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Strategic and Operational Strategies to Inform First- and Last- Mile Services: Case Studies for Robinson and Moon Townships

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Strategic and Operational Strategies to Inform First- and Last- Mile Services: Case Studies for Robinson and Moon Townships

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Executive Summary

Traditional public transit is designed to serve high-density, urban areas with concentrated travel patterns using fixed routes and schedules. Mobility gaps exist for populations who are captive to public transit and need to travel to locations where public transit does not cover. Emerging technologies enable bridging such a gap by providing flexible mobility services and informing travelers real-time service information. One such example is to complement public transit mainlines with first- or last-mile mobility services (FMLM).

This project developed a generalized model to evaluate user costs (wait time and in-vehicle time), agency costs (costs to provide mobility services), and system reliability for an integrated public transit, transportation network company (TNC), and FMLM service considering uncertain rider demand and network dynamics. Various supply (number of vehicles, TNCs) and operations strategies (stop aggregation, fixed-route + on-demand) are fully examined to provide performance insights for an existing FMLM service in Robinson Township, PA and a proposed FMLM service in Moon Township, PA, both of which are growing suburban areas in Southwestern PA.

First, level-of-service metrics were evaluated for the existing FMLM service in Robinson Township using three months of demand and vehicle trajectory data. The model was then used to compare user costs, agency costs, and reliability for various supply and operational strategies. Given the service area geometry and demand patterns, two on-demand 23-passenger vehicles (status quo) minimizes total user costs. Supplementing existing services with TNCs may increase total user costs by 19%, however, agency costs can be reduced by up to 26%.

Second, a proposed FMLM service in Moon Township was evaluated to compare various strategies under uncertain demand patterns. Demand for the service was simulated using the Robinson Township hourly demand profile and expected demand levels based on information provided by Ride ACTA. For the expected demand of 20 requests/day (40 total daily trips), incorporating TNCs can reduce user costs by 39% at an additional cost of approximately $50/day. Hiring a second shuttle can reduce user costs by 58% but would cost an additional $500/day. TNCs help reduce total user costs by serving trips that require shuttles to make large detours, thereby, reducing in-vehicle times for current passengers and wait times for future customers. Assigning a few, large-detour trips to TNCs can improve system-wide performance at minimal cost to the agency (average TNC trip cost of $8). While integrated services may not be currently feasible, study insights can help inform future strategies as FMLM services continue to grow and adapt.

Stop aggregation strategies for the Moon Township service were evaluated by creating one stop location for clusters of businesses within 1000-ft of one-another. Stop aggregation strategies were found to provide larger wait time improvements to system performance as the demand for the service grows. For the 40 request/day case, wait times improved by up to 16%. However, additional walk time costs are incurred by users under stop aggregation policies. We found that shuttle efficiency gains from stop aggregation did not fully offset additional walking costs until demand for the service eclipsed 40 requests/day. Since stop aggregation is easy to implement, it is recommended to incorporate such a policy, especially if demand is expected to increase to more than 40 requests/day in the future.

Lastly, fixed-route and on-demand strategies were compared for the Moon Township service. The fixed-route policies assigned one shuttle to a list of scheduled stops during the evening peak that included all

large businesses in the region. Either a second shuttle or TNCs were used to serve all remaining small business demand. On-demand strategies outperform their comparative fixed-route strategies until demand for the service reaches 40 requests/day. At this point, assigning one shuttle to a fixed schedule can improve overall system performance by drastically reducing wait times along the fixed route.

The model is developed to be flexible and replicable using simple operational decision rules to provide high-level insights for planning purposes. We find that adding flexible mobility services (e.g., TNCs) can improve system performance in a cost-effective way. We also show that simple operational strategies can considerably improve system performance. However, such improvements depend on realized demand patterns for the service.

1. Introduction

Traditional public transit is designed to serve high-density, urban areas with concentrated travel patterns using fixed routes and schedules. In recent years, development patterns, socioeconomic trends and demographic changes have resulted in travel behaviors that require more flexible service options (Koffman, 2004). To address this need, many transit agencies have adopted various forms of "flexible" transit, which range from on-demand, door-to-door services in low-density areas to flag stop polices along fixed routes in medium-density regions. Other flexible policies include flexible-route and flexible-stop and are typically implemented in low-to-medium density regions. Flexible-route policies operate with fixed-stops; however, the service vehicles can adjust their routes based on demand locations between fixed stop locations. Flexible stop policies do not require vehicles to make stops if demand is not present. In a 2010 survey, Potts et al (2010) revealed that approximately 40% of transit agencies in the United States provided some form of flexible transit service. The same study also concluded that in many low- to medium-density areas, flexible services could improve mobility, lower costs, and encourage mode shift from private automobiles when the services connected travelers to regional transit networks. In this study, we develop a model to evaluate various operation strategies for two first- and last-mile transit connector services in Pittsburgh, PA. Numerous scenarios are compared to provide insights and make recommendations for existing operations and planning for future FMLM services with similar characteristics.

Previous studies have explored various design polices for flexible-route and demand-responsive FMLM transit services. Quadrifoglio and Li (2009) compared fixed-route and demand-responsive connectors (DRC) using analytical methods. DRC was optimal up to demand levels of 30 customers/mi^2/hr and 70 customers/mi^2/hr in the one van and two van case, respectively. Similarly, Li and Quadrifoglio (2010) derived the critical demand to switch between DRC and fixed-route services, and found that at demand levels between 10-50 customers/mi^2/hr, DRC was optimal in terms of user costs (walking time + wait time + ride time). Nourbakhsh and Ouyang (2012) compared three services (taxis, flexible-route, and fixed-route) in a hybrid network and found flexible-route services to be optimal when demand fell in the range 10-100 customers/mi^2/hr. For demand levels less than 10 customers/mi^2/hr, taxis were found to be the most cost-effective operational strategy. Peak demand for services analyzed in this study fall between 5-15 customers/mi^2/hr, indicating that some combination of on-demand vans and taxi services will likely be optimal. Other studies have compared various flexible-route operational strategies such as dynamic stations (Qiu, Li, & Zhang, 2014), flag stops (Qiu, Shen, Zhang, & An, 2015), point deviation (Zheng, Li, & Qiu, 2018), and optimal cycle length (Chandra & Quadrifoglio, 2013). The studies find that flexible-route services can be improved under such policies. Previous studies all agree that flexible services outperform conventional fixed-route service when customer demand is between 10-50 customers/mi^2/hr. When demand falls below this range, on-demand, taxi-like services are shown to be the most cost-effective. It is important to note that previous studies develop analytical methods assuming uniform demand. However, in a real-world scenario, demand ranges for optimal policies are expected to shift based on the spatial layout of demand and transportation infrastructure.

In recent years, with the emergence of transportation network companies (TNC), many transit agencies are exploring partnerships to improve FMLM service quality at reduced costs. In 2019, Curtis et al (2019) surveyed 38 transit agencies currently partnered with TNCs and found that 75% of the respondents listed "improving first- and last-mile" services as a primary partnership goal. Using information technologies, algorithms, and data analytics, TNCs can provide convenient and reliable transportation services to many urban populations. In the FMLM setting, TNCs can increase access, reduce travel times, and encourage multi-modal trips by extending the effective transit catchment area (Shaheen & Chan, 2019). Under appropriate policies, other benefits, such as reductions to VMT and car ownership can also be realized if mode shift occurs. To date, limited studies have evaluated the success of TNC/public transit partnerships from a cost's perspective. In one case study, Dallas Area Rapid Transit (DART) partnered with TNCs and replaced low-ridership fixed-routes with TNC services. DART observed increased ridership and coverage with reductions in user and agency costs (Parks & Moazzeni, 2020). Other studies predict transit ridership increases (Yan, Levine, & Zhao, 2019; Zgheib, Abou-Zeid, & Kaysi, 2020) and reductions in vehicle miles traveled (VMT) (Alemi & Rodier, 2017) when TNCs are used as feeder services. Additionally, (Gonzales, 2019) estimated that net paratransit expenditures can be reduced by 26% when partnering with TNCs in a Boston, MA case study. While positive results can be observed through the integration of TNCs and public transit, limited tools exist to aid local transit agencies during the decision-making process.

In this study, we propose a generalized model to evaluate user costs, agency costs, and system reliability for an integrated transit/TNC FMLM service considering demand and network dynamics. User costs are defined by the summation of wait and in-vehicle times for each traveler. Agency costs are the costs to provide the service (e.g., hiring shuttles, paying for taxi trips). Several months of data were used to assess system reliability in terms of 95th percentile wait and in-vehicle times. System reliability is presented due to its importance on ridership retention. By comparing all three metrics (user costs, agency costs, reliability), we provide a more complete assessment for agencies to evaluate tradeoffs and select optimal strategies based on unique objectives.

2. Methods

A simulation model was developed to provide system performance insights under various strategic and operational policies for FMLM services. The model incorporates TNCs during the vehicle-to-request matching phase based on a pre-defined allowable user wait time. Vehicle-to-request matching is conducted by assigning requests to the vehicle with minimal marginal user costs. Routing is determined based on an insertion heuristic, which is found to be near optimal when requests per cycle are low (Li & Quadrifoglio, 2010). Simple decision rules are designed to be flexible to test various strategic and operational policies (e.g., varying supply and demand, incorporating TNCs, aggregating stops, etc.). In the following report, van refers to a 23-passenger shuttle with a center aisle, which are the current vehicles used in the Ride ACTA service region.

2.1 Simulation Algorithm

The simulation modifies van trajectories and assigns vehicles to incoming requests in one step. For each new request, the marginal cost is calculated for each in-service van. The new request is then assigned to the van that produces the lowest cost for the user. User cost is defined as a weighted combination of wait and in-vehicle time (α*wait time + β*in-vehicle time). α and β are model inputs based on transit agency objectives. Based on values of time for public transit from Wardman (2004) for short bus trips, the value of wait time is approximately three times the value of in-vehicle time. For this reason, we adopt $\alpha = 0.75$ and $\beta = 0.25$ for the following analysis. To compute the marginal cost for each new request, an insertion heuristic is used. The insertion heuristic simply inserts the new request's origin and destination at all feasible indices (e.g., the origin index must always be before the destination index) within the current van trajectory. For each insertion, total wait and in-vehicle times are summed for the entire trajectory. The "best" route is then selected as the trajectory that minimizes the weighted total wait and in-vehicle times. This method drastically reduces the computational time because all requests do not need to be optimized at each step.

However, instead of only passing in node information to determine the best route in terms of distance, a unique user ID and the user's request time is also stored at each node. With this information, user wait and in-vehicle times can be calculated for each user in each vehicle trajectory. User request times stored at each node also preserve time consistency throughout the van's trajectory. For example, if the node in a vehicle trajectory is a pickup node, the vehicle must leave the node after the requested pickup time. To ensure equity for all requests, maximum wait and in-vehicle times (30min) are defined, and a large cost penalty is applied if either the maximum wait or in-vehicle times are exceeded. By using an insertion heuristic, the "best" route can be computed for each van considering the new request, which is the one that minimizes the sum of the user costs. Once the "best" route is computed for each van considering the new request, the marginal cost can be computed by subtracting the sum of the user costs without the new request considered. This simple decision rule is meant to simulate existing conditions but also has some drawbacks. For example, if all new requests during a specific time window are coming from a specific area within the service region, one van will be assigned all those requests, even if the other van is idle at a different location. However, this method will reduce van travel time because it will be inefficient to move the idle van across regions, especially if demand is realized in the region where the idle van is located. The algorithm is designed to minimize user costs, as opposed to agency costs, because the agency is a public transit agency looking to improve the level of service for its users. Vehicle costs are hourly, and fares are minimal ($0.25).

To accommodate TNCs, a pre-defined wait time threshold is used at the time of request to either assign the new request to a van or a TNC. If the estimated wait time for the new request exceeds the threshold, then a TNC is assigned to the request. We elect to make this assignment at the time of request to notify the user and provide an estimated wait time. However, user wait times can subsequently pushed over this threshold if new requests get added to the trajectory because once a request is assigned to a van, then the request can no longer be assigned to a TNC, even if their respective wait time exceeds the TNC threshold.

Inputs to the model are designed to be flexible to allow for agencies to design FMLM services based on their own unique objectives. Model inputs are as follows:

- **α**: weight assigned to user wait times
- **β**: weight assigned to user in-vehicle times
- **δ**: look ahead time window
- **TNC threshold**: wait time threshold to assign a TNC to a request
- **G**: Time-dependent travel time graph

α and β can be altered if the service seeks to improve user costs based on either wait or in-vehicle time. For example, if the service operates in a region with poor weather conditions, a larger weight can be applied to wait time to reduce extra costs of waiting outside for a pickup. Using a look ahead time window (δ) is advantageous for system performance and routing decisions if requests are known in advance. The TNC wait time threshold can be altered to either minimize or maximize TNC use based on agency budgetary constraints. And G is pre-computed using either vehicle trajectories (if historical data is present) or the Google Travel Time API. One month of demand data was obtained, which allows for the simulation to consider day-to-day demand variation in time and space. Using real-world service data enables us to calculate system reliability metrics to be compared across scenarios in addition to user and agency costs. Under this modeling framework, agencies can customize on-demand FMLM services based on unique objectives (e.g., wait time, in-vehicle time, reliability, etc.). The simple decision framework also allows for numerous policies to be tested to either alter existing services or design new services.

2.2 TNC Cost Calculations

While TNCs provide flexibility to FMLM services, user and agency costs must be considered. According to Uber estimates for Pittsburgh in 2016, the average wait time for an Uber in the Pittsburgh region was 5 minutes (Moore, 2016). In this research, we will use an automatic 5-minute wait time penalty for all trips assigned to a TNC. In-vehicle time costs are determined from the time-dependent travel time graph. Agency costs are based on Uber cost estimates for the Pittsburgh region (Taxi How Much, 2020). Uber's formula for calculating base costs are as follows:

Uber cost = max{minFare, (baseFare + bookingFee + $0.32/min + $0.87/mi)}

Where **minFare** = $8, **baseFare** = $1.43, and **bookingFee** = $2.50. This estimate does not consider surge pricing and we realize that if the frequency of surge pricing in Robinson Township is high, then cost calculations will underestimate the costs incurred by the local transit agency. However, since TNC demand spikes are primarily observed between 10pm and 4am (Murphy & Feigon, 2016), it is estimated that the number of surge occurrences will be low during commute hours.

