The Feasibility of Citywide Public DRT: Door-to-door Bus Service in Tacoma

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This paper examines the feasibility of operating Demand Responsive Transit (DRT) as the primary mode of mass transit in Tacoma, WA. With the promise of door-to-door service anywhere within a region, DRT has the potential to attract new discretionary mass transit riders while serving demand more efficiently than fixed-route systems. We present an algorithm for generating realistic datasets of riders based on employment and demographic data at the census tract level, which are fed through a simulated dynamic DRT system in Tacoma (TacDRT). The TacDRT service is considered feasible if it can serve the same volume of demand that the extant local fixed-route system serves while remaining cost-comparable. Although the simulation results suggest that TacDRT is not feasible, other findings indicate that *a*) the cost or operating DRT significantly decreases as the system scales up, and *b*) the geographical distribution of demand significantly affects the efficiency of DRT.

1 Introduction

The increasing prevalence of mobile geographic technology in the hands of consumers and organizations alike is rapidly changing the urban transportation industry. In the public sector, buses and trains equipped with Automatic Vehicle Location (AVL) allow their movements to be tracked in real time. These data can be pushed to riders' smartphones in the form of real time vehicle location and arrival time estimates. But even with these changes, transit agencies continue to operate fundamentally inefficient fixed-route bus systems, and riders must still plan their schedules around inherently inflexible timetables and routes. Fixed-route systems are not able to meet transit demand dynamically. At a particular time, vehicles might waste resources visiting stops which don't have any riders, or they might miss stops that do have demand. To remedy this, public transit agencies should look to transit startups such as Uber, Lyft and Sidecar, which provide urban demand-driven taxi and shared-ride services.

This paper examines the feasibility of operating a public, citywide Demand Responsive Transit (DRT) service, which has several potential benefits over fixed-route systems. DRT vehicles do not operate according to a fixed route or a fixed schedule. Instead, passengers explicitly request trips between any two locations in the service area, and vehicles are dynamically routed to meet those requests. In this way, agency resources are only spent when and where there is explicit demand. In addition, one DRT vehicle is sufficient to serve any trip request anywhere within the service area. Therefore, DRT provides door-to-door service with no transfers, characteristics which have the potential to attract many new discretionary riders to mass transit.

To maximize the number of trips that a DRT system can serve, it must efficiently assign trips to vehicles. Determining the best allocation of n riders to m vehicles is referred to as the *Dial-A-Ride-Problem* (DARP) [3]. The static DARP assumes all trip requests are known to the agency when service hours begin, while the dynamic DARP allows for the modification of vehicle schedules as trip requests are made across the day. The general case of DARP is NP-Hard, and cannot be solved optimally on any system of reasonable size. The DRT service investigated here is a large-scale, dynamic system and is simulated in Tacoma, WA. We will thus refer to our service as Tacoma Demand Responsive Transit (TacDRT).

The rest of this paper is organized as follows. In *Section 2*, we review work related to DARP and large-scale DRT services. *Section 3* defines the problem and *Section 4* outlines the simulation we designed to address the problem. *Section 5* discusses the results of the simulation, and is followed by conclusions in *Section 6*.

2 Related Work

2.1 DARP Scheduling Algorithms

DARP is NP-Hard, so finding the optimal scheduling solution for TacDRT is not possible. Instead, we use a heuristic procedure.

DARP scheduling algorithms generally fall into one of several meta-heuristic categories including tabu searches, fuzzy logic algorithms, branch-and-cut algorithms and insertion algorithms. TacDRT implements an insertion algorithm for scheduling, so we'll focus our review on those.

Jaw et al. present ADARTW, one of the first static multi-vehicle insertion algorithms. When making a request, riders specify a time window on either their origin or destination stop. ADARTW then imposes a maximal travel time constraint which is a linear function of the minimum driving time of the trip. Trips are considered and scheduled sequentially, and once a trip is inserted into a schedule it cannot be moved to another [7]. Madsen et al. build on this work, generalizing the algorithm to the dynamic case to schedule a small-scale real world DRT service in Copenhagen [9]. They propose REBUS, a two-step insertion algorithm. The feasibility of a particular trip insertion is evaluated first, to ensure that no hard constraints regarding quality of service (e.g. passenger wait time) or regarding the vehicle (e.g. capacity) are violated. If the insertion is deemed feasible, a heuristic cost is calculated and the scheduling with the lowest heuristic cost is chosen. If no feasible insertions are found, the trip is rejected.

For a more comprehensive review of DARP scheduling algorithms, consult Cordeau and Laporte [3].

