Center for Advanced Multimodal Mobility Solutions and Education

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PRIORITIZING PEOPLE - MIXED EQUILIBRIUM ASSIGNMENT FOR AV BASED ON OCCUPANCY

Final Report

by

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EXCUTIVE SUMMARY

As transportation technology continues to evolve, Autonomous Vehicles (AV) have the potential to disrupt the way we travel and require adjustments to our traditional transportation operations mode choice models. As AV become more widely available and increase in market share, there are predictions that a significant portion of the AV fleet will be owned or utilized by private households. Regular traffic assignment in mixed environment of 1) human-driven vehicles, 2) occupied AVs and 3) unoccupied AVs will most likely result in routing of unoccupied vehicles that will reduce traffic flow for occupied vehicles. This type of routing would not be preferred as travel of occupied vehicles should be prioritized while unoccupied vehicles should take longer less congested routes to reduce their impact on the network. This study proposes a mixed equilibrium traffic assignment methodology to minimize the impacts of the unoccupied AVs on the network. Thus, focusing on high levels of service for occupied vehicles, AV or not, without disproportionally impacting households that will travel in an occupied AV. In this paper, the impacts of unoccupied vehicles are modeled under three different scenarios using the equilibrium route assignment methods for AV route choice and AV owners under both occupied and unoccupied conditions. To conduct this analysis two networks were considered, the Sioux Falls and Eastern Massachusetts networks. The methods devised and results obtained through the modeling and simulation process indicated that a) for the majority of the occupied vehicles there will be a reduction in travel times when compared to regular traffic assignment, b) there were no significant delays for any of the AV owners studied, and c) System is performing is improved, resulting in a reduction in total travel time.

Chapter 1. Introduction

1.1 Problem Statement

Autonomous vehicles (AVs) have the potential to bring a substantial safety and operational change to the current transportation system. There is wide spread optimism, and criticism, that introduction of AVs will have dramatic impacts on traffic congestion and may vastly improve safety. The exact impacts on traffic congestion are still debatable and highly reliant on how vehicles are utilized and prioritized in the future. While literature suggests that AVs will help mitigate traffic congestion and vastly improve safety [1] the transition to a fully autonomous fleet will take time. This era of a mixed fleet of self-driving and human driven vehicles will present many complex problems that will require new methods and models to solve. This progressively changing blend human-driven vehicles, occupied AVs, and unoccupied AVs will present new opportunities to achieve real-time route choice and traffic equilibrium decisions. This is due to connected and automated vehicles collecting, transmitting, and receiving real-time knowledge of current conditions at a scale and density that currently is not possible.

Existing literature suggests that as the concept of shared AVs becomes more prevalent, accessible, and possible the perceived benefits of a Shared Autonomous Vehicle (SAVs) will create a more dynamic ridesharing system [2]. The benefits of shared riding system were evaluated by Ford using fixed pickup and drop off stations. [3] Although there is an extensive research and literature related to SAVs, the transition will take significant time, effort, and a change in culture here in the United States. The United States has a strong desire to remain independent and the use of private AVs tend to still be the primary preference according to recent AV surveys. An internet-based survey was conducted in Austin concluded that only 41% of the respondents were willing to use shared AVs at a cost of 1$ per mile at least once a week [4].

One of the perceived benefits of an AV is that a single vehicle can meet all the travel needs of an entire family, thus allowing households to own fewer vehicles at a considerable cost savings. In theory, this SAV would be drive one family member to an initial destination, then leave unoccupied and travel to the pickup location of another family member. This model however only works efficiently if family members are willing to wait and plan their trips accordingly. Under this scenario a single AV could be used to meet the mobility needs of multiple household members. With vehicles that need a human driver, this shared mobility would be impossible. However, while the number of vehicles in a household may decrease, the number of trips made by an individual vehicle may increase dramatically. This shared mobility means that trips from drop off to pickup will be unoccupied and may actually increase the vehicle miles traveled for a household, depending on the activity level and commuting distance of the household. It is predicted that unoccupied AVs may impact congestion on heavily traveled routes and the travel times of occupied AV and human-driven vehicles will increase. Levin.et.al discusses the rerouting of unoccupied AV trips to less traveled routes or longer paths resulted in the reduction of the congestion on the downtown Austin network [5]. Levin et.al provided a genetic algorithm for shifting unoccupied AVs routes by encouraging AVs to park at cheaper locations further away from the travelers' destination. The findings of that study suggest adjusted parking fees results in reducing the congestion caused by the unoccupied AVs. [6]

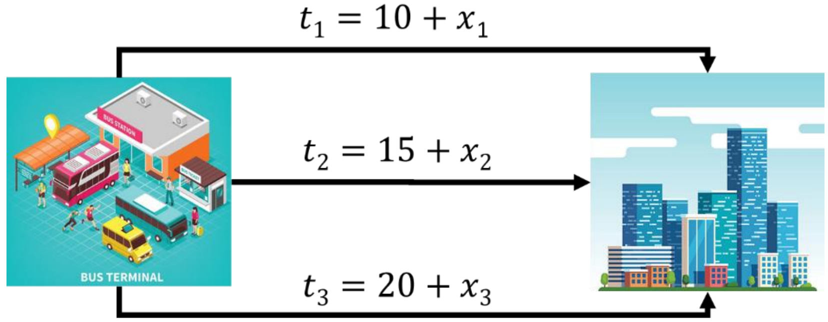


Figure 1: Example network

Imagine the following situation.

- 15 occupied vehicles wish to travel from a bus terminal (A) to the same office building (B) in the city.
- If they follow the user equilibrium UE assignment, $x_1 = 10$, $x_2 = 5$, $x_3 = 0$
- Then $t_1 = t_2 = t_3 = 20$.

Under that initial condition the travel time on each link is equal to 20.

- If we introduce an additional 15 vehicles traveling from A to B, the UE result is $x_1 = 15$, $x_2 = 10$, $x_3 = 5$ and $t_1 = t_2 = t_3 = 25$.

If these additional 15 vehicles are unoccupied, that means that the passengers of the original 15 vehicles will experience an additional 5 units of travel time each. This introduces an unreasonable burden considering the unoccupied AVs have a value of time equal to zero.

