Volume 14, No. 3, 2011

Journal of Public Transportation

USF University of South Florida

National Center for Transit Research

JOURNAL OF

Public Transportation

Volume 14, No. 3, 2011
ISSN 1077-291X

The *Journal of Public Transportation* is published quarterly by

National Center for Transit Research
Center for Urban Transportation Research
University of South Florida • College of Engineering
4202 East Fowler Avenue, CUT100
Tampa, Florida 33620-5375
Phone: (813) 974-3120
Fax: (813) 974-5168
Email: *jpt@cutr.usf.edu*
Website: *www.nctr.usf.edu/jpt/journal.htm*

Volume 14, No. 3, 2011
ISSN 1077-291X

CONTENTS

Quantitatively Understanding Transit Behavior from the Rider's Point of View

Colin Bick

Abstract

Arrival time uncertainty is a major source of negative perception by riders, yet how this uncertainty manifests in the rider's experience is not well-studied. While operators constantly make efforts to improve reliability, and real-time arrival predictions reduce uncertainty for riders in transit, it is also possible to lessen frustration by better informing riders of system behavior beforehand. This work introduces a new method for understanding transit behavior through an analysis of historical arrival time data from San Francisco. The results identify impacts of timeliness on rider experience, such as that average wait time is minimized by showing up five minutes early, or that a five-minute transfer window will be successful 80 percent of the time. Categories of rider experience also are discovered, such as between daytime and evening users. More importantly, it is demonstrated how operators and trip planners can make use of this method to improve rider experience.

Introduction

Of the many obstacles faced when using public transportation, one of the largest is the information barrier. Transit schedule and route information add several dimensions to what is already contained in a standard road map. The agencies responsible for distributing the information rarely are successful at communicating what one might call the intent of their system; in other words, it often is difficult to learn how a system is meant to be used.

Paper schedules that display route details and timetables are one of the most fundamental formats of transit information, yet using them to plan a trip is far from a simple task. Cain (2007), for example, found that 47.5 percent of sampled riders were unable to correctly plan a trip using only a system map and paper schedules. Some studies examine ways to improve presentation of the information, but rarely are there efforts that find new information to present. Even after significant improvements in presentation, one study (Sollohub et al. 2006) was unable to determine if improvements were effective since the riders generally were unable to correctly use them.

An online trip planner is a tool that improves on a schedule by providing a rider with step-by-step directions from one point to another for a given day and time. The trip planner tries to construct optimal answers using the same information provided in a paper schedule and decides on a priori costs for transfers, waits, walks, etc., before a well-defined optimization problem is possible, not to mention useful (Modesti et al. 1998, Sherali et al. 2006). An especially important parameter is that of minimum transfer time, defining a safety margin of time between vehicles to ensure the feasibility of a transfer.

What these tools do not take into account is that transit behavior is inherently random. The arrival times provided in a schedule are estimates only, making their use in trip planning much less straightforward. A rider must therefore draw heavily on experience and make guesses when creating and evaluating trip plans, weighing perceived risks against convenience. Online trip planners, similarly, must choose a minimum transfer time as a heuristic meant to compensate for nondeterministic behavior, and, consequently, the possibility of making shorter transfers is ignored.

Riders, on the other hand, are all too aware of the uncertainty involved in taking the bus. The uncertainty of arrival time is a major source of frustration (Caulfield et al. 2009), and the perception of time spent waiting or riding increases disproportionately whenever the actual time spent is longer than expected (Li 2003). Even the uncertainty of arrival time itself increases the perceived amount of time passing (Mishalani et al. 2006), and without any sources of information beyond schedules or schedule-based tools, the rider does not know what to expect. While these effects on perception and frustration are understood, precisely how the events in using transit are impacted by timeliness (or the lack thereof) is not well-studied.

The next bus predictor NextBus was developed to decrease this uncertainty. Approached in many manners, this tool uses real-time data to predict the time of arrival of the next bus of a given route, in a given direction, at a given stop. To make these predictions with reasonable accuracy, machine learning techniques are trained against historical data (see, for example, Chien et al. 2002; Jeong 2004; Shalaby et al. 2004; Wall et al. 1999). The value and utility of this tool has been investigated several times, due in large part to the costs involved; it is understandable that not every agency has invested in it.

While the next bus predictor reduces uncertainty during a trip (i.e., while at the bus stop), it does not help the rider anticipate behavior beforehand. This uncertainty —the uncertainty of transit behavior in general—has yet to be addressed. Riders and trip planners constantly are forced to make guesses that try to remediate the disagreement between scheduled and actual arrival times. Any treatment of transit as a discrete or deterministic process is bound to result in errors and frustration.

If transit behavior is approached mathematically and as a random process, on the other hand, not only can the guesswork in trip planning be removed, but the entire process of using public transportation can be made as exact and predictable as possible. The tradeoff is the added complexity of treating many aspects of riding the bus as probability distributions, including time spent waiting, actual arrival times, trip durations, and vehicle transfers. These distributions naturally all reduce to some combination of actual arrival times. Thus, by viewing actual arrival times in relation to the schedule—that is, how late the bus is—the true nature of transit behavior can be understood, and therefore communicated, from the rider's point of view.

This research introduces a new method for understanding transit behavior by modeling vehicle lateness as a random variable. An analysis is performed on data from four weeks of system-wide arrivals from San Francisco. The data were calculated by matching archived GPS data provided through NextBus with the corresponding schedule provided in GTFS (General Transit Feed Specification) format.

A similar work was performed by Berkow et al. (2009), but from the operator's perspective. They demonstrated an approach that provides far greater insight into a system's performance than the generation of performance measures, applying statistical as well as visual tools to a year's worth of data recorded by Portland's TriMet. Properties of performance-related random behaviors such as those exhibited by passenger boardings, lift use, overall ridership, vehicle headway, and lateness were investigated at several resolutions. Importantly, they noted that the large size of the dataset allowed the entire analysis to be done without making estimates or assumptions.

This work focuses on the rider's perspective. It identifies the quantitative impacts of lateness on rider experience, including waiting for the bus, making transfers, and overall trip time. It then discovers and explores categories of rider experience, showing how different groups of users are impacted by different behavior. Finally, it is demonstrated how the method and results can be used by operators and tools such as trip planners to provide the rider with better information.

Model and Data

Description of Model

Conceptually, the idea of lateness as a random variable is fairly straightforward, if one imagines a rider waiting for the bus with a schedule in hand. Addressing lateness as a property of the entire system requires a more careful definition. This study models lateness as measuring

$$lateness = t_{actual} - t_{scheduled}$$

where t_{actual} and $t_{scheduled}$ are the actual and scheduled arrival (or departure) times for a scheduled stop chosen at random, with uniform probability, from the population of all scheduled stops during the period of data collection. To make the results representative of a weekly schedule, a period of data collection was chosen such that its duration is precisely four weeks, without holidays.

Additionally, the study makes a distinction between lateness computed using arrival times and departure times. Each computation below states whether it is referring to arrivals or departures. When using arrival times, the first stop of each run is excluded from the population; similarly, when using departure times, the last stop of each run is excluded. This is done to make the model more meaningful.

Description of Data

San Francisco, by releasing both schedule and real-time data to the public, offers a valuable opportunity to explore this approach in a dense and heterogeneous transit system. San Francisco Municipal Rail (Muni) transports 200 million passengers per year inside an area of 47 square miles, employing bus, light rail, cable car, and a historic street car (San Francisco 2011). GPS tracking data collected every minute from Muni for a period of four weeks starting in March 2009 was matched to schedules described in a GTFS (General Transit Feed Specification) format for that month (see references for data sources). This match-up describes the actual arrival and departure times of each vehicle at each stop along its assigned route, as well as the scheduled arrival time. Much information about the routes is available from the GTFS data, including stop location, route shape, and vehicle type. The software written to perform the match-up has been made available online at *http://cbick.github.com/gps2gtfs*.

Of the approximately 14 million rows of raw GPS data, only around 40 percent were qualified to survive preprocessing. While equipment errors causing this may have been uniform, any human influence (for example, new drivers or incorrect use of tracking equipment) in creating bad data cannot be assumed uniformly distributed. For this reason, the data collected in some areas may be much less populated than in others. Additionally, the match-up of GPS data may be distorted by geographical (or geological) influences. For example, a visualization of the data shows that GPS signals neighboring bodies of water are an order of magnitude more erroneous than those between buildings. For this reason, data may be less accurate for certain stops than for others.

The GTFS data are far from perfect as well. Stops in close proximity often are given the same scheduled time, decreasing specificity in the meaning of the schedule in general. In other instances, detours can cause a vehicle to shift its schedule or miss designated stops entirely.

Treatment of Data

Computation of Lateness

To compute the arrival and departure time estimations, the GPS data points were projected onto the corresponding route's path and the times were interpolated. The arrival and departure of a vehicle at a stop were defined to be the points at which the vehicle entered and exited a 25-meter radius around the stop.

Outliers and Errors

Processing raw GPS data and matching it up to schedule data introduce many opportunities for error. Examining the data shows that 98 percent of the weighted distribution falls between 8 minutes early and 20 minutes late, but the remaining 2 percent ranges from 35 minutes early to 90 minutes late. While these outer bounds of lateness are suspiciously large, the following steps were taken to eliminate errors:

- Only vehicles whose signal existed for and matched a significant portion (>50 percent) of their designated route paths were considered admissible.
- All vehicles were put through a secondary processing to ensure there were no better matches in the schedule.

These steps establish confidence that there is an insignificant level of error in the matching process. Any errors in the GTFS data are impractical to eliminate, so its correctness must be assumed. Errors resulting as artifacts from abnormal events or incorrect GPS data cannot be eliminated using any consistent method. Therefore, any apparent outliers cannot be discarded and should be included in the distribution.

Sample Bias and Correction

From the nature of the data collection, it is clear that the data set is not representative of the population in the model. The observations, therefore, have been weighted and normalized to provide representative estimates of the population as defined by the schedule. In particular, for any particular scheduled stop, its weight w is defined as

$$w = \frac{f_{scheduled}}{f_{observed}}$$

where $f_{scheduled}$ is the number of occurrences of the stop according to the model's population, and $f_{observed}$ is the number of actual observations that were made for that stop.

Independence

As the model is constructed, observations in the data are not independent. Specifically, arrival times within the same run are highly correlated. While it may be reasonable to assume that lateness samples from different vehicle trips are (sufficiently) independent, several of the confidence interval widths shown below are potentially underestimated. Since calculating more accurate intervals would add computational complexity without contributing to the discussion, such efforts have not been made.

It is necessary, however, to at least provide a reasonable estimate of the true error bounds. For this, the reader is directed to examine the confidence intervals in Figure 10. These represent a meaningful upper bound on width, as each population in that figure consists of independent samples.

Analysis

The processing described above resulted in a little over 2 million recorded observations of lateness. With a large dataset such as this, rather than try to fit some analytical model, it is much more straightforward to simply compute an empirical cumulative distribution function (ECDF). From an ECDF, one can quickly compute quantiles and their confidence intervals, as well as take computationally simpler approaches to simulation. The ECDFs and their confidence intervals in this work were computed using Horvitz-Thompson estimates as described in, e.g., Diaz-Ramos et al. (1996).

This section proceeds by examining first some overall properties of lateness as a random variable, then a series of comparisons of hand-picked partitionings. In each case, it is identified how the extracted information is useful to a bus rider.

Overall Behavior of Lateness

Overall ECDF of Lateness

The overall (weighted) ECDFs of arrival lateness and departure lateness are shown in Figure 1. They are nearly identical. The 95 percent confidence interval for each ECDF is too small to discern in the figure, each having a width of only about 0.25 percent. The estimated means of lateness, the positions estimated by the schedule (i.e., that of lateness = 0), and the 5 percent quantiles have also been marked.

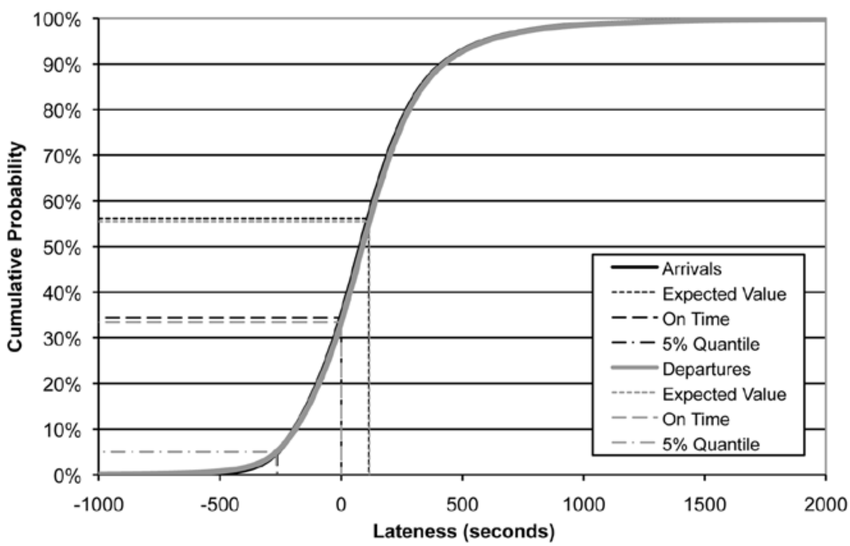


Figure 1. ECDF of lateness

From this plot, it is seen that the schedule is approximately equal to the 33 percent quantile for lateness of departure—in other words, a rider showing up (spontaneously) at a bus stop at precisely the scheduled time has only a 67 percent chance of catching that bus. To have a 95 percent chance of catching the bus, the rider must arrive 267 seconds, or about 5 minutes, early.

The 95 percent confidence interval for the average lateness of arrivals is between 113 and 114 seconds, while that for departures is between 116 and 117 seconds; that is, the bus is about 2 minutes late on average. The ECDFs also show that the rider can expect to arrive (or depart) 5 minutes or more past the scheduled arrival around 18 percent of the time; 10 minutes or more 5 percent; and 15 minutes or more 2 percent. Such knowledge can help the rider not only to better plan a trip, but also to experience less frustration since the behavior is now in a sense predictable.

Average Waiting Time

An interesting metric to consider at this point is that of expected waiting time, or how long a rider can expect to wait on average for a vehicle given the time he or she arrives at a stop relative to the schedule. To compute this, a simulation was constructed with scheduled arrivals occurring at a constant frequency of arrival (headway). The actual arrivals were simulated by sampling from the empirical distribution of departure lateness, implicitly assuming that the distribution does not change significantly for different headway values. The resulting values for expected wait time are depicted in Figure 2, which plots the average wait time as a function of the passenger's arrival time at the stop for various headways. The figure shows that the minimum average wait time is achieved by the rider arriving about five minutes early, with slightly earlier minimums for larger headways since the cost of missing the bus is higher.

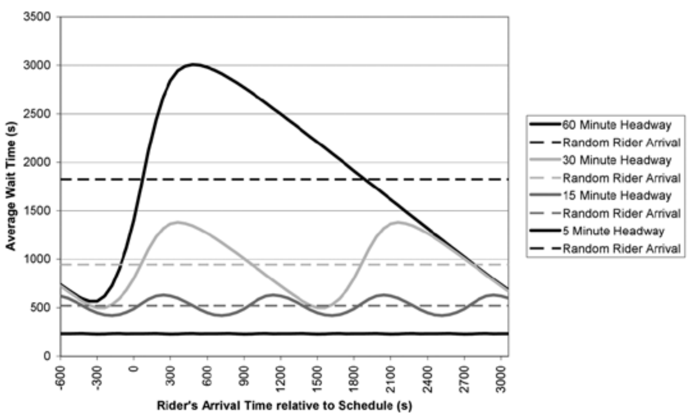


Figure 2. Average wait time

Figure 2 also shows a dashed line for each headway, marking the average wait time for a rider who arrives at the stop randomly without consulting the schedule. It is interesting to see that a rider arriving "on time" has approximately the same expected wait time as one arriving randomly. For the shorter headways, there is almost no practical difference between arriving randomly and consulting the schedule; it is clear from this why the behavior observed by Balcombe and Vance (1998, cited by Cain 2007) might occur, where riders arrive randomly for headways of 10 minutes or better, but consult the schedule for those of 15 minutes or more.

Making a Transfer

One of the critical determinations that must be made when planning a trip on public transportation is the feasibility of a transfer between two vehicles. Riders have only their experience to draw on, and software trip planners simply use a threshold minimum transfer time. Using the lateness data, however, it is simple to construct a simulation of a rider transferring from one vehicle (sampling from the arrival distribution) to another (sampling from the departure distribution), producing the informative plot displayed in Figure 3. Here, the likelihood of making a transfer—that is, the likelihood that the second vehicle will depart from the stop after the first vehicle arrives—is plotted against different transfer window sizes. The 90 percent mark is not reached until there is a 7-minute window between scheduled arrivals, and to be 95 percent sure of making the transfer requires a window of 10 minutes. This chart enables even a new rider to make an informed decision about the acceptability of a particular trip plan.

Figure 3. Overall probability of making a transfer

An element that is missing from this model is the concept of a designated transfer point, where transfers can be coordinated between vehicles (meaning that the second vehicle will wait for the first), or the transfer window is elongated by scheduling the departure of the bus to be some minutes later than its arrival. This element is missing, too, from the SF Muni GTFS data. We can hypothesize that the probability of making a transfer increases at these transfer points, but no empirical observations can be made.

Hour of Weekday Comparisons

This first set of comparisons examines the behavior of lateness exclusively on weekdays, partitioned according to which hour of the day an arrival is scheduled. This is determined strictly according to the clock hour of the scheduled arrival, meaning, for example, that a scheduled arrival of 7:59 a.m. belongs to the 7 a.m. category.

This kind of comparison is useful because it reveals categories of user experience. Riders using transit mainly to commute during rush hour will observe a different class of behavior than those who use transit in the evening or at night. As different categories of riders have different intents in their use of transit, it is important to understand the behavior of transit from each perspective.

Hour of Weekday ECDFs

The lateness ECDFs for the 8 a.m., 5 p.m., 8 p.m. and 1 a.m. blocks were selected for visual comparison as displayed in Figure 4. The overall ECDF is included as well. In all cases only the arrival lateness data was used.

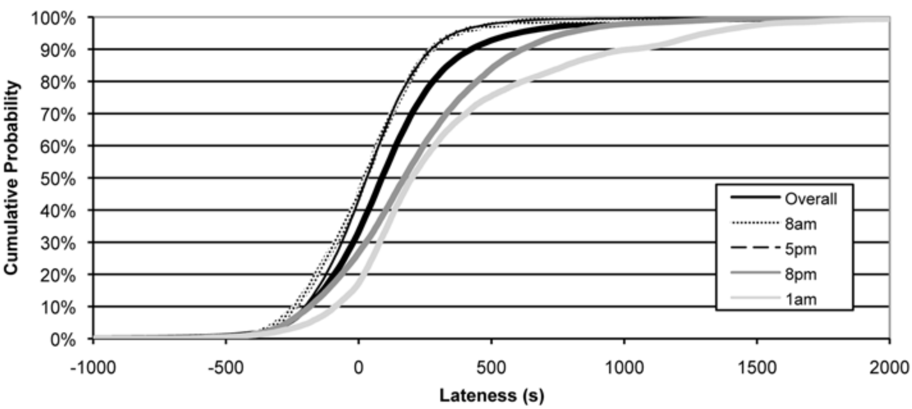


Figure 4. Hour of weekday ECDF comparisons

From these curves it can be seen that the 8 a.m. and 5 p.m. hours tend to be earlier than overall and have a lighter tail. The 8 p.m. hour shows the opposite, being considerably later than the overall and having a much heavier tail. The 1 a.m. behavior is the most distinct of the group, being quite late and wearing a long tail. It also has a wider 95 percent confidence interval (not shown), ± 1.4 percent compared to ± 0.6-0.8 percent for the others. Approximately 20 percent of the 1 a.m. data is more than 10 minutes late.

These differences in behavior during different phases of the day are quite important to the rider. Commuters are interested specifically in the rush hour behaviors. Late-night users should know that the behavior is significantly later and less reliable than during the daytime. The quantiles for late night behavior are especially useful when taking the last bus home. By making further analysis, it can be seen how the differences in behavior should influence the rider's use of the system.

Hour of Weekday Average Waiting Time

As in the overall case shown in Figure 2, Figure 5 plots average wait time as a function of the rider's arrival time at the stop. Only the departure data was used. For ease of comparison, the plot shows curves for the 5 p.m. and 1 a.m. hours only, alongside the overall lateness, and considers only a 30-minute headway. The 5 p.m. data show a lower minimum average wait than the overall for a rider arriving five minutes early and has a higher maximum average wait as well. These are due to the increased timeliness of that hour. The 1 a.m. data's minimum average wait, in contrast, are considerably higher than the other curves and occur where the rider arrives only two minutes early, as expected from the increased lateness of the hour (this assumes another bus is coming). It is interesting that the heavier tail in the 1 a.m. distribution actually causes the maximum average wait to be lower, since a rider arriving late is less likely to have missed the bus; but, of course, the variance of the wait time is much higher, though this is not shown in the figure.

There are several important messages for the rider in this plot. For one, a rider can expect to wait a long time for the bus at 1 a.m., which may be uncomfortable and possibly even dangerous. Rush hour riders, on the other hand, can expect short and pleasant waits—provided they arrive five minutes early.

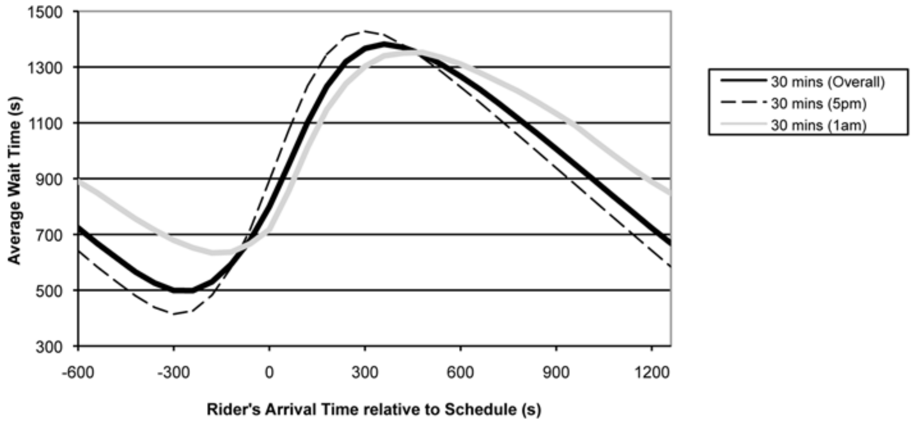


Figure 5. Average wait time comparison for hour of weekday

Hour of Weekday Probability of Transfer

We now inspect the differences the time of day on a weekday can make in the feasibility of a transfer. Figure 6 compares the probability of making a transfer for selected hours of arrival along with the overall probability. Note that the curves intersect near the 50 percent point where the transfer window is 0. This is an effect of using near-identical distributions for each transfer (e.g., the 8 a.m. line represents transferring from an 8 a.m. arrival to an 8 a.m. departure). As expected, the increased timeliness of the 8 a.m. and 5 p.m. data results in lower probability than the overall for negative transfer windows and in higher probability for positive windows. The opposite applies to the 8 p.m. and 1 a.m. hours. In fact, the 90 percent point is reached with windows as small as six minutes for the 5 p.m. data and as large as 15 minutes for the 1 a.m. data.

It is helpful to the commuter to know that transfers are easier to make during the rush hours. It is even more important, however, for the timeliness-concerned rider to note the probabilistic behavior: given (for example) a commute with a scheduled transfer window of five minutes during the 8 a.m. hour, the rider will make that transfer approximately 85 percent of the time—that is, the transfer will be missed 3 out of 20 times. By making this behavior predictable, the rider can expect and plan for its occurrence, removing much of the frustration associated with transfers.

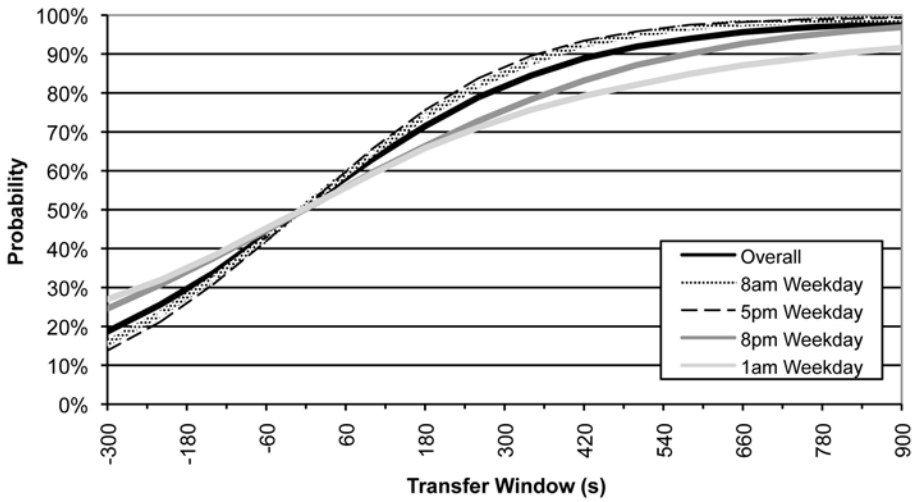


Figure 6. Probability of making a transfer for hour of weekday

Hourly Trend

It is instructive to look at information comparing all hours of the day, instead of just the four selected in the last few plots. Figure 7 compares the quartiles (25, 50, and 75 percent quantiles) and means, along with 95 percent confidence intervals, for each hour of arrival on a weekday. These values were computed using the arrival lateness ECDFs from each hour.

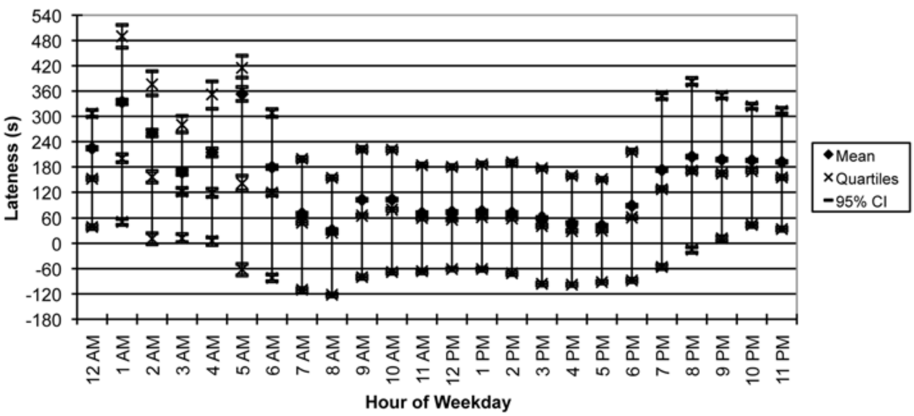


Figure 7. Quartiles and means: Hour of weekday comparison

The information here is both interesting and valuable. If "reliable" is defined as having a small distance between the first and third quantiles, then the most reliable times of bus operation are at 12:00 p.m. and 5 p.m. The level of reliability is, in fact, fairly good and does not vary much throughout the course of the workday. Then, the reliability deteriorates sharply from 5 p.m. to 8 p.m., and the skew of the distribution (as indicated by the distance between the mean and the median) increases. Between 9 p.m. and 12:00 a.m., there is a surprising increase in reliability, though the mean lateness stays relatively high. Finally, there is inexplicable behavior, as all reliability is lost between 12:00 a.m. and 1 a.m., rendering bus behavior almost unpredictable.

It should be noted that it is quite possible that the erratic behavior observed in the early hours is caused by erroneous GTFS data, leading to faulty treatment of the GPS data. The outlandishly large skew on the 5 a.m. data, in particular, is quite suspect. It is difficult to make any conclusions here, since routes run much less frequently at these hours and so there is much less data to draw upon.

It is clear, however, that a rider should expect distinctly different behavior when using public transportation during business hours and in the evening. Again, this is especially relevant to the commuter, who is typically highly concerned with timeliness and reliability.

Progress of Route Comparisons

This next set of comparisons splits the data according to how far along its route a transit vehicle has progressed at each stop. This can be done in a number of ways, and two were selected here: first is the stop number, which enumerates the stops along a route in sequence, and second is route portion, defined as the stop number divided by the total number of stops for the trip.

Route Portion ECDFs

Figure 8 shows the arrival lateness ECDFs for the start of the route (those stops having route portion between 0 and 0.25), middle of the route (0.25 to 0.75), and end of the route (0.75 to 1.0), as well as for overall arrival lateness. These curves are relatively similar, so it is difficult to make interesting conclusions offhand. They do demonstrate a trend of increasing lateness and a heavier tail as a route progresses, but whether this makes a perceptible effect is unclear.

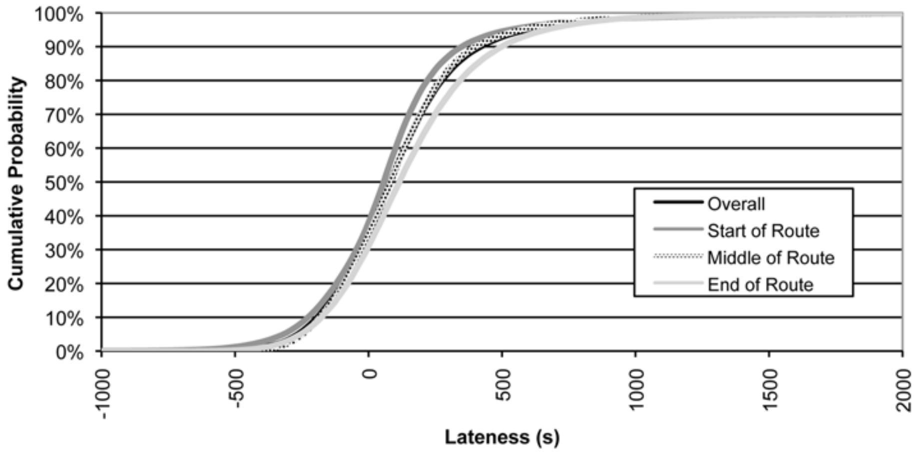


Figure 8. Route portion ECDF comparisons

Probability of Transfer between Route Portions

To better understand the effect of route progress on lateness behavior, the probability of making a transfer according to transfer window size was once more calculated. In this case, four scenarios were selected, representing transfers between different portions of the route, using the same definitions as the ECDFs plotted previously. The results are shown in Figure 9. The cases of making transfers from the beginning of a route or to the end of the route have been omitted, as they are ostensibly less useful.

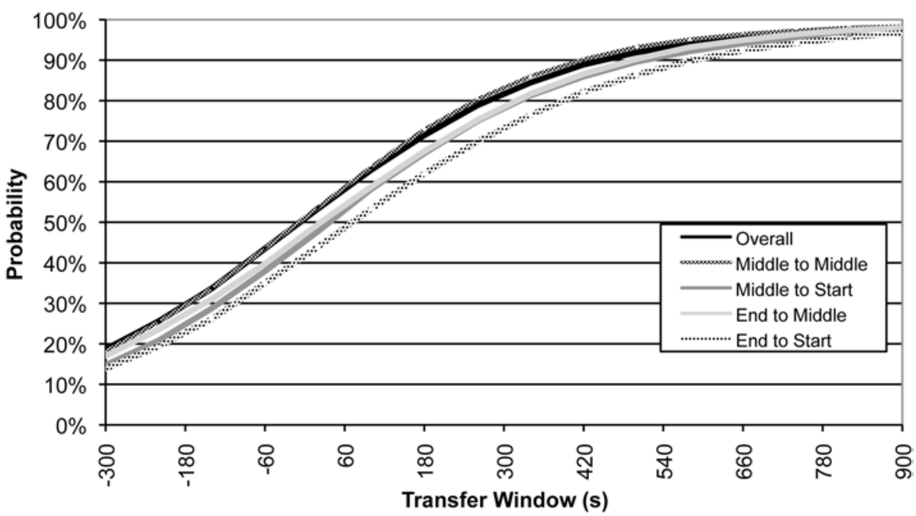


Figure 9. Probability of making a transfer for route portion

Observe that the curves no longer all intersect the 50 percent mark where the transfer window is zero, since the transfers are no longer symmetric. All but the middle-to-middle curve appear to have shifted below the overall curve in probability, suggesting that the previous results were optimistic. For some windows, there is as large as a 10 percent decrease in probability. Fortunately, the shift is not so large in the higher probabilities. To achieve 90 percent probability in the worst case (transferring from the end of one route to the start of another), the transfer window need only be 1 minute larger than in the overall case.

Trend along Route

We also can clarify the effect of route progress by looking more closely for a trend. Using the same type of plot that demonstrated an hourly trend, Figure 10 shows the quartiles and means of the arrival lateness distribution according to stop number. It is plain to see that lateness increases as a route progresses, and that reliability (again using the distance between the 1st and 3rd quartiles as an indicator) decreases. The lack of data in the higher stop numbers causes much larger confidence intervals, but the trend is still apparent, and a trip planner should account for it.

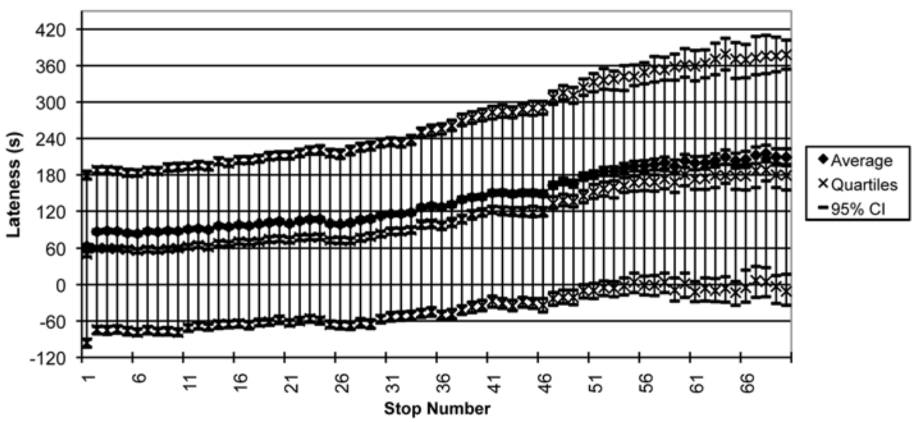


Figure 10. Quartiles and means: Stop number comparison

Trip Plan Evaluation

Taking a step further in our observations, this final analysis makes a quantitative evaluation of a simple trip plan. Suppose a commuter is evaluating the option of taking the bus to work and wishes to arrive at 8 a.m. Looking at the system map, the commuter finds that he must make one transfer. The schedule shows that the first bus is scheduled to arrive at the transfer point at 7:00 a.m., 7:30 a.m., and 8:00 a.m.

The second bus is scheduled to depart from the transfer point every 20 minutes beginning at 7:10 a.m. and to arrive at the final destination 20 minutes later.

The naïve conclusion is that there is no chance to make the transfer from the 7:30 a.m. arrival to the 7:30 a.m. departure, and so he must wait 20 minutes for the next bus, arriving at work at 8:15 a.m. (15 minutes late). To arrive on time, therefore, he must take the bus which arrives at the transfer point at 7:00 a.m., which is highly inconvenient.

Now, instead, it is possible to make a probabilistic evaluation using the knowledge of behavior derived thus far. Figure 11 shows the ECDF of the commuter's arrival time at his destination given the schedule data above, where he takes the first bus scheduled to arrive at the transfer point at 7:30 a.m. and then transfers to the next bus that he sees. This ECDF was generated through simulation on the 7 a.m. and 8 a.m. hour of arrival datasets, using the arrival and departure data as appropriate. The bimodal characteristic of this curve represents the two main outcomes of the trip plan: that half the time, the 7:30 a.m. transfer is successful, and half the time it is not. The commuter's arrival time, on average, is only 154 seconds, or about 3 minutes, past 8 a.m. There are occasions where he will be more than 20 minutes early, and occasions where he will be more than 20 minutes late; each of these represents less than 2 percent of occurrences, or about 1 day every 11 weeks. This method not only has discovered the reality of the situation to be better than initially thought, but it also has formed the correct expectations for the rider.

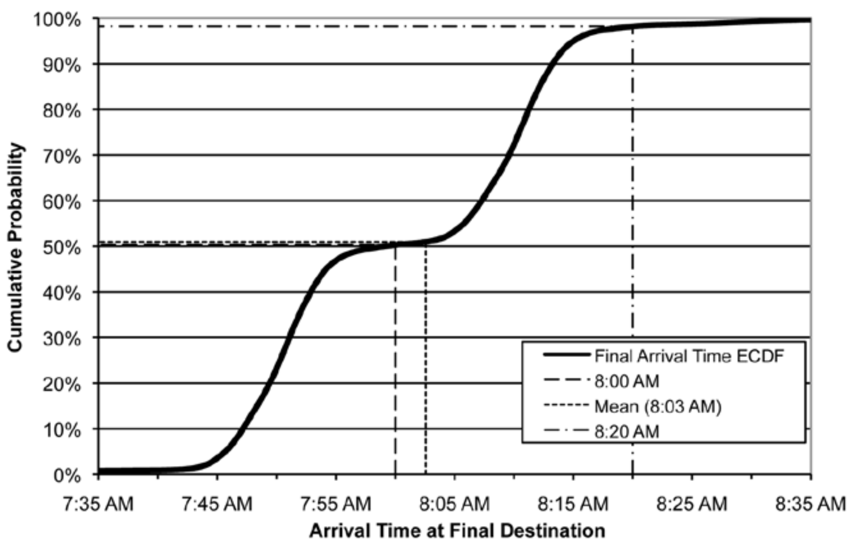


Figure 11. ECDF of trip plan for daily commute

Conclusions and Further Work

This work has demonstrated a new approach to the analysis of arrival data that creates an understanding of transit behavior from the rider's point of view. Using this approach, operators can understand precisely how on-time performance impacts their users and identify sources of frustration. By releasing timeliness or tracking data to the public, agencies can allow the community to use these methods to provide better information and to improve the rider's experience, in the same way that releasing schedule and arrival prediction data has seen growing success.

Online trip planners, or new tools entirely, can use the model from this research to provide better information to the rider. Incorporating it directly into the trip planner would make it possible to operate on explicit probabilities of transfer, instead of guessing a minimum transfer time. This easily could be extended to consider all outcomes and their probabilities, giving every trip plan an evaluation like that shown in Figure 11. From there, the optimization problem can be redefined in a very flexible and meaningful manner.

It also is desirable to communicate this knowledge in a more direct form, so that a rider is always equipped to form the correct expectations ahead of time. Of course, as is evident in the case of paper schedules, presenting information in a format that is easy to use and understand is a difficult problem. A small step is to provide simple rules of thumb that will guide expectations in a way that reduces frustration: show up five minutes early, give small transfer windows a (small) chance, expect poor behavior late at night. A more complete and utile form of communicating this information is worth pursuit.

Acknowledgments

The author would like to thank the reviewers for their effort in improving this paper. The author would also like to thank Robert Damphousse for his help in making sense of the initial GPS data. Finally, the author thanks the San Francisco Municipal Transit Agency for releasing their tracking and schedule data to the public.

References

Balcombe, R. J., and C. E. Vance. 1998. Information for bus passengers: A study of needs and priorities. *Transportation Research Laboratory*—Report 330.

Berkow, M., A. M. El-Geneidy, R. L. Bertini and D. Crout. 2009. Beyond generating transit performance measures: Visualizations and statistical analysis with historical data. *Transportation Research Record* 2111: 158-168.

Cain, A. 2007. Are printed transit information materials a significant barrier to transit use? *Journal of Public Transportation* 10(2): 33-52.

Caulfield, B., and M. O'Mahony. 2009. A Stated preference of real-time public transit stop information. *Journal of Public Transportation* 12(3): 1-20.

Chien, S. I., Y. Ding, and C. Wei. 2002. Dynamic bus arrival prediction with artificial neural networks. *Journal of Transportation Engineering* 128(5): 429-438.

Diaz-Ramos, S., D.L. Stevens, Jr., and A.R. Olsen. 1996. EMAP Statistics Methods Manual. EPA/620/R-96/XXX. Corvallis, OR: U.S. Environmental Protection Agency, Office of Research and Development, National Health and Environmental Effects Research Laboratory.

Google. 2009. General Transit Feed Specification (previously Google Transit Feed Specification). http://code.google.com/transit/spec/transit_feed_specification.html [accessed March 2009].

Jeong, R.H. 2004. The prediction of bus arrival time using automatic vehicle location systems data. PhD Dissertation, Texas A&M University.

Li, Y. 2003. Evaluating the urban commute experience: a time perception approach. *Journal of Public Transportation* 6(4): 41-66.

Massart, P. 1990. The tight constant in the Dvoretzky-Kiefer-Wolfowitz Inequality. *The Annals of Probability* 18(3): 1269-1283.

Mishalani, R. G., M. M. McCord and J. Wirtz. 2006. Passenger wait time perceptions at bus stops: Empirical results and impact on evaluating real-time bus arrival information. *Journal of Public Transportation* 9(2): 89-106.

Modesti, P., and A. Sciomachen. 1998. A utility measure for finding multiobjective shortest paths in urban multimodal transportation networks. *European Journal of Operational Research* 111: 495-508.

San Francisco Municipal Transit Agency. 2009. SFMTA GTFS transit data license agreement and download. http://www.sfmta.com/cms/asite/transitdata.htm [accessed March 2009].

San Francisco Municipal Transit Agency. 2010. SFMTA GPS vehicle location data. http://www.sfmta.com/cms/asite/nextmunidata.htm [accessed January 2010].

San Francisco Municipal Transit Agency. 2011. http://www.sfmta.com/cms/ahome/indxabmu.htm [accessed February 2011].

Shalaby, A., and A. Farhan. 2004. Prediction Model of bus arrival and departure times using AVL and APC data. *Journal of Public Transportation* 7(1): 41-61.

Sherali, H. D., C. Jeenanunta, and A. G. Hobeika. 2006. The approach-dependent, time-dependent, label-constrained shortest path problem. *Networks* 48(2): 57-67.

Sollohub, D., and A. Tharanathan. 2006. A multidisciplinary approach toward improving bus schedule readability. *Journal of Public Transportation* 9(4): 61-86.

Wall, Z. and D. J. Dailey. 1999. An Algorithm for predicting the arrival time of mass transit vehicles using automatic vehicle location data. 78th Annual Meeting of the Transportation Research Board, January 1999.

