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# Understanding Bus Service Reliability: *A Practical Framework Using AVL/APC Data*

By

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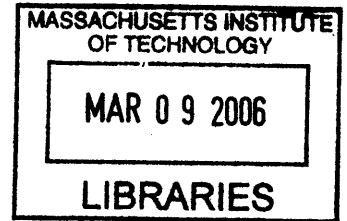
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**BARKER**



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## **ABSTRACT**

Service reliability on a transit system can have significant impacts on its provider and both existing and potential users. To passengers, unreliable service affects their perception of service quality and transit utility compared to other mode choices, while to transit agencies, this translates to loss of ridership and revenues and higher costs to provide additional service to compensate for poor service operations. The introduction of technologies such as Automatic Vehicle Location (AVL) and Automatic Passenger Counters (APC) provides the opportunity to gather large sets of data at relatively low cost and evaluate service to improve performance, schedule planning and operations control.

This thesis presents a comprehensive review of key elements of service reliability, focused on the measures of reliability, the causes of unreliability and the application of strategies to improve service. The most significant causes of service reliability are presented: deviations at terminals, passenger loads, running times, environmental factors (or externalities) and operator behavior. Each is reviewed in terms of how they impact service and the complexities and interrelationship between different causes are explored. Also reviewed are the potential preventive and corrective strategies, and the links between the causes of service unreliability and best strategy according to the source of problems.

A practical framework is developed to assess service reliability, exploring the uses of Automated Data Collection (ADC) systems to characterize service reliability and evaluate the causes of unreliability that may exist. Its goal is to serve as a guide for transit agencies to begin to analyze the large sets of data available from these systems to evaluate performance and implement efficient strategies to improve service planning and operations. The proposed framework consists of three blocks: 1) characterization of service reliability through service measures and performance reports; 2) identification of causes of reliability problems; and 3) selection of strategies which target critical causes of unreliability to improve service.

Characterization of service reliability involves examining five key elements an agency should analyze: a) data inputs, b) output calculations, c) service measures, d) threshold values, and e) performance reports. Identifying the causes of unreliability includes two sequential processes to infer the causes of service reliability problems. The first focuses on deviations at terminals, because good on-time performance and headway adherence is expected at the terminals and

deviations at this point tend to propagate down the route and create further reliability problems. The second process examines deviations at other points on the route, and follows a set of steps to infer the causes of unreliability: initial deviations at terminal, passenger loads, poor schedule planning, operator behavior and externalities. Application of strategies includes an assessment of the best strategies to prevent reliability problems and reduce the impacts on service performance, based on the results of the previous analysis.

The application of the proposed framework on the Silver Line Washington Street in Boston (MA) revealed that variability of running times and headway distributions are high. This indicates that bus arrivals and passenger wait times on this route are unpredictable and travel times are irregular. As a Bus Rapid Transit route, which is suppose to provide bus service with rail transit quality, headway adherence is poor on this route, with a tendency for buses to bunch together or leave gaps in service. Further analysis revealed that service reliability has recently deteriorated as a result of the implementation of a new Automatic Fare Collection (AFC) system. The new fare collection system presented delays in the boarding process, which resulted in increased travel times and passenger wait times.

The main cause of service unreliability on this route was identified to be deviations at the terminals. Trips are departing the terminal with poor headway adherence (and therefore, poor on-time performance), which propagates and creates further reliability problems down the route. The causes of these terminal deviations were inferred to be a combination of poor terminal supervision and operator behavior. Recovery times, externalities and passenger loads at this terminal are inferred to cause only minor problems. At other points in the route, operator behavior and passenger loads are observed to affect reliability in the inbound direction.

As for strategies to improve service reliability, emphasis is given to better supervision at the terminal. Supervisors at terminals are needed to enforce good operator behavior, balance headways, apply control strategies, and coordinate passenger loads to avoid poor departure headways and overcrowding of buses. Along the route, operator training, corrective strategies and traffic signal priority are highlighted as potential strategies to reduce the variability in running times and balance headways to reduce the occurrence of bunches and gaps in service.

Thesis Supervisor: Nigel H.M. Wilson

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To My Family



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# TABLE OF CONTENTS

---

<b>1. INTRODUCTION TO RELIABILITY .....</b>	<b>17</b>
1.1 Motivation .....	17
1.2 Objectives .....	18
1.3 Research Approach .....	19
1.4 Outline of Thesis .....	20
<b>2. LITERATURE REVIEW .....</b>	<b>21</b>
2.1 Reliability: The problem and its effects .....	21
2.2 The Role of Automated Data Collection .....	22
2.2.1 Key Dimensions in Data Collection .....	23
2.2.2 Analysis and Decision Support Tools .....	25
2.2.3 Software Development .....	26
2.2.4 Findings and Guidelines .....	27
2.3 Transit Reliability Study .....	29
2.3.1 Traveler Behavior .....	29
2.3.2 Transit Agency Perspective .....	30
2.3.3 Reliability Measures .....	30
2.3.4 Causes of Unreliability .....	32
2.3.5 Strategies to Improve Reliability .....	33
2.4 Portland, Oregon Studies .....	35
2.4.1 Improvements in Reliability .....	35
2.4.2 Schedule Efficiency and Operator Behavior .....	38
2.4.3 Headway Deviations and Passenger Loads .....	41
2.4.4 Operations Management .....	42
2.4.5 Operations Control .....	43
2.5 Research Potential .....	43
<b>3. A FRAMEWORK FOR ANALYZING TRANSIT RELIABILITY .....</b>	<b>45</b>
3.1 From Theory To Practice .....	45
3.2 Key Characteristics of Service Reliability .....	46
3.2.1 On-Time Performance .....	46
3.2.2 Headway Regularity .....	47
3.2.3 Passenger Loads .....	48
3.2.4 Overview of Interactions .....	49

3.3 Causes of Unreliability .....	49
3.3.1 Schedule Deviations at Terminals .....	49
3.3.2 Passenger Loads .....	52
3.3.3 Running times .....	54
3.3.4 Environmental Factors .....	54
3.3.5 Operator Behavior .....	55
3.3.6 Inter-relationships between Causes .....	56
3.4 Strategies.....	58
3.4.1 Preventive Strategies.....	58
3.4.2 Corrective Strategies .....	61
3.5 Relationships between Causes and Strategies .....	65
3.6 Proposed Reliability Analysis Process.....	70
3.6.1 Characterizing Service Reliability .....	70
3.6.2 Identification of Causes .....	83
3.6.3 Application of Strategies .....	94
3.7 Framework Summary .....	98
<b>4. CASE STUDY: APPLICATION TO MBTA .....</b>	<b>99</b>
4.1 MBTA Silver Line on Washington Street .....	99
4.2 Automated Data Collection Systems .....	105
4.2.1 Archived Data .....	105
4.3 Scope of Analysis and Data Assumptions .....	108
4.4 Silver Line Reliability Assessment.....	109
4.4.1 Running Times.....	109
4.4.2 Headway Adherence .....	114
4.4.3 Passenger Wait Times.....	116
4.4.4 Changes in Performance: May 2005 .....	117
4.4.5 Overall Reliability Assessment .....	119
4.5 Identifying the Causes of Unreliability.....	120
4.5.1 Performance at Terminal .....	120
4.5.2 Causes of Deviations at Terminals .....	125
4.5.3 Deviations at Other Points .....	131
4.6 Application of Strategies .....	134
4.7 Summary of Findings.....	135
<b>5. CONCLUSIONS .....</b>	<b>137</b>

Table of Contents

---

5.1 Framework Summary ..... 137

5.2 Major Findings ..... 138

5.3 Future Research ..... 139

**BIBLIOGRAPHY ..... 141**

**APPENDIX A: RUNNING TIME DISTRIBUTIONS ..... 143**

**APPENDIX B: TERMINAL ANALYSIS ..... 145**



# LIST OF FIGURES

---

Figure 3-1. Service Reliability Interactions.....	49
Figure 3-2. Effects of Late Departure from Terminal .....	50
Figure 3-3. Inter-relationships between Causes of Unreliability.....	57
Figure 3-4. Operator Behavior Strategies .....	66
Figure 3-5. Running Time Strategies .....	67
Figure 3-6. Deviation from Terminal Strategies .....	68
Figure 3-7. Passenger Load Strategies .....	69
Figure 3-8. Externalities Strategies.....	69
Figure 3-9. Sequential Process to Identify Causes of Deviations .....	94
Figure 3-10. Application of Strategies.....	96
Figure 4-1. Silver Line Washington Street Route.....	101
Figure 4-2. Passenger Demand Distribution.....	104
Figure 4-3. PM Peak Running Time Distribution: Dudley to E. Berkeley - Inbound .....	112
Figure 4-4. PM Peak Running Time Distribution: E. Berkeley to Temple - Inbound .....	112
Figure 4-5. PM Peak Running Time Distribution: Temple to E. Berkeley - Outbound .....	113
Figure 4-6. PM Peak Running Time Distribution: E. Berkeley to Dudley - Outbound .....	113
Figure 4-7. PM Peak Headway Ratio Distribution.....	115
Figure 4-8. PM Peak Headway Distribution (May 2005).....	118
Figure 4-9. Headway Ratio Distribution at Dudley - Inbound .....	121
Figure 4-10. Headway Ratio Distribution at East Berkeley by Initial Ratio at Dudley .....	123
Figure 4-11. Headway Ratio Probability at East Berkeley by Initial Ratio at Dudley.....	123
Figure 4-12. Analysis of Causes of Unreliability at Dudley Square.....	128
Figure 4-13. Analysis of Causes of Unreliability at East Berkeley - Inbound .....	132



# LIST OF TABLES

---

Table 2-1. Factors Affecting Reliability .....	22
Table 2-2. Levels of Spatial and Temporal Detail for Data Capture .....	24
Table 2-3. Decision Support Tools and Analyses .....	26
Table 2-4. System Design and Data Capture Issues.....	28
Table 2-5. Recommended Measures of Service Reliability .....	32
Table 2-6. Strategies to Improve Service Reliability .....	34
Table 2-7. Parameter Estimates for Running Time Model.....	36
Table 2-8. Running Time Model.....	40
Table 2-9. Operator Model Parameter Estimates .....	41
Table 3-1. On-Time Performance Levels of Service.....	47
Table 3-2. Fixed-Route Headway Adherence Level of Service .....	48
Table 3-3. Effects of a Late Departure.....	51
Table 3-4. Effects of an Abnormally High Passenger Load .....	53
Table 3-5. Types of Expressing .....	64
Table 3-6. Data Inputs for Analysis Process.....	71
Table 3-7. Example of Analysis of the Propagation of Deviations .....	86
Table 3-8. Time Point Schedule Deviations vs. Terminal Deviation .....	86
Table 3-9. Example of Headway Adherence Analysis.....	88
Table 3-10. Example of Headway Ratios per Terminal Headway Ratios .....	88
Table 3-11. Terminal Departure Schedule Deviation vs. Available Recovery Time.....	90
Table 3-12. Terminal Departure Deviation vs. Terminal Headway .....	92
Table 4-1. Silver Line Route Stops .....	102
Table 4-2. Scheduled Departure Times of Sample Trip.....	103
Table 4-3. Silver Line Washington Street Route Schedule .....	103
Table 4-4. Silver Line Route Time Point Information .....	106
Table 4-5. Data Items of Time Point Crossing Record* .....	107

## List of Figures

---

Table 4-6. Silver Line Time Periods.....	108
Table 4-7. Running Time Analysis: Dudley to E. Berkeley - Inbound .....	110
Table 4-8. Running Time Analysis: E. Berkeley to Temple - Inbound .....	110
Table 4-9. Running Time Analysis: Temple to E. Berkeley - Outbound.....	110
Table 4-10. Running Time Analysis: E. Berkeley to Dudley - Outbound.....	111
Table 4-11. Mean Scheduled and Actual Headways .....	114
Table 4-12. Coefficients of Variation of Headways .....	114
Table 4-13. Expected Passenger Wait Times.....	116
Table 4-14. Expected Excess Passenger Wait Times .....	116
Table 4-15. Headway Ratio at Inbound Time Points by Ratio at Dudley Terminal .....	122
Table 4-16. Mean Recovery Times at Dudley Square .....	125
Table 4-17. Available Recovery Time vs. Schedule Deviation at Dudley Square.....	126
Table 4-18. Poor Performance Operators.....	131
Table 4-19. Operator Behavior Analysis .....	133



# 1. INTRODUCTION TO RELIABILITY

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Service reliability significantly impacts transit agencies, their passengers and their potential users, and therefore is a major concern to transit managers. The degree of adherence to scheduled times and headways can significantly affect customer satisfaction and perception of service quality. If buses do not run on schedule, service is perceived as unreliable, and longer waiting times and crowding will result. To the transit agency, this translates to a decrease in ridership and revenue, as well as potentially higher costs for overtime and extra buses to provide enough capacity to avoid some buses from becoming overcrowded.

This research reviews key elements of service reliability and proposes a framework to analyze reliability using data from Automated Data Collection (ADC) systems. The practical framework is aimed to serve as a guide for transit agencies to characterize performance, identify the causes of service unreliability and select efficient strategies to improve service quality.

## 1.1 MOTIVATION

Everyday, transit agencies must deal with questions such as why buses are running late a large percentage of the time. They need to know what conditions lead to bus bunching on a route. It is clear that when two buses arrive within seconds of each other, after a long gap in service, there's a problem with service quality and schedule adherence. It is this variability and the resulting increase in waiting time, and less the bunched arrival of buses, that frustrates and annoys customers.

Service unreliability can have great impacts on the system and its users. Unreliable service increases waiting times for passengers (Wilson et al. 1992) and reduces the probability of on-time arrival at destinations, which frustrates passengers and decreases the disutility of transit in traveler mode choice (Abkowitz et al., 1978). It also impacts passenger loads, as buses bunch and the first bus picks up more passengers and becomes crowded while the next bus follows with far fewer passengers (Kittleson & Associates, 2003). Impacts on transit agencies include the increase in costs to provide additional service to compensate for imbalanced passenger loads (Strathman et al. 2003), and eventually, the loss of passengers and revenue (Strathman et al. 1999).

With the introduction of technologies such as Automatic Vehicle Location (AVL) and Automatic Passenger Counters (APC), large amounts of data is increasingly becoming available and it is important to pay attention to how this data can be used to improve service reliability. Analyzing this data can help characterize reliability problems and help improve service planning and operations control.

Archived data on vehicle operations and passenger activity is becoming widely available at relatively low cost (Strathman et al. 2003). The larger data samples allow the transit

agencies to perform statistically valid analyses to monitor performance and improve scheduling, operations control and traffic engineering (Furth 2000). Automated tools can be used to provide a better understanding of what creates problems in a system, prevent such problems through better service planning and operations management, and develop strategies to correct them once they appear. Automated data collection also reduces the need for expensive manual data collection, and the various types of performance reports that can be generated may benefit numerous areas within a transit agency in providing feedback to improve service (Kimpel et al. 2004).

The list below summarizes some of the benefits of automated data collection systems compared to traditional data collection practices:

- **Reduced labor:** automated data collection systems reduce the need for human data collectors (e.g. for manual ride checks and point checks) and for post processing tasks such as entering the data into a computer for analysis.
- **Lower marginal costs:** compared to manual collection, automated data collection systems have higher initial capital costs and lower marginal costs. For example, obtaining an extra day of data is less costly with automated systems because the data is collected continuously, in situations where paying the full cost of an extra day of manual collection could never be justified.
- **Fewer opportunities for human error:** the reduced reliance on manual collection and processing reduces the chance of human error in collecting and transferring data. Of course, automated data collection systems can also produce errors, but it should be easier to identify when the systems need repair or maintenance because of the large data sets typically available and the use of automated error-checking software routines.
- **Greater data accuracy:** data from automated systems needs to be evaluated for precision and bias, but higher accuracy is possible because of the large sample sizes. In addition, they eliminate the problem of false data reported by unmotivated traffic checkers.

## **1.2 OBJECTIVES**

This thesis explores the potential uses of Automated Data Collection (ADC) systems data to better understand the operation of bus routes and the dynamics of service reliability. With the availability of larger ADC datasets, there is an opportunity for transit agencies to answer important questions regarding service reliability, such as:

- What conditions lead to service reliability problems?
- What strategies can be applied to avoid or reduce poor service quality?

- How can data from ADC systems be analyzed to improve service planning and operations monitoring and management?

The objective of this research is to provide transit agencies with a framework to address these types of questions. By better understanding the dynamics of transit service, transit managers would be able to improve service through:

- Improved service delivery: provide promised level of service, and operate at scheduled times and headways. Respond to actual passenger demands, service environments and trouble spots.
- Improved service management: monitor system performance, including allocating resources efficiently and evaluating operators.
- Improved service planning: adjust timetables to reflect realistic vehicle running times and passenger demand.

This research recognizes that the levels of complexity surrounding service reliability and the very nature of transit systems do not allow for a clear, simple solution to the problems of reliability. One of its goals is to provide insight into the dynamics of service reliability and develop a practical framework through which transit agencies can better identify the causes of problems and select strategies to overcome them.

### **1.3 RESEARCH APPROACH**

The focus of this research is to develop a framework to measure and analyze service reliability of bus routes using automated data collection systems. The first step of this approach involves the evaluation of causes of service unreliability, considering the impacts of each on the bus route or system and their interactions. The framework identifies certain trigger events, both operational and external, which can cause vehicles to deviate from their scheduled times or headways and potentially lead to unreliability. This part of the approach is aimed at developing a means to describe how many unreliability problems can be explained by these trigger events and how these triggers propagate unreliability along the route. The triggers evaluated in this research are: late departure from terminals, unusual passenger loads, inadequate or too generous running times, traffic conditions and operator behavior.

The next step is to outline service metrics to characterize reliability and service quality. The metrics provide an overall picture of service reliability to help develop hypotheses about the causes of unreliability on a particular route. The metrics are intended to reflect the perceptions of service quality from the perspective of travelers and transit agencies, and thus they characterize service in terms of on-time performance and variability.

The framework then presents the potential uses of AVL and APC data in analyzing reliability and computing the relevant service metrics. The objective is to review available ADC systems and analyze what these systems can tell us about service

reliability and the effects of problems. The framework includes an outline of how data from these systems can be processed to calculate service reliability measures related to running times, and schedule or headway adherence.

The framework also considers strategies to counteract service unreliability with the goal of improving service quality. Evaluation of strategies is based on data analyses to identify causes of unreliability, and the strategy's ability to minimize the effects on passengers and to efficiently return to normal service. The strategies are categorized as preventive or corrective/restorative. Preventive strategies are aimed at preventing reliability problems through avoidance of its causes. Examples of preventive strategies are exclusive bus lanes and traffic signal priority schemes. Corrective or restorative strategies, such as holding or expressing buses, are implemented when problems have developed and are meant to restore normal service and avoid the propagation of problems down the route or day.

A case study of the Massachusetts Bay Transportation Authority (MBTA) Silver Line Washington Street bus route is presented. Various tools are developed in this process to use the available AVL data and summarize service reliability measures in order to evaluate the performance of this Bus Rapid Transit (BRT) line. The case study illustrates the application of the framework including proposed service measures, the causes of unreliability and potential strategies.

## **1.4 OUTLINE OF THESIS**

Chapter 2 summarizes and reviews previous work relating to service reliability, the measures and strategies used in operations control and service planning, and the use of automated data collection systems for service analysis. Chapter 3 describes the framework analysis process which is used to evaluate service reliability, identify service metrics, investigate possible causes, and select strategies. Chapter 4 presents a case study of the application of this methodology to the MBTA's Washington Street Silver Line. Chapter 5 completes this thesis with conclusions and suggests future research directions on service reliability.

## 2. LITERATURE REVIEW

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A review of previous studies reveals that considerable research exists on the effects of transit service reliability on passengers and transit agencies, on the selection of reliability measures, on the identification of the causes of unreliability, and on the application of strategies to improve service. However, the complexities of transit service and the limitations of data collection have made it difficult to fully understand service reliability and to identify the relationship between service attributes and reliability. In recent years, the development and implementation of automated vehicle monitoring and related data collection systems has sparked the opportunity for more detailed analyses.

A comprehensive study published in 1978 (Abkowitz et al.) provides perhaps the most detailed examination to date of transit service reliability. It presents a framework for the evaluation of techniques to improve operations, service management and schedule planning. This research builds on the findings of that study and goes further taking advantage of automated data collection systems. The prevalence of these new technologies has changed the fundamentals of data availability and the prior high costs of manual data collection.

The remainder of this chapter is organized as follows. The first section (2.1) introduces service reliability while Section 2.2 presents studies related to the roles Automatic Vehicle Location (AVL) and Automatic Passenger Counters (APC) systems play in measuring transit reliability. Section 2.3 summarizes the comprehensive transit reliability study (Abkowitz et al. 1978). Section 2.4 reviews the results of a number of studies focused on the application and potential of AVL and APC systems in the Portland, OR metropolitan area to improve service reliability. Section 2.5 summarizes the literature and the key findings which research builds upon.

### 2.1 RELIABILITY: THE PROBLEM AND ITS EFFECTS

Service reliability can be defined in terms of the variability of service attributes and its effects on traveler behavior and on agency performance (Abkowitz et al. 1978). Reliability problems are often attributed to the dynamic nature of the operating environment. (Abkowitz 1983). Providing reliable service means keeping buses on schedule, maintaining uniform headways and minimizing the variance of maximum passenger loads (Levinson, 1991).

An added complexity in measuring performance and the effects of improvements in reliability is the differences in the perceptions of reliability by travelers and operators. Several studies have explored the effects of transit reliability from the perspective of both transit customers (Abkowitz et al. 1978; Bates et al. 2001<sup>1</sup>; Prioni and Hensher 2000<sup>1</sup>)

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<sup>1</sup> As referenced in Strathman et al. 2003

and operating agencies (Abkowitz et al. 1978; Furth 2000). For frequent service, travelers tend to focus on headway regularity, on-time arrival at destinations, and wait time, while agencies often see schedule adherence as an important and easier-to-collect measure of the effectiveness of service delivery.

Table 2-1 summarizes a number of factors that affect service reliability. More detailed discussions of some of these factors is presented in Chapter 3.

**Table 2-1. Factors Affecting Reliability**

<b>Factor</b>	<b>Description</b>
Traffic conditions	For on-street, mixed-traffic operations, it includes traffic congestion, signal delays, parking, incidents, etc.
Road construction and track maintenance	Creates delays and may force detours
Vehicle maintenance quality	Influences the probability of breakdowns
Vehicle and staff availability	Involves the availability of vehicles and operators to operate scheduled trips
Transit preferential treatment	Includes exclusive bus lanes and conditional traffic signal priority
Schedule achievability	Reflects ability to operate under normal conditions and loads with sufficient recovery times to allow most trips to depart on-time
Evenness of passenger demand	Describes loads between successive buses and from day-to-day
Differences in operator driving skills	Involves route familiarity and schedule adherence (particularly in terms of early running)
Wheelchair ramp and ramp usage	Includes frequency of deployment and amount of time required
Route length and the number of stops	Relates to the exposure to events that may delay a vehicle
Operations control strategies	Application of actions to counteract reliability problems as they develop.

\* **Source:** *Transit Capacity and Quality of Service Manual – 2<sup>nd</sup> Edition*

Negative impacts of service unreliability include additional wait time for passengers (Wilson et al. 1992), overcrowding and the potential need to provide additional service to neutralize imbalanced loads due to headway irregularity (Strathman et al. 2003).

## 2.2 THE ROLE OF AUTOMATED DATA COLLECTION

Extensive research exists on the potential of automatic vehicle location (AVL) and automatic passenger counters (APC) systems to improve operations, performance monitoring, scheduling and planning (Wilson et al. 1992, Furth 2000, Furth et al. 2003, Wile 2003, Kimpel et al. 2004, Hammerle 2004).

It is generally agreed that automated data collection systems present the opportunity to do statistically valid analyses on service reliability for the first time (Furth 2000, Kimpel et al. 2004).

Furth et al. (2003) reviews past and potential applications of automatic data collection systems in service planning, scheduling, performance evaluation and system

management. The study describes a number of analysis and decision support tools that have been, or could be, developed using the output of these systems.

The first chapter of this study describes the historical uses of AVL and APC systems, the technological advances in recent years and a number of data capture and matching issues. Historically, for most AVL systems, the focus has been on its real-time application for operations control and emergency response. The authors state that many systems were not designed to provide useful archived data because the transit agencies did not specify such use during procurement and design. On the other hand, APC systems were designed for off-line analysis and have been used to evaluate performance. The limitations of APC systems have been the large costs of implementation and maintenance, and the need to develop software (mainly in-house) to analyze the data. Other systems that have been implemented include event recorders, which have been more popular in Europe, and standard vehicle monitoring devices, such as odometers, engine heat sensors and fareboxes.

Among the technological advances outlined in the study are:

- The development and improvement of location-based tools such as global positioning systems (GPS) and geographic information systems (GIS).
- The evolution of computers, making them smaller, faster, less expensive and with far more storage capacities. Communication has also improved with wireless network technologies and more efficient radio communications.
- The integration of systems and “smart bus” design, which combines the functionalities of various systems such as passenger information, fare collection and scheduling.

The study also outlines common issues of matching captured data with the corresponding schedule. Matching captured data with bus stop locations has been difficult because many agencies do not have an accurate “stops” database because it requires a lot of work to maintain and update. However, the introduction of stop announcements systems tied to GPS systems has increased the need for more accurate stop matching because errors are very obvious in real-time announcement systems. Problems also arise when trying to match data to schedule files for the current timetable. An automated process is needed which requires compatibility between the different systems. Matching is also limited by the need for valid entries for operator, run and trip numbers. Issues also exist with end-of-line data records because passenger counts may be skewed by confusion surrounding the end of the trip and the beginning of the next trip.

### **2.2.1 KEY DIMENSIONS IN DATA COLLECTION**

Furth et al. (2003) define four key dimensions in archived data: level of spatial and temporal detail, complete vs. exception data, fleet penetration and sample size, and data

quality control. The first is a hierarchy, summarized in Table 2-2, on the levels of details available depending on the type of automated systems deployed.

**Table 2-2. Levels of Spatial and Temporal Detail for Data Capture**

Level	Description	Event-Independent Records	Event Records	Between-Stop Performance Data
A	AVL without real-time tracking	Infrequent (typically 60 to 120s)	-	-
B	AVL with real-time tracking	Infrequent (typically 60 to 120s)	Each time point	-
C	APC or event recorder	-	Each stop	-
D	Event recorder with between-stop summaries	-	Each stop and between-stop events	Recorded events and summaries
E	Event recorder / trip recorder	Very frequent (every second)	All types	All events, full speed profile

**\* Source: *Uses of Archived AVL-APC Data to Improve Transit Performance and Management*. (Furth et al. 2003)**

Level A is representative of older AVL systems, where location data was obtained by polling for the location of buses at certain time intervals. Level B creates a data record when the vehicle traverses a timepoint, identified through GPS technology or dead reckoning, using the odometer. For Level B, the data may be transmitted over the air or stored on-board for later download. Level C, which is mainly applied for APC and stop announcement systems (rarely with AVL), creates a record for each stop which can include the time at stop, passenger counts, wheelchair lift or ramp use, and other special events. Data is typically downloaded at the end of the day, although newer systems are able to transmit the information through radio communications. Level D includes events at stops, just like level C, but also records other activities in-between stops, such as speed and direction change. Level E is the most complete, recording data about time, location, events and status in an almost continuous manner. It requires the greatest storage capacity.

The second dimension deals with whether data records are produced routinely, defined by a time interval or a location-related event, or it is triggered by an unanticipated time of an event or an unanticipated even itself. The latter is called exception reporting, in which any non-standard conditions are recorded. Headway and running time analyses are limiting with exception data because fewer data records are provided, typically with larger margins of error, which is why most agencies have moved away from developing performance analyses using exception data only.

The third dimension is fleet penetration and sample size. It is standard with AVL systems to have the entire fleet equipped, while it is typical to have only a subset of the fleet equipped with APC systems. The sample size is related to the fleet penetration and the rate of sampling. Having only a subset of the fleet equipped with an ADC system decreases the number of valid headways recovered and considerations in vehicle assignment become important to ensure route and daily variations are taken into



account. With the entire fleet equipped, transit providers benefit from larger sample sizes to estimate any significant variability as well as the response from any changes in service or demand.

The last dimension described by Furth et al. is the need for good quality control and post-processing to correct for any errors. Errors in identifiers and passenger counts are inevitable, and should be flagged and omitted from any analysis.

The study also states that good analysis using archived data from ADC systems depends on the availability of other useful data items and databases. The capabilities of AVL and APC systems are enhanced when other related data items are integrated. Potentially valuable data items include: door open and close times, start and stop times, time stamps on passenger entries and exits, off-route events, mechanical and security alarms, communications to and from the control center, traffic control messages, farebox transactions, and annunciation and destination signs. Related databases include schedule data, GIS, payroll, farebox, maintenance, weather or special events, and customer satisfaction.

### **2.2.2 ANALYSIS AND DECISION SUPPORT TOOLS**

Furth et al. also identify a number of analyses and decision support tools, as shown in Table 2-3, and used in current transit practice as well as potential functions that would improve service management and performance. The usage code indicates the level of use by agencies with AVL-APC data, where [4] indicates the tool is commonly used by agencies and [0] not used.

**Table 2-3. Decision Support Tools and Analyses**

Function	Tool / Analysis [Usage Code]	Detail needed
General service monitoring. - Did service operate as schedule?	- Missed trips [1]	A or B
	- Schedule adherence [4]	
Targeted investigation - "Replay" service to review customer service/complaints, security (incidents, accidents), operator performance	Trip investigation at gross level (was the trip there? Off-route?) [4]	A
	Trip investigation: early, late, overcrowded? [3]	C
	Trip investigation: speed, acceleration [2]	D or E
Schedule and Monitoring Running Time - Observing running times based on scheduled running times	Route and segment analysis (mean, distribution) [4]	B
	Suggesting running time [3] or half cycle [2] based on percentiles	B
	Analysis of net holding time [2]	C
	Speed and traffic delay [2]	D
	Unsafe operations monitoring [0]	D or E
	Relating running time to weather, incidents or special events [1]	B
Schedule Adherence and Connection Protection - Evaluating service and operation quality	Percent early, late by timepoint [4]	B (timepoint) or C (stop)
	Distribution of schedule deviation at timepoint [3]	B or C
	Graphical display of schedule deviation distribution along a route [2]	B or C
	Connection protection [1]	1
Headway Analysis - Evaluating service and operation quality	Headway deviations (mean, distribution) [3]	B (timepoint) or C (stop)
	Waiting time impacts (random passenger arrivals) [1]	C
	Plot successive trajectories (bunching analysis) [2]	C
Demand Analysis - Analysis of passenger counts	Load profile [4] and variations [3]	C
	Analysis of maximum loads and max load point [1]	C
	Time-dependent demand and load analysis [1]	C
	Analyze overload, lift and other events [3]	C
	Transfer and linked trip analysis [1]	C
Other Operations Analysis	Operator performance [1]	B (timepoint) or C (stops)
	Dwell time analysis [2]	C
	Layover and pull in/out analysis [0]	B
	Control effectiveness	By analysis
	Before/after study, special event or weather analysis	By analysis

\* **Source: Uses of Archived AVL-APC Data to Improve Transit Performance and Management. (Furth et al. 2003)**

### 2.2.3 SOFTWARE DEVELOPMENT

The study (Furth et al. 2003) also reviews practice relating to software development for data analysis for the following five sources of software used to analyze archived data.

- *In-house software*. This type of software provides the greatest flexibility because it is developed for the data needs of the transit provider. Examples of transit agencies that have developed their own software include King County Metro, Tri-Met and Metro Transit (Minneapolis/St. Paul). Software developed in-house has the drawback of requiring personnel and expertise to develop and maintain software, as well as resulting custom products that cannot be easily transferred to other agencies.
- *Equipment vendors*. Software from AVL and APC vendors has been limited to real-time applications (in the case of AVL) and basic report functionalities (for APC systems). These limit the flexibility and the types of analyses possible because the needs of the transit provider are not directly tied with generic software. There is also the risk of poor customer-support from the vendor or of the vendor going out of business.
- *Scheduling system vendors*. Software provided by scheduling system vendors also have limited flexibility, providing suggested scheduled running times but limited analysis of schedule or headway adherence. The risks and disadvantages are the same as software from equipment vendors.
- *Third party software*. The advantage of these is that they are not tied to any specific system, and have more room for improvement and flexibility. Examples of these include TriTAPT (Trip Time Analysis in Public Transport), developed at Delft University of Technology's Transportation Engineering Laboratory in the Netherlands. The disadvantage is that, in the US, funding issues do not allow transit agencies to purchase these software packages justified only by data analysis. One way to get around this is to procure these software packages as part of procurement of the larger AVL or APC systems.
- *Research-Oriented Analyses*. These are specialized tools developed by university research teams. Unless developed in conjunction with the transit agency, like the partnership between Tri-Met and Portland State University, there is the risk of staff analyst not being able to apply the specialized software and analyze future data.

## 2.2.4 FINDINGS AND GUIDELINES

The study develops findings and guidelines in four major areas: system design and data capture, analysis and decision support tools, quality and integration of other data sources, and organizational issues. Issues in system design and data capture are summarized in Table 2-4.

**Table 2-4. System Design and Data Capture Issues**

<b>Issue</b>	<b>Description</b>	<b>Finding and Guidance</b>
Stop vs. Timepoint level detail	Whether data is collected at every stop or only at timepoints is a key system design decision. Timepoint level detail is adequate for schedule planning and adherence analysis, while stop level detail is better for integration with other data items such as door open/close.	Stop level detail also has an advantage on: <ul style="list-style-type: none"> <li>- accuracy and end-of-line issues</li> <li>- wait times, holding time analysis</li> <li>- posted schedules at stops, support for signal priority</li> <li>- better integration with other data systems</li> </ul>
Time-at-location vs. Location-at-time	Time-at-location is usually captured through real-time tracking, while location-at-time is captured by polling vehicles.	The first is preferred because most performance reports refer to arrival and departure times at specific points along the route
Between-stop records	Are full details necessary in general analysis or are summaries sufficient?	Full details are helpful for incident investigation. Summaries sufficient for speed analysis
Exception data only	Capturing exception data only is useful in real-time operations, but very limiting for performance analysis using archived data.	Exception data cannot be used by itself for performance reporting, and must be complemented with other data items.
Central on-board computer with unified location capability and interface	The idea of a "smart bus" design, where location data is supplied by one central computer. It has integration capabilities, with a single interface and shares its location data with other systems.	Accuracy of location information improves and matching is easier. A single operator interfaces reduces the error rate in identifiers.
ID verification: real-time vs. off-line	Matching of observed and scheduled data is improved with valid sign-in data. Opportunities to maximize valid sign-in data: <ul style="list-style-type: none"> <li>- Single interface for operator sign-in</li> <li>- Range and validity checks during sign-in</li> <li>- Automatic sign-in, smart-card ID</li> </ul>	Real-time ID verification is preferred because remedial action is taken right away and the number of records affected is reduced. However, post-processing corrections can also be automated to improve data quality.
On-board data recording vs. over-the-air transmission	Radio transmission to central computer is needed for real-time operations control. Archiving done on-board or by central computer during transmission.	Limitations on radio bandwidth restrict the amount of real-time APC data that can be transmitted (on top of the AVL that is already being sent).
Data from single-purpose systems	Use of archived data captured from passenger information systems.	Trend is increasing towards the suppliers offering off-schedule data and reporting capabilities.
Size of equipped fleet	It is customary to equip 100% of the fleet with AVL systems, while only 10%-15% with APC systems.	Passenger count analyses can be done with only 10-15% of the fleet equipped with APC systems, (100% equipped fleet if there is a need to report extreme values). For operations data, it is better to equip 100% of the fleet.
Data on control decisions	Supervisors do not usually log any control action decisions in useful archived data files.	Need to capture and code any control actions to flag records and analyze effectiveness.
Location and fare-payment systems	Time-stamping and integration of location records with fare collection data.	Integration can be done in real-time or off-line, and benefits include origin/destination analysis.

**\* Source: Uses of Archived AVL-APC Data to Improve Transit Performance and Management. (Furth et al. 2003)**

In the area of analysis and decision support tools, the study notes the opportunities presented by the transition to a data-rich environment and its accompanying analysis possibilities. Service standards, limited previously by the data, can now be revised to reflect and evaluate the occurrence of extreme values and percentiles instead of just averages. The study highlights the need for good data integration with related databases of stop locations, schedule information and fare collection data.

## **2.3 TRANSIT RELIABILITY STUDY**

Abkowitz et al. (1978) present the first comprehensive assessment of transit service reliability. The study explored the impacts of transit unreliability on both travelers and transit agencies<sup>2</sup>. It presents a framework to develop appropriate measures of reliability, possible causes of unreliability and effective strategies to overcome the problems. The main parts of this study are summarized below.

### **2.3.1 TRAVELER BEHAVIOR**

Prior surveys indicated that reliability is ranked by travelers as one of the most important service attributes. The theoretical framework considers the influence of unreliability on travel behavior and mode choice, and potential benefits resulting from improvements in reliability.

The authors review previous studies of the relationship between reliability and travel behavior, in particular mode choice and departure time decisions. Travelers choose a travel alternative and departure time based on their perception of travel time variability and on their risk aversion. This choice reflects the assumptions that travelers associate a certain loss in value with being late at their destination. They aim to minimize total travel time, accounting for the variability of in-vehicle travel time and wait time. For the latter, it was found that travelers do not perceive a reliability problem if bus arrivals are predictable to some degree. Travelers tended to adjust their arrival time at bus stops to reduce their expected wait times. The theoretical view of departure time behavior was based on the travelers' need for on-time arrival at the destination, their familiarity with the system, and bus arrival patterns.

The authors state that a number of benefits to travelers can accrue from improved service reliability. The most important is the increase in the probability of on-time arrival, as the variability in total travel time, especially wait time, is reduced. This probability increase may decrease the disutility of transit relative to other modes and thus lead to more frequent use of the system. It may also attract new riders whose transit disutility is now lower than their prior travel alternative. Reducing travel time variability may allow travelers to choose a later departure time with the same probability of on-time arrival.

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<sup>2</sup> The 1978 Transit Reliability Study refers to transit agencies as "Operators". The terminology has been changed to follow the convention of this research in referring to "operators" as the vehicle drivers.

### **2.3.2 TRANSIT AGENCY PERSPECTIVE**

To transit agencies, reliability is most often defined in terms of schedule adherence. Prior surveys indicated that service reliability is important to transit agencies in maintaining efficient operations and providing good service to customers.

A survey of ten bus systems showed the variability in agency behavior regarding key issues in bus service. On scheduling practices, all ten systems kept a tight scheduled running time, with no slack time built in, and relied on recovery time to account for the variability in running times. Even so, only four of them stated that reliability, based on ensuring on-time departures for successive trips, was a primary factor in determining recovery times. Four agencies stated that recovery times were mainly set as a result of union contracts, and two agencies stated recovery times were set to achieve clock-face schedules. The survey also revealed differences in policies regarding the number of spare vehicles and drivers. Availability of these spares affects service reliability in terms of ability to cover vehicle breakdowns and additional service disruptions. All the systems assigned a certain percentage of their vehicle fleet as spares, but the strategies for assigning spare drivers varied widely, including a set number per garage, informal drafting, and daily variations. All agencies identified problems through customer complaints and monitoring techniques such as road supervisors, ride checks and point checks. The type, frequency of these monitoring techniques as well as the resulting actions. Control practices also varied, focusing mainly on recurring problems, and included adding extra service, rerouting and schedule adjustments.

The theoretical discussion presented in Abkowitz et al. (1978) examines agency behavior as it affected transit service reliability. Decisions of service operations managers involve a trade-off in resource allocation and operating policies such as setting frequency, running times and recovery times. To the agency, reliability strategies consist of maintaining schedules as reflected through on-time performance measures and ensuring an adequate availability of spare vehicles and drivers.

The authors state that improving service reliability may yield benefits in reduced capital and operating costs as a result of reduced travel time variability. Schedule adjustments to improve service may reduce the size of the spare fleet required. Improving service reliability also has the potential to increase ridership, and therefore, revenues.