One might argue that the AVs should simply be routed to the unchosen path 3, thereby imposing no cost on occupied vehicles and resulting in:

- $x_1 = 10$, $x_2 = 5$, and $x_3 = 15$
- Resulting in $t_1 = t_2 = 20$ and $t_3 = 35$.

However, if one or all of the unoccupied AVs is owned by a household that is using their AV as a SAV, those vehicles would need to return home to pick up another household member for another trip. This would result in delays imposed on the second household member waiting for an unoccupied vehicle returning to pickup the second household member. This type of assignment scheme would result in these household(s) absorbing the cost of a missed trip or other transportation services. Therefore, if unoccupied AVs are assigned routes that become too lengthy, or require significant delays, it defeat the all the benefits of unmanned vehicles. Planners are taking the obvious approach of prioritizing the travel time and needs of occupied vehicles, while minimizing the impacts of empty AVs on occupied vehicles. However, there needs to be parameters established to ensure that the penalty imposed on unoccupied vehicles is not so severe that it outweighs their benefits.

This paper develops a differential route assignment methodology based on AV vehicle occupancy, with the goal of reducing the impacts of unoccupied AV route choice on all drivers and while not discouraging SAV operations in the future. This was accounted for by rerouting unoccupied AVs to minimize the potential impacts on occupied vehicles without disproportionally influencing households that will utilize SAVs in the future.

The remainder of this paper is organized as follows. In Section 2, we brief the research related to the work. In Section 3, methodology of the section was discussed and a solution procedure was presented. In Section 4, numerical experiments were presented for different scenarios to study the performance of the system with the proposed methodology. Section 6 concludes the paper with a summary of major results and propositions for future research.

1.2 Objectives

The proposed research focuses on the following topics:

1) The mitigation of travel delays experienced by occupied vehicles by minimizing the impact of unoccupied AVs route choice.
2) Development of a differential route assignment methodology for occupied versus unoccupied AVs while accounting for the impacts of unoccupied AV route choice on SAV owners.
3) Conduct an analysis of this new methodology application based on sample networks as a case study.

1.3 Expected Contributions

The proposed project makes the following contributions:

- The new methods of assignment will treat vehicles based on their occupancy, instead of treating all AVs as equal
- The travel time restrictions of unoccupied vehicles are incorporated and accounted for in the proposed solution so that SAV are not discouraged through inflated travel penalties yet the trip making needs of the household can be achieved without adversely impacting occupied vehicles.

1.4 Report Overview

The remainder of this report is organized as follows. Chapter 2, outlines literature related to the work conducted. Chapter 3, describes that methodologies used and a solution procedure is presented. Chapter 4, details the numerical experiments that were conducted using two different networks to evaluate the performance of the system. Chapter 5 concludes the report, summarizing the major results and propositions for future research.

Chapter 2. Literature Review

2.1 Introduction

Autonomous Vehicles (AV) have the potential to revolutionize transportation operations mode choice. In June of 2017, Connecticut passed Public Act 17-69 entitled "An Act Concerning Autonomous Vehicles." This new act authorized the limited and state approved testing of AVs on Connecticut roads. In April 2018, Connecticut launched the Fully Autonomous Vehicle Testing Pilot Program (FAVTPP), which set the permitting and testing requirements for AVs on public roads. To date no municipality in Connecticut has been approved to test fully autonomous vehicles under this Public Act. However, there have been several applications submitted for review that are still being considered for approval. This chapter reviews and synthesizes the current practice and exploration of the potential impacts of autonomous vehicles on transportation planning methods and models. AV implementation has accelerated rapidly ober the last 10 years. With car companies like Tesla pushing the boundaries of what can be done and what is allowed to be tested on public roads. The impacts of this new mobility are predicted to have a wide variety of impacts on not only how we travel but how we have to plan the development of our cities as well as transportation policies and infrastructure. Most of the existing literature focuses on perception and adoption surveys focused on understanding demand and adoption rates or the price per mile tipping point at which vehicle ownership becomes unlikely due to cheap unmanned ride sharing services. Many forward looking mobility experts expect there to evolve a shared autonomous fleet which replicates the current human driven rideshare systems. However, the removal of a human driver is expected to drop the price per mile traveled to a rate at which individual vehicle ownership is no longer economically beneficial.

Menon et al. describes the likelihood a person would be willing to reduce their current household vehicle ownership by one vehicle in the presence of SAVs.[7] The results indicate that there are key parameters which differ by dingle vehicle and multivehicle homes with which indicate whether a person will adopt SAVs. However, Menon et al. caution that AV technology becomes more common, personal experiences, media reports, crashes, publicity, and information gathering will change an individuals perception of SAVs. Therefore, future studies are needed to track and understand shifts as they take place. Fatemeh et al.'s (2018) stated preference survey and socio-economic characteristics that effect choosing a shared versus private AV[8]. Finding that individuals with larger inter-trip travel times are more inclined toward SAVs. Hoboucha et.al developed a vehicle choice model that provided owners the ability to chose between regular, shared and private AVs. This stated preference survey across Israel and North America found that even if the SAVs were to be completely free, only 75% of the individuals would be willing to use SAV [9].

It is predicted that when AVs become available, private households will not own a signifiact portion of the fleet. Schoettle et.al used the 2009 U.S. National Household Travel Survey to observe a 43% reduction of vehicle fleet, while personal vehicle usage dropped from 2.1 to 1.2 per household. This was attributed to simply eliminating existing trip overlap [10]. Zhang et al. conducted a study which predicts a 9.5% reduction of private vehicles due to households switching to private AVs. Their study concluded household efficiency gains will be realized though a SAVs being able to serve multiple household trips. However, They also notied that this shift to SAVs will generate nearly 30 unoccupied Vehicle Miles Traveled (VMT) per day per vehicle eliminated [11].

