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A System Dynamics Approach on Sustainability Assessment of the United States Urban Commuter Transportation

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A SYSTEM DYNAMICS APPROACH ON SUSTAINABILITY ASSESSMENT OF THE UNITED STATES URBAN COMMUTER TRANSPORTATION

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ABSTRACT

Transportation sector is one of the largest emission sources and is a cause for human health concern due to the high dependency on personal vehicle in the U.S. Transportation mode choice studies are currently limited to micro- and regional-level boundaries, lacking of presenting a complete picture of the issues, and the root causes associated with urban passenger transportation choices in the U.S. Hence, system dynamics modeling approach is utilized to capture complex causal relationships among the critical system parameters affecting alternative transportation mode choices in the U.S. as well as to identify possible policy areas to improve alternative transportation mode choice rates for future years up to 2050. Considering the high degree of uncertainties inherent to the problem, multivariate sensitivity analysis is utilized to explore the effectiveness of existing and possible policy implications in dynamic model in the terms of their potential to increase transit ridership and locating critical parameters that influences the most on mode choice and emission rates. Finally, the dissertation advances the current body of knowledge by integrating discrete event simulation (multinomial fractional split model) and system dynamics for hybrid urban commuter transportation simulation to test new scenarios such as autonomous vehicle (AV) adoption along with traditional policy scenarios such as limiting lane-mile increase on roadways and introducing carbon tax policy on vehicle owners. Overall, the

developed simulation models clearly indicate the importance of urban structures to secure the future of alternative transportation modes in the U.S. as the prevailing policy practices fail to change system behavior. Thus, transportation system needs a paradigm shift to radically change current impacts and the market penetration of AVs can be one of the reforms to provoke this transition since it is expected to revolutionize mode choice, emission trends, and the built environment.

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Last but not least, I dedicate this dissertation to my wife Irem Ercan and our son Deniz Ercan. I am grateful to have such supportive and lovely wife Irem Ercan who encourage and support me with patience through this hard work. And, I am also grateful for my parents who support me from the beginning of my academic career. Without their love and support I would never be able to complete this work.

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LIST OF ACRONYMS (or) ABBREVIATION

ABM	Agent Based Modeling
APEEP	Air Pollution Emission Experiments and Policy Analysis
APTA	American Public Transportation Association
B20	Biodiesel with the blend of 20% bio and 80% conventional diesel
BAU	Business as Usual
BE	Battery Electric
BRT	Bus Rapid Transit
CLD	Casual Loop Diagram
CNG	Compressed Natural Gas
DALY	Disability-Adjusted Life Year
DES	Discrete Event Simulation
EIO-LCA	Economic Input-Output – Life Cycle Assessment
EMA	Explanatory Modeling Analysis
EPA	Environmental Protection Agency
EU	European Union

FHWA	Federal Highway Administration
GDP	Gross Domestic Product
GHG	Greenhouse gases
GREET	Greenhouse-gases Regulated Emissions, and Energy use in Transportation
IEA	International Energy Agency
LCA	Life Cycle Assessment
LCC	Life Cycle Cost
LDV	Light Duty Vehicle
MSE	Mean Square Error
NHTS	National Household Travel Survey
PMT	Passenger Miles Traveled
RMSEP	Root Mean Square Error Percentage
SD	System Dynamics
VMT	Vehicle Miles Traveled

CHAPTER ONE: INTRODUCTION

1.1 Overview

Urbanization in the U.S. has been rapidly increasing since World War II, but sustainable urban development was not considered as an applicable concept with respect to smart growth initiatives until Clean Air Act Amendments declaration (Bento et al. 2005). Therefore, urban passenger transportation in the U.S. has since become greatly dependent on private vehicle use, as demonstrated consistently by the results of the National Household Travel Surveys (NHTS) (1990, 1995, 2001, and 2009) for U.S. households (Santos et al. 2011). For instance, the average number of vehicle ownership per household increased from 1.77 in 1990 to 1.86 in 2009, and 23% of the surveyed households owned 3 or more vehicles in 2009 (Santos et al. 2011), which tripled the total number of vehicles on the U.S. highway from 1969 to 2009 (U.S. Department of Transportation 2015). As a result of this car mode dependency, the level of motorization is significantly higher on average in the U.S. compared to the average motorization of Europe (EU27), where there are 477 light-duty vehicles (2 axles - 4 tires) for every one thousand people in Europe, whereas the corresponding number for the U.S. is 763 light-duty vehicles for every one thousand people (European Commission 2011). Another statistic of car ownership comparison indicates that persons per privately owned vehicle rate is around 2 for France and United Kingdom, where U.S. rate is 1.3 (US DOT 2016).

As shown in Figure 1, which illustrates survey data from the 2009 National Household Travel Survey for approximately 150,000 U.S. households (Santos et al. 2011), the total number of personal trips is increasing, but transportation mode shares remain almost constant over time. Private vehicle usage decreased from 1995 to 2009, but only by about 5.9% of all trips. In order to mitigate traffic congestion impacts due to increasing number of vehicles on roadways, the federal and local governments spent 209 billion dollars in 2007, 218 billion dollars in 2008, and 160 billion dollars in 2009 to maintain and improve roadway systems every year (U.S. Bureau of Transportation Statistics 2015). In addition, land use is another critical issue; like fossil fuels, land availability for roadways is limited. To better sustain available natural resources; there is a need to reconsider the use of transportation modes. In addition to walk or cycling mode choices, public transportation, for example, could contribute to reduce fossil fuel usage, environmental impacts, and land use. Even though most public transportation modes use fossil fuels as their primary energy source, they tend to increase the passenger-miles traveled (PMT) exponentially compared to the corresponding amount of vehicle-miles traveled (VMT). Figure 1 also indicates that the ridership share of public transportation compared to those of other transportation modes is only about 1.7%, increasing by only 0.3% from 2001 to 2009. Therefore, it is clear that only a small number of people use public transportation in the U.S. as opposed to other transportation modes.

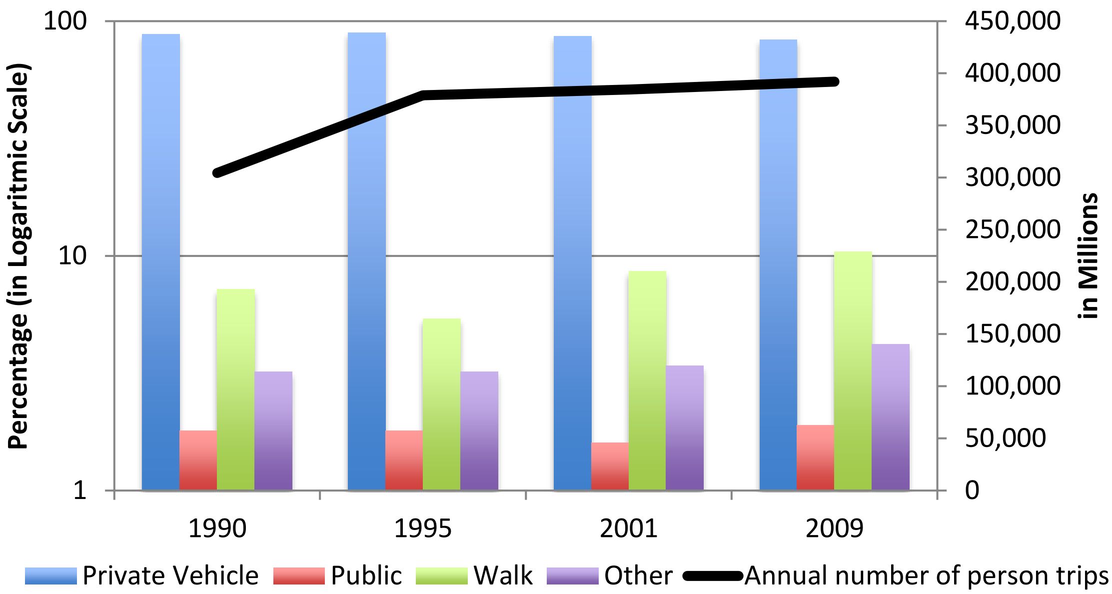


Figure 1: Transportation mode choice percentages and annual number of person trips from 1990 to 2009

As a result of this car-depended life style, transportation sector accounts for the 27% of annual GHG emissions in the US, which makes it second largest emission cause after energy generation sector (EPA 2017). In addition to the GHG emissions, combustion of fuels also causes conventional air pollutant emissions such as CO, NO_x, SO_x, PM_{10}, $PM_{2.5}$, and VOC. In addition to the climate change impacts of these emissions, their impacts on society can be measured in terms of externalities, which accounts for human health impacts, timber loss, and other relevant factors (Muller and Mendelsohn 2006, 2007b), which are specifically quantified for light-, medium-, and heavy-duty vehicle operations (Ercan et al. 2015; Michalek et al. 2011; Sen et al. 2017; Zhao et al. 2016a; b). Road transportation is the largest contributor of premature deaths in the US due to air pollutant emissions by causing 58,000 premature deaths annually (Caiazzo et al. 2013). Road transportation is not the largest contributor for total emissions in the air, however it is the number one responsible for mortalities due to emission occurrence in highly populated urban areas, which affect human health directly compare to mostly rural-based energy generation plants. In addition to emissions, significant energy consumption of inefficient transportation modes is another crucial concern in terms of energy insecurity (foreign oil, limited source of fossil fuels, etc.). Alternative fuel use for various road transportation vehicles has been studied in literature to propose solutions for energy efficiency and emission reductions. (Ercan et al. 2016a; Ercan and Tatari 2015; Onat et al. 2014b, 2015; Sen et al. 2017; Zhao et al. 2016a; b). Although these studies indicated significant emission and energy consumption related reduction results by shifting from fossil fuels to alternative fuels, it is an incomplete effort for decreasing the trends of vehicle miles traveled (VMT) and air pollutant emissions from transportation sector (Ercan et al. 2016c; b). The number of vehicles are increasing on the roads with growing population, so the society and infrastructure cannot supply the demand to the infinity. Thus, alternative fuel deployment should be merged with alternative transportation mode adoption efforts to decrease drive modes.

As Litman (1999) argues, sustainable transportation measures are not limited to mobility measures where most transportation studies account for. Sustainable transportation needs to be considered in more holistic perspective so social, health, environmental, and economic impacts of high car dependency as transportation mode choice can be presented (Onat et al., 2016a, 2016c). The U.S. society has very limited experience with transit-oriented and healthy communities, which cause more resistance on changes from behavior or habits of living (Litman 1999). Litman and Burwell's (2006) later study also underlines that in order to achieve sustainable transportation goals, holistic approach suggests institutional reforms, land use (built environment) changes, and economic incentives as opposed to individual technological (vehicle oriented) solutions of myopic perspective. The shared-idea in the minds of the society about how urban transportation should be (prevailing paradigm) played very important role on the development of today's urban structures using vast amount of land and requiring excessive trip lengths to meet basic needs, employee commuting, etc. In addition to these macro level literatures, some of the survey based studies also presented overlaying results as they pointed out the abnormalities in the existing paradigm. Rajamani et al. (2003) stated that even non-commute type travels tend to be significantly sensitive to urban form. Their study concludes that high residential density favors walking and transit modes for non-work travels. Similarly, Zhang (2004) emphasized that travel time and monetary cost related influences on mode choice is independent from land use related influences. Besides urban infrastructure and demographic information, transportation mode choice is a matter of decision making by individuals and this decision is affected by psychological behavioral and emotional models. Bamberg and Schmidt (2010) and Carrus et al. (2008) found similar results that previous behavior tends to influence later behavior for transportation mode choice since it is no longer a decision making but a habit of the person. The question is how are these actions become habits over the past decades of urban development in the U.S. There is a shared idea in the society's mind about how urban structures and transportation should be, which can be realized by looking at historical trends in urban structures and minimal increase in public transportation ridership. Despite the increased federal funds and investments in public transportation, the shared-idea, unstated assumptions, perceptions push right up against the accepted idea of "urban structure", which constitutes the society's paradigm. At what degree these external factors (exogenous factors) are effective on the transportation mode choice is one of the critical questions to be answered in this dissertation. Overarching goal of the systematic approach taken in this research is to reveal the underlying mechanisms feeding the current paradigm of the society and provide a complete picture of the problem.

The heavy dependence on privately-owned vehicles in today's society has become a particularly important topic to federal and local government agencies, scholars, and research institutes over the last few decades, and research efforts on this topic are still active today (Curtis and Headicar 1997; McIntosh et al. 2014; Newman and Kenworthy 2015; Oakil et al. 2014; Wickham and Lohan 1999). Real-world examples of alternative transportation mode incentives, congestion pricing policies, and other policy initiatives have demonstrated remarkable decreases in drive mode trends in many different parts of the world (Singapore, London, Paris, etc.) (Kim et al. 2013; Poudenx 2008; Sabounchi et al. 2014). Although efforts to definitively shift transportation mode choice trends in the U.S. using these policies has proven to be more difficult than expected, the availability of more drive mode choices has been increasing in recent years (Santos et al. 2011; US DOT 2016). As indicated in earlier literature studies, most of these research studies and policies indicate the same obstruction as the lack of "sustainable urban development" (Ewing and Cervero 2001; Poudenx 2008; Saunders et al. 2008), meaning that urban sustainability is the only possible marginal solution for a paradigm shift for the U.S. transportation sector (Banister 2008; Ercan et al. 2016c). Some of the authors of this study also proved this statement with respect to regions where public transportation mode shares are not increasing to the desired levels despite extensive government support for infrastructure investment and reductions in roadway network investments, but where a paradigm shift in urban development is still necessary for expanding public transportation networks and utilization rates (Ercan et al. 2016c; b).

Neither sustainable urban development nor definitive paradigm shifts for urban development are easy goals to accomplish, primarily because it may take decades to reform the predominant "American" lifestyle in any given time period. Nevertheless, the U.S. transportation sector is experiencing a revolution thanks to the combined advances in three transportation-related innovations in this generation: electric vehicles (EV), autonomous vehicles (AV), and ride-sharing options. The literature investigated of these new technologies and initiatives individually in detail, particularly with respect to their related effects on transportation-related environmental (i.e. air pollution emissions), economic, and social impacts; for instance, AV taxis have a great deal of potential to dramatically reduce the amount of overall light-duty vehicle (LDV) emissions in the U.S. (Greenblatt and Saxena 2015). However, as Fulton et al.'s (2017) recent report suggests, these three options should also be analyzed together to gather their potential impacts, and Fulton et al.'s study also indicates that deep carbonization is possible for the world's transportation-related emissions. Therefore, this study will include fuel economy improvement projections and autonomous vehicle additions to the transportation network as an additional policy scenario to be tested.

1.2 Research Objectives

In order to outreach the transportation related sustainability problems in the U.S. that are stated above; this research aims to integrate some of the powerful methods of transportation literature. Although numerous studies have looked at different aspects of sustainable transportation, no study has been found with a broader system perspective in which feedback relationships among climate change, the economy, travel time, and transportation mode choice shares are all simultaneously taken into consideration.

Discrete event choice methods estimate the impacts of key parameters that affect commuters'/society's transportation mode choice with logit models where SD is capable of quantitatively defining the feedback mechanisms, potential delays, and multi-dimensional causal relationships. Therefore, it is crucial to study these two powerful research "*engines*" for current problem.

In this regard, this dissertation aims to present future projections to reduce CO_2 emissions by considering increasing the ridership rate of public transportation, as well as the complex feedback relationships among key elements of the system as a whole, such as climate change and the economy. A combination of SD studies for urban development and studies that present factors affecting public transportation ridership can be beneficial to extend the literature with realistic and applicable policies (business as usual (BAU), marginal scenarios) to reduce transportation-related CO_2 emissions. Furthermore, the inclusion of various feedback relationships among the public transportation system, climate change, the economy, and the population can help to reveal the bigger picture and pave the way for future studies in this specific domain.

As the system boundary expands and new interconnections are introduced, the resulting degree of uncertainty in any analysis of the system will dramatically increase, compromising a policy maker's ability to develop more effective future transportation policies to increase adoption of public transportation. Therefore, deep uncertainty ranges for key model parameters can be introduced, followed by multivariate sensitivity analysis. The sensitivity analysis is crucial for urban passenger transportation to present the most sensitive model parameters that is not responding to prevailing policy efforts.

The DES method is a broad approach consisting of various methods used to study different behaviors with different types of discrete data sets, and has been the most widely used method for studying transportation mode choice problems. However, the DES method is limited with the given discrete data to estimate mode choice behavior. On the other hand, the SD method can model the system being studied in a macro-scale environment where endogenous (dynamic) and exogenous (deterministic) parameters work together to send and receive feedbacks among all relevant parts of the system. However, the SD method is limited to the use of macro-level data sets and may fail to capture case-by-case variations in certain parameters due to human-based behavioral changes (discrete), which are easy to model in DES. Therefore, a combination of the DES and SD methods as part of a hybrid simulation method would be ideal for simulating problems such as those associated with transportation mode choice, which consists of both individual human behaviors and macro-level system dynamics. The literature studied for this research includes studies on such hybrid modeling approaches, including applications in health care, operational research, and construction management problems (Alvanchi et al. 2011; Brailsford et al. 2010; Helal et al. 2007; Morecroft and Robinson 2005; Peña-Mora et al. 2008). However, to the author's knowledge, few literature studies thus far have applied any such hybrid simulation methodology to transportation problems (Mueller and Sgouris 2011; Struben and Sterman 2008). To do so, following tasks are defined and explained below for this dissertation.

Task 1: Developing a model with SD approach to simulate scenarios of CO_2 mitigation in the U.S. urban areas by adopting public transportation policies for future years. Based on the historical data and model validation processes, transportation behavior of the U.S. and transit transportation's potential for CO_2 emission mitigation forecasted for 2050 with several policy scenarios. (Chapter 3)

Task 2: Extending the developed SD model with social impacts consideration (i.e. air pollution externalities) and assigning uncertainty ranges for key model parameters to forecast mid-term and long-term sustainability impacts of urban passenger transportation (Chapter 4).

Task 3: Perform multivariate sensitivity analysis on developed SD model to present the effectiveness of prevailing public transportation policies and the root causes of inefficiencies. Besides, investigating the policy leverage points that influence drive mode, public transportation ridership, and urban passenger transportation related sustainability impacts (Chapter 4).

Task 4: Estimate the transportation mode choices of metro/micropolitan area commuters from the American Community Survey dataset by utilizing multinomial fractional split model (Chapter 5).

Task 5: Developing a novel hybrid simulation model that integrates DES and SD methods for transportation mode choice estimation of the U.S. metro/micropolitan area commuters to test and compare prevailing policy practices with AV adoption scenarios (Chapter 6).

1.3 Dissertation Organization

This proposal is organized as follows: Chapter two, following this chapter summarizes literature on system dynamics model and discrete event simulation model methodologies. Chapter three provides SD model development steps and finally scenarios analyses for (e.g. increasing capital investment funds of public transportation system and hypothetical transit ridership increase) CO_2 emissions mitigation results by switching private vehicle modes to public transportation in the U.S. Continuation of the model developed in chapter three, new policy practices of public transportation investment and fuel tax increase are developed as well as uncertainty and multivariate sensitivity analysis of overall system in Chapter four. Transportation mode choice of the metro/micropolitan area commuters and their demographic data is processed and multinomial fractional split model is developed in Chapter five. Finally, Chapter six integrate the DES model in Chapter five with SD modeling approach for hybrid modeling and forecasting AV's market penetration scenario impacts on mode choice and emission impacts. The overall findings and implications of policy practices, future of the U.S. urban transport, future study ideas, and study limitations are discussed in Chapter seven. Figure 2 summarizes the organization of the dissertation with a graphical illustration.

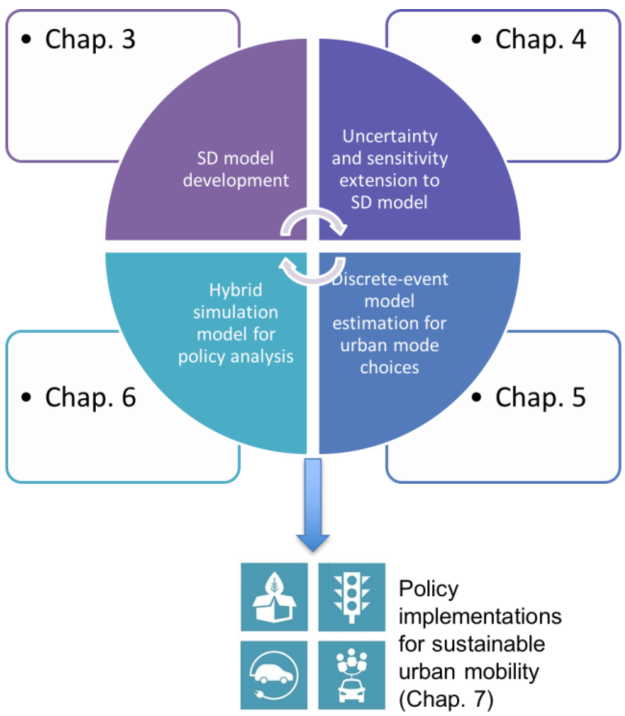


Figure 2: Organization scheme of dissertation

CHAPTER TWO: BACKGROUND INFORMATION ON URBAN SUSTAINABILITY SIMULATION MODELS

The possibility of increasing public transportation ridership for more environmental friendly cities has been investigated with various methods. Taylor and Fink (2003) stated the most of the factors that affect ridership are beyond the control of transit agencies, while factors under the control of such agencies (on-time performance, ride fare, etc.) have an insignificant effect on ridership rates. Vincent and Jerram (2006) studied the potential of Bus Rapid Transit (BRT) to reduce CO_2 emissions with the energy intensity of transportation modes as a functional unit. Paulley et al. (2006) investigated four factors (fare, quality of service, income, and car ownership) that could affect public transportation ridership demand, and found income and quality of service to be crucial contributing factors to public transportation ridership rates. A report submitted to the American Bus Association (M.J. Bradley & Associates LLC 2008) provided information on the energy intensity and CO_2 emissions of different transportation modes, which could be used to show the potential of public transportation as a sustainable transportation alternative. Taylor et al. (2009) outlined the external factors that affect ridership rates (regional geography, metropolitan economy, population characteristics, and auto/highway characteristics) as well internal factors (fare, service frequency, etc.), the latter of which were found to significantly increase public transportation ridership. A multi-criteria decision making method is applied to a similar focus to that of this study, investigating mode choice behaviors in switching from private vehicle usage to transit transportation (Jain et al. 2014). Lastly, Song et al. (2015) studied the environmental efficiency performance of high-speed rail transportation in China and indicated significant environmental efficiency results for rail transportation with regional differences.

2.1 System Dynamics Method for Transportation Mode Choice

System Dynamics (SD) was introduced to the research community by Jay Forrester in 1969 and since then it has been utilized in various research areas such as policymaking, sustainable development, healthcare management, etc. (Egilmez and Tatari 2012; Fong et al. 2009; Forrester 1969; Haghani et al. 2002; Han and Hayashi 2008; Laurenti et al. 2014; Onat et al. 2014a; Shen et al. 2009). Moreover, predicting or simulating the behavior of society as a whole in terms of transportation mode choice requires robust analysis, which may connect many different factors influencing such decision via complex relationships and feedback mechanisms (Struben and Sterman 2008). SD method is capable of doing such robust analysis and it has been utilized for some transportation mode choice models and these models provide a crucial perspective for selecting regional study boundaries (Fong et al. 2009; Han and Hayashi 2008; Shen et al. 2009; Wang et al. 2008). SD modeling approach fit to the concept of investigating such complex issues since it provides describing ability of feedback mechanisms, delays in system algorithm, and quantitative causal relations between attributes (Onat et al. 2014a). Quantitatively defining causal loops and feedback mechanism between variables also allow performing scenarios analysis on such complex models. Laurenti et al. (2014) also highlighted the importance of this modeling approach for scenario analysis. Due to SD approach's capability of controlling such complex issues, policy studies involving urban development and transportation related land use have utilized the SD approach for various scenario analyses in literature. As Abbas and Bell (1994) stated, the relation between environment impacts assessment and transportation system can be studied with SD modeling approach. SD modeling approach is utilized for transportation systems research in such areas of alternative fuel vehicles, supply chain management, infrastructure construction and maintenance, urban, regional or national scale policy making, air transportation, safety since 1994 (Shepherd 2014).

Increasing the share of transportation modes other than drive alone option is one of the major areas of focus in most urban development studies. Available literature on the subject includes a study by Haghani et al. (2002), who developed a holistic system dynamics model to analyze the relationship between transportation and land use. In a similar manner, Wang et al. (2008) concluded that sustainable urban development is possible if private vehicle ownership is restricted and the use of public transportation is encouraged. Han and Hayashi (2008) used a system dynamics approach to study the CO_2

mitigation potential of public transportation for inter-city travel in China while considering all possible scenarios. Fong et al.'s (2009) study implemented a 50% public transportation share for all transportation modes as a possible scenario, and their simulation results indicated that such a scenario could provide significant CO_2 mitigation compared to other aggressive policies tested in the study. Shen et al. (2009) recommended expanding rail transport for even compact city developments. Lastly, recent studies extended the literature by considering the whole U.S. transportation mode choice behavior, transportation emissions impacts, and sensitivity analysis of the system (Ercan et al. 2016c; b).

2.2 Discrete Event Choice Model Applications for Transportation Mode Choice

There are numerous transportation mode choice studies that utilized discrete event models which can include detailed behavior of certain modes (i.e. cycling in a small community) or consider all mode choices in regional scales. This section only discusses some of the recent literature that includes multiple mode choices as follows. Whalen et al. (2013) investigated the decision-making mechanism of Canadian university commuters and the results indicated interesting findings that affects decision such as psychological decision (i.e. joy of cycling, etc.), travel time, built environment (street, sidewalks, etc.). Schneider (2013) conducted a research to understand how to switch the routine of commuters' from driving to alternative modes by identifying the five key steps of leading a routine such as; awareness & availability, basic safety & security, convenience & cost, enjoyment, and habits. Chakrabarti's (2017) recent study also investigates how to improve transit ridership by shifting drive mode user in Los Angeles area. Sun et al. (2015) advanced the literature by using Copula-based method and their study indicated that built environment (residential and work-place density) has significant correlation with mode choice behavior. Similarly, Ding et al. (2017) also found that built environment should be designed for reducing drive modes, since the results indicate higher population and employment density areas are more likely to use alternative modes.

2.3 Hybrid Simulation Modeling of Discrete Event and System Dynamics

The method of this dissertation combines two widely utilized simulation and forecasting tools for transportation system problems. The use of the DES method allows the researchers to present "*sample paths*" of the desired discrete behavioral data for its behavior (Fishman 2013); Brailsford and Hilton (2001) describes the DES method as a stochastic approach that allocates distinct entities, scheduled activities, queues, and decision rules within a relatively narrow context. On the other hand, the SD method can cover a broader context and allocate external "outside world" interactions with the system being analyzed over longer periods of time (Brailsford and Hilton 2001). Consequently, Brailsford et al. (2010) has referred to the combined use of these two powerful methods as part of a hybrid modeling approach as a “holy grail” of simulation modeling.

SD and DES models are compared in Mak's (1992) dissertation and initialized an effort to develop a prototype computer based simulation. Sweetser (1999) also compared these two models and states that SD method fit well with continues events and feedbacks influence the behavior with dynamic changes. In contrast, Sweetser’s (1999) study defines DES approach a better method for providing more detail analysis of linear algorithms, which includes discrete changes in system. Therefore, the study concludes that both methods has large area of overlapping concept and could have much more potential together. Similarly, Morecroft and Robinson (2005) compared both methods with a case study of fishery design. Their result comparison of both methods indicates that these methods are not opponents but could be complementary. Tako and Robinson (2010) also compared two models by simulating the same problem with 10 modeling experts (5 of each). Their study implied the difference between modelers use for the way of approaching the problem, however, the results of simulations did not present significant differences. Finally, as it mentioned above sections, Brailsford et al. (2010) compared both models for health care management system and named their integration as “holy grail” for their great potential.

In addition to the comparison studies, hybrid simulation method framework is successfully integrated for manufacturing enterprise system (Helal et al. 2007). Another industry that deals with great amount of discrete and continuous events, construction management also benefited from this hybrid approach (Peña-Mora et al. 2008). Another example of hybrid model for construction management provided a framework to simulate real-world situation of mega construction projects for time and money constraints (Alvanchi et al. 2011). Borshchev and Filippov (2004) took a step forward in literature for hybrid simulation and introduced the combination of DES, SD, and Agent-based (AB) models. Similarly, Shafiei et al. (2013) combined SD and AB approaches for urban transportation problem simulation.

In the light of the findings and methods available from these literature, this dissertation chooses to use of the DES and SD modeling approaches to surpass the limitations of the modeling efforts in Section 3 and 4, which only use SD modeling for transportation mode choice problems, thereby limiting previous studies to only two mode choices being taken into account while also being unable to sufficiently account for the effects of behavioral changes on commuters' mode choice decision. Section 4 concludes that sustainable mobility is extremely sensitive to trip generation parameters, which also explains why current policy efforts have so far been unsuccessful in reaching sustainable mobility goals. It must therefore be noted that transportation-related impacts cannot be addressed with only subsidized or myopic policies, but should instead be addressed using policies that would actively involve all stakeholders in the transportation sectors. Similarly, Banister (2008) highlights the importance of stakeholder involvement at all possible levels in order to achieve the desired sustainability mobility goals. Banister's research is an important overlaying literature for this study, since it reinforces the dissertation's point as to the necessity of SD modeling, which can integrate the impacts and feedbacks of these stakeholders and other possible contributors into a macro-level simulation of the transportation sector as it applies to this problem. In other words, the stakeholders of this network complete the system loop by providing feedback with respect to discrete events corresponding to mode choice behavior.

Although transportation system modeling requires an interconnected macro-level design, the key component of the modeled system for purposes of this dissertation is travel mode choice, which is a personal behavior that can vary widely due to a variety of factors. A qualitative survey approach has provided valuable insight with respect to commuters' driving/transit choices, which can be affected by level of service, comfort, availability, and other related factors, but is still mainly a person's choice (Beirão and Sarsfield Cabral 2007). This finding is also in agreement with Innocenti et al.'s (2013) study, which likewise found that mode choice is not always a rational behavior but can still be affected by psychological (mental) models that may cause heuristic and biased decisions. Therefore, it is also crucial to include discrete event modeling estimations in this research with respect to mode choice behaviors.

CHAPTER THREE: A SYSTEM DYNAMICS MODEL TO INVESTIGATE CARBON FOOTPRINT REDUCTION POTENTIAL OF PUBLIC TRANSPORTATION

A partial work of this chapter has been published in the Journal of Cleaner Production with the title of "*Investigating carbon footprint reduction potential of public transportation in United States: A system dynamics approach*" (Ercan et al. 2016b).

3.1 Model Development

3.1.1 Problem Identification

Based on Taylor et al.'s (2009) defined factors that affect public transportation ridership (please see Section 2 for these factors), increasing ridership is expected to decrease private vehicle use, but using private vehicles generates tax revenues for the government from fuel purchases, vehicle registration fees, and driver's license fees. Moreover, the government needs funds in addition to public transportation fare revenues to sustain public transportation infrastructure, meaning that private vehicle ridership cannot rapidly decrease, or such a decrease will result in a collapse of the transportation mode system as a whole unless the government found another way to afford operation expenses of the transportation sector.

The relationship between the transportation modes and the total CO_2 emissions could be linked with the energy intensity of each mode, which is represented by the energy consumption required for each vehicle to move passengers a distance of one mile. The majority of current public transportation vehicles have large engines and body sizes, and so more energy is required to move these vehicles than that required to move private (i.e. light-duty) vehicles the same distance. However, the vehicle occupancy rate regulates energy intensity by dividing the total energy consumption by the number of passengers. Figure 3 illustrates transit bus occupancy and the energy intensity of light-duty vehicles and transit buses in the U.S. from 1990 to 2012 (U.S. Bureau of Transportation Statistics 2015). Until 2009, the energy intensity of transit buses was higher than that of passenger vehicles, which could be due to two main factors. First, the vehicle occupancy and PMT of transit buses was too low before then, making transit buses a non-efficient transportation mode option in term of energy consumption. Second, fuel economy technologies have been developed since 1990, after which even heavy-duty vehicles could be operated with less energy (fuel) required for the same travel demand. In addition, transit bus authorities have been adopting alternative fuel options for their fleet, whereas the per-gallon energy equivalents of alternative fuel options are less than those of gasoline or diesel. It is also especially crucial to highlight the relationship between transit bus occupancy and energy intensity, as the gap between energy intensities of different transportation modes becomes greater as transit bus occupancy decreases. As the Figure 3 indicated, the increase on transit bus ridership after 2008 resulted in more efficient points for energy intensity of transit buses.

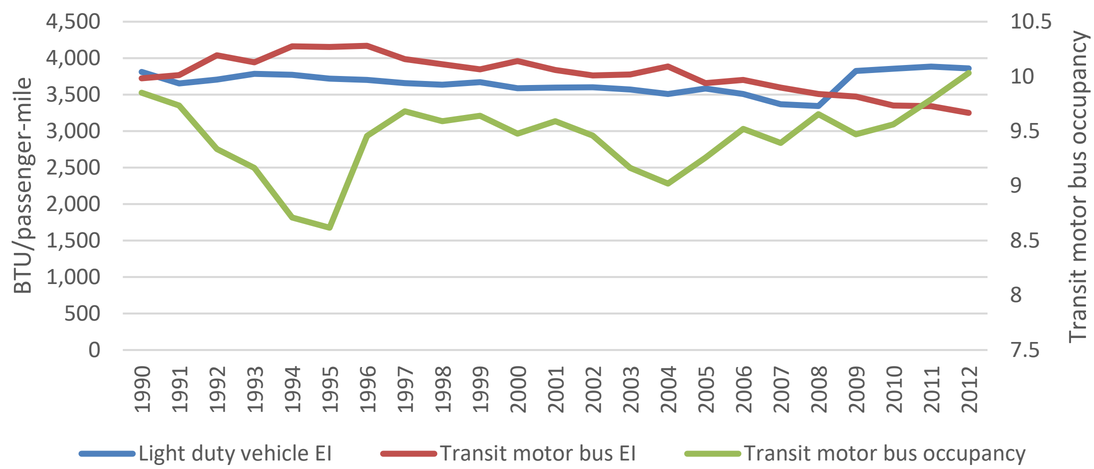


Figure 3: Energy intensity (EI) of light duty vehicles (passenger vehicles) and transit motor buses per passenger-mile, and average transit motor bus occupancy, from 1990 to 2012

The American Public Transportation Association (APTA) announced that public transportation ridership has reached its highest value in the last 57 years (American Public Transportation Association 2014). However, while public transportation ridership increased in 2008 following rapid increases in fuel prices, this ridership increase was not as much as that of last year. The reason behind that the U.S. employment rate is still recovering from its decline 2008, whereas the total number of workers has increased with respect to population growth, and the resulting growth in the workforce would lead to a possible increase in public transportation ridership. Figure 4 depicts the relationship between the number of employees, the total public transit ridership, and gasoline prices from 1990 to 2013. In this figure, the workforce exhibited a nearly constant linear increase over the course of 23 years. A slight decrease in the workforce can be seen from 2008 to 2009, corresponding to the 2008 U.S. economic crisis. However, the total public transportation ridership has an increasing trend, albeit closely related to gasoline prices. Figure 4, which will be used as the reference mode of this chapter, clearly indicates that any extraordinary changes in gasoline prices can likewise cause public transportation ridership to fluctuate. As explained in the previous sections, public transportation ridership has the potential to decrease private vehicle usage and CO_2 emissions, and so any important factor that could increase public transit ridership will be taken into consideration so as to yield a realistic simulation model (American Public Transportation Association Public Transportation Statistics 2015; U.S. Department of Labor Bureau of Labor Statistics 2015).

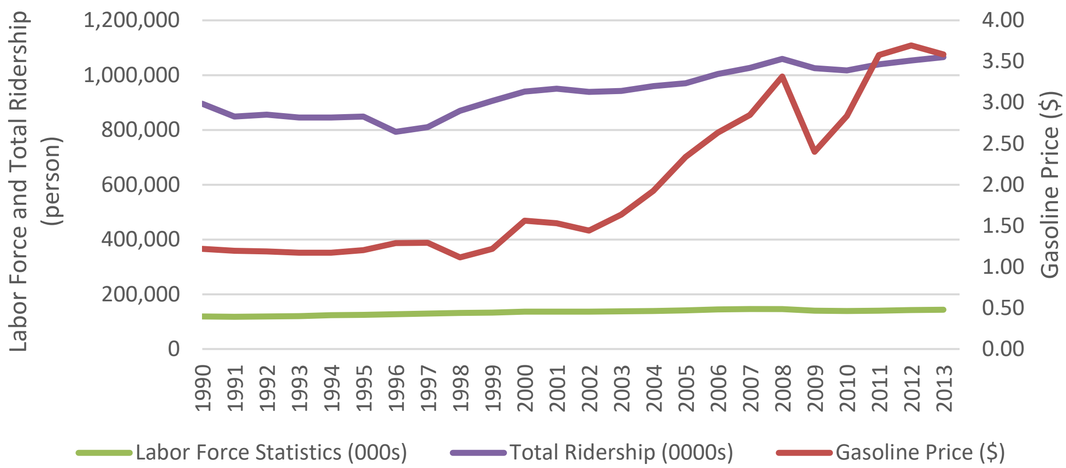


Figure 4: Reference Mode - Labor force statistics (in thousands), total ridership (in tens of thousands), and gasoline price ($) in the U.S.

3.1.2 Identification of Parameters

Parameters that could affect public transportation ridership are summarized in Table 1, along with their descriptions, types, and units. These parameters can be classified as either 'endogenous' or 'exogenous'; parameters expected to be affected by internal factors and/or other parameters within the defined system are classified as 'endogenous', while parameters affected only by external factors beyond the scope of the system as defined in this study are classified as 'exogenous'.

Table 1: Descriptions and units of first SD model parameters

Parameter	Description	Type	Unit
Private Vehicle Ridership	Percentage of person trip with private vehicle in transportation modes	Endogenous	Percentage
Public Transportation Ridership	Percentage of person trip with public transportation in transportation modes	Endogenous	Percentage
Traffic Congestion	Extra time that could be spent on traffic by commuters due to traffic congestion	Endogenous	- (Index)
CO_2 emissions	Vehicle use related annual CO_2 emissions	Endogenous	Ton
Tax Revenue	Tax related government revenue	Endogenous	Million $
Public transportation investments	Infrastructure or fleet investments	Endogenous	Million $
Public transportation travel time reliability and accessibility	Reliability of travel time and accessibility rate of public transportation	Endogenous	- (Index)
Public transportation revenue	Public transportation agency's revenue	Endogenous	Million $
Annual number of person trips	Population increases annual number of person trips	Endogenous	Person trips
Health effects of climate change	Human health impacts of GHG emissions in a given disability-adjusted life year (DALY)	Endogenous	-
Economic damage of climate change	Climate change impacts on the growth rate of the U.S. GDP	Endogenous	-
Labor force population	The employed U.S. population	Exogenous	Person
Alternative fuel adoption for public transportation vehicles	Percentage of public transportation vehicles that operates with alternative fuel source	Exogenous	Percentage

3.1.3 System Conceptualization

Based on the information and parameter definitions previously discussed, a causal loop diagram (CLD) is developed. Figure 5 presents the developed CLD with the corresponding relationships of each parameter. There are five loops that could be detected in the CLD, which are presented in Table 2 as follows.

