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Measurement and Evaluation of Transit Travel Time Reliability

Kari Edison Watkins, PhD Candidate, University of Washington

G. Scott Rutherford, Professor, University of Washington

Department of Civil and Environmental Engineering
University of Washington
Seattle, WA 98195-2700

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Transportation Northwest (TransNow)
University of Washington
112 More Hall, Box 352700
Seattle, Washington 98195-2700
www.transnow.org

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ABSTRACT

Transportation system customers need consistency in their daily travel times to enable them to plan their daily activities, whether that is a commuter on their way to work, a company setting up delivery schedules for just-in-time manufacturing, or a transit agency scheduling coaches and drivers. To understand the effects such variability has on transportation customers, performance measures must take typical travel times into account as well deviation from those typical travel times. Some travel behavior studies have even suggested that reliability in travel is more important than travel time. As we strive to figure out how to achieve a sustainable transportation system, further research into understanding reliability and how it influences mode choice is needed. Reliability research must include measures of reliability that can be used across modes, ways to incorporate travel time reliability into travel demand forecasting and analysis of competitiveness of modes partially based on travel time reliability. We would like to obtain automated vehicle location data from King County Metro, Sound Transit, Tri-met and other agencies. Our intent is to begin with an investigation of schedule adherence, a key measure of travel time reliability, to characterize which aspects of routes (exclusive lanes, CBD, monthly pass use) make them more or less reliable. However, the measure of schedule adherence doesn't go far enough to allow comparison to other modes in an effort to understand if it is perception or reality that causes potential riders to avert from transit. In addition to schedule adherence, we would like to consider other aspects of reliability such as the relationship between travel time and the allowance of extra time to ensure meeting a schedule. We would also like to develop a system which takes other factors such as ridership into account in ranking of route reliability to help agencies prioritize infrastructure improvements to maximize value.

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DISCLAIMER

Introduction

With the increase in congestion on America's roadways, travel time reliability has become a more critical measure of performance in recent years. Although measures of travel time reliability on freeways and arterials are receiving increased attention, transit travel time reliability often continues to be viewed by transit agencies solely on the basis of overall route-level on-time performance, if it is measured at all.

It is imperative to improve the reliability of public transportation, because the societal benefits of public transportation are numerous. Transit provides mobility to those who cannot or prefer not to drive, including access to jobs, education and medical services. Transit reduces congestion, gasoline consumption and the nation's carbon footprint (American Public Transit Association 2008). In 2007, public transportation saved 646 million hours of travel delay and 398 million gallons of fuel in the U.S., resulting in a savings of $13.7 billion in congestion costs (Schrank and Lomax 2009). Use of public transportation reduced U.S. CO_2 emissions by 6.9 million metric tons in 2005 (Davis and Hale 2007). While hybrid and electric vehicle technologies can reduce the carbon-footprint of single-occupancy vehicles, they cannot compete with public transit in reduction of traffic and promotion of compact, sustainable communities rather than low-density sprawl. By helping travelers move from single-occupancy vehicles to transit systems, communities can reduce traffic congestion and the environmental impact of transportation. However, from a customer perspective, a mobility choice is only a choice if it is fast, comfortable and reliable. Improvements to transit reliability measurement can lead to better evaluation of potential transit improvements that can increase ridership and load factors (Perk, Flynn et al. 2008).

Therefore, this research will investigate the causes of travel time variability in transit by comparing the runtime deviations and on-time performance of routes and portions of routes based on specific characteristics of the service (right-of-way, stop spacing, load factors, etc). The primary benefit from the comparison of on-time performance based on route characteristics is to allow transit agencies to prioritize infrastructure and other improvements based on their resulting impact on reliability.

Background

Travel Time Reliability

Transportation system customers need consistency in their daily travel times to enable them to plan their daily activities, whether that is a commuter on their way to work, a company setting up delivery schedules for just-in-time manufacturing, or a transit agency scheduling coaches and drivers. A frequent user of a facility can become accustomed to the typical travel time, but their continuing concern is punctuality, or the deviations from the expected travel time. A journey to work travel time that takes 20 minutes one day and 40 minutes another day takes an average of 30 minutes, but the individual making this trip would either have to plan for the 40 minute trip or plan for 30 minutes and be late certain days. The consequences of being late repeatedly could mean costs anywhere from daycare fines to the loss of a job.

To understand the effects such variability has on transportation customers, performance measures must take typical travel times into account as well deviation from those typical travel times. Measurement of typical travel time and deviation from that typical travel time is needed for a wide variety of operational decisions, input to modal choice models and decisions, analysis of the effectiveness of system improvements and measurement of the impact of congestion mitigation measures. Travel time reliability on freeways has recently become the subject of much research, including investigations of the value of reliability (Bates, Polak et al. 2001; Brownstone and Small 2005) and development of reliability performance measures (Lomax, Schrank et al. 2003; Cambridge Systematics, Dowling Associates et al. 2008; Lyman and Bertini 2008). The inclusion of travel time reliability in planning and operations analysis is becoming a critical element of understanding the customer perspective. Some travel behavior studies have even suggested that reliability in travel is more important than travel time (Rietveld, Bruinsma et al. 2001; Daskalakis and Stathopoulos 2008).

As we strive to figure out how to achieve a sustainable transportation system, further research into understanding reliability and how it influences mode choice is needed. Reliability research must include measures of reliability that can be used across modes, ways to incorporate travel time reliability into travel demand forecasting and analysis of competitiveness of modes partially based on travel time reliability.