2.2 Mixed Traffic Equilibrium Modeling

For this study the occupancy of the vehicle is studied and its impact on the network and other travelers is evaluated. Existing research on competition and cooperative traffic assignment was pioneered by Haurie in 1985 [12]. However, in 2017 Chen et al. proposed the use of a mixed equilibrium model, where segments of the road network were dedicated as AVs only [13]. At the same time, Balogee et al. proposed a UE-SO mixed equilibrium strategy which the network assignment was based Connected Vehicles being treated as SO users, and conventional vehicles were modeled as UE users. That research developed a mathematical formulation for the UE-SO mixed traffic assignment methods [14]. Zhang and Nie investigated the issue of a mixed fleet model where human-driven and AV are modeled and since AVs are controllable, they could be dynamically assigned suboptimal routes to prioritize and improve the travel time of human-driven vehicles. [15] They mad the assumption that human-driven vehicles will choose the shortest path and behave in a UE manner, but the AVs would be assigned a system optimal (SO) routing that minimizes the total travel time for all users. [16][17]

The proposed framework generates a bi-level model where one group of AVs are assigned using the UE method and the lower level unoccupied AVs are assigned a different class based on SO. Therefore, instead of treating all AVs as equal, classes are assigned based on occupancy. The priority in the assignment is set as the ability for household trip making and travel time restrictions of unoccupied vehicles are incorporated in the solution method to optimize their usage and benefit to the system.

2.3 Summary

The review of recent literature has indicated that the methods used for traffic assignment in a mixed fleet of occupied and unoccupied AVs needs to be updated. Our traditional models will not generate an optimal solution based on the number and frequency of unoccupied AVs trips generated and the potential use and benefits of SAVs. The next section of this report outlines the methods used to conduct the analysis and build this new form of traffic assignment model.

Chapter 3. Solution Methodology

3.1 Introduction

The user equilibrium (UE) assignment procedures are based on Wardrop's principle which makes the assumption that all drivers are uniform in their perception of costs. Therefore, no driver can reduce their cost, or travel time, by unilaterally changing their route. The introduction of AVs allows planners to introduce non-uniform decisions based on real-time information and historical traffic flow information. Therefore, new methods need to be developed to account for this shift in assignment. The increasing market share of AVs provides the opportunity to create different classes and assignment assumptions to vehicles based on their occupancy, or lack thereof. The methods described below work to generate a solution to this new traffic assignment theory.

3.2 Modeling Framework

In an effort to develop a new solution we must establish a baseline or network as a test bed. Therefore if we consider a transportation network G (N, L) with ‘N’ number of nodes and ‘L’ number of links, then assume there are two classes of vehicles wishing to use this network, we will need to make the following assumptions.

1) Occupied vehicles will follow the User Equilibrium traffic assignment approach
2) The objective of occupied vehicles is to minimize their own travel time
3) Unoccupied vehicles will follow a System Optimum traffic assignment approach
4) The objective of unoccupied vehicles is to minimize the total system travel time while serving the AV owner within the time window for the next pickup.

The following model has been adopted for this proposed research and it follows the traditional UE and SO formulations found in Sheffi (1985). However, there have been modifications similar to those found in Zhang and Nie (2018) [18]. The upper level objective function is:

$$\min_{x_o} z_1(x) = \sum_a \int_0^{x_a} [t_a(x_o + x_u)]\, dx$$

Where x_o and x_u represent the occupied and unoccupied vehicle contribution to the link flow, respectively. The lower level objective function is:

$$\min_{x_u} z_2(x) = \sum_a [t_a(x_0 + x_u)(x_0 + x_u)]$$

These are constrained by the standard path flow constraints requiring the flows across all paths k∈K between origin r∈R and destination s∈S satisfy demand between origin and destination.

$$\textstyle\sum_k f_k^{r,s} \geq q_k^{r,s} \qquad \forall k, r, s$$

The mapping $x_a = \sum_r \sum_s \sum_k f_k^{r,s}\, \delta_{a,k}^{r,s}$ produces link flows x_a using the path flows and a binary indicator δ which takes the value 1 if link is a on path k between origin r and destination s. This indicator can also be used to compute path travel time – which will be used to check whether path flows for unoccupied vehicles are falling within the necessary time windows for the household owners of the AVs.

To evaluate this new mixed model methodology there were three different scenarios developed.

- **Scenario 1:** Mixed Equilibrium Assignment for occupied and unoccupied vehicles with no time adjustment. 95^{th} percentile of the delay in minutes is calculated from this scenario.
- **Scenario 2:** Mixed Equilibrium Assignment for occupied and unoccupied vehicles with time adjusted such that no vehicle has more than 5 minutes delay.
- **Scenario 3:** Mixed Equilibrium Assignment for occupied and unoccupied vehicles with time adjusted such that no vehicle has more than 95^{th} percentile minutes delay from scenario 1.

3.1.1. **Scenario 1 Parameters:**

Input:

a. Network G with 'N' number of nodes and 'L' number of links,
b. Demand for each OD pair = D
c. Capacity of each link
d. Free flow travel time of each link
e. Gap = Total System Travel time/Shortest Path Travel time -1
f. Path travel times in standard Traffic Assignment using Frankwolfe method

Output:

a. Link travel times for occupied vehicles
b. Link travel times for unoccupied vehicles
c. Total system travel time
d. Shortest path travel time of each OD pair for occupied vehicles
e. Average shortest path travel time of each OD pair for unoccupied vehicles

Initialize:

a. Assume the demand of occupied Vehicles – i % of D, where i = [10,20,30,40…90]
b. Assume the demand of unoccupied vehicles – 100-i %
c. Link travel times are calculated using BPR function
d. Gap =infinity
e. Accuracy = 0.0001
f. Total system travel time (TSTT) = 0
g. Shortest path travel time (SPTT)= 0

While: Gap > accuracy,

a. All or nothing assignment of the demand for the shortest path of the occupied vehicles.
b. Recalculate link travel times using BPR function and recalculate occupied vehicle link flows.
c. Find the new 20 shortest paths from the updated times using Dijkistras method.
d. Run Mixed Integer Non Linear Programming (MINLP) solver to minimize the total system travel time of unoccupied vehicles such that
    - The flow on 20 shortest paths = unoccupied vehicle demand
    - Unoccupied Link flows = sum of the flows on the path if the link is present on the route[19]
e. Add the unoccupied vehicle flow to the occupied vehicle flow.
f. Calculate and update the travel times.
g. Line search: To find alpha (α) which is the portion of the occupied vehicle flow. Golden method is used here to calculate alpha.
    - Shift the path flow such that: updated flow (x) = $\alpha x^* + (1-\alpha)\, x$ where x^* is the previous shortest path flow.