### **2.3.3 RELIABILITY MEASURES**

The study reviews research prior to 1978, highlighting the typical service reliability measures. The evaluation of these measures revealed several weaknesses at the time of the study:

- Measures tended to focus on published schedules. As a result, inefficient schedules, with inadequate running times and recovery times, might have skewed the results of measures of lateness and deviations.

- A number of the reviewed measures did not capture the effects of reliability problems from the perspective of travelers.
- Variability across different time periods was often overlooked. Data collection limitations led to a lack of consideration of daily and seasonal variability, and result in inconsistent comparisons of measures.

The authors developed criteria to address the above weaknesses and proposed a set of service measures that characterize reliability and are useful to make appropriate comparisons, help identify problems and select effective remedial strategies. The reliability measures reflect both the perspectives of travelers and operating agencies, and focus on:

- Compactness of distribution to describe the deviations from the average value. Deviations from the average observed running time, and not printed schedules, are better measures of variability.
- Likelihood of extreme delays. To travelers, it measures the probability of long wait times and late arrival at a destination. For operators, it translates into the likelihood of a system failure and the need for extra vehicles to restore service due to delays.
- Normalization of measures. Standardization of indicators allows for comparative analysis between time periods and routes, and more accurately measure the “true” impacts of service attributes. For example, standard deviations for routes with very different headways cannot be usefully compared unless they are normalized by the average headway value.

The authors review some basic measures of travel time distributions, such as standard deviation, coefficient of variation, and percent of late trips, to evaluate their advantages and disadvantages in describing service reliability. Recommendations were against the use of extreme values for skewed distributions, on ensuring appropriate description of distributions using the mean and measures of compactness, and on including the mean value of the attribute for standardization.

Table 2-5 shows the recommended measures based on the arguments. The measures should account for time-of-day and day-to-day variability, and it was postulated that analyses ought to consider the interrelationships between different measures and the development of mathematical relationships to better understand the interactions and effects of service attributes.

**Table 2-5. Recommended Measures of Service Reliability**

Distributions of travel time (total travel, in-vehicle, wait times).	<ol style="list-style-type: none"> <li>1. Mean.</li> <li>2. Coefficient of variation (for skewed distributions, standard deviation should exclude extreme values).</li> <li>3. Percent of observations 'N' minutes greater than the mean value.</li> </ol>
Schedule adherence, measured at any point along the route.	<ol style="list-style-type: none"> <li>1. Average deviation from schedule</li> <li>2. Coefficient of variation (from average deviation, not schedules)</li> <li>3. Percent of arrivals N minutes later than average deviation from schedule</li> </ol>
Distribution of headways	<ol style="list-style-type: none"> <li>1. Mean.</li> <li>2. Coefficient of variation.</li> <li>3. Percent of headways: <ol style="list-style-type: none"> <li>a. Greater than X percent of average or scheduled headways, where <math>X \geq 1</math></li> <li>b. Lower than Y percent of average or scheduled headways, where <math>Y \leq 1</math></li> </ol> </li> </ol>
Seat Availability	<ol style="list-style-type: none"> <li>1. Passenger loads (demand and capacity)</li> </ol>

\* **Source: Transit Reliability Study. (Abkowitz et al. 1978)**

### 2.3.4 CAUSES OF UNRELIABILITY

The study classifies basic causes of unreliability as environmental or inherent. The authors consider environmental factors to be those resulting from the surrounding of the system and are generally random in nature, while inherent factors are those associated with the transit service itself. The authors separate the causes of unreliability common to all transit systems, as well as those specific to fixed route bus system.

Common factors for all transit operations included:

- General traffic conditions affect transit service, since transit vehicles typically operate in mixed-traffic. Variations in travel time result from interactions with other vehicles, including accidents, turning movements, illegal parking or speed changes.
- The presence of signalized intersections along the route interrupts the free flow of traffic and increases the probability of delays. Running times increase due to stop-and-go operations and stop times at red lights.
- Demand varies by day-of-week and season-of-year. Agencies account for systematic or known fluctuations in demand by adjusting schedules accordingly, but random variations in demand cause variability in dwell times and travel times.
- Vehicle and driver availability is related to the operating policies of the agency, but affects reliability in terms of being able to cover all scheduled trips and having spares in case of breakdowns, accidents or operator absences.



These causes are generally environmental in nature. While the availability of vehicles and drivers tends to be driven by operating policies and can be controlled to some extent, random externalities still exist, such as vehicle accidents and driver sickness.

The study identified the following as significant inherent causes of unreliable service considered to most significant:

- Initial deviation from scheduled times or scheduled headways caused by traffic conditions, late departures from origin points (garage or terminals), or uncommon volumes of passenger boardings and alightings. Such deviations tend to propagate, creating unbalanced loads and may worsen conditions downstream.
- Variation in speed (travel times) between consecutive buses caused by exogenous factors and operator behavior
- Unrealistic scheduled running times and recovery times that buses are unable to follow.
- Operator behavior and inadequate supervision that impedes proper headway control or schedule adherence, especially at terminals.

### **2.3.5 STRATEGIES TO IMPROVE RELIABILITY**

The study categorizes strategies to improve reliability as follows:

- 1) Priority strategies, where transit vehicles receive special treatment to reduce the influence of external factors.
- 2) Control strategies, which involve direct handling of active service operations.
- 3) Operational strategies, that relate to changes in route, schedule and resource allocation.

The authors also group strategies into two other categories, according to their application:

- a) Preventive strategies, aimed at reducing the likelihood of reliability problems developing.
- b) Corrective or restorative strategies, directed at avoiding further propagation of problems and restoring normal operations.

Strategies identified by the study are presented in Table 2-6.

**Table 2-6. Strategies to Improve Service Reliability**

	Preventive	Corrective
<b>Priority</b>		
Exclusive Lanes	X	
Signal Priority	X	X
<b>Control</b>		
Holding		X
Passing / Overtaking		X
Turnback		X
Skip stops		X
Speed Modifications	X	X
<b>Operational</b>		
Reserve vehicle and drivers	X	X
Schedule adjustments	X	X
Express service	X	
Improve vehicle access (fare collection, boardings/alightings)	X	

\* **Source: Transit Reliability Study. (Abkowitz et al. 1978)**

Previous studies evaluated the effectiveness of these strategies through empirical analyses and simulation models. However, the authors argue that these evaluations measured improvements in reliability by changes in mean values rather than other measures of reliability.

The previous studies showed that priority strategies, such as exclusive lanes and signal preemption, had the potential to reduce mean travel time. On control strategies, the review of studies found a reduction in mean travel and wait times due to roadside, central control or automated vehicle monitoring. Holding strategies were shown to have a positive effect on headway regularity, but a negative impact on travel times. Turnbacks and skip stops were shown to have negative effects on wait times and transfers. A full cost-effectiveness evaluation would be required to determine whether the extra resources needed for vehicle monitoring could be justified. For operational strategies, there was an emphasis on good schedule planning to reflect predictable variations and the use of the reserve fleet.

The authors conclude with a number of future research proposals to supplement and extend our understanding of service reliability. Research should focus on the relationships between reliability and behavior, for both travelers and operators, and the evaluation of service measures to improve transit reliability. Recommended studies include: 1) empirical models and simulation tools to determine the causes of unreliability; 2) evaluation of reliability measures and practical testing of those proposed in the study to examine appropriateness and cost-effectiveness; 3) development of relationships between reliability and travel behavior, and 4) the effects of unreliability on the cost of operations. Future studies should also focus on the implementation and effects of strategies to improve service reliability, such as control point holding, transit priority schemes, route restructuring and schedule planning.

## 2.4 PORTLAND, OREGON STUDIES

A number of studies conducted by Portland State University, in conjunction with TriMet, the transit provider for the Portland, Oregon metropolitan area, have highlighted the innovative applications of TriMet's Bus Dispatching System (BDS) to improve bus service. While other studies have looked at the use of AVL and APC systems to improve service reliability, particular attention is given to the TriMet studies because of their depth and quality.

One of the advantages of the BDS system is the integration of AVL and APC technologies to collect detailed stop-level information. This has supported both real-time and off-line applications, increasing the pool of potential users of the data and the potential opportunities in monitoring service, measuring performance, and schedule planning. The system is also widely deployed with AVL on all buses and APC installed on 72% of the buses (Strathman et al. 2004), which eases the sample size constraint.

### 2.4.1 IMPROVEMENTS IN RELIABILITY

One of these studies (Strathman et al. 1999) documents improvements in reliability and running times after the implementation of their AVL and Computer-Aided Dispatching (CAD) technologies. The study compared key indicators of service reliability, on-time performance, headway adherence and running time variations, for eight bus routes of different types (radial, cross-town and feeder). The service reliability measures were standardized (normalized with respect to the mean) for direct comparison given the key route characteristics (route type, service frequency, time of day).

The statistical results comparing the baseline and follow-up period showed an overall increase in on-time performance, from 61.4% to 67.2% of all trips, with improvements concentrated in the AM peak period (an increase of 129%). A closer look at the distribution of delay revealed that it had shifted to the right, with a decrease in early arrivals (by almost 37%) and an increase in late arrivals (by more than 14%). This indicated that although more trips were arriving at their destination within the window of one minute early and five minutes late, the average delay had actually increased.

The coefficient of headway variation throughout the day decreased by almost 5%, with improvements concentrated mainly in the PM peak (a reduction of 15%). The share of normal headway trips (those with headway ratios<sup>3</sup> between 70% and 130%) increased by only about 1%, while the cases of bus bunching (headway ratios below 70%)

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<sup>3</sup> Headway ratio was defined as:

$$\text{Headway Ratio (HR)} = (\text{Observed Headway} / \text{Scheduled Headway}) * 100$$

Source: Strathman et al. (1999) "Service Reliability Impacts of Computer-Aided Dispatching and Automatic Vehicle Location Technology: A Tri-Met Case Study"

decreased by 15%. Overall estimated excess wait-time<sup>4</sup> also decreased (nearly 7%) in the follow-up period, concentrated in the PM peak period.

Mean running time did not change significantly, but its coefficient of variation declined by 18%, concentrated mainly in the AM peak inbound trips. Comparing running times of the baseline and follow-up period, an increase (+12%) was observed in the percentage of buses completing their trip within +/- 7.5% of their scheduled run time.

Making use of the APC data, Strathman et al. also developed a bus running time model to control for the effects of route design and passenger demand and allow for a more careful examination of the effects of the BDS. The Ordinary Least Squares (OLS) regression model estimates running time as a function of departure delays, number of stops, route length, boardings and alightings, scheduled headway, peak periods and an After-BDS dummy variable. The parameter estimates of the model are presented in Table 2-7.

**Table 2-7. Parameter Estimates for Running Time Model**

Variables	Units of Variable	Parameter Estimates
Constant	--	5.19
Departure Delay	Observed minus scheduled departure time, in minutes, at terminal	- 0.30
Stops	Number of APC-recorded passenger stops in the trip	2.90
Distance	Route length, in miles	0.34
Boardings	Total passenger boardings in trip	0.01 *
Alightings	Total passenger alightings in trip	0.01 *
Scheduled Headway	Scheduled headway, in minutes	- 0.13
AMin	Dummy variable: 1 for inbound AM peak period trip, 0 otherwise	- 1.41
PMout	Dummy variable: 1 for outbound PM peak period trip, 0 otherwise	3.70
After BDS	Dummy variable: 1 for observations after BDS implementation, 0 otherwise	- 1.45

\* The t-ratios are insignificant at the 0.05 level.

\*\* Source: *Service Reliability Impacts of Computer-Aided Dispatching and Automatic Vehicle Location Technology: A Tri-Met Case Study.* (Strathman et al. 1999)

<sup>4</sup> Excess wait time was defined as:

$$\text{Ex. Wait Time (EW)} = ((\text{Variance}_{\text{HR}} / (2 * \text{Mean}_{\text{HR}})) / 100) * \text{Mean Observed Headway}$$

Source: Strathman et al. (1999) "Service Reliability Impacts of Computer-Aided Dispatching and Automatic Vehicle Location Technology: A Tri-Met Case Study"

The authors make the following comments on the results of the model:

- Under the assumption that schedules allow for buses to make up some of the initial delay along the route (by providing more than the average running time between each timepoint – a somewhat risky strategy which may encourage early departures downstream), the authors expected the “Departure Delay” parameter to range from zero (none of the delay is made up) to minus 1 (all of the delay is made up). The model affirmed this expectation and estimated that operators recover about a third of their initial delay. (Note: this seems somewhat counterintuitive, as one would expect running times to increase with late departures, due to the likelihood of an increased number of passenger boardings).
- Boarding and alighting coefficient estimates were not significant, implying loads are within the vehicles’ capacity limitations and do not significantly influence running times.
- The authors expected scheduled headway to be inversely related to running times on the basis of a greater need for control actions, such as holding, on higher frequency routes which increases travel time. This expectation proved to be correct as the model estimates a decline in running times with increased headway. However, a more general view would attribute this relationship to larger headways tending to have lower running times because of lower demand, and not the need for control actions.
- The authors expected higher running times during peak periods (positive model parameter estimates for the AMin and PMout variables). This expectation is contradicted in the AM peak period, where running times were estimated to be slightly lower (by almost 1.5 minutes). The PM peak period does show increased running times (by nearly 3.7 minutes) compared to other trips, showing congestion problems are worse later in the day.
- Running times for AM peak inbound trips were estimated to be slightly lower (-1.5 minutes) compared to other trips in the day. The parameter estimate for inbound AM peak period trips also contradicted the authors’ expectations of higher running times during peak periods due to traffic congestion.
- After controlling for the effects of the other variables, the model estimated that the BDS system reduces trip running times by almost 1.5 minutes on an average route. Benefits from the initial impacts of the BDS were analyzed as having cost-saving potential.

In general, average running times were shown to be slightly higher in the follow up period. Interpretation of the results was that the reductions in running times due to the BDS have been masked by the effects of changes in other operational characteristics, such as an increase in average number of stops, in scheduled headways and in average departure delays.

Strathman et al. organize benefits into three categories: 1) reductions in passenger wait times, 2) reductions in passenger in-vehicle travel times, and 3) improvements in operator running times. These translate to increased passenger satisfaction and cost savings, and when valued using average passengers' wage rate and operational costs, they yield savings up to \$5.4 million.

The study concludes that the impact of the automated bus dispatching system were positive, with improvements in on-time performance and in headway and running time variability. The system has the potential to yield greater benefits through further use in operations control and monitoring, and in service planning.

## **2.4.2 SCHEDULE EFFICIENCY AND OPERATOR BEHAVIOR**

Another study (Strathman et al. 2001<sup>1</sup>) uses archived data to analyze the efficiency of schedules and investigate the effects of operator variability on running times. The analysis consisted of comparing actual and scheduled running times and recovery times. The analysis was applied to one route (14 Hawthorne) characterized as a radial route with frequent service and heavy passenger loads, and external traffic conditions including moderate-to-heavy traffic, on-street parking on most of the route, numerous signalized intersections and random delays from openings of a river bridge crossing.

The analysis assumes the definition of optimal running time and recovery times described by Levinson (1991). Levinson argues that "running time for the route should be set at a value slightly less than the median/mean" and "appropriate recovery time is defined as the difference between the chosen [running time] benchmark and the running time associated with the 95<sup>th</sup> percentile trip in the frequency distribution." This ensures that, under normal operating conditions, 95 percent of the trips will be able to maintain their schedule. These "optimal" values were compared with their scheduled times for five different time periods (early AM, AM peak, mid-day, PM peak and evening).

The results showed that scheduled running times are lower than "optimal" for all outbound trips and that scheduled recovery times were higher than "optimal" for all trips except in the PM peak inbound trips. Even though these scheduled times follow standard practice of setting low running times with generous recovery times to avoid excess time and late departures, the total scheduled (running plus recovery) times were found to be excessive (higher than "optimal").

The authors also present a more detailed analysis of each scheduled trip on all bus routes in the system to account for different route types and service patterns. The analysis considers three different recovery benchmarks: 1) Levinson's optimal recovery time based on the 95<sup>th</sup> percentile value, 2) based on operators' contract requirements, recovery time equal to 10% of the median running time, and 3) the "rule-of-thumb" standard of 18% of the median running time. The analysis used running time data from 281,305 trip-level observations from 5,479 scheduled daily trips of 104 bus routes over 65 weekdays.

The results of this analysis found that the average scheduled running time conforms to Levinson's use of the median running time value. However, for all three recovery time benchmarks, there are excesses in scheduled recovery time and in total scheduled times, which includes running and recovery times. The latter were found to be in excess by 7.30, 7.92 and 3.82 minutes based on the benchmark values by Levinson, contract requirements and "rule-of-thumb" standard, respectively. Based on these excess time values and a marginal operating cost of \$42.00 per platform hour and 255 days of weekday service, the analysis presents estimates of potential annual cost savings of \$7.1, \$7.7 and \$5.1 million dollars, respectively. Using the standard "rule-of-thumb" value of 18%, 81 of the 104 routes had excess scheduled times. Limitations also exist in reducing recovery times, such as clock face schedules, labor contracts, transfer optimization and operator scheduling.

Nonetheless, the analysis suggests that adjustments towards a more efficient schedule could potentially yield cost-reduction by more efficiently scheduling vehicles while still providing the same level of service to customers. Also, the study clearly demonstrates the potential of using automatic data collection technologies in scheduling and service planning.

Another component of the study (Strathman et al. 2001<sup>1</sup>) is a model that explored the influence of operator behavior on running times. The model estimated run times as a function of route length, number of stops made, time period variability, route type, passengers boarding and alighting, scheduled headway, seasonal variability, and an operator-specific dummy variable. Fifteen bus routes, of different types, were selected and the study comprised of 110,743 valid weekday trips (49.7% of all scheduled weekday trips for the selected routes) in the summer and fall sign-up periods. The parameters estimates of the model are presented in Table 2-8 and the coefficients represent the change in running time associated with a unit change of the given variable.

**Table 2-8. Running Time Model**

<b>Variable</b>	<b>Coefficient (in seconds)</b>
Intercept	573.09
Distance (per mile)	206.00
Lifts (does not include 8.10 seconds to stop)	59.80
Stops (involving a single boarding / alighting)	8.10
Early AM (compared to mid-day)	- 256.66
AM Peak (compared to mid-day)	- 99.84
PM Peak (compared to mid-day)	138.43
Night (compared to mid-day)	- 248.04
Feeder (compared to radial route)	- 418.47
Crosstown (compared to radial route)	- 506.14
Peak Express (compared to radial route)	- 1088.90
Ons+Offs	3.36
Ons+Offs <sup>2</sup>	- 0.0016
Headway (per 1 minute reduction)	- 10.76
Summer	- 26.40

**\* Source: Evaluation of Transit Operations: Data Application of Tri-Met's Automated Bus Dispatching System. (Strathman et al. 2001<sup>1</sup>)**

With regard to the operator-specific variables, the results of the model indicate that 70% of the recovery time allocated (based on the standard of using 18% of the mean running time) is needed to account for variation in operator behavior, and 17% of running time variation can be attributed to operator behavior factors.

To further explore these factors, the authors specify a model to estimate the individual operator effects as a function of experience, average delays and work assignment type (trippers, extraboards and reliefs). The R<sup>2</sup> value of the model is 0.09 and the estimated parameters, along with the expectations, are shown in Table 2-9. Model parameters showed a decrease in nearly 0.57 seconds in running time per trip for each additional month (nearly 7 minutes for each year) of operator work experience (i.e, older drivers tend to drive faster). The departure delay parameter was not significant, and of the work assignment variables, only the tripper parameter was significant, estimated to increase running time by 40 seconds compared to duty types. Based on the results of these analyses, recommendations to reduce variability included operator training and increased field supervision, and that the cost effectiveness of these strategies be assessed.



**Table 2-9. Operator Model Parameter Estimates**

Variable	Expectation	Mean Value (Std. Dev.)	Coefficient (t-value)
Intercept	—	—	25.15 (1.07)
Experience (months of service)	Inversely related (increased driving skill, familiarity and operating conditions)	94.3 (88.7)	- 0.57 (- 5.69)
Complaints (number per year)	Unclear in relationship of complaints and adherence	3.9 (4.5)	- 1.43 (- 0.92)
Departure Delay (average delay over sampled trips)	Inversely related (makes up delay by running faster)	101.2 (54.9)	- 0.19 (- 1.49)
Regular Service		—	—
Tripper (1 if assignment is a tripper, 0 otherwise)	Require more time, typically filled by part-time operators during peak	0.20 (0.40)	40.01 (1.78)
Extraboard (1 if operator has extraboard assignment, 0 otherwise)	Unclear, but filled by full-time operators	0.21 (0.41)	- 5.54 (- 0.26)
Relief (1 if operator has relief assignment, 0 otherwise)	Require more, filled by newer operators	0.18 (0.39)	29.8 (1.34)

\* Source: *Evaluation of Transit Operations: Data Application of Tri-Met's Automated Bus Dispatching System.* (Strathman et al. 2001)

### 2.4.3 HEADWAY DEVIATIONS AND PASSENGER LOADS

Another study by Strathman et al. (2003) investigates the relationship between headway deviations and passenger loads using archived AVL-APC data. Deviations in passenger loads will tend to contribute to a deterioration in the headway distribution due to abnormally high or low dwell times. Simultaneously, extreme headway deviations will create disproportionate passenger loads. The study included ten of TriMet's 99 bus routes, providing cross-town (2 of the 10 routes) and radial services (8 of the 10 routes), and was limited to weekday service for a period of 6 months. The mean peak passenger load is normally lower than bus seat capacity, which is 43 for a standard 40 foot bus and 39 for a low-floor bus. However, the coefficient of variation in passenger loads for these routes range from 0.30 to 0.40. Routes with high mean loads and high coefficient of variation experience greater incidence of overloads. Scheduled headways for these routes ranged between 5-12 minutes<sup>5</sup>.

A two-stage least squares regression model was formulated to account for the simultaneity between passenger loads and headway deviations. The first-stage

<sup>5</sup> Range of headways determined from posted schedules on TriMet's website: [www.trimet.org](http://www.trimet.org) (July 2005)

equation estimated headway delay<sup>6</sup> at the peak load point as a function of headway deviation at the route origin (terminal point), operator experience and distance from route origin to peak load point. The second equation estimated passenger load at the peak load point as a function of headway deviation at the peak load point, scheduled headway and a low floor vehicle dummy variable. The two-stage regression model meant that instead of using the observed values of headway deviation, the estimates of headway deviations from the first equation were used in the second equation.

The model results indicated passenger overloads were indeed primarily caused by headway deviations. It is estimated that an increase of 1 minute in headway deviation at the peak load point increases load by 2.6 and 2.0 people for the AM peak and PM peak, respectively. Further analysis of the first equation estimates revealed that a one-minute increase in headway deviation at the terminal point generally resulted in an increase of approximately 45 second in headway deviation at the peak load point. Reductions in headway deviations, especially at the origin (terminal), would yield significant reductions in passenger load variation. The authors recommended that strategies to control for delays should be focused on improved field supervision or, in the case where running times and recovery times are insufficient, on schedule adjustments. The authors also argued that this type of analysis with archived data provides agencies with the data and tools to target potential problems and to implement control measures more efficiently.

#### **2.4.4 OPERATIONS MANAGEMENT**

Data availability at TriMet has also allowed analysis of archived data to improve schedule and operations management (Kimpel et al. 2004). The paper was a summary presentation of a number of performance reports used by TriMet to monitor service quality and operational efficiency. A summary of the key findings highlighted in the report are:

- The detailed design of the TriMet BDS has allowed for the generation of various reports analyzing different performance measures for multiple purposes.
- Agency staff are able to customize reports to monitor schedule efficiency, passenger loads and capacity, on-time performance and operator behavior, which can be broken down by route, direction and time of day.
- The potential exists to analyze the relationship between operator behavior and service reliability. The reports can track operator performance through measures such as percent of late departures and average minutes early or late. These allow peer comparisons among operators and help identify the effects of operator variability in order to improve schedules and supervisory actions.

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<sup>6</sup> Headway delays are referred to as positive or negative deviations from scheduled headways. A positive deviation means a greater-than-scheduled headway, while a negative deviation signifies a smaller-than-scheduled headway. To avoid confusion, this study will refer to headway delays as “headway deviations”

In summary, the service delivery reports generated by TriMet provide a detailed understanding of route performance in order to identify potential problems, investigate the effects of various service attributes and serve as feedback and diagnostic tools to improve scheduling, planning, and operations.

#### **2.4.5 OPERATIONS CONTROL**

In the area of operations control, Strathman et al. (2001<sup>2</sup>) present a review of previous operations control practice and an experiment to evaluate the potential of the TriMet BDS to manage headways. The review shows that previous studies had analyzed various strategies such as holding, short-turning, signal priority, but had been limited by availability of data due to the large costs of data collection and supervisory restrictions. Field supervisors are located at specific points and do not have easy access to information about the whole system. The study examined the potential of APC and AVL technologies to estimate the effects of real-time control strategies and implement them more effectively. The experiment involved comparing passenger load variations and headway variations for a baseline period and a control period, where various control strategies were undertaken by field supervisors. The statistical analysis performed did not provide significant evidence of the effects of the applied control strategies; although the desired outcome of more balanced passenger loads was attained. The authors conclude that the use of real-time APC and AVL for control purposes has been limited, and there is a need to develop a decision support system to more effectively aid dispatchers and field supervisors in maintaining and restoring service reliability.

#### **2.5 RESEARCH POTENTIAL**

The framework developed by Abkowitz et al. (1978) served as a theoretical discussion of transit reliability with the objective of achieving greater understanding of reliability. The framework recommends appropriate measures, identifies various causes of unreliability and reviews the potential strategies available to deal with unreliability. It recognizes that the characteristics of the distribution of service attributes give a better picture of reliability than just the mean value of the measures, and that the evaluation of the mean and variability combined is key to the understanding service problems. However, the structure and conclusions of the study were largely theoretical and had limitations in the analysis of real operating data to support its framework and apply these concepts in practice.

The studies conducted in Portland have taken advantage of this potential and explored the application of ADC systems to improve service planning, performance monitoring and operations management. The extensive disaggregate data provided by TriMet's Bus Dispatching System (BDS) have allowed analysts to study the impacts of AVL and APC systems on service operations and performance, and the relationships between certain service attributes. However, these studies do not provide a comprehensive examination of the causes of service unreliability and their complex relationships with service attributes.

This research builds upon the strengths and weakness of the studies reviewed and develops a practical framework to understand service reliability using archived AVL and APC data. With the introduction of ADC systems, the limitations of high cost and extensive manual labor involved with collecting and processing large data sets no longer hinder the potential for more detailed analyses and a deeper understanding of reliability problems. The data available from these systems provide the opportunity to extend our understanding of unreliability and how service problems can be analyzed.

The practical framework presented in Chapter 3 aims to be as comprehensive as the framework presented by Abkowitz et al. 1978, but based on the technological advances in data analysis and application of decision support tools using archived data, as described by Furth et al. (2003) and developed by TriMet and Portland State University.

Updates to the transit reliability framework include:

- A review and selection of appropriate service measures that adequately characterize service and help identify reliability problems. The effectiveness of the measures presented by Abkowitz et al. (1978) is evaluated further using more extensive and more detailed datasets.
- An in-depth framework to identify the causes of service unreliability and evaluate the complex relationship between them using archived data. These will go beyond those presented by Abkowitz et al. (1978) to reflect the recent data analysis capabilities available through automated data collection systems.
- The type of analyses developed by TriMet and Portland State University are brought together to analyze service reliability in a broader and more complex approach. Rather than looking at individual relationships between different service attributes, which is what these studies have evaluated, the framework attempts to take a step further and provides more detail on the interrelationships between the causes of service unreliability and the complexities inherent in their impact on service operations. Analysis tools are developed to help separate out the various contributions of interrelated service design and operations factors.

## **3. A FRAMEWORK FOR ANALYZING TRANSIT RELIABILITY**

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Previous research has laid a strong foundation for the analysis of service reliability, but gaps in understanding unreliability and its causes still remain. The implementation of automated data collection systems presents an opportunity to expand previous research and extend our understanding about reliability. The objective of this chapter is to develop a practical framework to assess transit reliability, with an emphasis on using data from automated collection systems.

The chapter is organized in the following manner. Section 3.1 reviews the need for a practical framework. Section 3.2 presents the key characteristics of transit service reliability. Sections 3.3 and 3.4 present the causes of service reliability problems and potential strategies to improve reliability, respectively, while Section 3.5 describes the relationships between these causes and strategies. Section 3.6 presents the proposed reliability analysis process to assess service reliability, describing the steps to characterize reliability, identify the causes of unreliability and apply appropriate strategies to improve service.

### **3.1 FROM THEORY TO PRACTICE**

Prior research has clearly shown that service reliability is a key objective for both travelers and transit agencies. It is clear that to efficiently implement strategies to avoid reliability problems or reduce their impacts, the fundamental causes of unreliability must be understood. However, it is clear that poor reliability can be triggered by many different and interrelated factors and so it is difficult to fully understand and address the underlying causes.

Abkowitz et al. (1978) acknowledged the need for further research to increase the understanding of reliability, especially the need to develop empirical models to evaluate their proposed measures and possible causes of unreliability. While the TriMet studies, reviewed in Chapter 2, have begun to take advantage of new technologies to increase our understanding of service reliability, a gap between the theoretical groundwork and practical applications remains.

The 1978 study (Abkowitz et al.) was based on knowledge of transit reliability at the time. Twenty-five years later, this research re-visits this framework to assess which features are still appropriate and applicable in light of our improved understanding based on better data.

The proposed framework includes:

- The overall picture of service reliability including the characteristics of unreliability, the causes of problems and potential strategies to improve service reliability.

- A review of data and possible service measures to characterize service unreliability. The service measures consider the perspective of both travelers and transit agencies, and what the trade-offs are between them.
- The distinction between systemic and random variations in archived data. Determining whether an observed variation, such as a long gap in service, is a random occurrence or a systemic problem. It is important in data analysis to determine the patterns of occurrence that help identify the underlying causes of unreliability.
- The development of performance reports and analysis tools that enable the transit agency to assess current service and identify the causes of unreliability problems.

## **3.2 KEY CHARACTERISTICS OF SERVICE RELIABILITY**

This section presents an overall picture of service reliability, highlighting the key characteristics of service unreliability and their impacts. A key aspect of transit reliability is the distinction between low-frequency and high-frequency routes. The attributes of transit reliability differ based on the frequency of the route because of the difference in passenger behavior and passenger perception of unreliable service. Passengers on low-frequency routes tend to time their arrival at a stop to catch a specific scheduled trip and minimize wait time. Service will be perceived unreliable if their specific trip is not running as scheduled, and they end up missing it or having to wait a long time because it is late. Passengers on high-frequency routes tend not to consult posted schedules because service is frequent enough they should not experience long wait times. Unreliability for these passengers will be in the form of very long wait times (especially if two buses arrive together after a large gap in service), and overcrowding.

As a reference, the *Transit Capacity and Quality of Service Manual (TCQSM)* considers the threshold of 10 minute headways at which point the passengers consult the posted schedules (low-frequency routes) or are assumed to arrive at random (high-frequency routes).

### **3.2.1 ON-TIME PERFORMANCE**

On-time performance is the measure of whether buses are operating as scheduled. From the passengers' perspective, on-time performance is critical on low-frequency routes, particularly for inexperienced travelers who base their departure time decisions on printed schedules in order to minimize the expected wait time (Abkowitz et al. 1978).

When buses do not operate as planned, travelers experience poor service quality due to increased wait times and higher likelihood of late arrival at destination. If a bus departs early, travelers who time their arrival at the stop in order to minimize wait time may end up missing the intended bus and have to wait a full headway for the next bus. If a bus departs late, travelers experience longer wait times. Transit agencies experience

inefficient operations, possible increases in operational costs (to compensate for poor service), and loss of patronage and revenues as a result.

The TCQSM argues that measures of on-time performance should be based on the interest of the passengers which will vary by location on the route as well as the scheduled headways. For most passengers, an early departure is not “on-time” because if they timed their arrival based on posted schedule, they will have to wait a full headway for the next bus. However, at points where more passengers are likely to alight than board, an early arrival does not have as great an impact. This study defines “on-time” performance as the range between 0 and 5 minutes late, with consideration of whether to measure departures or arrivals based on the likelihood of boardings and alightings. Table 3-1 presents the TCQSM proposed levels of service for on-time performance, with “on-time” performance defined as 0 to 5 minutes late applied to either arrivals or departures.

**Table 3-1. On-Time Performance Levels of Service**

Level of Service (LOS)	On-Time Percentage
A	95.0 – 100 %
B	90.0 – 94.9 %
C	85.0 – 89.9 %
D	80.0 – 84.4 %
E	75.0 – 79.9 %
F	< 75.0 %

\* Source: *Transit Capacity and Quality of Service Manual – 2<sup>nd</sup> Edition*

Benn (1995) presents a survey of transit agencies in North America that shows most agencies define an early bus as 1 minute early and a late bus as 5 or more minutes. The Chicago Transit Authority (CTA) defines on-time schedule adherence as buses within 1 minute early and 5 minutes late for headways over 10 minutes. New York City Transit (NYCT) uses the same 1 minute early and 5 minutes late window for on-time performance (NYCT website, 2005). The MBTA’s service delivery policy designates bus service as on-time for arrivals and departures within 0 to 5 minutes of published schedules (MBTA Service Delivery Policy, 1996)

### 3.2.2 HEADWAY REGULARITY

Headway adherence is often used to determine service reliability for high-frequency bus service since passengers often arrive randomly and headway irregularity can affect both expected waiting times and the variability of passenger loads. The variability of headways causes travelers to perceive service as unreliable, especially if two or more buses arrive in a platoon after a long gap in service. There is clearly a problem when buses drive along the route one right after the other, meaning somewhere there is a gap in service and resources are not being used efficiently.

The TCQSM considers headway adherence level of service (LOS) grades based on the coefficient of variation of headways and the probability of bunching (see Table 3-2). The coefficient of variation of headway is the standard deviation of headway divided by the mean scheduled headway. The probability is defined as the probability that a vehicle's headway will differ from the scheduled headway by more than 50%.

**Table 3-2. Fixed-Route Headway Adherence Level of Service**

Level of Service (LOS)	Coefficient of Variation of Headway	Probability	Comments
A	0.00 – 0.21	≤ 1 %	Service provided like clockwork
B	0.22 – 0.30	≤ 10 %	Vehicles slightly off headway
C	0.31 – 0.39	≤ 20 %	Vehicles often off headway
D	0.40 – 0.52	≤ 33 %	Irregular headways, with some bunching
E	0.53 – 0.74	≤ 50 %	Frequent bunching
F	≥ 0.75	> 50 %	Most vehicles bunched

\* **Source: Transit Capacity and Quality of Service Manual – 2<sup>nd</sup> Edition**

Benn (1995) reports that 28% of the transit agencies surveyed use headway adherence as a criterion for performance evaluation, but that attention to this criteria is increasing due to the availability of data from AVL technologies. The CTA defines regular headways as headways below a threshold value of 150% of scheduled headway (readings above are considered gaps in service) and above an absolute value of 1 minute (buses with headways lower than 1 minute are considered bunched). NYCT defines an “acceptable limit” for headways based on bus wait assessment, given as no more than 3 minutes greater than scheduled headway during peak hours, and 5 minutes during off-peak hours (NYCT website, 2005). This means, that headway deviations above 3 (or 5) minutes are considered unreliable because customers have to wait longer than scheduled. For MBTA bus service, the service delivery policy defines a good service adherence as 85% of all trips in a time period are within 1.5 (or 150%) of scheduled headway, for service with scheduled headways lower than 10 minutes (MBTA Service Delivery Policy, 1996)

### 3.2.3 PASSENGER LOADS

Service frequency is set to ensure demand is evenly distributed and buses do not exceed a given load factor<sup>7</sup>, a measure based on the bus seat capacity. Benn (1995) shows that seventy-two percent of transit agencies surveyed use a benchmark maximum number of standees as criteria in schedule design standards. This benchmark is a percent of the number of seats. When passenger loads are high, passengers experience a lower level of comfort, and boarding and alighting times generally increase, along with the dwell time at stops. Overcrowding eventually leads to a more severe problem when passengers are not able to board the first bus that arrives because it is

<sup>7</sup> Load factor is defined as the occupancy of a vehicle divided by its seating capacity.

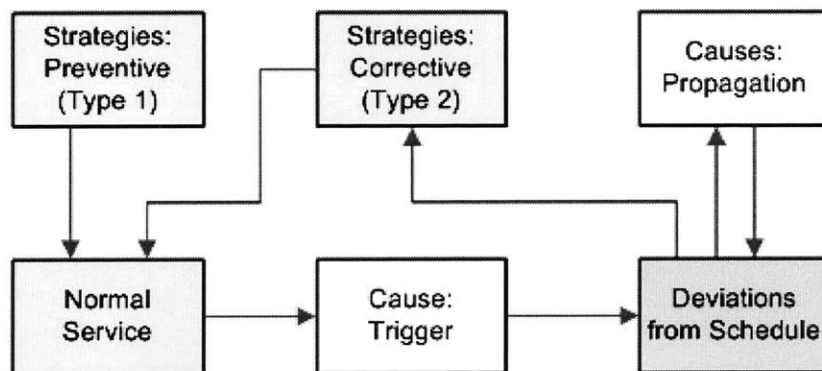


full and have to wait for the second vehicle. This obviously increases the wait time of passengers, the probability of late arrival at destination and the user's frustration.

### 3.2.4 OVERVIEW OF INTERACTIONS

Before discussing the causes of unreliability and strategies to improve service, it is helpful to provide a broad picture of the interactions affecting reliability of transit service. At a high level, Figure 3-1 shows how service unreliability develops and how the system may be restored to scheduled or normal service. Trigger events are defined as occurrences, whether operational or external, which cause an initial deviation of a vehicle from its scheduled time or headway. Many of these causes can also propagate unreliability once deviations have occurred. The strategies to improve service reliability are categorized as preventive and corrective, according to their application. Preventive techniques aim to avoid the occurrence of problems and maintain regular service, while corrective strategies aim to return service to normal and minimize the effects of deviations.

*Figure 3-1. Service Reliability Interactions*



The relationships between the different components are simplified in this diagram, since the interrelationship of service attributes, causal factors and potential strategies are quite complex. These complexities are discussed further in subsequent sections.

## 3.3 CAUSES OF UNRELIABILITY

This section describes the most significant causes of service reliability problems. The goal is to provide further understanding of why they are considered significant causes, how they impact service and how they are interrelated.

### 3.3.1 SCHEDULE DEVIATIONS AT TERMINALS

Schedule deviations (actual departure time minus scheduled departure time; thus, late departures are positive deviations while early departures are negative deviations) can be measured at any point along a route. Some buses may be able to make up a schedule

deviation and return to their scheduled times further down the route, but others may not be able to. A schedule deviation might propagate, with the vehicle falling further from schedule as it proceeds along the route, leading to further service deterioration.

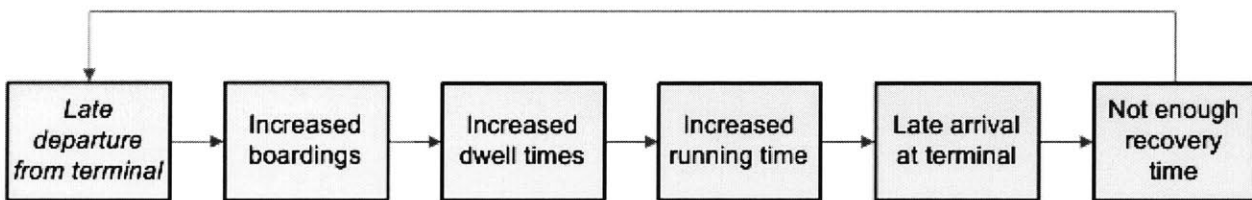
Emphasis is given to schedule deviations at the terminal because operators and supervisors have more control at these points than at intermediate points along the routes. Supervisors at terminals are able to monitor driver behavior and more disciplined behavior is likely to result. Recovery times at terminals are intended to allow buses to recover from earlier delays (i.e. late arrival on the previous trip) and still begin the next trip on-time. Recurrent late departures from terminals may be an indication of inadequate training, poor enforcement or supervision, or poor scheduling.

