DEPARTMENT OF TRANSPORTATION

Designing an Autonomous Service to Cover Transit's Last Mile in Low-Density Areas

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16. Abstract (Limit: 250 words)

Public transportation provides a safe, convenient, affordable, and environmentally friendly mobility service. However, due to its fixed routes and limited network coverage, it is sometimes difficult or impossible for passengers to walk from a transit stop to their destination. This inaccessibility problem is also known as the "transit last-mile connectivity problem." Such a lack of connectivity forces travelers to drive, thereby increasing vehicle miles traveled (VMT) on roads. The autonomous mobility-on-demand (AMoD) service, with characteristics such as quick fleet repositioning and demand responsiveness, as well as lower operational cost due to the elimination of operators' wages, has the potential to provide last-mile coverage where fixed-route transit can only provide limited service. This study presents research on designing an AMoD service to solve the transit last-mile problem in Greater Minnesota. After selection of the Miller Hill Mall (MMH) area in Duluth, MN, as the case study site, analysis on local transit services and demand data show that passengers may have to spend significant time walking and cross multiple streets to access stores from transit stops. To address this issue, an AMoD system for last-mile service was designed and integrated with the fixed route transit service. Novel mathematical models and AMoD control algorithms were developed, and simulation experiments were conducted for evaluation of the AMoD service. Simulation results showed that the AMoD service can improve transit quality of service and attract more riders to use transit to the MHM area, and therefore reduce the VMT in the region. These findings were consistent with the literature in that mode choice and first-/last-mile access were highly interdependent and AMoD can improve transit quality of service and reduce VMT. Research on riders' perception of AMoD service and field testing of the AMoD system using the developed models and algorithms are recommended to help agencies prepare for application of AMoD system in the region.

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Final Report

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List of Abbreviations

1. AMoD: Autonomous Mobility-on-Demand.
2. AV: Autonomous Vehicle.
3. DTA: Duluth Transit Authority.
4. EV: Electric Vehicle.
5. GTFS: General Transit Feed Specification.
6. MHM: Miller Hill Mall.
7. MoD: Mobility-on-Demand.
8. MPC: Model-Predictive Control.
9. SP: Stated Preference.
10. TAZ: Transportation Analysis Zone.
11. VMT: Vehicle Miles Traveled.

Executive Summary

Public transportation provides a safe, convenient, affordable, and environmentally friendly mobility service. However, due to its fixed routes and limited network coverage, it is sometimes difficult or impossible for passengers to walk from a transit stop to their destination. This inaccessibility problem is also known as the “transit last-mile connectivity problem.” Such a lack of connectivity forces travelers to drive, increasing vehicle ownership and vehicle miles traveled (VMT) on roads. The autonomous mobility-on-demand (AMoD) service with characteristics such as quick fleet repositioning and demand responsiveness, has the potential to provide last-mile coverage where fixed-route transit can only provide limited service. Particularly, autonomous vehicles have various advantages over human-driven vehicles when used in a mobility-on-demand (MoD) system. In this context, some of the advantages include the independence from drivers’ availability when there is a shortage of drivers, potentially lower operational cost, and full responsiveness to control algorithms (e.g., dispatching or repositioning) without being affected by drivers’ behavior. This study presents research on designing an AMoD service to solve the transit last-mile problem in Greater Minnesota. The study is organized in three chapters: 1) the review of literature on AMoD service design and evaluation, 2) site selection and analysis of the accessibility and safety of last-mile trips with the existing transit mode, and 3) design and evaluation of an AMoD service through mathematical modeling and simulation.

According to the literature, a notable amount of research has been conducted on autonomous vehicle (AV) services in recent years, some on the user/demand aspects of the service and some on the design aspects of the service. Past studies indicate that travelers are, in general, open to the adoption and use of AVs for last-mile service. Also, first-/last-mile access and travelers mode choice are highly interdependent, with waiting time being a significant factor affecting their choices. Users in different contexts were found to perceive the time spent on last-mile AVs less negatively than the time on regular transit vehicles such as buses or trains. Price of the last-mile service seems to be a concern in the adoption of AVs for last-mile access as some studies found users’ expectation of reasonably priced last-mile service in relevance to transit fare. On the supply side, various studies used mathematical or simulation models to optimize or evaluate AMoD systems, although very few of them are specifically on last-mile transit access. While the technical aspects of the studies vary, the overall finding is that last-mile service can contribute to improved quality of transit service, energy saving, and reduced VMT.

The University of Minnesota research team in consultation with the technical liaison (TL) and the Technical Advisory Panel (TAP) identified a case study site in the Miller Hill Mall (MHM) area in the Duluth, MN, region. The MHM area is a large, car-oriented commercial area with multiple retail stores and shopping plazas. The research team obtained data on transit service and ridership in the area and conducted analyses to identify service gaps and opportunities for improved last-mile access. According to the analysis, accessing the MHM area from other parts of the region by transit could take as much as four times longer than by personal vehicle, or in some cases, even be impossible. On a typical day, about 500 people travel to the MHM area with transit, but about 10 percent of them do not use transit for their return trip, implying the need for more convenient transportation options. A local accessibility analysis in the MHM area shows that riders may have to walk for 20-30 minutes to access the stores from transit stops or other stores, and may have to cross multiple highways or streets, being exposed to safety risks. The findings suggest improvements in last-mile transit access toward rider safety, convenience, and saving time, as well as potential attraction of new transit riders.

The third and novel part of the study was on designing and evaluating a new AMoD service for the last-mile transit connectivity in the MHM area. A new mathematical model was developed to optimize the operation of the AMoD service, including the calculation of minimum fleet size, dispatching and routing of customer-carrying AVs, and real-time rebalancing of empty vehicles to zones with higher passenger demand. A simulation experiment was developed to evaluate the AMoD service and integrate it with a transit mode choice model. For the simulation test, it was assumed that transit routes in the MHM area would terminate their service at a transit hub in the area, and the last mile of the transit services is replaced with an AMoD with 19, 25, or 31 small AVs in different scenarios. Optimal selection of the transit hub would require more investigation, but for the purpose of the simulation, an existing transit stop at the periphery of the area is assumed to serve as the transit hub. Simulation results indicate that the AMoD service can significantly improve transit quality of service namely travel and waiting times, potentially attract new riders to transit, and reduce VMT in the region. With the assumed AMoD fleet size, passenger waiting time at local zones or the transit hub did not exceed 2 minutes in most cases. Moreover, a mode-choice model shows that transit demand to the MHM area could increase by as much as 100 riders in the two-hour peak period. The mode shift from personal vehicles to the integrated transit-AMoD service could result in a reduction of 490 VMT. Overall, the simulation analysis confirms the great potential in advancing the mobility, safety, and convenience of riders, and improved well-being of residents in the region.

The study is an early step toward evaluating AMoD services as last-mile access in Greater Minnesota. There were limitations in this feasibility study, and further research is recommended for realization of the benefits of such an AMoD service. In summary, study limitations include:

- Use of a simplified, stand-alone mode choice model in lieu of a regional travel demand model
- Lack of attitudinal variables in the utility of the AMoD service, i.e., lack of evidence on how riders perceive AMoD in comparison to conventional MoD or transit buses,
- Simplification of real operational challenges of AMoD in the simulation model, e.g., interaction with traffic signals or pedestrians.

Based on the findings of this study and noting the limitations, the following next steps are recommended:

- Using the developed AMoD optimization algorithm within an existing travel demand model. This would include estimating the utilities of the AMoD service using real data and conducing scenario analysis with an enhanced regional model encompassing AMoD as a mode option.
- Deployment and field testing of the AMoD system in the area, using the developed models and algorithm to verify their effectiveness. The field testing would include data collection from riders to identify real-world challenges toward application of the AMoD service.

- Investigation of the use of electric vehicle fleets in the AMoD system to address operational issues such as charging scheduling and infrastructure planning and to evaluate the environmental benefits of the system.

Chapter 1: Introduction and Literature Review

Technological advances in the field of autonomous driving observed in past decades offer a new mobility paradigm: autonomous mobility on demand (AMoD). Autonomous mobility promises to bring various benefits to society, which include safer travel by avoiding crashes, equitable mobility for the elderly, disabled, low-income, and non-driver communities, increased road capacity, and the ability to use the driving time for business activities [1]. An AMoD system consists of a fleet of autonomous vehicles (AVs) that pick-up passengers and transport them to their destinations. A control system manages the fleet by simultaneously (i) assigning passengers to AVs, (ii) routing the AVs, and (iii) rebalancing the fleet by relocating customer-free AVs to re-align their geographical distribution with transportation demand. Due to its characteristics, such as quick fleet repositioning and demand responsiveness, it has the potential to provide coverage in areas where fixed-route transit can only provide limited coverage. Such an integrated AMoD-transit service can help reduce travel time, emissions, and operational costs as compared to a standalone AMoD service. In this chapter, we review studies related to the integration of AV and transit for the last-mile connection from two perspectives, namely, the adoption and design of this new service. Figure 1 describes a broad classification of studies related to AMoD systems.

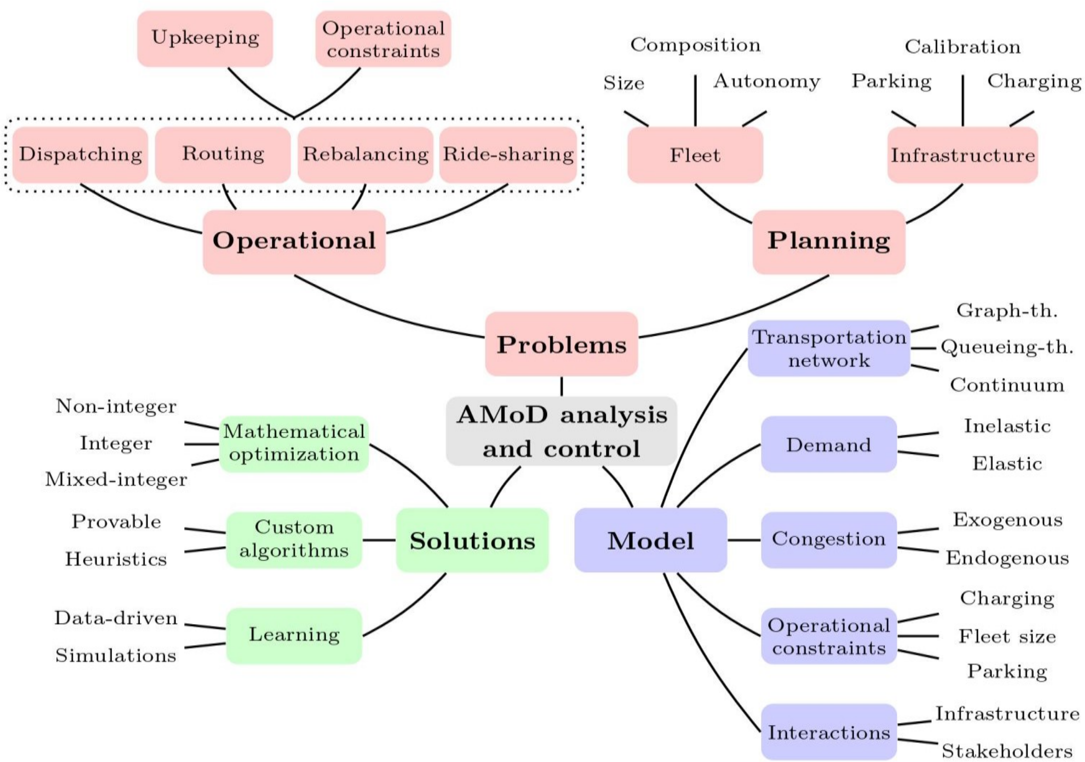

Figure 1. Taxonomy of studies on Autonomous mobility-on-demand systems.

1.1 Adoption of Integrated AV-Transit Service

The travel demand and travel satisfaction of transportation services are affected by the user's perception of the service quality attributes. Various studies have conducted both qualitative and quantitative analyses to understand the attitude and opinion of travelers towards adopting an integrated AMoD-Transit system. Song et. al., 2019 conducted a web-based survey in Eau Claire, Wisconsin, to assess the attitudes of residents towards AVs and transit [2]. They found that residents are not comfortable using a stand-alone transit service but generally welcome the deployment of an integrated AMoD-Transit service. Chee et. al. 2020 surveyed 584 potential users of a first- and last-mile automated bus service trial operated in Kista, Stockholm [3]. Respondents were found to be willing to pay more for a personalized service if it is safe, provides good ride comfort, and is competitively priced relative to the price of traveling by metro and train over the same distance. Other than service quality attribute perceptions, income level, existing travel modes for daily trips, familiarity with automated driving technology, and automated ride experience are important factors affecting willingness to pay for AV services. Yap et. al. 2016 estimated discrete choice models to understand the passenger sensitivity towards various attributes of a multimodal trip consisting of train and last-mile AV service [4]. They found that only first-class train passengers prefer AVs as an egress mode in comparison to buses, trams, and bikes. Moorthy et al. 2017 compared different modes of transportation, including personal vehicles, transit-only services, on-demand service shuttles, and integrated AV-Transit services, in terms of cost, performance metrics, and environmental friendliness [5]. They considered a case study of travel between five different locations in Ann Arbor and Detroit Wayne County Airport in Michigan. The results show that the energy savings from using AV as the last-mile connection to transit mode are as high as 37% as compared to a personal vehicle. Previous studies have found that access and egress to transit are significant factors affecting its modal share [6]–[8]. Accessibility is defined as a measure of the ease with which an individual can pursue an activity of the desired type at the desired location, in the desired mode, and at the desired time. It influences the modal choice of a tripmaker who prefers public transport. Moniruzzaman and Páez 2012 investigated the implications of accessibility to and by transit for mode shares in the city of Hamilton, Canada, and showed that accessibility by transit is a significant predictor of modal share in their case study [6]. Similarly, Brons et. al. 2009 evaluated the importance of the access-to-the-station part of a rail journey to passengers [7]. They found that satisfaction with the level and quality of access to the station is an important dimension of the rail journey. Kalaanidhi and Gunasekaran 2013 developed a framework for evaluating the accessibility of urban transportation networks and assessing their influence on the ridership of the bus transit system [8]. They showed that the temporal accessibility of the zones affects the number of passengers boarding and alighting at those zones. Therefore, various modes of transport have been studied and implemented to improve access and egress to transit modes. This includes integrating bikesharing and transit [7], [9] – [11], designing a responsive transit feeder service [12]–[14], and integrating ridesharing and transit [15] – [17]. Liu et. al. 2012 established a new scheme for the Beijing public bicycle system to solve the last-mile problem and connect users to public transit networks by analyzing the main reasons for the failure of the first generation of public bicycle systems [9]. Wang 2017 studied the operation of last-mile transportation system with batch demands that result from the arrival of groups of passengers who desire last-mile service at urban metro stations or bus stops [12]. It showed that routes and schedules for a multivehicle fleet of delivery vehicles can be determined by the policy of minimizing passenger waiting time and riding time. Moreover, it investigated how routing and scheduling approaches can potentially benefit last-mile transportation systems by providing operating plans that are both cost-effective and offer a higher LOS for passengers. Abe 2021 investigated the preference of transit passengers for last-mile AV services [18]. Using the stated choice survey data of 2,300 residents in the Tokyo metropolitan area, they estimated the access mode choice model incorporating demand service by shared AVs serving the last mile of transit trips. The access mode choice models are used to evaluate the elasticities of demand for access modes with respect to AV cost and wait time. Their analysis of results shows that price sensitivities of demand for AV service lie within a reasonable range of transit fares and elasticities. Riding an AV service for the last mile is preferred over other modes. The AV wait times also vary according to the surrounding area where the passenger is waiting. They emphasized that integrated AMoD Transit mobility will benefit those who do not have other ways of accessing transit services. By developing the simulation of the operation of an integrated AMoD -Transit system, various studies analyze the performance of such systems. Lau and Susilawati 2021 develops a simulation model of the mode choice and operation of a multimodal shared AV and transit system in Kuala Lumpur [19]. They showed that such integration would lead to a 3% increase in transit ridership and a 6% decrease in the overall VMT in the city. Similar predictions are also made based on a SUMO software simulation model of Austin, Texas [20]. Results of the study show that 3.7% of auto trips will shift to transit mode if an AV-last-mile service is provided.