Table 2: Feedback loop relations of causal-loop diagram

Feedback Loops	Relations
Public Transportation Revenues	
Reinforcing Loop 1 (**R1**) – Revenue	Public Transportation Ridership → + Public Transportation Revenue → + Public Transportation Investments → (Delay)+ Public Transportation Travel Time Reliability/Accessibility → + Public Transportation Ridership
Balancing Loop 2 (**B2**) – Fuel Tax	Private Vehicle Trips → + Tax Revenue → + Public Transportation Investments → (Delay)+ Public Transportation Travel Time Reliability/Accessibility → + Public Transportation Ridership → - Private Vehicle Trips
Traffic Congestion Effects	
Balancing Loop 1 (**B1**) – Congestion	Private Vehicle Trips → + Traffic Congestion → + Public Transportation Ridership → - Private Vehicle Trips
Environmental and Economic Impacts	
Reinforcing Loop 2 (**R2**) – Transit Emissions	Annual Number of Person Trips → + Private Vehicle Trips → + Tax Revenue → + Public Transportation Investment → + Public Transportation Travel Time Reliability/Accessibility → + Public Transportation Ridership → - CO_2 Emissions → + Economic Damage of Climate Change → - Labor Force Population → + Annual Number of Person Trips
Reinforcing Loop 3 (**R3**) – Transportation Emissions	[**Reinforcing Loop-3**] Annual Number of Person Trips → + Public Transportation Ridership → - Private Vehicle Trips → + CO_2 Emissions → + Health Effects of Climate Change → - Labor Force Population → + Annual Number of Person Trips

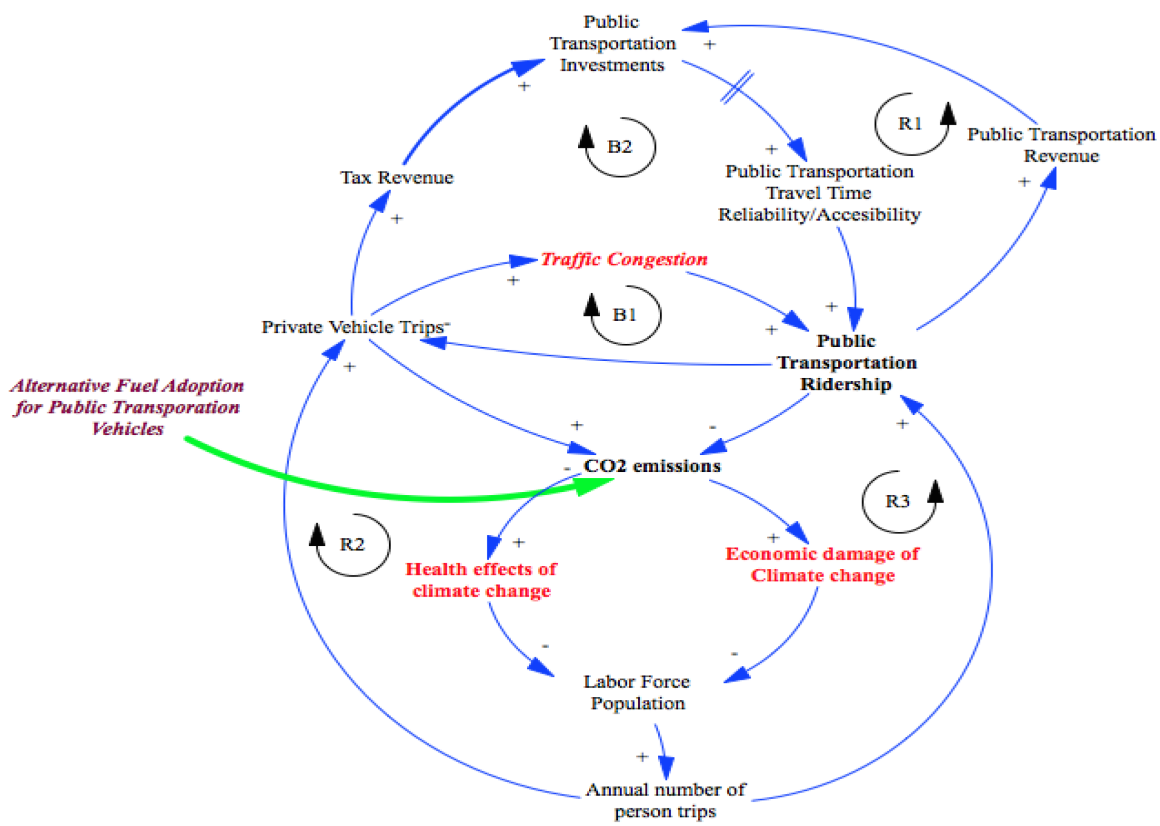


Figure 5: Causal-loop diagram for first SD model (impacts of transportation modes on CO_2 mitigation

3.2. Model Formulation

Based on the CLD presented and explained above, the model designed for this section must be formulated and developed iteratively. The stock and flow diagram of the model is presented in the following five subsections, as the model's stock and flow diagram is too large to show in one figure and had to be broken down into multiple sub-models. The following stock and flow figures illustrate the visual expression of model relationships as developed using the software VENSIM (please see Appendix Table for the meanings of each symbols on stock-flow diagrams). The highlighted variables (‘public transportation ridership’, ‘fuel consumption of private vehicles and transit transportation’, etc.) are the crucial variables used in this study to validate the model.

3.2.1 Population Sub-Model

The total population is the origin point for this model to start from, since people could use various transportation modes to make trips as needed. Figure 6 depicts the developed population sub-model with which to recreate the historical behaviors and values of the population in past years and also to project expected population values in future years. This system’s central focus is on the population of the labor force, which could be represented by the number of people between the ages of 15 and 65. It is assumed that the people within this age group generate the majority of trips, since people could start driving after the age of 16 and employed people typically make at least a two-way trip from home to work and back again. However, the labor force population could in turn be affected by various factors, including the Gross Domestic Product (GDP) of the U.S. economy, life expectancy, birth and mortality rates, and (indirectly) net migration rates. In addition, life expectancy determines the mortality rates at different age groups, which is also affected by the Disability-Adjusted Life Year

(DALY) due to CO_2 emissions. This model is adopted from the WORLD3 model (Bossel 2007; Meadows et al. 2004), and has been modified for the U.S.

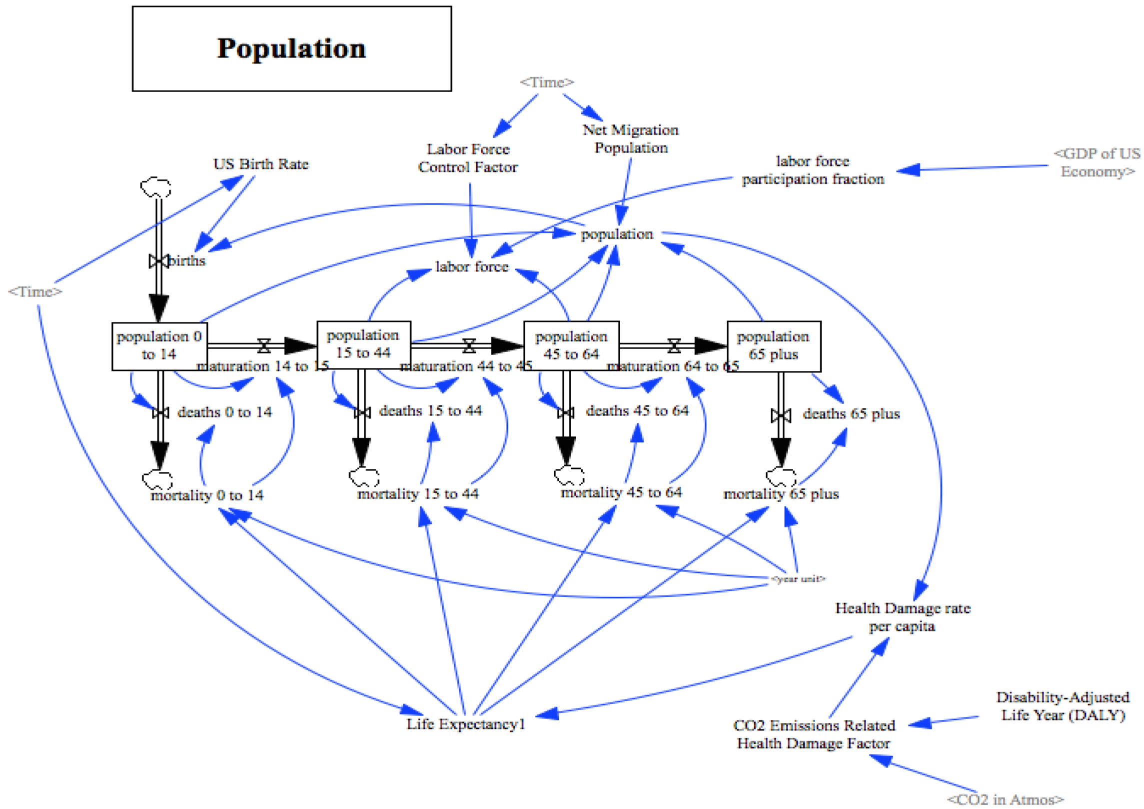


Figure 6: Population sub-model stock and flow diagram

3.2.2. Trip Generation and Public Transportation Ridership Sub-Model

The labor force population and the average trip rate of urban commuters could be used to generate the average daily number of trips made in the U.S. According to Santos et al.'s (2011) study, each person generates almost 4 trips per day. Therefore, it could be stated that the product of the labor force population, the per-person trip rate, and the number of workdays per year could be closely equal to the actual number of trips made in the U.S. per year. Beyond that, how a person chooses to make his or her trip considering all available transportation modes is a matter of preference. Some transportation modes (walking, bicycling, etc.) have been excluded from the model of this section for simplification purposes. Unfortunately, private vehicle usage per person per trip has dominated total ridership in the past with a ridership share of 90%; for the 22-year period covered in this study, this share has been decreased by almost 1%. The relative dominance of private vehicle usage and the ridership share of 3.5% for public transportation are then used to calculate the average number of trips completed with each transportation mode, which in turn provides the necessary information to determine the PMT and VMT by each transportation mode. Multiplying the average trip length of each transportation mode in this model by the number of trips yields the corresponding VMT for each mode. It is important to note that public transportation ridership is equal to the number of trips by the public transit mode specifically. As described in the above sections, transit ridership is the key variable for implementing policies in this model.

As can be seen in Figure 7, "Public transportation ridership" could increase linearly with any increase in the number of trips or in the labor force population. However, the mode choice share (percentage) for public transportation and private vehicle usage would remain constant. The annual revenue of the public transportation system could reinforce itself to extend its service, but it would not be enough to switch a given commuter’s transportation mode from private vehicle to transit on a marginal basis. Therefore, ridership could be increased significantly by introducing new marginal policy scenarios into the system; these policies are explained in further detail in following sections for policy development.

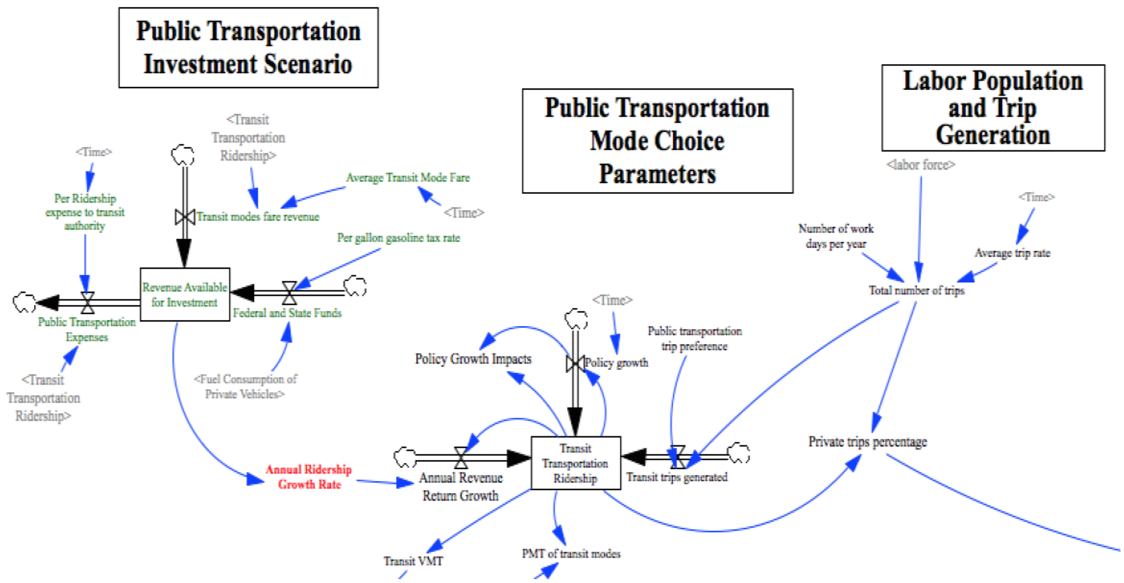


Figure 7: Trip generation and public transportation ridership sub-model stock and flow diagram

3.2.3 Private Vehicle Use and Traffic Congestion Sub-Model

The trip generation sub-model leads the system to generate private vehicle trips. The public transportation mode choice percentage regulates the percent share of private vehicle usage as a mode of transportation. In other words, the percent usage of private vehicles subtracts from the corresponding percent usage of public transportation from 1, with adjustments from the total set made as necessary for walking, cycling, etc.

Private vehicle usage is also regulated by traffic congestion, since people tend to switch from driving to using public transportation at some level of traffic congestion. Figure 8 depicts the relationships between these parameters. Traffic congestion impacts on people's mode choice provide a balancing factor to the system, since private vehicle VMT cannot increase linearly with respect to population growth because lane-mile growth is limited. Light-duty vehicle (LDV) fuel economy values are assumed to represent the fuel economy values of private vehicles in the U.S., which could determine the annual fuel consumption of private vehicles in the following sub-model.

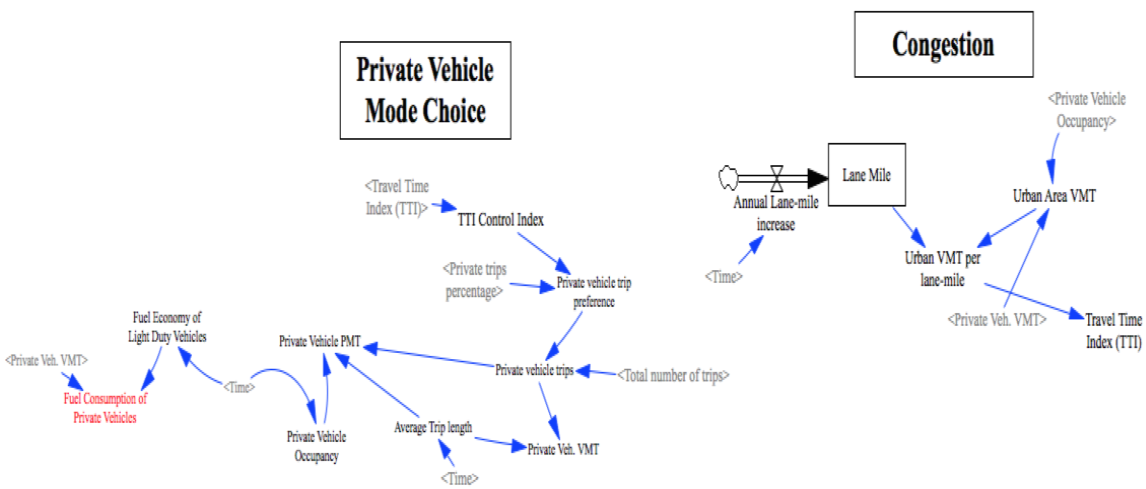


Figure 8: Private vehicle use and traffic congestion sub-model stock and flow diagram

3.2.4 Energy Consumption of Public Transportation Modes Sub-Model

The main energy consumers of the public transportation system are defined in this model as buses, heavy-and-light railways, commuter railways, and demand response. It is more complicated to determine the fuel consumption of transit modes, since available fuel types for public transit vehicles can include electricity, diesel, natural gas, and other fuel sources, compared to private vehicles, most of which are powered by gasoline powered. It is also important to note that each of these energy sources is used in different portions, and that the emission impacts of each source are likewise significantly varied. In order to overcome this variety issue, the energy equivalence of each fuel sources' consumption rates are gathered from historical data for public transportation operation (U.S. Bureau of Transportation Statistics 2015). This consumption per gallon of fuel or per kWh of electricity is then multiplied by the appropriate energy equivalence factor for each fuel source and by EPA's corresponding conversion factor in order to determine CO_2 emissions; applicable rates and reference information are given in Table 3 below. Therefore, Figure 9 is used to present and generate the overall fuel consumption and CO_2 emissions of different energy sources.

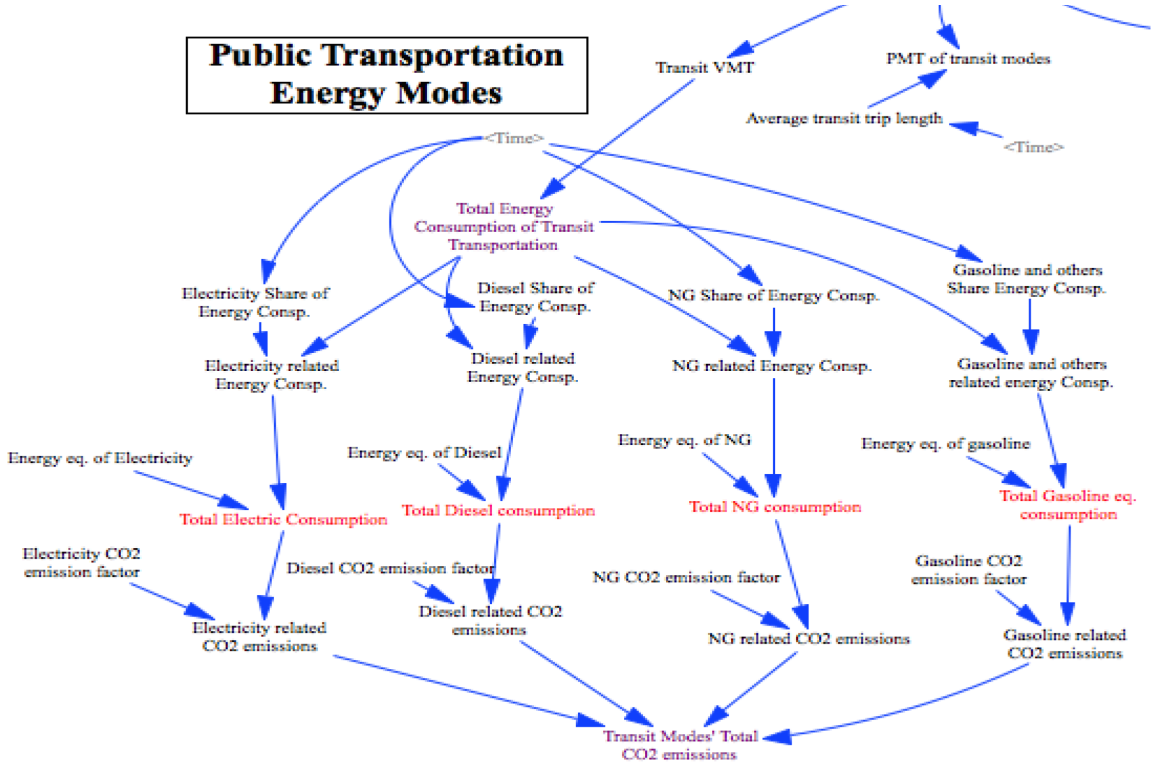


Figure 9: Public transportation related energy consumption sub-model stock and flow diagram

3.2.5 Transportation-related CO_2 Emissions and Climate Change Impacts on Economy Sub-Model

Private vehicle VMT values and average fuel economy values of Light Duty Vehicles (LDV) are used to determine the annual fuel consumption of private vehicles as previously explained in Section 3.2.3 the annual fuel consumption of private vehicles can be converted into CO_2 emissions values based on EPA's average gasoline consumption CO_2 emission conversion rate; this rate and other relevant information is provided in Table 3. Public transportation related CO_2 emissions are the other component of the total transportation-related CO_2 emissions, and is calculated based on each fuel type's CO_2 emission rates, which are explained in further detail in Section 3.2.4. Therefore, the sum of the respective CO_2 emissions from private vehicles and from public transportation modes can be used to find the total value of "*the U.S. transportation related CO_2 emissions*". The relationship between these values is shown in Figure 10. Transportation-related CO_2 emissions are one of the main contributors to global CO_2 emissions, but to fully capture the impacts of climate change on economic and health indicators, the total global CO_2 emission rate should also be considered. For this purpose, The World Bank's World Development Indicators database is used in this model to gather data for total global CO_2 emissions (The World Bank 2014).

After the annual rate of total CO_2 emissions is calculated, their economic impact on the U.S. GDP is calculated using a modified version of the DICE model (Nordhaus 2006). The economic damages from climate change include dislocations resulting from higher sea levels, losses in agricultural productivity, and the dollar-equivalent costs of increases in mortality, morbidity, and social disruption (Pindyck 2011). In current literature, most studies quantify the economic damage of climate change as a direct impact on GDP and consumption. However, these approaches fail to capture the permanent or long-term impacts of climate change. Similarly, the DICE model also assumes that increases in global temperature will affect GDP. On the other hand, Pindyck (2011) claims that global warming can have a permanent effect on future GDP values, and that the effects of climate change should therefore be modeled in such a way that climate change impacts in future years can also be taken into consideration. In the climate change model presented in this paper, the DICE model has been modified so that the impacts of increasing temperatures affect the GDP growth rate in accordance with Pindyck's equations. This modified climate change model was first applied in (Onat et al. 2016c).

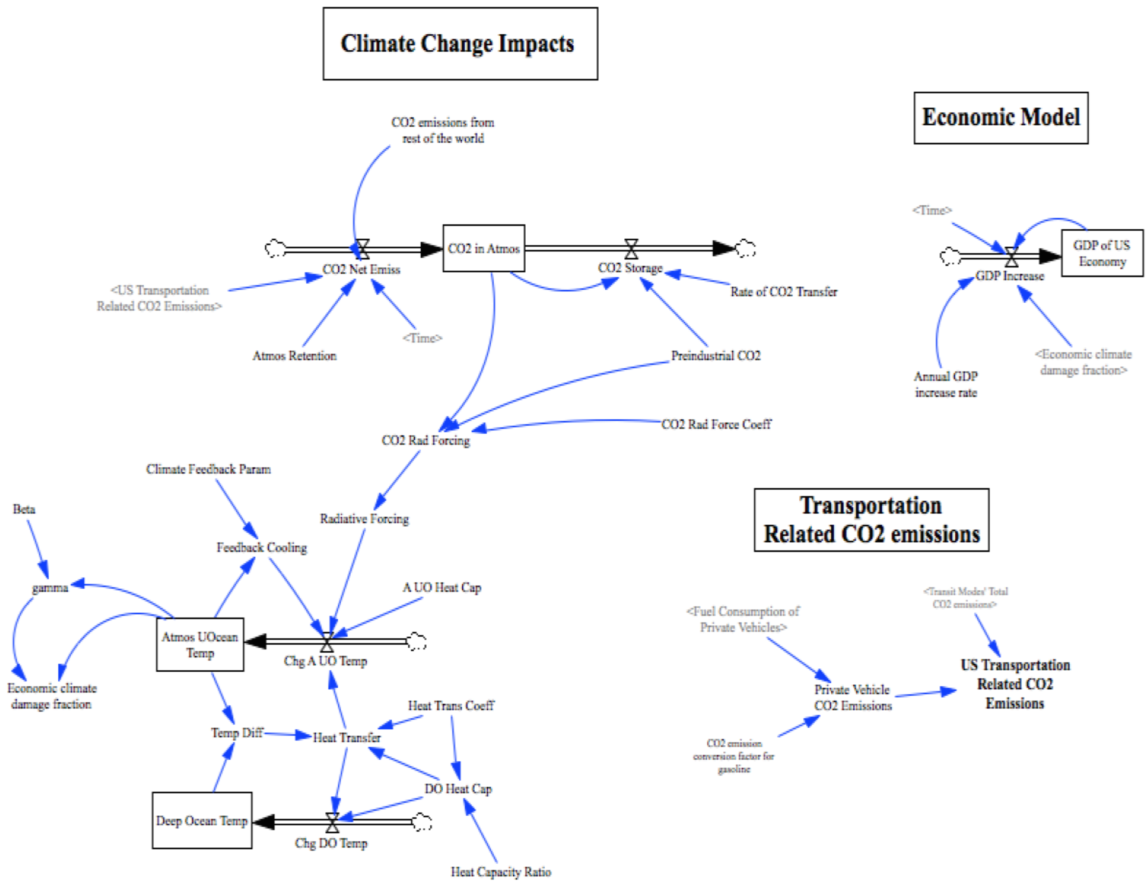


Figure 10: Overall transportation related CO_2 emissions and emissions-related climate change impacts sub-model stock and flow diagram

Some of the parameters seen and explained in the above-mentioned sub-models can be found in Table 3, with their values, units, types, and relevant reference information included as applicable. The model consists of parameters found in currently available literature and from the reports of government agencies. Most of the parameters is to model transportation behavior are gathered from the website of the U.S. Department of Transportation Research and Innovative Technology Administration Bureau of Transportation Statistics (2015). In addition, corresponding factors are used to convert fuel consumption values to energy equivalent values and CO_2 emissions. Since some parameters have been changed over the study period, these parameters are defined as 'auxiliary' variables in the model.

Table 3: Model parameters with unit and references

Parameter	Value	Type	Unit	Reference
Private Vehicle Occupancy	1.62 – 1.39	Auxiliary	person	U.S. Department of Transportation Research and Innovative Technology Administration Bureau of Transportation Statistics (2015)
Fuel Economy of Private Vehicles	20.3 – 23.3	Auxiliary	mpg	
Public Transportation Preference	3.5	Constant	percentage	
Private Vehicle Preference	90	Constant	percentage	
Average transit unlinked fare	0.67 – 1.33	Auxiliary	$/trip	
Diesel Share of Energy Consumption (EC)	82 – 62	Auxiliary	percentage	
Electricity Share of EC	16.2 – 14	Constant	percentage	
Natural Gas (NG) Share of EC	13.5 – 0	Auxiliary	percentage	
Gasoline and Others Share of EC	9 – 2	Auxiliary	percentage	
Average trip length	8.2 - 8.67	Auxiliary	mile	Santos, et al. (2011)
Average trip rate	3.76 – 4.30	Auxiliary	trip/day	
Average transit trip length	5.4	Constant	mile	
Per gallon tax rate	0.54	Constant	$/gallon	(U.S. Energy Information Administration 2015a)
Per PMT expense to transit authority	0.6	Constant	$/PMT	American Public Transportation Association (2014)
(***Energy eq. and CO2 emission conversion factors***)				
Electricity - Energy eq. factor	3,412	Constant	BTU/kWh	U.S. Energy Information Administration (2015)
Gasoline - Energy eq. factor	125,000	Constant	BTU/gallon	
Diesel - Energy eq. factor	138,700	Constant	BTU/gallon	
Natural Gas (NG) - Energy eq. factor	22,500	Constant	BTU/gallon	
CO2 eq. - Electricity/kWh factor	6.89E-04	Constant	t CO2 eq./kWh	(U.S. Environmental Protection Agency 2014a)
CO2 eq. - Gasoline/gallon factor	6.66E-03	Constant	t CO2 eq./gallon	
CO2 eq. - Diesel/gallon factor	1.02E-02	Constant	t CO2 eq./gallon	
CO2 eq. - NG/gallon factor	8.89E-03	Constant	t CO2 eq./gallon	

3.3 Model Validation

The overall development of this model is not complete without first presenting the model's validation results, which must prove that the model is adequate for policy implementation and testing. In other words, the model should be valid and correct with respect to applicable literature and historical data before it can be used for forecasting.

With the development of system dynamics in literature, model validation has since become the topic of several important articles. Barlas (1996) highlighted and defined the model validation process, and his work has been cited in most system dynamics articles today. Qudrat-Ullah and Seong (2010) summarized the validation methods in light of the work of Barlas (1996). Moreover, this paper will follow the validation steps described by Qudrat-Ullah and Seong (2010).

3.3.1 Structural Validation

The first step consists of five specific structural validation (or verification) tests; *boundary adequacy, structure verification, dimensional consistency, parameter verification,* and *extreme conditions*. Structural validation tests whether or not the model is an adequate representation of the real-life situation(s) being modeled, and therefore refers to the point where the model is first developed with the causal-loop diagram. Since this dissertation has provided some references with different perspectives regarding transportation mode problems, it can be safely stated that this model includes all of the necessary variables that affect the modeled system in reality. Furthermore, as a part of structural validation, providing references for the model boundary and variables affirms that this model meets the requirements of the "*boundary adequacy*" test.

The causal-loop diagram of the model shows that this model consists of feedback loops that affect the reference mode. Moreover, the developed stock and flow diagram as a whole was developed with variable relations and formulations that run on VENSIM without any errors. Thus, this model passes the "*structural verification*" test as well.

After adding all formulas and relations between variables of the model, it is also crucial to include their dimensions. Defining the exogenous variables' dimensions allows system thinkers to generate the endogenous variables' dimensions in order to check the real-life dimensions of these same endogenous variables. Table 3, as previously explained, defines the dimensions of the model and confirms that the model passes "*dimensional consistency*" validation test. The parameters of the model defined in Table 3 are gathered from reliable references, meaning that the "*parameter verification"* test is satisfied. Finally, some of the historically defined parameters used in the model include extreme conditions such as rapid increases or decreases for some years, such as 2008's economic crisis in the U.S. and its subsequent impacts on transportation modes.

However, neither parameters nor endogenous variables reflected any "*extreme conditions*" with such negative or zero data points.

3.3.2 Behavioral Validation

The structural validation process ensures that the model is developed correctly and is working properly, but does not determine whether or not the model exhibits the same behavior as the real-world historical data of the reference mode. Although behavioral validation could be simply presented with graphs, it should also be scientifically supported with statistical analyses. Figure 11 presents the "*behavioral reproduction*" test results with respect to public transportation ridership, and it is clear from the figure that the simulation behavior of the model is fairly similar to the historical behavior of the real-life data. The actual data for transit transportation ridership was gathered from the U.S. Department of Transportation Research and Innovative Technology Administration Bureau of Transportation Statistics (2015). The statistical relationship between the public transportation ridership data for the model simulation and for the reference mode is explained below.

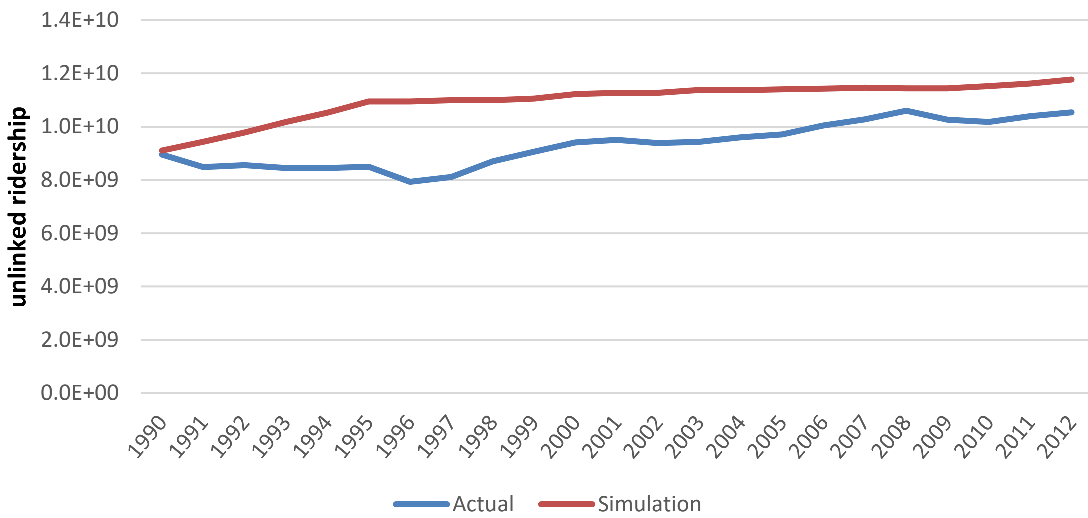


Figure 11: Behavioral Reproduction of Public Transportation Ridership

Fuel consumption is one the key components of the model, since it generates the energy consumption and CO_2 emissions previously discussed with respect to the modeled system. Therefore, Figure 12 depicts the behavioral reproduction test results for the annual fuel consumption of LDVs. The historical fuel consumption data from 1990 to 2012 was also gathered from the U.S. Department of Transportation Research and Innovative Technology Administration Bureau of Transportation Statistics (2015). Figure 12 indicates a significantly close relationship between the historical data and the simulation results.

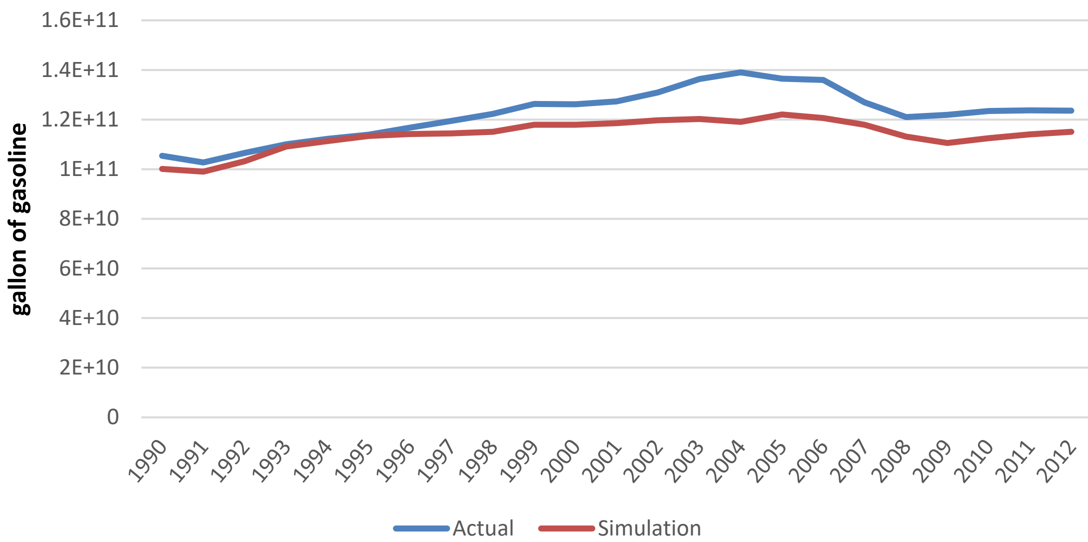


Figure 12: Behavioral Reproduction of Light Duty Vehicle Annual Fuel Consumption

As a major environmental emission contributor, VMT values related to private vehicle usage are critical to calculating valid overall CO_2 emissions. Therefore, Figure 13 presents the VMT values pertaining to private vehicles and compares the actual historical data and simulation results associated therewith. The figure depicts that the system dynamics model accurately captures the behavior of the real life VMT data over the study period. As with the other reference modes, the actual data for private vehicle VMT is gathered from the U.S. Department of Transportation Research and Innovative Technology Administration Bureau of Transportation Statistics (2015).

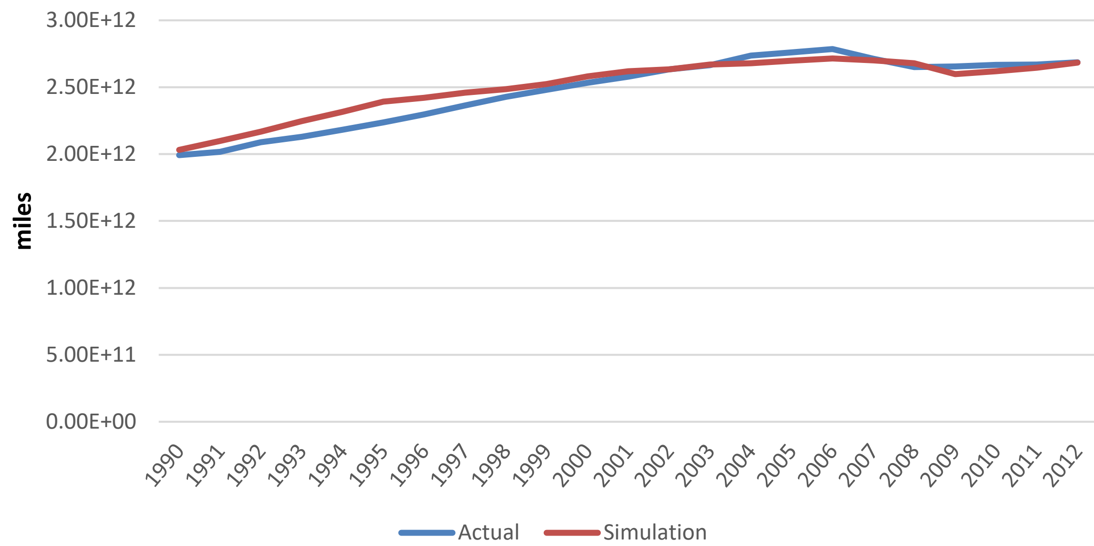


Figure 13: Private Vehicle's Vehicle-Miles-Traveled (VMT) Behavioral Reproduction Results

Finally, Figure 14 indicates a close behavioral relationship between the actual data and simulation results for annual transportation-related CO_2 emissions. The actual data values of annual CO_2 emissions from transportation activities are higher than the corresponding simulation results, but this is acceptable because the fluctuations of the historical data are sufficiently captured. As with all reference modes, the U.S. Department of Transportation Research and Innovative Technology Administration Bureau of Transportation Statistics (2015) database was used to access historical transportation related CO_2 emissions data.

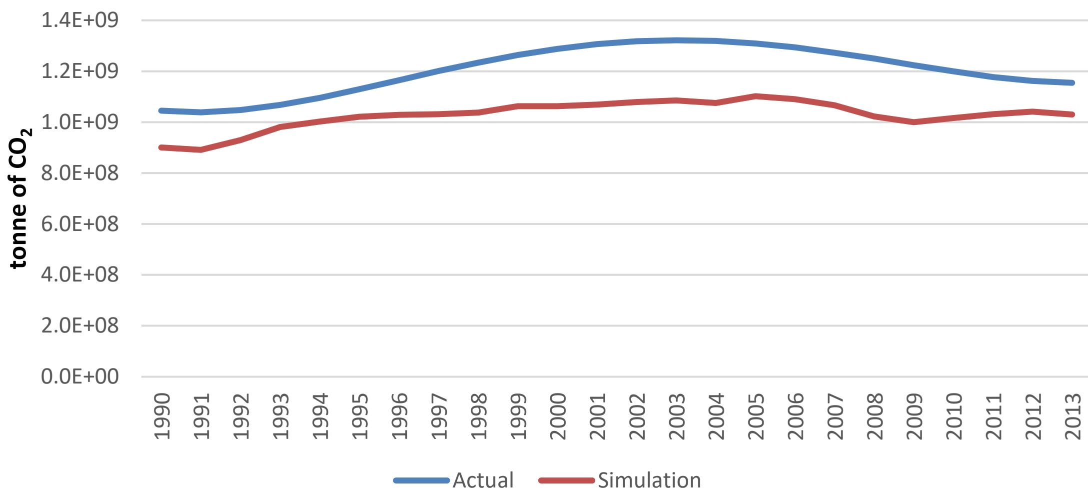


Figure 14: Behavioral Reproduction of transportation Related CO_2 Emissions

For a proper behavioral validation, the reference modes' behavioral reproduction tests should be supported with a thorough statistical analysis in order to prove that the model's behavior is statistically correct. There are many ways to statistically validate the significance of any differences between two datasets. Qudrat-Ullah and Seong (2010), for example, used the Mean Square Error (MSE) and Root Mean Square Error Percentage (RMSEP) methodologies to validate their simulation results. In another example, Egilmez and Tatari (2012) used normality tests and the one-way ANOVA test for behavioral validation. This study also used the one-way ANOVA test to validate the simulated behavior of transit transportation ridership values, and the results are presented in Table 4. In accordance with the model's hypothesis, the significance level is almost zero for all of the selected key variables of the model, so the simulated data can therefore be deemed behaviorally accurate with respect to the corresponding reference mode data. Likewise, the corresponding F values for each variable are substantially less than their respective mean square values.

Table 4: One-way ANOVA test results for validation of key parameters

	Significance Level	F	d_f		Mean Square
			Between Groups	Within Groups	
VMT	0.007	33.03	19	3	4.92E+22
Fuel Consumption	0.001	0	22	0	3.98E+19
Ridership	0.001	0	22	0	5.03E+17
CO_2	0.001	0	22	0	3.09E+15
Labor Force Population	0.001	0	22	0	3.04E+14

3.4 Policy Analysis

For the main objective of this section, the validated model is now used to forecast the potential of public transportation to mitigate transportation-related CO_2 emissions. There are several ways to implement policies into the model, but some of said policies could become irrelevant to the model or might make it impossible to define the applicable relationships between model variables. Therefore, this research considers some of the possible policies that could change the previously observed trends in the reference mode and especially in annual CO_2 emissions.

A report by the U.S. Federal Highway Administration and U.S. Federal Transit Administration (2014) proposed several investment scenarios that could increase public transit ridership annually, with the FHWA's report adopted for policy development with respect to public transportation. In order to increase public transportation usage, factors related to funding should be integrated to the model. Reinforcing Loops 1, 2, and Balancing Loop 2 from Figure 5 (causal loop diagram) highlight the funding-related variables and possible policy implementations for public transportation. These additional policy-related variables generate funds to the system in two ways such as; the public transportation system itself generates fare collection revenue and federal and/or state funds are implemented for system extensions.

However, the operational expenses associated with public transit will inevitably require some amount of deductions from one or both of these revenues. Nevertheless, the net revenue can then be used for public transportation system extensions. The FHWA's report states that public transportation agencies already invest in system developments in order to meet future ridership demand, but this investment cannot help to increase the accessibility or reliability of public transportation to more effectively persuade society to switch from private vehicles to public transit (U.S. Federal Highway Administration and U.S. Federal Transit Administration 2014). Table 5 presents the required annual investment values and their relative annual ridership growth rates. Expanding the transit transportation-related policy approach could provide feedback from the model, since it reduces private vehicle trips and increases fare-related revenues, which could provide more funding for investments as needed. The impacts of these investment policies on public transportation ridership are discussed in Section 3.5.