2.3 Performance Evaluation Metrics

System performance was evaluated using metrics that measure user costs, agency costs, and system reliability. User costs are a weighted combination of wait and in-vehicle times experienced by system users. These two metrics are considered during day-to-day simulation and are minimized to improve the level of service for travelers. Agency costs are the costs for the agency to provide mobility services within the service region. Currently, 23-passenger vans are used in an on-demand setting, and cost \$51 per vehicle hour. In the scenarios that involve TNCs, base fare cost estimates are included to determine total costs to the agency (in our case, Ride ACTA). For each day, the model considers network dynamics and demand uncertainty to simulate operations in real-time by minimizing total user costs. We use historical data and sampling to determine system reliability metrics in the long-term using one month of actual demand data obtained from Ride ACTA. 95^{th} percentile wait and in-vehicle times are computed to measure system reliability and make recommendations about operational strategies to balance user and agency costs in the long-term. System reliability is presented and compared across scenarios due to its importance on ridership retention. It is possible to reduce user and agency costs, while also observing higher 95^{th} wait and in-vehicle times. By comparing all three metrics (user costs, agency costs, reliability), we provide a more complete assessment for agencies to evaluate tradeoffs and select optimal strategies based on unique objectives.

3. Robinson Township Description and Performance

Robinson Township is located 8 miles east of downtown Pittsburgh and consists of mixed low-density residential and commercial. Robinson sits between the City of Pittsburgh and Pittsburgh International Airport and is home to 200 local businesses. The Port Authority of Allegheny County (PAAC) serves the region with route 28x, which both serves as airport transport and commuter service for travelers working in the Robinson area. Ride ACTA (Airport Corridor Transportation Association) is a public transit organization that provides FMLM connections for passengers boarding/departing the 28x at the Ikea Superstop to nearby businesses.

3.1 Service Description

Ride ACTA serves approximately 15 square kilometers (6 square miles) and consists of two 23-passenger shuttles that pickup and drop off riders at the Ikea Superstop for connections with PAAC fixed-route transit buses. In the following report, “van” and “shuttle” are both used interchangeably to represent a 23-passenger shuttle with center aisles. The service operates as a hybrid on-demand, flex-route service where users with origins other than the Ikea Superstop make requests via mobile application. Travelers departing the Ikea Superstop are not required to make trip requests beforehand. Two fixed stops are also provided to two large employers in the region during the evening peak. The average trip distance is 2 miles. A software platform is provided by a third party and is used to assign requests to vans and for routing assistance. The service region is shown in Figure 1.

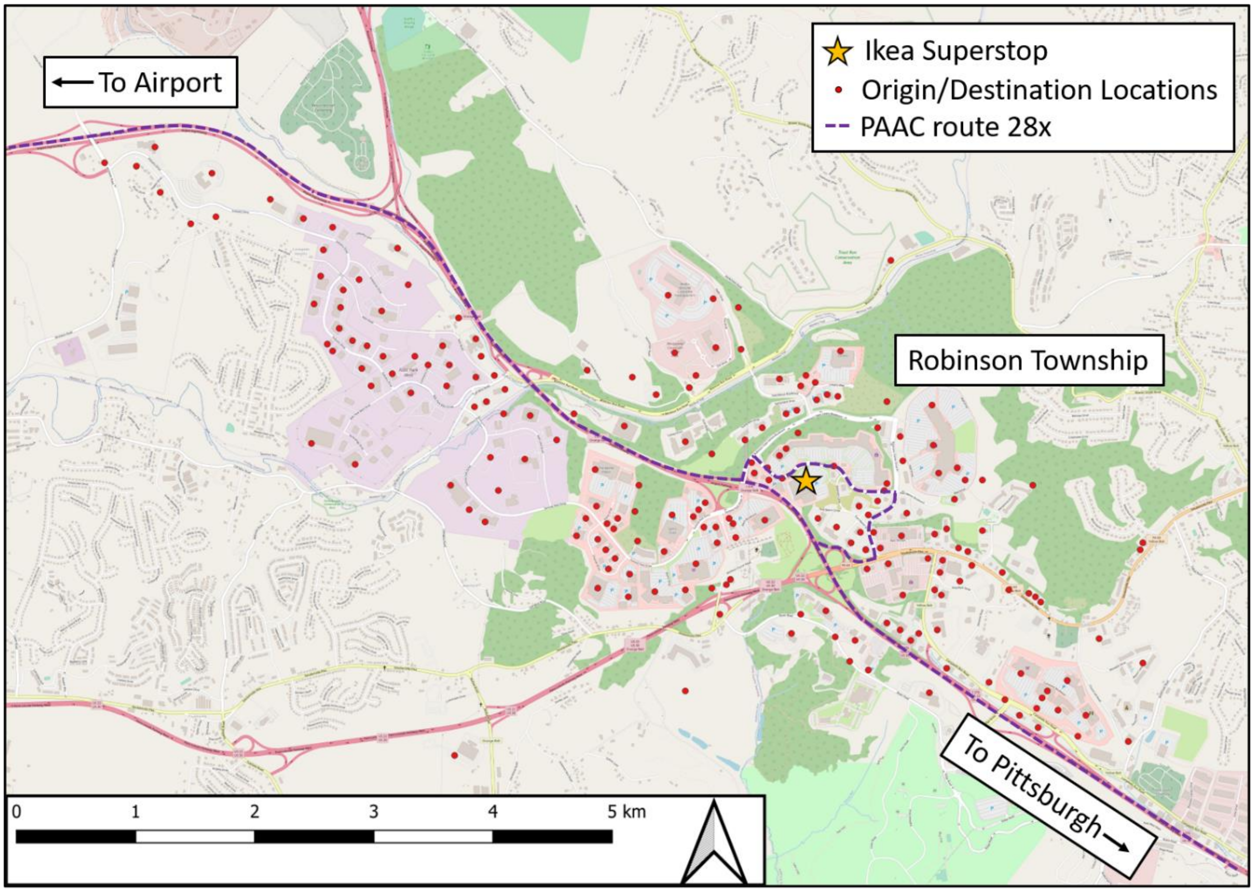

Figure 1: Robinson Township Service Area

3.2 Data and Descriptive Statistics

Request and vehicle trajectory data between May 1, 2019 - July 31, 2019 were provided by Ride ACTA. However, the software was still in its pilot phase, which translated to several data recording errors. Request data consisted of origin/destination information and departure time. Trajectory data provided coordinate points for each van every few seconds. However, it was not uncommon to observe one- or two-minute gaps in trajectory timestamps. Ride ACTA serves roughly 175-200 requests per weekday with morning and evening spikes in demand during commute hours. **Error! Reference source not found.** plots hourly demand for the Ride ACTA service considering the full three months of provided data.

Trajectory data was used to compute travel times between origin and destination locations at 15-min time intervals. To ensure travel time calculations were accurate, trajectory points located on major roadways were not allowed to connect to nearby businesses. This way, connections were only considered when the van diverted from a major roadway to directly serve the specific establishment. Since multiple traversal times between two node pairs were observed, the median travel time was used for each 15-minute period to compute time-dependent travel times. These travel time graphs are used to simulate various strategic and operational policies to accurately capture the dynamics observed in a real-world transportation network. **Error! Reference source not found.** plots the 20 most popular trips observed from the request data. While the service region does not observe typical peak-hour congestion, travel times still vary throughout the day and should be considered to produce more realistic results.

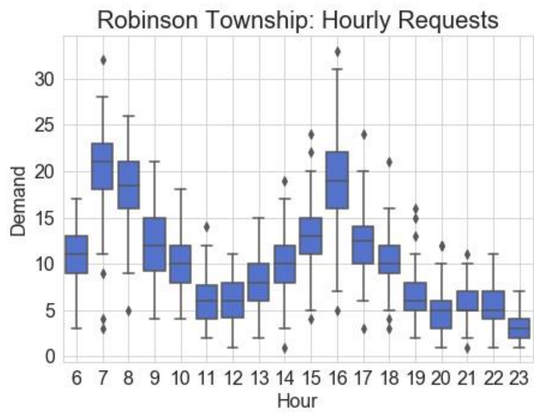

Figure 2: Hourly Demand

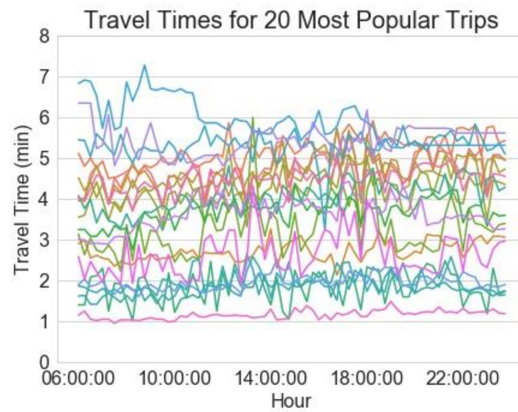

Figure 3: Hourly Travel Times

The FMLM service primarily serves two types of trips: those departing the Ikea Superstop and those arriving at the Ikea Superstop. Travelers departing the Ikea Superstop directly board waiting vans from the 28x PAAC stop and no advanced notice is required. Travelers arriving at the Ikea Superstop are required to make a trip request before a van picks up the passenger and returns to the Ikea Superstop. From Figure 4 and Figure 5, wait times for return trips experience higher wait times compared to trips departing the Ikea Superstop. This is because travelers directly board waiting vans when they depart the Ikea, thus experiencing minimal wait time. The highest wait times for Ikea arrivals are observed during non-peak hours. This is likely because only one van is working during these hours (6-7am and 10am-2pm). This insight here is that two vans are sufficient during peak hours. However, only operating one van during off-peak hours results in higher user wait times. During these time periods, assigning a few trips to TNCs might help reduce user wait times.

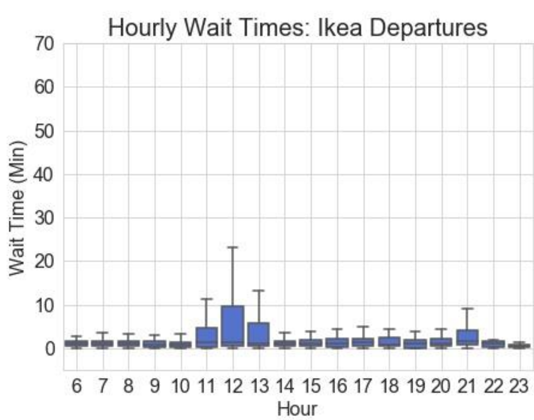

Figure 4: Ikea Departure Wait Times

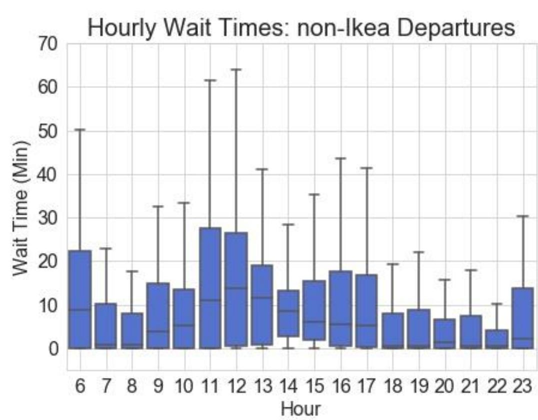

Figure 5: Ikea Arrival Wait Times

The total number of origins and destinations within the Robinson Township service region is well over 300. But this high number is likely due to input errors (either early/late inputs or incorrect addresses). This input error hypothesis is confirmed by the number of origins and destinations located on the freeway (I-376). An analysis was conducted, and it was determined that approximately 9% of records were infeasible based on vehicle trajectories and were therefore dropped from the analysis. Additional request records were either input either with wrong origin/destination or where input early or late. However, enough information about the request was provided to infer the origin/destination and departure time. While the software provider might not be flexible with requests from numerous partner agencies, one software improvement would be to restrict driver inputs to actual pickup and drop off locations. A quick check to verify the input address based on the vehicle location would also be beneficial. We approximate that the actual count of origin/destination locations to be closer to 100. We also find that 50% of the trips serve six locations (Ibex: 20%, Walgreens: 7%, FedEx: 7%, Marriott: 5%, Walmart: 4%, Cigna: 4%). Prioritizing service to these locations, either through scheduled stops or higher priority assignments, will be beneficial in improving service and retaining ridership. As of July 2020, Ibex has decided to move locations, which is the location that serves 20% of riders in the Ikea region. This reduction of riders will drastically impact agency goals to increase and retain ridership.

Existing system reliability was also evaluated using three months of data. Maintaining a reliable service is integral in retaining existing users. Again, reliability metrics were calculated by separating Ikea departure and arrival trips. Both 50th and 90th percentile wait times were computed and shown in Figure 6 and Figure 7. By observation, similar trends exist in that reliability suffers during non-peak hours. For Ikea departures, the mid-day period when only one van is in service produces 90th percentile wait times near 20 minutes while all other periods are below 10 minutes. For Ikea arrivals, a similar trend exists, but both morning and afternoon peaks also observe higher 50th and 90th percentile wait times compared to Ikea departures. This is expected because demand is spread across the entire service area instead of being aggregated at one point (Ikea Superstop). When demand is spread spatially, the probability of "expensive" trips (e.g., one trip requiring a large detour) is high. For this reason, integrating TNCs to serve a few "expensive" trips during peak-demand hours can have large impacts on system performance. In the following results, we use the word "expensive" to describe trips within a given shuttle's trajectory that require large detours to serve a request. For example, if five users are currently being dropped off at locations in the northwest region (e.g., Walgreens and Ibex) and a request enters the system from Settler's Ridge (southeast of Ikea), the shuttle would either have to make a large detour and pick up the passenger at Settler's Ridge (drastically increasing the in-vehicle times for all current riders) or first drop off all its current passengers before picking up the request from Settler's Ridge (drastically increasing the wait time for the passenger at Settler's Ridge). The request from Settler's Ridge would be considered an "expensive" trip because total user costs would increase drastically regardless of the operational strategy.

