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An Analysis of Commuter Rail Real-Time Information in Boston

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Abstract

Prior studies have assessed the impacts of real-time information (RTI) provided to bus and heavy rail riders but not commuter rail passengers. The objective of this research is to investigate the benefits of providing commuter rail RTI. The method is a three-part statistical analysis using data from an on-board survey on two commuter rail lines in the Boston region. The first analysis assesses overarching adoption, and the results show that one-third of commuter rail riders use RTI. The second part conducts difference of means tests and regression analysis on passenger wait times, which reveals that riders’ use of RTI is correlated with a decrease in self-reported “usual” wait times. The third part analyzes 12 quality-of-service indicators, which have a limited relationship with RTI utilization. The results suggest that the benefits of commuter rail RTI are modest. Despite this, many commuter rail riders choose to use this new information source, which has important implications for transit managers considering deploying RTI systems.

Introduction

Public transit providers often struggle with service reliability issues; when a transit vehicle does not arrive on time, passengers become frustrated and may be less likely to choose transit for future trips. Reliability can be improved in many ways, including improving rights-of-way, using service planning approaches, or implementing control strategies. While these supply-side strategies can be effective at improving reliability, they often come at a substantial cost.
As another way to address reliability concerns, transit agencies in the United States increasingly provide real-time vehicle location and/or arrival information (RTI) to riders. Providing RTI helps passengers adapt to the unreliability of transit service (Carrel et al. 2013). Moreover, RTI can be provided to passengers in an increasingly cost-effective manner. Over the past decade, the provision of RTI to passengers via web-enabled and/or mobile devices has become ubiquitous in urban bus and rail systems (Schweiger 2011; Rojas 2012).

This trend has spurred commuter rail operators to consider providing riders with similar levels of digital, dynamic transit information. Recently, some of the largest commuter rail providers in the U.S. have begun to offer RTI to passengers. Both the Long Island Rail Road and Metro-North Railroad in the New York region provide real-time train location information on a website known as “Train Time” (MTA 2013a; MTA 2013b). Similarly, New Jersey Transit provides information through its “Departure Vision” real-time train status service (New Jersey Transit 2013), and, in the Chicago region, Metra offers real-time train tracking on its website (Metra 2013).

In Boston, the Massachusetts Bay Transportation Authority (MBTA) has taken a different approach to commuter rail RTI. Instead of developing its own RTI platform, it released real-time commuter rail data to independent software developers, which has resulted in numerous third-party RTI applications on many different digital platforms, including websites and smartphone applications. Since commuter rail operators increasingly offer RTI options to passengers, this research aims to assess how riders may benefit from this information.

Prior Research
While the delivery of RTI has been possible for decades, until recently, such information tended to be delivered via electronic signs at stations, if at all. Two inter-related phenomena in the U.S. have begun to change this fixed-infrastructure, centrally-provided information model: the “open data” movement and the rapid adoption of the “smartphone.” The results are increasingly available transit information in a variety of formats for connected devices (Schweiger 2011).

In light of this trend, a growing body of literature has begun to assess the benefits of providing RTI to transit riders via web-enabled and/or mobile devices. This brief literature review focuses on prior research that uses actual behavioral data to understand rider benefits, since this will most likely provide more concrete conclusions needed to inform decision-makers. Prior studies that use stated preference methods (e.g., Tang and Thakuriah 2010) or simulation techniques (e.g., Cats et al. 2011; Fries et al. 2011; Fonzon and Schmöcker 2014) to evaluate the potential impacts of RTI on passenger behavior are not included in this review. Following the framework of a prior RTI study in Tampa, Florida (Brakewood, Barbeau, and Watkins 2014), this literature review divides potential rider benefits of RTI into three key areas: (1) decreased wait times, (2) increased satisfaction with transit service, and (3) increased ridership.
Decreased Wait Times

RTI enables riders to “time” their arrival at a stop/station to minimize wait time. Using RTI improves passenger awareness of the estimated actual arrival time of the vehicle at the stop/station, thus allowing them to more precisely time their arrival at the station and reduce wait time. Additionally, RTI may reduce passenger perception of waiting time once they have reached a stop/station because they are getting real-time updates of when the vehicle should arrive.

A recent study conducted in Seattle found that bus riders with RTI perceived wait times at the bus stop to be approximately 30 percent less than those who did not use RTI, and the actual wait times of RTI users were almost two minutes less than the wait times of non-users (Watkins et al. 2011). Another study of bus riders in Tampa found significant improvements in the “waiting experience” associated with use of mobile RTI, including reductions in self-reported wait times and decreases in levels of anxiety and frustration while waiting for the bus (Brakewood, Barbeau, and Watkins 2014).

Increased Satisfaction

If transit passengers spend less time waiting and/or perceive waiting time to be less, they may become more satisfied with overall transit service. A panel study conducted of the shuttle bus system on the University of Maryland campus showed increased satisfaction with transit service attributable to RTI (Zhang et al. 2008). Additionally, the results of two surveys of bus riders in Seattle who use mobile RTI revealed increased satisfaction with overall bus service (Ferris et al. 2010; Gooze et al. 2013).

Increased Ridership

If passengers spend less time waiting and/or are more satisfied with transit service, then RTI may increase the frequency of transit trips by existing passengers or potentially attract completely new riders to transit. In Chicago, a longitudinal analysis of bus ridership over a nine-year period found a modest increase in route-level ridership attributable to the provision of bus RTI (Tang and Thakuriah 2012). A follow-up study in Chicago found a small increase in train ridership over a six-year period attributable to the provision of bus RTI, possibly due to increased intermodal transfer efficiency between trains and buses (Tang et al. 2013).

Summary of Prior Research

This review of studies grounded in behavioral data reveals three key rider benefits of RTI: (1) decreased wait times, (2) increased satisfaction with transit service, and (3) increased ridership. However, these benefits were identified based primarily on studies of bus and urban rail systems, leaving at least one transit mode understudied: commuter rail. Commuter rail may be understudied for numerous reasons. First, bus and heavy rail systems carry the majority of public transit trips in the U.S. (APTA 2012); therefore, these systems may be studied more frequently simply because they are more heavily used. In addition, commuter rail systems generally operate at longer headways and run on dedicated right-of-way, whereas urban bus systems often have shorter headways and operate in mixed traffic. Because of differences in frequency and reliability of service, the value of using RTI on urban bus systems may be different (likely greater) than for commuter rail systems, which may be why they have been studied first. Regardless, by focusing on a mode that
has been largely excluded from previous research, this study adds to our understanding of RTI provision in transit systems.

**Objectives**

The overall objective of this research is to explore the utilization and passenger benefits of RTI provided to commuter rail riders through web-enabled and/or mobile devices. Three specific objectives are set forth, which focus on measures of RTI use and benefits in the short term. First, the overall levels of adoption and rates of utilization of commuter rail RTI are explored. Second, prior research indicates that reductions in passenger wait times are an important benefit of RTI in other modes of transit; subsequently, this study aims to determine if there are decreases in wait times associated with using commuter rail RTI. Third, the literature review revealed that increases in satisfaction with transit service are another possible benefit of RTI systems; therefore, this study aims to assess if there are increases in quality of service ratings associated with using RTI. It should be noted that the literature review suggested that increased ridership is a benefit of RTI; such analyses, however, require longitudinal analysis and are left for future research in the commuter rail case.

**Background**

Commuter rail service in Greater Boston includes fixed schedule, daily service on 12 heavy rail lines serving downtown Boston via 2 central city stations (North Station and South Station). Boston has the fifth largest commuter rail ridership in the U.S. based on the number of unlinked passenger trips (APTA 2012). The service is operated by the Massachusetts Bay Commuter Rail Company (MBCR) under contract with the Massachusetts Bay Transportation Authority (MBTA).

Three basic categories of information sources are available to commuter rail riders in Boston: (1) static information, (2) service alerts, and (3) real-time information. Static information consists of schedules and maps, which generally are updated on a quarterly or annual basis and are available online at the MBTA's website, through other websites (such as Google Transit, a free trip planner available worldwide), in printed form, and on signs at stations. Service alerts, known as “T-alerts” in Boston, include emails and text messages that report major delays (more than 15 minutes) to subscribers. Riders can sign up for mode- and line-specific alerts, which are automatically pushed to their mobile phone or email account in the event of a delay (MBTA 2013). Service notifications are also posted on the MBTA's website. Real-time information (RTI) refers to up-to-the-minute tracking of transit vehicle locations and often includes predicted arrival times for stops/stations. RTI is distinguished from service alerts because the latter are incident-based information “pushed” to the user, while the former are user-initiated inquiries to the system. RTI has increasingly become available to riders “on-the-go” due to the advent and widespread adoption of smartphones and smartphone-based applications (“apps”) and the “open data” movement.

In the U.S., the MBTA was an “early adopter” in the movement towards public disclosure of real-time data (Rojas 2012), gradually releasing real-time data to the public for each transit mode as part of the Massachusetts Department of Transportation's open data
An Analysis of Commuter Rail Real-Time Information in Boston

An analysis of commuter rail real-time information in Boston (MassDOT 2013) (Figure 1). In 2009, the MBTA released a real-time data feed for five “pilot” bus routes that included vehicle location and arrival information. In response to public demand, real-time data were released for all approximately 200 MBTA-operated bus routes in the summer of 2010. Shortly thereafter, the MBTA began publishing real-time data for the heavy rail lines (excluding the light rail Green Line). In June 2011, the MBTA added commuter rail to its real-time data initiative as a beta feed, which used a GPS-based tracking system originally designed for automated on-board announcements and station signage. Prior to the open release of data to third-party developers, LED signs at some commuter rail stations gave riders real-time updates by displaying “train approaching” messages.

![FIGURE 1. Timeline of transit data release in Boston](image)

Similar to other transit agencies, the MBTA makes available on its website the independently-developed applications (without endorsement) that draw from the real-time data feeds. On the MBTA’s webpage, more than 80 different web and mobile applications created by third-party software developers are showcased (as of 2014), and many of them integrate commuter rail data (MBTA 2014). Despite the great variety of transit information applications now available, little evidence exists on how many riders in Boston actually use RTI or how they access it, partly because the applications come from third parties instead of the MBTA. Therefore, this research aims to provide a more concrete understanding of RTI utilization on Boston’s commuter rail system.

**Data Collection**

Data for this analysis were collected via a short paper survey administered in June 2012. An on-board sampling method was selected to most easily reach the target population (commuter rail riders). This study does not explicitly attempt to detect potential modal shifts (e.g., from car to commuter rail), since the data collection was conducted only one year after the debut of the commuter rail RTI feed. Furthermore, capturing non-users of commuter rail would have required a sampling strategy well beyond the resources available.

The on-board survey was conducted on three weekdays in mid-June during the morning and evening peak periods (between 6:30–10:00 AM and 4:00–7:30 PM). Because ridership on the commuter rail is highly-peaked in the commuting direction (inbound in the morning, outbound in the evening), the off-peak direction (outbound in the morning, inbound
in the evening) also was sampled so both peak and off-peak riders could be included in
the analysis. Riders were sampled on 12 train trips: 6 outbound and 6 inbound. Once
on-board the trains, teams of two to three researchers distributed paper surveys to as
many riders as possible and collected them before riders alighted.

**Line Selection**

All 12 commuter rail lines could not be sampled due to resource constraints. Instead, two
lines were selected—the Worcester and the Newburyport/Rockport lines—based on four
factors: geography, ridership levels, ridership demographics, and service reliability. Geo-
graphy was defined based on the terminal stations in downtown Boston. As two large ter-
menal stations serve different geographic regions in the metropolitan area, one line from
each was selected to better represent the entire network. The Newburyport/Rockport
line terminates at North Station, and the Worcester line ends at South Station. Second,
only high ridership lines were considered, to increase the number of survey responses.
The selected lines have average weekday boardings of approximately 17,000–18,000 and
are among the highest ridership levels within the overall commuter rail network (MBTA
2010). Third, based on previous survey results, diversity in rider income levels and ethnic-
ities was considered, since these may impact the level of technology adoption and sub-
sequently, utilization of RTI. The Worcester line has relatively high levels of demographic
diversity, whereas the Newburyport/Rockport line has a more homogenous, high-income
ridership (CTPS 2010). Finally, the two lines differ in levels of service reliability, as defined
by the MBTA’s on-time performance metric. Monthly data for June 2012 show that the
Worcester line was on time for 91 percent of trips, above the commuter rail system
average of 89 percent, whereas the Newburyport and Rockport branches had on-time
performance measures of only 70 and 61 percent, respectively (MBTA 2012).

**Data Collection Constraints**

Although standard survey research procedures were followed, data collection faced
constraints. First, no survey mail-back option existed. Riders were instructed to com-
plete as many questions on the survey as possible during their commute, leaving surveys
incomplete because the rider alighted the train prior to completion. Additionally, since
the survey was administered only in English, a very small number of riders (fewer than 10)
declined participation because they did not speak English. Last, due to the constraints of
conducting an on-board survey in rail cars (which were often crowded), the rate at which
riders accepted or declined participation was not measured.

**Survey Content**

The survey instrument included questions about the awareness and use of commuter rail,
subway, and bus RTI; 2 questions about wait times; and 12 quality of service indicators.
Travel behavior questions about frequency of ridership, trip destination, and boarding
and alighting locations, as well as socioeconomic status of respondents, were included
to better account for relevant influencing factors. The survey also contained questions
about ticketing, which were used in a mobile ticketing analysis (Brakewood et al. 2014). A
copy of the questionnaire is available online (Brakewood 2014).
Responses
In total, 914 responses were collected during the fieldwork period, with 903 deemed sufficiently complete for the following analysis. Sufficient completeness means that the respondent answered questions up to the halfway point on the questionnaire, where the use of commuter rail RTI question was posed. The survey responses from both lines were pooled and used to conduct the following analyses.

Results
Three analyses were conducted to explore the impacts of RTI on commuter rail passengers. The first analysis assessed overall adoption and utilization of RTI by commuter rail riders. The second analysis aimed to understand if decreases in wait times are associated with using commuter rail RTI. The third analysis examined if increases in perceived quality of service are associated with using RTI.

Analysis 1: Awareness and Utilization of RTI
This analysis assessed three different aspects of RTI utilization by commuter rail riders: awareness and adoption of RTI for the three primary MBTA modes (commuter rail, bus, and subway); the interfaces used to access commuter rail RTI; and the reasons riders do not use commuter rail RTI.

Awareness and Utilization of RTI
Survey respondents were provided with a brief description of RTI and were asked if they were aware of RTI for commuter rail, MBTA buses, and MBTA subway trains. Figure 2 shows that 54 percent of respondents were not aware of commuter rail RTI, 63 percent had not heard of subway RTI, and 66 percent were not aware of bus RTI. Prior to the survey, commuter rail RTI had not been formally marketed by the MBTA or MBCR, likely contributing to the fact that more than half of surveyed riders were not aware of commuter rail RTI. For those who were aware of commuter rail RTI, this was likely due to word-of-mouth, press coverage, and marketing conducted by independent software developers (such as through social media).

FIGURE 2.
Awareness and utilization of RTI by commuter rail riders

Note: All percentages rounded to the nearest whole number.
The survey also asked commuter rail riders how frequently they used RTI for each MBTA mode. Figure 2 shows that 33 percent of riders used commuter rail RTI either on every ride (always = 1%), on most rides (often = 4%), or on a few rides (sometimes = 28%). However, 13 percent of surveyed riders were aware of commuter rail RTI but had not used it, and, as previously stated, 54 percent were not aware of commuter rail RTI.

Figure 2 also shows that 19 percent of commuter rail riders had used subway RTI (total of “always,” “often,” and “sometimes”), and only 15 percent used bus RTI (total of “always,” “often,” and “sometimes”). A large amount of overlap exists between riders who used commuter rail, bus, and subway RTI: 46 percent of riders who used commuter rail RTI also used either bus, subway, or both bus and subway RTI. This overlap may be attributable to RTI applications that integrate all three modes. At the time of the survey (in 2012), there were 44 third-party applications listed on the MBTA’s “App Showcase” website, many of which integrated commuter rail RTI with others modes (Rojas 2012). Additionally, bus and subway data were released prior to the commuter rail data (as shown in Figure 1) and, therefore, bus and subway RTI users may already have had the applications needed to use commuter rail RTI. Note that the on-board survey sampled only commuter rail riders; the utilization of bus and subway RTI would likely be much higher if passengers on subway trains and buses also were sampled. Last, only 5.5 percent of survey respondents reported having used commuter rail RTI prior to boarding the train on the day of the survey.

**Interfaces to Access RTI and Reasons for Not Using RTI**

Respondents could select all technologies that they had used to access commuter rail RTI, and they most commonly used a desktop or laptop computer (51%) (Figure 3). This may be because riders often were traveling to/from work and may have checked the real-time status of their train before leaving their office. The second most-common method was through smartphone applications (36%).

![FIGURE 3. How riders access commuter rail RTI (n=334)](image)

Riders who were aware of commuter rail RTI but stated that they “never” use it were asked why. The most common reason (38%) for not using commuter rail RTI was “I don’t have a smartphone” (Figure 4). Note that all respondents were asked which types of information and communication technologies they had used in the past 30 days, and smartphones had utilization rates of 76 percent of all respondents, a higher rate than the national average (46%) of smartphone owners at the time of the survey (Pew Research Internet Project 2012).
Another common reason for not using commuter rail RTI was “other.” This response had a write-in section, and the most frequent theme of write-in comments was that commuter rail RTI was not needed. Some examples of write-in responses include “haven’t needed to,” “don’t see the need to,” “not valuable info,” and “doesn’t matter.” These reasons may stem from the nature of commuter rail service, traditionally a fixed-schedule service operating at low frequencies. Commuter rail riders traditionally consult the schedule pre-trip, and riders may continue to be reliant on static schedule information for reasons of habit or simplicity. Additionally, some survey respondents noted the lack of other transportation alternatives in the event of a delay. Since the commuter rail network services many outlying suburbs without other transit options, riders may not have alternative means of getting to their destination if there is a delay in service.

Finally, 21 percent of riders who do not use commuter rail RTI selected the response that “it is not accurate.” Unfortunately, the accuracy of RTI was not monitored during the study period.

Analysis 2: Wait Times
Passenger wait times were analyzed because prior research indicated that reductions in wait times are a key benefit of RTI systems. RTI enables riders to “time” their arrival at the stop/station to minimize wait time. This is particularly important when a vehicle deviates from the posted schedule because passengers can then adjust their behavior to reduce wait time by leaving their origin (e.g., home) earlier or later than if they had simply consulted the schedule. The relationships between RTI use and passenger wait times were tested using difference of means tests and regression analysis.

Wait Time on the Day of the Survey
The first analysis compared wait times on the day of the survey for passengers who used commuter rail RTI before boarding the train and passengers who did not. Passengers were divided into groups based on their response to the following question: Before boarding the train today, did you use real-time commuter rail information on a phone or the web? [Yes/No]. Wait times came from responses to the following question: How long did you wait at the commuter rail station today? [Write number, e.g., 7 minutes].

FIGURE 4.
Reasons why riders do not use commuter rail RTI (n=144)
We hypothesized that RTI use on the day of the survey would be correlated with lower reported wait times because studies of other transit modes have found that passengers wait less with the real-time knowledge of train arrival times and/or they perceive the waiting time to be lower due to the reduced uncertainty about train arrival times. Table 1 shows that the data do not support this hypothesis, since there is no statistically-significant difference in reported wait times on the day of the survey (p=0.2557).

<table>
<thead>
<tr>
<th>Group</th>
<th>Observations</th>
<th>Mean (mins)</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Used real-time information today</td>
<td>48</td>
<td>6.43</td>
<td>4.77</td>
</tr>
<tr>
<td>Did not use real-time today</td>
<td>839</td>
<td>6.91</td>
<td>7.10</td>
</tr>
<tr>
<td>Total</td>
<td>887</td>
<td>6.88</td>
<td>7.00</td>
</tr>
</tbody>
</table>

\[ t = -0.6606, P(T < t) = 0.2557 \text{ (one-tail)} \]

Two notes should be made about this analysis. One important variable affecting passenger wait times is the reliability of the trains on the day the survey was administered; therefore, the teams distributing surveys were instructed to note any delays in service. None of the train trips for which the on-board survey was conducted experienced delays. Subsequently, passengers who consulted RTI before boarding would have seen the same information as passengers who consulted traditional information sources (i.e., schedules). Second, there were a few outlier responses to the wait time question (3 respondents said 60 minutes and 1 stated 90 minutes). These outliers were excluded from the analysis because commuter rail trains generally operate at headways less than one hour during the time period when data were collected.

Finally, we specified and estimated an ordinary least squares regression model of wait times on the day of the survey as a function of many variables, including mode used to access the station, line (Worcester, Newburyport/Rockport), time and direction of travel, destination, time sensitivity of the trip (can/cannot be late), use of wait time for other activities (reading/listening to music), frequency of travel on that commuter rail line, use of other information sources (schedules, T-alerts, posted schedules, LED signs), and socio-economic characteristics of the respondent (gender, age, ethnicity, household income, and household car ownership). The results confirm the previous finding of no statistically-significant difference in self-reported wait times on the day of the survey attributable to use of commuter rail RTI. Subsequently, this model is not shown for presentation.

**Usual Wait Time**

The second analysis compared the “usual” wait times of passengers who have used commuter rail RTI to the usual wait times of passengers who have not. Passengers were divided into two groups based on their responses to how frequently they use commuter rail RTI, with the RTI user group consisting of respondents who said they “sometimes,” “often,” or “always” use commuter rail RTI. The non-user group consisted of all respondents who said they “never” use commuter rail RTI. Usual wait times were measured based on responses to the question: How long do you usually wait at the commuter rail station? [Write number, e.g., 7 minutes].
This analysis aimed to capture the difference that RTI could have on passenger wait times over an extended period of time. We hypothesized that passengers who sometimes/often/always consult RTI would be able to adjust their wait times on days when the commuter rail experienced delays. Subsequently, their “usual” wait times would be less than for riders who consulted only traditional information sources (i.e., schedules). Table 2 shows that the data somewhat support this hypothesis, since the mean usual wait time of RTI users is almost one minute less than for non-RTI users (7.87 minutes vs. 8.45 minutes), a difference significant at a 90% confidence level (p = 0.0915 < 0.1).

<table>
<thead>
<tr>
<th>Group</th>
<th>Observations</th>
<th>Mean (mins)</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Real-time information user</td>
<td>295</td>
<td>7.87</td>
<td>5.65</td>
</tr>
<tr>
<td>Have not used real-time</td>
<td>573</td>
<td>8.45</td>
<td>6.81</td>
</tr>
<tr>
<td>Total</td>
<td>868</td>
<td>8.25</td>
<td>6.45</td>
</tr>
</tbody>
</table>

\[ t = -1.3328, P(T \leq t) = 0.0915 \text{ (one-tail)} \]

To control for potentially confounding variables influencing usual wait times, we again estimated an ordinary least squares regression model, with the results shown in Table 3. The independent variables included in different specifications were the same as the previous wait time analysis, plus one additional variable for respondents who sometimes/often/always consult commuter rail RTI. The overall goodness-of-fit of the model is moderately low (R-squared=0.16), which is not surprising given the individual-level data underlying it.

As can be seen in Table 3, the intercept term (11.92) indicates that when all other variables are zero, the usual wait time is approximately 12 minutes. The first independent variable, Peak, is a binary variable for traveling in the peak direction (inbound in the morning, outbound in the evening). The negative value of the peak direction coefficient (-3.53) shows that respondents who were traveling in the peak direction experience shorter typical wait times. This result may be explained, in part, because the peak direction has shorter headways than corresponding trips in the off-peak direction. The second set of independent variables, Access Mode, reveals that accessing the commuter rail by MBTA-operated bus, subway train, or boat significantly increases the usual wait time, as is indicated by the positive coefficient (1.98). This may be due to poor coordination between different transit modes and/or may result from higher perceived waiting times due to the disutility of transferring between fixed schedule transit services. The third set of variables, Frequency of Commuter Rail Trips, demonstrates that those who ride that commuter rail line more frequently (2–4 days/week or 5+ days/week) report shorter usual wait times. This may indicate that regular riders are more comfortable “cutting it short” or have better knowledge of schedules. The positive coefficient (1.42) for the Trip Destination variable representing home-bound trips indicates that respondents report higher typical wait times when traveling home compared to work-bound trips. The fifth set of variables, Time Sensitivity of the Trip, shows that riders who can be a few minutes late and those who have flexibility report shorter wait times typically. These results suggest that riders with some flexibility wait less, perhaps indicating a difference in perceived wait times.
and/or less concern with missing the train if they “cut it close” getting to the train station. Respondents also were asked how they used their wait time. Those who stated that they use the time to read, make calls, listen to music, etc., typically experienced longer wait times, as indicated by the positive coefficient (1.26). Two possible interpretations of this are that these riders think they spend more time waiting because they are otherwise occupied, or they may choose to wait longer as they find value in the use of that time. The only socioeconomic/demographic characteristic that was statistically significant was the set of variables for Ethnicity. The negative coefficient (-1.28) for Asian riders indicates that they report shorter typical wait times, which requires further investigation.

### Regression Model for Usual Wait Time

<table>
<thead>
<tr>
<th>Category</th>
<th>Independent Variable</th>
<th>Estimate</th>
<th>T-stat</th>
<th>Robust T-stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td></td>
<td>11.92</td>
<td>11.6 **</td>
<td>9.59 ***</td>
</tr>
<tr>
<td><strong>Peak Period</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Off-peak trip (reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Peak trip (inbound AM; outbound PM)</td>
<td></td>
<td>-3.53</td>
<td>-6.37 ***</td>
<td>-4.60 ***</td>
</tr>
<tr>
<td><strong>Access Mode</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Drove/dropped off via car (reference)</td>
<td></td>
<td>1.98</td>
<td>3.01 ***</td>
<td>2.82 ***</td>
</tr>
<tr>
<td>MBTA bus/subway train/boat</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Walk or bicycle</td>
<td></td>
<td>-0.36</td>
<td>-0.70</td>
<td>-0.77</td>
</tr>
<tr>
<td>Other (taxi, shuttle, etc.)</td>
<td></td>
<td>1.94</td>
<td>1.84 *</td>
<td>1.86 *</td>
</tr>
<tr>
<td><strong>Frequency of Commuter Rail Trips</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 day or less/week (reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2 to 4 days/week</td>
<td></td>
<td>-1.74</td>
<td>-1.88 *</td>
<td>-1.63</td>
</tr>
<tr>
<td>5 or more days/week</td>
<td></td>
<td>-1.73</td>
<td>-1.96 **</td>
<td>-1.68 *</td>
</tr>
<tr>
<td><strong>Trip Destination</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Work (reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home</td>
<td></td>
<td>1.42</td>
<td>2.86 ***</td>
<td>2.78 ***</td>
</tr>
<tr>
<td>Other (social/recreational activity, etc.)</td>
<td></td>
<td>0.77</td>
<td>0.89</td>
<td>0.77</td>
</tr>
<tr>
<td><strong>Time Sensitivity of Trip</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I cannot be late (reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I can be a few minutes late</td>
<td></td>
<td>-1.42</td>
<td>-2.87 ***</td>
<td>-2.83 ***</td>
</tr>
<tr>
<td>I have flexibility</td>
<td></td>
<td>-0.77</td>
<td>-1.26</td>
<td>-1.12</td>
</tr>
<tr>
<td><strong>Used Wait Time</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Did not used wait time (reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Used wait time to read/make calls/listen to music</td>
<td></td>
<td>1.26</td>
<td>2.93 ***</td>
<td>2.96 ***</td>
</tr>
<tr>
<td><strong>Commuter Rail RTI</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-user (reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Real-time information user</td>
<td></td>
<td>-0.80</td>
<td>-1.80 *</td>
<td>-2.02 **</td>
</tr>
<tr>
<td><strong>Ethnicity</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Caucasian (reference)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td></td>
<td>-1.28</td>
<td>-1.90 *</td>
<td>-2.09 **</td>
</tr>
<tr>
<td>Other ethnicity</td>
<td></td>
<td>1.08</td>
<td>1.29</td>
<td>1.15</td>
</tr>
<tr>
<td><strong>Summary Statistics</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>number of observations</td>
<td></td>
<td>811</td>
<td></td>
<td></td>
</tr>
<tr>
<td>degrees of freedom</td>
<td></td>
<td>796</td>
<td></td>
<td></td>
</tr>
<tr>
<td>F-statistic</td>
<td></td>
<td>11.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>R-squared</td>
<td></td>
<td>0.1627</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R-Squared</td>
<td></td>
<td>0.1480</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Significance codes: *p<0.1, **p<0.05, ***p<0.01

Most importantly for this research, the binary variable representing Use of Commuter Rail RTI reveals that RTI users typically experience shorter wait times. The magnitude of the coefficient (-0.80) implies that RTI users report that they typically wait, on average, about 1 minute less than non-users, which is approximately 10 percent of the average usual wait time.
In light of the statistically-significant relationship between the use of commuter rail RTI and usual wait times, two important caveats should be made. First, the survey instrument had free-form responses for both questions about wait time (today and usual). For the usual wait time question, many respondents wrote in a range (e.g., 8–10 minutes), as opposed to writing in a single number (e.g., 7 minutes), and when a range was provided, the average of the range was used. Future research should aim to more clearly capture this concept, since it may be indicative of the inherent variability of wait times. Second, as was previously noted, wait times used in both analyses were self-reported. Prior research has shown that self-reported wait times may not align with actual wait times due to the perception of time (Watkins et al. 2011). Accordingly, the finding that the usual wait times of RTI users were less than the usual wait times of non-users could actually be a difference in the perception of wait time attributable to RTI. To differentiate between the two (actual and perceived wait times), independent observations of passenger wait times would be necessary.

**Analysis 3: Quality of Service**

The third analysis pertains to the quality of transit service, since prior work revealed that increases in satisfaction with transit service are another possible benefit of RTI systems. Tables 4 and 5 show the results of the quality-of-service analysis that tests the differences between RTI users (defined previously as “sometimes,” “often,” or “always” using commuter RTI) and non-RTI users (defined as “never” using commuter rail RTI). The survey included nine specific elements of transit service (#1–6 in Tables 4 and #7–9 in Table 5) and three overall quality of service indicators (#10–12 in Table 5). Respondents ranked all 12 indicators on 5-point scales from “poor” to “excellent.” Some of these indicators were selected because of their use on previous MBTA surveys (CTPS 2010) and others were added to capture topics related to information provision, particularly RTI and T-alerts.

Tables 4 and 5 show the count and percentage of survey responses for each quality-of-service indicator for non-users, RTI users, and their combined total. Additionally, the percent above average (good/excellent) is shown for non-users, RTI users, and their combined total. The results of chi-squared tests used to assess differences between RTI users and non-users are also shown.

