JOURNAL OF ADVANCED TRANSPORTATION
J. Adv. Transp. (2010)
Published online in Wiley InterScience (www.interscience.wiley.com). DOI: 10.1002/atr.134

Analyzing transit service reliability using detailed data from automatic vehicular locator systems

Ahmed M. El-Geneidy[1*,†], Jessica Horning[2] and Kevin J. Krizek[3‡]

[1]*School of Urban Planning, McGill University, Suite 401, Macdonald-Harrington Building, 815 Sherbrooke Street West, Montreal, Quebec, Canada H3A 2K6*
[2]*Cambridge Systematics, Inc., 4800 Hampden Lane, Suite 800, Bethesda, MD 20814, USA*
[3]*University of Colorado, Denver, Campus Box 126, P.O. BOX 173364, USA*

SUMMARY

The widespread adoption of automated vehicle location (AVL) systems and automatic passenger counters (APCs) in the transit industry has opened new venues in operations and system monitoring. In 2005, Metro Transit, Minnesota, implemented AVL system and partially implemented APC technologies. To date there has been little effort to employ the collected data in evaluating transit performance. This research uses such data to assess performance issues along a cross-town route in the Metro Transit system. We generate a series of visual and analytical analyses to predict run time, schedule adherence and reliability of the transit route at two scales: the time point segment and the route level to demonstrate ways of identifying causes of decline in reliability levels. The analytical models show that while headways are maintained, schedule revisions are needed to improve run time and schedule adherence. Finally, the analysis suggests that many scheduled stops along this route are underutilized and recommends stop consolidation as a tool to decrease variability of service through concentrating passenger demand along a fewer number of stops. Copyright © 2010 John Wiley & Sons, Ltd.

1. INTRODUCTION

Transit users are demanding more from their transit providers these days. The old practice of sketching out a viable bus route, placing service on that route, and hoping that people ride the bus is currently insufficient. Users have several demands including but not limited to: fast and reliable service that can compete with the single occupancy vehicle, shorter walking distances to stops, low floor buses, inexpensive service, and friendly drivers. Transit operators are responding to such demands; they naturally collect and analyze transit operations data as a means to inform enhanced service quality. In particular, several agencies are employing automatic vehicle location (AVL) technology to aid in monitoring their buses, to better understand causalities of delay and avoid operational problems. In 2000 the number of transit systems with operational AVL system was 22. This number grew to 157 in 2004, a 614% increase. Adding planned deployments, the number of systems AVL properties grew from 86 in 1995 to 257 in 2004, and increase of 199% [1].

The widespread implementation of AVL and automatic passenger counters (APCs) in the transit industry has opened new venues in transit operations and system monitoring. Metro Transit, the main transit authority in the Twin Cities, Minnesota region, has been testing various intelligent transportation systems (ITSs) since 1999. In 2005, they fully implemented an AVL system and partially implemented an automated passenger counter (APC) system. To date, however, there has been little

*Correspondence to: Ahmed M. El-Geneidy, School of Urban Planning, McGill University, Suite 401, Macdonald-Harrington Building, 815 Sherbrooke Street, West Montreal, Quebec, Canada H3A 2K6.
E-mail: ahmed.elgeneidy@mcgill.ca
†Assistant Professor.
‡Associate Professor of Planning, Design, and Civil Engineering; Director, Active Communities/Transportation (ACT) Research Group.

effort to employ such data to evaluate different aspects of performance. This research capitalizes on the availability of such data to better assess performance issues of one particular route in the Metro Transit system. We employ the archived AVL and APC data from buses running on an example cross-town route between September 20, 2006 and December 1, 2006 to conduct a microscopic analysis to understand reasons for performance and reliability problems. We generate a series of analytical models to predict run time, schedule adherence and reliability of the transit route at two scales: the time point segment and the route level.

This work builds on the body of research on transit performance by taking a new approach to understanding the problem of service reliability. While previous studies have primarily relied on summary statistics to understand reliability issues, this research employs detailed statistical analysis to understand the reasons for decline in service reliability. The statistical models we describe examine the impact of multiple route characteristics such as length, number of stops served, and passenger activity on bus travel time and schedule adherence. The models also explore the relationship between variation in these characteristics and variation in travel time. This approach is advantageous over previous efforts because it allows transit planners to identify the impact of specific characteristics on a route's overall performance. Modeling variation in bus activity and performance also aids planners and managers to develop specific strategies to improve service reliability, which is often suggested as a more efficient and cost-effective way to improve rider satisfaction than increasing service frequency [2].

2. BACKGROUND

As of 2000, at least 88 transit agencies in the US had operational AVL systems in place; an additional 142 agencies were planning to implement AVL systems in the near future [3,4]. Although the data collected by these systems are similar, the manner in which the data collected has been used for analysis varies considerably, if it is analyzed at all. For example, many agencies gather the data but spend little effort to make sense of it; they continue to rely largely on professional judgment and "rules of thumb" to drive decision-making processes [5]. Transit agencies analyzing the data do so with myriad strategies to address a variety of applications.

For example, in Portland, Oregon, ITS technologies were first implemented in 1997 and have been extensively evaluated since implementation [3,6–12]. In 1997, the Ann Arbor Transportation Authority implemented an advanced operating and monitoring system and used the data collected to improve schedule adherence and increase system performance [13]. Similarly, in the late 1990s the Chicago Transit Authority began installing and operating AVL and APC devices on select buses. With the data collected by this system, they evaluated schedule adherence, calculated quality-of-service measures and identified where and why bus bunching occurs [13]. Milwaukee County Transit (MCT) has also used ITS data to improve communications with operators in efforts to reduce the number of off-schedule buses by 40% [14]. To our knowledge, however, research is bereft in its application of AVL data to diagnose transit service problems along routes using AVL data. The work developed in Portland, Oregon concentrated on evaluating system performance and technology implementations. Recent studies that focus on diagnosing a single route largely rely on observation and data visualization [15,16] and rarely incorporate statistical analysis. Thus, most of the above body of work is largely descriptive in nature, compared to the current study, which relies on both statistical analysis and data visualization. The following section provides more specific text explaining concepts of transit service reliability and predicting run time of select routes.

