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CONTENTS

The Effects of Perception vs. "Reality" on Travel Behavior after a Major Transit Service Change: The Case of Tallahassee, Florida

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Abstract

An individual's perception plays an important role in determining the decisions that people make involving the use of public transportation. An individual's perception about the qualities of transit service might differ from the objective measures ("reality") of service quality used by planners to make and evaluate decisions. This study explores the roles of perception and "reality" of transit service quality as influences on the attitudes and behaviors of two different groups of transit dependent riders after a major service change in Tallahassee, Florida. Using a combination of community surveys, key informant interviews, and agency data, the study finds that perception mattered more than "reality" as an influence on the attitudes and behaviors of the two groups. The need for more effective outreach to understand the reasons that individual perception might differ from the objective measures used and understood by transit professionals also emerges as an important lesson of the study.

Introduction

An individual's perception plays an important role in the decisions that people make every day, including decisions involving transportation. An individual's decision about travel routes, modes, times, destination choices, and the like depends on her/his perception of the quality, ease, and cost of travel, as well as the qualities of the destination opportunities available for that particular trip. Past scholarship suggests that, often, it is the perception of travel as opposed to the actual measurable attributes of travel that is the fundamental driver of individual decision-making (Goodwin and Lyons 2009). In short, perception can often trump reality, making perception the more appropriate lens through which to understand, and perhaps modify, individual travel decisions.

Perception and reality often do not align. This has become particularly noteworthy in the literature on public transit and travel behavior. Transit is frequently perceived as being less convenient, less accessible, and less safe than it objectively would seem to be based on measurable attributes (Kenyon and Lyons 2003; Loukaitou-Sideris 1999). Within transit, bus rapid transit (BRT) and rail modes are perceived as being more convenient, more reliable, and faster than bus services, when this may or may not actually be the case (Deng and Nelson 2012; Thompson, Brown, and Bhattacharya 2012). Clearly, the transit industry understands the importance of perception, and the need to alter perception, given the numerous examples of branding higher quality bus services such as BRT differently from traditional local bus services (Deng and Nelson 2012; Wirthlin Worldwide and FJCandN 2000). Frequent transit riders also tend to perceive transit service very differently from infrequent riders, who, in turn, have different perceptions than the larger, non-transit-using public (Mahmoud and Hine 2013). This adds an important group dimension to the understanding of the role of perception vs. reality in affecting individual attitudes and behavior.

This paper explores the similarities and differences between perception and reality and their relationship to transit use after a major service change in Tallahassee, Florida, where the previously downtown-focused transit system was entirely restructured overnight to serve a more dispersed array of travel destinations. This change was driven largely by a desire to increase the system's appeal to infrequent and discretionary riders. The local transit system, StarMetro, overwhelmingly catered to a transit-dependent ridership market dominated by two very different types of riders: university students, who are a transient population, and the long-term resident, lower-income community. Using a combination of quantitative

data about service quality and ridership, community surveys, and key informant interviews, the authors document the important role that perception played in affecting individual attitudes and travel behavior decisions and how these changed before and after the major service change. The results indicate the importance of perception over reality, which suggests the need for more effective outreach, listening, and engagement when transit agencies propose similar kinds of service changes in other locales. The results also suggest some important, if subtle, differences between the two groups of transit-dependent riders.

Case Study Setting

On July 11, 2011, StarMetro, the transit agency in Tallahassee, restructured its network from one focused on the downtown (a classic radial pattern) to one that was decentralized (a grid-like pattern) to serve a wider array of travel destinations in a decentralized community where population and employment growth is highest in outlying locations. The presence of two major universities to the west and southwest of downtown Tallahassee, Florida State University (FSU) and Florida Agricultural and Mechanical University (FAMU), as well as a major regional community college, Tallahassee Community College (TCC), and the presence of state government offices in downtown has maintained a strong core of activity at the center of the community, but in recent years the departure of many state agencies and private employers to the outlying districts has eroded downtown's role as a major activity center (see Figure 1). The Southwood area, a major New Urbanist style suburban development located southeast of the downtown, and Killearn, a more traditional post-war suburban development located northeast of the downtown, have been major centers for population and employment growth in recent years. Closer to the center of Tallahassee, however, the Frenchtown and Southside neighborhoods remain important centers of the local African-American community. Central Tallahassee remains the most important activity center in the region, although it is one in relative decline. Population and employment growth is expected to occur primarily in outlying areas, as has already been the case for the preceding several decades.
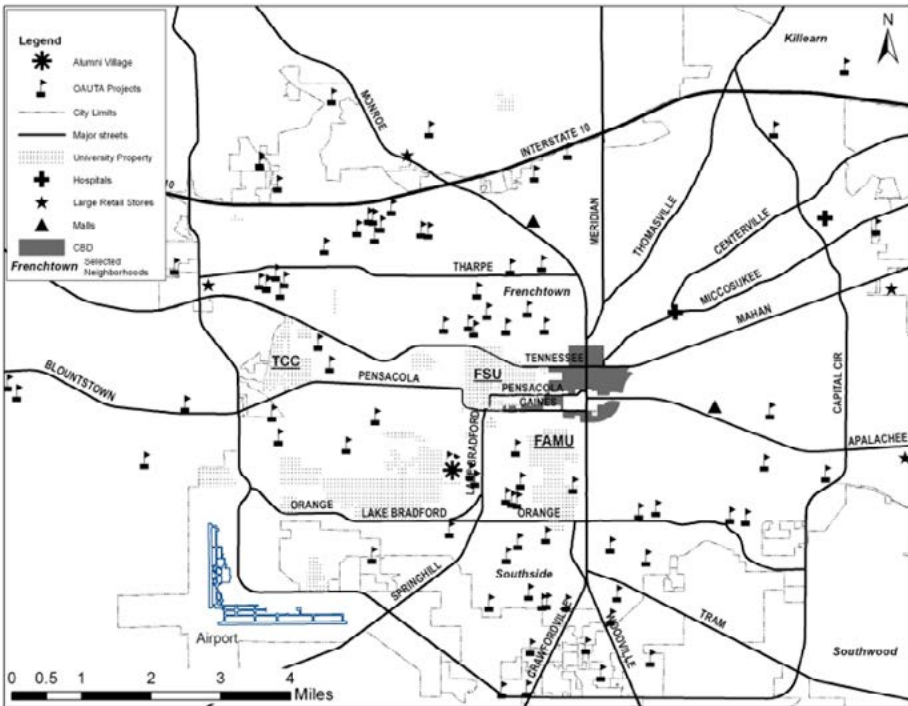
Figure 1. Major activity centers in Tallahassee, Florida

Many local observers believed there was a mismatch between the downtown-oriented transit system and the decentralized pattern of urban development, and local planners embraced the restructuring of the transit network as a means to increase transit's relevance and usefulness to the community. By making this major service change, planners sought to better align the geography of transit to the distribution of population and employment and to thus increase transit's appeal to potential riders. Planners also hoped to improve the agency's image in the community, thereby affecting the community's perception about the quality and convenience of transit service (StarMetro Transit Development Plan 2011). By changing the agency's image and providing service to new locations, planners hoped to increase use of the system by discretionary and infrequent riders in particular. Prior to the service change, more than 70 percent of StarMetro's riders were transit-dependent riders who lacked access to a car (Renaissance Planning Group 2009).

Figures 2 and 3 show the transit system before and after the July 2011 restructuring. Although visually similar, due to the overwhelmingly radial orientation of the local arterial road network, there are important differences between the two
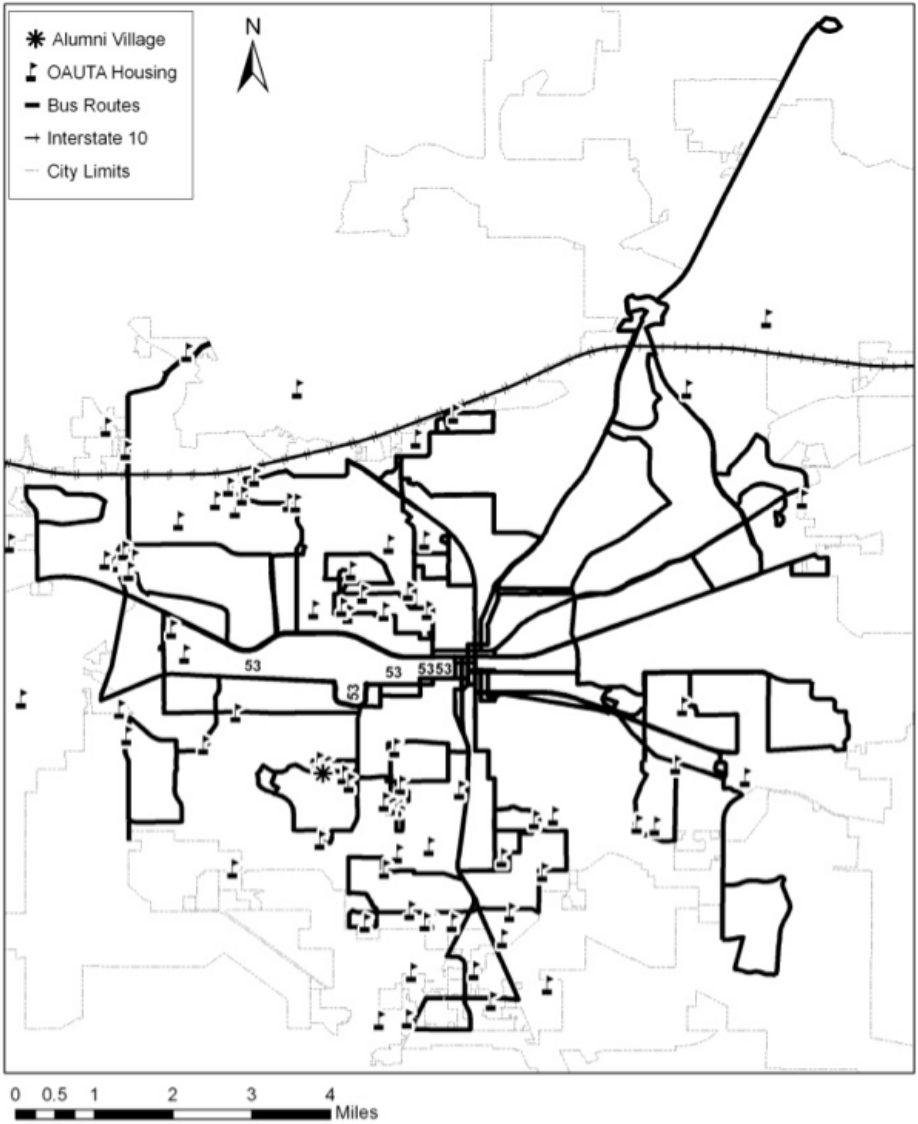
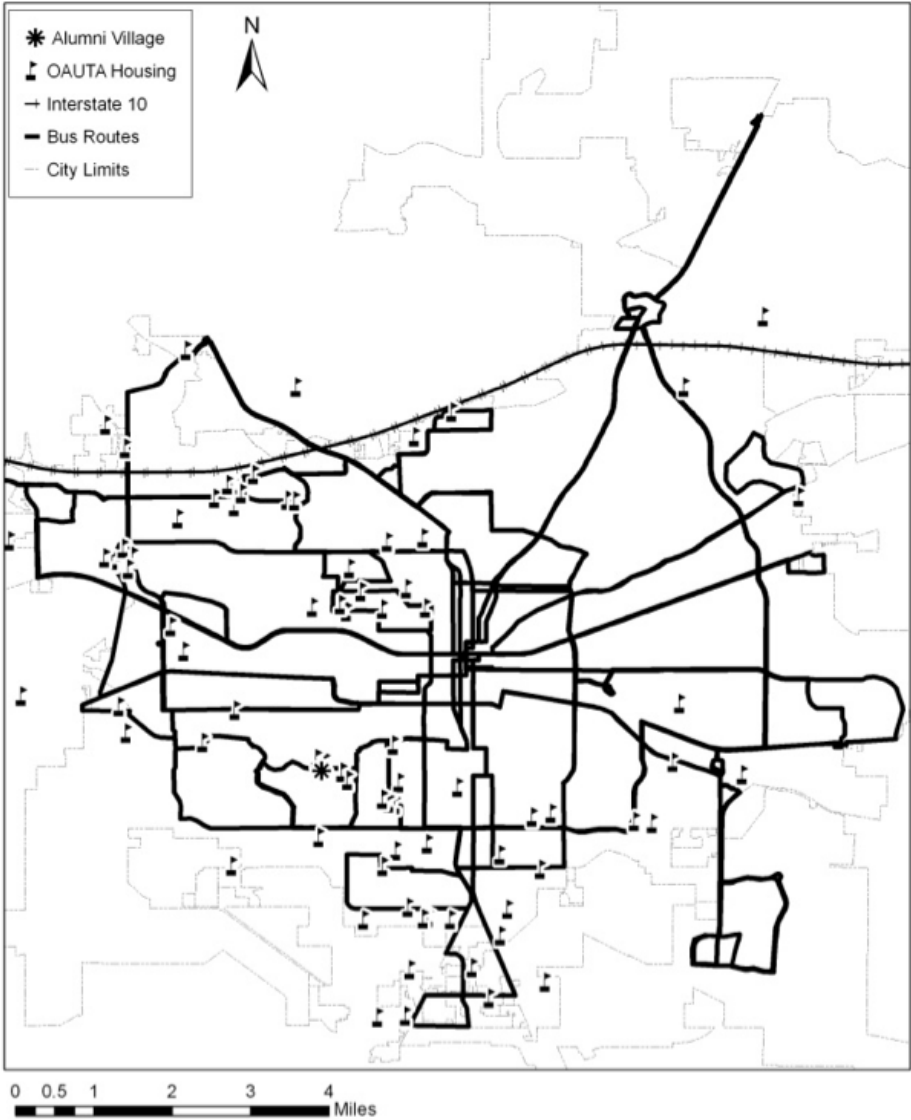**Figure 2. Transit system in Tallahassee before July 2011**

Figure 3. Transit system in Tallahassee after July 2011

network designs. The service restructuring removed many routes from within neighborhoods and placed them on arterial roads, so as to increase bus speeds and reduce travel times. New crosstown routes were added in several important north-south and east-west corridors, providing direct connections to and between outlying locations. In the old system, all routes terminated at a central terminal, where transfers had to be made for all crosstown trips. Through the restructuring, half of the new routes were removed entirely from the central terminal, with new transfer locations designated outside the center of Tallahassee that allowed riders to make their crosstown trips without making a deviation through the central business district (CBD). Planners believed that the net result of the route changes would be increased overall accessibility to destinations throughout the community, although the removal of routes from within neighborhoods would negatively affect some riders. StarMetro staff engaged in substantial public outreach during the two years preceding the actual service change, holding more than 100 public meetings, as they communicated their intentions to residents and made a series of adjustments to their plans based on public comments. These adjustments continued right up until implementation of the new system, and several additional minor route adjustments were made in the months that followed the service change.

A survey conducted prior to service restructuring demonstrated that StarMetro carried an overwhelmingly transit-dependent ridership consisting of two distinct groups of riders: a transient population of college students and a long-term population of low-income residents (Renaissance Planning Group 2009). Students accounted for more than 40 percent of riders, while other low-income, transit-dependent residents accounted for more than 30 percent. Both groups had low levels of vehicle access, which meant they relied heavily on transit service to meet their daily travel needs. They would, thus, be strongly affected by the service change, which was designed primarily with an eye toward increasing the system's appeal to infrequent and discretionary riders. Given their importance in the local transit market, the authors felt it would be particularly important to determine how these groups perceived and were ultimately affected by the service change.

To do so, the authors selected two large communities for targeted surveys and key informant interviews: Alumni Village, a student apartment complex, and the Orange Avenue Unified Tenant's Association (OAUTA), a tenant's group representing residents of local public housing complexes. Both communities consist overwhelmingly of low-income, transit-dependent residents. Their locations are denoted on Figure 1 shown earlier. Alumni Village houses the largest local concen-

tration of students within a single neighborhood. Many residents are international graduate students who do not have access to personal vehicles; some residents have families and, therefore, have varied travel needs.

Alumni Village residents are FSU students who must rely on a car or transit to reach classes and other community destinations due to the community's relatively isolated location. Residents are served by local bus routes and a dedicated campus shuttle route that operates on a limited basis only when classes are in session.

OAUTA is an organization of public housing tenants who reside in Tallahassee Housing Authority operated housing complexes located throughout the city. In general, however, most low-income housing complexes are scattered around the south and west of Tallahassee, as shown in Figure 1. Many housing complex residents lack easy access to a personal vehicle and depend on StarMetro to reach their employment or other important destinations. Residents are served by the local bus system whose routes were changed through the restructuring process.

Research Design and Methodology

The authors sought to address three questions with respect to the attitudes and behavior of residents of the two communities: Alumni Village and OAUTA. First, did perception of the service change affect the travel behavior of residents of these two communities? The authors use the results of surveys conducted in the two communities to address this question. Second, was perception more important than objective measures of service quality as a determinant of behavior? The authors relate results from surveys and interviews to quantitative indicators of service levels, and their change before and after the service change, to address this question. Finally, were there differences in perception, and/or in the influence of perception on behavior, between the two communities? The authors compare the survey results and interview results from key informant interviews in each community to one another to address this question.

The authors structure the analysis in three parts, each of which has a different set of data sources and methodologies. The first part, which the authors title "reality," represents the objective outcomes of the service restructuring in each of the surveyed communities in terms of the accessibility provided by transit to reach travel destinations. The second part, which the authors title "perception," consists of the results of community surveys and key informant interviews conducted in each of the communities. The third part, which the authors title "outcome," consists of the

measured travel behavior of community residents as obtained from community surveys and transit agency ridership data.

The authors use the concept of accessibility as a primary means of gauging the objective results of the restructuring on each community. This method involves calculating an accessibility score based on the number of transit-accessible destinations available from a particular location as discounted by the time it actually takes to reach these destinations (Handy and Niemeier 1997). The authors use employment as a measure of destinations, as is traditionally done in transportation analyses given its ability to represent employment destinations directly and to serve as a proxy for other destinations that are co-located with employment (Bhattacharya et al. 2013). To calculate the accessibility measure, the authors geocoded the locations of FSU student and low-income residential locations to their appropriate traffic analysis zone (TAZ) in a geographic information systems program, ArcGIS. The authors obtained student address data from the university registrar's office (FSU Office of University Registrar 2012) and low-income housing complex addresses from the Tallahassee Housing Authority website (http://www.tallha.org). The authors then obtained the travel time matrix from the regional transportation demand model for both transit networks (Travel Demand Model, http://www.crtpa.org/). The resulting zone-to-zone (TAZ) travel times were then linked to TAZ employment numbers acquired from U.S. Census Bureau (Longitudinal Employer-Household Dynamic, http://onthemap.ces.census.gov/) in the following accessibility formula:

$$A_i = \sum_{j=1 \text{ to } n} (Emp_j / T_{ij})$$

Where,

A_i = job accessibility from origin zone i to destination zone j

Emp_j = number of jobs within the destination zone j

T_{ij} = total transit travel time from origin zone i to destination zone j

The authors calculated the total accessibility for the combined sets of zones containing all FSU student housing and low-income housing complexes, before and after the service change. As part of the accessibility analysis, the authors consider the change in the locations of bus stops (which affects walk time to stops) and the service frequencies (headways) and locations of bus routes in the surveyed communities (which also affects the overall transit accessibility provided in the com-

munity). The authors obtained the stop location and service data directly from StarMetro staff (StarMetro 2011, 2012).

An important component of accessibility is travel time by transit. The authors use the regional travel model to calculate the change in three different components of transit travel time (walk time to a bus stop, in-vehicle travel time on the bus, and total travel time to begin and complete a trip) as a result of the restructuring to further investigate how each time component was affected by the transit system redesign and how each community experienced each of these changes in transit travel times. Such objective measures are useful tools for transit planners in understanding the effectiveness of transit, although the literature noted earlier suggests that perceptions are even more important determinants of individual behavior. For that reason, the authors pair the objective calculations just noted with a consideration of individuals' perceptions about transit service discussed below.

The perception analysis relies on the results of community surveys conducted in each of the two communities, as well as key informant interviews. The surveys focused on the respondents' satisfaction with 11 different aspects of transit service quality, including frequency, safety, accessibility, and amenities. Respondents graded each aspect of the transit system on an ordinal scale ranging from "very satisfied" to "very dissatisfied." The surveys were distributed electronically to residents of Alumni Village, using the complex's e-mail list serve, and by staff in the sampled OAUTA public housing complexes. There were 60 respondents for the Alumni Village survey and 76 respondents for the OAUTA survey. The authors also conducted 29 hour-long detailed interviews with key informants, including two from each of these communities to gain a better understanding of the prevailing perceptions of the community towards the service change as well as to learn about any outreach efforts conducted by StarMetro staff targeted towards these communities. Key informants were people in recognized leadership positions within each of the communities.

The outcomes analysis relies on measured effects on travel behavior as obtained from community surveys and stop-level monthly ridership data for a selected representative month for the neighborhoods surrounding the two communities obtained directly from StarMetro staff (StarMetro 2012).

The authors use the results of these two outcome analyses to understand the actual effects of the service change on travel behavior in the two communities and to understand the relative roles of perceptions vs. the objective measures

("reality") in influencing the travel behavior of community residents in each of the communities.

Results

The first part of the analysis is the objective examination of the service restructuring, which the authors label "reality." The removal of routes from within neighborhoods, decentralization of routes from the central terminal to outlying locations, and addition of new crosstown services through the restructuring did change the pattern of transit accessibility in the community. Figure 4 shows that 28 TAZs lost access to transit service, largely due to the removal of stops within neighborhoods, while 48 TAZs became accessible via transit service, due to the addition of new outlying service. It should be noted, of course, that this visual depiction ignores the reality that people residing in TAZs that lost service might still be able to walk to nearby bus stops located outside their home TAZ. The map indicates that TAZs added and removed are randomly distributed across the entire transit service area, with a few clusters in the east and south east, but, overall, there is no particular spatial pattern to the elimination or reduction of transit service.

The accessibility analysis indicates that both community groups enjoyed higher average transit accessibility to destinations as a result of restructuring. The average accessibility scores for the student community was 1076 before and 1162 after the service change. The average scores for the low-income community was 1363 before and 1451 after the change. Therefore, it can be concluded that the "real" change in accessibility after the service change was positive for both the groups, with the low-income community being made relatively better off, in terms of the ability to access more destinations via transit, than the student community, on average.

The travel time analyses indicate that the loss of stops within neighborhoods has led to increased walk times to bus stops for these communities. The average change in walk time was an added 3.15 minutes for the low-income residents but only an added 2.70 minutes for the students. However, the more direct routing led to lower in-vehicle travel times once riders reached their bus stops. The average reduction in total travel time was 9 minutes for low-income residents and 8 minutes for students. The net result of the restructuring was reduced overall travel times for both groups, with the benefits slightly greater for low-income residents than for students.

The analysis clearly indicates that some neighborhoods lost stops, and this very visible result of the restructuring emerged as an important issue in the surveys and

Figure 4. Change in service coverage before and after July 2011 restructuring

interviews discussed later. Given that people tend to value their time spent accessing or waiting for a bus as more burdensome than time spent actually in the vehicle (Thompson et al. 2012; Corradino Group 2008), the net results of the change with respect to travel time become much more difficult to evaluate. If riders value their time spent walking to the bus as two or three times as burdensome as time spent in the vehicle, which might be realistic considering the lack of significant sidewalk infrastructure in many of these communities, then the perceived net result of the restructuring might become closer to no effective change, or even negative.

Figure 5 shows the pattern of bus stop location change in several neighborhoods and corridors containing OAUTA housing complexes. Particularly noteworthy are the changes in the Southside community along the Orange Avenue corridor. It contained many public housing complexes that lost bus stops and, hence, its residents experienced longer walks. The other panels indicate changes in stop locations in the Northwest area, Frenchtown, and Alumni Village. From StarMetro's perspective, the addition of more frequent service and the addition of stops nearby might make up for the added inconvenience of the longer walk. But is it true from the rider's perspective as well?
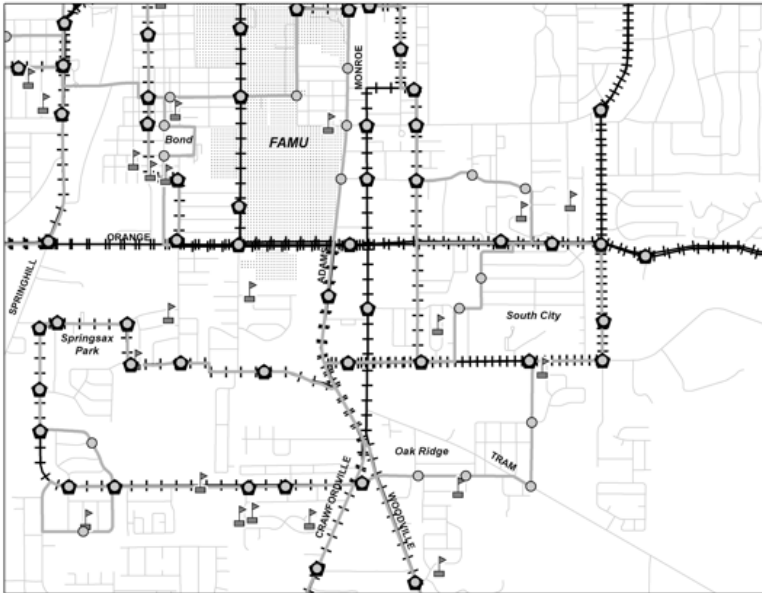
Southside
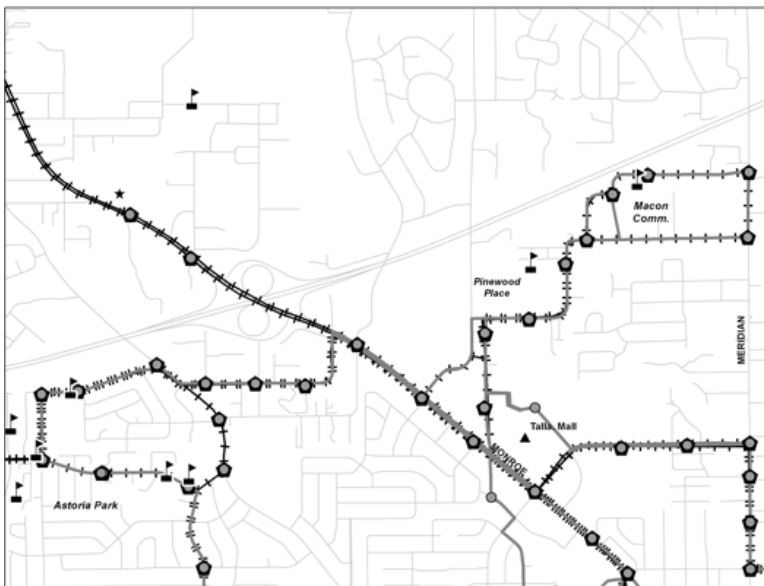
Northwest

Figure 5. Change in stop locations in selected neighborhoods
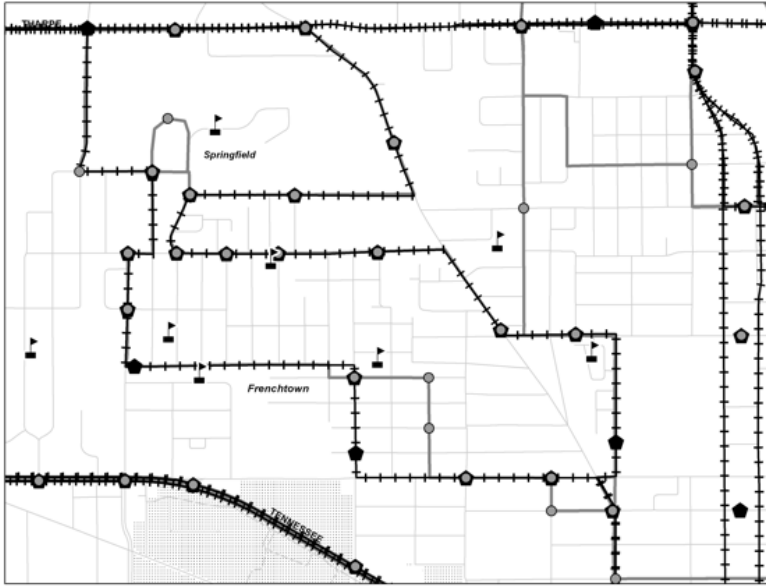
Frenchtown
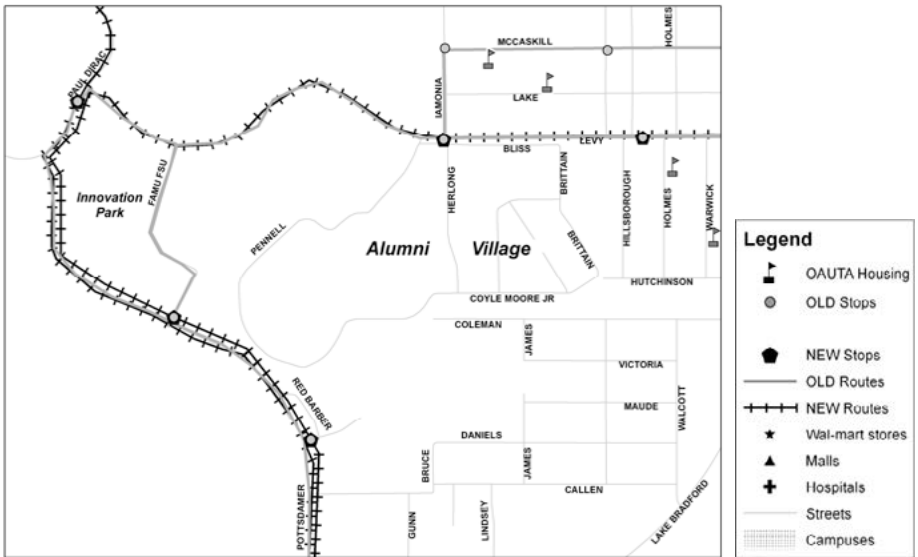
Alumni Village

Figure 5 (cont). Change in stop locations in selected neighborhoods

The authors relied on the community surveys and two key informant interviews from each of the two communities to document how residents in the two communities perceived the service change and its effects. The results from the two community surveys, conducted in summer 2012, are shown in Table 1.

Table 1. Resident Satisfaction with Transit Service Quality, Alumni Village (n=60) and OAUTA (n=76)

Category	Very Satisfied		Satisfied		Neutral		Dissatisfied		Very Dissatisfied	
	AV	*OAUTA*	*AV*	*OAUTA*	*AV*	*OAUTA*	*AV*	*OAUTA*	*AV*	*OAUTA*
Frequency of Service	15.0%	4.0%	45.0%	15.8%	13.3%	23.7%	18.3%	19.7%	8.3%	31.6%
Service to Destinations	27.6%	4.0%	22.4%	22.4%	22.4%	17.1%	17.2%	17.1%	10.3%	32.9%
Service in Neighborhood	26.7%	4.0%	46.7%	17.1%	16.7%	10.5%	16.7%	19.7%	3.3%	40.8%
Service Reliability	25.0%	1.3%	26.7%	13.2%	21.7%	19.7%	20.0%	23.7%	6.7%	36.8%
Night and Weekend Service	20.0%	4.0%	21.7%	10.5%	20.0%	19.7%	26.7%	15.8%	11.7%	38.2%
Sense of Personal Safety	35.0%	5.3%	45.0%	30.3%	11.7%	25.0%	3.3%	14.5%	5.0%	17.1%
Availability of Shelters, Benches, Sidewalks	25.0%	4.0%	36.7%	14.5%	18.3%	15.8%	11.7%	15.8%	8.3%	43.4%
Walking Distance to Bus Stop	28.3%	9.2%	41.7%	10.5%	16.7%	14.5%	8.3%	22.4%	5.0%	36.8%
Ease of Transfers/ Connections	13.3%	4.0%	25.0%	19.7%	36.7%	21.1%	13.3%	17.1%	11.7%	31.6%
Information on Service Changes	13.3%	5.3%	26.7%	10.5%	41.7%	21.1%	11.7%	23.7%	6.7%	30.3%
Overall Satisfaction with StarMetro Service	11.7%	4.0%	43.3%	10.5%	23.3%	21.1%	13.3%	25.0%	8.3%	32.9%

Source: Survey conducted by authors, 2012

Community Survey, 2012

Table 1 shows there are similarities and differences among the two sets of survey respondents in terms of their perceptions of the service change. On most questions, Alumni Village respondents expressed majority sentiment in the "satisfied" or "very satisfied" classes for each dimension of service quality. However, OAUTA respondents took an opposite view, with a majority falling into the "dissatisfied" or "very dissatisfied" categories on each dimension. The difference in perceptions was particularly striking with respect to the walking distance issue, with most Alumni Village residents satisfied or very satisfied about walking distance and OAUTA respondents dissatisfied or very dissatisfied. This distinction is particularly striking given the not-too-different actual changes in walk times to stops, noted earlier, for these two communities. Overall, Alumni Village respondents had an overall positive perception of transit service, whereas OAUTA respondents had an overwhelmingly negative perception. By and large, OAUTA respondents were quite dissatisfied with the results of the service changes.

Alumni Village respondents suggested service improvements that were very specific to their ease of reaching key destinations such as the FSU main campus, Walmart shopping centers, regional malls, and the airport, especially during weekend and off-peak hours. On the other hand, about half of the respondents in the OAUTA survey wanted StarMetro to bring back the old system. As a group, OAUTA respondents had much more specific complaints about the service change and suggestions for improvement than the Alumni Village respondent group, indicating their higher level of dissatisfaction with service restructuring. About 40 percent of Alumni Village residents were satisfied or very satisfied with Star Metro's outreach efforts, whereas more than 50 percent of OAUTA residents were dissatisfied or very dissatisfied with information provided to them regarding the service change.

The key informant interviews added additional insights into the perception of the restructuring, and of transit more generally, in each community. One particularly important issue that came up in the interviews was perception about the level and type of public outreach StarMetro conducted in each community in advance of the service restructuring. The Alumni Village interviewee voiced concern about the lack of advance warning from StarMetro staff about the relocation of bus stops from within the community to its periphery and about changes to evening service. This interviewee noted that Alumni Village staff and residents had to reach out to StarMetro, but that eventually StarMetro staff worked with the community

and seemed to be listening carefully to its needs. The interviewee at OAUTA also expressed concern about stop relocation but seemed to have a much more negative view of StarMetro's efforts to reach out to or address needs within this community around this and other service issues. Overall, StarMetro staff held more than 100 public meetings prior to restructuring the service, including some within close proximity to these communities. But there is still a clear perception among OAUTA respondents, in particular, that the outreach effort was insufficient or that staff did not adequately take into account their concerns raised during these outreach sessions.

The objective indicators indicate improved transit travel times and higher accessibility to destinations for each of the communities, with the low-income community having higher accessibility and more reduced total travel times than the student community, with the important caveat about residents experiencing longer average walk times to bus stops. However, the perception in one community (Alumni Village) was largely positive and the other was largely negative (OAUTA), which indicates an inconsistency between the objective indicators of service change and individual perceptions of the changes. So, what are the outcomes of the service change with respect to transit ridership and travel behavior in these communities? Do they differ? Is perception more important than reality?

At a system level, StarMetro was a primarily transit-dependent serving system prior to restructuring as well as afterward (Renaissance Planning Group 2009 and StarMetro Customer Satisfaction Survey 2012) (see Table 2). Those without regular access to vehicles dominated among respondents to surveys conducted both before and after the restructuring. However, the survey results also suggest that efforts to increase the system's appeal to infrequent and discretionary riders have succeeded to some degree, given modest increases shown in the number of infrequent riders and increased proportion of non-work and non-school trips. Overall, ridership on the new system is down slightly from the older system, on a month-to-month basis, although StarMetro staff caution that the short timeframe within which the new system has been operational has not provided sufficient time for riders to adjust. The average monthly decrease in systemwide ridership is around 12 percent. Still, the results in Tallahassee are similar to those found at similar points in time in other systems that made significant service changes (Jaroszynski et al. 2013).

Table 2. Results of Restructuring on Overall Transit Use in Tallahassee

	Before (2009)		After (2012)	
Car Access				
Yes	533	(27.08%)	82	(14.16%)
No	1,435	(72.92%)	497	(85.85%)
Total responses	1,968		579	
Frequency of Use (per week)				
More than 5 days	1,360	(69.11%)	348	(57.62%)
3–4 days	438	(22.26%	184	(30.46%)
2 days	89	(4.52%)	39	(6.46%)
0–1 day	81	(4.52%)	39	(6.46%)
Total responses	1,968		604	
Trip Purpose				
Work	1,095	(51.03%)	258	(31.77%)
School	744	(34.67%)	266	(32.76%)
Medical care	80	(3.73%)	99	(12.19%)
Leisure/other	227	(10.58%)	189	(23.28%)
Total responses	2,146		812	
Walk Distance to Bus Stop				
0–1/8 mile	191	(57.01%)	172	(29.66%)
1/8–1/4 mile	41	(12.24%)	128	(22.07%)
1/4–1/2 mile	23	(6.87%)	135	(23.28%)
More than 1/2 mile	80	(23.88%)	145	(25.00%)
Total responses	335	580		

Sources: Renaissance Planning Group 2009, StarMetro Customer Satisfaction Survey 2012

Table 3 explores the specific results in the two surveyed communities. Both sets of survey respondents consist overwhelmingly of individuals lacking vehicle access who use transit frequently for a diverse array of trip types. Both sets of respondents were also aware of the service change in July 2011. An overwhelming majority of the Alumni Village respondents are students (more than 83%; the remainder are spouses or dependents), whereas a plurality of the OAUTA respondents (just under 45%) are employed individuals. OAUTA respondents also included unemployed people, retired persons, and homemakers, representing a much more diverse group with diverse travel needs than the Alumni Village survey respondents. Nearly three-

quarters of Alumni Village respondents reported using transit about the same or more frequently than they did prior to the restructuring, while nearly two-thirds of the OAUTA respondents reported using transit less frequently than before restructuring. In general, the largely negative perception that OAUTA respondents have of the service change is indeed reflected in their lower use of the system, despite the objective indicators suggesting that the quality of the service provided to them has improved overall (based on the accessibility and total travel time measures).

