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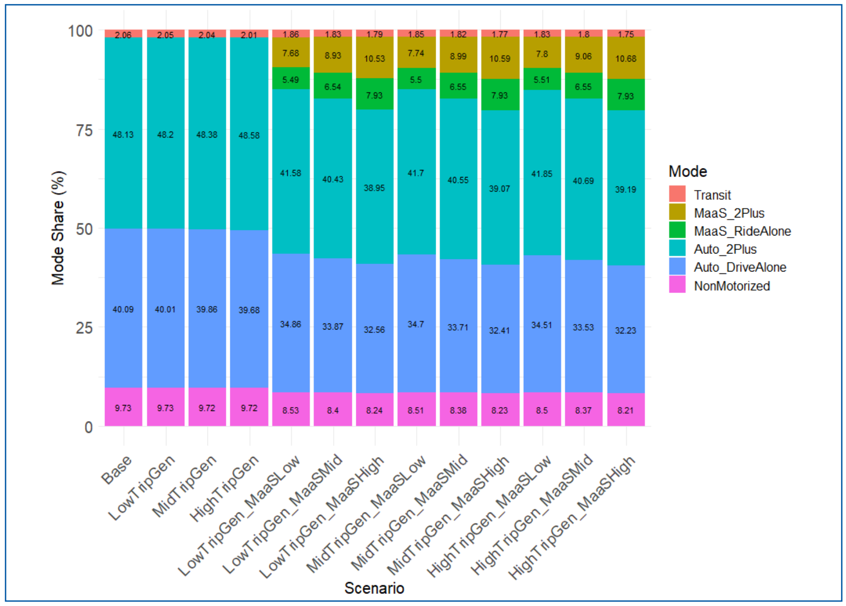
EXPLORATORY MODELING AND ANALYSIS FOR AUTOMATED VEHICLES IN UTAH



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16. Abstract

Autonomous Vehicles (AVs) have the potential to offer benefits and flexibility in travel, which can lead to significant reductions in the generalized travel cost, and possibly more demand. The combination of the AV technology with Mobility as a Service (MaaS) creates a new disruptive transportation mode – Shared Autonomous Vehicles (SAVs) that have the promise to re-define the transportation landscape by improving mobility and competing with conventional transportation modes. While it is foreseen that SAVs could potentially be on the market in the near future, the long-range transportation planning process has yet to account for their impact. We fill this gap by presenting a framework of modeling SAVs to seamlessly integrate them into the four-step travel demand models that are widely used by transportation agencies. Using the Wasatch Front region in the State of Utah as a case study, we present such modeling effort for the year 2040 forecast horizon. Delineated by different combinations of trip growth rates and SAV market attractiveness, the designed scenarios revealed that SAVs could increase the total number of trips by 1% to 7%. SAVs could shift travel away from conventional transportation modes. It is estimated that SAVs will increase daily Vehicle Miles Traveled (VMT) by 4% to 9% across designed scenarios due to improved mobility of underserved populations and additional repositioning trips.

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ABSTRACT

Autonomous Vehicles (AVs) have the potential to offer benefits and flexibility in travel, which can lead to significant reductions in the generalized travel cost and possibly, more demand. The combination of the AV technology with Mobility as a Service (MaaS) creates a new disruptive transportation mode – Shared Autonomous Vehicles (SAVs) that have the promise to re-define the transportation landscape by improving mobility and competing with conventional transportation modes. While SAVs could potentially be on the market in the near future, the long-range transportation planning process has yet to account for their impact. We fill this gap by presenting a framework of modeling SAVs to seamlessly integrate them into the four-step travel demand models widely used by transportation agencies. Using the Wasatch Front region in the State of Utah as a case study, this project presents such modeling effort for the year 2040 forecast horizon. Delineated by different combinations of trip growth rates and SAV market attractiveness, the designed scenarios revealed that SAVs could increase the total number of trips by 1%–7%. SAVs could shift travel away from conventional transportation modes. It is estimated that SAVs will increase daily Vehicle Miles Traveled (VMT) by 4%–9% across designed scenarios due to improved mobility of underserved populations and additional repositioning trips. The results will assist public agencies in understanding the impacts of SAVs on travel patterns to further consider the special needs of AV technology in long-range cost estimates and programming processes.

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EXECUTIVE SUMMARY

It is anticipated that ongoing advancement of computational capabilities will make it possible to build Autonomous Vehicles (AVs) with a high level of reliability operating under various complex situations. AVs can provide travelers with additional benefits and flexibility reducing the cost of travel, which, in turn, may lead to increased travel demand. In conjunction with the growth of AV technology is an evolving transportation service — Mobility as a Service (MaaS) — which can be seen in today's Transportation Network Companies. Combining the AV technology with MaaS creates a new transportation mode — Shared Autonomous Vehicles (SAVs), which have the promise to re-define the transportation landscape by generating more trips and competing with conventional transportation modes. While

SAVs could potentially be on the market in a decade or two, Metropolitan Planning Organizations (MPOs) and Departments of Transportation (DOTs) are just beginning to estimate the impacts of SAVs on travel behavior. This research fills this gap by investigating the impact of SAVs on travel demand in Utah in the 2040 horizon year.

In this project, we modified the Wasatch Front (WF) travel demand model to estimate the impact of SAVs on Vehicle Miles Traveled (VMT). These model modifications were made in the trip generation and mode choice modules of the WF travel model. To address the impact of SAVs on trip generation, we adjusted the mobility of seniors, people with disabilities or driving-restrictive medical conditions, and children — demographics that often encounter challenges when traveling independently. The research assumes that SAVs will improve the mobility of these populations for non-work and non-school trips. To accommodate SAVs in the mode choice module, a new mode — MaaS — was added within the motorized branch. The attractiveness of the MaaS mode — as expressed in a utility function — is calculated based on the burden of in-vehicle-time, initial pick-up time, and operating cost. To model the additional benefits and flexibility that SAVs offer, we reduced the generalized cost of this mode compared to conventional transportation modes. Finally, 12 scenarios were designed and analyzed to investigate the impact of various combinations of trip growth and SAV market penetrations on VMT.

Results revealed that SAVs can increase the total number of trips by a range 1%–7% across designed scenarios. Comparing mode shares across scenarios showed that while SAVs can shift mode shares from all conventional transportation modes, it competes most effectively with auto and non-motorized modes. Higher mode shifts were found for SAV shared ride modes when compared to SAV ride alone, partially due to Utah's demographics, with larger average household sizes.

Analysis of the modal shifts by trip purpose showed that for all trip purposes, except Nonhome-Based (NHB) trips, SAVs compete more with auto and non-motorized modes. For NHB trips, transit experiences the largest mode shift to SAVs. Among available transit modes, Bus, BRT, and Light Rail are estimated to experience the highest degree of shift to MaaS. An analysis of trip length distributions revealed that the SAV mode is more desirable for shorter trips than longer ones. Moreover, while reducing the generalized cost of SAVs makes it more competitive for longer trips, it does not significantly impact the share of SAVs for shorter trips. Eventually, it is observed that SAV increases daily VMT by 4%–9% across designed scenarios due to both improved mobility of underserved population and additional VMT from the repositioning of vehicles toward the next rider.

1. INTRODUCTION

1.1 Problem Statement

Recent advancement of computational capabilities in terms of hardware, algorithms, communication architecture, sensing, and navigation systems has made it possible to build Autonomous Vehicles (AVs) with a high level of reliability and to operate in complex driving situations. The Society of Automotive Engineer (SAE) International, building on the earlier work of National Highway Traffic Safety Administration (NHTSA), has defined automation levels from 0 to 5. Level 5 vehicles will have the maximum level of automation and can be operated without a supervised driver under all roadway and environmental conditions (Miller, et al., 2014). Vehicles with lower levels of automation currently available on the market are equipped with different automation features, such as adaptive cruise control, lane keeping systems, and parking assistance, etc. Since 2009, Google reported over five million miles driven with AVs, mostly on public roads (Lee, 2017). Moreover, most major automobile manufacturers including General Motors (LeBeau, 2013), Mercedes Benz (Andersson, 2013), Nissan (Nissan Motor Company, 2013), and Volvo (Carter, 2012), target to sell vehicles with automated driving features by 2020. Although fully automated vehicles are currently not available for purchase, it is foreseen that they could potentially be on the market in a decade or two (Levin and Boyles, 2015).

