IDEA

Innovations Deserving Exploratory Analysis Programs

Transit IDEA Program

Innovative Operating Strategies for Paratransit Services

Final Report for
Transit IDEA Project 73

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November 2013

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EXECUTIVE SUMMARY

Paratransit services are a very large industry providing transportation services for disabled and elderly customers across the country. Demand for these services has been drastically and continuously growing since the Americans with Disabilities Act (ADA, 1990) and there are no signs indicating a reversal of this trend. More than 30 million paratransit trips are requested yearly from the U.S. population. As these services are very costly and mandated by law, transit agencies work to deliver an adequate level of service in a cost effective manner and are always looking at ways to improve their performance and reduce their operating costs. However, the current operating policy adopted by most transit agencies is causing inefficiency. When an independently managed zoning operating strategy is adopted, cross-zonal customers need to be dropped off outside their pick-up zone; the service provider's vehicle will bring the customers at destination, but is not allowed to pick up customers outside its own service zone. This zoning strategy clearly causes to forbid some of the ridesharing and to increase the empty trip miles driven, eventually increasing the costs of these services considerably, as cross-zonal customers can be as high as 30% of the daily demand (Los Angeles County). Furthermore, customers having pick-up and drop-off locations in different zones are required to rely on two different providers for their round-trip, with potentially different booking rules, and, therefore, they might experience a reduced level of service.

To address the abovementioned issue, this project explores innovative strategies for operating ADA Paratransit services. Since an inefficiency of the paratransit services is due to the large amount of empty trip miles driven for serving cross-zonal customers, the goal of this research is to quantify the potential benefits of enabling service providers to serve both trips of cross-zonal customers in need of round trip rides. The main anticipated benefits due to the implementation of this innovative operating practice would be a significant reduction of the empty trip miles driven (and their associated costs) and an improvement of the level of service provided to customers. In this research project we explored whether allowing the innovative proposed strategy could benefit the overall operations and to what extent, by investigating both static and dynamic scheduling scenarios:

- Static: advance requests are generally scheduled the night before the day of operations. The new proposed strategies were implemented to test the difference of the static solutions.

- Dynamic: a portion of the demand may occur dynamically during the day of operations (according to the data currently in our possession, it is approximately 15-20% of the total demand).

This project had two stages. In the first stage, we specifically proposed three new policies allowing providers to serve a given zone to pick up out-of-zone passengers that are in need of their return trip to this zone. Among these new polices, two of them base the customer assignment decisions on the relative distance between pick-up and drop-off locations. The research team developed new algorithms that incorporate the proposed strategies into the scheduling and developed simulation models that replicate the paratransit operations. We completed the development of the static and dynamic model and validated them with simulated schematic cases.

In the second stage of the project, we evaluated the effects of implementing our proposed operation strategies using a simulation platform we developed and the real demand data we collected from Houston, Los Angeles and Boston. Simulations were first performed assuming Manhattan distances and then using real network distances calculated with ArcGIS geocoding and network

analyst software to carefully replicate real operations. Simulation results showed that, without sacrificing customers' level of service, our best policy can significantly reduce the inefficient empty trip miles by up to 23%. As a result, it can save up to 6.6% assigned vehicles, lower the total mileage by 9% and improving the passenger trips per revenue hour by 7.8%, indicating a significant saving in operation cost and improvement in productivity by adopting our policy while maintaining a reasonable level of service quality.

We expect that the implementation of our operation strategies will have these noticeable benefits:

- Maintain a zoning structure for easier overall management and better reliability (higher percentage of on-time performance), as already preferred by many agencies.
- Reduce the empty trip miles to lower operating costs.
- Improve the passenger trips per revenue hour, which is a productivity indicator frequently referred to by transit agencies.
- Allow cross-zonal customers to book both legs of their round-trip ride with the same provider, for an improved level of service.

Besides, the simulation model we developed can be served as a powerful and effective platform to test and evaluate different paratransit operation policies.

1. IDEA PRODUCT

The research team explored innovative strategies for operating ADA Paratransit services. Specifically, we allow paratransit providers serving a given zone to pick up out-of-zone passengers that are in need of their return trip to this zone.

Paratransit operations are large and complicated in nature, due to the combinatorial characteristic of their scheduling problem, which is intrinsically very hard to solve, and, therefore, approximate solution techniques are needed to find good applicable solutions. These are called heuristics algorithms. While multiple heuristic algorithms are already available in the literature for scheduling paratransit services, to our knowledge there are no algorithms performing the key novelty feature described in this research project. In order to evaluate and analyze the proposed innovative scheduling rules, a new simulation model for replicating the paratransit operations was developed in this project. Both static and dynamic simulation models were developed and implemented with the innovative scheduling rules. Both Manhattan distance-based simulation model (an assumption widely used by paratransit research community) and real network distance-based simulation model were developed. Thus the resulting product of this research also includes a powerful simulation package that can be used to test new policies which will be very helpful for paratransit practitioners. Experiments based on the actual data of Houston, Los Angeles and Boston paratransit services produced satisfactory results and proved the power of our proposed innovative policies.

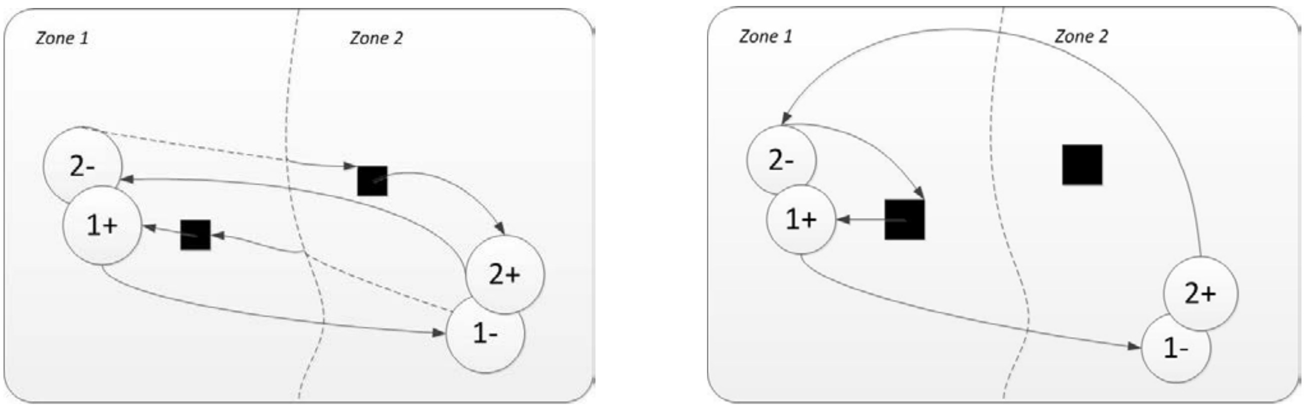
The implementation of this innovative operating practice potentially has several benefits for paratransit services, which are explained in detail in this report; the most important being: (1) the reduction of the amount of empty trip miles driven, as vehicles are now allowed to pick up some customers during their return trip from an out-of-zone drop-off; (2) the reduction of operation cost for paratransit services, as is indicated by total mileage and number of vehicles used; (3) the improvement of productivity, as is indicated by passenger trips per revenue hour, and (4) the improvement of the level of service, as out-of-zone customers may use the same service provider for booking their round-trip.

2. CONCEPT AND INNOVATION

Paratransit services are a very large industry providing transportation services for disabled and elderly customers across the entire nation. Demand for these services has been dramatically and steadily growing since the Americans with Disabilities Act (ADA, 1990) and there are no signs indicating a reversal of this trend. More than 30 million paratransit trips are requested yearly from the U.S. population. As these services are very costly and mandated by law, transit agencies work to deliver an adequate level of service in a cost effective manner and are always looking at ways to improve their performance and reduce their operating costs. Different operating practices and innovative ways to organize these services have been adopted to ease the management of these large daily operations. “Zoning” is one of them. The whole service area is divided in adjacent zones and operated by independent providers. Unfortunately, there is evidence that this organizational strategy also increases the operating costs, as the amount of empty trip miles is significantly increased.

This project explored innovative strategies in operating ADA Paratransit services. The key concept is modifying the rule currently identifying the service provider by the pick-up location of a customer request. We explored the potential benefits of allowing cross-zonal customers to use the same service provider for their round trip. In essence, providers are allowed to serve customers in need of the return trip whose drop-off location is within their service zone, even though their pick-up is not. We evaluated this proposed strategy for both the static and dynamic scenarios.

The innovative operating strategy for paratransit services that we proposed has some similarity with the independently managed zoning operating strategy, with a fundamental difference: allow providers serving a given zone to pick up out-of-zone passengers that are in need of their return trip to this zone. This means that cross-zonal passengers will use the provider operating in the zone of their pick-up location, and be dropped off out of their original zone (as already currently done). However, these customers may perform their return trip with the *same provider* and are not forced to use the other provider operating in their destination zone. The concept is better illustrated in the following **FIGURE 1**.



(a) **(b)**

FIGURE 1. The key difference between the operating strategies

A cross-zonal customer needs to be transported from its origin 1^+ to the destination 1^- (in another zone) and later needs a return trip from 2^+ (same location of 1^-) to 2^- (same location of 1^+). In Fig. 1(a), the independently managed zoning operating strategy would have the first vehicle (belonging to the left-side zone 1) pick the customer up at 1^+ and drop him/her off at 1^- (likely along other ridesharing customers, not shown here). The dash portion of the arrow going from 1^- to the depot in zone 1 has a high likelihood to correspond to an empty trip drive, as this vehicle is not allowed to pick up other customers in the right-side zone 2. Similarly, the return trip of the same customer would have a vehicle, belonging to zone 2, perform a similar trip, with the dash portion of the arrow going from 2^- to the depot in zone 2 representing the segment of the trip highly likely to be empty.

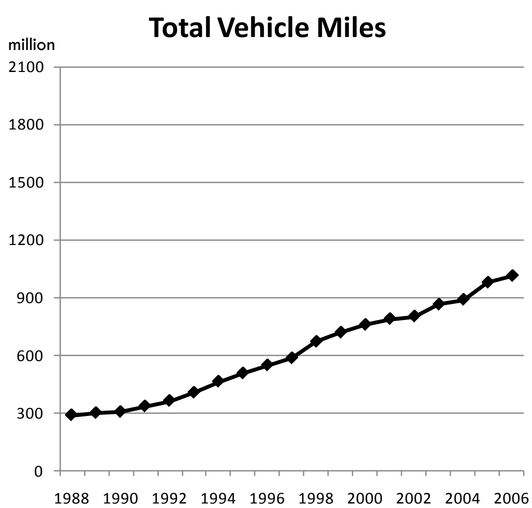
The new proposed strategy, shown in FIGURE 1(b), allows the first vehicle to pick up other customers returning to their original left-side zone 1 in the portion of the trip from 1^- to the depot in zone 1. Similarly, the represented customer could be served by a left-side zone vehicle for the return trip and the portion of the trip from the depot in zone 1 to 2^+ needs not to be empty as other cross-zonal customers from zone 1 can be dropped off in zone 2. In fact, most customers (not only the cross-zonal ones) are in need of daily round-trips, as opposed to one-way trips; therefore, modifying the rule affecting nearly all cross-zonal customers could potentially have a great impact on the performance measures.

3. INVESTIGATION

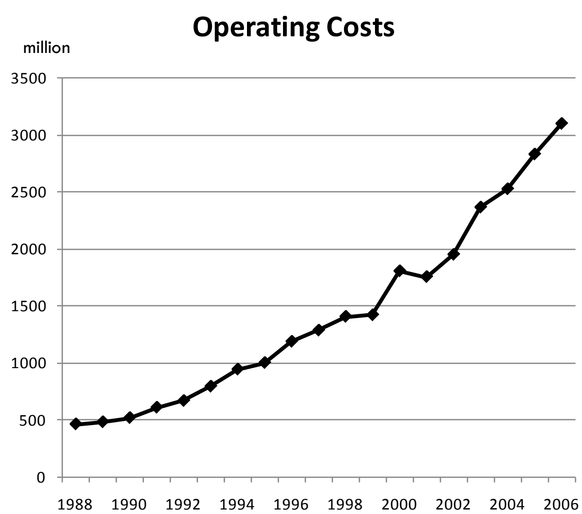
3.1 INTRODUCTION

The passage of the American with Disabilities Act (ADA) in 1990 essentially prohibited discrimination based on disability, revolutionizing the requirements and expectations for transit agencies. Section 223 of the Act requires that public entities which operate non-commuter fixed-route transportation services also provide complementary paratransit service for individuals unable to use the fixed route system, as their mental and/or physical disability prevents them “to get to or from the system or to board, ride, and disembark from the vehicles.”

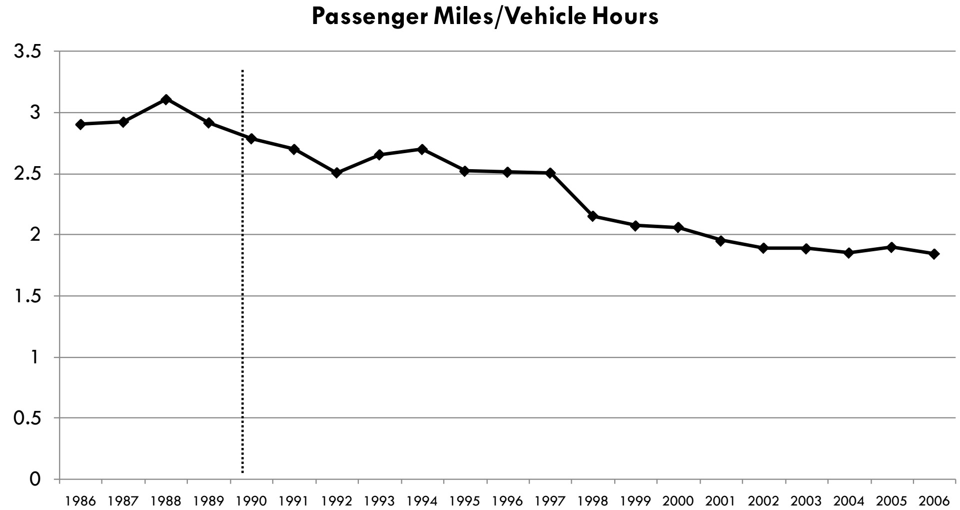
As a consequence, the demand for this type of service has experienced a tremendous growth in the last years (8%/yr), more than tripling their ridership in a 15-year period; see FIGURE 2(a). There are today over 5,500 providers of paratransit services for the elderly and persons with disability nationwide. Today in the city like Houston there are about 5,000 trip-requests per day and more than double for Los Angeles County. In parallel, the operating costs have raised even more (12%/yr), increasing by six times in the same 15-year time span; see FIGURE 2(b). Lastly, the ratio between passenger miles and vehicle hours, a major performance indicator commonly used for paratransit services, is showing a steady undesirable decrease, halving in 15 years; see FIGURE 2(c).