About the Author

Colin Bick (*colin.bick@gmail.com*) has used public transit almost exclusively for several years. Professionally, he is a software developer and holds an M.S. in applied mathematics from the Colorado School of Mines.

Using AVL Data to Improve Transit On-Time Performance

Fabian Cevallos, Xiaobo Wang, Zhenmin Chen, and Albert Gan
Florida International University

Abstract

This paper describes an approach for improving on-time performance at transit agencies. It takes advantage of the schedule adherence information from an AVL system. A methodology that can be used to update the bus timetables by using AVL schedule adherence data is described. Using statistical analysis, the main goal is to maximize the density area of the on-time performance range. From this distribution, the optimal value is obtained and used to update the times in the timetables. Then, a comparison process is used to assess the on-time performance improvements. In addition, a simulation process is presented to provide a different perspective than the statistical methodology. This approach also presents possibilities for further on-time performance improvements. To demonstrate the applicability of this research, a case study using data from Miami-Dade Transit is included. The on-time performance calculations for Routes 99 and 57 also are presented.

Introduction

To passengers, schedule adherence is a matter of service quality. From the service provider perspective, schedule adherence reflects the quality of the service plan (the schedule) and the operations control (Furth et al. 2003). Researchers have long noticed the importance of schedule adherence information contained in Automatic Vehicle Location (AVL) systems. Lee et al. (2001) studied the effect of an AVL system on schedule adherence and operator behavior and willingness to keep on schedule. In addition, Hammerle et al. (2005) pointed out that some transit agencies would like to use Automatic Passenger Counter (APC) and AVL data to inform service planning and management and ultimately provide more reliable service. Methods for extracting information from these data were developed to compute service reliability indicators. Also, some schedule adherence properties were observed and reported in their research. These studies show a general interest in improving schedule adherence.

It is important to clarify the difference between schedule adherence and on-time performance. Schedule adherence refers to the difference between real time and scheduled times of arrival or departures times, usually presented in minutes. On-time performance, on the other hand, is a percentage value used to indicate buses arriving or departing late, on time, or early. Depending on the AVL system and the transit agency, on-time performance can be calculated using arrivals, departures, or possibly a combination of both.

AVL systems are computer-based vehicle tracking systems that function by measuring the real-time position of each vehicle and relaying this information back to a central location. Many researchers also see the potential uses of analyzing AVL or APC data to improve service quality. A study that uses data from Tri-Met in Portland, Oregon, shows that scheduling can be improved through performance monitoring using AVL data and that very useful information has been retrieved (Kimpel et al. 2004). Shalaby and Farhan (2004) made efforts to use AVL and APC data to develop a bus travel time model capable of providing real-time information on bus arrival and departure times to passengers (via traveler information services) and to transit controllers for the application of proactive control strategies.

One continual question asked by researchers is how to use AVL data to improve on-time performance. The importance of on-time performance to both the transit customer and the transit providers has been discussed in many research projects. For instance, New York City transit established a customer-oriented bus performance indicators program to measure on-time performance. The program contains two schedule adherence indicators that measure different aspects of service performance: route on-time performance and service regularity. The purpose of this program is to measure the quality of service experienced by the customer (Nakanishi 1997).

This research attempts to fill the gap in the understanding of AVL data and presents another perspective on how the data can be used to improve on-time performance. With the availability of AVL data, it is possible to improve on-time performance by modifying the scheduled times in the timetables. Changes in the timetables will take effect in the following line-up period (also known as mark-up, shake-up, sign-up, bid, or pick). This paper makes use of the AVL schedule adherence data (measured in minutes) to calculate on-time performance expressed as a percentage of buses arriving or departing within an acceptable window. In other words, it uses disaggregate information to derive the aggregate information.

Research Methodology

This research focuses on the idea that transit agencies can maximize on-time performance by adjusting their published schedule timetables. First, the data from an AVL system need to be studied, cleaned, and prepared for use on this on-time performance methodology (OTPM). Second, the distribution of the data needs to be determined by using statistical analysis. Once the statistical distribution is known, the optimal value is calculated and used to update the times in the timetables. Finally, a computerized iterative validation and comparison process is provided to ensure that the updating takes effect and on-time performance is improved. In addition, an on-time performance simulation (OTPS) process is included to better understand the relationship between the time adjustments and their effect on on-time performance.

The distribution of the schedule adherence times (the difference between actual and scheduled arrival or departure times at time points) is used to make schedule adjustments that can maximize the on-time performance. The methodology assumes that the distribution is normal (which can be justified by the fact that normality tests fail to reject the normality assumption). The objective is to adjust the timetables such that the probability of on-time performance is maximized, where the probability of on-time performance is the area under the density function between the acceptable schedule adherence values.

The data process for the improvement of on-time performance is described in Figure 1. It starts with the AVL data to determine the statistical distribution of the schedule adherence data. Then the first adjustment, using the mean of normal distribution, is made, and the schedule adherence values are brought to the center (mean) of the on-time performance parameters. The details on how to determine the adjustment are described in the following sections. Since the values in the timetables are rounded to the nearest minute, a round function is used to change the adjustment values that can be tested; this is done for practical purposes. Transit agencies present the times in the timetables in minutes. In theory, using continuous values (decimals) or smaller intervals (e.g., ½ minutes), rather than discrete values (integers), could improve on-time performance even further. Then, on-time performance is calculated, using the rounded adjustments, and it is determined if the modifications increased on-time performance. If yes, then the timetables will be updated.

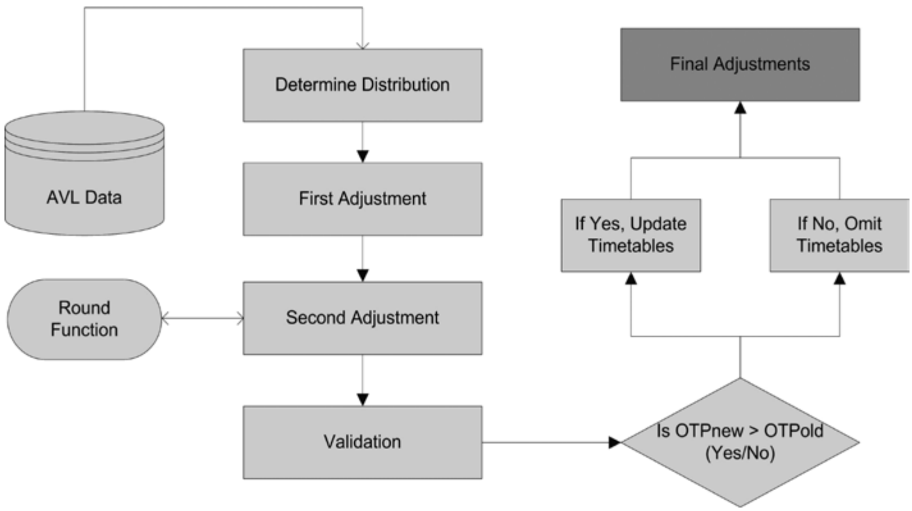


Figure 1. Data flow for the on-time performance improvement process

On-Time Density Area

As previously mentioned, the strategy is to maximize the on-time density area in order to improve on-time performance. Figure 2 displays two distribution curves. One is before the adjustments and the other is after the adjustments. The two shaded areas, which correspond to the on-time performance density areas, are different under the two curves.

As can be seen, the shaded area on the top is smaller than the shaded area on the bottom. For this example, the on-time performance parameters are assumed to go from -5 to 2, which are the limits of the density areas. Buses arriving within 2 minutes early to 5 minutes late are considered to be on time. To maximize on-time performance, the sample mean (0) of the curve on the left is shifted to [(2-5)/2 = -1.5], which is the center of the on-time range and depicted on the right curve.

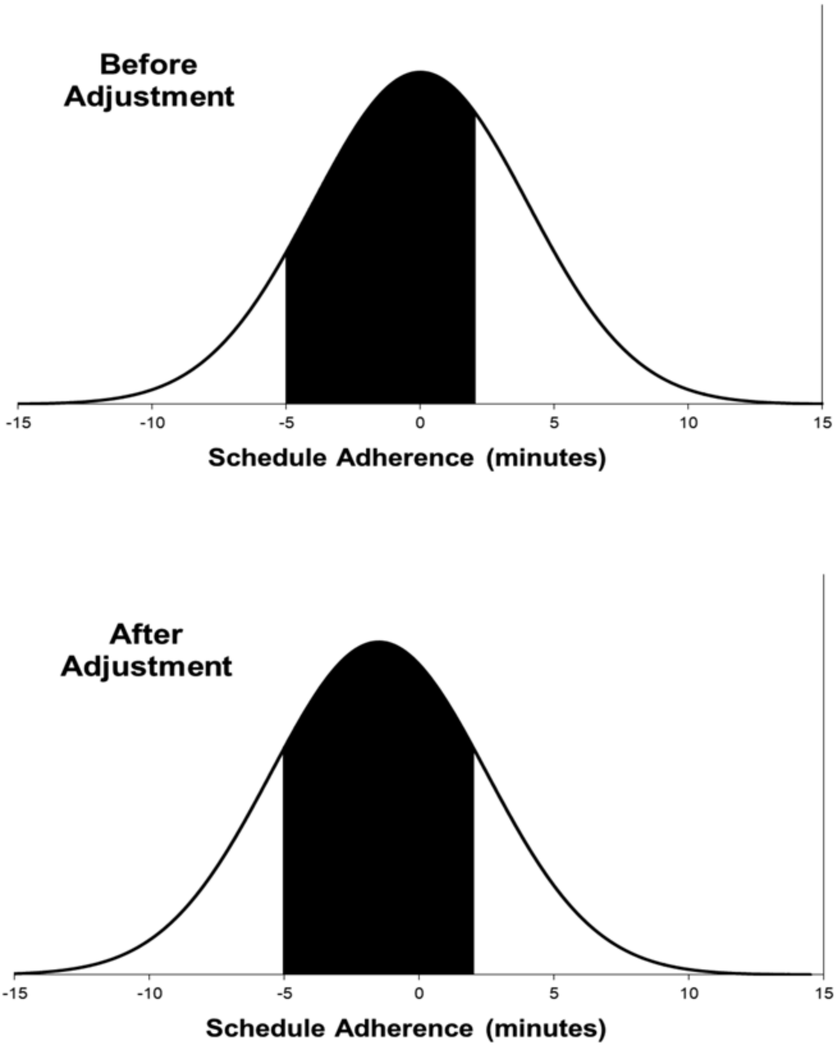


Figure 2. Density areas before and after adjustments

The explanation of why the density area will be maximized when the sample mean is in the center of on-time range is described below for the case that the distribution is normal.

Define:

x_1 = Lower value of the on-time parameters.

x_2 = Upper value of the on-time parameters.

$c: = x_2 - x_1$.

μ = Mean of the schedule adherence (ADH) data.

σ = Standard Deviation of the ADH data.

$D(x)$ = Cumulative distribution function for the normal distribution.

The density area in the on-time range is

$$G(x_2) = D(x_2) - D(x_2 - c) = \int_{x_2-c}^{x_2} \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left\{-\frac{(t-\mu)^2}{2\sigma^2}\right\} dt.$$

The first and second derivatives of $G(x_2)$ are

$$G'(x_2) = \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left\{-\frac{(x_2-\mu)^2}{2\sigma^2}\right\} - \frac{1}{\sqrt{2\pi}\,\sigma} \exp\left\{-\frac{(x_2-c-\mu)^2}{2\sigma^2}\right\}$$

and

$$G''(x_2) = -\frac{x_2-\mu}{\sqrt{2\pi}\,\sigma^3} \exp\left\{-\frac{(x_2-\mu)^2}{2\sigma^2}\right\} + \frac{x_2-c-\mu}{\sqrt{2\pi}\,\sigma^3} \exp\left\{-\frac{(x_2-c-\mu)^2}{2\sigma^2}\right\},$$

respectively. Letting $G'(x_2) = 0$, then $x_2 - \mu = \frac{c}{2}$. Note that

$$G''(x_2)\Big|_{x_2=\mu+\frac{c}{2}} = -\frac{c}{\sqrt{2\pi}\,\sigma^3} \exp\left\{-\frac{c^2}{8\sigma^2}\right\} < 0.$$

This implies that $G(x)$ reaches its maximum at $x_2 = \mu + \frac{c}{2}$. It means that the density area in the on-time range is maximized when x_1 and x_2 are symmetrically allocated about μ, and, finally, we obtain that when $\mu = \frac{x_1 + x_2}{2}$, the density area of the on-time range is maximized.

Another finding about the on-time density area is described in Figure 3. It is clear that the on-time density area is related to the data variance. We use kurtosis to measure the peakedness or flatness of the dataset distribution: a positive kurtosis indicates a relatively peaked distribution, while a negative kurtosis indicates a relatively flat distribution. Higher kurtosis is an indication that more of the variance is due to infrequent extreme deviations.

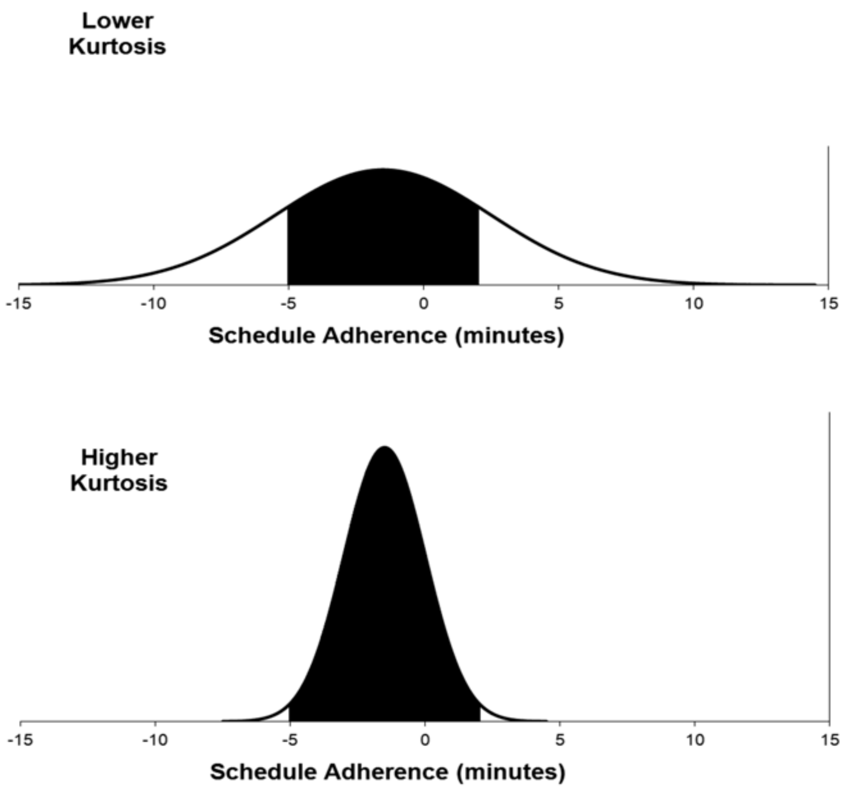


Figure 3. Data with different kurtoses (on-time parameters between -5 to 2)

In Figure 3, the bottom figure shows a higher kurtosis than the top one. From this figure, it is clear that the dataset with higher kurtosis will have more area within the on-time parameters area than dataset with lower kurtosis. Thus, one approach to increase on-time performance is to increase the dataset kurtosis value—in other words, reduce its variance.

As high variances have a negative impact on on-time performance, transit agencies can use different operational strategies to reduce this variability. For instance, the early and late arrival tails can be addressed with a combination of field and dispatch supervision as well as optimal timetable adjustments. Thus, improving on-time performance may require both better operations control and scheduling strategies.

Data Source and Distribution

The schedule adherence dataset used in this research comes from the Miami-Dade Transit (MDT) CAD/AVL system. MDT buses transmit data at a 2-minute poll interval. However, at the timepoints, a record is generated at the exact time of the event. These records, in combination with data from the Transit Operations System (TOS), are used to calculate schedule adherence. The schedule adherence dataset includes GPS location, date, time, and operational data such as Route, Direction, Run Number, Employee Number, Vehicle Number, and Time Point information (Cevallos et al. 2008).

Even though the schedule adherence data from an AVL system can be assumed to be normally distributed, the data can be skewed to the right or to the left (it most likely follows the log normal distribution), depending on how schedule adherence is calculated by the AVL system. This is dependent of the sign (i.e., + or -) used to represent lates or earlies.

The normality assumption, as justified by the normality tests, is very useful for practical purposes. Using the normal distribution, the timetables adjustments to maximize on-time performance can be determined easily. The goal of this strategy is to maximize the density area of the schedule adherence distribution, within the on-time performance parameters. Therefore, adjustments to the AVL data in the database are made to maximize the density area. By doing this, more buses will arrive or depart within the density area, which improves on-time performance. This process also reduces the number of buses arriving or departing early, which is an undesirable condition for both the transit agency and the passengers.

QQ plot diagrams were used as a graphical tool to diagnose differences between the probability distribution of a statistical population from which a random sample has been taken and a comparison distribution. To demonstrate the applicability of this research, Route 99 was selected. This is a simple route with only one pattern using the same running times throughout the day. Figure 4 shows the normal QQ plot diagrams for the time period of 16:00 - 19:00 at the 199S47AV (NW 199 St. & 47 Ave) time point in Route 99. According to the shapes, with the exception of lower and upper end points, it can be assumed that the statistical distribution is approximately normal.

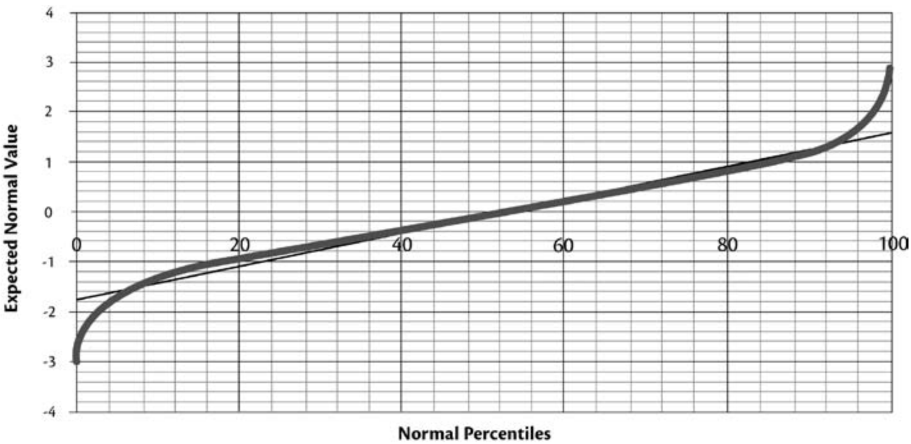


Figure 4. Normal QQ plot for schedule adherence for Route 99 at NW199 St. and 47 Ave.

In this research, the schedule adherence dataset used is considered to follow the normal distribution. This is supported by the shapes of the QQ plots. However, this may not be absolutely guaranteed for other datasets in the AVL database. Even though the normality assumption of the dataset plays an important role in this research, the key point in this paper is how to make the on-time performance area maximum by shifting the ADH values. In fact, even if the dataset does not follow normal distribution, it still is possible to find the approximate center of the schedule adherence values and shift the ADH dataset to improve on-time performance. If the dataset is close only to the normal distribution, the on-time performance area also is close to the maximum area possible. In this situation, simulation can be used to make sure that the adjustments made maximize the on-time performance area. This is further discussed in the Simulation Process section.

Depending on the AVL system, the data can be skewed to the right or to the left. Data generated from AVL systems that use negative numbers to represent late buses will tend to show data skewed to the right because it is expected that the majority of values be towards the left, whereas if late buses correspond to positive numbers and early buses to negative numbers, then the distribution is likely to be skewed to the left. Further, this distribution is likely to follow the log normal distribution (Cevallos and Zhao 2006). This is due to the fact that buses are likely to arrive or depart late rather than early most of the time. Early arrivals and departures is an undesirable condition, and it is controlled by most transit agencies. The reason for this is obvious. Transit agencies usually work hard to avoid early departures, as this can be very detrimental to passengers.

Hypothetical Transit Route

To better understand the framework of our research, a hypothetical transit route to better demonstrate the process is presented. Figure 5 is used for this purpose. The diagram depicts a schematic of a hypothetical transit route. The route is divided into a number of timepoints with a bus traversing along the route. When the transit bus arrives at stop i+1, the actual arrival time is known from the AVL system, and the schedule adherence is calculated at that particular location. If the bus arrival time falls outside the range of the on-time parameters, which are defined by the transit agency, the bus will be regarded as either late or early. This is depicted in Figure 5 under Actual Arrival Time, which shows a bus arriving early. However, if the schedule time is shifted a little earlier, chances are that the number of early arrivals is reduced. The question is, how much should the scheduled time be moved to improve on-time performance?

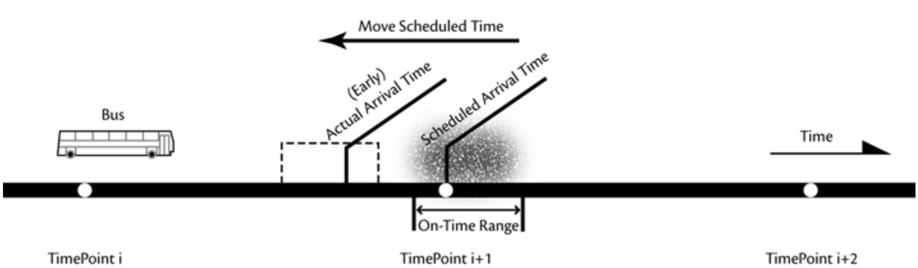


Figure 5. Moving scheduled times in a hypothetical transit route

Adjustment of Timetable

Before adjusting the timetables, some terminology needs to be defined first:

- *ADH*: Schedule adherence.
- *Before.Time*: The scheduled time before adjustments.
- *After.Time*: The new scheduled time after adjustments.
- *Adj.First*: First raw adjustment of the schedule adherence.
- *Adj.Second*: The second adjustment of the schedule adherence by applying round function.
- *On-Time.Period*: $-5 \leq ADH \leq 2$. A bus is considered to be on time if it is within 2 minutes early and 5 minutes late. These are the on-time performance parameters used by MDT. Different agencies may have a different definition for the on-time period. Other agencies may use 0 and -5 or 1 and -5. There appears to be no industry standards for on-time performance.
- *Adj.ADH*: This is a constant, based on the statistical distribution and time period. In the normal distribution, this corresponds to the middle value of the on-time range. In other distributions, it should be the number that maximizes the density area of the on-time range.
- *Layover/Recovery Time*: 10% of the trip time. The time used at the end of a trip (Pine et al. 1998).

To minimize the complexity of this methodology, some assumptions need to be made:

- *Assumption 1*: The schedule adherence follows the normal distribution. Since the schedule adherence distribution is close to the normal distribution, this assumption seems reasonable and it is supported by QQ plot diagrams.
- *Assumption 2*: Shifting the schedule does not change behavior. Operator behavior is not expected to change with the new schedule—that is, vehicle operators will drive as usual.

The method used in this research is to adjust the times in the timetables by shifting the *ADH* to *Adj.ADH* values, so that density area for the on-time range is maximized. For this, the following formulas were developed:

Adh.First = Mean.ADH - Adj.ADH
Adh.Second = Function Round (Changes.First)

After.TIME = Changes.Second + Before.TIME
After.ADH = Changes.Second + Before.ADH

The Round function is applied to the first change from a decimal to an integer value, because the minimum unit is one minute. For example, in the case of timepoint NW 199 St & 47 Ave in Route 99 in Table 1, *Adj.First* = 4.23. After applying the simple round function, *Adj.Second* will be 4, which means that the schedule time should be updated from 05:23 PM to 05:19 PM.

Adj.ADH is a very important constant in this model. Though the data are considered to follow the normal distribution, other distributions can be applied (like the lognormal distribution). In any case, the goal should be to maximize the area of the statistical distribution considering the on-time performance parameters. According to the on-time performance parameters used in this research, the vehicle is on-time if and only if *ADH* is less than or equal to 2 or *ADH* is more than or equal to -5. Since it is assumed that the data follows the normal distribution, the center of the on-time performance area is -1.5, which is the adjustment value that can maximize the on-time performance area. Therefore, in this particular case the *Adj.ADH* will be -1.5.

Figure 6 shows the fit curve of the schedule adherence on the right, compared to the ideal curve that maximizes on-time performance on the left. The solid line display the fitted normal distribution based on a sample data in this research. The discrete data are approximated and treated as normal distribution. The center of the solid curve is the mean of the sample data. According to the methodology, the mean of the schedule adherence values is shifted to -1.5. This value (-1.5) is the center of the on-time range [-5, 2]. This is depicted in Figure 6, where the right solid normal distribution curve is shifted to the left dotted line. After the adjustments, the on-time performance area is maximized.

After the second adjustments are calculated, the whole timetable is adjusted. The sample data selected consisted of seven timepoints in Route 99 in the Eastbound direction. Table 1 displays information of these time points. The first row shows the stop name of each time point, the second row shows the name of time points. The third row shows the schedule time before adjustments. The data collected is from the time period of 16:00 - 19:00. The fourth row shows the mean of the schedule adherence at the timepoints. The fifth row is the standard deviation of the schedule adherence data. The sixth row is the first adjustment and the seventh row is the second adjustment. The eighth row shows the schedule time after adjustments.

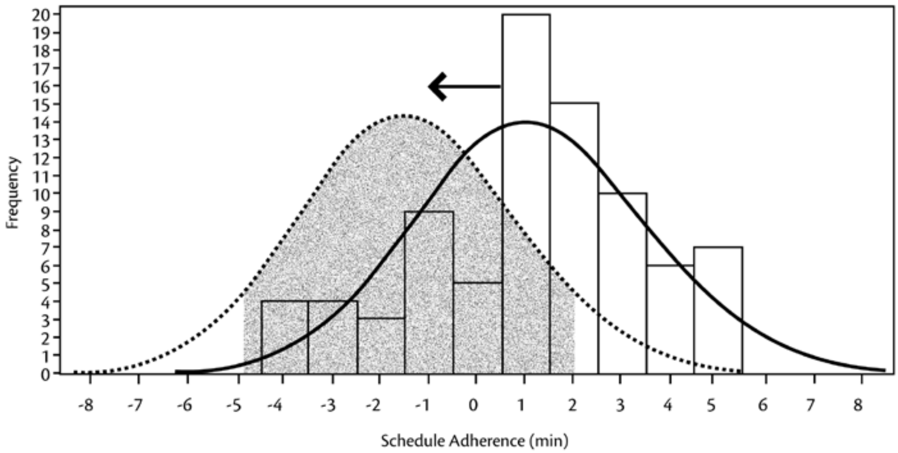


Figure 6. Adjustment diagram

Table 1. Adjustment of Timetable in Route 99

Stop Name		NW 199 St & 47 Ave	NW 199 St & 27 Ave	NW 215 St & 2 Ave	NE 199 St & 2 Ave	NE 199 St & 10 Ave	NE 203 St & 20 Ave	Aventura Mall
1	Time Point	199S47AV	199S27AV	U441215S	NE2A199S	199S10AV	203S20AV	AVEN-MALL
2	Before-Time	05:23 PM	05:29 PM	05:45 PM	05:53 PM	05:58 PM	06:06 PM	06:15 PM
3	Mean (adh)	2.73	-1.72	-0.05	-2.06	-0.94	-0.73	-0.67
4	SD (adh)	5.41	3.05	3.55	3.85	3.76	3.28	3.93
5	Adj. First	4.23	-0.22	1.45	-0.56	0.55	0.77	0.82
6	Adj. Second	4	0	1	0	1	1	1
7	After Time	05:19	05:29	05:44	05:53	05:57	06:05	06:14

For instance, the mean of the schedule adherence at NE 203 St & 20 Ave is -0.73. This uses the -1.5 constant, which is the center of the on-time period of -5 and 2. The first adjustment (*Adj.First*) should be 0.77, which is the result of -0.73-(-1.5).

After applying the round function, the second adjustment (*Adj.Second*) equals 1. Therefore, the new time would be 06:05 PM (06:06 PM – 1).

The final results, based on the adjustments implementation, are presented in Figure 7. By applying this methodology, the on-time performance for Route 99 in the Eastbound direction increased from 72.3 percent to 80.4 percent (i.e., an 8.1% increase) during the time period from 16:00 to 19:00.

Simulation Process

Though the timetable approach is described and the effect is proved by the on-time performance improvement results above, these results are based on a normal assumption and a rounding procedure. Ideally, a better solution could be obtained by using the best possible statistical distribution for the schedule adherence data as well as using continuous or smaller time intervals, instead of discrete integer values for the timetable adjustments. Nevertheless, a good solution can be obtained through simulation to get all possible outcomes for on-time performance using different schedule adherence adjustments. This is accomplished by introducing different adjustments until the best on-time performance value is obtained. The simulation uses schedule adherence adjustments at 1-minute intervals, since this is the basic unit used in the timetables and schedule adherence data.

A Structured Query Language (SQL) statement is built to perform the simulation. The output data contains columns that include old on-time performance, new on-time performance, average of *ADH*, variance of *ADH* and the changes of *ADH*. It calculates all possible on-time performance by changing the *ADH* values. Table 2 presents a partial outcome of the simulation test. According to this test, the highest on-time performance value at timepoint SOUTMIAM from Route 57 is reached when the ADH_CHANGE value equals to -2 and the AVG_ADH is -1.41. As it can be seen, this average value is close to the constant of -1.5.

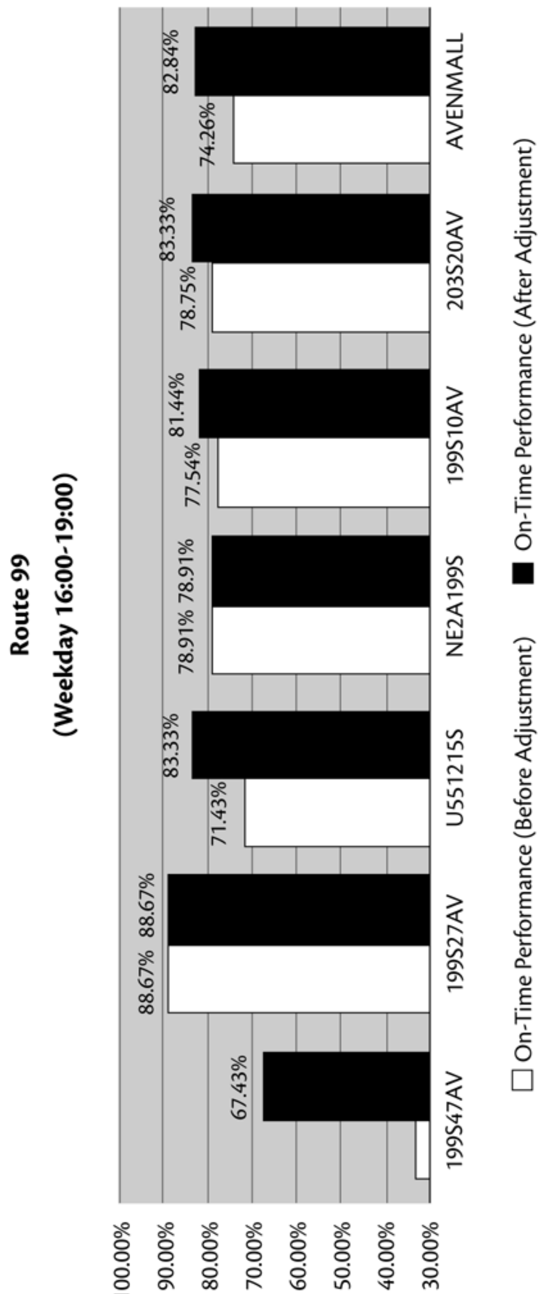


Figure 7. On-time performance comparisons of intermediate time points

Table 2. Partial Dataset from Simulation Process*

TP	ROUTE	AVG_ADH	PERF1	PERF2	ADH_CHANGE
SOUTMIAM	57	-4.41	47.85	61.21	-5
SOUTMIAM	57	-3.41	47.85	64.35	-4
SOUTMIAM	57	-2.41	47.85	64.55	-3
SOUTMIAM	57	-1.41	47.85	65.19	-2
SOUTMIAM	57	-0.41	47.85	57.48	-1
SOUTMIAM	57	0.59	47.85	47.85	0
SOUTMIAM	57	1.59	47.85	40.98	1
SOUTMIAM	57	2.59	47.85	34.55	2
SOUTMIAM	57	3.59	47.85	28.58	3
SOUTMIAM	57	4.59	47.85	23.70	4

*TP: time point; Route: route number; AVG_ADH: average of *ADH* values after changes; PERF1: on-time performance value before any changes; PERF2: on-time performance after *ADH* changes; ADH_CHANGE: changes of ADH value

Based on the methodology presented in this paper, the optimal on-time performance is obtained when the mean of the schedule adherence values is shifted to -1.5. Note that using simulation, the optimal value is the same as the one obtained from the previous methodology. However, it is not guaranteed that the optimal values that are obtained from both methodologies will be always the same.

Figure 8 presents the on-time performance comparison between the solutions of On-Time Performance Metrology (OTPM) and On-Time Performance Simulation (OTPS) for a 24-hour period. The chart in Figure 8 shows that there are no differences in four of the five timepoints. However, in time point U441215S, the solution by using OTPS increased the on-time performance. For practical purposes, there is no major difference from either method. Yet, the OTPS process produced a slightly higher on-time performance improvement.

As depicted in Figure 8, the OTPS approach improves the on-time performance of timepoint U441215S approximately 2 percent; the other timepoints remain the same. What this means is that using the simpler OTPM approach, good results can be obtained without having to go through the more elaborated OTPS process. Usually, the OTPS process generates better results, because it tries all possible adjustments. However, it is a more complicated than OTPM process. The changes obtained by either process can be used to adjust the time in the timetables, which

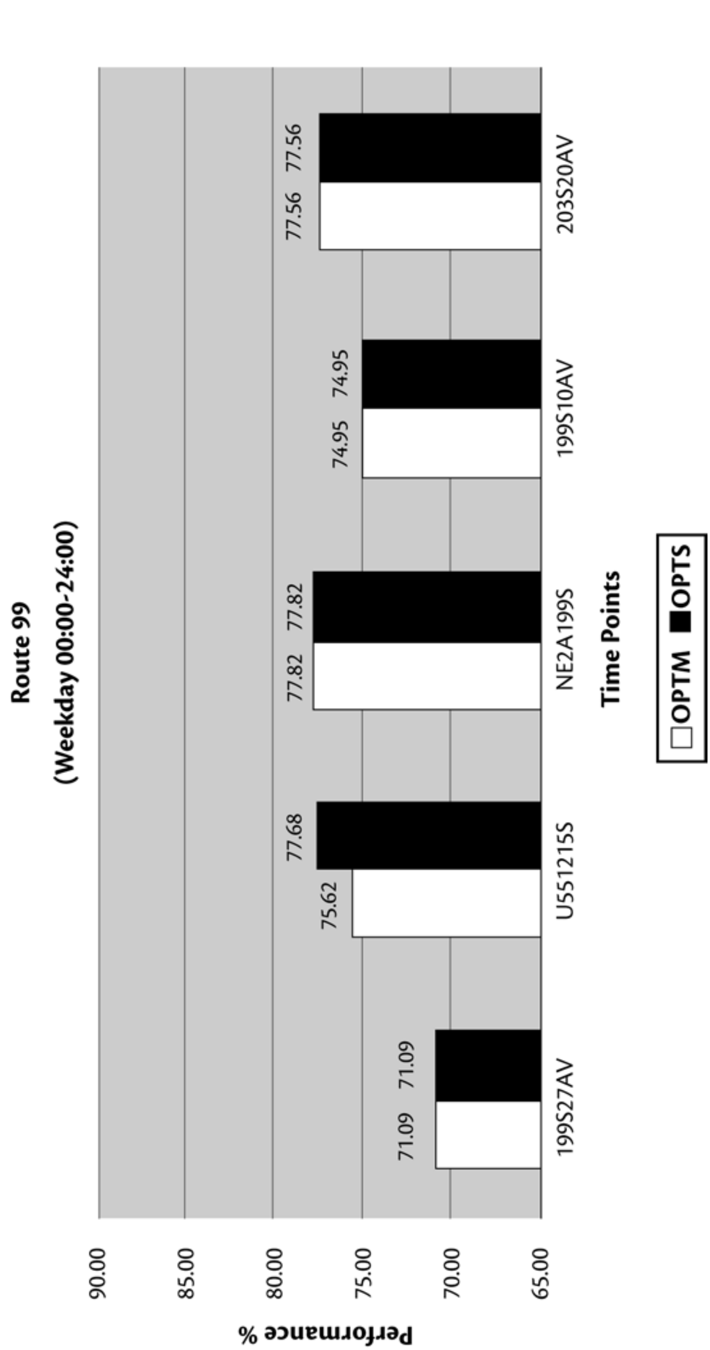


Figure 8. On-time performance results from OPTM and OPTS approaches

can take effect in the next line-up period. Based on this research, it is expected that adjusting the timetables on-time performance can be improved.

Summary and Conclusion

This paper presents a perspective on how to improve transit on-time performance by using schedule adherence data. It takes advantage of data from an AVL system, in particular, schedule adherence information. To demonstrate the applicability of this research, a case study using data from MDT is included, and on-time performance calculations for Routes 99 and 57 also are presented.

A methodology that can be used to update the times in the bus timetables by using schedule adherence data is described. The goal of this methodology is to maximize the on-time density area. The density area is maximized when the mean of the schedule adherence data is in the center of the on-time range. This is supported by a mathematical proof. A validation process is provided to ensure that the updating takes effect. Further, a comparison process is used to assess the on-time performance improvements, before and after the adjustments.

Before this methodology can be applied, the AVL data need to be cleaned, manipulated, and stored in a database to allow the processing of the data. Using statistical analysis, the distribution of the data is determined, and the mean and standard deviation are calculated. Once the statistical distribution is known, the main goal is to maximize the density area of the on-time performance range, which is based on the on-time performance parameters. From this distribution, the optimal value that can maximize on-time performance is obtained and used to update the times in the timetables. The updated timetable will take effect in the next line-up period, and the on-time performance is improved. This process also reduces the number of early arrivals and departures.

There were two assumptions in this research: normal distribution and operator behavior. The assumption of normal distribution is supported based on QQ plots and normality tests. Operator behavior can be attributed to many different factors, and it is assumed to be unchanged after the timetable modifications.

A simulation process is presented to demonstrate additional possibilities. Simulation is a good solution to obtain all possible outcomes for on-time performance using different schedule adherence adjustments and to finally obtain the optimal values. This is accomplished by introducing different adjustments until the best on-time performance value is achieved.

There are still many opportunities for improvements and optimization on this subject. For instance, the peakedness or flatness of the dataset distribution can be measured using the kurtosis statistic. This can be useful for developing strategies that reduce the variance of the data. Studying the relationship between the standard deviation (variability of arrivals/departures) and the schedule adherence adjustments would be beneficial. Including the standard deviation in the methodology may influence the outcome of the on-time performance results. In addition, developing a computerized application could assist with the automation of the described methodology.

In particular, there is potential for generating a more accurate distribution model. The statistical distribution of the schedule adherence data is important to this research. Therefore, better statistical techniques can be applied if a more accurate distribution model is obtained. Different distribution models will produce different adjustment factors, which makes the density area of the sample data maximized.

References

Cevallos, F., and F. Zhao. 2006. Minimizing transfer times in a public transit network with a genetic algorithm. *Transportation Research Record* 2034: 74-79.

Cevallos, F., K. Kirwin, and R. Pearsall. 2008. Using CAD/AVL data for performance management. *Proceedings of the 10th International Conference on Applications of Advanced Technologies in Transportation*, ASCE, Athens, Greece, May 27- 31.

Furth, P., B. Hemily, T. Muller, and J. Strathman. 2003. Using archived AVL-APC data to improve transit performance and management. Transit Cooperative Research Program.

Hammerle, M., M. Haynes, and S. McNeil. 2005. Use of automatic vehicle location and passenger count data to evaluate bus operations. *Transportation Research Record* 1903: 27–34.

Kimpel, T., and J. Strathman. 2004. Improving scheduling through performance monitoring using AVL and APC data. Submitted to University of Wisconsin-Milwaukee as a Local Innovations in Transit project report under the Great Cities University Consortium.

Lee Y., K. Chon, D. Hill, and N. Desai. 2001. Effect of automatic vehicle location on schedule adherence for mass transit administration bus system. *Transportation Research Record* 1760: 81-90.

Nakanishi, Y. 1997. Bus performance indicators-on-time performance and service regularity. 1997. *Transportation Research Record* 1571: 1–13.

Pine, R., J. Niemeyer, and R. Chisholm. 1998. Report 30 transit scheduling: basic and advanced manuals. Transportation Research Board of the National Academies, Washington, D.C.

Shalaby, A., and A. Farhan. 2004. Prediction model of bus arrival and departure times using AVL and APC data. *Journal of Public Transportation* 7(1).

About the Authors

Fabian Cevallos (*fabian.cevallos@fiu.edu*) is the Transit Program Director at the Lehman Center for Transportation Research. He holds a Ph.D. in Civil (Transportation) Engineering from Florida International University. His research interests include Advanced Public Transportation Systems (APTS), transit planning and operations, traffic safety, driving simulation, business intelligence, and information technology.

Xiaobo Wang (*xiaobo.wang@fiu.edu*) is a Software Engineer at the Lehman Center for Transportation Research. He holds an M.S. from Beijing University of Aeronautics and Astronautics and an M.S. in Transportation Engineering from Florida International University. His areas of interests include transportation software research and development.

Zhenmin Chen (*chenzh@fiu.edu*) is a Professor at Florida International University. He holds a Ph. D. in Statistics from the University of Texas at Dallas. His research interests include applied statistics, reliability, and clustering analysis.

Albert Gan (*gana@fiu.edu*) is an Associate Professor at Florida International University. He holds a Ph.D. in Civil (Transportation) Engineering from the University of Florida. His research interests include public transit, traffic simulation and control, ITS, highway safety, access management, and information technology.