On the other hand, the number of states in the United States considering legislation related to AVs is gradually increasing every year. In 2017, 33 states had introduced legislation and 21 states had passed legislation related to AVs. While current regulations in most places require the presence of a driver behind the steering wheel to take control of the vehicle in case of an emergency, it is likely that such requirements might change in the near future (Autonomous Vehicles, 2018). Given that AVs are increasingly heralded to re-define the transportation landscape, they are brought to the attentions of Metropolitan Planning Organizations (MPOs) and Departments of Transportation (DOTs) to be considered in their long-range transportation plans.

AVs could provide travelers with additional travel benefits and flexibility. For instance, travelers can engage in various activities, such as reading, playing video games, and sending emails, while traveling. They may also have AVs drop them off at their destinations, then park elsewhere to avoid excessive parking fee (Levin and Boyles, 2015). AVs might have the potential to increase the mobility of children, seniors, and people with driving-restrictive medical conditions by eliminating human involvement during driving (Harper et al., 2016). Moreover, AVs could substantially reduce the number of crashes due to various human errors, such as slow reaction time, speeding, driving under the influence, and lack of experience (Arvin et al., 2019). These benefits could lead to a significant reduction in the generalized cost of travel, and subsequently more demand for travel and a modal shift away from public transport, passenger train, and air (Wadud et al., 2016).

While the ownership of AVs can be a huge, fixed cost, another stream of research has been focusing on combining AVs with Mobility-as-a-Service (MaaS). MaaS presents people with different mobility options reducing or eliminating the need to own a private vehicle. It is also referred to as “shared mobility” in certain contexts and can come in various forms, such as personal vehicle sharing, bike sharing, carpooling, vanpooling, ride sourcing and ride hailing. Ride sourcing and ride hailing are typically served by Transportation Network Companies (TNCs), leveraging smartphone apps to connect drivers with passengers.

Combining AV technology with MaaS creates a new mode – Shared Autonomous Vehicles (SAVs), which could provide inexpensive and flexible, on-demand service. SAVs may operate on the TNC model, enabling travelers to obtain a ride through a smartphone application. SAVs can also reposition themselves to a more favorable location with lower parking cost and higher demand. These advances may provide environmental benefits in terms of reduced parking and vehicle ownership needs. However, there are potential downsides of such services. For instance, the inexpensive cost of this new mobility service could result in more trips and, in turn, higher Vehicle Miles Traveled (VMT). It could also cause modal shifts from conventional public transportation. Moreover, travelers could walk less due to the convenience of such on-demand mobility service, incurring adverse health effects. Consequently, while SAVs might have substantial positive impacts, such as improved safety, efficiency, accessibility, and mobility, they could also induce greater travel demand and modal shift from other active transportation modes.

Given the growing interests and promising market of SAVs, it is important for MPOs and DOTs to start modeling how SAV technology would impact the regional travel patterns and consider the special needs of AV in long-range cost estimates and programming process. This research paves the way by presenting a framework of modeling SAVs to seamlessly integrate it into the existing four-step, travel demand models. Using the Wasatch Front (WF) region in Utah as a case study, we propose various modifications to the regional travel demand model to explore the impact of SAVs on travel behaviors. A scenario-based analysis is then used to predict a range of VMT increase on the introduction of SAV within the study region in the year 2040 forecast horizon.

1.2 Objectives

The primary objective of this study is to estimate the impact of SAVs on VMT in Utah in the year 2040 forecast horizon. The results of this research will assist UDOT and WFRC to understand the impact of SAVs on travel patterns in terms of increased trip generation and shift from traditional modes of travel.

1.3 Outline of Report

The rest of the report is structured as follows. Chapter 2 summarizes the literature review. The proposed methodology, including a discussion on modifications to the Trip Generation and Mode Choice Models, are explained in Chapter 3. Chapter 4 details the results and discussion. Implications and conclusions are presented in Chapter 5.

2. LITERATURE REVIEWS

In recent years, there has been increased research interests in AVs. Yet, much of the literature has focused on technological hurdles in operating AVs safely on the road (e.g. sensing system). Here, we attempt to provide a comprehensive summary of recent research efforts in examining the impacts of AVs (or SAVs) on travel patterns from the travel demand modeling perspective.

Levin and Boyles (2015) developed a multiclass, four-step model and used a generalized cost function of travel time, monetary fees, and fuel consumption to assess the impact of AV ownership on trip, mode, and route choice behaviors. Three modes of transportation, including car, transit, and AV, are considered via a nested logit model. AV users were assumed to have the option of either parking the vehicle (with a parking fee) or sending it back to the origin (with no parking fee and incurring fuel costs). Static link performance functions were modified to predict capacity improvements due to AVs on each link. Travelers seek to minimize the generalized cost of travel time, fuel, and parking fees. It is assumed that market penetration, trip productions and attractions are known. The proposed model was tested on the Austin downtown network considering the presence of transit. Results revealed that parking cost was the main incentive for transit use, and the presence of AV round-trip caused a reduction in transit demand. They predicted a 61.4% reduction in transit ridership as a result of lower costs of AVs.

Hörl (2016) used an agent-based transport simulation model, MATSim, to simulate AVs. Four modes of transportation, including public transport, private car, autonomous taxi (AT), and walking, are considered in this study. Individuals selected their travel options such that travel disutility is minimized. Travel disutility for each mode is defined as "a function of mode-specific disutility, travel time, and travel cost." The classic Sioux Falls, South Dakota, network was selected as a test case for the proposed model. Results revealed that AV mode mainly decreased the share of public transport and walking; however, it enabled the shifts of previously private vehicle users to AVs. The presence of AVs reduced the average travel distance for public transport and walking agents because long trips using these modes will be replaced by AVs. Moreover, AVs were found to increase VMT, which has negative effects on environment and congestion. They concluded that availability of AVs without administrative regulations would attract mode shifts from all the other three modes (i.e. public transport, walking and private car), and attract more public transport users than private car users.

Zhang et al. (2015) applied an agent-based model to explore the potential benefits of SAVs with Dynamic Ride Sharing (DRS). Vehicle-trips were generated based on the 2009 National Household Travel Survey (NHTS) data for an imaginary 10-mile by 10-mile grid-based city. They assumed that two individuals might share their ride voluntarily if both are willing to share rides with strangers and the higher delay incurred by ridesharing can be offset by travel cost reductions. They reported that SAV with DRS could provide a better level of service compared to SAV without DRS by reducing trip delay and costs, offering more reliable service particularly in peak hours, and generating less VMT. The model results indicated that the average delay per trip is approximately 13% lower throughout the day with the presence of SAV with DRS, and around 37% lower during peak hours. Moreover, the availability of SAV with DRS was found to generate 4.74% less VMT compared to SAV without DRS.

Childress et al. (2015) assessed potential change in travel patterns in the Puget Sound, Washington, region using an activity-based model. They modeled AV under assumptions of four different scenarios. The first scenario assumes that AVs use existing facilities more efficiently and increase all freeway and major arterial capacities by 30%. The second scenario is built on the first one, assuming that with capacity improvements, travelers using AVs perceive in-vehicle time less burdensome compared to driving in regular vehicles. In the third scenario, it is assumed that all cars are self-driving and none are shared. Similar to the third scenario, all cars are assumed to be automated in the fourth scenario, but the main difference is the consideration of SAVs. Table 2.1 summarizes assumptions used in these four scenarios.

To investigate potential effects of AVs, the model outputs from scenarios 1 through 4 were compared against a year 2010 baseline. Scenarios with a capacity increase (scenarios 1 through 3) experienced increased VMT, ranging from 4% to 20%.

Bischoff and Maciejewski (2016a) assessed the impact of AT fleets on traffic congestion using an agent-based simulation model. They found that although ATs increase traffic volumes they can reduce traffic congestion assuming capacity increase by 50%.