(a)



(b)



(c)

FIGURE 2. U.S. Paratransit services data

[Source: Public Transportation Fact Book (APTA, 2010)]

Depending on location, local regulations, size/shape of the service area and management's choice, these demand responsive services are operated according to different rules and policies. Maximum service time-windows (for pick-up/drop-off) may be of different durations (usually between 20-40 minutes) and a maximum ride time is generally guaranteed to riders (usually 1.5-2.5 times the hypothetical "taxi" direct ride time). With the intent to ensure an easier, smoother and less costly management of the entire operations and to ensure a more reliable service to customers (higher percentage of on-time service), a number of transit agencies in the U.S., primarily the ones operating within very large sprawled cities, have begun adopting decentralized control strategies as opposed to centralized ones. Instead of considering a whole large unique geographical region within which customers are allowed to request their transportation service, the entire service area is divided into "zones." There are a number of possible alternative "zoning" strategies currently adopted by transit agencies in the US. Some systems may refer cross-zonal passengers to taxis or carriers that mostly provide cross-zonal rides. Others may have hybrid operating policies. These operating choices can have a significant impact on the overall service performance (Quadrifoglio et al., 2008). But the most common zoning strategies are independently managed zoning and zoning with transfer.

Smaller and independent zones are easier and less costly to manage; they ensure better on-time performance to passengers and they generally trigger better job satisfaction among call centers and drivers, which are more likely to be assigned with a more limited and familiar driving range. However, this apparently simplifying strategy comes at a price in terms of operating costs and/or level of service. It is known in fact that demand responsive services, such as these, rely heavily on efficient "ridesharing" to reduce their cost. A major part of the operating costs of these services is represented by the "empty trip miles," miles driven by the vehicle with no customer on board.

When an independently managed zoning operating strategy is adopted, cross-zonal customers need to be dropped off outside their pick-up zone; the service provider's vehicle will bring the customers to their destination, but is not allowed to pick up customers outside its own service zone. This zoning strategy clearly causes to forbid some of the ridesharing and to increase the empty trip miles driven, eventually considerably increasing the costs of these services, as cross-zonal customers can be as high as 30% of the daily demand (Los Angeles County). Furthermore, customers having pick-up and drop-off locations in different zones are required to rely on two different providers for their round-trip, with potentially different booking rules, and, therefore, they might experience a reduced level of service.

In essence, the original centralized strategy (still adopted in cities like Houston, for example) might have several drawbacks, primarily linked to their potentially extended geographical size, but it would be the one minimizing operating costs and maximizing level of service. The authors proposed zoning solutions overcoming the drawbacks of the currently-adopted strategy and thus maintaining an operating efficiency and a level of service closer to the centralized strategy.

3.2 LITERATURE REVIEW

In this section, we present a review of the paratransit scheduling problem, more formally, the dial-a-ride problem (DARP) and related pick-up and delivery problem (PDP) and traveling salesman problem (TSP). Both exact and approximate algorithms are reviewed. Then the two common operating strategies of paratransit, namely the zoning strategy and decentralizing strategy are reviewed, along with a comparison between the performances of different strategies. Last, the popular paratransit scheduling packages that are widely used in the industry are reviewed and compared.

The pickup and delivery problem (PDP, see (Savelsbergh and Sol, 1995) for a complete review) can be modeled as a mixed integer program (MIP). The PDP has been extensively studied and many of the exact algorithms are based on integer programming techniques. Sexton and Bodin (1985) reported a formulation and an exact algorithm using Bender's decomposition. Cordeau (2006) introduced an MIP formulation of the multi-vehicle Dial-a-Ride Problem (DARP), which is a variant of PDP. He proposed a branch-and-cut algorithm using new valid inequalities for DARP. This multi-vehicle DARP MIP formulation is a good reference for the multi-vehicle MAST MIP formulation. Cordeau and Laporte (2007) gave a comprehensive review on DARP, in which different mathematical formulations and solution approaches were examined and compared. Lu and Dessouky (2004) formulated the multi-vehicle PDP as an MIP and developed an exact branch-and-cut algorithm using new valid inequalities to optimally solve multi-vehicle PDP of up to 5 vehicles and 17 customers without clusters and 5 vehicles and 25 customers with clusters within a reasonable time. Cortes et al. (2010) proposed an MIP formulation for the PDP with transfers. Ropke and Cordeau (2009) combined the techniques of row generation and column generation and proposed a branch-cut-and-price algorithm to solve PDP with time windows (PDPTW). In their algorithm, the lower bounds are computed by solving the linear relaxation of a set-partitioning problem through column generation, and the pricing subproblems are shortest path problems. Berbeglia et al. (2010) reviewed the most recent literature on dynamic PDPs and provided a general framework for dynamic one-to-one PDPs. Quadrifoglio et al. (2008) proposed an MIP formulation for the static scheduling problem of a single-vehicle MAST system and solved the problem by strengthening the formulation with logic cuts. Other exact algorithms include dynamic programming. Psaraftis (1980, 1983) used dynamic programming to solve the single-vehicle DARP and its variant with time windows. Both algorithms has a time complexity of $O(N^2 3^N)$ (N for customers), and can solve an instance of N up to 20 in a meaningful time. Very recently, Fortini et al. (2011) proposed a new heuristic for TSP based on computing compatible tours instead of TSP tours. They proved that the best compatible tour has a worst-case cost ratio of 5/3 that of the optimal TSP tour. A branch-and-cut algorithm was developed to compute the best compatible tour.

Since the optimization problem of PDP is known to be strongly NP-hard (Lenstra and Kan, 1981), researchers have been studying on heuristic approaches to solve PDP with large in- stances in a reasonable (polynomial) time, while not compromising the quality of solution too much. Along these approaches, insertion heuristics are the most popular because they can provide good, meaningful results in very fast running time, thus are capable of handling problems with large instances. Another reason that justifies insertion heuristics in practice is that they can be easily implemented in dynamic environments (Campbell and Savelsbergh, 2004). Some other efforts in insertion heuristics include Lu and Dessouky (2006). A major disadvantage of the insertion heuristics is the difficulty to bound its performance. Another disadvantage is its myopic and greedy approach for current optimum at each time step without having an overview of all the requests. The insertion heuristic controlled by "usable slack time" resolved this issue efficiently (Quadrifoglio et al., 2007). To evaluate the performance of the proposed heuristics, worst-case analysis can be found for PDP and its fundamental or related problems such as traveling salesman problem (TSP), vehicle routing problem (VRP). Savelsbergh and Sol (1995) gave a complete review on PDP and discussed the several variants of the problem in terms of different optimization objectives, time-constraints, and fleet sizes. Both exact algorithms based on mathematical modeling and heuristics were reviewed. For traveling sales man problem (TSP), Christofides (1976) proposed a new heuristic of ratio 3/2 for metric-TSP based on constructing minimum spanning tree and Euler tour. Rosenkrantz et al. (1977) analyzed the approximation ratio of several heuristics, including the cheapest insertion heuristic for TSP. Archetti et al. (2003) studied the re-optimization version of TSP which arises when a new node is added to an optimal solution or when a node is removed. They proved that although the cheapest insertion heuristic has a tight worst-case ratio of 2, the ratio decreases to 3/2 when applied to the re-optimization TSP problem. So far the best result on TSP is Arora's polynomial time approximation scheme for Euclidean TSP (Arora, 1998).

Some other research on paratransit that can be found in the literature includes the study on the Mobility Allowance Shuttle Transit (MAST) system. The design and operations of the MAST system has attracted considerable attention in recent years. Quadrifoglio et al. (2006) evaluated the performance of MAST systems in terms of serving capability and longitudinal velocity. Their results indicate that some basic parameters are helpful in designing the MAST system such as slack time and headway. Quadrifoglio et al. later developed an insertion heuristic scheduling algorithm to address a large amount of demand dynamically (2007). Quadrifoglio and Dessouky (2008) carried out a set of simulations to show the sensitivity analysis for the performance of the insertion heuristic algorithm and the capability of the system over different shapes of service area. In 2008, Zhao and Dessouky (2008) studied the optimal service capacity for the MAST system. Although these studies investigated the design and operations of the MAST system from various aspects, they are all for the single-vehicle MAST system.

Categorized by the applicable tools to evaluate the performance of practical management strategies, the analytic analysis and simulation models are two major methods. The approximate analytical model of a demand responsive transportation system was first developed by Daganzo (1978). This study focused on the real-time algorithms for dial-a-ride systems. Fu (2003) provided an analytic model to predict the fleet size and quality-of-service measurements. Diana et al. (2006) proposed analytic equations to calculate the fleet size for a square service area. Li and Quadrifoglio (2009) developed an analytic model to determine the optimal service zone for feeder transit service. The analytic model is easier for parametric analysis of the system; however, it is hard to build a close form expression.

Compared to the analytical model, simulation methods have been applied to stochastic event analysis and the evaluation of performance measurements on dial-a-ride systems. Wilson et al. (1970) developed a computer aided routing system (CARS) which built the relationships between performance parameters and different scheduling algorithms. Xiang et al. (2008) adopted a simulation to evaluate the influence of different stochastic factors. In order to evaluate the operational improvement from the application of automatic vehicle location technology, Fu (2002) applied a simulation model to analyze. Shinoda et al. (2004) developed a simulation method to compare the performance of dial-a-ride systems and fixed route bus systems. Quadrifoglio et al. (2008) considered the impact of specific operating practices of zoning strategy and time window setting that is currently used by demand responsive transit providers.

In comparison, the performance evaluation of practical operation strategies such as zoning strategy on DARP has received meager attention. McKnight and Pagano (1984) explored the service quality of DARP by investigating 42 service providers in the United States. It was found that the quality of special transportation services for elderly and disable persons tends to increase as the ridership of the provider increases. Wilson and Hendrickson (1980) summarized the earlier models that predicted the performance of flexible routed transportation system. Paquette et al. (2009) concluded that the further study is needed for better understanding the trade-offs among costs, operational policies and quality in dial-a-ride systems.

The existing research dealing with paratransit operating policies is still limited, and the trade-offs decision analysis between centralized and decentralized strategies has not been determined. In the paratransit services, the transfer of passengers will always require more than one vehicle to fulfill a trip; therefore, the spatial and temporal synchronization constraints will, by necessity, be imposed on more than one vehicle. A schedule delay in one vehicle route may necessitate a change in all other routes. Therefore, it is computationally difficult even when simply trying to develop a heuristic algorithm. Shang and Cuff (1996) provide a concurrent heuristic approach to solve the PDP with transfer issue, using as an example a Health Maintenance Organization. They show that their proposed heuristic performs better than the HMO's scheduling heuristic, according to the overall lower number of delays, total travel hours, and total number of vehicles. However, this paper considered neither excess passenger travel times nor vehicle capacity constraints. Cortes et al. (2010) studied a PDP with transfers through the process of Mixed Integer Programming (MIP). They found that the transfers permitted a higher level of efficiency, over the total vehicle travel time. Due to the complexity of the problem, this solution can only handle very small instances, which are maximized at six customers. They suggested further developments of the transfer application on the strategic design and planning of paratransit system. Unlike DARP, PDP does not have travel times constraints to reduce customer dissatisfaction.

In comparison, the performance evaluation of practical operation strategies such as decentralized strategy on DARP has received meager attention. McKnight and Pagano (1984) explored the service quality of DARP by investigating 42 service providers in the United States. It was found that the quality of special transportation services for elderly and disabled persons tends to increase as the ridership of the provider increases. Wilson and Hendrickson (1980) summarized the earlier models that predicted the performance of flexible routed transportation system. Paquette et al. (2009) concluded that further study is needed for better understanding the trade-offs among costs and quality of different operational policies in dial-a-ride systems. Quadrifoglio et al. (2008) found the operating choices of a decentralized strategy to have a significant impact on the performance of demand responsive transit services. Utilizing paratransit data in Houston, Shen and Quadrifoglio (2010) showed that adopting a decentralized strategy increases the total vehicles used and empty backhaul miles driven against the centralized strategy.

Coordination of paratransit services increases not only efficiency and productivity but mobility. From the evaluation of Burkhardt (2004), around $700 million per year to transportation providers in the United States could be generated after implementing successful coordination. Consolidation of inter-zonal transportation will likely reduce trip costs by higher ridesharing rate and lower empty return miles (Cook et al., 2003). Malucelli et al. (1999) presented a flexible collective transportation system. They suggested a future study should deal with allowing the passenger to transfer from one vehicle to another. Häll et al. (2009) introduced the integrated DARP, where some part of journey may be carried out by a fixed route service. Aldaihani and Dessouky (2003) proposed a system that integrates fixed routes within a pickup and delivery problem (PDP). An integer programming formulation of cooperative PDP with time windows was analyzed by Lin (2008). It concluded that the cooperative strategy may achieve savings in both total cost and vehicles used, under the assumptions of all delivery locations are identical, the transfer is only allowed at the last pickup location of the returning vehicle, and the vehicle capacity is unlimited.

The size of the service area is one of the key factors that affect the productivity of Demand Responsive Transit (DRT). In general, the larger the service area, the longer the trip length, and thus DRT will not always be able to consistently serve a given number of passengers in a specified amount of time. The impact on the productivity of the different area sizes was first studied by Wilson et al. (1970). They demonstrated that the number of vehicles used is proportional to the size of the service area. Chira-Chavala and Venter (1997) adopt the data provided by the Outreach Paratransit Service in Santa Clara County, California, and observe that longer trip lengths contribute to an increase in empty trip miles in an expanding service area.