Figure 6: Ikea Departure Wait Time Reliability

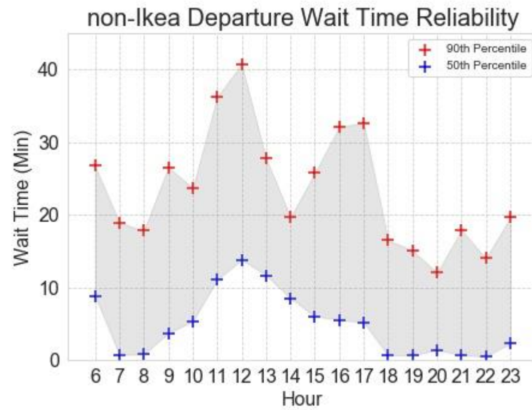

Figure 7: Ikea Arrival Wait Time Reliability

3.3 Results

3.3.1 Comparison with Observed Data

July ridership data was used to compute hourly total wait and in-vehicle times for three scenarios. First, raw data was downloaded directly from the Ride ACTA software that contained attributes for wait and in-vehicle time for each request. Since the software was still in its pilot phase, operations and data collection produced many errors and challenges for the Ride ACTA service. For example, drivers found the software difficult and work arounds (e.g., swapping trips between drivers, errors in input, poor route recommendations) were common. To verify system metrics (wait and in-vehicle times), a second scenario ("Observed") was created using van trajectories to infer pickup and drop off times. However, due to trajectory data granularity and input errors, both "Real Data" and "Observed" cases were only able to produce estimates of system wait and in-vehicle times. In Figure 8 and Figure 9, total hourly wait and in-vehicle times for three scenarios can be observed. "Real Data" plots metrics based on raw data downloads from the software provider. "Observed" is the case where verification was conducted, and corrections were made based on vehicle trajectories. "Simulation" plots results obtained from the simulation using time-dependent travel times and the algorithm presented in the previous section.

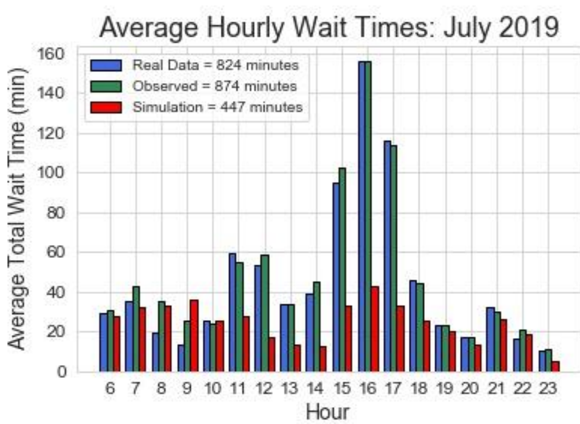

Figure 8: Total Hourly Wait Times

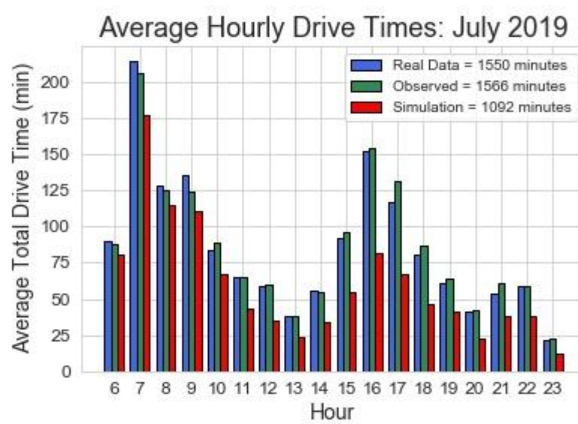

Figure 9: Total Hourly In-vehicle Times

The three scenarios produced similar temporal trends for both hourly total wait and in-vehicle times, however, reduced system wait and in-vehicle times were observed under the "Simulation" case. These results are expected because the algorithm simply observes the data and makes decisions that reduce user costs. It does not capture the various driver behaviors that may result in worse system performance. The "Simulation" case outperforms observed wait times significantly during the evening peak. Although demand requests are more spatially spread out during the evening peak (not all trips are originating from Ikea Superstop), we would still expect to see a closer agreement in terms of system performance for the two peak periods due to similar demand levels. For this reason, we hypothesize that both "Real Data" and "Observed" wait and in-vehicle times are likely due to a combination of driver behavior, poor routing, and input and data collection errors.

3.3.2 Vehicle Supply

The current service consists of two 23-passenger vans operating an on-demand FMLM commuter service. However, due to low demand throughout most of the day, we explore the feasibility of incorporating TNCs into the existing service. Three scenarios are simulated which include (i) the status quo ("2 vans"), (ii) removing one van and using TNCs to help accommodate high demand periods ("1 van + TNC"), and (iii) using only TNCs to serve all demand ("TNC only"). Figure 10 and Figure 11 plot total hourly wait and in-vehicle times comparing the three scenarios.

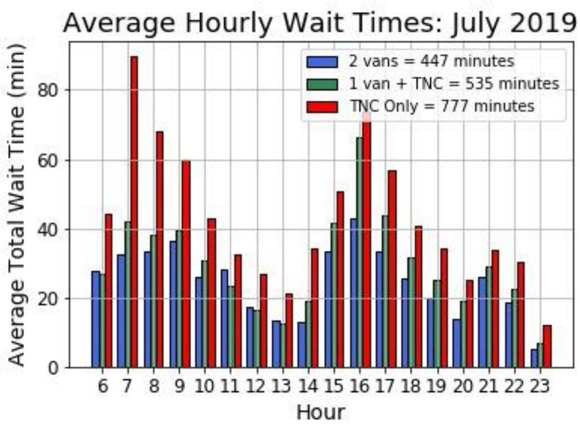

Figure 10: Total Wait Times

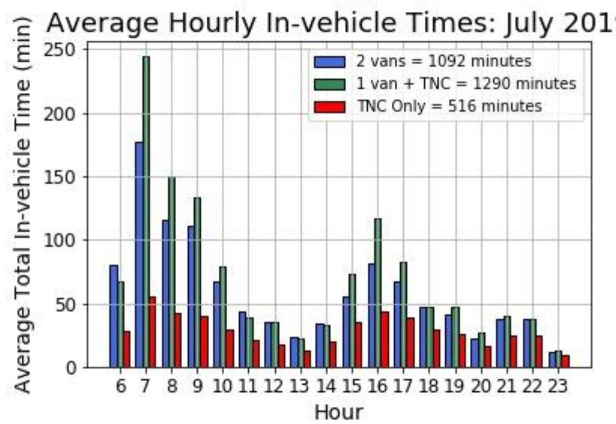

Figure 11: Total In-vehicle Times

The "2 van" scenario outperforms both TNC scenarios in terms of wait time, which provides confidence that two vans are sufficient to serve the service demand. A 20% increase in total average daily wait time is observed for the "1 van + TNC" case. Each request experiences a 5-minute wait time in the TNC only case, thus making this policy the worst in terms of wait time. In terms of in-vehicle time, the TNC only case outperforms the other two scenarios by a large margin. This is because no rides are shared, and no requests must make any detours between their respective origins and destinations.

Since the simulation objective function is defined as a weighted combination of wait and in-vehicle time (0.75*wait time + 0.25*in-vehicle time), total user costs are calculated and compared for the three scenarios in Figure 12. Figure 13 compares average daily agency costs for the three scenarios, which are the costs the agency pays to provide the FMLM service. While agency costs are constant when considering 23-passenger shuttles ($51/hour), the integration of TNCs introduces new costs that are dynamic and based on spatio-temporal demand. Agency costs for the "2 van" scenario considers one 14-hour shift split into two time periods (6am-10am, 2pm-12am) and one 17-hour continuous shift (7am-12am). In the "one van + TNC case", a continuous 18-hour (6am-12am) van shift is considered. TNC costs are calculated using the cost formula highlighted in previous section, which includes both travel time and travel distance costs.

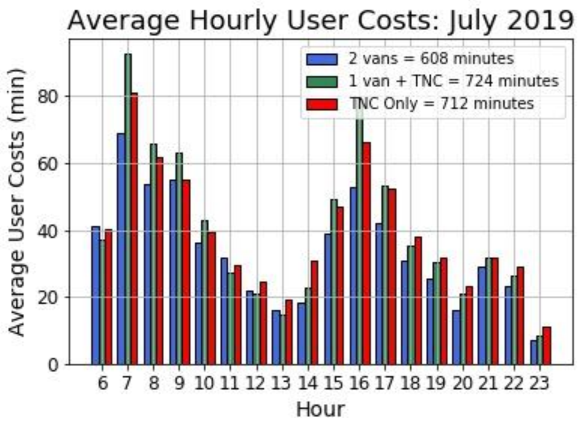

Figure 12: Average Daily User Costs

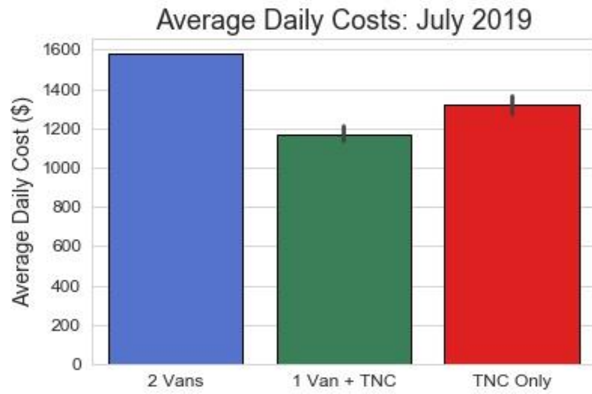

Figure 13: Average Daily Agency Costs

Based on these results, if Ride ACTA reduced their supply of vans from two to one and incorporated TNCs, agency costs can be reduced by 26% but user costs would increase by 19%. If they elected to use TNCs to serve all demand, agency costs can be reduced by 16% but user costs would increase by 17%. These costs only consider wait and in-vehicle times and do not incorporate service reliability.

3.3.3 Wait Time Reliability

Wait and in-vehicle time reliability was also evaluated for the three scenarios to capture system performance under day-to-day demand variability. It is important to remember that TNC wait times are assumed to be 5 min. This value can vary temporally and spatially, however, we use the average value provided by Uber in the Pittsburgh region for analysis purposes. Figure 14 and Figure 15 plot hourly 95th percentile wait and in-vehicle times, respectively.

The "1 van + TNC" scenario outperforms the status quo ("2 vans") during periods when only one van is operating (6am and 10am-2pm) because costly trips during these periods can be assigned to TNCs. However, during the evening peak, the "2 van" case produces lower 95th percentile wait times because more trips are being assigned to one van (in the "1 van + TNC" case) during this period. The flat line for the "TNC Only" case was due to the assumption of 5-minute wait times.

From an in-vehicle time perspective, the "2 van" scenario outperforms and "1 van + TNC" case during morning and evening peak periods. This is due to the additional riders assigned to one van during periods of high demand. Reliability in the "1 van + TNC" scenario can be improved with more riders being assigned to TNCs, however, agency costs would increase. These results emphasize the importance of knowing rider requests in advance to improve request-TNC matching, thereby improving reliability when integrating TNCs.

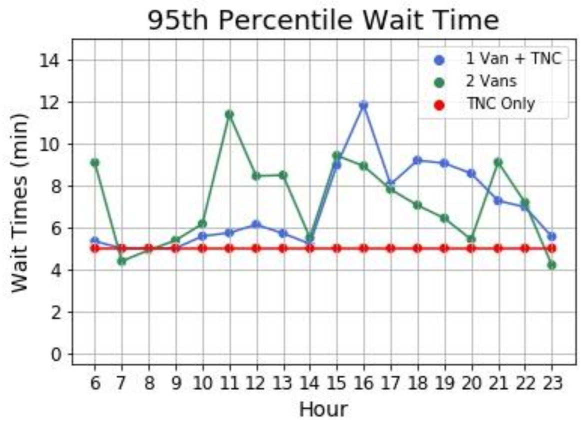

Figure 14: Wait Time Reliability

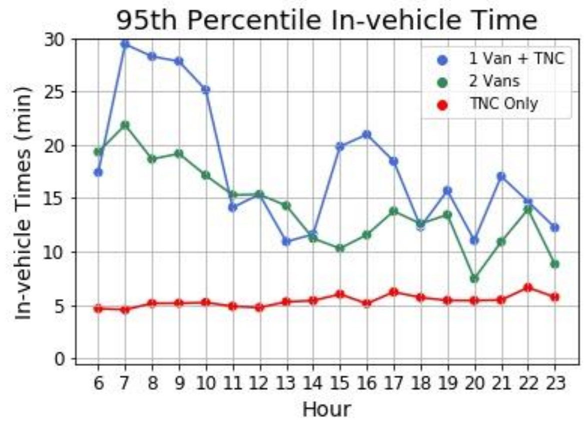

Figure 15: In-vehicle Time Reliability

5. Moon Township

Moon Township is located five miles northeast of Robinson Township and consists of mixed low-density residential and commercial. Compared to Robinson Township, Moon is smaller in size with fewer businesses. PAAC also serves the region with a peak-hour service (route G3), which is primarily used in conjunction with a park-and-ride to transport travelers to downtown Pittsburgh during commute hours. However, several large businesses and airport hotels are in Moon, which provide employment opportunities in the region. Ride ACTA is looking to design a similar FMLM service for reverse commuters that directly serves the park-and-ride, which is the terminal stop along the G3 route.

5.1 Service Description

The proposed service area would serve approximately 15 square kilometers (6 square miles), however, most of the demand is expected to fall within a 4 square kilometer (1.5 square mile) region directly around the park-and-ride. This is because all the large employers (office parks, airport hotels, and corporate offices) fall within this region. The proposed service will directly serve commuters from the park-and-ride facility looking to connect to nearby businesses. A similar on-demand system is proposed; however, it is expected that demand for the service will be much lower compared to Robinson Township. The goal of the service is to provide FMLM connections to all businesses not already served by PAAC route G3, which include all large and small businesses. The proposed service region is shown in Figure 16. Large business locations are presented in Table 1.

