Assessing the Impact of Real-Time Information on Transit Passenger Behavior

by

Mark David Hickman

S.B.C.E., Massachusetts Institute of Technology (1988)
M.S.T., Massachusetts Institute of Technology (1988)

Submitted to the Department of Civil and Environmental Engineering
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Transportation Systems

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

October 1993 [FEB 1994]

Author ....
Department of Civil and Environmental Engineering
October 6, 1993

Certified by ....
Nigel H. M. Wilson
Professor of Civil and Environmental Engineering
Thesis Supervisor

Certified by ....
David H. Bernstein
Assistant Professor of Civil and Environmental Engineering
Thesis Supervisor

Accepted by ....
Joseph Sussman
Chairman, Departmental Committee on Graduate Studies

Assessing the Impact of Real-Time Information on Transit Passenger Behavior

by

Mark David Hickman

Submitted to the Department of Civil and Environmental Engineering
on October 6, 1993, in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy in Transportation Systems

Abstract

This thesis develops a modeling framework to examine the impacts of real-time information on transit passenger behavior, particularly the passenger's choice of path and departure time. By examining how passengers may alter their travel decisions in response to various types of real-time information, the quantitative impacts of passenger information systems can be evaluated.

As a foundation for the research, an analytical framework for both transit service and passenger path and departure time choice is presented. A transit service model is developed that explicitly incorporates several elements which most influence the passenger's trip travel time reliability: stochastic departure and running times, connections between routes, and time-dependence. These elements are critical in examining travel times in a transit network where real-time information may be most useful. Based on these transit service characteristics, two path choice models are developed: a *static* model, which assumes that the passenger determines a vehicle boarding strategy upon his/her arrival at the origin terminal; and a *dynamic* model, which assumes that the passenger decides his/her boarding strategy as vehicles arrive at the terminal. The dynamic model is also shown to be useful in describing adaptive path choice decisions made during the passenger's trip. In addition, two passenger departure time choice models are considered: one in which passengers arrive at the origin stop entirely at random, and a second in which arrivals at the origin stop are coordinated with scheduled vehicle departures.

The passenger's path choice decision may also be affected by the availability of real-time information and the passenger's experience with the transit service. A set of scenarios is developed to examine several dimensions of real-time passenger information systems, including: the type of information given; the time when the passenger receives the information; and, the accuracy of the information in predicting network conditions. Variations in passengers' level of experience with the transit service and with the real-time information are also included in the modeling framework.

These scenarios are examined using a corridor-level network simulation that is based on the transit service model and incorporates the path and departure time choice models. A case study from the Massachusetts Bay Transportation Authority is used to assess the anticipated passenger response to different levels of real-time information, using the measures of origin-to-destination travel times and path choices. The results of the simulation model suggest that the potential reduction of travel times resulting from real-time information are very modest, on the order of 2% to 3% of the total origin-to-destination travel time. Yet, this amount accounts for 70% to 95% of the possible travel time savings in the selected networks. The results also suggest more significant changes in path choices from this real-time information. The overall magnitude of travel time savings, however, raises significant questions about the benefits of real-time passenger information systems to the transit passenger.

Thesis Supervisor: Nigel H. M. Wilson
Title: Professor of Civil and Environmental Engineering

Thesis Supervisor: David H. Bernstein
Title: Assistant Professor of Civil and Environmental Engineering

Acknowledgments

This work is much richer because of the many people who have contributed to my life and my research over these many years in Boston. The words below cannot begin to describe the influence they have all had in my life in Boston and at MIT. I owe them all my deepest gratitude.

As an advisor, I could ask for none more gifted than Nigel Wilson. He has been a faithful and wise advisor during my many years at MIT. He was a guide when I felt confused in a maze of details, always and consistently keeping perspective on the bigger picture. I am also thankful that he had me write things down regularly. It has made writing this thesis much easier than it could have been.

My other supervisor, David Bernstein, has provided me with the wisdom and insight of a "big brother." He is a man who knows how to ask questions; I only wish I could learn more of that art from him. Also, his sense of humor and ability to laugh at himself has helped me not to take myself so seriously.

I would also like to express my appreciation to the other members of my thesis committee for their insight and fresh ideas which contributed significantly to this thesis: Haris Koutsopoulos, a trusted and sympathetic advisor over these many years of graduate school, and Arnold Barnett.

I am thankful for the financial support of the University Transportation Centers (UTC) program and for the encouragement of my UTC project supervisor, Tom Humphrey. Various people at the MBTA, including Maureen Trainor, Rick Macchi, David Nelson, and Alan Castaline helped to develop the case studies and encouraged my interest in advanced technologies in public transit. The financial support of the Mitsui Career Development Chair is also gratefully acknowledged.

The encouragement of many friends, all of whom I take for granted almost all of the time, has been a blessing. Ted Botimer, Oh Kyoung Kwon, and Rabi Mishalani have been full of support and encouragement as we traveled the road together. Each has shared this thesis with me in small and large ways. When there seemed to be no one else, I could always count on Brent Chambers and John Evans for a sympathetic ear or at least a hot cup of coffee at the coffeehouse. Also, two kind roommates, David Williamson and Fred Hoth, have made these last few years in Cambridge much more comfortable. My family has also supported and encouraged me; I wish I had been closer to them during these years. Finally, Ken Larsen has helped me to grow in many new ways over the past year and a half. I am indebted to him for helping me find a way through some really dark places.

My wife, Amy (von Stamwitz) Hickman, has stood with me in my work for the past three years. She has patiently endured my long work hours, and encouraged me when things looked the worst. She has helped me to realize the value of enduring love and in following one's heart.

Finally, I am most grateful to God for helping me to find out who Jesus is. He has been a steady and strong Friend in the midst of a world that seems to be changing continually.

Contents

1 Introduction **14**

1.1 Travel Time Reliability 15

1.2 Real-Time Passenger Information 17

1.3 Research Question 19

1.4 Thesis Organization 21

2 Literature Review **23**

2.1 Glossary of Terms 24

2.2 Stochastic Transit Route and Network Models 25

2.2.1 Analytic Models 26

2.2.2 Simulation Models 27

2.3 Transit Path Choice Models 29

2.3.1 Transit Path Assignment 29

2.3.2 Common Route Segments (or Paths) 36

2.3.3 Shortest Paths in Stochastic Time-Dependent Networks 40

2.4 Transit Departure Time Choice Models 43

2.5 Information and Traveler Response Modeling 46

2.6 Real-Time Passenger Information in Public Transit 48

3 Transit Service Model **51**

3.1 Full Model Framework 51

3.2 Introduction to the Transit Service Model 53

3.3 Modeling Assumptions 55

3.3.1 Exogenous Variation in Travel Times 55

3.3.2 Independence of Vehicle Departure and Running Times from Vehicle Interactions . . . 57
3.4 The Shuttle Model . . . 58
3.4.1 Model Parameters . . . 59
3.4.2 Model Development . . . 60
3.5 The Shuttle Network . . . 64
3.5.1 Modeling Assumptions . . . 65
3.5.2 Model Development . . . 66
3.6 Other Networks . . . 74
3.6.1 Rapid Rail and Bus Travel Time Distributions . . . 76
3.6.2 Model Development (Outbound) . . . 78

4 Path Choice Modeling **80**
4.1 Passenger Travel Time Objectives . . . 80
4.2 Problem Definition . . . 82
4.3 Expected Passenger Travel Time . . . 85
4.4 The Static Path Choice Model . . . 89
4.4.1 Identification of the Choice Set . . . 90
4.4.2 Path Choice Probabilities . . . 94
4.5 The Dynamic Path Choice Model . . . 95
4.5.1 Identification of the Choice Set . . . 96
4.5.2 The Truly Optimal Dynamic Choice Problem . . . 103
4.6 Adaptive Path Choice Modeling . . . 107
4.7 Departure Time Choice Models . . . 109
4.7.1 Random Departure Times . . . 110
4.7.2 Arrivals Coordinated with Vehicle Schedule . . . 110
4.8 Analytic Difficulties . . . 112
4.8.1 Probability Distribution Form . . . 112
4.8.2 Dynamic Model Formulation . . . 113

5 Development Using Simulation **114**
5.1 Simulation Motivation and Objectives . . . 115
5.2 Real-Time Information . . . 117

5.2.1 Type of Information 119
5.2.2 Place of Information 121
5.2.3 Information Accuracy 123
5.2.4 Information Scenarios 126
5.3 Passenger Experience 127
5.4 Simulation Scenarios 130
5.4.1 Shuttle Operating Conditions 131
5.4.2 Statistical Design 131
5.4.3 Passenger Objectives 132
5.5 Implementing the Simulation 134
5.5.1 Distributions and Modeling of Vehicle Movements 134
5.5.2 Passenger Decision Models 139
5.5.3 Information Modeling 141

6 Results from the Shuttle Network 144

6.1 Simulation Parameters 144
6.1.1 Input Parameters 145
6.1.2 Empirical Departure Time Distributions 148
6.1.3 Information Parameters 151
6.1.4 Simulation Scenarios 152
6.1.5 Modeling Issues 154
6.2 Simulation Results 155
6.2.1 Path Choice Models 155
6.2.2 Information Scenarios 162
6.2.3 Alternate Passenger Objectives 171
6.3 Conclusions 176

7 MBTA Case Study 179

7.1 MBTA Case Study Characteristics 179
7.1.1 MBTA Service Schedules 180
7.1.2 MBTA Travel Time Data 181
7.2 Case Study Scenarios 184
7.2.1 Scenario Description 184

7.2.2 Modeling Issues 186
7.3 Morning Peak Inbound Results 190
7.3.1 Path Choice Models 191
7.3.2 Information Scenarios 193
7.4 Evening Peak Outbound Results 198
7.5 Conclusions 203

8 Conclusions and Future Research 206
8.1 Conclusions 206
8.1.1 Transit Service Modeling 208
8.1.2 Path Choice Methodology 209
8.1.3 Real-Time Information 211
8.1.4 Simulation Results 213
8.1.5 Research Contributions 217
8.2 Future Research 218
8.2.1 Model Extensions 219
8.2.2 Modeling of Pre-Trip Information 221
8.2.3 Behavioral Validation 225

Bibliography 227

List of Figures

3-1 Model Framework 52
3-2 A Single Shuttle 64
3-3 The Shuttle Network 64
3-4 The Arlington-Cambridge-Boston Corridor 74

6-1 The Shuttle Network 145
6-2 Departure Distribution for Route 1, from Time = 75.0 149
6-3 Departure Distribution for Route 1, from Time = 105.0 149
6-4 Departure Distribution for Route 1, from Time = 135.0 150
6-5 Departure Distribution for Route 1, from Time = 165.0 150

7-1 The Arlington-Cambridge-Boston Corridor 180

8-1 Model Framework 207

List of Tables

2.1 Some North American Real-Time Passenger Information Systems . . . 49

3.1 Routes for the Shuttle Network 66
3.2 Routes for Case Study Network - Inbound 75
3.3 Routes for Case Study Network - Outbound 75
3.4 Origin-Destination Paths for Case Study - Inbound 76
3.5 Origin-Destination Paths for Case Study - Outbound 76

5.1 Accuracy of Departure Time Projections by Time Until Departure . . . 125

6.1 Running Time Parameters 146
6.2 Parameters for Network 1 146
6.3 Parameters for Network 2 147
6.4 Parameters for Network 3 147
6.5 Expected Travel Times from Network 1 156
6.6 Expected Path Assignments from Network 1 157
6.7 Expected Travel Times from Network 2 158
6.8 Expected Path Assignments from Network 2 159
6.9 Expected Travel Times from Network 3 160
6.10 Expected Path Assignments from Network 3 160
6.11 Expected Travel Times with Information - Network 1 163
6.12 Expected Travel Times by Passenger Type - Network 1 163
6.13 Mean Daily Variance in Travel Times - Network 1 164
6.14 Probability of Completing a Trip in 37 Minutes - Network 1 164
6.15 Expected Path Assignments with Information - Network 1 165
6.16 Expected Travel Times with Information - Network 2 166

6.17 Expected Travel Times by Passenger Type - Network 2 167
6.18 Mean Daily Variance in Travel Times - Network 2 167
6.19 Probability of Completing a Trip in 37 Minutes - Network 2 167
6.20 Expected Path Assignments with Information - Network 2 168
6.21 Expected Travel Times with Information - Network 3 169
6.22 Mean Daily Variance in Travel Times - Network 3 170
6.23 Probability of Completing a Trip in 37 Minutes - Network 3 170
6.24 Expected Path Assignments with Information - Network 3 171
6.25 Probability of Completing a Trip in 37 Minutes - No Information 172
6.26 Expected Path Assignments with Probability Objective - No Information 172
6.27 Probability of Completing a Trip in 37 Minutes 173
6.28 Probability of Completing a Trip in 37 Minutes by Passenger Type . . 174
6.29 Mean Daily Variance in Travel Times - Probability Objective 174
6.30 Expected Travel Times with Probability Objective 174
6.31 Expected Path Assignments with Probability Objective 175

7.1 Morning Peak Operating Characteristics 180
7.2 Evening Peak Operating Characteristics 181
7.3 Red Line AM Inbound Travel Time Parameters 182
7.4 Red Line PM Outbound Travel Time Parameters 182
7.5 Bus Route AM Inbound Travel Time Parameters 183
7.6 Bus Route PM Outbound Travel Time Parameters 183
7.7 Accuracy of Departure Time Projections 189
7.8 Expected Travel Times with No Information - AM Inbound 191
7.9 Probability of a Trip Completed in 38 Minutes with No Information - AM Inbound 191
7.10 Expected Path Assignments with No Information - AM Inbound 192
7.11 Expected Travel Times - AM Inbound 194
7.12 Expected Travel Times by Passenger Type - AM Inbound 194
7.13 Mean Daily Travel Time Variance - AM Inbound 195
7.14 Probability of a Trip Completed in 38 Minutes - AM Inbound 195
7.15 Expected Path Assignments - AM Inbound 196

7.16 Expected Path Assignments by Passenger Type - AM Inbound 197
7.17 Expected Travel Times - PM Outbound 199
7.18 Mean Daily Travel Time Variance - PM Outbound 201
7.19 Probability of a Trip Completed in 37 Minutes - PM Outbound 201
7.20 Expected Path Assignments - PM Outbound 202

Chapter 1

Introduction

In recent years, there has been significant growth in the application of new information technologies in the field of transportation. Automated systems, information systems, vehicle control systems, and other technologies have advanced quickly in the past ten to fifteen years. Transportation researchers are mounting more detailed studies of these technologies, investigating both the theory and application of these technologies for all transportation modes, and both public and private interests have invested in developing these technologies.

In public transportation, specifically in urban public transportation, several major implementations of these types of technologies are now being planned. The last several years has seen a growing investigation of intelligent vehicle/highway systems (IVHS), covering private vehicle traffic management, driver information, and vehicle control systems. Urban mass transit also has a major research program in advanced public transportation systems (APTS), emphasizing operations control, customer information, and vehicle control systems.

The research components of IVHS and APTS have emphasized project implementation and, to a lesser extent, evaluation and modeling of traffic patterns and traveler behavior in response to these new information technologies. Particularly with respect to urban mass transit, there has been remarkably little research on evaluating the effects of real-time information on operations control and passenger information systems. The focus of the APTS effort has, instead, been on implementation, with less emphasis on research to assess these new technologies. This is in part because existing urban transportation planning methods are often inappropriate to assess these new information technologies. A fresh look at methods to evaluate transportation options with these new technologies is necessary.

This thesis examines planning models which may be used to assess the value, to the transit passenger, of real-time passenger information systems. These information systems have been proposed to reduce passenger uncertainty about travel conditions and improve passenger decision-making for transit trips. In particular, it seems likely that providing information about current transit system characteristics and projected vehicle travel times may reduce uncertainty and improve decisions about trip timing. The research presented in this thesis examines the latter hypothesis, i.e., that real-time information may improve passenger decision-making regarding their trip timing. To this end, it is necessary to examine the underlying operating environment in public transit that favors real-time information systems, including the factors of service reliability and travel time uncertainty. The following sections describe the context of travel time reliability and the relevance of real-time passenger information systems in transit. The third section poses the research question and a specific research plan to evaluate the role of real-time information in transit passenger decision-making. Finally, the last section outlines the organization of the remainder of the dissertation.

1.1 Travel Time Reliability

Anyone who has ever waited for a transit bus or train can attest to the fact that transit service can be unreliable. A trip which takes twenty minutes one day may take thirty minutes another day, because there are delays which result in longer waits or travel times for passengers. Mass transit operates in an inherently stochastic environment: travel times can depend on things such as traffic conditions, passenger loads, equipment and labor availability, and other external factors (e.g., weather). Because of this variation, vehicles may be delayed over the course of a route. This variability in travel times can make the transit operating environment much more uncertain for both transit operators and passengers.

In this context, transit service reliability may be defined as providing a transit service that is consistent and repeatable in its characteristics. One factor which is central to this concept of service reliability is the variation in the amount of time a vehicle or user spends in getting from one point to another in the network. The time spent waiting for a vehicle and in transit on that vehicle (hereafter referred to as "running" time) are both subject to stochastic variation. Travel time reliability, then, may be defined as a measure of the consistency and repeatability of the travel time between two points in the transit network.

This characterization of reliability is important to both the transit system operator and the transit passenger. However, the operator and the user quantify this travel time reliability in different ways: the operator tends to regard reliability in terms of vehicle performance, while the user regards reliability in terms of the trip itself and not in terms of specific vehicles. The operator is typically more concerned with measures of vehicle *schedule adherence*, while the passenger is more concerned with measures of variation in origin-to-destination (o-d) travel times. For transit passengers, these o-d travel times may not be linked with a single transit vehicle, or even with a single transit route. Instead, the passenger may be more concerned with the travel time characteristics on each route segment he/she may use, including multiple route segments if a transfer is necessary during the trip.

Moreover, the factor of route transfers may significantly affect travel time reliability for transit passengers. In any transit system, not all origins and destinations will be linked by direct service. Instead, at some point in many passenger trips, transfers may be required between routes, implying a change of vehicles. These transfer connections bring about even more uncertainty for passengers. Are the transfers coordinated so as to minimize the adverse impacts for passengers while waiting for a vehicle on the transfer route? Specifically, if a passenger misses a connection to another route due to the inherent uncertainty in trip timing, there is an additional cost associated with a longer wait or alternative travel arrangements.

This level of reliability of service may ultimately influence the decisions made by the passenger. Depending on when the passenger arrives at the origin stop, different paths may be most appealing, from the perspective of origin-to-destination travel times. If the passenger has a high probability of making a transfer connection, a certain transfer path may seem most attractive. At another time, though, the same path may not be preferred because of more adverse timing of the transfer. The desirability of different travel options depends on both the variability of travel times in the transit network as well as the time at which the trip is taken. Thus, the implicit or explicit schedules of transit service and the level of variability of travel times around those schedules may affect what paths the passenger may choose and also what his/her resulting travel time in the network will be.

More specifically, in the midst of a transit service environment which includes vehicle schedules and an associated reliability of travel times, passengers must make decisions about their trips. Decisions that seem to be most critical in day-to-day trip planning include the decision about what time to begin the trip, hereafter called the *departure time choice*, and the decision about what routes (or combination of routes) to take to reach the destination, hereafter called the *path choice*. The fundamental premise for this thesis is that the level of variability and time-dependence in transit network travel times will have an impact on how passengers make these path and departure time decisions.

For this analysis, the assumption is made that there is an implicit level of vehicle travel time reliability in the network. This is obviously a function of factors under direct control of the transit operator, such as vehicle and crew availability and real-time control strategies, as well as exogenous factors such as traffic congestion, weather, accidents, etc. Regardless of these endogenous and exogenous factors, this research assumes that the transit operating conditions are given for the planning horizon in question.

1.2 Real-Time Passenger Information

Assuming that there is some intrinsic level of uncertainty in transit travel times, providing additional information about transit services to passengers can reduce passenger anxiety and improve trip decisions. This research will examine passenger information systems which provide information to passengers in *real time*; i.e., in light of the current state of the system. Included in this characterization is any information, *in addition to existing route and schedule information*, provided to travelers regarding current or projected system conditions, such as vehicle locations, expected departure times and expected running times.

Much of the focus of transit passenger information systems to date has focused on more elementary, or static, forms of information for passenger trip planning, such as basic routes and schedules. Such information is indeed critical to passengers in making fundamental decisions on possible travel modes, paths, and departure times. Much less effort, however, has been focused on the value of real-time information for these decisions. Current vehicle location technologies, often described as automatic vehicle identification (AVI) or location (AVL) systems, allow accurate tracking of vehicle movements in the transit network. As the cost-efficiency of AVL and AVI technologies improves, so does the ability to provide information on vehicle movements to passengers in real time. Real-time information systems may have benefit, then, in reducing the level of uncertainty in vehicle movements and travel times in the network. Passenger decision-making may also be improved by this reduction in uncertainty.

More traditional passenger information systems provide passengers with route and schedule information, and perhaps provide some prescriptive information regarding sensible routes serving the passengers' origin and destination. This type of information allows the passenger to determine an itinerary, including a transit route (or routes), a stop or station near his/her origin and destination, and the scheduled timing of the trip. Passengers using this information can make reasonable decisions about what routes to use and how to schedule their trip among other activities they have planned on a given day.

When transit travel time reliability is low, however, the value of static information declines. When transit services adhere very closely to scheduled departure and travel times, static information is sufficient, and real-time information provides little additional value to the passenger. However, if there is more significant variation in travel times on transit routes, passengers may be uncertain of when (or even if) transit vehicles will arrive at a stop or station, how long the trip may last upon boarding the vehicle, and whether they can make certain connections between routes. In this context, passengers will have much more difficulty in planning their trips.

The basic premise of this thesis is that passengers' decisions about which routes to use and how to schedule their trips will depend on the level of information available to them. Particularly, the hypothesis of this thesis is that passengers' decisions about potential routes and travel times can be facilitated by accurate real-time information. Where there is the potential for significant variation in vehicle travel times, real-time information should allow passengers to plan their trips most effectively. In situations where passengers may choose among different routes serving their origin and destination, having the most current information on travel conditions on each route can assist in making better route decisions for a given travel objective. One may also restate this conjecture, suggesting that the value of real-time information to the passenger seems intuitively to be greatest when the passenger has a number of route and trip timing options for the chosen origin-destination pair.

Unfortunately, there has been little empirical or analytical evidence in support of the value of real-time information systems in public transit. The APTS program is currently developing a number of operational tests, but these are largely still in the conceptual or early planning stages. Furthermore, very little research has focused on assessing the value of these information systems before such systems are implemented. There is clearly a need for a more critical assessment of these information technologies.

1.3 Research Question

The above discussion has established that the transit operating environment is inherently stochastic. Specifically, in daily operations the travel times of vehicles and passengers through the transit network may be subject to significant variability. In this context, there are two general premises which guide this research. First, it is presumed that travel time uncertainty can have an impact on passenger decision-making, with respect to both path and departure time choices. Second, the level of real-time information provided to the passenger will affect his/her assessment of travel times and, as a result, will impact these path and departure time decisions.

The fundamental issue to be addressed in this research is as follows:

Research Question: Given the stochastic nature of travel times in public transit, how might real-time information on vehicle movements affect passenger decisions on path and departure time?

To this end, this thesis has two major objectives. First, it is necessary to develop path and departure time choice models which are sensitive to the uncertainty of timing in transit vehicle movements as well as to levels of real-time information provided to the passenger. This involves models of path and departure time choice which account for both the stochastic nature of path travel times as well as the time-dependence of these choices. The development must also provide a framework by which passengers can adapt these choices to new information on actual or projected conditions in the transit network. The objectives of the first major thrust of the research, then, are the following:

1. Investigate and develop an analytic model of transit vehicle movements on routes which incorporates time-dependence, based on the vehicle schedules, and uncertainty of travel times, corresponding to stochastic departure times and running times.

2. Investigate and develop an analytic model of passenger path choice which is based on intuition about path choice behavior in this same transit service environment. The path choice model, then, should make use of the above transit performance model.

3. Examine existing models of passenger departure time choice which may be consistent with these transit service and path choice models.

The second objective of this research is to use the resulting path and departure time choice models to examine the impacts of different types of real-time information. It is suspected that the impact of this information will depend upon the following factors: the type of information given to the passenger, when (or where) the passenger receives the information, and the level of accuracy of the information. In this context, then, the research seeks to measure the impact of this information on passenger path and departure time decisions. The criteria used to evaluate these impacts includes the resulting passenger decisions of different o-d paths and potential reductions in o-d travel times and their variability. Thus, this second research effort has the following objectives:

1. Identify a set of likely scenarios for implementation of real-time passenger information systems. These should include variation among:

- Types of information (current and/or projected travel conditions);
- Timing of information during the passenger trip (before or during the trip); and,
- Accuracy (or precision) of the information technology.

2. Investigate the effect of these different levels of information on passenger behavior. These effects may be quantified using the measures of o-d travel times and path choices.

3. Extend this type of analysis to a case study to demonstrate its potential in a real-world setting.

1.4 Thesis Organization

The thesis is organized around these two main objectives. The major emphasis of the next three chapters (Chapters 2, 3, and 4) is to develop and describe the necessary path and departure time choice models. The following three chapters (Chapters 5, 6, and 7) discuss a detailed simulation model used to assess the various aspects and impacts of real-time information. The organization of these chapters is described in the following paragraphs.

The next chapter (Chapter 2) reviews the literature in a number of relevant areas, including transit travel time reliability, transit service models, and transit path and departure time choice modeling. It also examines the state of the art of real-time information systems, particularly in their development and implementation in urban mass transit.

The third chapter develops a simple transit performance model for shuttle routes. The resultant analytical model describes the distribution of travel times from an origin to a destination in a shuttle network, based on vehicle movements which are both stochastic and time-dependent.

The fourth chapter develops path and departure time choice models for the shuttle network model presented in Chapter 3. Two different path choice models are presented. The first is a *static* model in which the passenger decides a boarding strategy upon arrival at a particular stop in the network. The other model is *dy-*

namic and describes the case in which the passenger decides a boarding strategy as vehicles arrive at the particular stop. Two different passenger departure time choice (i.e., choice of "arrival time" at a particular stop) models are also reviewed within the context of these two path choice models. The integration of the path and departure time choice models is also discussed.

Because of several analytic difficulties resulting from the generality of the shuttle network distributions and the path choice models, it is difficult to draw specific results from these models without a clearer definition of transit service characteristics. To draw more specific conclusions about the path choice models and about the impacts of real-time information, a simulation model is developed and analyzed in Chapters 5 and 6, respectively. A set of simulation scenarios is described which takes advantage of different possible sources of real-time information as well as variation in a passenger's level of experience with the system. The analysis examines the effect of the type, timing, and accuracy of the real-time information on passenger travel times and the resultant route assignment.

Chapter 7 extends the simple shuttle network to a case study using a radial corridor at the Massachusetts Bay Transportation Authority (MBTA). Using vehicle performance data from the MBTA, the effects of real-time passenger information on passengers in this travel corridor is assessed. Chapter 8 summarizes the major conclusions and contributions of this research, and also presents a number of ideas for future research in this and similar areas.

Chapter 2

Literature Review

In order to examine the effect of real-time information on passenger behavior, a merging of ideas must take place. That is, the literature on passenger behavior and information modeling is not well-integrated, at least in the field of public transit. For this reason, this chapter seeks to integrate this literature under some common themes. The first involves modeling of a traveler's choice of path and departure time in transit networks, under the assumption that vehicle movements in transit networks are subject to stochastic variation and time-dependence. To this end, there has been much prior research on models of transit service and passenger behavior. The second major theme, and the focus of current research in this area, emphasizes the role of information technology and how real-time information on vehicle locations and travel times might improve passenger decision-making.

In order to place the research in its appropriate context, this chapter reviews the literature on transit service modeling, passenger path and departure time choice models, and real-time information systems. After an initial glossary of terms, the second section discusses route and network models of transit service. In the context of these service models, the chapter reviews models of transit passenger behavior, focusing on path and departure time choice. The fourth section discusses research on the traveler's response to real-time information, within the context of urban transportation and IVHS research. Finally, the last section reviews the state of the art of real-time passenger information systems in public transit.

2.1 Glossary of Terms

The terms listed below are defined in a manner consistent with their usage in this thesis. Even a casual review of the literature indicates that each of these terms may have a wide variety of definitions.

Definition 1 *A* route *(or a* line*) is a set of nodes and connecting arcs which are served by set of transit vehicles which serve all nodes and arcs in the set in a pre-specified order and according to some schedule. As a description of transit service, this closely resembles traditional definitions of a transit route from an operator's perspective.*

Definition 2 *A* route segment *(or a* line segment*) is a subset of nodes and arcs on a route, including at least two nodes and their connecting arcs.*

Definition 3 *A set of* common routes *(or, alternatively, a set of* common route segments*) represents a set of routes (or route segments) which share two or more nodes. This definition generalizes the more standard assumption that common routes also include two or more nodes* and arcs.

Definition 4 *A* path *(or an* itinerary*) is a sequence of route segments which a passenger may use in traveling from an origin to a destination. A path will include at least one transit route segment.*

Definition 5 *Transit* path choice *(or the passenger's path choice* strategy*) is the process by which a passenger selects a single path for a trip, given the set of all paths serving the origin and destination.*

Definition 6 *A transit passenger's* path choice set *is a set of paths which the passenger may consider using for a given trip. An* optimal choice set *is that choice set which optimizes some passenger path choice objective (e.g., minimum expected travel time).*

Definition 7 *Transit* path assignment *is the process of assigning passengers to specific paths, based on certain criteria regarding the passengers' choice of paths from his/her path choice set.*

Definition 8 *A set of common routes is said to have* coordinated schedules *if the timetable for vehicle departures from a node is constructed so that the time-weighted* *average interval between vehicle departures on all routes is minimized. For example, if two routes have identical headways, a coordinated schedule would imply that one route be scheduled with departures at times one-half of the headway later than the other route. If the routes have different headways, the routes are scheduled such that the time-weighted average of vehicle inter-arrival times is minimized. Two routes, with a 10-minute and a 15-minute headway, for example, would be scheduled so that the first departure on the 15-minute headway route will leave the terminal 2.5 minutes after the first departure on the 10-minute headway route.*

Definition 9 *A set of common routes is said to have* uncoordinated schedules *if the route schedules are not coordinated.*

2.2 Stochastic Transit Route and Network Models

One of the most critical aspects of transit service which must be addressed in this research is the inherent level of service reliability. If transit service were perfectly reliable (e.g., always on time), there would be no need for real-time information systems. Indeed, the fundamental premise of the need for real-time information systems is that the transit environment is essentially one of uncertainty, particularly in the realm of travel times.

In contrast, most models of transit routes and networks assume that vehicle travel times and headways are deterministic, albeit perhaps unknown to the passenger. Much of the earlier literature on transit performance models assumes that vehicles travel exactly on schedule, and passenger origin-to-destination travel times depend only on these deterministic running times plus a waiting time which depends only on the frequency of routes serving that o-d pair. More recently, there has been some research to develop transit service models in which the vehicle travel time characteristics are explicitly stochastic. The following section reviews the stochastic models; the deterministic models are included as part of the discussion of transit path choice models in Section 2.3.

There are a number of transit route and network models in the literature which explicitly account for stochastic travel time characteristics. The most salient analytic models include Andersson and Scalia-Tomba [5], Powell and Sheffi [61] and

Marguier [48]. A considerable literature on simulation models also exists. As both analytic and simulation models of transit networks will be considered in this thesis, both of these types of models are reviewed below.

2.2.1 Analytic Models

Andersson and Scalia-Tomba [5] present a summary of the mathematics and statistics which were used in the simulation of Andersson et al. [4]. Their model examines the movement of vehicles on a single bus route, incorporating passenger boardings and alightings at each stop, as well as stochastic running times between stops. They establish a set of mathematical relationships regarding vehicle dwell times and running times and derive statistical relationships for computing various parameters of these dwell times and running times, both across a given day and across days of the week.

Powell and Sheffi [61] develop a model of bus route performance using probability distributions. Using the assumption that vehicle travel times may be correlated, the authors develop recursive relationships for travel time, boarding and alighting time, and vehicle load distributions for each stop on the route. Their model allows for vehicle bunching. [The topic of transit vehicle bunching is treated more substantially by Newell and Potts [54], Potts and Tamlin [60], Heap and Thomas [29], Newell [53], Chapman and Michel [14], and Boyd [12]]. A simple numerical model is developed, showing some statistical results from the probability model.

Marguier [48] also examined the performance of buses on a single bus route. His analysis is similar to that of Powell and Sheffi, in that he determines recursive relationships for the mean and variance of travel time and vehicle load distributions for each stop on the route. However, he assumes that there will be no bus pairing or bunching. Marguier also computes the variance of resulting dispatch times on successive trips at route terminals. Using the assumption that the parameters of passenger flows and travel times do not vary over the course of the day, Marguier derives non-recursive expressions of the means and variances of headways, loads, and dispatch delays. Marguier also uses these closed-form solutions to derive equations for various passenger and operator performance measures. Using a simulation model, Marguier compares the results of the closed-form solutions with those from a simulation of vehicle movements, with mostly positive results.

These studies suggest the following elements for transit route and network modeling:

- Stochastic running times and boarding/alighting times;
- Stochastic vehicle loads;
- Correlation of vehicle travel times and vehicle bunching; and,
- Dispatch delay at route terminals.

There are, however, several shortcomings of this research. First, these researchers have implicitly emphasized headway regularity rather than schedule adherence, in that route-level performance is measured in terms of variability of headways rather than variation about a particular schedule. Headway adherence is more significant for short headway service; however, for longer headways, schedule adherence may be a more appropriate measure of transit service quality. In addition, one of the major drawbacks of these studies is their implicit disregard for passenger behavior and o-d travel patterns. Typically, they assume random passenger arrivals at each bus stop, as well as a simple model of passenger alightings which disregards passenger o-d travel behavior. For this reason, it will be necessary in this thesis to develop an analytic model of transit service which is oriented toward the passenger's perspective on travel time reliability.

2.2.2 Simulation Models

Because of the great complexity required in rigorous analytic models of transit service, simulation is often preferred. There are a large number of transit route and network simulation models which have been developed over the past twenty years, following the growth of computer capabilities. Most of these simulations have been developed explicitly to examine transit operating performance and operations planning for single bus routes, using a stochastic framework similar to that of the analytic models presented above.

These route-level models often simulate vehicle control strategies to improve operations on these routes. Specifically, the models of Bly and Jackson [9], Koffman [37], Andersson et al. [4], Andersson and Scalia-Tomba [5], Abkowitz et al. [1] and Senevirante [63] examine route-level operating dynamics and different control strategies to improve bus on-time performance. These models typically assume a random pattern of passenger arrivals at each stop (i.e., Poisson arrivals) and a binomial distribution for the number of alighting passengers at each stop. Similar route models were combined in the research of Kulash [39] to produce a full network simulation. With this network model, Kulash examined vehicle allocation in the network to minimize each of several passenger-oriented performance measures, including waiting time, total travel time, and vehicle crowding.

Other models have explicitly examined passenger waiting times using simulation. Abkowitz and Engelstein [2] use data from Los Angeles to estimate passenger arrival patterns on routes of varying headways. Using these functions, they calibrated a route-level simulation model which examines vehicle holding strategies and the resulting impacts on waiting times for passengers, both on board and waiting for the bus. Bowman [10] and Turnquist and Bowman [69] explicitly consider passenger waiting times in their network simulation. Passenger arrival patterns are assumed to be correlated with scheduled vehicle arrivals. The authors examine different network designs and, in the work of Bowman [10], real-time operations control policies using the network performance measures of passenger waiting times, transfer times, and total o-d travel times.

The analytic and simulation models presented above offer some insight into the mathematical and probabilistic aspects of transit system dynamics. However, as with the analytic models, the simulation models assume an operator's perspective on transit service. Although the models often use passenger-oriented performance measures to evaluate operating plans and real-time control strategies, there are no models to date that specifically focus on analysis or simulation of passenger behavior in these types of networks. As a result, the models of passenger behavior used are relatively simple. This is especially true of the few network models which exist, primarily because of the significant complexity and host of assumptions necessary for network modeling. A more passenger-oriented approach to transit service modeling will be necessary for this thesis.

2.3 Transit Path Choice Models

Given the broad range of analytic models for transit networks, there are a correspondingly large number of models about how transit passengers choose a path from origin to destination. Early research in this area focused on "path assignment," meaning that individual passengers use some disaggregate method to choose a path with a resulting deterministic or stochastic aggregate assignment to o-d paths. This section summarizes the passenger assignment process in transit networks. There are several sections to this literature, covering deterministic transit path assignment, path choice for common route segments, and path choice in stochastic and time-dependent (transit) networks.

The review below is motivated by the observation that more accurate real-time information about vehicle locations, departure times, and travel times may improve the decisions made by passengers about which routes and paths to consider. In this regard, this review examines these models with a critical view toward how accurately the models intuitively reflect individual passenger behavior, and also how well information can be incorporated into the models.

2.3.1 Transit Path Assignment

A considerable literature exists in the area of transit service planning and demand modeling. This discussion will first consider models which fall into the area of *transit path assignment*, which is the manner in which a given aggregate o-d demand is "assigned" to various routes. While a larger discussion of these models appears subsequently in this section, it is important to begin this section by discussing these assignment models in terms of their assumptions about transit service. In particular, most of these models assume deterministic route travel times, and thus are particularly of interest here.

Deterministic Service Models

Robert Dial [21] was one of the first researchers to examine the problem of assigning passengers to transit paths. His simple network model assumed that vehicle running times are deterministic and headways are exponentially distributed. That is, there is no fixed schedule, and the number of passengers served by a particular route is directly proportional to that route's frequency share. Thus, for *any* random point in time, the a priori probability that a vehicle from one route will arrive next is equal to its frequency share. Mathematically, if f_i is the frequency of route i, and the set R includes all routes serving a stop, then,

$$\text{Prob(Route } r \text{ arrives next)} = \frac{f_r}{\sum_{i \in R} f_i} \tag{2.1}$$

Other authors assume similar service models in terms of deterministic running times and exponentially distributed headways, including le Clercq [42], Andreasson [6], and Mandl [46]. More recent path assignment models make similar assumptions about transit service, including Spiess [65], de Cea et al. [20], Nguyen and Pallottino [55], and Spiess and Florian [66].

Recently, Jansson [33, 32] and Jansson and Ridderstolpe [34] have explicitly questioned the assumption of exponentially distributed headways. Instead, they assume that headways are deterministic. In this case, the frequency share approach shown in equation (2.1) is not always valid; it is only true for specific vehicle arrival times. For example, if two routes serve a stop with identical 10-minute headways and with each route scheduled so that a vehicle arrives 5 minutes after the other route's scheduled arrival, the passenger share (assuming randomly arriving passengers) for each route will indeed be one half. However, if they are not timed in this way, a different share occurs: for example, if the second route is timed 4 minutes after the first, the passenger shares are 60% for the first route and 40% for the second.

Thus, under the assumption of deterministic headways, the resulting passenger shares depend upon the timetables. Jansson and Ridderstolpe work with the concept of *perfectly coordinated* schedules, which results in passenger shares being the same as the route frequency shares from equation (2.1). Their model also allows for *uncoordinated* schedules, in which the arrival time of any one vehicle is uniformly distributed between successive arrivals on any other route. Uncoordinated schedules do not necessarily imply a particular schedule, as the example above might suggest. Instead, Jansson and Ridderstolpe assume that the schedules are not perfectly correlated, and that the level of coordination is not specified by the vehicle operator. These models are incorporated in the transit planning software VIPS II [33, 32].

In practice, this assumption about schedule coordination is certainly not true; the operator will specify some schedule (coordinated or not). The difference between a specific schedule and the authors' assumption is most obvious for routes with equal headways. The authors' assumption about uncoordinated schedules, when used in the 2-route, 10-minute headway example above, yields a 50/50 passenger split between the two routes, although a specific schedule (which is not perfectly coordinated) can yield much different passenger shares. Thus, the approach of Jansson and Ridderstolpe [34] does not explicitly consider the effects of different vehicle schedules on transit path choices.

Summarizing, based upon the above research, many of the transit service models in use today (in packages such as VIPS II, UTPS, and EMME/2) assume deterministic vehicle travel times and either exponentially distributed or perfectly coordinated and deterministic headways. Both of these headway assumptions result in passenger shares equal to the route frequency shares. For uncoordinated schedules, the passenger shares depend on the specific schedule or on the assumptions about how the schedule is constructed. This last issue of schedule coordination has not been sufficiently addressed in the path assignment literature to date.

Path Assignment Methods

Transit path assignment techniques have existed for over twenty-five years, beginning with Dial's [21] transit path assignment (or "transit pathfinder") algorithm. Dial created an algorithm which generates "optimal" origin-destination paths in transit networks. Generally, his methodology is based on computing the shortest paths in the network using the more generic label-correcting algorithm. An improvement of Dial's algorithm was presented by le Clercq [42], who used a label-setting rather than label-correcting algorithm for determining shortest paths in the network; however, in most other respects, his approach is similar to that of Dial. The models of Dial [21] and le Clercq [42] assign passengers to a single path with the minimum expected travel time, except in the case of common routes (or paths) with equal travel times, in which case the assignment is proportional to route frequencies.

There are a number of common elements to the work of Dial [21] and le Clercq [42].

First, both authors use a network representation in which each pair of nodes in a route are connected using unique arcs. Both algorithms then use this representation of route segments, rather than more typical road links, to determine the shortest transit path from a given origin to all destinations. Link travel times are assumed to be constant, and waiting and transfer times are specifically assumed to be equal to one-half the headway, regardless of the headway value. When several transit routes operate on the same link, the expected waiting time (or transfer time) is equal to one-half of the inverse of the sum of the route frequencies; i.e., all routes are available and assignment to routes on common line segments is proportional to the relative line frequency.

Andreasson [6] and Mandl [46] separately formulated the transit network design problem. One of the phases in network design involves assigning passengers to paths in order to determine the allocation of vehicles to various routes in the network. The procedure discussed by Andreasson was later adopted as part of the Volvo transit planning package VIPS [28]. Both Andreasson's and Mandl's network design models assume that transit passengers arrive at stops randomly and that vehicle arrivals at stops are exponentially distributed.

Andreasson [6] expanded on the models of Dial [21] and le Clercq [42] by performing a path assignment based on a simple heuristic to include paths in the passenger's optimal choice set. If the travel time conditional upon boarding a given path is less than the minimum over all paths of the headway plus the travel time after boarding, that route is included in the path assignment. For example, if path A has a travel time conditional upon boarding of 30 minutes, and the shortest path travel time conditional upon boarding (path B) is 24 minutes and has a headway of 10 minutes, path A is included in the path assignment, since $30 \leq 24 + 10$. Once the optimal path choice set is determined, path assignment is again based on the relative route frequencies.

Mandl [46], on the other hand, used a heuristic devised by Chriqui and Robillard [16] (discussed later) to compute which routes should be included in a passenger's choice set over common route segments, and aggregates link running times for these common route segments using a frequency-weighted sum of route running times. Mandl also computes waiting times (and transfer times) based on one-half the inverse of the sum of combined route frequencies. Assignment to common routes, then, is based on the frequency share.

The model formulated by Jansson and Ridderstolpe [34] and used in the VIPS II software [33, 32] assumes the existence of a vehicle timetable, and that vehicle movements adhere perfectly to this schedule. As a result, depending on the level of coordination of routes, different path assignments may be inferred. Again, for routes which are not coordinated, the assignment is based on the presumption that vehicle departures on any route are uniformly distributed between departures on any other route. A heuristic is used to solve for the path assignment in the case of uncoordinated routes. For perfectly coordinated routes, a heuristic assigns passengers to routes based on frequency share, although such an approach is only correct when common routes have identical headways.

These models represent much of the state of the practice in path assignment. Path assignment techniques based on the work of Dial and le Clercq are used in the UPATH/UMODEL functions of the UTPS transit planning software by a number of large cities in the United States. Jansson and Ridderstolpe's assignment technique is used in the VIPS II software produced by the Volvo Corporation for transit service planning. However, there are several significant shortcomings to these models. First, they are unable to incorporate either the inherently stochastic nature or the inherent time-dependence of travel times and vehicle movements in the transit network. A related issue is the assumption that all expected waiting times may be approximated by one-half of the headway, which has been shown to be inappropriate for longer headways (over 10-12 minutes) by a number of authors (e.g., Jolliffe and Hutchinson [35], Bowman [10], and Bowman and Turnquist [11]).

One seeming inconsistency in several of the analyses presented above is the calculation of waiting times at one-half of the prevailing headway, while also assigning route shares on common route segments according to a route's frequency share. As noted by a number of authors (e.g., Turnquist [68] and Marguier and Ceder [49]), the assumption that waiting times are equal to one-half of the prevailing route headway is equivalent to assuming that schedule adherence is perfect; i.e., headways are maintained perfectly. Furthermore, the assignment of passengers to common routes according to a route's frequency share, when passenger arrivals are entirely random, must be based on the assumption that vehicle departures are perfectly coordinated. The assumption that vehicle departures (i.e., headways) are exponentially distributed is inconsistent with the assumption that waiting and transfer times are equal to one-half the prevailing headway. On the contrary, the mean waiting time with exponentially distributed headways is equal to the full prevailing headway. No one has noted this inconsistency to date.

More recent transit path assignment models incorporate some of the stochastic nature of vehicle headways by explicitly assuming that vehicle headways are exponentially distributed. Recent work by de Cea et al. [20] and Spiess and Florian [66] formulate the transit path assignment problem as a linear program, as a relaxation of a mixed integer program. The model of de Cea et al. is used in the TRANSCOM transit planning software, while Spiess and Florian's approach is used in the EMME/2 transit planning software.

In both of these works, the authors use the definitions of itinerary (i.e. path), route, and strategy as defined in Section 2.1. de Cea et al. [20] presents the mathematical programs from both Spiess [65] (which is very similar to Spiess and Florian [66]) and Chriqui [15], the latter being a mathematical formulation of Chriqui's approach determined by de Cea [19]. The formulations presented are very similar, except that the two formulations differ in the representation of "line segments": Spiess' network representation uses transit line segments connecting *adjacent nodes only*, while Chriqui's approach uses "line sections" which includes links for non-adjacent nodes that are connected by a bus route. The result in this case is that Spiess' formulation focuses on adding simple line segments to the optimal path choice strategy, while Chriqui's approach adds "line sections" to the optimal path choice strategy. As a result of these representations, Spiess' proposed solution algorithm is a form of a shortest path algorithm, while Chriqui's algorithm uses a network search to define feasible o-d paths, followed by a greedy heuristic (similar to Chriqui and Robillard [16]) to determine optimal o-d paths. Both approaches assign path choice probabilities based on relative route frequencies.

Both approaches represent a significant improvement over previous transit path choice models by modeling the possibility that passengers may consider multiple paths in an optimal passenger path choice set. Furthermore, the paper by de Cea et al. is helpful in its contrast of network representations and by emphasizing the importance of these in determining path assignments. However, both approaches still assume random passenger arrivals, lack of schedule coordination among overlapping bus lines, and sufficiently short headways to accommodate the assumption that vehicle inter-arrival times are exponentially distributed.

Nguyen and Pallottino [55] discuss the transit path assignment problem with the aim of improving the state of the art of network representation for model development. The authors present the concept of *hyperpaths*, which allows a fairly generic graph framework to accommodate transit path assignment in both deterministic and probabilistic settings. A hyperpath is a set of simple paths (for a single origin-destination pair) which are in a passenger's "optimal" choice set [16]. For each origin-destination pair, there is a graph consisting of any number of hyperpaths, based on the number of feasible choice sets on that o-d pair. The graph model is used in computing shortest paths and in determining passenger assignment for each origin-destination pair in the network. Each arc in a hyperpath has an associated "cost" and probability of being traversed. Once these hyperpaths are constructed, shortest path calculations and equilibrium traffic assignment can be performed. Shortest paths can be determined by taking the probability-weighted sum of arc costs within each hyperpath, then assigning all-or-nothing flow on the hyperpath with minimum cost. Waiting times or transfer times in this case are proportional to the inverse of the sum of the frequencies of all transit routes serving the origin in a hyperpath. The framework accommodates any number of path assignment techniques, including that developed later in this thesis. Time-dependence and stochastic running times are not explicitly treated by these authors.

To summarize, current path assignment techniques have considerable shortcomings in describing the assignment of passengers to paths. First, there is little consideration of the inherently stochastic nature of travel times, particularly running times. Second, in none of these assignment models is there any explicit consideration of the timetable or of scheduling of route-to-route transfers. Because the context of real-time information incorporates both time-dependent and stochastic service characteristics, it is not possible to use these models directly in this research.

2.3.2 Common Route Segments (or Paths)

The stochastic and time-dependent nature of transit service has been considered more explicitly in the research on common route segments, or common paths. In this problem, passengers are assigned to different routes serving a common origin and destination, based on the arrival patterns of vehicles at the origin stop, which are assumed to be inherently stochastic. Because of the centrality of this path choice problem to the development of this thesis, the models of Chriqui and Robillard [16], Marguier [47], Marguier and Ceder [49], and Jansson and Ridderstolpe [34] are reviewed in greater detail.

Chriqui and Robillard [16] examined the issue of how transit passengers might be assigned to various routes serving a common origin and destination. Their hypothesis is that passengers traveling on a common route segment will choose a certain subset of those lines on which they would be prepared to travel (i.e., an optimal choice set). Specifically, they will choose that set of routes which, when the passenger takes the first bus to arrive on any route of the set, minimizes the expected total travel time (wait plus in-vehicle time).

The problem is stated as determining a choice vector (of dimension r, where r is the number of common lines) containing elements 1 and 0, where $x_i = 1$ if the route is in the optimal subset, and $x_i = 0$ otherwise. Chriqui and Robillard assume a certain probability distribution for the waiting time for each route, and then derive an expression for the expected waiting time for the next vehicle, given the choice vector. [The mathematical formulation is presented later in equations (4.17) and (4.18).] It is assumed that routes on this common line segment are independent, and that passenger arrivals are random. Using explicit enumeration of all (common) routes, the authors suggest the following greedy heuristic:

1. Sequence the routes according to expected in-vehicle travel time (fastest route first).

2. Let X, the choice vector, be $(1, 0, 0, ...)$, and compute the expected total travel time with this choice vector.

3. Add the next (slower) route into the choice vector, and compute the expected total travel time. If the result yields a lower expected travel time, repeat this

step. Otherwise, terminate; the prior choice vector is "optimal."

The motivation for this heuristic is that "it is illogical for a passenger to let a bus of a given route go by and wait for a bus with longer in-vehicle time" (p. 119). The heuristic always produces the optimal solution for the following cases: when the waiting time distributions for all routes are identical; when all routes have the same in-vehicle travel time; and when all routes have exponentially distributed headways. They hypothesize, but are unable to prove, that under more general waiting time distributions, their heuristic produces an optimal solution. This assertion is later refuted by Marguier [47].