Transit Travel Time Reliability

Currently, the predominant performance measures collected in the transit industry are used to evaluate an agencies business. Measures collected for the National Transit Database, the largest national source for performance data, mostly include measures related to cost and utilization (Federal Transit Administration). The Transit Capacity and Quality of Service Manual (TCQSM), first produced in 1999, was an attempt by the industry to provide a guide for measurement of the quality of service provided to the passengers (Kittelson & Associates 1999). Quality of Service is defined as "the overall measurement of perceived performance of transit service from the passenger's point of view." The TCQSM breaks quality of service into two areas, availability and comfort & convenience, and further describes those areas as shown in Table 1 (Kittelson & Associates, KFH Group et al. 2003).

Table 1 Fixed-Route Transit Service Measures

	Transit Stop	Route Segment	System
Availability	Frequency	Hours of Service	Service Coverage
Comfort & Convenience	Passenger Load	Reliability	Transit-Auto Travel Time

Source: Transit Capacity and Quality of Service Manual, 2nd Edition, Exhibit 1-1

Reliability in transit, as defined by the TCQSM, has two components, the amount of time passengers spend waiting at a stop for their transit vehicle and the consistency of their arrival time at their destination. The perceived and actual reliability of service affects passenger choices about the time they will arrive at the stop and the trip they will choose to give them buffer for their destination. Travel time reliability is influenced by a number of factors, some of which are controlled by the transit agency, such as vehicle and maintenance quality, vehicle and staff availability, schedule achievability, and operations control strategies; some of which are partially controlled by the transit agency, such as differences in operator driving skills, route length and the number of stops and transit preferential treatments; and some of which are out of the agencies control, such as background traffic conditions, road construction, weather, evenness of passenger demand, and wheelchair lift and ramp usage (Kittelson & Associates, KFH Group et al. 2003).

Transit travel time reliability can therefore be improved by changes and improvements that take these factors into account. Agencies frequently adopt measures such as transit signal priority, proof-of-payment fare collection, increased layover times and operations control to improve travel times and reliability. The Transportation Research Board has published an entire series of documents about the effects of such changes called TCRP 95, Traveler Response to Transportation System Changes (Transportation Research Board 2003). The documents detail experiences with various improvements a transit agency can undertake and the gives elasticities for the resulting ridership. It includes items such as parking, transit-oriented development, road pricing, transit information, scheduling and others.

The two most common measures of fixed-route service reliability that passengers can relate to are on-time performance (or schedule adherence) and headway adherence. Transit agencies also often measure missed trips and distance between mechanical breakdowns, but these measures are not as readily seen by the passenger. On-time performance is a measure of percentage of on-time vehicles and is used by agencies for service operating on schedules, which is usually service with headways more than 10 minutes. Many agencies use the measures outlines in the TCQSM to analyze on-time performance (Perk, Thompson et al. 2001; El-Geneidy, Horning et al. 2007). Agencies differ, however, in their definition of on-time, with Canadian agencies typically having shorter windows for on-time performance (Benn 1995; Canadian Urban Transit Association 2001). King County Metro defines on-time as 1 minute early to 5 minutes late. More than half of the Canadian agencies only allow 3 – 4 minutes late with no early arrivals.

Headway adherence is used for service operating headway-based, typically for headways less than 10 minutes. Headway adherence uses the coefficient of variation of headways, which is equal to the standard deviation of headway deviations (actual headway minus the scheduled headway) divided by the mean scheduled headway. Both measures are graded similar to the Highway Capacity Manual guidelines with LOS A to LOS F. Some agencies also monitor travel speeds as a measure of reliability (Jacques and Levinson 1997) and the MTA in New York uses a specific measure of passenger wait assessment (New York Metropolitan Transit Agency).

Automatic Vehicle Location

Automatic Vehicle Location (AVL) data is collected by many transit agencies to allow real-time tracking of transit vehicles for supervision, safety and customer information. The data is typically archived for use in planning applications such as schedule adjustment and analysis of route performance. AVL data is frequently used by agencies to track on-time performance, also referred to as schedule adherence. As described above, on-time performance is the most frequently used measure of reliability for schedule-based transit service. Headway adherence is the most frequently used measure of reliability for headway-based service.

TCRP 113, entitled "Using Archived AVL-APC Data to Improve Transit Performance and Management, details the uses of archived automatic vehicle location data for planning, scheduling and performance measurement applications (Furth, Hemily et al. 2006). One major advantage of using AVL data is the ability to focus on extreme values in travel time, such as 95^{th} percentile travel time, that are frequently used in travel time reliability analysis. Therefore, using AVL data has become a major asset in the measurement of on-time performance, schedule adherence and other travel time reliability measures for transit service.

Although many newer AVL systems are GPS based, the current King County Metro (KCM) AVL system is a sign post beacon and dead reckoning system. This older type of AVL system was implemented before the US government began unscrambling military-based GPS signals. KCM's AVL system uses radio emitters (beacons) to serve as fixed-point location devices throughout the system. When a bus passes a beacon, its Mobile Data Terminal (MDT) on-board relays the bus number, the mileage and the current time to the beacon. The Data Acquisition and Control System (DACS) records this information and relays it for use in real-time supervision of the system. Between beacons, the MDT uses the odometer-based dead reckoning to determine the location of the vehicle.

The shortcomings of this type of system stem from the route that the bus must follow in order for data to be recorded. If the bus does not follow its assigned routing, data will not be collected about the vehicle's location. Therefore, with any kind of route deviation, such as alternate routings due to special events or weather, the vehicle is lost to the system. No real-time information can be provided to transit operations or to the public and no data can be stored for performance monitoring. In addition, the system may provide inaccurate data at trip terminals, wear and tear and topography may affect the mileage, and schedule adherence can only be tracked at the scheduled timepoints. For this reason, KCM is upgrading to a GPS-based system in the next few years.