Table 2.1 Assumptions for the four scenarios in Childress et al. (2015)

Assumptions	Scenario 1	Scenario 2	Scenario 3	Scenario 4
1	30% capacity increase on freeways and major arterials	30% capacity increase on freeways and major arterials	30% capacity increase on freeways and major arterials	All trips are provided by AV/SAVs
2		The value of time for AV mode was reduced from $24 to $15.6/hr for the highest income households	The value of time for AV mode was reduced from $24 to $15.6/hr for all households	The system provides the same service as private cars but at a higher rate ($1.65/mi)
3			50% parking cost reduction	

Fagnant et al. (2015) examined the implications of SAVs at a low market penetration (1.3% of regional trips). They used an agent-based model to simulate SAVs in a dense urban area of Austin, Texas. Results indicated that each SAV could replace nine private vehicles, but that increases VMT by 8% due to repositioning trips. In another study, Fagnant and Kockelman (2018) advanced an existing model by enabling DRS, optimizing fleet size, and anticipating profitability for private operators. They showed that the availability of SAVs with DRS could limit VMT increase to 4.5%. Moreover, they reported that DRS might significantly reduce waiting time, particularly during peak hours. A myriad of previous studies revealed that AV/SAV can increase VMT in the range of 4–40% (Brown et al., 2014, Gucwa, 2014, Childress et al., 2015, Fagnant et al., 2015, Harper et al., 2016, Wadud, 2016, Milakis et al., 2017, Fagnant and Kockelman, 2018).

Bischoff and Maciejewski (2016) investigated the potential replacement of private cars with AT in Berlin, Germany, using an agent-based simulation model. Results showed that a fleet of 100,000 ATs could replace the car fleet with high service quality. In another study, Bischoff et al. (2018) integrated parking search behavior to the existing agent-based simulation model to assess the impact of AV fleets on parking search. They reported that the introduction of AVs can reduce parking search time for conventional, private cars. Levin et al. (2017) studied replacing personal vehicles with SAVs in downtown Austin, Texas, using AM peak demand. They developed an event-based framework to integrate SAVs with traffic flow models; however, the impact of SAV on trip generation was not taken into consideration. They showed that SAVs could increase congestion due to empty repositioning trips.

Wen et al. (2018) proposed a modeling framework to simulate and evaluate possible integration of AV with public transportation systems. AV is modeled to provide first-mile connections to rail stations and also efficient service in suburban areas. An agent-based model of service, in combination with a discrete choice model of demand, were used to model the interaction between service operators and travelers. The proposed framework was implemented on a case study in Delft, Netherland.

Hörl et al. (2019) used an agent-based model to evaluate the performance of different operational polices for controlling and dispatching SAV fleets in Zurich, Switzerland. They found that SAVs can provide higher occupancy rates than conventional cars. Moreover, they reported that SAVs cannot compete with public transport or private cars in the short term if travelers' mode choice decision is solely based on monetary cost. The choice of efficient operational policy was found to have a significant impact on potential benefits that SAV service could offer.

As demonstrated, previous studies mainly focused on four-step planning models and, more recently, activity-based (or agent-based) models, to explore the impact of AVs (Levin and Boyles, 2015). The main advantage of activity-based models (when compared with traditional four-step models) lies in their capability to predict repositioning trips. However, due to constraint on data availability and computational requirements, most of these studies relied on unrealistic traffic flow models (Burns et al., 2013, Fagnant and Kockelman, 2014, Fagnant and Kockelman, 2016) and/or simplified transportation networks (Poulhès and Berrada, 2017, Zhang et al., 2015, Fagnant and Kockelman, 2014). Moreover, many MPOs are still heavily dependent on their respective four-step models for long-range transportation planning and do not intend to adopt agent-based models in the near future due to cost constraint and reliability concerns of these models. Consequently, there is a need to provide guidance toward incorporating AVs/SAVs into the existing four-step travel demand modeling, and a method to account for repositioning trips when modeling AVs/SAVs' impacts on VMT.

3. METHODOLOGY

SAVs can potentially increase VMT in two ways: 1) by incurring trips from currently underserved populations; and 2) by converting other modal trips to MaaS, which can result in higher VMT (e.g. transit or nonmotorized trips are shifted or when additional VMT is generated during a MaaS vehicle being repositioned after passenger drop-off). To estimate the range of VMT changes incurred due to SAVs, we adopted a scenario-based approach to account for SAVs' impacts. Using the WF travel demand model as an example, we assumed that SAVs will mainly affect the trip generation and mode choice modules as explained above. Correspondingly, a total of 12 scenarios were designed to investigate different combinations of trip growth rates and SAV market attractiveness (see Table 3.1). Detailed explanations of the parameters (i.e. β_i and TRR) will follow.

Table 3.1 Experimental design

Scenario	Trip Generation Effect	Mode Share Effect	Description
Base			The current WF Model without any modifications
LowTripGen	Low	Zero	$\beta_i = 0.1, TRR = 15\%$, MaaS is not included in the mode choice model
MidTripGen	Medium	Zero	$\beta_i = 0.5, TRR = 10\%$, MaaS is not included in the mode choice model
HighTripGen	High	Zero	$\beta_i = 1, TRR = 0\%$, MaaS is not included in the mode choice model
LowTripGen_MaaSLow	Low	Low	$\beta_i = 0.1, TRR = 15\%$, MaaS with low travel cost included in the mode choice model
LowTripGen_MaaSMid	Low	Medium	$\beta_i = 0.1, TRR = 15\%$, MaaS with medium travel cost included in the mode choice model
LowTripGen_MaaSHigh	Low	High	$\beta_i = 0.1, TRR = 15\%$, MaaS with high travel cost included in the mode choice model
MidTripGen_MaaSLow	Medium	Low	$\beta_i = 0.5, TRR = 10\%$, MaaS with low travel cost included in the mode choice model
MidTripGen_MaaSMid	Medium	Medium	$\beta_i = 0.5, TRR = 10\%$, MaaS with medium travel cost included in the mode choice model
MidTripGen_MaaSHigh	Medium	High	$\beta_i = 0.5, TRR = 10\%$, MaaS with high travel cost included in the mode choice model
HighTripGen_MaaSLow	High	Low	$\beta_i = 1, TRR = 0\%$, MaaS with low travel cost included in the mode choice model
HighTripGen_MaaSMid	High	Medium	$\beta_i = 1, TRR = 0\%$, MaaS with medium travel cost included in the mode choice model
HighTripGen_MaaSHigh	High	High	$\beta_i = 1, TRR = 0\%$, MaaS with high travel cost included in the mode choice model

The following sections describe the WF travel demand model and modifications made to the WF trip generation and mode choice modules to incorporate SAVs' impacts.

3.1 The WF Travel Model

The WF travel demand model maintained jointly by the Utah Department of Transportation (UDOT), Wasatch Front Regional Council (WFRC) and Mountainland Association of Governments (MAG) is a trip-based, travel model that estimates the movement of people and vehicles within the 4-County (Weber, Davis, Salt Lake, and Utah) urbanized area during an average spring/fall weekday. This classic demand model consists of four sub-models: trip generation, trip distribution, mode split, and trip assignment.

Figure 3.1 shows the conceptual overview of the WF model.

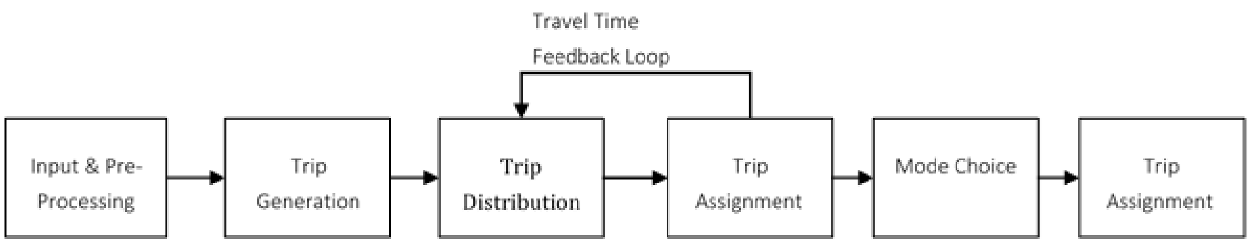

Figure 3.1 The conceptual overview of the WF travel model

The model has a feedback loop between the trip distribution and traffic assignment, which ensures consistency between congestion and travel times that influence trip distribution patterns. The trip generation model first estimates trip-ends by Transportation Analysis Zone (TAZ) based on household and employment characteristics. Households are stratified jointly by life cycle, income, household size, and the number of workers. Three different life cycle categories are considered in the model as follows:

- LC1: Households with no children and no seniors
- LC2: Households with children and no seniors
- LC3: Households with seniors (may have children)

The trip distribution model then pairs generated trip-ends into trips. In the mode choice model, a mode of travel is identified for each trip. Vehicle trips are assigned to the highway network in trip assignment, during which congestion levels on each road are estimated consistent with route choices. The WF model shows trips that fall into three main classifications: person trips, commercial vehicle/truck trips, and external vehicle trips. Person trips are further categorized by different trip purposes, as follows:

- **Home-Based Work Trips (HBW)**: Trips made between the traveler's home and the place of work in either direction.
- **Home-Based College Trips (HBC)**: Trips made between the traveler's home and college.
- **Home Based School Trips (HBSch)**: Trips made between the traveler's home and school. HBSch trips include kindergarten through high school.
- **Home Based Shopping Trips (HBShp)**: Trips made between the traveler's home and shopping (e.g. retail) locations.
- **Home Based Other Trips (HBOth)**: Trips made between the traveler's home and all other non-work-related destinations not already accounted for by the previously defined trip purposes.
- **Non-Home-Based Work Trips (NHBW)**: Trips made between the traveler's work and some other non-home location.

