Title

Modeling and Planning for Future Multimodal Transportation Systems with Household-owned Driverless Vehicles

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Modeling and Planning for Future Multimodal Transportation Systems with Household-owned Driverless Vehicles

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Civil and Environmental Engineering

by

Younghun Bahk

Dissertation Committee:
Assistant Professor Michael F. Hyland, Chair
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Professor R. Jayakrishnan

2024

DEDICATION

To

my parents, Dr. Jeongdong Bahk and Heegyong Jo

and

my wife, Dr. Sunghi An

for their true love and endless support

"If one wishes to BE, they shall DO; if one wishes to DO, they shall BE."

Myself, age 17, when I first dreamed of becoming a transportation planner

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Standing at end of this journey, echoing my sentiments from my master's thesis, I will always remember those who have readily assisted me during my studies.

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Bahk, Y., Hyland, M., and An, S. (2022). "Private Autonomous Vehicles and Their Impacts on Near-Activity Location Travel Pattern: Integrated Mode Choice and Parking Assignment Model," *Transportation Research Record: Journal of the Transportation Research Board*, 2676(7), pp. 276–295.

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ABSTRACT OF THE DISSERTATION

Modeling and Planning for Future Multimodal Transportation Systems with Household-owned Driverless Vehicles

by

Younghun Bahk

Doctor of Philosophy in Civil and Environmental Engineering

University of California, Irvine, 2024

Assistant Professor Michael F. Hyland, Chair

Driverless (or fully-automated) vehicles (AVs) are expected to fundamentally change how individuals and households travel and how vehicles interact with roadway infrastructure. Privately-owned AVs (PAVs), when operated within households, offer travel options that distinguish them from conventional vehicles (CVs), such as remote parking, returning home to park, and serving other household members. These options—available through deadheading—can lead to an increase in vehicle miles traveled (VMT). The goals of this dissertation are to (i) explore the expected travel patterns of PAVs, (ii) analyze their impacts on transportation system performance, and (iii) propose design and policy changes to mitigate the negative impacts of PAVs and leverage their benefits.

In this context, this dissertation presents three models and corresponding case studies. First, I propose a parking assignment model to analyze the impact of PAV parking behavior on travel patterns and parking facility demand and performance. The case study finds that significant VMT increases occur due to PAVs traveling to remote parking locations after dropping off travelers at activity locations, and that balancing fees and capacities of parking spaces can reduce the extra VMT.

Second, I introduce a new policy and infrastructure system aimed at reducing VMT that is similar to a park-and-ride (PNR) system. Instead of traditional fixed-route transit, my proposed system includes transfer stations where travelers can switch from their PAVs to on-demand, door-to-door shared-use AVs (SAVs) that enhance traveler convenience and service reliability. By optimizing transfer station locations, the case study demonstrates significant reductions in both VMT and vehicle hours traveled (VHT) within the region.

Third, I extend the routing and scheduling of PAVs to the decision-making process within households. I introduce the Household Activity Pattern Problem with AV-enabled Intermodal Trips (HAPP-AV-IT) that incorporates SAV, public transit, and transit-based intermodal travel options. The case study results reveal that travelers are likely to choose long deadheading options, such as returning home, to optimize household vehicle operations. The model also demonstrates that intermodal trips can reduce both the household's travel distance and overall travel costs.

Although the precise performance of AVs on road networks remains uncertain, the findings of this dissertation suggest that additional VMT from PAV deadheading could negatively affect transportation systems. As we move closer to the era of widespread AV adoption, it becomes increasingly important for planners and researchers to develop policies and infrastructure systems that reduce PAV deadheading miles. The methodological advancements and practical insights presented in this dissertation provide a strong foundation for addressing these challenges and preparing for the transformative impact of AVs.

Chapter 1 INTRODUCTION

1.1 Background

Automated or autonomous vehicles (AVs), including fully automated within narrow operational design domains, now exist in several cities. The terminology for AVs—such as driverless, self-driving, automated, and autonomous—are often used interchangeably, as there is no strict consensus on their definitions (Garsten, 2024; Levinson, 2017; Muscad, 2023). However, the various levels of automation and the additional self-routing capabilities of AVs will likely necessitate more precise definitions of these terms. In this dissertation, the terms "driverless vehicle" and "AV" refer to fully automated vehicles that do not require a driver and can accelerate, decelerate, and steer without any human assistance, but still require an external input for destination and route choices.

Over the last decade, a large volume of research has focused on modeling and predicting the impacts of AVs on travel behavior, travel demand, and transportation systems broadly. Two model-based findings are relatively common in the literature: the technological aspects of AVs and connected vehicles will improve traffic flow efficiency (Talebpour and Mahmassani, 2016), and AVs will increase overall vehicle miles traveled (VMT) (Harb et al., 2021). Given that AVs are not widely available, their overall impact on travel demand and traffic congestion is still uncertain (Anderson et al., 2016). However, to plan for AVs, including allocating resources for infrastructure investments and setting policies and regulations, it is important to model, understand, and forecast the potential impacts of AVs on transportation systems under a variety of different conditions. This dissertation focuses on the changes of travel patterns—the factors that can increase the usage of private vehicles and overall VMT.

The most distinguishable characteristic of AVs is that human drivers are not required, meaning vehicles can travel empty, and even when travelers are inside the vehicle, the traveler does not need to operate the vehicle or even know how to operate the vehicle. These changes imply that travel patterns of AVs are likely to diverge from travel patterns in conventional (i.e., non-driverless) vehicles. The existing literature identifies a variety of behavioral changes stemming from the introduction of AVs that may increase private vehicle usage and overall VMT. For example, people without a driver's license, seniors, and people with medical conditions preventing them from driving are expected to make more trips and increase their vehicle-based travel when AVs enter the market (Harper et al., 2016). From a long-term land use perspective, some people may change their home locations and work locations as a result of AVs reducing travel costs to/from major activity locations (Ahmed et al., 2020; Bansal and Kockelman, 2018; Kim et al., 2020). Also, the improved convenience of private vehicles will attract current transit users to switch trips to PAVs, thereby increasing VMT (Huang et al., 2020; Kröger et al., 2019).

Additionally, as drivers become riders in PAVs, PAV travel patterns are likely to involve dropping off travelers at their exact activity locations and traveling empty (i.e., deadheading or relocating) to another location to park during the activity or to serve another traveler. Although deadheading in PAVs is similar to current taxi and ride-hailing services, in the case of taxis and ride-hailing, the next location is likely to be a pickup spot for the next rider, whereas in the case of PAVs, the next location could be a parking spot (i.e., parking space or home) as well as a pickup spot for another household member.

As shown in Figure 1-1, there are, at least, four PAV deadheading options. First, the vehicle can move to a nearby or distant parking space. The parking space choice depends on the parking fee, vehicle operating cost per mile, and the duration of activity (Harper et al., 2018). The vehicle waits in the parking space until the original passenger completes their current activity. Second, the vehicle can go back to the home of its owner to avoid a parking fee (Levin and Boyles, 2015). When parking fees in the area are too expensive, and the distance between home and activity location is close enough or there is another household member planning to use the vehicle, this option is likely to be chosen (Correia and van Arem, 2016). Third, the vehicle can deadhead to another location to pick up another household member, just like ride-hailing services (Correia and van Arem, 2016; Khayati et al., 2021a). This is likely to occur if the locations of the household members are relatively close, and their activity schedules align. If PAV owners release their car to a mobility service provider to serve as a shared-use AV, the vehicle may also serve other passengers, while this dissertation assumes all PAVs are only shared within household members. Fourth, the vehicle can even cruise around nearly aimlessly to avoid parking, when the duration of activity is relatively short and parking costs are high (Millard-Ball, 2019). Along with vehicle electrification, cruising can be an economical choice for PAV users in downtown areas where and when parking fees are expensive relative to fuel costs. Of course, this fourth option is particularly harmful to the performance of the transportation system. However, this dissertation does not consider this last option, assuming intentional cruising is prohibited.

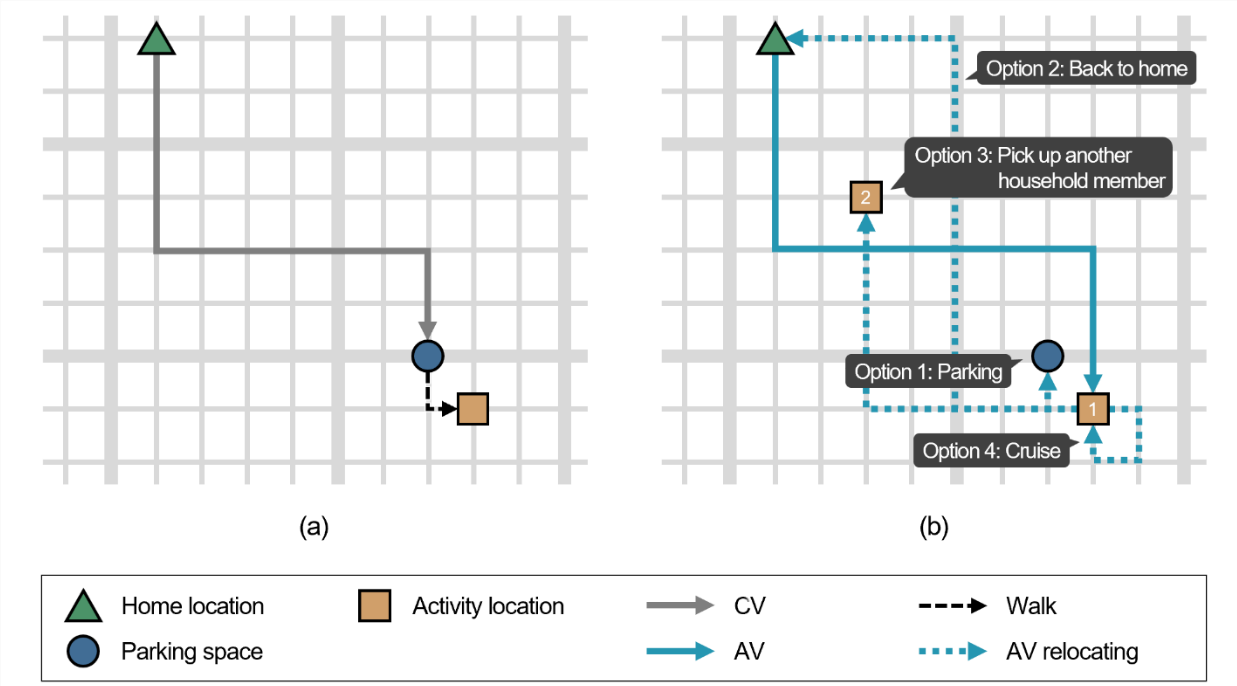


Figure 1-1: Difference in Travel Pattern: (a) PCV's Park-and-walk and (b) PAV's Flexible Deadheading Options after Drop-off

The four deadheading options in Figure 1-1 are also available in the case where the PAV owner/user takes the PAV to a transit station and transfers from PAV to transit before reaching his/her activity location. Transferring from PAV to transit is most likely to occur when there is congestion in the road network and the transit line has a separate right-of-way and therefore is not subject to roadway congestion and delays. If an individual's travel time saving or punctuality matters, the traveler can choose a better right-of-way transit mode, i.e., metro, LRT, or BRT. Considering that such modes require access/egress trips to/from the station by walk or another feeder mode, the PAV is clearly a useful feeder mode, as it does not need to park and can drop the traveler off very close to the transit station. Thus, the PAV drop-off point is not necessarily at the activity location but could be a transit station, which is illustrated in Figure 1-2.

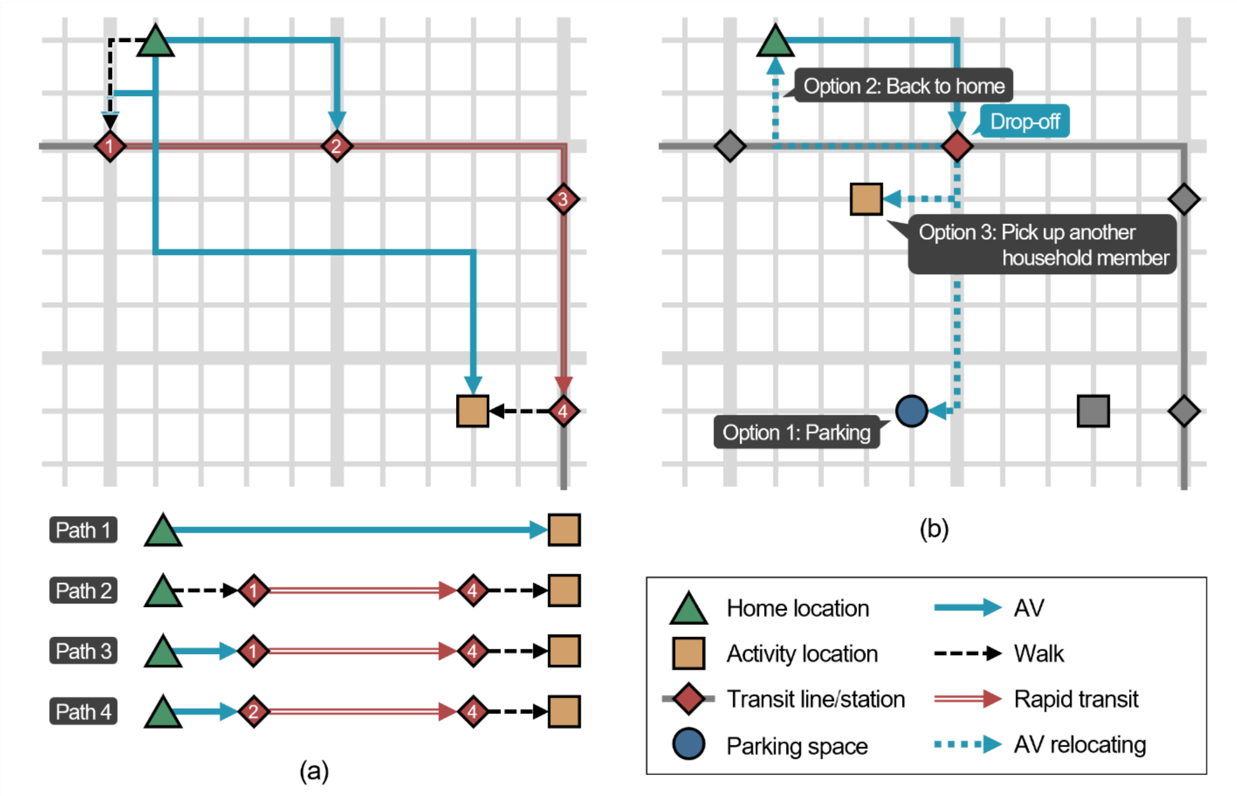


Figure 1-2: Dropping off at Transit Station: (a) Possible Paths for a Home-to-Activity Travel and (b) PAV Deadheading Options for Selected Path (Path 4)

One particular concern is that all the AV deadheading options will generate extra travel distance compared to a transportation system with all conventional vehicles. The increased travel distance for individual vehicles will result in an increase in overall VMT in the roadway network, thereby increasing congestion, energy consumption, and vehicle emissions. Thus, it is important for planners to analyze the impact of PAV travel patterns on the system and develop a modeling framework to analyze travel patterns across the four deadheading strategies.

1.2 Research Questions

Although many studies investigate PAV travel patterns and their impacts, there is no analysis that comprehensively covers household decision-making on vehicle operations, the impacts on transportation system performance, and the development of policies to mitigate negative impacts of new private vehicle travel patterns. Therefore, this dissertation proposes three research questions:

1. How will PAVs change private vehicle operating patterns?
2. How will the new PAV travel patterns affect transportation system performance?
3. What design and policy changes should planners make to leverage PAVs for mobility improvements?

The first question relates to the decision-making process for vehicle operation. Unlike shared-use AVs, where transportation network companies (TNCs) or public agencies can centrally control vehicle routing and scheduling, PAV usage is optimized by individual travelers or within households. Travelers will choose their shortest or least-cost path, regardless of overall system-wide performance. For example, a traveler might choose a distant but cheaper parking space, as they do not need to remain in the vehicle while parking, thereby increasing vehicle travel distance within the road network. Moreover, since households can separate the routing of PAVs from the travelers themselves, these empty-seat travels are not limited to parking but also include other household needs. In particular, when serving other household members, the routing and scheduling of PAVs should consider all activity-travels of the household members.

Given the aforementioned individual (person/household) decision-making process, the second question focuses on the system-wide impacts of PAV usage. These impacts include changes in performance metrics such as VMT, vehicle hours traveled (VHT), and other travel times and costs. Increased vehicle travel distance can lead to reduced travel speeds and increased travel times, which may cause shifts in mode and route choices, or even affect activity-travel scheduling.

The third question seeks ways to reduce the negative impacts of PAV travel patterns, whether through policy implementation or infrastructural investment. Based on extensive scenario analyses, several actions can be identified to prevent or mitigate expected traffic congestion resulting from individual decision-making that disregards system performance. For example, planners might adjust parking pricing policies to discourage remote parking travels or introduce a convenient intermodal pooling system to reduce the number of vehicles entering downtown areas.

In order to answer these questions, this dissertation presents three studies that investigate PAV travel patterns, their impacts, and planners' corresponding actions. Each study analyzes the PAV travels in different approaches and assumptions, as I can predict various scenarios based on different situations.

1.3 Contributions

This dissertation makes several contributions to the literature in both methodological and conceptual aspects. Additionally, the proposed modeling frameworks in this dissertation permit policy assessments aimed at improving transportation systems.

First, this dissertation presents a dynamic parking assignment model that routes parking travel near activity locations. The model captures parking space finding behavior, taking parking lot capacities and congestion into account. I integrate this parking lot choice model with a mode choice model, enabling analysis of the interaction between parking infrastructure performance, PAV parking demand, and mode choice.

Second, using the aforementioned model, this dissertation examines the impact of PAV deadheading (remote parking) and strategies to mitigate the negative effects. Specifically, I apply different parking capacity distributions and parking fees to reduce VMT.

Third, this dissertation proposes a novel future park-and-ride system connecting PAVs with on-demand shared-use AVs (SAVs). The system encourages single-occupancy vehicle (SOV) travelers to transfer to SAVs, reducing the number of vehicles entering downtown areas. Infrastructure investments, including PAV-SAV transfer stations and SAV-dedicated lanes, aim to provide convenient and reliable intermodal travel.

Fourth, the modeling framework and its components for the PAV-SAV transfer system include an innovative approach for integrating shared mobility (e.g. ridesourcing or SAV) trips within traditional trip distribution and network assignment models. The integrated model consists of vehicle distribution, traffic assignment, and service choice. Moreover, I propose an innovative method to incorporate the stochastic arrival of PNR users and the corresponding routing of SAVs based on the destination clusters.

Fifth, the case study for the PAV-SAV transfer system demonstrates significant reductions in VMT and VHT in the region, suggesting that the proposed infrastructure concept can serve as a transportation demand management (TDM) strategy for large and congested metropolitan areas.

Sixth, this dissertation introduces a new model of household activity-travel routing and scheduling behavior in a future world with AVs. In addition to existing mathematical programs that model household vehicle operations, my new formulation reflects multimodal and intermodal travel options available to household members, which are critical to capturing behavior in future transportation systems with PAVs, SAVs, and transit.

Seventh, the case study of the new household activity-travel routing and scheduling problem reveals that parking-at-home could become the dominant vehicle relocation choice, increasing VMT and decreasing parking occupancies in urban areas. The results also show that intermodal trips can reduce household travel costs.

Eighth, the regression models for the household activity-travel routing and scheduling problem analyze the impact of the number of vehicles, household members, and activities on vehicle travel distance and computational time. The results indicate how additional vehicles or activities affect VMT, as well as the computational complexity.

1.4 Outlines

I organize this dissertation as follows.

Chapter 1 motivates the dissertation topic and presents the research questions.

Chapter 2 introduces a parking assignment and mode choice model, assuming that travelers choose parking spaces based on their overall travel cost, including parking fees and the distance between the activity location and the parking space. This chapter specifically assumes that travelers only choose to park their vehicles during the activities. Using an iterative solution approach that integrates mode choice and parking assignment, the model identifies converged mode shares and performance metrics across different scenarios. Based on the case study using a virtual network and agents, this chapter demonstrates that balancing parking pricing and capacities can reduce the extra VMT associated with parking travels.

Chapter 3 introduces a new policy and system designed to reduce extra VMT. This chapter focuses on a transfer system that connects PAV with a shared-use AV (SAV) mode, proposing a new park-and-ride (PNR) system utilizing AVs. The solution approach in this chapter includes vehicle trip distribution, traffic assignment, and service choice, in order to consider the interactions between travel demand, service mode choice, and travel cost. Applied to the Greater Los Angeles area, the chapter finds that the proposed transfer system can significantly reduce both VMT and VHT in the region.

Chapter 4 extends PAV operations to include interconnected decision-making within households. Based on the Household Activity Pattern Problem (HAPP), which stems from mixed integer linear programming (MILP), this chapter models the household vehicle routing and scheduling problem, incorporating multimodal and intermodal trip options. Notably, this chapter introduces transit-based intermodal trips for the first time in household-level activity-travel optimization models, demonstrating that such trips could become viable travel options in the AV era.

Chapter 5 concludes the dissertation and discusses avenues for future research.

Chapter 2 PARKING TRAVEL PATTERN ANALYSIS

2.1 Overview

This chapter parallels Bahk et al. (2022) and focuses on the near-activity location travel associated with PAVs and their impact on VMT relative to the current world with only PCVs. Figure 2-1 displays potential travel patterns for PCVs and PAVs for the same person trip from a home location to an activity location. Figure 2-1 shows that PCV travel typically involves a traveler driving to a parking lot and then walking to the activity location from the parking lot. However, in the case of PAVs, the AV drives the traveler directly to work, negating walking, and then deadheads to a parking location. Notably, because the traveler does not need to walk from parking location to activity location, the traveler is more willing to choose parking locations farther away from the activity location (or allow the AV itself to choose further away parking locations) if they are cheaper.

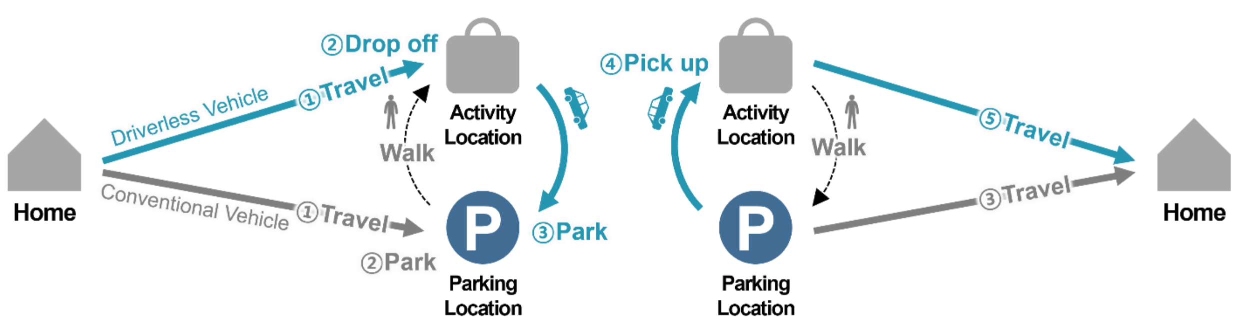


Figure 2-1: Travel Pattern of PCVs and PAVs

The goal of this chapter is to develop a modeling framework in order to analyze the potential impacts of PAVs on near-activity travel patterns and overall VMT. Near-activity travel patterns for PVs denote the travel between activity locations and parking lots by vehicles and people, in the case where the parking lot is not at the same location as the activity. To model this problem, this paper presents an integrated parking location choice and mode choice model. The parking location choice model considers factors such as parking fee, parking lot capacity and congestion, driving cost per mile, walking distance for PCV travelers, and waiting time for PAVs to pick up travelers for their return home trip. The mode choice model captures the potential shifts between transit, shared vehicles like ridesourcing and taxi, and PVs as a function of the cost and service quality provided by each of these modes. Moreover, by integrating the mode choice and parking choice model, the framework captures the balancing effects of mode shifts toward PAVs (and to a lesser extent PCVs) and parking lot capacity and congestion impacts on the attractiveness of PAVs and PCVs.

The study also presents an iterative solution approach to solve the integrated mode choice and parking location choice problem. The output of the model and solution algorithm includes mode shares, VMT, parking lot occupancy, traveler wait times, traveler walk distances, and traveler in-vehicle travel time (IVTT). By varying the percentage of PAVs and PCVs in various scenarios, the study aims to analyze the impact of PAVs on overall VMT. The authors believe integrating mode choice with parking location choice is critical for assessing the impacts of PAVs on near-activity VMT, since PV travel is likely to increase in a future with AVs compared to the current transportation system without AVs.

This chapter makes several contributions to the existing literature. First, it introduces an integrated mode choice and parking assignment problem with PAVs, and formulates it as a fixed-point problem, in order to analyze the impacts of PAVs on near-activity travel patterns and VMT in particular. Previous research aims to analyze the impacts of PAVs on travel patterns and VMT, but those studies do not explicitly integrate mode choice and parking assignment. Second, this chapter proposes a novel simulation-based parking assignment model to evaluate near-activity travel patterns, VMT, parking lot congestion, traveler walking distance, and other important travel attributes. Third, this chapter presents an efficient iterative solution approach to solve the integrated mode choice and parking assignment problem. Fourth, this chapter presents valuable insights into the trade-offs between VMT, travel time, and travel costs when comparing a system with PCVs vs. a system with PAVs. Fifth, this chapter provides insights into the role parking lot prices and the spatial distribution of parking lot capacity can have on VMT.

The remainder of this chapter is structured as follows. The next section (Section 2.2) provides a brief review of the existing literature. The following section (Section 2.3) presents the mathematical formulation of the integrated mode choice and parking location choice problem. Section 2.4 presents an iterative solution approach to solve the integrated model. A case study based on an artificial central business district is outlined in Section 2.5. Section 2.6 presents computational results from the case study and associated scenario analyses. Section 2.7 discusses the implications of the model results. Section 2.8 concludes this chapter.

2.2 Literature Review

Although many studies analyze factors related to AVs that impact travel behavior, relatively few studies analyze the impact of AVs on near-activity location travel and parking. Moreover, most parking studies related to AVs focus on microscopic topics such as optimizing parking lot configurations and how to find a parking location more efficiently (Abidi et al., 2015; Feeney, 1989; Han et al., 2017; Young et al., 1991). Conversely, the current study focuses on parking and AVs across a transportation network to understand and forecast the potential impacts of AVs on VMT, parking lot usage, and other relevant metrics for transportation planning purposes. This section provides a brief review of studies that analyze the relationship between parking, travel behavior, and transportation system performance for PCVs before reviewing the small set of recent studies that incorporate PAVs alongside the other factors.

The parking location choice problem for PCVs is well established in the literature. Feeney (1989) provides a review of studies in the 1970s and early 1980s covering the impact of parking policy measures on travel demand. The behavioral models (mostly logit models) show that factors such as parking fees and time costs (e.g., walking time) impact mode choice and travel behavior (Gillen, 1978). Unlike most of the literature that relies on revealed preference data, Axhausen and Polak (1991) employ stated preference data to estimate a parking choice model. Specifically, they create a parking type choice set that includes off-street, surface lot, and multi-story parking. Two other studies develop and use agent-based parking choice models within MATSim (Bischoff and Nagel, 2017; Waraich and Axhausen, 2012). Bischoff and Nagel (2017) find that incorporating parking choice in MATSim for Klausenerplatz in Berlin increase total VMT estimates by almost 20%. Nurul Habib et al., (2012) incorporate parking type choice alongside activity scheduling decisions within an activity-based travel demand model.

More recently, several studies analyze changes in parking behavior related to PAVs. Table 2-1 provides a summary of these studies alongside a summary of the current study.

Levin and Boyles (2015) adopt the conventional multi-class four-step trip-based model to predict PAV travel patterns assuming some PAVs will drive a traveler to their activity location before deadheading to the same traveler's origin (home) to avoid parking fees near the high-demand activity center. In a PAV-only scenario, Childress et al. (2015) find a 50% discount in parking fees results in a significant increase in VMT. Zhang et al. (2018) suggest that PAVs will generate unoccupied VMT due to the reduction of household vehicle ownership and deadheading. Zhang et al. (2018) develop an integrated parking choice and route choice model. Harper et al. (2018) predict that some PAVs will greedily search for more distant and economical parking spots including unrestricted parking areas rather than downtown parking lots, thereby increasing VMT. On the other hand, Zhao et al. (2018) propose a centrally controlled parking system that collects travelers' destination information and dispatches the vehicles to the parking lots and finds that this can reduce VMT.

It is not possible to compare the results of those studies directly since they each make different assumptions and employ different modeling approaches. However, there are several emerging key factors that illustrate the relationship between AVs, travel behavior, and VMT. For example, parking fees and walking time are the most important factors in parking location choice (Axhausen and Polak, 1991; Childress et al., 2015; Feeney, 1989; Gillen, 1978; Harper et al., 2018). A vehicle's cost per mile is a factor as well. For PAVs, waiting time should be included in behavioral models since travelers need to wait for pickup after calling the AV, unless the traveler summons the PAV to arrive at the pickup point first, in which case the PAV may have to wait for the traveler. The model in this chapter incorporates all these factors into a utility maximization framework for mode choice and parking location choice.

Table 2-1: Comparison of PAV Studies on Parking Behavior

Study	Purpose	Approach	Parking-related Findings
Levin & Boyles (2015)	Analyze impact of AVs on travel behavior and network performance	Four-step trip-based travel forecasting model	PAVs increase VMT due to deadheading to cheap parking
Childress et al. (2015)	Quantify impacts of AVs on travel behavior and network performance	Activity-based travel forecasting model	Improved road capacity, reduced VOT, and discounted parking fees increase PAV demand and VMT.
Zhang et al. (2018)	Quantify excess VMT stemming from vehicle deadheading	Household travel model. Greedy scheduling algorithm for required household vehicles. Mixed-integer program for unoccupied VMT.	Reduction of household vehicles increases VMT due to unoccupied PAV travel.
Zhang et al. (2019)	Quantify network equilibrium patterns under AV parking behavior	Integrated route choice and parking assignment choice model and solution approach	PAVs increase traffic congestion due to parking search. Some PAVs will park at home.
Harper et al. (2018)	Evaluate impact of AVs on VMT, emissions, and parking revenues	Agent-based parking simulation model on grid network with greedy parking lot selection	PAVs park at distant and economical parking locations and increase VMT.
Zhao et al. (2021)	Analyze improvements in congestion under centralized parking dispatch	Optimization of parking control with macroscopic fundamental diagram	Optimized parking assignment reduces cruising VMT for parking
This chapter	Estimate impacts of PAV parking travel patterns on VMT and PV demand	Integrated mode and parking location choice model. Iterative solution approach.	PAVs increase demand for PV travel and as a result, VMT increases.

2.3 Problem Formulation

This chapter presents the integrated mode choice and parking assignment problem, wherein the parking assignment model captures congestion and capacity constraints in parking lots throughout the analysis region. Since the demand for parking is a function of mode choice (i.e., higher PV demand increases parking lot congestion), and mode choice is a function of parking congestion (i.e., congestion in parking lots reduces demand for PVs), this chapter models the integrated mode choice and parking assignment problem using a fixed-point problem formulation. In general, a fixed point of a function $f(\cdot)$ is a value p such that $f(p) = p$, or put another way, the value p is unchanged by function $f(\cdot)$ (Boyles et al., 2022). The variable p can be a scalar or a vector.

Equation 2-1 displays the general form of the integrated mode choice and parking assignment model in the form of a fixed-point problem. A solution to Eqn. 2-1 is a multi-dimensional array of probabilities, $\boldsymbol{p}$**,** that when input into $f_m\left(f_p(\cdot)\right)$ remain unchanged. The parking function $f_p(\cdot)$ in this chapter does not have a straightforward functional form, rather, this chapter employs a dynamic simulation-based parking assignment model that is detailed in the next section. Equation 2-2 shows that the function $f_p(\cdot)$ is non-separable because the mode splits ($\boldsymbol{p_{odt}}$) between each origin $o \in O$ and destination $d \in D$ at time interval $t \in T$ impact the service quality, price, and therefore parking location choice for travelers using the parking system between all origins, all destinations, and all future time periods. Conversely, the mode choice function, $f_m(\cdot)$, displayed in Eqn. 2-3, which returns mode splits for travelers going from origin $o \in O$ to destination $d \in D$ at time interval $t \in T$, is separable by origin, destination, and time interval.

$$\boldsymbol{p} = f_m\left(f_p(\boldsymbol{p})\right) \tag{2-1}$$

$$\boldsymbol{q} = f_p(\boldsymbol{p}) \tag{2-2}$$

$$\boldsymbol{p_{odt}} = f_m(\boldsymbol{q_{odt}}) \tag{2-3}$$

The next section describes the detailed agent-based parking simulation model, $f_p(\cdot)$. The next section also provides the functional form and the parameters for the mode choice function, $f_m(\cdot)$, which is a standard multinomial logit model.

2.4 Solution Approach

Figure 2-2 displays the proposed iterative solution approach to solve the integrated mode choice and parking assignment problem. The remainder of the section describes the iterative solution approach along with the model input and output.

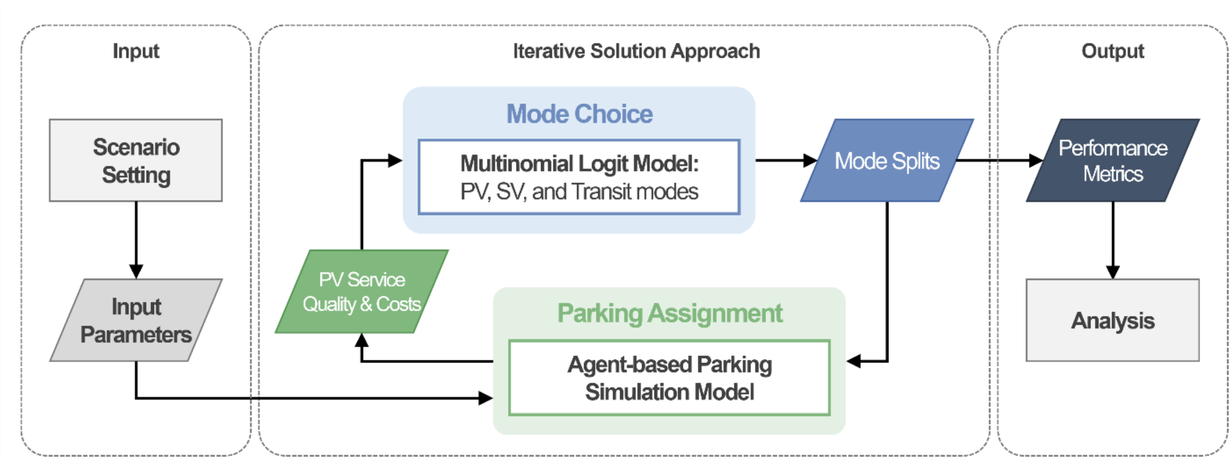


Figure 2-2: Solution Approach

2.4.1 Model Inputs

The left-most box labeled 'Input' in Figure 2-2 includes a scenario setting box that leads into an input parameters box. This chapter performs sensitivity and scenario analyses based on changes in a variety of model parameters. These parameters and the changes to them are detailed in later sections. The input data and parameters in this chapter include the available travel modes, mode choice model parameters, fixed modal attributes for non-PV modes, the location, capacity and price of parking lots, parameters for the parking congestion model, the transportation network, and demand data including trip origins and destinations. The following subsections provide details about the available travel models and the mode choice model parameters.

2.4.1.1 Travel Modes

This chapter incorporates three types of high-level travel modes, PVs, shared vehicles (SVs), and public transit. PV includes conventional PV (PCV) and PAV. SV includes shared-use automated vehicles (SAVs), ride-hailing and ride-sharing services, and taxis. SV travelers wait for a vehicle, travel inside an SV, pay a fare, and receive door-to-door service. Public transit effectively refers to high-capacity buses. Transit riders walk to a bus stop, wait for a bus, pay a fare, travel inside the bus as a rider, and walk to their destination—they may also need to transfer between routes, but this chapter assumes transfers are not necessary.

Specific scenario details are given in the Case Study section; however, it is important to note that each traveler has access to a single PV—either a PCV or PAV but not both—in this chapter. Additionally of note, in the scenarios with all PCVs, SVs are conventional vehicles (SCVs); conversely in the scenarios with all PAVs, the SVs are all SAVs.

2.4.1.2 Mode Choice Model Parameters

Important mode choice model parameters include the disutility of travel time for in-vehicle travel and out-of-vehicle travel (walking and waiting) and the disutility of travel costs. Combining the disutility of travel time and travel costs produces estimates of a user's value of time (VOT). According to previous studies and reports, VOT varies widely depending on a variety of factors (Axhausen and Polak, 1991; US Department of Transportation, 2016). Axhausen and Polak (1991) find a wide range of walking VOT estimates ranging from \$1.35/h to \$47.43/h in the mode choice context and \$7.67/h to \$58.21/h in the parking choice context. Caltrans (2021) uses the following VOTs: \$13.65/h for automobile and transit in-vehicle VOT and \$27.30/h for transit out-of-vehicle VOT in 2016 dollars. Kolarova et al. (2019) estimate the VOT from the German National household travel survey data segmented by mode and income class. Based on the middle-income class's PCV commuting trips (\$8.18/h), the other values of in-vehicle VOT are \$5.26/h, \$8.72/h, and \$4.89/h for PAV, SAV, and public transit, respectively. The walking VOT is \$12.03/h, while the AV and public transit waiting VOT are \$9.49/h and \$7.45/h, respectively. Zhong et al. (2020) provide ranges for the VOT for PCV, PAV, and SAV in the United States by place of living: \$9.36/h (rural) to \$53.71/h (urban) for PCV; \$7.71/h to \$40.89/h for PAV; and \$8.64/h to \$46.53/h for SAV. This chapter uses the values in Kolarova et al. (2019).

Moreover, this chapter uses \$0.50/mi as the cost per vehicle mile of travel, based on the 2020 electric vehicle cost provide by American Automobile Association (2020). Although PCV or PAV can maintain conventional fuel systems in the future, this chapter assumes that all private vehicles are electrified, in order to compare the route choices under the same vehicle unit-distance operating cost.

According to several studies, about 40% of a ride-hailing service travel is deadheading miles (Balding et al., 2019; Henao and Marshall, 2019). In other words, when one mile of PCV travel from an origin to a destination (except the parking travel distance) is changed to a ride-hailing vehicle travel, the travel distance becomes 1.67 miles (67% extra travel). Considering that PAVs do not cruise to find and then pick up another passenger, the PAV's VMT increase depends on the parking location finding travel distance.

2.4.2 Iterative Solution Approach

The middle portion of Figure 2-2 displays an overview of the proposed solution approach that involves iterating between the mode choice model and the dynamic simulation-based parking assignment model. In the iterative process, the outputs of the parking assignment model are the performance of the transportation system, specifically the costs and service quality attributes associated with PAV and/or PCV travel. Given that the parking model is agent-based, these cost and service quality attributes are available at the agent level and can easily be aggregated over time and space (e.g., travel analysis zones). The costs and service quality attributes for the other modes—transit and SV—are fixed in this chapter. The costs and service quality modal attributes for PVs from the parking assignment model are the inputs to the mode choice model, alongside the fixed modal attributes for SVs and transit. The outputs of the mode choice model are the modal splits, which are the inputs for the next iteration of the parking assignment model. This iterative process repeats until there is consistency between the mode choice model and the parking assignment model in terms of modal service quality/costs and modal splits.

The following two subsections describe the dynamic simulation-based parking assignment models and the multinomial logit mode choice model, respectively.

2.4.2.1 Dynamic Simulation-based Parking Assignment Model

The mode choice model returns modal splits, $\boldsymbol{s^n}$, where the n superscript denotes the current iteration number. Given that the modal attributes for SV and transit are fixed, and these modes do not use the parking lots, only the modal splits for PV are needed as input for the parking assignment model, $\boldsymbol{s^n_{m=PV}}$. The formula for the spatial (origin zone to destination zone) and temporal demand for PVs in the current iteration, $s^n_{o,d,t,PV}$, is displayed in Eqn. 2-4.

$$s^n_{o,d,t,PV} = p^n_{o,d,t,PV} \times D_{odt} \quad \forall o \in O, \forall d \in D, \forall\, t \in T \tag{2-4}$$

where D_{odt} denotes the total trip demand from origin zone o to destination zone d departing at time t, which is exogenous to the integrated model system, meaning it is independent of the iteration. Notably, the demand for origin zone o and to destination zone d is based on aggregating traveler agents with origin nodes that are inside origin zone o and destination nodes that are inside destination zone d.

Each traveler agent in the dynamic simulation-based parking assignment model must choose a parking lot, where A is the set of parking lots, indexed by $a \in A$. In this chapter, each traveler creates an ordered list of parking lot preferences, based on their own expected generalized cost of travel. Each traveler with a PCV drives from their origin to a parking lot before walking from the parking lot to their activity location. Each traveler with a PAV rides from their origin to their activity location (i.e., destination node) after which the vehicle deadheads to a parking lot. Eqns. 2-5 and 2-6 display the expected generalized cost functions for PCV travelers and PAV travelers respectively.

$$EC_{PCV,a} = VOT_{trv} \times t_{trv,a} + VOT_{wlk} \times t_{wlk,a} + CPM \times d_a \quad \forall a \tag{2-5}$$

$$EC_{PAV} = VOT_{wt} \times t_{wt,a} + CPM \times d \quad \forall a \tag{2-6}$$

where VOT_{trv} is the in-vehicle VOT, and $t_{trv,a}$ is the travel time between the origin and parking lot a; VOT_{wlk} is the walking VOT, and $t_{wlk,a}$ is the walking time between parking lot a and the traveler's destination; VOT_{wt} is the waiting VOT, and $t_{wt,a}$ is the length of time the traveler must wait at the activity location to be picked for their return home trip, when their PAV is in parking lot a; CPM is the vehicle's cost per mile, and d_a is the travel distance between the traveler's origin and parking lot a (via the destination in the case of PAVs).

The parking assignment model simulates the movements of PAV and PCV travelers and the vehicles themselves as well as the occupancy of parking lots, in a time-driven simulation. Hence, the simulation captures the current location of travelers, PAVs, and PCVs as well as the current occupancy of all parking lots in the transportation network, every time step, which is denoted $\Delta\tau$. This chapter applies six seconds for $\Delta\tau$ based on the network resolution and computational convenience.

Each traveler has an ordered list of parking lots because it is possible that a parking lot is full when the PV arrives at the parking lot entrance in the simulation, in which case the traveler or the traveler's PAV needs to travel to the next parking lot on their ordered list. Of note, this chapter assumes a traveler only becomes aware of a parking lot's occupancy when they arrive at the parking lot—future studies may assume travelers always have full knowledge of parking lot occupancies. Additionally, since travelers can go from parking lot to parking lot in the simulation, the expected costs for a parking lot a, EC_a, in a traveler's ordered list does not reflect the detour travel time and distance that occurs in the simulation. Hence, the ordered list of parking lots for an agent is fixed within the current iteration of the model, i.e., an agent does not update their ordered parking list during a simulation.

In addition to capturing hard capacity constraints at each parking lot in the transportation network, the parking assignment model also captures in-lot parking search time. This is an important model feature for dense urban areas with limited parking supply, as drivers can spend considerable time inside parking lots finding an open parking spot. In this chapter, the parking time after entering the parking lot (in-lot parking time) depends on the volume to capacity ratio of the parking lot. For example, this chapter uses a BPR function to reflect the in-lot parking time, expressed as Eqn. 2-7:

$$t_{prk}(v_a) = t_0 \times \left\{1 + \alpha \left(\frac{v_a}{C_a}\right)^{\beta}\right\} \tag{2-7}$$

where t_{prk} is the in-lot parking time; v_a is the number of vehicles currently in parking lot a (parking and searching for parking); C_a is the capacity of parking lot a; and α, β, and t_0 are model parameters to be calibrated based on data.

The parking assignment model also captures network IVTT and network walking time. The simulation model assumes both vehicles and pedestrians travel along the shortest network path. The model does not currently capture congestion in the road network, as the assumption is that parking lot capacity is the limiting constraint on PV mode demand. Additionally, the simulation model does not capture congestion or capacity at drop-off points (i.e., activity locations).

As noted in Figure 2-2, the simulation-based parking assignment model returns the service quality and costs for PV modes. It does so by taking the average values for service quality and cost from all traveler agents with origin o, destination d, departure time t, and PV mode m, as denoted in Eqn. 2-8.

$$q_{o,d,t,m,k}^{n} = \frac{\sum_{r\in R} \delta_{o,d,t,m}^{r,n}\, q_k^{r,n}}{\sum_{r\in R} \delta_{o,d,t,m}^{r,n}} \quad \begin{array}{l} \forall o \in O, \forall d \in D, \forall t \in T \\ \forall m \in M, \forall\, k \in K_m \end{array} \tag{2-8}$$

where, $\delta_{o,d,t,m}^{r}$ is an indicator variable equal to one if agent r has origin o, destination d, departure time t, and was assigned to mode m in iteration n; $q_k^{r,n}$ is agent r's experienced service quality or cost metric k's value in iteration n. The set of experienced service quality or cost metrics K_m, vary by PV mode m. For PCV, K_{PCV} includes IVTT from origin to parking lot, in-lot parking time, parking fee, walking time from/to the parking lot, the opposite direction IVTT, and vehicle travel distance to calculate vehicle parking cost. On the other hand, for PAV, K_{PAV} includes include IVTT from origin to destination, total vehicle travel distance, parking fee, and the waiting time for the PAV to pick up the traveler for the return home trip. The values in Eqn. 2-8 are then fed into the mode choice model.

2.4.3 Multinomial Logit Mode Choice Model

This subsection describes the mode choice model. The chapter employs the random utility maximization framework to model mode choice. The utility function for each mode can be written as Eqns. 2-9 through 2-13:

$$U_{PCV} = \beta_{IVTT,PCV}\left(t_{trv} + t_{prk}\right) + \beta_{wlk}t_{wlk} + \beta_{cost}\left(c_{opr}d + c_{prk}t_{dur}\right) + \epsilon \tag{2-9}$$

$$U_{PAV} = \beta_{IVTT,PAV}t_{trv} + \beta_{wt}t_{wt} + \beta_{cost}\left(c_{opr}d + c_{prk}t_{dur}\right) + \epsilon \tag{2-10}$$

$$U_{SCV} = \beta_{SV} + \beta_{IVTT,SCV}t_{trv} + \beta_{wt}t_{wt} + \beta_{cost}c_{fr} + \epsilon \tag{2-11}$$

$$U_{SAV} = \beta_{SV} + \beta_{IVTT,SAV} t_{trv} + \beta_{wt} t_{wt} + \beta_{cost} c_{fr} + \epsilon \tag{2-12}$$

$$U_{Transit} = \beta_{Transit} + \beta_{IVTT,Transit} t_{trv} + \beta_{wlk} t_{wlk} + \beta_{wt} t_{wt} + \beta_{cost} c_{fr} + \epsilon \tag{2-13}$$

where t_{trv} is path travel time (origin to the final parking lot entrance), t_{prk} is in-lot parking time from Equation 2-7, t_{wlk} is walking time, t_{wt} is waiting time, c_{opr} is vehicle operating cost per mile, d is vehicle driving distance (including parking lot searching travel), c_{prk} is parking fee per hour, t_{dur} is parking duration time, c_{fr} is the fare of shared vehicle or transit, β_{SAV} and $\beta_{Transit}$ are mode-specific coefficients, β_{IVTT} is IVTT coefficient, β_{cost} is cost coefficient, and β_{wlk} and β_{wt} are coefficients for each variable.

Among those variables, t_{trv}, t_{prk}, c_{prk}, and d change in the parking assignment model, and the other non-beta parameters and variables remain unchanged based on scenario settings. $\beta_{IVTT,PCV}$, $\beta_{IVTT,PAV}$, β_{wlk}, β_{wt}, and β_{cost} are frequently used variables in the mode choice model and can be found from many studies in the literature. Wardman (2004) and Pratt and Evans IV (2004) collect and list relative time valuations for transit travel from decades of studies in UK and US, respectively.

