walking, cycling, driving, public transit and trucks. Some statewide plans also include trips made by air and railroad.

The idea of using computerized deterministic models to predict social and economic patterns was introduced in the 1950s (Weiner, 1997). The basic approach has not changed much since then. Currently, the most common type of travel demand forecasting model considers a sequence of at least four models and the output from one model becomes the input to another. The first model (trip generation) is to determine the number of trips that will start or end in each zone (traffic analysis zone) based on the socio-economic and land use characteristics of those zones. The next step (trip distribution) is to model how many trips originating in each of the origin zones will end at each destination zone. A gravity-type of model is often used, which takes into the account of the relative activity at an origin and destination zone and the cost of traveling between the zones. The third step is to determine the trips conducted by each mode (e.g., automobile, public transit, carpool, etc.) from each origin zone to each destination zone. One important factor that determines travelers' mode choice is vehicle availability. For people whose households own at least one vehicle, they tend to drive for most trips, while people from a household that does not own a vehicle are more likely to choose public transit and non-motorized choices. The last step is known as traffic assignment. A procedure is used to estimate how many trips will take each possible path for each mode between each origin and destination (McNally, 2008).

These existing forecasting tools are complex, both in terms of data needs and calibration process. In order to develop such a model, an MPO requires demographic data on geographic zones, and representations of links in the transportation system for multiple travel modes. Additionally, the parameters of the models themselves, even if initially estimated perfectly, may not remain stable over time (Dewar & Wachs, 2006).

Over the years, as computer capabilities have increased, models have become more complex (Figure 2-1). Several planning organizations have moved from trip-based travel demand modeling to activity-based travel demand modeling to better capture trip chains (known as “tours”) and time constraints (Virginia Department of Transportation, 2009). Spatial and temporal resolution has also increased. Run times remain an issue, with it taking anywhere from several hours to several days to run the full model chain. Consider the integration of activity-based model (ABM) and dynamic traffic assignment (DTA) model as an example (S. Smith, Fong, et al., 2018). They are disaggregate models and the DTA can take trip information from the ABM and produce network performance at a specific time-of-day, which shows more disaggregated (better) spatial and temporal resolution of trips compared with the trip pattern generated from a traditional ABM. However, modelers face challenges to develop an integrated ABM-DTA model. The first major challenge is the requirement of detailed data on road network, socioeconomic and spatial factors of micro-analysis zones, travelers (e.g., value of time), and their travel pattern. A small sample of travelers and their travel patterns on a specific day collected through a household travel survey would not be sufficient to fit into such a disaggregated model. The long runtime is another significant drawback of the integrated ABM-DTA model.



Source: Volpe Center

Figure 2-1 Evolution of travel models

Motivation for new approaches

Analysis of the modeling literature reveals a concern that uncertainty is not adequately represented in travel demand models. Transportation Research Board (TRB) special report 288 (Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting, 2007) noted that, among other things, models need to do a better job of dealing with uncertainty, both in the data and in future conditions. However, improving representation of uncertainty has rarely been a motivation for suggested improvements in travel forecasting (Dewar & Wachs, 2006). However, a recent NCHRP report, “Updating Regional Transportation Planning and Modeling Tools to Address Impacts of Connected and Automated Vehicles, Volume 2: Guidance” (Zmud et al., 2018), has a chapter on planning in the context of uncertainty.

Dealing with uncertainty

One alternative approach to the traditional four-step model is to explore the scenario space (e.g., what happens if we make a particular investment today, and some future event occurs?). The objective is not to predict the future, but rather, to make decisions today that produce good outcomes under a wide variety of plausible futures. Many MPOs are examining a range of plausible futures using exploratory scenario planning. A few examples include Philadelphia (*Dispatches from Alternate Futures: Exploratory Scenarios for Greater Philadelphia*, 2020), San Francisco Bay Area (Association of Bay Area Governments & Metropolitan Transportation Commission, 2020), and Orlando (Metroplan Orlando, 2020).

The FHWA Travel Model Improvement Program has sponsored development of an exploratory modeling and analysis tool (TMIP-EMAT), to help with exploration of the entire scenario space (Milkovits et al., 2019). TMIP-EMAT was pilot tested at several locations, including Buffalo, New York (Greater Buffalo Niagara Regional Transportation Council) and Sacramento, California (Sacramento Area Council of Governments) (S. B. Smith, 2019).

Uncertainties considered in the Buffalo TMIP-EMAT pilot are listed in Table 2-2.