Development of a Mode Choice Model for Bus Rapid Transit in Santa Clara County, California

Chun-Hung Peter Chen and George A. Naylor
Santa Clara Valley Transportation Authority

Abstract

Bus Rapid Transit (BRT) is an enhanced bus service that offers many of the same service attributes as rail transit, such as specialized vehicles, large stations, real-time passenger information, and more frequent and reliable operations. The Santa Clara Valley Transportation Authority (VTA) intends to develop an integrated BRT network throughout Santa Clara County, California, to provide high quality service to areas not well served by the VTA Light Rail (LRT) system. Past research showed that many transit agencies in North America considered BRT the same as LRT in their demand models, and a few agencies treated BRT and local bus identically. Realistic BRT ridership forecasts are essential for selecting and sizing facilities, preparing service plans, estimating capital and operating costs, and assessing cost-effectiveness. This study applied the results of the transit preference survey in a Market Research Model prepared for the VTA and built the improved mode choice model that explicitly included the BRT mode in the VTA demand model. Instead of considering BRT the same as either LRT or local bus, the improved VTA model with an explicit BRT mode is expected to forecast more reasonable future BRT boardings. Eleven scenarios in the BRT strategic plan for Santa Clara County were developed using the BRT forecast results from the improved VTA model.

Introduction

Bus Rapid Transit (BRT) is an enhanced bus service that offers many of the same service attributes as rail transit, such as specialized vehicles, large stations, real-time passenger information, and more frequent and reliable operations. A more detailed definition developed by the Transit Cooperative Research Program (TCRP) as part of TCRP Report 90 (2003) is that "BRT is flexible, rubber-tired rapid transit mode that combines stations, vehicles services, running ways, and Intelligent Transportation System (ITS) elements into an integrated system with a strong positive identity that evokes a unique image ... In brief, BRT is an integrated system of facilities, services, and amenities that collectively improves the speed, reliability, and identity of bus transit."

Vuchic (2002) defined BRT based on combining mode performance (speed, reliability, capacity, image) and investment cost per kilometer of line for three categories of transit modes—rapid transit (Metro), semi-rapid transit (light rail transit, LRT), and street transit (regular bus)—and expresses the definition of BRT as the transit mode between LRT and regular bus. Levinson et al. (2002) proposed the comparisons of BRT and other transit modes as follows: "1. where BRT vehicles (buses) operate totally on exclusive or protected rights-of-way, the level of service provided can be similar to that of full Metrorail rapid transit; 2. where buses operate in combinations of exclusive rights-of-way, median reservations, bus lanes, and street running, the level of service provided is very similar to LRT; 3. where buses operate mainly on city streets in mixed traffic, the level of service provided is similar to a limited-stop tram/streetcar system." In general, BRT operating in combinations of exclusive bus lane and mixed traffic is considered to be a transit mode between LRT and local bus.

BRT is now a major trend in the development of public transportation systems worldwide. In the U.S., several BRT systems are in service, such as in Eugene (Oregon), Los Angeles, and Cleveland, and there are also other BRT systems under construction, in development, or planned. According to a Federal Transit Administration's study (2005), in areas with new BRT systems, about 24 to 33 percent of BRT ridership is new to transit. BRT ridership—and transit ridership forecasting in general—is an integral part of transportation planning. Realistic estimates of BRT ridership are essential for selecting and sizing facilities, preparing service plans, estimating capital and operating costs, qualifying benefits, and assessing cost-effectiveness (TCRP 2006). TCRP (2006) implemented BRT ridership surveys for 20 transit agencies in North America to ascertain how BRT was treated in their travel demand forecasting. This study found many agencies considered BRT the same as LRT in their demand models, and only a few agencies treated BRT and local bus identically. It was also found that no transit agencies had built new specific BRT modes in their models for analyzing BRT in the study survey.

The Santa Clara Valley Transportation Authority (VTA) intends to develop an integrated BRT network throughout Santa Clara County, California, to provide high quality service to the areas not served by LRT. VTA has developed the Santa Clara County BRT Strategic Plan (2009) in which different BRT alternatives, potential corridors, operating and infrastructure strategies were proposed. Near-term and long-term BRT corridors integrated with the existing transit system and road system within the county, including Caltrain, LRT, bus, and exclusive lanes with signal priority, will provide the community with more comprehensive and convenient transit service. Future BRT ridership forecasting is one critical element for BRT planning. The current VTA countywide model does not include a BRT mode in the mode choice model. Based on the current structure of the VTA models, if BRT is considered the same as LRT, the forecast ridership may be overestimated. Conversely, if BRT is considered the same as a local bus, the forecast ridership may be underestimated. Given the anticipated need for the level of detail required in developing future BRT plans, it was necessary for the VTA to develop a refined mode choice model that included the mode of BRT.

The purpose of this study was to develop an enhanced mode choice model including the mode of BRT into the VTA model so that the model can forecast future BRT ridership for the planning, development, and implementation of the BRT system in Santa Clara County. The model proposed in this study also is used for alternatives analysis, prioritizing BRT corridors, analysis of new transit trips, and examining impacts to background local bus services. The "previous model" used in this paper represents the original VTA countywide model without applying the procedures of the BRT mode choice model developed in this study; the "improved model" represents the revised model using the new BRT mode choice model.

Previous VTA Model

VTA has developed and maintained a countywide travel demand model for at least a decade, which has been applied to various countywide transportation planning and engineering projects. The VTA model initially was structured to be consistent with the Metropolitan Transportation Commission (MTC) regional model, BAY-

CAST (1997). MTC is the metropolitan planning organization (MPO) for the nine-county San Francisco Bay area. The VTA countywide model is an enhanced version of the MTC nine-county regional model, with the addition of more traffic analysis zones (TAZs) and more detailed highway and transit network coding within Santa Clara County. The MTC mode choice model also was enhanced for application in Santa Clara County and the greater modeling region. In the original MTC model, trips were first split into motorized modes and bicycle and walk-only modes. Motorized trips were then split into drive alone, shared ride 2, shared ride 3 plus, and transit. Last, transit trips were split into transit walk access versus transit auto access. All transit modes were treated identically in the MTC mode choice model, and the choice as to whether the trip used heavy rail, commuter rail, light rail, or express or local bus was dependent on the shortest time path. The enhancements from the MTC model to the VTA model included the implementation of a transit submode nest, allowing the models to estimate ridership on the different transit submodes of commuter rail, express bus, local bus, BART (heavy rail), and light rail as distinct choices based on relative costs and travel times that occur for each submode. The constants of the utility functions for commuter rail, express bus, local bus, BART (heavy rail), and light rail were calibrated based on the transit on-board survey data and transit boarding data. With the inclusion of distinct transit submodes as choices in the model structure, it was possible to calibrate mode specific constants in the VTA mode choice models for each submode. Typically, submode specific constants capture the importance of modal attributes not typically included in the mode choice utility equations, such as reliability, passenger comfort, and safety. During base year calibration, for home-based work trips, the addition of transit submode constants improved the level of validation for each submode. Home-based work calibration results yielded a less negative constant on light rail, followed by heavy rail, commuter rail, local bus, and express bus, in that order. This implies that, all things being equal with respect to travel times and costs, there is a higher probability that a trip will use rail over bus. For the non-work purposes, transit submodes behave in a much more generic manner, with only slight biases for rail in the home-based shop/other and home-based social recreational models. The exception in the non-work models was with the non-home-based trip purposes, as both heavy rail and light rail were shown to have less negative constants as compared to commuter rail or bus modes. Figure 1 without the dashed line box shows the mode choice structure at the previous VTA model.

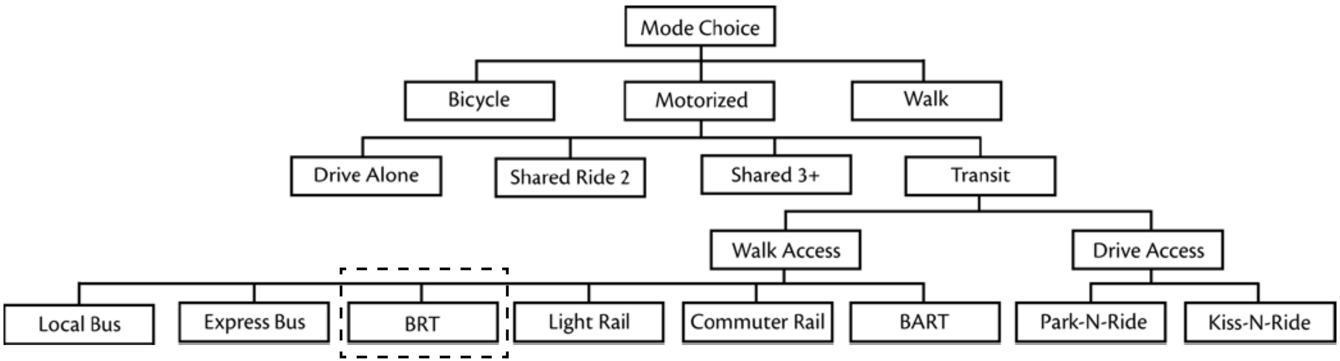


Figure 1. Mode choice structure of the previous and improved vta models

Improved VTA Model

The BRT mode was added into the VTA mode choice model for developing the BRT ridership forecasts to support the Santa Clara County BRT strategic plan. Figure 1 with the dashed line box of the BRT mode shows the mode choice structure of the improved VTA model. The important parameters used in the improved VTA mode choice model, i.e., BRT constants, were derived from the Transit Market Research Model (2007) developed for the VTA. This section addresses how the BRT mode was developed by applying the Transit Market Research Model into the VTA demand model while BRT was still in development and planned without any observed BRT operating data.

Transit Market Research Model

VTA developed a transit market research project, implemented by Cambridge Systematics, Inc., to support the Comprehensive Operational Analysis (COA), a major service redesign plan for the entire VTA bus system that was implemented in January 2008. Transit market research is used to develop market segments based on travelers' attitude towards everyday transportation experiences. The VTA transit market research project consisted of three distinct tasks: data collection, attitudinal-based market segmentation modeling, and mode choice modeling. Data collection included a stated-preference survey of 819 households throughout Santa Clara County. The survey collected attitudinal, demographic, and travel behavior data. The attitudinal-based market segmentation uses cluster analysis techniques to group individual travelers according to their attitudes toward transportation to identify market segments, and then expands the survey records to the entire population of Santa Clara County.

The importance of Transit Market Research Model introduced here is because a new mode of travel—BRT—was estimated in the market research mode choice models. Market research-based mode choice models were developed with the data collected from the market research household travel surveys, specifically from four customized mode choice experiments. Four experiments in the surveys have different values of time, costs, and amenities. Three transit service amenities to address packages of BRT and other transit modes include an electronic sign showing minutes until next train, distinctive-looking buses with comfortable interior, and well-lit, covered stations equipped with benches, maps, and guides. Because BRT was not in service currently, through attitudinal and stated preference surveys, the ridership of BRT likely transferred from current transit systems and potential new ridership from auto modes could be estimated by the market research-based mode choice models. The market research-based mode choice models are multinomial logit models for work and non-work trip purposes. The results of the mode choice models, including the coefficients of different variables in the utility functions and the bias constants for each transit mode (rail, BRT, and bus) are shown in Table 1.

Table 1. Market Research-Based Mode Choice Models

Categories	**Variables**	**Home-Based Work/University**	**Non-Work**
IVTT	In-Vehicle Travel Time	-0.0330	-0.0091
OVTT	Walk time-Access/Egress	-0.0650	-0.0233
	Wait time <= 7 mins	-0.0650	-0.0233
	Wait time > 7 mins	-0.0500	-0.0179
	Drive-Access Time	-0.0650	-0.0233
	Transfer Time	-0.0650	-0.0233
Cost	Cost	-0.0770	-0.0718
Attitudinal Factors	Pro-environment	0.5750	-
	Social Perception	-0.2430	-0.5512
	Travel Flexibility	-0.1450	-
Social-Economic Variable	Workers/ Household	-0.0630	-
	Vehicle/ Household	0.0000	-0.0670
	Age 18 to 24	1.5180	1.8589
	Income < $25,000	1.0360	1.4565
	Income $25,000 to $50,000	0.2520	-0.2244
	Female	-0.6210	-0.3754
Transit Amenities	Amenities -Signs	0.2140	0.5281
	Amenities -Buses	0.2930	0.0187
	Amenities Stations	0.4220	0.5100
Modal Constants	Drive Alone - base constant	0.0000	0.0000
	LRT– constant	0.0000	-1.7593
	BRT – constant	-0.0340	-1.8115
	Bus – constant	-0.7810	-1.8025
Perform Measures	Value of Time	$25.37	$7.64
	OVTT(wait time <= 7 mins) /IVTT	2.0	2.6
	OVTT(wait time> 7 mins) /IVTT	1.5	2.0

Note: OVTT: out-vehicle travel time; IVTT: in-vehicle travel time
Source: Santa Clara Valley Transportation Authority, 2007.

Translation of BRT Constants

Though the purpose of the market research project was to support the transit comprehensive operational analysis, and the market research-based mode choice models were not directly applied in the VTA demand model, the bias constants of BRT compared to (light) rail and bus can be applied to add the new BRT mode in the VTA demand model. Constant coefficients can be converted into bias time constants by dividing constant coefficient by in-vehicle time coefficient

$$b_m = \frac{c_m}{c_{ivt}} \tag{1}$$

where b_m is bias time constant for mode *m*; c_m is constant coefficient for mode *m* and c_{ivt} is in-vehicle time coefficient in Market Research Model. Bias time constants present the relative waiting time among different transit modes. For home-based work trips, the rail, BRT, and bus constants are 0, -0.034, and -0.781. Using Eq. (1), the bias time constants for rail, BRT, and bus are 0, -1.03 and -23.67 minutes, respectively. For non-work trips, the rail, BRT, and bus constants are -1.7593, -1.8115, and -1.8025. The bias time constants for rail, BRT, and bus converted to equivalent minutes of in-vehicle travel time are -193.33, -199.07 and -198.08 minutes, respectively. Due to home-based work passengers having a higher value of time at $25.37 compared to non-work passengers' value of time at $7.64, potential BRT passengers from home-based work trips consider BRT more like LRT, while non-work passengers consider BRT more like local bus. For home-based work passengers, BRT only provides one less minute travel time than light rail and 23 minutes travel time over local bus; for non-work passengers, BRT and local bus almost have no significant difference for equivalent time, -199.07 and -198.08 minutes. It was, therefore, assumed that BRT and local bus have the same bias time constants for non-work trips.

Bias time constants derived from Transit Market Model were used to estimate the BRT constants in the VTA demand model. Table 2 shows the coefficients of utility functions of the previous VTA mode choice model without BRT constants. Because the BRT mode is considered to be service between that provided by light rail and local bus, BRT constants are calculated by the linear interpolation method using the light rail constants, local bus constants, and bias time constants obtained above.

$$\Delta_{BRT} = \Delta_{LB} + (\Delta_{LRT} - \Delta_{LB})(\frac{b_{BRT} - b_{LB}}{b_{LRT} - b_{LB}}) \tag{2}$$

where Δ_{BRT} is BRT constant; Δ_{LB} is local bus constant; Δ_{LRT} is LRT constants; b_{BRT} is BRT bias time constant; b_{LB} is local bus bias time constant; and b_{LRT} is LRT bias time constant.

Table 2. VTA Mode Choice Models—Transit Walk Access

Variables	Home-Based Work	Home-Based Shop-ping	Home-Based Social/ Recre-ation	Non-Home Based	Home-Based School (Grade School)	Home-Based School (High School)	Home-Based School (College)
BART (heavy rail)	-0.86301	1.14089	2.48260	4.74364	0.59115	1.11067	0.76854
Commuter Rail	-0.86301	1.02982	2.22221	3.57032	0.59115	1.11067	0.76854
Light Rail	-0.96318	1.02982	2.22221	4.84000	0.59115	1.11067	0.76854
Express Bus	-1.84149	1.02982	2.22221	3.57032	0.59115	1.11067	0.76854
Local Bus	-1.70196	1.02982	2.22221	3.57032	0.59115	1.11067	0.76854
EMPD	0.546100						
Zero VHHD	0.550100	3.2910					
VHH		-0.3352	-0.7475				
PHH^3					0.004436		
Rurali					1.544		
Total Time		-0.05815					
IVT	-0.033260		-0.02745	-0.03232	-0.05855	-0.03228	-0.02731
Wait	-0.052330			-0.07836			
Walk	-0.093050			-0.07583			
Transfer	-0.033260						
OVTT			-0.06806		-0.06384	-0.03463	-0.03923
Cost	-0.002067						
LnCost		-0.2262	-1.1600	-0.9862	-1.9300	-2.0340	-0.6920
Corej		2.3750	0.9694				
LnAreaDen			0.3217				
Net ResDen						0.1442	
Value of Time	$9.65	$6.58	$0.78	$1.08	$0.36	$0.23	$0.67
Ratio of Wait/IVTT	1.57	-	-	2.42	-	-	-
Ratio of Wait/IVTT	2.80	-	-	2.35	-	-	-

Note: EMPD: employment density; Zero VHHD: zero vehicle per household; VHH: vehicle per household; PHH: population per household; Rurali: rural in production zone; Corej: core zone (CBD) in attraction zone; LnAeraDen: natual log of area density; Net ResDen: net residential density.

Source: Santa Clara Valley Transportation Authority, Valley Transportation Plan 2035, 2009; Transit Cooperative Research Program Report, Appendices to TCRP Report 118, 2006; VTA Model

Table 3 shows the results of BRT constants by applying Eq. (2). Estimated BRT constant for home-base work is -0.99530, close to the light rail constant -0.96318. For home-based shopping, home-based social/recreation, home-based grade school, and home-based high school, light rail constant and local bus are considered as the same mode in VTA model, so that the estimated BRT constants are the same as light rail and local bus constants. For non-home-based trips, BRT constant is equal to local bus constant because BRT and local bus has the same bias time constant for non-work trips.

Table 3. BRT Constant Calculation

Variables	Home-Based Work	Home-Based Shopping	Home-Based Social/ Recreation	Non-Home Based	Home-Based School (Grade School)	Home-Based School (High School)	Home-Based School (College)
Light Rail Constant Δ_{LRT}	-0.96318	1.02982	2.22221	4.84000	0.59115	1.11067	0.76854
Local Bus Constant Δ_{LB}	-1.70196	1.02982	2.22221	3.57032	0.59115	1.11067	0.76854
Light Rail Bias Time b_{LRT}	0	193.33	193.33	193.33	193.33	193.33	193.33
BRT Bias Time b_{BRT}	1.03	198.08	198.08	198.08	198.08	198.08	198.08
Local Bus Bias Time b_{LB}	23.69	198.08	198.08	198.08	198.08	198.08	198.08
Estimated BRT Constant Δ_{BRT}	-0.99530	1.02982	2.22221	3.57032	0.59115	1.11067	0.76854

BRT Strategic Plan

BRT ridership estimates for VTA's BRT Strategic Plan were developed based on the results of the improved VTA model with the added BRT mode in the mode choice model. Eleven different BRT alternatives and operating and infrastructure strategies were proposed. Six potential BRT corridors were identified by the recent Comprehensive Operations Analysis and from VTA's Long-Range Countywide Transportation Plan (Valley Transportation Plan 2035) (VTA 2009), and these included the Alum Rock, El Camino, King Road, Monterey Highway, Stevens Creek, and Sunnyvale-Cupertino BRT corridors, all shown in Figure 2. Six lines show the potential BRT corridors, which are not covered by the LRT. An assessment of new

BRT services was conducted on three corridors within the county as the most promising alignments for near-term BRT implementation. The three corridors included:

- Alum Rock—stretching from HP Pavilion to Eastridge Mall (6.9 miles) and currently served by Rapid 522 (15-minute headways), Local Route 22 (12-minute headways), and Local Route 23 (12-minute headways).
- El Camino—stretching from Palo Alto Transit Center to HP Pavilion (16.6 miles) and currently served by Rapid 522 (15-minute headways) and Local Route 22 (12-minute headways).
- Stevens Creek—stretching from De Anza College to Downtown San Jose (8.6 miles) and currently served by Local Route 23 (12-minute headways).

Rapid 522 has the same route alignment as Local Route 22 with less headway but longer stop spacing. In the previous model, all Rapid 522, Local Route 22, and Local Route 23 are considered as local bus mode. The operating plan in these three corridors is shown in Figure 3.

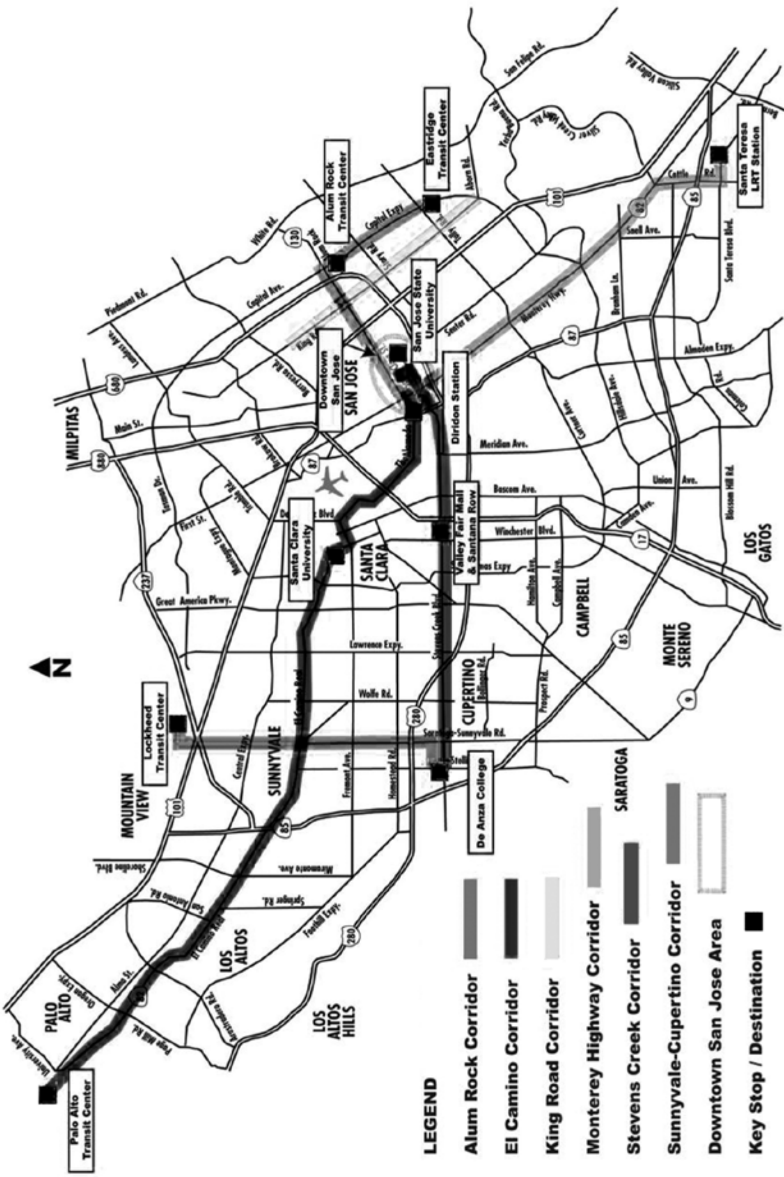
Two new BRT services were proposed in these three corridors: BRT 522 to replace Rapid 522 and overlay on the Local Route 22, and BRT 523 to overlay and complement Local Route 23. Eleven operating plans were developed seeking to achieve enhanced transit market share in the corridor, while making transit more efficient and effective at serving riders. The No Project and 10 operating plans were proposed based on different combinations of BRT and local bus service areas and headways. Note that:

(1) Option 6 considers BRT 522 and 523 modeled as an LRT mode using Option 4 as a base.

(2) BRT 522 in the No Project is the existing Rapid 522. The existing Rapid 522 currently provides 15-minute headways and fewer bus stops than Local Route 22 and is considered as a local bus in the previous VTA model;

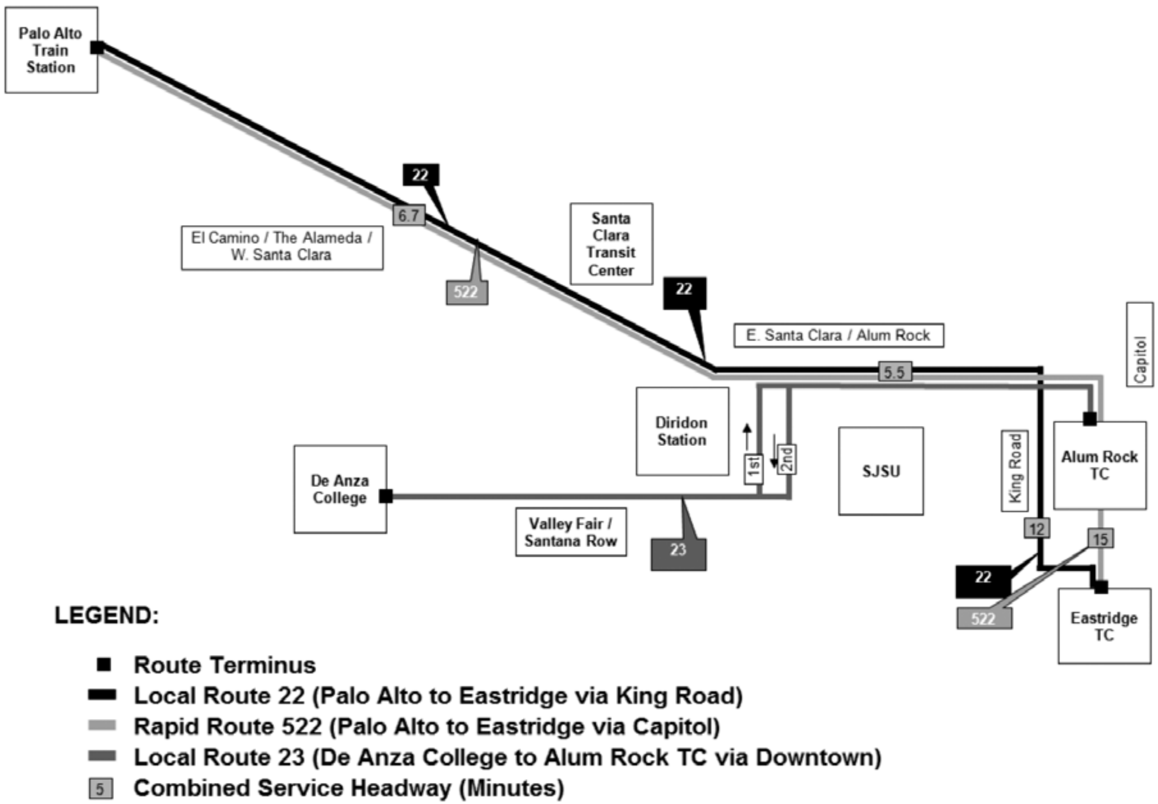
(3) BRT would operate a premium service with 10-minute headways.

(4) Local Route 22 service would be fixed at 15-minutes, a slight reduction in service from existing 12-minute, and Local Route 23 service would have a variable headway (between 15-30 minutes) to be tested in various service scenarios to gauge its impact on demand.



Source: VTA, Congestion Management & Planning Division

Figure 2. Six potential VTA BRT corridors



Source: VTA, Congestion Management & Planning Division

Figure 3. Existing Rapid 522, Local Route 22, and Local Route 23

It also was assumed that in order to claim the full BRT constant, the amount of capital infrastructure required to provide the travel time savings, through either dedicated lanes with signal priority, and vehicle and station passenger amenities must be accounted for in the BRT alternative definition and costs.

Table 4 shows the No Project and 11 operating plans by different operating combinations of BRT 522, Local Route 22, BRT 523, and Local Route 23 that were modeled. Table 5 shows the 2030 boardings for the No Project and the 11 BRT operating plans. Option 6 has the highest boardings for the 522/523 BRT corridors at 91,769 daily boardings, with VTA total transit system boardings of 409,859, because BRT was assumed to have the same constant as LRT in this option plan. Option 4 modeled as a BRT mode results in 79,494 daily boardings for the 522/523 BRT corridors; this translates to a 15 percent decrease in BRT ridership if BRT is treated as a separate BRT mode and not the same as LRT. Option 4a with BRT modeled as a local bus mode results in 65,985 daily boardings for the 522/523 BRT corridor routes and 375,713 VTA total transit system boardings. This represents a 17 percent decrease in BRT ridership over the BRT constant model if BRT is treated as a local bus mode.

Table 4. No Project and Eleven BRT Operating Plans

	BRT Route 522	Local Route 22	BRT Route 523	Local Route 23
No Project	Rapid, Palo Alto to Eastridge via Capitol (15-min headways)	Palo Alto to Eastridge via King Road (12-min headways)	N/A	De Anza College to Alum Rock via Downtown (30-min headways)
Option 1	Palo Alto to Eastridge via Capitol (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	Valley Fair/Santana Row to Eastridge via Downtown/Capitol (10-min headways)	De Anza College to SJSU via Downtown (30-min headways)
Option 2	Palo Alto to Eastridge via Capitol (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	Valley Fair/Santana Row to Eastridge via SJSU/Capitol (10-min headways)	De Anza College to SJSU via Downtown (30-min headways)
Option 3a	Palo Alto to SJSU via Downtown (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	Valley Fair/Santana Row to Eastridge via Downtown/Capitol (10-min headways)	De Anza College to Alum Rock via Downtown (30-min headways)

Table 4. No Project and Eleven BRT Operating Plans (cont'd)

Option 3b	Palo Alto to SJSU via Downtown (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	De Anza College to Eastridge via Downtown/Capitol (10-min headways)	De Anza College to Alum Rock via Downtown (30-min headways)
Option 4 (modeled as BRT)	Palo Alto to Eastridge via Capitol (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	De Anza College to Eastridge via Downtown/Capitol (10-min headways)	N/A
Option 4a* (modeled as Local Bus)	Palo Alto to Eastridge via Capitol (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	De Anza College to Eastridge via Downtown/Capitol (10-min headways)	N/A
Option 5	Palo Alto to Eastridge via Capitol (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	Valley Fair/Santana Row to Eastridge via Downtown/Capitol (10-min headways)	De Anza College to SJSU via Downtown (30-min headways)
Option 6** (modeled as LRT)	Palo Alto to Eastridge via Capitol (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	De Anza College to Eastridge via Downtown/Capitol (10-min headways)	N/A
Option 7 (BRT 10-20)	Palo Alto to Eastridge via Capitol (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	De Anza College to Eastridge via Downtown/Capitol (10-min headways)	De Anza College to SJSU via Downtown (20-min headways)
Option 7a (BRT 10-15)	Palo Alto to Eastridge via Capitol (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	De Anza College to Eastridge via Downtown/Capitol (10-min headways)	De Anza College to SJSU via Downtown (15-min headways)
Option 7b (BRT 10-30)	Palo Alto to Eastridge via Capitol (10-min headways)	Palo Alto to Eastridge via King Road (15-min headways)	De Anza College to Eastridge via Downtown/Capitol (10-min headways)	De Anza College to SJSU via Downtown (30-min headways)

*Note: * Option 4a considers BRT 522 and 523 as Local Bus mode using Option 4 as the base.*
*** Option 6 considers BRT 522 and 523 as LRT mode using Option 4 as the base.*

Table 5. 2030 Daily Boardings by Eleven BRT Operating Plans

Operator/Route	No Project	Opt 1	Opt 2	Opt 3 a	Opt 3b	Opt 4	Opt 4a	Opt 5	Opt 6	Opt 7	Opt 7a	Opt 7b
Route 22 (Local)	29,830	20,782	21,067	21,373	21,383	20,908	15,709	20,651	19,562	20,667	20,557	20,788
Route 23 (Local)	16,966	3,497	3,498	4,269	2,715	0	0	6,678	0	4,386	6,474	2,061
Route 522 (BRT)	12,883*	35,479	36,297	26,597	23,941	32,568	26,738	35,103	40,497	32,549	32,533	32,565
Route 523 (BRT)	0	15,568	12,278	18,469	28,049	26,018	23,538	15,415	31,710	24,834	24,013	25,450
Total BRT Boardings	**12,883**	**51,047**	**48,575**	**45,066**	**51,990**	**58,586**	**50,276**	**50,518**	**72,207**	**57,383**	**56,546**	**58,015**
522/523 BRT Corridor Routes	**59,679**	**75,326**	**73,140**	**70,708**	**76,088**	**79,494**	**65,985**	**77,847**	**91,769**	**82,436**	**83,577**	**80,864**
LRT System	**122,466**	**118,906**	**119,721**	**119,737**	**119,920**	**119,146**	**120,692**	**119,008**	**123,658**	**119,120**	**119,084**	**119,134**
VTA Local Bus (not including Routes 22/23)	145,358	153,280	153,658	152,198	151,005	153,152	147,636	151,923	152,807	150,983	150,525	152,295
VTA Community Bus	23,670	24,026	24,406	23,945	23,907	24,060	24,085	23,937	24,476	23,935	23,878	24,018
VTA Express Bus	16,545	16,323	16,312	16,339	16,239	16,226	17,315	16,314	17,149	16,216	16,213	16,223
VTA Total System	**367,718**	**387,861**	**387,237**	**382,927**	**387,159**	**392,078**	**375,713**	**389,029**	**409,859**	**392,690**	**393,277**	**392,534**

The ultimate preferred BRT Option 7a has the second highest boardings for the 522/523 BRT corridors at 83,577 daily boardings, with VTA total transit system boardings of 393,277, by using the BRT constants derived from Table 3 in the improved VTA model. Option 7a also would generate the second largest total new transit trips, including home-based work and non-work trips, as shown in Table 6. The potential new transit riders would be up to 36 percent of BRT ridership in the preferred operating plan Option 7a, which is a little higher than the 24 to 33 percent from the FTA's study of BRT systems currently in operation (Peak et al. 2005).

The operating costs and capital costs for the 11 BRT operating plans are listed in Table 7. Detailed operating and capital cost analysis can be found in the VTA BRT Strategic Plan (2009). Without considering Option 6 (BRT treated as LRT mode), after demand, operating cost, and capital cost analysis, Option 7a was selected as the preferred BRT operating plan, which would generate the highest demand and the largest number of new riders, but include the highest operating costs as well. The operating and routing plan of Option 7a is shown in Figure 4.

Conclusions

A state-of-the-practice travel demand model with a new BRT mode included in the mode choice model was developed by the Santa Clara VTA and now is used in planning and design phases for countywide BRT projects. Instead of considering BRT the same as LRT or local bus, the BRT constants derived from the Market Research Model fall between LRT and local bus constants. The application of the BRT constants results in BRT ridership between ridership estimates prepared with BRT having a local bus constant and for BRT having a LRT constant, with a variation of approximately 15 percent higher or lower, depending on which constant BRT employed in the forecasts. The improved VTA model was expected to forecast more reasonable future BRT boardings, which were an important consideration in light of the relatively high capital and operating costs associated with BRT services. The potential new transit riders after BRT lines open would be up to 36 percent of BRT ridership in the preferred operating plan.

Future extensions of the present work might include developing a peer review of before-and-after BRT implementation studies and an evaluation of how actual ridership compares to forecasted ridership for areas implementing BRT, either through passenger counts or on-board surveys reflecting the situation at least one year after BRT lines opens. The Alum Rock segment of the BRT lines 522/523 is currently in final design and scheduled for completion by 2013. The remainder

Table 6. 2030 Daily Linked Transit Trips – Santa Clara County

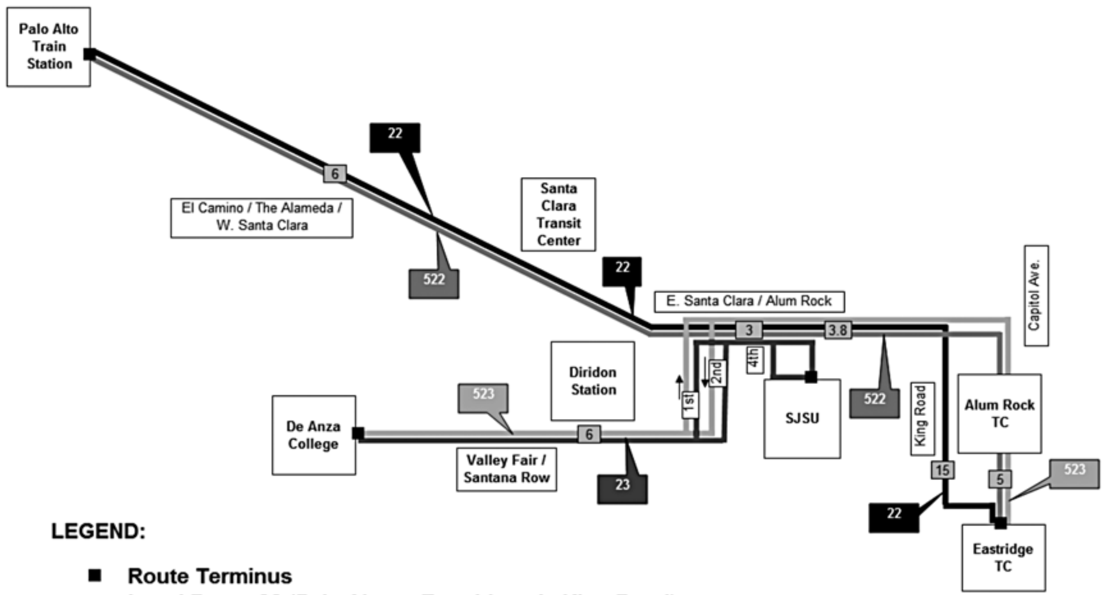
Linked Transit Trips	No Project	Opt 1	Opt 2	Opt 3a	Opt 3b	Opt 4	Opt 4a	Opt 5	Opt 6	Opt 7	Opt 7a	Opt 7b
Home-based Work	113,800	118,819	118,716	118,134	119,067	119,638	114,256	118,954	119,854	119,794	119,835	119,737
Non Work	204,865	216,234	216,238	215,262	217,945	218,552	208,659	216,727	224,524	219,107	219,154	218,877
Total	318,665	335,053	334,954	333,396	337,012	338,190	322,915	335,681	344,378	338,901	338,989	338,614
New Home-based Work Transit Trips (relative to No Project)		5,019	4,916	4,334	5,267	5,838	456	5,154	6,054	5,994	6,035	5,937
New Non Work Transit Trips (relative to No Project)		11,369	11,373	10,397	13,080	13,687	3,794	11,862	19,659	14,242	14,289	14,012
Total New Transit Trips (relative to No Project)		16,388	16,289	14,731	18,347	19,525	4,250	17,016	25,713	20,236	20,324	19,949
Percent New Transit Relative to Total BRT Boardings		32.1%	33.5%	32.7%	35.3%	33.3%	8.5%	33.7%	35.6%	35.3%	35.9%	34.4%

of the BRT 522 corridor along El Camino Real is scheduled for completion by 2015. Based on this schedule, it is expected that the VTA will be able to implement BRT in the county within three years, which will provide an opportunity to refine the BRT models in the relative near term and develop before and after studies of actual local experiences.

Table 7. Annual Operating and Maintenance Costs and Capital Costs for Eleven BRT Operating Plans

	Annual Operating and Maintenance Cost	Capital Cost
No Project	-	-
Option 1	$62,700,000	$412,200,000
Option 2	$62,600,000	$420,900,000
Option 3a	$58,900,000	$417,900,000
Option 3b	$64,600,000	$495,700,000
Option 4	$64,400,000	$490,000,000
Option 4a	$64,400,000	$490,000,000
Option 5	$64,700,000	$412,200,000
Option 6	$64,400,000	$490,000,000
Option 7 (BRT 10-20)	$70,400,000	$490,000,000
Option 7a (BRT 10-15)	$72,300,000	$490,000,000
Option 7b (BRT 10-30)	$68,400,000	$490,000,000
Option 7b (BRT 10-30)	$68,400,000	$490,000,000

Source: VTA BRT Strategic Plan, 2009.



LEGEND:

- Route Terminus
- Local Route 22 (Palo Alto to Eastridge via King Road)
- BRT Route 522 (Palo Alto to Eastridge via Capitol)
- BRT Route 523 (De Anza College - Eastridge via Downtown/Capitol)
- Local Route 23 (De Anza College to SJSU via Downtown)
- 5 Combined Peak Service Headway (Minutes)

Note: **Assumes Transit Center at San Jose State for layover and turnaround.**

Source: VTA BRT Strategic Plan, 2009

Figure 4. Preferred BRT operating plan – Option 7a (BRT 10-15)

References

Levinson, H. S., S. Zimmerman, J. Clinger, and Rutherford, C. S. 2002. Bus rapid transit: An overview. *Journal of Public Transportation* 5(2): 1-30.

Metropolitan Transportation Commission. 1997. Travel demand models for the San Francisco Bay Area (BAYCAST-90) technical summary. Oakland, California.

Peak, M., C. Henke, and Wnuk, L. 2005. Bus rapid transit ridership analysis, Federal Transit Administration, Report FTA-CA-26-7068-2004.1.

Santa Clara Valley Transportation Authority. 2001. Silicon Valley Rapid Transit Corridor MIS/EIS/EIR Deliverable #10: Travel demand modeling methodology report. Prepared by Hexagon Transportation Consultants. San Jose, California.

Santa Clara Valley Transportation Authority. 2007. Transit market research models. Prepared by Cambridge Systematics, Inc. San Jose, California.

Santa Clara Valley Transportation Authority. 2009. BRT strategic plan - Final report. Prepared by ARUP North America Ltd. San Jose, California.

Santa Clara Valley Transportation Authority. 2009. Valley Transportation Plan 2035. San Jose, California.

Transportation Research Board of the National Academies. 2003. Transit Cooperative Research Program Report 90. Bus rapid transit – Volume 1: Case study in bus rapid transit. Transportation Research Board, Washington D.C.

Transportation Research Board of the National Academies. 2006. Transit Cooperative Research Program Report - Appendices to TCRP Report 118. Bus Rapid transit practitioner's guide, *TCRP Web-Only Document* 39. Transportation Research Board, Washington D.C.

Vuchic, V. R. 2002. Bus semirapid transit mode development and evaluation. *Journal of Public Transportation* 5(2): 71-95.

Chun-Hung Peter Chen (*peter.chen@vta.org*) is a Transportation Planner in the Santa Clara Valley Transportation Authority, Santa Clara County, California. He received his Ph.D. in Civil Engineering from the University of Maryland, College Park, and his M.S. and B.S. degrees in Civil Engineering from the National Taiwan University. He has been with VTA since 2007 and worked at several light rail and BRT projects. He is a registered professional engineer in the states of Washington and

California and also has a certificate of PTOE (Professional Transportation Operations Engineer) from the Transportation Professional Certification Board Inc.