This chapter also assumes that the error terms, ϵ, are independent (across modes and agents) and identically distributed. Hence, the functional form for mode choice is the multinomial logit model. Given the modal attributes from the previous iteration of the parking assignment model, the exogenous modal attributes and other parameter values, as well as the beta coefficients, determining the mode choice probabilities, $\boldsymbol{p}$, from the multinomial logit model is straightforward and computationally inexpensive.

2.4.4 Model Output

After the iterative solution approach converges to a solution, there are a variety of system-level and agent-level performance metrics that can be output for analysis purposes. The system-level metrics include VMT, empty VMT, final mode splits, parking lot occupancy and parking lot revenue. The agent-level metrics include travel time, walk time, travel cost, generalized cost, and systematic utility.

2.5 Case Study

2.5.1 Network Configuration

This chapter uses a grid network describing an imaginary central business district (CBD). The network, displayed in Figure 2-3, has 8 external origin nodes (Nodes 1 to 8), 22 activity locations (Nodes 9 to 30), and 10 in-network parking lots (Nodes 31 to 40) with 1 out-of-network parking lot (Node 41) that accommodates unassigned vehicles. The size of a block is 600 ft by 500 ft and the width of the road is 60 ft. The main road links are unidirectional with a uniform vehicle speed (25 ft/s) and a uniform walking speed (4 ft/s).

Parking assignment requires a fine spatial resolution, particularly in the CBD. Each intersection is divided into four nodes to reflect intersection delays. Each internal short link in each intersection has additional travel times: 12 seconds for the *through* direction and 24 seconds for a left turn and a U-turn. Each activity location and parking lot has two bi-directional links connected with the main road that take 18 seconds to traverse and are accessible only from the adjacent direction links (i.e., only right turn is available) and a short detour (ex: U-turn at the downstream intersection) is required for the opposite direction travel. For example, assume a PAV with external origin 3 and activity location 21 parks in lot 36 in Figure 2-3, the node sequence of the path would be: [3, 539, 537, 122, 535, 533, 531, 529, 530, 549, 550, 212, 21, 211, 550, 552, 362, 36].

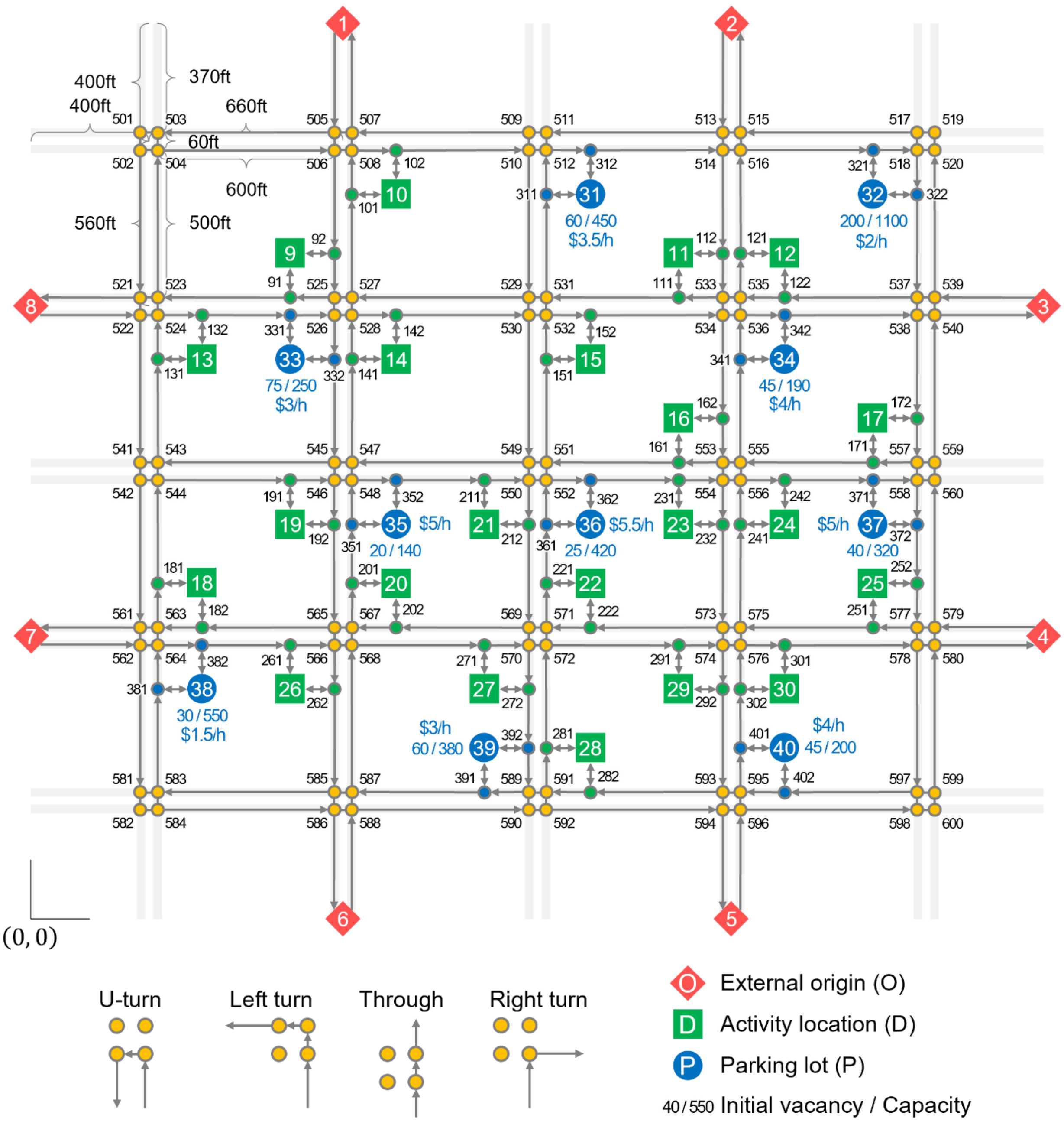


Figure 2-3: Grid Network for Parking Assignment Simulation

2.5.2 Trip Generation and Distribution

Vehicle trips are generated every six seconds ($\Delta\tau = 6sec$) and the simulation runs for four hours (i.e., there are 2,400 time steps during the process). To collect enough samples, each simulation runs three times (i.e., three days). There are 12,000 entering trips including PV and non-PV (SV or public transit) users per scenario. To balance the parking location availability throughout the day, 3,000 PVs randomly exit the parking lot during the analysis period. The 12,000 entering trips have uniformly distributed origin and destination nodes (and zones) and departure times. Additionally, the model does not explicitly model travel from activity location or parking lot to external origin. Rather, this chapter uses fixed values for PAV user pickup wait time and IVTT to external origin.

2.5.3 Parking Lots

Each parking lot has a fixed parking capacity and a fixed parking fee. The total parking capacity across the 10 parking lots is 4,000 and 15% of parking spots (600) are vacant at the beginning in the base scenario. The results section includes scenario analyses with respect to changes in parking fees and parking lot capacities. Parking fees range from \$1.5/h to \$5.5/h with mean (median) values of \$3.65/h (\$3.75/h). Parking lot fees are based on lots in major cities in Germany and the United States (Parkopedia, 2021). When all parking lots are full, vehicle must go to the out-of-network parking lot (Lot 41) that is 0.5 miles away, costs \$5.5/h, and has a capacity of 10,000.

For the in-lot parking space search time function (Eqn. 2-7), this chapter uses the following parameter values for all parking lots: $t_0 = 1$ minute and $\alpha = \beta = 2$. According to the function, parking time is 60 seconds when the parking lot is empty, 90 seconds at 50% vacancy, 120 seconds at 30% vacancy, and 180 seconds at 1% vacancy.

2.5.4 Model Parameters and Values of Time

The model parameters and VOTs used in this chapter are based on those in Kolarova et al. (2019). Since there is no experience of AV travel yet, the value of AV travel time in most studies relies on SP survey or assumptions. The San Diego Association of Governments (SANDAG) multiplies 0.75 from the PCV in-vehicle VOT as a modifier considering the improved convenience (Resource Systems Group, 2020), which is the same as Correia et al. (2019). Conversely, Kolarova et al. estimate that in-vehicle VOT in PAVs is 0.64 of in-vehicle VOT in PCVs. According to Singleton (2019), several simulation studies assume various VOTs of AVs, and the value ranges from 0% to 100% of PCV VOT. This chapter applies Kolarova et al. (2019)'s survey-based number in the base scenario and adjusts the number in alternative scenarios with different modifiers. Note that Kolarova et al.'s SAV refers to "driverless taxi" in their survey. The coefficient values used in this chapter are shown in Table 2-2.

Table 2-2: Model Parameters

Variable		PCV	PAV	SCV	SAV	Transit
Mode-specific constant		0	0	-0.927	-0.927	-3.23
Time-related	In-vehicle time (minutes)	-0.0966	-0.0621	-0.11	-0.103	-0.0577
	Walking time (minutes)	-0.142	-	-	-	-0.031
	Waiting time (minutes)	-	-0.112	-0.112	-0.112	-0.088
Cost-related	Operating cost and parking fee (USD)	-0.709	-0.709	-	-	-
	Fare (USD)	-	-	-0.709	-0.709	-0.709

2.5.5 Travel Costs for Mode Choice

The mode choice model includes out-of-network IVTT since the mode choice is not only based on the travel in the simulated network, but also affected by the whole travel path. For each traveler, the out-of-network IVTT time for two directions are added to the in-network IVTTs (including the parking lot searching time) determined by the parking assignment model. PV and SAV users' out-of-network IVTT is set to 20 minutes per one way, and transit users' out-of-network IVTT is set to 30 minutes per one way. Including the in-network IVTT, the total IVTT becomes around the US average (27.6 minutes for one-way commute) according to recent data (Helling, 2023). Assuming the average speed is 24 mi/h, the out-of-network one-way travel distance is 8 miles.

This chapter assumes 10 minutes (5 minutes in each direction) of waiting time for SAV and 20 (10+10) minutes of waiting time and 10 (5+5) minutes of walking time for transit. Transit fare is $5 (thus, $10 for the two-way trips). Uber fare consists of base fare ($2), cost per minute ($0.4/min), and cost per mile ($1/mi) (Chen and Kockelman, 2016), which can be changed when the company starts to run AVs. For SAVs, Chen and Kockelman (2016) use $0.75–1/mi, Kaddoura et al. (2020) assume $0.64–0.84/mi (€0.35–0.46/km), and An et al. (2019) estimate $0.66/min, which is a simplified cost estimation of the current Uber service. Considering those studies, this chapter uses $1.2/mi for SCV fare and $0.8/mi for SAV fare.

2.5.6 Scenarios

This chapter analyzes several scenarios that reflect various possible future conditions at different points in time. Table 2-3 displays the full set of scenarios. In the base scenario, all PVs are PCVs. Those PCVs are all converted into PAVs in Scenario A. Scenarios B1 and B2 are all PAV scenarios, but they apply different in-vehicle VOTs for PAV, 50% and 90% of PCV in-vehicle VOT, respectively. Scenarios C1 and C2 are also all PAV but uniformly apply $3.5/h fee to all parking lots, and Scenario C2 additionally attempts to evenly distribute parking lot capacity across the network.

Table 2-4 displays the parking lot fees, capacity, and initial vacancy across a variety of scenarios.

In the base scenario and Scenarios A–C2, the traveler agents are aggregated into a single origin zone and single destination zone for the mode choice model. However, in Scenarios D1–D5, the traveler agents are aggregated into four destination zones in the mode choice model. Scenarios D1 through D5 vary the proportion of PVs that are PAVs, as opposed to PCVs, between 0 and 1 in increments of 0.25.

Table 2-3: Scenarios

Scenario	Modes	PAV VOT	Parking fee	Parking lot capacity	PAV percentage	Description
One Origin and One Destination Spatial Aggregation in Mode Choice						
Base	PCV, SCV, Transit	-	Varied	Uneven	0%	CV default
A	PAV, SAV, Transit	64.3% of PCV	Varied	Uneven	100%	AV default
B1	PAV, SAV, Transit	90.0% of PCV	Varied	Uneven	100%	Variations in PAV VOT parameter
B2	PAV, SAV, Transit	50.0% of PCV	Varied	Uneven	100%	
C1	PAV, SAV, Transit	64.3% of PCV	Uniform	Uneven	100%	Variations in cost variable
C2	PAV, SAV, Transit	64.3% of PCV	Uniform	Even	100%	
One Origin and Four Destinations Spatial Aggregation in Mode Choice						
D1	PCV, SCV, Transit	64.3% of PCV	Varied	Uneven	0%	Variations in PAV Ownership Percentage
D2	PCV, PAV, SCV, SAV, Transit				25%	
D3	PCV, PAV, SCV, SAV, Transit				50%	
D4	PCV, PAV, SCV, SAV, Transit				75%	
D5	PAV, SAV, Transit				100%	

Table 2-4: Parking Lot Information across Scenarios

Parking lot	Default			Scenarios C1 and C2	Scenario C2	
	Parking fee (USD/h)	Capacity (veh)	Initial vacancy (veh)	Parking fee (USD/h)	Capacity (veh)	Initial vacancy (veh)
31	3.5	450	60	3.5	250	38
32	2	1,100	200	3.5	250	37
33	3	250	75	3.5	750	112
34	4	190	45	3.5	400	60
35	5	140	20	3.5	500	75
36	5.5	420	25	3.5	550	83
37	5	320	40	3.5	350	52
38	1.5	550	30	3.5	300	45
39	3	380	60	3.5	300	45
40	4	200	45	3.5	350	53
41	5.5	10,000	10,000	5.5	10,000	10,000

2.6 Results

2.6.1 No Spatial Disaggregation Scenarios

The Solution Approach section and Figure 2-2 describe an iterative solution approach to solve the fixed-point integrated mode choice and parking location choice problem, $\boldsymbol{p} = f_m\left(f_p(\boldsymbol{p})\right)$. However, when the variable p is a scalar or low-dimensional vector, and the function $f_m\left(f_p(\boldsymbol{p})\right)$ is relatively easy to evaluate, it is possible to use enumeration to solve the fixed point problem. The base scenario and scenarios A through C2 meet these criteria because the mode choice model does not include any spatial or temporal disaggregation; hence, the dimension of $\boldsymbol{p}$ is $1 \times 1 \times 1 \times |M|$. Using an enumeration method also has the added benefit of ensuring that all fixed points are identified, whereas the iterative solution approach may not identify all possible fixed points solutions.

Figure 2-4 shows the results of the enumeration approach for the base scenario and scenarios A through C2. The x-axis displays the input values for the PV mode share, $p_{m=PV}$. and the y-axis displays the evaluation of the integrated parking assignment and mode choice function, $f_m\left(f_p(p_{m=PV})\right)$. Values along the diagonal represent solutions to the fixed-point problem.

Using an increment of 1%, Figure 2-4 shows that there is a unique solution for the base scenario and scenarios A through C2. Unsurprisingly, the lines are all downward sloping. Moreover, the relative flatness of Scenario C1 and C2 likely stems from the fact that the parking fees across the network are uniform. The existence and uniqueness of a solution for all scenarios engenders a straightforward analysis of the fixed-point solutions across scenarios.

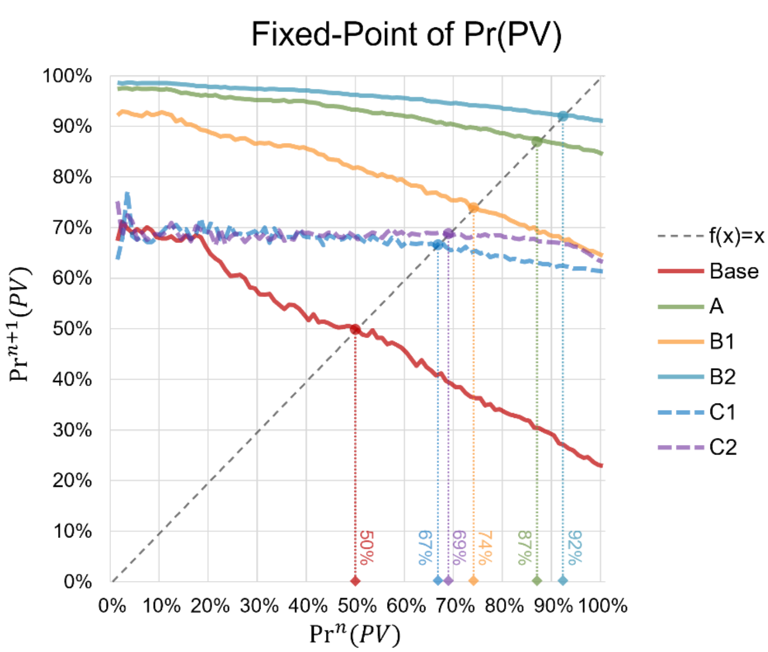


Figure 2-4: Fixed Point Solutions for Private Vehicle Mode Choice Probability--Pr(PV)

2.6.1.1 Mode Share Metrics

Figure 2-5 shows the mode shares for all modes in each scenario. The mode share for PV is lowest in the base scenario where the PVs are PCVs, and the mode share is 50%. In Scenario A, where all PVs are PAVs, PV mode share significantly increases to 87% due to eliminating walking time, potentially reducing parking fees, and the reduction in IVTT disutility.

In Scenario B2, the assumption is that PAV in-vehicle VOT is 50% of PCV in-vehicle VOT, and the PAV mode share increases all the way to 92%. In Scenario B1, when PAV in-vehicle VOT is 90% of PCV in-vehicle VOT, the PAV mode share is 74%. Taken together, Scenario A, B1, and B2 unsurprisingly indicate that PAV IVTT disutility has a significant impact on mode share.

The properties of parking lots also affect the choice probability. Instead of the varied parking fees that range from $1.5/h to $5.5/h in the base scenario, all parking fees are set to $3.5/h in Scenarios C1 and C2. In addition, Scenario C2 redistributes the parking lot capacities to be more evenly distributed in the network. In Scenarios C1 and C2, the PAV mode shares are 67% and 69%, respectively. This represents a notable reduction in mode share compared to Scenario A, in which the larger parking lots had lower fees.

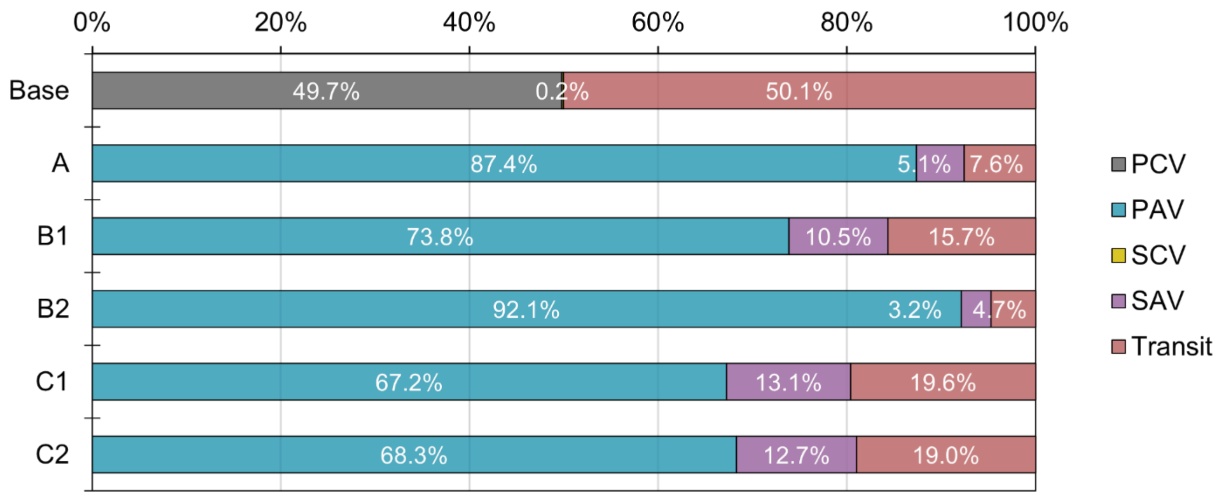


Figure 2-5: Mode Share by Scenarios

2.6.1.2 VMT Metrics

In addition to the increase of the travel demand (Figure 2-6a), total PV VMT substantially increases in PAV scenarios (Figure 2-6b). Note that I only consider in-network VMT (starting from external origin nodes), and do not include the VMT from the actual origin to external nodes. In-network VMT increases by 15,000–22,000 miles in Scenarios A, B1, and B2 compared to the base scenario. On the other hand, the increases are reduced when there is no difference in parking fees in Scenario C1 and C2.

As shown in Table 2-5 and Figure 2-6c, the average VMT for a PCV is 1.07 miles in the base scenario, and the average VMT for a PAV stretches from 1.18 miles to 2.57 miles in the other scenarios. The VMT per vehicle increases by 1.38–1.51 mi/veh in default parking lot settings compared to the base scenario. In Scenarios C1 and C2, VMT per vehicle increases by only 0.11–0.35 mi/veh. This clearly indicates that the spatial distribution of parking prices and parking supply have a significant impact on average VMT per vehicle. Hence, if policymakers and planners are interested in reducing VMT in a future era with PAVs, parking supply and pricing must be considered alongside other policy measures.

The increase in in-network VMT from PAVs shown in Figure 2-6b stems from both an increase in PV trips (shown in Figure 2-6a) and an increase in network VMT per vehicle (shown in Figure 2-6c). Hence, VMT in a future with AVs is likely to increase due to travelers switching to PV and also driving more miles in PAVs than they did or would have in PCVs. Policymakers interested in decreasing VMT will likely need a multi-pronged approach to address these two factors that are expected to increase VMT.

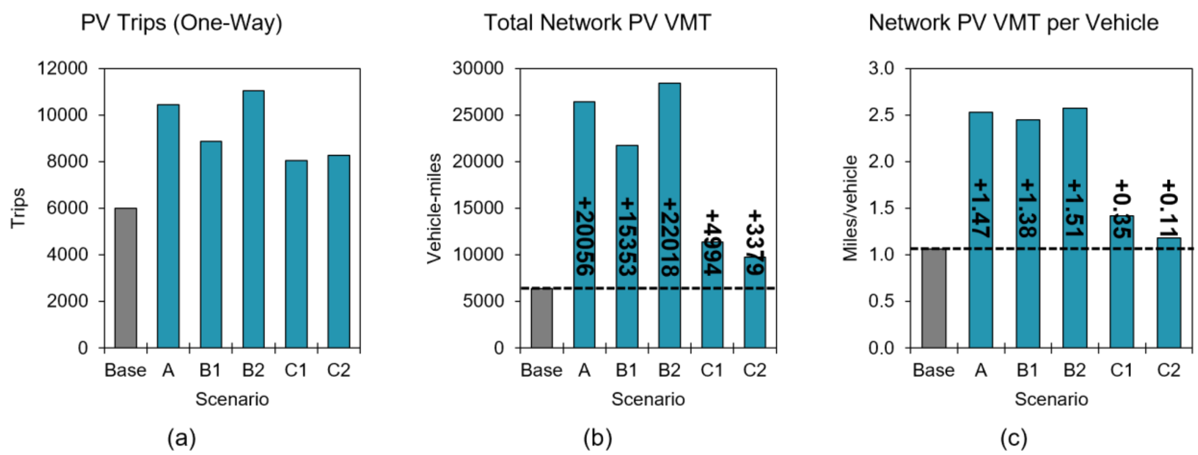


Figure 2-6: PV's VMT in the Network: (a) Number of PV Trips, (b) Total PV VMT, and (c) VMT per Vehicle

2.6.1.3 Travel Time and Travel Cost Metrics

Table 2-5 shows the average travel time components for travelers along several dimensions, along with average total travel time, and average travel distance. Travel distance is the distance in the grid network (counted from the external origin node) and includes the deadheading travel distance. The travel distance in every PAV scenario is longer than the distance in the PCV base scenario.

Since PCV travelers need to travel to parking lots and search for parking, while PAV travelers do not, the average IVTT of PCV travelers is 3.3 minutes longer than that of PAV travelers on average. On the other hand, PAVs spend more time searching for parking than PCVs. The reasons are twofold; first there are more vehicles in the PAV scenarios and second PAVs have more homogeneous parking lot preferences—they want cheap parking and are less sensitive to distance from activity location and parking spot search time—making cheaper parking lots more crowded.

The PCV users' average (one-way) walking time from parking lot to activity location is about 6 minutes in one direction, and nearly 13 minutes total including the activity location to parking lot return walk. Of course, walking time is zero minutes for the PAV scenarios. The average waiting time for PAVs to pick up PAV users is 1.2-2.4 minutes in Table 2-5. The variation across scenarios comes from the distance between parking lots and activity locations.

The final column sums average traveler IVTT, walking time, and waiting time to determine total travel time. The results show that the total roundtrip in-network travel time for PCV is significantly higher than total roundtrip in-network travel time for PAV users. Hence, there are significant time benefits associated with PAVs compared with PCVs.

Table 2-5: Average PV Traveler Distances and Times

Scenario	Number of PVs (veh)	Travel distance (mi/veh)	In-lot parking time (min/veh)	IVTT (min/prs)	Walking time (min/prs)	Waiting time (min/prs)	Total time (min/prs)
Base	6,000	1.07	2.45	8.19	12.73	-	20.9
A	10,440	2.53	2.71	4.83	-	2.37	7.2
B1	8,880	2.45	2.70	4.83	-	2.40	7.2
B2	11,040	2.57	2.72	4.84	-	2.35	7.2
C1	8,040	1.42	2.61	4.84	-	1.39	6.2
C2	8,280	1.18	2.45	4.85	-	1.22	6.1

Table 2-6 presents an even more holistic comparison of the travel experiences of PV users across scenarios; it includes average monetary costs and monetized travel time components based on the values of IVTT, walking time, and waiting time in the mode choice model. The final column of Table 2-6 displays the total generalized cost per traveler.

Table 2-6 shows that the in-network vehicle operating cost is \$0.06 to \$0.75 higher for PAVs than PCVs, depending on the scenario. This result stems from the deadheading distance that PAVs travel after dropping off travelers at their activity locations.

Scenarios A, B1, and B2 have higher average parking fees for travelers compared with the base scenario. Hence, despite PAVs being able to travel further to cheap parking lots, the increase in total PV demand in the PAV scenarios forces some travelers to pay for parking at the high-cost parking lots, which more than offsets their ability to access cheap parking lots. Since the parking fees are unified in Scenarios C1 and C2, the popular cheaper-than-average parking lots are not cheap anymore. Thus, the average parking fee increases in those scenarios.

The monetized IVTT, monetized walking time, and monetized waiting time columns of Table 2-6 parallel the IVTT, walking, and waiting time columns in Table 2-5. IVTT is higher and walking time is significantly higher for PCVs than PAVs, while waiting time is higher for PAVs.

The final column of Table 2-6 is the sum of all the cost and monetized cost components in the preceding columns. Interestingly, while Scenario A and B1 have the lowest total generalized costs, the base scenario has a lower generalized cost than Scenarios C1 and C2. This latter finding stems directly from the high parking cost per person in Scenarios C1 and C2.

Table 2-6: Average Monetized Traveler Costs

Scenario	Vehicle operating cost (USD/prs)	Parking fee (USD/prs)	Monetized IVTT (USD/prs)	Monetized Walking time (USD/prs)	Monetized Waiting time (USD/prs)	Total generalized cost (USD/prs)
Base	0.53	4.72	1.12	2.55	0	8.92
A	1.27 (+0.73)	5.34 (+0.62)	0.42 (-0.69)	0 (-2.55)	0.37 (+0.37)	7.40
B1	1.22 (+0.69)	5.07 (+0.35)	0.42 (-0.69)	0 (-2.55)	0.38 (+0.38)	7.10
B2	1.29 (+0.75)	5.46 (+0.74)	0.42 (-0.69)	0 (-2.55)	0.37 (+0.37)	7.54
C1	0.71 (+0.18)	7.77 (+3.05)	0.42 (-0.69)	0 (-2.55)	0.22 (+0.22)	9.12
C2	0.59 (+0.06)	7.84 (+3.12)	0.42 (-0.69)	0 (-2.55)	0.19 (+0.19)	9.05

Together with the VMT results, Table 2-5 and Table 2-6 illustrate trade-offs between PCVs and PAVs in terms of travel time, travel cost, and VMT. Compared with the base scenario, the PAV scenarios A, B1, and B2 significantly increase VMT, while reducing average traveler in-network time considerably and slightly reducing traveler generalized costs. On the other hand, compared with the base scenario, the PAV scenarios C1 and C2, only slightly increase VMT, while significantly reducing average in-network travel time. However, C1 and C2 have a higher total generalized cost than the baseline scenario because of the higher parking costs that are needed to reduce VMT.

2.6.1.4 *Vehicle Hours Traveled vs. Traveler In-vehicle Travel Time Results*

Figure 2-7 displays both total VHT and total traveler IVTT under the various scenarios. Figure 2-7a displays the total VHT for PVs and traveler IVTT. Even though the number of travelers and VHT increase in the PAV scenarios, there is no significant increase in total traveler IVTT. Understandably, this is because the PAVs are empty during the parking search process. Figure 2-7b shows that PV VHT per vehicle increases in Scenarios A, B1, and B2 relative to the baseline scenario; conversely, PV VHT per vehicle only increase slightly in Scenario C1, while Scenario C2 shows a slight decrease. Figure 2-7c displays the average IVTT per traveler, with the main result being that IVTT per traveler is lower in the PAV cases than the baseline PCV scenario. The results in Figure 2-7c partially explain the increase in PV mode share in the PAV scenarios despite the increase in VHT with PAVs.

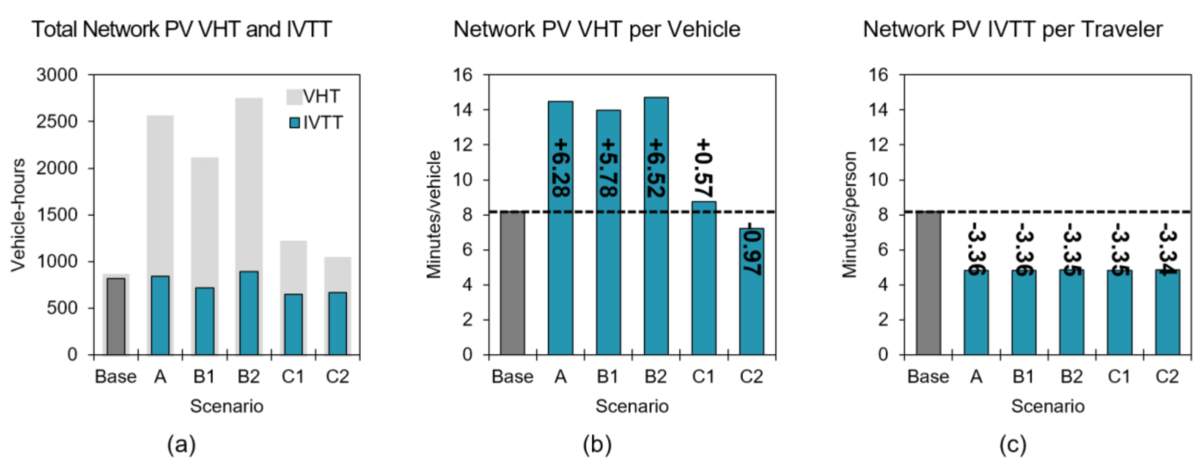


Figure 2-7: PV's VHT and IVTT in the Network: (a) Total PV VHT and IVTT, (b) VHT per Vehicle, and (c) IVTT per Traveler

2.6.1.5 *Impact from Shared AVs*

According to Balding et al. (2019) and Conway et al. (2018), using data from the 2017 National Household Travel Survey, the share of for-hire vehicles (taxi and TNC) is around

0.5% across the country and up to 1.7% in San Francisco and 1.5% in Washington DC. Since this chapter only considers travelers who have their own vehicles, the base scenario (PCV-SCV) shows an even lower mode share for SVs, 0.2%. However, the percentage increases in the PAV-SAV scenarios as the SV's travel cost per mile decreases significantly.

Naturally SVs, particularly SAVs, impact total network VMT in addition to PAVs. Assuming 40% deadheading miles for SVs (Balding et al., 2019; Henao and Marshall, 2019), SV travel adds 0.67 deadhead miles per in-service mile. Figure 2-8 illustrates the impact of SAVs on VMT. Figure 2-8a displays the number of SV trips across the scenarios. Interestingly, Scenarios C1 and C2 produce the highest number of SV trips. Figure 2-8b displays the total SV deadheading VMT, which parallels the results in Figure 2-8a. Figure 2-8c displays the total SV and PV VMT and finds that VMT increases substantially (5,000–22,000 miles, depending on the scenario) in the AV-based scenarios. However, the impact of SV VMT (green bars in Figure 2-8c) is relatively small compared to PV VMT (blue bars in Figure 2-8c) in nearly all scenarios.

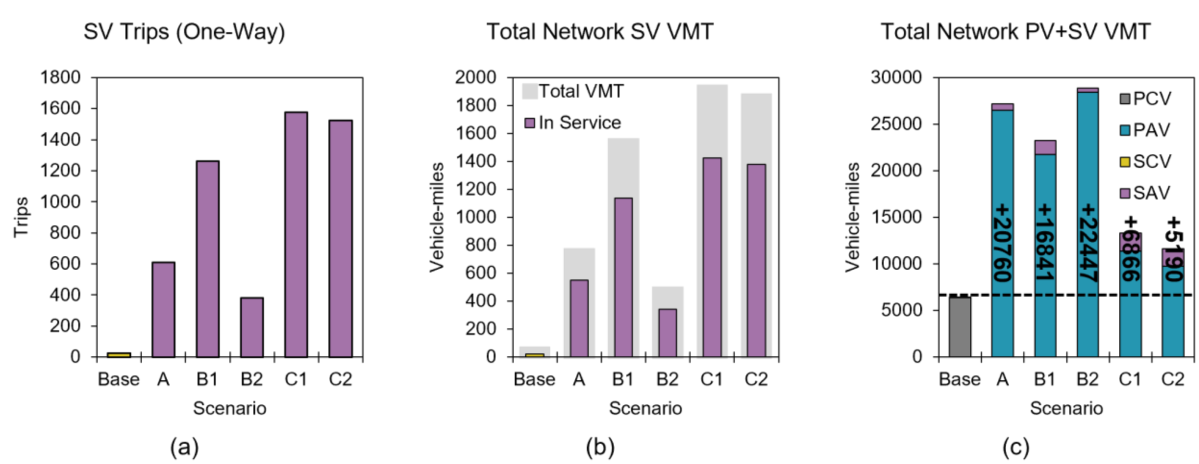


Figure 2-8: SV VMT in the Network: (a) Number of SV Trips, (b) Total SV Deadheading VMT, and (c) Total PV and SV VMT

2.6.2 Spatial Disaggregation Scenarios

While the results in the prior subsection were based on an enumeration-based solution approach to the integrated mode choice and parking assignment problem, this section presents results using the iterative solution approach proposed in the Solution Approach section. Notably, the iterative solution approach is necessary in this section because the mode choice model aggregates the travelers into four destination zones, rather than just one destination zone like in the prior subsection. This subsection illustrates the ability of the iterative solution approach to identify a solution to the fixed-point problem.

Figure 2-9 displays the mode choice results under a variety of different scenarios. The parameter α denotes the proportion of travelers who own a PAV, as opposed to a PCV. Each row of graphs in Figure 2-9 denotes a separate α value, whereas α does not vary across columns. The figure varies α between 0 and 1 in increments of 0.25. Each column in Figure 2-9 denotes a separate initial starting point for PV mode choice in order to determine if the iterative solution algorithm finds different fixed points as a function of the initial starting points.

The lines in each of the 15 graphs in Figure 2-9 indicate that the iterative solution approach converges to a fixed-point solution under all cases after less than 20 iterations. Moreover, given that the only thing that changes between the three graphs in each row is the initial starting point of PV mode choice, the 15 graphs indicate that the iterative solution approach finds the same fixed point, independent of starting point of the mode choice probabilities. The analysis below assumes a single fixed-point solution based on the empirical finding in Figure 2-9 that the algorithm converges to a single fixed point.

However, it is important to note that this chapter does not prove the model system always admits a unique solution.

The results in Figure 2-9 indicate that PAV owners are much more likely to choose PV than PCV owners, in all scenarios. However, an interesting finding is that as the proportion of travelers who own a PAV, α, increases, the mode choice probabilities for PAV owners decrease, while they increase for PCV owners. The reason for this stems from the fact that PAV and PCV owners prefer different parking lots. PCV owners are highly sensitive to the distance between a parking lot and their activity location, whereas PAV owners are not. This means that as the proportion of travelers owning a PAV increases, PAV owners must compete with more travelers who share their parking lot preferences (i.e., PAV owners who mainly care about price), while PCV owners compete with fewer travelers who share their parking lot preferences (i.e., PCV owners who are sensitive to walking distance in addition to price).

This logic also explains why the range of modal splits for PCV owners across zones narrows as α increases. When α is zero, the range of PV mode share across zones is as wide as 15%, indicating that PCV travelers going to a zone with congested parking lots and high parking costs are significantly less likely to choose PV than travelers going to zones with uncongested and lower cost parking lots. Conversely, the range of PAV mode shares across zones is quite small under all scenarios, because a traveler's destination does not heavily impact where they prefer to and do park their PAV.

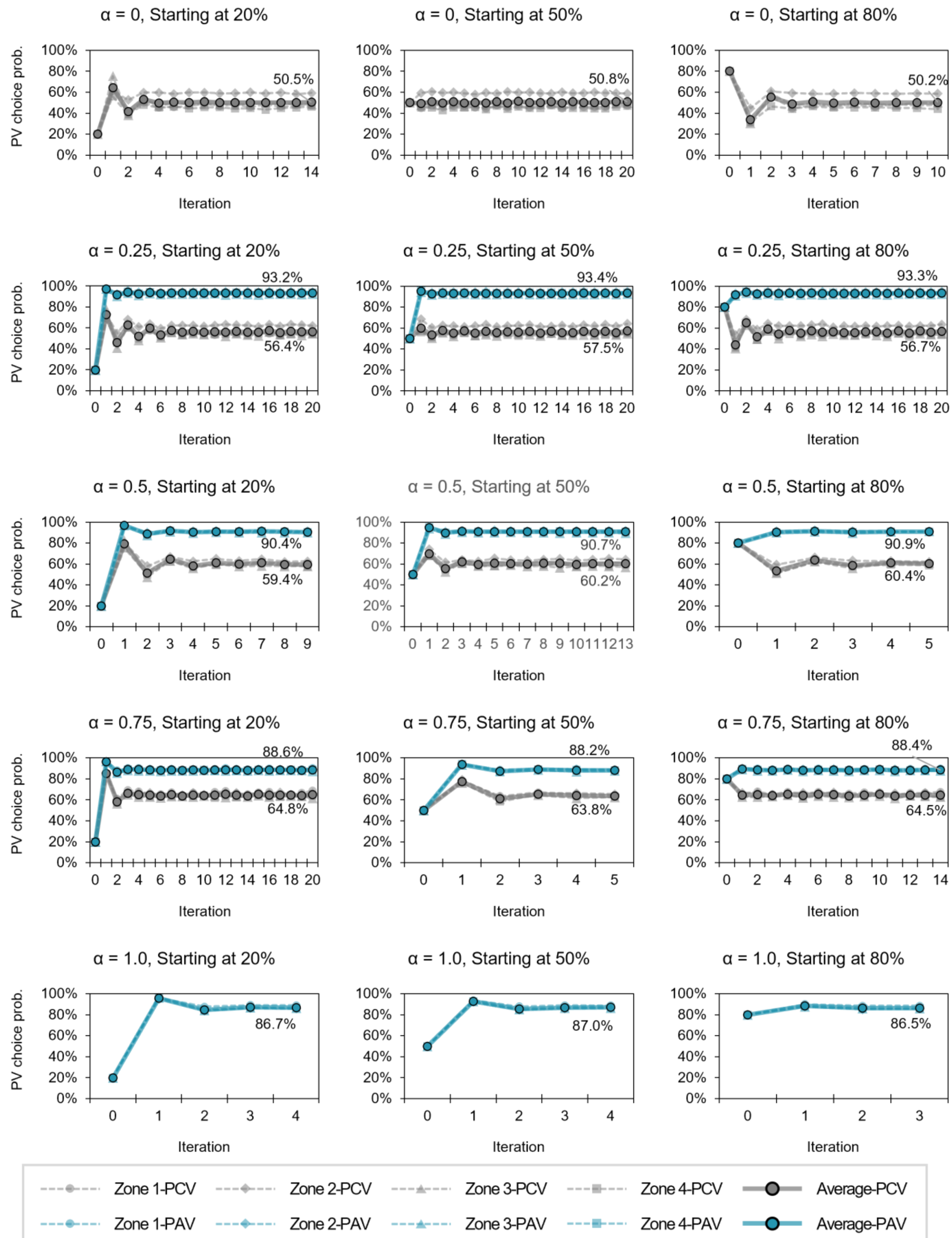


Figure 2-9: Mode Choice Convergence Plots Varying PV Mode Share Starting Points by Column from 20% to 80%, and PAV Ownership Proportion by Row from 0.0 to 1.0

2.7 Discussion

Although the case study presented in this chapter is based on a fictional CBD, the results section hopefully illustrates the power of the integrated mode choice and parking location choice model to provide valuable, transferrable, and generalizable insights into VMT, parking occupancy, transportation system performance and user costs and travel times in a future with PAVs and PCVs. Moreover, the model can be applied to any region if detailed data about the road network, parking lots, and travel demand (or trips) are available. The proposed solution approach, incorporating the simulation-based parking assignment model and the multinomial logit mode choice model, are computationally efficient and would easily scale to large metropolitan areas given data availability.

The proposed model should also be quite useful for policy and planning analysis and decision support. For example, compared to the current PCV-only case, redistributing parking spaces appears able to prevent dramatic increases in VMT while not reducing PV mode share in a future with PAVs. This suggests the spatial distribution of parking supply and parking pricing can significantly impact VMT in the future with PAVs.

Moreover, although not shown explicitly in the results section, the model can demonstrate, under certain scenarios, that parking pricing alone may struggle to reduce VMT and PV demand. Rather, joint parking pricing and roadway pricing is likely necessary in an AV future to reduce VMT and PV demand.

Another implicit finding from this chapter is that PAVs searching for parking would often look for the cheapest possible lot in the area, particularly when the driving cost per mile is low. Hence, if all PAVs want to access the same cheap lot(s) in the periphery of the CBD, this/these lot(s) will become full, and the other PAVs will need to search for and drive to the next cheapest lot. This finding has important technology, policy, and modeling implications. From a technology standpoint, providing accurate real-time information to travelers and/or PAVs about parking lot occupancy could be quite useful. From a policy standpoint, setting parking prices based on disaggregate spatial resolutions in CBDs may not decrease VMT in a world of PAVs. Moreover, there is clearly a value in promoting a reservation system of parking lots and even spaces in parking lots to reduce both parking lot search time and parking space search time, respectively. Finally, from a modeling standpoint, a future extension involves incorporating traveler/PAV knowledge of parking lot occupancy into the modeling framework to analyze the benefits of this information on VMT.

Another future modeling extension involves incorporating roadway congestion into the modeling framework. The results in this chapter clearly indicate a significant increase in roadway VMT as a result of the attractive attributes of PAVs as well as the increase in parking search distance for PAVs. However, at some point, if enough vehicles are driving around searching for the cheapest parking lot with available space, the network is going to experience congestion. This increase in congestion would normally have a leveling effect on parking search costs, as human drivers would perceive the time costs of sitting in congestion and likely choose more expensive parking locations and leave the roadway network. However, if the vehicles searching for a cheap parking spot are driverless, they will have much lower costs per minute in congestion and are much less likely to choose nearby parking lots and exit the roadway network. This is a particularly troubling insight for cities in the future. It suggests that congestion pricing in cities may become even more vital to prevent gridlock and vehicles may need to be charged not just per mile but per minute on the road network in order to avoid regular gridlock in CBDs.

A related future model extension includes incorporating congestion and capacity constraints at pickup and drop-off spots near activity locations in dense urban areas. With a large percentage of PAVs and/or SAVs in a dense urban area, large queues are likely to build at pickup and drop-off points associated with activity locations with high demand, such as large office buildings. These queues may even spillover into the roadway network; thereby requiring a response for traffic managers, planners, or regulators.

A final research area includes conducting stated preference surveys to better estimate model parameters used in this chapter. Parameters associated with willingness-to-pay, willingness-to-wait, and willingness-to-walk are likely to have a significant impact on model results related to mode share and VMT.

2.8 Conclusion

Modeling, understanding, and forecasting the potential impacts of AVs and PAVs on travel behavior, travel demand, and transportation systems under a variety of possible future scenarios is critical in terms of planning for AVs. This chapter focuses on the potential transportation system implications during the transition from PCVs to PAVs for near-activity travel in urban areas. Specifically, given the ability of PAVs to drop-off travelers at their activity location and then deadhead to a parking location, under certain assumptions it is conceivable that PAVs will drive far distances to park and/or drive around looking for an open parking space. This process would significantly increase VMT compared to PCVs that drive directly to a parking location close to the traveler's activity location.

To analyze the impacts of PAVs on near-activity location travel, parking lot usage, overall VMT, and traveler cost and travel time this chapter proposes an integrated parking assignment and mode choice modeling framework. The proposed mode choice model form is multinomial logit, while the parking model is a dynamic simulation-based model of the temporal dynamics of supply and demand for a system of urban parking locations. This chapter also proposes an iterative solution approach to solve the integrated mode choice and parking assignment problem. In the iterative solution approach, the parking simulation model calculates system performance and costs for travelers based on the demand for each mode—determined either by the mode choice model or the initial modal splits—while the mode choice model returns modal splits based on the travel costs from the parking simulation model.

The chapter applies the integrated model and iterative solution approach to an illustrative CBD network. The model results indicate that PAVs significantly increase VMT compared to PCVs. The reason for this result stems from the differential between parking prices and driving fees in the case study. As such, PAVs do not simply look at the stations nearby their traveler's activity location, instead they consider all parking locations and are highly price sensitive. Moreover, in the case where a few parking locations are particularly attractive to PAVs, these parking locations may reach capacity, requiring PAVs to detour and search for other parking locations, thereby further increasing VMT in dense urban areas. The results section also illustrates that PAVs significantly reduce in-vehicle travel time, eliminate walking time, but require travelers to wait a few minutes to be picked up.

The proposed modeling framework can provide valuable insights to researchers, planners, policymakers, and other city officials in terms of the potential implications of AVs on VMT, parking lot usage, mode share, and other measures of transportation system performance and user costs.

Chapter 3 PARK-AND-RIDE POLICY IMPLEMENTATION

3.1 Overview

The analysis results from the previous chapter demonstrate the excessive congestion by PAV deadheading miles, particularly in urban areas. In consequence, this chapter proposes a policy to reduce the number of vehicles entering downtown areas with infrastructural investments. Specifically, this chapter covers a future park-and-ride (PNR) system that connects urban and suburban areas using PAV and SAV. This chapter also parallels Bahk et al. (2024).

Park-and-ride systems provide facilities for travelers to transfer from a private vehicle to public transit and vice versa. Cities usually implement PNR systems to connect low- to medium-density urban and suburban areas to the urban core, because high-capacity transit modes are often unviable or difficult for residents of low-density areas to reach via walking. Moreover, within the urban core, private vehicles have limited space to operate and park.

Cities began implementing PNR systems to manage vehicle miles traveled (VMT) and congestion in dense areas in the 1960s, and the concept spread between the 1970s and 1990s (Parkhurst, 1995; Spillar, 1997). PNR systems have contributed to the alleviation of vehicles entering the urban core, to some degree. However, demand for PNR systems never grew dramatically, and today only a small portion of travelers use PNR systems for travel.

There are several reasons for the limited attractiveness of PNR systems. First, unless there is a parking space available close to the transit platform, walking from the parking space to the transit stop/station and then waiting for transit service is often more inconvenient and uncertain than driving directly to one's destination. Many travel models express the inconvenience of walking and waiting time by applying larger weights for out-of-vehicle travel times compared with in-vehicle travel time, consistent with empirical data (Wardman, 2004). Some studies even specifically include transfer penalties for the disutility of out-of-vehicle travel time when transferring transit modes (Bahk et al., 2021; Liu et al., 1997). Second, finding a parking space can be challenging with congested lots or when only on-street parking is available (Shirgaokar and Deakin, 2005). This delay in finding a parking space may even cause the traveler to miss their scheduled transit service, which may not operate frequently or on a reliable schedule.