h. Calculate the TSTT and SPTT.

i. Gap = $\frac{TSTT}{SPTT} - 1$

End:

a. Total link flow = occupied flow +unoccupied flow

b. Link travel time = Free flow travel time $* [1 + 0.15 * \left(\frac{Total\ link\ flow}{Cpacity}\right)^4]$

c. SPTT of each OD pair of the occupied vehicles

d. Average path travel time for each OD pair for the unoccupied vehicles

a. Change in travel times for each OD pair of the unoccupied vehicles = Average path travel time for each OD pair for the unoccupied vehicles - Path travel times in standard traffic assignment using Frankwolfe method

g. Calculate the 95th percentile of the change in time of the unoccupied vehicles.

3.1.2. **Scenario 2 Parameters:**

b. Change in travel times for each OD pair of the unoccupied vehicles = Average path travel time for each OD pair for the unoccupied vehicles - Path travel times in standard Traffic Assignment using Frankwolfe method

c. Find the OD pairs where the change in travel time is more than 5 minutes

d. Add the demand of the unoccupied vehicles to the occupied vehicles and unoccupied vehicle demand equals zero.

e. Repeat scenario 1 procedure until there are no OD pairs with more than 5 minutes change in travel time.

3.1.3. **Scenario 3 Parameters:**

a. Change in travel times for each OD pair of the unoccupied vehicles = Average path travel time for each OD pair for the unoccupied vehicles - Path travel times in standard Traffic Assignment using Frankwolfe method

b. Find the OD pairs where the change in travel time is more than 95th percentile minutes calculated in Scenario 1.

c. For these OD pairs, add the demand of the unoccupied vehicles to the occupied vehicles and make the unoccupied vehicle demand equals zero.

d. Repeat Scenario 1 procedure until there are no OD pairs with more than 95th percentile change in travel time.

To model these networks with the parameters outlined above Python 3.8 was used to script algorithms for each scenario. The Sioux Falls and Eastern Massachusetts transportation networks were used to conduct the Numerical experiments using one of UConn's Linux servers.

3.1.4. **Sioux Falls Network:**

Sioux Falls network has 24 nodes, 76 links and 528 Origin Destination pairs.[20]

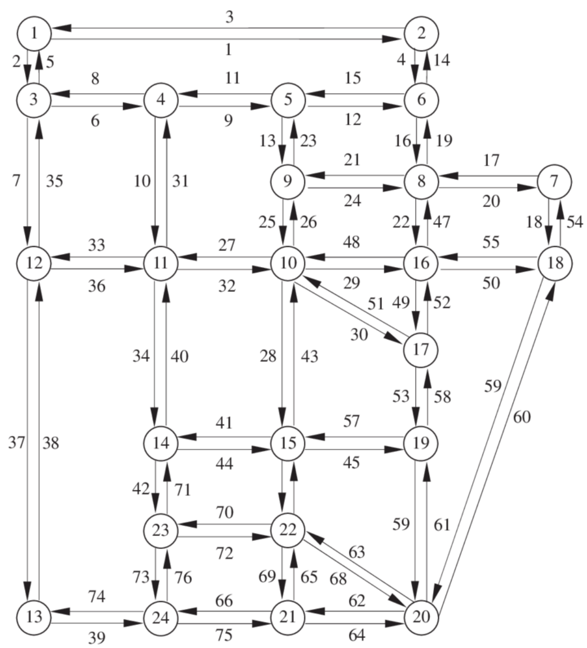


Figure 2: Sioux Falls Network

3.1.5. **Eastern Massachusetts Network:**

Eastern Massachusetts has 74 nodes, 258 links and 5402 OD pairs from Zhang et al. (2016) [20 and 21]

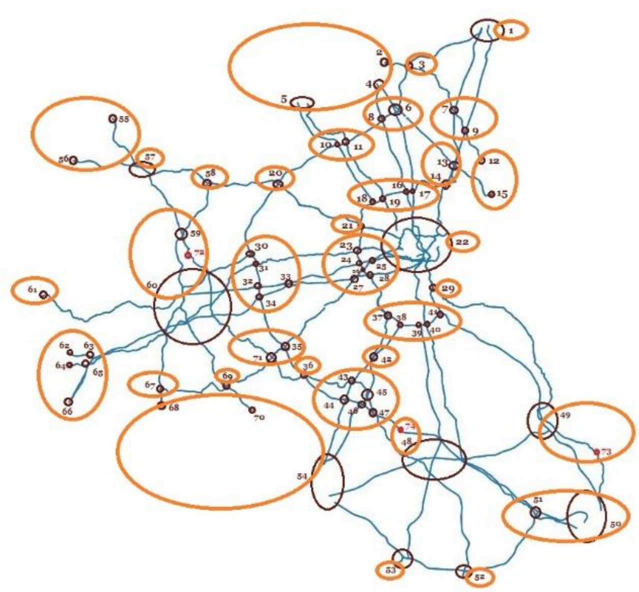


Figure 3: Eastern Massachusetts Network

3.3 Summary

The development of algorithms in python and then applying the corresponding code to two sample transportation networks was successful. The models created were able to generate travel times for links and calculate the predicted travel time and then corresponding delay experienced by each of the groups of vehicles. The next chapter outlines the results of each scenario, network, and system optimization.

Chapter 4. Results and Analysis

4.1 Introduction

Using the developed python code and the mixed model methodology, the three scenarios were run on each of the two different transportation networks. The results generated are described below. The next chapter will discuss the conclusions that were drawn from this analysis conducted in Chapter 4.