The authors also obtained stop-level boarding data for the areas within which these two communities reside to serve as an additional source of outcome data about ridership changes before and after restructuring (StarMetro 2012). In the Southside area, where many OAUTA housing complexes are located, there were 44 stops that recorded 3,245 average monthly boardings in February 2011 (before restructuring); in February 2012 (after restructuring), 59 stops recorded 5,221 boardings, a significant increase in ridership in this area—although the presence of two major transfer points in the area complicates the results. On balance, ridership in this area is, thus, only slightly changed from before restructuring. In the Frenchtown area, also the location of a large number of OAUTA housing complexes, 47 stops recorded 11,275 average monthly boardings in February 2011, and 53 stops recorded 6,811 boardings in February 2012, indicating a significant drop in ridership in this area. For the Alumni Village area, 6 stops recorded 431 boardings in February 2011 and 6 stops recorded 1411 boardings in February 2012, representing a significant increase in ridership. By and large, the results of the stop-level boardings analyses echo those reported through the community surveys. The student community has increased its transit ridership, while the low-income community has decreased its ridership (when the net results for the Southside and Frenchtown are considered as a single whole).

Table 3. Results of Restructuring on Transit Use in Alumni Village (n=60) and OAUTA (n=76)

	AV	OAUTA
Access to an Automobile		
Yes	35.0%	25.0%
No	65.0%	72.4%
No response		2.6%
Use of Public Transit		
Never	3.3%	10.4%
Less than Once per Week	11.7%	19.5%
1–2 Days per Week	11.7%	10.4%
3–4 Days per Week	20.0%	23.4%
5 or More Days per Week	53.5%	35.1%
Use of Public Transit for Different Trip Types		
Work	43.3%	42.1%
School	83.3%	35.5%
Medical	15.0%	46.1%
Other	53.3%	38.2%
Awareness of Service Change in July 2011		
Yes	68.3%	67.1%
No	31.7%	32.9%
Change in Use of Transit Service Since Change in July 2011		
Using More Frequently	21.7%	14.5%
Using About the Same	55.0%	18.4%
Using Less Frequently	23.3%	65.8%
No Response		1.3%
Status of Respondent		
Employed	16.7%	31.6%
Employed and a Student	43.4%	13.2%
Student	40.0%	9.2%
Homemaker		15.8%
Unemployed		19.7%
Retired		10.5%
Total Responses	60	76

Source: Survey conducted by authors, 2012

Discussion

The objective ("reality") analysis of the service change suggests that both communities received increased accessibility and reduced total travel times as a result of the service change. It also indicates that the low-income community is relatively better off than the student community as a result of the change. They do have to walk slightly further than the student riders to reach a bus stop, on average, but once they reach the bus stops, their travel is faster, on average. While both rider groups experience higher accessibility levels after the restructuring, the low-income community has a higher accessibility score than the student community. However, the perception of the Alumni Village respondents is overwhelmingly positive, whereas that of the OAUTA respondents is overwhelmingly negative. Respondents in Alumni Village were also more satisfied with StarMetro's outreach efforts and responsiveness to their concerns than OAUTA respondents. However, it must also be cautioned that the non-random nature of the two surveys might affect the results. It is possible that the most dissatisfied persons responded in disproportionate numbers to the OAUTA survey. This is a possibility, although the consistency of the survey responses with the key informant interviews and local press coverage suggest that the survey is reflective of a larger community sentiment.

The travel behavior results suggest that perception exercises a stronger influence than the objective "reality" on attitudes and behavior in both communities. The community that perceived the service change positively responded favorably in terms of its actual use of public transit, whereas the community that perceived the change negatively responded negatively in terms of its actual use, based on both the travel survey and stop-level results. These results occurred despite the fact that the community that perceived the changes most favorably (students in Alumni Village) was actually not made as better off as the community that perceived the changes less favorably (OAUTA). Perception definitely affected people's behavior in the two communities surveyed, and it proved more powerful an influence on behavior than the objective measures of service change ("reality"). These results clearly indicate that in these communities, and particularly among low-income residents, more outreach efforts targeted at influencing individual perceptions are needed to increase transit ridership. StarMetro staff made significant efforts at public outreach to explain the service changes prior to their occurrence, including hosting more than 100 public meetings, but the nature of that outreach was clearly perceived to be insufficient and turned out to be relatively ineffective in at least one of the two communities.

Recommendation

The study indicates that in the case of the transit restructuring in Tallahassee, perception matters and was a stronger influence on travel behavior than were objective measures of the service change. This case indicates the importance of effective outreach geared toward understanding how and why communities have particular perceptions of the effects of planning decisions, particularly perceptions that, at least superficially, appear to be different from the objective measures typically used by planners to make and evaluate decisions (Innes and Booher 2010). Effective outreach should involve a genuine dialogue with the community to better understand their issues and concerns and should not be limited to making presentations or delivering information. The more engaged the community is in the dialogue, the greater the ability to change their perceptions, or perhaps even for planners to change their own views to better reflect the needs and concerns of the communities for which they are planning (Wirthlin Worldwide and FJCandN 2000). Whenever members of a community feel left out of a decision making process that affects their day-to-day lives, there is much greater likelihood of detachment, negative perceptions, and a general lack of acceptance of the solutions defined by "others" who are not part of the community. The low-income community discussed in this study would appear to fall into this category, whereas the outreach done, albeit somewhat belatedly, in the student community appears to have been successful in helping to gain more acceptance of the service change by these individuals.

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Testing Individuals' Ability to Compare Emissions from Public Transport and Driving Trips

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Abstract

To make informed environmental choices, individuals must first understand the potential environmental impacts of the modes of transport available and be able to relate this information to their own internal reference points. This study examines the results of an on-line survey conducted to assess the ability of individuals in the Greater Dublin Area to estimate their potential carbon footprint for a variety of modes of transport. The results indicate that nearly one third of those surveyed stated that they simply did not know the carbon footprint of the modes in question, while those who provided emissions estimates showed a wide range of variance. Comparison with existing emissions factors indicates that respondents overestimate the environmental impact of bus journeys and underestimate the impact of small car and tram trips. The results of this study indicate the need for more specific emissions information to allow individuals to make informed and sustainable mode choices.

Introduction

Human economic activity is now recognized by the majority of scientists as a contributor to global climate change due to the emissions of greenhouse gases (GHGs) such as carbon dioxide (Bray 2010). In the Republic of Ireland, transport

emissions are estimated to have accounted for 19 percent of total emissions produced for the period 2008–2012 (EPA 2012). While there is an apparent awareness among the population about the impact of their carbon emissions, there are also a number of barriers to the desired behavior change, including lack of knowledge about the benefits of sustainable transport (Browne et al. 2011; Lorenzoni et al. 2007). If individuals are to be able to make decisions with the aim of reducing their transport-related carbon footprint, they need to be sure that they are choosing the most sustainable alternatives available to them, such as public transport and non-motorized modes. While there is an ever-increasing number of carbon footprint calculators available for a number of different technological platforms, offering comparisons between transport modes, it is still unclear to what extend these have educated the population with regard to carbon emissions, as these calculations are often far from consistent in terms of outputs (Kenny and Gray 2009). This study seeks to examine the ability of the general public to assign values and implicit rankings to the carbon emissions associated with driving and a number of different public transport modes available in the Greater Dublin Area (GDA) as defined by the National Transport Authority (NTA).

Public Transport in Dublin

The public transport system in Dublin is highly radial in nature and is centered upon the city center and Central Business District (CBD). The rise in low-density urban sprawl that accompanied the economic upturn, labeled the "Celtic Tiger," has resulted in a geo-spatial environment that is far from ideal in terms of the provision of public transport (Browne et al. 2011). Despite the construction of two new "Luas" tram lines and the upgrading of existing commuter rail services, large sections of the Greater Dublin Area remain accessible only by bus service. Existing bus networks are themselves highly radial, and service frequency levels vary widely across the network, leaving travelers certain areas of the GDA with little option but to drive (Caulfield 2012). This is reflected in recent census figures (Central Statistics Office 2012) which indicate the of the 529,812 residents Dublin making trips to work, 12.4 percent took bus, coach, or minibus and 7.5 percent took train or tram. In contrast, 49.2 percent stated that they drove to work, and this figure rises to 55.5 percent when accounting for car passengers and commercial vehicles. When compared to the Irish governments policy targets (DoT 2009) of a 20 percent reduction in car commuter trips nationally and the majority of the commuter trips being undertaken using sustainable modes, it is clear that significant behavior change is needed with regard to utilizing existing public transport.

Survey Methodology

The research questions discussed in this paper formed part of wider study concerning carbon dioxide emissions and transport choices in the Greater Dublin Area. An online questionnaire (n=503) was distributed to a number of large public sector institutions, including municipal councils and government departments, in November and December 2012. Special attention was paid to ensure that organizations outside the CBD were included to capture suburb commutes, as these are likely to be very different from those anchored in the CBD. Table 1 outlines the demographic characteristics of the sample. Partly as a consequence of the distribution methods employed, the sample is over-representative of younger individuals and those with higher levels of education. As this survey was conducted online, some respondents failed to provide demographic information; however, this was not deemed an adequate reason to eliminate their estimates from the analysis.

Table 1. Sample Properties

Gender	Male	Female	NA*			
	42.8 (34.8)	57.2 (46.5)	18.7			
Age	15-24	25-34	35-44	45-54	55+	NA
	15.7 (12.3)	25.5 (20.1)	24.7 (19.5)	25 (19.7)	9.1 (7.2)	(21.3)
Education	High school	Diploma	Bachelor's degree	Higher degree	NA	
	25.4 (20.5)	17.7 (14.3)	22.9 (18.5)	34 (27.4)	(19.3)	
Income	€0-24K	€25-49K	€50-74K	€75-99K	€100k +	NA
	22.2 (17.9)	44.6 (36)	20.9 (16.9)	6.4 (5.2)	2 (1.6)	(22.5)

* NA = no answer

Environmental Attitudes

As part of this survey, respondents were asked to give their opinions on a number of statements regarding their existing attitudes towards climate change and transport. The results in Figure 1 show that the majority of respondents agree that climate change is occurring and is a serious issue, and they have a personal responsibility in this area.
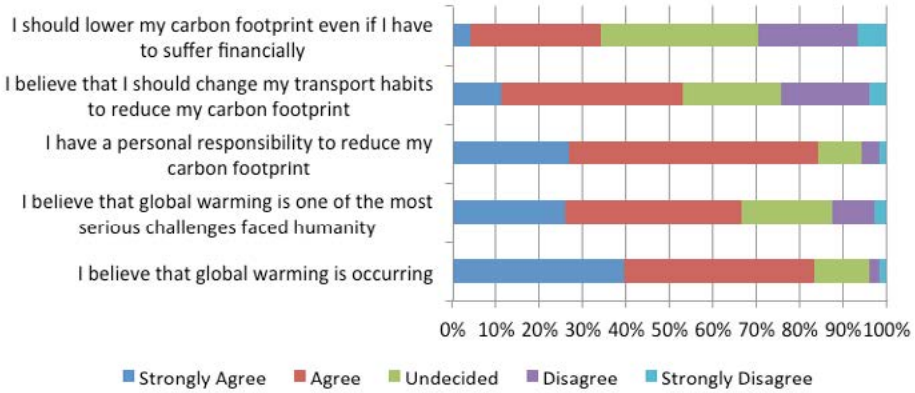
Figure 1. Attitudes towards climate change

Access to Sustainable Transport

While it appears that there is concern and appreciation of the need to take action with regard to transport behavior, there were also a number of barriers identified that prevent the necessary changes from occurring. The uneven geographical distribution of environmentally-friendly alternatives, alluded to previously, was reflected in the results of the respondents' perceived access to sustainable modes. Figures 2 and 3 indicate that perceived access to sustainable transport for both work/educational trips and non-work/educational trips declines with respect to distance of the respondents' homes from the city center. The issue of access to sustainable modes of transport becomes more acute as the length of commuting journeys increases with respect to distance from the city center. As journey length is a major factor in terms of the production carbon dioxide emissions, the result of this is that individuals produce much higher emissions in rural areas (McNamara and Caulfield 2011).
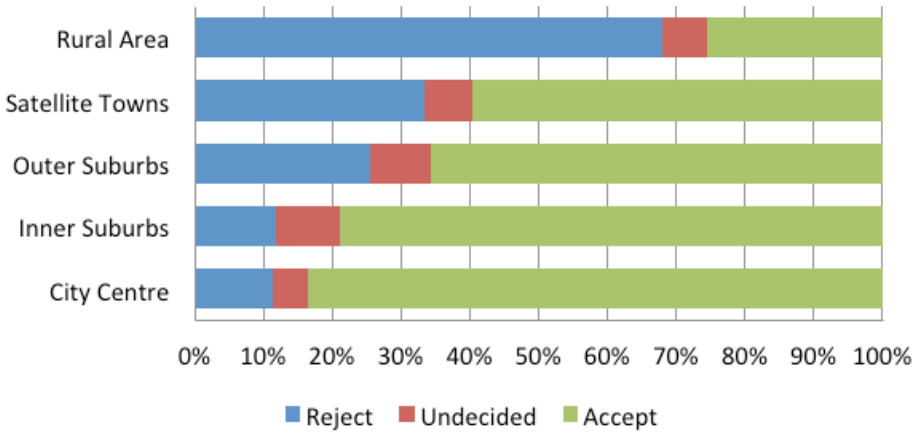
Figure 2. Access to sustainable transport vs. residence (commuting/educational trips)
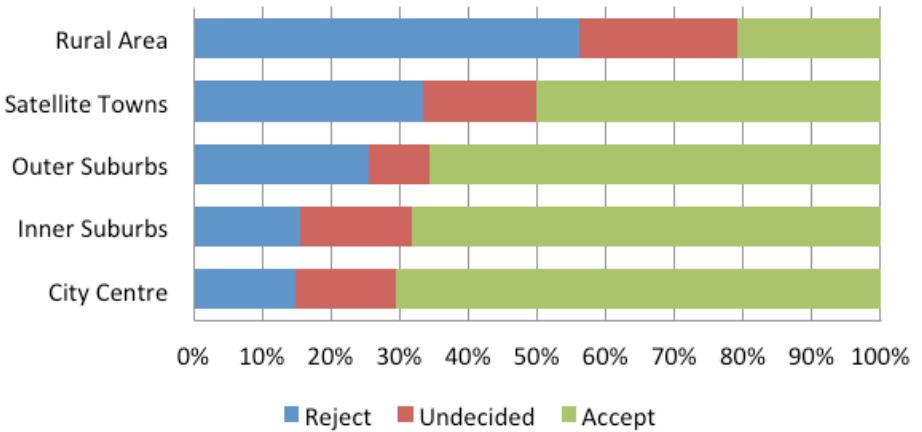
Figure 3. Access to sustainable transport vs. residence (non-commuting/educational trips)

Informed Decisions

Among the questions posed to respondents was the statement, "I have enough information to make informed transport choices." The responses displayed in Figure 4 indicate that the majority of respondents believe this to be true, with less than 20 percent disagreeing. However, due to concerns regarding the capacity of

individuals to assess their own abilities highlighted in the literature (Whitmarsh et al. 2011; Lorenzoni et al. 2007) and issues such as self report bias and social desirability bias, it was decided to test this assertion further.
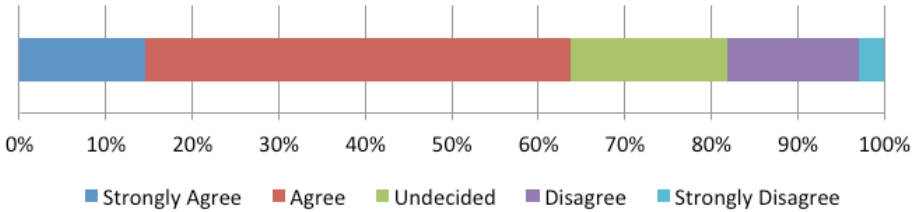
Figure 4. "I have enough information to make informed transport choices"

Testing Emissions Knowledge

While respondents may have been of the opinion that they are able to make informed choices with regard to sustainable transport options, this would appear to contradict findings from the literature (Whitmarsh et al. 2011; Gadema and Oglethorpe 2011). Carbon dioxide emissions have a number of specific features that make them harder to relate to than other aerosol pollutants. Carbon dioxide is both colorless and odourless, and emissions may be produced at a distance, both in terms in time and space, from the individual who benefits from the related economic activity. A prime example in public transport is the tram system in Dublin. The tram itself does not produce any emissions directly, as it is powered electrically. However, due to its operation, a large amount of electricity energy must be used, the majority of which is produced from fossil fuels (Howley 2009). To test this hypothesis, respondents were asked to estimate how much CO_2 six different modes would emit for a 10km journey. The six modes considered for this experiment were:

- Small car (defined as less than 1.6L)
- Large car (defined as 1.6L+)
- Tram (light rail system operating in the Greater Dublin Area)
- Heavy rail (DART/suburban rail system operating in the Greater Dublin Area)
- SUV (sports utility vehicle)
- Bus

These modes represented the majority of trips undertaken in the GDA (Central Statistics Office 2012). The decision to provide respondents with three driving options was due to the large proportion of trips accounted for by this mode (Gormley 2011). It is also important to consider that there are individuals who do not have access to sustainable modes of transport and, therefore, their only option, with respect to emissions reduction, may be to switch to car models with lower emissions ratings. Electric vehicles were omitted, as they are still uncommon in Dublin, and the emissions arising from non-motorized modes (Walsh et al. 2008) were not assessed, as it was felt that this may confuse respondents.

Although it could be possible that it that individuals may not possess knowledge of the precise emissions related to their trips, the format of the question allowed modes to be ranked in relation to one and another, in terms of associated carbon dioxide emissions.

The decision to present the respondent with categories that were non-uniform in size was due to the wide range in emissions that are related to different modes. As the average emissions of a mode increases, so does the range of values across which any given measurement may fall, resulting in a heteroscedastic pattern of possible emissions values.

The categories were intended to capture, as much as possible, the range into which modes were likely to fall—i.e., car trips usually fall between 1kg and 5kg and Luas tram trips between 250g and 1 kg (Walsh et al. 2008). Figure 5 displays the question interface that was presented to respondents as part of the survey. It clearly indicates that emissions are per passenger, rather than for the vehicle as a whole.
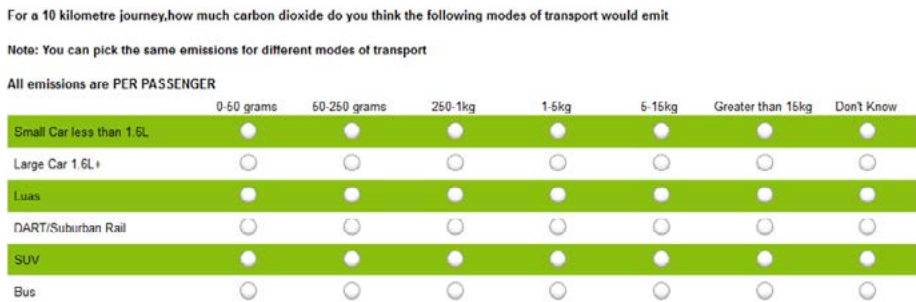
Figure 5. Emissions test

Results

Emissions Estimates

Table 2 displays the percentage of respondents who simply stated that they did not know the emissions associated with each mode. This represents roughly one third of overall respondents. This finding, in itself, indicates that a sizable proportion of the population is simply unable to provide any type of estimate, or even guess, regarding their transport emissions. As the question was presented in the first section of the survey, we can discount the influence of survey fatigue. For the rest of the paper, analysis was performed on only the respondents that provided emissions estimates (henceforth known as "participants"). It was found that the vast majority of individuals who stated that they did not know for any given mode also failed to provide estimates for any of the other modes. Therefore, it was decided to consider all emissions estimates provided for the purpose of further analysis.

Table 2. "Don't Know"

	Small Car	Large Car	SUV	Bus	Tram	Heavy Rail
Don't Know	32%	32.6%	32.6%	32%	32.4%	33.5%

Figure 6 displays the distribution of the participants' emissions selections for each of the modes under consideration. It is clear that participants, on average, assign higher emissions values to Large Cars and SUV than to public transport modes such as Bus and Heavy Rail (DART). It is also clear that the Tram option is the mode associated with the lowest emissions estimates.
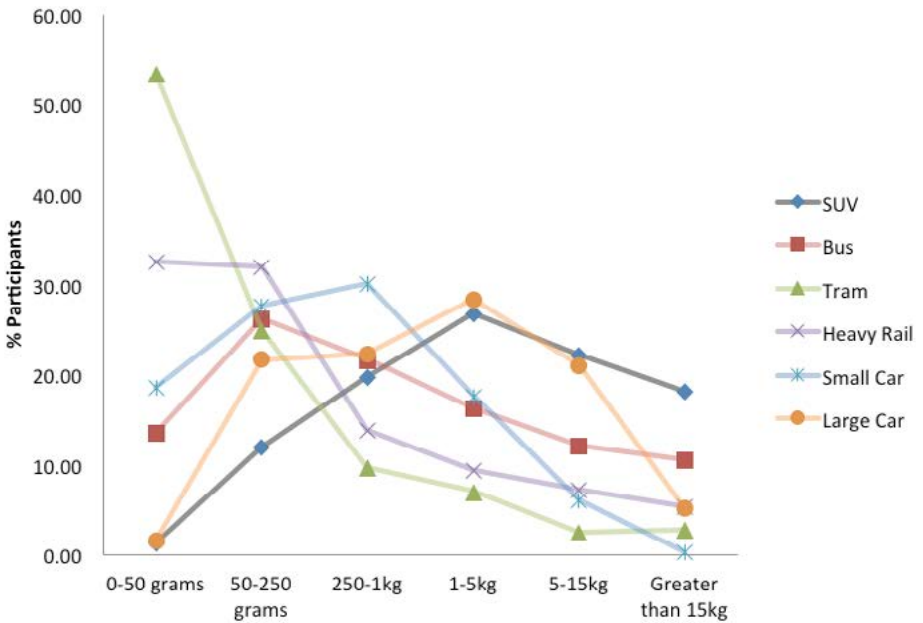
Figure 6. Participants vs. emissions estimates

Whereas Figure 6 presents the aggregate absolute category selection of respon-
dents, it is also important consider the perceived relative position of modes in
terms of associated carbon emissions. When an individual is faced with a decision
between modes based upon his/her environmental impact, it may not be impor-
tant that he/she is aware of the absolute emissions related to each mode, rather
that he/she is able to recognize the differences in scale between the emissions asso-
ciated by the available options. Acknowledging the need to assess relative emis-
sions placement, Figure 7 presents the results of emissions comparisons between
modes. Using the ordinal values assigned to categories in Table 3, it is possible to
assess the aggregate "distance" between emissions estimates. For example, if an
individual placed Small Car emissions in Category 4 and SUV emissions in Category
6, the distance between these estimates is +2. For results presented in Figure 7,
positive values relate to higher estimates and negative values to lower relative esti-
mates. For example, it can be observed that aggregate estimates place SUV higher
and Tram lower than all other modes and that the Bus option has higher associated
emissions relative to the Small Car option.
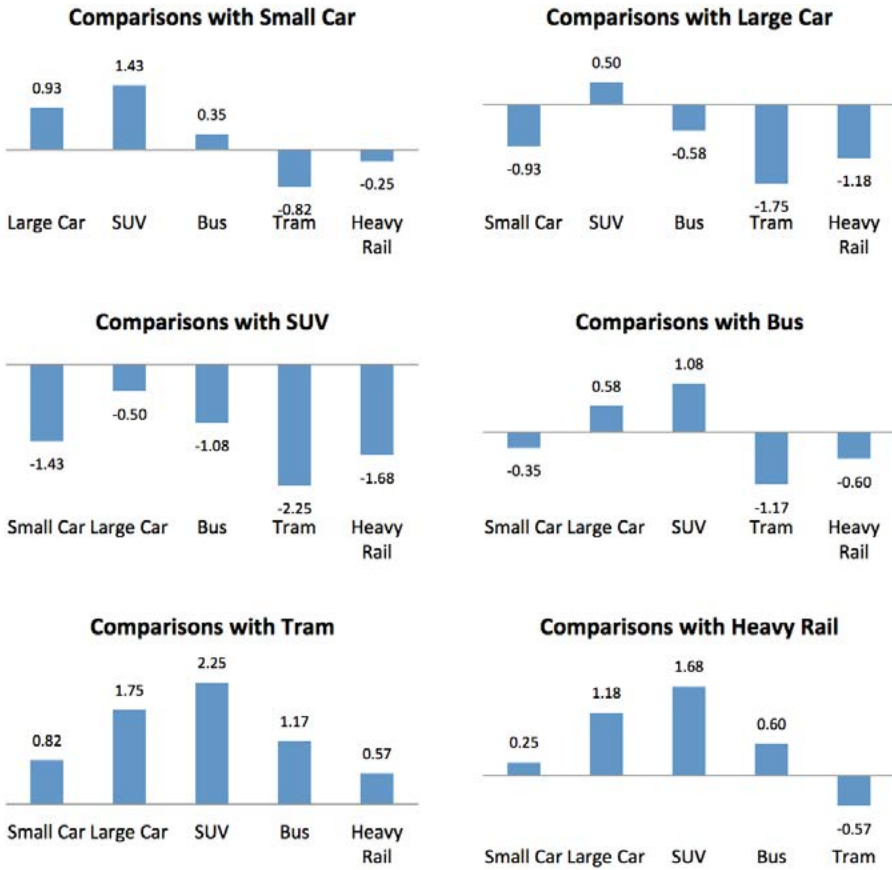
Figure 7. Mode comparisons

Table 3. Assignment of ordinal values

Category	0–50g	50–250g	250g–1kg	1–5kg	5–15kg	>15 kg
Ordinal Value	1	2	3	4	5	6

As the emissions estimates were bound by the need to acknowledge real-world conditions, where modes have emissions ranges rather than definitive values, and where it is possible that these ranges overlap, the respondent selections cannot be treated as ranked data. Within the sample, 161 distinct relative emissions ordering

patterns were observed, with none occurring more than 20 times. Further analysis of mode ranking with respect to emissions factors is presented in the next section.

Accuracy of Estimates

It was deemed important to provide a comparison with the participants' estimates and current emissions estimates for the Greater Dublin Area. Using the emissions values put forward by Walsh et al. (2008) concerning carbon emissions produced by transport modes in Ireland, it is possible to conduct a comparison between the participants' estimates and existing emissions factors. Values for Small Car and Large Car are taken as falling between 1–5kg. Walsh et al. (2008) gives a value of 0.120 per passenger for general cars in "normal" conditions. The United Kingdom's Transport Direct website (Transport Direct, accessed 2013) carbon calculator gives a small car value of 1.3kg for a 10km journey, and Transport for Scotland (Traffic Scotland, accessed 2013) gives a value of 1.7kg for a petrol car with an engine capacity of below 1.4 litres, so we can assume that both car categories are likely to fall within the 1–5kg range.

Tables 4, 5, and 6 indicate the categories into which each respective mode is most likely to fall and, based upon this, how accurate the participants' estimates were. To account for variances in per-passenger carbon emissions with regard to vehicle occupancy, the results were presented for modes at both average and full occupancy. Results assuming average vehicle occupancy are displayed in Table 4, and Table 5 presents the results associated with maximum occupancy. The adjusted results displayed in Table 6 represent a summation of the correct selections from the two categories and takes into account the respondents who stated that they were unable to assign values to the modes.

Table 4. Assuming Average Emissions Values

	Small Car (Av)	Large Car (Av)	SUV (Av)	Bus (Av)	Luas (Av)	DART (Av)
Emissions	1.2 kg	1.5 kg	1.8kg	0.35kg	0.8 kg	0.29kg
Category	1-5kg	1-5kg	1-5kg	250-1kg	250-1kg	250-1kg
% Correct	17.1%	31.1%	27.1%	21.9%	10.3%	15.1%

Table 5. Assuming Maximum Occupancy Emissions

	Small Car (Max)	Large Car (Max)	SUV (Max)	Bus (Max)	Luas (Max)	DART (Max)
Emissions	~0.4kg	~0.5 kg	0.68	0.16	0.64	0.11
Category	250-1kg	250-1kg	250-1kg	50-250kg	250-1kg	50-250g
% Correct	29.9%	19.3%	20%	29.1%	10%	32.3%

Table 6. Adjusted Accuracy

	Small Car	Large Car	SUV	Bus	Luas	DART
Sum	47%	50.4%	47.1%	50%	10%	47.4%
Adj.	32%	33.4	31.7%	34%	6.8%	31.5

For most modes, participants displayed an accuracy rate of 45–50 percent, which when adjusted for all respondents corresponds to a 30–35 percent rate. The most striking result appears to be with regard to the accuracy of Tram estimates, with only than 10 per cent of participants correctly estimating its associated emissions, even when both occupancy levels are assumed.

Treating both average and maximum occupancy values as correct, it is possible to categorize the remaining selections as either underestimates or overestimates. Results displayed in Figure 8 clearly indicate that a large number of participants underestimated emissions for both Small Car and Heavy Rail. However, the most striking result is that 81 percent of participants underestimated the emissions associated with the Tram option.

In both the case of assuming average or maximum occupancy, a number of logical relationships emerge, such as all public transport modes having lower emissions than driving modes or all driving modes falling into the same category. The results in Table 7 indicate the percentage of participants that correctly identified the emissions relationships between modes. Perhaps the most striking result is that only 34.6 percent of participants correctly stated that all driving modes produce higher emissions than all public transport modes. This can be considered somewhat worrying from a public transport perspective, as it appears that individuals may not be aware of the potential emissions reductions associated with switching from driving.
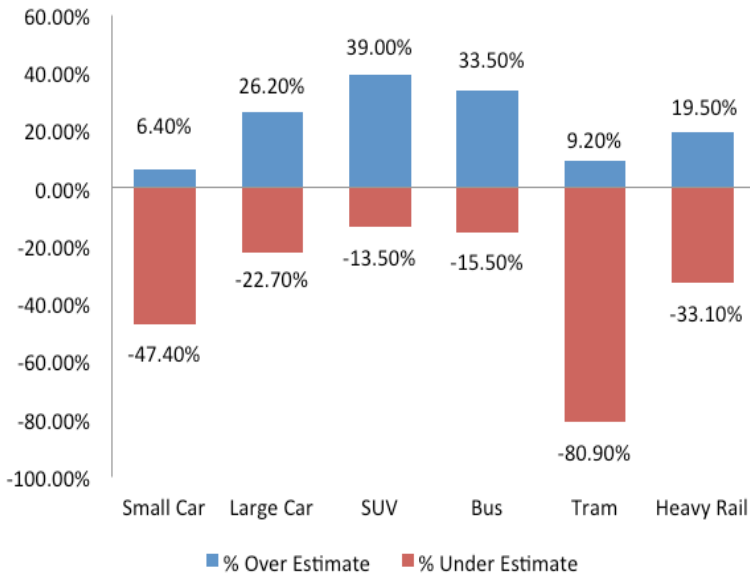
Figure 8. Underestimation and overestimation of emissions

Table 7. Comparisons

SUV= Large Car	SUV= Small Car	SUV> Tram	SUV> Bus	SUV> Heavy Rail	Large Car= Small Car
110	26	226	163	197	46
43.8%	10.3%	90%	65%	78.5%	18.3%
Large Car >Tram	**Large Car >Bus**	**Large Car >Heavy Rail**	**Small Car >Tram**	**Small Car >Bus**	**Small Car >Heavy Rail**
214	147	186	165	94	128
85.2%	58.5%	74.1%	65.7%%	37.4%	50.9%
Bus=Tram	**Bus >Heavy Rail**	**Tram >Heavy Rail**	**All Cars Equal**	**All Cars >All PT**	**All Correct**
73	123	12	20	87	0
29%	49%	4.8%	7.9%	34.6%	0%

Conclusions and Discussion

The results of the attitudinal statements contained in this research, presented in Figure 1, indicate that there is widespread recognition that climate change is a serious problem and that individuals acknowledge that they have personal responsibility with regard to tackling this issue. There are a number of barriers in terms

of changing transport behavior, including perceived lack of access to sustainable modes with respect to residential location. While public transport offers a realistic sustainable alternative to a considerable proportion of the population, this is tempered by the inability of respondents to make accurate estimates concerning the impact of their transport choices.

The results of the examination of emissions knowledge indicate that a minority of the population has a good knowledge of the carbon dioxide emissions associated with different modes of transport. Roughly one third of those surveyed stated that they simply did not know the levels of emissions for each mode. This is in contrast to the stated ability of respondents to make informed transport choices. This indicates that not only are individuals unable to make accurate comparisons between available modes, they are also overly confident of their own abilities.

For those respondents who did answer, the overall carbon footprint of public transport modes was estimated to be less than driving. Tram and heavy rail were estimated to produce fewer emissions than any driving categories; however, bus journeys were viewed as falling with the same categories as driving.

The environmental impact of small cars was underestimated suggesting that individuals may be of opinion that switching to a smaller car may be an effective method of reducing their carbon footprint, whereas substantial reductions can occur via only mode change. The environmental impact of the tram system was also greatly underestimated, while the carbon emissions attributed to buses were overestimated. One potential explanation for this is that the tram system is relatively new and has no visible emissions, whereas buses produce visible emissions that may be confused with GHGs. It may also be the case that respondents were unable to understand the idea of per-passenger emissions rather than total vehicular emissions. However, this would also be of concern with regard to taking personal responsibility for transport emissions as individuals should be able to acknowledge their own personal contributions to climate change.

If individuals are to be asked to make sustainable personal transport choices, they must have the ability to make accurate comparisons with regard to the environmental impact of the modes available to them. In general, public transport modes were viewed as more sustainable than driving, with the exception of bus journeys. The overestimation of carbon emissions associated with bus journeys may result in individuals overlooking this mode as a sustainable alternative.

This may be considered as an important research outcome, as individuals appear to be overestimating the environmental impact of the largest and most extensive public transport option in the Greater Dublin Area (Central Statistics Office 2012). The results of this study highlight that there is a need to provide better levels of education and information to transport users with regard to the environmental impacts of the alternatives available to them, in particular with regard to the city's bus network.

Acknowledgments

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Artificial Neural Network Travel Time Prediction Model for Buses Using Only GPS Data

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Abstract

Real-time and accurate travel time information of transit vehicles is valuable as it allows passengers to plan their trips to minimize waiting times. The objective of this research was to develop a dynamic artificial neural network (ANN) model that can provide accurate prediction of bus travel times to give real-time information at a given downstream bus stop using only global positioning system (GPS) data. The ANN model is trained off-line but can be used to provide real-time travel time information. To achieve this, care was taken in selecting a unique set of input-output combinations for prediction. The results obtained from the case study are promising to implement an Advanced Public Transportation System (APTS). The performance of the proposed ANN model was compared with a historical average model under two criteria: prediction accuracy and robustness. It was shown that the ANN outperformed the average approach in both aspects.

Introduction

Growing traffic congestion has posed threat to the quality of life of people in many countries over the past few decades. Congestion in general leads to a decrease in accessibility and mobility, travel time loss, and air pollution. Many different solution techniques have been suggested, including demand-side (congestion pricing, traffic management, etc.) and supply-side (constructing more roads, adding lanes,

etc.) or their integration, for mitigation of congestion. One potential supply-side tactic is to improve and expand public transportation service (Houghton et al. 2009; Dewan and Ahmad 2007). Public transport service can be enhanced by providing travelers with reliable travel information through the help of an Advanced Public Transportation System (APTS), which is one component of Intelligent Transportation Systems (ITS) (Houghton et al. 2009; Vanajakshi et al. 2009). Travel time information is the most preferred information by travelers. The provision of timely and accurate transit travel time is vital because it attracts more people to public transport and increases the contentment of transit users (Jeong and Rilett 2004). However, real-time travel time information cannot be measured directly. Therefore, to provide passengers with this information, mathematical models that can predict travel time with reasonable accuracy are required. A variety of prediction models for forecasting traffic states such as travel time and traffic flow have been developed over the years. The most widely-used bus travel time prediction models can be classified into four categories, which are discussed below.

1. **Historical Average Models** (Jeong and Rilett 2004; Farhan et al. 2002; Ramakrishna et al. 2006).   Historic data-based average prediction models give the current and future travel time from the historical bus travel time of previous journeys, and the current traffic condition is assumed to remain stationary. Therefore, a model of this kind is reliable only when the traffic pattern in the area of interest is relatively stable or where congestion is minimal, e.g., rural areas.

