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IDENTIFYING MICROTRANSIT SERVICE AREAS THROUGH MICROSIMULATION

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16. Abstract

Demand-responsive microtransit services have operated in Utah since a pilot program debuted in Fall 2019. The Utah Transit Authority (UTA) and its partners see such services as providing key mobility in transit-limited areas, but how to prioritize which areas receive such services is an open question. In this research, we present a multi-agent daily activity simulation of regional travel demand in the Wasatch Front– using the open-source BEAM simulation developed by Lawrence Berkeley National Laboratory – including on-demand microtransit services. Though unresolved methodological limitations surrounding sample size and choice methodology exist, the simulation we develop successfully replicates key indicators of the pilot program including ridership and utilization. An analysis of additional prospective deployment areas suggests that all proposed areas would be successful at the current level of investment. UTA and its partners should prioritize regions that enhance the ability to build multi-modal travel paths and focus on automobile-limited households to maximize system use.

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LIST OF ACRONYMS

ASC: Alternative-specific constant

BEAM: Behavior, Energy, Autonomy, Mobility

DAP: Daily activity pattern

GTFS: General Transit Feed Specification

LBNL: Lawrence Berkeley National Laboratory

MAG: Mountainland Association of Governments

MATSim: Multi-Agent Transportation Simulation

TAZ: Transportation analysis zone

UDOT: Utah Department of Transportation

UTA: Utah Transit Authority

WFRC: Wasatch Front Regional Council

EXECUTIVE SUMMARY

In 2019, the Utah Transit Authority launched an on-demand transit service in south Salt Lake County, Utah in cooperation with Via, a private mobility company. On-demand transit services—sometimes referred to as microtransit—are a mobility service in which passengers request shared rides from shuttles through a mobile application. Such microtransit services are relatively new, as the increasing penetration of smartphones and other location-aware mobile devices has enabled such services and created a larger potential market. Such systems hold great potential for improving first- and last-mile access to fixed route, mass transit systems and for enhancing mobility for households with limited automobile ownership (Shaheen et al., 2015). Initial research on such systems has included efforts to understand attitudes and preferences for such a system (Macfarlane, Hunter, et al., 2021) as well as general operations and utilization (Alonso-González et al., 2018). Many questions remain, however, about the long-term sustainability of such systems, and there are systems that have succeeded as well as those that have failed (Alonso-González et al., 2018; Helsinki Transit, 2016). Developing demand forecasting frameworks to understand and model these systems prior to deployment will improve the likelihood of successful deployments.

While some attempts have been made to model demand for microtransit, tools and practices to do this are still in the early stages of development. In this project, we apply the BEAM (Lawrence Berkeley National Laboratory, 2022)demand microsimulation framework to model ridership and wait times for the 2019 deployment in south Salt Lake County. The model produced daily ridership estimates and utilization rates in line with the observed data collected from the system between November 2019 and March 2020 (prior to the arrival of COVID-19 in Utah). We then apply this same model to several potential expansion areas along the Wasatch

Front. The model suggests that demand for the service is limited primarily by the resources allocated to it, with ridership scaling linearly with the number of vehicles in service. There are, however, unresolved methodological questions surrounding simulation scaling – how to appropriately scale down microtransit fleets with small numbers of vehicles and small capacity is an open research question. Similarly, the procedures by which BEAM identifies modes for its agents is constantly evolving in search of improved methods. Despite these limitations, the simulation models suggest that households with low vehicle ownership are most likely to use the service.

The results at face value suggest that microtransit may in fact work in any of the study regions, as BEAM predicts that the microtransit fleets are fully utilized in each scenario. The results also provide an illustration of the potential benefits of microsimulation for travel demand analysis, with the model providing an understanding of who is using the services and for what purposes. Further research is required, however, to develop the simulation inputs, refine methodologies, and analyze and interpret outputs.

CHAPTER 1 INTRODUCTION

In November of 2019, the Utah Transit Authority (UTA) began a partnership with VIA, a private mobility company. Under this partnership, UTA has supplemented its fixed-route services in south Salt Lake County with on-demand shuttles hailed through a mobile application. On-demand microtransit offerings of this kind have the potential to efficiently extend UTA services into low-density areas and function as last-mile services for the regular fixed-route rail and bus network. UTA is interested in examining other areas where microtransit services can be effectively deployed.

In September 2020, UTA released a report detailing a possible expansion of microtransit services to other areas in Utah following the UTA on Demand pilot program (Via Mobility, 2020). The report identified 19 zones between Brigham City and Santaquin as areas that could potentially benefit from these services. VIA estimated microtransit ridership based on number of residents and number of workers employed within each zone, as well as a mode share score that VIA developed based on their internal demand model. This model, however, has several limitations. The model itself is proprietary, and VIA gave little indication as to its mechanisms for predicting ridership. As such, there is no objective mechanism for UTA to evaluate the model or apply it to areas not included in the report.

In this report, we present an alternative method of forecasting microtransit ridership. We use the Behavior, Energy, Autonomy, and Mobility (BEAM) model developed by Lawrence Berkeley National Laboratory (LBNL) to directly simulate transportation demand, including mode choice. BEAM operates on an agent-based level, simulating individual agents traveling between daily activities with their vehicles traversing a provided network. The model seeks to minimize travel costs for the agents in the system, allowing the agents to dynamically replan their travel mode and departure times. An iterative replanning process allows agents multiple attempts at computing their most optimal day, while accommodating the consequences of the choices of others. For example, agents will learn to avoid over-capacity routes and transit systems. A particular advantage of BEAM for working with on-demand transit services is that agents can request a pickup from a dynamic agent, but if the wait time is too long or no vehicle is available, they will choose a different travel mode for their trip in a future iteration. This provides a mechanism to pair a limited number of drivers with limited capacity to simulated requests for rides, which a linear direct demand model cannot accomplish.

This research implements the BEAM model developed by LBNL with modifications developed under the Transit—Serving Communities Optimally, Responsively, and Efficiently University Transportation Center (T-SCORE, 2020). These modifications are described in Day, (2022) and summarized in this report. Additionally, this research modified the BEAM software to accept geofenced on-demand transit operations, which is both the current and proposed operating scheme for the UTA/VIA project implementation. Travel demand data in the form of daily activity plans for the Wasatch Front population was generated by ActivitySim, an activity-based travel demand model using inputs from the Wasatch Front Regional Council / Mountainland Association of Governments (WFRC / MAG) travel model outputs and supporting data.

The primary objective of this research project is to identify possible geographic areas along the Wasatch Front where a microtransit system might most effectively operate, while a secondary objective of this research will be to provide a template for the Utah Department of Transportation (UDOT) and UTA to examine projects of this kind with a microsimulation model. Utah has invested a great deal of resources into fixed route, high-capacity transit lines such as

UVX, TRAX, and FrontRunner. These services perform well and have relatively high ridership statistics, but many people not directly near the stations can have difficulty accessing them. UTA will use this research to identify other places on the Wasatch Front where microtransit systems could be successful. UDOT could also use this methodology to study the potential effectiveness of such services in other areas, such as Logan, Moab, and Cedar City.

1.1 Outline of Report

The report is organized into the following chapters:

1. **Introduction:** This introductory chapter.
2. **Literature Review:** An overview of previous efforts to understand microtransit systems and forecast their operations.
3. **Methodology:** Methods and data used to create the initial microsimulation scenario in the Salt Lake City region as well as a description of the study scenarios
4. **Results:** Results of the simulation scenarios, including an evaluation of the simulation against data collected from the south Salt Lake County project between November 2019 and February 2020 (prior to the onset of COVID). Additionally, an evaluation of three additional regions selected by UTA and UDOT for simulation analysis.
5. **Recommendations and Conclusions:** A final concluding chapter summarizes the findings of the study as well as the implications for UDOT and UTA.

CHAPTER 2 LITERATURE REVIEW

2.1 Overview

This chapter presents prior attempts in the academic and practical literature to understand, model, and predict ridership for on-demand transit systems. The literature highlights the power and flexibility of agent-based demand modeling while including examples of other methodologies. The Multi-Agent Transportation Simulation (MATSim) model is an agent-based simulation that models individuals' behavior through across-day planning, and BEAM (an extension to MATSim) extends this to within-day planning. As this project deals with modeling the UTA on Demand by VIA pilot program in Salt Lake City, the chapter additionally discusses this program.