Overall, the analysis shows limited relationships between the quality-of-service indicators and the use of commuter rail RTI. Of the 12 indicators, 8 were not correlated with use of commuter rail RTI (p>0.05). Two indicators had statistically-significant differences in which non-users reported higher rankings (“Arriving at your destination on-time” and “Overall MBTA service”), and only two had statistically-significant differences in which the RTI user group reported higher levels of quality of service (“Amount of time between trains” in Table 4 and “Availability of real-time train information” in Table 5). The higher ranking of the availability of commuter rail RTI by its user group is intuitive, since those who use RTI are more likely to rank it favorably since they value it enough to use it. The positive correlation of RTI use with the indicator for the amount of time between trains suggests that respondents who use RTI do not experience as much time between trains or are not as concerned by the time between trains, and subsequently, they may perceive the frequency of service as higher quality, even though frequency has not changed.
### TABLE 4. Results of Quality-of-Service Analysis for Indicators #1–6

<table>
<thead>
<tr>
<th>Service Quality Ranking</th>
<th>#1: On-time performance (reliability)</th>
<th>#4: Arriving at your destination on time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-User</td>
<td>%</td>
</tr>
<tr>
<td>1 – Poor</td>
<td>31</td>
<td>5%</td>
</tr>
<tr>
<td>2: Somewhat Poor</td>
<td>77</td>
<td>13%</td>
</tr>
<tr>
<td>3 – Average</td>
<td>201</td>
<td>34%</td>
</tr>
<tr>
<td>4 – Good</td>
<td>208</td>
<td>36%</td>
</tr>
<tr>
<td>5 – Excellent</td>
<td>66</td>
<td>11%</td>
</tr>
<tr>
<td>Total No. of Responses</td>
<td>583</td>
<td>100%</td>
</tr>
<tr>
<td>Percent Above Average</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Kruskal Wallis Test</td>
<td>Chi-squared = 3.5346, p-value = 0.060</td>
<td>Chi-squared = 4.8031, p-value = 0.028</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Service Quality Ranking</th>
<th>#2: How long you wait for train</th>
<th>#5: Personal safety at station</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-User</td>
<td>%</td>
</tr>
<tr>
<td>1 – Poor</td>
<td>19</td>
<td>3%</td>
</tr>
<tr>
<td>2: Somewhat Poor</td>
<td>46</td>
<td>8%</td>
</tr>
<tr>
<td>3 – Average</td>
<td>240</td>
<td>42%</td>
</tr>
<tr>
<td>4 – Good</td>
<td>201</td>
<td>35%</td>
</tr>
<tr>
<td>5 – Excellent</td>
<td>63</td>
<td>11%</td>
</tr>
<tr>
<td>Total No. of Responses</td>
<td>569</td>
<td>100%</td>
</tr>
<tr>
<td>Percent Above Average</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Kruskal Wallis Test</td>
<td>Chi-squared = 2.1997, p-value = 0.138</td>
<td>Chi-squared = 0.2932, p-value = 0.588</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Service Quality Ranking</th>
<th>#3: Amount of time between trains</th>
<th>#6: Availability of schedule and map information</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-User</td>
<td>%</td>
</tr>
<tr>
<td>1 – Poor</td>
<td>94</td>
<td>17%</td>
</tr>
<tr>
<td>2: Somewhat Poor</td>
<td>119</td>
<td>21%</td>
</tr>
<tr>
<td>3 – Average</td>
<td>211</td>
<td>38%</td>
</tr>
<tr>
<td>4 – Good</td>
<td>98</td>
<td>18%</td>
</tr>
<tr>
<td>5 – Excellent</td>
<td>38</td>
<td>7%</td>
</tr>
<tr>
<td>Total No. of Responses</td>
<td>560</td>
<td>100%</td>
</tr>
<tr>
<td>Percent Above Average</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Kruskal Wallis Test</td>
<td>Chi-squared = 3.9373, p-value = 0.047&lt;0.05</td>
<td>Chi-squared = 2.6342, p-value = 0.105</td>
</tr>
</tbody>
</table>
TABLE 5. Results of Quality-of-Service Analysis for Indicators #7–12

<table>
<thead>
<tr>
<th>Service Quality Ranking</th>
<th>#7: Availability of real-time train information (web &amp; mobile)</th>
<th>#8: Effectiveness of T-Alerts for incidents</th>
<th>#9: Explaining reasons for delays or other problems</th>
<th>#10: Overall commuter rail service on THIS line</th>
<th>#11: Overall commuter rail service on ALL lines</th>
<th>#12: Overall MBTA service (subway, bus, commuter rail)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Non-User %</td>
<td>RTI User %</td>
<td>Total Count</td>
<td>%</td>
<td>Non-User %</td>
<td>RTI User %</td>
</tr>
<tr>
<td>1 – Poor</td>
<td>37 9%</td>
<td>7 2%</td>
<td>44 6%</td>
<td>13 2%</td>
<td>64 14%</td>
<td>30 11%</td>
</tr>
<tr>
<td>2 - Somewhat Poor</td>
<td>50 12%</td>
<td>23 8%</td>
<td>73 11%</td>
<td>58 10%</td>
<td>32 8%</td>
<td>108 18%</td>
</tr>
<tr>
<td>3 – Average</td>
<td>182 45%</td>
<td>113 40%</td>
<td>295 43%</td>
<td>181 32%</td>
<td>108 18%</td>
<td>289 34%</td>
</tr>
<tr>
<td>4 – Good</td>
<td>102 25%</td>
<td>90 32%</td>
<td>192 28%</td>
<td>242 42%</td>
<td>117 41%</td>
<td>359 42%</td>
</tr>
<tr>
<td>5 – Excellent</td>
<td>36 9%</td>
<td>49 17%</td>
<td>85 12%</td>
<td>77 13%</td>
<td>29 10%</td>
<td>106 12%</td>
</tr>
<tr>
<td>Total No. of Responses</td>
<td>407 100%</td>
<td>282 100%</td>
<td>689 100%</td>
<td>571 100%</td>
<td>286 100%</td>
<td>857 100%</td>
</tr>
<tr>
<td>Percent Above Average</td>
<td>34%</td>
<td>49%</td>
<td>40%</td>
<td>34%</td>
<td>49%</td>
<td>40%</td>
</tr>
<tr>
<td>Kruskal Wallis Test</td>
<td>Chi-squared = 24.9232, p-value = 5.996e-07</td>
<td>Chi-squared = 1.6292, p-value = 0.202</td>
<td>Chi-squared = 1.0423, p-value = 0.307</td>
<td>Chi-squared = 1.6284, p-value = 0.202</td>
<td>Chi-squared = 1.5283, p-value = 0.216</td>
<td>Chi-squared = 5.4733, p-value = 0.019</td>
</tr>
</tbody>
</table>
Limitations and Future Research

A few caveats limit the results of this exploratory study, and many areas for future research can be identified based on the results.

One noteworthy limitation of the on-board sampling method was that the response rate of the survey was not measured due to manpower constraints and the difficulty distributing surveys in crowded train cars. Another limitation of this study is that the accuracy of RTI was not monitored during the study period, which could have been done by comparing real-time arrival predictions to actual train arrival times. Because 21 percent of surveyed riders who do not use commuter rail RTI stated that commuter rail RTI is not accurate, further study should be conducted in the area of data accuracy and its impact on passengers.

In terms of future research, to expand upon this research design, riders on other commuter rail lines in Boston or on commuter rail systems in other cities could be surveyed to identify trends in the use and benefits of commuter rail RTI. Additionally, the sampling frame could include travelers using other forms of transportation who may switch modes due to the possible conveniences afforded by the provision of RTI. This is particularly important area for future research because many rail providers want to understand if providing RTI increases rail ridership, which might occur in the long term.

The analysis of RTI utilization could be expanded in numerous ways. First, future research could assess disaggregate trends (i.e., RTI queries by line, station-specific RTI queries) using fine-grained, server-side data by working with RTI application developers. Similarly, as of October 2014, there were 80+ different applications that provide transit information in the Boston region, and these applications could be compared to assess the quality of information presentation and corresponding effects on users. Another area for future research is comparing the utilization of RTI with both schedules and service alerts, particularly when there are differing levels of delays in transit service.

There also are avenues for additional research pertaining to both the wait time and quality of service analyses. The finding that use of RTI is associated with reduced usual wait times relied on self-reported data. For more concrete measurements, wait time observations should be conducted and repeated over time, which may also distinguish between differences in perceived and actual wait times. Additionally, the quality-of-service analysis could be expanded using multivariate techniques, such as factor analysis, to tease out the many factors that affect a rider’s ranking of quality of service.

Conclusions

This research sheds light on the use of RTI on commuter rail services, offering initial insights on overall utilization of RTI, the relationship between RTI and passenger wait times, and the relationship between RTI and indicators of quality of service.

One year after the release of real-time data for Boston’s commuter rail, one-third of commuter rail riders used RTI either sometimes/often/always, despite the fact that commuter rail RTI had not been formally marketed by the MBTA or MBCR. However, on a daily basis, the percentage of surveyed riders using commuter rail RTI was much lower, with only 5.5 percent of riders using RTI on the days the survey was conducted. Additionally,
a large amount of overlap exists between riders who use commuter rail, bus, and subway RTI, which may be attributable to applications that integrate information from all three modes.

Two analyses of passenger wait times produced interesting results. First, wait times on the day of the survey were compared between passengers who used commuter rail RTI before boarding the train and those who did not, but the results did not support the hypothesis that RTI use lowers wait times. This may be partially attributed to the fact that there were no delays on the days when the survey was administered, and subsequently, passengers who consulted RTI before boarding would have seen the same information as passengers who consulted schedules. Conversely, the analysis of “usual” wait times showed that use of commuter rail RTI was associated with a decrease in self-reported usual wait times. This statistically-significant finding may capture the difference that RTI has on wait times over an extended period of time, since passengers who sometimes/often/always consult RTI can adjust their wait times on days when commuter rail service is delayed. Alternatively, it may be a difference in the perception of wait time attributable to RTI, since all wait time measures were self-reported.

An analysis of 12 quality of service indicators showed limited relationship with the use of commuter rail RTI. The only noteworthy finding is the positive correlation of RTI use with the indicator for the amount of time between trains, suggesting that respondents who use RTI do not experience as much time between trains or are not as concerned by the time between trains. The limited relationship between RTI use and the various quality-of-service indicators suggests minimal impacts of RTI on rider satisfaction with commuter rail service.

Overall, the results suggest that the benefits of commuter rail RTI are modest. This could be due to commuter rail’s relatively high levels of on-time performance, the common practice of passengers consulting commuter rail schedules, the regularity of travel patterns among commuting riders, and/or users’ limited possibilities to seek out wait time activities due to the design or location of stations. Transit providers may look to invest elsewhere if providing RTI to commuter rail passengers would be a costly endeavor. However, despite the modest benefits, many commuter rail riders choose to use this new information source, which may be due to generally increased expectations for refined, personalized transportation information sources. Therefore, where RTI is easily provided, agencies should consider offering it along with bus and rail RTI to provide a seamless information experience for the whole transit trip.

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References


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Effective Modeling for a Distance-Based Fare Structure with a Time-Expanded Network

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Abstract

This study addresses the appropriateness of a passenger assignment model for a distance-based fare structure that recently has received attention from transit agencies, along with technological advances in electronic fare payment and global positioning systems. Among the two major passenger assignment models, the study identifies that the schedule-based model has an advantage over the frequency-based model for representing a distance-based fare structure. The schedule-based model that explicitly traces passenger routes enables the accurate calculation of a distance-based fare and its variant. In addition, the study addressed the implementation issues associated with the schedule-based model. As the schedule-based model is considered to require more data than the widely-used frequency-based model, the study suggests a way to mitigate this data requirement issue by approximating the timetable at each stop with the same data used for the implementation of the frequency-based model. A case study on the field application of the schedule-based model and its availability as a ready-to-use option in most commercial software for travel demand modeling is described.

Introduction

Transit fare is a critical factor in transit planning that requires careful consideration from the viewpoints of both transit service providers and users. The major source of revenue for transit agencies is the fare collected from users, which naturally makes agency financial health dependent on fare level and demand. Fares constitutes the majority of the cost of an individual’s travel disutility, especially for transit users. Transit fares are out-of-pocket expenses; users are sensitive to fare changes, and such changes can affect ridership. Considering the complicated relationship transit fare has with other variables, it is important
to determine a fare appropriately according to a transit agency's fare policy and its goals (e.g., maximizing revenues, ridership, welfare) that guide customer-related decisions.

Of several fare structures that govern the fare level, a distance-based fare has been considered by transit agencies recently because of its positive impact on social equity as well as the transit agency's financial health, especially by switching from a flat fare model to a distance-based model. In light of the vertical equity defined by Bullard et al. (2004) that compares mobility need and the ability to cover the needs, a distance-based fare seems to effectively alleviate the disparate impacts caused by a flat fare on low-income and minority households (Farber et al. 2014). Such households often are characterized by short travel distances and high rates of transit usage; thus, the fare they pay may subsidize the cost of other transit user groups under a flat fare structure (Farber et al. 2014). Meanwhile, revenue expectations can increase by structural reform to a distance-based fare, as long-distance transit users are relatively insensitive to fare increases (Daskin et al. 1988). Electronic fare collection technology also fosters the attractiveness of a distance-based fare structure.

Despite efforts to explore its potential, whether a distance-based fare structure is appropriately represented in a planning model or not is in question when the frequency-based model is predominantly used among practitioners. Since a precisely-modeled transportation system provides a "common ground" for examining future system planning (Ortuzar and Willumsen 1994), it is imperative to choose the appropriate modeling scheme to represent the real world. Between the two representation schemes for simulating a transit system—the frequency-based model and the schedule-based model—this paper aims to address the model that is more appropriate for a distance-based fare structure.

The study is organized as follows. The next section discusses the historical perspective of a distance-based fare structure. The subsequent section describes how a distance-based fare structure is differently represented in two passenger assignment models. Next, the implementation issues associated with the schedule-based model, an application example in the field, and implementation in major software packages are addressed. The final section summarizes and concludes the paper.

Past and Present Distance-Based Fare Structure
In the recent past (the 1960s), a differentiated fare system was used in most cities in the U.S. (Cervero and Wachs 1982). This method gradually was replaced by a flat fare system to provide low-cost transportation to lower-income people as well as for the simplicity of fare collection. Almost all transit agencies in the U.S changed their system to flat fare (Cervero and Wachs 1982). This change became the primary cause of the 1980s transit fiscal crisis.

Cervero (1981) and Cervero and Wachs (1982) attributed the transit agencies’ financial difficulties to the insensitivity of the flat fare and suburbanization in 1960s and 1970s. They observed that the suburbanization of the U.S. exacerbated an unhealthy fiscal condition, as many transit operators expanded their service coverage to outlying areas while maintaining their insensitive fare structures. This observation was supported by the comparison of the average mileage between individual bus routes and the total number
of buses. From 1960 to 1974, the average mileage covered by individual bus routes more than doubled, but total bus mileage declined (Sale and Green 1979).

Although fare structure has gone through changes for many years, and there was a time when differentiated fare structures were widely implemented, once transit agencies adopt a flat fare because of its simplicity, they seem to be unwilling to change to alternatives, regardless of the financial impact. The initial capital costs associated with implementing a differentiated fare structure, such as global position system (GPS) devices and electronic payment systems, contribute to the resistance to change (Yook and Heaslip 2014).

However, recent technological developments in fare collection offer transit agencies the opportunity to reconsider these practices. Examples of successful implementation of a distance-based fare structure have been found (TCRP 2003), which can provide transit agencies with the motivation to reconsider the practicality of the structure.

A differentiated fare structure that was difficult to implement in the past now has become a viable option as a result of recent developments in fare collection technologies. In terms of fare media, the increasingly widespread usage of smart cards (TCRP 2003) has made a distance-based fare structure more practical. The smart card’s compatibility with multiple operators makes a distance-based fare structure implementable by consolidating transit systems and collecting fares based on the actual distance traveled by passengers. As for the monitoring technology that measures passenger travel distance, GPS is used to perform the tracking. Typically, card readers are installed at controlled entrances such as rail line platforms and buses. In addition, policies regarding technology are being developed to incorporate users’ ability to indicate the starting and end points of their trips. By requiring passengers to tap their electronic payment media to card readers at vehicles or on platforms, transit agencies can charge a fare based on passenger usage. With this policy, the travel distance of a trip can be tracked when the passenger boards and exits using a device that identifies the location.

**Effectiveness of Schedule-Based Model for Distance-Based Fare Structure**

To model a distance-based fare structure, it is critical to select an appropriate modeling scheme that effectively traces passenger route choices. Since the fare is based on the total passenger in-vehicle distance, a model that closely describes passenger flow is needed for representing the fare structure. This section describes the effectiveness of the schedule-based model for tracing the route choice of a passenger, which enables the precise calculation of a distance-based fare. The explicit tracing of the individual route choice is achievable because all possible time-considered routes, called a time-expanded network, are constructed in the schedule-based model.

In a time-expanded network, all possible ways of the passenger flow are created with virtual links and nodes. Figure 1 shows the conceptual representation scheme of the frequency model and the schedule-based model. As shown, the transit lines used for the frequency-based model are broken down into runs in the schedule-based model, where each run of the transit operation (dotted lines) and the temporal arrival of the runs (end of each arrow) build up all possible ways to the destination. In this structure, the
network-handling scheme becomes greatly similar to a conventional highway network. A route comprising the sequence of links is replaced by a sequence of runs in the time-expanded network. Tracing passenger route choices is intuitive by following the sequence of virtual links.

For example, in Figure 1, users who depart from the origin at 9:00 AM encounter many choices of vehicle runs as the number of virtual nodes after the temporal arrival of the thick dotted lines. However, they would choose the first or second departing vehicle (indicated by circles) to finish their journey in a time-minimized manner. In this case, if a passenger takes the first arriving vehicle, which is the second run of line 6, then he/she misses the line 7 bus that departs at 9:20 AM. Taking the second run of bus 5 that connects directly to destination B is the shortest route to the destination, according to the space-time graph.

**FIGURE 1.** Time-expanded network from line-based representation: frequency-based *(top)* and schedule-based *(bottom)*
In the meantime, consideration of the distance-based fare in the frequency-based model is not as flexible as in the schedule-based model. This is because of the line-based representation scheme in which the fare is assessed based on a line segment—the part of a line divided by a transit stop—before a passenger’s entire journey is determined. With this modeling scheme, the fare cost of a line segment shared by different routes should be adjusted depending on the routes.

The issue incurred by the frequency-based model for representing a distance-based fare structure is caused by the fact that the fixed fare is used for evaluating the travel cost of a line segment, which does not take into account the possible fare adjustment due to different route compositions. For example, when a different premium is charged for different transit vehicles and the travel distance is compromised by buffer distance, the fare should be assessed only after the route is determined. In this case, the frequency-based model, which considers the fare based on line segment, has a limitation of calculating the accurate distance-based fare. The following paragraphs describe how line-based fare calculation limits the frequency-based model’s capability to model the variants of a distance-based fare structure.

The introduction of buffer distance and different premiums for different transit services could produce the following variants of a distance-based fare structure. For the base model and Variant 1, the frequency-based model precisely reflects the actual payment of a user, as the individual fare calculation for a line segment is identical for all routes. On the other hand, a final fare is adjusted at the end of the passenger’s journey depending on the routes under Variants 2, 3, and 4. In case of Variants 2 and 4, the total in-vehicle distance is compromised by the buffer distance, which implies that the actual in-vehicle distance subject to fare charge is dependent on the route. However, the absence of route information in the middle of fare calculation for a line segment yields an inconsistent fare evaluation in the frequency-based model.

Figure 2 shows an example of different unit buffer distances applied to each line segment for different line combinations. In this example, a 1-mile buffer distance is applied to Variant 2, and the buffer distance is divided by the total distance to apply a 1-mile buffer for each line segment. For example, if the total in-vehicle distance is 5 miles, then the buffer distance per mile that amounts to the total 1-mile buffer is 0.2 miles.
Effective Modeling for a Distance-Based Fare Structure with a Time-Expanded Network

### TABLE 1. Variants of Distance-Based Fare Structures

<table>
<thead>
<tr>
<th>Fare Model</th>
<th>Description</th>
<th>Formulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base Model</td>
<td>Charge fare proportional to total distance</td>
<td>( C_p = d_p \times u )</td>
</tr>
<tr>
<td>Variant 1</td>
<td>Charge same base fare for different transit modes and additional fare proportional to total distance</td>
<td>( C_p = b + d_p \times u )</td>
</tr>
<tr>
<td>Variant 2</td>
<td>Charge same base fare for different transit modes and provide buffer distance that base fare covers</td>
<td>( C_p = b + (d_p - \text{buffer}) \times u )</td>
</tr>
<tr>
<td>Variant 3</td>
<td>Charge different base fares for different transit modes and additional fare proportional to total distance</td>
<td>( C_p = \max_{l \in L_p} b_l + d_p \times u )</td>
</tr>
<tr>
<td>Variant 4</td>
<td>Charge different base fares for different transit modes and provide buffer distance that base fare covers</td>
<td>( C_p = \max_{l \in L_p} b_l + (d_p - \text{buffer}) \times u )</td>
</tr>
</tbody>
</table>

where,

- \( C_p \) = distance-based fare of route \( p \)
- \( d_p \) = in-vehicle distance of route \( p \)
- \( u \) = unit fare per unit distance (e.g., mile, kilometer)
- \( b_l \) = base fare for line \( l \)
- \( \text{buffer} \) = buffer distance
- \( L_p \) = set of lines going through route \( p \)

There are three line combinations for the base network (top of Figure 2). The numbers above the line indicate the distance. Since one line segment is associated with different routes (in this case, the last 2-mile segment is the last segment for all three line combinations), one fixed unit buffer distance does not exist for Variants 2 and 4. Because the line segment fare calculation is conducted without consideration of route configuration, the fare charge will not be universal for all different routes. For example, when a unit buffer distance of \$0.2/mile is assumed, this is appropriate for line combination 2, yet the value does not properly assess the buffer distance for line combinations 1 and 3. Since the total route distance for line combinations 1 and 3 are 6 miles and 5.5 miles, respectively, the buffer distance will be 1.2 and 1.1 miles, respectively, which indicates that the actual in-vehicle distance is reduced by more than 1 mile and could result in underestimation of the fare.
A line segment fare calculation independent of route also causes a similar incorrect fare calculation for Variants 3 and 4. In these cases, the maximum premium fare will be charged to the passenger considering his/her vehicle riding history. For example, when a passenger transfers from the first transit vehicle and boards the second vehicle, an additional fare is charged if the second vehicle is premium service (e.g., express bus, commuter rail). This additional fare is dependent on the service level of the second transit vehicle and also the fare already paid when leaving the first transit vehicle. As the frequency-based model does not consider fare adjustment by a combination of different transit vehicles, the model is limited for reflecting the exact fare for a line segment.

The study has identified that the frequency-based model is incapable of representing all variants of a distance-based fare structure. The major factor that hinders the appropriate fare structure modeling is inherited from the line-based service supply system of the frequency-based model. On the other hand, the explicit representation of passenger flow by the schedule-based model can precisely assess all variants of the distance-based fare structure.

In spite of the intuitive feature of the schedule-based model, the modeling scheme has not been widely adopted by transit agencies. The next section focuses on the practical issues of implementing the schedule-based model.
Implementation

Data Requirements for Schedule-Based Model

In the planning stages, the operational details of future transit lines are not provided. This is one reason why the frequency-based model is preferred to the technique based on a time-expanded network. However, with the same level of information given to the frequency-based model, a time-expanded network also can be constructed.

Figure 3 presents typical transit route information for the frequency-based model for a future line in the planning stage. Included are the name of the bus line ("Route 472"), mode ("6" means express bus), one-way operation ("T" means true), frequency of the vehicle (30-minute interval), an indicator of the first node ("N"), and the route represented by the node sequence.

With the information shown in Figure 3, a timetable for a time-expanded network can be easily approximated. By estimating the travel time between nodes, the times of the bus arrival at each stop of the future line are calculated. The point of the time approximation is calculated by dividing the distance referred from the highway network by the given operation speed. Then, tagging the start time of the bus operation finalizes the timetable estimation at each stop.

A sample timetable has been constructed with a currently-operating bus route (#472) of the Utah Transit Authority. Comparison between the approximated timetable and the published timetable is presented in Figure 4. Some deviations are observed from the published timetable at each stop; however, the estimated schedule and the total journey time are well fitted to the published timetable overall. When further information becomes available, a more sophisticated method (Ceder et al. 2013) can be applied for constructing a timetable that minimizes passenger waiting time and number of empty seat hours.
FIGURE 4.
Comparison of estimated schedule to published schedule for Route 472

<table>
<thead>
<tr>
<th>Stop</th>
<th>Estimated Schedule</th>
<th>Published Schedule</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rivendale Park &amp; Ride</td>
<td>6:10</td>
<td>6:10</td>
</tr>
<tr>
<td>Layton Hills Mall</td>
<td>6:23</td>
<td>6:23</td>
</tr>
<tr>
<td>Kaysville Park &amp; Ride</td>
<td>6:30</td>
<td>6:34</td>
</tr>
<tr>
<td>North Temple &amp; 300 W</td>
<td>7:03</td>
<td>7:00</td>
</tr>
<tr>
<td>402 South &amp; State St</td>
<td>7:07</td>
<td>7:09</td>
</tr>
<tr>
<td><strong>Total journey time</strong></td>
<td><strong>57.7</strong></td>
<td><strong>59.0</strong></td>
</tr>
</tbody>
</table>
Time Segmented Transit Demand

Another implementation issue related to the schedule-based model is time-associated demand. Here, the time segmented transit demand means more disaggregated transit demand with a relatively short time interval. As mentioned earlier, the temporal segmentation of transit demand is desirable for its appropriate distributions into a network for the schedule-based model. In general, the travel demand model is framed by peak and non-peak hours, which is longer than two hours.

In this case, it is necessary to disaggregate the demand according to the temporal distribution of demands in the schedule-based model. Segmentation is not a significant issue, since the temporal distribution of travel demand is obtainable from a household travel survey. Determining a correct time interval is more influential for the appropriate distribution of demand into the network. However, densely-segmented demand (less than 15 minutes) can cause large computational burdens due to the large number of temporal zone centroids.

Field Application Cases of Schedule-Based Model

Field application cases rarely are found despite the rich academic research in the work based on schedule-based transit assignment (Nuzzolo 2003). However, a good pioneer study that models the time dynamics of the supply and demand sides of a transit system with a schedule-based model can be found with TransLink, a transit agency based on South Coast British Columbia, Canada. The study highlights the capability of the model that effectively analyzes the capacity issues of a transit system. The model evaluates the current operating plan’s optimality status, identifies future capacity of the critical segment, and determines the fleet strategy for SkyTrain operation. Also, the model helps to examine the impact caused by introducing a new light metro line into adjacent bus routes. The application estimates the ridership change for affected buses and provides an insight for desirable adjustment for the bus route design.

However, the input data considering the demand and supply sides of the transit system that are time-dependent requires considerable effort to construct and validate. As mentioned earlier, the supply side of a transit operation, the time-expanded network, should be prepared using the current operation schedule and fleet management plan. This step amounts to joining the network topology and operation schedule of all transit lines in the study network. The actual challenge for preparing the input data comes from the data construction of demand. Since the schedule-based model necessitates that demand be associated with time, the time-dependent demand should follow the distribution of desired departure times.

This study suggests a simple method to estimate the distribution using a household travel survey. However, if the sample size of the survey is not enough to make a distribution curve, other sources of data such Automated Passenger Count (APC) should be used. This applies to the case of TransLink, in which the departure time distribution was determined from boarding counts. It used four different time frames because the time distribution of the desired departure was different for geographical market segments. As the distance to the Central Business District increased, the peak of the distribution curve shifted to the left on the x-axis, representing time, to keep the desired arrival times. Once the time-
dependent demand is constructed using the time distribution of the desired departure, the demand should be validated with the observed data. In the case of TransLink, the demand was validated by total passenger trips, per mode, per line, and per stop based on the boarding and alighting counts. This validation process was successful for TransLink, as it was equipped with a relatively new, cutting-edge system that produces various aggregated and disaggregated statistics of passenger counts.

This study shows both promising and challenging aspects of the application of the schedule-based model. The promising side contains detailed outputs. As seen in TransLink’s case, the schedule-based model is useful for investigating the capacity issue at the planning stage. Considering that the general approach for capacity analysis engages a special process for constructing a load profile based on passenger itineraries, the run-based schedule-based model that simply yields the load profile on a time-expanded network provides a significant advantage. Also, without the modal split process, the schedule-based model estimates user behavioral changes caused by new transit lines, which is sufficient for providing a modification sketch for existing bus route design.

On the other hand, as the well-calibrated data are strongly linked to the validated results, the construction of time-dependent demand is a resource-demanding process. This may be one of the obstacles to agencies adopting the advanced scheme for transit system modeling, especially for those that do not have an APC system.

Schedule-Based Model, a Fully Implementable Option in Commercial Packages

The major travel demand modeling software, including TransCAD, EMME, Cube, and VISUM, are equipped with the schedule-based assignment model as well as the frequency-based model. Since the schedule-based model needs a time-expanded network for modeling the supply side of the transit system, timetable information associated with spatial route data is necessary. Similar to the suggested simple method that estimates the timetable at each stop, most software provide an internal mechanism to estimate the running time between stops using the given highway network or transit operation speed. In the case of VISUM, running time is calculated from the quotient of link length and link-specific speed (VISUM 2011), whereas EMME uses results from the evaluation of transit time functions (Florian 1999). When analysts use this scheme, no extra information is required other than the conventional input data, as presented in Figure 3 for the frequency-based model.

However, considering the time dynamics of the schedule-based model, if the highway network or the transit time function are not sophisticated enough to represent the temporal difference associated with each run of a transit vehicle, it is highly likely that discrepancies will be produced between the published timetable and the estimated timetable. It is recommended to examine the estimated running time based on the published timetable to minimize errors from transit operation modeling.

Most software provides supplemental tools to modify the estimated running time by means of a modification dialog box or a dedicated coding system. Table 2 shows the transit segment time coding scheme provided by EMME/2. When using the first 10 nodes of the sample route information given in Figure 3, the timetable coding is generated as shown in Table 2.
Since the node number followed by negative sign is not a stop, only a stop is tagged with published departure time; the coding scheme is straightforward.

Summary and Conclusions
Although a distance-based fare structure is regarded to achieve fairness and equity in fare charging, it has not been widely adopted by transit agencies. However, recent technological developments in electronic fare payment systems and GPS devices create a favorable condition for implementing a distance-based fare structure.

Following advancements in fare payment systems, the study investigated the appropriateness of passenger assignment models for a distance-based fare structure. Among the two major passenger assignment models, the study identified that the schedule-based model is more suitable for representing a distance-based fare structure. The schedule-based model explicitly traces passenger route and enables accurate calculation of a distance-based fare and its variants, whereas the frequency-based model has limited capability for handling all variations of a distance-based fare structure due to its line segment-based fare calculation method. In addition, the study addressed implementation issues for the schedule-based model. Even if the data requirements for the schedule-based model are higher than its counterpart, the study suggested a simple method that reduces the data requirements and explained the method as a ready-to-use option for most commercial travel demand modeling software.

References


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A Worldwide State-of-the-Art Analysis for Bus Rapid Transit: Looking for the Success Formula

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Abstract

This paper’s intended contribution, in terms of providing an additional angle in the existing Bus Rapid Transit (BRT) state-of-the-art knowledge spectrum, is a dual one. On the one hand, it provides a detailed description of the mode, re-defining BRT as an overall concept by identifying, discussing, and categorizing in a systematic way its strengths and its weaknesses in comparison with rail-based solutions and conventional bus services. On the other hand, it presents in detail a number of selected scheme-oriented applications from around the world, looking into some of the basic ingredients behind BRT’s success (or failure) stories. This is a scientific effort that could inform the reader about the current status of BRT internationally and about the challenges and opportunities that exist when trying to materialize BRT’s potential as an effective urban passenger solution that could challenge the merits of more conventional mass-transit options.

Introducing Bus Rapid Transit

Bus Rapid Transit (BRT) is a modern breed of urban passenger transportation with a consistently growing global importance due to evidence of an ability to implement mass transportation capacity quickly and at a low-to-moderate cost (Deng and Nelson 2011). Perhaps the most complete and focus-driven definition of what BRT intends to be is the one addressing it “as a rubber-tyred rapid transit service that combines stations, vehicles, running ways, a flexible operating plan, and technology into a high quality, customer focused service that is frequent, fast, reliable, comfortable and cost efficient” (Canadian Urban Transit Association 2004).

More specifically, BRT refers to schemes that apply rail-like infrastructure and operations to bus systems in expectation of offerings that can include high service levels, segregated rights-of-way, station-like platforms, high-quality amenities, and intelligent transport systems for a fraction of the cost of fixed rail (Currie and Delbosc 2011). This cautious phrasing means that BRT “does not necessarily represent transformation as such, but a means to achieve transformation” (Mejia-Dugand et al. 2013). A combination of infrastructure...
and service-oriented elements that, in principle, mean to bridge together the best that light rail and buses have to offer is the prerequisite to forming mass transit systems capable of responding to rapidly-changing mobility needs with a strong positive identity that evokes to a unique image (Levinson et al. 2003).

BRT applications are designed to be appropriate to the markets they serve and their physical surroundings, and they can be incrementally implemented in a variety of settings and types. Because of the inherent flexibility advantages of rubber-tired buses—e.g., unlike rail systems, the same vehicle that functions as a line-haul carrier also can morph into a neighborhood feeder—BRT also is suited for many lower-density areas (Cervero and Kang 2011). However, the vast potential of BRT could be used at its maximum rate in congested urban environments where adequate mass transit services could not be provided to road users by (or solely by) more expensive modal options such as light rail or metro.

BRT, thus, is a homogeneous system of facilities, services, and amenities that has the potential to become an alternative far more competitive to car-oriented mobility than conventional buses, to the degree that it could redefine the very identity of a city.

A BRT system is composed of the following ingredients:

- **Vehicles**, which not only contribute significantly to BRT’s image and identity, but also play a strong role in achieving measurable performance success (Zimmerman and Levinson 2004)

- **Stops, stations, terminals, and corridors**, which define the system’s area of operation

- **A wide variety of rights-of-way**, including bus priority in signalized intersections, dedicated lanes on surface streets, and, more importantly, special BRT busways completely separated from road traffic; BRT routes can be operated almost anywhere—on abandoned rail lines, within a highway median, or on city streets (Jarzab et al. 2002)

- **Pre-board fare collection**, to disengage ticketing from the on-board user experience and to provide a hypothecation mechanism for the system’s long term viability

- **The use of information and communication technologies**, to improve the quality of the services provided in terms of customer convenience, speed, reliability, integration, and safety

- **All-day service** that, according to Levinson et al. (2003), should operate at least 16 hours per day with peak headways of 10 minutes or less

- **Brand identity**, consisting of perceptual constructs substantiated by the strategic deployment, placement, and management of communication elements that allow people to recognize the unique qualities of a specific BRT system; these include visual and nominal identifiers (e.g., system name and logo), a color palette, and long-term strategic marketing and advertising plans (Hess and Bitterman 2008)

For the economy of the overall transport system of a city that employs BRT, some of the infrastructure facilities (e.g., busways and stationary settings) could be shared with light
The Advantages of BRT

BRT has been widely regarded as “one of the most wide-spread urban public transportation revolutions” of recent decades (Jiang et al. 2012; Levinson et al. 2003). This is because BRT is a mass transit choice with considerable advantages in terms of its implementation merits but also because of its vast potential to eventually benefit in a variety of ways the urban environment for which it has been chosen. Wright and Hook (1999) support the view that BRT is a transport mode rapidly expanding around the world because of its 1) low cost, 2) operating flexibility, 3) rapid implementation, and 4) high performance (i.e., reliability/speed) and impact (i.e., user satisfaction/environmental benefits). Based on a study by the Canadian Urban Transit Association (2004), Hensher and Golob (2008) also report as BRT advantages over other mass transit systems the potential for greater patronage and higher capacities, the possibility of incremental implementation, and the induction of land use changes. However, it has been well documented by
international experience, thus far, that all these advantages are not necessarily true for every BRT case (Filipe and Macario 2013).

The first significant advantage of BRT over rail-based transit options is that it needs considerably lower start-up capital investment while operational costs are moderate (Badami and Haider 2007; Campbell 2009; Hensher and Golob 2008). System costs are a fraction of those of comparable rail systems (Currie and Delbosc 2011; Hidalgo and Gutierrez 2013). Hodson et al. (2013) reported that the main antagonists of BRT, which are light rail systems when compared to bus-oriented schemes in purely economic terms, were found to be:

- too costly
- poor in terms of financial performance
- in need of significant local funding in addition to central government funding to become a reality

Figure 1 shows the capital costs per kilometer for selected BRT corridors around the globe. These costs range from the very moderate $1.4 million per kilometer for the scheme in Jakarta to Bogotá’s $12.5 million per kilometer.1 Rail systems with similar capacities cost 3 to 10 times more (Hensher 1999; Wright and Hook 2007).