In the meantime, KCM's current AVL system can be used for analysis on a timepoint basis for routes which are running on their usual pattern. Buses that are rerouted for special events or adverse weather are removed from the data. KCM's AVL system has 319 radio emitters throughout the system. Routes pass up to 16 emitters per trip, which means data can be provided at up to 16 scheduled timepoints per trip. However, most routes pass emitters and record at 5 to 9 timepoints per trip.

Related Work using AVL Data

Many transit agencies use AVL data to evaluate their bus operations. In most cases, routes are evaluated in their entirety in order to adjust schedules and layovers to account for variability. In both Portland and Chicago, the agencies are using AVL data to measure their performance on a system, route and even a stop level with the intent of recommending improvements to the service (Bertini and El-Geneidy 2003; Hammerle, Haynes et al. 2005). Many agencies also use AVL data to monitor their systems in real-time to respond to reliability issues (Furth, Hemily et al. 2006; Pangilinan, Wilson et al. 2008). Strathman and Kimpel used Portland's AVL and APC data to verify that reliability in the form of headway deviations are the primary cause of overloaded buses (Strathman, Kimpel et al. 2003). However, little research exists about the causes of the variability using AVL data.

A few studies have been done using AVL data to investigate the before and after effects of specific travel time and travel time reliability improvements. One study in Portland looked at the effects of bus stop consolidation using AVL and APC data, finding that combining stops had no significant effects on ridership, but running times were improved (El-Geneidy, Strathman et al. 2006). Similar studies were done in both Portland and Seattle to investigate the effectiveness of transit signal priority looking at AVL data before and after implementation (King County DOT Speed & Reliability Program 2002; Kimpel, Strathman et al. 2005). Both found that the improvements in travel time variability were mixed.

There are several factors widely believed to impact travel time reliability in transit and research about their impact has been undertaken for decades. In 1976, Sterman and Schofer found that the length of route had the biggest impact on reliability (Sterman and Schofer 1976). Levinson recommended minimizing the number of stops and speeding up fare collection (Levinson 1983), as well as minimizing the impact of traffic congestion (Levinson 2005). Abkowitz and Tozzi also summarized that traffic conditions and dwell time at stops were major factors in headway variation (Abkowitz and Tozzi 1987). More recently, Chen et al found a correlation between reliability and route length, headways, and exclusive bus lanes in China (Chen, Yu et al. 2009). Research conducted in the Netherlands showed the importance of taking reliability into account when planning the line length and stop spacing of a transit service (Oort and Nes 2008).

Using AVL data for travel time reliability research is ideal because of the large sample size available, which is necessary to look at extreme values (Furth and Muller 2007). However, because the widespread use of AVL is relatively new, few studies have been done to date (Okunieff 1997; Parker 2008). Strathman, et al. looked at the effects that the driver has on the reliability of the transit system in Portland (Strathman, Kimpel et al. 2002). They found that the operator had a significant effect on running time variation, but the only operator characteristic that was significant was years of experience. One study in Twin Cities, Minnesota, did a microscopic analysis of the reasons behind performance and reliability issues using regression models to predict run time, run time deviation, headway deviation, and coefficient of variation of run time (El-Geneidy, Horning et al. 2008). The authors used length of route, driver experience, number of stops served, and passenger activity in their multivariate regression model. The data was only for one route however and no stop-level data was used.

Problem Statement

With the increase in congestion on America's roadways, travel time reliability has become a more critical measure of performance in recent years. Although measures of travel time reliability on freeways and arterials are receiving increased attention, transit travel time reliability often continues to be viewed by transit agencies solely on the basis of overall on-time performance. Therefore, this research will be used to increase knowledge about the causes of travel time variability in transit by comparing the on-time performance and runtime deviation of routes and portions of routes based on specific characteristics of the service (right-of-way, stop spacing, load factors, etc).

Research Objectives

This research strives to answer three related questions:

1. What are the characteristics of route segments where travel times (as measured by runtime) are the least variable?

2. What are the characteristics of route segments where drivers are least likely to fall behind?

3. What are the characteristics of route segments where drivers are most likely to be able to catch-up if they have fallen behind schedule?

Method of Analysis

The basis for this study will be the King County Metro (KCM) Automatic Vehicle Location (AVL) data described in the background section. This data is archived by KCM for the use in transit planning applications. Examples of the use of this data are before and after studies of transit signal priority projects or the tracking of on-time status of the system over time. In addition, this data is used by Metro on a route by route basis to decide when additional time should be added to a schedule to improve on-time performance for a particular trip.

For this analysis, I have been working with John Toone and Sidney Quach of KCM to access the Speed and Reliability Analysis (SandRA) database currently under development. SandRA is an SQL-based data warehouse that consolidates data from multiple departments within KCM by linking the data and matching it to a common framework. The initial implementation of SandRA includes data from the AVL system, the Transit Enterprise Database (TED, which includes KCM scheduling data output from HASTUS) and TNET (the King County regional GIS system). In addition, KCM has made the Automatic Passenger Counting (APC) system data available for the project. Approximately 15 percent of the vehicles in KCM's fleet are equipped with APC and these vehicles are rotated throughout the system on random basis.

Using the AVL data and schedule data, the deviation from schedule can be determined for every route in the system for every trip that route makes and for every timepoint within that trip. This data on deviation from scheduled timepoints has been linked to the other data available through the links in SandRA to determine the impact that various characteristics of the routes and stops have on the travel time variability.

In addition to the AVL, APC, schedule and GIS data, KCM provided data on the characteristics of coaches and a listing of through-routed buses, both of which were imported into an Access database to connect with SandRA data. Local Climatological Data was obtained from the National Oceanic and Atmospheric Admistration (NOAA) National Data Centers and imported into the Access database as well.