2.2 Purposes and Description of On-Demand Transit

One aspect of traditional public transit is that the routes are usually fixed, and to achieve sufficient ridership to justify operations, are concentrated on areas with sufficient population or employment density. It is not always feasible to extend these fixed-route systems into less densely populated areas—at least, not in a way that would reasonably service most of the residents—due to the high costs of capital and operation and the relatively low ridership that would result (Ferrell & Mineta Transportation Institute, 2015). However, public transit has many benefits such as reduced carbon emissions per person-mile and less traffic congestion (Buchanan, 2019; Gershon, 2005), and the lack of transit options in many suburban areas requires residents to overwhelmingly use personal vehicles as their main form of transportation (Gershon, 2005). This raises the question of the most effective and efficient way to increase transit ridership and decrease dependence on personal vehicles in these areas.

One possible solution is the introduction of microtransit services. Microtransit is a form of shared on-demand transit in which passengers schedule rides and vehicle routing is updated in real time to efficiently transport users. Many implementations of such a service utilize a form of minibus that can hold several passengers at once (Shaheen et al., 2015). One proposed application of microtransit is for first- and last-mile transportation, connecting a wide area to the existing fixed-route network and taking less time than walking or cycling. Decreasing this first/last mile travel time can increase job accessibility by allowing individuals to travel farther with the same travel time budget, and some microtransit services have been shown to decrease this access time significantly (Kang et al., 2019). As smartphone ownership and usage continues to increase, microtransit is a promising option, as booking rides can be done within phone apps, making the user experience easier (Agatz et al., 2011).

2.3 Previous Attempts to Analyze On-Demand Transit

In order to assess the potential usefulness of microtransit services, some sort of analysis framework is needed. Alonso-González et al. (2018) set out to create such a framework useful in comparing microtransit services to existing systems. The framework presented requires identifying several characteristics of the microtransit system: coverage and routing, operating hours, vehicle characteristics, the booking system, and request acceptance criteria. Then several quantities are calculated or estimated, including generalized journey time and share of declined microtransit trips as well as usage values. The microtransit system is then compared on these metrics with other modes such as fixed transit and walking/biking. However, this method requires accurate data from a real-world or simulated microtransit implementation, and focuses mainly on comparing the implementation to existing services using a generalized cost of travel metric. This framework is not especially well-suited to be a predictor of microtransit operating characteristics such as ridership and wait time.

Many different researchers have developed methodologies to forecast microtransit ridership, and Vosooghi et al. (2017) 1/31/2023 1:16:00 PMpublished a literature review discussing several of these: Azevedo et al. (2016) used the software package SimMobility to model an autonomous taxi network, MobiTroop was used by Heilig et al. (2015) to simulate carsharing in the Stuttgart, Germany area. MATSim has been used to develop a carsharing model in Berlin (Ciari et al., 2014) and analyze one in Zurich (Balać et al., 2015), and it was used to model a shared autonomous vehicle system (Fagnant & Kockelman, 2014).

Ronald et al. (2015) looked at three software simulations in more detail: the basic simulation Delphi, the agent-based simulation MATSim, and the traffic microsimulation SUMOoD (SUMO on Demand). The study found that these simulations generally produced similar results with respect to number of vehicles and amount of demand, and noted that all simulations performed as expected based on real-world observations. They are also quick to point out that results of these simulations might be optimistic if simplifications to routing are made or if using an undirected network, where a vehicle could pick up passengers on either side of a road no matter the direction of travel. A simplified network does not model the potential difficulties of routing through local streets and can result in picking up passengers that are "close enough," which could result in over-predicting the mobility of the microtransit vehicles.

MATSim is an open-source framework for transportation modeling originally developed by Horni et al. (2016). The framework simulates traffic flows and congestion on a microscopic level, and simulates demand by creating agents and following their daily schedules and decisions. It is designed to model a single day in large-scale scenarios, and uses an iterative process to have each agent optimize their schedule and consider factors such as route choice, mode choice, time choice, and destination choice. This is similar to how many people would likely use a transportation network: either trying several options and sticking with what works best for them, or using a routing service (such as Google Maps) to find their optimal route. It is important to note that this is different than finding the optimal solution for the whole system (which likely would lead to some agents individually being assigned very poor routing/mode choice/etc.); instead, each individual tries to optimize their own travel, and MATSim outputs the overall equilibrium that results. MATSim has been used in numerous studies to model various scenarios: of relevance to the present research, Bischoff & Maciejewski (2016) simulated a city-wide replacement of personal vehicles with autonomous taxis in Berlin, Cyganski et al. (2018) introduced autonomous vehicles and microtransit to Brunswick via simulation, and Viergutz & Schmidt (2019) modeled microtransit vs public transit in the rural town of Colditz. In each of these situations, MATSim was configured to have agents request rides from mobility services, and then replan their day if the mobility services had unreasonably long wait or travel times.

BEAM is an extension of the MATSim framework, and is maintained by Lawrence Berkeley National Laboratory (Lawrence Berkeley National Laboratory, 2022). The BEAM documentation gives a description of some of its functions and purposes. The simulation is designed to simplify running full-scale transportation models, and places an emphasis on within-day agent mode choice and planning. As an example, after an agent requests a microtransit vehicle, they may decide the wait time is too long and choose another mode; in MATSim the agent would need to re-plan their day. It is—like MATSim—intended to find the equilibrium point where resource markets (including road capacity and fleet availability) match the demand for service through an iterative algorithm. Improvements from MATSim are largely related to convenience functions for analysts and performance enhancements for the simulation.

2.4 Real-World Microtransit

Microtransit has generally performed well in simulations, and there have been several real-world implementations. One of the earliest implementations studied was Kutsuplus, which ran from 2012–2015 in Helsinki, Finland. Helsinki Transit (2016) created a report of the system and considered it a success, with significant ridership, efficiency in combining trips, and high customer satisfaction despite Kutsuplus' small scale (only 15 vehicles were used). Other studies have also been done on microtransit implementations, including in Texas (Weinreich et al., 2020) as well as Canada (Sanaullah et al., 2021) and Dubai (Giuffrida et al., 2020). Microtransit systems are generally well-received and well-used, and real-world implementations such as these have confirmed some of the previously obtained, optimistic simulation results discussed previously.

2.4.1 UTA On Demand by VIA

Another real-world microtransit implementation began in November 2019, when UTA partnered with VIA to run a pilot program of microtransit service—called UTA On Demand—in southern Salt Lake County (Via Mobility, 2020). The two main goals of this program were to expand access to public transit, providing first- and last-mile connections, and increase mobility for all users, even on trips not involving fixed-route transit. The purpose of the pilot program was to determine if microtransit would achieve these goals.

Monthly reports on the pilot program are available from December 2019 through November 2020, as well as four quarterly reports (Utah Transit Authority, 2020). Several metrics were measured and compared to previously set goals in different areas, such as ridership, wait times, and cost per rider. At the end of the first quarter (December–February), the pilot program either met or was on track to meet the 6-month goals for each metric. However, due to the COVID-19 pandemic becoming prevalent in Utah beginning mid-March 2020, significantly fewer people have utilized the service since then, and average ridership from March through November was significantly lower than the 6-month goals. Though the pilot program ultimately did not meet the goals that were originally set due to the pandemic, UTA renewed its contract with VIA for an additional year. This is in part because the program was projected to have met its 6-month goals in absence of the pandemic, and also more generally for continued evaluation and testing.

In September 2020, UTA released a report detailing a possible expansion of microtransit services to other areas in Utah following the UTA on Demand pilot program (Via Mobility, 2020). Three characteristics for each potential area were considered: Transit potential, reflecting population and employment density; transit need, reflecting socioeconomic factors that indicate a higher propensity to use transit; and the existing transit service level, based on quality and quantity of transit already available in the area. Based on these characteristics, 19 areas were identified between Brigham City and Santaquin as areas that could potentially benefit from microtransit services. Ridership was estimated based on number of residents and number of workers employed within each area, as well as a mode share score that VIA developed based on their proprietary internal demand model. The report makes no definitive recommendation regarding expanding microtransit services, but does present several results of the analysis for each area, including how well microtransit would improve transit coverage, provide efficient transit, replace existing bus routes, and increase equity. The report also notes several considerations regarding accessibility (including paratransit) and operations, and that this study will inform UTA's future transit choices.