The system in Bogotá is considerably more expensive because it includes dual lanes, large stationary facilities, and some non-grade intersections, as well as a large fleet of articulated and bi-articulated buses, to provide for very high capacity and high commercial speeds (Hidalgo and Gutierrez 2013).

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1 These costs have not been adjusted to reflect inflation since the time of construction, the differences in labor costs in different regions of the world, and the differences in the nature and extent of planning studies required in various countries because BRT-related expenditure figures are extremely difficult to locate in a form that could be treated accordingly. Rather, these costs are indicative numbers given by the operators but could nonetheless allow rough comparisons between schemes.
Overall, accessing information about BRT costs is neither an easy nor a straightforward task. In many cases, capital costs for specific BRT applications are fully integrated in much broader transport improvement packages, and identifying the specific BRT-related figures is near to impossible. For instance, the TranSantiago project has three main components: the development of a BRT network, the expansion of the existing metro system, and the integration across all transit modes in the city. The initial conceptual framework, estimated at $250 million, was later revised to incorporate an extensive expansion of the metro network with total capital costs of almost $2.5 billion. No specific information solely related to the TranSantiago BRT framework per se is available.

Compared with other forms of mass transit, BRT systems are more flexible. The fact that BRT systems have the potential to use the same operating infrastructure that could have been already in place for light rail transit systems and, at the same time, allow conventional bus services to access certain BRT infrastructure sections to facilitate interconnection and performance enhancement (Deng and Nelson 2011) underlines the interoperability dynamics of this mode. Because BRT vehicles are rubber-tired, they can operate in a wide range of environments without forcing transfers or requiring expensive running way construction over the entire range of their operation. Through this flexibility, BRT can serve a geographic range much wider than that in which dedicated BRT guideways do exist (Levinson et al. 2002). BRT also may be implemented in combination with a variety of travel demand management measures, such as congestion charging or traffic calming. Moreover, BRT can be more adaptable to deal with changing travel patterns and is faster to build than any rail-based scheme.

The capability of BRT to be implemented rapidly make this type of system attractive to political leaders willing to complete systems before the next election cycle (Hidalgo and Carrigan 2010). In comparison, the planning timescales and consultation processes for rail-based systems are excessively long, and this is a key reason that a number of these schemes have failed already in the planning stages (Hodgson et al. 2013). When there was a clear BRT vision by a local champion or any other political leader, planning for implementation received priority and development cycles were short, at least for the initial phases of project implementation (Hidalgo et al., 2007). For instance, the city of Guadalajara, Mexico, completed a high-quality corridor 16 km long for 125,000 passengers per day in only 2 years from idea to implementation (Hidalgo et al. 2010). The successes of BRT in Curitiba, Bogotá, Guangzhou, Istanbul, and elsewhere also are helping decisionmakers in developing cities to adopt BRT concepts, although implementation in developed countries has been slower than elsewhere due to preferences of planners and decisionmakers for rail systems and also due to compliance with planning and funding regulations, including extensive public participation processes (Hidalgo and Gutierrez 2013).

Case studies summarized by Levinson et al. (2003) and Wright and Hook (2007) suggested that BRT could be the most cost-effective way of providing a high-performance public transit. The main indicators of performance of a BRT scheme are commercial speed, capacity, and productivity (Hidalgo and Gutierrez 2013). The qualities represented by these indicators are supported by special design features that BRT schemes offer. These operational features that can define the individual quality and performance potential of any local BRT application are described by the BRT Standard, a comparison tool meant
to assign points to BRT systems according to their serviceability. High points mean that a system is in line with international BRT best practice. The assessed aspects that are being considered in the latest BRT Standard designed from the Institute for Transportation and Development Policy (ITDP 2014) include:

- **BRT basics** (dedicated right-of-way, busway alignment, off-board fare collection, intersection treatment, platform-level boarding)
- **Service planning** (multiple routes, express/limited/local services, control center, located in top 10 corridors, demand profile, hours of operations, multi-corridor network)
- **Infrastructure** (passing lanes, bus emissions minimization, stations set back from intersections, center stations, pavement quality)
- **Stations** (distance between stations, safe and comfortable stations, number of doors on bus, docking bays and sub-stops, sliding doors in BRT stations)
- **Communications** (branding, passenger information)
- **Access and integration** (universal access, integration with other public transport, pedestrian access, secure bicycle parking, bicycle lanes, bicycle-sharing integration)

Point deduction also exists that penalize BRT schemes for poor performance in commercial speeds, service capacity, lack of enforcement of right-of-way, significant gap between bus floor and station platform, overcrowding, poor infrastructure maintenance, and low-peak and off-peak frequencies (ITDP 2014).

Regarding BRT transport-related impacts, most systems have showed better performance than the bus operations they replaced regarding passenger demand, user satisfaction, travel time, and reliability (Diaz and Hinebaugh 2009; Gutierrez 2010; Wright and Hook 2007). Currie and Delbosc (2011) report that BRT technologies not only improve service design compared to conventional bus services but could potentially act as door openers to increased ridership because of:

- their higher frequency and longer operating hours services
- their priority systems, which are known to reduce journey times and improve service reliability
- their better-defined network/corridors, branding, and provision of new technology information systems to improve the ease of understanding the system

An additional, positive impact related to BRT systems, which has been documented by international practice, is the improvement of environmental conditions in terms of air quality, noise reduction, and energy consumption; also, externalities such as traffic accidents have been reduced considerably. Moreover, when looking at the broader picture on a longer-term basis, one could suggest that some BRT projects, and especially those that have received significant capital investments, may have the potential to bring broader effects on urban economic, social, and environmental development (Deng and Nelson...
A Worldwide State-of-the-Art Analysis for Bus Rapid Transit: Looking for the Success Formula

The Problems with BRT

BRT is connected to a complex set of actors and networks within the social and technical dimensions of the city (Mejia-Dugand et al. 2013) and, thus, it is a system that could be difficult to implement and operate in a flawless manner. Filipe and Macario (2013) report that neither are all the advantages of BRT over other public transport modes always true, nor are the stories of implementing BRT systems always successful ones.

There are reports of BRT systems that fail to fulfill their objectives and have produced costly, in societal terms, side-effects—for example, the TranSantiago BRT system (in Chile) and its initial implementation. The system’s performance (even now), belying expectations, has been rather dismal, making it a traumatic process for the whole of Chile, to the extent that taboo policy discussions such as nationalizing or subsidizing the public transport of the country became mainstream (Muñoz and Gschwender 2008).

BRT systems do not have a single meaning and image; on the contrary, they reflect a broad spectrum of applications, spanning from supporting mechanisms that simply provide infrastructure or marketing improvements to existing bus services operating on mixed traffic to totally segregated systems. There is a need, thus, to refine the definition of BRT and BRT-like systems and create categories based on objective performance measures to improve the understanding among planners and decisionmakers (Hidalgo and Gutierrez, 2013). Notwithstanding the growing evidence that BRT could serve, if well-planned and well-executed, as a viable transport “savior,” pro-rail attitudes are still dominant in the public debate regarding best public transportation practice. BRT systems are still often regarded as “second best to rail-based alternatives,” even if this is not justified by an explicit evaluation analysis (Finn et al. 2011; Gutierrez 2010; Hensher 1999).

Despite the growing acceptance that BRT is a time-efficient mode to implement in urban environments that face rapidly-growing mobility needs (Badami and Haider 2007; Hensher and Golob 2008), especially in comparison with fixed rail schemes, the political economy is often favorable to those candidates offering rail alternatives as part of their
proposals in electoral debates (Hidalgo and Gutierrez 2013). BRT is, aside from the evidence provided to the contrary by Deng and Nelson (2011), still considered inadequate to foster urban development, and planners often cite this as a fact (Hidalgo and Gutierrez 2013). This is because the flexibility that enables BRT to be implemented in a wide range of environments—one of the system’s main advantages—is also one of its weaknesses since a bus service is generally perceived as being less permanent than a rail service. Local decisionmakers and transport planners may, based on this very reason, question its ability to stimulate land development. However, there is insufficient evidence, especially in developed countries, to prove that development is favored by rail over high-quality bus systems (Hidalgo and Gutierrez 2013). In addition, the fact that BRT is being prioritized over any other road-based transport mode is perceived negatively by car users, who tend to think that road space is reduced, even though, at least in theory, road capacity means to be increased significantly.

The fact that BRT is cheaper to implement than a rail system does not mean that this is not a capital-intensive system (Deng and Nelson 2011). On the contrary, BRT is far more expensive than any conventional bus system that lacks sophisticated design features and the need for dedicated road space. Actually, funding for some cities that introduced BRT in the past was so scarce that the cities needed to rely on donations, budget allocations from the national governments, and loans. The process of applying for funding could be time-consuming as well, reducing the time window for the actual project implementation (Hidalgo et al. 2007).

In addition, several BRT systems in developing countries suffer problems such as the following (see also Hidalgo and Gutierrez 2013; Hidalgo and Carrigan 2010; Hidalgo et al. 2007):

- **Rushed implementation** – several components could be incomplete at the time of commissioning, but gradual improvement over time has been observed
- **Tight financial planning** – systems usually do not receive operational subsidies; there are exceptions, however, such as TranSantiago
- **Very high vehicle occupancy levels** – six to seven standees per m², which is quite frequent nowadays and can make the user experience unpleasant
- **Early deterioration of infrastructure** – lack of road surface reinforcement or problems in design and construction result in maintenance issues
- **Delayed implementation of fare collection systems** – often requiring longer timetables than initially expected and very tight supervision
- **Poor communication during disruptions caused by construction** – can erode public support for the project, and **insufficient user information and education** prior to the system launch can lead to chaotic conditions or even protests (Carrigan et al. 2011)
- **Integration deficiencies** – for instance, in any urban transit system, the walking catchment area tends to be particularly important since walking is typically the primary access mode for urban stations (Hsiao et al. 1997); nonetheless, the reality is
that accessing BRT stations is not as easy or safe as it should have been (unpublished research by the authors and some of their students shows that providing better pedestrian safety is a significant issue for some BRT applications in China)—this creates a serious integration issue that could adversely influence ridership numbers.

These problems are associated with financial restrictions and institutional constraints, rather than intrinsic issues of BRT system concepts. Actually, many of them are local problems with unique topological character that could not be duplicated by similar schemes elsewhere. Nevertheless, these difficulties could influence to a certain point public attitudes reflecting the social acceptance of BRT.

Finally, the critics of BRT often cite comfort issues when comparing bus systems with rail. As a matter of fact, many past studies have found that, other things being equal, most public transport users prefer rail to bus because of its greater comfort (Abelson 1995). Due to the fact that most BRT systems in developing countries use very high occupancy standards, as a result of financial restrictions that would allow the provision of a level of service exceeding what customer fares can strictly finance for operation and vehicles, the standard of comfort can be neglected (Hidalgo and Carrigan 2010). However, Currie (2005) documents that there is actually evidence to support the fact that BRT has generally similar performance to light rail in the perceptions of passengers regarding comfort. Indeed, the average results of his study suggest that BRT may perform as well as rail with the other factors identified, depending on the scale of the BRT system and the quality of its stations and facilities.

Table 1 is a synopsis of the strengths and weaknesses and the opportunities and challenges that BRT represents today. It is a practical framework that looks into BRT from six different angles that refer to realistic concerns regarding BRT’s actual use: 1) economy, 2) technology, 3) flexibility, 4) implementation, 5) performance, and 6) impact.

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2 The authors recognize that some of strengths and weaknesses presented in Table 1 are of a broader nature and, thus, could be in some degree applicable or could be generalized to other mass-transit modes.
<table>
<thead>
<tr>
<th>TABLE 1. Synopsis of Strengths and Weaknesses of BRT Today</th>
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</thead>
<tbody>
<tr>
<td><strong>BRT Strengths</strong></td>
</tr>
<tr>
<td><strong>Economy</strong></td>
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<tr>
<td>Cost</td>
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<tr>
<td>Funding</td>
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<tr>
<td>Financial Planning</td>
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<tr>
<td><strong>Technology</strong></td>
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<tr>
<td>ICT</td>
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<td>Pre-board Fare Collection</td>
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<td>Priority Systems</td>
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<tr>
<td><strong>Flexibility</strong></td>
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<td>Operational Flexibility</td>
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<tr>
<td>Integration Flexibility</td>
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<tr>
<td><strong>Implementation</strong></td>
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<tr>
<td>Rapid Implementation</td>
</tr>
<tr>
<td>Straightforward Implementation</td>
</tr>
<tr>
<td>Road-User Engagement</td>
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<td>Political Leadership</td>
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<tr>
<td><strong>Performance</strong></td>
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<tr>
<td>High Capacity</td>
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<td>High Speed</td>
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<td>High Reliability</td>
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<tr>
<td>Comfort</td>
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</tbody>
</table>
TABLE 1. Synopsis of Strengths and Weaknesses of BRT Today (cont.)

<table>
<thead>
<tr>
<th>Impact</th>
<th>BRT Strengths</th>
<th>BRT Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environment</td>
<td>Improvement of environmental conditions in terms of air quality, noise reduction, and energy consumption</td>
<td>Can be argued that metro/light rail are even greener</td>
</tr>
<tr>
<td>Traffic Safety</td>
<td>Reduction in number of traffic accidents</td>
<td>Still not entirely disengaged by general road traffic; implies that there are still traffic accidents related to its use</td>
</tr>
<tr>
<td>User Satisfaction</td>
<td>Majority of BRT users have been fairly satisfied with service</td>
<td>Car users tend not to see significant BRT-related benefits, while some schemes have been deemed poor by their users</td>
</tr>
<tr>
<td>Image</td>
<td>With right patronage and political support, can become iconic for respective cities</td>
<td>Needs support to be publicly recognized as system much more complete and superior than slightly improved conventional bus service</td>
</tr>
<tr>
<td>Urban Development</td>
<td>May have potential to bring broader economic, social, and environmental benefits on urban development</td>
<td>Can be argued that BRT’s potential for positive societal impacts is not as significant as the potential of fixed-rail</td>
</tr>
<tr>
<td>Land Use</td>
<td>Can increase land values, rent values, and even promote high-density residential, office, and commercial land use</td>
<td>Metro and light rail could have an even greater positive land use impact</td>
</tr>
</tbody>
</table>
An Introductory Review of BRT Systems Globally

The development of BRT systems worldwide has witnessed tremendous growth in recent years (Delmelle and Casa 2012). Following a few pioneering implementations in the later 20th century, BRT has emerged as a leading mode of urban passenger transit in the first decade of the 21st century (Deng and Nelson 2011). Many of these new implementations are taking place in cities throughout the developing world, attributed largely to the relative inexpensive cost, easier implementation, and greater flexibility as compared to rail systems, and their promise to foster economic revitalization (Levinson et al. 2003).

Currently, there are 186 cities in 41 countries with BRT systems or corridors, serving almost 32 million passengers every day (www.brtdata.org, December 2014). New BRT systems and BRT extensions are under development as well.

The most important point of reference for BRT systems worldwide is South America, the birthplace of this mass transit mode. The South American schemes are widely appreciated as the most advanced and widely-used BRT systems in the world and provide a vision of how BRT can be used to radically change urban modal split in favor of public transportation. More specifically, BRT schemes have been implemented in 60 different locations in South America, hosting 62.4 percent of global BRT passenger trips (as of December 2014).

Recently, several cities in Asia have adopted BRT operations. The potential for BRT implementation in Asia is still huge, but this has been recognized only recently by Asian policymakers. Actually, the newer cities joining the list of the urbanities with BRT corridors are concentrated to China, followed by Indonesia, with the Latin American region coming in third. China, fostering one of the fastest-growing economies in the world and experiencing an unprecedented urbanization and motorization that has greatly transformed the nation’s urban landscape over the last years, is the most fertile ground for new BRT schemes to prosper. Currently, 18 Chinese cities host at least one BRT corridor, but most of these schemes are of minor scale for the magnitude of the Chinese mega-cities. This trend is even clearer in India, where BRT operates in 8 different cities, serving only 390,000 passengers per day.

<table>
<thead>
<tr>
<th>Regions</th>
<th>Passengers/Day</th>
<th>No. of Cities</th>
<th>Length (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Africa</td>
<td>242,000 (0.76%)</td>
<td>3 (1.61%)</td>
<td>80 (1.68%)</td>
</tr>
<tr>
<td>Asia</td>
<td>8,529,322 (26.93%)</td>
<td>38 (20.43%)</td>
<td>1,317 (27.68%)</td>
</tr>
<tr>
<td>Europe</td>
<td>1,804,829 (5.69%)</td>
<td>53 (28.49%)</td>
<td>822 (17.27%)</td>
</tr>
<tr>
<td>Latin America</td>
<td>19,769,380 (62.42%)</td>
<td>60 (32.25%)</td>
<td>1,646 (34.6%)</td>
</tr>
<tr>
<td>Northern America</td>
<td>894,821 (2.82%)</td>
<td>26 (13.97%)</td>
<td>798 (16.77%)</td>
</tr>
<tr>
<td>Oceania</td>
<td>430,041 (1.35%)</td>
<td>6 (3.22%)</td>
<td>94 (1.97%)</td>
</tr>
</tbody>
</table>

Source: www.brtdata.org, December 2014
TABLE 3. Complete List of Cities Hosting BRT Schemes

<table>
<thead>
<tr>
<th>Adelaide</th>
<th>Cannes</th>
<th>Evry</th>
<th>Joinville</th>
<th>Maubeuge</th>
<th>Port of Spain – Arima</th>
<th>Surat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ahmedabad</td>
<td>Cape Town</td>
<td>Fareham-Gosport</td>
<td>Jonkoping</td>
<td>Medellin</td>
<td>Porto Alegre</td>
<td>Swansea</td>
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<tr>
<td>Almere</td>
<td>Caracas</td>
<td>Feira de Santana</td>
<td>Juiz de Fora</td>
<td>Merida</td>
<td>Prague</td>
<td>Sydney</td>
</tr>
<tr>
<td>Amsterdam</td>
<td>Castellon</td>
<td>Fortaleza</td>
<td>Kansas City</td>
<td>Metz</td>
<td>Prato</td>
<td>Sydney</td>
</tr>
<tr>
<td>Auckland</td>
<td>Caxias do Sul</td>
<td>Gatineau</td>
<td>Kent</td>
<td>Mexico City</td>
<td>Puebla</td>
<td>Liverpool</td>
</tr>
<tr>
<td>Bangkok</td>
<td>Châlon-sur-saône</td>
<td>Goiania</td>
<td>Kesennuma-Tome</td>
<td>Monterrey</td>
<td>Pune</td>
<td>Toyota</td>
</tr>
<tr>
<td>Baranquilla</td>
<td>Changde</td>
<td>Gothenburg</td>
<td>Kunming</td>
<td>Quito</td>
<td>Taichung</td>
<td>Taipei</td>
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<tr>
<td>Beijing</td>
<td>Changzhou</td>
<td>Guadalhajara</td>
<td>La Rochelle</td>
<td>Rajkot</td>
<td>Tehran</td>
<td>Toulouse</td>
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<tr>
<td>Belém</td>
<td>Chiayi</td>
<td>Guadalupe</td>
<td>Lagos</td>
<td>Recife</td>
<td>Twente</td>
<td>Uberlandia</td>
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<tr>
<td>Belfort</td>
<td>Chicago</td>
<td>Guanzhou</td>
<td>Lahore</td>
<td>Rio de Janeiro</td>
<td>Rosario</td>
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<tr>
<td>Belo Horizonte</td>
<td>Chihuaha</td>
<td>Guarulhos</td>
<td>Lanzhou</td>
<td>Santos</td>
<td>Saint-Nazaire</td>
<td>Vancouver</td>
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<tr>
<td>Bhopal</td>
<td>Chongqing</td>
<td>Guatemala</td>
<td>Las Vegas</td>
<td>New Delhi</td>
<td>Salvador</td>
<td>Waterloo</td>
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<tr>
<td>Blumenau</td>
<td>Cleveland</td>
<td>Guayaquil</td>
<td>Leeds</td>
<td>New York</td>
<td>San Bernadino</td>
<td>Winnipeg</td>
</tr>
<tr>
<td>Bogotá</td>
<td>Crawley</td>
<td>Haifa</td>
<td>Leon de los Aldama</td>
<td>New York</td>
<td>Nice</td>
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<tr>
<td>Boston</td>
<td>Criciuma</td>
<td>Halifax</td>
<td>Lianyugang</td>
<td>Nick</td>
<td>San Diego</td>
<td>Xiamen</td>
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<tr>
<td>Bradford</td>
<td>Curitiba</td>
<td>Hamburg</td>
<td>Liège</td>
<td>Niteroi</td>
<td>Santiago</td>
<td>Yancheng</td>
</tr>
<tr>
<td>Brampton</td>
<td>Dalian</td>
<td>Hangzhou</td>
<td>Lille</td>
<td>Oakland</td>
<td>Santos</td>
<td>Yinchuan</td>
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<tr>
<td>Brasília</td>
<td>Diadema-Sao Paolo</td>
<td>Hefei</td>
<td>Lima</td>
<td>Oberhausen</td>
<td>Sao Paolo</td>
<td>York</td>
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<tr>
<td>Brescia</td>
<td>Douai</td>
<td>Indore</td>
<td>Lisbon</td>
<td>Olinda</td>
<td>Seoul</td>
<td>York Regional</td>
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<tr>
<td>Brisbane</td>
<td>Dublin</td>
<td>Ipswich</td>
<td>London</td>
<td>Orlando</td>
<td>Snohomish County</td>
<td>Zhengzhou</td>
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<tr>
<td>Bucaramanga</td>
<td>Ecatepec</td>
<td>Istanbul</td>
<td>Lorient</td>
<td>Ottawa</td>
<td>Strasbourg</td>
<td>Zurich</td>
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<tr>
<td>Buenos Aires</td>
<td>Edinburgh</td>
<td>Jaboatão dos Guararapes</td>
<td>Los Angeles</td>
<td>Panama</td>
<td>Stokton</td>
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<tr>
<td>Caen</td>
<td>Eindhoven</td>
<td>Jaipur</td>
<td>Luton</td>
<td>Paris</td>
<td>Stockholm</td>
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<td>Cali</td>
<td>Enschede</td>
<td>Jakarta</td>
<td>Lyon</td>
<td>Pereira</td>
<td>Stokton</td>
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<tr>
<td>Cambridge</td>
<td>Essen</td>
<td>Jinan</td>
<td>Maceió</td>
<td>Phoenix</td>
<td>Strasbourg</td>
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<tr>
<td>Campinas</td>
<td>Eugene</td>
<td>Joao Pessoa</td>
<td>Maua – Diadema</td>
<td>Pittsburgh</td>
<td>Sumare</td>
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</tr>
<tr>
<td>Campo Grande</td>
<td>Everett</td>
<td>Johannesburg</td>
<td>Maubeg — Maubeuge</td>
<td>Sumare</td>
<td></td>
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</tbody>
</table>

Source: www.brtdata.org, December 2014
Only three cities in Africa have introduced BRT: Johannesburg and Cape Town in South Africa and Lagos in Nigeria. In Oceania, there are six cities hosting a BRT scheme; five are in Australia. A seventh scheme in Melbourne (i.e., SmartBus) contains elements of BRT infrastructure but is no longer listed as such in the brtdata.org database. The introduction and usage of BRT in North America is limited compared to the potential opportunities that exist in the U.S. and Canada markets. Most schemes that are operating have small usage rates in relation to the dedicated BRT kilometers offered.

Europe, on the other hand, is a very different story when attempting to assess BRT’s operability, productivity, and success. In Europe, the bus sector has a long tradition of innovation and development in introducing bus lanes, bus-only roads, traffic management measures to assist buses, and automatic dispatch and control systems—in some cases, as early as the 1970s (Hidalgo and Gutierrez 2013). Nevertheless, BRT has not been embraced with the same enthusiasm. One explanation is that during the 1990s, tramways were favored and received a lot of attention, while buses and bus systems were left behind. Nonetheless, the number of BRT systems in Europe is steadily increasing, especially in France and the UK.

Researchers and practitioners in Europe prefer to use the term Buses of High Level of Service (BHLS) rather than BRT (Finn et al. 2011). This is the case because they want to differentiate the European applications, which are based on improving passenger experience rather than simply focusing their efforts on how to supply high-capacity mass transit. In the report from CERTU (2005), BHLS is defined as “a public road transportation concept for the structuring services of the network that meet a set of efficiency and performance criteria, coherently integrating stations, vehicles, circulation lanes, line identifications, and operating plans in an on-going manner.”

However, the BRT vs. BHLS theme is far from simply being a quantity vs. quality aspect. The advanced bus schemes across Europe, with the exception of Istanbul’s Metrobus, are not BRT systems that resemble Bogotá’s TransMilenio or Curitiba’s RIT but rather are BRT-Lite. BRT-Lite is a term that is more or less synonymous with BHLS, which explicitly refers to a system of buses with a high level of service that, despite its advanced characteristics, when compared with a conventional bus-line is not a fully developed BRT system, but rather a French/European BRT version of significantly smaller scale suiting European city needs. BHLS can have a considerable impact when implemented as part of the “co-modality” concept promoted by the EU—for example, working in cooperation between public transport fleet operations and parking management systems to promote BRT corridors (Deng and Nelson 2011).

A Brief BRT History Lesson
BRT is an evolution of bus priority measures, such as designated busways and bus lanes (Hidalgo and Gutierrez 2013) and reflects a vision that was inspired almost 80 years ago. The idea of using rubber-tired vehicles to provide rapid transit is well-documented in plans and studies that have been prepared since the 1930s, with growing emphasis on bus prioritization (Levinson et al. 2003). For example, in 1937, the so-called Chicago Plan called for converting three west‐side rail transit lines to express bus operation on super highways.
with on-street distribution in central areas (Levinson et al. 2003). The term BRT was initially used in 1966 in a study for the American Automobile Association by Wilbur Smith and Associates, but a proper full-scale implementation came almost two decades later.

The first real BRT system was implemented in Curitiba in 1963, although dedicated bus lanes were not operating until 1974 (Rabinovitch and Leitman 1996). Curitiba, with 1.85 million inhabitants occupying a total area of 435 km² (about 4,200 inhabitants per km²), is the seventh most populated city in Brazil and the largest in the southern region of the country. The city stands at the center of a metropolitan area that includes 26 municipalities with a total population of 3.17 million inhabitants. As early as the 1960s, Curitiba’s policymakers had the inspiration to direct the city’s growth by integrating urban transportation, land-use development, and environmental preservation using bus-based transit innovation as their main apparatus.

In a December 2013 discussion with the authors, the Mayor of Curitiba, Jaime Lerner, the political champion who introduced this first BRT application in the world, stated that “the inspiration behind the creation of a metro-nized, in terms of performance bus system,” was based on three parameters: 1) reflecting the restrictions of the local economy that could not cater to the massive financial needs for building and eventually sustaining a metro system; 2) understanding that the future of transportation was on the surface (and not underground)—he explicitly referred to “the need to have an interactive urban environment that integrates mobility, in a very visible way, with the overall sustainability focus of the city”; and 3) maximizing the potential of an already-existing bus system by transforming it in a cost-effective but yet unparalleled way that could fit his vision of a city working, living, and moving as a whole like a living organism.

As originally described by Lindau et al. (2010), the Curitiba bus system evolved from conventional buses in mixed traffic to busways, which were later fitted with floor-level boarding, prepayment, and articulated buses, creating the first full BRT system in the world. Later, the city introduced high-capacity bi-articulated buses and electronic fare ticketing systems. In 2007, RIT (the name of the scheme) had 2.26 million trips per working day transported by a fleet of 2,200 buses that produced 483,000 km per day. In 2009, the RIT was upgraded with the introduction of the Green Line, its sixth BRT corridor, which includes the operation of 100 percent bio-diesel articulated buses. As of 2010, some of Curitiba’s corridors had achieved performance to levels that are typical for metro systems (Lindau et al. 2010). The capacity of the Boqueirão Corridor, for example, serves up to 89,000 passengers per day, and its operating commercial speed for the express service is approximately 28 km/h. Today, RIT is responsible for 508,000 passenger trips per day over its 81 km (www.brtdata.org, December 2014).

Curitiba’s operational framework was adapted to a significant degree for introducing BRT corridors in places such as Quito (1995), Bogotá (2000), Los Angeles (2000), Mexico City (2003), Jakarta (2004), Beijing (2005), Istanbul (2008), and Guangzhou (2010), to name a few. Nonetheless, sufficient time passed for this public transit philosophy to disseminate to other locations. The vast majority of cities around the world that adopted BRT operations embraced this choice from 2000 onward, as illustrated in Figure 2.
FIGURE 2.
BRT Implementation History

Source: www.brtdata.org, December 2014

Presenting and Discussing Local BRT Applications
The main focus of this section is to present updated information on specific local BRT applications that could be representative of their geographical region, followed by appropriate discussions. These discussions could be generalized into wider context for cities with similar characteristics and could serve as valuable lessons for building future BRT applications. There are many more examples that could have been discussed, but due to space restrictions, this was not an attainable choice.

South America
TransMilenio, Bogotá, Colombia
Other than Curitiba, the influence of Bogotá has been particularly important in setting the standards for what BRT is really about. The TransMilenio BRT system is the most powerful BRT reference for planners and practitioners worldwide (Gutierrez 2010). Bogotá is the capital and largest city of Colombia, with 7,760,500 inhabitants. It is among the 30 largest cities in the world and has 20 localities, or districts, that form an extensive network of neighborhoods. TransMilenio, widely known as the “Jewel of Bogotá,” has received many tributes, including the Stockholm Partnership Prize in 2002. It is the largest investment in public transportation in Colombia in the last decade, with significant impacts on travel times, transportation costs, the environment, accidents, and urban development of the nation’s capital (Hidalgo et al. 2013). It was built in three years, effectively from scratch, as the answer to the persistent demand for a metro system (Gilbert 2008). On an average working day in 2014, the system carried 2.21 million passengers in 113 km of lanes in 11 corridors (www.brtdata.org, December 2014).

TransMilenio began operations in December 2000. Its key features as described by Gilbert (2008) include the following:

- The system was built in stages, aiming to cover 80 percent of the urban transport needs of the city (Gómez 2004).
- Each corridor is built along the city’s major roads, and the construction of the bus stations, garages, bridges and other infrastructure was financed by public funds.
TransMilenio operates using a public-private partnership mechanism. City administration is responsible for the construction and maintenance of the infrastructure (through the Urban Development Institute) and for the planning, management, and control of the service (through Transmilenio S.A., the private operator). The system operated originally on a commission of 3 percent of the fares collected, a percentage that has risen over time (Hidalgo et al. 2013).

- There is no operating subsidy.
- Red articulated buses operate along reserved corridors, with two exclusive lanes each way on most routes; a feeder system takes passengers to the main stations.
- In 2011, 1,262 articulated buses and 10 bi-articulated buses were operating 114 stations around the city, in addition to 519 conventional 12m buses that operated within the 83 different feeder routes (Hidalgo et al. 2013).
- Each articulated bus can carry 160 passengers, with 112 standing and the remainder sitting.
- The red buses belong to 7 “modern,” private companies that have contracts with the city; the green feeder buses belong to another 11 companies.
- Some buses stop at every station; others are express services.
- Passengers board and alight the buses at special stations, many of which can be reached by pedestrian bridges to avoid accidents and to speed up loading.
- Passengers purchase travel cards before boarding. A fixed fare is charged whatever the length of the journey. The use of the feeder bus system is free; passengers are charged only when they board on the articulated buses. The payment system also embraces the use of a smart card (Hidalgo et al. 2013). The fares are collected by Transmilenio S.A.
- Transmilenio S.A. monitors and controls the system through a GPS system and communicates with the drivers through a wireless telecommunications system.
- User information is achieved through a fixed signage and dynamic display panels (Hidalgo et al. 2013).
- The buses have to be replaced on a regular basis, approximately every 10 years, although this can be extended to 15 years if the buses have not completed an agreed mileage.
- The drivers are salaried employees of the bus companies.

TransMilenio may be a minor miracle, but Bogotá is still in need of improving its transport system. Perhaps the main lesson that other cities planning to invest in busways should learn is that TransMilenio-type systems can work efficiently and should be encouraged, but unless parallel changes are made to the rest of the transport sector, real progress will be slowed and, in a worst-case scenario, vested interests may actually undermine the viability of a new BRT system (Gilbert 2008).
MIO, Santiago de Cali, Colombia

Santiago de Cali (or Cali), the third largest city in Colombia, with a population nearly 2.5 million residents, is among the most recent South American cities to adopt a BRT system and is in the process of replacing its traditional bus public transit system with an integrated mass transit system. This city-wide transportation project is central to a larger urban revitalization plan intended to encourage economic growth and to alter the image of both the city and the country to residents and outsiders. What defines this scheme is the intention of planners to create a system that prioritizes equity over other potential goals. As Delmelle and Casa (2012) report, the policymakers’ ambitions focus on developing a scheme that promotes equitable access to all residents and access to a large number of urban opportunities. This is a scheme that on a daily basis accommodates 530,000 passenger trips in its 6 corridors that extend to 39 km (www.brtdata.org, December 2014).

Lessons to be Learned by South American Applications

Since BRT has a long tradition in South America, a discussion about South American scheme variety and success (or failure) as a whole is a meaningful process. This discussion, nonetheless, could be generalized into a wider context since these findings could be applicable to other systems that have not yet achieved the levels of maturity of the South American schemes.

After Curitiba opened the first BRT system, other cities in Brazil introduced systems with some of the same characteristics but with much lower speeds, capacities, and customer comforts. These light BRT systems—São Paulo’s passa rápido corridors, for example—brought some real benefits to passengers but were far less appreciated by the general public. As a result, Brazil lags behind Colombia in terms of leading BRT development (Weinstock et al. 2011).

BRT systems in South America (and in Asia, in this case, since there are similarities) feature a diversity of scope and level of integration. There are single-corridor projects that do not integrate with feeder services and other transport modes (e.g., Mexico City, Beijing), projects with sequential implementation of non-integrated corridors (Quito, Jakarta), schemes that gradually implement physically-integrated corridors (Bogotá, Guayaquil), and others that deploy extended route re-organizations (São Paulo, Santiago, León) (see Carrigan et al. 2011). A strong political champion has proven to be an asset in the development and implementation of BRT (Lerner 2013).

