Transfers and Path Choice in Urban Public Transport Systems

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Abstract

Transfers are endemic in public transport systems. Empirical evidence shows that a large portion of public transport journeys involve at least one change of vehicles, and that the transfer experience significantly affects the travelers' satisfaction with the public transport service, and whether they view public transport as an effective option. Despite their importance, however, transfers have long been overlooked by decision-makers, transportation planners, and analysts. Transfer-related research, practice, and investments are rare compared with many other aspects of transportation planning, probably because (1) the underlying transfer behavior is too complex; (2) the analysis methods are too primitive; and (3) the applications are not straightforward. This dissertation focuses on these issues and contributes to current literature in three aspects: methodology development, behavior exploration, and applications in practice.

In this research, I adopt a path-choice approach based on travelers' revealed preference to measure the disutility associated with transfer, or the so-called transfer penalty. I am able to quantify transfer experience in a variety of situations in great spatial detail, and reduce the external "noises" that might contaminate the model estimation. I then apply the method to two public transport networks: a relative small and simple rail network (subway and commuter rail) in Boston and a large and complex network (Underground) in London. Both networks offer a large variability of transfer environment and transfer activities.

Estimation results show high system-wide transfer penalties in both studies, indicating that transfer experience can have a very negative impact on the performance and competitiveness of public transport. They also suggest that the system-average value has limited applications in planning and operation because the transfer penalty varies greatly across station and movement. Such variation is largely caused by different transfer environments, not by different personal characteristics, attitudes, preferences, or perceptions, at least in the two investigated networks.

The two applications to the London Underground network illustrate that the lack of careful consideration of transfer effect can lead to inaccurate passenger flow estimation as well as less credible project evaluation and investment justification. The results further confirm the potential, as well as the importance, of transfer planning in major multimodal public transport networks.

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Chapter 1 INTRODUCTION

Transportation is about connecting activities, and the concept of connectivity is vital to developing a successful transportation system. Connectivity is especially important to public transport in major metropolitan regions, whose performance relies on effective coordination among various modal systems. Empirical evidence shows that a large portion of public transport journeys involve at least one change of vehicles, and that the transfer[1] experience significantly affects the travelers' satisfaction with the public transport service, and whether they view public transport as an effective option. Despite its importance, however, transfer has long been overlooked by decision-makers, transportation planers, and analysts. Transfer-related research, practice, and investments are few compared with many other aspects of operation and planning. The question is why? A simple answer is that the transfer topic is difficult to tackle. The underlying behavior is too complex; the analysis methods are too primitive; and the applications are not straightforward. These problems point to the importance of this research. This study is designed to increase our understanding of transfer behavior, to develop a methodological framework suitable for transfer analysis, and to demonstrate the potential benefits of these efforts to the operation and planning of public transport. It is one of the first comprehensive studies of transfers in public transport systems.

[1] In the United Kingdom, another term "interchange" is often used. In this research, transfer and interchange are interchangeable.

1.1 Transfers and Public Transport Systems

Public transportation can be an effective solution to the ever-increasing road congestion and vehicle emissions in many metropolitan areas worldwide. A well-performing public transport system provides a credible alternative to driving for many trips in a metropolitan region, and therefore has the potential to mitigate road traffic, alleviate auto dependency, and reduce greenhouse gas emissions. However, public transport is usually slow and unreliable, and is unable to compete with cars on many door-to-door trips. In the United States, its market share remains small despite strong support from all levels of government, development of new systems, and rebuilding of many older systems. In order to enhance the competitiveness of public transport, various solutions have been proposed and adopted by public transport agencies, including technology innovation, institutional reform, market restructuring, building supportive coalitions, flexible services, etc. In this study, I focus on an important but often ignored issue in public transport: service connectivity, which could be an important element in developing credible alternatives.

A great disadvantage of public transport, compared to private automobile, is that it is not able to provide direct door-to-door services for most trips. Passengers have to walk or take feeder services to access and egress public transport services. After boarding the system, they often have to transfer between different modes or services to reach their destinations. Transfers play a significant role in public transport, especially for the larger and more complex systems. For example, in Boston, 40 percent of bus and subway trips involve at least one transfer (CTPS 1991), while 75 percent of commuter rail trips transfer to or from other modes. In London, about 70 percent of Underground and rail trips and 30 percent of bus trips involve at least one transfer (LATS 2001). In New York City, about 30 percent of subway and bus trips and 80 percent commuter rail trips involve at least one transfer (NYMTC 1997). In Chicago, more than 50 percent of Chicago Transit Authority (CTA) passengers transfer during their typical trips (Crockett 2002). Connectivity of public transport services, either between modes or between lines, could have a significant impact on the performance of the entire system. How (in)convenient the transfer is can have an important influence on passenger satisfaction and on whether many passengers will find public transport an acceptable option.

Despite their importance, connectivity and transfers in public transport have been largely ignored by analysts and policymakers. In the public transport industry, improving transfers is seldom at the top of lists of investment priorities for major public transport agencies. In academia, only a handful of analyses so far have focused on transfer behavior. This lack of priority might partially be a result of the institutional structure of public transport agencies. Different public transport systems might be operated by different agencies. When they are managed by a single agency, operation, service planning, and performance evaluation are often done principally at the individual line level without much attention to coordination and integration. It might also be due to the complexity of the problem. Transfer behavior is complicated, has not been well documented in travel surveys, and requires a different set of analysis methods. Traditional mode choice models are limited in dealing with transfers as they often combine different modes or service lines. Given the situation, it is not surprising that transfer planning is still at a primitive stage for most public transport systems worldwide.

1.2 Transfer Planning and Public Transport Service

Most public transport systems do not perform transfer planning and for the few systems that have analyzed it, it is normally in an ad hoc way. Some operation and service planning efforts, such as fare media integration and real time information provision, do cover the issue of transfers, but they do not treat it as a main policy concern. The often cited stand alone practice of transfer planning is coordinated transfers, or coordination and synchronization of arrival and departure times at major transfer stations through planning or service control (Vuchic et al.1981, Clever 1997, Dessouky et al.1999). This strategy is most effective for transfers from high frequency to low frequency services or between low frequency services. It, also, focuses on only one part of the transfer process--transfer waiting time, with only a limited contribution to comprehensive transfer planning.

In many situations, transfer planning is focused on a few major transfer facilities in a public transport system, where transfer-related investments are concentrated (TfL 2002). However, when and how the investment should be made are generally case-by-case decisions. This model does not work well for large and complex systems because there might be many important transfer facilities in the system, while the resources for transfer planning are often limited. In this situation, the public transport agency normally does not have a clear idea of where to invest in the system, how much to invest, and most importantly, how to predict the benefit of an investment.

Part of the reason is the way projects are evaluated in transportation planning. Traditional evaluation methods rely on time savings, or how much travel time could be saved through the investment. This number can be easily converted into a monetary value by applying an estimated value of time. This monetary value is then applied to all users to estimate the direct benefit of the project. For transfer-related projects, this method does not work well because the benefit of improved transfer experience includes but often goes beyond time savings. In other words, time-saving oriented methods tend to under-value the benefit of transfer planning.

The difficulty of making and justifying decisions in transfer planning in turn contributes to the aforementioned inaction of public transport agencies, producing a vicious cycle. Although no quick change is expected, any solution to this problem must be comprehensive and user-oriented. Comprehensive means that the problem should be analyzed for the entire transfer movement process. Targeting a specific transfer component or focusing on a particular segment of a network will provide an incomplete or even biased answer. User-oriented means that the problem should be analyzed from the user's perspective—it is the *perceived* transfer inconvenience that matters most. Clearly, the two requirements are interconnected. They lead to a path-based analysis approach based on choice theory.

1.3 Path-based Research Approach

Transfers can affect travelers' decision to choose a particular mode, but they can also affect their decisions to choose a specific path given a particular mode or across multiple modes. An oft cited example is the trade-off between a slow but direct path and a fast but indirect (involving a transfer) path to the same destination.

Compared to mode choice, a path-based method has many merits for transfer analysis. It is able to cover diverse transfer situations with great detail. A path can incorporate both inter- and intra-mode transfers into one framework, and capture transfer movement-specific[2] attributes, which is the key to understanding transfer behavior and to improving transfer experience in practice. A path-based approach can better capture the transfer decision by providing a situation closer to an experimental design. Origin, destination, and mode can all be treated as given. In a

[2] For example, a transfer from Line A southbound to Line B westbound represents one transfer movement

perfect situation, a path choice decision is made solely based on transfer inconvenience; thus, external "noise" that may contaminate the transfer effect is excluded.

However, path choice decisions are complicated, and modeling them is extremely difficult and time-consuming. Unlike mode choice where available alternatives are clear and well defined, path choice alternatives are very hard to identify. A lengthy process is often required to generate the available paths with the results normally being unjustifiable due to the lack of data. Path alternatives may be correlated with each other in a complex way: they may overlap over common links, share the same node, and, in the case of public transport, take the same service line. Controlling for these correlations is highly challenging. These two issues are at the core of the path-based approach and have to be dealt with through careful research design and appropriate model specifications.

Choice theory assumes that a choice can be viewed as an outcome of a sequential decision-making process that includes the following steps: defining the choice problem, generating alternatives, evaluating alternative attributes, and making a choice. Each choice is assigned a single value as its utility, which is a function of all attributes of that choice. A decision maker is assumed always to select the alternative with the highest utility to him or her. Although this theory has been shown as an over-simplification of the choice decision process in reality, it is still the most widely used theory in travel behavior analysis. Some of the concerns with choice theory are solved by introducing the concept of random utility. In this study, the path-based approach takes a form of random utility models (RUM).

In RUM, a path is viewed as a choice. A traveler can make a path choice decision before the trip starts or along the trip. A path is judged based on its objective attributes such as speed, directional changes, scenic view, congestion, etc. and is adjusted by travelers' cognition of these attributes and their preferences and attitudes. Therefore, path choice is a very personal matter. Two travelers facing an identical choice set and the same external constraints might make different decisions. This dynamic process assigns a utility to the path, which often takes a cardinal form. A portion of this utility comes from transfers, which indicates the perceived inconvenience of transfer by a traveler. In this research, this transfer (dis)utility is defined as the transfer penalty. It includes time components (transfer walking and waiting), cost components (extra fare for transfer), and a residual that captures the remaining factors. The approach to understand transfer activities is to measure this transfer penalty in diverse situations through path choice models.

1.4 Research Objectives

The first objective of this study is to improve our understanding of transfer behavior in public transport systems. This task aims to answer the following questions:

1. What is the current pattern of transfer activities in major multimodal public transport systems, and what is the future trend?
2. What is the state of practice in transfer planning by public transport agencies, and what are the associated problems?
3. How much have we learned from prior studies on transfer analysis?

The second objective is to develop an effective methodology suitable for the transfer analysis. The task aims to answer the following questions:

1. What are the theories that underlie the transfer decision process from the demand point of view?
2. What is a suitable research design and analysis framework for the transfer analysis?

3. What types of datasets and models should be used in the analysis?
4. What are the merits and limits of the adopted methodology?
5. What are the criteria for selecting case studies?

The third objective is to apply the research findings to operation and planning in public transport networks, and to help improve passengers' transfer experience

1. What are the implications of the findings for public transport in general and to transfer planning in particular?
2. Can the proposed models be incorporated into the daily operation and planning process by the public transport agencies?
3. Can the developed approach be applied to systems other than the case studies? What adjustments are needed in order to make that happen?

In summary, the overall objective is to (1) summarize transfer-related activities such as demand and supply, planning, and research, (2) to develop a methodology for empirical studies, and (3) to apply results and outcomes to transfer-related practice in operation and planning.

1.5 Structure of Dissertation

I organize this study into six chapters. Chapter 2 provides the context of analysis describing the prevalence and complexity of transfer activities, discussing transfer planning practice in public transport systems, and summarizing the literature in this field. Chapter 3 proposes the methodology, including theory, research design, models, data sources, and measures. Chapter 4 introduces the first case study for a mid-size network—the rail systems (subway and commuter rail) in Boston, MA. Chapter 5 extends the empirical study to a much larger and more complex system—the Underground in London. In each case study, I discuss the policy implications.

Chapter 6 summarizes the main findings and contribution, and proposes directions for future research.

Chapter 2 TRANSFER ACTIVITIES, PLANNING, AND LITERATURE

In this chapter, I demonstrate the prevalence and complexity of transfer activities in major multimodal public transport networks, describe relevant planning practice within public transport agencies, and summarize literature on transfer behavior analysis. It provides the background for the proposed methodology and case studies in the following chapters. A detailed literature review of methodology will be presented separately in the following chapter. Section 2.1 summarizes transfer activities in multimodal public transport networks. Section 2.2 discusses transfer planning practice. Section 2.3 presents the literature.

2.1 Transfer Activities in Multimodal Public Transport Networks

Transfers are endemic in public transport systems. In car travel, a driver is the service provider as well as the service consumer, and each journey is unique and produced to meet a specific travel need of an individual traveler. However, in public transport systems, service is provided by an agency, and consumed by customers. If customers have different travel demands in terms of travel patterns, travel preferences, or budget constraints, service provision can be differentiated for each market segment. Transfer between different services is often inevitable. Therefore, transfer originates from the separation of service provision and consumption in public transport systems, and from the segmentation of the travel market in metropolitan areas.

Accordingly, large public transport networks often consist of multimodal systems: bus, light rail, subway, commuter rail, etc. Each has a distinct technology and service pattern, and serves relatively different travel markets. Bus has the dual-mode nature of car and rail with low capital costs, relatively high operating cost, and wide network coverage. It often serves short trips, and the service density varies from the urban center to the suburban edge. Rail has relatively high capital costs, high capacity, low operating costs, high service quality, and a stronger land-use influence. Among rail systems, urban rail normally serves densely developed areas with high service frequencies, while commuter rail serves long-distance trips into the urban center with long station spacing, low frequency, and a large imbalance between peak and off-peak service. The general pattern is that low travel volumes are best served by the low-investment/low capacity modes; with increasing volumes, high-investment/high-capacity modes become superior in terms of both performance and operating costs (Vuchic 2007).

Within each mode, service is provided on separate lines or routes. Because direct service for all origin-destination pairs is economically infeasible, these lines are connected at transfer points so as to cover a large area while maintaining a reasonable cost. For example, in Boston, the rail system has four urban lines and 12 regional lines intersecting at eight major transfer stations. In Chicago, the rail system has eight urban lines and 11 regional lines with about 20 major transfer stations. In London, the rail network is much more complex: the Underground and the regional rail services intersect at more than 100 transfer stations in the Greater London area, providing a large number of transfer and route options.

In addition to the multimodal nature of public transport systems, different public transport modes are often provided by different agencies or operators. For example, in London, Transport for London (TfL) is responsible for the Underground, bus, light rail, and tram, but most regional rail (National Rail) services are operated by private contractors under franchise agreements with the Department for Transport. In Chicago, the Chicago Transit Authority (CTA) operates city bus and rail services, but Metra operates regional rail and PACE is responsible for suburban bus services. In the New York metropolitan area, public transport is run by agencies from three states: New York, New Jersey, and Connecticut. For example, commuter rail is operated by Metro-North Railroad (MNR), Long Island Rail Road (LIRR), and New Jersey Transit; bus is operated by New York City Transit, Long Island Bus, MTA Bus, and New Jersey Transit; and urban rail is operated by New York City Transit, New Jersey Transit, and the Port Authority Trans-Hudson Corporation (PATH). In Atlanta, public transport is primarily operated by five agencies, four for suburban-oriented bus systems, and one for the urban bus and rail system (CPT 2005). In China, bus and subway systems are operated independently by different agencies in Beijing, Shanghai, Guangzhou, and Shenzhen. The segmentation of operation does not necessarily mean poorly coordinated services, but in many cases it does make transferring more complicated in a multimodal network. The prevalence and complexity of transfer activities are described in more detail in the following sections.

2.1.1 Prevalence of Transfer Activities

Given the system structure, it is not surprising that transfers are prevalent in public transport systems. For example, in Boston, an on-board survey that targeted only rapid transit passengers found that about half of the surveyed 38,881 trips involved at least one transfer (CTPS 1994). About 70 percent of the transfers were made with other modes (bus and regional rail), while 30 percent were within the rapid transit system. Of all trips with transfers, 16 percent involved both an inter- and an intra-modal switch on the same journey. In another survey of all travelers in the Boston metropolitan region, 43 percent of public transport trips (including rapid transit, regional rail, and bus) involved at least one transfer. Most of them were inter-modal transfers with many involving a private mode (park-and-ride, kiss-and-ride, and pick up) (Table 2-1).

In London, an on-board survey showed that 44 percent of all Underground trips involved at least one transfer, and 22 percent had two or more transfers (TfL 1998-2005). Another survey of all travelers in the London region found that 50 percent of all public transport trips (including bus, Underground, and regional rail) involved at least one transfer with two-thirds being intermodal (LATS 2001) (Table 2-1). In New York, a survey of all travelers in the region found about a third of all public transport trips (including local and express bus, subway, and regional rail) involved at least one transfer, most of which were inter-modal (Table 2-1).

Table 2-1 Transfers in Public Transport Systems in Boston, London, and New York

Modes	Surveyed Trips	Transfer Trips*			
		Total	Intra-mode	Inter-mode	Both
Boston					
Bus	673	270 (40%)	10 (1.5%)	257 (38%)	3 (0.5%)
Subway	1,348	533 (40%)	23 (2%)	497 (37%)	13 (1%)
Regional Rail	216	163 (75%)	0 (0%)	163 (75%)	0
Total	2,237	966 (43%)	33 (3.4%)	917 (95%)	16 (1.6%)
London					
Bus	22,387	7,386 (33%)	2,971 (13%)	4,306 (19%)	109 (1%)
Subway	14,213	9,435 (66%)	2,745 (19%)	5,153 (36%)	1,537 (11%)
Regional rail	7,887	5,558 (71%)	375 (5%)	4,959 (63%)	224 (3%)
Total	44,487	22,379 (50%)	6,091 (27.2%)	14,418 (64.4%)	1,870 (8.4%)
New York					
Local Bus	3,156	843 (27%)	94 (3%)	733 (23%)	16 (1%)
Express Bus	5,11	232 (45%)	0 (0%)	232 (45%)	0
Subway	4,106	1,294 (31%)	140 (3%)	1,096 (27%)	58 (1%)
Regional Rail	889	741 (83%)	4 (0.5%)	731 (82%)	6 (0.5%)
Total	8,151	3,110 (32%)	238 (7.7%)	2792 (89.8%)	80 (2.5%)

Note: * trips that involve at least one vehicle switch

Source: compiled by the author from LATS 2001, MTC 1998, CTPS 1991

2.1.2 Complexity of Transfer Activities

In addition to the prevalence of transfers in public transport systems is the complexity of transfer patterns. This complexity is reflected in two aspects: the diversity of transfer types and the complexity of transfer decisions.

Transfers are diverse because the transfer environment differs across stations, directions, and time of travel, and because passengers might be able to combine services in different ways to "personalize" their journeys. Transfer activities vary across space in public transport systems due to the hierarchy of modes, the network structure, and the design of transfer facilities. Transfers are more likely to happen between modes with different speeds. Lower-speed modes often provide feeder service to higher-speed modes, for example, bus to rail, or urban rail to regional rail with the latter normally having only a few stations in the urban center but being well connected to the urban rail network [3]. The higher speed of a public transport mode, the more transfers will typically be involved, because the extra inconvenience of transfer can be compensated by a shorter travel time, and because higher speeds typically imply longer stop or station spacing, placing more stress on access and egress links. For example, in Boston, only 30 to 40 percent of bus trips involve transfers, while more than 70 percent of commuter rail trips transferred. Another example is the local and express bus services in New York City with the latter having a significantly higher transfer share largely due to its higher speed.

Within the same mode, whether the network structure is radial, grid, or crisscross also matters. A radial network requires fewer transfers as long as there is a reasonable concentration of employment at the center. If activities become decentralized, radial networks often require a

[3] The commuter rail in Boston area has three stops in the central city: South Station, North Station, and Back Bay. The commuter rail from Maryland to Washington D.C only stops at the terminal, Union Station, after it enters the city. In New York, commuter rail has three stops at Manhattan: Penn Station, Grand Central, and Harlem 125 St. The commuter rail in Chicago has five termini: LaSalle Street Station, South Water Station, Millennium Station, Ogilvie Transportation Center, and Union Station.

transfer for passengers to travel back through the central point. Adding a circumferential line to a radial network can reduce the travel time, but is also likely to increase the number of transfers. The grid-type network often requires just one transfer in order to get from many origins to many destinations. One way to combine the better attributes of both radial and grid networks is to provide additional points where lines converge. This provides direct service to more activity centers, but at the cost of longer travel time (Gray and Hoel 1992).

A transfer station is often viewed as a point in a public transport network, but in many situations that "point" itself is a complex network. For a transfer station with just two intersecting lines, there are actually eight transfer movements involved. For large transfer stations, such as King's Cross or Waterloo in London, that involve four or five lines, the total number of transfer movements[4] can be 30 or more. For each movement, there might be multiple paths available with each path consisting of a complicated physical environment in terms of escalators, stairs, corridors, signs, facilities for the disabled, platform design, seat availability, change of level, concessions, lighting, etc. These attributes likely vary across both stations and movements, thereby affecting transfer behavior differentially.

Personalization of travel is a characteristic of private modes because they can usually meet the temporal and spatial desires of an individual. Personalization might also be an issue for public transport even though passengers are often assumed passively to take whatever service is provided. However, evidence on transfer behavior indicates that passengers can also personalize their travel, at least to some extent, by combing different modes or services to suit their preferences. The combinations can be very diverse in major public transport systems. For example, although there are only five major transport modes (car, bus, Underground, light rail,

[4] Movement here refers to a particular transfer direction, for example, from the Red Line southbound to the Green Line eastbound. For a station with two intersecting lines, there are a total of eight transfer movements at the station.

regional rail) in London, the 2001 travel survey reported up to 468 different ways of combining the five modes into a single journey. A 1998 New York survey recorded 422 such combinations, while in Boston with its smaller system, 88 such combinations were reported. Table 2-2 shows the top six combinations in the three metropolitan regions.

Table 2-2 Top Six Transfer Activities in Three Cities

Cities	Boston	London	New York
Top Six Transfer Activities	bus – subway (212)	subway – subway (4319)	bus – subway (471)
	auto – subway (187)	subway – rail (3306)	auto - rail (455)
	auto – rail (112)	bus – bus (3104)	rail – subway (247)
	subway – rail (83)	bus – subway (2501)	subway – subway (200)
	auto – bus (38)	bus – rail (1511)	auto – bus (123)
	subway – subway (36)	auto – rail (1009)	bus – bus (110)

Source: compiled by the author from LATS 2001, MTC 1998, CTPS 1991

The second aspect of complexity associated with transfers is that it is not known when and how travelers make transfer decisions. A transfer decision could be made either before the trip is started (a pre-trip decision) (Khattak et al. 1996), or during the trip based on information that a traveler acquires along the way (en-route decision). An example of the latter case is that a passenger on a regular bus might switch to an express bus when the two vehicles arrive at the same stop at the same time. It is unclear which decision prevails in transfers. In general, it is believed that the decision type is influenced by a traveler's familiarity with the network and the service reliability. The more familiar the passenger is with the system and the more reliable the service, the more likely passengers are to make pre-trip decisions (Lappin and Bottom, 2001).

Previous analysts indicated that pre-trip decision making might be more common. In a Dutch study of inter-urban commuter path choice, for example, 75 percent of the travelers made pre-trip decisions, while 25 percent made en-route decisions (Hoogendoorn-Lanser 2005). In the north of England, Benshoof (1970) also found that 69 percent of motorists reported choosing a path before getting into the car, 16 percent decided a path soon after getting into the car, and only 15 percent made decisions during the trip. However, these studies were conducted three decades ago for all travelers not just for public transport passengers. The recent development of information and communication technology has significantly changed the availability of travel information. Abundant real-time or off-line information might affect travel decisions in different ways. For example, online travel planning tools might encourage pre-trip decisions, while real-time information at a subway station might make en-route decisions more likely.

Why travelers decide to transfer is another question that has not been well analyzed by researchers. Transfers may happen because they provide some forms of economic benefit to a traveler in terms of time savings. Transfers may also happen because they provide amenities along the travel path other than time savings, such as seat availability, reduced crowding, more scenic view, safer environment, etc. Even for the economic argument, it is not always clear whether the time saving is for the entire trip or just for some components of the trip. For example, a passenger may board a short-turn service on line A and transfer at the terminal to line B that has more frequent services to get to the final destination. Here the trade-off is between one transfer and transfer waiting time, not necessarily the total travel time. Trade-offs could also happen involving access or egress walking, transfer walking, or other segments along the path.

In summary, transfers are an important and prevalent attribute of public transport systems, especially in large multimodal networks. However, transfer behavior is complicated, and is not yet well understood by practitioners and researchers, which partly explains the lack of transfer planning in most major public transport agencies worldwide.

2.2 Transfer Planning in Public Transport Agencies

Transfer-related transportation policy and planning has become an issue only very recently. In the past century, adding more capacity to the transportation infrastructure by building new roads and public transport systems has been one of the main themes of transportation planning. However, the land resources for transportation infrastructure have been increasingly constrained, especially in the major metropolitan regions. At the same time, people have also realized that you cannot build your way out of congestion. It is a natural trend to refocus on the existing infrastructure and try to make it more efficient. One general goal is to integrate different pieces of a multimodal network to make a "seamless" system.

Such a paradigm shift in the United States is best illustrated by the passage of the Intermodal Surface Transportation Efficiency Act (ISTEA) in 1991. In the European Union, intermodalism has been emphasized by the European Union (EU) Common Transport Policy since 1995, and investigated extensively by the EU Committee through various projects, such as PIRATE (Promoting Interchange Rationale, Accessibility and Transfer Efficiency), INTERCEPT (INTERmodal Concepts in European Passenger Transport), EU-SPIRIT (European System for Passenger Services with Intermodal Reservation, Information and Ticketing), MIMIC (Mobility Intermodality and Interchanges), etc. However, despite these high-profile policies at the national level, transportation agencies at the local level have not yet fully incorporated intermodalism in their planning and operation practices. While there are a few efforts in freight transport (Mahoney 1985, Dwyer 1994, Wiegmans et al.1999, Southworth et al.2000), standalone transfer planning for passenger transport is rare in most major metropolitan regions worldwide. In most cases, transfers are just one component of larger planning initiatives.

2.2.1 Transfer Component of Public Transport Planning

Public transport agencies have adopted various methods to integrate service and management, such as institutional consolidation, unified fare media, integrated travel information, and network design. Although these initiatives often emphasize reducing operation cost or minimizing total travel time, they also benefit transfer activities by making transfers more convenient. For example, in Hamburg, Germany, the Hamburg Transport Alliance (HVV), established in 1965, was the first Transport Alliance in the world to promote "One schedule, one tariff and one ticket." HVV is charged with the task of planning, organizing, and optimizing public transport in the region. This has become a common model in Germany and Switzerland. In London, London Bus, London Underground, and London Transport merged in 2001 under the new umbrella organization Transport for London (TfL), a transport agency in charge not only of multimodal public transport, but also of parking and major arterial roads.

Institutional consolidation has been brought to decision-makers' attention in a number of other metropolitan areas, such as San Francisco, Vancouver, and Seattle. In some other areas, different agencies have tried to share their infrastructure to facilitate the movement of people between different systems. For example, three adjacent bus systems in Southwest Connecticut developed a cooperative arrangement to operate jointly a single, inter-town regional bus route. The route has a single schedule, but is operated by all three systems using their own buses. The number of transfers between routes has dramatically decreased and at the same time ridership has increased. Similar efforts can also be seen in Washington DC, Dallas-Fort Worth, San Diego, and Portland (Miller et al. 2005).

Unified fare media make transfers between modes that previously had different fare media more convenient, often with reduced transfer cost. This topic has been investigated extensively

(Giuliano et al. 2000, Rivasplata and Zegras 1998). A typical catalyst is the adoption of Automatic Fare Collection (AFC) systems across multimodal public transport systems operated by a single agency as seen in New York City, Chicago, London, Boston, Washington DC, and San Francisco.

The third relevant effort is to provide passengers with integrated travel information on different modes to help them make sound travel decisions. For example, in Chicago, the Regional Transit Travel Information Center provides information for the three major regional systems: CTA, Metra, and PACE. In San Francisco, a single information source was launched in 2003 via phone (511) or web (www.511.org) with information on transit, traffic, rideshare, bicycling, and itineraries for all the region's transit agencies. The system is managed by the Metropolitan Transportation Commission. To what extent the integrated information provision affects transfer decisions remains to be determined.

Transfers can also be part of the objective function in transportation network design that aims to minimize the total travel cost (Shrivastava and O'Mohony 2006). The method is to develop the best bus routes from a given initial skeleton based on analytical models. However, despite the extensive literature on this topic, there is little evidence that these research findings have been applied in real planning practice.

2.2.2 Standalone Transfer Planning

Standalone transfer planning targets two main areas: service coordination and infrastructure improvement. The former has been investigated extensively by researchers, and different types of coordination have been adopted by many public transport agencies, while the latter has attracted little attention despite the fact that this is the principal area of transfer-related investments. Service coordination means coordinating and synchronizing arrival and departure times to facilitate transfers by reducing transfer waiting time. Coordinated service is most effective for transfers from high frequency to low frequency services or between low frequency services. Implementation has occurred in Chicago, San Francisco, Sacramento, New York City, etc. One example is the service coordination between Caltrain and BART in the San Francisco Bay Area after 2003. Since then ridership in Caltrain has increased 17 percent, although it is hard to know how much of this increase is attributable to the service coordination because there were a number of other programs going on at the same time (Miller et al. 2005). The limitation of service coordination in transfer planning is that it targets only certain types of transfers (e.g. between low-frequency services) and only a portion of the transfer experience (transfer waiting time).

The biggest challenge in transfer planning is on facility assessment and improvement. For a large public transport network, there might be many transfer facilities associated with different modes. Given the limited resources, it is critical to concentrate investments on transfer facilities that are underperforming or where they can be most cost-effective. However, little is known about these aspects: analysts often do not know which transfer stations are perceived as more or less convenient by passengers, and why; analysts do not know how to estimate and hence justify the benefit of transfer-related investments. The problem is partly due to the nature of transfer improvement. Although the traditional evaluation methods rely on time savings for project prioritization and evaluation, they are not compelling for transfer projects, because time savings might only be a minor objective of the investment. The consequence is, not surprisingly, for three reasons: (1) the lack of funding for transfer planning, (2) the inefficient use of available funding, and (3) the instability of funding resources in improving transfer experience.

Some public transport agencies have tried to deal with the problem given their increasing investments in transfer facilities. A good example is the Interchange Plan conducted by Transport for London which allocated £100 million to improve interchange facilities over the past five years (TfL's Business Plan 2002/03 to 2007/08). The Interchange Plan used a methodology to prioritize investments among more than 600 interchange stations. Basically, the method calculates two values for each interchange facility: policy value and quality value. Policy value was based on scores on 20 policy objectives identified in the Mayor's Transport Strategy (GLA, 2001). Physical quality value describes accessibility (stairs, escalators, lifts, etc.), environmental quality (perceptions of the condition and quality of signs, level of cleanliness, etc.), and security (CCTV, lighting, visibility of staff and level of graffiti). All the factors are given weights, and the quality value is estimated from Mystery Shopper Surveys (MSS). Then a Quality Gap index between the policy and the quality values is developed. A station with a high Quality Gap, or high policy value but a poor physical quality, will rank high in the list of priorities for investment.

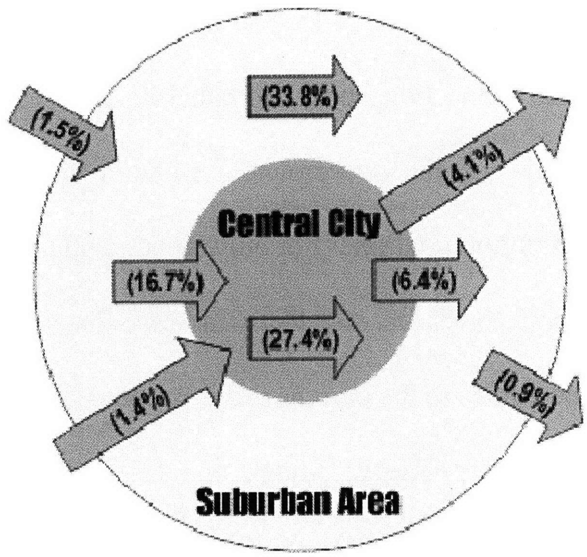
The Interchange Plan is the most comprehensive transfer-planning effort that the author has identified. It offers a valuable approach for transfer project selection. Transfer investments are guided by policy strategies, and the evaluation criteria could be expanded fairly easily, for example by including other types of indices such as the feasibility of implementation and support from local boroughs. However, using this approach, an analyst is unable to justify the benefit of transfer investment and has to rely on Customer Satisfaction Surveys (CSS) carried out before and after an improvement, which yields qualitative and descriptive conclusions. Furthermore, the CSS is expensive and is impractical to undertake at all interchange stations.

In summary, the diverse efforts to integrate institution, infrastructure, service, and information of public transport systems have yielded positive results. However, owing to exogenous factors, it has been difficult to attribute specific benefits to particular policies. In most cases, the transfer is analyzed as a component in a comprehensive planning effort in an ad hoc manner. Transfer planning does not receive serious attention in most public transport agencies, and standalone transfer planning efforts, such as service coordination and the TfL Interchange, can make a difference but should be improved to overcome their problems of being narrowly focused or unable to select and justify transfer investments.

2.2.3 Transfer Planning in the Future: Increasing Importance

The future of transfer planning is determined by the evolution of the urban structure, travel patterns, and transportation systems. The decentralization of jobs and housing has made metropolitan regions bigger, less dense, and more polycentric. People are traveling longer distances, spending more time trip-making, traveling more often, and becoming more dependent on automobiles (NHTS 2001). At the same time, travel patterns are more diverse. As Figure 2-1 indicates, there is no dominant commuting pattern in a typical metropolitan area. Reverse commuting, suburb-to-suburb, intra-central city commuting, and traditional suburb-to-central city commuting all take significant shares of the market.

The new travel patterns have created more need to transfer. First, increasing suburb-to-suburb trips, the largest cohort (33.8 percent) in the travel market, might increase the need to transfer in a public transport network, which largely follows a radial structure serving the urban center, though the extent of change is unclear because public transport remain uncompetitive to cars for this travel market. Second, ridership has redistributed inside the multimodal public



Source: Rodrigue, J-P et al. 2005

Figure 2-1 Destination for Work-Related Trips in the United States

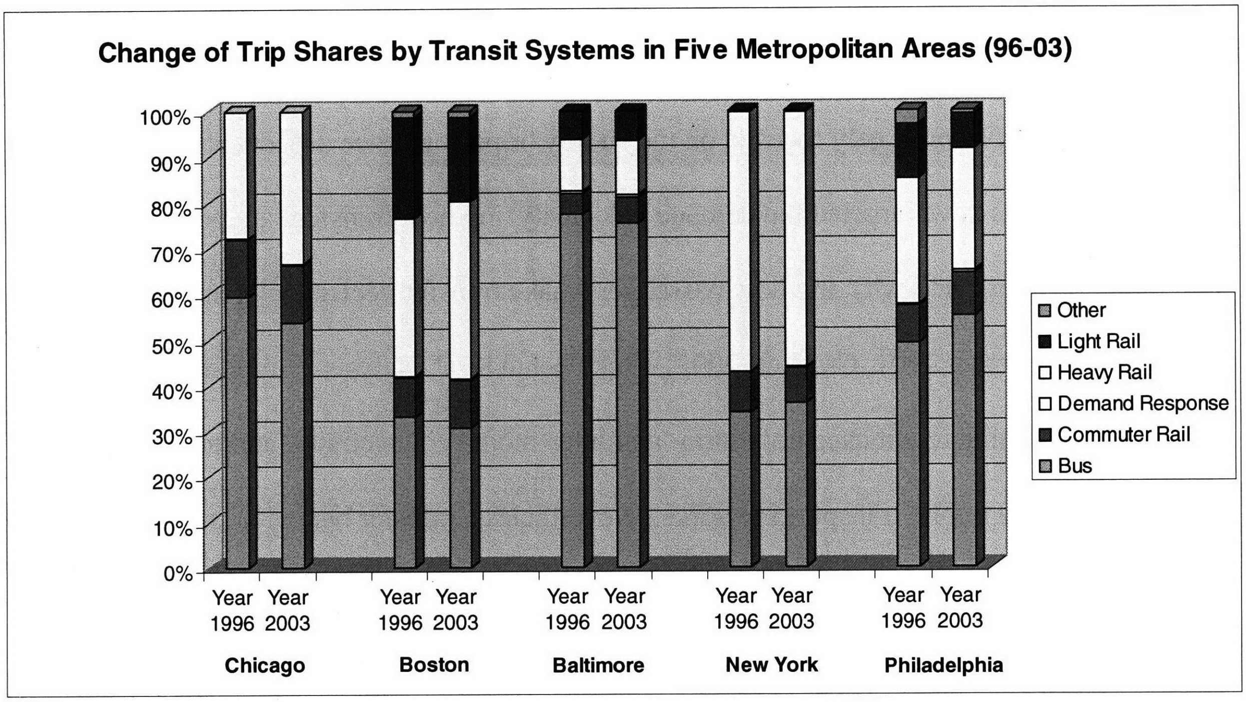
transport systems (Figure 2-2). In particular, commuter rail, primarily serving the outer suburban areas, has benefited from the decentralization. It has continuously gained ridership over the past twenty years, which significantly contributed to the total transit ridership increase in the 1990s. Nationwide, from 1990 to 2003, commuter rail ridership increased by 25 percent, followed by rapid transit 19 percent, while bus ridership was virtually unchanged (NTD 2005).

Given these trends, there has been increasing transfer activities between different public transport modes as well as between public and private modes. For example, in Chicago, park-and-ride ridership increased 14 percent in two years from 1998 to 2000 (CTA 1998, 2000). At the national level, the percentage of public transport trips that involve at least one transfer increased from 35 in 1990 to 50 in 1995[5](NPTS 1990, 1995).

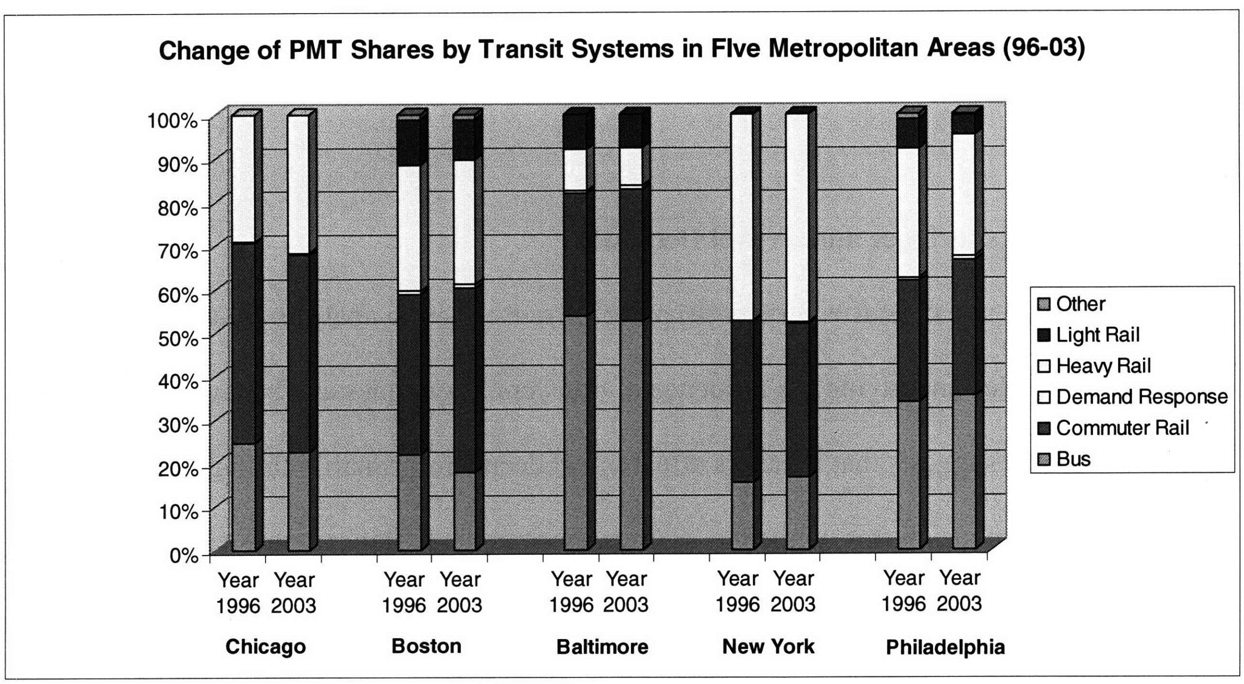
[5] Transfer information within transit is difficult to obtain at both the system and the national level. The only dataset containing this information is the National Personal Transportation Survey in 1995 and 1990, however, this information is not included in the 2001 survey. More data are necessary to confirm this trend.

Transfer activities will also be more important as public transport networks become more complex. For example, many major public transport agencies are investigating or implementing possible network elements to connect the spokes of radial lines, including the Urban Ring in Boston, the Circle Line in Chicago, the Overground in London, and the circumferential Triboro RX in New York City. Circumferential lines not only make public transport systems more attractive for suburb-to-suburb travel, but also likely increase the chance of transfers between radial corridors. Adding new lines to the current network could also generate more transfer trips as shown by the Green Line in Los Angeles (Mieger and Chu 2007). Similar increases are expected from the 2nd Avenue Subway in New York City, the Green Line in Dallas, and Crossrail in London.

In summary, transfers are critical to the competitiveness of public transport systems, and likely will become increasingly prevalent in the future. However, transfer planning has not been widely conducted in most public transport agencies, probably due to the complexity of transfer activities, and the lack of planning tools to help transfer-related decisions. The first step in tackling this problem is to improve our understanding of transfer behavior, which has been analyzed in only a few studies.



(a) Unlinked Trips



(b) Passenger Miles Traveled

Source: American Public Transportation Association (APTA)

Figure 2-2 Transit Travel Redistribution in Five Metro Areas

2.3 Literature on Transfer Behavior Analysis

Transfer analyses have largely focused on the supply or performance aspects of transfers, and only a few studies have targeted the demand side analyzing how transfers are perceived by individual travelers, and why and how passengers make transfer decisions (Han 1987, Liu et al. 1997, Wardman et al. 2001, Crockett 2002). Such behavioral analysis is important because it is the basis of planning to enhance both intra- and inter-modal connectivity, and to promote seamless travel in public transport networks. Nevertheless, transfer behavior is not an easy topic for investigation due to the lack of relevant theories and analytical methods, and the complexity of transfer decisions. This section summarizes the theories, models, measures, and empirical results from prior studies, and discusses the implications for the methodology that will be presented in the following chapter.

2.3.1 Transfer Experience and Travel Decisions

Why and how do transfers affect travel behavior? Transportation analysts assume that there are two related theories underlying the influence of transfers: economics and behavioral science. Economic theory suggests that transfers affect travel decisions primarily through travel cost either in time or money terms, while the later emphasizes the social and physical environment of transfers and their psychological and cognitive impacts on travelers. The two mechanisms often work together rather than separately. For example, information provision at a station may facilitate transfers by reducing transfer time as well as easing the anxiety associated with transfers. The two mechanisms might also be applicable to different components of transfers. For example, in general, the inconvenience of a transfer is believed to originate from three main sources: extra time spent on transfer, extra money spent on transfer, and an additional penalty associated with transfer (Han 1987, Liu et al. 1997, CTPS 1997, Wardman and Hine 2000, Wardman et al. 2001). The impact of extra time and money can be best explained by the economic theory, while that of the transfer penalty belongs primarily to behavioral science, which has been least studied in the context of transfer behavior analysis.

Transfer time includes walking time between two stops/platforms, and waiting time for the connecting vehicle. Transfer cost refers to the monetary value paid to make the transfer, which often can be zero or a reduced fare. The transfer cost could be complicated by a zonal fare system when a fare is charged based on the zone of origin and destination or through which zones the passenger passes.

There are many factors that might affect the transfer penalty. In their conceptual framework, Liu et al. (1997) mentioned exposure to weather, implication of handling luggage, physical environment of the transfer facility, and point of transfer in the context of overall trip as factors affecting the "penalty". Crockett (2002) listed en-route and pre-trip information, weather protection, road crossing, concessions, and the level of change in addition to the transfer time and cost. Iseki and Taylor (2007) included information provision, amenities, and security and safety. A few U.K. analysts cited maps and timetables, escalators or lifts, staff availability, crime and overcrowding, same-platform, ramp availability, cleanliness, etc. as factors that could affect the transfer experience (Harris Research 1993, Oscar Faber 1996, SYPTE 1996, GMPTE 1997, London Transport 1997). Some analysts summarized the many detailed attributes of a transfer facility that may affect the transfer penalty based on user interviews. For details, see Horowitz and Thompson (1994), Wardman and Hine (2001), and several documents from Transport for London (2001, 2002, 2004).

The transfer perception and/or experience might affect many different travel decisions including mode choice, path choice, time choice, travel frequency, and destination choice. Using household travel survey data for the Boston region, the Central Transportation Planning Staff (CTPS) (1997) found that a transfers could affect the mode choice between transit, single-occupant vehicle, and shared-ride. Based on a stated preference survey in Edinburgh, Wardman et al. (2001) found that convenient connection was viewed as the single most important factor that would make motorists switch to transit. In another survey, connectivity is one of the top three features of public transport that most concern auto drivers after service reliability and frequency (Wardman et al 2001). However, when the analysts tried to model the mode choice to work by either car or bus, transfers associated with bus became insignificant in travelers' decisions on which mode to choose (Wardman et al 2001). Liu et al. (1997) found a similar result when they examined the impact of transfers within a proposed light rail system on people's mode choice between the light rail and car traveling from New Jersey to New York City. However, they also found that transfers did affect the mode choice between the light rail and an existing subway system. Their explanation is that the modal bias between car and transit is so strong that transfers are not considered in the decision-making process.

The impact of transfers on path choice has been recorded by prior studies. Based on interviews of bus riders over a two-month period, Han (1987) found that the number of transfers along a bus path reduced the chance of that path being chosen by travelers. Hoogendoorn-Lanser et al. (2006) conducted a survey for inter-city train travel in an urbanized corridor in The Netherlands, to examine alternative combinations of regional rail and urban rapid transit, and the different access and egress modes. The authors found that transfers (time and types) did affect the path choice in the multimodal rail network.

2.3.2 Analysis Methods

There are two main methods to analyze transfer behavior: surveys and behavioral modeling, each with advantages as well as disadvantages. Surveys can provide rich information on transfer behavior in terms of individual decision-making process, perceptions and attitudes, and suggestions for improvement. However, surveys normally cover only a small sample of individuals and trips. The findings might be informative but offer little insight on the quantitative evaluation of transfer facilities or projects. Behavioral modeling is powerful in this respect but transfer related data are hard to collect, and the decision scenario can be hard to construct. This section explains these two methods in more detail.

Surveys: Focus Groups and In-depth Interviews

The oft-mentioned surveys include focus groups and in-depth interviews. The former is essentially a group interview, but relies on interaction within the group based on the topic supplied by a moderator. The latter targets an individual's thoughts and feelings from the respondent's own perspective rather than from the researcher's priorities or assumptions. Only a few analysts have used surveys to investigate transfer behavior with the most comprehensive being one by Hine and Strode (2000a, 2000b).

Hine and Strode undertook four focus groups in Edinburgh, Kilmarnock, and Glasgow in 1999. They found that transfers were viewed as a negative feature of travel, but its inconvenience could be reduced if the frequency of service is high, the connection is under one roof in a pleasant environment, and the transfer happens close to either home or the destination. The experience of transfer-related coordination between operations in general was poor. The authors also found that transfer was just one factor, albeit a large one, in a number of barriers to using public transport. Rail transfers were perceived more positively than bus transfers probably because the former provide a better transfer environment. Car drivers' perceptions of interchange problems were similar to those expressed by regular public transport users. There was a greater level of anxiety about wayfinding and the need for better information and signposting of services. For disabled or mobility-impaired users of public transport, quality information that can help them plan the trip in advance is a high priority.

Based on the insights provided by the focus group, Hine and Strode conducted in-depth interviews in the same regions. Interviewees stated or implied that they sought to avoid transfers, especially for commuting trips, by changing bus routes, switching to car or walk, or even changing housing location. Transfer facilities were perceived differently depending on their physical conditions. Interviewees also indicated that both car users and public transport passengers favored freedom, independence, and flexibility, things that could be considered as giving users control and that fit with modern lifestyles.

In both surveys, the sample sizes were very small: fifty-six persons in all were recruited for the focus groups, and 33 persons attended one of the four groups. In the in-depth interviews, a total of 32 people were interviewed, 17 public transport users and 15 car users. Researchers recruited participants on the street, in car parks, or at bus and rail stations without a sampling plan. It is not clear whether the results could be generalized to the population at large.

Another disadvantage of surveys is that they offer limited information on how to evaluate a transfer facility or investment. For example, it was not clear which transfer component needs to be improved and to what extent in order to achieve desired changes in travel behavior. This question can only be answered by quantitative methods, such as behavioral modeling.

Behavioral Modeling: Transfer Choice Decisions

A typical way to model transfer behavior is first to construct a decision scenario over several travel options that involve transfers, and then to compare the decision outcome with transfer attributes, controlling for all other factors. The underlying theory is random utility (Ben-Akiva and Lerman 1985), which is based on neoclassical economic theory. A competitive alternative is assumed to have a certain amount of utility to the person who is making a decision. The attributes associated with the alternative determine the amount of its utility, which includes a systematic component based on observed aspects and an un-observable random component. A rational decision maker will always try to maximize his or her utility by selecting the choice with the highest utility. Although random utility models are not representations of the actual choice process, they have proved to be useful tools to identify which aspects are relevant in the choice process and to predict choices (Hoogendoorn-Lanser 2005).

A random utility model consists of four main parts: a decision maker, a choice set, attributes of each choice, and the error term (Ben-Akiva and Lerman 1985). The most difficult part to define is the choice set for two main reasons: (1) transfer-related decisions tend to be more subtle (i.e. not as obvious), as the oft-examined mode-choice decisions, and (2) choice set generation that involves multimodal or multipath travel is more complicated than the traditional choice set generation process. To simplify the problem, many analysts rely on data collected from Stated-Preference (SP) surveys of travelers, not from their actual revealed behavior. For example Wardman et al. (2001) conducted a series of SP surveys for bus, car, and train commuters in Edinburg and Glasgow. For bus and train users, only those who had to transfer were included, while for car users only those who would have to transfer if they were to make their journey to work by bus were included. Up to 18 different questionnaires were designed in order to cover a large range of transfer activities. Choice models were applied and transfer-related attributes were quantified as the equivalent in-vehicle travel time. The interchange penalty for bus users is estimated to be 4.5 minutes of in-vehicle time, but with a 95 percent confidence interval of ± 44 percent (Wardman et al. 2001, p. 36).

Stated-Preference (SP) data were also used by Liu et al. (1997), who presented a hypothetical travel scenario that included light-rail transit (LRT) as opposed to the current travel mode. The attributes of the LRT option included in-vehicle time, walking and waiting time, fare, and number of transfers. Nine different LRT service configurations were compared with a base LRT option and the current public transport system. They found that respondents chose those options with fewest transfers even if they had longer walking and waiting times. Two binary logit models were estimated, one for car and one for public transport users.

Although Stated-Preference surveys and modeling can offer insight into transfer behavior, they normally target a small group of travelers due to the intensive nature of the data collection. The three surveys conducted by Wardman et al. (2001) in Edinburgh and Glasgow had 242, 182, and 132 respondents, respectively. Similarly, in Liu's research (Liu et al.1997), a total of 152 individuals completed questionnaires distributed by the New Jersey Transit Authority. The limited number of scenarios also offers small variation among the transfer attributes, which might make it impossible to differentiate transfer components in evaluation (Wardman et al., 2001).

Revealed-Preference (RP) data based on people's actual behavior can be used to avoid these constraints, but it is difficult to construct a transfer decision situation from RP surveys in an empirical context. That is why only a few studies of transfer behavior are based on RP data, and most have problems in defining a transfer decision situation.

Based on a 1991 household travel survey in the Boston metropolitan region, CTPS (1997) applied a multinomial logit (MNL) model to estimate the transfer effect on the mode choice between transit, single-occupant vehicle, and shared-ride auto. In addition to the chosen mode, they identified alternative modes or paths manually, which was time consuming and inefficient. They then calculated the attributes of all available options using a regional travel model and inserted the results into the MNL model.

Using a travel survey for inter-city travelers in the Netherlands, Hoogendoorn-Lanser et al. (2005) modeled the effect of transfers on both modal combinations and path choices. In addition to the chosen alternative, options were generated through a complex process using branch-and-bound techniques. The total number of available alternatives was unrealistically large, about 40 on average, which raised questions about whether the constructed decision scenario reflected reality.