2.5 Summary

Since microtransit has significant potential to increase mobility and provide first- and last-mile transit service, several methods have been used to analyze microtransit systems (both real-world and simulated) and compare them with existing systems. Alonso-González et al. (2018) compared generalized cost of travel between microtransit and other modes to determine the effectiveness of microtransit, but this approach is not focused on predicting ridership or wait time. In order to forecast these metrics, this study uses BEAM as the modeling tool of choice, due to its emphasis on within-day planning of on-demand transit services.

CHAPTER 3 METHODOLOGY

3.1 Overview

This chapter presents the methodology employed in this research to generate the simulation scenarios. Section 3.2 describes the BEAM software configuration and modifications made for this project to allow for geofenced microtransit operations. Section 3.3 presents information on the specific scenarios executed, including configuring a base (existing) scenario while Section 3.4 presents the various forecasting scenarios.

3.2 BEAM Configuration

BEAM is a transportation simulation model with a focus on adaptive planning for individual agents. Like MATSim, BEAM attempts to find an optimal path for individual agents' daily plans. BEAM takes a set of input plans, with information on activity schedule, location, and duration as well as initial mode choice determined by an activity-based transport model, and assigns a specific path for these plans on the provided network attempting to maximize trip utility. This utility value is "scored" by BEAM using values such as travel time and cost (Day, 2022). BEAM then simulates the plans with their assigned paths and notes the experienced utility. Based on these values, BEAM runs another iteration of the simulation, assigning new paths based on the updated predicted utility values. The difference between the predicted and experienced utility can be substantial, especially in the early iterations, and so it is important to run BEAM for multiple iterations to approach an equilibrium where the amount of change between iterations is small, though how much change should be allowed is not scientifically defined in the literature at this point.

BEAM may also adjust mode choice from the initial input plans in an attempt to improve a trip's utility and the overall agent score. This is done at the end of each iteration (end-of-day replanning), but can also occur dynamically during the simulated day (within-day replanning). This allows agents to change modes based on current predicted utility, for example to change from a transit trip to a car trip (if a vehicle is available) and vice-versa. This within-day planning is useful for ridehail modes (taxis, Uber/Lyft, etc.), as it allows agents to "change their minds" about a ridehail request if the wait time is too long or if no vehicle is available.

In this research, we represent microtransit as a pooled ridehail mode that simulated agents select on a trip-by-trip basis according to a heuristic supplemented by a multinomial choice model. The details of this heuristic are given in Day (2022) and are presented here in a simplified form. For within-day replanning, agents beginning a ridehail trip, a walk or drive access transit trip, or a walk trip will enter a multinomial logit (MNL) model that predicts their likelihood of using ridehail (microtransit) for this trip alongside those other modes. Agents who undergo end-of-day replanning – set to 10% of agents in each BEAM iteration – can choose from all possible modes for their trips using the same MNL model, but without mode restrictions. The parameters of this MNL match the ActivitySim / MTC model parameters in San Francisco, calibrated to the WFRC region as described below in Section 3.3.

If an agent is assigned microtransit as a mode, BEAM processes this in the form of a ridehail request. Agents request a pooled ridehail trip, and a ridehail vehicle services the request. BEAM contains internal algorithms to match ridehail requests with vehicles, and to intelligently pool multiple requests when feasible (Day, 2022). However, by default BEAM allows ridehail vehicles to travel anywhere within the network, but our implementation needs to confine microtransit vehicles to a specific area. BEAM natively offers some support for this “geofencing” of vehicles, but this is limited as an operating radius. We adapted BEAM’s implementation to allow a geofence in the form of an arbitrary polygon. BEAM will check that a request for microtransit originates and ends within the specified geofence, and only accept those requests that do. We were also able to allow for multiple geofence polygons, with a fleet specific to each one.

3.2.1 Computational Limitations

Because BEAM is an agent-based simulation with an emphasis on within-day planning and dynamic choice modeling, BEAM simulates each agent and vehicle individually so that real-time data is available. In our study area of 2.4 million individuals, this requires significant computational power. We chose to run our BEAM scenarios on the BYU supercomputer, which was our best access to high-power computing resources, but our access was not unlimited. In our case, a limit of 32 CPU cores, 2TB of memory, and a 72-hour runtime were imposed. This meant that we were unable to run a full BEAM scenario modeling the entire population. BEAM natively offers the ability to run a scenario with a sample of the full population, and we were able to run at least one iteration of scenarios with a population sample of up to about 50%.

However, while a larger population sample clearly would provide a more accurate simulation, we needed to find a good balance between sample size and number of iterations. Though BEAM places an emphasis on within-day planning, across-day planning typical of MATSim (which BEAM is an extension of) is still very important. BEAM will allow agents to change their plans based on information from the previous iteration, such as travel time and cost, and each iteration brings BEAM closer to a stable equilibrium. With a larger sample size, we were not able to run as many iterations, and vice-versa.

We ultimately decided to use a 20% population sample for our BEAM runs. This allowed us to run BEAM for around 11 iterations in each scenario. We decided that this was a good balance, as smaller-scale BEAM models tended to mostly converge by this time (see Figure 3.1) and the sample size was large enough to still be representative. In order to compensate for the much smaller population in our simulations, we additionally scaled the network capacity to 20% of its original value on a per-link basis, resulting in more accurate estimates of congestion and travel time.

Scaling the microtransit fleets, though, is not as straightforward. Generally, these are fleets of between 5 and 20 vehicles, so a change in fleet size would drastically affect the availability of the service. Wait time is a function of the distance from the nearest microtransit vehicle to the requester, and with vehicles so sparse this distance is likely to be artificially higher with a proportionally scaled-down fleet than it should be. Microtransit could theoretically be scaled similarly to other forms of transit: rather than adjust transit scheduling or frequency, capacity is reduced proportionally. However, microtransit often employs small vehicles, where the passenger capacity is no more than 6 or so. As such, it makes very little sense to scale down this capacity, since a key feature of microtransit is as a pooled service. We therefore left our microtransit fleets as-is, as this would give a better prediction of wait time and ridership than proportionally-scaled fleets would.

3.3 Scenario Description

A BEAM scenario requires the following inputs:

- Initial population daily activity patterns (DAP)
- Mode choice parameters
- A transportation network

- Transit information and schedules in the form of GTFS data
- A microtransit fleet (or fleets) with fleet size and operating hours

Figure 3.2 illustrates the process we used to generate and/or obtain these inputs. Many of these inputs are re-used from Macfarlane and Lant (2021), but we have modified some of the information to better suit our specific study. This process is discussed in detail in the following paragraphs.

To create the initial population DAP, we utilized the software packages PopulationSim (Association of Metropolitan Planning Organizations, n.d.-b) and ActivitySim (Association of Metropolitan Planning Organizations, n.d.-a). PopulationSim uses census data to create a synthetic population with individual home locations, where the total number of individuals matches the population of the study area. This synthetic population is designed to be representative of the area on metrics such as population density and income distribution, but avoids the privacy concerns of using data from actual individuals. This population can then be used as an input to ActivitySim. ActivitySim is an activity-based travel demand model in which individuals are assigned a set of daily plans based on area socioeconomic data and travel times/costs. The socioeconomic data is listed by Transportation Analysis Zone (TAZ) and includes information on job availability, number of workers, income, and other metrics. The travel times and costs are provided via network skims, detailing this information for trips between any given TAZs. ActivitySim uses this information, along with destination choice and mode choice equations, to assign trips to individuals coherently and with consistent mode choice (for example, an individual won't leave a personal vehicle at work and take transit home).