2.2 DRT

Although there has been substantial research into DARP scheduling algorithms, research into the feasibility of large-scale DRT systems is less robust. ADARTW and REBUS, for example, are developed and tested on simulations not exceeding 350 passengers.

Hyytiä et al. examine a large-scale DRT system, with an average of 72,000 trips and 500 vehicles [6]. They find that insertion algorithms perform well in comparison to route enumeration on systems of this size. Noda et al. compare the performance of DRT and fixed-route bus service in a simulated city [10]. They find that the usability of DRT increases along with the demand frequency, suggesting that DRT might work best in denser service areas.

Diana examines how several factors influence the quality of service and rejection rates in a DRT system [4]. He concludes that as the rejection rate of a system approaches 0%, the cost to serve the remaining trips becomes increasingly expensive. He also finds that increasing the DRT fleet size reduces rejection rates, but doesn't affect quality of service in the system.

Lastly, Jokinen et al. create an abstract DRT model, compare its usability to that of taxis and private vehicles, and conclude that large-scale DRT is the missing ingredient in urban transportation [8].

3 Problem Formulation

Tacoma is a city of 202,010 residents covering 49.72 square miles, and was chosen as the case study due to its population density and for the author's convenience [13]. It was our hypothesis that Tacoma's medium population density would allow for enough rider aggregation to make the DRT system efficient, but doesn't provide enough aggregation to necessitate the regular, high-capacity fixed-route service that is currently in operation.

Before formulating the problem, several terms should be defined:

- A trip's ***call-in time*** represents the time that the rider makes the request known to TacDRT
- A trip's ***request time*** represents the time that the rider desires to get picked up
- ***Service time*** represents the time that a TacDRT vehicle actually picks up a trip

Each TacDRT rider specifies a start and end point anywhere within Tacoma, as well as a *request time*. Trip requests can be made before service hours begin (static) or while service is running (dynamic). We assume that the majority of riders know when and where they will be traveling before service hours begin for a particular day. We settled on a ratio of 90% static trips and 10% dynamic trips, which falls within the range of ratios examined by Fu and Xu [5].

TacDRT must determine the best allocation of trips to vehicles. We impose several hard constraints on service scheduling to address the fact that riders have limited patience and that TacDRT vehicles have a finite capacity. In particular, we impose the following for each trip t:

- The ***excess ride time*** constraint, which ensures that the total ride time for a job will not exceed that job's direct driving time multiplied by a scalar, where direct driving time is the time required to drive directly from a trip's origin to a trip's destination. This is adapted from ADARTW [7]. The scalar A is bound at 3.5.

$$TRT_t \leq DDT_t * A$$

- The ***pickup deviation*** constraint, which ensures that the *service time* for a particular trip will occur between that trip's *request time*, and the *request time* plus a constant. Several DARP scheduling algorithms allow the rider to specify the maximum pickup deviation, however TacDRT will impose this constraint equally on all riders [7, 9]. The constant B is 45 minutes.

$$RT_t \leq ST_t \leq RT_t + B$$

And we impose the following for each stop i.

- The ***vehicle capacity*** constraint, which ensures that the vehicle load at every stop will not exceed its capacity. The capacity is set at 20 riders.

$$VC \geq L_i$$

Binding these hard constraints to values requires balancing the efficiency of the system against the convenience of the rider. For example, a large excess ride time scalar would allow the system to more flexibly schedule trips at the expense of the riders, who might be stuck riding very indirect routes. The values that we chose find the middle ground as much as possible, guaranteeing a decent minimal quality of service for riders while maintaining some flexibility in how the system can serve demand.

For TacDRT to be considered feasible, it must maintain the integrity of these hard constraints on each trip throughout the day and must also satisfy two criteria. First, it

for all Trip t **do**
  $t.age \leftarrow$ age weighted according to transit rider age distribution table
  $t.purpose \leftarrow$ purpose weighted according to trip purpose distribution table
  $t.direction \leftarrow$ inbound or outbound, randomly chosen
  $t.tract1 \leftarrow$ census tract weighted according to age of rider
  switch $t.purpose$
    case $shopping/dining$
      $t.tract2 \leftarrow$ census tract weighted according to Retail and Service employment
    case $shopping/dining$
      $t.tract2 \leftarrow$ census tract weighted according to Retail and Service employment
    case $medical/dental$
      $t.tract2 \leftarrow$ census tract weighted according to Service and Government employment
    case $commute$
      $t.tract2 \leftarrow$ census tract weighted according to total employment level
    case $social$
      $t.tract2 \leftarrow$ census tract weighted according to age of rider
    case $school$
      $t.tract2 \leftarrow$ census tract weighted according to Education employment
    case $other$ **or** $personalBusiness$
      $t.tract2 \leftarrow$ random census tract
  $t.endpoint1 \leftarrow$ random address within $t.tract1$
  $t.endpoint2 \leftarrow$ random address within $t.tract2$
  $t.pickupTime \leftarrow$ time weighted according to daily demand distribution
end for