Table 5: Public Transportation Investment Scenarios

Scenario	Annual Investment	Annual Ridership Growth Rate	Total Added New Ridership
B.A.U.	$6.2 Billion	1.8%	4.6 Billion
Low Growth	$7.1 Billion	2.1%	5.4 Billion
Med. Growth	$10.2 Billion	3%	8.5 Billion
High Growth	$14.4 Billion	4.3%	13.8 Billion
Marginal Growth	$30 Billion	9%	23 Billion

In addition to the FHWA's proposed policy scenarios on increasing transit ridership, some other ambitious scenarios could also be implemented in order to present the potential impact of reducing private vehicle usage on CO_2 emissions. Therefore, four hypothetical scenarios are implemented to simulate increases in public transportation ridership up to 25%, 50%, 75% and 100% compared to private vehicle usage. It is crucial to note that European Union (EU) countries have used 16% transit transportation in 2008 and currently have an increasing ridership trend (International Energy Agency (IEA) 2009). Therefore, it is not too practically infeasible to aim to increase public transit ridership in the U.S. to a share of 25% in future years.

Another possible policy scenario could be implemented with respect to the fuel consumption of public transportation vehicles. Alternative fuel options are increasing their market shares in the transportation industry. Although diesel is still the dominant fuel source for public transportation operations, the number of diesel-powered vehicles has already decreased from 82% in 1990 to 63% in 2012 (American Public Transportation Association 2014), while natural gas and electricity are both quickly emerging as popular fuel sources for public transportation. For instance, the market share of natural gas vehicles was almost 0% in 1990, but has since risen to 16.2% in 2012. This policy initiative could be especially important because diesel is considered to be one of today's most environmentally harmful fuel sources due to its environmental emissions (The Clean Air Act Amendments 1990). In addition to efforts to shift ridership shares away from private vehicles in favor of public transportation, ensuring that public transportation vehicles emit less pollution is also very important for CO_2 mitigation. Fortunately, in light of recent alternative fuel adoption rates, public transit market shares of electric and natural gas-powered vehicles are expected to increase by 4% and 2%, respectively. The potential outcomes of implementing this policy initiative can also be found in the recent literature (Ercan et al. 2015, 2016a; Ercan and Tatari 2015; Zhao et al. 2016a).

Finally, the fuel economy of private vehicles can also be improved as part of yet another policy initiative. Assuming that private vehicles comprise the light-duty vehicle (LDV) shares in the U.S., the fuel economy of the overall fleet has been improving. Based on the last 10 years of development, the fuel economy of LDVs is expected to improve by 25% from 2013 to 2030 (National Highway Traffic Safety Administration 2015).

3.5 Results

The results of all growth scenarios directly pertaining to public transportation ridership are presented in Figure 15. The FHWA's growth scenarios by improving transit system performance and service are examined along with more ambitious potential growth scenarios to generate these results. Although increasing transit system funding can increase public transit ridership, this cannot be seen clearly in Figure 15 because the ambitious scenarios increased ridership exponentially. Even the "*MarginalGrowth*" scenarios could not generate any significant results compare to these more ambitious scenarios. It is important to note that the "*MarginalGrowth*" scenario is expected to increase annual ridership by 9%, whereas the most conservative of the ambitious scenarios yields a corresponding increase of 25%.

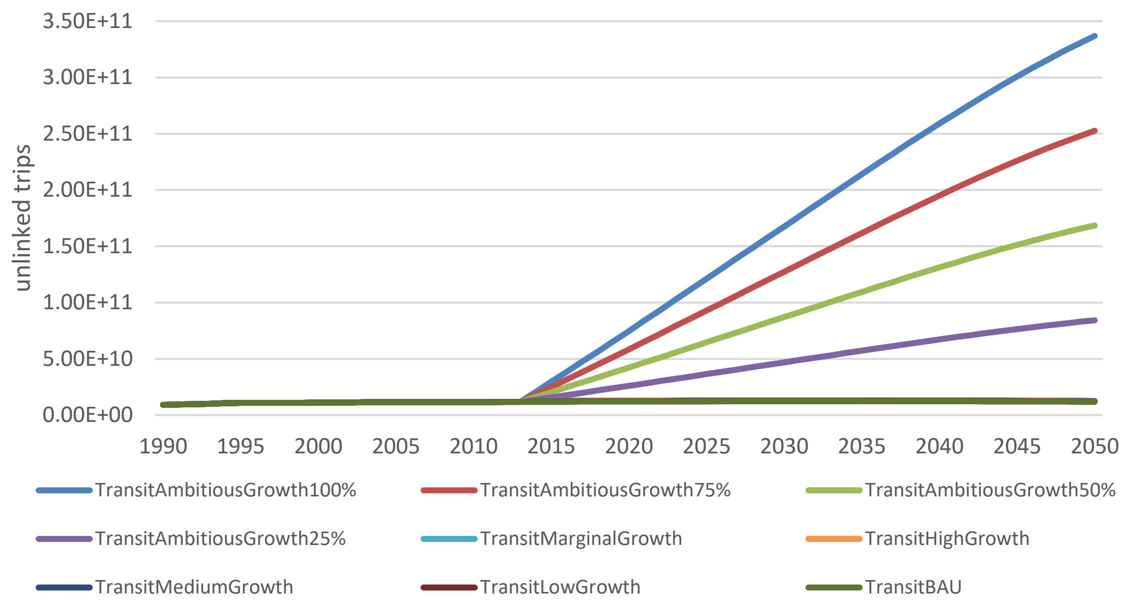


Figure 15: Unlinked public transportation ridership policy results

Private vehicle VMT projections for 2050 are presented in Figure 16. This figure indicates that currently predicted VMT trends will continue to increase until late into the year 2035. However, this increase is linearly dependent on the labor force population; it should be noted that the increase is not as deep as it was before 2008. Hence, it could be stated that the negative impacts of 2008's economic depression not only caused negative impacts on economic indicators, but also had positive impacts on public transportation ridership as opposed to private vehicle usage. Since the VMT values in this research are in billions, the transit development impacts are somewhat difficult to visualize from Figure 16 alone. Parallel to the increase of transit ridership, private vehicle VMT is decreasing, but this decrease is not enough for the FHWA's proposed growth scenarios to change increasing trends in VMT. On the other hand, the 25%

ambitious growth scenario as previously described is expected to significantly change the current trend in private vehicle VMT and thereby yield crucial environmental benefits.

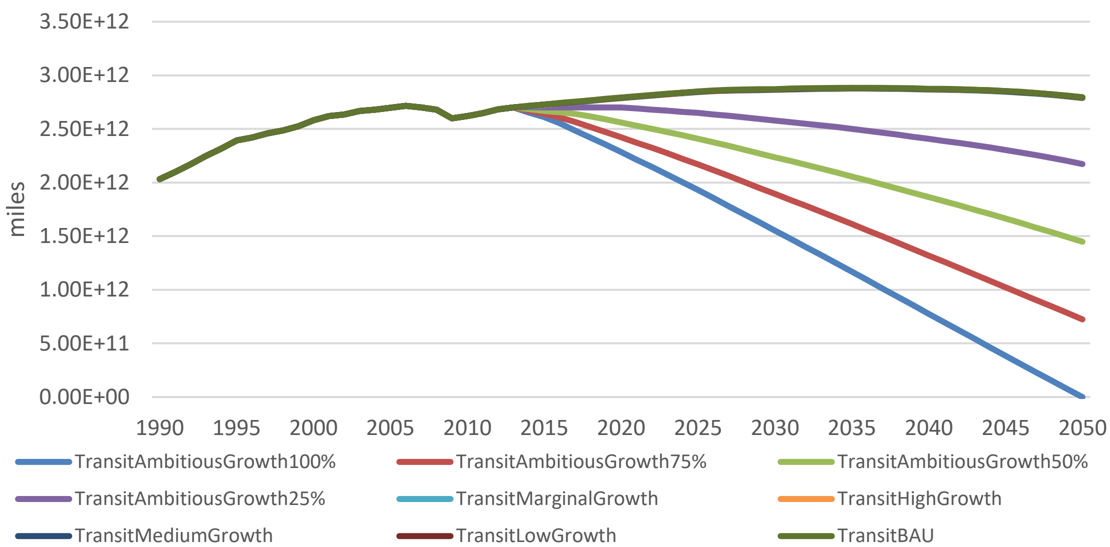


Figure 16: Private vehicle usage related annual VMT simulation

As stated in Section 3.4, the fuel economy of private vehicles regularly improves every year, and is expected to continue to do so in future years with the help of EPA's Tier regulations and the U.S. Department of Transportation's CAFE regulations (National Highway Traffic Safety Administration 2015; U.S. Environmental Protection Agency 2014b). Figure 17 presents the benefits of a mode shift in favor of public transit in terms of fuel consumption, as well as the possible benefits of fuel economy improvements. The graph also indicates that the 25% ambitious growth scenario could save as many as 18.4 billion gallons of gasoline per year in 2050 compared to the BAU scenario. On the other hand, the corresponding savings for the "*MarginalGrowth*" scenario compared to the BAU scenario are reduced to 227.4 million gallons of gasoline per year.

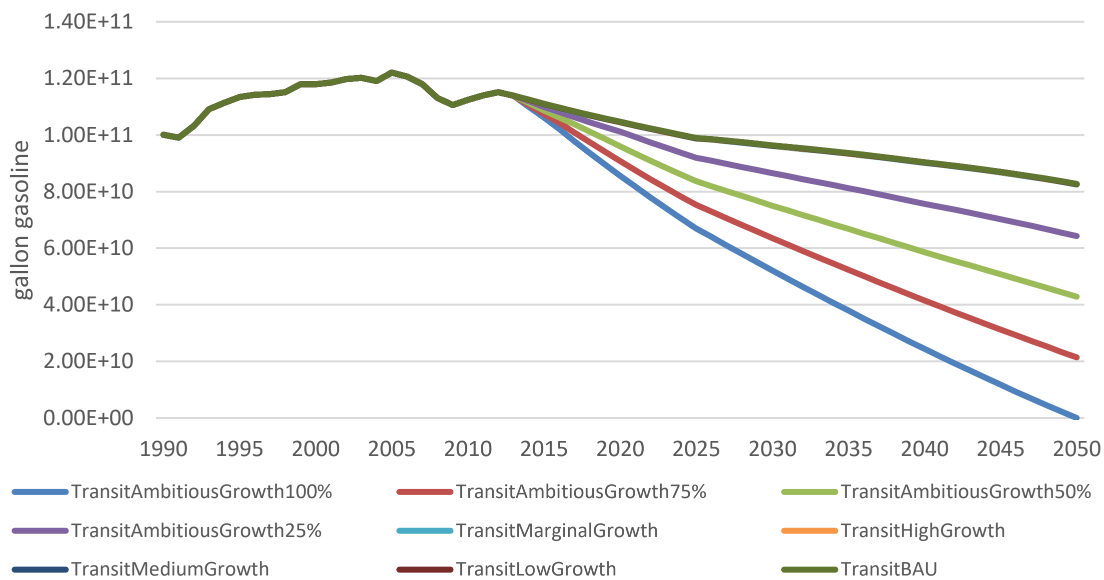


Figure 17: Private vehicle usage related annual fuel consumption simulation

Figure 18 presents the annual transportation-related CO_2 emissions for future years in tonnes of CO_2 equivalents. These results exhibit similar behavior to that of previous results with respect to transportation modes, and so the FHWA's proposed growth scenarios could not provide significant CO_2 mitigation compare to the BAU scenario. Conversely, it should be noted that the annual CO_2 emissions reduction under the "*MarginalGrowth*" scenario relative to the BAU scenario is 766,000 tonnes of CO_2 equivalents annually in 2050. Likewise, the 25% ambitious scenario is expected to contribute to CO_2 emission mitigation by 61.3 million tonnes of CO_2 equivalents annually in 2050.

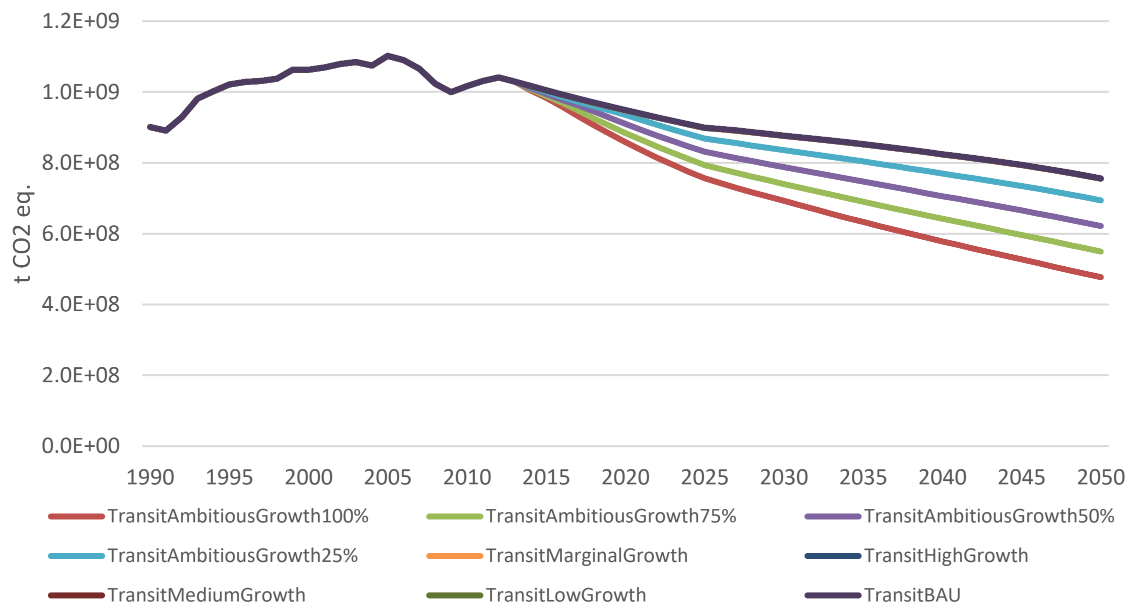


Figure 18: Annual CO_2 emissions of transportation modes simulation

It must be noted that CO_2 emissions have been accumulating in the atmosphere for decades. Figure 19 depicts the stock of transportation-related CO_2 emissions from 1990 to 2050 in terms of atmospheric accumulation. This figure also indicates that CO_2 emissions have a linear increasing trend under the BAU scenario and the FHWA's transit growth scenarios, whereas only the ambitious scenarios show any potential to change this. The "*MarginalGrowth*" scenario for transit ridership reduced CO_2 emission accumulation from 2013 to 2050 by 34.9 million tonnes of CO_2 equivalents, while the 25% ambitious growth scenario yielded a corresponding reduction of 1.4 billion tonnes. It should be noted that these scenarios are able to reduce the net increase in the accumulation stock of CO_2 emissions even with the anticipated increases in population and trips in the U.S. in future years.

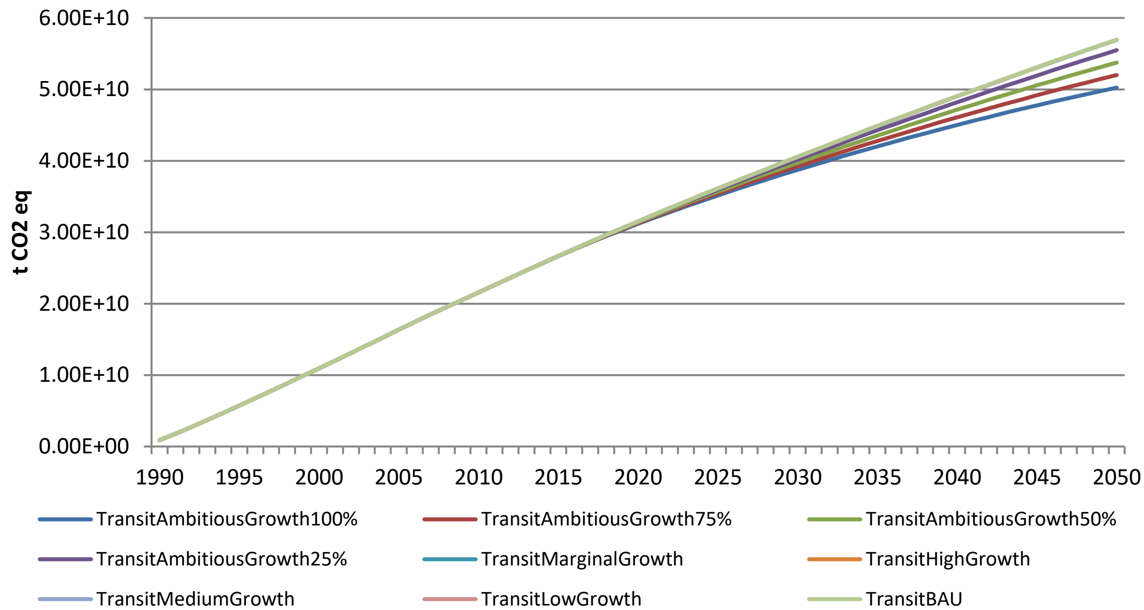


Figure 19: Stock of transportation-related CO_2 emissions of the U.S.

CHAPTER FOUR: MULTIVARIATE SENSITIVITY ANALYSIS ON URBAN TRANSPORTATION'S SUSTAINABILITY PERFORMANCE

A partial work of this chapter has been published in the Journal of Cleaner Production with the title of "*Public transportation adoption requires a paradigm shift in urban development structure*" (Ercan et al. 2016c).

4.1 Model Conceptualization

This chapter advances the model that is developed in Chapter 3 with dynamic generation of public transportation network funds with policy practices and multivariate sensitivity analysis on entire system. A dynamic modeling approach will allow this study to identify the feedback mechanisms of the U.S. transportation mode choice as an independent system, particularly those that divide the total number of trips made into those using private vehicles and those using public transit, depending on society's preference. Instead of quantifying and simulating the associated mode choice preference factors using separate discrete events, dynamic modeling uses relevant equations to connect and simulate the macro-level relationships of these factors. However, before formulating the model relations with the necessary equations, the system should first be analyzed from a conceptual standpoint, as illustrated with a

Causal-Loop Diagram (CLD) that simplifies and summarizes the observed complex relations in the system (Onat et al. 2014a).

As Sterman (2000) stated "*learning is a feedback process*" and real world provide feedbacks to decision makers in the forms of qualitative or quantitative data by the time. So, system thinking requires defining appropriate feedbacks in the form of causal links that are shown in arrows between "*cause*" and "*effect*" variables. These arrows are followed by polarity information where positive (+) or negative (-) indicate the influence between two variables. Positive (reinforcing) relation indicates that the "*effect*" and "*cause*" variables are both influenced in same polarity direction where negative (balancing) relation indicates opposite linkage (i.e. effect increases while cause decreases or effect decreases while cause increases) (Sterman, 2000). By identifying this polarity information, feedback loops can be defined for being reinforcing or balancing on CLD.

The proposed CLD for this system (Figure 20) identifies seven feedback loops within the system, five of which are reinforcing loops (where an increase in any single factor causes an additional increase) and two of which are balancing loops (where an increase in any single factor causes a subsequent decrease). Each of these loops are labeled with their names and rotation information on the figure.

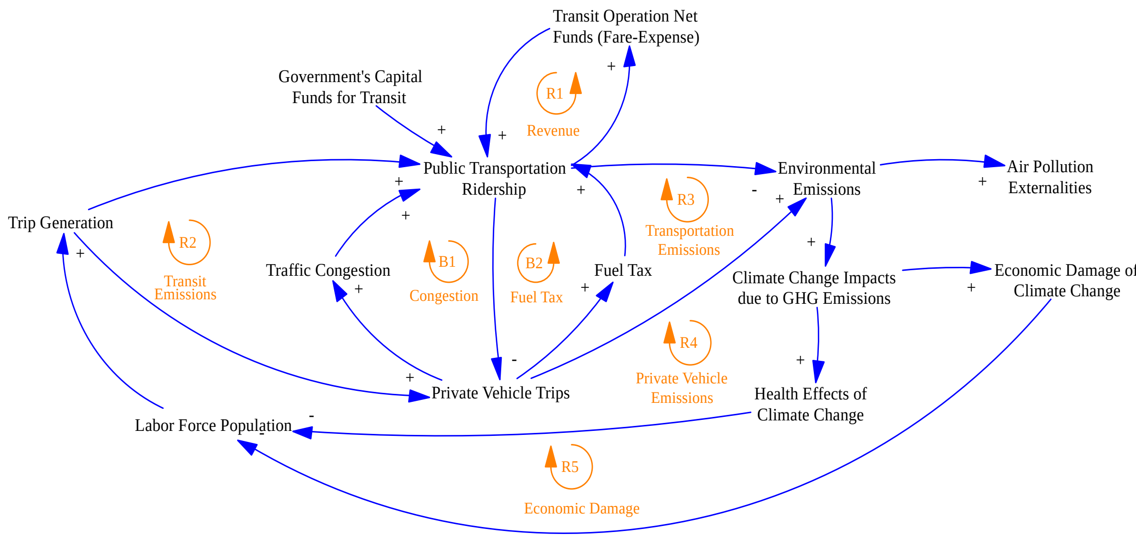


Figure 20: Causal-loop diagram (CLD)

The U.S. public transportation system has been supported by large amounts of federal, state, and local government funding for many years, and these funds are expected to increase transit ridership as a viable alternative to private vehicle use (U.S. Department of Transportation Federal Highway Administration and Federal Transit Administration 2014). In addition to system-generated net revenues (operation expenses, fare revenues, etc.) and partial fuel tax revenues (a portion of which is directed to transit funds), federal, state, and local governments also reserve funds for capital investments in public transportation. This external support of government entities to transit transportation system can be seen as a positive (reinforcing) relation on Figure 20. As can be seen from the polarity information (positive/negative) of the arrows in Figure 20, parameters related to funding and revenues will reinforce transit ridership ("Revenue" loop). However, there is also a balancing loop between private vehicle and transit use that must be noted, as decreasing private vehicle use can decrease fuel purchases and thereby reduce one of the sources of transit system funding ("Fuel Tax" loop). Each of these crucial feedback relations are defined in Table 6 (Please see feedback loops R1 and B2).

A similar balancing relationship with respect to transportation modes can also result from traffic congestion impacts, as people are more likely to switch to public transportation if traffic congestion increases to certain levels, thereby decreasing private vehicle use and decreasing traffic congestion. This effect is summarized in Balancing Loop 1 (B1) as shown in Table 6.

As more trips are generated, environmental emissions increase and incur greater life expectancy damages and economic damages for society as a whole. The remaining feedback relationships defined in this model focus primarily on these environmental and economic impacts from transportation modes. The use of either private vehicles or transit options will ultimately reinforce these environmental and economic damage impacts, albeit to different degrees; even transit modes are efficient primarily in that they can transport a greater number of people per trip, but are still significantly dependent on fossil fuels and will therefore emit some amount of air pollution. The feedback relationships corresponding to the environmental and economic impacts of the overall system are summarized in four reinforcing loops (R2 – R5) as shown in Table 6.

Table 6: Feedback loop relations of the causal-loop diagram

Feedback Loops	Relations
Public Transportation Revenues	
Reinforcing Loop 1 (**R1**) – Revenue	Public Transportation Ridership →+ Transit Operation Net Funds (Fare-Expense) →+ Public Transportation Ridership
Balancing Loop 2 (**B2**) – Fuel Tax	Private Vehicle Trips →+ Fuel Tax →+ Public Transportation Ridership →- Private Vehicle Trips
Traffic Congestion Effects	
Balancing Loop 1 (**B1**) – Congestion	Private Vehicle Trips →+ Traffic Congestion →+ Public Transportation Ridership →- Private Vehicle Trips
Environmental and Economic Impacts	
Reinforcing Loop 2 (**R2**) – Transit Emissions	Trip Generation →+ Public Transportation Ridership →- Environmental Emissions →+ Climate Change Impacts due to GHG Emissions →+ Health Effects of Climate Change →- Labor Force Population →+ Trip Generation
Reinforcing Loop 3 (**R3**) – Transportation Emissions	Trip Generation →+ Public Transportation Ridership →- Private Vehicle Trips →+ Environmental Emissions →+ Climate Change Impacts due to GHG Emissions →+ Health Effects of Climate Change →- Labor Force Population →+ Trip Generation
Reinforcing Loop 4 (**R4**) – Private Vehicle Emissions	Trip Generation →+ Private Vehicle Trips →+ Environmental Emissions →+ Climate Change Impacts due to GHG Emissions →+ Health Effects of Climate Change →- Labor Force Population →+ Trip

Feedback Loops	Relations
	Generation
Reinforcing Loop 5 (**R5**) – Economic Damage	Trip Generation →+ Private Vehicle Trips →+ Environmental Emissions →+ Climate Change Impacts due to GHG Emissions →+ Economic Damage of Climate Change →- Labor Force Population →+ Trip Generation

4.2 Model Development

The problem statement of this study emphasizes a high dependency on private vehicles for urban passenger transportation in the U.S. Based on the literature, the external factors affecting this problem include geographical features, socio-economic indicators (i.e. metropolitan economy, population characteristics, etc.), spatial factors (i.e. auto/highway characteristics, urban development, etc.), and travel behavior, while the internal factors include fare rate, quality of service, quantity factors, etc. (Taylor et al. 2009) Earlier research on identifying the most significant influencing factors on transit ridership indicates that external factors tend to have greater impacts on transit ridership than internal factors, although transit authorities have no control over said external factors in their efforts to increase transit ridership shares (Taylor and Fink 2003). However, the identification of relevant external and internal factors and the conceptualization of the system as a whole (as illustrated in proposed CLD) can guide the model development process in terms of parameter selection and model formulation. To this end, Table 7 summarizes the key parameters selected for model development, including their value(s), units, and any relevant reference information.

Table 7: Some of the critical model parameters and values

Parameter	Value	Type	Unit	Reference
Private Vehicle Occupancy	1.62 – 1.39	Auxiliary	person	(U.S. Bureau of Transportation Statistics 2015)
Fuel Economy of Private Vehicles*	23.11 – 40.18	Auxiliary	mpg	
Initial Public Transportation Preference	3.50	Constant	percentage	
Average transit unlinked fare	1.30 – 1.34	Auxiliary	2015 $/trip	
Diesel Share of Energy Consumption (EC)**	45.00 – 81.00	Auxiliary	percentage	
Electricity Share of EC**	14.86 – 27.50	Auxiliary	percentage	
Natural Gas (NG) Share of EC**	0.00 – 16.00	Auxiliary	percentage	
Gasoline and Others Share of EC**	3.83 – 11.50	Auxiliary	percentage	
Average transit trip length	4.70 – 6.37	Auxiliary	mile	(Santos et al. 2011)
Per gallon fuel sale tax rate*** (including federal and state/local tax shares)	0.28 – 0.90	Auxiliary	2015 $/gallon	(U.S. Energy Information Administration 2015a)
Federal Capital Funds	2.54E+09 – 7.30E+09	Auxiliary	2015 $/year	
State Capital Funds	6.30E+08 – 2.39E+09	Auxiliary	2015 $/year	
Local (County/City) Capital Funds	1.90E+09 – 6.34E+09	Auxiliary	2015 $/year	
Other Capital Funds	0.00 – 1.47E+09	Auxiliary	2015 $/year	
Per PMT expense to transit authority	0.866 – 0.711	Auxiliary	2015 $/PMT	(American Public Transportation Association 2014)

Table Notes: *"Fuel Economy of Private Vehicles" is assumed to be equal to the U.S. Light-Duty Vehicle (LDV) fleet's average fuel economy values, which are available from historical data and have been projected for future years in the VISION model. Therefore, the lowest fuel economy value (23.11 mpg) is from 1990, whereas the highest fuel economy value (40.18 mpg) is based on 2050 projections. The 2015 fuel economy value falls in between these two values at 29.98 mpg.

**Energy Consumption (EC) shares for each fuel type vary based on the historical data with the availability of alternative fuels. Following the similar trend in alternative fuel adoption, it is assumed that the use of diesel fuel will eventually lose its dominant place compared to other fuel sources, while use shares for all other fuel types will increase with respect to transit modes. The maximum EC shares for electricity, NG, and gasoline are based on 2050 projections, whereas their lowest EC shares are based on 1990 historical data. Diesel, electricity, NG, and gasoline have 2015 EC shares of 60%, 17%, 13%, 10%, respectively.

***The fuel sales tax rate is calculated in constant dollars. Using historical inflation rates, the 1990 tax rate is$0.90 in 2015 dollars. Based on inflation rate projections, the estimated total tax rate in 2050 will be $0.28 in 2015 dollars.

The SD model development is divided into eight sub-models: population, trip generation and public transportation mode choice, public transportation revenue calculations, public transportation emissions, private vehicle mode choice and traffic congestion impacts, air pollution externalities, CO_2 emission impacts on climate change, and total emission and externality calculations. Conceptual interconnection of these eight sub-models are summarized in Figure 21 in addition to detailed information and figures for each of these sub-models in previous chapter's sections and following sub-sections.

For validation purposes, the output data from a model simulation running from 1990 to 2015 will be validated with historical data. For policy analyses, the model aims to project the impacts of the U.S. transportation system (private vehicle miles traveled, public transportation ridership, CO_2 emissions, and externalities associated with U.S. transportation) until 2050. Therefore, the proposed transportation mode choice model will be initiated through the U.S. population sub-model. Labor force population variables, as a product of the population sub-model, can produce trip generation numbers based on society's trip characteristics (please see Fig. 21). The population sub-model will be the same as the sub-model described in Section 3.2.1 and Figure 6.

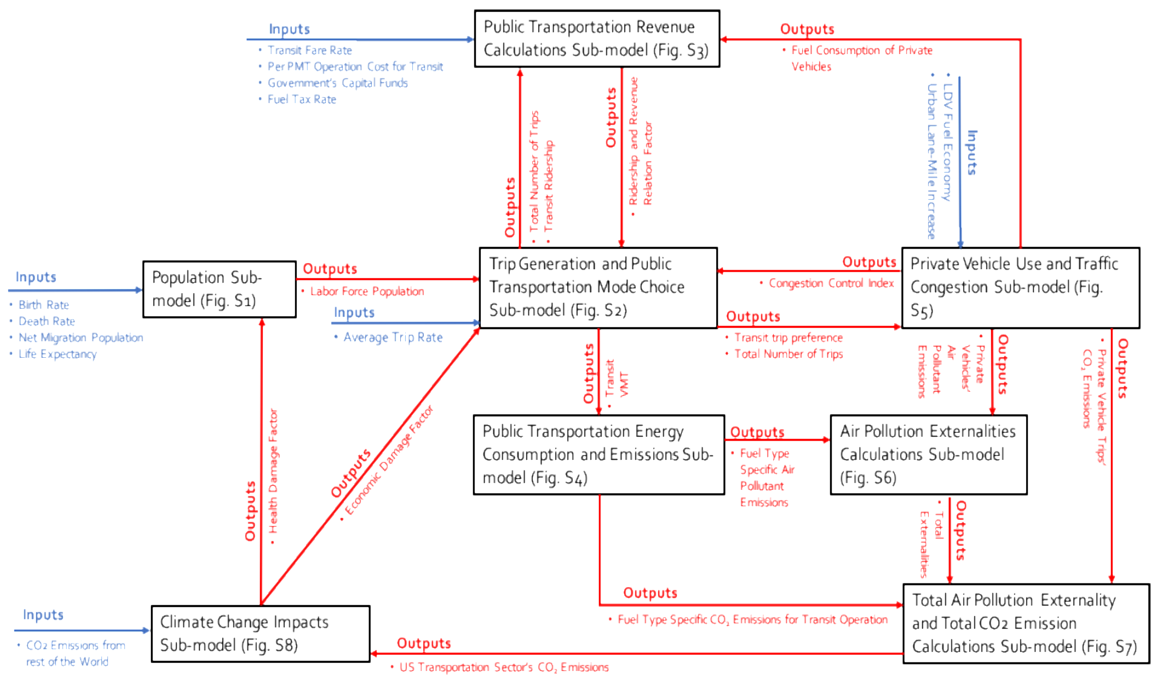


Figure 21: Conceptual interconnections of sub-models

4.2.1 Trip generation and public transportation mode choice

This sub-model is also similar with the sub-model in Section 3.2.2, however with this chapter's model extensions public transportation mode choice is affected by revenue generated and travel time index (TTI) related impacts. Therefore, the updated sub-model's stock and flow diagram can be seen in Figure 22 (please see Appendix Table for the meanings of each symbols on stock-flow diagrams).

Although other modes of transportation (walking, cycling, etc.) are available to commuters, this chapter's model only focuses on the use of private vehicles or transit use as the primary modes of transportation in the U.S. Even though many sustainability initiatives worldwide analyze and encourage transportation modes such as walking and cycling as potential alternatives to private vehicles or transit, walking and cycling as modes of transportation distinguish themselves from transit and private vehicles in that their practical applicability may be significantly limited by other attributes such as travel distance, weather conditions, safety concerns, and the availability of appropriate infrastructure (bike routes, sidewalks, etc.). These crucial attributes are beyond the scope this chapter's model, so walking and cycling modes of transportation are excluded from study's system boundaries (Ercan et al. 2016b; Gatersleben and Uzzell 2007) but considered in following extended model in Chapter 6.

The modeled labor force population (ages 15 to 64) is expected to make trips every day based on NHTS statistics, which estimate an average of almost 4 trips/day per person (Santos et al. 2011). The total generated annual trips in the U.S. (measured as a product of labor force population, average daily trip rate per person, and annual number of workdays) are then divided into two different mode choices (private vehicle driving and transit) based on societal preferences. Due to uncertainty considerations, the increasing rate variables for average trip rate and transit trip length will include this information after 2010. Two variables control the public transportation mode choice rate (Equation 1), which then generates all of the relevant statistics with respect to public transportation related, including transit ridership, transit VMT, transit PMT, and transit-related emissions. Therefore, the parameters "Transit revenue and ridership control factor" and "Travel Time Index (TTI) control index" are crucial for the entire model, as explained in later sub-sections.

Public transportation trip preference = Transit revenue and ridership control factor + TTI control index [1]

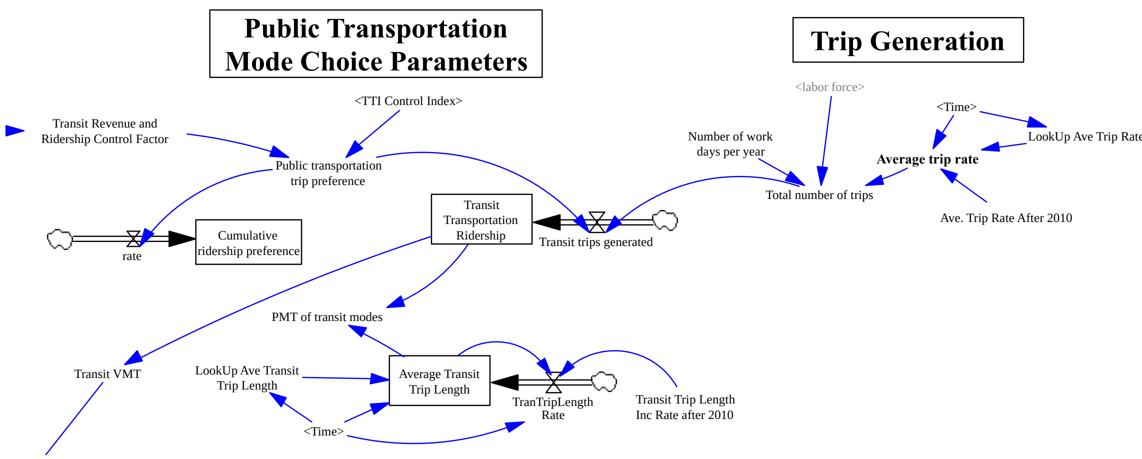


Figure 22: Trip generation and public transportation mode choice sub-model

4.2.2 Public transportation revenue calculations

As highlighted by the CLD in Figure 20, available funding and revenues for transit system will enforce transit ridership as an alternative to private vehicles, and this reinforcing relation will be controlled based on the projections of a report by the FHWA (U.S. Department of Transportation Federal Highway Administration and Federal Transit Administration 2014). This sub-model consists of two main objects, the first of which dynamically calculates the "operation-generated revenue" while the second provides deterministic values for the "capital funds" given to transit systems each year by various government organizations (please see Fig. 23 below). As has also been discussed above and in Table 7, the operational cost is calculated based on APTA's per-PMT operational expense rate (Equation 2), while fare revenue is calculated using the NTS value for average fare rate in the U.S. (Equation 3).

Fuel sales tax increase scenario: The fuel sales tax portion of transit system revenue is calculated as shown in Equation 4. The multiplication shown in Equation 4 indicates the portion of fuel sales tax that is contributed to transit system funding. One of the most crucial balancing loops in the transit system (Loop B2 in Figure 20) is supported by revenues from fuel taxes and federal fuel sale taxes, which first increased in the early 1930s from 1 cent per gallon of gasoline to 1.5 cents per gallon of gasoline. With the continuous increases in federal fuel taxes since then, the latest increase has brought the tax rate to 18.4 cents/gallon-gasoline in 1997, which is still the current fuel tax rate today (Weingroff 2015). Moreover, for every gallon of gasoline purchased, 2.86 cents are transferred from this tax revenue to the Mass Transit Fund account (U.S. Department of Transportation Federal Highway Administration and Federal Transit Administration 2014; Weingroff 2015). In addition to federal support, state and local (i.e. county, etc.) governments also collect taxes from fuel sales, bringing the average fuel tax rate per gallon of gasoline in the U.S. to 48 cents (U.S. Department of Transportation Federal Highway Administration and Federal Transit Administration 2014), while the Mass Transit Fund also receives support from state and local tax revenues depending on state-specific regulations. Although state and local governments have been increasing their fuel tax rates, as with the examples indexed to the Consumer Price Index (i.e. Florida), the federal fuel tax rate increases to be applied are still being debated today. It can therefore be argued that the Highway Trust and Mass Transit Funds are generally supported with tax revenues and, with a simple inflation rate of 18.4 cents per gallon of gasoline in 1997 dollars, equals almost 12 cents per gallon of gasoline in today's dollars (Bureau of Labor Statistics 2013). Therefore, this model assumes that the most ambitious federal fuel tax increase will be signed into law in 2020, increasing the federal fuel tax rate per gallon of gasoline from 18.4 cents to 33.4 cents, while also further increasing state and local fuel tax rates. This ambitious increase can also be included in the model's projections until 2050, with the consideration of constant dollar calculations.

Transit authorities are also supported with new investments ("capital investments") from federal, state, county, city, and other governmental organizations, which help to fund service/system expansions. Based on data from the National Transit Database website, the contributed capital funds in each study year are applied as inputs into the model, as summarized in Table 8. In this model, capital funds are expected to increase after 2016 by 593 million dollars (2015 $) per year. Finally, two revenue variables are used to generate the simulated revenues, which can in turn control the annual ridership rate of the U.S. transit system based on the FHWA's projections. These control values for the revenue and the transit ridership rate can be found in Table 9.