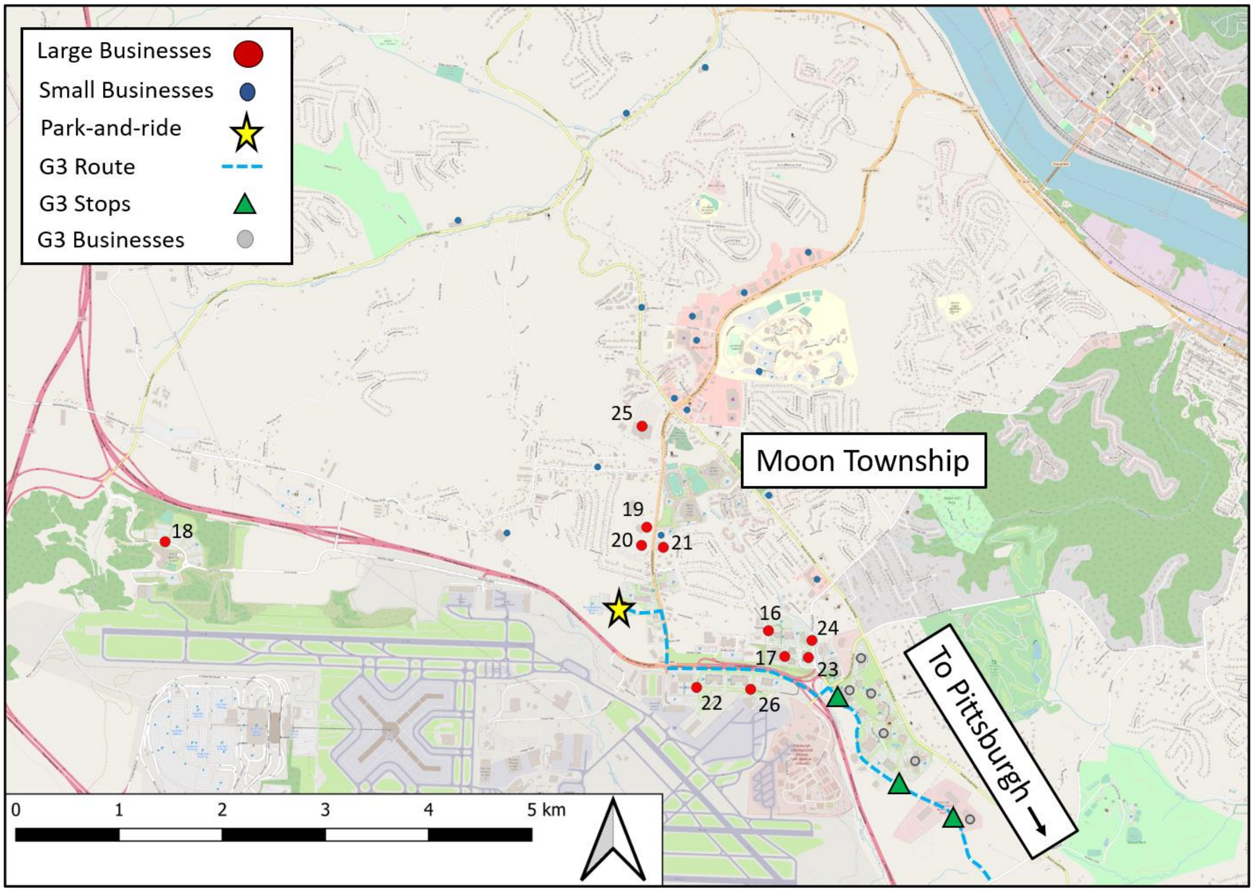

Figure 16: Moon Township Service Area

Table 1: Large Businesses

Node	Location
16	Airport Office Park 1
17	Airport Office Park 2
18	Dick's Sporting Goods
19	Double Tree
20	Hampton Inn
21	La Quinta
22	Michael Baker International
23	Quality Inn
24	Sheraton
25	Walmart
26	Adapt Health

The PAAC G3 route is a peak-hour service, with buses arriving at the Moon Township park-and-ride between 6:14am-7:57am and departing the park-and-ride between 3:41pm-5:58pm. The latest G3 schedule (provided by PAAC) is shown in Figure 17.

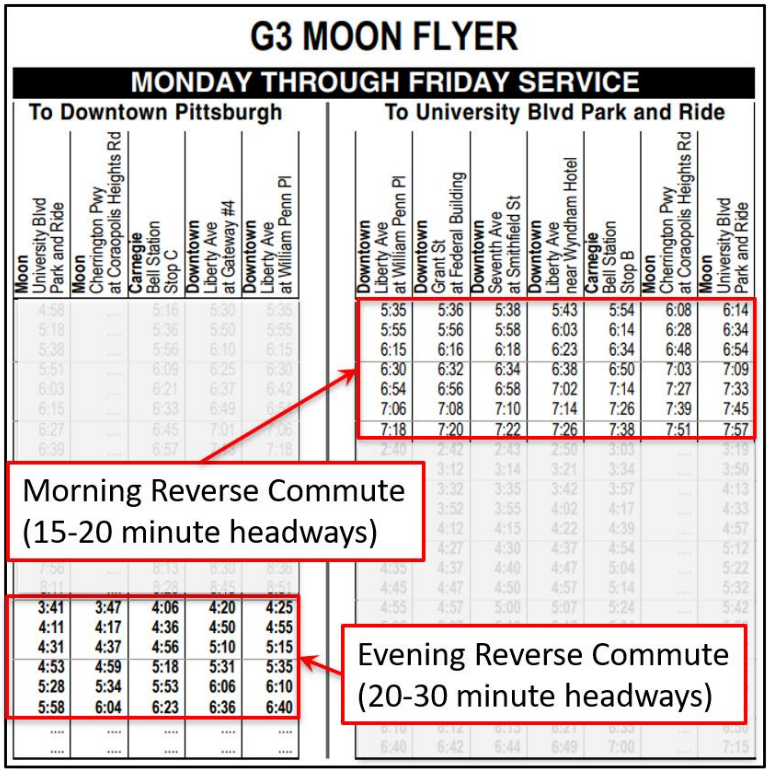

Figure 17: G3 Service Schedule

5.2 Data and Demand Estimation

Time-dependent travel times were obtained from the Google Travel Time API for each hour during morning and evening peak service (6am, 7am, 8am, 4pm, 5pm, 6pm). The travel time data is used to construct a time-dependent directed graph for simulation. Demand data is unknown because the service is not yet in operation. However, it is expected that most of the demand will originate from the large businesses within the service area. For the following analysis, we assumed 90% of the demand originates at large businesses and 10% of demand originates from small businesses. Large businesses are determined in two ways. First, locations provided by Ride ACTA where demand is expected be high (Dick's Sporting Goods, office parks, Michael Baker International) were classified as 'Large' businesses. Additionally, Robinson Township analysis was used to determine other locations where demand is expected to be high. From Robinson Township, hotels and Walmart observed significant demand for the Ride ACTA service. For this reason, we classify all airport hotels and the Walmart located in Moon Township as 'Large' businesses because we expect higher demand for the service from these locations. In Robinson Township, ten locations accounted for over 80% of the service requests. Since we expect similar patterns in Moon, we assume 90% of the demand originating from 'Large' businesses. The 90% value was determined because the Moon service area contains even fewer large businesses compared to Robinson Township. Additionally, small businesses in Moon Township have few employees and mostly include fast food restaurants and car dealerships. Because of this, we select only 10% of demand originating from such small businesses. While the 90%/10% selections seem to be arbitrary, since no demand is known at this time, the assumption serves as a likely estimate. These thresholds can be easily modified once demand for the service in Moon is better understood.

Demand is simulated hourly based on the demand profile for Robinson Township (see Figure 2). Since demand is expected to be small compared to Robinson Township, we use scaled hourly distributions to sample demand in Moon Township. For each demand level (e.g., 20 daily travelers), all requests are assigned to various G3 arrivals and 90% and 10% of total demand are randomly assigned to either large or small businesses, respectively. All the same travelers must also make return trips during evening peak G3 service, so 20 travelers correspond to 40 total trips. Evening peak request times are assigned to a departure hour (4pm or 5pm) based on the Robinson Township demand profile. The request minute is randomly assigned with equal probability. Sixty representative days are sampled, which is equivalent to approximately 3 months of weekdays.

It is expected that initial demand levels for the service will be approximately 20 requests per day (or 40 total trips). For this reason, we analyze performance metrics and costs based on this expected demand. To provide insights if demand grows in the future, we also analyze system performance for 30 requests per day (60 total trips).

5.3 Results

5.3.1 Vehicle Supply

The following results are presented for two demand scenarios: (i) 20 requests/day (40 total daily trips) and (ii) 30 requests/day (60 total daily trips). For Moon Township, we include the “1 van” scenario because demand levels are expected to be low compared to Robinson Township. Results are based on simulating 60 representative weekdays using the demand estimation methods highlighted in the previous section. Figure 18 and Figure 19 plot the resulting hourly wait times for the two demand scenarios and compare four supply scenarios (“1 van”, “1 van + TNC”, “2 vans”, and “TNC only”).

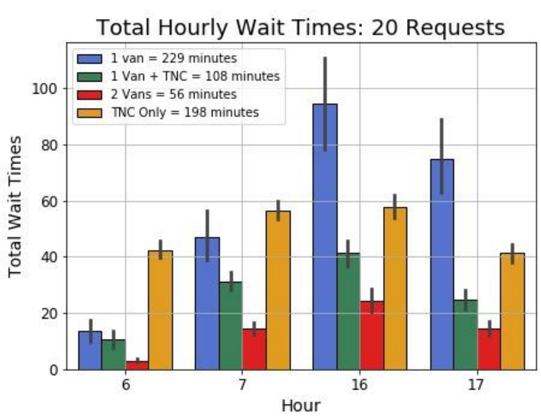

Figure 18: Total Wait Times - 20 Requests

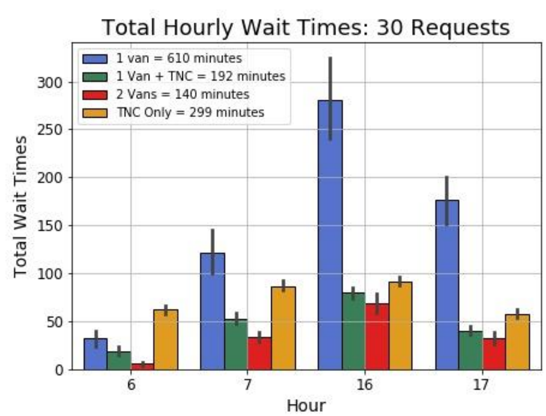

Figure 19: Total Wait Times - 30 Requests

The “1 van” scenario is the worst performer under both demand scenarios, however, as demand grows, wait times grow at a much faster rate compare to the other scenarios for the “1 van” case. This observation indicates that if demand is higher than 20 requests per day, using only one van might not be sufficient to serve all requests with an appropriate level of service. It is important to remember that while daily demand is lower for the proposed Moon Township service, all the demand is observed in four hours, while the Robinson Township demand is spread throughout the day. For example, Robinson Township experiences just over 30 trips during the 4pm-6pm demand window, which is similar to the afternoon peak for Moon Township in the 30 requests/day scenario. Because of this, it is expected that one van will not be sufficient for Moon when daily requests reach 30. This hypothesis is confirmed based on the figures above. Based on the hourly wait time results, a FMLM service that provides either one van with TNC services or 2 vans would be preferred.

In-vehicle times are also compared for the four scenarios. The time a traveler spends in a vehicle is much less important compared to wait times based on how travelers' value of time. However, providing more direct routes for users will help improve ridership levels and retain current users. Figure 20 and Figure 21 compare traveler in-vehicle times for the four scenarios of interest.

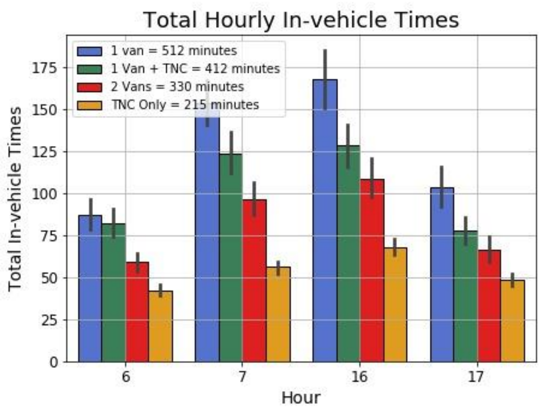

Figure 20: Total In-vehicle Times - 20 Requests

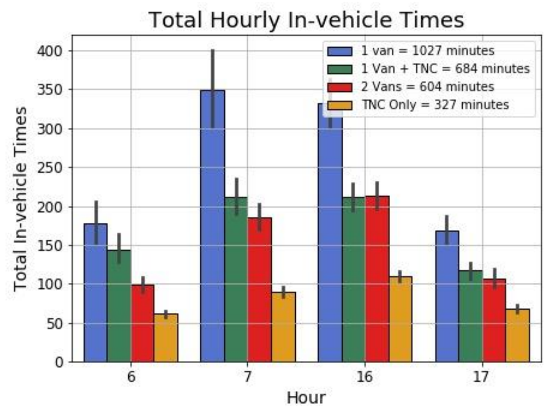

Figure 21: Total In-vehicle Times - 30 Requests

The "TNC only" case outperforms all other scenarios for both demand levels. This result is expected because no rides are shared, therefore, no detours are required. However, as demand grows for TNCs, it is likely that the level of service will drop, and prices could increase based on the mismatch of requests and available drivers. As demand grows from 20 requests/day to 30 requests/day, the "1 van" case observes much higher drive times due to the number of detours required for each trip. The "1 van + TNC" and "2 van" cases produce similar results because "expensive" trips are now being assigned to TNCs, thus freeing up the one in-service van to share more similar trips resulting in a more efficient service for the user. The key takeaway from this analysis is that flexible services (TNCs in this case) can accommodate "expensive" trips, thus reducing in-vehicle times experienced by the traveler.

Since riders value wait and in-vehicle time differently, we adopt the value of travel time proposed by Wardman (2004), which found that for short bus trips, riders valued wait time three times more than in-vehicle time. To obtain and compare total user costs, wait and in-vehicle time values were multiplied by 0.75 and 0.25, respectively. The following comparisons are shown in Figure 22 and Figure 23.