Figure 1: *The trip generation algorithm. The rider age and trip purpose distribution tables come from APTA transit rider surveys [1]. Daily trip distribution is derived from a transportation model run by PSRC [12]*

must serve the same volume of trips as the extant local fixed-route system operated by Pierce Transit (PT). That system serves 21,793 fixed-route trips within Tacoma each day. Secondly, TacDRT must be cost-comparable to the existing system. Estimating the cost of TacDRT is difficult, considering there are no similar large-scale public DRT services in operation for comparison. Instead, we base the cost off of the SHUTTLE paratransit service, which is PT's ADA accessible complement to their fixed-route service. Using the cost per service hour of SHUTTLE as an estimate, and pinning the total cost of TacDRT to that of PT's fixed-route system, allows us to operate 1496.5 service hours per day.

Lastly, the computational time required to schedule the trips will not be considered. Hyytiä et all have shown that entire large scale DRT systems can be scheduled in minutes, and it is assumed that any transit agency implementing a DRT service would have access to sufficiently powerful computers to accomplish this [6].

4 Model Design

The TacDRT model consists of two main components. The first component is the trip generator, which creates realistic data sets of trips within Tacoma. These trips are fed to the second component, the service simulator, which assigns these trips to vehicles.

4.1 Trip Generator

Most DRT studies evaluate service in square or disk-shaped regions with a perfect street grid and trip requests evenly distributed across the day [6, 8, 10]. In reality, transit demand varies throughout a service area according to housing and employment density, and request rates vary across the day in accordance with peak and non-peak periods. Therefore, evaluating DRT in a real city like Tacoma will require a more sophisticated trip generation methodology.

We have devised an algorithm that models ridership patterns within Tacoma at the census tract level but is generalizable to any service area where appropriate data can be gathered. The algorithm is outlined in *Figure 1.*

Each rider is assigned an age and a trip purpose, based on transit rider characteristics compiled by the American Public Transportation Association (APTA) [1]. APTA recognizes 7 trip purposes: *medical/dental, commute, social, school, personal business and other*. The age and purpose of the trip inform where that rider will travel within Tacoma. One of the trip's endpoints is anchored in a census tract weighted according the population of the age group of the rider. The second endpoint in anchored in a census tract weighted according to the employment level of sectors related to the trip purpose. For example, the second tract of a *school* trip will be chosen according to the number of people employed in *Education* in the tract. If the trip is inbound, it will run from a random address in the first census tract to a random address in the second census tract. If the trip is outbound, it will run the converse route. All trips have a minimum driving time of at least 5 minutes.

Period	% Daily	% Hourly
AM Peak (6AM - 8:59AM)	29%	9.66%
Midday (9AM - 2:59PM)	28%	4.66%
PM Peak (3PM - 5:59PM)	29%	9.66%
Evening (6PM - 9PM)	14%	4.66%

Figure 2: *Daily trip distribution, derived from a transportation model run by PSRC [12].*

The *request time* of each trip is generated according to the daily trip distributions specified in *Figure 2.* The daily service window is broken down into four periods: *AM peak, midday, PM peak* and *evening.* Demand during peak periods is almost double that of non-peak periods. These daily breakdowns are derived from a transportation model run by the Puget Sound Regional Council [12].

Lastly, each trip is assigned a *call-in time* which is the time that the rider makes the request known to the agency. Static requests are effectively assigned a call-in time of 0:00. Dynamic requests are assigned a call-in time between the beginning of the service window and the *request time* of the trip.

4.2 Service Simulator

TacDRT implements an event-based simulation to model service, where each event is a trip request. A schematic of the design is presented in *Figure 3.*

Dispatch batches trip requests by *call-in time*, and releases those batches to the scheduler. In this way, the scheduler receives and schedules the static batch before service hours begin, while the dynamic requests are scheduled as they trickle in across the day. The assignment