4.2 Simulation Results and Analysis

Sioux Falls Scenario 1 Results:

For each of the model runs there as a systematic increased the percentage of unoccupied vehicles with a corresponding decrease in the percentage of occupied vehicles. In the majority of cases, travel times for occupied vehicles increased due to the rerouting of unoccupied vehicles. According to the results generated and displayed in Table 1, the maximum delay experienced is around 3 minutes. Furthermore, the 95th percentile delay is approximately 2 minutes, which is not considered a significant delay. The results also indicated that there are some unoccupied vehicles that experience delay. However, if the unoccupied vehicle was able to reach its destination within the allotted window, the time value of the unoccupied vehicle is set to zero. The maximum delay, approximately 21 minutes for unoccupied vehicles, was seen in final case in Table 1. Where 10% of the fleet were unoccupied vehicles and 90% where occupied vehicles.

TABLE 1 Effect on occupied vehicles and unoccupied vehicles – SF Scenario 1

Occupied vehicles Demand (%)	Unoccupied vehicles Demand (%)	% of OD pair gained time		% of OD pair with delay		Delay when compared to standard Traffic assignment (minutes)					
		OV	UV	OV	UV	Average delay		Maximum		95% Delay	
						OV	UV	OV	UV	OV	UV
10	90	57.6%	40.2%	42.2%	59.8%	-0.803	0.16	3.34	11.16	2.04	2.88
20	80	56.6%	39.2%	42.4%	60.8%	-0.738	0.24	3.26	11.13	1.99	2.85
30	70	54.7%	35.8%	44.7%	64.2%	-0.631	0.32	3.18	11.16	2.06	2.84
40	60	54.2%	33.5%	45.3%	66.5%	-0.549	0.42	3.09	11.16	2.17	2.83
50	50	54.4%	35.6%	44.5%	64.4%	-0.451	0.45	3.19	11.10	2.14	2.87
60	40	53.4%	33.7%	46.0%	66.3%	-0.293	0.81	3.23	11.47	2.18	4.63
70	30	48.5%	29.9%	49.8%	70.1%	-0.085	1.00	2.86	11.65	2.19	4.64
80	20	45.3%	26.3%	52.7%	73.7%	0.014	1.06	2.07	11.93	1.55	5.19
90	10	44.9%	28.0%	52.1%	72.0%	0.217	1.72	2.89	21.62	1.81	9.84
OV –occupied vehicles, UV –unoccupied vehicles											

Sioux Falls Scenario 2 Results:

In Scenario 2, the maximum delay experience by unoccupied vehicles travel time was set to 5 minutes. The results in Table 2 indicate that there are limited impacts observed on occupied vehicles, and their maximum delay is still approximately 3 minutes under a nearly fully unoccupied AV network of vehicles. Similar results can be seen for unoccupied vehicles where the maximum delay is 4 minutes where the majority of the fleet are occupied vehicles.

TABLE 2 Effect on occupied vehicles and unoccupied vehicles– SF Scenario 2

Occupied vehicles Demand (%)	Unoccupied vehicles Demand (%)	% of OD pair gained time		% of OD pair with delay		Delay when compared to standard Traffic assignment (minutes)					
		OV	UV	OV	UV	Average delay		Maximum delay		95% Delay	
						OV	UV	OV	UV	OV	UV
10	90	59.7%	41.1%	44.3%	58.9%	-0.76	0.01	3.68	3.39	2.20	2.74
20	80	59.5%	40.6%	43.9%	59.4%	-0.70	0.07	3.48	3.33	2.08	2.56
30	70	58.0%	37.8%	45.8%	62.2%	-0.65	0.12	3.16	3.12	2.14	2.67
40	60	53.8%	36.2%	50.0%	63.8%	-0.40	0.25	2.97	4.39	2.10	2.69
50	50	57.0%	36.2%	46.4%	63.8%	-0.50	0.25	3.09	3.43	2.11	2.62
60	40	51.7%	32.6%	50.6%	67.4%	-0.26	0.45	2.61	4.53	1.83	2.88
70	30	51.9%	30.9%	50.6%	69.1%	-0.19	0.54	2.38	4.44	1.71	3.15
80	20	49.2%	28.7%	53.6%	71.3%	-0.02	0.61	1.91	4.62	1.44	3.12
90	10	42.8%	28.4%	54.5%	71.6%	0.05	0.47	1.68	4.09	0.61	2.89

OV –occupied vehicles, UV –unoccupied vehicles

Sioux Falls Scenario 3 Results:

The final scenario adjusts the unoccupied vehicles travel time to not exceed the 95th percentile minutes. This results in Table 2 show output similar to those observed in scenario 2. The 95% delay of the occupied vehicles is now less than 2 minutes, and the maximum delay is just under 4 minutes. The maximum delay experienced by unoccupied vehicles is around 10 minutes and there is minimal delay under other cases.

TABLE 3 Effect on occupied vehicles and unoccupied vehicles – SF scenario 3

Occupied vehicles Demand (%)	Unoccupied vehicles Demand (%)	% of OD pair gained time		% of OD pair with delay		Delay when compared to standard Traffic assignment (minutes)					
		OV	UV	OV	UV	Average Delay		Maximum Delay		95% Delay	
						OV	UV	OV	UV	OV	UV
10	90	58.1%	41.7%	45.6%	58.3%	-0.63	-0.02	3.91	2.88	2.13	2.24
20	80	58.1%	42.2%	45.8%	57.8%	-0.68	-0.09	3.78	2.77	2.01	2.03
30	70	50.0%	43.1%	53.2%	56.9%	-0.20	0.03	2.09	2.62	1.48	1.58
40	60	44.3%	34.5%	56.8%	65.5%	0.02	0.09	2.97	2.63	1.72	1.16
50	50	44.5%	33.8%	58.9%	66.2%	-0.09	0.20	2.21	2.54	1.62	1.72
60	40	51.5%	32.7%	51.3%	67.3%	-0.25	0.43	2.67	4.58	1.77	2.73
70	30	52.1%	33.1%	50.8%	66.9%	-0.18	0.54	2.42	4.49	1.76	3.28
80	20	49.1%	29.9%	53.4%	70.1%	-0.02	0.70	1.91	5.12	1.50	3.58
90	10	46.0%	27.7%	54.9%	72.3%	0.22	1.15	3.15	9.69	2.13	6.79

OV –occupied vehicles, UV –unoccupied vehicles

Sioux Falls Total System Travel Time Results:

In all the three scenarios, the total system travel time (TSTT) improved when compared to the traditional user equilibrium traffic assignment. (**Figure 4)**