Furthermore, analysts, who use RP-based mode choice, have difficulty with the inter-modal nature of many transfers and the weak relationship between mode choice and transfer attributes. From the perspective of consumer theory, transfer behavior is about consuming joint-products (e.g. car and rail, bus and subway), while mode choice models assume that a customer faces distinct products (e.g. bus, car, rail). If a transfer is treated as an attribute of a travel mode, it is not always clear to which mode the transfer should belong. Similarly, the distinction between access/egress and main modes is not always clear. If a mode combination is treated as an individual mode, correlation among these modes is often complicated, and hard to control for. Nevertheless, there are questions about whether mode choice is sufficient to determine the influence of transfers on travel decisions (Wardman et al. 2001; Liu et al.1997).

Han (1987) adopted a path choice model to test the influence of transfers on bus path decisions in Taipei, Taiwan, based on interviews of bus riders over two months. The survey identified the travel path for a previous trip and a potential alternative path. Detailed information of both paths were recorded and used to estimate a binary choice model. Path-choice modeling avoids the aforementioned problems of mode choice models, but it is more complex than mode choice in terms of alternative identification (choice set generation). I will discuss this issue in detail in the methodology chapter.

2.3.3 Assessment of Transfer Penalty

One of the major outcomes of behavioral modeling is to assess the transfer penalty quantitatively. In mathematical terms, the transfer penalty is the ratio between the coefficients of transfer variables and a non-transfer time/cost variable. In formulations with a transfer constant, the penalty is the coefficient ratio between the constant and a non-transfer time/cost variable. In formulations with no such constant, the penalty is the sum of coefficient ratios between transfer attributes and a non-transfer time/cost variable. It indicates how much people are willing to pay, or, how much further they would travel, in order to save one transfer – in other words, it measures the time or money that must be saved in order to justify one transfer (see Section 4.3.4 for equations). The definition suggests that the transfer penalty can possess different values depending on what transfer attributes are included in behavioral modeling. For example, if transfer walking and waiting times are not included in model specifications, the transfer constant would capture the entire transfer effect, and the estimated transfer penalty would include the influence of transfer walking and waiting. Comparisons between transfer penalties should be based on the same definition.

Prior studies show varying results on the transfer penalty assessment. Alger et al.(1971) used survey data for commuter trips in Stockholm to estimate the transfer penalty, including transfer walking and waiting, between subway, rail, and bus. They found a great variation of the penalty across different transfer types: 4.4 minutes of in-vehicle time for a subway-to-subway transfer and almost 50 minutes for a bus-to-bus transfer. In Taipei, Han (1987) measured the penalty for a bus-to-bus transfer as 30 minutes of in-vehicle time using the same definition. Hunt (1990) estimated a logit model of transit route choice behavior using data for commuters in Edmonton, Canada. The transfer penalty of a bus-to-light-rail transfer was valued as 18 minutes of in-vehicle time. MVA (1991) examined inter-city travelers in the United Kingdom, and estimated a penalty of 32 minutes from an SP survey. Jones (1993) examined route choice for travelers who could use Thameslink services to avoid transfers in London. He found a penalty of 37 minutes using actual route choice data and 47 minutes using SP data. Toner and Wardman (1993) estimated the RP mode choice model in Southwest England, and found a value of 23 minutes. In the New York-New Jersey metropolitan region, the transfer penalty of an auto-to-rail transfer was about 15 minutes of in-vehicle time, while that of rail-to-rail was only 1.4 minutes (Liu et al., 1997).

Several analysts estimated the transfer penalty after excluding the effects of the transfer walking and/or waiting time. London Transport (1988, 1995) evaluated the transfer penalty in the Underground in 1988 and found an average value of 5.7 minutes of in-vehicle time additional to transfer walking and waiting. In 1995, they repeated the analysis based on a new dataset and found a value of 3.7 minutes in the peak period additional to transfer walking and waiting. In both situations, transfer walking and waiting were constrained by weighting them at twice the rate of in-vehicle time. In Boston, CTPS (1997) estimated that the transfer penalty of an average transfer for all modes of 12 to 15 minutes of in-vehicle travel, after controlling for the transfer waiting time. Wardman et al., (2001) produced the most comprehensive estimates of the transfer penalty to date. Their research controlled not only for the transfer walking and waiting time, but also for fare type, physical, mental, and affective efforts, concentration, and worry. Therefore, the estimated value of transfer penalty might be smaller than a value controlled only for walking and waiting times. In Edinburgh, the transfer penalty of a bus-to-bus and an auto-to-bus transfer was 4.5 and 8.3 minutes, respectively, of in-vehicle time, while that of a rail-to-rail transfer was about 8 minutes in Glasgow (Wardman et al., 2001).

The major results are summarized in Table 2-3 and 2-4.

2.3.4 Variation of Transfer Experience by Person, Trip, and Time

Making a transfer is a personal experience, so the perceived inconvenience of a transfer is likely to vary across individuals depending on their personal and trip characteristics. Such a variation might have different policy implications for service planning compared with the variation caused by the physical transfer environment. If the former variation is more significant than the latter, improving transfer facilities might not be effective. Rather transfer-related incentives targeting particular market segments might work better. Studies on these topics are few. Some of the key findings are summarized below:

1. Commuters tend to have lower values of transfer penalty than non-commuters probably because they are more familiar with the transfer environment and because the generally higher service frequencies in the peak reduce the uncertainties involved in transfers. Oscar Faber (1993) estimated the transfer penalty in a joint RP-SP mode choice model for inter-urban travelers. He found that the penalty value for a rail transfer was 87 minutes, equivalent in-

Table 2-3 Previous Results on Transfer Penalty without Controlling for Walking and Waiting

Previous Studies	All Variables	Transfer Types	Transfer penalty
Alger *et al,* 1971 Stockholm	Walking time to stop Initial waiting time In-vehicle time Fare Number of transfers	Subway-to-Subway Rail-to-Rail Bus-to-Rail Bus-to-Bus	4.4 minutes in-vehicle time 14.8 minutes in-vehicle time 23.0 minutes in-vehicle time 49.5 minutes in-vehicle time
Han, 1987 Taipei, Taiwan	Walking time to stop Initial waiting time In-vehicle time Fare	Bus-to-Bus (Path Choice)	30 minutes in-vehicle time, or 10 minutes initial wait time, or 5 minutes walk time
Hunt , 1990 Edmonton, Canada	Walking distance Waiting time In-vehicle time Number of transfers	Bus-to-Light Rail (Path Choice)	17.9 minutes in-vehicle time
MVA, 1991 *			32 minutes in-vehicle time
Jones, 1993 London, UK *			37 minutes in-vehicle time 47 minutes in-vehicle time
Toner and Wardman, 1993, Southwest UK			23 minutes of in-vehicle time
Liu *et al,* 1997 New Jersey, NJ	Out-of-vehicle time In-vehicle time Fare Number of transfers	Auto-to-Rail Rail-to-Rail	15 minutes in-vehicle time 1.4 minutes in-vehicle time

Note: * from Wardman et al., 2001. Cost of Interchange: A Review of Literature, Institute of Transportation Studies, University of Leeds, United Kingdom

Table 2-4 Previous Results on Transfer Penalty Controlling for Walking and/or Waiting

Previous Studies	Transfer Attributes Controlled for	Transfer Types	Transfer Penalty
NBPI, 1970 Daly et al..1973, UK *	Transfer waiting time		3 to 4 minutes (waiting time)
London Transport, 1988, 1995 *	Transfer walking time Transfer waiting time		5.4 minutes (1988) 3.7 minutes (1995) (in-vehicle time)
CTPS, 1997 Boston, MA	Transfer waiting time	All modes combined (Path + Mode Choice)	12 to 15 minutes (in-vehicle time)
Wardman *et al,* 2001 Edinburgh, Glasgow, UK	Transfer walking time Transfer waiting time Fare type Perceptions, attitudes	Bus-to-Bus Auto-to-Bus Rail-to-Rail	4.5 minutes 8.3 minutes 8 minutes (in-vehicle time)

Note: * from Wardman et al., 2001. Cost of Interchange: A Review of Literature, Institute of Transportation Studies, University of Leeds, United Kingdom vehicle time, for a business trip but increased to 102 minutes for a leisure trip. The same pattern also holds for bus transfers. Other analysts using the SP approach in the United Kingdom (Steer Davies Gleave, 1981) calculated a transfer penalty of 19 minutes for business travel and 38 minutes for leisure trips in the National Rail system. Similar results were found by Wardman (1983, 1998). MVA (1985) estimated that business travelers found transfer time more onerous than leisure travelers. Wardman et al., (2001) found rail commuters in Glasgow had a 29 percent higher value of transfer waiting time than non-commuters, implying that commuters might be less tolerant of the inconvenience of transfers.

2. Travel frequency also matters. MVA (1991) estimated that season ticket holders had a transfer penalty of 11 minutes, while the average transfer penalty for all travelers whose journey is less than 50 miles was 45 minutes. Seasonal ticket holders generally travel more frequently than the average passenger. The United Kingdom Passenger Demand Forecasting Handbook recommends a transfer penalty for season tickets 30-35 percent less than those for other tickets. Wardman (1983) examined the transfer behavior of rail passengers and found an average transfer penalty of 35 minutes, with less frequent travelers having higher values. MVA (1985) also found the transfer penalty was 20 minutes of in-vehicle time for non-Londoners, while it was insignificant for Londoners. Wardman et al. (2001) found that the transfer penalty was 85 percent higher for rail users who make fewer than one trip a week in Glasgow.

3. The variation of transfer experience across demographic groups is less clear. MVA (1985) found that transfer time was perceived 2.7 times more onerous than in-vehicle time, but varied little across age and income groups. The value, as equivalent in-vehicle time, was somewhat higher for females (3.5 minutes) than males (2.6 minutes), and for those with luggage (4.0 minutes) than those with no luggage (3.1 minutes). In their comprehensive study in

Edinburgh and Glasgow, Wardman et al. (2001) found the transfer penalty for bus users was higher for women, for those with bags, and for those aged 50 and over. The same result also held for car and rail users. Female drivers had the transfer penalty 38 percent higher and worry rating valuation 3.3 times higher than for male drivers. Female rail passengers had a 26 percent higher value of waiting time and a 23 percent higher value of walking time than male passengers. A study by London Transport (1998) also found that the transfer penalty varied across individuals with about 30 percent travelers having virtually no penalty, 50 percent having a penalty of less than 3.5 minutes and 10 percent having a value over 14 minutes.

4. The only research on the variation of transfer experience over time was by London Transport (1995). It found that the transfer penalty value was 3.7 minutes in peak hours, versus 3.0 minutes in the off-peak. Possible explanations are that service in peak hours is often more crowded and less reliable, and people who travel in peak hours are normally more time sensitive.

In summary, current research on transfer behavior is still rudimentary. A methodology suitable for transfer analysis needs to be developed; the measurement of transfer experience needs to be expanded, especially in terms of the variation of the experience; and current analyses offer limited help to public transport agencies on transfer planning. This study examines these issues, and, in the next chapter, I propose a comprehensive methodology.

Chapter 3 METHODOLOGY AND RESEARCH DESIGN

Results from the above chapters suggest that a good method for transfer-behavior analysis should meet the following requirements:

1. be able to differentiate among the different transfer components such as the transfer time, cost, and the residual transfer penalty;
2. be able to measure the transfer penalty accurately, and to control for external factors such as modal bias;
3. be able to differentiate the transfer experience across different locations and directions within a network in order to provide guidance for project evaluation; and
4. be comprehensive enough to deal with the complexity of transfer behavior within a broad context.

Therefore, I develop a new methodology, which has the following key features:

1. it is based on random utility theory and covers both economic and psychological effects of transfers;
2. it relies on the concept of the "transfer penalty" for measurement of and comparison between transfer experiences and facility qualities;
3. it adopts a transfer-analysis framework based on revealed path choices;
4. it includes multiple case studies that cover some of the complexity and diversity of transfer activities and environments.

In this chapter, section 3.1 introduces discrete choice theory and random utility models (RUM) and their application to transfer behavior analysis. Section 3.2 explains path choice in public transport networks and path choice modeling. Section 3.3 explains why multiple cases are necessary and why the rail systems in London and Boston were selected for this study.

3.1 Discrete Choice Theory and Random Utility Models

According to discrete choice theory, a choice can be viewed as an outcome of a sequential decision-making process that includes the following steps: defining the choice problem, generating alternatives, evaluating alternative attributes, and making a choice[6]. Although discrete choice theory is just one of many theories that analysts have used to explain individual decisions, it is nevertheless the one most commonly used in demand analysis, which emphasizes "a wide range of applications and making operational predictions for a large number of individuals" (Ben-Akiva and Lerman, 1985).

3.1.1 Elements of Choice Process

There are four elements in a discrete choice process: decision maker, alternatives, alternative attributes, and a decision rule.

The decision-maker can be an individual person, a household, a firm, or an organization. In the transfer case, it is an individual traveler in a public transport network. The observable and un-observable differences among decision makers contribute significantly to the different decision outcomes, even in identical choice situations.

[6] Please note, not all observed behavior is an outcome of an explicit decision-making process, for example behavior that follows a habit, intuition, or preference where no alternative choices are available.

Alternatives are the options that are perceived to be available by a decision maker at the time of the decision. This group of available alternatives is called a choice set and the process of identifying them is called choice set generation. The core issue of choice set generation is to define the term "availability". In some situations, availability is clear. For example, car is not an available option for a traveler without a driver license, and certain road segments are not available to trucks. However, in many other cases, whether an alternative is available or not may be unclear for three reasons:

1. People's recognition of alternatives might spread across a wide range of levels rather than just between "available" and "unavailable". For example, Hoogendoorn-Lanser (2005) described six levels of recognition of alternatives: existing, logical, feasible, known, considered, and chosen, thus, it is not easy to decide at which level "availability" should be defined.

2. The availability of an alternative might depend on the value of a particular attribute, for example, the travel distance for walking. As distance increases, it is not clear when walking becomes unavailable or just available, but not favored by a traveler. Including it or excluding it from the choice set will likely affect the analysis results.

3. There are no data to verify the "availability" because is the choices not revealed by actual behavior, and not documented in travel surveys.

All these three issues apply to the path choice problem described later.

Attributes of alternatives measure the attractiveness of an alternative. Transportation analysts believe that a decision maker compares the values of attributes among alternatives in order to make a decision. In many situations, the attributes or unattractiveness of an alternative can be easily identified, for example, travel time and cost. In other cases, however, they are either not well defined due to the unobserved characteristics of transport supply and personal tastes, or are known but hard to measure.

The decision rule describes the internal mechanisms used by the decision maker in comparing the available alternatives leading to a choice. Researchers have proposed a great variety of decision rules (e.g., Slovic et al. 1977, Svenson 1979, Klein 2001, Lichtenstein and Slovic 2006). According to Ben-Akiva and Lerman (1985), there are four types of decision rules: dominance, satisfaction, lexicographic rules, and utility. An alternative is dominant if it is better for at least one attribute and no worse for all other attributes. This rule is often used to eliminate alternatives that are dominate over all attributes because no trade-offs are presented in this situation. The satisfaction rule acts similarly through defining a minimum expectation from a decision maker for every attribute of an alternative. An alternative can be eliminated if it does not reach this satisfaction level for at least one attribute. In lexicographic rules, attributes are ranked by their level of importance to travelers. The decision maker is assumed to choose the alternative that is the most attractive for the most important attribute. If no decision is reached at this stage, the decision maker will go on to the second most important attribute and continue until a choice is made. This process can be performed in the opposite direction by eliminating the most inferior alternative.

In the utility rule, the attractiveness of an alternative is expressed by a single objective function that a decision maker attempts to maximize. It is based on the notion of trade-offs, or compensatory offsets (Ben-Akiva and Lerman 1985). For example, the most expensive mode may be chosen if its price is compensated for by offering fast service. According to the utility rule, a decision maker always chooses an alternative with the best combination of attributes. Utility often takes a cardinal form, having no meaning except for the comparative relationships of greater than, less than, or equal to. It results in formulations of a choice process that is amenable to mathematical analysis and statistical application. The utility decision rule, which I adopted for this research, is most widely used in travel demand analyses. It provides a platform to compare attributes from different origins that are normally not comparable, for example, travel time, crowding, and safety.

The utility decision rule assumes that a decision maker is fully aware of all information pertaining to an alternative, and then makes a "rational decision". Rationality means a consistent and calculated decision process in which the individual follows his or her objectives (Ben-Akiva and Lerman 1985). However, these assumptions do not always hold in reality. Empirical studies in psychology and behavioral science suggest that people do not always act rationally (Muth 1961, Sen 1977, Simon 1978, Thaler 1992). This does not necessarily imply, however, that the rationality principle should not be applied in demand analysis. It is still the most parsimonious way to explain individual decisions consistently and in the long run (Kirchgässner 2004, Vanberg 2004). Furthermore there is no better theory to substitute for the rationality principle even though alternative explanations are diverse. I deal with these concerns, at least partially, by introducing the concept of random utility.

3.1.2 Random Utility Models

An analyst can argue that human behavior is inherently probabilistic. Individuals do not always select the same alternative if the same decision situation arises successively. An analyst can also argue that, from a research perspective, the probabilistic behavior originates from the lack of more precise knowledge about individuals' decision processes, including the unobserved heterogeneity among decision makers, unobserved attributes of alternatives, and the possible distortion during information acquisition and interpretation. One effective approach to control for this "probability" is to treat utility as a random variable (Manski 1977). In mathematical form, the utility, U, is decomposed into two terms: the first is a deterministic term, V, and the second term is random and not measurable, ε.

Depending on the specifications of the deterministic and random terms, different models can be derived. The specifications are often a result of sometimes contradictory criteria, e.g., balancing theoretical validity against computational convenience. For the deterministic terms, a linear function is often chosen by researchers. For example, if there are j alternatives, each with k attributes, the utility of alternative j can be written as follows where x is the attribute itself and β represents the weigh for that attribute:

$$V_j = \sum_k \beta_k x_{jk} \qquad (5)$$

For the random term, two types of distributions are widely used by researchers: the normal and Gumbel distributions. The model based on the normal distribution is called probit. It is intuitively reasonable and has some theoretical basis, but it does not have a closed form solution. The model based on the Gumbel distribution is called logit because the differences of two Gumbel-distributed random terms are logistically distributed. For example, assuming there are two alternatives j and i, then the distribution function of $\varepsilon_{j-i} = \varepsilon_j - \varepsilon_i$ is

$$F(\varepsilon_{j-i}) = \frac{1}{1+e^{-\mu\varepsilon_{j-i}}} \qquad (6)$$

$$f(\varepsilon_{j-i}) = \frac{\mu e^{-\mu\varepsilon_{j-i}}}{(1+e^{-\mu\varepsilon_{j-i}})^2} \qquad (7)$$

Therefore, the choice probability for alternative j is given by

$$P(j) = Probility(U_j \geq U_i) = \frac{1}{1+e^{-\mu(V_j - V_i)}} = \frac{e^{\mu V_j}}{e^{\mu V_j} + e^{\mu V_i}} \quad (8)$$

Equation (8) depicts a choice situation between two alternatives, referred to as the binary logit. It can be extended to a general form for multiple alternatives written as follows:

$$P(j) = \frac{e^{\mu V_j}}{\sum_j e^{\mu V_j}} \quad (9)$$

This model is called Multinomial Logit (MNL) (McFadden 1973), and is the most widely used demand model in the field of transportation. In this research, MNL is applied in the framework of path choice in public transport networks.

3.2 Path Choice

Path choice refers to a situation when a traveler faces multiple paths from a given origin to a given destination in a transportation network. It should be differentiated from the term "path search" and "route choice." The former refers to a process through which a traveler finds possible paths to reach his or her destination. The question in that case is how to acquire information to find a route on unknown terrain. The latter sometimes refers to a choice situation among different services in a public transport network even they follow the same physical path. In this case, the decision problem is whether to board an arriving vehicle or to wait for a later vehicle that will have lower in-vehicle time. Neither situation will be dealt with in this research, so that a different term, path choice, is adopted.

3.2.1 Basics of Path Choice

Path-choice analyses target questions such as: How do people choose paths in a network? What do they know? What do they look for? Which path attributes play a role. According to Bovy and Stern (1990), such analyses are useful in three areas. First, they might help "design quantitative models aimed at predicting the use of paths dependent on the path and travelers' characteristics". Therefore, traffic flows in the network can be estimated and the network performance evaluated.

The second application of path choice analyses is to predict travelers' reaction to proposed network changes: which alternative will they choose, and how will that affect congestion and travel time in the network? Such information can shed light on network and facility design, service and operational systems. There are two sub-questions: whether the individual decision is for the best interest of the traveler, and whether the aggregated decisions are in the best interest of society. If the answer is no, and if inconsistencies exist between individual and societal interests, guidance should be provided by public transport agencies to help travelers select "optimal" paths for the society. According to King and Mast (1987), the potential benefit from time savings, decreased accidents, and reduced air pollution might be significant, as high as $ 80 billion per year in the United States and about 600 million pounds a year in the United Kingdom.

Path choice is also a useful tool for transfer analysis in public transport networks for two main reasons. First, direction matters for transfers, and analysis at the travel-path level is able to provide researchers the spatial location and the detailed directional information for transfers. In contrast, mode choice models often ignore or are unable to incorporate such information. Second, transfer behavior will be better captured and understood if other types of travel decisions, such as mode choice, time-of-day choice, or destination choice, are better controlled for. In a perfect situation when only a transfer decision distinguishes two alternatives, the observed behavioral difference can be attributed only to that transfer decision. Theoretically, mode choice is not inferior to path choice in this regard, but empirically, mode choice tends to involve a wider range of factors than just transfers. For example, when mode choice is between private cars and public transport, transfers are often required in the public transport alternative, thus attitudes towards transfers are hard to separate from the modal preference for public transport. It is less problematic when mode choice is between different systems in a public transport network because transfers can occur in all systems. Path choice can minimize this problem when the alternative paths are within the same system.

There are two main approaches to collect path-choice data: stated preference (SP), and revealed preference (RP). The main difference between them is that in SP, the conditions, such as choice situation, choice set, and attributes, are known because they are manipulated and controlled by the researcher. In other words, the input is known, and only the output is yet to be observed. In RP, however, both conditions (input) and behavior (output) have to be observed. The relative advantage of SP is the controlled nature of the choice scenarios. This feature allows greater freedom in defining choice contexts, alternatives, and attributes; as well as direct comparison of the responses across individuals and over time (Bradley and Bovy 1986). However, SP also has a disadvantage by the fact that the choice situation is usually uni or bi-dimensional, which is not a realistic image of paths which, in reality, are often perceived in four-dimensional space (Bovy and Stern 1990). RP has the advantage of increasing realism and validity, which lead to more definitive results than SP, but RP has the disadvantage of difficulty in controlling for the variety of choice contexts, choice sets, and attributes. In transfer analyses, RP is especially advantageous over SP because it is able to provide a large variation of transfer behavior and environments and detailed spatial and directional information on transfers. Both are critical to transfer planning practice.

3.2.2 Path Choice in Public Transport Networks

Public transport networks differ from road networks in at least two respects. First, compared to road networks, public transport networks usually comprise fewer links, but each link is critical to the network performance. Second, and maybe more important, a public transport network has scheduled non-continuous services, which imposes constraints on travelers' travel decisions (Wilson and Nuzzolu 2004). With these two characteristics, path choice in public transport networks differs significantly from that in a road network, in terms of path definition, path correlation, choice set size, and choice set generation. I discuss the last two issues in the following section.

A travel path can be clearly and unambiguously defined in a road network for driving, walking, or cycling, but the situation is more complicated in public transport networks. With platforms, tracks, stations, and scheduled services (lines or branches), a public transport travel path can be defined in multiple ways. It can be a sequence of tracks or platforms, a sequence of service lines, or any possible combinations between the infrastructure and service, say a sequence of lines and stations. Analysts who use different definitions obtain relatively diverse results in measuring travel behavior in a public transport network.

For example, Figure 3-1 shows six simple network examples, each having two travel paths. Black dots represent origin and destination stations, and white dots represent a transfer or a pass-through station. If the path is defined as a choice, the two paths shown in (a) and (b) are viewed as identical by travelers, while paths in other situations are different from each other because they involve a travel decision. Suppose there are four possible path definitions: (1) sequence of platforms and tracks, (2) sequence of origin, transfer, and destination stations, (3) sequence of service lines, and (4) sequence of service lines and branches. The first two are strictly based on physical infrastructure, and the last two are solely based on service provision. Applied to the six cases in Figure 3-1, these definitions perform differently.

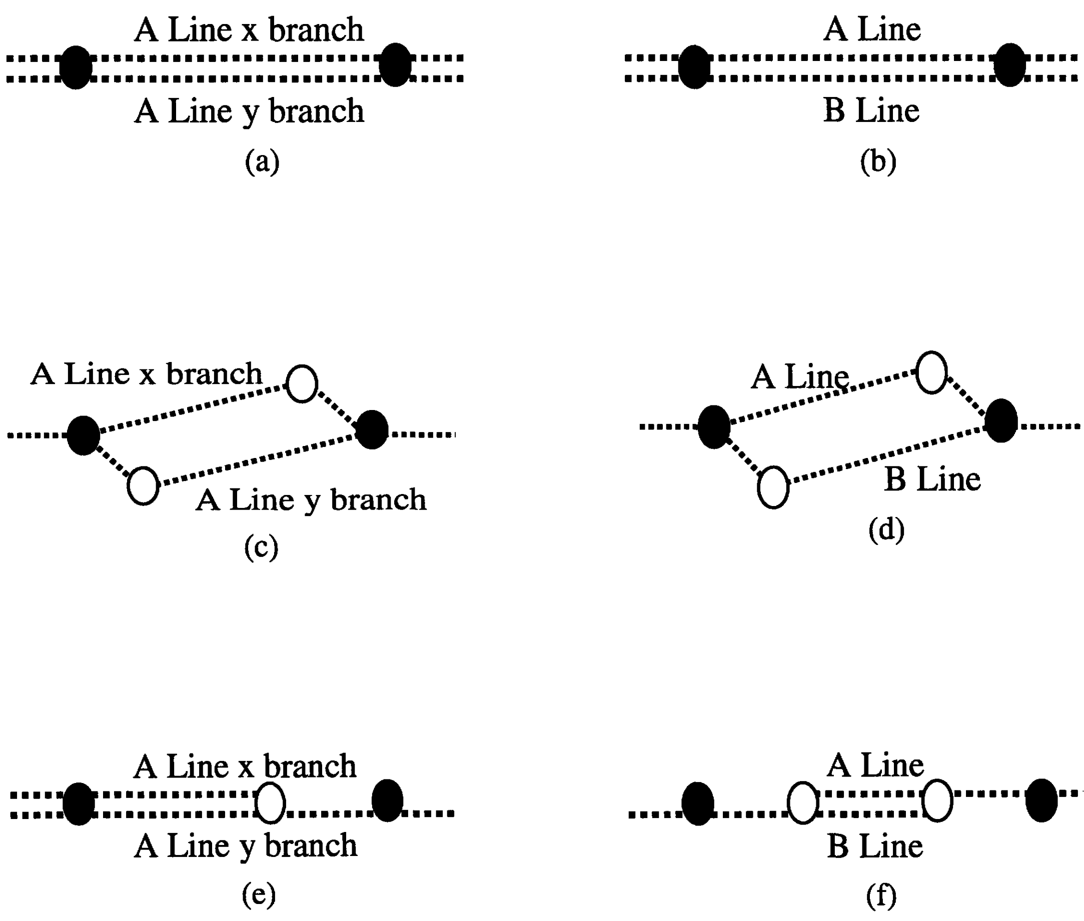


Figure 3-1 Travel Path Examples in a Public Transport Network

Definition 1 can differentiate between the two paths in cases (c), (d), (e), and (f), while treating cases (a) and (b) as having only a single path, which is reasonable. Definition 2 can differentiate paths in situations (e) and (f), while treating both paths in cases (a), (b), (c), and (d) as the same, which is correct for (a) and (b), but incorrect for (c) and (d). Definition 3 treats paths in all situations as different, which is, again, problematic for cases (a) and (b). Definition 4 can differentiate paths in cases (b), (d), and (f), but treats those in cases (a), (c), and (e) as the same, which is wrong for cases (b), (c), and (e).

Which definition is appropriate for this research depends on the characterization of transfer behavior, suitability of path choice analysis, resulting sample size, and data availability. I choose Definition 2 because it achieves a good balance among the four criteria. Definition 1 is able to provide detailed information for transfer and path choice analyses, but it tends to yield a larger size of a choice set than necessary, and obtaining data with such spatial detail is likely to be difficult. Definitions 3 and 4 are unable to support path-choice modeling and detailed transfer analysis. They tend to reduce the choice set size and the number of observations because many different paths might be consolidated under this definition. Furthermore, service and branch information is often hard to obtain from travel surveys.

Many paths overlap to varying degrees due to common road segments or nodes, which add complexity to path choice analyses. In public transport networks, if two paths share a common link, their services are likely to be affected by the similar demand pattern, infrastructure, or operation plans. If two paths pass through the same transfer station, they are likely to be affected by the same station design, crowding level, safety concern, and other transfer experience. Such a node overlap might be more influential to path choice in public transport networks than in road networks because (1) a road path might include many intersections, while a public transport path, in most case, involves two or fewer transfers, and (2) the travel inconvenience caused by a transfer is likely to be larger than that caused by an intersection.

Public transport networks also add another type of overlap to path choice: service. When segments of two paths take the same service line, the two paths are affected by the same level of reliability, crowding, or vehicle design from that line. The main issue associated with path overlap is the correlation between paths (alternatives) in path-choice modeling, which will be discussed in the following section.

3.2.3 Path Choice Decision Process

The decision process associated with path choice is well described by Bovy and Stern (1990). They define three categories of choice process: simultaneous choice, sequential choice, and hierarchical choice. The first refers to when a traveler decides the entire path between origin and destination before he or she starts the trip, and then does not change it. The latter two involve en-route decisions, but in different ways. In the sequential-choice process, a traveler needs to make a choice at each decision point along the trip among the sub-paths, but these follow-up decisions are independent of one another. In the hierarchical-choice process, the traveler needs to make a choice at each decision point, but that decision is dependent on previous choices.

Available evidence suggests that all three processes occur in reality, but the simultaneous choice process seems to outnumber the other two. For example, Bovy and Stern cited a Dutch study conducted Jansen and Den Adel (1987) who found that 75 percent of travelers followed a simultaneous process, while only 25 percent took en-route decisions. Benshoof (1970) sampled 1300 drivers in northern England, and asked them whether they chose their paths before getting into the car, soon after getting into the car, or along the journey. Sixty-nine percent of respondents chose the first alternative, 16 percent the second, and 15 percent the third. The share of simultaneous-choice decisions might be higher for travelers in public transport networks especially in urban rail systems, because it is more difficult to acquire travel information and change behavior accordingly in these systems than in a bus or car within a road network. In this research, I assume a simultaneous process in path choice decisions.

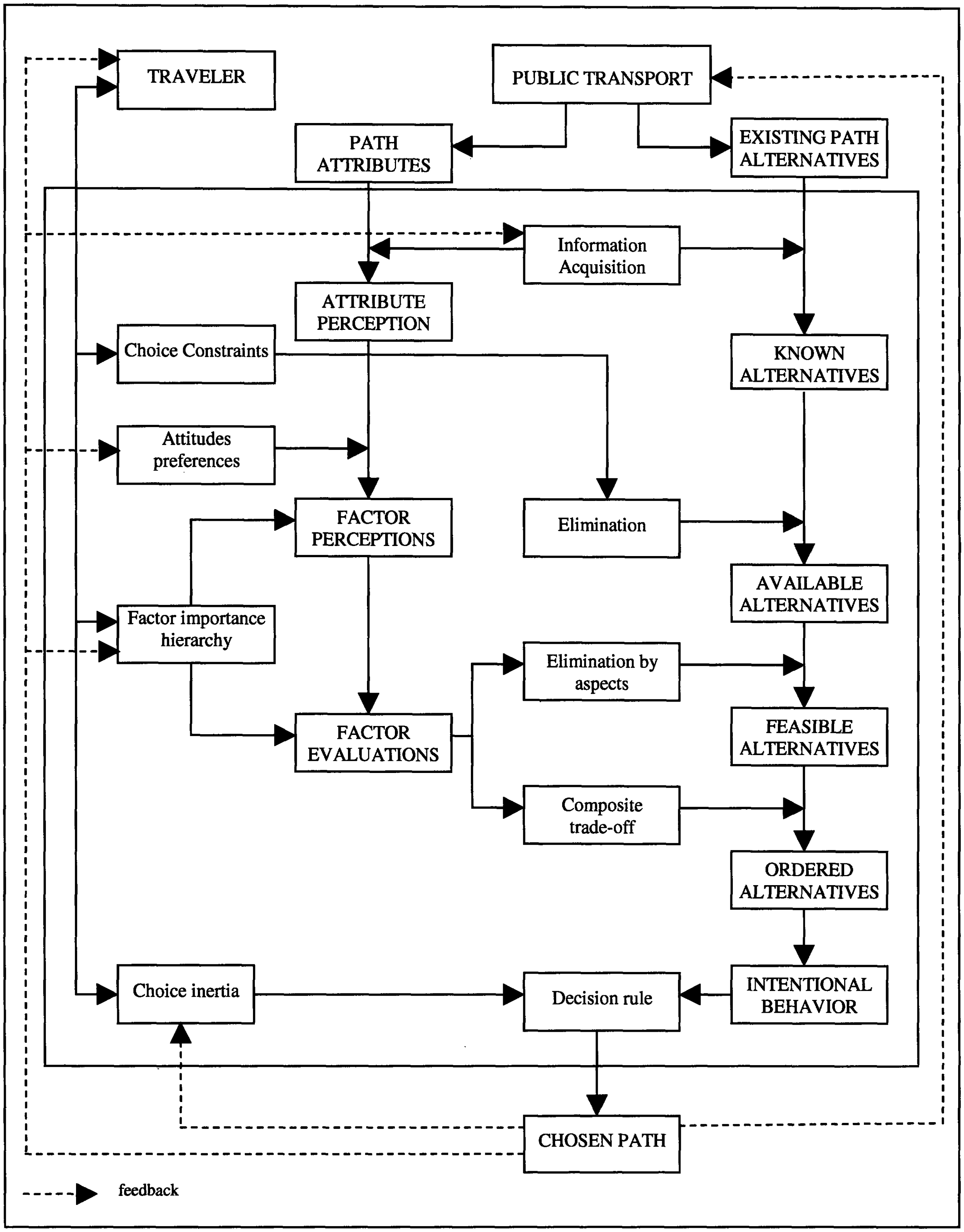
In terms of the detail of the choice process, I follow the conceptual framework proposed by Bovy and Stern (1990). Figure 3-2 shows the adaptation of such a framework to path choice in public transport networks.

The input to this generic framework consists of:

1. a traveler with his or her subjective needs, experiences, preferences, and perceptions;
2. a physical environment, i.e., public transport networks, with its objective opportunities and their characteristics.

The public transport network offers multiple options to travel from an origin to a destination. The number of alternatives available for a specific trip might not be as large as the set in a road network, but can still be significant due to the various types of spatial overlapping. Travelers only have limited knowledge (cognition) of all available alternatives. That cognition is associated with the previous travel experience (feedback from usage of chosen alternatives) and their manner of acquiring information like reading maps, checking timetable, and asking others. To some extent, this cognition is a distorted image of the actual situation: the acquired information is incomplete or inaccurate or the perception is affected by personal attitudes and preferences (Hoogendoorn-Lanser 2005).

Not all known alternatives are available to the traveler for a particular trip. There can be constraints that preclude the use of one or more paths in certain situations (referred to as



Source: adapted from Bovy and Stern (1990)

Figure 3-2 Conceptual Framework of the Path Choice Process

Elimination in Figure 3-2). They include system constraints, such as stop closure, service disruption due to maintenance, door closure due to over-crowding, etc., and personal constraints, such as time conditions, physical handicaps, safety concerns, etc. With these constraints, known alternatives are reduced to a sub-set of feasible alternatives.

Not all known and feasible alternatives are considered in the choice process. "Being considered" means attributes of alternative are evaluated by a traveler, and compared among alternatives. However, not all attributes of alternatives are equally important to a traveler in making a decision and some attributes may compensate for others to a certain degree. This may be expressed in the relative value that the traveler gives to them: high or low, positive or negative (Bovy and Stern 1990). Under such a factor-importance-hierarchy, many alternatives may prove not to be satisfactory or useful. Only after a limited number of feasible alternatives remains, will the traveler make a more in-depth evaluation, trade offing among counter-balancing attributes by creating a composite utility function to reflect the relative evaluation of all aspects of alternatives. Travelers then are able to put the alternatives into a preference rank order. According to certain rules, travelers can decide on the alternative to be used. In this process, inertia will play an important role, meaning that travelers tend to stick with earlier choices and only change routine behavior if certain annoyance or pleasure thresholds are crossed.

This process will further reduce the size of the choice set. Evidence suggests that, in reality, the number of alternatives evaluated or ordered in the choice process is relatively small. As Jansen and Den Adel (1987, cited by Bovy and Stern 1990) found in their in-depth interviews with 50 commuters in the Netherlands, the average number of known paths is 4. Benshoof (1970) also found that most motorists consider only two or three paths to be available.

Both studies targeted a road network, and the number might be even smaller in public transport networks, due to their limited number of links.

The choice process outlined above shows that path choice is not a direct and simple derivative of the observable characteristics of the traveler and the public transport network. It can be seen as a complicated system of filters through which information is selected and transformed. Two types of filters can be identified: perception and evaluation filters (Bovy and Stern 1990). The former formulates travelers' cognition of the existing alternatives and their known attributes, while the latter transforms these perceptions into a desirable scale.

This process is far from being static, the most important being feedback from the usage of previously selected paths. The learning process is thus involved in cognition and perception because information acquired through earlier experience is processed in the next decision. With respect to evaluation aspects, attitudes and preferences might be adapted due to discrepancies between anticipated and actual experience (Bovy and Stern 1990).

It is expected from the nature of the choice process that the path choice decision is a very personal matter. Therefore, strong individual differences in preference and behavior will occur, which cannot be easily reduced to observable demographic characteristics such as age or sex. Despite the strong idiosyncrasies, different individuals may reach the same path choice decision, though on different grounds. From the perspective of influencing behavior or evaluating policy initiatives, knowledge of underlying individual differences is desirable. I discuss this issue again under path choice modeling and in the following empirical case studies.

3.3 Choice Set Generation and Path Choice Modeling

Path-choice modeling is based on the discrete choice theory described earlier, and takes the form of random utility models (RUM). However, in contrast to other choice problems, such as mode or destination, a path through a network is a more complex object of choice (Fiorenzo-Catalano 2007). This is true especially for a public transport path for four reasons. First, path attributes affect the path disutility in complicated ways, some are simple and linear (distance and time) while others (fares or tolls) are not. Second, there exist attributes at the path level that do not have a corresponding attribute at the link or node level; thus, they cannot be derived from the constituent path elements. Examples include direction, angularity, hilliness, etc. Third, paths often overlap with each other to some extent causing the correlation problem in model estimation. Finally and most important, a choice set is more difficult to identify in path choice than in mode choice situations. The last two issues are critical to path-choice modeling, and I discuss them in detail in this section.

3.3.1 Path Choice Generation

The basic role of the choice set is to provide insight into available travel opportunities in particular network conditions. Based on the choice process described earlier, the choice sets play a critical role in choice model estimation and demand prediction, significantly influencing the validity of parameter estimates and predicted demand levels. As a first step in path choice modeling, an analyst needs to generate the choice set with a sound theoretical basis and make it consistent with empirical behavior. I first discuss the criteria or requirements for choice set generation, summarize current generation approaches, and propose a method suitable for this research.

According to Fiorenzo-Catalano (2007) there are three levels of requirements on choice set generation: individual path, individual traveler, and group of travelers. The generated paths should be reasonable in that they should meet logical, feasibility, behavioral, and perceptual conditions. A reasonable path does not contain loops, have detours from the shortest path that exceed a threshold, and has a hierarchical quality. For an individual traveler, the generated choice set should be such that:

1. any two paths should not have overlap beyond some threshold value; otherwise, they become too similar to allow a comparison;
2. any two paths should not differ by more than some threshold value because; otherwise, they become too different to allow a comparison;
3. the unique segments of two paths should be within a certain range to avoid unreasonable detours;
4. the choice set size should not contain either too many or too few paths.

For the generated choice set for all targeted individuals, these four requirements should still hold as well as an additional requirement on variability: or the generated paths should possess sufficient variation with respect to path types and attributes, and traveler characteristics.

Table 3-1 summarizes the three types of requirements adapted from Fiorenzo-Catalano (2007).

Most generation approaches are heuristic because it is very complex to specify clear objective functions for the best prediction of the path choice set. Nearly all procedures assume that path properties can be described by the properties of constituent links. Almost all approaches are based on shortest path search, except the one based on an enumeration approach with the Branch & Bound technique. This is prompted by the circumstance that any paths

Table 3-1 Requirements for Path Choice Generation

Type	Individual (OD Pair)	Group Level (OD Zone)
Single Path	Acyclic criteria Detour criteria Hierarchic quality	
Choice Set	Overlap criteria Comparability Detour-max criteria Detour-min criteria Choice set size	Overlap criteria Comparability Detour-max criteria Detour-min criteria Choice set size Spatial variability Preferential variability

Source: Fiorenzo-Catalano, 2007

between two given points can only efficiently be determined with the aid of shortest-path algorithms. There are two types of shortest-path search algorithms reported in the literature: single criteria and multiple objectives. The latter is more difficult to solve and requires much more computation time. Fiorenzo-Catalano (2007) also suggested that single-objective approaches might perform well not only in computation time but also in terms of quality of generated route.

In the reminder of this section, I evaluate five single-objective approaches based on the requirements mentioned above. Table 3-2 summarizes the results. For a detailed description, see Fiorenzo-Catalano (2007, pp.161 – 188).

The k-shortest path (Lawler 1976,_Shier 1979, Ziliaskopoulos 1994)

This approach generates choice sets that consist of the k-shortest paths according to a given criterion. The algorithm changes the network by excluding some links at each iteration in the process. The number k is determined so as to cover the chosen alternatives. This method is easy to understand, and can be applied to both road and public transport networks. However, the method relies on chosen alternatives, and those not revealed by surveys may be under-represented. Generated choices tend to be similar and they are not necessarily competitive (Park and Rilett 1997, Scott et al. 1997). This method is not flexible in the sense that it is difficult to force the method to generate particular alternatives. Each individual traveler has an equal number of generated alternatives. Finally, this method is applicable only to single OD pairs (Fiorenzo-Catalano 2007), and is computationally expensive on a network basis. For these reasons, the k shortest-path method is not applicable for the path choice generation problem at hand.

Constrained k-shortest path is an extension of the original k-shortest path method, which finds the k-shortest path(s) each of which satisfies predefined constraints. Generated paths have more variability than those from the original method. However, the check of all constraints during the generation process may slow down the performance of the method. It is also applicable only to single OD pairs, and it is not completely useful for the path choice generation required for my research.

Link elimination (Bellman and Kabala 1968, Martins, E.Q.V. 1984, Azevedo et al., 1993)
This method generates paths that are variations of the shortest path by removing some or all links from the current shortest path. The process stops when it generates a predefined number of paths or when no more paths are generated due to the removal of links. This approach may be computationally efficient compared with the k-shortest path method, but the quality of choice set might be very poor. One danger of eliminating some or all links on the shortest path is

Table 3-2 Comparison of Path Choice Generation Methods

Methods	Behavior knowledge	Requirements						Applicability to large networks	Estimated with Commercial Software?	Computation Effort Required	Appropriate Approach?		
		Acyclic	Overlap	Detour	Compara-bility	Choice set size	Variability				Generic	Flexibility	Parsimony
k shortest path	Heuristic	Yes	No	No	Yes	No	No	No	No	High	Yes	No	No
Link elimination	Heuristic	Yes	No	No	Yes	No	Yes	No	No	High	Yes	No	Yes
Branch & bound	Heuristic	Yes	Yes	Yes	Yes	No	Yes	No	No	High	No	Yes	No
Labeling	Theoretical	Yes	No	No	No	Yes	Yes	Yes	Yes	Moderate	No	Yes	Yes
Simulation	Theoretical	Yes	No	No	Yes	Yes	Yes	Yes	No	High	Yes	Yes	No

Sources: Fiorenzo-Catalano 2007, Ramming 2002, and Hoogendoorn-Lanser 2005.

removal of critical paths resulting in a disconnected network. On the other hand, eliminating one link at a time might result in very similar, highly overlapping paths. This method is only applicable to single OD pairs, and is not an effective method for path choice generation.

One adaptation of the elimination method is incrementally increasing the impedance of links on the current shortest path to find a new path. This is called the link penalty method (De la Barra et al., 1993). It shares many of the characteristics of the elimination method, without resulting in disconnected networks. The results are sensitive to the level of impedance, which may be too small or too large. A small penalty may not achieve sufficient dissimilarity, whereas a large penalty may eliminate many feasible paths from consideration. This method is also only applicable to single OD pairs, and it is not an effective method for generating path choice.

Branch and bound (Friedrich et al. 2001, Prato and Bekhor 2006)

This method adds a new link one node on and one node off the current shortest paths, while the generated paths are bounded by multiple constraints. It was originally developed for a public transport network, and has been used for multimodal network analyses (Hoogendoorn-Lanser 2005). The approach is flexible in the sense that the algorithm consists of a set of constraints that should be satisfied by separating partial and complete trips. This method can generate reasonable and heterogeneous paths. Tests conducted by other analysts suggest that this method performs better in reproducing the observed path than simple labeling or link elimination approaches. However, in some cases, this method may delete some active alternatives. It also tends to generate unrealistically large choice sets. This method is applicable only to single OD pairs. It is computationally inefficient because of the potential size of the branch-bound tree. For these reasons and because of the type and size of the public transport network analyzed in this research, exhaustive methods that try to determine and enumerate all available paths within constraints are not realistic.

Simulation (Sheffi and Powell 1982, Fiorenzo-Catalano 2007)

Researchers using this method find a choice set by repeating the shortest path search on the network while randomly drawing link and/or travel attributes from assumed distributions. The method can generate a relatively small choice set with large variability (Fiorenzo-Catalano 2005, Nielsen 2000). Ramming (2002) stated that the method resulted in a good coverage of observed paths with a reasonable computation time. This method is applicable to both single and multiple OD pairs. However, the method might be slow in computation because of the high number of iterations needed to generate an adequate choice set. In my research, because the purpose of choice set generation is to generate paths to estimate path attributes, the distributional parameters from which simulations are drawn must come from another source (Ramming 2002). One concern about this method is that the distributions used to draw attributes and preferences are often unjustified.

Labeling (Ben-Akiva et al.1984)

Researchers using this method find a choice set that consists of all labeled shortest paths that are each optimal for a specific label from a given label set. The method matches several of the requirements listed earlier. It takes taste variation into account, and includes heterogeneous path choices. Prior studies showed that this method performed well in generating reasonable routes and resulted in good coverage of observed paths (Ramming 2002). The method is applicable not only to single OD pairs, but also to multiple OD pairs simultaneously. It is flexible because it can easily analyze specific policy questions by specifying dedicated labels, e.g., by giving targeted link or link-type specific cost values. From a computational point of view, this method is very easy and efficient. The method can be easily implemented with commercial software using the Finding Optimal Path function. The only problems of this method are that it might generate identical paths; the choice set size is small; and sometimes it is difficult to define the labels. All in all, the labeling approach is an interesting method for generating a choice set (Fiorenzo-Catalano 2007).

There are other generation methods, and many are extensions of combinations from the five methods discussed above. Although there is no single perfect approach to meet all requirements, two methods stand out and outperform others in many respects: the labeling approach and the simulation method. Both yield satisfactory results while the simulation method is technologically more complex and computationally more demanding. For this research, I choose the labeling approach because of its sound theoretical base, reflection of actual decision process, simplicity in computation, and link to policy concerns. It can also be easily implemented in available commercial software, which is critical to its application in practice in public transport agencies.

3.3.2 Path Choice Modeling and Path Correlation

There are different approaches to model path choice in public transport networks, such as aggregate approximation, user equilibrium, and production-rule system. However, the most widely used path choice models are the random utility models (RUM), discussed earlier. The path-choice modeling I use is based on random utility models. In this section, I review a selected number of RUMs applicable to path-choice modeling and propose three models for the empirical studies. For a summary of all models, see Bovy and Stern (1990) and Ramming (2002).

The basic type of random utility models for path-choice modeling is the multinomial logit (MNL) model. Under this model structure, each path is treated as an alternative. However, MNL has a serious drawback in dealing with path choice. The most critical assumption with MNL is that the error terms are independent and identically distributed (i.i.d.). Clearly, this condition does not hold in the path choice situation since there will often be partial overlap between different paths (i.e. common links and/or nodes) leading to positive correlation among the error distributions of random utility models. This correlation between alternatives (paths) results from the assumption that the attractiveness of a leg contributes in the same way to the attractiveness of all paths containing that leg. Travelers' preference of a leg is assumed to be constant and independent of the paths containing this leg. Consequently, there is a positive correlation between travelers' preferences for the path with common legs (Hoogendoorn-Lanser 2005). Without controlling for the correlations, MNL would overestimate the use of paths with common links and would result in serious errors in predicted link flows (Fiorenzo-Catalano 2007).

Depending on how this correlation is controlled for, different MNL-based models are developed from the simple nested logit (Ben-Akiva and Lerman 1985), to the complex implicit availability/perception logit (Cascetta and Papola 1998), cross-nested logit (Vovsha and Bekhor 1998), and mixed logit (Ben-Akiva and Bolduc 1996, McFadden and Train 2000).

I review these models according to their technical complexity, availability in commercial software, and applicability to public transport networks. Paths in public transport networks usually involve fewer links and, in most cases, fewer than two transfer station nodes. The correlation across nodes (transfer stations) is likely to be more influential in public transport networks than in road networks. Based on the analysis, I finally adopted three types of models: modified MNL, nested logit, and mixed logit. They are not the most complex models, but they can still deal with correlation effectively but in a simple way.

Modified Multinomial Logit

I modified standard MNL in this research to have the traditional model structure, but specify explicitly the link or node correlation in the path utility function. Mathematically, the utility function of a typical MNL model expressed in Equation (5) is revised as

$$V_j = \sum_k \beta_k x_{jk} + f_n(N) + f_l(L) \qquad (10)$$

N is the set of nodes that are included in at least two paths, while L is the set of links that belong to at least two paths. f_n and f_l are functions specified for a particular node or link. The functions are then applied to all nodes and links in N and L, which have a value of 1 if a node or link is that particular node or link the functions refer to, and 0 otherwise. This process adds $N * N + L * L$ dummy variables to the utility function. Obviously, it is computationally infeasible if N and L are large. In practice, often a small subset of N and L is checked, which include the critical nodes and links in the network. In the London case study, the subset of N includes 23 major interchange stations.

The modified MNL might be an effective solution due to two reasons. First, the fewer possible overlaps, especially for the nodes, between paths in public transport networks makes it a feasible approach. In road networks, the large number of overlaps between many links and nodes (intersections) make it impossible to specify each individual node or link in the utility function. Second, as Bhat and Pulugurta (1998) found, sophisticated model structures might lead to worse estimation results if the model assumptions are too strong, the quality of collected data is poor, and the underlying travel behavior is not well understood. That is why even MNL models have been applied widely for path-choice modeling (Dial 1971). In this case, a simple model structure might perform better than a complex one. I apply the modified MNL to the London case study, as discussed in Chapter 5.

Nested Logit (NL)

The partial correlation among paths can also be viewed from a hierarchical perspective: two paths share a common trunk and then follow different sub-paths to reach the same destination. For this multi-dimensional choice, nested logit can be applied. All paths sharing the same trunk segment are viewed as belonging to the same "nest". The utility of this nest is based on the combination of the utilities of alternative (paths) within the nest, which is the expected value of the maximum utility of those paths. Ben-Akiva and Lerman (1985) have shown that the expected maximum utility can be calculated by the "logsum" formulation:

$$IV_k = \frac{1}{\mu} \ln \sum_{j \in k} e^{\mu V_j} \tag{11}$$

Where IV_k is the inclusive value of nest k with a value between 0 and 1. A value of 0 suggests that the two paths are completely overlapping with each other. A value of 1 means that the two paths are not correlated with each other and the nested logit model reduces to multinomial logit. A value greater than 1 generally suggests that another nesting structure is appropriate, for instance, reversing the hierarchical order of a multi-dimensional choice. Under the nest structure, the probability of choosing an alternative is revised:

$$P(j)=\frac{e^{\mu V_j}}{\sum_{j\in k} e^{\mu V_j}} * \frac{e^{\mu(V_j+IV_k)}}{e^{\mu(V_j+IV_k)}+\sum_{l} e^{\mu(V_l)}} \tag{12}$$

Where l refers to all choices additional to the nest. This example assumes one nest, but the model can have multiple nests at multiple levels.