The fares for South American BRT projects with competitive bidding for bus operating concessions (e.g., Bogotá’s TransMilenio, Pereira’s Megabus and TranSantiago) often have been determined through the bidding process itself. Initial user fares were calculated based on prospective operator bids, and the contracts then issued for operating have included adjustment formulas for future rises in labor and fuel costs over time. In other systems, political authorities defined fares that did not reflect the actual costs of the system or the required levels of subsidy. This approach can have adverse effects. For instance, Quito’s system was unable to generate enough funds to pay the operators of the Ecovía buses, and the BRT systems of Mexico City (and, similarly, Jakarta and Beijing) were financially challenged until fare increases were approved. Setting fares related to knowledge of the costs and an understanding of subsidy requirements are necessary to ensure financial
sustainability for operators and funding authorities as well as continued political buy-in (Carrigan et al. 2011).

It is also common for cities to incorporate existing operators into the new BRT system to minimize political and contractual risks referring to service operation. Cities in South America (and now in Asia and Africa as well) have encouraged small transport businesses and operators to organize themselves into formal companies through restricted bidding for operation contracts or through direct negotiations (Carrigan et al. 2011). This encourages local communities and businesses to engage more actively with the scheme of their city by sharing some responsibility for its functional operation. Even more important, however, this helps to secure working posts that could be in doubt if a large contractor was in command—something that influences local economic development positively. This is an operational issue that perhaps deserves a study on its own, but since it is an important success ingredient for BRT, it is reported as such for the sake of a more holistic approach.

Europe

Metrobüs, Istanbul, Turkey

A scheme that is considered among the most successful is Turkey’s Metrobüs, the only intercontinental BRT system in the world. This is a success story not related with South American schemes, although it was inspired by them. The implementation of Metrobüs started in 2007. It was initially built on the European side of Istanbul through a high-demand arterial and received criticism for being preferred over rail alternatives. The section that was built in 2009 runs over one of the two Istanbul Strait (Bosphorus Strait) bridges connecting Asia and Europe, by which Metrobüs has uniquely acquired the distinction of crossing a major water barrier and connecting two continents. Istanbul Strait is a major transportation bottleneck and source of congestion, and Metrobüs is the only transit system for crossings.

Shortly after the opening of the bridge section, the whole system recorded a directional capacity of 24,000 passengers per hour and patronage of 620,000 daily trips (Alpkokin and Ergun 2012). The one-corridor BRT scheme after its fourth phase in 2012 extends to 51.3 km (Yazici et al. 2013). Currently, Metrobüs carries 750,000 passengers per day serving Istanbul, one of the largest cities in the world, with a population of more than 13 million inhabitants (www.brtdata.org, December 2014), which, similar to other megacities in terms of size and complexity, has a metropolitan area even larger. Metrobüs uses the application of a median busway with center island stations that was built within the median of the freeway D100 by removing a travel lane in each direction. Bus operation is counter-flow to reduce costs and implementation times and uses conventional buses with right-hand doors. The entire Metrobüs system has a dedicated right-of-way in Istanbul, with the exception of mixed traffic operations on the Bosphorus Bridge.

Alpkokin and Ergun (2012) conclude their assessment of Metrobüs by reporting that “all the information of improved ridership and capacity proves that Istanbul Metrobüs achieves one of the highest patronage levels amongst similar BRT systems, which provides evidence to support the effective operation of BRT systems.”
Stombussar, Gothenburg, Sweden

Gothenburg has approximately 540,000 inhabitants and is divided by the Gothia River, with the south and the north parts crossed by two bridges and one tunnel. Public transport accounts for 29 percent of all trips; 48 percent are by private car, 14 percent by motorcycles and non-motorized vehicles such as bicycles, and 9 percent by walking. The public transport system in Gothenburg consists of trams, BRT-Lite routes, and other bus services including express buses. There is also a ferry service across the river and to/from the archipelago. Most public transport journeys are made by trams (60%), but the BRT system is gaining in popularity and carries around 15 percent of the passengers of all public transport trips (Trafikverket 2014), that equal approximately 25,000 passenger trips per day (www.brtdata.org, December 2014).

The BRT system, or, more precisely, the trunk bus system, was first introduced in 2003. Currently, eight lines are considered trunk bus lines or “stombusslinjer.” Line 16 initially had a 10-minute frequency during peak hours; the current frequency is 5 minutes during most of the day and 2.5 minutes in the most demanding directions during peak hours. The other seven BRT routes run with at least 10-minute frequencies during daytime, in some cases reinforcing traffic during peak hours. To minimize the times at each bus stop, travelers are allowed to get on and off through all doors, a so-called “open visa” regime. This corresponds to the principles that apply to trams in Gothenburg, but is not allowed in other, ordinary bus lines.

Buses are given priority at all traffic lights en route. The position of all bus stops was reviewed, leading to a minimum number of bus stops in relation to traveler needs, and special bus lanes and bus streets were created. When planning the routes, efforts were made to avoid sharp curves and lateral movements; this has been achieved by providing a straight line into and out of the bus stops and bus lanes, which run straight through roundabouts, etc. All these actions lead to a higher average speed. Most bus stops in the BRT system are equipped with real-time information displays, presenting information on next departure as well as disturbances and delays. On all buses, internal displays inform the passenger about the next two stops. A special road map presents the trunk bus lines together with the tram system to further stress the relationship between the two. The ticketing system is an electronic smart card system. Tickets cannot be purchased on board, but individual tickets can be purchased via SMS just before the trip and are valid for 90 minutes, or cards can be purchased from local shops. Approximately 65 percent of passengers use monthly passes.

The entire bus fleet consists of low-floor buses with wheelchair ramps. In addition, all stops have a raised platform to improve accessibility for mobility-challenged passengers. The buses have a unique and uniform design to make them easily detectable in city traffic. For interior design, care was taken in the choice of colors, materials, and lighting to make the travel experience more pleasant for travelers and to assist passengers with disabilities.

It should be noted that this BRT scheme is substantially scaled down compared to the world’s leading BRT schemes; it is not oriented towards dealing with higher capacities but, rather, emphasizes the provision of high-quality services. Conclusions from previous Swedish research on BRT indicate that there is no place for full-scale BRT schemes in
Sweden, even though Swedish towns and cities could benefit from the image, flexibility, speed, and quality that BRT symbolizes (Stojanovski 2013). The urban form, the road hierarchies, and the dispersed and fragmented urban structure of Swedish towns and cities and low densities were identified as main obstacles (Kottenhoff 2010).

**Asia**

**TransJakarta, Jakarta, Indonesia**

Jakarta is the capital and largest city of Indonesia and is located on the northwest coast of the island of Java. It is the country's economic, cultural, and political center and, with a population of around 10 million, is the 13th most populated city in the world. TransJakarta BRT System launched its first corridor on January 2004 on a trial basis, beginning revenue operation on February 2004 (Ernst 2005). This was the first fully operational BRT system in Asia. During its first year, it served 15.9 million passengers. Beginning with just 12.9 kilometers, TransJakarta is now 206 km (www.brtdata.org, December 2014), larger than the BRT systems in Curitiba and Bogotá (Yunita 2008).

This is a scheme that has all the key elements of a BRT system. It is founded on a designated busway that is physically separated from mixed traffic, except for very few cases where segregation was not feasible. TransJakarta offers facilities such as air-conditioning and pre-paid boarding that distinguish it from other buses. Currently, 12 corridors operate, serving 370,000 passenger trips per day (www.brtdata.org, December 2014). In its first year of operation, TransJakarta was responsible for a significant modal shift, with 14 percent of private car users using BRT (Susilo et al. 2007), a measurement that reflects the period occurring four months after the launching date of the first eight corridors.

TransJakarta’s ridership is rather low, with systems that have less than one-quarter of TransJakarta’s infrastructure carrying more passengers per day. For example, Belo Horizonte’s BRT system is approximately 5 times smaller than TransJakarta, with 5 fewer corridors and carrying 682,000 passengers per day on its articulated buses. One effort to improve the customer experience and attract ridership included the installation of water fountains in several stations, intended for passengers observing Ramadan, the Islamic month of fasting, to be able to break their fast in the station during their commute home. The cost of the water purifiers was about $2,136 each (Yunita 2008).

The main problems of the scheme are long queuing times and insufficient bus frequency. The initial corridors were constructed for buses with only one door, constraining the number of people who could get off or on the bus at one time. The new corridors will include a fix to this problem. Information provision is not efficient since it is provided only in stations by ticketing officers, security officers, and a display board. Cleanliness and maintenance are important concerns as well.

**BRT1, Beijing, China**

Beijing is the capital of China and one of the most populous cities in the world, with more than 20 million inhabitants. The metropolis is governed as a direct-controlled municipality under the national government, with 14 urban and suburban districts and 2 rural counties. Beijing Southern Axis BRT Line 1 (BRT1) is the first BRT system implemented in China and the first large-capacity rapid bus line based on the needs of developing public
transportation, which was designed using foreign advanced ideas and technology as reference (Lin and Wu 2007). BRT1 started commercial operations in December 2004 with a pilot line of only 5.5 km in length. In December 2005, BRT1 began full operations and was extended to 15.8 km. It should be noted that from proposal to trial operation, the time span of implementing BRT1 was relatively short. Most lanes are physically segregated in the median of the road, except for 2 km from Qian’men to Tian’an’men. Six of the 17 stations of the corridor are transfer stations (Deng and Nelson 2013). Accessibility to the city center has been significantly improved for residents along the BRT corridor.

The BRT system investment at Beijing Southern Axis Corridor included significant expenses for the creation of the necessary road-reconstruction project, stations, and intelligent transportation systems (ITS). The investment in the road reconstruction project was about 321.31 million yuan, and the investment for the stations and ITS (including operation for stations, parking lots, vehicles, etc.) was approximately 288.19 million yuan, for a total cost of 609.5 million yuan; construction cost per kilometer was about 38.1 million yuan (Lin and Wu 2007), a cost in American dollars (in 2014 values) of approximately $6.2 million.

In Beijing, the local authority has faced increasing difficulties in paying off debts for subsidizing its metro and light rail operations and for expanding the rail network to increase coverage. In a pre-implementation cost-benefit study on three transport improvement alternatives (busway, street-level light rail, and elevated rail) in a congested corridor in Beijing, it was found that only the busway showed a positive net present value (Deng and Nelson 2013). This rationale led Beijing policymakers to implement, on a relatively small scale (for the city standards), BRT to save costs and eventually provide high-quality services within a short implementation time.

Currently, Beijing has 4 corridors covering 74 km of routes and hosts on a daily basis 305,000 passenger trips (www.brtdata.org, December 2014). The lines use vehicles with a passenger capacity of 180 persons (Lin and Wu 2007), and all are low-floor buses and cost about US$250,000 each, including features such as automatic stop announcements, three double left-side doors, and air conditioning (FTA, 2006). The buses are mounted with GPS terminal equipment and meet universal emission standards. The speed of the buses reaches 26 km/h, and (according to Lin and Wu 2007) the overall travel speed of general traffic after BRT implementation of the Southern Axis Line has increased by 2.26 km/h.

A user survey conducted by Deng and Nelson (2012) suggested that passengers were generally content with the BRT service provided in the Beijing Southern Axis BRT Line 1, with 85.5 percent rating overall satisfaction as "very satisfied" or "satisfied." High speed and convenience were the main factors encouraging passengers to use BRT. It was also found that passengers who had a car alternative were more likely to give lower satisfaction ratings regarding the reliability, comfort, cleanliness, and overall satisfaction of the BRT service.

Overall, the implementation of BRT in Beijing is regarded as a considerable success because of its prominent flexibility, transit speed (close to that of the Beijing Metro), and user satisfaction (Deng and Nelson 2012, 2013; Lin and Wu 2007). However, some problems do exist. In Beijing, an impressive feature of BRT stations is a pedestrian overpass or
underpass, which provides safe pedestrian access; adding lifts and elevators would make these stations even more accessible to mobility-challenged groups. Fares are below the operation cost level, which has generated considerable financial difficulties for the operators. Currently, Beijing’s BRT is heavily subsidized by the local government, but because it has high passenger volume levels and low labor costs, it could be profitable, provided that the system operation structure is redesigned accordingly. The local authority needs to re-examine the effect of subsidies on operational efficiency and conduct a full review of its fare policy and structure to improve the operational sustainability of BRT. Adding more express buses at large stations and intersection services during peak-hours while reinforcing the fleet with super-capacity vehicles could, according to Lin and Wu (2007), bring immediate improvements to the system.

Unrealized Potential for BRT Investments in Asia

In many developing Asian cities, the growth of transportation needs is very rapid and uncontrolled, causing various impacts on the environment and human welfare (Satien-nam et al. 2006). The reality is that until recently, heavy investments have been made exclusively in building metro and light rail systems as a means to meet massive travel demand. Pucher et al. (2007) suggest that although metro and light rail projects have gained extensive political support in Asia, in some cases, this is mainly because “rail symbolizes modern, advanced technology and offers politicians tangible, highly visible achievements to impress their constituencies and the rest of the world.” Thus, the prioritization of rail-based solutions was primarily founded for image and national pride purposes and not on the provision of a mechanism adequate to deal with urgent traffic congestion problems.

BRT has recently emerged as an attractive urban transit alternative in many Asian cities due to its financial sustainable, ecologically-friendly character and its flexible implementation. However, it seems to be difficult to introduce BRT, at least on a scale that reflects the size and traffic challenges of Asian mega-cities. Ten countries and 38 cities in Asia have a BRT scheme to date, but none is comparable in size or performance to the schemes of South America. Some of them also lack innovation and are limited to unsuccessfully adapting BRT operations that do not fit the local needs of the city hosting them. For instance, after Indonesia opened TransJakarta, a system with significant problems of its own, other cities across Indonesia began opening copycat systems, the best of which brought about only marginal improvements and the worst of which made conditions worse. Chinese and Indian cities, after gaining some limited familiarity with Bogotá’s TransMilenio, also made a number of sub-optimal bus system improvements that were branded as BRT but which could not be judged as cost-effective (Weinstock et al. 2011).

Furthermore, the lack of upfront integration of road design, public transportation planning, land-use planning, and early-stage public consultation has created challenges to providing high-quality public transport services on many new urban corridors (Jiang et al. 2012). Deng and Nelson (2010) add that, despite the fact that BRT systems are successfully in operation across the world (and in Asia in particular), the image of BRT is not yet well understood by most decisionmakers. This means that it is difficult for them to transform a concept that is often misunderstood into new local applications that could genuinely
improve road traffic conditions. Yet, with more than 100 cities of more than 1 million
in population only in China, the urban transportation market in Asia is very large (FTA
2006)—too large to address by simply supporting car-orientated operations and conven-
tional public transport services.

North America

HealthLine, Cleveland, USA

The most successful example of BRT in the U.S. (with a BRT Standard score of 63/100 com-
pared to Eugene’s EmX 61, Los Angeles’ MetroRapid 61, Pittsburgh’s Martin Luther King,
Jr. East Busway 57, and Las Vegas’ MAX 50) is the 11.4 km Euclid Corridor Transportation
Project, also known as HealthLine. This is a scheme that is not really comparable to the
productivity, efficiency, or size of a scheme such as Bogotá’s, whose BRT Standard score
is 93. Healthline is a one-corridor scheme serving 15,000 passenger trips per day (www.
brtdata.org, December 2014).

This project was created in response to the need for providing an efficient public transit
service connecting the city’s main employment centers. The Greater Cleveland Regional
Transit Authority (RTA), the Northeast Ohio Areawide Coordinating Agency (NOACA),
and the City of Cleveland had studied transit options in Cleveland for four decades, cul-
minating with the consensus in 1995 that BRT would be the most cost-effective option
to provide high-capacity transit service for the city (Weinstock et al. 2011). The project
details for the Euclid Corridor Transportation Project were finalized in 1999 following a
series of 12 public consultation meetings.

Before the system opened, average bus speeds in the corridor were only 15 km/h. Line
6 on the Euclid Avenue corridor was one of the most heavily-used routes in the city,
accounting for 10 percent of the total passenger trips. Euclid Avenue also had lines 7 and
9 operating on part of the corridor. The operational plan for the HealthLine converted line
6 into an upgraded service with new articulated BRT buses that operate mostly within
a newly-constructed segregated right-of-way. The original low-floor 7 and 9 buses also
are able to use the BRT infrastructure at station stops with right-side boarding. A total
of 32 buses also use the BRT corridor in some places. Together, these 4 lines average an
interval of 2.1 minutes between buses during the peak, and speeds in the corridor average
a respectable 20.11 km/h (Curitiba BRT averages about 21.06 km/h and Bogotá averages
26.2 km/h). More than 13 additional routes that overlapped the corridor for short dis-
tances or were in the impact area of the corridor have been rerouted. Some of the speed
increase resulted from the elimination of stops, which some residents complained about
along with the inconvenience resulting from the changes in routes, but that was the only
negative side-effect.

Daily ridership increased by 60 percent after 2 years of operation. The project’s total
budget was approximately $200 million, but only $50 million was allocated for buses and
stations; the remainder was directed towards other corridor improvements such as road-
ways, utilities, new sidewalks, and street furniture. The cost of the busway itself, therefore,
was only about $7 million per mile, including rolling stock. The investment has resulted in
nearly $4.3 billion in economic development for the area (Zingale and Riemann, 2013) in
real estate investments along Euclid Avenue, one of the city’s most historically-significant corridors.

A very intriguing factor of the scheme (that perhaps could be a point of reference for more BRT schemes) relates to the fact that Greater Cleveland sold the naming rights of the line to help fund the system. The Cleveland Clinic and University Hospital jointly purchased the naming rights, resulting in the HealthLine name. This partnership will provide the system with $6.75 million in additional funding, dedicated to maintenance, over the next 25 years.

**North America is Still “Testing” BRT**

The development of BRT systems is relatively recent in the United States; however, several systems are operating, and many more are being planned (Perk et al. 2010). Until recently, the U.S. and Canada (partly because BRT is not ideal for the population density of the typical Canadian urban structure) have not yet relied heavily on BRT. Having witnessed the success of BRT schemes such as those in Curitiba and Bogotá, a number of American cities began developing BRT-type systems. Some of these systems have brought significant benefits and won public approval. However, even the best U.S. systems lack some key characteristics of the world’s best BRT systems, and none have fully captured the imagination of American motorists and voters (Weinstock et al. 2011).

American cities started investing in BRT as a viable alternative after it was solidified as a worldwide phenomenon. However, the concept of employing rubber-tired vehicle fleets to provide rapid transit and the term BRT itself could be of American origin (Levinson et al. 2003). Since there is still no consensus on what constitutes a full-scale BRT system (Wirasinghe et al. 2013), the not particularly infrastructure-heavy American BRT systems have been labeled by some (e.g., Weinstock et al. 2011) as “modest bus system enhancements corrupting the BRT brand.”

Nonetheless, each BRT system is a unique solution fitting the needs of the city in which it is implemented and should be addressed as such. The role BRT is asked to play in the U.S. because of federal and other cultural and institutional differences is that of a complement and not of a sole solution. Similar to Europe, there is a focus on quality rather than quantity. Perhaps, to allow for BRT to grow to its full potential in North America, more comprehensive understanding is needed of the relationship between land use and BRT, particularly in comparison with other fixed-guideway modes (Perk et al. 2010). Understanding the mode’s impacts on property values, in particular, could be another key for embracing the measure if the impact is somewhat comparable to that of rail-based services (Perk et al. 2013). The emergence of BRT, in this sense, should not be seen as a problem despite all its current limitations, but rather as “a unique opportunity to change negative perceptions regarding public transit in North America,” as Hess and Bitterman (2008) argue.

Currently, 18 cities in the U.S. host 32 corridors and 548 km of dedicated BRT road infrastructure, but only 365,000 passenger trips per day (www.brtdata.org, December 2014) take place, which, in comparison, is less than half of those completed daily in Istanbul’s Metrobüs. Canada, in respect, has 8 cities with BRT schemes, hosting 530,000 passenger trips in 18 corridors spanning 250 km (www.brtdata.org, December 2014).
Africa

Lagos BRT-Lite, Lagos, Nigeria

Among the three African BRT applications, the most recognizable is perhaps the one in Lagos, Nigeria. Lagos is one of the fastest growing cities in Africa. Data for “building up” urban area population is a particular concern in Nigeria; the 2006 census results were highly disputed. For example, the federal census indicated a population for the state of Lagos of 9.1 million; a parallel census conducted by the state found the population to be 17.5 million (Demographia 2014).

The 22 km Lagos route is Africa’s first BRT scheme and became operational in March 2008. It is termed “BRT-Lite,” meaning that it is not a scheme of the highest specification such as TransMilenio in Bogotá. It is a new form of BRT, focused upon delivering a system to meet key local user needs, with the aim of improving quality of life, economic efficiency, and safety within a clearly-defined budget. The implementation of a 15-month conception-to-operation program, together with its delivery at a cost of $1.7 million per km, makes its development unique internationally (Brader 2009).

The Lagos BRT-Lite carries almost 200,000 people per day (www.brtdata.org, December 2014). Its single route is 65 percent physically-segregated and 20 percent separated by road markings. However, its success is not purely based on its infrastructure but on a holistic approach that involved the reorganization of the city’s bus industry, financing new bus purchases, and creating a new institutional structure and regulatory framework to support it, together with the training of personnel to drive, maintain, enforce, and manage BRT (Brader 2009). An early evaluation of the scheme showed that users were saving journey time, had fewer interchanges en route, were traveling cheaper, and felt safer (Brader 2009). Adebambo (2009) also suggests that BRT has a significant impact on passenger satisfaction in Lagos metropolis; it has helped to improve the quality of life of not only its users but also those that travel along the corridor using other modes, as well as those who choose to locate their businesses there. Businesses within the corridor saw the scheme as a positive addition, improving accessibility and aiding their access to staff and the ability of their staff to travel for work-related duties (Brader 2009).

Negative aspects relate primarily to the need for more buses and more routes. Problems exist, and improvements relating to the system’s efficiency are necessary. According to Adebambo (2009), there is a need, for instance, to ensure greater coordination with local planning and operating agencies for the purpose of identifying BRT potential, and a need to conduct research, develop operational techniques, and promote the use of ITS technology to enable safe and efficient deployment of BRT. BRT implementation also may require policy and institutional reforms, such as changes in transportation planning and roadway management practices (to give buses priority in traffic), vehicle purchasing, transit regulations and contacting (to maintain a high quality of service), and urban design (to increase development near BRT routes). The scheme overall seems to have a beneficial effect upon the quality of life of the commuting population of Lagos.
Oceania

Brisbane Busway, Brisbane, Australia

Australia and New Zealand, due to their small populations compared to their vast land-masses, are more likely than most countries to have strict limits on public spending, including transport infrastructure and operations. This means that bus-based systems can be the only viable solutions for some Oceanic cities. Australian BRT systems have been noted as being particularly diverse in design (Currie 2006), with systems now operating in Sydney, Brisbane, Adelaide, and, to a lesser extent, Melbourne (Currie and Delbosc 2011). The system in New Zealand is the one-corridor Northern Busway in Auckland, operating 22 km and generating 22,900 passenger trips per day (www.brtdata.org, December 2014). The Adelaide O-Bahn is the oldest BRT system in Australia and one of the first BRT systems worldwide; it opened in 1989 (Currie 2006).

The Brisbane Busway is the largest BRT system in Oceania, with 3 corridors running on 28 km and serving 356,800 passenger trips per day (www.brtdata.org, December 2014), which is about the same passenger volume as the huge TransJakarta scheme that was built to cater the needs of a city five times the size of Brisbane. The system is recognized as one of the most successful BRT systems in a developed economy, and, by Australian standards, is regarded as one of the most successful mass transit systems, delivering fast, comfortable, and cost-effective urban mobility through the provision of segregated right-of-way infrastructure, rapid and frequent operations, and excellence in marketing and customer service (Gollota and Hensher 2008). For the high-level strategic criteria of value for money and increased accessibility, connectivity, and visibility, the Brisbane BRT excels, according to Gollota and Hensher (2008).

Conclusions

BRT systems are celebrated worldwide as an increasingly popular public transport development option (Currie and Delbosc 2011). This is due to their promise for delivering relatively low-cost, rapidly-implemented, flexible, and high service quality solutions to developing cities’ transportation needs (Wright and Hook 2007). There is an increasing number of highly-congested urban environments in need of a public transport mode with a vast potential for eco-innovation that could be assessing the merits of BRT. As pointed out herein, if BRT is well-designed and supported adequately by local policymakers, it can be a high-capacity public mode that could capture road-user loyalty. Furthermore, by reviewing BRT examples from all over the world, and especially concentrating on cases that have been revolutionary, this work provides an identification of prototype mechanisms for reconstructing success.

Combining the quality standards of a tram or metro system with the flexibility and ease of a conventional bus system at a significantly lower expense than that related to fixed rail operations could challenge the merits of car-oriented mobility in any eco-friendly society. International practice supported by current BRT user satisfaction levels (as reported, for example, for Beijing by Deng and Nelson 2012) suggest that BRT schemes could be highly-acceptable strategies for relieving traffic problems and promoting sustainable living conditions.
BRT is a very demanding public transit medium that could transform the whole transport system within a city with two distinctive approaches—by re-allocating road space and by reforming the priorities of the city’s urban development policy. In addition to BRT’s dedicated road space requirements that call for the introduction of bus lanes on existing streets and bus streets completely separated from traffic, BRT is based on a wide variety of other rights-of-way, including bus priority in signalized intersections. These could radically affect the current balance of traffic prioritization, minimizing the dominance of automobiles in streets. Thus, introducing a full-scale local BRT scheme could rearrange the entire dynamics of a city’s mobility and, ultimately, force dramatic changes in modal share.

Nonetheless, if the system fails to be attractive to the commuting audience, it could end up as an expensive fiasco. In such a case, the scheme could, instead of promoting alternative and greener mass transportation, worsen the inner-city road conditions in terms of traffic congestion by depriving road space from other more successful transport modes. Therefore, strong political consensus, branding, image-making, marketing promotion, and the provision of user education are of invaluable importance for 1) easing the transition from conventional bus services to BRT and 2) solidifying BRT as a tangible long-term solution that could provide vital societal services for all road users and eventually become iconic for the very identity of the city hosting it.

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Stranding Cycling Transit Users on Los Angeles’ Orange Line Bus Rapid Transit

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Abstract

The Los Angeles Metro Orange Line is a bus rapid transit (BRT) system that accommodates cycling transit users (CTU) with front-of-the-bus mounted bike racks. However, cyclists sometimes find these bike racks full and are stranded until the arrival of the next bus. By collecting CTU usage data at seven Orange Line stations, the following results were observed: (1) CTUs are more likely to be stranded during weekday nights due to the proximity to three major colleges; on weekends, CTUs are more likely to be stranded in the mornings; (2) Metro’s policy that increased evening service during 2013 successfully decreased the number of stranded cyclists; and (3) when the racks are two-thirds full, approximately 20 percent of buses will strand at least one cyclist.

Introduction

Bus rapid transit (BRT) has proven to be a popular alternative to rail-based transit, particularly for its cost effectiveness and the minimal time to build and start operations. BRT frequently is associated with Curitiba (Brazil), where it started in the 1970s as a lower capital alternative to light rail and subways (Duarte and Rojas 2012). This type of mass transit has since become more widespread throughout the world. While elements of BRT have been adopted by seemingly every local transit agency in the United States and Canada, the Institute for Transportation and Development Policy’s (ITDP) BRT Standard (2014) excludes most bus systems in the United States that purport to be BRT. The standard is based on accumulation of points for features present in an ideal BRT system, with high-scoring systems distinguished with Gold, Silver, or Bronze status. Common elements of BRT include a dedicated busway, pre-boarding fare collection, high-quality station
amenities, and bus headways similar to rail transit. Further, elements often are related to branding or imagery, including the BRT vehicles themselves being of distinctive designs and transit system maps elevating BRT lines to rail status. Within these criteria, only four BRT lines in the U.S. have ITDP designation: Cleveland, Ohio (Silver); Los Angeles Metro Orange Line (Bronze); Eugene, Oregon (Bronze); and San Bernardino, California (operational as of April 2014 and not assessed yet). Boston’s Silver Line excluded some planned elements and did not receive ITDP BRT status.

Cycling transit users (CTUs) are multimodal users of public transit (including BRT) that use their bicycles at one or both access/exit points of the transit system. It has generally been understood that CTUs are found most frequently in suburban areas (Krizek and Stonebraker 2010; Bachand-Marieau et al. 2011) because transit stations are less frequent in these low-density areas. CTU demographics have changed from being white, well-educated homeowners in single-family housing in 2001 to a more heterogeneous mix. By 2009, race was the only statistically-significant difference between CTUs (Wang and Liu 2013). However, even race may become less important as “invisible riders”—immigrants from Latin America who use bicycles because of affordability issues—increase in central city populations (Koeppel 2006). Understanding the changing face of CTUs will help transit agencies better manage their experience.

Transit agencies support integrating bicycle-transit travel in the United States as a method to increase transit ridership (Wang and Liu 2013). Biking extends the catchment area of transit stops far beyond walking range. A study of Portland’s Westside Express suburb-to-suburb commuter rail found that the median walking distance was 0.54 miles, whereas the median and mean cycling distances were 1.7 and 2.6 miles, respectively (Bergman et al. 2011). Accommodating cyclists is a lower-cost option compared to feeder-buses and automobile park-and-ride facilities (Krizek et al. 2011). Other benefits to increasing transit usage, with increased CTU ridership as a portion, include reducing greenhouse gas (GHG) emissions and creating a more active public. Vincent and Jerram (2006) estimated that BRT would be the most effective method to decrease carbon dioxide emissions from a hypothetical medium-sized U.S. city versus the base bus and private vehicle cases and even compared to adding a light rail system. Wener and Evans (2007) found that train commuters walked 30 percent more steps per day than car commuters.

To promote bicycle access to transit services, local bus agencies in the United States have installed bike racks on the front of most transit buses in the U.S. (Hagelin 2005). However, the same trend is not found with BRT, with transit agencies preferring to accommodate CTUs by providing bike sharing, bike racks, and bike lockers at stations rather than allowing cyclists aboard BRT vehicles. This is true in Europe (Martens 2004) as well as most of the U.S. Transit agencies prefer to accommodate CTUs at stations for multiple reasons, including passenger safety, space limitation, length limitations, and to decreased stop time. A bicycle that is held on a bus and not on a rack is a liability that might hurt other passengers, and this problem compounds as the buses become more crowded. Because on-board bicycle racks take away several seats, as ridership levels increase, transit agencies prefer external bike racks (Hillmer, personal communication, 2014). Transit agencies also may face vehicle length limitations, the case in California, so that front-of-the-bus racks can be only so long and additional racks cannot be added to the back of the vehicle.
Finally—and perhaps one of the largest considerations for transit agencies—bikes can take a while to load or off-load from the bicycle racks (Krizek and Stonebraker 2010), which increases dwell time at stations and reduces the performance of BRTs.

Although transit agencies prefer to accommodate CTUs with fixed infrastructure at stations, riders prefer to bring their bicycles with them (Pucher and Buehler 2009; Krizek et al. 2011). In Montreal, 45 percent of 1,432 survey respondents identified allowing bicycles on board buses as the best method to increase bicycle/transit shares (Bachand-Marieau et al. 2011). Hagelin (2005) found that 26 percent of bike-on-bus users indicated a major problem was full bike racks on buses when looking at 11 Florida transit agencies and 4 non-Florida agencies and their bus systems. Increased cycling accommodation aboard buses seems likely to increase CTU ridership.

Counting the number of CTUs is difficult, and counting the number of stranded CTUs is more difficult. Transit agencies regularly estimate ridership numbers by using actual farebox counts and performing field counts. Field counts usually are performed in two ways: all-day counts at a few stations and rush-hour counts at a larger number of stations. These are then extrapolated to determine counts at all locations and times (Hummer 1994). However, most do not estimate bicycle ridership, and only the Cleveland Metropolitan Transit Authority keeps track of bicycle ridership on its buses (Flamm 2013). Bicycle ridership is likely to be extrapolated from regular transit trends, but with such users as “invisible riders,” CTUs may not have the same use patterns. The literature does not indicate that transit agencies count the number of stranded CTUs.

Even with the exterior bicycle racks to accommodate CTUs, the local transit agency in Los Angeles County, commonly known as Metro, struggles to provide adequate bicycle capacity aboard its BRT service known as the Orange Line. Many cyclists are being left behind on the Orange Line due to full bike racks, with more left behind during weekday evenings and weekend mornings. Metro added more evening buses to the Orange Line’s 2013 schedule to better accommodate the CTUs. This paper discusses (1) CTU usage patterns and how they differ from pedestrian users, (2) the effectiveness of the added buses in reducing stranded cyclists, and (3) an evaluation of the relationship between the utilization of on-board bus racks and the number of stranded cyclists.

The paper is organized as follows. The next section discusses the history of Metro Orange Line. The data and descriptive statistics follow in the next sections. Analysis of the CTU usage patterns, increased BRT service effects, and the relationship between bike rack utilization and stranded cyclists follows. Finally, the paper ends with conclusions and recommendations.

**Background of LA Metro’s Orange Line**

The Orange Line is the only full-fledged BRT system in Los Angeles, despite the Metro Rapid service having some BRT elements (Cervero et al. 2013), because it has a dedicated exclusive busway and pre-boarding fare collection. The Orange Line serves the San Fernando Valley, a broad inland suburbanized area northwest of downtown Los Angeles and Hollywood (see Figure 1). The line’s area of service is notable for not directly connecting with the city center, but connecting to Amtrak and commuter rail at the western
Chatsworth terminus and the Los Angeles Metro Red Line (subway) at the eastern North Hollywood terminus. The line runs through a mix of older suburban areas of Los Angeles and passes by three major education institutions. Two campuses of the Los Angeles Community College District—Valley College, with enrollment of 18,789 students, and Pierce College, with 20,506 students—are along the Orange Line, and California State University, Northridge, with an enrollment of 36,911 students, is 4 miles from the Orange Line, connecting via the Reseda station (U.S. Department of Education 2013). These large colleges provide many possible CTUs, supporting the understanding of the demographic profile change of CTUs.