Small deviations from schedule at intermediate points are not as significant because the scheduled times are based on average running times and variability is known to occur. These deviations may also be the direct result of deviations at the beginning of trips from which drivers are unable to recover.

Problems at terminals are also significant because unreliability tends to propagate downstream, and any deviations from scheduled times or headways at the start of the trip will affect a greater number of passengers.

Figure 3-2 illustrates the effects late departures from terminals could have on service. Deviations have the potential to cause an increase in boardings at stops further downstream, if passengers arrive randomly at downstream stops, as is often the case with high frequency service. Increased boardings at stops result in higher dwell times, which increase total running times. If not enough recovery time is available at the end of trips, late arrivals of previous trips might carry over to the next trip and cause further late departures.

**Figure 3-2. Effects of Late Departure from Terminal**



An important concept here is the concept of *random incidence* when dealing with the relationship between headways and passenger loads. If passengers are assumed to arrive at random, which is the case for high-frequency route, the probability of a passenger arriving in a long headway is greater than that of a shorter headway. Therefore, if headways become imbalanced such that consecutive buses have alternating headways of 5 and 15 minutes, the probability of a passenger arriving during the 15 minute headways is 0.75. Thus, imbalanced headways will create an imbalance in passenger loads between consecutive buses.

The relationship between headway deviation and passenger boardings is illustrated in the following example. Assume a route with running time of 5 minutes between stops, and vehicles departing from the terminal every 5 minutes. Passengers are assumed to arrive at a rate of 2 passengers/minute at each stop, each passenger takes 5 seconds to board the bus and there are no alightings at any of the stops. Table 3-3 presents the resulting differences if one bus departs the terminal one minute late.

**Table 3-3. Effects of a Late Departure**

	Scheduled Service												
	Depart from Terminal	Bus Stop A				Bus Stop B				Bus Stop C			
		Arrive	Depart	Boardings	Load on Bus	Arrive	Depart	Boardings	Load on Bus	Arrive	Depart	Boardings	Load on Bus
Bus #1	3:00:00	3:05:00	3:05:50	10	10	3:10:50	3:11:40	10	20	3:16:40	3:17:35	11	31
Bus #2	3:05:00	3:10:00	3:10:50	10	10	3:15:50	3:16:40	10	20	3:21:40	3:22:25	9	29
Bus #3	3:10:00	3:15:00	3:15:50	10	10	3:20:50	3:21:40	10	20	3:26:40	3:27:35	11	31
Bus #4	3:15:00	3:20:00	3:20:50	10	10	3:25:50	3:26:40	10	20	3:31:40	3:32:25	9	29

	Actual Service												
	Depart from Terminal	Bus Stop A				Bus Stop B				Bus Stop C			
		Arrive	Depart	Boardings	Load on Bus	Arrive	Depart	Boardings	Load on Bus	Arrive	Depart	Boardings	Load on Bus
Bus #1	3:00:00	3:05:00	3:05:50	10	10	3:10:50	3:11:40	10	20	3:16:40	3:17:35	11	31
Bus #2	3:06:00	3:11:00	3:12:00	12	12	3:17:00	3:18:05	13	25	3:23:05	3:24:10	13	38
Bus #3	3:10:00	3:15:00	3:15:35	7	7	3:20:35	3:21:05	8	13	3:26:05	3:26:25	4	17
Bus #4	3:15:00	3:20:00	3:20:50	10	10	3:25:50	3:26:45	11	21	3:31:45	3:32:50	13	34

Bus #2 leaves the terminal one minute late, and begins its trip with a preceding headway of 6 minutes, not 5 minutes as scheduled. Because of the longer headway, there are more passengers waiting to board this bus at Stop A, increasing the dwell time and load on-board. In the mean time, Bus #3 leaves on-time with a 4-minute headway, and has a lower dwell time because fewer passengers have arrived at each stop. By the third stop, the headways have diverged from the scheduled 5:00 minutes to 6:35 minutes and 2:15 minutes for Buses #2 and #3, respectively. As the buses continue along the route, Bus #2 headway will increase, leading to crowding and falling even further behind schedule. Bus #3 will pick up fewer passengers, its headway will decrease and eventually it will catch up with Bus #2. Of course, this example is highly simplified. Passenger arrivals at stops are not a constant deterministic process, boarding and alighting times are not linear and are affected by other factors (for example, crowding and wheelchair accessibility), and other externalities, such as traffic conditions, cause other variations in running times between stops.

Late departures from terminals can be the result of various factors:

- Late pullout from the garage. A garage pullout is the start of a vehicle block, as buses deadhead from the garage to the route terminal. Any deviations from scheduled pullout times have the potential to carry over to the first revenue trip. Late pullouts from a garage may be due to:

- A. Operator or vehicle unavailability, which includes vehicle malfunctions or operator re-assignment due to absenteeism.
- B. Operator behavior, which involves operators reporting late for work or delays in starting workpieces (i.e. disregard for schedule).
  - Late arrival from previous trip. If recovery time at the terminal is insufficient, delays from a trip will propagate to the next trip. Late arrival from the previous trip may be the result of poor scheduling (inadequate schedule running time), major delays due to traffic conditions or passenger boardings, or operator behavior.
  - Operator behavior. Late departures may occur if operators disregard scheduled departure times, take a break time greater than the available recovery time, or report late for duty when relief occurs at the terminal.

### 3.3.2 PASSENGER LOADS

Poor service quality is experienced by passengers when buses are highly loaded and crowded. Many passengers find it uncomfortable to stand for a long time or they are unable to use their travel time productively (Transit Capacity and Quality of Service Manual). Transit disutility increases when passengers compare feeling cramped in a bus with the privacy and comfort of a single seat ride on a personal vehicle. Service quality also deteriorates with higher crowding levels because it becomes more difficult to move around inside the bus. The added interference increases the dwell times at bus stops as buses must wait longer for people make their way in and out.

Two passenger boardings conditions can affect service reliability:

- Abnormal loadings. These tend to affect the load on one vehicle and can disrupt the headway distribution. When one bus spends a significant amount of time at a stop, the preceding bus has the chance to increase the gap between them as it proceeds along the route, and the following bus is more likely to catch up with the first bus. A greater number of passengers will have accumulated at stops downstream because of the larger headway, so the bus will continue to fall further behind schedule. Eventually, this leads to bunched vehicles separated by large gaps in service.

Abnormal deviations in passenger loads thus tend to initiate schedule deviations. Take the example in the previous subsection. The same assumptions of passenger arrivals and travel times hold, except this time all buses depart from the terminal on-time but a group of 10 passengers arrive at stop A at 3:07:00. Other passengers still arrive at the stop at the assumed rate of 2 passengers per minute. The results of this random passenger load, shown in Table 3-4, are increases in headway and load variability.

**Table 3-4. Effects of an Abnormally High Passenger Load**

	Scheduled Service												
	Bus Stop A				Bus Stop B				Bus Stop C				
	Depart from Terminal	Arrive	Depart	Boardings	Load on Bus	Arrive	Depart	Boardings	Load on Bus	Arrive	Depart	Boardings	Load on Bus
Bus #1	3:00:00	3:05:00	3:05:50	10	10	3:10:50	3:11:40	10	20	3:16:40	3:17:35	11	31
Bus #2	3:05:00	3:10:00	3:10:50	10	10	3:15:50	3:16:40	10	20	3:21:40	3:22:25	9	29
Bus #3	3:10:00	3:15:00	3:15:50	10	10	3:20:50	3:21:40	10	20	3:26:40	3:27:35	11	31
Bus #4	3:15:00	3:20:00	3:20:50	10	10	3:25:50	3:26:40	10	20	3:31:40	3:32:25	9	29

	Actual Service												
	Bus Stop A				Bus Stop B				Bus Stop C				
	Depart from Terminal	Arrive	Depart	Boardings	Load on Bus	Arrive	Depart	Boardings	Load on Bus	Arrive	Depart	Boardings	Load on Bus
Bus #1	3:00:00	3:05:00	3:05:50	10	10	3:10:50	3:11:40	10	20	3:16:40	3:17:35	11	31
Bus #2	3:06:00	3:10:00	3:11:55	22	22	3:16:55	3:17:45	12	34	3:22:45	3:23:45	12	46
Bus #3	3:10:00	3:15:00	3:15:40	8	8	3:20:40	3:21:25	7	15	3:26:25	3:26:55	6	21
Bus #4	3:15:00	3:20:00	3:20:50	10	10	3:25:50	3:26:45	11	21	3:31:45	3:32:50	13	34

The scheduled headway of 5:00 minutes between buses diverges to headways of 6:10 minutes for Bus #2 and 3:10 minutes for Bus #3. Bus #2 will continue to pick up more and more passengers down the route, falling further behind schedule and increasing its headway. At the same time, Bus #3 will have less passengers arriving and waiting at stops, have lower dwell times and will catch up with Bus #2, creating the bunching effect of two vehicles platooning together and also creating large gaps in service.

- Inadequate frequency to meet demand. When actual demand is greater than expected, buses will run with higher than planned load factors which can lead to:
  - A. Crowding. Overcrowding decreases the level of comfort, slows down operations and may lead to passengers being unable to board the first bus that arrives. When this situation occurs, travelers may feel frustrated in having to wait another full headway for the next bus, especially after already waiting a long time, or having to seek an alternate mode of transportation.
  - B. Poor on-time performance. The higher boarding and alighting volumes make dwell times at bus stops greater than those scheduled. Vehicles fall behind schedule and service is not provided as promised.

In both cases, it is clear that any deviations in passenger loads disrupt the headway distribution, and problems tend to propagate. Even when passenger loads are light, buses might tend to run off-schedule because of the decreased time spent at stops or a decrease in the number of stops serviced. If buses are not required to serve all stops, only those requested by passengers, there is a time difference “saved” between the time it takes to drive by and the time it needs to decelerate, serve passengers and accelerate back into service.

### 3.3.3 RUNNING TIMES

The variability of running times, especially between consecutive buses, affects the headway distribution. Transit planners acknowledge such variability in running times and therefore schedule recovery time at the end of each trip to ensure subsequent trips have a high probability of on-time departure. If running times are inadequate, the majority of the buses will have a poor on-time performance.

When actual running times are lower than scheduled, buses will tend to run “early” for most of the route. Passengers who time their arrival at stops according to schedules will be left waiting for a bus that has already left, and will have to wait a lot longer than expected. If drivers are instructed to hold at certain time points and depart only at set scheduled times, passengers experience increased in-vehicle times. With very slack schedules, transit agencies then fail to benefit from the possibility of higher frequencies with the same level of resources, or the opportunity to reduce the total number of buses needed.

If too little running time is scheduled, buses will not run as scheduled. The system would have poor on-time performance, and passengers who time their arrival at stops to minimize wait time end up experiencing longer wait times and lower probabilities of on-time arrival at their destination. Buses are also likely to arrive “late” at terminals, and if not enough recovery time is allocated, late departures from terminals can result and reliability problems will propagate throughout the day.

Overall, the result of inadequate running times is poor on-time performance and inconvenience to passengers.

Running times are affected by traffic conditions and other externalities, and by operator behavior, which are evaluated in the next sections. Some operators tend to drive faster and more aggressively, while others tend to be slower. The speed differentials due to traffic conditions, intersections and operator behavior will cause deviations in headways throughout the route. Recovery times and operator behavior are also related. If recovery times are not adequate, drivers might tend to delay the start of the next trip.

### 3.3.4 ENVIRONMENTAL FACTORS

Environmental factors relate to traffic and the external context of operations (Abkowitz et al. 1978, Levinson 1991). These exogenous causes are generally random in nature, and cause variability in scheduled bus service.

- Weather. Lower visibility levels, cautious drivers or poor road conditions during inclement weather can reduce the speed of vehicles on the road and increase the probability of accidents occurring. During bad weather, boarding and alighting times tend to be above average. For example, when it is raining, passengers waiting for a bus with open umbrellas will not pack together as tightly and will take longer to board as they enter the bus and close their umbrellas.

- Interactions with other vehicles on the road. Buses operate on roads, and generally in mixed-use traffic. The presence of other vehicles on the road reduces travel speeds, and high volumes of traffic create congestion. Interference occurs in numerous forms, all of which disrupt normal service: vehicle movements, such as lane changes or turning movements, street parking, illegally parked vehicles or unexpected breakdowns and accidents.
- Speed differentials. Intersections force buses to decelerate and accelerate, reducing travel speeds and increasing total travel times. Signalized intersections add even more variability because of the random nature of arrival at the traffic light. Buses may be fortunate enough to catch the green light phase of the signal and easily traverse the intersection without having to stop. But at other times they may be unlucky to catch the beginning of the red light phase and have to spend extra time at the intersection.

### **3.3.5 OPERATOR BEHAVIOR**

As mentioned in previous subsections, variability in operator behavior affects on-time departures and vehicle speeds. More generally, operator behavior can have a great impact on running time and headway variability, and can affect reliability in the following respects:

- **Driver Availability.** Operator absenteeism can cause late departures or result in missed trips when not enough spare drivers are available to cover the absences. It has the greatest effects on reliability when operators disregard the agency's policies and procedures on advance notification of absence and supervisors are left to find a replacement at the last minute.
- **Running Time Variability.** Speed differentials are one of the main contributors to running time variability. These are the result of traffic conditions and stop-and-go operations, as mentioned previously, and of an operator's driving characteristics. It is unrealistic to expect that all operators will drive at the same speed, and differences in personal characteristics are inevitable. Some operators tend to drive faster and more aggressively, while others might be slower and more cautious. These differences in behavior may be the result of differences in driving experience or familiarity with the route.
- **Poor Performance.** Bad operators may report late to work, take long personal breaks or drive aggressively, and disregard the schedules. The result of reporting late to work is the late departure of that bus from the garage or terminal. If operator relief is made at mid-route, a late arrival from the succeeding operator also impacts passengers' total travel time as the bus must wait. If operators value longer personal breaks than those given as recovery times at terminals at the end of each trip, they are likely to disregard the scheduled departure time, take their desired break and depart late on their next trip. Operators also disregard scheduled times and

headways when they deliberately catch up with their preceding bus and ride along bunched in order to pick up fewer passengers and have an easier trip.

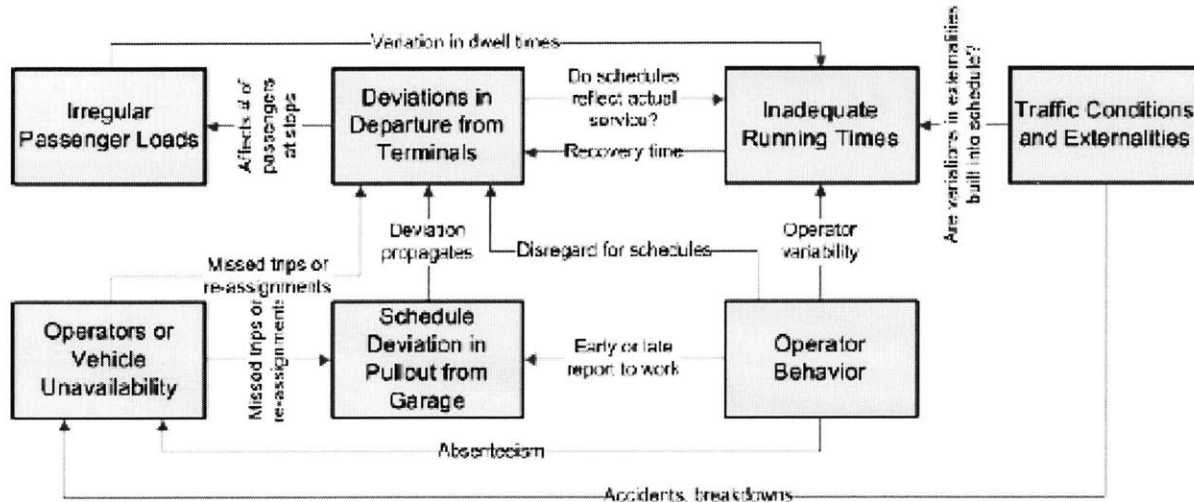
Because operator behavior can have an impact on service operations, it is interesting to analyze the effects of certain operator characteristics. Previous studies (Strathman et al. 2001, Kimpel et al 2004) identified the following operator characteristics as most affecting their behavior and performance:

- Years of experience. The longer operators have worked, the more experienced they are with the vehicles and the routes. The general observation is that older operators tend to drive faster than their younger counterparts because they are more comfortable with maneuvering the bus, and are more familiar with the route. Years of experience also factor in operator performance because senior operators may choose better shifts and vehicle blocks, and have a better performance record because they might tend to be happier at their jobs.
- Operator Type. Differences in characteristics of full-time and part-time operators may affect driver performance. Part-time operators tend to be less experienced than full-time operators, and may be subjected to different labor union work rules that could affect their overall performance.
- Duty type. The type of duty may affect the performance of operators. Trippers are short-duration runs, usually covered by operators working overtime. Performance is affected by overtime work as it is not the regular scheduled work of operators and they may be less familiar with the route operations or conditions. Relief and extraboard operators may also be unfamiliar with the route, as it may not be their usual route.

### **3.3.6 INTER-RELATIONSHIPS BETWEEN CAUSES**

It is important to recognize that the causes of unreliability tend not to be isolated and independent. As stated earlier, an event triggers an initial deviation from schedule, and further interactions tends to propagate the delay down the route. In many cases, the effects of one cause yield the occurrence of another cause of unreliability. Figure 3-3 shows the various relationships between the identified causes of unreliability. These interrelationships make it difficult to isolate the trigger event from the propagation effects.



**Figure 3-3. Inter-relationships between Causes of Unreliability**

As discussed earlier, deviations from scheduled times may be the result of poor schedule planning or variability in service conditions. Small deviations in arrival and departure times are expected because of variability in environmental factors, operator characteristics and passenger demand. The impacts of deviations from schedule depend on the frequency of service. For high-frequency routes, it is more the range of variability in deviations than the absolute value of deviation that causes reliability problems. If all buses are off schedule, but by approximately the same amount of time, the headway between consecutive buses remains regular and there is no adverse effect on passengers.

Operator behavior may be the cause that has the greatest effect on variability and service unreliability. All drivers will operate buses slightly differently and thus create variability in various aspects of service. Any negative deviations (late departures) will cause an imbalance in passenger loads between consecutive buses, which then propagate through to variations in running times. Externalities such as traffic and weather will affect running times, as well as driver and vehicle availability in case of accidents and difficulties reporting to work.

Taking into account these complexities in the causes of unreliability, a number of recommended solutions are presented. The recommended strategies are targeted towards preventing the causes of unreliability and correcting any deviations once some of the underlying sources of problems are identified.

## 3.4 STRATEGIES

This research will use the categorization presented in the 1978 transit reliability study (Abkowitz et al. 1978) which considers two categories of strategies to improve service reliability: 1) Preventive, aimed at reducing the likelihood of deviations from occurring, and 2) Corrective or Restorative, directed at restoring service to normal once deviations have occurred.

By identifying some of the possible causes of unreliability in bus service, transit agencies are able to target their efforts to minimize the occurrence of problems. Preventive strategies focus on reducing the variability of running times and dwell times, while corrective strategies focus on reducing the negative impacts on passengers. The strategies are evaluated based on the costs and feasibility of implementation, and the trade-offs to operations and passengers.

### 3.4.1 PREVENTIVE STRATEGIES

Preventive strategies can be grouped into five different categories: route design and lane priority, signal priority, operator-related, supervision, and scheduling.

#### ***Route Design and Lane Priority***

Exclusive bus lanes allow buses to operate without interference from general traffic. When traffic volumes are high, operators have less control over travel speeds and have a harder time pulling back into traffic after servicing a stop. Exclusive bus lanes, therefore, reduce the variability in running times due to traffic conditions and allow for greater control of speeds in order to adjust for early arrivals or late departures. However, introducing exclusive bus lanes is not always feasible, since it involves major capital costs in redesigning and reconstruction, and its implementation is constrained by current street dimensions, surrounding development and traffic volumes. In addition, exclusive lanes, unless fully protected or grade separated, are still subject to intersections, turning movements and illegally parked vehicles.

Previous running time models (Strathman et al 1999, Strathman et al 2001) have shown an increase in running time with respect to the route distance. Naturally, running times increase as the buses traverse a longer route, but the variability in running time is also expected to increase with distance as there is more chance for triggering events to occur and for initial deviations to propagate.

The models in these studies (Strathman et al. 1999, Strathman et al. 2001) also show an increase in running time with an increase in the number of bus stops. This increase in running time, along with an increase of its variability, is attributed to the stop-and-go factors of servicing a stop mentioned previously. Shorter routes or fewer stops as improvement strategies are limited by network design issues, available resources and service standards, such as maximum walking distance to bus service or maximum number of transfers.

## **Signal Priority**

Traffic signal priority aims to reduce running time variability by reducing delays at signalized intersections. General traffic conditions and the random arrival at an intersection with respect to the signal phase of the traffic light create variability in the amount of time buses spend at intersections. As previously mentioned, buses may be fortunate enough to catch all the green phases at intersections and whisk through intersections without having to stop, while unlucky buses may arrive at intersections during the red-phase of the signal and be forced to stop and wait. This running time variability among consecutive buses disturbs the headway distribution, eventually creating bunches and large gaps in service. Signal priority allows for greater control of traffic flow at intersections, reducing the variability in time buses must spend waiting at signalized intersections. Signal priority may also be used to speed up a bus that has a large preceding headway or that is behind schedule. In this case, passengers directly benefit from improved headway regularity and decreased travel times (Abkowitz et al 1978, Turnquist 1981).

There are two types of traffic signal priority: 1) absolute priority, where a green phase is given to all buses regardless of whether they are running early, on-time or late; and 2) conditional priority, providing a green phase only to buses that are running behind schedule. Furth and Muller (2000) examined the impacts of traffic signal priority on average delay, measured as the time difference between the actual crossing time and the time it would take a typical unimpeded vehicle to go through the intersection, for both transit buses and private vehicle traffic in Eindhoven, The Netherlands. The results showed conditional priority did not cause significant changes to private vehicle traffic. For buses, average delays were greater than with absolute priority, but lower than without priority. Another study (Kimpel et al. 2005) examined running times, on-time performance and passenger excess wait time with data from before and after the implementation of traffic signal priority. The analysis results were mixed with an overall improvement in average running times, but mixed outcomes at the individual route level and by direction and time-of-day. On-time performance decreased as the tendency for early arrivals increased, and headway variability and excess wait time increased.

## **Operator-Related**

Reserve operators and vehicles are intended to avoid missed trips or avert large schedule deviations. The absence of a scheduled operator or vehicle creates a gap in service, which can significantly decrease service quality. Extraboard personnel cover for operators who are on vacation, who call in sick or who are absent without leave. A reserve fleet of vehicles is maintained to replace a missing bus resulting from vehicle breakdowns, accidents or other emergencies. Standby buses can also be used to service a route where peak demand warrants extra capacity. These on-demand buses help avoid overloads and schedule deviations that can propagate unreliability throughout the route. The number of reserve operators and vehicles is important, and the disadvantage of this strategy is the extra cost of having reserve operators and vehicles.

If the number of reserves is too low, supervisors can either assign overtime work or adjust frequencies to cover for absent operators or broken-down vehicles, which increases operating costs and decreases service quality. If the number of reserves is too high, resources are underutilized as operators are not working while still getting paid and vehicles in the garage are not being used. A more detailed analysis of the trade-off between reserve policies and service reliability is described in Abkowitz et al. (1978).

Operator training serves to minimize the impacts of operator behavior on service reliability. While it recognizes that there will always be differences between operators that will cause variability in running times, it aims to make drivers aware of early signs of service deterioration and use their own best judgment to improve service quality. Operator training includes, but it is not limited to, review of operational policies and procedures, route familiarity, driving classes, emergency-situation programs and educational courses to emphasize the importance of good on-time performance and balanced headways.

Operator incentives and penalties also serve as a strategy to induce better service. Operator morale affects overall work performance and driving behavior. Thus, service quality can be maintained by keeping morale high and by giving operators incentives to perform well. On the other hand, stricter enforcement of policies regarding absenteeism and poor performance helps induce better service. Imposing penalties and disciplinary actions on operators who have a low performance grade serves to inhibit negative operator behavior. This includes disciplining operators who tend to report late to work, have a habit of early departures or tend to form platoons with the preceding bus in order to have an easier duty.

## **Supervision**

Service supervision serves as a strategy to both prevent and correct service reliability problems. Supervisors are able to monitor operations, especially at terminals, to ensure buses run on schedule and with reasonable headway spacing. Supervisors keep an eye on operator behavior, preventing operators from taking personal breaks longer than the allocated recovery time or avoiding early departures. These actions help reduce the number of service reliability problems triggered by late departures from terminals. Supervisors also exercise control to return service to normal after service reliability problems have occurred. They can instruct operators to speed up or slow down in order to follow schedules, adjust headways according to current demand, or employ any of the corrective strategies described in the following section.

The introduction of automated vehicle location systems enables supervisors to better monitor and control bus operations. Before, road supervisors only had information on the buses as they drove by their point on the route and could only obtain vehicle location information by polling operators through radio communications. This limited the ability to accurately evaluate the impacts of control strategies, which could lead to actually worsening the headway distribution. With AVL technologies, real-time information on vehicle location allows supervisors to evaluate the route and make better control

decisions. This improves the effectiveness of control and lessens the risk of negative impacts on passengers.

### ***Schedule Adjustments***

Adjusting schedules to reflect actual conditions also serves as a strategy to maintain reliability. This strategy is directed to avoiding inadequate running times triggering reliability problems, as described in Section 3.3.3. Passenger demand and traffic conditions will gradually change over time, causing the running time distributions to deviate from those used during schedule planning when vehicles and drivers were assigned. If these deviations become large enough, schedules become unrealistic. This disturbs the headway distribution, and causes early departures and/or unproductive time (if the schedule is too slack), or late departures, bunching and crowding (if the schedule is too tight). Periodic adjustments to schedules enable transit agencies to more efficiently assign available resources and publish schedules that better reflect actual service. Thus, the benefits of this strategy are more reliable service for passengers and more efficient operations for transit agencies.

## **3.4.2 CORRECTIVE STRATEGIES**

The most common corrective strategies are reviewed in this section: holding, expressing, short-turning and deadheading.

### ***Holding***

Holding is the control strategy of delaying a bus at a time point for a set amount of time. It aims to correct for a bus running early or prevent buses from forming bunches. Holding can be schedule-based to ensure on-time performance, or headway-based to maintain even headways between consecutive buses.

Schedule-based holding involves instructing buses that arrive at check-points early to wait until their scheduled departure time. The assumption is that, by keeping to schedules, the buses will run with more even headways. Implementation is subject to reasonable schedules that buses are able to keep and adequate supervision to ensure buses depart on-time (Turnquist 1981). If schedules are slack, a large percent of the buses will spend too much time idle, as they wait for their scheduled departure time, and passengers will get frustrated with the increase in travel time. If schedules are tight, buses will be running late most of the time and the holding strategy will be ineffective in achieving on-time performance or maintaining even headways.

Scheduled-based holding is more appropriate for low-frequency routes, where travelers tend to arrive at stops based on posted schedules to reduce their expected wait times. This type of holding is also appropriate for routes with important transfer connections. By holding a bus until its scheduled departure time, passengers are less likely to miss connections because the second bus departed earlier than scheduled.

*Headway-based holding* focuses on delaying selected buses to balance the headways. It involves holding a bus so that its preceding headway increases and its trailing headway decreases. The bus in front continues service down the route and moves away from the held bus, while the bus behind also continues regular service and moves closer to the held bus, evening out the space (and times) between consecutive buses when applied to buses with short headways. This prevents the occurrence of bus bunching and helps balance passenger loads. As a result, headway-based holding is more suitable for high frequency routes, where passenger arrivals are independent of the schedule and bus bunching is more likely to occur.

Headway-based holding also decreases average passenger wait time at stops. For high-frequency routes, passengers are assumed to arrive randomly at bus stops and rarely time their arrival based on posted schedules. For these passengers, Wilson et al (1992) references that the expected passenger waiting time is given by,

$$\bar{w} = \frac{\bar{h}}{2} [1 + \text{cov}^2(h)]$$

where  $\bar{w}$  is the average passenger wait time,  $\bar{h}$  is the mean headway and  $\text{cov}(h)$  is the coefficient of variation of headway, the standard deviation of headway divided by the mean headway. The equation shows that for balanced headways, the coefficient of variation is small and the expected wait time is approximately half the mean headway, and the expected wait time increases as the headway variance increases. Therefore, applying headway-based holding to balance out headways between consecutive buses decreases the aggregate passenger wait time.

Turnquist (1982), as cited in Strathman et al (2001<sup>2</sup>), analyzes two types of headway-based holding: "Single Headway", where a bus is held until its preceding headway is equal to its scheduled headway; and "Prefol", which consists of holding a bus until its preceding and trailing headways are approximately the same. The first strategy only requires headway information of the current bus, while the latter strategy involves knowing the location of the following bus. Turnquist (1982) also points out that for headway-based control strategies, wait time savings are maximized when all headways are known in advance (Strathman et al 2001<sup>2</sup>).

For both types of holding, passengers on board experience longer in-vehicle travel times and transit agencies absorb the cost of longer running times (Strathman et al. 2001<sup>2</sup>). Previous studies point out that holding strategies may produce minimal improvements, even negative impacts, and should be implemented early on the route, applied at an optimal point where on-board loads are low and passenger demand is heavy at immediate subsequent stops (Bly and Jackson, 1974, Koffman, 1978, Turnquist and Blume, 1980, as cited by Strathman et al, 2001<sup>2</sup>). The authors also point out that the next generation of operations control research should exploit the potential of APC and AVL systems to provide valuable information to decision-makers regarding the implementation of holding strategies.

A study by Wilson et al. (1992) evaluates the potential uses of automatic vehicle information (AVI) as decision-support tools for operations control strategies on the MBTA's Green Line. The authors found that control decisions by supervisors were mainly based on experience and communication with operators, and that occasionally these strategies actually increased aggregate passenger wait times. The authors also found that the results and effectiveness of control strategies varied widely because of the lack of real-time information available to supervisors and decision-makers.

Real-time AVL and APC systems can provide decision-makers with useful information about the buses in service, and enable them to better evaluate the impacts of implementing control strategies. These systems can provide decision-makers with a broader view of the route. Knowing the headways and the passenger loads on a bus allows decision-makers to assess whether it is beneficial to hold a bus, what time point to hold at, what length of time a bus should be held, and approximately how many passengers on-board will be impacted. Off-line data from these systems may also prove useful in helping decision-makers evaluate the effectiveness of holding strategies. Archived data may be used to analyze the impacts of control strategy decisions, and to develop decision-support tools that enable supervisors to estimate the conditions under which holding and other strategies are most appropriate. Boarding and alighting profiles generated from historical data would be helpful to approximate the number of passengers, both on-board and down the route, who would potentially benefit from holding a bus.

## ***Expressing***

Expressing involves sending a bus to a stop further downstream and skipping (not servicing) some, or all, intermediate stops. The objective of this strategy may be either to split bunched buses or to close a service gap further downstream, both in an attempt to balance headways and improve service past the end of the express segment. Wilson et al. (1992) state the ideal scenario for expressing a vehicle is when it has a long preceding headway and a short trailing headway, and passenger demand past the end of the express segment is high. This should minimize the negative impacts on passengers at intermediate stops because the next bus will not be far behind, and maximize the benefits of lower wait times on downstream passengers.

There are three types of expressing, categorized according to whether and how intermediate stops are serviced, as described below.

- Full expressing. The bus is expressed to a point downstream without serving any intermediate stops.
- Limited stops. The expressed bus services only a limited number of intermediate stops.
- Alighting-only. The expressed bus does not pick up any additional passengers and only drops off at intermediate stops.

Table 3-5 summarizes the pros and cons of each type of expressing.

**Table 3-5. Types of Expressing**

<b>Type of Expressing</b>	<b>Benefits</b>	<b>Penalties</b>
<i>Full Expressing</i>	Reduced travel times to on-board passengers whose destination is past the end of the express segment Reduced wait times to passengers waiting at stops downstream of the express segment	Inconvenience of transfer to on-board passengers whose destinations are intermediate stops Increased wait times for passengers at intermediate stops
<i>Limited Stops</i>	Reduced travel times to passengers whose origin AND destination are an intermediate stop or past the end of the express segment.	Inconvenience of transfer to on-board passengers whose destinations are skipped stops Increased wait times to passengers at skipped stops
<i>Alighting Only</i>	Reduced travel times to on-board passengers Reduced wait times to passengers waiting at stops downstream of the express segment	Increased wait times to passengers at intermediate stops

The trade-offs of expressing involve the passengers on board, passengers waiting beyond the express segment, and passengers at intermediate stops. Decision-makers must weigh the benefits to downstream passengers and to the overall performance of the route, considering the negative impacts on passengers at intermediate stops and those on-board affected by the extra transfer.

An expressing strategy involves selecting the intermediate stops that are skipped or served with limited service, considering the ability of a bus to express over a segment and pass regular-service buses, and informing passengers of the change in service.

Again, real-time information enables decision-makers to better evaluate the trade-offs regarding the decision to express a bus. Expressing a bus requires knowing the location of each bus on the route in order to assess the overall system. The location and load data from automated systems provide more detailed information to help supervisors decide whether expressing is appropriate, which of the three expressing strategies to apply, which bus is the most fitting to express, how long should the express segment be. Archived data may also provide support to supervisors by analyzing previous expressing decisions and assessing passenger demand estimates through load profiles.

### **Short-turning and Deadheading**

Short-turning involves directing a bus to end its current trip before it reaches the terminus, and service the route in the other direction. This strategy is employed to return a late bus to schedule, or when extra service is needed in the opposite direction, whether it is due to higher passenger demand or large gaps in service. The ideal scenario for short-turning a bus as a control strategy is, as described by Wilson et al (1992), when the bus carries a small load, its following headway is low, and there is a large gap in service in the reverse direction. This will minimize the negative impacts in



the current direction because the number of passengers forced to transfer is low and those waiting at subsequent stops will still have regular service, and it maximizes the benefits of better service to passengers in the opposite direction.

Short-turning is constrained by the ability of buses to short turn and serve the reverse direction. Route design and street layout may limit the number of control points at which buses are able to easily switch directions.

Deadheading involves pulling a bus from service and running it empty for a segment of the route. Deadheading is one of the most common control strategy employed in US transit systems, and if applied appropriately, it can be effective in reducing service irregularity (Eberlein et al. 1999). It is similar to expressing except that the vehicle runs without any passengers on-board.

Both strategies are similar to expressing as it instructs a bus to discontinue regular service in order to provide capacity at another location. All three strategies inconvenience passengers at stops that would have been served if the control strategy had not been implemented. On-board passengers are also troubled by the need to transfer and incur additional travel time.

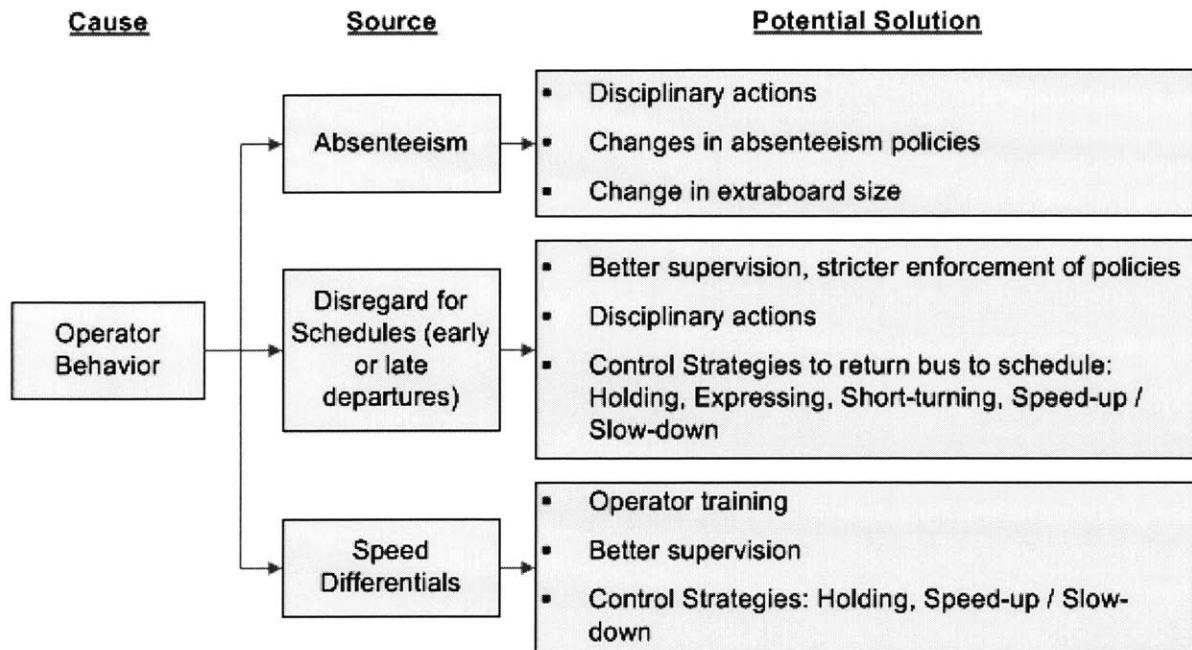
### **3.5 RELATIONSHIPS BETWEEN CAUSES AND STRATEGIES**

This section is focused on identifying the links between the causes of service unreliability and the best strategy according to the source of the problem. Taking into account the complex interrelations between the causes of unreliability described in Section 3.3.6, a number of recommended solutions are presented for each cause. While corrective strategies can be applied once the causes have triggered a deviation in service, emphasis is given to preventive strategies. These are targeted at reducing the occurrence of unreliability once the underlying sources have been identified.

Figure 3-4 shows that operator behavior related deviations are the result of absenteeism, disregard for schedules and speed differentials. Potential strategies for absenteeism are changes in policies regarding absenteeism, disciplinary actions and extraboard size. Stricter enforcement and disciplinary actions, along with control decisions by supervisors, are strategies for operators who disregard schedules. Speed differentials may be addressed through operator training, better supervision and control strategies.

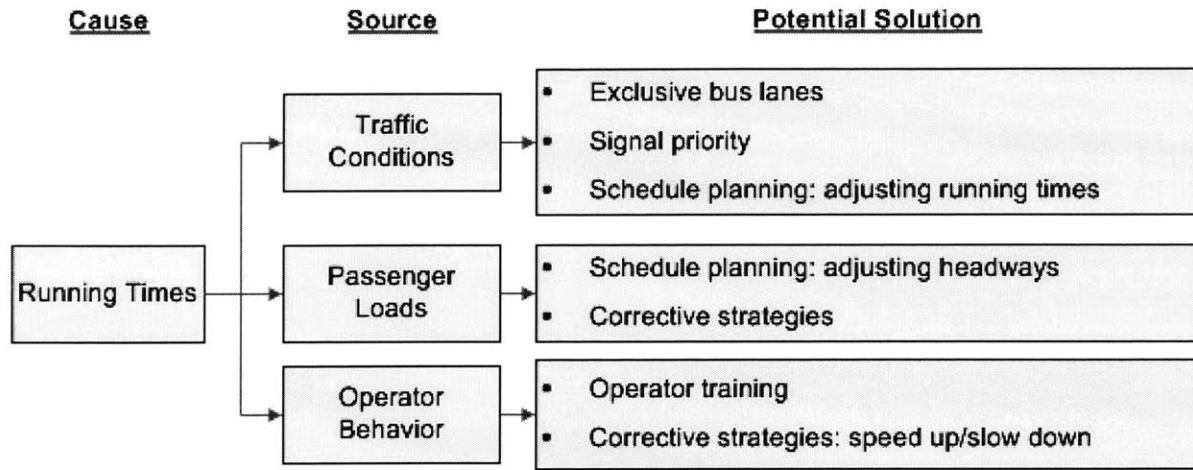
Supervision serves as both a preventive and corrective strategy to ensure service is running at an adequate level, and at the sign of any major problems, supervisors are the decision-makers regarding the application of control strategies. Operator training is a preventive measure to address operating policies and increase familiarity with the vehicle and route. This is aimed at decreasing the driving speed variability among operators and increasing focus on on-time performance.