Nested logit models have a more flexible error structure than MNL models and can account for the correlations between paths if these can be assigned exclusively to branches in a hierarchical-nesting structure. However, when alternatives cannot be partitioned into well-separated nests to reflect their correlation, nested logit models are not valid. This is the case of path choice problems because each alternative can only be assigned to a single nest. Therefore, they are not applicable to path-choice modeling in complex choice situations. I use nested logit models in the Boston case study.

Mixed Logit

Mixed logit models are also known as Logit Kernel, and have been introduced by Ben-Akiva and Bolduc (1996). The disturbance term of the utility includes both a probit-like portion and an additive i.i.d. extreme-value portion (i.e., the MNL disturbance). The result is an intuitive, practical, and powerful model that combines the flexibility of a probit model with the tractability of a logit model. For this reason, mixed logit is becoming extremely popular in the field.

The mixed-logit specification, known as random parameter specification, involves specifying each beta parameter associated with a path attribute as having both a mean and a standard deviation. In other words, it is treated as a random parameter instead of a fixed parameter. The general form of the Logit Kernel model (in vector notation) is given by Walker (2001) as:

$$U_j = X\beta + \varepsilon = X\beta + FT\xi + \upsilon \qquad (13)$$

where U is a J_n by 1 vector of utilities;

β is a column vector of K unknown parameters;

X is a J_n by K matrix of explanatory variables;

ξ is a column vector of M i.i.d. standard Normal variables representing unobserved factors;

F is a J_n by M factor loading matrix to be determined;

T is an M by M lower triangular matrix of unknown parameters to be determined; and

υ is a J_n by 1 vector of i.i.d Gumbel variables with scale parameter μ.

For details of mixed logit estimation and identification, see Walker (2001).

This flexible structure enables mixed logit models to capture the path overlap as long as identification is not a problem. However, a much more central use of the mixed logit model is to specify taste coefficients that are assumed to be randomly distributed across individuals. It provides a powerful way to specify individual unobserved heterogeneity. Although analysts may handle this heterogeneity through data segmentation, the challenge is in picking the right segmentation criteria. A random parameter represents the preference heterogeneity more generally, but the challenge is to choose the appropriate form of distribution. Recent studies on the mixed logit models showed that the mixed logit model improves the fit to the observed choices (Hensher and Greene 2003, Hess et al. 2005, Mabit and Nielsen 2006). However, mixed logit models often suffer from computation difficulties because of the high number of iterations required in the simulation. I apply the mixed logit models in the public transport network application in Boston.

3.4 Multiple Case Studies

For the empirical analysis, I conducted multiple case studies because of the diverse characteristics of transfer behavior across space, time, modes, travelers, and networks. A single case study is unable to cover the richness of all factors affecting transfer decisions. It would be ideal to focus on a multimodal network that includes all transport modes and lines, however, existing systems do not have detailed data adequate to support such an analysis. For example, when a travel survey covers all travel modes (car, bus, subway, regional rail, walking, cycling, etc.), it normally does not record detailed path information. Researchers have to make a trade-off between the depth and breadth of analysis. Hoogendoorn-Lanser (2005) conducted her own survey on multimodal travel in the Netherlands, but her research targeted intercity travel along one busy corridor, which is much simpler than intra-city travel in a major metropolitan region with multiple transport systems.

In this study, I focus on rail systems (urban and regional rail) rather than a complete multimodal network. I choose rail systems because their performance relies more heavily on transfers (see Table 2-1) than other public transport modes. Transfer facilities in rail systems are more complex, and their design is more likely to influence transfer behavior. Furthermore, most transfer-related investments are also in rail systems because most major transfer stations exist in rail systems (TfL 2003).

Given the rail focus, I consider five criteria in order to decide which rail systems should be included in the empirical analysis: system size, variability, data availability, local knowledge and local needs, and prior studies. System size matters because it significantly affects the path choice opportunities. A simple small rail system will have limited paths available for a given origin-destination pair, while a large and complex system might have many path options.

Variability matters because a large variation in the transfer environment would be necessary in order to explore the impact of the transfer environment on transfer behavior. Data availability is always a concern. Travel path information is normally not well collected by public transport agencies. A detailed inventory of transfer facilities is often missing in their databases. Although secondary data collected by public transport agencies will be a major source for this analysis, first-hand data collected through field trips might be a necessary complement. Fourth, one goal of my research is to help planning and operation practitioners. Involving local knowledge and local needs from a public transport system in the research process will help policy-makers understand the problem and develop appropriate solutions. Finally, I also prefer a system that has been investigated in prior studies because of the possibility of comparison.

I choose Boston and London as the case studies because they meet the above requirements very well. The Boston region has a comprehensive but mid-sized public transport network. The system is the sixth largest in the United States including bus, urban rail, and regional rail modes. Transfers happen frequently within the urban rail systems and between the urban and regional systems, but path options are limited because there are only a few transfer stations in the rail network. In contrast, the public transport system in London is large and complicated. The size is about 10 times that of Boston in terms of ridership and network length. Passengers transfer at more than 100 stations. In many situations, multiple paths are available between origins and destinations. For example, based on the London Underground Rolling Origin-Destination Survey (RODS) (TfL 1998-2005), a quarter of origin-destination pairs had more than two revealed paths. The maximum number of revealed paths for an origin-destination pair is 19.

Both rail systems in Boston and London have great internal variability in terms of station design, technology, and service operation. Part of the variability comes from great difference in system age. The Green Line in Boston is the oldest operating subway in the United States, dating back to 1897, while the Red, Blue, and Orange Line were constructed and extended during the 20th century. The three rapid transit lines are not fully compatible with each other: a train from one line cannot run on all other lines. The London Underground is the oldest subway system in the world. The first segment of the Metropolitan line opened in 1863, while the latest segment of the Jubilee line opened in 1998. Accordingly, there is great variation of the connection quality between lines even within the same station. For example, transfers between Victoria and Piccadilly lines at Green Park station are relatively convenient, while transfers at the same station between the Victoria and Jubilee lines are long and inconvenient.

Transfer-related data have been collected in both networks. Both conducted on-board surveys in their urban rail systems (Boston on the subway in 1994 and on the commuter rail in 1993, London on Underground from 1998-2005), which record travel paths (as a sequence of access, alighting, and egress stations) within the systems. The London annual Rolling Origin Destination Survey (RODS) has collected about 250 thousand trips in the London Underground, which represents about eight percent of daily trips in the system. London Underground also has a good inventory of station facilities, which documents the design (i.e. location, platform types, stairs, subway, etc.), equipment (lighting, escalators, lifts, etc.), and amenities (vending machines, cash machines, public phones, information display, waiting rooms, etc.) (TfL Station Database 2006). The Massachusetts Bay Transportation Authority (MBTA), operator of the subway system in Boston does not have such an inventory, but the system's relatively small size and proximity to the Massachusetts Institute of Technology (MIT) make field surveys a viable tool to collect such information.

Another important reason to select these two systems is the long-term collaboration between MIT and the two agencies, MBTA in Boston, and TfL in London. The multi-year program has focused on a jointly developed research agenda analyzing both agencies' critical needs, and resulted in a series of recommendations and/or planning techniques that provide public transport managers with the tools to analyze ongoing challenges. Internship opportunities in the two agencies gave the author first-hand experience of their networks and the transfer issue. Questions and feedbacks from both agencies have helped formulate and refine this research from the beginning. Such a platform provides wonderful opportunities to investigate path choice and transfer issues in Boston and London.

Another benefit of choosing Boston and London is that they represent the European and North American models of public transport. The public transport networks in Boston and London are among the few systems that have been investigated by prior analysts, which facilitates cross-study comparisons.

Chapter 4 BOSTON CASE STUDY

This case study covers the rail network in Boston including the subway and the commuter rail. The network is relatively small and simple: there are not many path options inside the network, and transfers concentrate at a few major stations in a small area in downtown Boston. This characteristic affects the particular questions of interest, methodology being applied, model specifications, and implications in planning and operation in three ways.

First, the relatively simple network allows the researcher to cover transfers in multimodal system: transfers within a single mode as well as transfers between different modes under a more complex transfer situation. However, the network is too simple to support a full path choice analysis. The challenge and one of the contributions of this case study is to develop and apply a method that overcomes these constraints and generates multiple-path options for transfer analysis. Such a method could be a prototype for similar analyses for the majority of public transport systems with small or mid-sized networks. Third, compared to the London case, this study emphasizes developing the new methodology and understanding behavior. It does not focus on direct applications of findings in planning and operation as does the London case. Therefore, in the Boston case I apply more sophisticated models, such as the nested logit and mixed logit models.

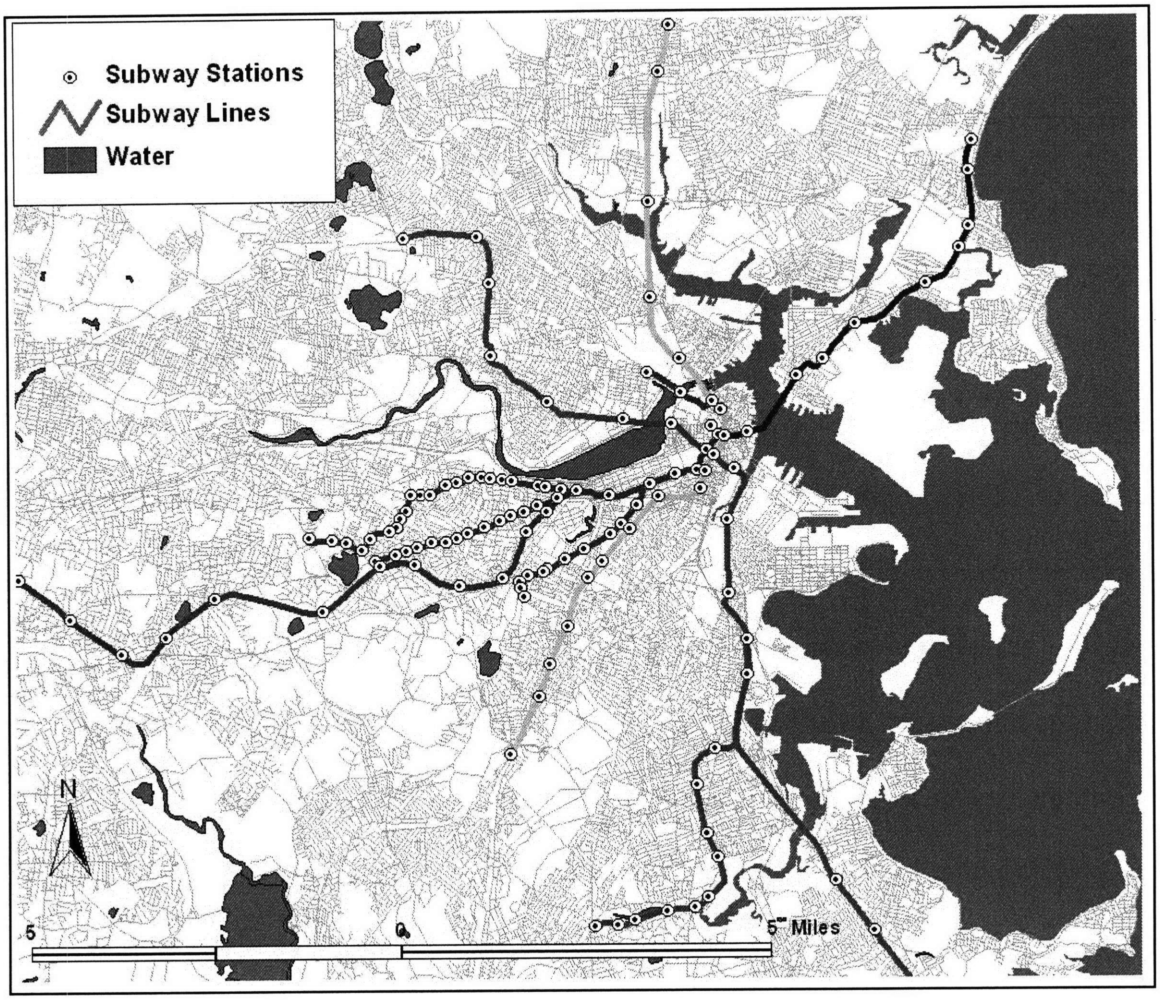
Section 4.1 describes the rail network in Boston. Section 4.2 introduces the new method for path-choice modeling for small or medium size networks. Section 4.3 explains the different emphasis in the subway and commuter rail analyses. Section 4.4 investigates transfers within the subway system, while Section 4.5 targets transfers between commuter rail and subway. Section 4.6 provides conclusions for the Boston case study.

4.1 Description of Rail Systems

The rail network in the Boston metropolitan area consists of two major systems: subway and commuter rail. Both are owned by the Massachusetts Bay Transportation Authority (MBTA), but the subway system is operated directly by the MBTA, while the commuter rail system is operated by Massachusetts Bay Commuter Rail (MBCR) under a contract with the MBTA. The subway system has a total length of 70 miles, and comprises 125 stations on four lines: the Red Line, the Orange Line, the Blue Line, and the Green Line. Daily ridership is approximately 664,000 trips per weekday. The commuter rail network has a total length of 265 miles, comprising 13 lines, with 67 stations and a daily ridership of 110,000 (MBTA website).

Each of the rail systems forms a simple radial network with the commuter rail serving exurban communities and the rapid transit serving the inner suburbs and the urban core (Figures 4-1 and 4-2). Commuter rail is actually two seperate sub-systems: the southern part has eight lines, which terminate at South Station, while the northern part has five lines which terminate at North Station. The lines in each sub-system do not connect with each other except at the terminals and a few other stations including Porter Square, Back Bay, Forest Hills, etc. The four rapid transit lines intersect with each other at four main transfer stations in downtown Boston: Park Street, Downtown Crossing, State Street, and Government Center[7]. The two rail systems connect at the two terminals, South Station and North Station, and at Porter Square and Back Bay (Figure 4-3).

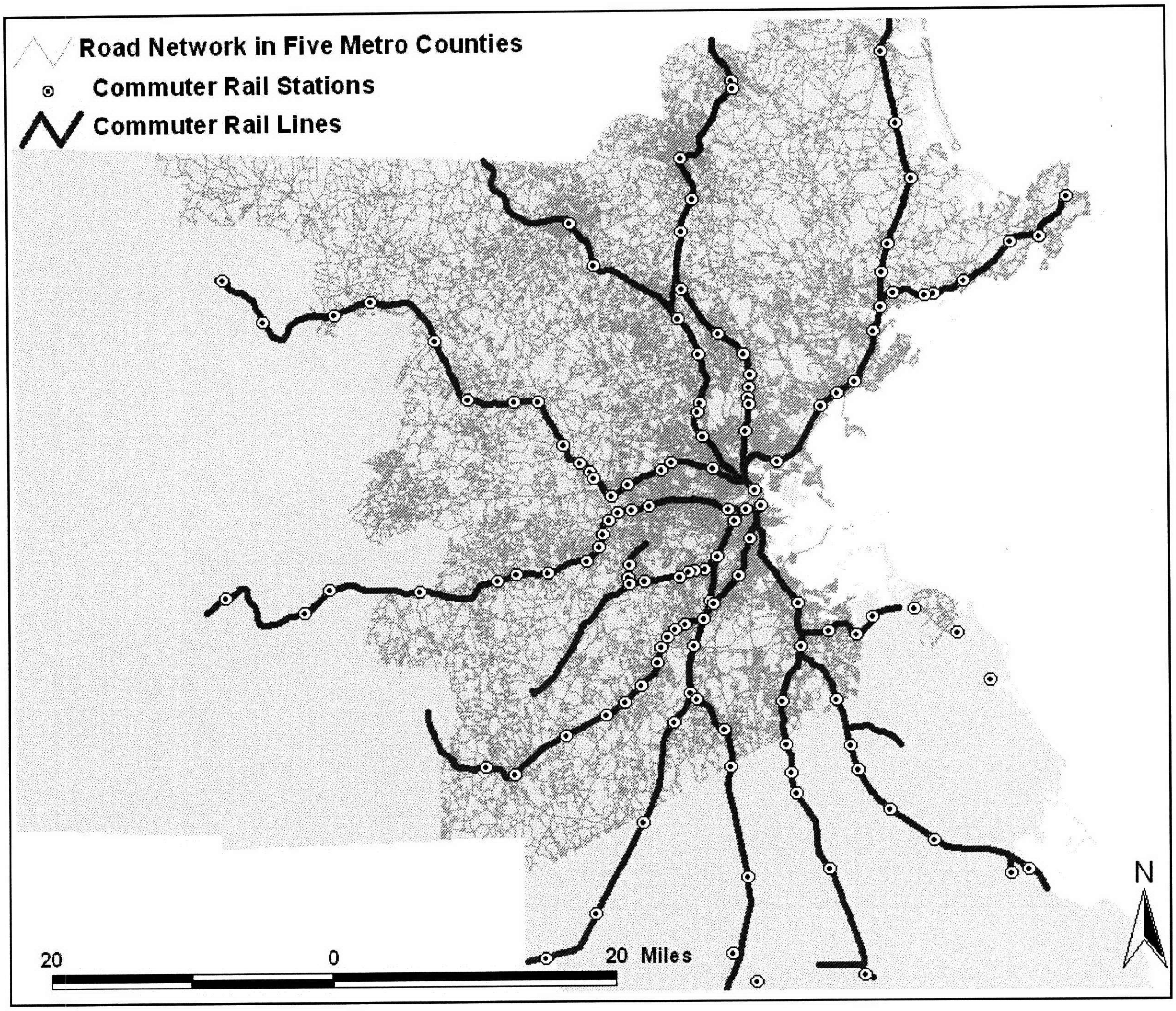
[7] The Orange Line and the Green Line also intersect at Haymarket station running in parallel. It is usually not viewed as a transfer station between the Orange and Green Lines due to its location between North Station and State Street, two main transfers stations between the Orange and Green Lines.



Source: MassGIS, created by the author

Figure 4-1 Boston Subway System

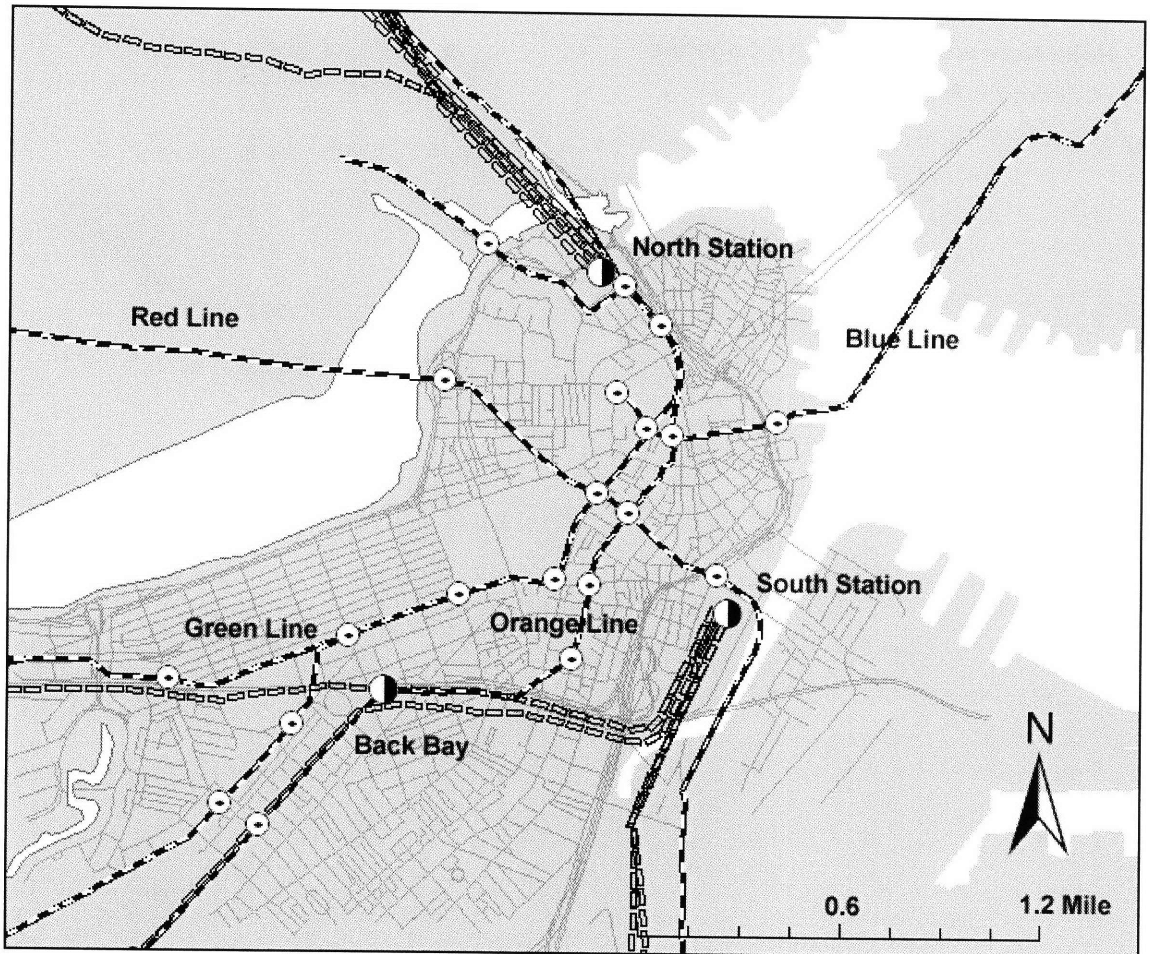
Transfers are frequent and important to the two rail systems. About half of rapid transit trips involve at least one transfer, 30 percent of which are within the system. More than half of the intra-modal transfers happen at Park Street station between the Red Line and the Green Line, which are the highest ridership and longest rail lines in the system (CTPS 1994). Both lines serve job centers outside the Boston CBD: the Red Line serves Cambridge and Quincy, while the Green Line serves Back Bay and Longwood in Boston. For commuter rail passengers, about one-third transfer to or from the rapid transit system because of the limited number of commuter rail stations in downtown Boston (CTPS 1993).



Source: MassGIS, created by the author

Figure 4-2 Boston Commuter Rail System

The simple network provides very limited path options to rail passengers. Most commuter rail trips have only one travel path within the system due to the lack of connections across commuter rail lines and the two sub-networks. The subway system offers multiple travel paths in some special situations, for example for trips that go to the area between the Green Line and the Orange Line, or for trips that involve transfers between the Red Line and the Blue Line.



Source: MassGIS, created by the Author

Figure 4-3 Connections between Commuter Rail and Subway in Boston

However, these trips account for only a small portion of all subway trips, and they provide little opportunity for analysts to investigate transfer behavior. In other words, the network is too simple to support a full path choice analysis. This problem is common to small and mid-sized public transport systems. Therefore, I develop a new method based on path choice at the sub-path level to overcome these constraints. The following section describes this method and applies it to both the rapid transit and commuter rail systems in Boston.

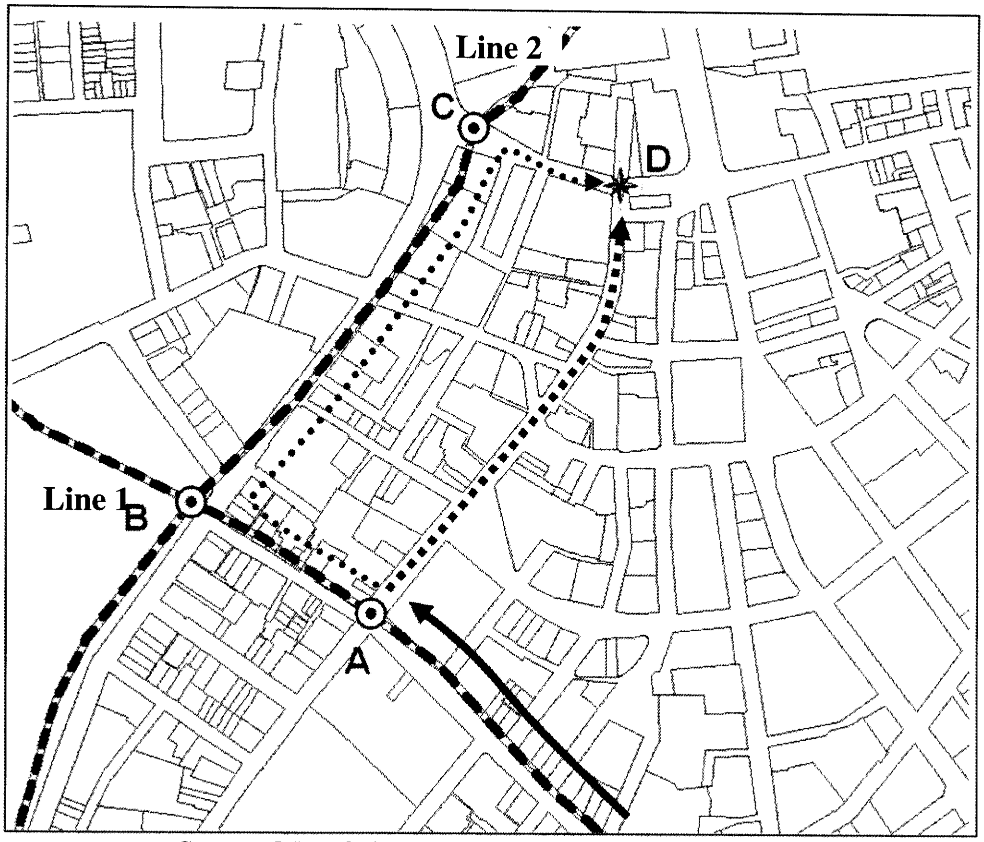
4.2 Analysis Framework

As discussed in the methodology chapter, a path-choice decision is a complex multi-dimensional process. A path often consists of segments in a hierarchical structure, i.e., freeways, arteries, and collectors in a road network, and feeder and long-haul services in a public transport network. These segments are likely treated differently during the decision process. A traveler may decide on the trunk segment first and then choose from connecting segments. In other words, the choice decision, pre-trip or en-route, may also follow a hierarchical structure. The process, however, may not always be complete. In cases where only a single trunk segment is available, travelers will decide only on the connecting segments. In other words, path-choice decisions are not always made at the full path level: they also occur at a sub-path level. Although multiple full-path options are rare in small or mid-sized networks, there might be many sub-path choice situations adequate to support the path choice and transfer analysis. This section describes the analysis framework based on this assumption. The first part introduces the concept, and the second part discusses its application to the subway and commuter rail systems.

4.2.1 Sub-Path Choice Decision

Assuming a trip has three portions: access, trunk, and egress, a traveler may have multiple-path options in the access or egress portions even if there is only one path available in the trunk portion. This partial path choice situation is conditioned on the mode and service the traveler selects for the trunk portion of the path. This will be referred to as sub-path choice. Figure 4-4 illustrates such a situation.

A, B, and C are stations on two separate subway lines, and D is the trip destination. Suppose the traveler enters the area on Line 1 comes from the south. When the traveler reaches



Source: MassGIS, CTPS 1994, created by the Author

Figure 4-4 Sub-Path Choice for the Egress Portion of Transit Trip

station A, he or she has two options to get to destination D. The traveler can leave the system at A and walk to D, or can continue traveling on Line 1 to Line 2, transfer at B, exit at C, and then walk a shorter distance to D which is closer to Line 2 than Line 1. Therefore, the traveler has two possible sub-paths: ABCD or AD. Which path is better depends on the perceived tradeoff by the passengers among four factors: extra in-vehicle time spent on path ABC, transfer penalty at station B, the walking time saved (AD - CD), and the quality of the walking environment along AD and CD. The more convenient the transfer at B, the more walking time saved, the less in-vehicle time from A to C, and the better the pedestrian environment on CD relative to AD, the more likely the traveler is to choose path ABCD. If the last three factors are well controlled, the influence of transfers on the sub-path choice will be captured, and the impact of service quality and facility design on transfer experience can be assessed.

Such a sub-path choice situation has several advantages: it is simple--we do not need to define clearly the attributes of the full path, which is often difficult and time-consuming. Path choice generation might also be easier because only a portion of the network is used, and the feasible sub-paths are constrained by a few available service lines, which can be easily identified manually. Another important benefit of conducting sub-path choice analysis in this type of situation is that it reduces the chance of path correlation because sub-paths ABCD and AD are unlikely to overlap with each other. This significantly reduces the modeling complexity. The sub-path choice focuses on the egress rather than the access portion of the trip. The egress portion is preferred by the author over the access portion because of the concentration of trips in a small geographic area, the lack of competing egress modes other than walking, and the multiple transfer paths available to passengers. This is particularly true of the Boston CBD, which offers little bus service that could be an alternative to rail for the egress portion, but has a concentration of transfer stations.

However, there is also the disadvantage of limited applicability to other contexts. Sub-path choice is for a special situation, and so the applicability of the results to other systems and populations may not be straightforward. I discuss the limitation in the following case studies.

4.2.2 Subway and Commuter Rail

The decision situation described above indeed exists in both subway and commuter rail systems as demonstrated in this chapter. However, there are significant differences between the two systems. First, transfers in the subway case are within the same system because the transfer line

(Line 2) is also a subway line. Transfers associated with commuter rail trips are between commuter rail and subway due to the difference of their system functions and network layouts. The choice situation is much simpler in the subway case: most qualified subway trips are well represented by Figure 4-4. Only a few passengers transfer twice in the system. In contrast, transfers from commuter rail to subway are more complicated, involving simultaneous decisions on station choice and/or line choice. The difference affects the choice generation process and leads to different model specifications with those for commuter rail being more sophisticated than those for the subway system.

I use the difference in the two Boston case studies to emphasize different aspects of the questions of interest. Both studies examine the variation of transfer behavior in addition to the average experience, but I use the subway study to focus on the spatial variation of transfer experience due to the differences in transfer facilities, while I use the commuter rail study to focus on the heterogeneity across individual travelers. The reason for such a differentiation is because, from a passenger point of view, there is little variation of transfer environment in the commuter rail case. First, due to the separation of the north and south sub-systems, commuter rail passengers often do not have multiple transfer stations to consider. For example, passengers from the north who plan to transfer to the subway have only one option, North Station. Second, the differences among transfer directions are minimized due to the long walk between commuter rail and subway platforms. In the subway case, four transfer stations and 34 transfer movements offer sufficient variation to support such an analysis.

In the following sections, the subway study covers the variation of transfer experience across space, time, trip purpose, and demographic characteristics, while the commuter rail study accounts for intermodal transfers, costs, and market heterogeneity.

4.3 Transfers within Subway System

There are three objectives in this case study. First is to test the proposed method—whether it can be used to explain the transfer behavior in the system. Second is to examine the contribution of different components to the transfer penalty: transfer walking, transfer waiting, extra in-vehicle time, walking time, physical environment, and the residual penalty. Understanding such contributions is important because this is the basis for identifying improvements that can reduce the transfer penalty. Previous analysts did not decompose the transfer penalty into different components because this type of information is transfer-facility-specific, and the previous datasets and methods were unable to incorporate this information. The third objective is to test the variation of the transfer penalty, in addition to the system average, across stations, movements, time, trip and demographic characteristics.

Sections 4.3.1 and 4.3.2 introduce the datasets and variables. Section 4.3.3 describes the path choice generation process. Section 4.3.4 develops a series of models. Section 4.3.5 and 4.3.6 discuss the estimation results and provide conclusions for the subway case study.

4.3.1 Datasets

The main dataset used is the Massachusetts Bay Transportation Authority (MBTA) 1994 subway on-board survey. On-board surveys, which are readily available in major transit authorities, interview individual travelers asking for trip origin and destination outside the system, and the access, interchange, and egress stations in the system. Their uni-modal focus limits the usage of on-board surveys in travel-demand analyses. They are, however, a good source to explore path choice behavior within a single mode given their rich information on travel path and travelers.

The on-board survey was conducted on the four lines in 1994 by the Central Transportation Planning Staff (CTPS 1994). Survey forms were distributed at station entrances on several workdays in November 1994. Surveyors asked for the origin and destination addresses and boarding and alighting stations of their current trip, as well as detailed trip and demographic characteristics and comments on service quality. There are a total of 38,888 trips in the data set. Because the survey was conducted from 6:00am to 3:30pm, evening peak trips were not included. These trips usually involve fewer time constraints, and more trip chains, so that transfers may be perceived differently in the evening peak.

In addition to the on-board survey, I also use two other datasets, mainly for the measurement of the quality of the walk path on the street (AD and CD in Figure 4-4). They are the Boston 1996 Assessor Parcel Database, and the Road Inventory database from Massachusetts Highway Department (MHD). Parcel data with basic land-use information from local assessor offices provide detailed information on the parcel type, value, and structural conditions with maps in GIS format. The road-inventory database describes individual road segments including number of lanes, central separation, curb presence, shoulder width, sidewalk width, speed limit, turn direction, etc. It is also associated with road-network maps in GIS format. Controlling for these attributes helps capture the influence of service quality and facility design on transfer decisions.

When information necessary for the analysis is not available in the above datasets, the author made field surveys in the system to acquire the information.

4.3.2 Variables

For each trip analyzed, I created two sets of variables: one for the transfer sub-path, and the other one for the non-transfer sub-path. Each set has three types of variables: transfer attributes, pedestrian environments, and trip and personal information.

I define three transfer attributes: transfer walking time, transfer waiting time, and escalator presence. I calculated transfer waiting time as half the headway of the subway line, adjusted by time of day, to which the rider transfers, which is a good approximation of waiting time because of the high frequency of service in subway. I used the 2004 subway timetable because the 1993 (when the survey was conducted) timetable was not available when this research was conducted, assuming there was no major changes on subway headways. For the Red Line, the headway estimate is the combined headway of both the Braintree and Ashmont trains. For the Green Line, it is the combined headway of the B, C, D, and E lines. Therefore, the headway of the Green Line at different downtown stations can be different: specifically Haymarket has longer headways than Government Center or Park because not all trains go to Lechmere. Table 4-1 lists the estimated waiting time for the four lines. The headway data are from the MBTA website.

Transfer walking time is defined as the walking time from the arrival platform to the departure platform, which varies across transfer stations and by transfer movement. This information has not been collected by the public transport agencies, and I calculated it based on my field survey. It is measured in seconds at a normal walking speed from the end of the first platform to the start of the transfer platform. I repeated the survey several times in both AM peak and midday, and used the average values (see Table 4-2).

In addition, I conducted a survey of the transfer environment. A required change of level without escalators may make a transfer less appealing, so that I include a dummy variable for escalator presence, which is 1 when there is an escalator to facilitate transfers, and 0 otherwise. I also considered other facility attributes, such as the availability of concessions at the transfer departure platform, the down/up direction of transfer, and overlap between the transfer and non-transfer paths. However, they proved to be either insignificant or unstable in the estimation process.

Table 4-1 Peak Hour Transfer Waiting Times in Boston Subway System

Line	Waiting Time	Transfer Stations
Red Line	112 seconds	Park and Downtown Crossing
Orange Line	150 seconds	State and Downtown Crossing
Blue Line	120 seconds	State and Government Center
Green Line Segment I	43 seconds	Park and Government Center
Green Line Segment II	97 seconds	Haymarket

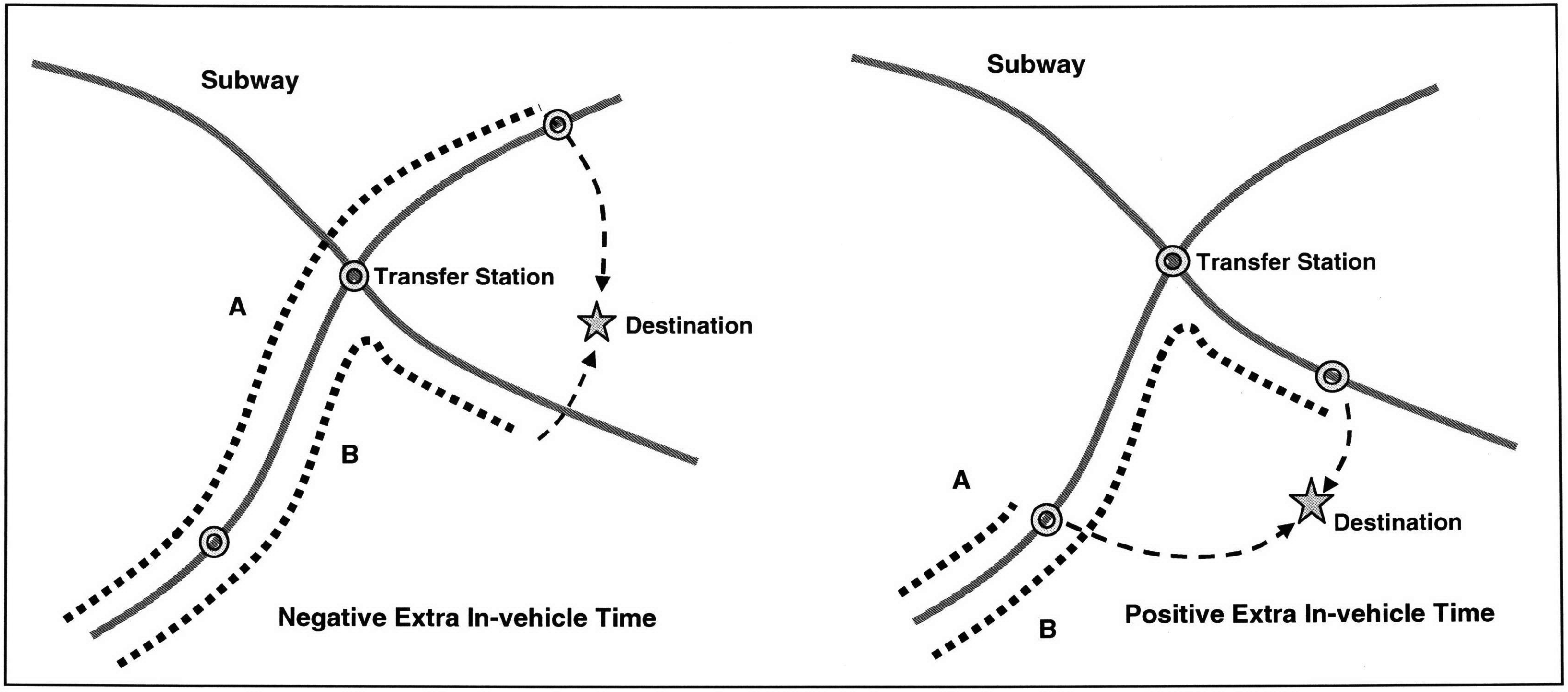
Source: compiled by the Author from the MBTA website

Table 4-2 Transfer Walking Times in Boston Subway System

From \ To		Red Line		Orange Line		Green Line		Blue Line	
		South	North	South	North	East	West	West	East
Green Line	West	17	14	31	50			20	20
	East	17	14	31	50			20	20
Orange Line	South	60	56			117	117	130	116
	North	50	57			217	217	32	30
Red Line	South			60	54	17	14		
	North			56	57	17	14		
Blue Line	West			130	32	20	20		
	East			116	30	20	20		

Note: all times are in seconds

Source: based on field surveys conducted by the author



Source: Created by the author based on the MBTA Subway On-board Survey (CTPS 1994)

Figure 4-5 Extra In-vehicle Time

In addition to transfer attributes, I also defined two other variables: extra in-vehicle time, and surface walking time. Extra in-vehicle time refers to the extra travel a passenger needs to take to the exit station on the transfer line, calculated as the transfer path in-vehicle time minus the non-transfer path in-vehicle time. In general this difference is positive, but in some cases it is negative (see Figure 4-5). Surface walking time refers to the walk to the destination after exiting the subway system. I assume that travelers follow the shortest walk path to their destinations, which is a dominant characteristic of pedestrian movement within a city (Zacharias 2001). For each path, the walking time is calculated based on a walking speed of three miles per hour. The difference in walking time between the transfer and non-transfer paths indicates the walk time saved by transferring.

Descriptive statistics of continuous travel variables are shown in Table 4-3.

Table 4-3 Descriptive Statistics of Independent Variables

Transfer Variables	Mean	Std Dev	Min	Max
Transfer Walking Time (seconds)	57.5	52.8	17	217.0
Transfer Waiting Time (seconds)	113.8	63.8	44	270.0
Surface Walking Time (Transfer path) (seconds)	190.7	137.9	1*	935.2
Surface Walking Time (Non-transfer path) (seconds)	620.1	402.9	67	2380.3
Extra In-vehicle Time (seconds) (if transferring)	174.7	186.2	-371	964.0

Note: * the destination is in the same building as the subway station

Source: calculated by the author based on field surveys and in GIS

The last challenge in variable definition is how to quantify the great variety of characteristics of pedestrian environments at the path level. Prior analysts have surveyed a number of characteristics of pedestrian environments, such as safety and security (Landis et al. 2001), topography (Rodriguez and Joo 2004), landscape and design (Stamps 2000), pedestrian generators (Zacharias 2001), street continuity (Kruger 1980), and infrastructure comfort and convenience (Sisiopiku 2001), etc. Some of these characteristics are hard to quantify; some are not path attributes; some do not vary much in downtown areas. Based on these concerns, I selected five measurable characteristics of the pedestrian environment: pedestrian friendly land use, sidewalk continuity, sidewalk convenience, open space, and topography. It should be noted that these variables only represent a small number of attributes of pedestrian environments.

In terms of parcel types, I assumed that retail, commerce, and mixed development were more conducive to walking than industrial, residential, and office, because these businesses rely on pedestrian access, and they likely provide amenities, such as window decoration, lighting, planting etc., to attract pedestrians. In this study, I defined Pedestrian Friendly Parcels (PFP) to include 22 out of 198 parcel types in the Boston 1996 Assessor database (see Appendix A). I defined the density of PFPs as the total number of PFPs along the walking path, calculated by intersecting the path line with the parcel polygons in GIS, divided by the length of the path (in multiples of 100 meters). The PFP variable is included for both the transfer and non-transfer options (Table 4-4).

The amenity of pedestrian infrastructure may include lighting, planting, sidewalk pavement, sidewalk width, curb situation, speed limits, traffic lights, etc. Some of the factors are not well recorded, and most of them do not vary much in downtown Boston. Finally, I select only one factor: average sidewalk width. A wide sidewalk is assumed to be more conducive to walking. Sidewalk width is included for both path options. Open space such as parks, plazas, playgrounds, or water bodies may also affect the willingness to walk (Giles-Corti et al. 2005). Specifically, Boston Common, which is adjacent to Park Street Station in downtown Boston, might affect the transfer decision for some trips. I created a dummy open space variable, which is 1 when a path crosses the Common, and 0 otherwise. People may not like to walk in hilly topography because it is physically more demanding. In downtown Boston, this applies to Beacon Hill. As with the open-space variable, I created a dummy topography variable, which is 1 when a path crosses the Beacon Hill, and 0 otherwise (Table 4-4).

Trip characteristics (trip time, trip purpose, trip frequency, and fare types) and demographic characteristics (age, driver's license, auto availability, occupation, gender, household size, income, and number of cars owned) may also affect the transfer decision. However, except for school trip, family size, car ownership, and round trip[8], most of them are not significant in the model estimation. Weather is another factor that may affect the transfer decision. Although the survey was conducted over several days, there is no record of the exact survey dates, so that I did not consider weather in this study.

Table 4-4 Descriptive Statistics of Pedestrian Environment Variables

Variables	Mean	Std Dev	Min	Max
# of PFPs per 100 meters (non-transfer path)	0.48	0.43	0	2.59
# of PFPs per 100 meters (transfer path)	0.59	0.95	0	13.80
Average Sidewalk Width (non-transfer path) (feet)	21.80	9.00	2.46	56.80
Average Sidewalk Width (transfer path) (feet)	18.93	8.06	0	59.00
Pass through Boston Common (non-transfer path)	0.26	0.44	0	1.00
Pass through Boston Common (transfer path)	0.03	0.17	0	1.00
Pass through Beacon Hill (non-transfer path)	0.31	0.46	0	1.00
Pass through Beacon Hill (transfer path)	0.01	0.08	0	1.00

Note: PFP = pedestrian friendly parcels

Source: calculated by the author in GIS based on Boston Assessor Database

[8] Although many of these factors affect mode choice, I only examine path choices for those who have already committed to using transit.

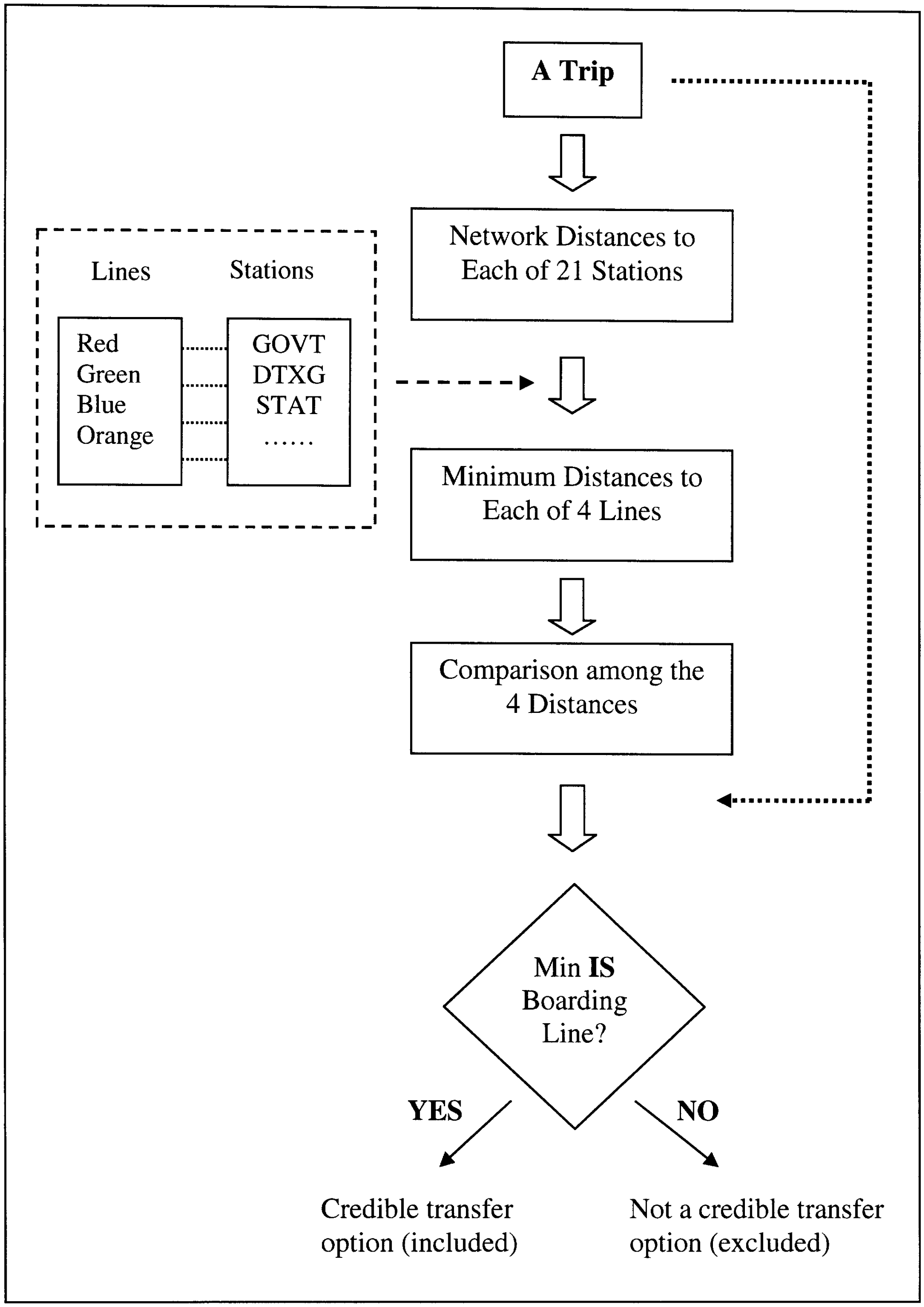
4.3.3 Choice set generation

In order to estimate the trade-offs between transfer and non-transfer paths, I analyze only those trips having a credible transfer alternative. I consider a 'credible' transfer path to be one where transferring allows a rider to exit from a subway station that is closer to the rider's destination than the closest stop on the originating subway line. Riders with destinations that are closest to subway stops on the original boarding line would not save time by transferring and are excluded from the analysis.

I created a look-up table to clean the destination addresses, thereby increasing the match rate of geocoding from 3 percent to almost 40 percent out of 38,888 Boston subway trips.[9] This process yielded about 15,000 identifiable destination points, of which 6,500 are located in downtown Boston. I developed a simple algorithm (Figure 4-6) to identify which trips to the 6,500 destinations had a credible transfer option. Applying this process to all 6,500 trips results in 3,741 trips with credible transfer options, of which 1,313 (33 percent) included a transfer. I assume that a rational traveler will exit from the closest station, either on the original boarding line or the transfer line, to reach their destinations. Those who did not are excluded from the analysis. These include 170 trips in the transfer case and 391 trips in the non-transfer case. I also exclude trips with two transfers because there are only 40 such trips, and this simplifies the analysis considerably. Eventually, 3,140 trips remain in the final dataset, representing 2,130 walking paths to 508 destinations.[10]

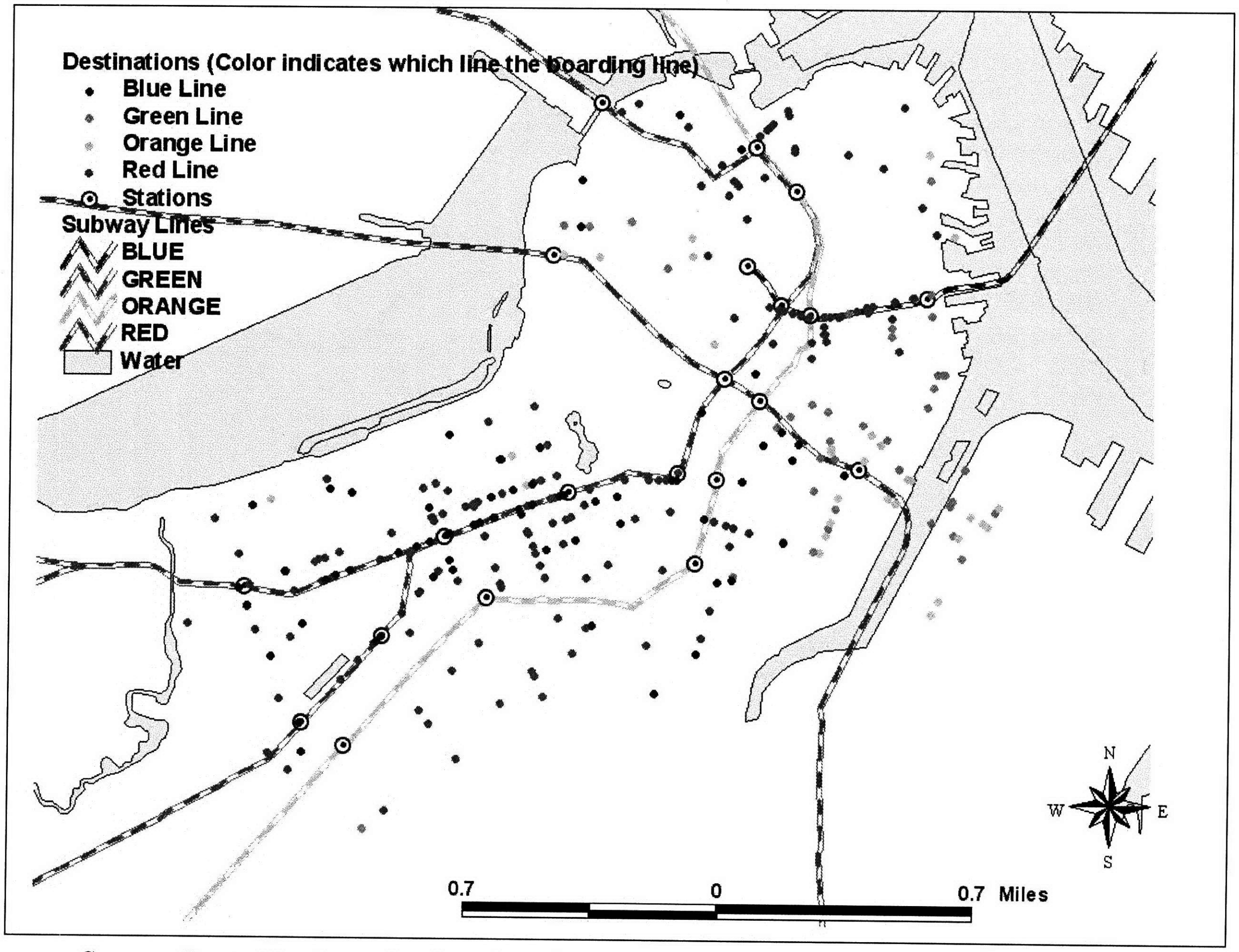
[9] About 7.5 percent of survey records do not have a destination address, 17 percent of records only have street names, and about 28 percent list a landmark, building, or institution as the destination address. Due to time constraints, only those landmarks, buildings, or institutions associated with a significant number of trips were manually identified with their street addresses. So the actual match rate for the *geocodable* records is between 60 and 70 percent.