In addition, a large area usually comes with more dispersed trips. Large service areas with dispersed trip patterns, which translate to a lower demand density, make it difficult to achieve the most beneficial of effects of ride-sharing. On average, larger service areas mean more dispersed origin and destination points than those enjoyed by more compact service areas. In low-density areas, DRT systems have a lower productivity level than those systems that function in a municipal area (Ellis and McCollom, 2009).

Quadrifoglio et al. (2008) performed a simulation study to test the productivity of zoning without transfer, comparing the performance of that strategy with a centralized, no-zoning case based on data obtained from Los Angeles. To retain the productivity by focusing on shorter trips within a denser area, some larger systems have outsourced operations to more than one contractor, with each contractor responsible for the service zone to which their vehicles have been assigned. This service design is called a zonal structure or zoning approach. Adjacent zones would have no overlapping or have shared buffer areas. The zoning approach is attractive not only because it creates more manageable pieces of work, but more importantly because it establishes an ongoing spirit of competition throughout the contract term (Lave and Mathias, 2000). Zonal demand responsive service is also used for dispatching, as well as for fare determination purposes *(*Burkhardt, 1995*)*.

We reviewed the current intelligent transportation system (ITS) techniques that can help with paratransit scheduling. With the rapidly growing demand of paratransit services and the expansion of service area, the routing and scheduling task is much more complicated so that the computer-aided tools are required to help manage both productivity and service quality. Paratransit operation software now has integrated customer reservation, vehicle scheduling and dispatching through real-time data communication and automatic vehicle location (AVL) techniques. The "Real-time" optimization is now applicable as new trip requests or cancellations are registered within minutes.

The following table lists some of the available software. For the scheduling algorithm, almost all of the software emphasizes the "Real-time" creation of the scheduling to ensure the serving of trips' requests.

TABLE 1. Current Paratransit Scheduling Packages

Product	Vendor
PASS	Trapeze
GIRO/ACCES	GIRO
RouteMatch TS/PM	RouteMatch
ADEPT	StrataGen
Touch Screen MDT	Ecolane

Trip Master	CTS Software

GIRO/ACCES is a scheduling package by GIRO Inc, a Canada-based company. Its most recent version is GIRO/ACCES 2010. GIRO/ACCES emphasize the immediate scheduling and confirmation while the customer is on the phone.. GIRO/ACCES features immediate scheduling, continuous optimization (which deals with taxi overbooking that is passed over to paratransit authority vehicles), and modal choice. It is also compatible with additional operational and contractual constraints, customers' specific needs, and marginal cost of adding new trip.

Routematch also features a multi-modal transit dispatch system. The RouteMatch software provides what-if planning tools to analyze the results and statistics associated with the planned schedule. It can handle both the operations of fixed-route transit and demand-responsive transit. Besides, it provides an extra function that helps transit agencies to make decisions on when and where to utilize the existing fixed routes for paratransit services. In other words, it allows deviated fixed route scheduling, which is the feature of the MAST system.

ADEPT is a batch-scheduling engine produced by StrataGen that specializes in managing the operations of paratransit and demand-responsive transit. ADEPT features a full service spectrum that allows managing everything from customer registration and trip-scheduling to automated dispatch. The ADEPT has the flexibility to construct specific scheduling strategies based on specific conditions and requirements.

PASS is a scheduling and dispatching application developed by Trapeze to support the operations and management of demand response transit services. It covers the whole range of DRT management including client registration, trip booking, real-time scheduling and dispatching. Besides the typical function that such a package can provide, PASS provides a robust schedule by monitoring daily operations closely and notifying operators of situations that affect service in real-time.

3.3 STATIC MODEL DEVELOPMENT

In this section, we introduce the algorithms that are used to distribute the static customers into different zones according to corresponding policies that we propose. Note that the algorithm in this section also serves as the fundamental for the dynamic model that is detailed in the following section. The insertion algorithm that is used to route and schedule the customers is also described.

3.3.1 Network Assumptions

The Manhattan (rectilinear) distance is used to calculate the travel distance between different locations. For example, $A(x_1, y_1)$ and $B(x_2, y_2)$ are two points that are either the pick-up or drop-off location respectively. The travel distance between A and B is calculated as $|x_1 – x_2| + |y_1 – y_2|$. The Manhattan distance is commonly used in urban road networks which follow a grid pattern. This estimated travel distance was verified to be reasonably close to the actual travel distance in the literature (e.g., Quadrifoglio et al, 2008). We also assume no traffic jams in the system, as a result the travel time between two points is only a matter of travel distance and vehicle speed.

3.3.2 Customer Generation

To evaluate the effects of our customer distributing policies, we generate round trips (the first trip and the back trip) for each customer. Each trip includes the following information: pick-up and drop-off locations, requested pick-up time, number of passengers, and the need of a wheelchair accessible vehicle. The pick-up and drop-off coordinates are independently generated from the service area according to the pre-specified pick-up and drop-off distribution.

3.3.3 Parameters

The following system parameters are used in the preliminary numerical tests:

- Vehicle travel speed: 25 miles/hour
- Service time of each customer: 1 minute
- Time-windows: 20 minutes minus and plus the requested time
- Maximum ride time factor: 2.5 (the ratio of actual ride time divided by direct ride time, as mandated by law)
- Unlimited number of vehicles are available
- Vans capacity: 4 wheelchairs or 10 ambulatory persons
- Cabs capacity: 1 wheelchair or 4 ambulatory persons

3.3.4 Innovative scheduling policies

We propose three new different policies regarding how we distribute the inter-zonal customers into different operation zones, as described below along with the old policy that is currently used by operating agencies. The logic behind redistributing the trips of a customer aims to construct more efficient routes by reducing inefficient “empty-trip” mileage as much as possible.

1. Old policy: Each trip is assigned to the zone according to its pick-up location. Take an inter-zonal customer as an example, the first trip is operated by zone A, the return trip is operated by zone B, as is shown in FIGURE 3.

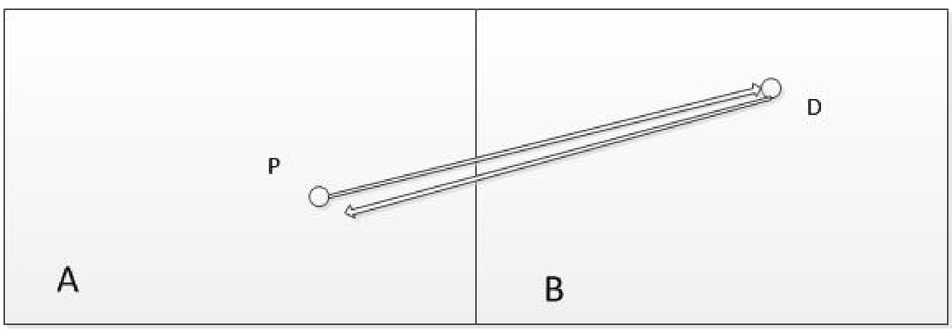


FIGURE 3. Old policy and new policy

2. New policy: both trips are operated by the zone that the customer is generated. In the case of Fig. 3, the operator is zone A for both trips under new policy.
3. Alternative policy 1: the two alternative policies distribute the customers according to their proximity to the border of the two zones, assigning a customer to one of the two zones to which he is more naturally belongs. As is shown in FIGURE 4, if the distance between the pick-up location and the border (L1) is less than the distance between the drop-off location and the border (L2), then the back trip is assigned to zone B, which is intuitively the more efficient carrier of the customer compared to zone A. The operator of the first trip remains zone A, because the pick-up location is generated in zone A.

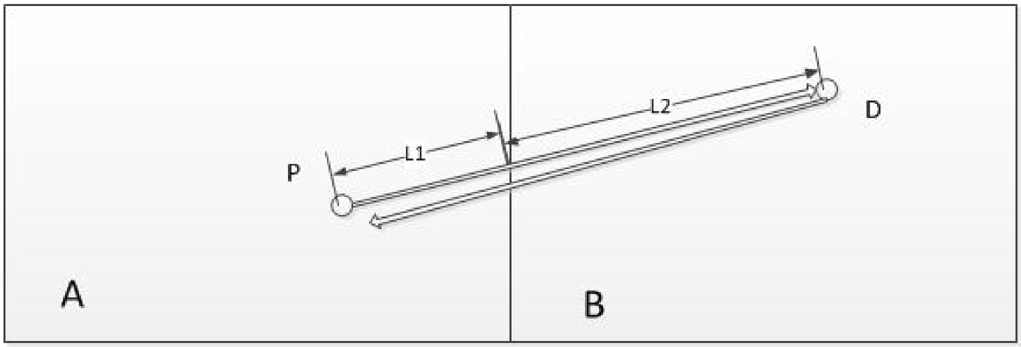


FIGURE 4. Alternative policies

4. Alternative policy 2: This policy is the most flexible one among all the policies. Using a similar manner of Alternative policy 1, we assign both the first trip and the return trip to the zone to which the customer is more naturally belongs. In the case of FIGURE 4, both trips are assigned to zone B.

<u>Pseudo code</u>
The algorithms of distributing trips and insertion is summarized as follows:

Step 0.
- (a) Generate customers according to the pre-specified distribution.
- (b) Distribute the trips of each customer to different zones according to different policies.

Step 1. For each of the zones, set i=0. (i represents the number of vehicles that are used)
While unassigned trips not equal to 0 do:
- (a) For each depot, generate one empty route from it.
- (b) Choose first trip in the unassigned trip list.
- (c) Check all the possible insertions for feasibility
- (d) If more than one feasible insertions are found, select the one the minimizes the additional travel distance for the existing route
- (e) Update the schedule of the inserted route and delete the trip that is just inserted from the unassigned trip list.
- (f) If feasible insertion cannot be found, set i=i+1 then go to Step 1(a); else stop.

3.4 DYNAMIC MODEL DEVELOPMENT

The simulation model that is able to handle the dynamic demand is introduced in this section. The dynamic feature allows customers to book the service during the service time. Comparing to its static counterpart who requires booking before the service date, it gives more freedom to customers while, at the same time, bringing scheduling challenge to transit agencies.

3.4.1 Customer Generation

In the dynamic paratransit model, customers are generally divided into two categories:
- (a) Static demand - passengers who book the seats before the service starts, typically one day before the service date.
- (b) Dynamic demand - passengers who book the seats on the day after the service starts.

Transit agencies usually require certain amount of advanced time ahead of the requested pickup. In our experiments we set this parameter to 30 minutes. For the whole time horizon of the paratransit service, dynamic demand occurs with a predefined probability. Note that the algorithm runs the static insertion first to get a basic schedule and then deal with the dynamic requests. This would require rescheduling of the fleets.

3.4.2 Parameters

The following system parameters are used in the numerical experiments for dynamic model, in addition to the ones described for the static model:

- Service time period: 24 hours. The paratransit service responds to customers' demand 24 hours a day.
- Minimum advanced request time: 30 minutes. Customers are required to book a trip at least 30 minutes before the pickup time.
- Dynamic demand generation probability: 0.10-0.20. This means 10%-20% of the total requests are dynamic.

3.4.3 Algorithm Description

Pseudo code

The modified algorithm that incorporates dynamic insertion is summarized as follows. It involves two stages of insertion - static and dynamic:

Step 0.
- (a) Generate customers according to the pre-specified distribution.
- (b) Distribute the trips of each customer to different zones according to different policies.

Step 1. For each of the zones, set i=0. (i represents the number of vehicles that are used)
While unassigned trips not equal to 0 do:
- (a) For each depot, generate one empty route from it.
- (b) Choose first trip in the unassigned trip list.
- (c) Check all the possible insertions for feasibility
- (d) If more than one feasible insertions are found, select the one that minimizes the additional travel distance for the existing route
- (e) Update the schedule of the inserted route and delete the trip that is just inserted from the unassigned trip list.

Step 2. If feasible insertion cannot be found, set i=i+1 then go to Step 1(a).

Step 3. Record the basic schedule after inserted all the static requests.

Step 4. While within the service time period, do
- (a) Generate dynamic customers with predefined probability.
- (b) Distribute the trips of each dynamic customer to different zones according to different policies.

Step 5. For each of the zones, do: (j represents the No. of existing routes)
While dynamic trips are not serviced do:
- (a) Choose first trip in the unassigned trip list.
- (b) Check all the possible insertions in each of the existing (or newly generated) routes for feasibility
- (c) Insert the trip into the first available route.
- (d) Update the schedule of the inserted route and delete the trip that is just inserted from the unassigned trip list.

Step 6. If none of the existing routes can accommodate the dynamic trip, then generate one empty route, let j represent the No. of existing routes, then set j=j+1 and go to Step 5(a).

3.5 PRELIMINARY EXPERIMENTS

3.5.1 Policies Comparison on Static Model

We evaluated the effects of our policies through simulation in this section. A rectangular service area is used in these preliminary experiments. We divided the service area into two zones from which the customers were generated. Uniform distribution is used for the pick-up and drop-off locations. Each zone has two depots in the center, one for vans and the other for cabs. The dimensions of the area are shown in FIGURE 5. The whole area is 42 mile × 26 mile = 1092 mile^2, which is approximately half the size of the Houston paratransit operation area that we'll be using in the real-data experiments.

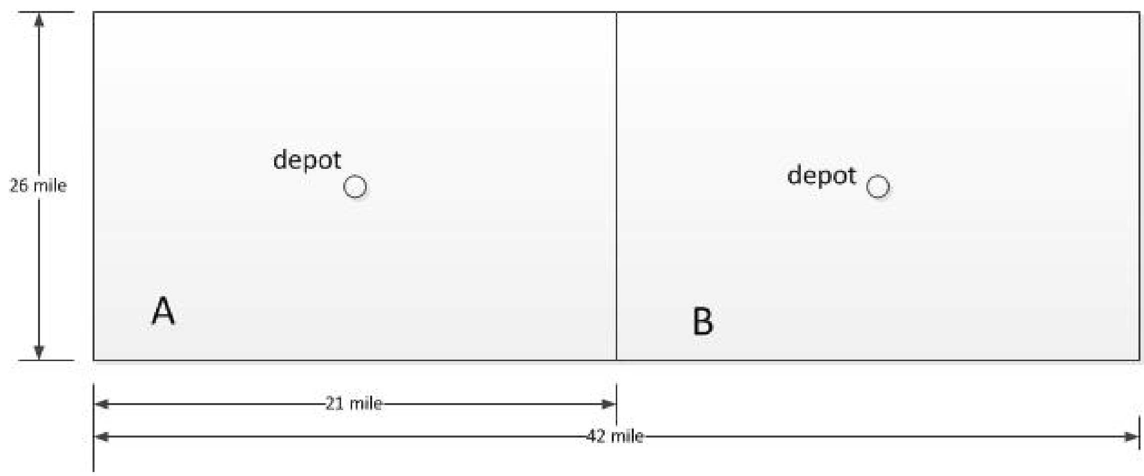


FIGURE 5 Illustration of the rectangular service area

We investigated the performance of policies from the perspectives of cost/productivity and service quality. In terms of cost/productivity, the number of vehicles and the total mileage are the most straightforward indicator when comparing the efficiency of different policies. We further divided the total travel mileage of each vehicle into two parts, namely the travel miles with no passenger on board from first pick up to last drop-off ("empty trip miles"), and travel miles with passengers on board. Since it's possible that vehicles arrive at the pick-up locations earlier than the requested pick-up time, we define the vehicle waiting time at a pick-up location as "Idle time".