- **Non-Home-Based Non-Work Trips (NHBNW):** Trips made between non-home and non-work locations.

The WF model was calibrated to represent 2011 base-year travel conditions by adjusting model input data, assumptions and parameters so intermediate and final outputs could closely match field observations. Model outputs are validated against real-world data. Origin-destination flows, roadway vehicle volumes, vehicular travel times and speeds, and transit ridership are some of the model outputs used for validation. For future forecast years, the model output is reviewed for reasonableness to validate model results.

3.2 Trip Generation Modifications

SAVs can potentially increase the mobility of underserved populations. Specifically, many seniors, people with travel restrictive disabilities or medical conditions, and children often encounter challenges traveling independently and must rely on family members, friends, and other service providers to meet their mobility needs. In this research, we assumed that SAVs would improve the mobility of these populations for non-work and non-school trips. Since work-based and school-based trips are among those necessary trips that every traveler, including underserved populations, regularly makes, it is expected that SAVs will not have a great effect on these specific trip purposes. SAVs may, however, increase trip making for other, discretionary trips. To address the improved mobility of the underserved population, the following modifications are made to the WF demand model:

3.2.1 Impact on Households with Children and Elderly

To capture the improved mobility of children and elderly members in the WF model, we increased the trip rates of households classified under LC2 and LC3 for non-work and non-school trip purposes. It is assumed that before the introduction of SAV, children and elderly members of high-income households have higher mobility than lower-income households, since they are less constrained by travel costs (WFRC/MAG Demand Model, 2016). Based on this assumption, we can expect that the availability of SAV mode offers the same level of mobility for lower income households. Thus, SAVs will increase trip generation rates for lower income households toward the trip generation rates of higher income households.

The 2012 household travel diary data is used to extract the high-income household trip generation rates by life cycle and household size for three trip purposes: HBO, HBShp, and NHBNW. Once these rates were calculated, the trips rates for different trip generation scenarios were calculated as follows:

$$TR_{LSP_i} = TR_{LSP_{Base\ Model}} + \beta_i * (TR_{LSP_{High\ Scenario}} - TR_{LSP_{Base\ Model}}) \quad (1)$$

where TR_{LSP_i} and $TR_{LSP_{Base\ Model}}$ denote the trip generation rates for households with life cycle L, size S, and trip purpose P in scenario i and base scenario (current version of the WF model without any modifications), respectively. $TR_{LSP_{High\ Scenario}}$ represents the trip generation rate for households with life cycle L, size S, and trip purpose P for high income population and β_i is the adjustment factor for scenario i. When β_i is 1, the trip generation rates for all income categories are set to those of high-income households. When β_i is 0, the trip generation rates for all income categories are set to those of the base model (null or "no build"). Different values for β_i are used to populate three scenarios with different trip generation growth. For low, medium, and high trip generation scenarios, β_i is set to 0.1, 0.5, and 1, respectively.

Figure 3.2 shows the trip rates of households under LC2 and LC3 categories for non-work and non-school trip purposes against household size. The blue and purple lines (TR_LC2 and TR_LC3) show the trends of trip rate increase before improving the mobility of LC2 and LC3. The red and green lines (NTR_LC2 and NTR_LC3) illustrate the same trends after improving the mobility for LC2 and LC3 households. As shown in this figure, for most households, trip rates increase as the household size increases. Moreover, the trends of the trip rate increase are generally consistent with the before and after mobility improvement. There are three cases (circled in black) where the trends of trip rate increase after mobility improvement are not conforming with that of before improvement. This might be explained by the small sample size of households within these categories in household travel diary data. These trip rates were adjusted to follow the same trend as before mobility improvement (as shown in the second column of graphs in Figure 3.2 titled "After Adjustment")

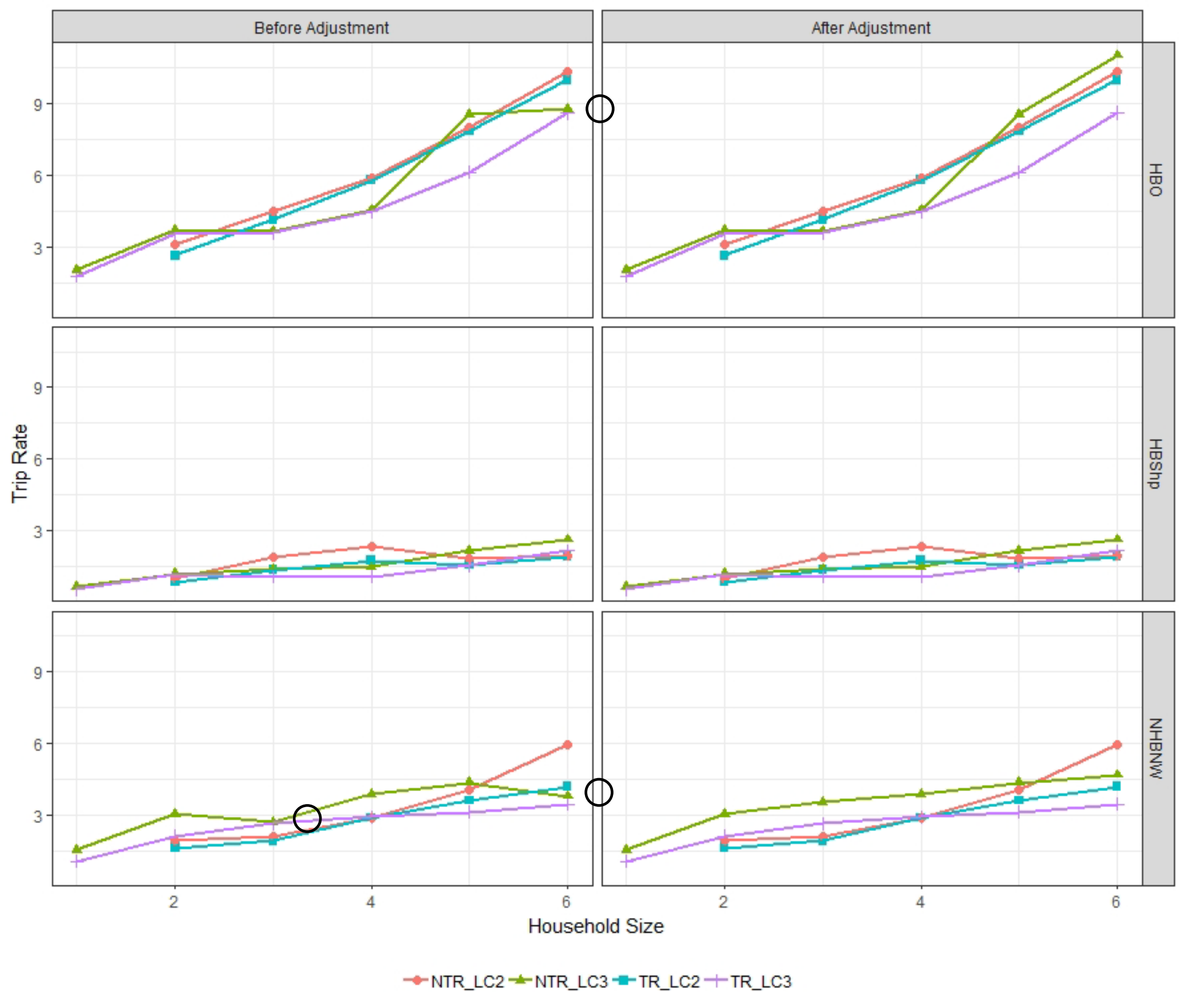

Figure 3.2 Trip rates before and after adjustments (TR: trip rate before SAV; NTR: new trip rate due to the introduction of SAV, considering improved mobility of children and elderly populations)