Table 2-2 Uncertainties in Buffalo TMIP-EMAT

Type	Uncertainty	How modeled
Economic	Regional household and employment growth	PERT distribution of percentage change from base socioeconomic data set
Technological	Change in roadway capacity due to automation	Triangular distribution of a 0 – 100% increase in capacity of freeways, expressways and ramps
Technological / Behavioral	Vehicle availability	PERT distribution of vehicle sufficiency categories (e.g., 0-car, vehicles < workers)
Technological / Behavioral	Auto in-vehicle travel time (IVTT) coefficient	Triangular distribution of a multiplier on the existing IVTT coefficient

Uncertainties in the Sacramento TMIP-EMAT analysis are listed in Table 2-3:

Table 2-3 Uncertainties in Sacramento TMIP-EMAT

Type	Uncertainty	How modeled
Economic	Price of gasoline	$1, $4 and $8 / gallon
Economic	Employment growth	Range from 21 – 61%
Behavioral	Millennial behavior	Binary variable, will this age cohort continue to drive less as they age?
Behavioral	Elasticity of amount of driving with respect to cost of driving	Vehicle Miles Traveled (VMT) elasticity with respect to the cost of driving (range from -0.762% to -0.026%)
Behavioral	Elasticity of amount of driving with respect to economic growth	VMT elasticity with respect to economic growth (0.6 to 0.7)
Technological / Behavioral	Zero-emission vehicle adoption	Adoption of zero-emission vehicle/plug-in hybrids (0 – 40%)
Technological	Fuel Efficiency	Average internal combustion engine fuel efficiency (15 – 50 mpg)

Outputs typically include distributions of the output measures of interest, given sets of input variables, both uncertainties and assumed policy levers. In a TMIP-EMAT analysis, output metrics will typically include amount of travel (VMT), transit use, accessibility and equity measures, and environmental measures, such as greenhouse gas emissions. One example given in the Buffalo analysis was that of understanding the scenarios where transit boardings are low, even when there is improved transit service. This analysis can help to identify the input uncertainties that have a significant effect (or do not have a significant effect) on the output measures of interest.

These TMIP-EMAT deployments were at the proof-of-concept stage. They demonstrated a methodology that can be used to support robust decision-making by identifying levers that perform well across a range of futures.

When discussing new approaches with MPO modelers, they indicated that they were not particularly interested in models that were more complex or took longer to run than their existing, in-house models. There is interest, however, in simple, fast models that help to explore the corners of the scenario space and to fill in the gaps in their current modeling frameworks. The next chapter presents an approach for how system dynamics can be applied to meet this need, and discusses results from applying this approach with modelers and planners from two regions – Boston, Massachusetts and the state of Oregon.

Chapter 3. Causal Models

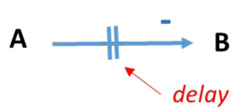
System dynamics basics

A system dynamics (SD) model can be useful to help practitioners explore the bigger-picture dynamics resulting from changes in parts of a larger system. The foundation of a system dynamics model is the *causal loop diagram* (CLD). CLDs are constructed using only two elements: variables and causal links. Variables 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.

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 otherwise would be*, and *a decrease in variable A will cause variable B to be larger than it otherwise would be*. Marks can also 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.

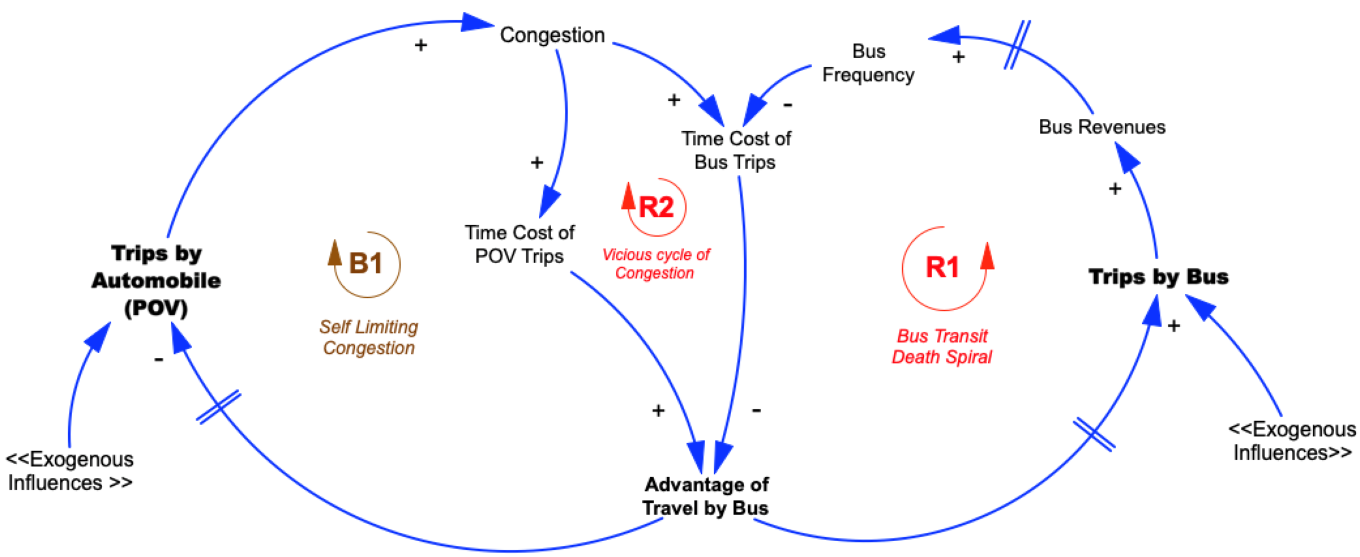
Once these CLDs are assembled, "loops" will arise when the causal links from one variable connect back to itself, after connecting to one or more additional variables. These loops play a central role in system dynamics modeling, so it is important to identify them and understand the role they may play in the overall behavior of the model. They are labeled to indicate: (a) the dynamic behavior that the loop illustrates 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, or decay to zero. In a balancing loop, they will tend to reach an equilibrium value. As will be seen later, the dynamics become more complex when reinforcing and balancing loops are combined.