George A. Naylor (*george.naylor@vta.org*) is a Transportation Planning Manager for the Santa Clara Valley Transportation Authority and manages the travel demand modeling activities for the Authority. He received his master's degree in Urban and Regional Planning from San Jose State University and his B.S degree in Petroleum Engineering from Texas A&M University.

The Effects of Articulated Buses on Dwell and Running Times

Ahmed M. El-Geneidy and Nithya Vijayakumar
McGill University

Abstract

Articulated buses are being operated more frequently on popular bus routes, as they can handle higher passenger loads and increase rider comfort. Dwell and running times associated with articulated buses are expected to be different from regular low-floor buses. We use archived bus operation and passenger information from three heavily-used bus routes operated by the Société de Transport de Montréal, Canada, to measure these differences. Operation of articulated buses yielded to savings in dwell time, especially with high levels of passenger activity and the use of the third door in alighting. These savings were not reflected in running time, due to increases in the time associated with acceleration, deceleration, and merging with traffic. This study gives transit planners and operators important information on the differences in operating environments between regular and articulated buses.

Introduction

Articulated buses are being used more frequently on popular bus routes, as they can handle high volume passenger loads. Articulated buses can increase the speed of boarding and alighting at each stop, as well as reduce the number of buses needed on a route. Experts recommend the use of articulated buses as part of bus rapid transit (BRT) systems and express routes (Levinson et al. 2002). It is expected that the use of articulated buses in BRT systems will help attract more choice riders (Pahs et al. 2002). This is related to the expected improvements associated to the use of this bus type, which include increases in the levels of comfort to existing users through more space on the bus per passenger and decreased dwell time (time associated to passenger activity) (Hemily and King 2008; Hemily 2008). To our knowledge, these benefits have not been quantified in terms of operational benefits to the transit agency or time savings to transit users. In Fall 2009, the Société de Transport de Montréal (STM), the transit provider on the Island of Montréal, introduced articulated buses on routes 69, 121, and 467 as a measure to improve bus services along these highly used routes. STM's main goal with this action was to increase passenger satisfaction and attract new choice riders by reducing overcrowding along heavily-used routes. This study compares the effects of articulated buses to regular low-floor buses on dwell and running times using archived Automatic Vehicle Location (AVL) and Automatic Passenger Counters (APC) data. It gives transit planners and operators important information on the operating environment of articulated buses. This information can be used to adjust the schedules of bus transit routes where articulated buses operate.

The paper begins with a literature review on the use of articulated buses and its expected effects. The next sections describe the data being used in the analysis and the methodology. These two sections are followed by a discussion of the model results and a conclusion and recommendation section.

Literature Review

Articulated buses frequently are used in BRT systems and heavily-used routes (Levinson et al. 2002; Jarzab et al. 2002). Articulated buses have an advantage over single-body low-floor buses because they can carry twice as many passengers during one trip (Kaneko et al. 2006). On high-capacity bus routes, articulated buses reduce staff and bus stock necessary to transport passengers (Smith and Hensher 1998). Compared to regular buses, articulated buses have higher loading speeds and can carry a higher passenger capacity (Levinson et al. 2002; Smith and Hensher 1998). In 2008, the Transit Cooperative Research Program (TCRP) published a report on the use of high-capacity buses, including articulated buses. The report provided a synthesis of experiences by different transit agencies in North America. Most transit agencies reported that maintenance cost for high capacity buses was greater than regular buses. Meanwhile, fuel economy and acceleration performance was lower. Passengers enjoyed the additional comfort of larger buses due to more available seating and reductions in crowding. (Hemily and King 2008; Hemily 2008).

The use of articulated buses is expected to have an effect on dwell and running time. The availability of archived AVL and APC data made it possible for various transit agencies to improve scheduling, develop performance measures, and evaluate various operational strategies (Strathman et al. 2002; Strathman 2002; El-Geneidy et al. 2010; Berkow et al. 2009; Bertini and El-Geneidy 2003; El-Geneidy and Surprenant-Legault 2010). These data were used by various researchers in generating statistical models to understand running time and dwell time (Bertini and El-Geneidy 2004; Dueker et al. 2004; Kimpel et al. 2005).

Dwell time is the time associated to passenger activity at each stop, including door opening and door closing times. Most dwell time analyses attribute increased dwell time to increased passenger activity (Cundil and Watts 1973; Levine and Torng 1994; Vandebona and Richardson 1985). One study looked at the factors affecting dwell time using archived AVL and APC data (Dueker et al. 2004). Dwell time is affected by passenger activity, which door is being used for this activity, the number of passengers paying with cash or change, stop sequence, and time of day (Kraft and Bergen 1974; Levinson 1983). Although the number of passengers using articulated buses is expected to be higher, due to the size of the bus and the nature of the routes being served by this bus type, the use of articulated buses is likely to have a negative effect on dwell time. The amount of time consumed per passenger is expected to decline with the use of articulated buses, due to the presence of a third door for alighting. However, dwells may not be significantly reduced if all boardings occur at the front door to pay a fare (Hemily and King 2008; Hemily 2008). Levinson's (1983) classical study estimated that each passenger boarding and alighting added 2.75 seconds to the constant dwell time of 5 seconds on any bus route. The height of the bus floor is expected to affect dwell time as well. Low-floor buses can shorten dwells by 13-15 percent (Levine and Torng 1994). Dwell time accounts for 9 to 26 percent of total running time (Levinson 1983). Reducing dwells at bus stations is expected to reduce overall running time and can improve reliability and speed (Levine and Torng 1994). \

Reductions in running time make transit services more attractive to existing and potential users (Levinson 1983; Krizek and El-Geneidy 2007). Levinson (2001) mentions the use of articulated and low-floor buses as the vehicle design of the future. Different-sized buses should be used on varying bus routes; articulated buses should be used on high frequency routes (Levinson 2001) with high levels of demand. However, high frequency routes and high variations in dwell times at each station can also lead to bus bunching (Yabe 2005). Slack often is added to improve bus on-time performance, but it adds to travel time (Daganzo 2009). Daganzo (2009) proposed having dynamic holding times based on AVL/APC data and many service points to maintain bus headways. The use of articulated buses on high frequency bus routes should be addressed in scheduling to avoid any decline in on-time performance and reliability of service.

Running time is known as the time that takes a bus to complete a trip between two defined points along a route (Ceder 2007). Shorter running times will make buses a more attractive mode choice. Running time models are used to understand existing transit performance in order to implement new operational strategies or adopt new technologies to improve services (Berkow et al. 2009; Bertini and El-Geneidy 2004; Kimpel et al. 2004). Determinants of running time include trip distance, number of bus stops, passenger boardings and alightings, time of day, weather, congestion, departure delays and nonrecurring events (Abkowitz and Engelstein 1983; Abkowitz and Tozzi 1987; Guenthner and Sinha 1983; Levinson 1983; Strathman et al. 2000; Tétreault and El-Geneidy 2010). The use of articulated buses is expected to have a mixed effect on running time. The first is a negative effect due to the likely decline in dwell times, and the second is a positive effect due to the size of the bus and the time associated to acceleration, deceleration, and merger with regular traffic.

Case Study and Data

Montréal, Québec, is the second most populous metropolitan area in Canada, with 3.7 million inhabitants. STM operates bus and subway services on the Island of Montréal, which is the home to about half of the region's population. Four subway lines served by 759 cars and 192 bus routes served by 1,600 vehicles comprise the STM network, allowing for over a million trips per weekday. In 2008, STM started a series of improvements to its existing service as part of an overall plan targeting an increase of transit ridership by eight percent in five years. These improvements included increasing service hours along several routes, implementing express (limited stop) service, offering new bus routes, and purchasing low-floor buses with wide doors as well as articulated buses. In fall 2009, the new articulated buses were delivered and operating along three heavily-used bus transit routes on the Island of Montréal (Routes 69, 121, and 467). These routes are shown in Figure 1. The routes had both articulated and regular buses serving them. STM noticed a mixed effect from implementing articulated buses along these routes. These effects included increases in running time along some of the trips operated by articulated buses.

Figure 1. Routes 69, 121, and 467

Accordingly, a comprehensive study was needed to understand the effects of articulated buses on transit operations, especially running time, to introduce some modifications to the existing schedules.

Route 69 runs east-west along Boulevard Gouin and Boul. Henri Bourassa; it passes by one métro (subway) station at its midway point, as well as a commuter rail line. Route 121 runs east-west as well, along rue Côte-Vertu and rue Sauvé; and it connects to two métro stations and two commuter rail lines. Route 467 is a limited stop service that runs north-south along Boul. St. Michel parallel to route 67. Both routes have a combined daily ridership of 42,000 passengers, and 20,000 of them board route 467. Route 467 connects to two métro stations, one at its southern terminus and another at its midway point. The built form around these routes is mostly three-story triplexes mixed with some commercial buildings near major intersections. Table 1 includes a summary of route characteristics. The daily boarding figures are derived from APC sampling between January and March 2010.

Table 1. Physical characteristics of Routes 69, 121, and 467

	Route 69		R121		Route 467	
Direction	E	W	E	W	N	S
Length (km)	15.56	15.5	11.21	11.56	9.13	9.97
Number of stops	72	70	49	52	15	16
Daily boardings	28,000		36,000		20,000	
Type of service	Regular		Regular		Limited stop	

Methodology

AVL and APC data use is widespread in transit research when changes in a service need to be measured or evaluated (Dueker et al. 2004; El-Geneidy et al. 2006; Kimpel et al. 2004; El-Geneidy and Surprenant-Legault 2010). As only 18 percent of STM's buses are outfitted with AVL and APC systems, STM samples its routes at different moments to obtain a complete picture of its network. The data recorded at both the stop and the trip levels then can be used to adjust schedules or to generate performance measures. AVL and APC data were collected for a sample of trips serving the three bus routes between January 4 and March 15, 2010. The entries from AVL and APC systems include bus arrival and departure times at each stop along the route, as well as passenger activity. A total of 487,588 individual stop records was obtained from this sample. These records were cleaned in order to remove incomplete trips, recording errors and layover times.

The objective of this paper is to measure the effects of operating articulated buses on dwell and running times along three bus routes operated by STM. The analysis is conducted at two levels of analysis; the first is the stop level (to measure the effects on dwell time), and the second is the trip level (to measure the effects on running time). Two datasets were generated after the data cleaning process was completed. The first dataset includes every stop with recorded passenger activity and a dwell time greater than five seconds. This dataset contains 253,260 records and will be used in the dwell time analysis. The second dataset is a trip-level data for routes 69, 121, and 467. This dataset includes 9,235 records; 4,350 trips were made using articulated buses, and 4,885 trips were made using regular low-floor buses.

The analysis includes two statistical models. Each model is concerned with a different level of analysis. The first is a dwell time model, while the second is a running time model. Table 2 includes a list of variables included in the dwell time model. It is important to note that the first, last and second to last stops along every route were omitted, due to the presence of longer dwells. This can be related to layovers or early layovers that were observed along certain routes.

The dwell time model measures the effects of a number of variables, including boardings and alighting at each door, stop sequence, and passenger load on dwell time. Dummies are included to control for time of day and route. Weather conditions are represented by the amount of snow cover in centimeters. The main policy variable, which is articulated bus, is included in the statistical model. In addition, an interaction variable is included, which is the total number of people alighting from a bus at a stop multiplied by the articulated dummy. This variable captures the effects of alightings from articulated buses on the dwell time. All the regular and articulated buses used are low-floor buses; accordingly, a low-floor dummy was excluded from this model.

In this model, it is expected that passenger activity will have a positive effect on dwell time. The square term is expected to be negative and statistically significant. This negative sign associated with positive sign from the passenger activity variables indicates that the amount of time used by each additional passenger will be less than the time associated with passenger alighting or boarding before him (Berkow et al. 2009). The passenger activity is separated by a door to enable isolation of the effects of the third door. Alighting along door 3 is expected to be statistically significant with the lowest coefficients compared to the other two

Table 2. Stop-Level Analysis Variables

Variable Name	Description
Dwell Time	The time in seconds from when a bus arrives at a bus stop and leaves a bus stop.
Board1	Total number of passengers that boarded at door 1 at a single bus stop.
Board1^2	The square of the total number of passengers that board at door 1 at a single bus stop.
Alight1	Total number of passengers that alighted at door 1 at a single bus stop.
Alight1^2	The square of the total number of passengers that alighted at door 1 at a single bus stop.
Board2	Total number of passengers that boarded at door 2 during a single trip.
Board2^2	The square of the total number of passengers that boarded at door 2 during a single trip.
Alight2	Total number of passengers that alighted at door 2 during a single trip.
Alight2^2	The square of the total number of passengers that alighted at door 2 during a single trip.
Board3	Total number of passengers that boarded at door 3 during a single trip.
Board3^2	The square of the total number of passengers that board at door 3 during a single trip.
Alight3	Total number of passengers that alighted at door 3 during a single trip.
Alight3^2	The square of the total number of passengers that alighted at door 3 during a single trip.
AM Peak	A dummy variable that is equal to 1 if the trip took place between 6:30am and 9:30am.
PM Peak	A dummy variable that is equal to 1 if the trip took place between 3:30pm and 6:30pm.
Midday	A dummy variable that is equal to 1 if the trip took place between 9:30am and 3:30 pm.
Articulated	A dummy variable that is equal to 1 if the bus is articulated.
R121	A dummy variable equal to one if the trip was made on bus route 121.
R467	A dummy variable equal to one if the trip was made on bus route 467.
Passenger Load	The total number of passengers on a bus.
Snow Cover	The amount of snow on the ground in centimeters on the day of the trip.
Alight Interaction	The total number of passengers alighting at a single station on an articulated bus.
Board Interaction	The total number of passengers boarding at a single station on an articulated bus.

doors. Meanwhile, boardings from door 1 are expected to increase dwell time the most compared to the other doors. This is due to fare-box transactions. STM uses a smart card system that requires every passenger to attach his monthly pass or tickets to a reader for a couple of seconds. Boardings from the second and third doors are rare and occur only when buses are full and do not require fare collection. Since passengers normally board from door 1, boardings on articulated buses are not expected to decrease dwell times; however, alighting from articulated buses should be statistically significant and shorten dwell time. The interaction variable will show the influence of each passenger alighting from an articulated bus on dwell time. It is expected that this variable will have a statistically significant negative effect on dwell time. The articulated bus variable is expected to shorten dwell time; however, since we do control for the alightings through the interaction dummy, this effect might change in the model. Route 467 is expected to be slower in terms of dwell time since each stop along this route is a time point (the route is a limited stop service) and the schedule of this route was not adjusted after the implementation of the service. So buses are generally holding at stops when they arrive early. Doors usually are closed if a bus is holding at a stop, thus the hold is not included in the dwell time analysis so as not to skew the results. Regarding passenger loads, it is expected that higher loads will lead to shorter dwells. This expectation is derived from previous research concentrating on dwell time (Dueker et al. 2004). Finally, the amount of snow on the ground is expected to increase the amount of time associated to dwell time. This is due to the presence of slippery sidewalks that requires more caution from passengers.

The second part of the analysis includes a run time model. This model is generated at the trip level. The trip-level analysis excludes data from the first and last stops in both directions to avoid the effects of layover time (Berkow et al. 2009). It was noticed through a detailed analysis of the studied routes that some drivers take their layovers at the stop before the last. Consequently, the trip is defined as departure from the first stop to departure from the third stop before the last. Passenger activity from the first and last stop and before the last stop were excluded because of higher risk of error for this variable due to a layover.

A number of factors have an influence on running time. These can be divided into factors that do not fall under the control of the transit agency, such as congestion or weather, and those that can be controlled by the agency, such as route design and the driver behavior (Strathman and Hopper 1993). Nevertheless, operators still can account for uncontrollable factors through scheduling and "real-time corrective actions" (Strathman and Hopper 1993). The factors affecting running time include trip distance, passenger activity, number of stops made, period of the day, driver characteristics, delay at the beginning of a trip, weather conditions, bus type (articulated or low-floor) and congestion (Abkowitz and Engelstein 1983; Abkowitz and Tozzi 1987; Guenthner and Sinha 1983; Strathman et al. 2000; Levinson 1983; Strathman and Hopper 1993; El-Geneidy and Surprenant-Legault 2010). Table 3 lists the variables used in this analysis.

In this model, running time is expected to increase with distance, passenger activity, peak hour trips, delay at the beginning at the trip, and adverse weather conditions, which is measured by the amount of snow on the ground. Trips running along Route 467 are expected to be faster than the other routes since this is a limited stop service route. Attributes of articulated buses are expected to have mixed effects on running times. The third door that allows the passenger activity to be faster will reduce running time. Acceleration, deceleration, and merger time are expected to consume more time for articulated buses relative to regular buses, thus contributing to a longer running time (Hemily and King 2008; Hemily 2008). Accordingly, an interaction variable is added to the model. This variable is expected to show that articulated buses decrease overall running time. Meanwhile, the articulated dummy is expected to increase running time due to the effects of acceleration and deceleration. During the AM peak and the PM peak, Route 467 is operated along an exclusive bus way. Accordingly, isolating the effect of the exclusive bus way is a must, which is done through two dummy variables. In previous research, snow cover has shown to be a variable that lengthens running time (Tétreault and El-Geneidy 2010). This variable is included to the model to control for adverse weather conditions and its effects on the operating environment.

Analysis

Table 4 includes summary statistics for the stop level data used in the dwell time model. The average dwells were 24.44 seconds for articulated buses and 24.41 seconds for regular buses. This shows a minor difference in terms of the amount of time associated to dwells. The articulated buses have a lower standard deviation, indicating less variance when compared to the regular buses. This is a key reliability factor, making the predictability of dwell time for articulated buses higher than regular buses. The average loads and passenger activity on an articulated bus were higher; the average load on an articulated bus was 24.89 passengers, while the average load on a regular bus was 22.48 passengers. It is clear that the difference

Table 3. Running Time Analysis Variables

Variables	Descriptions
Running time	The running time per trip in seconds, from the departure of the first stop before the designated trip to the departure from the last stop of the designated trip or segment.
Distance	The length of the studied route in kilometers.
Articulated	A dummy variable that equals to one if the trip observed is recorded uses an articulated bus.
Total Boardings	The sum of boardings for each trip.
Total Alightings	The sum of alightings for each trip.
R121	Dummy variable that equals to 1 if the trip observed is serving Route 121.
R467	Dummy variable that equals to 1 if the trip observed is serving Route 121.
Actual stops made	The number of actual stops that was actually made by the bus.
Delay Start	The delay at the start of the route in seconds (leave time – scheduled time).
AM Peak	A dummy variable for trips that took place between 6:30am to 9:30am.
PM Peak	A dummy variable for trips that took place between 3:30pm and 6:30pm.
Midday	A dummy variable for trips that took place between 9:30am and 3:30pm
AM Peak R467	A dummy variable for trips along Route 467 that used the exclusive bus way in AM peak.
PM Peak R467	A dummy variable for trips along route 467 that used the exclusive bus way in PM peak.
Alight Interaction	The total number of alightings on an articulated bus during a trip.
Board Interaction	The total number of boarding on an articulated bus during a trip.
Snow Cover	The amount of snow on the ground in centimeters.
	A dummy variable equal to one if the trip was made on bus route 121.
R467	A dummy variable equal to one if the trip was made on bus route 467.
Passenger Load	The total number of passengers on a bus.
Snow Cover	The amount of snow on the ground in centimeters on the day of the trip.
Alight Interaction	The total number of passengers alighting at a single station on an articulated bus.
Board Interaction	The total number of passengers boarding at a single station on an articulated bus.

in the number of boardings is minor between articulated and regular buses. The main advantage of using articulated buses is highlighted in the mean and standard deviation values associated to number of people alighting the bus from door 1 and door 2. This value was 1.29 for alighting from door 1 and 1.61 from door 2 for regular buses and 1.05 and 1.02 for articulated buses. Alighting on articulated buses is split between 3 doors, instead of just two, which interferes less with boarding from door 1.

Table 4. Summary Statistics at the Stop Level

	Articulated Buses		Regular Buses	
	Mean	Std. Deviation	Mean	Std. Deviation
Dwell Time	24.44	27.24	24.41	29.23
Board1	2.84	4.98	2.82	4.97
Alight1	1.05	1.63	1.29	2.06
Board2	0.002	0.08	0.01	0.15
Alight2	1.02	2.15	1.61	3.22
Board3	0.002	0.07	---	---
Alight3	0.82	2.02	---	---
Passenger Load	24.89	14.92	22.48	13.48
Number of Observations	123,859		129,401	

For the running time, Table 5 includes a summary statistics of the key variables aggregated at the trip level of analysis. The mean running time for trips using articulated buses was around 45.2 minutes, while for the regular buses it was around 43 minutes. This average leads to a difference of 2.2 minutes per trip. Observing the mean values, we can say that articulated buses are slower by around 2.2 minutes, on average, compared to regular buses. In addition, the standard deviation of running time for articulated buses is much higher than standard deviation of regular buses. The observation noticed in the decline in dwells is not reflected in the running time. This confirms the increase in running time that STM noticed along some trips operated by the articulated buses, but not for all trips. Total boardings and total alightings have increased along articulated buses, which were expected due to the added capacity. The increase was accompanied with increase in variation as well. Another variable that explains the increase in the variation of running time is the increase in the number of actual stops made. Finally, delay at start for articulated buses was much higher 11.53 seconds compared to 6.2 seconds for regular buses.

Table 5. Summary Statistics at the Trip Level

	Articulated Buses		Regular Buses	
	Mean	Std. Deviation	Mean	Std. Deviation
Running Time in Seconds	2,712.43	647.88	2,580.85	592.28
Total Boardings	85.24	39.90	79.83	37.58
Total Alightings	85.95	38.92	80.77	37.11
Actual Stops Made	32.49	13.32	30.54	12.05
Delay Start	11.53	71.68	6.20	60.35
Number of Observations	4,350		4,885	

To better understand the findings from Tables 4 and 5, a more detailed analysis of dwell and running times can help identifying determinants of time savings and observed changes. The following section includes dwell time as well as running time models.

Dwells and Running Time Models

A linear regression model is developed using dwell time in seconds as the dependent variable. Table 6 presents the results of the model. The t-statistics and the statistical significance are reported in the table along with the coefficients. This model explains 51 percent of the variation in dwell time.

For the first person that boards at door 1, 4.6 seconds is added dwell time, but each additional person boarding at the first door will take 0.027 seconds less time. The more people that board a bus, the less time it takes per passenger to board. Boarding at the second and third doors only adds 2.19 and 2.33 seconds, respectively, to the model. It takes far less time to board at the second and third doors, because passengers do not need to scan their cards. Alighting at the first door adds 2.74 seconds, alighting at the second door adds 1.65 seconds, and alighting at the third door adds 1.01 seconds to dwell time. It is clear that the use of the third door leads to a decline in the contribution of each passenger alighting to the total dwell time. Policies encouraging the use of a third door for alighting should be emphasized to increase the benefits of using articulated buses. For all the squared values for boarding and alighting, each additional passenger adds less time to overall dwell time compared to the passenger ahead of him.

Table 6. Dwell Time Model

Variable Name	Coefficient	t-stat	Stat. Sig.
Board1	4.05	206.20	0.00
Board1^2	-0.02	-47.60	0.00
Alight1	2.73	59.97	0.00
Alight1^2	-0.07	-15.82	0.00
Board2	2.19	5.17	0.00
Board2^2	-0.11	-2.35	0.01
Alight2	1.65	47.78	0.00
Alight2^2	-0.05	-30.96	0.00
Board3	2.33	1.81	0.07
Board3^2	-0.21	-1.34	0.18
Alight3	1.00	13.03	0.00
Alight3^2	-0.06	-15.68	0.00
AM Peak	-1.37	-10.56	0.00
PM Peak	-0.47	-3.71	0.00
Midday	0.24	2.15	0.03
Articulated	1.22	11.31	0.00
R121	0.61	6.01	0.00
R467	6.85	46.96	0.00
Passenger Load	-0.12	-40.60	0.00
Snow Cover	0.02	1.78	0.07
***Alight Interaction**	-0.16	-5.54	0.00
****Board Interaction**	0.28	14.87	0.00
Constant	10.89	69.72	0.00
R Square	0.51		
N	253,260		
Dependent Variable Dwell Time in Seconds			

** Alight Interaction = Total Alightings * Articulated dummy*
*** Board Interaction = Total Boardings * Articulated dummy*

Dwells taking place during the morning and afternoon peak hours are generally faster compared to late evening and early morning dwells. A trip during the morning peak takes 1.31 seconds less, while trips during the evening peak take 0.4 seconds less compared to late evening and early morning dwells. These lower dwells have been attributed to more routine passengers and directional traffic during morning routes (Dueker et al. 2004). A bus serving Route 121 consumes 0.6 seconds more per dwell compared to Route 69. However, dwell time is 6.8 seconds more on Route 467, compared to Route 69. This is because Route 467 is an express route and has 15 stops, but the schedule has not been changed since Route 467 was implemented and an exclusive bus-way was introduced. Drivers have excess time in the schedules, leaving more time at every stop. Moreover, the drivers have pressure to stay on schedule, compared to the other routes. An interesting finding is that increasing passenger loads lead to decreases in dwell times. This can be related to riders' behavior and their reaction to overcrowded buses. Previous research indicated a similar relationship with higher loads (Dueker et al. 2004). Snow on the ground showed statistical significance, but added only 0.02 seconds to dwells.

An articulated bus adds 1.22 seconds to the dwell time. However, the interaction variable, which looks at passenger alighting on an articulated bus, reveals that increased alighting on an articulated bus, compared to a regular bus, actually reduces dwell time by 0.15 seconds per passenger. Finally, the boarding interaction variable shows a positive and statistically significant effect on dwell time, which means that boarding on articulated buses increases dwell time. Accordingly, the articulated buses cause both increases and decreases in running time, which was hypothesized earlier. It is necessary to have a more precise estimate of the additional time required by articulated buses to run a complete route. This estimate should be used to adjust schedules in order to address the net effect of using articulated buses. Table 7 shows the output of a linear regression model using running time as the dependent variable.

This model explains 92 percent of the variation in running time. This high value is attributed mainly to the inclusion of the distance variable. For every meter in the route length, running time is expected to increase by 0.14 seconds, keeping all other variables at their mean values. This coefficient indicates an average speed of 25 km/h.

An articulated bus adds an additional 27.2 seconds to the total running time. This addition will require modification to the existing schedules to avoid delays and on-time performance problems. Each boarding adds 1.91 seconds and each alighting adds 1.04 seconds to the total running time while keeping all other variables at their mean values. Boarding on an articulated bus, which is represented by the Board Interaction variable, adds 0.81 seconds to running time. The Alight Interaction variable, which shows alighting activity on articulated buses, demonstrates that

Table 7. Running Time Model

Variable Name	Coefficient	t-stat	Stat. Sig.
Distance	0.14	15.69	0.00
Articulated	27.22	3.09	0.00
Total Boardings	1.91	8.45	0.00
Total Alightings	1.04	4.42	0.00
R121	70.81	1.89	0.06
R467	-305.34	-5.60	0.00
Actual Stops Made	8.30	19.13	0.00
Delay Start	-0.36	-13.18	0.00
AM Peak	142.34	22.15	0.00
PM Peak	307.69	46.92	0.00
Midday	202.57	36.43	0.00
Alight Interaction	-0.58	-2.03	0.04
Board Interaction	0.81	2.91	0.00
AM Peak R467	160.03	13.02	0.00
PM Peak R467	-66.69	-6.24	0.00
Snow Cover	2.90	4.94	0.00
Constant	217.25	1.55	0.12
R square	0.92		
N	9,235		

** Alight Interaction = Total Alightings * Articulated dummy*
*** Board Interaction = Total Boardings * Articulated dummy*

running time is reduced by 0.81 seconds for every passenger that alights from an articulated bus. Route 121 is faster than route 69 by 70 seconds per trip. Meanwhile, Route 467 is faster by 306 seconds relative to route 67. This is due to the nature of Route 467 as an express route. During the morning peak, Route 467 has its own exclusive bus-way, yet buses operating along this route during this period of time are slower by 160 seconds. On the other hand, the exclusive bus-way decreases running time by 66 seconds. This can be due to the difference in the levels of congestion during both periods. In addition, for every stop made along the studied routes, 8.30 seconds are added to the running time, which can be attributed to accelerating and decelerating at each stop. For every second of delay at the beginning of a trip running time is expected to decrease by 0.36 seconds. This indicates a recovery of 36 percent of delay by drivers during the trip. This finding is consistent with previous studies (El-Geneidy and Surprenant-Legault 2010; Tétreault and El-Geneidy 2010). In addition, morning peak trips are longer by 142 seconds, evening trips are longer by 307 seconds, while midday trips are slower by 202 seconds relative to early am and late evening trips. Finally, for every centimeter of snow on the ground, running time is expected to increase by 2.9 seconds per trip.

It is clear that the effects of operating an articulated bus on dwell and running times are complicated and cannot be isolated using a single variable. In order to understand these effects, a sensitivity analysis is introduced in the following section. This sensitivity analysis depends on multiplying the coefficients by the mean values to obtain the dwell and running times under various scenarios and conditions.

Sensitivity Analysis

The dwells for each scenario is estimated based on the model presented in Table 6. The scenarios for the dwell time estimates are presented in Table 8. Each simulation has a constant passenger load of 30 passengers. The estimate also is constructed for morning peak on Route 69. In the first scenario, the total passenger activity equals 20 passengers. These passengers are distributed as 5 boarding and 15 alighting. Distributing the 15 alighting among the three doors in articulated buses compared to two doors in the regular bus leads to 1.9 percent time saving. Meanwhile, passenger activity of 30 passengers at a stop leads to 4.5 percent of savings in dwell time when utilizing an articulated bus relative to a regular low-floor bus.

Table 8. Simulation of Dwell Gime at a Stop on Route 67 during AM Peak Hours

	20 Passengers		30 Passengers	
Variable Name	*Articulated*	*Regular*	*Articulated*	*Regular*
Boarding Door 1	5	5	5	5
Alighting Door 1	8	8	10	15
Boarding Door 2				
Alighting Door 2	3	7	10	10
Boarding Door 3				
Alighting Door 3	4		5	
Passenger Load	30	30	30	30
Dwell Time in Seconds	50.55	51.53	58.6	61.37
Percentage of Savings	1.9		4.5	

For each simulation, the number of passenger boarding and alighting at each door, boarding and alighting squared, the passenger load and stop sequence are multiplied by the coefficients from Table 6 to calculate the total dwell time per trip. The results indicate that articulated buses save more time per stop, especially with high levels of passenger activity.

The running time simulation uses the model presented in Table 7 to estimate the total travel time for one trip along Route 121 during the morning peak. The passenger load, actual stops, and passenger activity remain constant for each example. Meanwhile, the distance traveled is 11.21 km, which is the actual length of Route 121. The simulation results are presented in Table 9. It takes an articulated bus 39.3 seconds longer to complete a trip with 120 passengers boarding and alighting, compared to a regular bus. This is while having 30 passengers on board on average, serving 30 stops along the route, and starting 8 seconds late.

Table 9. Simulation of Running Time on Route 121 during AM Peak Hours

	120 Passengers		**80 Passengers**	
Variable Name	*Articulated*	*Regular*	*Articulated*	*Regular*
Total Boarding	120	120	60	60
Total Alighting	120	120	60	60
Mean Passenger Load	25	25	25	25
Number of Actual Stops	30	30	30	30
Delay at Start	8	8	8	8
Total Travel Time in Minutes	44.7	43.82	41.56	40.87
Difference in Seconds	39.00		41.2	

The second scenario uses 60 passengers as the input for passenger activity. Again, the articulated bus is slower by 41.26 seconds. Observing Tables 8 and 9 clearly indicates that articulated buses do save time at the stop level of analysis, yet the savings vanish when measured at the trip level. This can be attributed mainly to acceleration and deceleration time associated to articulated buses. Also, it can be related to the time an articulated bus consumes to merge back with traffic. This difference decreases with the increase in the total number of passengers using the articulated buses. In conclusion, adopting the use of articulated buses requires modifications in the existing schedules to address the additional time needed for operation to avoid delays and on-time performance issues, especially if the articulated buses are introduced along routes with medium levels of passenger activity per trip. The estimated numbers in this scenario are developed at the mean value.

Since schedules are written to accommodate 95 percent of all trips, adjustments need to be made to these estimations.

Building the relationship between the 95th percentile of running time and the estimated running time in the above scenario, it is estimated that two additional minutes need to be added to the scheduled running time. These two minutes need to be added to each trip serving the above route, if STM chose to keep operating articulated buses along this route at the same level of service. The TCRP report cited that one of the agencies in their study needed to a lot more time for articulated buses due to their slower acceleration (Hemily and King 2008; Hemily 2008). An addition of two minutes per trip will require major modifications in schedules as well as addition of new trips. Using Vuchic's (2005) model for estimating fleet size for a bus transit route with a uniform headway (5 minutes) and a constant travel cycle (120 minutes), it is estimated that 24 buses will be needed to operate this route, while an additional bus is needed if articulated buses will be operated along this route to maintain the same level of service. This calculation can be done for different time periods with varying headways to determine the added operational costs of using articulated buses. A different option is to adjust the schedules through increasing the existing headways and using fewer buses. This solution is expected to have an increase in passenger waiting time. TCRP reports on transit agencies implementing measures improve dwell times of articulated buses. These measures include operating articulated buses exclusively on a route to simplify scheduling and developing new fare collection procedures. The fare collection procedures included allowing passengers to use all three doors for boarding in order to take full advantage of increased passenger flow that articulated buses can facilitate(Hemily and King 2008; Hemily 2008).

Finally, another alternative is work on the mechanics of the articulated buses to decrease acceleration and deceleration time through adjustment in transmission systems of articulated buses. STM currently is conducting mechanical studies to measure the differences in acceleration and deceleration time between articulated and regular buses. Various mechanical changes are being tested to the transmission of both types of buses to account for some of these differences in travel time.

Conclusion

The objective of this research was to measure the effects of operating articulated buses along three bus routes operated by STM in Montréal Canada. The effects of using articulated buses was measured at two levels: the stop level and the trip level. The stop level analysis concentrated mainly on dwell time saving. It was clear that articulated buses do have a mixed effect on dwell time, yet overall, articulated buses decrease the amount of time associated per passenger alighting leading to major time saving at the stop level. These savings are maximized with higher levels of passenger activity (4.5% savings for 30 passengers). Meanwhile, articulated buses do cause delays at the trip level. So the amount of savings associated to passenger activity is offset by the loss in acceleration, deceleration, and time consumed to merge back in the regular traffic. Articulated buses impose an additional two minutes of delay on the existing schedule of the studied routes. To maintain the existing headway, these two minutes need to be added to the schedules. Accordingly, more buses are needed to operate the existing system with articulated buses while keeping the same level of service. STM has achieved one of its main targets through operating the articulated buses. The increase in the number of boardings on articulated buses compared to regular buses was around 5 passengers per trip. Although this number is small, the studied routes suffered from overcrowding. The use of articulated buses has lead to an increase in the level of comfort and has helped in attracting five new passengers per trip.

STM currently is implementing some tests for mechanical modifications in the transmission system of articulated buses. These modifications are expected to improve the speed of articulated buses. Driver experience plays a big role in running time and bus operations. A detailed study concentrating on differences in driver behavior is recommended to measure to what extent driver fear of collision or comfort in operating articulated buses is recommended. Such study will require simulator systems and on-board driver behavior monitoring systems.

Since the data obtained from the STM was collected from a sample of trips, it was not possible to measure the effects of using articulated service on either the reliability of service or on headways. It was clear that variation in dwell time declined while variation in running time increased. The use of articulated buses is expected to increase the level of bus bunching, which is noticed from the increase in the level of variation in running time. A headway variability analysis is recommended using actual headwaysTo do so, the entire fleet serving these routes will need to have AVL and APC systems, which is something that STM is trying to achieve in the next few years.

Acknowledgments

We would like to acknowledge the Société de Transport de Montréal (STM) for providing the funding and data for this project, especially Michel Tremblay, Jocelyn Grondines, and Sébastien Gagné for their feedback and support during this project.

References

Abkowitz, M., and I. Engelstein. 1983. Factors affecting running time on transit routes. *Transportation Research Part A 17*(2): 107-113.

Abkowitz, M., and J. Tozzi. 1987. Research contributing to managing transit service reliability. *Journal of Advanced Transportation* 21 (Spring): 47-65.

Berkow, M., A. El-Geneidy, and R. Bertini. 2009. Beyond generating transit performance measures: Visualizations and statistical analysis using historical data. *Transportation Research Record* (2111): 158-168.

Berkow, M., A. El-Geneidy, and R. Bertini. 2009. Beyond generating transit performance measures: Visualizations and statistical analysis using historical data. Paper read at Transportation Research Board 88th Annual Meeting, Washington, D.C.

Bertini, R., and A. El-Geneidy. 2003. Using archived data to generate transit performance measures. *Transportation Research Record* 1841: 109-119.

Bertini, R., and A. El-Geneidy. 2004. Modeling schedule recovery processes in transit operations for bus arrival time prediction. *Journal of Transportation Engineering* 130(1): 56-67.

Ceder, A. 2007. *Public Transit Planning and Operation, Theory, Modeling And Practice.* Burlington, MA: Elsevier Ltd.

Cundil, M., and P. Watts. 1973. Bus boarding and alighting times. In *TRRL Rep. LR 521.* Crownthorne, U. K.: Transport and Road Research Laboratory.

Daganzo, C. 2009. A headway-based approach to eliminate bus bunching: Systematic analysis and comparisons. *Transportation Research Part B* 43(10): 913-921.

Dueker, K. J., T. J. Kimpel, J. G. Strathman, and S. Callas. 2004. Determinants of bus dwell time. *Journal of Public Transportation* 7(1): 21-40.

El-Geneidy, A., J. Horning, and K. Krizek. 2010. Analyzing transit service reliability using detailed data from automatic vehicular locator system. *Journal of Advanced Transportation* 44 (4): 1-14.

El-Geneidy, A., J. Strathman, T. Kimpel, and D. Crout. 2006. The effects of bus stop consolidation on passenger activity and transit operations. *Transportation Research Record* 1971: 32-41.

El-Geneidy, A., and J. Surprenant-Legault. 2010. Limited-stop bus service: An evaluation of an implementation strategy. Paper read at Transportation Research Board 89th Annual Meeting, Washington, D.C.

Guenthner, R. P., and K. C. Sinha. 1983. Modeling bus delays due to passengers boardings and alightings. *Transportation Research Record* 915: 7-13.

Hemily, B. and King, R. 2008. Uses of higher capacity buses in transit service: A synthesis of transit practice. Washington, D.C.: Transportation Research Board.

Jarzab, J., J. Lightbody, and E. Maeda. 2002. Characteristics of bus rapid transit projects: An overview. *Journal of Public Transportation* 5(2): 31-46.

Kaneko, T., H. Iiuzuka, and I. Kageyama. 2006. Steering control for advanced guideway bus system with all-wheel steering system. *Vehicle System Dynamics* 44: 741-749.

Kimpel, T., J. Strathman, R. Bertini, P. Bender, and S. Callas. 2004. Analysis of transit signal priority using archived TriMet bus dispatch system data. Paper read at 84th Transportation Research Board Annual Meeting, Washington, D.C.

Kimpel, T., J. Strathman, R. Bertini, P. Bender, and S. Callas. 2005. Analysis of transit signal priority using archived TriMet bus dispatch system data. *Transportation Research Record* 1925: 156-166.

Kraft, W., and T. Bergen. 1974. Evalutation of passenger service-time distribution. *Transportation Research Record* 505: 13-20.

Krizek, K., and A. El-Geneidy. 2007. Segmenting preferences and habits of transit users and non-users. *Journal of Public Transportation* 10(3): 71-94.

Levine, J., and G. Torng. 1994. Dwell time effects of low-floor bus design. *Journal of Transportation Engineering* 120(6): 914-829.

Levinson, H. 1983. Analyzing transit travel time performance. *Transportation Research Record* 915: 1-6.

Levinson, H. 2001. Bus transit in the 21st century some perspectives and prospects. *Transportation Research Record* 1760: 42-46.

Levinson, H., S. Zimmerman, and J. Clinger. 2002. Bus rapid transit: An overview. *Journal of Public Transportation* 5(2) :1-29.

Pahs, M., M. Rohden, D. Hampsten, S. Gallant, and R. Bertini. 2002. Door-to-door mobility: Evaluating a bus rapid transit communit transport concept. *Journal of Public Transportation* 5(2): 137-161.

Smith, N., and D. Hensher. 1998. The future of exclusive busways: The Brazilian experience. *Transport Reviews* 18(2): 131-152.

Strathman, J. 2002. Tri-Met's experience with automatic passenger counter and automatic vehicle location systems. Portland OR: Center for Urban Studies, Portland State University.

Strathman, J., K. Dueker, T. Kimpel, R. Gerhart, and S. Callas. 2002. Evaluation of transit operations: Data applications of Tri-Met's automated bus dispatching system. *Transportation* 29: 321-345.

Strathman, J. G., K. J. Dueker, T. J. Kimpel, R. L. Gerhart, K. Turner, P. Taylor, S. Callas, and D. Griffin. 2000. Service reliability impacts of computer-aided dispatching and automatic location technology: A Tri-Met case study. T*ransportation Quarterly* 54(3): 85-102.

Strathman, J. G., and J. Hopper. 1993. Empirical analysis of bus transit on-time performance. *Transportation Research Part A* 27(2): 93-100.

Tétreault, P., and A. El-Geneidy. 2010. Estimating bus run times for new limited-stop service using archived AVL and APC data. *Transportation Research Part A* 44(6): 390-402.

Vandebona, U., and A. Richardson. 1985. The effects of fares-collection strategies on transit level of service. *Transportation Research Record* 1036: 79-87.

Vuchic, V. 2005. Transit operations and service scheduling. In *Urban Transit: Operations, Planning and Economics*, Hoboken, N.J.: John Wiley & Sons.