[10] In summary, the survey has 38,888 trips, of which 15,000 trips are geocoded, based on their destinations. 6,500 of these trips are in downtown Boston. In the final models, 3,741 trips have credible transfer options, and 3,140 trips are included in final model estimations.



Source: the author

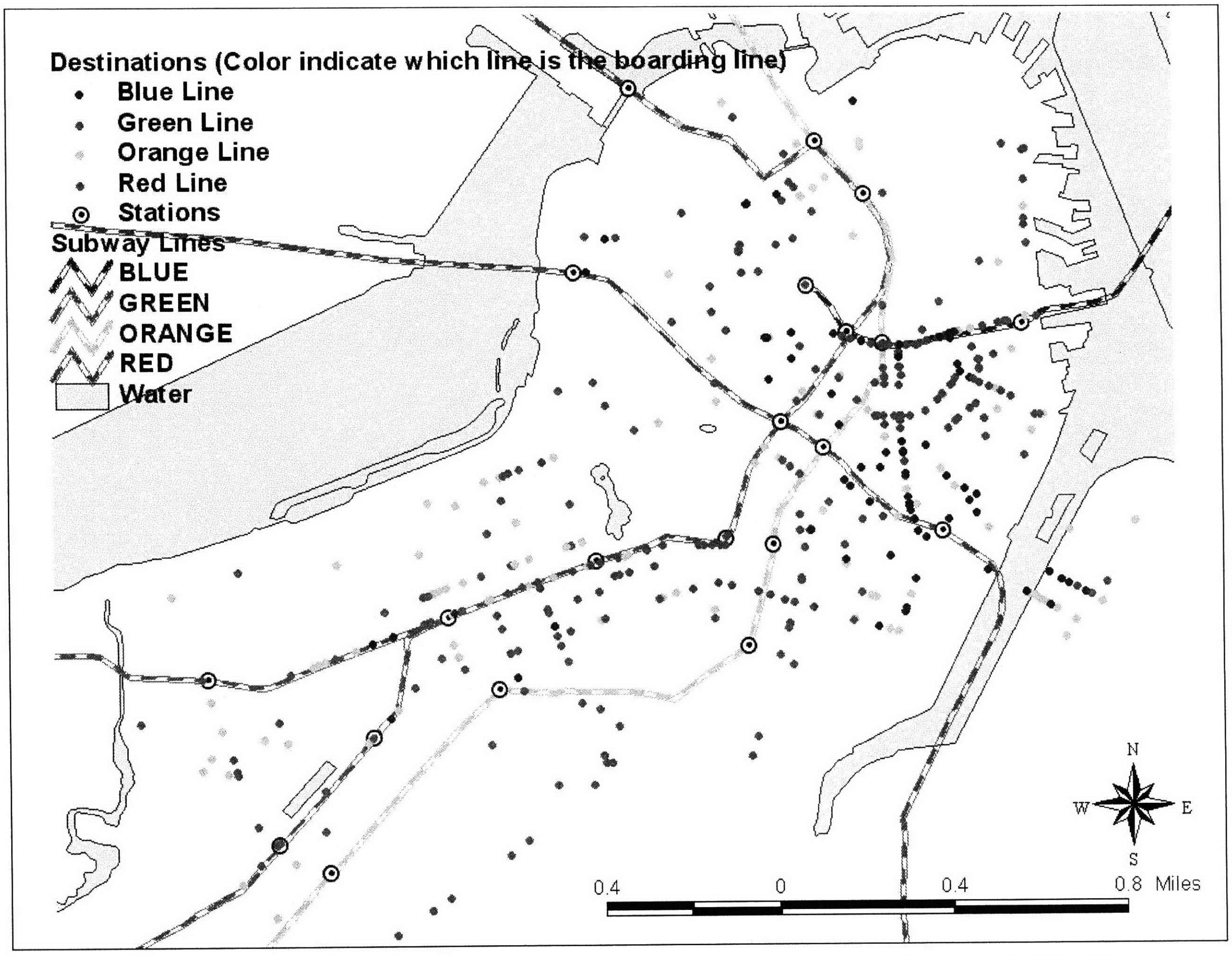
Figure 4-6 Algorithm to Identify Credible Transfer Options



Source: Created by the author based on the MBTA Subway On-board Survey (CTPS 1994)

Figure 4-7 Destinations of Transfer Trips

Figures 4-7 and 4-8 display these trips showing the destination of each trip in downtown Boston. All passenger trips provide the transfer option, but those in Figure 4-7 actually chose to transfer, while those in Figure 4-8 did not. The spatial patterns of destinations in the two figures are quite different. Destinations of the transfer trips tend to be far away from the original boarding line, but close to another subway line. The opposite is true for the destinations of the non-transfer trips. The difference clearly suggests a trade-off between transferring and walking time saved. The following section investigates the relationship quantitatively using random utility models.



Source: created by the author based on the MBTA Subway On-board Survey (CTPS 1994)

Figure 4-8 Destinations of Non-Transfer Trips

4.3.4 Model development

The dependent variable is a binary choice, defined as 1 if the traveler chooses the transfer option, and 0 otherwise. The choice probability is a function of differences in path attributes (extra in-vehicle time, transfer walking and waiting, street walking, etc) as well as trip and demographic values. The estimated models are all of the binary logit form presented below. The probability of an individual n selecting the transfer option ***i*** is given as:

$$P(i)=\frac{1}{1+e^{-\mu(V_i-V_j)}} \tag{13}$$

$$V_{in} = F(C,\ S_{in},\ E_{in},\ K_n\ ) \tag{14}$$

$P_n(i)$: the probability of person n selecting the transfer path
V_{in} : the systematic component of the utility for option i for person n
i, j : the transfer and non-transfer option
μ: the positive scale parameter
C: constant to reflect the difference between option i and j, all else being equal
S_{in}: subway path and transfer characteristics for option i for person n
E_{in}: attributes of pedestrian environment for option i for person n, and
K_n: trip and demographic characteristics for person n

In this model specification, I quantify the transfer penalty following a similar theory to the value of time (VOT), which is the marginal rate of substitution (MRS) of a transfer for time or money savings. The MRS can be estimated by observing how people make choices between the transfer and non-transfer paths. The transfer option may have the advantage of less total travel time or walking distance to the destination, but it also has disadvantages based on the extra time and inconvenience associated with the transfer. When the advantages exceed the disadvantages, passengers will choose to transfer; otherwise, they will not. The MRS of a transfer can be estimated in terms of travel time or money saved.

For example, assuming the utility of a transfer option is

$$U(Tsf)=\alpha+\beta_1*(Tsf-Time)+\beta_2*(Tsf-Cost)+\beta_3*(IV-Time)+\beta_4*(IV-Cost) \tag{15}$$

α is the transfer path specific constant, and β_1 and β_2 are coefficients of total transfer time and cost. Then the transfer penalty for trip n (TP_n) measured in equivalent in-vehicle time is:

$$TP_n=\frac{\alpha}{\beta_3}+\frac{\beta_1}{\beta_3}*(Tsf-Time_n)+\frac{\beta_2}{\beta_3}*(Tsf-Cost_n) \tag{16}$$

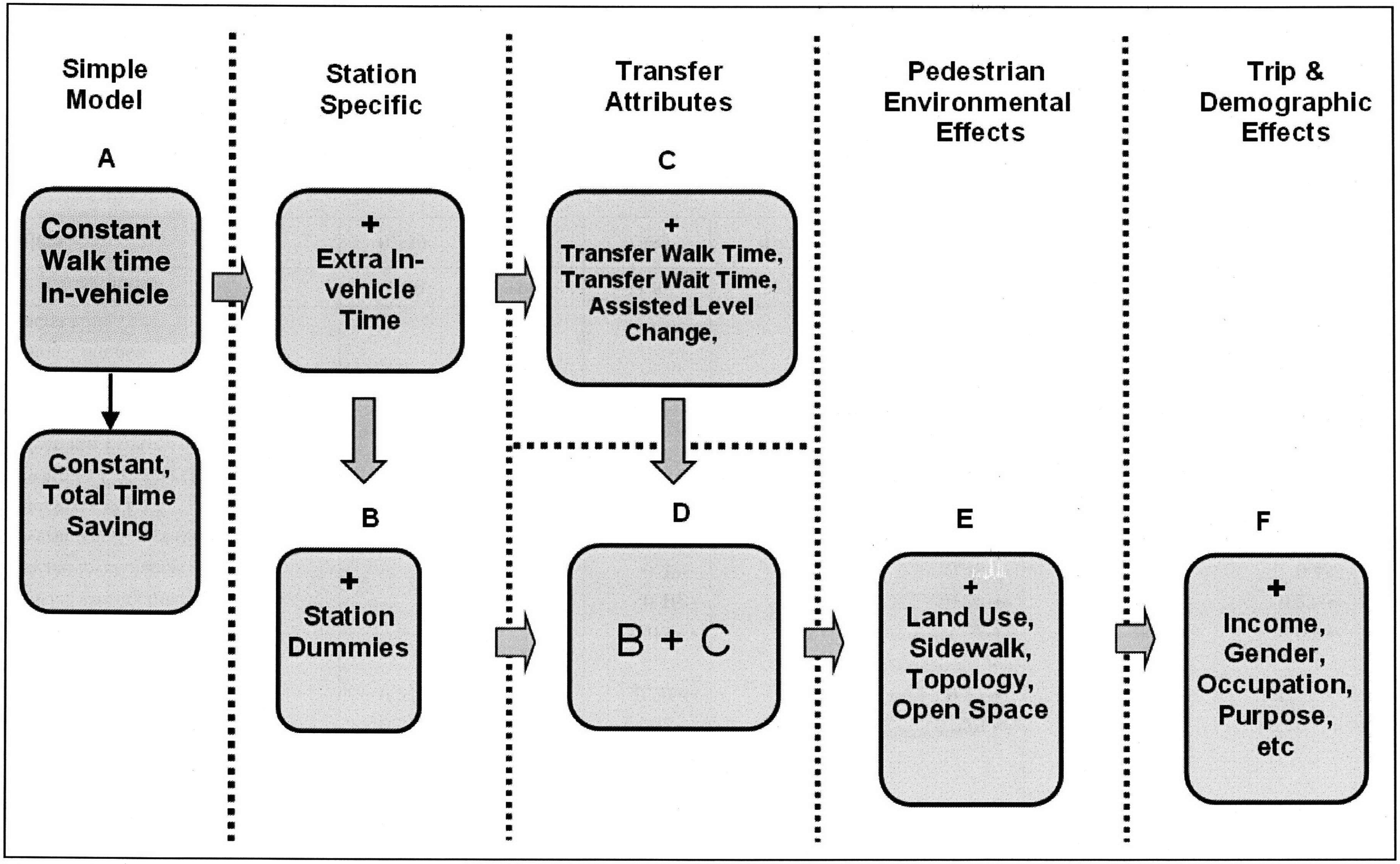
α / β_3 is the residual of transfer penalty additional to transfer time and cost. Therefore when the transfer penalties across different studies are compared, the difference in utility function must be considered.

I estimated a series of models. The simplest model (Model A) includes only a transfer constant, the walking time savings, and the extra in-vehicle time; thus, the effects of all the transfer factors are collapsed into the transfer penalty: referred to as the total transfer penalty. The next two models capture differences among transfer stations. In the second model (Model B), I include transfer station dummies. In the third model (Model C), I replace the station dummies with the transfer facility characteristics including transfer walking time, transfer waiting time, and assisted change in level. I then combine these two specifications to yield a model (Model D) that describes the transfer penalty strictly in terms of path attributes. The environmental variables are then included (Model E). Lastly, I include trip and personal characteristics (Model F). There are a total of ten model specifications. Figure 4-9 shows the series of models, and Table 4-5 shows the results of the model estimation process.

Simplest Model (Model A)

In this model, I assume that every transfer is perceived to be the same and there are only three variables in the model: a transfer constant, the walking time savings, and the extra in-vehicle time. The ratio of their coefficients represents the transfer penalty in terms of the equivalent walking time savings. This is the total transfer penalty capturing the effects of all the differences between the transfer and non-transfer paths at the transfer station.

This model confirms that there is indeed a trade off between making a transfer and walking time savings, with both coefficients having the expected signs and being highly significant. The constant term is negative, which means that, all else being equal, travelers will tend to avoid



Source: the author

Figure 4-9 Sequence of Model Development

Table 4-5 Model Estimation Results

Variables	Model A	Model B	Model C	Model D		Model E	
				Peak Hour	Non-Peak Hour	Peak Hour	Non-Peak Hour
Transfer Constant	-2.29***	-1.39***	-0.99***	-1.08***		-1.39***	
Transfer Path Variables							
Walking Time Savings (minute)	0.316***	0.289***	0.285***	0.315***	0.220***	0.286***	0.194***
Extra In-vehicle Time (minute)	-0.216***	-0.21***	-0.20***	-0.24***	-0.17***	-0.24***	-0.16***
Transfer Attributes							
Transfer walking time (minute)			-1.13***	-1.39***	-1.22***	-1.28***	-0.99***
Transfer waiting time (minute)			-0.16**		-0.29***		-0.27***
Assisted level change			0.27**	0.39**	0.48***	0.39***	0.45*
Government Center (GOVT)		-1.21***		-1.28***	-1.26*	-1.20***	-1.28**
State Street (STAT)		-1.41***					
Downtown Crossing (DTXG)		-1.09***					
Pedestrian Environment Variables							
Extra PFP density							-0.20**
Extra sidewalk width						-0.03***	-0.03***
Boston Common						0.73***	0.79***
Beacon Hill						-0.73**	-1.07***
# of Observations	3140	3140	3140	2173	967	2173	967
Adjusted ρ^2	0.339	0.369	0.385	0.414	0.357	0.425	0.376

Note 1. ***: $P < 0.001$; **: $P < 0.05$; *: $P < 0.1$

2. In model A, if the walking time saving is replaced by total travel time saving, the adjusted ρ^2 is 0.355

3. Coefficients that are statistically insignificant ($P > 0.1$) are not shown in the table.

4. Adjusted ρ^2 is the goodness-of-fit of the model. A higher value indicates an improved explanatory power of the model to the dataset

transfers. The positive sign of walking time savings confirms that the more walking time is saved by transferring, the more likely riders will be to transfer. With this estimated model, one transfer is equivalent to 7.3 minutes of walking (10.6 minutes of in-vehicle time). If the walking-time savings are replaced by total travel time saving, both the constant term and the total travel time are significant, with the expected signs and one transfer is equivalent to 3.8 minutes of travel time saving. The explanatory power of this model is higher (an adjusted ρ^2 of 0.355 compared to 0.339), which indicates that the total time saving is more significant than the walk time saving in determining the transfer decision (Appendix B).

However, because I am interested in the effects of different time components on the transfer penalty, I base the following model specifications on Model A, the walking time saving formulation. In discrete choice models, the adjusted ρ^2 is an informal goodness-of-fit index that measures the fraction of the initial log likelihood value explained by the model. A higher value of adjusted ρ^2 indicates improved explanatory power of the model to the dataset.

Transfer Station Model (Model B)

This model shows how the four transfer stations are perceived by riders in terms of differences in the transfer penalty. Model B includes only walking-time savings, the extra in-vehicle time, and three transfer-station dummies, which capture the variation of the transfer penalty between transfer stations. Park Street is used as the base case because it is the highest volume transfer station in the system. The model results show that one transfer is equivalent to 4.8 minutes of walking-time savings at Park Street, 9.0 minutes at Government Center, 9.7 minutes at State, and 8.6 minutes at Downtown Crossing. Park Street is perceived to be the best transfer station with only half the transfer penalty of State, the worst transfer station. Model B shows that the transfer penalty can vary greatly even within the same system and for the same type of transfer.

Transfer Attributes Model (Model C)

In this model, I include common characteristics of the transfer facilities in place of the simple dummy variables used in Model B. I assume that each transfer is characterized by the transfer walking time, transfer waiting time, and assisted change in level. I also test the total travel time saving in this model specification, but dropped it because it was not significant. The premise is that transfer walking time, transfer waiting time, in-vehicle time, and surface walking time are all perceived differently by passengers (this is supported by the differences in the estimated coefficients).

The three time variables are all negative and significant, which means the more time spent walking, waiting, or in-vehicle to transfer, the less likely riders are to transfer. Riders are more willing to transfer if escalators are available to assist the transfer. The model shows that there is a residual (or "pure") transfer penalty remaining, equivalent to 3.5 minutes of walking time savings. Transfer walking time, transfer waiting time, and assisted change in level contribute 3.8 minutes to the total 7.3 minutes penalty. The model shows that half (52 percent) of the total transfer penalty can be explained by including the characteristics of the transfer facilities and the transfer path, suggesting that the perceptions of transfers can be greatly affected by transfer facility design and by transit system characteristics.

Combined Transfer Attributes and Transfer Station Model (Model D)

This model is the combination of models B and C and shows how the quantitative characteristics (represented by transfer attributes and in-vehicle time) and intangibles (represented by the station dummy variables) of the transfer facility contribute to the transfer penalty. I apply this model specification separately to peak hour trips and off-peak hour trips because the transfer behavior might vary by time period.

As expected, the coefficients of the transfer attributes and in-vehicle time do not change much, but those of the transfer station dummies do change greatly. In the peak period, the pure transfer penalty decreases slightly to 3.4 minutes of walking time savings, while in the off-peak period the pure transfer penalty vanishes. The coefficients of the two transfer station dummies (State and Downtown Crossing with Park Street as the base case) are not statistically different from zero, which means that for off-peak trips transfer attributes, extra in-vehicle time, and station dummies capture the entire transfer penalty for State, Park Street, and Downtown Crossing, which appear to be similar in terms of the pure transfer penalty. This suggests that, even though State overall has a much higher transfer penalty than Park Street, this difference is totally explained by differences in the quantifiable characteristics of these stations. Government Center is now clearly the worst transfer station with a high residual transfer penalty. This implies that there are other factors not captured by the quantified transfer station characteristics, which are negatively perceived at Government Center. This needs further exploration.

The peak hour model shows a higher adjusted ρ^2 (0.414) than the off-peak model (0.357), and the transfer waiting time is not significant in the peak period. This suggests that the transfer waiting time does not affect the decision to transfer in the peak periods because subway waiting times are very short in this period.

Pedestrian Environment Model (Model E)

All four pedestrian-environment variables are significant at the five percent level with the expected signs. This suggests that the environment along street walking paths (AD and CD in Figure 4-4) can affect the sub-path choice. This model shows somewhat greater sensitivity to pedestrian environment for off-peak trips than for peak trips. Specifically for the off-peak, if there are more PFPs or wider sidewalks along the non-transfer path, all else being equal, riders are slightly less likely to transfer. If the non-transfer path passes through Beacon Hill while the transfer path does not, riders are more likely to transfer. Finally, if the non-transfer path crosses Boston Common but the transfer path does not, riders are less likely to transfer. For example, in the peak period, riders are willing to walk about 2.5 minutes further if the non-transfer path crosses the Common.

Trip and Demographic Model (Model F)

In this research, I tested trip and demographic characteristic variables from 12 categories; however most of them proved to have no significant explanatory power. Only four dummy variables were candidates for inclusion in the final specification: school trip purpose, a round trip, household size of three persons or greater, car ownership of zero or one. However, the overall explanatory power of the model changes only marginally and none of the new variables has strong logical support. Furthermore, the transfer penalty captured by the constant term does not change much. The estimation result is not presented in Table 4-5 because it is statistically insignificant.

Everything indicates that the trip and demographic characteristics do not significantly affect transfer behavior. This may be a reasonable result because the data set only includes travelers who already have chosen to use the subway system. Clearly, if this were a mode choice model, demographic and trip characteristics are likely to play a much greater role. Another explanation is that the model measures the trade-off between walking time and transferring. People may have different perceptions of transfers, but may have a similar attitude towards the relative disutility of transfers and walking time. For example, a person who is more averse to walking than the typical subway rider is also likely to be more averse to transferring. This would be consistent with the model findings.

4.3.5 Analysis and Interpretation

The sequence of model development shows that, with more variables included in the model, the transfer penalty as reflected in the constant term decreases, while the explanatory power of the model increases. The best model specification, Model E in the peak period, has an adjusted ρ^2 of 0.425, which is high for a discrete choice model. This confirms the findings that the approach developed provides a good understanding of the transfer penalty.

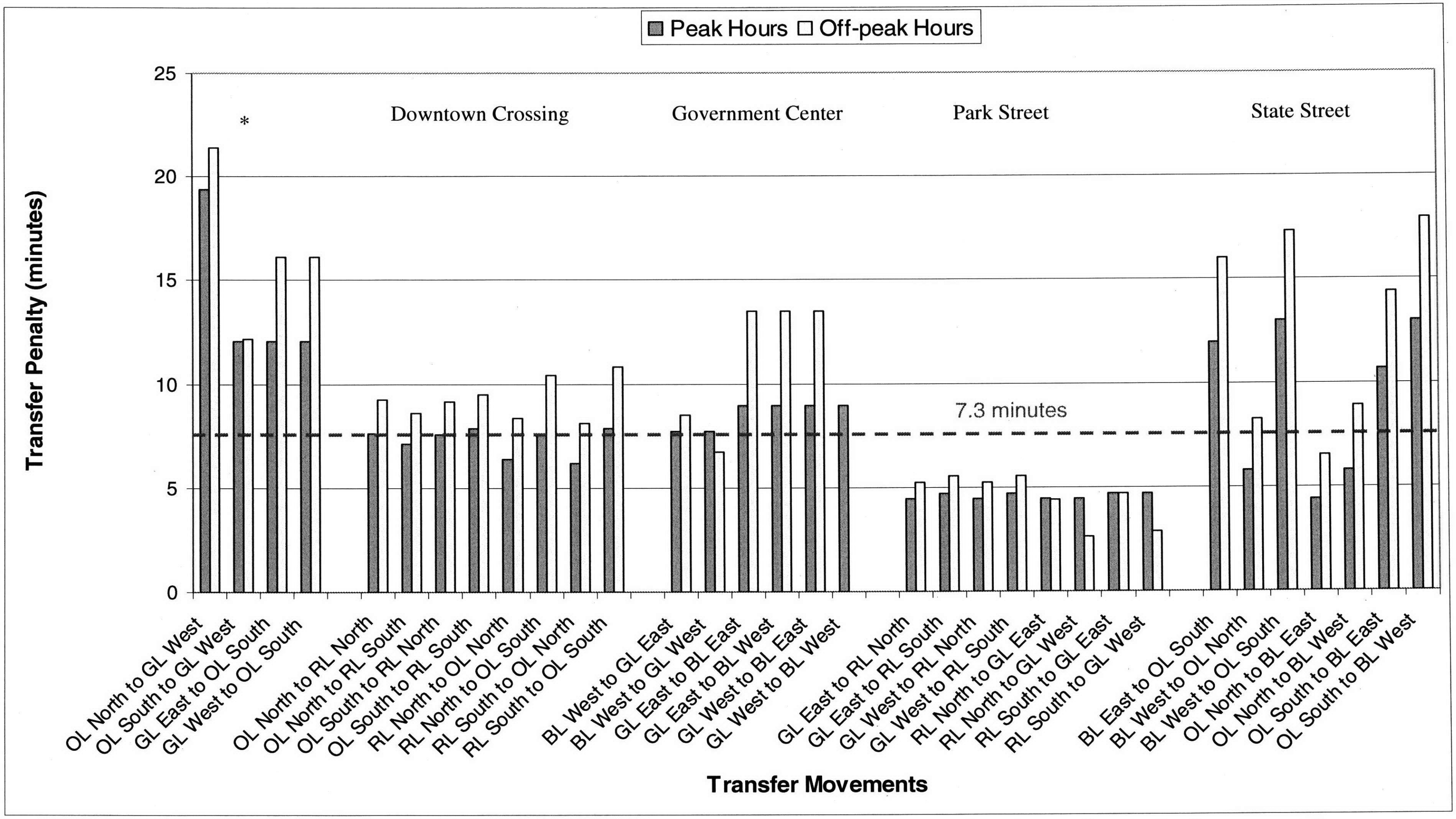
Because the transfer penalty is affected by multiple factors and varies with time, direction, and station, it is important to recognize that the transfer penalty has a range of variation rather than a single value. The single value of the transfer penalty generated from the simple model (Model A) as well as most previous research is misleading. Using the models estimated in this research, I can examine the range of the transfer penalty for a total of 32 transfer movements at the four transfer stations (Figure 4-10). With more variables included in the model, the range of the transfer penalty expands. Each transfer movement is characterized by transfer walking time, transfer waiting time, and assisted change in level. I calculate the transfer penalty for each

Table 4-6 The Range of the Transfer Penalty and the Goodness-of-Fit

Model Number	Underlying Variables	Adjusted ρ^2	The Range of the Penalty (Equivalent Value of)
A	Transfer constant	0.339	7.3 minutes of walking time
B	Transfer constant Extra In-vehicle time Station Dummies	0.369	4.8 ~ 9.7 minutes of walking time
C	Transfer constant Transfer walking time Transfer waiting time Assisted Level Change	0.385	4.3 ~ 15.2 minutes of walking time
D	Transfer constant Transfer walking time Transfer waiting time Assisted Level Change Station Dummy	0.414 (Peak) 0.357 (Off-peak)	4.4 ~ 19.4 minutes of walking time (Peak) 2.3 ~ 21.4 minutes of walking time (Off-peak)

transfer movement by summing the contributions of each transfer attribute and dividing the result by the walking-time-saving coefficient.

I apply this method to models C and D with the resulting ranges of the transfer penalty as shown in Table 4-6 along with the results for Model A and B. In model D, the range of the transfer penalty in off-peak hours is slightly greater than that in peak hours. The highest penalty exists at Downtown Crossing for the movement from the Orange Line northbound to the Green Line westbound, which requires a long walk through a passage connecting Downtown Crossing and Park Street. The wide range of the penalty shows the complexity of the transfer penalty, which has not been recognized in previous studies. Finally, Table 4-7 shows that the findings are consistent with the results of prior studies for urban rail systems. Specifically, the single values of the transfer penalty estimated from prior work falls within the range after it is converted to equivalent minutes of in-vehicle time. The CTPS study also gave a range of transfer penalty between 12 and 15 minutes of in-vehicle time for the entire MBTA system.



Note: * There is a long underground tunnel between Park Street Station and Downtown Crossing Station that raises the transfers penalty for some transfers, despite the relatively low transfer penalties of other movement directions at the two stations.

Source: calculated by the author based on model estimation results

Figure 4-10 Transfer Penalty for Different Movements

Table 4-7 Comparison of the Transfer Penalty for Urban Rail Systems

	Alger *et al.*1971		Liu, 1997	Wardman *et al,* 2001	CTPS 1997	This Research
City	Stockholm		New Jersey	Edinburgh	Boston	Boston
Transfer Type	Subway	Rail	Subway	Rail	All modes	Subway
Value of the Transfer Penalty*	4.4	14.8	1.4	8	12 to 18	3.5 ~ 31.8

Note: * Minutes of in-vehicle time

4.3.6 Discussion of Subway Study

The term transfer penalty describes passengers' perceptions of transfers on a transit system. A clearer understanding of the penalty can enhance ridership forecasting, network design, station design, service design, service management, and the marketing strategy of a transit system. In my research, I develop and apply a new method for evaluating the transfer penalty based on standard on-board survey data, a sub-path choice model, and geographic information system (GIS) techniques. I show that this new method reduces the complexity of data processing and increases our understanding of the transfer penalty. The limitation of this method is that it analyzes people who already use transit, so that, at least in this form, it does not shed light on how those who do not currently use transit perceive transfers. This understanding is critical to attracting new riders to transit.

In this case study, I estimate the average transfer penalty for the MBTA subway system to be equivalent to 7.3 minutes of walking time. The average waiting time for the MBTA subway is only about 4 minutes, while the average access time is between 6 and 10.5 minutes, which implies that transfers have a significant negative impact on the use of the system. Without including the transfer penalty appropriately, ridership forecasting models probably will over- or under-estimate demand for trips requiring transfers. The penalty is likely to be even larger for non-transit users because they are likely to have worse perceptions of transfers than current riders. Half (52 percent) of the total penalty can be explained by including characteristics of transfer facilities and the subway system. The quantitative characteristics of transfers, including transfer walking time and transfer waiting time, explain much of the variation observed between the transfer stations. However, important differences remain due to intangible factors. In the case of the Boston subway system, these intangibles manifest themselves most strongly in a negative perception of Government Center, which implies that there is a 6.9 minute perceived penalty for transferring at Government Center compared with the other three downtown transfer stations after controlling for the quantitative attributes of each station.

This case study also showed for the first time that there are significant differences in transfer behavior between the peak and off-peak periods with peak-period travelers generally perceiving a greater pure transfer penalty but being less affected by transfer waiting time.

The new approach also enables analysts to explore the range of the transfer penalty and the underlying factors that affect it, which is more meaningful than thinking only of the average transfer penalty in service planning, facility design, and marketing. With additional variables, the model shows that there can be a wide range to the transfer penalty. In the case of the MBTA subway system, the penalty ranges from 2.3 to 21.4 minutes of walk time. My research also shows that the environment and service components of the penalty contributed most to the transfer penalty (52 to 84 percent), which also has a great variation within the subway system. The range of variation can be 5.1 minutes across stations, and 20 minutes across transfer directions. Surprisingly, the transfer penalty varies modestly across demographic groups. The variation is only about 1 minute between work and non-work trips, and most other demographic variables are not significant at the five percent level. This indicates either the homogeneity of transit users, or similar preferences, attitudes, or perceptions among transit riders to transfers, or both. The result suggests that policies to improve the perceived transfer experience are feasible by changing transfer-station design, service frequency, and information provision, but they must be station- and time- specific; otherwise, policy intervention might lead to unexpected outcomes.

In this case study, I have only assessed the transfer penalty within the MBTA subway system, but the approach can easily be applied to other systems, as well as to other modes, for example, the transfer between commuter rail and subway, between bus and subway, between auto and subway, or between buses. I expect such studies will show that the transfer penalty can be substantially greater than the values found here, particularly when transfers occur in exposed and non-secure settings, when expected waiting times are high and when an additional fare payment is required for a transfer, none of which apply to the MBTA subway-to-subway transfers analyzed here.

4.4 Transfers between Commuter Rail and Subway

This analysis is an extension of the subway study looking at transfers between commuter rail and subway service, and examining the effects of fare payment, network familiarity and service reliability as well as differences in perceptions of transfers among individuals. For the subway research, I did not include the monetary cost of transfers because transfers were free within the subway network I analyzed. Neither did I analyze service reliability and network familiarity, which are both likely to affect transfer decisions. Furthermore, I did not look at the variation in attitude or preference across individuals, which is likely an important source of variation in the transfer penalty.

In this analysis, I examine transfers between commuter rail and subway, two major transit services that are connected but serve distinct markets. In Boston about one-third of current commuter rail riders transfer to subway after they leave the commuter rail, which represents about 17 percent of all subway trips that end in downtown Boston. About 61 percent of commuter rail customers walk to their final destinations after leaving the commuter rail system, and only a few transfers to buses. Transfers between the commuter rail and subway are vital to the performance of both systems.

The commuter rail system connects with the Green and Orange subway lines at North Station, with the Red Line at South Station, and with the Orange Line at Back Bay station. In addition, the Green Line runs close to Back Bay Station, and also becomes a potential transfer line even though it is not directly linked to the commuter rail station (see Figure 4-8). At North Station, at the time when these data were collected, commuter rail and subway used different station buildings with a long distance between them exposed to the weather. [11] Commuter rail riders had to exit the terminal, walk several minutes, and either climb up 30 stairs to board the Green Line, or go down two levels to take the Orange Line. There was no escalator at the time of the survey.

At Back Bay Station, the commuter rail and subway platforms are separated by a wall, but are close together in the same building. Transfer involved one change of level, and is assisted by escalators in both directions (up and down). At South Station, passengers have a long walk from the commuter rail platform to the subway platform, and must go down several levels. There is no escalator in that direction. In addition, there were construction activities going on at the time of data collection, which may have caused further inconvenience for passengers interchanging at

[11] North Station has since been redesigned with a much improved connection between commuter rail and the subway system.

South Station. The transfer path is also complicated with many turns and changes of levels, and it is easy to get confused especially for passengers unfamiliar with the system.

For this analysis, I further categorized the transfer penalty into two components. The first component refers to the observable factors associated with transfer station design, seating availability, lighting, burden of luggage, schedule flexibility, network familiarity, etc, and the second component refers to unobservable factors such as attitudes, preferences and perceptions. I use the method developed in the subway study to capture the first component and the random coefficient technique embedded in a mixed logit discrete choice model is used to analyze the second component.

The method I adopted in general is similar to the approach I used in the subway research, but is more complicated because multiple transit services are available at the egress commuter rail station, or there are several potential egress stations along the way. For example, in Boston for commuter rail passengers coming from the north, while there is only one commuter rail terminal (North Station), which is served by both the Green and Orange subway lines. Passengers coming from the south can leave the commuter rail system at either Back Bay or South Station in downtown Boston, which are served by different subway lines (Figure 4-3). In these situations, the individual travel choices might be made at two levels: to transfer or not and the path/station decision. Nested logit models are an appropriate tool to deal with such a decision hierarchy.

As discussed earlier, the perception of transfers may vary among travelers, and the decision-making process is likely to be idiosyncratic. If this is true, a constant estimated parameter might be a misleading description of transfer behavior. For example, if half the riders in a sample strongly dislike transfers while the other half actually enjoy transfers to the same extent, the transfer parameter will be estimated to be zero in a traditional choice model: obviously, not a good description of overall behavior. In this study, I develop mixed logit models to deal with this problem. In traditional discrete choice models, heterogeneity among individuals is assigned to the error term and not considered during the estimation process.

The basic concept of mixed logit is to restructure the error term into two additive parts. One part is correlated over alternatives and individuals, while the other part is independently and identically distributed (i.i.d.) over alternatives and individuals. This structure allows for the possibility that some unobserved information relevant to making a choice, such as attitudes, preference, and perceptions, may be sufficiently important to induce correlation across alternatives and individuals (Walker 2001). One application of this model structure is to specify each parameter associated with an attribute of an alternative as having both a mean and a standard deviation, i.e., to treat it as a "random" parameter instead of a fixed parameter. In this way, mixed logit models are able to capture a variety of sources of heterogeneity among individual, however, because they do not have a closed form, they have only become feasible in recent years with advances in simulation and numerical-analysis techniques.

4.4.1 Datasets and Variables

The major dataset I used in this analysis is the MBTA commuter rail on-board survey, which was conducted by Central Transportation Planning Staff in 1993 (CTPS 1993). The survey was distributed to all passengers on all trains due to arrive in Boston (inbound only) from the first train of the day until 9:00 PM. There are a total of 16,567 trips in the data set, representing about 15 percent of weekday daily boardings at the time. There are a total of 67 fields in the dataset providing abundant information on the spatial characteristics of commuter rail trips, and on the personal characteristics, attitudes and perceptions of customers. For example, the data includes

Table 4-8 Egress Modes for Commuter Rail Inbound Trips

System	Egress Station	# of Trips	Walk	Subway	Bus	Other
North	North Station	5,555	2,861 (52%)	2,358 (42%)	105 (2%)	231 (4%)
South	Back Bay	3,738	2,048 (55%)	1,465 (40%)	163 (4%)	62 (1%)
	South Station	5,918	4,476 (76%)	1,117 (19%)	119 (2%)	206 (3%)
Total		15,211	9,385 (62%)	4,940 (33%)	387 (2%)	499 (3%)

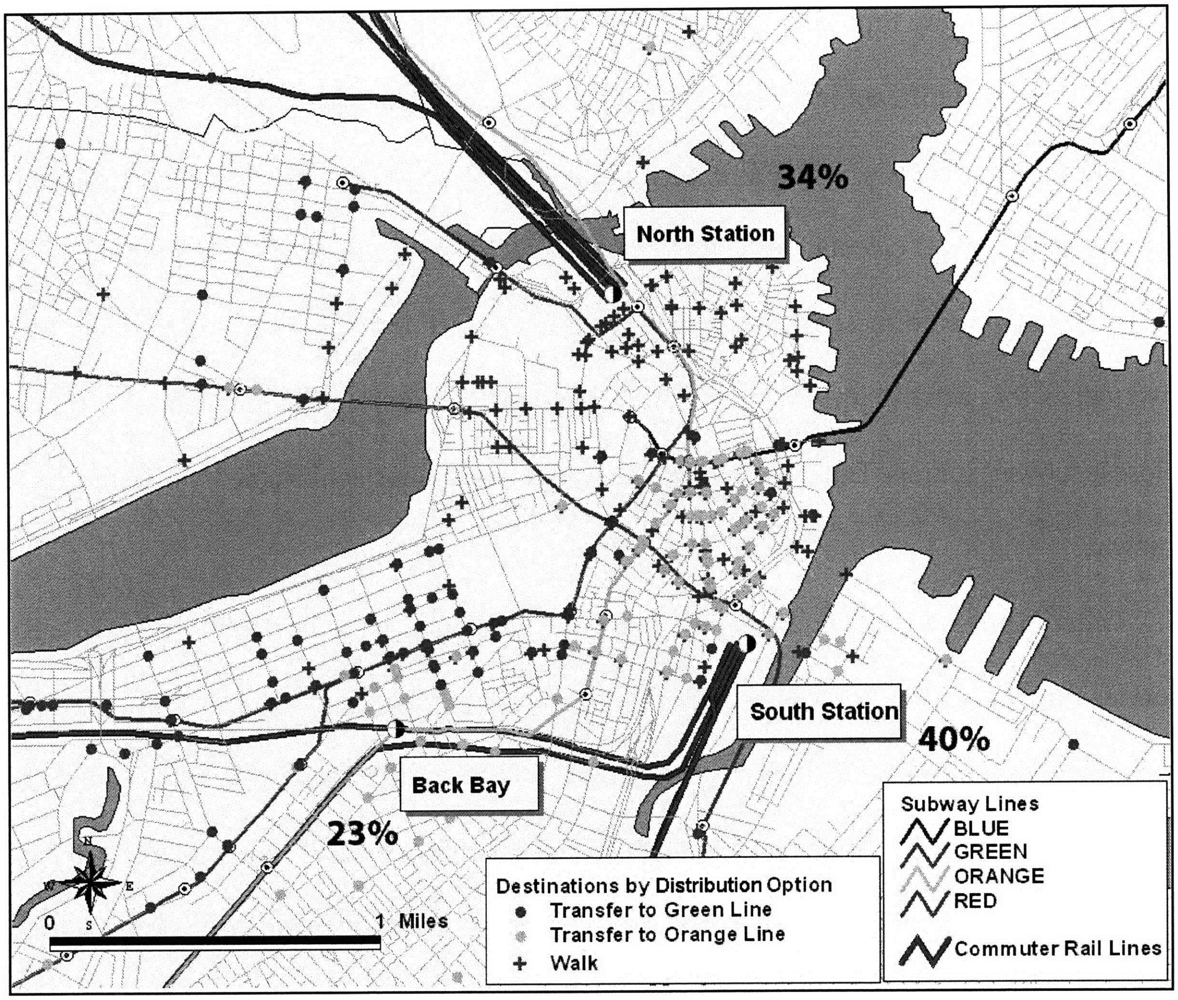
Source: MBTA 1994 Commuter Rail On-board Survey

the routes used as well as the boarding and alighting stations and the exact origin and destination for each trip surveyed.

According to this survey, about one-third of commuter rail passengers transfer to the subway after they exit commuter rail at one of the downtown stations, while most of the remainder walk to their destinations (see Table 4-8). Figure 4-11 displays the destinations of commuter rail passengers who exit at North Station by their egress options. Clearly, passengers with a destination close to North Station do not transfer, while those transferring tend to have a destination far away from North Station. For those transferring to the Green Line, their destinations are concentrated along the Green Line in Back Bay. For those transferring to the Orange Line, most have destinations in the Financial District, Chinatown, and South Boston, areas well served by the Orange Line. According to the survey, for passengers coming from the south,[12] 39 percent exit the system at Back Bay, with the remainder traveling to the South Station terminal. For passengers who transfer to the subway at Back Bay, most (85 percent) choose the Orange Line with a small number walking to the nearby Green Line station. At North Station, subway transfers are almost evenly split between the Green and Orange Lines.

Next, I define variables to be included in the utility functions of transfer and non-transfer options. The transfer walking time (distance) from commuter rail to subway is not separable

[12] Because the Fairmount Line does not go through Back Bay station, I did not included it in this analysis.



Source: created by the author based on the MBTA Commuter Rail On-board Survey (CTPS 1993)

Figure 4-11 Destinations by Egress Modes for Commuter Rail Passengers Exiting at North Station

from the transfer option itself due to its minimal variation across transfer movements. The difference in transfer walking among transfer movements within the same station is also minimized due to the long walk between commuter rail and subway platforms. For example, for all trips that transfer from North Station to the Green and Orange Lines, the different designs at the two subway stations might be viewed as insignificant compared to the long walk between them and North Station. The variation of transfer walking time is captured by the constant of the transfer option and the error term.

Transfer waiting time also has little variation across the subway lines (see Table 4-4). It also proved to be insignificant in affecting the subway transfer behavior in peak hours; thus, I did not include it in the analysis. Therefore, travel time variables include only in-vehicle time and surface walk time. I calculate in-vehicle time for each transfer path based on the subway time tables from the boarding station to the alighting station, adjusted by time of day. Walk time has two values for each trip, the direct walk time from the commuter rail station and that from the closest subway station. The difference is the walk time savings achievable by transferring to subway.

Other factors of interest include the fare type, familiarity with the transit network, and service reliability. There are three major fare types: cash, monthly pass, and 10-12 ride ticket. Of particular relevance here is that the commuter-rail monthly pass holders enjoy free access to the subway, while 10-12 ride ticket holders and cash customers need to pay the subway fare if they transfer. Accordingly, I expect the transfer penalty for cash customers and ticket holders to be higher than for pass holders.

Frequent commuter rail riders tend to be more familiar with both the subway system and pedestrian environment, and face less uncertainty about both transferring and walking. I define the familiarity proxy variable as the frequency of taking commuter rail. My analysis of the transfer share for each frequency group showed a jump in transfer rate from 2-days-or-less per-week riders to 3-days-or-more riders, so that I use the 3 days per week as the familiarity threshold. An alternative way is to define travelers riding 5 days per week as frequent riders, but those riders are also very likely to be commuters and pass holders. This might mix the impacts of familiarity, trip purpose, and fare type on transfer behavior. By using 3-days as the threshold, I reduce the correlation between travel frequency and fare type to 0.32 for the north model, and 0.41 for the south model. Both are acceptably small for model estimation purposes.

Service reliability may have a significant impact on the perceived transfer inconvenience. Unreliable service would increase the uncertainty and risk associated with transfers, thus raising the transfer penalty. However, service reliability is hard to define in a single term. Possible indicators of service reliability may include early or late arrival, service variability, and adherence to schedule. However, historical information on these measures is not available from either the on-board survey or the MBTA operations database. In this study, I use the riders' evaluation of service reliability as an indicator to explore the impact of reliability on transfers. I expect riders who view commuter rail service reliability as very poor (rating =1) to have a higher standard for reliability than other riders. Therefore, the risk and uncertainty associated with transferring from commuter rail to subway should also be higher for this group of people. In other words, they perceive a higher transfer penalty than those who are not as sensitive to service reliability.

4.4.2 Choice Set Generation

Because the transfer decision involves choices of mode, path, and station, it is critical to identify credible choice sets available to each individual rail passenger. Two issues arise: treatment of double transfers within the subway system, and rules governing choice set availability.

My analysis indicates that there are very few second transfers in the subway system after riders transfer from commuter rail. Although the commuter-rail on-board survey does not record the travel path inside the subway system, I can infer the incidence of second transfers based on the destination and results from the previous study. The subway case identified a threshold of

9.5 minutes of walk time savings to justify a subway-to-subway transfer, i.e. a typical subway rider will transfer to another subway line when he or she can save at least 9.5 minutes of walking to reach the destination.[6] In the commuter rail case, I expect an even higher threshold because the second transfer is likely to be perceived more negatively by riders.

After comparing the two network distances to reported destinations from the two closest subway stations, separately, on the first and second subway transfer lines, I found commuter rail customers could not save more than 9.5 minutes of walking by adding one more transfer within the subway system. This is due to the geography of the study area and the subway network structure (see Figure 4-8).

First, downtown Boston is on an east-west peninsula with the Green and Orange subway lines also running east-west. Therefore, most destinations in the study area are within a short distance of these two lines. Second, the Red and Orange lines intersect and cover most of downtown Boston. Therefore, commuter rail customers can choose one of the subway lines to reach their destinations directly. For example, if a commuter rail passenger can save a long walk by transferring one more time from the Red Line to the Orange Line after egressing at South Station, this customer will egress at Back Bay and transfer immediately to the Orange Line. Thus, the second transfer is not a credible option, so that it is reasonable to assume there are virtually no second transfers within the subway system for commuter rail trips ending in downtown Boston.

In determining the rules for choice set availability, I rely on the walk times and total travel times. The subway study demonstrated that these two times are dominant in determining the

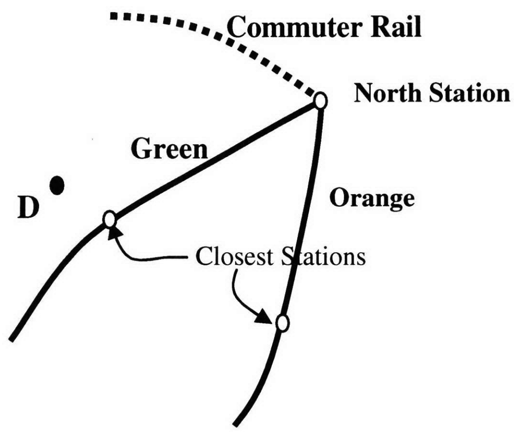
[6] This number is the average for the whole subway system, but the movement directions involved in the commuter rail-to-subway case have an above-on-average transfer penalty comparing to the whole subway system. These movement directions include Westbound Green Line to Red Line, Southbound Orange Line to Red Line, Northbound Red Line to Orange Line and Green Line.

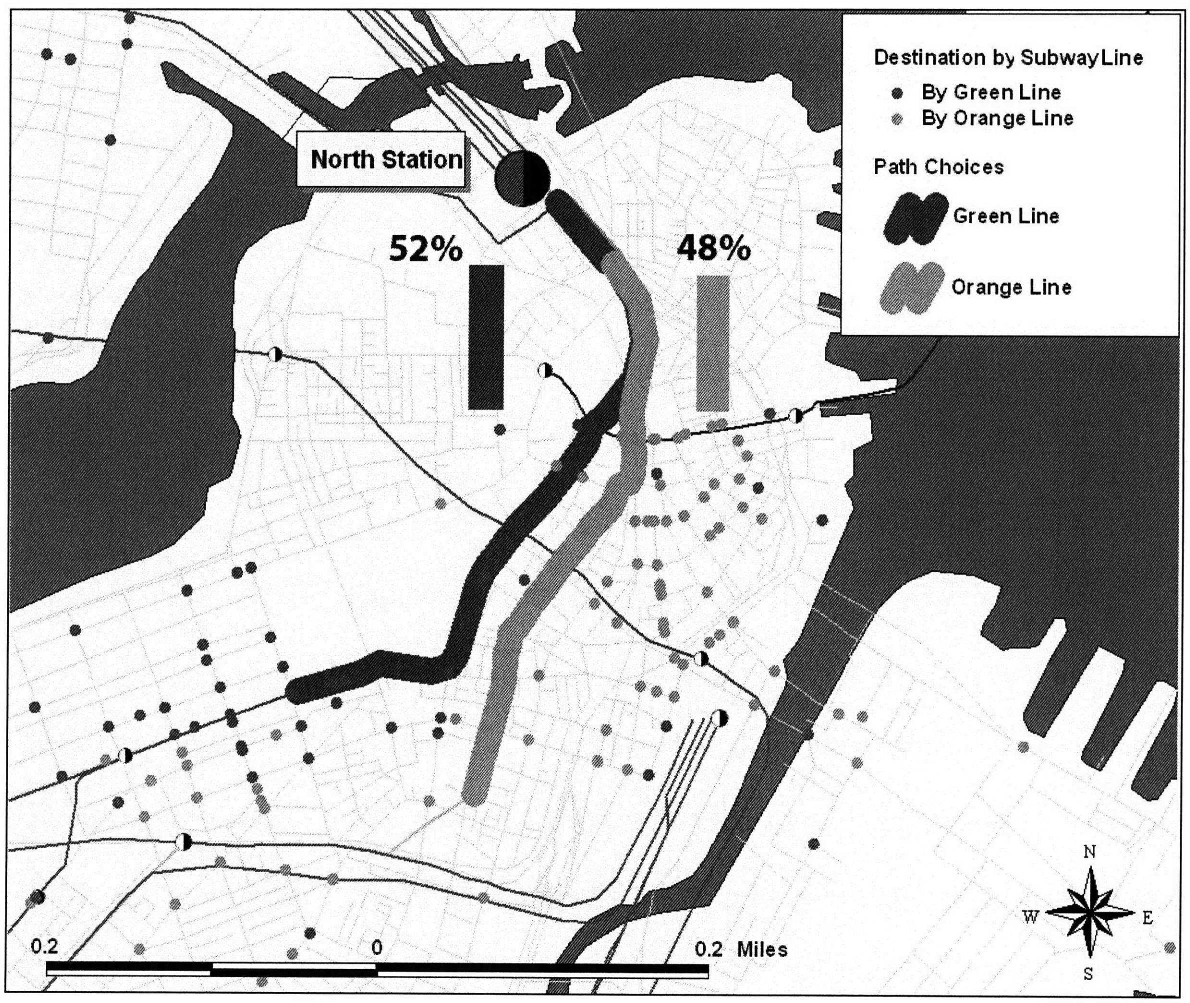
choice set, although other factors may have some influence. I assume a transfer option is available only if it brings additional benefits, either walk time or total travel time savings, because a transfer option usually involves extra transfer walking and waiting. Specifically, if an alternative has both the shortest walking distance and the shortest total travel time, the decision is assumed to be deterministic, and there is no need to model it. Passengers are assumed to have multiple options only when trade-offs among transfers, total travel time, and walking are involved.

For example, Figures 4-12 to 4-14 show three situations, each with a destination D. Figure 4-12 represents the choice between Green and Orange Line paths after transferring at North Station, and commuter rail passengers' choices from the on-board survey. D is a destination closer to the Green Line. The trip ending at D should not have a credible Orange Line option because it saves neither walk time nor total travel time compared to the Green Line option. The on-board survey clearly confirms this assumption. All passengers transferring to the Orange Line go to a destination south of the Orange Line, far away from the Green Line. The opposite is true for passengers transferring to the Green Line.

Figure 4-13 represents the choice between exiting the commuter rail at Back Bay or South Station. The destination D is closer to the South Station on the Red Line. In this example, Back Bay station is not a credible option for trips ending at D, because it involves both a longer in-vehicle travel time and a longer walk time compared to South Station. Results from the on-board survey indicate that passengers exiting at Back Bay end at destinations near the station and along the Green Line, while passengers exiting at South Station have destinations close to the Station.