2.1. Transit service reliability

A primary use of ITS data rests in assessing the reliability of transit service in terms of scheduling. In theory, improving transit service reliability has been linked to increases in transit demand for particular routes [5] and also should increase service productivity, given accurate schedules. At issue, however, is that transit service reliability is defined in a variety of ways. Turnquist and Blume [17] suggest it is "the ability of the transit system to adhere to schedule or maintain regular headways and a consistent travel time." In other words, reliability can be defined as the variability in the system performance measured over a period of time. Abkowitz [18] offers a broader definition of transit service reliability: the

DOI: 10.1002/atr

invariability of transit service attributes that affects the decisions of both the users and the operators. Strathman *et al*. [11] and Kimpel [19] relate reliability mostly to schedule adherence, keeping schedule related delays (on time performance (OTP), run time delay, run time variation, headway delay, and headway delay variation) to a minimum, which agrees with Levinson [20] and Turnquist [21]. Previous research examining transit service reliability using AVL systems concentrated on quantifying the benefits of AVL systems in improving reliability [19,11]; they did not aim to understand causes of decline in reliability along problematic routes. In theory, an increase in transit service reliability should lead to an increase in service productivity, given accurate schedules. Several researchers have outlined methods for improving transit service reliability [22–27]. These methods include: (1) implementing changes in driver behavior (through training), (2) better matches of schedules to actual service, (3) implementing control actions such as bus holding at time points, (4) implementing transit signal priority (TSP), and (5) modifying route design (route length, bus stop consolidation, and relocation).

Differences also exist between how reliability is perceived by transit agencies versus passengers. A reliable service for a passenger is one that: (1) can be easily accessed by passengers at both the origin and destination, (2) arrives predictably, resulting in short waiting time, (3) has a short in vehicle time, and (4) has low variance in run time [28,29]. This means that any deviation from these factors results in a decline in reliability; the key difference between the two perspectives is run time.

2.2. *Run time*

Run time is the amount of time it takes a bus to travel along its route. Abkowitz and Engelstein [22] found that mean run time is affected by route length, passenger activity, and number of signalized intersections. Most research agrees on the basic factors affecting bus run times. However, optimizing run time is challenging for all transit agencies because changes in run time have strong and often conflicting effects on service reliability and total travel cost [10,23,30–32]. If the primary goal of an agency is to increase service reliability and on-time-performance, the agency could conceivably allow for more time between stops along a route, increasing total run time. This increases the probability that the bus will arrive at stops early and, with bus holding at time points, increases the likelihood of on-time departure. Unfortunately, this strategy also lowers operating speed and increases riding time, which increases both user and operating costs [33]. An alternative strategy is to keep run time to a minimum. This strategy helps agencies to realize savings in recovery time and layover time, but can lead to decreases in reliability and subsequent increases in user cost. The general guideline for establishing optimal run times that is suggested by the Transit Capacity and Quality of Service Manual (TCQSM) and is supported by several transit planning software packages is to set run time between time points equal to the mean observed run time [33,34].

One indicator of deteriorating transit service reliability that can be identified by performance measures is the increase in variance in run time relative to the mean run time. This variation represents unpredictable service from the standpoint of passengers since it increases waiting time and in-vehicle time. Run time models are fairly common in the transit literature, while run time variation models tend to be rare. Passenger activity variables, such as boarding and alighting rates contribute to run time variance [10,31,32,35–39]. Agencies try to minimize these delays by consolidating bus stops, promoting smart-card based fare media, back door only policies for alightings, front door only policies for boardings, low floor buses, and requiring fare payment at the ends of trips. Headway adherence may also reduce run time delay created by passenger clustering and overloading [40].

Several researchers have outlined methods to improve transit service reliability, including but not limited to: (1) enhancing the training of drivers, (2) matching schedules to actual service, (3) implementing control actions such as bus holding at time points, (4) implementing traffic signal prioritization, (5) modifying route design (route length, bus stop consolidation, and relocation), and (6) implementing real-time operation controls and passenger information systems.

Recently, Furth *et al*. [41] reviewed the potentials of using ITS data and outlined future research in this area. His team focused on operations in nine transit agencies to demonstrate best practices in implementing ITS technologies. Metro Transit (Twin Cities, Minnesota) was one of the selected agencies. Metro Transit's system was implemented in 1999 and tested through 2002 under a project named Orion. The Orion system was upgraded recently to a fully functional archiving system that

DOI: 10.1002/atr

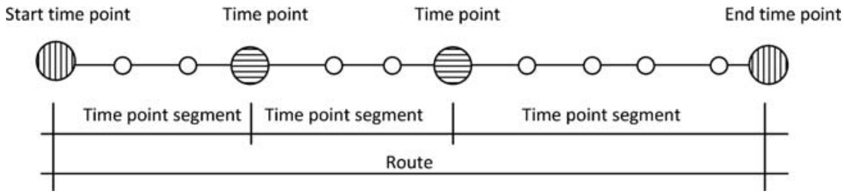

Figure 1. Levels of analysis.

enables archiving AVL data. In addition to the AVL, the archiving system records passenger, fare box, and lift activities. Metro Transit's current AVL system offers a unique opportunity for analysis and developing performance standards since it depends mainly on the radio system where bus AVL information is being sent every 60 seconds compared to other stop base systems. Such information allows one to perform microscopic analysis and better understand factors that affect bus service over the course of the trip; accordingly, improvements in reliability can be recommended through analyzing this information.

3. DATA AND RESEARCH METHODS

The primary motivation of this research was to demonstrate a proof-of-concept application for how AVL data can be analyzed at a microscopic level to inform matters of transit service reliability. After consulting representatives from Metro Transit, the research team decided to examine in detail one bus transit line that has been experiencing declines in ridership and has experienced problems with respect to adhering to schedules. The selected route can be used as a prototype to develop a methodology for analyzing other routes facing similar problems either in the Metro Transit system or in any other agency.

3.1. Data

Route 17 is a cross-town route serving two western suburbs, Hopkins and St. Louis Park, as well as the southern, downtown, and northeast sections of Minneapolis. It operates along sections of one of the most congested corridors in the Twin Cities region (Hennepin Avenue and Lake Street), proving an interesting route for conducting travel time and reliability analysis. Since not all of the Metro Transit bus fleet is equipped with APCs, Metro Transit's service and planning department agreed to direct the maximum possible number of APC equipped buses to serve Route 17 during the period between September 20, 2006 and December 1, 2006. During the study period no major weather issues were present (i.e., snow storms) that might have an effect on travel time and schedule adherence. The data collection process lead to a sample of over 658,000 stop level observations.[a]

After removing duplicate records, 650,938 stop level observations remained in the sample. Of these records, only 150,635 stop level observations (23%) were associated with APC equipped buses that served Route 17 during the study period. Only weekday observations and data obtained from APC equipped buses were used in this analysis. The stop level data include information related to when the bus arrived at a stop, when it left the stop, number of passengers on board, and several other variables. Since schedules are written to time points, schedule adherence is measured only at these points. It is not possible to interpolate between time points in this data set.

