AMERICAN UNIVERSITY OF BEIRUT

# OPTIMIZATION-BASED CONTROL ALGORITHM: DEVELOPMENT AND TESTING FOR DYNAMIC ON-DEMAND SAV OPERATION

by
YOUMNA MOHAMAD RAMADAN SHATILA

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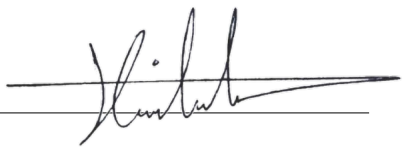

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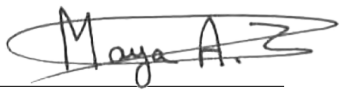

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# Abstract
# of the Thesis of

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Development and Testing for Dynamic On-Demand SAV Operation

Motivated by the growth of ride-sharing services and the technological evolution in autonomous vehicles (AV), this thesis seeks to develop and assess an operational platform for an on-demand autonomous vehicle hybrid sharing system (AVHS). The AVHS system is comprised of a fleet of AVs controlled by a Central Operation Manager (COM) that provides three levels of service to travelers ranging from a taxi-like service, to a flexible-route, flexible-schedule transit-like system. The proposed AVHS system operational platform is built as a dynamic, sequential, and time-dependent stochastic control problem whose objective is to simultaneously minimize the costs associated with the operator and the traveler. The system is developed and tested using an agent-based modeling and a simulation framework where the different agents and layers of the system interact with each other and react to the surrounding environment. The multi-layered system consists of three main components: i) the traffic network layer, ii) the vehicles fleet and the COM layer, and iii) the travelers layer. This study develops a complex dynamic optimization-based control algorithm for a dynamic on-demand shared autonomous vehicles operation and tests the system's flexibility and resilience, through a sensitivity analysis on different testing cases defined by the AV fleet size, travel demand rate, and demand composition by levels of service. The operational performance is assessed against different KPIs from both, operation and system user perspectives. The system showed its ability to entertain multiple levels of service where, to the best of the authors' knowledge, this has not been achieved before. Results showed that the developed system was able to maintain the quality of service among different levels of services by reducing the travelers' waiting time, increasing vehicle occupancy, and reducing the empty vehicles miles traveled.

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# Abbreviations

| | |
|---|---|
| AV | Autonomous Vehicles |
| SAV | Shared Autonomous Vehicles |
| DRS | Dynamic Ride-sharing |
| VMT | Vehicles Miles Traveled |
| AVHS | Autonomous Vehicle Hybrid Sharing System |
| COM | Central Operation Manager |
| SAMS | Shared-use AV Mobility Service |
| AVSR | Autonomous Vehicle Sharing and Reservation |
| SAEV | Shared Autonomous Electric Vehicles |

# Chapter 1

# Introduction

The increase in travel demand in urban areas is imposing new challenges facing urban transportation networks. While the opportunities to increase roadway capacities are limited, shifting to emerging transportation modes is a promising approach. The technological evolution in Autonomous Vehicles (AV) will upend traditional transportation systems, introduce unprecedented transportation modes, and change the current nature of transportation systems. Shared Autonomous Vehicles (SAVs) are a potential candidate as an emerging public transportation alternative. Besides, SAVs are envisioned to provide low-cost, more efficient, and safer services through eliminating the labor costs of human drivers [1]–[4], and probably reduce the need for personal autonomous vehicles ownership [5]–[7]. Dynamic Ride-sharing (DRS), which refers to sharing rides with strangers en route, holds promises to reduce the vehicles miles traveled (VMT) [8], decrease the trip cost through reducing the network's need for parking, and lead to an overall lower travel cost per-mile [9], [10]. Correspondingly, DRS is, in fact, a growing service sector that is being offered by large transportation companies [11].

Surveys conducted in urban areas showed a positive attitude toward using automated public transportation systems against using conventional ones [12]. Driverless public transportation system focuses on shifting the notion of commuting by traditional public transportation into demand-responsive SAVs [8]. SAVs are known for their adaptability to changes in the surrounding environment and their potential to reduce existing delays in the system [13]. Besides, the communication ability of SAVs, while incorporating the DRS system, allows the vehicles to reduce travel time [8], [14] congestion [11], and fuel consumption.

The concept of vehicle sharing where a group of people owns a number of vehicles that are spatially distributed [15] is becoming more popular. This alternative mode provides a decent level of comfort in comparison to private vehicles as well as reduces vehicle ownership significantly. However, the major disadvantage of this service is the unavailability of a nearby vehicle resulting in a long waiting time or long walking distance [7]. These issues can be addressed by adopting AV where travel requests can be made for relatively far vehicles to reduce the walking distance to available vehicles. Further, AVs have the ability to relocate upon the traveler's request. Further, [16] showed that SAVs can replace around eleven conventional vehicles. However, that

is associated with an increase in the VMT by 10% in comparison to non-SAV trips. Furthermore, the research utilized relocation strategies for unoccupied SAVs to meet potential future demands and decrease the VMT [8].

## 1.1 Motivation

The urban transit systems adapt to the strong temporal variations in passenger demand through the peak/off-peak based schedule [17]. However, that is usually accompanied by either longer waiting times or a waste of energy. The high demand rate during peak hours may result in waiting for multiple vehicles before boarding to destination [18] regardless of the efforts for improving the service quality through the aforementioned method. On the other hand, during off-peak hours, the occupancy of the vehicles is relatively low resulting in a significant waste of energy [19].

The aforementioned challenges are aggravated in low-density communities. Accordingly, transit companies envision the disappearance of conventional fixed-route, fixed-schedule transit services in most low-density communities and being substituted by new hybrid forms of transportation modes [2] motivated by the strong desire of the millennials for environmental sustainability [20] and dependence on mobile information technology. Thus, this research considers different levels of non-shared and shared AV services that guarantee a high-quality experience for the onboard passenger.

This study proposes a real-time operation of an autonomous vehicle-sharing system. The proposed Autonomous Vehicle Hybrid Sharing System (AVHS) is a hybrid system that combines the concepts of autonomous vehicles, dynamic ride-sharing, and public transit-like operations. In this system, travelers can request a service with a defined origin and destination, the request will be forwarded to the Central Operation Manager (COM) to assign an AV based on the existing AVs in the network, their location, capacity, and routes. The AVHS can be characterized as follows:

1. A fleet of AVs is distributed to be shared by different users over the road network
2. Traveler requests are made dynamically with defined pickup and drop-off locations
3. Each traveler request will be served with an overriding goal of maximizing the operator's profitability while constraining the traveler's waiting time
4. The system provides soft guarantees for waiting and travel times through a preset reward system
5. The system also offers three levels of service as follows:
    - No ride-share door-to-door service: A taxi-like system where requests utilize a full vehicle regardless of the number of passengers. Travelers

are served from their desired pickup location to their desired drop-off location.

- Ride-share door-to-door service: A ride-sharing system where travelers can share a vehicle with other passengers. Travelers are served from their desired pickup location to their desired drop-off location.
- Clustered ride-share service: A shuttle transit-like service where travelers are allocated to a virtual pickup location and drop-off location that lies within a certain distance from the traveler's desired origin and destination location.

## 1.2 Background

Several studies were conducted to assess the impact of SAV systems as an alternative transportation mode. The work in [8] studied the integration of SAVs and DRS using the Golden Section Search Optimization procedure assuming functional concavity. The study showed that the integration of both systems may increase the traveler's VMT due to vehicle rerouting. On the other hand, results showed that the DRS system reduces the travel cost for the system users. The authors in [11] studied the benefits associated with ride-sharing in SAV in the city of Austin, TX. The research used MATSim, an agent-based simulation tool, to simulate the travel patterns to analyze the fleet size, pricing, and fare level impacts on SAV. The results showed that a fleet size of one vehicle per 25 people can serve about 30% of the daily made trips.

On the other hand, [21] evaluated three taxi-dispatching strategies. The first strategy assigned travelers on a first come first served basis to the nearest idle vehicle; the other strategies included the idle vehicles and the en-route drop-off vehicles in the assignment. On the other hand, a dynamic taxi dispatch framework was developed for taxi dispatch [22]. Further efforts took place to define, model, and compare different vehicle assignment strategies for shared-use AV mobility service (SAMS) with no shared rides [23]. While the study did not allow travelers to be reassigned to another vehicle, the study defined the problem as a sequential, dynamic, and time-dependent stochastic control problem. The findings showed that the spatial distribution of traveler requests has a significant impact on the zero-occupancy VMT (referred to as empty VMT), where clustered demands result in a less empty VMT in comparison to uniformly distributed demands.

An SAV public transportation system that supports point-to-point services was proposed [24] where the authors focused on scheduling and admission control strategies of an AV-based public transportation system. The research formulated the scheduling problem as a mixed-integer linear program and the admission control as a bi-level optimization algorithm. Furthermore, a no-ride-share personal rapid transit (PRT) system that utilizes driver-less vehicles was designed [25] where the system requires predefined pickup and drop-off locations, as well as, a network of fixed guide-ways. Moreover, [7] explored an autonomous vehicle sharing and reservation (AVSR) system where the system optimizes AV pickup and delivery schedules

based on advanced travel requests. The study proposed a linear programming model to solve the AV trip chains and required fleet size over the AVSR network. The system showed that AVSR can significantly reduce vehicle ownership and increase the use rate. However, others evaluated the factors that might impact the implementation of Shared Autonomous Electric Vehicles (SAEV) using MATSim [26]. The findings showed that charging time and charging range significantly influence the service's operational performance due to its ability to accommodate greater traveling demands. Moreover, [27] developed a shared autonomous vehicle reservation system, where the reservation requests are divided into short-term and long-term requests. The developed system utilized an integer linear programming model and showed that allowing ride-sharing can significantly decrease the operating cost of the system. Additionally, [28] designed a flexible ride-sharing system that reduces congestion by allowing users to walk short distances to and from pick-up/drop-off points for increased efficiency. The adopted design approach significantly reduced traveler request rejections and travel time, especially for users in high-demand areas, with greater benefits as trip requests increase.

Table 1.1 provides a summary of the related literature review and the difference with the work conducted in this research. The literature review confirms that most of the analysis criteria have been addressed individually by different papers. For example, the research done by [23] allows for traveler reassignment and scheduling however the system does not include ride-sharing. Furthermore, [8] developed a ride-sharing that allows traveler scheduling but does not support flexible pick-ups and drop-offs for travelers. Additionally, none of the research papers integrated different services into a single system and this is the gap we intend to bridge in our proposed research. Moreover, we intend to develop more efficient algorithms for traveler assignment, ride-sharing, and flexible traveler pickups and drop-offs.

| Authors | Demand | Traveler Re-assignment | Traveler Scheduling | Ride-sharing | Flexible Pickup& Drop-off | Integrated Services | Assignment Strategy |
|---|---|---|---|---|---|---|---|
| Ma, Li, Zhou, *et al.* [7] | Reservation | ✗ | ✗ | ✗ | ✗ | ✗ | Optimization |
| Fagnant and Kockelman [8] | Real-time | ✗ | ✓ | ✓ | ✗ | ✗ | FCFS |
| Maciejewski and Nagel [21] | Real-time | ✗ | ✗ | ✗ | ✗ | ✗ | FCFS |
| Maciejewski, Bischoff, Nagel, *et al.* [22] | Real-time | ✗ | ✗ | ✗ | ✗ | ✗ | Optimization |
| Hyland and Mahmassani [23] | Real-time | ✓ | ✓ | ✗ | ✗ | ✗ | Optimization |
| Yang, Cui, Ma, *et al.* [27] | Reservation | ✗ | ✗ | ✓ | ✗ | ✗ | Optimization |
| Fielbaum, Bai, and Alonso-Mora [28] | Real-time | ✗ | ✗ | ✗ | ✓ | ✗ | Optimization |
| **Proposed Research** | Real-time | ✓ | ✓ | ✓ | ✓ | ✓ | Optimization |

Table 1.1: Summary of literature.

This research seeks to develop and evaluate an operational platform for an on-demand dynamic autonomous ride-sharing transportation system by tackling an emerging concept of urban mobility. Unlike previous studies, the proposed system incorporates the progress in information and communication technology and autonomous shuttle data analytics through a collaborative coordinated optimization technique. This research will evaluate the on-demand shared rides as a sequential, dynamic, and time-dependent stochastic problem. The proposed dynamic ride-sharing system proposes a dynamic programming vehicle assignment algorithm that targets minimizing the vehicle miles traveled (VMT) of the SAVs and the travel time of the passengers. The system is assumed to be operating in a congested urban network during a peak demand period.

The research evaluates the operational performance of the proposed system in terms of traveler waiting time, traveler and operator cost, vehicle occupancy, empty vehicle miles traveled, fleet utilization, and percentage of rerouted vehicles. The aforementioned metrics are evaluated for different demand levels, fleet size, and percentage of ride-shared requests.

# Chapter 2

# Methodology

This chapter details the methodology adopted to solve the AVHS problem. In Section 2.1, the AVHS problem statement is defined. Then, in Section 2.2, the mathematical problem is formulated and the system cost components are identified. Finally, section 2.3, the three levels of service offered by the AVHS system are defined along with their respective characteristics.

## 2.1 Problem Statement

The on-demand AVHS system is characterized by a fleet of AVs $V = \{1, 2, \ldots, |V|\}$ serving travel requests $R = \{1, 2, \ldots, |R|\}$ that arrive randomly and dynamically over a time period $T = [0, |T|]$. Let $r$ denote a traveler request where $r \in R$ and $v$ denote an AV $v \in V$. The system is controlled by a Central Operator Manager (COM) that is responsible for the request management, vehicle assignment, route choice, and operations of the AVHS system. Travel requests arrive according to a Poisson process with a travel demand rate $\lambda$, which is unknown to the COM. Each traveler has an origin $i_r$ and destination $j_r$ located in a defined service area and an arrival time $t_r \in T$ that denotes the time the COM becomes aware of a request. A traveler's wait time $w_r$ denotes the elapsed time from the moment a traveler's request is made to the moment a traveler is picked up by an AV. The system offers travelers different levels of service to choose from, where the requested type of service $\alpha_r \in \{\alpha_\text{n}, \alpha_\text{s}, \alpha_\text{cs}\}$; where $\alpha_\text{n}$ denotes a no ride-share door-to-door service; $\alpha_\text{s}$ denotes to a ride-share door-to-door service, and $\alpha_\text{cs}$ or a clustered ride-share service.

At any time $t \geq t_r$, a traveler $r \in R$ has a physical location $l_r$ and a state that is expressed by one of the following mutually exclusive subsets:

$$r \in \begin{cases} R_\text{u} & \text{If a traveler has made a request but has not yet been assigned to an AV} \\ R_\text{a} & \text{If a traveler has been assigned to an AV but has not yet been picked up} \\ R_\text{er} & \text{If a traveler has been picked up by an AV and is en route to their destination} \\ R_\text{s} & \text{If a traveler has been dropped off at their destination} \end{cases}$$

such that $R = \{R_\text{u} \cup R_\text{a} \cup R_\text{er} \cup R_\text{s}\}$. Similarly, at any time $t \geq 0$ an AV $v \in V$ has a physical location $l_v$ and a state that is expressed by one of the following mutually

exclusive subsets:

$$v \in \begin{cases} V_{\mathrm{p}} & \text{If an AV is en-route to pick up a traveler} \\ V_{\mathrm{d}} & \text{If an AV is en-route to drop off a traveler} \\ V_{\mathrm{idle}} & \text{If an AV is idle} \end{cases}$$

such that $V = \{V_{\mathrm{p}} \cup V_{\mathrm{d}} \cup V_{\mathrm{idle}}\}$.