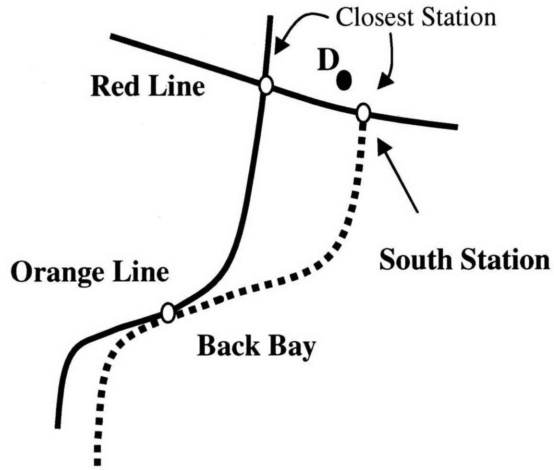
Figure 4-14 indicates the choice between transferring to the subway and walking directly to the destination. In this example, destination D is closer to the commuter-rail terminal; therefore,

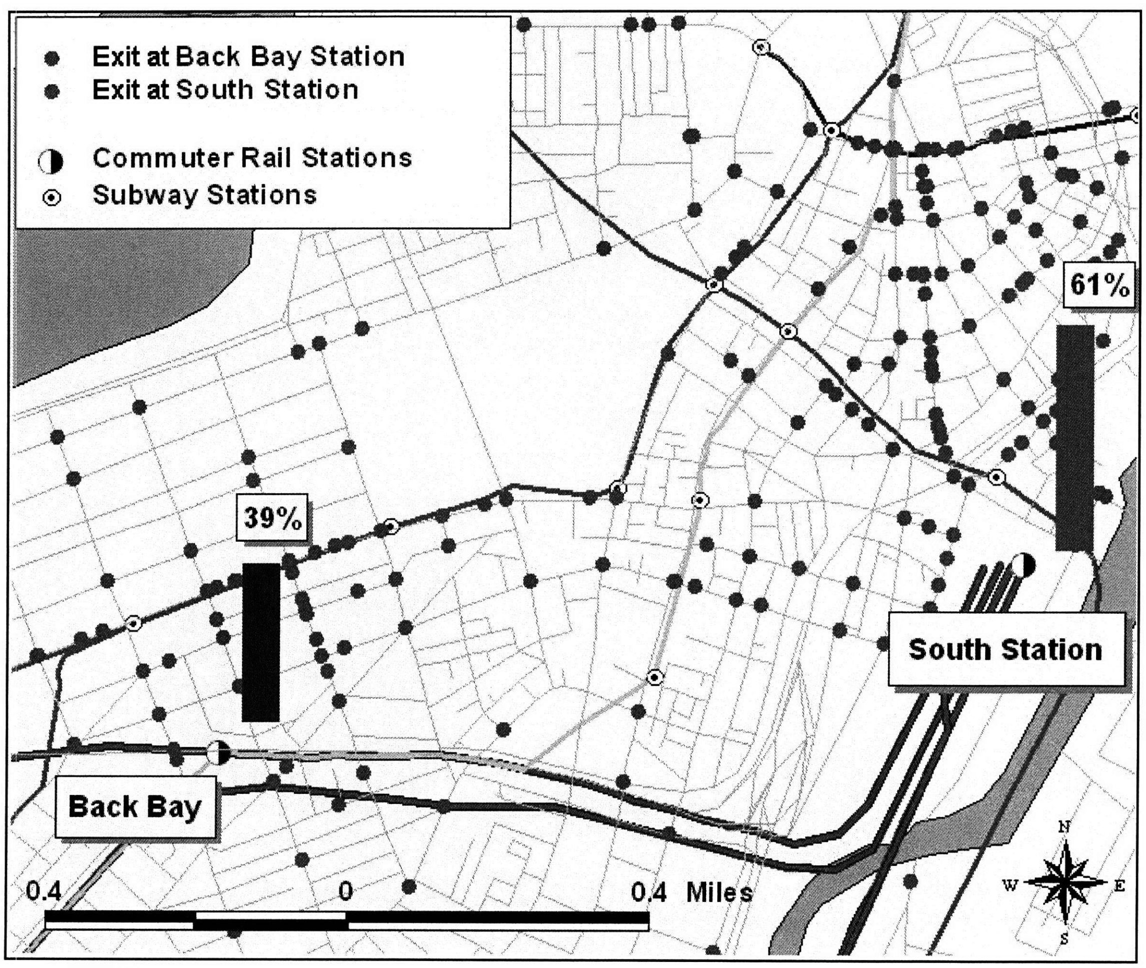




Source: created by the author based on the MBTA Commuter Rail On-board Survey (CTPS 1993)

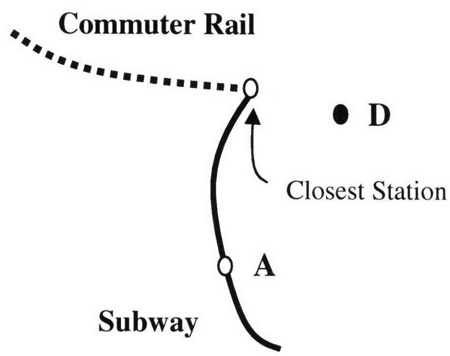
Figure 4-12 Choice between Green and Orange Lines at North Station

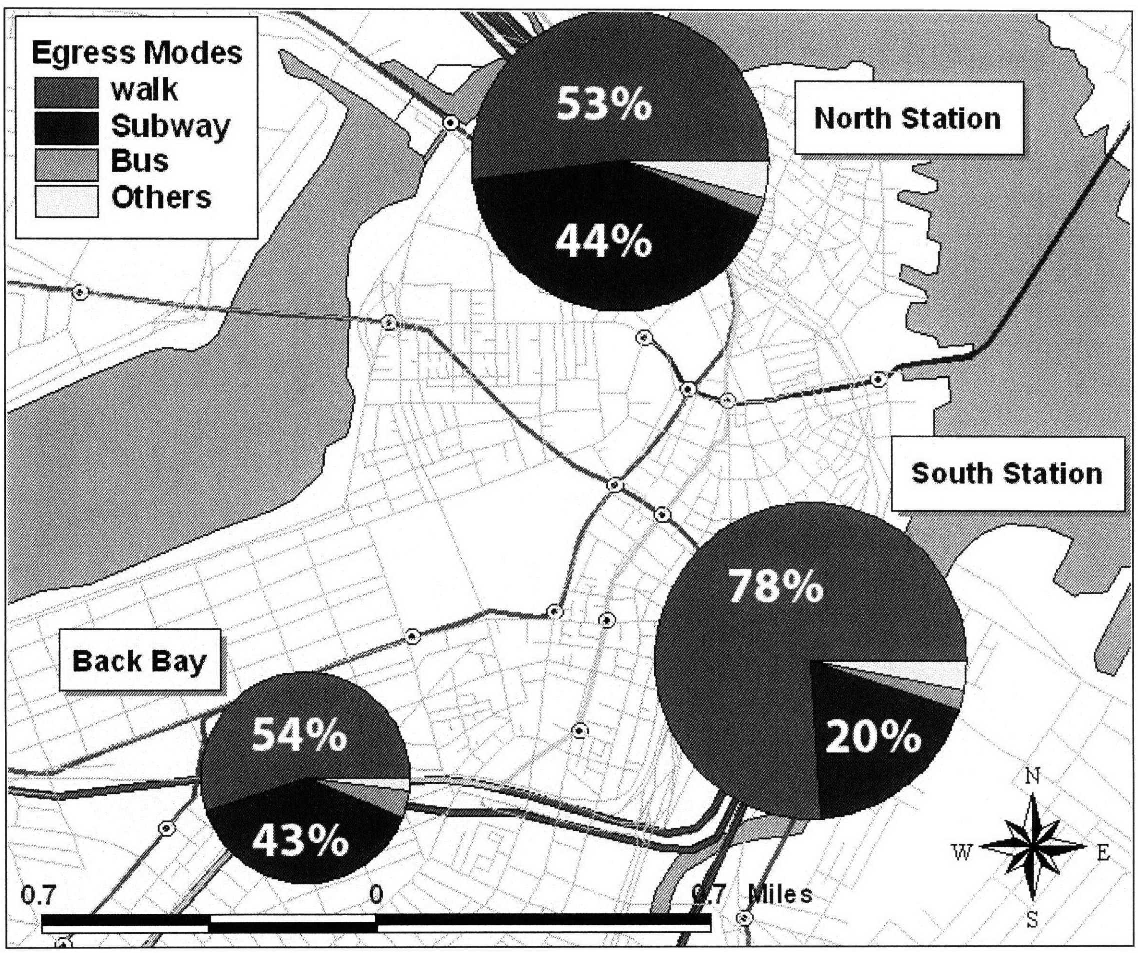




Source: created by the author based on the MBTA Commuter Rail On-board Survey (CTPS 1993)

Figure 4-13 Choice between South Station and Back Bay





Source: created by the author based on the MBTA Commuter Rail On-board Survey (CTPS 1993)

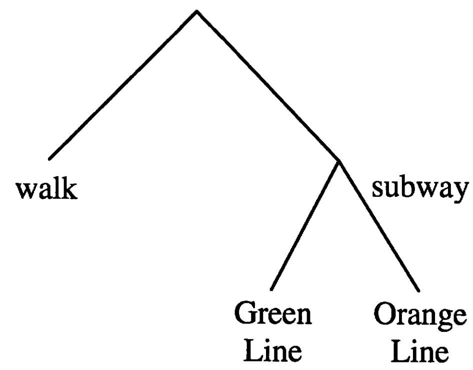
Figure 4-14 Egress Mode Choice at Commuter Rail Terminals

transferring to the subway and exiting at station A is not a credible option. Figure 4-14 also shows the share of commuter-rail passenger choices. The values are affected by the land-use pattern in the station area and the layout of subway lines. For example, South Station is very close to the Financial District, a major job center in downtown Boston, and many commuter rail passengers can walk to their destinations directly without transferring to the subway.

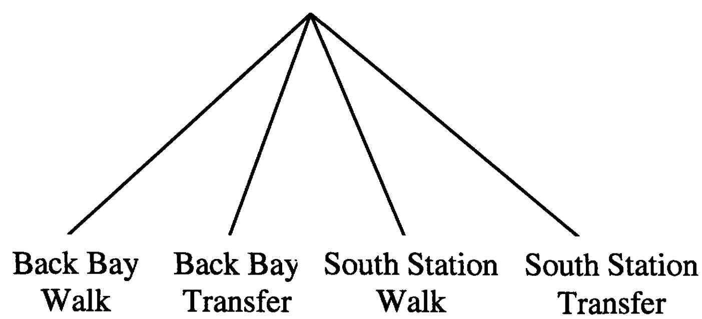
4.4.3 Model Specification

Because the north and south commuter rail lines belong to different sub-systems without any connection, I develop two separate models. On the north side, there are three potential choices available to commuter rail customers: (1) no transfer, (2) transfer to the Green Line, and (3) transfer to the Orange Line. Obviously, the latter two choices share some common characteristics because they both involve transfers to the subway. A commuter rail customer must first decide to transfer to select either of these options. In this case, a nested model structure is appropriate where the transfer decision acts as an input to the choice of subway line (see Figure 4-15 (a)).

On the south side, there are four choices available: Back Bay walk, Back Bay transfer, South Station walk, and South Station transfer. The on-board survey recorded a small number of trips transferring to the Green Line station from Back Bay, but they all ended outside the study area, and so I exclude these trips from the analysis. For the four choices, there are two main decisions: the decision between transfer and walk, and the decision about the exit station. I assume commuter rail customers may follow any of three potential decision processes: (a) decide about the exit station first, and then choose between the transfer and walk options; (b) decide to transfer (or not) first, and then choose from which station to exit; (c) the station and transfer



(a) North-Side



(b) South-Side

Source: the author

Figure 4-15 Model Structures for the Commuter Rail Systems

decisions are not interrelated, so that there are four unrelated options without a decision hierarchy. I test these three model structures. The Robust t-test for the scale parameter of the nest is -0.13 for the first structure, and 0.21 for the second structure. This means that the nested structures are not appropriate for the south models, i.e., the station and transfer choices are not interrelated. Choosing a particular exit station does not affect the transfer decision, and the transfer or walk decision does not influence the choice of exit. Therefore, a simple multinomial logit (MNL) model structure is appropriate (see Figure 4-15 (b)).

The models predict the probability of a particular commuter rail customer choosing among transfer, station, and service line options. Independent variables include the constants for each option, in-vehicle and walk time, fare type, familiarity, and service reliability. The constant for transfer alternatives depicts the impact of the transfer on choosing this alternative. The ratio between this constant and a travel time coefficient is the marginal rate of substitution, or the transfer penalty, measured in travel time equivalence. In the MMNL cases, the constant becomes a random parameter to be estimated.

The most challenging work in MMNL estimation is to define the distribution of the random parameter. Analysts have found that there is no single perfect distribution, and an inappropriate choice of the distribution may lead to serious bias in model forecast and in the estimated means of random parameters (Hess, Bierlaire, and Polak 2005, Fosgerau 2006, Hess and Axhausen 2005). They proposed different distributions depending on the particular question of interest. Fosgerau and Bierlaire (2007) also proposed a practical test to evaluate the performance of various distributions. The three distributions I used (Normal, Lognormal, and Triangle) are based on the prior work, primarily by Hess, Bierlaire, and Polak (2005) and Train and Sonnier (2004).

The normal distribution is an unbounded symmetrical distribution, which means that it has infinite tails on both sides, implying both positive and negative values for this parameter especially when the mean is close to zero. This might be inappropriate because no transit passengers are likely to view transfers positively as this might imply. In this situation, the lognormal distribution might be a better choice because it constrains the values to be non-negative. However, the lognormal distribution applicability is limited for two reasons: its long tail on the unbounded side, and problems with slow convergence in some cases. Sometimes it can lead to severe problems with overestimated standard deviations and means. Another problem with the Lognormal distribution is that it arbitrarily sets the lower bound at zero, which may or may not be the case. For example, passengers may have a minimum perceived transfer penalty larger than zero. For these reasons, the use of distributions bounded at both sides, with bounds directly estimated from the data, may be preferable.

An example is the triangular distribution, which allows for a peaked, but bounded, density function. The triangular distribution is rarely used with MMNL models, as the linear segments between its bounds and the mode are seen as restrictive. However, the Triangular distribution avoids the long tails of the normal distribution and the strict bounds of the lognormal distribution, and can be used to estimate both lower and upper bounds of the distribution. Another more complicated example is Johnson's S_B distribution (Train and Sonnier 2004). The S_B distribution is advantageous over other bounded distributions in that it can be used to approximate a number of very different distributions such as the normal, lognormal, beta, symmetric, asymmetric, flat plateau, or bi-modal. However, in my case, the flexibility of the S_B distribution might cause instability in model estimation, and, for this reason, I exclude it from the analysis.

Depending on the independent variables included on the right-hand side and the distribution assumptions for the random parameters, I developed five types of models: two MNL and three MMNL models. Model A includes only in-vehicle time and walking time as independent variables. Model B adds fare type, travel frequency representing familiarity with the transit network, and sensitivity to reliability, which will capture part of the variation of the transfer penalty. Models C-E include random parameters to examine possible taste variation among individuals. Model C assumes the Normal distribution, Model D the Lognormal distribution, and

Model E the Triangular distribution. I apply the five types of models to both the south and north commuter rail networks; therefore, I estimate a total of ten models.

4.4.4 Estimation Results and Interpretation

Tables 4-9 and 4-10 show the estimation results for the north and south commuter rail networks, respectively. All ten models have reasonable adjusted ρ^2, which indicates that the model specifications provide a good explanation of transfer behavior from commuter rail to subway in downtown Boston. The south models have significantly higher adjusted ρ^2 values than the north models, which indicate that the travel-time variables better explain transfer behavior on the south side. The transfer option in all models has the expected negative sign, which confirms the existence of a transfer "penalty." The constant for the transfer option also captures the modal preference for subway, and thus the negative sign actually comes from two sources: the transfer penalty and possible aversion to the subway of commuter rail riders. I assume the second source is not significant because commuter rail and subway are both rail transport systems, and riders likely see them similarly despite the differences between them.

Average Transfer Penalties (Model A)

For the north models, I estimated the transfer penalty based on Equation (16), to be equivalent to about 17 minutes of walking time, which is much higher than the subway-to-subway transfer penalty that I estimated in the subway study (see Table 4-5). The Orange and Green Lines are perceived similarly even though the Green Line is a fully grade-separated light-rail line with higher frequency, but lower speeds and reliability than the Orange Line, which is a standard heavy rail line.

Table 4-9 Estimation Results for the North Side Commuter Rail Network

Variables		MNL		MMNL		
		Model A	Model B	Model C Normal	Model D Lognormal	Model E Triangular
Intercept						
Green Line						
Mean:		-3.45 ***	-4.86 ***	-5.91 ***	-7.00 ***	-5.16 ***
Standard Deviation:				2.41 ***	3.82 ***	0.63 ***
Orange Line		-3.36 ***	-4.72 ***	-5.01 ***	-5.00 ***	-4.88 ***
Travel Time Attributes (Minutes)						
Walk Time (all three alternatives)		-0.20 ***	-0.21 ***	-0.22 ***	-0.21 ***	-0.20***
In-vehicle Time (two transfer alternatives)		-0.08 ***	-0.07 *	-0.05	-0.017	-0.022
Trip & Personal Attributes						
(specific to non-transfer alternative)						
Fare Type: Monthly Pass			-0.81 ***	-0.86 ***	-0.86 ***	-0.81 ***
Frequent Rider (>=3 days/week)			-0.56 *	-0.57 *	-0.60 *	-0.62 ***
Reliability Sensitive (rating=1)			-1.08 ***	-1.10 ***	-1.10 *	-1.1 ***
Reliability Insensitive (rating=5)			-0.23*	-0.22 *	-0.24 *	-0.23 *
Scale				34.4		3.26 ***
Transfer Penalty (minutes of walk)	**To Green Line**					
	Mean	17.25	23.14	26.9	33.3	25.8
	Standard Deviation			11.0	18.2	3.15
	Lower Bound			$-\infty$	0	18.1
	Upper Bound			$+\infty$	$+\infty$	33.5
	To Orange Line (mean)	16.80	22.48	22.8	23.8	24.4
Adjusted ρ^2		0.299	0.321	0.328	0.327	0.321

Note ***: P < 0.001; **: P < 0.05; *: P < 0.1. N=1725

Table 4-10 Estimation Results for the South Side Commuter Rail Network

Variables		MNL		MMNL		
		Model A	Model B	Model C Normal	Model D Lognormal	Model E Triangular
Intercept						
Transfer from Back Bay						
Mean		-2.83 ***	-3.01 ***	-3.08***	-5.23***	-3.52***
Standard Deviation				-1.46 ***	-4.15***	-0.685***
Walk from South Station		-1.05 ***	-1.04 ***	-1.14 ***	-1.24 ***	-1.18 ***
Transfer from South Station						
Mean		-4.49 ***	-4.69 ***	-4.89 ***	-5.02 ***	-4.96 ***
Standard Deviation				-0.002	1.005	0.016
Travel Time Attributes (Minutes)						
Walk Time (all four alternatives)		-0.33 ***	-0.33 ***	-0.35 ***	-0.36 ***	-0.35 ***
Subway In-vehicle Travel Time (two transfer alternatives)		-0.28 ***	0.29 ***	-0.28 ***	-0.24***	-0.27***
Trip & Personal Attributes (two walk alternatives)						
Fare Type: Monthly Pass			-1.21 ***	-1.28 ***	-1.33 ***	-1.31 ***
Frequent Rider (>=3 days/week)			0.76 **	0.82 ***	1.00 ***	0.85 ***
Reliability Sensitive (rating=1)			-0.51	-0.53	-0.52	-0.54
Reliability Insensitive (rating=5)			0.04	0.05	0.06	0.05
Transfer Penalty (minutes of walk)	Back Bay Mean	8.51	9.0	8.8	14.5	10.1
	Standard Deviation			4.2	11.5	1.96
	Lower Bound			$-\infty$	0	5.3
	Upper Bound			$+\infty$	$+\infty$	14.8
	South Station Mean	13.86	14.0	14.0	13.9	14.2
	Standard Deviation			0.0	0.0	0.016
	Lower Bound			$-\infty$	0	14.1
	Upper Bound			$+\infty$	$+\infty$	14.3
Adjusted ρ^2		0.498	0.511	0.512	0.513	0.512

Note ***: P < 0.001; **: P < 0.05; *: P < 0.1. N = 1560

For the south models, compared to subway-to-subway transfers, the penalty is much higher at South Station (14 minutes of walking), and only slightly higher at Back Bay (8.5 minutes of walking), but both are much lower than for North Station. This is reasonable because commuter rail and subway share the same station facilities at both South Station and Back Bay, while they are in separate locations at North Station, separated by a long walk. Back Bay station out-performs South Station in both walk and transfer choices: for transfer riders, the transfer penalty is about 5 minutes lower, and for non-transfer riders, Back Bay is also preferred to South Station by 3.2 minutes of surface walking.

There are probably two reasons why Back Bay is perceived to be a better station. First, the connection between commuter rail and subway at the Back Bay station is convenient. The second reason is that the Back Bay station is located between a commercial and a residential district, and it has good pedestrian access to the surrounding areas. The streetscape is well designed with plenty of plants, open space, and stores; furthermore, there is not much traffic, and its speed is usually low. In contrast, South Station is isolated by the central artery from the downtown area. Several major arteries intersect in front of the main station entrance and the streets are wide, traffic is heavy, and speed can be high. It is not easy to walk across these streets to get to adjacent destinations. Also, this area contains primarily high-rise offices towers, and few pedestrian amenities. The last but not least important reason is the construction activity at South Station at the time when the survey was conducted, which likely increased the inconvenience of transfer to subway at this station.

Variation of the Transfer Penalty: Fare, Frequency, and Reliability (Model B)

In these models, the monthly pass variable consistently has a negative sign as expected, which means that pass holders are less likely to walk directly to destinations from commuter rail than non-pass holders. Their transfer penalty is about 3.8 minutes walk time (0.81/0.21) less than the cash/ticket users for the north system, and about 3.7 minutes (1.21/0.33) less for the south. Given that the subway fare was $0.85 at that time (1993), the implied value of walk time (per hour) is (60/3.8)*0.85 = $13.40 for the north, and $13.80 for the south, in 1993 dollars. Using the regional average ratio (1.28) between out-of-vehicle travel time (OVTT) and in-vehicle travel time (IVTT) (CTPS 1997), the estimated value of IVTT is $10.50 for the north, and $10.80 for the south, very close to the value of $10.90 used for Boston in 1993.[8] This further supports the validity of the estimated model.

On the north side, frequent riders also have a smaller transfer penalty (by 2.7 minutes of walk time (0.56/0.21)) compared to infrequent riders, probably due to their greater familiarity with the transit network. On average, non-pass, infrequent, and reliability-insensitive riders have a transfer penalty equivalent to about 23 minutes of walking, 6 minutes higher than the population as a whole. For the south side, frequent riders are more likely to walk than transfer with an additional transfer penalty of 2.3 minutes (0.76/0.33). There are two possible explanations for these seemingly contradictory findings. First, frequency of travel may not strongly affect the transfer decision. Second, frequent riders may trade-off the familiarity with the pedestrian environment and the familiarity with the transit system. Frequent riders on the south side may prefer walking because they are familiar with the pedestrian environment as well

[8] Data are from the annual mobility report from Texas Transportation Institute: http://mobility.tamu.edu/ums/congestion_data/tables/boston.pdf

as the transit network. Reliability variables are not significant in most models, and thus do not affect transfer decisions.

On average, the transfer penalty for non-pass, infrequent, and reliability-insensitive passengers increases slightly at Back Bay (0.5 minutes from 8.5 to 9.0), and South Station (0.1 minute from 13.9 to 14.0). However, the trip and personal attributes included significantly increased the explanatory power from Model A to Model B. This further suggests that although these factors affect the transfer decision, they act in opposite directions and cancel each other out, leading to the unchanged transfer penalty. Therefore, dealing only with the average value not the variation of the transfer penalty can lead to misunderstanding of transfer behavior.

Variation of the Transfer Penalty: Attitudes, Preferences, and Perceptions (Models C-E)

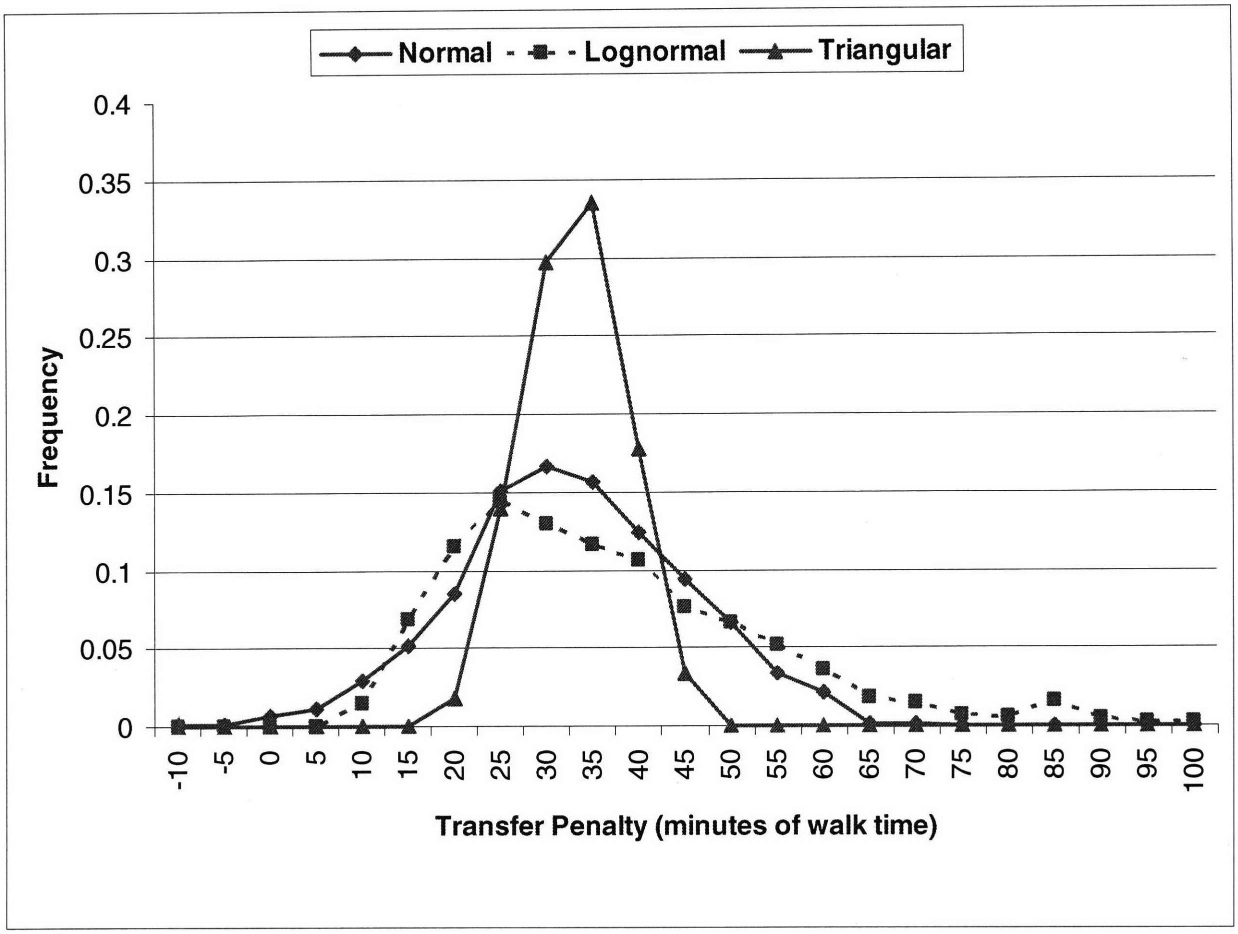
In these models, I allow the constant of the transfer alternative to have a random coefficient, so that I can estimate up to four additional parameters: the mean, the standard deviation, and the two bounds. Because the north models have only three alternatives with a nest, I can estimate only one more random constant parameter (Walker 2001). Therefore, I set only the constant of the Green Line transfer to be a random parameter because I expect the Green Line to have a larger variance than the Orange Line. The standard deviation represents the taste variation among riders with respect to the transfer option, while the bounds indicate the range of such variation.

For the three random parameters estimated, two have both means and standard deviations significant at the 1 percent confidence level: Green Line transfers, and Back Bay transfers. The mean of South Station transfer is significant, but the standard deviation is not. This indicates that perceptions of transfers at South Station are almost homogeneous among commuter rail riders.

The other two random parameters yield consistent results across all three MMNL models. For the Normal distribution model, the estimated means of the Green Line (27 minutes) and Back Bay (8.8 minutes) transfer penalty change only slightly from the MNL model (Model B). The standard deviation is 11.3 minutes for the Green Line transfer, and 4.2 minutes for the Back Bay transfer. This suggests that only about one percent of Green Line North Station commuter rail riders perceive the transfers positively, and two percent at Back Bay station. The small number of positive values might be due to the assumption of the Normal distribution discussed earlier.

This problem can be corrected by assuming a lognormal distribution, but this significantly overestimates the means and standard deviations for the Green Line (by 22 and 62 percent) and Back Bay transfers (by 68 and 162 percent). Thus, the lognormal assumption creates significant bias by setting an arbitrary lower bound of zero on the distribution. This problem can be avoided by using the triangular distribution, and allowing the lower and upper bounds to be estimated. The triangular assumption yields similar means as the Normal distribution and MNL models, but much smaller standard deviations, about 40 percent of those in the normal distribution. This suggests that the normal distribution also overestimates the standard deviation but less so than the lognormal distribution. The estimated lower and upper bounds of the transfer penalty are 18.1 and 33.5 minutes for the Green Line transfer, and 5.3 and 14.8 minutes for the Back Bay transfer. Therefore, the unbounded assumptions of both normal and lognormal are inappropriate. However, the symmetric Triangular distribution has the potential to underestimate the upper bound when the real distribution might be skewed to the right as in the transfer penalty case.

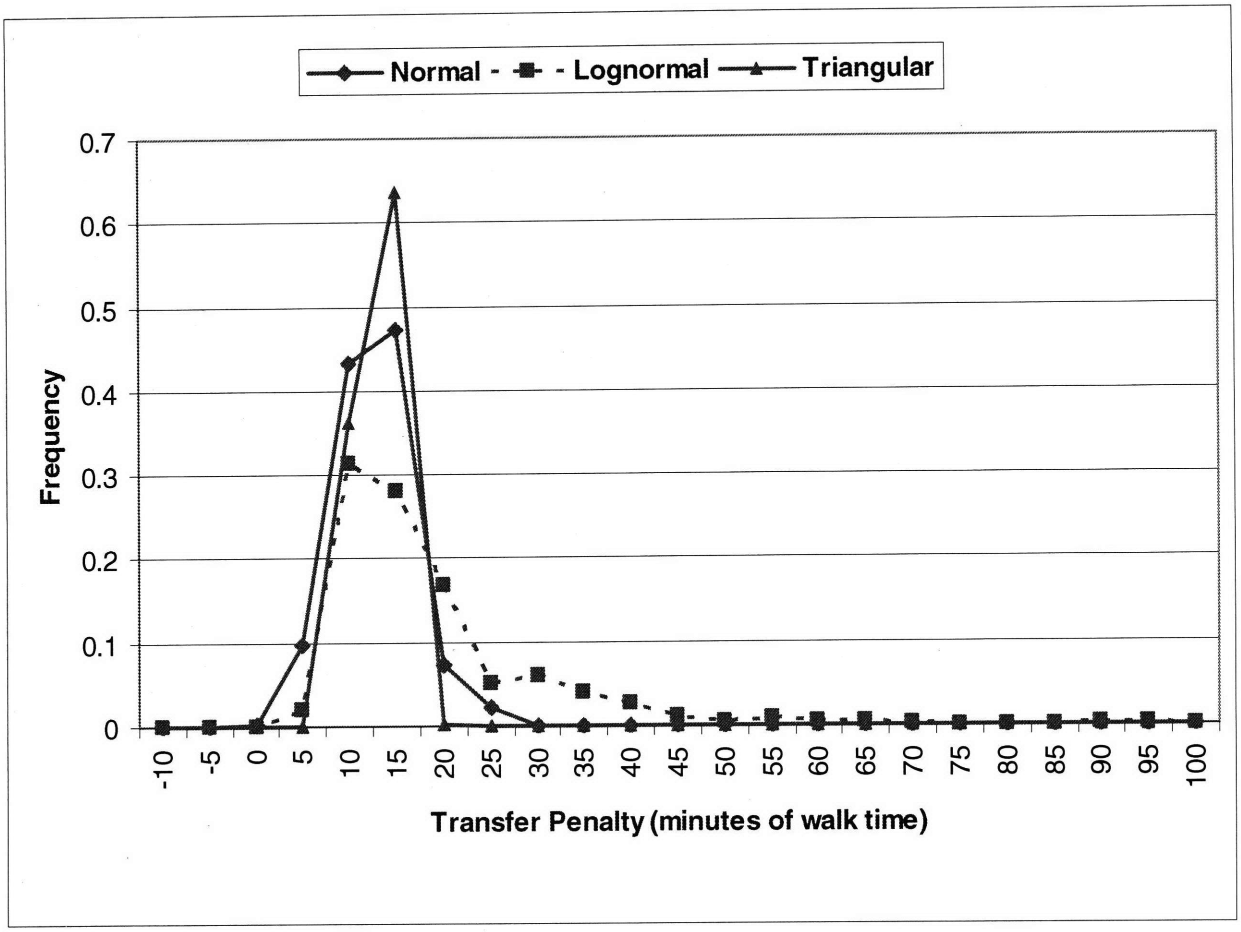
Figures 4-16 and 4-17 show the simulated distributions of the transfer penalties for the Green Line at North Station and Back Bay Station. The simulation is based on random draws from each of the assumed distributions, normal, lognormal, and triangular with the number of



Source: created by the author based on model estimated results

Figure 4-16 Distributions of the Implied Transfer Penalty at North Station for the Green Line

draws being the same as the number of observations in each model. In general, the variation of the transfer penalty is not wide with even the largest standard deviation being small compared to the mean. The goodness-of-fit is not improved significantly going from the MNL models to the MMNL models. Both indicate a relatively uniform perception among commuter rail riders of transfers to subway. The standard deviations of the transfer penalty from the Triangular distribution are 1.95 and 3.15 minutes respectively, which is much smaller than the differences of the average transfer penalties among different transfer stations and demographic groups. This suggests that the variation of the transfer penalty originates more from observable factors such as



Source: created by the author based on model estimated results

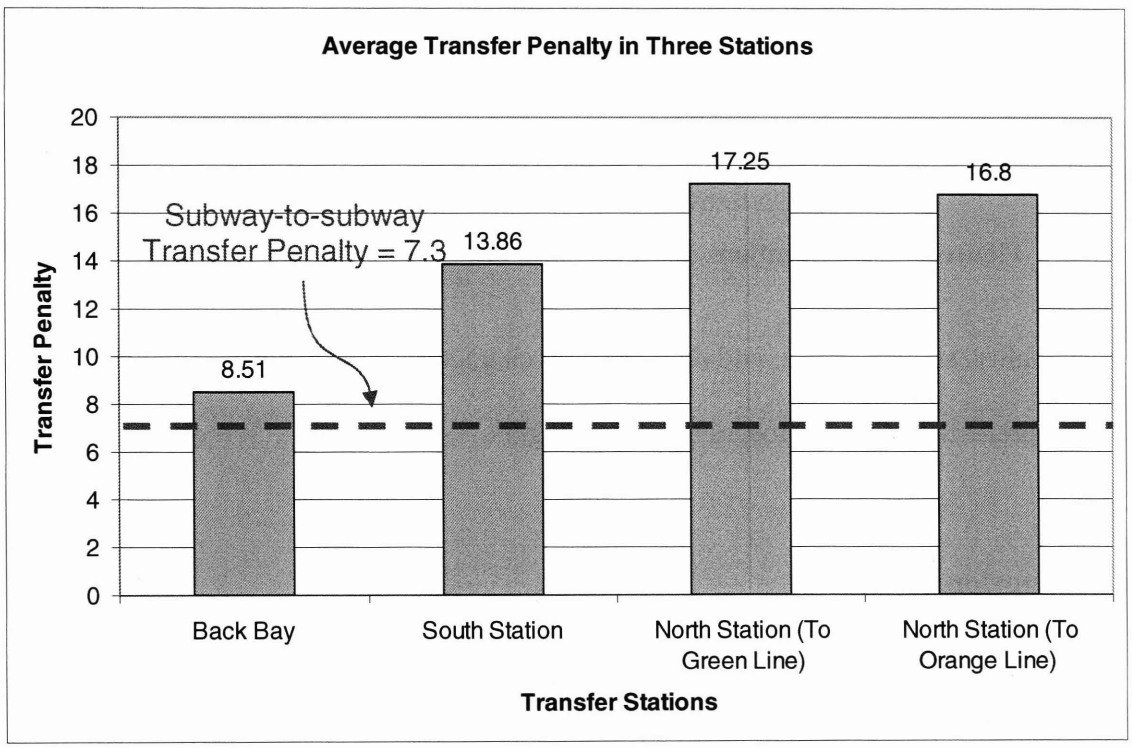
Figure 4-17 Distributions of the Implied Transfer Penalty at Back Bay Station

service quality, station design, and demographic characteristics, than from the unobservable attitudes, preferences, and perceptions of passengers.

4.4.5 Discussion

There are many passenger transfer trips between commuter rail and subway because commuter rail usually has only a few stops in the central city, and many passengers rely on the subway to reach their destinations. Considering the significant roles of commuter rail and subway in the entire transit network (they carry 70 percent of all transit ridership in Boston), a convenient connection between them is vital to the success of the entire system. However, transfer behavior is more complicated across systems than within an individual system. The transit path, exit station, and transfer choices might be interrelated, and all should be considered together.

This research indicates that commuter-rail-to-subway transfers are consistently more negatively perceived than subway-to-subway transfers. The transfer penalty ranges from 8.5 to 17 minutes of walking at four transfer situations, all being all higher than the 7.3 minutes in the subway case in previous research (Figure 4-18). Longer transfer walks, more complicated modal connections, and monetary cost of transfers all contribute to the increased "penalty". Among the four transfer situations in Boston, transfers on the north side have a higher "penalty" than those on the south side due to the separation of the commuter rail terminal and subway

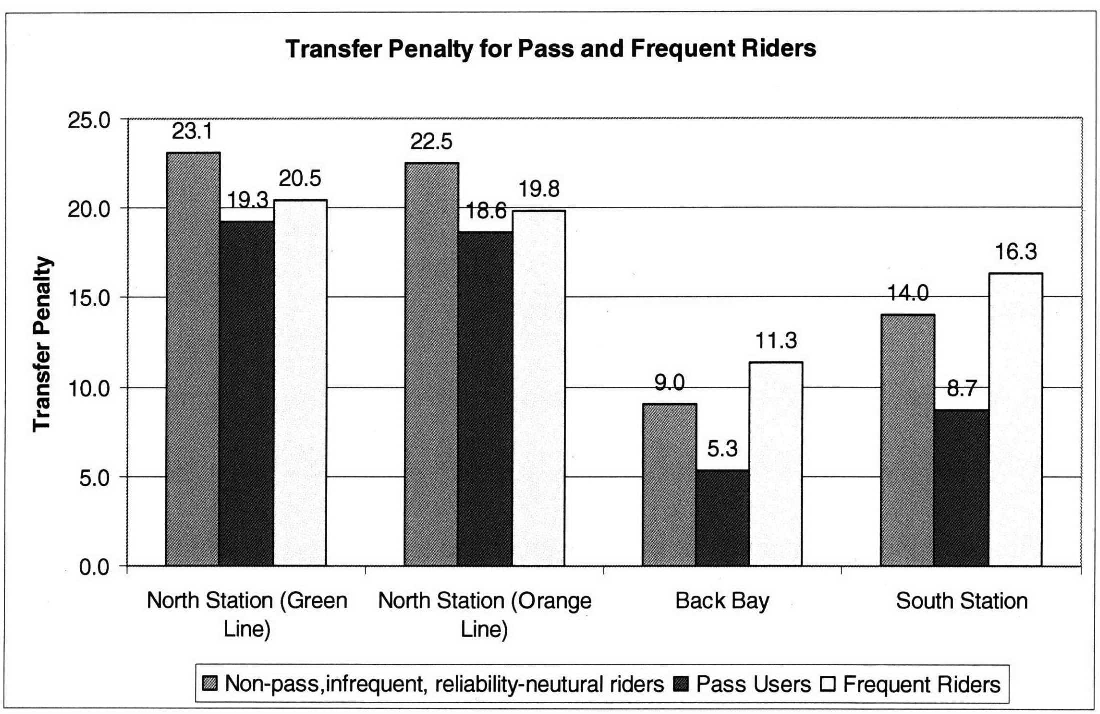


Source: created by the author based on the model estimated results

Figure 4-18 Transfer Penalty Across Stations

stations at North Station. While the transfer penalty is almost the same between the Green and Orange Lines at North Station, it is much lower at the Back Bay station (to the Orange Line) than at South Station (to Red Line): a 5 minutes difference. Back Bay is the best transfer station because it has the shortest walking distance between platforms, the simplest connection path, and availability of escalators.

Monthly pass users, who have free access to the subway, have consistently lower transfer penalties than cash riders, a 3.7 to 3.8 minutes difference (Figure 4-19). However, the influence of travel frequency on the transfer penalty is mixed. At North Station, frequent riders are more likely to transfer having a 2.7 minute (of walk time) lower transfer penalty, while at South Station, frequent riders tend to walk more, having a 2.3 minute extra transfer penalty. This is probably due to a problem with variable definition. I use frequency as a proxy for familiarity with the network, and perceptions of reliability not the actual reliability, which might be



Source: created by the author based on the model estimated results

Figure 4-19 Transfer Penalty across Rider Groups

inappropriate. For example, frequency may mean a familiarity not only with the transit network, but also with the pedestrian environment. An infrequent rider may choose to transfer because it may be easier to get lost walking in unfamiliar neighborhoods than riding a train. Clear and well-defined attitude variables would be very helpful in further studies.

To explore the variation of the transfer penalty among individual riders, I applied the random parameter method to investigate the distribution of the transfer penalty. In general the variation of the transfer penalty among individuals is small, which suggests that the simple MNL model form is adequate.

This research has extended our understanding of transfers to interchanges between commuter rail and subway. The research findings can benefit travel behavior modeling and hence appraisal of transportation projects. The next step might be to examine transfers between transit and non-transit systems like auto, walk, and bicycle because the eventual goal of this comprehensive study is to enhance the role of transit in the entire transportation system by improving the transfer experience within transit systems and between transit and non-transit modes.

4.5 Conclusion of Boston Case Study

In this Boston case study, I investigate path choice and transfer behavior in a mid-size rail network. Such a network affects the case study in two main ways. First, because the network is too simple to support a full path choice analysis, I had to develop a new method rather than follow the traditional approach to path choice analysis. Second, there are only a few major transfer stations in the network which are concentrated in a small area in the urban core. The transfer environment is usually simple, and the need for comprehensive transfer planning is not high, which suggests that applications of research findings to the operation and planning in the Boston rail systems are not a priority to operators as well as passengers. Therefore, compared to the London case study, in the Boston study, I focus on method development and understanding behavior.

I base the new method on sub-path choice on the egress portion of travel in a public transport system and apply it to the Boston subway and commuter rail networks. Because of the system differences, for the subway study, I focus on subway-to-subway transfers and the spatial variation of transfer experience across stations and movements, and for the commuter rail study, I focus on the commuter rail-to-subway transfers and the heterogeneity of individual transfer experience.

The proposed method can capture the transfer decision in a small or mid-sized public transport network. On-board surveys and statistical models clearly suggest a trade-off between transfer and walking at the sub-path level for both subway and commuter rail passengers. This method can be a useful approach for transfer analysis in other small or mid-sized networks.

In both studies, I find surprisingly high transfer penalties in the two systems. Subway-to-subway transfers, often viewed as the most convenient transfers in public transport networks, are perceived, on average, as 7.3 minutes of street walking, including transfer walking and waiting times. The commuter rail-to-subway transfers are even worse, about 17 minutes in North Station, and 14 minutes in South Station. The high values suggest that public transport systems may not be perceived to be as effective as planners have believed. Improving transfer experience has great potential to improve the service quality and competitiveness of public transport.

Meanwhile, my results also suggest that the average experience does not help much on policy implementation because there is a great variation of such experience across stations and movements, even in a small simple network like the Boston subway. For example, the worst transfer movement can be almost an order of magnitude worse than the best transfer movement (21.4 vs. 2.4 minutes). Interestingly, all passengers seem to have similar attitudes towards transfers. In other words, the spatial variation of transfer environment is more important than the taste differences among individuals in determining individual transfer experience. The variation of the transfer penalty across stations or movement indicates the quality differences of transfer environments. From a policy point of view, this suggests that transfer planning is more important than marketing in improving transfer experience. In the London case study, I analyze these issues in detail.

Chapter 5 LONDON CASE STUDY

The public transport network in London is much larger than its counterpart in Boston: the bus fleet is 9 times larger, bus passengers are 18 times greater,[13] the underground network is 4 times larger, and ridership is 7 times higher. It is also more diverse and complex with multiple well-connected modes: bus, Underground, Overground, National Rail, light rail, tram, coach, London riverbus, etc. Passengers often have multiple paths available for travel from their origin to destination, and many make one ore more interchanges along the journey at more than 600 major interchange facilities[14]. The number of interchanges[15] in one of the sub-systems, London Underground, actually exceeds the total ridership in the entire Boston network on a typical weekday.[16]

Such network characteristics have two implications for this case study. First, more diverse and complex decision situations exist in the path-choice process. Unlike the Boston study where I only consider the trade-off between interchange and walking time saved, I need to analyze many more types of trade-offs in the London study. Second, interchange is a critical element not only in service operation, but also in capital investment and planning. According to the TfL Business Plan (2002/03 -2007/08), a total of £100 million was allocated to interchanges over the plan period. Therefore, this case study emphasizes the application of research findings in

[13] In 2006, the annual ridership is 104 million (unlinked trips) for MBTA buses, and 1,816 million (linked trips) for London buses.

14 According to the 2002 Interchange Plan, it includes all rail stations, tram stops, Riverbus stops and coach termini, together with their nearest bus stops, and 33 major 'bus-bus' interchanges.

[15] In the U.K., interchange instead of transfer is commonly used by public transport agencies; therefore this term is used in the London case study, which is interchangeable with the term, transfer, in the Boston case study.

[16] Number of interchanges in the London Underground is 1.42 million on a weekday in 2004, while the total MBTA daily ridership is about 1.2 million in 2006.

operation and planning. Behavioral exploration and policy implications are equally important. The two implications suggest that a different approach should be adopted in the London study.

Section 5.1 describes the London public transport network in detail and explains why the London Underground is selected as the system for investigation. Sections 5.2 and 5.3 summarize path choice and interchanges in the Underground from the supply and demand perspectives, respectively. Section 5.4 introduces the research design, and Section 5.5 discusses the path choice generation process. Section 5.6 describes the datasets used, and defines the variables. Section 5.7 develops a series of choice models and analyzes the estimation results. Section 5.8 presents two applications of the research results in operations and planning. Section 5.9 concludes the London case study.

5.1 The London Public Transport Network

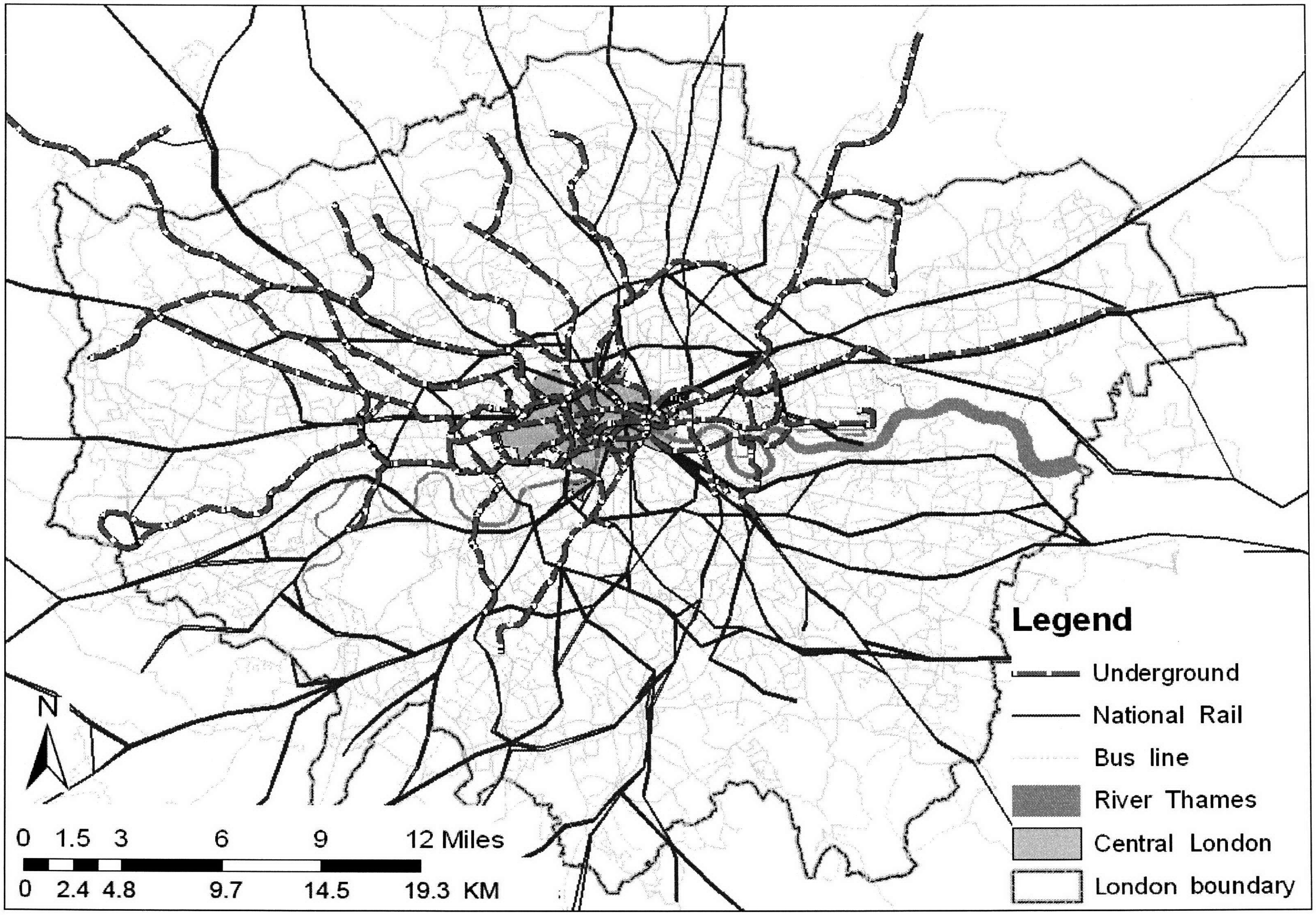
London has one of the largest and most complex multimodal public transport networks in the world. It consists of three major region-wide systems: bus, Underground, and regional rail, plus various other sub-systems including light rail and tram. Most commuter rail services are managed by National Rail as part of the nation-wide National Rail Network (NRN), while the other major modes are managed by Transport for London (TfL). All systems are well integrated in terms of timetable, fare media, infrastructure, and travel information, and they provide multiple travel paths and interchange options in the region. Figure 5-1 shows the layout of these systems, and Figure 5-2 displays the major interchanges in the region.

Bus serves the entire region within the Greater London Authority (GLA) boundary with one of the largest and most comprehensive bus networks in the world. Over 6,800 scheduled buses operate on over 700 different bus routes carrying over 1.5 billion passenger journeys annually. The network is managed by London Buses, an arm of Transport for London, although services are operated under contract by private companies. The bus network is connected to the rail network at all stations and provides feeder service as well as origin-destination service. Bus-to-bus interchanges are less frequent compared to bus-to-rail interchanges, but are still common. About 20 percent of bus trips involve at least one interchange with another bus and the interchange locations are more dispersed than the rail interchanges. Major bus-bus interchanges, however, tend to be in locations such as suburban town centers where a number of routes converge. There are 33 major bus-bus interchange hubs in London (London Transport Planning 1997).

The Underground serves London north of the river much more extensively than the south. This is the result of a combination of unfavorable geology, historical competition from surface railways and the historical development of London which was focused to the north of the Thames (Figure 5-1). It is the world's oldest underground railway system with services operating since 1863. The system has been continuously expanded in the past century and a half with the most recent addition being the extension of the Jubilee Line from Green Park to Stratford in 1999. The Underground has 268 stations and 407 km (253 miles) of track, making it the longest underground railway in the world by route length, and one of the largest in terms of stations. On a typical weekday, about 3.2 million people travel on the Underground. Unlinked trips total at least 4.6 million because many passengers will use more than one line to complete a journey. The size and complexity of the network offer ample travel options to Underground passengers with respect to path choice, and the network provides a solid platform to test the influence of interchange inconvenience on travel decisions.