The 150,635 stop level observations included represent data obtained from 2174 bus trips during peak and off peak periods traveling in both east- and west-bound directions. Surprisingly, these trips represent 28 different trip patterns distributed over the course of a day. A trip pattern is identified as

[a]Unfortunately, using the raw data obtained from the Metro Transit data archiving system directly in an analysis is not possible. Various problems were identified after carefully observing the data. For example, duplicate records exist in the data. The duplication is present when an unscheduled stop occurs right before or after a scheduled stop, recording both stops as the same regular scheduled stop and assigning the same arrival and departure time to both stops. However, the passenger activity variables (boardings, alightings, and passenger load) and odometer readings for both records differ. In addition, the authors removed any suspicious ''utlier'' observations from the data since they might have occurred to a non-recurring event (e.g., accidents).

DOI: 10.1002/atr

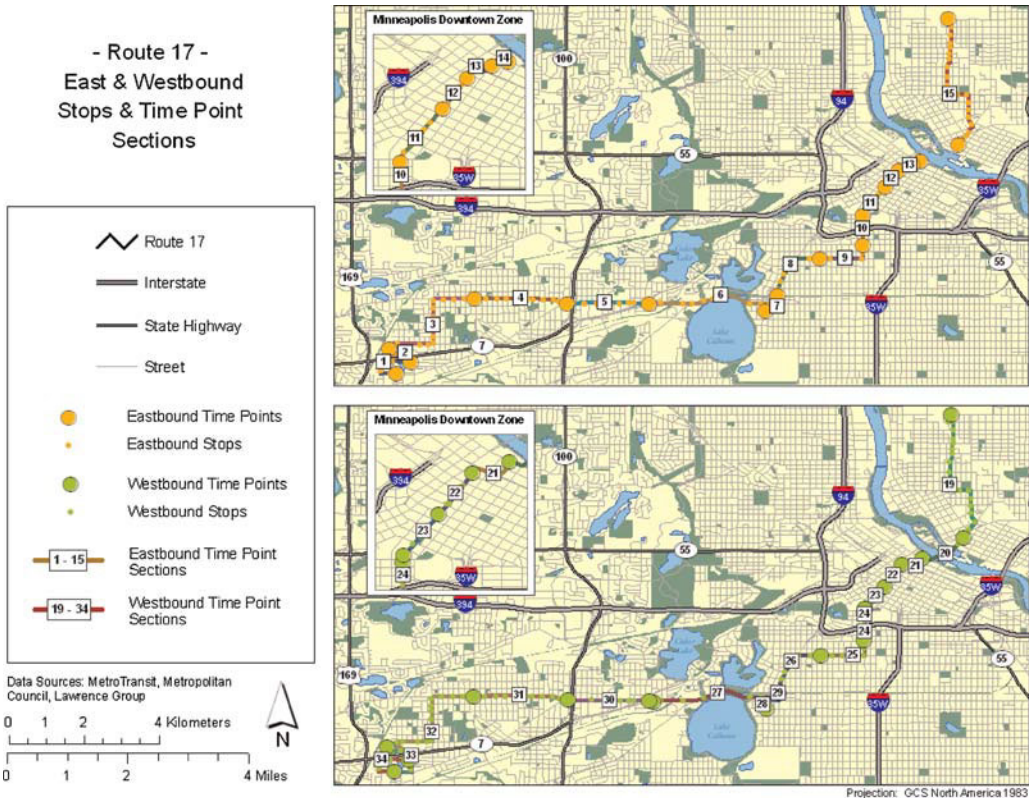

Figure 2. Route 17 time point segments.

having the same first and last stop, running during the same period of time, in the same direction, and serving the same number of stops. Due to the variance in the data caused by the large number of trip patterns and their differences, we divide the analysis into two sections: (1) the route level for a sample of two specific trip patterns, and (2) the time point segment level. A time point segment is identified as the segment between two consecutive time points. Figure 1 graphically shows the different levels of analysis.

The data at the time point segment level of analysis were obtained from various trip patterns and are combined based on the number of stops being served between each two time points. Figure 2 shows the 34 different time point segments used in the analysis. The source data were cleaned and aggregated to the trip pattern level by summarizing over each of the days in the study period. Assembling the data in this manner resulted in a sample of 21,257 records that can be analyzed while controlling for the variations introduced by the differences in patterns. The data was subjected to a detailed observation to remove any extreme travel time that might have occurred due to the presence of accidents or any other interruptions along the corridor.

Route 17 has 28 different trip patterns; conducting a generalized route level analysis without accounting for the differences among these patterns would impose a measurement error. It is also important to note that these patterns need to be treated as 49 different patterns based on the peak and off-peak classification. Accordingly, we analyzed the route level data considering specific patterns during the course of the day. The analysis at the route level allows us to generate different performance measures.

After cleaning and compiling the Route 17 data for analysis at both the time point segment and trip pattern levels, we also generated a series of variables showing variation in passenger activity, travel time, and other characteristics at the time point segment and trip pattern levels. This calculation was made possible because of the relatively long duration in which the Route 17 data were collected. The headway deviation, travel time deviation, and coefficient of variation (CV) of run time (standard deviation divided by the mean) are used as measures of reliability. The CV was calculated based on the time of day along each trip-segment. For example, data obtained from the trip departing at 8:00 from

DOI: 10.1002/atr

stop A along segment X in day 1 is combined with data obtained from the same location and the same time from day 2 and so on. To ensure robustness of the generated models, several sample sizes were tested to discern how many days should be included to derive the CV. A sample size threshold of 30-trip observations was found to be the point when the model retains its robustness. Accordingly, any data used in the headway deviation or the CV of run time had to be derived from at least 30 observations to ensure stability in the variation values.

3.2. Research methodology

Keeping in mind the two different units of analysis, our aim is to measure reliability and performance at both the macro- and microlevels. The first section focuses on the trip pattern to analyze run time and

Table I. Variable description.