3.2.2 Impact on Mobility-impaired Population

SAVs can potentially increase the mobility of mobility-impaired population (i.e., people with driving-restrictive medical conditions) for non-work and non-school trips. Ideally, SAVs would enable a mobility-impaired traveler to generate the same number of trips as a traveler with no impairment. The current WF travel model does not differentiate between people with driving-restrictive medical conditions and those without. Thus, it is reasonable to assume that the current trip generation rates are a weighted average of trip generation rates for the disabled and non-disabled populations as follows:

$$TR_{base} = TR_{WD} * P_{WD} + TR_{WOD} * P_{WOD} \tag{2}$$

where TR_{base} denotes trip generation rates in the base model, TR_{WD} and TR_{WOD} represent the trip generation rates of households with and without mobility-impaired members in the study region, and P_{WD} and P_{WOD} are the percentages of households with and without mobility-impaired members in the study region. We assumed a trip reduction (or suppression) rate (TRR) for households with mobility-impaired members and calculated trip rates for those households as follows:

$$TR_{WD} = TR_{WOD} * (1 - TRR) \tag{3}$$

Based on the finding of Sweeney (2004), the trip suppression rate for households with mobility-impaired members was assumed to be 20%, meaning that households with mobility-impaired members on average generate 20% fewer trips than households without mobility-impaired members.

The percentage of households with mobility-impaired members within the study region was obtained from 2012-2016 American Community Survey (ACS) where the data was collected at the census tract level. Finally, trip generation rates for households without mobility-impaired members are calculated as:

$$TR_{WOD} = \frac{TR_{base}}{(1 - P_{WD}) + ((1 - TRR) * P_{WD})} \tag{4}$$

To populate scenarios with various trip generation growth rates to account for the SAVs' impact, TRR was adjusted to reflect various levels of mobility improvements for households with mobility-impaired members. When TRR is 20%, the trip generation rates are equal to the base model trip generation rates; when TRR is 0%, households with mobility-impaired members are assumed to incur the same number of trips as households without mobility-impaired members. For this research, 15%, 10%, and 0% TRR are respectively assumed for low, medium and high trip generation scenarios.

Using Equation 2, the trip rate increase due to the improved mobility of households with mobility-impaired members is estimated. This can be translated into trip rate increase by 0.3%, 0.5%, and 1% for low, medium, and high trip generation scenarios, compared to the base scenario. Table 3.2 summarizes the modified trip rates and their increase percentages to capture the improved mobility of the underserved population in the WF trip generation model.

Table 3.2 Modified trip rates for different trip generation scenarios

HH Size	Life Cycle	Trip Purpose	Base Model Rates	Low Scenario		Medium Scenario		High Scenario	
				Increase Percentage	Trip Rate[1]	Increase Percentage	Trip Rate	Increase Percentage	Trip Rate
1	1	HBOth	1.301	0.30	1.305	0.50	1.308	1.00	1.314
2	1	HBOth	2.322	0.30	2.329	0.50	2.334	1.00	2.345
3	1	HBOth	3.569	0.30	3.580	0.50	3.587	1.00	3.605
4	1	HBOth	5.214	0.30	5.230	0.50	5.240	1.00	5.266
5	1	HBOth	7.265	0.30	7.287	0.50	7.301	1.00	7.338
6	1	HBOth	9.5685	0.30	9.597	0.50	9.616	1.00	9.664
2	2	HBOth	2.634	2.05	2.688	9.26	2.878	18.61	3.124
3	2	HBOth	4.128	1.15	4.175	4.75	4.324	9.54	4.522

4	2	HBOth	5.784	0.47	5.811	1.35	5.862	2.71	5.941
5	2	HBOth	7.826	0.54	7.868	1.71	7.960	3.42	8.094
6	2	HBOth	9.9762	0.64	10.040	2.22	10.198	4.46	10.422
1	3	HBOth	1.785	1.63	1.814	7.15	1.913	14.36	2.041
2	3	HBOth	3.558	0.68	3.582	2.40	3.644	4.83	3.730
3	3	HBOth	3.569	0.57	3.590	1.88	3.636	3.77	3.703
4	3	HBOth	4.461	0.50	4.483	1.48	4.527	2.98	4.594
5	3	HBOth	6.128	4.25	6.388	20.27	7.370	40.74	8.625
6	3	HBOth	8.6	3.11	8.868	14.59	9.855	29.32	11.121
1	1	HBShp	0.452	0.30	0.453	0.50	0.454	1.00	0.457
2	1	HBShp	0.72	0.30	0.722	0.50	0.724	1.00	0.727
3	1	HBShp	0.753	0.30	0.755	0.50	0.757	1.00	0.761
4	1	HBShp	1.075	0.30	1.078	0.50	1.080	1.00	1.086
5	1	HBShp	1.559	0.30	1.564	0.50	1.567	1.00	1.575
6	1	HBShp	2.15	0.30	2.156	0.50	2.161	1.00	2.172
2	2	HBShp	0.86	2.05	0.878	9.26	0.940	18.61	1.020
3	2	HBShp	1.355	4.25	1.413	20.28	1.630	40.75	1.907
4	2	HBShp	1.752	3.66	1.816	17.31	2.055	34.78	2.361
5	2	HBShp	1.58	2.11	1.613	9.56	1.731	19.20	1.883
6	2	HBShp	1.924	0.53	1.934	1.65	1.956	3.31	1.988
1	3	HBShp	0.57	1.92	0.581	8.63	0.619	17.34	0.669
2	3	HBShp	1.161	0.64	1.168	2.22	1.187	4.45	1.213
3	3	HBShp	1.075	3.36	1.111	15.83	1.245	31.81	1.417
4	3	HBShp	1.075	4.35	1.122	20.80	1.299	41.80	1.524
5	3	HBShp	1.559	4.25	1.625	20.27	1.875	40.74	2.194
6	3	HBShp	2.15	2.56	2.205	11.83	2.404	23.78	2.661
1	1	NHBNW	0.892	0.30	0.895	0.50	0.896	1.00	0.901
2	1	NHBNW	1.247	0.30	1.251	0.50	1.253	1.00	1.259
3	1	NHBNW	1.828	0.30	1.833	0.50	1.837	1.00	1.846
4	1	NHBNW	2.15	0.30	2.156	0.50	2.161	1.00	2.172
5	1	NHBNW	2.473	0.30	2.480	0.50	2.485	1.00	2.498
6	1	NHBNW	2.795	0.30	2.803	0.50	2.809	1.00	2.823
2	2	NHBNW	1.613	2.40	1.652	11.03	1.791	22.16	1.970
3	2	NHBNW	1.914	1.10	1.935	4.52	2.001	9.08	2.088
4	2	NHBNW	2.87	0.36	2.880	0.78	2.892	1.57	2.915
5	2	NHBNW	3.591	1.54	3.646	6.69	3.831	13.44	4.074
6	2	NHBNW	4.171	4.61	4.363	22.08	5.092	44.37	6.022
1	3	NHBNW	1.054	4.73	1.104	22.68	1.293	45.58	1.534
2	3	NHBNW	2.118	4.55	2.214	21.77	2.579	43.75	3.045
3	3	NHBNW	2.634	3.71	2.732	17.60	3.098	35.38	3.566
4	3	NHBNW	2.903	3.62	3.008	17.11	3.400	34.39	3.901
5	3	NHBNW	3.118	4.25	3.250	20.27	3.750	40.74	4.388
6	3	NHBNW	3.44	3.88	3.573	18.42	4.074	37.02	4.714

[1]: Number of trips per household

3.3 Mode Choice Modifications

The current WF travel model adopts a nested multinomial logit mode choice model to estimate the split among non-motorized (walk/bike) and motorized (auto and transit) trips. The mode choice model estimates the modes of travel separately for HBW, HBO, HBC and NHB trips. For this research, a new mode —MaaS – was created to incorporate SAVs into the mode choice model. The MaaS mode was added as a new branch within the motorized category. The layout of the new mode choice model is shown in Figure 3.3.