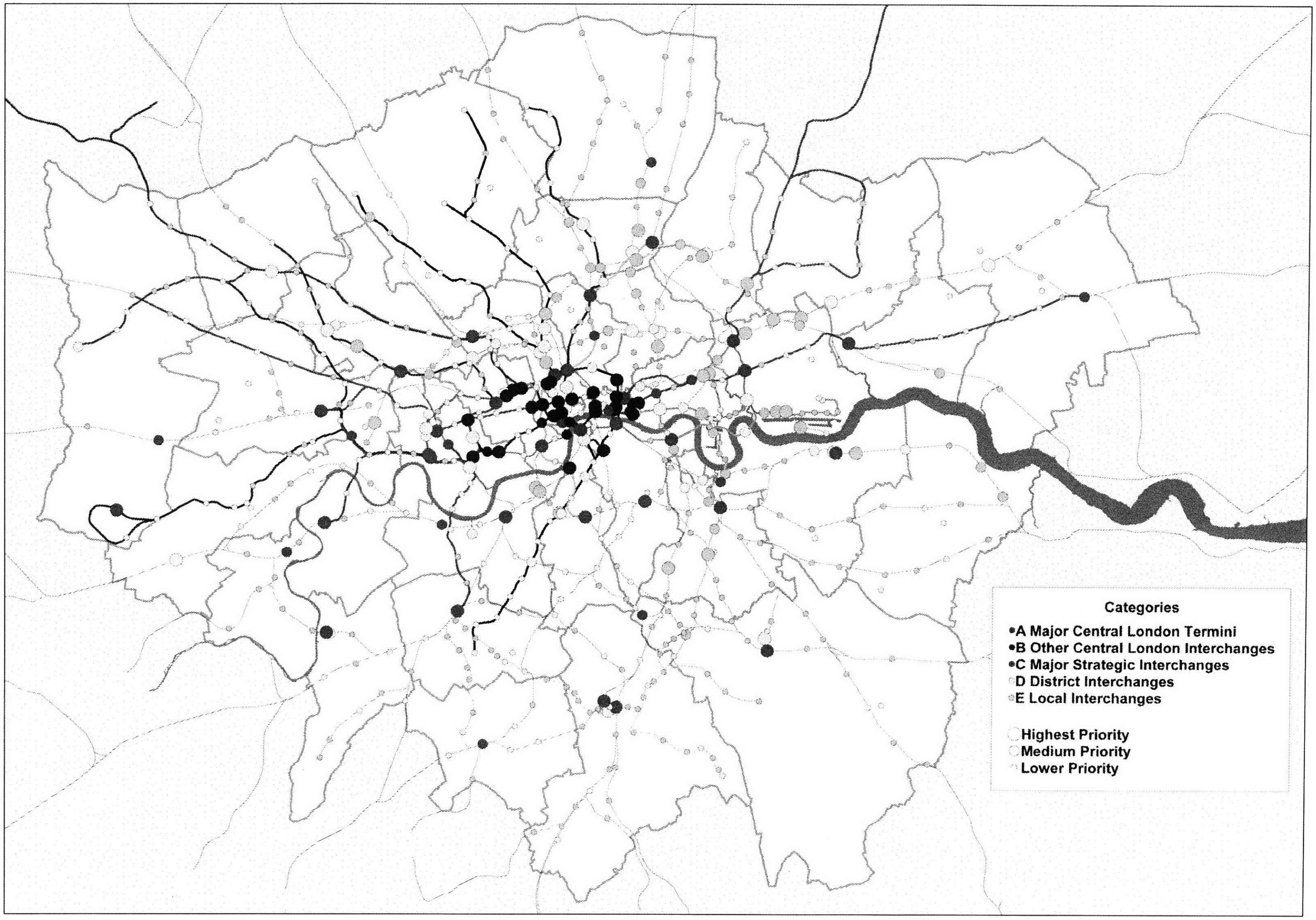
Regional rail forms another extensive network serving London as well as the surrounding metropolitan area. The network has nearly 2,000 miles of track and more than 700 stations on more than 40 lines. There are 0.47 rail stations per square mile (one for each 2.1 square miles) of developed land. Regional rail represents approximately 20 percent of public transport travel in London. The network connects to the Underground at major termini, most of which are on the circumferential rail line, the Circle Line. Because each terminus is associated with commuter services from a particular segment of this area, and there is no through running of trains on the network, interchange volumes at these termini between regional rail and the Underground are very high. In addition to its radial lines, there are also several orbital lines inter-connecting parts of the inner city such as the West London Line, the North London Line, and the Gospel Oak to Barking line linking inner North London to the northeastern suburbs. Work is also underway to extend the Underground's East London Line, converting it into a heavy rail line and linking its northern end to the North London line, while extending its southern end to south London. These extensions will eventually create an outer rail loop through the inner suburbs, named the London Overground, which will provide more alternative travel paths in the rail network.

Another recent development for the public transport network is Crossrail, a newly planned multi-billion pound new line. Crossrail will link services into Paddington in the west with Docklands and services out of Liverpool Street in the east, by constructing twin 16-km tunnels underneath Central London. New stations will be provided at key locations, linking to the Underground. This major new addition will provide more interchange locations and travel paths in the network.



Source: Transport for London 2006

Figure 5-1 London Public Transport Network



Source: TfL 2002 Interchange Plan

Figure 5-2 Strategically Important Interchange Locations

The complexity of the London public transport network makes it difficult to cover all these modes in a single study: path choice analysis is more complicated in a multimodal network than in a unimodal system (Hoogendoorn-Lanser 2005). The strategy I take here is to focus on one mode first, and expand the analysis to other modes if necessary. Of the three major modes, I choose the Underground as the system for investigation because (1) interchanges are more frequent and therefore more important in the Underground network than in the bus network[17], (2) the Underground network provides more path options between origin-destination (ODs) than the regional rail network, and (3) with exit control, both trip origins and destinations can be identified quite accurately in the Underground.

5.2 Transport Supply and Multiple Paths in Underground

Two characteristics of the Underground network are relevant to path choices within the system: a large number of connections and a viable circumferential service. Except for the short Waterloo and City Line, East London Line, and the Circle Line, all other lines run through Central London, and intersect with other lines at multiple locations (see Figure 5-3). Unlike the relatively small Boston system where all interchange stations are close together in downtown, these points of intersection are distributed over a wide area. Non-central interchange locations include Finsbury Park between the Piccadilly and Victoria Lines, Acton Town between the District and Piccadilly Lines, Stratford between the Central and Jubilee Lines, and Wembley Park between the Metropolitan and Jubilee Lines.

The highly connected nature of the network also results in multiple interchange stations between the same pairs of lines in Central London, such as Euston and Warren St between the

[17] 40 percent of Underground trips involve at least one interchange within the system, while the rate for bus trips is only 20 percent.

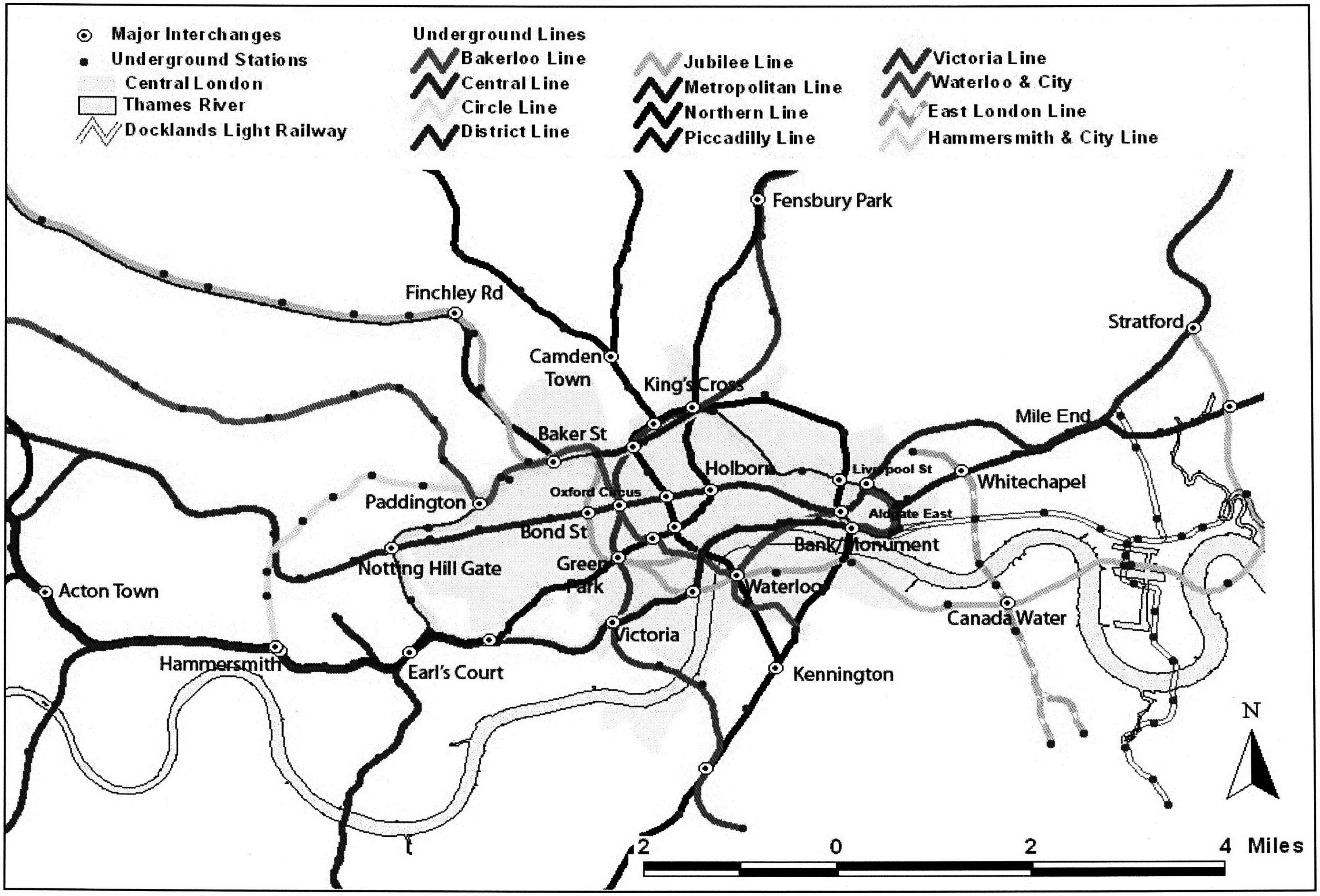
Northern and Victoria Lines, Baker St and Waterloo between the Jubilee and Bakerloo Lines, and Green Park and King's Cross between the Victoria and Piccadilly Lines. At the same time, the Circle Line together with segments of the District, Hammersmith, and Metropolitan Lines provide a "ring" service around Central London. These services link major National Rail termini including Paddington, Waterloo, King's Cross, Victoria, and Liverpool St. They are likely to provide more direct but sometimes slower connections between some origin and destination pairs. This type of network frequently offers multiple line choices at the start of a trip, and various options for most line-to-line interchanges.

This section focuses on multiple paths while the next section focuses on interchanges. The first two sub-sections summarize the transport supply in the Underground that affect multiple path options with section 5.2.1 focusing on infrastructure and technology and section 5.2.2 focusing on service and operations. The last sub-section 5.2.3 describes the multiple path choice behavior based on on-board survey results.

5.2.1 Infrastructure and Technology

Table 5-1 summarizes the number of interchange stations between the ten major Underground lines.[18] Except for the case of the Metropolitan and District Lines, all major Underground lines have interchanges with all other major lines. The Circle Line connects with each other major line at an average of 2.4 stations. This value is 2.2 for the District Line, but falls as low as 1.4 for the Victoria and Metropolitan Lines. Not surprisingly, along each major line, a large number of stations are interchange stations. For example, 8 out of 16 stations on the Victoria Line are interchange stations, while 8 of 25 Bakerloo stations are interchange stations. On average 36

[18] The Waterloo and City Line is not included because it acts like a shuttle service between Waterloo and Bank stations with no stops in between. The East London Line is also not included because it serves as a feeder service to the Hammersmith and District Lines.



Source: Transport for London 2006

Figure 5-3 Underground Lines and Major Interchanges

Table 5-1 Number of Interchange Stations by Underground Line

# of Interchange Stations	Bakerloo	Central	Circle	District	Hammersmith	Jubilee	Metropolitan	Northern	Piccadilly	Victoria
Bakerloo										
Central	1									
Circle	2	3								
District	2	3	4 *							
Hammersmith	1	2	3 *	4 *						
Jubilee	2	2	2	2	2					
Metropolitan	1	1	2 *	0	2	3				
Northern	4	2	3	2	2	2	2			
Piccadilly	1	1	3	3	2	1	2	2		
Victoria	1	1	2	1	1	1	1	3	3	
Summary										
# of Interchange lines	9	9	9	8	9	9	8	9	9	9
# of interchange stations	7	10	14	18	12	12	8	15	12	8
Average # of interchange stations per line pair	1.5	1.7	2.4	2.2	2	1.8	1.4	2.2	1.8	1.4

Note: *: for parallel services, only the first and the last stations on the common-shared trunk are defined as interchange stations

Source: Transport for London, 2008

percent of stations on a major Underground line are interchange stations. The good connections between Underground lines provide opportunities for multiple travel paths between many OD pairs.

The 12 Underground lines are different from each other in many respects: infrastructure, technology, operation, service quality, etc[19]. Even after travel time attributes are controlled for, they still offer diverse travel experiences. Based on the physical infrastructure, the lines can be classified into two types: subsurface and deep-tunnel. Subsurface lines include the entire Circle Line and segments of the District, Hammersmith, and Metropolitan lines. They were constructed using the cut-and-cover method (about 5 meters below the surface), while the deep-tunnel lines were bored using a tunneling shield about 20 meters below the surface, with each track in a separate tunnel. The deep-tunnel lines are for the most part self-contained, but the subsurface lines are part of an interconnected network: Each shares track with one or two other lines. The infrastructure difference affects the adopted technology and travel experience.

The subsurface and deep-tunnel lines use different types of rolling stock, most notably in terms of size (Table 5-2). The A, C, and D stock used by the subsurface lines have more interior space, while the stock used on deep-tunnel lines normally have little standing space due to the tunnel-size constraint. Besides size, other physical features such as curvature, platform length and in recent times the signaling system all mean that rolling stock increasingly can be used only on one specific line. For example, the Central and Victoria Lines platforms are 120 meters long and have different Automatic Train Operation systems specific to each train type. Most other Tube platforms are only 105 meters. The western part of the Circle Line has platforms that are too short to accommodate District Line D78 stock.

[19] Information is from the Transport for London (TfL) website: www.tfl.gov.uk, accessed in April 2008.

The stock type affects the level of congestion on trains. For example, the Jubilee Line extension serves a vast population in the East London/Stratford area with a huge passenger volume, but its 1996 stock is particularly small due to the size constraint of the deep- tunnel. Congestion has become a serious problem and causes many Jubilee Line passenger complaints. The infrastructure differences also affect the environment on the system, a major cause of travel disomfort in the Underground in the summer. Heat in the system is generated by the trains (motors and braking systems etc.), station equipment, and body heat from the passengers. Compared to the subsurface lines, the deep-tunnel lines are at a particular disadvantage: the heat accumulates due to poor ventilation, while conventional air conditioning could not be installed due to the lack of equipment on trains and the problem of dispersing the waste heat. [20] As a result, temperatures can reach very uncomfortable levels on parts of the systems under unfavorable conditions: 47 °C (116 ° F) were recorded at times in summer 2006.

5.2.2 Operation and Service Quality

Each Underground line operates differently with the most notable feature being the number of branches in each line. There are a total of 64 branch services formed by short-runs or split services (Table 5-2). The District, Northern, and Metropolitan Lines each have more than 10 branches, while the Central and Piccadilly Lines have 8 each. The District is one of the most complex Underground lines to operate, with only a single route running east to Upminster but three branches to the west to Ealing, Richmond, and Wimbledon (Table 5-3). The main central London tracks also accommodate the southern section of the Circle line. Additionally, there is a separate Wimbledon/Putney Bridge service to Edgware Road and a branch to

[20] Instead, massive blocks of ice have been used inside the trains. Source: http://www.undergroundcooling.net/, accessed on May 18, 2008

Table 5-2 Underground Line Characteristics

Lines	Important Dates**	Size		Structure		Cars		Average Weekday Passengers
		Length	Stations (interchanges*)	Branches	Type	Type	# of cars/Train	
Bakerloo	1906, 1907, 1917, 1939	23 km (15 miles)	25 (8)	3	Short-runs	1972 Mark-2 tube stock	7	302,869
Central	1900, 1908, 1920	74 km (46 miles)	49 (10)	8	Short-runs Split services	1992-tube stock	8	589,734
Circle	1863, 1868, 1875, 1884	22 km (15 miles)	27 (14)	1	Loop	C stock (1970s)	6	218,136
District	1868, 1879, 1884, 1902	64 km (40 miles)	60 (18)	10	Short-runs Split services	D and C stock (1970s, 1983)		556,252
East London	1869, 1876, 1913	8 km (5 miles)	9 (3)	2	Split services	A stock (1960s)	8	
Hammersmith and City	1864, 1884, 1936	27 km (17 miles)	19 (12)	1		C stock (1970s)	6	149,405
Jubilee	1979, 1999	36 km (23 miles)	27 (12)	7	Short-runs	1996 tube stock	6	405,878
Metropolitan	1868, 1879, 1892, 1904, 1932	67 km (42 miles)	34 (8)	10	Short-runs Split services	A stock (1960s)	8	186,271
Northern	1890, 1907, 1926, 1941	58 km (36 miles)	50 (15)	11	Short-runs Split services	1995 tube stock	6	660,395
Piccadilly	1906, 1933, 1977	71 km (44 miles)	52 (12)	8	Short-runs Split services	1973 tube stock	6	529,550
Victoria	1971	21 km (13 miles)	16 (8)	2	Short-runs	1967 tube stock	8	511,714
Waterloo and City	1898	2.4 km (1.5 mile)	2 (0)	1		1992-tube stock	4	37,173

Note: * interchange stations on parallel lines include only the first and last stations on the common section; ** indicate the years that the line was opened and major extensions occurred

Source: Transport for London, 2008

Table 5-3 District Line Branches (Eastbound)

District Line Branches	Name	# of Stations	Frequency
1E	Ealing Broadway to Upminster	43	15 minutes
2E	Richmond to Upminster	42	30 minutes
3E	Wimbledon to Upminster	41	6.7 minutes
4E	Richmond to DagEast	38	30 minutes
5E	Richmond to Barking	34	30 minutes
6E	Richmond to Tower Hill	22	60 minutes
7E	Wimbledon to DagEast	37	30 minutes
8E	Wimbledon to Edgware Rd	14	20 minutes
9E	Ealing Broadway to High Street	12	15 minutes
10E	Olympia to Edgware Rd	7	15 minutes

Source: Transport for London, RailPlan

Olympia. Some of these branches are so different that they act like distinct lines. Branch services further complicate travel options and decisions in the Underground. Passengers may trade-off between different short-run or split services with respect to waiting time and interchanges. These behavioral issues will be discussed in detail in later sections of this chapter.

Underground lines or branches often run at different speeds due to the different line alignments, technologies, and operation plans. System average train speed is 33km per hour (20.5mph), including station stops. In Central London, trains cannot reach speeds of more than 30-40 mph because of the short distance between stations. On the Victoria Line, where stations are further apart, trains reach speeds of up to 50 mph and on the express service of the Metropolitan line, trains can reach over 60 mph.

Service quality in terms of reliability, crowding, and frequency also varies across Underground lines. Transport for London developed a Journey Time Metric (JTM) to measure the time spent along each step of a journey within the Underground system including access and egress between station entrances and platforms, ticketing, travel times, etc. The values are estimated for 13 4-week periods annually from 1998 to 2007 (Table 5-4). JTM also compares the ideal and actual values for each time component, with the gap referred to as the excess time. Excess times for initial waiting and in-vehicle travel indicate the delay or unreliability of service, while such values for station walking and ticketing suggest the level of crowding. Table 5-5 summarizes the values for each Underground line. The Bakerloo, Piccadilly, and Central Lines are the three most crowded underground lines, and the Metropolitan, District, and Circle Lines have the least reliable service. Transport for London also records the number of delays for each of the 13 periods. In 2007, the District, Metropolitan, and Piccadilly are the worst lines in terms of total annual delays (Table 5-5).

Wait time differs significantly across Underground lines. Based on JTM, the most frequent line is Victoria: average passenger wait time is 2.2 minutes, almost 3 minutes less than that of the East London Line. This value recognizes that some passengers may not be able to board the first train to arrive, so is longer than the waiting time calculated based on headways. The Circle, Hammersmith, and Metropolitan Lines all have long waiting times, but because their services are parallel in many parts of the network, the actual passenger waiting times should be shorter than the values shown in Table 5-4. Accordingly, the second-least frequent line is the Northern Line with an average passenger waiting time equal to 3.5 minutes.

5.2.3 Multiple Underground Paths

This section describes revealed path choice behavior in the Underground based on the Rolling Origin and Destination Survey (RODS) conducted by Transport for London (or its predecessor organization London Transport) from 1998 to 2005. A detailed description of RODS is

Table 5-4 Journey Time by Underground Line

Line	AEI	TPT	Station Time	PWT	OTT	Train Time	Closures	Total
Bakerloo	7.22	0.13	7.35	2.55	9.43	11.97	0.17	19.48
Central	6.85	0.21	7.06	2.66	14.34	17.00	0.98	25.03
Victoria	4.84	0.24	5.08	2.23	10.76	12.99	0.24	18.31
Jubilee	5.11	0.19	5.30	2.54	13.21	15.75	0.18	21.23
Northern	4.99	0.26	5.25	3.51	13.55	17.05	0.31	22.61
Piccadilly	5.66	0.29	5.94	2.44	16.63	19.07	0.29	25.30
District	4.42	0.24	4.67	3.16	15.78	18.94	0.25	23.85
Metropolitan*	6.34	0.20	6.54	4.19	22.71	26.89	1.06	34.49
Circle*	NC **	NC	NC	4.69	11.09	15.78	0.35	22.26
Hammersmith & City*	NC	NC	NC	4.12	10.89	15.01	0.19	20.61
W&C	NC	NC	NC	2.75	4.53	7.27	0.59	11.64
ELL	3.94	0.23	4.17	5.17	6.06	11.23	0.10	15.51
System wide	5.54	0.23	5.77	3.05	13.73	16.77	0.36	22.91

Note: 1 values are average for 13 periods each year from 1998 to 2006, and 3 periods in 2007
2 * values are based on 13 4-week periods each year from 2002 to 2006 and 3 periods in 2007
3 ** NC: not calculated because performance is difficult to separate from other lines.

Notation:
AEI: access, egress, and interchange time; TPT: ticket purchase time; PWT: passenger waiting time; OTT: on-train time

Source: Journey Time Metric 2007 from Transport for London

Table 5-5 Reliability and Crowding Indices by Underground Line

Line	Crowding Index	Reliability Index	Annual Delays
Bakerloo	3.26	2.37	229
Central	2.75	3.01	276
Victoria	2.09	3.36	142
Jubilee	1.95	3.11	196
Northern	2.15	3.40	271
Piccadilly	2.49	3.62	360
District	1.58	4.04	456
Metropolitan *	1.79	5.12	354
Circle *	NC**	3.99	183
Hammersmith & City *	NC	3.65	
W&C	NC	1.41	46
ELL	0.82	1.25	37

Note: 1 values are average for 13 periods each year from 1998 to 2006, and 3 periods in 2007 weighted as equivalence of in-vehicle time

2 * values are based on 13 4-week periods each year from 2002 to 2006, and 3 periods in 2007; ** not calculated because performance is difficult to separate from other lines.

Source: Transport for London, Journey Time Metric (JTM), 2007

provided in Section 5.6. RODS is the only data source with detailed information on travel paths and interchanges within the Underground network.

In many situations, multiple paths in the Underground network are available between origin and destination stations. As revealed by RODS, on average Underground OD pair has revealed 1.4 paths. The number decreases to 1.2 if only the AM peak is considered. Of course, these numbers are based only on revealed RODS paths, which cover less than 10 percent of total daily trips in the Underground. So the actual numbers of paths (and indeed OD pairs) should be larger (Gordillo 2006, Chan 2007). The number of available paths varies greatly across OD pairs. About 75 percent of ODs have only one revealed RODS path, while eight percent of OD pairs have three or more paths with a few ODs having as many as nine revealed RODS paths (Table 5-6).

Such a variation in the number of multiple paths is determined by the number of lines, and the location and type of origin and destination stations in the Underground. Obviously, the more lines serving the two OD stations, the more travel paths are available. When each station is served by a single line, on average there are 1.3 paths between them. When each station has four lines, the average number of revealed paths increases to 3.7 (see Table 5-7). Note that passengers might be indifferent between some lines at certain stations, such as the Metropolitan and Hammersmith Lines at Moorgate, and the District and Circle Lines at Temple.

In terms of location, stations in Central London tend to involve multiple travel paths in the Underground network. Stations in East London are also more likely to be connected with multiple paths, especially when the other trip end is in Central or South London (Table 5-8). This makes sense given the Underground network configuration in South and East London. South London is served primarily by two Underground lines, the Northern and Victoria Lines,

Table 5-6 Multiple Underground Paths in RODS Database

RODS Revealed Path	# of OD Pairs All Day	Percent	# of OD Pairs AM Peak	Percent
1 path	50,867	75.2%	28,197	83.7%
2 paths	11,344	16.8%	4,251	12.6%
3 paths	3,563	5.3%	907	2.7%
4+ paths	1,834	2.7%	312	1%
Total	67,608	100%	33,667	100%
Average path/OD	1.4		1.2	

Source: compiled by the author from RODS (1998-2005)

Table 5-7 Multiple Paths by Number of Lines at OD Stations

Egress station / Access station	1 line	2 lines	3 lines	4 lines	5 lines	6 lines	Average
1 line	1.28	1.56	1.82	2.00	1.99	2.05	1.78
2 lines	1.60	1.80	2.13	2.61	2.5	3.07	2.29
3 lines	1.71	1.94	2.11	2.61	2.29	3.18	2.31
4 lines	2.05	2.49	3.24	3.68	3.4	3.60	3.08
5 lines	1.99	2.45	2.56	4.40	N/A	7.00	3.68
6 lines	2.67	2.84	4.78	4.80	11.00	N/A	5.22
Average	1.88	2.18	2.77	3.35	4.24	3.78	

Source: compiled by the author from RODS (1998-2005)

Table 5-8 Multiple Paths by OD Station Location

Egress station / Access station	Central	East	North	Outside	South	West	Average
Central	1.84	1.64	1.67	1.57	1.81	1.59	1.69
East	1.71	1.47	1.58	1.69	1.75	1.54	1.62
North	1.61	1.5	1.21	1.16	1.19	1.22	1.32
Outside	1.65	1.47	1.11	1.15	1.00	1.17	1.26
South	1.99	1.73	1.29	1.00	1.35	1.25	1.44
West	1.55	1.45	1.18	1.17	1.27	1.2	1.30
Average	1.73	1.54	1.34	1.29	1.40	1.33	

Source: compiled by the author from RODS (1998-2005)

which connect in South London, with three branches serving Central London. The same situation exists in East London where the Central, District, Hammersmith, and Jubilee lines connect and follow different routes to Central London.

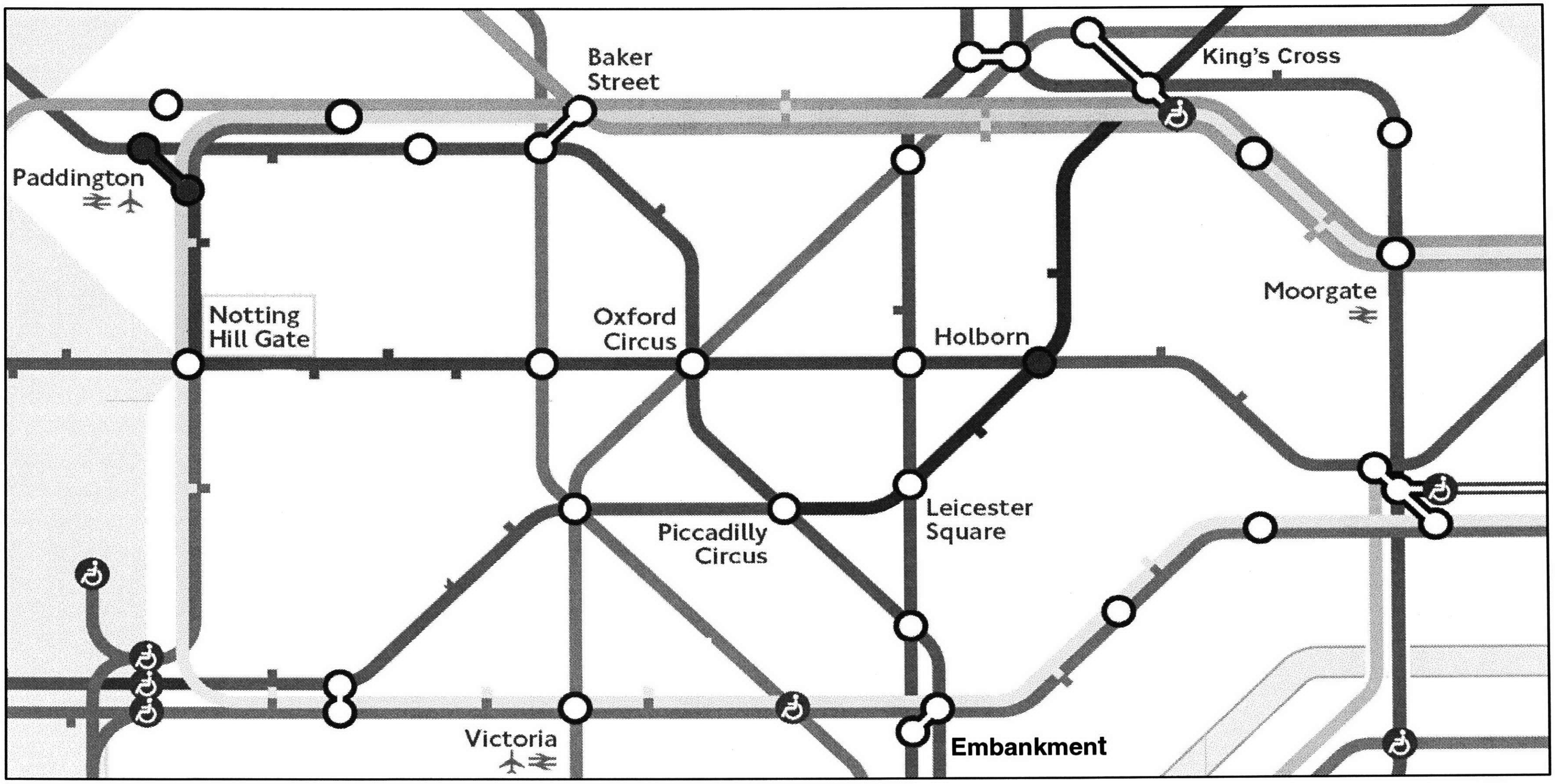
The type of station also matters: stations that serve as termini, major tourist sites, or shopping areas tend to have more multiple paths available, while stations that serve outer London tend to have fewer path options (Table 5-9). This is due to the correlation between

Table 5-9 Multiple Paths by Station Type

Egress station / Access station	City of London	Inner Suburb	Outer Suburb	Shopping	Teminus	Tourist	Average
City of London	1.97	1.75	1.84	2.09	3.25	1.89	2.13
Inner Suburb	1.78	1.35	1.27	1.96	2.06	1.64	1.68
Outer Suburb	1.76	1.25	1.20	1.78	2.10	1.68	1.63
Shopping	1.94	1.78	1.75	1.79	3.13	1.99	2.06
Teminus	2.73	2.12	2.13	2.44	3.61	2.56	2.60
Tourist	1.84	1.56	1.65	2.10	2.76	1.66	1.93
Average	2.00	1.64	1.64	2.03	2.82	1.90	

Source: compiled by the author from RODS (1998-2005)

station types, and station location and trip purposes. For example, terminus, shopping, and tourist stations are mainly in Central London, and serve a relative large portion of non-commuting trips, which tend to have multiple paths as suggested by the above analysis. Figure 5-4 shows an example of multiple paths between one Underground OD pair: Paddington to Holborn. Four travel paths are recorded by RODS: (1) Bakerloo then Central Lines, interchanging at Oxford Circus; (2) Bakerloo then Piccadilly Lines, interchanging at Piccadilly Circus; (3) Circle or District Lines then Central Lines, interchanging at Notting Hill Gate; (4) Circle then Piccadilly Lines, interchanging at King's Cross. Each path has advantages and disadvantages. Path 1 is the fastest option, but it involves a long walk to the deep Bakerloo platform, and an interchange at crowded Oxford Circus. Path 2 is slower than Path 1 but interchange at Piccadilly Circus might be easier. Paths 3 and 4 have the sub-surface Circle and District lines as the first leg of travel, but Path 3 has a shorter waiting time and longer travel time compared than path 4. RODS indicates that Path 1 is the popular option (81 percent of trips) followed by Path 3 (14 percent).



Source: Transport for London, London Underground RODS (1998-2005)

Figure 5-4 Multiple Underground Paths between Paddington and Holborn

OD pairs with multiple paths tend to, on average, involve more interchanges. RODS shows that, for OD pairs with a single RODS path, the average number of interchanges per path is 0.8, while for OD pairs with four or more RODS paths that value increases to 1.2. In other words, on average, every path involves more than one interchange. The issue of interchange is discussed in the following section.

5.3 Interchange Facilities and Activities in the London Underground

The transport supply in the London Underground, discussed in the above sections in terms of service provision and physical infrastructure at both the line and station levels, corresponds to the demand pattern with respect to multiple travel paths and frequent and diverse interchange activities. Of course, interchange and multiple paths are closely related because few origin-destination pairs have multiple paths that all offer direct service. In most cases, a path choice decision involves an interchange decision. This section describes interchange facilities in the Underground, and summarizes interchange activities in the network.

5.3.1 Interchange Stations

If an interchange is defined as a change of vehicle, an interchange station refers to a station where a passenger can make a rational decision to switch vehicles during travel. Such a station can be formed by the intersection of service lines, parallel services, or different branches on the same line. For example, the Piccadilly and District Lines run parallel between Acton Town and South Kensington; thus, a passenger can interchange between these lines at any station on this common trunk. On the Metropolitan Line, Baker Street station is the terminal of two short-run services. Surveys showed that people took the short-run service and then interchange at the station even though a direct service is available because Baker St is served by other lines. Based on this definition, about half of the 268 Underground stations are interchange stations, some of them combining all three situations: intersection, parallel, and branches.

Interchange stations vary greatly in terms of their size and complexity. Some major stations such as Paddington, Waterloo, and King's Cross also serve as termini for National Rail service. King's Cross connects six different Underground lines, while Waterloo and Paddington each connect four. Moorgate and Baker St are the most complicated interchange stations in terms of the number of platforms: each has ten platforms with different characteristics. Interchange becomes extremely complicated with so many platforms. At Baker St there are more than 40 different interchange movements, each representing different movement paths and environments. Attributes of the major interchange stations in Central London are summarized in Table 5-10.

The interchange movements are categorized into three types: same-platform, horizontal, and vertical. Same-platform interchanges often happen between parallel or branch services, such as Piccadilly to District at Hammersmith, Edgware District to Upminster District at Earl's Court, and Northern Charing Cross branch southbound to Northern City branch northbound at Kennington. They also occur in a few deep-tunnel stations between intersecting lines, such as Victoria southbound to Northern northbound at Euston, Victoria northbound to Piccadilly

Table 5-10 Central London Interchange Station Attributes

Station	# of Lines	# of Movements	# of Platforms ***						Facilities		
			Total	Tube	Sub	Sur	Shared	Island	Tkt	Esct	Lift
Baker Street	5	34*	10	4	2	4	2	2	2	6	
Bank/Monument	5	20**	8	6	2		2		3	15	6
Bond Street	2	16	4	4					1	30	
Earl's Court	2	12*	6	2	4			2	3	4	4
Embankment	4	24	6	4	2		2		1	10	
Euston	2	20*	6	6					1	10	
Green Park	3	24	6	6					1	11	
Holborn	2	16	4	4					1	7	
King's Cross	6	32	8	6	2		2		2	9	
Leicester Square	2	16	4	4					1	6	
Liverpool Street	4	16	4	2	2		2		3	9	
London Bridge	2	16	5	2				2	2	17	3
Moorgate	4	16	10		6		2	2	2	6	
Notting Hill Gate	3	16	4	2	2		2	1	1	6	
Oxford Circus	3	24	6	6					2	14	
Paddington	4	24	6	2	2	2	2		3	4	
Piccadilly Circus	2	16	4	4					1	11	
South Kensington	3	16	4	2	2		2		1	5	
Tottenham Court	2	16	4	4					1	6	
Victoria	3	16	4	2	2		2		2	6	
Warren Street	2	16	4	4					1	7	
Waterloo	4	28**	8	6				1	3	23	
Westminster	3	16	4	2	2		2	2	1	17	5

Note: * include interchanges between different branches of the same line; ** Waterloo & City starts and ends with reduced number of interchange movements; *** a platform may belong to multiple types

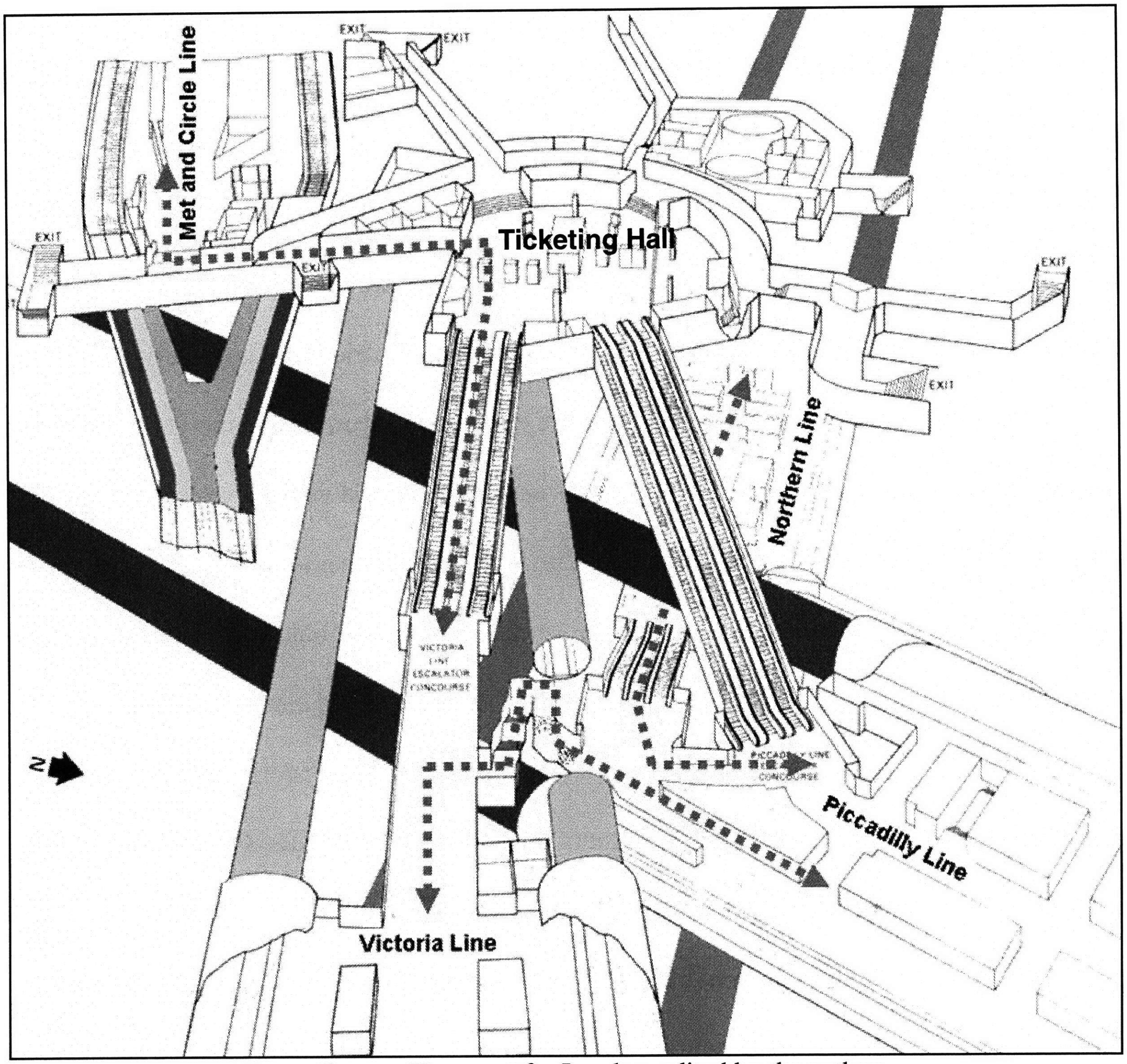
Notation:
Tube: number of platforms in the tube tunnel; Shared: number of shared platforms
Sub: number of platforms on sub-surface lines; Sur: number of platforms at surface stations
Island: number of island platforms; Tkt: number of ticketing halls at the stations
Esct: number of escalators at the stations

Source: Transport for London, Station Database westbound at Finsbury Park, and Bakerloo southbound to Northern northbound at Elephant & Castle. Horizontal interchanges include a walk between two platforms at the same level, so no vertical change is involved. They occur at a few stations such as Bakerloo southbound to Jubilee northbound at Waterloo, Hammersmith eastbound to Metropolitan northbound at Baker St. Most interchanges belong to the last category: vertical as well as horizontal interchange, which occurs for both parallel services (e.g., Piccadilly and District) and intersecting lines.

Three attributes of a vertical interchange are emphasized: connection methods, movement freedom, and directional change. The platforms can be connected vertically by escalator, lift, stairs, or some combination. Escalators facilitate vertical movement and help mitigate the interchange inconvenience. Lifts also help the vertical movement, but because passengers have to wait to take a lift and they have limited capacity, they are less popular than escalators. System wide, there are 412 escalators and 116 lifts installed in the Underground by 2008. [21] Based on a field survey conducted by the author and information obtained from Transport for London on 51 major interchange stations, 50 percent of the interchange movements have one or more escalators, whereas 19 percent have lifts. The average number of stairs involved per direction is 52, with a maximum value of 378 between District eastbound and Central eastbound at Bank/Monument.

Directional changes summarize the number and complexity of any interchange movement. Many directional changes make interchange way-finding more difficult, and increase the inconvenience of interchanges, especially to occasional Underground customers. For example, in order to interchange from Piccadilly eastbound to the Jubilee Line at Green Park station, a

[21] Information from Transport for London website: http://www.tfl.gov.uk/corporate/modesoftransport/londonunderground/1608.aspx, accessed on July 18, 2008

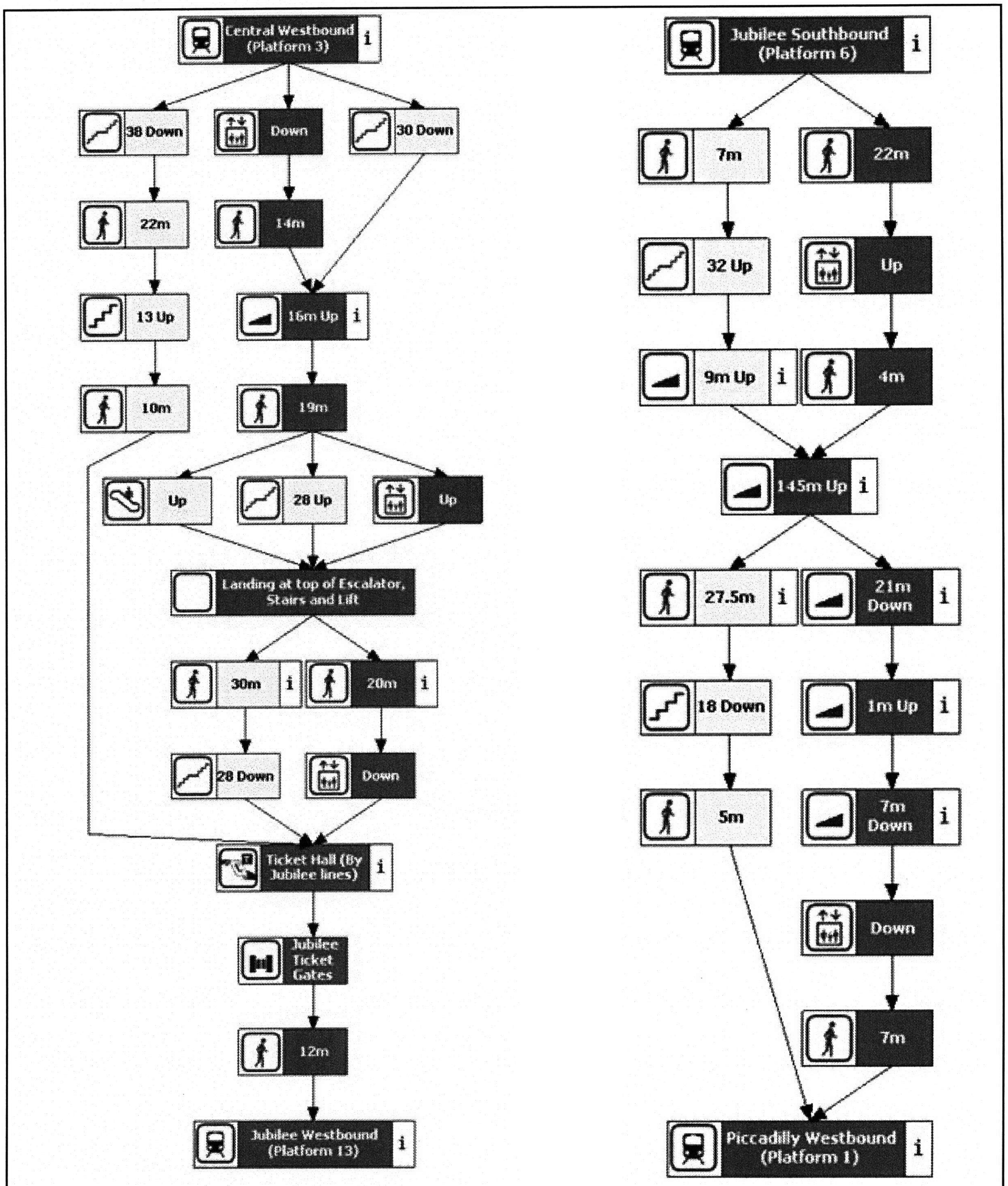


Source: Transport for London, edited by the author

Figure 5-5 Interchange Paths at King's Cross

passenger needs to go all the way up to the ticketing hall and then back down to the Jubilee platform. Directional changes also differ greatly across interchange movements.

As Figure 5-5 indicates, the interchange between Piccadilly and Northern Lines at King's Cross is straightforward, but interchanges between the sub-subsurface lines and the Northern Line are very complex, involving many directional changes. Another concern with interchanges is that multiple paths might be available between two platforms as illustrated in Figure 5-6.



(a) Green Park (b) Stratford

Source: Direct Access website, accessed on May 24, 2008

Figure 5-6 Interchange Paths between Two Platforms

These multiple paths normally involve different means of vertical connection, and add a further layer of complexity to characterizing an interchange path. In a few stations, passengers interchanging have to go through a ticketing gate because the two platforms are far apart, and it is difficult to connect them behind the fare gates. Although no fare is charged for interchange customers, this disrupts free interchange movement, and it likely causes confusion and inconvenience to customers. Currently, 19 percent of all interchange movements at the 51 surveyed stations belong to this category.

5.3.2 Interchange Activities

Frequent interchange activities are observed in RODS. Among all revealed travel paths on the Underground, almost 69 percent have at least one interchange. The share decreases to 44 percent at the trip level because paths that do not involve interchanges tend to have higher trip volumes than those that do (Table 5-11). The share corresponds to a total of 1.42 million interchanges between Underground lines on a typical weekday, 87 percent of which are the first interchange, and 12 percent are the second interchange along a journey. System wide, average interchange walking time is 2.4 minutes based on surveys of all interchange movements at 51 stations. Average interchange waiting time is 2.4 minutes, while average initial waiting time is 2.8 minutes.[22] Because interchange stations are concentrated in Central London where service frequency tends to be high, average interchange waiting time should be smaller than the average initial waiting time.

[22] Values are calculated based on 18,392 paths generated from 17 rules (see later sections for details). They are based on combined headways. The Journey Time Metric in 2007 uses a longer passenger waiting time, 3.85 minutes because it requires that passenger may not be able to board the first train due to crowding.

Table 5-11 Summary of RODS Interchanges

Number of Interchanges	By Path		By Trip	
	Number	Percent	Number	Percent
0	29,107	31.3%	139,608	56.1%
1	45,068	48.5%	88,162	35.4%
2	15,524	16.7%	17,885	7.2% *
3	2,579	2.8%	2,628	1.1%
4	592	0.6%	601	0.2%
Total	92,870	100%	248,884	100%

Note: multiple-interchange trips might be under-represented by RODS because a relative large portion of these long-distance trips start in early morning, a period that is not well covered in RODS.
Source: compiled by the author from RODS (1998-2005)

Interchange activities are distributed unevenly across the Underground network. About 74 percent of all interchanges occur in Zone 1, in Central London, while another 20 percent are in Zone 2. Among all Zone 1 interchanges, half are at the 27 stations on the circumferential services. At the station level, a few major interchange stations represent a large portion of all interchanges. The top 14 stations account for more than 60 percent of all interchanges (Table 5-12). Oxford Circus is the largest interchange station with 110 thousand interchange trips per weekday, followed by Baker St, King's Cross, and Green Park. In terms of share of interchange trips, about half of the passengers at Baker St are making interchanges. This ratio decreases to 1 out of 5 at Victoria. Even though both stations are extremely crowded at peak hours, mitigation solutions might be different due to the different shares of interchange passengers. For example, increasing the throughput at the fare gates and between the ticketing hall and platforms is critical for Victoria, while for Baker St, convenient high-capacity connections between platforms are key. The average interchange share of total volume at the 14 top interchange stations is 41 percent (Table 5-12).

Table 5-12 Weekday Entry, Exit, and Interchange Volumes at Interchange Stations

Station	Entry	Exit	Interchange	Share of Interchange
Oxford Circus	105,862	120,295	109,349	0.33
Baker Street	38,663	37,818	84,439	0.52
King's Cross	98,783	102,458	82,722	0.29
Green Park	46,339	53,304	81,514	0.45
Bank / Monument	76,119	78,854	66,755	0.30
Earl's Court	31,919	29,205	62,256	0.50
Mile End	19,967	18,755	59,079	0.60
Embankment	31,118	31,042	56,440	0.48
Stockwell	13,896	11,067	53,618	0.68
Victoria	119,294	122,344	52,006	0.18
Holborn	51,590	54,629	50,099	0.32
Finsbury Park	41,266	35,854	44,862	0.37
Euston	41,701	42,195	44,026	0.34
Westminster	26,901	27,512	38,576	0.41

Source: From Transport for London Tube Performance website:
http://www.tfl.gov.uk/tfl/corporate/modesoftransport/tube/performance/default.asp?onload=entryexit, accessed on May 18, 2008

In terms of demographics, female and male passengers have similar interchange rates of 44 percent. However, age does seem to matter: older passengers are less likely to interchange. The interchange rate is 47 percent for passengers under 25, 43 percent for passengers between 45 and 59, and 40 percent for passenger above 60. The elderly seems somewhat less likely to walk the physically challenging interchanges during Underground travel than younger travelers.

There are also interchange differences with respect to some trip attributes. The later in the day that a trip starts, the more likely it is to involve an interchange: the interchange rate is 37 percent for early morning trips, and increases to 41 percent in the AM peak, 43 percent at midday, and 47 percent in the PM peak and evening. Such differences might be due to the concentration of trips with different purposes at different times.

Based on the type of activities at the destination, trips to work are less likely to involve an interchange (39 percent), compared to school trips (46 percent), airport trips (47 percent), and trips visiting friends or museum (47 percent). Shopping trips tend to involve fewer interchanges with an interchange rate of 34 percent, probably because shoppers have the flexibility to select destinations to avoid interchanges. Based on the type of activities at origin, passengers doing home-based trips are less likely to interchange (41 percent), while those passengers whose trips originate at work places tend to interchange more (46 percent), probably because many after-work trips are for personal, social, and recreational activities that tend to involve more interchanges. [23]

Table 5-13 summarizes the interchange rates by destination and origin purposes. Based on RODS, the system-wide interchange rate is 44 percent.

Table 5-13 Interchange Rate by Trip Purposes

Purposes	At Destination		At Origin	
	Total Trips	Interchange Rate	Total Trips	Interchange Rate
Home	95,840	48%	124,356	41%
Work	91,944	39%	76,953	46%
Shopping	6,460	34%	3,807	38%
School	10,136	46%	7,994	49%
Airport	807	47%	394	49%
Personal, social, recreational overall *	27,905	44%	22,178	46%

Note: * include visiting friends, museum, social, personal, sports, theater, and sightseeing

Source: compiled by the author from RODS (1998-2005)

[23] This might be due to the spatial distribution of the activities and the possible trip chaining for after-work trips.

Travel frequency also seems to matter, although the differences are not as marked. Frequent travelers (at least one trip per week) tend to interchange less (43 percent), while occasional and first time Underground travelers interchange more, 44 and 51 percent, respectively. One possible explanation is that frequent users, who are more familiar with the system, are more experienced in mitigating inconveniences during travel such as avoiding interchanges. They may also be less tolerant of interchanges if they have to experience them frequently. This pattern is consistent with the research findings from the Boston case study.

Access and egress modes to/from the Underground are also correlated with interchange behavior within the Underground. The general rule is that the higher speed of the access (or egress) mode, the less likely an Underground trip is to involve an interchange (Table 5-14). For example, when the egress mode is walk, with the access mode being walk, bus, and National Rail, the interchange rate on the Underground decreases from 49 percent to 42 and 32 percent, respectively. Similar trends exist for egress modes. An exception is when the car is used for access or egress, in which case there is a much higher interchange rate on the Underground, especially for the drive egress mode.

Table 5-14 Interchange Rates by Access/Egress Mode

Egress Access	Walk (%)	Bus (%)	National Rail (%)	Drive (%)	Average (%)
Walk	49	45	26	62	47
Bus	42	36	32	51	41
National Rail	32	38	33	64	33
Drive	47	35	42	49	46
Average	44	42	29	61	

Source: compiled by the author from TfL Tube Performance profiles and RODS (1998-2005)

5.4 Research Design

This section elaborates the research design of the London study based on the principles described in the methodology and research design chapter, with a focus on path choice generation.