Figure 3-4. Operator Behavior Strategies



Variability in running times is inevitable, and such, deviations from average running times are accounted for in the schedule through the use of time points and recovery times. This variability can be caused by randomness in traffic conditions, passenger loads and operators. Figure 3-5 show the various strategies applicable to running time problems. Problems with traffic conditions may be resolved with lane priority, signal priority or better scheduling. Exclusive lane or signal priority will decrease the variability and randomness in externalities. Periodic adjustments of the timetable are important to define on-time performance, account for changes in externalities, and assess if the provided service meets current passenger demand and is operationally efficient. Passenger loads that affect running time variability can be addressed through schedule adjustments to ensure service meets demand, and corrective strategies to deal with passenger demand variability. Operator training and corrective strategies helps reduce the variability of operator characteristics.

Figure 3-5. Running Time Strategies



As described in Section 3.3.1, deviations from terminals tend to propagate down the route and disrupt the headways between consecutive buses. Deviations can be attributed to a number of possible sources: late pullout from garage, late arrival from previous trip, operator behavior and poor supervision. Figure 3-6 provides the potential solutions to problem of deviations from terminal. Strategies aim at: 1) correcting the schedule to account for the actual distribution of running times and required recover times to ensure an on-time departure for the following trip, and 2) decreasing the likelihood of operators missing or reporting late for a work duty. Corrective strategies also include a revision of the policies regarding the number of available operators (extraboard and overtime assignment) and vehicles (spare ratios and maintenance schedules), and how the agency handles the absence of an operator.

Figure 3-6. Deviation from Terminal Strategies

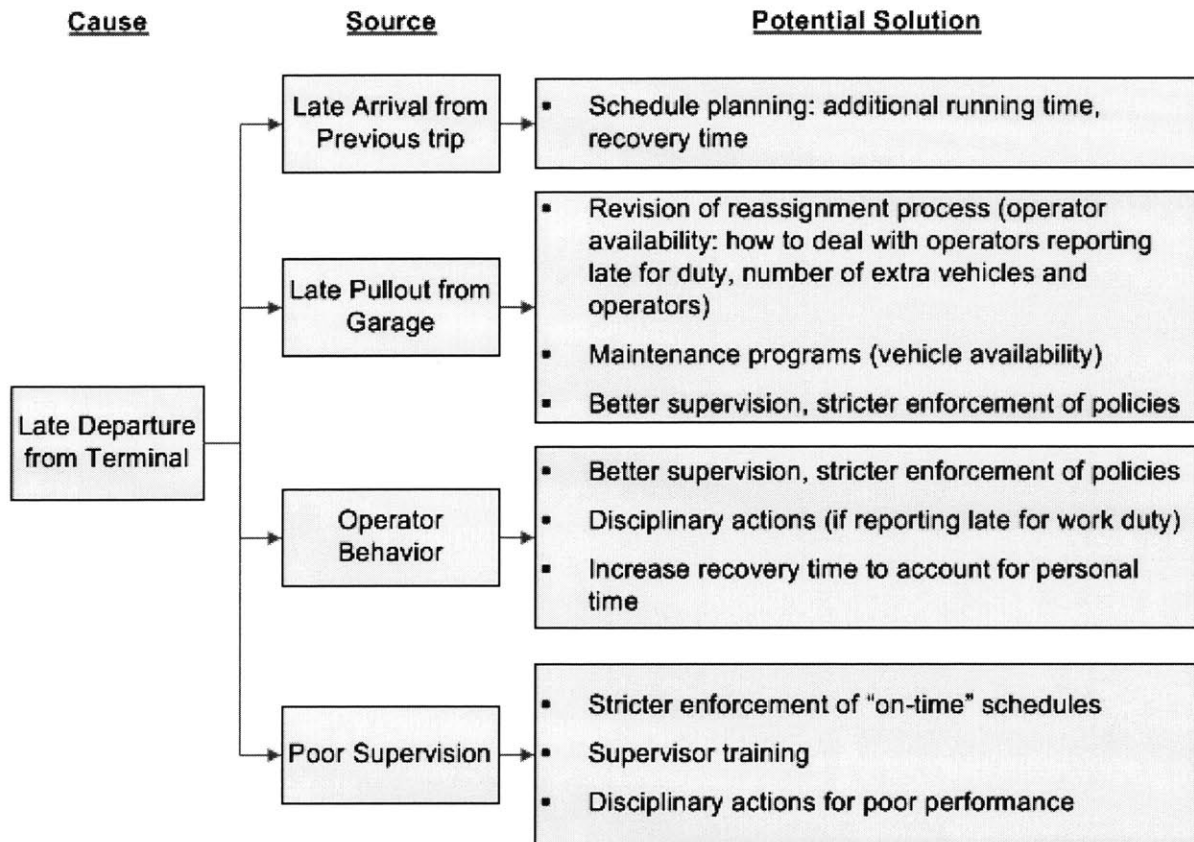
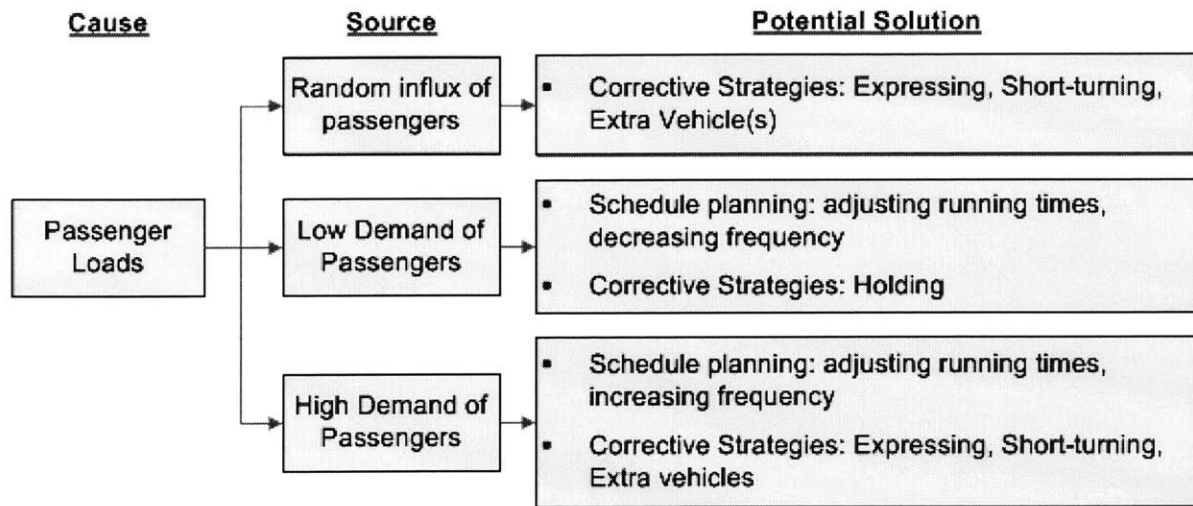


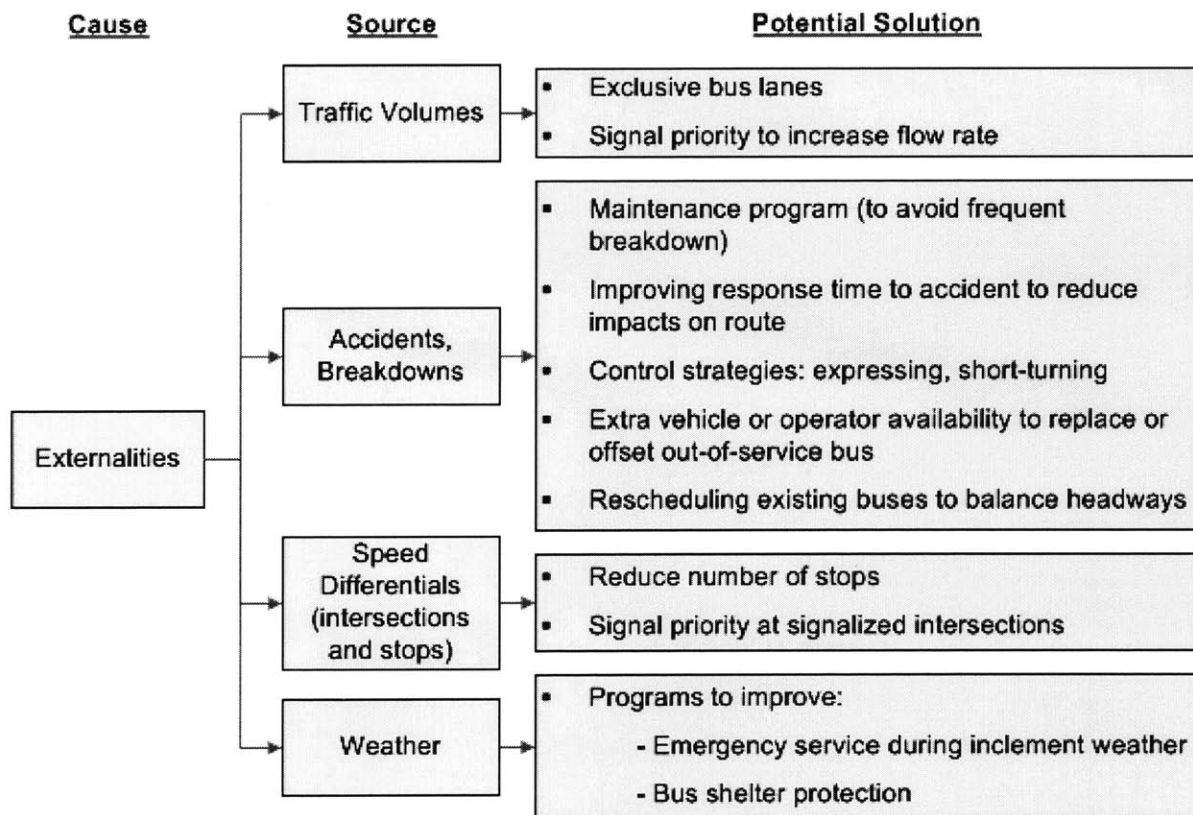
Figure 3-7 illustrates the potential strategies related to the effects of passenger loads on service reliability. Due to the level of randomness associated with passenger loads, the main strategies available are: 1) correcting for any deviations in schedules due to variability in loads and 2) adjusting the current scheduled times to account for expected average passenger loads.

**Figure 3-7. Passenger Load Strategies**



While externalities are beyond the operational scope of bus service, there are a number of strategies, mainly preventive, to offset the service problems that arise shown in Figure 3-8.

**Figure 3-8. Externalities Strategies**



## **3.6 PROPOSED RELIABILITY ANALYSIS PROCESS**

While the previous sections described the most common causes and strategies related to service reliability, this section describes the analysis process to use archived data from automated data collection (ADC) systems to evaluate service performance and identify and address reliability problems. The proposed process includes three blocks:

1. Characterization of service reliability. This block includes describing key data inputs and appropriate service measures, as well as outlining a number of performance reports to summarize service delivery and evaluate service reliability.
2. Identification of causes. Considering the complexities and relationships between causes of unreliability, the analysis looks at deviations from the terminal as a focal point, inferring the causes of such deviations and evaluating their effects down the route.
3. Selection of strategies. The last block involves identifying appropriate strategies which target the critical causes of unreliability so as to improve service reliability.

### **3.6.1 CHARACTERIZING SERVICE RELIABILITY**

The first block of the analysis process describes five key elements that an agency should carefully analyze in characterizing service reliability on a specific route:

- a) Data inputs
- b) Output calculations
- c) Service measures
- d) Threshold values
- e) Performance reports.

The goals of this block are to give transit providers a guide to determine delivered service quality from the reliability perspective.

#### ***A) Data inputs***

Different types of data are available through automated data collection systems, as well as other sources, useful in evaluating service reliability. This research identifies key data needed to characterize service reliability. Data inputs can be organized into four different groups related to the trips, timepoints, passengers and vehicle, as summarized in Table 3-6.

Not all these data items will be available through all automated data collection systems because the level of detail recorded and stored varies by system. A number of data

Items also require integration with other databases, such as schedules, operator work assignments and payroll, for more detailed follow up analyses.

As described by Furth et al. (2003), the greater the level of spatial and temporal detail, the more accurate will be calculation of running time and headway. If data is recorded based on time intervals or exceptions, it may prove difficult to estimate the time at a specific location in order to determine the headway. Running time and headway are more difficult to estimate from location-at-time data and the resulting errors will be larger. The data items described below are based on those systems that provide time-at-location data. The name and format of each data item vary across systems and transit providers, so typical variable names are adopted below.

**Table 3-6. Data Inputs for Analysis Process**

Data Group	Description	Data items
1. Trip	Identifiers for specific vehicle trip	- Date (calendar) - Route ID - Trip ID - Run ID - Block ID - Operator ID
2. Time Point	Attributes related to time-at-location data records	- Time Point ID - Direction - Scheduled time - Actual Arrival Time - Actual Departure Time
3. Passenger Activity	Information on passenger boardings and alightings	- Passenger Ons - Passenger Offs
4. Vehicle	Events relating to vehicle operations	- Doors open/close (time stamp, time spent) - Speed (maximum speed, zero speed, etc.) - Mechanical failures or vehicle alarms

### 1. Trip Data

Each data record has a set of identifiers needed for subsequent analysis:

Date and Route ID are the most basic identifiers, identifying the day and route of the data record.

Trip ID, Run ID and Block ID are data fields that identify the corresponding bus and work assignment. The trip, run and block IDs are based on the scheduled duties, which are typically integrated into the system from the schedule database. For bus service, a trip is the journey of a bus on a route from one terminal to the other terminal. A round trip consists of two individual trips. A run is comprised of various trips assigned to an operator, and a block is comprised of various runs and trips assigned to one vehicle. A block typically starts and ends at the garage.

Operator ID is also typically included in the ADC system record to associate a work assignment with the specific operator doing the work that day (one to one relationship for each unique Run ID). This data item is generally available on the on-board system

through operator log-in features. Operators may also be able to sign-in daily vehicle-block assignments and automatically pull-up scheduled trip information. This makes it easier to match the actual service data records with the scheduled assignments. Rescheduling adjustments must be noted and entered correctly in the system.

More information on operator assignments can be obtained from garage records and supervisor log sheets, as well as the payroll (human resource) database. Data such as years of experience and other operator characteristics are often vital in transit service analyses to examine the role that operator behavior plays in transit reliability.

## 2. Time Point Data

For time-at-location data records, the locations are defined by a set of time point identifiers. Transit providers use time points to post scheduled arrival times and estimated running times for route segments.

Time Point ID is the identifying number of each time point on the route. The time point identifier may be unique for each time point of each route and for each direction, or time points may be shared among different bus routes. In the latter case, individual data records are identified by the combination of the time point, route and direction identifiers.

Scheduled time at time point is the time at which the given vehicle is scheduled to be at a particular time-point. The information is based on the current timetable, which is either matched with actual data during post-processing or included automatically in the on-board system before hand. The latter is preferred since it reduces error and it also allows the system to serve as an Automatic Vehicle Announcement Systems (AVAS). Typically, AVL systems include the current route and schedule information to enable real-time tracking features such as indicating when a bus is running early or late. It is often difficult to ensure the accuracy of operator assignments, especially if there has been a reassignment, or other rescheduling. In some cases, it may also be hard to ensure that the scheduled trip data is correctly matched with the actual trip. Scheduled time point data is important for any reliability and other analysis of running times and schedule deviations.

Actual arrival at time point is the time the vehicle arrived at the time point. There are different ways in which this time-stamp is determined. Most AVL-systems record the arrival time of a bus when it enters an area surrounding the Global Positioning System (GPS) coordinates defining the time point. Care is needed to ensure the accuracy of the time-point coordinates, and calibration is required to ensure the actual arrival (and departure times are being recorded at the correct locations.

Actual departure time at time point is the time the vehicle departed the time point. As with the arrival time, the actual departure time is usually recorded as the vehicle leaves the area around the time point. These two data items, actual time point arrival and departure time, are available with most AVL systems that record time-at-location data, however, some systems may be less detailed and only record one timestamp at the



specific location. Having both an actual and departure timestamp allows for dwell-time analyses if data on door open and door close is not available.

It is noted that for both actual arrival and departure times, the AVL system records a time stamp as the bus enters and leaves an area around the time point and not an event record of door open/close. If the bus does not service the stop, time records are still created as the bus passes through the area (care is given that the area around the GPS coordinates must be big enough to record the bus as it passes through if it does not pull over to serve the stop).

### 3. Passenger Activity

*Passenger Ons* and *Passenger Offs* are the number of passengers that boarded and alighted at a given time point (or bus stop) on the route. Passenger-activity records are typically generated by APC systems and vary in detail according to the method of capture. If an APC system is not available, farebox transactions can provide data on passenger boardings (data on entries only, not exits). Typically, less detailed systems only record summary counts of passenger entry and exit with a time stamp, without a time point or bus stop identifier to fix the location at which the boardings and alightings occurred.

Matching passenger-activity records with location can provide detailed information on dwell processes as well as load profiles. Unless the APC system is equipped with location data or integrated with an AVL (or AVAS) system, post-processing is needed to match passenger count records and location data records, typically through the time stamp value. Problems can arise if the APC system captures data at the stop-level and the AVL system records data only at the time-point level. Thus, passenger activity analyses can benefit from integration with other systems such as AVL, AVAS, and AFC. The better integrated the systems are, the better reporting capabilities and analyses can be developed.

Passenger counts also need to be balanced and calibrated to ensure accuracy. APC systems can capture passenger boardings and alightings in a variety of ways: beam sensors around the frame of doors, pressure mats on the floor, etc. Inevitably, there will be errors in count records, depending on the system's level of sensitivity and ability to accurately distinguish on and off movements, especially in crowded vehicles. Thus, it becomes important to do post-processing to balance loads, ensuring that loads equal zero when it is known the bus was empty (for example, at the terminal) and below the capacity (it is impossible for a bus to carry more than a given number of passenger, both sitting and standing). Calibration may involve manually collected data from point-checks and ride-checks.

### 4. Vehicle Activity

Many AVL and APC systems create data records for certain vehicle activities. These data records include times such as the time a vehicle is not in motion (stopped), the doors open or close, and the speed of travel. More detail on these and related data

items are provided in Furth et al. (2003, page 20-21). These data items have the potential to give a better description of actual operations, and help identify the causes of deviations. For example, the use of a wheelchair lift at a stop would explain a high dwell time, the frequency of zero-speed (vehicle not in motion) records along the route could give insight into traffic conditions, or mechanical alarms or flags would make it easier to identify deviations from accidents and breakdowns.

## **B) Output Calculations**

From time-at-location data records containing valid data, the following service attributes are routinely calculated:

Actual running time for a trip is the difference in observed (arrival or departure) time between two time points. It is calculated for each trip between any two time points on the route.

Schedule deviation is the difference between the scheduled and the observed arrival (or departure) time of a bus at a time point. It is calculated for each trip at each time point on the route.

Dwell time is the time the bus spent at a time point. If time-at-location data is available, it is the difference between the actual arrival time and actual departure time at a time point. If events such as door open and door close are recorded, the dwell time can be inferred to be the time the doors remained opened at a stop.

Headways are calculated as the time between successive bus arrivals (or departures) at a time point. It is calculated for each trip at each time point, based on the arrival (or departure) of the previous (or next) bus at the same time point. Thus, a bus has a preceding and a trailing headway. Typically, the preceding headway is used for headway analyses since it is this headway that affects passengers served by a particular bus trip.

The time used can be either the actual arrival time or the actual departure time, depending on what the transit provider wants to evaluate. To transit providers, the headway is simply the time difference between consecutive buses, and thus, it does not matter much whether the arrival or departure time is used, as long it is consistent for all vehicles. Passengers tend to be concerned with the time between the departure of the last bus and the arrival of the next bus, which is not consistent with either the arrival or departure headway. The differences are most pronounced when buses experience long dwell times as a result of unusual passenger activity or holding actions.

Headway deviation is the time difference between the observed headway and the scheduled headway.

Headway Ratio is the ratio of the observed headway to the scheduled headway, for an individual trip. It compares actual service with promised service and is most useful for high-frequency routes. Headway ratio is a measure of headway adherence, where

values greater than 1 indicate a headway greater than scheduled and values less than 1 indicate a headway lower than scheduled.

This is also a good measure to identify large gaps in service and bunches, with the threshold value dependent on the transit provider's policies for high-frequency routes. Thus, a transit provider may consider a gap any headway greater than 1.5 the scheduled headway and a bunch any headway lower than 0.3 the scheduled headway.

Passenger Load is the number of passengers onboard the bus. Automatic passenger counters typically make a record of passenger boardings and alightings every time the doors open and close, which may not necessarily coincide with the time points in the route (typically not all stops are time points). Thus, passenger loads, calculated as the running total of passenger ons minus passenger offs, may be given for each record or at each time point. There are also two passenger load values per stop (or time point): the arrival load (passengers onboard when the bus arrives) and the departure load (passengers onboard at departure).

The mean and observed coefficient of variation of passenger loads may provide a good profile of the current demand distribution. These are also useful for service planning and operations control decisions.

### **C) Service Measures**

Service measures are the set of aggregate metrics used to characterize overall bus service, measure performance and evaluate service delivery. Service measures are needed to compare promised and actual level of service and are fundamental in characterizing service reliability. They consist of summaries of the individual trip outputs defined in the preceding section. Transit providers use them to assess current service and determine both the current level of reliability and whether it is improving or deteriorating over time.

Service measures are also useful both to identify causes and to select effective improvement strategies. As described by Abkowitz et al. (1978), measures are important to: 1) identify and understand reliability problems, 2) identify and measure improvements, 3) relate improvements to strategies, 4) modify strategies, methods and design to achieve greater improvements in reliability.

Abkowitz et al. describe the need for measures to accurately describe the variability in service, and reflect its impacts on both travelers and transit providers. The Transit Capacity and Quality of Service Manual base their recommended service measures on the following criteria: 1) best represents the passengers' perspective, 2) easily quantified, and 3) in current use by transit agencies.

Service measures for a route are calculated for a number of trips, grouped by time period and/or time point.

## 1. Distribution of Service Attribute

The distribution of a specific service attribute reflects the variability in that attribute and is at the heart of assessing reliability no matter what the attribute of interest. While the distribution itself has a great deal of information, it is often represented by statistical measures in the interests of quantification for ease of comparison. Service attributes of interest include running times, deviations from scheduled times, and deviations from scheduled headways.

The *running time distribution* is a good measure of reliability and is key in determining whether scheduled running times are adequate. The distribution should generally be centered on the scheduled running time because timetables are often built around the average running times. It should be analyzed for time periods having comparable running times reflecting similar traffic conditions and passenger demand. The typical time periods used are early morning, AM peak, mid-day, PM Peak and evening. However, more detailed analysis, such as hourly running time distributions, are possible with the large datasets available through automated data collection systems, leading to finer definitions of time periods. .

The *distribution of deviations from scheduled time* is a good measure to evaluate on-time performance and analyze arrival (or departure) time variability. It is a measure of how well service adheres to schedule and is most directly applicable to low-frequency routes, where the focus on reliability in meeting the posted schedules. If individual trips are typically early (or late), frequent passengers will adjust their arrival time to minimize their expected wait time. However, if there is significant variation in the bus arrival time, passengers are left frustrated because they find service unreliable, missing their scheduled bus or having to wait a long time.

The distribution will depend on whether scheduled departures from time points are strictly enforced. Some agencies, with the intention of maintaining schedules, do not allow any early departures from time points with operators instructed to hold until their scheduled departure time if they are running early. For this case, the expected average deviation should be small, but the distribution will be skewed to the right (towards late departures). On the other hand, for transit agencies that do not have strict schedule discipline at time points, a normal distribution centered on zero is expected. If the distribution shows a non-zero peak/average, unreliability may be the result of poor schedules, which might need to be revised to reflect actual conditions.

The *distribution of deviation from scheduled headways* is a good measure of headway adherence and service delivery on high-frequency routes, where the focus is typically on even vehicle spacing to minimize expected wait time. This distribution reflects how well buses are adhering to scheduled headways.

Deviations from scheduled headways may be calculated as an absolute value or a relative value. Absolute deviations are simply the difference between scheduled and actual headways, expressing, for example, a 1-minute deviation for an observed headway of 4 minutes with a scheduled headway of 5 minutes. Using this measure of

deviation, the center of the distribution is expected to be close to zero because the average headways should be close to the scheduled headways.

Relative headway values are the expression of the observed headways based on the scheduled headway. Thus, the same 4-minute observed headway can be expressed as “0.80 the scheduled headway” (*headway ratio value*) or the headway deviation as “-0.20 the scheduled headway”. For these values, the center of the distribution is expected to be close to 1 if the relative observed headway is used, and 0 for relative deviations.

## 2. Wait Times

The *expected wait time* measure reflects the impacts of headway or schedule variability on passengers. For low-frequency routes, passengers tend to time their arrival at a stop with the bus' expected arrival to minimize their wait time. The expected wait time on low-frequency routes is a function of on-time performance (schedule deviations) and the and the proportion of passengers that time their arrival to schedules and passengers that arrive at random (Bowman and Turnquist, 1981).

Expected wait time is a particularly good measure of service reliability for passengers on high-frequency routes, where passengers are assumed to arrive at random without consulting posted schedules. For perfectly even headways, the expected wait time is simply half the headway. However, the expected wait time increases as the headway variability increases, as described in Section 3.4.2.

$$\bar{w} = \frac{\bar{h}}{2} [1 + \text{cov}^2(h)]$$

Another measure of passenger wait time is the *excess passenger wait time* (EWT), which measures the difference between actual expected wait time and the expected wait time if headways were as scheduled. It is an appropriate measure to reflect the change in average expected wait time due to poor headway adherence and unreliable service.

$$EWT = \bar{w} - \frac{\bar{h}_s}{2} [1 + \text{cov}^2(h_s)]$$

where  $\bar{w}$  is the expected passenger wait time,  $\bar{h}_s$  is the mean scheduled headway and  $\text{cov}(h_s)$  is the coefficient of variation of scheduled headway (Wilson et al. 1992).

Another measure of excess headway time can be formulated by calculating the *percent of excess time*, *ET*, given as the sum of positive deviations over the total elapsed time.

$$ET = \frac{\sum_j (x_j - y_j)}{\sum_i x_i} \text{ for } i \in A, j \in B$$

where  $x$  is the actual headway,  $y$  is the scheduled headway,  $A$  is the set of all headways and  $B$  is the set of headways where the actual headway is greater than the scheduled headway (note that  $B$  is a subset of  $A$ ). For example, if scheduled headways are 5-minutes and actual headways were 8, 4, 7, 3, 9, 2 minutes, then the excess time is equal to 0.27. This can be interpreted as approximately 27% of the elapsed time was spent in excess. It is another measure of longer passenger wait times due to headway variability.

### 3. Overcrowding

Passenger loads are typically measured as the ratio of passenger load to the number of available seats. *Overcrowding* is a measure of high passenger loads, where the number of passengers exceeds a threshold value which affects passenger comfort levels. It also compares actual crowding levels with service standards on the maximum number of standees on each trip or averaged over a span of time. It is also related to reliability because high load levels increase dwell times and possibly wait times (see Section 3.3.2).

### 4. Percent of Unreliable Trips

These measures describe the number of trips falling outside some service reliability standard. The percent of unreliable trips is a useful measure to describe overall performance and the probability of unreliable service. Transit agencies may have service policies that promise service above a certain standard, such as “95% of trips arriving within 0-5 minutes late”. Thus, percent of unreliable trips is a measure of the extent of poor service. The percent of unreliable trips is measured for a number of service attributes, each with a given threshold value (or range) for what is considered a reliable (or unreliable) trip.

- Late departures. The percent of trips that leave the terminal (or time point) more than  $x$  minutes later than schedule, with the value of  $x$  determined by the transit provider.
- Early departures. The percent of trips leaving the terminal (or time point) early by  $x$  minutes from its scheduled departure time. The percent of early departures can be combined with the percent of late departures to determine the percent of trips with on-time departure from the given terminal (or time point).
- Late arrivals. The percent of trips arriving at the terminal (or time point) more than  $x$  minutes late. Because variability is known to occur in running times, this measure is typically applied to the terminal to evaluate recovery times necessary to ensure an on-time departure for the following trip. Another useful measure is the number of

trips arriving late by more than the scheduled recovery time. This indicates whether running times and recovery times are sufficient to avoid late departures for subsequent trips.

These measures are calculated for all trips each different time period, to account for time-of-day variability. The next two measures can be calculated for all headways within different time periods, where a headway is considered unreliable if it falls outside the threshold value (or range) at any point along the route.

- Bunches. Measured as the number of headways below a threshold value where the buses are considered to be “bunched”. The threshold value may be an absolute value, such as 1 minute, or a relative value based on the scheduled headway, such as the headway ratio or headway deviation.
- Large Gaps. With the above measure, it is an indicator of headway adherence. This measures the number of headways greater than a threshold value of what is considered a “large gap” in service. Again, the threshold value may be an absolute value, such as x minutes, or a relative value based on the scheduled headway, such as the headway ratio or headway deviation.

Late garage pull-out applies to specific work assignments that begin with a pull-out from the garage, not individual trips. It is the same as the late departure measure except taken at the garage, counting the number of work assignments that begin x minutes late. This is a good measure to identify possible problems regarding operator behavior, resource (driver or vehicle) availability or supervisory failures at the depot.

Late relief applies to operator duties that begin at a point in the route (street reliefs). It is similar to late garage pullout in counting the number of work assignments that begin x minutes late, and is an indicator of poor operator behavior or unrealistic scheduling.

## **D) Threshold Values**

For all of the service measures described above, the transit provider must make decisions on the threshold values or ranges of values to classify a service as reliable or unreliable. These should be based on the level of service the transit provider can cost-effectively deliver, as well as customer expectations, and may vary by type of route and time of day.

As previously noted, most customers on low-frequency routes will time their arrival at the stop based on the schedule modified by experience to reduce their expected wait time, while passengers on high-frequency routes are assumed to arrive at random because they place little confidence in the schedule but know their waiting time should be low. Thus, the threshold values of deviations should be different for low-frequency and high-frequency routes due to the different impacts on passengers. The same applies to trips across different times of the day with varying traffic conditions and passenger demands. Variability in passenger demand affects how many passengers are being affected by unreliable service. Variability in external conditions, especially during peak hours, may

be so great that it affects the ability of the transit provider to maintain on-time performance despite the best of schedule planning and service management.

The key points a transit provider should consider when making decisions on reliability threshold values are discussed below in four groups: on-time performance, headway adherence, passenger loads and percent of trips.

### **1. On-time performance**

The transit provider has to define the range around the scheduled time within which the bus is considered to be “on-time”. This is necessary to give meaning to on-time performance. These threshold values should depend on the type of route, scheduling practices and location on the route.

For low-frequency routes, where a strictly scheduled-based perspective on on-time performance is appropriate, schedule deviations affect passenger wait times. Early departures may cause passengers to miss their scheduled trips and be forced to wait a full headway for the next bus, while late departures simply increase the wait time of all passengers waiting at the stop. Because of this, early departures should be avoided and deviations in late arrivals kept to a minimum. The transit provider may implement a “no early departure” policy and instruct operators to hold at time points until their scheduled time, at the expense of increased travel times for passengers already onboard. Thus, the transit provider may choose deviations between 0 to  $x$  minutes late to be considered “on-time”, with  $x$  determined by scheduling practices, travel time variability, and customer expectations.

For high-frequency routes, the passenger concern is more on headway regularity, but minimizing schedule deviations may still be preferred since headways will certainly be balanced if schedules are maintained. The same criterion as for low-frequency routes may be applied, but without being as concerned with early departures. The range for “on-time” performance may then be given as  $(+/-) x$  minutes from the scheduled time, with  $x$  again determined by scheduling practices, travel time variability and customers expectations.

With regard to scheduling practices and travel time variability, the threshold value of  $x$  minutes depends on how scheduled times at time points are set and managed. Scheduled arrival times are typically set based on average running times, in some agencies slack is built-in based on the running time variability at the end of the route in the form of recovery time. If slack is built into the scheduled departure time at time points, early buses should be held to avoid buses running early and the value of  $x$  should be small. Otherwise, the value of  $x$  should account for the known variability in actual arrival or departure times at the point. Thus, a trade-off between on-time performance and travel times exists if the goal is to achieve tight on-time ranges. Timepoint scheduling sacrifices travel times and speeds, as early buses are held until their scheduled departure time.



There should also be a difference between the threshold values at the terminal and at other points in the route. As described in Section 3.3.1, good on-time performance is expected at the terminal because of recovery times and the higher degree of control at these points. And because deviations tend to propagate down the route, transit providers may want to have tighter departure time ranges at the terminal.

The review summarized in Section 3.2.1 reveals that the most common current practice is to set a 1 minute early to 5 minutes late range for “on-time” performance.

## 2. Headways

These values are used for high-frequency routes where the focus is on good headway adherence. Transit providers must consider whether to use an absolute value or a relative value to evaluate actual headways. Absolute values would be, for example, considering any bus with a 1-minute headway to be bunched, while relative values would consider a bunch any bus with an actual headway less than or equal to, for example, 0.30 of the scheduled headway.

Relative values may be preferred on routes on which consecutive headways are not equal (example, they range between 3 to 5 minutes), so that appropriate comparisons are made on actual and scheduled service and the true impacts on passengers are evaluated. However, caution is given in using relative values. For example, a gap in service might be considered as anything above 1.5 the scheduled headway. For service with 3 minute headways, this gap in service would be a 4.5 minute headway, which some passengers might still consider relatively frequent. But for service with 8 minute headways, the impact on passenger time is an increase of 4 minutes (12 minute headway).

## 3. Passenger Loads

Overcrowding threshold values are based upon seating capacity and an acceptable maximum number of standees. It can vary by length of route, frequency of route and time of day. For longer routes, the threshold value may be lower to ensure passengers do not feel crowded and are more likely to have a seat for longer journeys. Transit providers typically balance frequency with passenger loads. Low demand routes have higher headways to avoid maintain productivity but with enough service to provide a seat for all passengers, while high passenger demands justify the more frequent service, where buses might be crowded but close enough to avoid long wait times. In peak hours, threshold values for overcrowding tend to be set to higher values reflecting the higher cost of providing peak hour service, due to spread penalties and 8-hr guarantee work rules (Herzenberg, 1983).

Overcrowding threshold values may be set as the average maximum load over a time period (or span of time, like 30 minutes), or in terms of number of trips with loads exceeding a certain value. An example of the latter would be setting the threshold at no more than X-percent of trips with passenger loads over Y-percent of the seating capacity.

#### **4. Percent of Trips**

Another common threshold is the percent of on-time trips that are needed to still consider service quality as reliable. For each service attribute, this percent value may vary depending on frequency of service and time of day. For low-frequency bus routes and time periods, adherence standards may be lower given a good standard on schedule deviations and the lower passenger demand. For example, good schedule adherence may be stated as 75% of all trips with a schedule deviation of 0-5 minutes for each time period. This acknowledges early departures are unacceptable and some variability in departure times is inevitable. Deviations in schedule affect passenger wait times, but do not impact operations as greatly as on high-frequency routes. For high-frequency routes and time periods, transit agencies may want to be more aggressive in maintaining schedules or headways because of the higher levels of passenger demand and stronger tendency for problems to propagate. Typical percent threshold values that describe on-time performance and promised level of service follow those presented by the Transit Capacity and Quality of Service Manual summarized in Table 3-1.

#### ***E) Performance Reports***

Data recorded by automated collection systems are usually in formats that require both pre- and post-processing. The raw data must be transformed into useful information that operators and supervisors can use to analyze service reliability. Pre-processing includes piecing together all of the data recorded by the vehicle, and it can either be done automatically as the data is displayed for real-time tracking or when it is dumped each night at the garage, or it may require human intervention. Post-processing involves using these data items to calculate the service metrics previously described and generate service performance reports. The outputs of this analysis are the calculated service attributes that characterize service reliability for each trip, while performance reports are the summary of these outputs and service measures that evaluate current service for a given time period, and the extent of service unreliability.

Performance reports summarize the aggregate performance by time period accounting for the trip-to-trip and daily variations in service delivery.

##### **1. Running Time**

The performance report should summarize the distribution of trip running times for each time period, with the average, percentile and coefficient of variation (or standard deviation) for comparison of observed and scheduled values. Actual running times should be compared with scheduled running times, given by the current timetable, in order to determine whether schedule adjustments are needed. Evaluations may include calculating average (or percentile value) running time per time period to assess on-time performance, or determining appropriate time period boundaries to construct a timetable that reflects current conditions and the best possible values (minimizing variability) for scheduled running time.

## 2. Schedule Deviations

Reports on schedule deviations evaluate on-time performance of buses focusing on its distribution, along with the average and coefficient of variation by time period for terminals and/or time points on the route. If scheduled running times are appropriate, vehicles should closely follow the scheduled times, with small positive or negative deviations, knowing variability is inevitable. Large schedule deviations indicate problems such as inadequate running times, abnormal boardings, etc.

## 3. Headway Adherence

Performance reports on headway adherence include the distribution of headway deviation or headway ratios, and the calculation of average and coefficient of variation for comparison with scheduled values. Analysis also includes determining average passenger wait times and evaluating the likelihood of extreme headway deviations, such as bunching and large gaps. The evaluation of the likelihood of bunching and large service gaps is important in characterizing service as highly unreliable with unpredictable headways and with high probability of long wait times and crowding.

### 3.6.2 IDENTIFICATION OF CAUSES

The identification of the causes of service unreliability, the second block of the analysis process, involves a step-by-step approach to infer the underlying causes of the observed reliability problems found in the previous section. It focuses on the observed deviations from scheduled times and scheduled headways calculated using available trip data from ADC systems.

The first steps in this process focus on deviations at terminals, examining the different sources that may create such problems at the terminals and the effects of these deviations on the rest of the trip. The deviations at the terminal may be the result of: 1) deviation from previous trip, 2) operator behavior, or 3) supervision control. The later steps analyze deviations at points down the route, where the sources of the problems are different than at the terminal. Deviations developing along the route are likely to be the result of: a) the trip beginning off-schedule initially and not being able to recover, and/or b) a trigger somewhere between the terminal and the point of detection.

When analyzing a large set of data in order to identify the source of service reliability problems, it is important to distinguish between random and systematic occurrences. Random occurrences are hard to isolate and difficult to target because they are unpredictable in terms of where and when they will occur, and their severity. Regardless of how well designed or planned transit service is, random variations in demand, traffic and operators will naturally cause fluctuations to arise. Many of these may have no serious reliability impact. Systematic variations are easier to identify because of their predictability, although this does not necessarily imply that they are any easier to remedy.

Random variations are due to inadvertent events which may never be repeated in the same form. Their occurrence during the normal course of the daily operations does not contribute to any pattern of unreliability. For example, the service reliability problems of one morning peak period on one route may be attributed to a late departing bus. If this bus trip is usually on-time and no other service problems are reported (normal traffic conditions, no accidents, etc), the incidence may be isolated and the variation in service for that day is considered random in nature. It might just be the operator had a hard time starting the vehicle that day and was consequently late for his first trip. Delays due to accidents on the road are typically considered random events in service.

On the other hand, systematic variations in service attributes are those which are recurrent, for which a pattern of incidence can be identified. A single occurrence of service unreliability can be considered as a systematic variation when it has similar attributes of incidence, whether it is time of day or a causal trigger. For example, the same reliability problem as above can be shown to be due to a single late departing bus in the morning peak period. However, if performance reports show that the operator of this particular late departing bus is consistently late on all his work duties, the cause of unreliability may no longer a random variation, but a systematic problem caused by inappropriate operator behavior. Similarly, if operators in general have a tendency to be late on pullouts, this is systematic variation (caused by supervisory failures at the garage) even if it affects different operators, or trips and routes are affected in different days.

This distinction is also important in targeting strategies to avoid them, or at least lessen their impact. Systematic variations are typically somewhat predictable due to their nature. The service variation in question has a high probability of occurrence because of the similar factors involved. Random variations, on the other hand, are unexpected and can only be dealt with after they have already triggered reliability problems. Thus, systematic variations are usually better targeted by preventive strategies, and random variations are better dealt with through corrective strategies.