2. **Regression Models** (Jeong and Rilett 2004; Ramakrishna et al. 2006; Patnaik et al. 2004; Chien et al. 2002; Chen et al. 2004; Shalaby and Farhan 2003). Regression models predict and explain a dependent variable with a linear function formed by a set of independent variables. Unlike historical data-based prediction models, these are able to work satisfactorily under unstable traffic condition. Regression models usually measure the simultaneous effects of various factors, which are independent between one and another, affecting the dependent variable. Patnaik et al. (2004) proposed a set of multiple linear regression models to estimate bus arrival times using data collected by automatic passenger counters (APC). Distance, number of stops, dwell times, number of boarding and alighting passengers, and weather descriptors were used as independent variables. The study indicated that the models could be used to estimate bus arrival time at downstream stops. Jeong and Rilett (2004) and Ramakrishna et al. (2006) also developed multiple linear regression

models using different sets of inputs. Both studies indicated that regression models are outperformed by other type of models. However, one great advantage of multiple linear regression models is that they can reveal which inputs are less or more important for predicting travel times. For example, Patnaik et al. (2004) discovered that weather was not an important input in their model. Ramakrishna et al. (2006) also found out that bus stop dwell times from the origin of the route to the current bus stop in minutes and intersection delays from the origin of the route to the current bus stop in minutes are less important inputs. In general, the applicability of regression models is limited because variables in transportation systems are highly intercorrelated (Chien et al. 2002).

3. **Kalman Filtering Models** (Chien et al. 2002; Shalaby and Farhan 2003). Kalman filtering models have elegant mathematical representations (e.g., linear state-space equation) and the potential to adequately accommodate traffic fluctuations with time-dependent parameters (e.g., Kalman gain) (Chien et al. 2002). These models have been used extensively for predicting bus arrival time (Chien et al. 2002; Chen et al. 2004; Shalaby and Farhan 2003). Their basic function is to provide estimates of the current state of the system, but they also serve as the basis for predicting future values or for improving estimates of variables at earlier times, i.e., they have the capacity to filter noise (Kalman 1960).

4. **Machine Learning Models** (Jeong and Rilett 2004; Chen et al. 2004). Machine learning methods such as Artificial Neural Networks (ANN) can deal with complex relationships between predictors that can arise within large amounts of data, process non-linear relationships between predictors, and process complex and noise data. These models can be used for prediction of travel time without explicitly addressing the (physical) traffic processes. The ANN method is classified under this category. ANNs recently have been gaining popularity in predicting bus arrival time because of their ability to solve complex non-linear relationships (Jeong and Rilett 2004; Ramakrishna et al. 2006; Chien et al. 2002; Chen et al. 2004). ANNs, inspired by emulating the intelligent data processing ability of human brains, are constructed with multiple layers of processing units, named artificial neurons. The neurons contain activation functions (linear or nonlinear) and are highly interconnected with one another by synaptic weights. Information can be processed in a forward or feedback direction through fully or partially

connected topologies. Meanwhile, the synaptic weights can be adjusted to map the input-output relationship for the analyzed system automatically through a learning process (Hagan et al. 1996). However, results obtained using these models for one location are (typically) not transferrable to the next, due to location-specific circumstances (geometry, traffic control, etc.).

ANNs developed by different researchers in predicting bus travel time differ in their input-output combinations. In addition, they use explanatory variables such as flow, speed, weather, distance, etc., as inputs. However, few research efforts have been made in the area of bus travel time prediction using GPS technology in the absence of data on the stated traffic-stream variables. The purpose of this paper is, therefore, to explicitly consider arrival and departure time information at stops collected via GPS technology to predict bus travel time. The proposed bus travel time prediction model is based on historical arrival/departure time patterns and real-time arrival/departure time information. Hence, nonlinear correlations between travel times can be captured to predict bus travel time at downstream bus stops. The proposed ANN model is trained off-line but can be used to provide real-time travel time information. To achieve this objective, care was taken in selecting a unique set of input-output combinations for prediction while maintaining the reproducibility of the model.

ANN Model Structure

ANN

ANNs learn from examples and capture subtle functional relationships among data even if the underlying relationships are unknown or hard to explain. Thus, ANNs are well-suited for problems whose solutions require knowledge that is difficult to specify. Another advantage of ANNs is that they can generalize. After learning the data fed into them (a sample or example), ANNs can often correctly infer the unseen part of a population, even if the example data contain noisy information. However, to gain the maximum benefit from a neural network, there should be enough data or observations (Zhang et al. 1998).

Network Architecture

Many different ANNs have been proposed in the past few decades for forecasting purposes. The most popular connected multilayer perceptron (MLP) neural network architecture was chosen in this study because it can approximate almost any function if there are enough neurons in the hidden layers, i.e., it has a very good capability of arbitrary input-output matching (Haykin 1999). It is also easy to

implement. The ANN architecture is typically composed of a set of nodes and connections arranged in layers. In this study, three layers were used: input, hidden, and output. The first layer is an input layer when external information is received. The last layer is an output layer where the problem solution is obtained. Usually, one or two hidden layers are used in between the first and last layers to predict reasonably well. The actual processing in the network occurs in the nodes of the hidden layer and the output layer. The input layer is where the data vector is fed into the network. It then feeds into the hidden layer, which, in turn, feeds into the output layer. The connections are typically formed by connecting each of the nodes in a given layer to all of the neurons in the next layers. The hidden layer generates the weight of these connections and the bias parameter during the training process. It is the hidden nodes in the hidden layer that allow the neural network to detect the feature to capture the pattern in the data, to perform nonlinear mapping between input and output variables. A single hidden layer has proved to be sufficient for ANNs to approximate any nonlinear functions (Zhang et al. 1998). A suitable number of nodes in the hidden layer need to be determined by experiment. A fully-connected MLP with one hidden layer is presented in Figure 1.
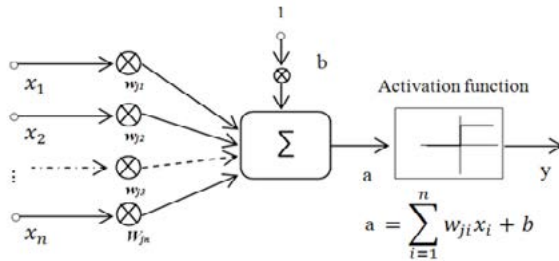
a) Neuron
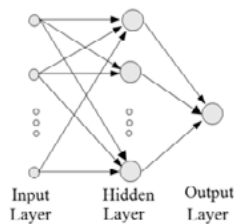
b) FeedForward Network

Figure 1. Multilayer perceptron (MLP) neural network architecture

ANN Model Development

Although the basic training procedure of ANNs is the same, the accuracy of the result is greatly dependent upon the type of input/output combinations. The input variables are presented in such a way that the function signal appearing at the output of neuron j is computed as:

$$Y_j = \psi(X_1, X_2, X_3, ..., X_n) \tag{1}$$

This can be written formally as:

$$Y_j = \psi_j(\sum_{i=1}^{m} w_{ji} X_i + b_j) \tag{2}$$

where,

  m is number of inputs applied to neuron j

  $\{X_i\}$ is set of input variables of neuron j

  Y_j is output of the jth neuron

  w_{ji} is the synaptic weight connecting the ith input to the jth neuron,

  b_j is error term and

  $\psi_j(\cdot)$ is an activation function

The activation function $\psi_j(\cdot)$ is usually needed to introduce nonlinearity into the network. It determines a nonlinear relationship between inputs and outputs of a node and a network. The sigmoidal functions such as logistic and hyperbolic tangent functions (tanh) are the most common choices. Functions such as tanh or arctan that produce both positive and negative values tend to yield faster training than functions that produce only positive values such as logistic in practice (Haykin 1999; Karlik and Olgac 2010). Hence, in this study, the tanh function is used to scale inputs and targets to (-1, 1). This function is given by:

$$\psi(X) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{3}$$

The training procedure chosen was the most commonly used back-propagation algorithm, which is arguably the most popular algorithm for transportation use (Jeong and Rilett 2004; Chien et al. 2002; Chen et al. 2004). The objective of the training process is to improve weights w_{ji} that minimize the mean squared error

(MSE) (Haykin 1999).The average error ε_{avg} at the output of neuron j at iteration n for N number of examples in the training set is defined by:

$$\varepsilon_{avg} = \frac{1}{2N} \sum_{n=1}^{N} \sum_{j} \left(d_j(n) - y_j(n)\right)^2 \tag{4}$$

where $d_j(n)$ is the desired output. The back-propagation algorithm applies a correction w_{ji} to the synaptic weight Δw_{ji}, which is proportional to the partial derivative $\partial \varepsilon_{avg}/\partial w_{ji.}$ That is:

$$\Delta w_{ji} = -\eta \frac{\partial \varepsilon_{avg}}{\partial w_{ji}} \tag{5}$$

where η is the learning-rate parameter of the back-propagation algorithm. It has typically a value between 0.001 and 1.0. If smaller learning rate is considered, smaller changes to synaptic weight will occur. If, on the other hand, one makes a large learning rate, the resulting large changes in the synaptic weights will follow such a form that the network may become unstable (Haykin 1999). Therefore, a simpler method of increasing the rate of learning was proposed by including a momentum term in the above equation (Rumelhart 1986):

$$\Delta w_{ji}(n) = \alpha \Delta w_{ji}(n-1) + \eta \delta_j(n) X_i(n) \tag{6}$$

where $\delta_j(n)$ is gradient and defined by:

$$\delta_j(n) = -\frac{\partial \varepsilon_{avg}}{\partial (\sum_{i=1}^{m} w_{ji}(n) X_i(n) + b_j)} \tag{7}$$

The ANN Prediction Algorithm

Consider the bus route shown in Figure 2. Suppose a journey for a bus k, equipped with GPS, is initiated from stop 0 at a certain time of day interval t and the bus is currently at location c, which may or may not be a bus stop after passing stop i. It

is required to provide travel time information for a person at stop *j*. Therefore, the travel time information from the current bus location *c* to stop *j* can be calculated as:

$$TT^k_{cj} = TT^k_{ij} - TT^k_{ic} \qquad (8)$$

Where,

TT^k_{cj} is predicted bus travel time from location c to stop j for bus k

TT^k_{ij} is predicted bus travel time between stop 'i' and 'j' for bus k

TT^k_{ic} is travel time to point c after passing stop 'i' for bus k
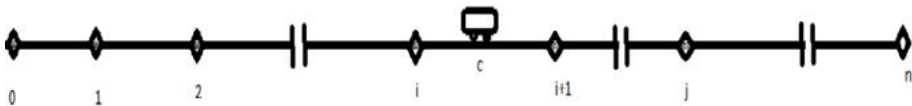
Figure 2. Hypothetical bus route

TT^k_{ic} value can be determined by deducting departure time at stop *i* from the current time when travel time information is requested. TT^k_{ij} is determined using ANN. As has been indicated earlier, a unique set of inputs and output that can be obtained from GPS are considered. The input variables chosen are:

X1 = the time of day interval *t*

X2 = coded id number of bus station *i*

X3 = coded id number of bus station *j*

X4 = the travel time taken from stop *0* to *i*

The output *Y* will be predicted bus travel time to reach stop *j* from stop *i*, which is equivalent to TT^k_{ij} in equation (8).

Training and learning functions are mathematical procedures used to automatically adjust the network's weights and biases (Mathworks). The training function dictates a global algorithm that affects all the weights and biases of a given network. The learning function can be applied to individual weights and biases within a network. Neural networks are trained so that a particular input leads to a specific target output. The network is adjusted based on a comparison of the output and the target until the network output matches the target. In this study, MATLAB

was used to train a network using the aforementioned set of inputs and a target variable, which is the observed travel time between stops *i* and *j*. Let the trained network be NEURAL_NET. The function *sim* simulates a network (Mathworks). It takes the network input vector $\{X_n\}$, and the network object NEURAL_NET, and returns the network output *Y*. That is:

$$TT^k_{ij} = Y = sim\ (NEURAL\_NET,\ \{X_n\}) \tag{9}$$

Usually, the input/target data sets need to be normalized before training. This is because the contribution of an input will depend heavily on its variability relative to other inputs. If one input has a range of 0 to 1, while another input has a range of 0 to 2,000,000, then the contribution of the first input will be swamped by the second input. Therefore, it is essential to rescale the inputs so that their variability reflects their importance, or at least is not in inverse relation to their importance. The choice of range to which inputs and targets are normalized depends mainly on the activation function $\psi_j\ (\cdot)$ of output nodes, with typically (0, 1) for logistic function and (-1, 1) for hyperbolic tangent function.

It is worth mentioning that the choice of input variables makes the algorithm possible to predict dynamically even when the neural network is trained off-line. The first input variable, for example, represents time of the day, which accounts for the variability of travel time between different hours of the day. The last input variable also takes the current travel time information from the origin up to the recently-visited stop.

In the development of a program for a neural network, several steps of algorithms presented above are followed. However, care should be taken while preparing input/target variables for training since one has to deal with a large amount of data sets. Another problem is when to stop the training. On one hand, under-training may occur and the training patterns may not be sufficiently representative of the true population. Hence, the network needs to be exposed to enough examples. On the other hand, over-training could cause memorization, where the network might simply memorize the data patterns and might fail to recognize other set of patterns. Thus, early stopping at the proper time is recommended to ensure that the network learns accordingly.

Case Study

GPS data were available from November 2008 to May 2009 for buses in Macae, Brazil. Bus line LT11 was chosen for the case study because it had the largest num-

ber of data sets compared to the other bus lines (1M+ records). The route, shown on Figure 3, has 35 stops, numbered 0 to 34. Data were collected using Automatic Vehicle Location (AVL) systems. In these systems, GPS receivers are usually interfaced with Global System for Mobile Communications (GSM) modems and placed in the buses. The systems basically record point locations in latitude-longitude pairs, speeds of the buses, date, and time. Arrival and departure time records at each bus stop are the most important.

Figure 3. Bus route LT11, Macae, Brazil

Preliminary Analysis

To calculate travel times, the travel times were pooled together in 30-minute intervals (e.g., 06:00–06:30, 06:30–07:00, etc.) and the average value of each interval was determined. This means that all data sets needed to be clustered by time period, because transit vehicles have different departure times by time period and, also, there might not be bus schedules, resulting in different travel patterns. Usually, the average travel time from historical data can be taken as a baseline prediction model, which can be used for comparison purposes later.

Figure 4 shows the travel time index as function of time of the day, i.e., the ratio of the average travel time per weekday and the average travel time over all days. The different lines correspond with different workdays, i.e., Monday–Friday. The upper panel demonstrates the line LT11 in the northbound direction (from stop 0 to stop 34), and the lower panel shows the southbound direction. From Figure 4, it can be seen that there is a significant variation in (average) travel time over different times of the day. In the evening rush hour (17:00–18:00), the travel times are about 30 percent higher than the average (over all time periods and all days). During the morning rush hour (around 07:00–07:30), travel times are about 20 percent higher than average for the southbound direction. Travel time variations during the day, thus, are significant and should be taken into account. This explains why we chose time of day as input variable in our proposed model.
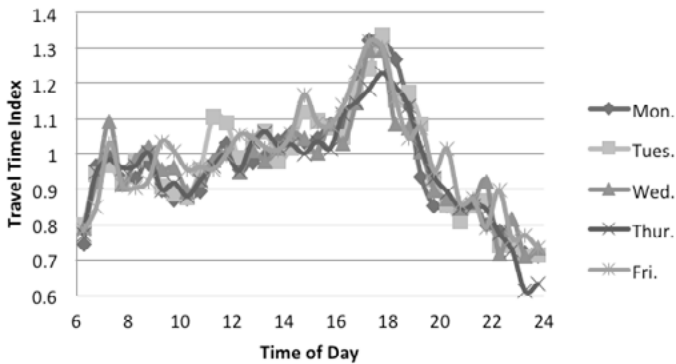
a) LT11 northbound direction
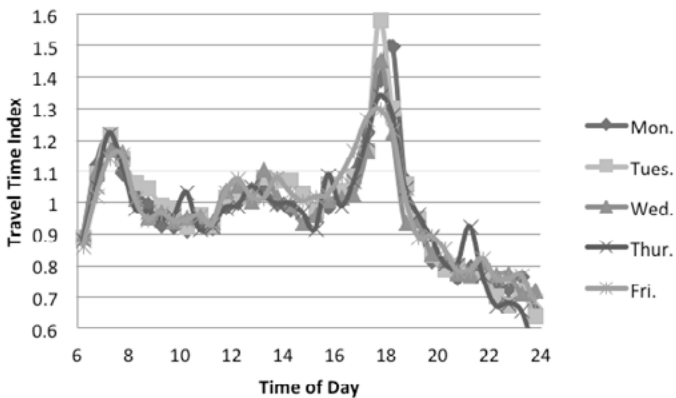
b) LT11 southbound direction

Figure 4. Travel time variation over time of day

Another observation is that travel time distributions over different days of the week are nearly the same without significant differences, as indicated and confirmed by performing Duncan's multiple range test. Thus, these variations were not considered in the model development.

It is possible to improve prediction models from average values by considering errors or variations and correlations between different values of the variable under consideration (Thomas et al. 2010). For example, if a bus is slower during the first section of the trip, it is likely that it will also be slower on the second section of the trip. Therefore, we say that travel time of successive buses or of successive trip sections may be correlated. If these correlations are found, the information about the travel time of a previous bus or trip section can be used to update travel time prediction of the next bus or trip section. To illustrate this, correlation analysis was conducted between observed travel times of successive sections. First, the whole trajectory was divided into four approximately equal sections. The average travel time in each section was around 20 minutes. Figure 5 presents correlation results of travel times between successive sections.
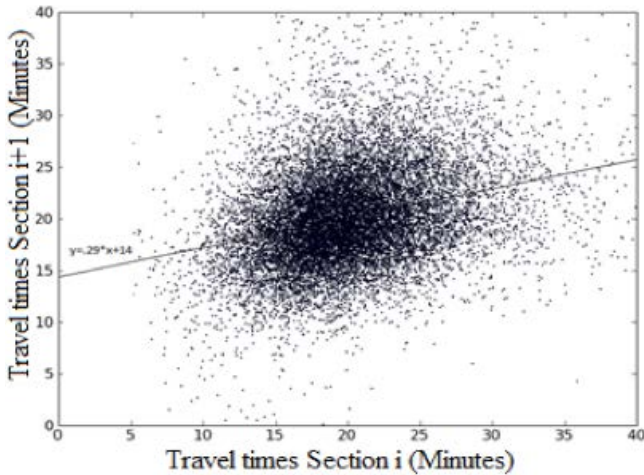
Figure 5. Correlation between travel times of successive sections

As can be seen from Figure 5, it was not possible to get satisfactory linear relationships (R^2=0.09) to improve the baseline prediction based on correlation. Hence, the proposed artificial neural network models were used to capture these highly nonlinear relationships and predict bus travel time at the downstream bus stops. Data reduction was done using Python(x, y) software, and the input/target data sets were prepared to be trained in MATLAB.

Training, Test, and Validation Data Sets

Training and test samples typically are required for building an ANN forecaster. The training sample is used for ANN model development and the test sample was adopted for evaluating the forecasting ability of the model or to measure its performance. A validation sample was also used to avoid the over-training problem or to determine the stopping point of the training process. The symptom of over-training is that the network performs well with data in the training set, while its performance over the test data set (those "unseen" by the network) starts to deteriorate. It is common to use one test set for both validation and testing purposes.

The first issue to deal with during ANN development is the division of the data into the training and test sets. Although there is no general procedure to do this, several factors, such as the data type and the size of available data, should be considered in the division. The whole data set was first sorted by week number. Then, the first 70 percent of the data set was taken as a training set and the next 30 percent as a testing set. This division has been used by most researchers (Yu et al. 2006; Patricia and Robert 2005). Of the testing set, 20 percent of the data set was taken as a validation test. It is worth mentioning that different percentage combinations of training, test, and validation sets had been investigated, and it was possible to get a minimum mean square error using the above combinations.

Training and Learning Functions

The training function dictates a global algorithm that affects all the weights and biases of a given network. The learning function can be applied to individual weights and biases within a network. MATLAB offers a number of training and learning functions. In this study, two training functions and one learning function were used. Of 12 training functions, Jeong and Rilett (2004) found that the Bayesian Regularization training function and the Levenberg-Marquardt Back propagation training function outperformed the other 10 training functions. In this study, it was found that the Levenberg-Marquardt Back propagation training function, which is commonly used by most researchers (Jeong and Rilett 2004; Chien et al. 2002, Chen et al. 2004), outperformed the Bayesian Regularization training function. Jeong and Rilett (2004) also showed that there were no significant differences in the results from the 14 tested learning functions. Gradient descent with momentum weight and bias learning function were used in this study to make it consistent with proposed algorithm.

Numerical Results

Model Performance

After the prediction model was developed, it was necessary to evaluate its performance in terms of prediction accuracy. Since regression prediction models are not good option in the absence of traffic data, and since there are several variations of Kalman filtering models that may complicate the evaluation process, as mentioned previously, the proposed ANN model was compared only with that of the historical average travel time model. The Mean Absolute Percentage Error (MAPE) was used as the measure of model performance, representing the average percentage difference between the observed value (in this case, observed arrival times at a bus stop) and the predicted value (in this case, predicted arrival times at a bus stop).

$$MAPE = \frac{100}{n} \sum_{t=1}^{n} \left| \frac{Y_t^P - Y_t^{Obs}}{Y_t^{Obs}} \right| \tag{10}$$

where,

Y_t^P is the predicted bus travel time from recent bus stop to target bus stop

Y_t^{Obs} is the observed bus travel time

n is the number of test sets

Figure 6 presents the average MAPE values (computed using Eq. [10]) for a range of observed travel times between stops. As can be seen, prediction of bus travel time in the study area could be given with an overall average MAPE value of 18.3 percent using the ANN model.
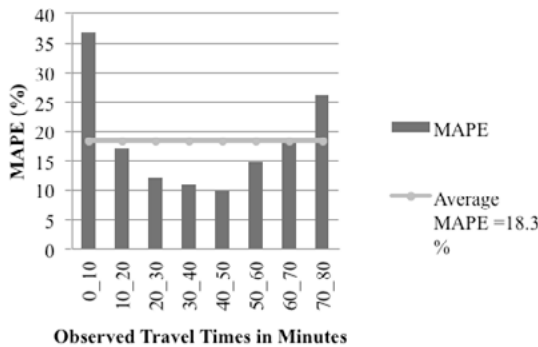
Figure 6. MAPE for a range of observed travel times

Around 25 percent of the test data set resulted in MAPE higher than the total average MAPE (i.e., 18.3%). Figure 6, thus, shows that only a few test data sets could be observed with a higher MAPE when the number of stops between the current bus location and the stop under consideration becomes too large or too small. It was discovered that the ANN model gave a better prediction of travel time when the station where the travel time information required is located at least five stops away from the current bus location. On one hand, for observed travel times with values of 20– 50 minutes, prediction can be given with less than 10 percent error. In other words, it is possible to provide real-time travel time information for a person who is 20–50 minutes away from the current bus location with a maximum 10 percent error. On the other hand, when the observed travel time becomes larger, i.e., greater than 50 minutes, the error in prediction starts to increase. This could be due to the fact that when a bus travels longer in a trip, there is a high probability that it stops at many bus stops, especially when demand is high during peak hours. Therefore, a person who is 20–50 minutes away from the current bus location receives the optimal travel time information. The error in prediction for smaller travel times, for example, 5–10 minutes, was found to be higher even for the ANN. This indicates that for short distance trips there is higher travel time variability, as one might expect, due to a number of factors. For example, a bus may wait for one minute at a traffic light on a link where the bus usually takes two minutes to cross it. So, the error for this situation could be exaggerated and may reach up to 40 percent, which, in turn, will increase the overall MAPE. However, it should be acknowledged that this kind of travel time information may be less important as it is within an acceptable range of waiting time.

Model Comparison

Three different sections were considered to show the comparison between the two models. The sections are defined for one direction, i.e., northbound, as shown in Table 1.

Table 1. Sections Compared

Trajectory	Stop ID's	Remark
Section 1	Stop 8 to Stop 16	Short section
Section 2	Stop 8 to Stop 26	Medium section
Section 3	Stop 0 to Stop 34	Long (whole section)
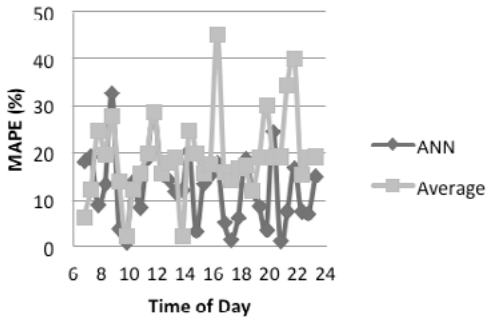
a) Short section (Section 1)
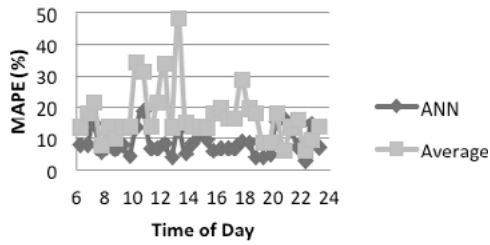
b) Medium section (Section 2)
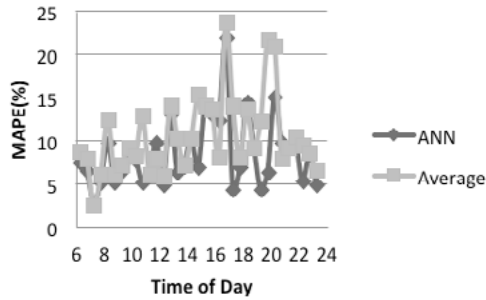
c) Long section (Section 3)

Figure 7. MAPE vs. historical average

Even though, there is no much difference in MAPE between the two models for large and small sections, the ANN outperformed the historical average model approach on more than 70 percent of the time intervals of the day for medium sections, as illustrated in Figure 7. Usually a low MAPE value is desirable for an algorithm. However, an algorithm with a low value of MAPE may occasionally yield a prediction with a large deviation. This is undesirable since it may divert passengers away from the bus stop and eventually cause them to miss the bus.

Therefore, it was important to define a second measure that could be used to detect this phenomenon. It examined the robustness of an algorithm such that its maximum deviation was within a certain range. Here, the robustness measure Ro is defined as: Ro = max {MAPE} of a section at a certain time interval of the day. As can be seen from Figure 7, the maximum MAPE of the historical average approach is greater that the corresponding MAPE of the ANN. Hence, the proposed ANN is more robust than the historical average approach in terms of this measure.

It has been noted that standard deviation of prediction errors can also be used as a means of performance measure to make further comparison between the ANN and average models. For each section, prediction errors, i.e., the difference between the actual travel time and the forecast travel time, was calculated for each time interval. Figure 8 shows the standard deviation of the prediction errors for the sections discussed above over time of the day.

As can be seen from Figure 8, there was not much difference for the small and large sections. However, for the medium sections, the ANN appears to outform the average model again, which reinforces our previous discussion. Therefore, it can be concluded that the ANN outperformed the average approach in terms of both prediction accuracy and robustness.
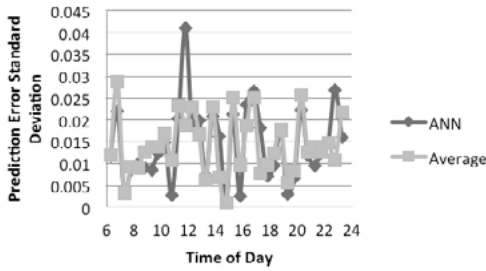
a) Short section (Section 1)
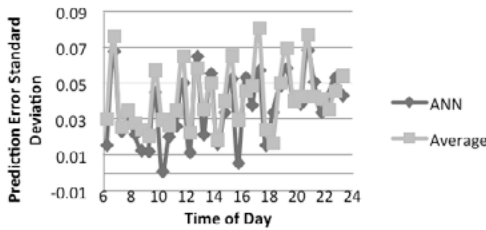
b) Medium section (Section 2)
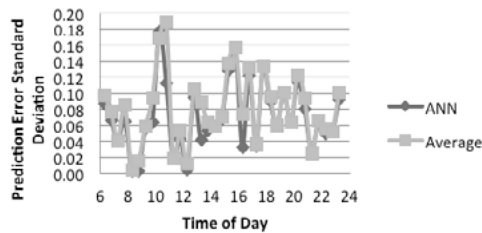
c) Long section (Section 3)

Figure 8. Standard deviation of prediction errors

Summary and Future Research

This paper presents an algorithm based on an artificial neural network using GPS data for predicting the travel time of transit vehicles between current bus location and any downstream bus stop under consideration. The predicted travel times between subsections of the route under consideration were compared with the measured data. The performance of the model was also tested and compared with a historical average approach, where the predicted travel time was taken to be the average of the travel times of previous buses that traveled between any

two stops under consideration. Prediction accuracy and robustness were used as performance measures. The overall precision measure determines the average deviation of the predicted travel time from the observed travel time. The robustness measure determines if an algorithm will occasionally give a prediction that is far off the actual arrival time.

The ANN outperformed the average approach in both performance measures. The standard deviation of the prediction errors reinforced this as well. The ANN model, which is trained off-line, enabled us to provide real-time travel time information at downstream stations with minimal error. The results obtained from the overall study are promising, and the proposed ANN model can be used to implement an APTS to predict the arrival time at bus stops in areas, even where there is undisciplined traffic flow. The implementation of this system will improve the reliability of the public transport system, thus attracting more travelers to buses and helping relieve congestion.

The study investigated the possibility of providing travel time information to transit users using departure and arrival time information at stops collected via GPS technology. Apart from prediction, creating an optimal bus schedule is also very important. Further study efforts may be directed towards incorporating schedule adherence information as an additional independent variable to improve the prediction model. Prediction with Kalman filtering algorithms in the absence of traffic data and comparing their results with the proposed model can also be conducted in the future. A user-interactive system may also need to be developed to provide the travel time information.

Acknowledgment

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Commuter Mode Choice and Free Car Parking, Public Transportation Benefits, Showers/Lockers, and Bike Parking at Work: Evidence from the Washington, DC Region

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Abstract

Municipalities and employers in the U.S. attempt to reduce commuting by automobile through commuter benefits for riding public transportation, walking, or cycling. Many employers provide a combination of benefits, often including free car parking alongside benefits for public transportation, walking, and cycling. This study evaluates the relationship between commuter benefits and mode choice for the commute to work using revealed preference data on 4,630 regular commuters, including information about free car parking, public transportation benefits, showers/lockers, and bike parking at work in the Washington, DC region. Multinomial logistic regression results show that free car parking at work is related to more driving. Commuters offered either public transportation benefits, showers/lockers, or bike parking, but no free car parking, are more likely to either ride public transportation, walk, or cycle to work. The joint provision of benefits for public transportation, walking, and cycling is related to an increased likelihood to commute by all three of these modes and a decreased likelihood of driving. However, the inclusion of free car parking in benefit packages alongside benefits for public transportation, walking, and cycling, seems to

offset the effect of these incentives. Benefits for public transportation, walking, and cycling, seem to work best when car parking is not free.

Introduction

Travel demand management (TDM) objectives include congestion mitigation, conservation of financial and energy resources, pollution reduction, and improvement in health outcomes and quality of life measures (Cervero 1991; Giuliano 1992; TCRP 2002, 2010; FHWA 2012b). At the local and regional levels, planning authorities have begun to implement policies to achieve TDM objectives and increase travel by public transportation, cycling, and walking, including changes to parking fee structures and requirements, zoning ordinances, building codes, and roadway regulations (TCRP 2010).

Another important policy tool to achieve TDM objectives has been the creation and expansion of commuter benefits—although the types and levels of these benefits has varied across both modes and time (Potter et al. 2006; TCRP 2003; EPA 2007; IRS 2013). Free car parking, however, generally continues to be the most prevalent type of benefit offered to commuters; only about 5 percent of auto commuters pay for parking in the U.S., and commuters, on average, avoid direct payment of the majority of actual parking costs (Wachs 1990; Shoup 2005; TCRP 2005; FHWA 2012a).

The interaction effects among commuter benefits have received relatively little attention in the literature, and few commuter mode choice studies jointly include benefits for driving, public transportation, and walking or cycling. However, the importance of policy interactions relating to travel behavior has long been recognized. For example, Pucher (1988) conducted an international comparison of transportation policies, and argued that public transportation benefits in the U.S. are largely rendered ineffective in the absence of complementary automobile taxation policies.

More recently, Washbrook et al. (2006) conducted a study of the effect of road pricing and parking charges on commuter mode choice in Vancouver, Canada, and concluded that effective TDM requires a combination of disincentives for driving and incentives for walking, cycling, and public transportation. Similarly, Habibian and Kermanshah (2011) highlight the push and pull factors for the decision to drive. Also, Marsden (2006) reviewed the literature on behavioral responses to various parking policies and suggested that substantial mode shifts among commuters

may be achieved when a package of alternatives is introduced along with changes to car parking pricing or supplies.

It remains a question whether, at the level of the individual commuter, packages that offer benefits for driving as well as walking, cycling, and public transportation may effectively promote TDM objectives. This study attempts to address that question and the growing need for understanding the cumulative effects of commuter benefits on travel behavior.

Until recently, commuter benefits for cycling and walking were often omitted from studies regarding transportation mode choice—typically due to their omission from data collection efforts as well as their relatively low level of provision. This study contributes to the literature through the inclusion of commuter benefits for driving, riding public transportation, and walking or cycling to work. In addition, this paper also supplements the existing literature on commuter benefits and mode choice by utilizing revealed preference data on how commuters traveled to work, rather than stated preference data regarding prospective or anticipated behavior.

The data for this analysis originate from the 2007/2008 Washington DC Household Travel Survey. The survey comprises information about free car parking, public transportation benefits, facilities/services for cyclists and pedestrians (such as showers and lockers), and secure bicycle facilities (such as bike parking) at work. A multinomial logistic regression analysis is used to examine the impact of these different types of commuter benefits on mode choice by comparing public transportation users, pedestrians, and cyclists to motorists.

The following section provides a brief overview of the literature on commuter benefits. Then, an empirical analysis investigates the relationship between transportation mode choice for travel to work and commuter benefits for motorists, public transportation users, pedestrians, and cyclists in the Washington, DC region.

Estimating the Impact of Commuter Benefits on Mode Choice

In recent decades, a substantial body of literature has focused on the effect of car parking pricing on commuter mode choice (FHWA 2012a). For example, Willson and Shoup (1990) conducted a review of empirical studies of car parking subsidies, and found that eliminating free car parking at work reduces single-occupancy vehicle commuting between 19 percent and 81 percent. Another study examined parking subsidies in Los Angeles and found that between 25 and 34 percent fewer

automobiles were driven to workplaces where workers had to pay to park their cars (Willson 1992). Shoup (1997) reviewed the effects of car parking "cash out" programs and found that single-occupancy vehicle commuting fell by 17 percent among 8 case study firms after they complied with California's cash-out requirement. More recently, an analysis of parking subsidies in Portland, Oregon, found that a daily car parking charge of $6 reduced single-occupancy vehicle commuting by an estimated 16 percent (Hess 2001).

Another important area of inquiry has been the effect of public transportation pricing on commuter mode choice. For example, two studies of the UCLA BruinGo fare-free program found increases in bus ridership and declines in driving corresponding to the launch of the program (Brown, Hess, and Shoup 2003; Boyd et al. 2003). Another study examined the efficacy of a proposed "mobility pass" at the Massachusetts Institute of Technology (MIT) that would combine parking and public transportation benefit programs, and predicted that both single-occupancy vehicle commuting and overall commuter costs would decrease (Block-Schachter 2009).

Increasing attention is being devoted to the effect of benefits for walking and cycling on commuter mode choice. Studies measuring the effect of direct subsidies for walking and cycling are still rare, likely due to the relatively scarce provision of these types of benefits and a related lack of available data. One study from the U.K. supplemented stated- and revealed-preference primary data with the National Travel Survey to forecast that direct payments could significantly increase cycling commuting rates (Wardman, Tight, and Page 2007). More commonly, studies focusing on cycling and walking assess the effect of facilities and services such as bicycle parking, workplace showers, and shared-use paths (Dill and Wardell 2007; Buehler 2012). In many studies, public transportation, walking, and cycling are considered complementary (Bachand-Marleau, Larsen, and El-Geneidy 2011; Pucher 2004). However, Boyd et al. (2003) found a decrease in walking and cycling to campus after the fare-free public transportation program's introduction. Dill and Wardell (2007) also found bike amenities to be negatively correlated with public transportation use in their study of factors affecting mode choice in Portland, Oregon. In addition, low-cost public transportation passes for students have corresponded with decreased cycling in some Dutch and German cities (Pucher and Buehler 2012).

Few studies on commuter mode choice concurrently include variables measuring benefits for driving, public transportation, walking, and cycling. One study randomly sampled firms identified as "best workplaces for commuters" in several metropolitan areas in the U.S. and found that comprehensive benefit packages could reduce vehicle miles traveled and pollutants by about 15 percent (Herzog et al. 2006). Another study modeled public transportation commuter mode share using worksite-level data from Portland, Oregon, and found public transportation benefits and bike amenities to be significant predictors for commuting by public transportation, walking, and cycling. The study did not assess the provision of worksite-specific free car parking; rather, it attempted to control for free car parking via a dummy variable for the downtown "Fareless Square" area, where free car parking was much less likely (Dill and Wardell 2007).

Overall, the relationship between commuter benefits and mode choice has been examined using a variety of methodologies and in a variety of settings. Some studies have surveyed employers, while others have surveyed commuters. The literature to date suggests a correlation between the provision of commuter benefits and a commuter's transportation mode choice, with free car parking associated with higher rates of single-occupancy vehicle commuting, public transportation benefits associated with higher rates of public transportation use, and walking and cycling benefits associated with higher rates of walking and cycling to work.

Selection bias continues to be a concern in interpreting these findings, as self-selection into residential and workplace settings may influence the perceived relationship between commuter benefits and transportation mode choice. Further, studies of this subject have typically relied on cross-sectional and observational data and that is also the case in our study. These types of studies suffer from the potential for endogeneity and selection bias, so findings suggest correlations, but cannot assess causality regarding the relationship between transportation mode choice and commuter benefits.