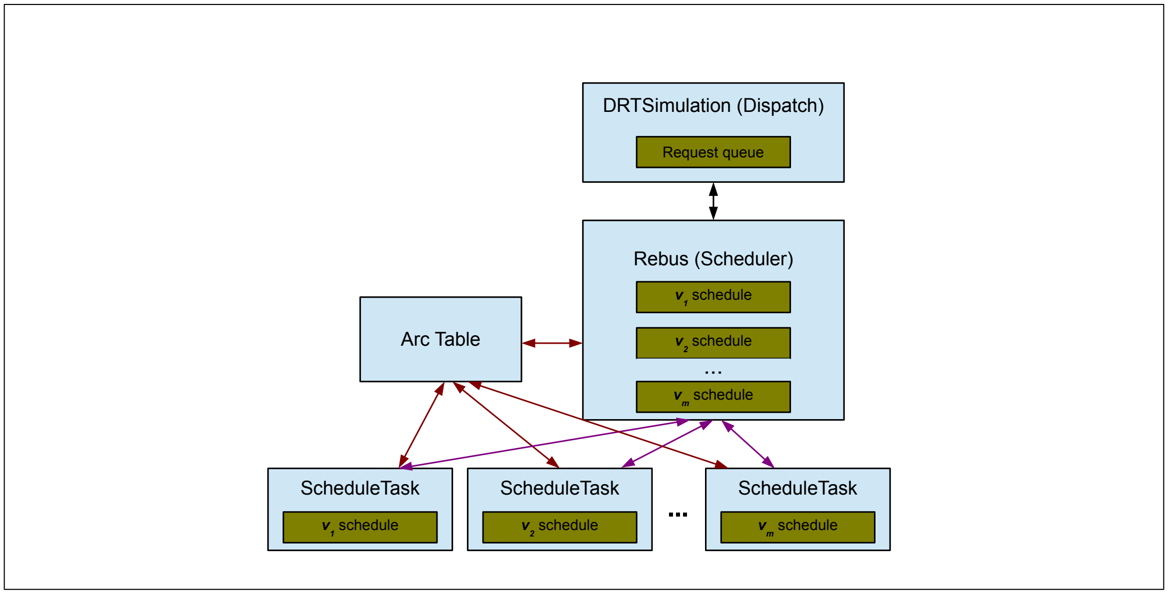

Figure 3: *Service simulator design*

of trips to vehicles in the scheduler is accomplished with a modified version of the REBUS algorithm developed by Madsen et al [9]. For details on the algorithm, we refer the reader to the publication. Here, it will suffice to discuss the modifications made for TacDRT.

REBUS queues trips according to a difficulty cost, and schedules them sequentially. To this end, three cost functions are summed to compute the trip's difficulty. We only use the *Maximal travel time* cost, which assigns a value based on the trip's expected duration. The others functions are not applicable for our purposes, as their value would be constant for each trip in our system.

REBUS consumes the request queue, and each trip is scheduled sequentially. The trip must be evaluated in every vehicle to determine the best insertion of that trip in the system. This is executed in parallel by worker threads (ScheduleTask), each of which is responsible for evaluating the trip in one vehicle schedule.

The quality of a particular trip insertion is determined by assigning the resulting schedule a heuristic value. REBUS proposes four heuristic functions, which are summed across every stop in the schedule. Preliminary tests of TacDRT with these insertion heuristic functions resulted in excessively high trip request rejection rates. This was potentially caused by the large difference in per-passenger resources between TacDRT and the system REBUS was developed and tested on (CFFS). To fully satisfy demand, each vehicle in the CFFS system must serve 12.5 people. TacDRT vehicles must serve roughly 234 people per day (this will be shown below). The greater flexibility of the CFFS system allows for the REBUS heuristics to weigh quality of service more heavily than possible with the limited resources of TacDRT. Recognizing the difficulties of fitting such a large quantity of trips into a vehicle schedule, TacDRT employs only the following function:

Let d be driving time between last job l and current job j

Let s be total number of jobs in the schedule

Let δ be a non-negative constant

Then the cost for a given job is computed as follows:

$$C(j) = \frac{\delta d}{s}$$

This function penalizes schedules with longer driving times between stops, with the intention that minimizing driving times between stops will allow more trips to fit into a schedule.

To find driving times between points, which is necessary for the above equation, the scheduler relies on an arc table. The arc table contains driving times between every pair of points that the scheduler might need. With 21,793 trips, each with 2 endpoints, the arc table has dimensions of 43,586 x 43,586. Each entry in the table contains a single byte of data, representing the driving time in minutes between a pair of points. To maximize thread safety and simulation speed, this table is precomputed and loaded into memory before the simulation begins.

After all the worker threads have finished evaluating a particular trip in their assigned vehicle, the scheduler examines the results. If at least one feasible insertion was found, the scheduler picks the insertion with the best heuristic cost and commits that trip to the vehicle. If no feasible insertions were found, the trip is rejected and will not be served.