In analyzing service reliability, even with large amounts of data, it is difficult to characterize each and every deviation from schedule as random or systematic. Indeed, there is a continuum of types of variations, ranging from completely random to completely systematic, and focusing only on these extremes understates the complexity of the problem. However, it is easier to determine whether there is a clear pattern of occurrence. If there are a number of deviations which all have the same root cause and share a common attribute, then the problem can be considered systematic.

Attributes include, but are not limited to, time of day, day of the week, location, operator and others. Thus, for example, the data may show that scheduled running times are insufficient during the morning peak hour period, or that a particular operator is late in reporting for 80% of his or her work duties.

The key is to determine a threshold beyond which to consider the overall problem as systematic and of importance to merit the implementation of strategies to improve service quality. If it is determined that X percent of deviations in a given time period

were the result of cause  $Y$ , then the decision must be made whether  $X$  is higher than some operational standard to conclude the deviations are systematic and cause  $Y$  is significant.

## **A. Deviations at Terminal**

As described in Section 3.3.1, emphasis in this process is given to terminals because they are the fundamental control points at which good schedule or headway adherence is rooted. The terminal is a “restart” point, such that any deviations at the end of a trip should not carry over to the next trip because of the scheduled recovery process. Also, supervisors are frequently based at terminals to monitor and control departures to ensure schedule (or headway) discipline. Thus, one expects very good on-time departure performance at terminals.

Care is needed to ensure accuracy of time-at-location data at the terminals because problems often exist in determining terminal times and passenger activities. Automatic Vehicle Location (AVL) systems tend to record the arrival and departure at a time point as the bus enters an area or zone (around a set of GPS coordinates). Typically, two time points are defined at the terminal, inbound and outbound, which may create an overlap in the catchment areas. This, as well as the fact that buses spend more time at this time point (passenger boarding/alighting and/or recovery time), may create problems if the system cannot accurately define (and distinguish) the arrival and departure time of the inbound and outbound trips.

The focus is first on evaluating performance at the terminal and describing the service reliability evolution process in terms of the effects of terminal deviations on the rest of the route. Although some buses may be able to make up for an early or late trip start, chances are these initial deviations will propagate further down the route and increase unreliability. Then the focus is on describing a process to examine the causes of deviations at the terminal. Terminal deviations from the schedule (time or headway) may be the result of insufficient recovery time to remedy previous deviations, or human factors related to operator behavior or supervision.

### **1. Performance and Effects of Deviations at the Terminals**

The process to analyze the effects of deviations at the terminal depends on the frequency of the route, with scheduled times the focus for low-frequency routes and headways for high-frequency routes.

*Schedule deviations.* For low-frequency routes, the analysis is focused on schedule adherence to investigate how departure behavior at the terminal affects performance at points down the route.

1. The schedule deviation is calculated at the terminal and specific points along the route for each scheduled trip. The trips are categorized based on the deviation at the terminal.

The average and standard deviation of schedule deviations of trips within each terminal deviation category are calculated for each specific point. This should provide insight into the propagation of deviations along the route. Table 3-7 is an example of the schedule deviation calculations at different points on the route. This analysis shows how schedule deviations propagate along the route, separating trips by their initial deviation at the terminal. This also helps identify points on the route where deviations are the worse (or more variable).

**Table 3-7. Example of Analysis of the Propagation of Deviations**

Deviation at Terminal	Number of trips	Point A		Point B	
		Mean schedule deviation	Standard deviation of schedule deviations	Mean schedule deviation	Standard deviation of schedule deviations
-2 to -1 minutes	23	-1.2	3.2	-0.8	3.5
-1 to 0 minutes	52	-0.5	2.1	0.1	2.2
0 to 1 minute	120	0.2	1.2	0.8	1.5
1 to 2 minutes	62	1.3	2.3	1.6	2.6
2 or more minutes	30	3.4	2.4	3.8	2.8

- To further analyze the impacts of deviations at the terminal, all trips in each terminal deviation category can be categorized according to the deviation at a specific time point (call this point B). The result is an  $n$  by  $n$  matrix, such as the example shown in Table 3-8, of the number of trips with a given combination of deviation at the terminal point and time point B.

**Table 3-8. Time Point Schedule Deviations vs. Terminal Deviation**

At Time Point B	Schedule Deviation at the Terminal						
	< -2 mins	-2 <= x < -1	-1 <= x < 0	0 <= x < 1	1 <= x < 2	2 <= x < 3	>= 3 mins
< -2 mins	7	5	12	53	4	0	1
-2 <= x < -1	3	1	4	49	11	3	0
-1 <= x < 0	2	1	7	71	36	6	0
0 <= x < 1	0	0	3	48	34	8	6
1 <= x < 2	2	0	0	29	26	13	8
2 <= x < 3	0	1	0	11	16	10	11
>= 3 mins	0	0	0	3	13	12	49

From the example above, the following observations can be made. Variability in deviations at time point B are significant given on-time departures at the terminal, if an on-time departure is considered a departure between 0 and 2 minutes after the scheduled time. Early departures seem to remain ahead of schedule down the route, while late departures have more variability but tend to remain behind schedule.

Using the transit provider's range of values for "on-time performance", one can also compare the number of trips that began "late", with those at points further

downstream. The distribution of trips would give a good indication of how many trips are able to make up for given initial deviations.

Trips that have been reassigned or that are out of the scheduled order must be discarded to avoid bias, unless adjustments in the scheduled-time data have been made to reflect the new scheduled trip.

*Probability of delay.* Schedule deviations can also be used to analyze the probability of delays at a specific time point given a deviation at the terminal.

1. For all trips with on-time departure at the terminal, the schedule deviation is calculated for both the terminal and the specific time point (call it point B).
2. The schedule deviation distribution can be computed, making sure there are a sufficient number of trips to support the level of data aggregation. From this distribution, the probabilities of on-time arrival at point B can be calculated.
3. The same distributions can be generated for each terminal departure deviation category. Then, the probabilities of deviations at point B are compared given the departure behavior at the terminal. The expectation is that the greater the positive (or negative) deviation at the terminal, the higher the probability of positive deviation at point B.
4. The distribution of trips with on-time departures also gives insight into the adequacy of the scheduled running time between the terminal and point B. If the probability of arriving at point B within an “on-time” range is low, it is a good indication that the scheduled times are unrealistic and need adjustment.

*Headway Adherence.* For high-frequency routes, the same type of deviation analysis can be made using the headway deviation values instead of the schedule deviation values. Instead of schedule deviation at time points, the headway ratio value is used to correlate departure behavior at terminals with problems at points down the route. The trips are categorized by their initial headway ratio.

1. The headway ratio (scheduled over actual headway) at the terminal and specific time points are calculated for each scheduled trip with valid headway data.
2. The average headway ratio and standard deviation of all trips are calculated for each category and at each time point. This provides a picture of whether vehicles maintain their initial headway throughout the route, and what the tendency is in terms of headway adherence problems. Table 3-9 is an example table of headway ratio calculations based on a trip's headway ratio at the terminal.

**Table 3-9. Example of Headway Adherence Analysis**

Headway Ratio at terminal	Total # of trips	At point A		At point B	
		Average HR	Std. Dev. of HR	Average HR	Std. Dev. of HR
$HR < 0.3$	20	0.15	0.20	0.10	0.23
$0.3 \leq HR < 0.5$	36	0.45	0.12	0.41	0.15
$0.5 \leq HR < 0.7$	35	0.65	0.23	0.58	0.26
$0.7 \leq HR < 1.3$	120	1.01	0.24	1.02	0.24
$1.3 \leq HR < 1.5$	20	1.24	0.23	1.35	0.26
$HR \geq 1.5$	25	2.0	0.52	2.3	0.57

3. Again, all trips in a given category are categorized once more according to the headway ratio at a specified time point (point B). A similar  $n$  by  $n$  matrix, such as the example provided in Table 3-10, summarizes the number of trips with a combination of its headway ratio at the terminal and at the given time point. This matrix provides some insight into the tendency of headway deviations to propagate and create bunches and gaps in service.

**Table 3-10. Example of Headway Ratios per Terminal Headway Ratios**

Headway Ratio at Time Point B	Headway Ratio at Terminal					
	0 - 0.5	0.5 - 0.75	0.75 - 1.00	1.0 - 1.25	1.25 - 1.5	$\geq 1.5$
0 - 0.5	32	21	38	24	5	2
0.5 - 0.75	8	22	21	18	2	3
0.75 - 1.00	2	9	37	19	10	4
1.0 - 1.25	2	4	20	22	7	7
1.25 - 1.5	0	1	12	26	11	12
$\geq 1.5$	1	2	14	37	22	34

This example shows high variability in headways at time point B even with good headway departure from the terminal. It also reveals that buses that depart bunched (0.5 or less of the scheduled headway) have a strong tendency to remain bunched, and those that depart with a large gap in service (1.5 or more) have a strong tendency to remain spaced apart.

## 2. Causes of Deviations at the Terminal

The causes of deviations at the terminal are evaluated focusing on the recovery time between trips. Recovery time is the time at the terminal between the end of a bus' previous trip and the beginning of its next trip. Recovery time is intended to ensure that buses are able to depart on schedule despite any deviations in its previous trip, as well as to give operators a break between trips.

Under normal operating procedures, operators are expected to use the recovery time to avoid any deviations from carrying over. However, if recovery time is not enough for buses to be able to start their next trip on-time or for operators to take a needed break, then the next trip will depart late from the terminal.



The scheduled, available and actual recovery times, as well as the scheduled and actual headways, are calculated for each trip and compared to determine the root cause of deviations in departure time.

Scheduled recovery time is the amount of scheduled time at the terminal between consecutive trips of a vehicle. Calculated as the time between the scheduled arrival time of the previous trip and the scheduled departure time of its subsequent trip, it is often determined by the variability in running times, minimum operating policies, or clock-face scheduling practices.

Available recovery time is the time between the actual arrival time at the terminal and the scheduled departure time of its subsequent trip. It is the time a bus has at the terminal if it were to depart its next trip on-time.

Actual recovery time is the time between the actual arrival time at the terminal and the actual departure time on its next trip. It is the time the bus actually spent at the terminal. The difference between the actual recovery time and the available recovery time is the schedule deviation in departure.

When analyzing the available recovery time and actual departure times at the terminal, it is important to consider the time needed for passengers to board and alight. It is unreasonable to expect an on-time departure for a bus that arrives with an available recovery time of 1 minute at a busy terminal, because there will likely be passengers in the bus who will be alighting and passengers at the terminal who are waiting to board. This terminal passenger processing time will depend on passenger demand as well as terminal configuration, and it will vary across routes and across transit agencies.

One approach to determine a reasonable range of time buses typically spend at the terminal boarding and alighting passengers is to look at the departure behavior of trips. An  $m$  by  $n$  table of the number of trips with a given combination of available recovery time and schedule deviation shows the variability of departure deviations based on the available recovery time. With a large enough sample to offset any bias from operator behavior, an estimate can be made of the time buses must spend at the terminal for passenger boarding and alighting. An example is presented in Table 3-11, where it is inferred that most buses take 2 to 3 minutes at the terminal. This estimate is based on the observations that buses with 1 to 2 minutes of available recovery time tend to depart the terminal 1 to 3 minutes late, and buses with an available recovery time of 2 to 3 minutes tend to leave 0 to 2 minutes late.

This analysis may also provide insight into the scope of problems at the terminal. The example below shows a large variability in departure deviations for trips with enough recovery time. For buses with 5 or more minutes of recovery time, one would expect a good on-time departure performance. However, deviations vary quite a bit, with some buses leaving very early, while others are very late. This indicates that there are other causes at the terminal triggering poor departure performance. The cause of such deviations may be operator behavior or control interventions by a supervisor.

**Table 3-11. Terminal Departure Schedule Deviation vs. Available Recovery Time**

Departure Schedule Deviation	Available Recovery Time								
	<= - 2 mins	-2 to -1 mins	-1 to 0 mins	0 to 1 mins	1 to 2 mins	2 to 3 mins	3 to 4 mins	4 to 5 mins	5+ mins
4+ mins early	-	-	-	-	-	-	-	0	8
3-4 mins early	-	-	-	-	-	-	0	0	2
2-3 mins early	-	-	-	-	-	0	0	5	3
1-2 mins early	-	-	-	-	0	0	1	6	5
0-1 mins early	-	-	-	2	2	3	4	16	39
0-1 mins late	-	-	3	0	5	14	19	121	115
1-2 mins late	-	2	1	3	12	6	11	52	40
2-3 mins late	0	0	3	7	8	1	8	15	8
3-4 mins late	1	1	4	4	1	2	2	7	4
4+ mins late	28	7	6	4	4	2	1	6	3

By comparing the three values of recovery time (scheduled, available and actual), inference on the causes of deviations at the terminal may be drawn. If a significant number of buses do not have enough available recovery time because of persistent late arrivals, then the late departures might be attributed to the current scheduled times and adjustments to the timetable may be needed. On the other hand, if most trips have an available recovery time (more than the determined minimum to account for variability in late arrivals, passenger demands and operator breaks), then deviations in departure may be due to operator behavior or control intervention.

However, this analysis does not account for the relationship between schedules and operator behavior. Schedule recovery times also serve as breaks for operators. If schedules are tight and available recovery times are typically lower than scheduled, operators will not be getting the amount of break time they are entitled to. This leads to low morale and added stress on operators, who may tend to take their scheduled breaks, regardless of the available recovery time and departure deviation. And while this may be viewed as operator behavior, it may be exacerbated by poor scheduling.

The following steps are proposed to make inferences about the cause of departure deviations at terminals, based on the recovery time, the schedule and the headways.

1. The scheduled, available and actual recovery times are calculated for all trips (with valid data) at the terminal. Determine the "minimum" recovery time, as described above, to infer the amount of time buses typically spend (and need) at the terminal for passengers to board and alight.
2. *Late arrival.* An available recovery time less than zero indicates that the trip could not depart on-time because of a late arrival. However, it is useful to examine the amount of actual recovery time that was taken. Beyond the time needed for passengers to board and alight, one would expect the bus to depart as soon as possible, given that it is already behind schedule. Thus, even though it is the late arrival that causes the late departure from the terminal, operator behavior may also

contribute by extending this time and causing further delay. If a large number of trips are arriving late and do not have enough recovery time, schedules need to be adjusted. Operator behavior may also be a result of tight schedules, if operators believe they deserve a break but are not getting it because they have to depart for their next trip almost immediately.

3. *With recovery time.* For other trips that have some recovery time at the terminal, the approach to infer the causes of unreliability depends on the route frequency (low-frequency and high-frequency routes) and whether there is a supervisor stationed at the terminal. Terminal supervisors are responsible to ensure good on-time performance or manage departures to balance headways.
  - A. For low-frequency routes, the focus is on on-time performance and schedule deviations. Buses ought to strictly follow schedules and headway-based control actions such as holding are inappropriate. In this case, deviations can be attributed to poor supervision and operator behavior. Poor supervision is responsible for poor on-time performance if there is a terminal supervisor. If there is no supervisor at the terminal to enforce on-time departures, then any schedule deviation beyond the acceptable on-time range of a trip with available recovery time, is the result of operator behavior.
  - B. For high-frequency routes, maintaining headways might be a more realistic objective than keeping to schedules and departures from terminals may be affected by headway-based control actions. Thus, schedule deviations at the terminal may be the result of headway-based control actions, and not entirely the result of operator behavior. In this case, there are four cases considered below. Documentation of control actions by terminal supervisors would help support the inference of causes of departure deviations for cases (2) and (3). This can be information on implemented control actions or a log of communications between supervisors and operators. If no information is available, a number of assumptions will have to be made regarding operator behavior and departure deviations at terminals.
    - a. An early departure with a smaller (than scheduled) preceding headway. It is likely that no control actions were implemented here because the headway would have been closer to scheduled if the bus had departed on-time. Thus, the early departure can be attributed to operator behavior or poor supervisor performance.
    - b. An early departure with a preceding headway greater than or equal to the scheduled headway. In this situation, the previous bus must also have left earlier than scheduled or that trip had been missed. There is the possibility that, if present, the supervisor instructed the operator to depart early in order to maintain headways. Otherwise, the early departure is attributed to operator behavior.

- c. A late departure with a preceding headway less than or equal to the scheduled headway. In this case, the previous bus must have left the terminal very late and it is possible that the supervisor instructed the operator to hold at the terminal and depart late to maintain more regular headways.
- d. A late departure with a large preceding headway. An on-time departure would have resulted in a more balanced headway. Thus, it is unlikely that holding was implemented as a control action, and the late departure can be attributed to operator behavior.

An example of this analysis on a high-frequency route is presented in Table 3-12. The trips analyzed have acceptable values of available recovery time. The example shows that many of the trips with a high departure headway also had a late departure, and most of the trips with a low headway departed before their scheduled time. For these trips, an on-time departure would have resulted on headways closer to schedule (ratio closer to 1). Therefore, these deviations are inferred to be caused by poor operator behavior because any control actions by terminal supervisors would have improved the departure performance (holding to balance headways or until scheduled). If it is known that the transit provider does not usually implement holding strategies at the terminal to maintain regular headways, then operator behavior can be inferred as the cause of the departure deviation.

**Table 3-12. Terminal Departure Deviation vs. Terminal Headway**

Terminal Departure Deviation	Departure Headway	
	Ratio > 1.5 (total number of trips = 100)	Ratio < 0.5 (total number of trips = 84)
5 or more minutes late	45	12
1 or more minutes early	7	60

A trend of early and late departures by an operator might give insight into the likelihood that the departure deviation in cases (2) and (3) was the result of operator behavior and not a holding strategy. The analysis helps infer the tendency of an operator to have poor terminal performance. It is unlikely that an operator is frequently going to be instructed to depart off-schedule or have extreme delays at the terminal due to passenger demand or traffic that prevent good on-time departure performance.

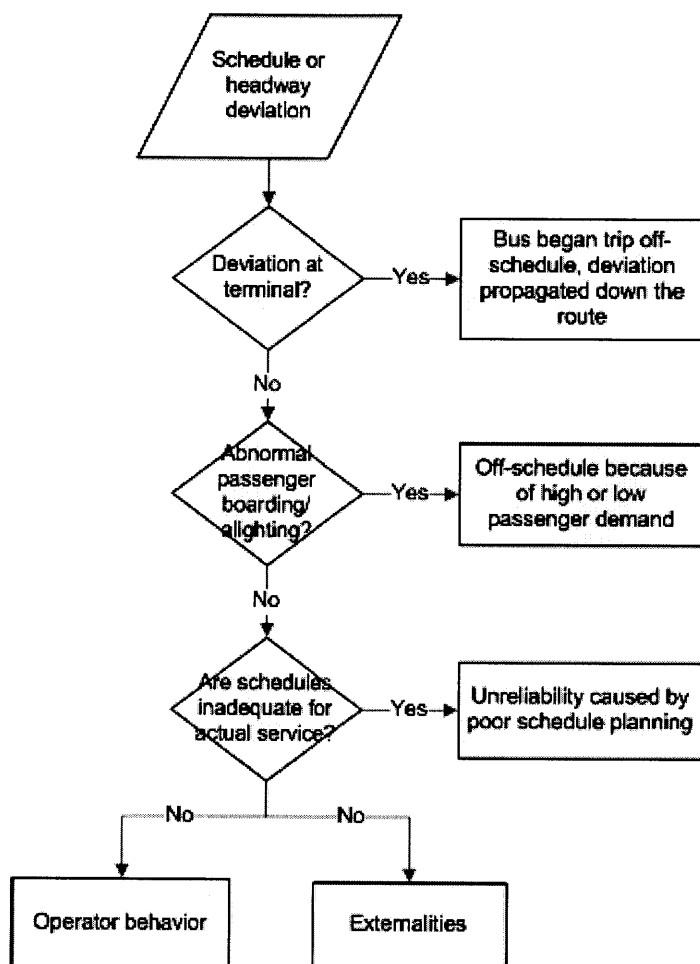
Missed trips present a problem in this analysis. If missed trips are not specifically marked in the data records, then it cannot be determined whether missing data is due to missed trips or errors in AVL recording. It is difficult to determine departure behavior from those trips with a preceding bus with missing data. One way to address this is to discard headway records with unknown headways, to avoid bias towards large headways that cannot be known to be missed trips or "ghost" buses.

### ***Deviations at Other Points***

For time points other than the terminal, a different analysis process is developed. It is applied to trips that fall out of the “on-time” window, determined by the transit provider’s threshold values. Illustrated in Figure 3-9, the analysis consists of the following sequential steps to infer the causes of deviations:

1. The first step is to determine whether there was a deviation at the terminal to cause the bus to begin its trip off-schedule. Because deviations tend to propagate along the route, deviations at other time points are likely to result from a departure deviation at the terminal. The terminal deviation is marked as the cause of unreliability for any trip with deviations down the route that began with an “off-schedule” terminal departure. For low-frequency routes, scheduled times at the time point and terminal are used, while for high-frequency routes, the focus is on the initial headway at the terminal.
2. If the bus departed the terminal on-time, a significant deviation from the norm in passenger loads somewhere on the route may cause the bus to deviate from schedule. Passenger counts and dwell time analysis help determine whether an abnormally high count of passenger boardings or alightings caused the bus to fall behind schedule, or low demand (not having to serve all stops) caused the bus to run ahead of schedule.
3. Schedule or headway deviations may be the result of inadequate scheduled times at time points. Previous running time and schedule deviations evaluations, as describe in Section 3.6.1, may show current scheduled times need adjustments, and therefore, such deviations can be attributed to problems with the timetable.
4. Operator behavior. If the bus had an on-time departure and current scheduled times are acceptable, then schedule deviations at time points may be due to operator behavior. The analysis is to look for operators that tend to deviate from schedules (tendency to be running early or late, or catch up to its leader and create a bunch).
5. Externalities. Event-records and speed profiles (level of detail D or E, according to Furth et al. 2003) may provide insight into traffic conditions to help make assumptions on the cause of the schedule deviations. For example, if the speed profile shows constant start and stop motions, high traffic volume may be the cause of service delays.

**Figure 3-9. Sequential Process to Identify Causes of Deviations**



The end-product of the analysis is a summary report on service reliability problems and the attributed causes of such problems based on the analysis findings. The goal is to provide a bigger picture of where major problem spots are in the route and what are the main causes of service unreliability in order to select effective preventive and corrective strategies to improve overall service.

### 3.6.3 APPLICATION OF STRATEGIES

The last block of analysis in the proposed reliability analysis process is the evaluation and application of strategies to improve service reliability. As described in Section 3.4, there are a number of potential strategies to improve service reliability, targeted at reducing the occurrence of reliability problems or lessening the impacts on service and passengers once service has deteriorated.

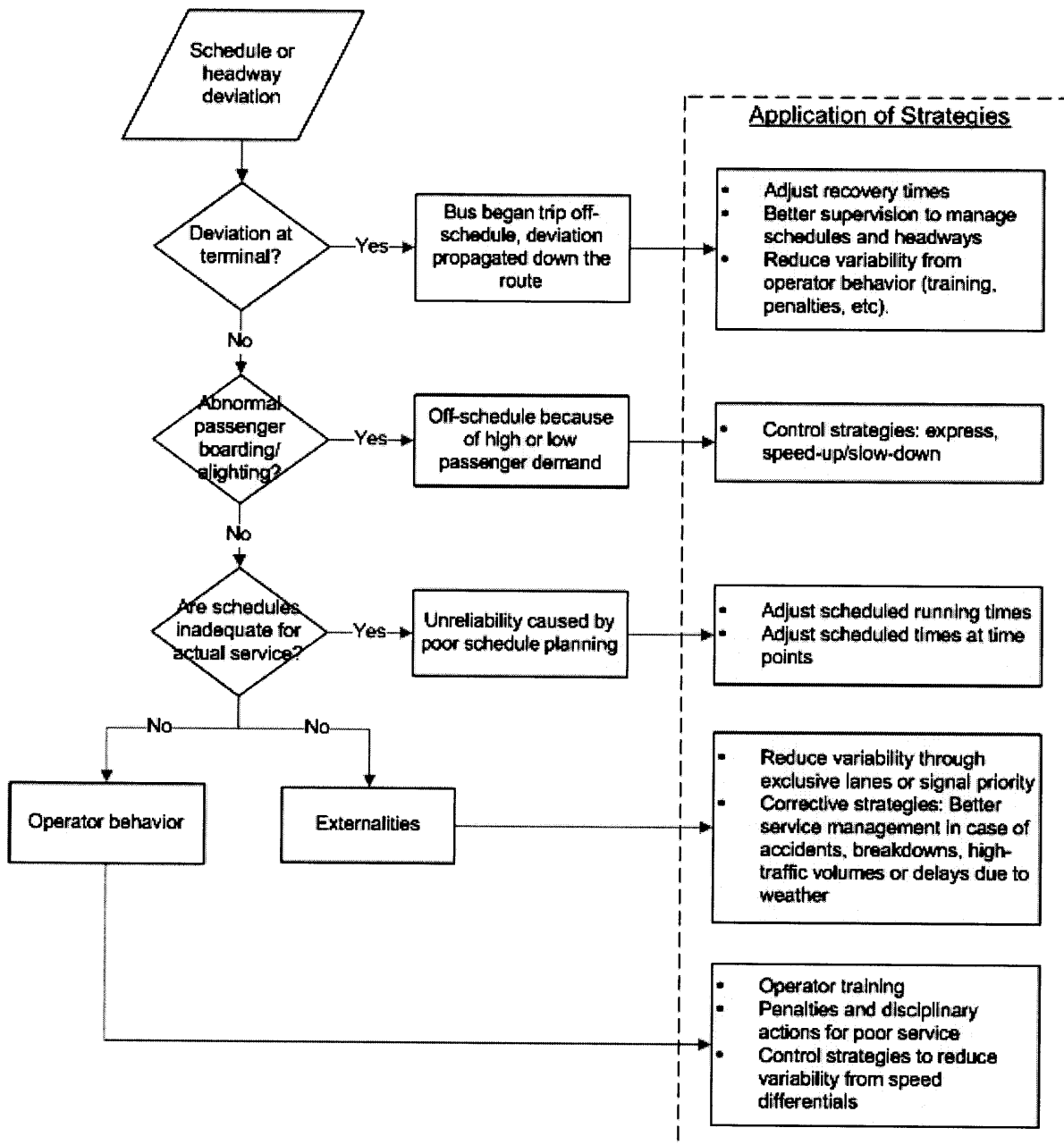
The analysis will show where and when problems have a tendency to develop, and which are the triggers or causes that have the greatest impacts on service reliability. Knowing what the causes of unreliability are on a route helps the transit provider's

decision-making process on what strategies are the most applicable to current service and most practical to implement.

This part of the analysis involves applying the theoretical relationships between causes and strategies described in Section 3.5 to the practical analysis results from Sections 3.6.1 and 3.6.2. Figure 3-10 illustrates the application of potential strategies based on the process to identify the causes of unreliability problems. A summary of the most applicable strategies are:

- Terminal procedures. Recovery times at the terminal are key to ensure trips begin on-time and do not create reliability problems that tend to propagate down the route. Good service management is needed by way of supervisors at terminal to ensure on-time departures or good headway control, and operator training helps operators understand the importance of following schedules and imparting better judgment on managing reliability.
- Schedule planning. If the cause of schedule deviations is unrealistic schedules that buses are not able to maintain, then schedule planning is needed to adjust the running times, scheduled times and headways to better reflect actual service and adjust for variability.
- Training and policies. This applies to both operators and supervisors. Variability due to operator behavior can be reduced by better training practices or stricter enforcement of policies regarding on-time departures and service performance. Penalties also apply to supervisors, especially at terminals, with poor performance in service management who do not enforce schedules or implement effective control strategies to reduce reliability problems.
- Corrective strategies. Variability in externalities and passenger demands, beyond those that can be accounted for in schedule planning, are unavoidable. These are better targeted through corrective strategies and service management to restore service back to normal as quickly as possible.

Figure 3-10. Application of Strategies



Transit providers must also assess the practicality and cost-effectiveness of potential strategies. There are some strategies that can easily be implemented and tested for effectiveness. Implementation of strategies such as changes in the schedule, on-time enforcements policies (no early departures, holding at terminal, etc), training, or corrective control-actions, can be assessed through before and after studies to analyze the resulting changes in service performance. There are capital costs involved with operator training and supervision, but these are not permanent changes and can be implemented as a test before full application. The cost of performing these types of analysis is low because of the availability of large data sets from automated data



collection systems. However, other strategies, such as exclusive lanes or signal priority, must be assessed before implementation. The high-cost of application and large-scale changes, does not allow these preventive strategies to be put into practice and then measured for effectiveness. These strategies are better assessed through predictive models.

### ***Predictive Models***

The identified causes and potential strategies can be analyzed further by developing and applying regression analyses and simulation models. This framework analysis serves as a guide to understanding service reliability and identifying the initial triggers of service reliability problems, and proposes the use of computer models to test the significance of the identified causes of service unreliability and to evaluate the effectiveness of specific strategies.

The large amounts of data available through automated data collection (ADC) systems allow for detailed analysis, such as those developed by Strathman et al. (2001, 2003), to provide more insight into the true impacts of each of the different causes on service variability. These regression models can contribute to the proposed framework analysis by determining more operator specific factors that affect running times and departure deviations, or evaluating the effects of deviations at the terminal on points further down the route. One useful model would be to estimate schedule deviation as a function of the initial deviation at the terminal point, time period, operator-specific characteristics, headway, passenger demands, and other variables.

Data from ADC systems can also be used to develop simulation models to analyze service reliability, test the significance of the identified causes, and evaluate the proposed strategies according the identified sources of problems. A simulation model using AVL and APC data from the Chicago Transit Authority was developed by Moses (2005) with the intent to evaluate the benefits of control strategies on a route. Moses was not able to calibrate and validate the simulation model, which showed significant differences between the simulated and actual service statistics of headway regularity and travel times. The simulation showed a stronger propagation of headway irregularity (bunching) than actual service, especially in the second half of the routes tested. The author concludes that this may be the result of operator behavior and service manager decisions to maintain headway regularity and schedule adherence, which are not included in the model. Perhaps, the simulator can be improved by the implementation and results from regression models on operator behavior, headway regularity and passenger loads, such as those by Strathman et al. (2001<sup>1</sup>, 2003).

While the simulation model (Moses 2005) could not be validated, the development of such simulation models using automated data collection systems remains a good approach to apply and test the characteristics of service reliability outlined in this research.

### **3.7 SUMMARY**

This chapter reviewed the most significant causes of unreliability, potential strategies to improve service reliability, and the complex interrelationships between them. A practical framework is developed to evaluate service performance and summarize service reliability. First, service reliability is characterized using data available from Automated Data Collection (ADC) systems and appropriate service measures, such as the distribution of running times and headways. Then, service performance is evaluated to infer the causes of unreliability. The framework first looks into performance at the terminal and then at other points on the route, following a number of sequential steps to infer the causes of unreliability. At the terminal, deviations may be caused by inadequate schedules (recovery time does not account for running time variability), poor operator behavior and poor terminal supervision. Causes of deviations at other points on the route include initial deviations at the terminal, passenger loads, unrealistic schedule times, operator behavior and externalities. Based on the results of these analyses, transit providers can evaluate what strategies are the most applicable to current service and most practical to implement.

The next chapter presents an application of the framework analysis using archived data from the Massachusetts Bay Transportation Authority (MBTA) Silver Line Washington Street route.

## **4. CASE STUDY: APPLICATION TO MBTA**

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The previous chapter outlined a process to analyze service performance and assess service reliability of a bus route. The chapter reviewed the most common causes of unreliability, their complex interrelationships and strategies to deal with them. It also proposed a process to use archived data collected from automated systems to analyze the extent of service unreliability on a bus route, identify the specific causes of problems and to guide transit providers in identifying effective strategies to improve service quality.

In this chapter, the proposed reliability analysis process developed in Chapter 3 is applied to a Bus Rapid Transit (BRT) route at the Massachusetts Bay Transportation Authority (MBTA) system: the Silver Line on Washington Street. The purpose is to examine service reliability on this route, and recommend improvement strategies based on the identified causes of the reliability problems. Section 4.1 presents a brief description of the case study route, while Section 4.2 describes the route's available archived data and Section 4.3 presents the scope of analysis and data assumptions. The results of the service reliability assessment analyses are presented in Section 4.4. Section 4.5 presents the results of the analyses to identify the causes of unreliability, while the strategies to improve service reliability on this route are presented in Section 4.6. A summary of the findings is discussed in Section 4.7.

### **4.1 MBTA SILVER LINE ON WASHINGTON STREET**

The Massachusetts Bay Transportation Authority (MBTA) is the oldest and one of the largest public transportation systems in the United States. The MBTA system serves 175 cities and towns, and comprises rapid transit, bus rapid transit, bus, commuter rail, water ferry, contracted bus and paratransit services. Ridership is over 1.1 million passenger boardings a day, with approximately 792,600 one-way passenger trips per day. Bus and trackless trolley service involves 162 routes and 9,000 stations/stops, and carries around 30% of the average daily passenger boardings (MBTA website, 2005).

The Silver Line is Boston's first Bus Rapid Transit service, and is currently being implemented in three phases. The Washington Street corridor is the first phase, which opened in June 2002, providing service between Dudley Square in the south-west of Boston, and the Downtown area. The second phase, the Waterfront line, began service in December 2004, and offers service between South Station (Red Line subway station) and South Boston, and to Boston's Logan International Airport. The final phase is currently in planning and design and is expected to connect the first two phases with a tunnel through the downtown area.

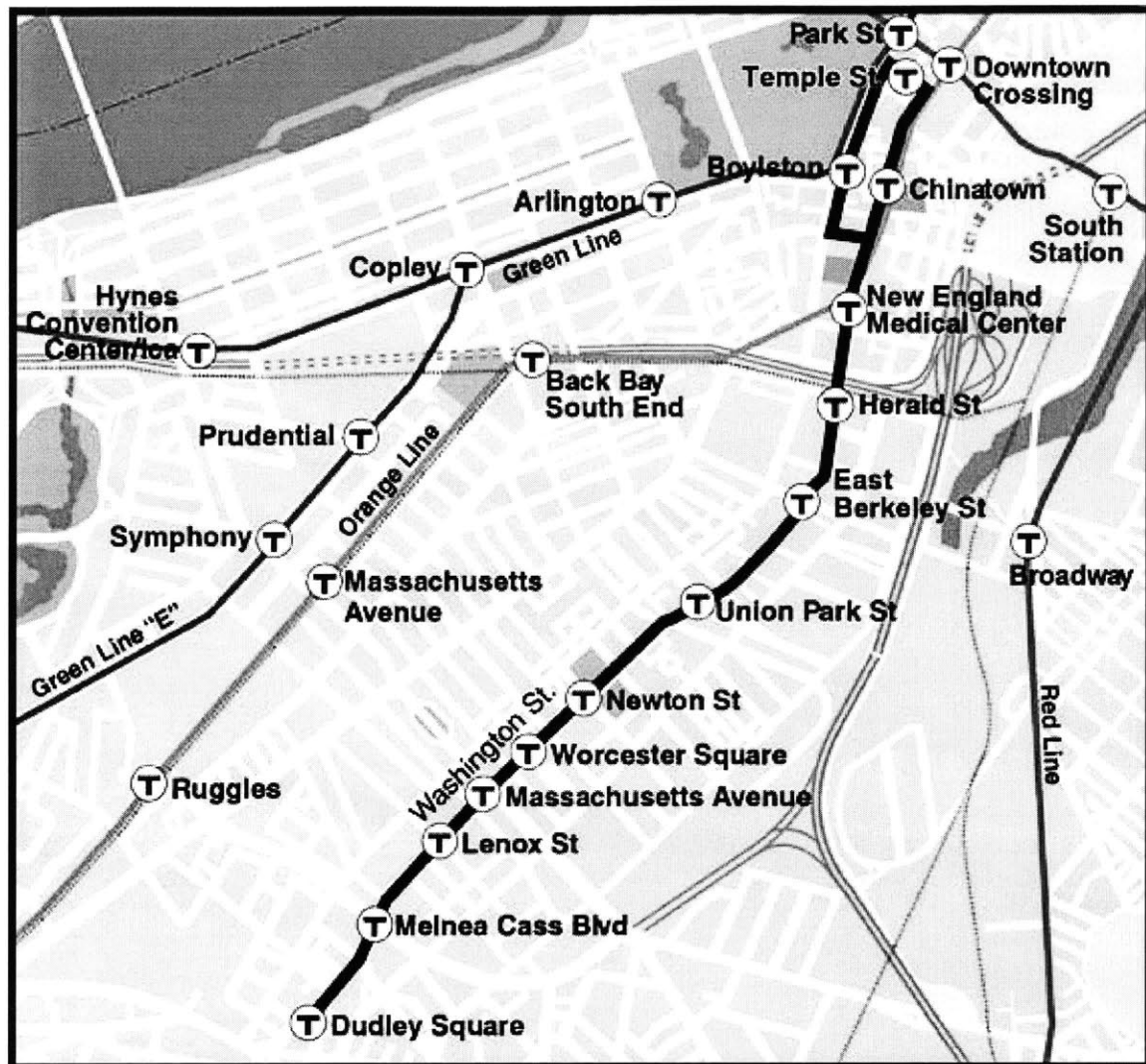
A Bus Rapid Transit (BRT) system is "a flexible, rubber-tired form of rapid transit that combines stations, vehicles, services, running ways and ITS elements into an integrated system with a strong identity" (Levinson et al. 2003). The main objective of a BRT system is to provide convenient, fast, frequent and high-quality bus service. Bus Rapid

Transit is typically characterized by dedicated lanes, distinctive stations and vehicles, off-vehicle fare collection, Intelligent Transportation Systems (ITS) technologies, and frequent service.

This case study focuses on the Silver Line on Washington Street because, as the MBTA's first BRT system and flagship bus service, it should provide exceptional service reliability. It is considered Boston's fifth rapid transit line, and major capital investments have been made to offer high-quality bus service on this corridor. The dedicated lanes allow for faster travel speeds and reduced travel times, state-of-the-art vehicles and stations provide higher levels of comfort and convenience to passengers, and the implementation of ITS technologies allow for better operations control and management.

The Silver Line on Washington Street (see Figure 4-1) is approximately 2.3 miles in each direction and serves around 14,100 weekday passenger trips (MBTA website, FY04). Connections to three of Boston's four rapid transit lines are available at the New England Medical Center (Orange Line), Downtown Crossing (Red Line and Orange Line) and Boylston (Green Line) subway stations.

Figure 4-1. Silver Line Washington Street Route



Service begins at the Dudley Square station, and runs inbound along Washington Street towards Downtown Boston, ending at Temple Place, close to the heart of the Boston commercial area at Downtown Crossing and Park Street. Outbound service begins at Temple Place, operating on Boylston Street, which forms a one-way pair with Washington Street in the downtown area, before returning to Washington Street and back to Dudley Square.

The buses operate on a non-protected exclusive bus lane for most of Washington Street and in mixed-traffic going through the Downtown area. Non-protected exclusive bus lane means that bus travel is still affected by turning movements at intersections, illegal travel and double-parked vehicles. The route is also equipped with signal priority technology; however, it is still in its testing phase and currently not being used. Each bus stop is sheltered, and provides seating and bike rack amenities. They are also equipped with a "smart kiosk" that provide passengers with schedule information,

variable message signs, area maps, and a police call box for emergencies. Table 4-1 presents the 12 bus stops in each direction and the approximate spacing between them.

**Table 4-1. Silver Line Route Stops**

	Stop Name	Approximate Distance (miles)
<b>Inbound</b>	Dudley Square	---
	Melnea Cass Blvd.	0.25
	Lenox St.	0.13
	Massachusetts Ave.	0.12
	Worcester Square	0.12
	Newton St.	0.12
	Union Park St.	0.30
	East Berkeley St.	0.25
	Herald St.	0.13
	New England Medical Center	0.30
	Chinatown	0.20
	Temple St.	0.20
<b>Outbound</b>	Temple St.	---
	Boylston St.	0.25
	New England Medical Center	0.35
	Herald St.	0.30
	East Berkeley St.	0.15
	Union Park St.	0.25
	Newton St.	0.30
	Worcester Square	0.12
	Massachusetts Ave.	0.12
	Lenox St.	0.12
	Melnea Cass Blvd.	0.13
	Dudley Square	0.15

The Silver Line on Washington Street has two terminal points: Dudley Square and Temple Place. Dudley Square is a major transfer station with high passenger activity from 7 other connecting bus lines, and station configuration allows for multiple Silver Line buses to be idle at this stop. Temple Place is also a major transfer point, located in the downtown area with nearby access to the Downtown Crossing and Park Street subway stations, and other connecting bus routes. It is located on a narrow, mixed-traffic one-way street, which makes it difficult to hold multiple buses at this terminal station.