The present study contributes to this literature by using revealed preference data via a household travel survey and incorporates commuter benefits for driving, public transportation, and walking or cycling. The literature review guided the selection of explanatory variables included in the analysis. Most studies of transportation mode choice for the commute include demographic, socioeconomic, and geographic measures as explanatory variables. Variations across studies are often due, in part, to differences in data availability and travel survey design.

Study Area: The Washington, DC Region

This study focuses on commutes in the urban core and inner suburbs of the Washington, DC region. The urban core of the Washington, DC metropolitan area comprises Washington, DC, along with Arlington County and the city of Alexandria in Virginia. In addition, Fairfax County in Virginia and Montgomery and Prince George's counties in Maryland are lower-density, inner-suburban jurisdictions bordering the urban core of the region. Together, these five jurisdictions have a population of approximately 3.8 million inhabitants (USCB 2010). Median household income is higher in the region than the national average, and except for Arlington County, area jurisdictions have higher shares of nonwhite populations than the national average. The share of households who do not own a vehicle varies significantly between the urban core and inner suburbs. For example, about 35 percent of households in Washington, DC do not own an automobile compared to only about 4 percent of households in Fairfax County (USCB 2010).

The Washington Metropolitan Area Transit Authority (WMATA) operates one of the most extensive public transportation systems in the U.S., including the second largest metro rail system and sixth largest bus system (WMATA 2011). According to the Metropolitan Washington Council of Governments (MWCOG) 2007 State of the Commute Survey Report, 83 percent of commuters in the region had bus or train service near their home at that time and 79 percent had some form of public transportation near their workplace (MWCOG 2007). The region has been recognized as an example of successful transit coordination, where transit agencies and the MWCOG metropolitan planning organization meet regularly (Rivasplata, Smith, and Iseki 2012). In addition, the region also has notorious automobile traffic congestion, ranking first in 2011 among the 15 largest areas in the country in yearly delay per auto commuter (TTI 2011) and has significantly increased levels of cycling and accompanying infrastructure and programming for active travel in recent decades (Buehler 2011).

Data Sources, Variables, and Model Development

Data for this analysis originate primarily from the 2007/2008 DC Household Travel Survey conducted by the Metropolitan Washington Council of Governments' (MWCOG) Transportation Planning Board. The survey is representative of the region and consisted of an introductory household questionnaire—which collected demographics and socioeconomics—as well as a travel diary to gather in-depth information on daily travel on a specifically assigned travel day for each household member (MWCOG 2010). The survey collected information on the

provision of free car parking, public transportation benefits, facilities/services for cyclists and pedestrians (such as showers and lockers), and secure bicycle facilities (such as bike parking) at work. The survey is particularly useful for assessing the relationship between commuter benefits and an individual's commute mode choice. The final sample includes 4,630 adult full-time workers living in the urban core or inner suburbs and commuting to regular workplaces using a reported usual mode to work. For this analysis, data on transit access, bikeway supply, population, and land area were merged with the travel survey dataset using 2,155 traffic analysis zone (TAZ) identifiers.

The analysis is comprised of a reduced multinomial logistic regression, which models the effect of commuter benefits on mode choice, and a full multinomial logistic regression, which models the effect of commuter benefits on mode choice while controlling for other relevant neighborhood-, household-, and person-level characteristics. The full model is the preferred specification, because it incorporates additional theoretically relevant variables beyond the commuter benefit measures. The dependent variable in both the reduced and full models is the commuter's transportation mode choice among driving, public transportation, walking, and cycling, based on the survey question, "How did you usually get to work last week?" Survey respondents who used more than one mode were directed to provide the mode used for the most distance or the mode that took the most time (MWCOG 2010). We used Hausman and Small-Hsiao tests to evaluate the Independence of Irrelevant Alternatives assumption for the multinomial logit models, and both produced mixed results. However, these tests are sensitive to model parameterization. Theory and judgment led us to determine that the four mode choices used in the multinomial logit could be treated as distinct choice sets for commuters. As a result, we chose to use the multinomial logit, although separately run binomial logit models produced similar results overall.

The key explanatory variables are commuter benefit measures of free car parking, public transportation benefits, bike/walk benefits (showers/lockers and/or bike parking), and combinations of these benefit types, as summarized in Table 1. Table 2 summarizes the variable names, definitions, and descriptive statistics for the model. The reduced model contains only the commuter benefit measures as explanatory variables.

Table 1. Commuter Benefit Combinations Used as Explanatory Variables

Variable Name	Description	Free Car Parking	Public Transportation Benefits	Showers/ Lockers and/or Bike Parking
Free Car Parking	Free car parking, no public transportation benefits, no showers/lockers or bike parking	X		
Public Transportation Benefits	No free car parking, public transportation benefits, no showers/lockers or bike parking		X	
Bike/Walk Benefits	No free car parking, no public transportation benefits, showers/lockers and/or bike parking			X
Public Transportation Benefits & Bike/ Walk Benefits	No free car parking, public transportation benefits, showers/lockers and/or bike parking		X	X
Free Car Parking & Public Transportation Benefits	Free car parking, public transportation benefits, no showers/lockers or bike parking	X	X	
Free Car Parking & Bike/Walk Benefits	Free car parking, no public transportation benefits, showers/lockers and/or bike parking	X		X
All Benefits	Free car parking, public transportation benefits, showers/lockers and/or bike parking	X	X	X

Table 2. Variable Names, Measurement/Description, and Descriptive Statistics

Variable Name	Measurement/Description	Descriptive Statistics
Mode Choice	Nominal variable. Value of 0 if respondent drove alone to work, 1 if rode public transportation, 2 if walked, 3 if cycled.	70.1% drove alone, 24.1% rode public transportation, 4.1% walked, 1.6% cycled
Free Car Parking	Nominal variable. Value of 1 if workplace provides free car parking and no other benefit, 0 otherwise.	20.7% have free car parking at work and no other benefit
Public Transportation Benefits	Nominal variable. Value of 1 if workplace provides transit or vanpooling benefits and no other benefit, 0 if otherwise	6.9% have transit or vanpooling benefits at work and no other benefit
Bike/Walk Benefits	Nominal variable. Value of 1 if workplace provides showers/lockers and/or bike parking, and no other benefit, 0 if otherwise	15.5% have showers/lockers and/or bike parking and no other benefit
Public Transportation Benefits & Bike/Walk Benefits	Nominal variable. Value of 1 if workplace provides transit or vanpooling benefits and showers/lockers and/or bike parking and no other benefit, 0 if otherwise.	12.2% have transit or vanpooling benefits and showers/lockers and/or bike parking and no other benefit
Free Car Parking & Public Transportation Benefits	Nominal variable. Value of 1 if workplace provides free car parking and transit or vanpooling benefits and no other benefit, 0 if otherwise.	2.4% have free car parking and transit or vanpooling benefits, but no other benefit
Free Car Parking & Bike/Walk Benefits	Nominal variable. Value of 1 if workplace provides free car parking and showers/lockers and/or bike parking and no other benefit, 0 if otherwise.	19.4% have free car parking and showers/lockers and/or bike parking and no other benefit
All Benefits	Nominal variable. Value of 1 if workplace provides free car parking, transit or vanpooling benefits, and showers/lockers and/or bike parking, 0 if otherwise.	2.3% have free car parking, transit or vanpooling benefits, and showers/lockers and/or bike parking
Race/Ethnicity	Nominal variable. Value of 1 if respondent is white, 0 if otherwise.	69.2% white
Gender	Nominal variable. Value of 1 if respondent is male, 0 if respondent is female.	49.5% male
Age	Integer variable.	Mean: 44 (Std. Dev.: 13)
Income	Nominal variable. Value of 1 if respondent lives in approximately wealthiest 25% (quartile) of households, 0 if otherwise.	35.4% in highest income quartile

Variable Name	Measurement/Description	Descriptive Statistics
Any Children in Household	Nominal variable. Value of 1 if respondent lives in household with one or more minors (under 18).	30.7% live in a household with at least one minor
Car Access	Ratio variable. Cars per household member.	Mean: 0.827 (Std. Dev.: 0.451)
Bicycle Access	Ratio variable. Bicycles per household member.	Mean: 0.536 (Std. Dev.: 0.623)
Commute Distance (Natural Log)	Continuous variable. Natural log of distance reported for commute trip.	Mean: 1.592 (Std. Dev.: 1.308)
Population Density	Ratio variable. Persons per acre of land area in home TAZ.	Mean: 15.741 (Std. Dev.: 16.537)
Urban Core	Nominal variable. Value of 1 if respondent lives in Washington DC, Arlington County, or Alexandria; 0 if respondent lives in Fairfax County; Montgomery County; or Prince George's County.	36.8% live in urban core
Transit Access	Count variable. Number of Metro Rail stations in home TAZ.	Mean: 0.051 (Std. Dev.: 0.246)
Bikeway Supply	Ratio variable. Centerline miles of bike lanes and paths per 1000 residents in home TAZ.	Mean: 0.097 (Std. Dev.: 0.955)
Season	Nominal variable. Value of 1 if travel day was between May and October, 0 if otherwise.	45.2% of respondents were interviewed between May and October

Several control variables are included in the full model. Measures of race/ethnicity, gender, and age are included as factors that may influence mode choice. Race/ethnicity has been examined as a relevant factor in mode choice, especially in the context of residential segregation and the spatial mismatch literature (Taylor and Ong 1995; Stoll 2005). Gender has been examined as an influence on travel behavior in relation to such factors as safety perceptions and child-caring responsibilities (Blumenberg 2002; Goddard et al. 2006). Age has also been examined in other mode choice studies relating to changes such as time availability (Cervero 1990; Hess 2001). Measures of income and car and bicycle access are included as factors related to resource availability that may influence mode choice. Car and bicycle access are not perfect measures, since they do not take into account whether the respondent has a driver's license or is able to drive a car or ride a bicycle. However, they are commonly-used control variables that approximate access to resources that may influence mode choice. A measure of commute distance is included.

Walking and cycling in particular are expected to be sensitive to distance, and mode choice studies often find it to be a significant factor (Cervero and Duncan 2003; Saelens, Sallis, and Frank 2003; Winters et al. 2010; Buehler 2012; Ewing and Cervero 2010). A logarithmic transformation was performed to improve the normality of the distribution of the distance variable. In addition, whether an individual lives in a household with one or more minors is included, since mode choice has been found to be sensitive to the presence of children, especially for women (Goddard et al. 2006).

Residential population density is included, as this measure has been found to be a significant environmental correlate for travel behavior and could relate to differences in street connectivity and urban design (Saelens, Sallis, and Frank 2003; Ewing and Cervero 2010). A dummy variable is also included to capture if a commuter lives in the urban core (Washington, DC, Arlington County, or Alexandria), as opposed to the inner suburbs (Fairfax County, Montgomery County, or Prince George's County). Residents of the urban core are likely to have access to higher levels of public transportation service and a more integrated and extensive active travel network. In addition, they may also interact with drivers who are more aware of pedestrians and cyclists due to heightened promotional programs for alternatives to driving and the more prevalent "safety in numbers" effect in urban areas (Ewing and Dumbaugh 2009; Pucher, Dill, and Handy 2010; Pucher, Garrard, and Greaves 2011).

In addition, a measure of transit access is included, based on the number of Metro Rail stations located in the residential traffic analysis zone (TAZ). While this is an imperfect measure, since TAZs vary in size, it is a general approximation of transit access and is expected to be positively correlated with public transportation use. Bikeway supply is also included, as measured by the miles of bike lanes and paths per 1,000 residents, and is expected to be positively correlated with cycling. Finally, a binary explanatory measure is included for whether the respondent was interviewed between May and October to control for potential seasonal effects on mode choice.

As presented in Table 2, the majority of commuters in our sample drove alone to work (70.1%). In addition, 20.7 percent reported the availability of free car parking and no other benefits, while about 6.9 percent reported the availability of public transportation benefits and no other benefits. In addition, roughly 15.5 percent reported being offered bike/walk benefits at work but no free car parking or public transportation benefits. About 36 percent reported receiving some combination

of benefits, including about 2.3 percent of commuters who reported being offered free car parking, public transportation benefits, and bike/walk benefits. Approximately 21 percent of the sample receives none of the benefits (neither free car parking, public transportation benefits, nor bike/walk benefits).

Results

Table 3 presents results for the reduced and full multinomial logit regression analyses, which examine the relationships between commuter benefits and mode choice. The reduced model includes only the commuter benefit measures as explanatory variables, while the full model comprises the commuter benefit measures and the additional control variables discussed above. Tests of model fit indicate all variables have joint significance in both models. In addition, both Likelihood-Ratio and Wald tests of the reduced versus the full model indicate that the full model adds significant explanatory power when compared to the reduced model (Likelihood-Ratio test statistic = 1,223.14, $p<0.01$; Wald test statistic = 917.9, $p<0.01$). The pseudo-R^2 for the reduced and full models, 0.231 and 0.398 respectively, are comparable to the model fits achieved in other transportation mode choice studies of similar subjects (Dill and Wardell 2007, Buehler 2012). In addition, we performed several multicollinearity tests, and found it is not a significant concern among the explanatory and control variables (Mean VIF = 1.25, Tolerance > 0.6, Condition Number = 18.2).

The results for each of the explanatory variables displayed in Table 3 can be interpreted based on sign, magnitude, and statistical significance. Coefficients have been transformed into odds ratios, which give the proportionate change in the relative risk of choosing a given alternative, rather than the reference category (Cameron and Trivedi 2010). In this case, they represent the likelihood of choosing to commute by public transportation, walking, or cycling relative to the base category of driving alone, while controlling for other variables in the analysis.

Table 3. Results of Multinomial Logit Model of Transportation Mode Choice and Commuter Benefits in the Washington, DC Region

Variable Name	Public Transportation		Walk		Cycle	
	Reduced Model	*Full Model*	*Reduced Model*	*Full Model*	*Reduced Model*	*Full Model*
Free Car Parking	0.082***	0.098***	0.213***	0.310***	0.102***	0.144**
Public Transportation Benefits	8.428***	11.337***	2.315**	2.006*	1.908	2.024
Bike/Walk Benefits	0.926	0.945	1.628**	1.503	2.464**	2.119*
Public Transportation Benefits and Bike/Walk Benefits	8.087***	9.627***	2.844***	2.549***	7.617***	6.257***
Free Car Parking and Public Transportation Benefits	0.622*	0.670	0.453	0.358	0.540	0.475
Free Car Parking and Bike/ Walk Benefits	0.096***	0.117***	0.340***	0.593*	0.387**	0.495
All Benefits	0.472**	0.479**	0.153*	0.267	1.639	1.171
Race/Ethnicity (white = 1)		1.021		2.550***		2.391**
Gender (male = 1)		1.163		1.414*		3.022***
Age		0.995		0.999		0.997
Income		0.719***		0.881		1.646*
Any Children in Household		0.285***		0.202***		0.658
Car Access		0.092***		0.079***		0.059***
Bicycle Access		1.093		1.007		4.191***
Commute Distance (Natural Log)		0.967		0.414***		0.679***
Population Density		1.011***		1.033***		1.019***
Urban Core		1.337**		1.493*		2.448***
Transit Access		1.475**		1.336		0.825
Bikeway Supply		0.983		1.065*		1.080***
Season		1.053		1.063		1.878**

*Significant at 10%; **Significant at 5%; ***Significant at 1%*
Odds ratios after multinomial logit for decision to commute.
Dependent Variable = Mode Choice
Base Outcome = Driving
Reduced Model Fit: Wald Chi^2 = 1056.4 (p<0.01); LR Chi^2 = 1,693.2 (p<0.01); pseudo-R^2 = 0.231
Full Model Fit: Wald Chi^2 = 1721.5 (p<0.01); LR Chi^2 = 2,916.3 (p<0.01); pseudo-R^2 = 0.398
N: 4,630

As described above, the full model is the preferred specification, since it incorporates control variables that are theoretically expected to be relevant for the commute mode choice. The signs and magnitudes of the commuter benefit variables are stable between the reduced and full models, but some shifts in significance occur. We emphasize the full model results in the presentation and discussion below.

Controlling for other variables and benefit combinations, commuters with free parking at work (but no public transportation benefits, or bike/walk benefits), were less likely to choose to commute by public transportation (odds ratio of 0.098), walking (odds ratio of 0.310), or cycling (odds ratio of 0.144) over driving.

Likewise, commuters with employers who only offer public transportation benefits are about 11 times more likely to take public transportation than to drive. Commuters with only public transportation benefits are also more likely to choose walking over driving. Bike/walk benefits were significantly correlated with choosing to cycle to work over driving (odds ratio of 2.119).

The combination of public transportation benefits and bike/walk benefits is strongly correlated with choosing public transportation (odds ratio of 9.627), walking (odds ratio of 2.549), or cycling (odds ratio of 6.257) over driving to work. The combination of free car parking and benefits for public transportation (but no bike/walk benefits) is not significantly correlated with transportation mode choice for the commute, while the combination of free car parking and bike/walk benefits is negatively correlated with choosing public transportation and walking. Simultaneous provision of all benefit types at work (free car parking, public transportation benefits, and bike/walk benefits) corresponds to lower odds for choosing public transportation and is not correlated with walking and cycling.

Summarizing key results regarding the additional control variables, the full model suggests that car access is associated with a strongly reduced likelihood of riding public transportation (odds ratio of 0.092), walking (odds ratio of 0.079), or cycling to work (odds ratio of 0.059), while population density and residence in the urban core are both associated with an increased likelihood of riding public transportation (odds ratios of 1.011 and 1.337, respectively), walking (odds ratios of 1.022 and 1.493, respectively), and cycling to work (odds ratios of 1.019 and 2.448, respectively). Race/ethnicity, gender, commute distance, and bikeway supply are associated with differing odds for walking and cycling to work, but not for riding public transportation, while the presence of children is associated with differing odds for riding public transportation and walking to work but not for cycling. Bicycle access

is associated with increased odds of cycling to work (odds ratio of 4.191) while transit access is associated with a greater likelihood of riding public transportation to work (odds ratio of 1.475).

In addition to odds ratios, the results may also be presented as predicted probabilities based on specific values assigned to the explanatory and control variables (Small and Verhoef 2007). Table 4 presents the predicted probabilities for mode choice outcomes based on the premise of a single commuter benefit package. For each row, the indicated benefit package is held at a value of one while the rest of the benefit categories are held at a value of zero and the control variables are held at their mean sample values.

Table 4. Predicted Probabilities for Mode Choice Outcomes Based upon Different Commuter Benefit Packages (Holding Other Commuter Benefit Packages at Zero and Control Variables at Mean Values)

Variable	Drive Alone	Public Transportation	Walk	Cycle
No Benefits	75.9%	22.3%	1.4%	0.5%
Free Car Parking	96.6%	2.8%	0.6%	0.1%
Public Transportation Benefits	22.8%	76.1%	0.8%	0.3%
Bike/Walk Benefits	75.9%	21.1%	2.1%	1.0%
Public Transportation Benefits & Bike/Walk Benefits	25.6%	72.3%	1.2%	1.0%
Free Car Parking & Public Transportation Benefits	82.9%	16.3%	0.5%	0.2%
Free Car Parking & Bike/Walk Benefits	95.4%	3.3%	1.0%	0.3%
All Benefits	86.8%	12.2%	0.4%	0.6%

Free car parking alone is associated with a 96.6 percent probability to drive alone to work—an increase of about 20 percentage points compared to when no benefits are provided. The simultaneous provision of free car parking, public transportation benefits, and bike/walk benefits is associated with an 86.8 percent probability of driving, an increase of about 10 percentages points compared to the probability when no benefits are provided. In general, the combination of free car parking with the other benefit categories is associated with an increased probability of driving alone to work. In contrast, benefits for choosing public transportation, walking, and cycling, when not combined with free car parking, are associated with either the same or reduced probabilities of driving alone.

To compare the model's overall predictive capacity relative to the mode choice sample summary statistics presented in Table 2, we account for the proportional presence in the sample of each benefit package presented in Table 4 and arrive at predicted mode shares of 74.6 percent for the drive alone outcome, 26.2 percent for public transportation, 1.2 percent for walking, and 0.5 percent for cycling. As a result, our model over-predicts the drive alone (4.5 percentage points) and public transportation (2.1 percentage points) outcomes, and under-predicts the walking (2.9 percentage points) and cycling (1.1 percentage points) outcomes. Since the walking and cycling mode choice outcomes are relatively rare events in our data set (4.1% and 1.6%), some degree of error in the model's prediction is expected.

Discussion and Limitations

The results from the multinomial logistic regression presented above suggest a significant correlation between commuter benefits and transportation mode choice. Specifically, the provision of free car parking and no other benefits is strongly associated with a reduced likelihood to ride public transportation, walk, or cycle to work. Public transportation benefits alone are associated with an increased likelihood of riding public transportation, as well as walking. The correlation between public transportation benefits and walking to work is unexpected, but it could be that the significance of the public transportation benefit for the choice between walking and driving is capturing some aspect of urbanity not otherwise measured by the control variables for urbanity in our model. It may also be related to the high share of federal workers with public transportation benefits in the Washington, DC, region. Federal workers who walk to work may still have a public transportation benefit available to them as a "backup," even though they only rarely ride public transportation.

Bike/walk benefits were significant for the choice between cycling and driving, as expected. Although some commuters who walk to work may also benefit from showers/lockers, this analysis did not find a significant effect for these facilities for the choice between walking and driving in the full model. It is likely that most regular pedestrians would not need a shower after walking to work.

Providing a public transportation benefit along with bike/walk benefits was associated with an increased likelihood to ride public transportation, walk, and cycle. Compared to all other benefit combinations, including bike/walk benefits alone, the odds ratios for walking and cycling were highest (odds ratios of 2.549 for walking and 6.257 for cycling) for this benefit combination. However, the odds ratio

for public transportation (odds ratio of 9.627) was lower with combined public transportation and bike/walk benefits than for commuters with public transportation benefits only (odds ratio of 11.337). This suggests that joint provision of public transportation and walk/bike benefits may encourage commuters to choose walking or cycling over driving while using public transportation as a "backup" alternative in case of inclement weather or unexpected emergencies. Moreover, the joint provision of public transportation and bike/walk benefits may attract at least some commuters away from public transportation to walking and cycling. These substitutions are more likely if commute distances are short enough for walking and cycling and if land-uses support walking, cycling, and public transportation. While our full model controls for commute trip distance, population density, household location in the urban core, transit access, and bikeway supply, we still find the combined provision of public transportation benefits and bike/walk benefits to be associated with the highest odds ratios for walking and cycling.

Combining free car parking with public transportation benefits and bike/walk benefits was associated with either the same or reduced odds for choosing one of the alternatives to driving. In other words, no benefit combination that included free car parking was associated with increased odds for riding public transportation, walking, or cycling to work. Providing free car parking alongside public transportation benefits was not associated with significantly differing odds compared to providing no benefits at all. Providing free car parking along with bike/walk benefits was associated with a lower likelihood of riding public transportation or walking to work. The joint provision of free car parking, public transportation benefits, and bike/walk benefits was associated with reduced odds of riding public transportation, but not differing odds for walking or cycling to work. This suggests that benefit combinations that include free car parking either overwhelm or render insignificant the positive effects of benefits for public transportation, walking, and cycling. Additional information about the 'quality' and 'quantity' of the benefits would strengthen such a finding. The MWCOG dataset only included dummy variables indicating the presence of a benefit, but did not include information about the quality or quantity of the benefit.

Regarding the additional control variables, findings are generally consistent with relationships reported in most other studies. Gender and ethnicity/race are associated with differing odds for walking and cycling, but ethnicity/race has a stronger correlation with walking while gender has a stronger correlation with cycling. Our results support other findings that men tend to be disproportionately represented

in U.S. cycling, and non-white populations tend to be disproportionately under-represented in U.S. cycling.

Income's negative association with public transportation is theoretically expected, and its positive association with cycling is consistent with other recent studies (Buehler 2012). The presence of one or more children in a household was associated with a reduced likelihood of riding public transportation and walking to work. This is theoretically expected, because households with children may have more rigid time budgets related to daycare and school schedules that lead to more trip-linking, among other factors.

Car access is negatively associated with riding public transportation, walking, and cycling. Transit access is positively associated with riding public transportation and bicycle access is positively associated with cycling. Car access makes driving a viable alternative to public transportation, walking, and cycling. Moreover, individuals who wish to drive to work may be more likely to own an automobile. Walking and cycling are related to shorter commute distances, as expected. Population density and living in the urban core are also positively correlated with public transportation, walking, and cycling. This finding likely captures differences in infrastructure as well as other policy and cultural factors associated with higher rates of public transportation use, walking, and cycling. Self-selection could also play a role in these findings, as individuals with unobserved preferences for riding public transportation, walking, and cycling may choose to live in the regional core in higher rates than the inner suburbs. Bikeway supply is positively associated with walking and cycling, and because shared-use paths are included it is reasonable to assume that these facilities could be used by both pedestrians and cyclists. Finally, cycling is affected by season of the year, with higher rates in the warmer months of the year. This is consistent with other studies that find cycling to be significantly correlated with weather features such as temperature and precipitation.

Future studies about the interaction of commuter benefits could overcome some of the shortcomings of this study. First, the travel survey only collected binary benefit data, so the quality and quantity of the benefits provided could not be assessed. Future analyses should attempt to refine this analysis by assessing the impact of changes in the magnitude of benefits on mode choice. For example, such studies could measure the amount of free car parking, the dollar value of public transportation benefits, the number and quality of showers and changing facilities, and the amount and type of bicycle parking. Studies already control for some of these variables individually, but very few are able to simultaneously control for

benefits for driving, riding public transportation, walking, and cycling. In addition, future analyses could identify distinct benefits for cycling and walking and treat them separately to further refine our understanding of the effect of these benefits.

Second, there are limitations related to several of the variables included in the model. The survey instrument only captured the usual main commute mode. As a result, the analysis could not evaluate the relationship between commute benefits and chained- or mixed-mode commuting. A future analysis of commute benefits and mode choice could examine whether the effect of combined benefit packages on mode choice is distinct for those commuters who combine multiple modes compared to those commuters relying on a single mode. In addition, the measures of transit access and bikeway supply did not incorporate quality measures that could relate to the impact of these measures on commute mode choice. Future studies could attempt to capture quality measures such as transit headways and traffic speeds or volumes along bikeways. Finally, commute travel time could be incorporated to assess the impact of travel time on mode choices, especially if travel time estimates for all commute modes are available.

Third, endogeneity and selection bias are limitations of our analysis, due to the cross-sectional and observational nature of the data. The potential for endogeneity and selection bias suggest caution should be taken in interpreting the results of our study. This study can report a correlation between mode choice and commuter benefits, but is not designed to assess a causal relationship. Structural Equations Models and other statistical techniques, combined with better data, could help shed light on the direction of causation.

Fourth, studies of this kind are vulnerable to omitted variable bias, and the analysis could potentially be improved by the addition of new explanatory measures or the improvement of measures already included in the model. For example, more controls for workplace neighborhood characteristics, such as density and transit access, may capture effects not included in this analysis.

Last, this study is based on the Washington, DC region, which is home to the U.S. federal government and is thus not necessarily representative of the rest of the U.S. Studies from other U.S. cities and regions could help solidify the results of this study.

Whatever the limitations of this study, it overcomes many shortcomings of previous studies in this field by including benefits for walking and cycling alongside benefits for driving and riding public transportation, as well as combinations of

these benefits. Moreover, it utilizes revealed-preference individual-level data and control measures for several neighborhood-, household-, and individual-level characteristics.

Conclusion

Overall, our results support earlier findings in the literature that suggest commuter benefits for walking, cycling, and public transportation may be effective at supporting TDM objectives. Free car parking tends to be associated with more driving to work, public transportation benefits tend to be associated with riding public transportation, and trip-end facilities at work such as showers/lockers and bike parking tend to support walking or cycling. Our results also add to the literature by presenting an evaluation of the joint supply of benefits. While benefits for alternatives to driving are associated with individuals choosing to walk, cycle, and ride public transportation, free car parking is associated with driving, and the joint provision of free car parking along with these other benefits may blunt the efficacy of efforts to get commuters to walk, cycle, and ride public transportation to work.

Acknowledgment

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Light Rail and Land Use Change: Rail Transit's Role in Reshaping and Revitalizing Cities

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Abstract

Planners and policymakers often cite the tangible objective of land use change as a primary motivation and justification for an investment in light rail transit (LRT). But how has light rail performed with respect to achieving this goal? This paper reviews and synthesizes the previous literature on LRT and other rail rapid transit systems in North America, demonstrating that rail transit alone is not a primary driver of land use change and that six beneficial factors affect the ability of these systems to have a measurable impact on reshaping and revitalizing cities.

Introduction

The past three decades have seen a remarkable growth in the number of light rail transit (LRT) systems in North America, with more route-kilometers of LRT constructed than any other type of rail transit technology. The development of these new systems provides an interesting opportunity to critically examine the LRT planning process, specifically the narrative crafted by policy and planning actors to motivate and justify investments in LRT. As a city considers such a project, the debate inevitably focuses on the benefits that can be achieved. This often includes tangible objectives such as lower levels of congestion and air pollution and the promotion of transit-oriented land use change, as well as intangible symbolic or emotional benefits, such as remaking the image of the host city as more modern

and competitive in the global economy. In some cases, the accumulation of these benefits has been true. However, the idea that these benefits are not only transferrable but inevitable in other host cities is at odds with of the North American rail transit experience. Making unsubstantiated claims of the transformative powers of these systems is both irresponsible and hazardous to short- and long-term public and political confidence in rapid transit as a tool for encouraging more sustainable patterns of growth and travel.

The impetus for this research is the $829 million 14km B-Line LRT in Hamilton, one of several LRT projects underway in the Province of Ontario. Currently in planning, the policy and planning narrative in support of the project is one heavily based in the goals of city building and revitalization (City of Hamilton 2010). These propositions employed by planners and policymakers in support of the B-Line LRT are valuable for helping to shape public and political support for the project and certainly laudable from a planning perspective. But the determination to market light rail as a driver of land use change raises important questions. How has light rail performed in relation to such goals? Can LRT act as a driver of land use change on its own? What factors must be in place to achieve such objectives? And is there an order of importance among these factors?

The present paper reviews and synthesizes the previous literature on rail rapid transit systems in North America with respect to their abilities to achieve land use planning objectives. This question has received considerable attention from a large number of authors, although this has resulted in a set of conclusions that are fragmented among several works. In response, this paper first presents an assessment of six factors that are beneficial for inducing land use change with rapid transit, factor impacts, and interactions and an examination of the land use impacts of recent LRT investments. The paper then discusses confounding influences and challenges associated with attributions of causality, finishing with conclusions that should be considered by planners and policymakers in *ex ante and ex post* evaluations of the expected benefits of such systems in other cities and regions in North America. But to begin, it is useful to theorize the two broad tangible rationales that inform an investment in rail transit. As Cohen-Blankshtain and Feitelson (2011) explain, the first is to achieve high levels of ridership by responding to existing travel demand, while the second is to create demand by affecting land use settlement patterns and travel behavior.

Existing Demand: Rapid Transit and Ridership

It is believed that the accessibility benefit obtained by providing rail transit service to a congested corridor will result in increased transit ridership and a cost-effective transit line, as well as result in a reduction in congestion, travel times, and harmful emissions (Cohen-Blankshtain and Feitelson 2011). However, previous research has been critical of the ridership and cost projections used to rationalize investments in rapid transit in a number of cities, finding them subject to systematic cost overruns and ridership shortfalls (Flyvbjerg et al. 2005; Mackett and Edwards 1998; Pickrell 1992; Siemiatycki 2009; Wachs 1987).

What factors have contributed to this trend in rail transit infrastructure projects? Several explanations have appeared in the literature. Public sector auditors have tended to view the inaccuracy of projections as a result of technical errors in fore-casting. Academic research has adopted another perspective, viewing the chronic overestimation of benefits and underestimation of costs as strategic misrepresentation, both conscious and unconscious, by project managers with a vested interest in a project's success (Flyvbjerg et al. 2005; Siemiatycki 2009).

Another explanation can be found in examining the connection between land use and transportation where, at its most basic, the existing built environment provides a foundation for activity patterns and travel demand in the urban system (Figure 1). Early research into the role of land use and travel demand established minimum densities required for cost-effective transit service (Pushkarev and Zupan 1977). In addition to density, later research has found the combined effect of several measures of the built environment to be important in affecting travel behavior, such as the diversity of land use mix, urban design, destination accessibility, and distance to transit (Ewing and Cervero 2010). For light rail specifically, recent work has further explored the link between LRT ridership and factors such as residential and employment densities, transit accessible destinations, and service quality in the United States (Kuby et al. 2004) and Europe, Australia, and North America (Currie et al. 2011). Constructing light rail in corridors where these factors are present is crucial to attracting high levels of initial transit ridership and realizing the congestion and emissions benefits associated with it.
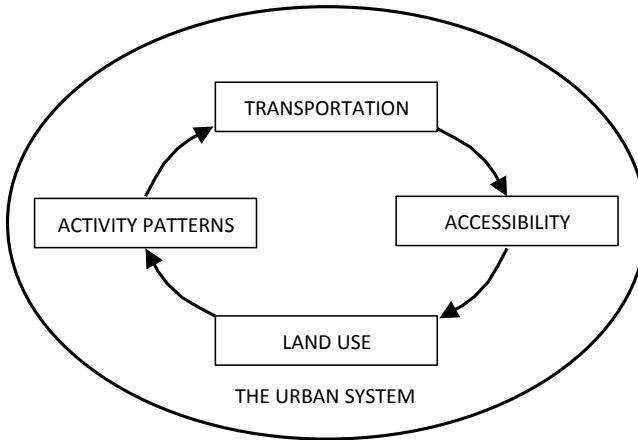
Source: Giuliano (2004)

Figure 1. Transportation–Land Use Connection

Induced Growth and Travel Demand: Land Use Impacts of Rapid Transit

The second rationale for an investment in light rail transit is to induce land use change in areas with unrealized developmental potential attributed to a lack of accessibility (Cohen-Blankshtain and Feitelson 2011). It is argued that once a light rail line is constructed, the accessibility benefits of the new transit facility will affect land use by increasing land rents and promoting higher density development, which, in turn, can alter travel patterns and mode choices over time within the urban system. Indeed, many proponents of light rail argue that an investment in LRT can spur urban growth, revitalize declining areas, and promote more transit-oriented development (TOD) in a city's downtown core, inner suburbs, and outlying areas. But what does the literature say regarding the impact of rapid transit investments on land use change?

Handy (2005) notes that, in theory, rapid transit can potentially have both a "generative" and "redistributive" impact on land use and development. However, a growing body of scholarly research challenges the generative land use effects of rapid transit, arguing that rail transit, at least on its own, is insufficient for generating new urban economic or population growth (Babalik-Sutcliffe 2002; Black 1993; Cervero and Landis 1997; Cervero and Seskin 1995; Hass-Klau and Crampton 2002; Knight and Trygg 1977a, 1977b; Vesalli 1996). Yet, there is evidence that light rail

and other rapid transit systems can have a substantial redistributive impact and influence where and how growth in a region occurs (Cervero 1984; Cervero and Seskin 1995; Handy 2005; Huang 1996; Knight and Trygg 1977a, 1977b; Vesalli 1996). As such, rapid transit should not be understood as a primary driver of new growth and revitalization, but rather as a tool to guide growth that would have occurred anyhow. But even the redistributive effect of rapid transit is greatly influenced by the presence of a number of basic factors.

Six Primary Factors Affecting Land Use Change

Knight and Trygg (1977a) were among the first to delineate several factors that affected the decision to develop land around rapid transit stations and their work has provided the foundation for research in this area since. Later studies tended to draw similar conclusions, although few appear to have specifically followed the approach of Knight and Trygg (1977a), instead formulating their own methodologies and settling on variations of which factors were most important. The end result has been a body of empirical research that is fragmented across several studies.

Nevertheless, several common themes are apparent. Our review of the literature has revealed six important factors that contribute to the ability of investments in rapid transit to promote land use change, without which rail transit is not likely to have a measurable impact on development. Each factor is outlined briefly below and their sources are presented in Table 1. From this base, we update and augment the work of Knight and Trygg (1977a) to display graphically the six primary factors and their associated determinants that affect the decision to develop land in rapid transit station areas (Figure 2).