Modeling path choice in the large and complex Underground network is challenging for three reasons: first, as discussed in the methodology chapter, analysts do not really know the detailed mechanism of the path choice decision process, i.e., what factors do they care about and how do they make the trade-offs? Second, monitoring such a complicated network and the associated service is extremely challenging. In the Underground case, nobody really knows passengers' exact travel paths except the sequence of entry, interchange, and exit stations.[24] In other words, the data cannot fully support such an analysis. Third, because this study emphasizes policy implications, the developed model will be used for forecasting and policy simulation. Compared to models focusing on understanding behavior, forecasting models have a higher requirement on path choice generation: the generated paths must be comprehensive and representative (Fiorenzo-Catalano 2007). So far, the author has identified few studies that conduct comprehensive and empirical path choice analysis for a large and complex public transport network.

These difficulties are best reflected in the process of choice set generation. Choice set generation is not just one of many steps in modeling path choice, rather, it is a process that is intertwined with every aspects of the analysis: theory, research design, data collection and sampling, attribute calculation, model specification and estimation, and prediction and applications. In the next three sections, I will discuss the path choice set generation problem in

[24] Multiple paths might occur for the same sequence of entry, interchange, and exit stations. For example, a passenger can take either the Victoria Line or the Piccadilly Line from Green Park to King's Cross or Finsbury Park.

detail for the Underground network. This section introduces the framework and the general process of choice set generation. Section 5.5 describes the generation process in detail, and section 5.6 calculates path attributes and concludes the generation process.

5.4.1 Framework of Path Choice Generation

This part describes the terminology, approach, principles, and tools used in path choice generation. First, three elements must be clearly defined and their interaction in the process should be clarified; the path, the OD, and the trip:

Path: defined as the sequence of entry, interchange, and exit stations in the Underground. It is an approximation of the real path because even given this information, it is still sometimes impossible to extract the exact travel paths, especially in identifying lines boarded. Such a definition is convenient for coding and generating paths, but not for calculating path attributes. A path belongs to an OD, and can have none, few, or many trips on it. There are two types of paths in the generation process: revealed paths (also called RODS paths in this study) and generated paths. Based on their combination, paths can be revealed (used by a passenger and documented by a survey) and generated (through a process in computers), revealed but not generated, and not revealed but generated. These distinctions are important and will be explained in detail later in this section.

OD: defined as a pair of stations in the Underground. An OD can be linked by one or multiple paths, and one or more trips. For the modeling purpose, all ODs included in the path generation process must have observed trips in surveys. An OD can have generated-but-not-revealed paths, but it must have at least one revealed path, otherwise the OD will be excluded from the process. In this study, about 5 percent of ODs fall in that category (see Section 5.5).

ODs enter the generation process several times: after the initial generation process (to narrow down generated paths by excluding ODs with a single dominant path), and at the end of the process (to organize generated and revealed paths into a suitable data set for model estimation).

Trip: is a documented journey along a particular path on a particular OD pair. The trip does not enter the generation process (though it is used to clean up the data set before the process starts), but it is included in modeling as the unit of decision. Models are estimated at the individual trip level. Each trip is associated with an OD and has multiple generated paths, and one revealed path. Some trips are identical, in a modeling sense, if they are on the same OD and take the same path.

Approach

The labeling approach, as discussed in the methodology chapter, is the method used to generate the path choice set. A label is based on an attribute or a combination of attributes; therefore label definition is highly constrained by data availability. For the Underground, the following path attributes are available from various data sources (see Section 5.6): in-vehicle time, entry and exit walking times, initial waiting time, interchange walking and waiting times, number of interchanges, number of stations, map distance[25], delay (at the line level) and design features. Based on the attributes, I categorize labels into three types: default weighting, single attribute, and combined attributes.

Default-weighting labels use the default weighting factors for path attributes to generate paths. These weighting factors, used by the London Underground for years, are assumed to be a close reflection of passengers' preferences; therefore, default weighting labels should capture

[25] Map distance refers to the distance of path measured on the Underground system map. The concept is explained in detail in Section 5.6.

the most popular paths between an OD pair. Single-attribute labels maximize or minimize a single path attribute. They should capture the idiosyncratic behavior of some passengers who might value one attribute very much, either positively or negatively. The total number of labels that belong to this category is limited by the total number of components that a network model can calibrate, which is seven in the case of RailPlan and TransCAD. The third type of label targets combinations of two or more attributes. The premise here is that some passengers make trade-offs among several travel attributes. It captures the grey zone between the extremes defined by the single-attribute labels.

Principle

Except for the single attributes, labels can be defined in indefinite numbers. The questions are which labels are credible and should be included, and when the generation process should stop. To answer these questions, I develop two measures for use in the labeling and choice set generation process. Defining C_R a set of paths revealed by RODS, C_L the set of paths generated through the labeling approach, and C_{RL} the overlap set between C_R and C_L, the two measures can be written:

$$B_1 = \frac{C_{RL}}{C_R}, \quad \text{and} \quad B_2 = \frac{C_{RL}}{C_L} \tag{17}$$

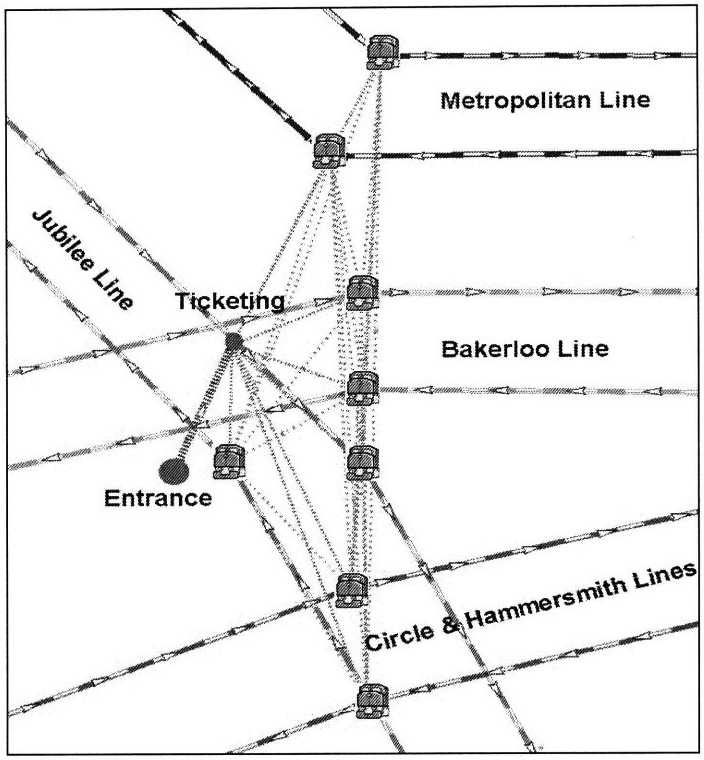
B_1 indicates how *effective* the method is in explaining the revealed behavior, while B_2 suggests how *efficient* the method is in explaining the behavior. The higher the value of B_1, the better because revealed paths C_R should be included in the generated paths C_L. For B_2, however, a large value indicates that the process generates few paths besides those which are revealed, while a small value suggests that the method might generate too many unrealistic paths that passengers are unlikely to consider in reality. As discussed in the methodology chapter, the number of paths viewed as available by travelers is usually small, i.e. between two to six. Therefore, I expect a credible value of B_2 to be at least 15 percent.

Tool for Generation

Finally, the generation process will be conducted in a network model calibrated for the Underground in TransCAD, a GIS-based transportation software. This network model originates from RailPlan, an EMME/2 based public transport model that has been developed over the past 15 years by Transport for London to model public transport users for the AM peak period only in London and the South East of England (RailPlan Modeling User Guide, 2006).

This model has a detailed representation of the public transport network, especially with respect to interchanges. For example, at an Underground station, three types of nodes and three types of links are defined in the network: station entrance, ticketing hall, and platform, entrance-ticketing hall links, ticketing hall-platform links, and platform-platform links. Each platform node corresponds to a direction for each line. All links have an associated type, mode (i.e. walk), and speed. Therefore, this model is able to capture each interchange movement in the network. As an example, Figure 5-7 shows the representation of Baker St in the model.

However, there are two concerns with this model in the context of this study. First, the representation quality of interchange stations might need to be improved. For example, platform nodes are not necessarily represented with "correct" co-ordinates. These have, in most cases, been represented diagrammatically within Railplan to make station layouts more easily understandable graphically. Station entrance nodes are the only station nodes with the correct co-ordinates so as to ensure compatibility with the bus network. Second, TransCAD does not



Source: Transport for London, RailPlan

Figure 5-7 Network Representation of Baker St

have a built-in function to generate paths for a large network with many OD pairs. A script is written to enable shortest-path search for many OD pairs simultaneously and to generate a path file with path attributes. The code is given in Appendix C, and the attributes are summarized in Section 5.6.

I use the Pathfinder algorithm to generate "optimal" paths. It is based on the assumption that passengers will take the first line which will get them to their destination in an acceptable amount of time. Then, multiple paths are utilized based on service times and frequencies. A line segment going out of a station will be used only if its addition to the optimal strategy will reduce the total expected travel cost from that station to the destination. The result is a sub-network, or "hyper-path" that contains all the paths that will be used. In most cases, these paths only differ in department times, and are the same path based on the path definition of this study, but sometimes it reflects multiple travel paths in the network. The parameter in Pathfinder is set to 0 in order to achieve a balance between capturing many identical paths and missing some distinct paths (TransCAD Travel Demand Modeling manual 2005).

5.4.2 Path Generation Process

This section describes the data processing, from a travel survey to a dataset ready for model estimation. The major steps are illustrated in Figure 5-8 and will be described in detail in Section 5.5.

The process starts and ends with individual trips, but the in-between processing is done at the path and OD pair levels. Paths and OD pairs are summarized from RODS, but not all of them can be used because some of them indicate "irrational" decisions caused by either coding errors or non-transportation related considerations such as meeting a friend at a particular station, or missing a stop. Because these factors cannot be analyzed through surveys and transportation network models, including these "irrational" paths in model estimation will weaken the results and lead to a less effective model for forecasting purposes.

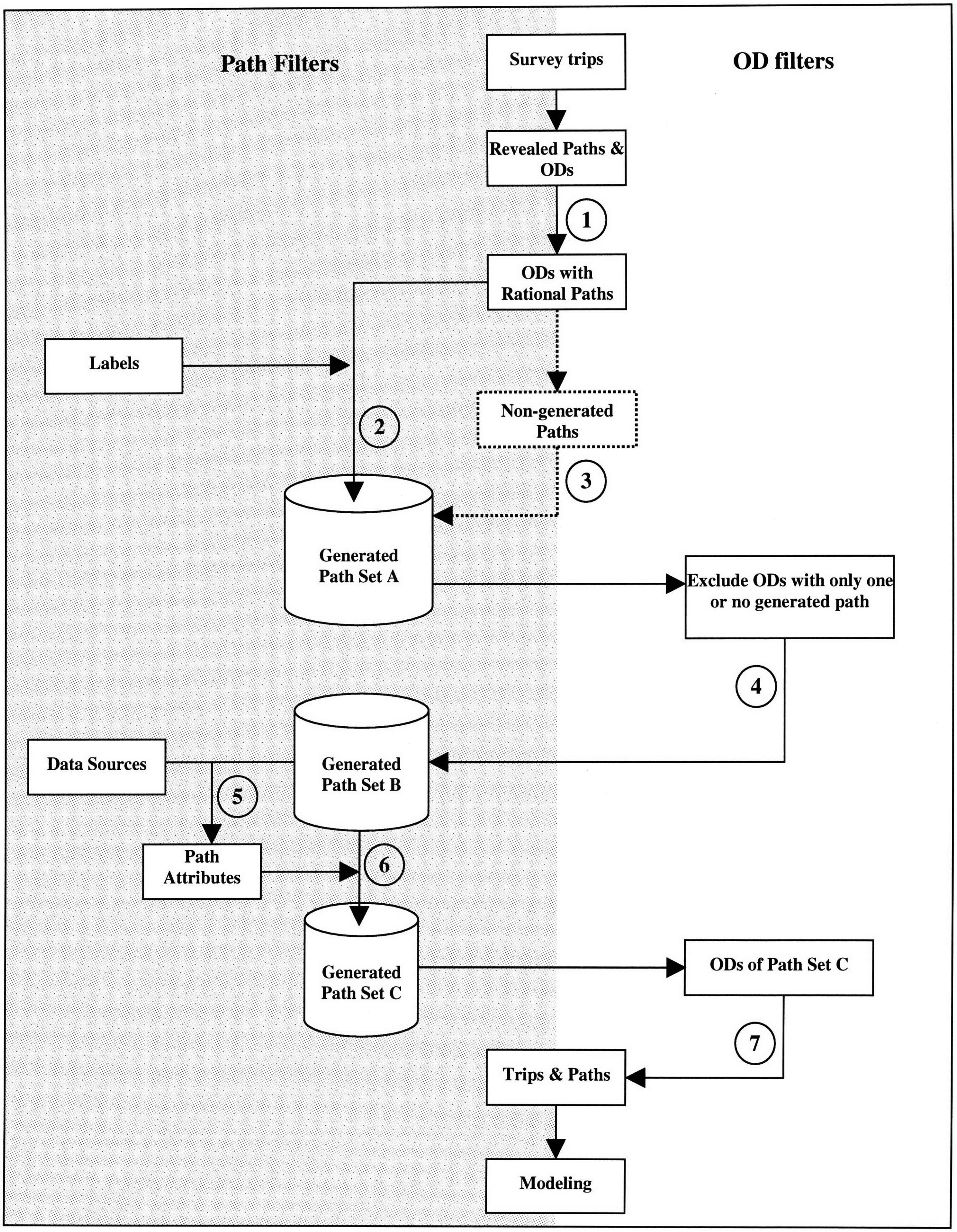
The first Step1 is screening, or identifying an initial group of revealed paths that can represent typical trade-offs made in path choice. Then, in Step 2, *OD pairs* associated with these rational paths are inserted into the TransCAD model to generate all possible paths between OD pairs using the Pathfinder algorithm (path set A). In Step 3, the generated paths are compared with the revealed rational paths in Step 1, and the non-generated rational paths are analyzed. Some of them will be generated manually (not through TransCAD) and then are added into path set A.

In Step 4, all OD pairs in the revised path set A are examined, and two types of OD pairs are excluded (path set B): those with one single generated path, which are assumed to have a dominant path, and those with no revealed path generated. In Step 5, attributes of all generated paths in set B are calculated or summarized from multiple data sources. Some of these paths do not have the same set of attributes because the labels in Step 2 are based on different TransCAD networks (see Section 5.5.2 for details). They are excluded from the process (path set C) in Step 6, because the same dataset is required for different model specifications to make estimation result comparable. Step 7 is purely formatting: paths in set C are organized by OD pair with path attributes, and then these OD pair and paths are linked back to corresponding individual trips in RODS, ready for model estimation.

A notable feature of this process is the need to maintain consistency among trips, paths, and OD pairs. The processing is done at the three levels, switching back and forth between them. The result is a clean dataset with each decision maker (trip) having multiple credible options (generated paths) and making a rational decision (revealed paths). Each of these steps is explained in detail in Sections 5.5 and 5.6 with the change of number of trips, generated paths, revealed paths, and OD pairs along the process.

5.5 Path Generation

This section discusses the above steps except Step 5, which will be presented in Section 5.6. It first introduces the dataset used, and then focuses on Steps 1, 2, and 3.



Source: the author

Figure 5-8 Process of Data Processing

5.5.1 Dataset for Path Generation

The main dataset used for path generation is the Rolling Origin and Destination Survey (RODS). It is the only large data set that documents travel paths in the Underground. RODS is a ten-year rolling survey program that begun in 1998 whose main output is an annual estimate of the origin-destination matrix for a typical day on the Underground. Each fall, planners select a set of 30 to 40 stations to survey. The selection of stations is based on where important changes in ridership and/or service have occurred subject to a budget constraint. Each station on the survey set is assigned a survey date. During that day, field workers hand out survey questionnaires to a random sample of passengers starting their journey from that station. Respondents are then expected to complete the surveys and return them by mail (Gordillo 2006). Questions asked include: origin, destination, and interchange stations, other modes in the trip, purpose and frequency of the trip, ticket type, and gender and age.

Apart from its use to estimate the general origin-destination matrix, the RODS survey is used to produce a series of reports on travel patterns including but not limited to: initial origin and final destination of customers using each underground station, other transportation modes used before and after taking the underground, purpose of travel to each underground station, and origin-destination matrices for different demographic groups (Gordillo 2006).

There are two concerns with RODS regarding path generation. First is the high non-response rate, between 70 and 80 percent, which raises the question of non-response bias in the sample. Second, since the surveys are handed out only between 7:00AM and midnight, the dataset does not capture the travel patterns of all customers, particularly those who begin their journeys early in the morning. This can result in significant bias in the dataset, as these customers are more likely to have longer commutes than customers traveling later in the morning. Therefore, OD pairs and revealed paths might not represent the population (all Underground passengers) accurately.

5.5.2 Identifying Rational (Revealed) Paths (Step 1)

A conservative screening process is performed in order to exclude possible errors in revealed paths. I select only 13,295 paths out of 92,870 RODS paths (15 percent) and 9,284 ODs out of 67,608 RODS ODs (14 percent), representing 139,091 RODS trips (56 percent of all RODS trips), which means that the screen favors popular OD pairs and paths in the Underground network. I apply three types of filters: Underground filters, error filters, and popularity filters.

The Underground filter makes sure included trips are purely Underground trips. Paths that involve National Rail in any of the journey segments or start/end outside the Greater London area are excluded, because I am interested in only the Underground network, and because data on the National Rail network is not readily available. This filter reduces RODS *paths* by almost 40 percent.

The error filter identifies coding errors in the dataset, such as the entrance or exit station is the same as an interchange station, an interchange is missing between two stations which are not on the same line, a non-interchange station is coded as an interchange station, etc. Because many three and four-interchange paths involve these problems but only represent a small fraction of total observations, I excluded them from the analysis at this stage, resulting in a further nine percent reduction of revealed RODS paths.

The popularity filter excludes unpopular RODS OD pairs and RODS paths because I assume they are more likely to be associated with "irrational" path behavior due to coding errors, decisions irrelevant to path attributes, etc. Several thresholds are tested for both OD and path popularity filters, and the resulting numbers of excluded paths and trips are summarized in Table 5-15. I chose five trips and 10 percent as the popularity filters for OD pairs and RODS paths, respectively.

Table 5-15 Popularity Filters and Reductions of ODs/Paths and Trips

Popularity Filter for ODs (N=67,608)			**Popularity Filter for Paths (N= 92,870)**		
Number of Trips	Reduction of ODs	Reduction of Trips *	Share of Trips	Reduction of Paths	Reduction of Trips
= 1	36,165 (54%)	36,165 (15%)	< 5%	2,539 (2.7%)	2,731 (1.1%)
< 5	55,602 (82%)	86,973 (35%)	< 10%	5,368 (5.8%)	6,035 (2.4%)
<10	62,404 (92%)	130,881 (53%)	< 15%	8,783 (9.5%)	10,215 (4.1%)

Note: * total number of RODS trips = 248,887

Source: compiled by the author based on RODS (TfL 1998-2005)

Table 5-16 shows an example of the selection process. RODS records a total of 13 trips from Aldgate East to Oxford Circus (Figure 5-3), which meets the OD popularity threshold (>=5 trips). Among the six revealed paths, three paths have a volume share less than 10 percent, and careful examination suggests that all three paths have problems. Path 1 is a coding error because there is no direct connection between the two stations. Path 4 also indicates a coding error because there is no need to interchange at Charing Cross to get to Oxford Circus from Embankment, which is connected by the Bakerloo Line (see Figure 5-4). Path 6 is not a coding error but rather a very unusual travel decision. There is no good reason why a passenger would interchange at Mile End to get to Oxford Circus when Liverpool Street station is available (Figure 5-3). So only paths 2, 3, and 5 are viewed as rational and retained in this process.

Table 5-16 Selecting Rational RODS Paths from Aldgate East to Oxford Circus

Path	1st Interchange Station	2nd Interchange Station	Trip Share	# of Trips	Selected?
1	Direct connection		7.7%	1	
2	Bank / Monument		15.4%	2	Yes
3	Embankment		30.8%	4	Yes
4	Embankment	Charing Cross	7.7%	1	
5	Liverpool Street		30.8%	4	Yes
6	Mile End		7.7%	1	

Source: compiled by the author from RODS (1998-2005)

5.5.3 Choice Set Generation (Step 2)

In this section, I define 19 labels under the three categories and two TransCAD networks used to generate available paths (Table 5-17), explain the generation process, and, finally, summarize the generation results at the path, OD pair, and trip levels.

Path generation is implemented in a network model based on the optimal-path algorithm, which calculates the generalized cost of travel paths and finds the one with the minimum value. If the weighting factors of path attributes are changed, their contribution to the generalized cost should change, as will the definition of "optimal". For example, if I increase the weight of walking time from three to 300, the generalized cost would be largely determined by walking time along a path, so that the optimal path found is actually the optimal (least) walking path. By changing the weights, I can create different labels to generate various optimal paths. TransCAD 5.0 allows users to define weights or values on seven path attributes: link time, dwell time, interchange penalty, initial wait, interchange wait, walk, and fare. Note TransCAD can not differentiate between different types of walking, such as interchange or entry/exit walking.

There are actually three default-weighting labels used:

1. Label 1 is the state of practice in RailPlan;
2. Label 2 is a revised version of Label 1 that emphasizes interchanges;
3. Label 3 values all time components equally, which indicates a situation where a passenger cares more about the total trip time than the individual components.

Seven single-attribute labels are defined:

4. Label 4 finds the minimum interchange time path by assigning a large weight to interchange waiting plus a 10-minute penalty for each interchange.
5. Label 5 finds the minimum number of interchange path by adding a 100-minute penalty to the generalized cost for each interchange while minimizing the contributions of all other attributes.
6. Label 6 finds the minimum walking path including entry, exit, and interchange walking.
7. Label 7 finds the minimum stations path by assigning a 10-minute penalty to each station along that path while setting all other weighting factors to be 0.01.
8. Label 8 finds the minimum initial waiting time path, by increasing its weight to 50, while reducing all other weighting factors to 0.01.
9. Label 9 finds the minimum interchange waiting time path by increasing its weight 10, , while reducing all other weighting factors to 0.01.
10. Label 10 finds the most reliable path. Since links in the TransCAD model do not have a reliability attribute, this label is implemented by converting the reliability index (Table 5-5) of each Underground line into a monetary cost, which is then treated as a fare for a path. So Label 10 is actually finding a modified least fare path.

Table 5-17 Weighting Factors and Values of Labels Defined in TransCAD

Label	Label Type	Link Time	Walk Time	Initial Wait	Interchange Wait	Interchange Penalty		Dwell		Delay Time
						Weighting	Value	Weighting	Value	
1	Default value A	1	3	2	2	1	2	0.01	0.01	0.01
2	Default value B	1	3	0.6	1	3	3.5	0.01	0.01	1
3	Default value C	1	1	1	1	0.01	1	1	0.01	0.01
4	Minimum interchange time	1	1	1	5	10	1	1	0.01	0.01
5	Minimum # of interchange	0.01	0.01	0.01	0.01	10	10	0.01	0.01	0.01
6	Minimum walking	1	10	1	1	0.01	0.01	1	0.01	0.01
7	Minimum # of station	0.01	0.01	0.01	0.01	0.01	10	10	1	0.01
8	Minimum initial wait	0.01	0.01	50	0.01	0.01	0.01	0.01	0.01	0.01
9	Minimum interchange wait	0.01	0.01	0.01	10	0.01	0.01	0.01	0.01	0.01
10	Minimum delay time	0.01	0.01	0.01	0.01	0.01	10	0.01	0.01	1
11	Combination 1	10	1	1	1	10	3.5	1	0.01	1
12	Combination 2	0.5	10	0.5	1	3	3.5	0.5	0.5	0.01
13	Combination 3	1	3	2	2	6	3	0.01	0.01	1
14	Combination 4	1	10	10	10	10	2	0.01	0.01	0.01
15	Combination 5	1	1	10	10	1	2	0.01	0.01	5
16	Combination 6	10	1	1	1	1	2	0.01	0.01	10
17	Combination 7	0.01	0.01	0.01	0.01	0.01	0.01	10	1	10
18	Combination 8	5	0.01	0.01	0.01	0.01	0.01	0.01	0.01	10
19	Combination 9	0.01	0.01	10	0.01	0.01	0.01	2	1	0.01

A large number of combined-attribute labels were tested, of which only nine are presented here. They are developed by setting the weighting factors randomly, which often indicate a trade-off among various path attributes. For example, Label 12 (Combination 2) increases the contribution of walk and interchange to the generalized cost but underestimates the contribution of in-train travel, waiting time, and reliability. This might be a strategy appropriate for a passenger with luggage. There are no pre-defined rules on how and how many of these labels should be developed, but their effectiveness in path choice generation can be determined using the two measures discussed in Section 5.4.1.

The labels are then applied to two different representations of the Underground network in TransCAD: the default network, and the map-based network. The default network is the one in RailPlan currently used by the London Underground, while the map-based network is created by the author based on the default network with only one difference: the link distance in the map-based network is the distance measured on the Underground system map, not the actual distance in reality. The argument is that some passengers may choose a travel path based on its length as shown on the map, which is very different from its actual length for certain segments of the network. The issue will be discussed in detail in Section 5.6.

Generation starts with the default-weighting labels, then the single-attribute labels, and lastly combined-attribute labels for the selected 9,284 ODs with 13,925 rational RODS paths. Results are summarized in Tables 5-18 and 5-19 with the labels ranked according to the effectiveness measure B_1. The default network, Label 1, based on default values in RailPlan, is the most effective single label, covering 65 percent of revealed paths, which is no surprise. However, the most efficient label is Label 5 that finds the minimum interchange path: almost nine out of 10 generated paths by this label are revealed RODS paths. On the map-based network, Label 19 (Combination 9) is the most effective as well as the most efficient label. Label 6 (minimum walking) and Label 8 (minimum initial wait) work well on the map network but poorly on the default network, while the opposite is true for Label 7 (minimum # of station) and Label 18 (Combination 8).

I decide to include only labels where the effectiveness measure, B_1, exceeds 50 percent: if a label cannot generate half of the RODS paths, it is viewed as ineffective. This threshold leaves 17 labels for both networks. The following discusses the results at path, OD, and trip levels. At the path level, the default network performs slightly better than the map-based network. Total coverage rate of 13,295 revealed RODS paths is 77 percent on the default network, and 75 percent on the map-based network. This result compares nicely to some prior studies. In Ramming's research (2002) for a road network, for example, the coverage rate is 72 percent for a combined labeling method, 60 percent for multiple-path algorithm, and 50 percent for a simulation method. Another recent study (Fiorenzo-Catalano 2007) achieved a coverage rate of 78 percent for a small multimodal network based on a combined simulation (Monte Carlo) and labeling approach with randomized link attributes and personal preference. Both studies used more sophisticated generation methods than in this research. With respect to the final efficiency, the map-based network outperforms the default network by eight percentage points (60 percent vs. 52 percent). Figure 5-9 shows the change of effectiveness and efficiency as more labels are applied following the order in Tables 5-18 and 5-19. Total effectiveness increases slowly while total efficiency decreases sharply on both networks.

Table 5-18 Path Choice Generation Based on Default Network

Ranking *	Revealed Paths $C_R = 13295$	Generated C_L	Overlap C_{RL}	Additional RODS Paths Captured	Additional Unique Paths Generated	Effectiveness $B_1 = C_{RL} \div C_R$	Efficiency $B_2 = C_{RL} \div C_L$
1	Default Value A	10,252 **	8,633	8,633	10,252	64.9%	84.2%
2	Min Initial Wait	9,471	8,354	224	1,021	62.8%	88.2%
3	Min # Interchanges	9,284	8,303	250	501	62.4%	89.4%
4	Min Interchange Time	9,285	8,057	72	496	60.6%	86.8%
5	Combination 3	9,284	7,940	125	584	59.7%	85.5%
6	Combination 1	9,285	7,936	226	826	59.7%	85.5%
7	Default Value B	9,284	7,868	15	202	59.2%	84.7%
8	Combination 5	9,284	7,833	77	608	58.9%	84.4%
9	Default Value C	9,284	7,822	245	753	58.8%	84.3%
10	Combination 4	9,284	7,773	55	403	58.5%	83.7%
11	Min Interchange Wait	9,284	7,571	65	634	56.9%	81.5%
12	Combination 2	9,284	7,457	37	653	56.1%	80.3%
13	Combination 6	9,284	7,355	44	637	55.3%	79.2%
14	Combination 7	9,284	7,270	35	337	54.7%	78.3%
15	Combination 8	9,284	7,097	1	221	53.4%	76.4%
16	Min Delay Time	9,284	7,046	17	414	53.0%	75.9%
17	Combination 9	9,284	6,347	98	1,050	47.7%	68.4%
Total				10,219	19,592 ***	76.9%	52.2%

Note: *: ranking is based on the effectiveness measure B_1; **: Pathfinder algorithm in TransCAD can find multiple paths; ***: distinct generated paths from all 17 labels

Table 5-19 Path Choice Generation Based on Map Network

Ranking *	Revealed Paths $C_R = 13295$	Generated C_L	Overlap C_{RL}	Additional RODS Paths Captured	Additional Unique Paths Generated	Effectiveness $B_1 = C_{RL} \div C_R$	Efficiency $B_2 = C_{RL} \div C_L$
1	Combination 9	9,284	8,256	8,256	9,284	62.1%	88.9%
2	Min Walk	9,284	8,159	608	1,305	61.4%	87.9%
3	Combination 3	9,284	8,146	171	545	61.3%	87.7%
4	Combination 4	9,284	8,099	140	609	60.9%	87.2%
5	Default Value B	9,284	8,081	21	121	60.8%	87.0%
6	Min Interchange Time	9,284	8,061	154	479	60.6%	86.8%
7	Min # Interchanges	9,289	8,018	50	133	60.3%	86.3%
8	Combination 2	9,285	7,942	49	350	59.7%	85.5%
9	Combination 1	9,284	7,911	138	556	59.5%	85.2%
10	Default Value C	9,285	7,865	18	228	59.2%	84.7%
11	Default Value A	9,284	7,818	23	277	58.8%	84.2%
12	Min # Stations	9,318	7,690	208	925	57.8%	82.5%
13	Min Interchange Wait	9,303**	7,624	69	722	57.3%	82.0%
14	Combination 7	9,284	7,580	5	264	57.0%	81.6%
15	Combination 5	9,284	7,555	33	346	56.8%	81.4%
16	Combination 6	9,284	7,471	3	60	56.2%	80.5%
17	Min Delay Time	9,284	7,101	13	504	53.4%	76.5%
Total				9,959	16,701 ***	74.9%	59.6%

Note: *: ranking is based on the effectiveness measure B_1; **: Pathfinder algorithm in TransCAD can find multiple paths; ***: distinct generated paths from all 17 labels.

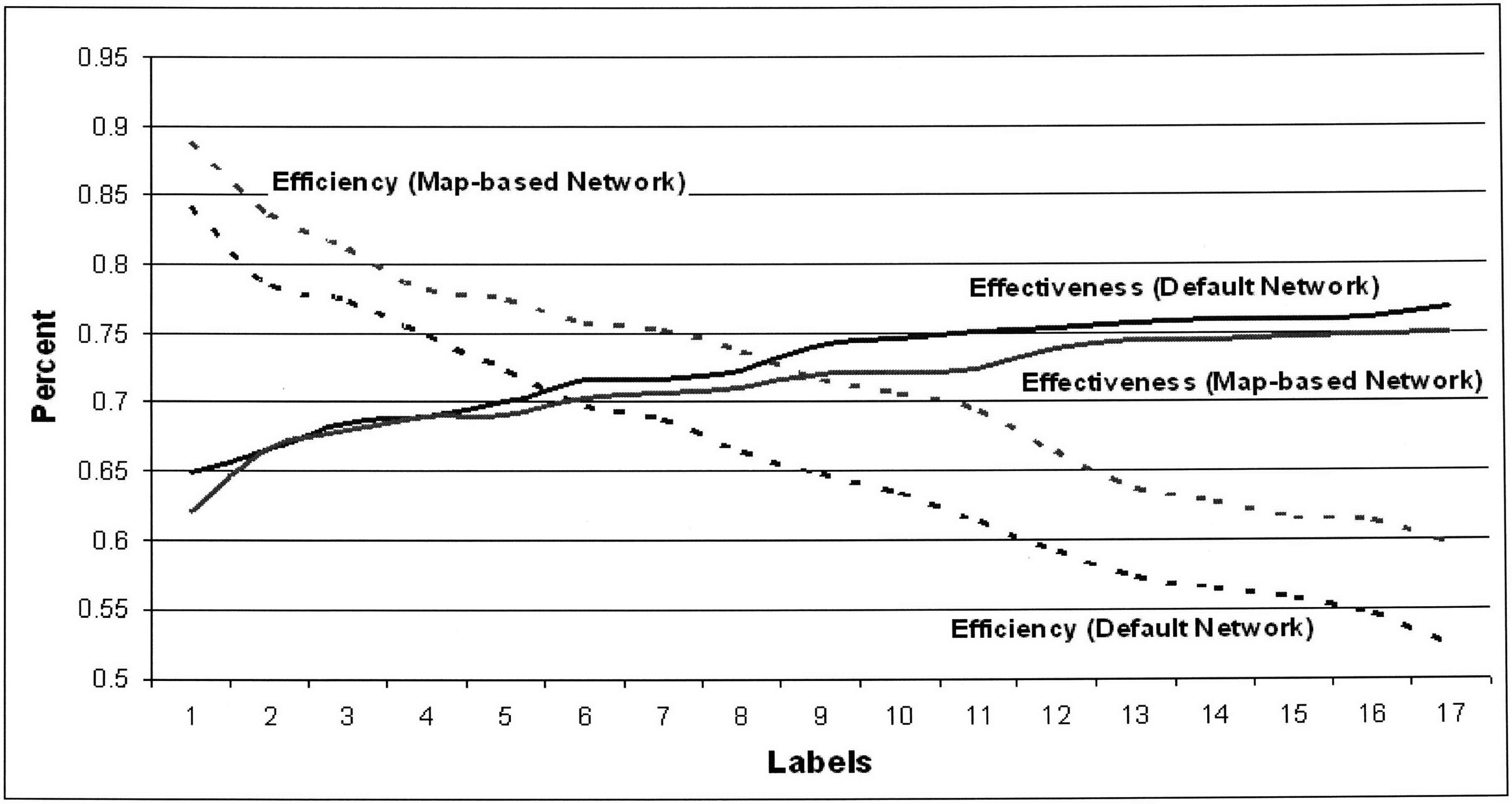
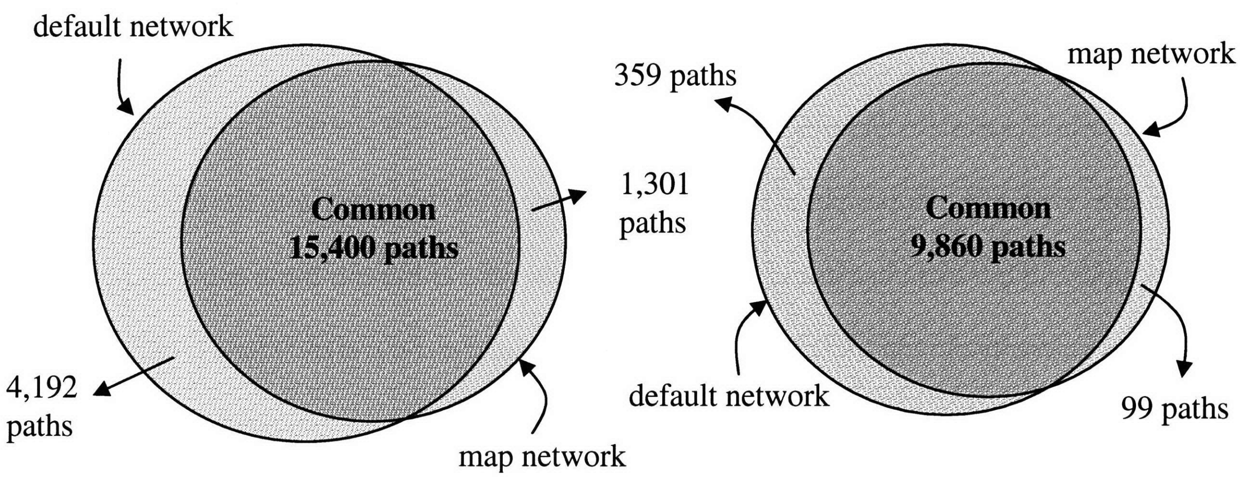


Figure 5-9 Effectiveness and Efficiency Measures for the London Network

The 17 labels with the default network generate a total of 19,592 paths. Labels on the map-based network generate about 3,000 fewer paths, but there is a large overlap between the two sets of generated paths: the common set of 15,400 generated paths, represents 92 percent of generated paths on the map network, and 79 percent on the default network (Figure 5-10 (a)). The overlap between two sets of generated RODS paths is even larger with the common portion counting for 99 and 96 percent of the generated RODS paths on the two networks (Figure 5-10 (b)).



(a) Generated Paths (b) Generated RODS Paths

Source: the author

Figure 5-10 Covered RODS Paths and Generated Paths for the London Network

At the OD level, I investigate both RODS paths and generated paths. For RODS paths, the key question is whether an OD pair has at least one RODS path generated in the process. Because both networks yield similar results in terms of the generated RODS paths, the discussion at the OD level does not compare the two networks. Based on the results from the default network, among the 9,284 RODS OD pairs targeted by the choice set generation process, 8,777 OD pairs (95.5 percent) have at least one RODS path generated, and none of the RODS paths are generated for the remaining 507 (4.5 percent) OD pairs. Careful examination of these 507 OD pairs shows that they tend to have more multiple revealed paths: 27 percent of them have multiple RODS paths as oppose to the 20 percent for the 8,777 OD pairs. Theoretically, OD pairs with multiple revealed paths are more likely to have at least one revealed path generated. This is not the case for the 507 OD pairs because the multiple revealed paths are often not generated for the same reason. For example, the link problem between the King's Cross and Old Street stations contributed three out of four non-generated revealed paths by the process.

For generated paths, the key question is how many paths are available for an OD pair: this indicates the average size of choice set. Table 5-20 summarizes the results for two networks. On average, each OD pair has about two paths available with the value from the default network being slightly higher than that from the map-based network. However, these generated paths are distributed unevenly among OD pairs. The maximum number of available paths for an OD pair is 11 on both networks, while the majority of OD pairs have only one generated path. The two networks perform differently on this matter: both have the same share of OD pairs with a single generated path, but the default network has more OD pairs (16 percent vs.11 percent) with a large choice set (4 or more generated paths), while the map-based network has more OD pairs with a medium-size choice set (29 percent vs. 23 percent).

ODs with only a single generated path or with no RODS paths generated could not be used for model estimation. The former indicates a dominant path—there are no alternative options for a passenger to consider, while the latter means that the decision is missing in the choice situation—we do not know which path is chosen by a passenger. The two issues correspond to Steps 3 and 4 in Figure 5-8.

Table 5-20 Generated Paths by OD Pair

# of Generated Paths / OD	# of ODs (N=9,284)	
	Default Network	Map-Based Network
1	5,645 (61%)	5,598 (60%)
2	1,330 (14%)	1,581 (17%)
3	833 (9%)	1,094 (12%)
4	583 (6%)	602 (7%)
5	425 (5%)	271 (3%)
6 or more	468 (5%)	138 (1%)
Average	1.98 generated paths / OD	1.8 generated paths / OD

At the trip level, the generated RODS paths have a total of 112,314 trips based on the default network, and 111,465 trips based on the map-based network, representing 80 percent of the original trips that enter the path choice generation process.

5.5.4 Dealing with Non-generated RODS Paths (Step 3)

Despite the good choice set generation results described above, there are still a significant number of RODS paths (3,076) not generated. Although, I could not use these paths for model estimation, they are still important. They may suggest potential problems of the choice set generation method, and indicate whether the generated choice set is biased and would weaken the path choice model estimation results. This section discusses (1) the reasons why these paths are not generated, (2) the potential problems in model estimation, and (3) potential solutions

First, I randomly selected one hundred non-generated paths from the pool of 3,076. Each of them was either checked manually on the Underground map or tested again in TransCAD using other labels until a possible explanation is reached. Although the specific reasons are diverse, they can be categorized into three types of problems: the branch problem, limited number of labels, and the network problem, each accounting for about a third of these non-generated paths. Table 5-21 gives six examples to illustrate these three problems.

The branch problem is associated with the trade-offs between waiting time (initial or interchange) and interchanges involved with branching services. A passenger may take the first train that is not a direct service and then interchange because (1) the interchange station offers more amenities than the boarding station, so that waiting there is more acceptable even though the total waiting time is the same, or (2) more frequent direct services are available at the interchange station, so that making an interchange there reduces the total waiting time for passengers. I could not capture these decisions using the TransCAD model because it does not characterize interchange amenities at stations and estimates waiting time based on combined headways without considering the board-the-first-train strategy.

The label problem is straightforward: the 17 labels I developed are certainly not sufficient to capture all revealed paths. A few of the 100 non-generated RODS paths are indeed found by applying more labels for several OD pairs. The network problem is purely technical: the Pathfinder algorithm used in TransCAD 5.0 has a program bug, which sometimes skips the first path it searches with multiple paths available, even though that path might be optimal.

The three problems affect model estimation differently. For the branch problem, because the non-generated RODS paths are often interchange paths, not including them in the choice set will over-estimate the influence of interchanges because fewer interchanges would occur in the sample. For the label and network problems, they are less likely to affect model estimations because the problems do not occur systematically in the Underground network and for particular trips.

In terms of solutions, there is no effective solution for the label problem, but it does not

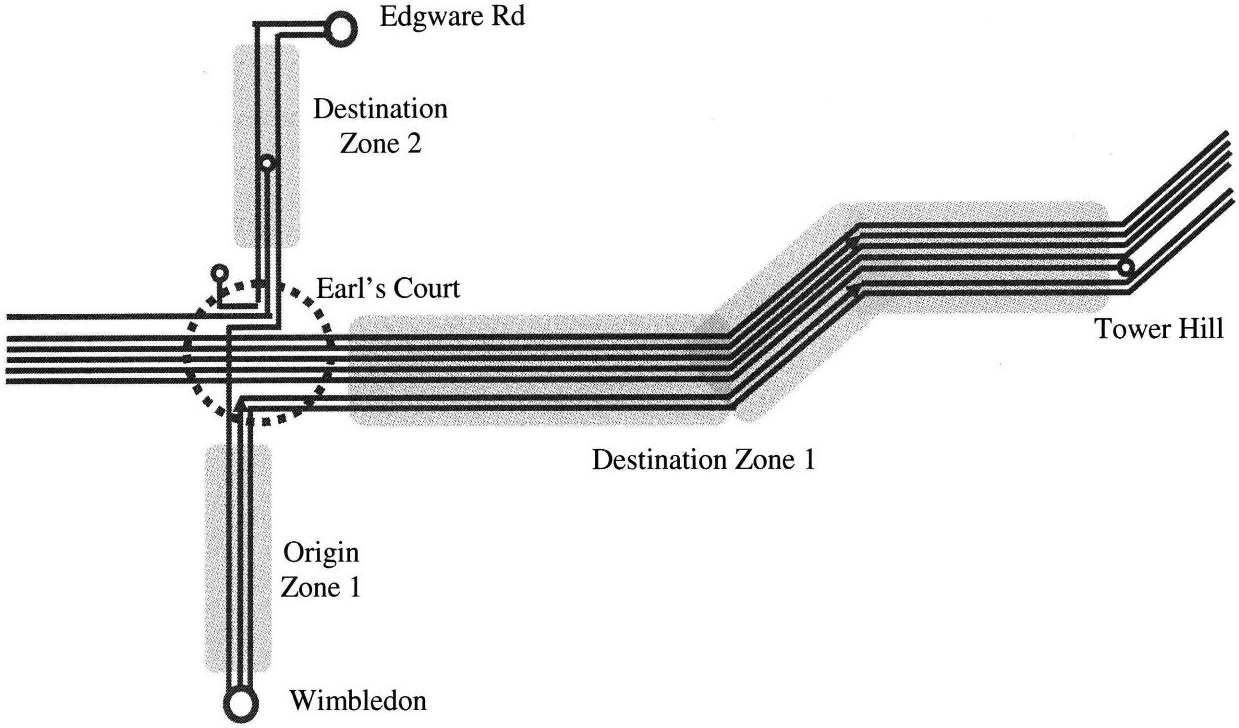
Table 5-21 Examples of Non-generated RODS Paths

Major Reasons	Non-generated Path			Explanations
	Entry Station	Exit Station	Interchange Station	
Branches	Tower Hill	Barons Court	Earl's Court	Board the first train that is not a direct service
	Leicester Sq	Balham	Kennington	More frequent services at Kennington
Too Few Labels	Bank-Monument	Green Park	Holborn	Found after more labels applied
	Paddington	Westminster	Embankment	Found after more labels applied
Network Problems	Oxford Circus	Old Street	King's Cross	TransCAD is unable to find the link from King's Cross to Angel due to a program bug
	Waterloo	Green Park		TransCAD is unable to find the link from Waterloo to Westminster due to a program bug

Source: compiled by the author from RODS (1998-2005)

significantly affect the results. For the network problems, no systematic patterns have been identified in terms of where they occur and on what type of links, so its presence is unlikely to result in a biased choice set and model estimation. The most challenging task is to solve the branch problem. Branches occur widely in the Underground, and it is unrealistic to tackle this problem for the entire network. I focus on The Earl's Court and Kennington due to the prevalence and complexity of branches on the District and Metropolitan lines, and the large number of interchanges at the two stations.

Figure 5-11 shows the layout of all District Line branches that pass through Earl's Court. (For the name of each branch, refer to Table 5-3). I identify three origin and destination zones: origin zone 1 on the Wimbledon branch (O1), destination zone 1 on the Edgware Road branch (D1), and destination zone 2 on the Gloucester Road-Tower Hill branch (D2). I examine two OD flows (O1 to D1 and O1 to D2) with the results summarized in Table 5-22.



Source: Transport for London; RailPlan

Figure 5-11 District Line Services at Earl's Court

Table 5-22 Direct and Indirect Services through Earl's Court

OD Zones	Number of Services		Combined Headway		RODS Interchange Rate
	Direct	**Indirect** (1st leg / 2nd leg)	**Direct Path**	**Interchange Path** (initial / interchange)	
O1 to D1 *	2	1 / 5	5.5	20 / 2.7	24%
O1 to D2**	1	2 / 2	20	5.5 / 5.5	37%

Note:
1 only a sample of OD stations in the origin and destination zones are examined
2 * **FROM** Wimbeldon, Wimbeldon Park, Southfields, East Putney, Putney Bridge, Parsons Green, Fulham Broadway, and West Brompton **TO** Monument, Blackfriars, Mansion House, Sloane Sq, South Kensington, St James Park, Temple, Tower Hill, Victoria, 1009 trips
3 ** **FROM** Wimbledon, Southfields, East Putney, Putney Bridge, Parsons Green, Fulham Broadway **TO** High Street Kensington, 100 trips

Source: calculated by the author based on headways in RailPlan

For the O1-D1 flow, three service paths are available at any O1 station: two direct services (Wimbledon to DagEast and Wimbledon to Upminster) and one indirect service (Wimbeldon to Edgware Rd) to Earl's Court where there are five more services from Ealing Broadway and Richmond to D1. If the first train to arrive at the O1 station is an indirect service, a passenger may board this train and then interchange at Earl's Court where the waiting time is short due to the additional services to D1. Thus, the trade off is between a potentially shorter total waiting time (including initial and interchange), given the first train is the indirect service, and one more interchange. Observations from eight stations (from Wimbeldon to West Brompton) in O1 indicate that 24 percent of the observed 1,009 passengers to D1 took the indirect service and made an interchange at Earl's Court.

This percentage indicates the existence of factors other than the waiting time and interchange in the decision process. If passengers choose between the direct and indirect services solely based on their headways on the Wimbeldon branch, the share of indirect services should be 21 percent. If the headways of interchange services at Earl's Court are also considered, the share is reduced to 19.5 percent. If the interchange penalty at Earl's Court is taken into account, the share should be even lower. One possible explanation of the high interchange share is crowding: the direct services may be too crowded so that some passengers choose the less crowded indirect services to Earl's Court, and then interchange.

In order to test this hypothesis, the share of indirect service for the O1-D1 flow is examined at the terminal station, Wimbeldon, and the down-stream stations before Earl's Court (Table 5-23). If the crowding hypothesis is true, the share should be lower at Wimbeldon than at the downstream stations. This is indeed the case as shown in Table 5-23. Only 12 percent of passengers at Wimbeldon took the indirect service, while the number is 26.3 percent at

Table 5-23 Shares of Transfer Trips by Access Station on the District Line Wimbledon Branch

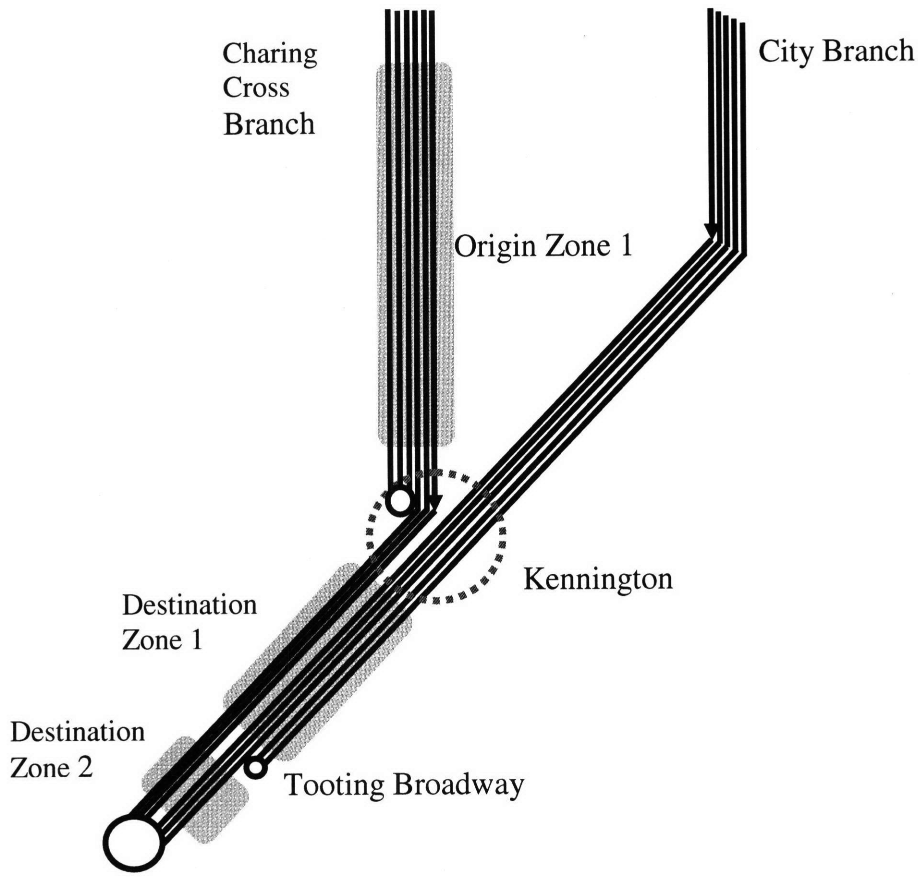
Access Station	Wimbledon	Wimbeldon Park	Southfields	East Putney	Putney Bridge	Parsons Green	Fulham Broadway	West Brompton
Total Trips	216	78	141	220	143	117	94	15
Transfer at Earl's	12.2%	25.6%	32.6%	17.7%	23.8%	36.7%	23.4%	60%

Source: compiled by the author from RODS (1998-2005)

the other seven stations. Some passengers at Wimbeldon Park and Southfield even took the southbound train and interchanged at Wimbeldon in order to avoid crowding.

The lower interchange rate for passengers at Winbeldom is largely caused by the interchange penalty at Earl's Court. In order to achieve the 12 percent share, the headway of the indirect service should be 40 minutes rather than the current 20 minutes, assuming passengers behave based on initial headway. In other words, we can convert this penalty into an extra headway of the indirect service at Wimbeldon. It is perceived as 40-20 = 20 minutes, or equivalent to 10 minutes of waiting. This penalty includes primarily interchange waiting time and other attributes because interchanges at Earl's Court occur on the same platform.

For the O1-D2 flow, the same three services are available in O1: one direct service (Wimbeldon to Edgware Rd) and two indirect services (Wimbledon to DagEast and Wimbledon to Upminster). At Earl's Court, two more District branches serve D2. The trade-off is the same as in the O1-D1 case. According to RODS, 37 percent of passengers from O1 to High Street Kensington interchange at Earl's Court, which is much smaller than an estimated share solely based on initial headway, 79 percent. This low value, again, is caused by the crowding on the indirect services and the interchange penalty at Earl's Court.