Public transportation expenses = Transit operation cost per PMT * PMT of transit modes [2]

Transit modes fare revenue = Average transit mode fare * Transit transportation ridership [3]

Federal and State Funds (Fuel) = Fuel Consumption of Private Vehicles * ((Per gallon gasoline tax rate + Gasoline Tax Increase) * 0.16) [4]

Table 8: Annual capital funds for transit system in the U.S. (in 2015 dollars)

Year	Federal	State	Local (County, etc.)	Other
1990	$2,540,000,000	$630,000,000	$1,900,000,000	$0
1991	$2,545,018,146	$638,116,164	$1,913,790,602	$0
1992	$2,599,687,278	$777,764,877	$1,906,476,526	$0
1993	$2,383,542,110	$1,316,737,793	$2,033,377,683	$0
1994	$2,518,082,125	$1,005,494,542	$2,074,813,017	$0
1995	$3,313,674,673	$989,168,123	$2,705,536,128	$0
1996	$3,506,283,691	$895,214,794	$2,553,413,923	$0
1997	$4,137,525,951	$1,006,749,807	$2,491,968,594	$0
1998	$3,679,503,579	$875,259,778	$2,855,740,912	$0
1999	$3,725,908,863	$857,509,862	$3,859,890,403	$0
2000	$4,274,908,313	$973,345,340	$3,807,655,288	$0
2001	$5,468,380,294	$1,011,145,805	$4,345,116,576	$0
2002	$4,993,714,432	$1,432,854,989	$5,639,423,262	$239,029,495
2003	$5,091,974,305	$1,622,719,347	$6,029,619,107	$30,759,386
2004	$4,930,228,302	$1,756,129,149	$5,772,417,019	$170,312,424
2005	$4,611,752,149	$1,494,168,982	$5,653,629,504	$77,122,788
2006	$5,552,125,521	$1,698,223,160	$5,393,610,839	$108,125,610
2007	$5,561,325,828	$1,517,464,945	$6,374,437,942	$117,558,767
2008	$6,418,647,652	$1,983,614,597	$7,588,742,794	$110,425,243
2009	$7,096,218,825	$2,414,311,718	$7,122,940,650	$198,079,375
2010	$6,813,141,491	$2,356,033,097	$7,280,920,050	$103,815,165
2011	$6,926,281,804	$2,047,571,278	$5,125,848,051	$1,619,323,531
2012	$7,515,782,462	$2,017,743,911	$5,585,749,997	$1,799,897,687
2013	$7,017,775,115	$2,850,442,204	$5,746,885,310	$1,624,464,311
2014	$7,306,446,959	$2,384,778,795	$6,343,077,250	$1,472,717,007

Table 9: Available transit system revenues (in 2015 dollars) and equivalent annual transit ridership rates

Revenue Available	Annual Ridership Rate
$6.63 Billion	0.90%
$7.59 Billion	1.05%
$10.9 Billion	1.50%
$15.4 Billion	2.20%
$21.4 Billion	3.08%
$64.1 Billion	9.75%

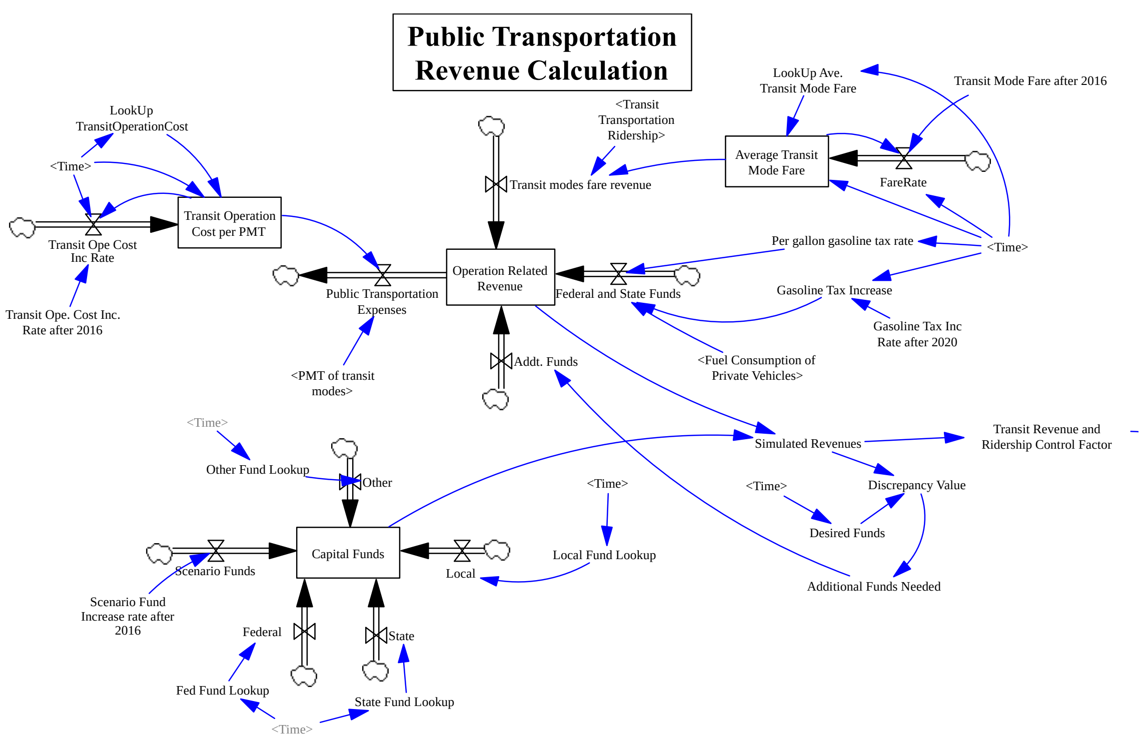


Figure 23: Public transportation net revenue calculations sub-model

4.2.3 Public transportation activity related energy consumption and CO_2 emission calculations

This sub-model is adopted from the previously defined relation in Section 3.2.4 and shown in Figure 9. The energy source for different type of engine/motors for transit vehicles are considered to adopt alternative energy source as it mentioned in Section 3.2.4. Instead of considering the alternative fuel adoption as a policy practice, this chapter considers the energy source shares as presented in following Table 10. Data on the total energy consumption of the transit system as a whole can be gathered from the NTS database, and these data values can be reproduced in this model via regression analysis for transit VMT values. Historical data on each fuel type's share in the total energy consumption can also be gathered from the NTS database, but values for future years should be predicted based on reasonable assumptions. As can be seen in Table 10, historical trends in fuel type use indicate a gradual shift away from diesel (which is currently the dominant fuel type) in favor of alternative fuels such as electricity and natural gas. Therefore, the utilization levels of different fuel types can be predicted for future years based on the available historical information. After calculating each fuel type's energy consumption, transit system emissions can be calculated using the emission conversation factors from Tables 7 and 11.

Table 10: Energy consumption shares of different transit vehicle fuel types

Year	Electricity	Diesel	Gasoline and others	Natural Gas (as CNG)
1990	14.86%	81.31%	3.83%	0.00%
1991	14.64%	81.60%	3.76%	0.00%
1992	13.89%	81.98%	4.01%	0.12%
1993	14.23%	80.69%	4.89%	0.19%
1994	14.50%	78.67%	6.27%	0.56%
1995	14.36%	78.11%	6.30%	1.24%
1996	17.54%	77.50%	3.30%	1.66%
1997	17.19%	76.76%	3.30%	2.75%
1998	16.69%	76.65%	2.72%	3.94%
1999	16.68%	76.19%	2.52%	4.61%
2000	16.80%	74.95%	2.70%	5.54%
2001	16.72%	73.86%	2.91%	6.51%
2002	15.00%	74.31%	3.44%	7.25%
2003	17.08%	69.98%	2.92%	10.01%
2004	17.49%	68.41%	3.22%	10.88%
2005	17.86%	67.03%	3.29%	11.82%
2006	17.21%	66.04%	3.33%	13.42%
2007	18.56%	65.14%	3.23%	13.07%
2008	18.72%	64.33%	3.41%	13.54%
2009	15.24%	62.78%	8.42%	13.56%
2010	15.70%	62.98%	8.75%	12.57%
2011	15.99%	62.15%	9.08%	12.78%
2012	16.19%	62.00%	9.26%	12.55%
2013	16.36%	60.84%	9.61%	13.19%
2015	**17.00%**	**60.00%**	**10.00%**	**13.00%**

Year	Electricity	Diesel	Gasoline and others	Natural Gas (as CNG)
2020	18.00%	57.00%	10.50%	14.50%
2025	20.00%	54.00%	11.00%	15.00%
2030	22.50%	50.00%	11.50%	16.00%
2040	25.00%	47.50%	11.50%	16.00%
2050	27.50%	45.00%	11.50%	16.00%

4.2.4 Private vehicle mode choice and traffic congestion impacts

The transit ridership rate simultaneously determines the private vehicle preference for trip generated, since the only transportation mode options for this model are private vehicles and transit. In other words, the private vehicle trip preference (measured as a fraction of total trips in a given year) is equal to one minus the public transportation trip preference. This sub-model is also adopted from Section 3.2.3 (Fig. 8) with slight changes, so please also see following Figure 24 for extended and updated version. Private vehicle VMT, of the most crucial outputs of the model as a whole, is calculated in this sub-model; private VMT is responsible for a majority of the emissions calculated in the model, and also controls feedback interactions related to traffic congestion. The fuel economy of Light-Duty Vehicles (LDVs) is applied to the model as a deterministic input based on historical averages and the Argonne National Laboratory's projections(Argonne National Laboratory 2016). Sufficiently large increases in traffic congestion are expected to discourage the use of cars, so this model uses the Texas Transportation Institute's method for calculating the travel time index (TTI) (Schrank. et al. 2015) and then dynamically chooses the degree of the resulting shift away from private vehicles based on the calculated TTI, which is factored into the "Trip generation and public transportation mode choice" sub-model (Figure 22) as previously discussed.

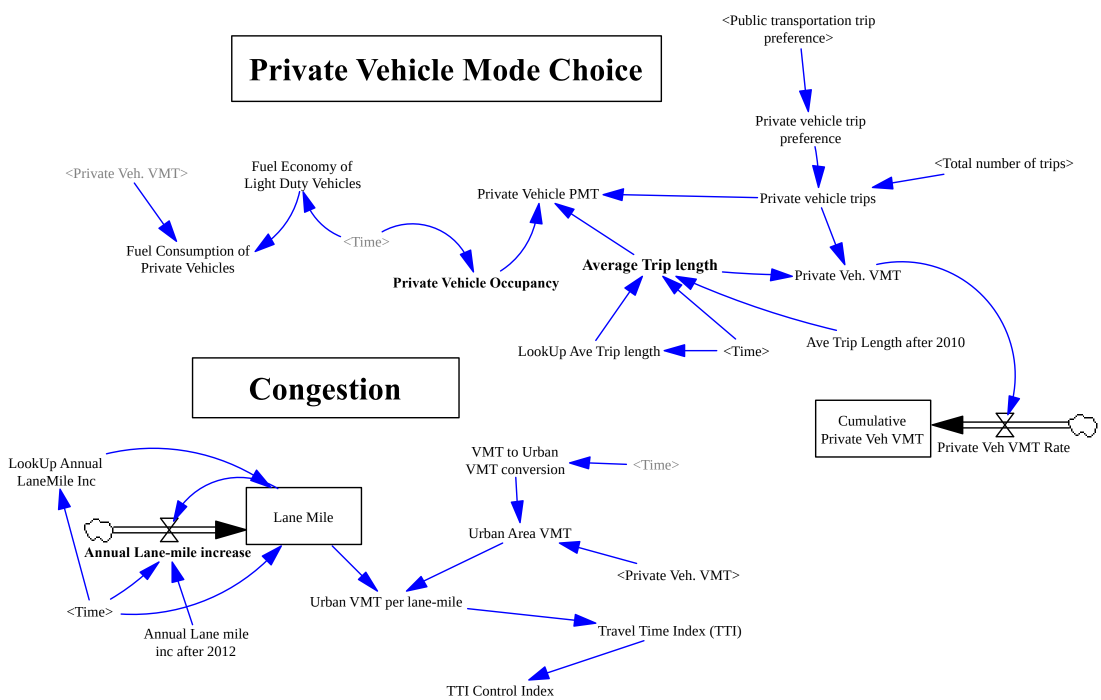


Figure 24: Private vehicle mode choice and traffic congestion impacts sub-model

4.2.5 Air pollution externality calculations sub-model

In addition to GHG emissions, other air pollutants may be generated from the U.S. transportation sector that can cause direct and indirect damage to human health and to the environment. As explained in Muller and Mendelsohn's research, pollutants such as CO, NO_x, SO_x, PM_{10}, $PM_{2.5}$, VOC must be taken into account in environmental impact studies (Muller and Mendelsohn 2007a; b). This research follows the methodology used in Michalek et al.'s study to quantify the externalities of these air pollutants, and the monetary value of the damages of these air pollutants to human health and the environment are presented in Table 12 (Michalek et al. 2011). Like in the calculation steps of life-cycle assessment studies with respect to alternative fuel powered vehicles (Ercan et al. 2015, 2016a), this study uses the unit emission rates of each fuel type and multiplied each emission rate by its corresponding monetary value multiplier (Table 12). Unit emission rates are derived from the Argonne National Laboratory's GREET Fuel Cycle Model (Argonne National Laboratory 2015).

Diesel, natural gas, and gasoline all have their own upstream (fuel production) and downstream (tailpipe) emission rates, as well as their own total consumption levels (in gallons for diesel and gasoline, and in mega joules [MJ] for natural gas), and the total VMT for each fuel type determines its respective total fuel-specific emissions. Since the emission calculations required for these three fuel types are all similar, Figure 25 only illustrates the modeling structure for diesel fuel emission calculations, but the same notations, equations, and modeling structure also apply to emission calculations for all other fuel types. Electricity consumption does not have downstream impacts and is therefore limited to upstream (electricity generation) impacts, so electricity-specific emission calculations are modeled as shown in Figure 25 and the accompanying notations and equations. Finally, externalities related CO_2 emissions are calculated separately from conventional air pollutant externalities, because CO_2 emissions will have already been calculated in previous sub-models, as seen in the bottom of Figure 25. It should be also noted that gasoline emissions and externalities are divided into those for transit and those for private vehicles, as the usage patterns for each of the two modes are significantly different, and the resulting emissions and externalities are therefore used separately.

Set *i* consists of the set of emission types, which is indexed on *i* as shown in Table 11. Likewise, set *k* consists of the set of fuel types, which is indexed on *k* as shown in Table 11.

Table 11: Notation of set indexes

Emission types	Index
CO	$i = 1$
NO_x	$i = 2$
SO_x	$i = 3$
PM10	$i = 4$
PM2.5	$i = 5$
VOC	$i = 6$

Fuel Types	Index
Diesel	$k = 1$
Gasoline	$k = 2$
Natural gas	$k = 3$

Table 12: Air pollution emission rates and externality values for different fuel sources

	Diesel		Natural Gas (NG)		Gasoline		Electricity
	(Emissions)						
	WTP [t/gallon]	*Tailpipe [t/mile]*	*WTP [t/gallon]*	*Tailpipe [t/mile]*	*WTP [t/gallon]*	*Tailpipe [t/mile]*	*WTP [t/kWh]*
CO	1.89E-06	1.28E-06	3.34E-08	2.30E-05	1.89E-08	7.63E-06	(Not necessary for externality calculations)
NO_x	4.21E-06	2.34E-06	4.28E-08	1.17E-06	3.99E-08	5.14E-07	
PM_{10}	2.77E-07	1.09E-07	9.78E-10	1.09E-07	3.23E-09	3.23E-08	
$PM_{2.5}$	2.24E-07	4.87E-08	6.30E-10	4.87E-08	2.14E-09	1.77E-08	
SO_x	2.75E-06	1.08E-08	1.78E-08	6.09E-09	3.40E-08	7.50E-09	
VOC	1.05E-06	2.62E-07	1.06E-08	2.62E-07	2.83E-08	2.85E-07	
CO_2	1.02E-02	N/A	9.32E-03	N/A	1.36E-02	N/A	6.90E-04
	(Externality of Emissions)						
	WTP [2015 \$/t]	*Tailpipe [2015 \$/t]*	*WTP [2015 \$/GJ]*	*Tailpipe [2015 \$/t]*	*WTP [2015 \$/t]*	*Tailpipe [2015 \$/t]*	*WTP [2015 \$/kWh]*
CO	\$708	\$968	\$0.17	\$968	\$708	\$968	\$0.00
NO_x	\$2,192	\$3,765	\$0.87	\$3,765	\$2,192	\$3,765	\$1.58
PM_{10}	\$7,336	\$12,726	\$0.00	\$12,726	\$7,336	\$12,726	\$0.81
$PM_{2.5}$	\$47,918	\$82,897	\$0.00	\$82,897	\$47,918	\$82,897	\$2.02
SO_x	\$19,690	\$27,882	\$110	\$27,882	\$19,690	\$27,882	\$17.05
VOC	\$4,520	\$7,824	\$0.00	\$7,824	\$4,520	\$7,824	\$0.01
CO_2	\$45.65	\$45.65	\$45.65	\$45.65	\$45.65	\$45.65	\$45.65

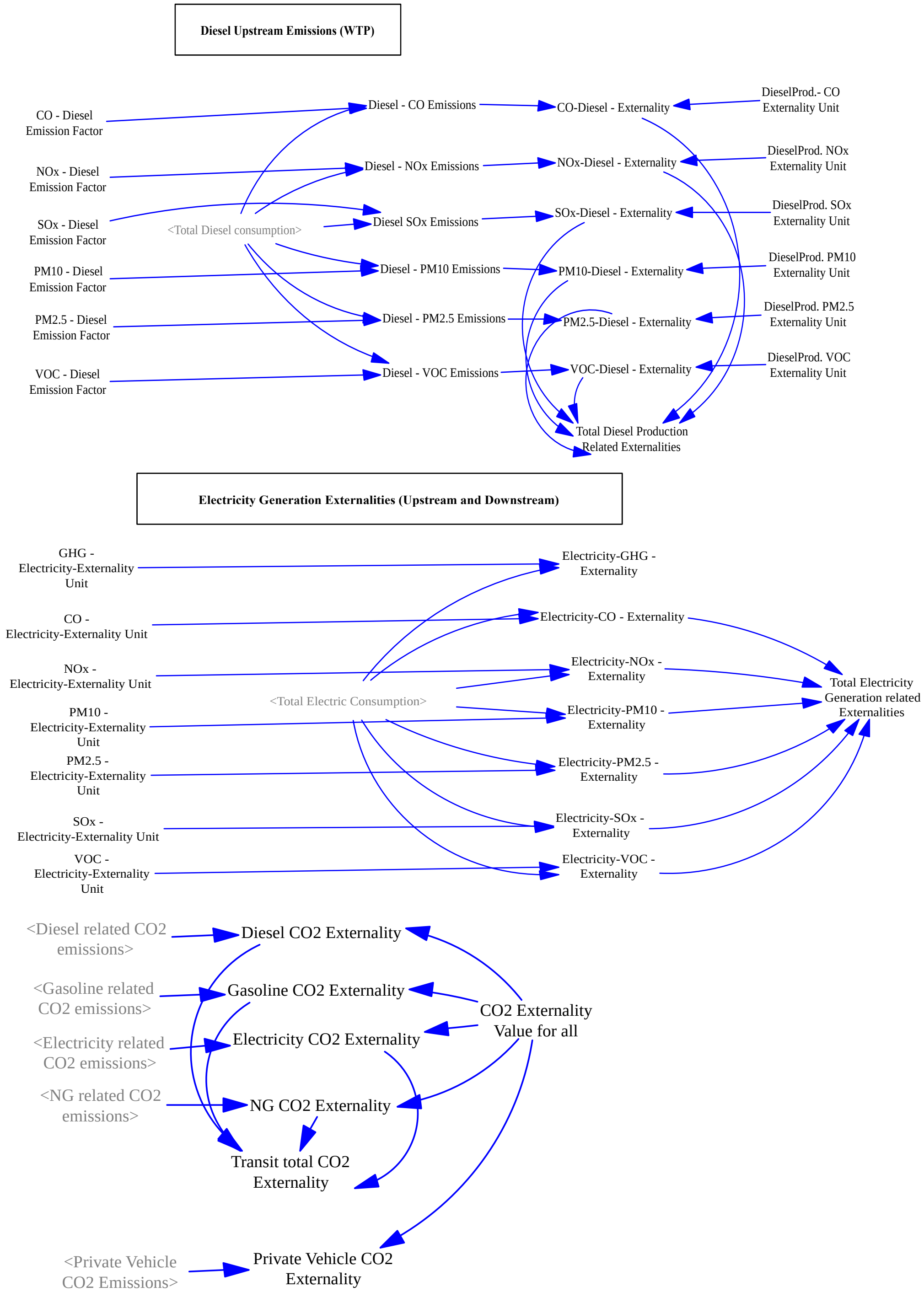


Figure 25: Partial presentation of the air pollution externality calculations sub-model

Notations:

TU_{ik} = the upstream emissions of the transit system of emission type *i* from fuel type *k*

TT_{ik} = the downstream (tailpipe) emissions of the transit system of emission type *i* from fuel type *k*

PU_{i2} = the upstream emissions of private vehicles of emission type *i* from fuel type *k = 2* (gasoline)

PT_{i2} = the downstream (tailpipe) emissions of private vehicles of emission type *i* from fuel type *k = 2* (gasoline)

E_i = the total emissions of emission type *i* from electricity consumption

$EXT.U_i$ = the externality unit value for fuel production emissions of emission type *i*

$EXT.T_i$ = the externality unit value for tailpipe emissions of emission type *i*

TM_{ik} = the total air pollution externality cost of the transit system (in 2015 dollars) for emission type *i* from fuel type *k*

PM_{i2} = the total air pollution externality cost of private vehicle use (in 2015 dollars) for emission type *i* from fuel type *k = 2* (gasoline)

The calculations used in this sub-model are summarized in Equations 5 through 11 below:

$$\sum_{i=1}^{6} TU_{ik} = Upstream\ emission\ factor_{ik} * Transit\ fuel\ consumption_{k} \qquad [5]$$

$$\sum_{i=1}^{6} TT_{ik} = Tailpipe\ emission\ factor_{ik} * Transit\ VMT_{k} \qquad [6]$$

$$\sum_{i=1}^{6} PU_{i2} = Upstream\ emission\ factor_{i2} * LDV\ fuel\ consumption_{2} \qquad [7]$$

$$\sum_{i=1}^{6} PT_{i2} = Tailpipe\ emission\ factor_{i2} * Private\ VMT_{2} \qquad [8]$$

$$\sum_{i=1}^{6} E_{i} = Electricity\ generation\ emission\ factor_{i} * Electricity\ consumption \qquad [9]$$

$$\sum_{i=1}^{6} TM_{ik} = \left(\sum_{i=1}^{6} TU * EXT.U_{i}\right) + \left(\sum_{i=1}^{6} TT * EXT.T_{i}\right) \qquad [10]$$

$$\sum_{i=1}^{6} PM_{i2} = \left(\sum_{i=1}^{6} PU * EXT.U_{i}\right) + \left(\sum_{i=1}^{6} PT * EXT.T_{i}\right) \qquad [11]$$

4.2.6 Total emission and externality calculations and Climate change impacts sub-models

After calculating all emissions and externality values, the results can all be summed together to obtain the final model outputs. For sensitivity analysis purposes, the annual emission and externality results are also calculated cumulatively as shown in Figure 26. The total externalities from public transit and from private vehicles can be found using Equations 10 and 11, respectively. In addition, the total CO_2 emissions from the U.S. roadway transportation system are also calculated so that the findings may be applied with respect to the specific feedback relationships corresponding climate change impacts.

The climate change impacts sub-model that is explained in detail in Section 3.2.5 is also used for this model (please see Fig. 10).

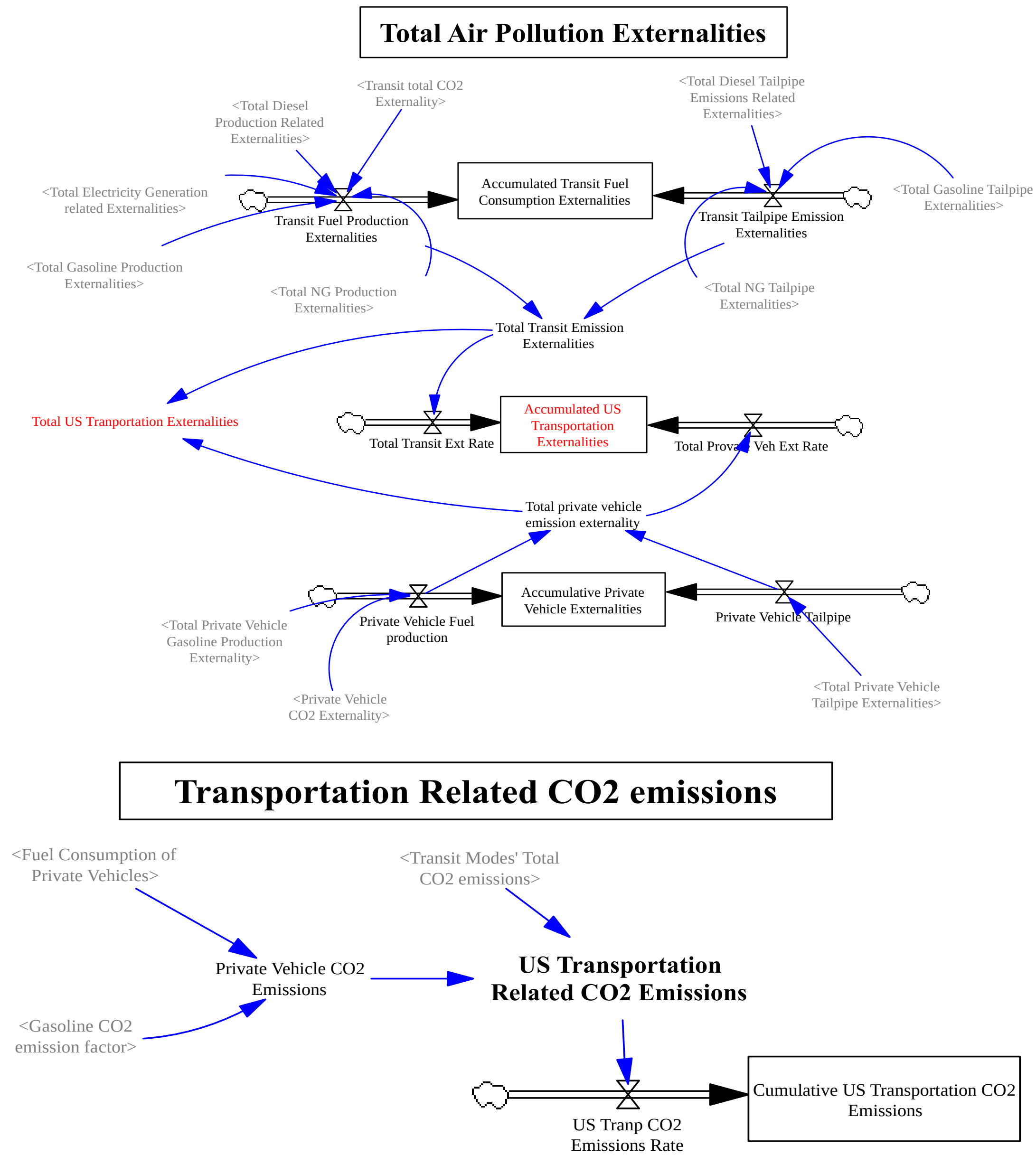


Figure 26: Sub-model of total air pollution externalities and CO2 emissions due to U.S. roadway transportation activities

4.3 Model verification and validation

Proper verification and validation is imperative for any modeling approach, so as to ensure that the developed model and its behavior adequately match what is known from available literature and historical data, thereby ensuring reliable projection results. Barlas's (1996) study summarizes a SD model verification and validation process that is still commonly cited and utilized in SD research today (Barlas 1996). Moreover, Qudrat-Ullah and Seong (2010) explained the validation process for SD models in light of the information provided in Barlas's study (Qudrat-Ullah and Seong 2010). Like in recent studies by Egilmez and Tatari (2012) and by Ercan et al. (2016), this model also follows Qudrat-Ullah and Seong's verification/validation process (Egilmez and Tatari 2012).

The verification process of this model consists of five structural validation tests: the boundary adequacy test, the structure verification test, the dimensional consistency test, the parameter verification test, and the extreme conditions test. To this end, this chapter identifies the problem statement and how to approach the problem from a modeler's perspective. Based on the available system information, a Casual Loop Diagram (CLD) is used to draw the system boundaries necessary for modeling. With proper reference information on model boundaries and variables, the model therefore meets the requirements of the boundary adequacy test. The developed model (stock and flow diagrams), which is designed using the CLD as a guide, can be successfully simulated in Vensim without any logical errors, confirming that the model is structurally valid and thereby passing the structure verification test. Tables 7 and 12 present some of the model parameters and their respective units, which are then applied to the model while Vensim's built-in unit check feature checks the model for dimensional consistency, confirming that the model passes the dimensional consistency test. Next, the parameter verification is used to confirm the validity of parameter selection during model development and the reliability of the selected parameters; based on available reference information, the model passes this test as well. Lastly, extreme conditions are tested on the model to see if any model variables incorrectly reflect negative or zero values, but no such issues were evident. Thus, the model passes all five structural validation tests and is therefore confirmed to be structurally valid.

After ensuring that the model works correctly and has been developed using proper data, the model should be tested for behavioral validity, meaning that the model's output data should statistically match the corresponding real-world historical data. First, behavioral reproductions of some of the key model variables are presented in Figures 27 through 29 from 1990 to 2013, and are then statistically compared to historical data (gathered from the website of the U.S. Bureau of Transportation Statistics, 2015) for the same variables over the same time period. As seen in Figures 27 through 29, the simulation data matches fairly well with the historical data, but a visual comparison alone is not enough to complete the validation process due to the potential for human error. To objectively confirm the behavioral validity of the model output, a one-way ANOVA test is also used to compare the model output and historical data for private VMT, transit ridership, and transportation-related CO_2 emissions. The results of this final test are presented in Table 13, clearly showing that the model's behavior is statistically valid at a significance level of zero.

Table 13: One-way ANOVA test results for critical model parameters

	p-value	**F**	**d_f**		**Mean Square**
			Between Groups	Within Groups	
Private VMT	0.000	0	23	0	5.429E+22
Transit Ridership	0.000	0	23	0	1.961E+18
CO_2 Emissions	0.000	0	23	0	2.506E+15

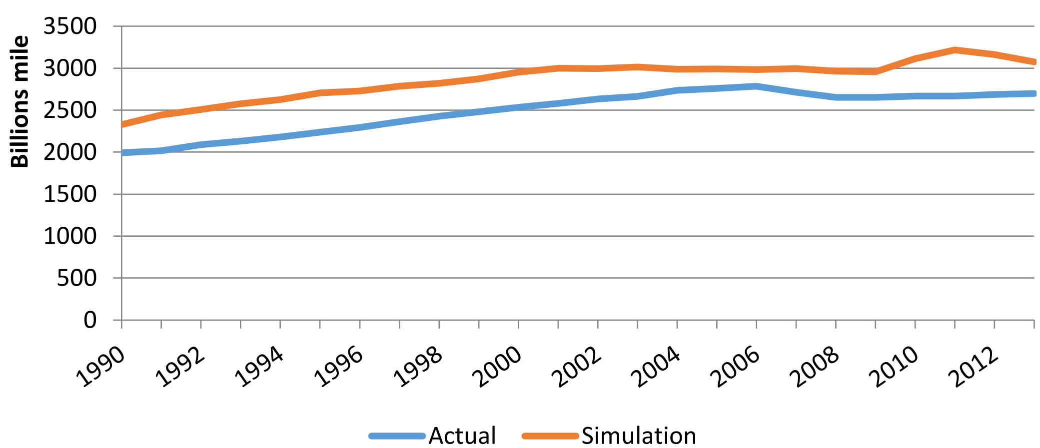


Figure 27: Behavioral reproduction (historical and simulation) of private VMT

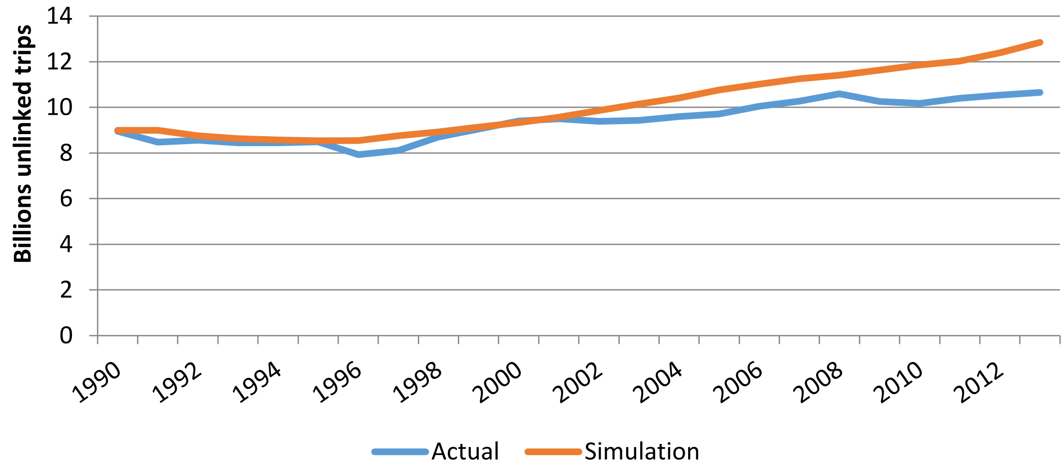


Figure 28: Behavioral reproduction (historical and simulation) of transit ridership

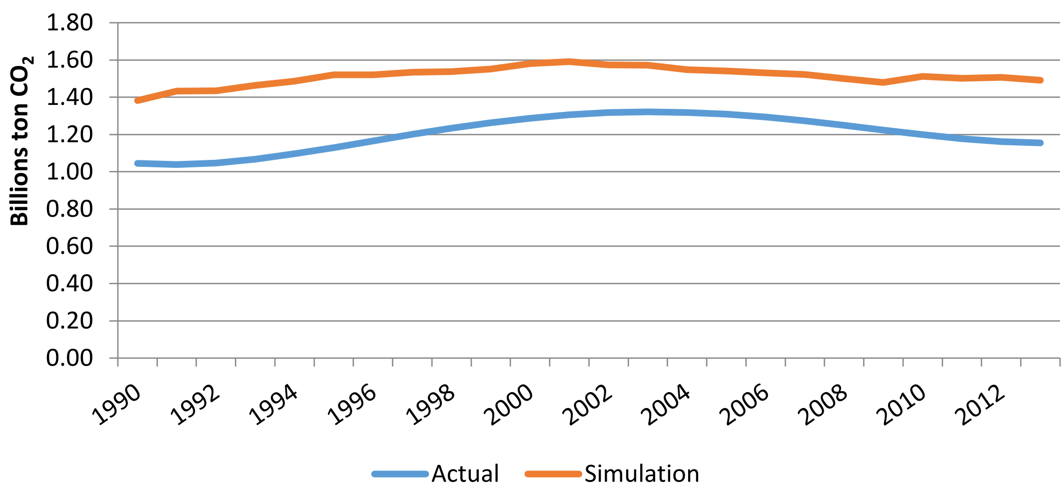


Figure 29: Behavioral reproduction (historical and simulation) of U.S. Transportation CO_2 emissions

4.4 Uncertainties and Policy Analysis

As Sterman stated in his article "*All models are wrong*" (Sterman 2002), the proposed models in a SD analysis are always limited by the provided information, and the reliability of any SD model is highly dependent on the deterministic parameters used as inputs into the model, whereas these deterministic parameter values often carry a great deal of uncertainty (Pruyt 2007). Furthermore, a comprehensive SD model will typically include numerous interconnections, further increasing the overall degree of uncertainty associated with the SD analysis. A recent study of Onat et al. (2016) also accounted for these uncertainties alternative fuel use on light duty vehicles and proved the significance of sensitivity analysis. Therefore, instead of assigning results to single points for future years, this chapter's model will account for this uncertainty by providing statistical distribution areas for the results. To do this, distribution information for key parameters in the model will be considered in simultaneous Monte Carlo simulations for all variables, providing results with their own unique distributions and confidence intervals.

This analysis is also known as a multivariate sensitivity analysis. Sensitivity analyses are often used to highlight the most influential parameters in a particular model. For this purpose, this study used a "global analysis" technique based on any and all possible variations in the input parameters, based on Sobol indices (Sobol 1990) which have already been used in environmental science (Wei et al. 2015). This global sensitivity analysis, again based on Sobol indices, was performed with respect to the parameters (X_i) that modeled the corresponding processes according to outcome (Y_j). The first-order Sobol indices of each parameter are as follows:

$$SI_i^j = \frac{\mathbb{V}\mathrm{ar}(\mathbb{E}(Y_j|X_i)}{\mathbb{V}\mathrm{ar}(Y_j)} \quad [12]$$

A meta-model $\widehat{Y}_j(X)$ of Y_j is then used to evaluate the Sobol indices:

$$\widehat{Y}_j(X) = \alpha_0^j + \sum_{k=1}^{12} \alpha_k^j X_k \quad [13]$$

This linear model fits the numerical data very well ($R > 0.99$), and allows the Sobol indices to be directly deduced as follows:

$$SI_i^j = \frac{(\alpha_i^j)^2}{\sum_{k=1}^{12}(\alpha_k^j)^2} \quad [14]$$

It should be also noted that Sobol indices are positive values, however we added the sign (plus or minus) of the correlation coefficients in order to specify positive or negative effects on the outputs. More specifically, this model will be run for 10,000 iterations simultaneously for the given distributions of parameters from 2015 to 2050, and the behavioral limitations of critical variables (model results) will be revealed accordingly.

Table 14: Distribution information for critical parameters

Parameter	Distribution Parameters	Unit	Distribution Type	Reference
Average Trip Rate	k = 2.222; θ = 0.615	Trip	Gamma	(Santos et al. 2011; U.S. FTA 2016)
Average Trip Length	Min = 8.99; Max = 9.69; μ = 9.40; σ = 0.24	Miles	Normal	(Santos et al. 2011; U.S. FTA 2016)
Average Transit Trip Length Increase Rate	Min = 0.0099; Max = 0.0102; μ = 0.01; σ = 0.000049	Percentage (for trip*miles)	Normal	(American Public Transportation Association 2014; Santos et al. 2011; U.S. FTA 2016)
Transit Mode Fare Increase Rate	Min = 0.009; Max = 0.011; μ = 0.01; σ = 0.0003	Percentage (for $/unlinked trip)	Normal	(U.S. Bureau of Transportation Statistics, 2015)
Transit Expense Increase Rate	Min = 0.0092; Max = 0.0107; μ = 0.0099; σ = 0.0003	Percentage ($/Transit PMT)	Normal	(American Public Transportation Association, 2014)
Annual Lane Mile Increase Rate	Min = 0.0099; Max = 0.0105; μ = 0.0102; σ = 0.00014	Percentage (lane-mile/year)	Normal	(U.S. Bureau of Transportation Statistics, 2015)
CO_2 Emission Factors:				
Diesel Emission Factor	μ = 8.92; σ = 0.1784	kg CO_2 emissions/gallon	Normal	(Venkatesh et al. 2011)
Gasoline Emission Factor	μ = 13.609; σ = 0.214	kg CO_2 emissions/gallon	Normal	(Onat et al. 2016b; Venkatesh et al. 2011)
Natural Gas Emission Factor	Min = 8.528; Max = 10.119; μ = 9.3235; σ = 0.0093	kg CO_2 emissions/gallon	Uniform	(Argonne National Laboratory 2015)
Electricity Emission Factor	a = 0; b= 0.696; p = 1.067	kg CO_2 emissions/kWh	Triangle	(Michalek et al. 2011; Onat et al. 2016b)

As it mentioned above and some of Pruyt's researches, SD approach is limited for conducting models that consists of deep complexity and uncertainty. However, this disadvantage of modeling can be turned to into an advantage by combining multivariate sensitivity analysis and SD model and provide all plausible outcomes/policies in given ranges of model parameters (Pruyt 2007; Pruyt and Kwakkel 2012). An example of deterministic policy analysis on SD model can argue the possible projections with the changes of given parameters, however multivariate analysis simultaneously accounts for tens of thousands possible scenarios in terms of changing all model parameters in the given ranges (as discussed in Section 4.5.1). Although, this research emphasizes on the uncertainty parameters for model, this analysis transforms the art of SD model into computational SD model, which provide comprehensive policy analysis (Pruyt and Kwakkel 2012).

For instance, for this study, the trip generation values will influence the ridership and the VMT (each consisting of their own separate degrees of uncertainty) based on the data source from the 2009 NHTS database (U.S. Department of Transportation Federal Highway Administration 2010). The deterministic parameters defined in a previous model in Chapter 3 are considered as the mean values, and proper (literature-based) distributions are assigned accordingly. Based on the proposed model in this chapter, the following parameters have statistical distribution: average trip rate (trip/day/person), average trip length (miles/trip), CO_2 emission rates for different energy sources such as electricity, natural gas (in the form of CNG), diesel, and gasoline (and/or other fuel types, all quantified in gasoline equivalents), average transit trip length (miles/transit trip), transit mode fare rate ($/trip), and transit operation cost per PMT ($/transit PMT).

In addition to the multivariate sensitivity analysis previously discussed, the sensitivity of critical parameters will be investigated to identify key policy leverage points for reducing the transportation-related impacts previously cited. The behavioral limit results from this analysis will guide a subsequent multivariate sensitivity analysis, which will use some of the key model parameters and other policy making parameters as inputs to provides future projections for four critical variables as outputs. As shown in the sensitivity input-output table (Table 15), each deterministic value is assigned a range of ±10%, thereby determining the parameters to which the resulting outputs are most sensitive.

Two separate sensitivity analyses are conducted to further investigate the importance of critical parameters, as explained further in Section 4.5 of this chapter. The second sensitivity analysis will follow a similar approach, in which the two most dominating (99%) parameters from the previous sensitivity analysis will be excluded. Therefore, average trip rate and average trip length parameters are neglected as shown in Table 16.