Finally, the concept of a "clever" passenger is introduced. Such a passenger might revise his/her choice set while waiting, based on the distributions of waiting time. The authors only raise this point in passing, remarking that in the case of exponentially distributed waiting times, the optimal set does not change over time.

The shortcomings of the analysis of Chriqui and Robillard [16] are discussed in Marguier [47]. Like Chriqui and Robillard, Marguier assumed that there could be a number of bus routes serving an origin-destination pair, with the object of the research being to examine how one might choose an "optimal" set of routes so that, upon taking the next vehicle arriving on any of those routes, the expected travel time to the destination is minimized.

Marguier examined the boolean decision vector proposed by Chriqui and Robillard. His first observation about this decision vector was that any optimal solution would necessarily include the route with the shortest expected in-vehicle travel time. [This was implicitly assumed by Chriqui and Robillard.] Yet, as mentioned above, Marguier determined that the heuristic proposed by Chriqui and Robillard was not necessarily optimal for all headway distributions. Even for the simple case of deterministic headways (in which the waiting time is uniformly distributed between zero and the headway), examples of a three-route case for which the Chriqui and Robillard heuristic fails to find the optimal strategy were shown. Specifically, Marguier demonstrates a case for which the strategy $(1,0,0)$ performs better than $(1,1,0)$, but $(1,0,1)$ is better than $(1,0,0)$, thus violating the heuristic.

Marguier went on to examine the 3-route case in greater detail, and found counter-examples to most of Chriqui and Robillard's implied logical relationships with respect to optimal route strategies. In many cases, it is slightly more advantageous to exclude some medium-speed routes from the optimal choice set if there are much higher frequencies on faster and slower routes. Using certain families of waiting time distributions, he demonstrates under what conditions such counter-examples will arise. He briefly describes similar results for a 4-route case, but it is clear that the level of effort required to examine proposed route choice sets rises exponentially with the number of common routes.

Marguier also examines the case of a "clever" passenger. This clever passenger updates his/her optimal set of routes based on the distribution of waiting times for each route and the amount of time they have already waited. Again, he shows that any optimal strategy over time will always include the shortest in-vehicle time route. However, through a brief examination of the 2-route case, Marguier determines that, depending on the form of the waiting time distribution, there are conditions under which the preference for $(1,1)$ or $(1,0)$ might change in either way. That is, there are conditions under which it might be advantageous to add routes to the optimal choice set after some waiting, while in other cases it is better to drop slower routes from the optimal choice set as waiting time increases.

There are several shortcomings to the two results presented above. First, both researchers focus on trips which can be completed without transfer over a number of routes. This allows the assumption that the expected travel time after boarding a chosen path does not vary as a function of time. However, such an assumption may be violated for trips which might include a transfer. In such situations, the optimal boarding strategy (i.e., the optimal choice set) is time-dependent. Another shortcoming which is evident from Marguier's work is that choosing such a subset of "optimal" routes is not as simple as applying a greedy heuristic. Explicit enumeration of paths will be necessary for more complicated passenger waiting time distributions.

Marguier and Ceder [49] describe how clever passengers might formulate a strategy in waiting for buses in this same case of overlapping bus routes. The distribution and mean of the waiting time is derived using two particular headway distributions: the "power" distribution and the gamma distribution. Their analysis assumes that the variation in bus arrival times is sufficiently large that passengers do not time their arrivals to coincide with vehicle arrivals (i.e., passengers arrive randomly). They also assume that passengers know both expected route headways and expected in-vehicle travel times.

The authors describe the distributions of waiting time for both the instant of arrival and conditioned on the amount of time already waited. For the most simple case of two routes sharing a common route segment, they define criteria under which a passenger might choose to include the slower route in the initial choice set. For the power and gamma distributions, as waiting time increases, the slower route will never be added to the optimal choice set. Finally, the authors derive formulas to describe the path assignment as a function of these two routes' frequencies and headway variations. The results suggest that the proportion of travelers on each route is a decreasing function of the coefficient of variation of headway on the route. However, the approach outlined by Marguier and Ceder is limited in that it only considers two routes and specific headway distributions.

Jansson and Ridderstolpe [34] consider the transit route choice problem for networks in which all headways and running times are deterministic. The stochastic nature of the problem arises from the assumption that there is no explicit coordination of headways on the transit routes, and thus the waiting time for any vehicle departure may be modeled using a uniform distribution over the period of one headway. In this context, the authors present a heuristic to determine path assignment. They use a greedy heuristic similar to that presented by Chriqui and Robillard [16]. However, rather than recomputing the expected travel time and the expected waiting time precisely at each iteration, routes are added to the choice set until the in-vehicle time of the route to be included exceeds an approximate "expected" travel time for the current set of routes. Because of this approach, it is not clear that Jansson and Ridderstolpe's approach will always produce the optimal choice set (i.e., with the minimum expected travel time).

The authors also use several examples to compare their heuristic with existing path assignment techniques, including Chriqui [15] and Spiess [65]. For these examples, their heuristic performs similarly to Chriqui's. However, since Spiess's formulation computes path assignment based on relative route frequencies, the results of the authors' heuristic differ significantly from those of Spiess. This difference results from two assumptions. First, as Jansson and Ridderstolpe note, Spiess' approach does not account for differences in in-vehicle travel times for routes covering common line segments. Second, Spiess' approach assumes that vehicle headways are exponentially distributed, not deterministic. For these reasons, significant differences are noted in both path assignments and in expected travel times.

From this path choice literature, several general comments can be made. First, the models make specific assumptions regarding the waiting time distributions for an arriving passenger, with results being dependent on the assumed distribution. In addition, none of the authors address the vehicle timetables, which will significantly impact waiting times and path assignment on common route segments. Because the greedy heuristic of Chriqui and Robillard [16] is optimal only for specific waiting time distributions, explicit path set enumeration seems necessary for more general waiting time distributions. Finally, these authors have not investigated the more general "clever" passenger's path choice problem posed by Chriqui and Robillard for more than a simple two-route case, and this approach lacked a more general model framework. A time-dependent model of transit path choice is necessary for this research, corresponding to the dynamic nature of real-time information systems.

2.3.3 Shortest Paths in Stochastic Time-Dependent Networks

There is a substantial literature on shortest paths. Of greatest relevance to the research in this thesis is the literature regarding shortest paths in both stochastic *and* time-dependent networks, as these two issues are the most constraining in defining scheduled service (i.e., transit) networks. The most relevant work is that of Hall [25, 27], who considered shortest paths in transportation networks where travel times are both stochastic and time-dependent. Furthermore, as Hall's work explicitly considered transit networks, his work is discussed in greater detail below.

[There is also a substantial amount of research in stochastic shortest paths; these authors, however, tend to generalize their results for communications networks where travel times are not time-dependent. In this respect, the literature on stochastic shortest paths is not particularly helpful to this research, and will not be covered explicitly here. The interested reader is referred to the works of Frank [24], Mirchandani [50], Sigal et al. [64], Loui [45], Eiger et al. [23], and Mirchandani and Soroush [51] for helpful discussions of the stochastic shortest path problem.]

[A similar literature exists for shortest paths where link travel times are time-dependent; i.e., travel times are a function of time. Such is the case for transit networks. A good discussion of these problems exists in Cooke and Halsey [17], Dreyfus [22], and Orda and Rom [57, 58]. The literature demonstrates how time-dependent problems may be reduced to problems solved through "standard" shortest path techniques. However, as noted by Hall [27], direct application of these time-dependent shortest path methods is not really feasible because of the stochastic nature of travel times in transit networks. This complication eliminates the effectiveness of the time-dependent analysis in the current context.]

Hall [25, 27] examines the issue of finding the shortest path in networks which have both stochastic and time-dependent travel times. In such networks, it is not always true that the shortest paths are simple and concatenated. That is, it is not always true that the shortest topological path from an origin to the destination includes the shortest topological paths from the origin to any nodes in that shortest origin-destination path. Hall demonstrates this concept through a simple counter-example, showing that the minimum expected time path on an o-d pair is not a simple extension of the shortest path to an intermediate node.

Hall proposes a simple algorithm to determine the shortest path in such cases. The algorithm assumes that each arc in the network has a lower bound on its travel time (i.e., a minimum possible travel time on each arc). The algorithm proceeds as follows:

1. Using the minimum possible travel times, a"shortest" path through the network is determined. From this "shortest" path, the expected o-d travel time of that path is calculated.

2. Again using minimum arc travel times, the *next* shortest path is determined. If its expected value is less than that of the current least expected value path, it becomes the new candidate optimal path.

3. The previous step is continued until the minimum travel time on the next candidate path is greater than the least expected travel time.

Hall demonstrates how this algorithm might work on a simple transit network in which all vehicles depart on time, but there is a random (exponentially distributed) delay of the vehicle before arrival at the next node in the network. In this example, the heuristic terminates with the optimal (i.e., least expected travel time) path from the origin.

Furthermore, Hall demonstrates a simple example where the optimal path chosen by the above method may be improved by using an adaptive decision rule, where the path choice at each node in the network is made once the passenger determines his/her arrival time at that node. Hall proposes an approach which convolutes the passenger's arrival time distribution at any node with the expected minimum travel time from that node to the destination (as a function of time). In this case, improvement in the minimum expected o-d travel time is achieved.

There are several shortcomings to Hall's approach, which shall be addressed later in this research. These include:

- It is not clear how much additional complexity is added to the problem by using continuous, rather than discrete, probability distribution functions. Hall's simple three-node example used a discrete probability function for computing expected values. When continuous distributions are used, this calculation of expected path travel times is considerably more difficult, and indeed cannot be done exactly except through explicit integration.

- The methodology assumes that vehicles depart their origins according to some fixed schedule. Path assignment, in this case, is in the form of all-or-nothing on the shortest route path. This assumption about vehicle departures constrains passengers to choose a single path from all paths serving the o-d pair. In this respect, Hall's formulation of the problem is somewhat limited, and should be extended to include the possibility of the passenger's (optimal) choice to consider more than one o-d path.

- Hall makes no mention of how passengers might choose their initial departure times. Obviously, for the case of deterministic vehicle departures, passenger arrivals can be timed perfectly with these vehicle departures. Stochastic vehicle departures would change waiting time distributions in the network, thus affecting shortest path calculations by increasing the complexity of calculating distributions of passenger o-d travel time.

2.4 Transit Departure Time Choice Models

In conjunction with the path choice models presented above, it is important to consider a passenger's departure time choice. In the context of real-time information systems, it may be possible for the passenger to improve his/her departure time choice by gaining better information about current vehicle locations or vehicle departure times. However, the applicability of existing transit departure time choice models is suspect. As noted previously, traditional transit modeling techniques assume that passengers arrive at the origin stop at a random point in time (i.e., with an exponential distribution of passenger inter-arrival times). In a few cases, a uniform distribution of arrivals is assumed; i.e., there are N passengers who arrive at random points in between times t_0 and t_1. These two approaches are most common in the transit planning literature. Typical justifications for these approaches are that service is at sufficiently short headways, or is so unreliable, that the passenger cannot effectively reduce his/her expected waiting time by means of any more clever arrival strategies. With real-time information, however, a passenger might have better information with which to make a more clever departure time decision.

Several researchers have observed correlations between passenger arrivals at a bus stop and vehicle arrivals. Several attempts to explain this phenomenon empirically have been put forth by Holroyd and Scraggs [31], O'Flaherty and Mangan [56], and Seddon and Day [62]. Each of these authors observed passenger arrival patterns at bus stops in various cities in the United Kingdom. They estimate regressions relating passenger waiting times with the mean route headway, and found that for headways of over 10 to 12 minutes, there were significant reductions in expected waiting time over that expected if passengers arrived randomly.

Jolliffe and Hutchinson [35] hypothesized a model in which there are three different types of passengers:

- Some passengers who arrive randomly because they are "unaware" of the service schedule, and thus incur an expected waiting time which depends on the mean μ and variance σ^2 of the vehicle headway according to the following relation:

$$E[W_{random}] = \frac{\mu}{2} \cdot (1 + \frac{\sigma^2}{\mu^2}) \quad (2.2)$$

- Other passengers who are "aware" of the schedule and thus time their arrival at the point of minimum expected waiting time during a bus headway, incurring a minimum expected wait time $E[W_{min}]$; and,
- The remaining passengers who, upon seeing the bus, rush to catch it and thus incur no wait at all.

Jolliffe and Hutchinson estimated the proportion of passengers in each category and the expected minimum wait time $E[W_{min}]$ using data from several bus routes in London. Again, they confirm the result that passengers are likely to time their arrivals at the bus stop when vehicle headways are over 10 to 12 minutes.

Turnquist [68] made several important extensions to the model of Jolliffe and Hutchinson [35]. In order to differentiate types of passengers based on passenger decision-making rather than purely empirical observation of behavior, Turnquist assumed two types of passengers: *random* arrivals, assuming passengers are unaware of the service schedule; and *planned* arrivals, which are correlated with the vehicle's scheduled departure. Persons decide on one strategy or the other, and then behave accordingly; however, no one "plans" to rush for the bus. Turnquist also assumes that vehicle arrivals at a particular stop may be modeled theoretically using a log-normal distribution. [No specific vehicle arrival distribution was assumed by Jolliffe and Hutchinson.] Finally, rather than having "aware" passengers choose their arrival time based on simply minimizing the expected wait time, a constraint was added such that the probability of a passenger missing the desired bus be less than some small probability. This methodology was validated empirically using several bus lines in the Chicago area.

Bowman [10] and Bowman and Turnquist [11] further extend the methodology of Turnquist [68]. Rather than the assumption that all "aware" passengers arrive at a single point in time, these works suggest that such passenger arrivals occur on a more continuous basis. The methodology for deriving such a model of passenger arrivals uses the logit model of random utility theory over a continuous domain of alternatives: the domain of all possible passenger arrivals times. The utility function for the logit model is a function of the expected waiting time, given the chosen departure time. In particular, the authors hypothesize a utility model of the form

$U(t) = a \cdot E[W(t)]^b$, where a and b are parameters of the utility function. This modeling approach, assuming the utility model and aware and unaware passengers, was calibrated with data similar to that used by Turnquist [68].

Abkowitz [3] examined the impacts of stochastic travel times on mode and departure time choice for the morning commute. Abkowitz assumed that the traveler has an ideal arrival time at the destination (e.g., 9:00 a.m.), and that there is some "loss function" for an early or late arrival at the destination. By integrating this loss function over the range of possible destination arrival times, an "expected loss" is computed for a given origin departure time. The optimal departure time, then, minimizes this expected loss function. Abkowitz deals with a discrete (i.e., finite) set of departure times to simplify these calculations and obtain a person's optimal departure time interval.

The research conducted by Sumi et al. [67] describes a model for commuters' choice of departure time and route for a morning commute. Assuming stochastic travel times, the authors define the traveler's objective in selecting a departure time as leaving home as late as possible such that the probability of arriving at work after a specified time is less than some value α. For a given set of route alternatives, the authors derive functions for the probability that a given route is the shortest for the o-d pair. As defined in the paper, the probability that a person chooses a given route is equal to the probability of that path being fastest of all paths, given the distribution of travel times on each path. Using this model for path choice, and assuming some distribution of the parameter α, the authors are able to derive a distribution of departure times over the population.

The critical elements of these departure time choice models which are incorporated into the present research are:

- Departure time choices may be correlated with vehicle departures. In this context, real-time information systems may improve passenger's information about vehicle departure times, and thus improve departure time decisions.

- Both path and departure time choice models should be integrated so that the departure time choice explicitly takes account of available paths.

- The network travel time distributions and calculations may be hampered by the accuracy of numerical integration techniques.

To elaborate on the second item, in each of the departure time models presented above, it is assumed that passengers have a single route for which they wait. In this case, it is reasonable to assume that "aware" passengers would arrive shortly before a scheduled vehicle departure in order to minimize their expected waiting time, and thus their expected trip travel time. Minimization of total travel time reduces to minimizing the initial waiting time. Such a strategy is not as obvious when there are a number of possible paths serving a given origin-destination pair. For this case, the minimum expected o-d travel time may not involve correlating arrivals with a particular vehicle's schedule, but rather some other arrival pattern. This possibility should be considered in this research.

2.5 Information and Traveler Response Modeling

To date, there has been no significant analytical or empirical results to demonstrate passenger response to real-time information in public transit. Instead, the literature in information and traveler response modeling has been limited primarily to the area of automobile travel. In particular, over the past several years, a large amount of research has been dedicated to modeling Advanced Traveler Information Systems (ATIS). Although this research is not directly related to public transit, there are several significant findings which are relevant to this thesis. The following section is by no means a complete review of the research in this area; however, the findings of relevance to this research are discussed briefly below.

An overall framework for analysis of traveler information systems is given in both Ben-Akiva et al. [8] and Kaysi [36]. In summarizing much of the research on driver information systems to date, these authors point out the most salient features and basic concepts associated with real-time information systems. The primary dimensions of these information systems, from their perspective, include the dynamic aspect of real-time information, the accuracy and reliability of that information, and the timing of information before or during the trip.

The term "accuracy" requires further elaboration. The information technology itself has an inherent level of precision which depends on such factors as: the frequency of updating vehicle information, the precision of vehicle location technology, the potential error inherent in forecasting travel times, etc. This type of accuracy depends largely on the technology and data processing hardware and software in the information system. Yet, this variability in prediction directly determines how reliable the information may be for the traveler in matching true travel conditions. That is, from the traveler's perspective, the accuracy of the information system affects how often the information matches experience. As suggested by Ben-Akiva et al., this will influence the ultimate acceptance or rejection of the information technology by the users.

The framework suggested in Ben-Akiva et al. [8] and Kaysi [36] also specifies a decision hierarchy which depends upon the point in time at which information is supplied to the passenger. In this hierarchy, a traveler's perception of system characteristics is initially based on historical experience. The traveler may then choose to supplement this knowledge base with real-time information on current or projected system conditions. This may occur before the trip (pre-trip information) or at some point during the trip (on-route information).

Also in the context of ATIS, several authors have investigated the effects of real-time information on the passenger's perceptions of travel characteristics. [A more systematic discussion of approaches to information processing and perception modeling for drivers is presented in Lotan [44].] Under the assumption of stochastic travel times, Mirchandani and Soroush [52] describe a model for traffic equilibrium which accounts for variation among passenger perceptions of the distribution of travel times. Under the assumption that link travel times follow some type of probability distribution, the authors hypothesize that there is also a distribution across the population of travelers in the perceptions of actual observations from these true travel time distributions. Specifically, Mirchandani and Soroush suggest that there are several groups with similar patterns of perception. For an individual belonging to a particular group, there is a particular distribution of error, called the *perception error distribution*, around the actual travel time on a link. This is then convoluted with the true distribution of link travel times to form a distribution of perceived travel times for a link. In this case, optimal traveler behavior assumes that the passenger will choose a path such that the perceived expected travel time on that path is less than or equal to that on any other path.

Koutsopoulos and Lotan [38] use a similar approach in examining the impact of ATIS on driver behavior. The authors assume that link travel times are stochastic, and, in addition, that travelers perceive that these distributions have a higher variance than they actually do. In effect, the authors apply a multiplier (≥ 1.0) to the true standard deviation of travel times, thereby simulating perception error. When the traveler receives perfect information, he/she perfectly understands the true distribution (multiplier = 1.0), and with minimum information, the multiplier is much greater than 1.0. The authors demonstrate that, as higher levels of information reduce the effect of this multiplier, travelers then make more accurate decisions.

2.6 Real-Time Passenger Information in Public Transit

As noted previously, there has been only limited investigation into real-time information systems in public transit. To my knowledge, there has been no investigation of the theory of real-time passenger information or its potential role in public transit. Several transit properties have developed and implemented real-time passenger information systems, but most of these are only beginning to analyze the impacts of the system in terms of passenger behavior and changes in demand. Furthermore, while a considerable number of transit properties have installed or are planning to install automatic vehicle location (AVL) or identification (AVI) systems to improve real-time operations control, few are considering the potential of these systems for passenger information.

There may, in fact, be considerable potential for these systems both to reduce passengers' uncertainty about the transit service and to improve passenger decision-making. The literature in this area suggests a number of possible benefits of real-time vehicle arrival and departure information:

- Reduce passenger anxiety about waiting or transfering;
- Allow passengers to make productive use of waiting time (e.g., make a phone call, run a short errand, etc.);
- Improve passenger movement and circulation in terminals;

Table 2.1: Some North American Real-Time Passenger Information Systems

Type of Information	Sources of Information: Pre-Trip	In-Terminal	Both
Vehicle Locations	Ann Arbor Champaign/Urbana		
Departure Times	Ann Arbor Columbus Hull, Quebec San Antonio	Anaheim Chicago Ottawa-Carleton San Francisco Tampa	Baltimore Halifax, Nova Scotia Houston Twin Cities

- Improve passenger decision-making when several alternatives (routes or modes) are available to travel from origin to destination; and,
- Ultimately reduce the passenger waiting time.

There are several good references on the state of the art in passenger information systems, including the Federal Transit Administration (FTA, formerly UMTA) [13, 40] and Castle Rock Consultants [18]. Real-time passenger information systems are currently being planned in a number of cities around the world. However, implementation of such systems is somewhat limited, both because of the novelty and the cost of these newer technologies. To date, most system implementations have been on rail networks, in which vehicle location information can be obtained relatively easily and inexpensively from track blocking systems. On route information systems have also been developed and implemented for a number of bus systems abroad: in several cities in France, and most recently in London [7], information on expected bus arrival times and their destinations is provided on displays at bus stops.

Table 2.1 lists a number of North American transit agencies which have implemented or are planning to develop such real-time passenger information systems [13, 40]. In addition, a number of larger North American cities have already implemented automatic vehicle location (AVL) systems, including Toronto (TTC), Norfolk (TTDC), San Antonio (VIA), and Los Angeles (SCRTD).

It may be suggested from the cursory listing of actual or planned real-time passenger information systems in Table 2.1 that little attention has been paid to more basic vehicle location information or to other types of forecast vehicle travel times such as running times. Intuitively, one might expect that the most beneficial information to reduce waiting times and improve path choices would be departure time information. However, such a hypothesis has not been tested to date.

One additional item currently in the planning stages in the United States is on-board passenger information systems. The FTA [40] notes that with the passage of the Americans with Disabilities Act (ADA), transit operators are required to have visual and/or audio information systems on board transit vehicles. With this requirement, real-time information may also be provided to passengers on board. On-board systems have already been developed which give information on expected arrival times at various stops and the schedules for connecting vehicles at each stop [13].

In the research to date, several dimensions of real-time passenger information systems come to the fore. These dimensions, which resemble those presented by Ben-Akiva et al. [8] and Kaysi [36] in research on ATIS, include: the level of accuracy of information, the timing of the information during the passenger trip (pre-trip, in-terminal, or on board the vehicle), and the type of information (current or projected travel conditions). The framework developed in this thesis focuses on these dimensions in assessing the relative merits of real-time information systems. Because most of the existing passenger information systems are relatively new, there has been little research to date investigating the magnitude of these benefits, either empirically or analytically. Part of the reason for this is that current transit planning and analysis techniques provide almost no real analytic framework for this evaluation (as noted in similar research by Hickman [30]). A systematic study of the costs and benefits of passenger information systems would include more empirical and perhaps analytical analysis of passenger behavior in this context. Potential benefits to be examined would include tangible evidence, such as reduced travel time, shorter waiting times, or improved passenger movement in terminals, as well as more intangible benefits such as reduced passenger anxiety or greater satisfaction with the transit service. This thesis focuses exclusively on analytic and empirical methods which may be used to assess the more tangible (or functional) benefits to transit passengers of real-time information.

Chapter 3

Transit Service Model

The central determinants of the transit level of service for passenger travel times are service reliability, transfers and time dependence, as discussed in Chapter 1. These elements define the resulting travel time characteristics of the transit network. Moreover, based on these characteristics (and any real-time information about those characteristics), passengers must make travel decisions. This chapter develops a model of transit service based on the three elements of travel time variability, time dependence, and transfers. Before developing this model, however, it is important to lay out the overall analysis framework for the thesis. For this reason, the following section introduces such a modeling framework. Subsequent sections develop the transit service model more specifically.

3.1 Full Model Framework

Chapter 1 draws attention to a number of important aspects of transit service, their potential effects on passenger behavior, and the possible advantages of real-time information to improve passenger's perceptions and decision-making in that transit service environment. The main goal of this research is to develop models of transit service and passenger behavior which allow analysis of passenger decision-making in the context of real-time information.

The modeling framework which has been adopted for this thesis is shown in Figure 3.1. A model of transit service is required which incorporates the issues of time-dependence in vehicle movements as well as the stochastic effects resulting from

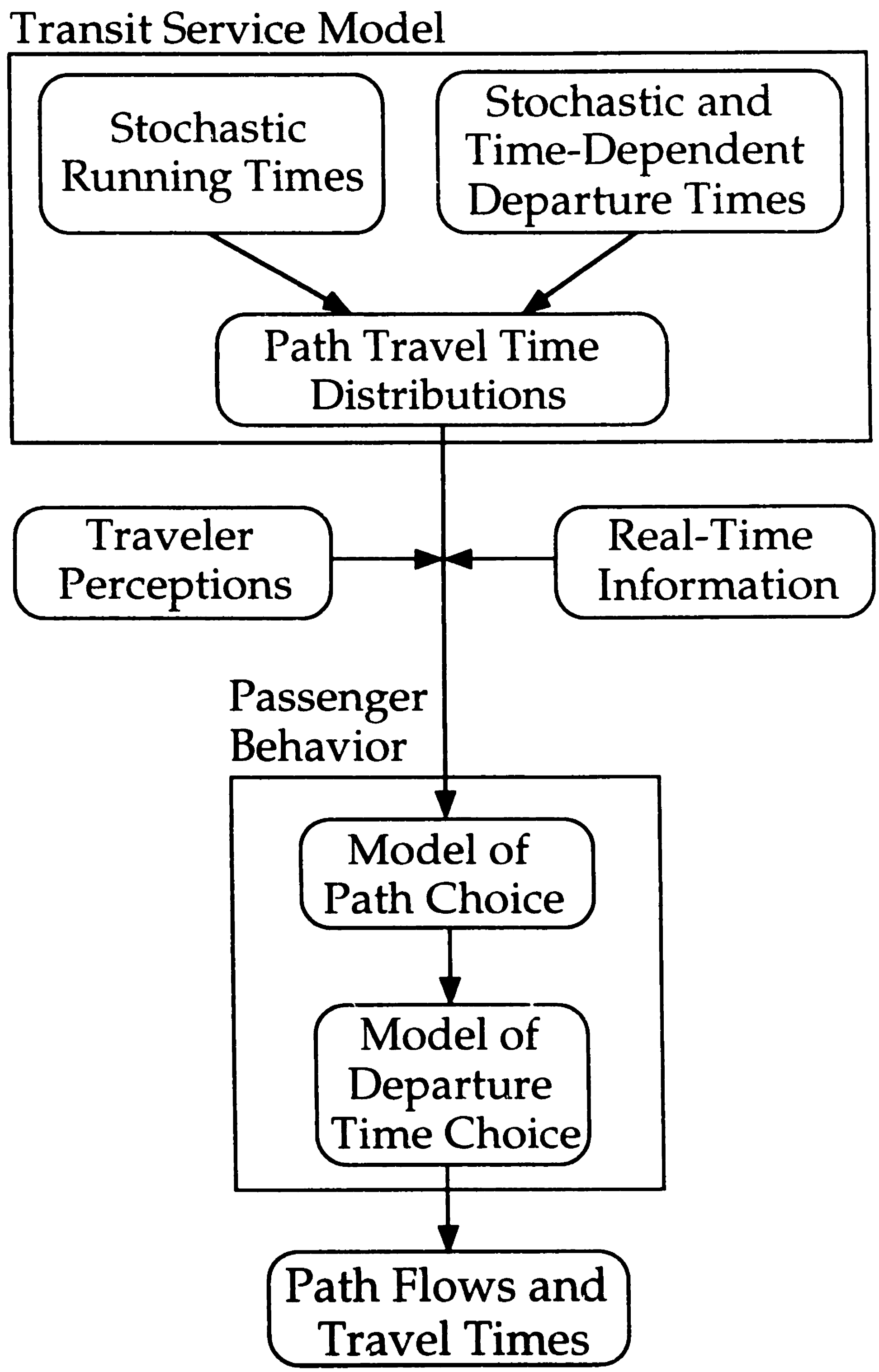

Figure 3-1: Model Framework

day-to-day variations in travel times. In this context, travel times include both vehicle departure times and vehicle running times. This model of transit service is developed in this chapter, and is used extensively in developing models for passenger path and departure time choice in Chapter 4. In this way, the impacts of stochastic and time-dependent transit service on path decisions can be measured.

Passenger decisions may also be influenced by the various dimensions of real-time information about and an individual's perceptions of travel times and transit service. This information and perception modeling is developed in Chapter 5. Using this framework, there is a resulting demand pattern which may be characterized through path decisions and origin-to-destination (o-d) travel times. As a result, potential changes in passenger behavior resulting from real-time information may be analyzed.

The full model framework from Figure 3.1 is developed using computer simulation. The motivation for this simulation and the scope of issues examined by the simulation model are discussed in Chapter 5. Two different networks are simulated under this modeling framework: a hypothetical network developed in detail in Chapter 6 and a real-world corridor network described in Chapter 7. Using this modeling framework, a detailed examination of the travel time impacts of real-time information for public transit passengers is possible.

3.2 Introduction to the Transit Service Model

The first main element of this analysis framework is a model of public transit service that is sufficiently flexible to accommodate the stochastic and time-dependent characteristics of network travel times. In considering models of transit service, then, it is notable that much of the literature describing transit service (discussed in Chapter 2) is oriented toward the transit operator. The route and network models defined by other researchers focus specifically on vehicle schedule adherence and loading. From the passenger's point of view, however, the overall performance of the transit system is measured in terms of that passenger's trip: the overall travel time, fare, level of comfort and convenience, number of transfers, etc. for a specific origin-to-destination (o-d) trip. This passenger orientation is not explicitly considered in most transit service models to date.

The transit service model developed in this thesis focuses on one specific aspect of the passenger's trip: the o-d travel time. Because of the effects of various exogenous and possibly endogenous factors, travel times between any two points in the network are subject to stochastic variation. In terms of vehicle operation, this variation might be caused by instability of traffic conditions, passenger loads, equipment and labor availability, and other external factors (e.g., weather). Because of this variation, vehicles may be delayed over the course of the route.

This variability affects the level of schedule adherence, as perceived by the transit operator, and the level of reliability in o-d travel times to the user. It is important to note that the operator and the user quantify this travel time reliability in different ways: the operator tends to regard reliability in terms of vehicle performance according to a given schedule, while the user regards reliability in terms of his/her trip itself, and not in terms of a specific vehicle's performance. Thus, it is supposed that a passenger's experience of travel time variation is inherent to the individual trip, depending on the chosen origin and destination as well as the possible transit paths connecting these two points.

This chapter, then, develops a transit service model which builds from more traditional models of transit service. Specifically, passenger-oriented distributions of travel times are developed which account for potentially numerous paths which serve a given passenger's origin and destination. The first section describes some of the modeling assumptions which will be necessary for analytical tractability. The second section discusses the model of a simple shuttle service, which is used to describe transit vehicle movements over particular route segments. In the third section, a shuttle *network* model is developed which applies the results of the simple shuttle service to an o-d pair which includes vehicle transfers. The final part of the chapter demonstrates how the shuttle model may be used to model additional networks; in particular, a corridor model is developed which is used later in the case study in Chapter 7.

3.3 Modeling Assumptions

All of the models developed in this thesis assume that transit service may be modeled as a shuttle service. From the point of view of the passenger, the trip over some route segment appears to them as an origin stop, a destination (or possibly a transfer) stop, and some measure of travel time between these two points. When passengers plan their trips, it would appear unlikely that they explicitly consider the boarding and alighting times or running times at intermediate stops on their particular o-d route segment. In this way, the passenger may examine travel times on a route segment using only the initial wait at the origin stop and the travel time from the origin stop to the destination stop upon boarding a vehicle on that route.

While these observations seem fairly obvious from the passenger's view, there are several assumptions made with respect to a shuttle service which need to be discussed before developing the shuttle models. The first major assumption is that the variability in transit travel times occurs because of exogenous factors alone; that is, the variation in travel times is caused by factors which cannot be controlled directly by the transit operator or by the user. The second major assumption is that vehicle departure and running times on routes are not impacted by transit vehicle interactions on that same route. In considering public transit service, one might argue that these assumptions are particularly strong. For this reason, they are discussed at greater length so that they may be more fully appreciated by the reader.

3.3.1 Exogenous Variation in Travel Times

There are both exogenous and endogenous factors which might affect vehicle travel times in a transit network. The exogenous factors affecting link travel times incorporate those factors generally considered beyond the control of the transit operator and the user. First, the level of traffic congestion and the degree of traffic signal control may cause considerable variation in transit travel times. In some cases, the resulting variation in travel times is easily understood: some travel times lie considerably above the daily average (i.e. during peak periods), whereas in off-peak times the travel times may be much lower than the daily mean. Yet, there can be considerable variation in shorter time periods which is not as predictable. For example, in a single peak hour, there can be significantly higher traffic densities during one ten-minute period than at other times in that same peak hour. To the extent that traffic congestion and signal delay are unpredictable, they add variation to travel times. Other exogenous factors such as the weather, accidents and other incidents may significantly disrupt service, often causing substantial delays.

There are other factors which contribute to travel time variability which are under the direct or indirect control of transportation operators and users. The operator has the opportunity to control vehicle and crew availability on a given route. The operator may employ various real-time control strategies to handle absent drivers (or crews) or significantly delayed vehicles. In the course of this analysis, it is assumed that such strategies are in place, to the point that there is *no missed service* on the route during the time period of interest. Furthermore, the impact of real-time control strategies on vehicle performance is assumed to be captured in the existing travel time characteristics (i.e., travel time variation) in the network.

A second endogenous factor which may influence vehicle travel times is the vehicle loading and boarding and alighting patterns. The passenger boarding and alighting processes may take up a substantial amount of the total route travel time. When passenger behavior or significant service delays lead to crowded vehicles, alighting times from the vehicle may increase substantially as passengers crowd the doorways and standing areas of the vehicle. Moreover, vehicle boarding affects travel times, as higher volumes of passengers take a longer time to board. Buses may incur even more delay by stopping at infrequently-used bus stops. When there is significant variance in the arrival patterns of passengers at stations or stops, there is a direct effect on the time vehicles spend picking up and discharging passengers. Many of the previous transit service models have explicitly incorporated the passenger boarding and alighting process (e.g., Andersson and Scalia-Tomba [5], Powell and Sheffi [61], and Marguier [48]). These models, of course, primarily focused on vehicle movements on a route and not on passenger behavior over certain route segments.

This research assumes that passengers view travel on a particular route segment as a shuttle service, with an initial waiting time and vehicle running between the endpoints of the route segment. Also, the potential variation in travel times on the shuttle service due to these exogenous and endogenous factors will be taken into account by the passenger. However, the passenger does not explicitly consider endogenous factors when considering travel time on that route segment. In other words, it is assumed that deviations in travels times may occur based on the operator's real-time control strategies and on the passenger boarding and alighting process, but also that this endogenous variation in travel times is not explicitly incorporated in any passenger decision process. This is consistent with the orientation of the research being toward the passenger's, rather than the operator's, notion of travel time variation on transit routes.

It may be argued that the implications of this assumption are not significant to the research. A passenger, in large part, may have some feel for the level of demand on a particular route segment, but the realization of every potential passengers' decisions on a given day is a very complex and highly stochastic process. At best, a transit passenger may have some idea of the operator's real-time control strategies, but it is unlikely they can effectively understand or predict passenger boarding patterns for a particular route segment on a given day.

The net result, then, is that the shuttle model assumes a given level of variability in transit travel times, for a given vehicle trip. This level of variability may be affected by passenger boarding and alighting patterns, but not in any systematic fashion that the passenger may accurately predict from one day to the next. In this way, the passenger's decision-making process assumes that travel time variation results from factors which are purely exogenous to these boarding decisions.

3.3.2 Independence of Vehicle Departure and Running Times from Vehicle Interactions

In addition to the above assumption about variability in travel times, it is also assumed that vehicle departure times and running times are independent of direct vehicle interactions. In particular, it is assumed that the headways are sufficiently long and the variability of running times sufficiently small that there is no vehicle "bunching" (forming pairs or clusters over the course of the route) or overtaking ("leap-frogging"). This is most likely a good assumption on routes with longer headways (e.g., 10 minutes or more), and where route running times are not very long (e.g., 30 minutes or less).

Routes with shorter headways or with long running times are likely to experience much more variability in service; in these cases, the assumption of no direct vehicle interactions is likely to be violated. Where route headways are small relative to the total travel time (or, more precisely, the total travel time variability) on the route, bunching is likely to occur (as discussed by Newell and Potts [54], Potts and Tamlin [60], Boyd [12], etc.).

The assumption of no direct vehicle interactions (no bunching or overtaking) does not restrict the analysis as much as assuming independence of travel times. Indeed, the models presented in this analysis explicitly allow for some level of correlation between vehicle running times. This permits a certain duration to these exogenous effects which influence vehicle running times. In this way, if one vehicle experiences significant delay over the course of a route, subsequent vehicles might also experience larger than average delays. As this situation is fairly typical in transit systems, the assumption of independence of vehicle running times and departure times is generally too strong.

A less constraining assumption, then, is that vehicles do not bunch over the course of a one-way trip, and that there is no vehicle overtaking. In this way, vehicles depart and arrive at route terminals in a FIFO (first-in-first-out) manner. In this case, vehicle running times might indeed be correlated, but vehicle movements are still FIFO and not constrained by other vehicle movements over the course of a route. Ways of incorporating the correlation of vehicle travel times will be discussed at a later point in this chapter.

3.4 The Shuttle Model

Given these two assumptions about the nature of transit service, this section develops the basic building block of the research, a model of a simple shuttle service between two points. This model represents vehicle movements in a stochastic and time-dependent manner. With this in mind, the goal of this section is to describe vehicle movements for this shuttle. To this end, the model yields an iterative approach so that, given a running time distribution between any two terminals in a network, distributions of vehicle departure times and arrival times for such a shuttle may be derived. This section first describes the basic parameters of the shuttle model and then demonstrates how the corresponding travel time distributions may be determined in an iterative fashion.

3.4.1 Model Parameters

For the analysis in this section, assume that there are two points (or nodes), labelled A and B, connected by a bi-directional route (or route segment) served at any given point in time by a set of N vehicles. In order to keep a consistent trip labelling scheme, vehicle trips are labelled in a one-directional fashion, yet with a round trip index j. In this case, the trip from A to B is trip j, and the subsequent trip from B to A is j'. Thus, a vehicle leaves A on trip j, arrives at B, and leaves B on trip j'. After it returns to A, it departs on trip $j+N$ from A to B, then on $(j+N)'$ from B to A, etc.

At each station, A and B, there is an assumed minimum layover time referred to as L_A and L_B, respectively. So, even if a vehicle is running behind schedule, it will be dispatched on its subsequent trip no earlier than L time units after its arrival at the terminal. The scheduled time of departure of the j^{th} vehicle round trip, leaving A, will be denoted TD_j, and similarly, its subsequent scheduled arrival time at B will be denoted TA_j. For the return trip from B, the scheduled departure time from B and the scheduled arrival time at A will be denoted $TD_{j'}$ and $TA_{j'}$, respectively. Of course, it is assumed that the schedules are constructed to account for the minimum layover time; therefore, $TD_{j'} \geq TA_j + L_B$ and $TD_{j+N} \geq TA_{j'} + L_A$. For the analysis, there is a presumed scheduled headway H_o between vehicles, where H_o is defined by $H_o \equiv TD_j - TD_{j-1}$, for $j > 1$. Without any loss of generality, one may also define $TD_1 \equiv 0$.

An "on-time" departure means that the vehicle is able to depart at its given scheduled departure time. In reality, it is assumed that on-time departures are distributed continuously over a (perhaps very short) time interval; e.g., 30 seconds or one minute. Given the minimum layover times L_A and L_B, it is helpful to define the latest time a vehicle can arrive at a terminal and still make its subsequent departure on time. This time is defined for each trip using the notation TA^*, which is the scheduled time of departure of the vehicle's next trip, minus the minimum layover time. Thus, $TA_j^* \equiv TD_{j'} - L_B$, where TA_j^* is the latest time of arrival of trip j so that the same vehicle can depart from terminal B on trip j' at $TD_{j'}$, its scheduled departure time. Similarly, $TA^*_{j'} \equiv TD_{j+N} - L_A$.

The discussion and derivation of distributions below will center around the distribution of running times of vehicles on the shuttle route. There is an assumed stochastic nature to the running times between the two points, A and B. As discussed above, the assumption is made that the stochastic variation in running times is caused by *exogenous* factors alone; i.e., variation in travel times is not caused by elements related to the vehicle, its operation, or the passenger demand.

Given this assumption, one further assumption is made that running times between the two endpoints of the shuttle route are independent of the time of day, *within the specified planning horizon*. This assumption implies that no matter what time a vehicle leaves its origin, the travel time to its destination is not related to that departure time. This assumption allows some flexibility in the model formulation, but ignores potential systematic differences in travel time distributions within the planning period (e.g., no systematic variation *within* a three-hour morning peak period).

3.4.2 Model Development

The following notation will be helpful to characterize the distributions presented in this section. The development follows the distributions of trip j from A to B, although the orientation of A and B is arbitrary. Trip j is chosen out of convenience of notation.

- τ or y = a time of day; τ may be defined as the time since $TD_1 = 0$.

- x or z = a duration of time; e.g., x minutes since the last departure.

- $f_0(x)$ = departure time distribution for an "on-time" departure from a given terminal. The variable x represents the time since a vehicle's scheduled departure time TD. An on-time departure is characterized by a continuous distribution, perhaps very steeply sloped and constrained to a very short time interval beginning at TD.

- $f_{td_j}(\tau)$ = departure time distribution of trip j from point A. Observe that the first N departures are on time; i.e., $f_{td_j}(\tau) = f_0(\tau)$ for $j \leq N$.

- $\phi_{AB}(x)$ = running time distribution from A to B. Note that this distribution is independent of the vehicle trip.

- $\phi_j(x)$ = actual running time distribution for trip j from A to B, assuming that there may be correlation between running times such that the distribution is dependent on the vehicle trip.

- $f_{ta_j}(\tau)$ = arrival time distribution of trip j at point B.

- G_j = the probability that a vehicle arrives at terminal A from trip $(j-N)'$ in time to make an "on-time" departure on its next trip, j. Formally,

$$G_j = \begin{cases} 1.0 & \forall j \leq N \\ \int_0^{TA^*_{(j-N)'}} f_{ta_{(j-N)'}}(y)\,dy & \forall j > N \end{cases} \tag{3.1}$$

Trip Indexing of Running Time Distributions

It is suggested above that the running time distribution for a given vehicle between nodes A and B, given that there is no correlation in vehicle running times, is given by $\phi_{AB}(x)$. The running time distribution of $\phi_{BA}(x)$ represents the similar distribution for the return trip from B to A. It is at this point that the additional assumption that vehicle headways are sufficiently long, and running times sufficiently short, that there is no vehicle bunching or overtaking is employed. If, on the other hand, vehicle travel times are correlated over time (which is indeed quite possible), it will be necessary to relate the running time distribution to each individual trip, using the notation $\phi_j(x)$. It is assumed in this case that correlation between vehicle running times will be of the first order, and is given by the parameter ρ. The model development uses the distribution ϕ_{j-1}, which is the running time distribution of the $j-1^{th}$ (with $j > 1$) vehicle trip from A to B, as well as a particular realization of that running time x_{j-1}. The running time x_j is then conditioned on the observed value x_{j-1}. Using the random variable z from the running time distribution $\phi_{AB}(x)$, the following formula may be used to determine the running time x_j (e.g., in a simulation experiment):

$$x_j = \rho \cdot x_{j-1} + (1-\rho) \cdot z \tag{3.2}$$

For a given value of x_{j-1}, the value of x_j has the desired level of correlation. Using equation (3.2), the conditional distribution of x_j may be derived. Using straightforward probability arguments,

$$\Pr\{x \leq X | x_{j-1}\} = \Pr\{\rho \cdot x_{j-1} + (1-\rho) \cdot z \leq X\} \tag{3.3}$$

And, using the distribution $\phi_{AB}(x)$ as the distribution of z, the following conditional distribution is attained:

$$\phi_j(x|x_{j-1}) = \phi_{AB}(\frac{x - \rho \cdot x_{j-1}}{1-\rho}) \tag{3.4}$$

Building on this conditional running time distribution, the unconditioned running time distribution for trip j is given as:

$$\phi_j(x) = \int_0^{\infty} \phi_j(x|x_{j-1}) \cdot \phi_{j-1}(x_{j-1})\, dx_{j-1} \tag{3.5}$$

By substituting equation (3.4) in equation (3.5), the final unconditioned running time for vehicle trip j may be computed as:

$$\phi_j(x) = \int_0^{\infty} \phi_{AB}(\frac{x - \rho \cdot x_{j-1}}{1-\rho}) \cdot \phi_{j-1}(x_{j-1})\, dx_{j-1} \qquad \forall j > 1 \tag{3.6}$$

Using the boundary condition that $\phi_1(x) = \phi_{AB}(x)$, equation (3.6) yields a set of iterative relationships to determine the running time distributions for each vehicle trip j, when first-order correlation of running times may occur. The discussions that follow simply use the notation $\phi_j(x)$ to denote the running time distribution on trip j, which is equal to $\phi_{AB}(x)$ if no correlation is present, or is given iteratively by equation (3.6) if correlation does exist. If there is no correlation of running times across vehicle trips, then the distribution $\phi_{AB}(x)$ may be substituted for $\phi_j(x)$, $\forall j$, in all subsequent equations to determine vehicle departure time and arrival time distributions.

Arrival and Departure Time Distributions

The first observation is that the distribution of departure times on subsequent trips can be computed in terms of the arrival time distributions. An additional assumption made here is that no vehicle will leave on a trip before its scheduled departure time. This assumption is made without loss of generality; the assumption here simply refers to the earliest possible departure time for a vehicle trip as its *scheduled* departure time. In this case, a vehicle will leave "on time," according to the departure distribution $f_0(x)$, if it arrives from its previous trip in time to do so, or else it will leave L time units after its arrival at the terminal. That is, the distribution of *departure times* for trip j can be characterized as

$$f_{td_j}(\tau) = \begin{cases} f_0(\tau - TD_j) & \text{for an on-time departure, and } \forall j \leq N \\ f_{ta_{(j-N)'}}(\tau - L_A) & \text{for a late departure, } j > N \end{cases} \tag{3.7}$$

or, using the associated probability of an on-time arrival from equation (3.1),

$$f_{td_j}(\tau) = G_j \cdot f_0(\tau - TD_j) + (1 - G_j) \cdot f_{ta_{(j-N)'}}(\tau - L_A) \quad \forall j > N \tag{3.8}$$

Thus, equations (3.1) and (3.8) are defined in terms of the distribution of vehicle arrival times, yet to be defined. The distribution of *arrival times* of trip j, then, is the convolution of this departure time distribution with the running time distribution $\phi_j(x)$, which may be trip-dependent. Then,

$$f_{ta_j}(\tau) = \int_{TD_j}^{\tau} f_{td_j}(y)\, \phi_j(\tau - y)\, dy \tag{3.9}$$

Based on the definition of an on-time departure given above, the following arrival time distribution is given for the first N trips:

$$f_{ta_j}(\tau) = \int_{TD_j}^{\tau} f_0(y - TD_j)\, \phi_j(\tau - y)\, dy \qquad j \leq N \tag{3.10}$$

Furthermore, using the departure time distribution as shown in equation (3.8), substituting in equation (3.9) yields:

$$\begin{aligned} f_{ta_j}(\tau) &= G_j \cdot \int_{TD_j}^{\tau} f_0(y - TD_j)\phi_j(\tau - y)\, dy \\ &\quad + (1 - G_j) \cdot \int_{TD_j}^{\tau} f_{ta_{(j-N)'}}(y - L_A)\, \phi_j(\tau - y)\, dy \quad \forall j > N \end{aligned} \tag{3.11}$$

So, equations (3.10) and (3.11) define a recursive relationship for computing the distribution of arrival times of a trip j, given the "on-time" departure time distribution

Figure 3-2: A Single Shuttle

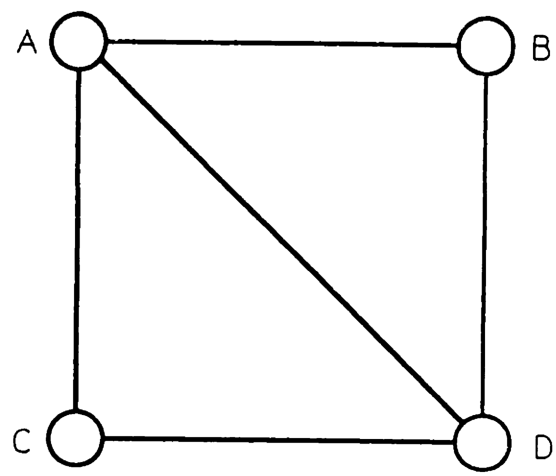

Figure 3-3: The Shuttle Network

$f_0(x)$ and a running time distribution $\phi_j(x)$. The arrival time distribution for a given trip can be determined based on that trip's running time distribution, convoluted with the previous trip's arrival time distribution.

3.5 The Shuttle Network

This section describes a model of a simple shuttle network, with transit service operating over five routes between four terminals. This model builds upon the one developed above, described as a simple shuttle operating between two terminals, A and B, which is shown in Figure 3-2. Figure 3-3 shows the obvious extension to the five shuttle routes and four terminals to be discussed in this section.

The goal of this section is to determine the distribution of travel times through this shuttle network for a given user. This is in contrast to the previous section, which was directed at examining the specific characteristics of individual vehicle trips over a single shuttle route. In this case, there are several paths composed of a shuttle or a sequence of shuttles going from the origin to the destination. By characterizing the distribution of travel times through this network, it is possible to examine how users might choose among various paths based on the stochastic and time-dependent travel times.

This shuttle network has several advantages. First, the network allows a fairly simple representation of a person's trip by transit, with the passenger choosing among several transit paths which serve his/her origin and destination, explicitly considering paths which include transfers. Second, the network allows a significant level of analysis for path choice and real-time passenger information. It is likely that particular sub-networks in the transit system, rather than the entire system, may be better suited for implementation of passenger information systems. Finally, for the purposes of this thesis, the network is small enough to allow more detailed analysis and investigation than might be possible on larger networks.