Table 1. Review of Factors Affecting Land Use Change with Rapid Transit

Source	City (Line)	1. Transit Accessibility	2. Positive Growth & Demand	3. Positive Social Conditions	4. Positive Physical Conditions	5. Available Land	6. Complementary Planning
Cervero (1984)	San Francisco (BART) Washington, DC (Metrorail) Calgary (C-Train) San Diego (Trolley)	✓	✓		✓	✓	✓
Cervero and Landis (1997)	San Francisco (BART)	✓	✓		✓	✓	✓
Cervero & Seskin (1995)	Literature review	✓	✓	✓	✓	✓	✓
Giuliano (2004)	Literature review	✓	✓				✓
Gómez-Ibáñez (1985)	San Diego (Trolley) Calgary (C-Train) Edmonton (ETS LRT)	✓	✓				✓
Handy (2005)	Literature Review	✓	✓		✓	✓	✓
Huang (1996)	Literature review	✓	✓			✓	✓
Knight and Trygg (1977a)	San Francisco (BART)	✓	✓	✓	✓	✓	✓
Knight and Trygg (1977b)	Toronto (TTC) Montreal (Metro) Philadelphia (SEPTA) Boston (MBTA Subway & Streetcar) Chicago (CTA Subway & Streetcar) Washington, DC (Metrorail) Cleveland (RTS) New York (PATH) Los Angeles (El Monte Busway) Seattle (Blue Streak Bus) Miami (Blue Dash Bus)	✓	✓		✓	✓	✓
Vessali (1996)	Literature review	✓	✓			✓	✓
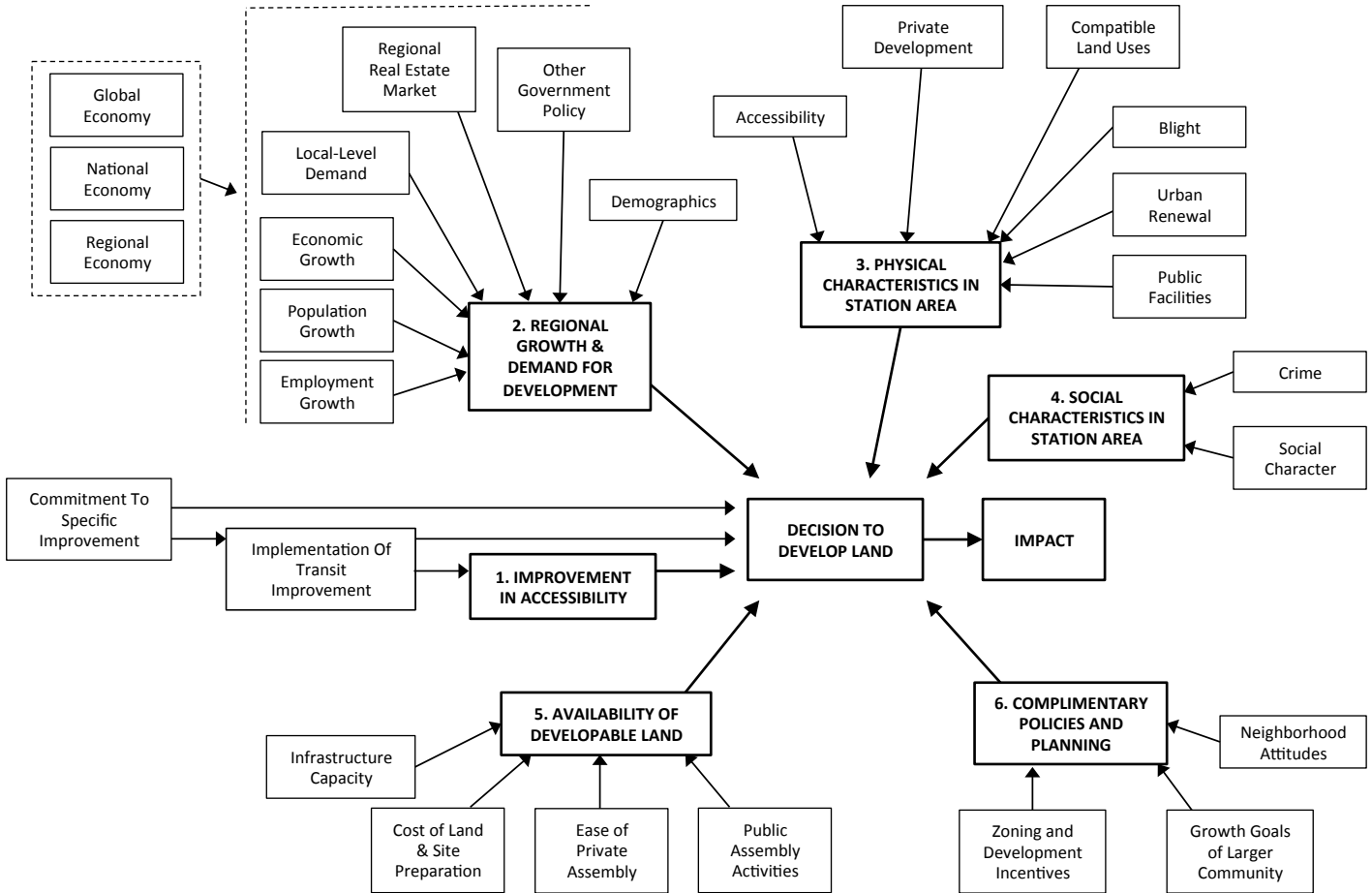
Source: Adapted from Knight and Trygg (1977a)

Figure 2. Factors influencing land use impacts

1. Improvement in accessibility

Accessibility lies at the heart of locational advantages in an urban market where individuals base their locational decisions on a tradeoff between transportation costs and housing consumption, and the attractiveness of higher-density, mixed use TOD is dependent on rapid transit offering a competitive alternative to other modes for reaching destinations in the city. This includes accessibility at the start and end of a transit journey, emphasizing the importance of transit-based employment in addition to transit-based housing as well as connectivity to transit at the neighborhood level. While there may be some latent demand from individuals who would self-select to locate in a station area, if rapid transit offers only a marginal or negligible improvement in accessibility and reduction in transportation costs it is unlikely to create a transit-based locational advantage which can in turn negatively impact by choice ridership and land use change. This is especially relevant in cities that are uncongested or where a spatially-dispersed and automobile-oriented built environment is prevalent. In some cases, development or speculation can occur in advance of a transit facility beginning service based on perceived accessibility benefits.

2. Positive regional economic, population, and employment growth and demand for development

The land use impact of transit is conditional on the presence of regional economic, population, and employment growth that can be redistributed to a transit corridor and a healthy real estate market with demand for higher-density living. Languishing growth and a soft real estate market can mean higher risks for developers and lenders and may require significant market intervention to increase the supply of transit-oriented housing, although this does little to increase demand for such development. Demand also matters at the local level, as even if a region is experiencing rapid economic, population, and employment growth, there must be demand from developers to construct and individuals to live within the transit corridor. Other broad factors such as demographics, government policies such as taxation and interest rates, and the structure of the global, national, and regional economy and labor market also come together to shape the nature of supply and demand in the urban land market. This prerequisite also suggests an element of timing, as the potential redistributive impact of rapid transit is stronger if the facility enters service just prior to a period of rapid growth.

3. Positive physical conditions in transit corridor and station areas

High quality physical environments that are friendly to pedestrians and feature amenities, public improvements, and streetscape enhancements are more hospitable to transit riders and thereby more attractive to developers, financers, and those presently or interested in living there. Conversely, a deteriorated housing stock or incompatible land uses can hurt demand for new development. This issue is related to the choice of transit corridor, as alignments in industrial areas or highway medians chosen for cost considerations can create a significant challenge to attracting transit-oriented land use change.

4. Positive social conditions in transit corridor and station areas

Social challenges, both real and perceived, can have long-lasting effects on the potential for land use change along a transit corridor, despite the best intentions of planners and policymakers. Positive social conditions play a vital role in the attractiveness of station areas for development for developers, financers, and prospective residents. Criminal activity can contribute to a perception of insecurity and other social issues such as poverty, unemployment, the quality of schools, or a general perception of disadvantage can all but erase market demand for certain locations.

5. Available land for development and ease of land assembly

Transit-oriented development is much more straightforward and profitable for developers if large parcels of land are already available, cheap, and suitable for development. Land assembly can be a costly and time-consuming process and can benefit from the help of the public sector. In some respects, development within established city cores may be at a natural disadvantage compared to greenfield locations, although development incentives may offset this.

6. Complementary government planning and policy

Policies designed to incentivize TOD and level the playing field for the transit mode are a critical factor in strengthening the relationship between rapid transit and land use change. This includes a package of zoning, financing, and planning policies to promote transit-oriented development, parking and road investment policies that restrict travel by automobile, and complementary regional policies such as urban growth boundaries and densification targets and the correction of market distortions such as the underpricing of automobile travel.

Complementary land use planning and policies have gained considerable attention in recent years. Planners of first-generation light rail and other rail transit projects

tended to view transit stations as natural "magnets" for development and saw land use planning as separate from transportation, preferring to leave development to the market. But the general underperformance of these systems in terms of land use change has resulted in increasing attention paid to TOD by academics, planners, and policymakers. A pivotal turning point came in 1998 when six explicit land use criteria became part of the Federal Transit Administration's (FTA) process for evaluating New Starts projects (Deakin et al. 2002). In response, concurrent and advance land use planning is now an integral part of the transit planning process within the vast majority of rail transit agencies in the United States (Cervero et al. 2004).

Factor Impact and Interactions

While the six primary factors listed above appear to be relatively straightforward, such an approach offers no information on the relative weight of each or interactions between them, leaving researchers with many unanswered questions regarding their effect in practice. For example, which factors are most important in tipping the balance towards development? Is there a point at which some factors can overcome others, such as using a suite of developmental incentives to overcome a less-than-ideal social or physical environment?

Definitive answers to these questions remain elusive, although the literature does offer some insight. A first consideration is the ability of rail transit to increase accessibility and create locational advantages. Previous authors consistently mentioned accessibility as an important condition for inducing land use change in transit station areas and rail has been shown to be a major driver of development in the 'streetcar suburbs' of the past (Bernick and Cervero 1997). But road systems in North American cities have become highly developed since that time, and the transit system is only a small portion of the entire transportation network (Giuliano 2004). Subsequently, the ability of light rail and other rapid transit to create an accessibility-based locational advantage within this context, particularly in highly automobile-oriented cities, is severely weakened, thus limiting one of rapid transit's strongest natural impacts on shaping land use within the urban system.

Nevertheless, rail is competitive in certain urban contexts, as the examples below will show. Reductions in automobility that result from congestion or targeted public policies can also benefit transit accessibility. Furthermore, the other five factors can augment accessibility to strengthen the ability of rail transit to induce land use change.

Given rail's potentially marginal effect on accessibility, the biggest emphasis in the literature for promoting land use change is on complimentary land use policies and planning. Meyer and Gómez-Ibáñez (1981) contend that a comprehensive package of land use planning policies and incentives can affect urban form far more than transit planning. But transit remains important as the process of transit planning is itself often a major catalyst for more intensive land use planning that might not otherwise have occurred (Vesalli 1996).

Regional growth and demand for development is also fundamental. As summarized by Vessali (1996): "Almost exclusively, transit systems' impacts on land use are limited to rapidly growing regions with a healthy underlying demand for development" (p. 97). In short, there must be growth to redistribute to a transit corridor if measureable land use change is to occur. Recent research by Hess and Almeida (2007) supports this position. Though transit-oriented land use change is considered most likely in central cities, the authors find a distinct lack of new projects in the downtown areas of slow growth and economically distressed cities. Meyer and Gómez-Ibáñez (1981) argue that positive growth is more important than complementary land use policies and planning as "if there is no underlying demand for high-density development, then almost no combination of public policies will elicit a compact urban structure" (p. 127).

The remaining factors of social and physical conditions and available land for development in station areas are cited with less frequency, suggesting they play a smaller role in the development decision. However, access issues, incompatible surrounding land uses, transit stations in highway medians, crime, and other related challenges have been shown to preclude development. Moreover, as recent experiences with light rail below demonstrate, all six of these factors continue to shape the land use impacts of LRT and other rapid transit.

Recent Experiences with Light Rail and Land Use in Practice

Previous research on experiences with light rail in several cities offers some more recent insight into the role of these factors in inducing land use change in station areas, though no one study has examined the impact of all six factors concurrently. While they can be low in some contexts and are generally accepted as less than that of heavy rail, accessibility benefits are cited as the root cause of significant new development along Jersey City's Hudson-Bergen LRT. The line, which opened in 2000, links several major residential and employment destinations and features

a direct connection to the PATH rapid transit system in New Jersey and New York City (Cervero et al. 2004; Robins and Wells 2008).

Cervero et al.'s (2004) review of experiences with TOD offer a number of insights into recent experiences with light rail and land use change in the United States. The authors cite strong market demand as a factor contributing to development around DART LRT stations in the Dallas metropolitan area, although they note that the functional connections to transit in the bulk of these projects is lacking. Outside of the city of Dallas, smaller cities such as Plano have used supportive planning policies to generate new transit-oriented development.

Two of the most widely-cited examples of complementary land use planning and policy are San Diego and Portland, the latter of which is considered by Cervero et al. (2004) to have among the most aggressive TOD programs in the nation. Although San Diego's southern leg of the Trolley to the Mexican border boasts impressive ridership, land use change along the line has been non-existent, largely due to its alignment along freight rail tracks in an industrial corridor. Future lines and extensions have been chosen based on developmental potential and, in concert with a strong real estate market, traffic congestion, demographics, population, and employment growth, as well as a progressive package of supporting public policies, new development in station areas has been commonplace

At the time of writing, Cervero et al. (2004) found that nearly every one of Portland's LRT stations saw some form of new development, thus increasing the multiplier effect of homes, jobs, and activity centers along its transit lines. Nevertheless, planners there are quick to point out that the City's policy and planning incentives did not create demand for TOD and instead credit demographics and individual preferences for driving the market for development in LRT station areas. But Portland's new Green Line LRT runs along Interstate 205, and experiences in other cities suggest that such an alignment can negatively impact prospects for new transit-oriented development. In this sense, it will be interesting to see if market demand and supportive public policies can overcome such a physical environment to promote land use change as the line matures.

Social challenges are less cited in the literature, although they have been found to have an effect on development. According to Loukaitou-Sideris and Banerjee (2000), poverty, unemployment, crime, and gang violence combined with physical issues such as inaccessible stations, poor pedestrian connections, incompatible surrounding land uses, and a deteriorated housing stock along the Blue Line LRT in Los Angeles have resulted in an environment described as "derelict and forbidding"(p.

10). This negative image was said to be a major factor precluding investment and development in many station areas.

Among new LRT systems, notable recent examples of land use change and revitalization attributed to complementary planning and policy include new lines and system extensions in Minneapolis, Denver, and Charlotte, which opened in 2004, 2006, and 2007, respectively (Fogarty and Austin 2011). Of these, both Minneapolis and Charlotte experienced considerable new investment around light rail stations in their central areas, and Fogarty and Austin (2011) attribute much of this to public policies in support of TOD as well as local factors such as accessibility and proximity to major employment areas, positive regional growth, a strong real estate market and demand for development, available land, and good physical connections to transit at the neighborhood level. However, these factors were not present at all stations along each line and, subsequently, development remains uneven, particularly outside of the central city. In Denver, there has been some development along the Southeast Corridor LRT, although it is not clearly due to transit and the developmental potential of the line is hurt by its location in a highway median (Fogarty & Austin 2011).

The land use impact of other recent LRT systems is less clear. Considerable land use planning was completed in advance of light rail in Phoenix, which began service in 2008 (Atkinson-Palombo and Kuby 2011). Kittrell (2012) has shown that these efforts have worked to some degree with a refocusing of development in downtown Phoenix, although in other cases new zoning incentives for TOD appear to have been ignored in favor of automobile-oriented projects. Valley Metro (2013) has released periodic economic development updates with the most recent detailing nearly $7 billion in new development near LRT stations since 2004. Land use change in Phoenix has likely been hindered to some degree by real estate speculation that occurred between 1998 and 2000 after station locations were announced (Kittrell 2012), a problem has previously been said to negatively affect land use development related to rapid transit elsewhere (Cervero 1985; Vesalli 1996). Other large-scale factors, such as the global economic crisis and recession of 2007–2008, have no doubt had an impact as well. However, no other empirical studies of the land use impact of LRT in Phoenix exist.

Property values have increased in Houston LRT station areas since METRORail began service in 2004 (Pan 2013). But like Phoenix, empirical research on new development associated with LRT remains sparse. Pan (2013) anecdotally notes one new condominium project within walking distance of a station. Research con-

ducted by the authors indicates some changes have occurred, with a small number of new condominium projects as well as significant new developments around the Texas Medical Center. However, many station areas throughout the system remain dominated by surface parking. METRORail's construction without federal funding means it was not subject to creating a land use planning program in line with FTA's evaluation criteria and the city's lack of traditional zoning regulations make it a relatively unique case in North America. This may change in the future, as Houston launched its Urban Corridor Planning initiative in 2009 and new system extensions approved in 2011 will receive almost $800 million in federal funds, although FTA (2009) rates the city's land use initiatives as medium to low.

After what Brown and Thompson (2009) characterized as a distinct lack of new TOD in TRAX station areas along its first phases of LRT, Salt Lake City is now aggressively pursuing several ambitious TOD projects on agency-owned land through FTA's joint development program at stations along new Green and Red Line extensions that opened in 2011 (Olson 2011). Several other cities have completed new light rail lines and system extensions since 2005, such as Los Angeles, Norfolk, Dallas, Portland, San Diego, and Sacramento. However, the relative immaturity of these systems means it will be some time before researchers are able to decipher their long-term ability to shape urban growth and development. Nevertheless, the information on the recent cases explored thus far suggests that the six factors that affect land use remain as relevant today as they did when they were first published several decades prior.

Causality, Confounding Influences, and the Effectiveness of Development

We began this paper questioning the role of light rail and other rail transit in promoting land use change and revitalization. But the evidence presented thus far paints only a partial picture of that process. Six important factors have been identified that influence land use development around rapid transit stations and some appear to carry more weight, though this conclusion is based simply on the frequency of their citations in the previous literature.

However, a more quantified analysis of the impacts of and interactions between the six factors identified above is beset by a number of challenges. A significant obstacle is the battery of confounding influences that inform each and local contextual factors in station areas. According to Giuliano (2004), the largest issues that plague attempts to clarify the relationship between rapid transit and land use

development are first the highly-dynamic nature of the urban system where many changes are occurring at any given moment in addition to the transit investment, and second, the long time horizon involved in market responses to these changes, which can span decades. A consequence of these issues is that it is especially difficult to determine the nuanced forces at work and the direction of causality in land use changes that have occurred as a result of land use planning in tandem with a transit investment, leading Giuliano (2004) to remark that "land use and transportation decisions are so closely tied together that it has been impossible so far to separate their effects" (p. 254). Subsequently, no authors have attempted to comprehensively disentangle the factors that have influenced development in station areas with previous work limited to "draw(ing) inferences by looking at a handful of time slices using less-than-complete data" (Cervero and Landis, 1997, p. 311).

Nevertheless, quantitative research using advanced statistical methods can isolate the six factors above while controlling for any additional influences that may be relevant to a particular case. This type of analysis is, of course, predicated on the availability of a longitudinal data set of sufficient scope and quality, one that has to date remained elusive. Still, such an approach is necessary for increasing our knowledge of which factors matter most and why.

Conclusions

If a rail transit system is to have high levels of initial ridership, it is essential that it be located along a corridor with high levels of existing demand. However, it is often the potential for promoting transit-oriented land use change that emerges as a central planning consideration for achieving long-term ridership goals. Many cities have witnessed new TOD associated with light rail and other rail transit over the past two decades, and there is no question that a narrative in pursuit of this objective is a fundamental factor in shaping public and political support for such a project. But it has been more than 35 years since Knight and Trygg (1977b) cautioned that "unreasonable claims of transit's power to induce major land use change must be avoided" (p. 245). Although these systems can bring considerable benefits to host cities, years of research demonstrate that local conditions must be receptive if these systems are to have a measurable impact on land use change. In response, rail transit is best understood not as a driver of new growth and land use change on its own, but as a singular element in a long-term effort to shape growth and revitalization in host cities.

In this paper we have delineated six important factors that influence land use change associated with light rail and other rapid transit, although no study to date has explicitly attempted to disentangle the role of each in the development decision and their piecemeal application in studies that have occurred leaves researchers with a fragmented set of conclusions. Factors such as an increase in accessibility, regional growth and demand for development, and supportive public policies are cited most frequently and appear to carry the most weight, although social and physical conditions and available land are also important.

Confounding influences, long time horizons, and the complexities of individual station area contexts will make greater quantitative determinations of association and causality among these factors challenging. Nevertheless, future quantitative research on the positive and negative influences associated with development in station areas should be conducted taking all six of these factors into account, thereby standardizing research in this area and providing more evidence as to their importance in the development decision This is particularly important for testing the impact and effectiveness of newer "second generation" light rail lines and extensions that are an outcome of the FTA's greater emphasis on concurrent land use planning. Only then can we surpass the limits of previous research to obtain a more complete picture of the role of light rail and other rapid transit in reshaping and revitalizing cities.

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Measuring Bus Service Reliability: An Example of Bus Rapid Transit in Changzhou

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Abstract

The objective of this paper is to analyze service reliability of bus rapid transit (BRT) taking Changzhou BRT as an example. Headway irregularity, potential waiting time, equivalent waiting time, and reliability buffer time are recommended to measure service reliability of BRT. Temporal and spatial distributions and comparisons are analyzed. Findings are that passengers of Changzhou BRT need to budget, on average, an extra 3–5 minutes beyond their typical journey time for selected origin-destination pairs to ensure on-time arrival at destinations with 95% probability. Extra time budgeted for bus waiting beyond mean waiting time contributes to more than 80 percent of extra time budgeted for a journey, while only 20 percent is budgeted for in-vehicle travel time. Service reliability is best near a route's origin terminal and gradually deteriorates along the route, then improves when approaching the route's end.

Introduction

Bus rapid transit (BRT) combines the efficiency and reliability of a rail service with the operating flexibility and lower cost of a conventional bus service. It has been implemented throughout Latin America, North America, Europe, Southeast Asia, Australia, China, and now, increasingly, in Africa and India (Deng and Nelson 2011).

In China, BRT has expanded faster than in any other regions over the last five years, with 320 km of BRT systems in 13 cities (Fjellstrom 2010). Service reliability of a transit system has significant impacts on its providers as well as existing and potential users (Cham 2006). The objective of this paper is to analyze service reliability of BRT taking Changzhou BRT as an example. Specifically, issues including the amount of time passengers need to wait, on average, and the amount of extra time passengers need to budget beyond typical wait time and journey time, on average. Temporal and spatial distributions of measures and comparisons between measures are examined. Potential wait time, which is proposed to measure service reliability but has not been applied yet, is put into practice in this paper. Some suggestions for improving service reliability of Changzhou BRT are brought forward. The framework for analyzing service reliability of Changzhou BRT includes measures and analysis dimensions that can be applied to other BRT systems.

Literature Review

Service reliability is defined as "the invariability of service attributes which influence the decision of travelers and transportation providers" (Abkowitz et al. 1978). The ability of transport operators to understand and improve reliability relies on their ability to measure it (Uniman 2009). Service reliability can be measured from multi-perspectives based on multi-levels.

Measures from operators' perspectives mainly include on-time performance (OTP) and headway regularity (Cham 2006, Kittelson & Associates, Inc. et al. 2003). OTP is the fraction of services with schedule deviation within some thresholds (Ryus 2003). Headway regularity is defined in terms of the fraction of observed headways that are within some absolute or relative deviation from the scheduled headway (Cramer 2008). Furth et al. (2006) consider it a coefficient of variation of headway, which is the standard deviation of headway divided by the mean.

Measures from the passenger perspective include waiting time-related measures such as excess waiting time, potential waiting time, and equivalent waiting time. They also contain journey time-related measures such as excess journey time, reliability buffer time, and excess reliability buffer time.

Excess waiting time represents the extra amount of time a passenger waits, on average, beyond the scheduled waiting time (Furth and Muller 2006). To have a high probability of arrival at their destinations on time, passengers must plan on waiting longer than the mean waiting time. The 95th percentile waiting time is often interpreted as budgeted waiting time, guaranteeing arrival at their destinations on time

at least 95 percent of trips (Furth et al. 2006). The difference between budgeted and mean waiting time is called potential waiting time, which is spent at the destination of the trip (Furth and Muller 2006). Equivalent waiting time is a weighted sum of mean and potential waiting time that expresses passenger waiting cost in equivalent minutes of waiting time spent at stops (Furth et al. 2006).

Journey time includes access, egress, and interchange time; ticket purchase time; platform wait time; on-train time; and closures. Each component has a scheduled value, which represents the amount of time a passenger should normally expect to take to complete this stage. The difference between the measured and scheduled times is an indication of service performance, expressed as excess journey time (Chan 2007). Journey time reliability also can be generally defined by quantifying the spread of journey time distribution. The measure quantifying the spread of journey time is known as the reliability buffer time. Reliability buffer time represents the extra time passengers need to budget beyond the typical journey time to ensure 95% probability of arriving at their destination on time. Uniman (2009) developed a new measure called excess reliability buffer time by proposing a methodology classifying performance into incident-related and recurrent conditions, which attempted to explain the causes of unreliability by isolating the effects of incidents.

BRT is defined as "a flexible, rubber-tired form of rapid transit that combines stations, vehicles, services, running ways, and ITS elements into an integrated system with a strong image and identity" (Levinson et al. 2003). Current studies in China mainly focus on the physical design and planning of BRT (Xu 2007; Mo 2007). In addition to passenger-carrying capacity, the integration of BRT with other modes and its implementation effectiveness were also studied. Current literature outside China pays more attention to the impacts of BRT on land development and land values (Perk et al. 2010). There is a growing body of evidence suggesting that BRT systems have a positive impact on land value uplift (Deng and Nelson 2011). Capability to lead bus-based transit-oriented development (TOD), impacts on travel behavior, environment, fuel consumption, construction, operation cost, and ridership were also studied.

Methodology
BRT in Changzhou, China
Vehicles of Changzhou's BRT are equipped with a Global Positioning System (GPS), and large-scale, archived Automated Vehicle Location (AVL) data provide the

opportunity for studying service reliability. This study employed one trunk route of Changzhou's BRT, called B1, as a specific study case. Archived AVL data of Route B1, consisting of nearly 700,000 records from August 17–23, 2009, were used. Route B1 is one of the busiest bus routes in Changzhou. Its length is 24.5km, there are 26 stops with an average space of 980m. Headway is 2–5 minutes during peak hours and 6–10 minutes during off-peak hours. Route B1 runs north and south and traverses downtown Changzhou, and its middle six stops are located in the downtown. Six origin-destination (OD) pairs were selected to study service reliability based on OD pair level. OD pair1 (length 5,880m) connects south and downtown, OD pair2 (6,860m) connects north and downtown, and OD pair3 (3,920m), pair4 (3,920m), pair5 (3,920m), and pair6 (4,900m) cover the entire route by connecting them together. Only OD pair5 covers downtown. Figure 1 illustrates Route B1 and the selected OD pairs.
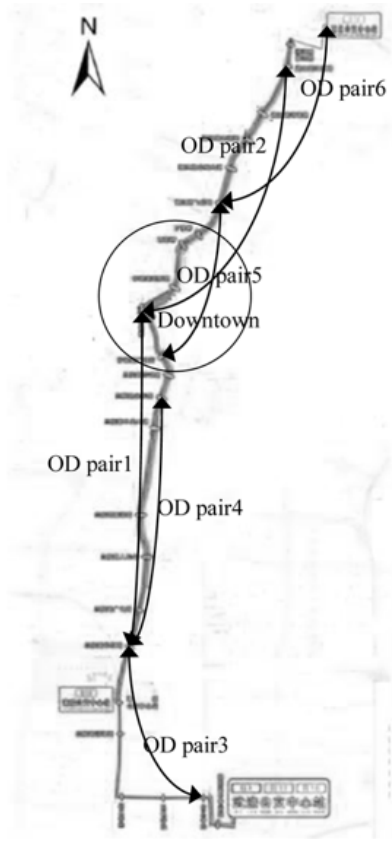

Figure 1. Route B1 and selected OD pairs

Measures Selection and Calculation

On-time performance, excess waiting time, excess journey time, headway regularity, potential waiting time (PWT), equivalent waiting time (EWT), and reliability buffer time (RBT) frequently are used for evaluating transit service reliability. On-time performance, excess waiting time, and excess journey time are related to schedule and are suitable for low-frequency services; the other four measures are suitable for high-frequency services. Most BRT systems are high-frequency services; therefore, headway regularity, PWT, EWT, and RBT were selected to measure service reliability of BRT. Headway regularity captures service reliability from the operator perspective based on stop level and is regarded as a coefficient of variation of headway in this paper. The higher the coefficient of variation of headway is, the more irregular the headway is. Headway regularity is called headway irregularity in this paper. PWT and EWT capture service reliability from the passenger perspective based on stop level. RBT captures service reliability from the passenger perspective based on OD pair level. To better understand each measure selected, the definitions, implications, and calculation methods are presented in Table 1.

Table 1. Definitions, Implications, and Calculation Methods for Measures Selected

Measures	Definitions and Implications	Calculation Methods
Headway irregularity	Regarded as coefficient of variation of headway ; called headway regularity in previous studies—the higher it is, the more irregular the headway is.	Standard deviation of headway divided by its mean (Furth et al. 2006)
Potential waiting time (PWT)	Difference between 95th percentile waiting time and mean waiting time; extra time that passengers need to budget beyond mean waiting time for bus waiting to ensure on-time arrival at destination with 95% probability (Furth and Muller 2006).	95th percentile waiting time minus mean waiting time
Equivalent waiting time (EWT)	Weighted sum of mean and potential waiting time that expresses passenger waiting cost in equivalent minutes of waiting time spent at stops (Furth et al. 2006).	Mean waiting time + $0.5 \times$ PWT
Reliability buffer time (RBT)	Difference between 95th percentile journey time and median journey time; extra time that passengers need to budget beyond typical journey time for entire journey to ensure on-time arrival at destination with 95% probability (Uniman 2009).	95th percentile journey time minus median journey time (50th percentile journey time)
Mean waiting time	Amount of time between passenger arrival and next vehicle departure, on average.	$0.5 \times$ mean headway $\times$ (1+) (Osuna and Newell 1972)

The 95th percentile waiting time, 95th percentile journey time, and median journey time are needed when calculating PWT and RBT. They can be obtained by interpolation from waiting time distribution and journey time distribution. Waiting time distribution can be estimated based on a set of observed headways according to Equation (1) (Furth and Muller 2006):

$$F_W(H_i) = F_W(H_{i+1}) + i\Delta H_i \bigg/ \sum_{i=1}^{n} H_i \qquad (1)$$

Where,

W = waiting time

H_i = *ith* observed headway; headways numbered in decreasing order

$F_w(H_i)$ = waiting time distribution, i.e., probability of W less than or equal to H_i $\Delta H_i = H_i - H_{i+1}$

n = number of observed headways

Journey time for an OD pair is considered the sum of waiting time at the origin stop and the in-vehicle travel time between the origin and destination stops in this paper. Journey time distribution can be estimated based on headways at the origin stop and the in-vehicle travel times of successive trips according to Equation (2) (Ehrlich 2010):

$$F_J(j) = \sum_{i=1}^{n} (j - T_i) \bigg/ \sum_{i=1}^{n} H_i \qquad (2)$$

Where,

J = journey time

j = given time

T_i = in-vehicle travel time of the *ith* trip

H_i = headway of *ith* trip

F_j = probability of J less than or equal to j

n = number of successive trips. If $j - T_i < 0$, let $j - T_i = 0$; if $j - T_i \geq H_i$, let $j - T_i = H_i$.

Analysis Dimensions

Issues including the amount of time passengers need to wait, the amount of time passengers need to budget beyond typical waiting time and journey time, their variations over time and space, and the relationships between measures can provide comprehensive understanding for service reliability. Therefore, analysis dimensions include value ranges of measures, temporal and spatial distributions of measures, and comparisons between measures. Temporal distribution can be carried on by time period within one day (analyzed here), a weekday and weekend, and a month. Spatial distribution can be carried on by direction, section (analyzed here), and area. The lower the headway irregularity, PWT, EWT, and RBT are, the more reliable the service is.

Results

Value Ranges of Measures

Mean headway, headway irregularity, mean waiting time, PWT, and EWT for each stop and RBT for each OD pair were calculated by taking the average number of each hour (06:00 to 21:00), day (August 17–23), and direction (Northbound and Southbound). To explain how the calculations were made, RBT's calculation process of an OD pair is provided below. First, the journey time distribution in each hour was calculated. AVL data were used for the Changzhou BRT for one week and in two directions, so 224 journey time distributions were obtained for each OD pair. Table 2 shows an example of a calculation of journey time distribution. The 95th percentile journey time and median journey time in each hour were gained from the journey time distribution by interpolation, and the RBT in each hour was obtained accordingly. Finally, the RBT of an OD pair was obtained by taking the average number of the 224 values of RBT.

Table 2. Example of Journey Time Distribution Based on Successive Trips

Trip$i$	Origin Stop Headway H_i (min)	In-Vehicle Travel Time T_i (min)	Max. Journey Time $H_i + T_i$ (min)	Give Time j (min)												
				18	19	20	21	22	23	24	25	26	27	28	29	30
				$j-T_i$												
Trip1	7.15	22.80	29.95	0	0	0	0	0	0.2	1.2	2.2	3.2	4.2	5.2	6.2	7.15
Trip2	1.87	21.52	23.39	0	0	0	0	0.48	1.48	1.87	1.87	1.87	1.87	1.87	1.87	1.87
Trip3	4.07	18.88	22.95	0	0.12	1.12	2.12	3.12	4.07	4.07	4.07	4.07	4.07	4.07	4.07	4.07
Trip4	5.65	17.35	23.00	0.65	1.65	2.65	3.65	4.65	5.65	5.65	5.65	5.65	5.65	5.65	5.65	5.65
Trip5	5.75	21.70	27.45	0	0	0	0	0.3	1.3	2.3	3.3	4.3	5.3	5.75	5.75	5.75
Sum	24.49			0.65	1.77	3.77	5.77	8.55	12.7	15.08	17.08	19.08	21.08	22.53	23.53	24.49
Distribution percentile $F_j(j)$				0.03	0.07	0.15	0.24	0.35	0.52	0.62	0.70	0.78	0.86	0.92	0.96	1

Mean headway was between 3.12–3.96 minutes, which means 15–20 buses are dispatched per hour. Headway irregularity was between 0.34–0.79. Its span is relatively large, which means headway is irregular from the entire route perspective. Passengers, on average, need to wait 2.17–2.82 minutes and need to budget an extra 3.29–4.54 minutes, on average, for bus waiting to guarantee arrival at their destinations on time with 95% probability. The extra 3.29–4.54 minutes is spent at destinations. This was transformed into the time spent at stops with a weight of 0.5. Along with mean waiting time, it was found that passengers need to wait an equivalent of 3.81–5.09 minutes at stops. RBT is between 3-5 minutes, which means passengers need to budget extra 3–5 minutes beyond their typical journey time to ensure 95% probability of arrival at their destinations on time.

Service Reliability by Time Periods

Figure 2 shows variations of mean headway, headway irregularity, mean waiting time, PWT, EWT, median journey time, and RBT for the Early, AM Peak, Inter-peak, PM Peak, and Evening periods for the Northbound and Southbound directions.

Mean headway is the lowest during AM and PM peaks and highest during the Early period. To be specific, buses are dispatched every 3 minutes during the AM and PM peaks, every 3.7 minutes during Inter-peak, every 4 minutes during Evening, and every 6 minutes during the Early period. Mean headway in the Northbound direction during Evening is higher, at 4.38 minutes.

Mean headway and headway irregularity are highest during the AM and PM peaks, especially during the AM Peak, at above 0.7; they are lowest during the Early period. This means that headways during the AM and PM peaks are less regular than other time periods. This likely is the result of more buses being dispatched during the AM and PM peaks, and traffic conditions during the AM and PM peaks being worse than other time periods.

Mean waiting time is the highest during the Early period, at 3.55 minutes Northbound and 4.05 minutes Southbound. Mean waiting time is also high during the Evening Northbound, close to 3 minutes. This can be attributed to lower service frequencies during these two periods. Mean waiting times during the AM and PM peaks and Inter-peak are below 2.5 minutes. Waiting time in Inter-peak is slightly higher than it is in AM and PM peaks.

Like mean waiting time, PWT and EWT are the highest during the Early and Evening periods Northbound. Relatively low service frequencies during these two periods push passengers to budget more extra time for bus waiting to ensure arrival at their
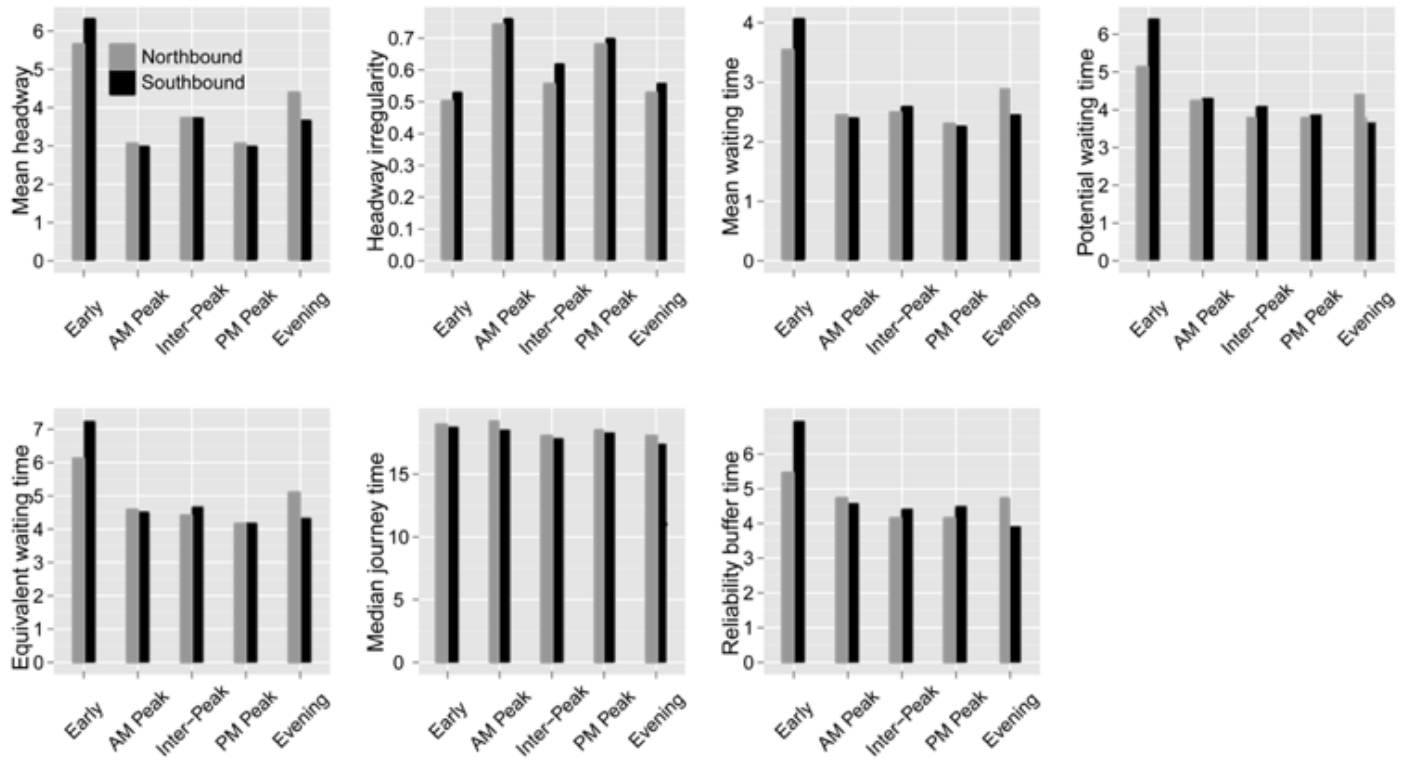
Figure 2. Service reliability by time periods

destination on time. Higher PWT together with higher mean waiting time during these two periods translates into higher EWT. In other words, equivalent waiting time spent at stops is the highest during the Northbound Early and Evening periods. PWT is slightly higher during AM Peak. This is reasonable because the primary passengers of BRT are office workers and students whose travel purposes during AM Peak are work or study and who want to arrive at their work/study place on time and are willing to budget more time.