Table 15: First sensitivity analysis input-output table

Input variables	Deterministic (mean) values	Min [-10%]	Max [+10%]	Output variables
Avg Trip Rate After 2010	3.9675	3.5708	4.3643	
Avg Trip Length after 2010	9.4033	8.4630	10.3436	
Transit Trip Length Increase Rate after 2010	0.0101	0.0091	0.0111	
Transit Mode Fare after 2016	0.0100	0.0090	0.0110	*Cumulative Private Vehicle VMT*
Transit Operation Cost Increase Rate after 2016	-0.0099	-0.0109	-0.0089	*Cumulative US Transportation CO2 Emissions*
Annual Lane Mile Increase after 2012	0.0051	0.0046	0.0056	*Cumulative US Transportation Externalities*
Electricity CO_2 emission factor	0.0007	0.0006	0.0008	*Cumulative Transit Ridership Preference*
Diesel CO_2 emission factor	0.0102	0.0091	0.0112	
NG CO_2 emission factor	0.0093	0.0084	0.0103	
Gasoline CO_2 emission factor	0.0136	0.0122	0.0150	
Gasoline Tax Increase Rate after 2020	0.4000	0.3600	0.4400	
Scenario Fund Increase rate after 2016	593,000,000	533,700,000	652,300,000	

Table 16: Second sensitivity analysis input-output table

Input variables	Deterministic (mean) values	Min [-10%]	Max [+10%]	Output variables
Transit Trip Length Increase Rate after 2010	0.0101	0.0091	0.0111	
Transit Mode Fare after 2016	0.0100	0.0090	0.0110	
Transit Operation Cost Increase Rate after 2016	-0.0099	-0.0109	-0.0089	*Cumulative Private Vehicle VMT*
Annual Lane Mile Increase after 2012	0.0051	0.0046	0.0056	*Cumulative US Transportation CO2 Emissions*
Electricity CO_2 emission factor	0.0007	0.0006	0.0008	*Cumulative US Transportation Externalities*
Diesel CO_2 emission factor	0.0102	0.0091	0.0112	*Cumulative Transit Ridership Preference*
NG CO_2 emission factor	0.0093	0.0084	0.0103	
Gasoline CO_2 emission factor	0.0136	0.0122	0.0150	
Gasoline Tax Increase Rate after 2020	0.4000	0.3600	0.4400	
Scenario Fund Increase Rate after 2016	593,000,000	533,700,000	652,300,000	

4.5 Results and Discussions

4.5.1 Multivariate sensitivity analysis: Exploring Behavioral Limits of Policy Implications

The outcomes of this model consist of the behavioral limits of key parameters for future years, and are then used to identify the most effective policy leverage points. Therefore, accounting for the relevant statistical distribution data, Figure 34 presents the historical data and corresponding model simulation behavior for key parameters related to the U.S. transportation sector (Figures 34a, 34c, 34e, and 34g) and the model simulation behavior with the relevant uncertainty ranges included (Figures 34b, 34d, 34f, and 34h). Additional results of the uncertainty analysis are provided below to numerically illustrate the behavioral limits of the results in 2050 (Table 17), with their corresponding histogram graphs presented in Figures 30 - 33.

Table 17: Statistics of distribution results in 2050

Variable	Unit	Min	Max	Mean	Median	StDev.	Norm. StDev.
Private VMT	Billion miles	3361.17	4100.87	3736.36	3736.79	152.80	4.1%
Public Transportation Ridership Fraction	% of total trips	6.23%	7.23%	6.71%	6.71%	0.17%	2.5%
US Transportation CO_2 Emissions	Billion ton CO_2	1.1529	1.4677	1.3087	1.3082	0.0579	4.4%
Cost of U.S. Transportation Externalities	Billion dollars	93.87	116.56	105.21	105.19	4.44	4.2%

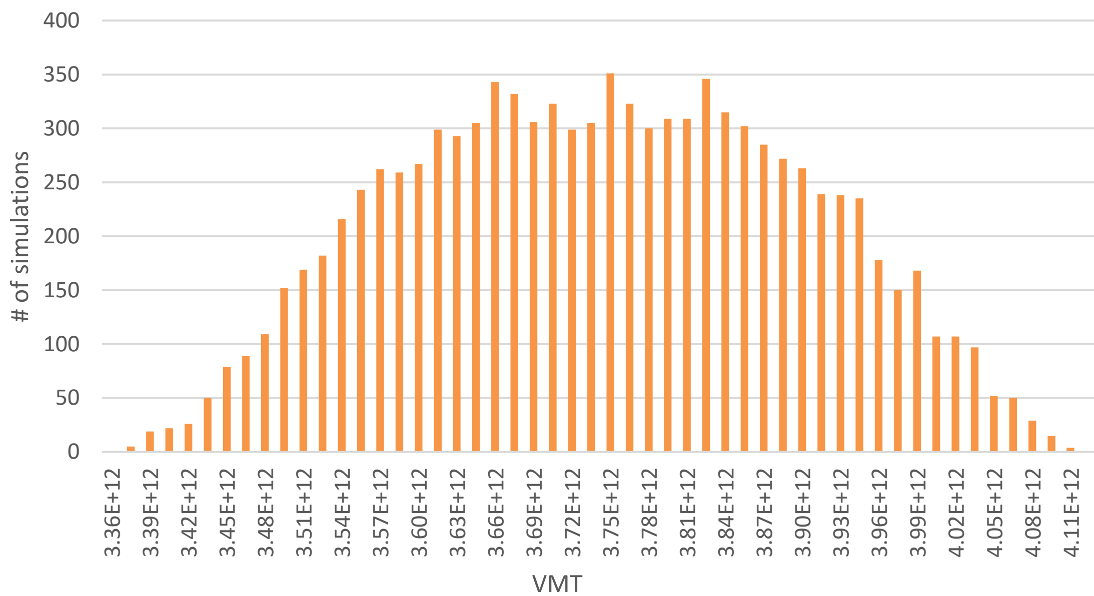


Figure 30: Histogram of private VMT in 2050

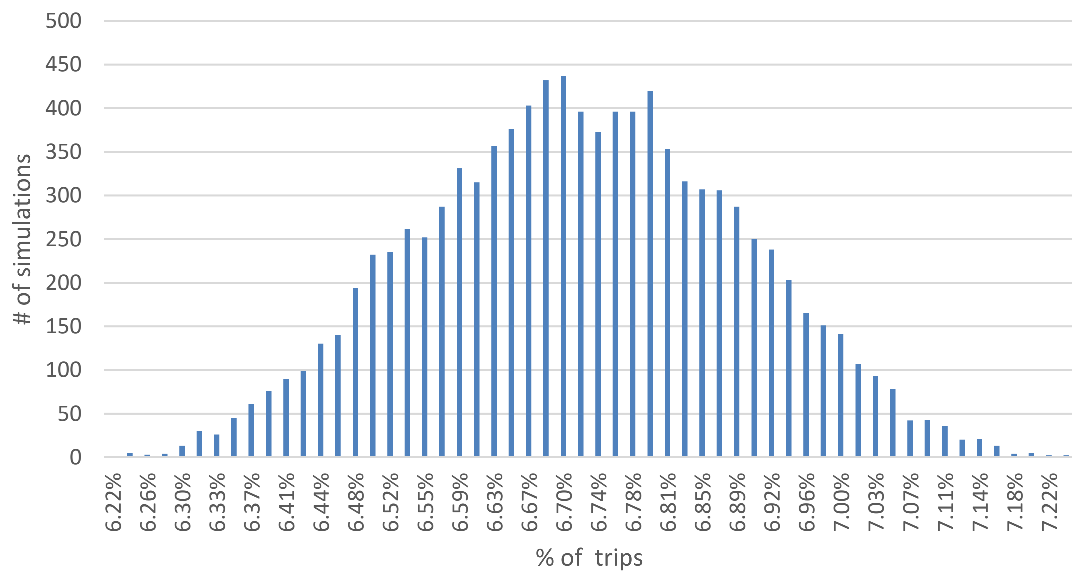


Figure 31: Histogram of public transportation ridership in 2050

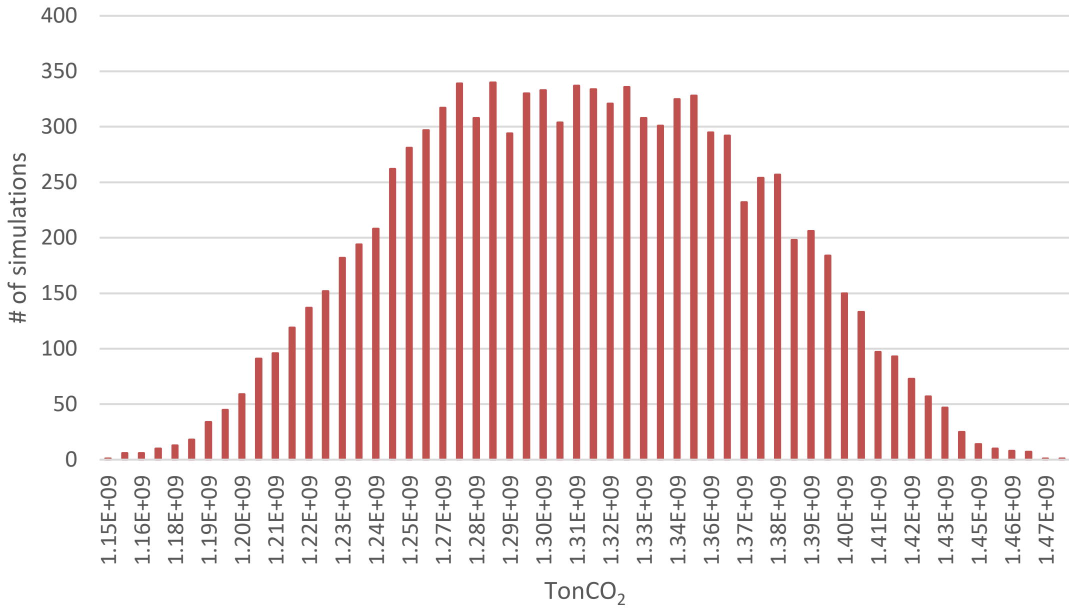


Figure 32: Histogram of transportation-related CO_2 emissions in 2050

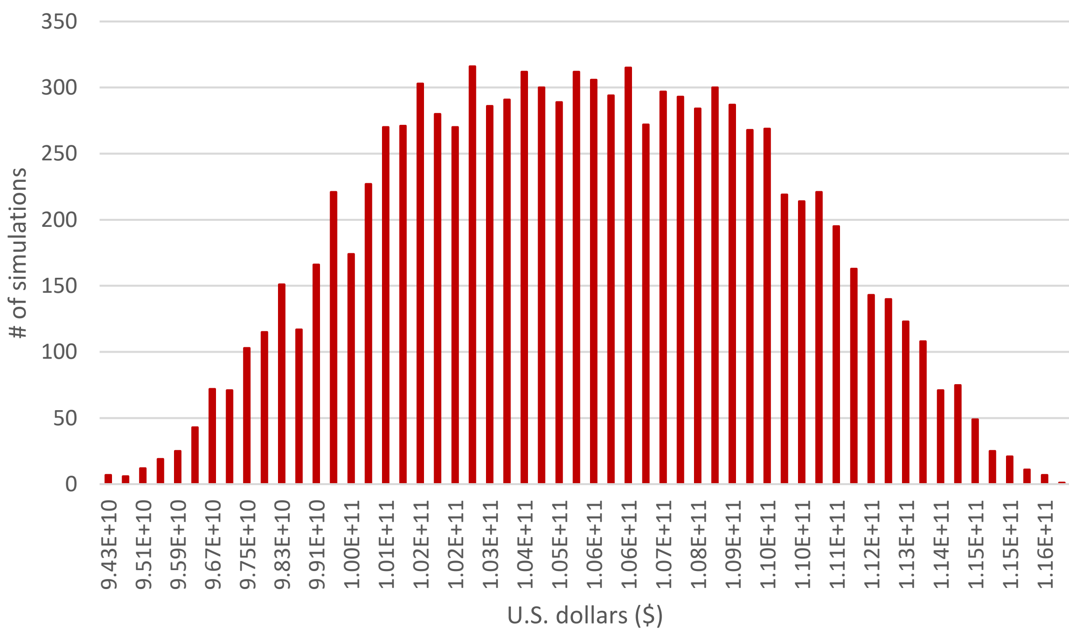


Figure 33: Histogram of total transportation-related air pollution externality in 2050

Figures 34a and 34b illustrate the increasing trend in private VMT from 1990 to 2050 and its behavioral limits from 2016 to 2050, respectively. The model results for the deterministic (mean) values show an increase in VMT from approximately 3.1 billion miles in 2016 to 3.7 billion miles in 2050. However, these projections can vary between 3.3-4.1 billion miles in 2050 based on projections with a 95% confidence interval, as shown in Table 17 and Figure 30 above. The variations in minimum and maximum values for the 2050 projections also emphasize the importance of uncertainty data, as the results from deterministic values alone were not able to capture this difference, which amounts to approximately 800 million miles. The analysis also indicates us that it is plausible to change private VMT by 800 million miles with various scenarios of changing given deterministic factors. Therefore, decision and policy efforts should consider all critical parameters of this model at the same time. Impacts related to private vehicles dominate the overall impacts of the U.S. transportation system due to its high dependency on private vehicle usage. Although the private vehicle preference (as a percentage of total trips) is almost constant or only slightly declining, the number of private vehicles is still increasing due to the increasing trend in the total U.S. population. As a result, private vehicle VMT in 2050 is almost twice as high as it was in 1990. As explained during the model development process, the relationship between lane-mile capacity and traffic congestion controls private vehicle usage shares based on the level of traffic congestion.

Transit and private vehicle use preference rates are complementary variables in the current U.S. urban passenger transportation profile (Figures 34a - 34d). Transit ridership has been increasing in the U.S. over time as the urban population has increased. However, this increase has never reached the levels needed to effectively decrease the dominant impacts of private vehicle usage on the overall U.S. transportation sector. Figure 34c also depicts this slight fractional increase in transit ridership preference. After 2016, the transit ridership preference rate is projected to remain almost constant at around 6.7% with only a few slight changes over time. As presented in Figure 34d and in Table 17, transit ridership rates can reach up to 7.25% in 2050, or can drop as low as 6.2%. One of the limitations preventing transit ridership from increasing to any significant degree can be traced back to Loop B2 in the CLD (Figure 20), meaning that a rapid decrease in private vehicle usage can also negatively impact the public transportation system, which is partially funded with fuel tax revenues.

U.S. transportation-related CO_2 emissions are presented in Figure 34e. The projections in this graph indicate that emissions can be reduced by 2050 to even lower levels than those in 1990. Due to the heavy dependency on fossil fuels in the U.S. transportation sector, transportation-related CO_2 emissions are the second largest contributor to the total U.S. CO_2 emission rate, and so many initiatives besides shifting toward public transit are being put into effect to decrease the current increasing trend in transportation-related CO_2 emissions in the U.S., such as government regulations to improve fuel economy. Although private VMT currently has an increasing trend while public transportation preference rates have yet to demonstrate a realistically significant increase trend, CO_2 emissions from the U.S. transportation sector have a decreasing trend due to projected fuel economy improvements from the Argonne National Laboratory's VISION model (Argonne National Laboratory 2016). The results in Figure 34f estimate a CO_2 emission rate of 1.3 billion tons in 2050, which can vary between 1.15 and 1.47 billion tons of CO_2.

Finally, Figure 34g presents air pollution emission externalities related to urban transportation activities each year in the U.S., while Figure 34h illustrates their large uncertainty range. It is worth noting that the graphs pertaining to transportation-related CO_2 emissions and externalities show very similar behavioral patterns, as CO_2 emissions account for a significant portion of the total externality costs as opposed to those of other air pollutants such as CO, SO_x, NO_x, PM_{10}, $PM_{2.5}$, and VOC. It should also be noted that transportation-related emissions cost approximately 105 billion dollars in 2016, whereas this value remains almost constant until 2050. However, this constant trend still has a wide variation range of ±11 billion dollars, which is also shown in Table 17 and Figure 33. This indirect cost to the public in the U.S. associated with passenger transportation activities is just crucial enough to highlight the importance of the problems related to mode choice and fossil fuel dependency.

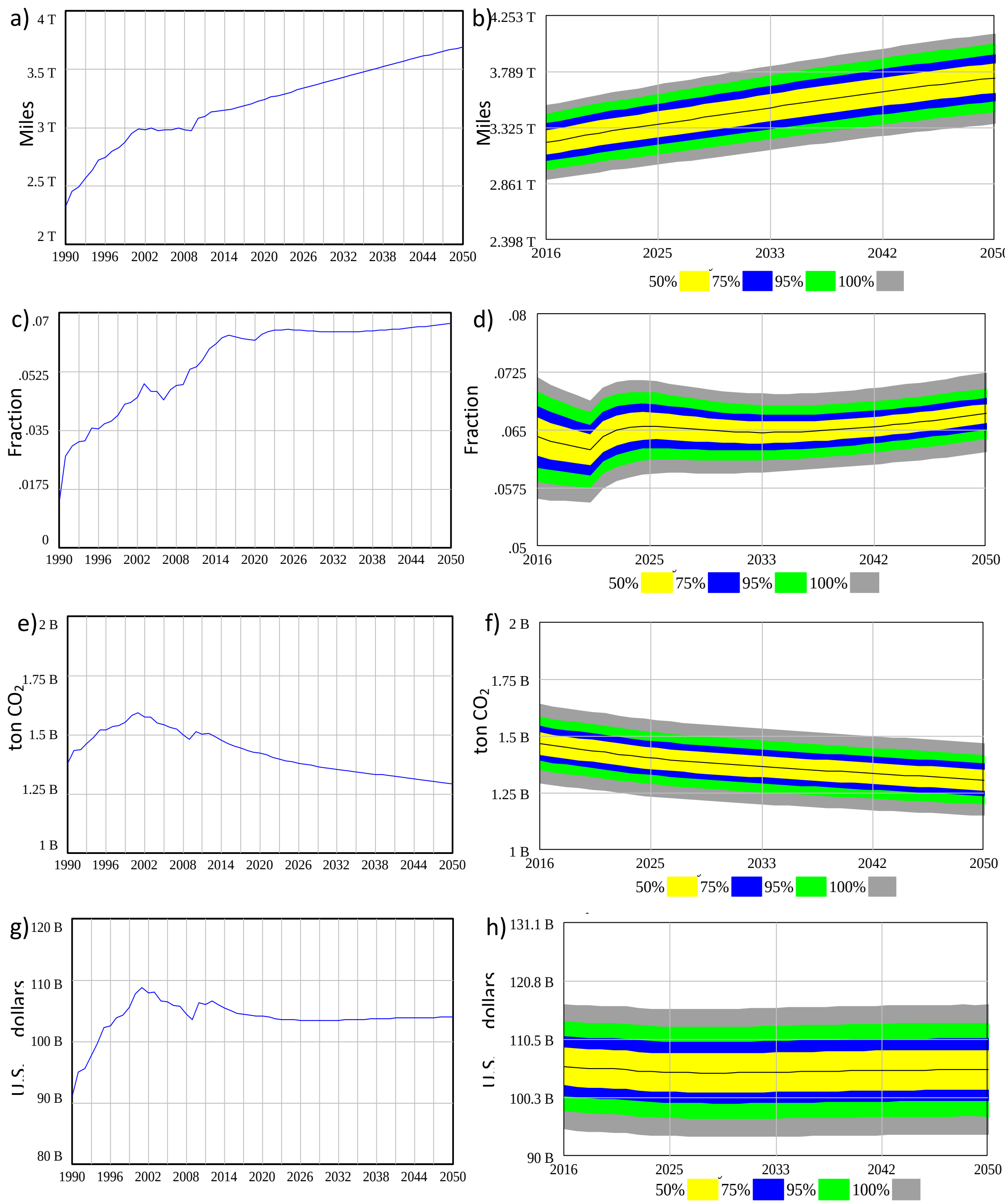


Figure 34: Critical parameter results based on average values and multivariate sensitivity analyses [per year]: a) Private vehicle miles traveled (VMT) average simulation values; b)

Private vehicle miles traveled multivariate sensitivity; c) Public transportation ridership average simulation values; d) Public transportation ridership multivariate sensitivity; e) U.S. urban passenger transportation CO_2 emissions average simulation values; f) U.S. urban passenger transportation CO_2 emissions multivariate sensitivity; g) U.S. urban passenger transportation emission externalities (in 2015 constant dollars) average simulation values; h) U.S. urban passenger transportation emission externalities (in 2015 constant dollars) multivariate sensitivity

4.5.2 Policy analysis: Exploring leverage points for policy implications

The applicable trends in critical parameters with respect to urban passenger transportation in the U.S. have been presented and discussed in the previous section. Although the uncertainty ranges and behavioral limits of these parameters can provide important insights, these values do not provide sufficient information for policy analyses unless the degrees of sensitivity to critical inputs (control variables) are also investigated. In other words, the parameters that directly and significantly affect urban transportation mode choice in the U.S should also be identified and analyzed in order to determine more effective policy strategies. Hence, Figures 35 and 36 will each depict the sensitivity of different model parameters (inputs) to the most critical model results (outputs).

Figures 35a through 35d present the most sensitive parameters with respect to private vehicle VMT, transit ridership rate, passenger transportation related CO_2 emissions, and passenger transportation-related externalities, respectively. These analysis results revealed that the average trip length and the average trip generation rate are the two most sensitive parameters with respect to transportation-related impacts, indicating that, although the SD model in this study accounts for feedback relationships that typically favor public transportation as opposes to private vehicle use (system generated funds for public transportation, traffic congestion, capital funds for public transportation, etc.), private VMT will still increase/decrease depending on the overall trip generation rate. Similarly, the average trip rate and average trip length are the two dominant influencing factors with respect to the public transportation ridership rate. Unlike Figure 35a, the average trip length governs the transit ridership rate with a sensitivity level of 61%, as shown in Figure 35b. This result is also in agreement with the results of many discrete event studies from the available literature (Bhat 1997; Eluru et al. 2012; Ewing 1995), where trip length was likewise found to be one of the most significant variables for commuters/travelers when choosing a transportation mode. Figure 35c also indicates that the average trip length and trip rate will also have a significant influence on urban passenger transportation-related CO_2 emission results, although these emissions are more heavily influenced by the per-gallon-of-gasoline CO_2 emission conversation factor. Therefore, as highlighted for other results, trip generation behaviors can be changed to more effectively reduce transportation-related emissions, although the main driving factor is the emission factor, which can nevertheless be reduced by using alternative fuels and/or more efficient vehicle technologies. Likewise, Figure 35d shows that air pollution externalities are almost equally sensitive to the average trip rate, average trip length, and per-gallon-of-gasoline CO_2 emission factor.

Since there are other types of air pollution that contribute to these externalities, the conversation factor for CO_2 emissions per gallon of gasoline shares its dominant role with average trip rate and length.

All of the sensitivity results (Figure 35) clearly indicate that trip generation and trip characteristics (e.g. average trip rate and length) will feature the most critical parameters for changing transportation mode choice patterns in the U.S., as the model outputs corresponding to transportation mode choice (i.e. transit ridership rate and private VMT) are heavily influenced by these parameters with a sensitivity coefficient of 99%. This study therefore predicts that the availability of transit funding will not affect mode choice in the U.S. unless the average trip length and/or the trip generation rate can be changed to accommodate such a shift in mode choice. This finding also supports the hypothesis previously stated in the first chapter of this dissertation, in that sustainable urban development (upon which trip generation rates and other trip-related characteristics will ultimately depend) is crucial for a more sustainable shift in transportation mode choice. Radical infrastructure accommodations and urban spatial changes are therefore urgently required to change trip generation metrics and thereby yield a more effective transportation mode shift.

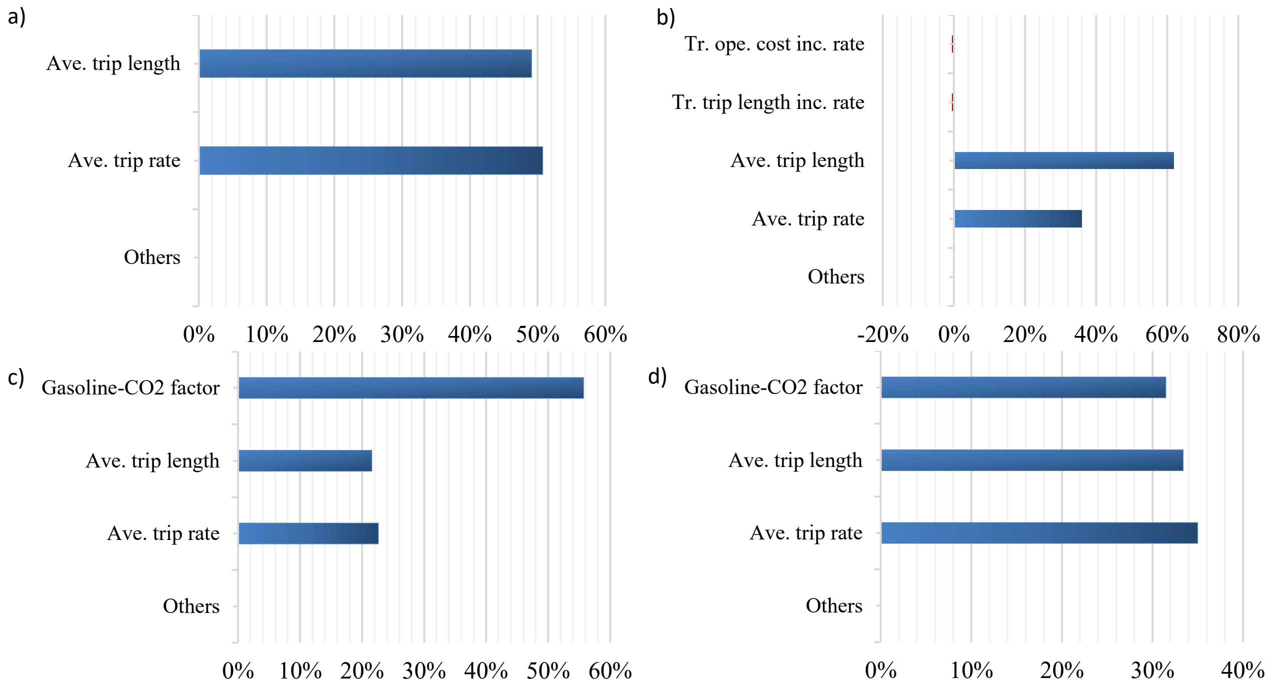


Figure 35: Sensitivity coefficients of critical parameters: a) Private vehicle miles traveled (VMT); b) Transit ridership c) U.S. urban passenger transportation related CO_2 emissions d) U.S. urban passenger transportation emission externalities [Figure legend abbreviations: "Ave.": Average; "Tr.": Transit; "inc.": increase].

The dominance of two particular parameters (average trip rate and length) in this sensitivity analysis demonstrates a clear need to unfold this analysis in a way that an additional sensitivity analysis is performed without these two dominant inputs with respect to the cumulative private VMT and transit ridership rate outputs. The results of this second sensitivity analysis are shown in Figure 36, which indicates similar results to those in Figure 35. For instance, transit trip length is still the most critical parameter with respect to both private VMT and transit ridership rate, with impact rates of +27% and -27%, respectively. It should be noted that, since private vehicle use and transit ridership are complementary factors (as private vehicles and public transit are the only two available mode choices in the developed model), any factor that increases transit ridership rate therefore decreases private vehicle usage, and vice versa.

Other parameters that influence the selection of a particular transportation mode target many different aspects of the mode selection process in the U.S. transportation sector. For instance, from the analysis results in Figure 36, transit operation cost is the second most sensitive parameter with respect to transportation mode choice, underlining the importance of a cost-effective transit system, especially in cities and other urban areas. In addition to the cost effectiveness of the transit system, the amount of capital funds dedicated to transit system development also contributes to the net available funds for the transit system, and therefore, two of the main contributing factors to net transit system revenues (transit operation costs and capital funds) have a combined sensitivity impact of ±42% (±26% and ±16%, respectively) with respect to private VMT and transit ridership rate. Transit mode fare prices also directly influence the transportation mode choice of many commuters/travelers, so increasing transit fare prices is typically expected to reduce ridership, but as shown in Figure 36, an increase in transit fares would actually result in a slight increase in transit ridership. This is again due to the resulting increase in net available revenues for transit systems, which encourages more transit ridership through system expansions, system improvements, advertising, and other possible improvements and incentives.

On a similar note, it is not surprising that increasing roadway capacity in the U.S. has a negative impact on public transportation ridership as shown in Figure 36, since such increases in road capacity are typically expected to reduce traffic congestion, thereby making private vehicle usage a more attractive option. However, increasing the roadway capacity to accommodate current trends in private vehicle ownership and usage is almost impossible due to limited funding and land for new roads and/or road expansions. Lastly, gasoline fuel sale taxes are also expected to influence mode choice behavior significantly due to their balancing feedback connection to mode choice, but the impacts of fuel taxes on transportation mode choice are limited to a sensitivity coefficient of 4%.

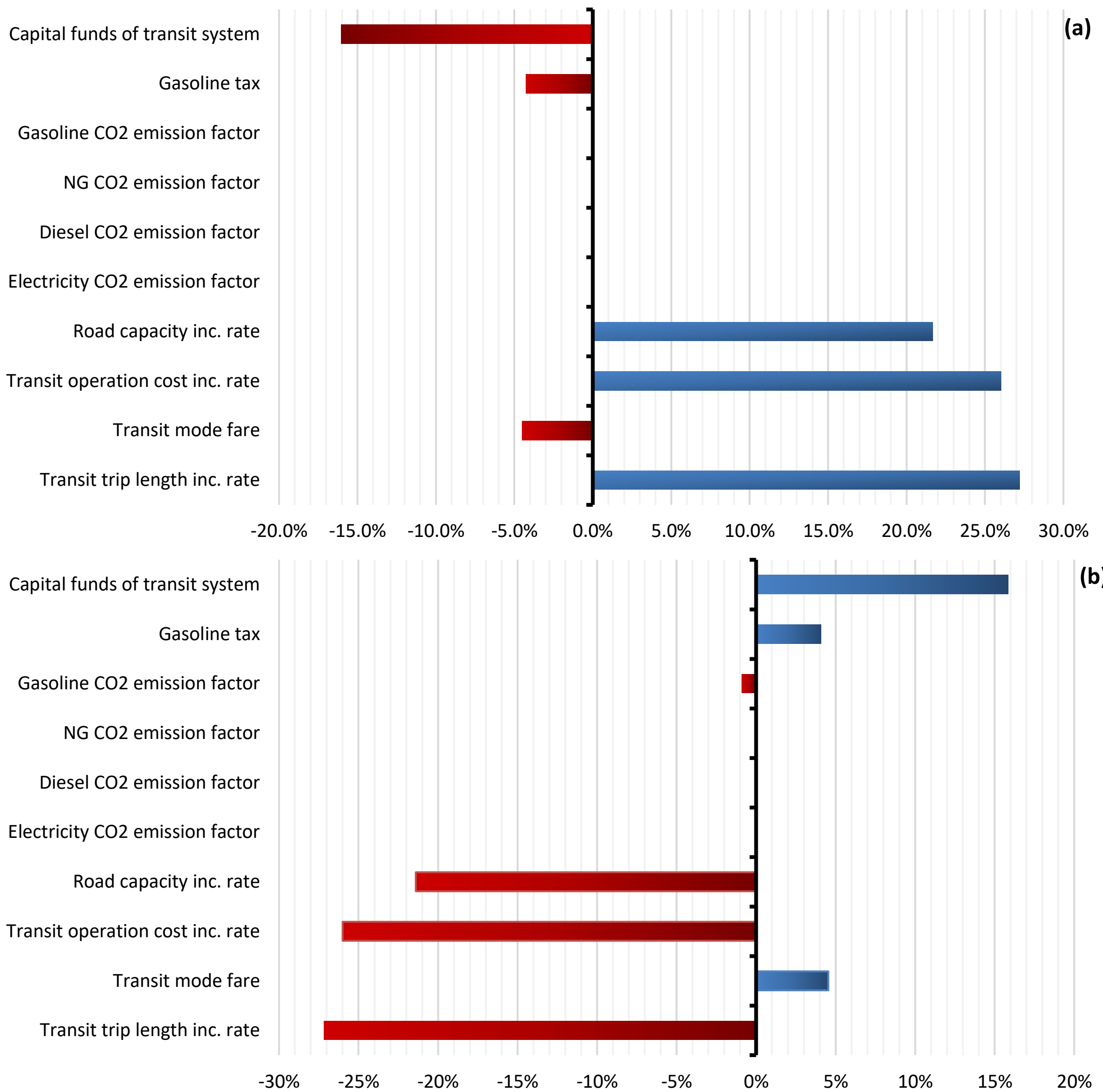


Figure 36: Sensitivity coefficients with respect to (a) cumulative private VMT and (b) cumulative transit ridership preference rate

CHAPTER FIVE: THE U.S. METROPOLITAN AND MICROPOLITAN AREAS COMMUTER TRANSPORTATION MODE CHOICE: A DISCRETE EVENT MODELING APPROACH

A partial work of this chapter has been submitted to the Transportation journal for publication and under review process with the title of "*Autonomous Vehicles or Prevailing Transportation Policies? An Integrated Modeling Approach Reveal Potential Environmental Benefits* ".

5.1 Discrete Event Simulation: Multinomial fractional split model

The analysis of mode choice at an urban region level cannot be accommodated with conventional discrete choice models because the dependent variable is a fractional mode share (as opposed to a single chosen alternative). Hence, we resort to the adoption of a fractional split multinomial model. The approach proposed by Papke and Wooldridge (1993) employs a quasi-likelihood based estimation approach for modeling fractional variables as a function of exogenous variables. The approach has received application in recent years in the transportation field (Eluru et al. 2013; Lee et al. 2016; Milton et al. 2008; Sivakumar and Bhat 2002). In this paper five modes of transportation (drive alone, car pool, public transit, walking and other mode) have been considered for each city. Let, y_{mi} be the fraction of transportation mode (m = 1, 2, …, M) used in city i (i

= 1, 2, …, I). The proportion of each mode ranges between 0 and 1 and the sum of the fractions across all the mode should add up to one.

$$0 \le y_{mi} \le 1$$

$$\sum_{m=1}^{M} y_{mi} = 1$$

Let, the fraction y_{mi} be a function of a vector x_i of relevant explanatory variables associated with attributes of the city *i*.

$$E\,[y_m \mid x] = G_m\,(x; \beta)$$

$$0 < G_m\,(.) < 1$$

$$\sum_{\mathrm{m}=1}^{M} G\,(.) = 1$$

Where G_m (.) (m = 1, 2, … M) is a predetermined function. The properties specified for G_m (.) assure that the predicted fractional mode choice will range between 0 and 1 and will add up to 1 for each city. The multinomial logit functional form for G_m in the fractional split model is as:

$$E\,(y_m \mid x) = G_m\,(x; \beta) = \frac{\exp(x\beta_m)}{\sum_{m=1}^{M} \exp(x\beta_m)}\,, \qquad m = 1, 2, \ldots, M$$

Given the probability expression above, the quasi likelihood function is as follows:

$$L_i\,(\beta) = \prod_{m=1}^{M} G_m(x_i; \beta)^{y_{mi}}$$

The quasi log-likelihood function for the sample is defined as:

$$\mathscr{L}(\beta) = \sum_{i=1}^{I} \ln[Li\ (\beta)]$$

5.2 American Community Survey (ACS) Data

The U.S. Census Bureau publishes American Community Survey (ACS) data that is also available thought American Fact Finder website that allow users to modify and set custom datasets (US Census Bureau 2016). Through many available geographic boundary selection, this study uses metropolitan and micropolitan statistical area to only consider urban areas in the US. The US Census Bureau defines urban areas that has population more than 20K and less than 50K as micropolitan statistical areas and 50K and above population as metropolitan areas. This geographic boundary selection consists of 929 urban areas of the US including Puerto Rico. The data included the population of each urban area and their following attributes:

- *Transportation mode choices (Drive alone, carpool, public transportation, walk, and other),
- *age groups (16 to 24, 25 to 44, 45 to 54, 55 to 64, and 65 years and older),
- *gender groups,
- native or foreign born information,
- *employment type (i.e. government, private sector, self-employed),
- *income levels ($1 to $24,999; $25K to $34,999; and $50K and above),
- employment industry (ACMT, sales, finance, education and others),
- occupation type (management, service, sales, and natural),

- poverty level (below 100, 100 to 149, and 150 and above),
- *time of leaving for work (12:00am to 6:59am, 7am to 7:59am, 8am to 8:59am, 9am to 11:59pm),
- *travel time (less than 10 mins, 10 to 14 mins, 15 to 19 mins, 20 to 24 mins, and 25 and above),
- *number of vehicles available in the household (no vehicle availability, 1 vehicle, 2 vehicles, 3 and more vehicles).

As it mentioned above, metropolitan area classification of the data consists of vast variation on population since the upper limit reaches up to almost 10 million for greater New York area. As one of the motivation of this study, city size has impacts on transportation mode choice, so the data is disaggregated into four major city size groups as follows (please see Table 18 for descriptive analysis results of each city size group and also Figure 37 for geographical presentation of each city size group):

- Very Large City: Population 1 million and above
- Large City: Population between 500K to 1 million
- Medium City: Population between 200K to 500K
- Small City: Population below 200K

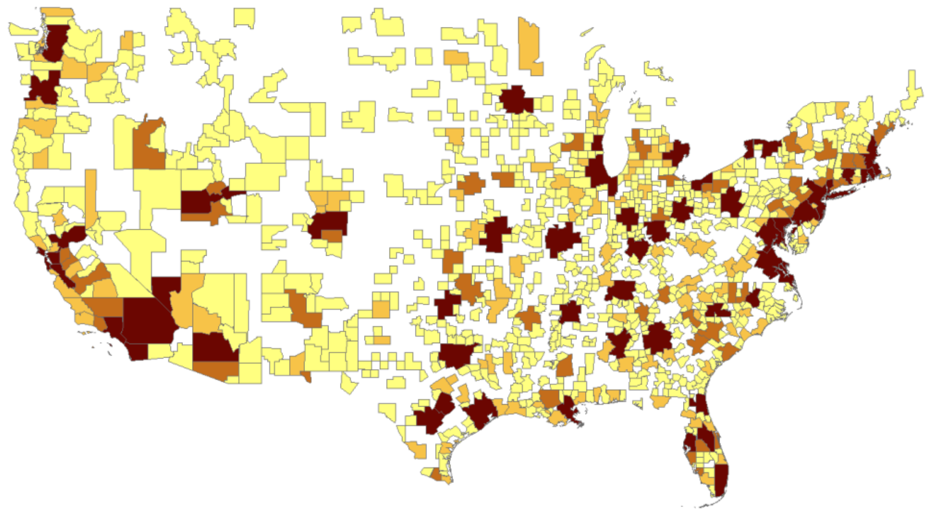


Figure 37: The U.S. metropolitan and micropolitan areas based on their population data (Urban area classification; darker colors represent larger population areas)

Table 18: American Community Survey data description and total population portion

	ACS Dataset for Urban-Labor Force Population				Portion in total population of 302.5M in 2015
	n (# of cities)	Total population of sample	Mean Population	Median Population	
Very Large City	27	63,506,084	2,352,077	1,795,123	21%
Large City	24	17,933,199	747,217	701,162	6%
Medium City	63	19,314,523	306,580	292,529	6%
Small City	815	34,784,904	42,681	25,337	11%
Total	**929**	**135,538,710**	**145,897**	**30,220**	**45%**

The dataset of ACS that is utilized in this study for metro/micropolitan areas of the U.S. only includes labor force population and commuters, which reduces the population representation to 45% of total population (please see Table 18). The reason behind this gap is due to rural area population and elderly and younger population groups that are not included in this study's data consideration. Although the population representation rate indicates less than total population, this portion can be considered as the major and routine contributors of transportation activities.

Due to the nature of using fractional split model the data should be converted to proportional form where each attribute group has their own percentages compare to each other (i.e. raw data provides male population in Orlando, FL area and this information is converted to a percentage of male and female population based on total population). Besides, some of the attributes have several parameters that can be grouped together for such as income level (reduced to 2 groups as "below 25K income" and "25K and above income"), time of leaving for work, travel time, number of vehicle in the household (please see following result Table 19 for their compromised groups). After the data preparation phase for DES, the model is designed and indicated that some of the attributes have no significant relation with transportation mode choice such as: native or foreign born information, employment industry, occupation type and poverty level. The statistically significant attributes are marked with asterisks (*) on above list.

5.3 Multinomial fractional split model results

Based on the exogenous variables available in ACS, fractional split multinomial model is estimated as explained in previous sections. The model provides significant associations of demographic attributes for different cities for transportation mode choice. Table 19 summarizes all of the significant attributes from the model of ACS dataset, which also guide the dynamic modeling parameter relations. Before moving to the dynamic modeling of the US urban areas in Chapter 6, Table 19 should be investigated closely and interpolated to understand interconnections of all attributes.