The COM aims to efficiently assign AVs to travelers as they arrive dynamically and randomly to the system. According to [29], this problem is classified as a sequential stochastic optimization problem because new travelers arrive to the system dynamically and their location and arrival are unknown by the COM. Also, [29] states that the Bellman Equation (2.1) is a solution approach to sequential optimization problems where it has been used as a solution for a vehicle assignment problem [23]. The Bellman Equation is expressed as follows:

$$\min_{x_t}\{C(S_t, x_t) + \sum_{s' \epsilon S} P(S_{t+1} = s' | S_t, x_t) V_{t+1}(s')\}. \tag{2.1}$$

However, [23] explained that since the system has no information about the spatial-temporal distribution of the travel requests, it only considers the information that is known exactly at each time step. For this reason, the term $P(S_{t+1} = s'|S_t, x_t)$ in (2.1) is unknown. Hence, to handle the dynamic aspect of the problem, the COM repeatedly re-solves a local optimization problem $\min_{xt} C(S_t, x_t)$ as new information enters the system.

## 2.2 AV-Traveler Assignment Problem Formulation

This section presents a mathematical formulation of the static local optimization problem $\min_{xt} C(S_t, x_t)$, referred to as the AV-Traveler assignment problem. Consider the optimization problem:

$$\min_{x_{v,r}} \sum_{v \in V'} \sum_{r \in R'} (c_{v,r} + c_r) x_{v,r}, \tag{2.2}$$

where $c_{v,r}$ is the vehicle operation cost incurred by the operator for AV $v$ and traveler $r$; $c_r$ is the trip cost charged to traveler $r$; and $R' \subseteq R$ and $V' \subseteq V$ are the sets of travelers and AVs considered in the assignment problem respectively. The decision variable of (2.2) is $x_{v,r}$ such that it is equal to 1 if AV $v$ is assigned to traveler $r$ and 0 otherwise. The objective function is defined such that the solution to the optimization problem minimizes the costs incurred by both, the operator and the traveler. The optimization problem is subject to a set of linear constraints that define its feasibility set, which will be detailed in the following sections.

The operator cost $c_{v,r}$ is the sum of the AV dispatch cost $c_{\mathrm{d},v}$, the AV parking cost $c_{\mathrm{p},v}$, the traveler pick-up cost $c_{\mathrm{k},v,r}$, and the traveler elapsed wait time cost $c_{\mathrm{w},r}$ such that

$$c_{v,r} = c_{\mathrm{d},v} + c_{\mathrm{p},v} + c_{\mathrm{k},v,r} + c_{\mathrm{w},r}. \tag{2.3}$$

The main factors of the operator cost are defined as follows:

- $c_{\mathrm{d},v}$ is the cost of dispatching AV $v$ from the depot station. By adding $c_{\mathrm{d},v}$ to the cost function of (2.3), COM will avoid dispatching new AVs from the depot station and will utilize AVs that are already in the network. In addition, $c_{\mathrm{d},v}$ inherently accounts for maintenance costs.

- $c_{\mathrm{p},v}$ is the parking cost of the idle AV $v \in V_{\mathrm{idle}}$ in the network. The $c_{\mathrm{p},v}$ is a function of the idle time spent by AV $v$ in the network and the parking price that is assumed to be a constant rate.

- $c_{\mathrm{k},v,r}$ is the cost incurred by AV $v$ as it travels to pick-up traveler $r$. $c_{\mathrm{k},v,r}$ is a function of the pick-up distance between the current location of the AV $l_v$ and the origin of the traveler $i_r$ and the AV travel distance price per kilometer.

- $c_{\mathrm{w},r}$ is a penalty applied to the operator if a traveler's elapsed wait time exceeds a threshold $\omega$ (i.e., the operator is penalized for each extra minute of wait time exceeding $\omega$). By adding $c_{\mathrm{w},r}$, the COM prioritizes assigning AVs to travelers who have been waiting a long time. The penalty imposed on the operator, denoted as 'cw,r,' serves as a reward for the traveler, as it translates into a reduction in the traveler's trip fare, effectively compensating them for their extended wait time beyond the threshold $\omega$.

The trip cost $c_r$ charged to a traveler $r$ of origin $i_r$ and destination $j_r$ is the sum of the trip base fare cost $c_{\mathrm{tb},r}$, the trip travel distance cost $c_{\mathrm{td},r}$, and the trip travel time cost $c_{\mathrm{tt},r}$ such that

$$c_r = c_{\mathrm{tb},r} + c_{\mathrm{td},r} + c_{\mathrm{tt},r}. \tag{2.4}$$

The components of the trip cost are defined as follows.

- The trip base fare cost is defined such that

$$c_{\mathrm{tb},r} = c_{\mathrm{b}} \times \delta_r, \quad \text{where} \quad \delta_r = \begin{cases} 1 & \text{if } \alpha_r = \alpha_{\mathrm{n}}, \\ \delta_{\mathrm{s}} & \text{if } \alpha_r = \alpha_{\mathrm{s}}, \\ \delta_{\mathrm{cs}} & \text{if } \alpha_r = \alpha_{\mathrm{cs}}. \end{cases} \tag{2.5}$$

  where $c_{\mathrm{b}}$ is a constant base fare and $\delta_r$ is a reduction factor associated to level of service $\alpha_r$. The values corresponding to $\delta_{\mathrm{s}}$ and $\delta_{\mathrm{cs}}$ will be detailed in their respective sections.

- The trip distance cost $c_{\mathrm{td},r}$ accounts for the cost of trip travel distance that is a function of the trip distance $d(i_r, j_r)$ and the trip price per kilometer.

- The trip time cost $c_{\mathrm{tt}_r}$ accounts for the cost of trip travel time that is a function of the trip duration $t(i_r, j_r)$ and the trip price per minute. The cost $c_{\mathrm{tt}_r}$ is introduced to accommodate the impact of traveling on congested links.

## 2.3 Levels of Service

In this section, the different levels of service offered by the AVHS system will be identified and detailed. The feasibility set of the problem (2.2) is altered depending on the LOS chosen by the traveler. The levels of service are **i)** No-ride-share door-to-door service, **ii)** Ride-share door-to-door service, and **iii)**Clustered ride-share service.

### 2.3.1 *No-ride-share door-to-door service*

The no-ride-share door-to-door service is a taxi-like system where travelers utilize a full vehicle by themselves and are picked up from and dropped off at their desired pickup and drop-off locations. At any time $t \geq t_r$ (i.e. a new travel request $r$ arrives to the system), the COM assigns an AV to the traveler according to one of the following cases:

- Case 1: Assign traveler $r$ to an idle AV $v \in V_{\text{Idle}}$.
- Case 2: Assign traveler $r$ to an assigned AV ($v \in V_{\text{p}}$) which is en route to pick up another traveler $r' \in R_{\text{a}}$, and reassign $r'$ to another AV. This case is referred to as "Vehicle Diversion" which contributes to reducing the empty VMT [23]. Figure 2.1 illustrates this case.

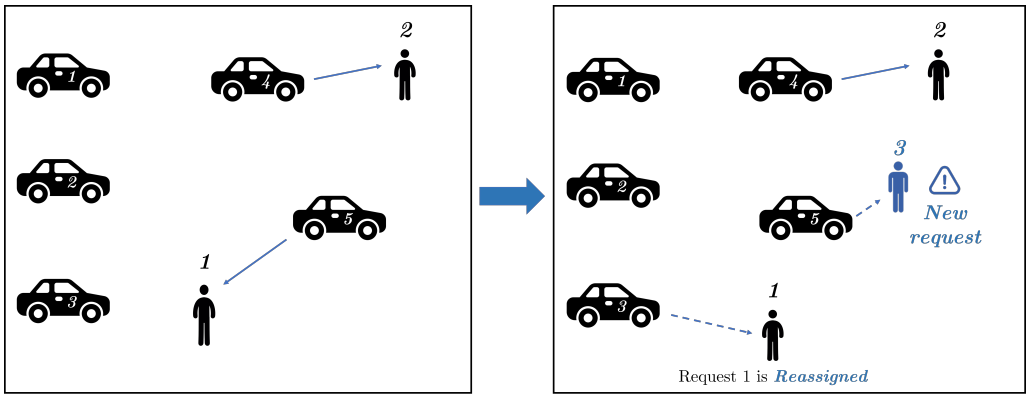



Figure 2.1: Illustration of Vehicle Diversion

- Case 3: Assign traveler $r$ to an AV ($v \in V_{\text{d}}$) which is en route to drop off another traveler $r' \in R_{\text{er}}$. This case is referred to as "two-person scheduling" which contributes to reducing empty VMT [23]. A traveler $r$ is assigned to an AV $v \in V_{\text{d}}$ can reach the origin $i_r$ faster than all the idle AVs. Figure 2.2 illustrates this case where a new request (traveler 3) is in the system where AV 1 is idle and AV 2 is dropping off traveler 1 at his destination. The COM assigns AV 2 to traveler 3 if AV 2 can reach the traveler's origin faster than AV 1.

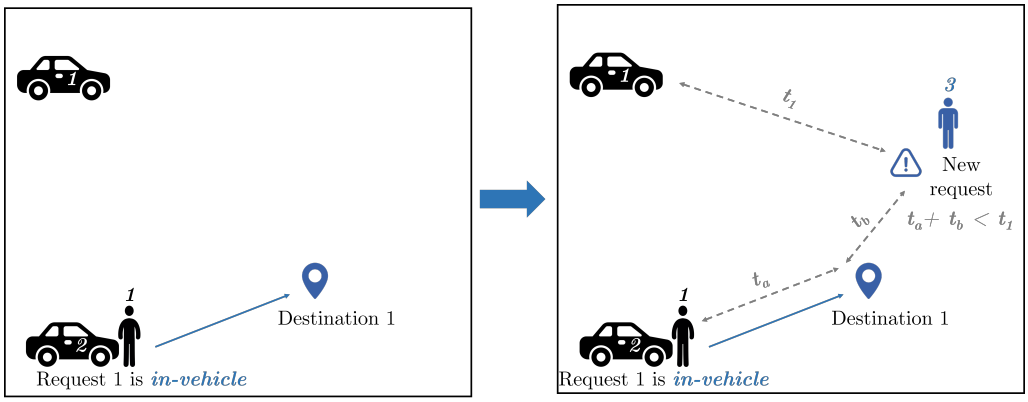



Figure 2.2: Illustration of Two-person Scheduling

The set of travelers considered in the assignment problem comprises the unassigned and assigned travelers such that $R' = \{R_\mathrm{u} \cup R_\mathrm{a}\}$. The set of AVs considered in the assignment problem comprises all the AVs (idle, en-route pickup, and en-route drop-off) such that $V' = \{V_\mathrm{idle} \cup V_\mathrm{p} \cup V_\mathrm{d}\}$. The definition of the feasibility set of Problem (2.2) depends on whether the number of travelers in the assignment $|R'|$ is less than or greater than the number of AVs $|V'|$ in the system at time $\tau \in T$.
If $|R'| \leq |V'|$ the feasibility set is defined by the following constraints:

$$\sum_{v \in V'} x_{vr} = 1 \quad \forall r \in R' \tag{2.6a}$$

$$\sum_{r \in R'} x_{vr} \leq 1 \quad \forall v \in V' \tag{2.6b}$$

Because the number of travelers is less than the number of AVs, the constraint in (2.6a) ensures that each traveler is assigned to one AV, and the constraint in (2.6b) ensures that each AV is assigned at most to one traveler.

noindent If $|R'| > |V'|$ the feasibility set is defined by the following constraints:

$$\sum_{v \in V'} x_{v,r} \leq 1 \quad \forall r \in R' \tag{2.7a}$$

$$\sum_{r \in R'} x_{v,r} = 1 \quad \forall v \in V'. \tag{2.7b}$$

In high demand scenarios, the number of travelers is greater than the number of AVs that results into not all travelers can be assigned. Hence, the constraint in (2.7a) requires that each traveler is assigned to at most one AV, and the constraint in (2.7b) requires that each AV is assigned to a traveler. Provided that the considered set of travelers in the assignment problem $R'$ includes assigned travelers $R_\mathrm{a}$, an additional set of constraints is required to prevent unwanted outcomes. To ensure that no assigned traveler becomes completely unassigned, the following equality constraint is enforced

$$\sum_{v \in V'} x_{v,r} = 1 \quad \forall \quad r \in R_\mathrm{a}. \tag{2.8}$$

To prevent travelers from being constantly reassigned to AVs, the following constraint is added to limit reassignment to once for each traveler.

$$m_r(y_{v,r} - x_{v,r}) \leq 0. \tag{2.9}$$

where

- $y_{v,r}$ is equal to 1 if AV $v \in V_{\mathrm{p}}$ is en route to pick up $r \in R_{\mathrm{a}}$ and is equal 0 otherwise, and
- $m_r$ equal to 1 if $r \in R_{\mathrm{a}}$ has been previously reassigned once and 0 otherwise.

### 2.3.2 *Ride-share door-to-door service*

The ride-share door-to-door service allows two or more independent travelers to share a single AV, provided that it doesn't cause significant inconvenience to any of the travelers. This approach aims to better utilize the AV fleet by maximizing the capacity of vehicles, as well as providing a more affordable travel option to the users. This is achieved by reducing the trip base fare and splitting the travel cost between the travelers.

As the system entertains more than one level of service, $R$ will be redefined to distinguish between the subsets of travelers with different LOS. At any time $t \geq t_r$, a traveler $r \in R$ belongs to one of the following mutually exclusive subsets:

$$r \in \begin{cases} R^{\mathrm{n}}_{\mathrm{u}}, R^{\mathrm{n}}_{\mathrm{a}}, R^{\mathrm{n}}_{\mathrm{er}} & \text{if} \quad \text{no-ride-share door-to-door service } (\alpha_r = \alpha_{\mathrm{n}}) \\ R^{\mathrm{s}}_{\mathrm{u}}, R^{\mathrm{s}}_{\mathrm{a}}, R^{\mathrm{s}}_{\mathrm{er}} & \text{if} \quad \text{ride-share door-to-door service } (\alpha_r = \alpha_{\mathrm{s}}) \\ R_{\mathrm{s}} \end{cases}$$

such that $R = \{R^{\mathrm{n}}_{\mathrm{u}} \cup R^{\mathrm{n}}_{\mathrm{a}} \cup R^{\mathrm{n}}_{\mathrm{er}} \cup R^{\mathrm{s}}_{\mathrm{u}} \cup R^{\mathrm{s}}_{\mathrm{a}} \cup R^{\mathrm{s}}_{\mathrm{er}} \cup R_{\mathrm{s}}\}$. The superscript of each subset corresponds to its associated level of service (n: no-ride-share door-to-door, s: ride-share door-to-door).