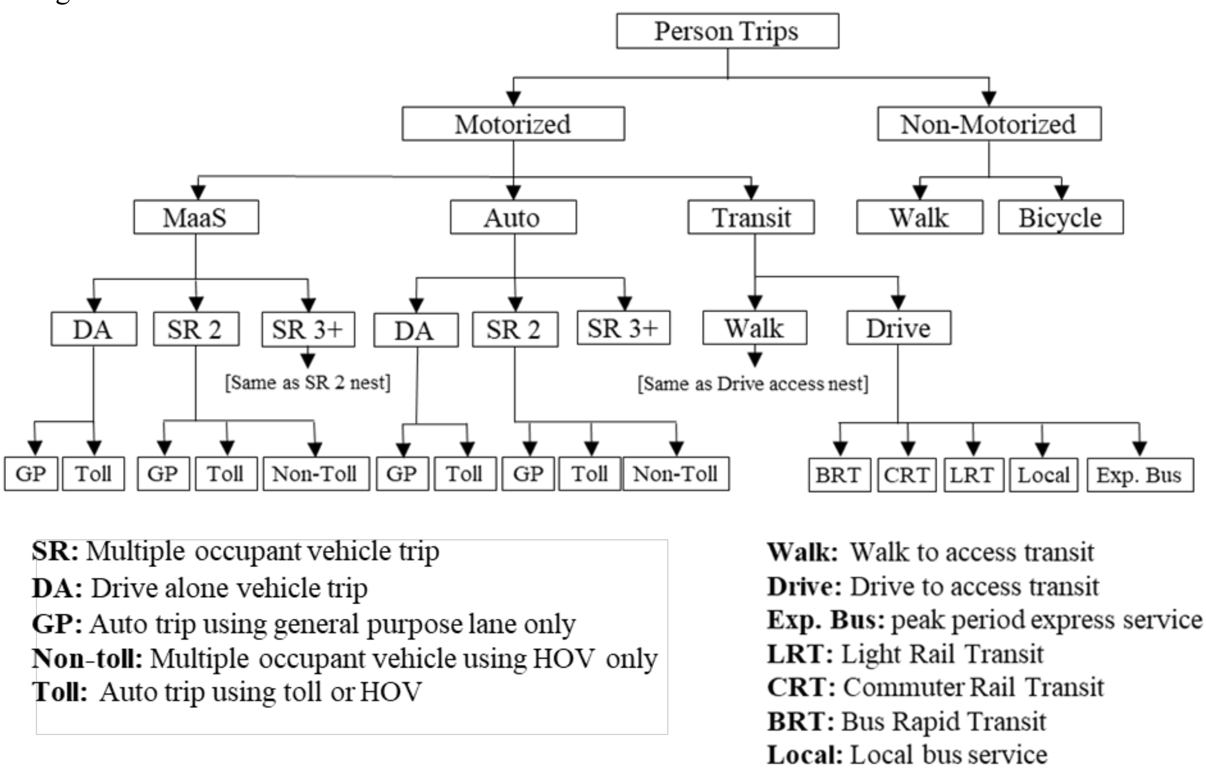

Figure 3.3 Modified WF mode choice model for accommodating SAVs

The MaaS utility function is calculated based on in-vehicle-time, initial pick-up time, operating cost (i.e. distance-based cost, time-based cost, and initial fee), cost split factor, and pick-up time factor. The utility function developed for MaaS_alone (Drive Alone) is as follows:

$$U_{MaaS\_alone} = (asc_{alone} + asc_{auto} + asc_{motor} + \beta_{ivt,purpose} * ivt + \beta_{pickup,purpose} * pt + \beta_{cost,purpose} * (trdist * dbc_{Maas} + ivt * tbc_{Maas} + inifee_{MaaS})/(nest_{alone} * nest_{auto} * nest_{motor}) \quad (5)$$

where asc_{alone}, asc_{auto}, and asc_{motor} represent alternative specific constants. ivt and pt denote in-vehicle time and pick-up time, respectively. $trdist$, dbc_{MaaS}, tbc_{MaaS}, and $inifee_{MaaS}$ represent trip distance, distance-based cost, time-based cost, and initial fee for MaaS trips. $nest_{alone}$, $nest_{auto}$, and $nest_{motor}$ denote nesting constants used in the mode choice model.

Table 3.3 through Table 3.6 show the values used for variables and coefficients across different scenarios in Equation 5. The current WF model in-vehicle-time coefficients are referenced and their absolute values are reduced in MaaS utility function to make travel time less burdensome for MaaS compared to conventional transportation modes (i.e. Auto and Transit modes). Table 3.3 shows default in-vehicle time coefficients (Base) currently used for Transit and Auto and those reduced coefficients for modeling MaaS mode under low, medium, and high impact scenarios. The operating cost of MaaS for the base scenario was estimated based on current Uber and Lyft fares in Salt Lake City, Utah. All rates are in 2010 dollar. For medium and high MaaS market penetration scenarios, operating cost was reduced by 10% and 20%, respectively, to reflect a less expensive SAV mode. The initial pick-up time is the time spent after a passenger is dropped off and prior to the next passenger pickup. This variable is included in MaaS mode and varies by area type. It is lower in the Central Business District (CBD) than in Urban and Rural areas due to the availability of more SAVs. For shared rides, cost split factor is used to split the operating costs between passengers. Moreover, a pick-up time factor is used to penalize initial pick-up time for MaaS shared ride modes. These two factors are multiplicators for $\beta_{cost,purpose}$ and $\beta_{pickup,purpose}$ in Equation 5 for MaaS SR2 and SR3+ modes.

Table 3.3 MaaS in-vehicle time values across different scenarios

Trip Purpose	In-Vehicle Time for Scenario			
	Base	Low	Mid	High
HBW	-0.045	-0.0405	-0.036	-0.0315
HBO	-0.035	-0.0315	-0.028	-0.0245
NHB	-0.04	-0.036	-0.032	-0.028
HBC	-0.025	-0.0225	-0.02	-0.0175

Table 3.4 MaaS operating cost across different scenarios

Cost Type	Operating Cost for Scenario		
	Low/Base	Mid	High
Distance-Based Cost ($/mile)	0.679	0.611	0.543
Initial Fee ($)	2.590	2.331	2.072
Time-Based Cost ($/min)	0.174	0.157	0.139

Table 3.5 MaaS initial pick-up time in different area types across scenarios

Area Type	Scenario		
	Low/Base	Mid	High
CBD Core	3	3	3
CBD	5	5	5
Urban	8	7.2	6.4
Urban-Rural	12	10.8	9.6
Rural	15	13.5	12

Table 3.6 Cost split factor and pick-up time factor for shared MaaS modes

Mode	Cost Split Factor	Pickup Time Factor
MaaS 2	0.7	1.5
MaaS 3+	0.6	2

3.4 VMT Estimation

Additional VMT induced by SAV repositioning occurs after a passenger is dropped off and prior to the next passenger pickup. Due to the macroscopic nature of the four-step model, it is challenging to accurately derive such additional VMT within the current modeling framework. To compensate, we performed offline post-model analyses to estimate such additional VMT incurred due to those repositioning trips. The additional VMT for each MaaS trip was estimated based on initial pick-up time and average speed within the trip's origin area type. Equations 6 and 7 show how this additional VMT was estimated for peak period and off-peak period.

$$VMT_{Repos,Pk} = \sum_{i=1}^{5} MaaS_{i,\,Pk} * Speed_{i,Pk} * PickUp_i \tag{6}$$

$$VMT_{Repos,Ok} = \sum_{i=1}^{5} MaaS_{i,\,Ok} * Speed_{i,Ok} * PickUp_i \tag{7}$$

where $VMT_{Repos,Pk}$ and $VMT_{Repos,Ok}$ denote additional VMT due to repositioning trips during peak and off-peak periods, $MaaS_{i,\,Pk}$ and $MaaS_{i,\,Ok}$ represent number of MaaS trips originating from area type i during peak and off-peak periods, $Speed_{i,Pk}$ and $Speed_{i,Ok}$ are average speeds within area type i for peak and off-peak periods, and $PickUp_i$ is the pick-up time within the area type i.

The total VMT considering repositioning trips for MaaS mode can be calculated as follows:

$$VMT_{Total,Pk} = VMT_{Repos,Pk} + VMT_{Model,Pk} \tag{8}$$

$$VMT_{Total,Ok} = VMT_{Repos,Ok} + VMT_{Model,Ok} \tag{9}$$

where $VMT_{model,Pk}$ and $VMT_{model,Ok}$ denote model VMT estimates for peak and off-peak periods. The daily VMT is consequently calculated as the sum of off-peak and peak periods VMT: as follows:

$$VMT_{Total,Daily} = VMT_{Total,Ok} + VMT_{Total,Pk} \tag{10}$$

4. RESULTS AND DISCUSSIOIN

We ran 12 scenarios (as shown in Table 3.1) consisting of different combinations of trip growth rates and MaaS modal attractiveness. This experimental design allowed us to estimate a range of VMT increase as a result of SAVs' introduction in the 2040 forecast year.