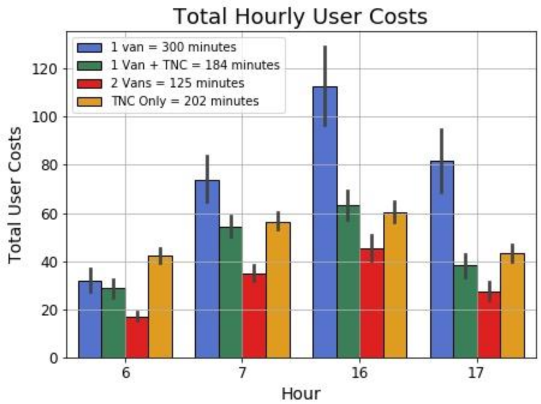

Figure 22: Total User Costs - 20 Requests

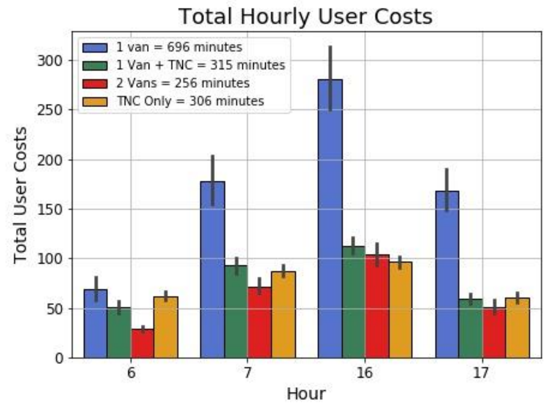

Figure 23: Total User Costs - 30 Requests

For the 20 request/day scenario, 2 vans provided the best service, however, both TNC scenarios are comparable. As demand grows, the “1 van” case is probably insufficient to provide reliable service. Similar user costs are observed for the three other scenarios. These results highlight the advantage of flexible services, especially under constrained van supply when demand grows.

System objectives are to reduce user costs and improve reliability. However, with any public transit agency, costs to provide services are limited. Such agencies are constantly evaluating tradeoffs between level of service and costs to provide the service. To provide a clearer picture, agency costs are also compared. By comparing both level of service and user costs, tradeoffs can be evaluated based on agency objectives. For the “1 van” and “2 Vans” scenarios, costs are constant and are based on two 5-hour shifts; one during the morning peak and one during the evening peak. Costs for TNC trips are calculated using methods highlighted in section “TNC Cost Calculations”, which are based on travel time and distance. Because trips are short within the Moon Township service regions, average costs for TNC trips were just over $8, which is the minimum base fare for an Uber trip in the Pittsburgh region (Taxi How Much, 2020). Only base fares are considered in this analysis, however, when demand in high in a specific region and requests outnumber available vehicles, fares increase to balance supply and demand. This is important, especially for the “TNC Only” case, because demand will be high during the morning peak from the park-and-ride. Since the Moon service is a commuter service, we would expect minimal “high fare” events (referred to as surge multipliers) because overall demand for TNCs during these times is low compared to weekend evenings when people are taking social trips. Average daily costs are compared in Figure 24 and Figure 25.

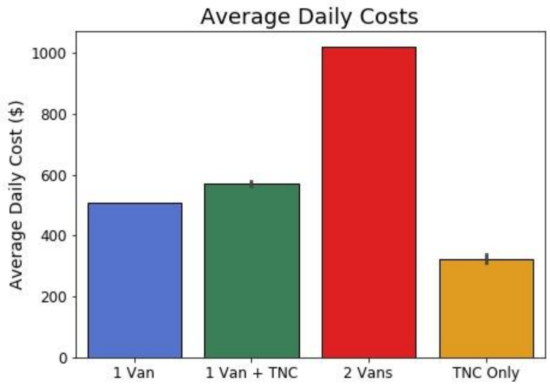

Figure 24: Agency Costs - 20 Requests

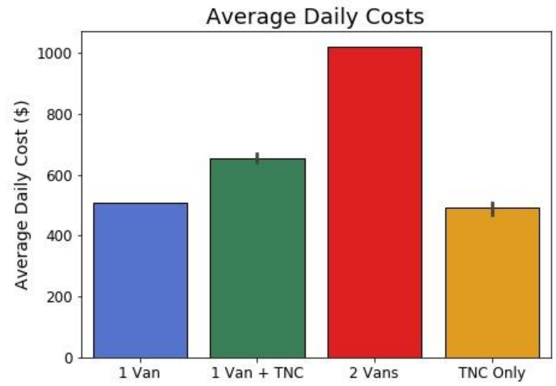

Figure 25: Agency Costs - 30 Requests

For the 20 request/day scenario, using only TNCs is optimal in terms of agency costs. By referring to Figure 22, user costs are reduced by 33% for the "TNC Only" case compared to the "1 Van" case. Agency costs are also 36% lower for the "TNC Only" scenario compared to "1 Van". This is because vans must be hired for minimum 5-hour shifts and the $51/hour is quite expensive when demand is low. For the cost to hire one van for one hour, a TNC can provide more than 6 trips. In other words, for the shift costs of one van ($255), TNCs can provide almost 32 trips, which would be equivalent to the 30 requests/day scenario. TNC costs are calculated based on current fares, however, since TNCs are private companies, future prices might increase. This fact should also be considered in the decision-making process. However, it is likely that costs would not suddenly increase by 33%, at least in the near term.

A second important observation is the total cost to hire two vans. For 20 requests/day, user costs for the "1 Van + TNC" was 184 minutes compared to 125 minutes for the "2 Van" case, which is an increase of 47%. However, costs for the "2 Van" are twice compared to the "1 Van + TNC" case. Because TNC trips are relatively cheap ($8/trip) and the service is flexible, incorporating them within a FMLM service would be beneficial in both user and agency costs.

Lastly, in addition to user and agency costs, reliability is compared between the four scenarios in terms of wait and in-vehicle time. Demand was sampled for 60 representative days to evaluate 95th percentile wait and in-vehicle times. Service reliability is an important factor that influences rider retention and comparing user costs alone cannot fully capture system reliability. Figure 26, Figure 27, Figure 28, and Figure 29 plot 95th percentile wait and in-vehicle times for both 20 and 30 requests per day.

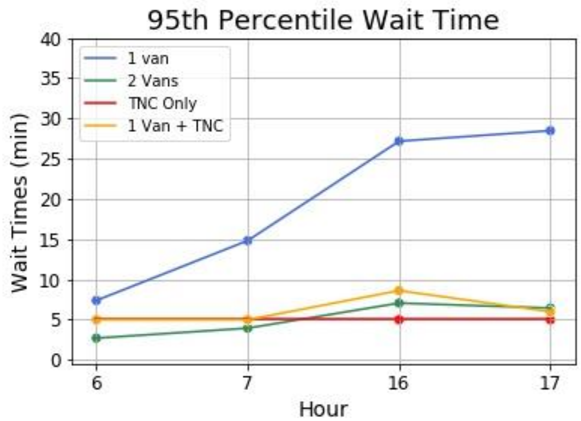

Figure 26: Wait Time Reliability - 20 Requests

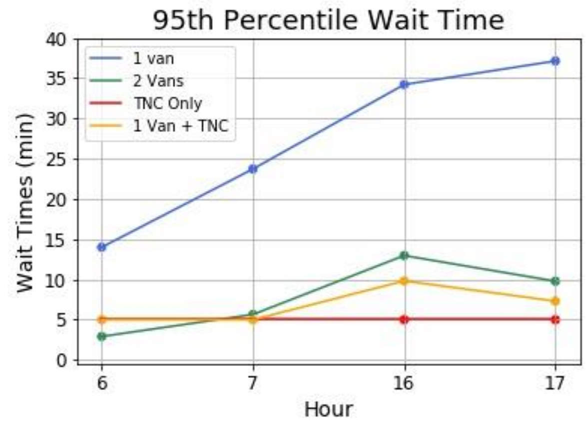

Figure 27: Wait Time Reliability - 30 Requests

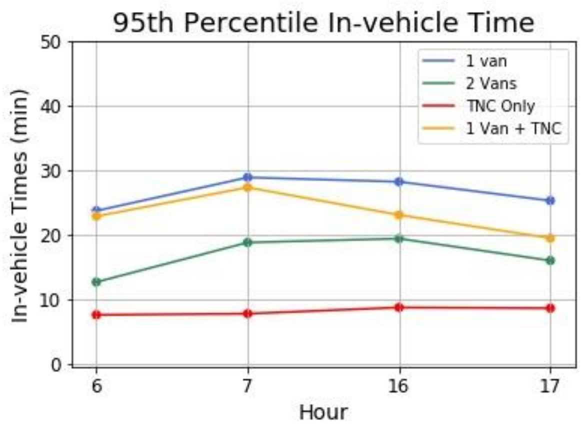

Figure 28: In-vehicle Time Reliability - 20 Requests

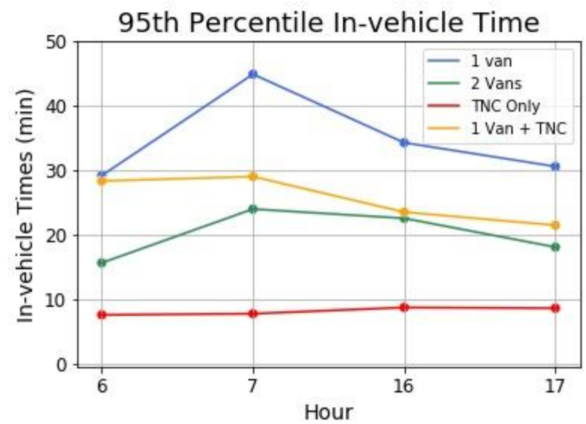

Figure 29: In-vehicle Time Reliability - 30 Requests

From a wait time perspective, based on demand assumptions during sampling, 95th wait times are quite high for the "1 van" scenario compared to other scenarios. Wait times increase during the evening peak because demand is spread throughout the region, as opposed to one demand location (park-and-ride). The flat line for the "TNC Only" case is due to the blanket assumption that all TNC trips will experience a 5-minute wait time based on average Uber wait times in the Pittsburgh region. The in-vehicle times are more spread out. It is important to remember that TNC trips are assigned using a wait time threshold, therefore, TNC assignment is "optimized" based on wait time, not in-vehicle time. The 95th percentile is a metric that determines almost a "worst case" because 95% of the time, values will be below this value. The takeaway here is that both TNC scenarios perform comparably to the "2 Van" scenario from a wait time perspective at much lower costs. In the higher demand scenarios (30 requests per day), the "1 Van + TNC" outperforms the "2 Van" scenario in terms of wait time. This is because at higher levels of demand, two vans are required to serve more requests, and thus suffer more when "expensive" trips enter the system. To summarize, user costs and reliability for both TNC scenarios are comparable to the "2 Van" scenario at lower costs. This is the advantage to designing a flexible system that incorporates TNCs to serve "expensive" trips.

5.3.2 Cost Comparison as Function of Demand

Since demand is uncertain for the proposed Moon service, we elected to plot service metrics (wait time, in-vehicle time, and reliability) and agency costs as a function of demand. Demand scenarios compared range from 20-45 requests per day. The “1 Van” scenario becomes insufficient once the daily demand eclipses 30 requests per day, therefore, we only plot this scenario between daily demand levels of 20-30 requests per day. Figure 30 and Figure 31 plot user and agency costs as functions of total daily travelers. User costs are calculated by weighting simulation wait and in-vehicle times by 0.75 and 0.25, respectively. Van costs are calculated using the hourly fee of $51/hour and two 5-hour shifts for each van in operation.

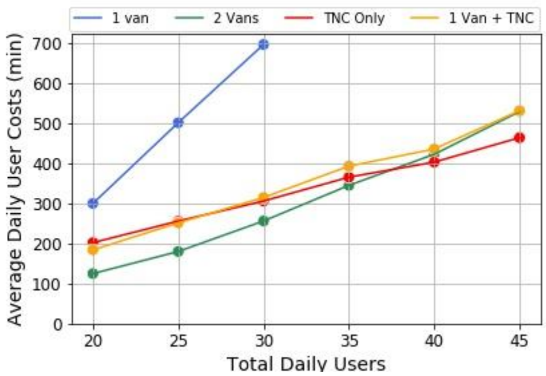

Figure 30: Average Daily User Costs

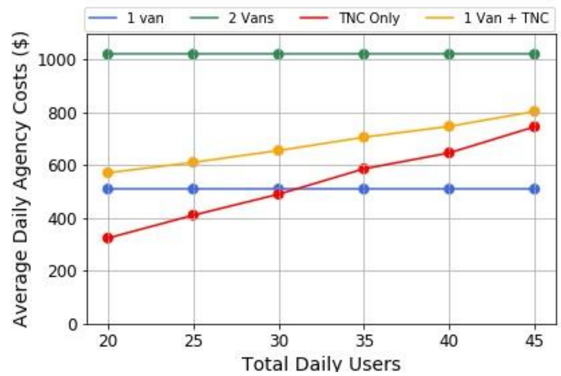

Figure 31: Average Daily Agency Costs

The important takeaway from the above figures is that the “1 Van + TNC”, “2 Van”, and “TNC Only” perform similarly for all demand levels, however, costs for both TNC scenarios are more cost-effective. For daily demand equal to 30 riders (60 total trips), user costs can be reduced by 60% (“1 Van” case) for an additional $150 per day by using TNCs. Of course, tradeoffs exist, and each agency must maximize their own objectives. From a user cost perspective, the "2-van" scenario outperforms all other scenarios until demand reaches 40 users per day (80 trips per day). This is counter-intuitive because we would expect multiple vans with excess capacity to become more efficient with growing travel demand (more similar trips and sharing of trips). However, this result is likely due to the on-demand operational strategy. Once the demand reaches a certain level (in this case 40 users/day), user costs begin to rise more quickly because two vans cannot effectively serve all the trips using an on-demand strategy. This is likely the threshold where a flexible route with fixed-stops strategy can improve the level of service using 2 vans.

Since reliability was not considered in the user cost calculations, a comparison of the 95th percentile wait and in-vehicle times are shown in Figure 32 and Figure 33, respectively. Increasing 95th percentile wait times are observed in both van only scenarios. This makes intuitive sense but also highlights the advantages of TNC flexibility in FMLM services. In terms of in-vehicle time reliability, the "2 van" scenario reduced the 95th percentile in-vehicle time compared to the "1 van + TNC" case, however, both scenarios approach a similar performance level as demand increased. Supplementing existing FMLM services with TNCs provides not only cost benefits (reducing van supply) but also improves service reliability in term of wait time (which is weighted 3x more than in-vehicle time).