Variable	Description
Run time	The travel time between two consecutive time points
Run time deviation	Actual run time divided by the scheduled run time
Headway deviation end	Actual headway measured at the end of the segment divided by scheduled headway at the end of the segment
CV run time	The coefficient of variation of run time between two consecutive time points
Distance	The distance between two consecutive time points composing the segment of analysis
Number of scheduled stops	The number of scheduled stops between two consecutive time points
West-bound	A dummy variable that equals one if the bus direction is west-bound
Order of first stop	The order of the first stop in the segment relative to the pattern that this stop is affiliated to
AM peak	A dummy variable that equals one if the observed trip started during the morning peak period
PM peak	A dummy variable that equals one if the observed trip started during the evening peak period
Number of actual stops	The number of actual stops being made by the bus along the studied segment
Boardings	The number of passengers boarding the bus along the studied segment
Boardings square	The number of passengers boarding the bus along the studied segment squared
Alightings	The number of passengers alighting the bus along the studied segment
Alightings square	The number of passengers alighting the bus along the studied segment squared
Lift use	The number of times the lift was used along the studied segment
Average passenger load	The average number of passengers onboard the bus during the trip
Delay at first stop	The delay relative to the schedule measured at the first time point along the studied segment
Headway delay at first stop	The headway delay relative to the schedule measured at the first time point along the studied segment
Driver experience	The experience of the driver who is operating the bus in years
CV number of actual stops	The coefficient of variation of the number of actual stops being made by the bus along the studied segment
CV boardings	The coefficient of variation of the number of passengers alighting the bus along the studied segment
CV alightings	The coefficient of variation of the number of passengers alighting the bus along the studied segment
CV lift use	The coefficient of variation of the number of times the lift was used along the studied segment
CV passenger load	The coefficient of variation of the average number of passengers onboard the bus during the trip
CV delay at first stop	The coefficient of variation of the delay relative to the schedule measured at the first time point along the studied segment
CV headway delay at first stop	The coefficient of variation of the headway delay relative to the schedule measured at the first time point along the studied segment
CV driver experience	The coefficient of variation of the experience of the driver who is operating the bus in years

DOI: 10.1002/atr

scheduling issues. The analysis is limited to specific patterns due to the complexity of the route. When selecting trip patterns to study, we adopted a criterion that the selected pattern needed to be present over the course of the entire day. Limiting the analysis to peak period allows us to make generalizations since the studied patterns are serving at least 80% of the stops along the studied route. The number of observations that can be present for this pattern was also part of the criteria. The second unit of analysis is the time point-segment (e.g., passenger activity per trip per segment). A time point segment is identified as the section of a trip between two consecutive time points.

We estimate four different multivariate regression models to inform different dimensions of service reliability. The first three models concentrate on run time and schedule adherence. Run time and headways vary among time point sections and time of the day; measuring both variables directly as headway delay and run time delay, without controlling for the variation in the schedule, imposes a measurement error. Accordingly, we add two new variables: run time deviation and headway deviation. Any delay that is measured is relative to the associated schedule. Run time deviation and headway deviation are ratios; for purpose of interpretation they can be used as percentages. The fourth model measuring variation in run time, captures the consistency in run time from day to day. Table I describes each of the dependent and independent variables used in the models, which are specified as follows:

(1) Run time $= f$ (AM, PM, west-bound, number of physical stops, number of actual stops, boardings, boardings squared, alightings, alightings squared, lift usage, driver's experience, schedule delay at start, headway delay at start, passenger load, order of first stop, and distance).
(2) Run time deviation $= f$ (AM, PM, west-bound, number of physical stops, number of actual stops, boardings, alightings, lift usage, driver's experience, schedule delay at start, headway delay at start, passenger load, order of first stop, and distance).
(3) Headway deviation $= f$ (AM, PM, west-bound, number of physical stops, number of actual stops, boardings, alightings, lift usage, driver's experience, schedule delay at start, headway delay at start, passenger load, order of first stop, and distance).
(4) CV of run time $= f$ (AM, PM, west-bound, number of physical stops, CV number of actual stops, CV boardings, CV alightings, CV lift usage, CV driver's experience, CV schedule delay at start, CV headway delay at start, CV passenger load, order of first stop, and distance).

The first model assesses the quality of the data used in the research and compares it to previous research being developed in the transit industry. The covariates in the regressions represent the most theoretically relevant variables included in empirical studies of this type. Run time is expected to increase with the number of possible stops in a segment, number of actual stops, the use of a passenger lift, and passenger activity; it decreases for morning and evening peak trips relative to off peak trips. The square terms that are associated with the passenger activity variables are expected to have a negative effect on run time. Headway deviation and schedule delay measured at the beginning of the time point segment could be either positively or negatively related to run time. A chronic delay is likely to have a positive effect on run time. Alternatively, if delay is circumstantial and operators utilize recovery opportunities, delay could be inversely related to run time.

For models predicting run time deviation and schedule deviation, we hypothesize that the same relationship exists with the independent variables, yet headway delay at the beginning is expected to be more crucial in these models. They can also be used to assess the extent to which schedules are well designed to accommodate the various operating conditions along the route. If several variables are statistically significant, then schedules need to be revised. If the magnitude is small, yet statistical significance still exists, then such a route has an efficient schedule and monitoring in the future is recommended. Likewise, it is hypothesized that variations in run time will be similarly related to variations in the same set of variables that were specified in the run time model. Driver experience variables are added to account for the variability in the performance of drivers. It is expected that drivers' experience would negatively affect run time and reliability measures. A dummy variable for the direction of travel is included in the models to control for these variations (going to or from downtown). Finally, two dummy variables representing the morning peak and evening peak are included to measure the differences between the operating environment among these time periods relative the off-peak time period.

DOI: 10.1002/atr

4. ANALYSIS

4.1. Route-level run time analysis

Following a methodology developed by Strathman *et al*. [9], route level analysis measures the effectiveness of the schedule in accommodating recovery time. Scheduled run time along any transit route consists of two main components, run time and layover (or recovery) time. The scheduled run time is usually equal to the mean or median value of the run time, while the recovery time is set as the difference between the selected benchmark (mean or median run time) and the run time associated to the 95th percentile in the frequency distribution of run time. Using trip level data, we compare the actual run time for the entire route to the scheduled run time to identify scheduling problems.

The first pattern starts from downtown Minneapolis heading west to the suburbs during the PM peak; the second pattern is coming from the suburbs during the morning peak going east to end in downtown Minneapolis. The selected AM peak (east-bound) pattern consists of 75 scheduled stops. On average, the bus serving this pattern only stopped at 38 stops during the morning peaks, serving an average of 57 passengers per trip. These numbers indicate that each time the bus serving this pattern completes a stop during the AM peak (east-bound), it serves approximately 1.5 passengers. On the other hand, the selected PM peak (west-bound) pattern consists of 77 scheduled stops. On average the bus serving this pattern during the evening peak period made 35 actual stops, serving an average of 45 passengers. These numbers indicate that each time the bus serving this pattern stops during the PM peak (west-bound) it serves 1.3 passengers.

