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Using Archived ITS Data to Improve Transit Performance and Management

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The widespread implementation of automated vehicle location systems and automatic passenger counters in the transit industry has opened new venues in transit operations and system monitoring. Metro Transit, the primary transit agency in the Twin Cities, Minnesota region, has been testing various intelligent transportation systems (ITS) since 1999. In 2005, they fully implemented an AVL system and partially implemented an APC system. To date, however, there has been little 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 data from the location systems of buses running on an example cross-town route to conduct a microscopic analysis to understand reasons for performance and reliability issues. 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. The methodology includes multiple approaches to display ITS data within a GIS environment to allow visual identification of problem areas along routes. The methodology also uses statistical models generated at the time point segment and bus route level of analysis to demonstrate ways of identifying reliability issues and what causes them. The analytical models show that while headways are being maintained, schedule revisions are needed to in order to improve run time. Finally, the analysis suggests that many scheduled stops along this route are underutilized and recommends consolidation them.

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Using Archived ITS Data to Improve Transit Performance and Management

Final Report

Prepared by:

Ahmed El-Geneidy
Jessica Horning
Kevin J. Krizek

Active Communities/Transportation (ACT) Research Group
Hubert H. Humphrey Institute of Public Affairs
University of Minnesota

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Executive Summary

In the past, measuring transit performance was very difficult and collecting the data necessary to evaluate transit systems was very costly. From the service planning perspective, a large number of employees were initially needed to obtain a small amount of data. Agencies often had to make strategic decisions regarding the amount of money to budget for data collection to support internal decision making, and many agencies chose to direct their funds toward other issues, such as providing more service, rather than data collection. Recently, as a result of the widespread implementation of intelligent transportation systems (ITS) and advanced public transit system technologies (APTS), data collection is no longer a limiting factor. Instead, there is concern relating to how we can meaningfully analyze the data these technologies make available and use it to create information relevant for service planning and control.

Metro Transit, the local transit authority in Minneapolis-St. Paul, MN, has implemented an APTS, which they have been testing since 1999. Metro Transit utilizes the data obtained from the APTS for live transit operations through its transit management center to identify early and delayed buses and apply some strategic decisions in the field to address such problems. Metro Transit also archives this information for future research that can help in improving its operations and planning process. This research utilizes this archived ITS data to introduce and explore various research methodologies that can help Metro Transit in improving service reliability, schedule adherence, and on time performance along Route 17. This research introduces a methodology on how various performance measures and indicators can be obtained from the archived ITS data. The methodology includes multiple approaches to displaying ITS data within a GIS environment to allow visual identification of problem areas along routes. The methodology also uses statistical models generated at the time point segment and bus route level of analysis to demonstrate ways of identifying reliability issues and causalities of such problems. The generated models have shown that schedule revisions are needed to Route 17 in terms of running time. Meanwhile, it is clear that headways were sustained over the course of the study. To conduct this analysis, Metro Transit agreed on directing APC equipped buses to serve this route. It is recommended that equipping the entire Metro Transit fleet with APC should be considered since generating similar research without having sufficient APC information is not possible. Finally, it is clear from the analysis that many scheduled stops along this route are underutilized and revisions in stop spacing, accompanied by careful consolidations are recommended.

Chapter 1: Introduction

The widespread implementation of automatic vehicle location (AVL) and automatic passenger counters (APC) in the transit industry has opened new venues in transit operations and system monitoring. Metro Transit, the local transit authority in the Twin Cities region, has been testing various intelligent transportation systems (ITS) since 1999. Metro Transit fully implemented an AVL system and archiving system and partially implemented an APC system in 2005. This research documents the first hand experience of using these systems to analyze the performance of a problematic bus route (Route 17) in the Metro Transit system. 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. Figure 1 is a map showing Route 17.

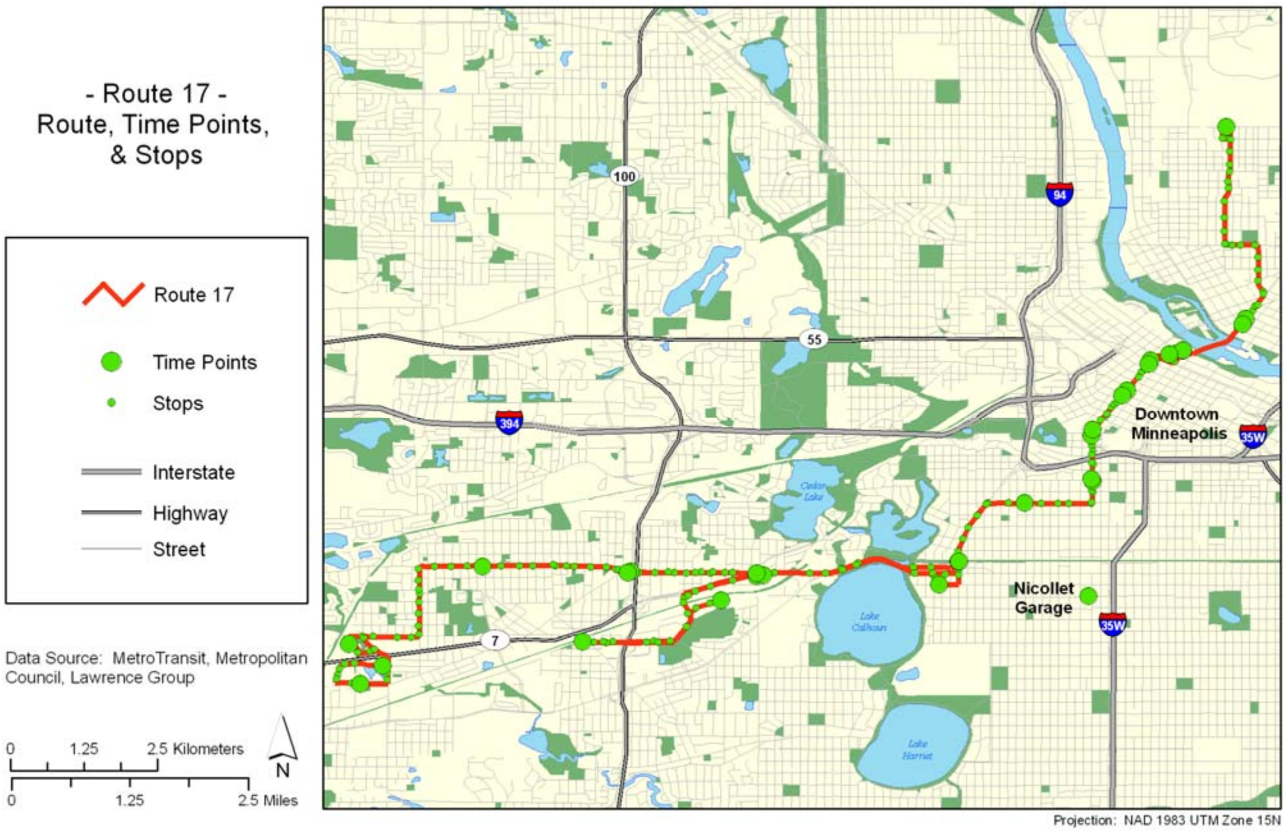

Figure 1: Route 17

We use the archived AVL and APC data from buses running on Route 17 between September 20 and December 1, 2006 to conduct a microscopic analysis to understand reasons for performance and reliability problems along this route being raised by the Metro Transit personnel. The research team generated a series of running time, schedule adherence and reliability models at both the time point segment and route level of analysis to help in understanding the factors causing the reliability and performance decline along this route, especially during the PM peak. These models were also used to generate a methodology that Metro Transit can use in the future when analyzing other bus routes.

This work expands upon previous research on transit performance by taking a new approach to understanding the problem of service reliability. While previous studies have primarily relied upon presentation of summary statistics to identify changes in performance, this research utilizes more detailed statistical analysis to understand the reasons for decline in service reliability. The statistical models presented in this report 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 preferable to that taken by earlier studies 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 will also assist planners and managers to develop specific strategies to improve service reliability, which Furth and Muller (2006) suggest may be a more efficient and cost-effective way to improve rider satisfaction than increasing service frequency.

This report is composed of four parts. Chapter 2 contains a comprehensive review of the literature on transit performance monitoring and the effects of transit service reliability on transit demand. This chapter also includes definitions of the terms used throughout this report and presents several case studies of how other agencies have utilized archived ITS data to monitor and improve transit operations and performance. Chapter 3 describes the methodology, data, and statistical analysis methods used to analyze the archived ITS data obtained for Route 17. This methodology includes an explanation of how the research team identified the appropriate statistical models for use in measuring running time and service reliability along the studied route. Chapter 4 presents several visualizations of the archived Route 17 data and includes the results of the statistical models developed for this route. Finally, Chapter 5 summarizes the findings of this study and makes several recommendations on how these findings can be used to improve the performance of Route 17 specifically and on how the methodology developed in this study can be applied to other routes by Metro Transit or by other agencies to improve transit operations and performance.

Chapter 2: Background

ITS Overview and Case Studies

Over the past decade, the Twin Cities and many other metropolitan areas have experienced population growth, large increases in traffic congestion, and changes in household size and distribution of employment. These changes have created many challenges for public transit agencies, which must develop long- and short-term strategies to adapt to changing conditions and provide reliable transit service at a reasonable cost to both the agency and users. Until recently, it was very difficult and costly to collect the necessary data to measure transit performance. A large number of employees were needed to obtain a small amount of data and transit agencies often had to make strategic decisions regarding whether to spend available dollars to expand services or for data collection to support internal decision making. Fortunately, the recent implementation of ITS and advanced public transit systems (APTS) means that data collection is no longer an issue. AVL systems use GPS to record the location of buses at various locations along the trip and APCs record the number of passengers boarding and alighting at each stop. This technology provides transit planners with an abundance amount of data that can be used for a variety of applications such as service planning and control and determining transit performance and level-of-service (LOS) measures.

Transit agencies around the world and especially in the United States have started to implement various ITS technologies to assist them in managing their systems. As of 2000, at least 88 transit agencies in the United States had operational AVL systems in place, and an additional 142 agencies were planning to implement AVL systems. At the same time, 339 transit agencies also used automated transit information systems or had plans for such systems (Schweiger 2003; Crout 2006). Although the data collected by these systems is fairly similar, the ways and extents to which it has been used vary greatly from agency to agency. According to TCRP Synthesis 66, despite the availability of ITS data the majority of transit agencies continue to rely largely on professional judgment and “rules of thumb” to drive forecasting and other decision-making processes (Boyle 2006). On the other hand, several transit agencies have tested the usefulness of ITS data in a variety of applications and utilize the data extensively.