1.2 Design of Integrated AMoD-Transit Service

Although there has been significant literature on analyzing passenger preference for an integrated AMoD-Transit service, only a few studies have considered designing such a service using mathematical modeling tools. The design of such a service evaluates the following aspects of such systems:

1. Determining the fleet size of AVs required to serve the demand.
2. Designing transit routes that integrate well with the AMoD systems.
3. Locating transit stations where passengers can switch to and from transit service.
4. Rebalancing of AVs to locations with high temporal demand.
5. Dispatching strategies for AVs to demand locations.
6. Efficient routing of AVs to serve the demand.
7. Matching passengers going to different destinations to a vehicle for ridesharing.

Cayford and Yim 2004 formulated a mixed-integer programming model for optimizing routing and scheduling decisions for a generic last-mile transportation system [13]. A mixed-integer program is an optimization model with both continuous and discrete decisions. They developed several computationally feasible heuristic approaches, including a myopic operating strategy and a metaheuristic approach based on a tabu search that employs demand information over the entire service horizon. Masoud and Jayakrishnan 2017 formulated the multi-hop peer-to-peer ride-matching problem as a binary optimization program [15]. To solve the problem in real-time, they proposed a preprocessing procedure to reduce the size of the problem and a decomposition algorithm that solves multiple smaller problems effectively. Stiglic et. al. 2018 showed that the integration of a ridesharing system and a public transit system can potentially enhance mobility and increase the use of public transport [16]. Several factors, including the location and number of transit stations with park-and-ride facilities as well as the use of different objective hierarchies, were necessary for investigating the potential benefits of the integration of ridesharing and public transit systems. They proposed a matching strategy for a transit-based ridesharing program. Kumar and Khani 2021 developed a labeling algorithm to integrate ridesharing and transit to solve the transit first-mile problem in real-time [17]. They applied their methodology to the Twin Cities region and found that VMT can be reduced significantly by such multimodal service. Shu et. al. 2021 proposed a data-driven method to design shuttle services for the last-mile transportation problem [21]. They identified the last-mile travel demands from various data sources, and the locations of bus stops were planned through an improved clustering algorithm. Raghunathan et. al. 2018 formulated the problem of scheduling passengers jointly on mass transportation and last-mile transportation services using a mixed-integer program [22]. In this problem, passenger itineraries were determined to minimize total transit time for all passengers, with each passenger arriving at the destination within a specified time window. Liang et. al. 2016 developed two mixed-integer programming models for the design of an automated taxi system for the last mile of train trips [23]. The first model considers acceptance and rejection of trip reservations based on the operator's profit, while the second model satisfies all the trip reservations. They found that AV fleet size influences the profitability of this integrated system. To satisfy all the requests in the second model, 33% more vehicles are needed in comparison to the first model. They also suggest that having electric AVs constrains the system for smaller fleets because vehicles do not have time for charging. Shehadeh et. al. 2021 proposed a robust model for optimizing the AV fleet required for transit last-mile service to deal with the uncertain demand [24]. They assume that passengers arrive in batches, and AVs are allocated to deliver these passengers to their destination. Since the demand is random and only a small dataset is available to calibrate its distribution, they propose a distributionally robust fleet sizing and allocation model. The distributionally robust consider a set of probability distributions of demand rather than assuming a normal distribution or a worst-case realization of demand. They emphasized that the quality of fleet allocation decisions is a function of fixed vehicle costs and passenger waiting and riding times. Due to the complexity of the model, only small-scale instances could be solved. Serra et. al. 2019 also developed a two-stage stochastic model for scheduling the transit last-mile service [25]. It captures a fixed demand and an uncertain demand using a finite number of scenarios. Zhang et. al. 2020 proposed a modular transit system that can serve passengers locally in a small region or connect them to transit systems for long-distance trips [26]. They model a modular transit system using the time-dependent vehicle routing problem and show its performance in a real-world case study. Kumar and Khani 2022 proposes a mixed-integer nonlinear programming model for designing an integrated AMoD and urban transit system [27]. It determines which transit routes to operate, the frequency of the operating routes, and the fleet size of AVs required in each TAZ to serve the demand and passenger flow on both road and transit networks. A Benders decomposition approach with several enhancements is proposed to solve the given optimization program. The results show a significant improvement in congestion in the city center with the introduction and optimization of the integrated transportation system.

For an easier understanding of the contributions made by various studies in designing the last-mile transportation service, Table 1 summaries the literature.

Table 1. Literature summary of design of integrated AV-transit service.

Reference	Problem	Investigated operational aspects	Modeling paradigm
[12]	Last-mile transportation	Routing and scheduling	Mixed Integer Programming
[15]	Ridesharing	Multi-hop peer-to-peer ridesharing and matching	Binary Optimization
[16]	Integrating ridesharing and public transit	Ride-share matching problem/synchronization of ridesharing and scheduled public transit	Binary Optimization
[17]	First-mile and last-mile transit	Ride-matching	Own algorithm/ Integer Linear Program
[18]	Last-mile AV services	Preference of the transit passenger	Multinomial/Mixed logit
[19]	First-mile and last-mile transportation	Optimize the SAVs implementation with public transit	Simulation-based
[20]	First-mile and last-mile transportation	SAVs coupled with ridesharing	Simulation-based (SUMO)
[21]	Last-mile transportation	Design Shuttle service	Data-driven
[22]	Last-mile transportation	Scheduling	Integer linear programming
[23]	Last-mile transportation	Design of an automated taxi system	Two mixed-integer programming models
[24]	Transit last-mile service	Optimizing the AVs fleet	Two-stage stochastic mixed-integer linear programming/ Two-stage distributionally robust
[25]	Transit last-mile service	Scheduling	Two-stage stochastic programming
[26]	Modular transit system	Modeling using time dependent vehicle routing	Two-stage stochastic programming
[27]	Integrated AMoD and urban transit system	Routing and AVs fleet size	Mixed-integer nonlinear programming

Chapter 2: Data Collection and Analysis

For the purpose of our analysis, various transportation agencies were approached to collect data related to transit service operations and passenger mobility in the Duluth area. After the receipt of data and careful considerations, the following datasets were finalized for their use in the the research:

1. Transportation analysis zones data
2. Road network data
3. General transit feed specification (GTFS) data
4. Stop-level transit ridership data.

A brief description of the datasets is provided below:

2.1 Transportation Analysis Zone (TAZ) data

The Duluth-Superior Metropolitan area is divided into several zones known as *transportation analysis zones* for the purpose of transportation planning. It is assumed that passenger demand is concentrated at the centroid location of the respective zones. This is geospatial data provided in the form of a shape file named "TAZ file".

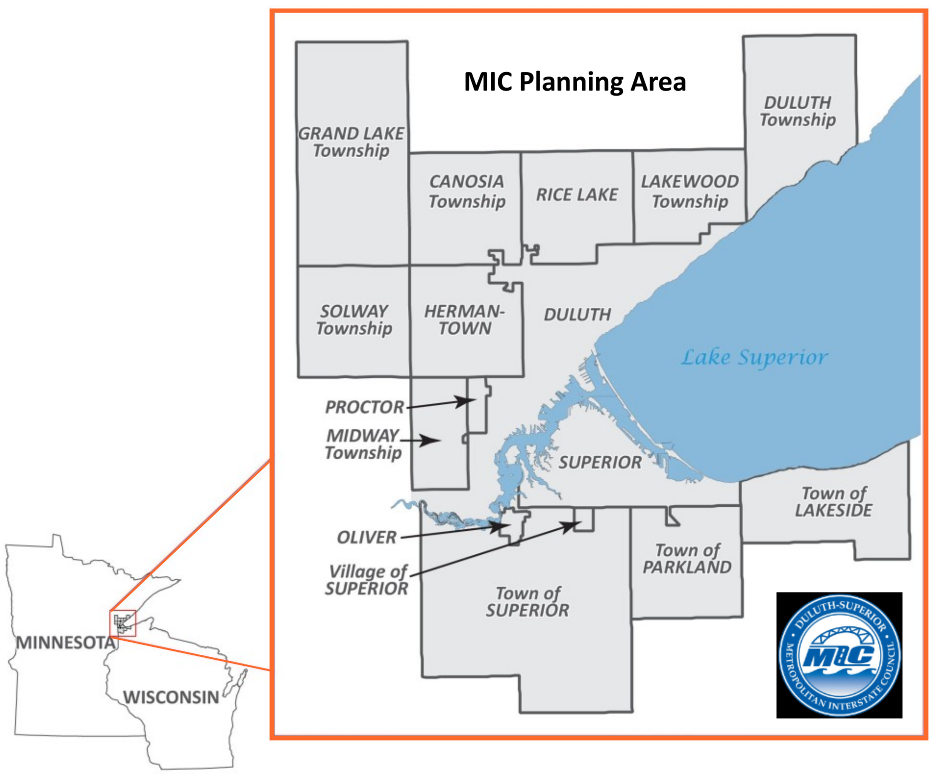

Figure 2 The Duluth-Superior Metropolitan Planning Area.

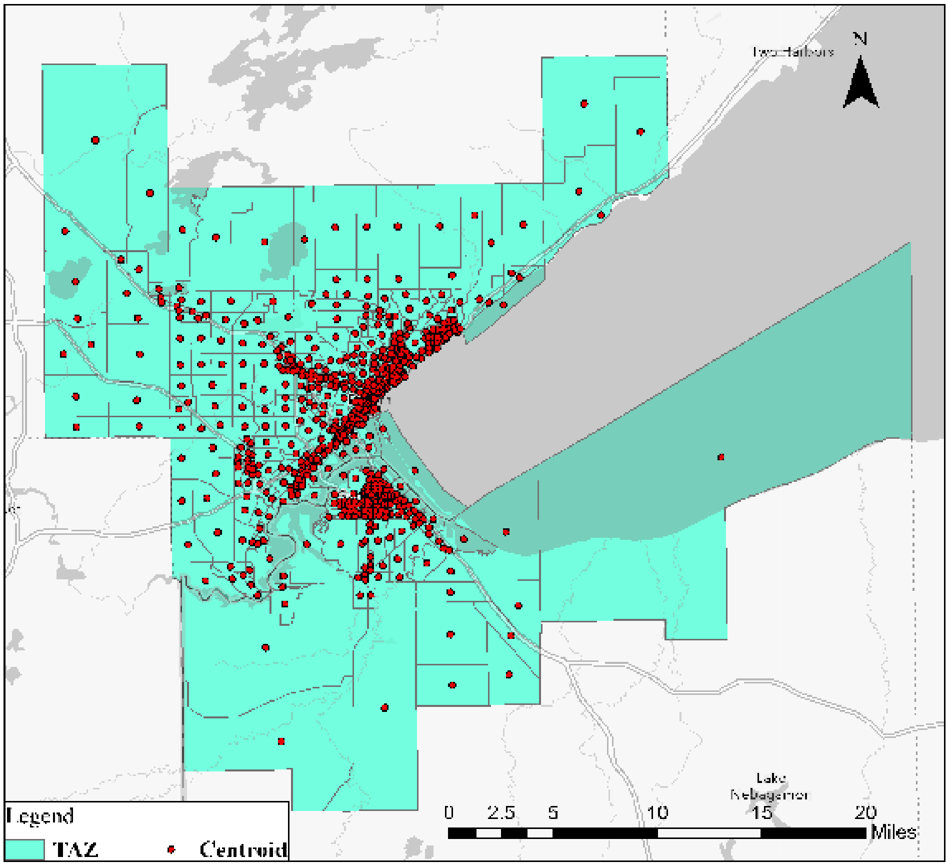

Figure 3. The Duluth-Superior Metropolitan TAZ.

The TAZ file has boundaries within the Duluth-Superior metropolitan planning area. It is provided by the Duluth Transit Authority (DTA), which is for the year 2018 (the most recent that the agency provided). Figure 2 depicts the boundary of the Duluth-Superior metropolitan planning area. The transportation analysis zones are shown in Figure 3. There are 639 TAZs shown in the figure. We will further use it to visualize the travel time from different locations to an area with the last-mile problem.