Recovery time at terminals allow for buses to recover from any previous delays and begin their next trip on-time, and also give operators a short break between trips. Ideally, the two terminals at the end of each direction would serve as a control point to ensure on-time performance or good headway control for both inbound and outbound trips. However, this route has an unusual two-terminal configuration that does not allow

this type of recovery capability to be fully implemented. The physical constraints at Temple Place limit the ability of buses to be held at this terminal point and the amount of recovery time that can be scheduled. Thus, recovery times at Dudley Square are greater, ranging from 3 to 11 minutes, while recovery times at Temple Place only range from 1 to 4 minutes.

Running times vary throughout the day, but are typically around 20 minutes in each direction. Table 4-2 shows the scheduled times of a trip in the AM peak hour period at the terminals and at three intermediate points. For this sample trip, the inbound running time is 17 minutes with 1 minute of recovery time at Temple Place. The outbound running time is 14 minutes with 5 minutes of recovery time at Dudley Square Station before the vehicle's next trip.

**Table 4-2. Scheduled Departure Times of Sample Trip**

<b><i>Inbound Service (Dudley Square to Temple Place)</i></b>				
<u>Dudley Square Station</u>	<u>Washington &amp; East Newton Sts.</u>	<u>Washington &amp; East Berkeley Sts.</u>	<u>New England Medical Center</u>	<u>Temple Place</u>
7:55	8:02	8:07	8:09	8:12
<b><i>Outbound Service (Temple Place to Dudley Square)</i></b>				
<u>Temple Place</u>	<u>New England Medical Center</u>	<u>Washington &amp; East Berkeley Sts.</u>	<u>Washington &amp; West Newton Sts.</u>	<u>Dudley Station</u>
8:13	8:16	8:19	8:22	8:27

Headways also vary throughout the day, with a maximum of 15 minutes in the early morning and late night time periods, and a minimum of 3 to 5 minutes in the peak hours. Table 4-3 shows the scheduled headways on the route, with the scheduled departure times of the first and last trips leaving Dudley Square and Temple Place.

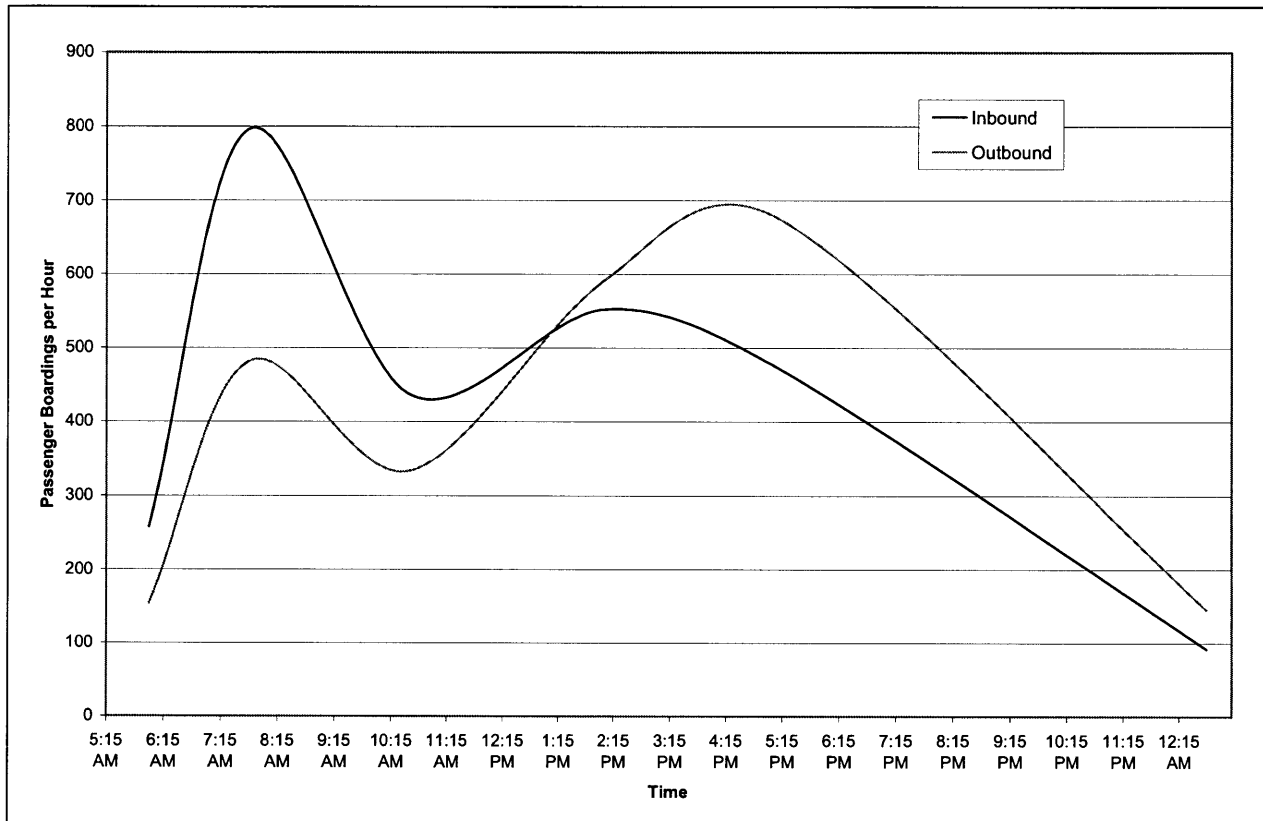
**Table 4-3. Silver Line Washington Street Route Schedule**

	<b>First Trip</b>	<b>Rush Hour Service</b>	<b>Midday Service</b>	<b>Evening Service</b>	<b>Late Night Service</b>	<b>Last Trip</b>
<b>Dudley Square</b>	5:15 am	5 mins	8 mins	10 mins	12 mins	12:43am
<b>Temple Place</b>	5:31 am	5 mins	8 mins	10 mins	12 mins	1:00am

Variability in scheduled headways makes this route both a high-frequency and low-frequency route. It is considered a high-frequency route in the rush hour and midday service time periods, where scheduled headways are less than 10 minutes. It is considered a low-frequency route during the early morning, evening and late night service time periods, when scheduled headways are 10 minutes or more.

Passenger demand typically follows the distribution illustrated in Figure 4-2, with an average maximum load of 45 passengers in the peak hours<sup>8</sup>. The inbound direction carries a higher volume of passengers in the AM peak and first half of the midday period, while the outbound direction carries more passengers in the afternoon and evening.

**Figure 4-2. Passenger Demand Distribution**



The vehicle fleet is composed mostly of low-floor, 60-foot, articulated buses that carry approximately 100 passengers, while smaller 40-foot buses are typically used in the late evening. The MBTA Silver Line buses are also low-emission Compressed Natural Gas (CNG) vehicles, which are more environmentally-friendly. The buses have an Automated Stop Announcement System (ASAS) and easy-access door ramp to comply with the American with Disabilities Act (ADA). The MBTA Silver Line buses are equipped with an Automatic Vehicle Location (AVL) system that uses Global Positioning System (GPS) technology that transmits vehicle location data to the MBTA's Control Center for real-time tracking and operations control. Also, buses have on-board sensors to monitor fuel levels, engine conditions, odometer reading and other vehicle condition indicators.

<sup>8</sup> Passenger boardings were obtained from ride checks recorded as part of a separate study on the Silver Line on Washington Street route.



## 4.2 AUTOMATED DATA COLLECTION SYSTEMS

The AVL system, provided by Siemens Transportation Systems, captures vehicle location data both through interval polling and time-point based technology. Using GPS technology, the system polls the location of each vehicle at time intervals to provide updated tracking data. This data is integrated with a Geographic Information System (GIS) that enables supervisors at the MBTA's Control Center to view the location data through a graphical user interface. The system also provides access to the current timetable and operator assignments which allows the interface to display whether a bus is running early, on-time or late, as well as the operator ID. Time-at-location information is also captured as buses traverse through a number of time points in the route. An arrival-at-point timestamp is recorded as buses enter a zone around a specific set of GPS coordinates that correspond to a time point in the route. The actual departure timestamp is recorded as the buses leave this zone. The system is not equipped to capture dwell time information such as the time stopped at a time point with the doors open.

Polled data is transmitted over the air to the control center, while time-at-location data is recorded in the on-board system, which is then downloaded at the garage at the end of the day and archived in a central database. Thus, the polled data is mainly used for real-time tracking, while the time-at-location data is used for off-line analysis.

The buses are not equipped with an Automatic Passenger Counter (APC) system. The analysis process and service reliability evaluations are still applied to the Silver Line route using the available AVL and integrated operator assignment data, but the lack of passenger loads limits the ability to conduct detailed analyses in determining the causes of unreliability on this route.

The system also displays real-time schedule information to passengers at each of the stations, which are equipped with variable message signs. The on-board computer system also has the capacity to capture information on fuel levels, odometer readings, wheelchair ramp usage, engine conditions and alarm triggers.

### 4.2.1 ARCHIVED DATA

The Automatic Vehicle Location (AVL) system installed in the MBTA Silver Line is configured with 10 time point locations in both the inbound and outbound directions, and at the Southampton Street garage. This means that almost all of the bus stops are considered time points in the system (only the Lenox Street and Worcester Square bus stops in both directions are not considered time points). Table 4-4 lists the 20 time points and the corresponding identification numbers. Note that time point identifiers are not unique for each direction, and both the Direction ID and Time Point ID must be used to properly identify the location of a data record.

**Table 4-4. Silver Line Route Time Point Information**

Stop Name	Time Point Sequence	Direction ID	Time Point ID
Southampton garage	---	---	24
<b><i>Inbound</i></b>			
Dudley Square	1	3	1
Melnea Cass Blvd.	2	3	6
Massachusetts Ave.	3	3	4
East Newton St.	4	3	12
Union Park St.	5	3	11
East Berkeley St.	6	3	5
Herald St.	7	3	9
New England Medical Center	8	3	7
Chinatown	9	3	8
Temple St.	10	3	3
<b><i>Outbound</i></b>			
Temple St.	11	4	3
Boylston St.	12	4	14
New England Medical Center	13	4	7
Herald St.	14	4	9
East Berkeley St.	15	4	5
Union Park St.	16	4	11
West Newton St.	17	4	26
Massachusetts Ave.	18	4	4
Melnea Cass Blvd.	19	4	6
Dudley Square	20	4	1

Data recorded by the on-board system is downloaded into the MBTA's databases at the end of service each night. The raw data is automatically pre-processed and sorted by the system, and archived into several database tables. This research uses the most comprehensive time-at-location data table, called "Time Point Crossing", where each row is a distinct data record of a scheduled bus trip crossing a specific time point location. Each data record contains values of the data items, listed in Table 4-5, that characterizes the route, time point location, scheduled and actual times at the time point, and vehicle and trip assignment.

**Table 4-5. Data Items of Time Point Crossing Record\***

Data Item	Description	Notes on Special Format
Unique ID	Unique identifier to characterize data record	Numeric value
Calendar ID	Date of data record	1yyyymmdd (y-year, m-month, d-day)
Route ID	Route identifier	Specific assigned numeric value
Route Direction ID	Value to indicate inbound or outbound direction	Specific assigned numeric value. For Silver Line Washington St.: 3 – Inbound, 4 – Outbound
Pattern ID	Combined with route ID, it identifies specific route traveled	Specific assigned numeric value. For Silver Line Washington St., there are only two pattern IDs that identify inbound and outbound travel.
Geo Node ID	Geographic location identifier	Assigned numeric value specific to each time point
Stop Offset	Numeric count of stops made so far per assignments	Cumulative numeric value. For Silver Line Washington St. for example, a bus' first trip will start at 1 for the garage, 2 for Dudley, 3 for Melnea Cass, and 5 for Mass. Ave. time point (4 is skipped because the Lenox St. stop is not a time point.
Scheduled Time	Scheduled time at time point	Numeric value corresponding to time in seconds past midnight of day of service. Service spans from approx. 5:15am-1:15am. Trips past midnight are same day service, where time values are greater than 86400.
Actual Arrival Time	Actual arrival time at time point	Same as Scheduled Time
Actual Departure Time	Actual departure time from time point	Same as Scheduled Time
Daily Work Piece ID	Run assignment identifier	Assigned numeric value
Time Point ID	Identifier associated with specific time point	Assigned numeric value (described in Table 4-1)
Vehicle ID	Identifier associated with bus operated	Assigned numeric value
Trip ID	Identifier associated with scheduled trip	Assigned numeric value
Pullout ID	Identifier associated with specific block	Assigned numeric value

\* There are six other data items in the table which do not contain any relevant data (PLANNED\_ADH\_WAIVER\_IND, ADHERENCE\_WAIVER, WAIVER\_ID, UPDATE\_TIMESTAMP) or contain inconsistent data (ODOMETER, IsRevenue)

Operator assignments for each scheduled trip are not included in the “Time Point Crossing” table. Information on operators was found to be limited in the MBTA’s automated data collection system databases and difficult to reliably integrate with the rest of the time point crossing location data<sup>9</sup>. However, operator assignments were recovered from operator log sheets maintained by supervisors at the garage and terminal and were manually entered for integration with the time point crossing data. These log sheets contain information on daily work assignments, including the day, departure time from garage or relief point (if work assignment begins at a point in the route), run number (or work assignment id), bus number (differs from vehicle identifier in

<sup>9</sup> At the time of this research, a definition of the data items of each table and the relationship between them was not available. This made it difficult to reliably interpret the bus operator data.

system), badge number, and operator's full name. The log sheets also indicate whether the trip was covered by the scheduled operator or whether a re-assignment occurred.

As previously mentioned, the on-board computer system also records information on wheelchair ramp usage and other on-board sensors and alarm systems. However, the data contained in these databases have rarely been used by the MBTA staff. This research considers this data to be unreliable due to the lack of calibration tests to ensure the archived data is accurate. While it would have been useful to determine whether a schedule or headway deviation was caused by the use of a wheelchair ramp, this research does not integrate these data items into the analysis process.

### 4.3 SCOPE OF ANALYSIS AND DATA ASSUMPTIONS

For this case study, the analysis process is applied to the Silver Line on Washington Street on weekdays for the period of September 13 to October 7, 2004, considering service throughout the entire day (5:15am to 1:15am). The first block of the analysis, the characterization of service reliability, is also applied for the period of May 2 to May 27, 2005 since some important changes had occurred in the fareboxes over this period which may have affected service reliability.

Daily time periods were those used by the MBTA and are as shown in Table 4-6. Categorization of scheduled trips by time period is based on the trip's departure time from the Dudley Square terminal.

**Table 4-6. Silver Line Time Periods**

Time Period	Start Time	End Time	Scheduled Headways (minutes)
1	5:00 AM	5:45 AM	15
2	5:45 AM	6:40 AM	6 – 10
3	6:40 AM	9:05 AM	3 – 5
4	9:05 AM	1:00 PM	6 – 8
5	1:00 PM	2:00 PM	6 – 7
6	2:00:PM	3:55 PM	5 – 6
7	3:55 PM	6:05 PM	3 – 5
8	6:05 PM	6:35 PM	5 – 6
9	6:35 PM	7:55 PM	10
10	7:55 PM	1:30 AM	12

For performance evaluation and analysis, three locations in each direction are considered: the Dudley Square terminal, the Temple Place terminal, and East Berkeley Street station. This allows for service reliability to be evaluated at the beginning, middle and end of each trip. East Berkeley Street is considered a good mid-route time point because it is near the transition point between the exclusive lane segment and the downtown area, and previous ride checks shows this to be the maximum load point on the Silver Line.

Time point crossing data was obtained for all 19 weekdays in the first study period and 20 weekdays in the second study period, although not all scheduled trips contained valid data. Data on actual trips may be missing due either to the trip not being made or the AVL system failing to capture the location data. Capture rates varied, but overall capture rates for the entire study period ranged between 70% and 95% of the scheduled trips per time period. These capture rates are lower for headway evaluations because two valid data records are needed to calculate the actual headway between consecutive buses.

Operator assignments were recovered from paper log sheets obtained from the MBTA staff for all days in the first study period except Monday, September 20, 2004. No operator assignments were obtained for the May 2005 study period. The operator assignments were manually entered into a database table and minor adjustments to the data were made to integrate it with the time point crossing data. Integration was based on departure time at the garage or scheduled departure time from the relief point in the route, and the "Daily Work Piece ID" value in the data records. It was found that some of the departure times were the same between the two sets of data and others were off by 5 minutes. Where scheduled times did not match, the first data record of each unique "Daily Work Piece ID" data item served to identify the first trip of an operator's assignment.

Assumptions also had to be made on operator assignments. Substitutions were assumed for any log sheet record where the name of the scheduled operator was scratched out and/or signed by a different operator. Records without a signature could not be assumed to be missed service since in many cases actual time point crossing data did exist. For these cases, where recorded data could not be matched with a known operator assignment, the trips were marked with an unknown operator. Operator type (part-time or full-time) was determined by the "Run Number ID" in the paper log sheets, where runs operated by part-time operators have an ID number starting with 9.

## **4.4 SILVER LINE RELIABILITY ASSESSMENT**

The proposed reliability analysis process discussed in Chapter 3 is applied to the Silver Line on Washington Street route to evaluate its service reliability. Service reliability on the Silver Line on Washington Street route is also evaluated using AVL data from May 2005. The results of both analyses are presented in this section.

### **4.4.1 RUNNING TIMES**

At the trip level, scheduled and actual running times are compared on two segments of the route: Dudley Square - East Berkeley Street, and East Berkeley Street - Temple Place. The running time distributions for the two segments in the inbound and outbound directions are calculated and summarized in Table 4-7 through Table 4-10. The tables present the capture rate (number of trips with valid data divided by the number of

scheduled trips), the scheduled and actual running time mean and standard deviations of both, for all time periods.

**Table 4-7. Running Time Analysis: Dudley to E. Berkeley - Inbound**

Time Period		# of Trips Sched.	# of Trips Obsv.	Capture Rate	Running Time (mins)			
Start Time	End Time				Mean		Std. Deviation	
					Sched.	Obsv.	Sched.	Obsv.
5:00 AM	5:45 AM	38	33	86.8%	8.0	6.2	0.0	1.0
5:45 AM	6:40 AM	116	106	91.4%	8.0	7.6	0.0	1.5
6:40 AM	9:05 AM	664	579	87.2%	10.8	10.0	1.5	2.2
9:05 AM	1:00 PM	614	529	86.2%	12.0	9.8	0.1	1.8
1:00 PM	2:00 PM	195	154	79.0%	11.9	9.5	0.6	2.0
2:00 PM	3:55 PM	445	369	82.9%	12.0	10.6	0.4	2.5
3:55 PM	6:05 PM	568	464	81.7%	11.9	10.1	0.5	2.2
6:05 PM	6:35 PM	76	72	94.7%	10.0	9.3	0.0	1.5
6:35 PM	7:55 PM	152	138	90.8%	10.0	8.2	0.0	1.7
7:55 PM	1:30 AM	476	333	70.0%	7.8	6.4	1.3	1.6

**Table 4-8. Running Time Analysis: E. Berkeley to Temple - Inbound**

Time Period		# of Trips Sched.	# of Trips Obsv.	Capture Rate	Running Time (mins)			
Start Time	End Time				Mean		Std. Deviation	
					Sched.	Obsv.	Sched.	Obsv.
5:00 AM	5:45 AM	38	33	86.8%	4.0	4.2	0.0	0.6
5:45 AM	6:40 AM	116	106	91.4%	4.0	4.9	0.0	0.9
6:40 AM	9:05 AM	664	579	87.2%	5.0	6.1	0.2	1.2
9:05 AM	1:00 PM	614	518	84.4%	5.0	7.9	0.0	2.0
1:00 PM	2:00 PM	195	152	77.9%	5.0	7.0	0.1	1.6
2:00 PM	3:55 PM	445	368	82.7%	5.0	7.0	0.1	1.6
3:55 PM	6:05 PM	568	460	81.0%	5.0	7.5	0.0	2.1
6:05 PM	6:35 PM	76	72	94.7%	5.0	6.6	0.0	1.3
6:35 PM	7:55 PM	152	138	90.8%	5.0	6.1	0.0	1.6
7:55 PM	1:30 AM	476	329	69.1%	4.3	5.0	0.4	1.6

**Table 4-9. Running Time Analysis: Temple to E. Berkeley - Outbound**

Time Period		# of Trips Sched.	# of Trips Obsv.	Capture Rate	Running Time (mins)			
Start Time	End Time				Mean		Std. Deviation	
					Sched.	Obsv.	Sched.	Obsv.
5:00 AM	5:45 AM	38	34	89.5%	6.0	5.4	0.0	1.0
5:45 AM	6:40 AM	116	108	93.1%	6.0	6.9	0.0	1.3
6:40 AM	9:05 AM	664	592	89.2%	6.1	7.7	0.3	1.3
9:05 AM	1:00 PM	614	510	83.1%	7.0	8.3	0.0	1.4
1:00 PM	2:00 PM	195	167	85.6%	7.9	8.5	1.3	1.4
2:00 PM	3:55 PM	445	398	89.4%	10.0	9.5	0.4	1.6
3:55 PM	6:05 PM	568	474	83.5%	9.4	9.2	1.2	1.6
6:05 PM	6:35 PM	76	70	92.1%	7.0	8.2	0.0	1.5
6:35 PM	7:55 PM	152	145	95.4%	7.0	7.9	0.0	1.6
7:55 PM	1:30 AM	476	330	69.3%	5.4	6.9	0.9	1.5

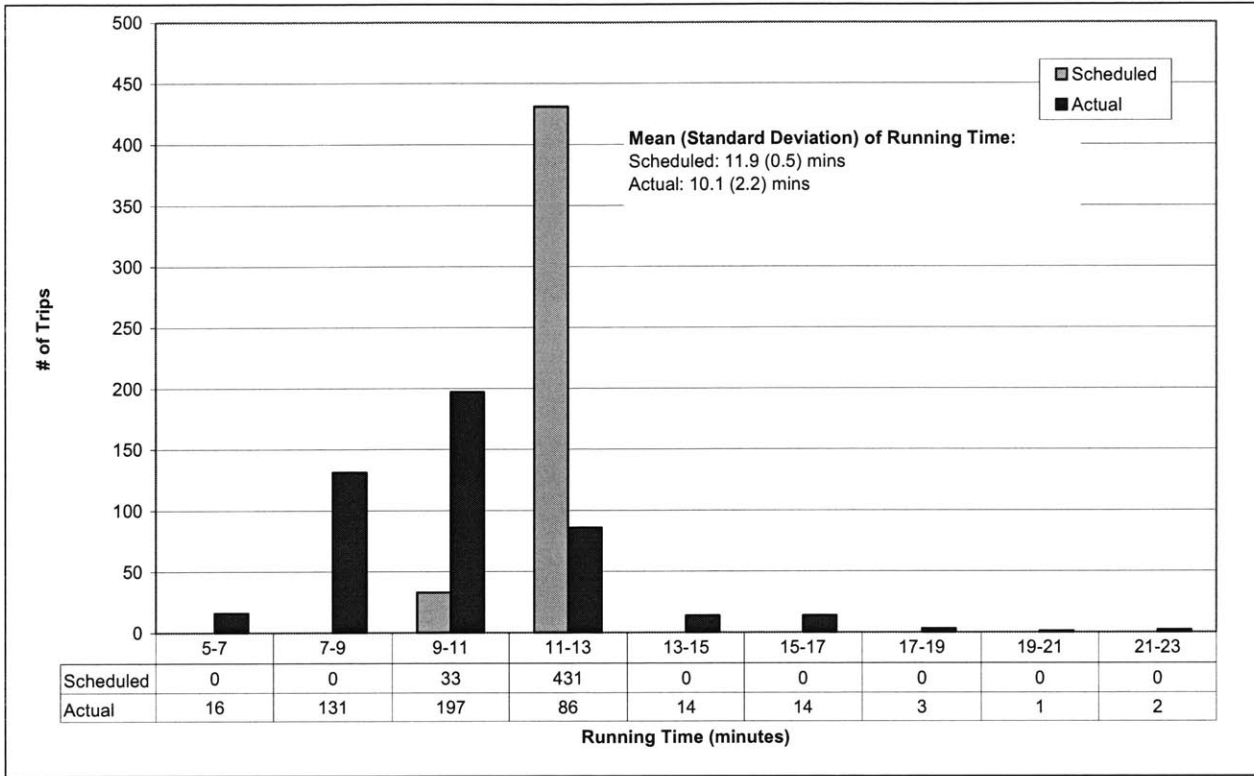
**Table 4-10. Running Time Analysis: E. Berkeley to Dudley - Outbound**

Time Period		# of Trips Sched.	# of Trips Obsv.	Capture Rate	Running Time (mins)			
Start Time	End Time				Mean		Std. Deviation	
					Sched.	Obsv.	Sched.	Obsv.
5:00 AM	5:45 AM	38	34	89.5%	8.0	5.6	0.0	2.0
5:45 AM	6:40 AM	116	108	93.1%	8.0	6.5	0.0	1.8
6:40 AM	9:05 AM	664	577	86.9%	8.8	7.3	1.1	1.9
9:05 AM	1:00 PM	614	477	77.7%	11.0	8.5	0.1	2.6
1:00 PM	2:00 PM	195	167	85.6%	10.4	8.0	0.7	2.0
2:00 PM	3:55 PM	445	396	89.0%	10.0	8.6	0.2	1.7
3:55 PM	6:05 PM	568	448	78.9%	9.7	8.6	0.4	2.2
6:05 PM	6:35 PM	76	69	90.8%	9.0	7.7	0.0	1.3
6:35 PM	7:55 PM	152	122	80.3%	9.0	7.1	0.0	1.5
7:55 PM	1:30 AM	476	309	64.9%	8.2	5.9	0.4	1.6

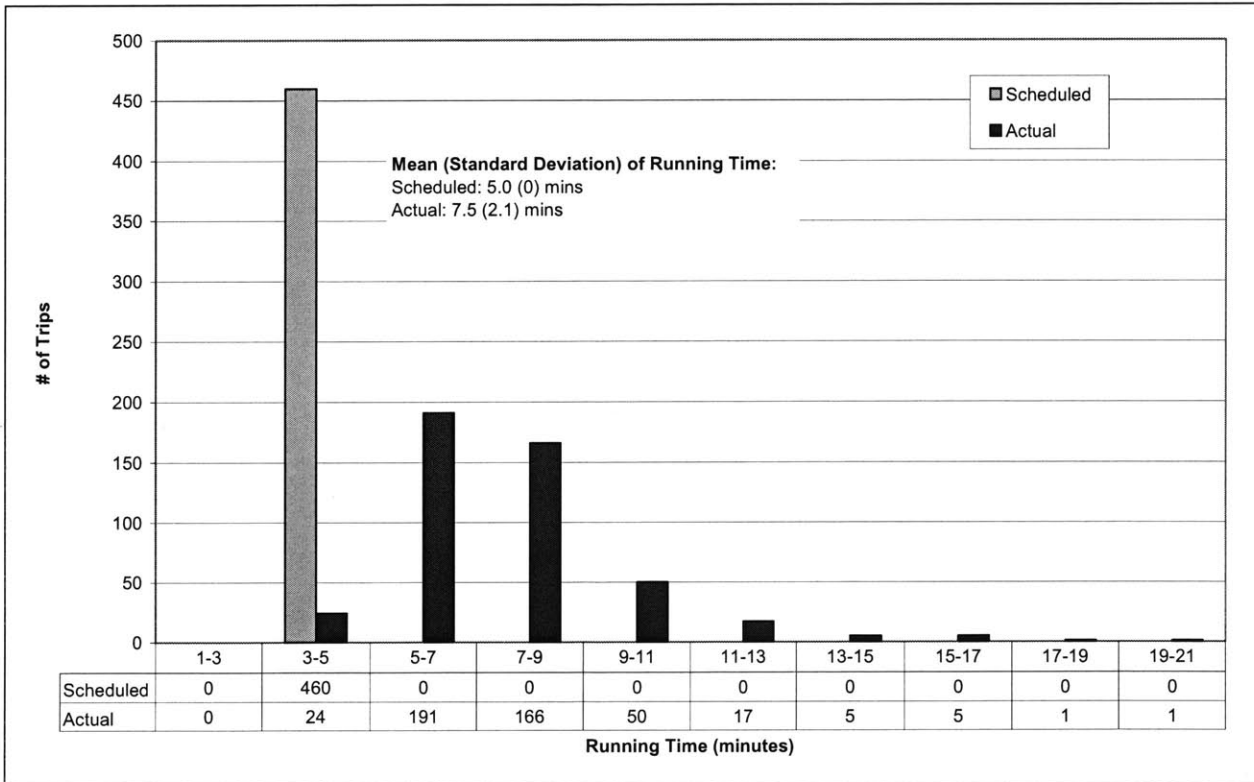
The running time analysis tables show that observed running time means are lower than scheduled for the Dudley Square to East Berkeley Street segment in both the inbound and outbound direction. For the East Berkeley Street to Temple Place segment, the observed running time means are higher than scheduled in both directions. Standard deviations vary across the route and throughout the day, with a tendency to be slightly higher for the Dudley Square – East Berkeley Street segment

The running time distributions for the PM peak hour for the two segments in the both directions are presented in Figure 4-3 through Figure 4-6. The AM peak hour graphs are shown in Appendix A.

**Figure 4-3. PM Peak Running Time Distribution: Dudley to E. Berkeley - Inbound**

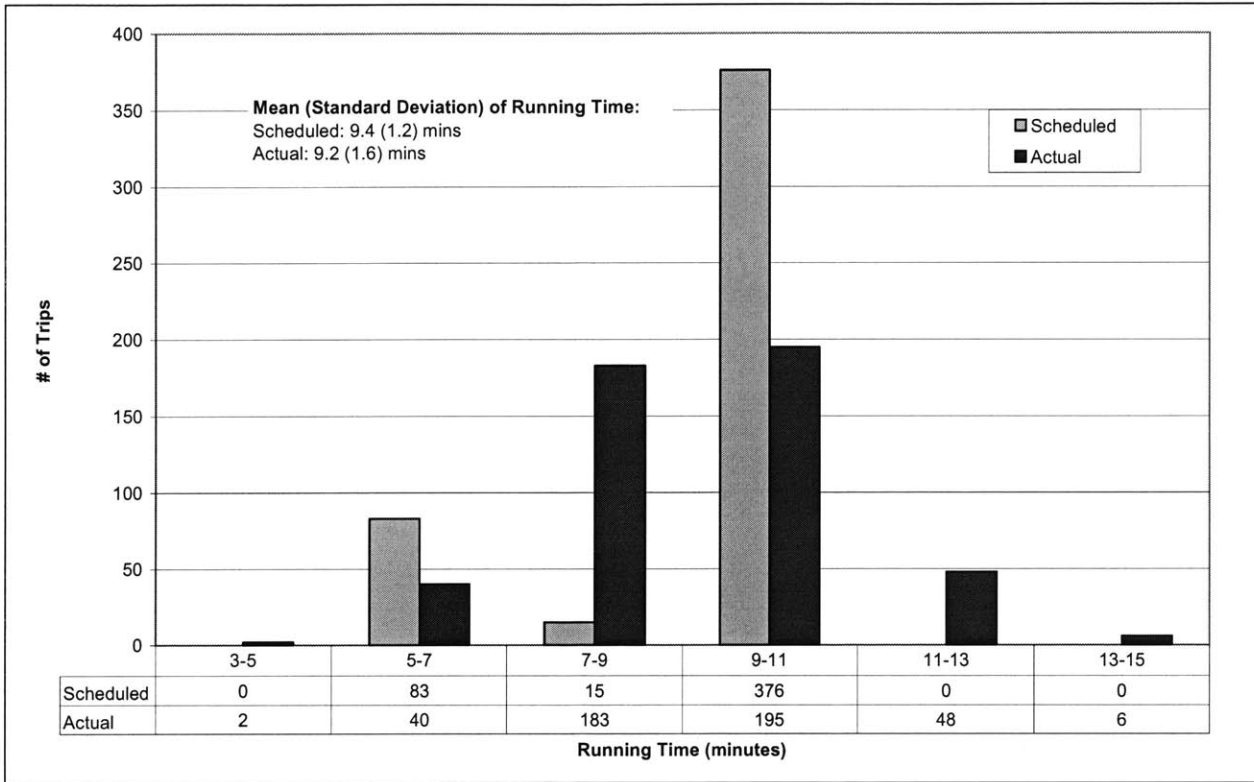


**Figure 4-4. PM Peak Running Time Distribution: E. Berkeley to Temple - Inbound**

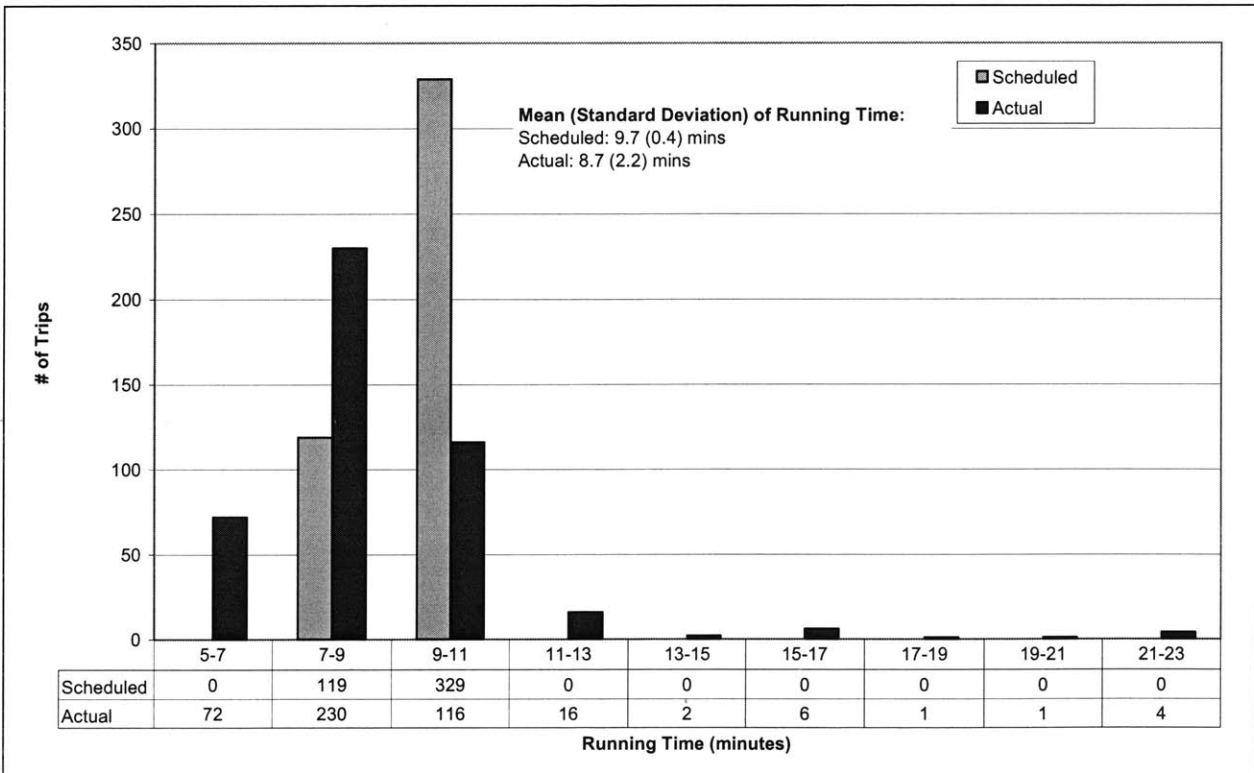




**Figure 4-5. PM Peak Running Time Distribution: Temple to E. Berkeley - Outbound**



**Figure 4-6. PM Peak Running Time Distribution: E. Berkeley to Dudley - Outbound**



The running time graphs for the PM peak hour show how the observed running time distributions for the Dudley Square – East Berkeley Street segment in both directions have an observed mean running time lower than scheduled, but a higher variability. For the East Berkeley Street – Temple Place segment, the observed mean and standard deviation of running time are significantly higher than scheduled in the inbound direction, and approximately equal in the outbound direction.

#### 4.4.2 HEADWAY ADHERENCE

For headway analysis, the schedule and actual preceding headway of each bus as it crosses a timepoint are calculated. Table 4-11 and Table 4-12 show the mean and coefficient of variation of both scheduled and observed headways for Dudley Square, East Berkeley Street and Temple Place in both directions for each time period. Scheduled headway coefficients of variation are non-zero because headways vary by 1 or 2 minutes in each time period.

**Table 4-11. Mean Scheduled and Actual Headways**

Time Period		Sched. (mins)	Actual (mins)					
Start Time	End Time		Inbound			Outbound		
			Dudley	E. Berkeley	Temple	Temple	E. Berkeley	Dudley
5:00 AM	5:45 AM	15.0	14.9	15.9	16.1	14.1	14.3	13.6
5:45 AM	6:40 AM	10.1	10.1	10.3	10.4	10.4	10.7	10.9
6:40 AM	9:05 AM	4.2	4.2	4.3	4.3	4.3	4.2	4.2
9:05 AM	1:00 PM	7.2	7.2	7.3	7.2	7.2	7.2	7.1
1:00 PM	2:00 PM	6.1	5.9	6.0	5.6	5.6	5.7	5.6
2:00 PM	3:55 PM	4.9	4.9	5.0	5.0	5.0	5.0	4.9
3:55 PM	6:05 PM	4.3	4.4	4.2	4.2	4.2	4.1	4.2
6:05 PM	6:35 PM	7.0	7.0	6.8	6.9	7.2	7.0	6.4
6:35 PM	7:55 PM	9.9	9.6	9.5	9.3	9.2	9.3	9.8
7:55 PM	1:30 AM	11.7	11.9	11.9	12.1	12.3	12.3	11.7

**Table 4-12. Coefficients of Variation of Headways**

Time Period		Sched.	Actual (mins)					
Start Time	End Time		Inbound			Outbound		
			Dudley	E. Berkeley	Temple	Temple	E. Berkeley	Dudley
5:00 AM	5:45 AM	0.00	0.24	0.27	0.24	0.13	0.18	0.38
5:45 AM	6:40 AM	0.21	0.31	0.29	0.32	0.31	0.37	0.44
6:40 AM	9:05 AM	0.23	0.46	0.63	0.68	0.64	0.76	0.81
9:05 AM	1:00 PM	0.12	0.41	0.62	0.68	0.66	0.73	0.82
1:00 PM	2:00 PM	0.08	0.39	0.54	0.60	0.53	0.66	0.79
2:00 PM	3:55 PM	0.08	0.50	0.70	0.75	0.76	0.87	0.98
3:55 PM	6:05 PM	0.13	0.57	0.72	0.78	0.77	0.86	0.95
6:05 PM	6:35 PM	0.14	0.37	0.47	0.55	0.51	0.55	0.64
6:35 PM	7:55 PM	0.03	0.33	0.41	0.47	0.44	0.54	0.58
7:55 PM	1:30 AM	0.07	0.18	0.24	0.27	0.33	0.35	0.35

Table 4-11 shows that mean observed headways are very close to scheduled values, with the largest deviation between the mean scheduled and observed headway occurring in the early AM peak period (5:15am-5:45am). However, the important observation (from Table 4-12) is the actual coefficients of variation are high for all time periods. This indicates headway variability is high, with buses tending to bunch together and creating large gaps in service.

Variability increases as the buses traverse the route, with the highest values at the end of the outbound trips. The exception, again, is at Temple Place, where a slight decrease is typically observed in the headway variability as vehicles begin their outbound trip. Thus, despite the heavily constrained nature of the Temple Place terminal, some headway regulation and correction is being achieved there during the day.