Similarly, the set of AVs $V$ is redefined to distinguish between the subsets of AVs serving travelers with different LOS. At any time $t$, an AV $v \in V$ belongs to one of the following mutually exclusive subsets:

$$v \in \begin{cases} V^{\mathrm{n}}_{\mathrm{p}}, V^{\mathrm{n}}_{\mathrm{d}} & \text{If an AV is serving a traveler with} \quad (\alpha_r = \alpha_{\mathrm{n}}) \\ V^{\mathrm{s}}_{\mathrm{p}}, V^{\mathrm{s}}_{\mathrm{d}} & \text{If an AV is serving a traveler with} \quad (\alpha_r = \alpha_{\mathrm{s}}) \\ V_{\mathrm{idle}} & \text{If an AV is idle} \end{cases}$$

such that $V = \{V^{\mathrm{n}}_{\mathrm{p}} \cup V^{\mathrm{n}}_{\mathrm{d}} \cup V^{\mathrm{s}}_{\mathrm{p}} \cup V^{\mathrm{s}}_{\mathrm{d}} \cup V_{\mathrm{idle}}\}$.

#### 2.3.2.1 Matching Algorithm

To determine whether two or more travelers can be matched together, the following *matching conditions* must be satisfied:

1. the number of travelers sharing a single AV must not exceed the vehicle's capacity.

2. the percentage increase in a traveler's trip duration must be $\leq 20$ % for all travelers sharing the same AV (total trip duration with ride-sharing vs. without ride-sharing), and

$$\frac{t^{\mathrm{s}}_{i_r j_r} - t_{i_r j_r}}{t_{i_r j_r}} \leq 20\% \quad \text{for } r \in \{R^{\mathrm{s}}_{\mathrm{u}} \cup R^{\mathrm{s}}_{\mathrm{a}} \cup R^{\mathrm{s}}_{\mathrm{er}}\},$$

Let $K$ be the number of groups of travelers sharing a single AV and define the sets $M_k$ for $k = 1, \ldots, K$ such that elements of $M_k$ correspond to the travelers belonging to the $k^{\mathrm{th}}$ group of matched travelers sharing a single AV. It should be noted that a group of matched travelers can include ones who are assigned awaiting pickup, or in-vehicle en-route to their destination. At any time $t \geq t_r$ for traveler $r \in R^{\mathrm{s}}_{\mathrm{u}}$, the COM assigns the traveler to an AV according to the methodology detailed in Figure 2.3.

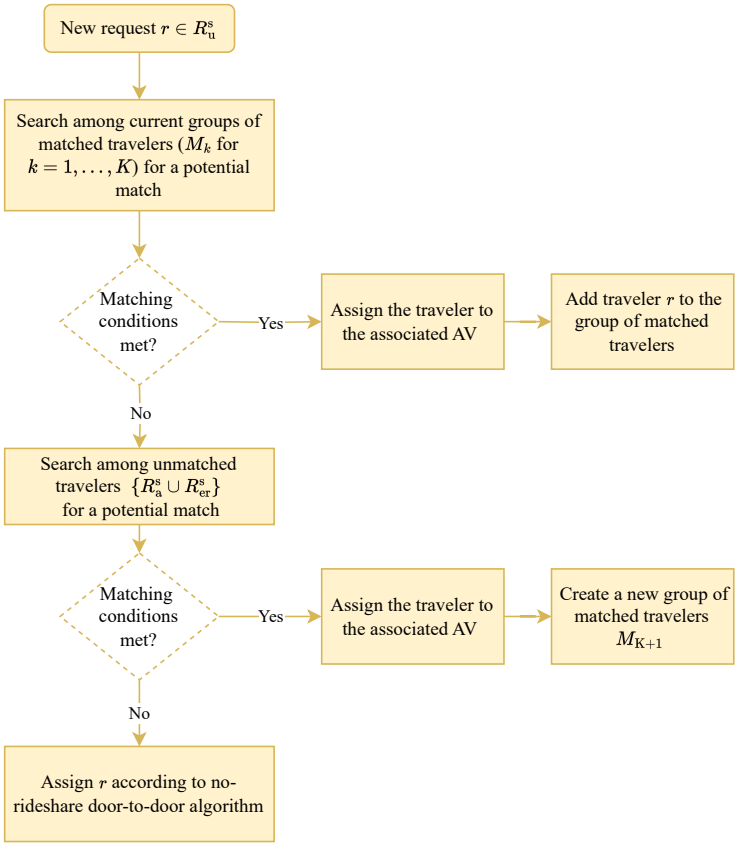



Figure 2.3: Travelers Matching Methodology

For each of the matching groups $M_k$, the COM evaluates the feasible routes to serve the travelers within the group such that the matching conditions are met. Then, the COM chooses the route that minimizes the travel time of the AV and consequently identifies the new sequence of pick-ups and drop-offs. Figure 2.4 illustrates the routing algorithm applied to two travelers requesting a ride-sharing service.

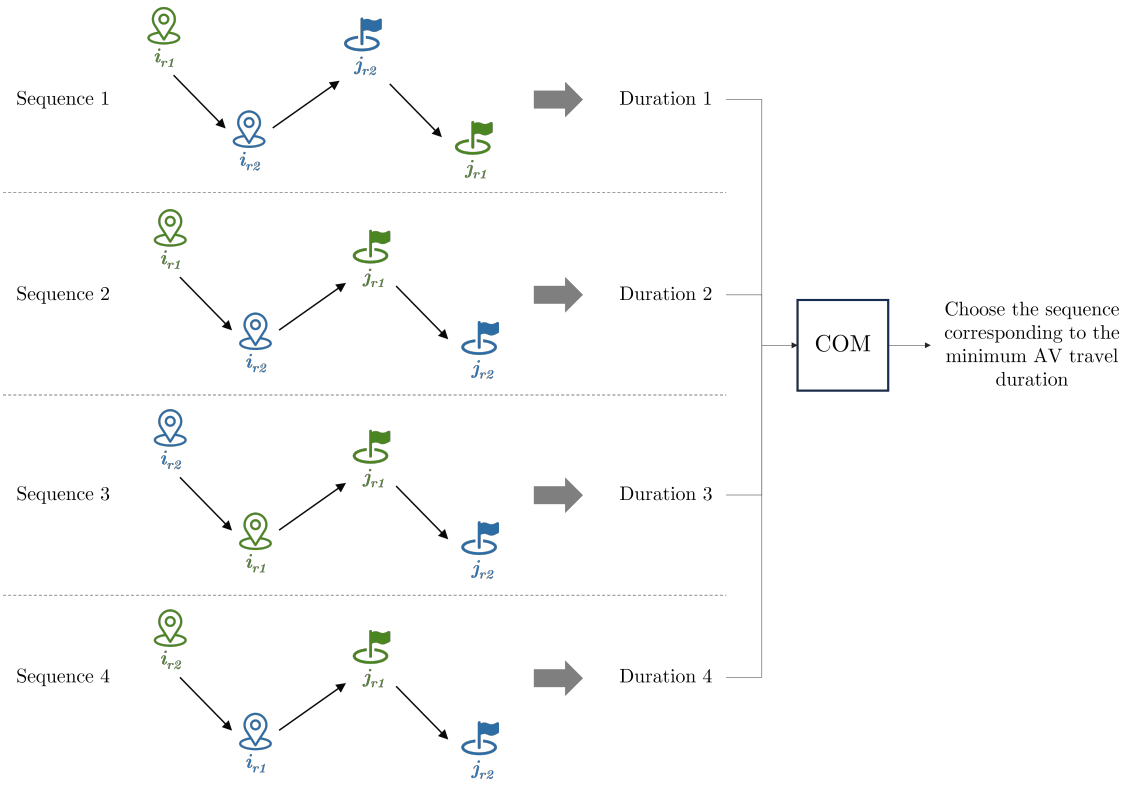



Figure 2.4: Routing algorithm illustration for two travelers

2.3.2.2 Cost Structure

As mentioned earlier, the ride-sharing service offers travelers a more affordable travel option. This is achieved by introducing a reduction factor $\delta_s$ to the trip base fare of those who choose the ride-sharing service. The reduction factor acts as an incentive to encourage travelers to use the ride-sharing service and takes into account their discomfort if an AV reroutes to pick up another traveler while sharing a single AV. Travelers benefit from the reduced base fare even if a match is not found throughout their trip.

Additionally, ride-sharing aims to make travel more affordable by splitting the trip cost among travelers sharing the same AV. The adopted pricing model for the ride-sharing service is a combination of an equal-split pricing model and a proportional-split pricing model. The equal-split pricing model divides the trip cost among the travelers sharing an AV, regardless of the distance and time traveled by each one of them throughout the trip. Despite its simplicity, this pricing model

suffers from unfair cost-sharing between travelers. For instance, it wouldn't be fair for a traveler whose trip makes up a small proportion of the route to pay equal to that of a traveler with a larger proportion. On the other hand, a proportional-split pricing model charges travelers based on their distance and time traveled on the route. In this pricing scheme, the ride-sharing option might not be appealing to travelers since they would be paying an amount similar to that of no ride-sharing, with the only incentive being the reduced base fare. On the other hand, the operator makes an additional profit because more than one traveler would pay for the shared portions of the route. The adopted pricing scheme combines elements from both the equal-split and proportional-split pricing methods. In the given scenario (as depicted in Figure 2.5), travelers $r_1$ and $r_2$ are sharing a ride, when each traveler is alone on a specific route portion, they will be charged for that corresponding portion of the route. For instance, traveler $r_1$ is charged $c_{12}$ and traveler $r_2$ is charged $c_{34}$. However, during route portions where multiple travelers are sharing the same vehicle, the fares will be equally divided among them. In this case, both traveler $r_1$ and traveler $r_2$ are charged half of the cost $c_{23}$ each. Consequently, the cost charged to traveler $r_1$ consists of the sum of $c_1$ and half the cost of $c_{23}$. Similarly, the cost charged to traveler $r_2$ comprises of the sum of $c_2$ and half the cost of $c_{23}$. This hybrid approach aims to ensure fairness and efficiency in cost distribution along the route, while keeping the operator's revenue unchanged compared to serving each traveler alone.

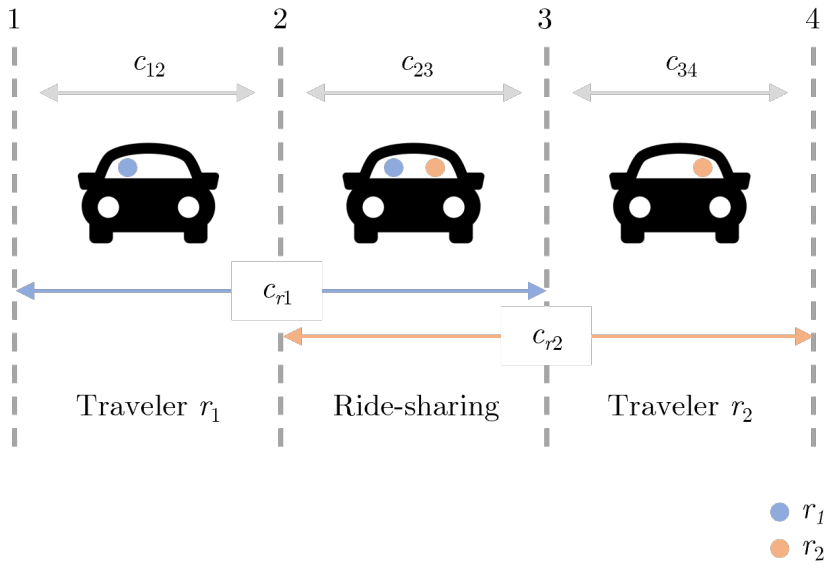



Figure 2.5: Cost-splitting illustration for two travelers

2.3.2.3 Mathematical Formulation

The ride-share door-to-door service introduces new subsets of travelers and AVs which consequently alters the feasibility set of problem (2.2). Let $V^s$ define the set of AVs serving more than one traveler at a time and let $R^s$ define the set travelers that

are sharing a ride. An AV $v \in V^{\mathrm{s}}$ is either en route to pick up travelers from their origins, en route to drop off travelers to their destinations, or both simultaneously. A traveler $r \in R^{\mathrm{s}}$ is either awaiting pick up (assigned to an AV) or en route to their destination.

Accordingly, $V' = \{V_{\mathrm{p}}^{\mathrm{n}} \cup V_{\mathrm{d}}^{\mathrm{n}} \cup V_{\mathrm{p}}^{\mathrm{s}} \cup V_{\mathrm{d}}^{\mathrm{s}} \cup V_{\mathrm{idle}}\}$ where $\{V' \cap V^{\mathrm{s}}\} = \varnothing$ . Similarly, the set of travelers $R' = \{R_{\mathrm{u}}^{\mathrm{n}} \cup R_{\mathrm{a}}^{\mathrm{n}} \cup R_{\mathrm{u}}^{\mathrm{s}} \cup R_{\mathrm{a}}^{\mathrm{s}}\}$ where $\{R' \cap R^{\mathrm{s}}\} = \varnothing$.
In addition to constraints (2.6)-(2.9) applied to $V'$ and $R'$, the following constraint are required to offer the ride-sharing service:

$$\sum_{v \in V^{\mathrm{s}}} x_{vr} = 1 \quad \forall r \in R^{\mathrm{s}}, \tag{2.10}$$

$$\sum_{r \in R^{\mathrm{s}}} x_{vr} \leq 4 \quad \forall v \in V^{\mathrm{s}}. \tag{2.11}$$

### 2.3.3 *Clustered ride-share service*

The AVHS system offers a public shuttle transit-like service, wherein travelers wait a few minutes before their trip begins and then walk a short distance to a nearby spot for pick-up and/or drop-off. This approach aims to reduce the number of stops and the VMT of AVs by grouping requests into clusters with a mutual pick-up and/or drop-off location. The clustered ride-share service provides travelers with a more affordable travel option than the door-to-door ride-share service by further reducing the trip base fare ($\delta_{\mathrm{cs}} > \delta_{\mathrm{s}}$) and splitting the travel cost between the travelers.

#### 2.3.3.1 Travelers Clustering Algorithm

Travelers cluster formation is an iterative process that recurs every clustering time period $T_{\mathrm{cs}}$ during which travel requests with $\alpha_r = \alpha_{\mathrm{cs}}$ are accumulated in $G_{\mathrm{cs}}$. At the end of the clustering time period, the COM evaluates the feasibility of clustering travelers within $G_{\mathrm{cs}}$ according to the following:

*1- Pickup Location Clustering*

For each traveler $r \in G_{\mathrm{cs}}$, the COM creates a pickup service area $A_{i_r}$ with radius $r_{\mathrm{cs}}$ and center $i_r$ (where $i_r$ is the pickup origin of each traveler). The travelers with intersecting service areas are clustered together for pickup. Let $K_{\mathrm{cs}}$ represent the number of pickup clusters formed and define the sets $P_{\mathrm{cs},k}$ for $k = 1, ..., K_{\mathrm{cs}}$ such that the elements of $P_{\mathrm{cs},k}$ correspond to travelers within the same pickup cluster. The number of travelers within each pickup cluster is a maximum of four, aligning with the capacity of utilized AVs. Then for each pickup cluster, the COM searches within the mutual service area for a mutual cluster pickup point $i_{\mathrm{cs}}$. The centroid of each cluster is obtained by minimizing the sum of squared distances between travelers' origins and their respective centroid using the Sum of Squared Errors method (SSE). Accordingly, the travelers walk from their original pickup locations to the pickup cluster centroid $i_{\mathrm{cs}}$ a distance that does not exceed the value of radius $r_{\mathrm{cs}}$.