Figure 4.1 illustrates the percentage of trip production increase that was due to the improved mobility of underserved populations for trip generation scenarios compared to the base scenario (without considering the impact of SAVs). Since the rates of work-based and school-based trips remain unchanged (compared to the base scenario) these trip purposes were intentionally excluded from the figure. The total number of trips increased by approximately 1%, 3.5%, and 7% for low, medium, and high trip generation scenarios, respectively. The higher trip production increase was observed for HBShp and NHBNW trips, compared to HBOth trip purposes. This is partially explained by the discretionary nature of HBShp and NHBNW trips, which makes these trips more sensitive to travel cost variation.

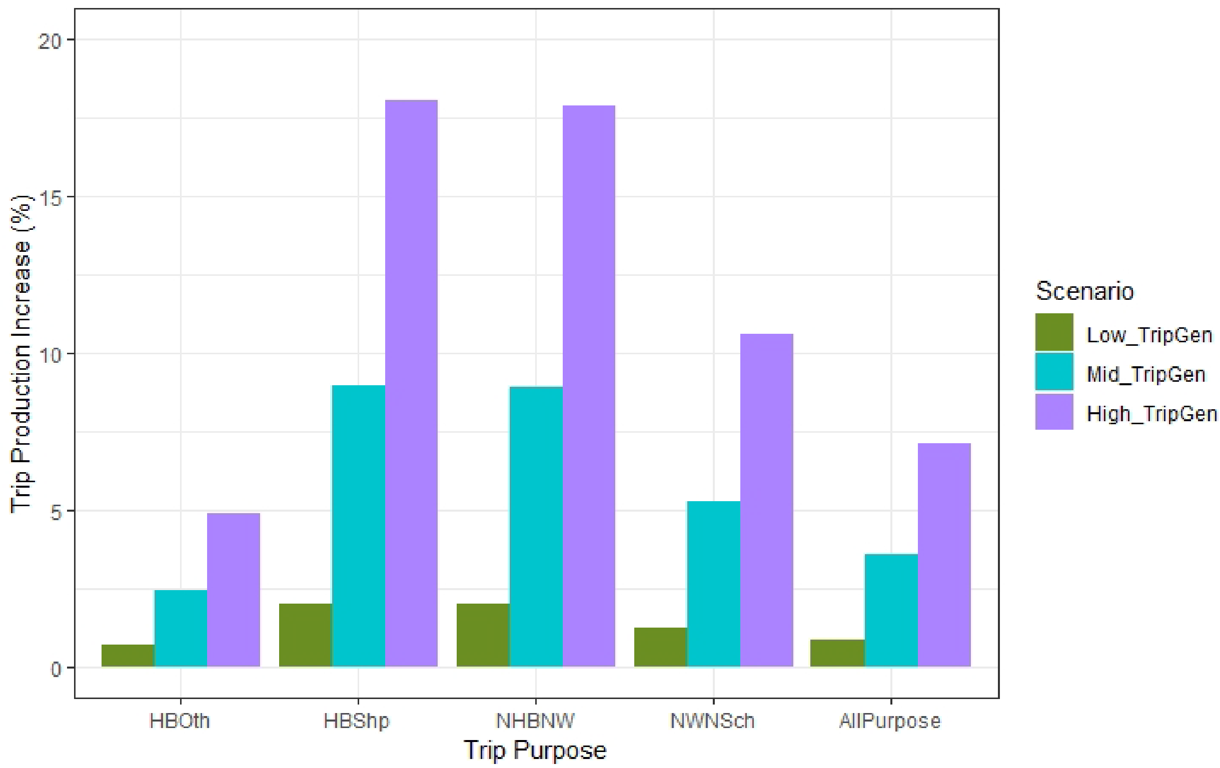

Figure 4.1 Designed scenarios trip production increase compared to the base scenario

Figure 4.2 illustrates daily mode shares across designed scenarios for all trip purposes. Auto_2Plus and MaaS_2Plus represent market shares of shared ride trips in Auto (SR2 and SR3 under Auto branch shown in Figure 3.3) and MaaS (SR2 and SR3 under MaaS branch shown in Figure 3.3), respectively. In the Base scenario, the market split is Auto, Non-motorized, and Transit (from high to low). The market share of shared ride mode (Auto_2Plus) is higher than non-shared ride mode (Auto_DriveAlone). This is partially explained by the unique demographics in Utah where the larger average household size creates more shared ride trips, usually with family members. Therefore, many of the shared rides can be attributed to household members traveling together. In those scenarios where MaaS mode is available, the market split is Auto, MaaS, Non-motorized, and Transit modes (from high to low). Auto_2Plus has a higher share than Auto_DriveAlone; similarly, shared ride MaaS mode (MaaS 2Plus) has a greater share than non-shared MaaS mode (MaaS-RideAlone). Comparing across scenarios, it reveals that MaaS gains most of its share from Auto mode. However, there is still some shift from Non-motorized and Transit modes to MaaS. It ws also observed that shared ride MaaS mode attracts more market share from total modal shifts than non-shared MaaS mode. As expected, comparing MaaS mode share across scenarios with a low, medium, and high MaaS market attractiveness shows that reducing the generalized cost of MaaS (i.e. in-vehicle time, initial pick-up time, and operating cost) makes MaaS more competitive against conventional modes of transportation.