Specific characteristics to be included on the route level include:

1. <u>Through-routing and length of route pattern</u> – Initial analysis at KCM has shown that buses which travel through the center of the city and begin another trip without laying over (waiting for the driver to take a break and get back on schedule) typically have worse on-time performance. In is unclear if it is the absence of a layover or simply the length of route that causes this variability in travel time.
2. <u>Ride Free Area</u> – The lack of the fare collection in the ride free area may cause transit service arrival times to be less variable, because greater numbers of boarding passengers would not slow the service down to the same degree.
3. <u>Coach type</u> (articulated vs. standard, low vs. high floor, trolley vs. diesel) – The type of transit vehicle can impact reliability based on the difficulty in boarding for low or high floor vehicles, the number of passengers versus doors for articulated (longer length) or standard vehicles or the type of propulsion and frequency with which buses are disabled for trolley-wire or diesel buses.
4. <u>Express vs. local route</u> – Express routing (buses which go longer sections without stopping) versus local routing impacts the stop spacing on portions of a route. Although this is accounted for in other variables below, this will be tested as a route characteristic as well.
5. <u>Weather</u> – Severe weather can impact both the underlying vehicular traffic and the transit service. During snow storms or flooding, many routes are rerouting and lose their ability to be tracked via KCM AVL. However, moderate amounts of rain or wind may impact transit travel time reliability and can be tested with the existing system.

Characteristics to be included on the stop level include:

6. <u>Passenger counts and passenger loads</u> (passenger count vs number of seats) – Using the APC data for the routes and runs available, passenger counts will be taken into

account. In addition, an analysis of the passenger count compared to the number of seats on the bus will be taken into account to determine the impact that an overloaded bus has on travel time variability.

7. Stop spacing and number of stops along route – Transit agencies commonly consolidate stops to improve travel time on routes because each stop along a route can take several seconds for acceleration, deceleration and opening and closing of doors regardless of the number of people boarding and alighting the bus. The impact of this stop spacing on reliability is unclear. The distance between stops and the number of stops along a route will both be considered as potential variables.
8. Stop location (near side vs. far side) – The location of stops before an intersection or after an intersection is a major factor in transit signal priority. However, it is unknown what the effect of near or far side stop locations will be on travel time variability.
9. Type of right-of-way (tunnel, HOV, BAT lane) – Giving buses exclusive right-of-way allows them to travel unimpeded by traffic congestion. Several forms of transit right-of-way exist within King County, including business-access and transit (BAT) lanes, high-occupancy vehicle (HOV) lanes and the downtown transit tunnel. The impact of these varying levels of exclusive right-of-way will be included as a variable.
10. Presence of transit signal priority – The presence of transit signal priority has been shown to improve travel time and the variability of travel time along severely congested routes in some cases, however little research has been done to quantify this impact. In addition, lanes at intersections that allow buses to jump the queue (move ahead of waiting traffic) can impact reliability. Frequently these measures are part of a larger bus rapid transit implementation project which includes multiple travel time improvements which cannot be separated.

The analysis uses data for weekdays during the summer 2008, fall/winter 2008 and winter/spring 2009 service changes to account for one year worth of transit service. In addition to variables listed above, the analysis uses control variables for the month, the time-of-day, and the direction of travel (inbound vs. outbound).

The analysis uses ordinary least squares (OLS) regression models of the form:

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon$$

The explanatory variables, x, are those in the list above. The explained variable, y, will be two measures that look at on-time performance: the difference between actual and scheduled arrival at a timepoint and the difference between actual and scheduled runtime on a route-level. The error term, ε, accounts for variation in the data that cannot be accounted for using the explanatory variables, including the three sources of variability for which data cannot be obtained (driver, fare payment, and underlying vehicular traffic).

Results

Analysis of Segment-level data

Due to the nature of the AVL system in King County, data is not available on the stop level. For many purposes, such as vehicle arrival predictions, data is interpolated to the stop level. However, we only know where the bus is when it passes a timepoint. For this reason, the finest level of analysis was conducted on the route segment, the distance from one timepoint to another timepoint. For all of the following analysis, the data was filtered to remove nighttime time periods, boarding and alightings greater than 50, stops per mile greater than 10 and travel times along a segment less than 1 minute to remove anomalies in the data that may indicate errors from the AVL tracking or extremely unusual conditions.

The first series of statistical tests are t-tests for each of the categorical variables comparing the on-time deviation of the bus at the timepoint. The on-time deviation is measured as:

On-time deviation = Actual Arrival Time – Scheduled Arrival Time

Table 2 Difference of Means Tests by Service Characteristic for On-time Deviation (in minutes)

	Mean	Std Dev	Observations	T (p-value)
Standard	2.21	4.15	390,875	3.69 (0.002)
Articulated	2.18	4.52	393,906	
Low Floor	2.09	4.41	283,604	-15.88 (0.000)
High Floor	2.25	4.30	501,177	
Diesel / Hybrid	2.15	4.43	672,425	-22.43 (0.000)
Trolley	2.46	3.78	112,356	
Local	2.43	4.31	598,074	84.28 (0.000)
Express	1.46	4.37	186,707	
Layover	1.86	4.09	666,193	-170 (0.000)
Thru Routed	4.08	5.17	118,588	
Few or No Standees	2.15	4.31	766,397	-66.18 (0.000)
Standees > 5	4.29	5.09	18,384	
No Service Alert	2.18	4.32	783,110	-51.15 (0.000)
Service Alert	7.62	8.99	1,671	
No Weather	2.20	4.34	646,774	2.58 (0.010)
Minor Weather	2.17	4.38	138,007	
No or Minor Weather	2.19	4.31	773,750	-12.35 (0.000)
Severe Weather	2.70	6.25	11,031	

As shown in Table 2, although all of the t-tests show significant differences between the means, the magnitude of these differences is substantial. For articulated versus standard buses and minor weather, little difference in the mean values is observed. High floor buses and trolley buses have a slight negative impact on the mean on-time deviation. Having a bus run express improves the mean on-time deviation. Severe weather also has an impact on the mean on-time deviation. The greatest impact from items under a transit agency's control are the improvement from not thru-routing and from running enough service that buses are not substantially overloaded. Having some sort of service problem, although a rare occurrence, has the greatest impact of all the variables shown.