Variability is highest in the PM peak period, suggesting that headway adherence problems seem to propagate throughout the day until after the PM peak period, where many buses return to the garage allowing headway performance to improve. Buses are likely to be able to maintain better headways due to the decrease in demand, frequency and traffic in the evening.

Figure 4-7 illustrates this variability by showing the headway ratio distribution for the PM peak period.

**Figure 4-7. PM Peak Headway Ratio Distribution**

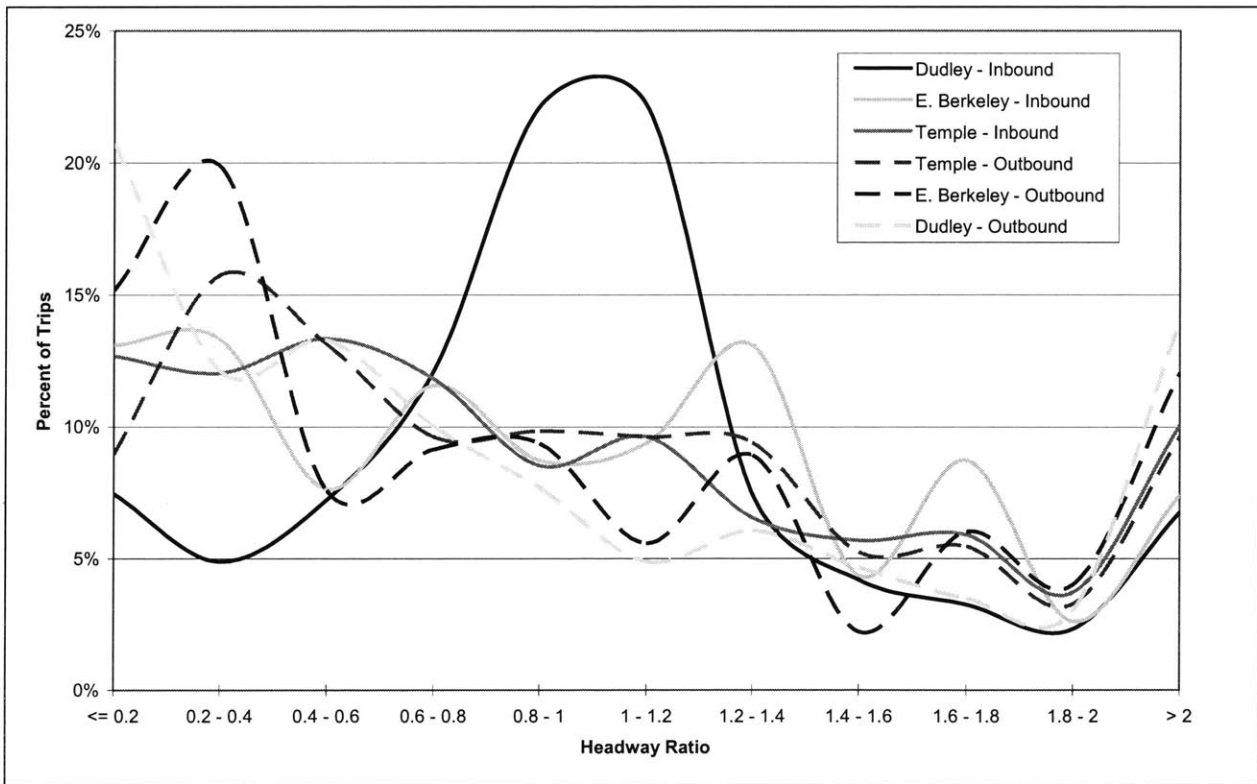


Figure 4-7 shows that most trips leave Dudley Square with a headway ratio between 0.8 and 1.2, and the distribution at this point has a relatively low variability. At other points on the route, the distributions show the variability of headway ratios, indicating poor headway adherence. The percent of trips with headway ratios between 0.8 and 1.2 is less than 20% at all points except Dudley Square inbound. Trips are observed to have a tendency for short headways (0.4 or less headway ratio) and very large headways (2.0 or more headway ratio).

### 4.4.3 PASSENGER WAIT TIMES

For high-frequency routes, the mean passenger wait time analysis is related to the mean headway and its coefficient of variation. Expected passenger wait times characterize reliability from the passengers' perspective, where the variability in headways affects the mean expected passenger wait time. The expected passenger wait time ( $\bar{w}$ ) and excess passenger wait time (*EWT*) equations, described in Section 3.6.1, are applied to all trips in each time period and for each time point, with the results shown in Table 4-13 and Table 4-14, respectively.

**Table 4-13. Expected Passenger Wait Times**

Time Period		Sched. Expect. Pass. Wait Time (mins)	Inbound (mins)			Outbound (mins)		
Start Time	End Time		Dudley	E. Berkeley	Temple	Temple	E. Berkeley	Dudley
5:45 AM	6:40 AM	5.3	5.5	5.6	5.8	5.7	6.1	6.5
6:40 AM	9:05 AM	2.2	2.6	3.0	3.1	3.0	3.3	3.5
9:05 AM	1:00 PM	3.7	4.2	5.0	5.3	5.2	5.5	5.9
1:00 PM	2:00 PM	3.1	3.4	3.9	3.8	3.6	4.1	4.5
2:00 PM	3:55 PM	2.5	3.1	3.7	3.9	3.9	4.4	4.8
3:55 PM	6:05 PM	2.2	2.9	3.2	3.4	3.3	3.6	3.9
6:05 PM	6:35 PM	3.6	4.0	4.2	4.5	4.5	4.5	4.5
6:35 PM	7:55 PM	5.0	5.3	5.5	5.7	5.5	6.0	6.6
7:55 PM	1:30 AM	5.9	6.2	6.3	6.5	6.8	6.9	6.6

**Table 4-14. Expected Excess Passenger Wait Times**

Time Period		Inbound (mins)			Outbound (mins)		
Start Time	End Time	Dudley	E. Berkeley	Temple	Temple	E. Berkeley	Dudley
5:45 AM	6:40 AM	0.3	0.3	0.5	0.4	0.8	1.2
6:40 AM	9:05 AM	0.3	0.8	0.9	0.8	1.1	1.3
9:05 AM	1:00 PM	0.6	1.3	1.6	1.5	1.9	2.3
1:00 PM	2:00 PM	0.4	0.8	0.8	0.5	1.0	1.5
2:00 PM	3:55 PM	0.6	1.3	1.4	1.4	1.9	2.4
3:55 PM	6:05 PM	0.7	1.0	1.2	1.1	1.4	1.8
6:05 PM	6:35 PM	0.4	0.6	0.9	1.0	1.0	0.9
6:35 PM	7:55 PM	0.4	0.6	0.7	0.5	1.0	1.6
7:55 PM	1:30 AM	0.3	0.4	0.6	0.9	1.0	0.7

These tables show deterioration in service as the buses traverse the route, with some improvements at Temple Place before beginning the outbound trip. Service reliability

continues to decrease in the outbound direction, with the highest value of excess passenger wait times at Dudley Square (Outbound). Of course, no passengers actually board at Dudley in the outbound direction since it is the end of the route, so these numbers are theoretical only.

Table 4-14 shows passengers in the outbound direction will tend to wait, on average, more than expected because headway variability at these points is higher. This will have a greater impact in the PM peak when passenger demand is higher in the outbound direction. Passengers in the midday period experience greater expected excess wait times, particularly right after the AM peak and before the PM peak. The ratio of excess wait time to scheduled expected passenger wait time is the highest for these time periods. This shows that passengers in this period experience very high wait times relative to that already expected (2 minutes of excess is significant if the scheduled expected wait time is 3 minutes). On the other hand, excess wait times are the lowest in the early morning and late night periods, where frequency is lower. This means that reliability from the passengers' view is good at these time periods as they should not expect to wait a lot more than scheduled (1 minute of excess wait time is not as significant if the scheduled expected wait time is 6 minutes).

#### **4.4.4 CHANGES IN PERFORMANCE: MAY 2005**

In January 2005, the MBTA installed a new Automatic Fare Collection (AFC) system on the Silver Line on Washington Street route as an initial test of the technology as part of deployment on the entire transit system. The AFC system created delays in the boarding process due to problems with the new equipment, which was designed to accept the new smartcard tickets, regular magnetic stripe cards, bills and coins. However, a lack of familiarity with the new equipment combined with its greater complexity and several design flaws contributed to an increase in dwell times and travel times for the route.

In response to these problems, the MBTA increased scheduled running times on the Silver Line on Washington Street corridor for certain time periods and segments of the route. The May 2005 data reflect such changes in scheduled times and the reliability analyses are intended to evaluate performance and assess any changes in performance due to the implementation of the new AFC system.

Mean scheduled running times have been increased from the September-October period in both segments in the inbound direction between 6:40am and 6:35pm (AM Peak, Midday and PM peak periods). In the outbound direction, the scheduled running times for in the East Berkeley Street – Temple Place segment have been increased for all time periods except in the evening and late night (6:35pm-1:30am), and are approximately the same for the Dudley Square – East Berkeley Street segment for all time periods.

Mean running times tend to be slightly higher for this analysis period (May 2005) compared to those in the previous analysis period (September-October), except for the early AM time period where mean actual running times have decreased.

With regard to the standard deviations of running times, they are significantly higher for the Dudley Square – East Berkeley Street inbound segment, especially in the PM peak period. Because the majority of boardings occur on the first half of the route, the new AFC equipment has impacted this segment of the route most negatively. Running time variability on the East Berkeley Street – Temple Place inbound segment did not change substantially, but variability has increased in the outbound direction.

The headway adherence results show that mean headways are close to scheduled, but the coefficients of variation reveal headways are highly variable and unreliable. Variability tends to be worse in the outbound direction than in the inbound direction.

Compared to the September-October period, headway variability has increased in May at most points and time periods. A decrease in headway variability is shown in the early AM and in the outbound direction for the PM peak (and the period right before the PM peak). This observation is unexpected, since variability should have increased for this period and direction because a high percent of boardings in the outbound direction occur in this segment of the route, and one would have expected the AFC equipment to negatively impact this segment. The headway ratio distribution for the PM peak is shown in Figure 4-8.

**Figure 4-8. PM Peak Headway Distribution (May 2005)**

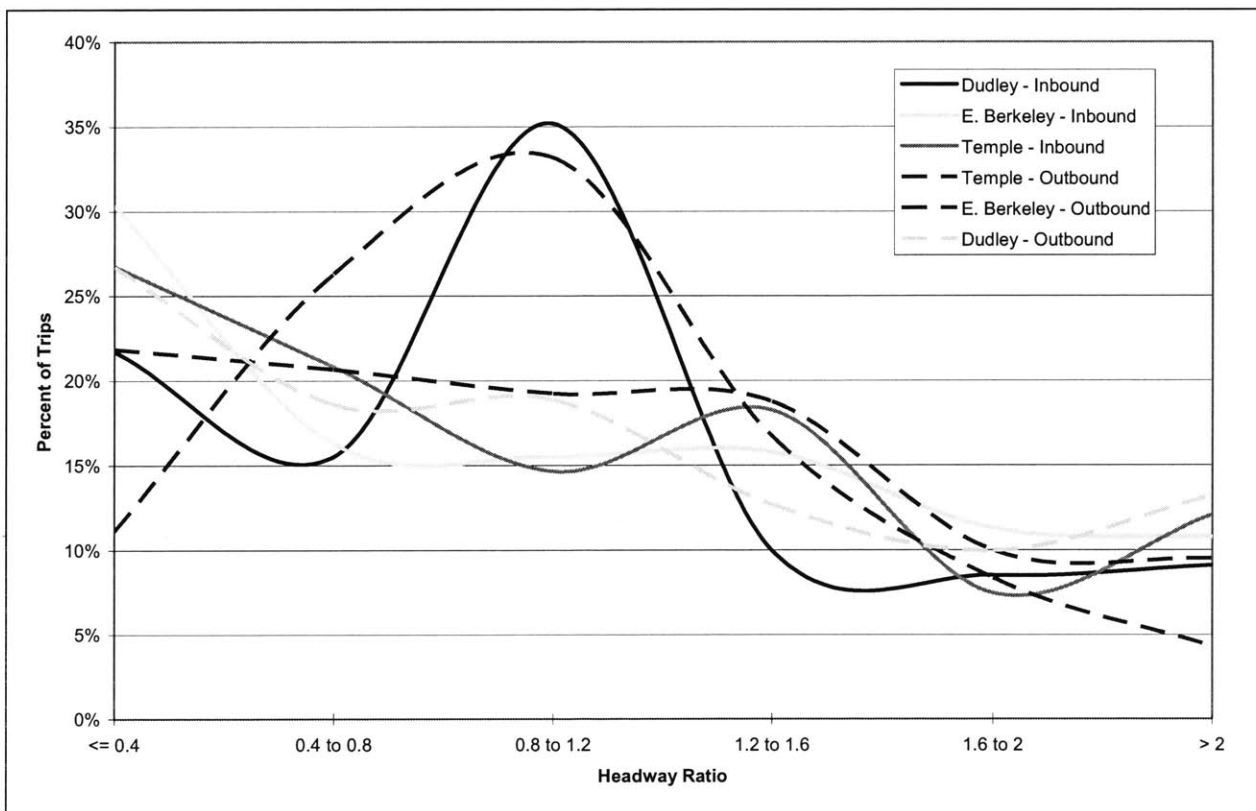


Figure 4-8 shows that headway variability in the PM peak is high at all points on the route. However, comparing this figure with Figure 4-7, it is observed that the headway ratio distribution for Temple Place in the outbound direction is less variable and has a more noticeable peak around better headway adherence.

As for expected passenger wait times, they are higher for the time periods between the AM peak and PM peak in the May 2005 analysis period compared to the scheduled values in the September-October period. Expected passenger wait times were observed to increase for most of the points, with the exception again of the PM peak in the outbound direction. The inbound direction in the early AM period is now shown to experience lower-than-scheduled expected passenger wait times.

Comparing the expected excess passenger wait times from September-October and May reveal an general increases, but a decrease in the inbound direction during the early AM and late night periods, and again, in the outbound direction in the PM peak. These results are consistent with those from the headway analyses, where a decrease in headway variability in the PM peak outbound reflects an improvement in expected passenger wait times for the same period and segment of the route.

#### **4.4.5 OVERALL RELIABILITY ASSESSMENT**

The characterization of service reliability of the Silver Line for both periods reveals the following:

- Running times between Dudley Square and East Berkeley Street are lower than scheduled, which indicate lower mean travel times for passengers in this segment. However, mean travel time between East Berkeley Street and Temple Place is higher than scheduled. This indicates that vehicles tend to slightly recover from late departures from Dudley Square in the inbound direction and improve on schedule performance upon arrival back at Dudley Square.
- The running times (and schedule deviations) standard deviations indicate a problem for passengers who are unable to adjust their departure times (decision on when to leave for a trip based on expected total travel time, including wait time and in-vehicle time) because travel times (and departures) are unreliable and inconsistent.
- Mean observed headways are close to schedule. However, the coefficient of variation shows that many buses operate with much lower or much higher headways, creating reliability problems for both operations and passengers. Headway variability increases as buses traverse the route (variability is higher in the outbound direction) and over the day until after the PM peak period (coefficient of variation is the highest highest in this period).

- The PM peak period is the worst in relation to operations (running times, schedule deviations and headway adherence). The midday period is the worst in terms of passenger wait times.

Comparing service reliability in May 2005 with September-October 2004, the following observations are made:

- Mean observed running times are higher in the May 2005, reflecting the aforementioned operational problems with the new Automated Fare Collection (AFC) system.
- Headway variability seems to have worsened for most of the route and day, compared to the September-October period, with more buses tending to bunch.
- Expected passenger wait times have also increased for all time periods except the early AM peak. Excess expected passenger wait times continue to be the worst in the early Midday period (9:05am-1:00pm). However, decreases in the excess wait time were observed in the early AM and late night (inbound direction) and the PM peak period (outbound direction).
- Reliability, as shown by the coefficient of variation of headways and passenger wait times, has actually improved in the outbound direction in the PM peak, and thus the scheduling adjustments appear to have had the desired effect for this period.
- Overall results show that service reliability has worsened since the September-October period, except for the outbound PM peak. Despite the increases in scheduled running times, running time variability has increased significantly, especially in the first half of the route (Dudley Square - East Berkeley Street). In addition to the increase in travel times, variability in schedule deviations and headway adherence has increased. This means that passengers experience higher expected passenger wait times and poorer service quality.

## **4.5 IDENTIFYING THE CAUSES OF UNRELIABILITY**

The second block of the proposed reliability analysis is applied to the Silver Line Washington Street route to identify the causes of service unreliability. The results of these analyses using the September-October 2004 data are presented in this section.

### **4.5.1 PERFORMANCE AT TERMINAL**

The first step of the analysis is to evaluate performance at the terminals. There are two terminals on the Silver Line Washington Street route: Dudley Square and Temple Place. As previously noted (see Section 4.1), Temple Place is a physically constrained terminal point and recovery times at this point are limited. Thus, only the results of the analysis of the Dudley Square terminal are presented.



As characterized in Section 4.4.2, the headway ratios at the Dudley Square terminal in the inbound direction have a mean value of roughly 1.0 and a coefficient of variation that varies between 0.18 and 0.57. The headway ratio distribution at the terminal is analyzed to examine the departure behavior at the beginning of trips. Figure 4-9 illustrates the number of trips that depart Dudley Square within a certain headway ratio range.

**Figure 4-9. Headway Ratio Distribution at Dudley - Inbound**

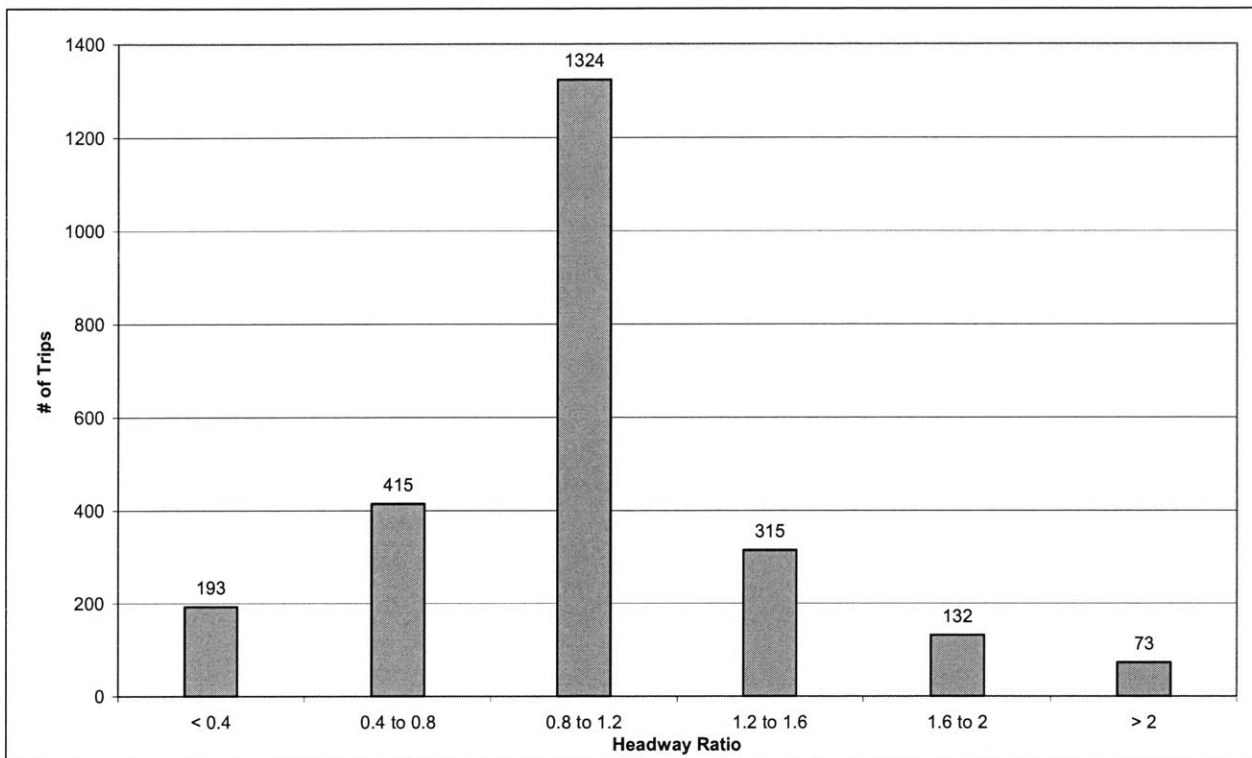


Figure 4-9 shows that most trips (54%) departed Dudley Square for their inbound journey within +/-20% of their scheduled headway. Extreme headway ratios (less than 0.4 and more than 2.0) were observed for around 10% of the trips.

While the departure behavior at Dudley Square is better than at Temple Place, there are still 46% of trips that are departing this terminal with short or long headways. This departure behavior has an effect on service reliability on the rest of the route, especially given the high trip frequency.

The next step in the analysis is to evaluate the effects of headway deviations at the terminal on other points along the route. This is to examine the headway adherence given the departure behavior from the terminal.

Trips are grouped by initial headway ratio at the Dudley Square terminal, and the mean, standard deviation and distribution of the headway ratio at East Berkeley Street and Temple Place are calculated for trips in each category. Because it cannot be determined whether missing data is due to a missed trip or errors in data capture, the analysis only uses records where valid headway data at the time point and the terminal

(i.e., when there is data on two consecutive buses at that time point are known) are available. The results of this analysis are summarized in Table 4-15.

**Table 4-15. Headway Ratio at Inbound Time Points by Ratio at Dudley Terminal**

Headway Ratio at Dudley Square	Dudley Square			East Berkeley			Temple Place		
	Mean	Std. Dev.	Coeff. Of Var.	Mean	Std. Dev.	Coeff. Of Var.	Mean	Std. Dev.	Coeff. Of Var.
0 to 0.4	0.23	0.12	0.51	0.38	0.38	1.02	0.38	0.30	0.80
0.4 to 0.8	0.64	0.11	0.17	0.55	0.37	0.67	0.58	0.40	0.69
0.8 to 1.2	1.00	0.10	0.10	1.02	0.42	0.41	1.03	0.52	0.50
1.2 to 1.6	1.35	0.11	0.08	1.33	0.53	0.40	1.31	0.58	0.44
1.6 to 2	1.80	0.11	0.06	1.61	0.57	0.36	1.61	0.70	0.44
> 2	2.38	0.40	0.17	2.15	0.64	0.30	2.14	0.84	0.39

The table shows that, as expected, mean headway ratios remain approximately the same along the route. The standard deviation shows that headway variability is higher for trips with greater departure headways at Dudley Square. However, relative to the mean, this variability is the highest for trips with initial headway ratios between 0 and 0.4 at Dudley Square.

The headway ratio distributions at East Berkeley in the inbound direction with respect to the headway ratio at the Dudley Square are shown in Figure 4-10 and Figure 4-11. The figures illustrate the distribution in terms of number of trips and probability of headway ratio at this point given an initial headway ratio at Dudley Square. The data table for Figure 4-10 and the distributions at Temple Place are shown in Appendix B. It is noted that for this analysis, overtaking and possible missed trips are not included in the analysis. Data records were included only where valid headway values (where actual data was recorded for two consecutive trips) existed, and there was the same preceding vehicle between the terminal and the time point in question.

Figure 4-10. Headway Ratio Distribution at East Berkeley by Initial Ratio at Dudley

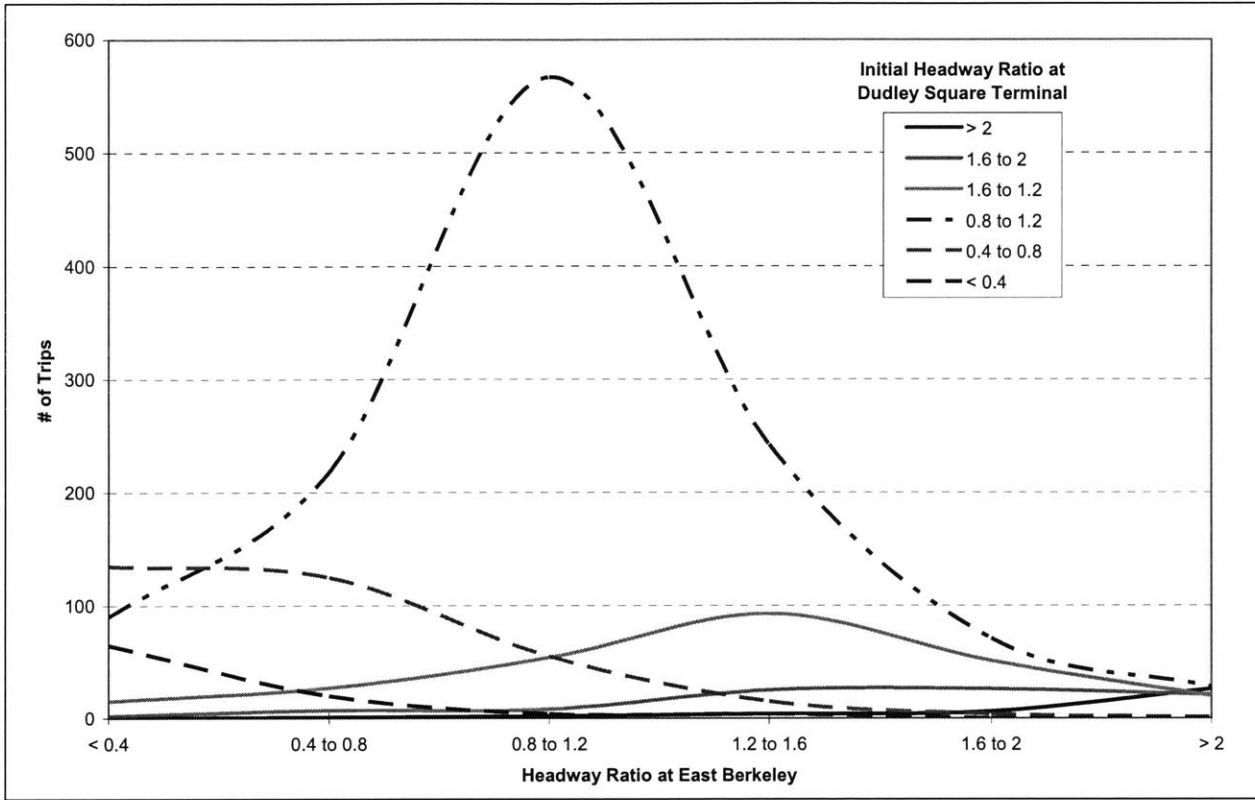
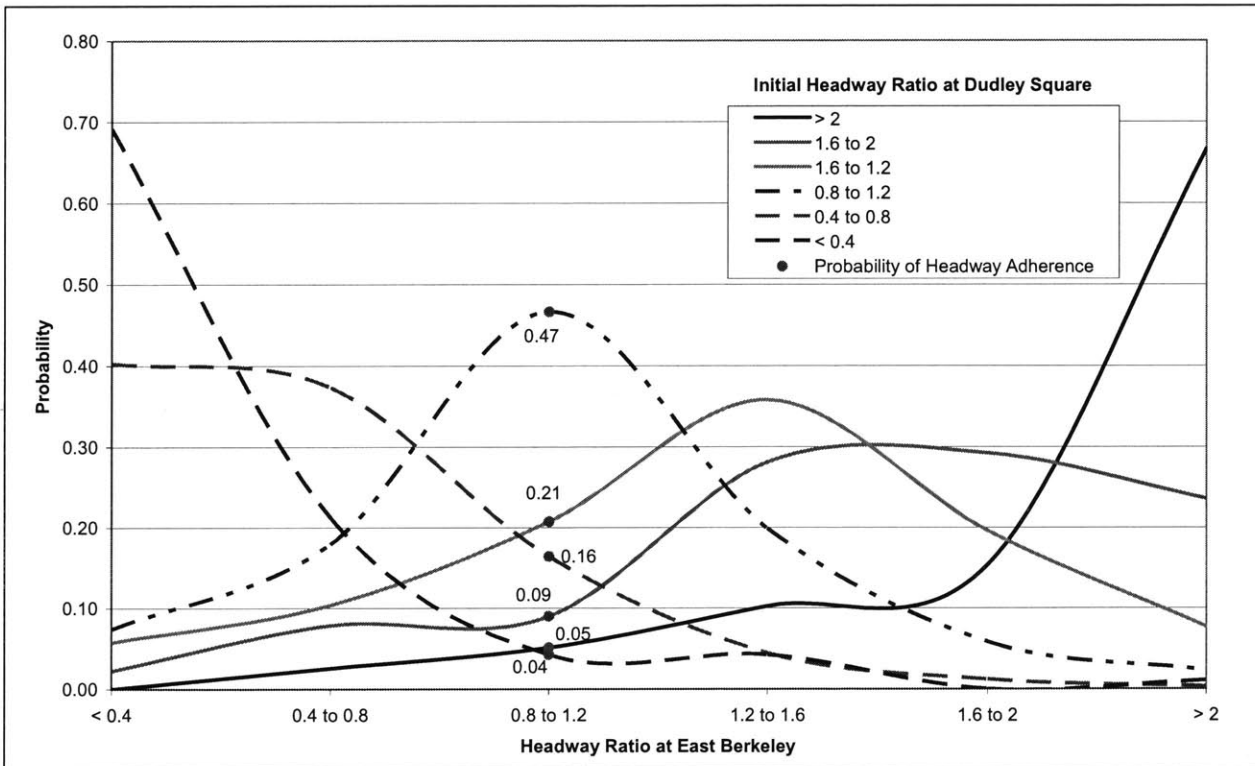


Figure 4-11. Headway Ratio Probability at East Berkeley by Initial Ratio at Dudley



As previously discussed, and as shown in Figure 4-10, about 54% of trips depart from Dudley Square terminal with an initial headway within 20% of the scheduled headway. Figure 4-10 also shows that most of these trips continue to have good headways at East Berkeley Street. Trips with lower-than-scheduled headways at Dudley Square tend to remain closely spaced, as shown by the distribution curve that is higher towards low headway ratio values, and the trips with initial higher-than-scheduled headways seem to continue with higher headways.

Figure 4-11 shows the expected behavior of headways at a point in the route given an initial headway deviation at the terminal in terms of probabilities. Trips that depart with an actual headway close to schedule tend to maintain a reasonable headway throughout the route, with variability likely due to externalities and passenger demand. Trips departing the terminal with a large preceding gap or bunched with its leader have a high probability of increasing this gap or remaining bunched.

An important observation made from Figure 4-11 (and the other distributions shown in Appendix B) is that the probability of actual headways being close to scheduled at other points in the route decreases by almost half if the headway deviation at the terminal is higher than 1.2 or lower than 0.8. This leads to the selection of these values as threshold values for what is considered good headway adherence.

A similar analysis of schedule deviations showed that probability of buses arriving close to the scheduled time at other points in the route varies along the route and by terminal departure behavior, but the results show that buses departing the terminal between 1 minute early and 3 minutes late tend to be on-schedule at other points on the route. Thus, these values are selected as the threshold values for what is considered good on-time performance.

The evaluation of performance at the terminal reveals the following:

- Approximately half of the inbound trips depart the Dudley Square terminal with an actual headway that is between 0.8 and 1.2 of their scheduled headway. A little less than half of these trips are likely to arrive at East Berkeley Street at approximately the scheduled headways (0.8-1.2 of the scheduled headway). This probability decreases to about 40% at Temple Place. Deviations from scheduled headways at the terminal are clearly a significant cause of unreliability.
- These observations indicate that there are other important causes that are triggering reliability problems, besides terminal deviations. As only about half of the trips that depart the terminals without major deviations in headway are able to maintain acceptable headway adherence, one must examine the data to determine other causes along the route.

The causes of this high incidence of deviations at the terminals are evaluated by applying the analyses described in Chapter 3. The process looks at schedules and recovery times, operator and terminal supervisor behavior, heavy passenger loads and other externalities. Limitations on available data from the MBTA, such as the lack of

passenger counts and operator data from an automated data collection system, constrain the level of detail in the analysis. Because data on passenger loads, terminal supervision (and any control actions taken or applied) and traffic conditions are not available, it is not easy to determine whether these elements are causes of unreliability on this route. These possible causes are evaluated based on certain assumptions and observations of the route, and not available AVL/APC data.

#### 4.5.2 CAUSES OF DEVIATIONS AT TERMINALS

The analyses of available recovery times at terminals can help assess whether scheduled times affect the departure behavior of trips from the terminal. If scheduled recovery times are not sufficient to cover excess travel times of most trips, then buses may not be able to begin their next trips following the scheduled headway.

Table 4-16 shows the mean scheduled, available and actual recovery times at Dudley Square by time period. Available recovery time is the time between the arrival of a bus at the terminal and the scheduled departure time of its subsequent trip. Actual recovery time is the time between the arrival of a bus at the terminal and the actual departure time of its next trip. The relative deviation in recovery is the difference between the mean available and scheduled recovery times divided by the mean scheduled recovery time. This represents the percent of deviation in recovery time, where a positive value means buses had, on average, more than the scheduled recovery time, while a negative value indicates they had less. For example, mean available recovery time was 28% lower than the mean scheduled recovery time in both the AM peak and evening periods. The mean observed schedule deviation is included as a reference to illustrate the mean delay in trip departures.

**Table 4-16. Mean Recovery Times at Dudley Square**

Time Period		Trips Observed	Mean Recovery Time (mins)			Relative Deviation in Recovery	Mean Observed Schedule Deviation (mins)
Start	End		Scheduled	Available	Actual		
5:45 AM	6:40 AM	53	6.8	8.9	9.0	31%	0.1
6:40 AM	9:05 AM	444	6.7	4.8	6.1	-28%	1.3
9:05 AM	1:00 PM	341	8.5	6.5	7.7	-24%	1.2
1:00 PM	2:00 PM	112	6.3	4.9	6.2	-23%	1.3
2:00 PM	3:55 PM	252	7.5	6.6	8.0	-12%	1.4
3:55 PM	6:05 PM	379	9.0	7.1	8.3	-21%	1.2
6:05 PM	6:35 PM	47	7.4	6.3	7.4	-16%	1.2
6:35 PM	7:55 PM	121	6.5	4.7	6.1	-28%	1.5
7:55 PM	1:30 AM	229	8.1	8.7	9.4	8%	0.7

The table shows that at Dudley Square, in early morning and late night mean available recovery times are higher than scheduled, and mean schedule deviations are the lowest. Mean available recovery time is lower than scheduled for all other time periods, and based on the relative deviation from the mean schedule recovery time, is the worst in the AM peak and evening periods. For these time periods, the mean actual recovery time is

higher than the mean available time, but close to the mean scheduled time (except in the early midday). Trips in the evening time period also have the highest mean schedule deviation from schedule. These trips are likely to be carrying over deviations from the PM peak, and this is not accounted for in the scheduled recovery time.

The analysis of recovery times includes inferring the time buses typically spend boarding and alighting passengers at the terminal. This is determined by estimating the time buses with tight or negative available recovery time take at the terminal. Although variability exists in the scheduled departure deviation, the analysis assumes that most buses depart as soon as possible when pressured by scheduled times. The results of this analysis are presented in Table 4-17, showing the number of trips within each category.

**Table 4-17. Available Recovery Time vs. Schedule Deviation at Dudley Square**

Schedule Deviation from Departure Time	Available Recovery Time				
	-4 to -2 mins	-2 to 0 mins	0 to 2 mins	2 to 4 mins	4 to 6 mins
3+ mins early	---	---	---	0	4
3-2 mins early	---	---	---	0	5
2-1 mins early	---	---	0	1	15
1-0 mins early	---	---	8	27	28
0-1 mins late	---	12	31	115	203
1-2 mins late	---	11	56	58	93
2-3 mins late	1	13	48	29	38
3-4 mins late	2	24	20	10	15
4-5 mins late	7	33	17	7	4
5-6 mins late	8	18	9	1	7
6-7 mins late	13	6	0	2	0
7-8 mins late	7	2	3	0	0
8-9 mins late	7	1	0	0	0
9-10 mins late	1	1	0	0	0

The distribution of schedule deviations given an available recovery time at Dudley Square suggests that buses spend 2-3 minutes at the terminal to board and alight passengers. This is inferred by observing that buses with negative available recovery time (i.e., the bus arrived after the scheduled departure time of its next trip) tend to leave 2-3 minutes later than their arrival, and buses with 0 to 2 minutes of recovery time tend to depart 1 to 3 minutes late.

By determining that buses typically need 2-3 minutes for passengers to board and alight at Dudley Square, then trips with available recovery times of less than 3 minutes do not have enough time to make an on-time departure. The late departure in this case cannot be attributed directly to operator behavior, and can be inferred to be the result of tight schedules. Of course, these values will vary by time of day because of variability in passenger demand, but a single value of 3 minutes is used because the analysis is applied to all trips (not detailed by time of day or day of the week).

The next step in the analysis is to infer the causes of unreliability by evaluating the amount of available recovery time and the departure behavior from the terminal. As described in Section 3.6.2:

- Late departures of trips from the terminal that had no available recovery time are caused by the late arrival of the previous trip.
- Trips with available recovery times are further separated between those with very short amount of recovery time, given by the threshold value determined as the time buses typically need to board and alight passengers at the terminal (3 minutes for Dudley Square), and those determined to have enough recovery time to account for regular passenger demand and depart its next trip on-time.
- For those trips which are determined to have enough recovery time, the actual headway is examined, counting the trips with headway ratios greater than 1.2 and those with a ratio lower than 0.8.
- The schedule deviation in departure time is also considered, to determine whether the bus had an on-time departure or not. This helps infer whether operators are following schedules or any type of headway-control actions might have been implemented by terminal supervisors. The trips are evaluated based on what the actual headway would have been if the bus had departed on schedule, compared to observed headway.

Figure 4-12 illustrates a flow diagram that presents the number (and percent) of trips that result at each level of the sequential analysis. The percent value shown is in relation to the number of trips in its parent category, and not the total number of trips.

Figure 4-12. Analysis of Causes of Unreliability at Dudley Square

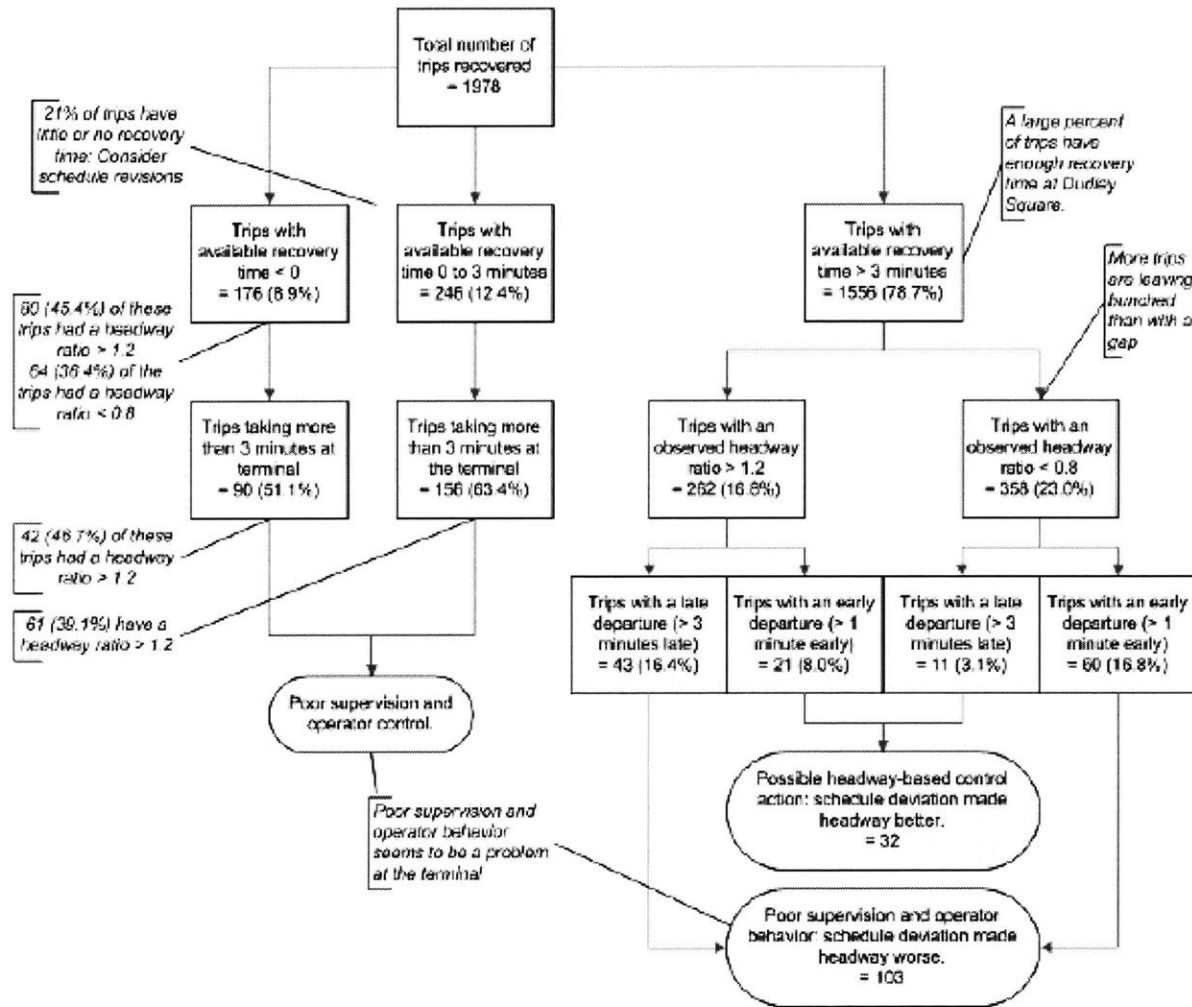


Figure 4-12 shows that the majority of the trips have an available recovery time greater than 3 minutes at Dudley Square. More than three-quarters of the inbound trips arrive from their previous trip before the scheduled departure time, with “enough” recovery time (more than 3 minutes) to account for normal passenger processing at the terminal and should depart on schedule. From these results, it can be inferred that: a) scheduled times and recovery times are not a significant cause of reliability problems at Dudley Square, as almost 78% of the trips had enough time at the terminal before their scheduled departure time; and b) there are other causes of reliability problems at the terminal because



approximately 40% of these trips with available recovery time have poor headway adherence (31% of the total trips) upon departure.