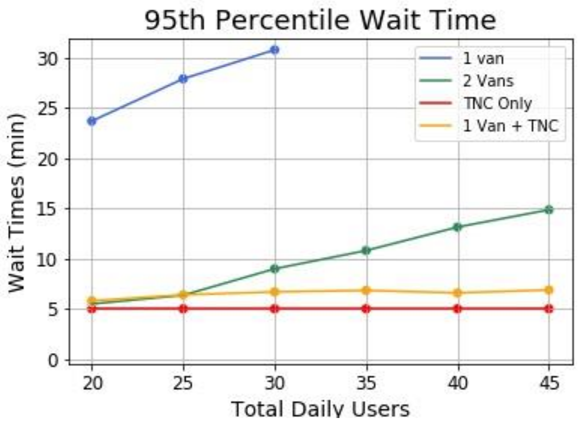

Figure 32: Wait Time Reliability

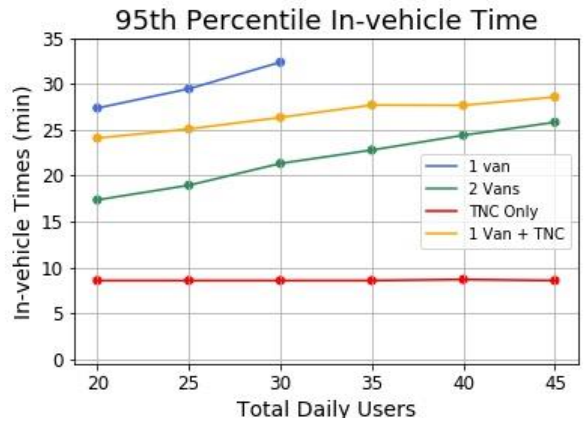

Figure 33: In-vehicle Time Reliability

5.3.3 Stop aggregation

The potential to aggregate stops and reduce the number of times each van must stop to make pickups and drop offs can improve system performance. However, this is dependent on the number of stops that can be aggregated and the associated demand at each of the aggregated stops. Because demand is expected to be low for the Moon service, the probability of multiple travelers making requests within clusters of potential aggregation points at similar moments in time is low. However, this strategy can improve performance as demand for the service grows.

In Moon Township, we restrict potential aggregation clusters to businesses within 1000-ft from one-another. Additionally, stops cannot be aggregated across roadways if not pedestrian infrastructure (crosswalks) are present. Based on aggregation criteria, four potential aggregation locations are identified and are shown in Figure 34.

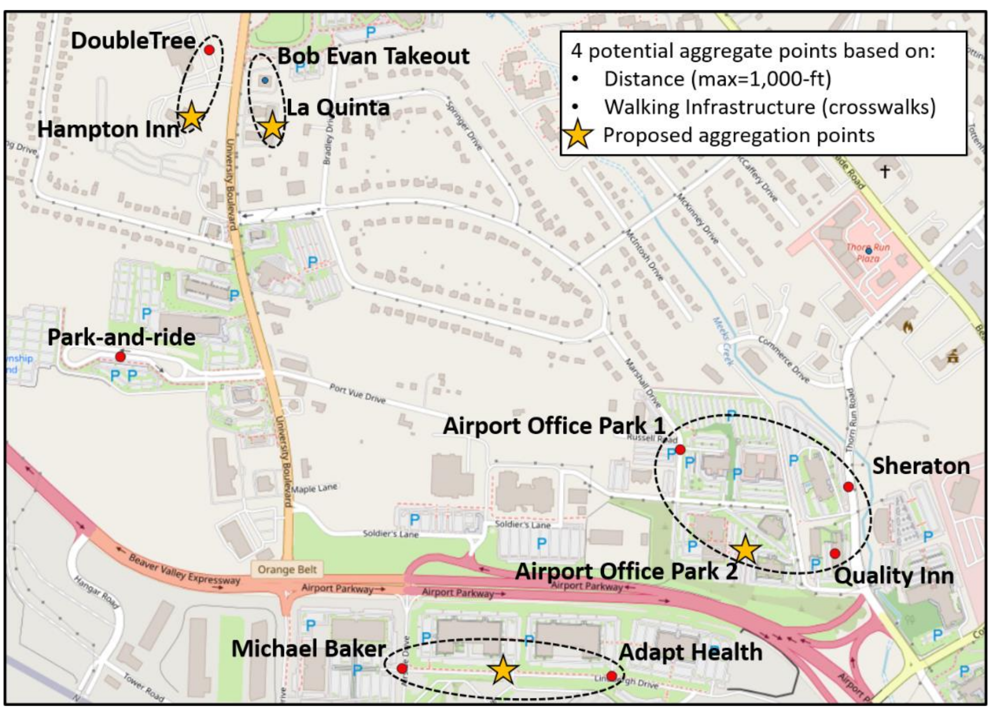

Figure 34: Potential Aggregation Points - Moon Township

The following results compare stop aggregation and no-stop aggregation for three demand scenarios: (i) 20 requests/day (40 total daily trips), (ii) 30 requests/day (60 total daily trips), and (iii) 40 requests/day (80 total trips). The “TNC Only” scenario was omitted from this analysis because trips are not shared, therefore, aggregating stops would have no effect.

In the 20 requests/day scenario, no wait or in-vehicle time improvements were observed. This is because of the low probability of observing more than one request from an aggregation cluster at a similar time. However, as demand increases, there is a higher probability of multiple requests coming from within potential aggregation clusters. Figure 35 and Figure 36 compare no stop aggregation with stop aggregation scenarios for three different vehicle policies.

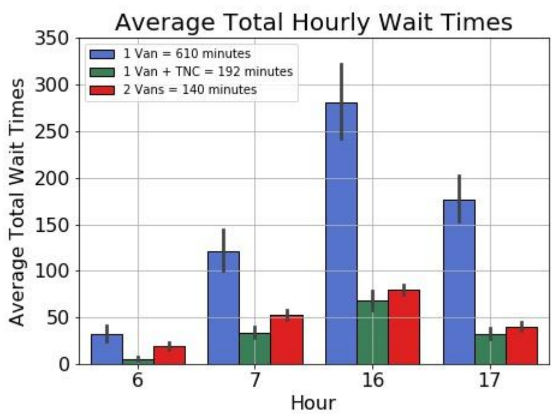

Figure 35: No Stop Aggregation (30 Requests)

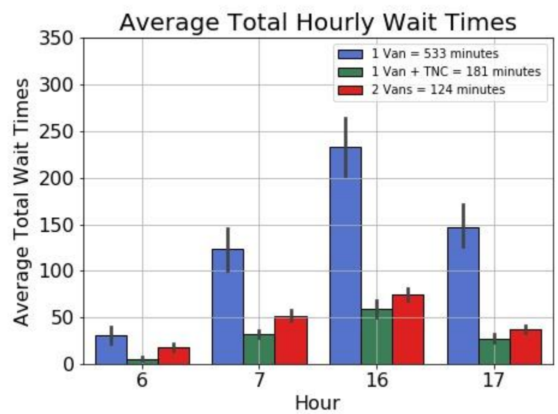

Figure 36: Stop Aggregation (30 Requests)

Wait time improvements are observed for all van policies. Wait times improve 13%, 6%, and 11% for the “1 Van”, “1 Van + TNC”, and “2 Vans” policies, respectively. The “1 Van + TNC” scenario observes the smallest improvement because trips are being assigned to TNCs, and therefore will not influence wait times. TNC trips are solo trips and no ridesharing is considered, which means that TNCs will not benefit from aggregating stops.

Average total hourly wait times are also compared for 40 requests/day. The “1 Van” scenario was omitted from the analysis because one van can no longer sufficiently serve all requests when demand reaches 40 requests per day. Figure 37 and Figure 38 compare “1 Van + TNC” and “2 Vans” cases for both no stop aggregation and stop aggregation scenarios.

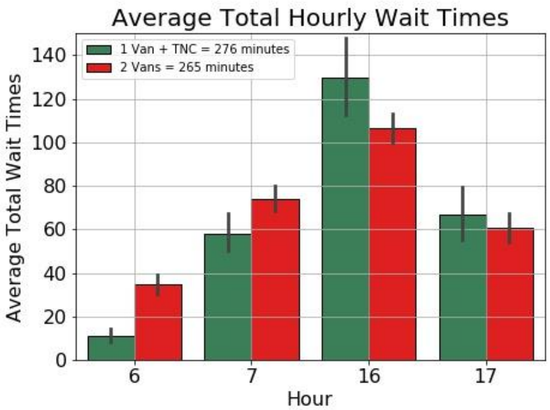

Figure 37: No Stop Aggregation (40 Requests)

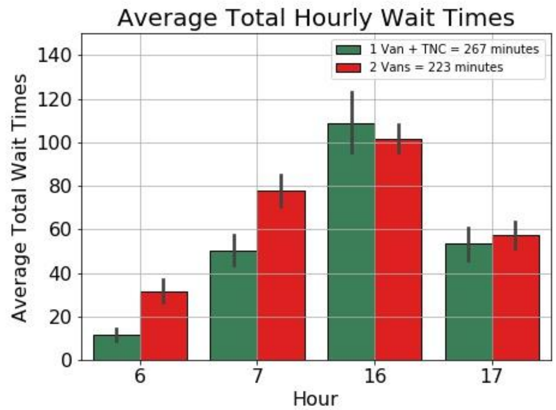

Figure 38: Stop Aggregation (40 Requests)

Wait times improve 3% and 16% for the “1 Van + TNC” and “2 Vans” policies, respectively. The “1 Van + TNC” scenario only improves 3%. This is because at higher demand levels, more trips are being assigned to non-shared TNCs. Trips that are not shared will not observe benefits from a stop aggregation policy. However, the “2 Van” observes a 16% reduction in hourly wait times when stops are aggregated. This improvement increased from the 30 request/day case (13%). When vans are operating and trips are shared, aggregating stops improved wait times significantly. This observation also confirms that stop aggregation will have larger impacts when demand for the service is high.

However, user costs for travelers required to walk will increase because additional travel time (walking time) is required for businesses within aggregation clusters. Using the value of walking time determined by Wardman (2004) for short bus trips, the value of walking time is approximately 0.7*wait time. Assuming a 5ft/sec walking speed, walking times for users departing from aggregations stops can be computed. For return trips, we assume that estimated wait times provided to each request by the app at the time of request is accurate, and that each request does not incur additional costs from waiting in inclement weather. Total user costs are then calculated by computing an equivalent wait time for walking times, which are then added to wait time costs. Total user costs are compared in Figure 39 and Figure 40.

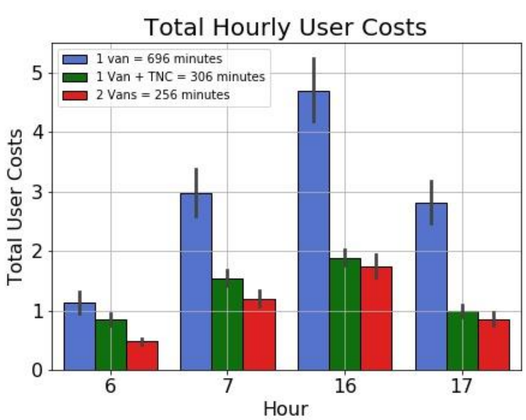

Figure 39: No-aggregation (30 requests)

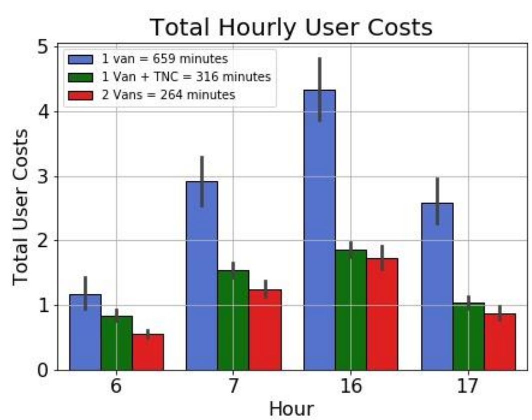

Figure 40: Aggregation (30 requests)

For the “1 Van” scenario, aggregation improved total user costs by 5%. However, in the “1 Van + TNC” and “2 Vans” scenarios, stop aggregation increased user costs for the 30-request case. This is due to the additional costs incurred by walking to aggregation points. The reason why we observe improvement for the “1 Van” case is because the improved travel times improved user costs for subsequent passengers by reducing future wait times. However, in the “2 Van” case, the extra shuttle provides improved service, and shuttle efficiency improvements (per shuttle) are smaller relative to the “1 Van” case. Smaller efficiency improvements do not fully offset the additional user costs incurred by walking to aggregation points.

For the 40 request/day case, total user costs are plotted in Figure 41 and Figure 42. The “1 Van” scenario is not shown because one shuttle is not sufficient when demand reaches 40 requests/day.

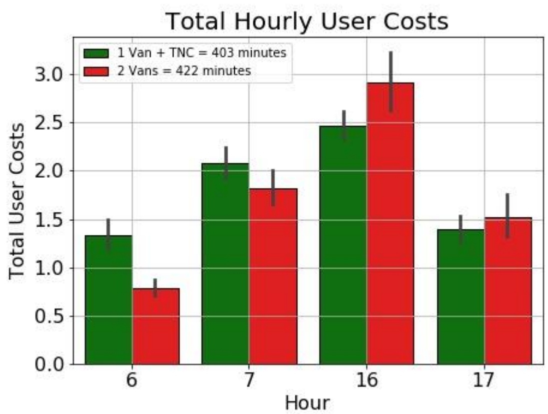

Figure 41: No-aggregation (40 requests)

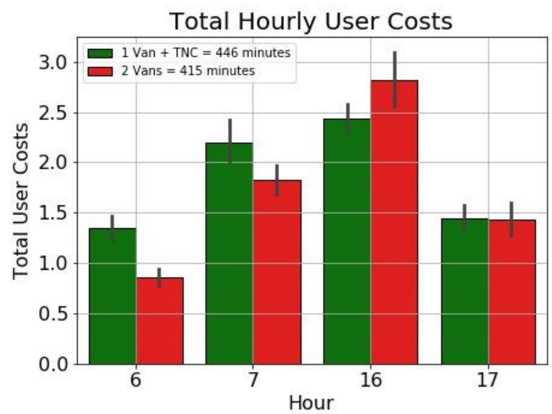

Figure 42: Aggregation (40 requests)

The “2 Van” scenario observes a 2% improvement in term of total user costs when demand levels reach 40 requests/day. This result indicates that shuttle efficiency improvements when stops are aggregated fully offset additional walking costs and provide a net benefit for users in the “2 Van” case.

Stop aggregation is a simple policy that can be implemented to improve overall level of service. However, additional walking costs are incurred by users that must be offset by vehicle efficiency gains. From this analysis, we find that a stop aggregation policy only provides a benefit when demand levels are greater than 40 requests/day.