While the conceptual model represented by a CLD is valuable in its own right, it can also form a basis for an "operational" SD model, where the variables are defined more precisely, and related to one another through algebraic equations and accumulations over time (i.e., integration). Such a model can be calibrated to real-world conditions, and is well suited to an exploratory scenario analysis.

Steps to building a CLD conceptual model

Similar to exploratory scenario modeling, CLD conceptual models can be a useful tool for organizing thinking and facilitating productive discussions. Steps in building a CLD model, and harvesting its insights, with an MPO/state DOT partner include the following:

1. **Work collaboratively to build CLDs.** This is a highly interactive step, as the Volpe team provides both SD expertise as well as more-general transportation modeling and planning expertise, while the MPO partner brings their own expertise with respect to their opportunities/challenges of interest in their region. Figure 3-3 is a basic example (greatly simplified here), illustrating some of the key dynamics involved in mode choice (between private personally-owned vehicles (POVs) and transit buses):



Source: Volpe Center

Figure 3-3 **CLD showing relationship between personally-owned vehicle and transit bus travel.**

2. **"Harvest" the insights of these CLDs**—e.g., through the following processes:
   - **Document the causal relationships**—e.g., in the tabular format shown in Table 3-1.

Table 3-1 Relationships in the CLD shown in Figure 3-3.

Causal Link: Independent Variable	Causal Link: Dependent Variable	+/- (polarity)	Notes (e.g., strength and certainty of each relationship; what data may be needed?)
Trips by Automobile	Congestion	+	The causal relationship is strong, but non-linear and complicated by many factors.
Congestion	Time Cost of POV trips	+	By definition, congestion
Time Cost of POV trips	Advantage of Travel by Bus	+	If a POV trip takes longer (presumably, due to congestion), bus becomes more attractive (assuming that its duration does not also increase)
Congestion	Time Cost of Bus Trips	+	Policy changes (e.g., providing a bus lane) could greatly affect the strength of this relationship. Also, increasing the comfort of the bus could reduce the time cost of bus trips, due to reduced value-of-time.
Time Cost of Bus Trips	Advantage of Travel by Bus	-	If a bus trip takes longer, in walk, wait, or in-vehicle time, using the bus becomes less attractive.
Advantage of Travel by Bus	Trips by Automobile (POV)	-	If the advantages of bus are clear, eventually some auto drivers will switch.
Advantage of Travel by Bus	Trips by Bus	+	If bus is more attractive, there will be more trips by bus
Trips by Bus	Bus revenue	+	With more trips by bus, more fares are collected.
Bus revenue	Bus frequency	+	Higher ridership and revenue justifies a higher service frequency, though there may be a lag.
Bus frequency	Time cost per bus trip	-	With more service, there is less waiting for the bus.

- **Create narratives of emergent dynamics—e.g.:**

  i. **B1: "Self Limiting Congestion".** An external factor (e.g., a pandemic) results in more people choosing to travel by automobile (over the long term) instead of the bus. This results in an increase in *Congestion*, which increases the *Time Cost of POV Trips.* This increases the *Advantage of Traveling by Bus,* which leads more people to make trips by bus, which reduces the number of *trips by automobile,* thereby reducing *congestion.* This completes a balancing feedback effect, which has a self-regulating effect on POV trips, suggesting that they will rise and gradually level off to an equilibrium.