In Portland, Oregon, ITS technologies were first implemented in 1997 and have been extensively evaluated from an empirical research standpoint since implementation. The research has focused mainly on bus dispatch system (BDS) evaluation, system performance, APC accuracy, TSP implementation, and many other related topics (Strathman, Dueker et al. 1999; Strathman, Dueker et al. 2000; Strathman, Kimpel et al. 2001; Kimpel, Strathman et al. 2002; Strathman 2002; Strathman, Dueker et al. 2002; Kimpel, Strathman et al. 2003; Crout 2006). In 1997, the Ann Arbor Transportation Authority (AATA) also implemented an advanced operating system. Analysis of data collected by this system has helped the AATA to increase schedule adherence for departures from transfer points and increase system performance (Hammerle, Haynes et al. 2005). Similarly, in the late nineties the Chicago Transit Authority began installing and operating AVL and APC devices on select buses as part of CTA’s automated vehicle annunciation system (AVAS). With the data collected by this system CTA has confirmed that peak demand and operating times match, evaluated schedule adherence, calculated quality-of-service measures related to on-time performance (i.e. headway regularity), and identified where and why bus bunching occurs and its impact on passengers (Hammerle, Haynes et al. 2005). CTA has more recently begun testing novel applications of its ITS data such as using archived screen messages from the CAD-AVL system to analyze the response times of dispatchers in the control room (Golani 2007). Milwaukee County Transit (MCT) has also used ITS data to improve communications with operators; providing point by point navigation for novice and paratransit operators. In addition to improving communications, MCT was able to reduce the number of off-schedule buses by 40% after the systems enabled them to spot chronic bottlenecks causing delays (Carter 2002).

ITS data has also been used in several cities to develop and test real-time passenger information systems. London's Countdown system, which began operation in early 1990, is the most well known of these systems, and similar systems have now been deployed and studied in Portland, OR; Denver, CO; Seattle, WA; Toronto, Ontario; and other areas (Smith, Atkins et al. 1995; Schweiger 2003; Shalaby and Farhan 2004; Tang and Thankuriah 2006; Crout 2007). These systems assist operators in proactively addressing scheduling issues and improve passenger satisfaction by providing them with accurate travel information. These systems have not been shown to create a significant increase in transit demand/ridership, however.

Metro Transit currently archives a vast amount of ITS data about the characteristics of the existing transit system. However, despite such rich data collection efforts, analysis of this data has not been fully explored. This research represents a comprehensive review of the literature of transit reliability measures and running time modeling. It examines how ITS data has been used to evaluate and improve bus transit reliability in other regions and presents methods that may be useful for the analysis of ITS data in the Twin Cities region.

Transit Service Reliability

As illustrated by the previous examples, one of the primary uses of ITS data is to determine transit service reliability and measure the impact of policy, scheduling, and technology changes on specific routes' level of reliability. However, transit service reliability has been defined in a variety of ways. Turnquist and Blume (1980) define transit service reliability as "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 measure over a period of time. Abkowitz (1978) provides a broader definition of transit service reliability. He defines transit service reliability as the invariability of transit service attributes that affects the decisions of both the users and the operators. Strathman et al. (1999) and Kimpel (2001) relate reliability mostly to schedule adherence, keeping schedule related delays (on time performance (OTP), running time delay, running time variation, and headway delay variation) to a minimum, which agrees with Levinson (1991) and Turnquist (1981). In theory, an increase in transit service reliability should lead to an increase in service productivity, given accurate schedules. Increase in service reliability has also been linked to increases in transit demand for particular routes. For example, a preliminary model developed for urban buses operated by the MTDB in San Diego found that service reliability-related variables overwhelmed demographic and economic variables in predicting ridership (Boyle 2006).

There are differences between reliability measured by agencies, however, and reliability as experienced by passengers. There is wide agreement in the literature regarding the definition of reliability to passengers. A reliable service for a passenger is one that: 1) can be easily accessed by passengers at both origin and destination, 2) arrives predictably, resulting in short waiting time, 3) has a short running time, and 4) has low variance in running time. This means that any change in these factors will be identified as a decline or improvement in reliability from a passenger perspective.

Transit reliability for passengers is strongly associated with transit accessibility, which is the suitability of a system to move people from their origins to their destinations with reasonable costs such as those based on time or distance (Koenig 1980; Murray and Wu 2003). Decline in service reliability subsequently translates into increased cost for transit users. According to Furth and Muller (2006; 2007), user cost has three components: 1) excess waiting time, 2) potential or budgeted travel time, and 3) mean riding time. Accordingly, passengers value minimization and consistency in travel times. Unreliable service results in additional travel and waiting time for passengers (Welding 1957; Turnquist 1978; Bowman and Turnquist 1981; Wilson, Nelson et al. 1992; Strathman, Kimpel et al. 2003). For long headway service routes reliability plays an even more important role, because passengers' perceived costs of using transit are determined by the extreme values of their experience. In an study of service reliability and passenger waiting time, Furth et al. (2006) found that passengers on routes with long headways base their budgeted travel times on the 95th percentile of arrival times for a particular route. Thus, even routes that have only occasional reliability issues are perceived as having a much higher cost to passengers. As a result, service reliability improvements can reduce passengers' perceived cost of using transit as much as more expensive adjustments such as large reductions in headway.

Excessive service unreliability can lead to loss of passengers using the service - especially choice riders - while improvements in reliability can lead to attraction of more passengers. Despite some differences, it is clear that an overlap exists in the understanding of transit service reliability by agencies and passengers. The key difference in the definition of reliability according to passengers and agencies is running time. Passengers consider running time a reliability measure, while agencies consider it an efficiency measure. This gap is gradually being bridged however, as transit agencies and academics increasingly acknowledge the link between running time scheduling, service reliability, and subsequent changes in user cost and demand.

Running Time

Running time is the amount of time it takes a bus to travel along its route. Abkowitz and Engelstein (1984) found that mean running time is affected by route length, passenger activity, and number of signalized intersections. Most researchers agree on the basic factors affecting bus running times (Abkowitz and Engelstein 1983; Guenthner and Sinha 1983; Levinson 1983; Abkowitz and Tozzi 1987; Strathman, Dueker et al. 2000). Table 1 contains a summary of factors affecting running times.

Table 1: Determinants of Bus Running Time

Variables	Description
Distance	Segment length
Intersections	Number of signalized intersections
Bus stops	Number of bus stops
Boarding	Number of passenger boardings
Alighting	Number of passenger alightings
Time	Time period
Driver	Driver experience
Period of service	How long the driver has been on service in the study period
Departure delay	Observed departure time minus scheduled
Stop delay time	Time lost in stops based on bus configuration (low floor etc.)
Headway	Scheduled headway
Headway Delay	Observed headway relative to scheduled
Nonrecurring events	Lift usage, bridge opening etc.
Direction	Inbound or outbound service
Weather	Weather related conditions

Since buses travel with regular traffic, they are affected by the overall dynamics of the transportation system, where changes occur on both regular (i.e. peak hour traffic congestion) and random (i.e. road construction, accidents, special events) bases. These changes influence the amount of time it takes a bus to travel from one stop to another and its ability to adhere to a schedule. Operating a transit service according to schedule helps in gaining the trust of passengers, insures that the system operates efficiently, and is an important measure of transit service reliability. It is important to understand schedule adherence from the perspective of bus running time, since the amount of schedule delay at a given stop is simply the amount of running time delay up to that point. Transit agencies face a hard challenge since the amount of delay caused by the transportation system cannot be controlled for through strategic changes in service. As a result, a large number of service hours at many transit agencies represents non-revenue service in the form of 1)layover or 2) recovery time which is needed to account for stochastic disturbances (Strathman, Dueker et al. 2002).

Optimizing running time is a challenge for all transit agencies, because changes in running time have strong and often conflicting effects on service reliability and total travel time; two main components of user cost. If the primary goal of an agency is to increase service reliability and on-time-performance, they will insert more slack time between stops along a route, increasing total running time. This increases the probability that the bus will arrive at stops early and, with bus holding at timepoints, increases the likelihood of on-time departure; thus, increasing service reliability and theoretically lowering user cost. Unfortunately, this strategy also lowers operating speed and increases riding time, which increases both user and operating costs (Furth 2006). An alternative strategy is to keep running 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 running 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 running time between timepoints equal to the mean observed running time (Kittelson & Associates 2003; Furth 2006). Researchers at the Delft University of Technology in the Netherlands have developed software known as TriTAPT, which uses a semi-automated analysis of “homogenous periods” to examine the feasibility of current running times and to suggest optimal running times and running time periods (Furth 2006). The software also allows users to evaluate scheduled running times for different periods of the day using Muller’s “passing moments” method. This method is most commonly used in the Netherlands, and is, “designed to achieve a high level of reliability and to create an incentive for operators to comply with timepoints by setting route running time at 85-percentile uncontrolled running time (essentially, mean plus one standard deviation), and using 85-percentile completion times as a basis for determining segment-level running time schedules” (Muller and Furth 2000; Furth, Hemily et al. 2003; Furth 2006).

Regardless of what method is used, ITS can play an important role in simplifying the problem of optimizing running times. One of the benefits of networked AVL equipped buses is that they enable transit operators to identify schedule/headway deviations as soon as they occur so that control strategies such as bus holding and expressing can be immediately implemented. According to Furth (2006), “AVL systems can help operators keep to schedule by displaying schedule deviation in real time, by triggering conditional priority at traffic signals, by providing management with a record of operators who habitually depart early, and by providing the archive of operations data needed to create well-tuned schedules.” In addition, several more recent real-time and “user-interactive” running time models have integrated archived and real-time AVL and APC data from specific routes in order to proactively control for regular and random variations in the transportation system when calculating bus running and arrival times, but these methods have not yet been tested on a large scale (Shalaby and Farhan 2004; Jeong and Rilett 2005).

Variance in Running Time

One indicator of deterioration in transit service reliability that can be identified by performance measures is the increase in variance in running time relative to the mean. This variation represents unpredictable service from the standpoint of passengers, since it increases waiting time and in-vehicle time. Running time models are fairly common in the transit literature, while running time variation models tend to be rare. Abkowitz and Engelstein (1984) compared the effects of average running time on the standard deviation of running time. They used mean average running time as a proxy for route characteristics in order to understand how much variance is imposed by the route itself.

Variations in running time associated with signalized intersections are being partially addressed by transit signal priority (TSP), which is a strategy mentioned in several studies that focused on transit service reliability and running time (Sterman and Schofer 1976; Levinson 1983). The most recent of these studies examined trip-level data collected from TriMet's Bus Dispatch System and found that TSP's impact on a variety of transit performance measures, including running time and OTP, are not consistent across routes and time periods, nor are they consistent across various performance measures. The authors believe that benefits of TSP will accrue only as the result of extensive evaluation and adjustment after initial deployment and that an ongoing performance monitoring and adjustment program should be implemented to maximize TSP benefits.