Motivated by the premise of PNR systems and aware of their shortcomings, this chapter proposes a similar system for an era of AVs. Like existing PNR systems, the proposed system involves a transfer from one mode to another. However, rather than transferring from a private vehicle to a fixed-route public transit line, I propose transfers from a privately owned AV (PAV) to a shared-use, shared-ride AV (SAV), which I call the PAV-to-SAV transfer system. The proposed system also includes exclusive SAV-only highway lanes connecting transfer stations to the downtown.

The PAV-SAV system addresses several shortcomings of existing PNR systems. First, the PAV can drop off the traveler at or close to the transfer point, minimizing walk time while eliminating the uncertainty of finding a parking spot. Existing kiss-and-ride (KNR) systems also have this feature, but they require a second person to drop off the transferring traveler. In the proposed PAV-SAV system, the PAV can park itself at or near the transfer station, or even back at the user's home. Second, because SAVs do not have drivers and are expected to be considerably cheaper (and smaller) than large-capacity buses, cities can acquire many SAVs and provide service more frequently than existing PNR transit lines. Third, the PAV-SAV system provides station-to-door service, reducing near-destination walking time compared to PNR.

The PAV-SAV transfer system can also address the same problems as PNR systems—private vehicle congestion and high parking costs in dense areas. The PAV-SAV system involves pooling travelers from several PAVs into one SAV, thereby increasing vehicle occupancy and reducing vehicles per person traveling downtown. SAVs also have the advantage, over large buses, of quickly entering and exiting pickup/drop-off locations (Huang et al., 2021). Moreover, like transit vehicles, SAVs will not park in dense urban areas. And even if some SAVs do park downtown, the parking space demand will be considerably lower than the private vehicles the SAVs replace. Not only is this important from a land use and societal perspective, but this feature is also highly valuable for users, as parking costs in dense urban areas can be prohibitively expensive for many individuals.

Notably PAV-only users could avoid downtown parking costs by having their vehicles travel empty to their home location or inexpensive parking lots in locations outside the city center (Bahk et al., 2022). While this might allow PAV users to decrease costs somewhat, they would still need to pay the per-mile fuel/energy costs of the two deadhead trips (downtown to home and home to downtown). Moreover, cities may respond to such behavior (i.e., PAV users sending their vehicles home empty while they participate in activities) through various regulations or pricing mechanisms that discourage deadheading.

The high volume of vehicles in downtown areas, both parked and moving, is already a problem for cities and may become a bigger problem in the future with AVs (Bahk et al., 2022). Research suggests that PAVs will dramatically change travel behavior and vehicle travel patterns, affecting trip generation, distribution, mode choice, and route choice. Specifically, PAVs are likely to lower or eliminate vehicle-based travel barriers for people without driver's licenses, seniors, and people with medical conditions, thereby generating more travel (Harper et al., 2016). Additionally, AVs may reduce in-vehicle travel time disutility, thereby increasing travel distances (Auld et al., 2018; Kolarova et al., 2019; Zhong et al., 2020). Moreover, people may even change home and work locations, such that they live and work further apart, thereby increasing travel distances further {Citation}. Researchers also predict that PAVs will cause substantial mode shifts away from transit modes (Huang et al., 2020; Kröger et al., 2019). Finally, AV deadheading miles for parking and pickup travel may significantly increase overall VMT (Bahk et al., 2022; Cramer and Krueger, 2016; Henao and Marshall, 2019).

The behavioral changes possible with PAVs that are likely to substantially increase VMT and congestion in dense urban areas further motivate this chapter and the proposed PAV-SAV transfer system. I hypothesize that the proposed PAV-SAV transfer system can reduce vehicle trips, congestion, and parking demand in dense urban areas or, at minimum, increase the number of travelers who can visit the urban core holding constant the number of vehicles and congestion.

Given the potential benefits of the proposed PAV-SAV transfer system to users and society, the goal of this chapter is to analyze the potential transportation system impacts of a PAV-SAV transfer system. In particular, this chapter aims to address the following three research questions:

1. How many travelers would use the PAV-SAV transfer system?
2. How much can the PAV-SAV transfer system reduce VMT and congestion?
3. What is the optimal, or at least a good, design for the PAV-SAV transfer system?

To meet the study's goal and address the first two research questions, I develop a model system that jointly captures travelers' service choices (PAV-only vs. PAV-SAV), route choices, and network congestion. Moreover, to answer the third research question, this chapter performs scenario analyses concerning the number and location of transfer stations, SAV capacity, and connection links between transfer stations and freeways and arterial roads.

This chapter assumes that AVs are ubiquitously available (in the future). As such, this implies that private-sector mobility service providers can offer their own SAV services. Moreover, given that SAVs do not require human drivers—the major cost in existing ride-hailing services—point-to-point private-sector SAV services are likely to be considerably cheaper than existing ride-hailing services. Hence, this introduction then implicitly assumes (i) most travelers will purchase their own AV, rather than rely exclusively on private-sector point-to-point SAV services for their travel needs, and (ii) hub-and-spoke systems with transfers between PAVs and public-sector SAVs will offer a competitive non-PAV alternative to private-sector point-to-point SAV service. I believe the first assumption is quite reasonable given survey data indicating that respondents are reluctant to forego private vehicles even if point-to-point SAVs are prevalent (Menon et al., 2019). Empirical evidence, even stated preference survey-based evidence, for the second assumption is lacking, in either direction. Hence, while it is plausible that the private-sector SAVs providing point-to-point service will dominate a system with PAV-to-SAV transfer stations, I believe the proposed system of PAV-to-SAV transfer stations offers notable advantages over point-to-point SAV service that will make the proposed system viable. First, in many suburban areas that would benefit the most from the PAV-SAV system, a point-to-point SAV service is unlikely to provide the short wait times (e.g., < 5 minutes) consistent with the convenience of a PAV. Second, given the public-sector nature of the PAV-SAV system, and its ability to significantly increase vehicle occupancies in dense urban areas, it is likely that cities will subsidize SAV travel in the PAV-SAV system, in addition to providing the public-sector SAVs exclusive highway lanes.

I structure the remainder of this chapter as follows. The next section introduces the literature on conventional PNR and PAV-related transfer services. Section 3.3 defines the PAV-SAV transfer system design, presents the underlying problem, and mathematically formulates the problem. Section 3.4 presents an iterative solution approach to solve the mathematical formulation. Section 3.5 describes a case study in Los Angeles based on real-world network and demand data. Section 3.6 presents the results of the case study and the scenario analysis. Section 3.7 discusses the model results and their planning and policy implications in relation to the three research questions. This section also discusses model limitations and the transferability of the results to other cities. The last section, Section 3.8, concludes this chapter with a summary and a discussion of the study's limitations and future research directions.

3.2 Literature Review

This section reviews the literature related to the current study. Hence, I review prior research on PNR systems, KNR systems, and transferring services with AVs.

Parkhurst (2000, 1995) investigates the impacts of bus-based PNR systems in the UK from the 1970s to the 1990s. According to the studies, reducing vehicles in downtown generally helps create a pedestrian-friendly environment and reduces the demand for parking facilities in the area (Parkhurst, 1995). However, congestion is not likely to decrease because new trips often replace the trips PNR travelers used to make (Parkhurst, 2000, 1995). Nevertheless, although PNR systems do not significantly reduce downtown congestion, they allow cities to accommodate more travelers without worsening the congestion level (Parkhurst, 1995), effectively increasing the productive capacity of cities. Given the similarities between PNR systems and the proposed PAV-SAV transfer station system, I expect comparable results for the latter system.

Karamychev and Van Reeven, (2011) suggest that the traffic-reducing effect of PNR is more prominent when more individuals prefer their private vehicles, and the redistribution of traffic from the urban area to the suburbs improves welfare. Based on their logic, the net social welfare impacts of PNR, KNR, and the proposed PAV-SAV transfer system can be positive even if the total VMT across suburban and urban areas increases.

Farhan and Murray (2008) introduce three major PNR station siting objectives—maximizing coverage, minimizing distances between stations and major roadways, and maximizing utilization. Their multi-objective spatial optimization model determines sites for PNR stations in Columbus, Ohio. While I do not formulate a PAV-SAV system design optimization model, I do use scenario analysis to determine a good system design. The main PAV-SAV system design variables are the location and number of transfer stations (along freeway corridors), the SAV capacity, and the connection links between the transfer stations and nearby roads. The system also includes SAV-only lanes on freeways that connect the transfer station to the dense urban core.

The catchment area is another essential system design variable. Ortega et al. (2020b) use a parabola method to visualize the catchment area of PNR facilities. Setting a PNR station as the focus of a parabola and the downtown area as the vertex, the study suggests the inner area of the parabola is the catchment area of the PNR station (Ortega et al., 2020b). Instead of relying on geometric shapes, this chapter assumes that every traveler utilizes one and only one transfer station—the one that minimizes the generalized travel cost from their trip origin to the destination.

The current study employs an integrated mode (i.e., service) split and traffic assignment model to determine the market share for the PAV-SAV system and the link flows at equilibrium. Liu et al. (2018) combine a cross-nested logit mode choice and traffic assignment model for PNR implementation and find that PNR services mitigate traffic congestion in congested areas.

Pineda et al. (2016) propose an integrated traffic-transit stochastic equilibrium model to analyze a PNR system where travel time changes with the number of PNR stations. The current study also adjusts the number and location of PAV-SAV transfer stations around the downtown area, through scenario analysis.

Several studies extend the PNR system to AVs. Zhou et al. (2019) consider SAVs combined with PNR and analyze system performance through an agent-based simulation. They focus on a suburban area and allow SAV-to-subway trips, subway-to-SAV trips, and SAV-only trips. Ortega et al. (2020a) also integrate AVs into their PNR study and simulate an SAV-to-transit transfer scenario within MATSim. Finally, two studies model joint SAV and public transit systems to analyze their impacts on transportation systems (Dandl et al., 2021; Pinto et al., 2020). A review of the existing literature indicates that no studies analyze a system similar to the PAV-SAV transfer system I propose in this chapter.

3.3 System Configuration and Problem Formulation

3.3.1 Definitions

Before introducing the PAV-SAV system of transfer stations and formulating the problem, this subsection introduces terminology that I will use throughout this chapter. Let us define a *person trip* as the human travel that occurs between a starting activity location (i.e., origin) and a terminating activity location (i.e., destination). A person trip is not dependent on mode, route, or vehicle type. In this chapter's system model, person trips are exogenous. Let us also define a *vehicle trip* as motorized car travel between two nodes in a road network wherein the occupancy of the car does not change. In this chapter, if the occupancy of the vehicle (PAV or SAV) changes at a node in the network, a vehicle trip has ended. A new vehicle trip might then begin at the same node, or the vehicle's travel might be complete. The vehicle trip definition does not differentiate between SAVs and PAVs. Importantly, vehicle trips are endogenous in this chapter's system model.

In the case of SAVs, let us define an *SAV route* as the ordered sequence of SAV trips (and therefore an ordered sequence of network nodes where vehicle occupancy changes at each node). An SAV route starts with one or more passengers entering the vehicle at a transfer station, and then a series of one or more passenger drop-offs at nodes in the downtown portion of the network, before terminating downtown when there are no passengers left inside. Finally, let an *SAV trip leg* denote a SAV vehicle trip. Person A traveling via SAV may experience multiple SAV trip legs before reaching her destination, as her SAV may drop off other passengers along its route before reaching person A's destination location.

Figure 3-1 displays a person trip from an Origin node to a Destination node. It shows a traveler has two service options to travel between her Origin node and her Destination node—the PAV-only option that includes one vehicle trip between her Origin and Destination nodes, and the PAV-SAV option that includes an Origin node to PAV-SAV transfer station node PAV trip, and a series of SAV trip legs between the transfer station node and her Destination node. Notably, the SAV route only includes drop-off stops in the Downtown region.

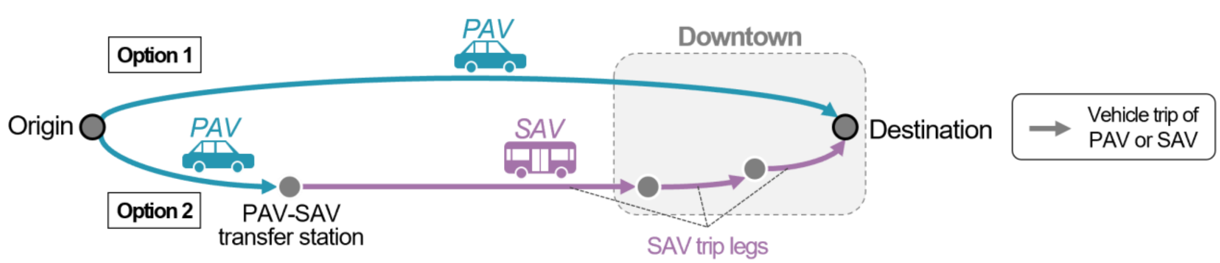


Figure 3-1: Segmentation of a Person Trip for both Mode/Service Options

3.3.2 System Configuration

The proposed PAV-SAV transfer system consists of facilities and vehicles and their operation. Locating transfer stations on freeway sections outside a city's urban core, the system operates SAVs from transfer stations to the downtown area. The system aims to reduce the number of vehicles entering the downtown area by pooling person trips into SAVs, thereby reducing congestion and parking demand during the peak period. Based on generalized travel costs, each traveler decides whether to use the PAV-SAV transfer system to complete their person trip or just use their PAV to travel directly from their origin to their destination. Thus, the model in this chapter includes two modes or service alternatives for travelers: (i) PAV-only and (ii) PAV-SAV transfer. As illustrated in Figure 3-2 and Figure 3-3, the PAV-SAV transfer system also includes an exclusive lane for SAVs on freeway sections between each station and the downtown area to induce more travelers to use the pooled service.

Figure 3-3 shows a station design example on a freeway section, with connections from both the freeway and an arterial. Setting up several platforms in both directions, the design minimizes walking distance from a PAV to a SAV. For the transfer station to downtown direction, each platform has several designated pickup locations, where each platform is associated with a cluster of downtown destination zones. Hence, PAVs should drop off travelers at the platform associated with the traveler's downtown destination zone.

Each SAV has a capacity (i.e., the number of seats), denoted $\rho_{\max}$. Moreover, SAVs have a maximum amount of time they will wait at the transfer station, τ, thereby ensuring no traveler waits for more than τ minutes. These are two critical design parameters. From a planning or societal perspective, increasing vehicle occupancies is an important goal, and increasing $\rho_{\max}$ and τ will increase average vehicle occupancies. On the other hand, from a traveler perspective, minimizing wait and total travel time (and possibly minimizing interactions with strangers) are relevant goals, and decreasing $\rho_{\max}$ and τ will decrease average wait and total travel times as well as interactions with strangers.

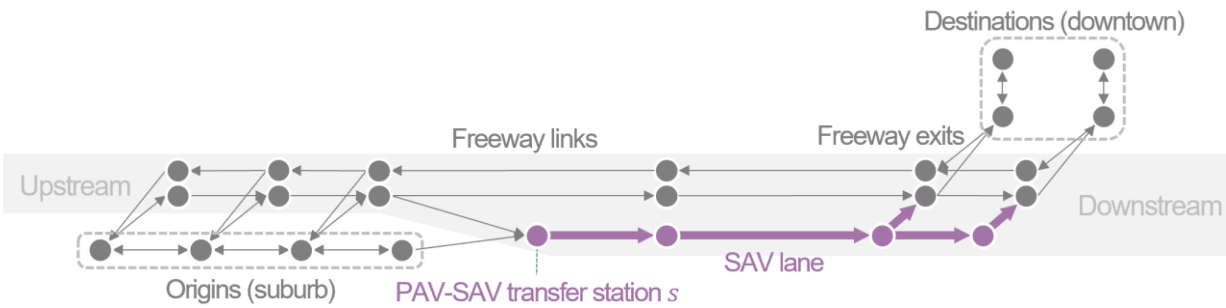


Figure 3-2: PAV-SAV Transfer System—Network Representation

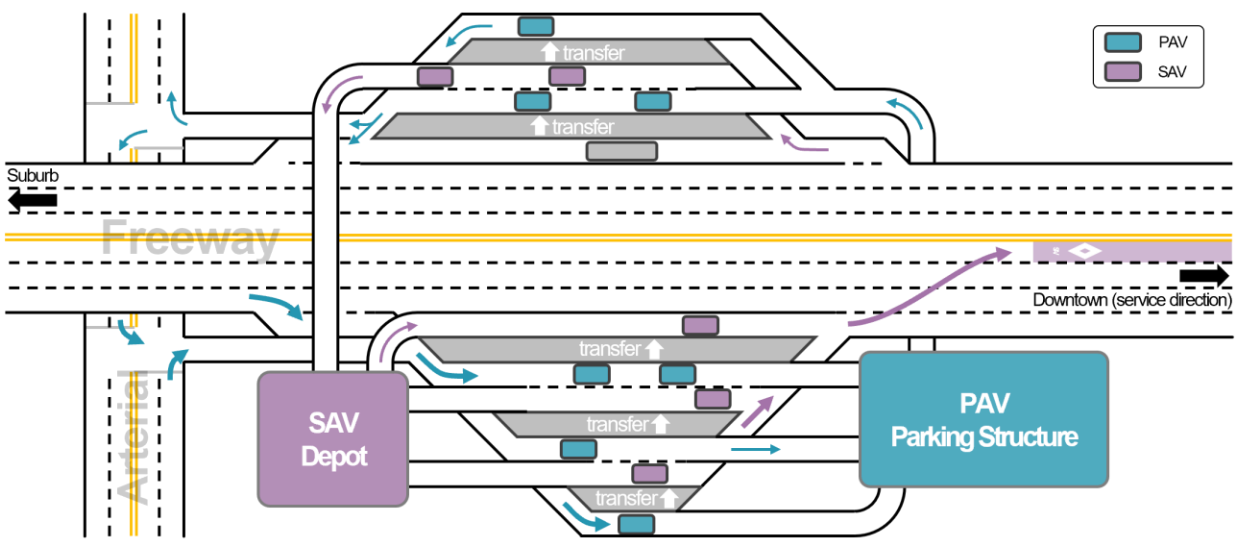


Figure 3-3: PAV-SAV Transfer Station—Planning-level Configuration

Another important design decision involves the clustering of destination zones for each platform and SAVs to serve. On one hand, the more zones clustered together (or the fewer total clusters), the easier it is to increase average vehicle occupancies given a fixed value of $\rho_{\max}$ and τ. Moreover, clustering more zones together should decrease user wait times, as SAVs become full at the transfer station more quickly. On the other hand, clustering more zones together is likely to increase in-vehicle detours for travelers, given a fixed value of $\rho_{\max}$ and τ.

As each platform is associated with a cluster of downtown destination zones, each SAV is also associated with a specific set of destination zones. I assume each platform/SAV has an ordered sequence of destination zones to visit. The model, presented in Subsection 3.4.2.2, captures the cases in which (i) multiple passengers in an SAV have the same destination, and (ii) an SAV does not visit each destination. In the second case, the ordered sequence of destination zones remains the same, the SAV just skips the zone(s) without any passenger drop-offs.

3.3.3 Problem Statement and Formulation

Consider a region, denoted by the graph $G(N, A)$, composed of a set of nodes N and a set of directed links A that connect the nodes. The region includes a set of traveler origins $O \subset N$ and set of traveler destinations $D \subset N$, as well as a set of PAV-SAV transfer stations $S \subset N$. This chapter assumes the traveler demand from origin $o \in O$ to destination $d \in D$, denoted $p_{o,d}$, is fixed and exogenous to the model system. Let the array $\boldsymbol{p}$ denote the $|O| \times |D|$ matrix of traveler demand flows.

Travelers in the system can choose one of two modal/service options, PAV-only and PAV-SAV, from the set of modes, denoted M, and indexed by $m \in M$. While person trips between activity locations are exogenous to the model system, vehicle trips between network nodes are not. Each traveler completes their person trip with either (i) a single PAV trip or (ii) a PAV trip and (one or more) SAV trip legs, depending on the traveler's service/mode choice. The SAV route determines how many SAV trip legs are associated with a person trip. Let $q_{i,j,m}$ denote the number of vehicle trips from node $i \in N$ to node $j \in N$ by mode $m \in M$. Given that travelers can choose between PAV-only and PAV-SAV, each PAV-only traveler goes directly from their origin node $o \in O \subset N$ to their destination node $d \in D \subset N$ via the PAV mode. However, each PAV-SAV traveler makes a PAV trip and is involved in one or more SAV trip legs. The PAV-SAV traveler does not transfer between SAVs, but SAVs may drop off other travelers first, thereby creating a sequence of SAV trip legs. The PAV-SAV traveler's PAV trip is one from their origin $o \in O \subset N$ to their assigned PAV-SAV transfer station $s \in S \subset N$. Their first SAV trip leg is from their assigned transfer station $s \in S \subset N$ to a destination $d \in D_{dt} \subset D \subset N$, where D_{dt} is the subset of destinations in the downtown or urban core. The other SAV trip legs for the traveler, if there is more than one, will be between destinations in the urban core, D_{dt}.

Given the focus of this chapter is on modeling the system and network impacts of a PAV-SAV transfer system, I introduce the following joint mode and route choice problem. Given the region $G(N, A)$ and exogenous traveler demand, $\boldsymbol{p}$, the problem is to determine (i) the market shares for PAV-only and PAV-SAV, (ii) vehicle trips by vehicle type, and (iii) route choices for each origin, destination, mode triad, such that no traveler can unilaterally change modes or routes and improve their utility. Equations 3-1 through 3-3 display the system of equations for the joint mode and route choice problem.

$$q_{i,j,m} = f_1(\boldsymbol{p}, \boldsymbol{r}) \quad \forall i \in N, \forall j \in N, \forall m \in M \tag{3-1}$$

$$r_{o,d} = f_2(\boldsymbol{c_{o,d}}) \quad \forall o \in O, \forall d \in D_{dt} \tag{3-2}$$

$$c_{o,d,m} = f_3(\boldsymbol{q}) \quad \forall o \in O, \forall d \in D, \forall m \in M \tag{3-3}$$

Equation 3-1 shows that the array of vehicle trips by mode, $q_{i,j,m}$ is a function of traveler demand $\boldsymbol{p}$, and also the market share of PAV-SAV from all traveler origins to all traveler destinations, $\boldsymbol{r}$, where the market share for traveler O/D pair o-d, denoted $r_{o,d}$, is endogenous to the model system. Equation 3-2 shows that $r_{o,d}$ is a function of the two-dimensional array of generalized costs for the traveler O/D pair o-d, across the two modes in M, denoted $\boldsymbol{c_{o,d}}$. Finally, Equation 3-3 shows that $c_{o,d,m}$, the cost for the traveler O/D pair o-d by mode m, is a function of $\boldsymbol{q}$, the multidimensional array of vehicle demand in the network.

The next section describes the functions $f_1(\cdot)$, $f_2(\cdot)$, and $f_3(\cdot)$ in more detail. However, at a high level, $f_1(\cdot)$ is a continuous function that converts person trips into vehicle trips, given the market share of the PAV-SAV system for each O/D pair. PAV-only travelers have just one PAV trip that goes directly from traveler origin to traveler destination, whereas PAV-SAV travelers have two sets of vehicle trips—one PAV trip from traveler origin to transfer station and an SAV trip leg, or series of trip legs, from transfer station to the traveler's destination. A series of SAV trip legs is possible as the SAVs need to make drop-offs at multiple locations in the dense urban core.

The function $f_2(\cdot)$ is relatively straightforward as $r_{o,d}$ should be decreasing with increases in $c_{o,d,m}$, and cannot exceed one. Hence, this chapter uses the logit function for $f_2(\cdot)$ but other functions are possible.

Finally, $f_3(\cdot)$ represents the vehicle traffic assignment problem, in particular, the static mixed-vehicle traffic assignment problem that returns, among other variables, the link costs for PAVs and SAVs at the deterministic user equilibrium. Given the link costs for each vehicle type, it is straightforward to calculate the costs of the used paths from each traveler origin to each traveler destination for both modes.

In order to find an equilibrium solution for this problem, I can reformulate the system of Eqns. 3-1 through 3-3 as a fixed-point problem, as displayed in Eqn. 3-4. Since I am primarily interested in the market share $r_{o,d}$ as a model output, I formulate the fixed-point problem over the set $\boldsymbol{r}$. Hence, Eqn. 3-4 shows $\boldsymbol{r}$ as a series of functions of $\boldsymbol{r}$ and can be expressed as one function $F(\boldsymbol{r})$. Solution(s) to the fixed-point problem occur at $\boldsymbol{r}$, if and only if $F(\boldsymbol{r}) = \boldsymbol{r}$ (Boyles et al., 2022). Note that the market share $\boldsymbol{r}$ is not a single value but an array of values from o-d pairs. The fixed-point problem lends itself to an iterative solution approach, which I describe in the next section.

$$r_{o,d} = f_2\left(f_3\big(f_1(\boldsymbol{p}, \boldsymbol{r})\big)\right) = F(\boldsymbol{r}) \quad \forall o \in O, \forall d \in D \tag{3-4}$$

Brouwer's fixed-point theorem states that a fixed-point solution *exists* for a continuous function defined over a compact (closed and bounded) and convex set (Fan et al., 2022). For Eqn. 3-4, the continuity condition is met as $f_1(\cdot)$ (vehicle trip counts between node pairs are a continuous function of traveler demand and market share), $f_2(\cdot)$ (origin-destination pair market shares are a continuous function of travel costs), and $f_3(\cdot)$ (mode-specific origin-destination travel costs are a continuous function of vehicle trips) are all continuous functions. Moreover, the domain and codomain of $F(\boldsymbol{r})$, the market shares in each origin-destination pair $r_{o,d}$, all have a range of $[0, 1]$, thus the function is defined over a compact and convex set. While Eqn. 3-4 satisfies the existence criteria for a fixed-point problem formulation, in the general case, it does not satisfy uniqueness criteria.

In similar contexts, several transportation modeling and analysis studies including Bahk et al. (2022), Chakraborty et al. (2021), and Pinto et al. (2020) adopt a fixed-point problem formulation similar to Eqn. 3-4 to model combined choices (e.g., route and mode, parking and mode). Chakraborty et al. (2021) employ a fixed-point problem formulation to model the share of AVs and conventional vehicles in a region, where the optimal location(s) of AV exclusive lanes is endogenous to the model system. Bahk et al. (2022) model the integrated mode choice and parking location choice problem with PAVs as a fixed-point problem.

3.4 Solution Approach and Model Details

3.4.1 Overview of Algorithm

Figure 3-4 displays an overview of the iterative solution approach to solve the fixed-point problem in Eqn. 3-4. Note that Eqn. 3-1 requires $r_{o,d}$ to obtain $q_{i,j,m}$ and begin the iterative solution approach. As an initialization (at iteration $n = 0$), I assume a zero percent market share for all origins $o \in O$ to each downtown area destination $d \in D_{dt}$, and the vehicle trip matrix $\boldsymbol{q}$ is the same matrix as the given travel demand matrix $\boldsymbol{p}$ at iteration 0. (I also test several other initial market shares.) After the first traffic assignment, the algorithm updates path travel costs for PAV-only and PAV-SAV routes for each O/D pair before determining the service choice (i.e., modal splits) for each O/D pair using a logit model. I use the service choice model output to calculate the market share for the system of PAV-SAV transfer stations for all O/D pairs. After calculating the market share, the algorithm performs a convergence check on the market shares. If the system converges, the algorithm outputs a series of performance metrics for analysis purposes. If the system does not converge, the algorithm must determine a vehicle trip matrix based on the original person trip matrix and most recent PAV-SAV market share before solving the traffic assignment problem again. This process repeats until the model system (i.e., the relationships in Eqn. 3-4) converges to a fixed point. Given the nature of Eqn. 3-4, I am unable to prove the algorithm will always converge; however, I empirically test the convergence properties of the algorithm in Subsection 3.6.1 and find that it satisfies the convergence criteria for all initial market shares, $r_{o,d}^{0}$, and scenarios, I test.

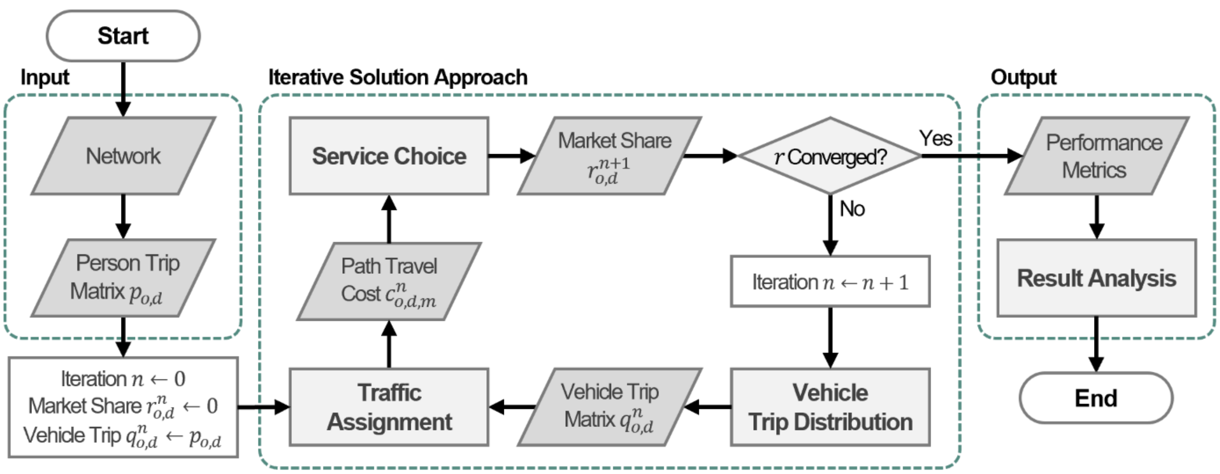


Figure 3-4: Solution Approach

I define an average relative gap G_{avgrel}^{n} and a maximum absolute gap G_{maxabs}^{n} as convergence criteria. As expressed in Eqn. 3-5, the average relative gap indicates the average of the absolute values of each O/D pair's relative market share gap between two consecutive iterations. Equation 3-6 displays the maximum absolute gap, which is the maximum of the absolute values of the market share gaps between two consecutive iterations among all O/D pairs. In theory, Eqn. 3-6 and therefore Eqn. 3-5, should reach a value of zero at a fixed-point solution to Eqn. 3-4.

$$G_{avgrel}^{n} = \frac{\sum_{o \in O} \sum_{d \in D_{dt}} \left| \frac{r_{o,d}^{n+1} - r_{o,d}^{n}}{r_{o,d}^{n}} \right|}{\|O\| \times \|D_{dt}\|} \tag{3-5}$$

$$G_{maxabs}^{n} = \max_{o \in O, d \in D_{dt}} \left\{ \left| r_{o,d}^{n+1} - r_{o,d}^{n} \right| \right\} \tag{3-6}$$

As planners are often interested in total demand, and total market share, alongside the market share of individual o-d pairs, I present Eqn. 3-7, which expresses the total market share $\bar{r}$ at iteration n.

$$\bar{r}^{n} = \frac{\sum_{o \in O} \sum_{d \in D} p_{o,d} r_{o,d}^{n}}{\sum_{o \in O} \sum_{d \in D} p_{o,d}} \tag{3-7}$$

The remainder of this section describes the vehicle trip distribution, traffic assignment, and service choice models in detail.

3.4.2 Vehicle Trip Distribution

The vehicle trip distribution model updates the vehicle trip matrix, $\boldsymbol{q}$, given the current market shares $r_{o,d}$ and the original person trip matrix $p_{o,d}$. The vehicle trip matrix consists of PAV-only trips and PAV-SAV trips.

For PAV-only trips, the vehicle trips are equivalent to the person trips because each PAV directly travels from the person's origin to the person's destination. On the other hand, a PAV-SAV travel consists of more than one vehicle trip. A PAV-SAV traveler first uses a PAV for origin-station vehicle trip and then transfers to a SAV for station-to-destination vehicle trip. When a SAV stops at multiple destination zones within a destination zone cluster, the passenger can even experience multiple SAV trip legs, such as station-to-destination and destination-to-another destination, where the first destination is another onboard passenger's destination.

In addition, the PAV-SAV transfer system can include multiple transfer stations in the region. This chapter assumes travelers from each O/D pair use the station, s, that minimizes the generalized travel cost from their origin to their destination. Let θ_s denote the set of O/D pairs where transfer station s minimizes their generalized travel cost, e.g., if s minimizes generalized travel costs for O/D pairs $\{o_1, d_5\}$ and $\{o_4, d_9\}$, then $\theta_s = \{\{o_1, d_5\}\{o_4, d_9\}\}$. Moreover, let s^*_{od} denote the optimal transfer station for O/D pair $\{o, d\}$.

Figure 3-5 shows an example of station s_1 users' vehicle trip matrix from origins $\{o_1, o_2, o_3\} \subset O$ to downtown $D_{dt} = \{d_1, d_2, d_3, d_4, d_5\} \subset D$ when there are two destination zone clusters, $D_{\Phi_1} = \{d_1, d_2\} \subset D_{dt}$ and $D_{\Phi_2} = \{d_3, d_4, d_5\} \subset D_{dt}$, for vehicle trips from station s_1. Please note that the destination clusters vary by transfer station in general, while all O/D pairs in this example only use s_1.

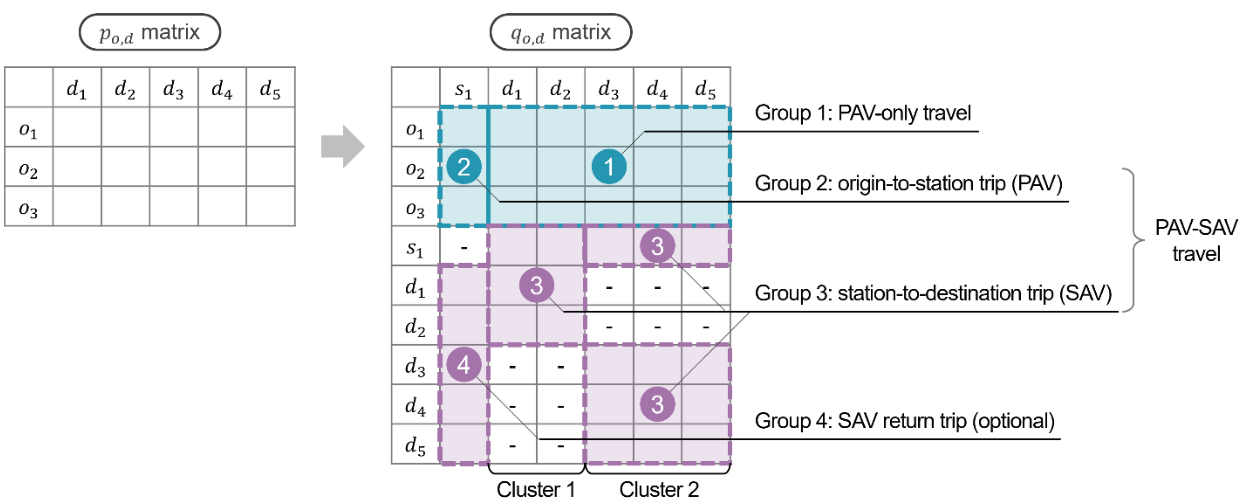


Figure 3-5: Person Trip Matrix and Corresponding Vehicle Trip Matrix

The following subsections describe and formulate each group of person-to-vehicle trip options displayed in Figure 3-5. Subsection 3.4.2.1 formulates PAV trips from origin to destination for PAV-only travels (Group 1 in Figure 3-5) and PAV trips from origin to station for PAV-SAV transfer travels (Group 2 in Figure 3-5). Subsection 3.4.2.2 formulate the SAV trip legs from station to destination cluster (Group 3 in Figure 3-5). Subsection 3.4.2.3 describes SAV trip legs after dropping off passengers (Group 4 in Figure 3-5).

3.4.2.1 PAV Trips: PAV-only Travel and Origin-to-station Trips of PAV-SAV Travel

Considering that all person trips heading downtown can choose between PAV-only and PAV-SAV transfer, and all PAV-SAV transfer service users visit a station, person trips $p_{o,d}$ is the sum of the two groups of PAV trips: from origin to destination trip of PAV-only travel (Group 1 in Figure 3-5) and from origin to station trip of PAV-SAV transfer travel (Group 2 in Figure 3-5). From Eqn. 3-1, these two vehicle trip groups are functions of $p_{o,d}$ and $r_{o,d}$, as shown in Eqn. 3-8 and Eqn. 3-9, respectively.

$$q_{o,d,PAV} = p_{o,d}\left(1 - r_{o,d}\right) \quad \forall o \in O, \forall d \in D_{dt} \tag{3-8}$$

$$q_{o,s_{od}^*,PAV} = p_{o,d} - q_{o,d,PAV} = p_{o,d} r_{o,d} \quad \forall o \in O, \forall d \in D_{dt} \tag{3-9}$$

where $q_{o,d,PAV}$ is a PAV-only demand for O/D o, d, and $q_{o,s_{od}^*,PAV}$ is PAV demand from origin o to the optimal transfer station for O/D pair $\{o, d\}$, s_{od}^* (i.e., PAV-SAV travel).

3.4.2.2 SAV Trips: Station-to-destination Cluster Trips of PAV-SAV Travel

Formulating the station-to-destination trips (Group 3 in Figure 3-5) is relatively complicated. Based on $p_{o,d}$ and $r_{o,d}$, the model needs to capture three challenging factors: (i) multiple passengers traveling to one destination zone in the same SAV, (ii) an SAV carrying travelers to multiple destination zones and (iii) an SAV skipping destination zones in a destination cluster.

First, the number of passengers heading to the same destination zone in an SAV is uncertain. Thus, the number of SAVs traveling to a destination zone depends on the probability of passenger pickups terminating at each destination zone. Second, a SAV's destination zone set is uncertain because a vehicle does not necessarily travel to every destination zone in the cluster, because the vehicles often have fewer travelers than zones or the travelers in the vehicle are going to the same zone or subset of zones.

To assist in model comprehension, I begin with a simple case with only two destination zones in a cluster and a fixed number of onboard passengers (ρ). Then I make the first in a series of two generalizations by allowing for more than two destination zones in a cluster. Finally, I further generalize the model by allowing for a variable number of onboard passengers. I use this final model to capture the total SAV trips between each transfer station and the downtown destinations, as well as between the downtown destinations.

Consider a destination zone cluster $D_\Phi = \{d_1, d_2\} \subset D_{dt}$ for the SAVs with origin station s, where $s \to d_1 \to d_2$ is the predetermined route for an SAV that includes travelers with destinations d_1 and d_2. Given this route, SAV trip legs between three network nodes pairs are possible. If there is at least one traveler with destination d_1, then there will be a SAV trip leg from station s to first destination zone d_1, denoted $q_{s,d_1,SAV}$. If there is at least one traveler with destination d_1 and at least one traveler with destination d_2, then there will be an SAV trip leg from destination zone d_1 to destination zone d_2, denoted $q_{d_1,d_2,SAV}$. Finally, if there is at least one traveler with destination d_2 and no traveler with destination

d_1, then there will be an SAV trip leg from station s to first destination zone d_2, denoted $q_{s,d_2,SAV}$. (In an alternative scenario where the predetermined SAV route for travelers with destinations d_1 and d_2 is $s \rightarrow d_2 \rightarrow d_1$, then the possible SAV trip legs include $q_{s,d_2,SAV}$, $q_{d_2,d_1,SAV}$, and $q_{s,d_1,SAV}$.)

Given the two uncertainties—(i) whether travelers in the same SAV share a destination, and (ii) whether a particular destination zone is in a particular SAV's route—the values for $q_{i,j,SAV}$ are uncertain. However, I can derive the values using probability theory and the concept of a complementary event (i.e., the probability that an event will not occur).

I first define a complementary event to reduce the length of the following equations (Eqns. 3-12 through 3-14 and Eqns. 3-16 through 3-17). Let E_{s,d_j} be the probability that the destination zone of a passenger in a SAV from station s is not d_j, which I express as a function of $p_{o,d}$ and $r_{o,d}$ in Eqn. 3-10. The numerator captures the number of PAV-SAV users from station s to destination d_j in the downtown over the whole analysis period. The denominator captures the number of PAV-SAV users from station s to all destinations within the cluster, D_Φ. Hence, this fraction is the probability that a passenger in a SAV is going to d_j, and the right-hand side of Eqn. 3-10 is the probability that a passenger in a SAV is not going to d_j.

$$E_{s,d_j} = 1 - \frac{\sum_{\{o,d\}\in\theta_s|d=d_j} p_{o,d} r_{o,d}}{\sum_{\{o,d\}\in\theta_s|d\in D_\Phi} p_{o,d} r_{o,d}} \tag{3-10}$$

Given Eqn. 3-10, the probability that a SAV with ρ passengers has at least one passenger heading to d_j is $1 - \left(E_{s,d_j}\right)^\rho$.

Equations 3-11 through 3-14 show the number of SAV trips when the number of passengers per vehicle is fixed at $\rho(\geq 2)$, for the case with two destination zones $D_\Phi = \{d_1, d_2\} \subset D_{dt}$ and predetermined route $s \to d_1 \to d_2$. Equation 3-11 states that the total number of SAV trips from station s to destination zones d_1 and d_2 is the sum of PAV-SAV travelers heading for d_1 and d_2 divided by the number of onboard passengers, ρ. From Eqn. 3-11, Eqn. 3-12 specifies the number of SAV trips from station s to destination zone d_1, which excludes the SAVs with no passengers traveling to d_1. Equation 3-13 shows the destination-to-destination (d_1 to d_2 in this example) SAV trips in the case where the SAV has passengers to both destinations. Equation 3-14 covers the case where the SAV skips d_1 because there is no passenger going to d_1 in the SAV.

$$q_{s,d_1,SAV} + q_{s,d_2,SAV} = \frac{1}{\rho} \sum_{o \in O | \{o,d\} \in \theta_s} \left(p_{o,d_1} r_{o,d_1} + p_{o,d_2} r_{o,d_2}\right) \tag{3-11}$$

$$q_{s,d_1,SAV} = \frac{1}{\rho} \sum_{o \in O | \{o,d\} \in \theta_s} \left(p_{o,d_1} r_{o,d_1} + p_{o,d_2} r_{o,d_2}\right) \times \left[1 - \left(E_{s,d_1}\right)^\rho\right] \tag{3-12}$$

$$q_{d_1,d_2,SAV} = \frac{1}{\rho} \sum_{o \in O | \{o,d\} \in \theta_s} \left(p_{o,d_1} r_{o,d_1} + p_{o,d_2} r_{o,d_2}\right) \times \left[1 - \left(E_{s,d_1}\right)^\rho - \left(E_{s,d_2}\right)^\rho\right] \tag{3-13}$$

$$q_{s,d_2,SAV} = \frac{1}{\rho} \sum_{o \in O | \{o,d\} \in \theta_s} \left(p_{o,d_1} r_{o,d_1} + p_{o,d_2} r_{o,d_2}\right) \times \left(E_{s,d_1}\right)^\rho \tag{3-14}$$

Now I generalize the two-destination-zone case in the prior subsection and allows for multiple destinations in a cluster. Equations 3-15 through 3-17 formulate the generalized case where there are $Z = |D_\Phi| \geq 3$ zones in a cluster, where the predetermined route is $s \to d_1 \to d_2 \ \to \cdots \ \to \ d_Z$. The destination indices themselves are ordered here from 1 to Z in order to simplify the mathematical formulations. Given the total SAVs serving cluster D_Φ

(Eqn. 3-15), $q_{d_i,d_j,SAV}$ is the number of SAV trip legs from the previous stop d_i to d_j, and $q_{s,d_j,SAV}$ is the number of SAV trip legs from station s to destination d_j (Eqn. 3-16 and Eqn. 3-17).

In this chapter, I assume a predetermined open vehicle route from depot s to serve all destinations assigned to a cluster, D_Φ. I do not consider the return trip to the depot because the SAV may not return to the depot (as described in Subsection 3.4.2.3), and, if it does, it might return empty and have considerably lower value of time than SAV trip legs with vehicle occupancies greater than zero. Notably, an SAV route is unlikely to serve every destination in D_Φ. Hence, it is conceivable to predetermine an optimal open vehicle route for every combination of subsets of destinations in D_Φ. Instead, I assume a vehicle always follows the same sequence of destination zone stops, with the SAV skipping destination zones that do not have a passenger drop-off. I make this assumption in order to model a mobility service where travelers have some travel time reliability between their transfer station and their final destination. Without an ordered sequence of destination zones, a PAV-SAV user may experience considerably different routes and therefore travel times on one day compared to the next.

Equation 3-16 is a generalization of Eqn. 3-13. The right-hand-side of Eqn. 3-16 multiplies the total number of SAVs serving a cluster by (i) the square bracket representing the probability an SAV serves both passengers going to d_i and d_j (at least one passenger per destination) and (ii) the last parenthetical representing the probability there are no passengers with destinations between d_i and d_j. Equation 3-16 exhaustively captures all SAV trip legs between all destination zones in a cluster. Note that the final parenthetical becomes 1 when $\rho = 2$ because the intermediate stops between d_i and d_j cannot exist.

Equation 3-17 represents the case where $d_i = s$, and is the generalized case of Eqn. 3-12 and Eqn. 3-14. Equation 3-17 measures the probability that an SAV has at least one passenger going to d_j and there are no passengers going to destinations between s and d_j.

$$\sum_{d \in D_\Phi} q_{s,d,SAV} = \frac{1}{\rho} \sum_{\{o,d\} \in \theta_s | d \in D_\Phi} p_{o,d} r_{o,d} \tag{3-15}$$

$$q_{d_i,d_j,SAV} = \frac{1}{\rho} \sum_{\{o,d\} \in \theta_s | d \in D_\Phi} p_{o,d} r_{o,d} \times \left[1 - \left(E_{s,d_i}\right)^\rho - \left(E_{s,d_j}\right)^\rho + \left(E_{s,d_i} + E_{s,d_j} - 1\right)^\rho\right] \times \left(\sum_{b=i+1}^{j-1} E_{s,d_b} + i - j + 2\right)^{\rho-2} \tag{3-16}$$

$$\forall i \in D_\Phi, \forall j \in \{D_\Phi | j > i\}$$

$$q_{s,d_j,SAV} = \frac{1}{\rho} \sum_{\{o,d\} \in \theta_s | d \in D_\Phi} p_{o,d} r_{o,d} \times \left[1 - \left(E_{s,d_j}\right)^\rho\right] \times \left(\sum_{b=1}^{j-1} E_{s,d_b} - j + 2\right)^{\rho-1} \tag{3-17}$$

$$\forall j \in D_\Phi$$

Equations 3-11 through 3-17 assume the number of passengers per vehicle is fixed at ρ. However, this is an unrealistic assumption because earlier I assumed that each SAV has a maximum waiting time, after the first traveler enters the SAV. I make this assumption to prevent low service quality in the PAV-SAV transfer system. Hence, in reality, ρ is random.