Figures 3 and 4 display the run time distributions for the selected Route 17 trip patterns during the AM peak (east-bound) and the PM peak (west-bound). For the 121 AM (east-bound) trips run time ranged from 42 to 66 minutes with a median value of 51.7 minutes. The median observed run time is 3.7 minutes (7%) longer than the mean scheduled run time of 48 minutes. This 7% difference in the morning peak requires careful revision in the scheduled run time. In addition, the amount of recovery/layover time incorporated into the schedule for this trip pattern requires revision. The observed 95th percentile run time for the selected AM peak (east-bound) trip pattern was 60 minutes, meaning that this pattern requires an average of 51.7 minutes of travel time and at least 9 minutes of layover and recovery time. Currently, the average actual layover time for this AM peak (east-bound) pattern is 2.5 minutes. A total of 6.5 minutes of difference exists between the actual and recommended layovers. These values indicate that at the end of this route, drivers do not have enough recovery time and schedules need to be revised. Maintaining a schedule with less recovery and layover time than what is recommended, suggests that the bus will be starting new trips already being delayed.

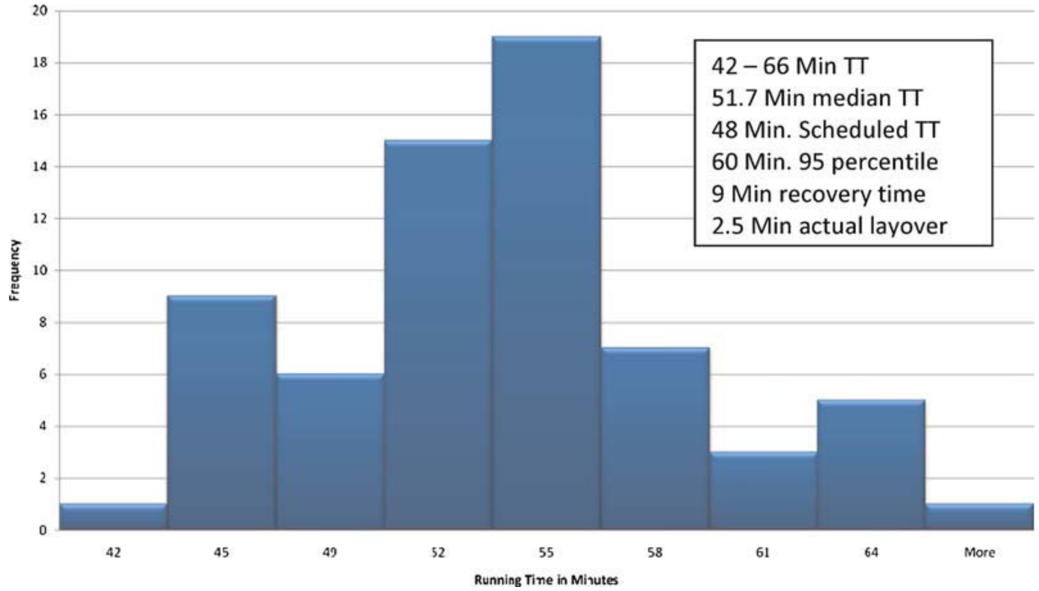

Figure 3. Route 17 run time distribution sample: AM east-bound.

DOI: 10.1002/atr

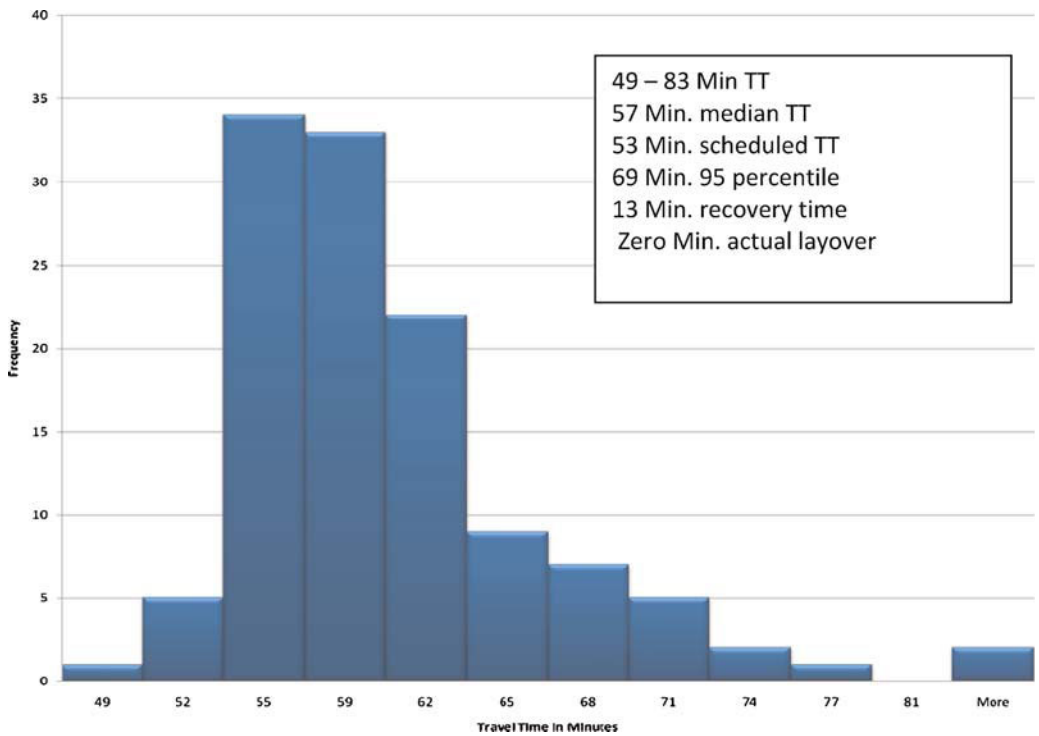

Figure 4. Route 17 run time distribution sample: PM west-bound.

The selected PM peak (west-bound) pattern observed in Figure 4 included 66 trips with run times ranging from 49 to 83 minutes and median value of 57 minutes. Similar to the first selected pattern, the median observed run time for this pattern is 4 minutes (7%) longer than the mean scheduled run time of 53 minutes. The observed 95th percentile run time is 69 minutes, meaning that this trip pattern (PM peak west-bound) requires an average of 57 minutes of travel time and at least 13 minutes of layover and recovery time. Currently there is no layover time for this PM peak (west-bound) pattern. Comparing the AM (east-bound) to the PM (west-bound) situation, more adjustments are needed for the selected PM peak (west-bound) trip schedules.