With respect to service quality, customers' waiting time and ride time are two of the major concerns. Waiting time is defined as the time difference between requested pick-up time and actual pick-up time. Note that we have a mandatory constraint that the actual ride time cannot exceed K=2.5 times of direct ride time, which is required by law. (K=2.5 is adopted in Houston)

The performance of alternative customer assigning policies is compared through a customer demand level=200 customers/day. We run 5 simulation replications, as is shown in TABLE 2. To evaluate the sensitivity of our results on the inter-zonal travel ratio, we run experiments based on two different inter-zonal ratios. TABLE 2, FIGURE 6, and FIGURE 7 show the results of inter-zonal ratio=50%, which means half of the customers' pick-up and drop-off locations are in different zones. TABLE 3, FIGURE 8, and FIGURE 9 show the results of inter-zonal ratio=100%.

TABLE 2. Performance of Policies – Interzonal Ratio=50%

		Total vehicles				Total customers
Policy	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time

Old policy	39.4	4166.9	7966	12132.9	2743.8	4955.2
New policy	39	3137.8	8211.4	11349.2	2801.2	5000.8
Alternative-1	37.2	3399.8	8043.4	11443.2	2652.4	5053.4
Alternative-2	36.6	3112.6	7970	11082.6	2829.8	4972

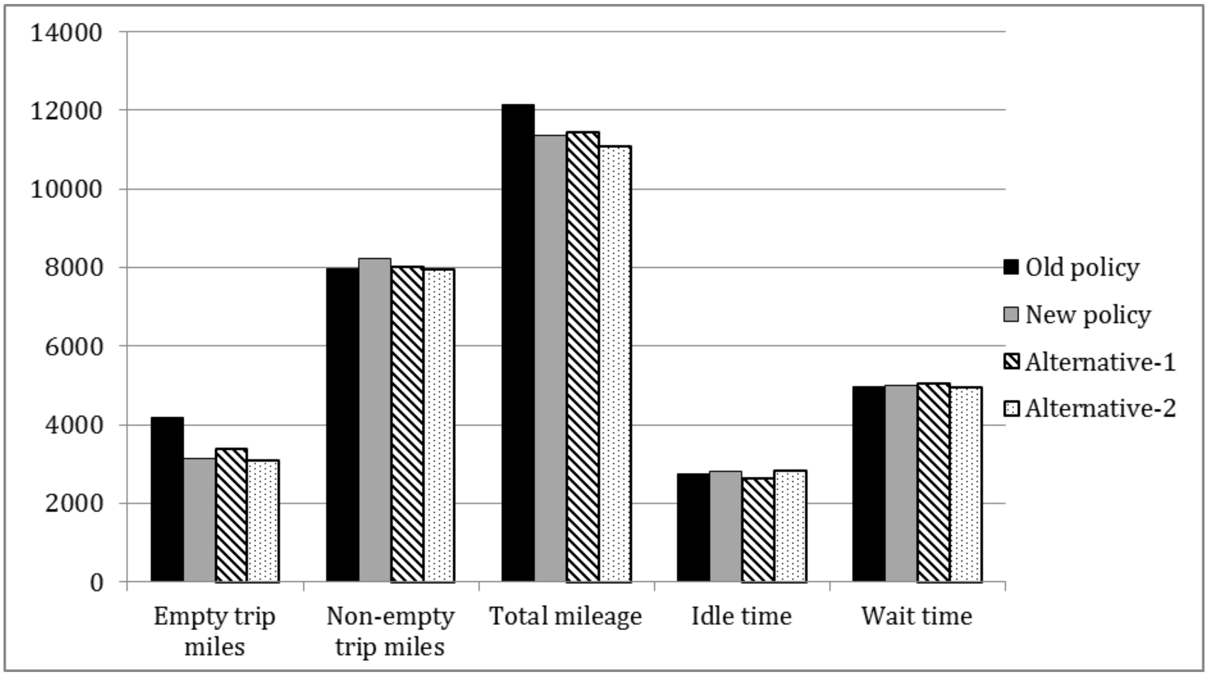


FIGURE 6. Performance comparison - interzonal ratio=50%

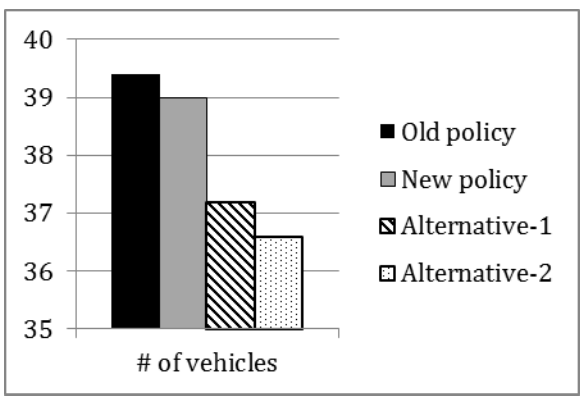


FIGURE 7. Number of vehicles - interzonal ratio=50%

TABLE 3. Performance of Policies – Interzonal Ratio=100%

		Total vehicles				Total customers
Policy	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time
Old policy	42.8	4975.4	8840.5	13815.8	2704.8	4896.2
New policy	39	2906.7	9437.0	12343.7	2839.2	5016
Alternative-1	40.8	3583.7	9150.6	12734.3	2622.2	5025
Alternative-2	37.8	2967.9	9121.5	12089.4	2789.2	5033.8

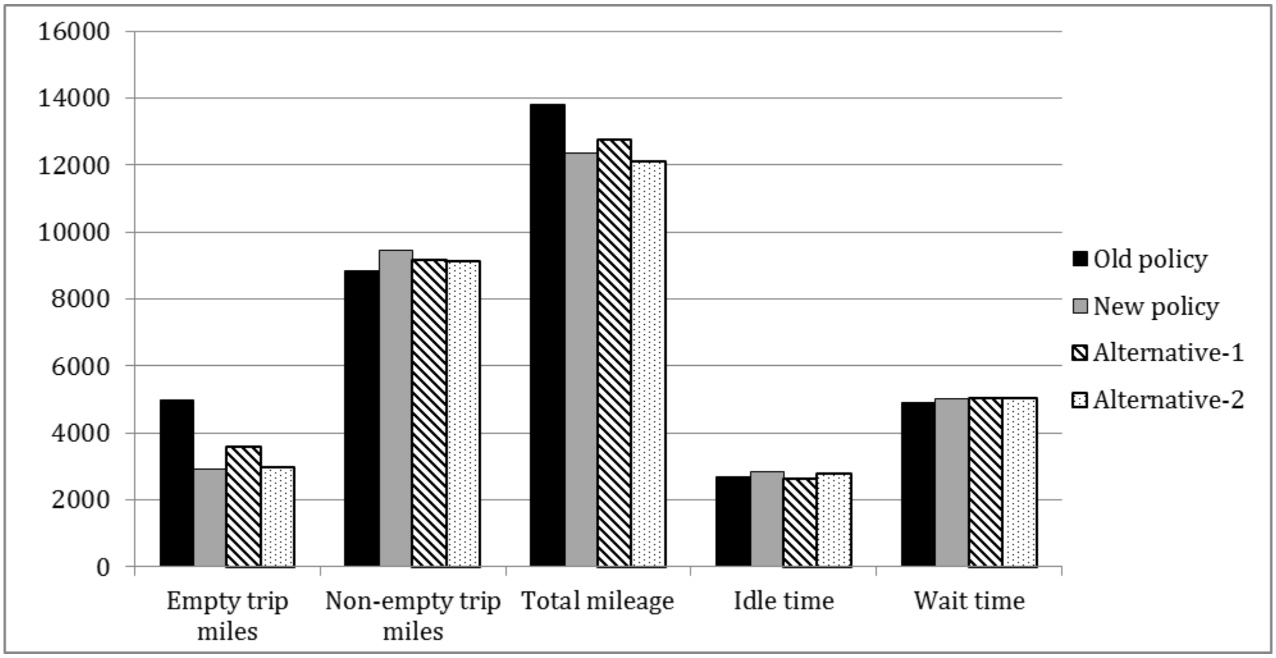


FIGURE 8. Performance comparison - interzonal ratio=100%

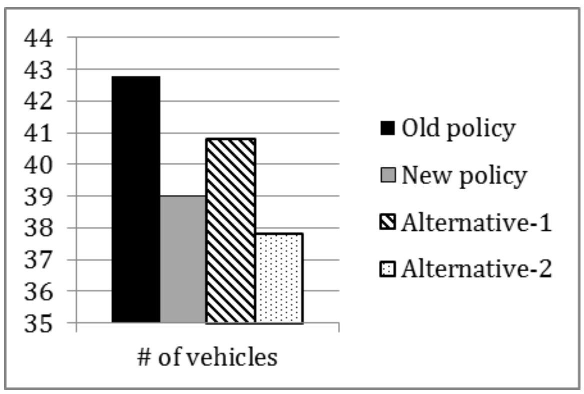


FIGURE 9. Number of vehicles - interzonal ratio=100%

Comparing the four different policies, Alternative-2 has the best performance in terms of number of vehicles used, total mileage, and empty trip miles. In the case of inter-zonal ratio=50%, Alternative-2 uses 8% less vehicles and travels 9% less mileage compared to Old policy. In the case of inter-zonal ratio=100%, Alternative-2 uses 12% less vehicles and travels 12% less mileage compared to Old policy. This implies a significant cost reduction when implementing the new policy we proposed. Taking a careful look at the results, it is found that the reduction of total mileage is due to the reduction of empty trip miles. There is a significant 25% drop in empty trip miles when applying Alternative-2 in the case of interzonal ratio=50%. The drop is even higher as 40% in the case of interzonal ratio=100%. It is also noteworthy that the significant improvement in the total mileage doesn't sacrifice the service quality, as is shown by the customer wait time.

3.5.2 Dynamic Model vs. Static Model

To validate and evaluate the dynamic model, we compare it with static model. All the experimental parameters are set the same and we have exactly the same requests for each of the model. The only difference is the dynamic model can only schedule dynamic requests one at a time and add them on top of the static schedule, while static model has the information of all the customers in advance.

Similar with the previous experiments, we test the performance of alternative customer assigning policies on each model through a static customer demand level=200 customers/day. Note that each customer has round trips and we have 10% additional dynamic customers so we totally have 400 static trips to be scheduled along about 40 dynamic trips. Ten simulation replications were conducted. We assume an inter-zonal ratio=50%, which means half of the customers' pick-up and drop-off locations are in different zones. The results are summarized in the following TABLE 4. FIGURE 10, FIGURE 11, FIGURE 12 and FIGURE 13 show the comparison results.

TABLE 4 Performance of Policies – Interzonal Ratio=100%

		Total vehicles				Total customers
Policy	Model	# of vehicles	Empty trip miles	Total mileage	Idle time	Wait time
Old policy	static	40.8	3355.4	14276.9	3669.2	5990.3
	dynamic	40.8	3361.4	14277.9	3677.5	5996.0
New policy	static	40.6	2555.5	13813.3	3856.0	6112.0
	dynamic	40.7	2560.2	13815.0	3857.7	6175.3
Alternative-1	static	39.6	2814.0	13617.1	3627.0	6046.5
	dynamic	39.8	2835.2	13697.5	3635.8	6069.0
Alternative-2	Static	37.8	2239.1	12657.3	4010.4	5939.5
	dynamic	37.4	2264.4	12718.5	4025.8	5940.2