I assume that PAVs arrive at each station following a Poisson process, with the assumption that access travel times from origins to the station are not significantly correlated. As such, Eqn. 3-18 displays the probability that κ PAVs arrive in τ minutes after the first PAV's arrival, when the PAV arrival rate is λ. Since each SAV collects passengers going to the same cluster, each station's destination cluster, D_Φ, has an arrival rate λ_{s,D_Φ}, as expressed in Eqn. 3-19.

$$P_\kappa = \frac{(\lambda\tau)^\kappa}{\kappa!} e^{-\lambda\tau} \tag{3-18}$$

$$\lambda_{s,D_\Phi} = \sum_{\{o,d\}\in\theta_s | d\in D_\Phi} p_{o,d} r_{o,d} \tag{3-19}$$

Thus, if the maximum SAV waiting time after the first passenger arrival is τ and the maximum number of onboard passengers for a SAV is $\rho_{\max}$, I can update Eqn. 3-16 and Eqn. 3-17 to Eqn. 3-20 and Eqn. 3-21, respectively, to capture uncertainty in vehicle occupancy. Note that $\rho = \kappa + 1$ because ρ counts the first boarding passenger while κ does not. The first term of the right-hand side of Eqn. 3-20 becomes 0 when $\rho = 1$ (see Eqn. 3-16) because there is only one destination zone in case.

$$q'_{d_i,d_j,SAV} = \sum_{\rho=1}^{\rho_{max}-1} P_\rho q_{d_i,d_j,SAV}(\rho) + \left(1 - \sum_{\rho=1}^{\rho_{max}-1} P_\rho\right) \times q_{d_i,d_j,SAV}(\rho_{max}) \tag{3-20}$$

$$q'_{s,d_j,SAV} = \sum_{\rho=1}^{\rho_{max}-1} P_\rho q_{s,d_j,SAV}(\rho) + \left(1 - \sum_{\rho=1}^{\rho_{max}-1} P_\rho\right) \times q_{s,d_j,SAV}(\rho_{max}) \tag{3-21}$$

where $q'_{d_i,d_j,SAV}$ is the number of SAV trip legs from d_i to d_j under the variable number of onboard passenger condition, and $q_{d_i,d_j,SAV}(\rho)$ is the number of SAV trip legs from d_i to d_j with ρ passengers, from Eqn. 3-16 and 3-17.

To capture SAV trips between each transfer station and each destination zone, as well as trips between destination zones in a destination cluster, I use the probability models in Eqn. 3-20 and 3-21. As far as I am aware, this is a novel modeling contribution that can convert stochastic passenger arrivals at transfer stations where there is a maximum passenger waiting time and fixed vehicle capacities, into node-to-node vehicle trip counts for network assignment purposes.

3.4.2.3 SAV Trips: After Dropping Off All Passengers

There are several options for relocating SAVs after dropping off all the passengers in the downtown area. First, the SAV can go to the nearest parking space to avoid causing additional deadheading traffic in the network during the peak period. This option would not increase overall parking demand relative to the PAV-only case because the PAV-SAV system will result in fewer vehicles downtown than in the case without the PAV-SAV system. Second, the SAVs can relocate to the nearest, the original (Group 4 in Figure 3-5), or the optimal PAV-SAV transfer station where they can continue to serve travelers. This is the most likely usage option, as it would significantly decrease the SAV fleet size compared to the first option. Moreover, it is possible that some SAVs on their return to transfer station trip could serve some travelers moving from inside the urban core to outside.

3.4.3 Traffic Assignment

The traffic assignment model determines the minimum path costs for each O/D pair for each service type, given the current vehicle trip matrix, $q_{o,d}$. This chapter adopts the conventional deterministic user equilibrium static traffic assignment approach to model the traffic assignment problem. Setting each station node as a new centroid and each link connecting to/from the station as centroid connectors, the network model only allows SAVs on the SAV lane links, as in Figure 3-2 and Figure 3-3. The vehicles on the SAV lanes must exit the lane and merge with general traffic at several freeway exits near downtown area. Despite the limitations of static traffic assignment models in terms of only permitting certain vehicle types on specific links, I can straightforwardly model this hybrid system (exclusive SAV traffic on freeways and mixed traffic on downtown streets) because every PAV-SAV transfer user has separated trips (o to s with PAV and s to d with SAV), and thus, only the o to s trips enter the station node and only s to d SAV trips are able to enter SAV-only links (see Figure 3-2). This is a highly convenient model property that permits the use of single-class, as opposed to multi-class, traffic assignment approach for private vehicles.

Equation 3-22 shows the objective function and constraints for the deterministic user-equilibrium traffic assignment problem (Sheffi, 1985).

$$min\, z(\boldsymbol{x}) = \sum_a \int_0^{x_a} t_a(\omega) d\omega \tag{3-22a}$$

subject to

$$\sum_k f_k^{o,d} = q_{o,d} \quad \forall o \in O, \forall d \in D \tag{3-22b}$$

$$\sum_o \sum_d \sum_k f_k^{o,d} \delta_{a,k}^{o,d} = x_a \quad \forall a \in A \tag{3-22c}$$

$$f_k^{o,d} \geq 0 \tag{3-22d}$$

where x_a is the volume on link a, $t_a(\omega)$ is link performance function (volume delay function) of link a, $f_k^{o,d}$ is the vehicle trips on path k connecting origin o and destination d, and $\delta_{a,k}^{o,d}$ is the link-path incidence array denoting whether link a is on path k for O/D pair o-d, or not.

I utilize the Bureau of Public Roads (BPR) link performance function, displayed in Eqn. 3-23.

$$t(x) = t_0 \left[1 + \alpha \left(\frac{x}{C}\right)^{\beta}\right] \tag{3-23}$$

where $t(x)$ is link travel time with volume x, t_0 is travel time with free flow speed, C is link capacity, and α and β are parameters. Based on the link performance function, the traffic assignment provides the path travel times for each o-d pair, $t_{o,d}$.

3.4.4 Service Choice

The service choice model determines the proportion of person trips from every O/D pair assigned to PAV-SAV and PAV-only, given the shortest path travel times and parking costs for each O/D pair, $c_{o,d}$.

Except for iteration $n = 0$, this model updates the market share $r_{o,d}$ using a choice model such as the binomial logit model, under the assumption that the error terms of the two alternatives are not significantly correlated. Equations 3-24 through 3-26 display the deterministic part of utility functions for the two alternatives (PAV-only and PAV-SAV) and the market share of PAV-SAV transfer service for each o-d travel.

$$c_{o,d,PAV} = \beta_{IVTT} t_{o,d} + \beta_{cost}\left[\gamma_{opr}\left(l_{o,d} + l_{prk}\right) + \gamma_{prk}\right] \tag{3-24}$$

$$c_{o,d,PSAV} = \beta_{IVTT}\left(t_{o,s} + t_{s,d} + t_{dtr}\right) + \beta_{wt} t_{wt} + \beta_{cost}\left(\gamma_{opr} l_{o,s} + \gamma_{fr} l_{s,d}\right) + \beta_{trsf}(1) \tag{3-25}$$

$$r_{o,d} = \frac{e^{c_{o,d,PSAV}}}{e^{c_{o,d,PAV}} + e^{c_{o,d,PSAV}}} \tag{3-26}$$

where $c_{o,d,m}$ is the generalized travel cost of alternative m from o to d at iteration n; PAV and $PSAV$ are PAV-only and PAV-SAV, respectively; β_{IVTT}, β_{wt}, β_{cost}, and β_{trsf} are model parameters for in-vehicle travel time, waiting time, monetary cost, and number of transfers (1 for PAV-SAV travel), respectively; $t_{o,d}$, $t_{o,s}$, $t_{s,d}$, and are in-vehicle travel times between origin o, station s, and destination d; t_{wt}, and t_{dtr} are waiting time and detour time due to other passengers in the same SAV, respectively; γ_{opr}, γ_{prk}, and γ_{fr} are PAV operating cost, parking fee, and SAV fare per distance respectively; and $l_{o,d}$, $l_{o,s}$, $l_{s,d}$ and l_{prk} are travel distances. Since the actual travel distances are unknown in static traffic assignments, I use the path with the shortest travel distance.

3.5 Case Study

This chapter implements the PAV-SAV transfer system in Greater Los Angeles area using the 2020 Regional Transportation Plan (RTP) dataset from the Southern California Association of Governments (SCAG) (Southern California Association of Governments, 2020).

3.5.1 Model Implementation Tool

I coded the service choice and vehicle trip distribution models in Python and used TransCAD 8.0 for traffic assignment. The TransCAD multiclass network assignment algorithm terminates when the relative gap reaches 0.001. The proposed algorithm in Section 3.4 (Figure 3-4) terminates when the average relative gap (Eqn. 3-5) $G^n_{\text{avgrel}} < 0.005$ and the maximum absolute gap (Eqn. 3-6) $G^n_{\text{maxabs}} < 0.01$.

3.5.2 Data Description

The SCAG 2020 RTP dataset consists of a transportation network and travel demand for the SCAG region (4,192 TAZs) for the base year of 2016. The study area includes Los Angeles and Orange counties, a subarea of the SCAG region (3,072 TAZs including subarea gate nodes). The travel demand data for the 2020 RTP includes eight classes of vehicles: single-occupancy vehicle (SOV), high-occupancy vehicle (HOV) with 2 or 3+ persons, and light/medium/heavy duty trucks. The RTP model also segments HOVs by whether they use HOV lanes. This chapter assigns all vehicle classes to the network but targets SOV person trips (excluding trucks) as potential users of the PAV-SAV transfer service. I integrate all truck classes into one class applying passenger car equivalent (PCE) values provided by the dataset. According to the SCAG 2020 RTP dataset, a light-duty truck is equivalent to 1.3 passenger cars, a medium-duty truck is equivalent to 1.5 passenger cars, and a heavy-duty truck is equivalent to 2.5 passenger cars. This chapter analyzes the AM peak period (from 6 AM to 9 AM) to represent the morning commute period and assigns 7,536,809 O/D person trips to the network during the period.

3.5.3 Model Parameters

The parameters for maximum waiting time, τ, and maximum onboard passengers, $\rho_{\max}$, are 5 minutes and 4 passengers, respectively in the case study. With the fixed τ and Eqn. 3-18, Table 3-1 shows the probability of a given number of onboard passengers as a function of the inter-arrival rates. Note that the probability of $\rho_{\max}$ includes the probability that more than $\rho_{\max}$ arrivals occur in τ. Considering λ represents arrivals over three hours in the morning, if λ for a destination cluster is 180 arrivals per 3 hours, $\lambda\tau$ becomes 5 arrivals per five-minute interval, and the probability that a SAV heading for that cluster collects four passengers would be 87.5%. $\rho_{\max}$ dramatically decreases when $\lambda\tau$ drops to 3. Thus, in order to achieve a significant VMT decrease, the system design should ensure a sufficient traveler arrival rate for SAVs traveling to each cluster of destination zones.

Table 3-1: Arrival Rates and Probabilities of the Number of Onboard Passengers

Arrivals (κ, person)	**Arrival Rates ($\lambda\tau$, person/5 min)**					
	10	7	5	3	2	1
0 ($\rho = 1$)	0.0%	0.1%	0.7%	5.0%	13.5%	36.8%
1 ($\rho = 2$)	0.0%	0.6%	3.4%	14.9%	27.1%	36.8%
2 ($\rho = 3$)	0.2%	2.2%	8.4%	22.4%	27.1%	18.4%
3 ($\rho = \rho_{\max}$)	99.7%	97.0%	87.5%	57.7%	32.3%	8.0%

The SCAG Regional Travel Demand Model provides model parameters for time, cost, and transfers ($\beta_{IVTT} = -0.025$, $\beta_{wt} = -0.063$, $\beta_{cost} = -0.003$, and $\beta_{trsf} = -0.250$) and vehicle operating cost ($\gamma_{opr} = 16.83$ cents per mile) (Southern California Association of Governments, 2020). This chapter applies parameters for the service choice model as follows. First, the parking fee for each PAV-only trip in downtown Los Angeles (DTLA) is 6 dollars based on parking fee information from the Downtown Center Business Improvement District website (Downtown Center Business Improvement District, 2022). Moreover, this chapter applies 0.4 USD/mile for SAV fares, based on prior research values for SAV and TNC fares that range between 0.64–1.00 USD/mile and Uber Pool fare that is about half the price of UberX (An et al., 2019; Chen and Kockelman, 2016; Doug H, 2022; Kaddoura et al., 2020). For PAV deadheading miles, I apply 2 miles per vehicle trip based on a prior PAV deadheading study (Bahk et al., 2022). This chapter also assumes that the SAVs serve other passengers around the area after dropping off the passengers in DTLA before they go back to the original station. Thus, I do not add SAVs return trips to the transfer station as I assume these return SAV trips could replace PAV trips on a one-to-one basis at minimum.

3.5.4 Scenarios

This chapter assumes PAV-SAV transfer stations exist along freeway axes (i.e., spokes in a hub-and-spoke network) emanating from DTLA as shown in Figure 3-6 and Figure 3-7. Each axis has an exclusive SAV lane to DTLA and two possible PAV-SAV transfer stations along each freeway. Through scenario analyses, I hope to identify a good combination of PAV-SAV transfer stations along the four freeway axes. Locating stations closer to DTLA increases potential PAV-SAV demand but it reduces the travel time savings from the exclusive SAV lane from transfer station to DTLA. The candidate station locations for each axis are as follows:

1. Axis 1: interchange of I-5 and SR 14 in Los Angeles (Station 1A) or interchange of SR 170 and US 101 in Los Angeles (Station 1B)
2. Axis 2: interchange of I-5 and SR 91 in Fullerton (Station 2A) or interchange of I-5 and I-605 in Santa Fe Springs (Station 2B)
3. Axis 3: interchange of I-405 and I-710 in Long Beach (Station 3A) or interchange of I-405 and I-110 in Carson (Station 3B)
4. Axis 4: interchange of I-10 and SR 57 in Pomona (Station 4A) or interchange of I-10 and I-605 in Baldwin Park (Station 4B).

In DTLA, each cluster contains four to six TAZs minimizing detours. As shown in Figure 3-7, this chapter applies the same clustering for each axis.

This chapter compares all scenarios to the do-nothing scenario, where all person trips are PAV-only trips. I first create and compare 16 base scenarios. In each of the sixteen scenarios, there is one and only one transfer station along each of the four axes. The sixteen scenarios capture all feasible combinations of transfer stations meeting this condition.

In addition to the 16-scenario set, I vary the number of stations (3 total stations with a maximum of one-station per axis for Scenario 17–20, and 8 stations for Scenario 21). Moreover, after identifying the best among the 16 baseline scenarios, I use this scenario and vary SAV capacity, $\rho_{\max}$ (6 and 8 seats per vehicle). Moreover, this chapter also compares how connections to transfer stations impact congestion around transfer stations and the network as a whole. In all previous scenarios, I connect transfer stations to both nearby arterials and the freeway. I then create two more scenario sets: access from freeway only and access from arterials to compare with the baseline transfer station connections. Finally, this chapter compares how destination zone clustering affects the performance. The baseline scenarios include five clusters (4–6 TAZs per cluster) and I add two alternatives—the nine clusters alternative (3 TAZs per cluster) and the no clustering alternative (1 TAZ per SAV).

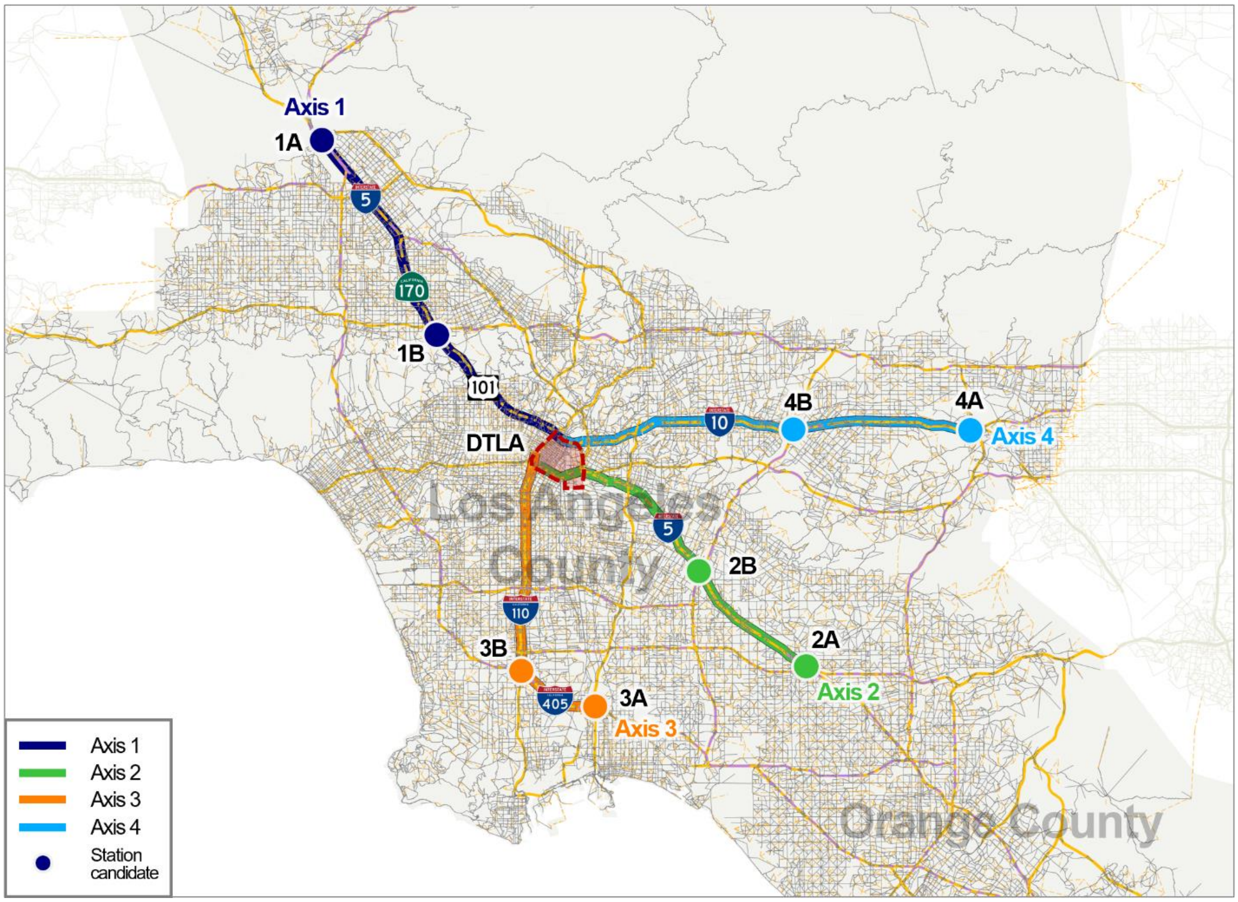


Figure 3-6: Possible PAV-SAV Transfer Stations along Four Axes into DTLA (TransCAD map)

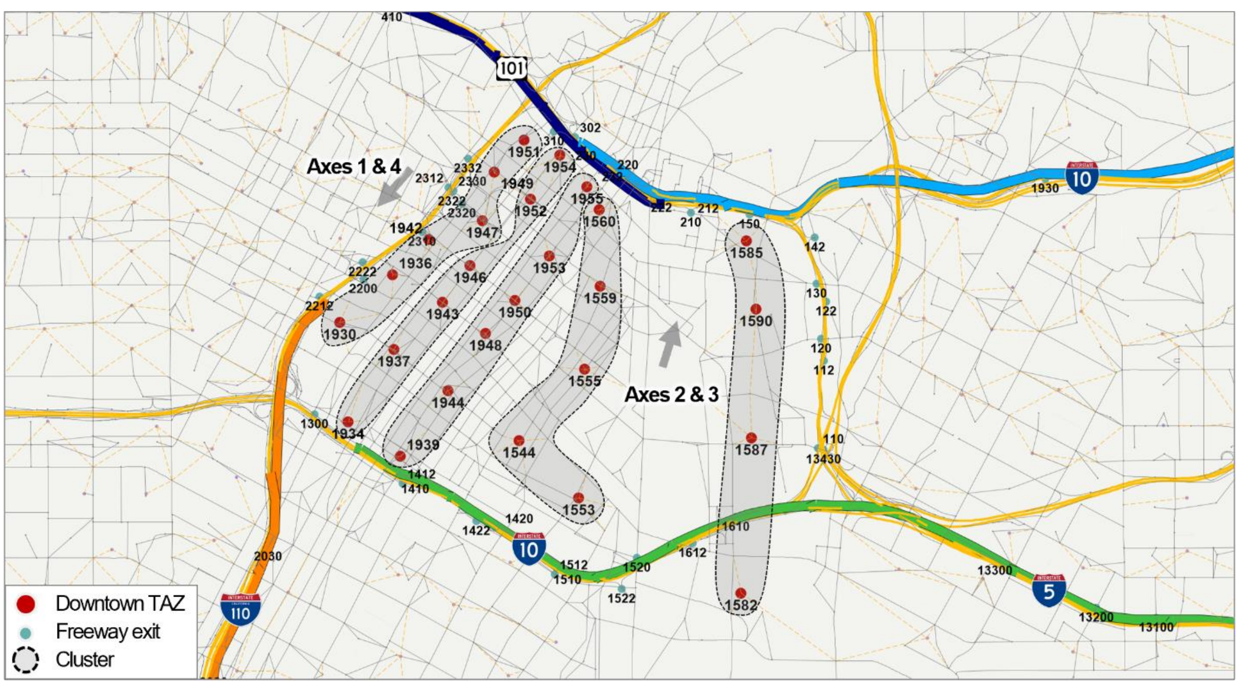


Figure 3-7: TAZs and TAZ Destination Clusters in DTLA (TransCAD map)

3.6 Results

3.6.1 Convergence Analysis

This subsection presents an analysis of the convergence performance of the iterative solution approach (Section 3.4) in terms of solving the integrated service and route choice problem (Section 3.3) for the Los Angeles and Orange County region (Section 3.5). Figure 3-8a and Figure 3-8b show the average relative gap and maximum absolute gap, respectively, for all sixteen scenarios. All scenarios meet both stopping criteria (Eqn. 3-5 and Eqn. 3-6 and Subsection 3.5.1) in 5 iterations or fewer. Figure 3-8d and Figure 3-8e show that increasing the number of iterations does not necessarily decrease the gaps across all O/D pairs, for Scenario 16.

Figure 3-8c and Figure 3-8f show the convergence properties for the PAV-SAV market shares across all 16 scenarios. These results indicate that the market shares across to-DTLA person trips stabilize by the third iteration in nearly every scenario.

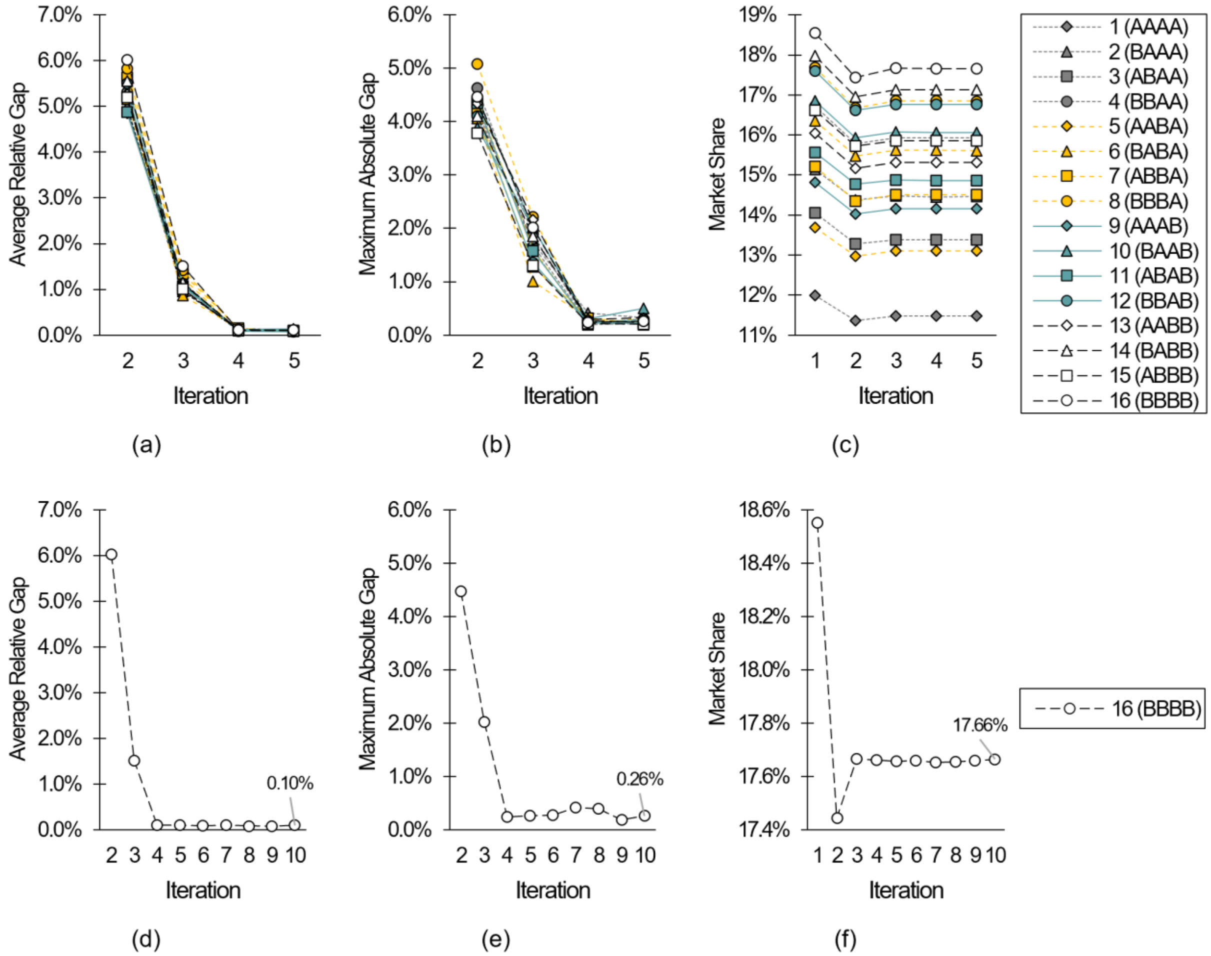


Figure 3-8: Convergence Analysis Results: Scenarios 1 to 16 with 5 iterations for Average Relative Gap (a), Maximum Absolute Gap (b), and Market Share (c), and Scenario 16 with 10 iterations for Average Relative Gap (d), Maximum Absolute Gap (e), and Market Share (f)

Table 3-2 displays an overview of PAV-SAV transfer service by scenario. The average relative gap, and maximum absolute gap columns display the respective gaps after five iterations, or ten iterations for Scenario 16. Overall, Figure 3-8 and Table 3-2 show that the iterative solution approach converges quickly to a small average relative gap across all sixteen scenarios.

Figure 3-9 shows convergence results for Scenario 16 with different starting values for the PAV-SAV market share (0% to 100% in increments of 10%). As shown in Figure 3-9c, all the starting values for PAV-SAV market share converge to small average relative and maximum absolute gaps and to a market share of $\bar{r} = 17.7\%$. The fact that all 11 starting points converge to the same total market share indicate that the total market share of $\bar{r} = 17.7\%$ is highly stable.

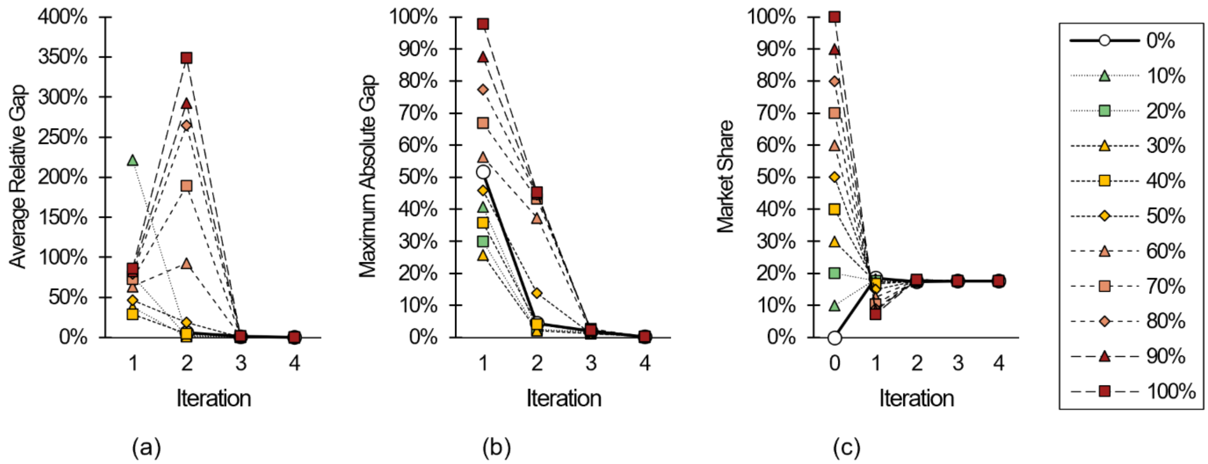


Figure 3-9: Convergence of Scenario 16 with Different Starting Points of Market Share (0% to 100%): (a) Average Relative Gap, (b) Maximum Absolute Gap, and (c) Market Share

3.6.2 Base Scenarios: One Station per Axis

Table 3-2 displays an overview of PAV-SAV transfer service across the sixteen base scenarios. The service users' column indicates the number of PAV-SAV transfer service users among the total 134,279 to-DTLA travelers during the three-hour AM peak period in the network. The SAV trips' column indicates the number of SAV trips in the network, including SAV trips between destination zones in DTLA. The SAV column indicates the number of SAVs needed to serve all SAV users and SAV trips. The average onboard passengers' column indicates the average number of passengers served per SAV. The remainder of this subsection describes the results in Table 3-2 in more detail.

Notably, the number of SAVs only exceeds 6,000 vehicles (2,000 veh/h) in a few scenarios (Scenarios 8, 12, 14, and 16) while the SAV lane capacity is 2,000 veh/h and I have four axes (8,000 veh/h in total) in the network. Considering that the freeway's BPR parameters α and β for the SCAG network are 0.8 and 8.0 (Eqn. 3-23), respectively, the SAVs rarely experience delays on SAV-only paths.

According to Table 3-2, the market shares range from 11–18% across the scenarios. Scenario 1 (1A-2A-3A-4A) shows the lowest share of 11.48%, followed by Scenario 5 (1A-2A-3B-4A). Conversely, Scenarios 16 (1B-2B-3B-4B, 17.66%) and 14 (1B-2A-3B-4B, 17.12%) attract over 17% and nearly 23,000 potential users. The main conclusion from Table 3-2 is that placing transfer stations closer to DTLA along the four main axes attracts more PAV-SAV travelers than scenarios with stations located farther away from DTLA. In the scenarios where the station is close to DTLA, travelers from TAZs near DTLA can utilize the transfer station, significantly impacting the total effective catchment area of the PAV-SAV transfer system along the axes. Figure 3-10 confirms that the demand for the PAV-SAV significantly increases when the station is close to DTLA compared to farther away.

Table 3-2: Overview of Convergence and PAV-SAV System Results for Scenarios 1-16

Scenario	Station Locations	Vehicle Seats (prs/veh)	Convergence			Market Share	Service Users (prs)	SAV Trips (trip)	SAVs (veh)	Avg. Onboard Passengers (prs/veh)
			Iter.	Avg. Rel. Gap	Max. Abs. Gap					
1	1A-2A-3A-4A	4	5	16.51	0.21%	11.48%	15,419	11,239	4,099	3.76
2	1B-2A-3A-4A	4	5	24.35	0.33%	14.46%	19,419	14,249	5,185	3.75
3	1A-2B-3A-4A	4	5	19.56	0.23%	13.38%	17,969	13,057	4,841	3.71
4	1B-2B-3A-4A	4	5	20.99	0.30%	15.93%	21,384	15,638	5,758	3.71
5	1A-2A-3B-4A	4	5	19.10	0.32%	13.10%	17,591	12,770	4,673	3.76
6	1B-2A-3B-4A	4	5	26.73	0.22%	15.61%	20,959	15,327	5,585	3.75
7	1A-2B-3B-4A	4	5	17.14	0.19%	14.50%	19,476	14,092	5,180	3.76
8	1B-2B-3B-4A	4	5	22.36	0.23%	16.84%	22,618	16,468	6,023	3.76
9	1A-2A-3A-4B	4	5	29.30	0.23%	14.16%	19,014	14,094	5,104	3.73
10	1B-2A-3A-4B	4	5	39.08	0.50%	16.07%	21,575	15,976	5,777	3.73
11	1A-2B-3A-4B	4	5	21.69	0.23%	14.87%	19,961	14,718	5,365	3.72
12	1B-2B-3A-4B	4	5	17.65	0.29%	16.76%	22,509	16,592	6,036	3.73
13	1A-2A-3B-4B	4	5	22.13	0.24%	15.32%	20,573	15,138	5,499	3.74
14	1B-2A-3B-4B	4	5	31.68	0.32%	17.12%	22,995	16,936	6,135	3.75
15	1A-2B-3B-4B	4	5	24.88	0.20%	15.85%	21,285	15,601	5,656	3.76
16	1B-2B-3B-4B	4	5	26.71	0.26%	17.66%	23,710	17,397	6,294	3.77
		4	10	25.32	0.26%	17.66%	23,720	17,404	6,296	3.77

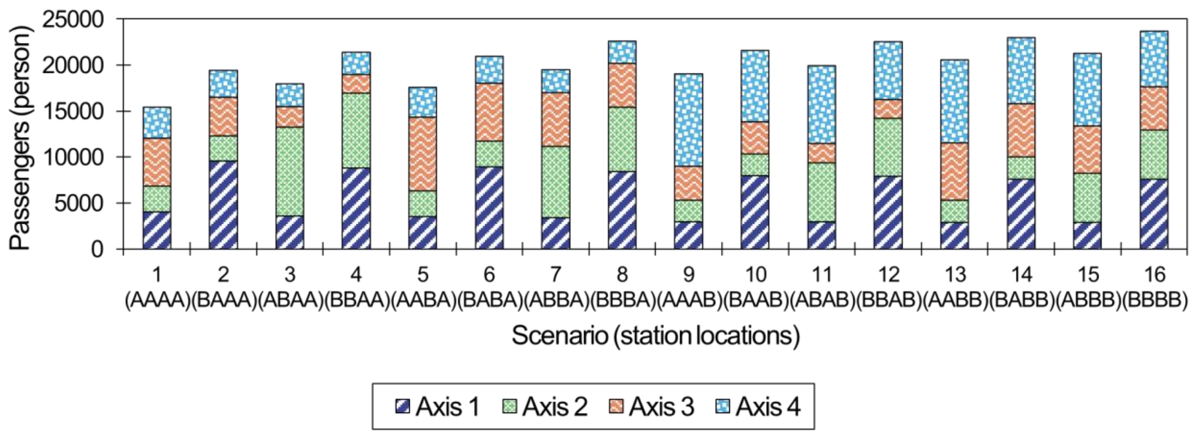


Figure 3-10: Number of PAV-SAV Service Users for Scenarios 1 to 16

Figure 3-11 shows the average number of onboard passengers by station when vehicle capacity $\rho_{\max} = 4$. Although the average number of onboard passengers per vehicle differs by station, the average across all four stations is above 3 in every scenario. Hence, the proposed system, in particular the five-minute time period before SAVs depart the station, appears to effectively pool together multiple travelers into SAVs.

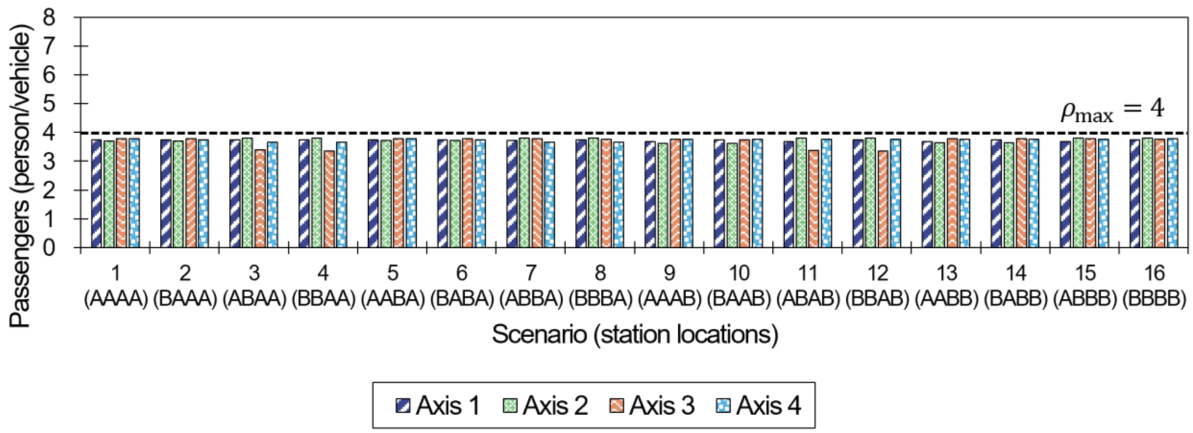


Figure 3-11: Average Onboard Passengers per Vehicle by Axis for Scenarios 1 to 16

Figure 3-12a shows each scenario's VMT change compared with the do-nothing scenario wherein the total network (Los Angeles and Orange counties) VMT is 67,417,000 vehicle-miles. The overall VMT decreases in all scenarios. Since Scenario 16 includes stations near DTLA, the PAV-SAV transfer service users do not need to detour significantly to reach their station, thereby minimizing the impact of traveler detours on VMT.

Moreover, considering PAV's deadheading miles after dropping off the passengers, the do-nothing scenario may underestimate VMT. Bahk et al. (2022) suggest that a PAV in downtown area may require 0.1–1.4 deadheading miles to search for a parking space. Although the overall impact on VMT is still uncertain for both PAV and SAV, the PAV-SAV transfer system can reduce the parking demand in the downtown area. Additionally, while both PAVs and SAVs involve deadheading, if the SAVs are controlled by a public agency, it will be considerably easier to implement rules that minimize the negative impacts of SAVs than privately-owned AVs.

Figure 3-12b shows that VHT (2,216,000 vehicle-hours in the do-nothing scenario) decreases across all scenarios. The results indicate that the SAV lane takes vehicles off the existing freeway sections thereby contributing to the increases in vehicles speeds. Once again, Scenario 16 outperforms the other scenarios in terms of VHT.

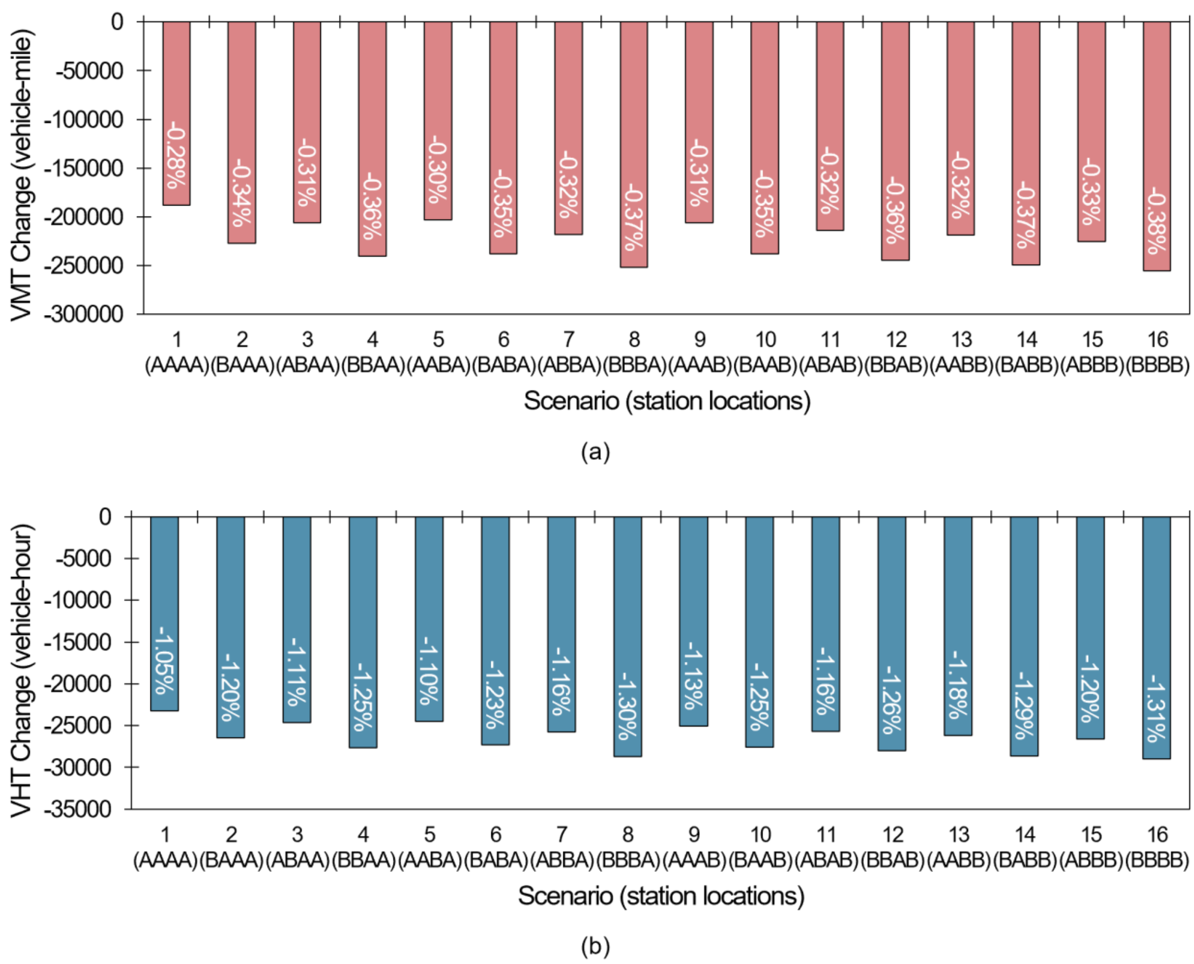


Figure 3-12: Network Performance Results: (a) VMT Change and (b) VHT Change from Do-Nothing Scenario

3.6.3 Variations in Number of Stations

This subsection considers other combinations of transfer stations along the four axes. The total number of transfer stations is a critical planning consideration, as the construction costs for each station and the surrounding infrastructure are likely to be quite expensive, as are the operating costs. Although this chapter does not analyze cost, this subsection does provide insights into the relative benefits of different numbers and configurations of transfer stations.

Building on the finding that Scenario 16 outperforms the other one-station per axis scenarios, I create and compare four new scenarios that remove one of the stations/axes from Scenario 16. I label these Scenarios 17 (XBBB), 18 (BXBB), 19 (BBXB), and 20 (BBBX), where the 'X' denotes an axis without a station. Finally, I also include Scenario 21 wherein each of the four axis has both stations.

Table 3-3 displays the results of Scenarios 17 to 21 alongside Scenario 16. Similar to Scenarios 1–16, the iterative algorithm meets the convergence criteria in four iterations for Scenarios 17–21.

Based on Table 3-3, Scenario 17, without a station on Axis 1, results in a 3-percentage point decrease in market share compared to Scenario 16. Interestingly, Scenarios 18 (no station on Axis 2), 19 (no station on Axis 3), and 20 (no station on Axis 4) only result in a 1.1–1.8 percentage point decrease in market share compared to Scenario 16. Together, these results suggest that the station on Axis 1 is a critical station in serving the demand for the PAV-SAV transfer system. The stations on the other three axes can each individually be removed without impacting total served demand for the PAV-SAV transfer system.

Table 3-3: PAV-SAV System Results for Scenarios 16 to 21

Scenario	Station Locations	Vehicle Seats (prs/veh)	Market Share	Service Users (prs)	SAV Trips (trip)	SAVs (veh)	Avg. Onboard Passengers (prs/veh)
16	1B-2B-3B-4B	4	17.66%	23,710	17,397	6,294	3.77
17	2B-3B-4B	4	14.42%	19,363	14,153	5,128	3.78
18	1B-3B-4B	4	16.52%	22,189	16,308	5,892	3.77
19	1B-2B-4B	4	16.38%	21,995	16,153	5,834	3.77
20	1B-2B-3B	4	15.84%	21,276	15,597	5,647	3.77
21	1A1B-2A2B-3A3B-4A4B	4	18.29%	24,561	18,398	7,135	3.44

Scenario 21, with two stations on each axis, has a higher market share than all scenarios with one station on each axis. This is because the larger number of stations can attract more users with improved accessibility and reduced overall travel time.

Figure 3-13 displays the VMT and VHT changes from the do-nothing scenario. The values in each figure indicate the percentage change compared to the do-nothing scenario. Except Scenario 17, the three-station scenarios show only a slight change in VMT. Although the eight-station scenario shows a higher market share, it does not decrease VMT (-255,023 vehicle-miles) as much as Scenario 16 (-255,551 vehicle-miles).

Scenarios 17–21 all reduce VHT; the magnitudes of the VHT reductions are almost consistent with the market share of PAV-SAV, with Scenario 17 reducing VHT the least and Scenario 21 reducing VHT the most.

In conclusion, the results in this subsection indicate that the eight-station scenario produces a higher market share and reduces VHT more than any of the three- and four-station scenarios, while the four-station scenario reduces VMT slightly more than the eight-station scenario. However, the gap across performance measures between Scenario 16 with four stations and Scenarios 18 and 19 with three stations is not particularly large. As such, if the estimated construction and operational costs of each station are substantial, the three-station option in Scenarios 18 or 19 provide good alternatives.

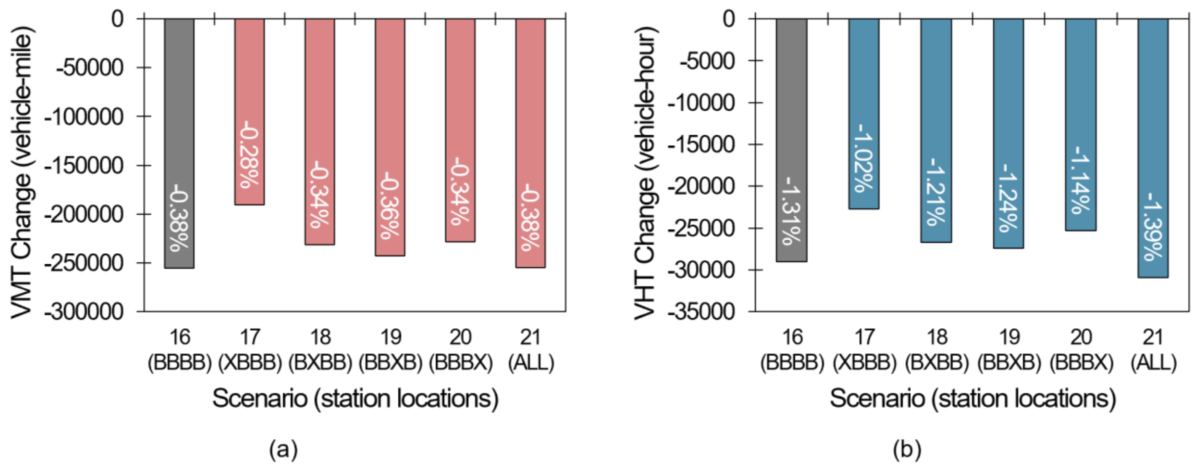


Figure 3-13: Network Performance Reuslts for Scenarios 16 to 21: (a) VMT Change and (b) VHT Change from Do-Nothing Scenario

3.6.4 Sensitivity Analysis on SAV Capacity

This subsection analyzes the impact of changes in SAV capacity. I create two scenarios, Scenarios 16-6 and 16-8, that extend Scenario 16 by increasing the vehicle capacity $\rho_{\max}$ from four seats in Scenario 16 to 6 seats and 8 seats, respectively. Larger vehicle capacities should further reduce vehicle trips into the urban core. However, having more travelers in a vehicle will increase detour times and distances for passengers in the vehicle, thereby making the PAV-SAV option less attractive.

Table 3-4 displays the results of this sensitivity analysis. According to the results, as vehicle capacity increases, the market share for PAV-SAV increases. However, the increase is minor—only a 0.04 percentage point increase from a vehicle capacity of 4 to a vehicle capacity of 8.

Table 3-4: PAV-SAV System and Network Performance Results for Scenarios 16, 16-6, and 16-8

Scenario	Station Locations	Vehicle Seats (prs/veh)	Market Share	Service Users (prs)	SAV Trips (trip)	SAVs (veh)	Avg. Onboard Passengers (prs/veh)	VMT Change	VHT Change
16	1B-2B-3B-4B	4	17.66%	23,710	17,397	6,294	3.77	-0.38%	-1.31%
16-6	1B-2B-3B-4B	6	17.70%	23,764	14,189	4,221	5.63	-0.42%	-1.35%
16-8	1B-2B-3B-4B	8	17.70%	23,769	12,521	3,855	6.17	-0.43%	-1.35%

While the number of PAV-SAV users is basically the same across the three scenarios in Table 3-4, as vehicle capacity increases, the number of SAV trips and SAVs required to serve those person trips decrease substantially. This result stems directly from the larger vehicle capacity and the average number of passengers per vehicle across the three vehicle capacities.