4.2. Time point segment analysis

The second analysis focuses on the detailed time point segment data. Actual run times range between 21 and 8869 seconds, a large range owed to the variance in the lengths of time point sections and several other factors included in the regression model. Run time deviation, which is the actual run time divided by the scheduled run time ranged from 0.18 to 18.48 with a mean value of 1.07. This means that on average actual run time is around 7% longer than the scheduled run time. On the other hand, headway deviation, the actual headway at the last stop divided by the scheduled headway at the last stop, ranged from 0.01 to 2.24 with a mean value of 1.00, meaning that on average there is no deviation from headway along the route. Combining the run time deviation and the headway deviation together we notice that a scheduling problem exists along the studied route. On average, buses are delayed yet the headway is maintained as scheduled. The variation from the mean in run time ranged between 8% and 57%. Table II includes the output of the regression models; *t*-statistics are indicated between parentheses below each coefficient.

4.2.1. Run time

The run time model (R^2 of 0.59) has almost all variables having a statistically significant effect on run time (barring direction). In addition, all variables in the model follow the transit operation theory in terms of direction and statistical significance. For example, the distance measured between two

DOI: 10.1002/atr

Table II. Regression model results.

Variable	Run time	Run time deviation	Headway deviation	CV run time
Constant	**102.601 (33.59)**	**1.072 (102.91)**	**0.996 (454.82)**	0.059 (1.61)
Distance	**68.507 (31.56)**	**−0.066 (−8.62)**	**0.003 (2.06)**	**−0.033 (2.27)**
Number of scheduled stops	**5.019 (10.61)**	**0.009 (5.49)**	**−0.001 (−4.25)**	0.002 (0.52)
West-bound	−0.281 (−0.16)	**0.025 (4.25)**	0.000 (0.36)	**0.044 (2.80)**
Order of first stop	**0.173 (4.45)**	**0.001 (6.71)**	**0.000 (3.00)**	**0.001 (2.79)**
AM peak	**−17.267 (−7.27)**	−0.006 (−0.67)	0.001 (0.56)	**0.155 (3.77)**
PM peak	**37.73 (18.46)**	**0.055 (7.68)**	**−0.011 (−7.28)**	0.022 (1.56)
Number of actual stops	**11.269 (17.02)**	**0.010 (4.29)**	**0.001 (2.46)**	—
Boardings	**13.485 (40.23)**	**0.004 (6.82)**	**0.001 (5.80)**	—
Boardings square	**−0.142 (−12.52)**	—	—	—
Alightings	**6.599 (16.64)**	**0.002 (2.23)**	**0.000 (2.27)**	—
Alightings square	**−0.043 (−2.90)**	—	—	—
Lift use	**67.252 (17.32)**	**0.241 (17.62)**	**0.039 (13.50)**	—
Average passenger load	**−0.34 (−4.31)**	0.000 (−0.99)	**0.000 (3.71)**	—
Delay at first stop	**0.21 (31.15)**	**0.001 (21.40)**	**0.000 (3.38)**	—
Headway delay at first stop	**0.028 (5.27)**	0.000 (1.35)	**0.000 (−96.68)**	—
Driver experience	**−0.340 (−3.05)**	−0.001 (−1.57)	**0.000 (−2.65)**	—
CV number of actual stops	—	—	—	**0.051 (2.97)**
CV boardings	—	—	—	−0.020 (−1.18)
CV alightings	—	—	—	0.026 (1.47)
CV lift use	—	—	—	0.003 (0.97)
CV average passenger load	—	—	—	**0.114 (1.86)**
CV delay at first stop	—	—	—	**−0.034 (−5.02)**
CV headway delay at first stop	—	—	—	0.000 (−0.29)
CV driver experience	—	—	—	**−0.056 (−2.43)**
Adjusted R^2	0.59	0.07	0.44	0.52
N	21,275	21,275	21,275	97

t-statistics reported in parenthesis.
Bold indicates statistical significance at the 0.05 level and higher.

consecutive time points is found to be statistically significant with a positive effect on run time. Run time increases by 68 seconds for every kilometer a bus must travel between time points. This can be translated as showing that buses travel at a speed of 51 km/hour (32 miles/hour) when all of the other variables in the equation are held at their mean values. Each scheduled stop adds 5 seconds to the travel time, regardless of a stop. On average, six scheduled stops exist along each time point segment, whereas only three stops are actually made. This means that at each time point segment an average of 15 seconds are spent at stops where no passenger activity is occurring. This represents approximately 4% of the average travel time along the studied time point segments.

The order of the starting time point in the segment along its pattern adds 0.17 seconds to the run time. A pattern with 80 scheduled bus stops means the run time along the first two time points should be faster by 13 seconds compared to the run time along the time point segment that starts with stop number 77 in the trip sequence, when keeping all variables at their mean values. Morning peak service is found to be faster than off-peak by 17 seconds. On the other hand, evening peak service is slower than off-peak by 37 seconds. This indicates a difference of 64 seconds in run time between the morning peak and the evening peak.

For each actual stop being made along a time point segment, 11 seconds is added to the run time. Each passenger boarding the bus adds 13 seconds to the run time while each alighting passengers adds 6.5 seconds. These three numbers are slightly higher than the regular numbers reported in previous research. This is due to the absence of a dwell time variable in the Metro Transit data. Accordingly, the time associated to acceleration, deceleration, door opening and door closing is included in the actual stops, boardings, and alightings variables. The squared terms for boardings and alightings indicate that the time associated with passenger boarding and alighting decreases with each additional passenger. For example, the first passenger boarding the bus at a stop takes 13 seconds to board; the second passenger boarding the bus will take slightly less time (because they have gotten their fare ready while

DOI: 10.1002/atr

the first passenger was boarding, etc.). Using the lift during a trip adds 67 seconds, while keeping all other variables at their mean values.

The average passenger load on the bus decreases the travel time by 0.34 seconds. If the bus is delayed at the first stop run time is expected to increase by 0.21 seconds for each second of delay, while the headway delay at the first stop adds 0.028 seconds of run time for each second of delay. Finally, drivers' experience has a statistically significant negative effect on run time with a value of 0.34 for each year of experience while keeping all other variables at their mean values.