The discussion in this section is organized into two parts. First, there is a review of the additional assumptions for the network analysis. The second part characterizes the distributions of travel times between two points in the shuttle network. Specifically, for a user traveling on any path from terminal A to terminal D, and arriving at A at a time T, this section characterizes the distribution of the waiting times for both the initial boarding and subsequent connections in the network, and the distribution of the arrival and departure times at each terminal in the network. As a result of these distributions, more specific passenger travel decisions can be examined. The reader is referred again to the definitions of route and path given at the beginning of Chapter 2, as they will be used quite extensively below.

3.5.1 Modeling Assumptions

It is assumed that each shuttle route runs more or less independently of every other shuttle. In other words, the vehicles which operate on each of the five shuttle routes operate only on that route. Several characteristics of these five shuttle routes are shown in Table 3.1. The "Index" column in this table describes the indices for random variables like the arrival times and departure times of specific vehicle trips. When a

Table 3.1: Routes for the Shuttle Network

Shuttle	Vehicle Trip Index	Headway	Number of Vehicles
A-B	j	H_{AB}	N_{AB}
A-C	k	H_{AC}	N_{AC}
A-D	i	H_{AD}	N_{AD}
B-D	l	H_{BD}	N_{BD}
C-D	m	H_{CD}	N_{CD}

certain variable corresponding to a shuttle is independent of the vehicle trip, it will simply be indicated by the two terminals of the shuttle; for example, the running time distribution from A to B (assuming independence of running times) is $\phi_{AB}(x)$. The notation here is consistent with that presented above; e.g., TD_j represents the scheduled departure time of vehicle trip j from A to B.

The two prior assumptions will also be used in this analysis. First, the running times and therefore the vehicle arrival and departure time distributions are caused by exogenous factors such as traffic congestion, weather, etc. Specifically, variation in travel times is not caused by elements related to the vehicle, its operation, or passenger demand. More importantly, due to resulting complexity of the problem when vehicle interactions (e.g., bunching and leap-frogging) are included, it is assumed that each vehicle does not interact with any preceding or subsequent transit vehicle on a given route. A direct result of this assumption is that a given user will always take the next vehicle to travel on a given route; there are no advantages to be gained by waiting for subsequent vehicle departures in this model.

For the analysis which follows, it is supposed that a single user arrives at terminal A at a time T. The traveler can simply ride from A to D on the A-D shuttle, or he/she can travel via two separate shuttles through either terminal B or terminal C. It will be helpful to define path 1 as A-B-D, path 2 as A-D, and path 3 as A-C-D. The object again is to examine the distribution of arrival times at the destination D for each of these three paths.

3.5.2 Model Development

The following notation (in addition to that described in Section 3.4.2) will be helpful to characterize the distributions presented in this section. The derivations below discuss the distributions of path travel times on shuttle A-D (path 2) or via the two-shuttle path A-B-D (path 1); results for the A-C-D trip (path 3) are similar to those for path 1.

- W_{AB} = the random variable for the waiting time for travel on shuttle A-B.
- $f_{W_{AB}}$ = the probability density function for the waiting time for the next vehicle to depart on shuttle A-B.
- $f_a^{Kp}(\tau)$ = the probability density function of the passenger's arrival time at node K at time τ, given that K is on path p. The goal of this analysis is to find f_a^{Dp} for paths p = 1, 2, 3. The cumulative distribution function of this arrival time is denoted as $F_a^{Kp}(\tau)$.
- $f_d^{Kp}(\tau)$ = the probability density function of the **user's** departure time from node K as a function of time τ, given that the passenger is on path p at node B.
- $g^p(x|T)$ = the probability density function of the total travel time from origin A to destination D using path p, assuming an initial passenger arrival at the origin A at time T. This distribution is the aim of the research described in this section.
- $I(AB, y)$ = the index of the most recent scheduled vehicle departure, on route AB, before time y. For example, if $TD_j \leq y < TD_{j+1}$, then $I(AB, y) = j$.

It is important to remember that *all of the distributions derived in the following sections are conditional upon the actual moment of arrival of the passenger to terminal A*; that is, all of the distributions are conditional on the passenger's arrival time T.

Initial Waiting Time Distribution

The transit passenger arrives at terminal A at time T. As noted above, if the passenger chooses to travel over a certain path from terminal A to terminal D, he/she will automatically board the next available vehicle on the first shuttle route in that path. Clearly, the time T falls between two different scheduled vehicle departures from A for each route having A as a terminal. For example, for route A-B, T falls between the scheduled departure for vehicle trip j and that for vehicle trip $j+1$; mathematically, $TD_j \leq T < TD_{j+1}$.

The assumption is made that there are no direct vehicle interactions on these shuttle routes. Under this assumption, given that a person arrives at time T and desires to board the next vehicle on path 1, he/she will board vehicle j if it has not yet departed or vehicle $j+1$ if vehicle trip j has already departed. This means that the set of possible vehicle trips on a given shuttle route for an arrival at time T includes only j and $j+1$. Clearly, in cases where vehicle trip j has already departed by time T (i.e., with probability 1.0), the possible vehicle trip set is reduced simply to $\{j+1\}$.

The time spent waiting for the next vehicle trip to depart on route A-B is the time between T and the departure time of the next vehicle. If the vehicle trip j has not yet departed, the waiting time W_{AB} is the time until the j^{th} vehicle trip departs. The probability of vehicle trip j not having departed by time T is simply $1 - F_{td_j}(T)$. If vehicle trip j has already departed (with probability $F_{td_j}(T)$, then the waiting time is the time between T and the departure time of vehicle trip $j+1$.

Mathematically,

$$\Pr\{W_{AB} \leq w\} = \Pr\{T \leq td_j \leq T + w\} + \Pr\{td_j, td_{j+1} : td_j < T, td_{j+1} \leq T + w\} \quad (3.12)$$

Assuming independence of vehicle departure times, the second expression in equation (3.12) may be rewritten as:

$$\Pr\{td_j, td_{j+1} : td_j < T, td_{j+1} \leq T + w\} = \Pr\{td_j < T\} \cdot \Pr\{td_{j+1} \leq T + w\} \quad (3.13)$$

The assumption that vehicle departures are independent may seem suspect, given that vehicle running times are correlated across vehicle trips. In particular, the assumption that vehicle running times may be correlated across vehicle trips may affect the waiting time distribution. Specifically, the departure time distribution for a vehicle as defined in equation (3.8) and the recursive equation (3.11) for vehicle arrival times use the running time distribution $\phi_j(x)$. Use of these equations in determining departure time distributions will explicitly incorporate the correlation between vehicle departure times. Thus, the waiting time distributions developed here will also explicitly allow for correlation in vehicle departure times. This allows the assumption of independence of departure times.

Replacing the second expression in equation (3.12) with equation (3.13), one arrives at the following equation:

$$\Pr\{W_{AB} \leq w\} = F_{td_j}(T+w) - F_{td_j}(T) + F_{td_j}(T) \cdot F_{td_{j+1}}(T+w) \tag{3.14}$$

Note that in the case where $W_{AB} < TD_{j+1} - T$, that is, where the waiting time W_{AB} is less than the time until the next scheduled departure, $F_{td_{j+1}}(T+w) = 0$, and the last term is 0. In the case where $F_{td_j}(T) = 1.0$, vehicle trip j has already departed and the waiting time W_{AB} is at least $TD_{j+1} - T$.

Taking the derivative of equation (3.14) with respect to w gives the following probability density function for the waiting time W_{AB}:

$$f_{W_{AB}}(w) = f_{td_j}(T+w) + F_{td_j}(T) \cdot f_{td_{j+1}}(T+w) \tag{3.15}$$

The assumption of no direct vehicle interactions (no bunching or overtaking) also means that departure delays will not exceed more than a single headway; i.e., $f_{td_j}(\tau) = 0$ for $\tau \geq TD_{j+1}$. This assumption is based on the hypothesis that a shuttle operator will schedule sufficient layover time at each terminal, and provide a sufficient level of on-route control, to avoid delays in vehicle departures of more than one headway. Under this assumption, equation (3.15) decomposes into the following form:

$$f_{W_{AB}}(w) = \begin{cases} f_{td_j}(T+w) & w < TD_{j+1} - T \\ F_{td_j}(T) \cdot f_{td_{j+1}}(T+w) & w \geq TD_{j+1} - T \end{cases} \tag{3.16}$$

Note that this distribution could be bi-modal, if the arrival time T is such that $0 < F_{td_j}(T) < 1$, or, alternatively, there is a positive probability (but less than 1.0) that vehicle trip j has not departed by time T.

In a similar derivation to that shown previously, the waiting times on other routes originating at terminal A may be described as follows:

$$f_{W_{AD}}(w) = \begin{cases} f_{td_i}(T+w) & w < TD_{i+1} - T \\ F_{td_i}(T) \cdot f_{td_{i+1}}(T+w) & w \geq TD_{i+1} - T \end{cases} \tag{3.17}$$

$$f_{W_{AC}}(w) = \begin{cases} f_{td_k}(T+w) & w < TD_{k+1} - T \\ F_{td_k}(T) \cdot f_{td_{k+1}}(T+w) & w \geq TD_{k+1} - T \end{cases} \tag{3.18}$$

Finally, the passenger's departure time distribution from terminal A on any given route can be characterized by the following expressions.

$$f_d^{A1}(\tau) = f_{W_{AB}}(\tau - T) \tag{3.19}$$

$$f_d^{A2}(\tau) = f_{W_{AD}}(\tau - T) \tag{3.20}$$

$$f_d^{A3}(\tau) = f_{W_{AC}}(\tau - T) \tag{3.21}$$

First Shuttle Arrival Time Distribution

With the arrival of a passenger at time T and a subsequent waiting time at the origin stop A, the user will travel on some initial shuttle route according to the distribution of running times over that route. The arrival time at the next terminal of one of these shuttles, then, is the current time T plus the sum of the waiting time for the given shuttle and the running time from terminal A to the other shuttle terminal. The probability of arriving at this intermediate (or final) terminal at a given time τ is simply the probability that the sum of the waiting time and the running time is less than or equal to $\tau - T$.

The arrival time at B may be characterized with respect to the waiting time at point A for the shuttle A-B and the running time from A to B. For a given waiting time of w and an arrival at B at time τ, the running time from A to B is equal to $\tau - T - w$. Integrating over all possible values of w, then, and assuming some generic running time distribution $\phi_{AB}(x)$, the following equation holds:

$$f_a^{B1}(\tau) = \int_0^{\tau - T} f_{W_{AB}}(w) \cdot \phi_{AB}(\tau - T - w)\, dw \tag{3.22}$$

Furthermore, by substituting the results of the previous section for the waiting time distributions (i.e., using equation (3.16) in equation (3.22) and by using vehicle-specific running time distributions, the resulting mathematical form of the arrival time distribution at B is given by:

$$
\begin{aligned}
f_a^{B1}(\tau) &= \int_T^{TD_{j+1}} f_{td_j}(y) \cdot \phi_j(\tau - y)dy \\
&\quad + F_{td_j}(T) \cdot \int_{TD_{j+1}}^{\tau} f_{td_{j+1}}(y) \cdot \phi_{j+1}(\tau - y)\,dy \qquad \tau \geq TD_{j+1} \qquad (3.23)
\end{aligned}
$$

Of course, if it is possible (with long headways and relatively short running times) to have vehicle trip j arrive at B before TD_{j+1}, then $f_a^{B1}(\tau)$ may have non-zero value for $\tau < TD_{j+1}$. In this case,

$$
f_a^{B1}(\tau) = \int_T^{\tau} f_{td_j}(y) \cdot \phi_j(\tau - y)\,dy \qquad \tau < TD_{j+1} \qquad (3.24)
$$

Similar derivations would show that the distributions of arrival times at D and C on paths 2 and 3, respectively, are:

$$
\begin{aligned}
f_a^{D2}(\tau) &= \int_T^{\tau} f_{td_i}(y) \cdot \phi_i(\tau - y)\,dy \qquad \tau < TD_{i+1} \qquad (3.25) \\
f_a^{D2}(\tau) &= \int_T^{TD_{i+1}} f_{td_i}(y) \cdot \phi_i(\tau - y)dy \\
&\quad + F_{td_i}(T) \cdot \int_{TD_{i+1}}^{\tau} f_{td_{i+1}}(y) \cdot \phi_{i+1}(\tau - y)\,dy \qquad \tau \geq TD_{i+1} \qquad (3.26)
\end{aligned}
$$

$$
\begin{aligned}
f_a^{C3}(\tau) &= \int_T^{\tau} f_{td_k}(y) \cdot \phi_k(\tau - y)\,dy \qquad \tau < TD_{k+1} \qquad (3.27) \\
f_a^{C3}(\tau) &= \int_T^{TD_{k+1}} f_{td_k}(y) \cdot \phi_k(\tau - y)dy \\
&\quad + F_{td_k}(T) \cdot \int_{TD_{k+1}}^{\tau} f_{td_{k+1}}(y) \cdot \phi_{k+1}(\tau - y)\,dy \qquad \tau \geq TD_{k+1} \qquad (3.28)
\end{aligned}
$$

Second Waiting Time (or Transfer Time) Distribution

As in the first waiting time, the passenger arrives at B on shuttle A-B at a certain point in time τ, which is between two different scheduled departures on shuttle B-D. That is, using the notation for the B-D shuttle from Table 3.1, $TD_l \leq \tau < TD_{l+1}$. However, in this case, depending on the domain of the arrival time distribution $f_a^{B1}(\tau)$ and the corresponding headway of shuttle B-D, H_{BD}, it is possible that a passenger might arrive on shuttle A-B during any number of such intervals.

It is reasonable to assume that a passenger arriving on shuttle A-B will take the next available shuttle vehicle on B-D to reach their destination D. If travel times on shuttle route A-B are relatively unreliable or the headway H_{BD} is relatively short (or both), then the passenger may have the possibility of a number of connecting vehicles at B.

To begin, one may examine the simple case of an arrival at B of τ, where $TD_l \leq \tau < TD_{l+1}$. As in equation (3.16), the waiting time can be characterized as follows:

$$fw_{BD}(w) = \begin{cases} f_{td_l}(\tau + w) & w < TD_{l+1} - \tau \\ F_{td_l}(\tau) \cdot f_{td_{l+1}}(\tau + w) & w \geq TD_{l+1} - \tau \end{cases} \quad (3.29)$$

Now, the result of equation (3.29) may be convoluted over all possible values of τ between TD_l and TD_{l+1}. This yields the following equation:

$$\begin{aligned} fw_{BD}(w) &= \int_{TD_l}^{TD_{l+1}-w} f_{td_l}(y + w) \cdot f_a^{B1}(y)dy \\ &+ \int_{TD_{l+1}-w}^{TD_{l+1}} F_{td_l}(y) \cdot f_{td_{l+1}}(y + w) \cdot f_a^{B1}(y)dy \end{aligned} \quad (3.30)$$

This equation naturally assumes that all potential arrival times from shuttle A-B fall between TD_l and TD_{l+1}. To account for the full range of potential connections, it is necessary to sum the right hand side of equation (3.30) over all the indices of possible connecting trips. Rather than a potentially complicated summation, the notation $I(AB, y)$ is used again, where $I(AB, y)$ is the index of the last scheduled vehicle before time y to depart on route A-B. Using this notation, the integrals in equation (3.30) may be revised to cover all vehicle departures:

$$fw_{BD}(w) = \int_T^\infty \left[f_{td_{I(BD,y)}}(y + w) + F_{td_{I(BD,y)}}(y) \cdot f_{td_{I(BD,y)+1}}(y + w)\right] \cdot f_a^{B1}(y)dy \quad (3.31)$$

In this equation, since vehicle departure time distributions are assumed not to overlap, only one of the terms in the large brackets will be non-zero, for a given y. The waiting time distribution for the transfer connection on path 1 is thus given by equation (3.31). Comparable results exist for connections from shuttle route A-C to route C-D:

$$fw_{CD}(w) = \int_T^\infty \left[f_{td_{I(CD,y)}}(y + w) + F_{td_{I(CD,y)}}(y) \cdot f_{td_{I(CD,y)+1}}(y + w)\right] \cdot f_a^{C3}(y)dy \quad (3.32)$$

Using the above characterization of the waiting time distribution for connections at B, it is also possible to define the probability density function for the departure time of the passenger from terminal B headed to terminal D. For a given arrival at B at time y, a passenger will depart on the next vehicle trip on route B-D at a time τ if his/her waiting time is $W_{BD} = \tau - y$. Integrating over all possible values of y, the following distribution of departure times is determined:

$$f_d^{B1}(\tau) = \int_T^\tau f_a^{B1}(y) \cdot f_{w_{BD}}(\tau - y)dy \tag{3.33}$$

The distribution of arrival times at B on path 1, $f_a^{B1}(y)$, is given in equations (3.23) and (3.24), while the distribution of waiting times at B $f_{W_{BD}}(\tau - y)$ is given in equation (3.31). A similar result holds for the distribution of departure times from terminal C on route C-D:

$$f_d^{C3}(\tau) = \int_T^\tau f_a^{C3}(y) \cdot f_{w_{CD}}(\tau - y)dy \tag{3.34}$$

Second Shuttle Arrival Time Distribution

The distribution of arrival times at terminal D for the paths with transfers (numbered 1 and 3) involves the final step of convoluting the running time distributions for these second shuttles with the departure time distributions shown in equations (3.33) and (3.34) above. Since the running time distributions on these final shuttle routes may be correlated and thus may be based on a particular trip index, the notation $I(BD, y)$ will be used to describe the index of the latest scheduled departure on shuttle route B-D before time y. Then, the calculation of the arrival time distribution for both path 1 through terminal B and path 3 through terminal C is given by:

$$f_a^{D1}(\tau) = \int_T^\tau f_d^{B1}(y) \cdot \phi_{I(BD,y)}(\tau - y)dy \tag{3.35}$$

$$f_a^{D3}(\tau) = \int_T^\tau f_d^{C3}(y) \cdot \phi_{I(CD,y)}(\tau - y)dy \tag{3.36}$$

Thus, the travel time distributions for each o-d path can be derived. The probability distribution of arrival times at D can be used together with the assumption of

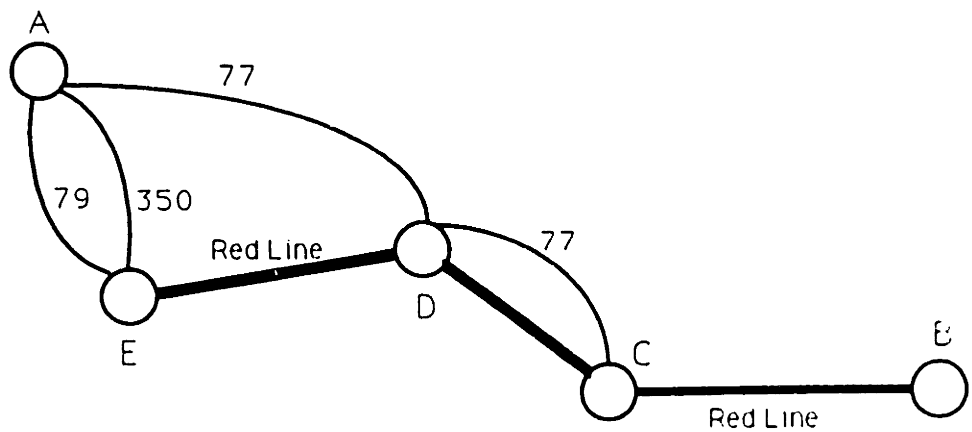

Figure 3-4: The Arlington-Cambridge-Boston Corridor

an initial arrival at the origin stop at time T to obtain:

$$g^1(x|T) = f_a^{D1}(T+x) \tag{3.37}$$

$$g^2(x|T) = f_a^{D2}(T+x) \tag{3.38}$$

$$g^3(x|T) = f_a^{D3}(T+x) \tag{3.39}$$

Equations (3.37), (3.38) and (3.39) are based on the results of equations (3.35), (3.25) with (3.26), and (3.36), respectively.

3.6 Other Networks

This section briefly describes an additional transit corridor which will be investigated as part of the case study for Chapter 7. In this case study, the network requires a transfer and there are a considerable number of o-d paths. The network shown in Figure 3-4 represents a particular corridor in the Massachusetts Bay Transportation Authority system, which will be described in greater detail in Chapter 7.

Table 3.2: Routes for Case Study Network - Inbound

Route Segment	Vehicle Trip Index	Headway
A-E (79)	i	$H_{AE(79)}$
A-E (350)	j	$H_{AE(350)}$
A-D	k, AD	$H_{AD(77)}$
D-C (77)	k, DC	$H_{DC(77)}$
E-D	i, ED	H_{EB}
D-C (Rail)	i, DC	H_{EB}
C-B	i, CB	H_{EB}

Table 3.3: Routes for Case Study Network - Outbound

Route Segment	Vehicle Trip Index	Headway
B-C	i, BC	H_{BE}
C-D (Rail)	i, CD	H_{BE}
D-E	i, DE	H_{BE}
C-D (77)	j, CD	$H_{CD(77)}$
D-A	j, DA	$H_{DA(77)}$
E-A (79)	l	$H_{EA(79)}$
E-A (350)	m	$H_{EA(350)}$

In this case, there are various paths available to a transit user traveling between Arlington Center (A) and Boston (B). There is a single rapid rail line (the Red Line) which serves stations at Alewife (E), Porter (D), Harvard (C) and Park Street (B). There is a bus connection from Arlington Center (A) to Alewife (E) using route 79 or 350, and to Porter (D) and Harvard (C) stations using route 77. Trips inbound and outbound require a transfer between one of the three bus routes and the Red Line. For the trip from A to B, there are four different paths, described in Table 3.2. The four different paths from B to A (the return trip) are described in Table 3.3.

The rapid rail line and each of the bus routes has constant scheduled headways for the period of analysis (i.e. the morning and evening peak). Specific vehicle trips on the rapid rail line have a consistent trip index over the whole line, but travel times are indexed with the additional nomenclature of the route segment. Other assumptions and notation will follow that presented in Section 3.5.1.

For the inbound trip, the assumption is made that a person arrives at A at a time T and desires to know the distribution of arrival times at the destination B.

Table 3.4: Origin-Destination Paths for Case Study - Inbound

O-D Path	Node Sequence
1	A-E (79), Transfer, E-D-C-B
2	A-E (350), Transfer, E-D-C-B
3	A-D, Transfer, D-C-B (Rail)
4	A-D-C (77), Transfer, C-B

Table 3.5: Origin-Destination Paths for Case Study - Outbound

O-D Path	Node Sequence
1	B-C, Transfer, C-D-A (77)
2	B-C-D, Transfer, D-A (77)
3	B-C-D-E, Transfer, E-A (79)
4	B-C-D-E, Transfer, E-A (350)

A similar assumption is made for the outbound trip from B to A. The traveler may choose among four (4) different paths in each direction, described in Table 3.4 for the inbound trip and Table 3.5 for the outbound trip. Again, the goal of this section is to describe the distribution of travel times in the network on each of these paths.

3.6.1 Rapid Rail and Bus Travel Time Distributions

A derivation similar to that presented in Section 3.5.2 may be used to develop the o-d travel time characteristics on each of these four paths. However, the running times on the rapid rail line should be discussed in greater detail. In particular, the simple shuttle network assumes that travel times on different shuttles are independent. In this case, this independence assumption is clearly violated; for example, the rail departures outbound from C depend on vehicle movements from B to C, and rail departures inbound from C depend on vehicle movements from E to D and from D to C.

To accommodate this issue, a modified network representation may be used, drawing from the literature in Chapter 2. Specifically, new arcs may be constructed representing connections of non-adjacent nodes on a common route. In this case, travel between Harvard (C) and Arlington (A) on the route 77 bus may be described by creating a new arc connecting A and C, and a new running time distribution for this node pair. Similarly, new arcs between B and D and between B and E may also be added for the Red Line, with new running time distributions for these arcs.

In terms of describing running time distributions for the rail line, it is assumed that $\phi_{l,ED}(x)$, $\phi_{l,DC}(x)$, and $\phi_{l,CB}(x)$ are given as the running time distributions for each inbound route link, respectively. The running time distributions for travel on the rail line for the route segments from D to B and from E to B for the inbound trip are then given by:

$$\phi_{i,DB}(x) = \int_0^x \phi_{i,DC}(z) \cdot \phi_{i,CB}(x-z)\,dz \tag{3.40}$$

$$\phi_{i,EB}(x) = \int_0^x \int_0^x \phi_{i,ED}(z) \cdot \phi_{i,DC}(y-z) \cdot \phi_{i,CB}(x-y-z)\,dy\,dz \tag{3.41}$$

For the outbound trip, the running time distributions are comparable, using the distribution notation set forth in Table 3.3. In this case, the running time distributions for travel on the rail line from B to stops D and E may be computed in a straightforward manner as follows:

$$\phi_{i,BD}(x) = \int_0^x \phi_{i,BC}(z) \cdot \phi_{i,CD}(x-z)\,dz \tag{3.42}$$

$$\phi_{i,BE}(x) = \int_0^x \int_0^x \phi_{i,BC}(z) \cdot \phi_{i,CD}(y-z) \cdot \phi_{i,DE}(x-y-z)\,dy\,dz \tag{3.43}$$

A similar derivation holds for the travel times on the route 77 bus from A to C inbound and from C to A outbound. Using the notation of Tables 3.2 and 3.3, the distribution of bus running times from A to C inbound is given by:

$$\phi_{k,AC}(x) = \int_0^x \phi_{k,AD}(z) \cdot \phi_{k,DC}(x-z)\,dz \tag{3.44}$$

and the distribution of bus running times from C to A outbound is given by

$$\phi_{j,CA}(x) = \int_0^x \phi_{j,CD}(z) \cdot \phi_{j,DA}(x-z)\,dz \tag{3.45}$$

By computing the distributions of running times for the rail and bus route segments, a simpler analysis of the distribution of running times on each of the inbound and outbound o-d paths is possible.

3.6.2 Model Development (Outbound)

Given the distributions of running time on the bus and rail lines shown above in equations (3.42), (3.43), (3.44) and (3.45), calculation of distributions on each path is straightforward, using the results of the transfer paths in the shuttle network described in Section 3.5.2. In particular, the following equations can be derived directly from previous equations. For this section, distributions for the outbound trip are developed; a similar set of derivations is used for distributions for the inbound trip.

Note that for the case of the rail line, the scheduled departure time TD_i and the departure time distribution $f_{td_i}(t)$ are used to describe departures *from node B only*. Then, using equation (3.16), the distribution of the initial waiting time at Park Street (B) for a train, given that a passenger arrives at a time T where $TD_i \leq T < TD_{i+1}$, is given by:

$$f_{W_{BC}}(w) = \begin{cases} f_{td_i}(T+w) & w < TD_{i+1} - T \\ F_{td_i}(T) \cdot f_{td_{i+1}}(T+w) & w \geq TD_{i+1} - T \end{cases} \tag{3.46}$$

The time of arrival at nodes C, D, or E on the rail line is simply a variant of equation (3.23), using the rail line running time distributions given in equations (3.42) and (3.43).

$$\begin{aligned} f_a^{C1}(\tau) &= \int_T^{TD_{i+1}} f_{td_i}(y) \cdot \phi_{i,BC}(\tau - y)dy \\ &\quad + F_{td_i}(T) \cdot \int_{TD_{i+1}}^{\tau} f_{td_{i+1}}(y) \cdot \phi_{(i+1),BC}(\tau - y)dy \end{aligned} \tag{3.47}$$

$$\begin{aligned} f_a^{D2}(\tau) &= \int_T^{TD_{i+1}} f_{td_i}(y) \cdot \phi_{i,BD}(\tau - y)dy \\ &\quad + F_{td_i}(T) \cdot \int_{TD_{i+1}}^{\tau} f_{td_{i+1}}(y) \cdot \phi_{(i+1),BD}(\tau - y)dy \end{aligned} \tag{3.48}$$

$$\begin{aligned} f_a^{E3}(\tau) = f_a^{E4}(\tau) &= \int_T^{TD_{i+1}} f_{td_i}(y) \cdot \phi_{i,BE}(\tau - y)dy \\ &\quad + F_{td_i}(T) \cdot \int_{TD_{i+1}}^{\tau} f_{td_{i+1}}(y) \cdot \phi_{(i+1),BE}(\tau - y)dy \end{aligned} \tag{3.49}$$

The transfer time distribution at nodes C, D, or E is given in an equation derived from equation (3.31). Thus, the waiting time distribution for a transfer at C would be given by:

$$f_{W_{CA}}(w) = \int_T^{\infty} \left[f_{td_{I(CA,y)}}(y+w) + F_{td_{I(CA,y)}}(y) \cdot f_{td_{I(CA,y)+1}}(y+w) \right] \cdot f_a^{C1}(y)dy \quad (3.50)$$

Similar equations for transfer times at D and E can be obtained.

The departure time distributions for the bus portions of the trip from B to A are derived using equation (3.33).

$$f_d^{C1}(\tau) = \int_T^{\tau} f_a^{C1}(y) \cdot f_{w_{CA}}(\tau - y)dy \quad (3.51)$$

$$f_d^{D2}(\tau) = \int_T^{\tau} f_a^{D2}(y) \cdot f_{w_{DA}}(\tau - y)dy \quad (3.52)$$

$$f_d^{E3}(\tau) = \int_T^{\tau} f_a^{E3}(y) \cdot f_{w_{BA,(79)}}(\tau - y)dy \quad (3.53)$$

$$f_d^{E4}(\tau) = \int_T^{\tau} f_a^{E4}(y) \cdot f_{w_{BA,(350)}}(\tau - y)dy \quad (3.54)$$

Finally, the arrival time at the destination A for each path is given by an adaptation of equation (3.35), yielding:

$$f_a^{A1}(\tau) = \int_T^{\tau} f_d^{C1}(y) \cdot \phi_{I(CA,y)}(\tau - y)dy \quad (3.55)$$

$$f_a^{A2}(\tau) = \int_T^{\tau} f_d^{D2}(y) \cdot \phi_{I(DA,y)}(\tau - y)dy \quad (3.56)$$

$$f_a^{A3}(\tau) = \int_T^{\tau} f_d^{E3}(y) \cdot \phi_{I(EA,(79),y)}(\tau - y)dy \quad (3.57)$$

$$f_a^{A4}(\tau) = \int_T^{\tau} f_d^{E4}(y) \cdot \phi_{I(EA,(350),y)}(\tau - y)dy \quad (3.58)$$

This finally yields the total travel time distributions, given as:

$$g^u(x|T) = f_a^{A\,u}(T+x) \qquad u = 1,2,3,4 \quad (3.59)$$

This, then, is sufficient to derive the distributions of origin-to-destination travel times in the MBTA case study corridor.

Chapter 4

Path Choice Modeling

This chapter develops path choice models which are consistent with the transit service model from Chapter 3. The models are developed in the most general sense and are applied more specifically for the simple shuttle network described in Chapter 3. It is assumed in this case that a traveler arrives at the origin terminal and desires to travel to the destination with the minimum expected travel time. This chapter first characterizes the problem faced by such a traveler, and then examines how one might solve for the passenger's path choice most generally and also specifically in the context of the shuttle network. Subsequent sections discuss different models for adaptive path choice decisions (i.e., path choices on route) and for different departure time choices. This chapter concludes with a discussion of the analytic complexities of these models.

4.1 Passenger Travel Time Objectives

There are a number of factors which may have a strong influence on a passenger's choice of routes and paths for a transit trip. Intuition would suggest that elements such as fare, level of crowding, route frequency, comfort and security of stations and vehicles, as well as travel time and trip timing would affect passenger path and departure time decisions. Much of the research into these factors is covered in the extensive literature on traveler behavior analysis and demand modeling.

However, this thesis has focused specifically on the passenger's travel time as the primary factor influencing path and departure time choice. The primary focus of the research is to investigate the potential incremental (or marginal) changes in passenger behavior resulting from real-time information about transit service. One of the most obvious roles of real-time passenger information systems is to provide passengers with information on trip timing and network travel times. Other factors such as fares and station and vehicle comfort are static and thus are not important factors in a real-time setting. Vehicle crowding, on the other hand, may be an important factor in real time, but is beyond the scope of what might be included in this thesis. [Its relevance is discussed more fully as an area for further research in Chapter 8.]

In the discussion that follows, then, it is assumed that the primary criteria passengers use in selecting paths is the overall time spent traveling, including waiting time, time spent transfering between routes, and time spent on board a vehicle. Even in this context, there are a number of appropriate measures of travel time and service reliability for the transit passenger. From the literature on transit service reliability, it is clear that the characteristics of the travel time which are of most interest include:

1. The expected travel time from origin to destination.

2. The variance of arrival times at the destination, around a certain expectation.

3. The probability of arriving at the destination (i.e. completing a trip) within X minutes of arriving at the origin stop. This quantifies the tail of the distribution of the o-d travel times.

In the discussion that follows, both path and departure time choice models will be examined using the passenger objective of minimizing the expected travel time from origin to destination. This may best reflect the passengers' objective when making non-work trips or work-to-home trips in the evening. For these trips, the passenger is not as concerned with problems or penalties arising from either a very early or very late arrival at the destination. Thus, if two paths have expected travel times of 25 and 28 minutes, the passenger would choose the one with a 25 minute travel time, regardless of the variability of this trip.

A similar framework can and will also be used for objectives which are more sensitive to the variability of travel times. In particular, in considering a morning commute or some other trips, the passenger may be interested in more consistent travel times or in the probability of arriving at the destination before a certain time. In such cases, an objective which explicitly considers the variability of travel times (e.g., the variance) or the probability of arriving by a certain time (e.g., arriving at work by 9:00 a.m.) could also be considered. These types of objectives will not be explicitly considered in this chapter, although the analytic framework presented below is sufficiently flexible to accommodate these objectives. For this thesis, the minimum expected travel time objective is used as an example, primarily because of its use by other researchers and because of its convenience in the analytic models developed here.

4.2 Problem Definition

The path choice problem, then, is to determine how passengers choose paths in the transit network. Most researchers approach this problem by computing a single shortest (i.e., minimum expected travel time) path in the network. The simplest model of path choice assumes that a passenger selects a single path based on minimizing the expected travel time, and then he/she waits until a vehicle on that path arrives (i.e. the passenger always boards the next vehicle on that path to arrive). In this case, it is assumed that there is a single path which is optimal for all points in time when the passenger might want to travel.

Chriqui and Robillard [16] were the first to address the issue of how transit passengers choose transit paths from their origin to destination when vehicle departures from the origin are explicitly stochastic. In this case, the transit passenger may be willing to use any of several paths, depending on the departure time and the expected travel time of the first vehicle on each path to arrive at the origin terminal. Considering the stochastic path choice model more specifically, Chriqui and Robillard suggested that a passenger chooses an "optimal" set of paths on the o-d pair such that, upon arrival at the origin terminal, he/she is willing to board the first vehicle from that set to depart. The term "optimal" in this case implies that the resulting path choice set minimizes the passenger's overall expected travel time from origin to destination.

Chriqui and Robillard constructed a mathematical model of this behavior. The problem is characterized by determining a choice vector (of dimension r, where r is the number of paths serving the origin and destination) containing elements 1 and 0, where $x_i = 1$ if path i is in the optimal set, and $x_i = 0$ otherwise. This choice vector will be referred to as the *path choice set*.

The problem as defined above represents a *static* model of path choice. In this case, upon arrival at the origin terminal, the passenger determines his/her optimal path set and then waits until some vehicle in the set arrives. Paths in the optimal set of this static model belong to the *optimal static choice set*. This static model is in contrast with what is called the *dynamic* model, in which passengers may update their optimal path sets while waiting for a vehicle. In this case, the passenger begins waiting for any of a set of possible vehicles, but may add or delete possible paths from the choice set as his/her waiting time increases. This time-dependent set of paths will be called the *optimal dynamic choice set*. As noted by Chriqui and Robillard,

> [T]he problem treated here [the static model] produces a suboptimal strategy. Indeed a 'clever' passenger would observe both the route r of the arriving bus and how long he had waited for it. On the basis of this information he would then compare t_r [the expected travel time upon boarding the vehicle on route r] with the conditional minimum trip time T for not taking the first vehicle given r and that no vehicle of type j, $j \neq r$ had arrived up to that time. The optimal strategy is to choose r if t_r is less than T.

In the dynamic path choice model, the optimal dynamic choice set would indicate, for a given point in time, whether or not a passenger would be willing to board a vehicle arriving at that instant in time. Such an optimal choice set would be determined by comparing the expected travel time upon boarding the arriving vehicle with some measure of the expected travel time if the arriving vehicle is not boarded.

Several researchers, including Marguier [47] and Marguier and Ceder [49], have examined the dynamic model for the simple case where there are only two possible paths. In this case, the optimal path set may change over time, depending on the probability distributions of the vehicle departures on each path. For most conventional passenger waiting time distributions, the optimal boarding strategy will usually involve dropping paths from the optimal dynamic choice set as the waiting time increases.

There are two critical issues which have not been addressed in this literature: stochastic vehicle running times and the impact of transfers and time-dependence on expected travel times. In the studies by Chriqui and Robillard [16], Marguier [47], and Marguier and Ceder [49], travel time after boarding a vehicle is assumed to be constant. Marguier [47] argues that these travel times (after boarding) may be treated as constant; however, his line of reasoning implicitly assumes that the random variable of the waiting time and the (possibly random) variable of the vehicle running time are statistically independent. When transfers are involved, this assumption is most likely violated. For example, as the waiting time at the origin terminal increases, the probability of making a specific connection on a transfer path decreases, and the expected travel time over that path would then increase. Thus, both stochastic running times and time dependence should be included in the path choice models.

Hall [25, 27] explicitly incorporated time-dependence in his proposed path choice model by including transfers in the transit network. His model also includes stochastic running times, but is limited in that he implicitly assumed that vehicle departures were deterministic (and known by the passenger). In such a case, there is only a single optimal path choice. Intuitively, variability in vehicle running times will also cause variation in vehicle departure times.

The desired path choice methodology, then, is a generalization of the above approaches to account for stochastic vehicle departure times and running times, as well as time-dependence in path travel times. With these assumptions, the static and dynamic path choice models will assume a more time-dependent nature.

One final issue in defining the path choice problem involves the possibility that vehicles may be on sufficiently long headways that both vehicle and passenger arrivals at a terminal are not well defined by the simpler distributions assumed in the literature. In the case of passengers, longer headways (i.e., over ten minutes) would imply that randomly arriving passengers may have substantial average waiting times. More likely, these passengers may try to coordinate their arrivals with the expected vehicle departures. Such a model has been proposed by many researchers, including Holroyd and Scraggs [31], O'Flaherty and Mangan [56], Seddon and Day [62], Jolliffe and Hutchinson [35], Turnquist [68] and Bowman and Turnquist [11]. Similarly, vehicles do not arrive entirely at random, but rather arrive sometime "close" to the scheduled vehicle departure times or "close" to the scheduled headway behind the previous vehicle. In this case, it is necessary to examine vehicle departure time distributions and the resulting passenger waiting time distributions which may be more complicated than the more simple distributions assumed in previous research.

Summarizing, the path choice methodology should allow more complicated vehicle departure time and running time distributions and time-dependent expected travel times. This research develops both static and dynamic path choice models in such a context. The foundation for both models involves computation of the expected travel time on each path as a function of time. The following section derives these expressions for the simple shuttle network. Subsequent sections outline how one might characterize both the static and the dynamic path choice problems and ultimately determine passenger boarding strategies using these optimal path choice sets.

4.3 Expected Passenger Travel Time

The first task in this analysis is to develop expressions for the expected travel time between the origin A and the destination D for each of the three possible paths in the shuttle network. These represent the fundamental elements to determining path choices, given the objective of minimizing the expected origin-to-destination travel time. Given that a passenger has arrived at the origin terminal at a time T, the desire is to know his/her expected travel time on each path at this arrival time, and the expected travel time on any path at the time of a vehicle departure on that path.

In this discussion, the following notation will be used (in addition to the notation previously defined in Chapter 3):

- $E[t^i_{AD}|T]$ = the expected travel time from A to D on path i given a passenger arrival at the origin A at time T.
- $E[t^i_{AD}|\text{dpt } td_j]$ = the expected travel time from A to D on path i given that the j^{th} vehicle departs A at the time td_j, which is a particular realization of a random

variable.

- $\overline{F}_{td_j}$ = complement of the cumulative distribution function of the departure time for vehicle j; i.e.,

$$\overline{F}_{td_j}(y) = 1 - F_{td_j}(y)$$

- R_j = expected running time for vehicle j.

- $\overline{td}_j$ = expected departure time for vehicle j. This may differ from the *scheduled* departure time TD_j.

$$\overline{td}_j = \int_{TD_j}^{TD_{j+1}} \tau f_{td_j}(\tau) d\tau$$

- $X(T)$ = path choice set for a particular time T.

- $T_{X(T)}$ = expected travel time at time T given the path choice set $X(T)$.

- $P_i(X(T))$ = probability of taking path i given a passenger arrival at time T, with the optimal path choice set $X^*(T)$.

The goal here is to describe the expected travel time on a path at each of the passenger arrival time T and the vehicle departure times td_j. Beginning with path 2, the single shuttle path directly from A to D, the expected travel time on path 2 given a vehicle departure time td_i is:

$$E[t^2_{AD}|\text{dpt } td_i] = E[\text{Running time for vehicle } i] = R_i \tag{4.1}$$

with the obvious restriction that td_i be a feasible departure time for the i^{th} vehicle, or $f_{td_i}(td_i) \neq 0$. As noted in Chapter 3, the expected running time R_i may be either dependent on the vehicle i or may simply be a constant for all vehicles, depending on level of correlation between consecutive vehicle running times on the shuttle route.

Given that a passenger arrives at A at time T, and assuming $TD_i \leq T < TD_{i+1}$, the total expected travel time may be divided into two parts, one being the expected travel time given that the i^{th} vehicle has not yet departed and the other being the expected travel time given that the i^{th} vehicle has departed by T. Mathematically,

$$\begin{aligned} E[t^2_{AD}|T] &= E[t^2_{AD}|\text{dpt } td_i \geq T] \cdot \text{Prob}(td_i \geq T) \\ &\quad + E[t^2_{AD}|\text{dpt } td_i < T] \cdot \text{Prob}(td_i < T) \end{aligned} \tag{4.2}$$

In this expression, the expected travel time given that vehicle i has not yet departed is given by:

$$E[t^2_{AD}|\text{dpt } td_i \geq T] = R_i + [\overline{F}_{td_i}(T)]^{-1} \int_T^{TD_{i+1}} \tau f_{td_i}(\tau)\, d\tau \; - T \tag{4.3}$$

Furthermore, the expected travel time given that vehicle i has already departed is simply the time until the $i+1$ vehicle arrives at D, or:

$$E[t^2_{AD}|\text{dpt } td_i < T] = R_{i+1} + \overline{td}_{i+1} - T \tag{4.4}$$

Noting that $\text{Prob}(td_i < T) = F_{td_i}(T)$, the total expected travel time (including wait time) from A to D using path 2 is given by:

$$E[t^2_{AD}|T] = R_i + \int_T^{TD_{i+1}} \tau f_{td_i}(\tau)\, d\tau \; + F_{td_i}(T) \cdot (\overline{td}_{i+1} + R_{i+1} - R_i) - T \tag{4.5}$$

This equation describes the expected travel time from A to D on path 2 given a passenger arrival at A at time T. A similar form could be used to describe the expected travel time from B to D given an arrival at B at time T_B:

$$E[t^1_{BD}|T_B] = R_l + \int_{T_B}^{TD_{l+1}} \tau f_{td_l}(\tau)\, d\tau \; + F_{td_l}(T_B) \cdot (\overline{td}_{l+1} + R_{l+1} - R_l) - T \tag{4.6}$$

Given a departure of the shuttle from A to B at a time td_j, and a vehicle running time from A to B of x_j, the expected travel time from A to D on path 1 integrates the sum of the running time x_j and the expected travel time from B to D given an arrival at B at time $td_j + x_j$ over all possible values of x_j.

$$E[t^1_{AD}|\text{dpt } td_j] = \int_0^{\infty} (x + E[t^1_{BD}|td_j + x]) \cdot \phi_j(x)\, dx \tag{4.7}$$

$$= R_j + \int_0^{\infty} E[t^1_{BD}|td_j + x] \cdot \phi_j(x)\, dx \tag{4.8}$$

To examine the total expected travel time on path 1, given a passenger arrival at the origin A at time T between TD_j and TD_{j+1}, the time between T and td_j is added to the expression in equation (4.8) and integrated over possible departure times after T. If it is known for certain that vehicle j has not departed as of time T, the distribution of departure times for vehicle j is given by:

$$f_{td_j|td_j \geq T}(\tau) = [\overline{F}_{td_j}(T)]^{-1} f_{td_j}(\tau) \tag{4.9}$$

Using this form of the departure time distribution, given that vehicle j has not yet departed, the expected travel time from A to D is given by the sum of the expected waiting time at A, the expected running time from A to B, and the expected running time upon arrival at B.

$$\begin{aligned} E[t^1_{AD}|T, \text{dpt } td_j \geq T] &= [\overline{F}_{td_j}(T)]^{-1} \cdot \Bigg[R_j + \int_T^{TD_{j+1}} \tau\, f_{td_j}(\tau) d\tau - T \\ &+ \int_0^\infty \int_T^{TD_{j+1}} E[t^1_{BD}|\tau + x] \cdot \phi_j(x) \cdot f_{td_j}(\tau) d\tau dx \Bigg] \end{aligned} \tag{4.10}$$

Similarly, if vehicle j has already departed, the expected travel time from A to D is given by:

$$\begin{aligned} E[t^1_{AD}|T, \text{dpt } td_j < T] &= R_{j+1} + \overline{td}_{j+1} - T \\ &+ \int_0^\infty \int_{TD_{j+1}}^{TD_{j+2}} E[t^1_{BD}|\tau + x] \cdot \phi_{j+1}(x) \cdot f_{td_{j+1}}(\tau) d\tau dx \end{aligned} \tag{4.11}$$

The net expected travel time from A to D using path 1 for a passenger arriving at time T is given by using a probability-weighted sum of equations (4.10) and (4.11). This may be written as:

$$\begin{aligned} E[t^1_{AD}|T] &= R_j + \int_T^{TD_{j+1}} \tau\, f_{td_j}(\tau) d\tau + F_{td_j}(T) \cdot (R_{j+1} - R_j + \overline{td}_{j+1}) - T \\ &+ \int_0^\infty \int_T^{TD_{j+1}} E[t^1_{BD}|\tau + x] \cdot \phi_j(x) \cdot f_{td_j}(\tau) d\tau dx \\ &+ F_{td_j}(T) \cdot \int_0^\infty \int_{TD_{j+1}}^{TD_{j+2}} E[t^1_{BD}|\tau + x] \cdot \phi_{j+1}(x) \cdot f_{td_{j+1}}(\tau) d\tau dx \end{aligned} \tag{4.12}$$

A similar set of expressions can be derived for the expected travel time on path 3, through C. In this case the expression for the expected travel time from C to D on path 3, given an arrival at C at time T_C, is given by:

$$E[t^3_{CD}|T_C] = R_m + \int_{T_C}^{TD_{m+1}} \tau f_{td_m}(\tau)\, d\tau \; + F_{td_m}(T_C) \cdot (\overline{td}_{m+1} + R_{m+1} - R_m) - T \quad (4.13)$$

This in turn may be used to derive the expected travel time from A to D on path 3, given a departure on the shuttle from A to C at time td_k.

$$E[t^3_{AD}|\text{dpt } td_k] = \int_0^\infty (x + E[t^3_{CD}|td_k + x]) \cdot \phi_k(x) dx \quad (4.14)$$

$$= R_k + \int_0^\infty E[t^3_{CD}|td_k + x] \cdot \phi_k(x) dx \quad (4.15)$$

In a manner similar to equation (4.12), the expected travel time from A to D on path 3 given a passenger arrival time of T at the origin is given by:

$$\begin{aligned} E[t^3_{AD}|T] = \; & R_k + \int_T^{TD_{k+1}} \tau\, f_{td_k}(\tau) d\tau \; + F_{td_k}(T) \cdot (R_{k+1} - R_k + \overline{td}_{k+1}) - T \\ & + \int_0^\infty \int_T^{TD_{k+1}} E[t^3_{CD}|\tau + x] \cdot \phi_k(x) \cdot f_{td_k}(\tau) d\tau dx \\ & + F_{td_k}(T) \cdot \int_0^\infty \int_{TD_{k+1}}^{TD_{k+2}} E[t^3_{CD}|\tau + x] \cdot \phi_{k+1}(x) \cdot f_{td_{k+1}}(\tau) d\tau dx \end{aligned} \quad (4.16)$$

The expected travel time expressions given in equations (4.1), (4.5), (4.8), (4.12), (4.15) and (4.16) will be used extensively in the following sections in development of the static and dynamic path choice models.

4.4 The Static Path Choice Model

In the static path choice model, the passenger makes a decision upon his/her arrival at the origin terminal (or perhaps before arrival, depending on when he/she receives information about service) of a certain set of possible paths. The passenger waits until the first vehicle among this set arrives and then boards that vehicle. This static optimal path set is determined using the criterion of minimizing the expected travel time from the passenger arrival at the origin terminal until arrival at the destination. Specifically, the following definition will be used.

Definition 10 *The* static path choice problem *is to determine the set of paths serving the origin and destination that the passenger would accept. A path is in this set if* *and only if the passenger will board the first vehicle to arrive on that path provided no vehicles on other acceptable paths have arrived previously. The passenger is assumed to minimize the expected travel time,* given this boarding strategy. *Vehicles are assumed to arrive at the origin terminal according to some stochastic process.*

In the following sections, it is shown how the optimal choice set may be identified and expressions are derived for the expected travel time and the path choice probabilities for a given passenger arriving at the origin terminal at time T. Note that, under the assumption that the vehicle arrivals are related to a schedule, the optimal set in the static case may vary as a function of the passenger arrival time T.

4.4.1 Identification of the Choice Set

The identification of the choice set is the problem examined by Chriqui and Robillard [16]. In their paper, they examine a mathematical formulation of the problem of determining a choice vector $X = \{x_1, x_2, ...x_n\}$ for n routes serving an origin-destination pair. This choice vector is determined using the objective of minimizing the expected total travel time, and is formulated as follows:

$$\min_X E[TT] = \sum_{i=1}^{n} \int_0^{\infty} (z + t_i) \cdot x_i \cdot f_{w_i}(z) \cdot \prod_{j \neq i} \left[\overline{F}_{w_j}(z)\right]^{x_j} dz \tag{4.17}$$

$$\begin{aligned} \text{subject to: } \sum_{i=1}^{n} x_i &\geq 1 \\ x_i &= 0 \text{ or } 1 \end{aligned} \tag{4.18}$$

In this formulation, t_i is the expected travel time after boarding a bus on route i, $(z + t_i)$ is the the total travel time, and the quantity

$$x_i \cdot f_{w_i}(z) \cdot \prod_{j \neq i} \left[\overline{F}_{w_j}(z)\right]^{x_j}$$

is the probability of a vehicle on route i arriving before any vehicle on all other routes with $x_j = 1$ in the choice vector X.