2.2 General Transit Feed Specification (GTFS) data

The GTFS is a data specification that allows public transit agencies to publish their schedule in a format that a wide variety of software applications can consume. The GTFS data for the transit service provided in the Duluth region is provided by the Duluth Transit Agency (DTA) through their website. This file consists of a series of text files collected in a ZIP file. Each text file models a particular aspect of transit information in the Duluth-Superior metro area, including stops, stop times, routes, trips, shapes, and other schedule data [28].

Table 2 shows the summary of the DTA GTFS data:

Table 2. Summary of the DTA GTFS data.

Service from	Dec. 5, 2021, to March 5, 2022
Number of routes	35
Number of trips	1,783
Number of stops	1,557

2.3 Stop-level ridership data

The transit stop-level average daily boardings and alightings were also obtained from DTA. The stop level ridership data comes from 1,376 stops, including the average weekday boarding and alighting as well as the weekend days. Note that this data is for the pre-pandemic years. This dataset will be used to estimate transit demand for the design of the last-mile service.

2.4 Duluth road network data

The road network for the Duluth-Superior area was obtained from the website of St. Louis County. This geo-spatial data is used to evaluate the auto travel time from various zones to the Miller Hill Mall area with last-mile connectivity problem. Figure 4 shows the snapshot of this dataset.

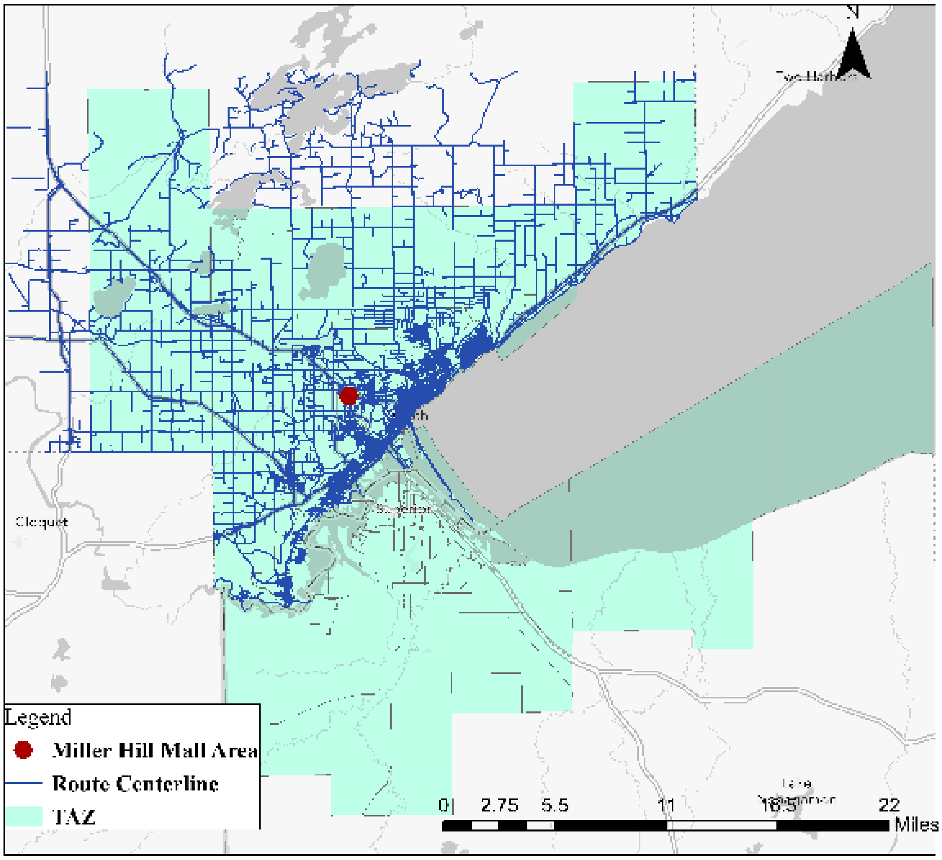

Figure 4. Duluth road network. MHM is shown by the red solid circle.

2.5 MHM area

After careful consideration and discussion with project champions, we identify the MHM area as the case study for this research. Even though the area is served by four different transit routes, longer travel times and indirect trips make transit unappealing. This is because the transit service does not provide a direct service to the stores and pedestrians feel unsafe crossing highways to get from one store to another. The car-oriented land-use and development patterns make it difficult to serve that area using a fixed-route transit service.

2.6 MHM area zoning

For the design of last-mile service, the MHM area is divided into 21 local zones, which are decided after observing nearby topology. Each zone has a specific drop-off location where last-mile service will drop passengers. Such zoning will help evaluate the demand for the last-mile service. Figure 5 shows various local zones with their respective drop-off location.

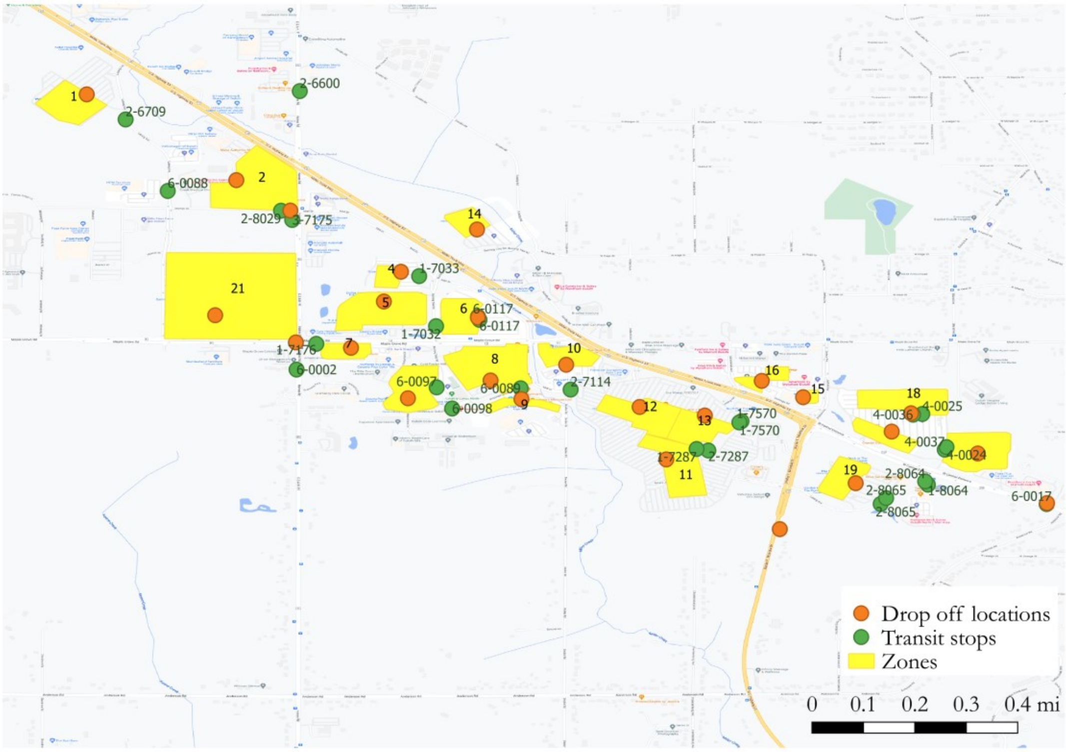

Figure 5. MHM area local zones and drop-off locations.

2.7 Ridership analysis

A summary of the transit stop-level average daily and also total boardings and alightings for the transit stops in the mall area is indicated in Table 3, Figure 6, and Figure 7.

Table 3. Summary of transit ridership for the stops in the mall area.

	Weekday	Saturday	Sunday
Service	Sept. 30, 2019, to Oct. 4, 2019 Oct. 7, 2019, to Oct. 11, 2019	Sept. 28, 2019 Oct. 5, 2019 Oct. 12, 2019	Sept. 29, 2019 Oct. 6, 2019 Oct. 13, 2019
Total Boardings	4,257	1,429	976
Total Alightings	4,769	1,615	1,068
Average Daily Boardings	426	476	325

Average Daily Alightings	477	538	356

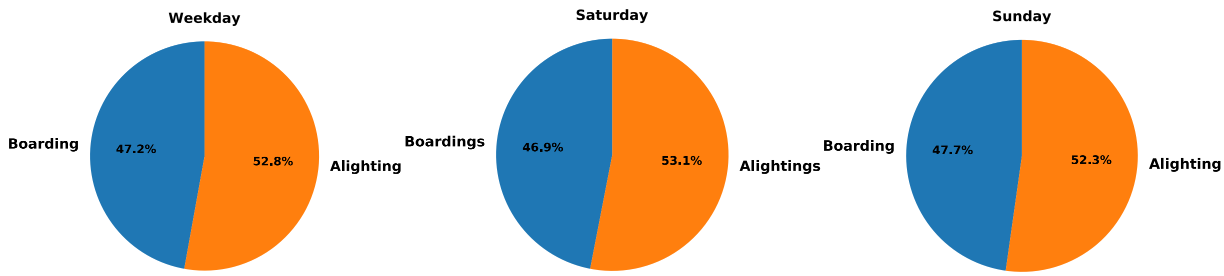

Figure 6. Average daily Boarding vs. alighting for weekday and weekend. (a) Weekday; (b) Saturday; (c) Sunday.

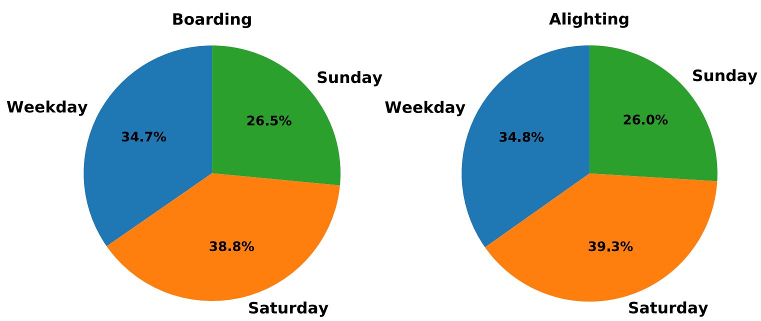

Figure 7. Weekday vs. weekend boarding and alighting. (a) Boarding; (b) Alighting.

Figure 6 reveals more alightings than boardings. This may be because passengers take transit to the mall area and later decide to go back using some other mode of transportation. Further, we observe that the average number of boarding and alighting on Saturday is more than a weekday. Moreover, the average number of boarding and alighting for a weekday is more than on Sunday (Figure 7).

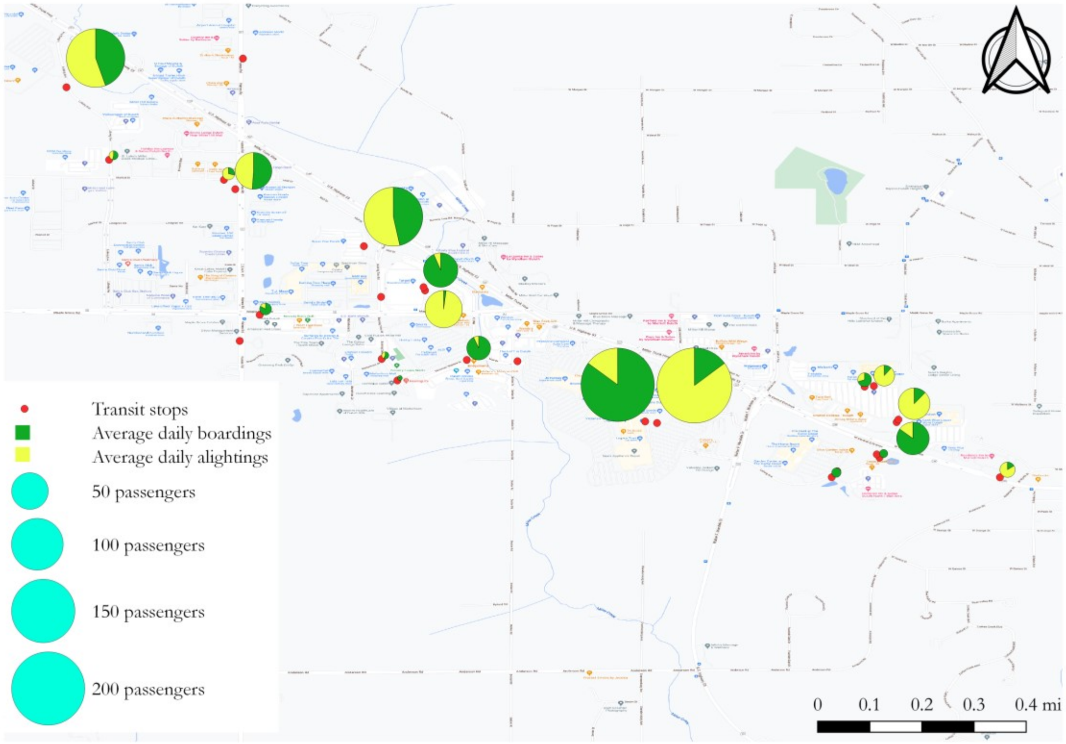

Figure 8. Average daily (weekday) ridership in MHM area.

Figure 8 shows the average number of boardings and alightings on various transit stops in the MHM area. The stops with high ridership are MHM/Northstar Ford, Cub Foods, Target Miller Hill, Burning Tree Rd - Super One, Mall Dr & Haines Rd, and Walmart - Hermantown.

2.8 Travel time analysis

To better understand the access to the MHM area, we conducted a travel time analysis. For this purpose, we visualize the travel time from different locations in the Duluth-Superior region to the MHM area by different modes using a heat map. Note that for the transit mode, the peak hours are from 7:00 AM - 9:00 AM and from 2:30 PM - 6:00 PM on weekdays. All other times are considered non-peak hours. In the driving mode, the peak hours occur from 7:00 AM - 8:30 AM and 4:00 PM - 5:30 PM. All other times are considered non-peak hours.

2.8.1 Transit travel time

Since transit service is time-dependent, we use a schedule-based transit shortest path routing algorithm to evaluate the travel time from various TAZs to the local zones in the MHM area. This is a routing algorithm that runs on a time-dependent transit network created using GTFS data. We use an R package named *tidytransit* for this purpose [29]. The walking times from transit stops to the actual drop-off location of local zones are calculated using the Google Maps API. After evaluating the travel time from a specific TAZ to various local zones, an average travel time value is calculated for the MHM area.