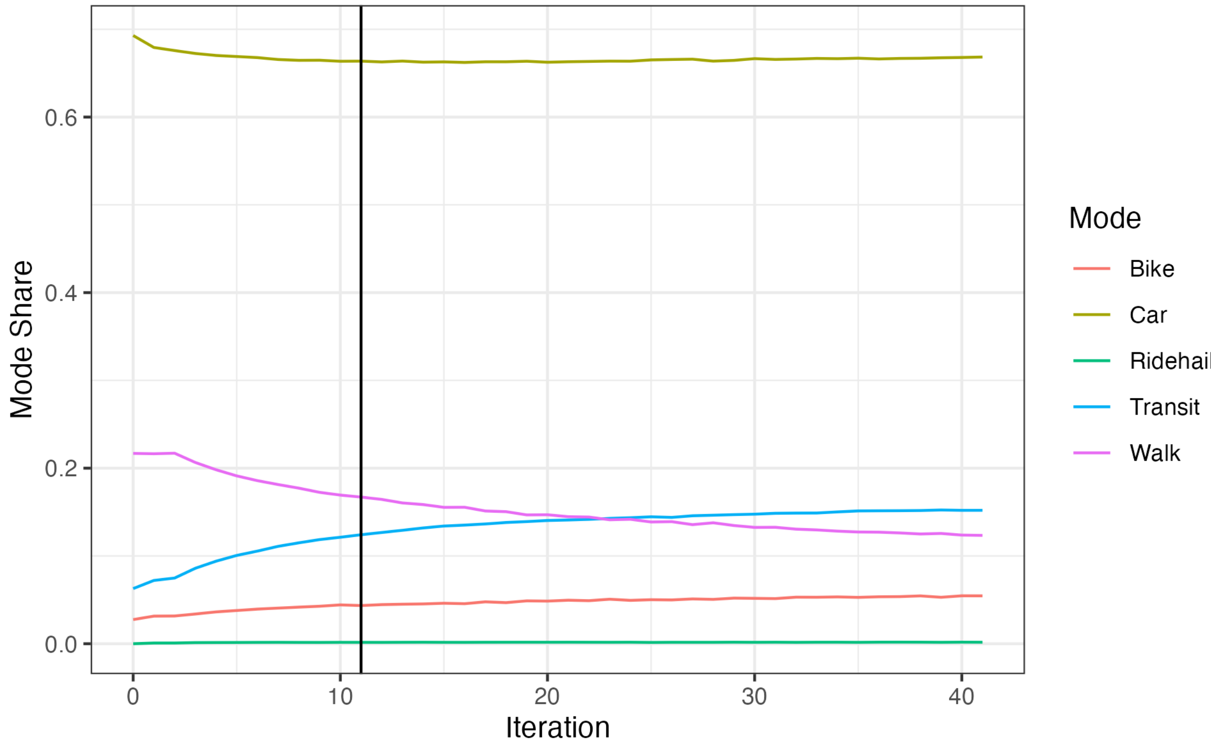

Figure 3.1. BEAM mode split for all trips by iteration in a 1% population scenario with the "Existing" microtransit fleet. The vertical line shows iteration 11; the BEAM scenarios in this research ran for 11 iterations each.

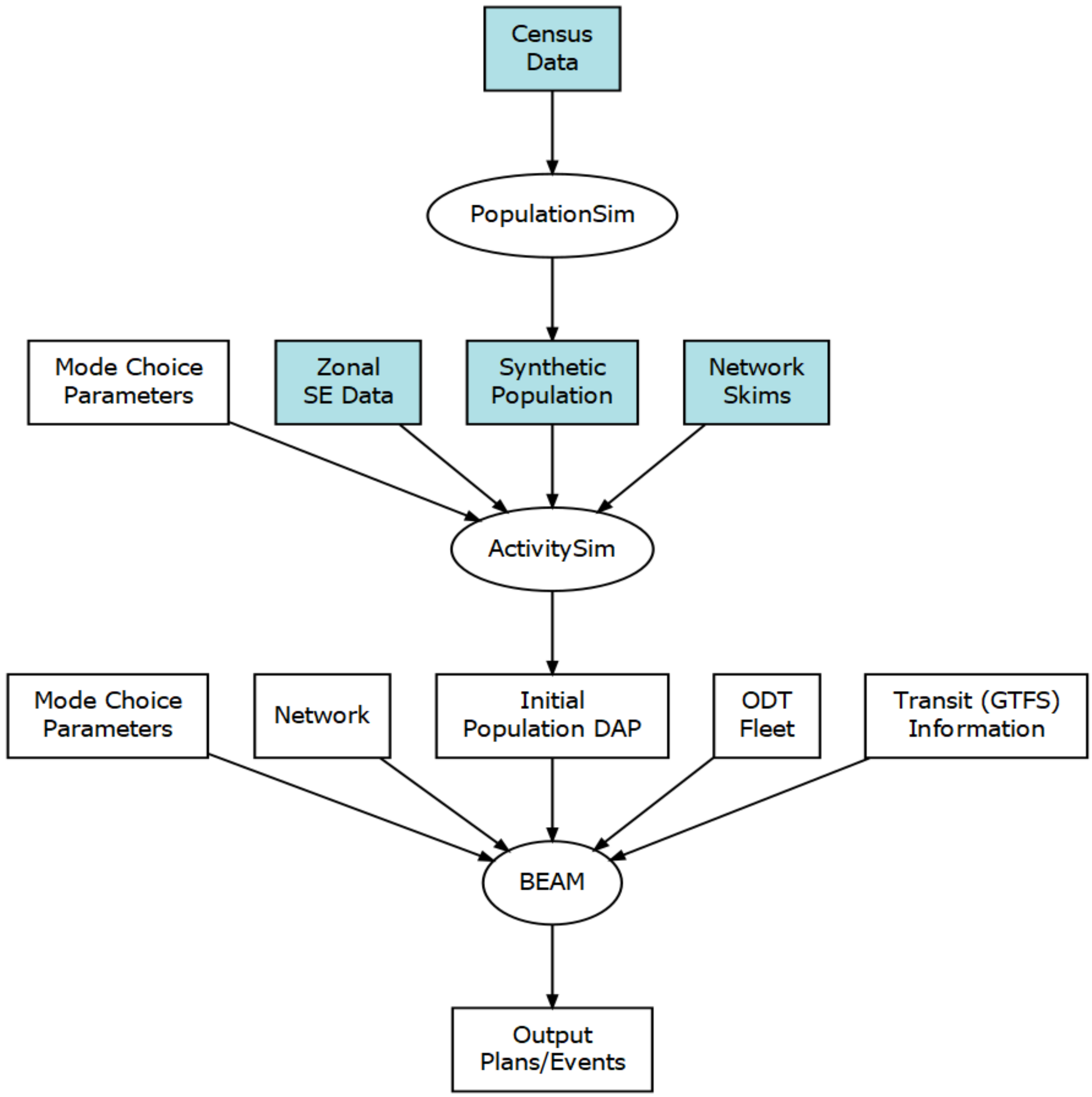

Figure 3.2. A diagram of our BEAM information pipeline.The shaded items are identical to those used in Macfarlane and Lant (2021).

Most of the work in creating/obtaining the data for PopulationSim and ActivitySim was done previously by Macfarlane and Lant (2021), and we are using this data in our study. That project adapted the ACS five-year census tract aggregation tables to create the input census data for PopulationSim and created a synthetic population modeling the Wasatch Front area in Utah. The network skims were obtained from the existing WFRC/MAG trip-based model, though some remapping of zones and modes to the ActivitySim mode choice model was necessary. Macfarlane and Lant also created the TAZ socioeconomic data using information from the WFRC/MAG travel demand model.

In addition to the population, skims, and socioeconomic data, ActivitySim relies on mode choice parameters to assign plans and transportation modes. Ideally, the mode choice output of ActivitySim would align with the existing WFRC/MAG model's mode distribution, and so we ran a calibration procedure, adjusting the alternative-specific constants (ASC's) in ActivitySim until the mode share roughly matched that of the WFRC/MAG model. This model estimates a 0.4% mode share of ridehail across all trip purposes: that is, 0.4% of trips in the WFRC/MAG model use taxis, Uber/Lyft, and other similar services. The initial ActivitySim outputs predicted a value much higher than this, given that ActivitySim was developed based on data collected and calibrated to San Francisco. We adjusted the ASC values in the tour mode choice model – which vary by purpose – using the same procedure as Macfarlane and Lant (2021) and described by Train (2009),

$$A_{ip} = \hat{A}_{ip} + \log\frac{T_{ip}}{P_{ip}} \tag{3.1}$$

where A is the adjusted ASC value to use in the next iteration, $\hat{A}$ is the ASC value used in the previous calibration iteration, T is the target share (from the WFRC /MAG) model, and P is ActivitySim's predicted share, for each mode i and purpose p. We ran this calibration procedure for 15 iterations, though ultimately the ridehail mode share converged around 1% (a larger share than our 0.4% target), with further ASC adjustments having little to no effect. One potential reason for this is that no matter how low the utility of ridehail is, it occasionally may be the only mode available in certain trip contexts in ActivitySim. For example, ActivitySim may assign a trip to an individual with no personal vehicle access, and if the trip is too far to walk, ridehail is the only mode the agent can take. Though this potentially could be resolved by adjusting the destination choice model used by ActivitySim, this was outside the scope of our research.