About the Authors

Ahmed El-Geneidy (*ahmed.elgeneidy@mcgill.ca*) is Assistant Professor in the School of Urban Planning at McGill University. His research interests include land use and transportation planning, transit operations and planning, travel behavior analysis including using motorized and non-motorized modes of transportation, and measurements of accessibility and mobility in urban contexts, with a special interest in transportation needs of disadvantaged populations. He received B.S. and M.S. degrees from the Department of Architectural Engineering at Alexandria University, Egypt, and continued his academic work at Portland State University, where he received a Graduate GIS Certificate and earned a Ph.D. in Urban Studies from the Nohad A. Toulan School of Urban Studies and Planning. After finishing his Ph.D., he moved to the Twin Cities to work as a post-doctoral research fellow at the University of Minnesota.

Nithya Vijayakumar (*nithya.vijayakumar@mail.mcgill.ca*) has a B.A. in Political Science and Geography from McGill University and currently is an MUP student and Graduate Research Assistant in the School of Urban Planning at McGill University. She developed a keen interest in bus operations and planning after working in Chennai and Bangalore, India, in 2007 and 2008. She currently is doing research on run time savings of articulated buses and factors that influence driving distance to commuter rail stations in Montréal.

System for Transit Performance Analysis Using the National Transit Database

Albert Gan, Feng Gui, and Li Tang
Florida International University

Abstract

The National Transit Database (NTD) includes comprehensive data on transit organization characteristics, vehicle fleet characteristics, revenues and subsidies, operating and maintenance costs, vehicle fleet reliability and inventory, services consumed and supplied, and safety and security. Some of these data have been used extensively to derive values for transit performance measures and have become the sole source of standardized and comprehensive data for use by all constituencies of the U.S. transit industry. An important application of NTD data has been in trend analysis, which requires multiple years of data. However, accessing NTD data, especially for multiple years, has not been an easy process. One reason is because the data were collected and distributed annually in separate files. This paper introduces a web-based system that integrates over 20 years of NTD data and provides user-friendly tools designed to facilitate the access and analysis of transit performance data.

Introduction

Performance analysis can help transit agencies to more objectively evaluate the performance of their systems, thus allowing them to better identify and prioritize problem areas for management actions (Gan et al. 2004). Whether a system is to be analyzed by looking at its performance trends over the years or by comparing its performances with those of other peer systems, a pre-requisite to these analyses is that the required data be available. In the United States, the National Transit Database (NTD) is increasingly being used for this performance analysis. Collected and distributed by the Federal Transit Administration (FTA), NTD has become the sole source of standardized and comprehensive data for use by all constituencies of the U.S. transit industry (Lyons and Fleischman 1991). NTD includes data on transit organization characteristics, vehicle fleet characteristics, revenues and subsidies, operating and maintenance costs, vehicle fleet reliability and inventory, services consumed and supplied, and safety and security. These data not only provide direct information on the transit systems, but can also be used to derive values for many useful performance measures such as farebox recovery, operating expense per passenger trip served, average speed, etc.

While the majority of the NTD data collected are made available by FTA to the public, access to these data was not easy. This can be attributed to four limitations:

1. NTD data are collected and distributed annually in separate files. To perform a trend analysis for a specific performance measure, one must learn about the file structures, which can vary from one year to another, identify the correct variables from the long list of NTD variables, and manually extract the corresponding data values from the specific files for each of the selected transit systems. For a 10-year trend analysis, for example, this process must be repeated 9 times. The process not only is time-consuming, but also is prone to human errors.
2. NTD data are reported and provided in the most original form while many performance measures must be calculated from the origin data. For example, average speed can be estimated by dividing the total actual revenue miles by the total actual revenue hours. The calculation will become more complicated and time-consuming with when a performance measure involves more than two variables, especially when these variables come from different NTD forms and thus, different files. In addition, the burden is also on the users to be knowledgeable about the correct formula to use and the correct variables to select from the files (Gan et al. 2002).
3. Many NTD variables are reported for individual transit modes and service types (i.e., directly operated or purchased transportation), making it difficult to compare transit performance for the entire agency or state. For example, an analyst may want to know the performance of a transit system without

differentiating between transit vehicles operated directly by the agency itself or by a subcontractor. Similarly, a state official may be interested in statewide transit performance in addition to those of individual transit agencies. Aggregating data is a very time-consuming process, and the user is burdened with using the correct methods of aggregation and selecting the correct variables to use.

4. There was no system that could provide the tools necessary to quickly select the input data and to perform analysis using these data.

This paper describes a web-based system designed to overcome these limitations. It allows the user to focus on the analysis rather than the data preparation and data access. The system is known as the Integrated National Transit Database Analysis System (INTDAS) and is a component program of the Florida Transit Information System (FTIS). The specific development efforts of the INTDAS system involve (1) integrating the NTD data from multiple years to form a single database that allows single access to multiple-year data, (2) developing a set of major performance measures from NTD, (3) aggregating agency-wide and statewide NTD performance data, and (4) developing a user-friendly interface and analysis tools for easy data access and analysis. The remainder of this paper elaborates each of these efforts.

Data Integration

As listed in Table 1, the latest NTD data are reported on a set of 21 standard forms covering 7 different reporting areas, referred to as modules in NTD. Among these forms, Forms B-10, B-20, B-30, F-10, F-20, and F-40 are reported for the entire transit agencies, while the other forms are reported for individual transit modes (motorbus, heavy rail, etc.) and/or service types. A service type can be either DO (directly operated), if the service is operated in-house by the transit agency itself, or PT (purchased transportation), if the service is subcontracted out to a service provider(s). When a service is subcontracted out, the NTD data may be reported either by the transit agency or by the subcontractor(s).

Table 1. NTD Reporting Forms

Module Name	Form Name	Form Title Description
Basic Information	B-10	Transit Agency Identification
	B-20	Transit Agency Contacts
	B-30	Contractual Relationship
Financial	F-10	Sources of Funds—Funds Expended and Funds Earned
	F-20	Uses of Capital
	F-30	Operating Expenses
	F-40	Operating Expenses Summary
Asset	A-10	Stations and Maintenance Facilities
	A-20	Transit Way Mileage
	A-30	Revenue Vehicle Inventory
Service	S-10	Transit Agency Service
	S-20	Fixed Guideway Segments
Resource	R-10	Employees
	R-20	Maintenance Performance
	R-30	Energy Consumption
Federal Funding Allocation Statistics	FFA-10	Federal Funding Allocation Statistics
Safety and Security	SS-10	Safety and Security Setup
	SS-20	Ridership Activity
	SS-30	Safety Configuration
	SS-40	Major Incident Reporting
		Non-Major Incident Reporting

From the perspective of database structure, NTD variables generally can be divided into two categories. The first involves variables that are used to identify the transit agencies and the transit systems (or modes) that they operate. These are herein referred to as the system variables. They include a unique four-digit ID that is used to identify a transit agency, a mode code, and a service type. The second category of variables consists of over 1,000 data attributes that are used to describe the various characteristics associated with each transit agency. They include such variables as service area population, unlinked passenger trips, operating expenses, etc.

Because NTD data are stored and distributed annually on different data files, the first step in the database development process was to combine these data files from different years for each form. Because multiple years of NTD data were integrated into a single data table, a fourth system variable must be added to every data record to identify the corresponding NTD data year. Combining data from different years was a major undertaking mainly because the NTD data have continued to evolve over the years, resulting in inconsistent data variables and file structures from year to year. These data must be reconciled before they could be combined.

Changes to the NTD data over the years have included NTD reporting forms that were added, dropped, combined, or restructured. In general, data were reconciled to match the latest version of the NTD forms. The reconciliation process included rearranging variables from different years, combining variables from multiple forms, moving variable from one form to another, standardizing inconsistent mode codes used in various years, standardizing measurement units, etc. Once the data from different years were reconciled and integrated, they were imported into a SQL Server database. The current database includes NTD data from 1984 through 2009 for most of the NTD forms and represents the most comprehensive database available for NTD data.

Performance Measure Development

After the NTD data were integrated, performance measures could be developed from these data. Below is a list of 20 commonly-used performance measures that are included in INTDAS (CUTR 2000):

1. Average Age of Fleet. This is a service quality measure based on the age of the vehicle fleet. It is derived by first multiplying the total number of active vehicles of each fleet of the same mode code and service type with their years in service (i.e., NTD reporting year subtracted by the year of manufacture), then summing up the totals from all fleets. The final number is then obtained by dividing this sum by the number of total active vehicles in all fleets. All of the variables involved in the calculations come from Form A-30.
2. Average Fare. This is an indicator of the average level of fare charged to transit riders and is calculated as the passenger fare revenues from Form F-10 divided by the total number of unlinked passenger trips from Form S-10.
3. Average Speed. This is the average speed of vehicles in revenue service operation (i.e., not including travel to and from the garage or any other deadhead) and is calculated by dividing the total actual vehicle (for non-rail modes) or train (for rail modes) revenue miles by the total actual vehicle/train revenue hours. Both of the variables come from Form S-10.

4. Average Headway (in minutes). This is an important measure of service frequency. It is computed by first dividing the total directional route mileage from Form S-10 by the system's calculated average speed, as defined above, to obtain an estimate of the number of hours it takes to traverse the entire system's total route miles. This time (in hours) is then divided by the system's average weekday total vehicles from Form S-10 to determine the amount of time in hours it takes for a vehicle to complete its portion of the total route miles, one time. The resulting time is then multiplied by 60 for conversion from hours to minutes.
5. Average Trip Length. This is the average trip length for all passenger boardings and is calculated as the total passenger miles divided by the total unlinked passenger trips. Both variables come from Form S-10.
6. Farebox Recovery. This is an indicator of the share of the total operating costs that is covered by the passenger fares. It is calculated by dividing the passenger fare revenues from Form F-10 by the total modal (operating) expenses from Form F-30. The resulting number is multiplied by 100 to express the share as a percent.
7. Operating Expense per Peak Vehicle. This is a measure of the resources required per vehicle to have one vehicle in operation for a year. It is calculated as the total modal expenses from Form F-30 divided by the number of vehicles operated in maximum service (i.e., peak vehicle) from Form S-10.
8. Operating Expense per Passenger Trip. This is a key indicator of the cost efficiency of transporting riders and is calculated as the total modal expenses from Form F-30 divided by the total unlinked passenger trips from Form S-10.
9. Operating Expense per Revenue Hour. This is a measure of the cost efficiency with which service is delivered. It is calculated as the total modal expenses from Form F-30 divided by the total actual vehicle or train revenue hours from Form S-10.
10. Operating Revenue per Operating Expense. This is a measure of how much the total operating expenses are covered by the total operating revenues, which include both directly generated fare and non-fare revenues. It is calculated as the ratio of the total operating revenue (including passenger fares, special transit fares, school bus service revenues, freight tariffs, charter service revenues, auxiliary transportation revenues, subsidy from other

sectors of operations, and non transportation revenues) reported in Form F-10 and the total modal expenses from Form F-30.

11. Passenger Trips Per Service Area Capita. This is a measure of the extent to which the public utilizes transit in a given service area and is calculated by dividing the unlinked passenger trips from Form S-10 with the total population living in the transit service area from Form B-10. The total service area population is usually taken as the sum of all population living within 0.75 mile of transit routes. However, because the number is reported for all modes operated by an agency, agencies that operate a demand response mode in a county may report the entire county population, making the measure difficult to compare across different modes and/or agencies. Accordingly, this measure should only be applied within an agency for comparisons across different years, i.e., trend analysis.
12. Passenger Trips per Revenue Hour. This is a key indicator of service effectiveness that is influenced by the levels of demand and the supply of service provided and is calculated by dividing the total unlinked passenger trips from Form S-10 with the total actual vehicle or train revenue hours, also from Form S-10.
13. Revenue Miles per Vehicle Mile. This is a measure that reflects how much of the total vehicle operation is in passenger service. It is calculated as the total actual revenue in vehicle/train miles divided by the total actual vehicle or train miles. All variables come from Form S-10.
14. Revenue Miles between Failures. This is an indicator of the average frequency of delays due to a problem with the equipment and is calculated as the total actual vehicle or train revenue miles from Form S-10 divided by the total revenue vehicle system failures from Form R-20.
15. Revenue Miles per (Total) Vehicle. This is measure of the level of vehicle utilization in terms of total revenue miles driven. It is calculated as the total actual vehicle or train revenue miles divided by the total vehicles available for maximum service. All variables come from Form S-10.
16. Revenue House per (Total) Vehicle. This is a measure of the level of vehicle utilization in terms of total revenue hours driven. It is calculated as the total actual vehicle or train revenue hours divided by the total vehicles available for maximum service. All variables come from Form S-10.

17. Revenue Hours per Employee. This is a measure of the overall labor productivity and is calculated as the ratio of the total actual vehicle/train revenue hours of service from Form S-10 and the total full-time employees from Form R-10.
18. Spare Ratio. This is an indicator of the level of spare vehicles available for service. It is calculated as the difference between vehicles operated in maximum service and vehicles available for maximum service, divided by vehicles operated in maximum service. Both variables come from Form S-10.
19. Vehicle Miles per Gallon or Kilowatt-Hour. This is an efficiency measure of energy utilization and is calculated as the total actual vehicle or train miles from Form S-10 divided by the total gallons or kilowatt-hour consumed from Form R-30.
20. Weekday Span of Service. This measure reports the number of hours that transit service is provided on a representative weekday. It is determined by calculating the number of hours between the average weekday time service begins and time service ends reported on Form S-10.

The values for these performance measures are pre-calculated and stored in the system, and can be quickly retrieved by the users for performance analysis.

Aggregated Performance Measures

Performance analysis does not necessarily have to be performed at the transit system level. Measures also can be compared at the state, regional, national, or any other geographic level of interest. For example, a state Department of Transportation (DOT) may be interested in comparing its statewide performance with the other peer states. For such comparisons, data collected at the transit system level must be aggregated to the specific level of interest. The system currently provides the aggregated performance measures for: (1) both service types combined, (2) all modes combined, (3) all rail modes combined, (4) all non-rail modes combined, (5) all fixed-route modes combined, (6) all transit systems within a state combined (i.e., statewide), and (6) all combinations of the above aggregates.

For illustration purposes, assume that a transit agency operates two modes, A and B. If a performance measure involves two variables, V1 and V2, and the formula for the performance measure calculation is V1/ V2, the aggregated value for both modes will be calculated as (V1A + V1B) / (V2A + V2B). It is obvious that one major issue with such aggregation has to do with the treatment for missing and incorrect values. A missing or incorrect value for one of the transit systems involved in the aggregation will have a direct impact on the final aggregated value.

In the case of a missing value, no aggregated values will be calculated when there is a missing value. This rule is applied on the basis that it is better to provide no data than to provide inaccurate or wrong data. A missing value simply could be because the number was not reported by the agency, or the agency is not required to report for a specific mode or service type. For example, for Revenue Hours per Employee, the measure is not calculated for the combined service types (i.e., DO + PT) because reporting of employee information is not required for purchased transportation.

In the case of potentially incorrect data, the detection is more difficult, as it is generally more difficult to look at a value and be able to tell if it is incorrect. However, an incorrect value is likely to be identified more easily after it is used in a formula. For example, an incorrect low value reported for the total actual revenue hours will cause the average speed to fall outside the normal speed range, e.g., a bus system with an average speed of over 80 mph. To further detect incorrect data, a major effort was taken to examine each calculated value by visually identifying sudden changes in the annual data trend. For example, it will be quite unlikely for a system to have its average speed jump by 10 mph from one year to another. Fortunately, INTDAS provides an interactive charting function (described in the next section) that can greatly facilitate this task. All calculated values that were deemed suspicious were subsequently removed from the database.

User Interface and Functionalities

This section introduces the functionalities of INTDAS via three case applications. The system is freely accessible at http://www.ftis.org/intdas.html upon user registration. The use of the web platform for the system not only facilitates user access, but also allows the developers to update the system quickly and as frequently as needed.

Case Application 1: Quick Information Lookup for Known Agencies

In this case application, the user would simply like to look up information for two major bus systems, the Miami-Dade Transit (MDT) and Metropolitan Atlanta Rapid Transit Authority (MARTA), located in the Southeast region of the United States. The user has registered to access the system, so she can quickly log on to the system using her assigned password. Upon entering the system, the user is first shown the main screen in Figure 1. On this screen, INTDAS selects the latest six years of NTD data, by default, for all individual transit modes, and all individual service types. The user can, however, choose to retrieve any years of data between 1984 and 2009 for any specific modes and service types.

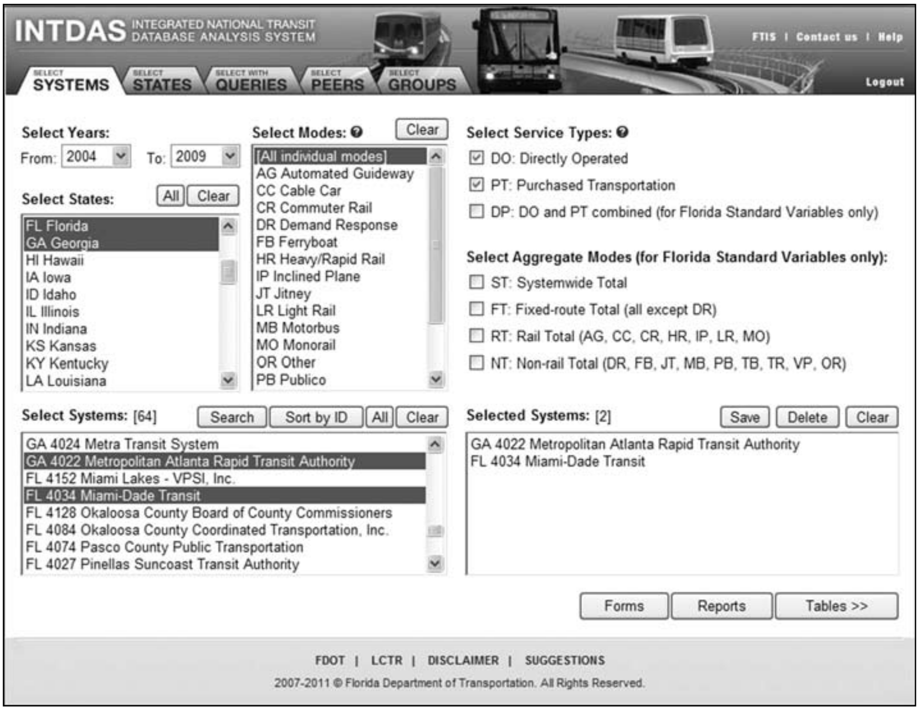


Figure 1. Screen for selecting transit systems

To select the two transit systems, the user clicks to select Florida and Georgia on the Select States list box to quickly shortlist the number of transit systems to only those in Florida and Georgia. The shortlisted systems are displayed in the Select Systems list box. The user then can identify the desired systems from the shortlist simply by clicking on the agency names. Selected transit systems are listed in the Selected Systems list box. Once the transit systems of interest are selected, data can be retrieved and displayed either on the NTD forms or on some pre-defined standard reports by clicking the Forms and Reports buttons, respectively, at the bottom right of the screen. Figure 2 displays some service related data on the top portion of the S-10 form. Figure 3 shows a standard report that includes six years of trend data for MDT for a set of efficiency measures. The user can click on any of the list boxes to get the same trend table for other system combinations, e.g., a directly operated heavy rail system for MARTA.

B10 | B20 | B30 | F10 | F20 | F30 | F40 | F50 | A10 | A20 | A30 | S10 | R10 | R20 | R30 | FFA10 | 405-1 | 405-2 | SS10 | SS20 | SS30 | SS40 | SS50

Transit Agency Service (S-10)

Year 2009 NTD ID 4034 Location Miami State FL Mode MB Type of Service DO

Item	Average Weekday				Average Weekday Total	Average Saturday Total	Average Sunday Total	Annual Total
	AM Peak	Midday	PM Peak	Other				
Maximum Service Vehicles								
01. Vehs operated in maximum service								716
02. Vehs available for maximum service								863
Periods of Service								
03. Time service begins	06:30	10:30	14:00		00:00	00:00	00:00	
04. Time service ends	10:30	14:00	19:00		24:00	24:00	24:00	
Service Supplied								
05. No. of veh/train in operation	687	448	716	448	716	341	290	
06. Total actual veh/train miles					113,983	70,239	72,742	37,092,499
07. Total actual veh/train hours					8,924	5,273	5,386	2,874,681
08. Total actual veh/train rev. miles					96,299	61,352	63,297	31,547,096
09. Total actual veh/train rev. hours					8,140	4,888	4,975	2,629,625

Figure 2. Retrived data displayed on an emulated NTD form

Analysis: Trend / Peer 2009 / << Back Page 1

Report: General Performance Indicators / Effectiveness Measures / Efficiency Measures

System: 4022 Metropolitan Atlanta Rapid Transit Authority / 4034 Miami-Dade Transit

Mode Code: AG / DR / HR / MB

Service Type: DO / PT

100%

Miami-Dade Transit
Directly Operated Motorbus

EFFECTIVENESS MEASURES	2004	2005	2006	2007	2008	2009	% Change 2004-2009	% Change 2008-2009	% Change 1984-2009
SERVICE SUPPLY									
Vehicle Miles Per Capita	15.36	16.77	18.02	17.49	16.28	15.44	0.52%	-5.17%	n/a
SERVICE CONSUMPTION									
Passenger Trips Per Capita	32.03	32.25	34.30	34.74	35.71	31.47	-1.73%	-11.87%	n/a
Passenger Trips Per Revenue Mile	2.42	2.24	2.22	2.34	2.57	2.40	-0.8%	-6.67%	-22.95%
Passenger Trips Per Revenue Hour	29.63	28.09	27.67	28.55	31.17	28.75	-2.96%	-7.74%	-27.11%
QUALITY OF SERVICE									
Average Speed (RM/RH)	12.26	12.53	12.48	12.20	12.14	12.00	-2.18%	-1.15%	-5.4%
Average Headway (in minutes)	13.05	12.26	11.44	11.33	n/a	12.90	-1.12%	n/a	n/a
Average Age of Fleet (in years)	4.62	4.77	4.53	5.16	5.36	6.31	36.46%	17.7%	n/a
Number of Incidents	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Number of Vehicle System Failures	13,097	15,808	18,951	15,248	15,926	13,933	6.38%	-12.51%	-55.53%
Revenue Miles Between Incidents	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Revenue Miles Between Failures	2,374.63	2,164.89	1,943.19	2,338.30	2,097.66	2,264.20	-4.65%	7.94%	245.52%
AVAILABILITY									
Revenue Miles Per Route Mile	17,587.78	17,800.13	19,085.46	18,448.00	n/a	17,079.07	-2.89%	n/a	n/a
Weekday Span of Service (in hours)	n/a	24.00	24.00	24.00	24.00	n/a	n/a	n/a	n/a
Route Miles Per Square Mile of Service Area	6.16	6.28	6.31	6.32	n/a	6.04	-2.03%	n/a	n/a

Figure 3. Retrived data displayed on a standard report

Case Application 2: Quick Information Lookup for Unknown Agencies

Unlike the previous application, the user in this application is not looking for information for some specific systems in mind, but any systems that meet a specific profile. In this case, the user would apply the query capability of the system by clicking the Queries tab on the main screen to open the screen shown in Figure 4. This screen provides the user with a user-friendly query editor to quickly construct SQL (Structured Query Language) queries. The top half of the query screen allows the user to specify the data years, states, mode codes, and service types. The bottom half of the screen allows the user to construct SQL query conditions that help to narrow down the system selection.

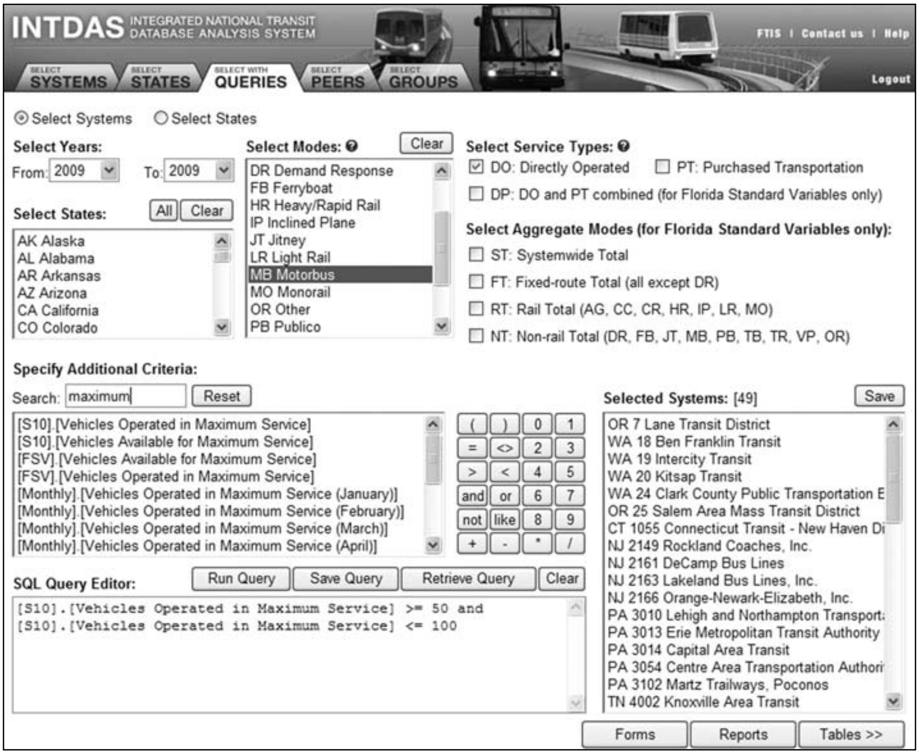


Figure 4. System selection by query

To add a query condition, the user first enters a keyword to narrow down the list of data variables. The user then clicks to select a variable from the variable list box and send it to the Query Editor box. A set of buttons are provided for selecting such common operators as "=" or ">=". Using a combination of the variable list, the math operator buttons, and the keyboard, the user can construct a series of SQL conditions. For example, the query shown in the Query Editor box in Figure 4 is to retrieve all directly operated (i.e., "DO") bus transit systems (i.e., "MB") in 2009 that operate a fleet size between 50 and 100 motorbus vehicles.

Once a query is constructed, the user clicks on the Run Query button to run the query to find transit systems that meet the query conditions. The output transit systems are listed in the Selected Systems list box. The user then looks up the information for these systems, as in the previous application, by clicking on the Forms or Reports button.

Case Application 3: Peer Selection and Comparisons

In this case application, the user is a transit planner from MDT who is interested in comparing the performances of MDT's bus system with those of its peer systems. As a first step of the analysis, the user needs to identify peer systems that are deemed comparable to MDT. To do so, the user first clicks the Peers tab on the main screen to open the screen shown in Figure 5. The screen allows the user to choose between two peer selection methods: TCRP or FTIS. The FTIS method was implemented prior to the development of the new TCRP method and is expected to be phased out. By default, the TCRP method, developed as part of the Transit Cooperation Research Program (TCRP) Project G-11 (Ryus et al. 2010), is selected.

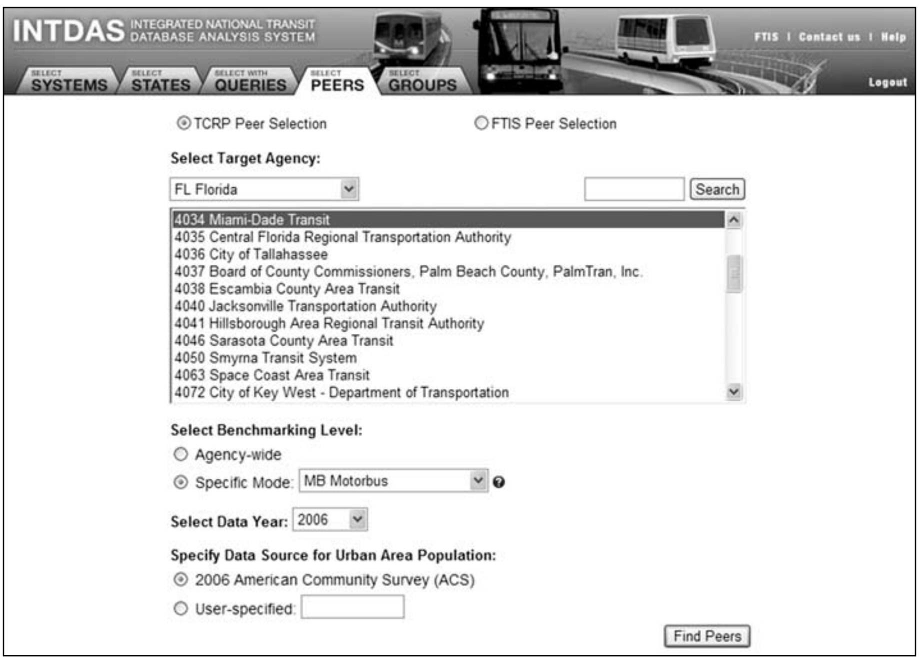


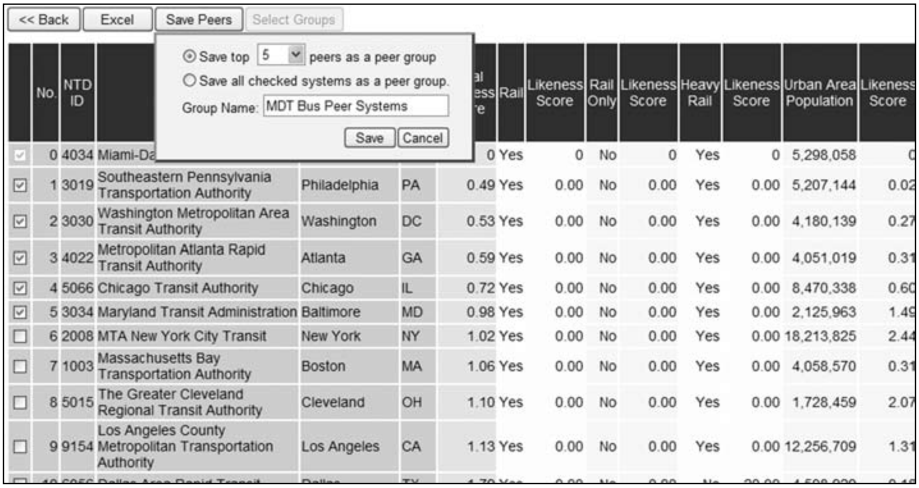
Figure 5. Peer selection input screen

The input screen for the TCRP method allows the user to first select Florida to shortlist the transit systems and then selects "Miami-Dade Transit" from the shortlist. The user can then choose to select peer systems based on agency-wide or mode-specific mode statistics for peer variables. In this application, the mode-specific option based on bus transit system (MB) is selected. The user then selects the data year for pear selection variables and the data source for the population size of the urban area in which the MDT is located. Next, the user selects the data year. As of the writing of this paper, only the 2006 data are available in the system for this peer selection method. Lastly, the user selects the data source for urban population. By default, the urbanized area (UZA) population from the American Community Survey (ACS) is used. However, the user may enter another population size. This allows the user to test different "what if" population scenarios. Once all of these inputs are specified, the user clicks the Find Peers button to search for peer systems based on their likeness scores, which are calculated from 3 screening factors and up to 14 peer grouping factors.

The three screening factors are whether an agency operates a rail system, only a rail system(s), and/or a heavy rail system. These variables ensure that potential peers operate a similar mix of modes as MDT. The peer grouping factors are used to determine which potential peer agencies are most similar to MDT in terms of service characteristics (e.g., vehicle miles operated, annual operating budget) and urban area characteristics (e.g., population density, percent low income). Based on these factors, a total likeness score is calculated for each potential peer system, as follows (Ryus et al. 2010):

$$\text{Total likeness score} \ \frac{\text{Sum (screening factor scores)} + \text{Sum (peer grouping scores)}}{\text{Count (peer grouping factors)}}$$

Based on this equation, the lower the score of a potential peer system, the more similar it is to MDT. Figure 6 shows the output screen, which lists all potential agencies from the lowest to the highest scores. In general, a total likeness score under 0.50 indicates a good match, between 0.50 and 0.74 represents a satisfactory match, and between 0.75 and 0.99 represents a potential match that may be used with additional investigation to determine major differences that may make them unsuitable. Scores beyond 0.99 are considered undesirable. Readers are referred to TCRP Report 141 for details on the peer selection process implemented in INTDAS (Ryus et al. 2010).



	No.	NTD ID				...al ...ess ...e	Rail	Likeness Score	Rail Only	Likeness Score	Heavy Rail	Likeness Score	Urban Area Population	Likeness Score
☑	0	4034	Miami-Da...			0	Yes	0	No	0	Yes	0	5,298,058	0
☑	1	3019	Southeastern Pennsylvania Transportation Authority	Philadelphia	PA	0.49	Yes	0.00	No	0.00	Yes	0.00	5,207,144	0.02
☑	2	3030	Washington Metropolitan Area Transit Authority	Washington	DC	0.53	Yes	0.00	No	0.00	Yes	0.00	4,180,139	0.27
☑	3	4022	Metropolitan Atlanta Rapid Transit Authority	Atlanta	GA	0.59	Yes	0.00	No	0.00	Yes	0.00	4,051,019	0.31
☑	4	5066	Chicago Transit Authority	Chicago	IL	0.72	Yes	0.00	No	0.00	Yes	0.00	8,470,338	0.60
☑	5	3034	Maryland Transit Administration	Baltimore	MD	0.98	Yes	0.00	No	0.00	Yes	0.00	2,125,963	1.49
☐	6	2008	MTA New York City Transit	New York	NY	1.02	Yes	0.00	No	0.00	Yes	0.00	18,213,825	2.44
☐	7	1003	Massachusetts Bay Transportation Authority	Boston	MA	1.06	Yes	0.00	No	0.00	Yes	0.00	4,058,570	0.31
☐	8	5015	The Greater Cleveland Regional Transit Authority	Cleveland	OH	1.10	Yes	0.00	No	0.00	Yes	0.00	1,728,459	2.07
☐	9	9154	Los Angeles County Metropolitan Transportation Authority	Los Angeles	CA	1.13	Yes	0.00	No	0.00	Yes	0.00	12,256,709	1.31

Figure 6. Peer output screen

Figure 6 also shows that the user can select the desired peer systems and then click the Save Peers button to save the peer systems for later use as a peer group. By default, the five most similar systems are selected. The user may, however, select any number of desired peer systems by checking the box in front of each listed system. The user then enters a group name for the set of peer systems selected to save. After the systems are saved, the user clicks on the Select Groups button to open the screen shown in Figure 7. This screen can also be opened by clicking the Groups tab on the main screen directly. On this screen, the user selects the peer systems she just saved by clicking on the group name. The saved peer systems in the group are displayed in the Select Systems window. The user can then select the peer systems by clicking the All buttons or clicking on the specific systems. The user then clicks on the Tables button to select the calculated performance variables as described above. This opens the screen shown in Figure 8, which allows the user to select specific data variables for retrieval and analysis.

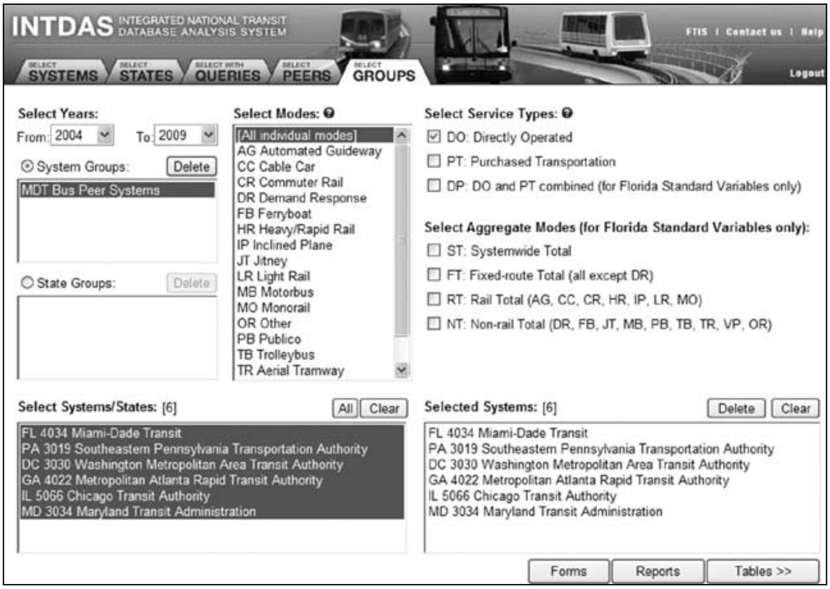


Figure 7. Screen for selecting saved peer groups

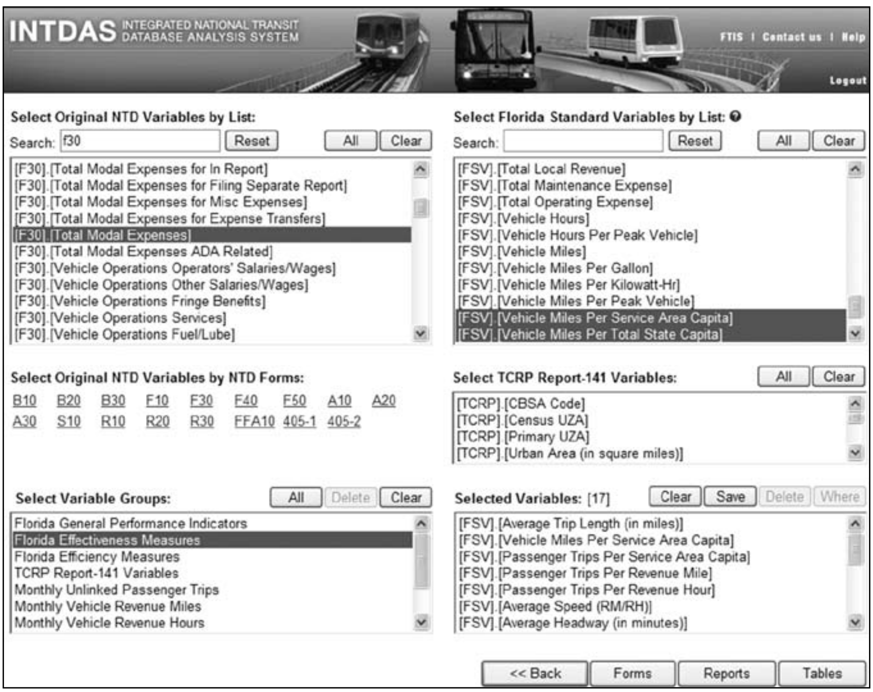
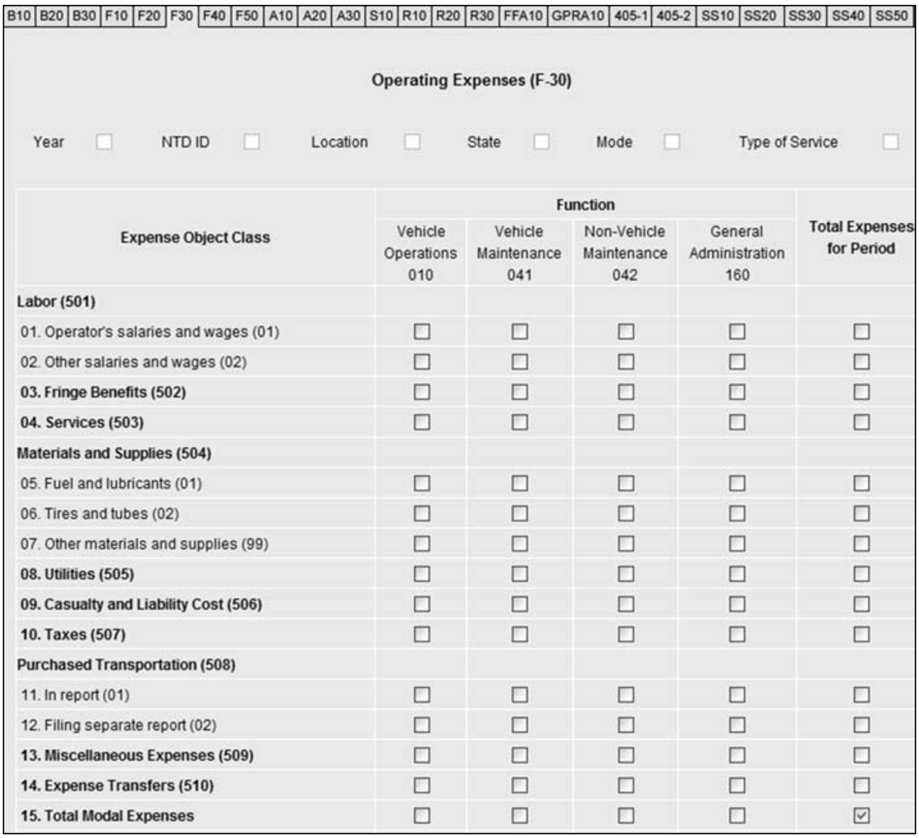


Figure 8. Screen for selecting data variables

INTDAS provides the following two selection options for variable selection:

1. Variable selection by list: This option allows the user to enter a keyword, or partial keyword, to search for variables that match the keyword. All variables that match the keyword are listed in the list box, as shown in Figure 8.
2. Variable Selection by NTD form: The second option for variable selection is through the emulated NTD forms. To select a variable, the user first selects the appropriate NTD form and then clicks on a check box to select a specific variable. Figure 9 shows that the users selected the total modal operating expenses on Form F-30.