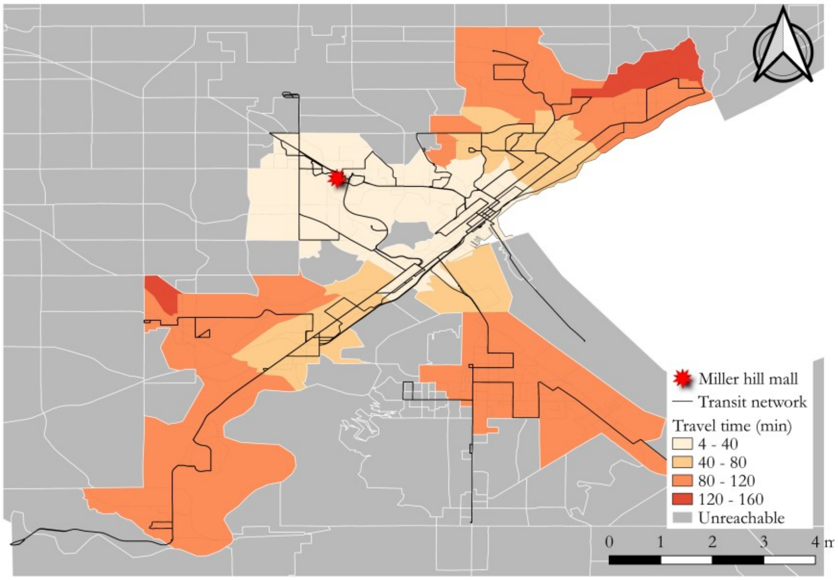

Figure 9. Transit travel time during morning peak hours.

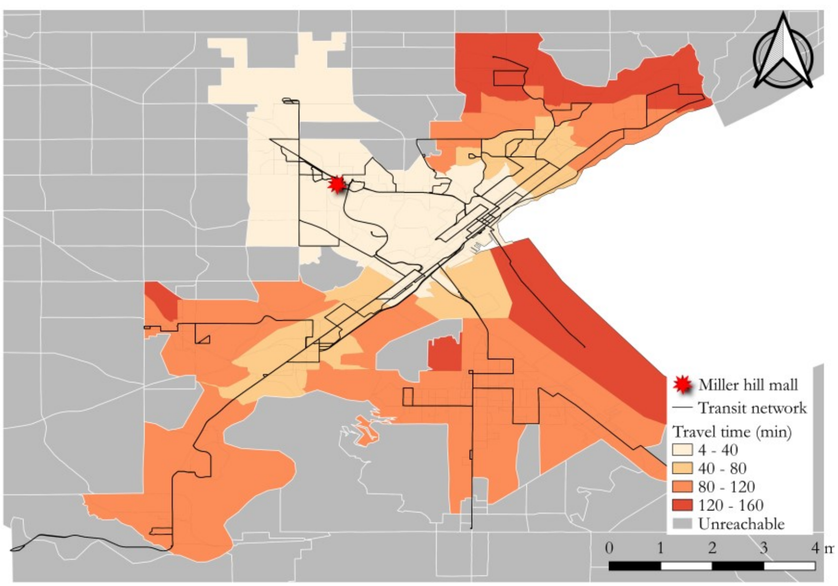

Figure 10. Transit travel time during morning non-peak hours.

The average travel time values for both morning peak and non-peak hours are visualized in Figure 9 and Figure 10, respectively. We observe that transit service provides more coverage during non-peak hours (due to the longer duration of non-peak hours). However, the average travel time during non-peak hours is higher than the peak hours. Due to less connectivity of the transit network, the MHM area is accessible from only a subset of TAZs.

2.8.2 Auto travel time

The auto travel time from various TAZs to local zones is evaluated using the Google Maps API. After evaluating the travel time from a specific TAZ to various local zones, an average travel time value is calculated for the MHM area. The average travel time values are visualized in Figure 11 during morning peak hours and in Figure 12 during morning non-peak hours. As expected, the travel time from some TAZs to the mall area during non-peak hours is lower as compared to peak hours. Comparing the auto and transit travel time, we find that for some of the zones, the transit travel time can be as high as four times the auto travel time.

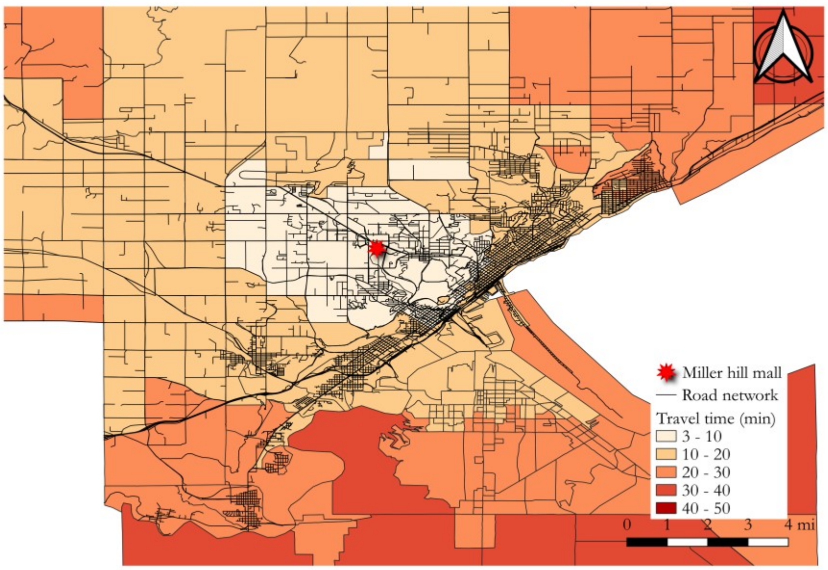

Figure 11. Auto travel time during morning peak hours.

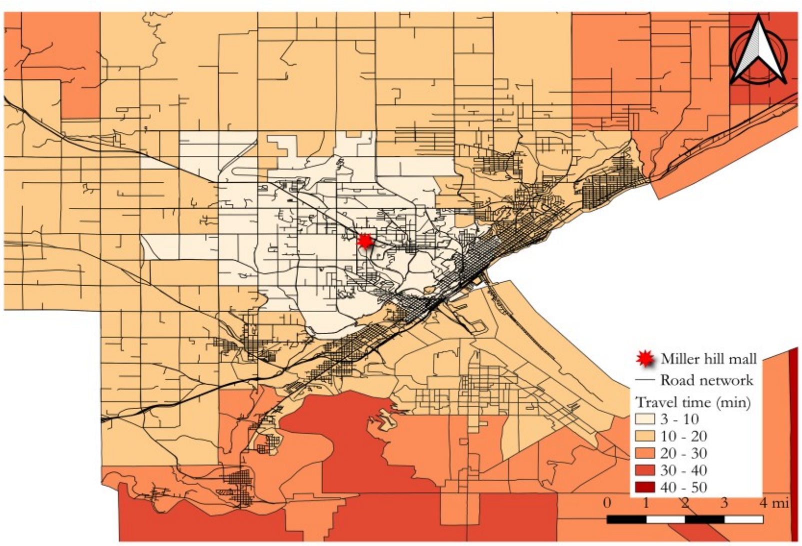

Figure 12. Auto travel time during morning non-peak hours.

2.8.3 Walking time

To analyze the walking accessibility across various stores around the mall area, we conduct a walking time analysis. For this purpose, we evaluate the walking travel time between various local zones in the MHM area and walking time between local zones and nearby transit stops using Google Maps API. Figure 13 shows walking time between transit stops and local zone drop-off locations. It shows that some of the stores are difficult to access using transit. For example, it is difficult to walk to Walmart if you alight at any other transit stop. Many of the stop-zone pair can take more than 30 minutes to walk. Figure 14 shows walking time between various local zone drop-off locations. The figure shows that a passenger must spend a significant amount of time to walk between various stores. It could be as high as 50 minutes in some cases.

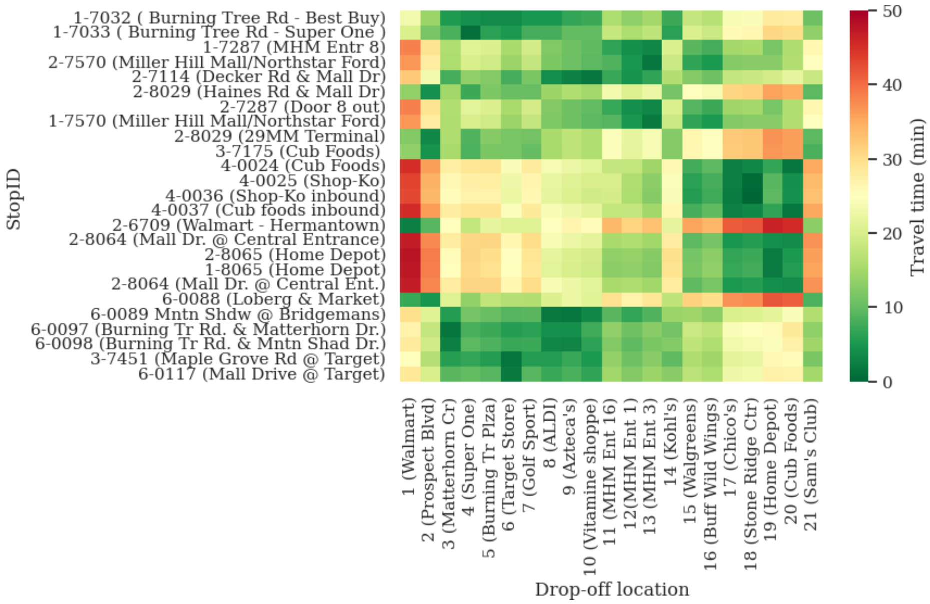

Figure 13. Walking time (min) between local zones and transit stops.

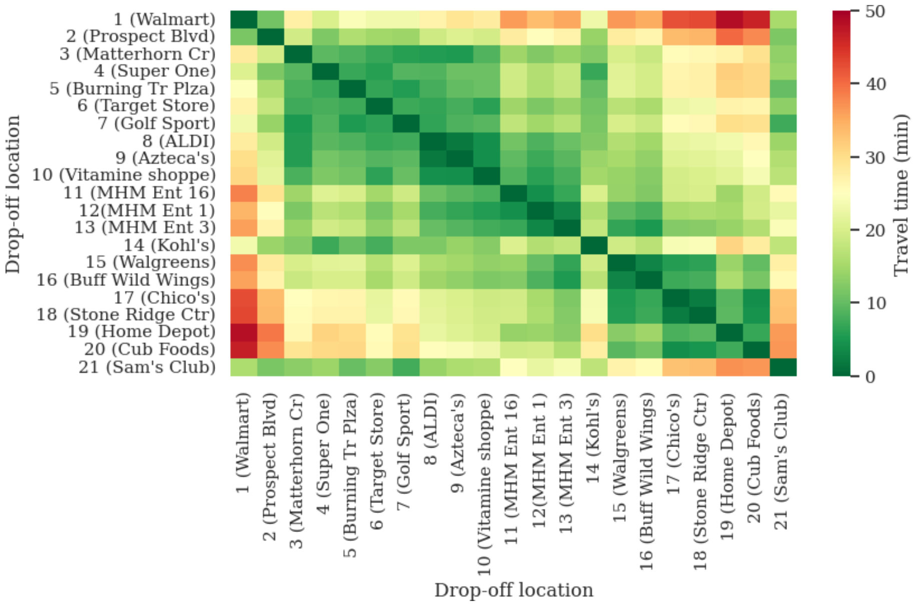

Figure 14. Walking time (min) between various local zones.

2.8.4 Safety analysis

To walk between stores, one must cross one or more roadways, which could be unsafe for pedestrians. We conduct a safety analysis based on how many major roadways and minor links should be crossed to walk between local zones or transit stops. A major roadway refers to any street, avenue, boulevard, or highway used for motor vehicle traffic, while a minor link represents a mall area parking lots link that one must cross while walking between various stores. Figure 15 and Figure 16 shows the number of major roadways and minor links crossing required to walk between various local zones. We can observe that it could be unsafe to walk between various zones, especially when the number of major roadways and minor links to be crossed is high.

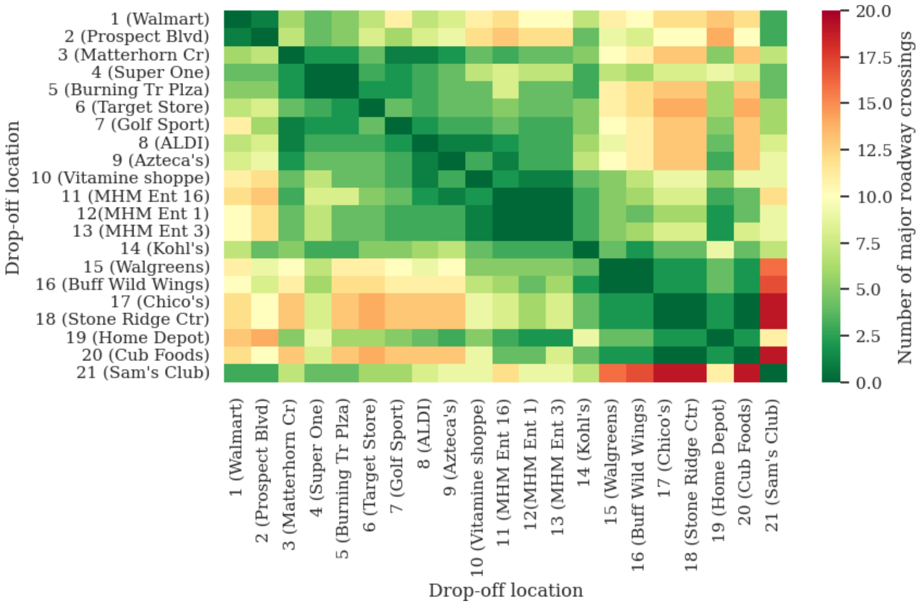

Figure 15. Number of major roadways crossing between zones.