The last two columns in Table 3-4 display the change in VMT and VHT, respectively. The results suggest that increases in vehicle capacity can significantly decrease VMT, due primarily to the reduction in SAV trips from nearly 17,400 in the four-seat case to around 12,500 in the eight-seat case.

Since there is almost no congestion on the SAV links to DTLA in Scenario 16, reducing the number of SAVs in Scenarios 16-6 and 16-8 does not significantly improve congestion in these parts of the network. Interestingly, increasing the vehicle capacity from 6 to 8 shows even less significant improvement in performance because the average pooling of passengers does not increase much in Scenario 16-8.

In conclusion, this subsection suggests that increasing SAV capacities has a negligible impact on demand, but it can decrease VMT and VHT via increasing vehicle occupancies and decreasing SAV trips.

3.6.5 Station Access Links

When some travelers change their primary destination to the PAV-SAV transfer station, the accessing PAVs may cause another congestion near the station. This subsection analyzes the congestion effect near transfer station access link connections. To analyze the impact on the system performance, I pivot from Scenarios 16, 19, 21, and 16-6 in prior subsections. These scenarios all include both freeway and arterial connection links to transfer stations. This subsection re-runs all these scenarios with freeway-only connection links (denoted by 'F') and arterial-only connection links (denoted by 'A').

Table 3-5 and Figure 3-14 show the results of the analysis. Unsurprisingly, the results show that the arterial-only and freeway-only alternatives perform worse than the alternatives with freeway and arterial connections. This is the case across Scenarios 16, 19, 21, and 16-6, as well as all performance metrics, including market share, VHT, and VMT. Also consistent across all alternatives and performance metrics is that the arterial-only option outperforms the freeway-only option.

The results in this subsection lead to a straightforward conclusion—having both arterial and freeway links to connect to transfer stations is preferable to arterial-only and freeway-only connection links. In general, more access connection links help avoid bottlenecks and congestion on links around transfer stations. With fewer access links, there are fewer routes that travelers can use to access a transfer station. Moreover, arterial-only connection links are preferable to freeway-only connection links. The reason for this finding is that congestion on arterial links is less harmful to the system than congestion on freeway links.

Table 3-5: PAV-SAV System Results for Transfer Station Access Link Connection Analysis

Scenario	Station Locations	Vehicle Seats (prs/veh)	Market Share	Service Users (prs)	SAV Trips (trip)	SAVs (veh)	Avg. Onboard Passengers (prs/veh)
16	1B-2B-3B-4B	4	17.66%	23,710	17,397	6,294	3.77
16F	1B-2B-3B-4B	4	17.18%	23,072	16,934	6,125	3.77
16A	1B-2B-3B-4B	4	17.42%	23,392	17,145	6,208	3.77
19	1B-2B-4B	4	16.38%	21,995	16,153	5,834	3.77
19F	1B-2B-4B	4	15.91%	21,360	15,689	5,666	3.77
19A	1B-2B-4B	4	16.15%	21,685	15,906	5,750	3.77
21	1A1B-2A2B-3A3B-4A4B	4	18.29%	24,561	18,398	7,135	3.44
21F	1A1B-2A2B-3A3B-4A4B	4	17.81%	23,921	17,956	6,992	3.42
21A	1A1B-2A2B-3A3B-4A4B	4	18.03%	24,211	18,137	7,046	3.44
16-6	1B-2B-3B-4B	6	17.70%	23,764	14,189	4,221	5.63
16-6F	1B-2B-3B-4B	6	17.21%	23,116	13,816	4,118	5.61
16-6A	1B-2B-3B-4B	6	17.46%	23,442	13,984	4,167	5.63

Note: ‘F’ denotes freeway access-only, and ‘A’ denotes arterial access-only

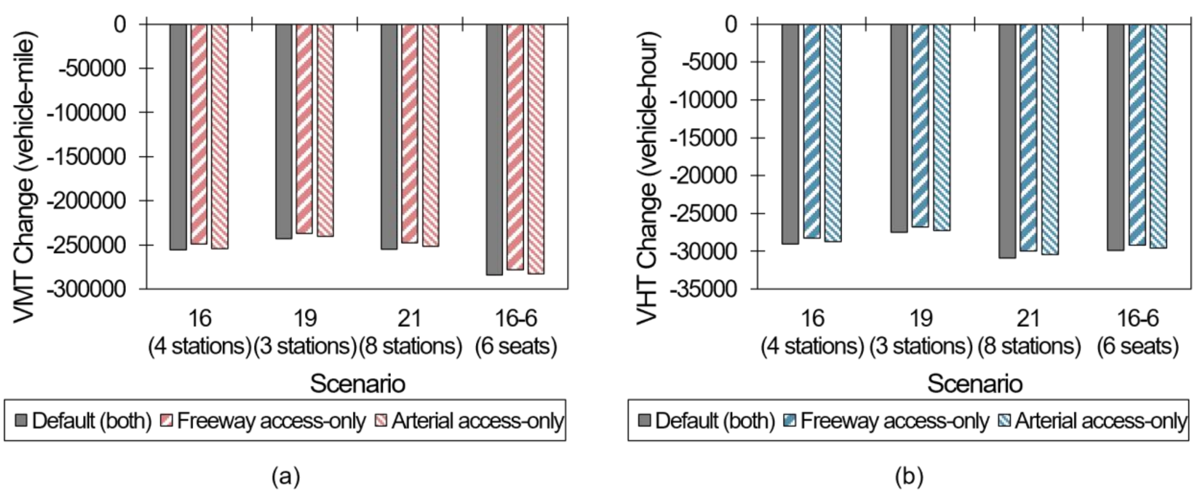


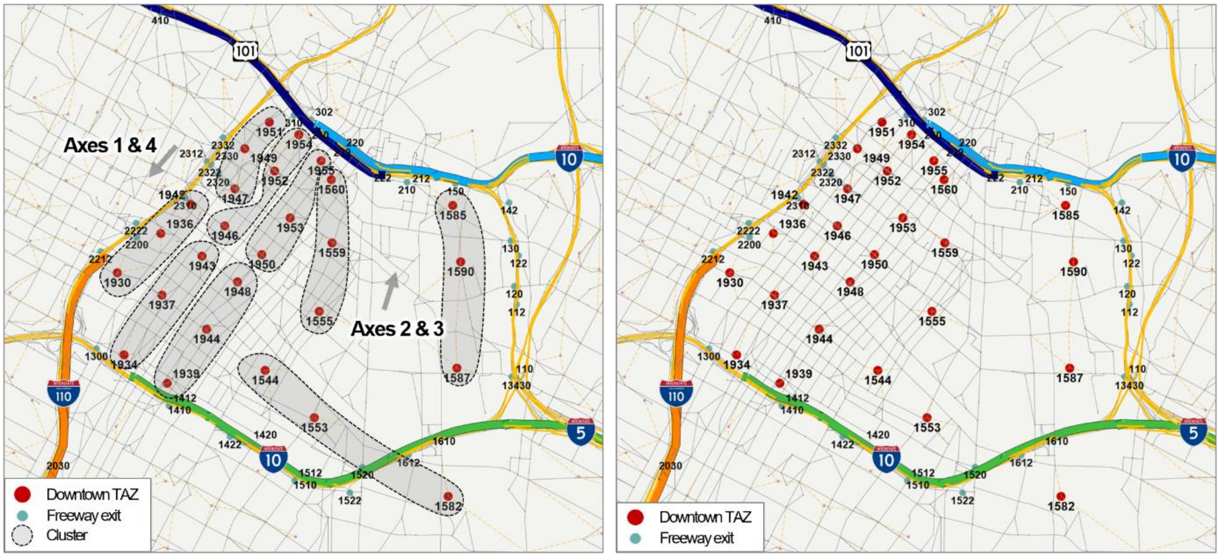
Figure 3-14: Variation in Station Access Links (Both, Freeway Access-Only, and Arterial Access-Only): (a) VMT Changes from Do-Nothing Scenario and (b) VHT Changes from Do-Nothing Scenario

3.6.6 Destination Zone Clusters

Figure 3-7 in Subsection 3.5.4 shows the clustering of TAZs used in all prior scenarios, with five clusters and four to six TAZs per cluster. In this subsection, I consider two alternative clustering approaches. Specifically, as shown in Figure 3-15, I split the clusters into nine clusters (three TAZs per cluster) in Figure 3-15a and eliminate clusters altogether (i.e., one TAZ per SAV) in Figure 3-15b.

Table 3-6 displays the results of the analysis, where 'N' denotes the no clustering alternative, and 'C' denotes the nine-cluster alternative. According to Table 3-6, the number of SAV trips in DTLA, in the no clustering alternative, decreases significantly compared to the clustering alternatives. I expected this outcome because SAVs will not travel between TAZs in the urban core if there is no clustering. On the other hand, the average number of onboard passengers also decreases in the no clustering alternative. Figure 3-16 provides a more detailed look at average vehicle occupancies across the alternatives (and Scenario 16, 19, 21, and 16-6) and across each station in the network. The reason for the decrease in vehicle occupancies in the no clustering alternative is that less clustering of destinations means it is less likely there will be enough demand to fill each SAV in each five-minute interval.

Table 3-6 also includes results related to the market share of the PAV-SAV system. The results clearly indicate that the no clustering alternative (i.e., the alternative where every zone is its own cluster) produces the highest market share. The higher market share for the no clustering alternative is primarily due to the reduction in detour distance and time, compared to the alternatives with clustering, making it the most attractive service offering for travelers.



(a) (b)

Figure 3-15: Variation in Destination Zone Clusters: (a) 9 Clusters and (b) No Clustering (TransCAD maps)

Table 3-6: PAV-SAV System Results for Destination Clustering Analysis

Scenario	Station Locations	Vehicle Seats (prs/veh)	Market Share	Service Users (prs)	SAV Trips (trip)	SAVs (veh)	Avg. Onboard Passengers (prs/veh)
16	1B-2B-3B-4B	4	17.66%	23,710	17,397	6,294	3.77
16C	1B-2B-3B-4B	4	17.44%	23,422	12,931	6,285	3.73
16N	1B-2B-3B-4B	4	18.37%	24,662	6,795	6,795	3.63
19	1B-2B-4B	4	16.38%	21,995	16,153	5,834	3.77
19C	1B-2B-4B	4	16.13%	21,655	11,957	5,795	3.74
19N	1B-2B-4B	4	16.86%	22,646	6,038	6,038	3.75
21	1A1B-2A2B-3A3B-4A4B	4	18.29%	24,561	18,398	7,135	3.44
21C	1A1B-2A2B-3A3B-4A4B	4	18.06%	24,247	14,850	8,129	2.98
21N	1A1B-2A2B-3A3B-4A4B	4	18.97%	25,479	8,238	8,238	3.09
16-6	1B-2B-3B-4B	6	17.70%	23,764	14,189	4,221	5.63
16-6C	1B-2B-3B-4B	6	17.47%	23,457	9,948	4,456	5.26
16-6N	1B-2B-3B-4B	6	18.39%	24,688	5,132	5,132	4.81

Note: 'C' denotes 9 clusters, and 'N' denotes no clustering

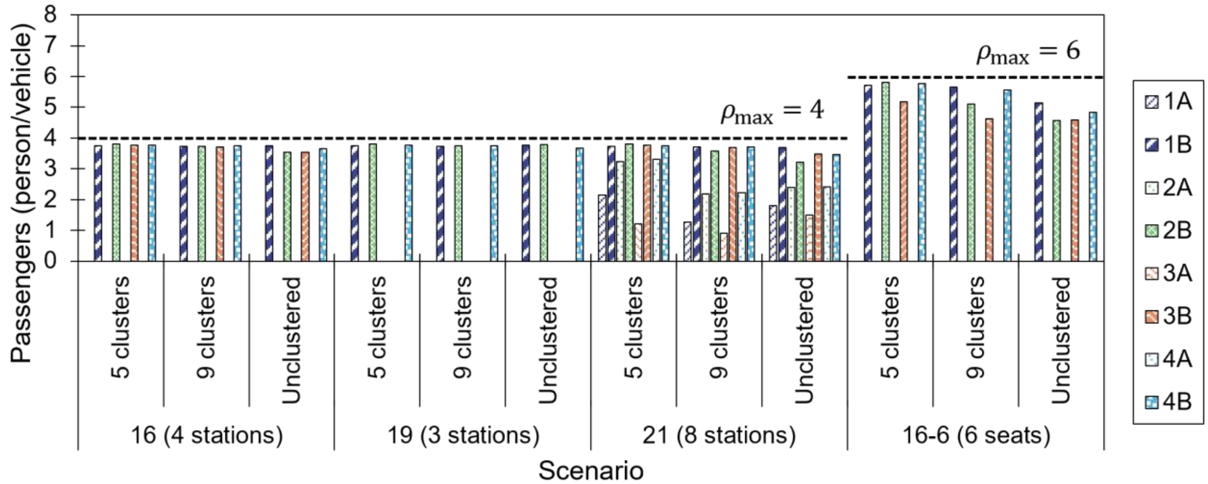


Figure 3-16: Average Onboard Passengers per Vehicle by Zone Clustering

Figure 3-17 displays the VMT and VHT changes across the scenarios and clustering alternatives. For the VMT in Figure 3-17a, there are two contradicting potential factors that affect total VMT. First, with fewer TAZs per cluster, the VMT decreases in DTLA because there are fewer TAZ-TAZ SAV trip legs in DTLA, as shown in Table 3-6. Second, however, with fewer TAZs per cluster, VMT increases since average vehicle occupancy in SAVs decreases, as shown in Table 3-6. The magnitude of these two competing factors varies across alternatives. The five-cluster alternative shows the largest VMT reduction with the highest number of onboard passengers. However, the no clustering alternative has the second largest VMT reduction due to the higher demand compared to the nine-cluster alternative. Hence, there is no consistent relationship between the number of TAZs per cluster and VMT.

VHT in Figure 3-17b shows similar patterns compared with VMT. The results indicate that the five-cluster alternative always reduces VHT more than the nine-cluster and no clustering alternative. The reason for this finding is that average vehicle occupancy has a significant impact on congestion, and the five-cluster alternative has the highest average vehicle occupancy. Hence, the benefits of fewer intra-DTLA vehicle trips do not outweigh the increase in transfer station to DTLA vehicle trips in terms of total congestion impact.

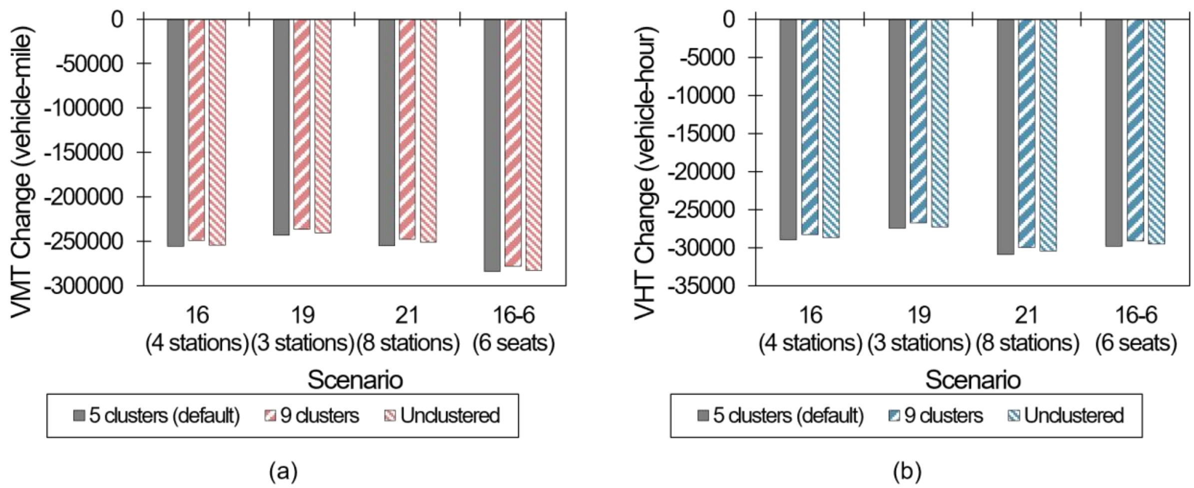


Figure 3-17: Variation in Destination Clusters: (a) VMT and (b) VHT Changes from Do-Nothing Scenario

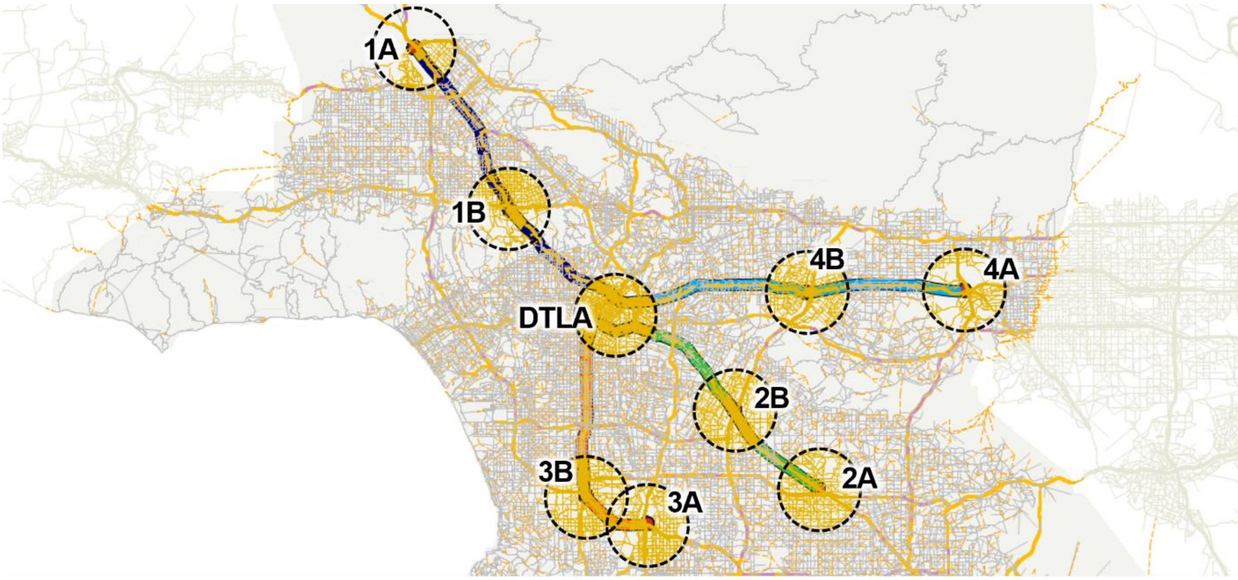
The results in this subsection illustrate that the PAV-SAV system can also work efficiently without clusters in AM peak. In fact, not clustering TAZs increases the market share for the PAV-SAV system. However, there is a practical factor that the model does not capture, which makes the no clustering alternative unattractive, namely, the number of platforms. As the number of clusters increases, more platforms will be needed in order to reduce friction at the PAV to SAV transfer station. More platforms would require a larger spatial footprint for the transfer station, thereby increasing costs.

A final point is that clusters do not need to be fixed and can vary throughout the day. The system operator can flexibly cluster the TAZs in DTLA in response to the time-of-day travel demand (e.g., no clustering in morning, nine clusters in afternoon, five clusters in midday, etc.).

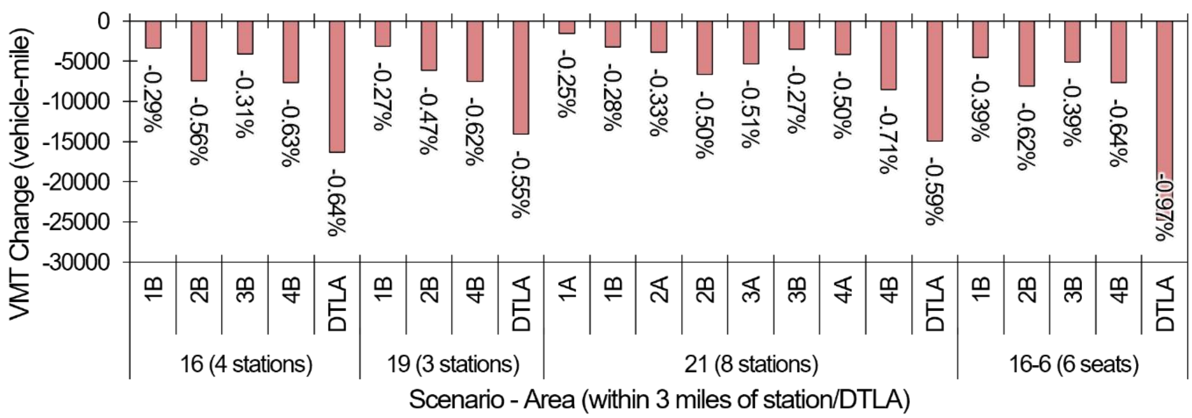
3.6.7 Spatial Variance in Performance Metrics

The prior subsections only include network-wide metrics. This subsection provides and analyzes VMT and VHT in different subregions of the network. Once again, I focus on Scenarios 16, 19, 21, and 16-6. Figure 3-18a shows the subregions that I analyze. Basically, I analyze DTLA as well as a three-mile radius around each transfer station.

Figure 3-18b and Figure 3-18c show a dramatic decrease in both VMT and VHT in the DTLA area across all scenarios. The results indicate that VMT and VHT do not change much around transfer stations in any of the scenarios, despite the significant decrease in DTLA across all scenarios.



(a)



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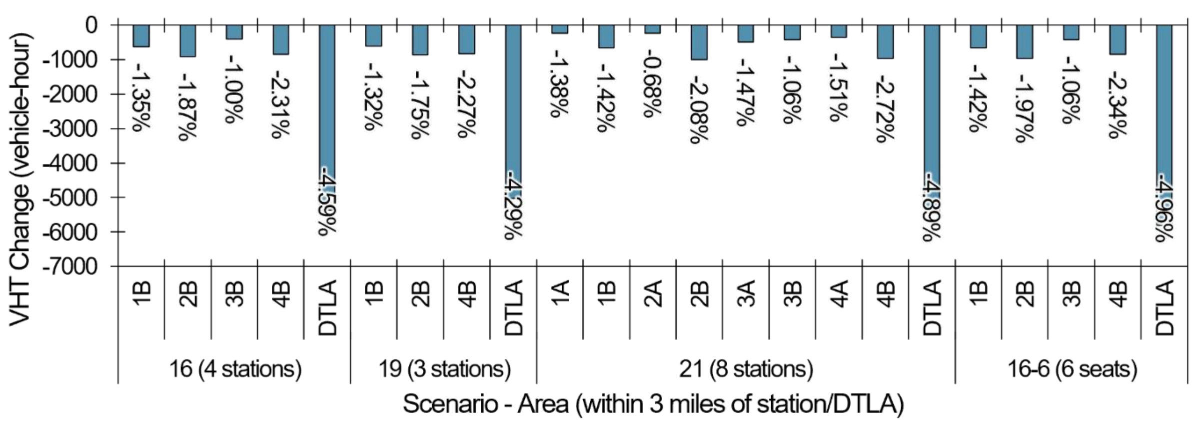


(c)

Figure 3-18: Spatial Variance in Performance Metrics: (a) Locations of 3-mile Radius Areas (TransCAD map), (b) VMT Changes by Area and Scenario, and (c) VHT Changes by Area and Scenario

3.7 Discussion

3.7.1 Answers to Research Questions

Section 3.1 of this chapter includes three research questions: (1) how many travelers would use the PAV-SAV transfer system? (2) how much can the PAV-SAV transfer system reduce VMT and congestion? And (3) what is the optimal, or at least a good, design for the PAV-SAV transfer system? The computational results address each of these questions. Below I discuss the answers to these research questions and their broader implications.

The best PAV-SAV transfer system designs have a market share close to 18% of person trips terminating in DTLA during the morning peak period, representing 24,000 person trips. This is clearly a sizable portion of person trips that would benefit directly from the proposed system (according to the model in this chapter). Hence, the preliminary analysis indicates that there would be a strong market to support a system of PAV-SAV transfer stations in a future with ubiquitous AVs. While these 24,000 clearly benefit directly, the second research question addresses the benefits and disbenefits other travelers acquire from the system of transfer stations.

The computational results indicate that the best PAV-SAV transfer system designs can decrease congestion, measured in terms of VMT, and VHT. However, the percentage change is relatively small, when considering all person and vehicle trips in Los Angeles and Orange counties. Nevertheless, for policymakers and planners interested in reducing VMT and VHT, they can use the proposed PAV-SAV transfer system alongside other travel demand management (TDM) strategies. In fact, combined with TDM strategies like parking and road pricing, the market share and secondary benefits of the proposed PAV-SAV transfer system would likely increase. Additionally, in the case study, the transfer stations and SAVs only serve a small number of DTLA zones; it is possible to expand the geographic region of possible destination zones.

In this chapter I performed extensive scenario and sensitivity analyses to answer the third research question and determine a good design for the system of transfer stations. According to the model results, and considering only market share, VMT, and VHT metrics (and not cost), the best design includes (i) four transfer stations, with one located along each of the four major (freeway) axes into DTLA and located relatively close to DTLA along the axes, (ii) a vehicle capacity of four or six passengers, (iii) connections between each transfer station and both nearby arterials and the freeway, (iv) no clustering of destination TAZs in DTLA.

3.7.2 Model and Analysis Limitations and Their Implications

The answers to all the research questions depend on the model system and analysis framework employed in this chapter. I believe the model system and analysis framework utilized in this chapter have been extremely useful, nevertheless they do have limitations that I will discuss.

First, the analysis framework only incorporates benefits and not costs. As the proposed transfer stations (see Figure 3-3) are likely to require significant land acquisition and construction costs if/when PAVs and SAVs become commonplace, a more detailed analysis is necessary to determine the best system design. For example, while the results suggest that stations closer to DTLA have larger benefits than stations farther away, land is likely to be more expensive closer to the urban core. Another example mentioned previously, is that clustering together destination TAZs is likely to reduce the number of platforms and decrease the construction and land acquisition costs. Additionally, while the results suggest connecting the transfer stations to more arterial and freeway links increases system benefits, each of these connections will increase system costs. In addition to facility/infrastructure costs, the number of SAVs required to serve PAV-SAV travelers impacts vehicle purchasing, financing, and operational costs. Hence, a detailed cost-benefit analysis is necessary in the future for making final design decisions and evaluating alternatives against the do-nothing alternative.

Second, the model system does not capture several second order factors, namely, intra-zonal person (and vehicle) trips in DTLA, non-personal vehicle modes (e.g., walking, bicycling, conventional transit), and changes in person trip distribution and person trip generation. Moreover, the model system focuses solely on person trips during the morning commute period, therefore it does not capture the space-time or inter-household constraints incorporated into existing activity-based travel demand models. Incorporating intra-zonal person trips would slightly increase VMT and possibly VHT. Notably the analysis in this chapter also ignores intra-zonal person trips for the do-nothing scenario. Forecasting the directional impacts of incorporating non-vehicle modes in the model system is difficult as both the real world and model system are complex. Incorporating changes in person trip distribution and generation would likely decrease the VHT benefits, particularly in the urban core, as well as some of the VMT benefits. Travelers would likely respond to the decrease in vehicle congestion in the urban core by changing their non-work activity locations to the urban core, as well as making more person trips to and within the urban core. However, incorporating these behavioral changes may increase the market share for the PAV-SAV transfer system.

I want to comment on the lack of non-personal vehicle modes in the model and the role of these modes in the final PAV-SAV transfer system design. I ignore walk to transfer station as the first-mile option because this chapter was motivated by the role a PAV-SAV transfer system can play in reducing VMT and VHT from private vehicles in a future with AVs, and walking trips are already the most sustainable mode of travel. Hence, in the final design of PAV-SAV transfer stations, it is critical that travelers can easily walk or bike to/from transfer stations, and that dense housing and business development can occur close to transfer stations in order for as many people and businesses to benefit from the mobility and accessibility these transportation facilities can offer. PAV-SAV transfer stations should not be built to only serve individuals with PAVs, even though the transfer stations are meant to reduce PAV trips to the urban core.

3.7.3 Transferability of Results

Another interesting area of discussion relates to the transferability of the results of this chapter to cities other than Los Angeles. Compared to other cities in the United States, Los Angeles (i) has the second largest population; (ii) is in the county with the highest population, but the metropolitan region lacks the high peaks of population and employment density in the urban core that are present in most East Coast cities and Chicago; (iii) has an extensive network of highways and major arterials that suffer from high congestion levels during the morning peak period; and (iv) has surface parking lots that consume a substantial portion of land in Southern California. The lack of concentration of employment opportunities and housing as well as the extensive roadway network and parking space has resulted in extremely low mode shares for transit, walking, and biking in the region, despite the moderate year-round weather. While these features contrast with the northeast and Midwest of the US as well as nearly all cities outside the US, cities in Texas and Arizona share features with Los Angeles.

3.8 Conclusion

Inspired by existing PNR and KNR systems, this chapter proposes a novel PAV-SAV transfer system wherein travelers move via PAV to a transfer station where they transfer to SAVs for the final leg of their person trips into the dense urban core. To further incentivize usage of the PAV-SAV transfer system, the chapter assumes there are dedicated lanes on expressways for SAVs. I hypothesize that the proposed PAV-SAV transfer system would provide significant value to travelers and decrease congestion in urban areas. To test these two hypotheses, I analyze the market share of the proposed PAV-SAV transfer system and VHT, respectively, for a model-based case study in Los Angeles. The model I develop is an integrated service choice (PAV-only vs. PAV-to-SAV) and traffic assignment model that includes an intermediary model to determine the number of SAV trips, given a particular PAV-SAV market share for every origin-destination pair. Additionally, this chapter aims to identify a good PAV-SAV transfer system design through scenario analysis.

The model-based case study results indicate that the proposed PAV-SAV transfer system can obtain a market share of 16–18% of all person trips terminating in downtown Los Angeles. Moreover, the proposed system can reduce VMT slightly and VHT considerably in Los Angeles. Finally, I use scenario analyses to identify a good PAV-SAV transfer system design with significant system performance benefits.

Future research directions include incorporating PAV and SAV deadheading trips into the analysis scope to improve the theoretical validity of the model. Additionally, future research can test PAV-SAV system designs using more advanced activity- and travel-behavior models. Examples include commercial disaggregate activity-based travel demand models, dynamic traffic and transit assignment models, and even stochastic PAV-SAV transfer station choice models. A final research direction includes developing a bi-level PAV-SAV system/network design problem with equilibrium constraints to optimally design a PAV-SAV transfer system.

Chapter 4 HOUSEHOLD-LEVEL ACTIVITY-TRAVEL PATTERN ANALYSIS

4.1 Overview

This chapter parallels Bahk and Hyland (2024). Developing systems models that capture the flexibility of PAVs and the downstream travel behavior changes enabled by PAVs is critical to understanding their potential impacts on transportation system performance. While this fact is well-recognized in the academic literature, there are shortcomings associated with the models proposed in the existing literature to understand the potential impacts of PAVs. Most notably, only a few studies in the existing literature capture the usage of AVs in household travel, considering the constraints facing individuals and their fellow household members as they travel to complete activities throughout the day (Cokyasar and Larson, 2020; Correia and van Arem, 2016; Khayati et al., 2021b, 2021a). Moreover, as far as I know, none of these studies that model household travel with AVs and capture spatial and temporal constraints facing travelers permit intermodal trips. Given the potential role of PAVs and shared-use AVs (SAVs) as transit feeder modes, I view this as a significant shortcoming.

The first goal of this chapter is to develop a holistic and high-fidelity transportation systems modeling framework that (i) includes a multimodal transportation network, (ii) permits intermodal trips, and (iii) captures the detailed spatial and temporal constraints facing household members and vehicles as the household members complete activities during a typical weekday. Specifically, I want the framework to capture the key features of

PAVs, SAVs, transit, walking, and intermodal AV-transit travel. The second goal of this chapter is to apply the proposed modeling framework to analyze the potential impacts of AVs—PAVs and SAVs—on household travel, vehicle usage patterns, and transit usage, as well as the potential benefits of AV-transit intermodal travel.

To meet these goals, I propose a generalization of the Household Activity Planning Problem (HAPP) proposed by Recker (1995) and the HAPP with AVs and Ridesourcing (HAPPAV-RS) proposed by Khayati et al. (2021b). In the HAPP model, households make travel decisions by solving a pickup and delivery problem with time-windows (PDPTW), wherein household members use their vehicles to pick up "activities" at activity locations and deliver them to their home location. The HAPPAV-RS model generalizes the HAPP model by treating household members and vehicles as separable, given the ability of AVs to deadhead. I generalize the HAPPAV-RS by allowing household members to use transit and to use PAVs and SAVs as first- or last- mile transit feeder modes. Hence, I refer to my model as the HAPP with AV-enabled intermodal trips (HAPP-AV-IT). I provide more details about each of these HAPP-based models in Subsection 4.2.1.1.

This chapter makes several contributions to the academic literature. These contributions stem from generalizing the HAPP to incorporate intermodal trips, more realistic transit networks, and multimodal travel. Most importantly, I incorporate intermodal PAV-transit and SAV-transit trips into a HAPP-based math programming formulation.

From a practical perspective, these model capabilities are critical to capturing travel behavioral more realistically and understanding, evaluating, and forecasting the potential impacts of AVs on household travel, vehicle kilometers (or miles) traveled (VKT or VMT;

Note that this chapter uses VKT, unlike the other chapters.), and transit. Prior models fail to capture the possibility that AVs will serve as a first- or last-mile transit mode—a distinct possibility in cities with rail systems or bus rapid transit systems that are more efficient than private cars on key corridors. Moreover, as transit agencies consider re-designing their transit networks in an era of shared and private AVs, these agencies need models that realistically capture the behavior of travelers in terms of person-level mode, path, and schedule choices, as well as vehicle-level routing and scheduling decisions.

From a methodological perspective, incorporating intermodal trips in a HAPP-based formulation is not straightforward. To address this modeling challenge, I enhance the HAPP model through the following changes: (i) I establish a distinct transit network, separated from the road network, and I connect the two networks using transfer links; (ii) I introduce transit hub nodes in the HAPP graph between a home location and the household's activity locations, and (iii) I introduce several novel constraints to permit intermodal transit-based trips.

Finally, while this chapter focuses on intermodal AV-transit travel, the modeling framework, which incorporates intermodal trips and multiple distinct travel modes, represents a valuable starting point for developing more comprehensive HAPP-based models. Based on the modeling framework, incorporating new modes like microtransit and shared micromobility and enabling connections between these new modes and conventional travel modes should be straightforward.

The remainder of this chapter is structured as follows. Section 4.2 reviews the literature most relevant to this chapter. Section 4.3 describes the decision problem facing households as they determine the modes, routes, and travel schedules of all household members who must conduct a given set of activities. Section 4.4 describes the HAPP-AV-IT model formulation. Section 4.5 presents a case study to illustrate HAPP-AV-IT's capabilities and analyze the impacts of AV deadheading and intermodal trips on household travel, VKT, and transit usage. Finally, Section 4.6 concludes this chapter with a summary and a discussion of future research directions.

4.2 Literature Review

This section reviews the current literature on household AV routing and scheduling problems, as well as vehicle routing problems involving en-route transfers. Given that most of the relevant studies involve HAPP-based models, I organize the review into subsections distinguishing between HAPP- and non-HAPP-based models. Additionally, I highlight the gaps in the existing literature that this chapter addresses.

4.2.1 Household Vehicle Routing and Scheduling Models

4.2.1.1 HAPP-based Models

As mentioned in the introduction, Recker (1995) proposes the HAPP and formulates it as PDPTW. In the HAPP, a household member 'picks up' an activity at an activity location and travels back home to complete the activity 'delivery'. Starting from a base formulation that allows any household member to travel alone to perform any activity, Recker (1995) formulates more realistic cases such as restricting activity participation to specific household members and allowing car-pooling within the household. The HAPP objective function incorporates household travel costs such as travel time, and the household-level decision problem is to determine the cost-minimizing travel routes and schedules across household members on a given day.

Several studies extend the original HAPP formulation—see Table 4-1 for a list. Gan and Recker (2013, 2008) propose the Household Activity Rescheduling Problem (HARP) and the Stochastic Preplanned HAPP with Uncertain Activity Participation (SHAPP) that capture uncertainty in activity scheduling and enable travelers to reevaluate their preplanned schedules and decide if they should modify their remaining schedule. Chow and Recker (2012) propose an inverse optimization problem to calibrate HAPP (Inverse HAPP, InvHAPP). In addition, Kang and Recker (2013) propose the Location Selection Problem for HAPP (LSP-HAPP) that models household members choosing among several activity locations to conduct a particular activity type, e.g., grocery shopping. Kang and Recker (2014) also suggest HAPP-Refueling (HAPPR) and HAPP-Charging (HAPPC) to consider refueling and recharging travels for alternative fuel vehicles such as hydrogen fuel cell vehicles (HFCVs) and battery electric vehicles (BEVs). Chow (2014) improves the computational efficiency of HAPP using two reoptimization algorithms in the Generalized Selective Household Activity Routing Problem (G-SHARP), enabling activity location selection as well. Yuan (2014) incorporates time-of-day activity utility and duration utility in HAPP (UHAPP) to consider the temporal variations in activity-related utility. Yuan (2014) also includes a transit mode in the model, expanding the HAPP to consider multiple modes. However, the specification of the transit network in the current study is much more detailed than the one in Yuan (2014). Chow and Nurumbetova (2015) suggest an inventory routing problem (Inventory-based Selective Household Activity Routing Problem, iSHARP) to consider needs satisfaction over a period of days, which captures heterogeneity in travel time across days. Chow and Djavadian (2015) propose the multimodal HAPP (mHAPP) and determine the market equilibrium for each mode using a discrete choice model. Khayati and Kang (2019, 2015) propose the HAPP with Electric Vehicles (HAPPEV) to capture and simulate the potential activity-travel patterns of BEVs. They conduct scenario analysis to understand EV-induced behavioral changes under different charging conditions. Xu et al. (2018) propose a random utility-based estimation framework for HAPP and provide a tool for estimating utilities for work and shopping and disutilities for travel times. Furthermore, several HAPP-based studies consider road congestion, including J. Liu et al. (2018) and Najmi et al. (2020), who assign trips from the HAPP model to a road network using conventional traffic assignment methods.

Two recent HAPP studies incorporate AVs. Khayati et al. (2021a, 2021b) propose the HAPP with Autonomous Vehicles (HAPPAV) and the HAPPAV with Ride Sourcing (HAPPAV-RS) to capture driverless vehicle operations. The HAPPAV-RS accommodates shared AVs (SAVs) as a travel option and Khayati et al. (2021b) conduct scenario analysis under different PAV operating cost and SAV fare parameters. As mentioned in Section 4-1, I generalize the HAPPAV-RS model to incorporate transit travel and intermodal PAV-transit and SAV-transit trips.

Table 4-1: HAPP Studies

Study	Application	Mode Choice	Carpool in Household	Intermodal Trip
Recker (1995)	Household Activity Pattern Problem (HAPP)	PV	Yes	No
Gan and Recker (2008)	HAPP with rescheduling problem (HARP)	PV, walk	No	No
Chow and Recker (2012)	Inverse HAPP (InvHAPP)	PV	No	No
Gan and Recker (2013)	Stochastic preplanned HAPP with uncertain activity participation (SHAPP)	PV	No	No
Kang and Recker (2013)	Location selection problem for HAPP (LSP-HAPP)	PV	No	No
Kang and Recker (2014)	HAPP for refueling (HAPPR) and for charging (HAPPC)	PV (HFCV, BEV)	No	No
Chow (2014)	Generalized selective household activity routing problem (G-SHARP)	PV	No	No
Yuan (2014)	Travel time-dependent HAPP (TUHAPP)	PV, transit	No	No
Chow and Nurumbetova (2015)	Multi-day inventory routing model with space-time-needs constraints (iSHARP)	PV	No	No
Chow and Djavadian, (2015)	Multimodal HAPP (mHAPP)	PV, walk, walk+transit	No	No
J. Liu et al. (2018)	HAPP with DTA	PV	Yes	No
Xu et al. (2018)	Random utility-based estimation framework for HAPP	PV	No	No
Khayati and Kang (2019)	HAPP with electric vehicle (HAPPEV)	PV	No	No
Najmi et al. (2020)	Multimodal HAPP with demand calibration and network assignment	PV, bicycle, walk, transit	No	No
Khayati et al. (2021a)	HAPP with autonomous vehicles (HAPPAV)	PAV	Yes	No
Khayati et al. (2021b)	HAPPAV with ride sourcing (HAPPAV-RS)	PAV, SAV	Yes	No
This chapter	HAPP with AV-enabled intermodal trips (HAPP-AV-IT)	PAV, SAV, walk+transit	Yes	Yes

Figure 4-1 illustrates the possible mode and route choice options captured in existing HAPP models and the model in this chapter for the same activity profile. In the example, starting from home, three household members travel to three different activity locations using the available travel options in each HAPP-based model. Figure 4-1a displays the original HAPP Recker (1995) that includes conventional private vehicles travel with carpooling as an option. Figure 4-1b displays the mHAPP (Chow and Djavadian, 2015;

Najmi et al., 2020) with PV, walking, and transit modal options. The mHAPP considers access/egress walk trips between activity locations and parking spaces or transit stations. However, the mHAPP does not consider carpooling as an option. Figure 4-1c displays the HAPPAV-RS Khayati et al. (2021b) that considers carpooling, mode choice (PAV and SAV), and PAV deadheading. Figure 4-1d displays my model, HAPP-AV-IT, which include mode choice with transit (PAV, SAV, and transit), carpooling, AV deadheading, and PAV-transit and SAV-transit transfers.

Figure 4-1 illustrates that as the capabilities of the model change, I can expect notable changes in the routing and scheduling of both vehicles and travelers. Hence, in regions with robust transit networks, and in future scenarios with SAVs and PAVs, prior models will fail to capture the modal options available to travelers, and therefore are likely to fail to forecast vehicle usage and transit demand.

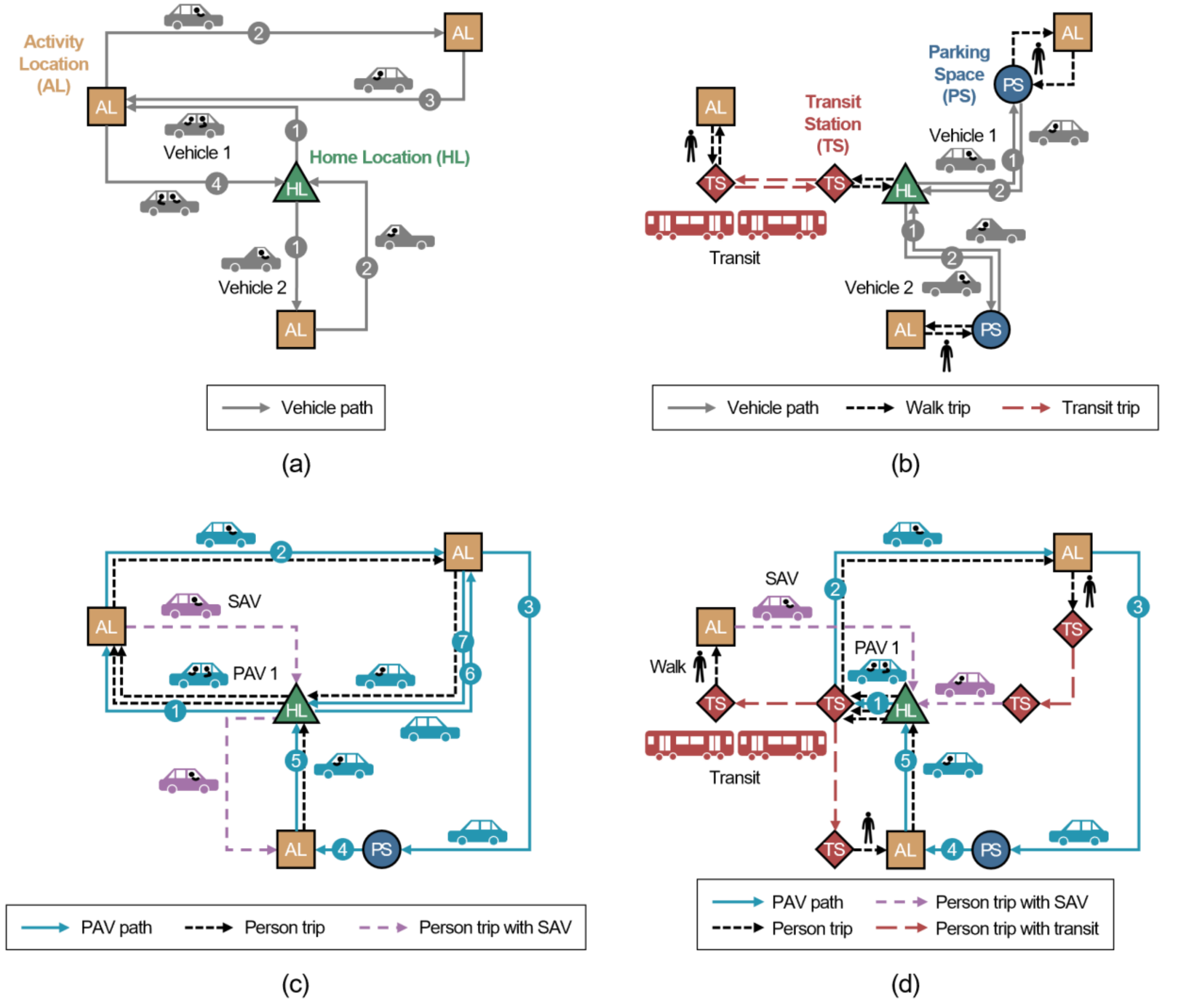


Figure 4-1: Comparing Possible Activity Travel Patterns among Studies for a 3-activity Case: (a) HAPP, (b) Multimodal HAPP, (c) HAPP with AV and Ride Sourcing, and (d) HAPP with AV and Intermodal Trip

4.2.1.2 Other PAV Routing and Scheduling Models

There are two studies that develop PAV routing and scheduling models that are not primarily based on the HAPP (Cokyasar and Larson, 2020; Correia and van Arem, 2016). Correia and van Arem (2016) propose and formulate the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP) as a Mixed Integer Program (MIP). Their model captures the expected travel patterns of PAVs and they assign PAV trips to the roadway network based on user-equilibrium traffic assignment principles. Like in HAPP-based models, the objective in Correia and van Arem (2016) is to minimize total generalized household travel costs. They capture temporal constraints on activities through late and early arrival time penalties, rather than through hard time-window constraints as in HAPP-based models. The household travel costs in the UO-POAVAP include (i) distance-based costs for PAVs, (ii) public transit fares for trips not satisfied by PAVs, (iii) PAV parking costs, and (iv) penalties for arriving early or late to each activity location. The study analyzes the activity profiles of 29 households assuming they all have at least one PAV, with a small network and two competing modes: PAV and public transit. However, unlike the model purposed in this chapter, Correia and van Arem (2016) do not consider SAVs, carpooling in PAVs, or inter-modal trips.

Cokyasar and Larson (2020) also develop a PAV routing and scheduling problem using a Mixed Integer Linear Program (MILP). The objective in their model is to minimize total household travel costs, including the fixed daily PAV costs, in-vehicle travel costs, deadheading costs, early and late arrival penalties, and parking costs. Household members can choose travel modes between PAV and SAV in their model, but their model does not include transit or intermodal transit-based trips. They also do not separate persons and vehicles.

As a concluding note, neither of these two studies (Cokyasar and Larson, 2020; Correia and van Arem, 2016) incorporate intermodal travel. This is an important gap that the proposed model in this chapter addresses.

4.2.2 Vehicle Routing Problems with En-route Transfers and Intermodal Trips

For traveling to out-of-home activities, travelers often use multiple modes to travel between consecutive activity locations (e.g. park-and-ride between home and work locations), and certainly to travel between multiple activity locations within a multi-stop trip chain or home-based tour (e.g., taking transit to the grocery store, then taking ride-hail back home). In this subsection, I discuss research that tries to model this type of behavior.