Dwell time and passenger activity variables, such as boarding and alighting rates also contribute to running time variance (Guenthner and Sinha 1983; Levinson 1983; Guenthner and Hamat 1988; Strathman, Dueker et al. 2000; Rodriguez and Ardila 2002; McKnight, Levinson et al. 2003; Bertini and El-Geneidy 2004; Dueker, Kimpel et al. 2004). 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 (Shalaby and Farhan 2004). However, according to previous research, the amount of time associated with each passenger declines with the increase in passenger activity (Dueker, Kimpel et al. 2004). Overall, reductions in dwell, boarding, and alighting time can lead to changes in mean running time and running time variation. Reductions in mean running time are equally important as reductions in the variation in running time, since average running time affects not only system attractiveness, but the overall costs of providing service as well.

Demand and Reliability

There are two general types of people who ride transit. The first are captive riders who do not have other modes to choose from except transit. The second type is people who have access to alternative modes for their activities but they choose transit because it is either convenient, cost efficient, or for other reasons. The factors affecting passengers' decision to use transit versus other modes are affected by several costs including monetary costs (fares), the cost of travel time, cost of access and egress time, effort, and finally the cost of passenger discomfort. The Transit Capacity and Quality of Service Manual (TCQSM) provide a comprehensive approach to understanding the transit trip decision making processes, which includes several transit availability factors. These factors addresses the spatial and temporal availability of service at both ends of the trip (origins and destinations) (Kittelson & Associates 2003). The presence or absence of transit service near origin and destination is found by Murray (2001) to be a major factor in choosing transit as a mode for travel.

Transit demand is also related to the number of potential users along a route (e.g. place of residence, place of work, and various transit amenities such as park and ride or transfer).

Levinson (1985) developed a model to forecast ridership along bus transit routes. His model is based on the following variables: passenger activity, population; employment, travel time, and demand elasticity factors. Levinson estimates bus ridership as a function of car ownership and walking distance to bus stops. Some scholars relate ridership to access, the more accessible the bus stops are the higher the usage (Hsiao, Lu et al. 1997; Polzin, Pendyala et al. 2002). This might not always be the case since ridership depends on additional variables such as service variability and /or socio-demographic information. The variability and frequency of service represents two additional basic factors that affect demand at a stop.

Several studies have contradictory outputs regarding the elasticity of demand for transit. Some studies indicate that average running time increases passenger demand more than other variables (Lago, Mayworm et al. 1981; Rodriguez and Ardila 2002), however this is based on the understanding that most of transit users are captive riders. Other studies indicate that passengers are more sensitive to out of vehicle time (Kemp 1973; Pushkarev and Zupan 1977; Lago and Mayworm 1981; Mohring, Schroeter et al. 1987). Two comprehensive studies regarding the elasticity of demand with respect to fare change found that demand for transit service is inelastic when it comes to changes in price (Goodwin 1992; Oum, Waters II et al. 1992). The value associated to time is usually higher than the fare. Mohring et al. (1987) found the value associated with in vehicle time is around half the equivalent of an hourly wage, while wait time is valued at 2-3 times that of in vehicle time. Domencich, Kraft, and Valette (1968) estimate the elasticities of demand for public transit in relation to all aspects of time and cost. They found that passenger demand will decrease by 3.9% for a 10% increase in travel time, while demand will decrease by 7% for each 10% increase in access, egress, and waiting time. These findings were reported and validated later by Kraft and Domencich (1972) and O'Sullivan (2000).

Conlon, Foote, O'Malley, and Stuart (2001) conducted a study to measure passenger satisfaction after implementation of major changes along a bus route in the Chicago area. The implemented changes led to a decrease in service variation along the studied route. Passengers were satisfied with the service in the areas of running time, waiting time, route dependability, and OTP. It is important to note that wait time is directly related to the size of the amount of headway variation (Hounsell and McLeod 1998). Variation in running time and headway is considered a reliability measure for both passengers and operators. Another recent study used a service quality index to quantify passenger satisfaction with bus service in New South Wales, Australia. This study concludes that running time and fare are the greatest source of dissatisfaction, while frequency of service and seating availability had the largest positive impact on passenger satisfaction. The study indicates that access time to bus stops when combined with the frequency of service are important aspects of reliable service from a passenger perspective (Hensher, Stopher et al. 2003).

Improving Transit Reliability and Performance

Several researchers have outlined methods for improving transit service reliability, including but not limited to: 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 TSP, 5) modifying route design (route length, bus stop consolidation, and relocation), and 6) implementing real-time operation controls and passenger information systems. Since the implementation of APTS, monitoring the transit system and testing which of these policies can lead to an increase in reliability is achievable through various performance measures that can be generated from the archived ITS data. For example, driver behavior can be dealt with through performance monitoring, by providing feedback information to training, and through field supervision.

Enabling field supervisors to take make effective control actions can also improve reliability. A headway-based control such as bus holding at time points is one strategy for increasing transit service reliability by decreasing passenger wait time (Abkowitz and Tozzi 1987). The effectiveness of this policy depends on the nature of passenger activity along routes and route configurations, however. Headway control should be implemented on routes with passengers boarding near the beginning and alightings anywhere from the middle to the end of routes. The savings will be minor or even nonexistent if the passenger patterns are different from what was mentioned above (Abkowitz and Tozzi 1986).

Modifications in route design have been recommended by various researchers as means to improve reliability. One example of this approach is to design shorter routes with fewer stops to decrease overall route complexity (Abkowitz and Engelstein 1984; Strathman and Hopper 1993). However, it should be noted that this approach might lead to an increase in total trip time for some passengers, since they might need to transfer more with shorter routes. Most previous researchers use simulation to demonstrate the effects of bus stop consolidation on service reliability (Furth and Rahbee 2000; Saka 2001). These studies predicted improvements in service reliability and savings in running time following bus stop consolidation.

Recently, Furth et al. (2003) have reviewed the potentials of utilizing such ITS data and outlined future research in this area. Nine agencies were selected by Furth et al. to demonstrate best practices in implementing ITS technologies. Metro Transit 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 enables archiving Advanced Vehicle Location (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 enables the conduction of microscopic analysis and better understanding of the externalities that affects bus service throughout the trip, accordingly, improvements in reliability can be recommended through the analysis of such information.

The transit performance measures and running time models developed by other agencies mentioned above should be used as models by Metro Transit to maximize usage of available ITS data and to improve service reliability. According to these studies, performance measures that can be derived from this data that will likely have the greatest impact on service reliability for Metro Transit passengers and operators are: decreasing running time and headway variation, increasing OTP, and evaluating route design and service timing. These measures can assist Metro Transit to reduce wait time, which passengers value more than other aspects of transit trips, and to increase service reliability, which will attract additional choice transit riders and improve efficiency in overall operations.

Chapter 3: Data and Research Methods

Several transit routes in the Twin Cities have faced decline in ridership and reliability-related problems. An initial meeting was held between the research team and Metro Transit personnel in the spring of 2006. The main agenda in this meeting was to identify a route of special interest to Metro Transit from a performance standpoint to be analyzed by the research team. Route 17 is one of the major routes identified by Metro Transit personnel as a route with reliability and schedule adherence issues that can be used as a prototype to develop a methodology for analyzing other routes facing similar problems. In this Chapter we discuss issues related to the data collected, the unit of analysis, and the research methodology used.

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 is important to note that Route 17 operates along one of the most highly congested corridors in the Twin Cities region (Hennepin Avenue and Lake Street), which makes it 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 this period of time no major weather issues were present (i.e., snow storms) that might have an effect on travel time and schedule adherence.

This data collection process lead to a sample of over 658,000 stop level observations. Unfortunately, utilizing 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. When this occurs the system records both stops as the same regular scheduled stop and assigns the same arrival and departure time to both stops, however, the passenger activity variables (boardings, alightings, passenger load) and odometer readings for both records differ.

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. Table 2 shows a sample of the stop level data obtained from the Metro Transit data archiving system. The stop level data includes 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 time points. Interpolation between time points is not present in the Metro transit data set. Appendix 1 includes a detailed description for each field in the stop level data. Appendix 2 includes a list of variables generated by the research team at the time point level of analysis and the data preparation and cleaning process used for this study.

Table 2: Sample of AVL data

Date	Direction	Driver Experience	Vehicle	Block Number	Bus Stop
9/20/2006	WEST BD	5	0518	347960	7 ST NE & CENTRAL AV NE
9/20/2006	WEST BD	5	0518	347960	CENTRAL AV NE & HENNEPIN AV E
9/20/2006	WEST BD	5	0518	347960	CENTRAL AV & 4 ST SE / UNIVERSITY AV
9/20/2006	WEST BD	5	0518	347960	CENTRAL AV & 2 ST SE
9/20/2006	WEST BD	5	0518	347960	2 AV S & 1 ST / 2 ST S
9/20/2006	WEST BD	5	0518	347960	2 AV S & 2 ST S
9/20/2006	WEST BD	5	0518	347960	2 AV S & WASHINGTON AV S
9/20/2006	WEST BD	5	0518	347960	NICOLLET MALL & 3 ST S
9/20/2006	WEST BD	5	0518	347960	NICOLLET MALL & 4 ST S
9/20/2006	WEST BD	5	0518	347960	NICOLLET MALL & 5 ST S
9/20/2006	WEST BD	5	0518	347960	NICOLLET MALL & 6 ST S
9/20/2006	WEST BD	5	0518	347960	NICOLLET MALL & 7 ST S
9/20/2006	WEST BD	5	0518	347960	NICOLLET MALL & 8 ST S
9/20/2006	WEST BD	5	0518	347960	NICOLLET MALL & 8 ST / 9 ST S
9/20/2006	WEST BD	5	0518	347960	NICOLLET MALL & 9 ST / 10 ST S
9/20/2006	WEST BD	5	0518	347960	NICOLLET MALL & 11 ST S

The 150,635 stop level observations included in this analysis represent data obtained from 2,174 trips during peak and off peak periods traveling in both east and westbound directions. Surprisingly, these trips represent 28 different trip patterns distributed all over the day. A trip pattern is identified as 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. Figure 2 shows the starting and ending stops of these different patterns.