4.2.2. Run time deviation

The run time deviation model (R^2 of 0.07) has a relatively large sample size; furthermore the variance in run times and lengths of the different time point segments this model is acceptable to be reported. The low R^2 value is not an issue of concern since we are mainly interested in understanding the causes of deviation from run time along the studied route. In the remaining section of the interpretation of the models we will mainly concentrate on interpreting the statistically significant variables that have higher magnitude and/or policy relevance. For each scheduled stop run time is expected to deviate from schedule by 0.9%. On average there are six scheduled stops per time point segment meaning that a deviation of 5.4% is expected, which can be translated to 16 seconds of delay per trip per segment. The distance traveled along the studied segment is found to have a statistically significant negative effect on run time deviation. For each kilometer traveled along the segment run time deviation is expected to decline by 6%. Run time deviation during the PM peak is found to be 5% more than the off-peak period. This indicates that PM peak run time is usually behind schedule. For each actual stop being made along the studied segment run time deviation is expected to increase by 1%. Each boarding adds 0.4% to run time deviation, while each alighting adds 0.2%. Each lift activity along the studied segment adds 24% to run time variation. Finally for each second of delay at the first stop in the time point segment, run time deviation is expected to increase by 0.1%. This means that if a time point segment has a scheduled run time of 310 seconds and the bus arrived 20 seconds delayed at the first stop, run time is expected to deviate from schedule by 30 seconds at the end of the segment adding 10 more seconds of delay compared to the beginning of the segment.

4.2.3. Headway deviation

The headway deviation model (R^2 of 0.44) revealed that majority of the studied variables have a statistically significant effect on headway deviation. In this model, lift activity has by far the strongest effect, increasing headway deviation by 3%. This model suggests that headway is well sustained along the studied route, which indicates consistency in the amount of delay along the consecutive trips. The buses are delayed in terms of run time yet they are maintaining the scheduled headways.

4.2.4. Coefficient of variation run time

Finally, the CV of run time model (R^2 of 0.52) revealed that distance traveled along each time point segment is found to have a statistically and significant negative effect on run time variation. Accordingly, designing routes with longer distances between time points is recommended to decrease the variability in run time. The variability in run time is larger for buses traveling westbound (away from downtown) relative to those traveling eastbound (towards downtown). Morning peak buses experience higher levels of variability in run time compared to buses running during the off peak time period. A 1% increase in the variability of the number of actual stops being made leads to a 5% increase in the variability of the run time between time points, while keeping all other variables at their mean values. The variance in the passenger load adds 11% in the variability of the run time. On the other hand, the variance in the delay at the beginning of the segment is found to have a statistically significant negative effect on run time variation. Also a 1% variation in drivers' experience leads to 5% decline in the run time CV.

5. CONCLUSIONS AND RECOMMENDATIONS

Transit agencies are increasing realizing the merits of collecting and analyzing data that automatically record the location of buses as a means to enhance service quality. In particular, several agencies are

DOI: 10.1002/atr

employing AVL technology to aid understanding such matters. This research focuses on AVL and APC data collected along Route 17, traversing the western suburbs to downtown Minneapolis. Currently, this route is served by 28 different patterns of bus service. The multiple trip patterns make service evaluation at the route or trip pattern level difficult. Our research presents methods to analyze performance of this route at two levels of analysis, the trip-pattern and the trip-time point segment. We conducted statistical analysis at the time point segment level, while calculations based on observed run times were derived at the trip-pattern level. We recommend that the number of patterns serving this route be reduced. Our examination of two select trip patterns shows that in addition to changes in the number of patterns serving Route 17, it may be important to consider scheduling changes. The scheduled run times for both the AM peak (east-bound) and PM peak (west-bound) trip patterns examined in this paper were shown to be 7% shorter than the median observed run times and had insufficient layover/recovery time scheduled after their last stops. We therefore recommend increasing recovery time for the existing patterns.

It was also clear that only 50% of the scheduled stops were used in both analyses. Revisiting the number of scheduled stops and reevaluating the spacing between stops could possibly lead to substantial savings in run time and run time deviations. Each scheduled stop adds 0.9% to the schedule deviation; when translated to seconds per trip segment, this equals approximately 3 seconds of additional run time. Since not all stops are used, as was made clear from the route and the time point segment analyses, we recommend consolidating bus stops.

The run time model at the trip time point segment level of analysis follows the transit operations theory in a manner that data add confidence and reliability to the data being used. For example, run time is longer at the end of the pattern even though the distance traveled might be the same. Also, delay at the beginning of the segment increases run time and the amount of delay at the end of the segment, which was reflected in the run time deviation model. It is important to note that TSP was not implemented during the data collection period and also information related to signal coordination was not present. Knowledge of traffic signal location and its cycle can yield to better models, yet we are confident about the generated models since they are comparable to previous research.

In addition to the scheduling problems at the route level addressed above, Route 17 is facing several schedule issues at the time point segment level that require revision, especially during the PM peak. According to this analysis, the run times assigned to segments along this route are not sufficient and revisions to the schedules for this route are a must. The models presented in this paper show that run time, run time deviation, and headway deviation are affected by almost all the same variables. Accordingly, schedulers should consider all the variables introduced in this analysis when preparing schedules – a difficult task indeed.

One other strategy to address some schedule problems includes assigning more experienced bus drivers to Route 17. The experience of drivers affects run time, headway deviation, and run time variation. Although this is not a strategy that is possible through the current route assignment policies at Metro Transit, it is recommended that experienced drivers be assigned to Route 17 in the future.

Finally, in order to conduct this analysis, Metro Transit agreed on directing APC equipped buses to serve this route. We recommend equipping as much of the Metro Transit bus fleet with APC; generating similar research without having sufficient APC information is not possible. This research demonstrates the advantages of analysis based on such data applied analysis that can be used to directly inform performance related issues for Metro Transit in future planning.

ACKNOWLEDGEMENTS

This research has been funded by Minnesota Department of Transportation (Mn/DOT). The research team would like to thank Wayne Babcock, Janet Hopper, Gary Nyberg, and Kevin Sederstrom from Metro Transit for directing several APC equipped buses to the studied route to enable the success of this project, supporting technical advice at various stages in the project, and for providing the data being used in the study. Also acknowledgments should go to Sarah Lenz and Nelson Cruz at Mn/DOT for their help and support throughout the project. In addition the authors would like to thank Prof. Jim Strathman, Portland State University for reviewing the statistical models.