The variation of median journey time is small across all time periods. The difference between its maximum, appearing in AM Peak Northbound, and its minimum, appearing in Evening Southbound, is less than 2minutes. Like PWT, RBT is the highest during the Early period, close to 7 minutes Southbound. RBT is also slightly higher during AM Peak, for the same reason as PWT.

In conclusion, service frequency during the Early period is the lowest, which, to a certain extent, results in the highest mean waiting time, PWT, EWT, and RBT during this period. However, headway during the Early period is more regular than any other periods. For the AM and PM peaks, service frequencies are the highest and headway regularity is the worst. Although mean waiting time is the lowest, the difference is negligible compared to other time periods except the Early period. For AM Peak, PWT and RBT are slightly higher than other periods, except for the Early and Evening periods Northbound. From the perspective of operators, i.e., based on headway irregularity, service reliability is the worst during AM and PM peaks. However, from the perspective of passengers based on PWT and RBT, service reliability is the worst during Early period followed by the AM Peak. Relatively worse service reliability during the AM Peak is mainly related to passengers' subjective inclination to budget more time for work or study.

Service Reliability by Directions

As mentioned above, Route B1 traverses through Changzhou's downtown. Directions are classified into To Downtown (going to downtown from both sides of the route) and From Downtown (leaving downtown from both sides). To analyze mean headway, headway irregularity, mean waiting time, PWT, and EWT by direction, stops in the Downtown were excluded. To analyze median journey time and RBT by direction, OD pair1, OD pair2, OD pair4, and OD pair6 in Figure 1 were selected. Figure 3 shows service reliability by To Downtown and From Downtown. The abscissas of the first five figures in Figure 3 represent stop order regarding the first stop in Northbound as 1.
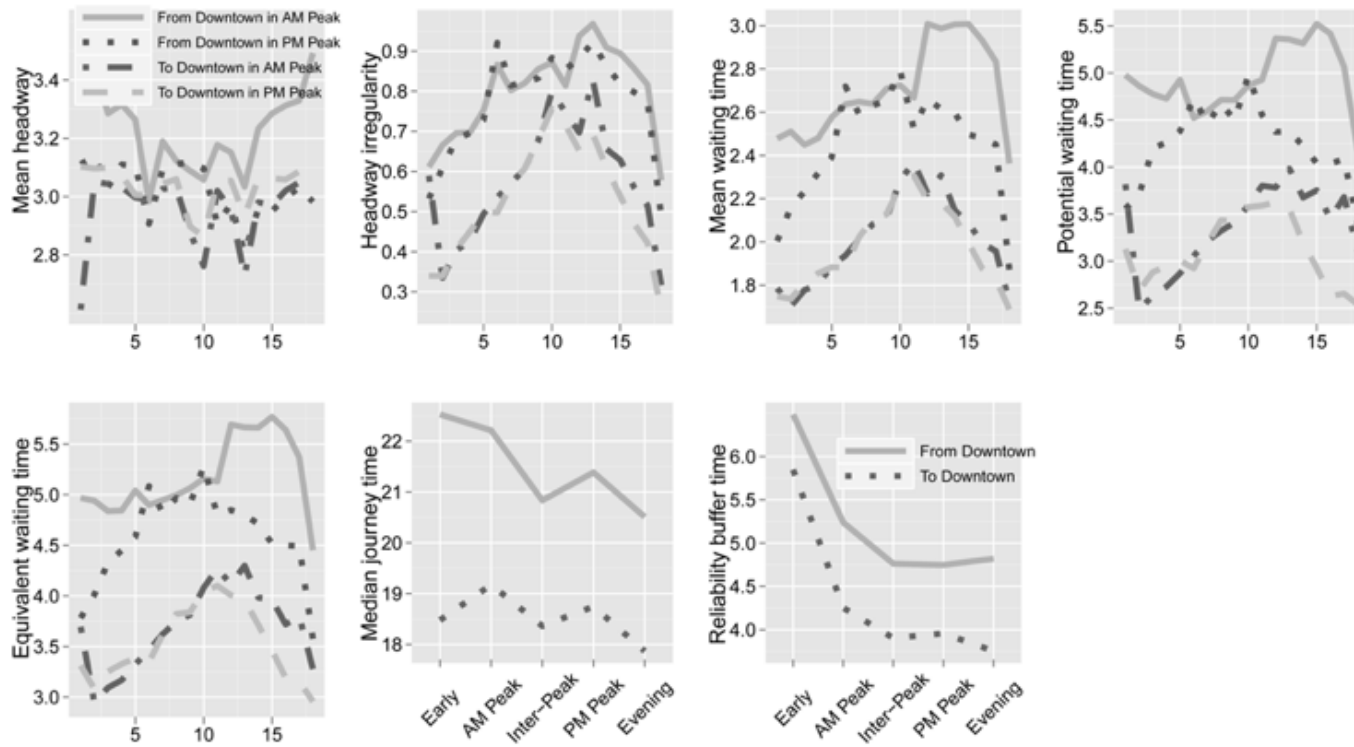
Figure 3. Service reliability by direction

The common characteristic of headway irregularity, mean waiting time, PWT, EWT, median journey time, and RBT is that they are lower To Downtown than they are From Downtown. Mean headway is lower To Downtown only during the AM Peak. During the AM Peak, higher service frequency To Downtown should be one of the reasons that other measures in this direction are lower. Passengers who travel To Downtown during the AM and PM peaks experience lower mean waiting time, PWT, and EWT, and they also experience lower median journey time and RBT the whole day. Headway is also more regular To Downtown. As a result, service reliability is better To Downtown than it is From Downtown both from the operator and passenger perspectives.

Service Reliability by Sections

To analyze mean headway, headway irregularity, mean waiting time, PWT, and EWT by section, Route B1 was separated into six sections for Northbound and Southbound, shown as Figure 4. Each section includes 3–5 stops. Sections are named Section1 to Section6, with the section closest to the route's origin terminal designated as Section1. Figure 5 shows mean headway, headway irregularity, mean waiting time, PWT, and EWT for Section1–Section6 for the Northbound and Southbound directions.

Headway irregularity, mean waiting time, PWT, and EWT in Section1 are the lowest and gradually increase from this section until they reach the maximum in Section4 and Section5, then begin to decline from Section5. In other words, these measures are lowest at the stops closest to the route's origin terminal, gradually increase as the distance from the route's origin terminal increases, and reaches the maximum at the stops whose distances to the origin terminal account for 80–90 percent of the entire route length. Changzhou BRT sets a schedule for two terminals only, and there is no schedule control for each stop. Buses depart the route's origin terminal according to the schedule, so headway is regular near it. Bus operation is influenced by the external environment, and together with no schedule control en-route, it is difficult to guarantee regular headway en-route near the terminal; the influence gradually cumulates as the distance to the route's origin terminal increases, which translates into increasing headway irregularity, mean waiting time, PWT, and EWT en-route. Drivers want to comply with the schedule when approaching the route's end, so the headway becomes regular again, which results in decreasing headway irregularity, mean waiting time, PWT, and EWT. Mean headway does not show the same variation trend as the other four measures; it is almost the same from Section1 to Section6, especially Northbound. From a temporal perspective, mean headway shows a difference from the Early to the Evening periods, as shown in Figure 2, which means mean headway is sensitive to time rather than space.
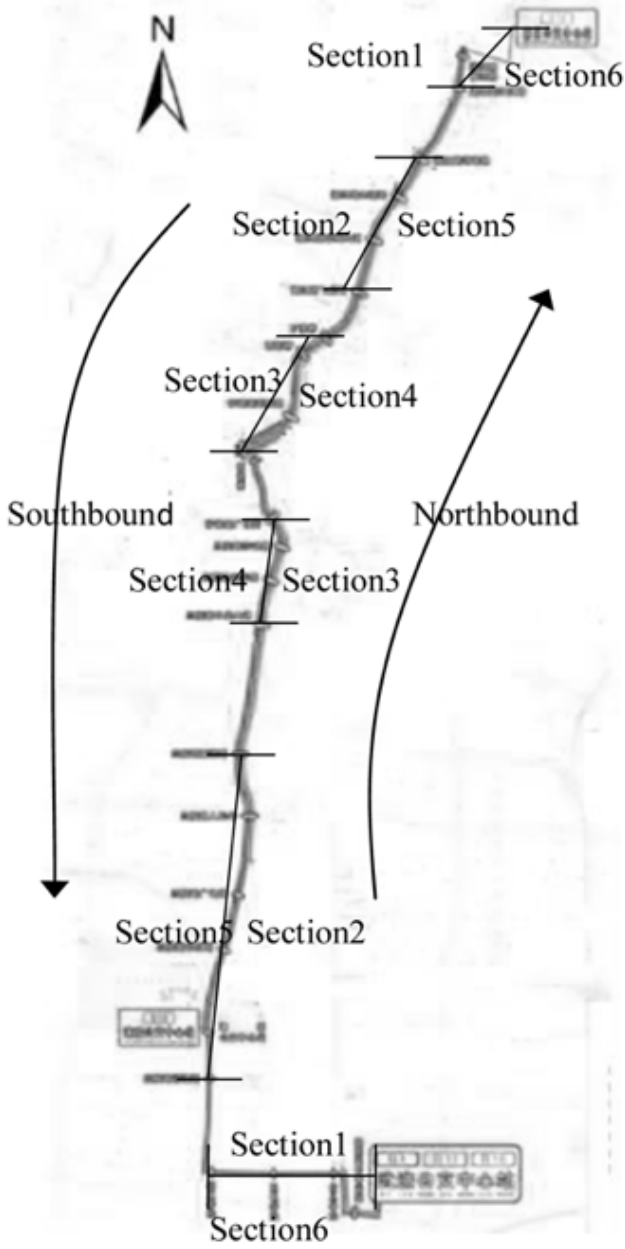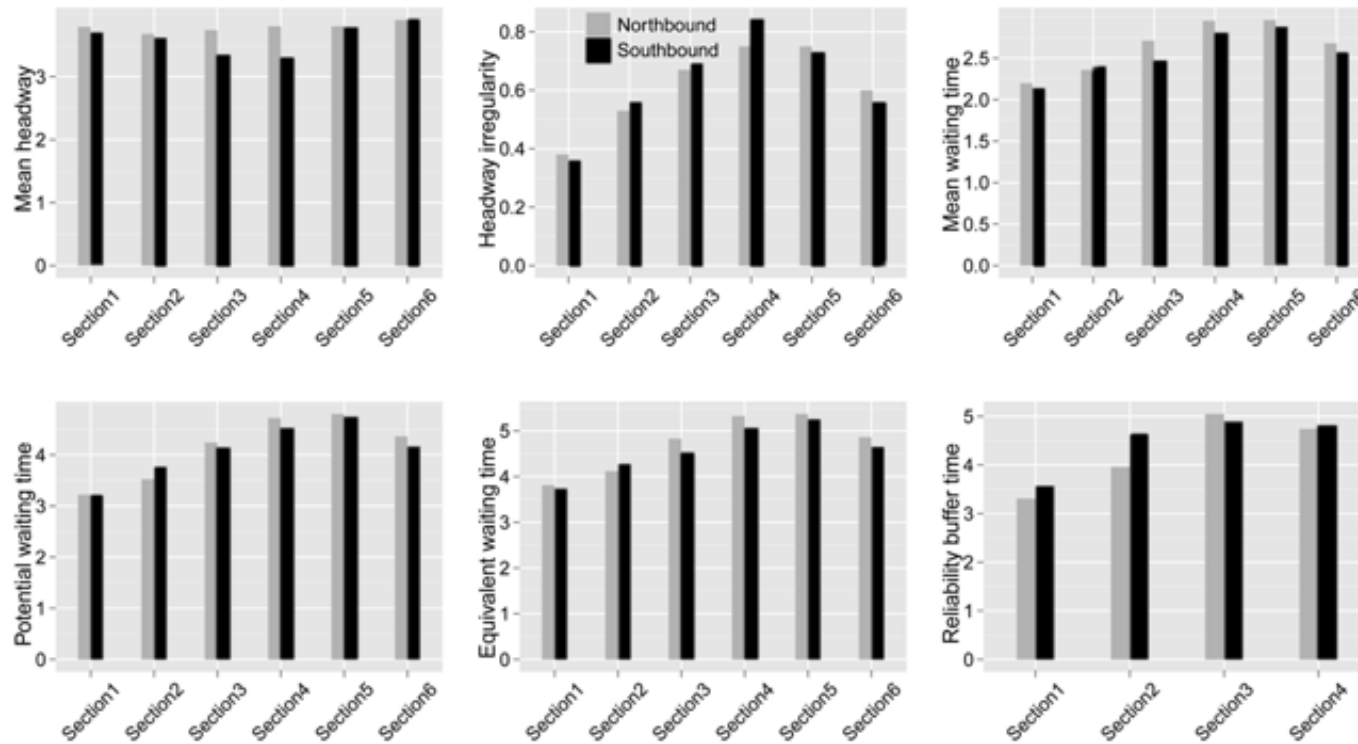
Figure 4. Section distribution for stops

Figure 5. Service reliability by section

Section4 Northbound and Section3 Southbound in Figure 4 are the most congested sections. Service reliability should be the worst in these sections. Correspondingly, headway irregularity, mean waiting time, PWT, and EWT should be the highest. For Southbound, these four measures in Section3 are not the highest; however, they are the highest in Section4 and Section5. Therefore, it is possible that the effect of distance to the route's origin terminal on service reliability is stronger than the effect of the congestion level of areas where stops are located. Buses reaching Section4 and Section5 have traversed through the most congested section Southbound, and congestion may be propagated down, so this conclusion needs to be confirmed in future studies.

To analyze RBT by sections, OD pair3–OD pair6 in Figure 1 were selected. They are named Section1 to Section4; the first OD pair closest to the route's origin terminal is Section1 for Northbound and Southbound, as shown as Figure 6. RBT from Section1–Section4 for Northbound and Southbound are shown in Figure 5. RBT in Section1 is the lowest, reaches the highest in Section3, then begins to decline. In other words, RBT for OD pairs near the route's origin terminal is the lowest, gradually increases as the distance to the route's origin terminal increases, and becomes lower for OD pairs near the route's end, which also can be attributed to no schedule control for each stop.

Taking the variation trends of headway irregularity, mean waiting time, PWT, EWT, and RBT by sections into consideration, it appears that service reliability from both the operator and passenger perspectives is the best near the route's origin terminal, gradually deteriorates along the route, then improves when approaching the route's end.

Comparison between Measures

The ratio of PWT to mean waiting time is 1.5 to 1.71. In other words, passengers, on average, need to budget an extra 1.6 times mean waiting time to guarantee on-time arrival at their destinations with 95% probability. Passengers have experienced unreliable conventional bus service in China. When they use BRT, they budget a lot of extra time, which is longer than the actual waiting time. Changzhou BRT had operated only for 20 months as of August 2009. This phenomenon may change with the popularization of BRT.

The ratio of PWT at its origin to RBT for each OD pair is between 0.8 and 1.0. PWT accounts for more than 80 percent of RBT and indicates that passengers budget extra time beyond typical their journey time for the entire journey to arrive at their
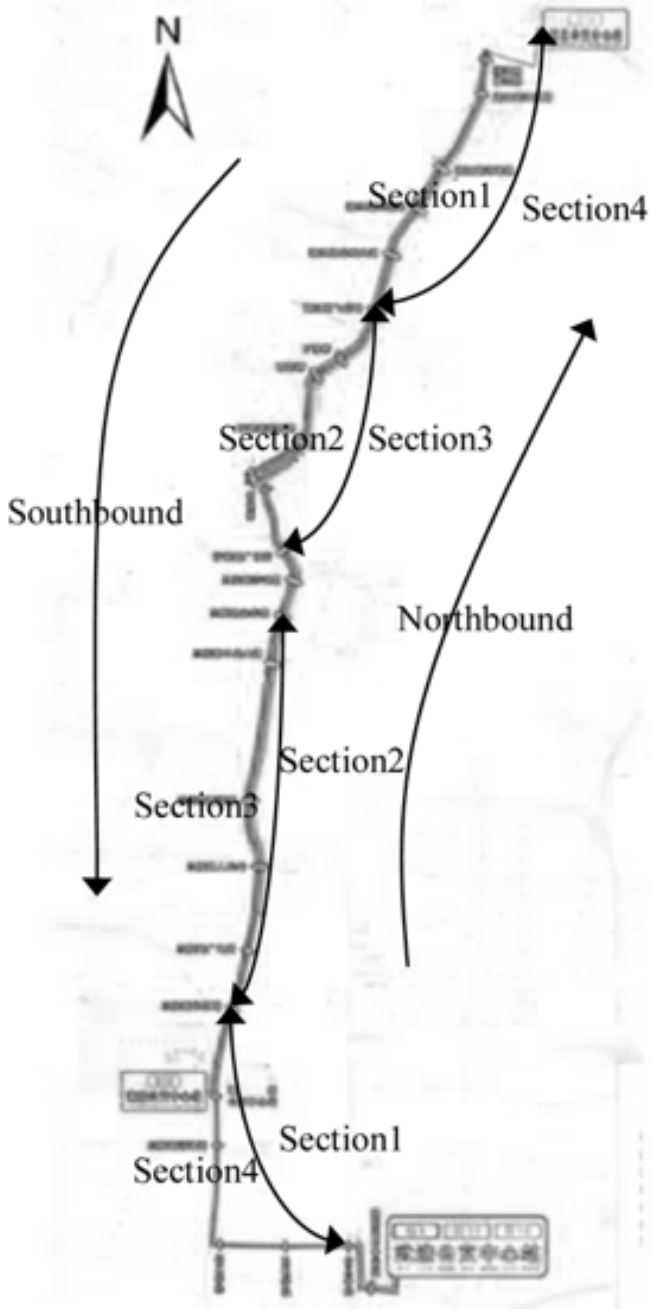
Figure 6. Sections distribution for OD pairs

destinations at a high probability, primarily to ensure boarding the target bus. They believe in-vehicle travel time has low variation and, thus, they budget only small proportion for it. In other words, the extra time budgeted for bus waiting beyond mean waiting time contributes to more than 80 percent of the extra time budgeted for the entire journey, while only 20 percent of it is budgeted for in-vehicle travel time.

Passengers possibly rarely consider travel distance when deciding the extra time budgeted for an entire journey because no special relationship was found between travel distance and RBT. For example, the distance of OD pair2 is the longest in six OD pairs; its RBT Northbound is the highest, but second lowest Southbound. This conclusion needs to be further confirmed in future studies. To some extent, it can be implied from the conclusion that only 20 percent of the extra time budgeted for the entire journey is budgeted for in-vehicle travel time.

Conclusions

The service reliability of BRT was analyzed taking Changzhou BRT as an example, including value ranges of measures, temporal and spatial distributions, and comparisons. This framework can be applied to other BRT systems. Findings on the service reliability of Changzhou BRT are summarized below, and for each improvement, measures for the Changzhou transit agency are suggested.

Mean headway and mean waiting times for the Changzhou BRT are low, at 3.12–3.96 minutes and 2.17–2.82 minutes, respectively. Transit passengers often budget extra time for bus waiting and for the entire journey beyond typical waiting and journey times to ensure arrival at their destinations on time at a high probability. Passengers of Changzhou BRT need to budget an extra 3–5 minutes for their journey. The extra time budgeted for bus waiting contributes to more than 80 percent of the extra time budgeted for the entire journey, while only 20 percent is budgeted for in-vehicle travel time. Measures to reduce potential waiting time should be taken by the Changzhou transit agency, such as enhancing stop accessibility and educating passengers to board in an orderly manner. Headways of BRT are not as regular as expected; headway irregularity is between 0.34–0.79.

Service reliability of BRT varies from the Early to Evening periods. From the perspective of operators (i.e., headway irregularity), service reliability is the worst during the AM and PM peaks. However, from the perspective of passengers based on PWT and RBT, service reliability is the worst during the Early period followed by the AM Peak. Sometimes service reliability is different from the operator and pas-

senger perspectives, so transit agencies should use multi-perspective measures to comprehensively evaluate service reliability. Specifically for the AM and PM peaks, headway irregularity is the highest and mean waiting time is the lowest, which are related to high service frequencies during these two periods. The Changzhou transit agency should implement some special traffic control treatments during peak hours, such as police guidance of traffic.

The spatial distribution of service reliability was analyzed by direction and section. For the direction dimension, service reliability is better To Downtown than it is From Downtown from both the operator and passenger perspectives. The Changzhou transit agency can improve service reliability through increasing service frequency From Downtown. For the section dimensions, service reliability from the operator and passenger perspectives is the same and is the best near the route's origin terminal, gradually deteriorating along the route, then improving when approaching the route's end. This can be partly attributed to no schedule control for each stop in China's bus service. The Changzhou transit agency should establish a schedule for each stop to improve en-route service reliability. Other improvement measures, such as using transit signal priority technology, dividing long routes into sub-routes, avoiding departure delays, and balancing passenger at bus doors, also can improve en-route service reliability.

Acknowledgment

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Optimizing Skip-Stop Rail Transit Stopping Strategy using a Genetic Algorithm

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Abstract

With skip-stop rail transit operation, transit agencies can reduce their operating costs and fleet size and passengers can experience reduced in-transit travel times without extra track and technological improvement. However, since skip-stop operation does not serve all stations, passengers for certain origins-destinations could experience increased access time, waiting time, total travel time, and/or transfer. Only when the stopping and skipping stations are carefully coordinated can skip-stop service benefit passengers and transit agencies.

This research developed a mathematical model using a Genetic Algorithm that coordinated the stopping and skipping stations for skip-stop rail operation. Using the flexibility of a Genetic Algorithm, this model included many realistic conditions, such as different access modes, different stopping scenarios, different collision constraints, and different objective functions. Passengers were put into three types and nine groups depending on their origin-destination pairs and the station and transfer

choices. Four types of collision constraints were developed depending on the skip-stop strategy.

For this research, Seoul Metro system Line No. 4 was used as an example. With skip-stop operation, total travel time became about 17–20 percent shorter than with original all-stop operation, depending on the stopping constraints. In-vehicle travel time became about 20–26 percent shorter due to skipping stations, although waiting, transfer, and additional access times increased by 24–38 percent.

Introduction

Both transit agencies and passengers can benefit from increased transit operating speed; in particular, passengers can enjoy shortened travel time. Transit agencies can benefit from accelerated rail transit operation's shorter cycle time, which, consequently, lowers operating costs and reduces fleet size. If a transit agency decides to keep the same fleet size and the same operating costs, then it can increase service frequencies. Eventually, all these advantages can attract more passengers and increase the agency's revenue.

New technology, new rolling stock, and/or better alignment can increase operating speed; however, they usually require a huge investment. In addition to those hardware upgrades, the accelerated operational scheme can increase operating speed by skipping stations. Although accelerated service can increase operating speed, passenger total travel time may not decrease, as shown in Figure 1. Good selection and coordination of skipping stations are necessary to reduce passenger travel time.

Three operational methods can increase rail transit operating speed without requiring technological investment: express/local service, zonal service, and skip-stop service. Despite the potential advantages of these accelerated methods, except for some rail transit lines in New York City and Chicago, most current rail transit in the United States uses local or regular service, which is the all-stop operational scheme. This is often due to operational complexity and the lack of methodology in modeling an optimal operational scheme. Nonetheless, there is considerable interest in combining the regular scheme with different accelerated methods to improve operating speed and efficiency.
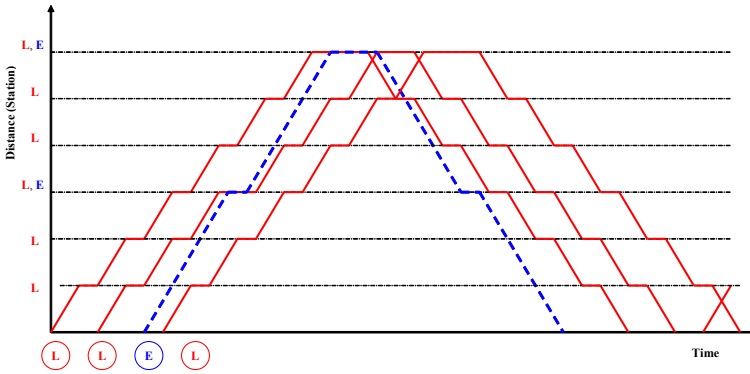
(a) Operational time-distance diagram for express service
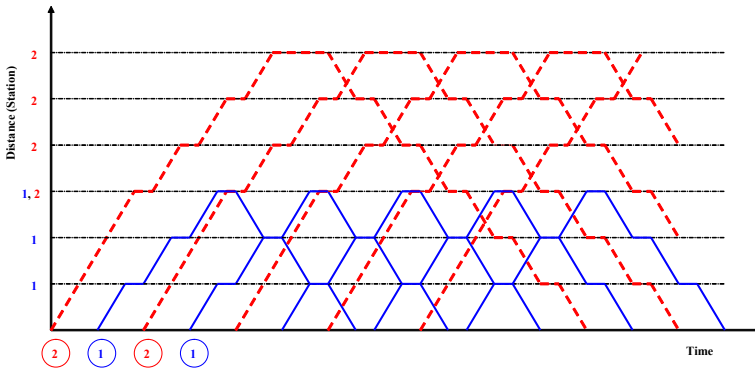
(b) Operational time-distance diagram for zonal service
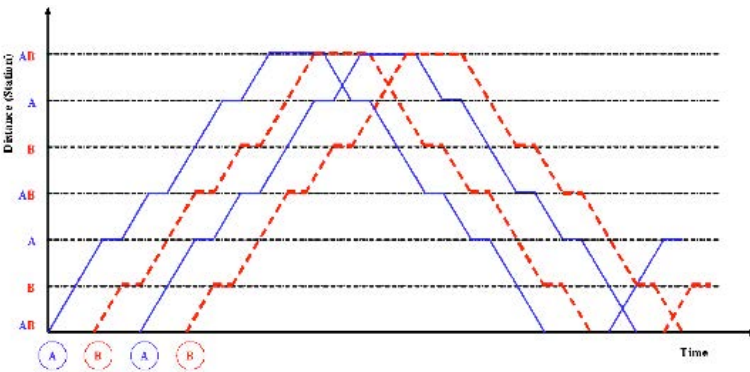
(c) Operational time-distance diagram for alternate stations stopping service

Figure 1. Operational time-distance diagram for accelerated rail operation

Although both express/local service and zonal service do not require technological investment, they require additional track so that express trains can pass local trains, and trains that serve farther zones can pass trains that serve nearer zones (Figures 1a and 1b). Only the skip-stop operation scheme can be implemented without additional track and technological investments, because two different trains—A train and B train—can keep safe separation between trains with proper coordination of stopping stations, as shown in Figure 1c. However, since the trains do not stop at all stations, passengers at skipped stations may experience increased access time or waiting time and may experience transfer.

This research found the optimal coordination of skipping and stopping stations mathematically that can increase and improve the overall benefits of the skip-stop operational scheme and minimize its disadvantages. To do so, passenger station and travel choices were closely analyzed. This research used a Genetic Algorithm (GA), which prevents huge potential computational efforts by the all-enumeration method, to find the optimal coordination of the skipping and stopping stations.

Literature Review

Station-to-Station Travel Time Components (Vuchic 2007)

Rail transit's station-to-station travel time consists of five components: acceleration, constant speed, coasting, braking, and standing time. Acceleration and braking take more time than travel time with a constant speed for the same distance traveled. If a train can skip a station, it can maintain a constant speed, avoid braking and accelerating, skip standing time, and consequently, reduce its travel time.

The following equations were used to compute acceleration time, accelerating distance, braking time, braking distance, travel time with constant speed, and travel distance with constant speed.

$$V = 3.6 \cdot a \cdot t_a \tag{1}$$

$$s_a = \frac{a \cdot t_a^2}{2} \tag{2}$$

$$s_v = \frac{V \cdot t_v}{3.6} \tag{3}$$

$$V = 3.6 \cdot b \cdot t_b \tag{4}$$

$$s_b = \frac{a \cdot t_b^2}{2} \tag{5}$$

where,

V = Speed (km/h)

a = Acceleration rate (m/sec^2)

t_a = Acceleration time (sec)

s_a = Distance traveled with acceleration (m)

t_v = Time traveled with constant speed (sec)

s_v = Distance traveled with constant speed (m)

b = Braking rate (m/sec^2)

t_a = Braking time (sec)

s_a = Distance traveled while braking (m)

Accelerated Rail Service (Vuchic 2005)

Although accelerated rail operation provides many benefits to users and operators, accelerated rail transit operational schemes may not be implemented with the existing two tracks. As shown in Figures 1a and 1b, express and zonal services require a third track (at or between the stations) so that the following train can pass the previous train.

However, as shown in the Figure 1c, skip-stop operation can be implemented without additional track when stopping stations are properly coordinated. Although the distance between two consecutive trains can be narrower at certain sections, they do not collide unless the headway is shorter than a technical minimum headway plus time savings by skipping a station.

Skip-Stop Operation
Skip-stop operation can increase operating speed and, consequently, it reduces passenger in-vehicle travel time and the rail transit cycle time. Reduced cycle time

also decreases the number of trains and operating costs. However, since the trains do not stop at all stations, passengers at skipped stations may experience additional access/egress time and/or increased waiting time. Also, they may experience transfer if they want to avoid additional access/egress time. Because of these trade-offs, only well-coordinated skip-stop stations can reduce user total travel time and total society costs eventually.

Because of the difficulty in selecting skipping and stopping stations and the complexity of the skip-stop operation, only a few rail systems use skip-stop operation, such as J/Z line in New York City Transit and the rail system in Santiago, Chile. However, there have been no rigorous efforts to optimize skip-stop operation, and most research has been based on empirical analysis.

Suh et al. (2007) evaluated the effects of skip-stop operation using the Korean Subway system as a case study. Although this study tried various operational scenarios to determine the most efficient operational strategy, it was based on predetermined sets of skipping and stopping stations as well as predetermined sets of operational scenarios. This research developed a methodology for evaluating the given sets of skip-stop operational strategies; however, it was developed empirically, not mathematically,

Zheng et al. (2009) developed an optimization model for the skip-stop strategy to minimize total travel time using a Tabu search algorithm. Although the model considered the trade-off between in-vehicle travel time and waiting time of passengers, the model did not include two other major disadvantages of skip-stop operation—additional access and egress times and transfer time, which are essential elements for the model because they occur for some passengers, depending on coordination of skipping and stopping stations and passenger choices.

Some research has studied skip-stop services for bus operation, including Niu (2011), who proposed bilevel GA-based skip-stop scheduling for a congested transit case, in which the outer GA searches the departure time and the inner GA skip-stop operations. However, the nature of rail transit operations and bus transit operations are very different, and rail transit operation requires many more constraints regarding collision and safety. As a result of the literature review, it was confirmed that there have been no rigorous efforts to optimize skip-stop operation and the sequence of skipping and stopping stations.

Genetic Algorithm

A Genetic Algorithm (GA) is a heuristic search method that imitates the process of natural evolution. It is motivated by the principles of natural selection and survival-of-the-fittest individuals (J. C. Jong 1998). This method is commonly used to generate useful solutions to optimization problems. There is now considerable evidence that GAs are useful for global function optimization and NP-hard problems despite continuous arguments.

The common benefit of a GA is its capability to improve the internal knowledge of an environment. This corresponds to a clear understanding of the possible structural changes and the legal operators for selecting and making changes.

In GAs, the problem is treated as the environment, and a set of possible solutions is treated as the population. In evolution, a child inherits good features from its parents via gene recombination or mutation. In GAs, recombination and mutation play key roles in the search space (K. D. Jong 1998).

Initially, the process starts by generating random individuals from the entire range of possible solutions (the search space) to form an initial population. The population size depends on the nature of the problem. Each individual in the population is represented by an encoded solution, called a chromosome. The individuals then compete with each other to produce children. In each generation, the fitness of every individual in the population is evaluated. Individuals are selected from the current population based on their fitness, recombined, and randomly mutated to form a new population. The new population is used in the next iteration of the algorithm (Goldberg 1989).

The process stops when a terminating condition is reached. This condition could be defined based on the nature of the problem. Some common terminating conditions include the following: a solution is found that satisfies the minimum criteria; a fixed number of generations is reached; the allocated budget (computation time/money) is reached; the highest-ranking solution's fitness is reaching (or has reached) a level such that successive iterations would not produce better results; or a combination of those conditions is achieved (Goldberg 1989).

Methodology

This research considers skip-stop operation as a choice for an accelerated rail transit operational scheme since it does not require additional track. Trains using this scheme increase their speed by skipping stations. However, to minimize

inconveniences for passengers due to skipping stations, stopping stations must be selected properly and coordinated carefully.

To find the best coordination of stopping stations, this research developed the optimization process. The optimization process includes four main components—objective function, constraints, cost estimation, and GA—to generate potential solutions.

This research uses a GA for searching a near-optimal solution, because the all-enumeration method requires huge computations (3^X, where X is the number of stations). Like a general GA, generated solutions are evaluated and compared using the fitness test with the previous optimal solutions. Then, the process keeps searching for the better solution until there is no better solution or until the algorithm reaches the given number of iterations, as shown in Figure 2.

Variables such as origin-destination (O-D) demand data, station-to-station distances, access modes, access times, etc., are needed to estimate user travel time. The mathematical model in this research will use those variables as inputs for the model, and the results of the model will show the best coordination of stopping stations to minimize the objective function and travel time estimation.