To efficiently meet peak and off-peak demand, the TacDRT fleet consists of all-day and peak vehicles. All-day vehicles are in service for the entirety of the service window, while peak vehicles are only in service during peak periods (see *Figure 2*). We must also factor in slack time to account for any trips that a vehicle might have to drop off as it's going out of service (peak vehicles go out of service twice each day). Experimentation indicates that each all-day vehicle requires 1 hour of slack time and each peak vehicle requires 3 hours of slack time. Therefore, each all-day vehicle is in service for 16 hours and each peak vehicle is in service for 9 hours. Depending on the allocation of service hours between all-day and peak vehicles, each TacDRT vehicle must serve roughly 234 trips to fully satisfy demand.

5 Results

Results were obtained by running simulations on three trip datasets. A dataset includes information regarding each trip (as specified in *Section 4.1*) as well as the fully computed arc table, and requires three days to compute. With a given dataset, each simulation required roughly ten hours to complete. All computation was carried out on several Dell Optiplex 790s, each with 8GB of memory and 8 processors at 3.4GHz.

The best allocation of service hours between all-day and peak vehicles is not known a priori. Therefore, 6 simulation rounds were executed with different service hour allocations between the vehicle types. Most of the results discussed below are situated against these simulation rounds, where each round is measured by the percent of service hours allocated to all-day vehicles.

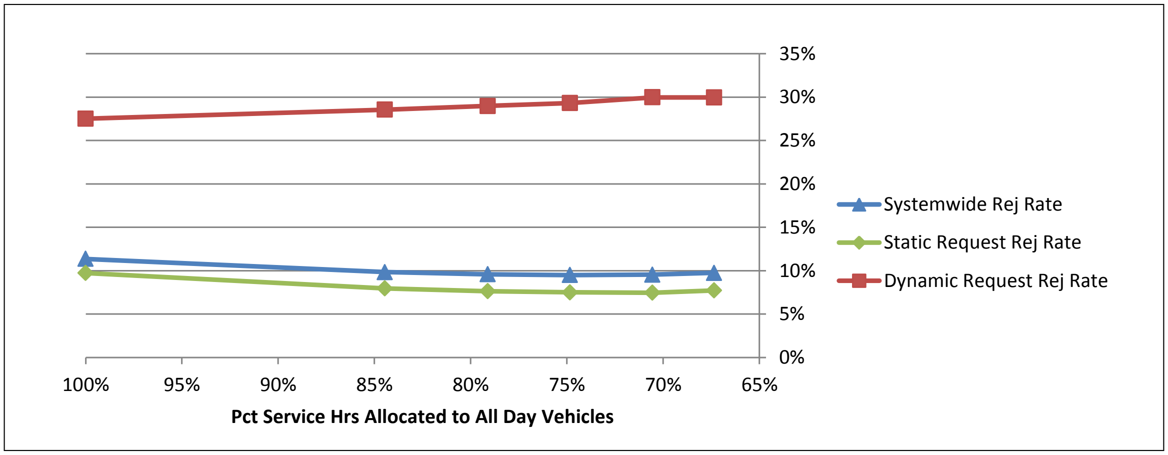

Figure 4: *Rejection rate by service hour allocation*

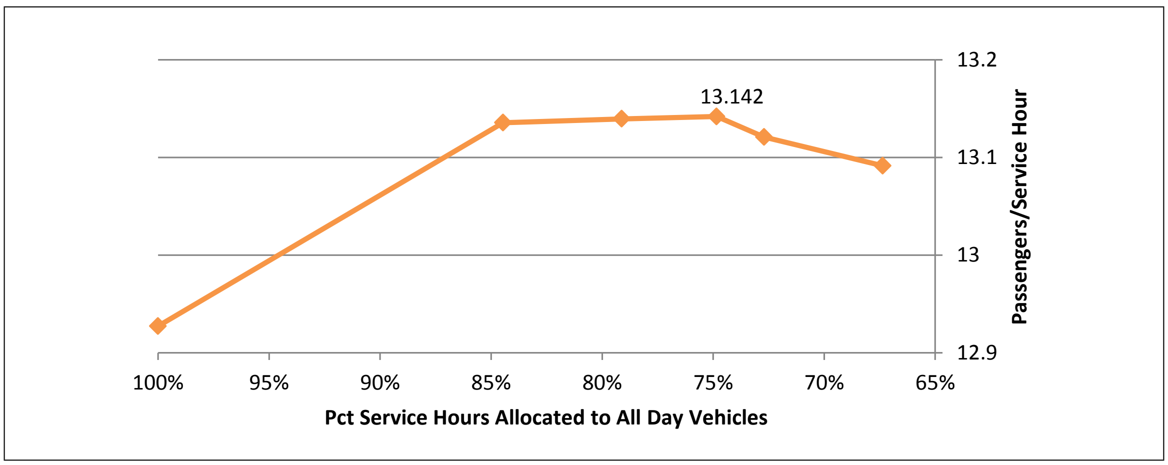

Figure 5: *System efficiency by service hour allocation, where efficiency is measured by passengers per service hour*