All city sizes only affect public transportation mode with positive relation. In other words, medium, large, and very large city group commuters more likely to choose transit than small city commuter, but this effort is stronger if the city is larger in terms of population. Moreover, this result is not surprising since larger metropolitans of the US has the highest transit ridership ratio compared to smaller cities. The only other city size related impact on mode choice is affecting carpool from large city commuters and it is a negative relation. Therefore, the model indicates that large city commuters slightly less likely to choose carpool mode.

In addition to large city related impact, carpool is positively affected by male population, commuters who are 55 years and older, and commuters who rent their house. It can be interpreted that male population does not prioritize their safety as much as female population, so male commuters are more likely to carpool. The relation between commuters who live on rental property and carpool mode choice can be connected with economic reasons, since carpool can be a mode that save money. Finally, commuters who travel more than 20 minutes are less likely to choose carpool. Travel time increase may lead to difficulty of finding other commuters that travel to identical area.

City size related significant positive relation for public transportation ridership is followed by other attributes such as male proportion, time of leaving home for work (8am – 8:59 am proportion), and rental house occupants. Similar to carpool mode, female proportion of study groups is less likely to use transit mode compare to male population, which again can be relate with discomfort and insecurity issues of transit system for female commuters. Compare to other early time groups (12:00-6:59am and 7:00-7:59am) for leaving to work, 8 – 8:59am group commuters may find it more convenient to ride transit modes, which can explain the positive relation for public transportation mode choice. Lastly, rental home occupant commuters tend to use more public transportation than home-owners and this could be again associated with economic reasons or higher density of residential communities available as rental house and their easy access to transit system (i.e. high-rise apartment communities that). On the other hand, number of vehicles in the household and travel time of 20 and more minutes decreases the willingness of commuting with public transportation. It is not surprising that as the number of commuters who has 1 or more vehicles in the household increases there is likely a reduced use of public transportation. Similarly, longer commute distance discourage public transportation use for commuters.

As an alternative and active mode choice for commuters, walking is affected negatively by many attributes but only employment type and late morning commute hours (8-8:59am group) tends to increase walking mode. Personal vehicle availability in the household has negative relation with walking mode, and it overlays with transit mode choice results. All available age groups for this analysis (25-44 years old, 45-54 years old, and 55 years and older) are less likely to choose walking compare to age group proportion of 16-24 years old. There is no statistical evidence for connecting this impact with vehicle availability but the youngest population group might not have personal vehicle and/or choose this active mode of transportation for personal reasons. Commute time of more than 10 minutes tends to discourage commuters from walking and it could be reasonable for commuters with the consideration of weather impacts (heat, cold, rain, snow, etc.) throughout the year. The two groups of time of leaving for work attribute affects the walking mode choice in a controversial way. The early commute hours of 7-7:59 am decreases the walking mode choice where 8-8:59 am commuters tend to choose walking more than base group of 12:00-6:59 am commuters.

Table 19: Fractional split multinomial model results

Variable	Drive Alone		Car Pool		Public Transit		Walking		Other Mode	
	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value
Constant	0	-	-3.88	-19.36	3.4	0.82	10.18	5.4	-3.21	-4.35
City Size (Base: Small City)										
Medium city	-	-	-	-	0.62	4.8	-	-	-	-
Large City	-	-	-0.07	-2.36	0.95	7.28	-	-	-	-
Very Large City	-	-	-	-	1.81	7.31	-	-	-	-
Proportion of Gender (Base: Proportion of Female)										
Proportion of Male	-	-	2.37	8.28	5.53	2.61	-	-	2.63	3.86
Proportion of No. of Vehicle in Household (Base: Proportion of 0 vehicle)										
Proportion of 1 vehicle	-	-	-	-	-13.61	-2.74	-4.9	-2.29	-	-
Proportion of 2 or 3 vehicles	-	-			-12.88	-3.1	-6.79	-3.67	-2.5	-3.72
Proportion of Age Group (Base: Proportion of 16 to 24 years old)										
Proportion of 25 to 44 years	-	-	-	-	-	-	-8.32	-9.78	-2.45	-3.87
Proportion of 45 to 54 years	-	-	-	-	-	-	-4.56	-3.8	-3.77	-3.06
Proportion of 55 years and over	-	-	1.21	4.3	-	-	-6.09	-7.02	-	-
Proportion of Income (Base: Proportion < $25K)										
Proportion > $25K	-	-	-	-	-	-	-	-	0.78	2.5
Proportion of Travel Time (Base: proportion of commuters with travel time less than 10 minutes)										
Proportion of 10 to 14 minutes	-	-	-	-	-	-	-3.45	-3.41	-	-
Proportion of 15 to 19 minutes	-	-	-	-	-	-	-1.71	-2.49	-	-
Proportion of 20 minutes and more	-	-	-0.28	-3.71	-1.22	-2.4	-2.14	-4.91	-	-

Variable	Drive Alone		Car Pool		Public Transit		Walking		Other Mode	
	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value
Proportion of Employment Type (Base: Proportion of Private Sector)										
Proportion of Government	-	-	-	-	-	-	1.29	4.68	-	-
Proportion of Self Employed	-	-	-	-	-	-	4.5	5.82	4.64	6.51
Proportion of Time of Leaving for Work (Base: Proportion of 12.00 am to 6.59 am)										
Proportion of 7.00 am to 7.59 am	-	-	-	-	-	-	-2.67	-5.73	-	-
Proportion of 8.00 am to 8.59 am	-	-	-	-	5.97	3.56	2.21	3.81	-	-
Proportion of House Occupied (Base: Proportion of Owner)										
Proportion of Rented	-	-	1.48	11.43	3.99	4.34	-	-	2.73	6.03
Number of cities	929									
Log Likelihood of constant only Model	-544.86									
Log Likelihood at Convergence	-538.36									

*All the coefficients are statistically significant at 95% confidence level

The early time commutes might cause discomfort for walking on dark in some times of the year in certain regions, which may also increase security concerns of commuters. Lastly, government employed and self-employed commuters tend to use more walking than private sector employed commuters.

The other modes of transportation include taxicab, motorcycles, bicycle, and others for this dataset. Therefore, it is more difficult to interpret this mode related results since it has many different modes that can have their own reasoning. Like other modes, male commuters tend to use more other modes of transportation such as cycling, taxicab, etc. The mode is also positively affected by income level of commuter $25K and more, self-employed commuters compare to government and private employed commuters, and rental house occupants compare to house-owner commuters. Number of vehicle availability of 2 and more vehicles in the household proportion again decrease the use of other modes of transportation. Lastly, two age groups of commuters (25-44 and 45-54 years old) are less likely to use other modes compare to 16-24 years old commuters.

CHAPTER SIX: A NOVEL INTEGRATION OF DISCRETE EVENT AND DYNAMIC MODELING APPROACHES: A COMPLETE PICTURE FOR SUSTAINABLE URBAN MOBILITY

A partial work of this chapter has been submitted to the Transportation Research Part A: Policy and Practice journal for publication and under review process with the title of "*Prevailing Transportation Policies or Autonomous Vehicles? Transportation Mode Choice Projections of the United States Urban Areas*".

6.1 Model Development

As it explained in research objectives of this dissertation, hybrid simulation modeling necessary to estimate all transportation mode choices in the U.S. for future sustainability performance under various policy practices. Previous chapter defined the discrete event method, data preparation, and model results interpretations. Following these inputs of Chapter 5, this chapter extends the developed SD models in Chapter 3 and 4 and generate hybrid model. Figure 38 illustrates the general concept of hybrid modeling in this study. 2015 American Community Survey's (ACS) demographic and commuter mode choice characteristics for the US metropolitan and micropolitan areas are gathered and converted to a proportional dataset. Thus, SD model can be formed with the inclusion of significant attributes and other parameters that complements the transportation system in the US. By the formation of "holy grail" (as it defined by

Brailsford et al. (2010)) in VENSIM (SD modeling software), transportation mode choices, vehicle miles traveled (VMT), CO_2 emissions, air pollution externalities of city types and the nation can be projected until 2050.

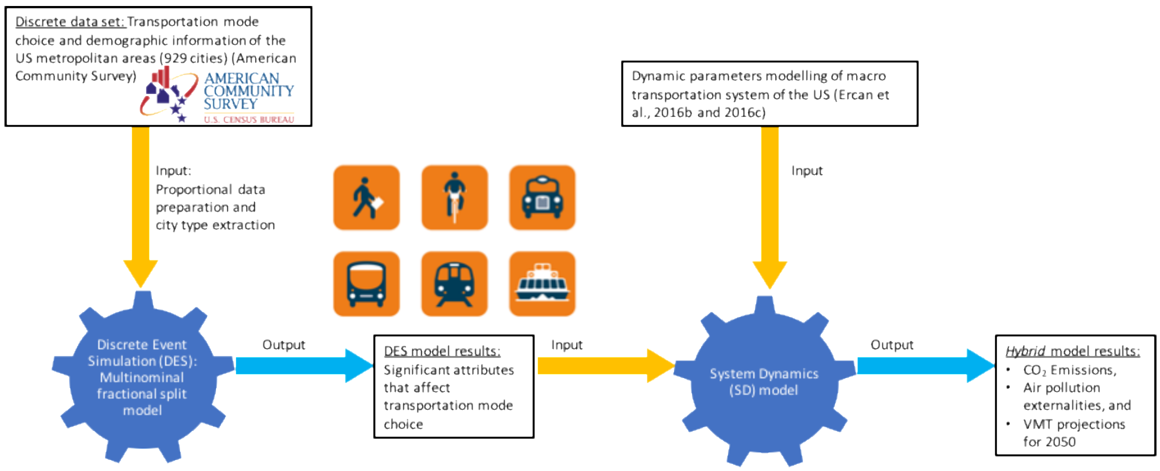


Figure 38: Concept illustration for hybrid modeling of simulation methods

6.1.1 System conceptualization (SD model)

Considering five modes of transportation for commuters, dynamic modeling approach allows this study to identify the feedback mechanism of transportation sector and its related components as a whole in the U.S. This macro-level relation identification provides an opportunity to simulate key outcomes of the system (i.e. air pollution emissions, economic and social impacts) and test policy initiatives for long-term spans. However, in order to start formulating and identifying dynamic model's parameters, the problem should be explored in conceptual level. Thus, CLD presents the interconnections and feedback loops of the system in Figure 39. As it explained in

Section 4.1 with Sterman's (2000) quote, real-world problems progress with feedbacks that decision makers gather in the forms of qualitative or quantitative by the time. Therefore, it can be stated that parameters are connected with cause and effect relations. As can be seen in Figure 39 parameters are linked with each other and the influence that is transferred through those links are presented with polarity symbols (Sterman 2000).

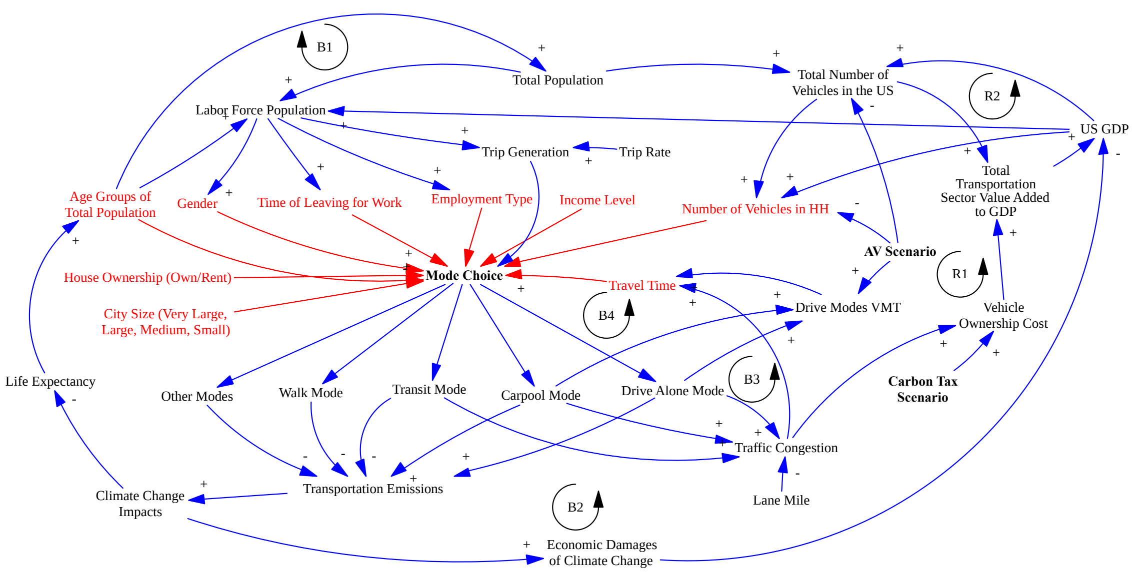


Figure 39: Causal-loop diagram (CLD) for hybrid model

This diagram provides guidance to see and formulate the impacts of the transportation sector for urban area commuters of the U.S. that also provides feedback to the system (i.e. climate change's drawback impact on life expectancy and so population and GDP). The CLD shows six feedback loops within the system where four of them are balancing and two of them are reinforcing loops. Balancing loop (B) represents a loop that an increase in any single factor cause subsequent decrease. Moreover, reinforcing loop (R) indicate a loop that an increase causes an additional increase (Ercan et al. 2016c; Sterman 2000). Each loop is presented with their rotation and labels in the figure.

Each of the feedback loop relation of the CLD is summarized in following Table 20. Due to nature of the identified system, most the loops share many of their parameters with each other and it may be difficult to locate some of the loops, so following table can guide the readers. As can be seen from the figure that mode choice variable is in the center of diagram and all nine significant parameters that influence mode choice behavior according to discrete event model is labeled with red color. The conceptual model has two general feedbacks that are caused by climate change impacts which create "population (**B1**)" and "economy (**B2**)" loops. These two loops are identified as balancing, since transportation emission increase has negative impacts on life expectancy and economy (GDP and labor force). Drive modes (drive alone and carpool) and on-road transit modes increase traffic congestion and travel time parameters which cause negative on drive mode choices, hereby this loop is identified as another balancing loop (**B3**). Similarly, increase on drive modes' VMT generate balancing relation with travel time and mode choice (**B4**) (drive mode commuters tend to switch their mode choice with the increase of travel time). However, economic impacts of traffic congestion indicate reinforcing relation since vehicle ownership cost increase also increases transportation related GDP, which enforces number of vehicles on the roadways (**R1**). Finally, economy model of the US GDP generation enforces itself with more vehicle sales and transportation related GDP generation (**R2**).

Table 20: Feedback loop relations for CLD

Feedback Loops	Relations
Emissions Related Damage Loops	
Balancing Loop 1 (**B1**) – Population	Total Population →+ Labor Force Population →+ *Discrete Model Related Parameters* (Gender, Time of Leaving for Work, Employment Type) and Trip Generation →+ Mode Choice (Drive Alone, Carpool, Transit, Walk, and Other) →± Transportation Emissions →+ Climate Change Impacts →- Life Expectancy →+ Age Groups of Total Population →+ Total and Labor Force Population
Balancing Loop 2 (**B2**) – Economy	Labor Force Population →+ *Discrete Model Related Parameters* (Gender, Time of Leaving for Work, Employment Type) and Trip Generation →+ Mode Choice (Drive Alone, Carpool, Transit, Walk, and Other) →± Transportation Emissions →+ Climate Change Impacts →+ Economic Damage of Climate Change →- US GDP →+ Labor Force Population
Traffic Congestion Effects	
Balancing Loop 3 (**B3**) – Congestion	Mode Choice →+ Drive Alone, Carpool, and Transit Modes →+ Traffic Congestion →+ Travel Time →± Mode Choice
Balancing Loop 4 (**B4**) Drive Mode VMT	Mode Choice →± Drive Alone and Carpool Modes →+ Drive Modes VMT →+ Travel Time →± Mode Choice
Reinforcing Loop 1 (**R1**) – Congestion (Economy)	Traffic Congestion →+ Vehicle Ownership Cost →+ Total Transportation Sector Value Added to GDP →+ US GDP →+ Total Number of Vehicles in the US →+ Number of Vehicles in HH →± Mode Choice →± Drive Alone, Carpool, and Transit Modes →+ Traffic Congestion
Economic Impacts	
Reinforcing Loop 2 (**R2**) – GDP Model	US GDP →+ Total Number of Vehicles in the US →+ Total Transportation Sector Value Added to GDP →+ US GDP

6.1.2 Hybrid simulation model development

With the guidance of aforementioned modeling concept information in Chapters 2-5 and necessity of hybrid modeling approach, model development and formulation can be formed conceptually as it shown in Figure 40. The development model consists of several sub-models that interconnects with each other as it summarized in CLD, so this Figure 40 explains the details of each sub-model and their input-output parameter relations. Some parts of the sub-models are adopted from the previous chapters such as population, trip generation, public transportation mode choice related emissions, air pollution externality calculation, total emission and externality, and climate change sub-models (Chapters 3 and 4).

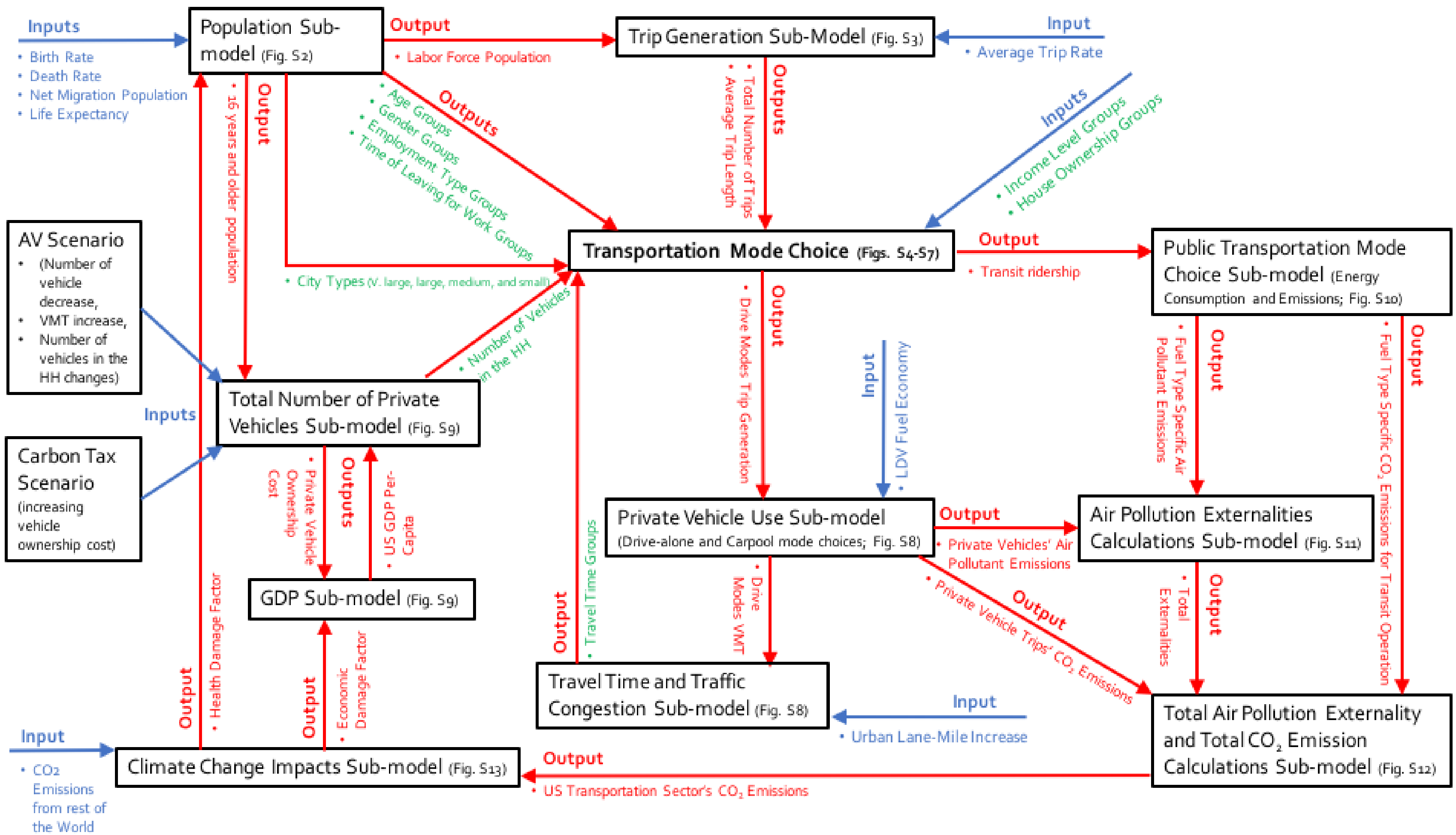


Figure 40: Conceptual interconnections of sub-models and scenarios

(Legend: Red; outputs of the sub-model that input for associated sub-model, Blue; Exogenous inputs to the sub-models, Green; Output parameters but also significant parameters that are gathered from discrete model.)

The journey of the model starts with population sub-model where age groups, mortality and birth rates, and immigration rates comprise total population and also labor force population from the age groups of 16 to 65 years old. The labor force population is a key component in the model since it determines the total trip generation figures with the trip demand statistics (a.k.a. in model: average trip rate) from NHTS (Santos et al. 2011). The population sub-model also generates age and gender groups that are significant demographic attributes for discrete event model's estimation. As can be seen from Figure 41 below, the population sub-model is adopted from Chapter 3. The discrete event model also indicates significant statistical relation with employment type and time of leaving for work on some of the mode choices. Although these two parameters can be modeled dynamically within the system, it may require extensive sub-model efforts and do not provide significant improvement to the accuracy of the model. Besides, these two parameters cannot be controlled or manipulated by the policy makers (i.e. employment type of a city cannot be changed to make differences on mode choice behavior). Therefore, employment type and time of leaving for work parameters are inputted to the model as a deterministic function of population based on historical trends of ACS (US Census Bureau 2016). Population sub-model generated city group classification and other ACS related data information are explained in detail in previous Section 5.2.

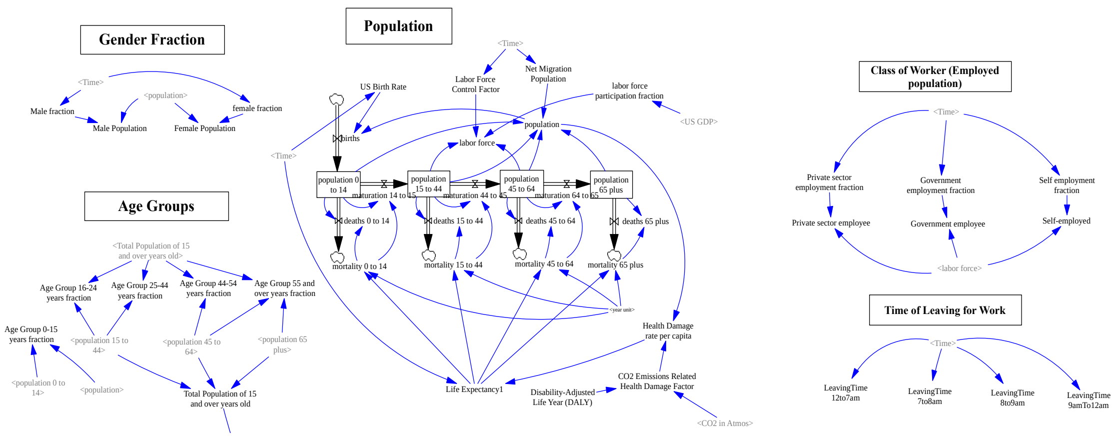


Figure 41: Population sub-model with attribute outcomes

Trip generation and public transportation mode choice sub-model follows a similar path with Chapter 3 and 4 by only adding city size related changes into the sub-model as can be seen in Figure 42.

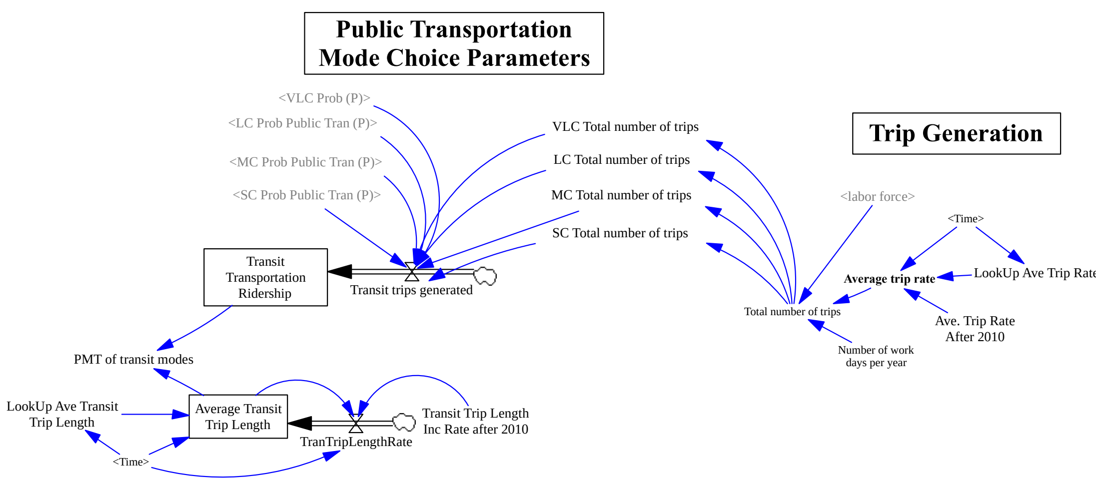


Figure 42: Trip generation sub-model and public transportation ridership generation

The significant attributes that are highlighted in Table 19 leads the city size specific transportation mode choice simulation as shown in following Figures 43 – 46. All of the statistically significant attributes are converted to city size specific proportions, which then inputted to the utility function.

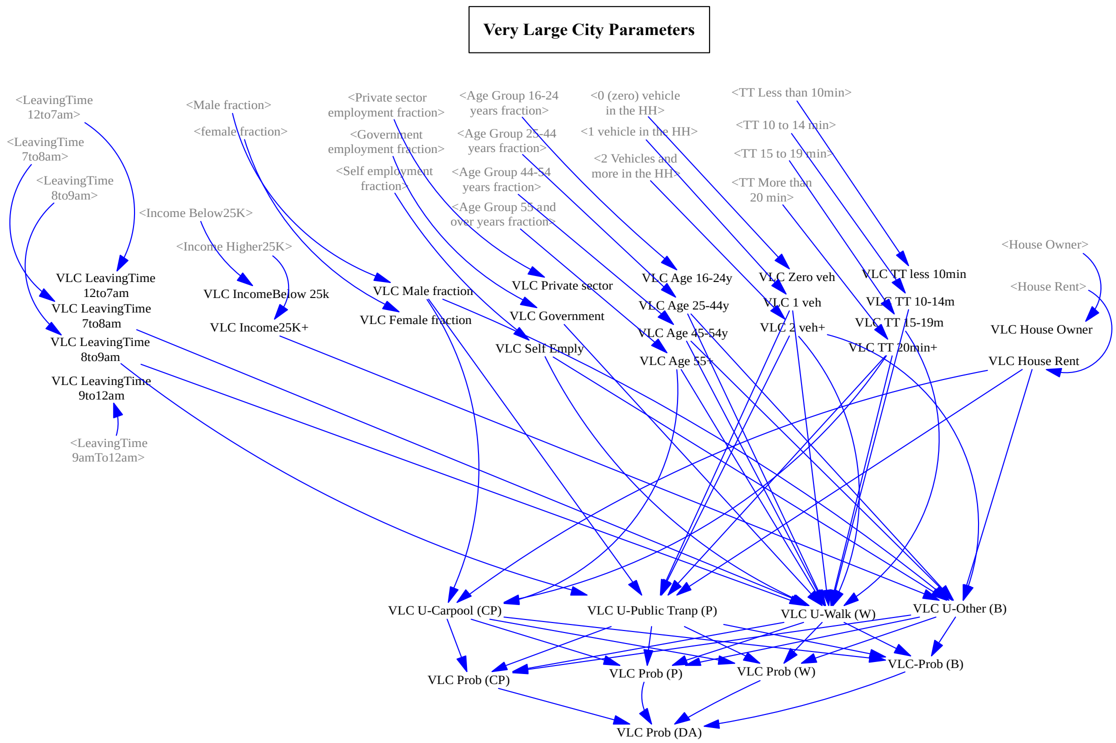


Figure 43: Very large city (VLC) group's utility function and mode choice probability calculations

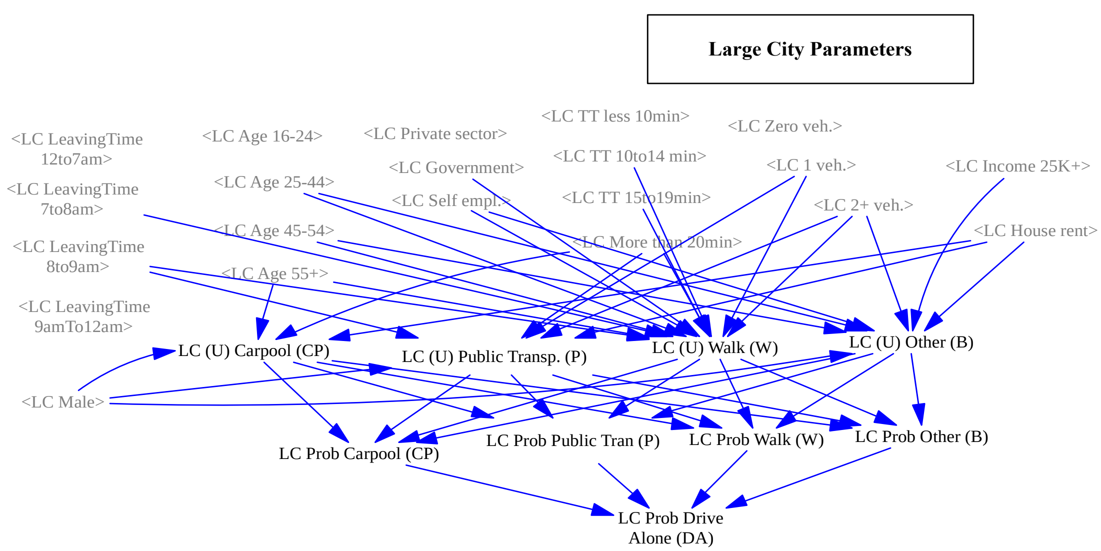


Figure 44: Large city (LC) group's utility function and mode choice probability calculations

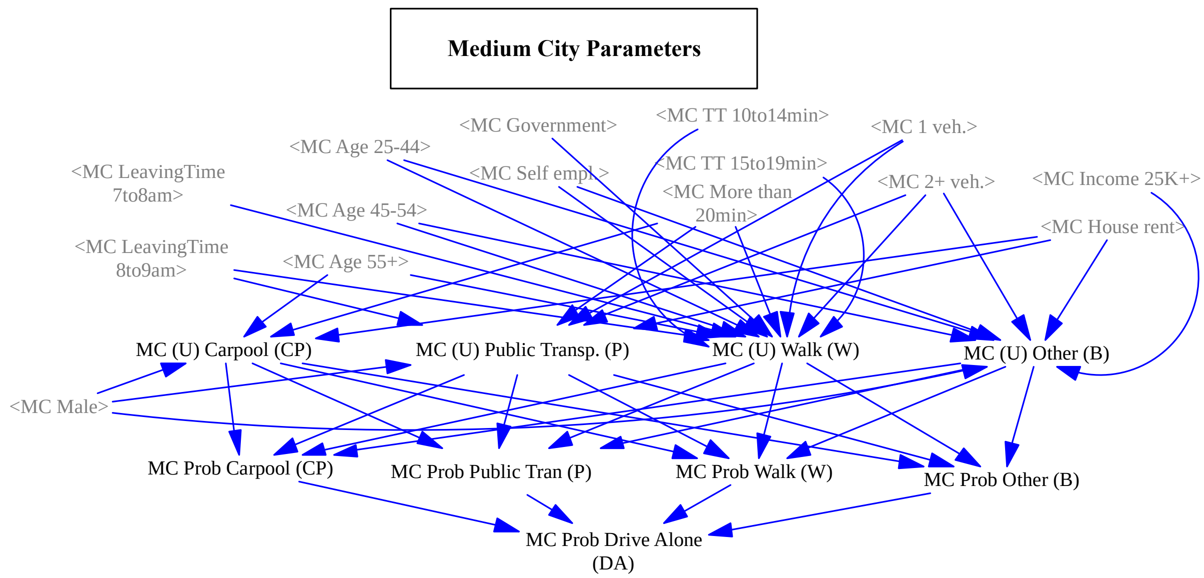


Figure 45: Medium city (MC) group's utility function and mode choice probability calculations

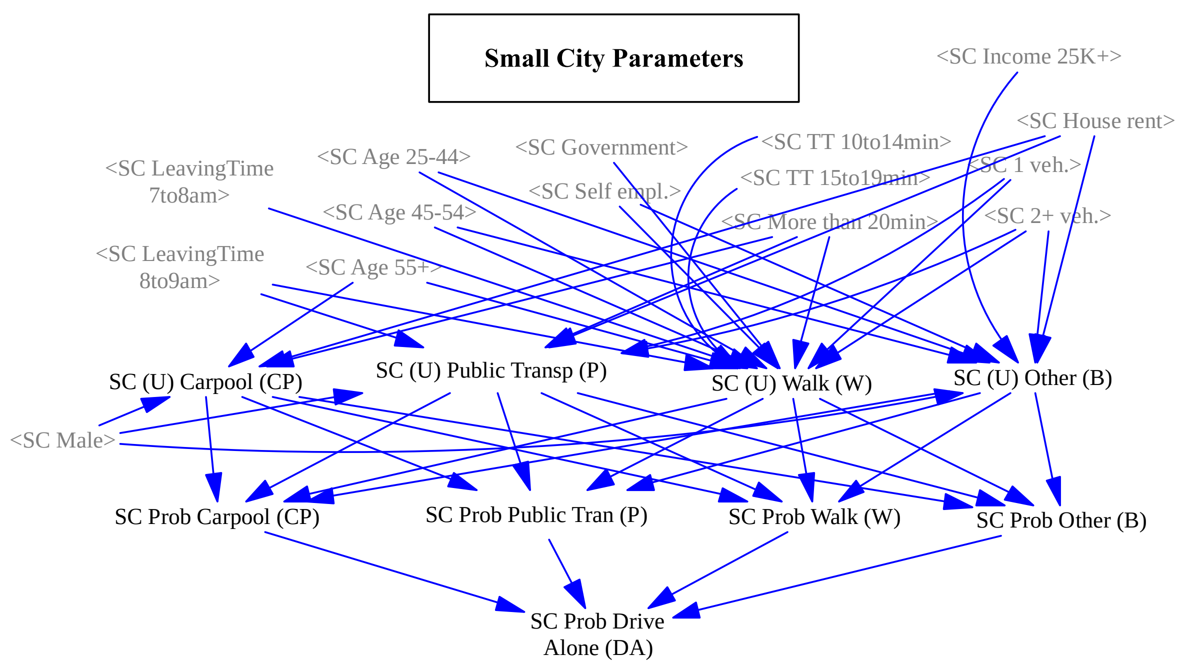


Figure 46: Small city (SC) group's utility function and mode choice probability calculations

Another attribute that DES model highlight is number of vehicles in the household (HH) and mode choice can be affected the groups of having zero, one, and two or more vehicles in the household. In order to model this attribute, total number of personal vehicles and GDP (economy) sub-models are formed. As can be seen from the Figure 40, GDP and total number of vehicle sub-models exchange feedbacks in the forms of "the US GDP per capita" and "per private vehicle cost of ownership" variables. And beyond that point, GDP sub-model receives feedbacks from climate change related economic damage factors, which is affected by the overall emission impacts of transportation passenger network (please see Fig. 47 for graphical illustration of these connections). Thus, total number of personal vehicle's dynamic sub-model determines the proportions of the number of vehicles in the household by a linear regression model (please see following Equation 15). The determination of total number of vehicle variable provide accurate and statistically significant relation for determining 2 and more vehicles in the household and zero vehicle in the household proportions with the U.S. GDP per capita variable. The linear regression model parameters for predicting number of vehicle availability in the household is also can be found below in Equations 16-18 [Eq. 16-18]. This sub-model is also affected by one of the policy scenarios and AV addition changes the patterns of number of vehicles in the household variables, as it explained in following Section 6.2.

Personal vehicle ownership cost sub-model is designed with the reference of American Automotive Association's (AAA) annual vehicle ownership cost reports (American Automative Association (AAA) 2016). The AAA's calculation for cost includes, maintenance, fuel consumption, tire replacement, and fixed cost (loan or lease payment, insurance, depreciation, etc.) items as it shown in Figure 47. As it mentioned above section, red color variables indicate policy scenario addition, so Carbon Tax (CT) scenario related additional cost of personal vehicle ownership is added after 2025.

Finally, all of these transportation related activities generate economic value and this value can be added to the overall annual GDP of the U.S. as it shown in Figure 47. Climate change related impacts on economy parameters is utilized on GDP increase rate to complete one of the feedback loops.

Total number of vehicles = (2.51175E+08 + (9.76E-06 * US GDP) + (-0.961 * Total Population of 15 and over years old)) [*15*]

2 vehicles and more in the HH = (0.548 + (9.547E-07 * US GDP per capita) + (-1.368E-05 * (Total number of passenger vehicles/100,000) [*16*]

Zero vehicle in the HH = 0.117 + (-9.588E-07 * US GDP per capita) + (1.182E-05*(Total number of passenger vehicles/100,000)) [*17*]

1 vehicle in the HH = 1 - ("0 (zero) vehicle in the HH" + "2 Vehicles and more in the HH") [*18*]

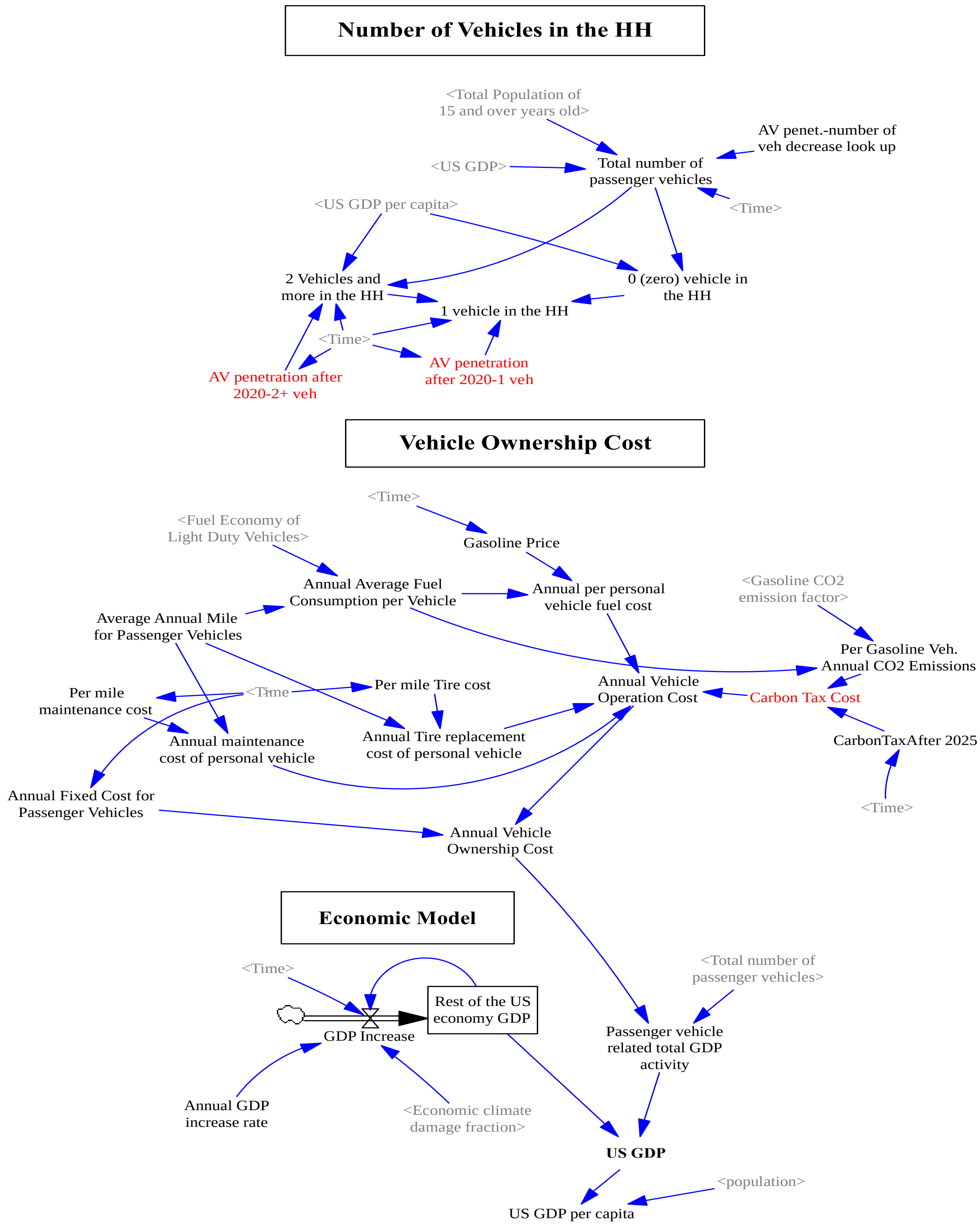


Figure 47: Total number of private vehicles, number of vehicles in the household, and GDP sub-models

Based on the mode choice estimations for different city types, drive modes proportion can be calculated (drive alone and carpool modes are both considered as drive modes). Private (personal) vehicle use trips generate models' private vehicle VMT variable, which can influence traffic congestion and travel time parameters. Urban Mobility Reports of the Texas Transportation Institute defines congestion index of cities based on VMT and available roadway infrastructure (Lomax et al. 2011). Hereby, the model formulates the dynamics of urban lane-mile infrastructure and its increase rate for projection years for traffic congestion score estimates. Generation of private vehicle (drive mode) VMT, the total emissions of personal vehicles can be determined with average fuel economy estimation of light-duty vehicle fleet of the U.S. As it explained in following Section 6.2, alternative fuel adoption (fuel economy improvement) is considered as the BAU scenario. So, the average fuel economy of LDV fleet variable uses U.S. Bureau of Transportation Statistics (2015) for historical data series and Argonne National Laboratory's (2016) VISION model estimations for future years. Lane-mile is an important parameter of traffic congestion measures and it increases with the help of government agencies' funds in order to supply the demand of increasing VMT (Schrank. et al. 2015). Therefore, lane-mile, private vehicle VMT, and total number of personal vehicles parameters are utilized to form a linear regression that estimates travel time intervals. Following Equations 19 - 22 presents the variables of linear regression model estimation. Please also note that the variables shown in red color in Figure 48 imply the policy scenario related changes. For instance, AV policy related external VMT increase prediction is inputted to the 'private vehicle VMT' variable, as well as the average fuel economy (FE) improvement on LDV fleet prediction. Similarly, Lane-Mile (LM) policy scenario related limiting lane-mile increase rate at certain levels is affecting 'annual lane-mile increase' rate. Private vehicle VMT variable is also an important variable for overall air pollution emissions determination, since it leads to calculate overall fuel consumption based on fuel economy values and projections for the total passenger vehicle fleet in the U.S.