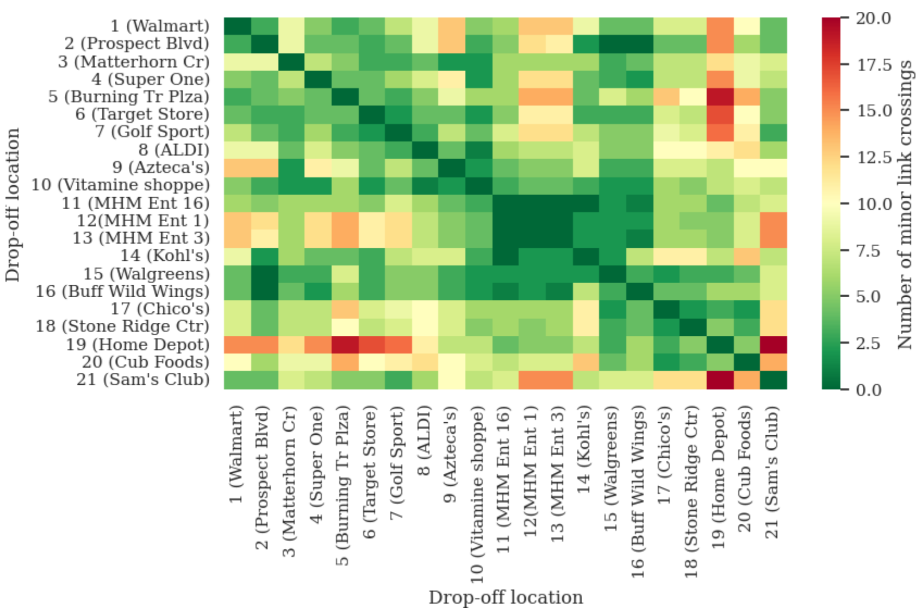

Figure 16. Number of minor link crossing between zones.

2.8.5 Data Analysis Summary

In this chapter, we presented the details of the collected data for this research. The data related to transit operations and passenger mobility in Duluth area, including transportation analysis zones (TAZ) data, road network data, GTFS data, and stop-level transit ridership data were presented and visualized. Then, ridership analysis, travel time analysis and safety analysis were conducted to understand the passenger mobility around the MHM area. The stop-level ridership shows that many stores such as the mall, Cub Foods, Super One, and Walmart attract a large number of transit trips. The travel time analysis shows that transit travel time which consists of access, egress, transfer, and in-vehicle time is higher than the auto travel time to the mall from different TAZs. The walking time between some of the local zones in the mall area is significantly high. Finally, the safety analysis shows that to walk between stores, one must cross many streets, which could be unsafe. Overall, the analysis reveals that the car-oriented development makes it difficult for the transit passenger to access their desired destinations in the mall area.

Chapter 3: Design and Control of an AMoD Service

This chapter aims to address the last-mile problem by developing an online demand-responsive AMoD service integrated with fixed-route transit. A linear time-delay dynamical system is proposed to model the AMoD system, and a Model-Predictive Control (MPC) methodology is adopted to regulate the system around an equilibrium point with minimum vehicle rebalancing. To assess the impact of this new mobility service on travel demand, a simulation study is developed and integrated with a mode choice model capturing a combined transit-AMoD model. The experiment results reveal the potential to enhance transit efficiency, reduce VMT, and accommodate the increased transit demand while maintaining quality of service.

3.1 Modeling Overview

We develop a method for designing an AMoD system to capture system efficiency gain and potential demand attracted to the system. The design will include the selection of a transit hub near the study area, for passenger transfer (from fixed route transit to AMoD) and vehicle dispatching. We will then simulate the proposed last-mile service (LMS) with the AMoD.

We assume the existence of two modes of transportation: i) automobile and ii) integrated transit and the AMoD system. In other words, people traveling to the study area can either drive their own personal vehicle or take the transit to the transit hub and transfer to the AMoD for the last-mile access.

The modeling procedure is as follows: First, we consider an initial transit demand and simulate the AMoD system. Then, we measure the performance of the AMoD system and aggregate the data, including travel times, waiting times, and other relevant factors. We define utilities for each mode and by employing a logit model, we update the demand for each mode. The procedure will be repeated in an iterative framework, i.e., demand will be updated until convergence is achieved. The procedure is shown in Figure 17.

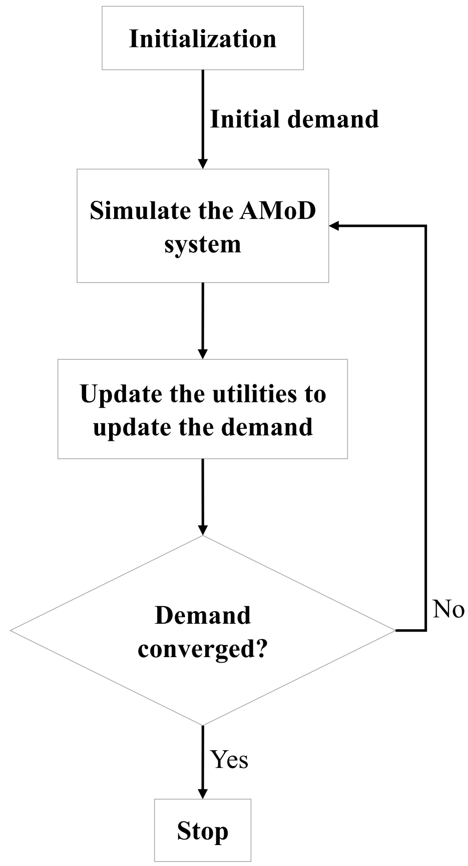

Figure 17. Proposed structure to evaluate the induced demand by implementing a new mobility service.

To model the framework depicted in Figure 17 particularly the simulation of the AMoD system, a linear discrete-time time-delay dynamic system is developed. The dynamic system discretizes the simulation horizon (e.g., a 2-hour peak period) into smaller time steps (e.g., 5-minute simulation intervals). It also incorporates various state variables at each time step, such as the number of customers waiting at each station, the availability of vehicles at each station, and the number of vehicles in motion along the links, including both customer-carrying and rebalancing vehicles. The control variables encompass the real-time dispatching of vehicles from each station to different destinations, with or without customers (customer-carrying and rebalancing vehicles). Additionally, the arrival of customers in a given time step is assumed to follow a Poisson process with parameter λ. The Poisson process is a statistical model for a series of discrete events where the average time between events is known but the exact timing of events is random. In the AMoD system, we know the average number of customers arriving at the station (e.g., λ=10 customers per unit of time), but the exact arrival time of each customer is random. More details on the AMoD system modeling is available in Appendix A.

3.2 Simulation Methodology

After developing the AMoD model, we implemented a control framework to maintain a balanced state of the system in terms of waiting customers and vehicle availability at each station. Note that the terms "control" and "simulation" may be used interchangeably in this report, and both refer to the optimal dispatching and repositioning of AVs in the AMoD system toward an objective. Given that the system is based on a linear model and is subject to a set of convex constraints, a natural approach to achieve this is through model predictive control (MPC).

MPC is a sophisticated control strategy that utilizes a mathematical model of a system to predict its future behavior and make optimal control decisions in real-time. Unlike traditional control methods, MPC takes into account not only the current state of the system but also the predicted future states, enabling it to optimize control actions over a defined time horizon. By continuously updating the model and adjusting control actions based on desired performance criteria, MPC can effectively handle complex systems with constraints and uncertainties. This approach has found applications in various fields, such as process industries, robotics, and AVs, where precise control and optimization are crucial. Through its predictive capabilities and ability to incorporate constraints, MPC offers a powerful and flexible solution for achieving optimal system performance in real-time applications.

MPC is a well-suited approach for optimizing vehicle dispatching and rebalancing in the AMoD system. Since we predict the model and demand for a set number of future time steps, optimal rebalancing is performed to respond to the incoming demand. It also ensures that system constraints such as fleet size are satisfied. One advantage of MPC is its robustness, attributed to its rolling-horizon structure. By incorporating recurrent state feedback, MPC prevents the accumulation of errors over time and tries to keep the system stable. More details on the MPC framework applied to the AMoD system is available in Appendix B.

3.3 Integrated AMoD System with Public Transit

To design the last-mile service to the MHM area, the area is partitioned into 10 zones or subsystems. This approach is implemented to reduce the computational complexity of the control system and to allow for faster simulation of the entire system. By structuring the area in this manner, the computational complexity is equivalent to that of a system with 13 zones, compared to the original design with 22 zones. Figure 18 shows the AMoD system zones with their respective subsystems.

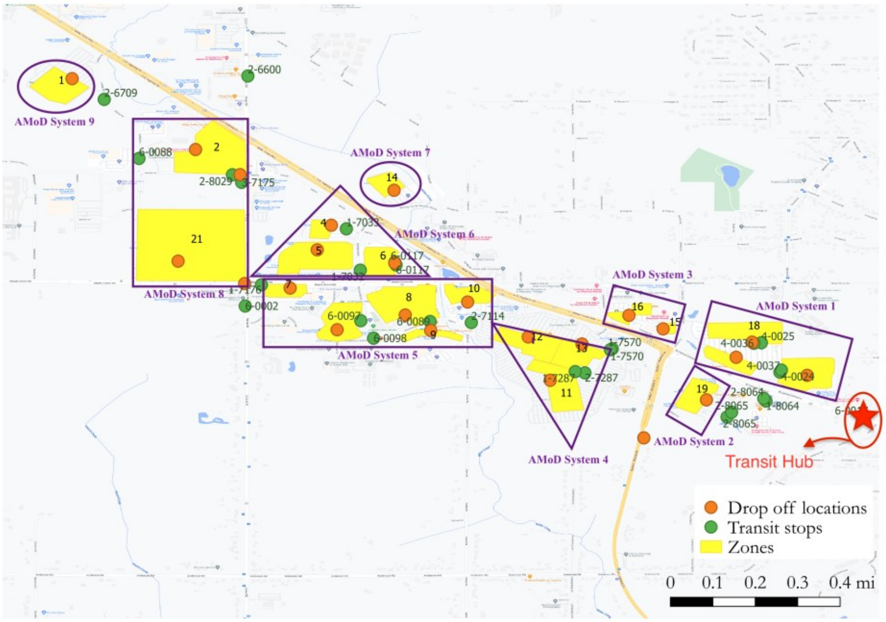

Figure 18. MHM area AMoD system. Yellow areas represent points of demand generation, while green dots indicate existing transit stops that are intended to be consolidated into the transit hub marked by a red star. The orange dots are considered potential drop-off in the AMoD system.

We designate a location near the MHM area as the transit hub, serving as the destination for transit passengers traveling from 23 different districts in the Duluth region as shown in Figure 19. Instead of relying on fixed-route services that follow predetermined routes at fixed intervals, transit passengers will transfer to the AMoD system at the transit hub and will be taken to the MHM stores with AMoD vehicles seamlessly. Optimal location of the transit hub would require thorough investigation of the area and coordination with local agencies, businesses, and residents. For the simulation study, we assume an existing transit stop near the MHM area can serve as the transit hub. This selection could change in future studies, or even more than one hub could be selected for the area.

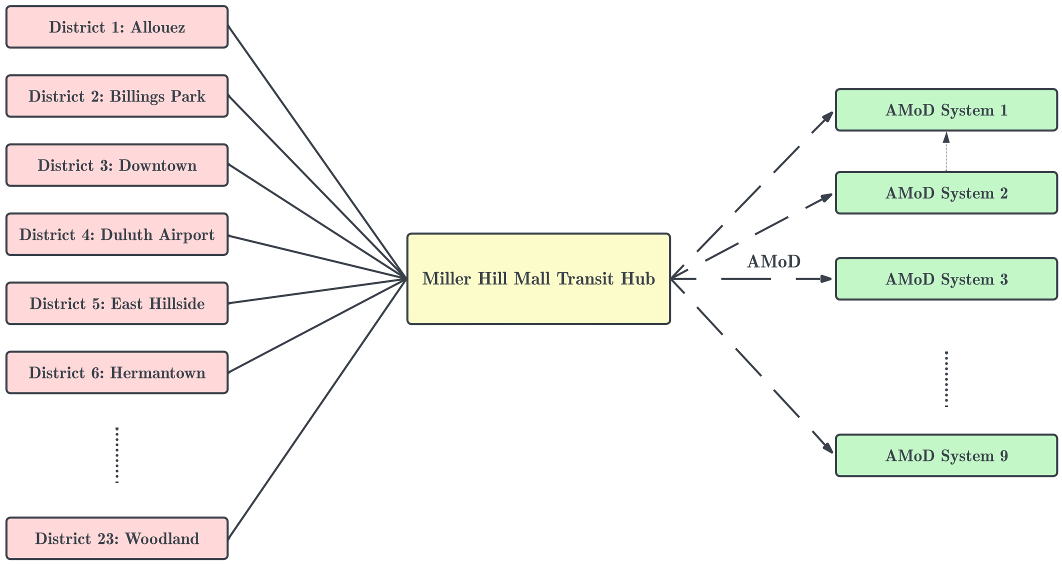

Figure 19. Integrated AMoD System with Public Transit. Passengers first take public transit to the MHM transit hub, and then they use the AMoD system to reach their final destination.

3.4 Utilities

For reference in this section, Table 4 shows the mathematical notation and the parameters of the utility functions for each travel mode.

Table 4. The parameters and variables used in the utility functions.