5.1 Rejection Rate and Efficiency

For TacDRT to be deemed feasible as an alternative to the fixed-route system, it must serve the vast majority of trip requests. The rejection rate across different allocations of service hours is shown in *Figure 4*. The lowest systemwide rejection rate that TacDRT achieved was 9.49%, when 74.8% of service hours were allocated to all-day vehicles.

The rejection rates also indicate that dynamic requests were harder to serve than static requests. More than 25% of dynamic requests were rejected across all service hour allocations, while the rejection rate of static trips stayed below 10%. Further, the static and dynamic rejection rates trended in opposite directions. As the static rejection rate decreased, the dynamic rate increased. That is, the increasing number of trips successfully scheduled in the static batch before service hours began led to less room in the schedules for the dynamic trips which are revealed later in the day. These findings confirm Fu and Xu's observation that dynamic requests are harder to serve than static requests [5].

System efficiency across different service hour allocations is shown in *Figure 5*. System

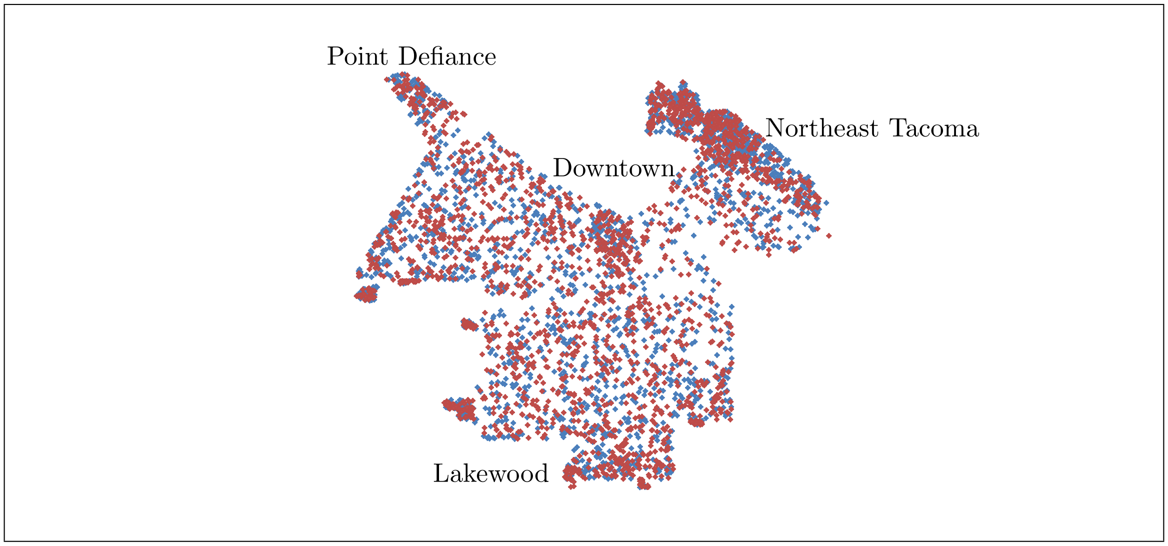

Figure 6: *Endpoints of all rejected trips*

efficiency is inversely proportional to rejection rate. As more passengers are served using the same number of service hours, rejection rates decrease while system efficiency increases. Therefore the service hour allocation that led to the lowest rejection rate also led to the highest efficiency of 13.14 passengers/service hour. In comparison, PT's fixed-route system averages 22.7 passengers/service hour [11]. However, the operational cost per service hour of TacDRT is less than that of PT fixed-route. So although PT fixed-route is 57% more efficient than TacDRT according to the passengers/service hour metric, it is only 10.7% less expensive than TacDRT. PT fixed-route spends \$5.03 on each passenger, while TacDRT spends \$5.57 [11].

5.2 Rejected Trips

It is worth examining the characteristics of rejected trips to determine if any policy changes might further reduce the rejection rate. We've already established that dynamic trips are rejected at a much higher rate than static trips.