For the travelers in $G_{\text{cs}}$ who are not clustered with others, the COM attempts to match them with travelers who have requested the door-to-door ride-share Level of Service (LOS) as depicted in Figure 2.3. If a ride-sharing match is not found, the travelers are then assigned according to the no-ride-share door-to-door algorithm.

*2- Clustering Drop-off Location*

After identifying the pickup cluster groups, the COM proceeds to check if the drop-off locations of travelers in the cluster groups can be clustered as well. For each of the pickup cluster groups formed, a drop-off service area $A_{i_j}$ is defined of radius $r_{\text{cs}}$ and center $j_r$ (where $j_r$ is the drop-off destination of each traveler). Upon obtaining the drop-off service area of travelers, the drop-off cluster process is done according to either one of three scenarios presented in figures 2.6 - 2.8.

- Scenario 1: Consider Figure 2.6 where travelers $r_1$, $r_2$, and $r_3$ are clustered for pickup. The drop-off service areas $Aj_{r1}$, $Aj_{r2}$, and $Aj_{r3}$ of all the travelers within the cluster are intersecting. The COM then searches for a cluster centroid $j_{cs}$ within the mutual service area that serves as a mutual drop-off point. The method of obtaining the drop-off cluster centroid is similar to that of the pickup cluster centroid. The travelers walk from their original drop-off destinations to the drop off cluster centroid location $j_{\text{cs}}$ a distance that does not exceed the value of radius $r_{\text{cs}}$.

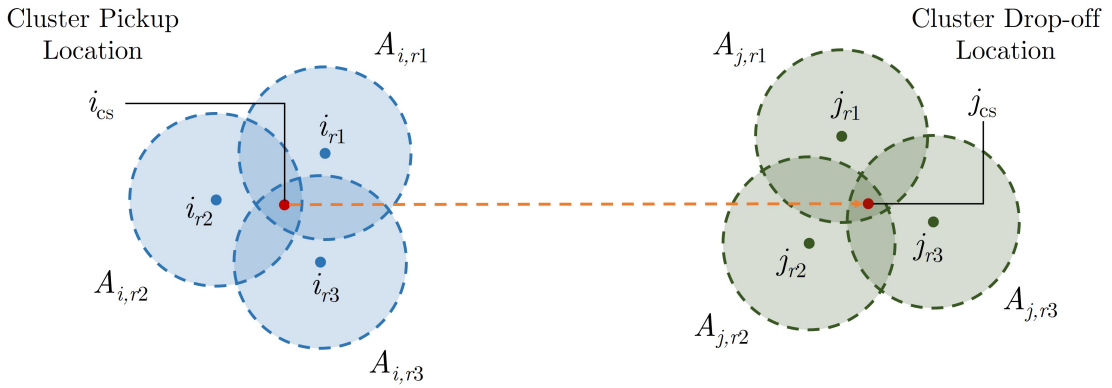



Figure 2.6: Cluster Drop-off Scenario 1

- Scenario 2: Consider Figure 2.7 where travelers $r_1$, $r_2$, and $r_3$ are clustered for pickup. Only the drop-off service areas $Aj_{r1}$ and $Aj_{r2}$ are intersecting. Accordingly, the COM searches for a cluster centroid $j_{cs}$ within the mutual area of $Aj_{r1}$ and $Aj_{r2}$ to serve as a drop-off point for travelers $r_1$ and $r_2$. Although traveler $r_3$ cannot be included in the drop-off cluster, it is possible to pick up all travelers at a mutual pickup point together and drop them off at different locations. In other words, the three travelers are picked up at $i_{cs}$ then travelers $r_1$ and $r_2$ are dropped off at $j_{cs}$ and traveler $r_3$ is dropped off at $j_{r_3}$. However, dropping off travelers at different locations might increase their

travel time if an AV reroutes to drop off other travelers. Hence, to maintain a high level of service, dropping-off travelers in different locations is permitted, only if the increase in the trip duration of all travelers does not exceed a certain threshold. If the condition is met, the COM arranges the drop-off in a sequence that minimizes the time traveled by the AV. Whereas if the condition is not met, only the requests with intersecting drop-off service areas, travelers $r_1$ and $r_2$, will be clustered together and $r_3$ is assigned according to Figure 2.3.

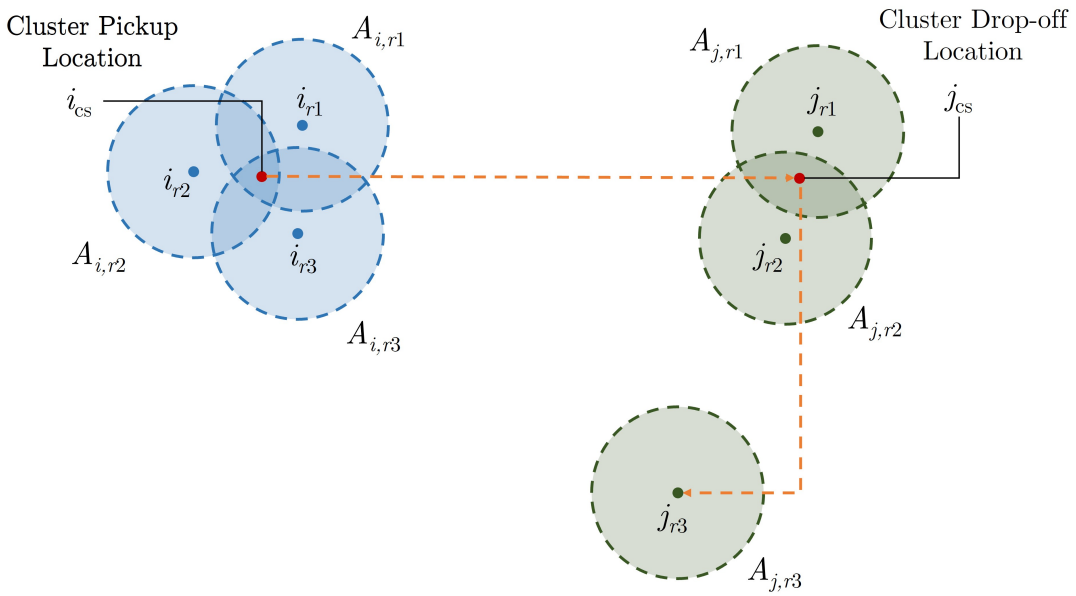



Figure 2.7: Cluster Drop-off Scenario 2

- Scenario 3: Consider Figure 2.8 where travelers $r_1$, $r_2$, and $r_3$ are clustered for pickup. None of the drop-off service areas $Aj_{r1}$, $Aj_{r2}$, and $Aj_{r3}$ are intersecting. Accordingly, the COM checks whether it is possible to cluster the travelers for pickup and drop them off separately at their destination. Similar to Scenario 2, dropping off travelers at different locations might increase their travel time if an AV reroutes to drop off other travelers. Hence, dropping-off travelers in different locations is permitted, only if the increase in the trip duration of all travelers does not exceed a certain 20%. If the condition is met, the COM arranges the drop-off in a sequence that minimizes the time traveled by the AV. If the condition is not met, the COM checks if it is feasible to drop off some of the travelers separately without violating the constraint. For example, picking up $r_1$, $r_2$, and $r_3$ from $i_{cs}$ and dropping off the three travelers at their destinations might increase the travel time beyond the allowable limit. However, picking up $r_1$ and $r_3$ from $i_{cs}$ and dropping them separately might not violate the condition and hence only travelers $r_1$ and $r_3$ are clustered together whereas traveler $r_2$ is assigned according to according to Figure 2.3.

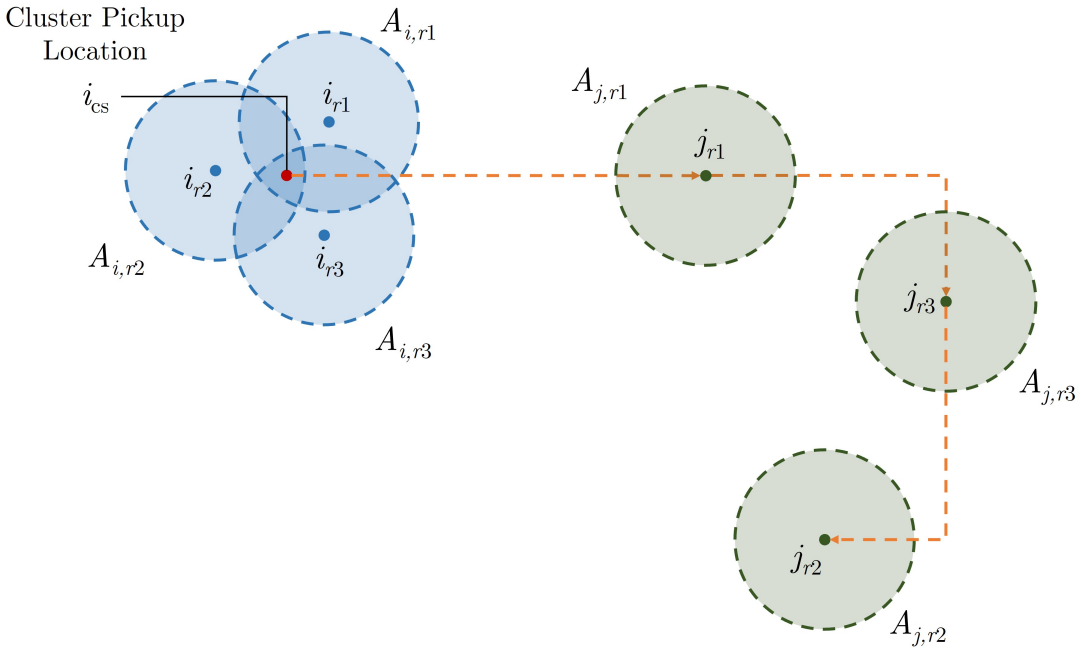



Figure 2.8: Cluster Drop-off Scenario 3

As for the pick up cluster groups that do not fall under any of the aforementioned scenarios, the travelers within these groups will no longer be considered for clustering and are assigned according to to Figure 2.3.

#### 2.3.3.2 Cost Structure

Additionally, travelers who are clustered together can split the trip cost among each other. As indicated earlier, all travelers within a cluster are picked up from a mutual location but not necessarily dropped off at a mutual location. Hence, cost-splitting among clustered travelers happens according to one of the following scenarios:

- Scenario 1: If all the travelers within a cluster are dropped off at a mutual location $j_{cs}$ (refer to Figure 2.6), the trip cost will be evenly split among them.
- Scenario 2: If some of the travelers within a cluster are dropped off at a mutual location $j_{cs}$ and some at separate destinations (refer to Figure 2.7), the cost of the route segments shared by multiple travelers will be divided equally among them. However, for the segments where the travelers are alone, they will be responsible for the corresponding route cost in addition to their share of the split cost.
- Scenario 3: If all the travelers within a cluster are dropped off at separate destinations (refer to Figure 2.8), the cost of the route will be divided among the travelers in the same manner as described in Scenario 2.

2.3.3.3 Mathematical Formulation

Now that we have another LOS introduced to the system, we will redefine $R$ to distinguish between the subsets of travelers with different LOS. At any time $t \geq t_r$, a traveler $r \in R$ belongs to one of the following mutually exclusive subsets:

$$r \in \begin{cases} R^{\mathrm{n}}_{\mathrm{u}}, R^{\mathrm{n}}_{\mathrm{a}}, R^{\mathrm{n}}_{\mathrm{er}} & \text{if} \quad \text{no-ride-share door-to-door service } (\alpha_r = \alpha_{\mathrm{n}}) \\ R^{\mathrm{s}}_{\mathrm{u}}, R^{\mathrm{s}}_{\mathrm{a}}, R^{\mathrm{s}}_{\mathrm{er}} & \text{if} \quad \text{ride-share door-to-door service } (\alpha_r = \alpha_{\mathrm{s}}) \\ R^{\mathrm{cs}}_{\mathrm{u}}, R^{\mathrm{cs}}_{\mathrm{a}}, R^{\mathrm{cs}}_{\mathrm{er}} & \text{if} \quad \text{clustered ride-share service } (\alpha_r = \alpha_{\mathrm{cs}}) \\ R_{\mathrm{s}} \end{cases}$$

such that $R = \{R^{\mathrm{n}}_{\mathrm{u}} \cup R^{\mathrm{n}}_{\mathrm{a}} \cup R^{\mathrm{n}}_{\mathrm{er}} \cup R^{\mathrm{s}}_{\mathrm{u}} \cup R^{\mathrm{s}}_{\mathrm{a}} \cup R^{\mathrm{s}}_{\mathrm{er}} \cup R^{\mathrm{cs}}_{\mathrm{u}} \cup R^{\mathrm{cs}}_{\mathrm{a}} \cup R^{\mathrm{cs}}_{\mathrm{er}} \cup R_{\mathrm{s}}\}$. The superscript of each subset corresponds to its associated level of service (n: no-ride-share door-to-door service, s: ride-share door-to-door service, cs: clustered ride-share service). Similarly, the set of AVs $V$ is redefined to distinguish between the subsets of AVs serving travelers with different LOS. At any time $t$, an AV $v \in V$ belongs to one of the following mutually exclusive subsets:

$$v \in \begin{cases} V^{\mathrm{n}}_{\mathrm{p}}, V^{\mathrm{n}}_{\mathrm{d}} & \text{If an AV is serving a traveler with} \quad (\alpha_r = \alpha_{\mathrm{n}}) \\ & \text{or non-clustered traveler with} \quad (\alpha_r = \alpha_{\mathrm{cs}}) \\ V^{\mathrm{s}}_{\mathrm{p}}, V^{\mathrm{s}}_{\mathrm{d}} & \text{If an AV is serving a traveler with} \quad (\alpha_r = \alpha_{\mathrm{cs}}) \\ & \text{or non-clustered traveler with} \quad (\alpha_r = \alpha_{\mathrm{cs}}) \\ V_{\mathrm{idle}} & \text{If an AV is idle} \end{cases}$$

such that $V = \{V^{\mathrm{n}}_{\mathrm{p}} \cup V^{\mathrm{n}}_{\mathrm{d}} \cup V^{\mathrm{s}}_{\mathrm{p}} \cup V^{\mathrm{s}}_{\mathrm{d}} \cup V_{\mathrm{idle}}\}$.

The clustered ride-share service introduces new subsets of travelers and AVs which consequently alters the feasibility set of problem (2.2).

Let $V^{\mathrm{cs}}$ define the set of AVs serving a clustered group of travelers and let $R^{\mathrm{cs}}$ define the set of travelers that are clustered together a ride. An AV $v \in V^{\mathrm{cs}}$ is either en route to pick up travelers from their origins or en route to drop off travelers to their destinations. A traveler $r \in R^{\mathrm{cs}}$ is either awaiting pickup (assigned to an AV) or en route to their destination.

Accordingly, $V' = \{V^{\mathrm{n}}_{\mathrm{p}} \cup V^{\mathrm{n}}_{\mathrm{d}} \cup V^{\mathrm{s}}_{\mathrm{p}} \cup V^{\mathrm{s}}_{\mathrm{d}} \cup V_{\mathrm{idle}}\}$ where $\{V' \cap V^{\mathrm{cs}}\} = \varnothing$ . Similarly, the set of travelers $R' = \{R^{\mathrm{n}}_{\mathrm{u}} \cup R^{\mathrm{n}}_{\mathrm{a}} \cup R^{\mathrm{s}}_{\mathrm{u}} \cup R^{\mathrm{s}}_{\mathrm{a}} \cup R^{\mathrm{cs}}_{\mathrm{u}} \cup R^{\mathrm{cs}}_{\mathrm{a}}\}$ where $\{R' \cap R^{\mathrm{cs}}\} = \varnothing$.