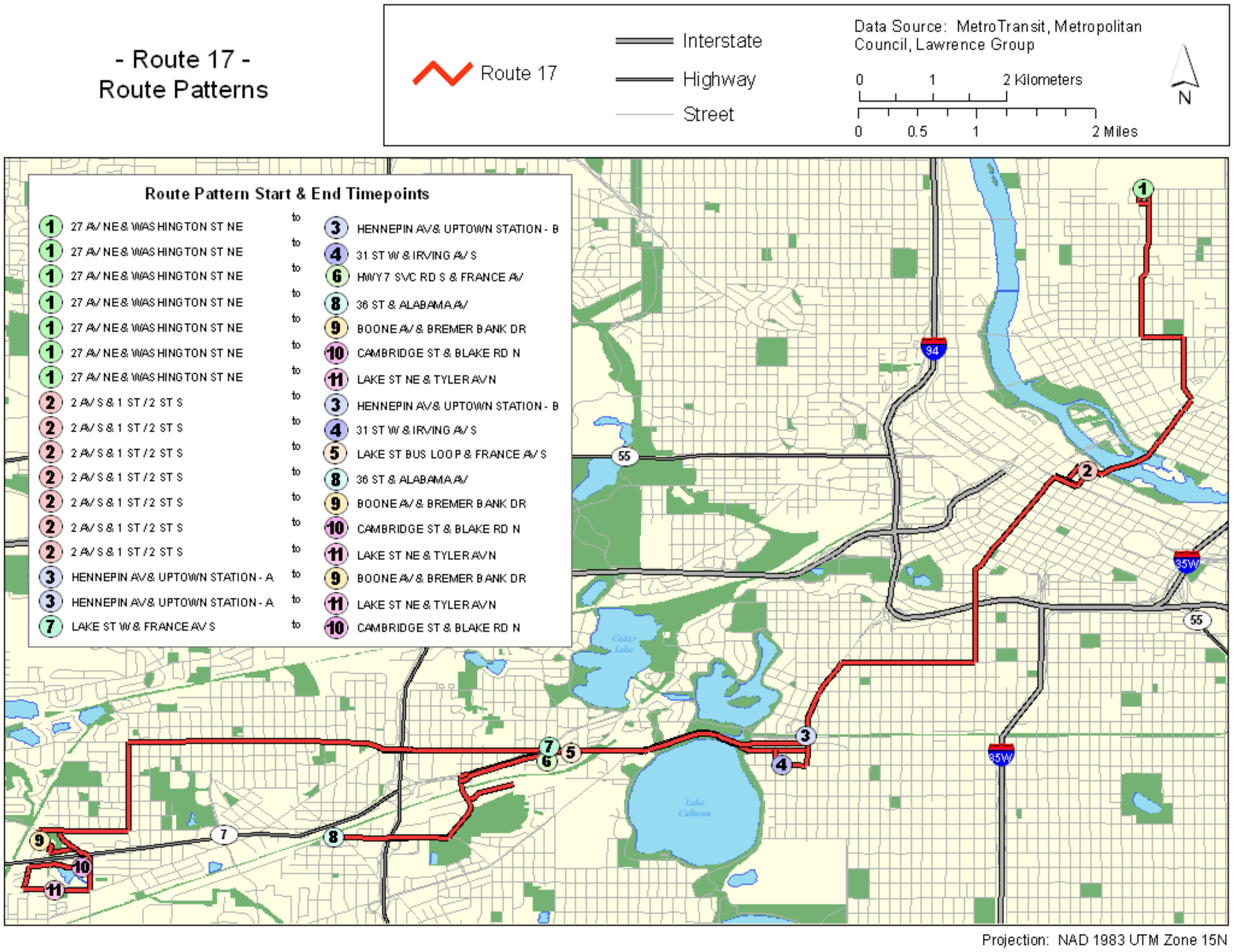

Figure 2: Route 17 trip patterns

Due to the variance in the data caused by the large number of trip patterns and the differences among them this analysis is divided into two main sections, analysis at the route level for a sample of two specific trip patterns and analysis at the time point segment level. A time point segment is identified as the segment between two consecutive time points. Figure 3 shows the differences between the various levels of analysis.

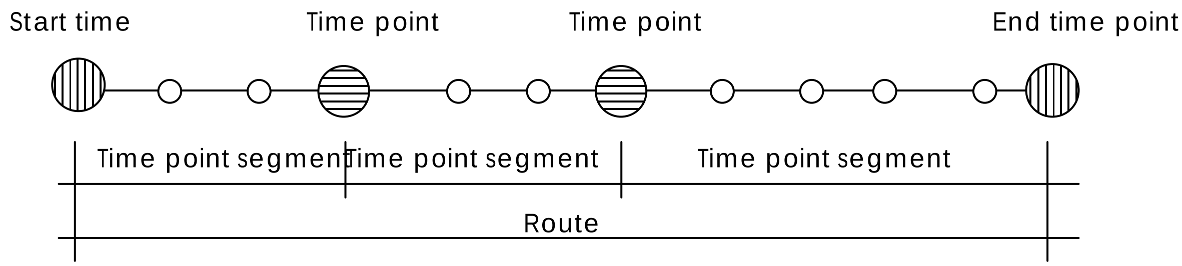

Figure 3: Levels of analysis

The data at the time point segment level of analysis were obtained from various patterns and combined based on the number of stops being served between each two time points. The source data were cleaned and then aggregated to the trip pattern level by summarizing over all of the days in the study period. Summarizing the data under this unit of analysis enabled the generation of a reliable sample (*N = 21,257*) to be used in a statistical analysis, while controlling for the variations introduced by the differences in patterns. It is important to note that the time point sections between the 36th & Alabama stop and the Lake St. & France Ave. stop (served by Route 17F buses) were excluded from the time point section analysis due to sample size issues associated with trips serving this section. Accordingly, 34 different time point segments are used in the analysis as shown in Figure 4.

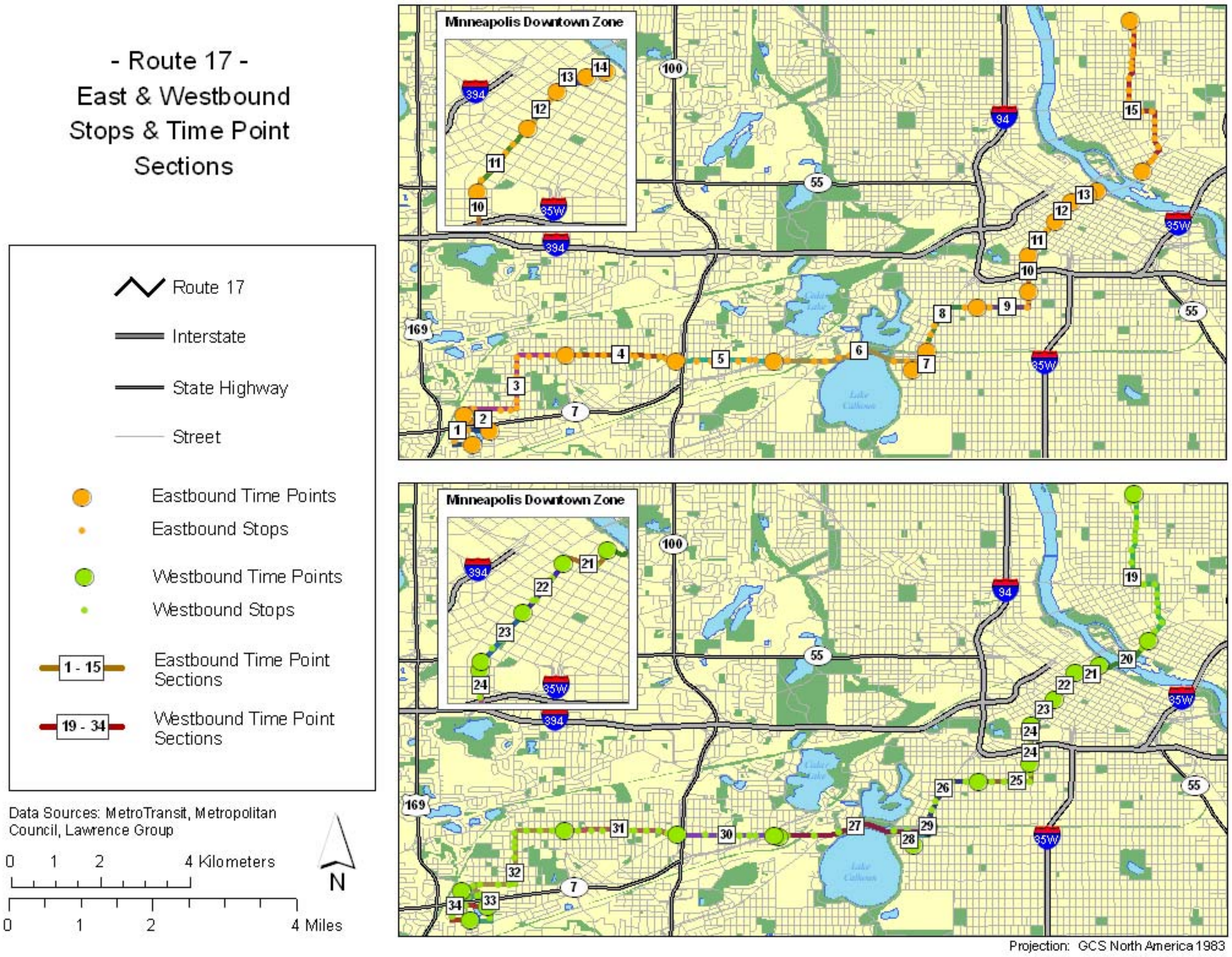

Figure 4: Route 17 study sections

Since Route 17 has 28 different patterns, conducting a generalized route level analysis without controlling for the differences among these patterns would impose a measurement error. It is also important to note that these patterns should be treated as 49 different patterns based on the peak and off-peak classification. Accordingly, analysis at the route level was directed mainly towards specific patterns during the course of the day. The analysis at the route level will enable the generation of different performance measures highlighting major problems related to scheduling and performance.

After cleaning and compiling the Route 17 data for analysis at both the time point segment and trip pattern levels, the research team 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 long period of time for which the Route 17 data was collected. The headway deviation, travel time deviation and coefficient of variation of running time (standard deviation divided by the mean) are used as measures of reliability. The coefficient of variation was calculated based on the time of day along each trip-segment. For example, data obtained from the trip departing at 8:00 from stop A along segment

X in day one is combined with data obtained from the same location and the same time from day two and so on. To ensure robustness of the generated models several sample sizes were tested related to how many days should be included to derive the coefficient of variation. A sample size threshold of 30-trip observations was found to be the point when the model retains its robustness.

Research methodology

The objective of this research is to analyze and understand the performance of Route 17 and generate a methodology that can be replicated by Metro Transit personnel when analyzing routes with similar problems. Two units of analysis are being used, as discussed earlier. The first section of the analysis is conducted at the trip pattern level of analysis to demonstrate a methodology for analyzing running time and scheduling issues. The analysis is limited to specific patterns due to the complexity of the route. The second unit of analysis, which is used in the detailed statistical 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. The specifications of the regression models are as follows:

Running 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, Segment location along the pattern, Segment length} (1)

Running 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, Segment location along the pattern, Segment length} (2)

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, Segment location along the pattern, Segment length} (3)

Coefficient of variation (CV) of running 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, segment location along the pattern, Segment length} (4)

A detailed description of each variable used in the models is presented in Table 3. The first model is used to assess the quality of the data being used in the research and compare 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 the determinants of running time and service reliability. Running time is expected to increase with the number of possible stops in a segment, number of actual stops, lift usage and passenger activity, and decrease 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 running time. Headway deviation and schedule delay measured at the beginning of the time point segment could be either positively or negatively related to running time. If delay is chronic and persistent it is likely to have a positive effect on running time. Alternatively, if delay is circumstantial and operators utilize recovery opportunities, delay could be inversely related to running time.