  ii. **R1: "Bus Transit Death Spiral".** Starting at the placeholder variable for "Exogenous Influences", on the right hand side, we can read this as: Some external factor (e.g., a pandemic) causes a decrease in *Trips by Bus*, which results in lower *Bus Revenues.* The loss of revenue will, ultimately (subject to a potentially significant time-lag) result in a decrease in *Bus Frequency*, which directly and immediately increases the *Time Cost of Bus Trips.* Having to wait longer for the bus causes a reduction in the *Advantage of Travel by Bus*, which ultimately (again, subject to some delay and other exogenous influences) causes some people to choose to travel by POV instead of a bus. This completes a reinforcing feedback loop, which (in the absence of other interventions) will have potentially powerful harmful effects on bus ridership and system performance. Note that in happier circumstances, this loop could go the other way, with more ridership leading to more bus service, leading to more ridership.

iii. **R2: "Vicious Cycle of Congestion".** Starting at "Exogenous Influences" on the left hand side, we can read this as: An external factor (e.g., a pandemic) results in more people choosing to travel by automobile (over the long term) instead of the bus. This results in an increase in *Congestion*, which increases the *Time Cost of Bus Trips.* This reduces the *Advantage of Traveling by Bus,* which leads more people to make trips by POV, which further increases *Congestion.* This completes a reinforcing feedback effect, which if not countered by other influences or interventions (e.g., no traffic management or pricing strategies), makes traveling by bus increasingly unattractive and worsens overall congestion.

- **Discuss key questions that emerge from the dynamics evident in the CLD.** For example, an important question immediately evident in this CLD is the following:

  i. Which effect of congestion will be more powerful—the balancing effect (B1), by which congestion makes driving less appealing and therefore pushes people to ride the bus instead? Or the reinforcing effect (R2), where congestion has a powerful negative effect on bus ridership?

     - Will people prefer to be stuck in traffic in the privacy and comfort of their own car? Or will they prefer to spend that "wasted" time on a bus, where they can engage in non-driving activities?
     - Are there other factors (policies, technologies, or other interventions) that could alter the strength of these effects and determine which feedback loop dominates the overall dynamics?
     - At what time scale would people change their mode choice decisions? At what time scale would local public transit agencies change their plans to accommodate the adjustment on demand due to various external factors (e.g., congestion, new mobility technologies, pandemic, etc.)? What is the time lead/lag between the changes of demand and changes of supply for each external factor?

  With more-elaborate CLDs, more dynamics will prompt more questions, more uncertainties, and help identify key areas for further investigation.