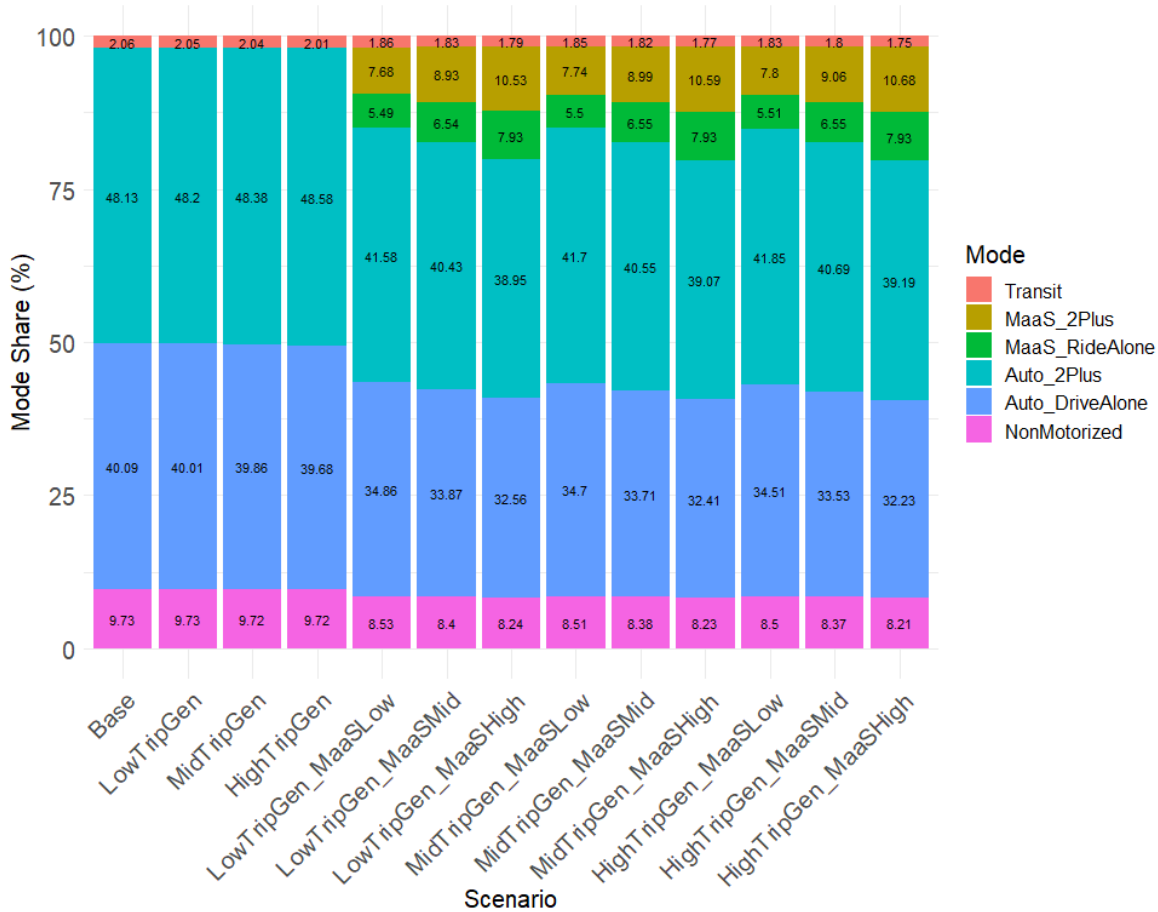

Figure 4.2 Daily mode split across designed scenarios

Figure 4.3 shows the daily VMT estimated by the model and post offline analysis (adding repositioning trips) across all scenarios. Note that MaaS mode is not available in Base, LowTripGen, MidTripGen, and HighTripGen scenarios. Comparing VMTs of LowTripGen, MidTripGen, and HighTripGen scenarios with that of Base scenario shows the increase in daily VMT due to improved mobility of underserved populations as a result of the availability of AVs. As expected, the higher increase in trip rates is associated with a greater increase in daily VMT.

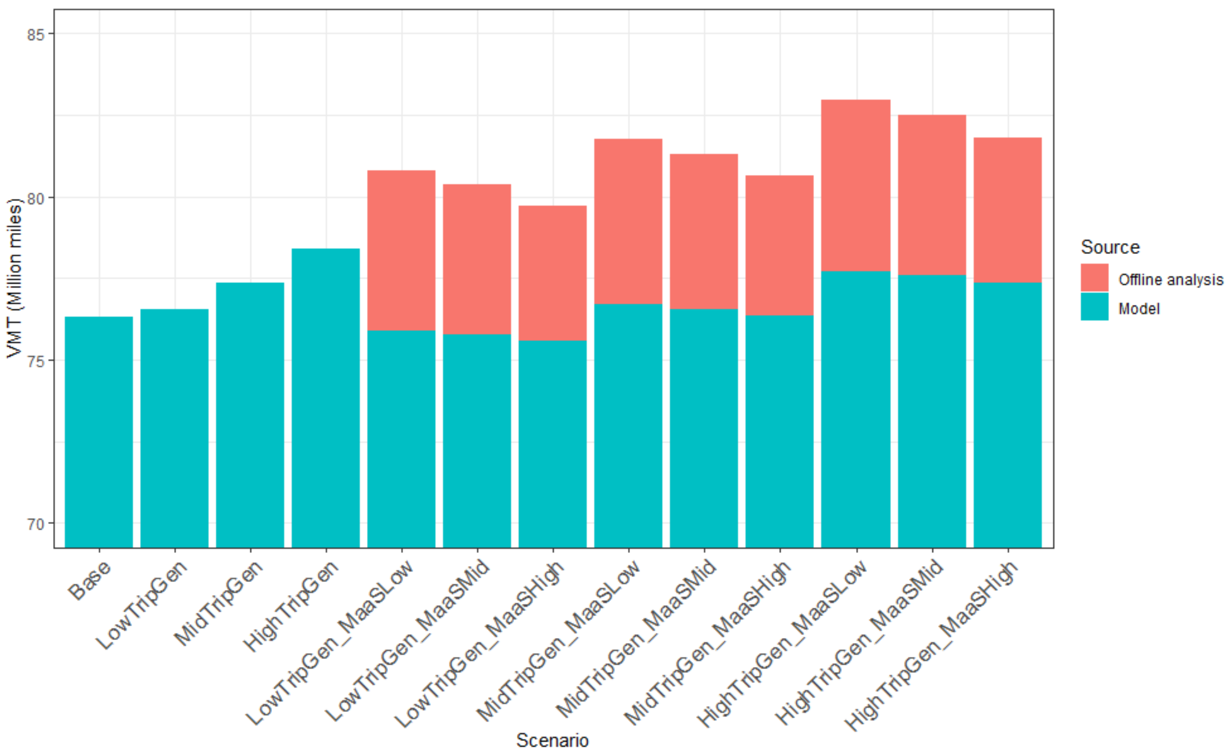

Figure 4.3 Daily VMT across designed scenarios

Introducing MaaS as a new mode to the mode choice model led to a slight decrease in VMT for all scenarios with MaaS available (compared to the "zero" scenarios, namely, LowTripGen, MidTripGen, and HighTripGen in **Table 3.1**). For example, as shown in **Figure 4.3,** low trip generation with MaaS (LowTripGen_MaaSLow, LowTripGen_MaaSMild, LowTripGen_MaaSHigh) scenarios have lower VMT compared to the Base scenario, which might appear to be counterintuitive. The reason lies in the slightly higher shifts from non-shared modes to shared ride modes. As discussed above, this finding is attributable partially to the unique demographics in Utah households and may not accurately account for additional factors discouraging a "pool" mode, such as discomfort in traveling with strangers. Given the current modeling framework, reducing the generalized cost of MaaS across scenarios to represent the low, medium, and high MaaS attractiveness, leads to a reduction in VMT, which is largely due to the shift from drive alone to MaaS2+.

Yet, the post offline analysis added the daily VMT from trip repositioning for scenarios with the MaaS mode, as shown in red in Figure 4.3. For the MaaS scenarios, significant VMT increase due to repositioning trips was observed. Moreover, higher MaaS penetration resulted in smaller VMT increase. This is because when MaaS is readily available, the repositioning trips have a shorter length (as the more distant passengers could be picked up by other MaaS). The daily VMT was estimated to increase in the range of 4%–9% across designed scenarios.

5. CONCLUSIONS

SAV is defined as "the combination of AV technology with MaaS," which offers a new ridesharing option for travelers. The growing interests and promising market of SAVs over the past several years urge the need for public agencies to model their impact on the regional travel patterns for long-range transportation planning cost estimates and programming. In this research, we presented a framework of modeling SAVs to seamlessly integrate it into the four-step travel demand models that are widely used by the public agencies.

Using the WF region in Utah as a case study, we captured the effects of SAVs on travel behavior through modifying its regional travel demand model. The model modifications were made mainly on the trip generation and mode choice modules. In the trip generation module, trip rates of households with children, elderly, and mobility-impaired members were increased to reflect the improved mobility that the AV technology can offer. Overall, a range of — MaaS -— was added, which competes with the conventional modes of automobile, transit, and non-motorized. Finally, 12 scenarios were designed to investigate different combinations of trip growth rates and MaaS market attractiveness. This experimental design yielded an estimate of a 4%–9% range of VMT increase due to SAVs in the year 2040 forecast horizon. Our results revealed that SAVs could increase the total number of trips by 1%–7% across designed scenarios. Mode share comparison among scenarios showed that while MaaS can take market shares away from all conventional transportation modes, it competes more with auto. Reducing the generalized cost of MaaS makes the mode more appealing against conventional modes. Higher market shares were found for shared ride MaaS due, in part, to the larger average household size in Utah. This finding, however, does not account for potential disbenefits of sharing a ride, such as discomfort in traveling with strangers.

In this study, several assumptions were made in regard to the trip rate increase and SAV utility function. In the future, there will be a need to verify these assumptions via survey. In addition to that, while SAV fleet size might have a significant impact on pick-up time, it is not considered in the modeling process. Regarding repositioning trips, an offline, post-processing analysis was performed to estimate the number and length of repositioning trips. Due to such post-process, repositioning trips were not assigned to the modeled network such that their impacts on congestion and traffic flow were not assessed during the modeling process. While SAV might also affect roadway capacity and auto ownership, we did not incorporate these impacts in our study — we left them for future research attempts. Further, we modeled the MaaS mode choice as MaaS Alone, MaaS2, and MaaS3+. Given how ridesharing decisions are currently made (e.g. Uber and Lyft), a more appropriate modeling approach would be to include only two MaaS choices: MaaS Alone and MaaS Pool. Such a shift of paradigm may affect the attractiveness of MaaS Pool, leading to a slight change of results from this research. Additionally, security and safety concerns might present themselves due to SAV's vulnerability to hacking and/or sharing a ride with strangers when there is no driver. Such impedance is not modeled in this study, and future research could investigate the impacts of these factors on SAV attractiveness.

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