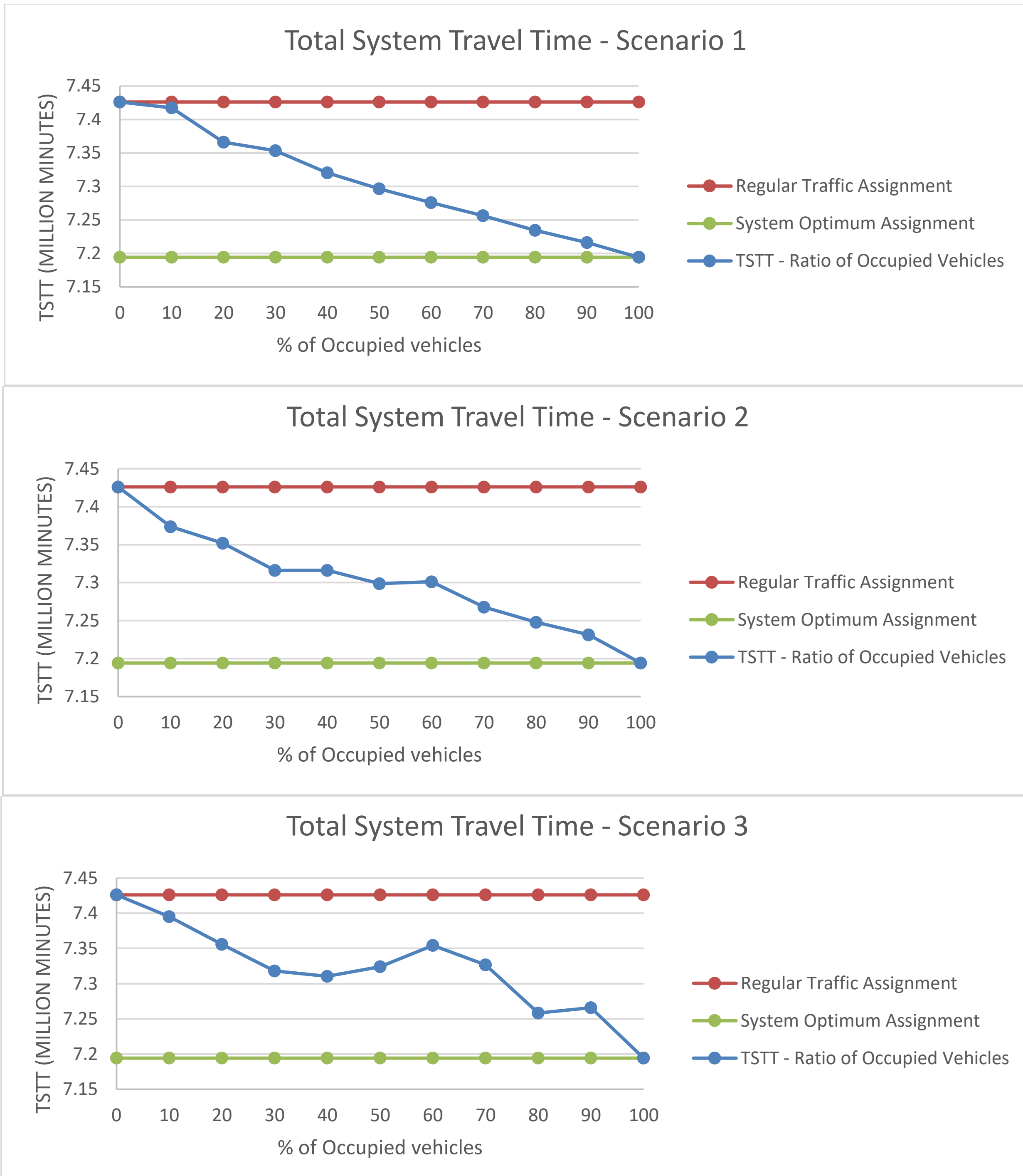


Figure 4: Sioux Falls Total System Travel Time Plots

Eastern Massachusetts Scenario 1 Results:
Most of the occupied vehicles gained time due to the rerouting of the unoccupied vehicles. Even for the vehicles that experience delay, the maximum delay is not significant and around 5 minutes. In Table 4, the 95th percentile delay is not significant for unoccupied vehicles at approximately 3 minutes and nearly zero for occupied vehicles. The maximum delay for unoccupied vehicles may have a delay of up to 12 minutes but the delay is within the acceptable window.

TABLE 4 Effect on occupied vehicles and unoccupied vehicles – EM Scenario 1

Occupied vehicles Demand (%)	Unoccupied vehicles Demand (%)	% of OD pair gained time		% of OD pair with delay		Delay when compared to standard Traffic assignment (minutes)					
		OV	UV	OV	UV	Average Delay		Maximum Delay		95% Delay	
						OV	UV	OV	UV	OV	UV
10	90	72.9%	60.0%	26.6%	40.0%	-0.552	-0.13	2.52	4.86	0.04	1.53
20	80	74.0%	59.8%	25.5%	40.2%	-0.534	-0.13	2.58	4.99	0.05	1.59
30	70	73.4%	56.3%	26.2%	43.7%	-0.492	-0.13	2.58	6.38	0.05	1.63
40	60	67.8%	55.8%	31.7%	44.2%	-0.51	-0.01	1.98	6.37	0.04	1.56
50	50	63.7%	49.6%	35.9%	50.4%	-0.45	-0.09	1.98	6.31	0.05	1.63
60	40	60.9%	45.6%	38.7%	54.4%	-0.39	-0.04	1.08	10.28	0.10	2.38
70	30	60.1%	40.0%	39.5%	60.0%	-0.282	0.22	0.48	10.30	0.05	2.38
80	20	57.3%	38.3%	42.3%	61.7%	-0.21	0.40	0.66	12.26	0.06	2.41
90	10	60.7%	35.5%	38.9%	64.5%	-0.126	0.60	0.3	4.85	0.04	2.47
OV –occupied vehicles, UV –unoccupied vehicles											

Eastern Massachusetts Scenario 2 Results:
For Scenario 2 the maximum delay for unoccupied vehicles was set to 5 minutes. The results in Table 5 for the Eastern Massachusetts network indicate that there is limited, impact observed on the occupied vehicles. Their maximum delay is still under 3 minutes and unoccupied vehicles meet their maximum delay restriction even when the fleet is nearly all unoccupied vehicles.