![Figure 1. Orange Line BRT stations included in study](image)

The Orange Line is noted for its multimodal capture, particularly of cyclists (Vincent and Callaghan 2007; Hensher and Thomas 2008), because it has good access to bike routes (including being paralleled by a Class I bike path), has both bike racks and lockers at stations, and accommodates bicycles on vehicles using exterior racks. In comparison, Curitiba and Bogota’s world-famous BRT systems have poor bicycle access, with only 6 of Curitiba’s 22 terminals being reached by bicycle paths and 8 of 13 in Bogota (Duarte and Rojas 2012). The Orange Line is similar to transit systems in Europe, in that there are facilities such as guarded bicycle parking and racks (Martens 2004).
Line exceeds is that it includes on-vehicle racks. These combined improvements increase the use of bicycles as a feeder mode to transit (Martens 2004) and are part of the wider multimodal alternative to private cars (Hine and Scott 2000).

The Orange Line opened in October 2005 and quickly exceeded expected ridership figures. Metro had projected ridership of 5,000–7,500 average weekday boardings for the first year of service, but was serving more than 21,000 average weekday boardings within 6 months of operations (Vincent and Callaghan 2007). Ridership has continued to grow and experienced a growth spurt between 2011 and 2012 when the Orange Line was extended north to reach the Chatsworth station, especially affecting the stations closer to Chatsworth (Reseda and Pierce College) (see Figure 2).

Originally, Orange Line buses met cycling demand with on-board interior bike racks, but because of high pedestrian ridership levels, they were removed to add seating. Racks were placed on the front of buses and quickly were expanded from two to three slots because of continued increases in CTU ridership. Despite the larger racks, cyclists were being left behind because the bus racks were full. An impediment to increasing interior or exterior bike rack capacity is the California Department of Transportation regulation limiting bus vehicle length to 60 feet (CA Vehicle Code 35400 sec B-3).

With limitations in accommodating cyclists on the Metro Orange Line, the sight of cyclists being forced to wait for the next bus became more common to casual observers. This pattern of occurrences prompted our original 2012 research to determine the mismatch between demand for bike rack space and supply of bike slots. Metro increased service during evening hours because it also was aware of stranded CTUs and, with high enough overall evening ridership issues, could justify the increased service. While Metro considered allowing bicycles aboard the buses, safety concerns could be met only by removing permanent seating, which was not considered a viable option (Hillmer, personal communication, 2014).
Methodology and Data
In 2012, data were collected for two-hour periods during weekday evenings (Tuesday to Thursday) at the North Hollywood, Van Nuys, Sepulveda, Reseda, and Pierce College station. For 2013, the sampling was expanded to include the Valley College and Chatsworth stations for both weekends and weekdays (Tuesday through Thursday) and included more time periods. As Table 1 shows, more complete collection was obtained at North Hollywood and the Van Nuys station to better understand overall cyclist behavior through the course of a day.

<table>
<thead>
<tr>
<th>Effort</th>
<th>Hours</th>
<th>North Hollywood</th>
<th>Valley College</th>
<th>Van Nuys</th>
<th>Sepulveda</th>
<th>Reseda</th>
<th>Pierce College</th>
<th>Chatsworth</th>
</tr>
</thead>
<tbody>
<tr>
<td>2012</td>
<td>8:30 PM–10:30 PM</td>
<td>D</td>
<td>D</td>
<td>D</td>
<td>D</td>
<td>D</td>
<td>D</td>
<td>D</td>
</tr>
<tr>
<td>2013</td>
<td>6 AM–8 AM</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
</tr>
<tr>
<td></td>
<td>8 AM–10 AM</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
</tr>
<tr>
<td></td>
<td>10 AM–12 noon</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
</tr>
<tr>
<td></td>
<td>12 noon–2 PM</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D</td>
<td>E</td>
<td>D/E</td>
<td>D/E</td>
</tr>
<tr>
<td></td>
<td>2 PM–4 PM</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
</tr>
<tr>
<td></td>
<td>4 PM–6 PM</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
</tr>
<tr>
<td></td>
<td>6 PM–8 PM</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
</tr>
<tr>
<td></td>
<td>8 PM–10 PM</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>E</td>
<td>D</td>
<td>D/E</td>
<td>D/E</td>
</tr>
<tr>
<td></td>
<td>10 PM–11 PM</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
<td>D</td>
<td>D/E</td>
<td>D/E</td>
<td>D/E</td>
</tr>
</tbody>
</table>

Note: D = week(D)ay; E = week(E)nd

In 2012, data were collected in 20-minute increments and included number of buses, direction of the buses, number of empty slots leaving the station, and number of cyclists left behind. For 2013, the methodology was slightly revised so that data were collected for each bus: time of arrival, direction, number of bikes arriving, number of bike alighted, number of bikes loaded, number of bikes leaving, and whether a cyclist was left behind by the bus. The improved methodology increased our ability to check and analyze the data. The data were collected between October 24 and November 8, 2012, and from October 16 to December 12, 2013.

Descriptive Statistics
A total of 2,102 buses were counted in 2013. However, some arrived outside the official time ranges, and others did not have departures: North Hollywood eastbound is the end of the line, so all riders must alight, and boarding begins when the bus starts its westbound trip. Similarly, the Chatsworth station is the western end, so there are only western alightings and no boardings. Of the remaining 1,704 buses counted during the 2013 effort, a total of 70 left a cyclist behind (4.1%). From the sample, 2,168 slots were full upon departure from the stations out of 5,104 available slots, a utilization rate of 42.5 percent. The results of percent cyclists left behind and slots full on departure are shown in Table 2.
### TABLE 2. Percentage of Buses Stranding at Least One Cyclist and Percentage of Slots Full When Bus Is Departing

<table>
<thead>
<tr>
<th>Day</th>
<th>Direction</th>
<th>Station</th>
<th>Buses Leaving Cyclists Behind</th>
<th>Slots Full on Departure</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>East</td>
<td></td>
<td>6 AM – 8 AM</td>
<td>12 noon – 2 PM</td>
</tr>
<tr>
<td>Weekday</td>
<td>East</td>
<td>Valley College</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Van Nuys</td>
<td>4%</td>
<td>7%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Sepulveda</td>
<td>0%</td>
<td>8%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Reseda</td>
<td>0%</td>
<td>4%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Pierce College</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Chatsworth</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td></td>
<td>6 AM – 8 AM</td>
<td>12 noon – 2 PM</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>North Hollywood</td>
<td>0%</td>
<td>7%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>Valley College</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>Van Nuys</td>
<td>4%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>Sepulveda</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>Reseda</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>Pierce College</td>
<td>0%</td>
<td>7%</td>
</tr>
<tr>
<td>Weekend</td>
<td>East</td>
<td>Valley College</td>
<td>0%</td>
<td>8%</td>
</tr>
<tr>
<td></td>
<td>East</td>
<td>Van Nuys</td>
<td>0%</td>
<td>33%</td>
</tr>
<tr>
<td></td>
<td>East</td>
<td>Reseda</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>East</td>
<td>Pierce College</td>
<td>18%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>East</td>
<td>Chatsworth</td>
<td>33%</td>
<td>0%</td>
</tr>
<tr>
<td>Weekend</td>
<td>West</td>
<td></td>
<td>6 AM – 8 AM</td>
<td>12 noon – 2 PM</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>North Hollywood</td>
<td>20%</td>
<td>17%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>Valley College</td>
<td>0%</td>
<td>8%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>Van Nuys</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>Reseda</td>
<td>0%</td>
<td>0%</td>
</tr>
<tr>
<td></td>
<td>West</td>
<td>Pierce College</td>
<td>0%</td>
<td>0%</td>
</tr>
</tbody>
</table>
On weekdays, no more than 25 percent of buses strand a cyclist during any time period. However, these high rates occur during the night and night-time period, suggesting that CTU travel behavior may not match the overall service levels suggested by pedestrian ridership. Also, the stations that hit these high numbers are the Valley College, Reseda, and Pierce College stations, all of which are near large colleges, suggesting that students taking evening classes are being left behind. This is corroborated by the highest slot full on departure occurring at the college stations at the night and late-night periods, with the Pierce College station at night having the maximum value of 83 percent full. The other station of note is the North Hollywood station, at which a cyclist most likely will need to wait for the next bus, regardless of the time of day. North Hollywood is a busy station because it connects with the northern terminus of the Red Line (subway).

On weekends, the patterns change. During the morning and lunch periods, cyclists are left behind, with Chatsworth and Van Nuys having 33 percent of the stranded cyclists, presumably because of increased recreational riding of bicycles. In fact, the percentages of slots full reached a maximum of 89 percent at the Van Nuys station during the lunch period. These high levels also suggest that CTU usage is not consistent with Orange Line service levels, which more closely match pedestrian usage levels.

**Cyclist Ridership vs. Pedestrian Ridership**

Typically, when transit agencies determine ridership levels, they collect data for peak hours and interpolate usage for the other time periods (Hummer 1994). This means that CTU estimates would be based on peak morning, lunch, and afternoon rush-hour periods, which may or may not coincide with peak CTU usage. By comparing pedestrian and CTU usage data collected in this study, we can determine if peak-hour testing is adequate to identifying stranded cyclist issues.

To evaluate if CTUs have similar use patterns as pedestrians, pedestrian user data were obtained from Metro, whose daily data is reported for five time periods: morning (5–9 AM), business hours (9 AM–3 PM), afternoon rush hour (3–7 PM), night (7 PM–12 midnight), and overnight (12 midnight–5 AM). Metro's overnight period is excluded because CTU ridership data were not collected during this time period. The pedestrian data used are an average of the October to December 2013 daily data. In Tables 3 and 4, pedestrian data were adjusted as a percent of time represented to be comparable to the bike data collected. Table 3 shows the stations at which longer time periods were kept, and Table 4 shows two-hour intervals (except the night period, which is three hours).

### Table 3.

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Weekday</th>
<th></th>
<th>Weekend</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>West</td>
<td></td>
<td>East</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Bike</td>
<td>Ped</td>
<td>% Bike</td>
<td>Bike</td>
</tr>
<tr>
<td>6 AM–9 AM</td>
<td>40</td>
<td>1,201</td>
<td>3.3%</td>
<td>24</td>
</tr>
<tr>
<td>9 AM–3 PM</td>
<td>42</td>
<td>2,004</td>
<td>2.1%</td>
<td>75</td>
</tr>
<tr>
<td>3 PM–7 PM</td>
<td>74</td>
<td>2,450</td>
<td>3.0%</td>
<td>39</td>
</tr>
<tr>
<td>7 PM–11 PM</td>
<td>39</td>
<td>892</td>
<td>4.4%</td>
<td>21</td>
</tr>
<tr>
<td>Chi-Square</td>
<td>11.211</td>
<td>**</td>
<td>4.83</td>
<td>14.434</td>
</tr>
</tbody>
</table>

Note: Chi-square Significance at * 0.10 level, ** 0.05 level, *** 0.01 level; otherwise not statistically significant.
### TABLE 4. Bike, Pedestrian, and Percentage Bike Ridership at Orange Line Stations with Data Collected for Four Standard Time Periods (2013 data)

<table>
<thead>
<tr>
<th>Time Period</th>
<th>Chatsworth</th>
<th>Pierce College</th>
<th>Sepulveda</th>
<th>Valley College</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Bike</td>
<td>Ped</td>
<td>% Bike</td>
<td>Bike</td>
</tr>
<tr>
<td>6 AM–8 AM</td>
<td>2</td>
<td>98</td>
<td>2.0%</td>
<td>16</td>
</tr>
<tr>
<td>12 noon–2 PM</td>
<td>8</td>
<td>72</td>
<td>11.1%</td>
<td>18</td>
</tr>
<tr>
<td>4 PM–6 PM</td>
<td>8</td>
<td>149</td>
<td>5.4%</td>
<td>47</td>
</tr>
<tr>
<td>8 PM–11 PM</td>
<td>5</td>
<td>50</td>
<td>10.0%</td>
<td>26</td>
</tr>
<tr>
<td>Chi-Square</td>
<td>6.39</td>
<td>*</td>
<td></td>
<td>12.33</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time Period</th>
<th>North Hollywood</th>
<th>Valley College</th>
<th>Sepulveda</th>
<th>Pierce College</th>
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<tr>
<td></td>
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<tr>
<td>6 AM–8 AM</td>
<td>25</td>
<td>801</td>
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<td>32</td>
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<tr>
<td>12 noon–2 PM</td>
<td>16</td>
<td>668</td>
<td>2.4%</td>
<td>19</td>
</tr>
<tr>
<td>4 PM–6 PM</td>
<td>51</td>
<td>1,225</td>
<td>4.2%</td>
<td>24</td>
</tr>
<tr>
<td>8 PM–11 PM</td>
<td>23</td>
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<td>3.4%</td>
<td>25</td>
</tr>
<tr>
<td>Chi-Square</td>
<td>4.11</td>
<td>8.10</td>
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<tr>
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<tr>
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<td>6</td>
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<td>26.1%</td>
<td>11</td>
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<tr>
<td>12 noon–2 PM</td>
<td>8</td>
<td>45</td>
<td>17.8%</td>
<td>13</td>
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<td>4 PM–6 PM</td>
<td>5</td>
<td>49</td>
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<td>15</td>
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<tr>
<td>6 AM–8 AM</td>
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<tr>
<td>12 noon–2 PM</td>
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<td>458</td>
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*Note: Chi-square Significance at * 0.10 level, ** 0.05 level, *** 0.01 level; otherwise not statistically significant*
Table 4 shows more stations but with data collected for fewer hours during each day. In this case, the westbound ridership behavior of cyclists and pedestrians from North Hollywood is statistically equivalent. However, what can be observed is that the statistically significant patterns occur at the Pierce and Valley College stations, both east and westbound, with higher evening and morning ridership levels. Student evening cycle ridership seems to be higher. However, on the weekends, in either direction, the statistically-significant ridership distribution occurs with an increase in morning ridership, most likely a reflection of increased recreational ridership. There are also higher evening ridership levels, perhaps an indicator of the invisible riders who need to use bicycles for the last mile due to reduced weekend bus service. The Chatsworth station has very high CTU percentages, a reflection of the low pedestrian ridership levels at this suburban terminus. The area is immediately surrounded by industrial uses, so most users are likely to either come via car, transit, or bicycle. With reduced car commuters on weekends, the overall usage at this station declines.

The results suggest that transit agencies should more closely monitor cyclist behavior in the mornings and evenings when there are higher percentages of CTUs but generally lower pedestrian ridership levels, the usual indicator for decreased service levels. To minimize monitoring, a transit agency can start by monitoring at colleges and at stations that are highly industrial to determine if there is an issue.

Effects of Increased Evening Service Levels

Between 2012 and 2013, the evening Orange Line service increased from three buses per hour to four buses per hour (see Table 5). The number of eastbound cyclists decreased from 53 to 47, and the westbound cyclists increased from 34 to 51. Overall, CTU usage increased at all stations except two: eastbound Sepulveda and Reseda. CTUs at these stations found that 100 percent of the slots were full and appear to have changed their transit behavior. There is a statistically-significant drop in the percentage of eastbound buses that strand a cyclist (paired-t = 6.657, p=0.022, df=2) and almost significant considering both directions (paired-t = 2.343, p=0.058, df=6). The question is, how much of the change in the percentage of stranded cyclists is due to change in cyclist ridership levels and how much is due to the increased bus service?

| TABLE 5. Comparison of 2012 and 2013 Bike Data to Understand Effects of Increased Night Service |
|--------------------------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|-------------------|
| Direction   | Station          | Total Buses 2012 | Total Buses 2013 | Bikes Leaving Station 2012 | Bikes Leaving Station 2013 | Percent Slots Full 2012 | Percent Slots Full 2013 | Percent Buses Stranding a Cyclist 2012 Model 2013 | Change in Percent Stranded Due to Ridership | Change in Percent Stranded Due to Increased Service |
| East        | Sepulveda        | 6               | 7               | 18               | 13               | 100%               | 62%               | 67%               | 21%               | 14%               | -45%               | -7%               |
|             | Reseda           | 6               | 8               | 18               | 16               | 100%               | 67%               | 100%              | 54%               | 25%               | -46%               | -29%              |
|             | Pierce College   | 7               | 8               | 17               | 18               | 81%               | 75%               | 71%               | 46%               | 25%               | -25%               | -21%              |
| West        | North Hollywood  | 7               | 8               | 16               | 19               | 76%               | 79%               | 29%               | 32%               | 13%               | 4%                 | -20%              |
|             | Sepulveda        | 7               | 8               | 9                | 12               | 43%               | 50%               | 0%                | 4%                | 0%                | 4%                 | -4%               |
|             | Reseda           | 6               | 9               | 5                | 8                | 28%               | 30%               | 0%                | 0%                | 0%                | 0%                 | 0%                |
|             | Pierce College   | 5               | 8               | 4                | 12               | 27%               | 50%               | 0%                | 0%                | 0%                | 0%                 | 0%                |
To answer this question, a model was designed that started with the 2013 raw data and estimated the number of buses that would strand a cyclist, assuming the 2012 bus level had occurred instead. Because the order of the buses was known for 2013, the riders on the skipped bus were assigned to the next bus (both the cyclists arriving via the bus and those wanting to board) and are left in the queue until enough open slots are available. Table 5 shows that the significant reduction in stranded cyclists was due to fewer cyclists using the Orange Line. However, it also shows that the increased service reduced stranded cyclists by up to 29 percent. With the reduced stranded cyclists in 2013, it would be interesting to see if eastbound ridership increased in 2014.

**How Full is Too Full?**

The final question is determining if there is a rule of thumb on when the bike racks are so full that cyclists are consistently being stranded. The 2012 and 2013 data for each station, time period, direction, and day of the week were used to compare the percentage of slots full on the bus bicycle racks and the percentage of buses that stranded a cyclist. Figure 3 shows that whereas bus rack utilization can be as high as 70 percent and still have no stranded cyclists, it is still possible for 33 percent of buses to strand cyclists with the rack utilization rate only being 33 percent.

Running Ordinary Least Square regression on these data indicates that a quadratic model is a better fit than the linear model and supports the assertion that a greater number of cyclists will be stranded as bus bicycle rack utilization increases (see Table 6). Tobit model regressions to account for censored data actually produced lower R-squared values, and creating an exponential model is mathematically infeasible due to the inability to take the logarithm of 0 (the lowest and most frequent percentage of the people left behind). Based on the best-fit equation, a bike rack utilization rate of 69 percent leads to 20 percent of buses stranding a cyclist.
**Conclusions and Recommendations**

The literature has shown that CTUs prefer to bring their bicycles with them on public transit rather than leave them at bicycle racks at transit stations (Bachand-Marieau et al. 2011). Metro, the operator of the Los Angeles Orange Line, has implemented policies to accommodate those CTU preferences by having exterior vehicle racks so that the bus interiors are not too full. In the summer of 2013, Metro also increased its evening service on the Orange Line to help decrease the number of stranded cyclists. This study has three main findings.

First, cyclist behavior is indeed different than pedestrian behavior. CTUs are more likely to use the Orange Line during weekday evenings at the Valley College and Pierce College stations, suggesting that the influx is due to students attending evening classes. It is possible that evening ridership is higher because bus service is less frequent, making the last mile more difficult to connect and increasing the viability of bicycles. Also, automobile traffic is lighter during the evenings, making it safer to use bicycles to finish the last mile. Unfortunately, we can only surmise these postulations as the data collected does not directly address these issues. CTU behavior is not the same as pedestrian transit user behavior, so we recommend counting CTUs during weekday evening hours near college campuses, as they are more likely to be a location with stranded cyclists.

On weekends, the mornings and early afternoons are more used by cyclists, most likely a reflection of weekend recreational cycling, especially considering the Orange Line has a Class I bicycle path paralleling it. Weekends are also a period of increased non-commuting trips, and Bachand-Marieau et al. (2011) found that CTUs who are regular commuters are more willing to leave their bicycles at a station, whereas CTUs on irregular trips, such as shopping and visiting, prefer to take their bicycles with them. The higher weekend usage also may be due to changes in trip purpose. We recommend that transit agencies count cyclist behavior during weekend mornings because of recreational cyclists influencing CTU ridership levels.

Second, increased evening service reduced the number of stranded cyclists. Because Metro cannot readily increase on-vehicle bicycle storage due to length limitations and crowded buses, it added an extra bus per hour in 2013. The extra service decreased the number of stranded cyclists, but not after losing some CTU ridership that was a response to the high probability of being left behind in 2012 in the eastbound direction. The west-
bound service did not have a stranded cyclist problem and saw an increase in usage levels. With fewer stranded in the eastbound direction as of 2013, CTU usage may increase. Increased service levels will continue to decrease the number of stranded cyclists, but it is an expensive fix. An alternative would be to find a method to engineer a bike rack onto the back of the Orange Line bus; however, both design considerations and legal restrictions limiting vehicle length would need to be addressed.

Third, a more generalized exponential trend occurs between the percentage of full bike racks and the number of buses stranding cyclists. Performing this study required many hours of data collection to monitor who is left behind at a station. Although the Greater Cleveland Regional Transit Authority is the only agency that collects bike rack loadings with detailed information including time, bus line, and location, it does not count cyclists left behind (Flamm 2013). Our data show a quadratic relationship between the percentage of full racks during a time period and the percentage of buses that strand a cyclist. Although it is difficult to generalize to a rule of thumb, it might be reasonable to assume that if there is normally a 66 percent rate of full racks, there should be less than 20 percent of the buses stranding a cyclist. But if two of the three racks are normally full, with occasionally all the racks full, then there should be consideration of increasing on-vehicle bicycle storage or increasing service levels.

A better understanding of cyclist choice behavior also would be beneficial. This would require interviews and surveys to determine when cyclists choose to use their bicycles and why. It could answer questions on what they do if they are stranded and at what level do they reach a point where they shift to an all-bicycle mode because of being stranded. Understanding the demographics of users could answer how many are part of the “invisible riders” and how many are represented by cycling advocates. They also may generate ideas on how to increase the desirability of using station bike racks. Providing space for cyclists aboard transit is difficult, and the Metro Orange Line successfully did so with its increase in evening service during the summer of 2013.

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A Cautionary Tale of Two Streetcars: Little Rock’s River Rail and Tampa’s TECO Line

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Florida State University

Hilary Nixon, Ph.D.
San Jose State University

Abstract

Planners and policymakers in dozens of U.S. cities are considering making streetcar investments in the hope of promoting economic development, encouraging tourism, carrying transit riders, and/or achieving a host of other local objectives. Most observers look to Portland, Oregon, as a model of successful streetcar development, but this paper considers the experiences of two less successful communities, Little Rock, Arkansas, and Tampa, Florida. Using a combination of key informant interviews and local and national transit data, the authors assess the goals of streetcar implementation and the performance of the streetcars in these two cities, seeking to understand the reasons for their performance and identify lessons for other communities.

Introduction

Planners and policymakers in dozens of U.S. cities are considering making streetcar investments in the hope of promoting economic development, encouraging tourism, carrying transit riders, and/or achieving a host of other local objectives. Advocates frequently point to the example of Portland, Oregon, as a model for their own community’s streetcar aspirations, because of the Portland streetcar’s purported role in promoting hundreds of millions of dollars in economic development near the streetcar line and its relatively high ridership and stronger transportation performance among the modern-era U.S. streetcar systems (Hovee and Gustafson 2012; Ramos et al. 2014). Among modern-era U.S. streetcars, Portland is indeed the standout performer, with the highest ridership and most productive service (Ramos et al. 2014), and its claimed economic development effects are the most widely touted (Golum and Smith-Heimer 2012). However, the authors suggest that planners and policymakers in cities that are considering building their own streetcar
This paper examines the cautionary experiences of two streetcar cities: Little Rock, Arkansas and Tampa, Florida. In both cities, planners and policymakers implemented streetcars to promote economic development and encourage tourism in their respective communities. The streetcars’ potential roles as transit services were secondary considerations in local decisionmaking (Brown et al. 2014). However, the experiences of both Little Rock’s River Rail and Tampa’s TECO Line streetcar have not lived up to their proponents’ original expectations. The economic development and tourism promotion results are questionable, and the ridership results are poor and worsening over time. The authors examine the experiences of these two less successful streetcar cities using a combination of insights gained from key informant interviews and transit data obtained from local agencies and national data sources. The objective was to better understand how these two less successful modern-era streetcars are doing and, more importantly, why, as well as to derive lessons from their experiences that might be of use to other cities that are considering making streetcar investments.

Basic Characteristics of the River Rail and TECO Line Streetcars
The two streetcar systems of interest are Little Rock’s River Rail streetcar, consisting of two lines (Blue, Green) operated by the Central Arkansas Transit Authority (CATA), and Tampa’s TECO Line streetcar, a single-line service operated by Hillsborough Area Regional Transit (HART) (Tampa Electric Company [TECO] purchased naming rights for the line). Photos of streetcars in the two cities are shown in Figures 1 and 2.
River Rail streetcars operate on a 3.4-mile alignment that serves 15 stops in the downtowns of Little Rock and North Little Rock. The streetcar system cost $28.8 million to build, and the streetcars operate in mixed traffic, except for a 0.4-mile dedicated segment on a bridge over the Arkansas River that connects the two downtowns. The first River Rail line opened in the latter part of 2004, with a new extension opening in 2007.

The River Rail streetcar line was built principally to serve visitors and promote economic development in the downtowns of Little Rock and North Little Rock (Brown et al. 2014). River Rail functions as a short circulator system within and between the two downtowns (see Figure 3). Service operates on consistent 25-minute headways throughout the day, and service hours start after the morning rush hour on weekday mornings to avoid conflicts between streetcar vehicles and automobile commuter traffic. The streetcar fare is $1 per ride; travelers can transfer free from CATA buses to River Rail, but streetcar riders must pay an additional fare to ride a CATA bus.
TECO Line streetcars operate on a 2.7-mile exclusive alignment (Figure 4) that cost $60+ million to build, including a rail facility and vehicles (personal communication, HART Board member, September 2014); the line serves 11 stops in areas east and south of downtown Tampa and links the nearby Ybor City tourism/historic district to the still-underdeveloped Channelside district. The TECO Line opened in the latter part of 2002 and originated as the proposed “first leg” of a larger light rail transit (LRT) system, but it soon evolved into a redevelopment and tourism-focused service of much shorter length (Brown et al. 2014). However, there were no system plans, no formal long-range plans, nor any designs prepared for future extensions for this particular vision of the streetcar (personal communication, HART Board member, 2014).
Although regional and transit planners reported that significant real estate investments, estimated by some observers to total nearly $1 billion, had been made near the streetcar alignment, the line still serves what most interviewees characterized as a largely underdeveloped waterfront district (Channelside) located between the entertainment/tourist-oriented Ybor City area and Tampa’s Convention Center (see Figure 4). Between these major destinations are several activity centers oriented towards serving tourists and visitors, including hotels, cruise terminals, an aquarium, a waterfront shopping mall, and a sports arena. Streetcar service operates on consistent 20-minute headways on weekdays and 30-minute headways on weekends starting at 12:00 noon Sunday through Thursday and at 11:00 AM Friday and Saturday. The fare is $2.50 per ride, and streetcar riders can transfer to HART buses without paying an additional fare.
Research Objectives, Methodology and Data Sources

The research objective of this study was to better understand how the streetcars in the two cities are performing and to identify possible explanations for their performance. It became clear during the early phases of the research that economic development, tourism promotion, and other non-transportation objectives were the most important objectives for streetcar development in these two cities, so the authors decided to investigate these issues. The authors were struck by the fact that few formal assessments of the performance of the streetcar systems with respect to these issues had been conducted in either city. The sole exception was an economic development study conducted by Little Rock’s CATA that used geographic information systems (GIS) analysis to estimate a total of about $1 billion in development activity within close proximity of the streetcar alignment (Central Arkansas Transit Authority 2012). However, the study did not attempt to control for other factors that might explain the level of development activity. There were no similar studies available for Tampa.

The lack of such formal assessments of non-transportation streetcar performance led the authors to rely on key informant interviews for this part of the investigation; these one-hour semi-structured telephone interviews are discussed below. The transportation performance assessment relied on ridership, productivity, and other performance data for a period extending from 2005, the first full year that both streetcars were in operation, to 2012, the most recent year for which data were available from the National Transit Database (accessed via Florida Department of Transportation [FDOT] 2013). The sections that follow discuss the non-transportation performance of the streetcars and their transportation performance.

Interviews about Streetcar Non-Transportation Goals

The authors conducted one hour semi-structured telephone interviews with key informants in both cities to better understand the goals and objectives of streetcar implementation and their assessment of the streetcar’s performance in meeting these objectives. These interviews proved particularly useful in understanding the non-transportation roles the streetcars were intended to play, which proved to be the critical factors driving local decisionmaking around the streetcars in both cities. The authors selected the interviewees to represent a diverse set of key local actors, including transit planners, regional planners, developers, business leaders, and streetcar advocates; the specific individuals were identified through a snowball process in which interviewees were asked to identify other potential candidates for interview. Most had been involved in streetcar issues for several years in their community. The authors conducted three interviews for Little Rock and seven interviews for Tampa (see Table 1); there were fewer interviews in Little Rock due to the difficulty in identifying informants who were willing to be interviewed. The informants are identified in Table 1 by role to maintain their anonymity. The authors first considered the interviewees’ identification of streetcar goals and then their assessment of goal attainment, for each city in turn.
Streetcar Non-Transportation Goals in Little Rock

The interviewees identified two sets of goals for streetcar implementation in Little Rock. The first goal was to promote downtown development; the second was to promote tourism and visitorship.

The regional planner interviewed recalled River Rail’s emergence as part of a downtown development strategy articulated in a study undertaken by local business leaders and developers in partnership with the Urban Land Institute; the mayors of Little Rock and North Little Rock were engaged in this effort as well. Participants viewed the streetcar as a potential “catalyst” for development. It was observed that the streetcar was supported by a “few big players” that included local developers and key elected officials who were interested in downtown revitalization. These key figures were able to secure federal funding earmarks to aid in streetcar construction. Major entities such as the Clinton Presidential Library and Heifer International participated in the second phase of streetcar construction, with the Library designing, building, and maintaining its own stop. The transit planner interviewed thought that former President Clinton’s influence helped the community obtain the funding for the second streetcar phase that included extending service to the Clinton Library.

The transit planner noted the primarily tourism and visitor orientation of the streetcar service and stated that the service was tourism-oriented and not transit-oriented. This focus is reflected in policy decisions such as starting service on weekday mornings at 8:20 AM, after much of the morning commute is over, to avoid streetcar conflicts with motor vehicle congestion. The streetcar does not have its own right-of-way and often is hindered by congestion as well as vehicles parked within its right-of-way. It also was noted that streetcar operators serve as tour guides who identify points of interest along the streetcar alignment to streetcar riders, which further indicates the primarily visitor orientation of the service.

The third interviewee, who promotes tourism and convention activity in the community, spoke of the streetcar’s role in connecting the two downtowns and enabling people to easily reach the major visitor attractions located there. Tourism promotion figured prominently in his assessment of the streetcar’s goals; he noted that the local convention and visitors bureau worked closely with the other agencies involved in streetcar planning and operations to develop and promote major events around the streetcar geared toward visitors.
Informant Assessment of Non-Transportation Goal Attainment in Little Rock

The informants offered a mixed assessment of the River Rail streetcar’s attainment of its original goals, with two more favorable and one more pessimistic in their assessments. These assessments tended to rely much more on observations and perceptions than on any formal evaluations. The tourism and visitors expert characterized the streetcar as playing a positive role as an “amenity” of the city and as an attraction itself for visitors because of the “sense of nostalgia” associated with streetcars. He also pointed to economic development that had occurred in the downtowns since the streetcar began operations, although he conceded that it was hard to know if the streetcar was responsible for the development activity. His comments pointed toward the Clinton Presidential Library as a driving factor for development activity in the downtowns more than the streetcar. Nevertheless, his overall assessment of the streetcar was largely favorable.

The transit planner focused his assessment both on the streetcar’s economic development effects and its performance as a tourism and visitorship promotion method. With respect to economic development outcomes, he pointed to its “outstanding development effects,” as documented in the local study by CATA that found about $1 billion in development activity within ¼ mile of the streetcar line (Central Arkansas Transit Authority 2012). Although he conceded that other factors undoubtedly also were important, he still viewed the streetcar as a critical “catalyst” for development.

With respect to the tourism and visitorship goals, the transit planner interviewee thought the streetcar had been very successful in this regard as well. As evidence, he pointed to the streetcar’s strongest ridership months (April and May) being tied to visitors and tourists; the streetcar patronage has a strongly seasonal pattern and is closely tied to major visitor-focused events, including conventions, fairs, school events, and other major public gatherings. He also noted the streetcar’s role as an icon of the city that is featured prominently in media coverage of the community.

The regional planner agreed that the streetcar had been embraced as an icon of the city, but he also noted frustrations with the streetcar’s performance, including the service’s underutilization as a streetcar service as well as one that served the larger community. He expressed frustration with local decisions that undercut the streetcar’s ability to attract visitor riders, such as the City of Little Rock’s decision to suspend service for “safety” reasons during major public events. The transit planner thought these decisions often were made to increase the supply of on-street parking.

Finally, the regional planner expressed frustrations with the process of trying to move the streetcar beyond the visitor-serving market. He noted that CATA and the metropolitan planning organization have studied extending the streetcar alignment into neighborhoods both north and south of the current alignment, as well as to the airport. He believes the extensions would increase the ridership for the service, but he noted that efforts to pursue funding to permit these extensions to go forward have been unsuccessful. He pointed to CATA’s two failed efforts to get a local sales tax passed to support local transit investments and felt that CATA leadership had failed to articulate a vision for how the tax revenue would be used to supplement what they are able to do with their regular, locally-appropriated revenue sources. Nevertheless, he also recognized that CATA has its
hands full in simply upgrading and maintaining a long-neglected bus system. The most positive assessment he offered was simply that the streetcar had been built.