For the travel time deviation and schedule deviation models, it is hypothesized that the same relationship exists with the independent variables, yet headway delay at the beginning is expected to be more crucial in these model. These models can also be used to assess to what extent schedules are well designed to accommodate the various operating conditions along the route. If several variables are statistically significant with a high magnitude 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 running time will be similarly related to variations in the same set of variables that were specified in the running time model. Driver experience variables are added to account for the variability in the performance of drivers. It is expected that drivers' experience would have a negative effect on running time and reliability measures. A dummy variable for the direction is included in the models to control for directional 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.

Table 3: Variable description

Variable	Description
Running time	The travel time between two consecutive time points
Running time deviation	Actual running time divided by the scheduled running time
Headway deviation end	Actual headway measured at the end of the segment divided by scheduled headway at the end of the segment
CV running time	The coefficient of variation of running 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

Chapter 4: Analysis

Basic Running Time Analysis

Following a methodology developed by Strathman et al. (2002), a route level analysis can be conducted to measure the effectiveness of the schedule in accommodating recovery time. Scheduled running time along any transit route consists of two main components. The first is actual running time and the second is the layover/ recovery time. The scheduled running time is usually set to be equal to the mean or median value of the running time, while the recovery time is set as the difference between the selected benchmark (mean or median running time) and the running time associated to the 95^{th} percentile in the frequency distribution of running time. Using trip level data an analysis can be conducted to compare the actual running time for the entire route to the scheduled running time to identify current scheduling problems. Figure 5 shows a sample of two patterns being selected from Route 17 for the detailed route analysis.

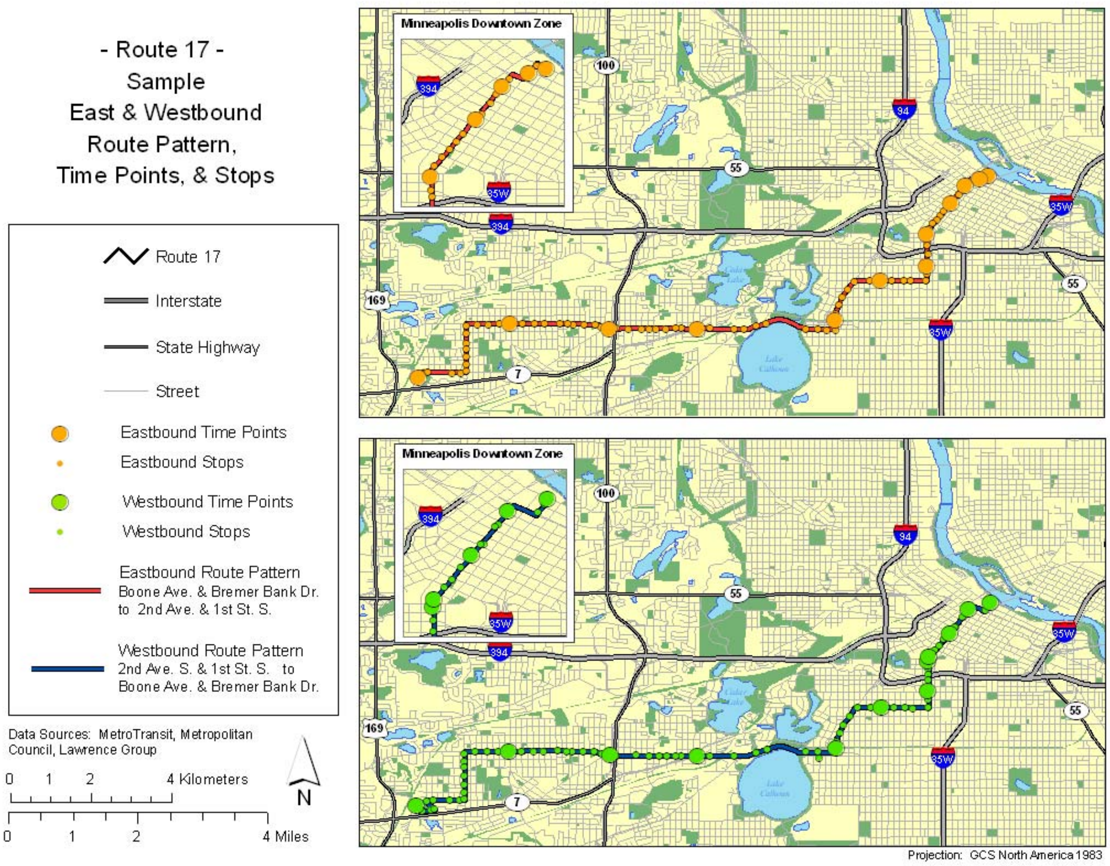

Figure 5: Sample Trip Patterns

The first pattern starts from downtown Minneapolis going west to the suburbs during the PM peak, while 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 stops 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 around 1.2 passengers.

Figures 6 and 7 show the running 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 running time ranged from 42 to 66 minutes with a median value of 51.7 minutes. The median observed running time is 3.6 minutes (7%) longer than the mean scheduled running time of 48 minutes. This 7% difference in the morning peak requires careful revision in the scheduled running time. In addition, the amount of recovery/layover time incorporated into the schedule for this trip pattern requires revision. The observed 95th percentile running 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. This indicates 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 means that the bus might be starting new trips already delayed.

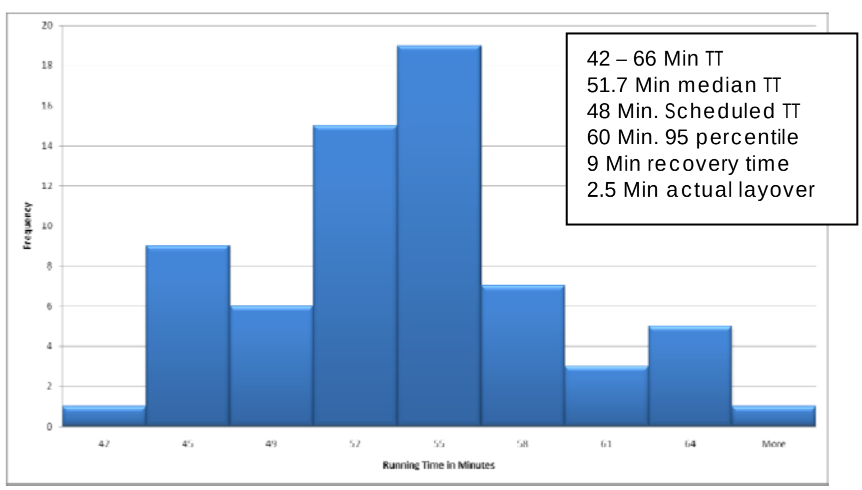

Figure 6: Route 17 run time distribution sample: AM East-bound.

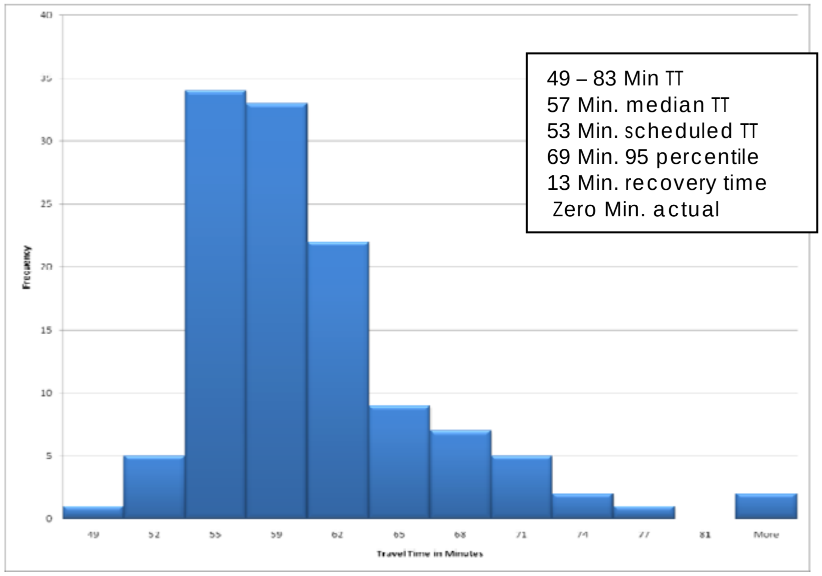

Figure 7: Route 17 run time distribution sample: PM West-bound.

The selected PM peak (West-bound) pattern observed in Figure 7 included 66 trips with running times ranging from 49 to 83 minutes with a median value of 57 minutes. Similar to the first selected pattern, the median observed running time for this pattern is 3.8 minutes (7%) longer than the mean scheduled running time of 53 minutes. The observed 95th percentile running 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.

Statistical analysis

The second analysis that the research team conducted using the Route 17 data is a detailed statistical analysis of the time point segment data. Table 4 includes a list of summary statistics of all variables used in this analysis. Actual running times range between 21 to 8869 seconds. This large range is due to the variance in the lengths of time point sections and several other factors that will appear in the regression model. Running time deviation, which is the actual running time divided by the scheduled running time ranged from 0.18 to 18.48 with a mean value of 1.07. This means that on average actual running time is around 7% longer than the scheduled running 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 running 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 running time ranged between 8% and 57%.

Table 4: Descriptive statistics

	Units	Minimum	Maximum	Mean	Std. Deviation
Running Time	Seconds	21.00	8869.00	312.90	178.83
Running Time Deviation	Percentage	0.18	18.48	1.07	0.42
Headway Deviation at last stop	Percentage	0.01	2.24	1.00	0.11
CV Running Time	Percentage	0.08	0.57	0.18	0.07
Distance	Km	0.27	3.90	1.50	0.96
Number of scheduled stops	Stops	1.00	20.00	6.47	4.60
West-bound	Dummy	0.00	1.00	0.49	0.50
Order of first stop	Dummy	1.00	99.00	40.09	24.21
AM peak	Dummy	0.00	1.00	0.15	0.35
PM peak	Dummy	0.00	1.00	0.23	0.42
Number of actual stops	Number	0.00	17.00	2.18	1.98
Boardings	Passengers	0.00	62.00	3.93	5.45
Boardings square		0.00	3844.00	45.10	142.66
Alightings	Passengers	0.00	51.00	3.82	5.14
Alightings square		0.00	2601.00	40.99	121.07
Lift use	Count	0.00	3.00	0.04	0.21
Average passenger load	Passengers	0.05	76.00	15.03	10.98
Delay at first stop	Seconds	-1671.00	8101.00	-124.63	160.83
Headway delay at first stop	Seconds	-1275.00	8215.00	-2.96	200.42
Driver experience	Seconds	0.00	30.00	7.02	7.17
CV number of actual stops	Percentage	0.20	4.00	0.65	0.51
CV boardings	Percentage	0.32	2.82	0.99	0.50
CV alightings	Percentage	0.30	3.38	0.98	0.56
CV lift use	Percentage	0.00	5.92	2.63	2.36
CV average passenger load	Percentage	0.25	0.91	0.48	0.15
CV delay at first stop	Percentage	-9.29	-0.41	-1.03	0.92
CV headway delay at first stop	Percentage	-151.22	176.98	0.80	33.35
CV driver experience	Percentage	0.44	2.08	0.86	0.41

Table 5 includes the output of the regression models developed for the study.