The solution technique proposed by Chriqui and Robillard is a simple heuristic based on a greedy algorithm which adds paths with the shortest in-vehicle travel times t_i to the optimal set until no further reduction in the expected travel time occurs. The algorithm terminates when an additional route in the choice set adds more to the expected in-vehicle travel time than it reduces the expected waiting time.

This simple heuristic finds the optimal solution if the shortest in-vehicle travel time path has exponentially distributed headways and all other paths have exponentially distributed or uniformly distributed headways. Although conjectured by Marguier [47], there is no formal proof that the heuristic attains the optimal solution for uniform waiting time distributions. Furthermore, the heuristic fails for certain instances of more general waiting time distributions (Marguier [47]). Moreover, it is fairly simple to show instances in which, assuming that vehicle arrivals are correlated with a schedule, this heuristic performs very poorly.

A generalization adopted in this research is that this static choice set X may be time-dependent. In this case, the decision variables and waiting and travel time functions of the formulation in equations (4.17) and (4.18) are explicitly functions of the time T at which a passenger arrives at the stop. The following problem is thus defined as the time-dependent static path choice problem:

$$\min_{X(T)} E[TT|T] = \sum_{i=1}^{n} \int_0^{\infty} (z + E[t_i|T+z]) \cdot x_i(T) \cdot f_{w_i}(z|T) \cdot \prod_{j \neq i} \left[\overline{F}_{w_j}(z|T)\right]^{x_j(T)} dz \quad (4.19)$$

$$\begin{aligned} \text{subject to: } \sum_{i=1}^{n} x_i(T) &\geq 1 \\ x_i(T) &= 0 \text{ or } 1 \end{aligned} \quad (4.20)$$

where $E[t_i|T+z]$ is the expected travel time after boarding a vehicle on route i at time $T+z$.

In this case, it seems reasonable to resort to explicit enumeration of all possible path sets, particularly since it is rare for an o-d pair to be served by a very large number of possible transit paths. As Chriqui and Robillard noted,

> When the number of common routes is not too large (less than eight or ten) the problem P can usually be solved by complete enumeration. Indeed T_X [the expected travel time for a solution X] can be automatically

evaluated for a given X with the aid of standard numerical integration techniques. In practice we have met very few cases of more than five or six common routes.

The approach here, for the case of three possible o-d paths in the shuttle network, is to enumerate paths explicitly. For the static problem, a specific path belongs in the optimal choice set if including that path in the static choice set reduces the expected travel time. Let us denote the optimal choice set using vector notation, with $X(T) = \{x_1, x_2, x_3\}$ being the choice set for a passenger at time T and $x_i = 1$ if path i is in the choice set and $x_i = 0$ otherwise, $i = 1, 2, 3$. Ignoring the case $X(T) = \{0, 0, 0\}$, there are seven (7) candidate choice sets.

From the formulation shown in (4.19) and (4.20), the expected travel time for any choice set, $T_{X(T)}$ is the sum over all paths in the choice set of the expected travel time on each path, given that a vehicle on that path arrives first, times the probability that a vehicle on that path arrives first. For choice sets with a single route, the following expected travel times can be determined, based on equations (4.12), (4.5) and (4.16), respectively.

$$T_{X(T)} = \begin{cases} E[t^1_{AD}|T] & \text{if} \quad X(T) = \{1,0,0\} \\ E[t^2_{AD}|T] & \text{if} \quad X(T) = \{0,1,0\} \\ E[t^3_{AD}|T] & \text{if} \quad X(T) = \{0,0,1\} \end{cases} \tag{4.21}$$

For cases with multiple paths in the choice set, the calculations suggested in (4.19) make use of the expected travel times conditional on a vehicle departure for each path, found in equations (4.1), (4.8) and (4.15). The expected travel time for a choice set with multiple paths computes the travel time over each path, assuming that an arrival on that path occurs first among all paths in the choice set. A probability-weighted sum of these conditional expectations gives the proper expected travel time for the full static path choice set.

In order for a vehicle on a particular path to arrive first, it is necessary that the waiting time for the next vehicle on that path be less than that for any other path in the choice set. Using the result of equation (3.16), the probability density function for the initial waiting time on path 1, for example, is given by

$$f_W^1(w|T) = \begin{cases} f_{td_j}(T+w) & \text{for } w < TD_{j+1} - T \\ F_{td_j}(T) \cdot f_{td_{j+1}}(T+w) & \text{for } w \geq TD_{j+1} - T \end{cases} \tag{4.22}$$

and the cumulative distribution of this waiting time is given by

$$F_W^1(w|T) = F_{td_j}(T+w) - F_{td_j}(T) + F_{td_j}(T) \cdot F_{td_{j+1}}(T+w) \tag{4.23}$$

Using these waiting time distributions for each path, the following expressions yield the expected travel times for each multiple-path choice set:

$$\begin{aligned} T_{\{1,1,0\}} &= \int_0^{TD_{j+2}-T} f_W^1(z|T) \cdot \overline{F}_W^2(z|T) \cdot (z + E[t_{AD}^1|\text{dpt } T + z])dz \\ &+ \int_0^{TD_{i+2}-T} f_W^2(z|T) \cdot \overline{F}_W^1(z|T) \cdot (z + E[t_{AD}^2|\text{dpt } T + z])dz \end{aligned} \tag{4.24}$$

$$\begin{aligned} T_{\{1,0,1\}} &= \int_0^{TD_{j+2}-T} f_W^1(z|T) \cdot \overline{F}_W^3(z|T) \cdot (z + E[t_{AD}^1|\text{dpt } T + z])dz \\ &+ \int_0^{TD_{k+2}-T} f_W^3(z|T) \cdot \overline{F}_W^1(z|T) \cdot (z + E[t_{AD}^3|\text{dpt } T + z])dz \end{aligned} \tag{4.25}$$

$$\begin{aligned} T_{\{0,1,1\}} &= \int_0^{TD_{i+2}-T} f_W^2(z|T) \cdot \overline{F}_W^3(z|T) \cdot (z + E[t_{AD}^2|\text{dpt } T + z])dz \\ &+ \int_0^{TD_{k+2}-T} f_W^3(z|T) \cdot \overline{F}_W^2(z|T) \cdot (z + E[t_{AD}^3|\text{dpt } T + z])dz \end{aligned} \tag{4.26}$$

$$\begin{aligned} T_{\{1,1,1\}} &= \int_0^{TD_{j+2}-T} f_W^1(z|T)\overline{F}_W^2(z|T)\overline{F}_W^3(z|T) \cdot (z + E[t_{AD}^1|\text{dpt } T + z])dz \\ &+ \int_0^{TD_{i+2}-T} f_W^2(z|T)\overline{F}_W^1(z|T)\overline{F}_W^3(z|T) \cdot (z + E[t_{AD}^2|\text{dpt } T + z])dz \\ &+ \int_0^{TD_{k+2}-T} f_W^3(z|T)\overline{F}_W^1(z|T)\overline{F}_W^2(z|T) \cdot (z + E[t_{AD}^3|\text{dpt } T + z])dz \end{aligned} \tag{4.27}$$

The optimal choice set for the static path choice model involves finding the minimum of the $T_{X(T)}$ over the choice sets enumerated in equations (4.21), (4.24), (4.25), (4.26) and (4.27). The resulting choice set is optimal in the sense that it minimizes the expected o-d travel time, and the expected travel time is the corresponding value of $T_{X(T)}$. Let $X^*(T)$ be the choice set corresponding to this minimum travel time, $T_{X^*(T)}$.

4.4.2 Path Choice Probabilities

Given the choice set $X^*(T)$ determined in the previous analysis, computing path choice probabilities for a passenger arriving at time T is fairly straightforward. The probability of taking a particular path, given the optimal choice set $X^*(T)$, is simply the probability that the waiting time for a vehicle on a path in that choice set is the minimum. In the simple cases where only one path is in the optimal choice set, the path choice probabilities are unity for the path in the choice set and zero for the other paths.

For each of the multiple-path choice sets, a few integrations are necessary, in the same manner as in the previous analysis.

$$P_1(X^*(T) = \{1,1,0\}) = \int_0^{TD_{j+2}-T} f_W^1(z|T) \cdot \overline{F}_W^2(z|T)\, dz \quad (4.28)$$

$$P_2(X^*(T) = \{1,1,0\}) = \int_0^{TD_{i+2}-T} f_W^2(z|T) \cdot \overline{F}_W^1(z|T)\, dz \quad (4.29)$$

$$P_1(X^*(T) = \{1,0,1\}) = \int_0^{TD_{j+2}-T} f_W^1(z|T) \cdot \overline{F}_W^3(z|T)\, dz \quad (4.30)$$

$$P_3(X^*(T) = \{1,0,1\}) = \int_0^{TD_{k+2}-T} f_W^3(z|T) \cdot \overline{F}_W^1(z|T)\, dz \quad (4.31)$$

$$P_2(X^*(T) = \{0,1,1\}) = \int_0^{TD_{i+2}-T} f_W^2(z|T) \cdot \overline{F}_W^3(z|T)\, dz \quad (4.32)$$

$$P_3(X^*(T) = \{0,1,1\}) = \int_0^{TD_{k+2}-T} f_W^3(z|T) \cdot \overline{F}_W^2(z|T)\, dz \quad (4.33)$$

$$P_1(X^*(T) = \{1,1,1\}) = \int_0^{TD_{j+2}-T} f_W^1(z|T) \cdot \overline{F}_W^2(z|T) \cdot \overline{F}_W^3(z|T)\, dz \qquad (4.34)$$

$$P_2(X^*(T) = \{1,1,1\}) = \int_0^{TD_{i+2}-T} f_W^2(z|T) \cdot \overline{F}_W^1(z|T) \cdot \overline{F}_W^3(z|T)\, dz \qquad (4.35)$$

$$P_3(X^*(T) = \{1,1,1\}) = \int_0^{TD_{k+2}-T} f_W^3(z|T) \cdot \overline{F}_W^1(z|T) \cdot \overline{F}_W^2(z|T)\, dz \qquad (4.36)$$

4.5 The Dynamic Path Choice Model

The static path choice model developed above suffers from two drawbacks. First, it assumes that the traveler does not update the choice set as he/she waits for a vehicle. As an example, suppose that the user has two paths in his/her choice set upon arriving at the origin terminal. After waiting for some period of time, it may be advantageous for that passenger to wait for the faster vehicle only, rather than for both vehicles. Such an example was developed in greater detail by Marguier and Ceder [49], suggesting that for certain waiting time distributions, the passenger may do better to update their path choice set as the time spent waiting increases; and, by updating this strategy, the passenger certainly will do no worse than if he/she had used the static choice set.

A related drawback of the static model is that it does not explicitly consider the effects of time-dependence in evaluating travel times on various paths. For the case when both the origin and destination are served directly by several transit routes, time-dependence in travel times is not a significant issue over a given planning horizon (e.g., during the morning commute). However, where there are o-d paths with connections (i.e., transfers), and with somewhat longer vehicle headways, the issue of time-dependence can be significant. Consider the following two-route example:

1. A passenger can take a very frequent bus, with negative exponentially distributed headways with mean 5 minutes, connecting to a suburban feeder bus with a fixed thirty minute headway.

2. A passenger can take a slower service on approximately fifteen minute headways directly to the destination.

In this example, a person may be willing to take the faster transfer trip if he/she has a high probability of making the connection with a small transfer time. However, at another point in time, choosing the transfer trip may lead to a long expected wait for the feeder bus. At that time, the slower direct service may be a better path choice. Therefore, it is possible that the passenger may improve his/her expected travel time by updating the path choice set as a function of time.

In this section a dynamic path choice framework is developed, first by outlining how one may identify the path choice set as a function of time. A modeling approach is suggested which relaxes some of the more difficult analytic aspects of this path choice problem. However, a separate section examines the formulation of the "true" (mathematically rigorous) dynamic path choice model.

4.5.1 Identification of the Choice Set

The basic idea behind the dynamic path choice model is the observation that the passenger may further improve upon the static decision rule by evaluating the amount of time he/she has already waited for an arriving vehicle and by updating the expected travel times accordingly. Ultimately, the question for the passenger becomes, given that I have waited since T and a vehicle on path r is about to depart, should I board this vehicle or wait for a subsequent vehicle? In the static case, the time spent waiting is irrelevant for the boarding decision. In the dynamic model, though, the decision to board relies on comparing the expected travel time given that the passenger boards the vehicle on path r with the possibly minimum expected travel time given that the passenger does not board the vehicle. The dynamic model assumes the passenger updates this expected travel time as he/she waits. Formally, the dynamic choice problem may be defined as follows.

Definition 11 *The* dynamic path choice problem *is to determine at any point in time whether the passenger would be willing to board a vehicle departing the origin at that point in time, given all the passenger has learned since his/her arrival at the origin terminal. This is done by comparing the expected travel time upon boarding with the (minimum) expected travel time given that a vehicle is not boarded.*

In this analysis, the choice set may be identified simply by looking at a given point in time and identifying whether a path does or does not belong in the choice set for that point in time. In this case, it is not necessary to enumerate all possible path choice sets explicitly as in the static model.

From this problem definition, there are two different ways of quantifying the "minimum" expected travel time given that the passenger does not board a vehicle on path r. The method suggested by Chriqui and Robillard (from Newell) would be to use the minimum expected travel time on some *new* set of paths, given that the person boards the first vehicle in that set to arrive after the vehicle on path r. This assumes that if the passenger chooses not to board the vehicle on path r, he/she would board the next vehicle to come along on another (possibly different) set of paths.

Actually, this strategy is not necessarily strictly optimal. The truly clever passenger would calculate the minimum expected travel time for not boarding, knowing that at each point in time in the future when there is a subsequent vehicle arrival he/she will perform a similar analysis. This may be modeled as a functional analysis problem, and would assure that the expected travel time given the passenger does not board is truly the minimum. Such a formulation is outlined later in Section 4.5.2.

From the point of view of decision analysis, however, it seems very unlikely that passengers will perform such a complex analysis. In this case, the simpler model suggested by Chriqui and Robillard [16] of computing the minimum expected travel time, assuming that the passenger would board the next vehicle to arrive from some new "optimal" set of paths, is more appealing. This approach is assumed for the development of the dynamic path choice model in the remainder of the thesis.

This approach does not imply, however, that passenger behavior necessarily follows this line of reasoning. It is assumed that the passenger makes the choice of whether to board a vehicle or not based on a comparison with the travel time assuming they will board the next arriving vehicle out of an optimal set of paths. However, when a subsequent vehicle from this set arrives, the passenger will (potentially) disregard the results of this prior decision process. Instead, the passenger will perform the same analysis for these new arrivals, comparing the expected travel time for the arriving vehicle with the minimum expected travel time given that he/she boards the next vehicle from some other "optimal" set of paths. The passenger performs this comparison for all arriving vehicles. The decision process is somewhat more difficult than the static path choice model but is considerably less complex than the true optimal dynamic path choice model.

It may be helpful to restate the proposed characterization of the dynamic path choice model. At the time of arrival of a vehicle at the origin, each waiting passenger compares the expected travel time upon boarding with an optimal static path choice set, assuming the passenger does not board. This decision process is used to determine the passenger boarding decision for all vehicle arrivals at the origin. However, it is possible (under more extreme conditions) that a passenger may "change his/her mind" by deciding to board (or not to board) vehicles that were not (or were) in this optimal static choice set during a previous boarding decision. Such a change in strategy is a low probability event, most likely occurring only for extremely late vehicle departure times or bad transfer connections. In most cases, this dynamic path choice model seems to allow considerable improvement over the static path choice model and yet may be interpreted more easily, both behaviorally and analytically, than the true dynamic path choice model.

The other intuitively appealing aspect of this approach is that there tends to be a potential bias in favor of boarding. In this dynamic model, a static model is used to determine expected travel times from not boarding a vehicle. Also, the static path choice model presented in (4.19) and (4.20) represents a constrained version of the true dynamic path choice problem (Section 4.5.2 demonstrates this relationship). In this case, then, the expected travel time computed using the static choice model will be greater than or equal to the expected travel time if the vehicle is not boarded using a the optimal dynamic path choice strategy for subsequent vehicle arrivals. Thus, when comparing the expected travel time upon boarding with the expected travel time from this static model, there is a possible bias causing the individual to board, rather than delay boarding, based on this criteria.

On the other hand, it is possible to show seemingly paradoxical situations where this dynamic path choice strategy may lead to very long waiting times, and a resulting poor decision on whether to board a vehicle or not. Consider the following two-path example.

- Path 1 goes from A to D with a transfer at B; Path 3 goes from A to D with a transfer at C.

- Running times on each route may be considered deterministic, with shuttle A-B taking 15 minutes, shuttle A-C 12 minutes and shuttles B-D and C-D both 20 minutes.
- Route A-B buses depart from A uniformly over 4:45-4:50, 5:02-5:07, etc.
- Route A-C buses depart from A uniformly over 4:54-4:59, 5:18-5:23, etc.
- Route B-D buses leave deterministically at 5:00, 5:20, 5:40, 6:00, etc. on 20 minute headways.
- Route C-D buses leave deterministically at 4:45, 5:10, 5:35, 6:00, etc. on 25 minute headways.

A passenger traveling from A to D arrives at A at 4:40. The first bus to arrive is shuttle A-B, at 4:47. The travel time to D if the passenger boards is $15 + 18 + 20 = 53$ minutes. If the passenger does not board, but waits for the A-C bus, the expected travel time is

$$0.8 \cdot (23 + 20) + 0.2 \cdot (48 + 20) = 48 \text{ minutes.}$$

So, the passenger would do better to wait, and he lets the A-B shuttle bus go without boarding. However, the shuttle A-C arrives at 4:59, and the passenger then could board with an expected travel time of 68 minutes or wait for the next A-B shuttle, which has the expected travel time (at 4:59) of

$$0.6 \cdot (21 + 20) + 0.4 \cdot (41 + 20) = 49 \text{ minutes.}$$

So, again the passenger passes up the A-C shuttle and waits for the A-B shuttle. Unfortunately, the A-B shuttle arrives at 5:06, and the expected travel time if the passenger boards is $15 + 19 + 20 = 54$ minutes. However, his expected travel time if he waits for the next A-C shuttle is $29 + 20 = 49$ minutes. Again, the passenger does better to wait for the next A-C shuttle. Already, the passenger has waited 26 minutes and is now guaranteed of having an expected total trip time of at least $26 + 49 = 75$ minutes. It is possible to conjecture situations where this poor passenger may never get home.

In this case, the passenger had already passed up the first set of vehicle departures for all candidate routes. What caused this paradoxical situation? Primarily, the passenger assumed he would board a subsequently arriving vehicle when, in actuality, he did not board. The example leaves a positive probability of passing up the first vehicles to depart on both routes which was not explicitly considered in choosing whether or not to board the A-B shuttle at 4:47. In reality, these kinds of factors will certainly influence the passengers' boarding decisions much more than the dynamic path choice model (in its present form) can capture. Obviously, such an example is pretty unlikely, in that two different shuttles departed at times on the later tails of their distributions, and the scheduled transfer connections were particularly horrible for these late departures. This paradoxical result suggests that it is necessary to examine more closely situations in which the dynamic model predicts that passengers can and do change their minds about the eligible paths while waiting for vehicles.

At this point, having defined the dynamic path choice model conceptually, it is also valuable to develop the model mathematically. Specifically, a passenger would like to determine whether to board a vehicle on any particular path at a specific instant in time τ. For this evaluation, a new optimal static choice set may be defined for a given vehicle arrival at τ as $X^{*}(\tau, T)$. Note that this choice set is a function of both the passenger arrival time T and the subsequent vehicle departure time τ. In the static choice set $X^{*}(\tau, T)$, the passenger has accrued information about vehicle arrivals since T. In the static model presented before, it is implicitly assumed that the passenger has no idea about the pattern of vehicle arrivals before T. However, for this dynamic model, the optimal static model at time τ adjusts the distributions of vehicle arrivals based on the vehicle arrivals since T. This is an important distinction between the static and dynamic path choice models.

The adjustment necessary from the static choice model presented in the previous section involves adjusting the waiting time densities and distributions $f_W^i(x)$ and $F_W^i(x)$ for a path i. Equation (4.22) gives the waiting time distribution for a given point in time T when the passenger first arrives. At some subsequent time $t_0 > T$, the waiting time distribution for that passenger for path 1 has two possible forms. If vehicle j on path 1 has not come while the passenger has been waiting (i.e., between

T and t_0), the waiting time density will take the following form:

$$f_W^1(w|t_0,T) = \begin{cases} [\overline{F}_{td_j}(t_0)]^{-1} \cdot \overline{F}_{td_j}(T) \cdot f_{td_j}(t_0+w) & w < TD_{j+1} - t_0 \\ F_{td_j}(T) \cdot f_{td_{j+1}}(t_0+w) & w \geq TD_{j+1} - t_0 \end{cases} \quad (4.37)$$

In the first expression of equation (4.37), the additional condition that $\overline{F}_{td_j}(t_0) \neq 0$ is also necessary. This condition implies that vehicle j may arrive at time t_0 or later. If t_0 is later than the maximum departure time for vehicle j, or if vehicle j had arrived while the passenger was waiting but the passenger refused to board that vehicle, the distribution of waiting times for the next vehicle on path 1 would be given by:

$$f_W^1(w|t_0,T) = f_{td_{j+1}}(t_0+w) \quad (4.38)$$

Thus, by substituting the appropriate forms from equations (4.22), (4.37) and (4.38) into the expressions for T_X in equations (4.24–4.27), the expected travel time for this static choice set $X^*(\tau,T)$ may be computed. At some point in time t_0, the expected travel time for this static choice set is $T_{X^*(t_0,T)}$.

In this manner, the dynamic model may be formulated mathematically. The passenger boards a vehicle on route i arriving at time t_0 if the following criteria holds:

$$E[t_i|\text{dpt } t_0] \leq T_{X^*(t_0,T)} \quad (4.39)$$

According to the decision model described in equation (4.39), then, a passenger in the shuttle network would be willing to board a vehicle on path 1 at time t_0 if:

$$E[t_{AD}^1|\text{dpt } t_0] \leq T_{X^*(t_0,T)} \quad (4.40)$$

and, similarly, the passenger would be willing to board a vehicle on path 2 or path 3, respectively, if:

$$E[t_{AD}^2|\text{dpt } t_0] \leq T_{X^*(t_0,T)} \quad (4.41)$$

$$E[t_{AD}^3|\text{dpt } t_0] \leq T_{X^*(t_0,T)} \quad (4.42)$$

This, then, is sufficient to characterize the dynamic path choice model. In this case, the paths in the dynamic choice set, for a given time t_0, are all paths for which the expected travel time on the path at that point in time is less than or equal to the minimum expected travel time for an "updated" static choice model at that same point in time.

Again, it is important to observe that the dynamic path choice model is oriented toward the times of *vehicle* arrivals, while the static path choice model is oriented toward the times of *passenger* arrivals. Path membership in the dynamic choice set at a given time t_0 is determined by looking at the expected travel times when a vehicle arrives on that path at time t_0. In this way, a passenger will always choose to board the path with the minimum expected travel time upon boarding at time t_0. However, while a passenger using the dynamic model might be willing to board a vehicle arriving at t_0 (i.e., the path is in the dynamic choice set at t_0), this does not necessarily imply that a passenger arriving just before t_0 who uses the static model to make path decisions would make the same decision to board the vehicle. The static choice set would depend on the waiting time distributions and the expected travel time functions for each path, *at the time the passenger arrived at the terminal.* Decisions with the dynamic path model are model only when vehicles arrive at the terminal.

It was hoped that the dynamic model would yield results to determine the probability of a passenger boarding a given route, given his/her arrival time T and also some kind of characterization of the times when paths enter and leave the dynamic choice set. Indeed, in the static choice model, it is possible to describe these path choice probabilities explicitly using the waiting time distributions for each path. However, a comparable analytic characterization of the dynamic choice model is extremely difficult. The hypothesis stated earlier, that there may be some kind of fixed *time-dependent choice set*, is not true in the most general sense because path preferences are conditional upon everything the passenger has learned between his/her time of arrival T and the current time t_0. It is not difficult to construct a simple two-route (A and B) example in which the willingness of a passenger to board a vehicle on route B arriving at a time t_0 depends on whether a vehicle on route A has arrived in the time between T and t_0. Thus, it is not true that there is a fixed time-dependent choice set for this dynamic model, and therefore it is very difficult analytically to characterize the choice set and to estimate the resulting path choice probabilities for this dynamic path choice model.

4.5.2 The Truly Optimal Dynamic Choice Problem

A slight extension at this point seems appropriate. None of the research to date has suggested how to formulate, let alone solve, the passenger's optimal path choice problem in the context of stochastic and time-dependent travel times. As the dynamic path choice model is described above, a passenger would make a decision whether or not to board a vehicle by comparing the expected travel time upon boarding the vehicle with the minimum travel time given that he/she does not board the given vehicle. A truly minimum expected travel time, given that the passenger does not board, differs from the above approach in that the passenger calculates that upon each possible vehicle arrival in the future, he/she will perform the same comparison in deciding whether or not to board.

This section formulates this optimal dynamic path choice problem. The following additional notation will be used:

- θ and τ = arguments denoting time.
- $x_r(\theta)$ = a time-dependent binary switch, which equals 1 when the passenger would be willing to board a vehicle on path r at time θ and equals 0 if the passenger would not board a vehicle on path r at time θ.
- $I(r,\theta)$ = the index of the most recent scheduled vehicle departure, on path r, before time θ. For example, if $TD_j \leq \theta < TD_{j+1}$, then $I(r,\theta) = j$.
- $\overline{P}_r(\theta|t_0)$ = the probability of not boarding a vehicle on path r before time θ, relative to the present time t_0.
- $\overline{P}(\theta|t_0)$ = the probability of not boarding *any* vehicle before time θ, relative to the present time t_0.
- $f_{td_j}(\theta)$ = probability density function of the departure time for vehicle j. Again, by assumption, any vehicle departs within one headway of its scheduled departure time; i.e., $TD_j \leq td_j < TD_{j+1}$.

It is helpful first to outline the overall approach to the formulation before going through the mathematics. The objective is to determine the minimum expected travel time at time t_0, given that there is a vehicle ready to go at t_0 and the passenger is unsure whether or not to board. Ultimately, it is necessary to determine the minimum expected travel time given that the passenger does not board the vehicle at t_0. This expected travel time upon not boarding is the sum of the expected waiting time and the expected travel time upon boarding a subsequent vehicle. In order to find the minimum expected travel time, it is necessary to know the probability that a passenger has not yet boarded a vehicle at any point in time in the future. Furthermore, in order to get this probability, it is necessary to specify when in the future the passenger is willing to board a departing vehicle on any particular path. So, the approach to the formulation develops the probability, denoted $\overline{P}(\theta|t_0)$, that a person has not boarded any vehicle before time $\theta > t_0$. Using this probability, the expected travel time can be calculated, given that the passenger has a time-dependent boarding strategy for each path r, denoted $x_r(\theta)$.

In order for a passenger to board a vehicle at a time θ, two things must happen. First, it must be in the passenger's strategy to board a vehicle at time θ if it departs then; i.e., $x_r(\theta) = 1$. Furthermore, there must be a positive probability (or probability density) that a vehicle will depart at that instant in time; i.e., $f_{td_j}(\theta) > 0$.

For a single path, say path 1, the assumption is made that the time now is t_0, where $TD_j \leq t_0 < TD_{j+1}$. The probability that a passenger has *not* boarded a vehicle on path 1 by time some time τ, for $\tau < TD_{j+1}$, is given by:

$$\overline{P}_1(\tau|t_0) = 1 - [\overline{F}_{td_j}(t_0)]^{-1} \int_{t_0}^{\tau} x_1(\theta) \cdot f_{td_j}(\theta) d\theta \tag{4.43}$$

In this case it is important to note that the distribution functions here should consider all vehicle arrivals and departures since the passenger first arrived at the origin at time T. That is, the probability density function of vehicle arrivals after time t_0 will be a function of what the passenger has learned since their arrival at time T. So, if the passenger knows that vehicle j has already departed by time t_0,

$$\overline{P}_1(\tau|t_0) = 1.0 \quad \tau < TD_{j+1} \tag{4.44}$$

If no vehicle has arrived since T, then equation (4.43) may be revised:

$$\overline{P}_1(\tau|t_0) = 1 - [\overline{F}_{td_j}(t_0)]^{-1} \cdot \overline{F}_{td_j}(T) \int_{t_0}^{\tau} x_1(\theta) \cdot f_{td_j}(\theta) d\theta \qquad (4.45)$$

The adjustments suggested by equations (4.44) and (4.45) would be carried through the first term of each of the expressions presented below. For the ease of presentation, however, the derivation continues using the form of equation (4.43).

A similar expression for points in time in the midst of the next headway interval ($TD_{j+1} \leq \tau < TD_{j+2}$) uses the fact that the passenger has not boarded a vehicle before time TD_{j+1}. Thus, the probability that the passenger has not boarded before some time $\tau \geq TD_{j+1}$ is the product of the probability that he has not boarded before TD_{j+1} times the probability that he/she has not boarded before τ, given that he/she has not boarded before TD_{j+1}. This probability is given by:

$$\overline{P}_1(\tau|t_0) = \left[1 - \int_{t_0}^{TD_{j+1}} x_1(\theta) \cdot \frac{f_{td_j}(\theta)}{\overline{F}_{td_j}(t_0)} d\theta\right] \cdot \left[1 - \int_{TD_{j+1}}^{\tau} x_1(\theta) \cdot f_{td_{j+1}}(\theta) d\theta\right] \qquad (4.46)$$

Generalizing this result for for $\tau \geq TD_{j+2}$ yields:

$$\begin{aligned} \overline{P}_1(\tau|t_0) &= \left[1 - \int_{t_0}^{TD_{j+1}} x_1(\theta) \cdot \frac{f_{td_j}(\theta)}{\overline{F}_{td_j}(t_0)} d\theta\right] \cdot \prod_{n=j+1}^{I(1,\tau)-1} \left[1 - \int_{TD_n}^{TD_{n+1}} x_1(\theta) \cdot f_{td_n}(\theta) d\theta\right] \cdot \\ & \left[1 - \int_{TD_{I(1,\tau)}}^{\tau} x_1(\theta) \cdot f_{td_{I(1,\tau)}}(\theta) d\theta\right] \qquad (4.47) \end{aligned}$$

Assuming that vehicle departures on each path are independent of departures on other paths, the total probability of not boarding a vehicle by time τ, given that it is now t_0, is given by:

$$\overline{P}(\tau|t_0) = \prod_r \overline{P}_r(\tau|t_0) \qquad (4.48)$$

The probability of boarding any vehicle, arriving at some time θ in the future, is the probability of a vehicle on a specific path r arriving at θ, times the probability that no vehicle has been boarded before θ, multiplied by the binary variable of whether the passenger would board a path r vehicle at time θ. Mathematically,

$$\text{Prob(Boarding path } r \text{ at } \theta) = \overline{P}(\theta|t_0) \cdot x_r(\theta) \cdot f_{td_{I(r,\theta)}}(\theta) \qquad (4.49)$$

The expected travel time, *once having boarded a vehicle*, is then given by:

$$E[\text{Post-board time}|t_0] = \sum_r \int_{t_0}^{\infty} \overline{P}(\theta|t_0) \cdot x_r(\theta) \cdot f_{td_{I(r,\theta)}}(\theta) \cdot E[t^r_{AD}|\text{dpt } \theta]d\theta \qquad (4.50)$$

By interpreting $\overline{P}(\theta|t_0)$ as the complement of the cumulative distribution of the waiting time until any vehicle is boarded, the expected waiting time at t_0 is given by the expression:

$$E[\text{Waiting time at } t_0] = \int_{t_0}^{\infty} \overline{P}(\theta|t_0)d\theta \qquad (4.51)$$

So, in order to minimize the total expected travel time from t_0, it is necessary to minimize the sum of the expected waiting time from equation (4.51) and the expected travel time upon boarding from equation (4.50). In other words, finding the minimum travel time, given that a passenger does not board a vehicle at t_0, is equivalent to minimizing

$$E[t_{AD}|t_0] = \int_{t_0}^{\infty} \overline{P}(\theta|t_0)d\theta + \sum_r \int_{t_0}^{\infty} \overline{P}(\theta|t_0) \cdot x_r(\theta) \cdot f_{td_{I(r,\theta)}}(\theta) \cdot E[t^r_{AD}|\text{dpt } \theta]d\theta \qquad (4.52)$$

This equation would then be minimized using the decision variables $x_r(\theta)$, for $t_0 \leq \theta < \infty$. The decision variables appear not only in the explicit form for the expected travel time upon boarding, but also in the calculation of the probability $\overline{P}(\theta|t_0)$. The decision to board at t_0, then, is based on comparing the expected travel time upon boarding (assumed known) and the minimum expected travel time from equation (4.52). This represents a formulation of the optimal dynamic path choice problem.

It is possible to relate the formulation in equation (4.52) to the static model presented in (4.19) and (4.20). The optimization problem here is an unconstrained version of the passenger's static path choice problem. In the static model, some additional constraints are added to the formulation of equation (4.52). First, the static model performs a single minimization at T, the time at which the passenger arrives. In this way, the limits of integration in equation (4.52) would be from T to ∞. Furthermore, the values of $x_r(\theta)$ are constrained to be either 0 or 1, *for all* $\theta \geq T$. Because of this additional constraint, it is clear that the minimum expected travel time from the static choice model is greater than or equal to the expected travel time from this minimization problem. That is, the expected travel time which results from the solution of the static choice problem is at least as large as that from the optimal dynamic path choice model presented in equation (4.52).

4.6 Adaptive Path Choice Modeling

The static and dynamic path choice models presented above are formulated for the passenger's path choice from the origin terminal. It is also possible that the passenger may be able to make a number of different path choices in traveling from origin to destination. In particular, it is possible that the passenger may be able to choose from a number of routes in making a transfer. For example, in the simple shuttle network, suppose there were two bus routes providing service between nodes B and D. In this case, a passenger choosing to travel from A to D in the network would choose not only the boarding strategy at A, but also may consider a second boarding strategy at B, if the A-B route is taken. In this case, the boarding strategy at B is obviously a function of the time when the passenger arrives at B from the A-B shuttle. Thus, the particular path choice at subsequent stops may be dependent on the time of arrival at these stops.

The passenger then may improve their expected travel time by making these subsequent path decisions upon arrival at a transfer terminal. As was suggested by Hall [25, 27], this "adaptive" decision-making will reduce the expected travel time to the passenger, relative to making the full path choice at the "upstream" terminal. The adaptive path choice model assumes the passenger waits until his/her arrival at the transfer terminal to choose a subsequent route. At that transfer terminal, the static or dynamic path choice models described above may be used in choosing this subsequent route.

In some situations, including the MBTA case study, the passenger may arrive at a transfer point at a time t_0 and be faced with the alternatives of getting off the current vehicle or staying on board. In such cases, the dynamic path choice model is most appropriate to compare the expected travel times for both options. The expected travel time calculations are identical to calculating the expected travel time on that route, given a departure at t_0. In a similar manner, the expected travel time for getting off and transfering to another route may be computed using a static path choice model for a passenger arrival at t_0. Thus, the dynamic path choice model can be applied directly in this case.

A question which naturally arises in determining paths at an "upstream" node is how to model the expected travel time at these transfer terminals when multiple paths connect the transfer point to the destination. What is needed at an upstream node (e.g., node A in the shuttle network) is an expected travel time at the downstream node (e.g., node B). The formulation in equation (4.6) assumes that an expected travel time at transfer node B is given. When several routes are available, it will be necessary to determine an expected travel time function based on subsequent path choices at the transfer node.

The path choice at these transfer terminals may be made using either the static or dynamic path choice models. Because of the analytic complexity of the dynamic path choice model, it is advantageous to assume that the passenger will evaluate the expected travel time at such transfer nodes using the static path choice model. In this case, then, given an arrival time at the transfer terminal t_0, the expected travel time from the transfer terminal to the destination is $T_{X^*(t_0)}$, from the static optimal choice set $X^*(t_0)$ upon arrival at the transfer terminal. This choice set $X^*(t_0)$ can be determined using explicit enumeration, as was done for the static choice model in Section 4.4.1.

When the passenger is evaluating a path choice at an upstream node (say, node A), the computation of the expected travel time using a particular transfer path uses the expected travel time function at the transfer node. Specifically, it is necessary to integrate the expected travel time function at the transfer node, $T_{X^*(t_0)}$ over all possible arrival times at the transfer node t_0.

Computationally, this calculation may be fairly complex. Numerical integration may require determining the static optimal choice set at the transfer node for each small interval (δ) in the numerical integration technique, which may be very tedious and computationally time-consuming. Some computational simplifications of this procedure may be possible, such as:

- Storing values for $T_{X^*(t_0)}$ in an array, for small increments (δ) in time.

- Determining times when routes enter and leave the static choice set at the transfer point. In this way, only a single choice set calculation is necessary for each interval δ, rather than explicit enumeration of all choice sets for each interval.

Again, the passenger will make a decision about possible paths at the transfer terminal assuming they will board the first bus to arrive from a static choice set. In the case where the passenger boards vehicles on these connecting routes based on the dynamic path choice model, the passenger may not actually behave as predicted by the static model. Instead, the passenger disregards this decision and uses the dynamic model in subsequent boarding decisions at the transfer terminal. This mimics the modeling approach taken in the dynamic path choice model presented in Section 4.5.1.

4.7 Departure Time Choice Models

Both the static and the dynamic path choice models developed above assume a given passenger arrival at time T. This presupposes that the passenger has already chosen to arrive at T; and, as shown above, his/her resulting strategy and expected travel time is conditional on T. The additional question of how the passenger might choose a time of arrival at the origin terminal, or, alternatively, a time to depart the origin, will be called the passenger's departure time choice. When there is some flexibility in trip scheduling, a departure time choice model is practical.

Given a time-dependent boarding strategy from the path choice models discussed above, this section examines two different departure time choice models. Traditionally, passengers are assumed to arrive randomly in time; that is, their departure time choice occurs independently of path choice, and independently of vehicle timing. Alternatively, a second model assumes that passengers choose departure times which are more strongly correlated with scheduled vehicle departure times. In this case, passengers may time their arrivals to minimize their waiting time or expected travel time. Typically, this involves arriving close to some scheduled vehicle departure time; such behavior has been noted in a number of previous studies (e.g., Jolliffe and Hutchinson [35], Turnquist [68], and Bowman and Turnquist [11]). Both of these models are discussed in greater detail below.

4.7.1 Random Departure Times

Traditional transit planning models assume that passengers arrive randomly at a stop. That is, passengers arrive according to a Poisson process (i.e., inter-arrival times between passengers are exponentially distributed random variables) or according to a uniform distribution over a fixed time interval. Both models assume that passengers basically choose their departure times at random. Typically, the assumptions used to justify the use of randomly arriving passengers include:

1. The headways on the transit service are sufficiently short (i.e., under 10 minutes), or the service sufficiently irregular, that there is little or no advantage to more clever arrival strategies; or,

2. Passengers are not aware of the service schedule and thus arrive randomly at the stop to begin their wait for a vehicle.

It is assumed for this analysis that passengers are aware of service schedules, which renders the latter argument moot. With regard to the first assumption, however, there is some dispute in the literature as to what actually constitutes either sufficiently short headways or sufficiently irregular service. Both factors will influence the amount of benefit to be gained by the passenger through more deliberate timing of arrivals at the terminal. Given the correlation between higher travel time variability and supposed higher value of real-time information, situations in which there is high variability in travel times are of interest in this thesis. For this reason, it is important to examine the case where passenger departure times are random.

4.7.2 Arrivals Coordinated with Vehicle Schedule

One might also expect that passengers may reduce their waiting times (and their total travel times) by timing their arrivals with specific vehicle departures. This section briefly describes how an experienced passenger might choose when to arrive at the origin terminal. This approach resembles that suggested by Abkowitz [3], who chose a utility maximization objective in determining a traveler's selected departure time. Several other authors have investigated passenger arrivals at bus stops for services with higher service reliability and longer headways (e.g., Jolliffe and Hutchinson [35], Turnquist [68], Bowman [10], and Bowman and Turnquist [11]). Under these conditions, it seems advantageous to the passenger to select an arrival time at the origin stop so that the waiting time (or disutility) at the origin would be minimized, for a particular vehicle departure. However, the utility formulations presented by these authors required a significant amount of empirical analysis, which is beyond the scope of this thesis. Moreover, the models which minimize the expected waiting time disregard both the multiple-route waiting phenomenon and possible time-dependence in travel times upon boarding vehicles on particular routes.

The assumption made for this thesis is that passenger arrivals are coordinated with specific vehicle schedules. However, the behavioral intuition behind exactly how passengers choose departure times is far from intuitive. Previous researchers (such as Holroyd and Scraggs [31], O'Flaherty and Mangan [56], Seddon and Day [62], Jolliffe and Hutchinson [35], Turnquist [68], Bowman [10], and Bowman and Turnquist [11]) have focused on empirical estimation of arrival patterns, rather than developing a more theoretically grounded analysis of passenger behavior. Furthermore, it is difficult to develop a theory on how passengers are really making these types of departure time decisions, in the context of other uses of a person's time.

To summarize, then, the research on transit passenger departure time choice lacks a behavioral representation of passenger decision-making and also lacks empirical evidence regarding arrival patterns for stops served by multiple routes. A more rigorous treatment of this passenger departure time choice is not possible as part of this thesis, but is clearly necessary. A more detailed discussion of this issue is included in Chapter 8 under Further Research.

For the purposes of this thesis, it is assumed that passengers are able and willing to time their arrivals at a stop with some scheduled vehicle departure. Rather than selecting some "optimal" arrival time, as was suggested by Turnquist [68], it is assumed that passengers arrive uniformly over a two-minute period just prior to the scheduled departure of a vehicle. In this case, since the service model of Chapter 3 assumes that all vehicles depart on or after their scheduled departure times, the passengers arriving in this manner will always arrive in time to meet a particular vehicle trip on the given route. This model of passenger arrivals is perhaps the simplest model possible; however, without more empirical and theoretical research in this area, this seems to be at least as credible as any other model.

4.8 Analytic Difficulties

There are a number of analytic difficulties which occur in the investigation of these path and departure time choice models. These difficulties mainly result from the complication of stochastic travel times and some of the various assumptions made regarding vehicle dynamics. In particular, two significant analytic difficulties are discussed below. These include the analytic complexities of vehicle departure time and running time distributions, as well as the formulation of the dynamic path choice model. For these reasons, many of the questions raised thus far about network dynamics, passenger behavior, and real-time information cannot be answered through straightforward analytic techniques alone. Instead, simulation (discussed in Chapter 5) represents a better approach for investigating these questions.

4.8.1 Probability Distribution Form

The primary complication to the analytic models discussed in Chapters 3 and 4 result from the assumptions of the shuttle model of transit service. In the development of the service model, the distribution of vehicle departure times were derived in an iterative manner. The departure time distributions for a given vehicle trip were shown to be related to similar distributions for the same vehicle on its previous trip. This iterative procedure to determine vehicle departure distributions requires iterative integration of these distributions, which does not yield closed form solutions except for specific probability distribution functions.

However, the functional form of departure time and running time distributions for this analysis are limited by the model assumptions. In particular, the exclusion of the possibility of vehicle bunching means that the probability distributions for vehicle departure times and running times must have finite domains. Otherwise, it might be possible for vehicles to bunch or overtake. This finite domain characteristic of the vehicle travel time distributions causes considerable difficulty in integrating waiting time and running time distributions in closed form. Either the number of cases to be examined in integration increases very quickly, or the analytic form of the distribution function makes integration very difficult without very specific assumptions about distribution parameters. Therefore, without a more specific definition of travel time characteristics for the shuttle network, it is very difficult mathematically to determine these distributions in closed form.

4.8.2 Dynamic Model Formulation

The dynamic path choice model discussed in Section 4.5.1 is difficult to model analytically. Specifically, as discussed at the end of that section, it is not possible to characterize a time-dependent choice set for the dynamic model. In this case, the path choice decision at a time t_0 is a function of not only the state of the system at time T, when the passenger arrives at the stop, but also the particular vehicle departures that occur while the passenger is waiting between T and t_0. Because of the stochastic nature of the vehicle departures between T and t_0, it is indeed very difficult to draw specific conclusions about the willingness of a passenger to board an arriving vehicle at time t_0. The decision to board a vehicle at time t_0 depends on the timing of vehicle departures on other routes up until time t_0. Thus, the stochastic nature of vehicle arrivals at the terminal makes analytic characterization of path choices in the dynamic path choice model extremely difficult.

Chapter 5

Development Using Simulation

This chapter describes the basic questions to be investigated using the simulation model. As outlined in the previous chapter, the analytic complexities of the transit service supply model developed in Chapter 3 and the path choice models developed in Chapter 4 require other techniques to analyze passenger path choice in the context of stochastic and time-dependent transit service. For this reason, a simulation model has been developed which incorporates these transit service characteristics and the path choice methodologies. This simulation model may be used to assess more accurately passenger path choice behavior and the value of real-time information to improve passenger decision-making.

This chapter is organized as follows. The first part describes some of the motivation and objectives of the simulation. Next, there is a discussion of different levels of real-time information that might be provided to the passenger in the course of his/her trip. The dimensions of this real-time information include the type of information given, when the passenger receives the information, and the accuracy of that information. The effects of real-time information on path choice are discussed for each of these dimensions. The third section of this chapter addresses how passenger experience and familiarity with the transit service affects the path choice models, and how this element will be treated in the simulation. The fourth section summarizes the treatment of real-time information by outlining the information scenarios to be tested using the shuttle network described in Chapter 3 and the set of simulation scenarios to be examined with the shuttle network. The fifth section concludes the chapter with a more detailed discussion of how the shuttle and path choice models are implemented in the simulation.

5.1 Simulation Motivation and Objectives

The goal of this thesis is to examine transit passenger path choice in the context of stochastic and time-dependent travel times, particularly looking at the potential impacts of real-time information on this decision process. In Chapter 1, the research question for the thesis was described as follows:

Research Question: Given the stochastic nature of travel times in public transit, how might real-time information on vehicle movements affect passenger decisions on path and departure time?

Given the development of the transit service models and passenger path choice models in the previous chapters, the following objectives are specified for the simulation phase of the research (from Chapter 1):

1. Identify a set of scenarios for implementation of real-time passenger information systems. These should include variation among:
   - Types of information (current and/or projected travel conditions);
   - Timing of information during the passenger trip (before or during the trip); and,
   - Accuracy (or precision) of the information given to the passenger.
2. Using appropriate passenger behavior models and a suitable form of analysis, investigate the effect of these different levels of information on passenger behavior, using the measures of o-d travel times and path choices.
3. Extend this type of analysis to a case study to demonstrate its potential in a real-world setting.

This chapter develops a framework for addressing these three issues in the context of a simulation model. The case study proposed in item 3 above will be mentioned only briefly in this chapter, but is discussed in much greater detail in Chapter 7. Specifically, the modeling framework from Figure 3.1 is developed using a simulation model. A "baseline" for this model assumes that passengers receive no real-time information. This baseline may be analyzed by using the the operating characteristics of transit service given in Chapter 3 and the path choice methodology described in Chapter 4. Under these decision criteria, there is a resulting demand pattern which may be characterized through path choices and origin-to-destination (o-d) travel times.

This modeling framework is the foundation to which the additional elements of passenger experience and real-time information may be added. This chapter examines the additional modeling needs to include the assumptions that passenger decisions may also be influenced by the various dimensions of real-time information and an individual's perceptions of service. With this extended modeling framework, the potential value of real-time information on passenger decision-making may be assessed. A fundamental question which should be answered through this approach is the following: will real-time information have a significant impact on passenger decision-making? Related questions to be addressed include:

1. What changes in passenger behavior may be caused by different types of real-time information?

2. What are the relative merits of providing real-time information to the passenger before the trip versus on route?

3. What are some of the benefits of providing more accurate information to the passenger?

Using the measures of o-d travel times and path choices, these questions can be addressed in a quantitative manner.

The tool to answer these questions is a simulation model which simulates vehicle movements and analytically determines different types of passenger behavior. The primary objective of the simulation is to look at real-time information, while variations in passenger perceptions and different decision-making criteria are intended to augment looking at this primary objective.not to look at variations in passenger perceptions or different types of behavior. In this context, though, a range of passenger behaviors can be modeled:

- Different path choice criteria: the static and the dynamic path choice models.
- Different passenger objectives in path choice: minimizing the expected travel time or some other objective relating to the variability of travel times.
- Different passenger arrival patterns at the origin stop: random arrivals and arrivals coordinated with the vehicle schedules.
- Different levels of passenger experience with the transit service and with the real-time information system.

The objective is to make statements such as the following:

> Assuming that passengers arrive at a stop randomly, in-terminal information about expected vehicle departure times will improve passenger path choices. Specifically, expected travel times for experienced passengers may be reduced by $X\%$ over the case with no real-time information, while passengers with less familiarity with the system experience smaller net reductions in travel times. In all cases, real-time information brought about a shift in passenger path choices from path 1 to path 2.

In this way, conditional answers to the critical questions on the value of real-time information can be determined. The additional elements necessary for modeling these types of scenarios is described in greater detail below. The next section discusses the dimensions of real-time information, and the following section discusses the treatment of passenger's level of experience and perceptions of the transit service.

5.2 Real-Time Information

In the path and departure time choice framework developed above, it was assumed that the underlying character of the transit system is stochastic and time-dependent. That is, vehicle departures and travel times between points are random variables which add uncertainty to passengers' travel times through the network. When more information is provided to the passenger about these random variables, some of this uncertainty may be eliminated. This reduction in uncertainty may result in improved passenger decision-making and overall reductions in origin-to-destination travel times.

This thesis assumes that all passengers have access to route maps and schedules. Other authors (e.g., Hall [25, 26]) have investigated the value of this static transit information to passengers who are not familiar with transit services. However, beyond simple route and schedule information, it may be helpful for the passenger to learn about the real-time status of transit vehicles and expected travel times in the network. Simply knowing the current location of vehicles may be a valuable form of real-time information, helping passengers to infer expected vehicle departure times and running times. However, the type of information which may be most useful to the passenger is information about predicted travel times for his/her trip; e.g., when the next bus will arrive at the bus stop, or how long it will take to get from point A to point B on that bus, given current traffic conditions.

By providing information about expected travel times (waiting times, running times, time of arrival at the destination, etc.), passengers are able to make the best possible choices of path and departure time. In the ideal case, when all these expectations are known with 100% certainty, the traveler's choice of path and departure time reduces to a time-dependent shortest path problem. If these expected travel times are not known with certainty, the problem becomes more complicated. Yet, even when such predictive information has limited accuracy, passenger decision-making may be improved.