Like ActivitySim, BEAM has several mode choice parameters that required calibration. We ran a similar calibration exercise for 15 iterations, again using Equation 3.1 to adjust the ASC values in BEAM. A major difference from the ActivitySim calibration described above is that BEAM does not have the same concept of trip purposes as ActivitySim (or the WFRC / MAG model for that matter). Note that the “Car” mode has no ASC value: the ASC values of the other modes are relative to this mode. Figure 3.3 shows the mode split at each iteration in this process along with the calibration targets, and Table 3.1 details the results of the calibration after the final iteration. The 0.4% mode share of ridehail in the WFRC model is an estimate of current ridehail usage, and so a representative ridehail fleet for the entire Wasatch Front was used in calibrating BEAM. This fleet and calibration process is described in more detail in Day (2022). It is worth noting errors remain in the resulting mode distribution when compared with the targets from WFRC / MAG. Like in our calibration efforts with ActivitySim, further ASC adjustment had little to no effect on the resulting mode split.

Though the resulting ridehail mode share after calibrating BEAM was closer to the target than after ActivitySim calibration alone (0.6% versus 1%, with a target of 0.4%), this is still not an ideally calibrated model. Like with ActivitySim, BEAM may conclude that an agent’s only available mode option is a ridehail mode. Although, considering that there are significant errors in many modes relative to the target mode spilt, it is more likely that there are non-alternative-specific coefficients in the mode choice model that ought to be adjusted to better reflect the study area.

BEAM also requires an input network and transit information and scheduling. We used the network in the WFRC/MAG travel demand model. This network contains several attributes for each link, including roadway capacity, free-flow speeds, number of lanes, and road type. A drawback of this network is its limited spatial resolution of streets: the travel model network only contains freeways, arterials, and connecting streets and omits local roads. The daily activity plans input to BEAM include latitude/longitude points of home locations for home activities and WFRC / MAG TAZ centroids for other activities. BEAM then locates the nearest roadway link to the activity point, which may be some distance from the actual location of the activity, especially when local roads are not included. This spatial error might distort the measured walking distance and the ridehail vehicle allocation procedures, among other similar issues. That said, alternative methods including networks from OpenStreetMap and the Utah Geographic Resource Center (UGRC) lacked accurate connectivity and reliable speed or capacity information.

Table 3.1: Results of BEAM Calibration (Final Iteration)

Mode	**Target Mode Share**	**Actual Mode Share**	**Percent Error**
Bike	0.026	0.042	61.9%
Car	0.783	0.656	-16.1%
Ridehail	0.004	0.006	57.3%
Transit	0.073	0.122	65.6%
Walk	0.114	0.174	52.6%

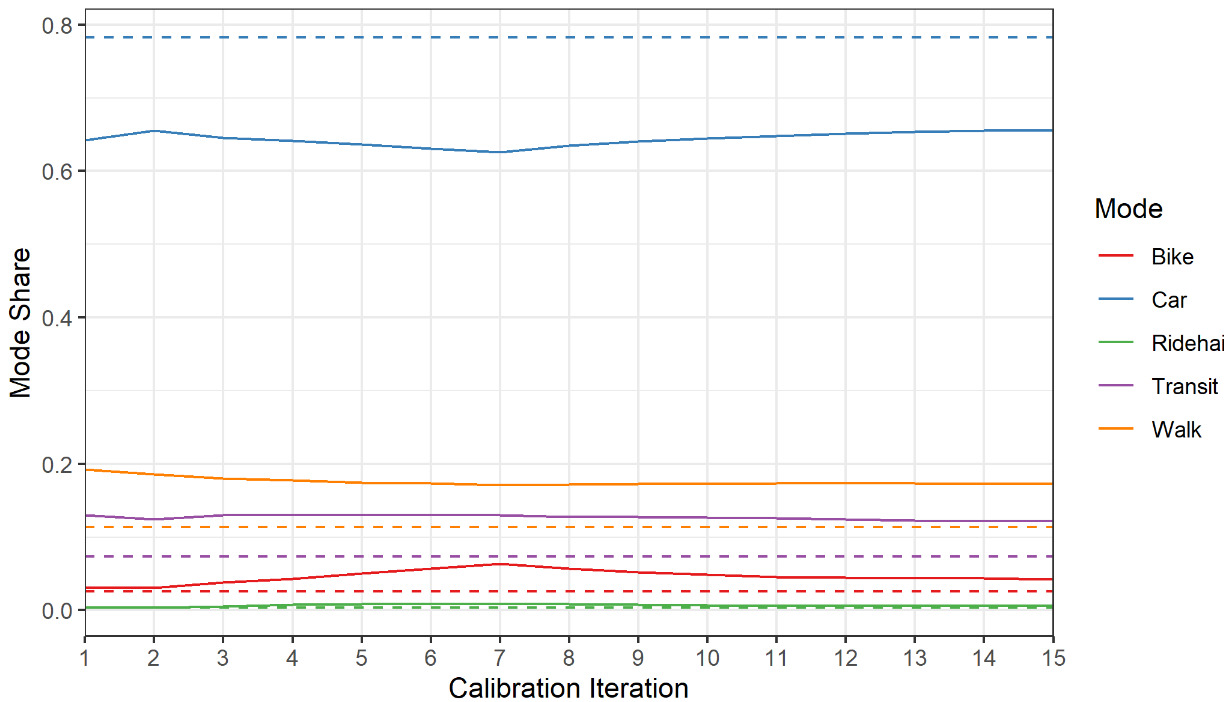

Figure 3.3. Mode split during BEAM calibration. The dashed lines indicate mode split targets, and the solid lines indicate the simulation results after each calibration iteration.

BEAM uses transit schedules provided in the GTFS standard. The simulations in this project used GTFS archives provided by UTA, valid for March–April 2022. In this configuration of BEAM, we chose the date of March 30, 2022, which is a Wednesday. We chose this date to be a typical weekday not near any major holidays since the model simulates an average weekday.

Information on a microtransit fleet/fleets may also be provided to BEAM. The primary purpose of this research is to evaluate the effects of microtransit availability in several study areas, and so we created multiple BEAM scenarios with various microtransit fleets. The first of these was a scenario we could use to assess the performance of BEAM relative to real-world data. UTA recently has completed a microtransit pilot program in southern Salt Lake County, so we used this as our comparison scenario. UTA's Office of Innovative Mobility Solutions informed us that typically 12 vehicles provided service at a time during this pilot program, and we found the microtransit vehicle shifts on UTA's website for the service (Utah Transit Authority, 2020). As the program shifted from a pilot to a permanent offering, the number of vehicles in service increased to 17.

3.4 Additional Scenarios

In addition to modeling the existing pilot program, the research aims to examine several other potential areas UTA is considering for deployment; Figure 3.4 shows these areas as well as the existing deployment area. These areas were originally described by Robertson, et al. (2020). Simulating these areas in BEAM requires an understanding of the microtransit vehicle fleet, which was not included in the Robertson, et al. analysis. Using the number of households from American Community Survey 2019 estimates and area of each of these areas as shown in Table 3.2, we scaled the existing South Salt Lake County scenario to generate a comparable number of vehicles for each deployment region; in general, the ratio of households led to larger vehicle deployments, and was selected as the fleet definition for the scenarios.