Optimization Process Using a GA

To use a GA for optimization, the concepts of genes and chromosomes and their fitness should be defined. In this project, chromosomes are the stations and Matrix S is the gene containing the station types (A, B, or AB chromosomes). The fitness of each gene is estimated based on the objective function. The objective function in this project is the total travel time. It is based on the developed models for calculating the total travel time, which is the fitness of Matrix S. Figure 2 presents the overall view of the optimization process in this project using a GA, and Table 1 shows the operators used to generate the children for the GA in this research.
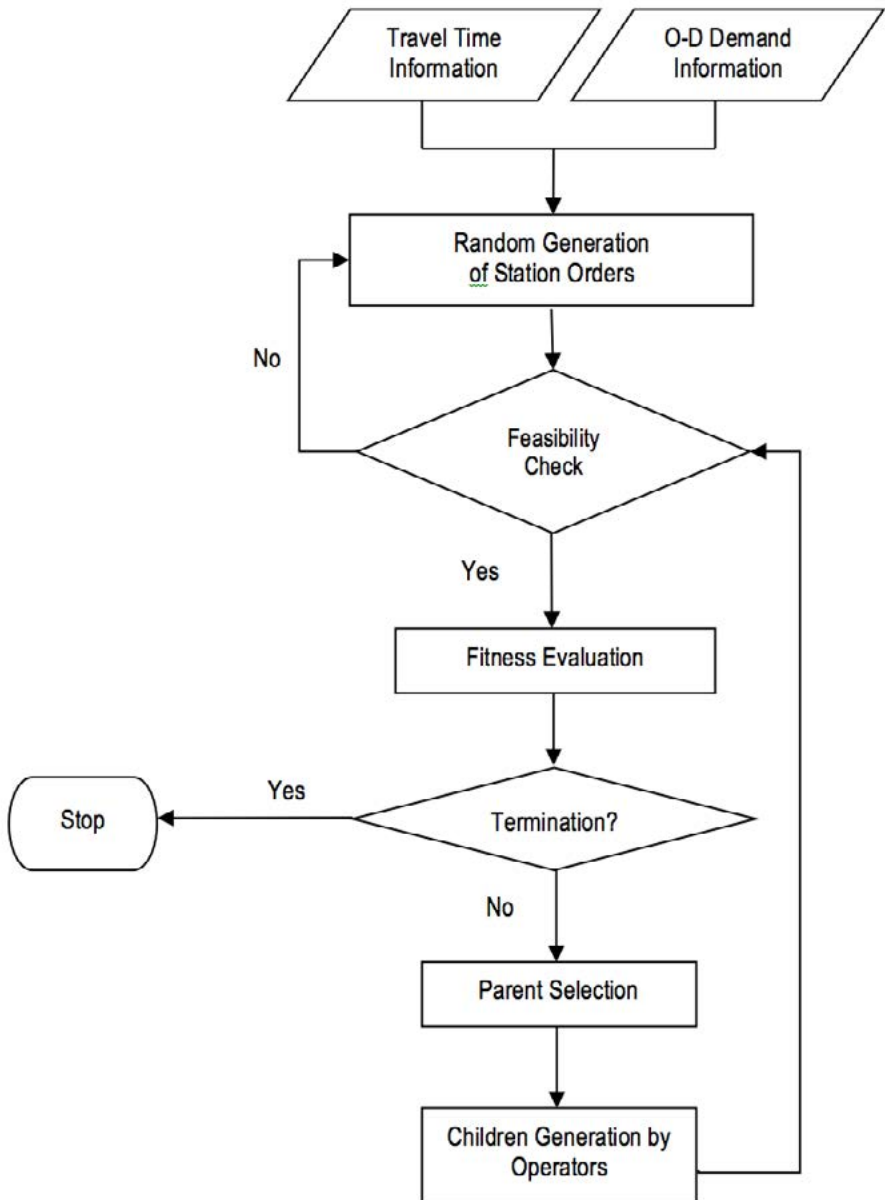
Figure 2. Overall procedure for finding an optimal solution

Table 1. Operators for GA Used in this Model

	Type	Explanation	Figure
1	Crossover	Creates child that inherits odd cells from Father and even cells from Mother	
2	Crossover	Creates child that inherits even cells from Father and odd cells from Mother	
3	Customized crossover	Creates child that inherits best genes (40%) from Mother and others from Father	
4	Customized crossover	Creates child that inherits best genes (40%) from Father and others from Mother	
5	Customized crossover	Creates child in which worst genes (40%) from Father are omitted and replaced by Mother gene	
6	Customized crossover	Creates child in which worst genes (40%) from Mother are omitted and replaced by Father gene	
7	Combined crossover and mutation	Creates child that inherits best Mother and Father genes (40% each) and other genes are random	
8	Combined crossover and mutation	Creates child in which worst genes (40% each) from Mother replaced by Father and worst genes from Father replaced by Mother; other genes replaced randomly	
9	Whole non-uniform mutation	Creates child that inherits random genes (maintaining diversity of genes in population)	
10	Mother saver	Creates child that inherits all Mother genes (replacing Mother in new generation)	
11	Father saver	Creates child that inherits all Father genes (replacing Father in new generation)	

For this particular optimization model, in addition to the general operators for the GA, customized crossover operators were designed to find the optimal solution more efficiently, which are types 3–6 in Table 1. Since it is important to keep the better O-D pairs together (instead of as a single chromosome), the better 40 percent of chromosome pairs were kept and others were replaced with operators 3 and 4. In addition, the worse 40 percent of chromosome pairs were replaced with operators 5 and 6. The 40 percent comes from experiments with different numbers

in this research; however, it will be necessary to find the optimal number in a future study.

Objective Function

There can be three types of objective functions: user travel-time minimization, operator benefit maximization, and total cost minimization.

As mentioned, well-coordinated skip-stop operation reduces in-vehicle travel time for users and increases operating speed for operators. However, some users will experience increased waiting time, access time, egress time, and, possibly, transfer time. Thus, there is no guarantee that skip-stop operation will reduce the total travel time of all users.

The selection and coordination of stopping stations can be done based on the objective function. If the objective function is user travel-time minimization, the proper selection and coordination of stopping stations will minimize the total travel time of all users, including their in-vehicle travel time, access time, egress time, waiting time, and transfer time.

Skip-stop service always increases operating speed, which results in reduced operator costs and fleet size. However, it does not mean that this service always produces advantages for operators. If passenger total travel time increases because of bad coordination of skip-stop stations, fewer people will use the transit service and transit agencies will lose revenue. Since operator benefit consists of operator reduced costs and increased revenue, under the objective function of operator benefit maximization, the selection and coordination of stopping stations will maximize the operator benefit, which is the difference between operator revenue and costs.

The last possible objective function is minimization of total costs, including user travel time and operator costs. The selection and coordination of stopping stations can be developed to minimize total costs.

In this research, user travel-time minimization was used; however, in future research, other objective functions can be applied, and the results of the different objectives can be compared and evaluated. Also, a combination of different objective functions for different times of the day, such as minimizing travel time for peak hours and maximizing revenue for off-peak hours, can be examined.

Cost Estimation (Fitness)

The mathematical model estimates passenger total travel time through coordination of stopping stations, which is also the objective function of the model. Each passenger's total travel time, which includes access time, waiting time, in-vehicle travel time, transfer time, and egress time, is formulated for each selection of the stopping stations. As a result, the model will suggest the best coordination of the stopping stations for the skip-stop operation strategy.

Three Types of O-D Pairs

For skip-stop operation, stations were categorized as Stations A, B, and AB. The A trains stop at A stations and AB stations, and the B trains stop at B stations and AB stations. Consequently, O-D trips are categorized into nine groups, such as A-A, A-B, A-AB, B-A, B-B, B-AB, AB-A, AB-B, and AB-AB. If the O-D pair is AB-AB, then passengers have the same headway, access, and egress time, while enjoying reduced in-vehicle travel time (Type I in Table 2).

Table 2. Three Types of O-D Trips for Nine O-D Combinations

OD Type	Orig.	Dest.	Decision	Penalty
Type I	AB	AB	Take any coming train.	None
Type II	A	A	Take A train.	$h^{new} = 2h$, $w^{new} \leq 2w$
	A	AB	Take A train.	$h^{new} = 2h$, $w^{new} \leq 2w$
	B	B	Take B train.	$h^{new} = 2h$, $w^{new} \leq 2w$
	B	AB	Take B train.	$h^{new} = 2h$, $w^{new} \leq 2w$
	AB	A	1. Wait for A train. 2. Take B train and walk to A station.	Min {($w^{new} \leq 2w$) or (additional egress)}
	AB	B	1. Wait for B train 2. Take A train and walk to B station	Min {($w^{new} \leq 2w$) or (additional egress)}
Type III	A	B	1. Take A train and transfer to B train at AB station. 2. Go to B station to take B train. 3. Take A train, go to A station, and walk to B station.	($w^{new} \leq 2w$) + Min{Min (additional access time or additional egress time) or transfer time}
	B	A	1. Take B train and transfer to A train at AB station. 2. Go to A station to take A train. 3. Take B train, go to B station, and walk to A station.	($w^{new} \leq 2w$) + Min{Min (additional access time or additional egress time) or transfer time}

h = headway, w = waiting time

If an O-D pair is other than AB-AB, then passenger headway will be twice as long as that of the AB-AB passengers because they can take only either an A train or B train, not both. If headway becomes twice as long, then waiting time can be up to twice as long. If there is no scheduling information, then waiting time becomes twice as long. However, if scheduling information is available, then average waiting time can be less than half of the headway because passengers can arrive at stations just before the train arrives.

If the O-D pair is either A-B or B-A, then the passenger will need a transfer to reach the destination station or will need to change the origin or destination station to avoid transfer. Passengers will choose to transfer or change their origin or destination to minimize their travel time depending on their exact origin and destination location (Type III in Table 2). The rest of the cases require headway and waiting time that are up to twice as long (Type II in Table 2).

Reduced Travel Time by Skipping a Station
The amount of reduced travel time depends on acceleration rate, braking rate, maximum constant speed, operation strategy (e.g., whether there is coasting), dwell time, and the distance between stations. Consequently, computation of the saved time can be complicated and has many variables.

According to transit agencies including Washington Metropolitan Area Transit Authority (WMATA) and Seoul Metropolitan Rapid Transit Corporation (SMRT), acceleration rate and braking rate range from 0.75 to 3 mph per second, and maximum speed ranges from 40–80 mph.

Assuming 2 mph per second (3.2 km/h/sec) for acceleration and braking rates, to reach the assumed maximum speed of 60 mph will take 30 seconds while traveling 0.25 miles, according to equations 1 and 2. From 60 mph, it also will take 30 seconds to stop while traveling 0.25 miles according to equations 4 and 5. Using equation 3, it will take 15 seconds to travel 0.25 miles with a 60 mph constant speed. As a result, not accelerating and not braking can save 15 seconds each. Standing time is about 30 seconds at each station. Under those assumptions, skipping one station can save a total of one minute. Therefore, this research assumed that one minute is saved each time a train skips one station.

However, this computation is based on the above assumptions, so the real time savings by skipping one station vary by station and operation strategy. If the maximum speed and/or the acceleration rate are lower, then the time saved by skipping one station is less than one minute.

Transfer

Type III passengers need to transfer or change their origin or destination station. There are two types of transfers. If the AB station is inside the origin and destination, then passengers can transfer at the AB station and will spend only additional transfer time, which is headway between two trains, in addition to their original travel time. If there is no transfer station, then passengers need to find a transfer station outside the origin and destination. In this case, passengers not only will spend transfer time but also will add in-vehicle time (to go to the transfer station and come back) to their original travel time.

Access Modes and Additional Access Time for Changing Origin or Destination Stations

There are other concerns in the estimation of the total passenger travel times. The first concern is the access mode to the train station for the Type III passengers. Train users can access stations by foot, car, bicycle, or feeder bus. Depending on their access mode, their additional access time to their origin or destination stations varies, and their decision to transfer or change the origin/destination is based on their additional access time and transfer time.

In this research, two groups—those who walk to the station and those who access it by car or feeder bus—were considered to compute the access time to other origin or destination stations. Since passengers who use park-and-ride, kiss-and-ride, or a feeder bus have a shorter additional access time to the new origin station that does not require transfer to go to their destinations, their average access time to the other origin station will be shorter than passengers who walk to the new origin station. However, the exact amount of additional access time depends on the locations of the origins.

For simplicity, this research assumed that passengers were uniformly distributed throughout the area. When users chose their origin stations, they selected stations that required the shortest total travel time.

Depending on the origin's location, going to the other station increases a different amount of travel time. For the one extreme case, changing an origin station will not increase total travel time at all when passenger origin is equidistant from the two stations. Thus, passengers choose an origin station arbitrarily, and changing the origin station will not add any additional access time.

When the origin is at the station, changing the origin station requires the whole distance traveled from the original station to the new station. The additional access

distance is the whole distance between the two stations, and the additional travel time is the additional access time to the other station minus station-to-station, in-vehicle travel time. For example, if it takes 15 minutes to walk to the new origin station and station-to-station and in-vehicle travel time is 3 minutes, then the additional access time is 12 minutes. If the access mode is auto and the additional driving time is 4 minutes, then the additional access time is only 1 minute.

Therefore, in the above situation, the minimum additional access time is zero minutes, and the maximum additional access time is 12 minutes by foot or 1 minute by auto. Since uniform distribution of total passengers is assumed, the additional access time is uniformly distributed between minimum additional access time and maximum additional access time. The distribution of walking passengers and driving passengers is a variable for this model, and this distribution rate can be set differently for each O-D pair.

Transferring vs. Changing the Origin or Destination Stations
For Type III origin-destination pairs, each pair was examined to determine if passengers would take a transfer or change their origin or destination. Access modes and origins determine the additional access times resulting from an origin or a destination change, so their decision between transfer and changing origin/destination can be made based on their additional access time and transfer time.

To estimate the number of passengers who will change their origin station and the number of passengers who will stick to their original station and transfer, the research compared the transfer time and additional access time of Type III passengers. Since transfer time is fixed, regardless of whether the transfer station is inside, outside, or between the origin and destination stations, transfer time was used as a standard. The range of additional access time to the other station that avoids the transfer was estimated based on access modes and passenger origins. Using transfer time and additional access time, it was assumed that passengers would change their origin if a transfer would result in longer travel time, and passengers would stay at their origin and transfer if a transfer would result in shorter travel time.

Different Weights for Travel Time Components
Total travel time consists of access time, waiting time, in-vehicle travel time, transfer time, and egress time. Although their units are the same, the perception of passengers may vary. Some researchers show that access time, waiting time, transfer time, and egress time can be as costly as three times in-vehicle travel time for the same amount of time (Kittleson & Associates 2003).

Although this algorithm can handle different weights for different travel time components, the same time value for all travel time components was applied to this example to show the absolute time amount for each travel time component and show how the trade-off between travel time components works.

Planning Horizon
The other concern is continuous transit operation during the day. The optimal solution for a certain period, such as morning peak, is not necessarily the optimal solution for a whole day or whole week. To make the precise evaluation, O-D demand for each hour and each hour's headway must be available. However, for simplicity, this research used one peak-hour demand and headway to find the optimal coordination of the stopping stations. Consequently, the result is optimal for that period only. Once the data are available for a whole day, it would not be difficult to find an optimal solution for a day or week.

This research developed a mathematical model that suggested optimal stopping stations for the skip-stop operational scheme. The model considers the nine aforementioned cases to minimize total passenger travel time on the route. Obviously, some passengers will have longer travel times due to longer headway and transfers, but a good selection of the alternate stopping stations can save travel time for more passengers. If a particular route is not suited for the skip-stop operation, then the results will show all stations as AB, which means that all trains must stop at all stations. The all-cost estimation process is shown in Figure 3.

Constraints
The most important constraint in this algorithm is the avoidance of collisions between the two trains. Unlike regular service, in which trains stop at all stations, skip-stop operation allows trains to skip stations. Once a train skips a station, its distance from the preceding train, which stops and skips at different stations, becomes shorter. Since two trains should not collide, this constraint is critical. In this study, for two trains to avoid collision, four scenarios were suggested based on the rules for stopping stations and initial headways in Table 3.
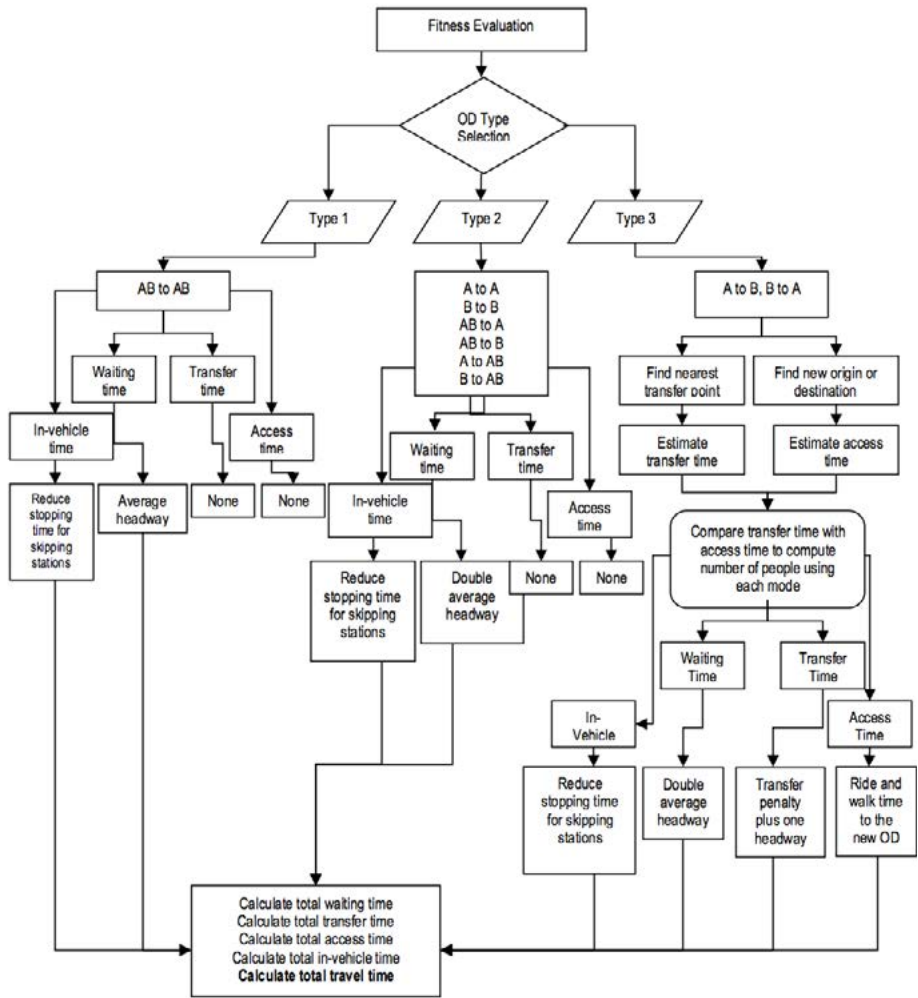
Figure 3. Fitness evaluation process

Table 3. Four Types of Collision Constraints

Collision Constraints	Definition	Constraints
Scenario I	Different type of exclusive stopping station between exclusive stopping stations	$-1 \leq (\sum CIS_i \times \text{saving time by skipping}) \leq 1$, (Headway – Saving time by skipping) $\geq$ Safety gap time
Scenario II	No consecutive same type of exclusive stopping stations	$-2 < (CIS_i - CIS_{i-1}) + (CIS_{i+1} - CIS_i) < 2$, $-($Headway – Safety gap$) \leq (\sum CIS_i \times \text{Saving time by skipping}) \leq ($Headway – Safety gap$)$
Scenario III	Uniform headway between different types of trains	$-($Headway – Safety gap$) \leq (\sum CIS_i \times \text{Saving time by skipping}) \leq ($Headway – Safety gap$)$
Scenario IV	Uniform headway between same type of trains	$Min_i \leq (\sum CIS_i \times \text{Saving time by skipping}) \leq Max_i$, $Max_i \leq 2 \times ($Headway – Safety gap$)$, $Min_i \geq -2 \times ($Headway – Safety gap$)$, $(Max_i - Min_i) \leq 2 \times ($Headway – Safety gap$)$

CIS: Collision Index Score

Scenario I has the most restricted constraint, as it provides the least number of feasible solutions. The constraint does not allow two consecutive types of exclusive stations, even if there is a general station between two same types of exclusive stations. For example, the A-AB-A combination is not allowed; there must be a B station between A stations, even if there is an AB station between them. In other words, after an A station, there must be a B station before an A station is located. Since this scenario requires a different exclusive stopping station between other kinds of stopping stations, users can accept this scenario relatively easily because the distribution of the stations looks uniform. Because no train skips two more stations than the other type of train skips, two different types of trains will not collide as long as the headway is longer than the sum of safety distance between the two trains and the time saved by skipping one station.

However, if the same type of exclusive stopping stations are allowed to repeat whether there is a general station in between them or not, it is necessary to check whether two trains will collide at every station. To check whether the two trains will collide, the arrival times of two different, consecutive trains (A train and B train) must be checked. If the difference is greater than safety time and standing time, then the two trains can operate without collision. If the difference is less than safety time and standing time, then the two trains will collide and the selection of stopping stations is infeasible.

Scenario II does not require a different kind of exclusive stopping station between two of the same kind of stopping stations as long as there is a general stopping station between them. As long as there are not two consecutive, same types of stopping stations, this scenario is acceptable. For example, this scenario will allow A-AB-A combination. Since this scenario relaxes the constraint of Scenario I, Scenario II provides more feasible solutions and better results.

Although it does not distribute the stopping stations as uniformly as Scenario I, users can comfortably accept Scenario II because they can easily access different types of stations. For example, if users want to go to the other type of station to catch another type of train because the original station requires transfer, they can go to the adjacent station, which is either another type of station or a general stopping station.

Scenarios III and VI do not restrict the distribution and coordination of stations as long as the coordination of stopping stations prevents collisions. The difference between scenarios III and IV is the initial headway. Scenario III keeps the initial headway between the two different types of trains. Scenario IV keeps the initial headway between the two same types of trains, but not necessarily between two different types of trains (i.e., A-A trains should have the same headway as B-B trains, but headway between A-B trains and B-A trains does not need to be the same).

To consider those four scenarios, "1" was assigned to A stations, "0" was assigned to AB stations, and "-1" was assigned to B stations. Then, at each station, the cumulative score from the terminal—called "Collision Index Score"—was used to compute the separation between the two trains. If the number becomes bigger, positively or negatively, one train is going much faster than the other and the chance of collision becomes higher. If headway, safety distance between trains, and time saved by skipping are given, then the feasible area for each collision constraint can be defined (Table 3).

As can be seen, Scenario I has fewer feasible solutions than Scenario II, Scenario II has fewer feasible solutions than Scenario III, and Scenario III has fewer feasible solutions than Scenario IV. Later, the results and time savings from all four scenarios are presented and discussed.

Formulation
This problem has many "ifs" in the algorithm for different scenarios; thus, it is not a traditional mathematical format, so there is a difficulty in formulation in a simple

format. The following is the formulation of this problem in a simple format, as discussed in previous sections.

Minimize: F(X(i)),*i*=1,2,...,*n*

$$X(i) = \begin{cases} 1, i \equiv A & (if\ Only\ Train\ "A"\ stops\ at\ station\ i^{th}) \\ -1, i \equiv B & (if\ Only\ Train\ "B"\ stops\ at\ station\ i^{th}) \\ 0, i \equiv AB & (if\ Both\ Trains\ "A"\&\ "B"\ stop\ at\ station\ i^{th}) \end{cases}$$

$$F\left(X(i)\right) = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} OD(i,j).T(i,j)$$

$$T(i,j) = ITT(i,j) - ST(i,j) + WT(i) + TT(i,s_t) + AT(i,s_o) + ET(s_d,j)$$

Travel time cost estimations based on OD types (I, II, III) are as follows:

Type I (AB-AB) and Type II (A-A , B-B , AB-A , AB-B , A-AB , B-AB)

$$T(i,j) = ITT(i,j) - ST(i,j) + WT(i)$$

$$AT(i,s_o) = 0$$

$$ET(s_d,j) = 0$$

$$TT(i,s_t) = 0$$

Type III (A-B, B-A)

$$T(i,j) = ITT(i,j) - ST(i,j) + WT(i) + TT(i,s_t) + AT(i,s_o) + ET(s_d,j)$$

$$TT(i,s_t) = WT(s_t) * T_P(i,s_t)$$

$$AT(i,s_o) = \left(\overline{R_T(i,s_o)} * R_P(i,s_o)\right) + \left(\overline{W_T(i,s_o)} * W_p(i,s_o)\right)$$

$$ET(s_d,j) = \left(\overline{R_T(i,s_d)} * R_P(i,s_d)\right) + \left(\overline{W_T(i,s_d)} * W_p(i,s_d)\right)$$

$$O_p(i,s_o) = W_p(i,s_o) + R_P(i,s_o)$$

$$D_p(i,s_d) = W_p(i,s_d) + R_P(i,s_d)$$

$$T_P + O_p + D_P = 1$$

Constraints are as follows:

Scenario 1

$$\forall i \in n: \begin{cases} \left| \sum_{i=1}^{n-1} X(i).ST(i,i+1) \right| - 1 \leq 0 \\ HT(i) - ST(i,i+1) - SF(i) \geq 0 \end{cases}$$

Scenario 2

$$\forall i \in n: \begin{cases} \left| \sum_{i=1}^{n-1} X(i).ST(i,i+1) \right| - \left(HT(i) - SF(i) \right) \leq 0 \\ |X(i+1).ST(i+1,i+2) - X(i-1).ST(i-1,i-2)| - 2 < 0 \end{cases}$$

Scenario 3

$$\forall i \in n: \begin{cases} \left| \sum_{i=1}^{n-1} X(i).ST(i,i+1) \right| - \left(HT(i) - SF(i) \right) \leq 0 \end{cases}$$

Scenario 4

$$\forall i \in n: \begin{cases} \left| \sum_{i=1}^{n-1} X(i).ST(i,i+1) \right| - \left(Max(i) - Min(i) \right) < 0 \\ Max(i) - 2\left(HT(i) - SF(i) \right) \leq 0 \\ Min(i) + 2\left(HT(i) - SF(i) \right) \geq 0 \\ \left(Max(i) - Min(i) \right) - 2\left(HT(i) - SF(i) \right) \leq 0 \end{cases}$$

Where:

OD(i,j): Origin-Destination Demand between stations i^{th} & j^{th}

ITT(i,j): Initial Travel Time between stations i^{th} & j^{th} without skipping any station

ST(i,j): Saved (Stopping) Time by skipping certain stations between stations i^{th} & j^{th}

HT(i): Headway Time between two consequent trains at station i^{th}

WT(i): Average Waiting Time at station i^{th} considered as half of the headway time and maximum of 5 minutes

SF(i): Safety Time considered between the two sequential trains at station i^{th}

s_o: Closest station to the origin with the identical train to destination

AT(i,s_o): Access Time to the station (s_o) with identical train to the destination: (i < s_o << j , X(s_o) = X(j))

s_d : Closest station to the destination with the identical train to origin

ET(s_d, j): Egress Time from the station (s_d) with identical train to the origin: (i << s_d < j , X(s_d) = X(i))

s_t : Transfer station between the origin and destination with stops for both trains

TT(i,s_t): Transfer Time required changing the train in the transfer station (s_t): (i < s_t < j , X(s_t) = 0)

WT(s_t): Waiting Time at station (s_t): WT(s_t) = Min (½ HT(i), 5)

T_p (i,s_t): Percentage of OD(i, j) transferring at station (s_t)

O_p (i, s_o): Percentage of OD(i, j) changing their origin to (s_o)

D_p (i, s_d): Percentage of OD(i, j) changing their destination to (s_d)

R_T (i, s_o): Average Riding Time to station (s_o)

R_p (i, s_o): Percentage of O_p (i, s_o) riding to station (s_o)

W_T (i, s_o): Average Walking Time to station (s_o)

W_p (i, s_o): Percentage of O_p (i, s_d) walking to station (s_o)

R_T (i, s_d): Average Riding Time to station (s_d)

R_p (i, s_d): Percentage of D_p (i, s_d) riding to station (s_d)

W_T (i, s_d): Average Walking Time to station (s_d)

W_p (i, s_d): Percentage of D_p (i, s_d) walking to station (s_d)

Example and Results

After the mathematical model was developed, the real data from Seoul Metro in Korea was applied to see if accelerated service was feasible for that rail transit line. This research selected Seoul Metro's Line No. 4 as an example, which includes the Gwacheon-Ansan line. Korea Railroad serves Line No. 4, which has 48 stations, and the total travel time between the two terminals during the morning peak is 1 hour and 52 minutes, with 2.5–3 minutes of headway. Line No. 4 currently provides local service, zonal service, and express service. Because there were limited data for this model, this example tested only the applicability (or functionality) of skip-stop operation for the metro line, not the actual feasibility.

To run this model, hourly O-D demand was essential. However, the only available data was monthly O-D demand and each hour's number of boarding and alighting passengers. As a result, it was necessary to manipulate the data to get the hourly O-D demand from the monthly O-D demand and each station's morning peak hourly boarding and alighting ratio. This analysis used the O-D demand from October 2008. The Geum Jung station was missing from the O-D data, so O-D data for only 47 stations was used with 3-minute headway.

The assumptions for the examples were as follows:

- Because standing time at the station is 30 seconds from the schedule, a train can save 1 minute (including acceleration time, deceleration time, and standing time) if it skips 1 station.

- Safety distance between 2 trains is 1 minute.

- Access time to the other station by foot is 6 times longer than rail's in-vehicle travel time.

- Access time by auto or feeder bus is 1.5 times longer than rail's in-vehicle travel time.

- Total passengers are uniformly distributed; accordingly, their additional access time is distributed uniformly between minimum additional access time and maximum additional access time.

- A total of 70 percent of passengers walked to the station, and 30 percent of passengers arrived at the origin station via a car or a feeder bus.

Table 4 shows the four optimal coordinations of stopping stations after 5,000 iterations, in addition to the original all-stop scenario, using different feasibility constraints to avoid collision.

As programmed, Scenario I always has B stations after A stations, even when there are AB stations in between the A and B stations. Scenario II has A station (19th station) after A station (16th station) with no B station between them because there are AB stations (17th and 18th stations) between A stations.

In Scenario III, since skipping a station saves one minute and the safety distance between two trains is one minute, skipping two stations is allowed when two different types of trains have uniform headway under the three-minute headway assumption. If one type of train skipped two stations, then the other type of train can skip as many as four stations before the previous train skips another station.

Table 4. Coordination of Skipping and Stopping Stations

Station/Scenario	Original	I	II	III	IV
1	AB	AB	AB	AB	AB
2	AB	AB	AB	AB	AB
3	AB	AB	AB	AB	AB
4	AB	AB	AB	B	AB
5	AB	AB	AB	AB	AB
6	AB	AB	AB	AB	AB
7	AB	B	B	A	AB
8	AB	AB	AB	AB	AB
9	AB	A	A	A	B
10	AB	B	B	B	B
11	AB	A	A	B	B
12	AB	B	B	A	B
13	AB	A	A	A	A
14	AB	B	B	A	B
15	AB	AB	AB	AB	AB
16	AB	AB	A	AB	AB
17	AB	AB	AB	AB	A
18	AB	AB	AB	AB	AB
19	AB	AB	A	AB	AB
20	AB	AB	B	AB	AB
21	AB	AB	AB	AB	AB
22	AB	AB	B	AB	A
23	AB	AB	AB	B	B
24	AB	A	AB	AB	A
25	AB	AB	A	AB	B
26	AB	AB	B	AB	B
27	AB	B	AB	AB	A
28	AB	A	AB	AB	B
29	AB	AB	AB	AB	AB
30	AB	AB	A	B	AB
31	AB	AB	AB	AB	AB
32	AB	AB	AB	B	AB
33	AB	AB	AB	AB	AB
34	AB	AB	AB	AB	AB
35	AB	AB	AB	A	AB
36	AB	AB	AB	AB	AB
37	AB	AB	AB	AB	AB
38	AB	B	A	B	AB
39	AB	AB	AB	AB	AB
40	AB	AB	AB	B	AB
41	AB	AB	AB	AB	AB
42	AB	AB	B	A	AB
43	AB	AB	AB	B	AB
44	AB	AB	AB	AB	AB
45	AB	A	AB	AB	AB
46	AB	AB	AB	A	AB
47	AB	AB	AB	AB	AB

In this example, stations from 12th station to 14th station were allocated as A stations, because before 12th station, there was one more B station than A station from the terminal.

Scenario IV does not require uniform headway between the A and B trains. As a result, the headway between A and B trains can be as long as five minutes. (The five-minute figure is based on the six-minute headway between two A trains minus the one-minute safety distance between A and B trains.) Since the maximum allowable headway between A and B trains is five minutes, the maximum number of consecutive A stations is four, which is five-minute headway minus one minute of the safety distance. In this example, stations from the 9th station and 12th station are all B stations. To make this service safe and feasible, the headway between the B and A trains should be five minutes, and headway between A and B trains should be one minute. For feasibility and safety, the cumulative number of A stations at any station will not be more than that of B stations.

In this example, the results of all four scenarios met the programming constraints.

Table 5 shows the total in-vehicle travel time, total waiting time, total transfer time, and total additional access and egress time for all four cases with the original all-stop case. As can be seen, total travel time becomes shorter with more relaxed constraints.

Table 5. Travel Time Characteristics of Skip-Stop Operation

Scenario	Original	I	II	III	IV
Number of AB stations	47	35	31	30	33
Number of A stations	0	6	8	8	5
Number of B stations	0	6	8	9	9
In-Vehicle Time (min)	3,688,169.62	2,946,771.66	2,929,213.27	2,847,704.26	2,811,122.13
Waiting Time (min)	272,744.43	334,290.85	342,502.14	367,530.57	327,646.25
Transfer Time (min)	0.00	1,935.99	3,185.69	6,032.21	2,144.89
Additional Access/ Egress Time (min)	0.00	1,256.20	1,955.11	3,486.26	1,268.45
Total Travel Time (min)	3,960,914.05	3,284,254.71	3,276,856.22	3,224,753.29	3,142,181.72
Average Total Travel Time (min)	21.78	18.06	18.02	17.73	17.28
Travel Time Reduction (min)	-	-17.08%	-17.26%	-18.60%	-20.66%

In this example, 181,830 passengers traveled during the one-hour morning peak, and their average total travel time with the original all-stop operation was 21.78 minutes. With skip-stop operation, depending on the stopping constraints, their total travel time became 17–20 percent shorter than that with original all-stop operation. While in-vehicle travel time became 20–26 percent shorter due to skipping stations, waiting time, transfer time, and additional access time were 24–38 percent longer.

Each train skipped 5–9 stations, which reduced 5–9 minutes (up to 8%) in operating time. As mentioned, this model was built to minimize the total travel time. If the objective of the model was minimization of operating time or total cost, the model could reduce operating time further.

Figure 4 shows the convergence of the searching process for all four scenarios. Except in the Scenario IV case, optimal results converged relatively quickly (about 100, 300, and 600 iterations). Only Scenario IV case took about 2,000 iterations to be converged.

Conclusions

Well-coordinated skip-stop service can reduce passenger total travel time and improve overall service, since it can increase operating speed. However, the selection and coordination of stopping and skipping stations requires extensive effort since it is a very large combinatorial problem.

This research showed how the optimization process for the selection and coordination of the stopping and skipping stations could be pursued. As discussed, this model used a Genetic Algorithm, which can handle different objective functions and include different constraints for preventing a collision. This model also considered different access modes, as well as different passenger options and choices (including access modes) when the same train does not serve the origin and destination stations. Passengers were put into three types and nine groups depending on their O-D and skip-stop strategy. Also, four types of collision constraints were developed depending on the skip-stop strategy. Since this model considered those components, the results were more realistic.

In this example, 181,830 passengers traveled for one-hour during the morning peak, and their average total travel time with the original all-stop operation was 21.78 minutes. With skip-stop operation, depending on the stopping constraints, their total travel time became about 17–20 percent shorter than that with the origi-
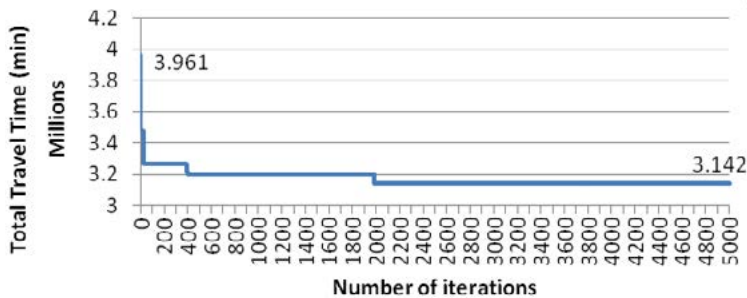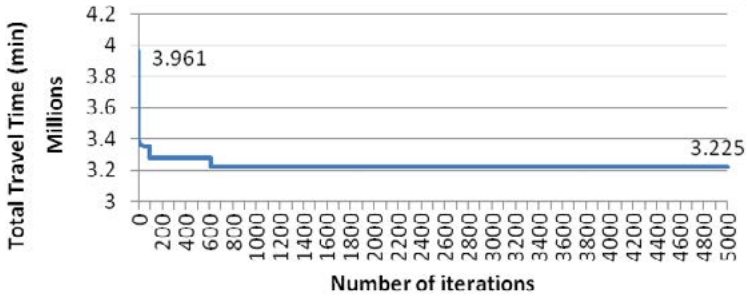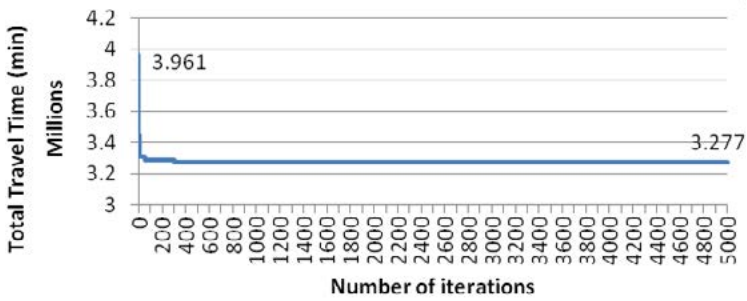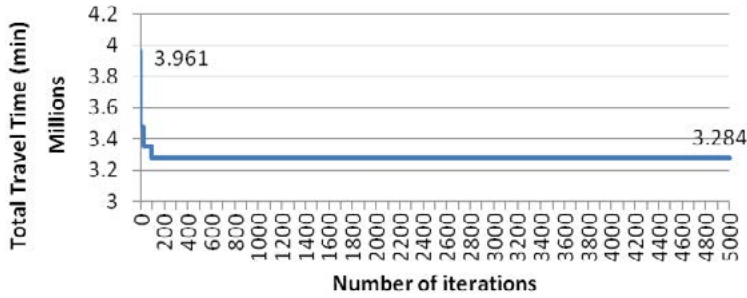
Figure 4. Fitness trends

nal all-stop operation. While in-vehicle travel time became about 20–26 percent shorter due to skipping stations, waiting time, transfer time, and additional access time became 24–38 percent longer.

Each train skipped 5-9 stations, which reduced 5–9 minutes (up to 8%) of operating time. As mentioned, this model was built to minimize total travel time. If the model's objective was minimization of operating time or total cost, the model could reduce operating time more.

Although skip-stop operation is vulnerable to delays and disruptions, is complicated, can confuse passengers at the beginning stage of the service, it can reduce passenger total travel time and operator investment and operating costs.

This research concentrated on the modeling and solution processes. In the future, this research can be used in many different ways by changing input values to create feasible conditions for skip-stop operation. For example, this research categorized passengers into two groups—those who walk to stations and those who ride to stations. In the future, research could be conducted to determine if skip-stop operation is more suitable for a walking-oriented environment or a driving-oriented environment. The minimum number of stations and the minimum average trip length for the feasible skip-stop operation could be defined as well. In addition, research could determine the difference between the results of skip-stop operation with total cost minimization and with passenger travel time minimization.