Note that t-statistics are indicated between parenthesis below each coefficient and statistically significant variables are in bold.

Table 5: Regression model results

Variable	Running Time	Running Time deviation	Headway deviation	CV Running Time
(Constant)	**102.601**	**1.072**	**0.996**	0.059
	(33.59)	**(102.91)**	**(454.82)**	(1.61)
Distance	**68.507**	**-0.066**	**0.003**	**-0.033**
	(31.56)	**(-8.62)**	**(2.06)**	**(2.27)**
Number of scheduled stops	**5.019**	**0.009**	**-0.001**	0.002
	(10.61)	**(5.49)**	**(-4.25)**	(0.52)
West-bound	-0.281	**0.025**	0.000	**0.044**
	(-0.16)	**(4.25)**	(0.36)	**(2.80)**
Order of first stop	**0.173**	**0.001**	**0.000**	**0.001**
	(4.45)	**(6.71)**	**(3.00)**	**(2.79)**
AM peak	**-17.267**	-0.006	0.001	**0.155**
	(-7.27)	(-0.67)	(0.56)	**(3.77)**
PM peak	**37.73**	**0.055**	**-0.011**	0.022
	(18.46)	**(7.68)**	**(-7.28)**	(1.56)
Number of actual stops	**11.269**	**0.010**	**0.001**	--
	(17.02)	**(4.29)**	**(2.46)**	
Boardings	**13.485**	**0.004**	**0.001**	--
	(40.23)	**(6.82)**	**(5.80)**	
Boardings square	**-0.142**	--	--	--
	(-12.52)			
Alightings	**6.599**	**0.002**	**0.000**	--
	(16.64)	**(2.23)**	**(2.27)**	
Alightings square	**-0.043**	--	--	--
	(-2.90)			
Lift use	**67.252**	**0.241**	**0.039**	--
	(17.32)	**(17.62)**	**(13.50)**	
Average passenger load	**-0.34**	0.000	**0.000**	--
	(-4.31)	(-0.99)	**(3.71)**	
Delay at first stop	**0.21**	**0.001**	**0.000**	--
	(31.15)	**(21.40)**	**(3.38)**	
Headway delay at first stop	**0.028**	0.000	**0.000**	--
	(5.27)	(1.35)	**(-96.68)**	
Driver experience	**-0.340**	-0.001	**0.000**	--
	(-3.05)	(-1.57)	**(-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)
R2	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

The running time model has an R-square of 0.59 with almost all variables having a statistically significant effect on running time except for the direction variable. 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 consecutive time points is found to be statistically significant with a positive effect on running time. Running 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 32 miles/hour when all of the other variables in the equation are held at their mean values. For each scheduled stop, 5 seconds is added to travel time. The 5 seconds are added no matter if a stop is made or not. On average, 6 scheduled stops exist along each time point segment, whereas only 3 stops are actually made on average. 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 running time. For example, if we have a pattern with 80 scheduled bus stops, the running time along the first two time points should be faster by 13 seconds compared to the running 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 running 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 running time. Each passenger boarding the bus adds 13 seconds to the running 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, while the second passenger boarding the bus will take slightly less time (because they have gotten their fare ready while 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 running 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 running time for each second of delay. Finally, drivers’ experience has a statistical significant negative effect on running time with a value of 0.34 for each year of experience while keeping all other variables at their mean values.

The running time deviation model had an R square of 0.07. Due to the large sample size and the variance in running times and lengths of the different time point segments this model is acceptable to be reported. Also, the low R square value is not an issue of concern since we are mainly interested in understanding the causes of deviation from running 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 running time is expected to deviate from schedule by 0.9%. On average there are 6 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 running time deviation. For each kilometer traveled along the segment running time deviation is expected to decline by 6%. Running time deviation during the pm peak is found to be 5% more than the off-peak period. This indicates that pm peak running time is usually behind schedule. For each actual stop being made along the studied segment running time deviation is expected to increase by 1%. Each boarding adds 0.4% to running time deviation, while each alighting adds 0.2%. Each lift activity along the studied segment adds 24% to running time variation. Finally for each second of delay at the first stop in the time point segment, running time deviation is expected to increase by 0.1%. This means that if a time point segment has a scheduled running time of 310 seconds and the bus arrived 20 seconds delayed at the first stop, running 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.

The headway deviation model had an R-square of 0.44. The majority of the studied variables were found to 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 in general indicates 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 running time yet they are maintaining the scheduled headways.

Finally, the coefficient of variation of running time model has an R-square of 0.52. Distance traveled along each time point segment is found to have a statistically significant negative effect on running time variation. Accordingly, designing routes with longer distances between time points is recommended to decrease the variability in running time. The variability in running time is larger for buses traveling westbound (going away from downtown) relative to those traveling eastbound (going towards downtown). Morning peak buses experience higher levels of variability in running 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 running 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 running 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 running time variation. Also a 1% variation in drivers' experience leads to 5% decline in the running time coefficient of variation.

Chapter 5: Conclusions and Recommendations

The analysis introduced in this paper highlights several issues related to Route 17 in specific and to transit operations in general. In this research paper we discussed methods for analyzing a transit route at two levels of analysis, the trip-pattern level and time point segment levels. Statistical analysis was conducted mainly at the time point segment level, while calculations based on observed running times were derived at the trip-pattern level. Currently, Route 17 is served by 28 different patterns of bus service, which makes service evaluation at the route or trip pattern level difficult. As a result, it is recommended that the number of patterns serving this route should be reduced. Our examination of two select trip patterns shows that in additional to changes in the number of patterns serving Route 17, scheduling changes may be necessary at the route level. The scheduled running 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 running times and had insufficient layover/recovery time scheduled after their last stops. It is recommended that recovery time be increased.

It was also clear that only 50% of the scheduled stops were utilized in both analyses. A revision to the number of scheduled stops and a reevaluation of spacing between stops can lead to substantial savings in running time and running time deviations. Each scheduled stop adds 0.9% to the schedule deviation, and when translated to seconds per trip segment this equals approximately 3 seconds of additional running time. Bus stop consolidation is one of the policies that are recommended since not all stops are utilized, as was made clear from the route and the time point segment analyses. Stop consolidation is one of the policies that when done carefully has proven to have a substantial effect on running time and running time variation with minor effects on demand.

The running time model generated for this paper using time point segment data adds confidence and reliability to the data being used. The running time model followed the theory discussed earlier in the literature review section. For example, running 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 running time and the amount of delay at the end of the segment, which was reflected in the running time deviation model.

In addition to the scheduling problems at the route level addressed above, Route 17 is facing several schedule problems at the time point segment level that require revision, especially during the pm peak. According to this analysis, the running 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 running time, running time deviation and headway deviation are affected by almost all the same variables. Accordingly, schedulers should consider all the variables being introduced in this study when writing schedules, which will be a difficult task.

In addition to adjusting running and recovery times, one method of addressing some schedule problems may be assigning more experienced bus drivers to Route 17 shifts. Drivers experience seems to have an effect on running time, headway deviation and running 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. It is recommended that equipping the entire or a high percentage of the Metro Transit bus fleet with APC is to be considered since generating similar research without having sufficient APC information is not possible. This research documented a first hand-experience of dealing with archived ITS data at Metro Transit. Although some problems did exist in the data the study shows a great potential for the future usage of such data in generating reliable analyses.

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Appendix A: Field Definitions Raw Data

Date - Date of Event

Route Number - The bus route

Direction - This is the Trip direction, not the actual necessarily the actual direction the bus is facing.

Driver Experience - this is the driver's experience in years, rounded up to the next year for partial years.

Vehicle - This is the vehicle number doing the route. This field may occasionally be unpopulated.

Block Number - This is the block ID number given by SMARTCoM

Trip Number - This is the sequential trip number within a block

Bus Stop - This is the name of the bus stop or time point.

Block Stop Order - This is a sequential number showing which stop number within a trip.

Departure Time - The time the bus departed the stop. **Departure Time** is only recorded if there was a passenger count. This is different from **Actual Departure Time**, which records departure from a time Point.

Latitude - This is the SMARTCoM Latitude measurement. To get actual latitude, divide by 10,000,000.

Longitude - This is the SMARTCoM Longitude measurement. To get actual Longitude, divide by 10,000,000.

Odometer - This is the distance the bus has traveled since start up in hundredths of a mile. A bus odometer will reset if the bus is turned off for 40 or more minutes.

Time Table - This is the schedule version in use. Only important if the data spans over a schedule change.

Pattern - This is the ID for the particular route this trip is taking. There may be many patterns for any given route.

Boarding - The number of passengers that boarded at this stop.

Alighting - The number of passengers that alighted at this stop.

Passenger Load - The current number of passengers on the bus.

Scheduled Time - The time, in seconds after midnight, that the bus was supposed to depart. Only available at time points

Adherence - The adherence, in seconds, of the bus. A negative number is late, and a positive number is early. Only available at time points.

Actual Arrival Time - The time, in seconds after midnight, that the bus arrived at the time point. Only available at time points.

Actual Departure Time - The time, in seconds after midnight, that the bus Departed the time point. Only available at time points.

Dwell - The time, in seconds, that the bus stayed at the time point. Only available at time points.

Lift Cycled? - Whether the lift was cycled at the stop. A null field indicates false, a number indicates true.

Layover? - Whether this stop is a layover or not. This does not indicate Terminals, only layovers where a bus turns around and goes the other direction on the same route.

Bus Type - The bus type. List manufacturer, model, and whether bus is Coach, Low Floor, or Articulated.

Appendix B: Time Segment Travel Time Methodology

In GIS…

1. Created a Route 17 shapefile in ArcGIS using TLG roads and broke this line into sections based on the locations of timepoints (did this separately for east and westbound timepoints because their locations differ).

2. Gave each section a number ID and begin stop and end stop fields containing the names of the timepoints at the beginning and end of the section.