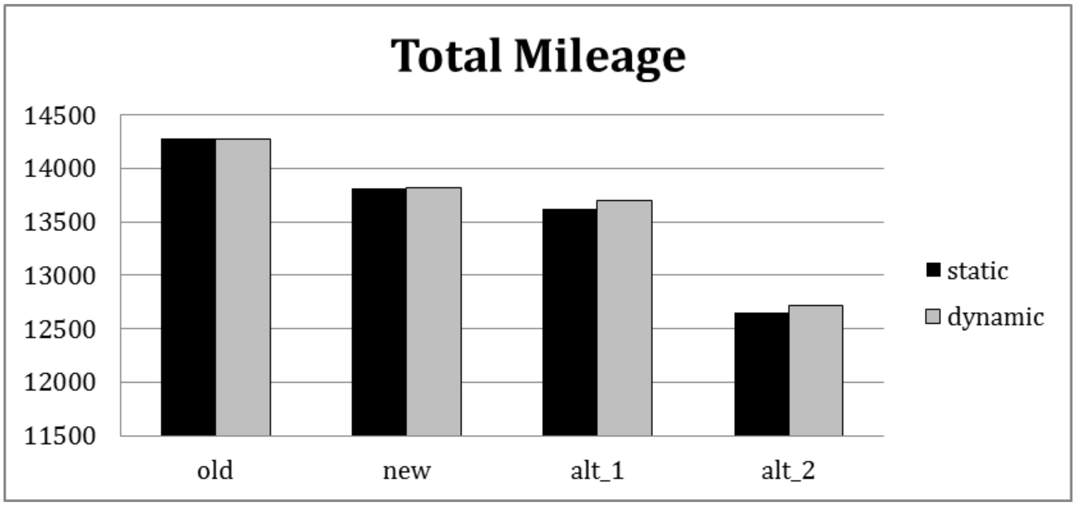


FIGURE 10 Dynamic vs. static - mileage

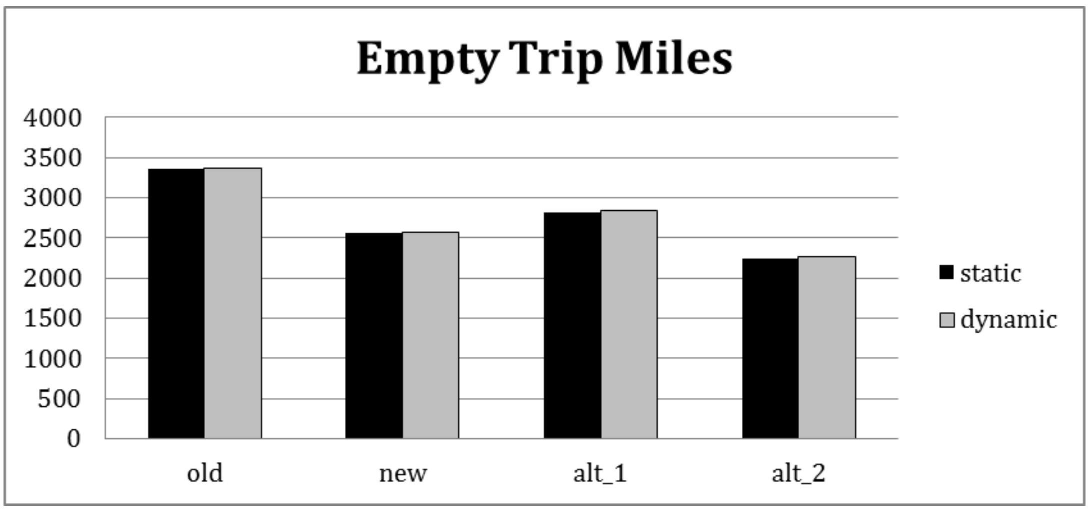


FIGURE 11 Dynamic vs. static – empty mileage

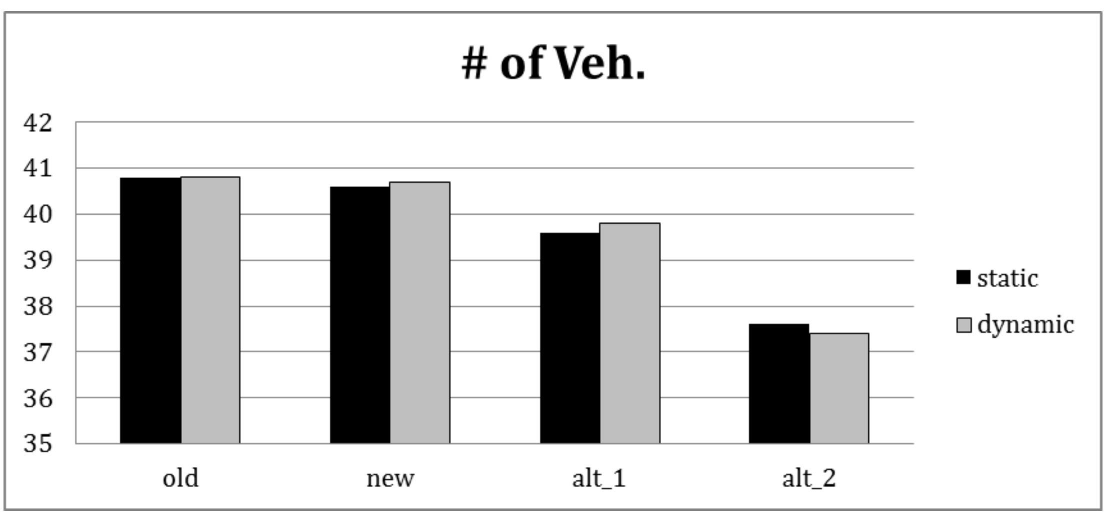


FIGURE 12 Dynamic vs. static – # of vehicles

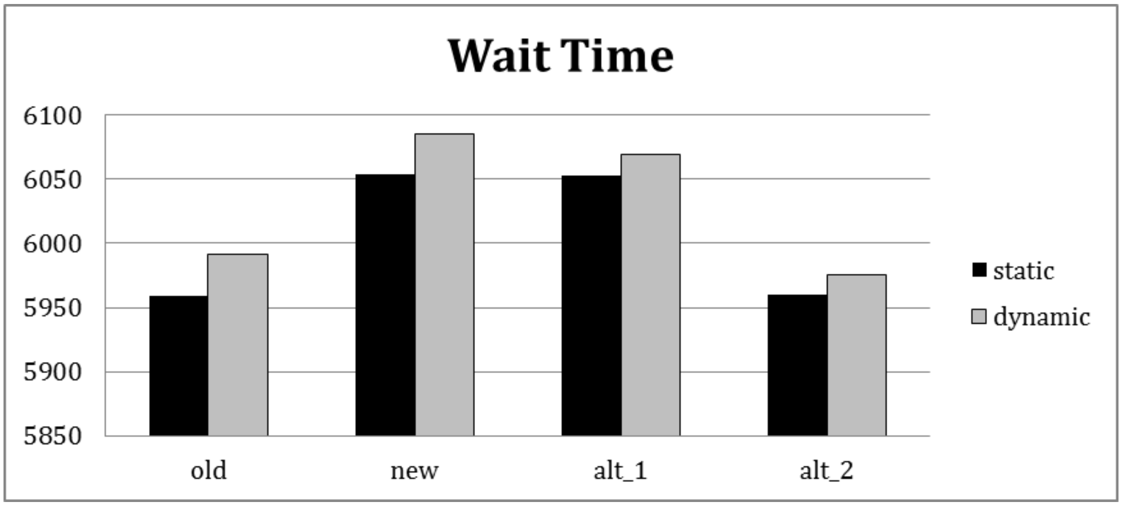


FIGURE 13 Dynamic vs. static – wait time

Comparing them, we find that static model has a slightly better performance than dynamic model in terms of total mileage, empty trip miles, and wait time. This is expected as that static model has all the information of customers in advance, thus it can construct a better schedule than the "myopic" dynamic model. The static model also performs better in terms of number of vehicles used for any adopted policy with the exception of alternative-2, which would require additional investigation and more statistically significant results, since we only conducted 10 simulation replications.

3.6 EXTENSION OF THE TWO-ZONE MODEL

To implement our policies into practice, we need to extend the 2-zone customer distribution model to multiple-zone model. In the four-zone model (FIGURE 14(a, b)) the whole service area is divided into four zones, namely the northern region (N), the eastern region (E), the western region (W) and the southern region (S). For zones that have common borders (e.g. N and W, W and S), the customer distribution follows the same logic as in the 2-zone model for the four policies. For the zones that are not close to each other (i.e., N and S), distribution is a little tricky as is described below for the four policies.

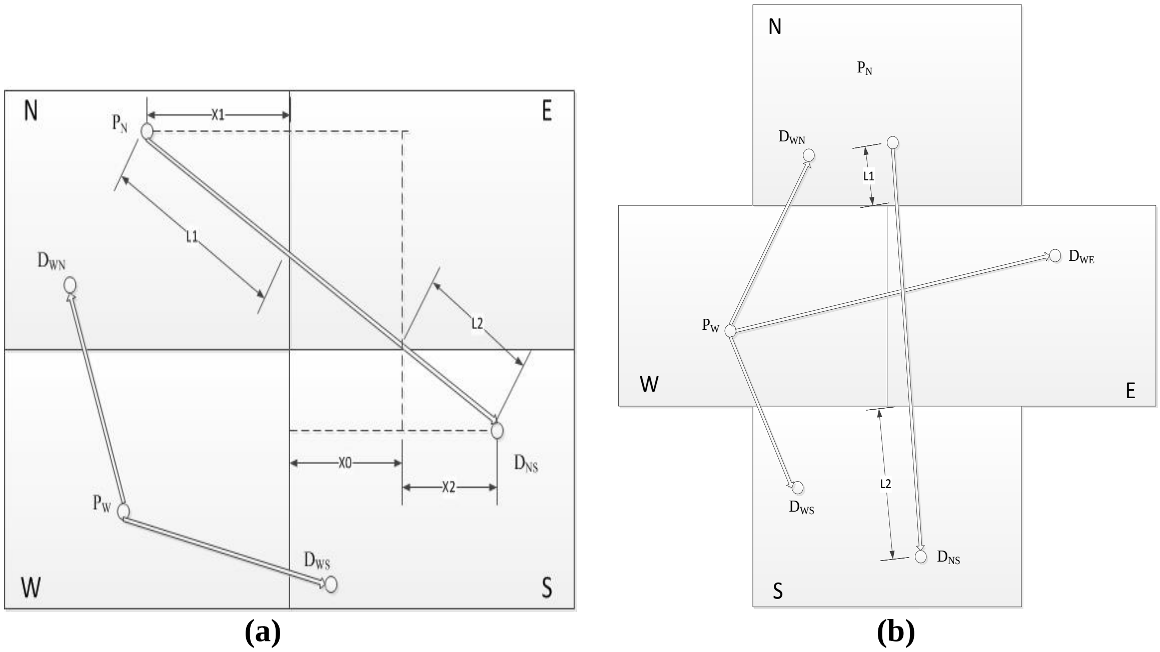


FIGURE 14 Four-zone customer distribution – (a) Houston and (b) Los Angeles.

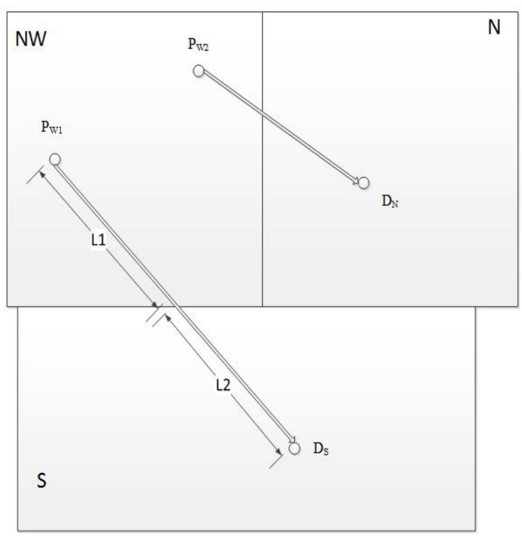


FIGURE 15 Three-zone customer distribution - Boston

The old policy and the new policy in a multiple-zone model follow a similar manner as in the two-zone model. For Alternative policy 1, it still assigns a customer according to his proximity to the border of the two zones (his pick-up zone and drop-off zone). Take the four-zone model of Houston as an example, geometry told us that L1>L2 if and only if X1>X2, i.e. (X1+X0>X2+X0) (see FIGURE 14(a)). This geometric relation gives us a simplified way to compare L1 and L2. The Alternative policy 2 is extended naturally from the two-zone model. It's still the most flexible policy among the four. The four-zone model of Los Angeles (FIGURE 14(b)) and the three-zone model of Boston (FIGURE 15) follow the similar logic as the Houston model.

3.7 DEMAND DATA FOR CASE STUDIES

The actual demand data from Houston, Los Angeles and Boston was used to generate the test samples. It was provided by METROLift in Houston, Access Services Inc. (ASI) in the Los Angeles County and MBTA in Boston. On average weekdays, there are about 5,000 trips for METROlift, 8000 trips for ASI and 6000 trips for MBTA. Currently, METROLift uses no-zoning strategy. Four hypothetical zones (see FIGURE 16) were generated according to the rules developed by Shen and Quadrifoglio (2013). For MBTA, it has three providers covering four zones in the whole service area, with the central Boston area shared by all providers (see FIGURE 17). For ASI, it has six zones over the service area, we consider only the Northern (N), Southern (S), Eastern (E) and West/Central (W) zones because the demand of Santa Clarita and Antelope Valley zones is less than 5% of the total daily average demand. There are in total 41,241 trips within 5 days period. TABLE 5, TABLE 6 and TABLE 7 show the daily average number of trips in each zone for each of the three cities.

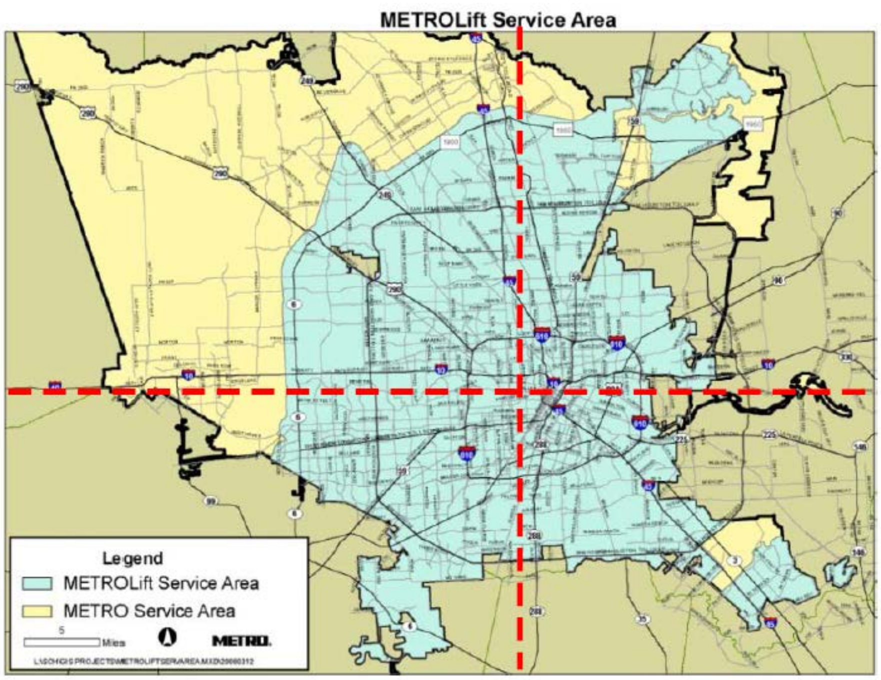


FIGURE 16 Houston Paratransit Service Area

FIGURE 17 Boston Paratransit Service Area

[source: http://www.mbta.com/riding_the_t/accessible_services/default.asp?id=7108#rideserv]

TABLE 5 Daily Average Trips of Four Zones in Houston

Zone	Daily average trips
Northwest	1208
Southwest	1510
Southeast	1272
Northeast	1010