Tables 3 and 4 show the mean on-time deviations by time of day and day of week. Clearly, PM peak into the evening has the worst on-time deviation, as well as days later in the week.

Table 3 Mean On-time Deviations (in minutes) by Time of Day

	Mean	Standard Error	Observations
AM	1.45	0.008	229,398
Midday	2.24	0.007	326,926
PM	2.88	0.011	229,036
Evening	3.07	0.011	175,481
Night	1.47	0.012	94,387

Table 4 Mean On-time Deviations (in minutes) by Day of Week

	Mean	Standard Error	Observations
Monday	1.93	0.011	150,618
Tuesday	2.10	0.010	167,509
Wednesday	2.18	0.010	163,812
Thursday	2.33	0.011	151,054
Friday	2.45	0.012	152,367

Figures 2 to 7 show the correlations between the continuous variables and the mean on-time deviations. As shown in Figure 2, as the stops per mile increase, the mean on-time status worsens. The relationship between the percentage of HOV and Business Access Transit (BAT) lanes is not as obvious, with a slight decline in mean on-time deviation with greater exclusive lanes along a corridor. The relationship with transit signal priority is even worse, although TSP is not widely implemented in KCM's service area, so this could be a function of the limited number of TSP corridors. In Figure 5, the percentage of farside (versus nearside or mid-block stops) seems to make no difference in the mean deviation at all. The number of boarding passengers (ons) does not seem to have a substantial impact until the number is above 40 (Figure 6), at which point the on-time deviation worsens. However, relatively few observations occur beyond 70 ons, as shown by the very large confidence interval. Similarly, in Figure 7, as the passenger loads reach numbers above 90, the confidence interval widens due to the relatively few observations. Prior to this, however, there is a clear relationship between on-time deviation and passenger load.