Parameter	Definition	Value
$\beta_{T,\text{Auto}}$	Coefficient of auto travel time	1
$\beta_{T,\text{Transit}}$	Coefficient of transit travel time	1
$\beta_{T,\text{Walk}}$	Coefficient of walking time	2
$\beta_{T,\text{Wait}}$	Coefficient of waiting time	2
$\beta_{T,\text{AMoD}}$	Coefficient of AMoD travel time	1
$\beta_{X,\text{Transit}}$	Coefficient of transit transfer	15
Variable	**Definition**	
F_{Transit}	Transit fare	$1.5

CPM	Driving cost per mile	\$0.2
VOT	Value of time (per minute)	\$0.25
L_{Auto}	Auto trip mileage	varies for different trips
T_{Transit}	Transit travel time	varies for different trips
T_{Auto}	Auto travel time	varies for different trips
T_{AMoD}	AMoD travel time	varies for different trips
T_{Walk}	Walking access time	varies for different trips
T_{Wait}	Waiting time for transit	varies for different trips
X_{Transit}	Number of transit transfers	varies for different trips
W_{AMoD}	Waiting time for AMoD	varies for different trips

3.4.1 Auto Utility

The utility of auto mode is defined by travel time and driving cost. Therefore, its utility function is defined as:

$$U_{\text{Auto}} = \text{VOT} \times \left(\beta_{\text{T,Auto}} T_{\text{Auto}}\right) + \text{CPM} \times L_{\text{Auto}}.$$

The first term in the equation takes the auto travel time and multiplies it by the coefficient of travel time, and subsequently converts it to monetary cost by multiplying it by the value of time. The second term multiplies the trip length by the cost-per-mile to calculate the auto trip cost.

For instance, the utility of a 15-minute auto trip with a 10-mile length will be calculated as follows:

$$U_{\text{Auto}} = 0.25 T_{\text{Auto}} + 0.20 L_{\text{Auto}} = 0.25 \times 15 + 0.20 \times 10 = 5.75$$

3.4.2 Integrated Transit and AMoD Utility

The utility of integrated transit and AMoD trips is defined as the combination of the utility of the two modes. A typical trip from any origin in the Duluth region to the MHM area using the integrated mode is presented in Figure 20.

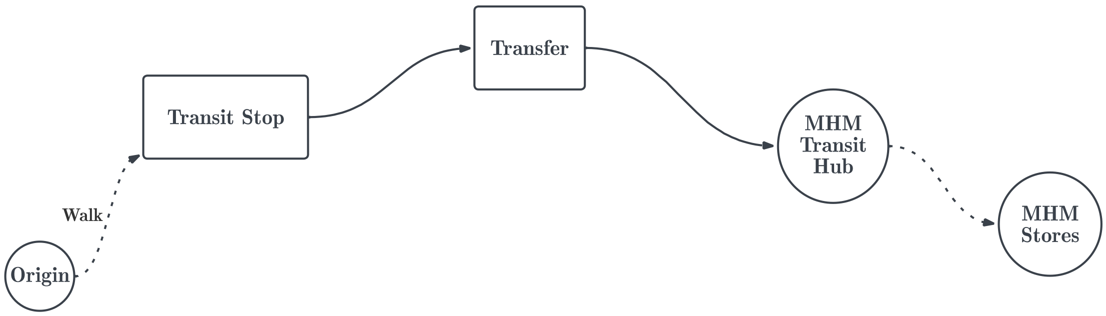

Figure 20. Illustration of a typical trip using an integrated mode. The breakdown of the trip to different legs helps with the calculation of the trip utility.

3.4.2.1 Transit Utility

We consider the utility from trip origins to the MHM transit hub as the utility of the transit. We assume a 5-minute average walking time from the origins to transit stops to board transit buses. We developed a shortest path algorithm to calculate the transit travel time, waiting time, and the number of transfers it takes to go from any point in the Duluth region to the MHM area. This step was explained in more detail in the previous chapter. Applying the coefficient to each trip attribute, the transit mode utility is defined as below:

$$U_{\text{Transit}} = \text{VOT} \times \left(\beta_{\text{T,Walk}} T_{\text{Walk}} + \beta_{\text{T,Wait}} T_{\text{Wait}} + \beta_{\text{T,Transit}} T_{\text{Transit}} + \beta_{\text{X,Transit}} X_{\text{Transit}}\right) + \text{F}_{\text{Transit}}.$$

Similar to the auto utility, transit utility is calculated based on perceived times and costs. The first term in the equation combines all the times spent on a transit trip as well as the transfer penalty and then converts it to monetary cost using the value-of-time coefficient. The second term is simply the transit fare, which is constant in this case.

For instance, the utility of a transit trip with 3 minutes waiting time, 20 minutes in-vehicle transit time, and one transfer will be calculated as follows:

$$\begin{aligned} U_{\text{Transit}} &= 0.25 \times (2T_{\text{Walk}} + 2T_{\text{Wait}} + T_{\text{Transit}} + 15X_{\text{Transit}}) + 1.50 \\ &= 0.25 \times (2 \times 5 + 2 \times 3 + 20 + 15) + 1.50 = 12.75 \end{aligned}$$

3.4.2.2 AMoD system utility

The AMoD system itself has 10 zones and 90 links connecting these zones. In other words, there are 90 origin-destination pairs within the AMoD system. In order to calculate the utility of AMoD for the integrated system, an aggregate utility, i.e., the average utility over all the links needs to be calculated. Assuming W_{AMoD} is the time-averaged waiting time for AMoD, and T_{AMoD} is the AMoD travel time along the links, first we define the AMoD utility as below:

$$U_{\text{AMoD}} = \text{VOT} \times \left(\beta_{\text{T,Wait}} W_{\text{AMoD}} + \beta_{\text{T,AMoD}} T_{\text{AMoD}}\right)$$

The above equation is similar to auto and transit utility functions, in that, different time components are added with the corresponding coefficients, and then converted to cost using the value-of-time parameter. We then use the log-sum formula to aggregate the AMoD utility values:

$$\mathrm{LS}_{\mathrm{AMoD}} = -\frac{1}{\mu}\mathrm{Ln}\sum_{i} e^{-\mu U_{\mathrm{AMoD}}}$$

where $\mathrm{LS}_{\mathrm{AMoD}}$ is the log-sum value to be calculated, μ is a nested logit parameter, Ln is the natural logarithm function, and i is the index representing links in the AMoD system, in this case, $\mathrm{i} \in \{1, 2, \ldots, 90\}$.

3.4.2.3 Integrated Mode Utility

Given the utility of transit and AMoD separately as explained above, the utility of the integrated transit and AMoD trips will be simply the sum of the two utilities:

$$U_{\mathrm{Int}} = U_{\mathrm{Transit}} + \mathrm{LS}_{\mathrm{AMoD}}.$$

3.5 Mode Choice and Demand Updating

During the simulation experiment, we assume the total travel demand to the MHM area is constant and will not change. However, the following logit mode choice equation is used to determine what proportion of the total demand will be attracted to the integrated mode after implementing the new AMoD service. Note that the mode choice equation is repeated for each origin district in the Duluth region.

$$d_{\mathrm{Int}} = d_{\mathrm{Total}}\frac{e^{-\theta U_{\mathrm{Int}}}}{e^{-\theta U_{\mathrm{Int}}} + e^{-\theta U_{\mathrm{Auto}}}}$$

The above equation calculates a proportion (between zero and one) and by multiplying it by the total demand, calculates the demand of the integrated mode. The process of updating the utilities and updating the mode choices continues iteratively until convergence is reached. Convergence is defined as achieving a gap value of less than 2 percent. The gap is calculated as the changes in new demand compared to the existing demand in the previous iteration.

$$\mathrm{Gap} = \frac{\left\| d_{\mathrm{Int}}^{\mathrm{new}} - d_{\mathrm{Int}}^{\mathrm{old}} \right\|_1}{\left\| d_{\mathrm{Int}}^{\mathrm{old}} \right\|_1}$$

To initialize the algorithm, the proportion of transit users in the current conditions needs to be estimated. Due to the lack of access to mode choice models, we made an estimate of total and transit demand, but the numbers should be calibrated in future studies. Based on the data in Table 3, the average number of daily passengers alighting at the MHM area is 477. From the "Duluth Travel Patterns Assessment" data provided by the Duluth-Superior Metro Interstate Council, the total number of trips to the MHM area on a weekday is 43,400. Therefore, we estimate that under the base condition, approximately one percent of the total trips to the MHM area are made by transit.

3.6 Simulation Experiment

3.6.1 Simulation Time Horizon

A simulation experiment was designed with a two-hour simulation horizon representing an afternoon peak period from 4-6. The simulation time step is 4 minutes, i.e., AMoD vehicle dispatching and rebalancing are performed every 4 minutes. Since we are simulating 120 minutes in 4-minute steps, the simulation horizon is $\mathrm{N_{hor}} = \frac{120}{4} = 30$.

3.6.2 AMoD Demand

As explained earlier in the report, the parameter λ^{0i} represents the average demand from the transit hub to zone i in the AMoD system. In the simulation experiment, and due to the lack of data for internal trips within the mall area, we assume that AMoD demand exists from the transit hub to the zones and from the zones to the transit hub, but not between the zones. This is a limitation of the study due to lack of input data, and it is recommended to be addressed in future studies.

3.6.3 AMoD Fleet Size

It has been shown in our research that a lower bound for the AMoD fleet size can be calculated using mathematical derivation with λ as the demand matrix, $\mathbf{T}$ as the travel times vector and $\overline{\mathrm{R}}$ as the optimal number of rebalancing vehicles in an equilibrium state of the system. Given the total demand coming to the transit hub (≈ 140 for two hours), the lower bound for the fleet size to serve customers is 10. Since this is the theoretical lower bound, we consider a 25% higher value ($\mathrm{M} = 12.5$) as the minimum fleet size for the simulation experiment.

Three fleet size scenarios were considered to evaluate the performance of the system and the potential demand for the integrated system: i) $1.5 \times \mathrm{M} \approx 19$ vehicles, ii) $2 \times M = 25$ vehicles, and iii) $2.5 \times M \approx 31$ vehicles in the AMoD fleet.

3.6.4 Initial Conditions

The initial conditions for the passenger queue and the number of vehicles along each link are set to zero. Also, the entire fleet is assumed available at the transit hub at the beginning of the simulation run. Finally, after several trials and evaluation of the results, parameters μ and θ were selected as 0.1 and 0.3, respectively. The uncalibrated model is another limitation of the study, and full calibration is recommended before applying the model in practice.

3.6.5 Simulation Results

Figure 21 and Figure 22 depict the median and average waiting times, as well as queue lengths for the AMoD system in different scenarios. These figures reveal a consistent trend: larger fleet sizes are associated with lower interquartile ranges. In other words, larger fleets exhibit reduced mean and variability in waiting times and queue lengths. This suggests that increasing the fleet size improves system performance, resulting in more consistent and efficient service delivery and higher quality of service to customers. Interestingly, in all the scenarios, the average queue length hardly exceeds one person, and the average waiting time does not exceed one minute. However, note that these are average values and there could be instances with longer queue lengths and higher waiting times during the simulation horizon.

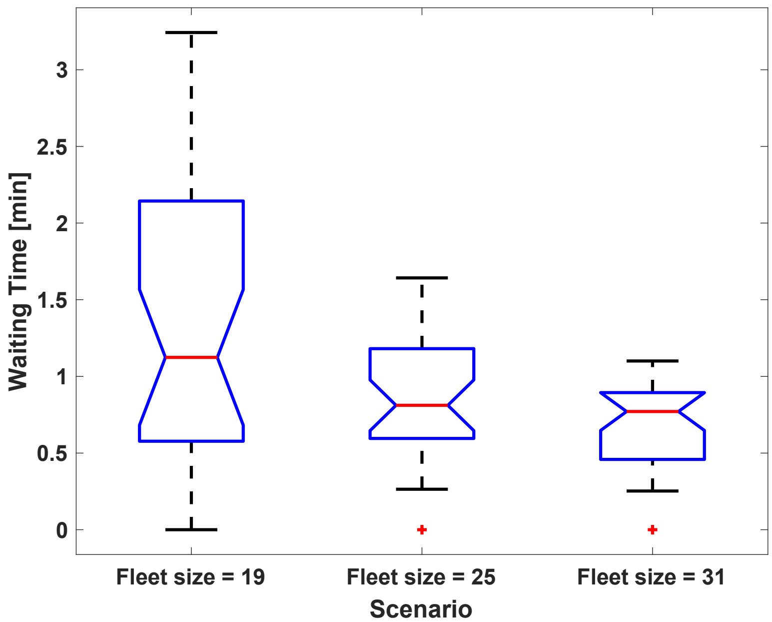

Figure 21. A box plot showing the variations of the average waiting time for the AMoD system in different scenarios.

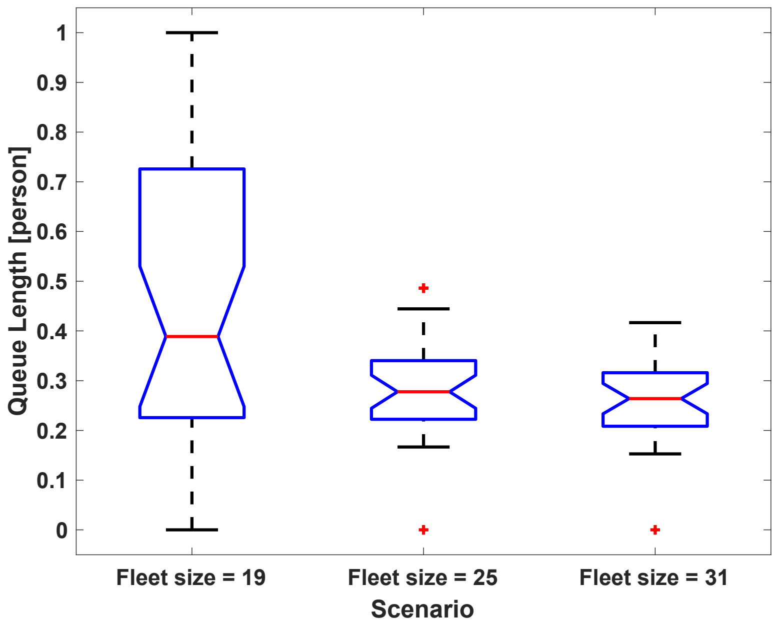

Figure 22. A box plot showing the variations of the average queue length for the AMoD system in different scenarios.

Figure 23 and Figure 24 display box plots of average customer-carrying and rebalancing vehicles, respectively. Both figures show that larger fleet sizes result in increased customer dispatching and more active rebalancing. This explains the lower waiting time and queue length depicted in Figure 21 and Figure 22. However, note that the higher customer-carrying vehicles are primarily due to the higher demand attracted to the system, explained later in the report.