Travel Time (TT) less than 10 min = 0.235 + (-1.15E-08 * Lane Mile) + (-1.92E-14*"Private Veh. VMT") + (-4.82E-11 * Total number of passenger vehicles) [*19*]

TT_10 to 14 min = 0.222 + (1.74E-08 * Lane Mile) + (-3.18E-14*"Private Veh. VMT") + (-1.32E-10 * Total number of passenger vehicles) [*20*]

TT_15 to 19 min = 0.224 + (1.64E-08 * Lane Mile) + (-2.96E-14*"Private Veh. VMT") + (-1.03E-10 * Total number of passenger vehicles) [*21*]

TT_More than 20 min = 0.39 + (1.73E-08 * Lane Mile) + (-8.75e-16 * "Private Veh. VMT") + (7.59e-10 * Total number of passenger vehicles) [*22*]

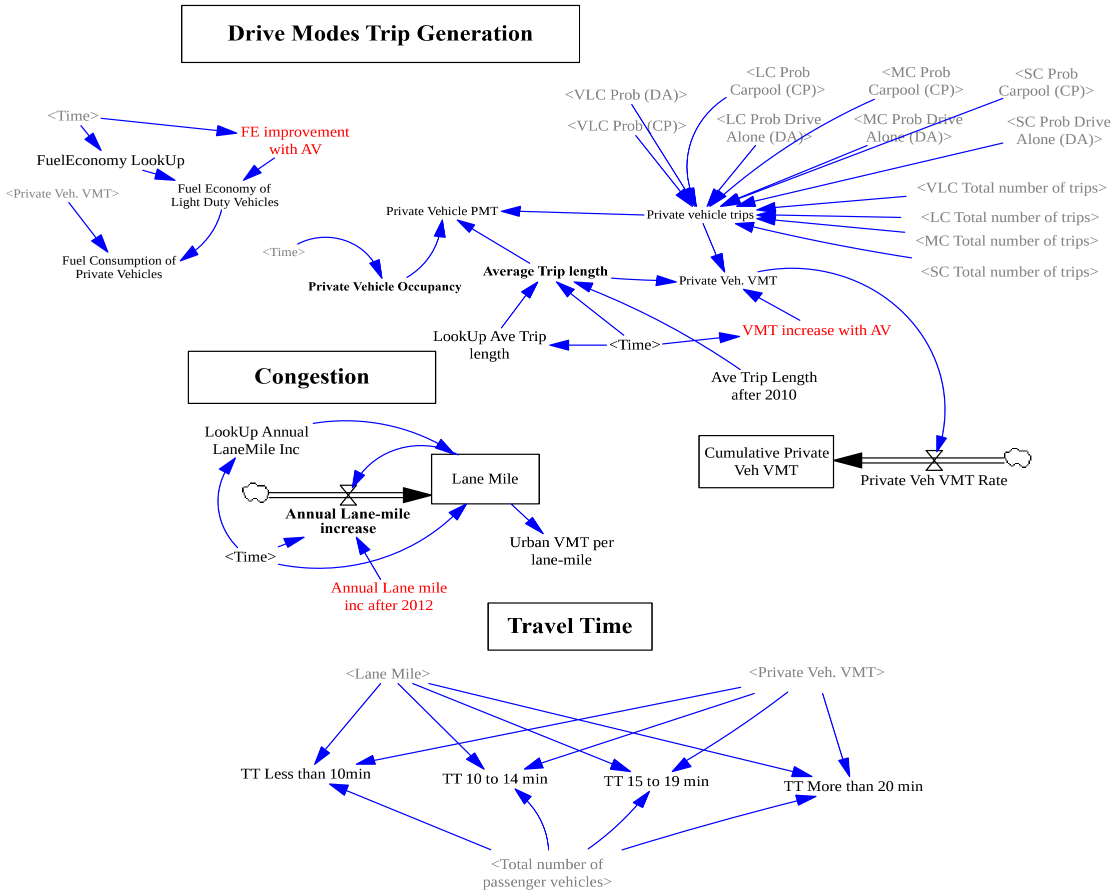


Figure 48: Drive modes trip generation, traffic congestion, and travel time sub-models

The overall impact calculations for drive modes and public transportation are determined similar to the sub-models that are explained in Chapters 3 and 4 (please see Fig. 9 and Section 4.2.3 for public transportation related emission calculations; Fig.10 and Section 3.2.5 for climate change impacts; Fig.25 and Section 4.2.5 for air pollution externalities; Fig. 26 and Section 4.2.6 total emission and externality calculations).

6.2 Policy Scenarios

As a great advantage of utilizing SD modeling approach, this chapter aims to test various policy scenarios on the U.S. urban transportation system for future references on transportation modes, emissions, and social impacts. Policy scenarios that are considered in this study are listed as follows:

- Alternative fuel adoption and fuel economy increase [Default Scenario] (*BAU*)
- Lane Mile (*LM*) (decrease of usual lane mile decrease)
- Carbon Tax (*CT*) (federal policy to collect tax revenue from vehicle owners based on their annual emission estimates)
- Automated Vehicle (*AV*) penetration (AV deployment related VMT, number of vehicle, and overall fuel economy changes).

The model considers that the vehicle efficiency will be improving in the U.S. with alternative fuel deployment and federal policy/incentives due (Noori et al. 2016; Noori and Tatari 2016; Onat et al. 2015, 2016c). Therefore, the average fuel economy of passenger vehicle fleet projections from the U.S. DOE is considered as a default scenario. In addition, energy source shares' for transit vehicles is considered to be shifted to alternative fuel as the current trends indicate (Ercan and Tatari 2015; Neff and Dickens 2015).

Lane mile (roadway expansion projects) increases in order to supply the demand of increasing number of vehicles and VMT, so that the level of service and traffic congestion measures can be lowered. However, alternative transportation modes cannot be competitive with the convenient of driving if the average travel time is not increasing significantly. Besides, lane mile increase will reach its limits due to land use limitations. Therefore, historical lane mile increase rate is considered as reduced around 50% after 2020 (U.S. Bureau of Transportation Statistics 2015).

Metcalf (2009) reviews the potentials and critics of carbon tax policy for the US, which is a policy effort that applies mandatory tax based on vehicle’s annual carbon emission estimates. It is highlighted as a necessary step to reduce emissions and also support the economy that is going through challenges due to climate change impacts (Stern 2007). However, as Metcalf (2009) also indicates, \$15/tone CO_2 can only increase the price of per gallon gasoline by 13 cents, which is equal to under 7% price increase. Therefore, this slight price increase is not expected to significantly change drive mode or travel demand behaviors. This study adopts \$13/tone CO_2 emissions policy scenario that starts on 2025 and applies with a constant rate until 2050 (WorldBank 2014).

Finally, in order to captivate with current technology developments in transportation sector and foresee the future of transportation revolution, AV penetration scenarios are tested. The literature is still in developing stage for AV related policy since there is still fully AV is not available in market but in testing stage so the research only relies on estimation data. Fagnant and Kockelman (2015) provides remarkable AV penetration level related behavioral change estimations such as VMT increase, total number of vehicle decrease, and overall fleet's fuel savings. Litman (2017) completes this effort for estimating the benchmark years that the market penetration levels. Following Table 21 summarizes the AV scenario related changes on the key parameters. Litman (2017) projects that AV's market penetration level will reach up to 50% in 2045 and defines further development as uncertain since it can increase exponentially after certain market levels. Therefore, in order to complete the estimations for our study's 2050 target year, all parameters are interpolated from both studies results (Fagnant and Kockelman 2015; Litman 2017). The model also combines lane-mile and carbon tax policy scenarios to present their overall impacts compare to only AV scenario and finally, combination of all three scenarios.

Table 21: AV scenario addition parameters

	Estimated Year for Market Penetration					Reference
	2020	2030	2045	????	2050	(Litman 2017)
Market Penetration	1% - 2%	10%	50%	90%	60%	(Fagnant and Kockelman 2015)
VMT Increase	1%	2%	8%	9%	8%	
Total number of vehicles	-1%	-5%	-24%	-43%	-28%	
Fuel Savings	11%	13%	18%	25%	20%	
Fuel Savings in overall fleet	0.17%	1.30%	9.00%	22.50%	11.85%	

6.3 Model validation

6.3.1 Multinomial fractional split model validation

Table 22: MAE and RMSE values at city level by mode

	Small City		Medium City		Large City		Very Large City	
Mode	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**	**MAE**	**RMSE**
Drive Alone	0.038	0.049	0.034	0.044	0.033	0.039	0.046	0.071
Car Pool	0.016	0.021	0.012	0.015	0.010	0.012	0.011	0.015
Public Transit	0.006	0.011	0.009	0.013	0.009	0.011	0.039	0.058
Walk	0.010	0.014	0.008	0.009	0.005	0.006	0.008	0.011
Other	0.006	0.009	0.005	0.007	0.004	0.006	0.003	0.005

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |actual - predicted| \qquad [23]$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(predicted - actual)^2}{n}} \qquad [24]$$

6.3.2 System dynamics model verification and validation

This chapter's model also follows the similar path of verification and validation approaches by Qudrat-Ullah and Seong (2010). Thus, one-way ANOVA test is performed on some of the selected key parameters of the model to provide statistical validation results. As the Table 23 presents, all of the selected parameter and/or results of the study are statistically valid. Similarly, figures of these four parameters are also illustrated below (Figures 49 - 52) to show how the model simulation results and historical behavior of that parameter matches. Although some of the figures indicate large value differences with simulation and actual data, it is due to the study boundaries and available historical data. For instance, Figure 49 implies that actual CO_2 emissions of the transportation system is higher than model's estimates. This model only considers urban commuters where the U.S. has tremendous amount of rural roadway activity that cause CO_2 emissions. It is crucial to highlight here that the value gap on the figures does not necessarily indicate non-valid model, as long as the lines matches for the behavior, which can be supported by statistical analysis.

Table 23: One-way ANOVA test results for some key results of the model

	p-value	**F**	**d_f**		**Mean Square**
			Between Groups	Within Groups	
Private veh. of VMT	0.000	242.99	24	1	2.041E+22
Total number of vehicles	0.000	313.58	23	1	5.171E+14
Transportation CO_2 Emissions	0.000	104.208	24	1	1.103E+15
Population	0.000	3720.28	24	1	3.397E+14

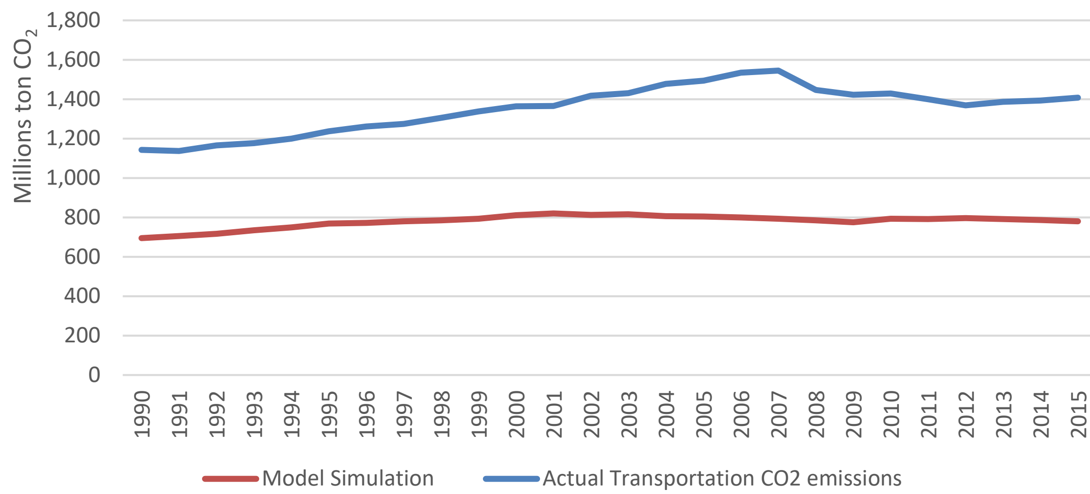


Figure 49: Behavioral reproduction of the U.S. transportation sector's CO_2 emissions

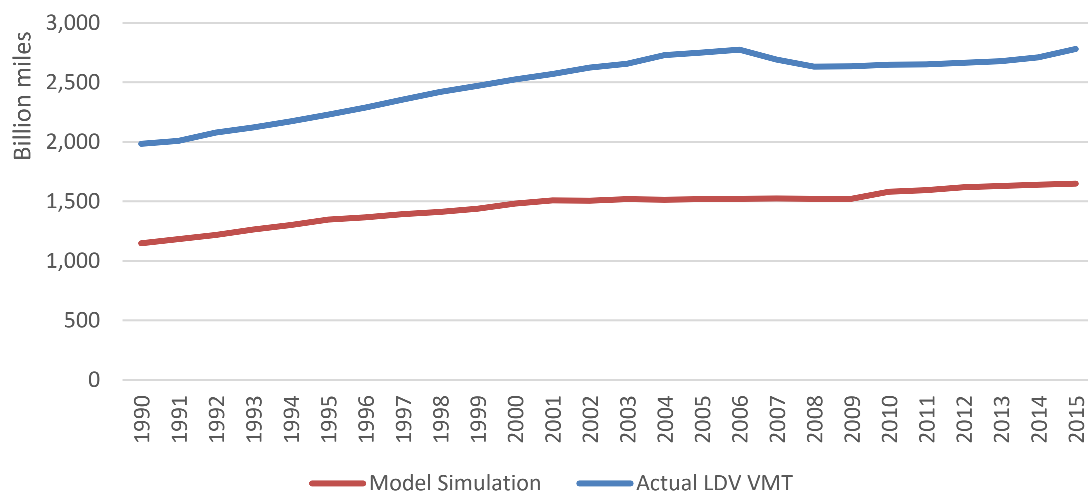


Figure 50: Behavioral reproduction of personal vehicle (or LDV) VMT

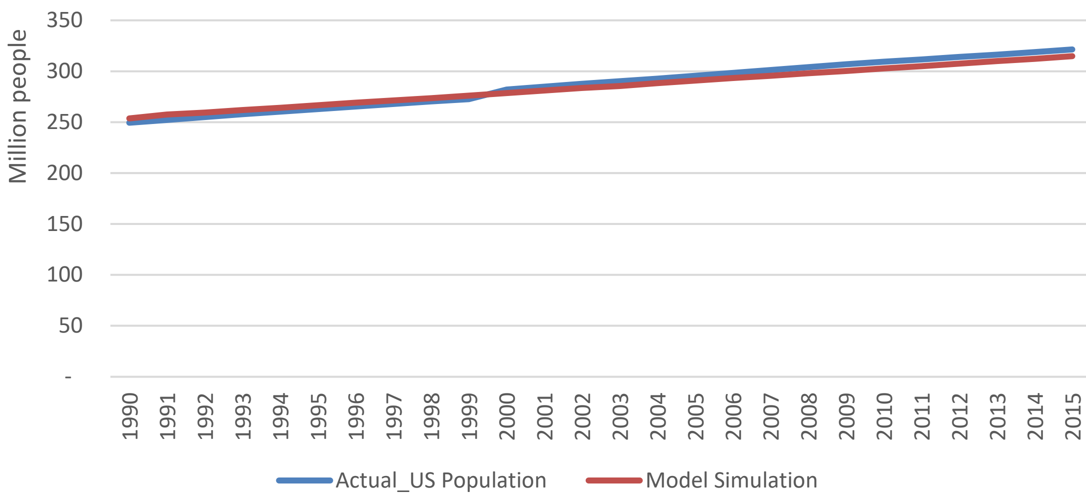


Figure 51: Behavioral reproduction of the U.S. population

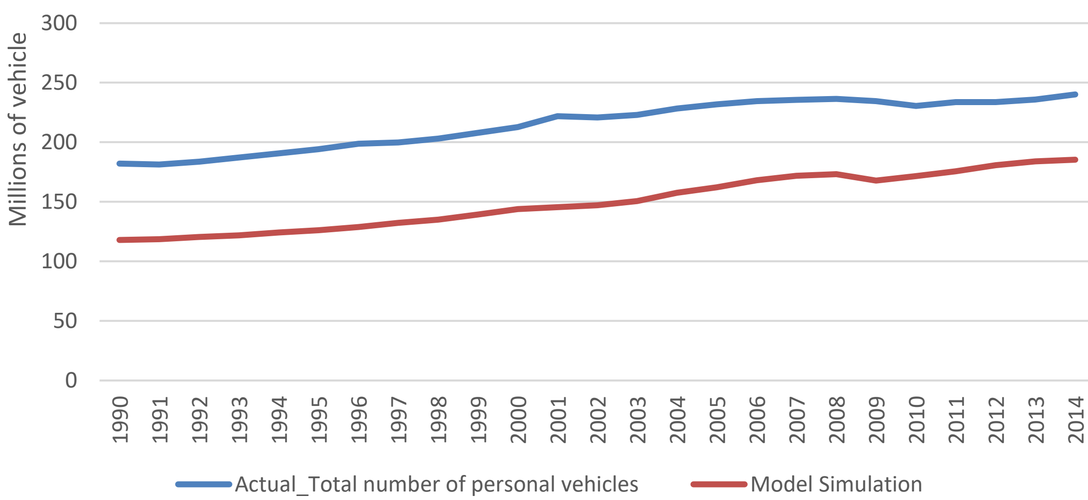


Figure 52: Behavioral reproduction of total number of the personal (or LDV) vehicles in the U.S.

6.4 Policy implementations for different city sizes

The outcomes of DES guide the hybrid modeling parameter selection and generate utility functions for each mode choices. Finally, the model run for overall urban transportation system in the U.S. reveals city size specific mode choice and impacts results with various policy scenarios. The combination of four city size groups and five mode choices with various impacts to present generates many crucial result graphs, however the manuscript is limited to show only some of these results such as city size specific mode choice changes and overall transportation system impacts (CO_2 emissions, air pollution externalities, marginal CO_2 emission changes) as follows.

6.4.1 Very Large City

Compare to average U.S. urban area transportation mode choice trends, very large cities are expected to present less drive alone mode but more public transportation mode choice (US Census Bureau 2016). Moreover, Figure 53a and 53b present this expected behavior for very large cities, where drive alone (DA) mode choice is between 73% and 78% and public transportation (P) mode varies from 5% to 11%. As can be seen from the graph, BAU and Lane Mile (LM) and Carbon Tax (CT) policy scenario results are quite similar, yet LM+CT scenario decreases DA mode choice by 0.1% in 2050. This slight impact of LM+CT policy scenario is also observed for all other modes in very large cities and does not present any behavioral change. However, AV scenario indicate interesting trends where it shifts the behavior of DA, P, walk (W), and other mode choices.

As opposed to LM+CT policy, AV scenario decreases the increasing trend of DA mode by almost 3% in 2050. Although there are 27 very large cities, they represent a great portion of the commuter population (21% of the total population as shown in Table 18) and this rate change of each year can provide tremendous energy consumption savings and emission reductions from personal vehicles. The only mode choice that is not significantly affected by AV scenario is CP mode choice. This insignificant relation of AV scenario and CP mode can be explained with the statistical relation that is indicated in Section 5.3., which shows that CP mode is only affected by gender, the oldest age group, longer commute time, and rental house attributes. AV scenario does not directly affect any of these attributes so the decrease is limited with 0.13% in 2050 compare to BAU scenario.

Public transportation trends are already decreasing for very large cities and this decrease is associated with increasing number of personal vehicle ownership and travel times. With the AV scenario addition, this decreasing trend becomes even more severe and reach around 3.5% in 2050. AV penetration scenario dictates that at least one vehicle ownership in the household will be increasing and this attribute becomes the dominant effect on the system to cause this decrease. It can be interpolated that VMT increase projection and transit ridership decrease for AV scenario overlay with each other since commuters can choose DA or other modes.

For BAU or LM+CT scenarios, W mode indicates decreasing trend where other modes continue with steady trend over the study period. However, AV penetration imply surprising impacts on these modes by changing their behavior and increase both mode choices. Along with other attributes that significantly affect W mode choice, proportion of two or more vehicles in the household cause the dominant impact and dramatic decrease of this attribute with AV penetration cause the W mode choice increase. It can be highlighted here that this increase indicates a behavioral change on the graph, however it is 1.2% of difference in 2050 compare to BAU scenario results. It is more difficult to interpret the results of other mode choices, since it consists of several different modes (i.e. cycling, taxi, etc.) and each of these modes have its own dynamics. Dramatic change of number of vehicles again cause the dominant impact on other mode choice, where remaining significant attributes neutralize each other. With the absence of many vehicles in the household, it can be observed that commuters tend to switch their mode to alternative modes.

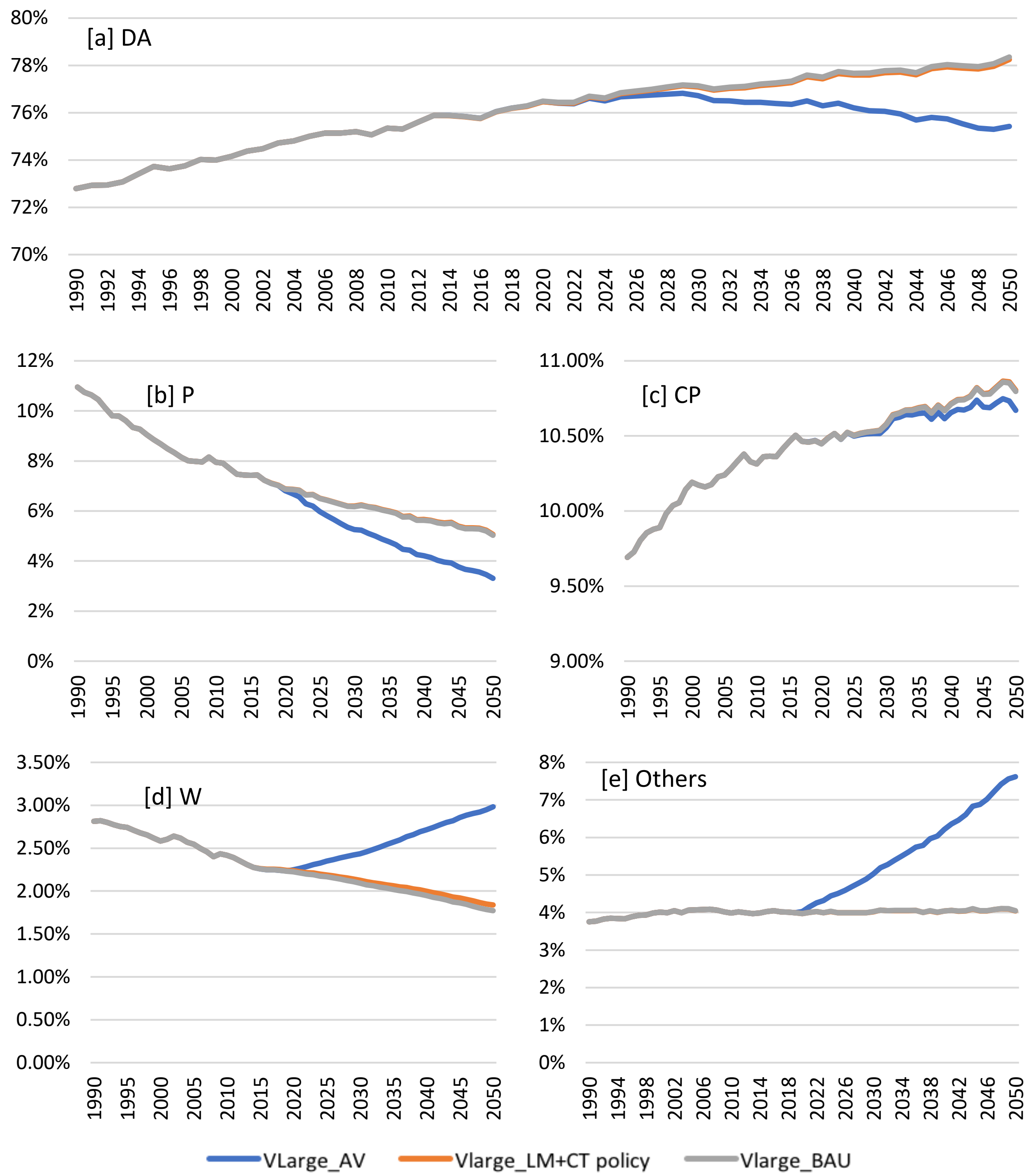


Figure 53: Transportation mode choice of *Very Large* cities: [a] Drive Alone (DA) mode choice; [b] Public Transportation (P) mode choice; [c] Carpool (CP) mode choice; [d] Walk (W) mode choice; [e] Other mode choice

6.4.2 Large City

Large cities consist of 24 metropolitan areas of the U.S. in this research and represent 6% of the total population. As oppose to very large cities, large cities already have more than 80% of DA mode choice and this rate tends to increase linearly for future years. LM+CT policy scenario indicate a slight effort to decrease this trend by 0.08% in 2050. However, AV penetration can change this trend drastically and lower the DA rate by 3.25% in 2050 as shown in Figure 54a. As the base mode choice for the DES model, all of the significant attributes of the model have impact on the estimates of DA mode choice over study period. In addition, due to the feedback relation of dynamic model, it can be stated that DA mode is under the influence of all model parameters. However, the drastic change of number of vehicles in the HH can be responsible for the dramatic decrease with AV penetration, since LM+CT policy scenario does not provide significant changes although it increases the travel time and vehicle ownership costs. As another drive modes, CP mode choice indicate a slight increase for BAU scenario in future years and AV scenario also causes a decrease on this behavior (please see Fig. 54c). However, the changes in CP mode choice is only limited with 0.16% in 2050 between BAU and AV scenarios. Moreover, the overall CP mode choice change from 1990 to 2050 is only 0.67%.

Transit ridership for large cities already less than the half of very large cities' P mode choice and it is expected to decrease over the study period as shown in Figure 54b. AV penetration impacts cause a stepper decrease on the mode choice, however this impact is not even greater than 1%. Therefore, the impacts on the P mode choice is limited due to its small scale. Similar to other cities behavior on W and other mode choices, these modes are increasing with AV scenario addition. However, only other mode related changes can be considered significant with 3.3% difference in 2050 between BAU and AV scenarios, since W related difference is limited to 0.8%.

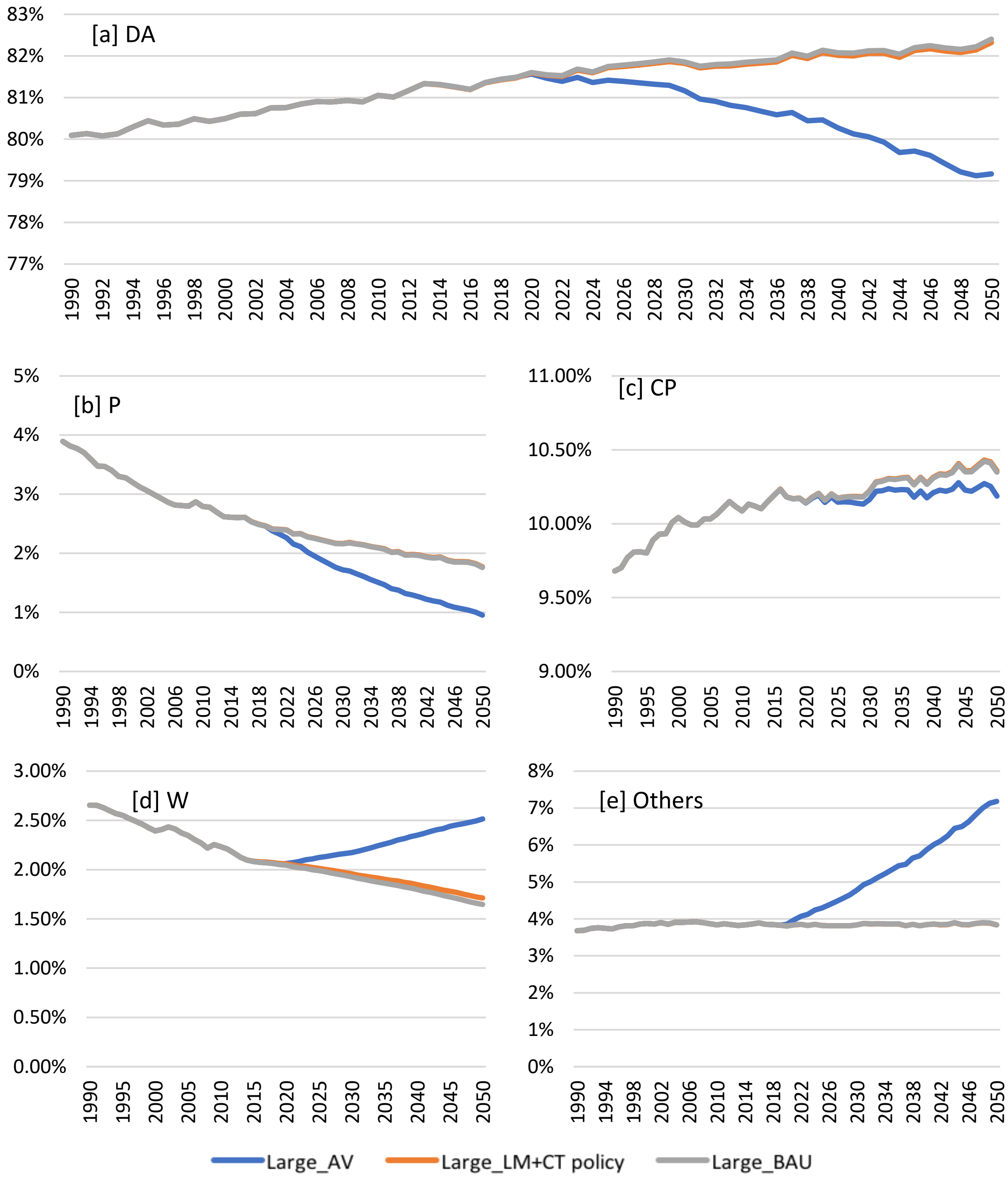


Figure 54: Transportation mode choice of *Large* cities: [a] Drive Alone (DA) mode choice; [b] Public Transportation (P) mode choice; [c] Carpool (CP) mode choice; [d] Walk (W) mode choice; [e] Other mode choice

6.4.3 Medium City

Medium cities consist of 63 metropolitan areas of the U.S. in this research and represent 6% of the total population. Medium and large cities present similar mode choice results in terms of scale and representation area. For instance, DA mode choice for both of these cities are around 80%-82% range for BAU scenario and this similar scale can be observed in remaining mode choice graphs of Figure 55a-e. AV addition related decrease on DA mode is more significant for medium cities, since it reaches up to 4.2% in 2050 compare to BAU scenario. Likewise, AV influence on W mode choice is around 1.5% and reaches up to 3.35% for other mode choices.

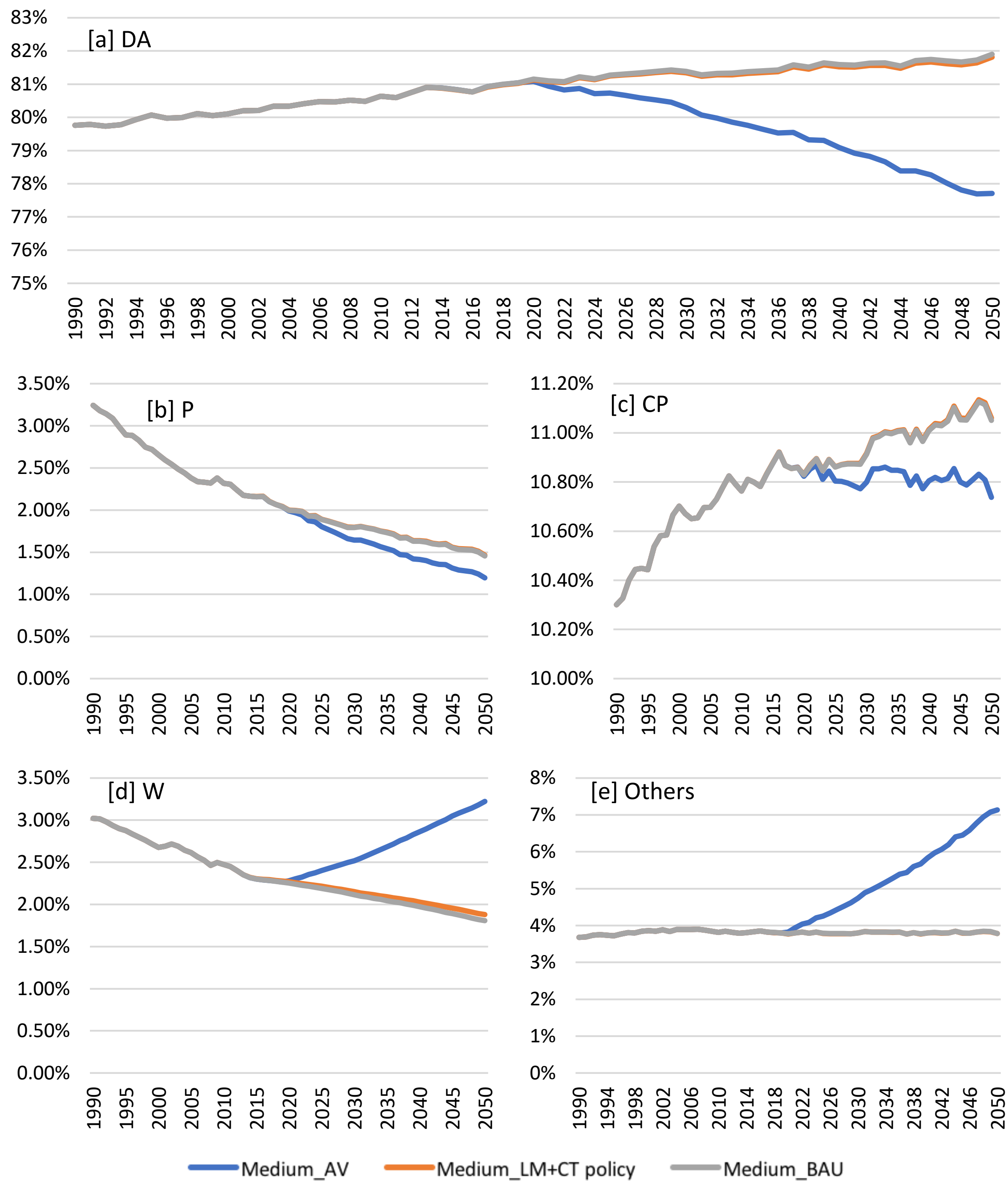


Figure 55: Transportation mode choice of *Medium* cities: [a] Drive Alone (DA) mode choice; [b] Public Transportation (P) mode choice; [c] Carpool (CP) mode choice; [d] Walk (W) mode choice; [e] Other mode choice

6.4.4 Small City

Finally, small cities consist of 815 metropolitan and micropolitan areas of the U.S. in this research and represent 11% of the total population. Although it consists of majority of urban areas, the population total does not exceed the total population of very large cities. LM+CT and AV policy scenarios both decrease the BAU scenario's DA mode choice projections, however LM+CT related impacts are limited almost 0.1% where AV cause 4.4% decrease. The DA mode choice reaches the highest level compare to other city groups, however it also does not significantly differ from large and medium cities' DA range.

In Figure 56b, P mode choice extents the lowest rate compare to other city groups, due to lack of transit system existence in some of the urban areas in the dataset. Moreover, the existence of transit system for small cities can be questioned here, since it only ranges from 0.8% to 1.6 % throughout the study period. The DES results also support these findings since small city has the highest negative relation on P mode choice. AV addition reduce the already decreasing P mode by 0.1% in 2050. Therefore, it is not durable to discuss any policy impact on this mode choice.

CP mode choice has identical behavior with other city groups and varies in less than a 1% range. LM+CT policy has a noticeable impact on W mode in Figure 56d by 0.09% in 2050, but this is still negligible compare to AV related 1.76% increase compare to BAU scenario. Small cities also react to other mode choice increase with AV addition in to the market and extents up to 6.8% in 2050.

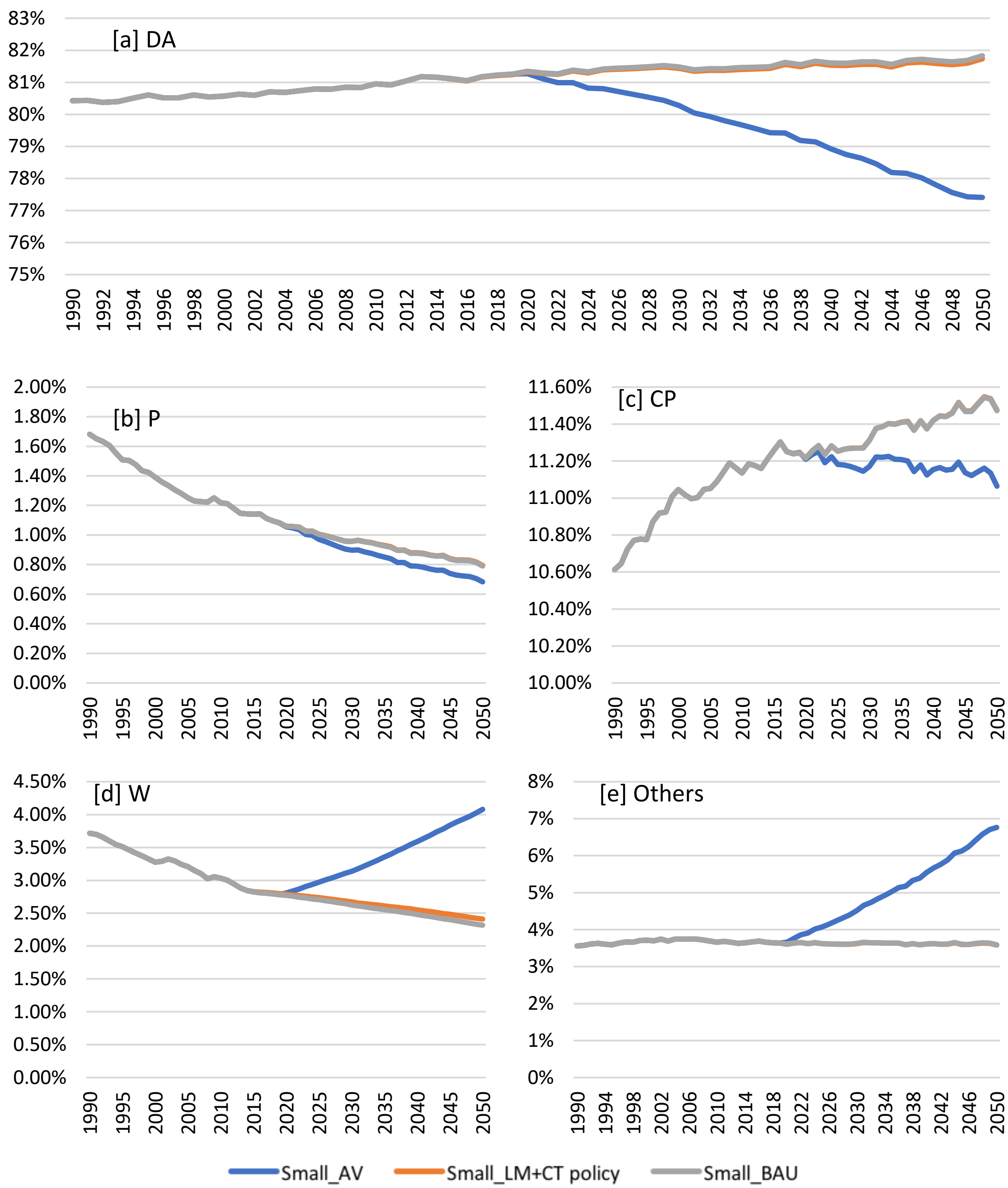


Figure 56: Transportation mode choice of *Small* cities: [a] Drive Alone (DA) mode choice; [b] Public Transportation (P) mode choice; [c] Carpool (CP) mode choice; [d] Walk (W) mode choice; [e] Other mode choice

6.5 Overall Transportation System Impacts

As a result of the mode choice trends for urban area commuters, the two drive modes (DA and CP) and the public transportation (P) mode all contribute to the overall impacts of the U.S. transportation system as previously described in Section 6.1.2. It should be noted here that other mode choices ("Other") include taxi cabs and motorcycles, both of which also have air pollution impacts, but these impacts are beyond the scope of this study. Recalling the policy scenarios previously described in Section 6.2, four policy scenarios (BAU, LM, LM+CT, and AV) are tested from 2017 to 2050. As indicated in previous mode choice estimates for different cities, the LM and CT scenarios are simulated together rather than separately due to their limited influence on their policy results compared to the results under the BAU scenario. The detailed results of the AV scenario for emissions and externalities are presented in the following figures for each city group.