In addition to constraints (2.6)-(2.9) applied to $V'$ and $R'$, we require the following constraint to offer the clustered ride-sharing service:

$$\sum_{v \in V^{\mathrm{cs}}} x_{vr} = 1 \quad \forall r \in R^{\mathrm{cs}}. \tag{2.12}$$

# Chapter 3

# Agent-Based Simulation Framework

An agent-based simulation framework is developed to model the dynamic system of AVs, travelers, and the COM under the different levels of service in the system. We consider four testing cases that are defined by the demand rate and fleet size such that:

- Case 1: Demand Rate: 100 traveler/hr, fleet size: 15 AVs,
- Case 2: Demand Rate: 100 traveler/hr, fleet size: 20 AVs,
- Case 3: Demand Rate: 200 traveler/hr, fleet size: 25 AVs,
- Case 4: Demand Rate: 200 traveler/hr, fleet size: 30 AVs.

For each of the testing cases, we run the simulation over 6 different scenarios that are defined by the composition of the demand ( NS: the travelers with $\alpha_r = \alpha_{\mathrm{n}}$, RS: the travelers with $\alpha_r = \alpha_{\mathrm{s}}$, and CS: the travelers with $\alpha_r = \alpha_{\mathrm{cs}}$) such that:

- Scenario 1: NS: 100 %, RS: 0 %, CS: 0 %,
- Scenario 2: NS: 80 %, RS: 10 %, CS: 10 %,
- Scenario 3: NS: 60 %, RS: 20 %, CS: 20 %,
- Scenario 4: NS: 40 %, RS: 30 %, CS: 30 %,
- Scenario 5: NS: 20 %, RS: 40 %, CS: 40 %,
- Scenario 6: NS: 0 %, RS: 50 %, CS: 50 %.

The travelers' origins and destinations throughout the simulation, in addition to the distribution of the AVs at the start of the simulation ($t = 0$) are randomly generated. To remedy the bias stemming from accounting to one demand and fleet distribution for every case, 5 different distributions for every testing case is considered. Hence, for every case-scenario pair, we run the simulation over 5 distinct

randomly generated demand and fleet distributions (5 iterations). Figure 3.1 summarizes the simulation cases, scenarios, and iterations. The simulation is coded in MATLAB2022a. The MATLAB toolbox YALMIP is embedded in MATLAB and is used to solve the optimization problem.

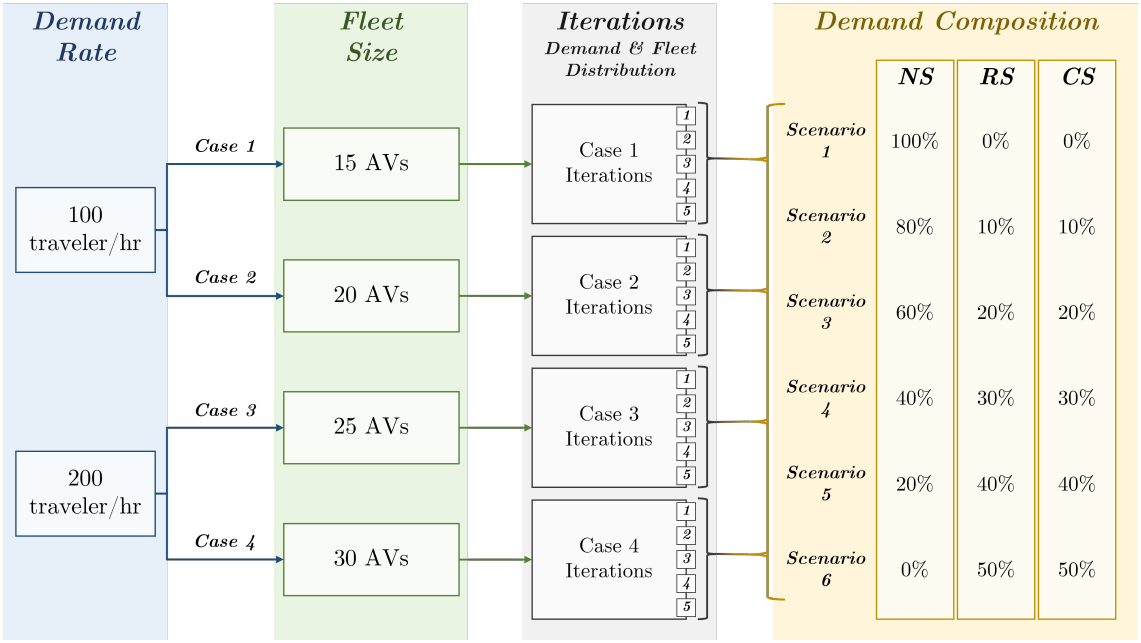



Figure 3.1: Simulation Cases

**Traffic Network:** A service area which expands over a Manhattan grid-based network. The area of the grid is 25 km$^2$ and is comprised of 781 nodes that represent pick-up locations, drop-off locations, and parking locations for AVs. Travel links (edges) are defined such that the grid can be divided into 100 blocks (with an area of 0.25 km$^2$ each) as illustrated in Figure 3.2. Therefore, each travel link has a length of 125 m.

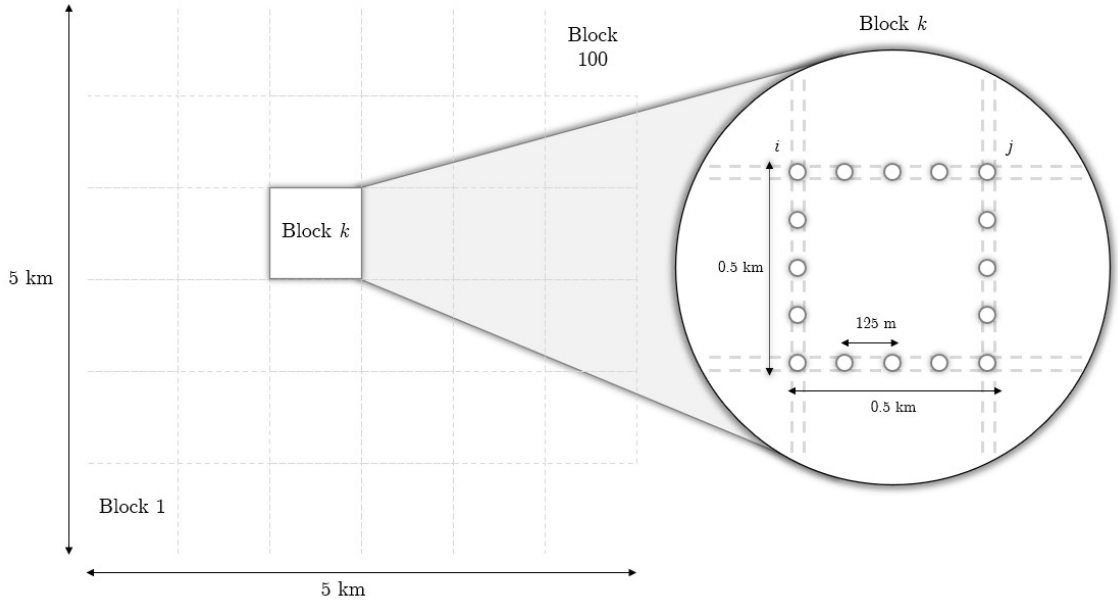



Figure 3.2: Manhattan Grid-based Network

**Analysis Period:** simulation analysis period $T$ during which the system is assumed to be operating in a congested urban network during peak demand period. Throughout the simulation, traveler requests arrive according to an arrival rate $\lambda$. Each traveler has an origin location $i_r$, a destination location $j_r$, and a requested level of service $\alpha_r$, all of which are randomly generated.
**Fleet Size:** the fleet of AVs where each AV has a passenger capacity of four. At the beginning of each analysis, it is assumed 30% of the AV fleet is located in the depot while the start location of the rest is randomly distributed over the grid-based network. The AVs travel at a constant speed on the links of the defined service area.

At every time step $\Delta T$ in $T$, the simulation runs according to the flowchart depicted in Figure 3.3.

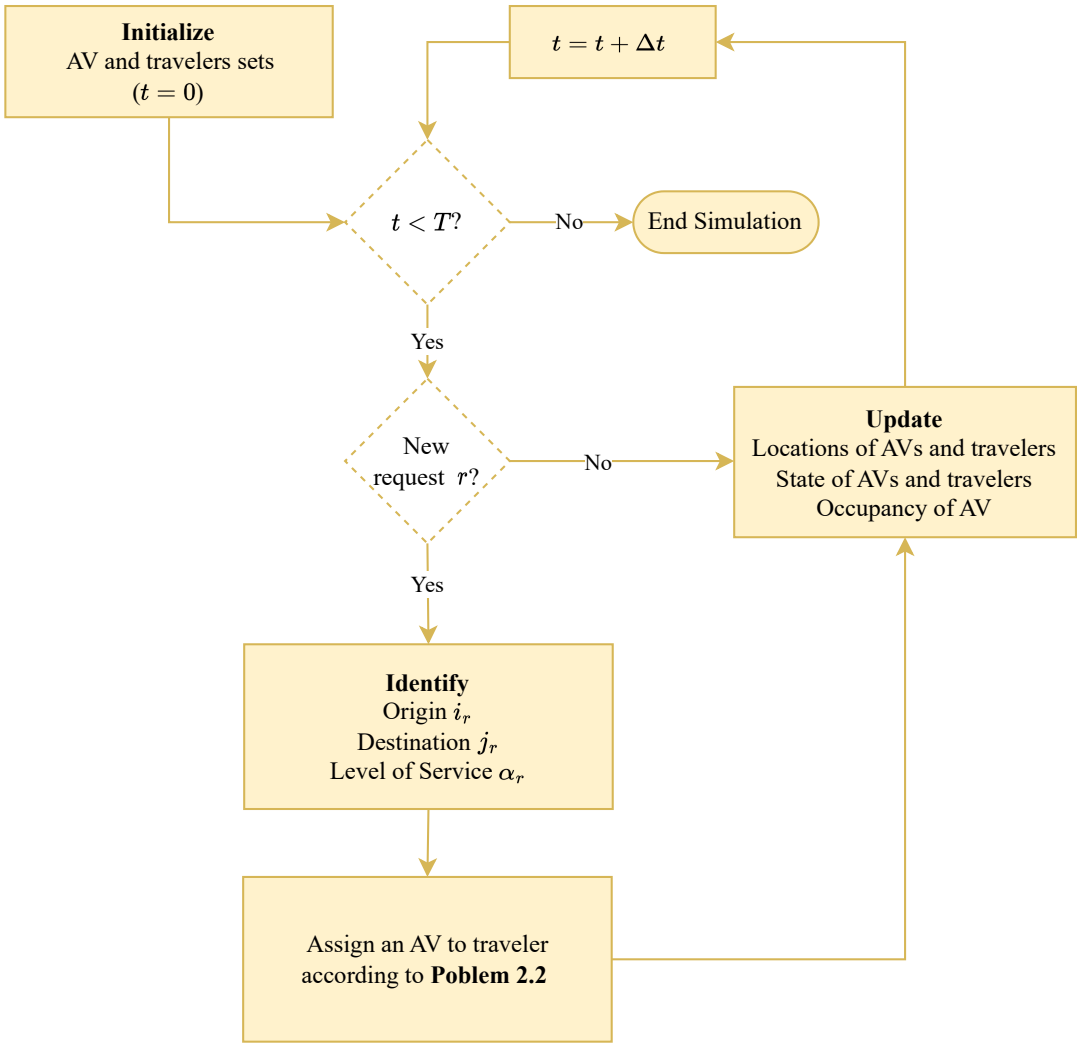



Figure 3.3: Overall Simulation Algorithm

The parameters associated with the AV-Traveler assignment problem are detailed in tables 3.1, 3.2, and 3.3. It should be noted that the trip base fare, trip price per kilometer, and trip price per minute (in Table 3.3) are adopted from Uber's fare pricing scheme [30].

Table 3.1: General simulation parameters

| **General Parameters** | **Value** | **Unit** |
|---|---|---|
| Simulation length ($T$) | 2 | hours |
| Simulation time step ($\Delta T$) | 5 | seconds |
| Service area size | 25 | $km^2$ |
| Vehicle travel speed | 45 | km/hour |
| Clustering time period ($T_{cs}$) | 10 | minutes |
| Clustering service area radius ($r_{cs}$) | 0.5 | km |
| Travel demand arrival rate | Case 1: 100<br>Case 2: 100<br>Case 3: 200<br>Case 4: 200 | traveler/hour |
| Fleet size | Case 1: 15<br>Case 2: 20<br>Case 2: 25<br>Case 4: 30 | AVs |

Table 3.2: Traveler cost parameters

| **Traveler Cost Parameters** | **Value** | **Unit** |
|---|---|---|
| Trip base fare | 4.25 | $/ride |
| Trip price per kilometer | 1.15 | $/km |
| Trip price per minute | 0.13 | $ /minute |
| RS base fare reduction factor $\gamma_{rs}$ | 0.35 | |
| CS base fare reduction factor $\gamma_{cs}$ | 0.45 | |

Table 3.3: Operator Cost Parameters

| **Operator Cost Parameters** | **Value** | **Unit** |
|---|---|---|
| AV dispatch price | 10 | $/AV |
| AV parking price | 5 | $/hour |
| AV travel distance price | 0.5 | $/km |
| Traveler wait time threshold ($\omega$) | 5 | minute |
| Traveler elapsed wait time penalty | 0.125 | $/minute |

# Chapter 4

# Simulation Results

## 4.1 Simulation Key Performance Indicators

To evaluate the efficiency of the AV-traveler assignment problem across the different LOS in the system, simulation cases of varying demand levels, fleet sizes, and demand compositions are simulated. The performance of the AVHS system is assessed according to the several key performance indicators (KPI's) that include **(1)** trip characteristics, **(2)** traveler-focused indicators, and **(3)** operator-focused indicators.

1. Trip characteristics include:
   (a) Average trip distance.
   (b) Average trip duration.
2. Traveler-focused indicators include:
   (a) Average wait time which is the elapsed time between the traveler's request initiation time and the traveler's pick-up time. The travelers' wait time is a metric that represents the customer service quality and should be evaluated in various system conditions (fleet size, travel demand, etc.).
   (b) Average traveler cost per trip.
3. Operator-focused indicators include:
   (a) Average operator cost per trip (2.3).
   (b) Empty VMT which is defined as:

$$\text{Empty VMT} := \frac{\sum_{v \in V} d_v}{\sum_{v \in V} d_{v,\text{p}}}, \tag{4.1}$$

   where for $v \in V$, $d_v$ is the total distance traveled by AV $v$ over the period $T$, and $d_{v,\text{p}}$ is the total distance traveled to pick-up travelers by AV $v$ over the period $T$. Empty VMT is a metric that represents system operational costs. A lower empty VMTs reduces traveler pickup costs, increases the life of AVs, and reduces maintenance costs.