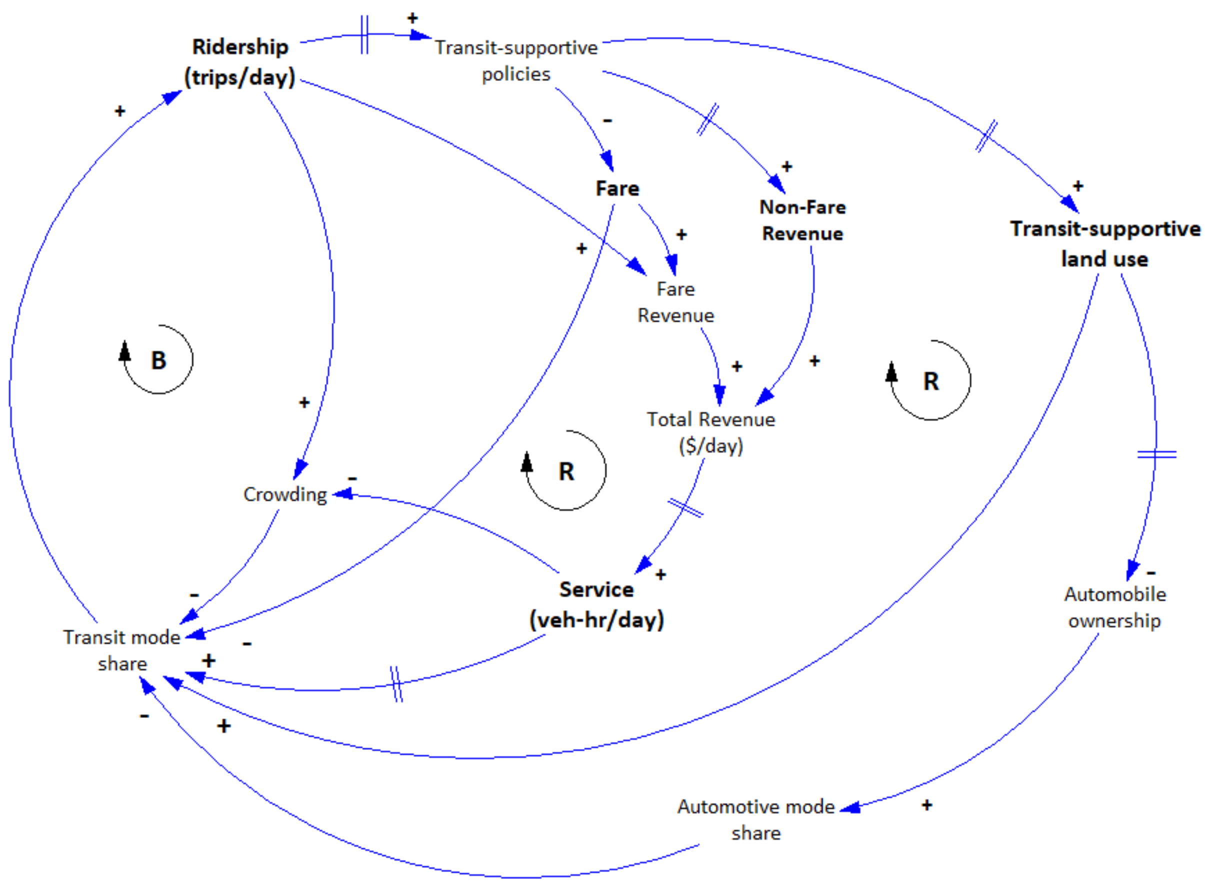
Common baseline model

Volpe's conversations with MPOs and other regional modelers have led to two ongoing collaborations in the fall of 2020 and winter of 2021 where Volpe and its partners have begun to apply SD to specific problems or scenarios.

These partners include staff at the Metropolitan Area Planning Council (MAPC) and Central Transportation Planning Staff (CTPS) in Boston, MA, and members of the Oregon Modeling Steering Committee's (OMSC) work group on emerging technology in the state of Oregon (including MPO, state DOT, and transit agency staff).

Since automated vehicles are not yet seeing widespread use, the model building had to focus on proxy modes. This is similar to the approach taken in our previous report (Berg et al., 2020), where we used transportation network companies to gain insights into user response, and dockless bike share to gain insights into fleet management. The current collaboration focused on two areas, both applied to transit. The first is the financial sustainability of a mode of travel, considering both fare policies and other sources of funding. The second is the overall land use ecosystem, including road design and transit oriented development, which supports a particular mode of travel. The ideas are relevant for any form of automation that involves shared fleets.

Figure 3-4 shows the simplified general model, applied to transit, coming out of these collaborations. The polarity signs and delay marks are as defined in the "System dynamics basics" section, above. Table 3-2 contains descriptions of each of the links in the diagram.



Source: Volpe Center

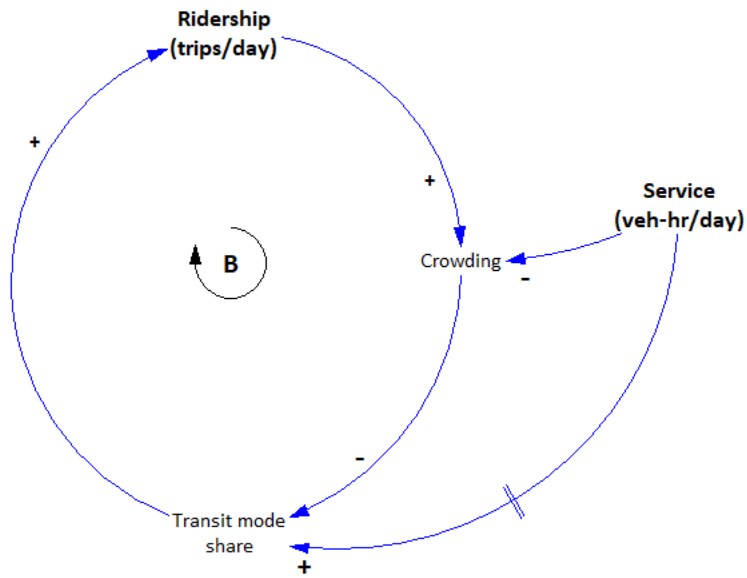
Figure 3-4 Simplified general model

Table 3-2 Relationships in the CLD shown in Figure 3-4.

Causal Link: Independent Variable	Causal Link: Dependent Variable	+/- (polarity)	Notes (e.g., strength and certainty of each relationship; what data may be needed?)
Ridership (trips / day)	Transit supportive policies	+	With higher transit ridership, there is more of a natural constituency for transit-supportive policies
Ridership (trips / day)	Fare revenue	+	More riders leads to more fares collected
Ridership (trips / day)	Crowding	+	Higher ridership (in the absence of a service change), leads to more crowded vehicles
Transit-supportive policies	Transit-supportive land use	+	Transit-supportive policies may include policy changes to encourage transit oriented development, as well as road designs that encourage transit use.