Before presenting the impacts of policy practices on emissions and externalities, the AV policy influence on total number of vehicles and personal vehicle ownership rates should be presented. As expected from AV scenario parameters, vehicle ownership is decreasing significantly, which can be seen in following Figure 57. Vehicle availability rates in the household are presented in Figures 58 – 60.

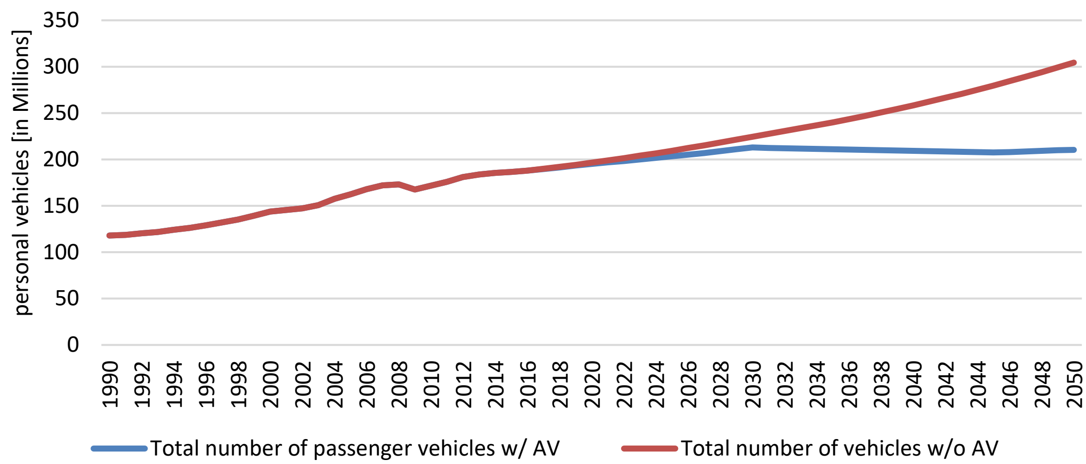


Figure 57: Total number of vehicles with and without AV market penetration scenario

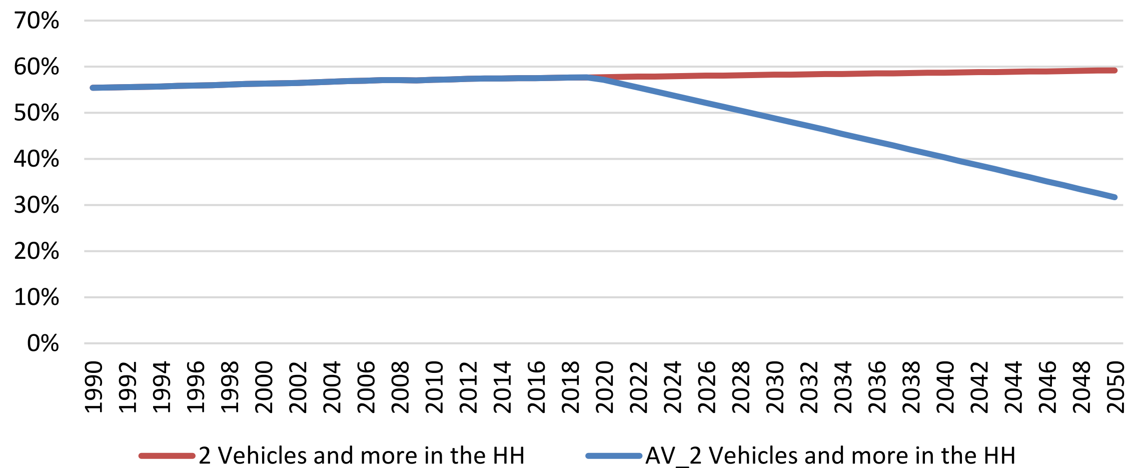


Figure 58: Percentage of households (HHs) two or more vehicles available with and without AV market penetration

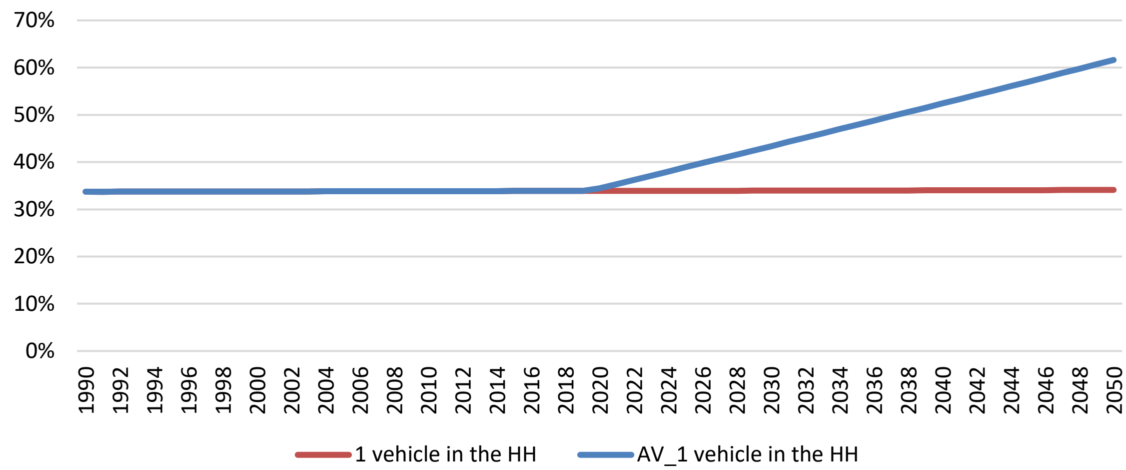


Figure 59: Percentage of households (HHs) one vehicle available with and without AV market penetration

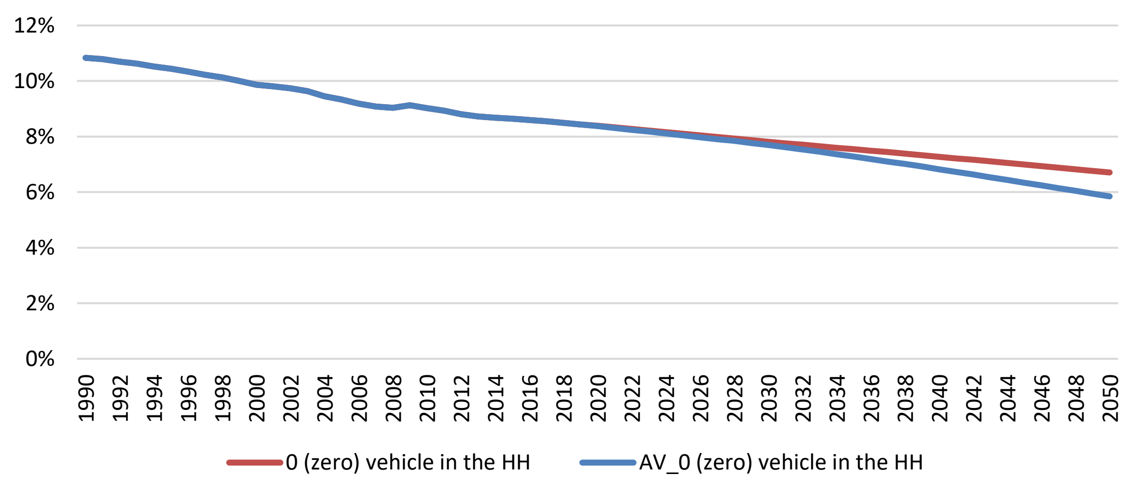


Figure 60: Percentage of households (HHs) zero vehicle available with and without AV market penetration

Figure 61 presents a cumulative graph of the total transportation-related annual CO_2 emissions under the AV scenario for all four of the city groups considered in this dissertation. The total annual CO_2 emissions under the BAU and LM+CT scenarios are shown as a single line that indicates the total emission rate from all city groups. These CO_2 emissions are already experiencing a decreasing trend due to fuel economy improvements and alternative fuel adoption, which has already been included in the BAU scenario. The LM+CT scenario follows the same path in the graph as the BAU scenario, but only yields 0.64 million tons annual CO_2 emission reductions by the year 2050. Conversely, the total CO_2 emissions under the AV scenario demonstrate a much greater reduction of up 51.3 million tons (a 7% decrease) between the BAU and AV scenarios by the year 2050. Although the emission reduction potential of the LM+CT scenario is not negligible despite being much smaller than that of the AV scenario, the CO_2 emission results clearly illustrate the potential of AV market penetration to reduce the number of vehicles on the roadway and improve energy efficiency despite its increases in the overall VMT of the U.S. transportation sector.

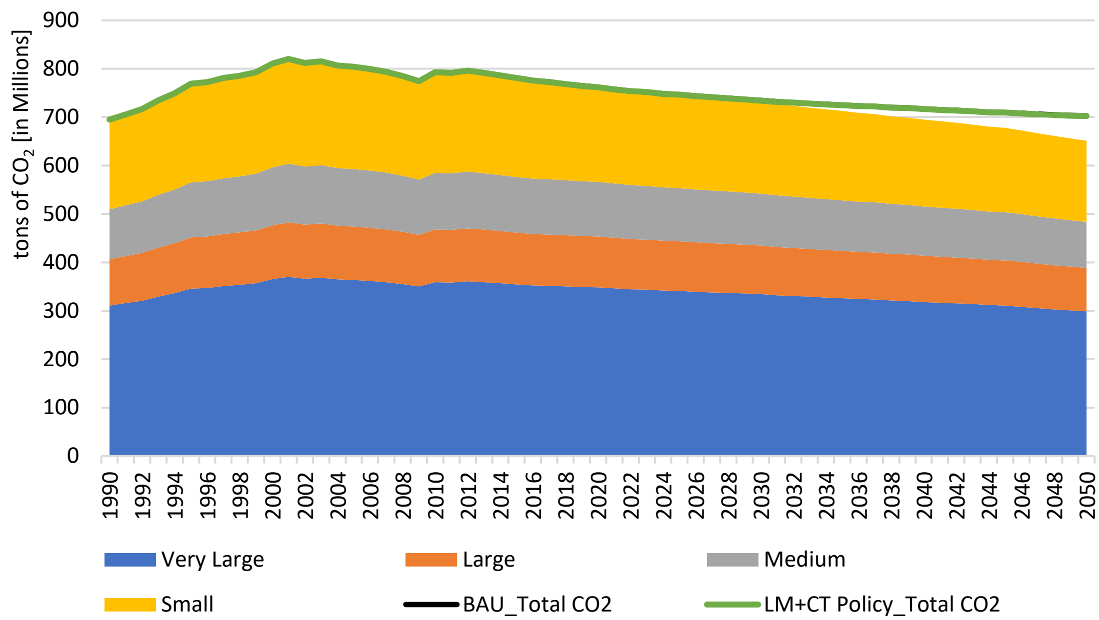


Figure 61: Total annual CO_2 emissions from urban passenger transportation in the U.S. under the AV adoption scenario: Cumulative emissions of city sizes, Business as Usual (BAU) scenario, and Lane mile + Carbon Tax (LM+CT) Policy Scenario

Figure 61 presents the annual CO_2 emission rates from commuter transportation activities, this time illustrating emission reductions and increases as a cumulative impact on the environment in addition to the emissions from the rest of the world. Therefore, illustrating the cumulative marginal differences in the LM+CT and AV scenarios relative to the BAU scenario for the duration of the study period can provide insightful information. Figure 63 illustrates these marginal differences for each city group with respect to the AV and LM+CT scenarios separately, adding up each year's CO_2 emission differences compared to the results of the BAU scenario. Hence, due to the increase in

VMT (as can be seen in Figure 62) and the slight benefits of the AV scenario in the initial years of AV market penetration, CO_2 emissions are increased, and this increase accumulates to almost 13.5 million tons of CO_2 for very large cities only. However, with the AV market penetration benefits previously observed, this behavior changes exponentially until the cumulative marginal difference for very large cities alone reaches up to almost 200 million tons of CO_2; the total summation of the corresponding marginal emission difference for all city groups under the AV scenario is 474 million tons of CO_2 by the year 2050, although it must be noted that this value is a net difference that accounts for the initial drawback impacts. On the other hand, the LM+CT scenario also yields crucial emission savings, but these savings cannot be seen in the graph due to their smaller scale; the total emissions from all city groups not shown in this regard for this scenario is limited to 13.7 million tons of CO_2.

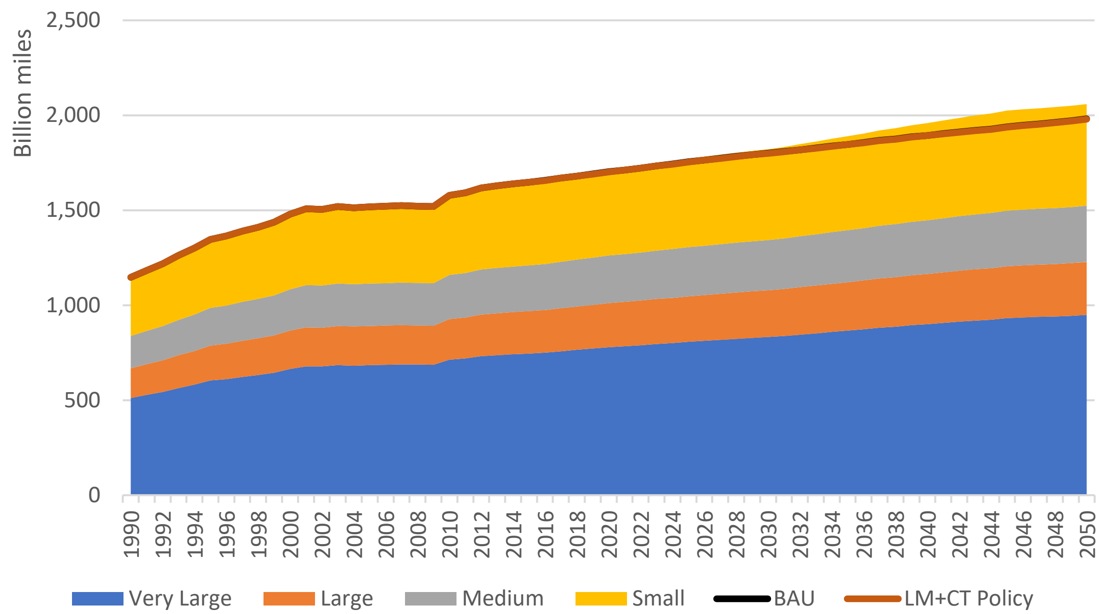


Figure 62: Annual VMT of drive modes (DA and CP) for urban area commuters

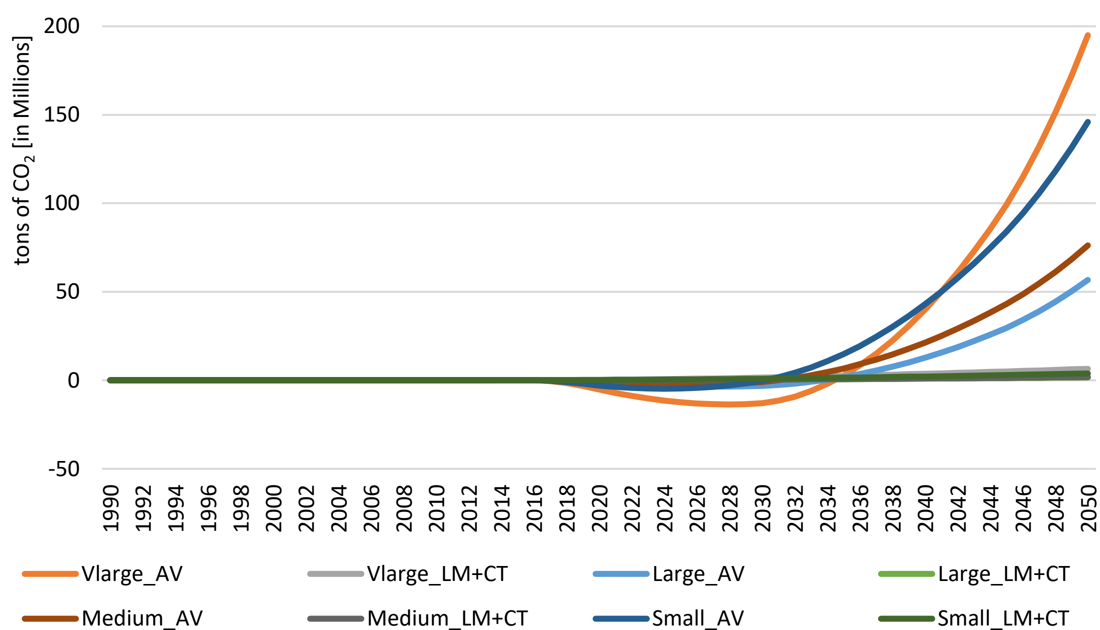


Figure 63: Marginal cumulative differences in CO_2 emissions compared to the BAU scenario for all city groups

All of the hybrid-modeling results corresponding to the aforementioned insignificant impacts are shown in the remainder of this section with respect to three possible policy scenarios. Figure 64 present these results in terms of the per-capita change in CO_2 emissions from 2017 to 2050 under all policy scenarios. As previously observed in Figure 61, CO_2 emissions are already experiencing a decreasing trend, and this trend alone yields a 28% emission reduction per capita under BAU scenario. This emission reduction is not noticeably different from those of the LM or LM+CT policy scenarios, each of which only yields a change of 0.07% compared to the BAU scenario. Conversely, the AV scenario yields a much more significant change of almost 34% from 2017 to 2050, which amounts to a difference of 5% relative to the BAU scenario. The model also tested the impacts of all three scenarios combined in order to test the possibility of a greater collaborative impact from all policies operating simultaneously, but this combination (the AV+LM+CT scenario) does not demonstrate any noticeable difference from the results of the AV scenario.

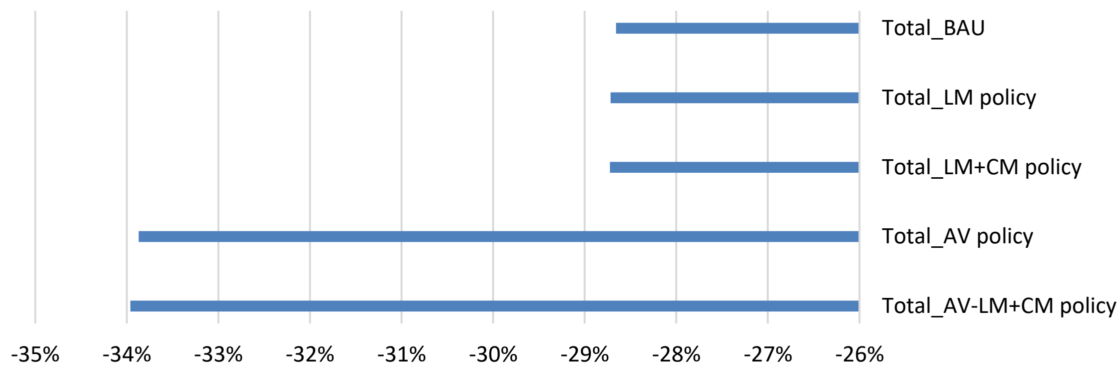


Figure 64: Marginal per-capita CO_2 emission changes by all policy scenarios from 2017 and 2050

The model also calculates the air pollutant emissions from personal vehicles (considered in this study to be light-duty vehicles) and transit vehicles in terms of CO, NO_X, SO_X, PM_{10}, $PM_{2.5}$, and VOC emissions in addition to CO_2 emissions. The marginal damages of these air pollutants (i.e. social cost or externalities) are converted into monetary values as explained in Section 6.1.2. These externalities are crucial for sustainability assessment of urban transportation design, since the ultimate goal of all of the accumulated literature and research in this regard is to improve air quality and (by extension) overall quality of life. Figure 65 summarizes the results of the externality calculations under the AV scenario, which are shown as cumulative areas for each city group while the total BAU and LM+CT scenario results are shown as single lines. The improved energy efficiency projections under the BAU scenario already contribute to a relatively steady behavioral pattern in externality values, while the impacts of AV market penetration begin to show a visible influence in overall externality levels after the year 2040, although the AV scenario still shows an optimistic reduction trend in future years. Although the overall decrease under the AV scenario may seem limited, the difference between the externality results under the BAU and AV scenarios is approximately $1.5 billion in the year 2050. It should also be noted that this number only corresponds to a one-year difference, while the decreasing trend under the AV scenario predicts promising externality savings for future years at higher AV market penetration levels.

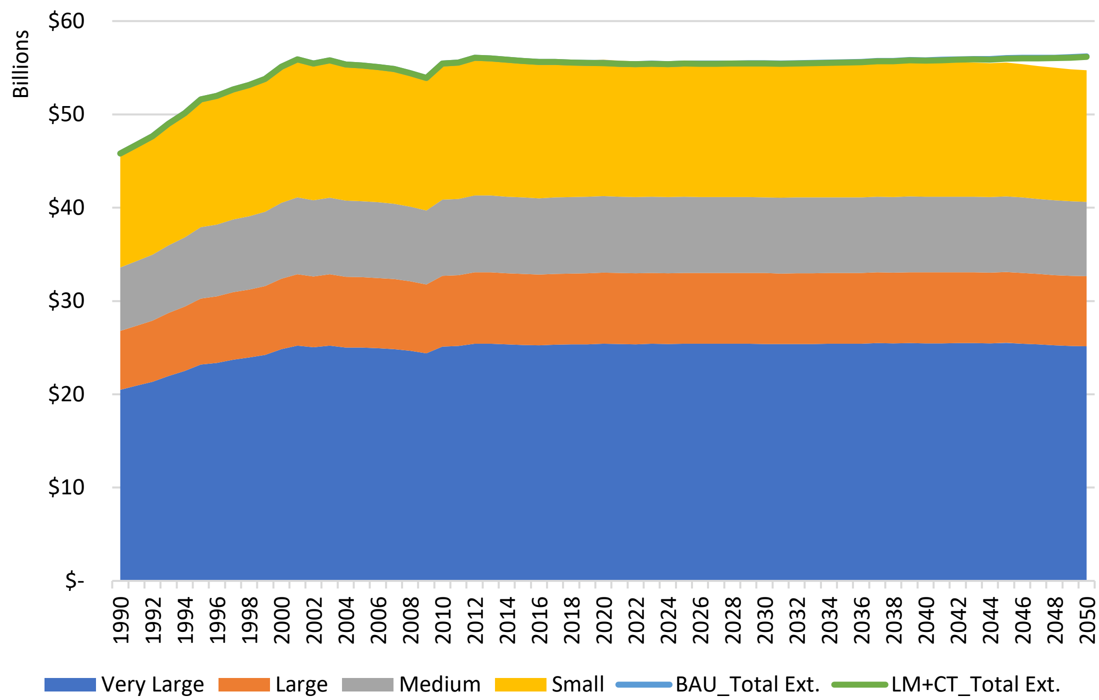


Figure 65: Total annual air pollution externalities of urban passenger transportation in the U.S. under the AV adoption scenario: Cumulative emissions of all city sizes, Business as Usual (BAU) scenario, and Lane mile + Carbon Tax (LM+CT) Policy Scenario

CHAPTER SEVEN: CONCLUSIONS AND LIMITATIONS

As the population of the U.S. grows and people make more trips per day, the number of vehicles on roadways is increasing every day. Moreover, today's transportation sector is still highly dependent on limited resources such as fossil fuels, land use, etc. As has already been highlighted in literature and government reports, it is expected that society will need to move away from private vehicles in favor of public transportation, walking, cycling, and other more sustainable alternatives in order to mitigate GHG emissions and climate change impacts. Overall modeling efforts and related policy practice results are summarized in following Figure 66. As it indicated in previous chapters each model and policy tests agreed on a single conclusion that paradigm shift is mandatory from current transportation system, urban development, and prevailing policy practices. Key findings, policy implementation, and detail discussions of the overall dissertation can be found below.

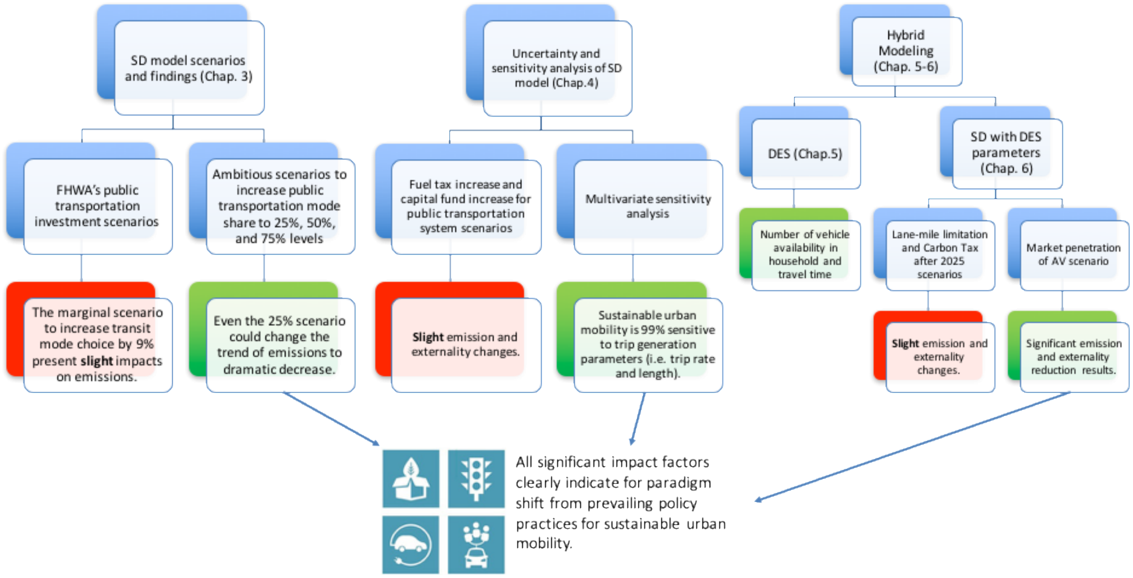


Figure 66: Overall dissertation findings summary

The first SD model in this dissertation (Chap. 3) simulated the labor force population, number of person-trips, transportation mode preferences, fuel/energy consumption, and CO_2 emission impacts. The SD approach allowed the author to forecast future CO_2 emission impacts given predicted population growth trends and private vehicle usage trends in the U.S., and possible policy implementations were examined in order to evaluate their potential to reduce or eliminate increasing trends in CO_2 emissions and energy consumption. The results of this first model (Chap. 3) indicated that public transportation has the potential to reduce or even partially eliminate the currently increasing trends in CO_2 emissions and energy consumption. Although the pre-defined scenarios prescribed for increasing funding for public transportation did indeed have an influence on CO_2 emissions that reduced the increasing annual trends to an extent, these scenarios on their own were not enough to change the currently increasing annual emissions trend to a decreasing trend. It was also noted that the adoption rate of alternative fuel options for public transportation vehicles has been increasing, and an additional policy can be implemented to this effect in order to reduce fossil fuel usage. In conclusion, these two policies should be supported by more aggressive policies, which might cause political challenges for decision makers. However, the ambitious scenarios prescribed in this study are not too unrealistic to consider, since even the most conservative of these ambitious scenarios (25% transit growth) has potential to significantly change current trends in fuel consumption and CO_2 emissions to decreasing trends. Expected private vehicle fuel economy improvements have also been included in the developed model, and these improvements contributed significantly to reductions in the currently increasing trend in CO_2 emissions. Moreover, due to the current predominance of private vehicle usage, it is safe to say that public transportation policies alone are not enough to change this high degree of dependency. That said, it must be noted that, because this first model only focuses on public transportation as a means to mitigate CO_2 emissions, future projections of alternative fuel market shares for private vehicles as a separate policy initiative are not included in this chapter.

Most public policy decisions are made in inherently uncertain situations. Although the first model analyzed the public transportation from a systems thinking perspective, which can provide insights with which to better understand the dynamic complexity of the U.S. public transportation system and its interactions with the economy and the environment, the model created in that chapter needs to be improved with an integration of uncertainty analysis. To this end, Chapter 4 advanced the SD model to test the robustness of applied policies and to deal with deep uncertainties not accounted for in Chapter 4.

In the light of second SD model's multivariate sensitivity analysis (Chap. 4), the most critical parameters influencing the model outputs (private VMT, transit ridership rate, transportation related CO_2 emissions, and externalities) are the average trip generation rate and the average trip length, which influenced mode choice outputs greatly with a combined sensitivity coefficient of 99%. Even though the initial sensitivity analysis was later redone (excluding these two most sensitive parameters) in order to analyze the impacts of other parameters, transit trip length was found to be the dominant parameter as shown and explained in Figure 36. Although the developed SD model consists of reinforcing/balancing feedback relationships that quantify transportation mode choice behavior, none of these relationships cause impacts on mode choice as significant as those due to changes in trip generation rates and/or characteristics. For example, the available funding (i.e. gasoline fuel taxes and/or capital funding) for transit systems, the discouraging effects of traffic congestion on private vehicle use, and the negative impacts of emissions on life expectancy and GDP all have minor impacts on mode choice. Overall, the findings in Chapter 4's model support the initial hypothesis as stated in the first chapter of this dissertation, and highlight the importance of urban infrastructure as the current root cause of excessive trip generation and increasing average trip lengths.

According to the analysis, a sustainable urban mobility in the U.S. will require radical infrastructure changes in urban transportation structure, which demands a paradigm-shift in society's perceptions and beliefs about how urban structures should be. The required changes in urban structure might be implemented through policy initiatives to modify the current standard for the typical 'American lifestyle' so as to reduce private vehicle dependency and preference levels (e.g. increasing the cost of car ownership) or making urban areas more transit-oriented by creating more compact communities, among other possibilities. Such radical changes cannot realistically be implemented in the near future, but should at least shape the society's perception of the problem. As an alternative near-future solution option, autonomous vehicles are the most promising initiatives to increase the existing infrastructure capacity and encourage ride share mode for urban areas, which is tested in Chapter 6. Pointing out the anomalies and failures in the old paradigm, working with the vast middle ground of people who are open-minded, education future generations aware of the anomalies in the old-paradigm are some of the ways for a paradigm shift in urban structures as well as U.S. transportation system (Kuhn 2012).

The overall SD model results indicate that, under current policy practices, urban transportation mode choice behaviors in the U.S. are not expected to shift from private vehicles to public transportation in the foreseeable future, but the encouragement and regulatory implementation of greater fuel economy may result in a decreasing trend in transportation-related CO_2 emissions. This decrease in CO_2 emissions does not ensure a similar decrease for air pollution externalities, but will nevertheless provide a steady trend. The emission-related findings emphasize the importance of using alternative fuels and improving fuel economy whenever possible. Although these findings are not directly related to the problems currently pertaining to transportation mode choice, they nevertheless illustrate an important part of the problem of transportation-related pollutant emissions worldwide. Therefore, the currently high fossil fuel dependency of the U.S. transportation sector means that future vehicles and transportation systems should switch to alternative fuel sources as quickly and as effectively as possible, and more efficient fuel technologies should also be utilized in marginal levels.

A comprehensive cash flow analysis (Chap. 4) of transit transportation systems indicates large operation costs, which are often higher than total fare revenues. Therefore, transit systems should also be supported with additional funding, including fuel tax revenues, federal/local government funds, and additional capital funds. Transit systems should also be operated with more cost-effective policies, at least to a sufficient degree that the fare revenues can balance out the operation costs. Like with alternative fuel use initiatives, operation cost reductions can be implemented with more efficient fuel systems, including alternative fuel systems such as hybrid and battery-electric vehicles.

Although roadway transportation infrastructure capacity and traffic congestion relief policies are beyond scope of this dissertation, the corresponding feedback relationship defined in this model indicates that traffic congestion should be relieved primarily by implementing new technologies (Intelligent Transportation Systems (ITS), autonomous vehicles, etc.) and not solely by attempting to expand current roadway infrastructure. In addition, efforts to reduce traffic congestion should also be used to guide future policies for shifting transportation mode choice away from private vehicles in favor of alternative modes.

The DES modeling (Chap. 5) results indicated that city size only influences public transportation mode choice, whereas the number of vehicles owned per household was found to significantly impact almost all of the considered mode choices, which can provide a great deal of insight regarding the aforementioned vehicle dependency statistics in the U.S. As more vehicles are available per household, the more likely commuters are to become heavily dependent on dive modes, among other urban development impacts. Travel time is another key factor (particularly with respect to the carpool, public transportation, and walk modes), which overlays with current trends in U.S. transportation mode choice. These travel times are typically long due to low-density residential developments, disproportions between the residential and employment densities of a particular area, and increasing traffic congestion due to growing numbers of vehicles on roadways. The above-cited factors all strengthen the already-predominant share of the drive alone mode choice and reinforce the urban development factors that worsen the current problems with today's transportation industry. These problems, therefore, cannot be properly addressed using only short-term policy resolutions, but will instead require a more long-term paradigm shift.

Other significant attributes in the DES model that cannot be realistically controlled or tested for polices included gender, age groups, employment, house occupancy (rental VS ownership), and the time when a commuter leaves home for work. Some might argue that the time when one leaves for work can be changed using workplace policies to encourage starting work at more optimal times of the day, and there are indeed some examples of such policies being implemented in several cities around the world. However, such policy applications aim mainly to reduce traffic congestion by distributing the peak-hour traffic load across a larger time span. Such policy application impacts can still be tested, but this dissertation has limited its scope by considering the time of leaving for work as an exogenous variable. The primary reason for this boundary limitation is that this model considers 929 urban areas nationwide whereas to model and test this policy would require very specific data from each urban area, thus requiring an overly extensive modeling process for only one attribute.

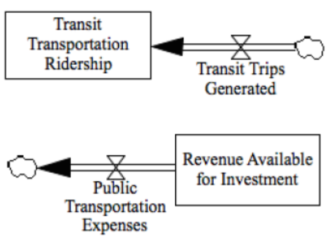
The developed hybrid model simulated in this dissertation (Chap. 6) was first used to illustrate the business-as-usual (BAU) results for transportation mode choice and emission impacts from 1990 to 2050. The BAU scenario itself showed interesting findings in terms of the mode choice behaviors of each city type, as the drive alone mode choice share increased while the public transportation and walk shares decreased and the shares of the carpool and other modes remained almost steady throughout the study period. This behavior in the BAU scenario, which matched the aforementioned current trends, was then subjected to a policy scenario analysis in order to identify the most efficient policies for decision makers to resolve these issues. As previously explained in detail, the nearly negligible effects of the LM+CT policy scenario indicated that traditional policy efforts that subsidize and/or punish different mode choices do not adequately support any meaningful long-term behavioral change. These policies are both considered "traditional" policies in this study because the transportation sector is currently undergoing a revolution by exponentially adopting electric vehicles, autonomous vehicles, and ride-share mode. Furthermore, past research efforts over the last few decades have already examined similar traditional policy scenarios, but have all failed to produce any significant shift from drive modes to alternative transportation modes. Today's reformist era of transportation, in contrast, has the potential to radically change many of the factors and indicators related to transportation mode choice behaviors, including the built environment, vehicle ownership, air quality measures, and several other key factors. To simulate an example of this technological revolution, AV market penetration was tested as an external policy factor for its possible impacts on the transportation system. The results of the AV market penetration scenario in this regard indicate significant promise for considerable reductions in emissions and externalities, decreasing drive alone mode shares while also increasing the walk and other mode choice shares. However, AV market penetration also caused a rebound effect by increasing the VMT, most notably because a growing number of households own at least one vehicle and society as a whole (especially vehicle owners) are expected to benefit from the relative convenience of AVs. This finding also aligns with a recent literature study that expects to add non-drivers, the elderly, and people with travel-restrictive medical conditions to the roadway commuter population in future roadway systems (Harper et al. 2016). This impact was observed in the model as a decrease in public transportation mode choice shares with increasing AV market penetration. The AV scenario also resulted in an increase in mode choice shares for the walk and other modes by decreasing the number of households that has more than one vehicle available. It is therefore important to note that more active transportation modes (walking, cycling, etc.) are not only alternative transportation modes but also potentially crucial contributors to improvements in health and overall quality of life. Two well-cited articles highlight the critical impacts of mobility (or lack thereof) on human health due to increases in obesity, blood pressure, and other serious health problems, and both of these studies recommend improving the built environment by increasing the "walkability index" of U.S. neighborhoods to encourage more people to use active modes of transportation (Frank et al. 2004, 2006). The extent to which AV market penetration may or may not encourage commuters to use less active travel modes is still unclear in today's literature, but future research efforts can investigate the impacts of increased and more convenient mobility that may reduce harmful pollutants but may also decrease or increase activity levels. Next, although AV market penetration can trigger a more dramatic decreasing trend in CO_2 emissions, its effectiveness is still limited in terms of reaching the desired deep carbon reduction goals, which Fulton et al.'s (2017) report has stated is possible with the full and combined adoption of the three aforementioned transportation reforms (EVs, AVs, and ride-sharing). This study and other recent literature studies have clearly revealed that transportation-related impacts can only be changed with a paradigm shift in the current practices of today's transportation industry. Fortunately, this paradigm shift can become a reality in the near future with the introduction of the three aforementioned reforms, which will also bring about marginal improvements in the built environment and in urban mobility.

In the future, the SD model from this dissertation can benefit from specific attributes connected to the urban area that respond to and provide feedback from the use of policy scenarios to address the problems being analyzed. Such research data can be processed using geospatial analysis tools and included as SD model inputs; this may be possible in future research with the use of an Agent Based Modeling (ABM) approach, which would integrate well with SD modeling. Lastly, the research in this dissertation can also be extended in the future with a worldwide case study of successes and/or failures of transportation policies intended to encourage the use of alternative transportation mode choices and reduce the current dependence of the U.S. on conventional drive modes.

APPENDIX: SYSTEM DYNAMICS MODELING SYMBOLS

The figures that present stock and flow diagrams of the developed models have symbols that is specific with Vensim software's system dynamics modeling. Therefore, following table is provided in order to explain the meanings of each modeling symbol of Vensim software.

Table 24: Appendix table for system dynamics modeling symbols in Vensim software

Symbol	Name	Description
Life Expectancy	Variable – Auxiliary/Constant	It is a variable that can be defined as auxiliary, constant, data. This variable information can consist of equation of connected other variables, constant value, or time series of data points with look up function.
Transit Transportation Ridership	Box Variable - Level	It is level variable where it is a product of connected rates and its initial value (if applicable).
	Arrow	Defines the relation between variables.
	Rate	Defines a flow to the level variables. The software is sensitive with the direction of flows so if the direction of flow goes into the box variable it indicates an in-flow (positive) where the opposite direction indicates out-flow (negative) relation.
<Life Expectancy>	Shadow Variable	Creates an existing model variable without adding its causes. This feature is useful for such large models to present in organized way so the arrows are not overlapping each other. And it is also useful to follow the cause within sub-models.
Population	Comment Box	Creates explanatory comments in the model for organization. It can be created in many forms of without border boxes, plus/minus signs, etc.

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