Acknowledgments

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Reduced Fare Programs for Older Adults and Persons with Disabilities: A Peer Review of Policies

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Abstract

A significant but understudied activity of transit agencies is managing reduced fare programs for older adults and people with disabilities. The laws that mandate these programs afford transit agencies substantial latitude in designing implementations. Although the resultant program variation offers an excellent opportunity for agencies to learn from each other's experiences, there has been little comparative analysis. This paper addresses this knowledge gap by providing, for the first time, a systematic consideration of reduced fare policies at the major transit agencies in the 10 most populous metropolitan regions in the United States. This work combines the findings of a structured, open-ended survey with information gleaned from transit agency websites to identify the core components of a reduced fare program, illustrate extant program variation, and discuss the attendant tradeoffs. The goal of this paper is to assist agencies seeking to re-examine and refine their reduced fare program practices.

Introduction

A nearly universal feature of transit in developed economies is the provision of reduced fares for older adults and people with disabilities. Such concessionary fares help public transportation meet its public objective of expanding mobility for disadvantaged populations. The number of people currently enrolled in concession-

ary fare programs is substantial. Chicago, for example—the third largest metropolitan area in the United States—has more than a half million registered reduced fare riders. These numbers are going to grow as demographic shifts continue to increase both the absolute numbers and the relative shares of eligible populations.

While it is always recommended practice for transit agencies to review their policies, the current transition to contactless fare media and open fare payment systems has focused attention on reduced fare programs. Successful reviews entail examining alternative models implemented by peer agencies. Unfortunately, there are no extant comparisons of concessionary fare policies to guide agencies seeking to revise and refine their own reduced fare programs. Alternative models do exist, as the laws that require concessionary fares be offered generally do not specify how those fare reductions are to be offered; however, the absence of a systematic comparison increases the likelihood that the innovations and unique adaptations developed in one place are not known elsewhere.

This paper seeks to fill this knowledge gap. This research surveys reduced fare policies among a pre-existing peer group of 10 major transit properties in the United States. Through analysis of the data collected, the core activities that characterize a reduced fare program are clustered into three areas: fundamentals, administration, and fraud prevention. This tripartite taxonomy is then used to structure the comparison of concessionary fare practices. This effort is designed to illustrate the range of practices and their attendant trade-offs without elevating any individual approach as a "best" practice. The goal of this work is to provide a framing grammar and illustrative vocabulary of reduced fare policy to enable interested transit agencies to discuss and define the practices that fit them best.

Background

United States law since 1976 requires, in somewhat dated language, that all transit agencies receiving federal funds give satisfactory assurances that "the rates charged to elderly and handicapped persons during non-peak hours … will not exceed one-half of the rates generally applicable to other persons at peak hours" (U.S. Department of Transportation 1976).

The regulations do not mandate any specific program administration. To date, studies of concessionary fares have only obliquely addressed the resultant policy variation. For example, Metz (2003) notes that in England, "there has been wide variation in the terms of the [older adult reduced fare] schemes that have been offered," but does not examine that variation. Instead, studies on reduced fare programs for older adults and persons with disabilities focus on ridership and revenue (Roszner and Hoel 1971; Ling and Howcroft 2007; Morlok, Kulash, and Vandersypen 1971; Hoel and Roszner 1972; Rye and Mykura 2009; Baker and White 2010; Truelove 1984; Andrews et al. 2012; Schmöcker et al. 2008; Shmelzer and Cantilli 1970; Rye et al. 2002) or equity impacts (Rock 1979; Andrews et al. 2012; Shmelzer and Cantilli 1970). The one exception (Ketron, Inc., and Urban Mass Transportation Authority 1981) catalogs the variation in reduced fare schemes then operating in the greater New York City region; however, the purpose of that cataloging was as a basis for a proposal to align the policies rather than explore their distinctions.

The current research takes a different tack and focuses on the reduced fare policies themselves with an appreciation of their diversity and a consideration of the associated trade-offs.

Methodology

This qualitative research combines a structured, open-ended survey of managers of reduced fare programs for older adults and persons with disabilities with materials available on the agency websites. The study sample consists of the largest transit agencies in the 10 most populous U.S. metropolitan areas. Table 1 lists these regions, which comprise an existing peer comparison group (Gallucci and Allen 2011) and the surveyed transit agency. For ease of expression, the region name is used in place of the transit agency throughout this text.

The survey results were analyzed to identify core elements common to all reduced fare programs. These elements were organized into a tripartite structure of fundamentals, administration, and fraud prevention. This structure provides a frame for considering all the activities associated with a concessionary fare policy. Fundamentals define the underlying program benefits as well as the technology for proving authorization for those benefits. Administration defines the three key processes of registration, renewal, and card replacement necessary for customers to obtain and maintain authorization for participation in the program. Fraud prevention includes all techniques and practices to prevent abuse and limit the benefit of the program to authorized users.

Table 1. Regional Information and Transit Agencies Surveyed

Region*	Population	Area	Boardings	Agency Surveyed**
Atlanta	5,359,205	8,339	144,324,818	Metropolitan Atlanta Rapid Transit Authority (MARTA)
Boston	4,591,112	3,487	380,694,311	Massachusetts Bay Transportation Authority (MBTA)
Chicago	9,504,753	7,197	641,388,305	Regional Transportation Authority (RTA)
Dallas	6,526,548	8,928	70,820,990	Dallas Area Rapid Transit (DART)
Houston	6,086,538	8,827	81,085,192	Metropolitan Transit Authority of Harris County (Metro)
Los Angeles	12,944,801	4,848	660,858,338	Los Angeles County Metropolitan Transportation Authority (LACMTA)
Miami	5,670,125	5,077	157,722,546	Miami-Dade Transit (MDT)
New York City	19,015,900	6,687	3,787,042,294	New York City Transit (NYCT)
Philadelphia	5,992,414	4,602	369,349,558	Southeastern Pennsylvania Transportation Authority (SEPTA)
Washington	5,703,948	5,598	455,528,801	Washington Metropolitan Area Transit Authority (WMATA)

Region: Populations are for associated metropolitan statistical area (MSA) in 2011. Areas are in square miles for associated MSA. Boardings are for selected transit agencies within an MSA based on their reporting for 2011 to the National Transit Database. The selection procedure is described by Allen (2013) and includes most operators reporting at least 4 million annual boardings. The one exception is the exclusion of NJ Transit, whose contribution to both New York and Philadelphia cannot be appropriately broken out. The enumerated list of included providers can be found in the "2011 Regional Peer Report Card" (RTA Department of Finance and Performance Management 2013).

**Agency Surveyed: Represents largest transit agency of MSA. In places such as Chicago, Los Angeles, and New York, selected agency runs reduced fare program for multiple operators.*

Fundamentals

Reduced fare programs offer the benefit of a cost reduction to authorized users. Those users demonstrate their authorization by presenting a permit issued by the transit agency. This section introduces those benefits and the accompanying permit technologies.

Benefits

United States law requires that transit properties offer half-price fares only during off-peak hours. The surveyed agencies all exceed this minimum temporal requirement and offer reduced fares throughout the day. Extending the hours of reduced rates is politically popular and facilitates handling of the discounts, particularly as relatively few systems maintain peak/off-peak distinctions in their pricing structures; however, such policies are theoretically problematic from a system performance perspective since they likely marginally increase transit demand during peak periods when transit supply is most limited (and most costly to provide).

Two systems do tweak their policies to better match demand and supply. Los Angeles offers deeper fare reductions during the off-peak period to encourage ridership when more capacity is available. Conversely, New York does not offer fare reductions on express buses during the morning rush when capacity is most desired. No respondent mentioned any system interest in scaling back the benefits to only off-peak periods.

The surveyed agencies also all exceed the minimum reduction requirement and offer free transit to at least one population group, as shown in Table 2.

Free transit is most commonly offered to people eligible for ADA paratransit service as a cost-saving measure designed to shift their trips to the far less subsidized fixed-route service. For example, New York, which started its free trip program in 2013, anticipates saving up to $90 million per year in subsidies (Newman 2012), and Washington claims $25 million in savings for fiscal year 2011 (Metro Staff 2012). Such programs are not without reported problems including large increases in ADA paratransit applicants (and consequently in labor costs for completing the additional eligibility determinations), illegal use of ADA paratransit permits by ineligible people, and counterfeiting of such permits. To limit these abuses, Washington restricts the free transit benefit to conditionally eligible riders (i.e., certified as physically able to use the fixed-route system for some trips) (Metro Staff 2012); Boston restricts the benefit to riders who have been in the ADA paratransit program for at least a year; and, New York restricts free travel to a maximum of four fixed-route trips per day (Goldstein 2013).

Table 2. Reduced Fare Policy Comparison

Policy	Atlanta	Boston	Chicago	Dallas	Houston	Los Angeles	Miami	New York	Philadelphia	Wash DC
Fundamentals										
Free fixed-route transit for:										
All ADA paratransit eligible	●	●	○	●	○	●	●	●	○	○
Conditionally eligible for ADA paratransit	○	○	○	○	○	○	○	○	○	●
All older adults (in Houston those over age 70)	○	○	○	○	●	○	●	○	●	○
Older adults/persons with disabilities who pass a means test	○	○	●	○	○	○	○	○	○	○
Card technologies in use:										
Identification-only card	○	○	○	●	○	○	○	○	●	●
Combined identity and fare card: smartcard	●	●	○	○	●	●	●	○	○	○
Combined identity and fare card: magnetic stripe	○	○	●	○	○	○	○	●	○	○
Administration										
Accepts applications for persons with disabilities by mail	○	●	●	○	○	●	○	●	●	○
Accepts older adult applications by mail	○	○	●	○	●	●	○	●	○	—
Maintains multiple transit agency customer service centers	●	○	○	○	○	●	○	○	●	○
Maintains mobile registration program	●	○	●	○	○	○	○	●	○	○
Maintains external service centers through partnerships	○	●	●	●	○	○	●	○	●	○
Transit agency prints/distributes reduced fare cards	●	●	○	●	●	○	●	●	●	●
External vendor prints/distributes reduced fare cards	○	○	●	○	○	●	○	○	○	○

● = yes; ○ = no; — = not applicable

Free transit is frequently offered to older adults as a political expediency. For example, the programs in Chicago and Miami both originated as part of successful campaigns to increase local sales taxes hypothecated for transit. Given the size of the older adult population, this benefit can be quite costly, and transit systems have developed different solutions for restricting the class of eligible users. All cities have a residency requirement. Chicago introduced a means test after the transit agency found its "all seniors ride free" policy cost $30 million a year in lost fares (Hilkevitch 2011). Houston set the threshold for free travel at age 70. Chicago also provides free fixed-route transit to people with disabilities who pass a means test. This program originated as part of the legislation that introduced the now curtailed "all seniors ride free" policy. No other surveyed system offers free rides to non-ADA paratransit eligible riders with disabilities.

While offering free fixed-route travel to ADA paratransit users results in a net gain for transit agencies, offering the same benefit to non-ADA paratransit users, whether older adults or people with disabilities, results in a net loss. Ideally, the transit agency would be fully reimbursed for these free trips; however, the only program to explicitly do so was found in Philadelphia. There, the state reimburses the transit operator on a full fare basis for each free trip made by an older adult with proceeds from the state lottery. These reimbursement rates are higher than the actual per-trip revenues collected by paying customers, which incentivizes the transit agency to promote the free ride program (Fish 1996). By contrast, in Chicago, transit agencies receive only partial reimbursement from the state for lost fare revenues.

Technology
There are two types of reduced fare permit technologies, as shown in Table 2. The first type, which is less prevalent today, is a simple identity card that functions as a flash pass the user shows the driver or ticket agent to claim the reduced fare benefit. These cards are entirely distinct from existing transit fare media. Dallas, Philadelphia, and Washington issue such cards for riders with disabilities and Dallas and Philadelphia issue them for older adults. Many regions allow older adults to use a government identification card to claim the reduced fare benefit. Washington relies exclusively on government identification cards and does not issue its own reduced fare permits for older adults, a policy that reduces administrative demands.

The second type of permit technology, which is currently predominant, combines an identity card with the transit system's fare media. This merger is typically accomplished by personalizing the back of a standard fare card. These cards function as

fare media coded to automatically offer the appropriate reduced fare benefit. This permit technology typically still functions as the simpler identification-only card on commuter rail.

The general technology trend has been to move towards the combined cards, which reduces the total number of products needed to be carried by customers. Philadelphia, which is currently transitioning to a contactless open fare payment system, is planning to issue a combined identity and fare smartcard for people with disabilities. Dallas may also be inching in this direction, as the region has recently begun selling an annual pass for older adults that merges identity and fare elements.

Administration

Administration refers to the central processing tasks transit agencies undertake to enroll and authorize participants in a reduced fare program. These tasks are registration, renewal, and replacement. Registration is the process through which potential users apply to participate in the program and receive their initial reduced fare card. Renewal is the process at the end of the program term through which existing users' accounts are updated and new permits are distributed. Replacement is the procedure through which an existing user receives a new permit for any reason other than the expiration of the program term.

Registration

Registration is the most labor intensive of the three "Rs" of administration, as it involves processing applications to determine eligibility and printing and distributing the reduced fare cards.

The applications themselves are quite consistent among the surveyed agencies. People with disabilities must produce documentation, typically a note from a medical professional, which attests to the nature and mobility impact of the disability. Older adults must produce government identification showing they have met an age threshold. That threshold is age 65 in all surveyed regions except for Los Angeles, which exceeds the federal requirement and qualifies older adults at age 62.

Agencies vary, however, on how they interact with applicants. Transit agencies must balance the desire to run an efficient operation with the competing need to make the program accessible to applicants. This tension is present in the federal regulations, which state that the Federal Transit Administration (FTA) "strongly encourages operators to develop procedures that maximize the availability of off-peak half-fares to eligible individuals. Requiring individuals to travel to a single office

that may be inconveniently located is not consistent with this policy, although it is not strictly prohibited. FTA reserves the right to review such local requirements on a case-by-case basis" (U.S. Department of Transportation 1976).

One option is to offer multiple agency service centers within a region, which reduces the average distance customers will need to travel. Table 2 demonstrates that although most systems maintain a single, centrally-located, agency-staffed customer service center, Atlanta maintains two and Los Angeles maintains four. Philadelphia maintains one center for accepting applications from persons with disabilities, but has four centers for accepting older adult applications.

Another approach is for agencies to come to the applicants. Several systems offer mobile registration services through which an agency employee will bring the necessary registration forms and equipment (computer, digital camera, card printer, etc.) to different locations around the region. Atlanta and New York offer this service regularly, whereas Chicago does so occasionally, and Boston did so in the past. Offering mobile services requires coordination with the hosting location as well as additional capital and setup costs. New York has streamlined this process by retrofitting two 40-foot buses and three 20-foot vans as mobile sales and customer service centers (Parker, Timson, and Henning 2000).

A third approach is partnering with external agencies. Miami allows applications from persons with disabilities and older adults to be completed at three customer service centers of the county government, and Philadelphia allows older adult reduced fare card applications to be completed at more than 20 state representatives' district offices. In both cases, the applications are then forwarded to the transit agency for processing. Boston, Chicago, and Dallas have extended these relationships more broadly and incorporate non-government agencies. Boston maintains more than 50 external centers for older adult applications. Chicago maintains 52 external centers for reduced fare card applications for persons with disabilities and 185 centers for older adult reduced fare card applications. Dallas maintains 45 external centers for reduced fare cards for persons with disabilities. These external locations include social service organizations, town halls, senior centers, bank branches, etc., that volunteer their efforts to assist in the preparation of reduced fare card applications. In Boston and Chicago, these centers prepare and mail applications to the transit agency. In Dallas, these centers not only prepare applications but certify disability status on the spot.

The Dallas example warrants special mention. Dallas Area Rapid Transit (DART) actively trains (and audits) its partner agencies. These DART-Approved Certifying

Agencies (DACAs) enter approved applicant information directly into the DART database via the Internet. The local DACA retains hard copies of the application material and prints out a receipt for the approved applicant. That applicant then takes this receipt to DART's main office to pick up his or her reduced fare card. DART's high level of training and supervision allows the transit agency to outsource disability certification to volunteers. Furthermore, those trusted partners are able to avoid extra paper handling and the attendant delay by electronically (and instantly) entering applicant information into DART's database. The requirement to come downtown to pick up the actual card may be burdensome, as only 73 percent of certified applicants actually claimed their card in 2011. This disjunction suggests that the current policies are either inadequately serving patrons or, alternatively, sorting out the people most likely to use the reduced fare card.

A final option is to accept applications by mail. Table 2 shows that half the surveyed agencies accept applications by mail, while the other half requires in-person applications. Offering the mail option makes it easier for the customer, who does not have to travel to a registration site, but reduces the agency's ability to ensure that the applications are filled out correctly and truthfully. In-person applications can be corrected on the spot and allow the agency to better verify applicant identity. Furthermore, in-person applications allow for digital photography, which makes for more consistent, higher-quality cards than scanning externally-submitted pictures. Agencies with larger numbers of reduced fare users reported that offering the mail option was necessary, as there would not be sufficient staff to handle the demand of in-person only applications.

Once an agency has approved an application, a permit must be produced. Agencies vary on whether they print these cards themselves or outsource the task. Outsourcing always adds an extra process, which extends the time until the card is in the hand of the user. Los Angeles and Chicago have chosen to outsource permit printing and deal with the long turnaround times by giving in-person applicants an interim reduced fare card good for 60–90 days. In-house printing may leave an agency vulnerable to staffing reductions. New York, for example, reduced its staff and has had trouble getting cards to customers (Donohue 2012). Agencies also vary on whether they charge for printing the permits. Dallas charges a $2 fee for both older adults and persons with disabilities to cover the cost of photo. Los Angeles charges a $2 processing fee for reduced fare cards for persons with disabilities, but not for older adults. No other system charges a printing fee, which might be seen as an undue impediment to receiving a legally-guaranteed benefit.

The third and final step to registration is distributing the permits to customers. These can be either mailed or picked up in person. Generally, cards are returned in the same way that the initial application was delivered. If the application was mailed to the agency (either by the applicant or a remote center), the card is mailed to the applicant. The distribution time ranges from two to eight weeks. (The number of weeks required to return the card to the patrons reported in surveys tended to be longer than those advertised on agency websites, sometimes by a factor of two.) If the application was delivered in person, the card is often produced on the spot. There are some exceptions. As noted above, Chicago and Los Angeles do not print their own cards, so their walk-in applicants receive their cards in the mail in about a month; Philadelphia returns all reduced fare cards exclusively by mail even though they do not accept older adult applications by mail; and Boston requires that all riders with disabilities pick up their permits in person, even if the applications were delivered by mail.

Some systems, like Atlanta and Dallas, distribute cards only in person. This approach puts a travel burden on the user, but has several advantages for the transit agency. The agency can be certain that the permit has been received and that it has been received by the actual applicant. The applicant can sign a statement acknowledging receipt, which may head off future legal problems. In-person distribution eliminates the need for issuing temporary cards as well as any mailing costs. In Miami, people who apply at remote government centers need to return to those centers to pick up the reduced fare permit in-person. In-person distribution can strain agency staff and was reported to not be feasible in regions with high numbers of both residents and transit trips (see Table 1), as such systems, consequently, have high numbers of reduced fare applicants.

Renewal

Every agency surveyed except Philadelphia requires that reduced fare permits for older adults and persons with disabilities be renewed on a regular basis. This requirement keeps the registration lists current by eliminating people no longer interested or eligible to remain in the program. It also forces a turnover in the card stock, which reduces fraud by capping the length of time that cards can be used illegally (i.e., by someone other than the named cardholder). This turnover may be necessary, as electronically-coded media, such as smartcard and magnetic stripe cards, are designed with limited useful life expectancies. Philadelphia does not currently use electronically-coded cards for its reduced fare media and, therefore, is able to offer lifetime terms of card validity.

Term lengths are set to balance the costs of processing renewals with the costs of lost revenue from fraudulent use of the cards. Figure 1 demonstrates that there is substantial variation in permit term lengths. Part of that variation can be attributed to the condition that warrants the reduced fare. On average, temporary disabilities (i.e., those for which recovery is expected) have the shortest terms and older adults have the longest terms, with permanent disabilities in the middle. In practice, only Boston reflects this tripartite variation, as regions tend to coordinate the terms either for temporary and permanent disabilities or for permanent disabilities and older adults. Most agencies offer fixed terms for all conditions; however, fixed terms for temporary disabilities may result in time periods when a rider who no longer has a disability can legally enjoy a reduced fare. To address this problem, Chicago, Houston, Los Angeles, and New York offer riders with temporary disabilities a variable term based on the expected recovery time, up to a limit ranging from one to four years, as shown in Figure 1.

Renewing reduced fare permits requires agencies to alert their permit holders to the impending card expiration. The lowest cost approach is to simply print the expiration date on the reduced fare card itself, which is done by all the surveyed systems except Atlanta and Miami. Atlanta plans to embrace this practice soon. Miami alerts customers by flashing a digital message on the farebox or turnstile when the permit is used. Since Miami structures all of its disabled reduced fare cards to expire the same day (September 30), the agency can further alert those customers through advertisements. A more expensive approach taken by Atlanta, Chicago, Houston (only for older adults), and Los Angeles is to mail notices to permit holders. This approach has the advantage of reaching people who may not be active card users. There is variation in how much warning time agencies provide. Atlanta provides 30 days, Chicago provides 60 days, and Los Angeles provides 90 days.

Renewing reduced fare cards also requires agencies to verify that current permit holders should remain in the program. Agency policies trade off convenience for a high certainty of verification. At the two extremes, Dallas and Los Angeles require customers with permanent disabilities (as well as older adults in Dallas) to repeat the entire certification process at the end of every term (which in Dallas is one year), while Houston automatically sends out new cards. Miami represents a middle ground by requiring proof of ongoing permanent disability by fax, mail, or in person, but not full recertification.
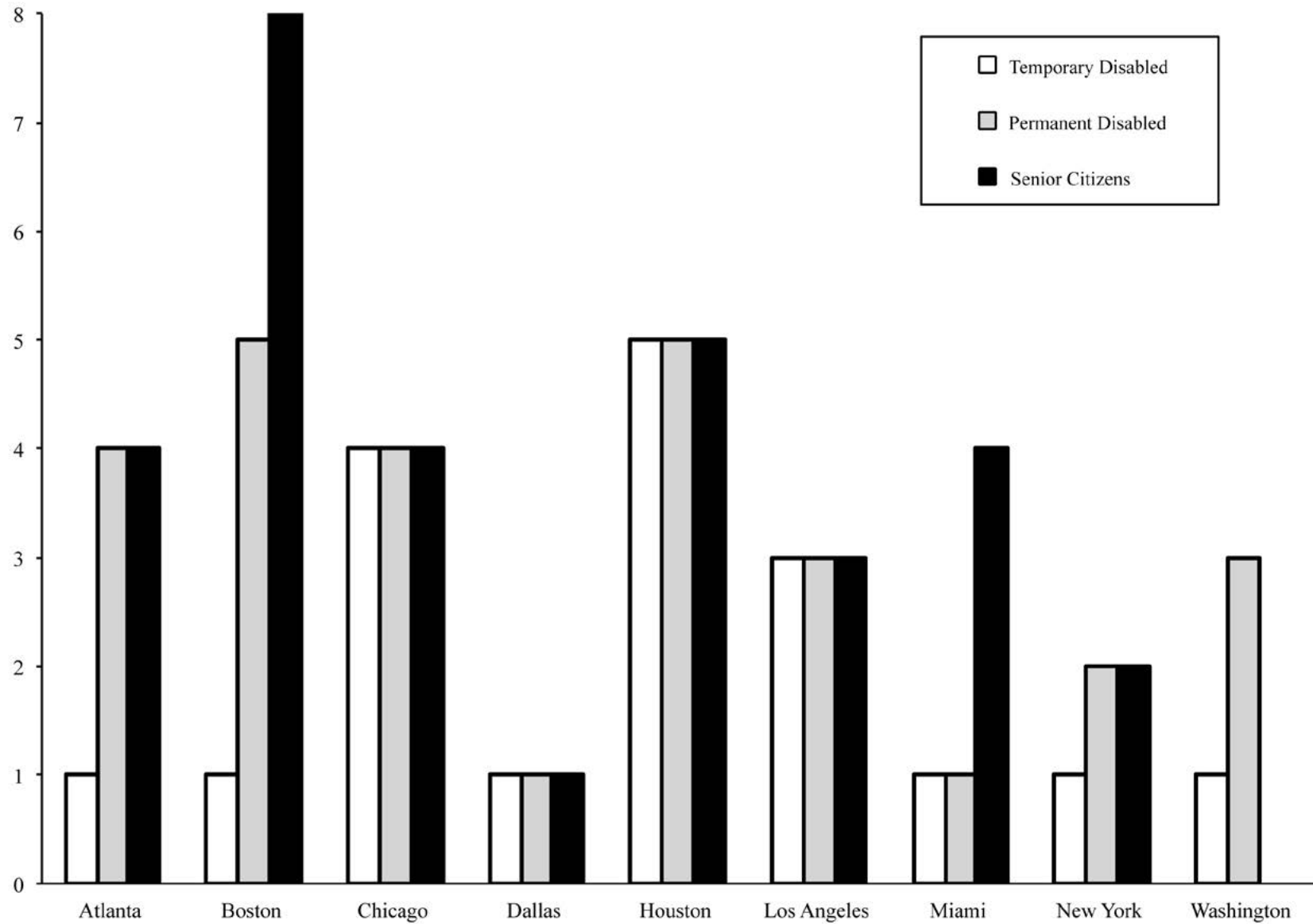
Notes: Washington does not register older adults. All terms are fixed except for temporary disabled terms in Chicago, Houston, Los Angeles, and New York, where they vary up to the limit shown in this figure. Philadelphia is not included in this chart since there are no fixed terms; instead, the card is issued either for the expected length of a temporary disability or for life.

Figure 1. Reduced fare card renewal terms (in years)

A main concern for many systems is verifying that the cardholder is alive and wants to remain in the program. Atlanta and Washington (for riders with disabilities) require the customer to visit a customer service center in person to get a permit renewal. Chicago and Los Angeles (for older adults) send a form that the customer must fill out and return. Boston allows cardholders to call in their verification. New York automates verification by checking the Social Security Administration database to ensure that the cardholder is still alive before sending out a new permit.

Replacement

A portion of reduced fare cards will need to be replaced before they reach the end of their term, either because the card is missing or because the card is no longer usable. The former occurs when the card is lost, stolen, or never received through the mail. The latter occurs when the card has been confiscated due to improper use, damaged to the point of inoperability, captured in a fare box or ticket vending machine, or needs to be replaced due to a technology change.

The general replacement approach is to, ideally, deactivate missing cards or destroy unusable cards and then place any remaining value on a new card. Deactivation is possible for those cards that incorporate electronic fare media, whether magnetic stripe or smartcard. These cards can be remotely deactivated by adding their identification number to a "hotlist" of invalidated card numbers to be rejected by fare readers. This approach does not prevent reduced fare cards from functioning as flash passes, does not affect identification-only cards, and entails some data storage limitations. Destruction is the preferred solution but can be used only for cards whose whereabouts are known. Many transit agencies will seek to have unusable cards returned to them for shredding before issuing a replacement.

Since replacement entails processing expenses and may introduce the possibility of fraud, transit agencies prefer that patrons hold on to and take care of permits. A variety of disincentives are used to discourage the need for replacement from arising. The most common disincentive is to charge replacement fees.

Figure 2 shows that 8 of the 10 agencies surveyed charge such fees. Most of these charge only when the customer can reasonably be held culpable, i.e., he or she has misplaced the card or "loaned" it to someone from whom it was later confiscated; however, Los Angeles also charges if the customer has damaged a card—for example, by punching a hole in it to thread a lanyard—and Miami charges if a customer claims he or she never received the card, but the card was sent to the correct address and the card was used. The fee amounts vary rather significantly,

from $1 to $25, and four of the systems charge escalating fees for subsequent replacements. Both the fee amounts and the incidence of escalation have gone down with the ability to remotely deactivate electronic fare media and, therefore, reduce the potential revenue losses from the fraudulent use of missing cards. For example, both Atlanta and Boston used to charge higher and escalating fees, but dropped the base level (in Atlanta to a token dollar and in Boston entirely) and the escalation framework with the transition to smartcards. (Boston's decision was also motivated by a concern that the fees fell disproportionately on riders whose disabilities, particularly cognitive, make it difficult to manage their cards.) By contrast, Philadelphia and Washington, which both use identity cards that cannot be remotely deactivated, charge the highest replacement fees and maintain escalation structures. Transit agencies typically have the right to waive these fees either at their discretion or as part of a structured program. An example of the latter is Houston, which allows a one-time fee waiver.

Several systems offer administrative disincentives to replacement. For example, Dallas requires riders to repeat the entire application procedures to receive a replacement card, regardless of the reason for replacement. Philadelphia will not issue a second replacement card for older adults until a year elapses from the time of the first replacement. In the case of confiscated cards, Atlanta delays replacement for 30 days and increases that delay by 30 days for each subsequent confiscation. New York has such patrons wait 60 days for a replacement card. Boston allows one "freebie" of fraudulent use and then can cut such owners from the reduced fare program altogether, a rarely-implemented policy provision of Massachusetts state law unlikely to pass a federal challenge.
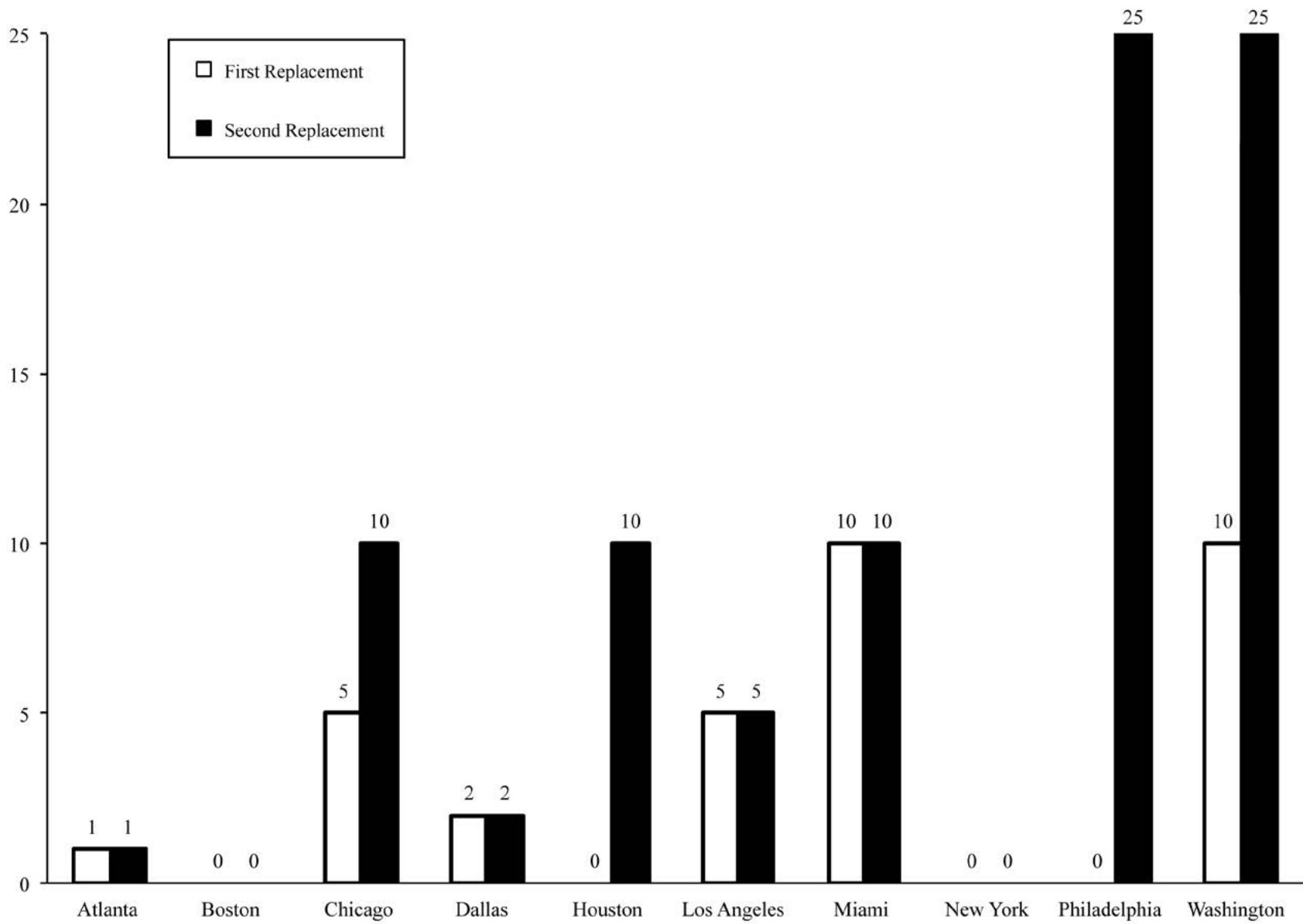
Figure 2. Reduced fare card replacement fees ($)

Fraud Prevention

Since reduced fare cards offer significant savings, they incentivize fraud. The main reported agency concern is non-eligible people using legitimate reduced fare permits obtained either as a loan/gift/bequest from the eligible user or through robbery. (A secondary concern, raised by one respondent as justification for requiring in-person applications, is that ineligible people may be fraudulently registering for legitimate permits. This concern does not appear to be widely shared as systems seem confident of their registration processes.) The administration procedures discussed above provide a general framework for making sure that permits initially go to the right people and that errant permits are deactivated. This section addresses how transit systems enforce use of the permits by the authorized cardholder.

Enforcement first requires that the reduced fare permit be sufficiently personalized to identify that the card user is the legitimate cardholder. At the same time, agencies are concerned about possible downsides for the user of too much data collection. For example, Chicago does not currently put the user's name on the card to protect the cardholder's identity in the case of theft. (Chicago has decided to include names as part of a new permit policy starting in late 2013.) Houston does not put the user's picture on the older adult card to not burden those users with the inconvenience of coming to a service center to be photographed. Many systems use card design to augment the personalization. The most sophisticated approach is used in New York, where reduced fare cards come in four background colors that distinguish between men and women as well as between older adult riders and riders with disabilities. These markings facilitate spot checking by enforcement agents.

Such enforcement is critical to preventing fraud, but varies significantly, particularly among the rail portions of the surveyed systems. The most secure rail systems, such as Philadelphia, require everyone using a reduced fare card to be manually checked upon entry. This approach slows boardings but is thought to result in very little abuse of the cards. Less-secure rail systems, such as Dallas, Houston, and Los Angeles, have (at least for now) barrier-free entry but maintain teams of roving fare inspectors to check for fraud and similarly report limited abuse of the reduced fare cards. The remaining rail systems in the sample all allow anonymous entry, which is the least secure approach. These systems consequently report greater concerns about fraud. Boston, Chicago, Miami, and New York note that their fare gates have indicator lights or specified tone sequences that mark when someone pays a concessionary fare. These agencies send roaming inspectors to challenge suspi-

cious users for proof of reduced fare eligibility. Atlanta and Washington have no structured monitoring program at their rail stations.

There is slightly more enforcement consistency on buses as, at least in theory, the driver is supposed to keep tabs on reduced fare use. Dallas and Philadelphia, which require the driver to check for a reduced fare permit before offering discounts, are the most secure. Many systems have fareboxes that emit different tones or lights to identify when a reduced fare payment is being made; however, it is up to the discretion of a bus driver to challenge potentially fraudulent use. New York is unique in sending fare inspectors onto buses to improve reduced fare permit enforcement.

The shift to electronic fare media does afford some new possibilities for data mining to combat fraud. New York is the only system to report examining usage patterns to identify fraudulent behavior and target enforcement locations. Chicago and New York hotlist the cards of people that have died, based on Social Security records. In Chicago, this practice began after an audit exposed one older adult reduced fare card being used more than a thousand times after its owner had passed away (Regional Transportation Authority Research, Analysis & Policy Development Department 2010). Hotlist capacity is often limited and, at a certain point, new additions bump off older numbers, which raises the specter of deactivated cards once again becoming useable. Chicago has addressed this storage limitation by splitting the hotlist in two. An active list maintains the current crop of bad card numbers for several weeks before transferring them to an offline passive list. Card use is monitored, and if a card number from the passive list appears in the usage records, then that number returns to the active hotlist.

Accessing the Social Security database requires transit agencies to collect cardholder Social Security numbers. Some agencies, such as Miami, find such unique identifiers critical for tracking program registrants in a region where many people have the same names. Other agencies report concerns about handling such sensitive information. Boston, for example, has ceased collecting Social Security numbers, having decided that the costs of possible data exposure outweighed the fraud prevention benefits.

Conclusions

The variation in reduced fare card policies across the United States offers an excellent opportunity for transit agencies to learn from each other's experience and to mix and match approaches that best meet their specific needs. This paper provides a framework for understanding that variation and then illustrates it with examples

from the largest metropolitan areas in the United States to illuminate policy trade-offs. This work is aimed at helping agencies review and refine their reduced fare policies.

The need for such policy reconsideration is likely to grow. The aging of the population will continue to strain reduced fare program administration, as can be seen in New York; the transition to contactless fare payment technologies will require many agencies to reissue reduced fare permits *en masse* and foster a rewriting of the associated policies, as is currently underway in Chicago; and, finally, the slow shift from paper-based to electronic information management will offer new opportunities for streamlining program administration as demonstrated in Dallas. Even in the absence of external impetus for change, the information presented in this paper will assist in the always useful practice of policy revision.

Acknowledgments

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