TABLE 5 Effect on occupied vehicles and unoccupied vehicles – EM Scenario 2

Occupied vehicles Demand (%)	Unoccupied vehicles Demand (%)	% of OD pair gained time		% of OD pair with delay		Delay when compared to standard Traffic assignment (minutes)					
		OV	UV	OV	UV	Average Delay		Maximum Delay		95% Delay	
						OV	UV	OV	UV	OV	UV
10	90	72.9%	60.0%	26.6%	40.0%	-0.55	-0.13	2.54	4.99	0.04	1.59
20	80	74.0%	59.8%	25.5%	40.2%	-0.53	-0.08	2.59	3.88	0.05	1.62
30	70	70.6%	55.9%	29.0%	44.1%	-0.45	-0.13	2.45	4.23	0.05	1.42
40	60	65.8%	52.9%	33.8%	47.1%	-0.46	-0.08	1.91	4.73	0.07	1.57
50	50	62.1%	49.1%	37.4%	50.9%	-0.40	0.22	1.92	4.71	0.05	2.38
60	40	58.4%	45.5%	41.2%	54.5%	-0.35	0.26	1.44	4.68	0.10	2.37
70	30	57.2%	41.2%	42.4%	58.8%	-0.27	0.38	0.50	4.66	0.06	2.38
80	20	57.1%	39.5%	42.4%	60.5%	-0.21	0.44	0.49	4.85	0.06	2.47
90	10	60.7%	35.5%	38.9%	64.5%	-0.13	-0.13	0.28	4.86	0.04	1.52
OV –occupied vehicles, UV –unoccupied vehicles											

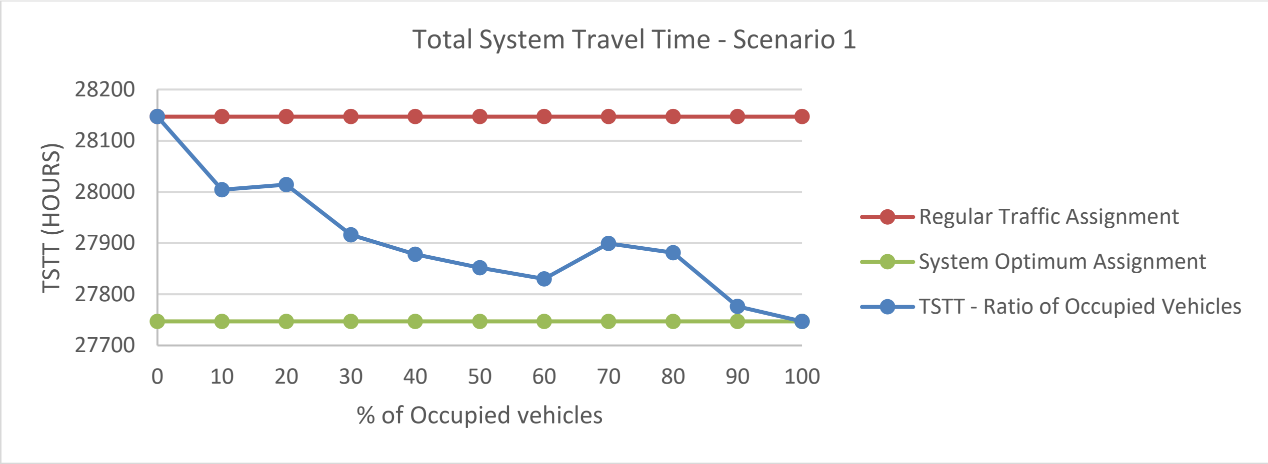
Eastern Massachusetts Scenario 3 Results:
After adjusting the unoccupied vehicles travel time delay to not to exceed the 95th percentile values, the maximum delay outlined in Table 6 is minimal at less than 2.5 minutes. Furthermore, unoccupied vehicles which are restricted in their delay reached a maximum delay of around 3 minutes.

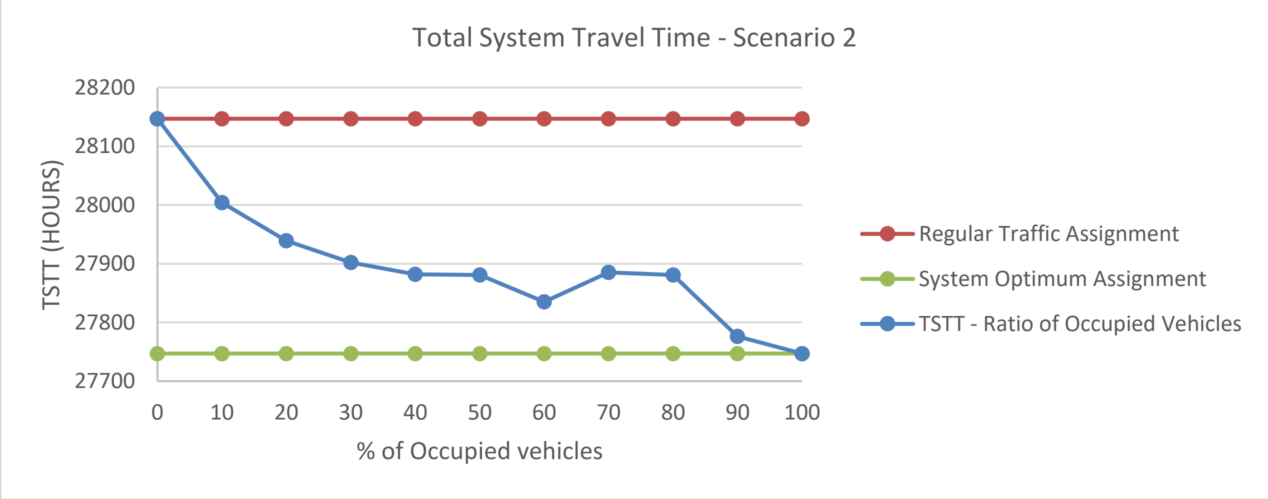
TABLE 6 Effect on occupied vehicles and unoccupied vehicles – EM Scenario 3