3. Used Hawth's tools to calculate the length of each section (network distance from each timepoint to the next timepoint).

4. Used Hawth's tools to snap the bus stops (excluding timepoints) shapefile to the route 17 shapefile and spatially joined the stops to the route sections to get a count of the number of stops between each set of timepoints (again, did this separately for east and westbound sections and stops)

In Access…

5. Import all route 17 data, save as "route17_ORIGINAL"

6. Created a unique ID for each bus run by concatenating the pattern, direction, run number, trip number, and date fields for each record

7. Replace records with duplicate UniqueID, Bus Stop, and Scheduled Time values with single record with max odometer value, sum of boarding and alighting values, max of passenger load if boarding > alighting or min of passenger load if alighting>boarding

8. Created a crosstab of bus patterns and stops, showing the stop order number of each stop for each pattern.

Example:

pattern3	2 AV S & 1 ST / 2 ST S	2 AV S & 1 ST S	2 AV S & 2 ST S
211850-EAST BD			
211851-EAST BD		58	
212079-WEST BD	1		2
212080-WEST BD	24		25
212081-WEST BD	24		25
212082-WEST BD	24		25
212083-WEST BD	2		3
212084-WEST BD	23		24
212085-WEST BD	1		2
212086-WEST BD	2		3
212087-WEST BD	23		24
212088-WEST BD	1		2
212089-WEST BD	23		24
212090-WEST BD	1		2

9. Queried the crosstab for patterns that serve all of the stops along a section. (For example, section 1 starts at the Lake Street stop, ends at the Cambridge stop, and has 6 stops in between timepoints, so I queried the crosstab for all patterns where the stop order number for the Cambridge stop equals the stop order number for the Lake Street stop plus 7.)

10. Created a series of queries that select the data for each stop along the section (for patterns that serve every stop along that section). These queries also calculate a dummy variable for whether or not the bus actually stopped at the station based on whether or not the departure time field is null.

11. Joined these queries based on the unique ID I created so that I have a table with a row for each bus run with information about each of the stops it did/could make along the section.

12. Created a final data table for each section that includes the following fields:

    UniqueID: The unique ID created to identify each bus run

    Date:

    Direction: (same for all records in a table)

    SectionID: The ID for the timepoint to timepoint section (same for all records in a table)

    Sec_Length: Distance from the first timepoint to the second timepoint (same for all records in a table)

    Stops_Betw: # of stops between the first and second timepoint (same for all records in a table, doesn't include either of the timepoints)

    ActualStop: The # of stops the bus actually made between the first and second timepoint (based on whether or not there was a departure time)

    TotalBoarding: The total number of boardings that occurred between the bus leaving the first timepoint and leaving the second timepoint

    TotalAlighting: The total number of alightings that occurred between the bus leaving the first timepoint and leaving the second timepoint

    DriverExpe: This is the driver's experience in years, rounded up to the next year for partial years.

    Bus Type: The bus type. List manufacturer, model, and whether bus is Coach, Low Floor, or Articulated.

BeginDelay: The schedule adherence, in seconds, of the bus at the first timepoint. A negative number is late, and a positive number is early.

AvgLoad: The average passenger load of the bus between the first regular stop and second timepoint. Buses with an average passenger load of zero are removed from the table.

TravelTime: The travel time, in seconds, between leaving the first timepoint and leaving the second timepoint. Records with negative travel times are removed from the table.

FirstStopOrder: The order of the first timepoint in the pattern's stop sequence.

AMPeak: A dummy variable equal to 1 if the bus departed either timepoint between 6:00-9:00AM, MetroTransit's morning peak period

PMPeak: A dummy variable equal to 1 if the bus departed either timepoint between 3:00-6:30 PM, MetroTransit's evening peak period.

OffPeak: A dummy variable equal to 1 if the bus did not depart either timepoint during the AM or PM peak period.

SchedStart: Scheduled departure time from the first timepoint

ActualStart: Actual departure time from the first timepoint

SchedEnd: Scheduled departure time from the second timepoint

ActualEnd: Actual departure time from the second timepoint

Scheduled Headway first: Scheduled headway measured at the beginning time point.

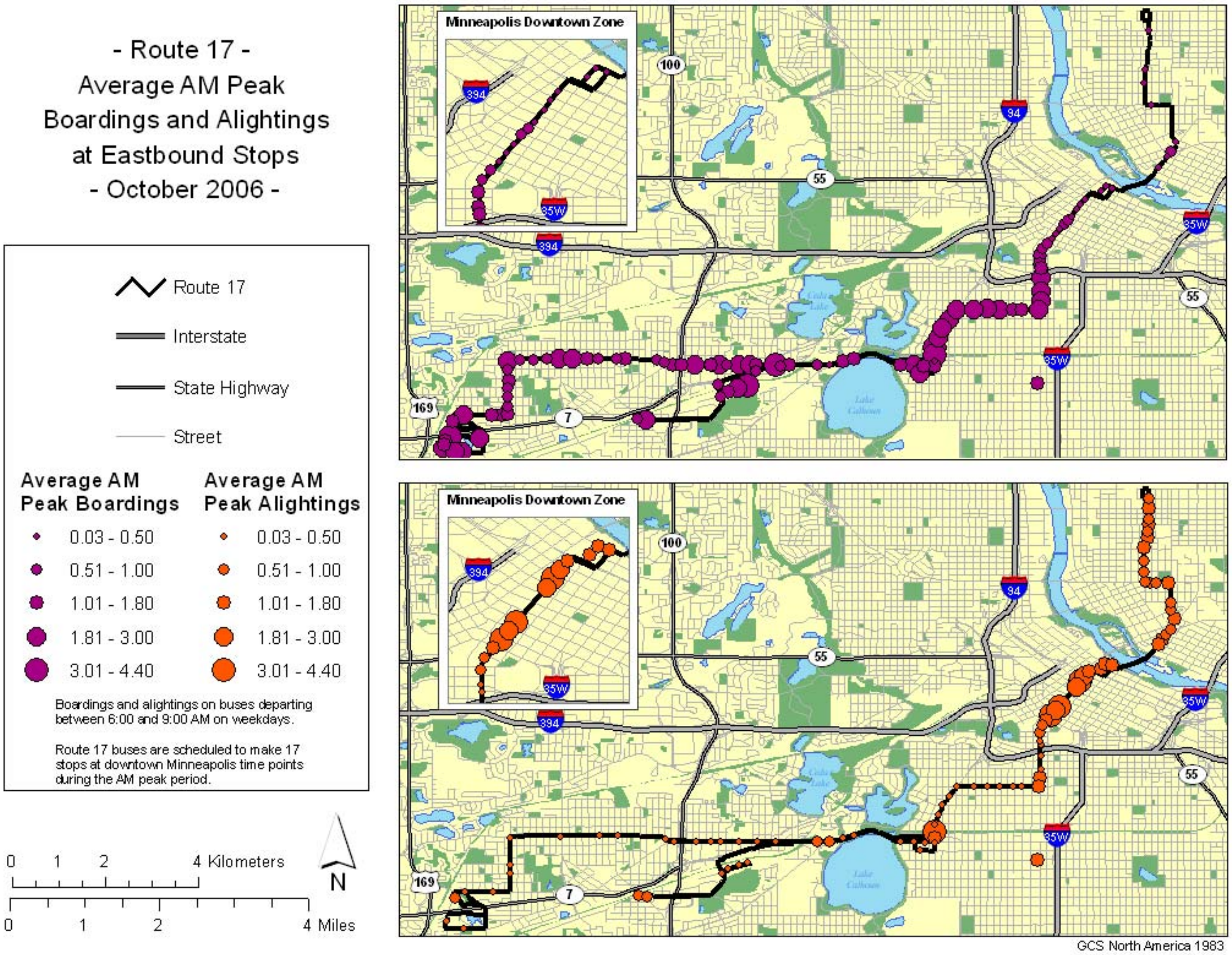
Scheduled Headway end: Scheduled headway measured at the ending time point.

Actual Headway first: Actual headway measured at the beginning time point.

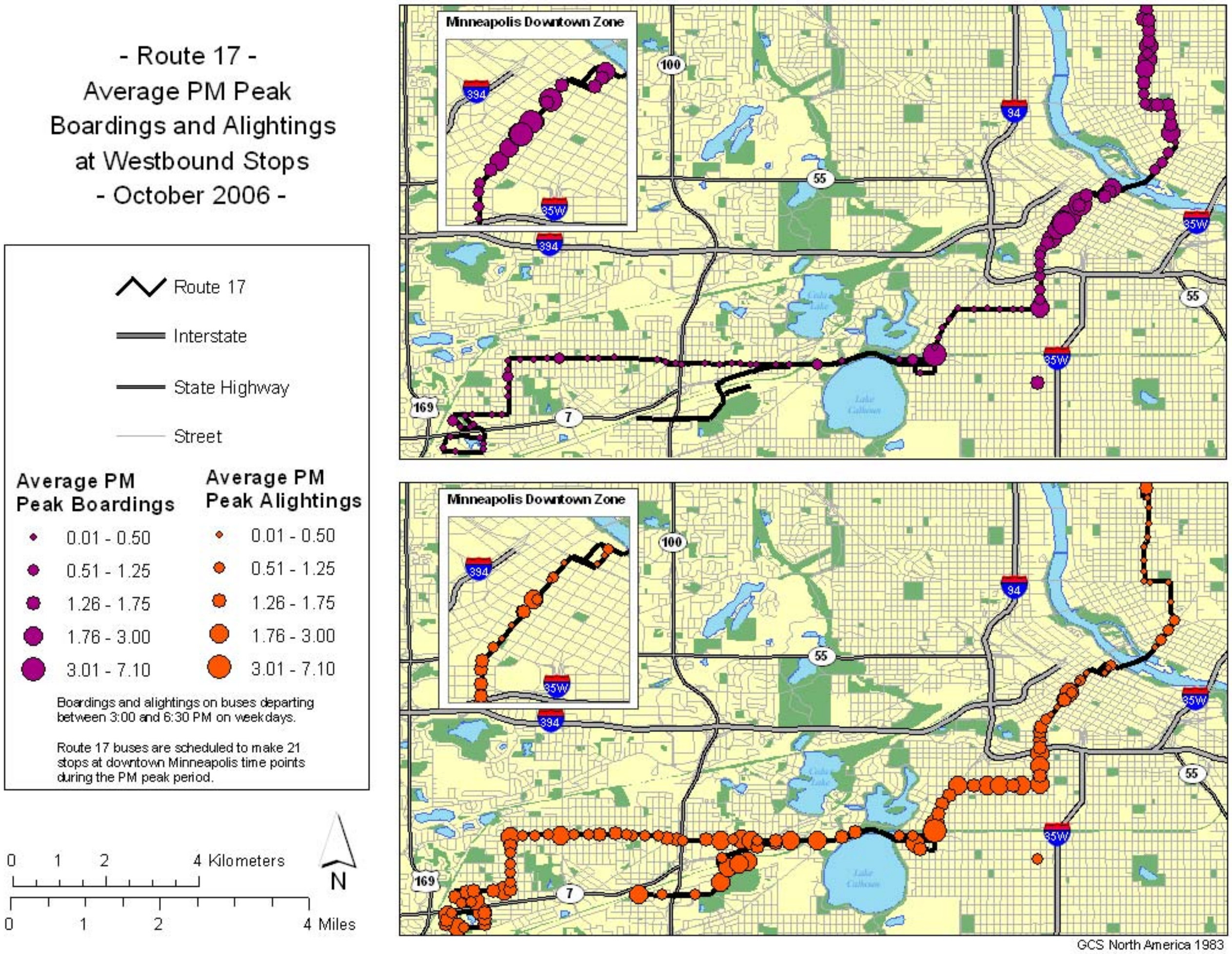
Actual Headway end: Actual headway measured at the ending time point.