Causal Link: Independent Variable	Causal Link: Dependent Variable	+/- (polarity)	Notes (e.g., strength and certainty of each relationship; what data may be needed?)
Transit-supportive policies	Fare	-	Transit-supportive policies may also include fare reductions.
Transit-supportive policies	Non-fare revenue	+	Transit-supportive policies may include direct financial support for transit services
Transit-supportive land use	Transit mode share	+	All else being equal, transit-supportive land uses will lead to a greater mode share for transit
Transit-supportive land use	Automobile ownership	-	Transit supportive land uses make it less necessary to own a car, and may make car ownership more difficult (e.g., via parking restrictions)
Fare	Transit mode share	-	A higher fare leads to lower mode share for transit, and vice-versa
Fare	Fare revenue	+	A higher fare leads to higher fare revenue per rider. Total fare revenue is a function of both ridership and fare.
Fare revenue	Total revenue	+	Having more revenue from fares increases total revenue, all else equal.
Non-fare revenue	Total revenue	+	Having more revenue from non-fare sources increases total revenue, all else equal.
Total revenue	Service	+	Having more revenue of all types (fare and non-fare) enables more service to be provided.
Automobile ownership	Automotive mode share	+	Higher auto ownership makes the automobile mode more attractive
Automotive mode share	Transit mode share	-	If other modes, such as auto, are more attractive, it leads to lower mode share for transit
Transit mode share	Ridership	+	Higher transit mode share leads to higher ridership (assuming the total number of trips by all modes is fixed)
Service	Transit mode share	+	More service leads to transit being an attractive option for more travelers, and hence, higher mode share for transit
Service	Crowding	-	More service, all else being equal, leads to less crowding
Crowding	Transit mode share	-	A more crowded service is a less comfortable service, leading to lower transit mode share.

The general model contains several balancing and reinforcing loops. First, there is a short-term balancing loop between ridership, crowding and mode share (Figure 3-5). Here, service is treated as exogenous, as it does not change in the short term. This loop says that given a level of service, ridership cannot increase indefinitely, as the system will then become too crowded, and thus, less attractive.



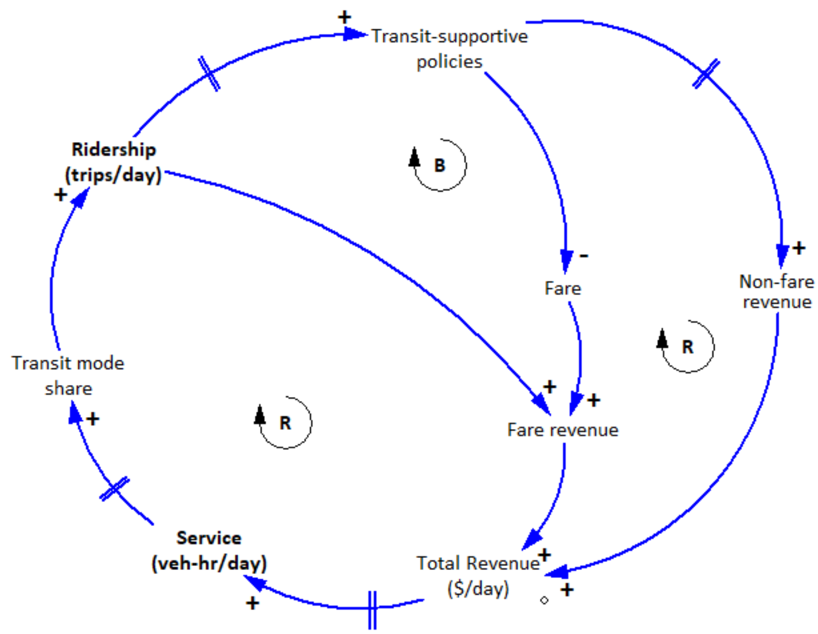
Source: Volpe Center

Figure 3-5 Short term balancing loop: ridership, crowding and mode share

Several loops connect ridership and level of service (Figure 3-6). All have time lags, as indicated by the lines crossing the arrows. These loops assume that changes in service depend on both the fare and non-fare revenue received. There are two reinforcing loops and one balancing loop. In all of the loops, more service leads to higher mode share, and thus more ridership.

1. Higher ridership leads directly to more fare revenue, which enables more service.
2. Higher ridership may also enable more transit supportive policies, which may take the form of reduced fares. However, in the absence of significantly increased ridership, the reduced fare will reduce fare revenue, thus constraining increases in service (this is the balancing loop). Note that transit ridership is generally considered to be inelastic with respect to fare[6], reduced fares will lead to reduced revenue (even with an increase in ridership).
3. Finally, transit supportive policies may also take the form of increased non-fare revenue, enabling service to be increased without a fare increase. This is the second reinforcing loop.