Streetcar Non-Transportation Goals in Tampa

Several Tampa interviewees stated that the TECO Line streetcar originated as the proposed “first leg” of a larger LRT system, but they also noted that it soon evolved into a redevelopment and tourism-focused service of much shorter length. According to one business community interviewee, however, the shift in purpose from transit to tourism/development is not yet completely settled as “groups [in charge of streetcar planning/operations/finance] are still trying to identify and concur on the main goals for the streetcar; they are not clear and the groups don’t understand each other on that aspect; ... some people are still debating if the streetcar should be transit or a cultural piece, or both.” This conflict has important consequences for decisionmaking about streetcar planning and operations, given the very different needs and concerns of visitors versus traditional transit riders.

Despite some uncertainty about the streetcar’s primary purpose, the interviews indicated that urban redevelopment and tourism historically have driven most decisions made around the streetcar. An economic development interviewee observed that the notion that “urban redevelopment follows transit investment” has been one of the guiding principles of streetcar implementation in Tampa. This idea was based on his understanding of Portland’s experience with streetcar implementation and the adjacent development activity that some observers have attributed to the streetcar lines in that city. He believes the Portland experience is replicable in other cities, including Tampa.

Several others pointed to significant development activity along the alignment during the period immediately preceding and shortly after the line’s opening, estimated to total about $1 billion by one individual. However, most interviewees’ overall assessments pointed to a lack of significant development results to date in Tampa’s Channelside district. Their assessments pointed particularly to a significant decline in economic activity, including new development, along the alignment since the recession of 2008.

Several interviewees emphasized the role of the streetcar in serving tourists and in providing an identity for Tampa. Many noted that the streetcar has now become a visible image, or icon, of the city. One noted that the streetcar had been featured during national television coverage of major events such as the Super Bowl, while another noted that local residents have embraced the streetcar as a city icon. Whether the idea of creating an icon was in the minds of early streetcar promoters or not, its role as one today is widely perceived among those interviewed for the study. One person even characterized the streetcar as being “transportainment.” Clearly, a utilitarian transportation role is not the key role played by the service.

Interviewee Assessment of Non-Transportation Goal Attainment in Tampa

Many interviewees believe that streetcar implementation in Tampa played a role in encouraging residential and commercial development in the Channelside district and that it has benefited businesses in Ybor City, yet they also recognize that its influence is partial and complementary to other development factors, such as a developer’s overall
economic assessment, building regulations, and local zoning. Special subsides or incentives for promoting development were not used in Tampa, although one interviewee noted that at least one hotel located in the area served by the streetcar did expect the streetcar to be present as a condition for development. Others also pointed to their perception that the streetcar had been a positive amenity in attracting hotel, restaurant, residential, and other developments to the area. It is important to emphasize that all of these assessments derived from observations or perceptions rather than detailed, systematic assessments.

One recurring theme among multiple interviews was the emergence of the streetcar as an icon of the city of Tampa and particularly the Ybor City area. The interviewees noted that the streetcar is featured frequently in news reports and marketing materials prepared for a diversity of purposes. Some perceived this as a positive consequence that contributes to the city’s image, has a beneficial effect on Tampa’s culture, and possibly encourages visitorship and commercial activity in Ybor City. Another noted that such publicity is “free marketing” that should help encourage streetcar use.

The interviewees also emphasized the role of the economic recession, which had a significant negative impact on Tampa’s cruise industry, number of conventions, and commercial activity along the Channelside district. Given Tampa’s tourist-oriented service characteristics (i.e., alignment, replica historic vehicles, operating hours, and headways), it also was expected that ridership would decline along with diminished tourism activities. This pattern suggests a greater vulnerability for tourism-oriented streetcar systems to larger-scale economic conditions as compared to streetcar systems that cater to a more diversified ridership market.

**Streetcar Transportation Performance**

The authors assessed the transportation performance of the two streetcars by considering ridership, service productivity, cost effectiveness, and other standard performance indicators. They focused on 2012 as the primary year of analysis, but also considered performance trends for certain key indicators over the period from 2005, the first full year in which both streetcars were in operation, until 2012, the most recent year for which data were available at the time of the study.

Table 2 shows the annual ridership and service data for streetcar in both cities from 2005 to 2012 for which data were available from the National Transit Database (accessed via FDOT 2013). Ridership is reported both for unlinked passenger trips, or boardings, and passenger miles; service is reported as service hours and service miles. In 2012, annual ridership in Tampa was nearly three times that of Little Rock. Service hours were virtually identical, and service miles were somewhat higher in Tampa due to slightly higher average streetcar operating speeds (5.4 miles per hour in Tampa vs. 4.4 miles per hour in Little Rock). There are higher levels of population and employment in the immediate vicinity of Tampa’s streetcar than in Little Rock (see Table 3), which might explain some of the differences in ridership levels.
## TABLE 2.
Annual Ridership and Service for Streetcar in Little Rock and Tampa (2005–2012)

<table>
<thead>
<tr>
<th>Year</th>
<th>Unlinked Passenger Trips (UPT)</th>
<th>Vehicle Revenue Hours (RH)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Little Rock</td>
<td>Tampa</td>
</tr>
<tr>
<td>2005</td>
<td>154,745</td>
<td>422,536</td>
</tr>
<tr>
<td>2006</td>
<td>154,432</td>
<td>406,393</td>
</tr>
<tr>
<td>2007</td>
<td>154,644</td>
<td>431,701</td>
</tr>
<tr>
<td>2008</td>
<td>134,204</td>
<td>439,555</td>
</tr>
<tr>
<td>2009</td>
<td>119,758</td>
<td>446,743</td>
</tr>
<tr>
<td>2010</td>
<td>107,088</td>
<td>399,637</td>
</tr>
<tr>
<td>2011</td>
<td>136,380</td>
<td>358,737</td>
</tr>
<tr>
<td>2012</td>
<td>104,868</td>
<td>301,516</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Year</th>
<th>Passenger Miles (PM)</th>
<th>Vehicle Revenue Miles (VRM)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2005</td>
<td>249,060</td>
<td>919,513</td>
</tr>
<tr>
<td>2006</td>
<td>248,950</td>
<td>838,421</td>
</tr>
<tr>
<td>2007</td>
<td>249,052</td>
<td>862,224</td>
</tr>
<tr>
<td>2008</td>
<td>206,572</td>
<td>728,890</td>
</tr>
<tr>
<td>2009</td>
<td>183,751</td>
<td>776,734</td>
</tr>
<tr>
<td>2010</td>
<td>165,718</td>
<td>789,244</td>
</tr>
<tr>
<td>2011</td>
<td>240,083</td>
<td>685,934</td>
</tr>
<tr>
<td>2012</td>
<td>162,616</td>
<td>523,031</td>
</tr>
</tbody>
</table>

Between 2005 and 2012, streetcar ridership in both cities fell between 30 and 40 percent. Streetcar service levels increased by about 50 percent in Little Rock and declined by about 20 percent in Tampa. In Tampa, part of the decline in streetcar ridership is no doubt attributable to the decline in service, although this is clearly not the case for Little Rock. The decline in streetcar ridership in both cities stands in stark contrast to bus ridership trends over the same time period. In Little Rock, bus ridership increased about one-third between 2005 and 2012, and bus service increased by only about 3 percent. In Tampa, bus ridership increased about 40 percent between 2005 and 2012, as bus service increased by about 10 percent (FDOT 2013).
Streetcar ridership in both cities is highly seasonal (see Figure 5). This stands in stark contrast with streetcar service, bus ridership, and bus service levels, none of which exhibit seasonal patterns (Federal Transit Administration 2013). The seasonality of streetcar ridership can be seen clearly in the monthly ridership data presented in the figure. Little Rock’s busiest ridership months are between March and July; ridership in the busiest month (May) is more than three times that of several other months of the year, thus indicating the strong visitor orientation of the service. Tampa’s busiest months are from December through April; ridership peaks in March, when it reaches levels about twice that of the lowest ridership months (August and September). Tampa’s busiest riding months correspond with the peak of the tourism season in the city. In 2012, average weekday streetcar ridership was about 400 boardings per day in Little Rock and 880 boardings per day in Tampa (HART 2012).

In recent years, both cities experienced deteriorating streetcar service performance. Between 2005 and 2012, service productivity (passenger kilometers per vehicle kilometer) declined 56 percent in Little Rock (from 6.73 to 2.97) and 30 percent in Tampa (from 10.98 to 7.74) (FDOT 2013). Operating expense per passenger trip increased significantly over the same time period in Little Rock (131% increase from $4.16 to $9.61 per trip, in 2012 dollars) and in Tampa (21% increase from $4.94 to $5.89 per trip, in 2012 dollars) (FDOT 2013).

Streetcar service has become less productive and less cost effective in both cities. In 2012, streetcar service productivity was below that of the average bus route in both cities (2.97 vs. 6.84 in Little Rock; 7.74 vs. 9.76 in Tampa); streetcar operating costs per passenger trip exceeded those for bus in both cities ($9.61 vs. $4.45 in Little Rock; $5.89 vs. $3.84 in Tampa) (FDOT 2013). In 2012, Little Rock and Tampa ranked last and next to last, respectively, among the modern-era streetcar cities on ridership and cost effectiveness,
and ranked among the bottom three streetcar cities in service productivity (see Table 3) (FDOT 2013; Ramos et al. 2014). The streetcars in these two cities are poor transit performers.

The authors assessed the two cities against three streetcar peers (Portland, Memphis, and Seattle) on several different factors that the transit literature has linked to ridership (see Table 3) (FDOT 2013; Ramos et al. 2014). On each factor, cities receive a higher score for better performance and a lower score for worse performance. The totals for all scores are shown at the bottom of Table 3. Not surprisingly perhaps, Little Rock and Tampa fares the worst when assessed over the entire set of factors; they are particularly noteworthy for the low population and employment levels in the areas near the streetcar lines, the low number of connections at streetcar stops to other transit services, and the relatively infrequent service and short hours of service. By contrast, Portland emerges as the standout performer on this assessment; it is also known for its high ridership and productive service among modern-era streetcar cities (Ramos et al. 2014).

In short, the Little Rock and Tampa streetcars do not appear to be located in areas with strong transit riding potential, and planners have not made decisions in a way that maximizes the streetcars’ utility for serving transit riders by making the service easy and convenient to use. This makes the streetcars even more dependent on visitors and tourists and on the generation of economic development to generate potential ridership. The ridership data clearly indicate that they have not been particularly successful in doing so to date, and the lack of any careful assessment or documentation of economic development or tourism promotion effects also raises serious questions about their actual performance in those areas.

**Discussion and Lessons**

Little Rock’s River Rail and Tampa’s TECO Line streetcars stand out as being among the poorest transportation performers among the modern-era U.S. streetcar cities and pale in comparison to Portland, whose streetcar lines carried about 12,000 riders per day during the same time that Little Rock and Tampa carried 400 and 880 riders per day, respectively. The two streetcars have much lower service productivity and offer much less cost-effective service than the average local bus in their communities. Some of these poor transportation results are due to external factors, including the health of the local economy, but conscious policy decisions have played a role as well, particularly the selection of alignment length and location and the decision (either explicitly or implicitly) to focus on serving tourist riders as opposed to a wider array of transit riders. Because this particular rider market is more sensitive to the overall health of the economy, tourism-oriented modern-era streetcars are more vulnerable to economic downturns and ridership decline, and this has occurred in both cities.

Although the key informant interviews emphasized the streetcars’ use as tools to serve tourism promotion and economic development, as opposed to their utility as transit services, their performance in these areas is not strongly supported by technical studies. Save for a single study commissioned by CATA that relied on a very simple GIS analysis of economic development activity around the River Rail lines, anecdotal observations and
individuals perceptions are all that can be found in support of the purported economic development effects associated with the streetcar investments. Still, available data do indicate that they are carrying some tourists, at least in part due to their roles as local amenities or novelty attractions that are being promoted as part of the city’s image; it is unlikely that bus transit could play such a role for this rider market. However, these tourist riders are being carried at a fairly high cost per ride and after making significant capital investment in the streetcar. Thus, the net benefit of the investment is an open question that would benefit from more careful analysis (Brown et al. 2014).

What should other cities take away from the experiences of these two cities? First, the authors suggest that streetcars need to carry riders to deliver benefits to the community, whether in the form of economic development, tourism promotion, or transportation service. The streetcars in Tampa and Little Rock carry few riders, and the ridership trends are in a declining direction. Policy and planning decisions should work toward making transit service more attractive to riders through the provision of convenient schedules and attractive fares. If the focus is on the visitor rider market, using the streetcar as a key transportation piece of events catering to visitors would seem a logical strategy, and one not always followed in Little Rock in particular. If the focus is on serving a broader array of riders, paying attention to connections to other transit services and implementing attractive transfer policies to encourage rider use of connecting services; neither of these objectives appear to be priorities in these two cities. On the other hand, planners in Portland have paid attention to these concerns by providing the frequent service and network connections that transit riders value and that planners in Little Rock and Tampa have ignored (Brown et al. 2014).

Second, decisionmakers should understand the uniqueness of their community and not simply assume that the experiences of other communities can be easily replicated. Decisionmakers in Little Rock and Tampa were inspired by the example of Portland and thought they could easily replicate what they saw as the outcomes of Portland’s investment in streetcar services. They did so despite really understanding that Portland’s experience was the result of a combination of factors, of which the presence of a streetcar line was merely one. Little Rock and Tampa lacked many of the other attributes that Portland possesses that encourage greater transit ridership by residents of that community, such as higher densities of population and employment, a strong local real estate market, a history of coordinating land use and transportation policies, and a transit system known for operating frequent, well-coordinated, convenient services. The decisionmakers in Tampa simply saw the economic development activity and attractive mixed-use urban environments around the Portland streetcar line and assumed that building their own streetcars would lead to the same results.

This has not been the case. In Little Rock, it appears that recent investments near the streetcar alignment can be attributed to several factors. As mentioned by one of the interviewees, the opening of the Clinton Library and the Farmer’s Market have exerted influence on recent developments downtown, with the streetcar serving as an additional amenity (Brown et al. 2014).
Planners and policymakers in other cities should think very carefully before making similar decisions for their communities, as this cautionary tale could also apply to other capital-intensive transit projects currently undergoing planning or implementation efforts. Transit investments can serve multiple transportation and non-transportation objectives, yet the authors suggest that their achievement depends primarily on their ability to move people conveniently from where they are to where they wish to be. For this to happen, planners and decisionmakers need to pay attention to streetcar transit service, connectivity to other transit systems in the region, regional economy trends, real estate trends, land-use characteristics, and development incentives. These need to be considered in the early planning stages and in ongoing streetcar operation decisions while catering to a wider set of users beyond tourists and visitors.

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An Adaptive Long-Term Bus Arrival Time Prediction Model with Cyclic Variations

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Abstract

Real-time bus arrival information systems at transit stops can be useful to passengers for efficient trip planning and reducing waiting times. The accuracy of such systems depends upon the ability of the model to account for variations in the data series and to adjust according to changing traffic conditions. Many of the existing studies on passenger information systems have modeled the system based on stationary relations, not taking into account the cyclic variations in data, which is often suitable for demonstration purposes but not for long-term implementation. The present study models the changing relationships using Double-Seasonal Holt-Winter’s Exponential Smoothing approach, which allows for self-updating parameters at four levels. It accounts for both long-term and short-term seasonal fluctuations in data while maintaining the dynamic treatment of real-time bus information. The model also takes into account delays using the real-time running information of the bus and incorporates it into subsequent forecasts for better accuracy. Real-time data from GPS transmitters in buses were used for validation of the proposed model. The results show that the proposed model performs better than the currently-used elementary field methods and is able to forecast bus travel times with a reasonable accuracy.

Introduction

Traffic congestion is a problem that affects transportation networks in many major cities in terms of reduced mobility and system reliability. In practice, particularly in transit-oriented cities, passengers often are faced with a choice between different modes of transport—for instance, buses and metro rail in Delhi. Bus systems often suffer a disadvantage, as rail and other transportation networks often have fixed schedules that are fairly accurate.

In densely-populated cities (e.g., Mumbai, Delhi, and Kolkata), with heavy passenger demands, real-time Passenger Information System (PIS) on arrival times of buses can be
very helpful to the commuters. This can prove to be useful, particularly at major bus stops with large numbers of transfer passengers to other modes (rail, BRT etc.). The availability of real-time transit arrival information can help in efficient trip planning and making smart choices for travel. Further, real-time information can attract potential transit users to the system due to the inherent advantages of the system.

In recent times, advances in the field of Information and Communication Technologies (ICT) have opened up new avenues for integrating real-time information in passenger information systems. Recently, transit agencies also have started implementing ICT-related technologies in their operations to help in improving operational efficiency and the quality of information (Yu 2011).

Such advanced systems are lacking in most Indian cities, and the few that have been implemented are very elementary in nature and have focused largely on technology demonstration. However, the reliability of such systems greatly depends on the ability of the system to account for different variations in the data series and to adjust to dynamic traffic conditions. Hence, there is an urgent need to develop a robust real-time bus arrival time prediction model that can be applied under dynamic Indian conditions (Vanjakshi et al. 2009; Ramakrishna et al. 2006; Padmanaban 2010)

Literature Review

In the recent past, various sophisticated techniques and algorithms have been employed to forecast bus travel time or arrival time by using Global Positioning Systems (GPS) or bus triangulation data. These may be categorized as elementary (non-recursive) or advanced (recursive algorithms) based on the way they process the input data.

Elementary Algorithms

A variety of elementary approaches have been applied in the past studies to forecast travel times. Some of these include:

- Simple averages
- Linear regression
- Non-parametric regression (Zhang and Rice 2003)
- k-Nearest Neighbor (k-NN) (You and Kim 2000; Smith et al. 2002; Chang et al. 2010; Park et al. 2007; Baker and Nied, 2013)

These elementary algorithms process the whole data set after every new observation and often are computationally inefficient in practical applications.

Advanced Algorithms

Moving Averages Models

This model assumes that the forecast for period \( i + 1 \) is the average of observations in the previous \( n \) periods.

\[
F_{i+1} = \sum_{k=i-n}^{i} \frac{T_k}{n}
\]  

(1)
The value of \( n \) is chosen based on the nature of the data series. For a relatively stationary data series, a large value of \( n \) is desirable. For a data series which is volatile, a small value of \( n \) is chosen.

**Kalman Filter**

Kalman filter is an efficient recursive procedure that estimates the future states of dependent variables using a linear quadratic estimation model. It uses modern control theory to apply state space representations in the prediction scheme. Several studies have been carried out in the past using the Kalman Filter for bus travel time predictions using three components—a track, a filter, and a predictor (Chien and Kuchipudi 2003; Shalaby and Farhan 2004; Cathey and Dailey 2003; Son et al., 2004).

The predictor–corrector form of the Kalman filter that is used to calculate the filtered estimate is as follows:

\[
\hat{x}_{ij}(k|k) = \hat{x}_{ij}(k|k-1) + K_{ij}(k)\hat{y}_{ij}(k|k-1)
\]

Where for the dynamic model \( \hat{y}_{ij}(k|k-1) \) is the measurement residual and is defined as:

\[
\hat{y}_{ij}(k|k-1) = y_{ij}(k) - \hat{x}_{ij}(k|k-1)
\]

\( K_{ij}(k) \) is the Kalman gain of arc \((i,j)\) at time \( k \), which is specified by the following set of equations where \( r_{ij}(k) \) is the measurement error in the system:

\[
K_{ij}(k) = \frac{cov\left(x_{ij}(k),\hat{y}_{ij}(k|k-1)\right)}{var\left(\hat{y}_{ij}(k|k-1)\right)} = \frac{var\left(\hat{x}_{ij}(k|k-1)\right)}{var\left(\hat{y}_{ij}(k|k-1)\right) + r_{ij}^2(k)}
\]

**Support Vector Machine Models (SVM)**

SVM is a learning algorithm that maps the input-output relationship in a non-linear system using statistical learning theory. In addition, SVM solves the model as a quadratic programming problem with linear constraints, thus always giving a unique and globally optimal solution. Therefore, SVM shows a high general performance by resisting the over-fitting problem (Richman and Parks 1998; Cristianini and Shawe-Taylor 2000; Vapnik 1999, 2000; Bin et al. 2006; Yu et al. 2010).

**Exponential Smoothing (ES) Models**

Simple exponential smoothing (SES) models are infinite order weighted averages and are used to predict the future state recursively based on the following relations:

\[
s_0 = x_0
\]

\[
s_t = \alpha x_t + (1-\alpha)s_{t-1}
\]

Where \( \alpha \) is the weight assigned to the most recent observation and a weight \((1-\alpha)\) assigned to combined past observations. This factor is chosen to achieve the best fit among the actual and the forecasted values. As a rule of thumb, if the data series is relatively stable, then a small value of the weight is used; a large value is used if the data series is volatile.

Although a very powerful prediction tool, SES models are based on the premise that the level of time series should fluctuate about a constant or change little over time. Li et
al. (2008) used an Adaptive Simple Exponential Model (ASES) that could detect bias in forecasts and give an indication to re-calibrate the parameters. An ASES model was developed for highway travel time prediction using Kalman Filter to update the parameter weights (Liu et al. 2012). Also, various models have been developed to incorporate multiple factors into the forecasts. Holt-Winter’s ES model uses three smoothing factors to forecast a time series with a linear time trend and single order cyclic variations. A double seasonal Holt-Winter’s method was also used to predict short-term electricity demand (Miranda et al. 2006). This method is discussed further in subsequent sections.

Artificial Neural Network (Effects across Space)
An ANN model is used to find solutions for complex non-linear models by stimulating the intelligent capabilities of human brain. It tries to model the interaction between neurons and the connections by assigning weights. Using this interconnected link approach, it is able to model complex relationships and find patterns in the data series. Its implementation comprises two phases: the learning phase used to train the model and assign weights, and the recalling phase used to apply the weights assigned in the learning phase. Several studies in the past have employed the link-based to the stop-based ANN model to forecast bus arrival time (Chien et al. 2002; Chen et al. 2004; Jeong and Rilett 2004). Mazloumi et al. (2009) developed two models based on travel time data obtained from GPS traces of buses and traffic signal saturation flow data to predict the bus travel time using ANNs.

Shortcomings of Current Models
Many studies have been carried out on forecasting bus travel/arrival time for a single bus route. Most of the previous studies used some factors related to road traffic (e.g., traffic speed and volume) for modeling the system. However, very few studies accounted for cyclic fluctuations in data. Traffic data are influenced by several factors such as time of day and day of the week and might show an upward trending pattern in the long run. The arrival time prediction model can be improved by integrating these inputs into an adaptive prediction scheme. Also, most of the studies have broken down the travel route into different segments and then treated these as independent for the purpose of prediction. However, correlation among different segments can provide useful insights about the congestion state of the route and can be useful to improve prediction accuracy as bus progresses along the route.

Moreover, none of the studies have accounted for the changing nature of the traffic characteristics in both the short and long run. In the long run, the average traffic is expected to grow, resulting in an overall increase in travel time; in the short run, the dependence/interaction of traffic streams across different periods may change according to time. The current models, once initialized and validated, assume functions that are stationary and do not change with time. Although these can successfully model and forecast travel times in the short run for research/demonstration purposes, the need for a more stable adaptive system for successful field implementation is evident.

\[1\] Long-term data cover all cyclic fluctuations—for instance, a week if only the daily fluctuations are being modeled or a year if seasonal fluctuations are being modeled. Short-term data are a subset of long-term data, which are insufficient to capture the entire cycle of fluctuations.
Objective and Scope

The focus of this study was to improve forecasting in uncertain and dynamic environments by developing techniques that can be easily implemented in real time using robust and reliable methodologies. The study aims to achieve the following objectives:

- To arrive at a reasonable travel time estimate based on the real-time running information of the bus taking into account variations in traffic conditions on different times of the day and on different days of the week.
- To develop a computationally-efficient model that can perform the above tasks and also update (correct) itself automatically to adjust to changing traffic conditions.
- To implement and test the model on data from an existing route.
- To evaluate the performance of the proposed model with respect to the actual observed travel times and with other existing forecasting algorithms in use.

Data Collection

The route chosen for this study was Delhi Transport Corporation (DTC) bus Route 78 in New Delhi, India. This is one of the important routes in the city, with a length of approximately 20 km and a travel time of 40–60 minutes. The route comprises 15 bus stops connecting Azadpur Bus Terminal to Inderpur via Wazirpur, Punjabi Bagh, and Naraina, all of which are important and relatively crowded bus stops. Table 1 shows the details of the bus stops along with their relative distances from the starting bus stop.

<table>
<thead>
<tr>
<th>Stop No.</th>
<th>Stop Name</th>
<th>Distance between Stops (km)</th>
<th>Cumulative Distance (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Azadpur Terminal</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>2</td>
<td>Shalimar Bagh</td>
<td>1.30</td>
<td>1.30</td>
</tr>
<tr>
<td>3</td>
<td>Ashok Vihar</td>
<td>0.40</td>
<td>1.70</td>
</tr>
<tr>
<td>4</td>
<td>PerambariPul</td>
<td>0.75</td>
<td>2.45</td>
</tr>
<tr>
<td>5</td>
<td>Wazirpur Depot</td>
<td>0.70</td>
<td>3.15</td>
</tr>
<tr>
<td>6</td>
<td>Brittania Factory</td>
<td>1.70</td>
<td>4.85</td>
</tr>
<tr>
<td>7</td>
<td>Punjabi Bagh</td>
<td>3.80</td>
<td>8.65</td>
</tr>
<tr>
<td>8</td>
<td>Rampura</td>
<td>2.20</td>
<td>10.85</td>
</tr>
<tr>
<td>9</td>
<td>Zakhira</td>
<td>1.20</td>
<td>12.05</td>
</tr>
<tr>
<td>10</td>
<td>Swatantra Mills</td>
<td>0.24</td>
<td>12.29</td>
</tr>
<tr>
<td>11</td>
<td>Moti Nagar</td>
<td>2.60</td>
<td>14.89</td>
</tr>
<tr>
<td>12</td>
<td>Sp. Depot</td>
<td>1.80</td>
<td>16.69</td>
</tr>
<tr>
<td>13</td>
<td>Naraina Depot</td>
<td>0.85</td>
<td>17.54</td>
</tr>
<tr>
<td>14</td>
<td>Loha Mandi</td>
<td>1.00</td>
<td>18.54</td>
</tr>
<tr>
<td>15</td>
<td>Inderpurji Colony</td>
<td>0.60</td>
<td>19.14</td>
</tr>
</tbody>
</table>

For the present study, GPS data were provided by Delhi Integrated Multimodal Transit System (DIMTS), which was recorded by GPS units placed in the buses along the given route. A total of 30 days’ data were available for the study (January 1–31, 2013). The GPS
unit was inbuilt with a general packet radio service (GPRS) modem, which sent the location details to the remote server at a time interval of 10 seconds. The same objective also has been achieved using a GPS-enabled smart phone application (Biagioni et al. 2010). Zhou et al. (2014) demonstrated the use of crowd-sourced smart phones for collecting data and helped predict the expected arrival times of buses. This method seems interesting, given the fact that it is based on commuter participation.

**Methodology**

Forecasting travel time is a complex method. In this study, the process was divided into the following steps:

- **Step 1** – Break down the route into smaller segments, usually between two bus stops. These smaller segments are subsequently treated as independent units.

- **Step 2** (*variations across time*) – Forecast travel time (or speed, etc.) for each segment using an appropriate forecasting algorithm (Holt-Winter’s Exponential Smoothing in the present case)

- **Step 3** (*variations across space*) – Combine the travel time estimates from different segments with the spatial state of the route to account for the current traffic conditions.

- **Step 4** – Combine the above with the current status of the bus to predict arrival time.

**Prediction Framework**

**Nature of Traffic Data**

Traffic patterns across the route follow complex patterns depending upon different inputs, which can be difficult to account for. The present study accounted for the following to approximate for the variations in the data series, which can account for long-term variations in the data:

- **Level Component** – constant component of traffic/travel time

- **Linear Time Trend** – linearly increasing slope in traffic demand/travel time

- **Hourly Variations** – depending upon time of day

- **Daily Variations** – depending upon day of week.

Thus, the model recognizes the time-related variations in data series and correspondingly splits the space into corresponding factors while forecasting. In the study, the data series was directly dealt in terms of travel time, which automatically incorporated the variations in the traffic mix and other factors in different states. Traffic conditions were assumed to remain consistent in any given state.

**Forecasting Algorithm**

The study used the Double-Seasonal Holt-Winter’s Exponential Smoothing model to carry out the prediction across segments. It is time series based on self-learning recursive algorithm based on non-linear relations that update its parameters based on real-time
data inputs. It is a relatively new statistical model that, until now, has been tested to forecast highly seasonal fluctuations in time series data. The model allows for the above cyclic variations in the data series, which makes it suitable for the traffic data. Despite being computationally efficient, it is an infinite memory model; each forecast carries information about all of the past information even though the weights follow an exponentially decreasing trend, thus automatically discarding irrelevant informant from distant past.

**Estimate Function**

The algorithm assigns the following form to the estimate function:

\[ D_t = (S_t + G_t) \cdot d_t \cdot h_t + e_t \]  

Where,

- \( D_t \): estimated variable; bus travel time in the current case
- \( S_t \): level component
- \( G_t \): slope/trend component
- \( d_t \): daily seasonal factor
- \( h_t \): hourly seasonal factor
- \( e_t \): random error component

**Linear Model Parameters**

\( S_t \) and \( G_t \) represent the intercept and components of the travel time function. This basically represents the change in traffic conditions over longer periods of time when the travel time is expected to increase due to increase in traffic on the road. In the short run, it represents average travel time across the route after filtering out the corresponding cyclic variations.

**Cyclic Variations**

The model has the linear component superimposed by two multiplicative seasonal factors that take into account the variations in traffic: hourly (\( h_t \)) and daily (\( d_t \)). Correspondingly, the data set has been split into eight two-hour intervals throughout the day and one hourly factor allotted to each period. Similarly, there are seven different daily factors, one for each day of the week.

First, the data are split into their different components and with different information filtered out, which are then combined to arrive at a forecast (see Figure 4). Thus, the model captures variations at four different levels in real time.

**Real-Time Updating of Parameters**

The model follows a two-stage filter-predictor approach to update its parameters:

- **Filter (Stage 1)** – The data from the actual travel time are de-seasonalized, corrected for time trend, and given a weight, \( \alpha \). This is done by using the observed data and the most recent values of all other parameters to arrive at an estimate of the observed value of the parameter. Thus, the filter estimates the vehicle’s dynamic state based on real-time observation.
• **Predictor (Stage 2)** – The previous value of the parameter being updated is assigned a weight \((1 - \alpha)\). Since these past data are a weighted average of all past information, the updated parameter is also a weighted average of all past data points.

The following relationships show how the parameters are updated in real time. Each factor uses its own weight to update itself after every new observation.

<table>
<thead>
<tr>
<th>Level</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Level</strong></td>
<td>( S_t = \alpha \cdot \frac{D_t}{d_{t-n_1} \cdot h_{t-n_2}} + (1 - \alpha) [S_{t-1} + G_{t-1}] )</td>
</tr>
<tr>
<td><strong>Time-Trend</strong></td>
<td>( G_t = \beta [S_t - S_{t-1}] + (1 - \beta) G_{t-1} )</td>
</tr>
<tr>
<td><strong>Hourly</strong></td>
<td>( h_t = \delta \frac{D_t}{S_t \cdot d_t} + (1 - \delta) h_{t-n_2} )</td>
</tr>
<tr>
<td><strong>Forecast</strong></td>
<td>( F_{t+n} = (S_t + n \cdot G_t) \cdot d_{t+n-n_1} \cdot h_{t+n-n_2} )</td>
</tr>
</tbody>
</table>

Where \( n_1 \) and \( n_2 \) represent the number of days in the week and the number of time intervals in the day defined in the model. In the current simulation, \( n_1 = 7 \) and \( n_2 = 8 \).

The weights are chosen depending upon the sensitivity of the data series to changes. Optimal values of these parameters are worked out by minimizing the mean squared errors on the validation data set. Given the current data series, it is intuitive to feel that these parameters should have a low value, as traffic conditions are expected to stay stable during one month observations of the data.

**Initialization of the Model**

Since the model is based on recursive relationships, it needs starting estimates of the parameters. These can be worked out using the following approach:

• A regression was carried out on the first week of data. Seasonality averages out to 1, and the slope and the intercept of the regression gives an initial estimate of the respective components of the demand function. Thus, we obtain starting estimates of \( S_t \) and \( G_t \).

• Divide the observed values by these calculated linear components to get estimate of \( h_t, d_t \).

• To calculate \( d_t \), take average of all the observations for that particular day. The hourly factor averages out to 1, and \( d_t \) remains constant.

\[
d_t = \frac{\sum_{k=n_2 t+1}^{n_2 t+n_1} h_k \cdot d_k}{n_2}
\]
An Adaptive Long-Term Bus Arrival Time Prediction Model with Cyclic Variations

• To calculate \( h_t \), take the average of all observations for that particular period for all days of the week. \( h_t \) remains constant, and daily factor averages out to 1. Thus, we have a starting estimate of \( h_t \).

\[
h_t = \frac{\sum_{k=0}^{n_1-1} h_{n_2 k+t} \cdot d_{n_2 k+t}}{n_2}
\]

With the initial parameter estimates for the first cycle \((t = 0 \text{ to } 52)\) determined as above, the estimates can be recursively updated through time to estimate the system state at any given time.

Computational Efficiency
The relationships used in the proposed model require a fixed number of mathematical operations to be carried out on the most recent observation to update the estimation of the system state, which is independent of the volume of the past data. Also, the model requires only past one cycle of data to be known to update itself, which is independent of the forecasting horizon or the volume of past data available. Once initialized, the model has a time and space complexity of \( \Theta(0) \) and thus is computationally-efficient.