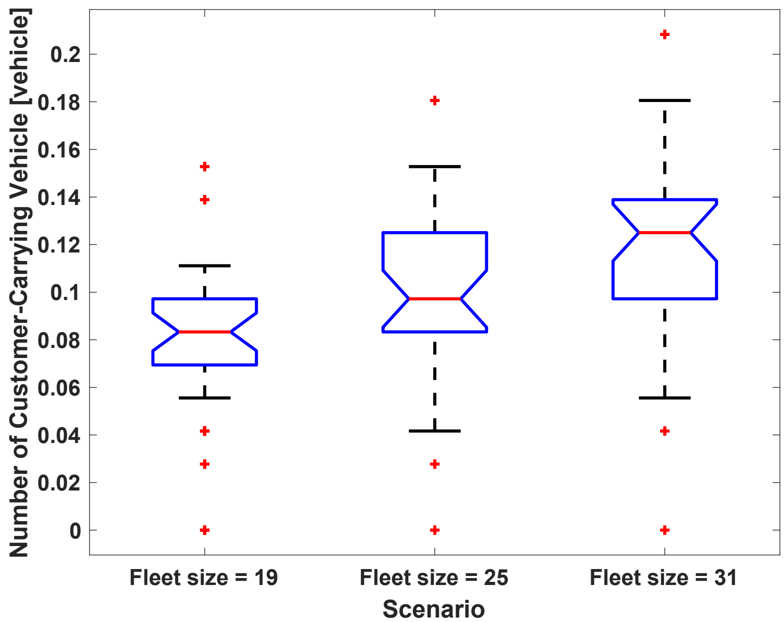

Figure 23. A box plot showing the variations of the average customer-carrying AMoD vehicles in different scenarios.

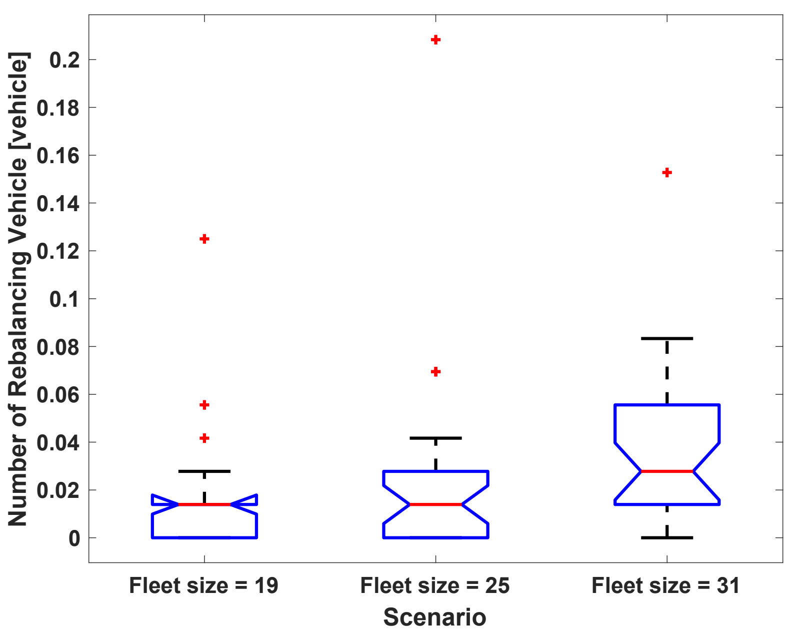

Figure 24. A box plot showing the variations of the average rebalancing AMoD vehicles in different scenarios.

Figure 25 depicts the total transit demand to the MHM area from all districts in the Duluth region, across various scenarios. The graph reveals a gradual increase in demand with larger fleet sizes, rising from 140 to 228, 248, and 260 for fleet sizes of 19, 25, and 31, respectively. These findings highlight the need for efficient transit last-mile service and the potential to attract demand to the integrated system.

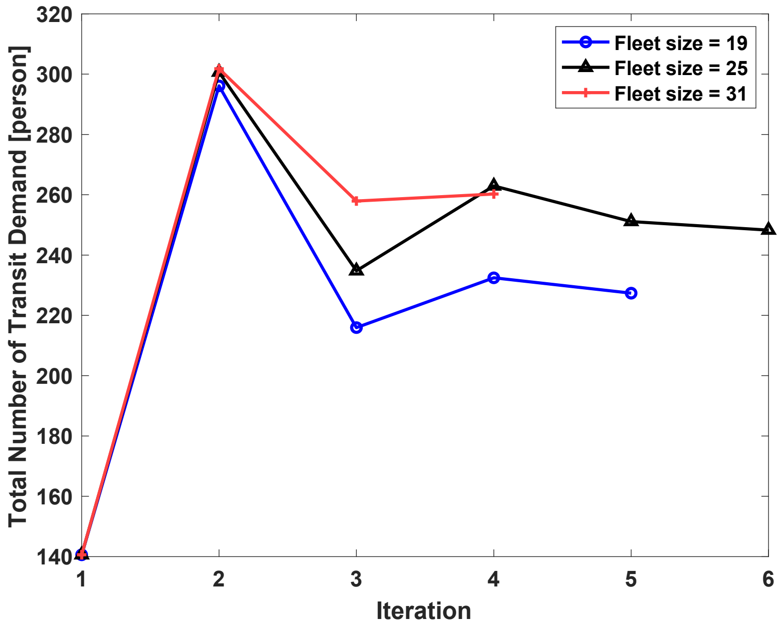

Figure 25. The total number of transit demand from all the districts in Duluth region to the MHM area in different scenarios.

Figure 26 shows how the relative gap decreases in different scenarios. For all the scenarios, the relative gap reaches a value of less than 2% within a small number of iterations, showing the convergence of the implemented algorithm.

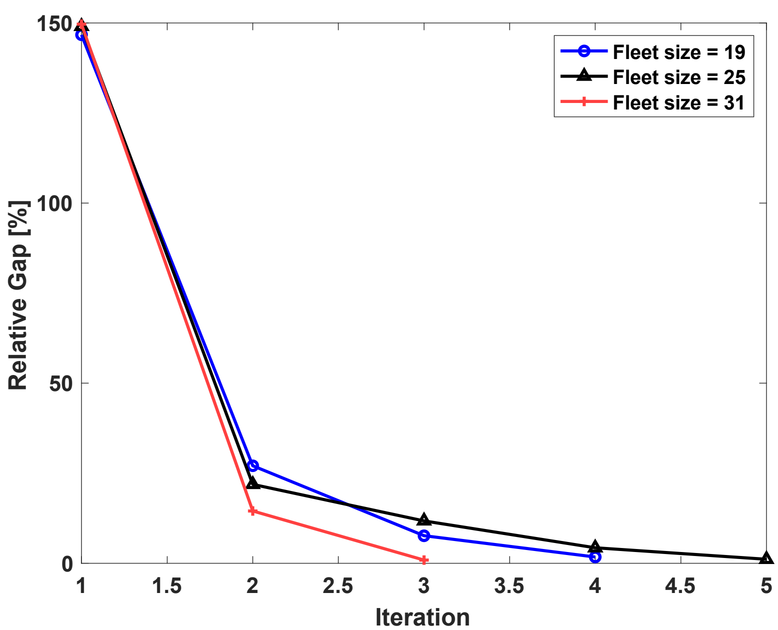

Figure 26. The reduction of the demand gap in different scenarios, showing the convergence of the algorithm.

In Table 5 the average queue length, average waiting time, total transit demand, and change in transit demand are presented for the final iteration of each scenario. The values on the table confirm the trend in higher demand and higher quality for the service as AMoD fleet size increases. It should be noted that since most of the elements of the demand vector (λ) and consequently the waiting time vector $\mathrm{W}_{\mathrm{Ave,AMoD}}$ are zero, we calculate the weighted average of the waiting time as $\frac{\lambda^{\mathrm{T}} \mathrm{W}_{\mathrm{Ave,AMoD}}}{\lambda^{\mathrm{T}} 1}$, where 1 is a vector with the same dimension as λ with all elements equal to 1.

Table 5. Comparison of the scenarios in terms of different performance metrics.

AMoD Fleet Size	19	25	31
Average queue length at AMoD stations [persons]	0.47	0.29	0.26
Average waiting time at AMoD stations [minutes]	4.39	2.47	2.14
Total transit demand to the MHM area [persons]	228	248	260
Percentage of the transit demand from the total demand*	1.62	1.77	1.85

* Note that transit mode choice and the demand values are not calibrated.

Table 6 represents the VMT for the auto mode before and after implementing the AMoD system. In the scenario with a larger AMoD fleet size of 31 vehicles, more trips are attracted to the integrated system, and fewer people drive to the mall area. This leads to a reduction of 490.5 VMT for a two-hour afternoon peak. It is important to note that this reduction already includes the addition of new VMT by AMoD vehicles but does not include the bus VMT reduction from shortening the fixed-route transit routes to the transit hub.

Table 6. Simulated VMT comparison before and after implementing the AMoD system.

AMoD Fleet Size	19	25	31
$\mathrm{VMT}_{\mathrm{AMoD}}$	126.9	177.1	214.6
$\mathrm{VMT}_{\mathrm{Auto,\ new}}$	83,878.6	83,759.5	83,687.9
$\mathrm{VMT}_{\mathrm{AMoD\ +\ Auto,new}}$	84,005.5	83,936.7	83,902.5
$\mathrm{VMT\ saving}\left(\mathrm{VMT}_{\mathrm{old}} - \mathrm{VMT}_{\mathrm{AMoD\ +\ Auto,new}}\right)^{*}$	387.5	456.3	490.5

* VMT for auto mode before implementing the AMoD system is estimated as $\mathrm{VMT}_{\mathrm{Auto,\ new}} = 84{,}393.02$.

3.7 Simulation Analysis Summary

A novel simulation method was developed in this study to facilitate the design of an AMoD service for transit last-mile access. Various factors, including passenger demand, and vehicle dispatching and rebalancing policies were incorporated into the simulation. Passengers traveling between the 23 districts of the Duluth region and the MHM transit hub were efficiently catered to by integration of the existing fixed route transit service and the designed demand-responsive service.

To assess the effectiveness of the AMoD service compared to traditional transit systems, a comparative analysis was conducted. The results of the analysis revealed significant benefits, with reductions of 387.5, 456.3, and 490.5 VMT observed for a two-hour afternoon peak and for different AMoD fleet sizes of 19, 25, and 31, respectively. It's important to note that these values do not include the reduction in bus VMT resulting from shortening the fixed-route transit routes to the transit hub exclusively. In other words, the implementation of the AMoD service has the potential to decrease both personal vehicle and bus transit VMT. Apart from that and based on the findings, it was concluded that the AMoD service has the potential to significantly affect transit demand. An increase in transit demand from 1% to 1.62%, 1.77%, and 1.85% for different fleet sizes of 19, 25, and 31, respectively, was observed. In summary, these results emphasize the potential of AMoD systems to enhance transit efficiency, reduce VMT, and accommodate increased transit demand.

As one of the earlier research on AMoD systems especially for transit access, the study faced some limitations that could be addressed in future investigations. Below is the list of the major limitations as well as potential ways to address them:

- Firstly, the demand resolution was limited to the MHM area from only 23 districts in the Duluth region, some of which comprise multiple transportation analysis zones (TAZs). Given the 639 TAZs in the Duluth-Superior Metropolitan area, using demand from the TAZs in the region would lead to a more accurate estimation of demand shift from auto mode to the integrated transit and AMoD system modes.
- Secondly, the demand between local zones in the MHM area is currently unknown, and including this data would allow for a more accurate determination of required fleet size, passenger waiting time, queue length, and other relevant metrics.
- Thirdly, the values of the parameters in the utility functions have not been estimated from any real data. A stated preference (SP) survey could be used to gather the necessary data and estimate the parameters. Alternatively, models developed in other regions could be adopted, but that should be done with diligence and proper accounting for contextual adjustments. In either case, factors such as privacy, convenience, safety concerns, and other technology-related factors should be properly incorporated into the mode choice with AVs.

Potential future works may involve incorporating Electric Vehicles (EVs) into the system, taking advantage of their environmental-friendly characteristics. Adjusting the model to accommodate EV charging scheduling is crucial to promote efficient and sustainable utilization of EVs within the system. Furthermore, allowing ridesharing in the AMoD system is another aspect to consider. This addition holds the promise of increasing vehicle occupancy and reducing the frequency of rebalancing trips across the network, potentially leading to a reduction in VMT.

Chapter 4: Conclusions and Discussion

This study tackled the potential application of AMoD services for last-mile access in Greater Minnesota by designing and simulating an AMoD service in a selected case study site. The research team obtained data on transit service and ridership and conducted descriptive analyses to identify service gaps and opportunities for last-mile access in the MHM area. According to the analysis results, accessing the MHM area from other parts of the region by transit could take as much as four times longer than by personal vehicle, or in some cases, even be impossible. A local accessibility analysis in the MHM area shows that riders may have to walk for 20-30 minutes to access the stores from transit stops and have to cross multiple highways or streets, exposing them to safety risks. These findings suggest improvements in last-mile transit access toward rider safety, convenience, and saving time, as well as potential attraction of new transit riders.

A new mathematical model was developed to optimize the operation of the AMoD service, including the calculation of minimum fleet size, dispatching and routing of customer-carrying AVs, and real-time rebalancing of empty vehicles to zones with higher passenger demand. A simulation experiment was developed to evaluate the AMoD service and integrate it with a transit mode choice model. Simulation results indicate that the AMoD service can significantly improve transit quality of service, namely travel and waiting times, potentially attract new riders to transit, and reduce VMT in the region. Evaluating scenarios with AMoD fleet sizes of 19, 25, and 31, passenger waiting time at local zones or the transit hub did not exceed 2 minutes in most cases. Moreover, a (uncalibrated) mode-choice model report that transit demand to the MHM area could increase by as much as 100 riders in the two-hour peak period. The mode shift from personal vehicles to the integrated transit-AMoD service could result in a reduction of 490 VMT. Overall, the simulation analysis confirms great potential for advancing the mobility, safety, and convenience of riders, and improved well-being of residents in the region by adopting an AMoD service.