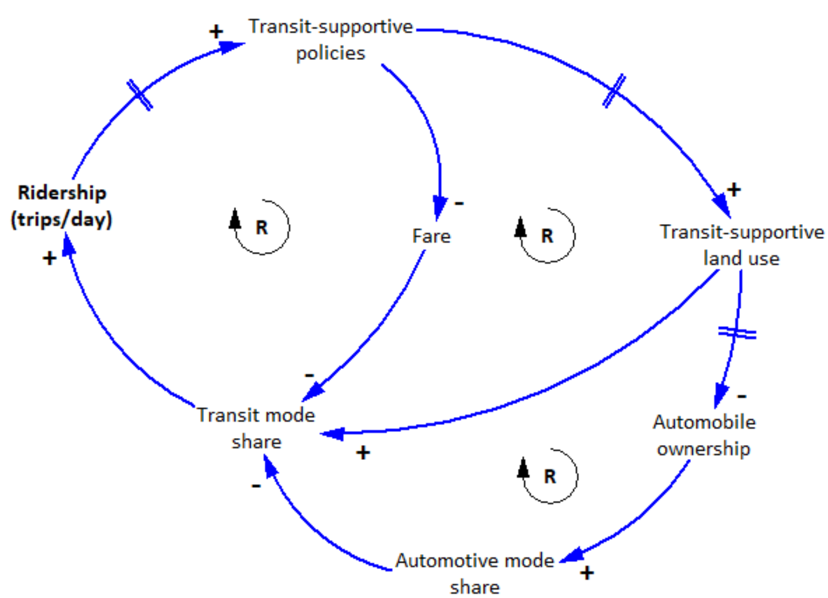
[6] Transportation Research Board, & National Academies of Sciences, Engineering, and Medicine. (2004). *Traveler Response to Transportation System Changes Handbook, Third Edition: Chapter 12, Transit Pricing and Fares*. Transportation Research Board. https://doi.org/10.17226/13800



Source: Volpe Center

Figure 3-6 Loops affecting service

Several additional reinforcing loops involve ridership and transit-supportive policies (Figure 3-7).



Source: Volpe Center

Figure 3-7 Reinforcing loops with transit-supportive policies

Transit-supportive policies may include direct fare reductions, or even free service. The reduced fare makes the service more attractive, thus leading to increased mode share. In the diagram the two negative relationships combine to form a positive relationship from transit-supportive policy to increased mode share (via reduced fare). Transit supportive policies may also lead to transit supportive land uses. Examples include:

1. Encouraging more development close to transit, thus leading to increased transit mode share
2. Discouraging development that leads to increased automobile dependence. For example, parking minimums could be removed. This will tend to lead to less automobile ownership, making automobile use less attractive. Again, the two negative relationships (from transit supportive land use to auto ownership, and from auto mode share to transit mode share) combine to form a net positive relationship.

Additional Considerations

Although the transit-oriented loops described above will also apply to an automation service with a shared vehicle fleet, one additional consideration for automation is the reinforcing loop of new product adoption. In the context of electric vehicles, this is described in (Struben & Sterman, 2008). There is a reinforcing loop, that they call social exposure, which models the number of potential users that become willing to consider the new product, via word-of-mouth from existing users. With a new mode, such as automation, this reinforcing loop will be important.

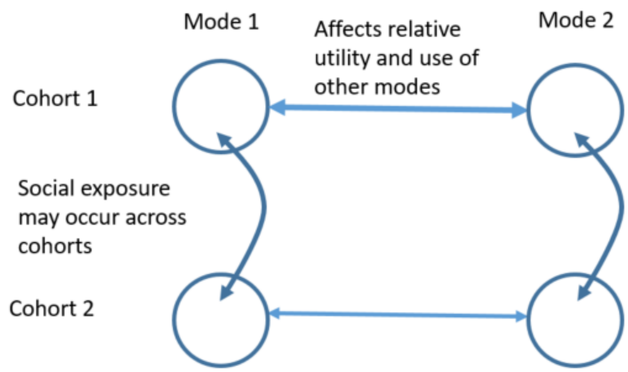
A complete model will also need to incorporate the externalities that arise from travel mode choices; these externalities may help to drive policies that either support or discourage a mode. They include

- Safety, does encouraging a particular travel mode improve safety in the community?
- Congestion, does encouraging a particular travel mode increase road congestion?
- Emissions, does encouraging a particular travel mode increase emissions, including greenhouse gas emissions?
- Public health, what is the effect of a mode on public health
    - Access to medical care, jobs, shopping
    - Effect on active travel
    - Noise and emissions that affect air quality in neighborhoods

A model will also need to consider that there are several modes of transportation, all competing with each other, each with its own characteristics and externalities.

Finally, different user and household cohorts might be affected differently by the new mode of transportation. Equity effects should be considered, at a minimum between motorists and non-motorists, and among various income groups. The full model will include several connected sub-models (Figure 3-8), each corresponding to a mode and cohort.