Figure 2 Change in Mean On-time Deviations by Stops per Mile

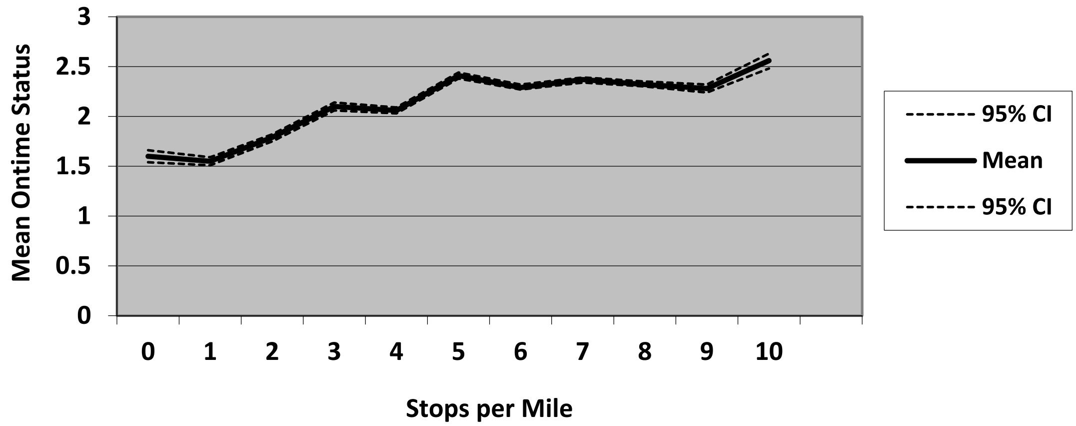


Figure 3 Change in Mean On-time Deviations by Percent HOV & BAT lanes

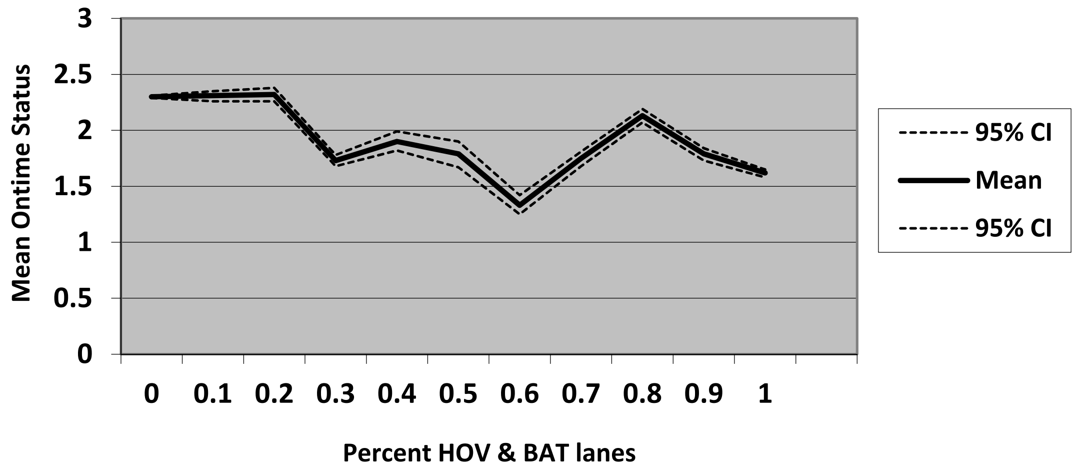


Figure 4 Change in Mean On-time Deviations by Percent TSP

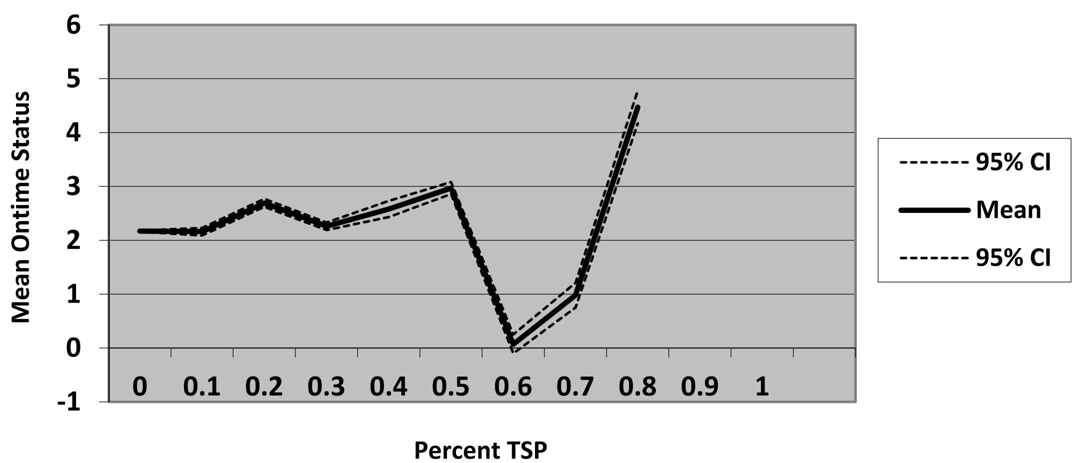


Figure 5 Change in Mean On-time Deviations by Percent Farside Stops

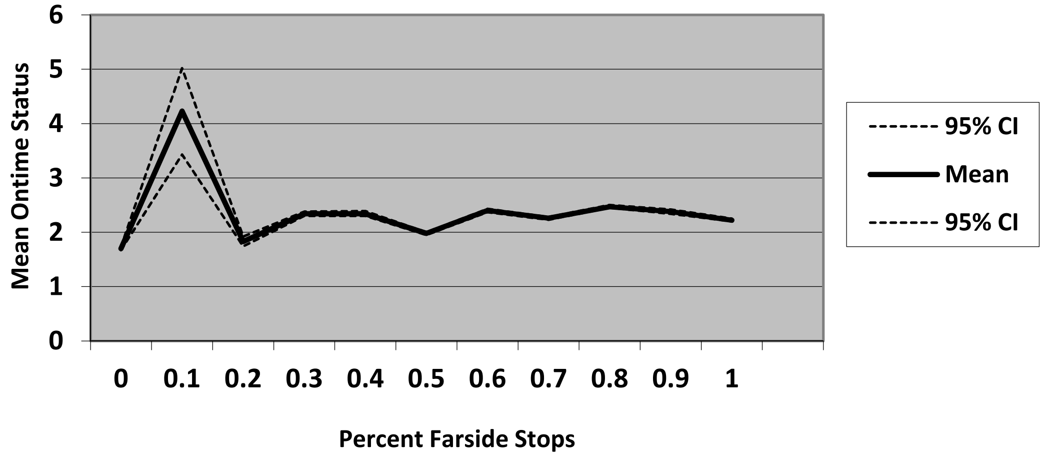


Figure 6 Change in Mean On-time Deviations by Rounded Ons

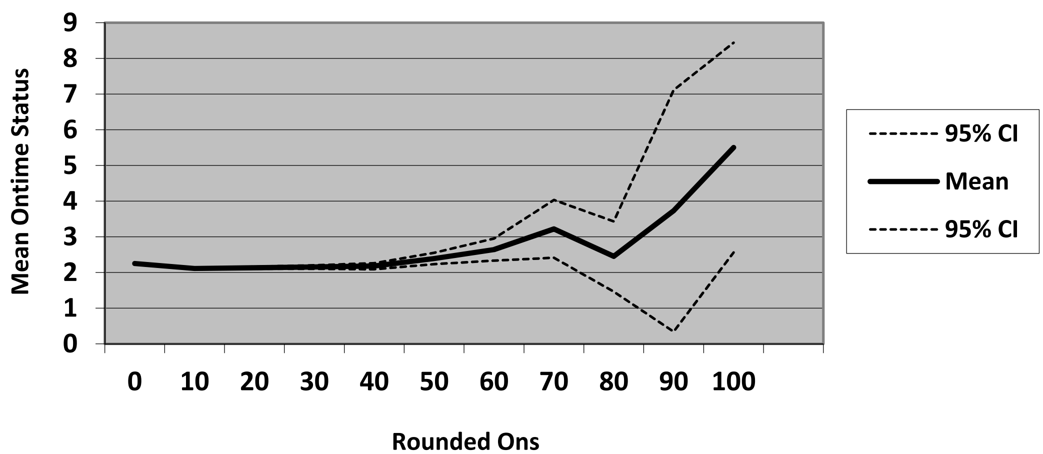
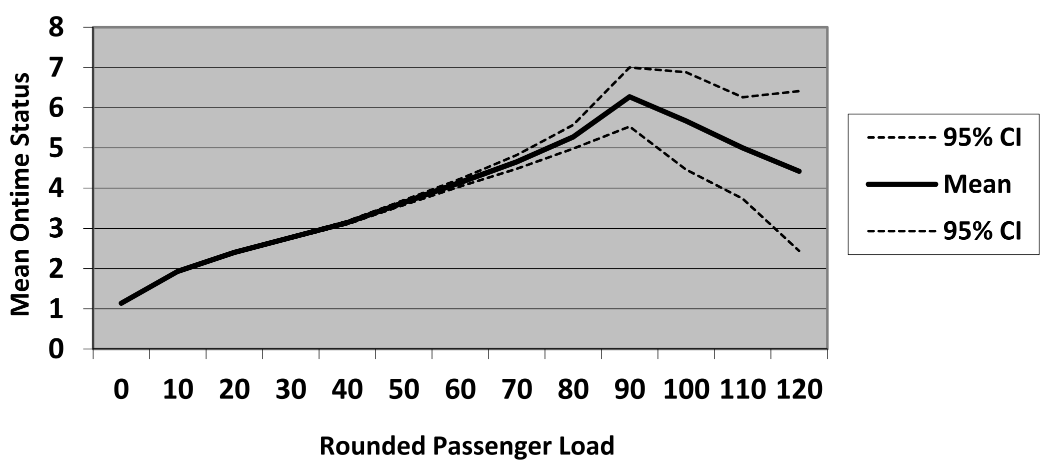