Studies that enable transfers in the Pickup and Delivery Problem (PDP) model framework mainly focus on freight deliveries. However, there are a few passenger transport examples. Cortés et al. (2010) introduce the Pickup and Delivery Problem with Transfers (PDPT) that involves predetermined transfer points where passengers can switch vehicles. Masson et al. (2014) extend the PDPT and develop the Dial-A-Ride Problem with Transfers (DARPT). The DARPT also allows travelers to change vehicles at specific locations, and computational experiments show that transfers can reduce costs by 8%. Additionally, Fu and Chow (2022) propose the Pickup and Delivery Problem with Synchronized En-route Transfers (PDPSET) for microtransit services. Utilizing MILP, they provide an en-route transfer option between two vehicles to reduce the total travel cost. However, while these PDP- or PDPTW-based models address general passenger routing problems, they do not specifically focus on the household activity-travel routing and scheduling problem.

Moreover, with the availability of AVs, a new viable option emerges: PAV-transit intermodal trips, which can potentially replace current park-and-ride and kiss-and-ride services (Bahk et al., 2024). For example, if a household's home location is far from a transit station, a household member can use a PAV to travel to the transit station, and transfer to a transit mode. Following the drop-off, the PAV can either return home or proceed to another location to transport other household members. Such flexibility from PAVs can: 1) increase accessibility to transit and destinations along transit lines, 2) produce significant vehicle deadheading and VKT, and (3) further increase vehicle productivity in terms of household activities completed per vehicle per day. Importantly, the total VKT impacts before and after the introduction of PAV are not straightforward to determine and analyze—a detailed model of activity-travel behavior and vehicle usage is necessary, particularly one that captures intermodal travel.

Similar to PAV-to-transit intermodal trips, SAV-to-transit intermodal trips can complement the limited transit service coverage in some cities. When an SAV-to-transit intermodal trip replaces an SAV-only trip, it not only increases transit usage but it also reduces total system VKT. Liang et al. (2016) present integer programming models for a last mile SAV system designed for SAV-transit intermodal trips, aiming to maximize the total profit from the SAV system operation. However, Liang et al. (2016) do not extend their models to incorporate other modes or household-level AV routing and scheduling.

There are currently no holistic models of household member and household vehicle travel that consider intermodal trips. The model in this chapter, the HAPP-AV-IT, aims to address this shortcoming.

4.3 Problem Statement

In this chapter, I address the problem of a household collectively making *travel decisions* to complete a set of given activities over the course of a day. Each activity has a time-window for when a person can arrive, a time-window for departure, a duration, a location, and a non-empty set of household members who can complete the activity. Each household includes a non-empty set of household members and a home location where all household members and household PAVs begin their day.

To complete all activities, household members make one or more home-based tours. To travel between locations, household members can choose a single mode such as PAV, SAV, or transit (including en-route transfers between transit lines) or intermodal trips (e.g., PAV-transit and SAV-transit). Moreover, household members can carpool in a PAV. The PAVs transport household members between the home location, activity locations, and transit stations. In addition to traveling between the home location, activity locations, and transit stations, empty PAVs can also travel to/from parking locations. And, to clarify, PAVs can choose among many parking locations within a city, and PAVs can also drop-off one household member and deadhead to another location to serve a second household member. Hence, the specific household *travel decisions* include the routes and schedules for each household member and PAV, where household member routes between activity locations are multimodal paths.

I assume the household wants to minimize its combined travel costs. I include the following household travel costs: in-vehicle and out-of-vehicle (e.g., walk and wait) travel time, PAV operating costs, PAV parking fees, SAV fares, and transit fares. I assume that the household has full information about network travel times and travel costs for all travel modes.

In terms of constraints, I assume that both vehicles and household members face numerous logical constraints based on the physical reality of how humans and vehicles can and cannot move through space and time. Additionally, I require a household to complete all activities, and the time-window constraints on activities are hard constraints. Finally, I assume that PAVs can only wait curbside for a few minutes, τ, before they must travel home, to a parking location, or another activity location.

4.4 Modeling Framework

In this section, I formulate the HAPP-AV-IT described in Section 4.3.

4.4.1 The Activity-travel Graph

This subsection describes the HAPP-AV-IT graph's entities and activity nodes (A-nodes). There are three entity types in the model: activities ($a \in \mathbf{A} = \{1, 2, \dots, A\}$), PAVs ($v \in \mathbf{V} = \{1, 2, \dots, V\}$), and household members ($p \in \mathbf{P} = \{1, 2, \dots, P\}$). Each activity $a \in \mathbf{A}$ has its assigned household member, $p \in \mathbf{P}_a \subset \mathbf{P}$ and each household member travels by PAV, SAV, transit, PAV-transit, or SAV-transit. The number of activities, PAVs, and household members are A, V, and P, respectively.

Table 4-2 displays the A-nodes defined in the HAPP-AV-IT. Each A-node type indicates whether the node is a home location, activity location, transit station, or parking space and whether the node is for pickup, drop-off, parking, or an at-home activity.

Table 4-2: Definition of Activity Nodes

A-Node Type	Notation	Description
Initial node	$\mathbf{N}_0 = \{0\}$	Initial departure node
Home pickup	$\mathbf{N}_{hp} = \{1, 2, \dots, A\}$	Home pickup node for each activity
Activity drop-off	$\mathbf{N}_{ad} = \{A + 1, \dots, 2A\}$	Activity drop-off node for each activity
Transit drop-off	$\mathbf{N}_{td} = \{2A + 1, \dots, 4A\}$	Transfer node for PAV-to-transit and SAV-to-transit - Transit station nearest from $\mathbf{N}_{hp}$ ($\{2A + 1, \dots, 3A\}$) - Transit hub ($\{3A + 1, \dots, 4A\}$)
Activity pickup	$\mathbf{N}_{ap} = \{11A + 1, \dots, 12A\}$	Activity pickup node for each activity
Transit pickup	$\mathbf{N}_{tp} = \{12A + 1, \dots, 14A\}$	Transfer node for transit-to-PAV and transit-to-SAV - Transit station nearest from $\mathbf{N}_{hp}$ ($\{12A + 1, \dots, 13A\}$) - Transit hub ($\{13A + 1, \dots, 14A\}$)
Parking space	$\mathbf{N}_{pk} = \{4A + 1, \dots, 11A\}$	PAV parking space node - Parking space nearest from each node in $\mathbf{N}_{ap}$ and $\mathbf{N}_{tp}$ ($\{4A + 1, \dots, 7A\}$) - Nearest cheapest parking for each node in $\mathbf{N}_{ap}$ and $\mathbf{N}_{tp}$ ($\{7A + 1, \dots, 10A\}$) - Parking at home ($\{10A + 1, \dots, 11A\}$)
Home drop-off	$\mathbf{N}_{hd} = \{14A + 1, \dots, 15A\}$	Home drop-off node for each activity
At-home activity	$\mathbf{N}_{hs} = \{15A + 1, \dots, 16A\}$	Household member stays at home between out-of-home activities
Final node	$\mathbf{N}_f = \{16A + 1\}$	Tour terminating node (f)
Set of A-node types	$\mathbf{N}_{PU} = \mathbf{N}_{hp} \cup \mathbf{N}_{ap} \cup \mathbf{N}_{tp}$	All pickup nodes
	$\mathbf{N}_{DO} = \mathbf{N}_{ad} \cup \mathbf{N}_{td} \cup \mathbf{N}_{hd}$	All drop-off nodes
	$\mathbf{N}_{PUDO} = \mathbf{N}_{PU} \cup \mathbf{N}_{DO}$	All pickup and drop-off nodes
	$\widehat{\mathbf{N}} = \mathbf{N}_{PUDO} \cup \mathbf{N}_{pk} \cup \mathbf{N}_{hs}$	All activity nodes but initial and final nodes
	$\mathbf{N} = \widehat{\mathbf{N}} \cup \mathbf{N}_0 \cup \mathbf{N}_f$	All activity nodes

The home pickup node is the starting node for each household member. An activity drop-off node corresponds to a physical activity location that an assigned household member must visit. An activity pickup node also corresponds to a physical activity location. However, in the HAPP-AV-IT graph, the drop-off and pickup A-nodes associated with a physical activity location are distinct, as the two nodes have distinct time-windows, and the traveler must visit the drop-off A-node before the pickup A-node. Transit drop-off and pickup nodes represent a transit station where a household member is dropped off or picked up, respectively, if the person chooses a PAV-transit or SAV-transit intermodal trip.

Before providing further information on the A-nodes, I want to illustrate the relationship between the A-nodes in the HAPP-AV-IT graph and a physical network with travel modes and activity locations. Figure 4-2 shows the physical network nodes and corresponding A-nodes for an example where $A = 2$. Two household members (Persons 1 and 2) travel, and each has one activity (Activities 1 and 2) to complete.

Figure 4-2a and Figure 4-2b show the physical network and their A-nodes for the example household activities, respectively. The home location and activity locations are given, and those locations determine the candidate transit pickup/drop-off stations and parking spaces. As shown in Figure 4-2b, the two transit stations (nearest to home and transit hub) have drop-off and pickup nodes for each activity. Hence, each household member can use the same transit station more than once during their tours in a day, while they can only visit each A-node (except for the initial and final nodes) once during the day. Likewise, the nearest parking spaces from transit stations and cheap parking spaces also have an A-node for each household activity.

Figure 4-2c and Figure 4-2d show the result of the optimization. Figure 4-2c displays the activity-travel tours for the two household members. Persons 1 and 2 use a PAV together from the home pickup nodes (A-nodes 1 and 2) to a transit hub (A-node 8: $3A + 2$). Person 2 gets out of the PAV at the transit hub while Person 1 stays in the PAV to reach their activity location (A-node 3: $A + 1$). Before Person 1 finishes their activity, the PAV goes to a parking lot (A-node 9: $4A + 1$) nearest to Person 1's activity location. When Person 1 finishes their activity, the PAV picks up Person 1 (A-node 23: $11A + 1$), returns home (A-node 29: $14A + 1$), and completes a tour (A-node 33: $16A + 1$). In the meantime, Person 2 finishes their activity (A-node 24: $11A + 2$), takes an SAV home (A-node 30: $14A + 2$) and terminates their tour (A-node 33: $16A + 1$). Figure 4-2d displays the corresponding activity-travel routes on the physical network.

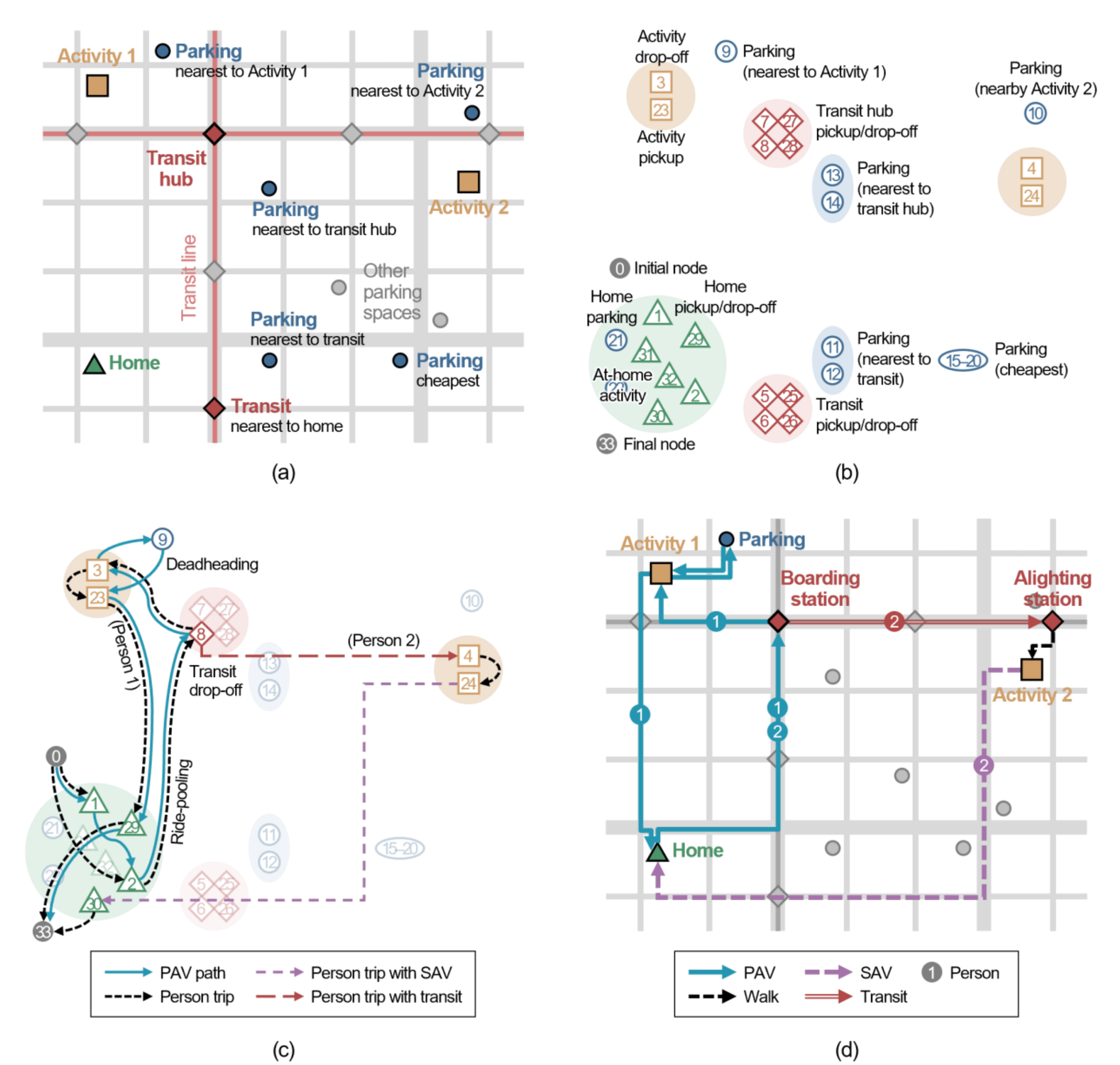


Figure 4-2: An Example of Two Household Members with Two Activities in HAPP-AV-IT: (a) Locations on the Physical Network, (b) Corresponding Activity Nodes, (c) Optimized Activity-travel Routes, and (d) Corresponding Activity-travel Routes on the Physical Network

The home pickup node is the starting node for each household member. An activity drop-off node corresponds to a physical activity location that an assigned household member must visit. An activity pickup node also corresponds to a physical activity location. However, in the HAPP-AV-IT graph, the drop-off and pickup A-nodes associated with a physical activity location are distinct, as the two nodes have distinct time-windows, and the traveler must visit the drop-off A-node before the pickup A-node. Transit drop-off and pickup nodes represent a transit station where a household member is dropped off or picked up if the person chooses a PAV-transit or SAV-transit intermodal trip. In the HAPP-AV-IT, I assume travelers use the nearest station from their home or a transit hub in the urban core where they can transfer to various transit routes, thereby enabling PAVs to access multiple convenient transit routes. If there are multiple transit hubs, I assume travelers consider the transit hub nearest to the home location. A parking space node is where PAVs can visit between any activity drop-off and pickup. The home drop-off node is where a household member returns after they complete one or more activities. The at-home activity node is the waiting node for household members before they depart for their next activity.

The nodal structure for the HAPP-AV-IT graph is similar to in the original HAPP model (Recker, 1995). For example, if a household member travels from home to the activity location for Activity 2, the person visits A-node 2 and then heads for A-node $A + 2$. Performing the activity, the household member virtually moves from A-node $A + 2$ to A-node $11A + 2$, the activity pickup node for Activity 2. After the completion of Activity 2, the household member travels from the activity pickup node to the corresponding home drop-off node, A-node $14A + 2$.

4.4.2 Decision Variables

Table 4-3 displays the decision variables in the HAPP-AV-IT. Several decision variables capture the movements of persons and vehicles over arcs connecting A-node pairs; these include movements on arc (i, j) by:

1. a household PAV v, $X_{i,j}^{v}$
2. a household member in an SAV, $Y_{i,j}$
3. a household member using transit, $Z_{i,j}$
4. a household member p, $H_{i,j}^{p}$.

The model also includes temporal decision variables. T_i denotes when node i is visited. Given that I have an initial node, $i = 0$, and final node, $i = f$, where all P household members and all V household PAVs start and end their day, respectively, I need to denote the times that each household member $p \in \mathbf{P}$ and each household PAV $v \in \mathbf{V}$ start and end their day. I define these variables—T_0^v, T_f^v, T_0^p, and T_f^p—in Table 4-3.

I also define a temporal variable, Q_i, which tracks how long a household member must wait for a vehicle at node i. Similarly, I define a variable, K_i, which tracks how long a vehicle parks at node i.

Finally, I define a variable, ρ_i^v, that tracks the number of passengers onboard PAV v, when it departs from node i. Only when the PAV is empty (i.e., $\rho_i^v = 0$), can the PAV go to a parking space.

Table 4-3: Decision Variables

Decision Variable	Type	Description
$X_{i,j}^{v}$	Binary	1 if PAV $v \in \mathbf{V}$ travels from $i \in \mathbf{N}$ to $j \in \mathbf{N}$
$Y_{i,j}$	Binary	1 if a household member uses SAV to travel from $i \in \mathbf{N}$ to $j \in \mathbf{N}$
$Z_{i,j}$	Binary	1 if a household member uses transit to travel from $i \in \mathbf{N}$ to $j \in \mathbf{N}$
$H_{i,j}^{p}$	Binary	1 if household member $p \in \mathbf{P}$ travel from $i \in \mathbf{N}$ to $j \in \mathbf{N}$
T_i	Continuous	Arrival time of visited node i
T_0^v	Continuous	Time that PAV $v \in \mathbf{V}$ leaves the initial node, 0
T_f^v	Continuous	Time that PAV $v \in \mathbf{V}$ arrives at the final node, f
T_0^p	Continuous	Time that household member $p \in \mathbf{P}$ begins their tour from initial node, 0
T_f^p	Continuous	Time that household member $p \in \mathbf{P}$ terminates their tour at the final node, f
Q_i	Continuous	Household member's waiting time for PAV arrival at $i \in \mathbf{N}_{ap} \cup \mathbf{N}_{tp}$
K_i	Continuous	PAV parking duration time at $i \in \mathbf{N}_{pk}$
ρ_i^v	Integer	Number of onboard passengers of PAV $v \in \mathbf{V}$ when departed from visited node i

4.4.3 Model Parameters

Table 4-4 lists the parameters used in the HAPP-AV-IT. I segment the parameters into network information (e.g., arc travel times), modal attributes (e.g.., wait time by mode), activity information (i.e., activity durations and time windows), policy parameters (i.e., parking fees and maximum curb loading/unloading time), behavioral parameters (e.g., value of time savings broken down by mode and in-vehicle, waiting, and walking time), and one "big M" parameter for the math program.

I can obtain network information from open-source data including mapping services (e.g. Google Maps) and for transit most agencies publish their routes and schedules using the General Transit Feed Specification (GTFS). For modal attributes, vehicle manufacturing companies, transportation network companies (TNCs), and transit agencies can provide travel time and travel cost information. Information related to activity durations is available through the American Time Use Survey (ATUS), and I can infer the time windows for each activity type (purpose). Parking fees are available on parking information websites, and I can refer to TNCs for maximum curbside loading time. For behavior parameters, I can use the stated preference (SP) survey data and discrete choice models for the target region.

Table 4-4: Model Parameters

Type	Parameter	Description	Possible Data Source
Network Information	$t_{i,j}$	Travel time from $i \in \mathbf{N}$ to $j \in \mathbf{N}$ on road network	Google Maps, HERE Maps, other APIs. Alternatively, a travel forecasting model with equilibrated link travel times.
	$d_{i,j}$	Travel distance from $i \in \mathbf{N}$ to $j \in \mathbf{N}$ on road network	
	$t_{i,j}^{TRN}$	Transit travel time from the nearest transit station from $i \in \mathbf{N}$ to the nearest transit station from $j \in \mathbf{N}$ on transit network	General Transit Feed Specification (GTFS)
	$t_{i,j}^{TRNwk}$	Access walk time between node i and the nearest transit station *plus* egress walk time between node j and the nearest transit station	
Modal Attributes	t^{SAVwt}	Average wait time for SAV arrival	Transportation network companies (TNCs)
	t^{TRNwt}	Average wait time for transit arrival	General Transit Feed Specification (GTFS)
	β_{op}^{PAV}	PAV operating cost per unit distance	Bureau of Transportation Statistics (BTS), vehicle manufacturing companies
	β_{fb}^{SAV}	SAV base fare per trip	TNCs
	β_{fd}^{SAV}	SAV fare per unit distance	
	β_{fr}^{TRN}	Transit fare per trip	Transit agencies
Activity Information	e_i	Earliest arrival time at $i \in \mathbf{N}_0 \cup \mathbf{N}_{ad} \cup \mathbf{N}_{ap}$	American Time Use Survey (ATUS)
	l_i	Latest arrival time at $i \in \mathbf{N}_{ad} \cup \mathbf{N}_{ap} \cup \mathbf{N}_f$	
	s_i	Activity duration time at $i \in \mathbf{N}_{ad}$	
Policy Parameters	ω_i	Parking fee per unit time at $i \in \mathbf{N}_{pk}$	Parking information websites (e.g., Parkopedia)
	τ	Maximum curbside loading time at each pickup or drop-off node	TNCs
Behavioral Parameters	β_{wt}^{PAV}	Value of PAV waiting time	Stated preference (SP) survey data
	β_{iv}^{PAV}	Value of PAV in-vehicle travel time	
	β_{wt}^{SAV}	Value of SAV waiting time	
	β_{iv}^{SAV}	Value of SAV in-vehicle travel time	
	β_{wk}^{TRN}	Value of transit access/egress walk time	
	β_{wt}^{TRN}	Value of transit wait time	
	β_{iv}^{TRN}	Value of transit in-vehicle travel time	
Math Programming Parameters	M	A large number	

$t_{i,j}^{TRN}$ and $t_{i,j}^{TRNwk}$ are transit travel time and transit access plus egress walk times from A-node i to A-node j. In this case, the A-nodes can be either home, activity location, or transit station. Note that the routes in the HAPP-AV-IT use transit station A-nodes only for PAV-transit and SAV-transit intermodal trips. When traveling by transit-only, the transit travel time between the home/activity location to activity location/home is directly calculated by designating the nearest transit station for each location.

The PAVs cannot stay at a pickup or drop-off node longer than τ, which is the maximum curbside loading time. Thus, if there is no upcoming service in τ, the PAVs must find a parking space.

Unlike PAVs, SAVs and transit have fixed wait times, t^{SAVwt} and t^{TRNwt}, respectively. I assume fixed wait time values for modeling convenience.

4.4.4 Objective Function

The objective of HAPP-AV-IT is to minimize total household travel costs, as shown in Eqn. 4-1. Household travel costs include wait time for each mode, in-vehicle travel time for each mode, access/egress walk time for transit, operating cost for PAV, fares for SAV and transit, and parking fee for PAV.

$$\min \ \beta_{wt}^{PAV}\sum_{i} Q_i + \beta_{iv}^{PAV}\sum_{i,\,j,p} t_{i,j}H_{i,j}^{p} + \beta_{op}^{PAV}\sum_{i,j,v} d_{i,j}X_{i,j}^{v} + \sum_{i}\omega_i K_i + \beta_{wt}^{SAV}\sum_{i,\,j} t^{SAVwt}Y_{i,j}$$
$$+ \left(\beta_{iv}^{SAV} - \beta_{iv}^{PAV}\right)\sum_{i,j} t_{i,j}Y_{i,j} + \beta_{fb}^{SAV}\sum_{i,\,j} Y_{i,j} + \beta_{fd}^{SAV}\sum_{i,\,j} d_{i,j}Y_{i,j}$$
$$+ \beta_{wk}^{TRN}\sum_{i,j} t_{i,j}^{TRNwk}Z_{i,j} + \beta_{wt}^{TRN}\sum_{i,j} t^{TRNwt}Z_{i,j} \tag{4-1}$$
$$+ \left(\beta_{iv}^{TRN} - \beta_{iv}^{PAV}\right)\sum_{i,j} t_{i,j}^{TRN}Z_{i,j} + \beta_{fr}^{TRN}\sum_{i,j} Z_{i,j}$$

4.4.5 Constraints on Travel Modes

Naturally, the household faces several constraints that prevent illogical and physically impossible trips. Spatial conditions include flow conservation rules and mode-specific node-visiting constraints. Temporal conditions include the sequence of activities and time windows to ensure the timely completion of each activity. Additionally, I incorporate constraints for AV travel patterns, such as parking and relocating without passengers. Finally, I set constraints to link vehicles and household members, ensuring that PAVs serve the passengers accordingly.

The base of the vehicle constraints derives from the PDPTW (Solomon and Derosiers, 1988) and HAPP (Khayati et al., 2021a; Recker, 1995) studies. HAPP-AV-IT reformulates and adds several constraints to enable multimodal and intermodal trips.

4.4.5.1 Spatial Connectivity Constraints

As described below, the spatial connectivity constraints on vehicles (Eqns. 2 through 20) ensure logical movements for all travel modes (PAV, SAV, and transit).

Equations 4-2 through 4-4 are basic PDPTW constraints that ensure each PAV has one connected tour (or no tours if not used) from initial node to final node during a day. Equation 4-2 ensures that at most one outflow is allowed for each node. Equation 4-3 ensures that each PAV has a connected path and there are no revisited A-nodes. Equation 4-4 requires all used PAVs to come back home at the end of the day.

$$\sum_{j \in \widehat{\mathbf{N}}} X_{i,j}^{v} \leq 1; \quad i \in \mathbf{N},\ v \in \mathbf{V} \tag{4-2}$$

$$\sum_{j \in \mathbf{N}} X_{i,j}^{v} - \sum_{j \in \mathbf{N}} X_{j,i}^{v} = 0; \quad i \in \widehat{\mathbf{N}},\ v \in \mathbf{V} \tag{4-3}$$

$$\sum_{j \in \mathbf{N}_{PU}} X_{0,j}^{v} - \sum_{i \in \mathbf{N}_{DO}} X_{i,f}^{v} = 0; \quad v \in \mathbf{V} \tag{4-4}$$

Equations 4-5 through 4-10 are connectivity constraints within A-nodes. Equation 4-5 connects home pickup nodes with their corresponding activity location drop-off nodes. The drop-off node can be the activity location or one of the three nearest transit stations from the pickup node. Equations 4-6 and 4-7 ensure that all activities are accessed by a PAV, SAV, transit, PAV-transit, or SAV-transit trip. Equations 4-8 and 4-9 connect the AV origin-to-transit station trip and the transit station-to-AV destination trip for each PAV-transit or SAV-transit intermodal trip. Equation 4-10 connects the activity drop-off trips and their corresponding activity pickup trips. Any mode can complete these trips.

$$\sum_{i \in \mathbf{N}} X_{i,j}^{v} - \sum_{i \in \mathbf{N}_{PUDO}} \sum_{k \in \{1,\,2,\,3\}} X_{i,j+kA}^{v} = 0; \quad j \in \mathbf{N}_{hp},\ v \in \mathbf{V} \tag{4-5}$$

$$\sum_{v \in \mathbf{V}} \sum_{i \in \mathbf{N}_{PUDO}} \sum_{k \in \{0,1,2\}} X_{i,j+kA}^{v} + \sum_{i \in \mathbf{N}_{PU}} \sum_{k \in \{0,1,2\}} Y_{i,j+kA} + \sum_{i \in \mathbf{N}_{hp} \cup \mathbf{N}_{ap}} Z_{i,j} = 1; \quad j \in \mathbf{N}_{ad} \tag{4-6}$$

$$\sum_{v\in\mathbf{V}}\sum_{j\in\mathbf{N}_{PUDO}}\sum_{k\in\{0,1,2\}} X^v_{i+kA,j} + \sum_{j\in\mathbf{N}_{DO}}\sum_{k\in\{0,1,2\}} Y_{i+kA,j} + \sum_{j\in\mathbf{N}_{ad}\cup\mathbf{N}_{hd}} Z_{i,j} = 1; \quad i\in\mathbf{N}_{ap} \tag{4-7}$$

$$\left(\sum_{v\in\mathbf{V}}\sum_{i\in\mathbf{N}_{PUDO}} X^v_{i,j+kA} + \sum_{i\in\mathbf{N}_{PU}} Y_{i,j+kA}\right) - Z_{j+kA,j} = 0; \quad j\in\mathbf{N}_{ad},\ k\in\{1,\ 2\} \tag{4-8}$$

$$\left(\sum_{v\in\mathbf{V}}\sum_{j\in\mathbf{N}_{PUDO}} X^v_{i+kA,j} + \sum_{j\in\mathbf{N}_{DO}} Y_{i+kA,j}\right) - Z_{i,i+kA} = 0; \quad i\in\mathbf{N}_{ap},\ k\in\{1,\ 2\} \tag{4-9}$$

$$\begin{aligned}
&\sum_{v\in\mathbf{V}}\sum_{i\in\mathbf{N}_{PUDO}}\sum_{k\in\{1,2,\,3\}} X^v_{i,j+kA} + \sum_{i\in\mathbf{N}_{PU}}\sum_{k\in\{1,2,\,3\}} Y_{i,j+kA} + \sum_{i\in\mathbf{N}_{hp}\cup\mathbf{N}_{ap}} Z_{i,j+A} \\
&\quad - \sum_{v\in\mathbf{V}}\sum_{i\in\mathbf{N}_{PUDO}}\sum_{k\in\{11,\,12,\,13\}} X^v_{j+kA,i} - \sum_{i\in\mathbf{N}_{DO}}\sum_{k\in\{11,\,12,\,13\}} Y_{j+kA,i} \quad j\in\mathbf{N}_{hp} \\
&\quad - \sum_{i\in\mathbf{N}_{ad}\cup\mathbf{N}_{hd}} Z_{j+11A,i} = 0;
\end{aligned} \tag{4-10}$$

Equations 4-11 through 4-14 prohibit illogical PAV trips to form a complete vehicle tour, which are similar to the constraints in PDPTW and original HAPP. Equations 4-11 and 4-12 prevent preceding and succeeding nodes for the initial and final nodes, respectively. Equations 4-13 and 4-14 ensure all vehicles start travel from a pickup node and terminate the travel after drop-off.

$$\sum_{i\in\mathbf{N}} X^v_{i,0} = 0; \quad v\in\mathbf{V} \tag{4-11}$$

$$\sum_{j\in\mathbf{N}} X^v_{f,j} = 0; \quad v\in\mathbf{V} \tag{4-12}$$

$$\sum_{j\in\mathbf{N}\backslash\mathbf{N}_{PU}} X^v_{0,j} = 0; \quad v\in\mathbf{V} \tag{4-13}$$

$$\sum_{i \in \mathbf{N} \setminus \mathbf{N}_{DO}} X_{i,f}^{v} = 0; \quad v \in \mathbf{V} \tag{4-14}$$

Equations 4-15 through 4-20 are additional prohibition constraints for PAV, SAV, and transit trips. Equations 4-15 and 4-16 ensure every SAV trip starts at a pickup node and ends at a drop-off node. Equation 4-17 prohibits unnecessary trips within home location. Equations 4-18 through 4-20 restrict transit trip starting and ending nodes.

$$\sum_{i \in \mathbf{N} \setminus \mathbf{N}_{PU}} \sum_{j \in \mathbf{N}} Y_{i,j} = 0 \tag{4-15}$$

$$\sum_{i \in \mathbf{N}} \sum_{j \in \mathbf{N} \setminus \mathbf{N}_{DO}} Y_{i,j} = 0 \tag{4-16}$$

$$\sum_{i \in \mathbf{N}_{hp}} \sum_{j \in \mathbf{N}_{hd}} \left(\sum_{v \in \mathbf{V}} X_{i,j}^{v} + Y_{i,j} \right) = 0 \tag{4-17}$$

$$\sum_{i \in \mathbf{N} \setminus \{\mathbf{N}_{hp} \cup \mathbf{N}_{td} \cup \mathbf{N}_{ap}\}} \sum_{j \in \mathbf{N}} Z_{i,j} = 0 \tag{4-18}$$

$$\sum_{i \in \mathbf{N}} \sum_{j \in \mathbf{N} \setminus \{\mathbf{N}_{ad} \cup \mathbf{N}_{tp} \cup \mathbf{N}_{hd}\}} Z_{i,j} = 0 \tag{4-19}$$

$$\sum_{i \in \mathbf{N}_{hp}} \sum_{j \in \mathbf{N} \setminus \mathbf{N}_{ad}} Z_{i,j} = 0 \tag{4-20}$$

4.4.5.2 Temporal Constraints

Equations 4-21 through 4-26 ensure that the arrival time at each visited node is later than the preceding node's arrival time plus the travel time between consecutive nodes. Equations 4-21 through 4-23 apply to PAV travel (pickup and drop-off nodes, initial node, and final node). Equation 4-24 applies to SAV travel, accounting for SAV waiting time at pickup. Equations 4-25 and 4-26 apply to transit travel, considering walk access and egress times and transit waiting time at station.

$$T_i + t_{i,j} - T_j \leq M\left(1 - X_{i,j}^v\right); \quad i,j \in \widehat{\mathbf{N}},\ v \in \mathbf{V} \tag{4-21}$$

$$T_0^v - T_j \leq M\left(1 - X_{0,j}^v\right); \quad j \in \mathbf{N}_{PU},\ v \in \mathbf{V} \tag{4-22}$$

$$T_i - T_f^v \leq M\left(1 - X_{i,f}^v\right); \quad i \in \mathbf{N}_{DO},\ v \in \mathbf{V} \tag{4-23}$$

$$T_i + t_{i,j} + t^{SAVwt} - T_j \leq M\left(1 - Y_{i,j}\right); \quad i \in \mathbf{N}_{PU}, j \in \mathbf{N}_{DO} \tag{4-24}$$

$$T_i + t_{i,j}^{TRN} + t_{i,j}^{TRNwk} + t^{TRNwt} - T_j \leq M\left(1 - Z_{i,j}\right); \quad i \in \mathbf{N}_{hp} \cup \mathbf{N}_{td} \cup \mathbf{N}_{ap},\ j \in \mathbf{N}_{ad} \tag{4-25}$$

$$T_i + t_{i,j}^{TRN} + t_{i,j}^{TRNwk} + t^{TRNwt} - T_j \leq M\left(1 - Z_{i,j}\right); \quad i \in \mathbf{N}_{ap},\ j \in \mathbf{N}_{ad} \cup \mathbf{N}_{tp} \cup \mathbf{N}_{hd} \tag{4-26}$$

Equation 4-27 ensures the activity duration time between activity drop-off node and corresponding activity pickup node.

$$T_i + s_i \leq T_{i+10A}; \quad i \in \mathbf{N}_{ad} \tag{4-27}$$

Equations 4-28 through 4-37 require trips to arrive at the destination within the time windows given for each activity drop-off and pickup.

Equations 4-28 and 4-29 are the earliest home departure time and the latest home return time for the household.

$$e_0 \leq T_0^v; \quad v \in \mathbf{V} \tag{4-28}$$

$$T_f^v \leq l_f; \quad v \in \mathbf{V} \tag{4-29}$$

Equations 4-30 through 4-33 are the time windows for PAV, SAV, and transit single modal trips.

$$e_j - T_j \leq M\left(1 - \sum_{v\in\mathbf{V}}\sum_{i\in\mathbf{N}} X_{i,j}^{v} - \sum_{i\in\mathbf{N}} Y_{i,j} - \sum_{i\in\mathbf{N}_{hp}\cup\mathbf{N}_{td}\cup\mathbf{N}_{ap}} Z_{i,j}\right); \quad j \in \mathbf{N}_{ad} \tag{4-30}$$

$$T_j - l_j \leq M\left(1 - \sum_{v\in\mathbf{V}}\sum_{i\in\mathbf{N}} X_{i,j}^{v} - \sum_{i\in\mathbf{N}} Y_{i,j} - \sum_{i\in\mathbf{N}_{hp}\cup\mathbf{N}_{td}\cup\mathbf{N}_{ap}} Z_{i,j}\right); \quad j \in \mathbf{N}_{ad} \tag{4-31}$$

$$e_i - T_i \leq M\left(1 - \sum_{v\in\mathbf{V}}\sum_{j\in\mathbf{N}} X_{i,j}^{v} - \sum_{j\in\mathbf{N}} Y_{i,j} - \sum_{j\in\mathbf{N}_{ad}\cup\mathbf{N}_{tp}\cup\mathbf{N}_{hd}} Z_{i,j}\right); \quad i \in \mathbf{N}_{ap} \tag{4-32}$$

$$T_i - l_i \leq M\left(1 - \sum_{v\in\mathbf{V}}\sum_{j\in\mathbf{N}} X_{i,j}^{v} - \sum_{j\in\mathbf{N}} Y_{i,j} - \sum_{j\in\mathbf{N}_{ad}\cup\mathbf{N}_{tp}\cup\mathbf{N}_{hd}} Z_{i,j}\right); \quad i \in \mathbf{N}_{ap} \tag{4-33}$$

Equations 4-34 through 4-37 are the time windows for PAV/SAV and transit intermodal trips, which determine the arrival time windows at intermodal transit drop-off and pickup nodes.

$$\begin{aligned} &\left(e_j - t_{j+kA,j}^{TRN} - t_{j+kA,j}^{TRNwk} - t^{TRNwt}\right) - T_{j+kA} \\ &\leq M\left(1 - \sum_{v\in\mathbf{V}}\sum_{i\in\widehat{\mathbf{N}}} X_{i,j+kA}^{v} - \sum_{i\in\widehat{\mathbf{N}}} Y_{i,j+kA}\right); \end{aligned} \quad j \in \mathbf{N}_{ad},\ k \in \{1,\ 2\} \tag{4-34}$$

$$\begin{aligned} &T_{j+kA} - \left(l_j - t_{j+kA,j}^{TRN} - t_{j+kA,\ j}^{TRNwk} - t^{TRNwt}\right) \\ &\leq M\left(1 - \sum_{v\in\mathbf{V}}\sum_{i\in\widehat{\mathbf{N}}} X_{i,j+kA}^{v} - \sum_{i\in\widehat{\mathbf{N}}} Y_{i,j+kA}\right); \end{aligned} \quad j \in \mathbf{N}_{ad},\ k \in \{1,\ 2\} \tag{4-35}$$

$$\begin{aligned} &\left(e_i + t_{i,i+kA}^{TRN} - t_{i,i+kA}^{TRNwk} - t^{TRNwt}\right) - T_{i+kA} \\ &\leq M\left(1 - \sum_{v\in\mathbf{V}}\sum_{j\in\widehat{\mathbf{N}}} X_{i+kA,j}^{v} - \sum_{j\in\widehat{\mathbf{N}}} Y_{i+kA,j}\right); \end{aligned} \quad i \in \mathbf{N}_{ap},\ k \in \{1,\ 2\} \tag{4-36}$$

$$T_{i+kA} - \left(l_i - t^{TRN}_{i,i+kA} - t^{TRNwk}_{i,i+kA} - t^{TRNwt}\right) \leq M\left(1 - \sum_{v\in\mathbf{V}}\sum_{j\in\widehat{\mathbf{N}}} X^{v}_{i+kA,j} - \sum_{j\in\widehat{\mathbf{N}}} Y_{i+kA,j}\right); \quad i \in \mathbf{N}_{ap},\ k \in \{1,\ 2\} \tag{4-37}$$

4.4.5.3 Parking and Relocating Constraints

Equations 4-38 through 4-42 keep track of onboard passengers for each PAV. Accordingly, an empty PAV can enter a parking lot, as shown in Eqn. 4-43. Equation 4-44 requires all vehicles to leave the pickup or drop-off node within τ minutes, which is the maximum curbside loading time.

$$\rho^v_0 = 0; \quad v \in \mathbf{V} \tag{4-38}$$

$$\rho^v_i + 1 - \rho^v_j \leq M\left(1 - X^v_{i,j}\right); \quad i \in \mathbf{N},\ j \in \mathbf{N}_{PU},\ v \in \mathbf{V} \tag{4-39}$$

$$\rho^v_j - \rho^v_i - 1 \leq M\left(1 - X^v_{i,j}\right); \quad i \in \mathbf{N},\ j \in \mathbf{N}_{PU},\ v \in \mathbf{V} \tag{4-40}$$

$$\rho^v_i - 1 - \rho^v_j \leq M\left(1 - X^v_{i,j}\right); \quad i \in \mathbf{N},\ j \in \mathbf{N}_{DO},\ v \in \mathbf{V} \tag{4-41}$$

$$\rho^v_j - \rho^v_i + 1 \leq M\left(1 - X^v_{i,j}\right); \quad i \in \mathbf{N},\ j \in \mathbf{N}_{DO},\ v \in \mathbf{V} \tag{4-42}$$

$$\rho^v_i + \rho^v_j \leq M\left(1 - X^v_{i,j}\right); \quad i \in \widehat{\mathbf{N}},\ j \in \mathbf{N}_{pk},\ v \in \mathbf{V} \tag{4-43}$$

$$T_j - T_i - t_{i,j} - \tau \leq M\left(1 - X^v_{i,j}\right); \quad i \in \mathbf{N}_{PUDO},\ j \in \widehat{\mathbf{N}}, v \in \mathbf{V} \tag{4-44}$$

Equations 4-45 and 4-46 prohibit unnecessary deadheading between parking spaces and accessing at-home activity node, respectively.

$$\sum_{i\in\mathbf{N}_{hp}\cup\mathbf{N}_{pk}}\ \sum_{j\in\mathbf{N}_{pk}} X^v_{i,j} = 0; \quad v \in \mathbf{V} \tag{4-45}$$

$$\sum_{v \in \mathbf{V}} \sum_{j \in \mathbf{N}_{hs}} X_{i,j}^{v} = 0; \quad i \in \mathbf{N} \tag{4-46}$$

Equations 4-47 and 4-48 calculate parking duration times. The parking duration time and hourly parking fee, ω_i, determine the total parking fees in the household.

$$\frac{T_j - T_i - t_{i,j}}{60} + 1 - K_i \leq M\left(1 - \sum_{v \in \mathbf{V}} X_{i,j}^{v}\right); \quad i \in \mathbf{N}_{pk},\ j \in \widehat{\mathbf{N}} \tag{4-47}$$

$$K_i - \frac{T_j - T_i - t_{i,j}}{60} - 1 \leq M\left(1 - \sum_{v \in \mathbf{V}} X_{i,j}^{v}\right); \quad i \in \mathbf{N}_{pk},\ j \in \widehat{\mathbf{N}} \tag{4-48}$$

4.4.6 Constraints on Household Members

4.4.6.1 Spatial Connectivity Constraints

Equations 4-49 through 4-66 cover household members' tours. Many of the constraints have the same format as vehicle spatial constraints in the previous subsection.

Equations 4-49, 4-51, and 4-52 parallel Eqns. 4-2 through 4-4. Equation 4-50 indicates that a person can either perform out-of-home activities or not. Equation 4-53 ensures that only the assigned household member can perform the activity. Equations 4-54 and 4-55 ensure that the assigned household member arrives/departs at/from the activity drop-off/pickup node at least once, respectively. Equations 4-56 and 4-57 ensure that each household member visits transit drop-off/pickup nodes when they choose an intermodal trip.

$$\sum_{i \in \mathbf{N}} H_{i,j}^{p} \leq 1; \quad j \in \widehat{\mathbf{N}},\ p \in \mathbf{P} \tag{4-49}$$

$$\sum_{j \in \mathbf{N}} H_{0,j}^{p} \leq 1; \quad p \in \mathbf{P} \tag{4-50}$$

$$\sum_{j \in \mathbf{N}} H_{i,j}^{p} - \sum_{j \in \mathbf{N}} H_{j,i}^{p} = 0; \quad i \in \widehat{\mathbf{N}},\ p \in \mathbf{P} \tag{4-51}$$

$$\sum_{j \in \mathbf{N}_{hp}} H_{0,j}^{p} - \sum_{i \in \mathbf{N}_{hd}} H_{i,f}^{p} = 0; \quad p \in \mathbf{P} \tag{4-52}$$

$$\sum_{p \in \mathbf{P}_a} H_{a+A,a+11A}^{p} = 1; \quad a \in \mathbf{A}, i \in \mathbf{N}_{ad} \tag{4-53}$$

$$\sum_{p \in \mathbf{P}_a} \sum_{i \in \mathbf{N}_{PUDO}} H_{i,a+A}^{p} \geq 1; \quad a \in \mathbf{A} \tag{4-54}$$

$$\sum_{p \in \mathbf{P}_a} \sum_{j \in \mathbf{N}_{PUDO}} H_{a+11A,j}^{p} \geq 1; \quad a \in \mathbf{A} \tag{4-55}$$

$$1 - \sum_{i \in \mathbf{N}_{PUDO}} H_{i,a+kA}^{p} \leq M\left(1 - H_{a+kA,a+A}^{p}\right); \quad a \in \mathbf{A},\ k \in \{2,\ 3\},\ p \in \mathbf{P}_a \tag{4-56}$$

$$1 - \sum_{j \in \mathbf{N}_{PUDO}} H_{a+kA,j}^{p} \leq M\left(1 - H_{a+11A,\, a+kA}^{p}\right); \quad a \in \mathbf{A},\ k \in \{12,\ 13\},\ p \in \mathbf{P}_a \tag{4-57}$$

Equation 4-58 connects previous activity tour and next activity tour via at-home activity node. If a household member has another out-of-home activity after being dropped off at home, the person can stay at home before being picked up at another home pickup node. Equations 4-59 through 4-61 prevent unnecessary trips within home nodes. Household members cannot directly travel from home pickup node to home drop-off node (Eqn. 4-59), they can visit home pickup node only when they begin the first trip or when they are at at-home activity node (Eqn. 4-60), and they can only visit at-home activity node or final node when they are dropped off at home drop-off node (Eqn. 4-61).

$$\sum_{i \in \mathbf{N}_{hd}} H_{i,a+15A}^{p} - H_{a+15A,a}^{p} = 0; \quad a \in \mathbf{A},\ p \in \mathbf{P}_a \tag{4-58}$$

$$\sum_{i \in \mathbf{N}_{hp} \cup \mathbf{N}_{hs}} \sum_{j \in \mathbf{N}_{hs} \cup \mathbf{N}_{hd}} H_{i,j}^{p} = 0; \quad p \in \mathbf{P} \tag{4-59}$$

$$\sum_{i \in \widehat{\mathbf{N}} \setminus \mathbf{N}_{hs}} H_{i,a}^{p} = 0; \quad a \in \mathbf{A},\ p \in \mathbf{P}_a \tag{4-60}$$

$$\sum_{j \in \widehat{\mathbf{N}} \setminus \mathbf{N}_{hs}} H_{a+14A,j}^{p} = 0; \quad a \in \mathbf{A},\ p \in \mathbf{P}_a \tag{4-61}$$

Equation 4-62 prohibits performing activity by household members other than the assigned person. Equation 4-63 prohibits household members visiting parking spaces. Equations 4-64 and 4-65 ensure that every tour starts at the initial node and ends at the final node, which are equivalent to Eqns. 4-11 and 4-12. Equation 4-66 ensures that household members visit home pickup node after the initial node.

$$\sum_{p \in \mathbf{P} \setminus \mathbf{P}_a} H_{a+A,a+11A}^{p} = 0; \quad a \in \mathbf{A} \tag{4-62}$$

$$\sum_{i \in \mathbf{N}} \sum_{j \in \mathbf{N}_{pk}} H_{i,j}^{p} = 0; \quad p \in \mathbf{P} \tag{4-63}$$

$$\sum_{i \in \mathbf{N}} H_{i,0}^{p} = 0; \quad p \in \mathbf{P} \tag{4-64}$$

$$\sum_{j \in \mathbf{N}} H_{f,j}^{p} = 0; \quad p \in \mathbf{P} \tag{4-65}$$

$$\sum_{p \in \mathbf{P}} \sum_{j \in \mathbf{N} \setminus \mathbf{N}_{hp}} H_{0,j}^{p} = 0 \tag{4-66}$$

4.4.6.2 Temporal Constraints

Equations 4-67 through 4-69 are arrival time constraints paralleling Eqns. 4-21 through 4-23.

$$T_i + t_{i,j} - T_j \leq M\left(1 - H_{i,j}^{p}\right); \quad i, j \in \widehat{\mathbf{N}},\ p \in \mathbf{P} \tag{4-67}$$

$$T_0^{p} - T_j \leq M\left(1 - H_{0,j}^{p}\right); \quad j \in \mathbf{N}_{hp},\ p \in \mathbf{P} \tag{4-68}$$

$$T_i - T_f^{p} \leq M\left(1 - H_{i,f}^{p}\right); \quad i \in \mathbf{N}_{hd},\ p \in \mathbf{P} \tag{4-69}$$

Equations 4-70 and 4-71 are the earliest and latest arrival times according to the given activity's time window, paralleling Eqns. 4-28 and 4-29.

$$e_0 \leq T_0^{p}; \quad p \in \mathbf{P} \tag{4-70}$$

$$T_f^{p} \leq l_f; \quad p \in \mathbf{P} \tag{4-71}$$

Equations 4-72 through 4-74 calculate each household member's waiting time at home pickup, activity pickup, and transit pickup nodes, respectively.

$$Q_i \geq T_{i+kA} - t_{i,i+kA} - T_i; \quad i \in \mathbf{N}_{hp},\ k \in \{1,\ 2,\ 3\} \tag{4-72}$$

$$Q_i \geq T_i - (T_{i-10A} + s_{i-10A}); \quad i \in \mathbf{N}_{ap} \tag{4-73}$$

$$\begin{aligned} Q_{i+kA} \geq\ & T_{i+kA} - (T_{i-10A} + s_{i-10A}) \\ & - \left(t_{i,i+kA}^{TRN} + t_{i,i+kA}^{TRNwk} + t^{TRNwt}\right); \end{aligned} \quad i \in \mathbf{N}_{ap},\ k \in \{1,\ 2\} \tag{4-74}$$

4.4.7 Travel Mode and Household Member Coupling Constraints

The last set of constraints involves coupling the vehicle and household member trips. Equation 4-75 ensures that a household member uses at least one mode to complete a trip. Equations 4-76 through 4-79 connect vehicle trips with household member trips when the household member uses a vehicle for travel (Eqn. 4-76: home pickup and activity pickup nodes, Eqn. 4-77: activity drop-off and home drop-off nodes, Eqn. 4-78: transit pickup nodes, and Eqn. 4-79: transit drop-off nodes). Equation 4-80 allows only one person per SAV trip.

$$1 - \left(\sum_{v \in \mathbf{V}} X_{i,j}^{v} + Y_{i,j} + Z_{i,j}\right) \leq M\left(1 - H_{i,j}^{p}\right); \quad i \in \widehat{\mathbf{N}} \backslash \mathbf{N}_{ad},\ j \in \mathbf{N}_{ad} \cup \mathbf{N}_{td} \cup \mathbf{N}_{ap} \cup \mathbf{N}_{tp},\ p \in \mathbf{P} \qquad (4\text{-}75)$$

$$H_{a+kA,j}^{p} - \left(\sum_{v \in \mathbf{V}} X_{a+kA,j}^{v} + Y_{a+kA,j} + Z_{a+kA,j}\right) = 0; \quad a \in \mathbf{A},\ j \in \widehat{\mathbf{N}},\ k \in \{0,\ 11\},\ p \in \mathbf{P}_a \qquad (4\text{-}76)$$

$$H_{i,a+kA}^{p} - \left(\sum_{v \in \mathbf{V}} X_{i,a+kA}^{v} + Y_{i,a+kA} + Z_{i,a+kA}\right) = 0; \quad a \in \mathbf{A}, i \in \widehat{\mathbf{N}}, k \in \{1,\ 14\},\ p \in \mathbf{P}_a \qquad (4\text{-}77)$$

$$H_{a+kA,j}^{p} - \left(\sum_{v \in \mathbf{V}} X_{a+kA,j}^{v} + Y_{a+kA,j}\right) = 0; \quad a \in \mathbf{A}, j \in \widehat{\mathbf{N}},\ k \in \{12, 13\},\ p \in \mathbf{P}_a \qquad (4\text{-}78)$$

$$H_{i,a+kA}^{p} - \left(\sum_{v \in \mathbf{V}} X_{i,a+kA}^{v} + Y_{i,a+kA}\right) = 0; \quad a \in \mathbf{A}, i \in \widehat{\mathbf{N}},\ k \in \{2,\ 3\},\ p \in \mathbf{P}_a \qquad (4\text{-}79)$$

$$\sum_{p \in \mathbf{P}} H_{i,j}^{p} - 1 \leq M\left(1 - Y_{i,j}\right); \quad i \in \mathbf{N}_{PU},\ j \in \widehat{\mathbf{N}} \qquad (4\text{-}80)$$

4.5 Case Study

In this section I present a two sets of case studies to illustrate the relationship between HAPP-AV-IT inputs and outputs, and also evaluate the computational complexity of the HAPP-AV-IT. Subsection 4.5.1 describes the fictitious network and lists the model parameter values I use for the two case studies. Subsection 4.5.2 briefly describes the optimization solver I use to solve the HAPP-AV-IT. Subsection 4.5.3 presents the results of three fictitious households that I created to illustrate the capabilities of the HAPP-AV-IT model. Subsection 4.5.4 presents the results from a synthetic population of households based on households and activity patterns in San Diego California. This subsection also analyzes the computational run time of HAPP-AV-IT with respect to household size, number of household vehicles, and number of activities. Finally, Subsection 4.5.5 provides additional insights into deadheading and PAV parking using the HAPP-AV-IT model.