The endpoints of all rejected trips are shown in *Figure 6*. In general, TacDRT had trouble serving the periphery of Tacoma. Northeast Tacoma contained the highest density of rejected endpoints. This is likely due to its isolation from the rest of the city. Any trip with either a destination or origin in Northeast Tacoma must pass through Tacoma harbor on SR 509, or around the harbor on Interstate 5. The lack of transit demand in and around the harbor limits the ability of TacDRT to effectively aggregate demand as its vehicles are passing through. Routes between downtown and Northeast Tacoma essentially constitute wasted time.

There were also high concentrations of rejections towards Lakewood at the southern end of the city and Point Defiance in the northwest corner of the city. Although these regions aren't isolated from the city like Northeast Tacoma, the nature of the periphery makes these regions more difficult to serve. Vehicles have less flexibility when they near the edge of the service area.

Downtown Tacoma also featured a higher concentration of rejected trips. Downtown has the highest density of residences and employment in the city, so the concentration of rejections is most likely due to the volume of trips with an origin or destination in the area.

5.3 New Vehicle on Rejection

The best allocation of service hours caused a 9.49% rejection rate. It's worth examining then how many additional resources TacDRT would require to serve every trip request. This can be achieved by adding a new vehicle to the fleet every time a trip is rejected, and then re-attempting to schedule the rejected trip. These new vehicles remain in the fleet, ready to serve other trips for the rest of the day.

The results of this modification are shown in *Figure 7*. Reducing the rejection rate to 0%, which means serving 2,046 more trips, required 537 extra service hours spread across 39 vehicles. This amounts to a rate of 3.81 passengers/service hour for the last 9.49% of trips, whereas the first 90.51% of trips were served at a rate of 13.14 passengers/service hour. These findings confirm Diana's observation that as the rejection rate of a DRT service approaches 0%, the remaining trips become increasingly expensive to serve [4].

Simulation	Rejection Rate	Service Hours
Standard	9.49%	1500.9
New Vehicle on Rejection	0%	2042

Figure 7: *A comparison of the standard simulation and the modified simulation which adds a new vehicle to the fleet every time a trip is rejected*

5.4 Quality of Service

Quality of service was measured with two metrics: average pickup deviation and average excess ride time.

Average pickup deviation represents the average difference between *service times* and *request times* across all served trips t.

$$APD = \sum_{t=1}^{n} \Big(ST_t - RT_t\Big)/n$$

For the simulation round with the lowest rejection rate, average pickup deviation was 21.6 minutes.

Average excess ride time represents, on average, the total time each trip t took from pickup to dropoff (total ride time), minus that trip's direct driving time. Direct driving time is the time required to drive directly from a trip's origin to a trip's destination.

$$AERT = \sum_{t=1}^{n} \Big(TRT_t - DDT_t\Big)/n$$

For the simulation round with the lowest rejection rate, this was 34.9 minutes.

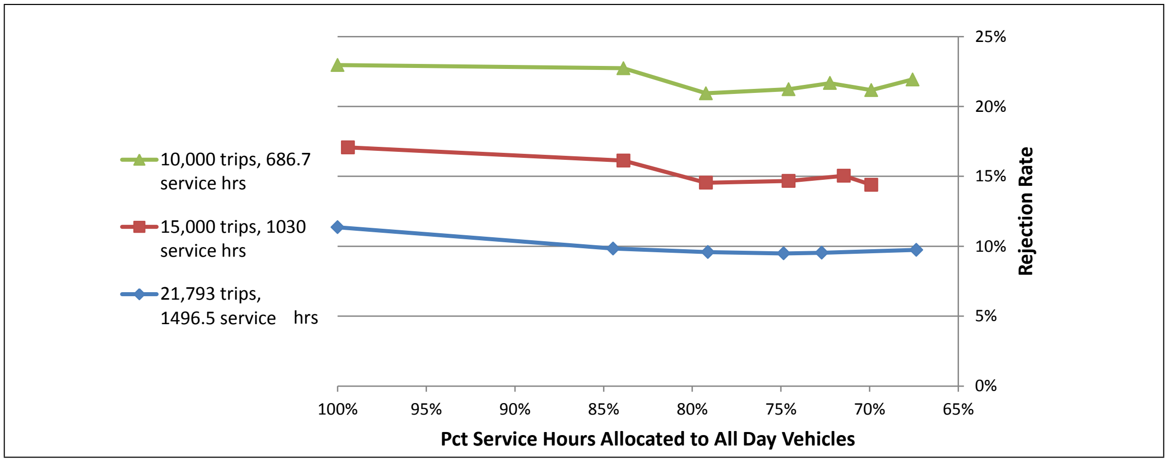

Figure 8: *Rejection rates of differently scaled systems*

5.5 System Scaling

To address our hypothesis that Tacoma's medium population density would lend itself well to DRT, we ran several simulations with systems of reduced scale. That is, transit demand and service hours were scaled down proportionally, while the geography and size of the service area remained constant. The results of these simulations are presented in *Figure 8*, where each line represents a differently scaled system.