Figure 7 Change in Mean On-time Deviations by Rounded Passenger Load



In order to determine the interaction between these variables and their overall affect on on-time deviation, an ordinary least squares regression analysis was performed using on-time deviation as the explained variable. Based on Table 2 to 4 and Figures 2 to 7, highfloor, express, through routing, standees, service alert, severe weather, percent HOV and BAT lanes, ons, passenger loads, AM peak period, PM peak period and month and day fixed effects were used as explanatory variables. Stops per mile and express were very highly correlated and therefore only express was used, because it was a better predictor. Table 5 shows the results from the OLS regression on on-time deviations with significant explanatory variables. It is of note that December and Thursday were the default values and are therefore not included.

Table 5 OLS Regression on On-time Deviations

	Coefficient	Standard Err	t	P>t	95% Conf. Interval	
On-time Lag	0.910	0.001	1280.4	0.000	0.909	0.912
Highfloor	0.097	0.006	16.5	0.000	0.086	0.109
Express	-0.161	0.007	-23.5	0.000	-0.174	-0.147
Thru Route	0.186	0.008	22.0	0.000	0.170	0.203
Standees	0.276	0.020	14.0	0.000	0.238	0.315
Service Alert	1.492	0.062	24.0	0.000	1.371	1.614
Severe Weather	0.206	0.024	8.5	0.000	0.159	0.253
% HOV/BAT	-0.166	0.009	-17.5	0.000	-0.185	-0.148
Ons	0.019	0.000	53.9	0.000	0.019	0.020
Passenger Load	0.008	0.000	36.6	0.000	0.008	0.009
AM	-0.017	0.007	-2.5	0.011	-0.030	-0.004
PM	0.269	0.007	39.9	0.000	0.256	0.282
January	-0.265	0.015	-18.2	0.000	-0.294	-0.237
February	-0.322	0.014	-22.5	0.000	-0.350	-0.294
March	-0.364	0.014	-25.9	0.000	-0.392	-0.337
April	-0.361	0.015	-24.7	0.000	-0.390	-0.332
May	-0.209	0.015	-14.0	0.000	-0.238	-0.180
June	-0.194	0.014	-14.0	0.000	-0.221	-0.167
July	-0.175	0.015	-12.1	0.000	-0.204	-0.147
August	-0.201	0.014	-14.2	0.000	-0.229	-0.173
September	-0.121	0.014	-8.5	0.000	-0.149	-0.093
October	-0.176	0.014	-12.3	0.000	-0.205	-0.148
November	-0.172	0.015	-11.8	0.000	-0.200	-0.143
Monday	-0.132	0.009	-14.6	0.000	-0.149	-0.114
Tuesday	-0.072	0.009	-8.2	0.000	-0.089	-0.055
Wednesday	-0.048	0.009	-5.5	0.000	-0.065	-0.031
Friday	0.021	0.009	2.3	0.021	0.003	0.038
Constant	0.465	0.014	32.3	0.000	0.436	0.493

F (29, 623840) = 69032 (Prob > F = 0.0000)
R-squared = 0.7492

As shown in the table, the R-squared indicates that about 75% of the variation in on-time deviation is being explained by the model. The most significant explanatory variable is by far the lagged on-time deviation. In other words, if a bus is already late at one timepoint, it tends to be late by a similar amount at the next timepoint. However, in addition to this, all of the other variables are significant and explain additional deviation in the on-time status. Highfloor buses, through-routed buses, those with standees, and those operating in severe weather tend to be delayed more, each accounting for about 6 to 17 seconds of delay per segment. As expected, express buses and those with HOV or BAT lanes tend to be delayed less, with each variable accounting for about 10 seconds less delay per segment. Service alerts also increase the delay, accounting for 1.5 minutes per segment when significant problems occur. The number of boarding passengers and passengers already on the bus both increase delay, accounting for about 1 second per boarding and 0.5 seconds per passenger already aboard.

Analysis of Route-level data

In addition to analyzing the data on the timepoint level, a route level analysis may give additional information about the effect of each characteristic of service. For this analysis, we have collapsed the data by trip to obtain a travel time for the entire distance of the trip for each time a bus makes a trip along a route. Table 6 shows the prediction of the actual travel time or runtime along the route based on the scheduled travel time (ie. runtime) and the same characteristics as the previous analysis using OLS regression. It is again of note that May and Friday were the default values and are therefore not included.