Effects across Space (ANN Approach)
Once the trend, daily, and hourly variations are accounted for in the model, there still exist some residuals in the Holt-Winter’s model that are due to factors not accounted for in the model. Part of this can be explained as the influence of traffic conditions from one segment to another. For instance, if one segment is experiencing abnormally high travel time due to congestion, then it is likely to influence the traffic conditions on the next segment as well (depending upon the nature of traffic flow from one segment to the next) and will lead to higher-than-expected travel time on the next segment. However it must be noted that if there is no significant traffic flow from one segment to another across the bus route, then this correlation might be absent.

Mathematically, after controlling the observed data for the daily and hourly variations, the residuals from the model represent the noise due to correlation effects across space and the interaction of traffic streams across various segments. Taking a hint from the ANN approach, we can improve the quality of our forecast by including correlation effects between the residuals across different segments. Since the mean travel time across different segments varies depending upon the length of the segment, it is a good idea to carry out the above check after controlling for the above factor—that is, taking the residuals as a percentage of the expected travel times.

We define a corresponding Performance Factor \( (P_i) \) for each segment \( i \) at time \( t \) expressing the residual from the model as a fraction of the expected value.

\[
P_{i,t} = \frac{u_{i,t}}{F_{i,t}} = 1 - \frac{d_{i,t}}{F_{i,t}}
\]
Where:

\[ u_{i,t} = \text{residual term from the model} \]
\[ D_{i,t} = \text{observed value} \]
\[ F_{i,t} = \text{forecasted (estimated) value} \]

For each segment, we check for its correlation with the previous segment \( i - 1 \) using the following hypothesis:

\[ P_{i,t} = k \cdot P_{i-1,t} \]  
(7)

Wherever the correlation is significant within the accepted significance level, the effect was considered and captured in the correlation factor \( k \).

**Dwell Time**

Dwell times at a bus stop usually vary from a few seconds to less than a minute, with the average being less than half a minute. Thus, a rigorous time series analysis, as was done in the travel time data, is not required.

The approach that the model uses is to group the travel time into eight two-hour intervals, as done previously. Since the variations are fewer, a simple average of dwell times can be taken for each period to estimate the dwell time at different times of the day.

\[ t_{dwell,i} = \frac{\sum_{k=1}^{n} \frac{d_{i,k}}{n}}{n} \]
(8)

**Performance Measures**

The study uses the following measures to evaluate the forecasts—the mean absolute error (MAE), the mean absolute percentage error (MAPE), and the root mean square error (RMS). The three terms can judge the difference between the observed and the predicted running time in different aspects.

- \[ \text{MAE} = \frac{1}{N} \sum |t_a - t_f| \]
- \[ \text{MAPE} = \frac{1}{N} \sum \frac{|t_a - t_f|}{t_a} \times 100\% \]
- \[ \text{RMSE} = \sqrt{\frac{\sum (t_a - t_f)^2}{N-1}} \]

Where \( t_a \) is the running time of the bus and \( t_f \) is the forecasted (estimated) running time.

**Validation Results**

For the study, one month of GPS data were available for DTC Route 78, as discussed above. The route comprises 15 bus stops. For the study, three stops were omitted—Wazirpur Depot, Punjabi Bagh Depot, and Swatantra Mills—as their GPS coordinates were not clear from Google Maps.

Data extraction was carried out using MATLAB code, which was then put into a spreadsheet file. Holts Winter’s Double Seasonal Model was applied separately to each segment.
The parameters were optimized using the Solver add-in available in Excel using Generalized Reduced Gradient (GRG) method. The processed data matrix then was imported back into Excel, which was then used to arrive at the arrival time estimates for bus. The forecasting functions were developed in this way to use only the past data for predictions.

**Individual Segments**

Table 2 shows the results when the model was applied to different segments across the route along with the minimized error estimates. The linear part of the model estimates the increase in average travel time across the segment due to long-term changes in traffic conditions. Since the observation set has only one month of data, the parameters $\alpha$, $\beta$ are estimated to be zero, as no significant change in average traffic conditions was expected over one month. This implies that the average traffic for the month is constant. The linear parameters are estimated to be non-zero for the first segment. This might be due to permanent change in traffic conditions on the segment owing to construction/other obstructions on the segment. The parameters updating the daily and hourly factors have very low values. This represents the low effect of a single observation on the model definitions and more importance is given to the cumulative past information. This validates our assumption about consistency in traffic condition in the same state.

### TABLE 2.

<table>
<thead>
<tr>
<th>Segment</th>
<th>Start Stop</th>
<th>End Stop</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\lambda$</th>
<th>$\delta$</th>
<th>RMSE (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Azadpur</td>
<td>Shalimar Bagh</td>
<td>0.003</td>
<td>0.125</td>
<td>0.132</td>
<td>0.115</td>
<td>1.003</td>
</tr>
<tr>
<td>2</td>
<td>Shalimar Bagh</td>
<td>Ashok Vihar</td>
<td>0.000</td>
<td>0.000</td>
<td>0.080</td>
<td>0.067</td>
<td>1.871</td>
</tr>
<tr>
<td>3</td>
<td>Ashok Vihar</td>
<td>PreambariPul</td>
<td>0.000</td>
<td>0.000</td>
<td>0.130</td>
<td>0.068</td>
<td>0.476</td>
</tr>
<tr>
<td>4</td>
<td>PreambariPul</td>
<td>Britanna</td>
<td>0.000</td>
<td>0.000</td>
<td>0.059</td>
<td>0.056</td>
<td>1.218</td>
</tr>
<tr>
<td>5</td>
<td>Britanna</td>
<td>Rampura</td>
<td>0.000</td>
<td>0.000</td>
<td>0.201</td>
<td>0.133</td>
<td>1.568</td>
</tr>
<tr>
<td>6</td>
<td>Rampura</td>
<td>Zakhira</td>
<td>0.000</td>
<td>0.000</td>
<td>0.056</td>
<td>0.125</td>
<td>0.651</td>
</tr>
<tr>
<td>7</td>
<td>Zakhira</td>
<td>Moti-Nagar</td>
<td>0.000</td>
<td>0.000</td>
<td>0.146</td>
<td>0.079</td>
<td>1.277</td>
</tr>
<tr>
<td>8</td>
<td>Moti-Nagar</td>
<td>Shadipur Depot</td>
<td>0.000</td>
<td>0.000</td>
<td>0.204</td>
<td>0.061</td>
<td>1.454</td>
</tr>
<tr>
<td>9</td>
<td>Shadipur Depot</td>
<td>Naraina Depot</td>
<td>0.000</td>
<td>0.000</td>
<td>0.082</td>
<td>0.017</td>
<td>1.250</td>
</tr>
<tr>
<td>10</td>
<td>Naraina Depot</td>
<td>LohaMandi</td>
<td>0.000</td>
<td>0.000</td>
<td>0.267</td>
<td>0.000</td>
<td>1.266</td>
</tr>
<tr>
<td>11</td>
<td>LohaMandi</td>
<td>Inderpuri</td>
<td>0.000</td>
<td>0.000</td>
<td>0.300</td>
<td>0.138</td>
<td>1.341</td>
</tr>
</tbody>
</table>

Using the above standard errors, following performance estimates were worked out for the model:

- Std. error for route: 4.22 min
- Average total travel time: 42.8 min
- Average error: 9.8%

Figure 1 shows the typical observation vs. forecast trend for a given segment across time. It can be seen that in the initial periods, the errors were large, as the model was training. However, after multiple inputs, the quality of the forecasts improved with time.

---

2 The GRG Non-Linear method is a popular mathematical approach used to optimize multi-variable problems under multiple constraints and is available as an in-built feature with the Solver add-in.
Dwell Time

Since the observed dwell times were usually small for different segments, it was decided to follow a stationary model superimposed with different seasonal factors for different times of the day. The seasonal factors were calculated by dividing each observation by the overall average of the data series, since we are assuming a stationary data series.

It was found that mean dwell time is less than half a minute for all the bus stops on the route. Thus, a simple model for the stationary series was used to predict the dwell time, as a few seconds' error in the model would not introduce many errors in the forecast.

Correlation Effects

After accounting for trend and seasonality in Holt-Winter's model, the residuals were tested for correlation to study the interaction between different segments. Thus, we defined appropriate performance factor for each observation, which were tested for correlation with the immediate predecessor.

Correspondingly, a regression was carried out and all the correlation factors within the significance level of 20% were accepted. The results are summarized in Table 3.

<table>
<thead>
<tr>
<th>Seg.</th>
<th>Corr</th>
<th>T-Stat</th>
<th>Sig. (%)</th>
<th>Inference</th>
<th>k</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-2</td>
<td>0.18</td>
<td>1.68</td>
<td>9.33</td>
<td>Sig.</td>
<td>0.184</td>
</tr>
<tr>
<td>2-3</td>
<td>0.00</td>
<td>0.02</td>
<td>98.48</td>
<td>Insig.</td>
<td>0.000</td>
</tr>
<tr>
<td>3-4</td>
<td>0.07</td>
<td>0.83</td>
<td>40.89</td>
<td>Insig.</td>
<td>0.000</td>
</tr>
<tr>
<td>4-5</td>
<td>-0.07</td>
<td>-0.89</td>
<td>36.97</td>
<td>Insig.</td>
<td>0.000</td>
</tr>
<tr>
<td>5-6</td>
<td>-0.089</td>
<td>-1.13</td>
<td>25.82</td>
<td>Insig.</td>
<td>0.000</td>
</tr>
<tr>
<td>6-7</td>
<td>0.03</td>
<td>0.62</td>
<td>53.53</td>
<td>Insig.</td>
<td>0.000</td>
</tr>
<tr>
<td>7-8</td>
<td>-0.05</td>
<td>-0.49</td>
<td>62.20</td>
<td>Insig.</td>
<td>0.000</td>
</tr>
<tr>
<td>8-9</td>
<td>0.15</td>
<td>4.74</td>
<td>0.00</td>
<td>Sig.</td>
<td>0.154</td>
</tr>
<tr>
<td>8-10</td>
<td>0.33</td>
<td>3.75</td>
<td>0.02</td>
<td>Sig.</td>
<td>0.329</td>
</tr>
<tr>
<td>10-11</td>
<td>1.03</td>
<td>31.99</td>
<td>0.00</td>
<td>Sig.</td>
<td>1.026</td>
</tr>
</tbody>
</table>

Prediction along the Route

Table 4 shows the cumulative error estimates as the bus travels across the route, and Figure 2 shows the evolution of the total error as the bus travels across the route. It should
be noted that the cumulative error stays below the standard error predicted for the route, and the absolute percentage error also remains largely within the 10% limit.

**TABLE 4.** Cumulative Error Estimates for Route on January 31, 2013, for Journey Starting at 2:15 PM

<table>
<thead>
<tr>
<th>Stop</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dist (km)</td>
<td>1.3</td>
<td>1.7</td>
<td>2.45</td>
<td>4.85</td>
<td>10.85</td>
<td>12.05</td>
<td>14.89</td>
<td>16.69</td>
<td>17.54</td>
<td>18.54</td>
<td>19.14</td>
</tr>
<tr>
<td>Cumm. Error (min)</td>
<td>0.19</td>
<td>0.46</td>
<td>0.29</td>
<td>2.75</td>
<td>1.07</td>
<td>1.38</td>
<td>1.14</td>
<td>0.60</td>
<td>0.68</td>
<td>1.46</td>
<td>1.66</td>
</tr>
<tr>
<td>MAE (min)</td>
<td>0.19</td>
<td>0.43</td>
<td>0.34</td>
<td>0.87</td>
<td>1.46</td>
<td>1.27</td>
<td>1.12</td>
<td>1.05</td>
<td>1.07</td>
<td>1.05</td>
<td>0.97</td>
</tr>
<tr>
<td>MAPE (%)</td>
<td>5.75</td>
<td>7.17</td>
<td>3.37</td>
<td>26.24</td>
<td>6.03</td>
<td>6.69</td>
<td>4.79</td>
<td>2.36</td>
<td>2.41</td>
<td>4.85</td>
<td>5.16</td>
</tr>
<tr>
<td>RMSE (min)</td>
<td>0.19</td>
<td>0.92</td>
<td>0.72</td>
<td>1.08</td>
<td>1.35</td>
<td>1.23</td>
<td>1.14</td>
<td>1.09</td>
<td>1.10</td>
<td>1.08</td>
<td>1.03</td>
</tr>
</tbody>
</table>

**FIGURE 2.** Real-time forecasting across whole route

**Multiple Step Ahead Forecasts**

Table 5 contains the performance measures of the proposed model with the moving averages model (most commonly-used field method). For the moving average, three categories were used: Past Three Periods (MA3), Past One Day (MA8) and Past One Week (MA56; long-term average). Standard performance measures were calculated and compared for different models. To compare different models, Real-time, 5-day ahead, and 10-day ahead forecasts were developed for the bus travel times.

**TABLE 5.** Comparison of Different Algorithms for Multiple Step Ahead Forecasts for January 29, 2013

<table>
<thead>
<tr>
<th>Proposed Model</th>
<th>MA3 (Past 1 Day Data)</th>
<th>MA56 (Past 1 Week Data)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Actual Obs. (min)</td>
<td>Real-Time</td>
<td>5-day</td>
</tr>
<tr>
<td>Forecast (min)</td>
<td>39.88</td>
<td>38.03</td>
</tr>
<tr>
<td>MAE</td>
<td>1.07</td>
<td>0.78</td>
</tr>
<tr>
<td>MAPE</td>
<td>2.75</td>
<td>2.02</td>
</tr>
</tbody>
</table>

The value of 10% on MAPE is the expected value of MAPE in the general case. The value of 26% is for one particular instance of the algorithm in which distortions in travel time could have been caused by unforeseen circumstances on the concerned segment. This is a one-time random error that is associated with that particular instant at that segment.
Figure 3 graphically compares the performance of the two models by plotting the percentage error estimates. It can be seen that the performance of the current algorithm is consistently better than that of the commonly-used methods with significantly fewer errors.

**Different Times of the Day**

Table 6 shows how the model performed at different times of the day. It can be seen in Figure 4 that the errors lie within the range that was predicted and, thus, the model is successfully able to account for variations arising due to different times of the day.

**Implementation**

The predicted travel time obtained from the proposed algorithm can be easily formatted to suit any mode of arrival time information displays such as at bus stops, within bus, or through websites.
The decision of an appropriate display depends on the requirements of the end user. For example, a passenger standing at a bus stop would be interested in knowing about the arrival time of the next bus in a particular route, whereas a passenger traveling on a bus would be interested in knowing about the arrival time of that bus at a specific bus stop. A sample display, which conforms to these requirements, has been generated for the current study and is shown below.

- **At the bus stop:**
  - Current time – 2:04 PM
  - Arrival time bus 78 – 2:13 PM

- **Inside the bus:**
  - Current time – 2:04 PM
  - Estimated time of arrival:
    - Rampura – 2:13 PM
    - Zakhira – 2:17 PM
    - Moti Nagar – 2:21 PM
    - Shadipur Depot – 2:24 PM

Similarly, the results from the model can be incorporated into different forms of inquiry systems and can cater to a wide range of end users through different media.

**Conclusions**

The present study developed a model-based algorithm for real-time automated bus arrival prediction, taking into account the time and space variations involved during travel. The main contributions of this study include automated travel time prediction, explicitly incorporating information about seasonality in the data series (time of day and day of week) and real-time updating using GPS data from the buses, thus making it possible to incorporate the changes in the field in real time. The prediction scheme used the Double Seasonal Holt-Winter’s Exponential Smoothing technique to predict the travel time of buses, which keeps track of real-time parameters at four different levels in the data series and is able to account for time-trend and seasonality in the data series. The proposed model also checked for correlation in the residuals from the model to account for space effects in the data series different segments.

The results show that the proposed model is able to estimate the travel times within an accuracy of approximately 10%, which is better than the traditionally-used elementary moving average models. The incorporation of real-time data and the complete automation make the proposed scheme ready for field implementation. This scheme can be adopted for real-time bus arrival time prediction under Indian conditions for reliable PIS implementation.

**Acknowledgments**

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References


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Measuring Passenger Loyalty to Public Transport Modes

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Yotam Barlach
NTA Metropolitan Mass Transit System Ltd.

Daniel Shefer
Technion – Israel Institute of Technology

Abstract

This paper incorporates insights from relevant consumer behavior research in marketing to travel mode choice by adopting the loyalty model, a decision-making model, to better understand and evaluate passenger attitudes toward public transport modes. This paper describes the loyalty model and demonstrates and validates its use in transportation using a case study of a choice between two modes, rail and bus. Based on factor analysis, two factors from the loyalty model were identified: loyalty, which measures the repeat purchase of the service and the passenger’s attitude toward it; and hedonic commitment, which measures the emotional feeling after using a mode. The full loyalty model was validated for both rail and bus passengers. The research shows that, like other consuming products toward which subjective emotional feelings affect the consumer’s behavior, passenger choice is significantly affected by subjective emotional feelings toward the mode. Additionally, the subjective effect can be measured easily using marketing research techniques.

Introduction

The marketing literature, and modern research on consumer behavior, in particular, includes some well-established theories for dealing with the mechanism of choice among products (see, for example, Oliver 1999; Babin et al. 1994; Anderson and Mittal, 2000; and Dick and Basu 1994). This study adopts the loyalty model from the field of marketing as a measurement tool for better understanding and evaluating passenger attitudes toward public transport (PT). Considering PT modes as a product and passengers as consumers allows us to use this tool when investigating consumer attitudes toward this product. Some researches show that PT level-of-service attributes are evaluated differently for different PT and private vehicle modes, and these also differ between PT and private vehicle users (Wearden et al. 2007). This paper demonstrates the application of the loyalty model
as a transport-service measurement tool and tests its validity toward this end, using a case study of the choice between two PT modes, rail and bus.

**Loyalty Model**

The consumer choice process, according to the marketing literature, is motivated by three types of product values: a utilitarian value, which captures the functionality of the product for the consumer; a switching value, which reflects the technical effort in switching from one product to another; and a hedonic value, which captures the experience of emotion associated with the product in the consumer's mind. The outcome of the model yields the level of satisfaction and the repeated choice of the product; i.e., the consumers' loyalty to the product. Satisfaction is the "consumer fulfillment response ... a judgment that a product or service feature, or the product or service itself, provided a pleasurable level of consumption...", whereas loyalty is a "deeply held commitment to re-buy or re-patronize a preferred product or service consistently in the future" (Oliver 1996, pp. 178, emphasis added). While satisfaction is a short-term judgment of the product, loyalty reflects the consumer's attitude and commitment toward the product in the long term. Levinson (Oliver 1996, pp. 173) divided loyalty creation into four stages:

1. **Cognitive loyalty (knowing)** – the loyalty created after a short experience with the product, based on the level of satisfaction with the product's physical characteristics.
2. **Affective loyalty (attitude)** – the creation of an attitude toward the product after a significant period of experience, including a personal commitment toward the product.
3. **Conative loyalty (intention)** – the creation of intention to re-buy the product and an emotional feeling toward the product.
4. **Action loyalty (re-buy)** – the highest level of loyalty; involves automatic re-purchasing of the product and a blindness to competitors.

Marketing research usually deals with selected links among the loyalty model factors: satisfaction and loyalty (Oliver 1996), utilitarian and hedonic values (Babin et al. 1994), product utility and loyalty level (Oliver 1999) and others.

In classic utility theory, passengers will prefer a PT mode that provides a higher level of service (LOS) in terms of time, cost, and other attributes. Considering a corridor with rail and bus service, this theory holds that if the bus service is significantly improved relative to rail service, passengers will shift from rail to bus. However, investigation of passenger behavior using the loyalty model, which includes the loyalty attitude and the subjective emotional preferences toward PT modes, may show that fewer passengers will switch to bus transport due to their loyalty and emotional attitude toward rail.

**Loyalty Model in Transportation Research**

Although marketing research treats loyalty and satisfaction as outcomes of a decision-making process, these characteristics are rarely used in transportation research as powerful explanatory factors to evaluate passenger attitudes toward PT modes. The transportation research literature, for its part, mostly ignores modern marketing research...
and its measurement tools; passengers are frequently asked directly about their loyalty and satisfaction toward a PT service. The mean results are used as a quality measure for level of service (Morface International and Cambridge Systematics 1999; Hargroup 2004); even when measured indirectly in factor analysis (Tyrinopoulos and Antoniou 2008; Basuki and Kubota 2007), these factors are not used as part of mode-choice modeling.

Loyalty and satisfaction normally are measured in transportation without taking into account the full loyalty process, which includes a deeper investigation of the subjective and emotional effect on consumer choice. Eboli and Mazzulla (2007) investigated passenger satisfaction with PT level of service while ignoring the loyalty factor and other marketing factors that function as measurements of emotional value in marketing research. An attempt also was made to measure a service experience factor, which is related both to affective and cognitive variables (Olsson 2012). An indirect measurement for loyalty and satisfaction was made in Greece (Tyrinopoulos and Antoniou 2008), but without a thorough investigation of the effect of those factors. The effect of LOS variables on loyalty strength was investigated in Taiwan (Wen et al. 2005). However, they did not include a hedonic value or other factors that could measure the emotional effect on mode choice.

**Methodology**

The methodology aims to establish some practical tools that will enable an easy assimilation of the loyalty model from marketing research in transportation. The methodology has two main purposes:

1. Establish measurement tools (scales) for marketing research factors in transportation.
2. Validate the loyalty model in transportation, using a case study of a choice between two PT modes.

This investigation comprised six stages:

1. **Theory** – developing a full loyalty theory as a basis for the research.
2. **Measurement scales** – identifying measurement scales from marketing to measure the factors included in the loyalty model and adopting these scales to the mode-choice problem in transportation.
3. **Level-of-service factors** – identifying some level-of-service factors to be included in the model.
4. **Survey** – creating a database of a representative sample of PT users to measure the factor scales.
5. **Measurement** – measuring the factors using the factor-analysis technique.
6. **Validation** – validating a full loyalty model in transportation using the structural equation model (SEM) technique.

Each of these stages is described in detail in the following subsections.
Theory: The Loyalty Model

Based on the marketing research, we developed a full loyalty model. This model, shown in Figure 1, was synthesized from the various literature reviews presented above (references for each element are shown in the figure).

![Developed customer loyalty theory](image)

This theory assumes that the impressions that arise in the consumer’s mind after using a product affect his/her level of satisfaction with the product, and long-term satisfaction leads to a loyal consumer’s behavioral pattern. The first impression takes into account not only practical utilitarian value, but also emotional-hedonic value.

Measurement Scales

The loyalty model shown in Figure 1 identifies various factors in the loyalty attitude-building process. In marketing research, special attention is given to measurement scales that are used to construct various factors, using the factor-analysis technique. An internal consistency index, $\alpha$, measures the consistency level between the direct questions and the factor value, with a value of 0.8 considered a satisfying value (Harris and Goode 2004).

The current research adopted appropriate scales from marketing theory to measure loyalty model factors in transportation. This was done in two steps:

1. Choosing an appropriate scale from marketing to adopt in this research.
2. Transforming the scales, which were developed for different products, to PT products (rail and bus).

The following factors play a critical role in loyalty theory and also have a well-established scale in marketing research:

- **Loyalty** — there are a large number of measurement scales to measure consumer loyalty strength toward a product. We selected an accepted scale based on Oliver’s four-stage theoretical model of loyalty—cognitive, affective, conative, and action.
loyalty (Morface International and Cambridge Systematics 1999). The scale was validated by a consistency $\alpha$ value of 0.88 (see Table 1).

- **Satisfaction** – a widely-used term in marketing and, as such, has a large number of measurement scales. Continuing with Oliver’s theory (Oliver 1996), which explored the relationship between loyalty and satisfaction, we chose a measurement scale that had been developed by Allen and Mayer (1990) based on Oliver’s theory. It is a validated 5-stage Likert scale composed of 6 questions ($\alpha=0.89$) (see Table 1).

- **Hedonic Value** – has been evaluated by various marketing researchers. A measurement of hedonic value developed by Babin et al. (1994) is frequently cited and accepted as the most common measure (see Mathwich et al. 2001; Ferrell and Beatty 1998). Babin’s scale is a validated 5-stage Likert scale consisting of 12 questions ($\alpha=0.91$) that explore emotional feeling as adventure and escapism, which are generated in the passenger mind when using the PT mode (see Table 1).

- **Utilitarian Value** – based on a scale that was developed by Babin et al. (1994). The questions on this scale explore the extent to which passengers like or dislike the PT service and the time spent inside the vehicle. The original scale is a validated 5-stage Likert scale comprising 5 questions ($\alpha=0.80$).
### TABLE 1. Factors and Variables included in the Research: Bus Passenger Questionnaire

<table>
<thead>
<tr>
<th>Factor</th>
<th>Code</th>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Affective</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>la1</td>
<td>I’m satisfied with the bus service.</td>
</tr>
<tr>
<td></td>
<td>la2</td>
<td>I have a negative attitude toward buses.</td>
</tr>
<tr>
<td><strong>Conative</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>lc1</td>
<td>Bus tickets are very expensive.</td>
</tr>
<tr>
<td><strong>Action</strong></td>
<td>Loyalty</td>
<td></td>
</tr>
<tr>
<td></td>
<td>lp1</td>
<td>Buses will remain my favorite mode choice in the future.</td>
</tr>
<tr>
<td></td>
<td>lp2</td>
<td>I prefer now and will prefer in the future bus service characteristics.</td>
</tr>
<tr>
<td></td>
<td>lp3</td>
<td>I prefer a bus on new bus routes when rail service is also provided.</td>
</tr>
<tr>
<td></td>
<td>lp4</td>
<td>I will always prefer this bus line even when competing rail lines will become available.</td>
</tr>
<tr>
<td><strong>Cognitive</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>lc1</td>
<td>Bus is a better option compared to rail.</td>
</tr>
<tr>
<td></td>
<td>lc2</td>
<td>Bus offers the best value for the money.</td>
</tr>
<tr>
<td></td>
<td>lc3</td>
<td>I prefer bus service compared to rail.</td>
</tr>
<tr>
<td></td>
<td>lc4</td>
<td>I’m satisfied with the bus trip.</td>
</tr>
<tr>
<td><strong>Satisfaction</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>s1</td>
<td>It is a smart decision to travel by bus.</td>
</tr>
<tr>
<td></td>
<td>s2</td>
<td>This bus service didn’t meet my expectations.</td>
</tr>
<tr>
<td></td>
<td>s3</td>
<td>The bus service is well managed.</td>
</tr>
<tr>
<td><strong>Hedonic value</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>ca1</td>
<td>I feel a strong belonging to buses.</td>
</tr>
<tr>
<td></td>
<td>ca2</td>
<td>I will continue to travel by bus, since I am happy to be a bus passenger.</td>
</tr>
<tr>
<td></td>
<td>ca3</td>
<td>I’m in a good mood when traveling by bus.</td>
</tr>
<tr>
<td></td>
<td>ca4</td>
<td>I feel part of the bus user’s family.</td>
</tr>
<tr>
<td></td>
<td>ca5</td>
<td>I have an emotional feeling toward buses.</td>
</tr>
<tr>
<td></td>
<td>vh1</td>
<td>I enjoy traveling by bus.</td>
</tr>
<tr>
<td></td>
<td>vh2</td>
<td>Using buses is a free willing choice, and not a forced necessity.</td>
</tr>
<tr>
<td></td>
<td>vh3</td>
<td>I have an escapism feeling when using buses.</td>
</tr>
<tr>
<td></td>
<td>vh4</td>
<td>I’m updated with timetables and new bus services.</td>
</tr>
<tr>
<td></td>
<td>vh5</td>
<td>I have a feeling of adventure when using buses.</td>
</tr>
<tr>
<td></td>
<td>vh6</td>
<td>I rest during bus trips.</td>
</tr>
<tr>
<td></td>
<td>vh7</td>
<td>It is not really a pleasure to travel by bus.</td>
</tr>
<tr>
<td><strong>Utilitarian value</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>vu1</td>
<td>My travel time is well utilized.</td>
</tr>
<tr>
<td></td>
<td>vu2</td>
<td>I am disappointed with the service.</td>
</tr>
<tr>
<td></td>
<td>vu3</td>
<td>Arriving on time is all that concerns me when traveling by bus.</td>
</tr>
<tr>
<td><strong>Comfort</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>c1</td>
<td>Bus is not overcrowded.</td>
</tr>
<tr>
<td></td>
<td>c2</td>
<td>I’m satisfied with the temperature inside the bus.</td>
</tr>
<tr>
<td></td>
<td>c3</td>
<td>I’m satisfied with the smoothness of the ride.</td>
</tr>
<tr>
<td></td>
<td>c4</td>
<td>The seats are comfortable.</td>
</tr>
<tr>
<td><strong>Convenience</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>co1</td>
<td>Waiting conditions at stops are comfortable.</td>
</tr>
<tr>
<td></td>
<td>co2</td>
<td>I feel safe and protected from threats when using the bus.</td>
</tr>
<tr>
<td></td>
<td>co3</td>
<td>I am secure from accidents when using the bus.</td>
</tr>
<tr>
<td></td>
<td>co4</td>
<td>I feel relaxed when traveling by bus.</td>
</tr>
<tr>
<td></td>
<td>co5</td>
<td>Bus is environmentally friendly.</td>
</tr>
<tr>
<td></td>
<td>co6</td>
<td>There is seat availability inside the bus.</td>
</tr>
<tr>
<td></td>
<td>co7</td>
<td>I’m able to read when traveling by bus.</td>
</tr>
<tr>
<td><strong>Reliability</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>r1</td>
<td>Bus service is as fast as possible.</td>
</tr>
<tr>
<td></td>
<td>r2</td>
<td>I feel confident that the bus will not need to stop for repairs.</td>
</tr>
<tr>
<td></td>
<td>r3</td>
<td>Bus travel time is unaffected by traffic congestion or frequent stops.</td>
</tr>
<tr>
<td></td>
<td>r4</td>
<td>Bus travel time varies by less than 5 minutes from day to day.</td>
</tr>
<tr>
<td></td>
<td>r5</td>
<td>Bus is available in no more than 5 minutes from the time scheduled.</td>
</tr>
<tr>
<td></td>
<td>r6</td>
<td>I’m able to estimate the actual time of arrival at destination.</td>
</tr>
<tr>
<td></td>
<td>r7</td>
<td>Bus travel time performance is not influenced by weather.</td>
</tr>
</tbody>
</table>
Level-of-Service Factors
The literature includes some well-established measuring scales of LOS factors. The Transit Capacity and Quality of Service Manual (TCRP 2013) evaluates the components of each LOS factor in terms of its equivalent in-vehicle travel time. The reports supply objective measures for the different levels of service components such as availability (which includes reliability), comfort, and convenience. A former report includes some measurement scales for different levels of service factors using factor analysis technique (Morface International and Cambridge Systematics 1999). These manuals are the basis for some applicable research being conducted (for example, see Olsson et al. 2012, and Kuppam et al. 1999).

In addition to marketing factors, we explored some perceived LOS factors that are not customarily used in transportation research. These factors explore the passenger’s perceived quality of the PT level of service (Table 1):

- **Comfort** – measures the level of trip comfort for the passenger. The questions explore the perceived physical comfort of bus seats, air conditioning, and crowdedness of the mode. The measurement scale is borrowed from the Morface International and Cambridge Systematics report (1999, Table 8.1).

- **Convenience** – measures the level of convenience of the service felt by the passenger. The questions explore the passenger’s feeling about safety, relaxation, and other convenience issues. The scale is based on research conducted in Washington, DC (Kuppam et al. 1999).

- **Reliability** – measures the level of the trip’s perceived reliability. The scale, originally developed by Prashker (1978), explores the passenger’s view of service reliability (arriving at destination on time, etc.). The scale is a 5-level, 9-question Likert scale ($\alpha=0.85$).

Survey
A survey was conducted among bus and rail passengers along the Haifa–Tel Aviv corridor (100 km apart). TelAviv is the largest metropolitan area in Israel and the business core of the country, and Haifa is the third-largest metropolitan area and features a port, industry, hi-tech centers, and two major research universities. Until two decades ago, this corridor was served mostly by buses. In the past two decades, a parallel rail service was introduced, and it has achieved a large share of the PT passengers in the corridor even though the bus service remained competitive with the rail service and the availability of both modes is similar, including the time of journey, access to stations, and service headway.

The questionnaire comprised three parts:

1. Questions concerning the trip being made: origin, destination, access and egress modes, and purpose.
2. Questions concerning passenger characteristics: age, level of income, number of persons and children in the household, and availability of a vehicle for the specific trip.
3. Questions concerning the passenger’s attitude toward both rail and bus modes.
Respondents were asked to evaluate their attitudes toward each mode through 50 questions (variables) according to the scales developed, which are detailed in Table 1. This evaluation served as the basis for the marketing research and the perceived LOS factors.

In all, 505 respondents completed the questionnaire—286 rail passengers and 219 bus passengers.

**Measuring Marketing Factors with Factor Analysis**

Factor analysis classifies attitudinal variables in such a way as to reduce the number of these variables and detect structural relationships among them while retaining the explanatory power of each manifest attitudinal statement. This process groups the various attitudinal questions into a series of attitudinal factors. The factor analysis for the present study is based on the last part of the questionnaire, which asked passengers about their attitude toward both modes and included two stages:

- **Exploratory factor analysis (EFA)** – a process that explore the survey data to determine the nature of factors accounting for the covariance among variables, without imposing any a priori hypothesis about the number and structure of factors underlying the data.

- **Confirmatory factor analysis (CFA)** – a process in which judgment is applied in regard to the structure and content of the factors, and then the statistical results of these established factors are estimated.

We present here only the confirmatory factor analysis results.

**Validation of the Model using SEM**

The aim of the last part of the study was to test the validity of the loyalty model in transportation, using the Simultaneous Equation Model (SEM) technique (using MX software). SEM is a modeling technique that enables the simultaneous testing of a set of linear equations. Two types of variables are used in the SEM:

- **Manifest variables** – observed variables that are directly measured from the questionnaires and can be classified to two groups: (1) attitudinal variables, which are the ratings that travelers gave to their attitude toward various travel statements, and (2) socioeconomic and demographic variables.