Evaluations of trips with adequate recovery time and poor headway adherence (both less than and greater than scheduled headway) reveal that most do not have a schedule deviation outside the “on-time performance” threshold values (1 minute early to 3 minutes late). This indicates that operators are following scheduled departure times, but headway control is poor on the part of the terminal supervisor maintaining balanced headways. For the off-schedule trips, headway-based control actions as a reason for the departure deviations could explain only a few (32 of 620) trips where the deviation made the actual headway better than it would have been if the trip had departed on-time. But the deviation from schedule made the headway worse for a much greater number of trips (103 out of 620). Operator behavior is then inferred to be the cause of this poor departure performance.

For the other 21% of the trips with little or no recovery time at Dudley Square, the number of trips that spent more than 3 minutes at the terminal are evaluated. This helps suggest whether operator behavior and poor terminal supervision are causing reliability problems at this terminal by buses waiting at the terminal longer than normal. The assumption is that trips, despite already being behind schedule, should depart the terminal as soon as passenger boardings and alightings permit, in order to reduce the magnitude of deviations. The threshold value to account for any passenger demand at Dudley Square is 3 minutes. Any time spent after that is assumed to be caused by poor operator behavior and poor terminal supervision.

The analysis shows that more than half of the trips (51.1%) with no available recovery time spend more than 3 minutes at the terminal. For trips with 0 to 3 minutes of recovery time, this percentage is 63%. The majority of these trips have poor headway adherence.

These observations lead to the conclusion that schedules (recovery times) are not a major cause of poor performance at the terminal, but operator behavior and poor terminal supervision are likely causes of reliability problems at Dudley Square.

However, this does not account for the effects that tight schedules might have on operator behavior. Operators might consider that if available recovery times (also operator breaks) are shorter than scheduled,, they have an added stress of keeping to tight schedules and are not getting their deserved/scheduled break time, and will take this time, regardless of the departure deviation. And while this behavior is controlled by the the operators, it may still be a consequence of poor schedule planning.

While externalities and heavy passenger loads may also affect service performance at the terminal, it is observed that the characteristics of Dudley Square station avert the systematic incidence of these as major causes of unreliability at this terminal. Silver Line buses have their own passenger bay at Dudley Square station, with two lanes and capacity for 3-4 buses at any time. This means that buses can pass-up other parked/idled buses, and are not affected by traffic conditions and private vehicles within the terminal area. Even though Dudley Square is a major bus transfer station, schedule

times are such that there is typically more than one Silver Line bus at the terminal, and heavy passenger loads may be diverted to board the second bus to avoid overloading one bus and causing major deviations in departure. The terminal supervisor is responsible for this type of headway control and enforcement, instructing buses to depart on schedule (or headway-based) and informing passengers to board the other available buses.

A summary of the results of the analyses of Dudley Square reveals:

- Recovery times at Dudley Square do not seem to be a significant cause of reliability problems, as most trips have 3 or more minutes of available recovery time before their inbound departure. Most of these trips are observed to have good headway adherence and on-time performance. Poor departure performance appears to be correlated with poor operator and terminal supervisor behavior, based on the number of trips with high or low headways. This analysis does not account for the effects that tight schedule planning might have on operator behavior with regard to unofficial break times at the terminal.
- Characteristics of Dudley Square station make it unlikely that externalities or heavy passenger loads are systematic problems at this terminal. Accidents/breakdowns or high passenger demand should not cause major departure time deviations at this terminal, and should be handled by terminal supervisors, who can instruct buses to overtake or depart despite passenger demand (instructing passengers to board the next bus).

### ***Operator Behavior***

An analysis of operators is applied to trips at Dudley Square where operator behavior is a potential cause of poor headway adherence. This analysis looks at the frequency of poor performance of operators to help infer whether operator behavior is a systemic problem. For trips with little or no recovery time and taking more than 3 minutes at the terminal, only those with a large headway (greater than 1.2) are considered for this operator analysis. Those with headway ratios lower than 0.8 are not counted because inferring operator behavior is not easy, as the headway would have been smaller if the trip had departed earlier (and not stayed at the terminal as long as it did).

Of the 206 trips with operator behavior as a possible cause of unreliability, operator assignments (known to be covered by particular operator<sup>10</sup>) were determined for 148 of them. The number of poor performance trips is compared to the total number of trips with valid headway data (actual headway is known) and the assigned operator, only 13 operators are observed to have performed poorly on more than 10% of their assigned trips, as shown in Table 4-18.

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<sup>10</sup> Because operator assignments were obtained from supervisor log sheets from the garage, only duties with a valid signature could be known to be covered by that particular operator.

**Table 4-18. Poor Performance Operators**

Badge ID	# of Trips with Poor Headway	# of Assigned Trips (with known headway data)	# of Assigned Trips	Percent Of Assignments Recovered	Percent Of Poor Trips (known headway)
2595	5	15	15	100.0%	33.3%
2929	1	4	4	100.0%	25.0%
7483	22	90	121	74.4%	24.4%
7748	2	17	20	85.0%	11.8%
8407	13	54	90	60.0%	24.1%
9577	4	16	24	66.7%	25.0%
9703	13	95	138	68.8%	13.7%
65230	2	18	21	85.7%	11.1%
65376	1	1	8	12.5%	100.0%
65501	5	37	50	74.0%	13.5%
65541	3	16	24	66.7%	18.8%
65619	4	32	42	76.2%	12.5%
67178	10	84	96	87.5%	11.9%

It should be noted that this analysis only includes operator behavior as it affects departure times at Dudley Square. Specifically, it does not take into account operator behavior that affects running times. For example, it does not include operators that tend to run fast (and bunched) to arrive early at the terminal and enjoy longer breaks (and still depart on their next trip on-time). However, the results suggest the general tendencies in terms of operator behavior, such as frequency of late trips, especially in the next step of the analysis.

### 4.5.3 DEVIATIONS AT OTHER POINTS

The analysis now focuses on the causes of unreliability at other points on the route. Previous sections noted that headway deviations at the terminals trigger reliability problems on this route, but poor performance is still observed at points on the route even when good headway adherence is observed at the terminal.

As described in Chapter 3, the process looks at deviations at the terminal, abnormal passenger boardings and alightings, operator behavior and externalities. Reliability is examined at East Berkeley, in both directions as a mid-route point, and headway adherence is evaluated for headways within 20% of the scheduled headway.

Again, limitations on available data constrain the level of detail in the analysis. Inference of abnormal passenger loads and traffic conditions as causes of unreliability on this

route are not easy to determine and are evaluated based on certain assumptions and observations (not available AVL/APC data). Results of the sequential steps to infer the causes of deviations at East Berkeley Street are presented in the flow diagram shown in Figure 4-13. The total number of trips reflects the number of trips with valid headway data for both the terminal and East Berkeley Street.

**Figure 4-13. Analysis of Causes of Unreliability at East Berkeley - Inbound**

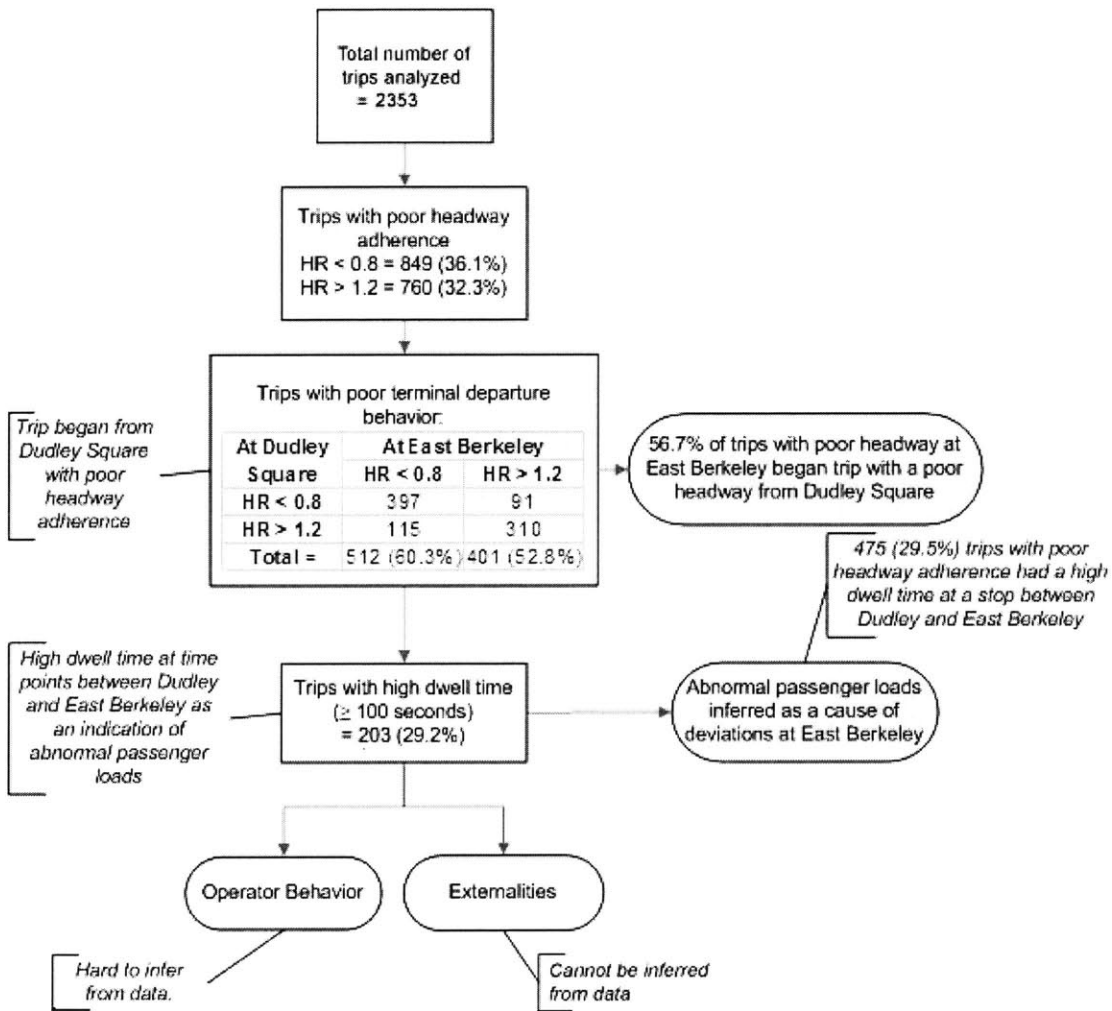


Figure 4-13 shows that 68.1% of the trips have poor headway adherence at East Berkeley, and of these, nearly 57% had an initial headway deviation at the terminal. This indicates that reliability is a big problem at East Berkeley Street station, and the main cause of these is the poor headway adherence at the terminal that propagates and disrupts the headways at other points in the route.

For trips that departed the terminal within 20% of their scheduled headway, but still showed poor headway adherence at East Berkeley, the results show that 29.2% of these trips spent more than 100 seconds at a previous time point before arriving at East Berkeley (time points in between include: Melnea Cass Blvd., Massachusetts Ave., Newton St. and Union Park St.). Because "door open" dwell times or passenger boarding data is not recorded by the Silver Line's automated data collection systems, dwell times are calculated indirectly using the actual arrival and departure time of vehicles at time points. It is suspected that large dwell times are the result of abnormal passenger loads, due to heavy passenger demand or the use of the wheelchair ramp, although in some cases they may be caused by traffic signal delays.

Detailed analyses of the remaining 493 trips could not be applied to infer whether operator behavior or externalities are a cause of poor headway adherence at this time point.

Operator behavior is difficult to determine given the limited data available. However, using the counts of trips with poor terminal departure that were inferred to be caused by poor operator behavior (from the previous section) and the assignments of these 493 trips, a total number of possible off-schedule trips due to operator behavior are calculated for each operator. The results of this analysis reveal that 44 operators (of 59 operators found in the dataset) have more than 10% of assigned trips (with valid headway data) within this set of possible deviated trips caused by operator behavior. A sample set of these operators and resulting number of trips are shown in Table 4-19. While 44 out of 59 operators having poor headway performance is a significant percent, it is noted that the capture rate of trips with known operator assignment and valid headway data is low for a large number of these operators. This indicates that there is a large percent of an operator's total assigned trips that are not included in this analysis due to missing AVL data. Therefore, the analysis on operator behavior remains inconclusive and difficult to interpret.

**Table 4-19. Operator Behavior Analysis**

Badge ID	# of Trips with Poor Headway	# of Assigned Trips (with known headway data)	# of Assigned Trips	Percent Of Assignments Determined	Percent Of Poor Trips (known headway)
1943	19	88	222	39.6%	21.6%
2036	20	148	315	47.0%	13.5%
2112	23	112	216	51.9%	20.5%
2300	24	162	324	50.0%	14.8%
2595	5	15	15	100.0%	33.3%
2630	26	124	351	35.3%	21.0%
2703	11	80	150	53.3%	13.8%
2929	1	4	4	100.0%	25.0%
2957	16	130	204	63.7%	12.3%

Externalities are also hard to infer as a cause of poor reliability on this route without available data on speed profiles or reports on accidents or breakdowns. However, this segment of the route is a semi-exclusive lane (bus-only and right-turn where permitted), that is also at-grade and not protected (no barriers), which lessens the impacts of the regular traffic stream but is still affected by illegal vehicle movements, double parking and accidents.

A summary of the results of the analyses of causes of unreliability at East Berkeley reveals:

- Headway deviation at the terminals is the main cause of poor headway adherence at East Berkeley. The analysis shows that both negative (lower than scheduled) and positive (greater than scheduled) deviations of headways create variability in headways at East Berkeley.
- In the inbound direction, high dwell times at stops affect approximately 30% of the trips that had good headways departing from Dudley Square but arrived at East Berkeley with poor headway adherence. The lack of passenger load data, wheelchair ramp usage and door open/close times, impedes the determination of whether these high dwell times at time points between Dudley Square and East Berkeley were due to abnormally high passenger loads, the use of the wheelchair ramp, or long traffic signal delays.
- Based on observations, aside from terminal deviations, it is believed that service reliability problems on the inbound segment are caused by passenger loads, light cycle delays, and operator behavior. Most boardings occur in the first half of the routes, and the semi-exclusive lane allows operators to have a bit more control over speeds (it also hinders the likelihood of traffic volumes affecting operations).

## 4.6 APPLICATION OF STRATEGIES

The following strategies are highlighted for application on this route, based on the results of the previous analyses.

- Terminal procedures. Terminal deviations were found to be the major cause of unreliability on this route.
  - o At Dudley Square, trips tend to have more than 3 minutes of available recovery time but have poor headway adherence because they are not departing on-time or are remaining at the terminal for a long time. Thus, good headway management by terminal supervisors is needed to maintain regular headways (which were observed to be both large and small upon arrival at Dudley Square). Terminal supervisors need to enforce better operator behavior to avoid early or late departures that affect departure headways and create problems on the route. Better terminal supervision would also need to include enforcement to maintain the route clear of

obstructions such as illegally parked vehicles or help buses depart the station. Terminal supervisors should also be able to balance passenger demand to avoid overcrowding and high dwell times. If supervisors know the arrival of the next bus, they can instruct passengers to avoid loading one bus and wait x minutes for the next one.

- Operator behavior, though it could only be directly inferred on a few trips in the analysis, is still believed to cause service reliability problems, especially at the terminals and in the semi-exclusive lane, where they have greater control of travel speeds. Better operator training, along with improved supervision tactics to enforce on-time performance and good headway adherence, are also noted as strategies that would improve service reliability on this route.
- Corrective Strategies. Applied to both directions, corrective strategies would help reduce the impacts of passenger demands and externalities on headway adherence at points along the route, which were found to be the cause of poor headway adherence at East Berkeley. Though more difficult in the mixed-traffic segment of the route, the available AVL/CAD system provides the location of all buses and helps target specific buses for corrective strategies to improve service reliability if traffic conditions worsen or passenger demand increases.
- Traffic signal priority. Signal priority, especially in the mixed-traffic segment of the route would improve service reliability and help maintain more balanced headways by reducing the impacts of externalities such as heavy traffic volumes. Conditional signal priority could also be applied to reduce the impact of operator behavior with regard to running time variability (tendency of some operators to run early, drive slower, etc.).
- Schedule planning. Although the results do not present much detail on this, schedule adjustments are also recommended in order to better account for time of day variability. Poor service reliability was observed in the time periods surrounding the peak hours, which may be the result of inadequate schedule times that do not account for possible peak demand or traffic conditions extending to these periods.

## 4.7 SUMMARY OF FINDINGS

The application of the proposed reliability framework described in Chapter 3 on the Silver Line route was limited by the availability of data from the Silver Line Washington Street route. The timepoint Automated Vehicle Location (AVL) data was useful in assessing the service reliability on this route and make some inferences on the causes of unreliability. However, data on passenger boardings, more detailed operator assignments, travel speeds or accident/breakdown reports would have improved the level of detail of this case study.

The assessments of service reliability of the Silver Line Washington Street corridor reveals that although mean travel times and headways are close to schedule, variability is quite significant on this route.

Running times are lower than scheduled for the first half of the route (between Dudley Square and East Berkeley Street), which allows buses to make up some of the deviations with respect to schedules. However, variability in running times affects the headways, leading to buses either becoming bunched or creating large gaps in service. This variability, and overall service reliability, deteriorates along the second half of the route between East Berkeley Street and Temple Place, where buses operate in mixed traffic. Running times are higher than scheduled, and recovery times at Temple Place do not give buses the opportunity to return to schedule. Thus, service unreliability continues to deteriorate and is worse in the outbound direction, with high variability of service attributes (running times, headways, expected wait times).

The results of the May 2005 Silver Line reliability assessment show further deterioration of service reliability due to the introduction of the new Automatic Fare Collection (AFC) system. Although scheduled running times were increased between September-October 2004 and May 2005, variability in running times and headways increased for this period, creating greater problems in service reliability and increases in travel times and expected wait times for passengers.

The main cause of service reliability problems are initial deviations from the terminal. Buses are beginning their trip with poor headway adherence, which tends to propagate and deteriorate service reliability as the buses traverse the route. Deviations at Dudley Square are observed to be the result of poor operator behavior and terminal supervision.

Poor service reliability in the inbound direction is inferred to be caused by passenger loads and operator behavior that deteriorates the headway of consecutive buses. In the outbound direction, service reliability problems are inferred to be triggered by externalities (traffic volumes, illegal vehicle movements, etc.) and passenger loads.

In terms of service operations, buses tend to be irregularly spaced (unbalanced headways) and experience highly variable running times. Passengers seem to experience unpredictable wait times and total travel times, and overcrowding, especially in the peak hours where reliability deteriorates. For a Bus Rapid Transit (BRT) route, characterized with features such as a semi-exclusive bus lane, high-capacity low-floor vehicles, and Intelligent Transportation Systems (ITS) technologies, service reliability is below the expected quality, and improvements such as better terminal headway controls and corrective strategies are needed.



## **5. CONCLUSIONS**

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This chapter summarizes the main elements of the proposed framework for analyzing service reliability, the major findings from the application of the framework to the Massachusetts Bay Transportation Authority's (MBTA) Silver Line Washington Street route, and future extensions and research.

Section 5.1 briefly describes blocks of the proposed framework and key elements to assess bus service reliability. The results of the case study on the Silver Line Washington Route are presented in Section 5.2, along with a summary of recommendations to the MBTA based on the major findings of this case study. Finally, Section 5.3 suggests extensions to the proposed framework and areas of future research.

### **5.1 FRAMEWORK SUMMARY**

The proposed practical framework to assess service reliability explores the uses of Automated Data Collection (ADC) systems characterize service reliability and evaluate the causes of unreliability that may exist. It serves as a guide for transit agencies to begin to analyze the large sets of data available from these systems to evaluate performance and implement efficient strategies to improve service planning, operations monitoring and management procedures.

A detailed review of the most significant causes of service reliability summarizes how they impact service and outlines the complexities and interrelationship between different causes. Also reviewed are the potential preventive and corrective strategies, and the links between the causes of service unreliability and best strategy according to the source of problems.

The proposed framework consists of three blocks: 1) characterizing service reliability through service measures and performance reports; 2) identifying the causes of reliability problems, starting with terminal deviations; and 3) selecting strategies which target critical causes of unreliability to improve service.

Characterization of service reliability involves examining five key elements an agency should analyze: a) available data inputs from ADC systems; b) output calculations from data analysis; c) appropriate service measures; d) threshold values, and e) performance reports.

Identification of causes includes two sequential processes to infer the causes of service reliability problems. The first is focused on deviations at terminals because they serve as control points to ensure on-time performance or headway adherence. Terminal deviations also have a larger impact down the route as deviations tend to propagate. The second process examines deviations at other points on the route, following a set of

steps to infer the causes of unreliability: initial deviations at terminal, passenger loads, poor schedule planning, operator behavior and externalities.

Application of strategies is based on the findings of the previous analysis, and includes an assessment of the best strategies to prevent reliability problems and reduce the impacts on service performance. This process also involves evaluating the practicality of implementing such strategies, based on the cost of implementation and effectiveness to improve service reliability on the route.

## **5.2 MAJOR FINDINGS**

The application of the proposed framework to analyze service reliability on the Silver Line Washington Street in Boston, MA served as the case study for this thesis.

The characterizations of service reliability reveals mean running times and mean headways have a tendency to be close to schedule. However, the standard deviations and coefficient of variations of the distributions show that variability of service attributes is high. This indicates that bus arrivals and passenger wait times are unpredictable and travel times are irregular. As a Bus Rapid Transit route, headway adherence is poor on this route, with a tendency of buses to bunch together and leave gaps in service.

The case study also included an analysis of service reliability with recent data (May 2005) to evaluate the impacts of the implementation of a new Automatic Fare Collection (AFC) system. The results of this analysis showed that mean running times and headway variability increased from the previous assessment. This indicates that service reliability has deteriorated, with increased travel times and expected passengers wait times.

The main cause of service unreliability on this route was identified to be deviations at the terminals. Trips are departing the terminal with poor headway adherence (and therefore, poor on-time performance), which propagates and creates further reliability problems down the route. At Dudley Square, a major bus transfer point with a dedicated loading area for Silver Line buses, a combination of poor terminal supervision and operator behavior are inferred to be cause of most of the deviated trips. Recovery times, externalities and passenger loads at this terminal are inferred to cause only minor problems. However, the analysis does not account the effects that scheduled times might have on operator behavior. At other points in the route, operator behavior and passenger loads are observed to affect reliability in the inbound direction.

As for strategies to improve service reliability, emphasis is given to better supervision at the terminal. Terminal supervision is needed to enforce good operator behavior and balance departure headways to prevent poor headway adherence from propagating down the route. Supervisors at terminals are also able to apply control strategies, such as holding or instructing buses to depart regardless of schedule times, to maintain headways, and able to coordinate passenger loads to avoid overcrowding of buses.

Along the route, preventive strategies such as operator training and corrective strategies are highlighted as potential strategies to reduce the variability in running times and balance headways to reduce the occurrence of bunches and gaps in service. Traffic signal priority would also improve service reliability by reducing variability, especially in the mixed-traffic portion of the route.

### **5.3 FUTURE RESEARCH**

The case study application of the proposed framework for reliability assessment revealed a number of areas for future extensions to the framework and bus service reliability research.

Application of the framework on another route. The Silver Line Washington Street route provided limited time-at-location and operator assignment data. The lack of passenger loads (boardings and alightings), more detailed event records, such as doors open and doors close, and speed profiles constrained the analysis on inferring the causes of unreliability on this route. A case study of the proposed framework on a route which has more detailed data available would prove useful and necessary to evaluate the practical application of this process.

Follow-up reliability assessment of the Silver Line. The first block of the analysis was applied to the Silver Line in May 2005 to characterize reliability after the implementation of a new Automatic Fare Collection (AFC) system. The second part of the analysis, the identification of causes, can be applied to this period to compare the results of inferred causes of unreliability of this route and further evaluate the impacts of the AFC system on service reliability.

Development of models. Empirical and simulation models ought to be developed to further explore the interrelationship between causes of service unreliability. The complexities of the most significant causes of service unreliability were not fully analyzed. The proposed framework explored the most basic interrelationships to provide a guide for transit providers to begin understanding the dynamics of service reliability on a route. Regression models would provide a more detailed analysis quantifying the impacts of each cause in a more simultaneous process, rather than the sequential steps described. Simulations models could also be developed to better integrate variations by time of day, operator behavior, traffic conditions and weather, into the analysis of service reliability.



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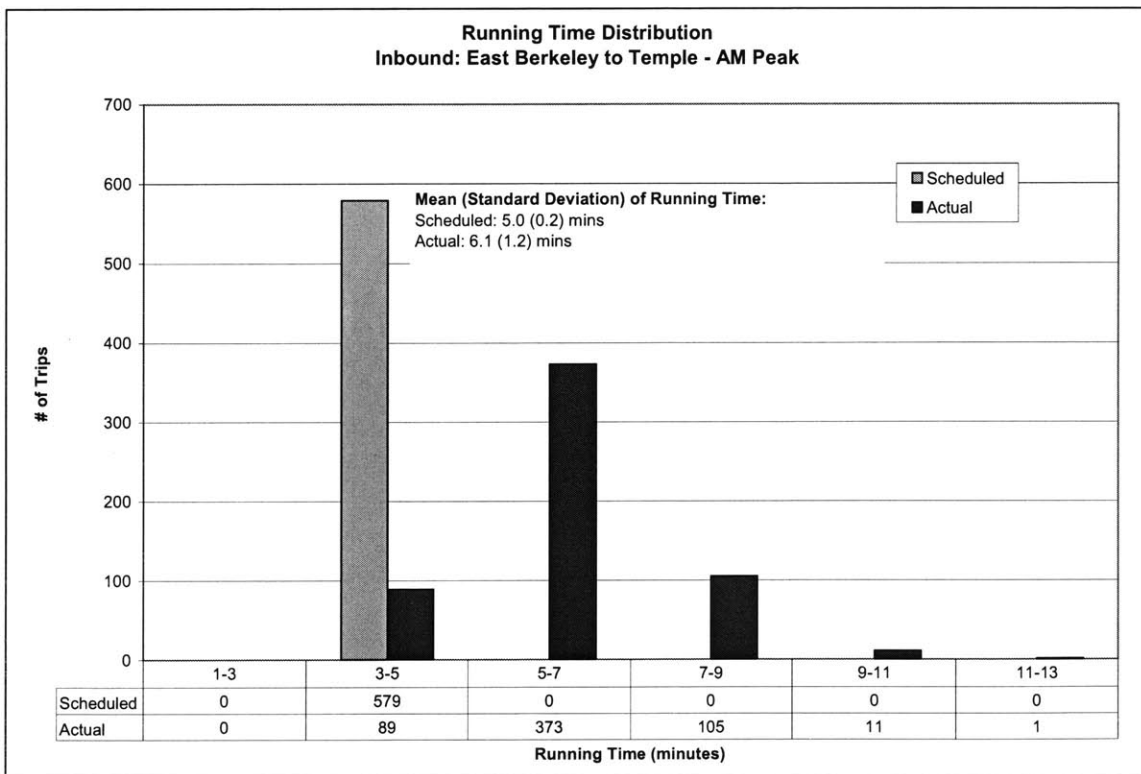
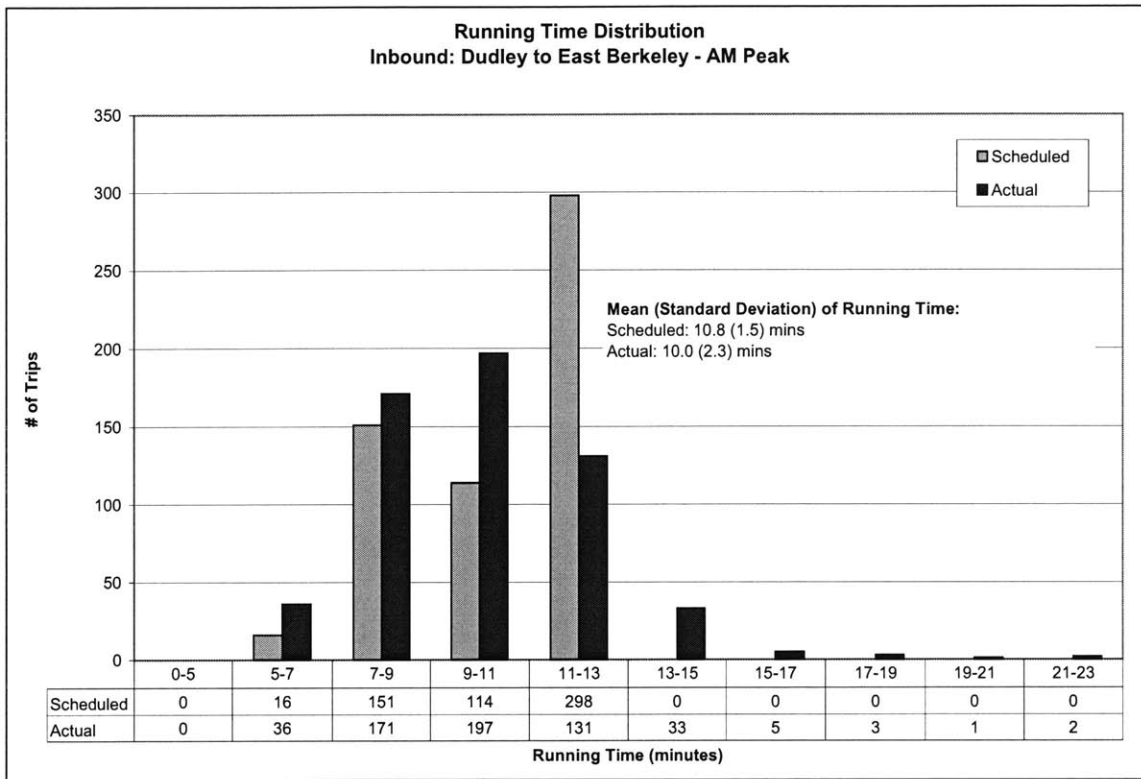
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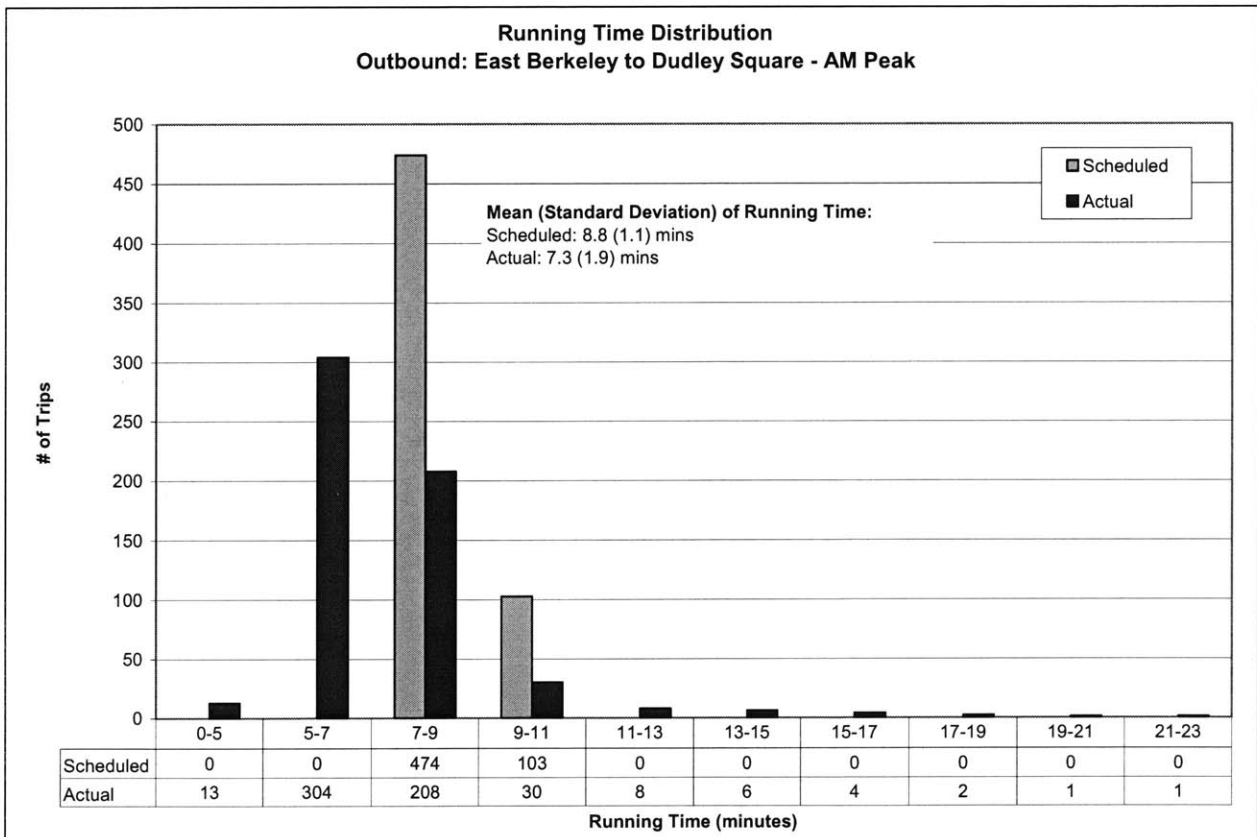
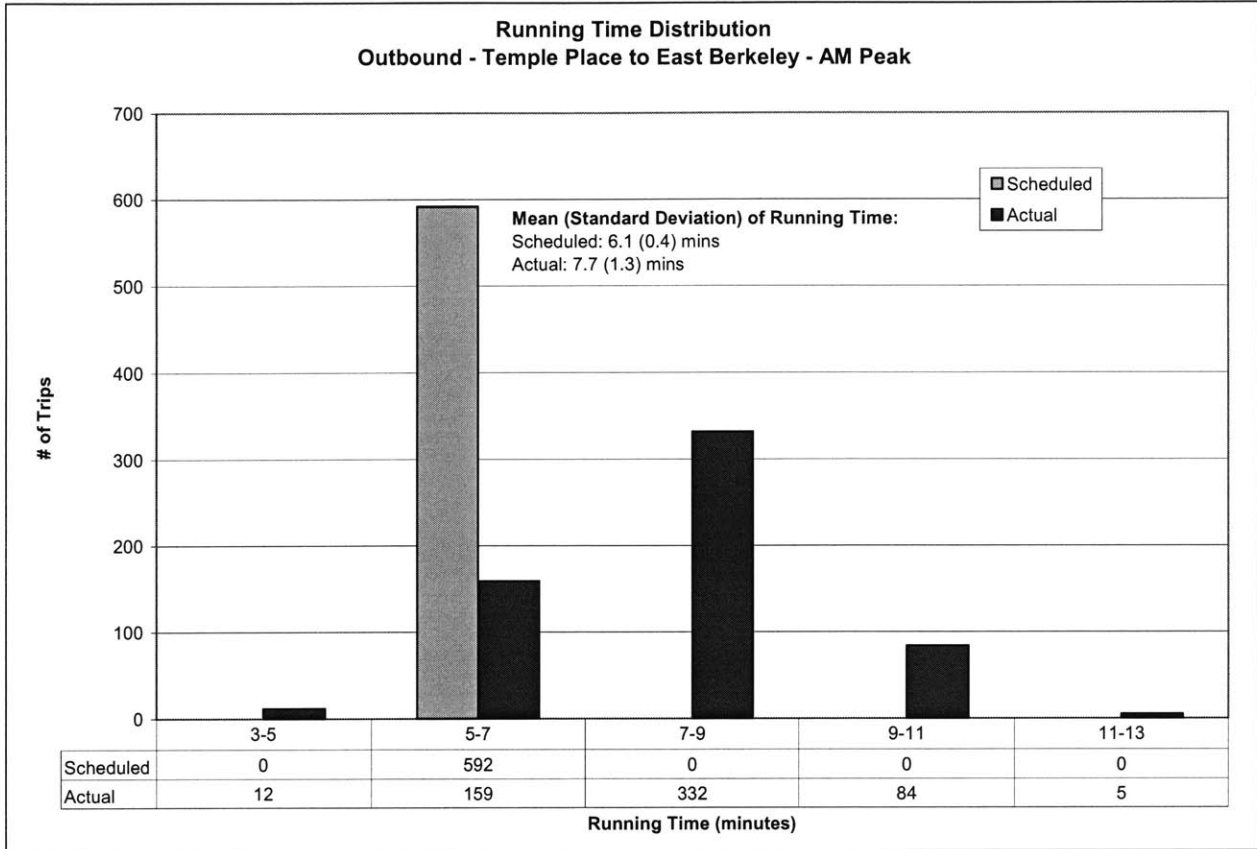
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# APPENDIX A: RUNNING TIME DISTRIBUTIONS







# APPENDIX B: TERMINAL ANALYSIS

Headway Ratio at East Berkeley	Headway Ratio at Dudley Square Terminal						Total #
	> 2	1.6 to 2	1.6 to 1.2	0.8 to 1.2	0.4 to 0.8	< 0.4	
< 0.4	0	2	15	90	135	65	307
0.4 to 0.8	1	7	27	218	125	20	398
0.8 to 1.2	2	8	54	567	55	4	690
1.2 to 1.6	4	25	93	242	15	4	383
1.6 to 2	6	26	51	71	4	0	158
> 2	26	21	20	28	1	1	97
<b>Total # of Trips</b>	<b>39</b>	<b>89</b>	<b>260</b>	<b>1216</b>	<b>335</b>	<b>94</b>	<b>2033</b>

Headway Ratio at Temple Place	Headway Ratio at Dudley Square Terminal						Total #
	> 2	1.6 to 2	1.6 to 1.2	0.8 to 1.2	0.4 to 0.8	< 0.4	
< 0.4	1	4	18	121	136	58	338
0.4 to 0.8	1	8	32	248	98	24	411
0.8 to 1.2	3	13	49	455	63	8	591
1.2 to 1.6	8	17	76	211	21	0	333
1.6 to 2	5	21	52	76	3	1	158
> 2	20	22	24	66	1	0	133
<b>Total # of Trips</b>	<b>38</b>	<b>85</b>	<b>251</b>	<b>1177</b>	<b>322</b>	<b>91</b>	<b>1964</b>