4.5.1 System Configuration

4.5.1.1 Virtual Base Network

This chapter uses a virtual network that is 9.6 km (6 mi) × 8 km (5 mi) with a higher density downtown area surrounded by a lower density uptown area. Figure 4-3 illustrates the base network with two rail transit lines. The road system consists of a grid street network and two crossing freeways. The block sizes in downtown and uptown are 400 m × 400 m and 800 m × 800 m, respectively. Free flow link travel speeds are 100km/h (freeway), 60 km/h (freeway ramp), 50 km/h (uptown street), 40 km/h (downtown street), and 30 km/h (street intersection). I apply 30% speed reduction from the free flow speed to reflect traffic congestion, and thus the actual link travel speeds are 70 km/h (freeway), 42 km/h (freeway ramp), 35 km/h (uptown street), 28 km/h (downtown street), and 21 km/h (street intersection). With the fixed link travel times, each trip uses the shortest path. I separate the rail transit lines from the road system, and transit stations connect the road and transit systems.

In the base network, there are 50 home locations (Nodes 401 to 450), 50 activity locations (Nodes 201 to 250), 17 transit stations (Nodes 301 to 317), and 40 parking spaces (Nodes 101 to 140). The transit network has a fixed travel speed of 40 km/h with a headway of 6 minutes. The transfer time at the transfer station (Nodes 306 and 313) is 2 minutes, which is shorter than the initial wait time because I assume a timed transfer is available. Walk assume the walk speed is 80 m/min (4.8 km/h). For a transit trip, there is an additional 1 minute of walking time for platform access and egress.

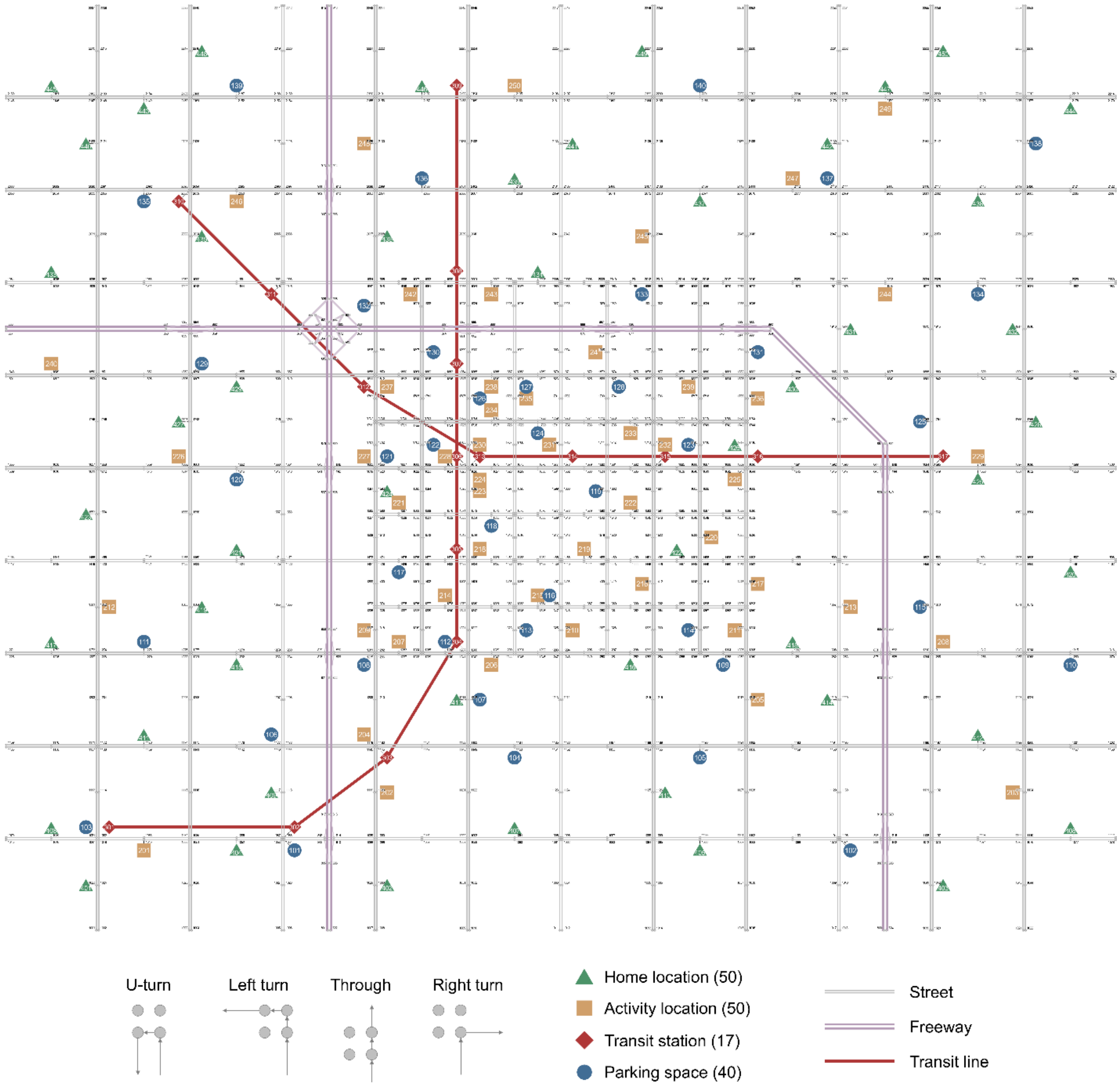


Figure 4-3: Base Network

4.5.1.2 Parameters

This subsection lists the model parameter values I use. For PAV and transit, I adopt \$4.8/h as the value of in-vehicle travel time (β_{iv}^{PAV} and β_{iv}^{TRN}), and \$7.8/h for SAV (β_{iv}^{SAV}). I adopt \$9.6/h for the PAV and SAV value of wait time (β_{wt}^{PAV} and β_{wt}^{SAV}) and \$7.2/h for transit (β_{wt}^{TRN}). I adopt \$13.2/h for the transit value of walk time (β_{wk}^{TRN}). I based these values on prior studies (Correia et al., 2019; Singleton, 2019). I set the wait times for SAV and transit (t^{SAVwt} and t^{TRNwt}) 6 minutes and 3 minutes, respectively, while the PAV wait time is a decision variable in the HAPP-AV-IT. For the PAV operating cost, USDOT provides a range of $0.3/mi to $0.5/mi for AV operating costs in the next decade (Cortright, 2017). I use $0.3/mi as the PAV operating cost (β_{op}^{PAV}). The SAV base and distance fares (β_{fb}^{SAV} and β_{fd}^{SAV}) are $1.0/trip and $1.5/km ($2.4/mi), respectively, which more accurately represents current TNC prices (Helling, 2023). I set the transit fare (β_{fr}^{TRN}) to $1.75/trip. The hourly parking fee (ω) for each parking space ranges from $1 in the periphery to $6 in the urban core. The maximum curbside loading time (τ) is 5 minutes.

4.5.2 Optimization Tools

For the case study, I used Gurobi in Python to solve the HAPP-AV-IT instances with 12 logical processors and 16 GB memory. The computational time for each household varies by the household's number of PAVs and activities. I investigate the relationship between household attributes (i.e. number of PAVs, number of activities, and number of household members) and computational time in Subsection 4.5.4.6.

4.5.3 Case 1: Three Fictitious Households

This section presents the results of three fictitious household and activity patterns I designed to demonstrate the capability of the HAPP-AV-IT model. Subsection 4.5.3.1 presents the base model inputs, Subsection 4.5.3.2 presents the outputs from the base model, and Subsection 4.5.3.3 presents sensitivity analysis results.

4.5.3.1 Base Model Inputs

Table 4-5 displays the model inputs for three distinct households. The model inputs include information about the household and the activities the household members must complete.

Household 1 includes three persons (Persons 11 to 13) and one PAV. All three household members have a work/school activity with nearly the same drop-off time window and pickup time window. With only one PAV, I expect household members to carpool in their PAV, and for some members to possibly use SAV, transit, PAV-transit, or SAV-transit.

Household 2, with three persons (Persons 21 to 23) and two PAVs, has four activities with different time windows; thus, I expect heavy utilization of the two PAVs. Person 22 has two activities (personal and shopping); they can go home between activities or perform both activities without returning home. Note that time windows for shopping are very flexible.

Household 3, with two persons (Persons 31 and 32) and 0 PAVs, has three activities. This household must use SAV or transit (or SAV-transit) to complete tours because they do not have any PAVs.

Table 4-5: Household Activity Profiles of Case 1

Household ID	Activity ID	Activity Type	Physical Network Node ID	Assigned Household Member ID	Earliest Drop-off	Latest Drop-off	Activity Duration (min)	Earliest Pickup	Latest Pickup
1 (1 PAV, 3 persons)	Home		409	Trip available time 06:00–23:30					
	1	Work	246	11	08:50	09:00	510	17:30	17:40
	2	Work	229	12	08:50	09:00	510	17:30	17:40
	3	School	212	13	09:00	09:10	480	17:10	17:20
2 (2 PAVs, 3 persons)	Home		424	Trip available time 06:00–23:30					
	1	Work	225	21	08:40	09:00	510	17:30	17:50
	2	Personal	217	22	20:00	21:00	90	21:30	22:30
	3	School	212	23	07:50	08:30	480	16:30	17:00
	4	Shopping	202	22	10:00	20:00	30	10:00	20:00
3 (0 PAVs, 2 persons)	Home		432	Trip available time 06:00–23:30					
	1	Work	201	31	10:30	11:00	240	14:30	15:00
	2	Shopping	241	32	14:00	17:00	60	14:00	17:00
	3	Personal	218	31	14:40	15:10	120	16:40	17:10

4.5.3.2 Base Model Outputs

Figure 4-4 through Figure 4-6 display the model outputs for Households 1 through 3, respectively.

Household members in Household 1 use PAV, SAV, and PAV-transit for their activities. As Household 1 owns only 1 PAV, and the three household members have overlapping activities each with tight time windows, the PAV cannot serve all trips. As shown in Figure 4-4b, Person 12 uses the PAV to access the nearest transit station (Node 302) and transfers to the transit network, using two transit lines (transit-transit transfer between Node 306 and Node 313) to go to work at Node 229. The PAV comes back home and picks up Persons 11 and 13 together and drops the two travelers off at their respective activity drop-off nodes: work (Node 246) and school (Node 212). Then, the vehicle parks at home until school finishes. Then the vehicle picks up Person 13, and drops them off at home. After another park-at-home phase, the PAV picks up Person 11 from work, comes back home, and terminates its tour. Person 12 uses transit for their return-home trip. In fact, Person 12 walks home from the transit station instead of using a PAV because lone PAV is serving another household member when Person 12 arrives at the transit station.

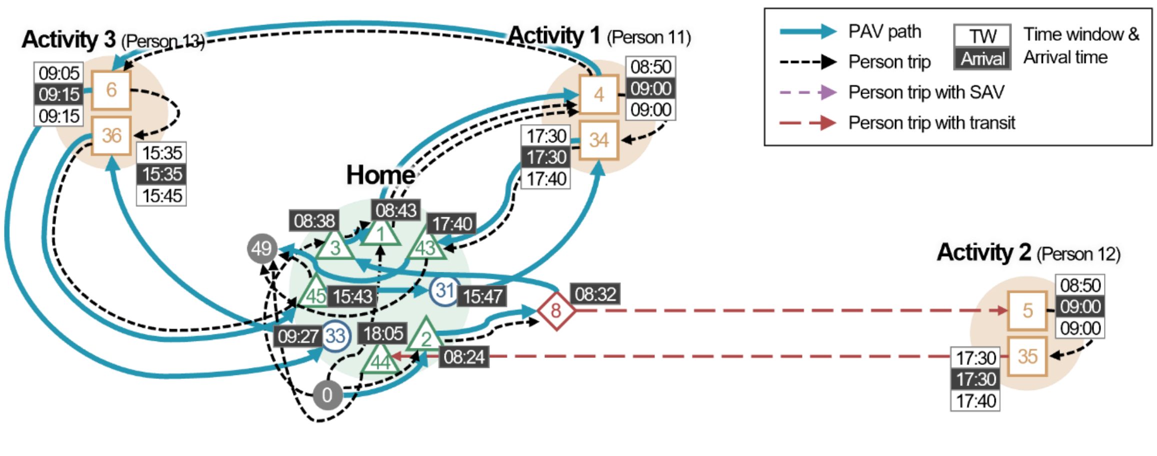
The members of Household 2 complete all their activities with their two PAVs; they do not make any SAV or transit trips. PAV 1 serves Persons 21 and 23, and PAV 2 serves Persons 21 and 22. After dropping off the household members at activity locations, both vehicles deadhead home to park. Due to the flexible time windows for Person 22's shopping activity, the vehicle drops off Person 22 before Person 23's school pickup and then goes back to pick up Person 22. As a result, PAV 2 moves directly from the shopping drop-off location to the school pickup location without parking at home.

The members of Household 3 travel exclusively via SAV and transit, because the household does not own any PAVs. As the home location (Node 432) is far from transit stations, household members use SAV for each first- and last-mile transit leg. From Figure 4-6b, I observe that Person 31's work (Node 201) and personal (Node 218) activity locations are close to transit stations (Nodes 301 and 305, respectively), and those activities are temporally adjacent. As a result, Person 31 completes the two activities in one tour, with a transit-SAV intermodal trip when returning home. On the other hand, Person 32 makes an SAV round trip for the shopping activity since the shopping location (Node 241) has no nearby transit stations.

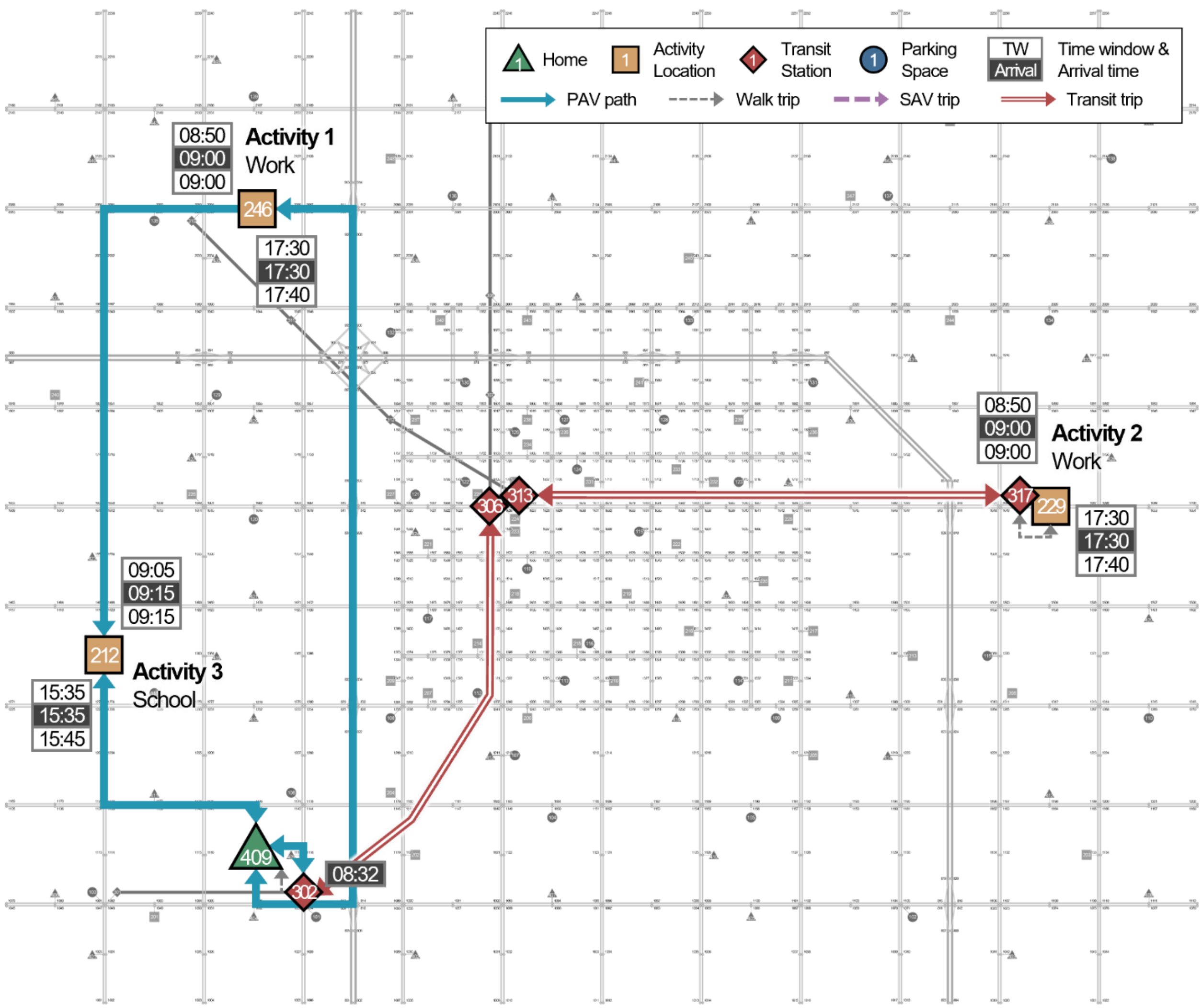
By analyzing all three households collectively, I can draw several conclusions. In terms of the HAPP-AV-IT modeling framework, collectively the three households use every mode

(PAV, SAV, transit, walking) and modal combination (SAV-transit and PAV-transit) at least once. Given the constraints that the three fictitious households face in terms of vehicle availability and activity time-windows, the HAPP-AV-IT produces quite reasonable mode, path, pooling, and schedule decisions for persons as well as routing and scheduling decisions for household vehicles.

In terms of potential changes in travel in a future with PAVs, while I do not want to make any strong conclusions because I did not calibrate the model parameters, it is clear that the flexibility that PAV deadheading provides will increase VKT. Moreover, the number of PAVs a household has will dramatically impact usage of transit and SAVs, not unlike the current situation with private non-automated vehicles.



(a)



(b)

Figure 4-4: Activity Pattern of Household 1: Tours on (a) Activity-travel Graph and (b) Physical Network

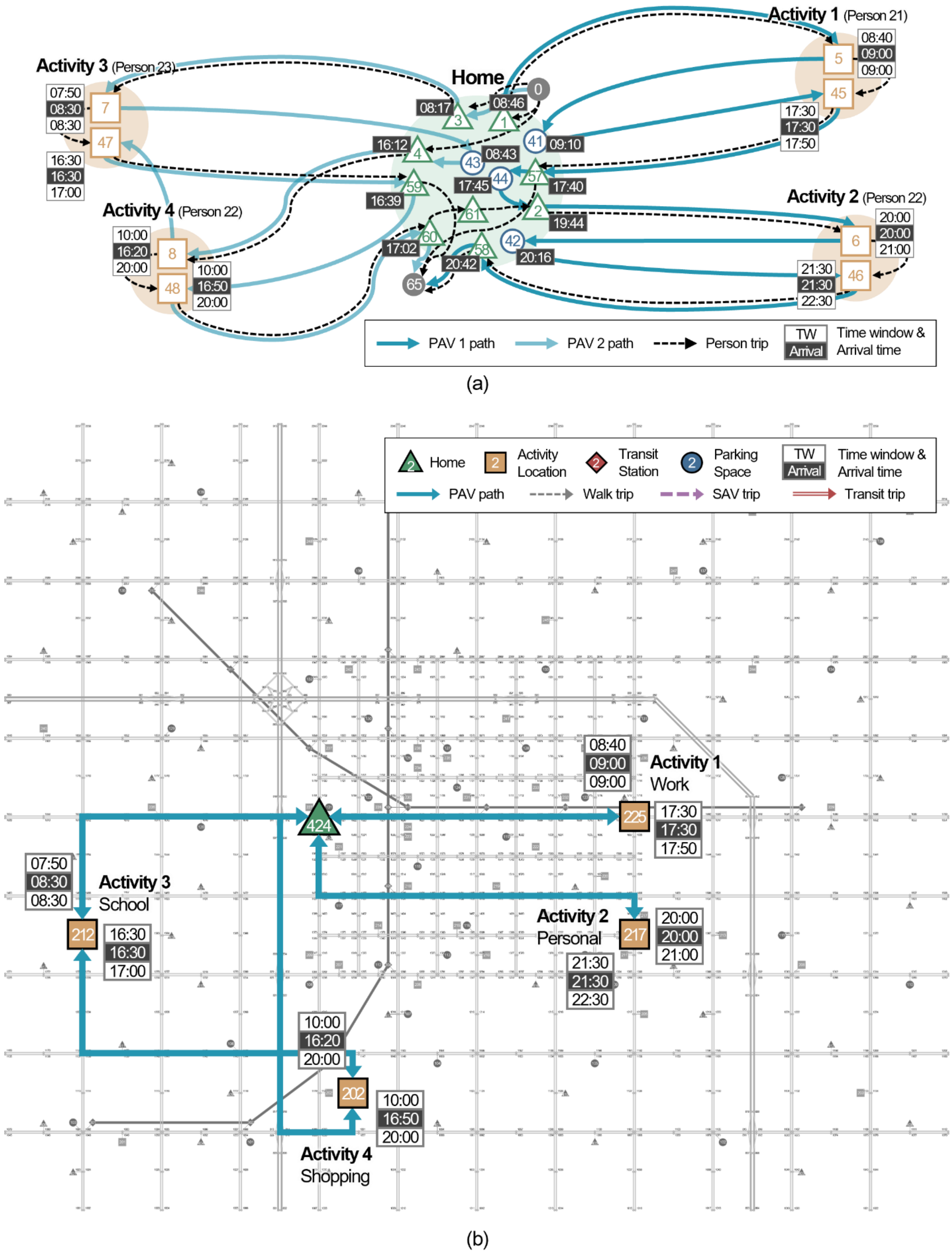
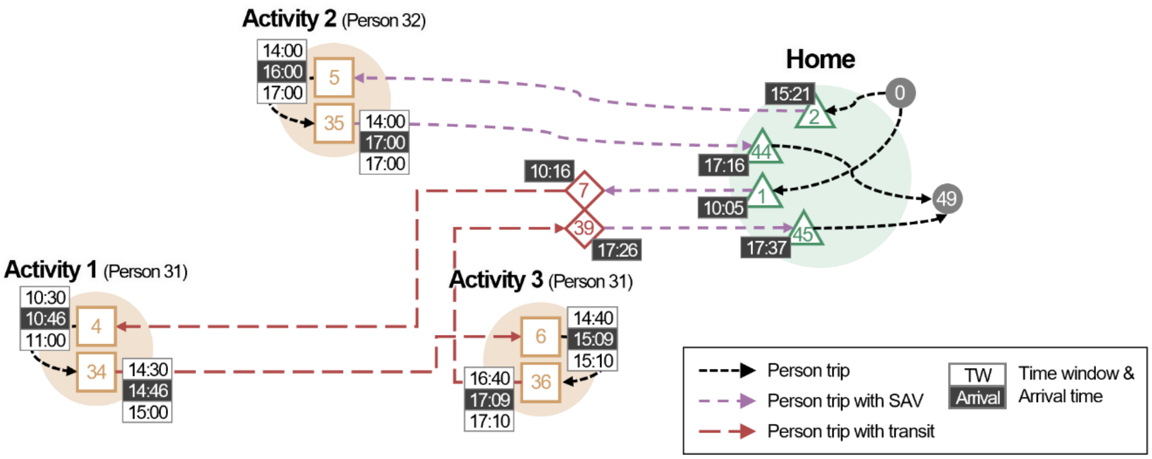
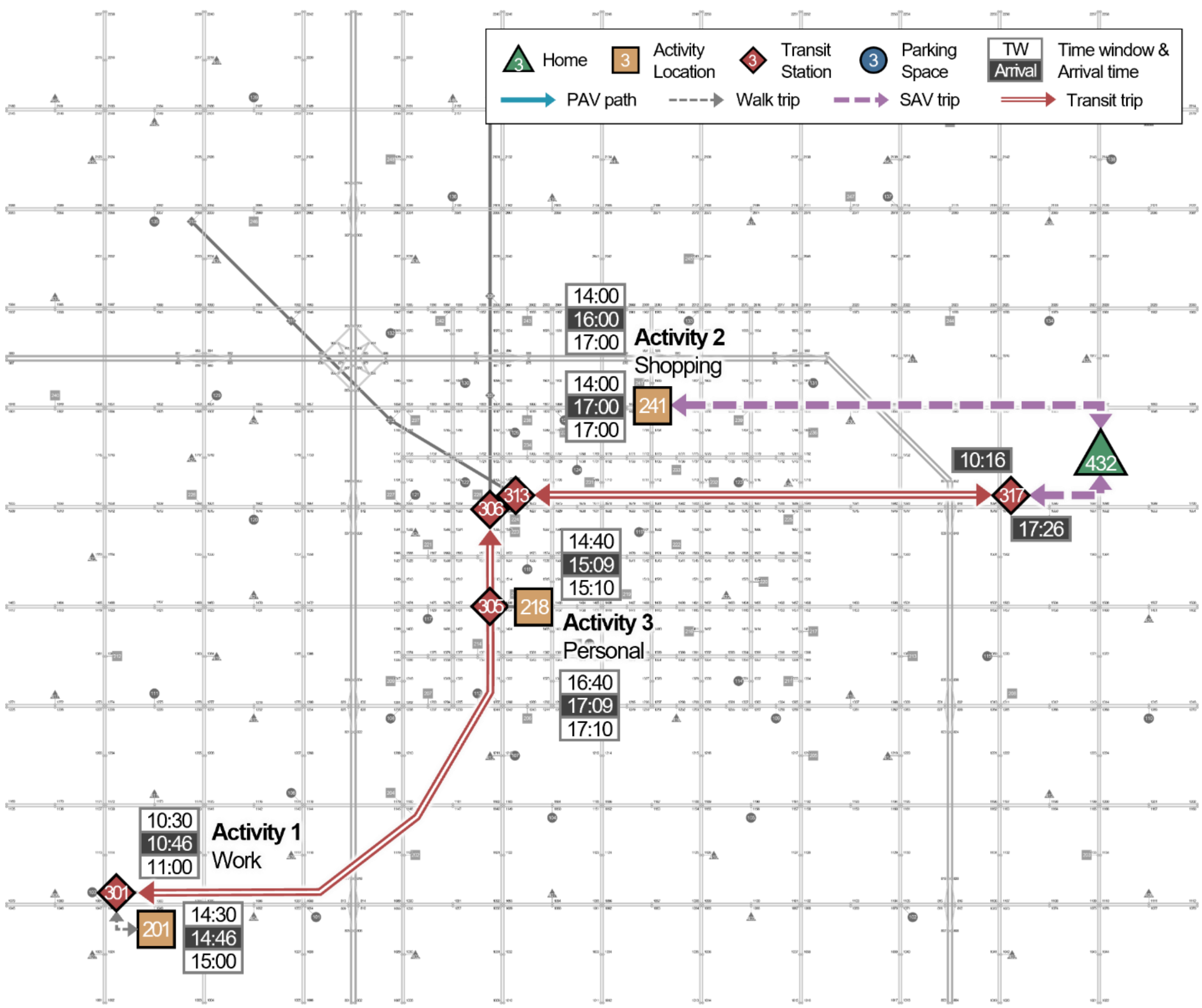


Figure 4-5: Activity Pattern of Household 2: Tours on (a) Activity-travel Graph and (b) Physical Network



(a)



(b)

Figure 4-6: Activity Pattern of Household 3: Tours on (a) Activity-travel Graph and (b) Physical Network

4.5.3.3 Sensitivity Analysis Results

In this subsection, I conduct sensitivity analyses on the three fictitious households. For Household 1, I consider three variations: (i) the number of household PAVs increases to two, (ii) there is a 50% discount on SAV fare, and (iii) transit is not available. For Household 2, I consider one variation: the number of household PAVs reduces to one. For Household 3, I consider two variations: (i) PAV household ownership increases to one and (ii) there is a 50% discount on SAV fare. Table 4-6 shows the baseline results and the results of the various scenarios analysis, for all three households.

Table 4-6: Sensitivity Analysis on Simple 3 Households

			Household 1 (1 PAV base)				Household 2 (2 PAV base)		Household 3 (No PAV base)		
			(base)	+1 PAV	SAV dis-count	No transit	(base)	-1 PAV	(base)	+1 PAV	SAV dis-count
Number of trips	PAV	Single-occupant	12	16	12	11	22	22	N/A	9	N/A
		Carpool	1	1	1	0	0	0	N/A	1	N/A
	SAV		0	0	1	2	0	0	4	0	4
	Transit		2	0	1	N/A	0	0	3	1	1
Inter-modal trips	PAV-transit		1	0	1	N/A	0	0	N/A	0	N/A
	SAV-transit		0	0	0	N/A	0	0	2	0	0
Travel time (min)	Person	Wait	10	0	11	12	0	0	37	3	27
		In-vehicle	78	77	76	62	73	73	57	53	50
		Walk	27	0	10	N/A	0	0	27	13	13
	PAV	Total	71	117	71	77	140	143	N/A	71	N/A
		Onboard	42	64	42	40	73	73	N/A	36	N/A
		Dead-heading	29 (41%)	52 (45%)	29 (41%)	38 (49%)	67 (48%)	70 (49%)	N/A	35 (49%)	N/A
	SAV	Onboard	0	0	10	22	0	0	28	0	43
	Transit	Onboard	24	0	12	N/A	0	0	29	7	7
Travel distance (km)	PAV	Total	36.7	64.3	36.7	42.2	61.2	62.6	N/A	36.3	N/A
		Onboard	22.1	35.9	22.1	23.2	31.9	31.9	N/A	17.5	N/A
		Dead-heading	14.6 (40%)	28.4 (44%)	14.6 (40%)	19.0 (45%)	29.3 (48%)	30.7 (49%)	N/A	18.9 (52%)	N/A
	SAV	Onboard	0	0	5.1	11.4	0	0	14.3	0	21.4
Out-of-home parking	Number of parking		0	0	0	0	0	1	N/A	1	N/A
	Parking time (min)		0	0	0	0	0	0.1	N/A	32	N/A
	Parking fee (USD)		0	0	0	0	0	0.003	N/A	0.54	N/A
Fare (USD)	SAV		0	0	4.34	19.13	0	0	25.45	0	18.04
	Transit		3.50	0	1.75	N/A	0	0	5.25	1.75	1.75
Total travel cost (USD)			29.55	25.42	29.09	42.21	24.21	24.64	52.21	21.44	37.30

For Household 1, compared to the base scenario, in the first new scenario when the number of PAVs increases to 2, household members no longer take transit. As a result, PAV operating time and distance dramatically increase, while person travel time decreases as the replaced transit trip takes longer than the PAV trip. In the second new scenario, I consider a 50% discount on SAV fare. In this new scenario, Person 12 returns home via SAV instead of transit. Replacing the transit trip with a SAV trip significantly reduces walk time, thereby reducing overall household travel cost. Finally, in the third new scenario wherein transit service is not available, Person 12's work tour (previously PAV-transit and transit-only) switches to a PAV trip and a SAV trip, and Person 11 uses SAV and PAV for their work tour. The total household travel cost increases due to the extended PAV operation and the SAV fare.

For Household 2, compared to the base case with two PAVs, with only one household PAV total household travel cost only reduces slightly. The household members can complete all four activities with one PAV. Interestingly, in the case of this household, one fewer PAV slightly increases PAV operating time and VMT. Another interesting finding is that despite the number of out-of-home parking events increasing from zero to one, the parking time is nearly zero indicating that the PAV immediately leaves the parking lot once it enters.

For Household 3, when going from 0 to 1 PAV, household travel drastically changes. The household members can complete all their activities with one PAV and one transit trip. Moreover, adding the PAV reduces the total household travel cost significantly. This is mainly due to avoiding SAV and transit fares and reduced person travel times. For the SAV discount case (with no PAVs), the members of Household 3 mainly use SAV for all three activities, while only Person 31 uses transit when traveling between work and a personal activity.

The sensitivity analysis results show that vehicle ownership is the most critical factor in household travel behavior. An additional PAV always significantly increases the amount of PAV travel as an additional PAV can reduce person travel time in nearly all cases. In a further analysis, I vary the number of PAVs for each household to determine the minimum number of PAVs needed to complete all their activities without using other modes. According to the results, Households 1, 2, and 3 require 2, 1, and 2 PAVs, respectively.

4.5.4 Case 2: Synthetic San Diego-based Households

4.5.4.1 Generating Synthetic Households and Activity Patterns

In this subsection, I generate household activity profiles using output from the activity-based travel forecasting model (ABM), ActivitySim, employed by the San Diego Association of Governments (SANDAG). Like most ABMs in use by planning agencies, ActivitySim determines activity locations and also person tours and travel schedules for household members. Below, I describe how I use the SANDAG ABM model to generate the inputs for the HAPP-AV-IT model.

I extract 200 synthetic households and aspects of their activity-travel profiles from ActivitySim. Since I do not use the SANDAG network, I randomly assign each household a home location in the virtual network in this chapter and also randomly assign non-home-activity locations to non-home-activity locations in the virtual network.

ActivitySim outputs the type and location of every activity. Unfortunately, it does not output activity duration or activity start time, which I need for the model in this chapter. Rather, it only outputs the departure time of trips from activity locations and travel times between activity locations. Hence, I need to modify ActivitySim output to create activity durations as well as activity drop-off and pickup time-windows.

Table 4-7 displays the rules I implement to convert the information available from ActivitySim into HAPP-AV-IT inputs. SANDAG classifies the ActivitySim activities into mandatory activities (work, school, and university), maintenance activities (escorting, shopping, and other maintenance), or discretionary activities (social/recreational, eating out, and other discretionary). For each activity type, I have different rules for generating HAPP-AV-IT inputs for the earliest drop-off (e_{DO}), latest drop-off (l_{DO}), activity duration (s), earliest pickup (e_{PU}), and latest pickup (l_{PU}).

Most of the rules pivot around "D", the time at which the household member departs for a given activity, and "D'", the departure time for the household member's next activity. Unfortunately, the temporal resolution for D and D' is one-hour in ActivitySim. As such, I create different rules for cases where $D = D'$ and $D \neq D'$. Also, to obtain temporal values with a higher resolution, I draw uniform random variates for times within the hour.

Table 4-7 shows 30-minute pickup and drop-off time-window lengths for mandatory activities. The time-window lengths for escort and discretionary activities are 60 minutes and 6 hours, respectively. For shopping, the time windows are very large, as household members often have considerable flexibility in terms of when they complete these activities.

Table 4-7: Generating Household Activity Profile for Case 2 Households

<table>
<tr><th colspan="2">Activity Type</th><th>Earliest Drop-off, e_{DO} (min)</th><th>Latest Drop-off, l_{DO} (min)</th><th>Activity Duration, s (min)</th><th>Earliest Pickup, e_{PU} (min)</th><th>Latest Pickup, l_{PU} (min)</th></tr>
<tr><td rowspan="3">Mandatory</td><td>$U[D-60, D]$</td><td rowspan="3">$e_{DO} + 30$</td><td rowspan="3">$U[5, 15]$ if $D = D'$, otherwise, $U[D' - D - 50, D' - D - 30]$</td><td rowspan="3">$l_{DO} + s$</td><td rowspan="3">$e_{PU} + 30$</td><td rowspan="3">$a_{PU} + 30$</td></tr>
<tr><td>School</td></tr>
<tr><td>University</td></tr>
<tr><td rowspan="3">Maintenance</td><td>$U[D-60, D]$</td><td>$e_{DO} + 60$</td><td>5</td><td>$e_{DO} + s$</td><td>$l_{DO} + s$</td><td>$b_{DO} + s$</td></tr>
<tr><td>$U[360, 600]$ (6 AM–10 AM)</td><td>$e_{DO} + 840$ (8 PM–12 AM)</td><td>$U[5, 15]$ if $D = D'$, otherwise, $U[D' - D - 50, D' - D - 30]$</td><td>$e_{DO}$ (6 AM–10 AM)</td><td>l_{DO} (8 PM–12 AM)</td><td>b_{DO} (8 PM–12 AM)</td></tr>
<tr><td>$U[D-180, D]$</td><td rowspan="4">$e_{DO} + 360$</td><td rowspan="4">$U[5, 10]$ if $D = D'$, otherwise, $U[D' - D - 50, D' - D - 30]$</td><td rowspan="4">$e_{DO} + s$</td><td rowspan="4">$l_{DO} + s$</td><td rowspan="4">$b_{DO} + s$</td></tr>
<tr><td rowspan="3">Discretionary</td><td>Social/ recreational</td></tr>
<tr><td>Eat out</td></tr>
<tr><td>Other discretionary</td></tr>
</table>

Note1: D and D' are departure times for the activity and the next activity, respectively, in minutes.

Note2: $U[a, b]$ denotes a continuous uniform distribution with parameters a and b.

I sample households this way to obtain a reasonable representation of the activities a household conducts within a day and the temporal distribution of those activities. Note that some ActivitySim household activity profiles were infeasible. Infeasibility often arose when households had more than ten activities (up to 15 activities), as schedule conflicts were common in these cases. As a result, I excluded these households and resampled to obtain 200 households in total.

4.5.4.2 Scenario Analysis Set-up

For the synthetic SANDAG households, I have a baseline scenario and two additional scenarios. The first additional scenario includes more transit lines in order for us to analyze the relationship between key performance metrics (e.g., mode choice) and transit supply.

In the base network, two transit lines cross each other. Figure 4-7 displays a transit-enhanced network with three more transit lines: two horizontal lines and one vertical line. As a result, the number of transit stations increases from 17 to 40 (Nodes 318 to 340 added), and there are 7 transit transfer stations (i.e., transit hubs) in the network. (Note that the transit hub nearest to the home location becomes a possible drop-off or pickup station for an intermodal trip.) With the transit-enhanced network, I expect more transit-only, PAV-transit, and SAV-transit trips.

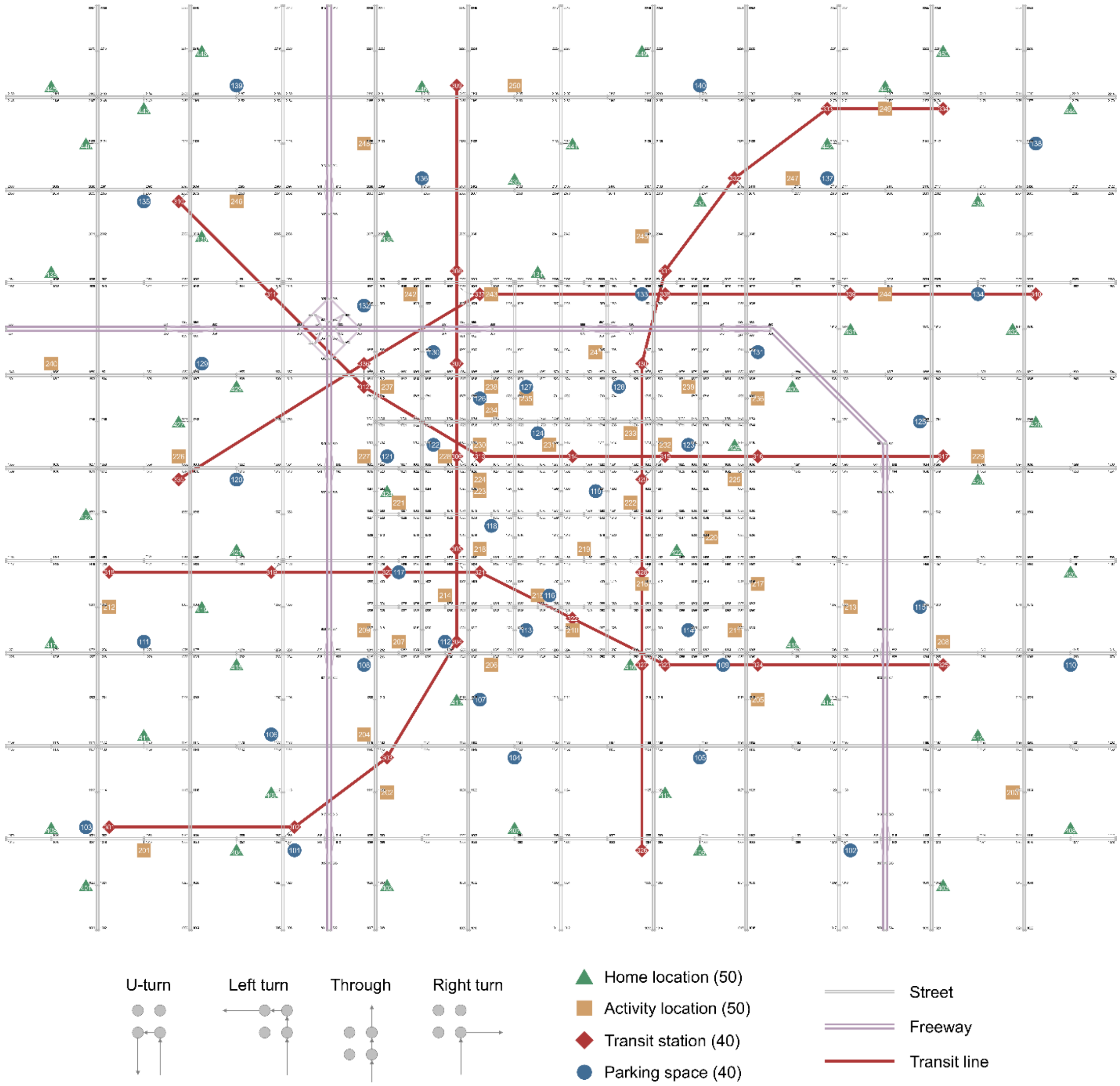


Figure 4-7: Transit-enhanced Network

The second additional scenario involves household PAV ownership. The San Diego ABM includes a statistical model (i.e., a discrete choice model based on survey data) that forecasts household vehicle ownership for synthetic households in the region. While the model forecasts non-automated vehicles for the base year, vehicle ownership may differ in the AV era since PAVs do not require a driver. As such, some households may consider owning fewer vehicles. Considering the possibility of reduced vehicle ownership, I analyze a second scenario that includes the transit-enhanced network and one fewer vehicle per household.

Table 4-8 shows the scenario settings and summarizes the household activity profile inputs. The household size ranges from 1 to 7 persons, and the average number of household members is 2.44. The number of activities is around 4 on average, with a maximum of 10. Household vehicle ownership ranges from 0 to 4 PAVs, averaging 1.92 vehicles per household. The average number of household vehicles decreases to 0.95 in Scenario B, where I decrease household vehicles by one vehicle per household.