The usefulness of microtransit can be enhanced when more than one area is in operation; trips can be made where an agent uses microtransit in one region, travels to another zone by mass fixed-route transit, and then uses microtransit on the other end. UTA is therefore interested not in the regions independently, but how these regions might be paired in the existing system. Since the beginning of this project, UTA has launched full-time microtransit service in the original "South SL Co" pilot program area as well as in the "Westside SLC" area. As such, we included both of these areas in an "Existing" scenario. The other regions were grouped into scenarios in cooperation with the TAC overseeing the project, and described in Table 3.3

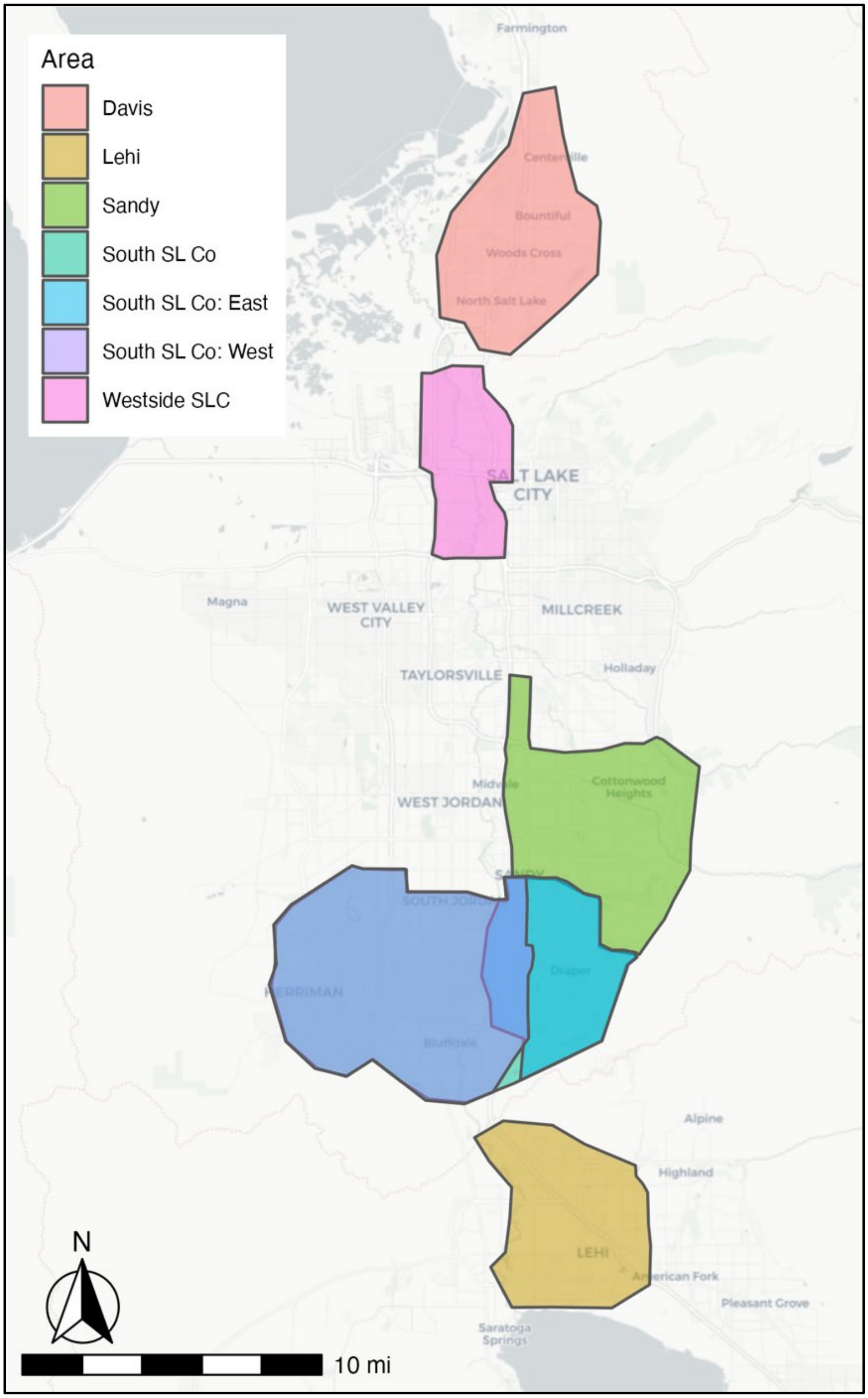

Figure 3.4. A map showing the study areas. Note that the South SL Co area is additionally divided into an East and West area; the combined (existing) region is largely hidden by the outlines of the other two.

Table 3.2: Information on Fleets Used in Each Area

Area	Households	Area (km^2)	Area / S.SLCO	Est. Vehicles: Area	Households / S.SLCO	Est. Vehicles: Households
Davis	32741	77.25	0.43	8	0.47	8
Lehi	24757	70.48	0.39	7	0.35	7
Sandy	65966	89.96	0.50	9	0.94	16
South SL Co (S.SLCO)	**70099**	**181.3**	**1.00**	**17**	**1.00**	**17**
South SL Co: East	27985	58.93	0.32	6	0.40	7
South SL Co: West	54412	139.5	0.77	14	0.78	14
Westside SLC	29909	41.45	0.23	4	0.43	8

Table 3.3: Areas Corresponding to Each Scenario

Name	Zones
Pilot (comparison)	South SL Co (12 vehicles)
Existing	South SL Co, Westside SLC
Split	South SL Co: East, South SL Co: West, Westside SLC
Existing + Davis	South SL Co, Westside SLC, Davis
Existing + Lehi	South SL Co, Westside SLC, Lehi
Existing + Sandy	South SL Co, Westside SLC, Sandy
All	South SL Co, Westside SLC, Davis, Lehi, Sandy

3.5 Performance Measures

The outputs of the BEAM simulation are complex and detailed. Understanding the performance of a scenario requires comparable performance measures. The UTA pilot program reports included daily ridership, vehicle utilization, and average wait times; similar measures are used in this report, though the specific calculation methodology for each measure is by necessity different. Ridership is relatively straightforward to calculate: whenever a person enters a vehicle in the simulation, BEAM logs an event containing information on the person and the vehicle. Daily ridership is therefore simply the number of times a person enters a microtransit vehicle at any point during the simulation day. UTA calculates utilization as the number of passengers per vehicle-hour of operation, and we did the same. Note however that the utilization statistics might be somewhat different given that the simulation fleet has a constant size and operating hours, and the actual microtransit fleet may change size throughout the day in response to varying demand. Microtransit wait time is calculated by observing the difference in time between BEAM recording the agent request and the agent entering a microtransit vehicle. However, it is possible for an agent to make a microtransit request but then cancel the request and choose another mode; these were not included in the wait time calculation.

It is important as well to understand the demographic characteristics of microtransit users in the simulated outputs to ensure that the system is targeting those who might benefit most from improved mobility options. The synthetic population produced by PopulationSim and used in this simulation includes household income, vehicle ownership, age, and similar information on each agent in the BEAM simulation. We noted the IDs of individuals who used microtransit at least once in the day and calculated the median income of this group using the information directly from the synthetic population.

3.6 Summary

Altogether, we created 7 scenarios to simulate in BEAM, one modeling the UTA on Demand pilot program, one modeling the existing microtransit implementation in the study area, and 5 with potential future microtransit implementations. Our implementation, though, is not without limitations. Our calibration efforts were unable to match our initial WFRC mode split targets, and computational limitations required us to use a small sample of the total population in our simulations. We scaled some of the model properties such as network capacity to compensate, but an open question remains regarding other scaling factors, especially of the microtransit fleets. However, because we are largely concerned with relative performance rather than absolute performance, we proceeded with the research, as the limitations will be the same for each of our scenarios. We calculated daily ridership, utilization, average wait time, and median income as metrics to compare our results with the observed data from UTA's pilot program and between scenarios.

CHAPTER 4 RESULTS

4.1 Overview

This chapter presents the results of the scenarios described in Chapter 3. First, Section 4.2 presents a comparison between the pilot program in the South Salt Lake County scenario with data reported in UTA reports. Section 4.3 then describes the results of the additional scenarios proposed in Section 3.4. This analysis includes some initial attempts to understand the equity issues in the proposed microtransit deployment areas by examining the scenarios based on income and automobile ownership of the travelers.