(c) Average idle time spent by an AV during the simulation. The average AV idle time ratio is defined such that

$$\text{Avg. AV Idle Time Ratio} \coloneqq \frac{\sum_{v \in V} \left(t_{v,\text{idle}}/T\right)}{|V|}, \tag{4.2}$$

where $t_{v,\text{idle}}$ is the total idle time spent by AV $v \in V$ during the simulation period $T$. This metric provides an understanding of the AV fleet utilization and operational effectiveness. It is also a representation of the system's operational costs, as higher AV fleet idle time results in higher parking costs.

(d) AV fleet utilization rate which is the ratio of active AVs, that are the AVs that have been utilized at least once during the simulation period $T$, to the total fleet size. AV Fleet Utilization is defined by

$$\text{AV fleet utilization rate} \coloneqq \frac{|V| - |\{v \in V | v \in V_{\text{Idle}},\ \forall t \in (0,T)\}|}{|V|}. \tag{4.3}$$

A high fleet utilization rate indicates that the majority of the vehicles in the fleet are actively engaged in providing rides. Additionally, the AV idle time ratio along with the AV fleet utilization rate helps determine the optimal fleet size required.

(e) Ride-share (RS) match rate which is the ratio of travelers sharing a vehicle to the travelers who requested the ride-share LOS and is defined as

$$\text{RS Match Rate} \coloneqq \frac{|R^{\text{s}}_{\text{All}}|}{|\{r \in R | \alpha_r = \alpha_{\text{s}}\}|} \tag{4.4}$$

where $R^{\text{s}}_{\text{All}}$ is defined such that $r \in R^{\text{s}}_{\text{All}}$ if and only if $r \in R^{\text{s}}$ for any $t \in (0,T)$. The matching rate is an indicator of the effectiveness of the adopted matching algorithm. A higher matching rate means that more travelers get served in a given unit of time and that the system operates more efficiently.

(f) Clustered ride-share (CS) match rate which is the ratio of clustered travelers to the travelers who requested the clustered ride-share LOS and is defined as

$$\text{CS Match Rate} \coloneqq \frac{|R^{\text{cs}}_{\text{All}}|}{|\{r \in R | \alpha = \alpha_{\text{cs}}\}|} \tag{4.5}$$

where $R^{\text{cs}}_{\text{All}}$ is defined such that $r \in R^{\text{cs}}_{\text{All}}$ if and only if $r \in R_{\text{cs}}$ for any $t \in (0,T)$. Analogous to the RS match rate, the CS match rate is an indicator of the effectiveness of the adopted clustering algorithm.

(g) Average ride-share AV occupancy which is the average number of travelers in a single AV during a ride-sharing trip and is given by

$$\text{Avg. RS AV Occupancy} \coloneqq \frac{|R^{\text{rs}}_{\text{All}}|}{P^{\text{rs}}}, \tag{4.6}$$

where $P^{\text{rs}}$ is the total number of completed shared trips over the simulation period $T$.

(h) Average clustered ride-sharing (CS) AV occupancy which is the average number of travelers in a single AV during a clustered ride-sharing trip and is given by

$$\text{Avg. CS AV Occupancy} := \frac{|R^{\text{cs}}_{\text{All}}|}{P^{\text{cs}}}, \tag{4.7}$$

where $P^{\text{cs}}$ is the total number of completed clustered trips over the simulation period $T$.

## 4.2 Simulation Results

In this section, we test the AVHS system designed in Chapter 2 on the test system proposed in Chapter 3. Then, we evaluate the performance of the AVHS system according to the KPIs detailed in the previous section. We first start by laying out the simulation results of all simulated cases and scenarios, then we analyze each KPI and validate the expected outcomes.

The simulation results are presented below in tables 4.1 - 4.4. These results are the averages of the iterations conducted for each respective case.

Table 4.1: KPIs corresponding to Case 1 - Average of 5 Iterations

| **Case 1** \| **Demand Rate:** 100 travelers/hr — **AV Fleet Size:** 15 | | | | | | |
|---|---|---|---|---|---|---|
| **Scenarios:** | **1** | **2** | **3** | **4** | **5** | **6** |
| No-Ride-Share (%) | 100 | 80 | 60 | 40 | 20 | 0 |
| Ride-Share (%) | 0 | 10 | 20 | 30 | 40 | 50 |
| Clustered Ride-Share (%) | 0 | 10 | 20 | 30 | 40 | 50 |
| **KPIs:** | | | | | | |
| Avg. Trip Distance (km) | 4.11 | 4.11 | 4.11 | 4.12 | 4.12 | 4.12 |
| Avg. Trip Duration (min) | 5.48 | 5.48 | 5.48 | 5.49 | 5.49 | 5.49 |
| Avg. Wait Time (min) | 4.1 | 3.79 | 3.6 | 3.64 | 3.65 | 3.73 |
| Avg. Traveler Cost ($/trip) | 9.69 | 9.21 | 8.63 | 7.98 | 7.42 | 6.79 |
| Avg. Operator Cost ($/trip) | 1.25 | 1.24 | 1.19 | 1.16 | 1.09 | 1.02 |
| Empty VMT (%) | 48.74 | 45.81 | 42.33 | 40.02 | 36.73 | 32.76 |
| Avg. AV Idle Time Ratio (%) | 4.94 | 5.58 | 8.29 | 8.56 | 11.4 | 13.11 |
| AV Fleet Utilization (%) | 100 | 100 | 100 | 100 | 100 | 100 |
| RS Match Rate (%) | 0 | 21 | 38.04 | 55.64 | 60.11 | 74.77 |
| CS Match Rate (%) | 0 | 43.52 | 56 | 60.84 | 57.61 | 53.4 |
| Avg. RS AV Occupancy (%) | 25 | 41.25 | 53.03 | 51.12 | 51.65 | 53.18 |
| Avg. CS AV Occupancy (%) | 25 | 50 | 50.72 | 55.11 | 57.71 | 57.77 |

Table 4.2: KPIs corresponding to Case 2 - Average of 5 Iterations

| **Case 2** \| **Demand Rate:** 100 travelers/hr — **AV Fleet Size:** 20 | | | | | | |
|---|---|---|---|---|---|---|
| **Scenarios:** | **1** | **2** | **3** | **4** | **5** | **6** |
| No-Ride-Share (%) | 100 | 80 | 60 | 40 | 20 | 0 |
| Ride-Share (%) | 0 | 10 | 20 | 30 | 40 | 50 |
| Clustered Ride-Share (%) | 0 | 10 | 20 | 30 | 40 | 50 |
| **KPIs:** | | | | | | |
| Avg. Trip Distance (km) | 4.11 | 4.11 | 4.11 | 4.12 | 4.12 | 4.12 |
| Avg. Trip Duration (min) | 5.48 | 5.48 | 5.48 | 5.49 | 5.49 | 5.49 |
| Avg. Wait Time (min) | 3.11 | 3.11 | 3.19 | 3.37 | 3.39 | 3.6 |
| Avg. Traveler Cost ($/trip) | 9.69 | 9.2 | 8.61 | 7.99 | 7.39 | 6.79 |
| Avg. Operator Cost ($/trip) | 1.22 | 1.16 | 1.12 | 1.11 | 0.97 | 0.89 |
| Empty VMT (%) | 46.75 | 43.85 | 41.45 | 39.11 | 35.11 | 32.29 |
| Avg. AV Idle Time Ratio (%) | 27 | 26.68 | 28.39 | 29.35 | 35.31 | 36.91 |
| AV Fleet Utilization (%) | 85 | 85 | 83 | 82 | 75 | 73 |
| RS Match Rate (%) | 0 | 18 | 37.37 | 55.64 | 60.87 | 74.18 |
| CS Match Rate (%) | 0 | 45.52 | 60 | 61.51 | 58.19 | 53.4 |
| Avg. RS AV Occupancy (%) | 25 | 45 | 52.13 | 50.61 | 51.85 | 53.11 |
| Avg. CS AV Occupancy (%) | 25 | 50 | 50.72 | 55.09 | 57.91 | 57.77 |

Table 4.3: KPIs corresponding to Case 3 - Average of 5 Iterations

| **Case 3** \| **Demand Rate:** 200 travelers/hr — **AV Fleet Size:** 25 | | | | | | |
|---|---|---|---|---|---|---|
| **Scenarios:** | **1** | **2** | **3** | **4** | **5** | **6** |
| No-Ride-Share (%) | 100 | 80 | 60 | 40 | 20 | 0 |
| Ride-Share (%) | 0 | 10 | 20 | 30 | 40 | 50 |
| Clustered Ride-Share (%) | 0 | 10 | 20 | 30 | 40 | 50 |
| **KPIs:** | | | | | | |
| Avg. Trip Distance (km) | 4.17 | 4.17 | 4.17 | 4.18 | 4.18 | 4.18 |
| Avg. Trip Duration (min) | 5.56 | 5.56 | 5.56 | 5.57 | 5.57 | 5.57 |
| Avg. Wait Time (min) | 6.81 | 6.59 | 4.75 | 3.82 | 3.87 | 3.77 |
| Avg. Traveler Cost ($/trip) | 9.76 | 9.34 | 8.68 | 7.96 | 7.36 | 6.78 |
| Avg. Operator Cost ($/trip) | 1.13 | 1.15 | 1.06 | 0.98 | 0.93 | 0.87 |
| Empty VMT (%) | 41.03 | 41.45 | 38.4 | 33.96 | 30.18 | 25.21 |
| Avg. AV Idle Time Ratio (%) | 6.51 | 6.54 | 9.3 | 11.73 | 11.8 | 13.14 |
| AV Fleet Utilization (%) | 100 | 100 | 100 | 100 | 100 | 98.67 |
| RS Match Rate (%) | 0 | 52.09 | 74.52 | 72.64 | 84.22 | 89.81 |
| CS Match Rate (%) | 0 | 13.17 | 41.26 | 54.9 | 54.93 | 50.75 |
| Avg. RS AV Occupancy (%) | 25 | 53.45 | 53.9 | 53.53 | 54.76 | 54.06 |
| Avg. CS AV Occupancy (%) | 25 | 55.17 | 56.64 | 58.98 | 60.63 | 60.92 |

Table 4.4: KPIs corresponding to Case 4 - Average of 5 Iterations

| **Case 4** \| **Demand Rate:** 200 travelers/hr — **AV Fleet Size:** 30 | | | | | | |
|---|---|---|---|---|---|---|
| **Scenarios:** | **1** | **2** | **3** | **4** | **5** | **6** |
| No-Ride-Share (%) | 100 | 80 | 60 | 40 | 20 | 0 |
| Ride-Share (%) | 0 | 10 | 20 | 30 | 40 | 50 |
| Clustered Ride-Share (%) | 0 | 10 | 20 | 30 | 40 | 50 |
| **KPIs:** | | | | | | |
| Avg. Trip Distance (km) | 4.17 | 4.17 | 4.17 | 4.18 | 4.18 | 4.18 |
| Avg. Trip Duration (min) | 5.56 | 5.56 | 5.56 | 5.57 | 5.57 | 5.57 |
| Avg. Wait Time (min) | 2.98 | 2.86 | 3.01 | 3.18 | 3.38 | 3.75 |
| Avg. Traveler Cost ($/trip) | 9.73 | 9.2 | 8.57 | 7.96 | 7.49 | 6.98 |
| Avg. Operator Cost ($/trip) | 1.08 | 1.11 | 1.07 | 0.96 | 0.84 | 0.82 |
| Empty VMT (%) | 37.05 | 35.43 | 36.07 | 32.71 | 27.6 | 24.4 |
| Avg. AV Idle Time Ratio (%) | 13.95 | 15.71 | 17.52 | 17.11 | 24.19 | 22.76 |
| AV Fleet Utilization (%) | 100 | 100 | 96.67 | 96.67 | 86.67 | 90 |
| RS Match Rate (%) | 0 | 30 | 59.26 | 70.59 | 88.68 | 95.98 |
| CS Match Rate (%) | 0 | 57.5 | 66.25 | 63.87 | 52.83 | 49.5 |
| Avg. RS AV Occupancy (%) | 25 | 50 | 51 | 51.67 | 52.63 | 52.88 |
| Avg. CS AV Occupancy (%) | 25 | 52.27 | 53 | 57.58 | 60 | 59.52 |

### 4.2.1 *Average Trip Distance and Average Trip Duration*

From tables 4.1 and 4.2 , the average trip distance remains relatively stable at 4.11 km in cases 1-2 and at 4.17 in cases 3-4 . Similar to trip distance, the average trip duration remains fairly constant at 5.48 minutes in cases 1-2 and 5.56 minutes in cases 3-4. The slight difference in the values of the average trip distance and average trip duration across the scenarios within each case roots back to the clustered ride-share service.

### 4.2.2 *Average Wait Time*

The average traveler wait time for Cases 1 and 2 are shown in Figure 4.1. Although the travel demand rate is the same in both cases, the system is less stressed in case 2 due to the relatively large fleet size compared to the demand rate. As depicted in Figure 4.1, the system's performance across scenarios 2-6 is better than that in scenario 1 in terms of average traveler wait time. This suggests that the inclusion of shared rides in the system reduces the average waiting time for travelers.

Additionally, it is evident from Figure 4.1, that the system performance in terms of the average wait time declines a bit in scenarios (2-6) as compared to scenario 1. This decline in performance is accompanied by a decrease in the fleet utilization rate across the scenarios (1-6). Due to the abundance of AVs in this case, the COM

did not dispatch all AVs in the depot and utilized the ones that are already roaming in the network. The average operational cost in case 2 is lower than that of case 1, as we have fewer AVs that are subject to dispatch cost. However, this comes at a slightly higher wait time because AVs roaming in the network may be located away from the origins of the travelers. This trade-off is acceptable as the increase in the average wait time did not exceed the wait time threshold.