From a modeling standpoint, Chapter 3 discussed models of stochastic and time-dependent transit service, resulting in probability distributions of the random variables of vehicle departure times and running times. These same distributions can be used to model both the range of passenger experience and potential information about future travel conditions on the transit system. It is assumed that passengers are given information, and this information is at least as accurate as what passengers may discern from their own experience. For example, passengers are told that the next bus on route 6 will arrive in 5 minutes. Depending on the accuracy of the information system, the passenger might believe that the expected arrival of that bus is in 5 minutes, but the bus could arrive as soon as 4 minutes or as late as 8 minutes from now. By having this information, though, the distribution of vehicle departures as perceived by the passenger is updated: without this information, the passenger may have believed that the route 6 bus could arrive at any time in the next 15 minutes; however, with the more accurate real-time information, the range of uncertainty is reduced. This is incorporated directly into the path choice models by adjusting the vehicle departure time (or vehicle running time) distributions accordingly. In this way, the behavioral response to real-time information may be assessed.

The goal of this section is to define a relevant set of scenarios to examine the potential benefits of real-time information systems. Below is a discussion of the key aspects of real-time passenger information systems in public transit: the type of information, the place of information, and information accuracy. In each case, the modeling technique for the simulation is discussed in detail.

5.2.1 Type of Information

The first aspect of real-time information systems is, what information is supplied to the passenger? First, and most obviously, the passenger can only process a limited amount of information. Providing detailed real-time information on the entire network is not practical because passengers would become overloaded by information, most of which is irrelevant to their particular trip. A second issue is whether to supply real-time information on current vehicle locations and travel times or predictive information about projected vehicle departure times and/or running times. There can be a significant difference in the level of effort required to report current network conditions as opposed to predicting future travel times with reasonable levels of accuracy.

In terms of network travel times, the types of information that may be given to the passenger fall into three broad categories:

1. Current vehicle locations;
2. Expected departure times of vehicles; and,
3. Expected travel times to the next terminal for specific vehicles.

Item 1 above reflects information regarding the most recent "snapshot" of the transit network, including the most recent estimated location of relevant vehicles in the network. Information on current vehicle locations would be used by the passenger to estimate the departure times of vehicles at the origin stop. By knowing the current location of a vehicle, the passenger can estimate when the vehicle will arrive at the stop at least as accurately as when no real-time information is given to the passenger. In this way, the domain of potential departure times on each route may be reduced, from the passenger's viewpoint. The modeling technique closely resembles that of item 2, in which the operator actually gives the passenger an estimate of the expected vehicle departure time. As a result, the discussion below first describes that alternative (item 2) and then describe how vehicle location information might be incorporated. In the simulation modeling in this thesis, however, current vehicle location information is not treated separately from the expected vehicle departure time information in item 2.

In the second case, the passenger is given information about expected vehicle departure times. Associated with this estimate is a related distribution (e.g., range of that estimate) reflecting the accuracy of that expectation. For example, information technology and forecasting error might allow an estimate that the next vehicle on route 1 will leave in five minutes, give or take one minute. In this case, the passenger is not given this distribution, but only the expectation. The passenger's level of experience with the information system will affect how well he/she is aware of the "true" distribution of departure times around this given expectation. That is, associated with an expectation is an *accuracy distribution* describing the distribution of true departure times around the given expectation. This expectation and the (passenger's perceived) accuracy distribution are then used in the path choice models to mimic passenger decisions in light of this information. How the passenger perceives this accuracy distribution is discussed in Section 5.3.

For scenarios with vehicle location information, the accuracy (as perceived by the passenger) of this projected vehicle departure time is likely to be less than that when the expected vehicle departure time is provided by the operator. The operator will generally have better information for estimating vehicle departure times, and thus may forecast departure times with greater accuracy than the passenger. In effect, this may be modeled by increasing the variability (e.g., the domain) of the accuracy distribution for vehicle departure times, relative to the scenarios where expected vehicle departure times are given by the operator directly. Again, real-time information on current vehicle locations is not modeled explicitly in this thesis.

The final type of information, the expected travel time to the next node, is treated similarly in the simulation. The passenger is given the expected departure time and the expected running time of the next vehicle on each route serving the origin terminal. Although the passenger may not know the distributions of these estimates with certainty, there is an associated level of accuracy (i.e., the accuracy distribution) for each of these estimates. These distributions are then be used in the path choice models, adjusted for the different levels of passenger experience with the real-time information system.

Since one of the fundamental premises of the research is to examine transit path choice in the context of transfers, it may also be of interest to provide passengers with information about transfer connections. In particular, it may be possible to provide information to the passenger about expected departure times and expected travel times on transfer paths. This information may influence passenger path decisions, especially where there might be considerable uncertainty about making a connection on a transfer path. Thus, scenarios examining different types of real-time information on transfer routes should be included.

5.2.2 Place of Information

Another issue in passenger information systems is, at what point should information be given to the passenger? Pre-trip information, provided using television, computer, or telephone at the passenger's home or work, may improve both departure time and path choices for the passenger. By having pre-trip information, passengers can reduce the amount of time spent waiting for vehicles and thus reduce their expected travel times. Additional benefits might be realized if the passenger can choose between different stops providing service near the trip origin. These advantages over in-terminal information systems may be weighed against the fact that pre-trip information is likely to be somewhat less accurate that in-terminal information for a given passenger trip, since pre-trip information must be provided further in advance. In-terminal information, on the other hand, is not likely to influence passenger's departure time choice (except perhaps to allow some productive activity within or near the terminal), but may significantly impact a passenger's path choice. Information on board the vehicle may influence adaptive path choice when the passenger may choose between different transfer connections for a trip.

There are a number of issues associated with pre-trip information that make its analysis rather difficult in the current context. First, the question arises as to how passengers actually choose departure times for the trip. This question has not been adequately addressed in the literature, and clearly depends on other activities the passenger may have planned around the given trip. In particular, it is not obvious when a passenger may access pre-trip information or how this information is used by the passenger to organize activities around the trip to take advantage of better trip timing. It is difficult to develop solid intuition about the value of pre-trip information without a coherent picture of how passengers choose departure times. The other issue which may arise is the choice of stop when the passenger has access to a number of different stops, potentially served by different routes. A coherent station choice modeling framework in the context of time-dependent and stochastic travel times in transit is also beyond the scope of this thesis. [Both of these issues are discussed in greater detail in Chapter 8 under Future Research.]

For this reason, the research here looks at information sources available during the trip: information systems at the stop or station and also on board the vehicle. These information scenarios may directly influence passenger path choices as passengers wait for vehicles to arrive. For the shuttle network, it is assumed that the passenger may receive information at the terminal only; for the case study, both in-terminal and on-board information systems are investigated. The following paragraphs discuss the in-terminal information systems for the shuttle network in greater detail. A final paragraph briefly touches on in-vehicle information sources to be developed in the case study.

In-terminal Information

When in-terminal information systems are available, the passenger's path choice decision is based on the type of information available at that terminal. The two path choice models proposed, the static and the dynamic model, may be used for this evaluation. However, in the context of real-time information at the terminal where boarding decisions are made, the dynamic path choice model seems to be the more reasonable model of passenger path choice. Basically, the static model assumes that passengers do not update their choice sets after arriving at the terminal. The dynamic model, on the other hand, assumes that passengers make boarding decisions based on the most current information available, and thus is more applicable in this situation.

More formally, as information at the terminal is updated, the waiting passenger using the static path choice model should be free to update his/her choice set. As a vehicle approaches the terminal, it seems reasonable to assume that the accuracy of the projected departure time for that vehicle might improve. In this way, the person might continuously update their static choice set, with refinement occurring as vehicles approach the terminal. In the limit, as information accuracy approaches 100% for an arriving vehicle, the static choice model thus reduces to the dynamic path choice model. For this reason, only the dynamic path choice model is used for scenarios in which real-time information is provided in the terminal.

In-Vehicle Information

An alternative is to provide the passenger with information while on board vehicle. Obviously, the value of such information would be limited to situations where the passenger must make a transfer on route and has a choice of several connections at different stops. In this case, the adaptive path choice methodology discussed in Section 4.6 may be applied. That is, the passenger may wait until his/her arrival at a stop before making a decision about whether to disembark to make a transfer at that stop, or to continue on the vehicle to some subsequent stop. In this case, the dynamic path choice methodology can be applied directly. This issue will be developed further as part of the case study in Chapter 7.

5.2.3 Information Accuracy

One of the key issues in implementing a passenger information system is the inherent accuracy of the information. Obviously, passengers can be more certain about the timing of their trip when there is greater accuracy of real-time information. Things like the type of vehicle location system used, the frequency of updating location data, the techniques for information processing, and travel time forecasting will influence the overall level of accuracy of real-time information. Clearly, real-time information provides no help to the passenger if it is not at least as accurate as passengers' expectations based on their own experience.

For the purposes of this thesis, information *accuracy* is defined as a distribution around a given expected travel time which comes from the inherent inaccuracy of the technology and forecasting technique used to predict vehicle locations or expected travel times. It is assumed that the information given to the passenger has a certain level of accuracy, characterized by an *accuracy distribution* associated with the expected travel time given to the passenger. This assumes that a certain accuracy distribution may be accurately projected, and that, given this accuracy distribution, the observed travel time will *always* fall within this distribution. For example, one scenario might have expected vehicle departure times accurate to plus or minus one minute. In this case, the accuracy of the information is given in the range of plus or minus one minute. The assumption that travel times may be accurately projected, then, assures that the vehicle will truly depart at some time within that distribution, but clearly not necessarily at the expected value. Finally, this accuracy distribution of projected travel times is known with certainty by the operator, but is only known by the passenger inasmuch as he/she has experience with the real-time information system. In this way, the accuracy distribution is subject to possible bias in passenger perceptions.

It has been suggested that the level of accuracy of the expected departure times are a function of the time until the true vehicle departure. For example, a vehicle departure which is 5 minutes away may be more accurately predicted than a departure time 10 minutes from now. Clearly, since the variation of travel times may be considerable for running times on a transit route, there is likely to be higher variance for estimated departure times or running times which are further in the future.

Ideally, this would best be modeled as a continuum: the variance (or domain) of the distribution of expected departure times would increase proportionally with the time until the departure. However, due to some difficulty of modeling this continuum in the simulation, it may be reasonable to assume certain discrete intervals and corresponding levels of accuracy, such as those suggested in Table 5.1. Two different

Table 5.1: Accuracy of Departure Time Projections by Time Until Departure

Low Accuracy

Time Until Event	Distribution Domain
Over 10 mins	-2.0 to +5.0 mins
7-10 mins	-1.5 to +3.0 mins
4-7 mins	-1.0 to +2.0 mins
1-4 mins	-0.5 to +1.0 mins

High Accuracy

Time Until Event	Distribution Domain
Over 10 mins	-1.0 to +3.0 mins
7-10 mins	-1.0 to +2.0 mins
4-7 mins	-0.5 to +1.0 mins
1-4 mins	-0.5 to +0.5 mins

levels of accuracy are proposed, in order to model different levels of technical precision in forecasting travel conditions. The levels of accuracy shown in Table 5.1 are consistent with the experience of existing passenger information systems in Europe, and thus may be applicable in the case study developed in Chapter 7.

The shuttle network, however, assumes a simpler accuracy distribution. For shuttle systems, it is likely that service is more or less predictable, in that it is often known with a pretty high degree of certainty that if a vehicle has a late departure from one terminal, it is very likely to have a delay at the opposite terminal before the next trip. For this reason, departure delays may be known with a fairly high degree of certainty, without regard to the time until the next vehicle departure. For the shuttle network, then, it is assumed that departure time projections have an accuracy of -0.5 to +1.5 minutes for all service.

For vehicle running times, it is assumed that these projections have a margin of error of -1.0 to +3.0 minutes for the low accuracy case and a margin of -1.0 to +2.0 minutes in the high accuracy case. Furthermore, information on connecting routes has an assumed accuracy distribution ranging from -1.0 to +3.0 minutes for projected departure times and from -1.5 to +4.0 minutes for projected running times on these routes.

5.2.4 Information Scenarios

The simulation scenarios trade off the various dimensions of real-time information described above. Two different scenarios examine path choice at the stop assuming no real-time information is available to the passenger, comparing the static and the dynamic path choice models. Models with real-time information assume that passengers use the dynamic model of path choice, as passengers will take advantage of the most current information on transit services when making vehicle boarding decisions. The total information scenarios for the shuttle network are listed below.

1. No real-time information. Passengers are assumed to choose paths based on the static model of path choice.

2. No real-time information. Passengers are assumed to choose paths based on the dynamic model of path choice.

3. Real-time information on expected departure times for origin routes only. A single level of accuracy is assumed for these expectations.

4. Real-time information on expected departure times for all routes in the network. A single level of accuracy is assumed for these expectations, consistent with scenario 3.

5. Real-time information on expected departure times and running times for origin routes only. A low level of accuracy is assumed for running time projections.

6. Real-time information on expected departure times and running times for origin routes only, with a high level of accuracy on running time projections.

7. Real-time information on expected departure times and running times for all routes in the network. A high level of accuracy on running time projections is assumed.

For the shuttle network, two scenarios examine provision of vehicle departure time information to the passenger: one for departures on routes serving the origin stop (scenario 3), and one for departures on all shuttle routes (scenario 4). A single level of accuracy in forecasting vehicle departure times is assumed for all information scenarios. Three scenarios examine the provision of both vehicle departure time and running time information to the passenger. Of these three, two scenarios (5 and 6) assume the passenger receives this information about routes serving the origin only, differentiated by the level of accuracy of predicting vehicle running times (scenarios 5 and 6). The final scenario (scenario 7) looks at real-time information on vehicle departure times and running times for all routes in the network.

Additional scenarios would be investigated using the MBTA case study. In particular, the restrictive service assumptions of the shuttle network can be relaxed, allowing investigation of different scenarios, such as the following:

- Different levels of accuracy for vehicle departure time projections, as suggested in Table 5.1.

- The availability of real-time information on board the vehicle for adaptive decisions about where to make a transfer.

A more detailed discussion of information scenarios for the case study is presented in the Section 7.2.1.

5.3 Passenger Experience

Each transit passenger making path choice decisions bases these decisions on his/her own perceptions about the travel time characteristics which may or may not be consistent with the true system characteristics. Passengers who have used transit for a long time will tend to have an accurate perception of the service, based on information gained from previous experiences. These passengers' historical knowledge of travel times and service reliability may be close to true travel time distributions. Other passengers with different levels of experience, may have perceptions which differ significantly from the true travel time characteristics.

Passengers less familiar with the transit network may have little or no information about historical patterns of travel time variability. In this case, their perceptions about travel times and system reliability may vary much more significantly: they may greatly exaggerate or underestimate travel times or travel time variability. At the one extreme, passengers with no experience on a given transit system may have little concept of true travel times or reliability beyond the printed route schedule, in addition to their own limited (or anecdotal) experience with other public transit services.

Intrinsically, then, it seems reasonable to assume that each passenger has some perception of the travel time characteristics of transit service connecting his/her origin and destination. This perception is a function of primarily the level of experience of the user but also the manner in which the user processes the information from that experience. A full range of perceptions, from a view based on the printed schedule, to a completely accurate understanding of the travel time characteristics of the system, are likely.

One technique presented in the literature (e.g., Lotan [44] and Mirchandani and Soroush [52]) is to model various passenger perceptions by using different parameters in perceived travel time distributions. Modeling different levels of passenger experience in making travel decisions, then, involves using modified distributions in the path choice models of Chapter 4. The more closely the passenger's perceived distributions match the true travel time characteristics, the more actual passenger behavior matches the "ideal" passenger behavior assumed in the path and departure time choice models. It is possible to compare how the behavior of passengers with varying perceptions of travel time distributions differs from the behavior of "experienced" passengers who have accurate knowledge of the true distributions of vehicle travel times.

The following three different passenger categories (or "types") are investigated further:

1. Experienced (or "realistic") passengers, whose perceptions of vehicle travel time distributions perfectly match the true system characteristics;

2. Less experienced passengers with some negative experiences, whose perceived mean and variance of travel times in the system are greater than their true values; and,

3. Less experienced passengers with more positive experiences, whose perceived mean and variance of travel times are less than the true values.

To incorporate these passenger types into the simulation, it is possible to associate a particular set of distribution parameters with each passenger. This is done by associating a single multiplier or set of multipliers with each passenger, corresponding to changes in the perceived domain of the vehicle departure time and running time distributions. For example, experienced passengers have a multiplier of 1.0, while less experienced passengers who overestimate the variance (or range) of travel times may have a multiplier of 1.3. The path choice calculations use these revised distributions in determining each passenger's behavior. There may also be a similar effect of experience influencing the passenger's perception of the accuracy of real-time information, specifically for the distributions of expected vehicle departure times and expected running times. In such a situation, the distribution parameters for the information on expected vehicle departure and travel times are adjusted based on these same three types of passengers.

The "bias" associated with these different passenger types (i.e., levels of experience) is modeled differently for existing network conditions as opposed to real-time information. In particular, it seems likely that, in the absence of real-time information, passengers with more positive experiences may have a more optimistic bias in their expectations about current vehicle departure times and running times than passengers with more negative experiences. However, when real-time information is available to the passenger, in the form of an expected vehicle departure time or running time, both passenger types will have similar expectations (equal to the expected departure time or running time provided by the operator).

To model this in the simulation, the following approach is used. When no information is given to the passenger (the baseline), it is assumed that passengers differ in their perceptions of the right tail of the vehicle departure time and running time distributions. Passengers with mostly positive experiences have shorter tails on their perceived distributions, while those with significant negative experiences have longer tails on these distributions. This is accomplished by multiplying the true domain of the distribution with the passenger-specific multiplier, and adjusting the maximum of the distribution accordingly. For example, a distribution on [0,3] would become a perceived distribution on [0,3.9] for passengers with a multiplier of 1.3. In effect, increasing the probability in the right tail of a distribution will increase the variance and slightly increase the mean of the distribution (as perceived by the passenger).

In the case of real-time information, the distributions of departure times and running times are adjusted in a slightly different manner. When the passenger is given an expected vehicle departure time or running time, their perceived distribution around this expectation will be a function of both the information accuracy and the perception "bias." Assuming a certain distributional form for the accuracy distribution, the bias associated with passenger experience moves **both** the left and right limits of the distribution in or out, depending on the passenger's positive or negative experience. For example, a true accuracy distribution on [-1,2] with a mean of 0 would become a perceived distribution on [-1.3,2.6] with a mean of 0, for passengers with a multiplier of 1.3. The expectation remains the same for all passengers, as the variance changes based on the type of passenger. Passengers with positive experiences have lower variance and tighter limits; passengers with negative experiences have higher variance and greater limits.

Because of economies of scale, it is easier to process these three passenger types in parallel through the simulation. Thus, a given information scenario from Section 5.2.4 can accommodate all three passenger types. In the simulation, a passenger arrival at the origin stop is, in reality, three passengers arriving simultaneously, one for each passenger type. In the discussions that follow, a single passenger type (e.g., 60 passengers arrive at random) is assumed for ease of presentation. However, in the simulation, three times as many passengers are moving around; in this example, a full 180 passengers are arriving at random at the origin stop, in groups of 3.

5.4 Simulation Scenarios

For the shuttle network, Section 5.2.4 presented a total of seven scenarios. In terms of running these scenarios through the simulation, a number of additional issues need to be addressed. This section briefly describes some of the experimental design for the simulation scenarios. The paragraphs below outline the operating conditions for the shuttle network, the statistical design of the experiments, and other passenger objectives that are investigated.

5.4.1 Shuttle Operating Conditions

In designing experiments for the simulation, the trip in the shuttle network is intended to represent a "typical" trip on public transit. In general, such an o-d trip may take on the order of 30 minutes. To examine possible differences in path choices under different operating conditions, each of the seven information scenarios described in Section 5.2.4 is run for two different types of service schedules: first, the routes leaving the origin node have coordinated schedules; second, there is no coordination of scheduled vehicle departures from the origin. Varying the service schedules provides additional insight into the value of real-time information in different service environments, particularly in evaluating variations in path loading and passenger travel times based on schedule coordination. By varying the service characteristics in the network, the seven information scenarios would be run for two different sets of input data, resulting in a total of 14 different simulation runs for the shuttle network.

5.4.2 Statistical Design

There are two issues to consider in determining statistically significant results from the simulation scenarios. First, there must be a sufficient number of observations for a single simulation run (i.e., for a given service day) to determine useful statistics on the o-d travel times and the path assignment on that day. Furthermore, the simulation should be run a number of times (i.e., for a sample of "days" of transit service) so that the results will also have statistical significance across days.

To deal with these two issues, a substantial number of passengers should use the transit service on a given (simulated) day, and a large number of days should also be modeled. The simulation period chosen for the shuttle network involves 60 passengers arriving during a 120-minute (two hour) period. Vehicle operations are assumed to continue past this two hour period, so that all passengers arriving in this window complete their trips. Because of the computational effort required in calculating expected travel times for the path choice models, the time to run a simulation on the computer is basically a function of the number of passengers. Furthermore, in order to gain results that are statistically significant, each simulation is run for 30 replications (i.e., days) to get a statistically meaningful sample of observations.

Several statistics are measured for each information scenario, including:

- The total travel time from origin to destination, including all waiting times, for a given day (i.e. replication).
- The variance of travel times among the set of passengers on a given day.
- The probability of a passenger arriving at the destination more than X minutes after beginning their trip, for a given day.
- The number of passengers choosing each path in the network on a given day.

These four statistics were calculated for a given day (replication), averaging or totalling over all passengers on that day, for 30 days. In order to compare the travel times and path choices between different information scenarios, a differencing technique described by Law and Kelton [41] was employed. Basically, these four statistics were compared across different scenarios in the following manner.

1. Two scenarios were chosen for comparison: a baseline (e.g., no information) and a test case (e.g., departure time information with a high level of accuracy).
2. Each scenario is run for 30 days (replications).
3. The days are matched between the two scenarios, and the difference between statistics for each day are calculated (for a total of 30 observed differences).
4. The mean and standard error of the mean *of the differences* is calculated.
5. These differences have statistical properties based on the t-distribution, and thus are subject to hypothesis tests using standard t-statistics.

This technique may be applied for any desired pairwise comparison of information scenarios. The results of these statistical comparisons are reported with the simulation results in Chapters 6 and 7.

5.4.3 Passenger Objectives

Two other aspects of passenger decision-making may also be addressed using the simulation model: the objective in passenger path choice, and the passenger departure time choice. First, there is room for debate regarding a passenger's objective in making path choices. Through the course of development of the path choice models in Chapter 4, the passenger is assumed to have the objective of minimizing the expected origin-to-destination travel time. As discussed at the beginning of that chapter, a number of other objectives may also be appropriate for certain types of passenger trips. In particular, passengers may also consider the level of variability in o-d travel times in making travel decisions, especially for the morning commute when desired arrival times at the destination are more rigid.

In order to test the sensitivity of these path choice models to the selected passenger objective, a set of scenarios examining an alternative objective are also presented. Specifically, the research considers the passenger objective of minimizing the probability of an o-d trip longer than X minutes. In this way, passengers that are averse to very long trips may choose to avoid paths where there is considerable potential for delay. As the o-d trip takes on the order of 30 minutes, a reasonable upper limit of $X = 37$ minutes is used for the objective of minimizing the probability of a trip longer than X minutes. This objective is included, for comparison purposes, in the shuttle network scenarios that assume coordinated vehicle schedules (as discussed in Section 5.4.1).

Second, as discussed in Chapter 4, it seems reasonable to model two different passenger departure time choices (i.e., arrival processes at the origin stop) in the simulation:

1. Random arrivals. In essence, passengers arrive uniformly over the specified planning horizon (e.g., two hours).

2. Arrivals correlated with vehicle schedules. Passenger arrivals are correlated with scheduled vehicle departures. Specifically, passengers are assumed to arrive uniformly during a two minute period before the scheduled departure of a vehicle.

Each of these two arrival patterns is used for the full set of scenarios.

Summarizing, the seven information scenarios presented in Section 5.2.4 are run for a number of different service and passenger decision-making options. The following list describes a total of 42 scenarios:

- Coordinated vehicle schedules, expected travel time objective, and random passenger arrivals. Total of 7 scenarios.

- Coordinated vehicle schedules, expected travel time objective, and timed passenger arrivals. Total of 7 scenarios.
- Coordinated vehicle schedules, probability objective, and random passenger arrivals. Total of 7 scenarios.
- Coordinated vehicle schedules, probability objective, and timed passenger arrivals. Total of 7 scenarios.
- Uncoordinated vehicle schedules, expected travel time objective, and random passenger arrivals. Total of 7 scenarios.
- Uncoordinated vehicle schedules, expected travel time objective, and timed passenger arrivals. Total of 7 scenarios.

5.5 Implementing the Simulation

The simulation model itself builds directly upon the analytic framework developed in Chapters 3 and 4. This section discusses more specific details about how those analytical results were used in the simulation model. For the information of the reader, the simulation language SIMAN [59] was used for the simulation; this language allowed fairly easy modeling of both passenger and vehicle movements as well as accommodating more complicated decision logic through user code (using the C programming language). The first part of this section discusses the modeling of vehicle movements in the simulation, and the second section discusses how the passenger path and departure time choice models are implemented. The final part discusses implementation issues with the distributions for real-time information.

5.5.1 Distributions and Modeling of Vehicle Movements

Two different corridor networks were described in Chapter 3: the shuttle network and the MBTA case study corridor. The modeling of vehicle movements for these networks within the simulation consists of defining distributions for vehicle movements in the network and then generating vehicles in the simulation. The first part below describes how these vehicle movements were generated for the shuttle network, followed by a discussion of the vehicle movements in the MBTA case study.

Shuttle Network Movements

Section 3.4.2 discusses the development of the shuttle model. For this model, there is an assumed "null" departure time distribution defined as $f_0(x)$ that defines departures for "on-time" vehicle arrivals at a shuttle terminal. Similarly, there is a running time distribution $\phi_{AB}(x)$ describing running times between shuttle terminals A and B (for example). In the case of the shuttle network, it was assumed that vehicle running times are independent and uncorrelated, and thus may be drawn from a single distribution, $\phi_{AB}(x)$, which is independent of the vehicle trip. Using the two distributions, $f_0(x)$ and $\phi_{AB}(x)$, departure time distributions for vehicle movements in the shuttle network may be derived iteratively.

However, because of the analytic complexity of this iterative derivation of departure time distributions, these distributions were determined empirically using the network simulation. Specifically, vehicle movements from 200 days over each shuttle route in the shuttle network were simulated. The simulation drew random numbers from the two distributions $f_0(x)$ and $\phi_{AB}(x)$ to model vehicle movements for each shuttle (e.g., between A and B). In this case, the first N_{AB} vehicle departures from A were drawn from $f_0(x)$, along with a running time drawn from $\phi_{AB}(x)$. As with the model developed in Section 3.4.2, subsequent departures from B and A were based on whether the vehicle arrived in time to make an "on-time" departure from that terminal. If so, the vehicle departed at a time based on a random draw from $f_0(\tau)$; if not, the vehicle departed L time units (the layover time) after its arrival at the terminal. All vehicle running times (in both directions) were drawn independently from $\phi_{AB}(x)$. A significant number of round trips were modeled for each shuttle vehicle, until the departure time distributions began visually to exhibit a steady-state behavior. The departure times for specific vehicle trips were then recorded, and a piecewise continuous distribution function was fitted for each vehicle trip departure. In total, 200 observations of specific vehicle trip departures were recorded and used in deriving the empirical departure time distributions for the shuttle network. The results of this experiment are illustrated and discussed later in Chapter 6.

When passenger movements are added to the the shuttle network, these fitted departure distributions are used directly. For each anticipated vehicle departure, the trip index of that departure is determined, and a random draw from the appropriate fitted distribution is selected as the actual vehicle departure time. All vehicle running times are based on a random draw using the trip-independent running time distribution $\phi_{AB}(x)$ (for shuttle trips from A to B).

When running the simulation with passengers, the vehicle departure times and running times are generated at the very beginning of the simulation, so that the network travel times may be known in advance. This is helpful so that the real-time information given to passengers is based on *true* vehicle departure times and running times. The departure times and running times of shuttle vehicles thus become scheduled events in the simulation.

MBTA Network Movements

Vehicles movements in the MBTA corridor described in Section 3.6 are modeled much differently than those for the shuttle network. In order to model reality as closely as possible, the vehicle departure time and running time distributions were derived directly from MBTA service data. Data on true vehicle departure times and running times is collected for each route on the MBTA on an annual basis, but, typically, only one day per year is sampled. For this reason, it is virtually impossible to estimate the day-to-day variation in travel times for individual vehicle trips. In this case, aggregating vehicles within a specific time period for a given day (i.e. the peak period) is necessary, rather than aggregating specific vehicle trips across different days.

Departure time distributions in the MBTA case were developed by collecting information on bus and subway departure times at the appropriate terminals in the network, and estimating distributions from this data directly. In the simulation, random draws from these departure time distributions are used to determine "true" vehicle departure times.

For vehicle running times, two different running time distributions may be derived: assuming vehicle movements are independent, and assuming some correlation exists in vehicle running times. In the case of the bus and subway lines of the MBTA, there is often traffic congestion which propagates for successive vehicles traveling on a route. For this reason, running time distributions incorporate possible correlation in vehicle travel times. Furthermore, the possibility of vehicle bunching also needs to be incorporated in the travel time distributions.

Equations (3.2) and (3.6) in Chapter 3 suggested that the correlation in vehicle running times for a specific vehicle trip could be generated as the weighted sum of the previous vehicle running time and a running time independent of correlation. In this case, the existing data from the MBTA already included correlation between successive vehicle running times for a number of route segments. However, because there was no data on specific vehicle trips across a number of days, a distribution indexed by vehicle trip was not possible. Instead, two new distributions were used. First, a running time distribution $\phi_A(x)$, corresponding to $\phi_{AB}(x)$ in equation (3.6), assumes no correlation or bunching. Second, a "long-run" distribution $\phi_B(x)$ explicitly includes the effects of correlation and bunching. The latter distribution, corresponding to the expression $\phi_j(x)$ as $j \to \infty$ in equation (3.6), was estimated directly from the MBTA data for each route segment.

The former distribution, $\phi_A(x)$ was determined by removing the first-order serial correlation from the existing MBTA vehicle running time data. The technique to remove this first-order correlation was to use a linear regression technique based on equation (3.2). Specifically, using the substitution

$$(1 - \rho) \cdot Z = \alpha + \epsilon_j \tag{5.1}$$

in equation (3.2), the correlation coefficient ρ may be estimated as follows:

$$X_j = \alpha + \rho \cdot X_{j-1} + \epsilon_j \tag{5.2}$$

By standard assumptions of ordinary least squares (OLS) regression, the error terms ϵ_j from the a regression based on equation (5.2) are uncorrelated. Thus, by running this regression and using the computed residuals

$$\hat{U}_j = X_j - \hat{\rho} \cdot X_{j-1} \tag{5.3}$$

the uncorrelated travel times may be estimated by

$$\hat{Z} = \frac{\hat{U}_j}{1-\hat{\rho}} = \frac{X_j - \hat{\rho} \cdot X_{j-1}}{1-\hat{\rho}} \tag{5.4}$$

The estimates $\hat{Z}$ from equation (5.4) are in turn used to approximate the uncorrelated travel time distribution $\phi_A(x)$.

The approach suggested by equation (3.2) may in turn be used to compute the running time for a given vehicle trip on these route segments:

$$X_j = \begin{cases} Z & \text{if } j = 1 \\ \hat{\rho} \cdot X_{j-1} + (1-\hat{\rho}) \cdot Z & \text{if } j > 1 \end{cases} \tag{5.5}$$

where Z represents a random draw from the distribution of running times assuming no correlation (i.e., from the estimated distribution $\phi_A(x)$.

The technique described in equation (5.5) is not entirely correct, however. The parameters of the vehicle departure time and running time distributions for two routes in the MBTA case study also yielded the possibility of vehicle "leap-frogging," although such behavior was not exhibited in any of the MBTA data. In reality, leap-frogging is either not permitted or physically impossible on the MBTA routes, so it was assumed instead that vehicle bunching may occur on these routes. For the Red Line and bus route 77, vehicle running times in the simulation were determined based on the following equation:

$$X_j = \begin{cases} Z & \text{if } j = 1 \\ \max\{X_{j-1} + \eta,\ \hat{\rho} \cdot X_{j-1} + (1-\hat{\rho}) \cdot Z\} & \text{if } j > 1 \end{cases} \tag{5.6}$$

where η is some parameter based on the closest vehicle spacing: $\eta = 0.0$ for bus route 77 and $\eta = 1.0$ minutes for the Red Line. Thus, the true manner of deriving vehicle running times for the MBTA case study is given in equation (5.6). This equation is used directly for generating vehicle movements in the simulation.

From the passenger's perspective, however, the original observed distribution for a specific route segment, $\phi_B(x)$, is no longer sufficient to describe the actual distribution "seen" by the passenger in the case of bunching. Again, lacking vehicle-specific data across days, a steady-state bunching phenomenon was assumed. In order to incorporate bunching in the passenger's experienced distribution $\phi_B(x)$, separate steady state departure time distributions (at Porter outbound) and running time distributions (for the Red Line and route 77 inbound and outbound) were derived in the following manner:

- Data was generated using 30 simulated days on each route, in which vehicle running times X_j were determined using equation (5.6) and recorded.
- A revised running time distribution $\phi_B^{\text{new}}(x)$ was estimated based on these new observations of X_j.
- Departure time distributions at intermediate stops for the route 77 bus were also estimated based on the observed running times X_j.

These estimated distributions $\phi_B^{\text{new}}(x)$ are then used directly for passenger decision-making in the MBTA case study.

5.5.2 Passenger Decision Models

In the simulation, passenger arrival times at the origin stop and path choice decisions are modeled explicitly. In this section, the implementation of these two processes is discussed. In terms of the passenger arrival process, both random and "timed" passenger arrivals are simulated. For random passenger arrivals, a set of N passengers is generated uniformly over the time period of interest (i.e., two hours). For the timed arrivals, passengers are again generated uniformly over this same time period. However, at that generated point in time, a passenger is then "assigned" to a particular route and is given an actual arrival time at the stop. This arrival time falls uniformly in a two-minute period before the scheduled arrival of the next scheduled bus on that assigned route. In effect, passengers are assigned to a route and then are "assigned" to a particular vehicle on that route in a totally random manner. In the shuttle network, passengers are assigned to routes directly, with one-third of all passengers assigned to route 1, one-third to route 2, and one-third to route 3. In the MBTA case, passengers are assigned to routes in a stochastic manner, with a fixed probability of being assigned to each route.

Once the passenger has arrived at the origin stop, they are placed in a queue to wait for subsequent bus arrivals. In the scenarios where passengers simply choose to board the next bus, there is a single waiting queue which empties when a bus arrives. For the static path choice model scenarios, passengers are placed in one of seven queues, corresponding to the seven different path choice sets shown in Section 4.4.1. When a bus arrives, the passengers from the appropriate queues board the bus. For the dynamic path choice model, passengers are placed in a single waiting queue, and upon arrival of a bus, each passenger is placed either on the bus or back in the waiting queue, depending on their boarding decision.

For the static and dynamic path choice models, the selection of the boarding strategy is based entirely on the computation of expected travel times outlined in Chapter 4. Specifically, when the passenger arrives at the origin terminal, the static path choice model requires calculation of the expected travel time for each possible choice set. For these scenarios, supplemental computer code was written that calculates the expected travel times for each choice set, given in equations (4.21), (4.24), (4.25), (4.26) and (4.27). In these computations, the calculations of the expected travel time for a given departure time *td* are taken directly from equations (4.8), (4.1) and (4.15). The resulting calculation, then, is a two-dimensional integration, solved in the computer code using Simpson's method for numerical integration in both dimensions (e.g., Lerman [43]). The necessary waiting time density and distribution functions are taken directly from equations (4.22) and (4.23), respectively. Once the minimum expected travel time set is determined, the passenger is placed in the corresponding waiting queue at the origin stop.

For the dynamic path choice model, a similar approach is used. All passengers in the waiting queue are processed upon arrival of a vehicle. The expected travel time for the arriving vehicle is taken directly using equations (4.8), (4.1) and (4.15). At the same time, the seven different static path choice models from equations (4.21), (4.24), (4.25), (4.26) and (4.27) are also evaluated. In this case, however, the waiting time density and distribution functions from equations (4.22) and (4.23) are not appropriate, since the passenger may have learned something about vehicle arrivals while waiting. Instead, the waiting time density functions in equations (4.37) and (4.38) are used, along with their corresponding distribution functions.

As before, the calculations for the dynamic path choice model are made in supplemental computer code using a two-dimensional numerical integration technique following Simpson's method. Once these calculations are performed, the minimum expected travel time from each static choice set is compared to the expected travel time for the arriving vehicle. If the expected travel time for the arriving vehicle is less than the expected travel times for all static choice sets, the passenger boards; otherwise, the passenger stays.

5.5.3 Information Modeling

Section 5.2.3 discussed some of the issues associated with modeling information accuracy. Specifically, bounds for information accuracy were given so that expected vehicle departure times and running times given to the passenger were sufficiently close to the true (or actual) departure times and running times. As mentioned above, the actual vehicle departure and running times in the simulation consist of random draws from the corresponding estimated or assumed departure time or running time distributions.

The exact technique used in the simulation to report information to the passenger is as follows. It is necessary that the true value of the vehicle departure time (or running time) fall within the accuracy ranges (or accuracy distribution) given in Section 5.2.3. The passenger, however, uses both the expected value and the accuracy distribution around that expectation. The expectation, however, is not the true value; rather, the expectation comes from another random process, so that the inherently stochastic nature of the forecasting process is incorporated in the model. In this way, the expected value and its associated distribution is stochastic, based on the inaccuracy of the projected departure and running times.

The parameters of information accuracy given in Section 5.2.3 define distributions of information accuracy. Specifically, it is assumed that the distribution of accuracy is triangular in form. For example, a running time tolerance of -1.0 to +3.0 implies a triangle distribution with minimum, mode, and maximum of -1.0, 0.0, and +3.0, respectively. However, the specific "location" of this distribution, relative to the actual running time, is stochastic. In order to incorporate the inaccuracy of the real-time information, a separate draw is made from this distribution to determine the distribution "location" and the resulting expectation given to the passenger.

The following process is used for determining the information given to the passenger. [For the sake of simplicity, it is assumed that departure time information is desired; running time information is determined in an identical manner.]

1. A random draw from the vehicle's departure time distribution is taken, and that becomes the *true* or *actual* departure time of the vehicle. As an example, assume that a vehicle departure at 10.5 is determined from the (triangle) departure distribution (8.0, 10.0, 14.0).

2. The appropriate level of accuracy for that information is determined (as presented in Section 5.2.3), in the form of a triangle distribution, with associated parameters. In this case, suppose the parameters of the distribution are -1.0, 0.0, and +3.0.

3. A random draw from this accuracy distribution is made (e.g. from the triangle distribution on -1.0, 0.0, and +3.0). In this case, let $u = 1.7$ represent the value of this random draw.

4. The accuracy distribution is then "located" relative to the *true* departure time, based on u. That is, the mode of the accuracy distribution is placed at the *true value* minus u. If the true departure time is 10.5, with $u = 1.7$, the accuracy distribution is then "located" on (7.8, 8.8, 11.8).

5. Parameters of this new accuracy distribution which exceed the true departure time distribution are shifted to the minimum and/or maximum values of the original departure distribution. For example, since buses cannot leave before 8.0 in the original departure time distribution, the minimum of the accuracy distribution is shifted from 7.8 to 8.0, yielding the accuracy distribution (8.0, 8.8, 11.8).

6. The parameters of this accuracy distribution are then used by the passenger in the path choice models. Furthermore, the passenger is given the associated expectation of the accuracy distribution. In this example, the expected departure time from (8.0, 8.8, 11.8) is 9.53.

In step 4, the accuracy distribution is "located" relative to the true observed departure time. This technique ensures that the true departure time does fall within the accuracy distribution around the expected departure time given to the passenger;

hence, the inaccuracy of the forecasts of departure times are incorporated directly in the simulation. By using the random draw u from the accuracy distribution, it is possible to work backwards to find the location of the accuracy distribution, given the true value. Thus, the first random draw locates the true value, and the second locates the accuracy distribution. A different (but equally effective) technique would select the location of the expected value from the information system first, followed by a separate draw from the accuracy distribution to find the true departure time. The technique described in step 4 was chosen due to the relative merits of generating network departure times and running times at the very beginning of each simulation.

The truncation of information parameters in step 5 is appropriate, since it is reasonable to assume the information system is aware of existing historical departure patterns and will adjust the information parameters based on existing limits of the departure (or running time) distributions.

Algebraically, the information modeling may be described as follows. Assume that td is the true departure time, and that a random draw u is taken from the accuracy distribution $(A,\ 0.0,\ B)$ (a triangle distribution). In this case, $A < 0.0$ and $B > 0.0$. The parameters of the accuracy distribution, (a, h, b), are then initially estimated by:

$$\hat{a} = td - u \tag{5.7}$$

$$\hat{h} = \hat{a} - A \tag{5.8}$$

$$\hat{b} = \hat{h} + B \tag{5.9}$$

Using the truncation technique described in step 5, the final parameters used in the simulation are given by:

$$a = MAX(\hat{a}, A) \tag{5.10}$$

$$h = MAX(A, MIN(\hat{h}, B)) \tag{5.11}$$

$$b = MIN(\hat{b}, B) \tag{5.12}$$

The expected value from this distribution, $(a + h + b)/3.0$, is given to the passenger as the expected vehicle departure time (or running time).

Chapter 6

Results from the Shuttle Network

This chapter discusses results from the simulation of the shuttle network described in Chapters 3, 4, and 5. The first section of this chapter discusses the parameters of the simulation experiments, covering network parameters and issues associated with the analytic modeling of passenger behavior. The second section discusses the results of the simulation experiments, and the third section draws conclusions from this phase of the research.

6.1 Simulation Parameters

The shuttle network required a large set of parameters. The first part in this section describes three different sets of shuttle operating characteristics corresponding to three example networks based on the shuttle service model from Chapter 3. One of the important elements of the shuttle network is the simulation-generated empirical distributions of vehicle departure times, which are presented in the second section. The third section discusses the parameters for real-time information which were used in the shuttle network simulations. The fourth section describes the set of scenarios for the analysis, and the fifth section discusses other modeling issues relating to the analytic path choice models.

It is important to keep in mind that the shuttle network is intended to represent a corridor in which real-time information systems may be implemented. Basically, the

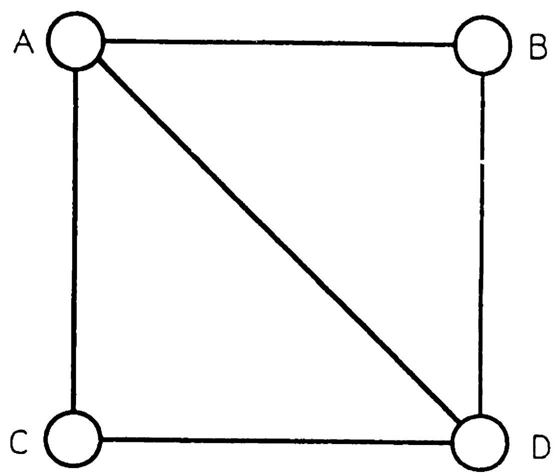

Figure 6-1: The Shuttle Network

parameters and operating conditions for the shuttle network are intended to provide insight into situations where real-time information may provide the most benefit: corridors in which travel time variance is relatively high, and in which there are a number of different paths with comparable origin-to-destination travel times. It is felt that these conditions are most favorable for examining travel time benefits from real-time information, as there may be opportunities to improve path choices in this context. The parameters discussed in this section reflect this orientation.

6.1.1 Input Parameters

The shuttle route model and the shuttle network are based on a simple model of a transit route operating between two terminals. The shuttle network is depicted in Figure 6-1, and the corresponding running time parameters for vehicle movements (which are common to all the simulation experiments) are described in Table 6.1. The times listed in Table 6.1 are the minimum, mode, and maximum for triangle distributions, which are assumed to be reasonable representations of vehicle running times. Overall, the network parameters were selected for a transit trip of approximately 30 minutes from origin to destination. It is further assumed that the direct route (path 2, or the A-D shuttle) is sufficiently circuitous that its overall running time from the origin to the destination is somewhat greater than the sum of running times on the connecting routes.

Table 6.1: Running Time Parameters

Shuttle	Minimum	Mode	Maximum
A-B	8.0	10.0	14.0
A-D	27.0	29.0	34.0
A-C	10.0	12.0	16.0
B-D	9.0	10.0	13.0
C-D	10.0	11.0	14.0

Table 6.2: Parameters for Network 1

Shuttle	Schedule Offset	Headway	Number of Vehicles	Layover Time
A-B	0.0	10.0	3	4.00
A-D	1.0	12.0	6	5.50
A-C	2.5	15.0	2	2.00
B-D	10.0	15.0	2	4.25
C-D	3.0	9.0	4	6.25

Three different sets of operating characteristics were chosen to reflect a variety of network conditions. The first network (Network 1), described in Table 6.2, contrasts the direct service with two transfer paths; the first transfer path (path 1) connects a higher frequency to a lower frequency service, and the second (path 3) connects a lower frequency to a higher frequency service. The schedule offsets are chosen such that the average time between scheduled vehicle departures from the origin is minimized. In this case, two vehicles scheduled to depart at the same time count as only one scheduled departure in minimizing this quantity. In fact, the schedule offsets are selected so as to minimize the average wait of a randomly arriving passenger who boards the next bus at its scheduled departure time. In this sense, the schedules of vehicles serving terminal A are coordinated between the three shuttle routes.

The second network (Network 2) is described in Table 6.3. The only substantive differences between this network and Network 1 are the schedule offsets. For this network, the routes serving the origin are assumed to have "uncoordinated" schedules; in this example, the offset times are chosen so as to maximize (rather than minimize) the average wait of a passenger boarding the next bus to depart the origin terminal. This case was developed to gain insight into different path choice strate-

Table 6.3: Parameters for Network 2

Shuttle	Schedule Offset	Headway	Number of Vehicles	Layover Time
A-B	0.0	10.0	3	4.00
A-D	4.0	12.0	6	5.50
A-C	5.0	15.0	2	2.00
B-D	10.0	15.0	2	4.25
C-D	3.0	9.0	4	6.25

Table 6.4: Parameters for Network 3

Shuttle	Schedule Offset	Headway	Number of Vehicles	Layover Time
A-B	0.0	10.0	3	4.00
A-D	1.5	12.0	6	5.50
A-C	5.0	10.0	3	2.00
B-D	0.5	10.0	3	4.25
C-D	9.5	10.0	4	8.25

gies and differences in travel times resulting from changes in the level of schedule coordination.

Finally, based on preliminary results of the first two networks, a third network (Network 3) was developed, and is described in Table 6.4. From the first two networks, it seemed possible to improve the value of real-time information by designing a network in which transfer connections would be somewhat problematic, with a 50% chance of making an earlier connection. To facilitate this schedule design, the headways on connecting routes (A-B and B-D, or A-C and C-D) were set equal and the schedule offsets were selected so that a trip on either of the transfer paths (1 or 3) has approximately a 50% chance of making an earlier connection.

The development of the shuttle model in Chapter 3 required a null distribution of vehicle departures, representing the distribution of departure times for an "on-time" departure from the shuttle terminal. In particular, following the notation of Chapter 3,

$$f_0(x) \sim \text{Uniform}\,[0, 2]$$

Thus, if a vehicle arrives at the terminal in time to make an "on time" departure on its next vehicle trip, it is assumed to leave the terminal sometime over a two minute interval, beginning at the scheduled departure time.

6.1.2 Empirical Departure Time Distributions

The shuttle model derived in Chapter 3 is analytically intractable because of the recursive nature of vehicle departure time distributions. However, using the simulation model, it is possible to develop empirical distributions for these departure times. Based on the running time distributions of Table 6.1, the layover times suggested in Table 6.2, and using the null departure distribution $f_0(x) \sim U[0,2]$, empirical distributions of vehicle departure times can be determined.

For each route in the shuttle network, 200 vehicle operating days were simulated according to these operating parameters (as described in Section 5.5.1). The resulting departure times of specific vehicle trips were recorded, yielding an empirical distribution of departure times for each vehicle trip in the network. By definition, vehicle departures on the first trip at the beginning of the simulation occur according to $f_0(\tau)$, and several vehicle trip cycles are necessary to allow the shuttle network to "warm up." For the purposes of this analysis, an initial warm up period of approximately 75 (simulated) minutes allowed the system to reach a more steady state condition.

Several histograms of departure time distributions are shown in Figures 6-2, 6-3, 6-4, and 6-5. These histograms correspond to each set of 3 departures on shuttle route A-B, as $N_{AB} = 3$. Thus, Figure 6-2 corresponds to the first three vehicle departures at the beginning of the two-hour period when passengers arrive, while Figure 6-5 corresponds to departures (numbers 10 through 12) near the end of that period. The histograms shown here (*not* the fitted curves) are used directly to simulate vehicle departure patterns. That is, random draws from these histograms are used as the true vehicle departure times in the simulation.