4.2 Existing scenario evaluation

UTA, in partnership with VIA, ran a pilot program of microtransit service in south Salt Lake County from December 2019–November 2020. UTA reported several metrics from this program, which are presented in Table 4.1. Much of the data in that report, however, is not necessarily representative, due to the COVID-19 pandemic and its onset in late March 2020. We also considered that the data for December was not necessarily valuable: since the service was new, people who would otherwise have used it may not have been accustomed to or even known about it. We therefore decided to use the average of the data from January through March as our benchmark. Table 4.2 presents these average daily ridership, utilization, and wait time metrics in comparison with the results of our BEAM model of this program (calculated as in Section 3.5). At first glance, these results seem to be quite good, as the simulated scenario reports similar ridership and wait time metrics to the real-world data. However, it is important to consider that our model scenario uses a 20% population sample, and the observed data reflects the entire

Table 4.1: Metrics Reported by UTA for the
Microtransit Pilot Program in Salt Lake County

Month	Avg weekday ridership	Utilization[1]	Avg wait time (minutes)
DEC	224	1.33	9.0
JAN	334	2.00	11.0
FEB	392	2.31	12.0
MAR	316	1.88	11.0
APR	275	1.52	10.0
MAY	105	0.67	8.0
JUN	162	1.10	9.0
JUL	155	1.10	9.0
AUG	193	1.50	12.0
SEP	214	1.60	12.0
OCT	200	1.70	13.0
NOV	169	1.70	13.0
Average	**228**	**1.53**	**10.8**
Average JAN–MAR	**347**	**2.06**	**11.3**

[1]Utilization is measured as passengers per vehicle operating hours

Table 4.2: Comparison of Observed Data
with 'Pilot' BEAM Scenario

Source	Ridership	Utilization[1]	Avg. wait time (minutes)
UTA Observed Data	347	2.06	11.3
BEAM 'Pilot' Scenario	314	1.29	10.1

[1]Utilization is measured as passengers per vehicle operating hours

population. The model microtransit fleet, on the other hand, was not scaled down to match the population sample size, and so represents the full fleet available in the real-world pilot program.

There is also a significant discrepancy in the utilization measurements. Because of the way utilization is calculated (passengers per hour per vehicle), the vehicle operating hours can greatly affect this metric. In our model scenario, all 12 of the microtransit vehicles are operational nearly all day, and it is likely that in off-peak hours the actual pilot program had fewer vehicles available. However, we do not have information on the exact operating hours of each vehicle in the pilot program, and so our utilization measure is more useful as a comparison between our simulated scenarios rather than a comparison to the observed data. An analysis that tried to dynamically scale the microtransit fleet based on demand would be an interesting analysis, as would one where the shifts of microtransit vehicles in the simulation matched the real-life shifts of the vehicles. In fact, in any real-world implementation of such a microtransit fleet, the number of vehicles operational during off-peak hours is likely to change over time to reflect demand (possibly even dynamically). In that sense, these utilization values are a potentially useful measure, but not necessarily good as a comparison with real-world data.

Despite these qualifications, however, the fact that the predicted ridership and wait time are so similar to the actual, measured values is nevertheless encouraging. This suggests that the predicted ridership and wait times in the other modeled scenarios may be a somewhat realistic forecast, albeit a rough approximation.

4.3 Candidate scenario comparison

We ran each of our scenarios as described in Section 3.4 and compared several metrics. These metrics include total ridership, utilization, and wait time, as in the comparison to the observed data from the pilot program, but also includes median income of microtransit users. These comparisons are given in Table 4.3. It is clear that in the scenarios with more microtransit vehicles available, ridership greatly increases. Interestingly, utilization does not vary much at all, which implies that at least in these specific scenarios there is a roughly linear relationship between number of vehicles and number of riders. This relationship can also be seen in the ratios

Table 4.3: Comparison Across BEAM Scenarios

Scenario	Fleet size	Ridership	Utilization[1]	Avg. wait time (min)	Median income of microtransit users[2]
Existing	25	667	1.32	9.7	$42,266
Split	29	781	1.33	9.7	$41,830
Existing + Davis	33	932	1.39	9.6	$49,554
Existing + Lehi	32	833	1.29	9.7	$41,170
Existing + Sandy	41	1079	1.30	9.6	$42,770
All	56	1571	1.39	9.5	$40,919

[1]Utilization is measured as passengers per vehicle operating hours
[2]The median income of all persons in each scenario is $53,100

of passengers to fleet size, as the vehicle operating hours are identical between scenarios. Additionally, wait times for microtransit services are very similar in each scenario. Not only are the average wait times nearly identical between scenarios (as shown in Table 4.3), the distribution of wait times is essentially the same as well. Figure 4.1 shows the statistical density of wait times in each scenario; the difference between scenarios is not large, but it is important to observe that the distribution of wait times within a scenario can vary considerably. Still, in no scenario are more than 5 to 10 percent of wait times longer than fifteen minutes. It is important to note though that these wait times represent only *fulfilled* microtransit requests. In BEAM, when an agent makes a microtransit request they may afterward re-plan and choose a different mode. This decision is largely based on the projected wait time for the microtransit vehicle, so a request that returns a long wait time will often result in a change to mode choice. Table 4.4 compares the proportion of fulfilled requests in each scenario.

Table 4.4: Comparison of Fulfilled and Unfulfilled Microtransit Requests

Scenario	Microtransit Requests			Proportion of Fulfilled Requests
	Total	Fulfilled	Replanned	
Existing	1066	642	424	0.602
Split	1319	752	567	0.570
Existing + Davis	1633	899	734	0.551
Existing + Lehi	1419	801	618	0.564
Existing + Sandy	1850	1038	812	0.561
All	2605	1515	1090	0.582

The proportion of microtransit requests that were fulfilled does not vary much between the scenarios, though none of these values are particularly high. This shows that around 40%–45% of microtransit requests return wait times considered too long, which results in a replanning of mode choice. The demand for microtransit is clearly much higher than the supply, and so in our simulations the microtransit fleets are fully saturated, regardless of which scenario is being run. This is further evidenced by the roughly linear relationship between fleet size and ridership (Table 4.3). With a larger fleet available, more microtransit requests would be able to be fulfilled, and so the proportion of fulfilled requests would likely increase. In fact, the proportion of unfulfilled microtransit requests may be a good measure of fleet over-saturation, which could be useful in determining the optimal fleet size to match demand. It should be noted, however, that a larger fleet might influence agents to make more microtransit requests, in which case the number of fulfilled *and* unfulfilled requests would increase. Such an analysis though is outside the scope of this project.

In addition to the ridership, utilization, and wait time comparisons, we also compared the median income of agents who used microtransit in each scenario. We used median income as a measurement of equity: lower incomes tend to be associated with lower auto ownership, and therefore lower mobility in car-centric areas (which much of the study area is). It stands to

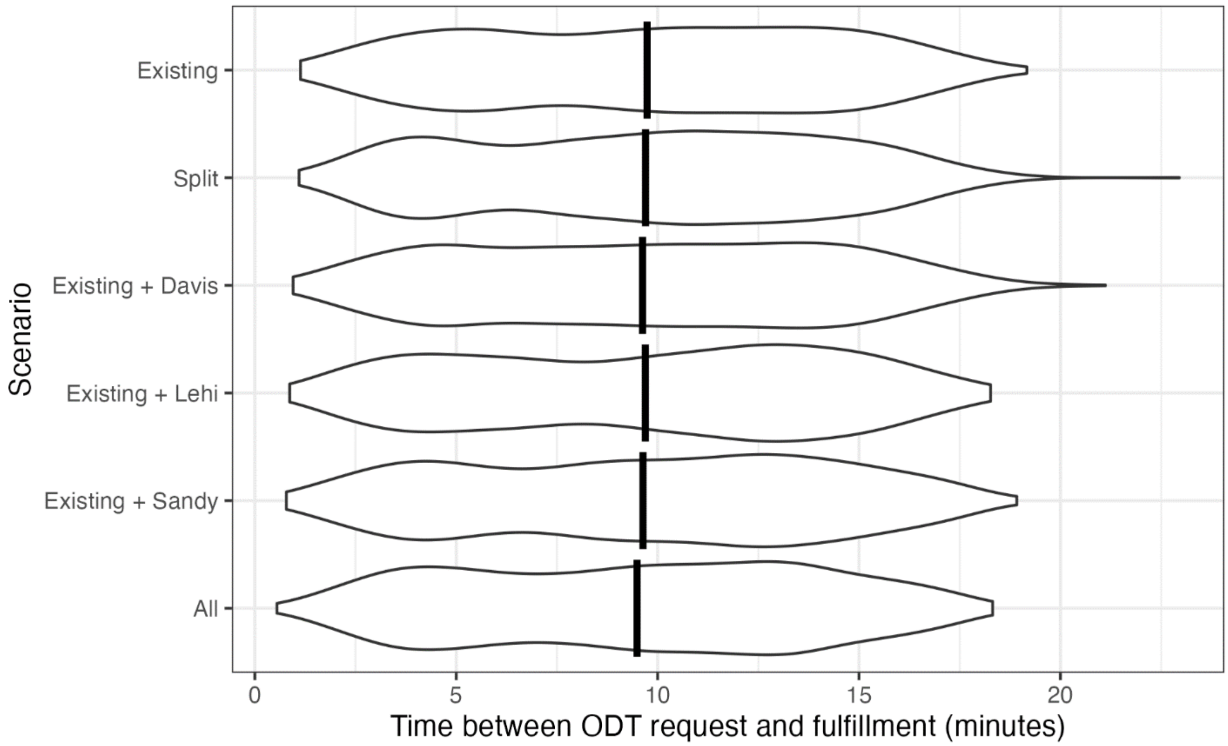

Figure 4.1: Comparison of microtransit wait times in each scenario. The width of the enclosed area represents the statistical density of observations, and the vertical bars represent the mean wait time in each scenario.