Occupied vehicles Demand (%)	Unoccupied vehicles Demand (%)	% of OD pair gained time		% of OD pair with delay		Delay when compared to standard Traffic assignment (minutes)					
		OV	UV	OV	UV	Average Delay		Maximum Delay		95% Delay	
						OV	UV	OV	UV	OV	UV
10	90	66.6%	58.7%	32.9%	41.3%	-0.51	-0.25	2.26	1.51	0.03	0.40
20	80	65.4%	60.5%	34.2%	39.5%	-0.50	-0.23	2.25	1.52	0.04	0.40
30	70	66.8%	54.3%	32.7%	45.7%	-0.34	-0.05	0.47	1.59	0.02	0.40
40	60	67.3%	56.9%	32.2%	43.1%	-0.31	-0.05	0.44	1.55	0.05	0.40
50	50	63.7%	51.6%	35.9%	48.4%	-0.27	-0.03	0.16	1.60	0.02	0.41
60	40	57.8%	42.6%	41.8%	57.4%	-0.24	0.18	0.53	2.38	0.05	1.53
70	30	57.5%	38.8%	42.1%	61.2%	-0.17	0.20	0.45	2.38	0.04	1.70
80	20	57.6%	37.4%	41.9%	62.6%	-0.14	0.27	0.36	2.38	0.05	2.17
90	10	60.3%	37.4%	39.2%	62.6%	-0.11	0.26	0.26	2.39	0.04	2.00
OV –occupied vehicles, UV –unoccupied vehicles											

Eastern Massachusetts Total System Travel Time Results:

In all the three scenarios for the eastern Massachusetts network, the total system travel time improved over the regular user equilibrium traffic assignment models. (**Figure 5**)





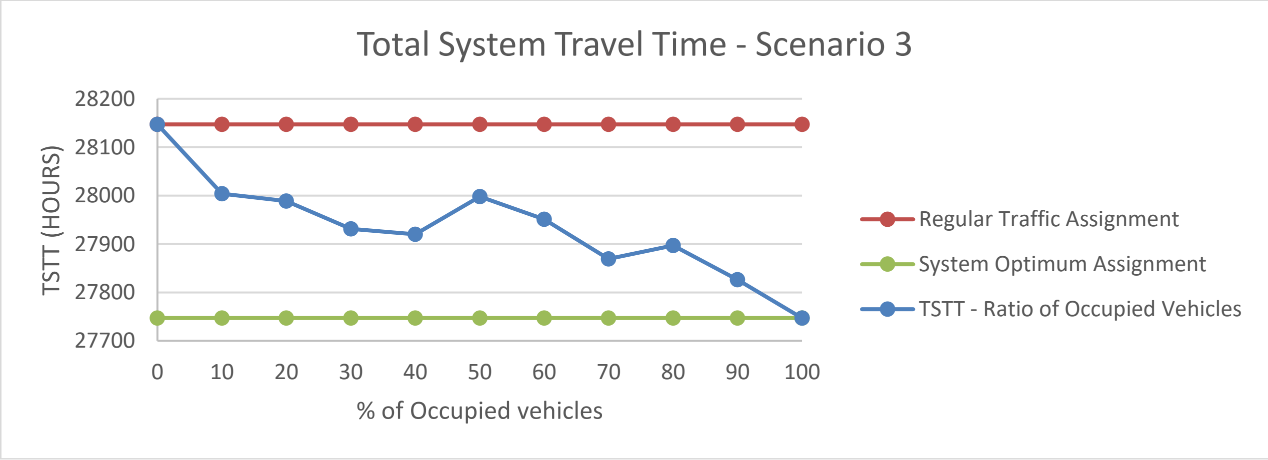


Figure 5: Eastern Massachusetts Total System Travel Time Plots

4.3 Summary

The results from the algorithms developed and deployed on the two sample networks indicated that there is an overall improvement in travel times when compared to the standard user equilibrium model. This method of using a mixed model approach appears to be successful, and promising when developing new models to account for AVs and SAVs scenarios. The final chapter discusses conclusions and outcomes from the this research.

Chapter 5. Summary and Conclusions

5.1 Introduction

The methods and analysis conducted as part of this research effort are critical to understanding how the future for planning and modeling the impacts of AVs on our system. Furthermore, tis research is important when quantifying and achieving the full benefits of AV adoption.

5.2 Discussion and Conclusion

The objectives of this research effort were to minimize the travel delays experienced by occupied vehicles by minimizing the impact of unoccupied AVs route choice. This was conducted through the development of a mixed model, differential route assignment methodology, and then validated by conducting an analysis of this new methodology using sample networks (Sioux Falls and Eastern Massachusetts) as case studies. The improvements of a mixed equilibrium model changed the regular selfish routing of occupied vehicles to allow for unoccupied AVs follow the system optimum traffic assignment. Thereby rerouting unoccupied vehicles to optimize based on a variety of parameters and scenarios. Another important aspect of this study was to confirm that future AV owner will not face inconveniences due to this dynamic rerouting of unoccupied vehicles.

By adapting the assignment methodology to account for the behavior and ability to assign unoccupied vehicles to preferred routes, the major findings are:

a) Occupied vehicles will most often see a reduction in travel times when compared to regular user equilibrium traffic assignment.
b) AV owners who want to use their vehicles as SAVs will not face any significant delays and the unoccupied vehicles delays can be restricted to less than 5 minutes without significant negative impacts on occupied vehicles.
c) The benefits of AVs can be realized since the total system travel time is predicted to be less when compared to regular traffic assignment output from in any of the scenarios tested.

5.3 Directions for Future Research

For future research, the algorithms developed can be applied to larger more complex networks. Furthermore, the parameters for each of the scenarios can updated and refined to generate a more real time pickup tolerance time windows based on travel survey studies. The expansion of this research can be used to enhance the algorithms developed and allow for more accurate benefits. Future enhancements would be beneficial to understand the real-time benefits that dynamic assignment of vehicles might have on travel times and network efficiency.

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