It is interesting to note from these figures that their overall shape is strongly skewed to the left, favoring departures which are reasonably close to the scheduled departure time. This pattern results from the assumed running time and layover time parameters, yielding a high probability (about 75% to 80%) that a vehicle arrives at each terminal in time to make an "on-time" departure. Using software which fits standard probability distributions to empirical data, these distributions tend to be

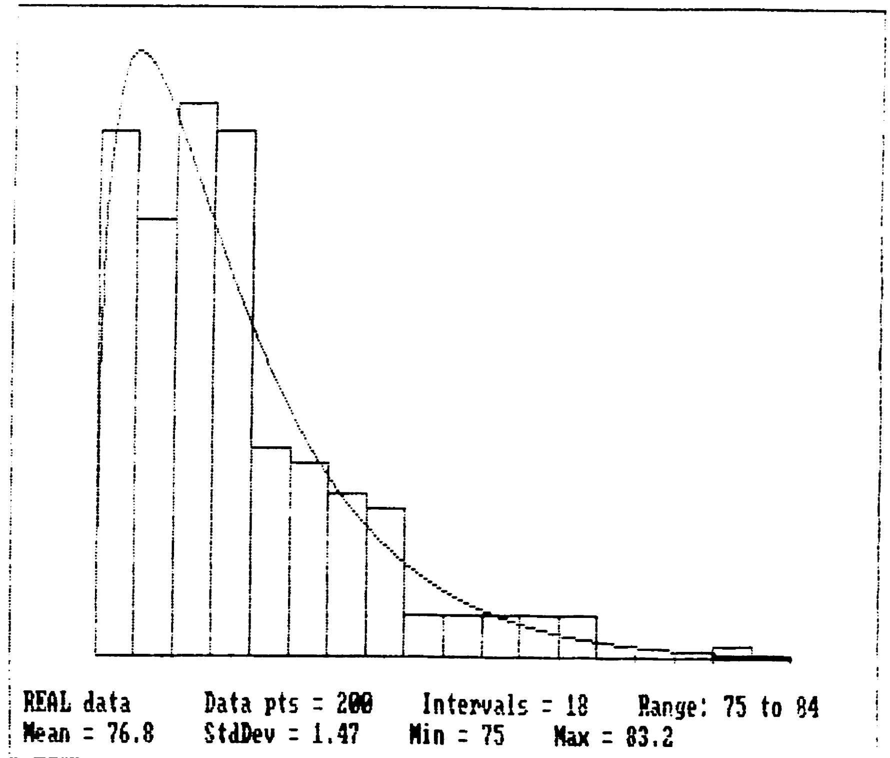

Figure 6-2: Departure Distribution for Route 1, from Time = 75.0

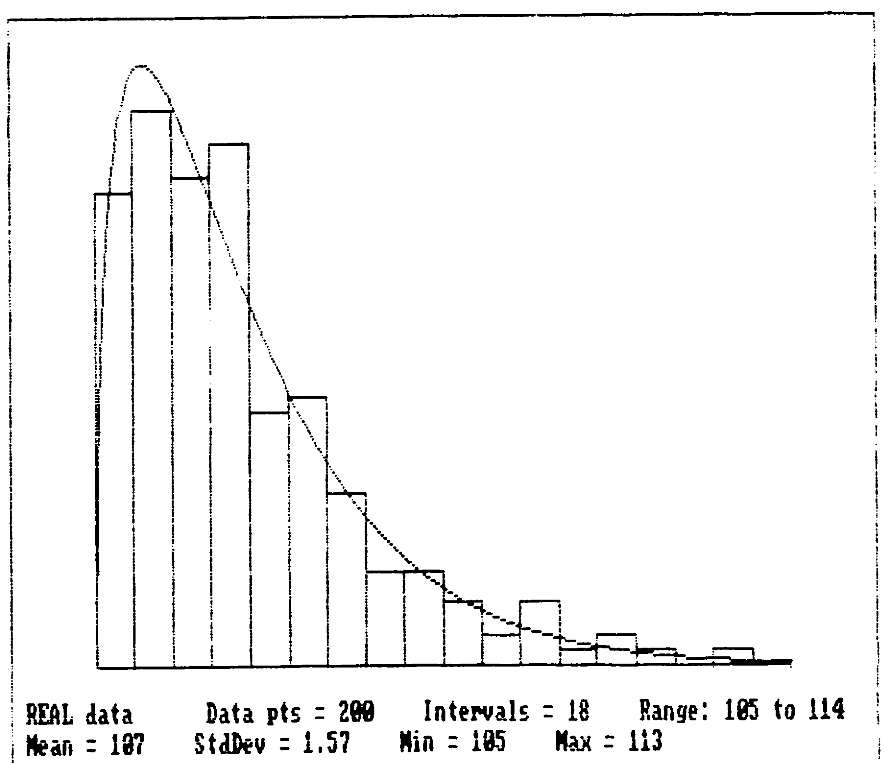

Figure 6-3: Departure Distribution for Route 1, from Time = 105.0

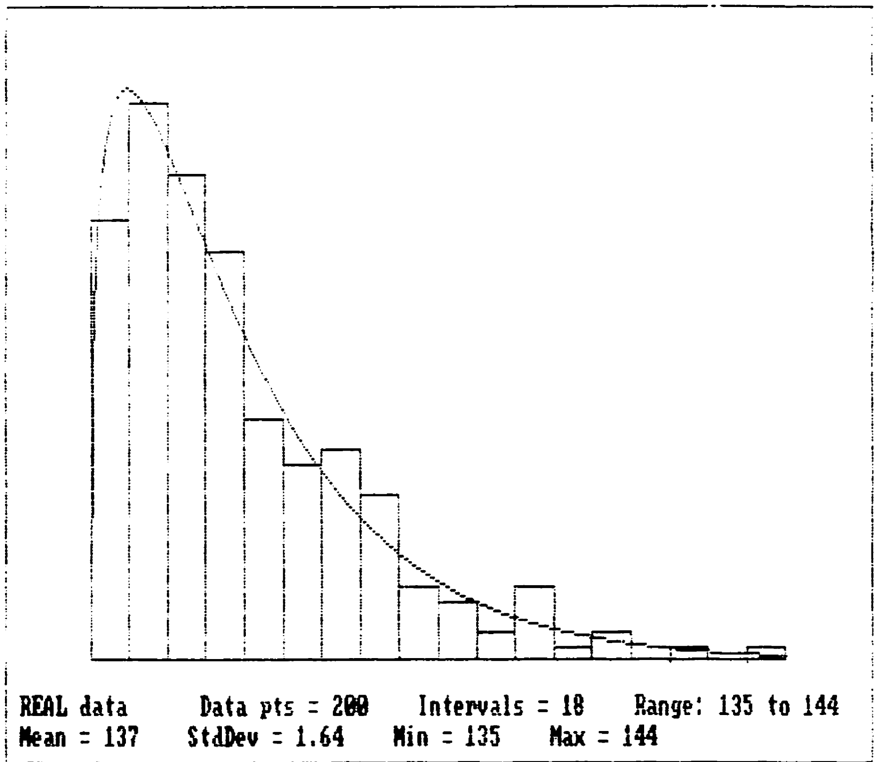

Figure 6-4: Departure Distribution for Route 1, from Time = 135.0

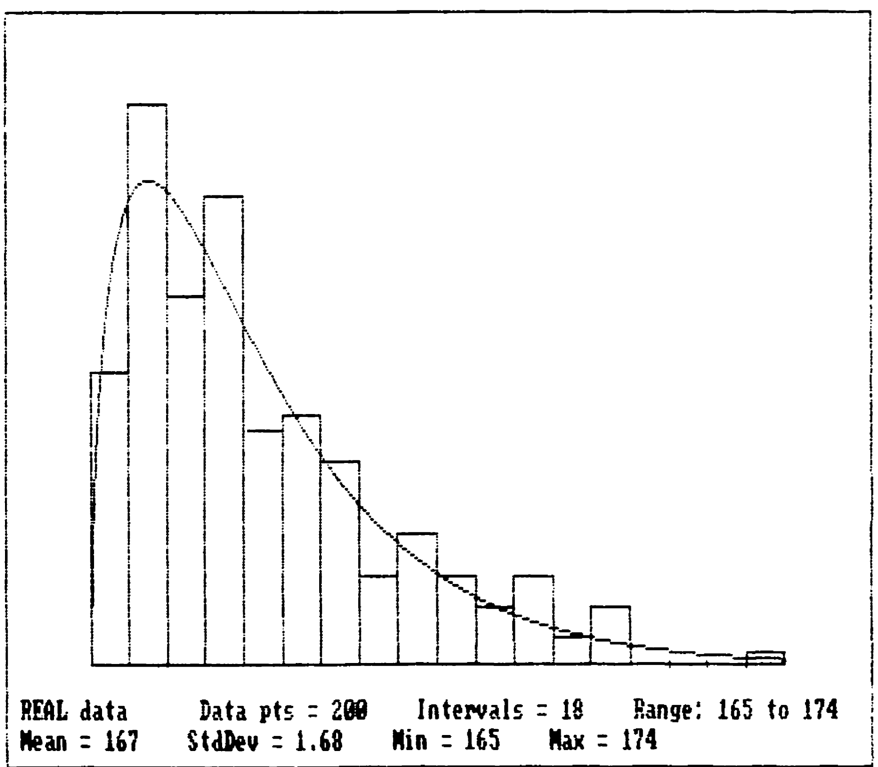

Figure 6-5: Departure Distribution for Route 1, from Time = 165.0

classified as Gamma distributions. These distributions also have a relatively long tail for significantly late departures. To this extent, the distributions seem to match intuition about the shape of vehicle departure time distributions.

More specifically, the parameters of these distributions may be fairly realistic. Departure delays have a mean of approximately 2.0 minutes for each of the distributions shown above, with standard deviations of 1.4 to 1.6 minutes, yielding a coefficient of variation of departure delay of about 0.7 to 0.8. The data for the bus routes from the MBTA case study suggests average departure delays from route endpoints of 2.0 to 3.0 minutes, with coefficients of variation of about 0.7. Thus, the departure time distributions for the shuttle routes seem to match actual bus terminal departures reasonably well.

6.1.3 Information Parameters

The information scenarios assumed that the passenger would be given an expected vehicle departure time and (possibly) an expected vehicle running time. The expectations given to the passenger in these scenarios were not "true" in the sense that they were completely accurate; instead, they were assumed to be accurate within some range for that information. The accuracy of information was assumed as follows (from Chapter 5):

- Departure times from the origin: -0.5 to +1.5 minutes.
- Running times from the origin: -1.0 to +3.0 minutes (low accuracy) and -1.0 to +2.0 minutes (high accuracy).
- Departure times from transfer points: -1.0 to +3.0 minutes.
- Running times from transfer points: -1.5 to +4.0 minutes.

The form of the accuracy distribution was assumed to be a triangular distribution with the above parameters and a mode of 0.0. In all these cases, it was assumed that the accuracy distribution would be no worse than the known distribution (as discussed in Section 5.5.3). Thus, the minimum (or maximum) value for the accuracy distribution was not less than (or greater than) the minimum (or maximum) value from the travel time parameter's true distribution.

As mentioned in Section 5.5.3, a sampling technique was used to "locate" the accuracy distribution about the true travel time value. That is, using a random draw from a triangle distribution, the accuracy distribution can be "located" around this true value. The expected value from this distribution is given to the passenger as the expected vehicle departure time (or running time). The passenger is also assumed to be aware of the accuracy distribution, although perhaps with altered parameters based on their level of experience with the information system (as discussed in Section 5.3).

6.1.4 Simulation Scenarios

For all simulations of the shuttle network, the following nine scenarios were run:

- Scenario 0: Passenger boards the next vehicle to arrive, regardless of route.
- Scenario 1: Passenger uses the static path choice model to determine his/her boarding strategy.
- Scenario 2: Passenger uses the dynamic path choice model to determine his/her boarding strategy.
- Scenario 3: Passenger uses the dynamic path choice model and receives additional information on vehicle departures from the origin.
- Scenario 4: Passenger uses the dynamic path choice model and receives additional information on vehicle departures from all terminals.
- Scenarios 5 and 6: Passenger uses the dynamic path choice model and receives additional information on vehicle departures and running times from the origin. Scenario 6 assumes a higher level of accuracy on the running time information than Scenario 5.
- Scenario 7: Passenger uses the dynamic path choice model and receives additional information on vehicle departures and running times at all terminals. A high level of accuracy for running time information is assumed.
- Scenario 8: Passenger receives perfect information from which to make an optimal path choice.

Scenarios 0 and 8 were added to this list to examine performance under extreme conditions. In Scenario 0, the passenger employs the simple path choice strategy of boarding the next bus to arrive at the origin, without regard to route or travel time. At the other extreme, the passenger with perfect information about vehicle departure and travel time information (Scenario 8) can make an optimal path decision to arrive at the destination in the shortest amount of time.

This set of nine scenarios was repeated for two different passenger arrival patterns. The first set of runs assumed that passengers arrived at the origin randomly. In this case, sixty (60) passengers arrived at the origin terminal uniformly over a period of two hours (120 minutes). The selection of 60 as the number of passengers was based on trading off computation time with statistical accuracy; the computation time for the path choice models is directly proportional to the number of passengers. Sixty passengers appeared to balance statistical accuracy for results on a given day with adequate computational speed for the simulation.

The second set of runs assumed that passengers timed their arrivals at the origin terminal with vehicle schedules. In particular, it was assumed that passengers arrived at the origin terminal uniformly during a two-minute period before the *scheduled* arrival of a given bus. The sixty passengers were assigned to routes in equal proportions, with 20 passengers timing their arrivals with scheduled departures on route 1, 20 passengers with route 2, and 20 passengers with route 3. Without any further research on passenger departure time choice models, this technique at least provided a rough estimate of the potential value of coordinating passenger arrivals with vehicle departures.

The scenarios above were run on the three networks described in Section 6.1.1, using the objective that the passenger makes path choice decisions trying to minimize his/her expected travel time. This yields 18 scenarios per network, multiplying 9 scenarios by 2 passenger arrival patterns. In addition, the second objective of maximizing the probability of arriving at the destination within 37 minutes of arrival at the origin was also used to compare model results for different passenger objectives. This "probability objective" was used only with the first set of network parameters (Network 1), yielding 18 more scenarios.

6.1.5 Modeling Issues

It is worthwhile to mention briefly several issues which arose in coding the static and dynamic path choice models. First, vehicle departure time distributions were modeled explicitly using the associated histograms shown in Section 6.1.2 with an interval width of 0.5 minutes. These histograms were used explicitly both in simulating vehicle movements and in calculating the expected travel time in the static and dynamic path choice models.

In performing the expected travel time calculations, a numerical integration technique was necessary. In particular, because of the form of the waiting time distributions both at the origin and at the transfer terminals, expressions for the expected travel time on the paths with transfers were extremely difficult to handle analytically. For these calculations, Simpson's method for numerical integration was used in two dimensions (e.g., Lerman [43]). It was apparent in running these simulations that the total computation time for the simulation runs was directly proportional to the number of function evaluations used in this integration technique.

Because of questions of accuracy of the numerical integration technique, a tolerance was built into the path choice decision criteria. In comparing the numerical integration technique versus explicit evaluation for expected travel times on path 2 (the direct route), travel times seemed to be accurate to within ± 0.05 minutes and probability measures to within ± 0.005. In comparing different path choice sets in the static model, then, a tolerance of 0.05 minutes (or 0.005 for the probability objective) was adopted, favoring choice sets with higher cardinality. In making boarding decisions in the dynamic model, these same tolerances were used, favoring the decision to board.

Finally, different passenger levels of experience were incorporated. Passengers who underestimate the variance of travel times, called simply "low" variance passengers, make their travel time calculations with distribution ranges that are 80% of the true range of each departure time and running time distribution. In effect, these passengers have multipliers of 0.8 which are used in modifying these travel time distributions. Passengers overestimating this variance are assumed to make calculations based on distribution ranges that are 120% of each distribution's true range (i.e., a multiplier of 1.2). The changes in distribution parameters resulting from these different passenger types have been discussed in Section 5.3.

6.2 Simulation Results

The following sections present the results of the simulation model in greater detail. First, under the assumption of no real-time information, the static and dynamic choice models are compared with both the "take the next bus" and the optimal path choice strategies. The second section examines the value of information to the passenger across the set of information scenarios. Finally, the results for Network 1 based on the probability objective are presented and compared with the similar results from the expected travel time objective.

The results presented below are taken from a simulation of 30 replications (i.e., days). The statistics that are presented, then, reflect the observations from a given day, averaged over the set of 30 days. The simulation model produces the following statistics:

- Expected travel time for a given day (60 passengers per day);
- Variance in passenger travel times for a given day;
- The number of passengers arriving at the destination in 37 minutes; and.
- Path choices for all 60 passengers for a given day.

The sections below compare and contrast these statistics across different networks, path choice models, and information scenarios.

6.2.1 Path Choice Models

For the three shuttle networks defined previously, four scenarios were used to evaluate the static and dynamic path choice models developed in Chapter 4, including:

- Scenario 0: Passengers board the next vehicle to arrive, regardless of route.
- Scenario 1: Passengers use the static path choice model to determine their boarding strategies.

Table 6.5: Expected Travel Times from Network 1

Passenger Arrivals	Scenario 0 (Base)	1	2	8
Random	32.194	32.168	32.167	30.909
Decrease		0.026	0.027	1.285
Std Error		(0.019)	(0.068)	(0.138)
Timed	31.675	31.575	31.505	30.295
Decrease		0.100	0.170	1.381
Std Error		(0.035)	(0.082)	(0.127)

- Scenario 2: Passengers use the dynamic path choice model to determine their boarding strategies.
- Scenario 8: Passengers receive perfect information from which to make optimal path choices.

Network 1

Table 6.5 shows the expected travel time statistics for Network 1 for this set of scenarios, from which several observations may be made. First, for this set of network parameters, there is little difference between the static and dynamic path choice models and the simple "board the first bus" strategy. Travel time improvements are very modest and not statistically significant for passengers arriving randomly, while improvements in travel times for passengers with timed arrivals are also modest. The travel time differences between scenario 0 and scenario 1 and between scenario 0 and scenario 2, given in Table 6.5, are statistically significant for timed passenger arrivals, but the average travel time savings are very small: about 10 seconds, or 0.17 minutes, with the dynamic model. For this network, then, the potential improvements in travel times by using more sophisticated path choice strategies is very limited, with improvements on the order of 0.5% to 0.6% of the total travel time. The maximum possible improvement in travel times over the "board the next bus" strategy, based on the optimal path choices from scenario 8, are on the order of 4.1% to 4.6% of the total trip time, or 1.28 to 1.38 minutes.

Somewhat larger differences in the expected travel times (on the order of 1.6% to 2.1%) are noted by comparing the randomly arriving passengers with those who

Table 6.6: Expected Path Assignments from Network 1

Passenger Arrivals	Path	Scenario 0	1	2	8
Random	1	26.30	26.43	26.07	26.53
	2	18.33	17.50	16.53	15.20
	3	15.37	16.07	17.40	18.27
Timed	1	21.07	20.40	19.33	20.73
	2	22.23	21.60	21.50	18.27
	3	16.70	18.00	19.17	21.00

time their arrivals with the vehicle schedules. In this case, passengers who use a simple form of trip timing as well as the static or dynamic path choice strategy may improve their average travel times by about 2%. This suggests that there may be some value to passengers timing their trips with at least the scheduled vehicle departures. Furthermore, the passengers who time their arrivals at the origin stop in this case are assigned one-third to each route; this constraint infers that these benefits underestimate the possible benefits if passengers actually exercised a specific choice of routes in this simple timing strategy. Moreover, in cases where better planning of trip times is possible (e.g. with pre-trip information on actual vehicle departure times), travel time improvements in this range seem possible.

In terms of path assignments, there are only small differences among these four scenarios. Table 6.6 shows the average number of passengers per day (out of 60) which chose each of the three paths. Under the condition of random passenger arrivals, approximately 26 passengers choose path 1, 15-18 choose path 2, and 15-18 choose path 3. A more traditional path assignment model, assigning passengers to paths based on frequency share alone, would average 24 passengers on path 1, 20 on path 2, and 16 on path 3. The differences in assignment in Scenario 0 result from the close coordination of vehicle departures at the origin. With stochastic vehicle departures, the probability of route being next is slightly greater than the frequency share for higher frequency routes (e.g. route 1), resulting in higher passenger shares for these routes. The shift of passengers from path 2 to path 3 in scenarios 1, 2 and 8 results primarily from the somewhat shorter expected travel times on path 3 relative to path 2.

Table 6.7: Expected Travel Times from Network 2

Passenger Arrivals	Scenario 0 (Base)	1	2	8
Random	32.568	32.527	32.714	31.371
Decrease Std Error		0.042 (0.036)	-0.146 (0.153)	1.198 (0.086)
Timed	31.682	31.596	31.686	30.461
Decrease Std Error		0.087 (0.073)	-0.004 (0.136)	1.221 (0.094)

As might be expected, passengers timing their arrivals with vehicle schedules yield approximately equal market shares across all three paths. Again, for stochastic vehicle departures, higher frequency routes have a higher probability of arriving "next," yielding slightly higher shares for paths 1 and 2. This effect is reduced slightly as passengers realize the travel time advantages from path 3 relative to path 2 in the more complicated path choice models (scenarios 1, 2 and 8). For both random and timed passenger arrival patterns, the standard deviation of the number of passengers on each path is on the order of 4 to 5, indicating that there is a significant amount of variation in path choice from day to day.

Network 2

The schedule for Network 1 was designed so that the average time a passenger waits before the next scheduled vehicle departure from the origin is minimized. On the other hand, vehicle schedules for Network 2 are selected so as to maximize this average time a randomly arriving passenger waits before the next scheduled vehicle departure. [In this case, two vehicles scheduled to depart at the same time count as a single vehicle departure. For example, only a single vehicle departure is modeled at time 20.0, covering both the scheduled departures on route 1 and route 3 (using the parameters in Table 6.3). Under these conditions, one might expect somewhat higher travel times, especially for randomly arriving passengers, as well as somewhat different path choices. Tables 6.7 and 6.8 reveal the expected travel times and path choices from Network 2.

Comparing Network 2 with Network 1, the fact that schedules are not coordinated

Table 6.8: Expected Path Assignments from Network 2

Passenger Arrivals	Path	Scenario 0	1	2	8
Random	1	25.23	24.93	23.13	24.63
	2	19.97	18.63	19.00	16.50
	3	14.80	16.43	17.87	18.87
Timed	1	22.30	20.30	18.17	22.80
	2	21.20	19.77	20.27	15.67
	3	16.50	19.93	21.57	21.53

tends to increase the overall expected travel time on the order of 20 to 30 seconds (or about 0.35-0.55 minutes) for randomly arriving passengers. It is also intuitively appealing that the value of timed versus random arrivals is greater for Network 2, on the order of 2.9% to 3.3% of the total expected travel time. However, the more sophisticated path choice methodologies (the static and dynamic path choice models) do not have any statistically significant impact on expected travel times for either passenger arrival pattern. This result is similar to Network 1, and may be supported more strongly here as there are likely to be fewer reasonable path options when schedules are less coordinated. Finally, optimal travel time improvements from perfect information are on the order of 1.2 minutes, or about 4% of the total trip time, when compared with the "next bus" strategy.

In general, the path assignments in Table 6.8 for passengers in Network 2 are more in line with what might be expected from a relative frequency assignment. Again, diversion to path 3 is noted, this time at the expense of path 1, when the travel time advantages of that path are considered (scenarios 1, 2 and 8). Diversion from path 1 is noted more strongly in this case because of the overlap of vehicles between path 1 and path 3: the schedule offsets for this network are such that every other route 3 vehicle has a scheduled departure time coinciding with that from path 1. Finally, as with Network 1, there is significant variation in day-to-day path choices, with a standard deviation on the order of 4 to 5 passengers per day.

Table 6.9: Expected Travel Times from Network 3

Passenger Arrivals	Scenario 0 (Base)	1	2	8
Random	31.140	30.942	30.859	29.464
Decrease		0.198	0.281	1.675
Std Error		(0.077)	(0.124)	(0.118)
Timed	30.812	30.511	30.495	29.098
Decrease		0.301	0.317	1.714
Std Error		(0.089)	(0.116)	(0.124)

Table 6.10: Expected Path Assignments from Network 3

Passenger Arrivals	Path	Scenario 0	1	2	8
Random	1	23.50	32.17	39.87	32.03
	2	14.00	9.43	7.87	9.93
	3	22.50	18.40	12.27	18.03
Timed	1	20.33	31.13	35.63	29.93
	2	19.37	12.33	11.57	12.40
	3	20.30	16.53	12.80	17.67

Network 3

Expected travel time and path choice results from Network 3 are shown in Tables 6.9 and 6.10. In this network, the connecting shuttle routes (on paths 1 and 3) are explicitly coordinated and have identical headways. Path choices in scenario 0 are close to the relative frequency shares, which would yield about 21.5 passengers on each of paths 1 and 3. Again, higher frequency routes have slightly higher market shares in this "next bus" scenario, due to the stochastic variation in departure times. Path 1 has the shortest travel times when a connection can be made at terminal B; as a result, passengers tend to choose path 1 much more than the other two paths in scenarios 2 and 8. This effect is particularly strong in scenario 2, where passengers using the dynamic path choice model are more likely to pass up other routes to improve their expected travel times on path 1. Again, considerable day-to-day variation in path choices is evident, with a standard deviation of passengers on each path of approximately 4 to 5 passengers per day.

More noticeable in this network is a greater value of the static and dynamic path choice models. It appears that the high frequency of service at the origin terminal implies that the path choice models may improve passengers' travel times over simply boarding the first vehicle to arrive. However, the effect is modest, on the order of 0.7% to 1.0% of the total travel time, or approximately 12 to 20 seconds (on average) per trip. For this high frequency service, however, the travel time improvements for passengers who time their arrivals with vehicle schedules (versus random arrivals) are somewhat smaller for Network 3 than the first two networks: average time savings amounts to approximately 1.1% to 1.4% of the total travel time (0.33 to 0.43 minutes, or 20 to 25 seconds). This result is due to the higher frequency of service at the origin in Network 3. Finally, as anticipated, the travel time improvements from perfect information (scenario 8) are larger for Network 3 relative to Networks 1 and 2, with potential time savings of about 1.7 minutes, or about 5.5% to 5.7% of the total travel time.

In summary, there is only some evidence in these three networks that the static and dynamic path choice models offer improvement over the most simple path choice strategy of taking the next bus to depart. Comparing the results of Network 3 with those of Networks 1 and 2, it might be suggested that the static and dynamic models may be more advantageous under higher frequency service and when travel time differences between routes are more substantial. However, the results from these networks do not offer conclusive evidence for this conjecture. A more rigorous analysis of situations in which the static and dynamic path choice models yield more substantial travel time advantages is not pursued here.

In terms of path choices, however, these results do offer more conclusive evidence. First, a simple "next bus" strategy seems to yield higher average market shares for high frequency routes than the simple relative frequency share model, within the context of stochastic travel times. This result seems to contradict that of Marguier and Ceder [49], who conjecture that market shares decrease with the coefficient of variation of route headways. The static and dynamic path choice models also have the desired effect of assigning more passengers to routes with shorter expected travel times, relative to the simple "next bus" strategy. This effect was apparent in all three networks. Furthermore, in Network 3, where route headways are short and travel time differences are slightly greater between paths, the dynamic path choice model seems particularly sensitive to vehicle arrival patterns. In this case, the dynamic model assigned many more passengers on the shortest travel time path (path 1).

6.2.2 Information Scenarios

The information scenarios presented in Section 6.1.4 were run on each of the three networks shown above. For the sake of clarity, the results of scenarios 3 through 7 presented below are shown relative to the baseline of scenario 2, in which the passenger uses the dynamic path choice model to determine his/her boarding strategy. This baseline is chosen because the dynamic choice model allows passengers to update their boarding decisions virtually continuously in time, as real-time information will also allow.

Network 1

Table 6.11 gives the expected travel times from Network 1 for the range of passenger information scenarios. For both passenger arrival patterns, departure time information (scenario 3) offers no travel time advantages over the dynamic path choice model. For the scenarios where information about departures of connecting vehicles (scenario 4) or running time information (scenarios 5 and 6) is provided, average travel time savings are on the order of 0.32 to 0.44 minutes (or 1.0% to 1.4% of the total passenger travel time). In each of these scenarios, the expected travel time savings is significantly different from zero, with t-statistics of at least 2.2. No substantial differences in these values is noted, however, across scenarios 4 through 6. In particular, the improved accuracy in running time information has no impact on expected travel times; in this case, the differences are negative (but not statistically significant) for both passenger arrival patterns.

The most statistically significant improvements in the expected travel times are noted for scenario 7, with information about departures and running times for both the origin and connecting routes. Travel time improvements under scenario 7, at 0.95 and 0.86 minutes for random and timed passenger arrivals, respectively, represents approximately 2.8% to 3.1% of the total trip time. These results represent average time savings of about 70% to 75% of the total possible time savings under perfect information in scenario 8. In this light, a real-time information system with detailed

Table 6.11: Expected Travel Times with Information - Network 1

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	32.167	32.173	31.730	31.754	31.789	31.214	30.909
Decrease		-0.005	0.437	0.413	0.378	0.953	1.258
Std Error		(0.072)	(0.143)	(0.144)	(0.130)	(0.150)	(0.143)
Timed	31.505	31.606	31.179	31.186	31.190	30.649	30.295
Decrease		-0.101	0.326	0.320	0.315	0.857	1.210
Std Error		(0.088)	(0.149)	(0.127)	(0.108)	(0.113)	(0.136)

Table 6.12: Expected Travel Times by Passenger Type - Network 1

Passenger Arrivals	Pass. Type	Scenario 2	3	4	5	6	7
Random	Low	32.262	32.190	31.813	31.853	31.838	31.229
	High	32.068	32.134	31.632	31.854	31.719	31.241
Timed	Low	31.691	31.585	31.293	31.234	31.201	30.678
	High	31.482	31.623	31.096	31.279	31.156	30.673

(but not entirely accurate) information on connecting services yields significant improvements in travel times relative to optimal path decisions. This would suggest, then, that if a transit operator could take advantage of real-time network information, passenger information systems could prescribe paths to passengers which yield more substantial improvements in passenger travel times.

Table 6.12 shows the travel times for passengers in Network 1 based on different levels of passenger experience; i.e., different perceptions of travel time variance (low and high). In this network, travel times for these passengers do not differ substantially, or in a statistically significant way, from the results for passengers with "perfect" perceptions of the service (Table 6.11). This suggests two conjectures. First, the results presented in Table 6.11 are fairly "robust" with respect to the variance of vehicle departure time and running time parameters. Second, the potential magnitude of time savings for less experienced passengers, using the dynamic path choice model, is comparable to those for very experienced passengers.

One might expect that real-time information may not only reduce the expected travel times of passengers, but might also reduce the variance of travel times, at least

Table 6.13: Mean Daily Variance in Travel Times - Network 1

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	22.01	21.80	19.57	19.45	20.00	16.42	13.67
Decrease		0.22	2.44	2.57	2.01	5.59	8.35
Std Error		(0.80)	(1.39)	(1.17)	(1.13)	(1.40)	(1.46)
Timed	15.48	16.39	15.30	15.94	16.28	13.00	11.21
Decrease		-0.91	0.17	-0.46	-0.81	2.48	4.27
Std Error		(1.05)	(1.23)	(1.33)	(1.34)	(1.16)	(1.25)

Table 6.14: Probability of Completing a Trip in 37 Minutes - Network 1

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	85.7%	85.7%	88.4%	88.0%	87.8%	91.6%	94.2%
Increase		0.0%	2.7%	2.3%	2.1%	5.9%	8.6%
Std Error		(0.6%)	(1.0%)	(0.9%)	(0.7%)	(1.1%)	(1.1%)
Timed	92.3%	90.9%	93.0%	92.8%	92.5%	96.6%	98.9%
Increase		-1.4%	0.7%	0.6%	0.2%	4.3%	6.7%
Std Error		(0.7%)	(1.2%)	(1.0%)	(0.9%)	(1.1%)	(1.2%)

reducing the likelihood of poor path choices. Improvements in travel time variance from the information scenarios are noted in Table 6.13. Small improvements in travel time variance are noted in scenarios 4 through 6 for randomly arriving passengers, with statistical results that do not yield t-statistics over 2.0 (except for scenario 5). There is no significant reduction in travel time variance for passengers timing their arrivals. More substantial (and statistically significant) reductions in travel time variance occur in scenario 7, the full network information case, for both passenger arrival patterns. Table 6.14 also shows the probability of a trip greater than 37 minutes. Scenarios 4 through 7 provide statistically significant improvements in the tail of the distribution for randomly arriving passengers, while improvements for passengers timing their arrivals is significant only for scenario 7. In most practical cases, the improvements in the probability of an arrival in 37 minutes are small. These results suggest that, in the absence of more comprehensive information on network travel times, the variability of trip times is not significantly reduced with real-time information.

Table 6.15: Expected Path Assignments with Information - Network 1

Passenger Arrivals	Path	Scenario 2	3	4	5	6	7	8
Random	1	26.07	26.17	26.90	25.23	25.40	26.77	26.53
	2	16.53	15.10	14.07	17.00	17.10	14.93	15.20
	3	17.40	18.73	19.03	17.77	17.50	18.30	18.27
Timed	1	19.33	19.67	20.47	19.10	19.47	20.50	20.73
	2	21.50	18.60	16.93	20.33	20.20	18.40	18.27
	3	19.17	21.73	22.60	20.57	20.33	21.10	21.00

For Network 1, the path assignments for each information scenario shown in Table 6.15 are broadly comparable to the base case (scenario 2). As more accurate information is given to passengers, there is a very slight shift from path 2 to path 3, again most likely due to better passenger perception of the travel time advantages on path 3. Perhaps the most interesting deviations in this table occur in scenarios 5 and 6, where running time information is given to the passenger on all origin routes. Because the passenger receives full information about path 2 (a direct service) in these scenarios, the desirability of this path improves relative to the more uncertain connections on paths 1 and 3. One may hypothesize that running time information favors direct routes more strongly than transfer paths.

Network 2

It was suggested in Section 6.2.1 that as the level of coordination of routes at the origin decreases, the value of more sophisticated path choice strategies may fall, at least in the case of no real-time information. However, there does seem to be slightly greater travel time advantages to real-time information for Network 2 relative to Network 1. Table 6.16 shows statistically significant (at a 90% confidence interval) travel time benefits across all scenarios.

In this network, expected travel time improvements are on the order of 0.22 to 0.99 minutes (approximately 0.7% to 3.2% of the total trip time) for randomly arriving passengers and 0.27 to 0.86 minutes (about 0.9% to 2.8%) for passengers timing their arrivals. Basic departure time information for the origin (scenario 3) yields more modest time savings (0.7% to 0.9%), while information on connecting depar-

Table 6.16: Expected Travel Times with Information - Network 2

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	32.714	32.494	32.159	32.404	32.323	31.725	31.371
Decrease Std Error		0.220 (0.131)	0.555 (0.147)	0.310 (0.165)	0.391 (0.164)	0.990 (0.137)	1.344 (0.139)
Timed	31.686	31.417	31.308	31.322	31.234	30.831	30.461
Decrease Std Error		0.269 (0.132)	0.379 (0.117)	0.364 (0.146)	0.453 (0.152)	0.855 (0.119)	1.225 0.139)

tures (scenario 4) and on running times for the origin routes (scenarios 5 and 6) are greater (1.0% to 1.8%). As with Network 1, the most significant benefits of passenger information appear in scenario 7, representing about 70% to 75% of the potential improvement in travel times when compared with perfect information (scenario 8).

The differences in expected travel times between scenarios 5 and 6, representing the value of improved information accuracy, statistically significant at a 90% confidence interval: a difference (standard error) of 0.081 (0.043) for randomly arriving passengers and 0.088 (0.045) for passengers timing their arrivals. These figures suggests only very small marginal benefits from improved information accuracy on vehicle running times. However, the net benefits of trip timing are substantial (around 1.0 to 1.1 minutes or 3.2% to 3.4% of the total trip time), but this statistic does not vary significantly based on different types of information. This again supports the value of passenger trip timing, and suggests at least some models benefits from pre-trip information to reduce passenger waiting and total travel times.

Two other results from Network 2 seem to confirm those suggested by Network 1. First, the expected travel times and improvements from information noted in Table 6.16 compare very closely with the same measures for passengers with different perceptions of departure and running time variances, listed in Table 6.17. The travel time results are thus very robust with respect to different passenger perceptions of service variability. Second, the variance of travel times experienced each day is given in Table 6.18. These results suggest more strongly that the only statistically significant reductions in travel time variance are for scenario 7, when real-time information on the full network is available. Furthermore, there is only modest (and

Table 6.17: Expected Travel Times by Passenger Type - Network 2

Passenger Arrivals	Pass. Type	Scenario 2	3	4	5	6	7
Random	Low	32.814	32.496	32.225	32.337	32.324	31.714
	High	32.562	32.523	32.153	32.345	32.289	31.695
Timed	Low	31.707	31.457	31.330	31.314	31.299	30.822
	High	31.520	31.459	31.284	31.331	31.285	30.789

Table 6.18: Mean Daily Variance in Travel Times - Network 2

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	23.62	22.72	20.97	22.44	21.72	18.25	15.70
Decrease		0.91	2.66	1.19	1.91	5.38	7.92
Std Error		(1.97)	(2.04)	(1.82)	(1.91)	(1.75)	(1.90)
Timed	14.74	13.38	12.60	13.71	12.67	10.31	8.83
Decrease		1.36	2.13	1.03	2.07	4.43	5.91
Std Error		(1.69)	(1.75)	(1.56)	(1.75)	(1.73)	(1.73)

in many cases statistically insignificant) reduction in the tail of the travel time distribution, as evidenced by the statistics on the probability of an arrival in 37 minutes in Table 6.19. Thus, as observed for Network 1, there are no significant reductions in the variability of travel times or in the tail of the total travel time distribution based on realistic scenarios of real-time passenger information.

The path choices for passengers in Network 2, presented in Table 6.20, do not seem to vary in any systematic way with the level of information available. In all information scenarios, there is a slightly higher proportion of travelers on path 3,

Table 6.19: Probability of Completing a Trip in 37 Minutes - Network 2

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	83.0%	83.7%	86.1%	83.7%	84.4%	88.7%	91.3%
Increase		0.7%	3.1%	0.7%	1.4%	5.7%	8.3%
Std Error		(0.8%)	(1.0%)	(1.1%)	(1.1%)	(1.1%)	(1.1%)
Timed	92.1%	92.6%	93.4%	93.6%	94.5%	97.1%	98.8%
Increase		0.5%	1.3%	1.5%	2.4%	4.9%	6.7%
Std Error		(0.9%)	(1.1%)	(0.8%)	(0.9%)	(1.0%)	(1.1%)

Table 6.20: Expected Path Assignments with Information - Network 2

Passenger Arrivals	Path	Scenario 2	3	4	5	6	7	8
Random	1	23.13	24.17	25.73	24.53	23.87	23.87	24.63
	2	19.00	16.17	15.53	16.93	17.53	17.00	16.50
	3	17.87	19.67	18.73	18.53	18.60	19.13	18.87
Timed	1	18.17	20.57	22.57	21.33	20.53	21.10	22.80
	2	20.27	16.63	15.33	17.20	18.00	16.90	15.67
	3	21.57	22.80	22.10	21.47	21.47	22.00	21.53

relative to scenarios without information. Again, this may be explained by the value of real-time information in helping passengers to realize the travel time benefits of path 3, the path with the shortest expected travel time. This was also more notably true on Network 1. Another trend common to Networks 1 and 2 (although less obvious for Network 2) is the inclination of passengers toward direct service when given information about vehicle running times (scenarios 5 through 7). Diversion to path 2 is evident in both networks. Generally, the results of both cases imply that accurate real-time information on vehicle running times from the origin tends to favor direct service as opposed to transfer paths.

Network 3

Finally, Network 3 was suggested as a model in which the value of information might be more pronounced. In this case, connections for transfer routes were timed in a problematic way, so that real-time information on service into and out of the transfer points may be of greatest benefit. The travel time results in Table 6.21, however, show travel time benefits which are more in line with those realized in Networks 1 or 2, relative to the base case of scenario 2, the dynamic path choice model with no information. Yet, relative to the simple strategy of taking the next bus (scenario 0), the results of Network 3 are more substantial. In this network, the dynamic model in scenario 2 yielded larger improvements in expected travel times (about 0.3 minutes) over scenario 0 (reported in Table 6.9). Thus, the dynamic path choice model with no information seems to compensate for at least some of the potential problems with poorly timed transfers. With this baseline, the benefits of real-time information are

Table 6.21: Expected Travel Times with Information - Network 3

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	30.859	30.835	30.464	30.618	30.576	30.066	29.464
Decrease Std Error		0.023 (0.193)	0.394 (0.103)	0.240 (0.139)	0.282 (0.169)	0.792 (0.099)	1.394 (0.093)
Timed	30.495	30.403	30.127	30.206	30.155	29.725	29.098
Decrease Std Error		0.093 (0.159)	0.369 (0.108)	0.289 (0.142)	0.341 (0.164)	0.770 (0.116)	1.397 (0.109)

considerably reduced.

Simple departure time information (scenario 3) yields little benefit over the dynamic path choice model with no information. However, relatively more significant time savings (about 0.4 minutes, or 1.3% of travel times) are realized with information about departures on connecting service (scenario 4). The scenarios with running time information (5 and 6) show more modest gains of about 0.24 to 0.34 minutes, indicating that running time information has a smaller effect in reducing uncertainty about making connections than information about departures on transfer routes. Real-time information on all departures and running times in the network (scenario 7) yield the greatest travel time benefits, which are still fairly modest at 0.77 and 0.79 minutes (about 2.6% of the total travel time) relative to the baseline of scenario 2.

For network 3, then, it appears that under conditions where connections are close, there may be considerable advantages to passengers adopting a dynamic path choice strategy, and even more so in the cases where real-time information about departures on connecting routes is available. Running time information for routes leaving the trip origin has much less of an impact in reducing expected travel times. Moreover, improved accuracy of running time information between scenarios 5 and 6 does not yield statistically significant differences in expected travel times: the difference (standard error) in travel times is 0.042 (0.073) for randomly arriving passengers and 0.051 (0.081) for passengers who time their arrivals with the scheduled vehicle departures.

The results for Network 3 show slightly greater reductions in travel time variance and the probability of a long trip than Networks 1 and 2. The expected daily vari-

Table 6.22: Mean Daily Variance in Travel Times - Network 3

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	22.53	22.79	19.46	20.14	20.55	17.40	14.58
Decrease		-0.26	3.07	2.39	1.98	5.13	7.95
Std Error		(1.67)	(0.69)	(0.76)	(1.48)	(0.65)	(0.62)
Timed	21.06	21.25	18.93	19.02	19.31	16.54	13.33
Decrease		-0.19	2.12	2.04	1.75	4.52	7.73
Std Error		(1.44)	(0.69)	(0.68)	(1.13)	(0.78)	(0.60)

Table 6.23: Probability of Completing a Trip in 37 Minutes - Network 3

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	89.1%	89.9%	92.4%	91.5%	91.8%	94.5%	97.1%
Increase		0.8%	3.3%	2.4%	2.7%	5.4%	8.1%
Std Error		(1.2%)	(0.8%)	(0.9%)	(1.0%)	(0.7%)	(0.8%)
Timed	92.4%	92.7%	93.9%	93.4%	93.9%	96.1%	98.8%
Increase		0.3%	1.6%	1.0%	1.5%	3.7%	6.4%
Std Error		(1.0%)	(0.7%)	(1.0%)	(1.1%)	(0.9%)	(0.7%)

ance in travel times, listed in Table 6.22, show statistically significant reductions in travel time variance on the order of 10% over most information scenarios, with the exception of a more pronounced 25% reduction in variance occurring in scenario 7. Improvements in the probability of arriving at the destination in 37 minutes are shown in Table 6.23. Even in the base cases, the probability of arriving in 37 minutes is relatively high, at 90% to 92% of trips arriving before that time. Given this base, more modest reductions in the tail of the travel time distribution are noted: 2% to 5% (in absolute terms) improvement for randomly arriving passengers and 1% to 4% for passengers timing their arrivals with vehicle schedules. The slightly more significant reductions in travel time variability here, relative to Networks 1 and 2, is attributed to the value of real-time information in helping passengers discern the likelihood of making connections in the network when these connections are timed problematically.

Real-time information also has a modest effect on path choices in Network 3, as suggested by Table 6.24. As was the case in Networks 1 and 2, the scenarios with

Table 6.24: Expected Path Assignments with Information - Network 3

Passenger Arrivals	Path	Scenario 2	3	4	5	6	7	8
Random	1	39.87	36.67	36.60	34.30	35.07	35.80	32.03
	2	7.87	8.73	8.80	10.87	10.50	9.63	9.93
	3	12.27	14.60	14.60	14.83	14.43	14.57	18.03
Timed	1	35.63	34.70	33.67	33.43	33.83	33.37	29.93
	2	11.57	11.53	11.10	13.90	13.77	12.70	12.40
	3	12.80	13.77	15.23	12.67	12.40	13.93	17.67

real-time information about running times from the origin (scenarios 5 and 6) show a greater attraction to path 2, away from the transfer paths. Information on connecting services (scenarios 4 and 7) has no obvious aggregate effect in diverting passengers toward or away from the transfer paths. However, as one might suspect some shifting to or from the transfer paths based on the real-time information about connections, this shifting occurs totally on a disaggregate (i.e. individual passenger) level. This is likely the case, given the travel time improvements noted in Table 6.21 for scenarios 4 and 7. The net result, however, yields no discernible aggregate changes in path choice.

6.2.3 Alternate Passenger Objectives

Network 1 was also examined using an alternative passenger objective. In this case, the passenger desires to minimize the probability of arriving at the destination later than 37 minutes after he/she arrives at the origin terminal. In this case, the expected travel time is of less concern than arriving at the destination by a certain time. Using the probability objective, passengers can indeed improve the probability of being on time by using better path choice strategies than the simple "next bus" strategy of scenario 0. The probability of arrival in 37 minutes for the no information scenarios is shown in Table 6.25. With this objective, the static and dynamic path choice model results do show clear improvement over the simple strategy of taking the next bus. The probability measure increases (in absolute terms) by approximately 3.5% for passengers arriving randomly and by about 6% for passengers who time their arrivals with vehicle schedules. In all cases, these improvements are statistically significant.

Table 6.25: Probability of Completing a Trip in 37 Minutes - No Information

Passenger Arrivals	Scenario 0 (Base)	1	2	8
Random	85.2%	88.7%	88.8%	94.2%
Increase		3.4%	3.6%	9.0%
		(1.0%)	(1.0%)	(1.0%)
Timed	90.5%	96.1%	96.8%	98.9%
Increase		5.6%	6.3%	8.4%
		(1.2%)	(1.3%)	(1.1%)

Table 6.26: Expected Path Assignments with Probability Objective - No Information

Passenger Arrivals	Path	Scenario 0	1	2
Random	1	26.30	19.43	19.73
	2	18.33	21.53	21.53
	3	15.37	19.03	18.73
Timed	1	21.07	11.73	11.50
	2	22.23	29.73	30.27
	3	16.70	18.53	18.23

Path assignments for the no information cases are shown in Table 6.26. The static and dynamic models produce very similar results, but these differ greatly from the results of the "next bus" scenario. With the improved path choice models, there are substantial shifts in passengers from path 1 to paths 2 and 3 for both passenger arrival patterns. The shift to path 2 may be explained in that the uncertainty of a transfer is removed for passengers choosing this path, while the shift toward path 3 results from its generally faster travel times. Thus, the probability objective seems to influence the path choice models to select more direct and faster paths in the network. These path assignments show strong shifts from path 1 to path 2, compared with the results in Table 6.6 for the expected travel time objective.

In Table 6.27, the results of scenarios 3 through 6 suggest that the probability measures do not vary substantially between different information scenarios. For this objective function, it seems that more accurate or more thorough real-time information provides little reduction in the tail of the passengers' travel time distributions. The relatively modest increases in the expected travel time shown in Table 6.30 allow

Table 6.27: Probability of Completing a Trip in 37 Minutes

Passenger Arrivals	Scenario 2	3	4	5	6	7	8
Random	88.8%	88.8%	90.6%	90.6%	90.8%	93.6%	94.2%
Increase vs. Net1	3.1% (0.9%)	3.2% (1.0%)	2.2% (0.6%)	2.6% (0.9%)	3.0% (0.9%)	1.9% (0.6%)	0.0% (0.0%)
Timed	96.8%	96.8%	97.3%	97.3%	97.7%	98.6%	98.9%
Increase vs. Net1	4.6% (1.3%)	5.9% (1.1%)	4.3% (0.9%)	4.5% (1.1%)	5.2% (1.1%)	2.0% (0.6%)	0.0% (0.0%)

the reductions in "late" trips by about 3% for passengers arriving randomly and about 5% on average for passengers timing their arrivals with vehicle schedules. Again, more substantial improvements in the objective appear in scenario 7, with improvements (in absolute terms) of about 4.8% for random passenger arrivals and 1.8% for timed passenger arrivals.

Three other comparisons are worth noting for the probability objective. First, Table 6.28 shows the value of the objective function for different passenger types. As with the expected travel time objective, there are only very minor differences in the probability of arriving "on time" based on different levels of passenger experience. Again, these results suggest that the value of information is similar for passengers with varying awareness of travel time characteristics. Second, the average variance in travel times for a single day is shown in Table 6.29. As with the probability measure derived for Table 6.27, there is little systematic difference in these variance measures across the range of real-time information scenarios. Finally, Table 6.30 compares the expected travel times resulting from the probability objective versus those from the expected travel time objective, presented in Table 6.11. In general, the probability objective has the effect of increasing expected travel times on the order of 0.9% to 2.6%, from 0.30 to 0.86 minutes, for both random and timed passenger arrivals. Under this objective, passengers are willing to trade off expected travel time improvements for a reduction in the variability and in the tail of the travel time distribution.

Finally, Table 6.31 presents the path assignments for trips in Network 1 using the probability objective. Several more insights emerge from these results. Clearly,

Table 6.28: Probability of Completing a Trip in 37 Minutes by Passenger Type

Passenger Arrivals	Pass. Type	Scenario 2	3	4	5	6	7	8
Random	Low	88.9%	89.2%	90.8%	90.2%	90.7%	93.6%	94.2%
	High	89.4%	88.9%	90.2%	90.8%	91.2%	93.6%	94.2%
Timed	Low	96.4%	96.8%	97.6%	97.5%	97.6%	98.6%	98.9%
	High	96.7%	96.7%	96.9%	97.3%	97.5%	98.6%	98.9%

Table 6.29: Mean Daily Variance in Travel Times - Probability Objective

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7	8
Random	17.88	16.92	17.34	16.07	16.25	15.39	13.67
Decrease		0.97	0.54	1.81	1.63	2.50	4.22
Std Error		(0.53)	(0.69)	(0.79)	(0.79)	(0.61)	(1.09)
Timed	8.46	8.07	8.36	8.16	8.32	8.31	11.21
Decrease		0.39	0.11	0.30	0.15	0.16	-2.74
Std Error		(0.19)	(0.33)	(0.33)	(0.33)	(0.45)	(0.77)

Table 6.30: Expected Travel Times with Probability Objective

Passenger Arrivals	Scenario 2	3	4	5	6	7	8
Random	32.579	32.587	32.186	32.464	32.439	32.041	30.909
Increase	0.411	0.414	0.456	0.710	0.650	0.826	0.000
vs. Net1	(0.142)	(0.139)	(0.111)	(0.139)	(0.131)	(0.116)	(0.000)
Timed	31.871	31.901	31.673	31.890	31.852	31.558	30.295
Increase	0.366	0.295	0.494	0.704	0.662	0.910	0.000
vs. Net1	(0.141)	(0.130)	(0.120)	(0.150)	(0.132)	(0.128)	(0.000)

Table 6.31: Expected Path Assignments with Probability Objective

Passenger Arrivals	Path	Scenario 2	3	4	5	6	7	8
Random	1	19.73	20.13	22.40	19.50	19.67	21.07	26.53
	2	21.53	23.07	20.63	24.90	24.87	22.20	15.20
	3	18.73	16.80	16.97	15.60	15.47	16.73	18.27
Timed	1	11.50	11.03	12.10	10.43	10.13	12.20	20.73
	2	30.27	32.57	29.87	34.50	34.87	30.17	18.27
	3	18.23	16.40	18.03	15.07	15.00	17.63	21.00

passengers tend to prefer path 2 (the direct route) more so than when using the expected travel time objective (comparing with Table 6.15). This makes intuitive sense, as there is considerably higher variation in travel times when transfers are involved. Path 2 is even more desirable when running time information is provided (scenarios 5 and 6), which supports the hypothesis made earlier that running time information from the origin will favor direct routes over transfer paths. In the cases where information on departures on transfer paths is available (scenarios 4 and 7), there is a slight increase in preferences for the transfer paths.