B10 | B20 | B30 | F10 | F20 | F30 | F40 | F50 | A10 | A20 | A30 | S10 | R10 | R20 | R30 | FFA10 | GPRA10 | 405-1 | 405-2 | SS10 | SS20 | SS30 | SS40 | SS50

Operating Expenses (F-30)

Year ☐ NTD ID ☐ Location ☐ State ☐ Mode ☐ Type of Service ☐

Expense Object Class	Function: Vehicle Operations 010	Function: Vehicle Maintenance 041	Function: Non-Vehicle Maintenance 042	Function: General Administration 160	Total Expenses for Period
Labor (501)					
01. Operator's salaries and wages (01)	☐	☐	☐	☐	☐
02. Other salaries and wages (02)	☐	☐	☐	☐	☐
03. Fringe Benefits (502)	☐	☐	☐	☐	☐
04. Services (503)	☐	☐	☐	☐	☐
Materials and Supplies (504)					
05. Fuel and lubricants (01)	☐	☐	☐	☐	☐
06. Tires and tubes (02)	☐	☐	☐	☐	☐
07. Other materials and supplies (99)	☐	☐	☐	☐	☐
08. Utilities (505)	☐	☐	☐	☐	☐
09. Casualty and Liability Cost (506)	☐	☐	☐	☐	☐
10. Taxes (507)	☐	☐	☐	☐	☐
Purchased Transportation (508)					
11. In report (01)	☐	☐	☐	☐	☐
12. Filing separate report (02)	☐	☐	☐	☐	☐
13. Miscellaneous Expenses (509)	☐	☐	☐	☐	☐
14. Expense Transfers (510)	☐	☐	☐	☐	☐
15. Total Modal Expenses	☐	☐	☐	☐	☑

Figure 9. Selecting variables from NTD forms

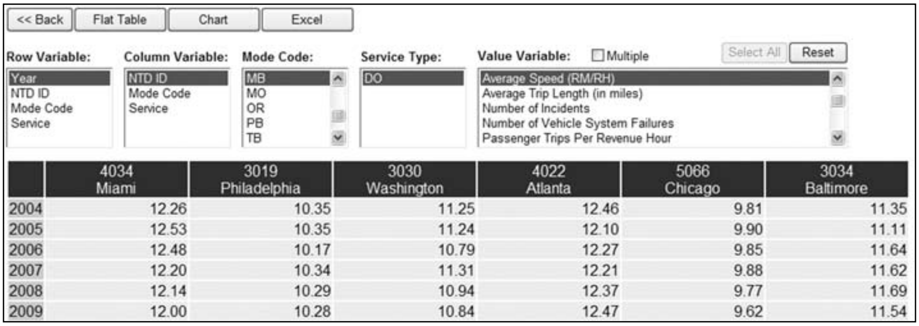
Once the variables of interest are specified, the data for the selected systems can be retrieved and displayed in a Flat Table, Cross Table, or Chart. Figure 10 shows an example of a flat table. It can be seen that the tenth column gives the total operating expenses after they are adjusted for inflation. The adjusted values could be quickly calculated in INTDAS by applying the Inflation function and specifying a target year to adjust to.

<< Back | Cross Table | Chart | Excel | Sort | Inflation | Summation | Statistics | Regression | Calculate | Reset

No.	Year	NTD ID	Company Name	Location	State	Mode	Service	Total Modal Expenses	Average Age of Fleet (in years)	Average Headway (in minutes)	Average Speed (RM/RH)	Average Trip Length (in miles)
1	2004	4034	Miami-Dade Transit	Miami	FL	AG	DO	$18,672,871	13.93	3.33	10.20	1.02
2	2004	4034	Miami-Dade Transit	Miami	FL	HR	DO	$61,437,722	22.00	5.30	23.58	7.79
3	2004	4034	Miami-Dade Transit	Miami	FL	MB	DO	$229,427,318	4.62	13.05	12.26	3.95
4	2004	3019	Southeastern Pennsylvania Transportation Authority	Philadelphia	PA	CR	DO	$186,242,753	28.90	11.40	27.05	14.32
5	2004	3019	Southeastern Pennsylvania Transportation Authority	Philadelphia	PA	HR	DO	$125,380,076	11.70	4.42	19.56	4.46
6	2004	3019	Southeastern Pennsylvania Transportation Authority	Philadelphia	PA	LR	DO	$46,088,287	23.59	3.79	9.45	2.51
7	2004	3019	Southeastern Pennsylvania Transportation Authority	Philadelphia	PA	MB	DO	$400,367,435	6.64	13.20	10.35	2.90
8	2004	3030	Washington Metropolitan Area Transit Authority	Washington	DC	HR	DO	$525,516,163	17.27	3.97	25.17	6.01
9	2004	3030	Washington Metropolitan Area Transit Authority	Washington	DC	MB	DO	$395,725,481	8.82	12.43	11.25	2.99
10	2004	4022	Metropolitan Atlanta Rapid Transit Authority	Atlanta	GA	DR	DO	$10,094,433	2.97		17.89	10.32

Figure 10. Retrieved data displayed in a flat table

It can be seen from Figure 10 that the tabulated data with multiple systems and multiple years are somewhat difficult to read. As such, INTDAS provides the ability to generate cross-table view that is cross-classified by two system variables at a time. Figure 11 shows such an example. The figure shows six years of average speeds for MDT and its five selected peer systems. The five list boxes on top of the cross-table screen allow the variables to be selected in different manners. The first two list boxes define the row and column variables, respectively, while the third and fourth list boxes list all of the possible data items for each of the remaining two system variables. The last list box lists all of the data attributes selected for analysis. The value for the selected data attribute is displayed on the cross table shown under the list box. The cross table is immediately updated as soon as a change occurs in any of the list boxes; this allows different data combinations to be examined quickly.



	4034 Miami	3019 Philadelphia	3030 Washington	4022 Atlanta	5066 Chicago	3034 Baltimore
2004	12.26	10.35	11.25	12.46	9.81	11.35
2005	12.53	10.35	11.24	12.10	9.90	11.11
2006	12.48	10.17	10.79	12.27	9.85	11.64
2007	12.20	10.34	11.31	12.21	9.88	11.62
2008	12.14	10.29	10.94	12.37	9.77	11.69
2009	12.00	10.28	10.84	12.47	9.62	11.54

Figure 11. Retrieved data displayed in a cross table

Instead of displaying data in a cross table, the user may also choose to display the data graphically, as shown in Figure 12. In this example, the user can quickly examine 25 years of average speed trends for MDT and compare them with those of the peer systems. Similar to the cross table, the plot is also refreshed immediately after any of the variables in the list boxes are changed, allowing the user to plot charts of all possible variable combinations.

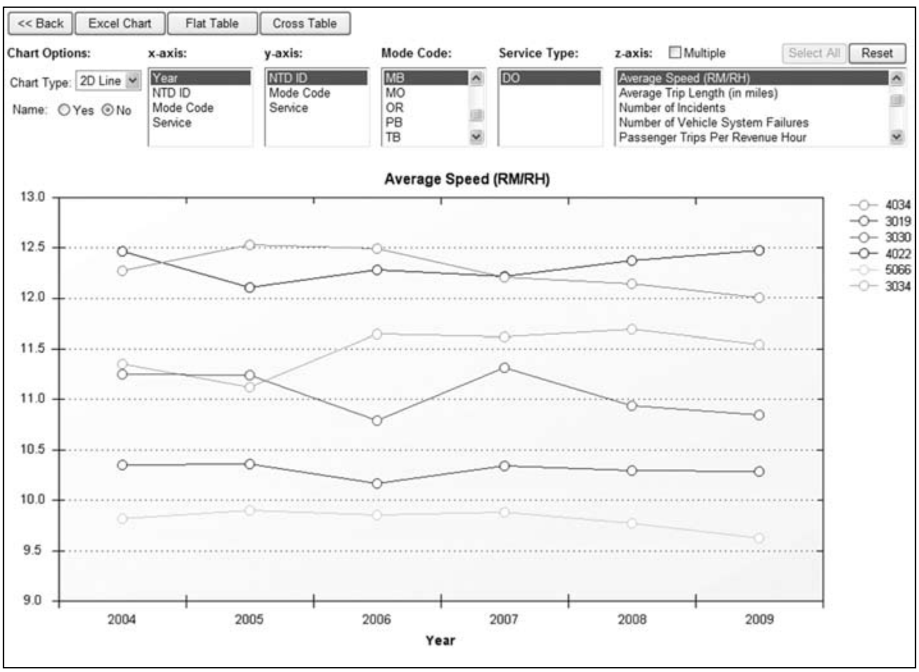


Figure 12. Retrieved data displayed in a chart

Summary and Further Developments

The National Transit Database (NTD) is an important database for the transit industry. These NTD data, however, were not easily accessible. Using three case applications, this paper described a web-based system designed to facilitate the retrieval and analysis of NTD data. The system is useful for both practitioners and researchers who use the NTD data to improve transit performance and services. The system provides user-friendly functions that allow multiple years of NTD data to be quickly retrieved and analyzed for multiple transit systems. The data retrieval functions allow the user to quickly select transit systems and NTD variables of interest, retrieve data for the selected systems and variables, and display the data in forms, tables, charts, and reports. The system also includes a peer selection process that allows one to quickly identify peer systems for peer comparisons.

The development of INTDAS remains an ongoing process. The original NTD data and the calculated performance measures will continue to be added to the system annually. While the system is quite user-friendly, an online web training system is being developed to help the users get started quickly and allow them to use the system more effectively. Current planned activities include the addition of rural NTD data, where were first collected in 2006, and the research and implementation of data mining tools to discover patterns and relationships from the vast amount of NTD data collected over the years.

Acknowledgements

The development of the INTDAS system was sponsored by the Public Transit Office of the Florida Department of Transportation. The peer selection feature in the system was implemented as part of Transit Cooperative Research Program (TCRP) Project G-11.

References

Center for Urban Transportation Research (CUTR). 2000. “Performance evaluation of florida’s transit systems.” Final Report Prepared for the Florida Department of Transportation.

Gan, A., I. Ubaka, and F. Zhao. 2002. “Integrated National Transit Database Analysis System (INTDAS),” *Transportation Research Record* 1799: 78-88.

Gan, A., I. Ubaka, and J. Zheng. 2004. "Automated transit peer selection and analysis," *Proceedings of the 2004 Annual Meeting of the Transportation Research Board*, Washington, DC.

Lyons, W. M., and E. R. Fleischman. 1992. "New future for the Federal Transit Administration Section 15 Program," *Transportation Research Record* 1349: 18-27.

Ryus, P., K. Coffel, J. Parks, V. Perk, L. Cherrington, J. Arndt, Y. Nakanishi, and A. Gan. 2011. *A Methodology for Performance Measurement and Peer Comparison in the Public Transportation Industry*, TCRP Report 141, Transit Cooperative Research Program, Transportation Research Board.

Ryus, P., K. Coffel, J. Parks, V. Perk, L. Cherrington, J. Arndt, Y. Nakanishi, and A. Gan. 2010. "Development of the TCRP G-11 transit agency peer-grouping methodology," *Proceedings of the 90th Annual Meeting of the Transportation Research Board*.

About the Authors

Albert Gan (*gana@fiu.edu*) is an Associate Professor with the Department of Civil and Environmental Engineering at Florida International University. He received his Ph.D. in Civil Engineering from the University of Florida in 1996. His areas of research have included traffic simulation, intelligent transportation systems (ITS), transit planning, demand modeling, and highway safety.

Feng Gui (*feng.gui@gmail.edu*) has been a System Programmer with the Lehman Center for Transportation Research at Florida International University (FIU) since 2006. He is the chief programmer of the INTDAS system and received his Ph.D. in Computer Engineering from FIU in 2009.

Li Tang (*ltang001@fiu.edu*) is a Graduate Research Assistant with the Department of Civil and Environmental Engineering at Florida International University. He received his B.S. and M.S. in Computer Science from Northeastern University of China and is working on his Ph.D. dissertation on transit data mining.

An Empirical Investigation of Passenger Wait Time Perceptions Using Hazard-Based Duration Models

Ioannis Psarros, Konstantinos Kepaptsoglou, and Matthew G. Karlaftis
National Technical University of Athens

Abstract

Waiting time in bus stops heavily affects traveler attitude towards public transportation and therefore is an important element for consideration when planning and operating a bus system. Furthermore, what passengers perceive as waiting time is often quite different from their actual waiting time at a bus stop. In this context, we present an empirical investigation of actual and perceived waiting times at bus stops for the case of a large bus network, using hazard-based duration models. The analysis is based on a questionnaire survey undertaken at bus stops of the Athens, Greece, bus network. Results indicate that age, trip purpose, and trip time period seem to have an impact on that perception, with older individuals, work, and education trips being factors that increase perceived waiting time and lead to an overestimation of actual waiting, while perceived waiting time decreases during morning time periods.

Introduction

Transit is an important element of a city's transportation system; transit systems offer sustainable and equitable transportation services to all travelers at low cost.

However, despite advantages of transit usage for societies, its share in ridership is often significantly lower compared to that of private vehicles, a fact usually attributed to the reduced performance and quality of services offered by transit systems. Bus systems are the most common among transit systems in cities worldwide (Vuchic 2004); however, these systems exhibit considerably lower attraction to passengers, which is mostly a result of problematic operations and their interaction with the rest of traffic. Indeed, operational characteristics such as low travel speeds, inadequate frequencies, and lack of punctuality and schedule reliability do have a negative effect in bus transit ridership.

Waiting times in bus stops are among those elements heavily affecting the attitude of passengers towards using bus transit, as well as their opinions on the quality of transit services. Riders are expected to wait at stops for buses to arrive, being exposed to adverse weather conditions, crowding, and a surrounding environment of poor quality, while being stressed by waiting anxiety. As a result, what passengers perceive that waiting time is often much larger compared to the actual waiting time imposed by bus operations, especially when no information is given to them on expected bus arrivals (Mishalani et al. 2006).

In that context, this paper provides an empirical investigation of actual and perceived waiting times at bus stops in the case of a large bus network with the use of duration models. The analysis is based on a survey undertaken at over 30 bus stops of the Athens bus network, which consists of over 300 lines and serves 1.3 million passengers on a daily basis. The remainder of the paper is structured as follows: the next section provides a brief background of past work on bus waiting times. Next, a description of the dataset and the methodological aspects of the paper are given. Empirical findings are then presented and discussed. The paper concludes with major insights drawn from the preceding analysis.

Background

The issue of waiting times at bus stops has been a topic of interest for researchers for at least three decades, with efforts concentrating both on the actual and perceived waiting times. Jolliffe and Hutchinson (1975) offered a behavioral explanation of the relationship between bus and passenger arrivals at bus stops and their impact on waiting times, considering random and not random passenger arrivals. Turnquist (1978) identified the effects of service frequency and reliability on waiting times, and Bowman and Turnquist (1981) developed a model based on passenger decision making for analyzing the sensitivity of waiting time against service frequency and reliability. Lam and Morral (1982) examined the impact of weather on waiting times, and Van Evert (1987) developed a relationship between service frequency and waiting time. Zahir et al. (2000) analyzed the bus system of Dhaka based upon field surveys and offered observations on actual passenger waiting times. Salek and Machemehl (1999) used experimental data from the city of Austin, Texas, and developed a model for predicting bus passenger waiting time, and Hall (2001) described a survey for collecting passenger waiting time information with the support of Automatic Vehicle Location systems for verification.

Perception of bus waiting time was investigated by Baldwin et al. (2004). Passengers were presented with the opportunity to pay for immediate service rather than wait. The study indicated that waiting times are overestimated by a factor of two when imposed by the transit system. Michalani et al. (2006) investigated passenger wait time perception on bus stops and attempted to quantify the relationship between perceived and actual wait time with the use of linear regression. Their results indicated an overestimation of waiting time by passengers compared to their actual waiting time. Currie and Csikos (2007) focused on the impacts of transit reliability on waiting times and drew interesting conclusions on their relationship. Another study on passenger perception of waiting time by Iseki and Taylor (2008) indicated that passengers mostly want short and predictable waits in a safe environment and do not give much notice to the attractiveness of bus infrastructures. Fan and Machemehl (2009) investigated different operating characteristics as potential predictors of passenger waiting time and concluded that a linear model which related waiting times to headways was the preferred case. They also reported differences between their model and the traditional random model for passenger waiting time estimation.

Overall, the review revealed past work focusing on either prediction of actual waiting time or the analysis of perceived waiting time. In that context, this research contributes to the existing literature by examining the relationship between actual and perceived travel time, based on data collected by a combination of observations and personal interviews and the use of appropriate statistical methods (hazard-based duration models) for analyzing the effect of various explanatory factors to the passenger perception of waiting time.

Dataset and Preliminary Statistical Analysis

The dataset used is based on an extensive field survey, which combined observations of actual waiting times for passengers at bus stops and personal interviews on their perception of waiting time. Passengers arriving at bus stops were randomly selected and their arrival time was recorded by interviewers. Shortly after their arrival, passengers were asked by the interviewers about their perception of waiting time at the bus stop, along with other information, while the interview starting time was recorded. Then, when the passengers boarded a bus, a note of their total actual waiting time was made. This way, both the actual and perceived waiting times were collected for the time up to the initiation of the interview, as well as the overall actual waiting time. The survey took place at 30 bus stops in Athens area, from 8 A.M. to 8 P.M. Bus stops with both frequent and infrequent bus arrivals were selected as survey locations, and a total of over 1,000 passengers were interviewed. Collected data included actual passenger arriving and interview time, total actual waiting time, perceived time, gender, age and trip purpose, while the period of the day for each interview (morning, afternoon, evening) was also indicated.

Preliminary statistical analysis of the results revealed a relative balance between male and female passengers (47% versus 53%), while most passengers were of age between 18 and 65. Further, over 35 percent of the respondents were traveling to or from their place of work. Tables 1 and 2 summarize actual and perceived average waiting times for different time periods, gender and age groups, and trip purposes.

By inspecting Table 1 and 2 results, it can be seen that perceived waiting time is, in most cases, increased by at least 50 percent compared to the actual waiting time. Furthermore, older age groups and passengers traveling to work or for personal affairs tend to overestimate their waiting time, compared to other categories. The same applies to passengers interviewed in the morning period. A preliminary interpretation of these overestimations by specific passenger groups can be qualitatively attributed to factors such as limited patience by older passengers and work anxiety affecting passengers traveling to work or for personal affairs. However, a detailed, model-supported statistical analysis would reveal the actual effects of the aforementioned factors to the actual and perceived waiting times.

Table 1. Actual and Perceived Average Waiting Times for Different Time Periods

Time period	Average Perceived Waiting Time (min)	Average Actual Waiting Time (min)	Ratio of Average Perceived to Average Actual Waiting Time
Morning	6.18	3.56	1.74
Afternoon	6.48	4.58	1.41
Evening	6.25	3.83	1.63

Table 2. Actual and Perceived Average Waiting Times for Different Sex and Age Groups and Trip Purposes

Group	Average Perceived Waiting Time (min)	Average Actual Waiting Time (min)	Ratio of Average Perceived to Average Actual Waiting Time
AGE GROUP			
< 18	7.65	5.56	1.38
18- 30	5.76	4.06	1.42
31-45	6.30	3.85	1.64
46-65	7.21	4.19	1.72
> 65	6.81	3.84	1.77
GENDER			
Men	6.22	3.87	1.61
Women	6.53	4.30	1.52
TRIP PURPOSE			
Return Home	6.60	4.72	1.40
Work	7.23	4.73	1.53
Education	8.80	7.73	1.14
Personal	8.08	5.49	1.47
Entertainment	6.58	5.17	1.27
Shopping	7.91	5.86	1.35
Other	9.29	4.57	2.03

Model

Overview

Duration data refer to time (or duration) until or between occurrence of events (Hensher and Mannering 1994). Such data are often encountered in transportation, with examples such as the duration between traffic accidents or vehicle purchases, waiting time in traffic queues, and so on (Hensher and Mannering 1994;

Washington et al. 2003). Hazard-based models have been developed especially for describing duration data (Hensher and Mannering 1994). In detail, consider an episode as the time period until the occurrence of an event (or the time period between successive events); a hazard function expresses the probability that this episode starting at time t is terminated within a time interval (t, $t+\Delta t$) provided that the event has not occurred before the beginning of the interval. For example, in the particular case investigated in this paper, waiting time refers to the time period (episode) until a passenger boards a bus (event). As a result, the probability of boarding the bus after waiting for a duration Δt is represented by the hazard function.

Hazard-based duration models have been exploited in a field of transportation for modeling the duration between traffic accidents, the time up to capacity restoration following a traffic incident, the duration of trip decision making activities, automobile ownership time etc. (Hensher and Mannering 1994; Washington et al. 2003). As noted by Hensher and Mannering (1994), duration models "focus on the probability of an end-of-duration occurrence, given that the duration has lasted to some specified time." This implies that the terminating event is assumed to be related to the duration of an episode. As such, the underlying advantage of duration models compared to other approaches) is the fact that they allow the occurrence of an event to be formulated in terms of conditional probabilities with respect to factors affecting the duration of its preceding episode and therefore offer a "tight link between theory and an empirical approach" (Hensher and Mannering 1994). Similarly, in the context of this paper, any answer to the question on perceived waiting time asked as part of the personal interviews (occurrence of the event) is related to those factors affecting the perception of waiting time. Therefore, we consider duration models to be more appropriate for the problem at hand compared to other approaches (e.g., regression).

Theoretical Background

Following Washington et al. (2003), let T be a nonnegative random variable that represents (a) the perceived waiting time (duration) and (b) the difference between the perceived and actual waiting times. The probability distribution of T can be represented in a number of ways, of which the survival and hazard functions are the most useful. The survival function is defined as the probability that T is of *length at least t* (i.e. perceived waiting time or the difference between perceived and actual waiting time at least t min) and is given by (Washington et al. 2003):

$$F(t) = P(T \geq T),\ 0 < t < \infty \tag{1}$$

The notation used here suggests that *F(t)* is a monotone left continuous function with *F*(0) = 1 and $\lim_{t \to \infty} F(t) = 0$. The probability density function (p.d.f.) of *T* is (Washington et al. 2003):

$$f(t) = \lim_{\Delta t \to 0^+} \frac{P(t \leq T < t + \Delta t)}{\Delta t} = \frac{-dF(t)}{dt} \tag{2}$$

The hazard function specifies the instantaneous failure rate at *T* = *t*, conditional upon survival to time *t*, and can be defined as follows (Washington et al. 2003):

$$\lambda(t) = \lim_{\Delta t \to 0^+} \frac{P(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t} = \frac{f(t)}{F(t)} \tag{3}$$

It is important to note that hazard functions are extremely useful in practice. They indicate the rate at which perceived waiting time increases after lasting for time *t*, and for this reason is more interesting than the survival or the c.d.f. functions. Also, from Eq. (3) it can be seen that *l* (*t*) specifies the distribution of *T* since,

$$\lambda(t) = \frac{-d \log F(t)}{dt}$$

by integrating and setting *F(0)* = 1

$$F(t) = \exp\left(-\int_0^t \lambda(u)\,du\right)$$

and the p.d.f. of *T* becomes

$$f(t) = \lambda(t) \exp\left(-\int_0^t \lambda(u)\,du\right) \tag{4}$$

The literature suggests a wide variety of functional forms for the duration distributions such as the exponential, the Weibull, the Lognormal, the inverse normal, the Loglogistic, and others (*Washington et al*. 2010). Interestingly, these distributions display very different behaviors, and the selection of the functional form to be used will have important implications in the practical significance of the results.

Variables

Selected dependent variables are (a) the perceived waiting time by passengers and (b) the difference between the perceived and actual waiting times. Explanatory variables include sex, age, time period, travel purpose, and actual waiting time (when the dependent variable is the perceived waiting time). Both dependent and explanatory variables are shown in Table 3.

Table 3. Dependent and Explanatory Variables

Variable Name	Description	Values
Dependent Variables		
LOGPER	Perceived wait time difference	Any
LOGDIF	between perceived and actual wait times	Any
Explanatory Variables		
GENDER	Gender (male, female)	0 for male, 1 for female
AGE18	Age	1 for ages < 18, 0 otherwise
AGE1830		1 for ages 18-30, 0 otherwise
AGE3045		1 for ages 18-30, 0 otherwise
AGE4565		1 for ages 18-30, 0 otherwise
AGE65		1 for ages < 18, 0 otherwise
HOME	Trip purpose	1 for "return home," 0 otherwise
WORK		1 for "work," 0 otherwise
EDUC		1 for "education," 0 otherwise
PERS		1 for "personal affairs," 0 otherwise
ENTERT		1 for "entertainment," 0 otherwise
SHOP		1 for "shopping," 0 otherwise
TRAVEL		1 for "travel," 0 otherwise
OTHER		1 for "Other," 0 otherwise
QUE1	Time period	1 for 8:00 to 12:00, 0 otherwise
QUE2		1 for 12:00 to 17:00, 0 otherwise
QUE3		1 for 17:00 to 20:00, 0 otherwise
REALTIME	Actual wait time up to interview initiation	Any

In particular, five variables correspond to age groups of under 18, 18–30, 31–45, 46–65, and over 65; eight variables correspond to trip purposes (return home, work, education, shopping, entertainment, travel out of town, and other) ; and three variables are assigned to time periods (8:00–12:00, 12:00–17:00, 17:00–20:00).

Empirical Findings

Using previously described data and the duration model methodology, Tables 4 and 5 present model results for two duration distributions, Weibull and Loglogistic.

Table 4. Model Results with Perceived Wait Time as Dependent Variable

	WEIBULL			*LOGLOGISTIC*		
Explanatory Variables*	**Coefficient**	**t-statistic**	**Hazard ratio****	**Coefficient**	**t-statistic**	**Hazard ratio****
CONSTANT	0.687	40.19	1.988	0.691	28.27	1.996
AGE18				0.066	2.40	
AGE3045	0.037	2.39	1.038			1.000
AGE4565	0.084	5.81	1.088	0.040	2.82	1.041
AGE65	0.077	4.12	1.080			
HOME	0.175	8.49	1.191	0.082	2.85	1.085
WORK	0.241	12.21	1.273	0.091	3.47	1.095
EDUC	0.361	10.84	1.435	0.164	4.32	1.178
PERS	0.265	12.61	1.303	0.135	4.94	1.145
ENTERT	0.196	9.01	1.217	0.068	2.35	1.070
SHOP	0.262	11.64	1.300	0.137	4.56	1.147
OTHER	0.367	8.81	1.443	0.164	3.92	1.178
QUE1	-0.041	-2.18	0.960			

**Non-significant variables for both distributions are omitted.*
***Proportional change in hazard given a unit change in explanatory variable (all other variables assumed fixed).*

Table 5. Model Results with Difference Between Perceived and Actual Wait Times as Dependent Variable

	WEIBULL			*LOGLOGISTIC*		
Explanatory Variables*	**Coefficient**	**t-statistic**	**Hazard ratio****	**Coefficient**	**t-statistic**	**Hazard ratio****
CONSTANT	0.648	44.25	1.912	0.491	30.15	1.634
GENDER	0.000	4.82	1.000	0.000	4.43	1.000
AGE1830	-0.040	-3.21	0.961	-0.030	-2.17	0.970
AGE3045	-0.051	-3.22	0.950	-0.035	-2.11	0.966
HOME	0.127	6.20	1.135	0.146	7.30	1.157
WORK	0.146	10.03	1.157	0.152	9.12	1.164
EDUC	0.285	9.48	1.330	0.172	4.60	1.188
PERS	0.150	7.55	1.162	0.162	8.20	1.176
ENTERT	0.183	11.66	1.201	0.159	7.37	1.172
SHOP	0.238	13.21	1.269	0.187	7.40	1.206
OTHER	0.185	3.62	1.203	0.184	4.21	1.202
QUE1	-0.060	-3.92	0.942			
QUE2				0.054	3.35	1.055
QUE3	-0.030	-2.47	0.970	0.043	2.47	1.044
REALTIME	0.010	4.38	1.010	0.000	3.42	1.000

**Non-significant variables for both distributions are omitted.*
***Proportional change in hazard given a unit change in explanatory variable (all other variables assumed fixed).*

It should be noted here that the hazard functions for the Loglogistic and Weibull distributions are given by $l\ p(l\ t)^{p-1}/\ 1+(l\ t)^{p}$, $l\ p\ (l\ t)^{p-1}$, respectively; for the same distributions, the survival functions are $1/\ 1+(l\ t)^{p}$, $e^{-(l\ t)^{p}}$.

It is evident from Tables 4 and 5 that the different functional forms of the Weibull and Lognormal distribution lead to very different qualitative conclusions. For example, as can be seen from Figure 1, the Weibull distribution is monotonically increasing, indicating a continuously increasing hazard rate over time, while the Loglogistic suggests an initial increase and then a decrease in the hazard rate (Washington et al. 2010).

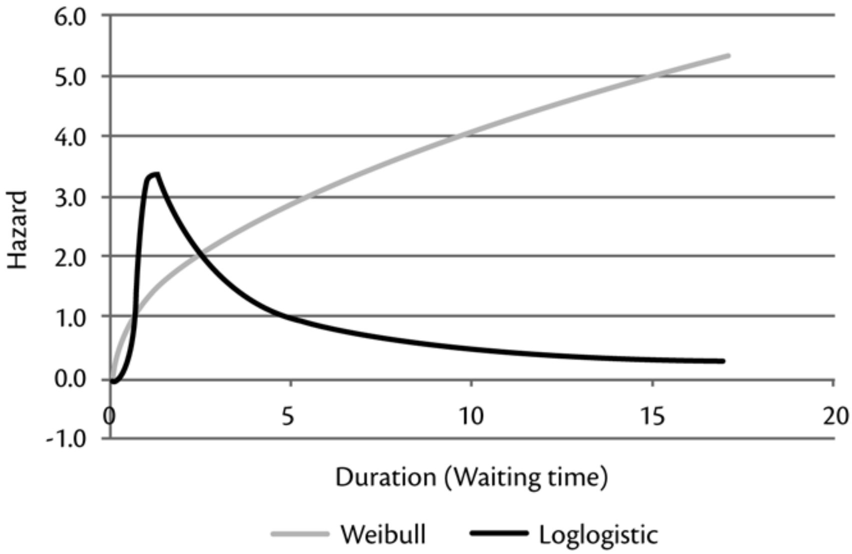


Figure 1. Weibull and Loglogistic hazard functions

The obvious question then becomes, how can the "best" fitting distribution be selected? Besides theoretical arguments, the statistical answer to this question is not straightforward. In general, for a model to be appropriate for the data, the graph for each of the functional forms needs to be a straight line through the origin (for the exponential model, for example, it is the graph of the log of the survival versus *t*). However, it is interesting to note that the Weibull and Loglogistic functional forms are all nested within the generalized gamma model, making it a simple matter to evaluate them with the likelihood ratio test (Lee and Wang 2003; Cleeves et al. 2008). Final likelihood values indicate that the Weibull distribution is more suitable for describing both the perceived waiting time and the difference between the perceived and the actual waiting time.

With respect to the interpretation of results, Table 4 presents those factors affecting perceived waiting time. According to Table 4 results (for the Weibull distribution), perceived waiting time increases for ages of over 18 years (positive coefficients of 0.037, 0.084 and 0.077, respectively), while a larger effect on the length of perceived waiting time is observed for ages over 45 years. Indeed, for ages between 45 and 65, a hazard ratio of 1.088 implies that for this age category, perceived waiting time increases by 8.8 percent. All trip purposes appear to have a strong positive effect on the length of perceived waiting time. In particular, trip purposes directly related to certain activities (such as trips made for work, education, and personal affairs) tend to have a stronger effect on increased perceived waiting times. Trips to work, for example, lead to an increase in perceived waiting time of 27.3 percen,t while the corresponding percentages for education and personal affairs are 43.5 percent and 30.3 percent, respectively. Interestingly, shopping activities have a similar effect on perceived waiting time by 30 percent. On the other hand "return home" and entertainment seem to have a lower (yet positive) impact on the length of perceived travel times compared to other purposes (hazard ratios of 1.191 and 1.217). Finally, the morning time period seems to have a negative effect on perceived waiting times (with a coefficient of -0.041), a fact that can be attributed to more frequent bus arrivals at the bus stops. In particular, the hazard ratio value of 0.96 implies that perceived waiting time is reduced by 4 percent during morning periods.

Table 5 results refer to the difference between perceived and actual waiting times and practically indicate the degree of waiting time overestimation by travelers. Results (again for the Weibull distribution) show that younger passengers (up to 30 years of age) tend to have a better perception of waiting times (coefficients of -0.040 and -0.051). Hazard ratios indicate that for these categories, the difference between perceived and actual waiting time is 4 percent-5 percent. Trip purpose seems to positively affect overestimation of travel time perception, particularly for work-related trips, shopping, and entertainment. For example, for work trips, passengers tend to overestimate their waiting time by 15.7 percent, while for education trips this percentage rises to 33 percent. We also find that at morning and afternoon periods, there is a better perception of waiting times. Overall, age, trip purpose and the morning and afternoon periods seem to affect perception of waiting time in bus stops.

Conclusions

Waiting time at bus stops is evidently one of those key factors affecting the attractiveness and performance of bus systems. Nevertheless, its perceived value practically dictates rider discomfort and preference towards bus services. In this context, this paper focused on investigating the effects of various factors on perceived waiting time using appropriate hazard-based duration models. The use of duration models was dictated by the nature of the problem at hand, which fits the underlying theoretical rationale behind using these models. Results indicated that age, trip purpose, and trip time period seem to have an impact on that perception, with older individuals, work trips, and education trips being factors that increase perceived waiting time and lead to an overestimation of actual waiting, while perceived waiting time decreases during morning time periods.

References

Baldwin Hess, D., J. Brown, and D. Shoup. 2004. Waiting for the bus. *Journal of Public Transportation* 7(4): 67-84.

Bowman, L.A, and M. A. Turnquist. 1981. Service frequency, schedule reliability and passenger wait times at transit stops. *Transportation Research Part A: Policy and Practice* 15A(6): 465-471.

Cleeves, M., R. Guttierez, W. Gould, and Y. Marchenko. 2008. An *Introduction to Survival Analysis Using Stata, 2nd Ed.* Stata Press, College Station, TX.

Currie, G., and D. R. Csikos. 2007. The impacts of transit reliability on wait time: Insights from automated fare collection system data. *Proceedings of the 86th Transportation Research Board Annual Meeting*, Washington, D.C., USA.

Evert, V. 1987. Relatie tussen frequentie en werkelijke wachttijd. Verkeerskunde 38(10): 430-433.

Fan, W., and R. Machemehl. 2009. Do transit users just wait for buses or wait with strategies? Some numerical results that transit planners should see. *Transportation Research Record* 2111: 169-176

Hall, R. W. 2001. Passenger waiting time and information acquisition using automatic vehicle location for verification. *Transportation Planning and Technology* 24(3): 249-269.

Hensher, D. A., and F. L. Mannering.1994. Hazard-based duration models and their application to transport analysis. *Transport Reviews* 14(1): 63-82.

Iseki, H., and B. Taylor. 2008. Style versus service? An analysis of user perceptions of transit stops and stations in Los Angeles. *Proceedings of the 87th Transportation Research Board Annual Meeting*, Washington, D.C., USA.

Jollife, J.K., and T. P. Hutchinson. 1975. A behavioural explanation of the association between bus and passenger arrivals at a bus stop. *Transportation Science* 9(3): 249-282

Lam, W., and J. Morrall. 1982. Bus passenger walking distances and waiting times: A summer-winter comparison. *Traffic Quarterly* 36(3): 407-421.

Lee, E. T., and J. W. Wang. 2003. *Statistical Methods for Survival Data Analysis 3rd Edition*. Wiley and Sons, Hoboken, NJ.

Mishalani, R., M. McCord, and J. Wirtz. 2006. Passenger wait time perceptions at bus stops: Empirical results and impact on evaluating real-time bus arrival information. *Journal of Public Transportation* 9(2): 89-106.

Salek, M-D, and R. Machemehl. 1999. Characterizing bus transit passenger wait times. Report SWUTC/99/167211-1, University of Texas at Austin and Southwest Region University Transportation Center, USA.

Turnquist, M. A. 1978. A model for investigating the effects of service frequency and reliability on bus passenger waiting times. *Transportation Research Record* 663: 70-73.

Vuchic, V. 2004. *Urban Transit: Operations, Planning and Economics*. John Wiley and Sons Inc. Hoboken, NJ, USA.

Washington, S., M. Karlaftis, and F. Mannering. 2003. *Statistical and Econometric Methods for Transportation Data Analysis*. Chapman & Hall/CRC Press, Boca Raton, FL, USA.

Washington, S., M. Karlaftis, and F. Mannering. 2010. *Statistical and Econometric Methods for Transportation Data Analysis – 2nd Edition*. Chapman & Hall/CRC Press, Boca Raton, FL, USA.

Zahir, U., H. Matsui, and M. Fujita. 2000. Investigation of the effects of bus and passenger arrival patterns and service frequency on passenger waiting time and transit performance of Dhaka metropolitan area. *Proceedings of the Sixth*

International Conference on Urban Transport and the Environment for the 21st Century, Cambridge University, Cambridge, UK: 55-64.

About the Authors

Ioannis Psarros (*psmmpg@yahoo.gr*) is a master's student at the School of Civil Engineering of the National Technical University of Athens. His research interests include transportation planning and design of public transportation systems.

Konstantinos Kepaptsoglou (*kkepap@central.ntua.gr*) is a post-doctoral researcher at NTUA. He holds a Civil Engineering diploma from NTUA, a master's degree from Purdue University, and a PhD from NTUA. His research interests include public transportation, transportation planning, railway planning and design, and operations research.

Matthew G. Karlaftis (*mgk@central.ntua.gr*) is an Associate Professor of the School of Civil Engineering of NTUA. His educational background includes B.Sc. and M.Sc. degrees from the University of Miami and a Ph.D. from Purdue University. His research has focused on a variety of aspects related to transportation planning, traffic engineering, operations research, and statistics. He is a co-author of over 70 publications in peer reviewed journals and an area editor of ASCE's *Journal of Transportation Engineering.*

What Do Passengers Do During Travel Time? Structured Observations on Buses and Trains

Marie Russell, Rachel Price, Louise Signal, and James Stanley
University of Otago, Wellington
Zachery Gerring and Jacqueline Cumming
Victoria University of Wellington

Abstract

Structured observation is one way to assess how public transport passengers actually use their travel time. This study reports on 812 adult passengers in Wellington, New Zealand. Researchers recorded passenger characteristics and behavior over a 4-minute period, on a range of routes and times, using 12 pre-set codes. Most passengers (65.3%) were "looking ahead/out the window" at some point in the observation period, more on buses than on trains. About one-fifth of all passengers observed were seen reading, more on trains. Other activities included listening on headphones, talking, texting, and sleeping/eyes closed. Activities were compared on the basis of gender, age group, mode, and time of day. Comparisons are made with recent observational and survey studies, with discussion of both methods and results.

Introduction

This article discusses structured observation as a method to assess what people do during their public transport travel time and reports on a study of bus and train passengers in New Zealand. Particular attention is given to some methodological challenges of data collection on public transport, and methods and results are compared with other observational studies.

The standard way travel time is valued in transport appraisal, through valuation of travel time savings (essentially, travel time is treated as wasted time), provides the overall context for this research (Wardman 1998; Mackie, Jara-Díaz et al. 2001; Wardman 2001; Hensher 2001a; Hensher 2001b; Mokhtarian 2005; Metz 2008). The study reported here does not engage with the monetary valuation of travel time; it is a social and not an economic study. The lead researcher's Ph.D. research investigates how public transport passengers use and value their travel time and its impact on health and well-being. As a preliminary investigation, observations of bus and train passengers were undertaken in the Wellington area during November-December 2008.

Ways of Observing Passengers

There is little in the transport literature about observation of passengers during travel as a method. Clifton and Handy (2001) pointed out that participant observation "has not often been used in travel behaviour research, but it has a rich tradition in studies of behaviour in urban space" (Clifton and Handy 2001). Observation is not appropriate if we seek to know what passengers are thinking or feeling, of course; it can be used only to assess manifest behavior. Further, observed behavior cannot often be interpreted: for example, a person reading a novel could be doing so for leisure or for study, or even for work.

Several useful ethnographic observational studies of passengers have been carried out (Nash 1975; Delannay 2001; Fink 2006; Watts 2008; Jain 2009). That method, however, would not yield information about the range of activities among large numbers of bus and train passengers or show which behaviors were more common and how they were shared across different population groups and different modes.

Naturalistic observation is assumed to "not interfere with the people or activities under observation" (Angrosino 2005) and people "are free to vary their individual and social responses" (Sackett, Ruppenthal et al. 1978). Still, "people may behave quite differently when they know they are being observed versus how they behave naturally when they don't think they are being observed" (Patton 2002).

To systematically observe passengers in a completely covert way, a hidden video camera might be used. But there are methodological and cost reasons, as well as the more compelling ethical arguments, against this approach (Sackett 1978).

Structured observation is a "way of quantifying behaviour" (Robson 1993) as it "focuses on the frequency of ... actions" (Gray 2004) and "employs explicitly formulated rules for the observation and recording of behaviour" (Bryman 2008). Unlike ethnographic studies, it produces quantitative data. The coding scheme and observation schedule are central to the method. At the time of the research, the team had not seen studies elsewhere using this method with passengers. Three reports since came to attention: Ohmori and Harata (2008), Timmermans and Van der Waerden (2008), and Thomas (2009). Comments on these studies, below, include remarks about methodology and data collection protocols.

Timmermans and Van der Waerden (2008) discussed the advantages and disadvantages of observation as opposed to surveys, diaries, and similar self-reports, which are common in time-use research. While self-reports may be useful and reliable for most activities and appropriate for questions about how people spend their time at home where observation is not feasible, travel activities may be rather different. Short-duration or non-routine activities while traveling may be especially subject to poor recall. Observation is economical and unobtrusive and yields a lot of fairly reliable data in a short time.

Problems with structured observation as a method may arise when there is more than one observer, in the degree of agreement between the observations (inter-rater reliability); but having more than one observer is desirable as reliability can be checked. An observer's attention may flag (affecting intra-rater reliability), or the consistency of observations over time by each observer may change (Martin and Bateson 2007). Hence "observer drift" (Robson 1993), "observer fatigue" (Martin and Bateson 2007) or "observer decay" (Hollenbeck 1978) are of concern. The ethnographer Watts (2008) described the challenge of maintaining the observer's role and location as a researcher.

Observational and Survey Studies of Passengers

In their study of 161 passengers on San Francisco trains, Timmermans and Van der Waerden (2008) found almost all were "doing nothing." Although this was a pilot study (Timmermans and Van der Waerden 2008) and the sample size was too small to detect significant effects, the authors reported differences in activities: "doing nothing, sleeping, talking, reading and [listening to] music" by socio-demographic and contextual variables: gender, race, age, travel party (alone, couple or group), trip duration, and time of day. That almost all of the people observed were "doing nothing" "casts doubt on the prevalence of multitasking while travelling on trains, at least for this sample, which concerned travelling for relatively short distances" (Timmermans and Van der Waerden 2008).

Other activities discussed were sleeping (more common among women and non-Caucasians and in the morning commute, less common among 18-25 year olds, and almost half of the sample) and talking (more common among women and Caucasians).