Table 4-8: Household Activity Profile Overview and Scenarios for Case 2

<table>
<tr><th colspan="2">Scenario</th><th>Baseline</th><th>Scenario A</th><th>Scenario B</th></tr>
<tr><td colspan="2">Network</td><td>Base</td><td>Transit-enhanced</td><td>Transit-enhanced</td></tr>
<tr><td colspan="2">PAV ownership</td><td>Base</td><td>Base</td><td>1 PAV reduced</td></tr>
<tr><td colspan="2">Number of households</td><td colspan="3">200</td></tr>
<tr><td rowspan="3">Household size</td><td>Minimum</td><td colspan="3">1</td></tr>
<tr><td>Mean</td><td colspan="3">2.44</td></tr>
<tr><td>Maximum</td><td colspan="3">7</td></tr>
<tr><td rowspan="3">Number of activities</td><td>Minimum</td><td colspan="3">1</td></tr>
<tr><td>Mean</td><td colspan="3">3.80</td></tr>
<tr><td>Maximum</td><td colspan="3">10</td></tr>
<tr><td rowspan="3">Number of PAVs</td><td>Minimum</td><td colspan="2">0</td><td>0</td></tr>
<tr><td>Mean</td><td colspan="2">1.92</td><td>0.95</td></tr>
<tr><td>Maximum</td><td colspan="2">4</td><td>3</td></tr>
</table>

4.5.4.3 Model Complexity and Stopping Criteria

As an NP-hard problem, previous HAPP studies generally apply relatively simple household activity profiles, similar to Case 1 in this chapter. Table 4-9 shows the complexities of household activity profiles in HAPP-based studies. The table indicates that compared with prior studies, the households in the numerical experiments in this chapter have the most people, conduct the most activities, have the most vehicles, and have the greatest number of modal options.

Table 4-9: Comparison of Household Activity Profile Complexities among HAPP Studies

Study		Number of Households	Max. Household Size	Max. Number of Activities	Max. Number of PVs	Number of Mode Options
Recker (1995)		1	2	3	2	1
Gan and Recker (2008)	Example	1	2	6	2	2
	Real-world	1	2	7	2	2
Chow and Recker (2012)		78	1	4	2	1
Gan and Recker (2013)		1	1	3	1	1
Kang and Recker (2013)	Example	1	2	2	2	1
	Real-world	13	1	1	1	1
Kang and Recker (2014)		302	1	2.4 (mean)	1	1
Chow (2014)		500	1	4	1	1
Yuan (2014)		1	2	3	2	2
Chow and Nurumbetova (2015)		510	1	4	1	1
Chow and Djavadian (2015)	Example	1	1	2	1	3
	Real-world	166	1	1	1	3
Liu et al. (2018)	Medium case	1	3	7	2	1
	Large case	1.35M	1	1	1	1
Xu et al. (2018)		1	1	4	1	1
Khayati and Kang (2019)		92	2	3	2	1
Najmi et al. (2020)		600	1	3 (mean)	1	4
Khayati et al. (2021b)	Example	1	2	3	1 (AV)	1
	Real-world	300	3	6	1 (AV)	1
Khayati et al. (2021a)		300	3	5–6 (mean)	1 (AV)	2
This chapter	Case 1	3	3	4	2 (AVs)	5
	Case 2	200	7	10	4 (AVs)	5

Computational effort is undoubtedly an issue with HAPP-based formulations. Khayati et al. (2021b) mention that optimizing a household with 3 household members, 5 activities, and 1 PAV takes more than 3 days with a commercial solver, and they reduce the runtime by 48% with their proposed algorithm. Similarly, I face long run times on laptop and desktop computers.

In this case study, I apply two stopping criteria to prevent long run times: (i) maximum unchanged incumbent solution time threshold and (ii) maximum running time threshold, to prevent extremely long runtimes. If the current best incumbent integer solution does not improve within the specified maximum incumbent solution time threshold, or if the optimization is not complete before two pre-defined time values, the optimization terminates, providing the current solution. I set the maximum unchanged incumbent solution time threshold to 900 seconds and the maximum running time threshold to 1,800 seconds.

4.5.4.4 Scenario Analysis Results

The following two tables (Table 4-10 and Table 4-11) give an overview of the results from the synthetic SANDAG households. Table 4-10 shows the average travel costs across households, and Table 4-11 shows the total costs among the 200 households.

The number of trips for each mode varies across scenarios, consistent with the changes in transit accessibility and PAV ownership. In the baseline case, there are 35 transit trips (or 0.2 per household). Scenario A has 29 more transit trips than the baseline scenario due to the enhanced transit network. However, the availability of PAV is a more critical factor, as the number of transit trips increases to 202 (or 1 transit trip per household) in Scenario B.

The travel time and distance metrics mostly follow the number of trips. In the baseline case, the average household operates PAVs for 95.3 minutes in a day, and all the household PAVs travel 48.0 km during that time on average. Total PAV distance decreases as transit accessibility improves in Scenarios A and B and as PAV ownership decreases by one vehicle per household in Scenario B.

Compared with the baseline case, personal travel time increases while total household travel costs decrease in Scenario A. I certainly expect both of these findings. Regarding total household travel cost, as transit service improves and all other modes remain the same in Scenario A compared to the baseline, household travel cost should decrease. Although less intuitive, as transit service improves, more people use transit, and since transit is typically slower than a personal vehicle and more people take transit in Scenario B, person travel time increases in Scenario B.

According to Table 4-11, the total number of intermodal trips increases in the transit-enhanced network scenarios. Interestingly, in Scenario A, the number of PAV-transit trips is the highest, while in Scenario B, the number of SAV-transit trips is the highest. The reduction in PAV-transit trips in Scenario B compared to Scenario A is likely because PAVs per household decrease in Scenario B.

Table 4-10: Scenario Output: Per Household

Scenario		Baseline	Scenario A	Scenario B
Number of trips	PAV	17.3	16.9	14.0
	SAV	0.4	0.3	0.6
	Transit	0.2	0.3	1.0
Travel time (min/hh)	Person	69.3	70.7	82.8
	PAV	95.3	92.5	76.1
	SAV	1.7	1.0	2.6
	Transit	1.0	2.6	9.6
Travel distance (km/hh)	PAV	48.0	46.6	38.2
	SAV	0.7	0.4	1.2
Out-of-home parking time (min/hh)		19.1	16.1	15.0
Fare (USD/hh)	SAV	1.48	0.91	2.32
	Transit	0.31	0.56	1.77
Total travel cost (USD/hh)		24.13	23.74	28.07

Note: Multiple transit trips with transit-transit transfer(s) are counted as 1 transit trip.

Table 4-11: Scenario Output: Total 200 Households

Scenario		Baseline	Scenario A	Scenario B
Number of trips	PAV	3,450	3,381	2,794
	SAV	77	61	117
	Transit	35	64	202
Number of intermodal trips	PAV-transit	2	10	5
	SAV-transit	5	1	14
Travel time (h)	PAV	317	309	254
	SAV	6	3	9
	Transit	3	9	32
Travel distance (km)	PAV	9,605	9,311	7,649
	SAV	146	81	231

Note: Multiple transit trips with transit-transit transfer(s) are counted as 1 transit trip.

Given the computational complexity of the HAPP-AV-IT model, solving the problem for every household in a metropolitan region (although feasible with the stopping criteria) would require significant computational resources. Hence, I use a multiple linear regression model to understand the relationship between a key transportation system performance metric, VKT, and the attributes of a household, including household size, household vehicle count, and household activity count. I also include a binary variable for whether the transportation system includes an enhanced transit network or not, to differentiate between observations in Scenarios A/B and the baseline Scenario. As a reminder, VKT includes occupied and unoccupied PAV travel distance, as well as occupied SAV travel distance. It does not include SAV deadheading.

Table 4-12 presents the parameter estimates for the multiple linear regression model. Interestingly, the results indicate that, while adding transit routes to the network decreases VKT, the effect is not statistically significant. This finding is not surprising, given the dominance of PAVs in each of the scenarios in Table 4-10 and Table 4-11.

The parameter estimates also indicate that as the number of household members increases, VKT increases. The same relationship is true of the number of household activities and VKT. It is somewhat surprising that there is a positive statistically significant relationship between the number of household members and VKT even after controlling for the number of household activities.

The relationship between the number of activities and VKT is quite interesting. The parameter estimates indicate that the relationship is monotonic but nonlinear. However, this finding is reasonable. Each additional activity is likely to require additional VKT. However, for a household already conducting many activities, an additional activity can most likely be incorporated into an existing activity-travel chain.

The relationship between the number of household PAVs and VKT is also interesting. The result indicates that going from zero household PAVs to one or more household PAVs drastically increases VKT. However, as a household increases their number of PAVs beyond 1, VKT remains steady or even slightly decreases. This result is due to the ability of PAVs to deadhead. For a household with just one PAV, the PAV can most likely serve a lot of household member trips, but serving those trips will require significant deadheading. If the household has another PAV, maybe they complete a couple more activities via PAV, but the two PAVs do not need to deadhead nearly as much as with one household PAV.

Finally, I interact the transit enhancement indicator variable with each of the other explanatory variables, to determine if the different transportation network in Scenarios A and B (compared to the baseline scenario) impacts any relationships. Although not statistically significant, the results indicate that a transit-enhanced network does decrease the strength of the positive relationship between household size and VKT. Additionally, the results indicate no practical or statistically significant difference between number of household activities and VKT when accounting for the enhanced transit network. However, there is a statistically significant impact of transit enhancement on the relationship between number of household vehicles and VKT. Surprisingly, with an enhanced transit network, the size of the relationship between household vehicles and VKT actually increases.

Table 4-12: Linear Regression Model on VKT with the Numbers of Household Members, Activities, and PAVs

	Explanation of VKT (600 Households in 3 Scenarios)		
Estimation Result			
	Coefficient	Std. Error	P-value
Constant	-6.12	6.295	0.332
Base: baseline scenario			
Transit enhanced scenarios	-4.67	6.969	0.503
Base: baseline scenario + 1 HH member			
2 HH members	5.33	5.706	0.351
3 HH members	7.85	6.337	0.216
4 HH members	10.91	6.823	0.110
5 HH members	21.67	10.427	0.038
6 HH members	27.39	11.945	0.022
7 HH members	50.46	16.472	0.002
2 HH members × Transit enhanced scenarios	-9.98	6.843	0.145
3 HH members × Transit enhanced scenarios	-8.26	7.596	0.277
4 HH members × Transit enhanced scenarios	-10.04	8.198	0.221
5 HH members × Transit enhanced scenarios	-11.12	12.675	0.381
6 HH members × Transit enhanced scenarios	-16.50	14.564	0.258
7 HH members × Transit enhanced scenarios	-7.58	20.001	0.705
Base: baseline scenario + 1 Activity			
2 activities	10.74	4.511	0.018
3 activities	20.78	4.644	0.000
4 activities	29.30	4.469	0.000
5 activities	31.70	5.000	0.000
6 activities	36.95	5.033	0.000
7 activities	50.68	5.795	0.000
8 activities	64.76	7.328	0.000
9 activities	45.32	15.665	0.004
10 activities	34.12	15.290	0.026
2 activities × Transit enhanced scenarios	-1.45	5.522	0.793
3 activities × Transit enhanced scenarios	-1.64	5.681	0.773
4 activities × Transit enhanced scenarios	-5.65	5.468	0.302
5 activities × Transit enhanced scenarios	-5.25	6.122	0.391
6 activities × Transit enhanced scenarios	-4.55	6.145	0.459
7 activities × Transit enhanced scenarios	-3.59	7.083	0.612
8 activities × Transit enhanced scenarios	-13.02	8.968	0.147
9 activities × Transit enhanced scenarios	-1.73	19.104	0.928
10 activities × Transit enhanced scenarios	-24.14	18.706	0.197
Base: baseline scenario + 0 PAVs			
1 PAV	26.44	6.811	0.000
2 PAVs	23.76	7.023	0.001
3 PAVs	24.14	7.789	0.002
4 PAVs	19.59	9.888	0.048
1 PAV × Transit enhanced scenarios	13.65	7.281	0.061
2 PAVs × Transit enhanced scenarios	16.28	7.521	0.031
3 PAVs × Transit enhanced scenarios	16.99	8.679	0.051
4 PAVs × Transit enhanced scenarios	17.51	12.186	0.151
Model Fit			
Observations			600
R-squared			0.666
Adjusted R-squared			0.643
Log-likelihood			-2436.0

4.5.4.5 *Usefulness of Intermodal Trips*

Given that incorporating intermodal travel in a household person and vehicle routing and scheduling problem is a key contribution of this chapter, this subsection explores the households that benefit from intermodal travel in Case 2.

Across the three scenarios in Case 2, there are 37 intermodal trips made by 19 out of 200 households. In this subsection, I re-run the model in Section 4.4 for these households but change the constraints such that intermodal travel is impossible. Table 4-13 lists all intermodal trips in Case 2 scenarios and shows the travel cost differences between with and without intermodal trips.

According to Table 4-13, intermodal trips decrease household travel costs by significantly reducing AV travel distance. Intermodal travel does increase person travel time on average due to additional walk and transit transfer wait times. Intermodal travel decreases household travel costs by 15% for one household, while most households save 2–5%.

The bottom of Table 4-13 shows the reduction in AV travel distance across the households that benefit from intermodal travel in the baseline scenario and Scenarios A and B. The results indicate that intermodal travel has the potential to decrease VKT.

Table 4-13: Comparison of With and Without Intermodal Trips

HH ID	Scenario	Intermodal Trips	Person Travel Time (min)			AV Travel Distance (km)			Total Travel Cost (USD)		
			Without	With	Change	Without	With	Change	Without	With	Change
35	B	1 SAV-transit	260	277	+7%	20.2	16.3	-19%	96.45	94.72	-2%
76	B	3 SAV-transit	331	378	+14%	27.2	11.6	-57%	123.43	112.36	-9%
87	B	1 PAV-transit	80	91	+14%	73.0	58.5	-20%	28.32	28.23	-0%
111	B	2 SAV-transit	294	332	+13%	10.5	4.1	-61%	88.17	87.96	-0%
329	A	2 PAV-transit	49	71	+45%	56.8	21.2	-63%	20.91	19.95	-5%
345	A	1 PAV-transit	132	139	+5%	62.2	49.0	-21%	33.75	33.71	-0%
	B	1 PAV-transit	132	139	+5%	62.2	49.0	-21%	33.76	33.71	-0%
360	A	1 PAV-transit	94	105	+12%	61.7	44.0	-29%	27.49	27.02	-2%
	B	1 PAV-transit	94	105	+12%	61.7	44.0	-29%	27.57	27.10	-2%
367	A	1 SAV-transit	136	152	+12%	8.2	4.2	-49%	45.55	43.30	-5%
	B	1 SAV-transit	136	152	+12%	8.2	4.2	-49%	45.55	43.30	-5%
369	A	1 PAV-transit	186	188	+1%	79.2	74.1	-6%	47.88	47.21	-1%
445	Baseline	3 SAV-transit	142	149	+5%	25.5	18.9	-26%	74.49	68.70	-8%
475	Baseline	1 PAV-transit	132	140	+6%	76.7	62.1	-19%	37.69	37.56	-0%
	A	1 PAV-transit	132	140	+6%	76.7	62.1	-19%	37.69	37.56	-0%
577	Baseline	1 PAV-transit	147	151	+3%	62.5	60.6	-3%	34.37	33.64	-2%
	A	1 PAV-transit	147	151	+3%	62.5	60.6	-3%	34.50	33.64	-2%
	B	1 PAV-transit	147	151	+3%	62.5	60.6	-3%	34.37	33.64	-2%
796	B	1 SAV-transit	104	122	+17%	17.1	9.3	-46%	51.25	43.75	-15%
805	Baseline	2 SAV-transit	66	62	-6%	5.7	4.6	-19%	24.53	23.41	-5%
809	A	2 PAV-transit	121	144	+19%	112.4	80.4	-28%	43.41	43.00	-1%
	B	1 PAV-transit	121	134	+11%	112.9	96.9	-14%	44.60	44.35	-1%
859	A	1 PAV-transit	114	108	-5%	85.7	72.9	-15%	35.11	34.42	-2%
	B	2 SAV-transit	238	273	+15%	12.4	3.0	-76%	75.07	69.61	-7%
903	B	2 SAV-transit	181	175	-3%	15.7	15.6	-1%	69.61	69.27	-0%
961	B	1 SAV-transit	54	68	+26%	13.2	10.1	-23%	33.90	33.27	-2%
1030	B	1 SAV-transit	71	89	+26%	21.3	17.5	-18%	50.24	49.28	-2%
Totals by Scenario											
Baseline		PAV-transit	279	291	+4%	139.2	122.7	-12%	72.06	71.20	-1%
		SAV-transit	208	211	+1%	31.2	23.5	-25%	99.02	92.11	-7%
		Total	487	502	+3%	170.4	146.2	-14%	171.08	163.31	-5%
Scenario A		PAV-transit	975	1,046	+7%	597.2	464.3	-22%	280.74	276.51	-2%
		SAV-transit	136	152	+12%	8.2	4.2	-49%	45.55	43.30	-5%
		Total	1,111	1,198	+8%	605.4	468.5	-23%	326.29	319.81	-2%
Scenario B		PAV-transit	574	620	+8%	372.3	309.0	-17%	168.62	167.03	-1%
		SAV-transit	1,669	1,866	+12%	145.8	91.7	-37%	633.67	603.52	-5%
		Total	2,243	2,486	+11%	518.1	400.7	-23%	802.29	770.55	-4%

Note: AV travel distance does not include SAV deadheading distance.

4.5.4.6 Computational Time Analysis

To determine the key factors affecting computational time, I systematically vary model inputs (i.e., household size, number of household activities, and number of PAVs) to create 200 HAPP-AV-IT instances. For each instance, I store the computational run time and then regress the computational run time against the model inputs. Given that the model terminates some households based on the stopping criteria in this chapter, I created two datasets with separate dependent variables: (i) the full optimization time for households with 4 or fewer activities and (ii) the time to find the first feasible solution for all 200 households.

Table 4-14 summarizes the descriptive statistics of each dataset. For the first dataset, note that I use two relaxed stopping criteria: (i) 86,400 seconds (1 day) of maximum running time and (ii) 10% gap tolerance. The second dataset has no stopping criteria. The average optimization time for households with 4 or fewer activities is around 15 minutes, while the range is between 0.1 seconds and the maximum running time, 86,400 seconds. On the other hand, the first feasible solution searching time is relatively short across all households.

Table 4-14: Computational Time Analysis: Descriptive Statistics

Variable	Fully Optimizing Time (138 households with four or fewer activities)					First Feasible Solution Time (All 200 households)				
	Mean	Std. Dev.	Min.	Median	Max.	Mean	Std. Dev.	Min.	Median	Max.
Runtime (sec)	904	7,424	0.1	3.0	86,400	32	184	0.1	2.3	2,424
Household size	2.3	0.7	1	2	5	2.4	0.9	1	2	7
Activities	2.7	1.1	1	3	4	3.8	1.9	1	4	10
PAVs	1.9	0.7	0	2	4	1.9	0.7	0	2	4

In each regression model, the dependent variable is computational time, while the independent variables include household size, the number of activities, and the number of PAVs. Due to the exponential nature of the computational times (optimization time and first feasible solution searching time), I log-transform the dependent variables. For the independent variables, I use ordinal/categorical variables considering the discreteness of the data.

Table 4-15 presents the multiple linear regression model estimates for the two datasets. The estimates for the first dataset indicate that neither the number of household members nor the number of PAVs explains the optimization time. However, I can infer that the number of activities has a statistically significant impact on the optimization time. As the number of activities increases, the optimization time dramatically increases. For example, a household with 4 activities is likely to have a runtime approximately 6 times longer than a household with 1 activity.

The estimates from the second data set indicate that the number of activities and PAVs impact the time to obtain a feasible solution. However, it is challenging to conclude that the number of PAVs is a significant variable since households with 2 PAVs and 3 PAVs show no significant difference in computational time. On the other hand, runtime increases consistently as the number of activities increases, where the only exception is that the runtime is relatively short when the number of activities is 9. This result is because there is only one household with 9 activities, and the household has 3 PAVs.

Therefore, I can conclude that the number of activities is the most critical factor in terms of finding the optimal solution and the first feasible solution for the HAPP-AV-IT.

Table 4-15: Computational Time Analysis: Log-linear Regression Model Estimation Result

	Fully Optimizing Time (Households with four or fewer activities)			**First Feasible Solution Time** (All 200 households)		
Estimation Result						
	Coefficient	Std. Error	P-value	Coefficient	Std. Error	P-value
Constant	-1.79	0.744	0.018	-2.42	0.309	0.000
Base: 1 HH member						
2 HH members	0.10	0.644	0.882	0.05	0.280	0.869
3 HH members	-0.14	0.738	0.847	0.42	0.311	0.184
4 HH members	-0.20	0.819	0.806	0.51	0.335	0.130
5 HH members				0.90	0.512	0.080
6 HH members				0.30	0.587	0.609
7 HH members				1.03	0.810	0.207
Base: 1 Activity						
2 activities	1.19	0.472	0.013	0.92	0.222	0.000
3 activities	2.59	0.486	0.000	1.67	0.228	0.000
4 activities	5.66	0.473	0.000	2.37	0.220	0.000
5 activities				3.20	0.246	0.000
6 activities				4.08	0.247	0.000
7 activities				4.91	0.285	0.000
8 activities				5.74	0.360	0.000
9 activities				3.97	0.770	0.000
10 activities				7.37	0.751	0.000
Base: 0 PAVs						
1 PAV	0.35	0.823	0.667	0.56	0.335	0.097
2 PAVs	0.80	0.850	0.347	1.03	0.345	0.003
3 PAVs	1.95	0.956	0.043	1.02	0.383	0.008
4 PAVs	0.66	1.216	0.591	1.83	0.486	0.000
Model Fit						
Observations	138			200		
R-squared	0.725			0.860		
Adjusted R-squared	0.701			0.845		
Log-likelihood	-241.83			-205.77		

4.5.5 Additional Activity-travel Pattern Analysis: Deadheading and PAV Parking

I can obtain the deadheading times and distances from the sensitivity and scenario analyses. Figure 4-8a shows household-level PAV travel distances from the Case 1 sensitivity analysis. In all variations, more than 40% of PAV travel distance consists of empty-seat travel. The large portion of deadheading is because the PAVs tend to park at home to avoid parking fees. If the parking fees are free or very cheap in the downtown area, the empty PAVs might not choose to return home. However, cheaper pricing for downtown parking is likely not a wise public policy decision given the inherent value of space downtown. Instead, planners may consider area-based congestion pricing or mileage-based pricing policies to mitigate the expected congestion from AV deadheading.

Figure 4-8b shows the aggregated VKT for each mode in the Case 2 scenarios. In all scenarios, 32% of PAV travel distance is deadheading, which is smaller than in Case 1. There are several possible reasons for this. In Case 2, households have more activities to complete, which might increase carpooling and, therefore, decrease the number of empty vehicle trips back home. Also, the activity duration of some activities in Case 2 is 5 minutes, which allows PAV to wait curbside at activity locations for the household member(s) because the maximum curbside loading time is 5 minutes.

This chapter does not calculate SAV deadheading distances. According to Henao and Marshall (2019), the proportion of deadheading in TNC services is nearly 40%. If I apply the same proportion to SAVs, VKT exceeds 9,800 km in the baseline, while the VKT decreases to under 9,500 km and 8,000 km in Scenarios A and B, respectively.

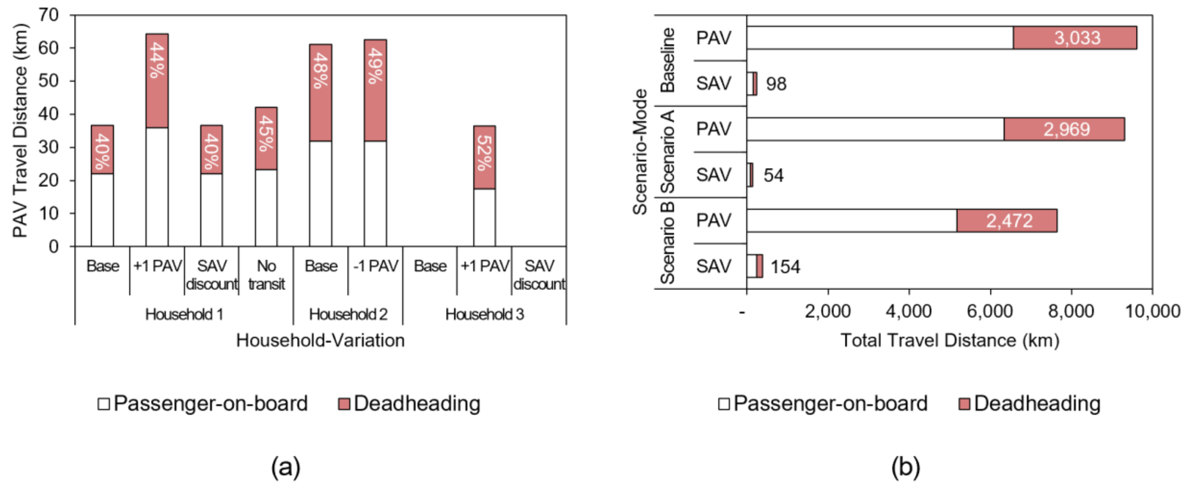


Figure 4-8: Deadheading Distance and VKT: (a) Household-level PAV Travel Distances from Case 1 Sensitivity Analysis and (b) Aggregated VKTs (PAV and SAV) from Case 2 Scenario Analysis

In the meantime, parking PAVs at home dramatically reduces occupancies in parking spaces. Figure 4-9a shows the PAV location by time of day for Case 1. Throughout all PAVs, only Household 3 has out-of-home parking, which amounted to 0.54 hours. Figure 4-9b illustrates the average PAV parking durations from the Case 2 scenarios. Even though Scenario B reduces 1 PAV for each household from Scenario A, the out-of-home PAV operating time does not exceed 2 h/day on average.

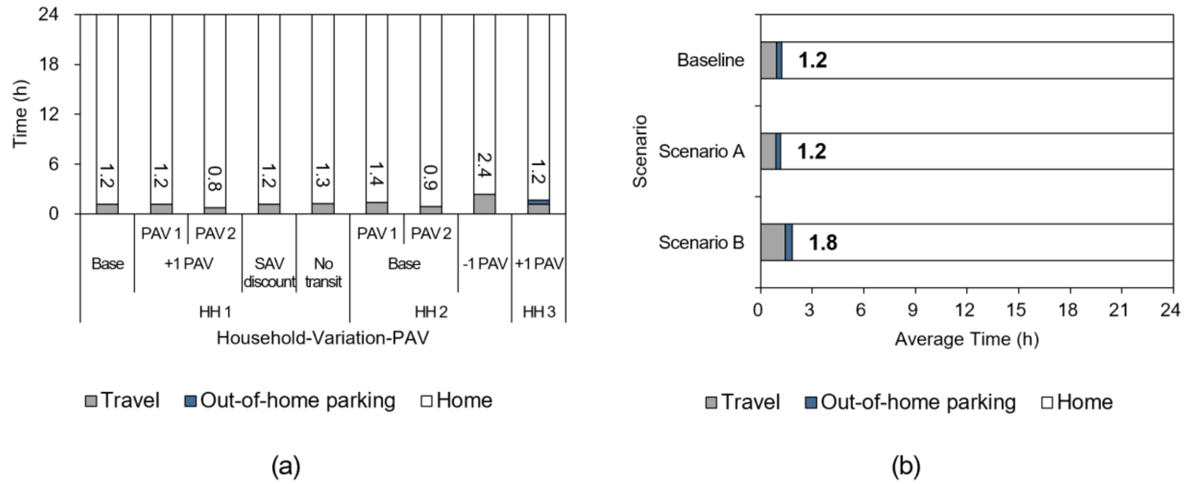


Figure 4-9: PAV Parking Duration by Location: (a) Household-level PAV Parking Durations from Case 1 Sensitivity Analysis and (b) Aggregated Parking Durations from Case 2 Scenario Analysis (HH: Household)

Note that the parking duration and travel time may vary based on regional commuting patterns, particularly travel distance. This change in commuting patterns, in turn, affects the feasibility of parking the PAV at home rather than in a nearby parking space. For instance, if a household member travels a considerable distance from home, the PAV may remain parked until the activity is complete. Nevertheless, I observe that most activity-travel choices in the case study involve parking at home to avoid parking fees, an option not available with conventional vehicles. However, PAVs can free up parking spaces in downtown areas, leading to more efficient use of urban space.

4.6 Conclusion

In this chapter, I introduce and formulate the HAPP-AV-IT. The HAPP-AV-IT models travel decisions for a household with access to AVs, consistent with household members' activity participation constraints as they complete daily activities. Only a few other studies in the literature model activity-constrained household-level travel decisions wherein the household has access to AVs (Cokyasar and Larson, 2020; Correia and van Arem, 2016; Khayati et al., 2021a, 2021b), and of these studies, none incorporate intermodal travel.

The HAPP-AV-IT jointly models the mode, route, and schedule decisions of all household members and the route and schedule decisions of all household vehicles. The model permits travel by PAV, SAV, walk-transit, PAV-transit, and SAV-transit. The incorporation of PAV-transit and SAV-transit travel represents a valuable methodological contribution, given the potential impacts of AVs on future transportation systems. I believe the HAPP-AV-IT represents the state-of-the-art in terms of capturing household-level activity-constrained travel in a future era of AVs, particularly for researchers, analysts, planners, and decision-makers interested in the potential for AVs to impact transit systems.

This chapter includes two case studies using a fictitious but detailed multimodal transportation network and synthetic household-level activity participation. The two case studies show that: (i) AVs generate excess VKT due to deadheading, particularly from AVs deadheading back home to park after dropping off a household member at an activity location, (ii) this "parking-at-home" behavior reduces the demand for downtown parking spaces, and (iii) AV-based intermodal trips can reduce both VKT and household travel costs. The first result implies that policy or infrastructure changes are necessary to mitigate VKT increases from AVs in the future. Potential policies to reduce VKT include distance-based road-user pricing and relaxing land use and zoning regulations to permit more housing and more land uses in urban areas. Potential infrastructure changes include enhancing major transit stations to more easily permit intermodal AV-transit trips and reducing space in urban areas dedicated to large, motorized vehicles. Improving transit infrastructure can further reduce household travel costs according to the third result.

The current study's limitations are similar to many other detailed activity-constrained household-level travel forecasting models (e.g., HAPP). These limitations include inflexible activity locations, reliance on hard time-window constraints, and challenges with model calibration. Another limitation of the study is that travel times are exogenous. Given the substantial changes in travel behavior and roadway usage that may occur due to AVs, link travel times are likely to change. Future research should integrate network assignment models with the HAPP-AV-IT. Lastly, the model requires more precise input data, including household activity profiles and model parameters. If the starting and ending times and the duration of activities are available, I can frame the time windows more accurately. Moreover, calibrated model parameters, such as the value of time, will provide a better reflection of real-world household travel patterns. Future research can consider integrating the model parameter calibration process into the HAPP-AV-IT model, as Chow and Recker (2012) demonstrated using inverse optimization.

In terms of future research, the HAPP-AV-IT is ideal for evaluating transit network design alternatives and policies related to parking and pricing. In particular, HAPP-AV-IT can serve to evaluate alternative designs in an algorithm that seeks to find the optimal multimodal transit network with AVs providing first-/last-mile service. Additionally, future research can improve the HAPP-AV-IT model by capturing walk-only and pooling in SAVs. Finally, in future research, I plan to compare the results from this chapter with scenarios where only non-automated vehicles exist. Similarly, I plan to model the case where a household has a mix of automated and non-automated vehicles.

Chapter 5 CONCLUDING REMARKS

5.1 Summary and Answers to Research Questions

This dissertation forecasts the future of transportation systems with the integration of household AVs. The introduction of AVs has the potential to improve traffic flow by reducing headway (Swaroop et al., 1994), decreasing accidents (Koopman and Wagner, 2017), mitigating bad driving behaviors (Talebpour and Mahmassani, 2016), and even eliminating the need for traffic signals (Zohdy et al., 2012). However, in terms of travel demand, AVs may increase VMT due to more frequent trips (Harper et al., 2016), longer trips (Ahmed et al., 2020; Auld et al., 2018; Bansal and Kockelman, 2018; Kim et al., 2020; Kolarova et al., 2019; Zhong et al., 2020), mode shifts to light-duty vehicles (Huang et al., 2020; Kröger et al., 2019), and AV deadheading/relocating. This dissertation specifically focuses on the impact of the latter, which arises from the assumption that individuals or households optimize PAV operations for their own benefit, without considering overall system performance. Such “selfish” vehicle operations include remote parking, returning home, and serving other household members. Since vehicle owners do not directly experience deadheading, each vehicle prioritizes minimizing generalized travel costs over travel time during deadheading.

Based on the motivation above, Chapter 1 outlines three research questions aimed at: (i) predicting travel behaviors and patterns with PAVs, (ii) analyzing their impact on transportation systems, and (iii) proposing effective designs and policies to leverage PAVs for mobility improvements. The following three chapters address these questions comprehensively.

PAV deadheading/relocating can significantly increase VMT. The parking assignment model in Chapter 2 shows that remote parking can increase vehicle travel distances by 1.38–1.51 miles per activity. Moreover, the household activity-travel routing and scheduling problem (HAPP-AV-IT) analyzed in Chapter 4 demonstrates that household AVs are more likely to return home for free parking or to serve other household members, resulting in deadheading accounting for 30–40% of total AV travel distance. Given that the deadheading proportion for TNC vehicles is nearly 40% and is known to exacerbate traffic congestion (Henao and Marshall, 2019), it is crucial for planners to develop policies aimed at reduce extra PAV travel distance.

This dissertation suggests several potential policies to reduce VMT and traffic congestion. Chapter 2 explores adjustments in parking fees and parking space capacities, which reduce extra VMT from 1.38–1.51 miles per activity to 0.11–0.35 miles per activity. Chapter 3 proposes a PAV-SAV transfer system, which shows a VMT decrease of up to 0.43% and a VHT decrease of up to 1.39% in the case study area, based on the optimal positioning of transfer stations. Chapter 4 suggests that encouraging intermodal trips can reduce both household travel costs and vehicle travel distance. The case study demonstrates that households utilizing intermodal trips can reduce vehicle travel distance by 23% and household travel costs by 5% due to the transit-based intermodal trips.

Answering the research questions forms the core contributions of this dissertation. Additionally, this dissertation advances methodological progress in travel behavior research. First, the iterative solution approaches in Chapter 2 and Chapter 3 propose robust integrated mode and route choice models that incorporate AV travel patterns. More importantly, the vehicle trip distribution step in Chapter 3 efficiently integrates stochastic PAV arrivals at transfer stations and the redistribution of travel demand from PAV trips to SAV trip legs via these stations. Researchers can apply this method to general park-and-ride or other intermodal systems, extending beyond just AVs. Chapter 4 not only proposes a multimodal AV routing problem but also incorporates intermodal trips, which previous household vehicle routing problems do not consider. Given that intermodal trips demonstrate benefits in terms of transportation system performance, the intermodal-related models presented in Chapter 3 and Chapter 4 will be valuable for future studies.

5.2 Future Research Areas

Based on the analyses in this dissertation and previous studies, I anticipate that exploring potential travel patterns in the AV era will remain a key issue in travel behavior research. However, before reaching the fully automated era, we will experience a transition stage with mixed use of PCVs and PAVs. Therefore, it is also important to consider both conventional and driverless vehicles as alternatives within households.

In an ongoing study, I extend the HAPP-AV-IT model by adding PCV options, such as PCV-as-a-driver, PCV-as-a-rider, and PCV-transit intermodal trips (park-and-ride and kiss-and-ride) to the activity-travel route and schedule choices. I implement the extended model in the San Diego area to analyze how travelers choose between PCV and PAV modes, and how these choices will alter travel patterns in the region. Figure 5-1 illustrates the routing and scheduling results for a household on both an activity-travel graph and the San Diego network. In this example, a household with two members and two PCVs undertakes six activities, utilizing drive-alone, carpooling, park-and-ride, kiss-and-ride, transit, nearby parking, and home parking all within the same day. Using this model, the research will conduct a broad scenario analysis involving households with varying demographics, numbers of activities, and vehicle ownership levels.

Additionally, to capture changes in traffic congestion and VHT, the research should incorporate traffic assignments. The new model will provide sophisticated origin-destination pairs, enabling more accurate traffic assignments. These results will demonstrate how the mixed use of PCVs and PAVs affects transportation system performance and how travelers adjust their travel mode, route, and schedule choices accordingly.

Moreover, applying dynamic traffic assignments will capture the different travel times and speeds on each activity-travel path. This dissertation excludes a possible PAV deadheading option: cruising. Cruising will heavily impact transportation system performance, especially when vehicles intentionally travel at low speeds to save their fuel and align with pickup times. Planners and researchers should analyze the effects of cruising and develop appropriate restrictions on PAV operations without destinations.

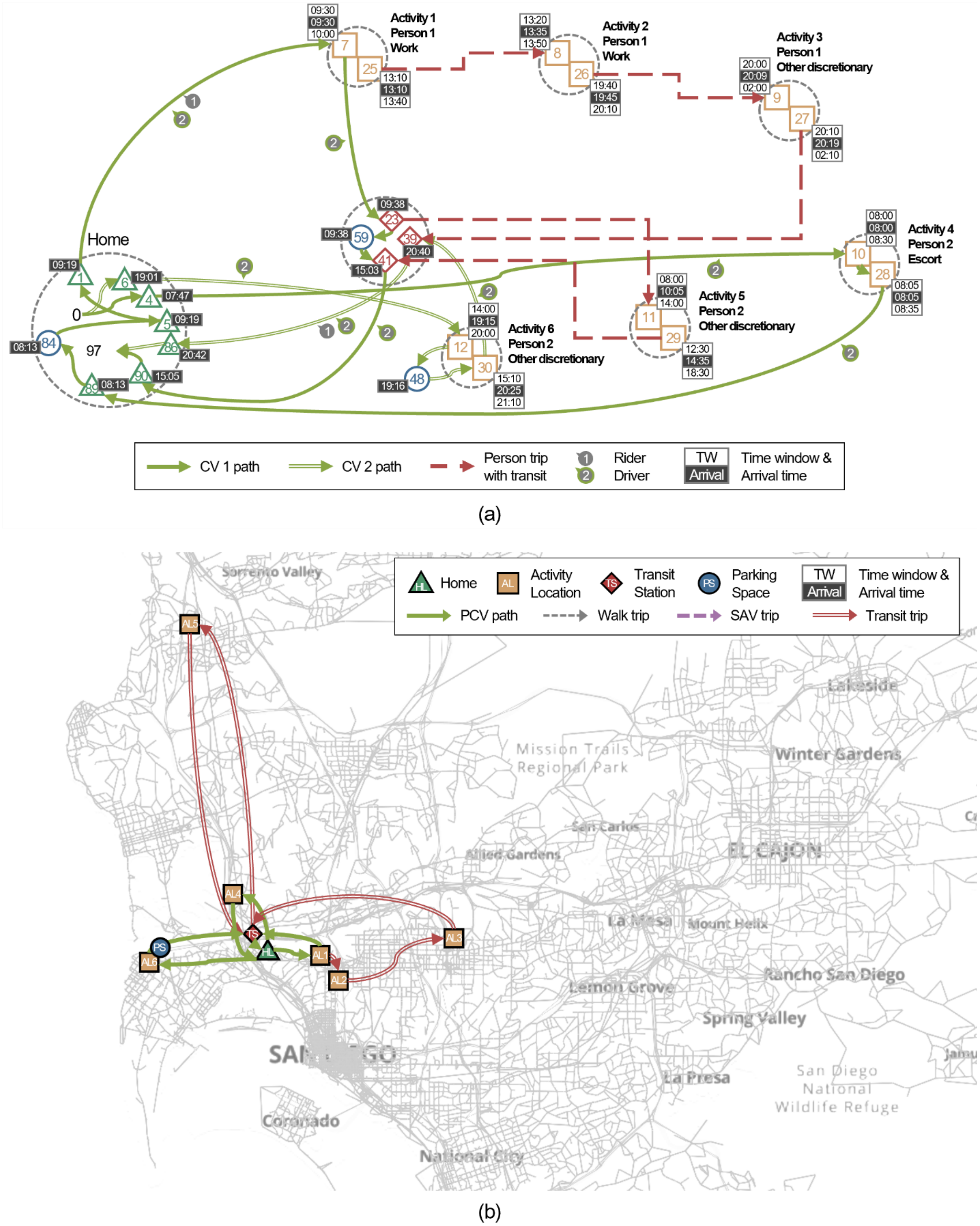


Figure 5-1: An Example of Household Activity Pattern in Ongoing Research: Tours on (a) Activity-travel Graph and (b) San Diego Network

Traffic assignments will also enable us to capture more diverse travel patterns with PAVs. Another future research topic involves the concept of dynamic mode shift, where travelers can change their mode during their trips. For example, if travelers encounter unexpected severe traffic congestion while traveling in a PAV, they could redirect the vehicle to a nearby metro station or BRT stop and transfer to a rapid transit mode. The "abandoned" vehicle would then start an unplanned deadheading trip. This behavior is already possible when a traveler is using a shared mobility vehicle (e.g., taxi or TNC) or a bus in mixed traffic. PAV travelers will also be able to choose this option since the vehicle can operate autonomously. Figure 5-2 illustrates dynamic mode shifts to rapid transit from various travel modes. However, dynamic mode shifts with PAVs could worsen traffic congestion, as the number of vehicles on the road remains unchanged while the traveler adds more load to the transit system.

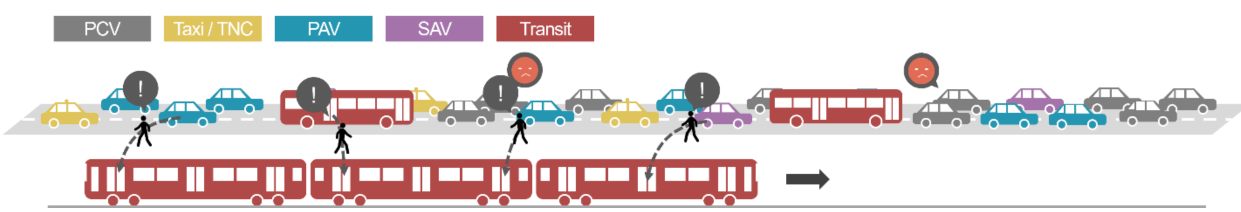


Figure 5-2: Dynamic Mode Shift

It is critical to investigate the performance of AVs on the road system. Although this dissertation does not account for efficiency improvements brought by AVs, future research should incorporate new road capacity parameters that reflect AV performance. Homogeneous vehicle movements, connected AV fleet operations, and dynamic operations are expected to significantly increase road capacities. Therefore, incorporating these factors into future studies will enable more precise forecasting and help identify equilibrium points in travel choices.

Exploring travel behavior with PAVs goes beyond macroscopic aspects. The concept of "driverlessness" will lead to dramatic changes in building and site designs, road alignments, and land use. While the results in this dissertation indicate a significant decrease in parking demand in urban cores, I anticipate that the space demand for pickup and drop-off will increase, much like the current use of TNC vehicles for individual travel. Figure 5-3 graphically compares between the current parking-and-walking system with PCVs and pickup-and-drop-off system with PAVs (and shared mobility vehicles). Designers should account for arrival and departure rates at buildings and facilities to prevent serious spillbacks onto local streets or arterials.

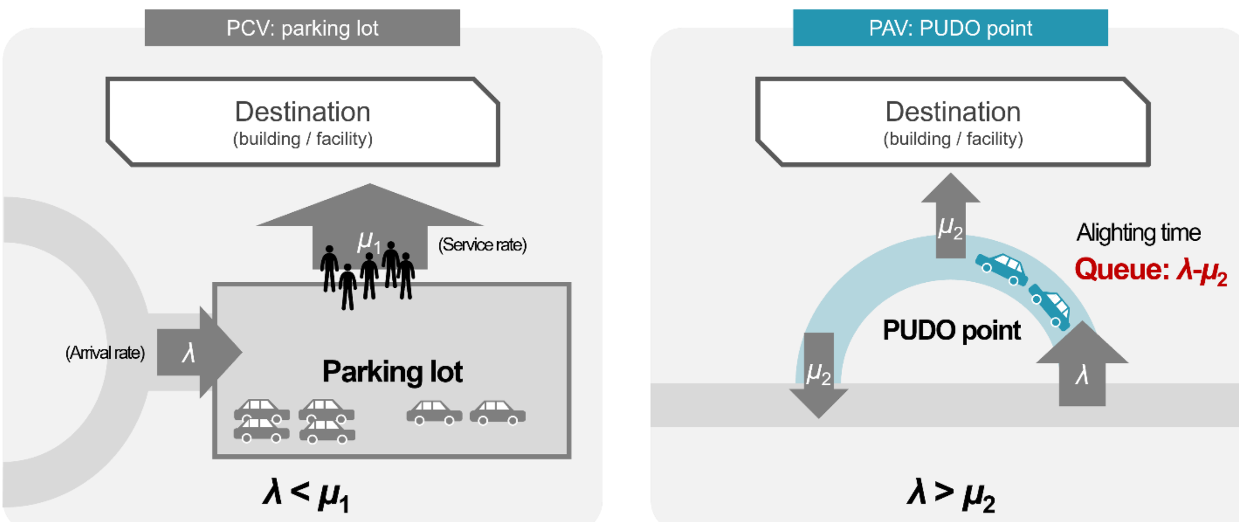


Figure 5-3: PAV Pickup and Drop-off (PUDO) Point Delay in a Facility

Additionally, PAV pickup zones require multiple slots to avoid long waiting lines. Considering the uncertainties in individuals' arrival times, vehicle-finding times, and boarding times, spillback could become a significant issue in the future (see Figure 5-4). Thus, researchers need to investigate PAV travel patterns from both microscopic traffic control and macroscopic travel demand forecasting perspectives.

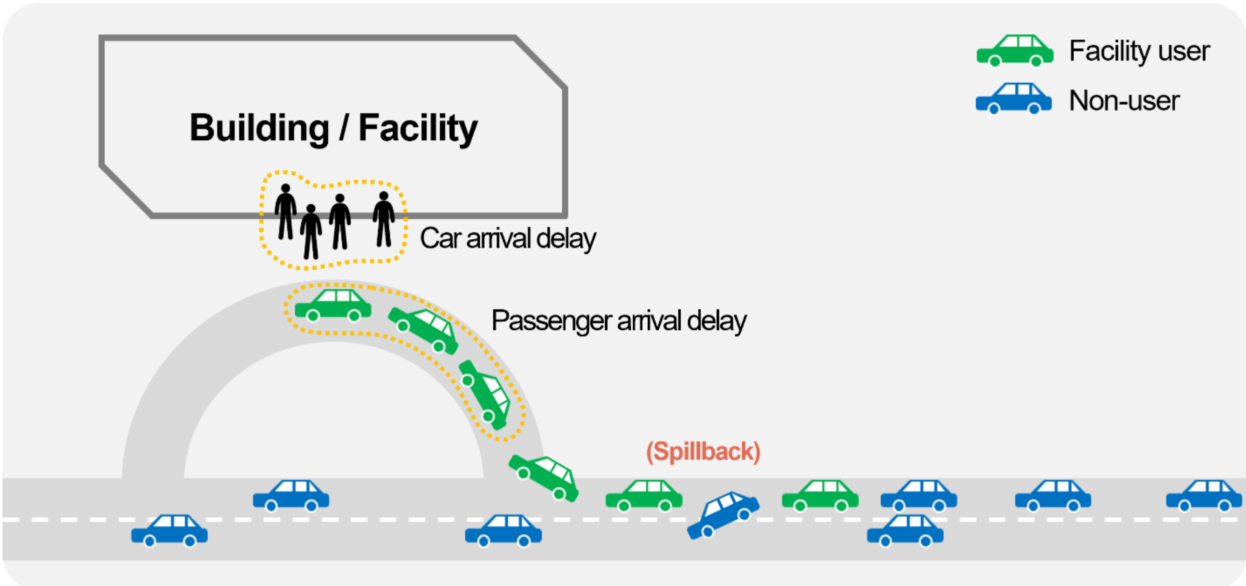


Figure 5-4: Spillbacks Due to Vehicle/Passenger Delays in a Facility

The era of AV is approaching. As a transportation planner and engineer, I am eager to continue investigating and forecasting our future travel patterns and contribute to the effective utilization of this emerging technology.

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