Transitions in one direction (e.g., from non-motorists to motorists) are often more likely to happen to households than other direction (from motorists to non-motorists). Households' decisions on changing vehicle ownership often are triggered by other key decisions, such as changing residential locations, changing jobs, getting married or having a child (Clark et al., 2016). Once households become vehicle owners, they tend to stay vehicle owners for a long time. The stickiness of switching across cohorts in certain directions will have important implications for transportation and housing policies that try to nudge users to switch from using personally-owned vehicles to shared or non-motorized modes.



Source: Volpe Center

Figure 3-8 Models for different modes and social cohorts

Chapter 4. Lessons learned for modeling and planning practices

The initial exploratory phase of this project involved extensive outreach to MPOs, and a series of interviews with several of them. The latter phase involved longer-term engagement and model building with two specific MPO partner-teams. Both of these phases provided valuable insights regarding system dynamics and its potential role in regional planning—particularly regarding its value to the practices of transportation modeling and planning.

Major themes from initial MPO interviews:

General utility (for MPOs) of system dynamics:

- Staff at MPOs of all sizes appeared interested (and often eager) to learn about system dynamics, as most of them expressed a general interest in new approaches to modeling. Many of them also currently engage with academic partners in their regions to expand modeling capabilities.
- Many of the MPOs expressed that the problems they currently face require holistic systems-thinking approaches, and they see system dynamics as a potentially useful tool. This is often true regardless of whether or not the MPO has begun to consider the impacts of automated vehicles.
- Several MPOs indicated that they would see value in system dynamics if the models are able to adapt to their local/regional context and either identify and/or help to fill gaps in their current modeling capabilities.
- MPOs also expressed the importance of linking models such as system dynamics to policies that they can actually influence. This goes to the policy levers, the “L” in the XLRM framework discussed earlier in this report.

Value (to Volpe) of engaging with practitioners:

- Communicating with MPO staff has also brought more real-world examples into the project, illuminating a wide range of local concerns, and providing insights about how system dynamics might function both as a generalized conceptual tool as well as one tailored to a specific area.

Applicability of system dynamics to issues related to automated vehicles:

- MPOs expressed interest in using system dynamics to explore longer-term impacts of AVs, where links to current conditions are less clear, there are a wide range of interacting and highly uncertain factors, and important indirect effects (e.g., on land use) will need to be examined.

Lessons learned from working with MPO partners:

Applicability of system dynamics to issues related to automated vehicles:

- Models created to represent MPOs' current concerns can usually be readily adapted to investigate the impacts of AVs. Furthermore, such models that start with realistic representations of current conditions appear to do a better job of representing "on-the-ground" conditions than models that begin with assumptions about future conditions relating to AVs. They provide a better foundation for building models of future scenarios.

Value (to Volpe) of working with practitioners:

- Working directly with state DOT and MPO partners has helped to ensure that Volpe's exploratory work with system dynamics is relevant. Providing technical assistance directly to staff who work with local/regional planning and modeling has enabled the Volpe team to rapidly sharpen their focus on the most important applications of system dynamics.

Value (to MPOs) of working with system dynamics:

- Both groups expressed an appreciation for ***the unique potential of system dynamics to bridge the gap between modelers and planners**,* help them share each other's' views, and use a common language. The primary benefit of such a convergence is that it enables integration of goal-setting with an understanding of the logic/mechanics of modeling:
    - *From a planner's perspective:* understanding the logic of a model may help inform the planners' goals (and the objectives to support those goals).
    - *From a modeler's perspective:* a better understanding of the planners' goals might help identify opportunities to achieve them, and ways to model potential solutions.
- Causal loop diagrams, especially when built collectively, provide a uniquely effective tool for developing and reinforcing common mental models. They allow users to make fast, holistic assessments of the potential impacts of proposed interventions. One of the MPO partners expressed that the models tell an integrated story of things "we all know and agree on," but never really see clearly connected in one place.
- Causal loop diagrams can provide a useful outreach tool—for agency staff, policymakers, and the general public. A well-designed causal loop diagram can represent a complex system (with multiple feedback effects and overlapping causal relationships) in a simple readily-comprehensible manner.
- Group model-building provides an effective way to structure engagement with MPOs. Several of them observed that the basics of system dynamics are simple enough that an MPO could quickly learn how to build a causal loop diagram, then turn around and use that process as a way to engage with key stakeholders and even the general public.
- Building a causal loop diagram can bring issues to light that may not be covered in an MPO's current modeling capabilities. Rather than asking, "What can our <u>existing</u> models tell us?" system dynamics gives modelers and planners the opportunity to identify a range of potential concerns

and questions, unconstrained by current modeling capabilities, thereby helping to identify gaps in current models.

- An operational (quantitative) system dynamics model can be useful when data is unavailable (the situation currently facing efforts to understand AV impacts), as it can quickly and easily be applied to “explore the corners of the scenario space.” Simple software tools provide real-time “dashboard-type” interfaces that a modeler or planner can use to explore various scenarios.

Appendix A. References

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