A Japanese study by Ohmori and Harata (2008) included an observation of 84 and a survey of 503 passengers on "normal" and "high grade" trains. The observations showed sleeping and reading as the most frequent activities; sleeping was at a high rate (67%). But the observation study did not appear to include a "doing nothing" category. The ensuing survey evidently did have such a category, however, and a quarter to a third of passengers reported "thinking of something" for work or leisure. Some activities differed by trip length: the longer the trip, the more likely passengers were to be sleeping or reading, especially if they had a seat. Not having a seat did not prevent sleeping, though.

Thomas's recent New Zealand study (2009) included observations of 1,703 passengers on Wellington buses and trains. Thomas was not examining the range of behaviors *per se* but looked at passenger characteristics, seat selection, movement within the vehicle, verbal interaction, and "defensive behaviors," in which category he included listening to music, reading, etc. (Thomas 2009). Results showed that about a quarter of passengers had verbal interactions, and a quarter engaged in activities, the most common being reading/writing (11% of the total sample) and listening to music (9%).

In a large British survey (N=26,221 train passengers) about different activities while traveling, reading for leisure (34%), window gazing/people watching (18%), and working/studying (13%) were the frequent activities reported by passengers (Watts and Urry 2008). For British passengers, unlike those in the U.S. observational study, sleeping/snoozing happened more on the "return" journey (Lyons and Chatterjee 2008). Window-gazing was high on short journeys (Lyons, Jain et al. 2007), and the authors suggest there may be "a possible travel duration threshold below which there is not a suitable amount of time to do other than window gaze/people watch" (Lyons, Jain et al. 2007).

In Norway, Gripsrud and Hjorthol's (2009) train survey (N=1196) found well over a third of passengers using travel time for work, with nearly a quarter of commuters having their travel time paid as work time.

Aim

The aim of this study was to assess the frequency of passenger activities during bus and train travel using structured observations of passengers in a purposive sample of bus and train routes and times in the Wellington area.

Method

Observing Passengers in Wellington: The Setting

Car ownership is high in New Zealand (2,306,921 cars in a population of under 4.2 million in 2009) (New Zealand Transport Agency 2010), but public transport also is used. In Wellington, 17 percent of residents used buses, trains, and harbour ferries to get to work in 2006, with about twice as many trips by bus as by train (Metlink). In New Zealand overall, about 5 percent of all travel time is on a bus or train (Ministry of Transport 2008). Wellington, the capital city, is set mostly on hills around a harbor.

There is only one class of carriage on any train route in New Zealand; except for the long-distance trains, those in Wellington were old and noisy. The train system was neglected and run-down in the 1990s. Replacement rolling stock is expected from 2011 (Greater Wellington Regional Council 2010). The most comfortable and well-equipped train observed was on the two-hour commuter trip between Wellington and Palmerston North, with power-points for computer connections; tables or trays; comfortable, well-padded seats; and food and drink available (the only service observed with such facilities). The buses in Wellington include older and newer vehicles. They are single-deckers and run either by overhead trolleys or diesel.

Sample

A purposive sample of bus and train routes and times was selected. Purposive sampling is a type of non-probability sampling that provides for a "strategic" sample (Bryman 2008). Bus and train routes selected were short (20-minute) or long (up to 2-hour) distances, downtown and suburban routes, encompassing wealthier and poorer areas (according to the NZ Index of Deprivation, Salmond, Crampton et al. 2007) and included routes where passengers had a clear choice of bus or train mode. Observations also were made opportunistically, e.g., while en route by bus to the Wellington railway station to begin collecting train data.

Both morning (before 9.00 AM) and evening (3.00 PM to 6.30 PM) peak commuting times (New Zealand Transport Agency 2008) were included for observations, as were several night and midday times.

Data Collection

Public transport providers were contacted to explain the research, including Go Wellington (a bus company owned by Infratil) and KiwiRail (the recently re-nationalized provider of local Tranz Metro rail services). The managers of both operations generously provided free passes for the two researchers and a covering letter of support. The two researchers worked together for safety reasons and avoided late night trips.

Developing a reliable and workable way to gather data was the most challenging aspect of this research. Some of the issues are described below and compared with methods described in other research reports.

Who and What to Observe: Passenger Types and Activity Categories

The coding scheme for structured observations is very important—exactly what and who will be observed? Interestingly, there was considerable accord between the categories of train passenger activities used in studies in Japan (using observation and a self-report survey) (Ohmori and Harata 2008), the U.S. (using observation only) (Timmermans and Van der Waerden 2008), and New Zealand (Thomas 2009) and those from two surveys (*not* observational studies) in Great Britain (Lyons, Jain et al. 2007) and Norway (Gripsrud and Hjorthol 2009). Of these, only the British study was available the schedule was designed. The activity categories were worded with subtle differences, e.g., the activity called "window gazing/people watching" in the British study (Lyons, Jain et al. 2007) is called "seeing advertisements, scenery and people" by Ohmori and Harata (2008). In addition, categories may reflect different cultural practices (the Japanese study includes "singing" as an activity) and varying national regulatory differences (for example, about smoking). Table 1 lists the activity categories used by six studies.

Gender, race and age of passengers were noted by Timmermans and Van der Waerden (2008). In the observational part of their study, Ohmori and Harata

Table 1. Activity Categories in Studies from Japan, U.S., UK, Norway, and New Zealand

Passenger Activity Categories	Ohmori & Harata (2008)	Timmermans & Vander Waerden (2008)	Lyons et al. (2007)	Gripsrud & Hjorthol (2009)	Thomas (2009)	Russell et al. (present study)
Reading for leisure/ newspaper/book/etc.	*	*	*	*	*	*
Talking to other passengers socially	*	*	*	*	*	*
Sleeping/snoozing	*	*	*	*	*	*
Listening to music/radio	*	*	*	*	*	*
Window gazing/watching people, advertisements, scenery	*		*	*		*
Working/studying			*	*		
Talking on phone	*	*	*	*	*	*
Text messaging	*	*	*	*	*	*
Nothing/staring ahead		*				*
Personal care		*				
Work computer		*			*	*
Game (various)		*	*			
Romancing		*				
Eating/drinking	*		*			*
Smoking cigarettes	*					
Singing songs	*					
Thinking	*		*	*		
Using PC/PDA, playing video game, watching video	*		*	*		
Care of children			*	*		
Knitting, needlework				*	*	
Writing					*	*
Handling wallet, equipment, etc.						*
Being bored			*			
Being anxious about the journey			*			
Planning onward or return journey			*			
Other (describe)				*		*

(2008) seem not to have noted passenger characteristics. Thomas (2009) noted gender and age group.

In deciding what to observe in the New Zealand study, we used our own and advisors' local knowledge and noted some of the items from Gray's list of high-level "features of social situations as a basis for observational data sources" (Gray 2004). Categories were developed, based on Lyons et al.'s work, but we added the category "handling wallet, equipment, etc." after a pilot study, having observed people rummaging in their bag, wallet, or purse apparently rearranging, examining, or stashing objects. As the list was plainly not exhaustive, we also added the category "Other (describe)."

In the study, only adults were observed. Gender and broad age group were noted (young = about 18 to 30-35; middle age = 35 to 60; older = over 60). In New Zealand, it is considered inappropriate to guess at people's ethnicity, which is constructed as meaningful only through self-identification (Statistics New Zealand 2005), so race or ethnicity were not included.

How to Observe: Field Work

There are many ways to conduct observations of passengers, as the literature shows. It was initially intended that two researchers sit or stand together on the public transport vehicle, then, at an agreed time and beginning with the same passenger, separately observe and record (using pen and paper) all the passengers in the vehicle. For each passenger, their general age range and their gender would be noted, as would whether or not they appeared to be a "single" or a "with" (meaning "with other people" [Goffman 1963]) and what they were doing. This is the general method described by Timmermans and Van der Waerden (2008) and similar to that used by Thomas (2009).

During the pilot period, the proposed method was found to be unworkable, even after repeated attempts. First, the buses, even when half full, were very busy with people getting on or off at stops every few minutes, and researchers' note-taking could not keep up. Second, there was a marked lack of inter-rater agreement on a range of points, but particularly about passengers' age group. An age gap of 32 years between the two observers probably contributed to this divergence. Third, in a crowded vehicle, the researchers could not see all of the passengers or had a partial view only. This was even more challenging in long train carriages (seating over 70).

Observing Passengers Over Time

Aware from the pilot that people varied their activities over time, and on suggestion from advisors, the researchers elected to observe individuals five times over a period of four minutes, noting passenger characteristics beforehand, and then, once per minute, viewing the passenger and immediately recording what the passenger was doing at that instant. Martin and Bateson (1986) call this approach "instantaneous sampling," "point sampling," or "fixed interval time point sampling"; they also advise on choosing the sample interval. The length of time for observing each passenger (four minutes) allowed us to record some of the variability in behavior and was long enough to obtain a large amount of data. However, it was not so long that many passengers were lost to observation in the frequent, busy movement of people on and off buses in particular.

Thomas (2009) appeared to observe all the passengers who boarded the vehicle (behavior sampling). Ohmori and Harata's observer recorded six to eight passengers' activities every minute (Ohmori and Harata 2008). Our study showed a researcher can comfortably observe two people at a time. More than two passengers at a time would be feasible in our view, but we think eight per minute would be demanding. The two-passengers, four-minutes, five-observations protocol was appropriate to elicit a large amount of data and gave as broad a sample as possible within the time and research resources available.

Each of the observers, taking one side of a vehicle, usually selected the passengers nearest to her, but also bore in mind a wish to observe roughly equal numbers of men and women, and sometimes individuals were purposefully selected on the basis of gender.

There were still difficulties, as, for example, when passengers boarded and stood in the aisle at peak times, completely blocking the researchers' view of passengers already under observation. One of the observers noticed that even if the observer could not see the passenger directly, bus and train windows had reflecting glass, which, especially at night, was useful in reflecting adequately what passengers were doing.

An attempt was made to address observer fatigue by taking breaks and ending a session when the researchers were tired. On the basis of this experience, a half-hour break after two hours is recommended for this kind of work, as well as doing no more than five hours of observations at a time.

During the four-minute observation period, a passenger might be recorded as carrying out only one or more than one activity at a time (multitasking), for example, reading a book while wearing headphones or texting while eating. In addition, a passenger might undertake several different activities sequentially over the observation period, for example, reading at Times 1 and 2, talking at Time 3, and texting at Times 4 and 5. Or a passenger might have alighted after two minutes. To accommodate this diversity, the data analysis refers to the numbers of passengers who were "ever observed" doing the activity. A passenger reported as "ever-texting" may have been reading at four of the times she was observed and texting only at the fifth, or eating while texting.

An effect of the "ever observed" approach may be to inflate some of the data. For example, in virtually every journey, a passenger is likely to look ahead or out the window at some point, and our method may count this activity more than its duration in reality would suggest. Results around this, therefore, could be an artefact of the method. Another category where a behavior is so integral a part of the journey that it may be distorted in the study is the handling of a wallet or purse. This is especially the case where passengers have a ticket clipped or pay cash in exchange for a paper ticket, thus handling their wallet or purse, removing money, or stowing a clipped ticket. Note, however, that many passengers in Wellington on both buses and trains show a pre-paid token and do not present cash or require change.

The differences in methods, as well as cultural and other differences in the studies from the U.S. and Japan, render the comparison of results unhelpful, but the Wellington study by Thomas is of considerable interest. Thomas did not fully explain his method, but it included, for most of his observations, one person observing all the passengers boarding a bus or one half of a train carriage, noting any subsequent seat changes and departure, gender, age, couple relations, seat location(s) and patterns, as well as activities such as verbal interaction, bag placement, and activities (reading, headphones, etc). Without greater detail than is given in his thesis, it is difficult to know exactly how this was accomplished but since he observed 1,142 bus passengers on 38 trips, an average of 30 people observed per trip; on trains, the average would be 24 people per trip. Hence, different results between Thomas's and the current study may arise from the different methods used.

Table 2 compares the observational studies reported by Timmermans and Van der Waerden (2008), Ohmori and Harata (2008), Thomas (2009), and the current study.

Table 2. Comparison of Scope of Four Observational Studies

	Timmermans & Van der Waerden (2008)	Ohmori & Harata (2008)	Thomas (2009)	Russell et al. (present study)
Area	San Francisco, U.S.	Tokyo Metropolitan Region, Japan	Wellington Region, New Zealand	Wellington Region, New Zealand
Mode	Train	Train	Train and bus	Train and bus
Vehicles and Routes	Bay Area Rapid Transport; line not specified; both directions	Odakyu Support #60, from Machida to Shinjuku on Odakyu Odawara line	Randomly selected bus service numbers; 4 train lines	5 bus routes 4 train routes
Time Period	1 day in June 2007; early morning peak, middle of the day and early evening commute	11 weekdays in November-December 2003; morning commute trips: 0630 AM to 0704 AM	8 weekdays in winter; 38 trips (bus), 23 trips (train); 0630 AM to 0600 PM	9 weekdays in November-December 2008; 24 trips (bus) 22 trips (train); early morning from 0700 AM; mid-late morning, early evening, night (to 1000 PM)
Method	Observer used layout map of carriage to record each passenger in sequence; passenger age, gender, race and activities; what station they got on and off; activities after each of the frequent stops; new passengers getting on were added and recorded	Observer recorded activities of only 6-8 passengers simultaneously every 1 minute from start to end of route	1 observer except for observations of n=31; train carriages treated as 2 for convenience; observer placed to view passengers boarding, sequentially recorded each passenger movement, gender, age, seat location, who sat next to, couple/single, defensive behaviors, vehicle percent full, weather, interpersonal distance	2 observers in each bus/carriage or separate carriages if few passengers; each took one side of the bus/carriage; selected 2 nearest visible adult passengers; recorded gender, age; activities once every minute for 4 minutes (5 times); then selected next 2 passengers; attempt to select approx. equal numbers of men and women; noted weather
People Observed	161	84	1,703 Buses: 1,142; Trains: 561	812 Buses: 353; Trains: 459

Analysis

Data were entered into Excel and analyzed in SPSS. Bus and train data were amalgamated to produce a single dataset, and the five time intervals were listed in a single column for analytical purposes. Computation of descriptive statistics using SPSS was carried out, followed by binary logistic regression analysis for the association of observed activity against the covariates (gender, approximate age group, transport mode, and peak/off-peak travel time). Odds ratios from the logistic regression are reported to examine the relationship between the covariates and each activity. A critical P-value of .05 and 95% confidence intervals were included to test for significance.

Results

Age and Gender of Passengers Observed

Table 3 shows the age-groups and genders of passengers by mode. Although no formal inter-rater reliability check was made, a lack of agreement about passengers' age was noted during informal checking: the reliability of coding in the "middle-age" and "older" groups is doubtful. From a cursory view, there seemed much better agreement about the "young" assessments (people age about 18 to 30-35) than about the middle-age group (35 to 60 years) and the older group (over 60). Accordingly, a conservative approach was taken in the statistical analysis: the middle-age and older groups were combined, providing a comparison between these and younger passengers.

Activities: How Did Passengers Spend Their Travel Time?

Table 4 shows the number and percentage of passengers observed doing different activities on buses and trains. The most striking result shown here is that nearly two-thirds of the passengers observed spent some of their travel time looking ahead or out the window (65.3%), but this was seen more on the bus (76.5% of bus passengers) than on the train, where just over half of train passengers (56.6%) were looking ahead or out at some point during the observation. About a fifth of the passengers were observed reading (21.7% overall), with more than twice the proportion seen reading on the train (28.8%) than on the bus (12.5%). A similar proportion was seen with headphones on (20.9% of train passengers and 17% of bus passengers). Slightly more people were observed talking to other passengers on the train (16.8%) than on the bus (13.6%). Texting was more commonly observed (9.2% of all passengers) than talking on a cell phone (1.5%). Activities observed more frequently on trains than on buses were reading, using a computer, sleeping/eyes closed, writing, and handling wallet, bag, etc. Writing included using a pen or pencil to work on crosswords or puzzles as well as writing in notebooks or on printed sheets.

Table 3. Age Group and Gender of Passengers Observed on Buses and Trains (N=812)

	Buses		**Trains**		**Total Passengers**	
	Count	*% of Total Sample*	*Count*	*% of Total Sample*	*Count*	*% of Total Sample*
Women						
Young	76	9.4	88	10.8	164	20.2
Middle-Age	72	8.9	126	15.5	198	24.4
Older	23	2.8	17	2.1	40	5.0
Totals	171	21.0	231	28.4	402	49.5
Men						
Young	77	9.5	61	7.5	138	17.0
Middle-Age	82	10.0	119	14.7	201	24.8
Older	23	2.8	48	5.9	71	8.7
Totals	182	22.4	228	28.1	410	50.5
Total	**353**	**43.4**	**459**	**56.6**	**812**	**100**

Table 4. Ever-Observed Activities on Bus and Train (N=812)

Activities	**Bus**		**Train**		**Total**	
	Number	*% of Total Sample*	*Number*	*% of Total Sample*	*Number*	*% of Total Sample*
Looking ahead/out window	270	76.5	260	56.6	530	65.3
Reading	44	12.5	132	28.8	176	21.7
Headphones in	60	17	96	20.9	156	19.2
Talking	48	13.6	77	16.8	125	15.4
Texting	29	8.2	46	10	75	9.2
Sleeping/eyes closed	15	4.2	57	12.4	72	8.9
Handling wallet, etc.	16	4.5	42	9.2	58	7.1
Other	15	4.2	28	6.1	43	5.3
Eating/drinking	13	3.7	25	5.4	38	4.7
Using computer	1	0.3	34	7.4	35	4.3
Writing	4	1.1	22	4.8	26	3.2
On phone	6	1.7	6	1.3	12	1.5

The observers could not always tell if two people talking together were acquainted before getting on the bus or train, although, in some cases, it was clear from behavior or overheard conversation that they were a couple, a group of friends, or strangers who started chatting en route.

The category "Other" included some rarely seen activities, for example, a group of four women, each accompanied by small children, began taking photographs of each other. Applying makeup, brushing hair, rocking a baby's push-chair, nose-blowing, looking at a watch, buying a ticket from the guard, and drumming with a stick were among "other" activities recorded.

Table 5 shows the results of the logistic regression models for each activity, with odds ratios for the explanatory variables: gender, age, transport mode, and time of day. An odds ratio compares whether the probability of an event is the same for two groups; an odds ratio of 1 means that the event is equally likely for each group.

The difficulty about age group in the data collection was described above. Here, older adults are contrasted with the "young" group—adults who appeared to be up to about 35 years of age (the reference category). The time of day compares off-peak with peak time (the reference category).

The results in Table 5 show how activities interacted with the demographic and contextual factors of gender, age, mode, and time of day. Women were significantly more likely to be talking and less likely to be using a computer than men. Older people were significantly less likely to be texting, using headphones, eating/drinking, or looking ahead/out window than younger people but significantly more likely to be reading. As noted above, more people were looking ahead/out window on buses than on trains, and the odds ratio for this showed a statistically significant difference. Train passengers were significantly more likely to be reading, using a computer, sleeping/eyes closed, writing, and handling their wallet or belongings than bus passengers. Time of day reveals fewer clear-cut differences, with passengers significantly more likely to use a computer at peak travel times and more likely to be looking ahead/out window at off-peak times of day.

Of interest is the extent of multitasking by passengers. The observations showed some passengers were doing one, two, or three other activities at the same time as traveling. As an example, Figure 1 shows data from the Time 1 observations only of the numbers of passengers ever-observed undertaking two activities: listening on headphones and one other activity. Although this count is for Time 1 only, the numbers were not markedly different from the other observation points.

Table 5. Odds Ratios (OR) and 95% Confidence Intervals from Logistic Regression for Ever-activity according to Gender, Age Group, Transport Mode, and Time of Day

Activities	OR Gender: Female	OR Age: Older	OR Mode: Bus	Time of day: Off-peak
Looking ahead/out window	1.018 (0.760;1.363)	**0.564** (0.413;0.770)	**2.490** (1.831;3.386)	**2.523** (1.617;3.938)
Reading	1.236 (0.879;1.738)	**2.732** (1.837;4.063)	**0.353** (0.242;0.513)	0.668 (0.415;1.074)
Headphones on	0.797 (0.556;1.143)	**0.332** (0.232;0.476)	0.774 (0.542;1.107)	1.521 (0.939;2.464)
Talking	**2.070** (1.391;3.080)	0.812 (0.549;1.201)	0.781 (0.528;1.154)	0.774 (0.436;1.373)
Texting	0.709 (0.563;1.479)	**0.333** (0.204;0.544)	0.804 (0.494;1.308)	1.469 (0.771;2.799)
Sleeping/eyes closed	0.853 (0.524;1.388)	1.040 (0.628;1.723)	**0.313** (0.174;0.563)	0.756 (0.392;1.456)
Handling wallet, etc.	1.596 (0.924;2.756)	0.926 (0.535;1.602)	**0.471** (0.260;0.853)	0.811 (0.386;1.702)
Other	**1.909** (1.001;3.638)	0.631 (0.340;1.172)	0.683 (0.359;1.300)	1.271 (0.559;2.889)
Eating/drinking	1.077 (0.559;2.076)	**0.464** (0.240;0.896)	0.664 (0.335;1.317)	1.260 (0.530;2.998)
Using computer	**0.205** (0.084;0.500)	1.590 (0.730;3.464)	**0.036** (0.005;0.261)	**0.238** (0.071;0.792)
Writing	1.238 (0.564;2.717)	1.658 (0.687;4.000)	**0.228** (0.078;0.667)	0.768 (0.277;2.128)
On phone	1.033 (0.329;3.239)	1.190 (0.354;3.999)	1.305 (0.417;4.083)	1.327 (0.240;7.334)

Results significant at p < .05 are indicated in bold.

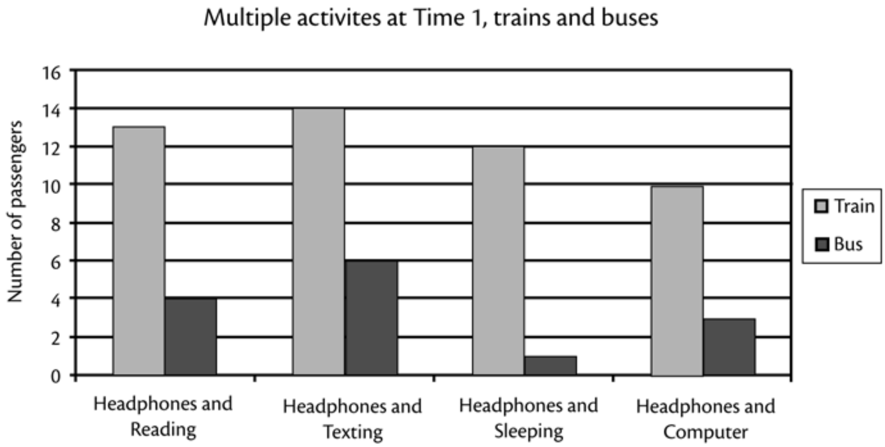


Figure 1. Number of bus and train passengers observed carrying out multiple activities at time 1 (n=812)

Other Observations

On the suggestion of passengers encountered on the long-distance Wellington-Palmerston North train, one of the researchers returned to travel part of the trip on this train on the last Friday evening before Christmas in 2008. Although many passengers appeared to undertake usual activities, others were partying around tables that, in parts of each carriage, unite four seats in pairs facing each other, sometimes with another four across the aisle. Seven or eight groups in different carriages had laid out bottles of wine and glasses, Christmas cake, and other party food; others added Christmas party hats, paraphernalia, and tinsel draped overhead and across the carriage lintel. These were groups of friends or acquaintances who regularly traveled and socialized together, usually celebrated on the Friday night train, and were making especially merry at Christmas. Evidently, considerable planning had gone into the preparations.

A further insight from the field work expands on Timmermans and Van der Waerden's (2008) reference to a travel time activity they call "romancing." During the observations, we saw couples and others traveling with a loved one and developed a conception of bus and train travel time as "relationship time" (Russell 2010), referring not only to romantic/couple relationships but also to other close relationships, those relationships that in Granovetter's terms are "strong ties" rather than "weak ties" (Granovetter 1973, 1983). Traveling with a loved one on public transport may be precious and meaningful for the relationship (Russell 2010). This extends beyond romantic relationships to traveling with one's child, parent, sibling, or close friend when there may be both physical closeness and significant emotional intimacy even in such a public place as a bus or train.

Discussion

Discussion of Results

The passenger activity data reported here arose from a purposive sample of routes and times of day, allowing a comparison between bus and train trips in the Wellington region. The study explored the association of activities performed on public transport with demographic variables (gender, age), and transport variables (mode of transport and time of day.)

Observational studies in Japan (Ohmori and Harata 2008) and the U.S. (Timmermans and Van der Waerden 2008), a large British survey (Lyons, Jain et al. 2007), and a Norwegian survey (Gripsrud and Hjorthol 2009) were all studies of train passengers only. Thomas's (2009) Wellington study, like ours, included both bus and train passengers. The considerable differences in data collection and analysis preclude direct comparisons with our findings, but contrasting some of the results enables us to better understand the challenges of the method and contributes to future work.

Some findings are in accord with other studies and are not startling, in particular, that many people appeared to be "doing nothing," "thinking," "window gazing/people watching," or, in our terminology, "looking ahead/out the window." Our results for activities differ from Thomas's for basically the same population; for example, he found about a quarter of Wellington passengers engaged in "verbal behavior," reducing to 15 percent if couples were excluded, whereas we observed 15 percent altogether talking. Thomas observed a quarter of his sample engaged in "activities," whereas we found a quarter on buses but nearly a half on trains doing something other than looking ahead/out the window. Our observations of reading (22%) and listening on headphones (19%) were much higher than Thomas's, at 11 percent and 9 percent, respectively. It is unclear whether these differences relate to different times of year (we collected data in summer, Thomas in winter), different times of day, or, more likely, methodological differences.

The study found people on the bus were much more likely than train passengers to be looking ahead/out the window. Some of the differences between bus and train passenger activities may be owing to the frequency of the service, the nature of the vehicle, or the length of the trip, as suggested by Lyons et al. (2007) above. On a short journey, one may not bother to get out a book or newspaper. Wellington trains run less frequently than many buses. Eating and drinking is formally prohibited on buses and some trains. In Wellington, many of the bus routes are through winding, hilly roads, possibly discouraging passengers who are even slightly subject to motion sickness from reading or writing. Activities also are constrained by whether or not one has a seat; it is difficult to read a newspaper while standing on a moving bus. The train offers a smoother ride, and more people were reading on the trains. The two-hour commuter train provided power-points and tables/trays, facilitating computer use and writing.

Another possible explanation comes from the notions put forward by Jain and her colleagues of the "equipped" passenger (Lyons and Urry 2005; Jain and Lyons 2008) and by Watts and her colleagues of the "packed" traveler, who comes prepared for the journey and unpacks in the vehicle, whose "bags and belongings" (Watts 2008) contain objects (book, pen, phone, food) that enable the journey to be spent in some way other than "doing nothing." Gripsrud and Hjorthol trace a link between passengers' enjoyment of travel and their "degree of preparedness, as measured by the number of items" they bring (Gripsrud and Hjorthol 2009).

A possible reason for smaller numbers of older passengers being observed is that the data collection mostly concentrated on peak-hour travel. Older people would be less likely to travel at this time if they are retired or in part-time employment, and the SuperGold Card, allowing free travel to New Zealanders 65 years and over, may be used only outside peak hours.

Differences in ticket purchasing on buses and trains may explain the difference in the extent of "handling wallet, etc." On buses, the ticket is shown or bought on entry, but on the Wellington trains, passengers' tickets are checked or sold by the train manager/conductor while the train is in motion, so some of the rummaging we observed may relate to this.

Discussion of Structured Observation as a Method

Using structured observation as a method for travel time use research was challenging. The vehicles have their set course and time frames, passengers are intent on their own lives and needs, and observers must work around these. The U.S. study seemed to gloss over some of the difficulties of data collection, stating that "because the data collection involves field observations, some mistakes will be made" (Timmermans and Van der Waerden 2008). Our experience on the Wellington buses and trains suggests that the field observation method described by these authors would be almost impossible to carry out, particularly at peak time. Ohmori and Harata (2008) note more realistically that "it would be difficult to conduct the on-board observation in highly congested normal trains where seats are full and many passengers are standing" (Ohmori and Harata 2008). Reviewing the methods sections of some observational studies, and knowing the practical challenges of working in crowded vehicles, we were sometimes puzzled as to how exactly data were collected in the time available.

As ethnographers of travel time have already shown (Nash 1975; Delannay 2001; Fink 2006; Watts 2008), actually getting out and about on public transport with a researcher's eye can yield rich information about how people behave and spend their time on the bus or train. We developed the new category "Handling wallet, etc." because we saw how frequently passengers were doing this. This shows the value of observation, as a passenger who is asked an open question about travel time use may be unlikely to spontaneously mention this activity, and even if it is suggested as a category, it may not register as meaningful. This activity, perhaps, relates to Watts' (2008) "packed" traveler in the very act of unpacking or repacking.

Strengths, Limitations, and Further Research

This study adds to existing knowledge about travel time use. The strengths of the study are its size, the comparison of bus and train passengers, the attention to method and frankness about methodological challenges, and the inclusion of a pilot phase. A limitation of the study is that each passenger was observed by only one researcher. Another is that waiting time activities were not observed. Waiting is a significant and often overlooked component of travel time.

An underlying limitation of the study is the nature of the method itself. Recording observable behavior cannot reveal people's intentions, attitudes, or feelings. Hence, the main question arising from the research concerns the meaning and value of activities. What are the 65 percent of passengers observed looking ahead or out the window really doing? From the outside, it appears that these people are "doing nothing," not reading, writing, or listening on headphones, not talking or eating, just sitting or standing there. Are they really "doing nothing," and, if so, how do they feel about that time? Are they bored, anxious, or content? Or are they "doing something"—thinking, planning, remembering, praying, daydreaming—and, if so, what does that mean for them in their everyday life? Is Thomas (2009) correct in identifying reading, wearing headphones, etc., as essentially "defensive" activities? How do passengers themselves understand travel time and how it affects their well-being? These questions can be answered only by asking passengers themselves. Future research will use qualitative methods to answer some of these questions, and further quantitative (survey) research will assess any differences between self-reported travel time use and the observational data reported here.

Conclusion

Adult passengers on buses and trains in the Wellington region, New Zealand, were engaged in a range of activities. While most spent some or all of their time simply "looking ahead/out the window," many were reading, sleeping/eyes closed, talking, using a computer, or listening on headphones, among other activities. In some cases, passengers appeared to be doing several things at once. There were differences between activities on buses and trains, with more people observed simply "looking ahead/out the window" on buses than on trains. This may relate to the length of trips or to the hilly and winding terrain covered by buses in Wellington, compared to trains, or the extent to which passengers come prepared for the journey.

Structured observation is a challenging but rewarding method for researching passengers' use of travel time. Greater frankness about methods and more detail about data collection protocols would be a welcome contribution in the literature.

The prevailing assumption in transport planning and transport economics that travel time is a "disutility to be minimised" (Mokhtarian 2005) is open to challenge. Passengers are not always "doing nothing" while traveling, and even if they are, this inactivity may have value for them. Similarly, the activities many engage in while traveling also may have value to them as individuals and in terms of wider economic and social wellbeing. Further research is needed to explore and explain the meaning and value of public transport travel time use and to develop ways in which transport planners and economists can address these realities.

Acknowledgments

Thanks to Juliet Jain and Patricia L. Mokhtarian for their comments and encouragement. Thanks also to two anonymous reviewers who made very useful comments on an earlier version of the article.

Funding Sources

Ms. Russell's research was supported by a scholarship from SPEaR Social Policy Evaluation and Research, New Zealand Ministry of Social Development. Ms. Price was sponsored by the Maurice and Phyllis Paykel Trust. Mr. Gerring's work was supported by the Wellington City Council. The funders had no involvement in the research.

References

Angrosino, M. V. 2005. Recontextualizing observation: Ethnography, pedagogy, and the prospects for a progressive political agenda. In Denzin, N. K., and Y. S. Lincoln, *The SAGE Handbook of Qualitative Research*. Thousand Oaks: SAGE Publications.

Bryman, A. 2008. *Social Research Methods*. Oxford: Oxford University Press.

Clifton, K. J., and S. L. Handy. 2001. Qualitative methods in travel behaviour research. *International Conference on Transport Survey Quality and Innovation*. Kruger National Park, South Africa.

Delannay, M. C. 2001. Maintaining anonymity: the social organization of riding the bus (unpublished thesis).

Fink, C. N. Y. 2006. Self in everyday transit life: Ethnographic study of Los Angeles bus culture. *TRB 85th Annual Meeting Compendium of Paper*, Washington D.C.

Goffman, E. 1963. *Behavior in Public Places: Notes on the Social Organization of Gatherings*. New York: Free Press.

Granovetter, M. 1983. The strength of weak ties: a network theory revisited. *Sociological Theory 1*: 201-233.

Granovetter, M. S. 1973. The strength of weak ties. *American Journal of Sociology*. 1360-1380.

Gray, D. E. 2004. *Doing Research in the Real World*. London: SAGE Publications.

Greater Wellington Regional Council. 2010. First new train en route to Wellington. Press Release. Wellington.

Gripsrud, M., and R. Hjorthol. 2009. Working on the train: from "dead time" to contractual time. Network- ICT: Mobilizing Persons, Places and Spaces. Fourth Specialist Meeting of the Network. Quebec Institute of Transport Economics.

Hensher, D. A. 2001a. Measurement of the valuation of travel time savings. *Journal of Transport Economics and Policy* 35(1): 71-98.

Hensher, D. A., Ed. 2001b. *Travel Behaviour Research: The Leading Edge*. Amsterdam: Pergamon.

Hollenbeck, A. R. 1978. Problems of reliability in observational research. In Sackett, G. P. *Observing Behavior: V 2, Data Collection and Analysis Methods*. Baltimore: University Park Press.

Jain, J. 2009. The making of mundane bus journeys. In Vannini, P. *The Cultures of Alternative Mobilities: Routes Less Travelled*. Farnham: Ashgate.

Jain, J., and G. Lyons. 2008. The gift of travel time. *Journal of Transport Geography* 16(2): 81-89.

Lyons, G., and K. Chatterjee. 2008. A human perspective on the daily commute: costs, benefits and trade-offs. *Transport Reviews* 28(2): 181 - 198.

Lyons, G., J. Jain et al. 2007. The use of travel time by rail passengers in Great Britain. *Transportation Research* Part A 41: 107-120.

Lyons, G., and J. Urry. 2005. Travel time use in the information age. *Transportation Research Part A* 39(2-3): 257-276.

Mackie, P. J., S. Jara-Díaz et al. 2001. The value of travel time savings in evaluation. *Transportation Research Part E: Logistics and Transportation Review* 37(2-3): 91-106.

Martin, P., and P. Bateson 1986. *Measuring Behaviour: An Introductory Guide*. Cambridge: Cambridge University Press.

Martin, P., and P. Bateson. 2007. *Measuring Behaviour: An Introductory Guide*. Cambridge: Cambridge University Press.

Metlink. Public transport statistics. Retrieved 9 March, 2009, from http://www.metlink.org.nz/story21978.php?

Metz, D. 2008. The myth of travel time saving. *Transport Reviews* 28(3): 321 - 336.

Ministry of Transport. 2008. Comparing travel modes In *Household Travel Survey v1.4 revised Jan 2008*. Wellington: Ministry of Transport.

Mokhtarian, P. L. 2005. Travel as a desired end, not just a means. *Transportation Research Part A*: Policy and Practice 39(2-3): 93-96.

Nash, J. 1975. Bus riding: Community on wheels. *Journal of Contemporary Ethnography* 4(1): 99-124.

New Zealand Transport Agency. 2008. General Circular – Policy No. 08/09 on public transport concession scheme for SuperGold Card holders.

New Zealand Transport Agency. 2010. New Zealand motor vehicle registration statistics 2009.

Ohmori, N., and N. Harata. 2008. How different are activities while commuting by train? A case in Tokyo. *Tijdschrift voor economische en sociale geografie; Royal Dutch Geographical Society* 99(5): 547-561.

Patton, M. 2002. *Qualitative Research & Evaluation Methods*. Thousand Oaks: SAGE.

Robson, C. 1993. *Real World Research: A Resource for Social Scientists and Practitioner-Researchers*. Oxford: Blackwell.

Russell, M. 2010. Convivial public transport: Six theories about travel time and social wellbeing. In Howden-Chapman, P., K. Stuart, and R. Chapman. *Sizing Up the City: Urban Form and Transport in New Zealand*. Wellington: Steele Roberts for Centre for Sustainable Cities.

Sackett, G. P. 1978. Measurement in observational research. *Observing Behavior: V 2, Data Collection and Analysis Methods*. Baltimore: University Park Press.

Sackett, G. P., G. C. Ruppenthal et al. 1978. Introduction: An overview of methodological and statistical problems in observational research. *Observing Behavior: V 2, Data Collection and Analysis Methods*. Baltimore: University Park Press.

Salmond, C., P. Crampton et al. 2007. NZDep2006 Index of Deprivation. Wellington: Department of Public Health, University of Otago.

Statistics New Zealand. 2005. Understanding and working with ethnicity data: A technical paper.

Thomas, J. 2009. The social environment of public transport. Department of Psychology, Wellington, Victoria University of Wellington.

Timmermans, H., and P. Van der Waerden. 2008. Synchronicity of activity engagement and travel in time and space: descriptors and correlates of field observations. *Transportation Research Record* 2054: 1-9

Wardman, M. 1998. The value of travel time: A review of British evidence. *Journal of Transport Economics and Policy* 32(3): 285-316.

Wardman, M. 2001. *Public transport values of time*. Leeds, Institute of Transport Studies, University of Leeds.

Watts, L. 2008. The art and craft of train travel. *Journal of Social and Cultural Geography* 9(6): 711-726.

Watts, L., and J. Urry. 2008. Moving methods, travelling times. *Environment and Planning D: Society and Space* 26: 860-874.

About the Authors

Marie Russell (*marie.russell@otago.ac.nz*) is a Ph.D. candidate in the Health Promotion and Policy Research Unit in the Department of Public Health at the University of Otago, Wellington, New Zealand.

Rachel Price (*rachel.price@otago.ac.nz*) is a medical student at the University of Otago, Wellington, New Zealand. She participated in the observations project as a University of Otago Summer Student.

Zachery Gerring (*zachery.gerring@vuw.ac.nz*) is a Research Assistant at the Health Services Research Centre, Victoria University of Wellington, New Zealand.

Dr. Louise Signal (*louise.signal@otago.ac.nz*) is an Associate Professor and co-director of the Health Promotion and Policy Research Unit in the Department of Public Health, University of Otago, Wellington, New Zealand.

Dr. Jacqueline Cumming (*jacqueline.cumming@vuw.ac.nz*) is an Associate Professor and Director of the Health Services Research Centre, Victoria University of Wellington, New Zealand.

Dr. James Stanley (*james.stanley@otago.ac.nz*) is a Research Fellow and biostatistician in the Department of Public Health, University of Otago, Wellington, New Zealand.

The Effect of City Bus Maneuvers on Wheelchair Movement

Michael J. Turkovich, Linda van Roosmalen,
Douglas A. Hobson, and Erik A. Porach
University of Pittsburgh

Abstract

A state-of-the-art four-point tiedown system, a prototype automatic docking system, and a prototype rear-facing wheelchair passenger station (RF-WPS) were installed in a large accessible transit vehicle (LATV). A manual wheelchair, powered wheelchair, and a three-wheeled scooter were used to test the securement performance of each wheelchair securement system during LATV normal driving, hard braking, and rapid turning maneuvers. All test wheelchairs were loaded with an ISO 7176 Part 11 compliant loader gage representing the weight of an average male wheelchair occupant. A tri-axial accelerometer measured vehicle acceleration during driving maneuvers, and a low-tech movement tracking system measured wheelchair movement during driving maneuvers. Results show that each wheelchair securement system limited wheelchair displacement to less than the 51-mm Americans with Disabilities Act (ADA) displacement limitation, and none of the securement systems showed visible signs of failure. Accelerations during LATV normal driving, hard braking, and rapid turning did not exceed 0.76 g.

Introduction

Regulations and Standards

With the passage of the 1990 Americans with Disabilities Act (ADA), public transportation is required to be available and accessible to people with disabilities. The

U. S. Department of Transportation (DOT) 49 CFR Part 38 requires public buses or large accessible transit vehicles (LATVs) to be outfitted with a wheelchair station consisting of a wheelchair securement and an occupant restraint system (U.S. Department of Transportation 2007). This regulation requires that the wheelchair securement system limit the movement of a wheelchair to a maximum of 51 mm (2 in.) during normal vehicle operating conditions. Although the ADA does not require wheelchairs to be secured, vehicle operators are to be trained to use the safety equipment on board public transit vehicles, and transit providers may have written policies in place requiring wheelchairs to be secured in the best possible way with the available equipment (U.S. Department of Transportation 2007).

Despite the advancement in legislation regarding accessible public transportation and the development of standards and compliant wheelchair transportation safety technology, vehicle operators and wheelchair users of public transportation systems have been reporting difficulties (Buning et al. 2007; Frost and Bertocci 2009). Lack of use of wheelchair securement systems has been attributed to the fact that many wheelchairs are difficult to secure. Buning et al. (2007) surveyed public transit wheelchair users and reported that over 50 percent had difficulty securing their wheelchairs. Lack of securement use also can be attributed to a lack of bus driver training in the proper use of wheelchair securement systems and a lack of compatible wheelchair securement hardware and wheelchair securement systems (Foreman et al. 2001). Currently, the most common type of wheelchair securement system installed in public buses is the four-point, strap-type tiedown system (Wolf and van Roosmalen 2007) due to the system's ability to accommodate a wide range of wheelchair types and sizes. A shortcoming of this securement system often cited by wheelchair users is that they have to rely on someone else to secure their wheelchair, thus not allowing independent use of the system. In addition, the bus driver has to secure the tiedown straps in hard-to-reach places on the wheelchair due to non-WC-19-compliant wheelchairs, which often impose on the user's personal space, further increasing the likelihood that wheelchair users will refuse the use of securement systems (Buning et al. 2007).