In summary, the probability objective offers several insights into a passenger's travel time and path choice behavior. First, the modeling approach suggests that alternative passenger objectives, such as the probability objective, may be included easily in the static and dynamic path choice framework. Furthermore, the improvements in path choices from these models versus the "next bus" strategy are more apparent with this objective function, as evidenced by the improvements in probability measures in scenarios 1 through 7 over the simplest path choice strategy (scenario 0). As was expected, the probability objective tends to draw passengers to faster and more direct paths, which, in this example network, had the effect of increasing expected travel times modestly. In general, improvements in the objective function for this network are also very modest, reinforcing the results from the expected travel time objective.

6.3 Conclusions

There are several important conclusions that can be drawn from these simulation results. One of the primary motives for examining the shuttle network was to develop some insight into the factors affecting the value of real-time information in a path choice setting. In this context, the results presented here do not a represent a comprehensive analysis of different factors. However, the results do support a number of conclusions.

First, the evidence for the three networks above shows little potential benefit of real-time information in reducing the expectation or the variability of passenger travel times. Real-time information yielded modest reductions of 2% to 3% of the expected travel time for a "typical" transit trip of about 30 minutes. Furthermore, only very small reductions in the variance of travel times for a given day and in the probability of a trip longer than 37 minutes were noted for each network. The small magnitude of these benefits is partially a function of the network parameters, as perfect information only provides travel time savings on the order of 4% to 5% of the total travel time. From this perspective, real-time information under more realistic levels of information accuracy allowed passengers to recover about 70% to 80% of the possible travel time savings in each of the networks. Yet, the overall magnitude of travel time benefits is small.

Second, for these three networks, the static and dynamic path choice models developed in Chapter 4 were shown to have some value. First, these path choice models are sufficiently flexible to accommodate different passenger objectives. In this case, both an expected travel time objective and a maximum probability of arriving in X minutes were modeled. Second, these path choice models demonstrated virtually no substantial travel time improvements for passengers minimizing their expected travel time for Networks 1 and 2; however, more significant improvements were noted for both the static and dynamic models both in Network 3 with the expected travel time objective and in Network 1 with the probability objective. In this way, the static and dynamic path choice models show potential for modest improvements in the objective function relative to more simple path choice strategies. Furthermore, the path choices from these path choice models showed substantial differences. In general, the models assign more passengers to higher frequency routes than a simple frequency share model when vehicle departure times are stochastic. Explicitly incorporating expected travel times in the static and dynamic models draws passengers to the faster paths.

The results paint an interesting picture of the value of different types of information. In the network examples above, simple departure time information offered no noticeable changes in the assumed passenger decision-making. Real-time information on vehicle running times from the origin (scenarios 5 and 6) and departure time information for connecting services (scenario 4) gave similar, and more significant, improvements in passengers' travel times. Furthermore, the analysis of Network 3 suggests that in situations where transfer connections are timed fairly closely, real-time information on vehicle departures from transfer points can have a more significant impact on passenger travel times than running time information out of the origin.

In terms of the path choices resulting from different types of information, there are several hypotheses which can be presented. As has been mentioned, the information which seems to be of greatest value in reducing travel times in the shuttle network is information about travel times into and out of the transfer points. When such information is provided, passengers are more likely to use transfer paths in the network (although this effect is very slight). When running time information is provided for vehicles at the origin, the direct routes appear to be more attractive than the transfer paths. In this way, passengers tend to choose these direct services more often if running time information is available than if it is not available.

At the same time, the value of real-time information did not really vary based on a passenger's level of experience with the transit service, on the vehicle schedules, or on the level of information accuracy. First, in all three networks, no substantial or statistically significant differences were noted between passengers based on different levels of possible bias in perceiving travel time variance. Passengers who underestimate the domain of travel times by 20% or who overestimate these domains by 20% made decisions which were, for the most part, indistinguishable from passengers who accurately perceived the true travel time (or accuracy) distributions. In this case, the results seem fairly robust to variations in perceived service characteristics in the transit network. Moreover, the results of Networks 1 and 2 suggest that similar travel time savings are realized virtually independently of whether or not the service schedules are coordinated. In these examples, however, transit service at the origin runs fairly frequently (on the order of one bus every 4 minutes), tempering the validity of this conclusion. Also, only modest and statistically questionable differences in the expected travel time were noted based on different levels of information accuracy in running time information from scenarios 5 and 6 for all three networks.

On the other hand, the passenger objective does seem to influence the conclusions significantly. With a probability (or "on time" arrival) objective, passengers tend to favor direct and relatively faster paths. With the operating characteristics of Network 1, the probability objective resulted in slightly higher net travel times, on the order of 1% to 3% higher than with the expected travel time objective. However, more substantial reductions in the travel time variance and the probability of arriving after 37 minutes were achieved with this objective.

Finally, the results also suggest that there is considerable advantage for passengers to time their arrivals at the origin stop with the vehicle departures. In all three networks, a simplistic coordination of passenger arrivals at the origin with scheduled vehicle departures provided average improvements of 2% to 3% of the total travel time. With pre-trip information, passengers may experience reductions in travel times in this same magnitude. These results are not conclusive, however, and much more research is necessary to evaluate pre-trip information systems in a similar manner.

Because of the design of the shuttle network and the information scenarios to date, little insight has been gained into the value of different levels of information accuracy or into the value of real-time information at different times during the trip. The case study at the MBTA, to be discussed at greater length in Chapter 7, provides much greater insight into these issues. That case study also allows further investigation of many of the conclusions drawn here.

Chapter 7

MBTA Case Study

There are still a number of questions about the role of information, the value of the path choice models presented in the thesis, and the practical application of the modeling framework which may be addressed through a case study. Hence, this chapter describes a case study at the Massachusetts Bay Transportation Authority (the MBTA). The first section considers the operating characteristics for the MBTA's Arlington-Cambridge corridor and also the set of scenarios to be investigated using the simulation model. The last three sections of the chapter discuss the model results for both the inbound and outbound commuting trips and the conclusions about real-time information that can be drawn from this example.

7.1 MBTA Case Study Characteristics

The case study examines MBTA transit service in the northwest corridor of the Boston metropolitan area, between Arlington Center and downtown Boston (Park Street station). The specific network is illustrated in Figure 7-1. Passengers traveling inbound to Boston from Arlington Center may choose from bus routes 79 and 350 traveling to Alewife station, and route 77 traveling to both Porter and Harvard stations to access the Red Line. Passengers traveling outbound from Boston may choose among this same set of routes in the reverse direction.

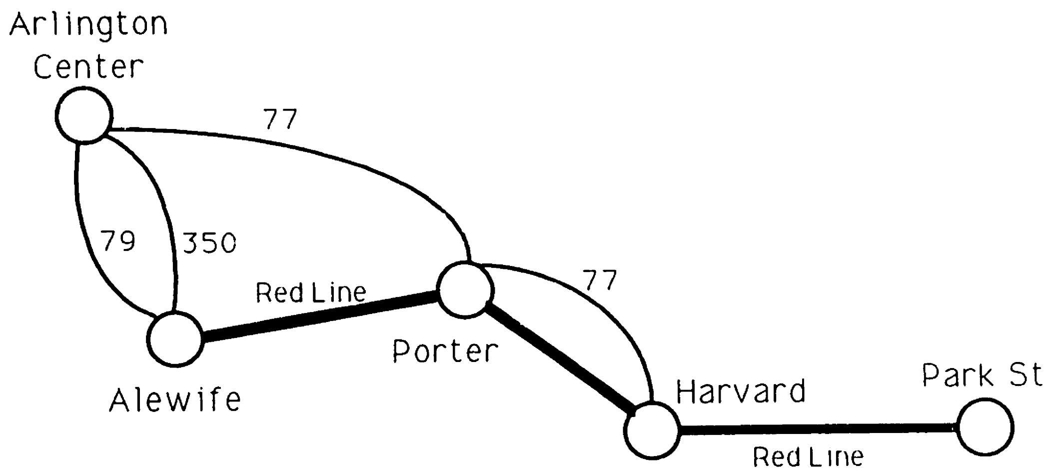

Figure 7-1: The Arlington-Cambridge-Boston Corridor

Table 7.1: Morning Peak Operating Characteristics

Route	Schedule Offset	Headway	Scheduled Run Time	Note
77	:02	8.0	14.0	Arlington to Porter
			6.0	Porter to Harvard
79	:10	10.0	10.0	Arlington to Alewife
350	:02	14.0	10.0	Arlington to Alewife
Red Line	:00	4.0	4.5	Alewife to Porter
			3.5	Porter to Harvard
			10.5	Harvard to Park Street

7.1.1 MBTA Service Schedules

In this corridor, two different travel patterns are examined. First, morning peak period (between 7 a.m. and 9 a.m.) trips from Arlington Center to Park Street are modeled. During this period, all three bus routes are operating at peak levels. A summary of the morning peak operating characteristics on the associated bus routes and the Red Line are given in Table 7.1. The second travel pattern includes trips from Park Street to Arlington Center during the evening peak, defined as 5 p.m. to 7 p.m. at Harvard station. The operating characteristics of the bus routes and Red Line during these hours are given in Table 7.2.

Table 7.2: Evening Peak Operating Characteristics

Route	Schedule Offset	Headway	Scheduled Run Time	Note
77	:00	8.0	6.0	Harvard to Porter
	:06		15.0	Porter to Arlington
79	:04	12.0	12.0	Alewife to Arlington
350	:00	20.0	12.0	Alewife to Arlington
Red Line	:00	5.0	9.5	Park Street to Harvard
			4.0	Harvard to Porter
			4.5	Porter to Alewife

7.1.2 MBTA Travel Time Data

Transit service characteristics in the Arlington-Cambridge corridor show considerable variability in vehicle departure and running times. The northwest extension of the Red Line serves Harvard through to Alewife station on the Cambridge/Arlington border with high frequency service (i.e., 4 to 5 minute headways during peak periods). Irregularities in Red Line headways occur often due to short turning of trains in the downtown portion of the line and minor mechanical problems, resulting in potentially considerable variation in headways and vehicle running times between stations. In addition, Massachusetts Avenue, the main street through this section of Arlington and Cambridge, is subject to considerable congestion during peak travel times. As a result, there is a high level of variability in travel times on bus routes traveling on Massachusetts Avenue.

The distributions for Red Line running times and vehicle headways are shown in Tables 7.3 and 7.4. [In these and subsequent tables, the triangle distribution has parameters of the minimum, mode, and maximum, respectively. The parameters for the lognormal distributions are the mean and standard deviation.] Vehicle headways are measured directly using vehicle sensors at Alewife station inbound for the morning peak and at Harvard station outbound for the evening peak. There are also vehicle sensors at a few points on the Red Line which provide some information about train running times between stations. However, because these sensors are not located with sufficiently high density in the northwest corridor, the running times between stations were approximated using the coefficient of variation of the running times be-

Table 7.3: Red Line AM Inbound Travel Time Parameters

Statistic	Location	Estimated Distribution
Headway	Alewife	1.0 + Lognormal(3.04, 1.72)
Run Time	Alewife-Porter	Triangle(4.95, 5.55, 6.25)
	Porter-Harvard	Triangle(3.55, 4.1, 4.6)
	Harvard-Park St	Triangle(10.35, 11.55, 13.25)
Run Time Correlation	All Segments	0.766

Table 7.4: Red Line PM Outbound Travel Time Parameters

Statistic	Location	Estimated Distribution
Headway	Harvard	2.0 + Lognormal(3.04, 4.31)
Run Time	Park St-Harvard	Triangle(9.85, 10.7, 12.7)
	Harvard-Porter	Triangle(3.55, 4.3, 5.15)
	Porter-Alewife	Triangle(4.45, 5.05, 5.95)
Run Time Correlation	All Segments	0.414

tween sensors at Alewife and Charles Street station inbound. Vehicle running time correlation and "bunching" on the Red Line was simulated separately, as described in Section 5.5.1. The running times of that simulation were used directly in defining the empirical running time distributions in Tables 7.3 and 7.4.

It is assumed that the initial starting time of the Red Line departures relative to the beginning of the morning and evening peak periods are arbitrary. That is, the initial offset of the first Red Line departure after 7 a.m. from Alewife (AM Inbound) or after 5 p.m. from Harvard (PM outbound) is arbitrary. To model this, a random draw from the lognormal headway distributions shown in Tables 7.3 and 7.4 (without the constant term) is drawn as the initial vehicle departure time after the beginning of each peak period. Red Line dwell times are assumed to be 0.3 minutes at each station (18 seconds), which is slightly less than the book time of 20 seconds. The smaller value does seem plausible, however, since passengers are almost always simply boarding (morning) or alighting (evening) at these stations during peak periods.

The travel time characteristics of bus routes in the Arlington-Cambridge corridor are described in Tables 7.5 and 7.6. Routes 79 and 350 travel over a common route segment between Alewife station and Arlington Center, and thus are assumed to have common running time characteristics (although leap-frogging between routes

Table 7.5: Bus Route AM Inbound Travel Time Parameters

Route	Measure	Location	Estimated Distribution
77	Dpt. Delay	Arlington	Triangle(0.0, 3.0, 9.0)
	Run Time	Arlington-Porter	Triangle(8.9, 12.2, 19.5)
	Run Time	Porter-Harvard	Triangle(2.6, 3.95, 6.4)
79	Dpt. Delay	Arlington	Triangle(0.0, 3.0, 10.0)
	Run Time	Arlington-Alewife	Triangle(6.0, 9.5, 14.0)
350	Dpt. Delay	Arlington	Triangle(0.0, 6.0, 12.0)
	Run Time	Arlington-Alewife	Triangle(6.0, 9.5, 14.0)

Table 7.6: Bus Route PM Outbound Travel Time Parameters

Route	Measure	Location	Estimated Distribution
77	Dpt. Delay	Harvard	Triangle(0.0, 0.5, 6.0)
	Run Time	Harvard-Porter	Triangle(6.0, 12.2, 14.1)
	Run Time	Porter-Arlington	Triangle(9.1, 10.9, 14.9)
77	Run Time	Harvard-Porter	Correlation of 0.554
79	Dpt. Delay	Alewife	Triangle(0.0, 0.1, 9.0)
	Run Time	Alewife-Arlington	Triangle(6.0, 9.5, 13.0)
350	Dpt. Delay	Alewife	Triangle(0.0, 0.1, 5.5)
	Run Time	Alewife-Arlington	Triangle(6.0, 9.5, 13.0)

is permitted). Passengers traveling outbound at Alewife are assumed to board the first bus on route 79 or 350 to depart from Alewife. Note that there is considerable variability in bus departure times, particularly on the morning inbound segments. All three bus routes begin significantly upstream of Arlington Center, and, as a result, there is considerable variation in actual vehicle departure times in Arlington Center. Similarly, the 77 and 79 buses traveling outbound in the evening are subject to considerable traffic congestion on Massachusetts Avenue. As a result, both routes have the potential for significant dispatch delays at Harvard and Alewife stations outbound, respectively.

For bus to rail transfers inbound in the morning, it is assumed that transfer times at each station (Alewife, Porter and Harvard) are identical. Thus, there is no observed walking or waiting time advantages to any of the three stations. A similar assumption is made for the evening peak outbound, except for the transfer from the Red Line to the 77 bus at Porter. In this case, an additional 3 minutes is added to the walking time from the train platform to the 77 bus stop, due to the location of the bus stop on Massachusetts Avenue. It is also assumed that the 77 bus incurs a 0.2 minute dwell time (or 12 seconds) as passengers board (or alight) at Porter. For the inbound trip, no passenger boardings on the 77 are permitted at Porter, so all passenger flows are out of the two doors on the bus. On the outbound trip, no passenger alightings are permitted, and passenger volumes are generally small enough, that the 12 second dwell time is not unreasonable.

7.2 Case Study Scenarios

For each operating network described above, there are several scenarios to be examined. This section outlines the set of scenarios and discusses some of the modeling issues associated with these scenarios.

7.2.1 Scenario Description

Because of the service characteristics in this corridor, the morning and evening peak are treated differently with respect to both the types of information provided to the passenger and the passenger response to information. For the inbound morning peak, the following set of scenarios appear to be of most interest:

- Scenario 0: Passengers in Arlington Center use the simple strategy of boarding the next bus to arrive.
- Scenario 1: Passengers use the static path choice model to select a set of routes to board.
- Scenario 2: Passengers use the dynamic path choice model to decide on a boarding strategy.
- Scenario 3: Passengers use real-time information on projected vehicle departures from Arlington Center to make a boarding decision (using the dynamic path choice model). A low level of accuracy of departure time information is assumed.
- Scenario 4: Identical to Scenario 3, but assuming a higher level of accuracy in predicting vehicle departure times.

- Scenario 5: In addition to the information on vehicle departures (with the low level of accuracy assumed in Scenario 3), passengers receive information about projected running times for each of the bus routes serving the Red Line. A low level of accuracy of running time information is assumed.

- Scenario 6: Identical to Scenario 5, but assuming a higher level of accuracy in predicting both vehicle departure times and vehicle running times.

- Scenario 7: Passengers receive perfect information on vehicle departure times and running times for bus routes out of Arlington Center.

The scenarios above are loosely comparable to those of the shuttle network described in Section 6.1.4. In this case, the scenarios with no information (numbers 0, 1 and 2) are identical for both the case study and the shuttle network. Scenario 3 above is similar to scenario 3 of the shuttle network, except that the accuracy of departure time information is time-dependent for this case study, whereas it was static for the shuttle network. To examine the effects of higher accuracy for departure time information, scenario 4 above was added to the list of scenarios, and has no direct comparison in the shuttle network. Scenarios 5 and 6 in the case study are similar to the similarly-numbered scenarios for the shuttle network, again with a time-dependent, rather than a static, level of accuracy on departure time information. Finally, the perfect information case, scenario 7 here and scenario 8 of the shuttle network, are somewhat similar, except that in this case, perfect information is constrained to the bus routes only, with no real-time information for the Red Line. The assumption of no real-time information about the Red Line has eliminated what were scenarios 4 and 7 in the shuttle network from the analysis here.

The evening peak scenarios are substantially different because the passenger decision point is not the trip origin. In particular, in the journey from Park Street to Arlington Center, all passengers take the Red Line from downtown and do not need to make a bus route choice until the train reaches Harvard station. Thus, information may be provided on board the train regarding bus connections to Arlington Center that allow passengers to make better decisions about their trips. Scenarios for the outbound trip are listed below.

- Scenario 1: Passengers choose routes adaptively upon arriving at each station on the Red Line. In particular, at Harvard and Porter stations, the passenger decides whether or not to disembark from the Red Line to take the next route 77 bus, based on the expected travel times for each alternative. At Alewife, the passenger simply chooses to get on the next bus to depart for Arlington Center. The passenger receives no real-time information about vehicle departures or running times.

- Scenario 2: Passengers receive information about the expected departure time of buses at each station on the Red Line, at a low level of accuracy. Using the adaptive path choice strategy as in scenario 1, a path is selected.

- Scenario 3: Identical to scenario 2 but with a higher level of accuracy on predicted vehicle departure times.

- Scenario 4: Passengers receive information on both expected departure times and running times for bus routes serving each of the Red Line stations. A low level of accuracy is assumed for both types of information.

- Scenario 5: Identical to scenario 4, with a higher level of accuracy on predicted departure and running times.

- Scenario 6: The passenger receives perfect information about bus routes from which to make a path choice upon entering each Red Line station.

Because in-vehicle information systems were not investigated for the shuttle network, these six scenarios for the MBTA have no direct comparison with the shuttle network scenarios of Chapter 6.

7.2.2 Modeling Issues

To model these scenarios, the models of passenger behavior and real-time information must be revised. This is discussed in greater detail below.

Choice Behavior Modeling

Section 4.6 introduced the concept of adaptive decision making in the context of the static and dynamic path choice models. In that discussion, a method was describe for using a static path choice model at "downstream" nodes in the network to get the expected travel time for path options at nodes further "upstream." In the MBTA case study corridor, such an adaptive decision model is critical to determining passenger decision making and path choice modeling. The following paragraphs briefly describe the modeling framework for both the morning and the evening peak scenarios.

In the morning peak, passengers traveling inbound from Arlington Center may choose either the 79 or 350 routes serving the transfer at Alewife, or route 77, allowing the passenger a transfer at either Porter or Harvard. When determining the expected travel time for boarding a route 77 bus in Arlington Center, some expectation of travel times from Porter to Park Street is necessary. In this case, a simple shortest path model may be used at Porter to determine the expected travel time from Porter to Park Street. Expected travel times for both staying on and getting off the route 77 bus at Porter are constant (but obviously dependent on running time information provided about the 77 bus). The expected travel time from this shortest path calculation at Porter may be used in calculating the expected travel time via route 77 from Arlington Center. This is a very simple application of the adaptive path choice model described in Section 4.6, where the decision at Porter, while perhaps made upon arrival at Porter, is really known in advance from Arlington Center.

For the evening peak trip from Boston to Arlington Center, the path choice modeling is more complicated. The entire process of path choice is based upon an adaptive decision made when the passenger arrives at Harvard, Porter, and Alewife stations. As suggested in Section 4.6, the static path choice model can be used to determine the expected travel time at "downstream" nodes, but passengers are assumed ultimately to use the dynamic path choice model upon reaching these nodes.

Upon arriving at Harvard, the passenger will make a decision whether or not to get off the Red Line and take the next route 77 bus. This decision is based on comparing the expected travel time on route 77 with that of staying on the Red Line to Porter. In turn, the expected travel time at Porter depends upon an adaptive decision, made upon arrival at Porter, whether to board a route 77 bus there or to continue on the Red Line to Alewife. Once at Alewife, the passenger simply boards the next bus to depart for Arlington Center (either the route 79 or the route 350 bus).

Summarizing, this framework entails a fairly complicated choice process, especially at Harvard. For this outbound trip, the adaptive choice model at Harvard must accommodate a subsequent adaptive choice at Porter on the Red Line, while adaptive decisions at Porter must accommodate a subsequent static path choice at Alewife. This adaptive decision-making may be explained most easily in reverse order.

- **At Alewife:** A passenger always boards the next bus to depart. The expected travel time for this decision is the (time-dependent) expected travel time $T_{X(t_A)}$ from the static path choice set $X(t_A) = \{1,1\}$, where t_A is the the time the passenger arrives at Alewife on the Red Line.
- **At Porter:** The expected travel times for transfering and for staying on the Red Line both depend on the time of arrival at Porter, t_P. However, given t_P, the expected travel times for both options may be calculated, and the minimum used to make path decisions. Expected travel times for the transfer to route 77 are straightforward. Expected travel times for the Red Line option integrate the expected travel times from Alewife, $T_{X(t_A)}$, over all possible arrival times t_A at Alewife. Obviously, $t_A = t_P +$ running time to Alewife from Porter.
- **At Harvard:** The expected travel times for transfering to the 77 bus and for staying on the Red Line depend on the time of arrival at Harvard, t_H. Expected travel times for both decisions are calculated, and the minimum is used to determine the path decision. The expected travel time for the transfer to route 77 is calculated in a straightforward manner. However, expected travel times for staying on the Red Line integrate the expected travel times at Porter (calculated as above) over all possible arrival times t_P at Porter. Obviously, $t_P = t_H +$ running time from Harvard to Porter.

Information Accuracy

From the discussion of information accuracy in Section 5.2.3, the parameters in Table 7.7 are used to model information about departure times for expected departure times in both the morning inbound and evening outbound scenarios. For vehicle running times, it is assumed (as before) that a low level of accuracy projects the expected running times with a margin of error of -1.0 to +3.0 minutes, whereas a higher accuracy forecast may predict the expected running times with a margin of

Table 7.7: Accuracy of Departure Time Projections

Low Accuracy:

Time Until Event	Distribution Domain
Over 10 mins	-2.0 to +5.0 mins
7-10 mins	-1.5 to +3.0 mins
4-7 mins	-1.0 to +2.0 mins
1-4 mins	-0.5 to +1.0 mins

High Accuracy:

Time Until Event	Distribution Domain
Over 10 mins	-1.0 to +3.0 mins
7-10 mins	-1.0 to +2.0 mins
4-7 mins	-0.5 to +1.0 mins
1-4 mins	-0.5 to +0.5 mins

-1.0 to 2.0 minutes. No time-dependence in the accuracy of running time information is assumed.

Other Modeling Assumptions

Three additional assumptions of the case study need mention. First, two different passenger arrival processes are modeled for the inbound trip. A total of sixty passengers (for each passenger type) are assumed to arrive in Arlington Center either randomly or timed with scheduled bus departures. For the case of timed arrivals, the shuttle network assumed that one-third of all passengers would time their arrivals with each of the three routes serving the origin. For the MBTA Case Study, however, passengers were "assigned" to wait for routes in different proportions. In particular, forty percent of the passengers were assigned to each of routes 77 and 79, with the remaining twenty percent assigned to route 350. This assignment was based very loosely on the frequency share of each route, while also discounting the attraction of route 350 because of the very large departure delays on this route. In particular, because such a large proportion (about 75% to 80%) of the 350 route occurs prior to Arlington Center, its share was reduced slightly.

For outbound travel in the evening peak, it is necessary to model only a single passenger arriving on each Red Line train in Harvard, destined for Arlington Center.

The decision process for that one individual would be identical to other passengers on the same train. Furthermore, for a two-hour peak period, with trains arriving on (approximately) five-minute headways, 25 train arrivals were modeled for the outbound scenarios.

For all of the information scenarios, the passenger is presented with information on departure and running times *on bus routes only*. This assumption was made because of the high frequency of service on the Red Line. In this case, passengers are less dependent on specific Red Line trains to complete their trips, and the timing of transfers from the bus routes is not important. In terms of modeling the accuracy of bus departure times, bus terminals (i.e., Harvard and Alewife) were treated similarly as intermediate stops (Porter and Arlington Center). Even though Alewife and Harvard stations are bus route terminals, there is significant likelihood of departure delays, and the accuracy of predicting departure delays at these terminals is most likely no better than at intermediate stops. Thus, the accuracy distributions at these terminals matches those for buses en route.

Finally, three passenger types were also modeled. As discussed in Section 5.3, passengers may have varied perceptions of the transit service. Some passengers may have considerable experience with the service, and thus accurately perceive the distributions of travel times in the network. On the other hand, persons with less experience may underestimate or overestimate the true variability. For the case study, it is assumed that passengers with less experience underestimate the domains of the vehicle departure time and running time density functions, using a multiplier of 0.7 (i.e., domains were reduced by 30%). Passengers who have had negative experiences with the transit service may overestimate these domains by some factor. For those persons, a multiplier of 1.3 is used, implying that the domains of the density functions were increased by 30%. Again, changes in distribution parameters resulting from the different passenger levels of experience are detailed in Section 5.3.

7.3 Morning Peak Inbound Results

The eight morning peak scenarios described in Section 7.2.1 were investigated using the simulation model. This section discusses the results of these simulation runs,

Table 7.8: Expected Travel Times with No Information - AM Inbound

Passenger Arrivals	Scenario 0 (Base)	1	2
Random	35.534	35.542	35.594
Decrease Std Error		-0.008 (0.006)	-0.059 (0.056)
Timed	35.682	35.689	35.722
Decrease Std Error		-0.007 (0.005)	-0.041 (0.068)

Table 7.9: Probability of a Trip Completed in 38 Minutes with No Information - AM Inbound

Passenger Arrivals	Scenario 0 (Base)	1	2
Random	77.6%	77.5%	77.0%
Increase Std Error		-0.1% (0.1%)	-0.6% (0.8%)
Timed	75.3%	75.3%	76.7%
Increase Std Error		0.0% (0.1%)	1.3% (1.0%)

first examining the path choice models with no real-time information and then the scenarios with real-time information.

7.3.1 Path Choice Models

In general, the morning inbound trip takes between 25 and 45 minutes, with a mean around 35 minutes. For the case of no information (described in Tables 7.8 and 7.9), expected travel times and the probability of a trip longer than 38 minutes are virtually identical for the simplest path choice model (scenario 0) and the static and dynamic models. In this case, more sophisticated path choice techniques do not yield travel time advantages. Furthermore, both the expected travel time and the probability measures are comparable for both passenger arrival patterns, with slightly worse values observed for timed arrivals. There seems to be no potential benefit to passengers in timing their arrivals with bus schedules, most likely due to the high variability of vehicle departure times from Arlington Center (as shown in Table 7.5).

Table 7.10: Expected Path Assignments with No Information - AM Inbound

Passenger Arrivals	Path	Scenario 0	1	2
Random	79	19.53	19.33	15.57
	350	12.90	12.73	10.67
	77a	27.57	27.93	33.77
	77b	0.00	0.00	0.00
Timed	79	20.40	20.13	14.10
	350	12.50	12.27	9.77
	77a	27.10	27.60	36.13
	77b	0.00	0.00	0.00

The path assignment for the first three scenarios corresponding to the different path choice models are listed in Table 7.10. [In Tables 7.10 and 7.15, route 77a is the segment of route 77 from Arlington to Porter, while route 77b is the segment from Porter to Harvard.] The first obvious result is that no passenger remains on the route 77 bus from Porter to Harvard; the expected running time on the bus is greater than the expected running time on the Red Line, without any further information about bus travel times into Harvard. In terms of the path choices in Arlington Center, the distribution on the three routes seem fairly comparable between the "next bus" strategy and the static path choice model. An assignment based on frequency shares would assign 25.3 passengers to route 77a, 20.2 passengers to route 79, and 14.5 passengers to route 350. As was noted for the shuttle network, the path choice models here (including the "next bus" strategy) seem to favor more frequent routes when bus departures are stochastic, with passengers shifting toward route 77 and, to a lesser extent, route 79.

However, path choices for the dynamic model (scenario 2) favor the route 77 bus more strongly, with about 55% to 60% of travelers choosing to take route 77 to Porter. It seems that some passengers are more likely to board the 77 bus with the dynamic path choice model. This seems to be a function of the shorter headways on route 77 and its significant variability in departure times from Arlington Center. Such an effect was also noted for Network 3 of the shuttle model. The dynamic path choice model may tend to overstate the effect of drawing more passengers to paths with high frequencies and high departure time variability; in part, there may be numerous occasions where the departures of the 77 bus closely follow route 79 or route 350 bus departures. It is interesting to note, also, that even as scenario 2 proposes a significant shift toward the 77 bus, travel times and the probability of arriving "on time" are virtually unchanged. Indeed, the shift from the 79 and 350 to the 77 bus in scenario 2 is probably *not* a function of the expected travel time advantage once boarding, since travel times are unchanged. Rather, there seems to be very similar travel times on all three routes from Arlington.

7.3.2 Information Scenarios

Real-time information may be applied to the bus routes in this corridor. The expected travel times for the information scenarios (3 through 7) and the dynamic path choice model with no information (scenario 2) are shown in Table 7.11. Travel time savings are on the order of 1.7% of the total trip time, or 0.57 to 0.59 minutes, for the perfect information scenario (scenario 7). Information about bus departure times, in scenarios 3 and 4, gives very modest improvements in travel times relative to scenario 2, with time savings on average of 0.15 minutes (0.4%) for the case of random passenger arrivals; timed arrivals show no statistically significant improvement with departure time information. Slightly greater improvements in passenger travel times are noted in scenarios 5 and 6, with average time savings of 0.42 to 0.55 minutes (1.2% to 1.6%). All of these differences are statistically significant. In spite of these modest gains, in the case of the more accurate departure and running time information (scenario 6), about 87% to 97% of the total potential travel time savings (suggested in scenario 7) may be recovered. All of the travel time reductions from real-time information shown here are similar in magnitude to the results of the three shuttle networks, with average travel time savings for scenario 6 of 0.50 to 0.55 minutes (1.5% to 1.6%), relative to time savings in the shuttle networks of 0.35 to 0.45 minutes (1.2% to 1.5%).

In these scenarios, however, there seems to be little benefit to improved information accuracy, comparing scenario 3 with 4 and scenario 5 with 6. Travel time differences from scenario 3 to scenario 4 are actually negative but statistically insignificant: mean differences (and standard errors) of -0.007 (0.007) and -0.003 (0.011) for random and timed arrivals, respectively. Time differences for scenarios 5 and 6 are at least positive but still very modest, and are only statistically significant for random

Table 7.11: Expected Travel Times - AM Inbound

Passenger Arrivals	Scenario					
	2 (Base)	3	4	5	6	7
Random	35.594	35.439	35.446	35.177	35.086	35.008
Decrease		0.154	0.147	0.416	0.507	0.586
Std Error		(0.060)	(0.061)	(0.066)	(0.064)	(0.065)
Timed	35.722	35.649	35.653	35.207	35.169	35.152
Decrease		0.073	0.070	0.515	0.554	0.571
Std Error		(0.050)	(0.051)	(0.090)	(0.093)	(0.054)

Table 7.12: Expected Travel Times by Passenger Type - AM Inbound

Passenger Arrivals	Pass. Type	Scenario					
		2	3	4	5	6	7
Random	Low	35.822	35.519	35.511	35.120	35.082	34.990
	High	35.624	35.457	35.445	35.162	35.088	35.014
Timed	Low	35.896	35.707	35.698	35.218	35.175	35.137
	High	35.777	35.655	35.661	35.240	35.163	35.150

arrivals: 0.091 (0.035) and 0.038 (0.022) for random and timed arrivals, respectively.

Surprisingly, for this corridor, the expected travel times for passengers arriving randomly do not differ greatly from those when passengers arrive with scheduled vehicle departures. This result is likely a combination of several factors: high variability in bus departure times on all routes; the lack of schedule coordination of bus departures from Arlington Center; and, the chosen proportional assignment of passengers to particular bus routes. In addition, no statistically significant differences in travel times were noted among the different passenger types who underestimate (Low) and overestimate (High) the level of travel time variation, shown in Table 7.12. There are only very small differences (less than 0.1 minutes) noted in travel times for different levels of passenger experience, except for less experienced passengers who underestimate the travel time variation in the no information case (scenario 2).

Besides expected travel times, one might expect that real-time information reduces the variability of travel times and perhaps reduces the probability of particularly late trips. Table 7.13 shows the mean within-day variance of travel times, while Table 7.14 shows the probability of completing a trip in 38 minutes or less for each information

Table 7.13: Mean Daily Travel Time Variance - AM Inbound

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7
Random	12.34	12.06	12.07	11.31	11.13	11.13
Decrease Std Error		0.29 (0.32)	0.28 (0.32)	1.03 (0.48)	1.22 (0.45)	1.22 (0.40)
Timed	11.60	10.98	11.04	10.71	10.63	10.51
Decrease Std Error		0.62 (0.34)	0.56 (0.35)	0.89 (0.58)	0.97 (0.59)	1.08 (0.53)

Table 7.14: Probability of a Trip Completed in 38 Minutes - AM Inbound

Passenger Arrivals	Scenario 2 (Base)	3	4	5	6	7
Random	77.0%	78.5%	78.5%	80.8%	81.7%	82.3%
Increase Std Error		1.5% (0.7%)	1.5% (0.7%)	3.8% (0.9%)	4.7% (0.9%)	5.3% (0.9%)
Timed	76.7%	77.2%	77.1%	79.9%	80.3%	81.1%
Increase Std Error		0.6% (0.7%)	0.4% (0.7%)	3.2% (1.2%)	3.7% (1.2%)	4.4% (0.9%)

scenario. The most statistically significant reductions (i.e., t-statistics over 2.0) in variance seem to be for randomly arriving passengers who are given running time information. For these passengers, the variance in travel times is reduced by about 10%. Other reductions in the variance are seen in Table 7.13, but the statistical significance of these results is more questionable.

Table 7.14 shows the probability of completing a trip in 38 minutes or less for each scenario. For the base case of no information (scenario 2), the tail of the distribution indicates that about 23% of all passengers have travel times above 38 minutes. Very modest improvements in the probability measure are noticeable over the scenarios with only departure time information (scenarios 3 and 4). These results are statistically significant for random arrivals, but not for timed arrivals. However, more statistically significant improvements in the probability measure occur with running time information. In these scenarios, the probability of a trip under 38 minutes improves by 3.2% to 4.7%, which is fairly high relative to the perfect information case (scenario 7). This suggests that the information about traffic conditions and projected

Table 7.15: Expected Path Assignments - AM Inbound

Passenger Arrivals	Path	Scenario 2	3	4	5	6	7
Random	79	15.57	13.37	13.67	13.03	13.13	12.77
	350	10.67	8.73	8.63	8.77	8.70	8.43
	77a	33.77	37.90	37.70	38.20	38.17	38.80
	77b	0.00	0.00	0.00	18.53	16.93	17.67
Timed	79	14.10	12.47	12.73	13.03	12.87	13.27
	350	9.77	8.47	8.47	7.97	7.63	7.87
	77a	36.13	39.07	38.80	39.00	39.50	38.87
	77b	0.00	0.00	0.00	18.00	17.97	19.37

travel times in to each of the Red Line stations can reduce some of the variability of the travel time to the destination. Still, improvements in probability of arriving "on time" are very modest across the range of information scenarios.

Differences in the path assignments across scenarios are shown in Table 7.15. As noted previously, path assignments from the dynamic path choice model (scenarios 2 through 6) tend to favor route 77 more heavily, and all the more so (up to about 65% of all passengers) with additional real-time information. The more realistic information scenarios (2 through 6) and even the perfect information case (scenario 7) show very similar path assignments from Arlington Center.

One of the most striking results of the path assignment in Table 7.15 is that, lacking improved running time information, passengers will always choose to transfer from route 77 to the Red Line at Porter, rather than stay on the 77 bus. This is due mainly to the fact that running times on the Red Line (from Table 7.3) are much less variable than those on route 77, where the bus operates in mixed traffic from Porter to Harvard. As a result, the expected travel time on the bus is slightly higher than for the Red Line. Only with real-time information on running times (scenarios 5 through 7) is the bus a viable option. Yet, from the perfect information case, staying on route 77 from Porter to Harvard may be beneficial almost 50% of the time. In reality, both behaviors may be observed, with some passengers transfering from the bus at Porter and others who continue on the bus to transfer to the Red Line at Harvard.

In addition, there are some differences in passenger path choices based on pas-

Table 7.16: Expected Path Assignments by Passenger Type - AM Inbound

Passenger Arrivals	Pass. Type	Path	Scenario 1	2	3	4	5	6
Random	Low	79	14.20	10.97	12.73	12.73	13.07	13.43
		350	10.70	7.47	8.10	8.00	9.20	8.83
		77a	35.10	41.57	39.17	39.27	37.73	37.73
		77b	35.10	41.57	39.17	39.27	14.97	15.37
	High	79	19.30	17.67	13.80	13.90	12.67	12.70
		350	12.70	11.47	8.97	8.83	8.43	8.63
		77a	28.00	30.87	37.23	37.27	38.90	38.67
		77b	0.00	0.00	0.00	0.00	21.80	19.40
Timed	Low	79	12.90	9.43	11.67	11.67	13.37	13.13
		350	10.27	7.37	7.90	7.83	8.33	8.30
		77a	36.83	43.20	40.43	40.50	38.30	38.57
		77b	36.83	43.20	40.43	40.50	15.60	16.57
	High	79	20.00	17.17	12.93	13.33	12.40	12.23
		350	12.23	10.50	8.93	8.77	7.90	7.60
		77a	27.77	32.33	38.13	37.90	39.70	40.17
		77b	0.00	0.00	0.00	0.00	20.67	19.60

senger levels of experience, shown in Table 7.16. [Again, the "Low" passenger types underestimate travel time variance, while "High" passenger types overestimate this variance]. Passengers with little experience who may underestimate the level of travel time variation consistently remained on route 77 to Harvard in the scenarios without running time information (1 through 4). This is a result of the technique chosen to model these passengers' perceptions, discussed in Section 5.3. Specifically, in these scenarios, the technique reduces the maximum but does not change the minimum or mode of a particular distribution if no real-time information is received about that distribution. Thus, the expected travel time on the bus is less than that for the Red Line, for these passengers. Across the set of information scenarios (3 through 6), the passenger path choice patterns from the "low"and "high" perceptions of variance generally are reasonably similar to those presented in Table 7.15 for passengers with accurate perceptions of distributions.

Additional insight is gained by comparing the path choices of the no information scenarios (1 and 2) in Table 7.16 with those presented for experienced passengers in Table 7.10. From this comparison, it is remarkable that the path assignments with no information (scenarios 1 and 2) differ greatly between the three passenger types. As might be expected, those who overestimate travel time variability prefer the shorter, and thus slightly more reliable, routes traveling to Alewife (routes 79 and 350). On the other hand, route 77 (including continuing on route 77 from Porter to Harvard) is preferred more strongly by passengers who underestimate travel time variation,. This result provides some explanation why less experienced passengers have slightly higher travel times in the no information scenarios (e.g., scenario 2 from Table 7.12). Nonetheless, once more accurate information is provided, the differences in path choices and in expected travel times between different passenger types are significantly smaller, as might be expected.

Summarizing, the morning inbound case study supports many of the conclusions from the shuttle networks. The path choice models offer only modest improvements in expected travel times over the "next bus" strategy, but significant changes in path assignment are noted with the static and dynamic models. In addition, the no information scenarios yield path choices which match expectations. First, higher frequency routes receive higher market shares with the static and dynamic path choice models. Second, passengers who underestimate travel time variability may be more likely to delay a necessary transfer, while those who overestimate this variability seem more likely to take an earlier transfer.

In support of the conclusions from Chapter 6, the impact of real-time information on expectations and the variability of travel times is very modest. However, relative to the "perfect information" scenario, more realistic real-time information scenarios allow passengers to recover (on average) about 90% to 95% of possible travel time savings. These results are comparable for different levels of passenger experience. Finally, improving the level of information accuracy has only a very slight effect in improving travel times with the dynamic path choice model.

7.4 Evening Peak Outbound Results

Scenarios for the evening outbound trip are described in Section 7.2.1. Trips in the reverse direction are slightly shorter than the inbound trip, due to less "peaking" of congestion along Massachusetts Avenue for the bus routes. A typical trip takes between 25 and 45 minutes, with a mean of about 34 minutes. One might expect that

Table 7.17: Expected Travel Times - PM Outbound

Statistic	Scenario 1 (Base)	2	3	4	5	6
Mean	34.164	33.528	33.363	33.409	33.225	33.147
Decrease Std Error		0.636 (0.064)	0.801 (0.072)	0.755 (0.071)	0.939 (0.078)	1.017 (0.077)
Mean, Low Var	34.300	33.504	33.378	33.411	33.260	33.154
Mean, High Var	34.150	33.575	33.402	33.417	33.247	33.162

real-time information about transfer connections may be of great use to passengers in this corridor. Specifically, knowing about the departures of buses at the transfer points may improve path decisions and resulting travel times. The results support this conjecture. Table 7.17 shows the expected travel times for the six scenarios for the outbound trip. The travel time improvements resulting from real-time information provided on board the Red Line are on the order of 1.9% to 2.8% (0.64 to 0.94 minutes) of the total travel time. In all the scenarios, travel time differences (from the baseline of scenario 1) are statistically significant. Bus departure time information alone improves travel times by 0.64 to 0.80 minutes, and at the higher level of accuracy recovers about 80% of the possible travel time improvements resulting from perfect information (scenario 6). Running time information provides incremental benefits over the departure time information on the order of 0.12 to 0.14 minutes, increasing the recovery to about 93% of the possible travel time savings. These statistics indicate that, under the dynamic path choice model, more typical levels of information accuracy can yield significant improvements in travel times relative to the perfect information case. Yet, the overall level of travel time improvements noted for these scenarios is still modest at 2% to 3% of the total travel time for the outbound trip. In this sense, however, real-time information provided on board yields travel time benefits of the same order of magnitude as in-terminal information systems from the inbound case.

For the on board information, a statistically significant difference in the results based on information accuracy is noted. For accuracy levels on the departure time information (between scenarios 2 and 3), a mean difference of 0.165 minutes (standard error of 0.033) is noted, while a similar difference of 0.183 (0.039) is noted between scenarios 4 and 5. In this case, information accuracy does seem to have a more significant role in improving travel times when compared with the morning inbound case. Travel time improvements are modest, providing on the order of about ten to twelve seconds of additional reductions in travel times relative to the low accuracy scenarios.

As in previous networks, there are only small differences in travel times for different passenger types, as shown in Table 7.17. Furthermore, while these differences are modest, the differences become smaller as more real-time information is supplied, from a spread of 0.15 for the base case (scenario 1) to only 0.015 in the perfect information case (scenario 6). Nonetheless, one might argue that these differences are not statistically significant, and no real discernible differences between passenger types exist. Again, the travel time results seem robust across different passenger levels of experience.

The mean daily travel time variance for the outbound trip is shown in Table 7.18. First, one may observe that the magnitude of the variance in travel times for this network is small relative to previous network results: a standard deviation of travel times in this case is on the order of 2.7 to 3.0, whereas it was about 4.5 for previous networks. This was expected in that there is less congestion during the evening peak, providing somewhat less variability in bus departure times and running times over the three routes (as shown in Table 7.6). In this case, however, statistically significant reductions in the travel time variance occur for all scenarios, and considerably more so for scenarios with higher accuracy information (scenarios 3 and 5). In this case, reductions in travel time variance of up to 25% are observed in scenario 5, reducing the standard deviation of travel times from 3.05 to 2.65. This reduction is much higher than that observed in the shuttle networks or in the MBTA inbound case study, and is due to the high level of uncertainty in making connections on the outbound trip.

In addition, Table 7.19 shows the probability of completing a trip in under 37 minutes for each scenario. Each of the standard information scenarios (2 through 5) have significantly higher probabilities than the base case with no information (scenario 1), with absolute improvements of about 5.2% to 7.6% from the baseline of 83.9%. Comparing scenarios 2 and 3 and scenarios 4 and 5, there is also a significant reduction in the tail of the distribution resulting from improvements in the level of information

Table 7.18: Mean Daily Travel Time Variance - PM Outbound

	Scenario					
Statistic	1 (Base)	2	3	4	5	6
Mean	9.27	7.92	7.27	8.09	7.02	6.54
Decrease		1.35	2.01	1.18	2.25	2.73
Std Error		(0.54)	(0.68)	(0.53)	(0.68)	(0.68)

Table 7.19: Probability of a Trip Completed in 37 Minutes - PM Outbound

	Scenario					
Statistic	1 (Base)	2	3	4	5	6
Mean	83.9%	89.1%	90.3%	90.1%	91.5%	92.0%
Decrease		5.2%	6.4%	6.3%	7.6%	8.1%
Std Error		(1.1%)	(1.1%)	(1.1%)	(1.1%)	(1.1%)

accuracy. Combining these results with the reductions in variance noted above, there is a more significant and quantifiable reduction in the variability of travel times and in the tail of the total travel time distribution for this network.

Finally, Table 7.20 shows the path assignments for each scenario for the outbound trip. [In this case, route 77a is the segment of route 77 between Harvard and Porter, while 77b is the segment from Porter to Arlington Center. Passengers traveling on route 77a *are also included* as travelers on route 77b. Thus, the total of 25 passengers may be obtained by summing passengers on routes 79, 350 and 77b.]

In the base case (scenario 1) and the information scenarios (2 through 5), about 60% of the travelers switch from the Red Line to the 77 bus at Porter, while the remaining 40% travel on to Alewife. A path assignment based on the relative bus frequency share would allocate 12.1 passengers to route 77, 8.1 passengers to route 79, and 4.8 passengers to route 350. Again, as noted in all the previous networks, incorporating stochastic departure times in the path assignment (in scenario 1) does tend to favor the higher frequency routes: in this case, route 77 has a much higher share of passengers.

In the information scenarios, some of the preference toward route 77 (especially noticeable for passengers with perceptions of greater variance) may be attributable to information accuracy. In this case, passengers arriving at Harvard or Porter receive

Table 7.20: Expected Path Assignments - PM Outbound

Passenger Type	Path	Scenario 1	2	3	4	5	6
Experienced	79	6.07	6.00	6.50	6.73	6.97	6.70
	350	4.47	3.50	3.73	3.50	3.63	3.80
	77a	0.00	1.40	0.37	1.40	0.33	0.07
	77b	14.47	15.50	14.77	14.77	14.40	14.50
Low Var	79	6.40	6.77	7.00	7.27	7.27	6.97
	350	4.43	3.87	4.00	3.87	3.87	3.87
	77a	2.27	0.37	0.10	0.47	0.13	0.03
	77b	14.17	14.37	14.00	13.87	13.87	14.17
High Var	79	6.13	5.03	5.83	6.23	6.33	6.53
	350	4.80	3.10	3.43	3.27	3.40	3.60
	77a	0.00	2.67	0.97	2.30	0.97	0.10
	77b	14.07	16.87	15.73	15.50	15.27	14.87

fairly accurate information about bus travel times on route 77, but much less accurate information about travel times on routes 79 and 350 from Alewife. In this light, an argument might be made that passengers arriving at Harvard or Porter would rather make a more certain connection to the 77 than risk a more uncertain transfer at Alewife. Clearly, the connections at Alewife are much less certain, particularly for the route 79 bus which has a very wide and flat distribution of departure times at Alewife. Without more accurate information about routes at Alewife, the passenger would much rather have a definite connection (if known with very high accuracy) than much greater uncertainty about possible future connections.

In the real-time information scenarios, very little difference is noted in the path assignments (shown in Table 7.20), except for a slightly higher tendency to take the route 77 bus from Harvard to Porter. Obviously, better departure time information in scenarios 3 and 5 has the effect of reducing the number of passengers on that route segment, since it is rarely a better choice than waiting until Porter to make a decision about the 77 bus. Passengers with higher perceptions of travel time variance are obviously more likely to make this connection to the 77 at Harvard (and also at Porter) in the real-time information scenarios, since the time-dependent level of information accuracy causes a tendency to take the "sure bet" as opposed to a much more uncertain transfer downstream. Conversely, passengers who underestimate travel time variability have a slightly higher tendency than other passenger types to travel to Alewife in the information scenarios. For these passengers, connections at Alewife compare more favorably with the route 77 bus at Porter and even more noticeably at Harvard.

One of the obvious differences between the path assignments from Table 7.20 and reality is that the transfer from rail to bus at Porter is much more onerous than simple travel time calculations suggest. The walk to the bus stop at Porter requires crossing several busy intersections, and the bus stop has no shelter. This differs significantly from the more comfortable bus terminals at Harvard and Alewife which are connected directly to the Red Line platform. Such impacts are obviously not captured in the current formulation of the path choice models.