- **Latent variables** – unobserved variables that are not directly measured, but are inferred by the relationships or correlations among manifest variables in the analysis. There were two groups of latent variables in the SEM: (1) marketing factors representing the most important attitudinal and emotional dimensions for traveler behavior and, in our case, also include the perceived level of service factors; and (2) error terms associated with each variable involved in the SEM model.

Using SEM, we were able to examine the structure of the loyalty model and the significance of the relationships among the factors composing it. We examined separately the attitudes of users of each mode toward their chosen mode: bus users toward bus and rail users toward rail.
Results
This section includes an investigation of two main issues:

1. The existence of marketing behavioral phenomena (such as loyalty and satisfaction) in the PT mode-choice process; this was done by identifying such factors in the factor analysis investigation.

2. The validity of the loyalty model in transportation; this was done by examining the full loyalty-model structure (including the factors and the links among them), using SEM.

Descriptive Statistical Results
Table 2 shows mode choice according to certain socio-economic variables and access modes. As can be seen, rail users are wealthier than bus users and have higher levels of income, education, and motorization rate. Rail passengers use their private vehicles more frequently than bus users (either as a driver or as a passenger) as an access mode to the station.

### TABLE 2.
Socio-Economic Variables – Rail and Bus Users

<table>
<thead>
<tr>
<th>Variable</th>
<th>Category</th>
<th>Rail</th>
<th>Bus</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car availability</td>
<td></td>
<td>53%</td>
<td>29%</td>
</tr>
<tr>
<td>Education</td>
<td>&lt; 12 years</td>
<td>34%</td>
<td>47%</td>
</tr>
<tr>
<td></td>
<td>&gt;= 13 years</td>
<td>66%</td>
<td>53%</td>
</tr>
<tr>
<td>Income</td>
<td>Low</td>
<td>56%</td>
<td>69%</td>
</tr>
<tr>
<td></td>
<td>&gt;= Average</td>
<td>44%</td>
<td>31%</td>
</tr>
<tr>
<td>Access mode</td>
<td>Bus</td>
<td>25%</td>
<td>60%</td>
</tr>
<tr>
<td></td>
<td>Private vehicle</td>
<td>48%</td>
<td>17%</td>
</tr>
<tr>
<td></td>
<td>Walk</td>
<td>20%</td>
<td>15%</td>
</tr>
<tr>
<td>Transit-use frequency</td>
<td>&lt;= 1 time per week</td>
<td>41%</td>
<td>26%</td>
</tr>
<tr>
<td></td>
<td>2–3 times per week</td>
<td>32%</td>
<td>32%</td>
</tr>
<tr>
<td></td>
<td>&gt; 3 times per week</td>
<td>27%</td>
<td>41%</td>
</tr>
</tbody>
</table>

Factor Analysis Results
Factor analysis was conducted for bus and rail passengers separately. The inputs for these procedures were the scales described in Table 1. The values, which are shown in Table 3, are the loading values of each variable for each factor. The value ranges from 0 (no correlation between the variable and the factor) to 1 (full correlation between the variable and the factor). The analysis identified two marketing factors and two level-of-service factors that were significant for both rail and bus users. These factors were used in the marketing model that was tested in the structural equation model (SEM) phase described later.

- **Loyalty attitude** – originally, four loyalty factors, representing the four loyalty stages included in Oliver’s theory, were measured (Oliver 1996). Another factor, measuring the passenger level of satisfaction—a satisfaction factor—also was measured. The analysis found the satisfaction factor to be insignificant. It also found no difference in passenger attitudes toward the four stages of loyalty. The loyalty factor, which
was accepted in the factor analysis stage, combines variables representing the four loyalty components. This factor describes the level of loyalty, in terms of both attitude and behavior, of a passenger toward the PT mode; therefore, it was termed the *loyalty attitude*.

- **Hedonic value** – this factor captures the emotional value associated with each mode in the consumer’s mind.

- **Comfort and convenience** – the analysis included two factors that reflect the perceived comfort and convenience of the PT mode. The factor analysis found no difference in passenger attitude toward these two factors. Therefore, the perceived comfort factor combines variables from both factors.

- **Reliability** – this factor measures the perceived reliability of the PT mode.

- **Utilitarian value** – this was found to be insignificant for both rail and bus users.

### TABLE 3.
Factors and Loading Variables: Loading Values in Confirmatory Factor Analysis

<table>
<thead>
<tr>
<th>Factor</th>
<th>Code</th>
<th>Rail</th>
<th>Bus</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Loyalty</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>la1</td>
<td>-</td>
<td>0.62</td>
<td></td>
</tr>
<tr>
<td>lp1</td>
<td>0.64</td>
<td>0.62</td>
<td></td>
</tr>
<tr>
<td>lp2</td>
<td>0.52</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>lp3</td>
<td>-</td>
<td>0.53</td>
<td></td>
</tr>
<tr>
<td>lp4</td>
<td>0.65</td>
<td>0.63</td>
<td></td>
</tr>
<tr>
<td>lc1</td>
<td>0.44</td>
<td>0.54</td>
<td></td>
</tr>
<tr>
<td><strong>Hedonic Value</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ca2</td>
<td>0.91</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>ca3</td>
<td>-</td>
<td>0.62</td>
<td></td>
</tr>
<tr>
<td>ca4</td>
<td>0.99</td>
<td>0.54</td>
<td></td>
</tr>
<tr>
<td>ca5</td>
<td>0.86</td>
<td>0.56</td>
<td></td>
</tr>
<tr>
<td>vh1</td>
<td>0.82</td>
<td>0.59</td>
<td></td>
</tr>
<tr>
<td>vh2</td>
<td>0.99</td>
<td>0.62</td>
<td></td>
</tr>
<tr>
<td>vh3</td>
<td>0.71</td>
<td>0.53</td>
<td></td>
</tr>
<tr>
<td>vh5</td>
<td>0.75</td>
<td>0.63</td>
<td></td>
</tr>
<tr>
<td><strong>Comfort &amp; Convenience</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>c1</td>
<td>-</td>
<td>0.54</td>
<td></td>
</tr>
<tr>
<td>c2</td>
<td>0.52</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>c3</td>
<td>0.53</td>
<td>0.59</td>
<td></td>
</tr>
<tr>
<td>c4</td>
<td>0.57</td>
<td>-</td>
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A summary of the confirmatory factor analysis results is shown in Figure 2.

**FIGURE 2.** Confirmatory factor analysis results

![Factor Analysis Diagram](image)

**SEM: Model Structure and Validity**

The third part of the study aimed at testing the validity of the loyalty model using the SEM technique (MX software). Using this technique enabled us to test the significance of the relationships between the factors composing the model. The factors included in the investigation are those that were found to be significant in the confirmatory factor analysis investigation (see Figure 2). Since the utilitarian value factor was found to be insignificant, but it was important to include some LOS variable in the SEM, we decided to include a time-proportion variable (TIMPOR) that measured the ratio between the time by rail and the time by bus for each origin-destination as the representative variable of the utilitarian value.

We separately examined the passengers’ attitudes toward their chosen mode: bus users toward the bus mode and rail users toward the rail mode. The two models were tested using two statistics (Kuppam et al. 1999):

1. *Root Mean Square Error Approximation* (RMSEA statistic), which measures the extent of the fitness of the model to the data: a value of zero reflects perfect fitness between the data and the model; a value lower than 0.08 is accepted as sufficient to accept the model’s validity (Kuppam et al. 1999).

2. *Comparative Fit Index* (CFI statistic), which measures the extent of improvement of the model compared to a base model that assumes no links between the factors; a value higher than 0.9 is accepted as sufficient to accept the model’s validity (Mathwick et al. 2001).

The full loyalty theory, as shown in Figure 1, could not be investigated in this research, because it was impossible to measure all the factors composing it. The model shown in Figure 3 checks the most important links from loyalty theory that were found significant:

1. Link between utilitarian value (TIMPOR variable) and loyalty – link a
2. Link between other LOS values (reliability & comfort) and loyalty – links b and c
3. Effect of the emotional value (hedonic value factor) on loyalty – link d
4. Link between LOS values (reliability & comfort) and the emotional value (hedonic value factor) – links f and g
5. Internal link of LOS values (reliability and comfort) – link e
These links attempt to explain the generators of the emotional attitude toward a PT mode.

This model is the platform for the bus and rail models that were tested using the RMSEA and CFI statistics.

**FIGURE 3.**
Model structure investigated by SEM technique

**Rail Loyalty Model**
The rail loyalty model, which investigated rail passengers’ attitudes toward the rail mode, is shown in the left side of Figure 4. The loading value and its significance (t-test in parentheses) are written on the arrows representing the links between the factors.

**FIGURE 4.**
Loyalty model link system, rail passengers toward rail mode compared to bus passengers toward bus mode
The rail passengers loyalty model shows that the strong loyalty attitude that exists among rail users is derived from both emotional and utilitarian sources. The emotional source is shown in the link between the hedonic value factor and the loyalty attitude (with a loading value of 0.53). The utilitarian source (time, reliability and comfort) is shown in the links between the time variable and the reliability factor to the loyalty attitude factor (with loading values of -0.59 and 0.55, respectively). The negative value for the time-loading value is a result of the time-definition variable, whereby the higher the value, the slower the rail service is compared to bus for a selected trip. The model also shows the links between utilitarian and emotional factors. The perceived comfort of the service increases the hedonic value factor. The model is validated through the CFI and RMSEA statistics.

**Bus Loyalty Model**

The bus loyalty model, which investigated bus passenger attitudes toward the bus mode, is shown in the right side of Figure 4. The loading value and its significance (t-test in parentheses) are shown on the arrows representing the links between the various factors.

The lower loyalty-attitude value of bus passengers compared to rail passengers can be explained by the absence of a link between the time variable and the reliability factor to the loyalty attitude. The utilitarian source exists only in the link between the comfort factor and the loyalty-attitude factor (loading value of 0.6). The perceived comfort of the service increases the hedonic value factor. The model is validated with the CFI and RMSEA statistics.

**Discussion**

This research explored the loyalty theory from marketing and tested its validity to travel behavior in regard to choosing between two alternative PT modes, bus and rail. The research had two main goals: 1) to show the existence of loyalty and other attitudinal and emotional factors from marketing in transportation, and 2) to validate the loyalty process mechanism in choosing between two alternative PT modes.

**Loyalty Phenomena in Transportation**

Four marketing research phenomena were investigated: utilitarian and emotional values, satisfaction, and loyalty, which are the outcomes of the process. Two factors were identified in the factor analysis investigation:

1. **Loyalty attitude** – the investigation could not differentiate among the four loyalty stages. The joint factor, therefore, includes the four loyalty stages and was termed the loyalty attitude. This factor measures the repeated use of the PT service, as well as passenger attitudes toward it.

2. **Hedonic value** – this factor measures the emotional feeling that is created among passengers as a result of using a PT mode.

Utilitarian value and satisfaction factors were not identified among bus and rail passengers. The main phenomena we were seeking to find among passengers—loyalty and emotional value—were identified in passenger attitudes. The loyalty phenomenon indicates that passengers develop an attitude toward a PT mode that may affect their behavior and the probability of choosing the selected PT mode. The emotional value shows that pas-
Passengers develop a feeling, and not just a consideration of its utilitarian value, that might affect their mode choice.

**Validity of Loyalty Model in Transportation Research**

Of the two factors that were not identified in the factor analysis investigation, the utilitarian value factor was essential for the SEM investigation. In the absence of a marketing scale measurement, we used the level-of-service factors that were measured: perceived comfort and perceived reliability of the PT mode. In addition, a direct variable that calculates the relative travel time between the two modes was used. The objective was to identify the effects of utilitarian and emotional values on passenger loyalty toward a PT mode in the same way that these effects have been found in marketing research (Babin et al. 1994).

The mechanism by which an emotional value is created in a passenger’s feeling after using a PT mode, thereby increasing the loyalty attitude toward this mode, was shown for both rail and bus passengers. We were mainly interested in the link between emotional value and loyalty, a link that shows a similarity to other consumer products; just as subjective emotional feelings affect a consumer’s behavior, a passenger’s choice is significantly affected by subjective emotional feelings toward the mode. This effect was found to be highly significant in both the rail and bus models, with a higher coefficient for the rail model, showing a stronger effect of hedonic value on loyalty for rail users than for bus users.

Governments, local authorities, and PT operators are seeking a measurement tool that will provide them with a deeper and better understanding of passenger attitudes toward a PT service. This research supplies a measurement tool that is:

1. Based on a solid theory that was deeply explored by marketing researchers.
2. Measures not only the current attitude toward the service but also forecasts future attitude and long-term passengers choice.
3. Includes detailed academic-based measurement scales.
4. Is efficient in developing a policy and strategy that are based on a deeper understanding of passenger attitude sources, whether hedonic (emotional) or utilitarian (practical).

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Citizens or Customers?
Transit Agency Approaches to Community Engagement

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Abstract

Aristotle, in his work Politics, expressed his view that a citizen attains his or her fullest humanity by engaging in the work of the government by accepting ownership of the policymaking apparatus of the work of the polis. Such a perspective contrasts with those who consider citizenship to be merely a legal status, unconcerned with the affairs of the public and passive recipients of government services. This research considers what public administrators at mass transit agencies say they do in pursuit of engagement with their communities. The decisions that public administrators in transit agencies make regarding service retrenchment or expansion have deep, profound consequences on poor and vulnerable transit-dependent populations. Such transit administrators exercise a great deal of power over their ridership’s lives since agency decisions have real-world consequences. Therefore, it is a critical research question to examine the methods, techniques, and underlying rationale of transit administrators’ pursuit of community engagement. This research finds that public transportation agency approaches to community engagement can be typified into two broad perspectives of how the agency views individuals in their community: Community as Citizens and Community as Customers.

Introduction

Mass transit in the United States provides many opportunities for community enrichment and development. As a public service and utility, it provides access to quality-of-life issues, including access to healthcare, cultural institutions, education facilities, and employment opportunities. Public transportation also has the potential to alleviate societal ills such as environmental degradation, traffic congestion, the regressive nature of the cost of private vehicle ownership and maintenance, and the physical isolation of the young, older adults, and persons with lower incomes (Lutz 2014). Therefore, public transportation in the United States is an indispensable component of community development and social improvement efforts.
How transit administrators engage their ridership and local communities in the agency’s policy- and decision-making processes varies significantly among agencies. While required by Title VI to undertake some form of community engagement and public participation in agency decisions, how that is defined and operationalized is largely left up to individual agencies. Naturally, therefore, community outreach exists across a broad spectrum. Drawn from interviews with 30 transit administrators across the United States, this research categorizes their community engagement efforts, which will assist the reader in better understanding the extent to which mass transit agencies are actively involved in sustainable community engagement in urban areas.

Citizenship and Community Outreach
The United States’ federalistic system of governing is arguably designed to reflect and create an active, involved citizenry that contributes to the policies governing them (King, Felty, and Susel 1998; Triplett 2013). What King and her coauthors (1998) term “administrative legitimacy” depends wholly on accountability of citizens to respect and adhere to basic values such as transparency and democratic governance; administrative states are legitimate when they are responsive to active citizens. The term “citizen,” as embodied in such a perspective and throughout this article, does not refer to a legal status bestowed upon selected individuals (for example, those born in the United States or who moved here legally); rather, it refers to joining “each other in making decisions where each decider respects the authority of the others, and all join in obeying the decisions ... they have made” (Pocock 1995, 31). Citizenship, also called democratic citizenship, can be seen as engaging in the work of the public, seeking to benefit all rather than a powerful few. De Tocqueville terms this “self-interest properly understood” (1969, 526-627) whereas Denhardt and Denhardt (2011) succinctly describe democratic citizenship as “a way of life that involves a commitment to the community and to its members, a significant level of involvement in public affairs, and an occasional willingness to put one’s own interest below those of the broader society” (47). In this tradition, a citizen is simply an individual actively engaged in the policymaking procedures of public agencies and institutions, and, indeed, can be accomplished by individuals who do not possess traditionally-recognized citizenship documentation.

When the administrative state is gathering citizen feedback from such citizens, democratic theorists assert that public trust in their institutions will rise (Halvorsen 2003; Shipley and Utz 2012); when administrators engage the public in a “dialectical exchange” (Fischer 1993, p. 183) or in bidirectional discourse (Fox and Miller 1995), they are truly reflecting democratic values. This implies that agencies seeking public input must allow that input to guide decision-making; “a history of participation with no visible impact on agency decisions can be worse than no participation at all” (Halvorsen 2003, p. 540).

Participation in this context is ineffective and conflictual, and it happens too late in the process—that is, after the issues have been framed and most decisions have been made. Therefore, rather than cooperating to decide how best to address issues, citizens are reactive and judgmental, often sabotaging administrators’ best efforts. Administrators are territorial and parochial; they resist sharing information and rely on their technical and professional expertise to justify their
role in administrative processes. Citizen participation is more symbolic than real (King et al. 1998, 320; Arnstein 1969).

Therefore, a democratic model of public participation envisions administrators as liaisons between administrative issues and the public, using public feedback to shape responses to public problems (King et al. 1998; Patten 2001) and allowing citizens to, in essence, govern themselves (Box 1999). However, true dialogue is bidirectional (Fox and Miller 1995; O’Connor et al. 2000), and therein lie opportunities for administrators to use information to shape participants’ beliefs regarding challenges and opportunities for the public agency itself (Halvorsen 2003; Triplett 2013). This research presupposes that community involvement in public transportation agency decision-making is a vital component of democratic governance, and this view has been shared, at least partially, by the framers of the 1964 Civil Rights Act and its Title VI stipulations.

Title VI and Community Involvement

Among the Title VI requirements for transportation agencies receiving federal funds are that the public be involved intentionally, that the community’s concerns are taken under advisement by administrators, and that minority populations are included, and even targeted, for agency feedback (FTA 1999). Such community involvement is achieved, at least partially, through stipulations requiring that agencies hold a series of meetings with members of affected communities every time a major route or fare change occurs. Such provisions do not specify the types of meetings required but do necessitate advance notice of the meetings and, to some degree, where the meetings can be held.

What Title VI requirements do not stipulate is the amount of community feedback that is required to identify such changes. For example, ridership or farebox recovery ratios on a route that decline below a certain threshold may automatically be presented by agency staff as a route or corridor in need of restructuring. Reliance on quantitative data, in this case, rather than community input triggers required public meetings, which occur after changes have already been proposed. Thus, it is legally left to the agency to determine what changes—route, fare, or otherwise—to make, so long as affected communities are provided advance notice and opportunities to comment before the changes take effect. In spite of a democratic normative theory of citizen involvement, there is no requirement to allow members of the public to propose service changes or that agencies seek their involvement prior to proposing service changes.

Under Title VI guidelines, agencies are left to a “justifiable” standard to explain the level of community involvement they seek on proposed transit service changes; that is, if they can justify that changes were made to which the community did not object within a specified period of time, then the changes will likely receive Federal Transit Administration (FTA) approval. As one interviewee in this research stated, “Title VI does not rule the day. We’ve got a four-inch thick [interagency] policy manual that we adhere to.” FTA Circular 4702.1A on Title VI compliance states, “Recipients and subrecipients have wide latitude to determine how, when, and how often specific public involvement measures should take place, and what specific measures are most appropriate” (FTA 2007, p. IV-5, emphasis added).
It can be surmised that, short of the requirement that public transportation agencies seek community feedback and that such feedback be justifiably sufficient, transit operators are left with wide latitude to define, engage in, and pursue stakeholder involvement in their services. A wide variety of approaches to community involvement can be evidenced by the different approaches undertaken by agencies in this research, with resounding implications for democratic governance.

Methodology
Qualitative research presents a prime opportunity for analyzing and reconstructing perceptions of public engagement in public transportation decision-making for several reasons. Harding (1987) points out that qualitative research is better-suited for examination of problems such as mobility faced by women, minorities, and those with lower incomes because, like the transit agencies’ outreach methods under scrutiny here, it allows for a deeper analysis of individual thoughts, does not discard outliers, and actively listens to all the voices that contribute. Further, as suggested by Hedges and Duncan (2000), qualitative research is invaluable to public sector research because of the richness of dialogue it can facilitate. The type of dialogue used in semi-structured interviewing, just as in citizen participation, is bi-directional and multi-faceted.

Using semi-structured interviews, this research focuses on what transit administrators say they do in pursuit of citizen engagement in agency decision-making. To answer this research question, 96 public transportation agencies were selected from the Integrated National Transit Database Analysis System at Florida International University. Criteria for inclusion in this study were that the agencies must be in metropolitan areas whose population is between 500,000 (on the assumption that many metropolitan areas smaller than 500,000 people frequently lack the resources necessary to maintain a robust transit system) and 4 million (on the premise that transit operators in very large metropolitan areas may face complicating, multifactorial hindrances beyond the scope of this research). Of the 96 United States transit agencies that meet these criteria, potential participating agencies were randomly selected via an Internet-based random numbers generator to create a geographically-representative sample. After identifying the transit agencies, high-level administrators were asked to participate in interviews on the basis of their job function or participation in prior academic research or through an expressed interest in community engagement. Of the 96 agencies meeting these criteria, 46 were contacted for interviews, of which 16 declined and 30 participated. Participating interviewees’ job titles largely included CEOs, Executive Directors, Assistant General Managers, Chiefs of Operations, Directors of Administration, and Assistant General Managers, among others. Having insight into the administrative functions, planning, and vision of the agency was a requirement of interviewees. Interviewees were overwhelmingly male (74%) and Caucasian (80%). While Caucasian males accounted for slightly fewer than two-thirds of all interviewees, unfortunately, no specific effort could reasonably be made to include members of minority groups since a representative sample of transit administrators in the United States was desired.

In accordance with Institutional Review Board guidelines, participants were promised confidentiality and anonymity prior to participating in the research interview. Woods
and McNamara (1980) found that confidentiality and anonymity encouraged openness, accuracy, and honesty. Further, because of the requirements of FTA through Title VI, a few questions of the interview could affect the interviewee’s agency compliance with Title VI; therefore, interviewees’ names, locations, or employing agency names are not disclosed below.

Agencies represented by the interviewees span all regions of the United States, with a predictable greater representation of more populous states and regions. Interviewees’ metropolitan areas ranged from just over 500,000 to 3 million in population, and their agencies’ annual operating budgets saw a similar wide dispersion from $11.3 million to $320 million. Interviews with participants primarily occurred over the phone (27), and three occurred face-to-face; all occurred solely with the author of this research. Interviews were recorded, transcribed, and hermeneutically analyzed using MaxQDA software.

Findings

Community outreach is undertaken by every transit agency in this research, with some agencies reporting Title VI compliance as their motivation and others claiming to seek transparency and stakeholder involvement. Naturally, such outreach exists across a broad spectrum with various approaches, definitions, and philosophies about whom the targets of such outreach should be, what should result, and, of course, how it should be done. This research categorizes the types of community outreach by transit agencies into two broad categories based on the perceived motivation for seeking to engage members of the public: 1) “Community as Citizens,” in which the transit agency seeks input, feedback, and direction from the community; and 2) “Community as Customers,” in which the administrators seek to build local rapport to grow the agency’s choice ridership or to tend their community relations with those who do not use their services but may still have the opportunity to vote on a transit bond or tax levy. As is discussed below, the differences between these approaches revolve around how transit administrators perceive the “public” they are seeking to engage.

It is important to note, however, that there are specific outreach activities undertaken by agencies in this research which, while the administrators interviewed considered them community outreach, could more accurately be classified as benevolent community service. One Southern agency shared a service-minded, “good neighbor” approach to community outreach in which the agency partners with community health organizations to offer free AIDS testing, diabetes checks, nutrition consultation, and other health-based services at transit transfer centers. Two agencies, one Midwestern and Southwestern, operate free mini-libraries on board the agencies’ buses, in which riders are welcome to take home books for free and return them on subsequent transit trips. Another Midwestern agency specifically seeks to hire non-violent ex-criminal offenders who frequently face difficulty finding employment after release from prison. This program is done in conjunction with local neighborhood organizations, and the agency has become a resource for those seeking to help returning ex-criminal offenders re-assimilate and reduce recidivism. Such examples of benevolent community service reflect a strong commitment to the agencies’ communities. Thus, it should be clearly noted that the distinction between community service and community outreach is blurry in certain instances.
Of the ways interviewees describe their agencies’ community outreach efforts, 54 percent of specific activities mentioned in interviews are classified in this research as "Community as Citizens"—activities in which transit administrators seek effective community involvement in decision-making, priority development, and strategic planning. (The reader will recall that “citizenship,” as described below, does not refer to a legal status, but rather engagement with public policymaking.) Such community engagement includes instances in which administrators view their community members as citizens exercising their right to govern themselves (Box 1999).

One East Coast interviewee illustrated this category through an exercise in which those attending public meetings were simultaneously asked to prioritize routes and corridors in which transit should be placed while learning about the limitations of the agency’s budget:

[We did] “draw on the map” exercises where you give people … a length of yarn, tell them the length of yarn equals a bus every half hour—so if you want to draw a new route that goes from point A to point B and you want it to go every 15 minutes, you’ve got to double up your yarn. Partly it’s an exercise that makes people have to prioritize and understand budget constraints…. They understand that there is a trade-off between frequency of service, frequency and span of service, and geographic coverage. And you can only get so much with two yards of yarn.

A Western interviewee demonstrated the desire to mitigate political consequences that potentially could occur with transit expansions in certain neighborhoods.

On one corridor, in particular, that runs through largely minority or disadvantaged populations, we actually went out multiple times through the study process and attempted to contact every household in the neighborhoods directly impacted by … both negative and positive impacts by this project…. [We] attempted to get information to every citizen, essentially “Here’s websites in English and Spanish where you could get more information about our projects on our website, here’s a map, here’s where you can come. We’ll have daycare, food, all of that at neighborhood meetings.”

A Midwestern agency head directly contradicted common assertions that public meetings are held so that agencies can inform the public of their plans rather than elicit feedback from them: “Every time you go to these hearings, people will stand up and say, ‘I don’t know why I’m talking—you’ve already made up your mind.’ And the interesting thing is that every time we’ve done this, we’ve never made up our minds.”

A smaller West Coast agency goes “to transit centers, some of our bigger rail stations, and bus stations, and we set up a booth and try and get feedback about different changes or proposals there for passengers and it’s actually been very effective.”

Another West Coast agency perhaps represents one of the most comprehensive views of community involvement in projects by targeting certain neighborhoods for employee recruitment:

[The General Manager of the agency] recognized the fact that a number of minority groups were not happy with the results of past public works projects.
So he set out to ... make the community a partner on [a new project], and the first thing he did was to hire individuals from the community, who had community ties and relationships.... [He] understood the value of bringing people in who have those community ties and have the ability to talk to the community and can really set up a community dialogue where the community feels like they're being heard and represented.

A Northeast agency undertook an exercise at a community meeting:

We give everybody in the room five sticky dots. You can put all five dots on one thing if that's the single thing that you want to see accomplished out of this route restructuring, or you can spread them around. We did that exercise 40 to 50 times at different neighborhood groups, tenant associations.

The unifying factor in each of these activities is the presumption that a portion of responsibility for decision-making rests upon the community. While professional administrators still exercise expertise, community groups and citizens are used in the decision-making process and given a voice in policymaking. Such a view of community as “governing citizens” contrasts with views in which community members are simply customers, or passive recipients of transit services, affected by—rather than affecting—transit administrators’ decisions.

Within the “Community as Customers” category, accounting for 46 percent of interviewees’ outreach efforts, are different perspectives on the value or purpose of community outreach. For example, outreach designed to educate the public on services offered or personal safety perhaps meets the perceived intent of the Title VI guidelines on community engagement; examples of “Community as Customers” below, however, occur without partnering with community members to create or change agency policy and contain few opportunities for citizens to impact agency policy, implying an administrative view of the community as customers awaiting service instead of empowered citizens shaping policy (Box 1999).

Outreach aimed specifically at increasing ridership and farebox revenue closely resembles private-sector marketing efforts. One Southwestern agency has “a team that does nothing but community and business development,” which seeks to build “community relationships” with large employers to offer reduced fare to employees. A Midwestern transit agency illustrates the educational approach and operates a transit bus outfitted solely for community outreach.

When that bus goes out, it goes to schools, it goes to community groups. We talk about the [agency], how to use the [agency’s transit services]. We talk about safety. It’s an education program. We go to the schools, for example.... We teach kids on how to pay the fare, how to ride the bus safely. When you get off the bus, for example, make sure there’s no traffic when you run around the front of the bus.

Some agencies’ actions can be characterized by their desire to control the public’s perceptions of the agencies. As an East Coast participant succinctly said, “The more we can educate the public about what we’re doing and why we do things, the better off we are.
If people understand what you’re doing, there are fewer complaints and there’s a better understanding when you have to make hard decisions.”

Another East Coast interviewee similarly “had this thing called the ‘Community Conversation,’ and we’re going literally everywhere anyone will listen to our story, whether it’s a Rotary Club, [or] an Optimist Club.”

A West Coast transit agency recognized the potential of its transit services to meet the mobility needs of a group of Vietnamese refugees:

We’ve used a variety of techniques to outreach to this community, including pictogram-type graphics that show the concept of what we’re trying to advance, bringing in dedicated [language services] staff, meeting with community organizations and grassroots leadership to explain what we’re doing, respond to questions, concerns, or issues that have been brought up by the community. [Also] meeting with them at community venues like their community center, which is where the soccer field is, and scheduling them to coincide with a major soccer game so there will be a lot of people from the community.... Just examples of that, of really getting in there and trying to connect to people at their level in their own language.

A Southwestern agency was direct in their community-outreach-as-marketing-efforts, saying, “We are currently trying to reach out to our Hispanic community because our Hispanic ridership numbers are not where we think they should be.”

A Southeastern agency appears to bridge the gap between community outreach and outright customer recruitment with its travel trainer-staff who, if someone is new to the region or if he/she is new to public transit, actually will go out and ride the bus with the person, show him/her how to use the fare box, where to change buses, and so on, just to make them feel comfortable.

Many transit administrators in this research were extremely aware of the politics of their region and the political predisposition of area voters and tailor their community outreach accordingly. In many areas, voters, regardless of whether they use transit, participate in elections on tax levies and proposals to raise sales taxes to fund new transit projects. Because of this, transit administrators often find themselves in unique positions of trying to lead public agencies while simultaneously catering to constituencies and potential voters. Thus, about 10 percent of community outreach efforts discussed by interviewees are as much about reaching potential voters as reaching potential transit users.

A Midwestern interviewee illustrated the duality some administrators describe:

We’re reaching out to all [people who vote] to show the value of the proposition.... We even go to places where we don’t have service. [Outreach] is building community support, which helps because we have to go back to the voters every once in a while.... We have an ongoing building support in the community because we want to be the public organization in the area that has value, that provides value.... So that means you have to go out and tell people what you’re doing.
A Midwestern interviewee, in discussing where routes should be cut due to low ridership and farebox recovery ratios, alluded to a situation in which an underutilized suburban route would be spared at the expense of an urban one to mollify voters:

Even though ridership is really high [on the hypothetical route in the city], I take that route out, and I leave a route out in the suburbs that’s got far less ridership. That’s a political decision…. It can’t be purely on the basis of [ridership]. You’ve got … a political issue here because of the economics of the funding.

Similarly, a Southern agency meets “with neighborhood associations on a regular basis to talk about transit services” and attends “a metro council member’s district meeting” in conjunction with elected officials.

In situations such as those described above, community engagement arguably emphasizes political considerations rather than service provision decision-making. However, as interviewees readily noted, this reflects the funding realities of many transit agencies in the United States.

Conclusion

Authentic public participation is a goal of many mass transit agencies in the United States. Community engagement in the “Community as Citizens” category provides administrative legitimacy, public accountability, and bidirectional dialogue that informs the public of the agency’s needs and administrators of ridership’s needs. “Community as Customers” represents a private-sector, New Public Management orientation to outreach in which the community and the agency’s ridership are regarded as “customers” rather than democratic citizens and in which agency decision-making tends to be removed from active community engagement. Although increasing ridership and more effectively marketing transit services is certainly a worthy goal of transit administrators, it does not reflect the democratic intent of community outreach, nor does it fully legitimize transit services as a citizen-owned enterprise (Box 1999; Innes and Booher 2004; Patten 2001).

What can transit agencies do to ensure they are fully and completely engaging with members of their community and valuing their input as democratic citizens? This research yields a number of normative public participation recommendations specifically for transit agencies:

- Make public feedback and involvement a goal of the agency. Actively listen to community groups, neighborhood associations, or religious organizations to understand their community’s transit needs.

- Engage local universities and academics in pinpointing needs and underserved communities. Many universities are looking for ways to partner with community organizations such as transit agencies, and such relationships rarely cost agencies money.

- Offer internships or other employment opportunities to youth from specific communities or high schools. Such an approach has yielded helpful results for agencies that have used it.
• Use “draw on the map” or similar exercises at community meetings, which can facilitate bidirectional dialogue, both educating the public on the agency’s constraints and identifying priorities of the public.

• Ask top transit agency officials and board members to use public transportation on a monthly basis to understand the mobility constraints inherent in most mid-size U.S. cities’ transit systems.

High-quality community involvement by public transportation agencies is vital for both a functioning democracy and the legitimacy of transit agencies themselves. As this research shows, many transit agencies are actively engaging members of their community. While “Community as Customers” approaches to community engagement are necessary to attract ridership, reduce the stigma of transit usage in mid-size metropolitan areas, and improve farebox ratios, they should be used in tandem with vigorous engagement approaches that value public input and feedback in policymaking.

Transit administrators’ decisions about service expansions or retrenchments can have profound consequences for when and how long—and whether—transit dependents can access important quality of life institutions such as education, healthcare, cultural, and employment facilities. It is imperative their voices be heard when their stake in the outcome can be life-altering. When robust methods of engagement from both “Community as Citizens” and “Community as Customers” are used, the democratic legitimacy of transit agencies will be realized, and transit users will have a voice in the policies that bear considerable consequences for their life chances.

References


About the Author

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