The results indicate that the DRT system becomes less efficient as the density of demand decreases along with the service hours. The system with 10,000 trip requests and 686.7 service hours experienced a rejection above 20% across all simulation rounds. The rejection rate for the system with 15,000 trip requests and 1030 service hours remained above 14%. The full scale model with 21,793 trip requests, discussed in *Section 5.2*, had rejection rates below 12%.

6 Conclusion

This study set out to evaluate whether a citywide, public DRT system could serve the same volume of trips as fixed-route at a comparable cost. The results of the simulations suggest that such a system would not be a feasible replacement for fixed-route, largely due to the 9.49% rejection rate. Although determining an acceptable rejection threshold is arbitrary and would vary between DRT implementations, it is clear that 9.49% is too high. Public transit must be capable of serving those who are dependent, and TacDRT does not provide service with a high enough degree of reliability.

Although TacDRT was not capable of serving all riders, it was able to efficiently serve the vast majority of riders (90.51%) with a high quality of service. TacDRT spent $5.57 on each passenger that was served, while PT fixed route spends $5.03 per passenger [11]. This is an important finding, and calls into question the commonly held assumption that DRT is necessarily expensive to operate. The real issue with DRT then is not its cost in general, but its cost in serving the final minority of demand. In our case, the cost per passenger of the final 9.49% of demand was almost 3.5 times more expensive than that of the first 90.51%. These findings confirm those of Diana [4].

The riders that were served experienced a high quality of service. Pickup deviations averaged 21.6 minutes. In a fixed-route system, this time could easily be equivalent to walking to an origin bus stop, waiting for the bus, and walking from the destination stop. Average excess travel time, which was 34.9 minutes, also appears reasonable, considering that riders of DRT never need to transfer vehicles, nor wait for transfers.

Our results also indicate that the characteristics of the service area strongly affect the effectiveness of DRT. Northeast Tacoma experienced the highest concentration of rejected endpoints, largely due to the harbor separating the neighborhood from the rest of the city. This finding emphasizes the importance of a service area's geography and its distribution of transit demand, both of which are not addressed in the majority of DRT literature. For DRT to work efficiently, vehicles must be able to aggregate demand anywhere they travel within the service area. Vehicles passing through portions of the service area with minimal transit demand, such as the harbor, are unable to accomplish this.

Lastly, we hypothesized that Tacoma's medium population density would lend itself well to DRT. However, the results of scaling the TacDRT system indicate that DRT functions more efficiently as it scales up. As the density of trips requests increase with a proportionate increase in service hours, the system experiences a lower rejection rate. The full size simulation experienced rejection rates below 12% across all rounds, while the smallest system with 10,000 trips experienced a rejection rate above 20% across all rounds. If this trend continues as the system scales up past our full-size simulation, and there's no reason to believe it shouldn't, then perhaps DRT would work better in areas with denser transit demand.

The results from this study point to several policy changes that could be evaluated in future work.

- The higher rejection rate of dynamic trips suggests that DRT services should incentivize static trips. Perhaps this could be accomplished by offering a reduced fare for riders who request trips before service hours begin, or by loosening the hard constraints on dynamic trips.

- TacDRT was unable to efficiently serve the periphery of the service area. This could be potentially remedied by maintaining fixed-route feeder lines that would transport riders in and out of a more confined DRT service area. However, this would create a hybrid system that would lose some of the benefits of pure DRT, such as the introduction of transfers.

- DRT might be better able to aggregate demand if instead of offering door-to-door service, it offered service between any pair of pre-designated locations. Existing bus stops are a natural choice. This way, if trip endpoints are in a sufficiently close proximity, a vehicle could satisfy them all with one stop. Although removing the door-to-door aspect would reduce the service's appeal, walking times could still be limited with a decent spread of the pre-designated locations.

If the main problem with DRT is its failure to efficiently serve the final minority of demand, then perhaps large-scale, urban DRT would function better as a private service.

Such a system would not have the same obligation to serve all demand, and could complement existing modes of transit by providing a cheaper alternative to taxis and a more flexible alternative to fixed-route transit. Kutsuplus, a DRT service with these qualities, was recently launched in the Helsinki city center, and has received largely positive feedback [2]. It will be interesting to see how well the service develops, and if similar concepts can be applied to other cities.

7 Acknowledgments

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