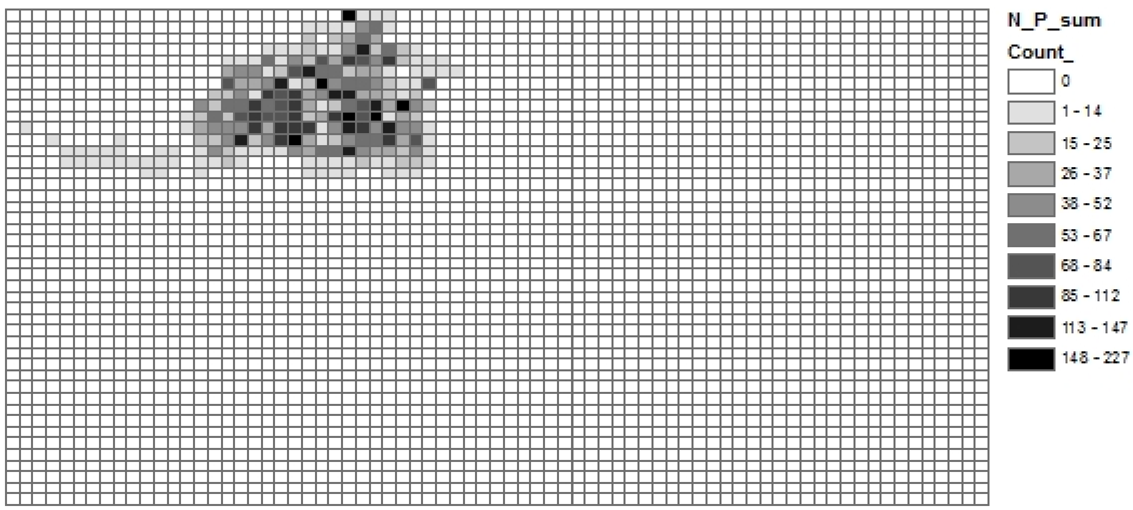
TABLE 6 Daily Average Trips of Six Zones at Los Angeles County

Zone	Daily average trips
Northern	1813
Southern	2780
Eastern	2253
West/Central	1402
Santa Clarita	144
Antelope Valley	273

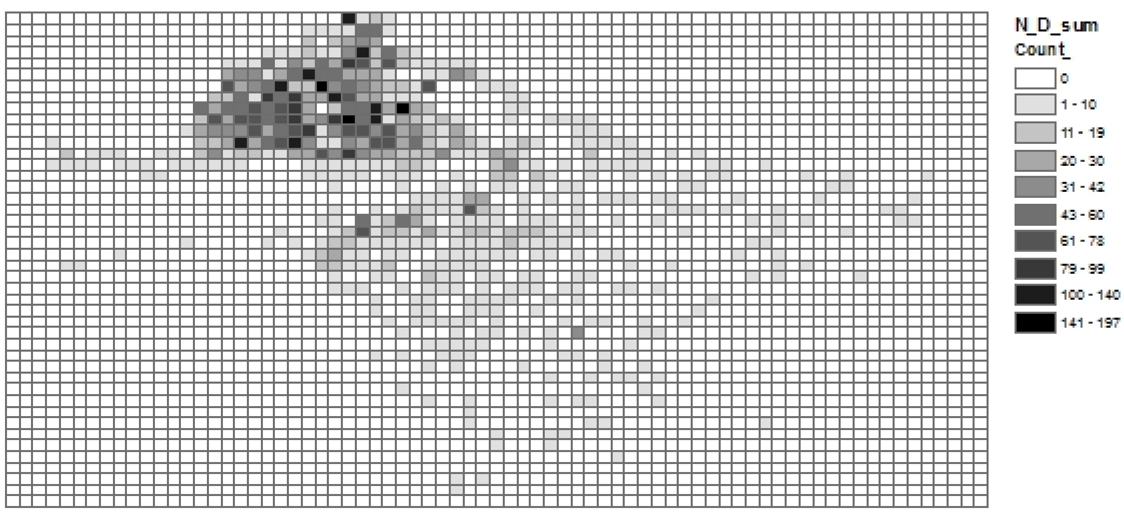
TABLE 7 Daily Average Trips of Three Zones in Boston

Zone	Daily average trips
North	1886
Northwest	2400
South	1918

We use the example of Los Angeles to illustrate the distribution of our data sets. FIGURE 18 shows the pickup and drop-off distribution for northern zone of Los Angeles. Other zones have their distinct distributions of pickup and drop-off locations.



(a)



(b)

FIGURE 18 Distribution of (a) pickup and (b) drop off location from northern zone in LA.

In Los Angeles County, the service area was divided by six zones. Each zone has its designated service provider. Providers can only pick up customers whose origins are within their service area. On the other hand, the drop off locations has no geographical restrictions. FIGURE 18(a) shows the pickup locations are all within northern zone; FIGURE 18(b) shows the drop-off locations are mainly within northern zone but some drop-off locations are out of northern zone. The pickup time distribution of northern zone is shown in FIGURE 19.

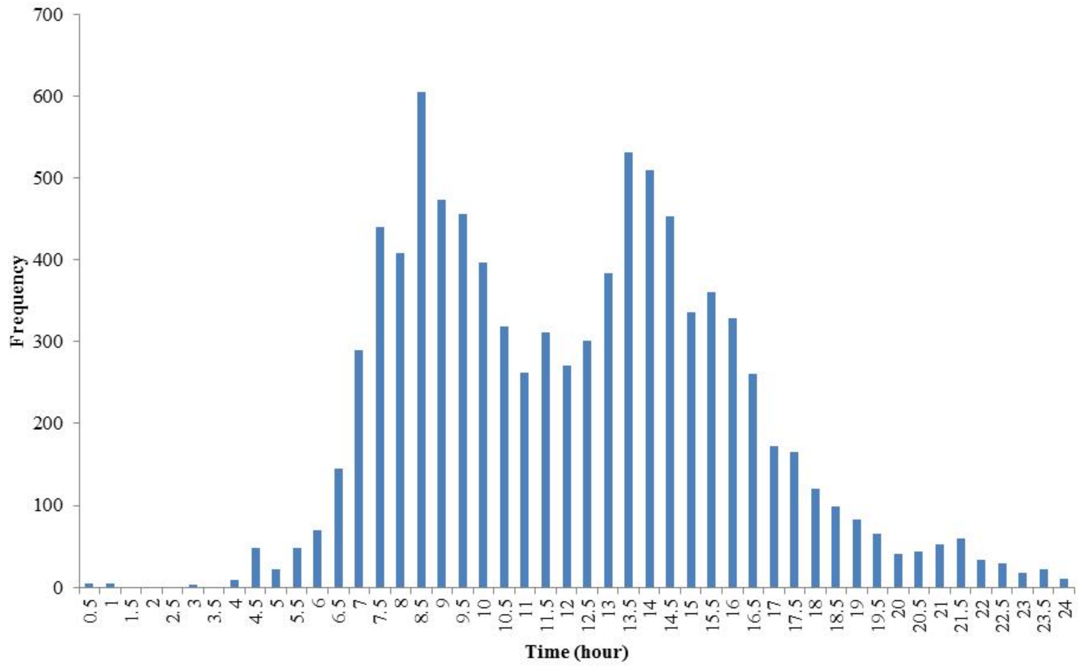


FIGURE 19 Distribution of pickup times for northern zone.

3.8 CASE STUDIES

This section will investigate the comparisons among policies using real demand data from our three selected cities. All comparisons will be made on the dynamic model and then compared against a static model. All analyses are conducted first assuming Manhattan distance among any pair of points and then using real distance calculated using the ArcGIS Network Analyst software for a very realistic simulation analysis.

3.8.1 Customer Generation

Customers are generated as done for the preliminary experiments but following the above real distributions. Note that our simulation model is able to handle dynamic requests that are randomly generated during a simulation. In our simulation model, customers are generally divided into two categories:

(c) Static demand - passengers who book the seats before the service starts, typically one day before the service date.

(d) Dynamic demand - passengers who book the seats on the day after the service starts.

Transit agencies usually require certain amount of advanced time ahead of the requested pickup. In our experiments we set this parameter to 30 minutes. For the whole time horizon of the paratransit service, dynamic demand occurs with a predefined probability. Note that the algorithm runs the static insertion first to get a basic schedule and then deal with the dynamic requests. This would require rescheduling of the fleets.

3.8.2 Policy Comparison on dynamic model

We investigated the performance of policies from the perspectives of cost, productivity and service quality. In terms of cost, the number of vehicles and the total mileage are the most straightforward indicators when comparing the efficiency of different policies. We further divided the total travel mileage of each vehicle into two parts, namely the travel miles with no passengers on board (Empty trip miles) and travel miles with passengers on board (Non-empty trip miles). Since it's possible that vehicles arrive at the pick-up locations earlier than the requested pick-up time, we define the vehicle waiting time at a pick-up location as "Idle time".

With respect to service quality, customers' waiting time and ride time are the two major indicators. Waiting time is defined as the time difference between requested pick-up time and actual pick-up time. Note that we have a mandatory constraint that the actual ride time cannot exceed K=2.5 times of direct ride time, which is required by law (K=2.5 is adopted in Houston).

With respect to productivity of a demand responsive system, transit agencies usually refer to passenger trips per vehicle hour. Higher values usually means more trips can be scheduled within a given time period.

The performance of competing policies is compared based on the data from Houston, Los Angeles and Boston. We run 10 simulation replications for each case. The results are summarized in TABLE 8.

TABLE 8 Policy Comparison

(a) Houston	Total vehicles					Total customers	Productivity
Policy	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	283.1	34649.1	61362.9	96012.0	10851.9	83259.4	1.61
New policy	277.7	28081.4	63661.9	91743.3	12495.8	82723.6	1.64
Alternative-1	276.7	29785.7	62918.4	92704.1	10832.2	83763.6	1.66
Alternative-2	264.9	26517.4	61949.4	88466.8	11409.1	82983.1	1.71
(b) LA	Total vehicles					Total customers	Productivity
Policy	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	520.9	59498.2	126268.7	185766.8	13527.7	137344.4	1.44
New policy	513.9	51437.8	125217.7	176655.5	13756.7	140365.9	1.46
Alternative-1	505.9	51986.1	123283.9	175270.0	13495.5	139225.7	1.47
Alternative-2	496.3	49358.7	121952.9	171311.5	13053.3	139818.0	1.50
(c) Boston	Total vehicles					Total customers	Productivity
Policy	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	379.5	32920.8	64280.6	97201.5	9000.9	103776.7	2.05
New policy	363.3	28725.3	63402.5	92127.8	8192.2	104987	2.15
Alternative-1	360.4	27836.8	62966.9	90803.7	8057.6	105564.8	2.18
Alternative-2	354.4	25970.1	62441.4	88411.4	7829.2	105028	2.21

Comparing the four different policies, Alternative-2 has the best performance in terms of number of vehicles used, total mileage, empty trip miles and passenger trips/hour. In the case of Houston, Alternative-2 uses 6.4% fewer vehicles and travels 7.9% less mileage compared to the current policy (old policy). In the case of LA, Alternative-2 uses 4.7% fewer vehicles and travels 7.8% less mileage compared to old policy. In the Boston case, Alternative-2 uses 6.6% fewer vehicles and travels 9% less mileage compared to old policy. This implies a significant cost reduction when implementing the new policy we proposed. Taking a careful look at the results, it is found that the reduction of total mileage is due to the reduction of empty trip miles. There is a significant 23% drop in empty trip miles when applying Alternative-2 in the case of Houston. The drop is a little lower as 17% in the case of LA and 21% in the case of Boston, possibly due to the lower inter-zonal trip rates in these two cities. It is also noteworthy that the significant improvement in the total mileage doesn't sacrifice the service quality, as is shown by the customer wait time. For the passenger trips per revenue hour, which is the productivity indicator a transit agency often refers to, our proposed policies all outperform the old policy. Comparing the best player, namely Alternative-2 with the current policy, the improvement percentage for the three cities is 6.2%, 4.2%, and 7.8% respectively.

We conducted statistical tests to further compare the performance of the four policies. Pair-wise confidence intervals are constructed for four variables that are most related to the operation cost and productivity, namely number of assigned vehicles, empty trip miles, total mileage, and passenger trips per hour. The numbers in TABLE 9, TABLE 10, and TABLE 11 represent the 95% confidence intervals of differences for each performance measurement. Note that those intervals with asterisks beside the bracket indicate that zero is not in the interval, meaning the corresponding pair of strategies have statistically significant difference in the measurement.

Note that all three data sets are showing similar performance relations for the measurements. For all the performance measures, the most flexible policy "Alt-2" beats all the other three policies. Again, this is because the flexibility we allowed efficiently reduced the "empty-trip" and promoted ridesharing, thus lowered both the total mileage and needed vehicles to fulfill the requests. The performance of the "New" policy and the "Alt-1" policy seems to be close as none of them is showing a statistical edge over the other for most of the measurements for the three cases except the empty trip miles, total mileage and passenger trips/hour in the Boston case, where "Alt-1" is a better player compared to "New".