As shown in the table, the scheduled runtime is predicting much of the actual runtime, as should be the case. In addition, high-floor buses add a small amount of runtime at 17 seconds for the entire trip. Express buses add runtime, about 43 seconds per run, as opposed to the previous analysis. Through-routed buses add runtime at almost 1 minute per run. Having standees and severe weather also add runtime, both about 48 seconds per run. In contrast, articulated buses reduce runtime at about 23 seconds per run. Service alerts are again among the most influential, adding almost 4 minutes per run. The total number of boardings along the route added a small amount per boarding at about 1.5 seconds per boarding. Finally, having the run occur in the PM peak period accounted for another 1 minute of additional runtime. The percentage of HOV / BAT lanes, passenger loads, and AM peak period were not significant predictors in this analysis.

Table 6 OLS Regression on Actual Travel Time

	Coefficient	Standard Err	t	P>t	95% Conf. Interval	
Scheduled TT	1.076	0.001	959.1	0.000	1.074	1.078
Highfloor	0.278	0.035	8.0	0.000	0.210	0.346
Express	0.721	0.040	17.9	0.000	0.642	0.800
Thru Route	0.923	0.043	21.6	0.000	0.839	1.007
Articulated	-0.381	0.035	-10.9	0.000	-0.450	-0.313
Standees	0.788	0.075	10.5	0.000	0.641	0.935
Service Alert	3.730	0.243	15.3	0.000	3.253	4.207
Severe Weather	0.805	0.121	6.7	0.000	0.568	1.042
Ons	0.026	0.001	33.3	0.000	0.025	0.028
PM	1.026	0.034	30.3	0.000	0.959	1.092
January	-0.159	0.081	-2.0	0.051	-0.319	0.000
February	-0.461	0.080	-5.8	0.000	-0.618	-0.304
March	-0.661	0.078	-8.4	0.000	-0.815	-0.507
April	-0.784	0.079	-9.9	0.000	-0.939	-0.628
June	-0.183	0.077	-2.4	0.017	-0.334	-0.032
July	-0.194	0.080	-2.4	0.015	-0.350	-0.038
August	-0.149	0.079	-1.9	0.059	-0.303	0.006
September	-0.033	0.079	-0.4	0.674	-0.188	0.122
October	-0.204	0.079	-2.6	0.009	-0.358	-0.050
November	-0.076	0.081	-0.9	0.349	-0.234	0.083
December	0.874	0.084	10.5	0.000	0.710	1.037
Monday	-0.561	0.050	-11.2	0.000	-0.659	-0.463
Tuesday	-0.358	0.049	-7.4	0.000	-0.454	-0.262
Wednesday	-0.330	0.049	-6.8	0.000	-0.425	-0.234
Thursday	-0.187	0.050	-3.8	0.000	-0.284	-0.090
Constant	-0.040	0.083	-0.5	0.631	-0.203	0.123
						F(25,139021) =53255 (Prob > F = 0.0000)
						R-squared = 0.9055

Conclusions and Recommendations

The underlying goal of this research is to help transit agencies improve the usability of public transportation by focusing on an aspect of travel that is a key element to the customer, reliability. This research has taken into account a number of variables that impact reliability in transit, as measured by on-time performance and runtime.

Based on this analysis the characteristic of service that has the highest impact on on-time status and additional runtime beyond scheduled is the presence of some kind of issue with service that would cause a service alert to be issued within the agency. This shows the importance of getting information about service alerts out to customers via a variety of means to ensure riders know that their bus is likely to be delayed.

In terms of policy decisions that agencies can make, the presence of high-floor buses increased the delays by several seconds per trip segment. Through-routing buses had an even greater impact, adding almost a minute to the actual runtime beyond that scheduled. Standees on a bus had a similar negative impact on both on-time status and overall runtime, indicating that agencies should pay attention to their passenger loads and work to add service along lines that become severely overloaded to avoid delays.

Interestingly, express buses and the percentage of exclusive lanes in the form of HOV lanes or Business-Access Transit (BAT) lanes had inconsistent impact on reliability. Although both had a negative impact on the on-time deviation on the segment level, they were either insignificant or positive on the runtime level. These substantial investments can significantly impact the scheduled runtime however, even if they do not substantially impact the difference between scheduled and actual runtime. By including exclusive lanes, the runtime will be less, which means transit planners can schedule a shorter travel time for the route. However, the impact on the variability of the actual runtime was found to be inconsistent in this research. Likewise other variables which are not included in the regression because they were not significant, including percentage of TSP or far-side stops may greatly impact the scheduled travel time even if they do not impact reliability.

Three obvious sources of travel time variablility have not been used in this analysis, including driver, fare payment (routes with more monthly passes versus those with cash), and underlying vehicular traffic. These variables either cannot be included for legal reasons or have no reliable data source to date. Although data about the driver is available, because of union agreements, it cannot be used for analysis by researchers outside of KCM. The data on fare payment will improve with time as the ORCA card is phased into service, however at present the method of fare payment is not accounted for accurately enough to use it in this analysis. Finally, although researchers are making progress in obtaining underlying traffic data, there are no robust sources of general traffic volume or speed data on arterials in Seattle available for this project.

The results presented for this analysis have two major caveats. First, there are a large number of observations in this analysis due to the large number of bus runs which are made throughout the county on a yearly basis. This large number of observations can have an impact on the t-tests and f-tests used, making everything seem significant, when in fact a more rigorous analysis would show that certain variables are not significant. In addition, the variables in this analysis represent several levels of variation, those on a route level, those on a trip level and those on a stop or segment level. For both of these reasons, early consultation with the statistics department at the University of Washington has indicated that a hierarchical random effects model that moves beyond ordinary least squares regression is a better approach for this analysis. The next steps for this study will therefore be to partner with a researcher in the statistics department to improve upon and verify the results reported here.

By investigating the causes of unreliability in transit, agencies will have the ability to prioritize improvements to the service. Our hope is that this research will prove useful to King County Metro and that through publication and presentation of the results, other agencies will be able to improve the usability of their public transportation systems as well.

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