DOI: 10.1002/atr

REFERENCES

1. Volpe National Transportation Systems Center. *Advanced Public Transportation Systems Deployment in the United States: Year 2004 update*; Federal Transit Administration, US Department of Transportation: Washington DC, 2005.
2. Furth P, Muller T. Service reliability and hidden waiting time: insights from automatic vehicle location data. *Transportation Research Record* 2006; **1955**:79–87.
3. Crout DT. Accuracy and precision of TriMet's Transit Tracker system. *Paper Presented at the Transportation Research Board 87th Annual Meeting*, 2006.
4. Schweiger CL. *Real-Time Bus Arrival Information Systems*; Transportation Research Board: Washington, DC, 2003.
5. Boyle D. *Fixed-Route Transit Ridership Forecasting and Service Planning Methods*; Transportation Research Board: Washington, DC, 2006.
6. Kimpel TJ, Strathman JG, Griffin D, Callas S, Gerhart RL. *Automatic Passenger Counter Evaluation: Implications for National Transit Database Reporting (no. PR124)*; Portland State University, Center for Urban Studies: Portland OR, 2002.
7. Kimpel TJ, Strathman JG, Griffin D, Callas S, Gerhart RL. Automatic passenger counter evaluation: implications for transit database reporting. *Transportation Research Record* 2003; **1835**:93–100.
8. Strathman JG. *Tri-Met's Experience with Automatic Passenger Counter and Automatic Vehicle Location Systems*; Center for Urban Studies, Portland State University: Portland OR, 2002.
9. Strathman JG, Dueker KJ, Kimpel TJ, Gerhart RL, Callas S. Evaluation of transit operations: data applications of Tri-Met's automated bus dispatching system. *Transportation* 2002; **29**:321–345.
10. Strathman JG, Dueker KJ, Kimpel TJ, *et al*. Service reliability impacts of computer-aided dispatching and automatic location technology: a Tri-Met case study. *Transportation Quarterly* 2000; **54**(3):85–102.
11. Strathman JG, Dueker KJ, Kimpel TJ, *et al*. Automated bus dispatching, operations control, and service reliability. *Transportation Research Record* 1999; **1666**:28–36.
12. Strathman JG, Kimpel TJ, Dueker KJ, Gerhart RL, Callas S. Bus transit operations control: review and an experiment involving Tri-Met's automated bus dispatching system. *Journal of Public Transportation* 2001; **4**:1–26.
13. Hammerle M, Haynes M, McNeil S. Use of automatic vehicle location and passenger count data to evaluate bus operations: experience of the Chicago Transit Authority, Illinois. *Transportation Research Record* 2005; **1903**:27–34.
14. Carter A. GPS keeps transit agencies on track. *Metro* 2002; **98**(3):32–37.
15. Mazloumi E, Currie G, Sarvi M. Assessing measures of transit travel time variability and reliability using automated vehicle location data. *Paper Presented at the 87th Transportation Research Board Annual Meeting*, 2008.
16. Pangilinan C, Wilson N, Moore A. Bus supervision deployment strategies and use of real-time automated vehicle location for improved bus service reliability. *Paper Presented at the 87th Transportation Research Board Annual Meeting, Washington DC*, January, 2008.
17. Turnquist M, Blume S. Evaluating potential effectiveness of headway control strategies for transit systems. *Transportation Research Record* 1980; **746**:25–29.
18. Abkowitz M. *Transit Service Reliability (No. UMTA/MA-06-0049-78-1)*; USDOT Transportation Systems Center and Multisystems, Inc: Cambridge, MA, 1978.
19. Kimpel TJ. Time point-level analysis of transit service reliability and passenger demand. Unpublished Doctor of Philosophy in Urban Studies, Portland State University, Portland, OR. 2001.
20. Levinson H. *Supervision Strategies for Improved Reliability of Bus Routes (Synthesis of Transit Practice No. 15)*; Transportation Research Board: Washington DC, 1991.
21. Turnquist M. Strategies for improving reliability of bus transit service. *Transportation Research Record* 1981; **818**:7–13.
22. Abkowitz M, Engelstein I. Methods for maintaining transit service regularity. *Transportation Research Record* 1984; **961**:1–8.
23. Abkowitz M, Tozzi J. Research contributing to managing transit service reliability. *Journal of Advanced Transportation* 1987; **21**(spring):47–65.
24. El-Geneidy A, Strathman J, Kimpel T, Crout D. The effects of bus stop consolidation on passenger activity and transit operations. *Transportation Research Record* 2006; **1971**:32–41.
25. Furth P, Rahbee A. Optimal bus stop spacing through dynamic programming and geographic modeling. *Transportation Research Record* 2000; **1731**:15–22.
26. Saka AA. Model for determining optimum bus-stop spacing in urban areas. *Journal of Transportation Engineering* 2001; **127**(3):195–199.
27. Strathman JG, Hopper J. Empirical analysis of bus transit on-time performance. *Transportation Research Part A* 1993; **27**(2):93–100.
28. Koenig JG. Indicators of urban accessibility: theory and application. *Transportation* 1980; **9**:145–172.
29. Murray A, Wu X. Accessibility tradeoffs in public transit planning. *Journal of Geographical Systems* 2003; **5**(1):93–107.
30. Abkowitz M, Engelstein I. Factors affecting running time on transit routes. *Transportation Research Part A* 1983; **17**(2):107–113.
31. Guenthner RP, Sinha KC. Modeling bus delays due to passengers boardings and alightings. *Transportation Research Record* 1983; **915**:7–13.

DOI: 10.1002/atr

32. Levinson H. Analyzing transit travel time performance. *Transportation Research Record* 1983; **915**:1–6.
33. Furth P. *Using Archived AVL-APC Data to Improve Transit Performance and Management*; Transportation Research Board: Washington, DC, 2006.
34. Kittelson & Associates. *Transit Capacity And Quality Of Service Manual*; US Department of Transportation: Washington DC, 2003.
35. Bertini RL, El-Geneidy AM. Modeling schedule recovery processes in transit operations for bus arrival time prediction. *Journal of Transportation Engineering* 2004; **130**(1):56–67.
36. Dueker KJ, Kimpel TJ, Strathman JG, Callas S. Determinants of bus dwell time. *Journal of Public Transportation* 2004; **7**(1):21–40.
37. Guenthner RP, Hamat K. Transit dwell time under complex fare structure. *Journal of Transportation Engineering* 1988; **114**(3):367–379.
38. McKnight CE, Levinson HS, Ozbay K, Kamga C, Paaswell RE. *Impact of Congestion on Bus Operations and Costs (No. FHWA-NJ-2003-008)*; Region 2 University Transportation Research Center: Trenton, NJ, 2003.
39. Rodriguez D, Ardila A. An empirical exploration of bus travel time and dwell times in highly competitive exclusive busway. *Journal of Public Transportation* 2002; **5**(1):39–60.
40. Shalaby A, Farhan A. Prediction model of bus arrival and departure times using AVL and APC data. *Journal of Public Transportation* 2004; **7**(1):41–61.
41. Furth P, Hemily B, Muller T, Strathman J. *Uses of Archived AVL-APC Data to Improve Transit Performance and Management: Review and Potential (TCRP Web Document No. H-28)*; Transportation Research Board: Washington DC, 2003.

DOI: 10.1002/atr