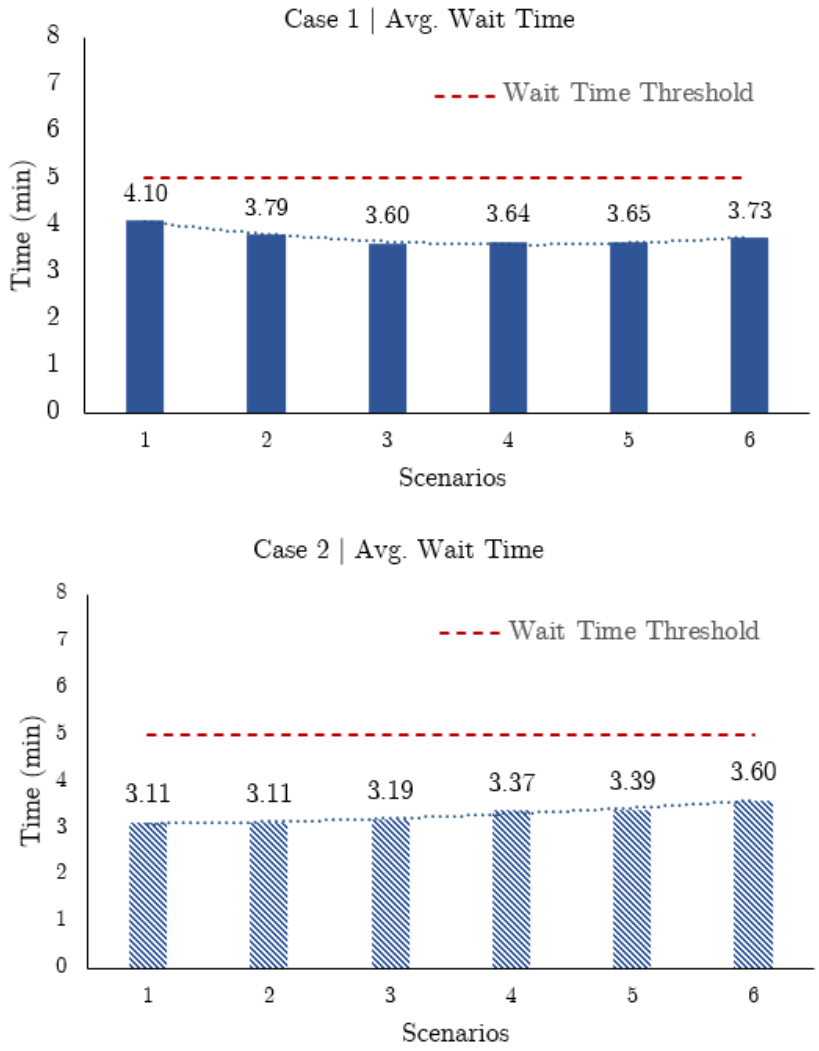



Figure 4.1: Case 1-2 — Average Traveler Wait Time

The average traveler wait time for cases 3 and 4 is depicted in Figure 4.2. In the initial scenario of case 3 (without shared rides in the system), the performance in terms of average wait time is notably inefficient, exceeding the allowable threshold. However, the system's performance improves significantly across scenarios (2-6) with the integration of ride-sharing. In the context of case 4, the system's performance closely mirrors that of case 2.

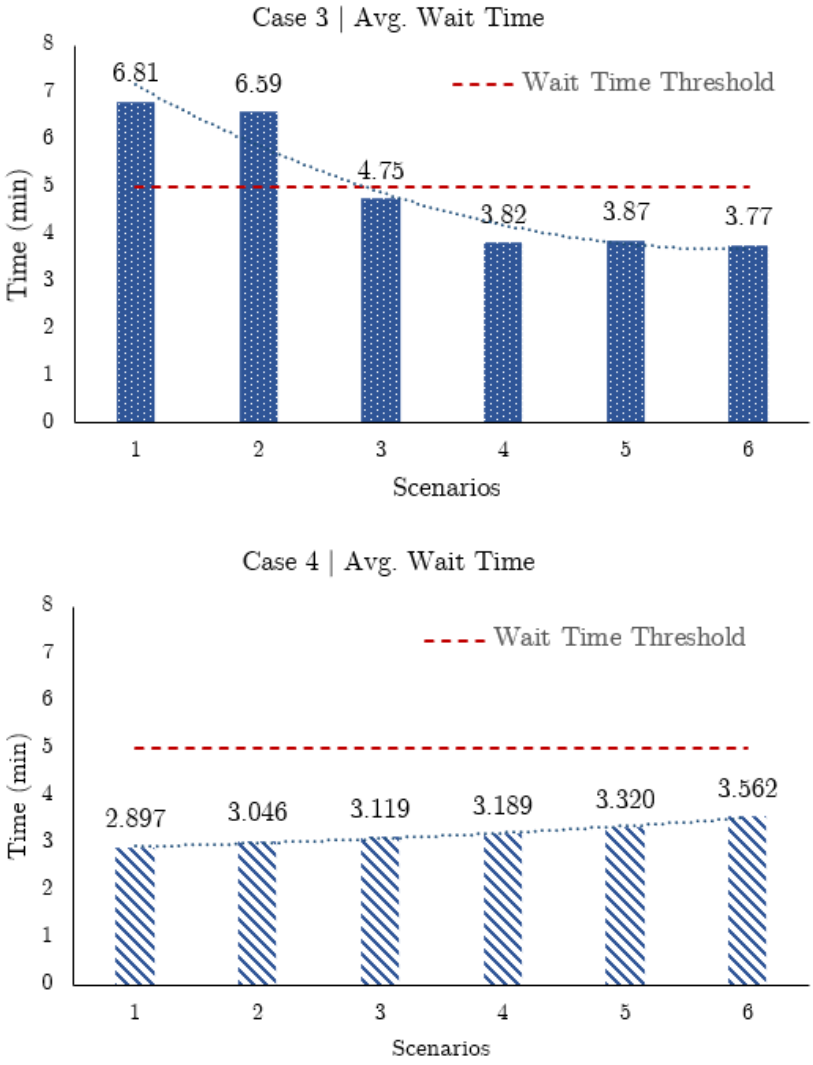



Figure 4.2: Case 3-4 — Average Wait Time

### 4.2.3 *Average Traveler Cost*

The traveler average cost per trip, as shown in Figure 4.3, has a consistent trend across the four cases. The traveler cost decreases as the ride-sharing in the system increases where this decrease in value aligns with the implemented trip base fare reduction scheme in addition to the trip cost-splitting in shared rides.

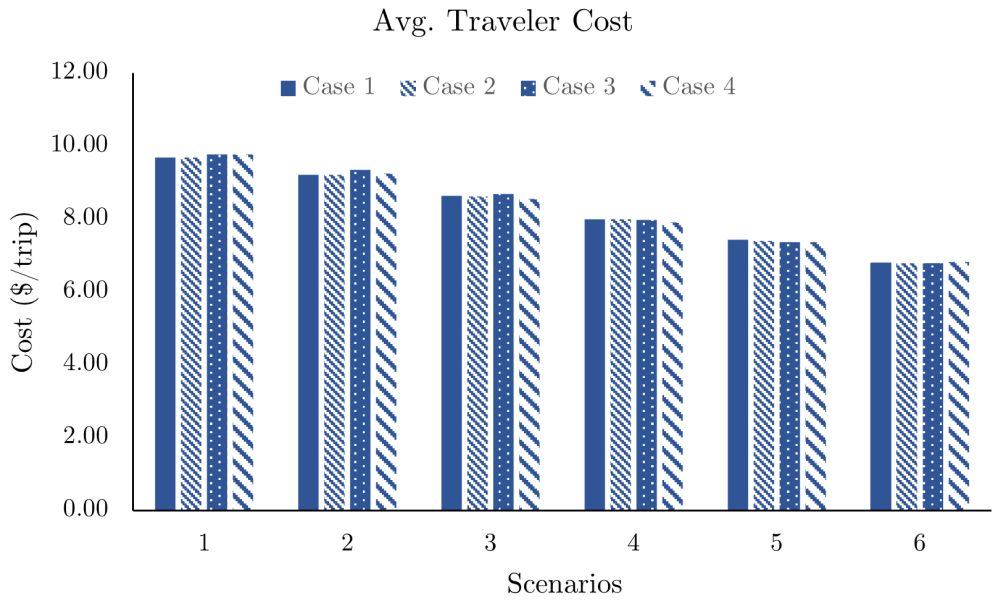



Figure 4.3: Case 1-4 — Average Traveler Cost

### 4.2.4 *Average Operator Cost*

Similarly, the average operator cost per trip decreases as ride-sharing increases as depicted in Figure 4.4. The decrease across the cases is associated with two factors: the empty VMT and the AV utilization rate which will be analyzed in the following sections.

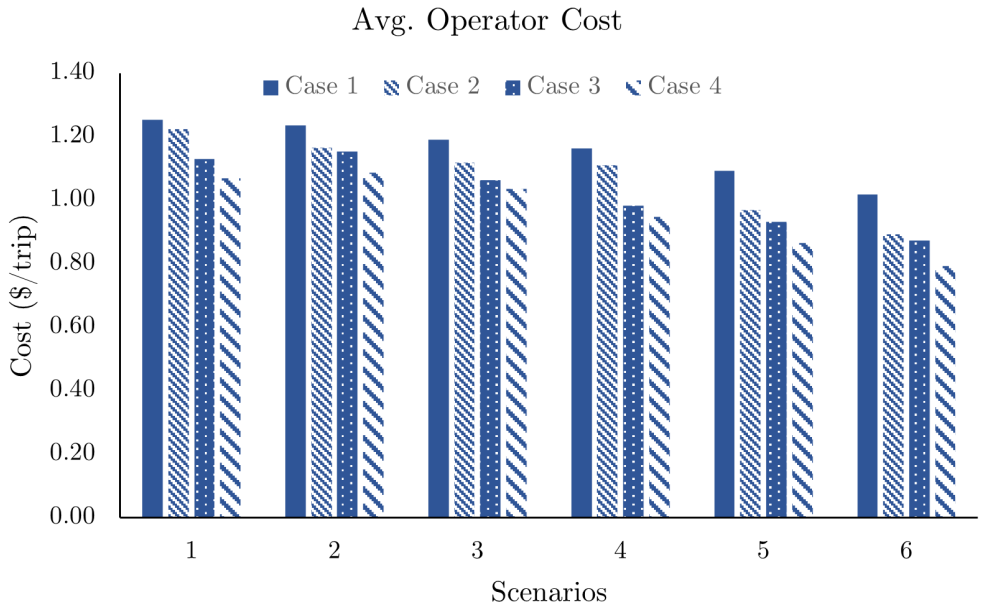



Figure 4.4: Case 1-4 — Average Operator Cost

### 4.2.5 *Empty VMT*

The empty VMT decreases as the ride-sharing in the system increases across the four cases as shown in Figure 4.5. The anticipated trend of the empty VMT is a result of the improved efficiency of AVs, achieved through optimized routing that reduces the need for unnecessary detours when picking up travelers. Consequently, the decrease in the empty VMT leads to a lower average operator cost.

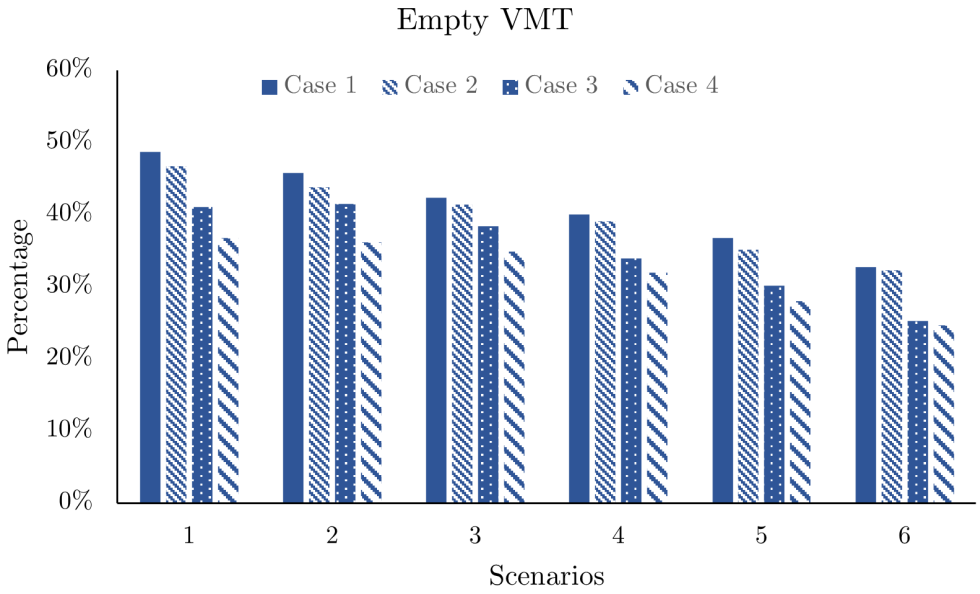
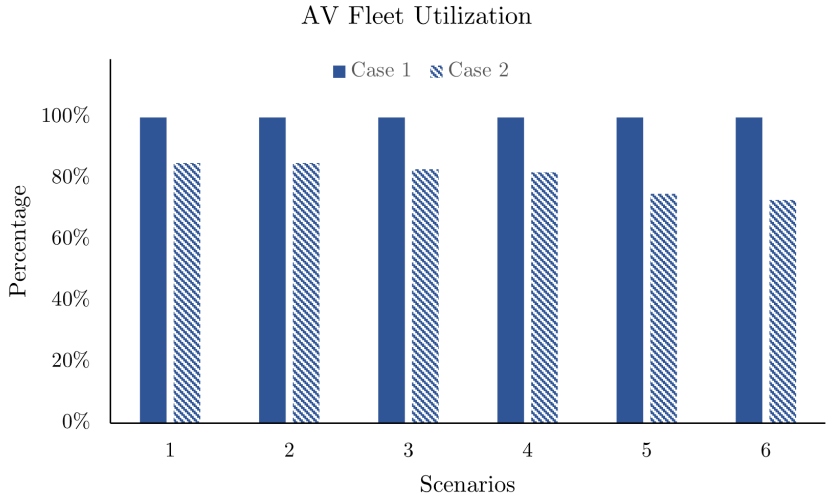


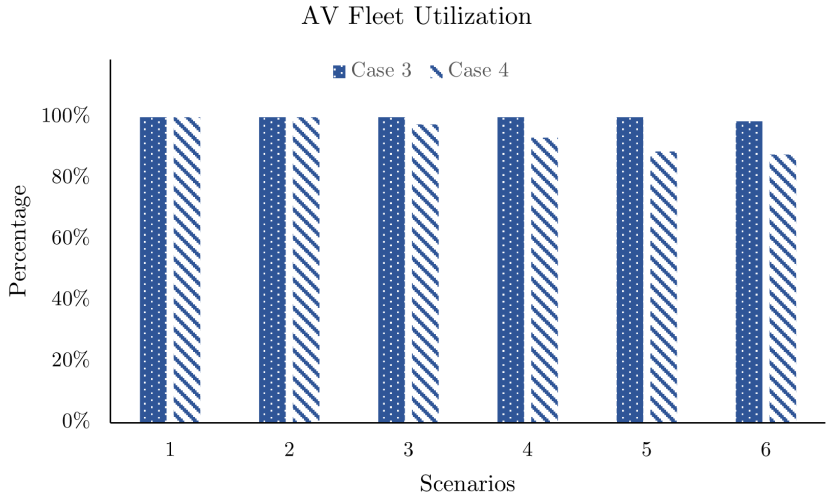

Figure 4.5: Case 1-4 — Empty VMT

### 4.2.6 *AV Utilization Rate*

Given a constant travel demand rate, the AV fleet utilization rate decreases as the fleet size increases as shown in Figure 4.6-a and Figure 4.6-b. Additionally, the increase in shared rides in across Scenarios 2 to 6, enabled the system to meet the same travel demand with fewer vehicles. As a result, the need to dispatch additional AVs from the depot becomes obsolete as the system can rely on the AVs that are already in service in the network and hence the average operator cost decreases.