Note that headways should be equal to zero when measured for the first trip in the day so the first trip in the day should be deleted from any analysis being done later.

Appendix C: Visualization of archived ITS data



- Route 17 -
Average AM Peak
Boardings and Alightings
at Eastbound Stops
- October 2006 -
Route 17
Interstate
State Highway
Street
Average AM Peak Boardings
0.03 - 0.50
0.51 - 1.00
1.01 - 1.80
1.81 - 3.00
3.01 - 4.40
Average AM Peak Alightings
0.03 - 0.50
0.51 - 1.00
1.01 - 1.80
1.81 - 3.00
3.01 - 4.40
Boardings and alightings on buses departing between 6:00 and 9:00 AM on weekdays.
Route 17 buses are scheduled to make 17 stops at downtown Minneapolis time points during the AM peak period.
0 1 2 4 Kilometers
0 1 2 4 Miles
N
Minneapolis Downtown Zone
394
35W
100
94
55
169
7
Minneapolis Downtown Zone
394
35W
100
94
55
169
7
GCS North America 1983



- Route 17 -
Average PM Peak
Boardings and Alightings
at Westbound Stops
- October 2006 -
Route 17
Interstate
State Highway
Street
Average PM Peak Boardings
Average PM Peak Alightings
0.01 - 0.50
0.51 - 1.25
1.26 - 1.75
1.76 - 3.00
3.01 - 7.10
Boardings and alightings on buses departing between 3:00 and 6:30 PM on weekdays.
Route 17 buses are scheduled to make 21 stops at downtown Minneapolis time points during the PM peak period.
0 1 2 4 Kilometers
0 1 2 4 Miles
N
Minneapolis Downtown Zone
394
35W
100
94
55
169
7
GCS North America 1983

- Route 17 -
Coefficient of Variance
for AM Peak
Boardings and Alightings
at Eastbound Stops
- October 2006 -

Route 17

Interstate

State Highway

Street

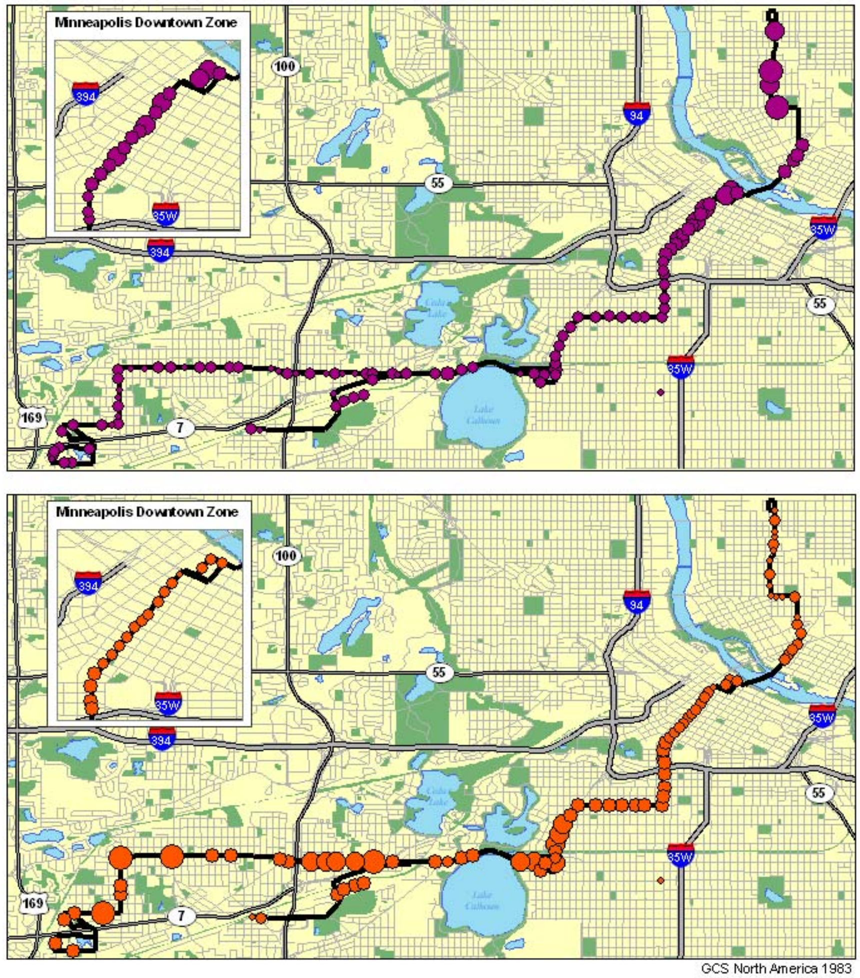
CV for AM Peak Boardings	CV for AM Peak Alightings
0.00 - 0.50	0.00 - 0.50
0.51 - 1.00	0.51 - 1.00
1.01 - 3.50	1.01 - 3.50
3.51 - 7.00	3.51 - 7.00
7.01 - 15.00	7.01 - 15.00

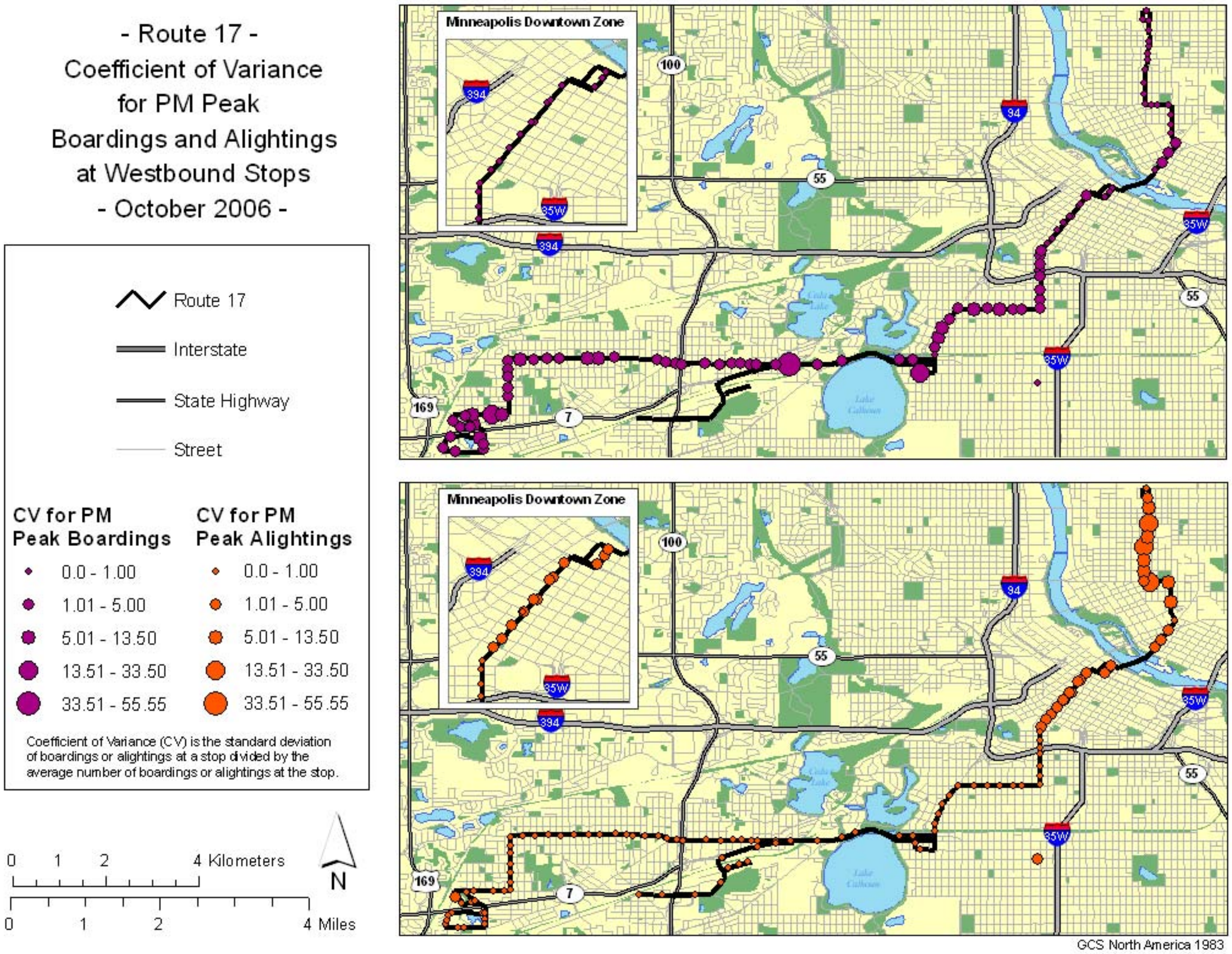
Coefficient of Variance (CV) is the standard deviation of boardings or alightings at a stop divided by the average number of boardings or alightings at the stop.

0 1 2 4 Kilometers

0 1 2 4 Miles

N




- Route 17 -
Coefficient of Variance
for PM Peak
Boardings and Alightings
at Westbound Stops
- October 2006 -
Route 17
Interstate
State Highway
Street
CV for PM Peak Boardings
0.0 - 1.00
1.01 - 5.00
5.01 - 13.50
13.51 - 33.50
33.51 - 55.55
CV for PM Peak Alightings
0.0 - 1.00
1.01 - 5.00
5.01 - 13.50
13.51 - 33.50
33.51 - 55.55
Coefficient of Variance (CV) is the standard deviation of boardings or alightings at a stop divided by the average number of boardings or alightings at the stop.
0 1 2 4 Kilometers
0 1 2 4 Miles
N
Minneapolis Downtown Zone
394
35W
100
94
55
169
7
Minneapolis Downtown Zone
394
35W
100
94
55
169
7
GCS North America 1983