reason then that lower-income individuals are likely to benefit more from a microtransit implementation. The median income of all persons is the same in each scenario, namely $53,100. In nearly all the model scenarios, the median income of microtransit users is at least $10,000 less than this value. This result matches our intuition: microtransit services seem to offer significantly more benefit to lower-income individuals. This suggests that microtransit services would be most effective, at least from an equity standpoint, in lower-income areas.

CHAPTER 5 RECOMMENDATIONS

There are two facets of the research worth discussing here. The first is what the research suggests at face value, assuming that the simulation results are a somewhat accurate, if rough, prediction of the results a real-world implementation would see. The second deals with the validity of the results. We made several assumptions in our methodology, including in our calibration efforts, that may significantly influence the results, and these are discussed in Section 5.2

5.1 Suggestions Based on the Results

We will assume for now that our results are a valid approximation of real-world microtransit implementations matching our test scenarios. What do these results mean? Firstly, as discussed in Chapter 4, In addition to the ridership, utilization, and wait time comparisons, we also compared the median income of agents who used microtransit in each scenario. We used median income as a measurement of equity: lower incomes tend to be associated with lower auto ownership, and therefore lower mobility in car-centric areas (which much of the study area is). It stands to reason then that lower-income individuals are likely to benefit more from a microtransit implementation. The median income of all persons is the same in each scenario, namely $53,100. In nearly all the model scenarios, the median income of microtransit users is at least $10,000 less than this value. This result matches our intuition: microtransit services seem to offer significantly more benefit to lower-income individuals. This suggests that microtransit services would be most effective, at least from an equity standpoint, in lower-income areas.

Table 4.4 shows an excess of demand for microtransit (or rather, insufficient supply of microtransit vehicles). Table 4.3 additionally shows that microtransit ridership in our scenarios is proportional to fleet size, with little to no variance based on any other characteristics of each area. Based on this, it seems that a microtransit implementation might work essentially anywhere; there aren't many area-specific traits we can identify that significantly affect ridership in this research. Of course, the areas we studied are not random, and a microtransit implementation outside of the Wasatch Front (or even in a different area within the Wasatch Front) could produce quite different results. However, our results here indicate that a microtransit implementation matching any of these scenarios would be about as effective as any other.

In terms of *who* uses the microtransit service, Table 4.3 shows that microtransit services disproportionately benefit lower-income individuals and households. As discussed previously, income is often correlated with auto ownership, and microtransit services appear to be effective in improving mobility for those who may not have access to a car. A microtransit implementation could also do a great deal to mitigate the first-/last-mile transit problem, greatly increasing the catchment area for existing transit services, especially when car access is limited. Because of this, we suggest that UDOT consider the demographics of any potential microtransit service area and ensure that low-income individuals especially have adequate access to the system.

5.2 Validity of the Results

However, while our results suggest some firm conclusions, the limitations of the study (and of BEAM itself) must be taken into account. Firstly, there is a dearth of real-world data regarding microtransit usage in our study area. The only real-world data available to us for model comparison was that of the UTA on Demand pilot program, and we considered much of that data unrepresentative due to the COVID-19 pandemic. Though full-time microtransit service has since begun in the pilot program area, with an additional service area in west Salt Lake City, we did not have observed metrics from these implementations to compare our model against. Our comparison with the data from the pilot program proved somewhat encouraging, but additional comparisons would allow us to determine whether our model is simply over-calibrated to one specific scenario. In particular, very limited systematic research has been conducted on the behavioral dynamics at play among microtransit users. Macfarlane et al. (2021) conducted a limited analysis of this question, but more detailed answers are unlikely until after the next household travel survey is complete.

In terms of calibration, as mentioned previously we were unable to calibrate the ASC values in either ActivitySim or BEAM to reach our target mode split exactly. The scope of our research was to take ActivitySim and BEAM as-is, and so we did not perform more thorough calibration efforts. The mode choice model, beside ASC values, includes non-alternative-specific coefficients on variables such as travel time/cost and individual income. These values are taken from BEAM natively, and as BEAM is developed by Lawrence Berkeley National Laboratory, these values are calibrated to the Berkeley-San Francisco area. Our study area is quite different from this in terms of demographics, population and job density, and employment types, and so it is likely that the values for the mode choice coefficients are not especially accurate to the Wasatch Front. If UDOT were to use BEAM as a modeling tool in the future, we strongly suggest fully updating and calibrating the mode choice model based on observed data in future study areas.

In addition to the limitations of our calibration efforts, the computational resources required to run BEAM necessitated in our case a significant down-scaling of the population. While in theory a completely accurately scaled model could potentially produce perfectly proportional results, the effects of scaling any given parameter are not always clear. For example, while we did scale the network capacity proportionally to approximate accurate congestion, there are other, more subtle factors in determining travel time and cost, such as network link storage capacity. If a link is full, other vehicles will not be able to enter that link, causing a traffic backup. We could not simply scale this value proportionally, however, as very short links would now have a storage capacity of less than one vehicle. It is unclear how exactly to obtain accurate predictions from these results due to these scaling discrepancies.

Another major question around scaling is regarding the microtransit fleets. Leaving the fleet sizes as-is was not necessarily the conceptually ideal approach, but we believe it to be better than a proportionally-scaled fleet with very few vehicles, as described in Section 3.2.1 . It would seem that the proper scaling factor would be between these values, but it should be noted that the microtransit ridership and wait times in our model closely match observed values, even with the unscaled microtransit fleet. This is likely largely because in calibrating BEAM we used the full microtransit fleet of the "Existing" scenario with a 20% population sample, so microtransit ridership was somewhat "forced" to match observed values regardless of fleet size. Considering BEAM also shows microtransit demand to be almost twice the supply (Table 4.4), we believe BEAM's mode choice model gives a higher preference to microtransit than it ought to. However, we have no data indicating what proportion of microtransit requests are fulfilled in the current real-world implementation, and so it is entirely possible that these are reasonable results. But as mentioned previously, we have very little observed data to validate our simulations against, and our ridership values may be over-calibrated.

5.3 Conclusions

In conclusion, our research has significant limitations, but there are still conclusions that we can draw. The primary objective of this research was to identify areas along the Wasatch Front that could benefit from implementing microtransit services, and our results suggest that microtransit may work essentially anywhere. It is notable though that microtransit ridership increases as more service areas are implemented, as the service can be used more for both home-to-transit and transit-to-destination connections. Observing trip paths that can be build upon existing implementations will make the system more effective generally. Microtransit especially benefits lower-income people in our model as a result of the low transit level of service and limited automobile availability, and so we recommend that any implementation have a strong focus on equity.

However, another research objective was to provide a template for UDOT to use in future evaluations. Because of the difficulties of using BEAM, including the computational requirements, the sub-optimal mode choice processes as applied to the Wasatch Front, and open questions regarding scaling factors (especially of the microtransit fleets), we do not recommend that our process as currently constituted be used in further evaluations. While BEAM does have its advantages, many other modeling packages and approaches exist that require less intensive computation and offer simpler interfaces for use. It may be that these simpler approaches are better for applications such as this. This is not to wholly discount BEAM as a transportation simulation, though. If further efforts to adjust the mode choice model to better match the Wasatch Front are successful, along with research and solutions to the questions of scaling, BEAM may be a useful modeling tool for UDOT in the future.

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