(a) Case 1-2

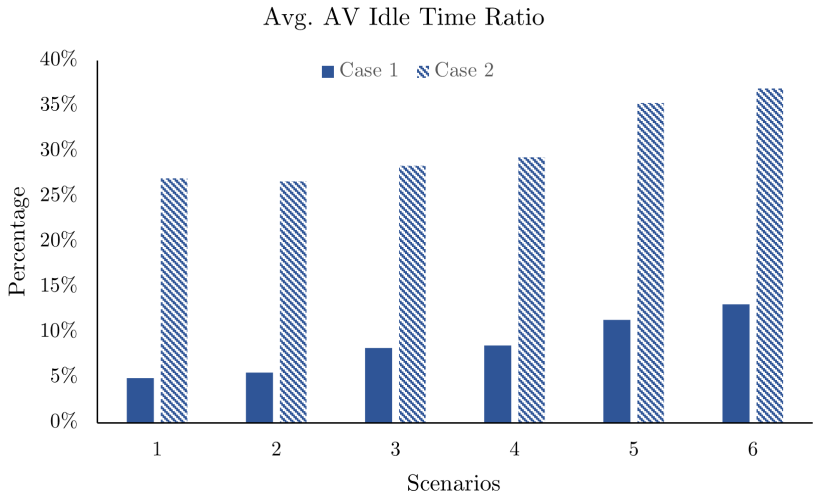



(b) Case 3-4

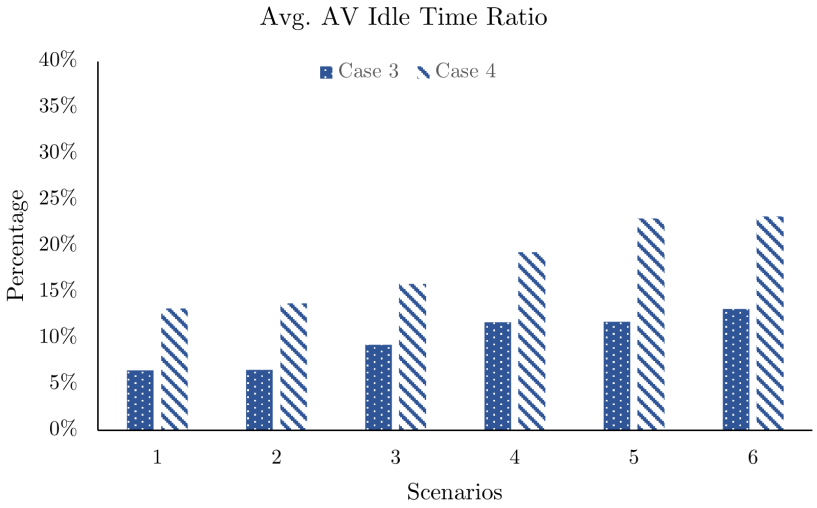
Figure 4.6: Case 1-4 — AV Fleet Utilization Rate

### 4.2.7 *Average AV Idle Time Ratio*

On another hand, the average AV idle time ratio increases as the shared rides increase as evident in Figure 4.7 across cases 1-4. This aligns with that in ride-sharing multiple travelers are served by the same AV hence increasing the idle time of other AVs. Moreover, under the same travel demand, increasing the AV fleet size results in a higher average AV idle time due to the abundance of AVs in the system as depicted in Figure 4.7-a and Figure 4.7-b.




(a) Case 1-2




(b) Case 3-4

Figure 4.7: Case 1-4 — Average Idle Time Ratio

### 4.2.8 *Match Rate*

The ride-sharing match rate is composed of the following:

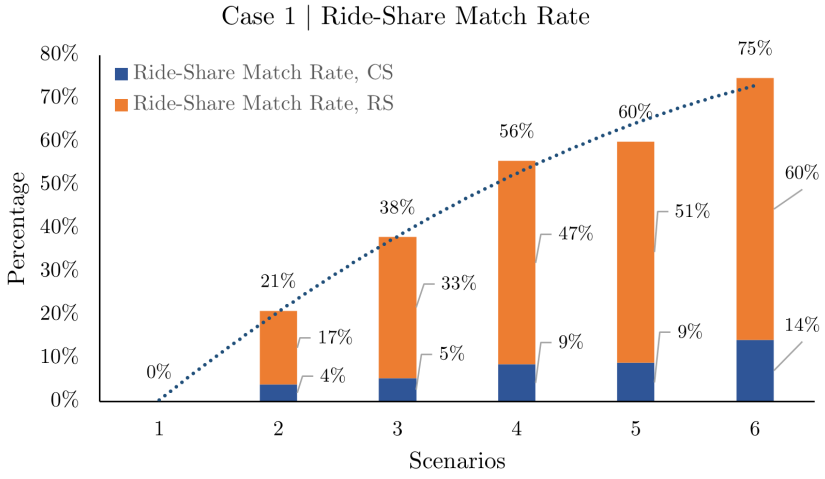
1. Travelers who requested the ride-sharing service and were successfully matched with other travelers (Ride-Share Match,RS).

2. Travelers who requested the clustered ride-share service but weren't successfully clustered with other travelers. Instead, the travelers were matched with others requesting ride-sharing (Ride-Share Match,CS).

The ride-sharing match rate across the four simulated cases shows a consistent increasing trend as depicted in figures 4.8 and 4.9. The match rate increases as

the demand for ride-sharing services increases across scenarios 2-6. The flexibility inherent in the AVHS system allowed for a better utilization of the AVs through the integration of the three levels of service. The figures below confirm that unsuccessfully clustered ride-sharing requests were automatically switched to the ride-sharing door-to-door service which allowed for efficient use of AVs and reduced operator cost. In the case where the COM is unable to to provide the travelers with a shared ride, the COM then resorts to treating the travelers as no-ride-share door-to-door requests. Switching to ride-sharing before resorting to no-ride-share is cost efficient as the travelers benefits from clustered ride-sharing discounts regardless of the service provided.

The clustered ride-share match rate varies across the scenarios of the different cases simulated as shown in tables 4.1 - 4.4. The fluctuation in the percentage matching rate for clustered ride-sharing can be attributed to the inherent randomness in the generation of origin and destination points for travelers and their requested level of service. In scenarios where the distribution of travelers' locations is conducive to effective clustering, a higher matching rate can be achieved. Conversely, when the distribution leads to more dispersed travel requests, finding optimal clusters becomes more challenging, resulting in a lower matching rate.



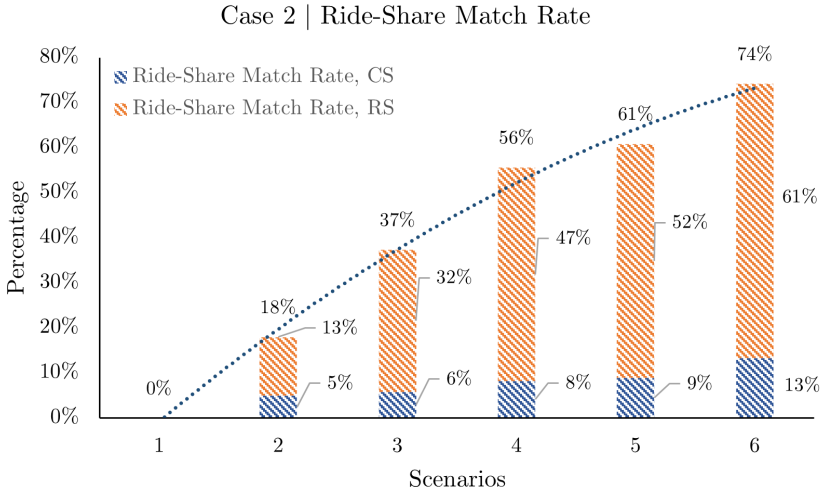




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Figure 4.8: Case 1-2 — Ride-share Match Rate

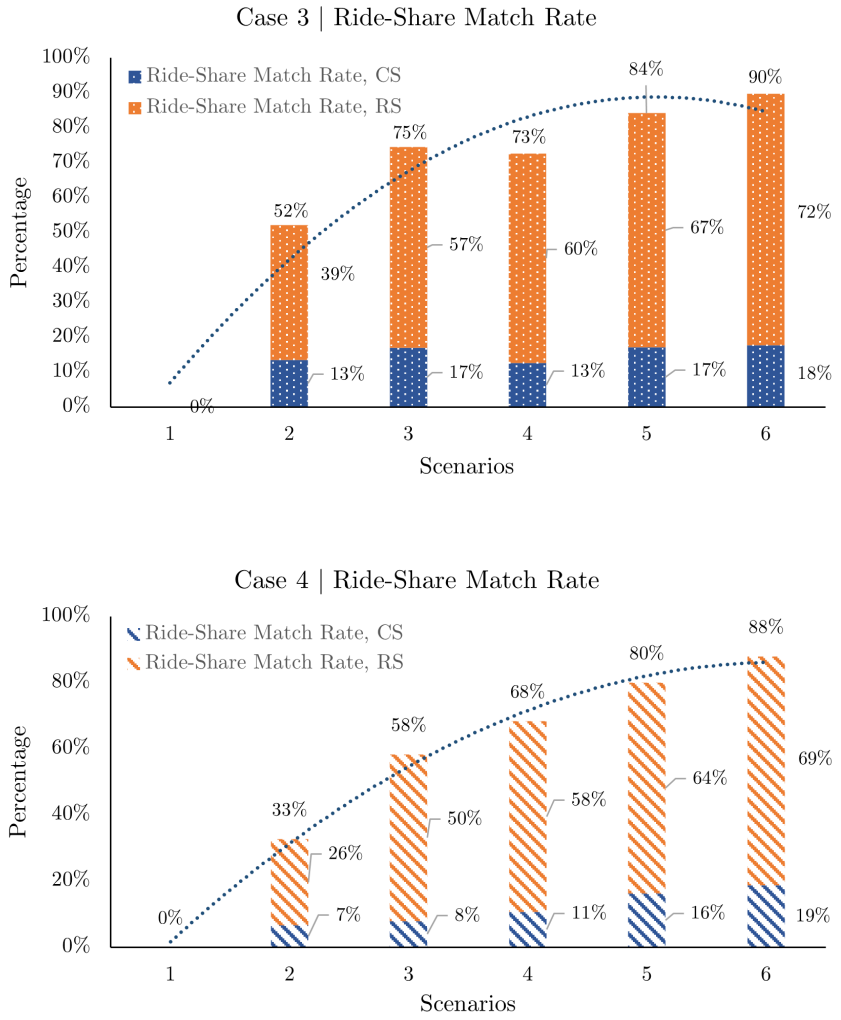


Figure 4.9: Case 3-4 — Ride-share Match Rate

### 4.2.9 *AV Occupancy*

The average occupancy of AVs serving ride-share trips across various scenarios in the simulated cases is depicted in Figure 4.10. Likewise, the average occupancy of AVs serving clustered ride-share trips across different scenarios in the simulated cases is shown in Figure 4.11. The average occupancy of AVs remains consistently on the rise for both service levels as the proportion of travelers opting for ride-sharing increases across the scenarios. Increasing the average occupancy of AVs enhances the system's performance through a more efficient utilization of the AV fleet which contributes to the reduction of average operational costs. Furthermore, as average occupancy rises, each trip can accommodate more travelers, thereby reducing empty vehicle miles traveled . This reduction in empty VMT contributes to the overall reduction of average operational costs as well.

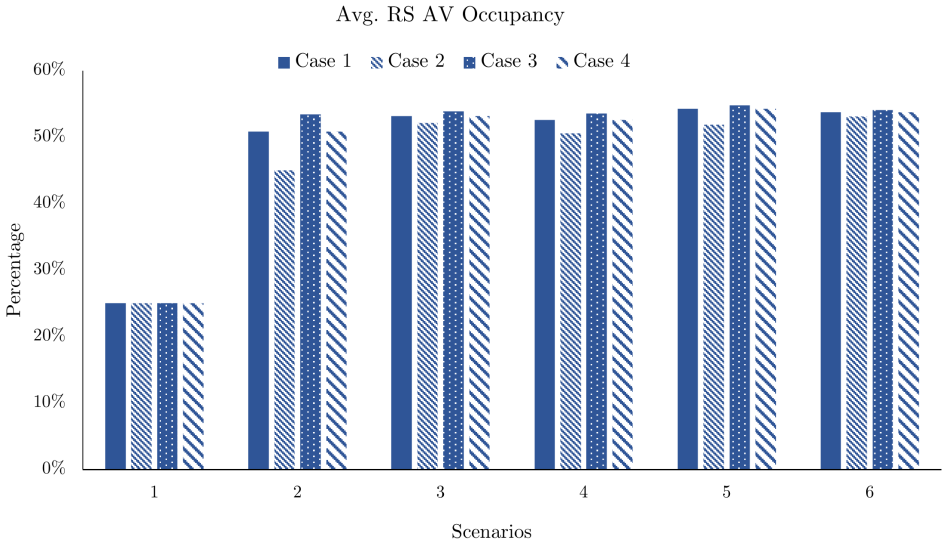


Figure 4.10: Case 1-4 — Average RS AV Occupancy

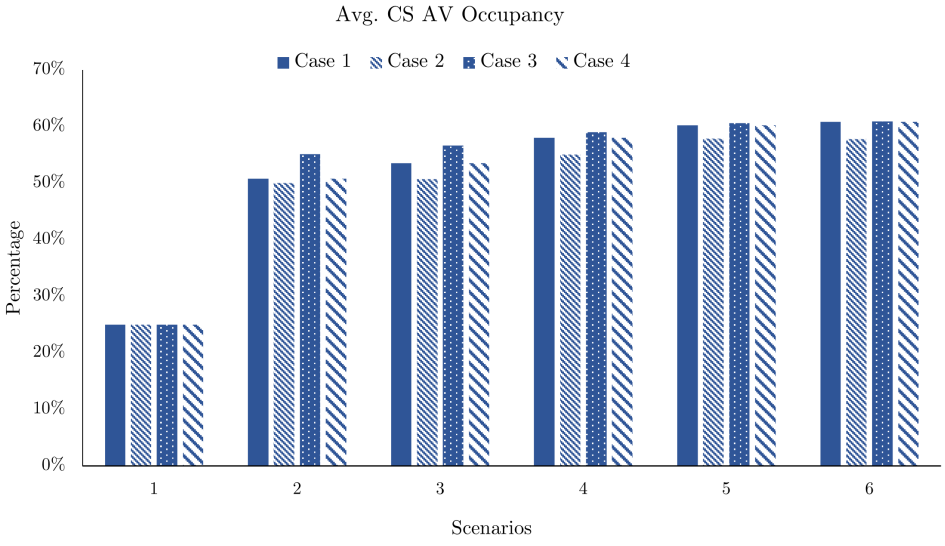


Figure 4.11: Case 1-4 — Average CS AV Occupancy

# Chapter 5

# Conclusion and Future Work

Fully-autonomous vehicles promise to increase the competitiveness of shared-use mobility services via eliminating the costs and performance limitations of human drivers. As such, this thesis examines an on-demand AVHS system that is defined by by a fleet of AVs that provide several transportation services to travelers ranging from a taxi-like service, to a flexible-route, flexible-schedule transit-like system service. The research focuses on modeling and evaluating the on-demand AVHS operational problem. The underlying problem is as a dynamic, sequential, and time-dependent stochastic control problem where the developed system aims to simultaneously minimize costs for both operators and travelers. An evaluation of operational performance is conducted from both operational and user perspectives, according to defined KPIs. The system demonstrated the ability to cater to the different service levels while maintaining a consistent service quality to travelers and improving the system's overall performance.

In future, the work presented in this thesis can be improved and expanded by the following:

- The conducted research uses a Manhattan grid network to represent an urban road network. However, going forward, it is necessary to model real, congestible road networks.
- The developed AVHS system in this thesis has proven it's ability to enhance overall system performance in a small-scale network, to assess the developed algorithm's robustness, the system should be tested in a large-scale network using real travel demand data.
- The AV fleet size considered in this research is homogenous with a passenger capacity of four. The inclusion of AVs of varying capacities is beneficial to examine the algorithm's performance in diverse scenarios.

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