An AMoD system, if implemented properly and optimally, can potentially be more cost-effective than a similar MoD system with conventional vehicles. While the exact cost of autonomous vehicles is still uncertain as technology matures and the market evolves, studies indicate that autonomous taxis would have a lower per-mile cost than conventional taxis due to the elimination of operator wages. A comprehensive study by Bosch et. al. in 2018 evaluated the cost of various transportation modes and technologies in Switzerland [30]. The report's calculations (Fig. 27) showed that an individual taxi had a high cost of $4.37 per passenger-mile, 88 percent of which was associated wtih operator salaries. With autonomous vehicles, the cost would fall to $0.66 per-mile after accounting for differences in the initial purchase cost, fuel cost, insurance cost, cleaning cost, etc. For reference, the cost of private vehicles was calculated at $0.77 for conventional and $0.80 for autonomous vehicles. Therefore, in the long run, AMoD would be expected to reduce transportation costs significantly, although the full benefit may not be readily realizable in the early stage of deployment. Lastly, it should be noted that the calculations in Bosch et. al. were based on assumptions (e.g., wages or vehicle utilization rates) from Switzerland and could be slightly different in the United States.

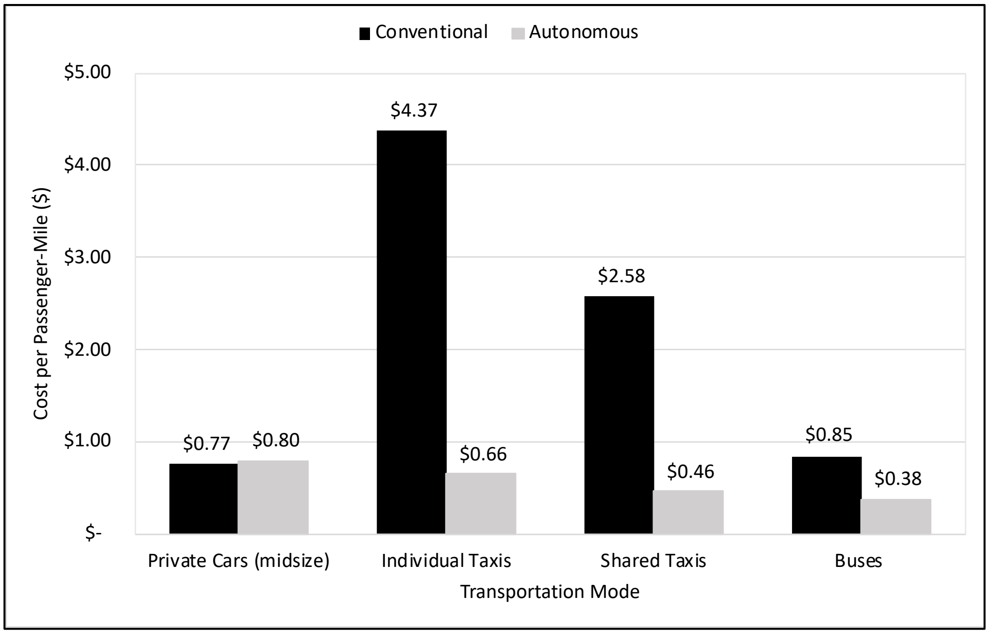

Figure 27. Cost of different transportation modes and technologies calculated by Bosch et. al. 2018.

The study is considered an early step toward evaluating AMoD services as last-mile access in Greater Minnesota. There were limitations in this feasibility study, and further research is recommended for realization of the benefits of such an AMoD service. In summary, study limitations include:

- Use of a (uncalibrated) stand-alone mode choice model as an approximation to a regional travel demand model
- Lack of attitudinal variables in the utility of the AMoD service
- Simplification of the operational challenges of AMoD in real applications

Based on these limitations, the following next steps are recommended:

- Use of the AMoD optimization model in a regional travel demand model. This would include estimating the utility of the AMoD service and conducting scenario analysis within an enhanced regional model.
- Deployment and field testing of the developed AMoD control algorithm in the area along with rider data collection to identify real-world challenges in the application of the service.
- Investigation of the use of electric vehicle fleets in the AMoD system to address operational characteristics, such as charging scheduling and infrastructure planning as well as evaluating the environmental benefits of the system.

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Appendix A: AMoD Modeling

The symbols $\mathbf{1}_m$ and $\mathbf{0}_n$ denote column vectors of dimension m and n with all entries equal to 1 and 0, respectively. Given a vector $\mathbf{p} \in R^n$, we define $\tilde{P} = \mathrm{diag}(\mathbf{p}) \in R^{n\times n}$ as a diagonal matrix with the elements of the vector $\mathbf{p}$ on the diagonal.

Consider a directed graph $G(N, A)$ where $N = \{1, \dots, n\}$ is the set of nodes and $A = \{1, \dots, m\}$ is the set of links. Let E_{in} and $E_{\mathrm{out}} \in \{0,1\}^{n\times m}$ be the in-neighbors and out-neighbors' matrices. If a link enters a node, the associated entry is one in E_{in}. Similarly, if a link exits a node, the associated entry is equal to one in the matrix E_{out}. The incidence matrix $E \in \{-1,0,1\}^{n\times m}$ can be derived by $E = E_{\mathrm{in}} - E_{\mathrm{out}}$.

A discrete-time linear dynamic model is formulated for the AMoD system. The linear discrete-time time-delay dynamic system is as follows:

$$w_{rs}(t+1) = w_{rs}(t) + d_{rs}(t) - U_{rs}(t),$$

$$p_r(t+1) = p_r(t) - \sum_{s\in N}\big(U_{rs}(t) + R_{rs}(t)\big) + \sum_{q\in N}\Big(U_{qr}\big(t - T_{qr}\big) + R_{qr}\big(t - T_{qr}\big)\Big),$$

$$g_{rs}^U(t+1) = g_{rs}^U(t) + U_{rs}(t) - U_{rs}(t - T_{rs}),$$

$$g_{rs}^R(t+1) = g_{rs}^R(t) + R_{rs}(t) - R_{rs}(t - T_{rs}),$$

for $\forall\, r, s \in N$ where state variable w_{rs} denotes the waiting customers at station r aiming to go to station s. State variable p_r characterizes the waiting or available vehicles at station r. State variables g_{rs}^U and g_{rs}^R denote customer-carrying and rebalancing vehicles moving along the link $\{r, s\}$. Control input U_{rs} is the number of available vehicles at station with a customer that will be dispatched to link $\{r, s\}$. R_{rs} is the number of available vehicles at station r that will be dispatched to link $\{r, s\}$ for rebalancing. The term $d_{rs}(t)$ represents the arrival of customers in a time step given by the realization of a Poisson process of parameter λ_{rs}. We also assume that the travel times T_{rs} are constant and exogenous. The reason is that the number of AMoD vehicles is much less than the rest of the traffic.

Delays in the AMoD model pose a challenge in deriving the control law. By considering a first-order lag approximation of the time delays, it is assumed that the number of vehicles exiting a link is proportional to the number of vehicles on that link. In other word, at each time instant t, the quantity $g_{rs}^U(t) + g_{rs}^R(t)/T_{rs}$ leaves the link $\{r, s\}$. Therefore, $U_{rs}(t - T_{rs})$ and $R_{rs}(t - T_{rs})$ can be replaced by $g_{rs}^U(t)/T_{rs}$ and $g_{rs}^R(t)/T_{rs}$, respectively.

Consequently, the AMoD model can be rewritten as follows:

$$w_{rs}(t+1) = w_{rs}(t) + d_{rs}(t) - U_{rs}(t),$$

$$p_r(t+1) = p_r(t) - \sum_{s\in N}\big(U_{rs}(t) + R_{rs}(t)\big) + \sum_{q\in N}\left(\frac{g_{qr}^U(t) + g_{qr}^R(t)}{T_{qr}}\right),$$

$$g_{rs}^U(t+1) = \left(1 - \frac{1}{T_{rs}}\right) g_{rs}^U(t) + U_{rs}(t),$$

$$g_{rs}^{R}(t+1) = \left(1 - \frac{1}{T_{rs}}\right) g_{rs}^{R}(t) + R_{rs}(t).$$

This AMoD system is subject to some constraints that enforce the non-negativity of state and control input variables. The global system associated with graph G is represented as

$$\mathbf{x}(t+1) = \mathcal{A}\mathbf{x}(t) + \mathcal{B}\mathbf{v}(t) + \mathcal{L}\mathbf{d}(t),$$

where the vector of all state variables $\mathbf{x} \in R^{2n^2-n}$ is $[\boldsymbol{w}(t)^T, \boldsymbol{p}(t)^T, \boldsymbol{g}^U(t)^T, \boldsymbol{g}^R(t)^T]^T$ and the vector of all control input variables $\mathbf{v} \in R^{2n(n-1)}$ is defined as $\mathbf{v}(t) = [\mathbf{U}(t)^T, \mathbf{R}(t)^T]^T$. $\mathbf{d} \in R^{n(n-1)}$ represents arriving customers. Matrices $\mathcal{A}$, $\mathcal{B}$, and $\mathcal{L}$ can be written as below:

$$\mathcal{A} = \begin{bmatrix} I_{n(n-1)} & 0 & 0 & 0 \\ 0 & I_n & E_{\text{in}}\tilde{T}^{-1} & E_{\text{in}}\tilde{T}^{-1} \\ 0 & 0 & I_{n(n-1)} - \tilde{T}^{-1} & 0 \\ 0 & 0 & 0 & I_{n(n-1)} - \tilde{T}^{-1} \end{bmatrix}, \quad \mathcal{B} = \begin{bmatrix} -I_{n(n-1)} & 0 \\ -E_{\text{out}} & -E_{\text{out}} \\ I_{n(n-1)} & 0 \\ 0 & I_{n(n-1)} \end{bmatrix}, \quad \mathcal{L} = \begin{bmatrix} I_{n(n-1)} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

If graph G is strongly connected and $d^{rs} = \lambda^{rs}\ \forall \{r,s\} \in N$, where λ^{rs} represents the Poisson arrival rate for the link $\{r,s\}$, then equilibrium points of the system are given by $\bar{\mathbf{x}} = (\bar{\mathbf{w}}, \bar{\mathbf{p}}, \bar{\mathbf{g}})$, where $\bar{\mathbf{w}}$ and $\bar{\mathbf{p}}$ can be any arbitrary positive vector, $\bar{\mathrm{g}}^U = \tilde{T}\lambda$, $\bar{g}^R = \tilde{T}\bar{\mathbf{R}}$, $\bar{\mathbf{U}} = \lambda$, and $\bar{\mathbf{R}}$.

$$E(\bar{\mathbf{R}} + \lambda) = 0$$

If the number of nodes, n, is greater than 2, there will be an infinite number of equilibrium points. The desired equilibrium point that minimizes the number of rebalancing vehicles ($\bar{\mathbf{R}}^{\star}$) can be found by solving the following optimization problem:

$$\min_{\boldsymbol{R}} \ \left\|\tilde{T}\bar{\boldsymbol{R}}\right\|_1$$

s.t. $E(\bar{\boldsymbol{R}} + \lambda) = 0, \quad \bar{\boldsymbol{R}} \geq 0.$

By changing the coordinates, we aim to regulate the AMoD system around the desired equilibrium points.

Appendix B: MPC Implementation

The MPC framework for regulation around the equilibrium point $\overline{\mathrm{x}} = (\overline{\mathrm{w}}, \overline{\mathrm{p}}, \overline{\mathrm{g}}^{U}, \overline{\mathrm{g}}^{R})^{\mathrm{T}}$ and $\overline{\mathrm{v}} = (\overline{\mathrm{U}}, \overline{\mathrm{R}}^{\star})^{\mathrm{T}}$ is expressed by the finite-horizon control problem and as follows:

$$\min_{\Delta v} \sum_{i=0}^{N_{\mathrm{hor}}-1} J(\Delta x_{t+i}, \Delta v_{t+i})$$

$$\text{s.t.} \quad \Delta \mathrm{x}_{\mathrm{t+i+1}} = \mathcal{A}\Delta \mathrm{x}_{\mathrm{t+i}} + \mathcal{B}\Delta \mathrm{v}_{\mathrm{t+i}}$$

$$(\overline{\mathrm{x}} + \Delta \mathrm{x}_{\mathrm{t+i}}, \overline{\mathrm{v}} + \Delta \mathrm{v}_{\mathrm{t+i}}) \in \mathcal{X} \times \mathcal{V}$$

$$\Delta \mathrm{x}_{\mathrm{t+N_{hor}}} = 0$$

$$\mathrm{i} = \{0, \ldots, \mathrm{N_{hor}} - 1\}$$

where $\Delta \mathrm{x(t)} = \mathrm{x} - \overline{\mathrm{x}}$ and $\Delta \mathrm{v(t)} = \mathrm{v} - \overline{\mathrm{v}}$. $\mathrm{N_{hor}}$ is the optimization horizon.

The objective function $\mathrm{J}(\Delta \mathrm{x}_{\mathrm{t+i}}, \Delta \mathrm{v}_{\mathrm{t+i}})$ is defined as a linear penalty function as follows:

$$\mathrm{J}(\Delta x_{t+i}, \Delta v_{t+i}) = \|Q\Delta \boldsymbol{x}_{t+i}\|_1 + \|S\Delta \boldsymbol{v}_{t+i}\|_1.$$

Q and S are positive semidefinite and positive definite matrices, respectively.

Since we are interested in considering transit waiting time, we are weighing the customers headed to the transit hub noted by h as $\mathrm{U_{rh}(t - T_{rh})}$, and an approximation of $\mathrm{U_{rh}(t - T_{rh})}$ will be $\mathrm{g_{rh}^{U}/T_{rh}}$. We are also emphasizing the high-demand routes as well as longer paths compared to the other paths. Consequently, weights matrices Q and S as

$$\mathrm{Q} = \begin{bmatrix} \tilde{\lambda} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \mathrm{Q_u} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \qquad S = \begin{bmatrix} \widetilde{\mathrm{T}} & 0 \\ 0 & \widetilde{\mathrm{T}} \end{bmatrix}.$$

where $\mathrm{Q_U} \in \mathbb{R}^{n(n-1) \times n(n-1)}$ is a diagonal matrix, and the elements associated with $\mathrm{U_{rh}}$ are one and rest of the elements are zero.