7.5 Conclusions

There are a number of observations which can be made regarding the results of the MBTA case study. First, it appears that, at least for this corridor in the MBTA system, there is little opportunity for substantive time savings resulting from a real-time information system. In spite of the various paths available in the corridor, potential time savings under perfect information amount to only about 3% to 4% of the total trip time of 34 to 35 minutes. Putting this most simply, it appears that the variability of transit service is high in this corridor, and the existing transit options do not allow significant travel time savings. Travel time improvements under more realistic information scenarios are limited to about 1% to 3% of the total trip time for the inbound and outbound commutes. In these cases, though, scenarios with a more realistic level of information accuracy provided up to 75% to 95% of the possible travel time improvements in the corridor. Moreover, these results assume that real-time information is supplied only for bus routes in the corridor, so that larger gains may be possible if real-time information were also available for the Red Line subway service. However, the magnitude of time savings from real-time information in this corridor seems to be limited to at most 3% to 4% of the total travel time, or 1.0 to 1.4 minutes for a typical (one-way) trip. One other observation that may be made, however, is that in-terminal information for the inbound trip and in-vehicle information for the outbound trips have comparable (though modest) levels of benefit.

Travel time differences by the level of information provided some additional insight. In the inbound case, departure time information alone provided very little substantive improvements in travel times. As with the shuttle network results, though, larger travel time improvements were noted for scenarios with real-time running time information, although these time savings are still a modest 2% to 3% of the total travel time. In the outbound case, both departure time and running time information yielded comparable travel time improvements on the order of 2.5% to 3% of the total travel time, with very small marginal gains resulting from additional real-time information on running times to information on vehicle departure times. It would seem that for adaptive path decisions, the simple information about making a certain bus connection is of much greater value than knowing bus running times once the connection is made.

The MBTA case study also demonstrated modest reductions in trip time variability resulting from real-time information. In the morning inbound case, statistically significant but very modest reductions in travel time variance and the probability of a trip greater than 38 minutes were noted only for the scenarios with running time information. More substantial and statistically significant reductions in travel time variance and the probability of arriving late were noted from the evening outbound case: 5-7% improvements (in absolute terms) in the probability of arriving in 37 minutes and 20% to 25% reductions in travel time variance. Some relatively modest improvements in trip time variability appear possible in this real-world setting.

The changes in path assignment in this corridor resulting from the dynamic path choice model and real-time information seem mixed. In the "no information" scenarios (0, 1 and 2 inbound and 1 outbound), passengers seem to have a propensity to use the route 77 bus. This supports a similar result for the shuttle networks: path assignment in the context of stochastic departure times tends to favor more frequent routes, relative to a simple frequency share assignment. Furthermore, in the inbound case, more dramatic differences are noted between the "next bus" and static path choice models (scenarios 0 and 1) and the dynamic path choice model (scenario 2) are noted. In this case, the dynamic path choice model yields a path assignment which favors route 77 more strongly, as route 77 is most frequent and shows a high level of departure time variation. Similar results were shown for a comparable path of Network 3 in Chapter 6. The reason for this strong shift to these paths with the dynamic path choice model is most likely due to more significant travel time advantages on these paths relative to other paths in the network.

This effect (of shifting to more frequent buses with high variability in departure times) is also apparent for both the inbound and outbound scenarios with real-time information. In fact, the advent of real-time information seems to heighten this effect, comparing scenarios 3 through 6 with scenario 2 in the inbound case and scenarios 2 through 6 with scenario 1 in the outbound case. For the inbound trip, real-time information about vehicle departures presents more credible evidence to the passenger wait for the next route 77 bus. For the outbound case, the fact that the level of information accuracy is based on the time until the event yields strong tendencies toward a "sure bet" connection (i.e. to the route 77 bus at Harvard or Porter) than a more uncertain transfer further down the line. On the whole, however, different levels of real time information have basically no effect on aggregate path assignment, relative to the baseline of the dynamic path choice model with no information. This is true across the whole range of real-time information scenarios for both inbound and outbound trips in the MBTA corridor, and was also noted for the three networks in Chapter 6.

It is difficult to provide a full assessment of real-time information using only a single case study corridor and constraining the assessment to look at travel time benefits alone. However, it is clear that potential reductions in the expectation and variability of travel times resulting from real-time information are very modest in this corridor. These results may be typical of other transit systems in situations where passengers have the choice of multiple paths serving their origins and destinations. The results here do seem to cast doubt on the value of these information systems to provide travel time benefits in these types of transit service corridors.

Chapter 8

Conclusions and Future Research

A modeling framework has been developed in this thesis which incorporates many different elements of transit service and passenger behavior modeling. The contributions of this work cover the range of service modeling, passenger behavior modeling, and assessment of the potential value of real-time passenger information systems. Each of these areas is discussed in greater detail in the first section of this chapter. The latter section discusses several limitations of the research and outlines some suggestions about related future research.

8.1 Conclusions

The primary motivation of this thesis has been the development of a modeling framework in which to analyze transit passenger decision-making in a stochastic and time-dependent environment. It is precisely to this type of environment that real-time passenger information systems are well-suited. Real-time information may affect passenger decision-making, and the modeling framework should provide the necessary tools to evaluate these impacts. To this end, the modeling framework proposed in the thesis is summarized in Figure 8.1.

A model of transit service is required which incorporates time-dependence in vehicle movements as well as the stochastic effects resulting from day-to-day variations in travel times. Such a model uses vehicle departure time and running time distri-

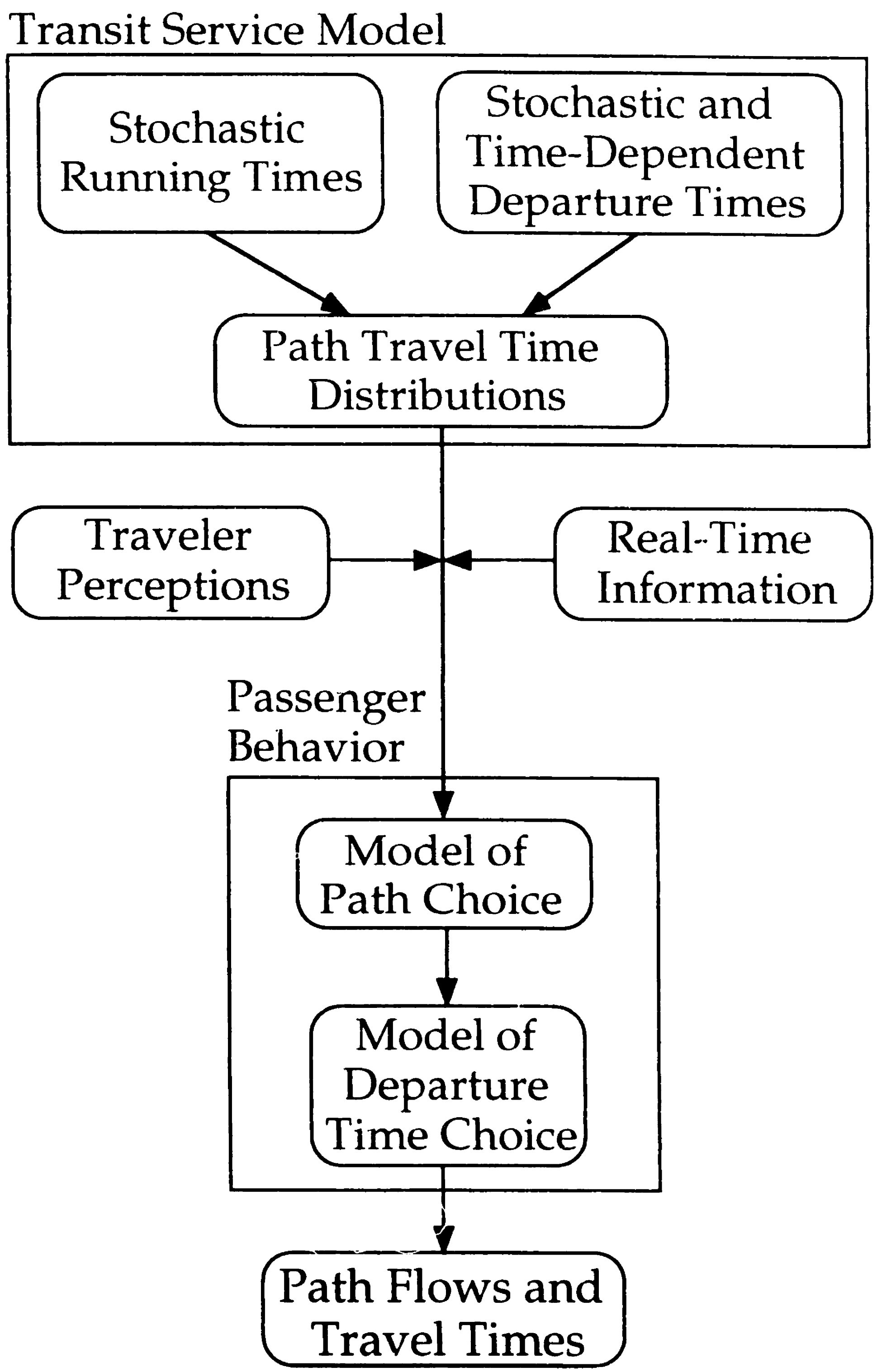

Figure 8-1: Model Framework

butions to analyze the characteristics of travel times for specific origin-to-destination paths. This transit service model, which was developed in Chapter 3, is the foundation for a model of passenger behavior, developed in Chapter 4. Specific decisions examined in this thesis include a passenger's choice of path and the choice of when to arrive at the origin stop. Passenger decisions may also be influenced by the various dimensions of real-time information and an individual's experience with and perceptions of the service characteristics. Chapter 5 described these dimensions and how they were connected to the transit service model of Chapter 3 and the path choice methodology of Chapter 4. This modeling framework was applied in a corridor-level network simulation, which is presented in Chapters 5, 6, and 7. The following sections discuss the particular conclusions of each of these elements in greater detail.

8.1.1 Transit Service Modeling

Two different aspects of transit service seem to be most salient in looking at real time information systems. First, transit service is in many cases inherently stochastic: travel times between stops are largely dependent on exogenous and endogenous factors that influence vehicle movements on a route. Travel times on a route may vary during any given day and also may vary from one day to another.

The second major characteristic of transit service is that services are usually scheduled. In particular, services running on longer headways (i.e., of 10 minutes or more) are generally operated on a schedule for both the operator's and the passengers' benefit. This structured timing of services means that travel times within a network may be time-dependent: the time spent traveling depends on when the trip begins. From the passenger's perspective, this is especially true when trips involve a transfer, as often the particular timing of that connection is critical.

The transit service models developed in Chapter 3 accommodate these two elements. In particular, a shuttle model is presented which accounts for both the stochastic and time-dependent elements of transit service. This shuttle model is based not on the operator's perspective on transit service, but rather on the passenger's perspective on his/her trip from origin to destination. In this context, each route of the journey appears to the passenger as a single shuttle from their point of origin to a (perhaps intermediate) destination. Such a shuttle model was developed in the first part of Chapter 3.

From this shuttle model, a small network model was developed in which a passenger trip from origin to destination is modeled as a series of shuttle trips. A shuttle network was designed which allowed both direct shuttle routes to the destination and also connecting shuttles through transfer points. In developing this model, then, time-dependent distributions of vehicle departure times and running times were derived. The net result of the shuttle network was the time-dependent distributions of travel times from an origin to a destination on each possible o-d path. These distributions describe the travel time characteristics on a particular origin-destination pair, and are appropriate for examining how travel times influence passenger behavior in a trip-making context.

The shuttle model is intended to serve as a planning tool, and is clearly limited in two ways. First, the model is oriented toward passenger behavior, and not toward vehicle operations. Such a model does not provide great insight into the specific transit vehicle movements or loads along a particular route. Second, the model is limited to a single corridor, which may not be sufficient for more network-wide transit planning. From the passenger's perspective, such a model may be sufficient to describe certain o-d trips, but it obviously lacks the scale to describe transit service on larger networks.

8.1.2 Path Choice Methodology

The path choice methodology developed in Chapter 4 describes how passengers might choose between different origin-destination paths within the context of stochastic and time-dependent path travel time characteristics, developed in the transit service model. A path choice model is needed which incorporates the stochastic and time-dependent elements of the transit service model and which allows the passenger to consider any number of transit paths serving their origin and destination. Existing path choice models have ignored at least one of these three elements:

1. Stochastic departure and running times;
2. Time-dependent travel times; and,
3. Multiple paths serving the origin and destination.

Two separate path choice models are developed which incorporate these three elements: the static and dynamic path choice models. The static path choice model is based upon the original formulation of the path choice problem suggested by Chriqui and Robillard [16], with the addition of the possibility that travel times may be time-dependent. In this case, the set of routes a passenger is willing to board may depend on the time at which he/she arrives at the origin terminal.

The inclusion of time-dependence in the static path choice model suggested that passengers may improve their path decisions by updating their choices while they are waiting at a stop. In this case, the passenger could potentially make the best path choice by waiting as long as possible before making a decision about which route to travel. While waiting, a passenger may learn about travel time characteristics on each path. In the limit, a passenger might simply begin waiting at the terminal, noting as much as possible about the vehicle delays until a bus finally arrives, and then making a decision whether or not to board the arriving bus, based on what he/she has learned. This kind of passenger behavior, which has a more obvious behavioral intuition, is more formally presented as the dynamic path choice model of Chapter 4. The dynamic path choice problem is formulated, both in its strict mathematical form, and also in a more functional and behavioral relaxation of its mathematical form. The latter model is adopted for reasons of analytic tractability.

Furthermore, in the context of real-time information, the passenger would seem to use such a dynamic path choice model. One may assume that any information that might be relayed to passengers regarding expected departures and running times in a corridor may improve their decisions about which path to take. Further, one might also expect that this information may become more accurate as the time to the event decreases. For this reason, a passenger may do considerably better by waiting at the stop and gaining more accurate (i.e., real-time) information before deciding whether to board a bus. This behavior corresponds directly to the dynamic path choice model.

The dynamic model is also shown to be useful in modeling adaptive path decisions. Passengers may be able to improve their travel times by making path decisions while on route, in cases where the passenger must make a transfer at some point during his/her trip. The passenger may do better to wait until arriving at a transfer point before making a subsequent path decision. This matches the essence of the dynamic path choice model.

The static and dynamic path choice models are also subject to a number of limitations. Foremost, since the models are sufficiently general to accommodate various travel time distributions and vehicle schedules, there is no obvious method to characterize these models analytically, in the most general form. This research has not discovered a form of analysis or any algorithm or heuristic that might be used to determine path choices in this more general context. Instead, the mathematical expressions for these path choice models are calculated explicitly, based on a specific set of network characteristics. The complexity of these computations also rises exponentially with the number of potential origin-destination paths, rendering the path choice models much more cumbersome for use on larger networks.

Finally, two departure time choice models were proposed. In the first, passengers are assumed to arrive at the origin stop randomly during the time period of analysis. A second model suggested that passenger arrivals at the origin stop are correlated with the scheduled vehicle departure times.

8.1.3 Real-Time Information

With recent advances in information technologies, it is technically feasible to provide passengers with up-to-the-minute information about transit service and to predict vehicle departure times and running times in the transit network. This information may be of considerable use to passengers in improving their travel decisions, including their decisions about which paths to take and when to begin their trip. However, there is substantial expense in installing these types of passenger information systems, and therefore, to the extent possible, it is helpful to determine what kind of quantifiable benefits might be realized by these systems.

Chapter 5 outlined a number of salient features of these proposed information systems. The important dimensions for evaluation may be summarized as follows:

1. What information is given to the passenger?

2. When does the passenger receive that information?

3. How accurate is the information?

The first question addresses the types of information the passenger may find useful, including information on current vehicle locations, projected vehicle departure times, projected vehicle running times, and information about connecting routes. Second, the passenger may receive information before beginning their trip (e.g., at home or work), at the stop, or even on board a vehicle. Real-time information may have different impacts, depending on what decisions the passenger can make at each point along his/her trip. Finally, the information also has a certain level of accuracy, depending on the level of technical accuracy in determining vehicle locations as well as the ability to predict future traffic conditions with an acceptable level of precision.

To evaluate these impacts, Chapter 5 also describes a modeling framework in which this real-time passenger information may be incorporated into the models of passenger path choice from Chapter 4. Specifically, it is possible to use the expectations and related distributions, based on the information accuracy, to describe future vehicle departure and running times. In turn, these expectations and distributions may be used directly in the dynamic path choice model. A set of scenarios were developed that examined the two dimensions of the type of real-time information given to the passenger (item 1) and the level of accuracy of that information (item 3).

The dimension of when (or, alternatively, where) the passenger receives real-time information became a difficult issue to address. Scenarios in which real-time information is given at the stop (in the terminal) were developed for the shuttle network of Chapter 3. Pre-trip information, however, requires considerably more research to understand how passengers might make decisions about travel before initiating a trip. To maintain a reasonable scope of the thesis, investigation of pre-trip information was not pursued. However, scenarios with on-route information were developed in a case study for the MBTA, in which a passenger must make a transfer and receives information about connecting services while traveling.

One other factor which influences passenger behavior is the passenger's level of experience with the transit service. Based on this experience, each passenger has their own perceptions of the level of service in the transit network. One method proposed in the literature, and adopted for this research, is to vary the parameters of travel time distributions according to how passengers might truly perceive services. Three different passenger types were identified:

- Experienced passengers who have an accurate perception of travel time distributions and parameters;
- Less experienced passengers who underestimate the variability of travel times in the network; and,
- Less experienced passengers who overestimate the variability of travel times in the network.

Thus, a set of scenarios was developed which incorporated real-time information about transit services as well as different levels of passenger experience in the passenger's understanding of travel time characteristics. For both elements, the modeling technique modifies the travel time distributions used in the path choice models from Chapter 4.

8.1.4 Simulation Results

Due to the analytic complexities of the shuttle network travel time distributions and the dynamic path choice model, simulation was selected as the preferred tool to analyze both the path choice models and the effects of real-time information. Two corridor-level networks were used to analyze the value of real-time information: a hypothetical shuttle network (from Chapter 3) and a case study corridor from the MBTA. The results of these simulations are reported more fully in Chapters 6 and 7, but several broad conclusions are made here.

Before discussing these conclusions, a caveat may be appropriate. The conclusions drawn here are, of course, a function of the assumed or estimated travel distributions on each of the networks. As discussed in Chapter 6, the networks for this analysis were chosen based on parameters which seemed to favor real-time information: there are several o-d paths; travel times on each path are in a common range (i.e., 25 to 45 minutes); and, travel time reliability in the corridors is a significant issue. Furthermore, the dynamic path choice methodology assumes that passengers make the best possible use of real-time information to improve their travel times. To this extent, the results presented in the thesis represent almost ideal conditions under which real-time information may be most beneficial. These results are not comprehensive; they merely suggest what changes in travel behavior might occur if real-time information is provided to transit passengers.

Path Choice Models

The simulation allows a preliminary examination of the static and dynamic path choice models from Chapter 4. For the shuttle networks and the MBTA case study, a base scenario (scenario 0) examined the simplest strategy in which the passenger takes the first bus to arrive. As the networks were designed, this option is not bad; in fact, the simulation results suggest that, in general, travel times are not substantially improved over this strategy by using the static or dynamic path choice models. This result, however, is not a characteristic of the path choice models, but rather is a function of the network examples chosen for the analysis. Indeed, the results of Network 3 with the expected travel time objective and for Network 1 using a probability objective gave more significant improvements in the objective function value with the static and dynamic path choice models.

In each of the shuttle network examples and the inbound scenarios for the MBTA case study, path distributions showed significant differences between the three different path choice strategies. In all cases, the share of passengers choosing routes was markedly different from more traditional route assignments based on relative frequency share. It seems that passengers tend to favor higher frequency routes in situations where vehicle departure times are stochastic, even with the "take the next bus" strategy. This tendency is particularly noticeable for the dynamic path choice model, since passengers may have a better sense of pending vehicle arrivals than the "next bus" or static path choice strategies. The static and dynamic models also demonstrated high sensitivity to the time-dependence of expected travel times, a characteristic not true of the frequency share and "next bus" models.

One important caveat must also be added regarding passenger path choices. The static and dynamic path choice models assume that passengers are willing to choose one of several different routes to make a certain trip. In all of the example networks, there was considerable day-to-day variation in path choices, with a coefficient of variation of about 0.2 for the number of individuals choosing a path on a given day. This variation was consistent across each of the scenarios, both with and without real-time passenger information. This level of path variation is most likely not consistent with actual passenger behavior, as passengers are most likely greater creatures of habit in choosing paths.

Real-Time Information

Some general conclusions may be made regarding the impacts of real-time information. First, in corridor networks where real-time information may be most beneficial to the passenger, only very modest time savings, on the order of 2% to 3% of the total travel time, are shown. This result is a function both of the value of information and also the particular network characteristics: the most optimistic scenarios assuming a more realistic level of information accuracy yielded reductions in travel times from 70% to 95% of that achievable using perfect information. However, from the overall magnitude of these results, the travel time savings to passengers of real-time information systems do not appear to be very large, and the results call into question the cost-effectiveness of these systems to improve traveler decisions. More specific conclusions in this regard are presented in the following paragraphs.

One of the primary measures of benefit for real-time information is potential travel time savings for passengers. Using the corridor-level shuttle network with an average travel time of approximately 30 minutes, average time savings of 1% to 2% (0.3 to 0.6 minutes) of the total travel time were achieved for in-terminal information systems. The extent of these time savings differed somewhat across information scenarios. As might have been expected, the more information available to the passenger, the greater the time savings. Running time information provides slightly more benefit than departure time information, but information on connecting routes (either departure times or running times) proved to be the most beneficial of all types of information, considering corridors where transfer paths have competitive travel times. In general, the scenario with real-time information on all route departure times and running times (scenario 7) yielded the greatest reductions in travel times, at about 3% of the total trip time. This represents 70% to 75% of the potential time savings achievable under perfect information.

Similar time savings were shown for a comparable corridor on the MBTA (Morning Inbound). In that case, however, information was provided only on the first leg of the trip, a bus trip connecting to a rail line. Benefits were on the order of 0.5% for basic departure time information and about 2% for running time information. For this case study, a realistic information scenario (high accuracy with departure time and running time information) realized about 90% to 95% of the time savings possible with perfect information.

The MBTA corridor also allowed a preliminary assessment of on-board information systems. In particular, an outbound trip with a transfer from a rail line to various bus routes was modeled. In this case, real-time information on bus routes was shown to have comparable results as in-terminal information systems: time savings on the order of 2% to 3% of the total travel time. In this case, adaptive decision-making on the part of the passenger is greatly aided by departure time information at each station, informing the passenger of the timing of connections at that station. Again, about 85% to 95% of the potential time savings was realized under information scenarios with high (but realistic) levels of information accuracy.

However, the level of accuracy of information seems to have only a very modest impact on travel times. The shuttle networks yielded little or no significant improvements in travel times with a higher level of accuracy. In the MBTA case study networks, the level of accuracy was assumed to be time-dependent for bus departure times, allowing improved information accuracy as a function of the time until departure. However, a comparison of low and high accuracy cases in both the inbound and outbound scenarios showed very modest (5 to 10 seconds on average) differences in travel times. This might lead one to the conjecture that in most corridors where travel time variability is a significant issue, the marginal benefit of more accurate information is relatively small. Simply having real-time information at a lower level of accuracy may be sufficient to improve passenger path decisions. A more thorough analysis of the trade-offs in costs and benefits from different levels of information is necessary to evaluate these systems.

In all the example networks with the expected travel time objective, comparably modest reductions in the mean daily travel time variance and in the probability of a long trip (e.g., a trip over 37 minutes) were noted. More substantial reductions in travel time variance and the probability of a long trip were noted for an objective which minimized the probability of a long trip. In this latter case, however, expected travel times increased by about 2% to 3% over those with the expected travel time objective. This example using the probability objective demonstrated the flexibility of the path choice models to accommodate different passenger objectives.

In the network simulations of Chapters 6 and 7, path distributions in general did not vary significantly based on the level of real-time information. In the shuttle networks, real-time information provided only very small shifts in path choices from the transfer paths to the direct service when running time information is available. This is a function of the fact that with running time information, the direct service is more of a "sure bet" than more uncertain connections. Information on connections, in the form of vehicle departure and running time information on connecting routes, had little effect to draw more passengers to these transfer paths.

Similar results were also noted for the MBTA case study, with little change in path choices across the real-time information scenarios. By passenger type, however, more noticeable changes in path choices were shown. Passengers who underestimate travel time variability have a greater tendency to choose transfers further downstream; conversely, passengers who over-estimate the variability in travel times had the tendency to transfer earlier in the trip.

Finally, in the hypothetical shuttle networks, the results suggest that passengers may do better to coordinate their arrivals at the stop with the vehicle departures. With the naive model that passenger arrivals are simply correlated with *scheduled* vehicle departure times, time savings on the order of 2% to 3% were realized over a more simple pattern of random passenger arrivals. More accurate information on vehicle departures, provided to the passenger at the trip origin, may improve passenger departure time choices, thereby reducing travel times in the same magnitude as this 2% to 3%. In the shuttle network examples, it appears that pre-trip information systems could provide trip time reductions that are on par with those possible with in-terminal systems. However, greater investigation of passenger behavior in trip timing decisions is required to evaluate pre-trip information systems.

8.1.5 Research Contributions

The major contribution of this thesis has been a modeling framework which evaluates transit passenger path choices in a stochastic and time-dependent service environment, with a natural extension to consider the effects of real-time information on these path choices. Such a model framework was presented in Figure 8.1 and discussed throughout the first part of this chapter. Moreover, the thesis has made two significant contributions to research in the field of public transportation. The first contribution is a model of transit passenger path choice which incorporates the three elements mentioned previously: time-dependence, stochastic vehicle departure and running times, and multiple paths serving the origin and destination. The static and dynamic path choice models of Chapter 4 represent a novel approach to modeling passenger path choice. The second major contribution of this thesis has been to demonstrate a method of assessing real-time passenger information systems in public transit. The methodology presented in Chapter 5 and illustrated in several examples in Chapters 6 and 7 demonstrate a method for assessing the potential benefits and impacts of real-time information systems. The results, although constrained by the parameters of the example networks, at least provide a preliminary assessment of these systems under almost ideal conditions. Furthermore, the results from this methodology raise serious questions about the quantifiable benefits of these real-time passenger information systems.

8.2 Future Research

Time and resources did not allow investigation of a number of issues which grew naturally out of this research. In most cases, more restrictive assumptions about the models and their implementatic · 'ere necessary to complete the research in a reasonable amount of time. Several ideas for extensions are described in the following sections. They are classified into three more general areas:

1. Limitations and extensions of the models developed here;
2. Modeling of pre-trip information and passenger decision-making; and,
3. Research and validation of behavioral models in public transit.

8.2.1 Model Extensions

The models in this thesis suffer from a number of necessary but restrictive assumptions. Specifically, there were several assumptions made about transit service which clearly limit the applicability of the models presented here. The first part of this section discusses how these assumptions may be relaxed in the service models. The second part discusses the implementation of the optimal dynamic path choice problem presented in Section 4.5.2.

Service Assumptions

In the models of transit service developed in Chapter 3, a number of assumptions were made about transit service. In particular, there were three assumptions made in the model development which made the problem more easily tractable for the thesis. These included:

- No vehicle bunching (or "pairing") is allowed.
- Travel times on all routes are assumed to be exogenous to passenger behavior.
- Vehicles are assumed to have infinite capacity.

Clearly, these assumptions are often not very realistic in many public transit systems. For vehicles traveling on longer routes with relatively short headways (e.g., under 10 minutes), vehicle bunching is a common problem. Because of service disruptions, vehicles have the tendency to form pairs and bunches as they move along these types of routes. The shuttle model of Chapter 3 may be extended to incorporate the effects of bunching. This might be done either by assuming a certain fixed probability that a vehicle will "catch" the preceding vehicle, or by explicitly modeling detailed vehicle movements in the network, as has been done in previous research (e.g., Newell and Potts [54], Potts and Tamlin [60], Heap and Thomas [29], Newell [53], Chapman and Michel [14], and Boyd [12]). The crude model adopted for the MBTA case study (presented in Section 5.5.1) assumes "steady-state" and not vehicle-specific effects of bunching, and thus is not entirely satisfactory for a more accurate transit service model.

Certainly one of the elements which affects vehicle bunching is the amount of time required for passengers to board and alight. When passenger loads are heavy, or when passenger arrival patterns at a stop show some "peaking" during different times of the day, it is likely that transit vehicles will experience longer dwell times at stops along the route. The route-level models of Bowman [10] and Marguier [48] provide some additional insight for possible extensions of the research in this area. Basically, endogenous travel times (i.e., vehicle dwell times) may be incorporated directly in the models shown here by using an iterative procedure for path assignment. Once initial path choices are made, the travel times on each path can be updated. The changes in path travel times may in turn be used in the path choice models to re-assign passengers to routes. Such an iterative procedure is a common solution technique in path choice problems in transportation.

Finally, the element of vehicle capacity may also come into question. During peak periods, transit vehicle capacity may be taxed to the point that a passenger is denied boarding on an arriving vehicle. To incorporate this situation in the models, there are two possible approaches. First, one can assume some fixed probability that a vehicle cannot be boarded and explicitly incorporate this probability in determining the passenger's boarding strategy. This approach is most easily incorporated in the shuttle network model. A second approach is to model each stop along the route and each passenger's boarding strategy explicitly to determine the loads on each vehicle at each stop on the route. Based on these loads, it is possible to assign a probability that each vehicle is filled to capacity. Based on this probability, the passenger selects a boarding strategy. This second approach would also require an iterative path assignment to accommodate the fact that passengers may divert to other routes based on the likelihood of being denied boarding.

Optimal Path Choice

The true dynamic path choice model presented in Section 4.5.2 furthermore, represents a fairly sophisticated decision process on the part of the passenger. In its true form, the optimal dynamic path choice model assumes that the passenger will be able to determine their boarding strategy for all routes for any point in time in the future. While such a problem was formulated mathematically in this thesis, its analytic solution is not at all apparent. One obvious area of research, for those more mathematically inclined, is to study and critique this model formulation, develop a characterization of solutions, and develop a solution technique for this problem.

8.2.2 Modeling of Pre-Trip Information

One of the potential advantages of pre-trip information is that it allows the passenger greater flexibility in making travel decisions before he/she leaves the point of origin (e.g., home in the morning). Two of the most important travel decisions that must be made at the origin include the time at which to leave the origin and an initial destination. In public transit, the passenger ultimately chooses some time to leave their home or work and travel to a local bus or train stop. Both of these decisions may be aided by pre-trip information, which, as was suggested in the examples of Chapters 6 and 7, may offer time savings to passengers of the same magnitude as was shown for in-terminal or on-board information systems. However, modeling passenger behavior in these cases is rather difficult. In this research, the questions of departure time choice and station choice surfaced on a number of occasions, and are discussed in greater detail in the following paragraphs.

Departure Time Choice

Both the static and the dynamic path choice models developed in Chapter 4 assume a given passenger arrival at a transit stop at time T. This presupposes that the passenger has already chosen to arrive at T; and, as shown in Chapter 4, his/her resulting path choice strategy and expected travel time is conditional on that arrival time. In situations when there is some flexibility in trip scheduling, a departure time choice model may be practical. This section discusses a *disaggregate* departure time choice model, where the objective of the model is to determine how individuals might select the time to depart their origin under various conditions.

Traditionally, passengers are assumed to arrive at the origin stop randomly in time; that is, their departure time choice occurs independently of path choice, and independently of vehicle timing. Alternatively, a more detailed departure time choice model assumes that passengers choose a departure time based on minimizing (to some extent) their expected travel time. In this case, a clever passenger may time their arrivals in order to minimize their origin-destination travel time. Typically, this may involve arriving close to some scheduled vehicle departure time; such behavior has been noted in a number of empirical studies to date (e.g., Jolliffe and Hutchinson [35], Turnquist [68], and Bowman and Turnquist [11]). These studies, however, have not been generalized to the case where multiple routes serve a single bus stop.

The most common approach in the literature simply uses simple statistical techniques to describe arrival patterns. A number of authors, however, have suggested more theoretical analysis of passenger departure times. In each case, the passenger is assumed to minimize his/her expected waiting time (e.g., Turnquist [68]) or some measure of utility based on the waiting time or total travel time (e.g., Bowman [10] and Abkowitz [3]). Under these conditions, it is assumed to be advantageous to the passenger to select an arrival time at the origin stop so that the waiting time (or disutility) at the origin would be minimized. However, the utility formulations presented by these authors required a significant amount of empirical analysis, which (at this time) is not feasible to assess the potential for pre-trip information systems. Moreover, the existing models which minimize the expected waiting time disregard both the multiple-route waiting phenomenon and possible time-dependence in travel times upon boarding particular routes. Thus, more detailed models are necessary.

A very crude model of departure time choice might assume that the passenger chooses a departure time in order to minimize some associated trip "cost," such as total travel time, waiting time, or a measure of trip disutility. In the context of the static and dynamic path choice models presented in Chapter 4, a clever passenger might choose his/her departure time based on minimizing the total expected travel time. In this case, the objective is achieved by simultaneously considering the path choice strategy as well as the origin departure time. It is assumed that the passenger knows how the expected o-d travel time varies over time, for a given boarding strategy once they arrive at the stop. Selecting an optimal departure time, then, involves finding that departure time which minimizes this function over time.

Such a model, however, is not very practical. First, the expected travel time function is not likely to be analytically tractable, especially for stops served by multiple routes. It is also likely that such a function will not be convex, but will have a large number of local optima, with no real criteria with which to judge whether such a point is either a local or a global optimum.

Furthermore, such a model is also not very realistic from a behavioral standpoint. This type of model would assume that passengers can choose to take their trips at virtually any point in time during a day. This is clearly not always possible, as people have many scheduled and unscheduled activities during a day which constrain the time available for the given trip. A person traveling to work still has to get in to work some time during the day, and is likely constrained (to some extent) about what hours he or she must be at the workplace.

How one might actually model a "trip timing" constraint is far from intuitive. It might be suggested that passengers consider departure times within a certain "window." For example, if a person must be in to work by 9 a.m., they may choose to depart home sometime between (say) 7:30 and 8:00 a.m. The passenger is assumed to make a decision about possible departure times at a time T. At this point in time, the passenger will scan the expected o-d travel time function over some travel horizon; for example, at 7:30 a.m., the traveler examines travel times for the period 7:30-8:00 a.m. The passenger then chooses to depart at the point in time that minimizes (say) the expected o-d travel time. This type of planning horizon, however, will vary considerably from one person to another, and is obviously very dependent on the person's activities and the associated priority of those activities for the given day. As a result, such a model of disaggregate departure time choice is difficult to formulate.

To make matters even more complicated, one may add the whole concept of pre-trip information to this discussion on departure time choice. In the context of the arguments made above, it is not clear how pre-trip information may actually influence a traveler's departure time choice. Intuitively, one might expect that pre-trip information allows the passenger to choose a better time to arrive at the local stop. In this regard, though, there are three additional questions which arise:

1. When does the passenger access the pre-trip information?
2. Do passengers "re-schedule" their trips based on this information?
3. If passengers change their trip timing, how is this done?

One idea is to assume that the passenger will choose to access the real-time information up to a few minutes before their planned departure time (T) from the origin, and may revise their chosen departure time according to this new information. Just how long such "revisions" might continue is not at all clear, and is obviously subject to similar constraints as the more general departure time choice models discussed above.

There are clearly both behavioral issues and mathematical modeling issues which must be addressed in examining a person's departure time choice. In public transit, the modeling to date has assumed more general aggregate passenger arrival patterns which generally defy any assessment of disaggregate departure time choices or of the potential of real-time information to influence individual behavior.

Station Choice

It is also important to consider the value of pre-trip information in the context of a station choice model. It is possible, in larger transit networks, that the passenger is not only selecting a set of routes for boarding, but also a particular stop to begin waiting for a vehicle. In such situations, a station choice model might also be formulated. Traditional station choice models exclude time-dependence in selecting a particular stop; yet, it seems that such a station choice should depend on the schedule(s) for route(s) serving that station.

As an alternative, if the passenger has (somehow) determined a departure time T, a station choice model may be derived based on the path choice models presented in Chapter 4. From T, the passenger may calculate his/her travel time to each potential stop (say, x), plus the expected travel time upon arriving at that stop at that point in time, $T + x$. In this way, the stop with the lowest expected travel time, *given the associated departure time* T, may be selected. For example, a passenger may choose between two stops. If the expected travel time at time T, including access time, is 25 minutes for stop 1 and 29 minutes for stop 2, the passenger will choose stop 1. Pre-trip information about travel times at each possible station could be incorporated into the path choice models directly, in the same way as in Chapter 5 in this thesis.

In this case, it has been assumed that the chosen departure time T is independent of the resultant choice of stop 1 or stop 2, which is not entirely plausible. Obviously, such a station choice model is heavily dependent on a disaggregate model of departure time choice. If such a departure time choice model could be formulated, then some iterative method could be used to solve both the station choice and departure time choice models simultaneously.

8.2.3 Behavioral Validation

Finally, one of the most salient objections of the research presented in this thesis is that it lacks behavioral validation. To what extent do passengers really behave according to the path and departure time choice models presented here? In many cases, data is simply not available about transit passenger behavior, and fielding surveys to develop this kind of data is a formidable task for any transit agency (or research group). In spite of these clear obstacles to model development and validation, there is a clear need for better modeling in this area. More empirical data should be collected and analyzed to understand the passenger's decision process.

As suggested in the beginning of Section 4.1, there may be any number of factors affecting a passenger's choice of route. This research has focused specifically on the trip characteristic of travel time. Clearly, this is the one aspect of the trip which may be most influenced by real-time network information, but it is certainly not the only factor affecting path choices. Behavioral science and disaggregate demand forecasting have more to say on these issues than may be covered reasonably in this chapter.

However, there are two different aspects to the behavioral validation which may be suggested. First, there is the question of how passengers actually make decisions about their trips on transit in the absence of real-time information. This thesis proposes a mathematical approach to modeling these types of decisions. It seems necessary that any type of models, be they mathematical, statistical, or perhaps purely behavioral, incorporate the elements of trip transfers and travel time reliability in passenger decision-making. These elements do seem to deter both regular transit users as well as potential transit riders from using public transit.

The second aspect required to validate models of passenger behavior in this context relates to how the passenger actually processes real-time information. In this thesis, it is assumed that the passenger would make optimal use of the data to determine their boarding strategy. In reality, the manner in which reported information about bus services is converted into a decision by the transit passenger is not well understood. Indeed, this same question is being asked in the realm of intelligent vehicle-highway systems (IVHS), where many of the proposed traveler information systems require decisions by the traveler in real time. Such research is obviously necessary to determine if these advanced information systems really will be of use to travelers, and what kind of improvements in mobility might be achieved with these systems.

Finally, this thesis has examined the impacts of real-time information on transit passengers only. One obvious area of research is the impact of real-time passenger information on other travelers. One might suggest that one benefit of these information systems may be in drawing travelers to public transit who would otherwise not make such a mode choice. Will real-time information systems have the effect of drawing more passengers to the transit service? One area of future research, then, would be to examine the relevance of accurate real-time information on traveler mode choice. Potentially, such information may improve the value of transit service, at least from the traveler's perception of service reliability. Very little research has been done in this area, but it does seem that real-time passenger information could be a factor in a traveler's mode choice as well.

Bibliography

[1] Mark Abkowitz, Amir Eiger, and Israel Engelstein. Optimal control of headway variation on transit routes. *Journal of Advanced Transportation*, 20(1):73–88, 1986.

[2] Mark Abkowitz and Israel Engelstein. Methods for maintaining transit service regularity. *Transportation Research Record*, 961:1–8, 1984.

[3] Mark D. Abkowitz. *The Impact of Service Reliability on Work Travel Behavior*. PhD thesis, Massachusetts Institute of Technology, 1980.

[4] Per-Ake Andersson, Ake Hermansson, Erik Tengvald, and Gian-Paolo Scalia-Tomba. Analysis and simulation of an urban bus route. *Transportation Research - Part A*, 13A:439–466, 1979.

[5] Per-Ake Andersson and Gian-Paolo Scalia-Tomba. A mathematical model of an urban bus route. *Transportation Research - Part B*, 15B(4):249–266, 1981.

[6] Ingmar Andreasson. A method for the analysis of transit networks. In Marc Roubens, editor, *Advances in Operations Research: Proceedings of the Second European Congress on Operations Research*, pages 1–8, 1977.

[7] Steven Balogh and Richard Smith. Real-time bus information - the London Transport route 18 demonstration. In *Proceedings of the PTRC Conference*, 1992.

[8] Moshe Ben-Akiva, Andre de Palma, and Isam Kaysi. Dynamic network models and driver information systems. In *U.S. - Italy Joint Seminar on Urban Traffic Networks*, June 1989.

[9] P. H. Bly and R. L. Jackson. Evaluation of bus control strategies by simulation. Technical Report 637, Transportation and Road Research Laboratory, 1974.

[10] Larry A. Bowman. *Analysis of Network Effects on Bus Transit Reliability and the Potential for Real Time Control*. PhD thesis, Northwestern University, 1979.

[11] Larry A. Bowman and Mark A. Turnquist. Service frequency, schedule reliability and passenger wait times at transit stops. *Transportation Research - Part A*, 15A(6):465–471, 1981.

[12] Colin W. Boyd. Notes on the theoretical dynamics of intermittent public passenger transportation systems. *Transportation Research - Part A*, 17A(5):347–354, 1983.

[13] Robert Casey, Lawrence Labell, Simon Prensky, and Carol Schweiger. Advanced public transportation systems: The state of the art. Technical report, Urban Mass Transportation Administration, April 1991.

[14] R. A. Chapman and J. F. Michel. Modelling the tendency of buses to form pairs. *Transportation Science*, 12(2):165–175, May 1978.

[15] Claude Chriqui. Reseaux de transport en commun: les problemes de cheminement et d'acces. Technical Report 11, Centre de Recherche sur les Transports, Universite de Montreal, 1974.

[16] Claude Chriqui and Pierre Robillard. Common bus lines. *Transportation Science*, 9(1):115–121, May 1975.

[17] Kenneth L. Cooke and Eric Halsey. The shortest route through a network with time-dependent internodal transit times. *Journal of Mathematical Analysis and Applications*, 14:493–498, 1966.

[18] Peter Davies, Chris Hill, Neil Emmott, and Jeremy Siviter. Assessment of advanced technologies for transit and rideshare applications. Technical report, Castle Rock Consultants, July 1991. Final Report.

[19] Joaquin de Cea. Rutas y estrategias optimas en modelos de asignacion a redes de transporte publico. In *IV Congreso Panamericano de Ingenieria de Transito y Transporte*, December 1986. Santiago, Chile.

[20] Joaquin de Cea, Juan Pablo Bunster, Lourdes Zubieta, and Michael Florian. Optimal strategies and optimal routes in public transit assignment models: An empirical comparison. *Traffic Engineering and Control*, 29(10):520–526, October 1988.

[21] Robert B. Dial. Transit pathfinder algorithm. *Highway Research Record*, 205:67–85, 1967.

[22] Stuart E. Dreyfus. An appraisal of some shortest-path algorithms. *Operations Research*, 17:395–412, 1969.

[23] Amir Eiger, Pitu B. Mirchandani, and Hossein Soroush. Path preferences and optimal paths in probabilistic networks. *Transportation Science*, 19(1):75–84, February 1985.

[24] H. Frank. Shortest paths in probabilistic graphs. *Operations Research*, 17:583–599, 1969.

[25] Randolph W. Hall. *Traveler Route Choice Under Six Information Scenarios: Transit Level of Service Implications*. PhD thesis, University of California, Berkeley, 1982.

[26] Randolph W. Hall. Traveler route choice: Travel time implications of improved information and adaptive decisions. *Transportation Research - Part A*, 17A(3):201–214, 1983.

[27] Randolph W. Hall. The fastest path through a network with random time-dependent travel times. *Transportation Science*, 20(3):182–188, August 1986.

[28] Dick Hasselstrom. *Public Transportation Planning - A Mathematical Programming Approach*. PhD thesis, University of Goteborg, 1981.

[29] R. C. Heap and T. H. Thomas. The modelling of platooning tendencies in public transport. *Traffic Engineering and Control*, 17:360–362, August/September 1976.

[30] Mark D. Hickman. Modeling transit path choice in the presence of real-time information. Paper presented at the 92nd Annual Meeting of the Transportation Research Board, January 1993.

[31] E. M. Holroyd and D. A. Scraggs. Waiting times for buses in Central London. *Traffic Engineering and Control*, 8(3):158–160, 1966.

[32] Kjell Jansson. VIPS II: A computerized system for public transport planning - Recent developments. Working Paper, Stockholm Transport Development Department.

[33] Kjell Jansson. VIPS II: New computer system for public transit planning. Paper presented at the American Public Transit Association Annual Meeting, 1987.

[34] Kjell Jansson and Bosse Ridderstolpe. A method for the route-choice problem in public transport systems. *Transportation Science*, 26(3):246–251, August 1992.

[35] J. K. Jolliffe and T. P. Hutchinson. A behavioural explanation of the association between bus and passenger arrivals at a bus stop. *Transportation Science*, 9(3):248–282, 1975.

[36] Isam Adnan Kaysi. *Framework and Models for the Provision of Real-Time Driver Information*. PhD thesis, Massachusetts Institute of Technology, 1992.

[37] David Koffman. A simulation study of alternative real-time bus headway control strategies. *Transportation Research Record*, 663:41–46, 1978.

[38] Haris N. Koutsopoulos and Tsippy Lotan. Motorist information systems and recurrent traffic congestion: Sensitivity analysis of expected results. *Transportation Research Record*, 1281:148–158, 1990.

[39] Damian J. Kulash. *Routing and Scheduling in Public Transportation Systems*. PhD thesis, Massachusetts Institute of Technology, 1971.

[40] Lawrence Labell, Carol Schweiger, and Mary Kihl. Advanced public transportation systems: The state of the art - Update '92. Technical report, Federal Transit Administration, April 1992.

[41] Averill M. Law and W. David Kelton. *Simulation Modeling and Analysis*. McGraw-Hill, second edition, 1991.

[42] F. le Clercq. A public transport assignment method. *Traffic Engineering and Control*, 14(2):91–96, June 1972.

[43] Steven R. Lerman. *Problem Solving and Computation for Scientists and Engineers: An Introduction Using C.* Prentice-Hall, 1993.

[44] Tsippy Lotan. *Modeling Route Choice Behavior in the Presence of Information Using Concepts from Fuzzy Set Theory and Approximate Reasoning.* PhD thesis, Massachusetts Institute of Technology, 1992.

[45] Ronald Prescott Loui. Optimal paths in graphs with stochastic or multidimensional weights. *Communications of the Association of Computing Machinery*, 26(9):670–676, September 1983.

[46] Christoph E. Mandl. Evaluation and optimization of urban public transportation networks. *European Journal of Operational Research*, 5:396–404, 1980.

[47] Philippe Henri Joseph Marguier. Optimal strategies in waiting for common bus lines. Master's thesis, Massachusetts Institute of Technology, 1981.

[48] Philippe Henri Joseph Marguier. *Bus Route Performance Evaluation under Stochastic Conditions.* PhD thesis, Massachusetts Institute of Technology, 1985.

[49] Philippe Henri Joseph Marguier and Avishai Ceder. Passenger waiting strategies for overlapping bus routes. *Transportation Science*, 18:207–230, 1984.

[50] Pitu B. Mirchandani. Shortest distance and reliability of probabilistic networks. *Computation and Operations Research*, 3:347–355, 1976.

[51] Pitu B. Mirchandani and Hossein Soroush. Optimal paths in probabilistic networks: A case with temporary preferences. *Computation and Operations Research*, 12(4):365–381, 1985.

[52] Pitu B. Mirchandani and Hossein Soroush. Generalized traffic equilibrium with probabilistic travel times and perceptions. *Transportation Science*, 21(3):133–152, August 1987.

[53] G. F. Newell. Unstable brownian motion of a bus trip. In Uzi Landman, editor, *Statistical Mechanics and Statistical Methods in Theory and Application*, pages 645–667, 1976.

[54] G. F. Newell and R. B. Potts. Maintaining a bus schedule. *Second Conference Australian Road Research Board*, 2(1):388–393, 1964.

[55] Sang Nguyen and Stephano Pallottino. Equilibrium traffic assignment for large scale transit networks. *European Journal of Operational Research*, 37:176–186, 1988.

[56] C. A. O'Flaherty and D. O. Mangan. Bus passenger waiting times in central areas. *Traffic Engineering and Control*, 11(9):419–421, 1970.

[57] Ariel Orda and Raphael Rom. Shortest-path and minimum-delay algorithms in networks with time-dependent edge-length. *Journal of the Association of Computing Machinery*, 37(3):607–625, July 1990.

[58] Ariel Orda and Raphael Rom. Minimum weight paths in time-dependent networks. *Networks*, 21:295–319, 1991.

[59] C. Dennis Pegden, Robert E. Shannon, and Randall P. Sadowski. *Introduction to Simulation Using SIMAN*. McGraw-Hill, 1990. SIMAN is a licensed product of Systems Modeling Corporation.

[60] R. B. Potts and E. A. Tamlin. Pairing of buses. *Second Conference Australian Road Research Board*, 2(2):3–9, 1964.

[61] Warren B. Powell and Yosef Sheffi. A probabilistic model of bus route performance. *Transportation Science*, 17(4):376–404, November 1983.

[62] P. A. Seddon and M. P. Day. Bus passenger waiting times in Greater Manchester. *Traffic Engineering and Control*, 15(9):442–445, 1974.

[63] Prianka N. Senevirante. Analysis of on-time performance of bus services using simulation. *Journal of Transportation Engineering*, 116(4):517–531, July/August 1990.

[64] C. Elliott Sigal, A. Alan B. Pritsker, and James J. Solberg. The stochastic shortest route problem. *Operations Research*, 28(5):1122–1129, September 1980.

[65] Heinz Spiess. On optimal route choice strategies in transit networks. Technical Report 286, Centre de Recherche sur les Transports, Universite de Montreal, 1983.

[66] Heinz Spiess and Michael Florian. Optimal strategies: A new assignment model for transit networks. *Transportation Research - Part B*, 23B(2):83–102, 1989.

[67] Tomonori Sumi, Yoshiji Matsumoto, and Yasuyuki Miyaki. Departure time and route choice of commuters on mass transit systems. *Transportation Research - Part B*, 24B(4):247–262, 1990.

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

[69] Mark A. Turnquist and Larry A. Bowman. The effects of network structure on reliability of transit service. *Transportation Research - Part B*, 14B:79–86, 1980.