5.3.4 Fixed-route + On-demand

Previous studies have concluded that fixed-route policies perform best when demand density is high. One study found that the critical switching point between on-demand and fixed-route service was between 10-50 customers/mi^2/hr (Li & Quadrifoglio, 2010). The range is determined for different service area shapes. When considering only large businesses and 30 customers per day, the Moon demand density falls at the lower end of this range. Since demand still must be served as small businesses, a complementary service (either an on-demand van or TNCs) is required to ensure all requests are served. For this reason, we test two potential scenarios to quantify the performance of different fixed-route/on-demand policies. The two scenarios tested are “fixed-route + on-demand van” and “fixed-route + TNC”. We compare these results to the “2 Van” scenario where both vans operate in an on-demand setting.

The fixed-route service is designed to serve all large businesses. Because destinations for all requests are known in the morning when a van picks up riders at the park-and-ride, a fixed-route service makes little sense. However, if fixed pickup times are designated to large businesses for pickups during the afternoon peak, wait times can be reduced because riders will arrive at the designated time, and will therefore not experience any wait time. An additional advantage is that users will not have to make advanced requests. The fixed-route policy also has some disadvantages. First, afternoon trips are less flexible because each rider will have to choose between two evening pickup times (one between 4pm-5pm and one between 5pm-6pm). Second, a one van scenario will not be possible to serve all requests. Either a second van or TNCs must be used to complement the fixed route to serve demand from small businesses. Last, the van must make all stops for any given circuit, even if no requests show for a given stop. This leads to longer drive times for all van passengers. There is a tradeoff when operated a fixed route service. Smaller wait times can be observed, but drive times will be longer.

Figure 43 presents the fixed-route service region that serves all large businesses (90% of the demand) in Moon Township. The demand sampling techniques are adjusted for the fixed-route service. When return trips are sampled for park-and-ride return trips, departure times are assigned to one of the scheduled pickup times. The simulation assigns all riders from a large business to the fixed route service and all small businesses either to the on-demand van or a TNC service depending on the scenario being tested. A fixed route service design is assumed based on a feasible trajectory. The fixed route service cycle length is 45 minutes based on travel times between the large businesses. Three aggregation points are assumed to limit the number of stops for the fixed-route van. One stop is provided for locations 26 and 26, locations 16, 17, 23, and 24, and locations 19 and 20. Figure 44 presents the proposed fixed route service along with the scheduled pickup times for each location. When demand for the service is better understood for each large business, the fixed-route schedule can be altered to provide a more efficient service. For example, if no demand is realized from Michael Baker (node 22), then this stop can be eliminated from the fixed route, thus providing a more efficient service.

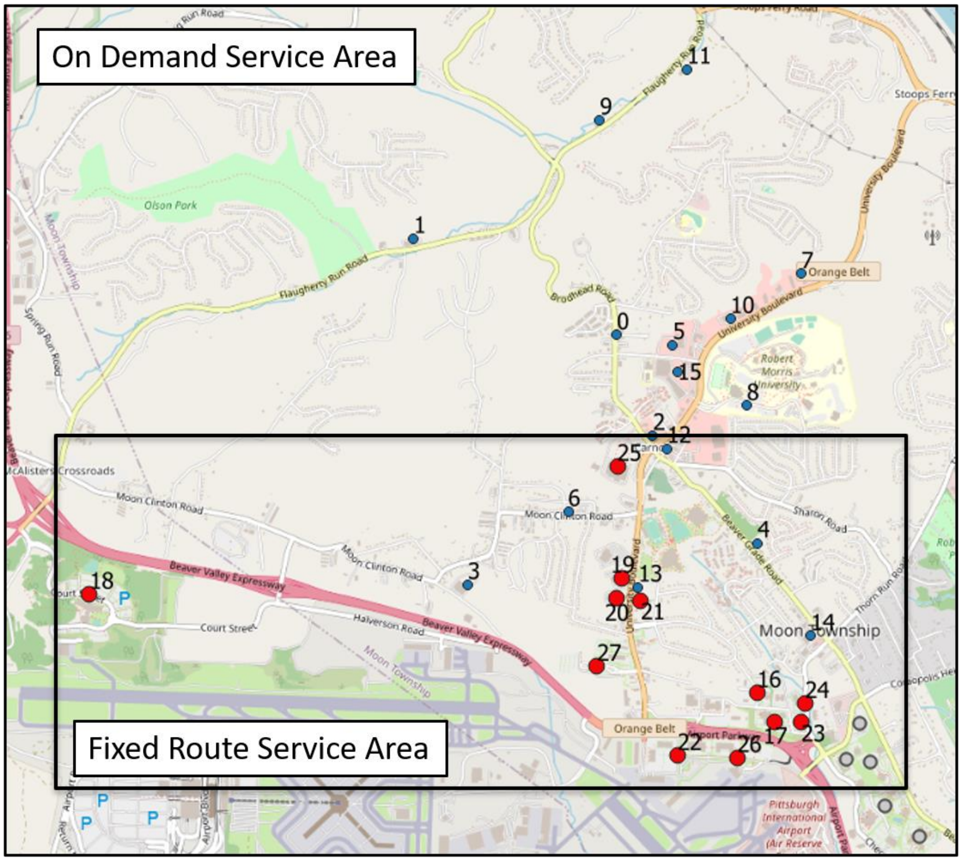

Figure 43: Fixed-Route Service Area

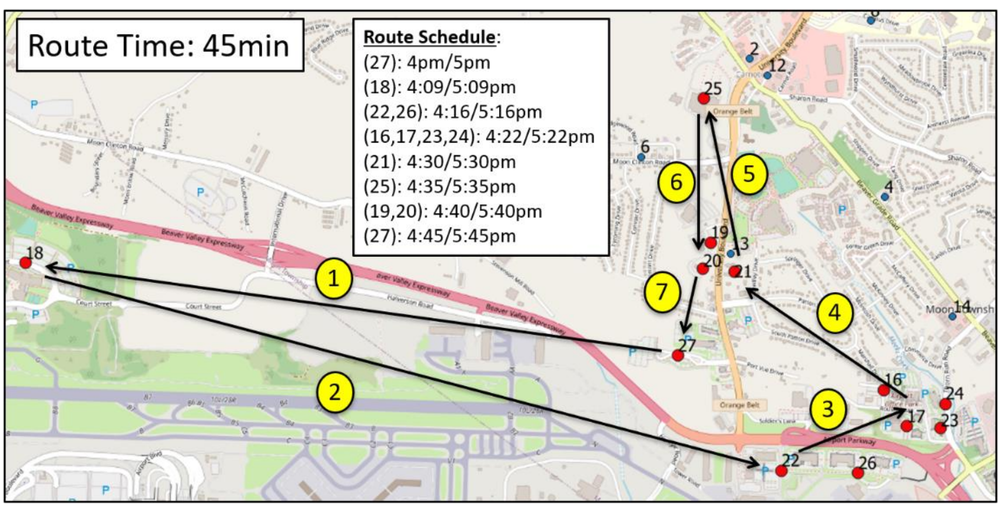

Figure 44: Fixed-Route Service Design

The following results compare four different scenarios: “2 Vans (OD)”, “1 Van + TNC (OD)”, “2 Vans (Fixed)”, and “1 Van + TNC (Fixed)”. The first two scenarios are the same results from previous sections when the vans are on-demand (OD). The next two scenarios assume that one van is providing a fixed-route service (Fixed). In the “2 Vans (Fixed)”, one van is operating on a fixed schedule during the evening peak while the other van is on-demand to serve small business requests. The “1 Van + TNC (Fixed)” uses

TNCs to serve small business demand. Two demand levels are selected (20 customers per day and 40 customers per day) to analyze how the results change and demand for the service grows. Figure 45 and Figure 46 compare average total hourly wait times. The hashed bars represent the fixed-route scenarios.

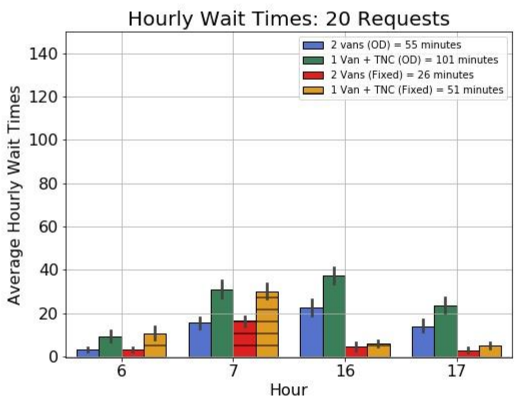

Figure 45: Fixed Route Wait Times - 20 requests

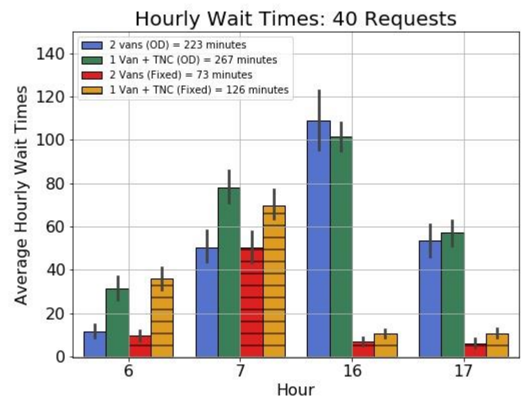

Figure 46: Fixed Route Wait Times - 40 requests

During the morning peak, all shuttles are on-demand for all scenarios. Because of this, we would expect similar wait times between the two van scenarios (red and blue) and the one van plus TNC scenarios (green and yellow). The small differences are because sampled demand is different between the two scenarios. Demand for the fixed-route services must be sampled and matched to a fixed schedule in the "Fixed" scenarios. Because all demand is sampled, each set of samples will have some natural variation, thus producing small changes in the results. From the above figures, we observe a drastic decrease in wait times during the evening peak when the fixed-route service is in operation. The large reductions in wait times depend on the vans arriving on time, however, we use time-dependent travel times to determine the route, so we would expect high on-time performance. The key takeaway from the above figures is that wait time improvements increase for fixed-route policies as demand grows. This is highlighted in Figure 46 with large improvements to wait time during the evening peak for the fixed-route strategies.

However, one disadvantage with fixed-route services is that each van must make all stops along a route, even if no demand is present at specific locations. This will result in larger in-vehicle times experienced by the traveler. For example, if three passengers board the van at Dick's Sporting Goods (the first stop along the route), they must traverse all other stops in the route before being dropped off at the park-and-ride. Since each route cycle lasts 45 minutes, this would translate to three customers each experiencing a 45-minute travel time. Average hourly in-vehicle times for 20 requests/day and 40 requests/day are plotting in Figure 47 and Figure 48, respectively.

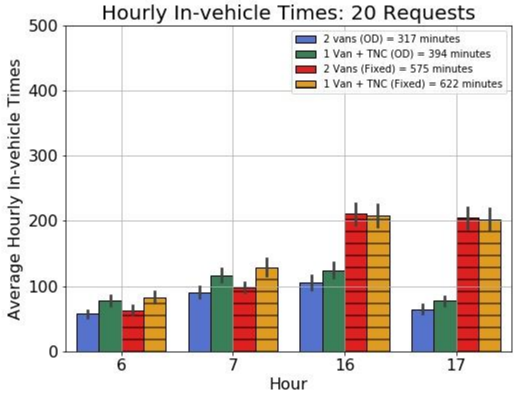

Figure 47: Fixed-route In-vehicle - 20 requests

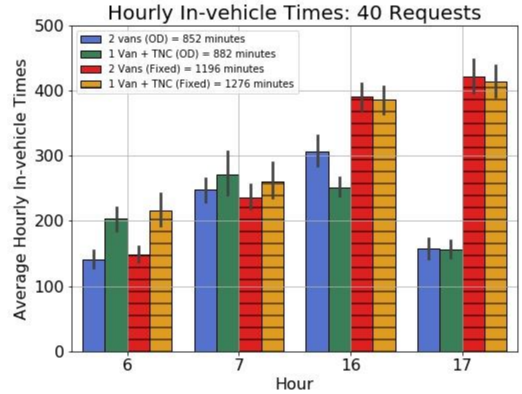

Figure 48: Fixed-route In-vehicle - 40 requests

In-vehicle times increase during the evening peak when using a fixed-route strategy. A tradeoff exists between on-demand and fixed-route strategies. Wait times are reduced at the expense of increased in-vehicle times. Since travelers are more concerned with wait times, we compute total user costs by weighting wait times by three times compared to in-vehicle times. This weighting was determined by previous value of travel time research for short bus trips (Wardman, 2004). Figure 49 and Figure 50 compare user costs for 20 requests/day and 40 requests/day, respectively.

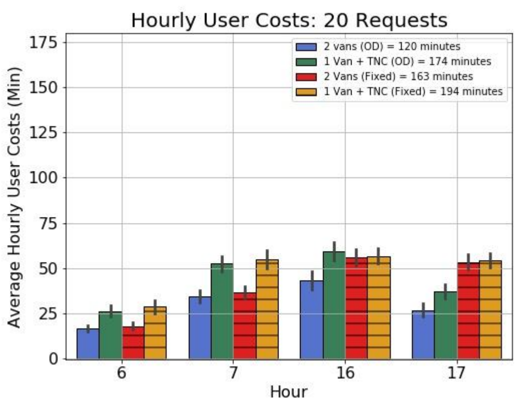

Figure 49: Fixed-Route User Costs - 20 requests

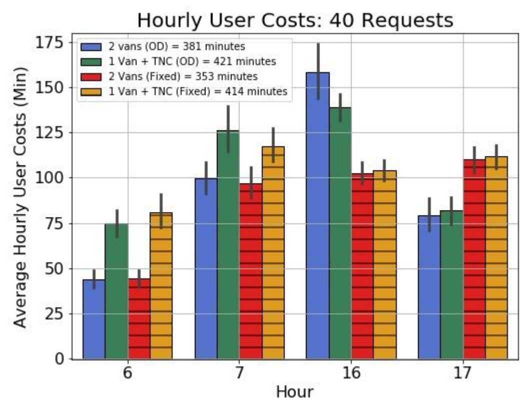

Figure 50: Fixed-Route User Costs - 40 requests

The on-demand scenarios outperform fixed-route strategies for the 20 requests/day scenario. However, when demand grows to 40 requests/day, both fixed-route strategies outperform their comparative on-demand strategies. As demand grows, more rides are "shared" on the fixed-route and more travelers experience minimal wait time because of the fixed schedule. Fixed-route travelers experience increased in-vehicle times, however, because wait times are more important, the choice to reduce wait times for more travelers with a fixed-route service improved total user costs when demand reached 40 requests per day.