Voluntary standards that include design and performance requirements of wheelchair tiedowns and occupant restraint systems (WTORS) have been developed to improve the safety and ease of use of wheelchair transportation safety technology (ANSI/RESNA 2001; International Standards Organization 2001). Standards also are being developed for WTORS that will be used only in LATVs, such as the draft international standard (ISO-10865-1) on rear-facing wheelchair passenger systems

(RF-WPSs) for use in low-g environments (International Standards Organization 2010). The purpose of ISO-10865-1 (which at the time of this writing is a Draft In Standard [DIS]) is to establish design and performance requirements for RF-WPS in a low-g environment (<1 *g*) such as in LATVs. The standard specifies dimensional, design, performance, and installation requirements for an RF-WPS and its components. In addition, guidelines are provided for use by vehicle and/or WTORS manufacturers seeking to design RF-WPS components (International Standards Organization 2010). This standard is intended to promote the development and implementation of alternative wheelchair transportation safety systems that can be used independently by wheelchair-seated passengers of LATVs.

Development of Alternative Wheelchair Securement

Earlier attempts have been made to increase the usability and independent use of wheelchair securement systems. Several alternative securement devices have been developed, including an automated docking system created by Oregon State in the 1990s and, more recently, an auto-docking system with a Universal Docking Interface Geometry (UDIG) developed and tested by the University of Pittsburgh (UPITT) and Sure-Lok. The UPITT/Sure-Lok system can be used independently by a wheelchair user and incorporates an anti-rotation lock to ensure that once the wheelchair is secured, the docking system will not rotate during rapid turning (Hobson and van Roosmalen 2007). This system was tested successfully according to SAE J2249 test methods with a surrogate wheelchair and a 48 kph/20 *g* crash pulse (Society of Automotive Engineers 1999). User testing of the auto docking system resulted in positive responses from wheelchair users and bus drivers on its ease of use (Hobson and van Roosmalen 2007).

RF-WPSs also have been developed for independent use by wheelchair-seated occupants using LATVs in Europe, Canada, and the U.S. (Rutenberg et al. 2005). RF-WPSs use a forward excursion barrier (FEB) that prevents the wheelchair and occupant from moving forward in the event of a sudden stop. Although some of these rear-facing systems include optional restraint systems that attach to or around the wheelchair, it remains unclear what level of containment is needed to protect the wheelchair and occupant from moving and/or tipping over during rapid vehicle turns and accelerations.

LATV Accelerations

Several studies have analyzed the accelerations that are experienced on board LATVs during various driving maneuvers. Hunter-Zaworski et al. (1992) measured in-vehicle accelerations during normal driving operations of LATVs. Their results indicate that during normal driving conditions, maximum accelerations reach 0.40 *g* and 0.10 *g* for forward acceleration and turning, respectively (Zaworski et al. 2007). Rutenberg (1995) reported that accelerations did not exceed 0.24 *g* in any direction (Rutenberg 1995). Fournier (1997) measured accelerations on LATVs as well and concluded that accelerations can be as high as 1.53 *g*, but it was suggested that the high values seen were likely due to vibrations of the vehicle (Fournier 1997). Finally, Zaworski et al. (2007) recorded normal driving and extreme driving accelerations of LATVs and found that during normal driving conditions, accelerations averaged 0.20 *g* and rarely exceeded 0.40 *g*. During extreme maneuvers, vehicle accelerations averaged 0.40 *g* and sometimes reached as high as 0.80 *g* during hard stops (Zaworski et al. 2007).

The combination of large vehicle size and relatively low travel speeds leads to a low likelihood of LATVs being involved in a collision of significant magnitude (Shaw and Gillispie 2003; Shaw 2008). Blower et al. (2005) examined accident reports from LATVs in Florida over a two-year period. They estimated that LATVs are involved in a collision of greater than 5 *g* every 27 million vehicle-miles traveled and in a 10 *g* collision every 455 million vehicle miles traveled. The likelihood of an LATV being involved in a crash event of 5 and 10 *g* is 16 and 250 times less, respectively, than for private vehicles (Blower et al. 2005). Given this low likelihood of a severe crash, the low *g* environment of LATVs, and the large size of LATVs, alternative wheelchair containment methods may offer a reasonable level of occupant safety to wheelchair users traveling in LATVs while allowing for greater freedom in the design of these systems and for designs that promote independent use by wheelchair-seated passengers.

A 20g/48kph (20g/30mph) frontal impact test with a surrogate wheelchair and Hybrid III Anthropomorphic Test Device is commonly used to evaluate wheelchair securement system safety. Alternative test methods that evaluate wheelchair securement system safety and assess wheelchair movement under lower accelerations commonly seen in LATVs are needed to improve wheelchair-seated passenger safety during normal driving conditions.

Objectives

The primary goal of this study was to determine if a prototype auto-docking system and a prototype RF-WPS are compliant with ADA maximum displacement requirements of 51 mm (2-in.) when exposed to accelerations associated with LATV normal driving, hard braking, and rapid turning. Secondary goals were to evaluate wheelchair securement performance by comparing the wheelchair displacement allowed by the two prototype systems with the displacement allowed by a standard four-point tiedown securement and no wheelchair securement. A final goal was to document the magnitude of LATV accelerations during normal driving, hard braking, and rapid turning conditions.

A follow-up project to this study includes having wheelchair users and LATV operators use and evaluate each wheelchair securement system on an LATV over a predetermined route and give feedback as to their likes and dislikes of each system. Findings of these wheelchair user and bus operator perceptions on wheelchair securement usage are being published separately.

Methods

Three types of wheelchair securement systems were installed in a high-floor LATV. Each wheelchair securement system was tested with a manual wheelchair, a powered wheelchair, and a scooter that were slightly modified to accommodate the securement systems tested (modifications of the test wheelchairs are described later on in the Methods section). The wheelchair securement systems were evaluated under three driving conditions: normal driving, hard braking, and rapid turning. The wheelchairs also were tested under each driving condition without any form of wheelchair securement. Wheelchair displacement and LATV accelerations were recorded during all testing conditions.

Wheelchair Securement Setup

1. Four-Point Tiedown System

The four-point tiedown system that was installed in the LATV consists of four straps with self-tensioning retractors (QRT Deluxe Retractor System, Q'Straint, Ft. Lauderdale). The straps have securement hook end fittings that each attach to four securement points on the wheelchair. The retractors contain a manual tension mechanism that allows a person to tighten the straps to minimize wheelchair movement. Two straps are secured to the rear and two to the front of the wheelchair (Figure 1).

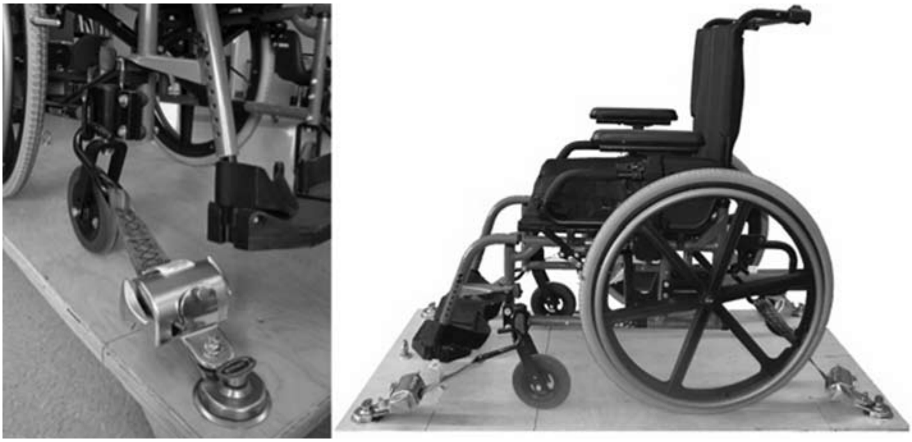


Figure 1. Retractor-type four-point tiedown system (left); side view of manual wheelchair secured by four-point tiedown system (right)

2. Auto Docking System

The prototype forward-facing auto docking system that was installed in the LATV was developed by the University of Pittsburgh and Sure-Lok (Sure-Lok, Bethlehem, PA). It consists of a pneumatically-powered docking mechanism that engages with an UDIG adaptor on the rear frame of each wheelchair (Figure 2). When a wheelchair user backs into the auto-docking system, the UDIG provides a means for securing the wheelchair to the docking securement device (Figure 3).

Figure 2. UDIGs attached to manual wheelchair (left), powered wheelchair (middle), and scooter (right)

Figure 3. Auto docking system installed in LATV (left); scooter equipped with UDIG adaptor, backed into and secured by auto docking system

3. RF-WPS System

A prototype RF-WPS developed by the University of Pittsburgh and Q'Straint was installed in the LATV (Figure 4). This system consists of a vehicle-anchored FEB and two pneumatically activated lateral barriers. On the aisle side, the lateral barrier consists of a padded arm that rotates from a vertical (downward) stored position to an in-use (45-degree) position, while on the wall side the lateral barrier consists of a padded movable block. The pneumatic lateral barriers move laterally to accommodate different wheelchair positions and widths. These lateral barriers squeeze the sides of a wheelchair to provide containment and to prevent lateral and rearward movement of the wheelchairs during low *g* non-crash accelerations of an LATV. The RF-WPS system does not require wheelchair-mounted hardware (e.g., UDIG adaptor), and the system does not include an occupant restraint system.

Figure 4. Rear-facing wheelchair passenger station (RF-WPS)

Test Wheelchair Setup

Three commonly-used wheeled mobility devices were selected for the purpose of examining the effectiveness of the three wheelchair securement systems. Each test wheelchair was equipped with four tiedown securement points (to work with the four-point tiedown system), a UDIG adaptor (to work with the auto docking system), and a wheelchair-anchored pelvic belt (to restrain the loader gages in each wheelchair). Pelvic belt prototypes were provided by BodyPoint (BodyPoint, Seattle) and Q'Straint. Each wheelchair was loaded with an ISO 7176-11 (International Standards Organization 1992), 76 kg (168 lbs) loader gage, representing a 50th percentile male occupant.

The three test wheelchairs included in the study were a manual wheelchair, a powered wheelchair, and a three-wheeled scooter. An ISO 7176-19 compliant Quickie II manual wheelchair (Sunrise Medical, Longmont, CO) had WC19 compliant securement points and was modified to include a prototype UDIG adaptor and a wheelchair-anchored pelvic restraint (Figure 5a). A WC19 compliant Invacare TDX-SP powered wheelchair (Invacare, Cleveland) was modified with a prototype UDIG adaptor wheelchair (Figure 5b). An Amigo-RD scooter (Amigo Mobility International, Bridgeport, MI) was modified with four tiedown securement points, a prototype UDIG adaptor, and a UDIG-mounted pelvic restraint (Figure 5c). The securement points on the scooter were designed and placed to allow for easy and effective securement by the bus operator with the four-point tiedown system. Although the securement point geometry on the scooter complied with WC19 dimensional requirements, the securement point locations on the scooter were not in compliance with the fore-aft and side-side WC19 requirements due to restrictions of suitable scooter frame mounting positions (ANSI/RESNA 2001).

Figure 5. (a) Modified Quickie II manual wheelchair, (b) Invacare TDX-SP powered wheelchair, (c) Amigo-RD Scooter with ISO 7176-11 Test Dummy

In-Vehicle Test Setup

The Pittsburgh Port Authority (PAT) provided a 12.2 m (40 ft) transit bus (ORION Bus Industries Inc., Oriskany, NY) and a licensed PAT bus driver for testing purposes. The test vehicle was a high-floor vehicle without internal wheel wells. The test vehicle had a front mounted platform lift, and some seats were removed from the vehicle to allow for installation of the three wheelchair securement systems to be evaluated. The four-point tiedown system was placed in the row behind the driver seat and installed according to Q'Straint WTORS installation instructions. The prototype automated docking system and prototype RF-WPS were placed opposite each other on the right side of the vehicle. Figure 6 shows a diagram of the securement system setup in the LATV.

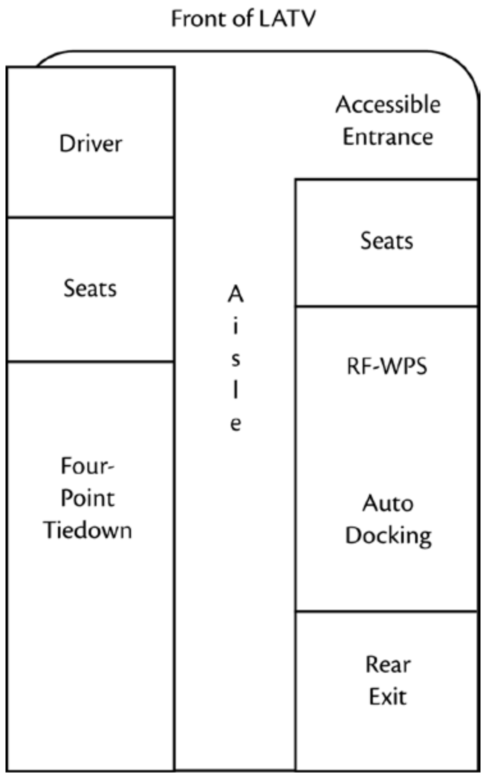


Figure 6. Layout of securement systems in LATV

Driving Conditions

Each securement system was tested under three driving conditions: normal driving, hard braking, and rapid turning. An urban course approximately 15 minutes in duration was mapped out for use during normal driving conditions. The course consisted of multiple left and right turns, starts, stops, and steep inclines and declines with a maximum grade of 17 percent. Hard braking trials are defined by LATV braking at a starting speed of about 32 km/h (20 mph) to an end speed of 0 km/h (0 mph) in approximately 3 seconds. Rapid turning trials are defined by a 90 degree left or right turn at a starting speed of about 32 km/h (20 mph) along a marked 15 meter (50 ft.) radius (Mercer and Billing 1990; Hobson and van Roosmalen 2007). LATV speeds and actual paths were not documented during the test trials.

Test Protocol

The three test wheelchairs were evaluated in three securement stations during three driving trials (normal driving, hard braking/ rapid turning, no securement):

- Three trials were conducted for the normal driving condition. Each wheelchair was tested on this course in each securement system to understand securement system performance for each wheelchair type during normal driving conditions.
- Eighteen trials of hard braking and rapid turning testing were conducted. Each wheelchair was tested three times in each station for both hard braking and rapid turning. A hard braking test was performed during the initial positioning of the wheelchairs to make sure the setup was appropriate. Thus, there were some cases where the systems were tested three times and others four.
- Wheelchairs also were tested when unsecured during normal driving, hard braking and rapid turning. Wheelchairs were unsecured with the hand brakes on (manual wheelchair) and power off (powered wheelchair and scooter). The wheelchairs and loader gages were loosely tethered to the vehicle walls by ropes to prevent excessive movement of and damage to the wheelchairs and loader gages.

Data were collected for a total of 28 trials. Throughout the testing, maximum vehicle accelerations and maximum wheelchair displacement were recorded for each wheelchair. A stationary video camera was used to observe general wheelchair motion.

Data Collection and Analysis

To capture wheelchair displacement, a low-cost, previously-validated test method was used (Hobson and van Roosmalen 2007). A target designed to contain a 51 mm (2 in.) radius circle, representative of the ADA displacement requirement, was fixed to the vehicle floor. The ADA does not specify how or where the displacement of a wheelchair should be measured from, so for the purposes of this study a spring-loaded pen was attached to the front of the wheelchair frame at the centerline of each wheelchair and 780 mm (30.7 in.), 830 mm (32.7 in.), and 1110 mm (43.7 in.)

forward of the vertical securement bars of the UDIG, for the manual wheelchair, powered wheelchair, and scooter respectively. Prior to the start of each trial, the pen was positioned at the center of the 51 mm (2 in.) radius target so that any movement from the original position would scribe a line that could be measured post-test (Figure 7). The displacement magnitude (mm) was measured from each of the marked targets located beneath each wheelchair. The furthest deviation from the target center was recorded as the maximum displacement. Displacement was measured to the nearest mm. If wheelchair displacement exceeded the width/length of the chart–108 mm (4 in.) in the lateral direction and 140 mm (5.5 in.) in the forward/rearward direction–it was labeled as "off the chart," or if the wheelchair tipped over, it was labeled as "tipped over."

Analysis of Variance (ANOVA) was used to determine statistical differences in displacement values of the test wheelchairs and scooter during various driving conditions when secured by each wheelchair securement system. An alpha level of 0.05 was used to determine significance. Additionally, maximum values of forward and lateral test wheelchair movement were measured and tabulated for the various driving conditions for each test wheelchair and each wheelchair securement scenario. Acceleration time histories were recorded for each test trial, and maximum LATV accelerations and average LATV accelerations were tabulated for normal driving, hard braking, and rapid turning conditions.

Figure 7. Spring-loaded pens and targets used for recording displacements of wheelchairs

A 2.5 *g* tri-axial accelerometer (GP1 Sensr, Elkader, IA) was fixed to the floor of the bus and positioned so that the axes (x, y, z) of the accelerometer were aligned with the longitudinal axis of the vehicle, the lateral horizontal axis of the vehicle, and the vertical, respectively. The accelerometer was positioned on the left side (driver side) of the bus, directly behind and in line with the center of the four-point tiedown station. Acceleration data were recorded for all trials at a frequency of 100 Hz.

Accelerometer data were processed similar to that of Zaworski et al. (2007). The accelerometer data first were averaged to 20 Hz, and voltage offsets were adjusted, and the raw voltage signal was converted to units of *g* in accordance with SAE J2181 (Society of Automotive Engineers, 1993). Maximum vehicle accelerations were obtained for normal driving, hard braking, and rapid turning maneuvers, and all accelerations were reported in units of "g." Then x, y and resultant accelerations were computed and reported for hard braking, rapid-turning, and normal driving conditions, respectively.

Results

Wheelchair Displacement during Normal Driving

Table 2 shows the maximum wheelchair displacement values recorded for each securement system during normal driving conditions. During the normal driving trials, no extraordinary events such as "jumping curbs" took place, and the route did not include steep uphill and downhill slopes of more than 17 percent. The maximum displacement recorded during normal driving was 18 mm (0.7 in.). This displacement was recorded on the target beneath the scooter when it was secured by the four-point tiedown system. The average maximum displacement experienced by the three wheelchairs was 12 mm (± 4 mm) (0.47 in. ± 0.16 in.). Displacements measured during normal driving trials were not synchronized with LATV accelerations at which maximum wheelchair displacements occurred.

Table 2. Maximum Wheelchair Displacement For All Normal Driving Trials

Wheelchair Type	RF-WPS (mm)	Four-Point Tiedown (mm)	Auto Docking (mm)
Manual	13	13	14
Powered	11	6	11
Scooter	13	18	6
Average (SD)	11.67 (1.15)	12.33 (6)	10.33 (4)

Wheelchair Displacement during Hard Braking

Table 3 shows the wheelchair displacements and accelerations for the three securement systems during hard braking. The maximum displacement during hard braking was 44 mm (1.7 in.). This displacement value was recorded on the target beneath the scooter during hard braking when secured by the four-point tiedown system.

Table 3. Maximum Wheelchair Displacement And Associated Vehicle Acceleration During Hard Braking

	RF-WPS		Four-Point Tiedown		Auto Docking	
	(mm)	*(g)*	*(mm)*	*(g)*	*(mm)*	*(g)*
Manual Wheelchair						
Trial 1	0	0.62	0	0.60	0	0.62
Trial 2	6	0.72	0	0.66	0	0.69
Trial 3	0	0.68	0	0.56	0	0.56
Trial 4	0	0.68	n/a	n/a	n/a	n/a
Powered Wheelchair						
Trial 1	19	0.60	13	0.62	0	0.62
Trial 2	13	0.66	13	0.69	0	0.72
Trial 3	13	0.56	13	0.56	0	0.68
Trial 4	n/a	n/a	n/a	n/a	0	0.68
Scooter						
Trial 1	13	0.62	44	0.62	0	0.60
Trial 2	13	0.69	24	0.72	0	0.66
Trial 3	6	0.56	24	0.68	0	0.56
Trial 4	n/a	n/a	24	0.68	n/a	n/a
Average (SD)	8.3(6.8)	0.64(0.1)	12(10)	0.64(0.1)	0(0)	0.64(0.1)

Wheelchair Displacement during Turning

Table 4 shows the wheelchair displacements and accelerations for the three securement systems during turning trials. The powered wheelchair secured by the four-point tiedown system showed the largest displacement of 41 mm (1.6 in.). The four-point tiedown system also allowed 37 mm (1.5 in.) of displacement of the manual wheelchair.

Table 4. Maximum Wheelchair Displacement And Associated Vehicle Acceleration During Rapid Right Turning

	RF-WPS		Four-Point Tiedown		Auto Docking	
	(mm)	*(g)*	*(mm)*	*(g)*	*(mm)*	*(g)*
Manual Wheelchair						
Trial 1	13	0.46	37	0.47	13	0.38
Trial 2	13	0.51	25	0.46	18	0.52
Trial 3	13	0.56	19	0.45	13	0.45
Powered Wheelchair						
Trial 1	13	0.47	13	0.38	13	0.46
Trial 2	13	0.46	41	0.52	13	0.51
Trial 3	13	0.45	19	0.45	13	0.56
Scooter						
Trial 1	8	0.38	0	0.46	8	0.47
Trial 2	13	0.52	0	0.51	6	0.46
Trial 3	13	0.45	0	0.56	6	0.45
Average (SD)	12 (1.7)	0.47 (0.1)	17 (16)	0.47 (0.1)	11 (4.0)	0.47 (0.1)

Maximum Wheelchair Displacement

Maximum displacement values of the test wheelchairs and scooter during various driving conditions (normal driving, hard braking and rapid turning) when secured by each wheelchair securement system are displayed in Figure 8. The auto-docking system allowed significantly less wheelchair displacement than the four-point tiedown system (p=0.0004) over all driving conditions. The displacement allowed by the RF-WPS during all driving conditions was not significantly different from that of the four-point tiedown system (p=0.1178) and the auto-docking system (p=0.105).

Unsecured Wheelchair Displacement

Table 5 shows the displacement of the three test wheelchairs when they were unsecured under normal driving, hard braking, and rapid turning conditions when facing forward and rearward. As expected, all wheelchairs experienced increased displacement when unsecured. During normal driving, the manual wheelchair moved a large enough distance that the excursion indicator was off the chart. This movement occurred during vehicle braking on a downhill grade of 17 percent. During a rapid right turn, the manual wheelchair tipped into the aisle until the safety rope stopped the movement, and the scooter tipped towards the vehicle wall and the dummy impacted and fractured a side window (Figure 9).

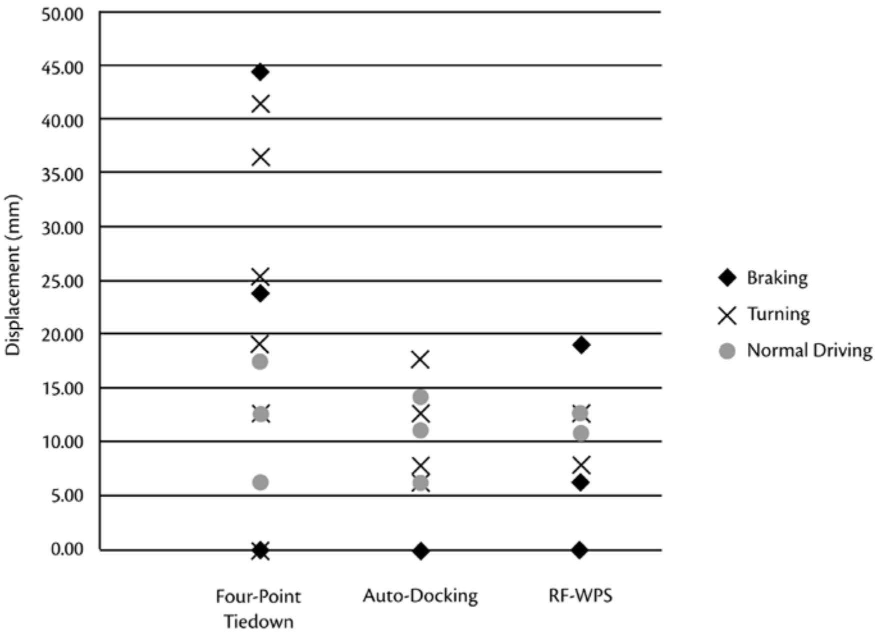


Figure 8. Maximum wheelchair displacement for four-point tiedown system, auto-docking system, and RF-WPS for test wheelchairs and scooter

Table 5. Maximum wheelchair displacements for unsecured trials during normal driving, hard braking, and rapid turning

	Manual	**Powered**	**Scooter**
	mm	*mm*	*mm*
Hard Braking			
Forward Facing	off the chart	off the chart	off the chart
Rear Facing	0	13	19
Rapid Turning			
Forward Facing	off the chart	off the chart	tipped over
Rear Facing	tipped over	14	off the chart
Normal Driving			
Forward Facing	off the chart	19	48
Rear Facing	25	18	20

Note: "Off the chart" indicates that the wheelchair moved sideways or forward outside the 51 mm (2 in.) target area and out of the wheelchair securement station, resulting in potential bodily injury to (wheelchair-seated) passengers. "Tipped over" indicates that the wheelchair or scooter tipped over sideways, resulting in potential bodily injury to (wheelchair-seated) passengers.

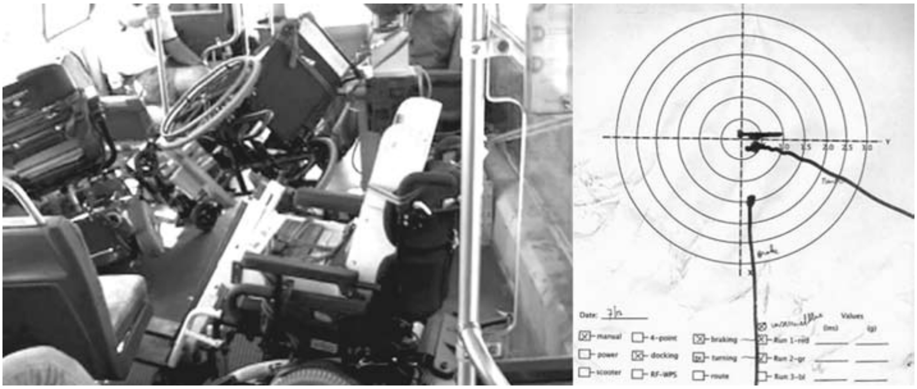


Figure 9. Final locations of unsecured wheelchairs during a right turn (left) and example of "off the chart" displacement (right)

LATV Accelerations

The maximum LATV accelerations were measured during normal driving, hard braking and rapid turning trials with the test wheelchairs and scooter. During normal driving conditions, the maximum acceleration measured was 0.60 *g*. Since the normal driving trials were all approximately 15 minutes in length, time history curves displayed merely a flat line. The maximum acceleration measured during hard braking was 0.75 *g*. Figure 10 shows the time history curves of all accelerations in the longitudinal (x-axis) direction for hard braking. The maximum acceleration recorded during rapid turning was 0.56 *g*. Figure 11 shows the time history curves of all accelerations in the lateral (y-axis) direction for rapid turning.

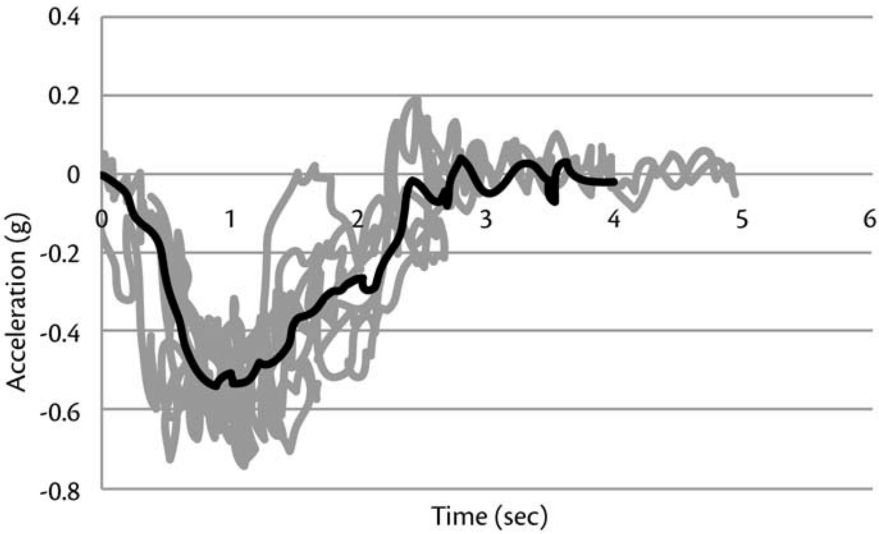


Figure 10. Time history acceleration curves in longitudinal (x-axis) direction for 13 hard braking trials, and average time history acceleration curve (black line)

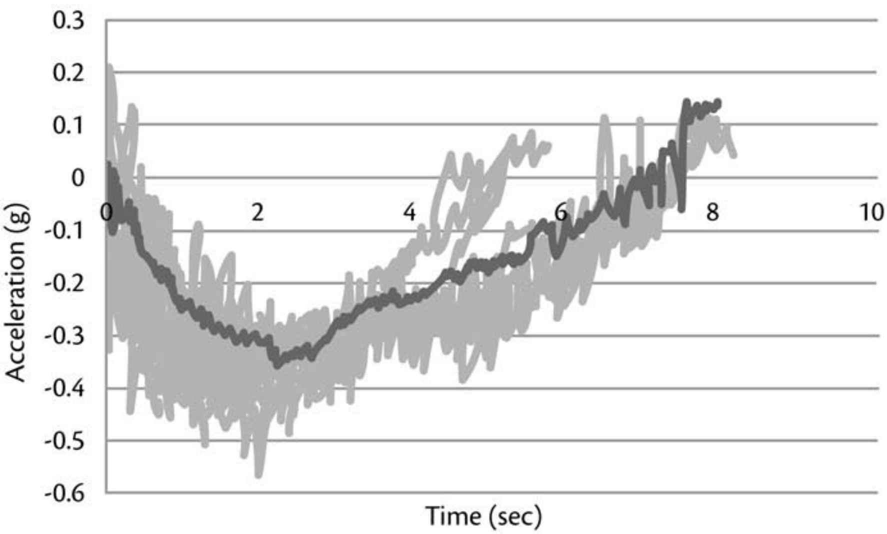


Figure 11. Time history acceleration curves in lateral (y-axis) direction for 12 rapid turning trials, and average time history acceleration curve (black line)

Discussion

Wheelchair Displacement

Maximum wheelchair displacement measured on the test wheelchairs and the scooter that were secured by either a four-point tiedown system, a RF-WPS, or an auto-docking system were all within the maximum ADA allowed limit of 51 mm (2 in.). The highest displacement of 44 mm (1.7 in.) occurred with the scooter secured in the four-point tiedown system, followed by 19 mm (0.8 in.) with the powered wheelchair in the RF-WPS, and 18 mm (0.7 in.) with the manual wheelchair in the auto-docking system. Based on the 51 mm (2 in.) displacement criteria, all three systems would be ADA compliant. During normal driving, the maximum displacement was 18 mm (0.7 in.), and all systems had similar average displacements of 12 mm (0.5 in.), 12 mm (0.5 in.), and 10 mm (0.4 in.) for the RF-WPS, four-point tiedown system and auto-docking systems, respectively.

The auto-docking system performed best under hard braking conditions, allowing 0 mm (0 in.) of wheelchair displacement across wheelchair types. It allowed more movement during rapid turning conditions (average 11 mm [0.4in.]), but this is to be expected, as the UDIG interface to the docking system is located at the rear of each wheelchair. This rear anchoring arrangement would allow for the wheelchair's center of mass to rotate more in a turning than in a braking condition. The docking system allowed a maximum of 18 mm (0.7 in.) of lateral displacement, but this maximal displacement was well below the ADA maximum 51 mm (2 in.) displacement limit. Most of the variability in the movement allowed by an auto-docking system could possibly be attributed to the differences in pen location with respect to the UDIG, which was different for the test wheelchairs and scooter.

The RF-WPS design also was effective in retaining wheelchairs, as the maximum forward (powered) wheelchair displacement was 19 mm (0.8 in.), which occurred during hard braking. This is most likely due the fact that the padding on the FEB and wheel locks on wheelchairs allow for some movement of the (powered) wheelchair even when it is backed up against the FEB. The RF-WPS generally allowed more displacement during rapid turning (avg. 12 mm [0.5 in.]) than hard braking (avg. 8 mm [0.3 in.]) and there was no significant difference between the displacement allowed by the RF-WPS and the displacement allowed by the four-point tiedown system and auto-docking system. Wheelchairs contained by the RF-WPS prototype stayed within the ADA displacement limit of 51mm (2 in.), thus the RF-WPS can be an effective alternative to securing wheelchairs and scooters in a low g environment.

The four-point tiedown system was effective at securing wheelchairs, but tended to allow the most displacement of the three systems and allowed significantly more movement than the auto-docking system (avg 12 mm [0.5 in.] for hard braking, 17 mm [0.7 in.] for rapid turning). This could have been due to the variability in the tension of the tiedown straps, which was not controlled for during the study.

The unsecured wheelchair trials conducted during this study show the importance of wheelchair securement or containment systems in LATVs. Even during normal driving conditions, an unsecured manual wheelchair experienced an excessive amount of displacement and slid forward in the vehicle when braking downhill. During hard braking and rapid turning trials, all unsecured test wheelchairs and scooters either tipped over or slid across the bus floor. These movements increase the risk of injury to wheelchair users and other near-by passengers (Wolf et al. 2007). This experiment showed that there is a need for wheelchairs to be secured or contained appropriately in LATVs during normal driving conditions, not only to protect the user but also other passengers traveling on LATVs. The unsecured trials also indicate that, as expected, scooters and manual wheelchairs are most likely to move, and a heavier power wheelchair is least likely to move under low acceleration LATV maneuvering.

LATV Accelerations

LATV accelerations recorded in this study were all less than or equal to 0.75 *g*. The maximum *g* levels experienced in this study during normal driving conditions averaged 0.46 *g*. These values approximate those measured in several previous studies that reported maximum accelerations near 0.40 *g* (Rutenberg and Association 2000; Zaworski et al. 2007). The current study recorded a maximum normal driving acceleration of approximately 0.60 *g*, which is slightly higher than that reported by previous studies (Rutenberg and Association 2000; Zaworski et al. 2007). The type of vehicle and the course traversed during the normal driving trials may explain the difference between accelerations.

During hard braking and rapid turning, the current study reported maximum accelerations of 0.75 *g* and 0.56 *g*, respectively. These values are similar to those found by Zaworski et al. (2007), who reported a maximum of 0.85 *g* for braking, and a maximum of 0.39 *g* for turning. The slight differences found in the accelerations between studies are most likely due to the difference in the types of buses used (high-floor versus low-floor buses) and the differences in testing procedures. Regardless of the slight differences in the maximum accelerations reported in the literature, all acceleration values remained below 1 *g*.

Study Limitations

This study did not examine the effect of the vehicle-anchored occupant restraint on wheelchair displacement. Vehicle-mounted occupant restraints could provide additional securement, further reducing the displacement of wheelchairs during all driving conditions. The ISO loader gages in this study were restrained to each of the test wheelchairs and could have affected the wheelchair measurements during normal driving, hard braking, and rapid turning trials. In this study, the amount of tension applied to the four-point tiedowns was not measured. The wheelchairs also were secured randomly by various researchers; although this represents real usage of tiedowns, it also may have influenced the magnitude of displacement of the test wheelchairs and scooter when secured by the four-point tiedown system. The ISO loader gages used in this study represent the mass of a 50th percentile male only. They are not representative of how an actual wheelchair-seated individual would respond in low *g* conditions and how this may influence wheelchair displacement.

This study was not conducted to make recommendations on wheelchair types that are appropriate and safer for use in LATVs. Additional research is needed to better understand how wheelchair type (manual, powered, scooter) and wheelchair securement use affects wheelchair displacement and occupant safety in LATVs.

Conclusions

All wheelchair securement systems tested in this study met the ADA displacement requirement by limiting wheelchair displacement to less than 51 mm (2 in.) during normal driving conditions. In addition, all systems met the ADA requirement for wheelchair displacement during hard braking and rapid turning maneuvers. The auto-docking system allowed significantly less displacement than the four-point tiedown system. Accelerations recorded in the LATV remained below 0.76 *g*, providing further justification, in addition to the low frequency of large impacts reported by Blower et al. (2005), for wheelchair securement performance requirements of 1 *g*.

New standards specifying methods to test wheelchair containment systems for use in LATVs are presently under development (ISO 10865). Results also indicate that there is a need to secure wheelchairs in LATVs even during normal driving conditions to prevent possible injury to the wheelchair occupant and other vehicle passengers. A follow-up project to this study includes having wheelchair users and LATV operators use and evaluate each wheelchair securement system on an LATV over a predetermined route and give feedback as to their likes and dislikes of each system. This feedback will be important for optimizing wheelchair securement systems for independent use by wheelchair seated passengers riding on LATVs.

Acknowledgements

Support for this study was provided by the Department of Education, National Institute on Disability and Rehabilitation Research and the Rehabilitation Engineering Research Center on Wheelchair Transportation Safety (Grant #H133E060064). The opinions expressed herein are from the authors and do not necessarily represent those of the funding agency.

The authors express their thanks to Pittsburgh Port Authority Transit for securement system installation and providing a vehicle and drivers for testing purposes. The authors acknowledge BodyPoint, Q'Straint, Invacare, Amigo, Sunrise Medical, and Sure-Lok for their support with designing prototypes, manufacturing components, and donating wheelchairs, securement systems, and seat belts.

References

ANSI/RESNA. 2001. ANSI/RESNA WC-19: Wheelchairs Used as Seats in Motor Vehicles. Arlington, American National Standards Institute (ANSI)/Rehabilitation Engineering Society of North America (RESNA).

Blower, D., L. Schneider et al. 2005. Characterization of transit-bus accidents resulting in passenger injuries for use in developing alternative methods for transporting wheelchair-seated travelers. International Truck & Bus Safety & Security Symposium, Itasca (IL), National Safety Council.

Buning, M., C. Getchell et al. 2007. Riding a bus while seated in a wheelchair: A pilot study of attitudes and behavior regarding safety practices. *Assistive Technology* 19(4): 166-179.

Foreman, C., J. Hardin et al. 2001. The challenges of wheelchair securement: Searching for solutions. Tampa, FL: National Center for Urban Transportation Research-Center for Transit Research, University of Southern Florida.

Fournier, E. 1997. In-vehicle evaluation of a wheelchair head and back support for use on inter-city buses. Toronto, Ontario, Canada City Province: Biokinetics and Associates, Rhodes & Associates.

Frost, K., and G. Bertocci. 2009. Wheelchair securement and occupant restraint practices in large accessible transit vehicles. RESNA, New Orleans.

Hobson, D. A., and L. van Roosmalen. 2007. Towards the next generation of wheelchair securement. Development of a demonstration UDIG-compatible wheelchair docking device. *Assistive Technology* 19(4): 210-222.

International Standards Organization (1992). ISO7176-Wheelchairs - Part 11: Test dummies. Geneva, Switzerland, International Standards Organization.

International Standards Organization. 2001. ISO7176-Part 19:Technical systems and aids for disabled or handicapped persons—Wheelchairs : Wheeled mobility devices for use in motor vehicles. ISO. Geneva, Switzerland, International Standards Organization.

International Standards Organization (2010). ISO/DIS 10865 Part 1: Assistive products for persons with disability—Wheelchair containment and occupant retention systems for motor vehicles designed for use by both sitting and standing passengers—Part 1: Systems for rearward facing wheelchair-seated passengers. ISO. Geneva, Switzerland, International Standards Organization.

Mercer, P. W., and J. R. Billing. 1990. Assessment of a transportable mobility aid in severe driving conditions - An exploratory test. Ontario, Vehicle Technology Office Transportation Technology and Energy Branch: 1-53.

Rutenberg, U. 1995. Urban transit bus accessibility considerations. Toronto, Ontario, Canada, Canadian Urban Transit Association.

Rutenberg, U. 2000. Accommodating mobility-aids on Canadian low-floor buses using the rear-facing position design: Experience, issues, and requirements. STRP Report 13, November.

Rutenberg, U., R. Baerg et al. 2005. Assessment of low floor transit bus g forces on rear-facing wheelchair securement systems. Montreal, Quebec, Canada, Transportation Development Centre.

Shaw, G. 2008. Investigation of large transit vehicle accidents and establishing appropriate protection for wheelchair riders. *Journal of Rehabilitation Research and Developmen*t 45(1): 85-108.

Shaw, G., and T. Gillispie. 2003. Appropriate protection for wheelchair riders on public transit buses. *Journal of Rehabilitation Research and Development* 40(4): 309-320.

Society of Automotive Engineers. 1993. SAE J2181: Steady-state circular test procedure for trucks and buses. Warrendale, PA, SAE.

Society of Automotive Engineers. 1999. SAE J2249: Wheelchair tiedowns and occupant restraint systems - Surface vehicle recommended practice. Warrendale, PA, SAE.

U.S. Department of Transportation. 2007). Part 38 - Accessibility specifications for transportation vehicles. Title 49, Volume 1. Code of Federal Regulations, Federal Transit Administration.

Wolf, P., and L. van Roosmalen. 2007. Wheelchair tiedown and occupant restraint system issues in the real world and the virtual world: Combining qualitative and quantitative research approaches. Assistive Technology 19(4): 188-196.

Zaworski, U., K. Hunter-Zaworski et al. 2007. Bus dynamics for mobility-aid securement design. *Assistive Technology* 19(4): 200-209.

About the Authors

Michael Turkovich, Ph.D. (*mjt52@pitt.edu*) received his doctoral degree from the University of Pittsburgh Department of Bioengineering and collaborates on projects in the Rehabilitation Engineering Research Center on Wheelchair Transportation Safety.

Linda van Roosmalen, Ph.D. (*info@lincdesign.biz*) is a Visiting Assistant Professor at the University of Pittsburgh Department of Rehabilitation Science and Technology and Department of Bioengineering. She is one of the lead investigators in the Rehabilitation Engineering Research Center on Wheelchair Transportation Safety and is Principal of LINC Design, LLC.

Douglas A. Hobson, Ph.D. (*dhobson1@mac.com*) is Emeritus Associate Professor at the University of Pittsburgh in the Department of Rehabilitation Science and Technology.

Erik Porach, B.S. (*eap26@pitt.edu*) is a Research Specialist at the University of Pittsburgh Department of Rehabilitation Science and Technology. He supports projects in the Rehabilitation Engineering Research Center on TeleRehabilitation, the RERC on Spinal Cord Injury, and the RERC on Wheelchair Transportation Safety.