TABLE 9 Pair-wise Confidence Intervals of Measurements - Houston

Houston Data			
Paired-t	(a) Number of Assigned Vehicles		
	New	Alt-1	Alt-2
Old	[1.61,9.19]*	[3.05,9.75]*	[15.31,21.09]*
New		[-3.07,5.07]	[9.05,16.55]*
Alt-1			[8.51,15.09]*
Paired-t	(b) Empty Trip Miles		
	New	Alt-1	Alt-2
Old	[6074.88,7060.37]*	[4340.68,5386.01]*	[7646.55,8616.72]*
New		[-2110.17,-1298.39]	[1217.66,1910.35]*
Alt-1			[2872.89,3663.68]*
Paired-t	(c) Total Mileage		
	New	Alt-1	Alt-2
Old	[3460.93,5076.37]*	[2426.87,4188.92]*	[6632.48,8457.87]*
New		[-1723.76,-197.75]	[2474.27,4078.78]*
Alt-1			[3361.02,5113.55]*
Paired-t	(d) Passenger Trips per Hour		
	New	Alt-1	Alt-2
Old	[0.01,0.05]*	[0.02,0.07]*	[0.07,0.12]*
New		[-0.01,0.04]	[0.03,0.10]*
Alt-1			[0.02,0.08]*

* denotes a significant difference

TABLE 10 Pair-wise Confidence Intervals of Measurements – Los Angeles

Los Angeles Data			
Paired-t	(a) Number of Assigned Vehicles		
	New	Alt-1	Alt-2
Old	[1.20,12.80]*	[9.67,20.33]*	[18.67,30.53]*
New		[2.03,13.97]*	[11.11,24.09]*
Alt-1			[3.50,15.70]*
Paired-t	(b) Empty Trip Miles		
	New	Alt-1	Alt-2
Old	[7336.74,8783.98]*	[6584.29,8439.76]*	[9398.46,10880.54]*
New		[-1429.19,332.51]	[1407.26,2751.01]*
Alt-1			[1733.76,3521.20]*
Paired-t	(c) Total Mileage		
	New	Alt-1	Alt-2
Old	[3816.28,6406.28]	[5053.93,7939.66]	[9101.46,11809.13]
New		[-19.84,2790.87]	[4031.81,6656.22]
Alt-1			[2501.08,5415.91]
Paired-t	(d) Passenger Trips per Hour		
	New	Alt-1	Alt-2
Old	[0.02,0.04]*	[0.02,0.04]*	[0.05,0.07]*
New		[-0.00,0.02]*	[0.02,0.05]*
Alt-1			[0.02,0.04]*

* denotes a significant difference

TABLE 11 Pair-wise Confidence Intervals of Measurements – Boston

Boston Data			
Paired-t	(a) Number of Assigned Vehicles		
	New	Alt-1	Alt-2
Old	[11.75,20.65]*	[14.39,23.81]*	[20.64,29.56]*
New		[-1.12,6.92]	[5.20,12.60]*
Alt-1			[1.97,10.03]*
Paired-t	(b) Empty Trip Miles		
	New	Alt-1	Alt-2
Old	[3751.40,4639.70]*	[4592.41,5575.57]*	[6524.49,7377.04]*
New		[515.27,1261.60]*	[2500.13,3010.30]*
Alt-1			[1517.53,2216.03]*
Paired-t	(c) Total Mileage		
	New	Alt-1	Alt-2
Old	[4269.24,5878.09]*	[5513.43,7282.11]*	[8004.50,9575.56]*
New		[674.26,1973.95]*	[3252.97,4179.76]*
Alt-1			[1769.17,3015.35]*
Paired-t	(d) Passenger Trips per Hour		
	New	Alt-1	Alt-2
Old	[0.08,0.11]*	[0.11,0.14]*	[0.15,0.18]*
New		[0.02,0.05]*	[0.06,0.08]*
Alt-1			[0.02,0.05]*

* denotes a significant difference

3.8.3 Individual Zone Analysis

The overall analysis in the previous section gives a big picture of how our proposed policies compared with the current policy in terms of operating cost, customer service level, and productivity. In this section we broke down the performance measures into individual zones to see how each paratransit provider is affected under different operating policies. The individual zone performance analysis is summarized in TABLE 12, TABLE 13, and TABLE 14. Note that the column "# of Trips" shows the passenger trip gain/loss for each of the zones after adopting a certain policy relative to the current (Old) policy.

TABLE 12 Individual Zone Performance - Boston

			Total vehicles					Total customers
Policy	Zone	# of Trips	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time
Old	N	0	84.8	7394.1	13744.5	21138.6	2337.2	22242.7
	W	0	105.5	9074.8	17512.4	26587.2	2485.6	28954.3
	S	0	189.2	16452.0	33023.7	49475.6	4178.1	52579.7
New	N	652.5	108.1	8087.6	18928.6	27016.2	2583.3	31443.2
	W	788.5	129.5	10581.7	22634.3	33216.0	2895.1	40756.3
	S	-1441	125.7	10056.0	21839.6	31895.6	2713.8	32787.5
Alt-1	N	626.7	106.4	7727.5	18475.7	26203.2	2405.2	31164.9
	W	664.6	126	9973.8	21699.7	31673.6	2797.5	39685.4
	S	-1291.3	128	10135.5	22791.4	32926.9	2854.9	34714.5
Alt-2	N	560.4	101.1	6794.9	17800.9	24595.7	2333.7	30277.1
	W	529.7	120.3	8813.8	20411.1	29224.8	2521.8	37583.2
	S	-1090.1	133	10361.4	24229.5	34590.8	2973.7	37167.7

TABLE 13 Individual Zone Performance - LA

			Total vehicles					Total customers
Policy	Zone	# of Trips	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time
Old	N	0	102.5	11560.8	23462.2	35023.0	2988.7	30988.4
	W	0	82.3	9688.4	16280.3	25968.7	2460.2	18306.6
	S	0	174.8	20522.6	43172.7	63695.3	4093.3	47048.4
	E	0	161.3	17726.3	39353.5	57079.8	3985.5	41001
New	N	46.7	102.6	10343.5	24039.8	34383.2	2907.4	31034.3
	W	227.6	87.8	8845.1	19231.2	28076.3	2821.3	21936.3
	S	-66.3	170.2	17592.0	42509.8	60101.8	4153.7	47923.9
	E	-208	153.3	14657.2	39437.0	54094.2	3874.3	39471.4
Alt-1	N	-17.3	98.2	10022.4	22953.9	32976.3	2866.9	30723.3
	W	38	78	8197.1	16329.8	24526.9	2369.4	19097.7
	S	37.2	172.1	18371.1	44139.0	62510.1	4237	48805.3
	E	-57.9	157.6	15395.5	39861.2	55256.7	4022.2	40599.4
Alt-2	N	-68.1	95.5	9249.5	21982.9	31232.3	2663.7	30344.8
	W	-152.9	65.6	6482.0	14120.3	20602.4	2312.6	16290.3
	S	97	173.9	17993.5	44757.3	62750.8	4038.9	50282.4
	E	124	161.3	15633.6	41092.4	56726.0	4038.1	42900.5

TABLE 14 Individual Zone Performance - Houston

			Total vehicles					Total customers
Policy	Zone	# of Trips	# of Vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time
Old	N	0	73.6	9071.4	15800.3	24871.7	2997.9	20109.5
	W	0	84.4	10151.2	18646.7	28797.9	2770.7	27689.2
	S	0	69	8289.4	14759.5	23048.8	3018.9	20794.8
	E	0	56.1	7137.1	12156.5	19293.6	2064.4	14665.9
New	N	-6.6	71.5	7219.6	15902.7	23122.3	3411.7	19776.4
	W	-113.9	77.8	7812.0	18186.1	25998.1	2895.2	25072.7
	S	46.6	70.4	7135.7	16464.0	23599.7	3553.6	21530.9
	E	73.9	58	5914.2	13109.0	19023.2	2635.3	16343.6
Alt-1	N	156.8	76.4	8287.5	18180.8	26468.3	2932	22115.2
	W	-14.8	82.2	8728.7	18817.9	27546.5	2772	27586.6
	S	-146.4	62	6634.5	13467.8	20102.3	2944.2	19193.6
	E	4.4	56.1	6135.1	12451.8	18586.9	2184	14868.2
Alt-2	N	284	81.8	8614.1	19874.6	28488.7	3280	23302.3
	W	40.3	80.5	8054.4	18858.6	26912.9	3117.2	28578.9
	S	-285.5	49.8	4625.3	11183.0	15808.3	2378.6	17136.0
	E	-38.8	52.8	5223.7	12033.1	17256.8	2633.3	13965.9

It is clearly seen that there's a redistribution of customers and resources (in terms of # of Vehicles used to service all the requests) among the paratransit providers in different zones. Take Boston as an example (TABLE 12), all three proposed policies redistributed some of the customers of the provider in the South zone to North and West. As a result, the vehicles used by each zone are redistributed accordingly. The result is a more balanced fleet size for each of the zone in Boston. For the other two cases (TABLE 13 and TABLE 14), the pattern for customer gain/loss in each zone is more random. However, the number of vehicles used by each zone increases (decreases) accordingly as it gains (loses) customers. The mechanism of how each of the operating zones gains (loses) customers under different policies in different cities is likely explained by geographical demand distribution: proximity to the borders, high level of demand concentration in certain areas, etc. The research team believes this would be an interesting future topic to be investigated.

3.8.4 Dynamic Model vs. Static Model

To evaluate the effect of allowing dynamic requests (i.e., requests that are made during the service day), we compare it with static model, in which requests are made before the service date. For the comparison, all the experimental parameters are set the same and we have exactly the same requests for each of the model. The only difference is that the dynamic model can only schedule dynamic requests one by one at the time they are made while static model has the information of all the customers in advance.

Similar to the preliminary experiments, we test the performance of alternative customer assigning policies on each model using the same datasets of the three cities. Ten simulation replications are conducted. The results are summarized in the following table.

TABLE 15 Dynamic (D) vs. Static (S) model

(a) Houston	Total vehicles					Total customers	Productivity
Policy (D) (S)	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	283.1	34649.1	61362.9	96012	10851.9	83259.4	1.61
	280.5	33908.4	61190.7	95099.1	10823.5	83098.5	1.62
New policy	277.7	28081.4	63661.9	91743.3	12495.8	82723.6	1.64
	275.0	27543.9	63159.0	90702.9	12432.0	82499.8	1.64
Alternative-1	276.7	29785.7	62918.4	92704.1	10832.2	83763.6	1.66
	273.1	29036.0	62708.1	91744.1	10805.6	83521.2	1.66
Alternative-2	264.9	26517.4	61949.4	88466.8	11409.1	82983.1	1.71
	262.8	26034.3	61653.6	87687.9	11388.4	82830.8	1.72
(b) LA	Total vehicles					Total customers	Productivity
Policy (D) (S)	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	520.9	59498.2	126268.7	185766.9	13527.7	137344.4	1.44
	514.3	58154.5	125085.9	183240.4	13466.2	137023.5	1.44
New policy	513.9	51437.8	125217.7	176655.5	13756.7	140365.9	1.46
	507.6	50682.1	124347.4	175029.5	13684.1	139260.1	1.46
Alternative-1	505.9	51986.1	123283.9	175270	13495.5	139225.7	1.47
	500.8	51031.3	122098.5	173129.8	13362.7	138700.2	1.48
Alternative-2	496.3	49358.7	121952.9	171311.6	13053.3	139818.0	1.50
	491.2	48452.4	120872.4	169324.8	13021.0	139621.4	1.52
(b) Boston	Total vehicles					Total customers	Productivity
Policy (D) (S)	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	379.5	32920.8	64280.6	97201.4	9000.9	103776.7	2.05
	372.6	32206.7	63922.4	96129.1	8962.2	103428.9	2.07
New policy	363.3	28725.3	63402.5	92127.8	8192.2	104987.0	2.15
	358.9	28083.4	63233.2	91316.6	8143.6	104249.5	2.15
Alternative-1	360.4	27836.8	62966.9	90803.7	8057.6	105564.8	2.18
	356.6	27309.8	62820.0	90129.8	8018.5	105390.1	2.19
Alternative-2	354.4	25970.1	62441.4	88411.5	7829.2	105028.0	2.21
	350.2	25877.1	62311.5	88188.6	7805.4	104682.3	2.22

Results are similar to what found on the preliminary experiments. The static model has a slightly better performance than dynamic model in terms of total mileage, empty trip miles, wait time and productivity. It is also found that the conclusions on the effect of different policies is not dependent on whether we adopt a static or dynamic model. That is to say, we still have the order of performance for the four policies is again: Alternative-2>Alternative-1>New>Old.

3.8.5 Simulation Based on Real Network Distance

In this section, we modified our assumption on Manhattan distance. We implemented our customer distribution algorithm and insertion algorithm based on real network distance. The real network distance is the distance calculated on a real road network that consists of turns, signals, barriers, etc. See FIGURE 20 for an example. Note that this is a step-up because with real network distance our simulation results will be more plausible than under the assumption of Manhattan distance. This is especially the case for cities that have a lot of bridges, Boston for example. We conducted simulation experiments for the policies we proposed. The simulation results are compared with those under Manhattan distance assumption.

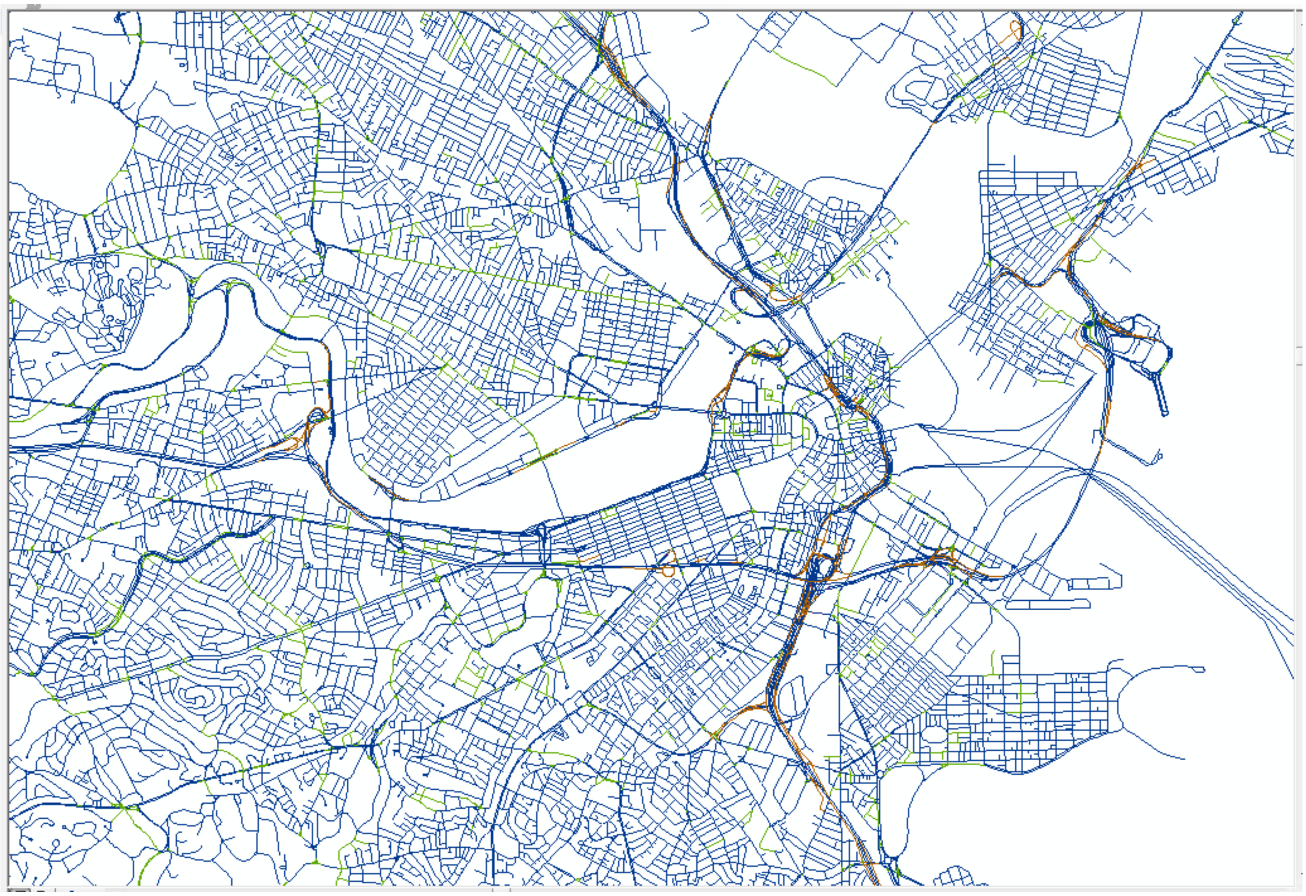


FIGURE 20 Boston road network

We divided the whole service area into 1 mile × 1 mile squares. For any origin – destination pairs, the distance is calculated using ArcGIS Network Analyst. For any origin-destination (OD) pairs that are generated based on the real demand, their actual distances that are used in our insertion scheduling algorithm are calculated in one of the following two ways:

1. If the OD pair belongs to different squares, we calculate the Manhattan distances between the O (D) and the closest centroid. Then, the OD pair's actual distance is calculated using the network distance from the centroid of the origin square to the centroid of the destination square (FIGURE 21(a)). In practice, we have: Manhattan distance from O to closet centroid plus real distance from centroid to centroid plus Manhattan distance from centroid to D.
2. If both the origin and the destination are in the same 1×1 square, the OD pair's actual distance is calculated using Manhattan distance (FIGURE 21(b)).

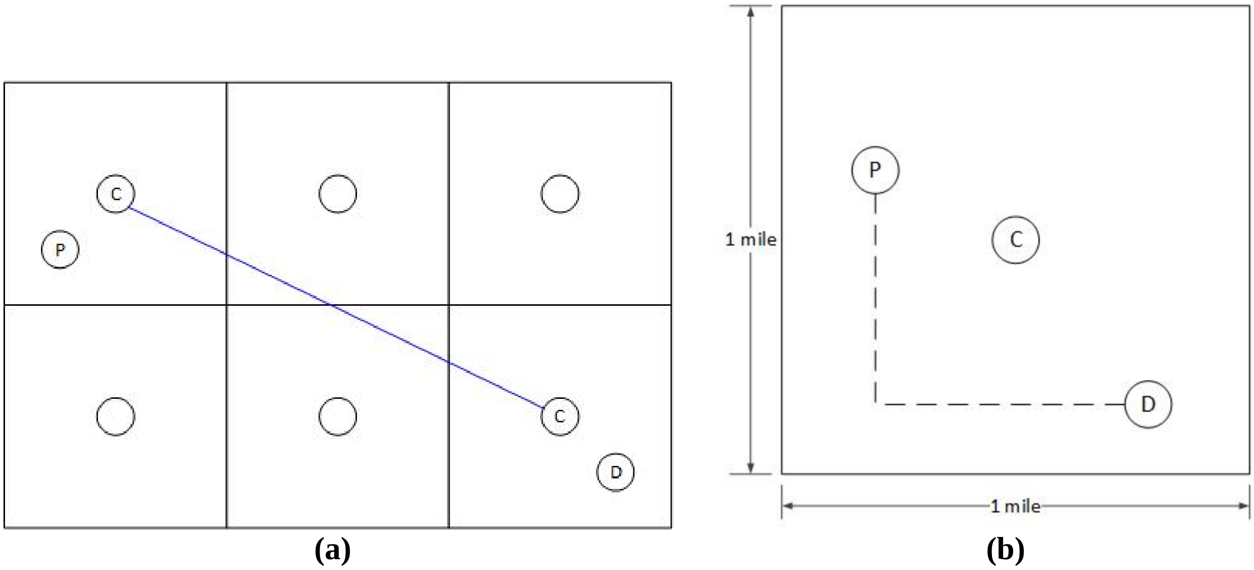


FIGURE 21 Actual distance

Our simplification can be justified by two facts: 1) as we showed in FIGURE 18, most of the demands are concentrated in a few squares, inside where the requests are randomly generated according to a uniform distribution. So statistically speaking, this treatment won't make a big difference compared to "strictly" real distance; 2) the largely predominant part of the total mileage is correctly calculated between zone centroids along the actual road network. By adopting this approximation we only need to calculate the centroid-based distance once for all the simulation runs. As a result, this treatment will cause a much lighter computational burden than strictly real distance treatment.

We ran simulation experiments similar to the previous section. The performance of alternative customer assigning policies is compared based on the data from Houston, Los Angeles and Boston. We run 10 simulation replications for each case. The results are summarized in TABLE 17.

Comparing the four different policies, Alternative-2 still has the best performance in terms of number of vehicles used, total mileage, empty trip miles and passenger trips/hour. In the case of Houston, Alternative-2 uses 5.8% fewer vehicles and travels 7.2% less mileage compared to the current policy (old policy). In the case of LA, Alternative-2 uses 4.3% fewer vehicles and travels 5.2% less mileage compared to old policy. In the Boston case, Alternative-2 uses 9.9% fewer vehicles and travels 10.8% less mileage compared to old policy. For the passenger trips per revenue hour, comparing the best player, namely Alternative-2 with the current policy, the improvement percentage for the three cities is 5.8%, 3.6%, and 8.9% respectively, as is shown in TABLE 17.

TABLE 16 Policy Comparison – Real Network Distance

(a) Houston	Total vehicles					Total customers	Productivity
Policy	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	302.3	36583.6	60337.3	96921.0	13453.5	92676.6	1.54
New policy	298.6	30647.3	62603.5	93250.8	14751.8	91344.6	1.57
Alternative-1	294.3	31820.8	61583.7	93404.5	14013.8	91379.1	1.58
Alternative-2	284.7	28794.0	61152.2	89946.1	13935.7	90343.1	1.63
(b) LA	Total vehicles					Total customers	Productivity
Policy	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	542.1	61261.1	119397.1	180658.3	16438.1	157521.2	1.39
New policy	537.6	54034.2	122702.5	176736.7	17488.8	159285.0	1.40
Alternative-1	532.0	54751.3	120969.3	175720.7	16521.3	157440.4	1.41
Alternative-2	519.0	51867.0	119461.9	171328.9	16564.5	157304.5	1.44
(c) Boston	Total vehicles					Total customers	Productivity
Policy	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	391.6	32786.9	57393.0	90180.0	9190.3	96310.0	1.90
New policy	364.5	27155.0	55473.7	82628.6	8717.0	96249.7	2.04
Alternative-1	375.8	28699.7	57318.2	86017.9	8594.1	99028.7	1.97
Alternative-2	352.8	25813.0	54615.5	80428.4	8580.2	96322.4	2.07

3.8.6 Real Distance vs. Manhattan Distance

To evaluate the effect of using real network distance in our simulation, we compare it with the Manhattan distance model. For the comparison, all the experimental parameters are set the same and we have exactly the same requests for each of the model. The only difference is in the distance calculation we used in our insertion algorithm.

Similar with the previous experiments, we test the performance of alternative customer assigning policies on each model using the same datasets of the three cities. Ten simulation replications are conducted. The results are summarized in the following table.

TABLE 17 Manhattan Distance (M) vs. Real Distance (R)

(a) Houston	Total vehicles					Total customers	Productivity
Policy (M) (R)	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	283.1	34649.1	61362.9	96012	10851.9	83259.4	1.61
	302.3	36583.6	60337.3	96921.0	13453.5	92676.6	1.54
New policy	277.7	28081.4	63661.9	91743.3	12495.8	82723.6	1.64
	298.6	30647.3	62603.5	93250.8	14751.8	91344.6	1.57
Alternative-1	276.7	29785.7	62918.4	92704.1	10832.2	83763.6	1.66
	294.3	31820.8	61583.7	93404.5	14013.8	91379.1	1.58
Alternative-2	264.9	26517.4	61949.4	88466.8	11409.1	82983.1	1.71
	284.7	28794.0	61152.2	89946.1	13935.7	90343.1	1.63
(b) LA	Total vehicles					Total customers	Productivity
Policy (M) (R)	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	520.9	59498.2	126268.7	185766.9	13527.7	137344.4	1.44
	542.1	61261.1	119397.1	180658.3	16438.1	157521.2	1.39
New policy	513.9	51437.8	125217.7	176655.5	13756.7	140365.9	1.46
	537.6	54034.2	122702.5	176736.7	17488.8	159285.0	1.40
Alternative-1	505.9	51986.1	123283.9	175270	13495.5	139225.7	1.47
	532.0	54751.3	120969.3	175720.7	16521.3	157440.4	1.41
Alternative-2	496.3	49358.7	121952.9	171311.6	13053.3	139818.0	1.50
	519.0	51867.0	119461.9	171328.9	16564.5	157304.5	1.44
(b) Boston	Total vehicles					Total customers	Productivity
Policy (M) (R)	# of vehicles	Empty trip miles	Non-empty trip miles	Total mileage	Idle time	Wait time	Passenger trips/hour
Old policy	379.5	32920.8	64280.6	97201.4	9000.9	103776.7	2.05
	391.6	32786.9	57393.0	90180.0	9190.3	96310.0	1.90
New policy	363.3	28725.3	63402.5	92127.8	8192.2	104987.0	2.15
	364.5	27155.0	55473.7	82628.6	8717.0	96249.7	2.04
Alternative-1	360.4	27836.8	62966.9	90803.7	8057.6	105564.8	2.18
	375.8	28699.7	57318.2	86017.9	8594.1	99028.7	1.97
Alternative-2	354.4	25970.1	62441.4	88411.5	7829.2	105028.0	2.21
	352.8	25813.0	54615.5	80428.4	8580.2	96322.4	2.07

We found that Manhattan distance model resulted in slightly lower (<10% difference) vehicle usage and slightly higher (<5% difference) productivity than real distance model in the cases of Houston and LA. For the Boston case, Manhattan distance model also has a slightly higher (<10% difference) productivity. For Houston and LA, the total mileage using real distance and Manhattan distance is very close (<3% difference). For the Boston case, the total mileage under different distance assumptions is still very close (<10% difference), with Manhattan distance model has the slightly higher value. This can be explained by the non-Manhattan-like road network in the Boston metropolitan area, and the bridges that actually shorten the distance between two locations.

Note that the close results under different distance assumptions are not only a justification of our real network distance simulation model, it also has the implication that Manhattan distance is a close-enough approximation for real network distance.

4. PLANS FOR IMPLEMENTATION

We expect that the results obtained from this project will encourage transit agencies and scheduling software companies to consider implementing the innovative rules we proposed to operate paratransit services. While this project will not be a full implementation to practice, we are confident that our results will lead to it in the future.

The implementation of our strategies will have these noticeable benefits:

- Maintain a zoning structure for easier overall management and better reliability (higher percentage of on-time performance), as already preferred by many agencies.
- Reduce the empty trip miles to lower operating costs.
- Improve the passenger trips per revenue hour, which is a productivity indicator frequently referred to by transit agencies.
- Allow cross-zonal customers to book both legs of their round-trip ride with the same provider, for an improved level of service.

This project focused on evaluating and particularly quantifying the above benefits (especially the reduction of operating costs and improvement of productivity) by conducting extensive simulation analysis of the proposed operating strategies. The promising results obtained from our simulation should encourage transit agencies to consider our innovative policies. Besides, the simulation model we developed can be served as a powerful and effective platform to test and evaluate different paratransit operation policies.

5. CONCLUSIONS

In this research project, innovative operating strategies for paratransit services are proposed. Specifically, we proposed three new policies allowing providers to serve a given zone to pick up out-of-zone passengers that are in need of their return trip to this zone. Among these new polices, two of them base the customer assignment decisions on the relative distance between pick-up and drop-off locations. The authors developed new algorithms that incorporated the proposed strategies into the scheduling algorithm and developed simulation models to replicate the paratransit operations. In the first stage of this project, we conducted simulation experiments to validate our models and preliminarily evaluated our proposed policies using artificial data. In the second stage of the project, we collected actual paratransit demand data from the transit agencies of Houston, Los Angeles and Boston. To evaluate and analyze the proposed operating strategies, we conducted computational experiments using the simulation model we built based on these three data sets. Since assuming Manhattan distance might seem unrealistic under certain circumstances (e.g. cities like Boston), we implemented our customer distribution algorithm and insertion algorithm based on real network distance using ArcGIS Network Analyst software, allowing us to consider very realistic scenarios. Experimental results showed that the proposed strategies use fewer vehicles (up to 6.6%), have less total mileage (up to 9% reduction), and have higher values of passenger trips per revenue hour (up to 7.8%) than the current policy. The results reinforced our preliminary conclusions that applying the operating strategies we proposed can both reduce the operations cost of paratransit services and improve the productivity significantly without sacrificing the level of service. Paired-t tests confirmed our inferences statistically.

Finally, we conducted two more interesting analyses. The first one looked into the effect of the re-scheduling in each zone. While the overall system benefited from it, the redistribution of customers and resources (in terms of # of Vehicles used to service all the requests) within each zone was different. This will undoubtedly generate discussion and negotiation among independent providers, which would gain or lose customers as a result of the redistribution.

Finally, we compared our real distance (using ArcGIS) results with the Manhattan distance model. Comparable outputs were found, in particular the conclusions reached in evaluating the effects of the different policies were the same. Therefore the study also showed that assuming Manhattan distances is a close-enough approximation (and much easier to implement) as a substitute for real network distance.

We believe our results could provide valuable insights to ADA transit agencies who are working hard to save operating cost and improve productivity. Future research might include conducting experiments for other cities.

6. INVESTIGATOR PROFILE

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