Figure 51 and Figure 52 compare 95th percentile wait times and Figure 53 and Figure 54 compare 95th percentile in-vehicle times for on-demand and fixed-route strategies. The results are similar to total hourly wait and in-vehicle times presented above. The fixed-route strategies have lower percentile wait times but higher 95th percentile in-vehicle times are observed.

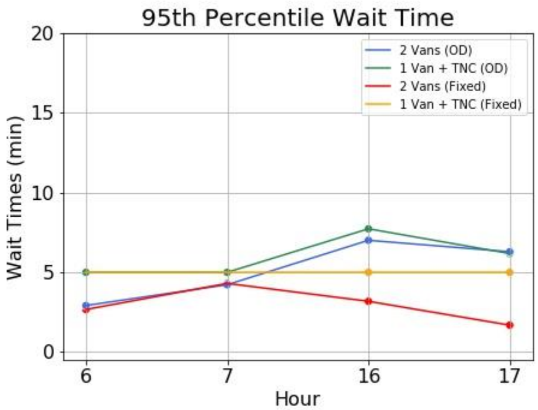

Figure 51: Wait Time Reliability - 20 requests

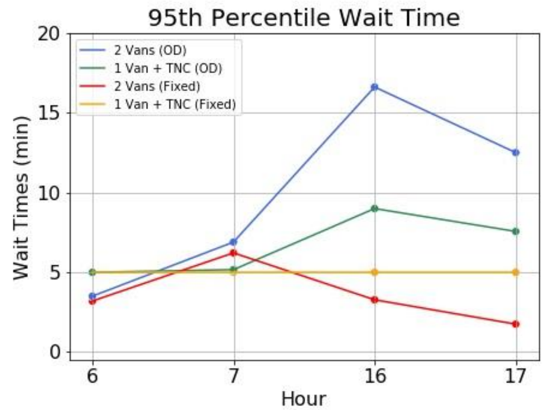

Figure 52: Wait Time Reliability - 40 requests

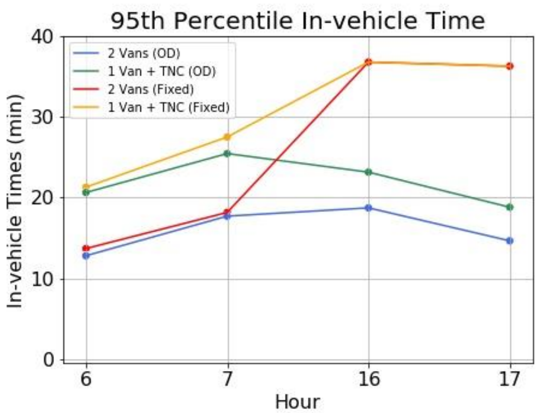

Figure 53: In-vehicle Time Reliability - 20 requests

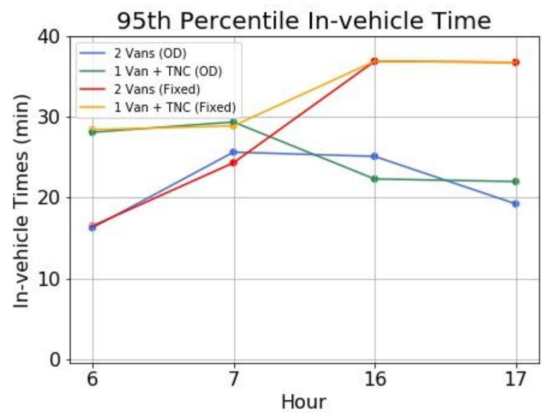

Figure 54: In-vehicle Time Reliability - 40 requests

6. Discussion

A general model was developed test various strategic and operational strategies for FMLM services in both Robinson Township and Moon Township. Various performance metrics (wait times, in-vehicle times, and reliability) were calculated and compared for the different strategies. User costs (wait and in-vehicle times), agency costs (costs for the agency to provide service), and reliability were compared to highlight tradeoffs between different service options and provide recommendations for both existing services and proposed future services.

The strategies tested focused on vehicle supply (number of vans, TNCs), operational strategies (stop aggregation and fixed route), and demand (20-45 requests per day) for the proposed Moon Township service, where demand for the service is unknown. All the scenarios are compared in terms of user costs, agency costs, and reliability to provide valuable insights and service recommendations to help improve existing and proposed FMLM services in the Pittsburgh region.

6.1 Robinson Township

Existing FMLM services in Robinson Township consist of two on-demand, 23-passenger vehicles either departing or arriving at the Ikea Superstop. The FMLM services provide connections from PAAC route 28x to nearby businesses in Robinson Township. Typical weekday demand for the Robinson Township service falls between 150-200 trips. Peak morning demand occurs between 7am-9am and evening peak demand occurs between 5pm-6pm. 35% of the total daily requests occur during either morning or evening peak periods.

Median wait times for trips departing Ikea are near zero for all hours expect 11am-2pm. During the lunch hours, slightly higher wait times are observed. This is likely due to the reduction of in-service shuttles during the lunch hours. The low wait times are a product of the service because all riders directly board waiting shuttles from the 28x, therefore, experience no wait time. Often, a shuttle idles at the Ikea to wait for additional riders, which results in higher in-vehicle times for direct boarding passengers. For Ikea return trips, the highest passenger wait times are also observed during the lunch hours, which is due to reducing in-service vans from two to one. Return trips experience wait times between 0-20 minutes depending on the hour of day. The higher wait times, compared to Ikea departing trips, can be attributed to the spatial spread of demand across the service region.

50^{th} and 90^{th} percentile wait times were computed for the existing service as a reliability measure. Results mirror the patterns of the total hourly wait times, in that, reliability suffers during lunch hours and for Ikea return trips. 90^{th} percentile wait times are close to 40 minutes for return trips during lunch hours. A large variation in wait times affects rider retention because (i) riders do not like waiting and (ii) there are risks involved for time-inflexible trips. Even though trip requests are low during lunch hours, reducing vans from two to one affect both wait times and reliability. Supplementing the existing van during lunch hours with flexible TNC services can help improve both wait times and reliability at relatively low costs. Using TNCs for “expensive” trips (trips with large detours to pick up a passenger) can reduce system wait times at the cost of a few TNC trips (~$8/trip).

A general model was developed to test three vehicle supply scenarios for the existing FMLM service in Robinson Township. Various tradeoffs exist between user costs (wait time and in-vehicle time) and agency costs for the three strategies tested. These tradeoffs must be evaluated by each agency to improve their own unique objectives. Because, on average, travelers assign costs that are three times higher for wait times compared to in-vehicle times, total user costs were computed combining both wait and in-vehicle times into one metric. The 2-van service (status quo) had the lowest total user costs, but the agency costs were almost $1,600/day. By incorporating TNC services and reducing van supply from two vans to one van, agency costs can be reduced by 26%, but total user costs increased by 19%. Additionally, the 2-van service outperformed the 1 van service with TNCs in terms reliability under current demand conditions. If the current service priority is to provide the highest level of service under the existing budget constraint, then the existing 2-van service is recommended at current demand levels.

6.2 Moon Township

A new FMLM service is proposed in Moon Township that has many similar characteristics to the Robinson Township service. All requests will either depart or arrive at the park-and-ride centrally located in Moon Township. PAAC route G3 will service the park-and-ride during peak hours to provide transit service between downtown Pittsburgh and Moon Township. Since demand for the service is uncertain, we assume the majority of demand (90%) will come from large businesses (corporate headquarters, hotels, office parks) and the remaining demand (10%) will come from small businesses in the service region. Robinson Township hourly demand profiles are used to generate demand from local Moon Businesses during the peak-hour G3 service. Vehicle supply (number of vans, TNCs) and operational strategies (stop aggregation, fixed route) were simulated to compare user costs, agency costs, and reliability across a range of likely demand scenarios.

Wait and in-vehicle times were compared for the different scenarios, and tradeoffs exist between the scenarios. As expected, more vehicle supply (2 vans or 1 van with TNCs) resulted in lower wait times, and in-vehicle times were minimized when using TNCs only because no trips are shared. In terms of user costs, the 2-van scenario minimized total user costs at an agency cost of approximately $1000/day because of the 5-hour minimum shift lengths. Daily agency costs using TNCs are similar to the one van scenario (i.e., much cheaper than the 2-van alternative), and both TNC scenarios resulted in lower user costs compared to the 1 van scenario. Lastly, using only one van becomes insufficient when demand grows to 30 requests per day (or 60 total trips).

Total user and agency costs were also compared as a function of demand ranging from 20-45 requests per day. The key takeaway from this analysis was that the performance of both TNC scenarios was similar to the 2-van case in terms of user costs, but both were more cost-effective for the agency providing the service. This highlights the advantage of incorporating flexible services (TNCs) to serve "expensive" trips (trips with large detours), thus reducing total user costs and improving the overall level of service.

Stop aggregation scenarios were also tested to compare the various supply scenarios with and without stop aggregation in terms of wait times and user costs. Because the businesses were spread out throughout the service region, only four aggregation points were identified that included ten total businesses. Aggregation points were identified considering a maximum walking distance of 1,000-ft and presence of pedestrian crosswalks when businesses were located on opposite sides of major roadways.

Three demand scenarios were compared (20, 30, and 40 requests/day) for three supply scenarios (1 Van, 2 Van, and 1 Van + TNC). At low demand levels (20 requests/day), no wait time improvements were observed. At 30 requests per day, stop aggregation improved each supply scenario wait times (1 van, 2 van, 1 van + TNC) by 6-13%, with larger improvements for scenarios that do not consider TNCs. This is expected because rides are not shared with TNCs. At 40 requests per day, wait time improvements up to 16% were observed for the 2-van case. However, system users incur additional walking costs when stops are aggregated. We found that total user costs did not improve until demand reached 40 requests/day, and this improvement was only observed for the "2 Van" scenario. Even in this case, only a 2% improvement was observed, which is an estimate that does not include additional costs of walking in inclement weather. The key takeaway from this analysis is that stop aggregation improved vehicle efficiency, but efficiency gains did not fully offset additional user costs until demand reached 40 requests/day. Since stop aggregation is a relatively easy policy to implement, it is recommended to consider such a policy when demand for the service eclipses 40 requests/day.

Previous research has shown that fixed-route services are optimal when demand is greater than 10-50 customers/mi^2/hr. This range was provided because each service area has different characteristics (size, demand locations, etc.). The proposed Moon Township service falls within this range when demand reaches approximately 40 requests/day. Because of this, fixed-route policies are tested and compared for different levels of vehicle supply (1 Van + TNC, 2 Vans). Both supply scenarios (2 vans, 1 van + TNC) were compared considering on-demand for all vehicles and one fixed-route van + on-demand during the evening peak. Results indicate that wait times can be improved when fixed-route policies are implemented, however, in-vehicle times are higher because each request must complete the full fixed-route cycle before being dropped off at the park-and-ride. Two demand scenarios were tested (20 requests/day and 40 requests/day) to compare the policies for different levels of demand. When demand is low (20 requests/day), the on-demand strategies outperformed their comparative fixed route strategies in terms of total user costs. However, at higher demand levels (40 requests/day), both fixed-route strategies outperformed their comparative on-demand strategies. The key takeaway here is that fixed-route strategies reduced total user costs when demand reached 40 requests/day. This result corroborates previous research, in that the critical switching point between on-demand and fixed-route strategies fell between 10-50 customers/mi^2/hr.

7. Conclusion

The purpose of this research was to compare various supply and operational strategies to help inform existing and proposed FMLM services in terms of user costs, agency costs, and system reliability. As expected, tradeoffs exist between the various strategies, and appropriate service designs are unique to the specific objectives outlined by specific agencies. While all strategies tested in this research might not be feasible now, we hope that the insights provided can inform future strategies as public FMLM services continue to adapt and grow.

The first key takeaway from this research is that emerging technologies can provide increased flexibility to existing FMLM services. TNC scenarios are tested, and results indicate that TNCs can improve the overall level of service at reduced costs. The study assumed Uber wait times and trip costs in the Pittsburgh region because data was available. However, information about other flexible services (e.g., zTrip) could not be acquired, therefore, results are only accurate if other flexible services have similar wait times and costs to Uber.

It is important to note that there are some disadvantages to using private TNCs (Uber/Lyft). First, the current software platform does not incorporate TNC services. For the service to work as simulated, TNC trips must be built into the real-time decision process. For example, if a request enters the system, the software must evaluate both the additional costs of serving the trip with an existing in-service van and with TNCs. The software then must decide in real-time whether to pick up the passenger with a van or a TNC. This is not feasible now, but as these services continue to adapt, it is expected that more software providers will provide this feature. Numerous public transit/TNC partnerships exist now and it is expected that service outcomes of such partnerships will continue to be published in the coming years. Second, TNC only scenarios are evaluated and show promising results in terms of user costs, agency costs, and reliability. However, we assume base costs and average wait times for all simulations highlighted in this research. In a TNC only scenario, it is likely that demand for TNCs would eclipse TNC supply during various times of day because all trips must be assigned to TNCs. This would result in higher wait times and increased costs. For this reason, a TNC only case would only be recommended for services with low expected demand.

In both Robinson Township and Moon Township, all riders must be served, which means that “expensive” trips can never be rejected. Additionally, constraints are added to ensure that individual wait and in-vehicle times do not eclipse 30 minutes. For these reasons, incorporating a flexible service to accommodate “expensive” trips can have large positive impacts in terms of overall level of service. Without such services, a request that enters the system that requires large van detours not only results in high wait times for the individual requests, but also ensures that the van assigned to the request is busy for longer periods of time. The large detour will affect all current van passengers in terms of in-vehicle time and will also result in larger wait times for future passengers. If the few “expensive” trips can be removed from in-service van trajectories, numerous travelers will benefit. In this study, we consider TNCs to supplement existing vans for the full day, however, other more conservative strategies can also improve overall level of service. For example, allowing requests to be assigned to TNCs only during lunch hours can help improve both wait times and reliability during low demand hours when only one van is in service.

Other operational strategies (stop aggregation, fixed route) can also improve overall level of service, however, both strategies observe larger improvements at higher levels of demand. The initial expected daily demand for Moon Township is 20 requests/day. At this level of demand, neither stop aggregation nor fixed routes improved the system level of performance. However, as demand grows for the service, additional operational strategies should be explored. Additionally, demand is sampled based on limited information. Once demand for the service is better understood, operational strategies can be optimized resulting in larger improvements to user costs and reliability.

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