Source: Transport for London; RailPlan

Figure 5-12 Northern Line Services at Kennington

Table 5-24 Direct and Indirect Services through Kennington

OD Zones	**Number of Services**		**Combined Headways**		**RODS Interchange Rate**
	Direct	**Indirect** (1st leg / 2nd leg)	**Direct Path**	**Interchange Path** (initial / interchange)	
O1 to D1 *	3	3 / 5	7.0	6.3 / 2.2	33%
O1 to D2**	3	3 / 3	7.0	6.3 / 2.4	35%

Note:
1 only a sample of OD stations in the origin and destination zones are examined
Source: Transport for London, RailPlan
2 * **FROM** Mornington Crescent , Goodge St, Tottenham Court Road, Leicester Sq, Charing Cross, Waterloo, Embankment **TO** Oval, Clapham North, Clapham Common, Clapham South, Balham, Tooting Bec, Tooting Broadway. Note Warren Street, Euston, and Kennington are not included. 782 trips
3 ** **FROM** Mornington Crescent, Goodge St, Tottenham Court Road, Leicester Sq, Charing Cross, Waterloo, Embankment **TO** Colliers Wood, South Wimbledon, Morden. 225 trips

Source: calculated by the author based on headways in RailPlan

Figure 5-12 shows the corresponding situation on the Northern Line at Kennington where the Charing Cross and City branches of the Northern Line meet. Three services from the Charing Cross branch stop at Kennington, while other three continue to the Morden terminal. From the City branch, two services end at Tooting Broadway, while three others continue to Morden. Applying the same analysis, 33 percent of passengers traveling from O1 (Figure 5-12 and Table 5-24) to D1 chose to take indirect services and interchange at Kennington. Based on the ratio of headways, the indirect services should capture 53 percent of passengers. The low interchange rate is largely caused by the interchange penalty because crowding is not a concern in this situation, which is equivalent to 7.9 minutes extra headway (to achieve the 33 percent share), or 4 minutes of waiting.

The two examples confirm that passengers do make trade-offs between direct and indirect services caused by short-runs or split services under certain conditions. Interchange is an intrinsic element of this decision-making process; therefore, these paths should be included in the choice set for model estimation. Because most of these interchange paths are not generated by the method described earlier, a sample of these paths are recovered manually and added to the generated choice set. Only those paths with more than 8 trips are included, which represents 129 paths with 1673 trips. This is Step 3 in Figure 5-8.

After this step, both the numbers of generated paths and the revealed paths increase slightly. Now, the revised choice set, based on the default network, has 10,348 RODS paths, representing 79 percent of revealed paths and 82 percent of revealed trips. Not all the ODs and paths in this choice set could be used for model estimation because some of the ODs only have a single generated path meaning that these passengers did not make a choice (from the model's perspective). The next step, or Step 4 in Figure 5-8, is to exclude these ODs from the process. Then, Step 5 consolidates the generated and revealed paths from the default and map-based network, leaving 2,969 RODS ODs with multiple generated paths corresponding to 3,564 RODS paths and 25,036 trips. This is the final dataset used for model estimation. The attributes of these paths are calculated in the following section.

5.6 Path Attributes and Variables

This section focuses on step 5 in Figure 5-8, the calculation of the attributes for all generated paths in the choice set. The attributes are categorized into four types: time attributes, map attributes, interchange time attributes, and interchange decision attributes. The following section first introduces datasets used and then describes in detail how each attribute is defined and calculated.

5.6.1 Datasets for Path Attribute Calculation

Although RODS is the key dataset to generate path choice set, it does not contain path attributes except the number of interchanges. Most path attributes have to be obtained from other data sources including RailPlan (TransCAD), Network Journey Time Metric (JTM), Station Inventory Database, Direct Enquiries Database, and field surveys.

The RailPlan model developed by the London Underground is the major data source for travel time. In the model, each link is assigned a specific time value. For track links, the value is from the Underground 2001 working timetable. Dwell time is treated as a uniform value for all stations. For walk links, the value is calculated based on an average walking speed adjusted by the type of walking: level walking, escalator, stairs, or lift (see Section 5.6.4 for detail). Each track link also has a crowding factor that adds extra time to the link in a crowding situation. All times are for the AM peak from 7AM to 10AM because RailPlan is calibrated only for that period of time.

The Network Journey Time Metric (JTM) is a system developed by the London Underground for measuring customers overall journey time experience on the network. Each journey is broken down into its constituent parts namely; access from entrance to platform, ticket queuing and purchase, platform wait time, on train time, platform to platform interchange and egress from platform to exit (Table 5-6). These figures are calculated for each line and for 13 individual timebands, six on weekdays and seven on weekends. Because JTM values can not be disaggregated at the link level, its application in path choice analysis is limited. Only one variable, excess time (reliability index) (see Table 5-7), is included in model estimations. JTM uses RODS to weight the impact of a delay at a particular node, and gate counts to assess demand volume in the period of interest (London Transport 1999).

Station Inventory Database is developed by the Underground, which records the design characteristics of 273 stations such as station and platform types, facilities (escalators, lifts, waiting rooms, etc.), amenities (clocks, help points, toilets, information, commercial, phone, etc.), and accessibility in terms of number of stairs, escalators or lifts between platforms, ticketing halls, and streets. However, the database represents the interchange movement quite simply, and does not cover all movements at these stations.

The other data source, Direct Enquiry Database, provides a more comprehensive review of the interchange environment. It is developed by a non-profit organization in London to facilitate disabled access a variety of activities including transportation, key attractions, pharmacy, post office, etc. The database describes, in text and diagram, every segment of the interchange movement at all Underground stations such as ticketing gate, level walking, ramp, escalator, lift, door, etc. The two datasets provide most information of station design. When there was ambiguity for a particular station or movement, the author conducted field surveys to collect data, which was conducted in January 2007, June 2007, January 2008, and May 2008.

5.6.2 Time Attributes

Time attributes include in-vehicle time, entry and exit time at station, and initial waiting time. Table 5-25 shows the descriptive statistics for these travel time attributes. In-vehicle time includes run time between stations and dwell time at stations. Average in-vehicle time for the revealed paths, is 17.9 minutes, 3 minutes shorter than the average value of 21.1 minutes for all generated paths, but 1 minute longer than the system average based on the Journey Time Metric (Table 5-4). Entry and exit time within stations refers to walking time between a platform and a station entrance or exit. As illustrated in Figure 5-5, this time varies across platforms and stations. On average, exit time is slightly longer than entry time. The average value is between 1.8 and 2.8 minutes with a standard deviation between 0.9 and 1.6 minutes. Generated paths tend to have larger averages and standard deviations, a pattern that holds for other travel time attributes. Initial waiting time takes a simple form of half the combined headway. It does not consider the situation when passengers could not board the first train due to crowding. The value is slightly smaller than the system average passenger waiting time estimated by JTM, 3.05 minutes (Table 5-4).

Table 5-25 Descriptive Statistics of Time Attributes for RODS and Generated Paths

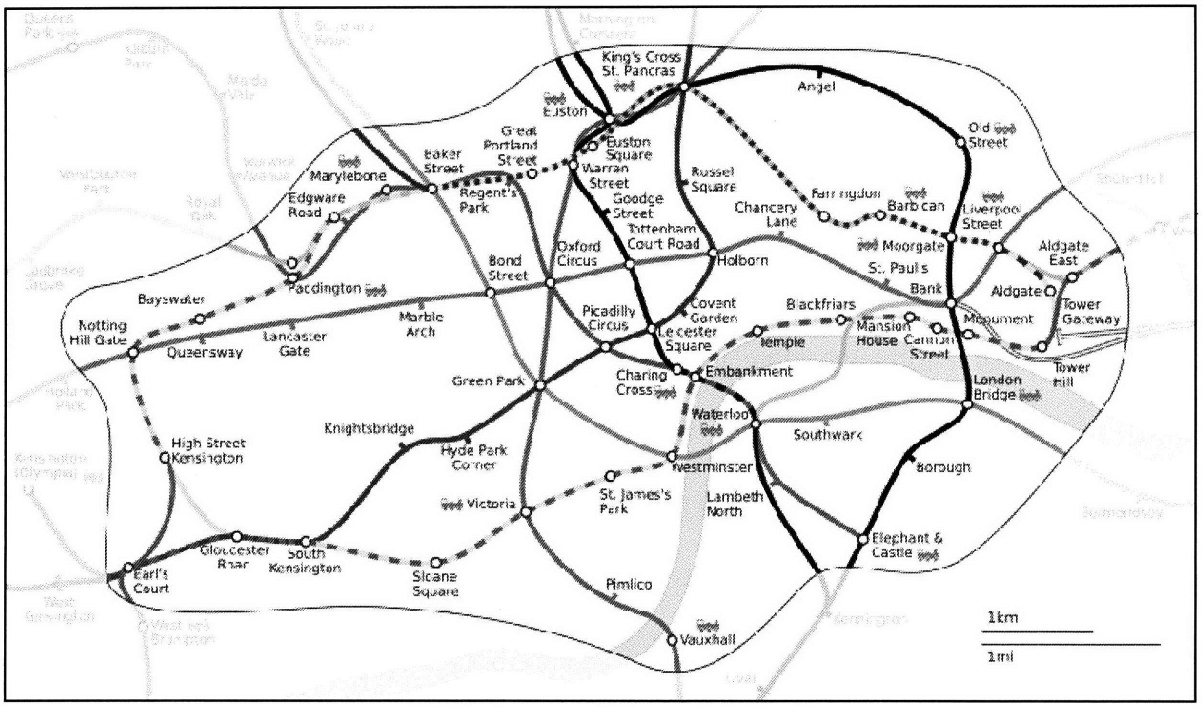
Path Attributes (minutes)		Average	Max	Min	Standard Deviation
In-vehicle	Chosen	17.9	55.5	1.5	8.3
	Generated	21.1	88.6	1.0	10.5
Entry within Station	Chosen	1.8	6.6	0.2	1.0
	Generated	2.1	7.1	0.1	1.3
Exit within Station	Chosen	2.6	7.1	1.0	0.9
	Generated	2.8	8.6	1.0	1.6
Initial Waiting	Chosen	2.2	16.6	1.0	1.6
	Generated	2.6	30.2	1.0	1.9

Note: N = 3,564 for chosen paths, and 8,126 for generated paths

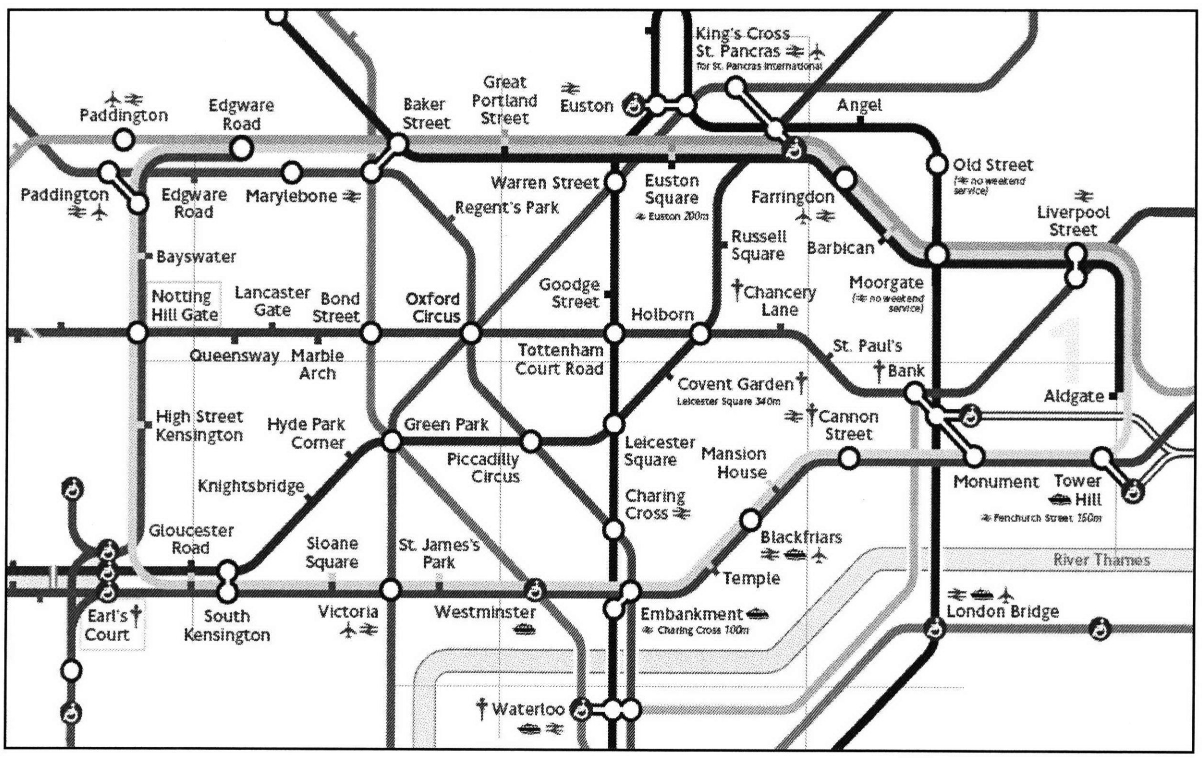
5.6.3 Map Attributes

A system map represents the network in a graphical form with respect to the location of stations, distance of links, direction of travel, and interaction between lines. For ease of understanding, the representation does not always reflect reality exactly: system maps often distort the spatial information they convey and the Underground map is no exception. Figure 5-13 compares the real Underground network and the map representation in Central London. Clearly, there exist significant differences in orientation and length of links. For example, the Paddington-Notting Hill Gate segment of the Circle and District lines runs east-west, but is shown as north-south on the system map. The same happens on the Westminster-Waterloo segment. On map, the link between King's Cross and Moorgate has almost the same distance as the link between Moorgate and Liverpool St, but in reality the former link is almost five times as long as the latter. Such distortion occurs widely on the map.

Not surprisingly, there is evidence that some travelers do indeed make travel decisions based on map information. For people who are not familiar with the system, they may check the



(a) Underground Network in Reality

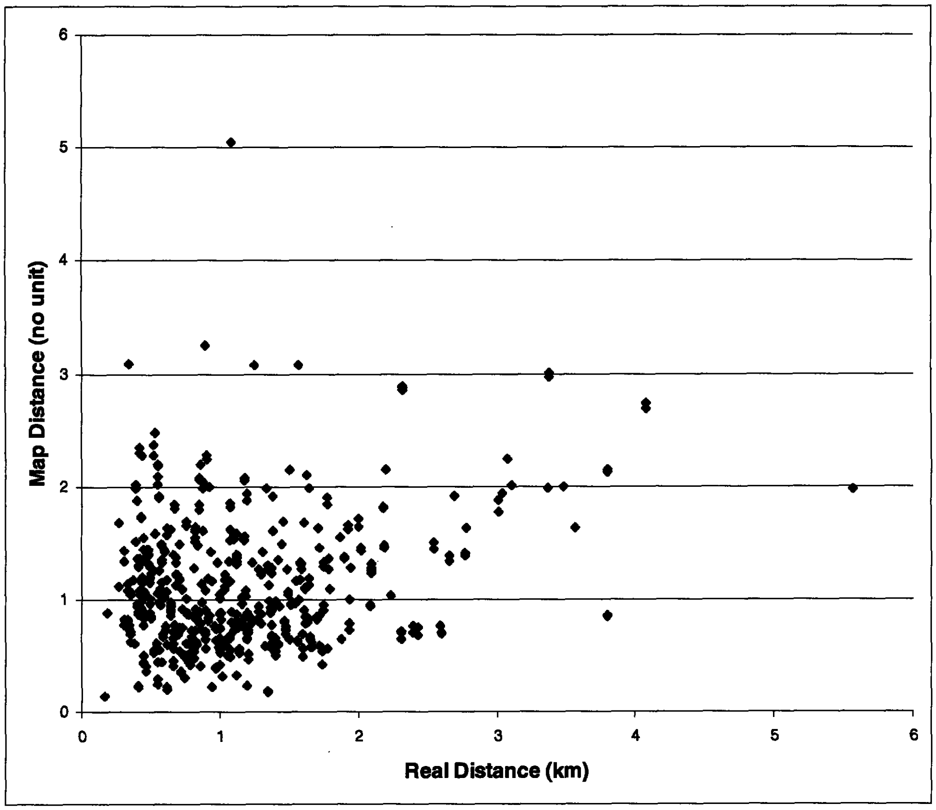


(b) Underground Network on System Map

Figure 5-13 Underground Network: Reality vs. Representation

map to find the best route of travel. The route distance on the map or number of station on the route might be the only information available to help them judge which route is quicker to get to a destination. Some scholars have even proposed a more profound influence of system maps. Using London as an example, Vertesi (2008) argues that the Underground map actually helps reshape Londoners' concept of space. Unlike Paris or New York, London above-ground offers few critical landmarks for wayfinding and making sense of the urban geography, while the Underground map may act as a backbone of spatial cognition. The map is highly stable over years, heavily copyrighted and controlled by the London Underground, and alternative views of the network are strictly prohibited and rarely seen by Londoners. Through in-depth interviews, Vertesi illustrated how Londoners often use the Underground map to organize space in the city. For example, they may use the number of stations as a proxy for distance rather than miles or kilometers. It would be no surprise if frequent Underground travelers also make decisions based on map information.

Two map attributes are defined: map distance and number of stations along a path. Map distances for the 691 Underground links are measured manually on the system map, and then inputted into the TransCAD network. Its unit is the map unit in Photoshop where the map distance is measured. The correlation between the map distance and actual distance is only 0.22, which indicates how seriously the map distorts real distances. Figure 5-14 plots the two distances, and the dots show considerable scatter. The number of stations is calculated through the choice generation process. Table 5-26 shows the descriptive statistics of these travel time attributes.



Note: N = 691

Figure 5-14 Relationship between Real and Map Distance

Table 5-26 Descriptive Statistics of Map Attributes for RODS and Generated Paths

Path Attributes (minutes)		Average	Max	Min	Standard Deviation
Map Distance*	Chosen	19.3	54.8	1.9	8.3
	Generated	24.3	105.6	1.1	12.0
# Stations	Chosen	9.7	28.0	1.0	4.1
	Generated	11.7	43.0	1.0	5.6

Note: * Photoshop map unit; N = 3,564 for chosen paths, and 8,126 for generated path

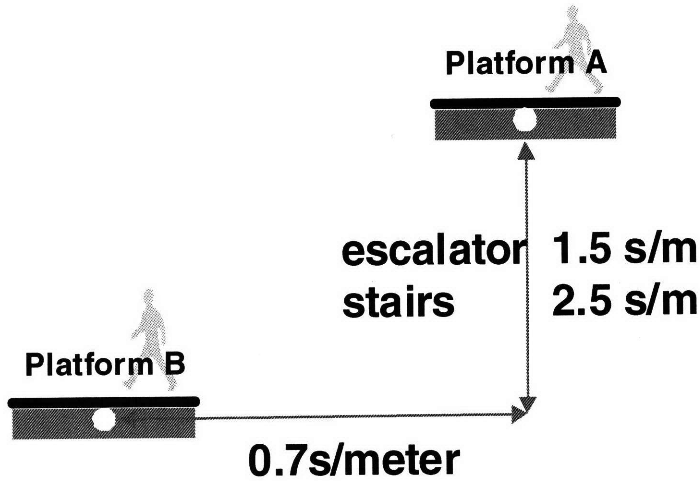
5.6.4 Interchange Attributes

Because interchanges within the Underground are free, the number of interchanges and the time spent on interchanges is vital to interchange-related decision. There are two time components:

interchange waiting and interchange walking. Interchange waiting time is calculated based on the same method as initial waiting time, but the value is smaller than initial waiting (see Table 5-27). I also computed the number of interchanges from the choice set generation process. The core part of defining interchange time attributes is to calculate interchange walking time.

Interchange walking time should not be difficult to calculate, however, interchange walk paths between platforms are complicated, and multiple paths might occur in three-dimensions. Transit agencies usually do not have a good database on the length of these links. Furthermore, that type of walking also matters: depending on whether it is walking on a level surface, escalator, stairs, or lift, walking time can be perceived very differently. Recording the walking conditions along interchange walking paths can be extremely time consuming and difficult, and the author is not aware of any transit agency that has done this. Instead, in general a simplified method is used to calculate interchange walking time.

The way I calculate interchange walking time in the Underground is shown in Figure 5-15. First, the X, Y coordinates of two platforms are identified; then, the Euclidian horizontal and vertical distances are computed. Second, the number of stairs and the length of escalator are recorded. Walking on the level is assumed at an average speed of 0.7 seconds per meter, escalator movement at an average speed of 1.5 seconds per vertical meter, and stairs are assumed at a speed of 2.5 seconds per vertical meter. Obviously, this is just an approximation of the actual time passengers spend walking between platforms. How accurate this method is will affect the model development and estimation to be presented. Table 5-27 summarizes the descriptive statistics of interchange time attributes.



Source: RailPlan Modelling User Guide, page 53

Figure 5-15 Interchange Walking Time Estimation

Table 5-27 Interchange Time Attributes Descriptive Statistics

Path Attributes (minutes)		**Average**	**Max**	**Min**	**Standard Deviation**
# Interchange	Chosen	0.95	2	0	0.33
	Generated	0.97	3	0	0.36
Interchange Waiting Time	Chosen	1.7	30.2	0	1.8
	Generated	2.1	30.2	0	2.1
Interchange Walking Time	Chosen	1.6	10.1	0	1.2
	Generated	2.2	13.7	0	2.2

Note: N = 3,564 for chosen paths, and 8,126 for generated path

Source: RailPlan

5.6.5 Interchange Facility Attributes

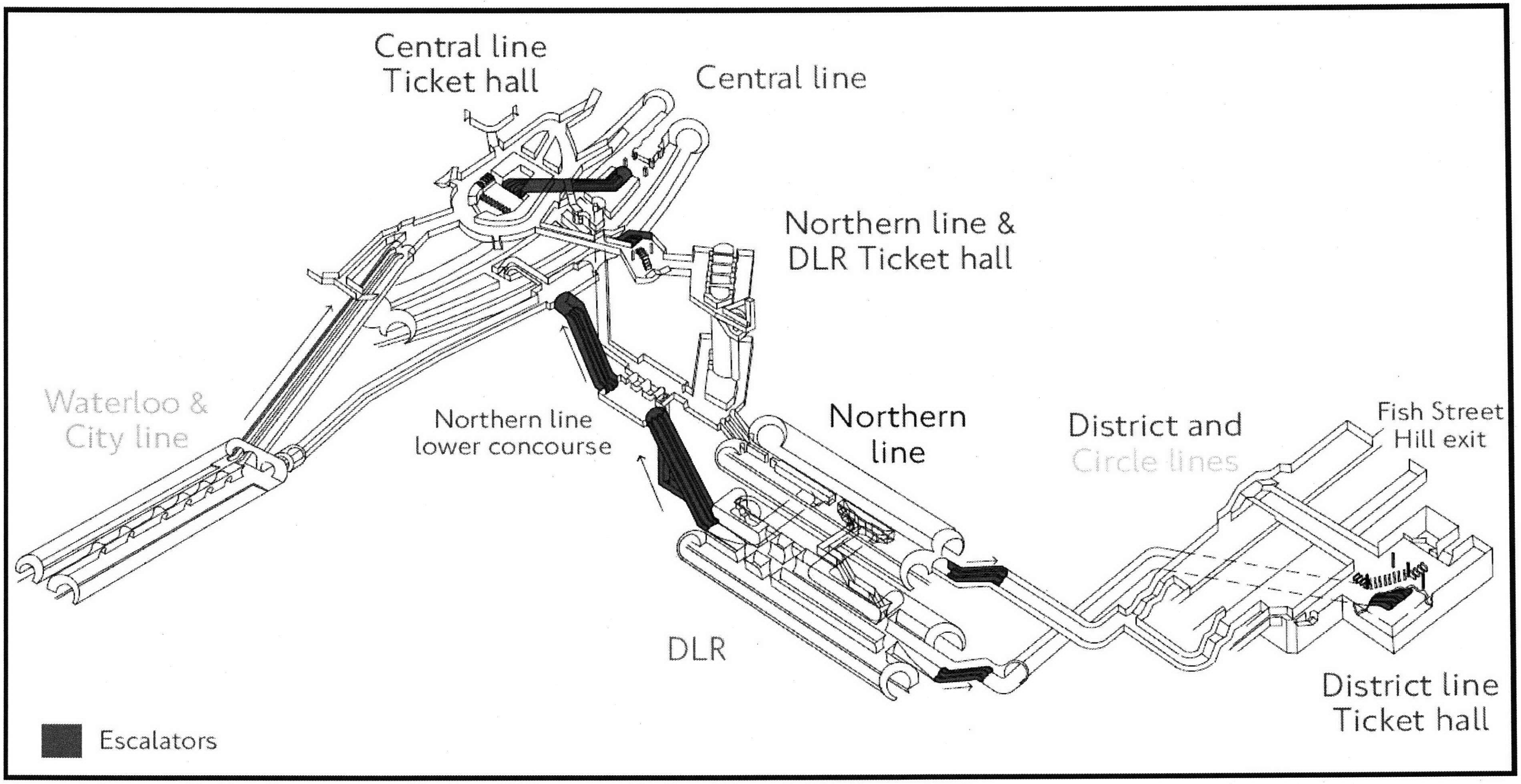
Although interchange walking time in general describes the (in)-convenience of interchanges, it misses many other attributes that may be important in interchange decisions. For example, when an interchange involves an up and down movement or significant directional changes at the same horizontal level, the time will be underestimated in RailPlan. As Figure 5-16 shows, Central Line platforms are at almost the same level as Circle/District platforms, but passengers need to go down to the deep Northern Line or Docklands Light Rail (DLR) platform and then up again.

Interchange design attributes refer to the non-time design elements of an interchange path that may affect the ease of interchange movement. There are endless ways to define these attributes: seating, signs, lighting, ventilation, stairs, concessions, directional change, etc. Due to the constraint of data availability, I considered only a dozen attributes in this analysis. Because many of them involve definition and measurement issues, I included about half of them in the final analysis. The following analysis is based on a field survey by the author of 24 Underground stations, the station inventory database from Transport for London, and a mobility survey conducted by Direct Enquiries, an organization aiming to provide Underground access information to the disabled.[26]

As suggested by the Boston case study, escalator presence is important. It is defined as a dummy variable with a value of 1 when there is at least one escalator available along the path, and 0 otherwise. The number of escalators might be a better measure but complete information on this is not available. The second attribute is stairs. There are two types of stairs: stairs that passengers cannot avoid, and stairs that passengers can avoid by taking an escalator or a lift. Note that this attribute refers to all stairs that a passenger has to use, often including both up and down stairs. I use total stairs in model specifications.

One particular type of level changes is explored: even interchange, which includes two situations: cross-platform interchanges and cross-track interchanges. The former does not involve any vertical movement: basically the two lines share the same physical platform, while

[26] Website: http://www.directenquiries.com/default.aspx?st=



Source: Transport for London, report on Bank and Monument Stations Upgrade Work.

Figure 5-16 Interchanges at the Bank and Monument Station

the latter refers to a situation where the interchange platform is at the same level but a bridge or tunnel must be used to cross the tracks. Most cross-track interchanges occur on the sub-surface and surface line. Among the 1,044 interchange movements investigated, 38 percent are cross-platform interchanges.

Other attributes include total length of horizontal walking considering level changes, and total length of ramp, which is assumed to be better perceived than stairs. Ramp usually has a slope ratio 1:20, a standard used by the Underground. There are two types of ramps: the one for the general public and the alternative path for the disabled, and the ramp definition here refers to the former one. I also explored share of ramp, lift availability, through ticketing gate, etc., but did not include them in the final results. Table 5-28 summarizes the descriptive statistics of the final five interchange-design attributes.

Table 5-28 Interchange Facility Attributes Descriptive Statistics

Design Attributes	Average	Max	Standard Deviation
Escalator	0.38	1.00	0.49
Stairs	42.78	378.00	55.72
Horizontal distance	45.68	292.00	58.15
Ramp length	12.80	154.00	25.44
Even interchange	0.50	1.00	0.50

Note: N = 1,044

5.7 Model Development and Estimation

A series of models are formulated and estimated considering two dimensions: (1) controlling for non-interchange variables, and (2) the spatial scale of the interchange behavior. The more non-interchange variables specified, the better the interchange's influence on path choice decisions can be captured. Due to the constraint of data availability, only five non-interchange variables are finally included: in-vehicle time, within-station entry and exit time, initial waiting time, map distance, and number of stations.

The three spatial scales are investigated for interchanges: system, station, and movement. The first level captures the interchange inconvenience at the system level. It indicates how well the different Underground lines and services are integrated with each other overall. The resulting value can be compared with other urban rail systems. The second level reveals the variation of the interchange experience across individual stations within the Underground. It consolidates all interchange attributes into one value, and suggests how well or poorly the interchange environment at a particular station is perceived by an average traveler. It allows the comparison with a traveler's intuition, and also has the advantage in avoiding specifying the interchange environment in detail, which has proven to be extremely time-consuming and data-intensive. However, station scale does not explain why one station is better than another in terms of interchange experience. The third level addresses this question by decomposing the interchange process into several components, and by specifying the physical interchange environment at the movement level. It also suggests potential ways to improve the interchange experience in the Underground.

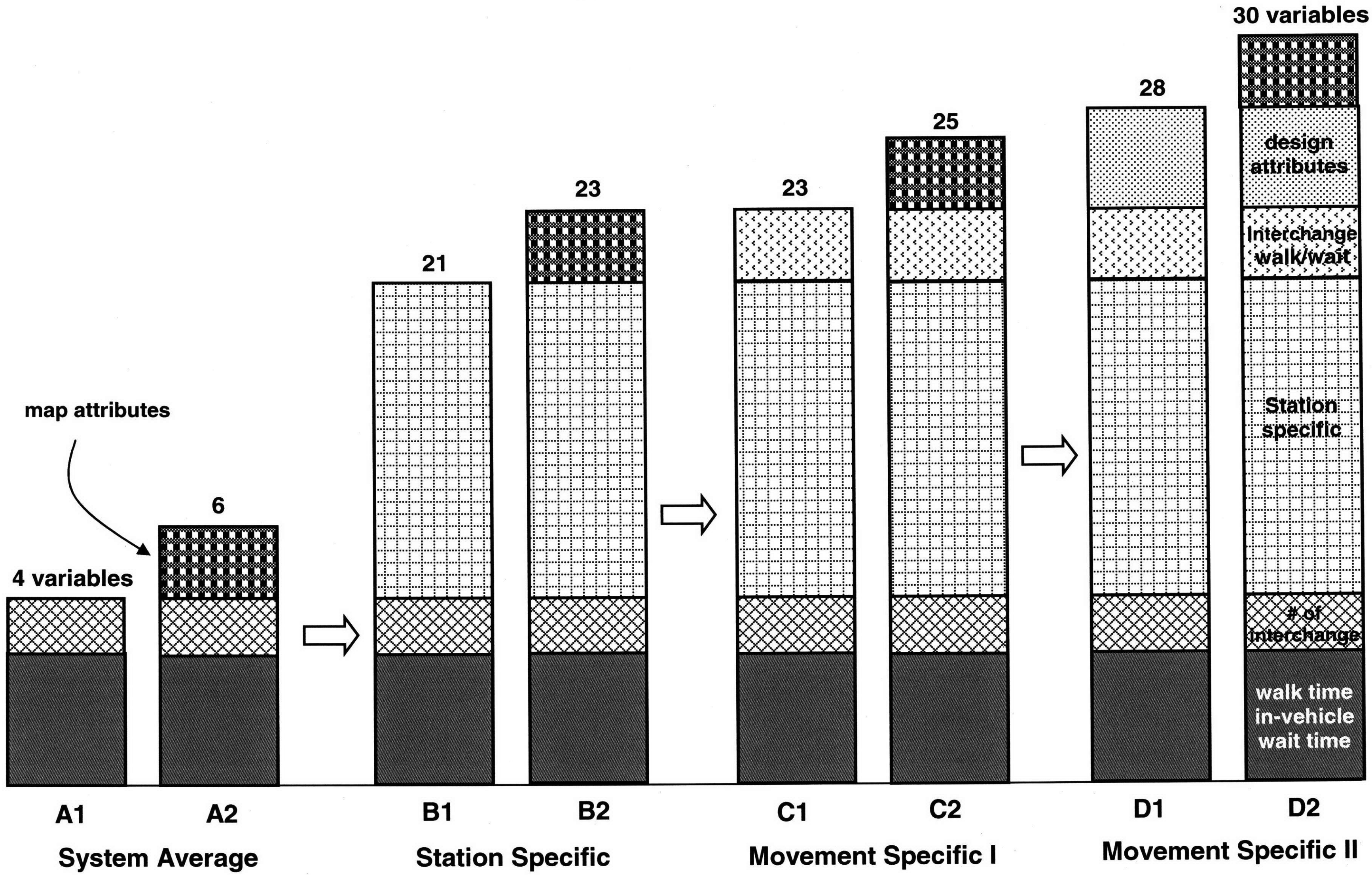
Accordingly, a total of eight models are estimated, four with map attributes and four without, as shown by Figure 5-17. Each bar represents a model with different categories of variables. The horizontal axis indicates the spatial scale dimension, while the vertical axis is the number of variables included in the specification. Models A1 and A2 are system-wide models with and without the two map attributes. Model B1 is the only station specific model with 17 station dummy variables, 1 indicating that the path involves an interchange at that particular station, and 0 otherwise. Models C1 is the movement-specific model with two interchange time variables, while model D1 is the movement-specific model with interchange time as well as design attributes. The results are presented in two tables (Tables 5-29 and 5-30). Models in Table 5-29 have similar specifications as those in the Boston case study, which can be used for comparison.

5.7.1 System Average Models: A1 and A2

In the base model A1, all four variables are significant at the 5 percent level with the expected signs. The more a path takes in terms of entry, exit, in-vehicle, or waiting time, the less likely that path is to be chosen by travelers. Initial waiting time is slightly more onerous (1.14 times) than in-vehicle time, which is expected but the premium is smaller than the current value of two used by TfL. Surprisingly, entry and exit walking are perceived to be 13 percent less onerous than in-vehicle time since walking on the street for either access to or egress from a station is generally viewed as more onerous than in-vehicle time.

It does necessarily mean that passengers prefer walking to in-vehicle travel. There are two possible explanations. First, entry and exit walking have small variation in the sample with standard deviations less than 1 minute for the revealed paths and between 1.3 and 1.6 minutes for generated paths (Table 5-24). Second, the in-vehicle time might capture the effects of other factors such as crowding and unreliability. The London Underground uses weights between 1 and 2.48 depending on the level of crowding in the system, while walking on platform has a weight of 2 (London Transport 1999). This issue will be discussed further later in this section.

On average, one interchange is viewed by the Underground passengers as equivalent to 2.217/0.395 = 5.6 minutes of entry/exit walking time (4.9 minute of in-vehicle time), including both interchange walking and waiting. Note that this value is the system average across all



Source: the author

Figure 5-17 Model Development Sequence

Table 5-29 Model Estimation Results (without map attributes)

Variables \ Models	A1	B1	C1	D1
Base Path Attributes				
Entry/exit walking	-0.395 (-12.6)	-0.382 (-11.2)	-0.288 (-9.0)	-0.247 (-7.3)
Actual in-vehicle time	-0.452 (-22.1)	-0.498 (-22.7)	-0.554 (-21.1)	-0.571 (-20.1)
Initial waiting	-0.516 (-11.0)	-0.436 (-8.1)	-0.362 (-7.4)	-0.367 (-6.9)
# of interchanges	-2.217 (-13.5)	-2.457 (-12.7)	-2.270 (-11.6)	-1.874 (-8.5)
Station Variables				
Baker St		-0.342 (-1.9)*	-0.512 (-2.8)	-0.685 (-3.4)
Bank/Monument		-0.608 (-3.2)	-0.638 (-3.0)	-0.679 (-2.5)
Bond St		1.454 (5.5)	1.198 (4.4)	1.077 (3.8)
Earl's Court		2.186 (6.6)	1.417 (3.9)	1.668 (4.0)
Embankment		-0.119 (-0.3)**	-0.301 (-0.9)**	-0.197 (-0.6)**
Euston		-0.401 (-1.8)*	-0.462 (-2.0)	-0.516 (-2.0)
Green Park		0.644 (3.9)	0.763 (4.0)	0.353 (1.5)**
Holborn		0.669 (3.3)	0.620 (2.8)	0.569 (2.5)
Leicester Sq		0.814 (2.6)	-0.120 (-0.5)**	0.418 (1.3)**
London Bridge		0.116 (0.31)**	0.096 (0.2)**	0.602 (1.3)**
Oxford Circus		0.917 (5.8)	0.592 (3.3)	0.565 (2.6)
Paddington		-2.013 (-5.0)	-1.896 (-4.7)	-1.999 (-5.1)
Piccadilly Circus		0.137 (0.44)**	-0.516 (-1.7)*	0.252 (-0.8)**
Victoria		0.339 (1.7)*	-0.060 (-0.3)**	-0.251 (-1.2)**
Warren St		-1.675 (-4.7)	-1.523 (-4.3)	-1.205 (-3.1)
Waterloo		-0.836 (-3.6)	-0.501 (-2.1)	-1.592 (-4.6)
Westminster		0.093 (0.4)**	0.249 (0.9)**	0.158 (0.6)**
Interchange Time				
Interchange walking			-0.322 (-8.9)	-0.299 (-7.7)
Interchange waiting			-0.197 (-4.6)	-0.176 (-4.4)
Interchange Environment				
Total interchange stairs				-0.0038 (-3.2)
Total horizontal distance				0.0021 (1.1)**
Presence of escalator				0.935 (3.9)
Ramp length				0.009 (5.6)
Same level interchange				0.827 (4.4)
Adjusted ρ2	0.504	0.543	0.579	0.592

Note: ** insignificant at 10 percent level, * significant at 10 percent level but insignificant at 5 percent level. Number in parentheses is t value.

Table 5-30 Model Estimation Results (with map attributes)

Variables \ Models	A2	B2	C2	D2
Base Path Attributes				
Entry/exit walking	-0.401(-12.2)	-0.387 (-11.0)	-0.281 (-7.9)	-0.240 (-6.5)
Actual in-vehicle time	-0.176 (-22.7)	-0.165 (-4.3)	-0.169 (-3.8)	-0.153 (-3.3)
Initial waiting	-0.475 (-10.0)	-0.395 (-7.1)	-0.299 (-6.4)	-0.290 (-5.8)
# of interchanges	-2.379 (-11.7)	-2.848 (-12.6)	-2.690 (-12.1)	-2.322 (-9.2)
Map Attributes				
Map distance	-0.742 (-7.7)	-0.856 (-7.9)	-1.129 (-8.8)	-1.184 (-8.9)
# of stations	-0.183 (-3.6)	-0.256 (-5.5)	-0.259 (-5.4)	-0.300 (-6.4)
Station Variables				
Baker St		-0.068 (-0.4)**	-0.298 (-1.6)**	-0.556 (-2.8)
Bank/Monument		-0.457 (-2.4)	-0.430 (-2.1)	-0.568 (-2.3)
Bond St		1.335 (5.1)	1.110 (3.9)	0.855 (2.9)
Earl's Court		2.419 (7.3)	1.671 (4.7)	1.893 (4.6)
Embankment		0.463 (1.3)*	0.469 (1.3)**	0.524 (1.6)*
Euston		-0.570 (-2.3)	-0.618 (-2.3)**	-0.631 (-2.2)
Green Park		0.630 (3.6)	0.766 (3.7)	0.407 (1.7)*
Holborn		0.524 (2.6)	0.448 (2.1)	0.289 (1.2)**
Leicester Sq		1.217 (3.8)	0.107 (0.4)**	0.776 (2.2)
London Bridge		-0.050 (-0.1)**	-0.073 (-0.2)**	0.422 (1.0)**
Oxford Circus		1.189 (7.8)	0.960 (5.7)	1.096 (5.0)
Paddington		-2.111 (-5.0)	-2.178 (-4.8)	-2.581 (-5.8)
Piccadilly Circus		0.404 (1.3)**	-0.275 (-1.0)**	0.642 (2.0)
Victoria		0.976 (4.8)	0.683 (3.1)	0.525 (2.2)
Warren St		-1.436 (-3.7)	-1.211 (-3.0)	-1.034 (-2.4)
Waterloo		-0.889 (-4.0)	-0.560 (-2.2)	-1.941 (-5.2)
Westminster		0.264 (1.0)**	0.452 (1.6)**	0.321 (1.1)**
Interchange Time				
Interchange walking			-0.350 (-9.6)	-0.299 (-8.1)
Interchange waiting			-0.193 (-6.4)	-0.176 (-4.0)
Interchange Environment				
Total interchange stairs				-0.0038 (-2.7)
Total horizontal distance				0.0021 (1.2)**
Presence of escalator				0.935 (4.9)
Ramp length				0.009 (5.6)
Same level interchange				0.995 (5.1)
Adjusted ρ2	0.523	0.565	0.604	0.619

Note: ** insignificant at 10 percent level, * significant at 10 percent level but insignificant at 5 percent level. Number in parentheses is standard error.

interchanges at the more than 200 Underground stations for both the first and second interchanges.

In order to compare with prior studies, a model with interchange walking and waiting is estimated, so their effect is excluded from the interchange penalty (Appendix D). The new penalty is 4.2 minutes of in-vehicle time, compared nicely with 5.2 minutes from the 1985 London Transport report, and 3.7 minutes from the 1995 report. TfL currently uses a boarding penalty of 3.5 minutes for the Underground after excluding interchange walking and waiting times. Model A1 is the base model for comparisons with subsequent model forms.

In the map attribute model A2, the two map-attribute variables, map distance and number of stations, are significant at the five percent level with the expected sign. The longer a path appears to be on the system map, and the more stations it passes through, the less likely that path is to be chosen. The goodness-of-fit of the model is also improved significantly from 0.504 to 0.523. More interestingly, other variables are largely unaffected by including the two map attributes except the in-vehicle time, whose coefficient is reduced significantly from 0.452 to 0.176. The likely explanation is that map attributes capture part of the in-vehicle time influence on path choice decisions. In other words, although travelers value the shortness of a travel path, they rely on multiple information sources, such as personal travel experience and the system map, to make that judgment. This result further explains why the in-vehicle time in Model A1 is viewed more onerously than entry and exit walking time.

Although system maps appear to affect passengers' path choice, whether this can be used as a planning and operations tool to change travel behavior for the benefit of both travelers and the transit system remains unclear. A system map needs to provide clear visual representation of the transport network, and should not be changed frequently. The London Underground system map has remained relatively stable for decades, and become the trademark of the system and sometimes even the symbol of the city. Changing the system map to guide travelers' behavior might not be easy for large public transport agencies like Transport for London (the governing body of the London Underground).

5.7.2 Station Specific Model: B1 and B2

A total of 23 major interchange stations are included in this station-specific formulation, representing 69 percent of all interchanges in the Underground. Only 17 stations remain in the final specification following the backward delete process. Those not included act as a base for comparison whose value is captured by the variable number of interchanges. A positive value of the dummy variable for a particular station indicates that the station is better than the base, a negative value means the opposite, while an insignificant value implies that the station is statistically no different from the base.

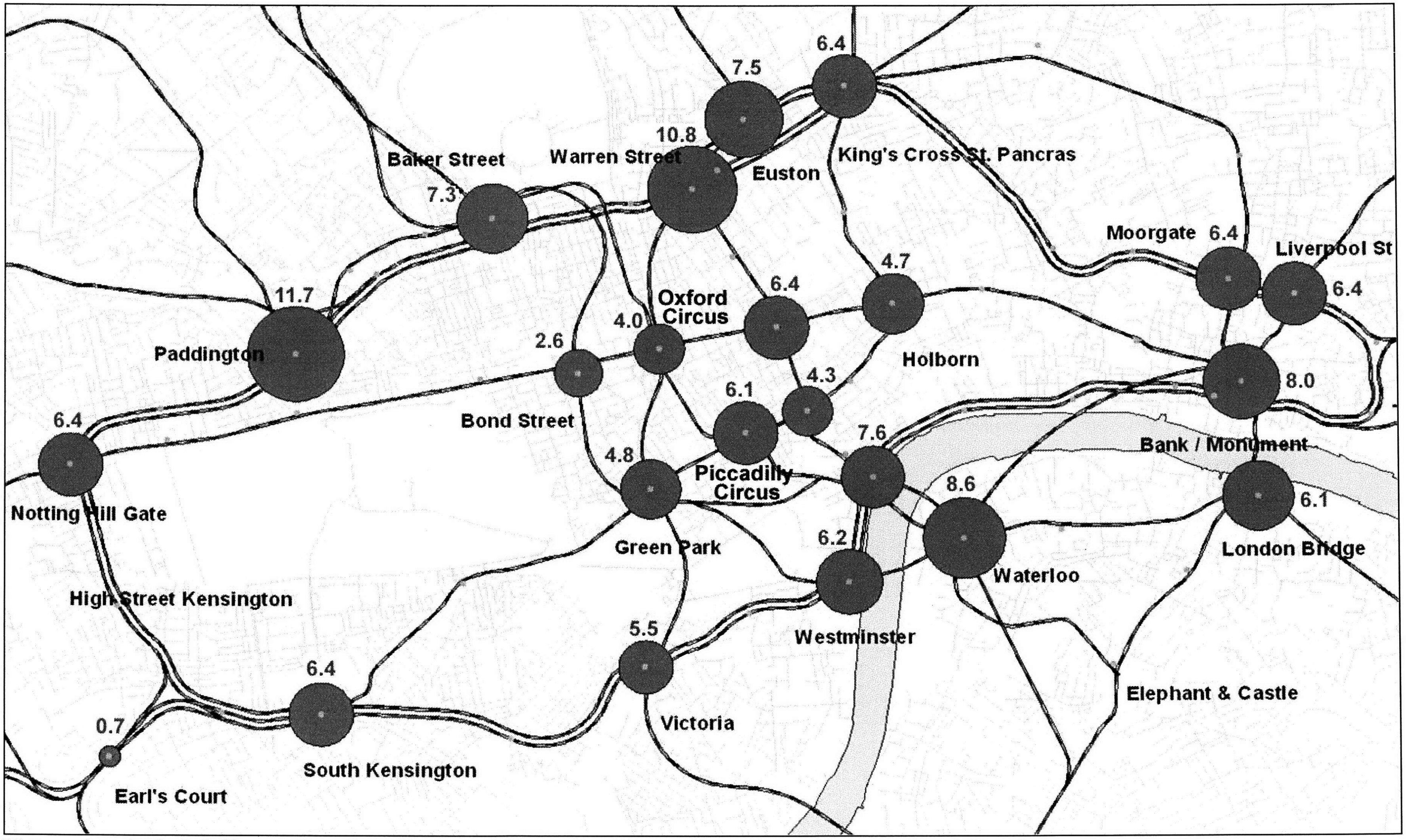
The results in Table 5-29 suggest that the worst interchange stations are normally some of the big, complex, National Rail terminal stations: Waterloo, Paddington, and Euston. Bank/Monument and Warren St also perform poorly probably because the former is basically a combination of two stations, while the later has a competitive disadvantage compared with Euston. When passengers interchange between the Victoria and Northern lines, Euston tends to be their first choice because interchange there is *more* convenient than at Warren St, which renders Warren St unpopular even though its interchange environment compares nicely with other interchange stations.

The five best interchange stations are Earl's Court, Bond St, Leicester Sq, Oxford Circus, and Victoria, which is understandable given their simple interchange environments and heavy use. In general, stations within the circumferential service tend to have smaller transfer penalties, probably because their interchange environments are relatively simple and straightforward. The station variation captured in this model significantly enhances its explanatory power with the goodness-of-fit increasing from 0.523 to 0.543.

I calculated the interchange penalty at each station using walking time as a base. The base interchange penalty is 6.4 minutes, while the worst station, Paddington, has 11.7 minutes, and the best station, Earl's Court, has only 0.7 minutes. Figure 5-15 shows the 17 interchange stations in Central London with the size of the circle representing the interchange penalty.

Next, the interchange penalty is multiplied by the total number of interchanges at each station. The value is the time loss due to the interchange penalty at these stations in the Underground. Figure 5-16 shows the results for a typical weekday. The ranking is different from Figure 5-17 with large interchange station, such as Baker St, King's Cross, Oxford Circus, Green Park, and Bank/Monument, moving up the list. These stations are also where improvement of interchange experience can result in the largest benefits. For example, assuming a value of time is \$21.2 (£10.6) per hour, monetary cost of interchange inconvenience at Baker St is about \$218,000 (£109,000) per typical weekday and almost \$70 million (£35 million) annually. The total social cost of interchange in the Underground can be tremendous. Although not all the interchange cost can be eliminated through design, planning, and operation, the number suggests the significant impact of interchange on public transport as well as the great potential of interchange improvement.

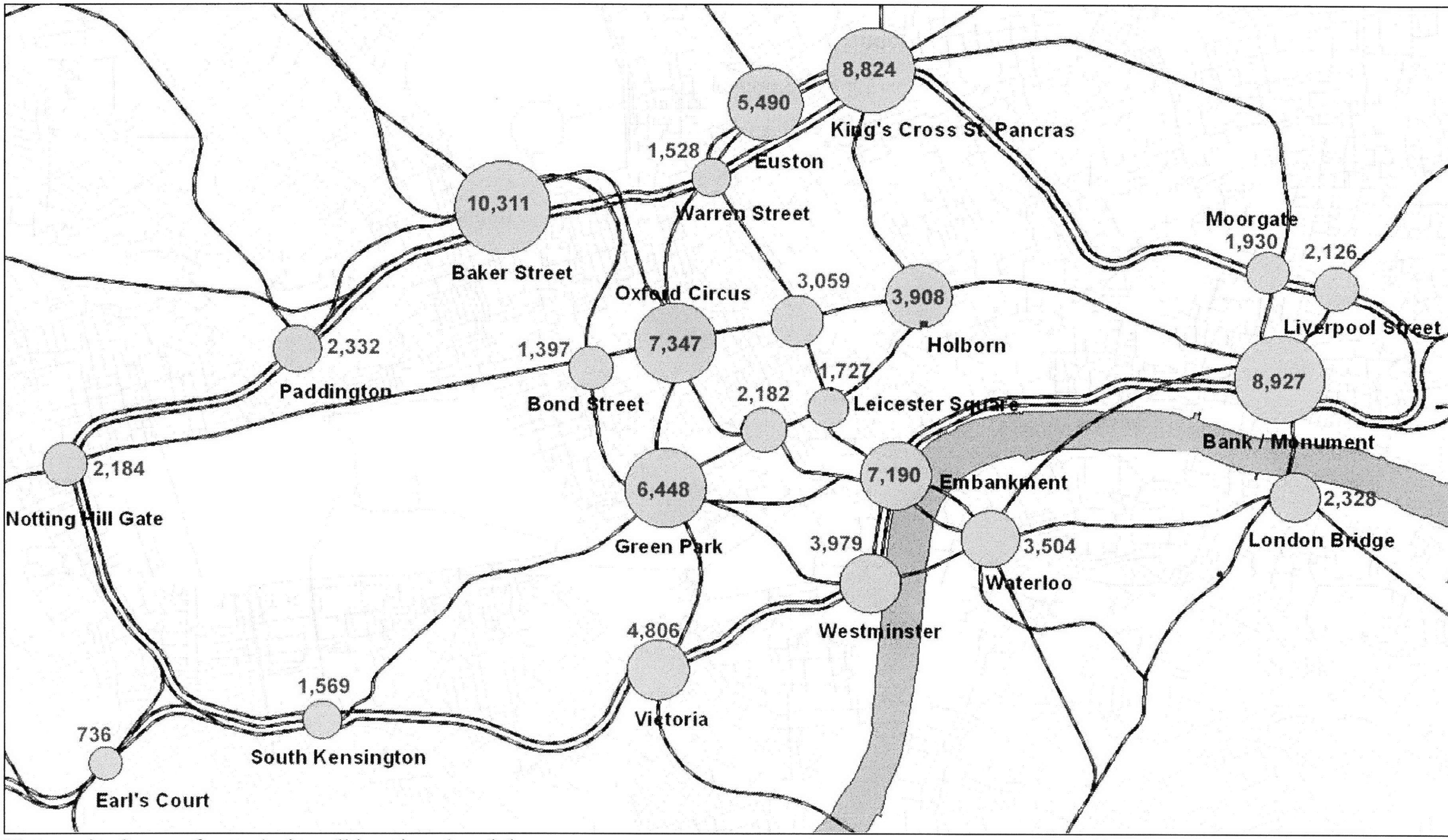
The map attribute model B2 has a better goodness-of-fit than B1, following a similar pattern as A2 to A1 (Table 5-30).



Note: values include influence form interchange walking and waiting; unit = minute of entry-exit walking time

Source: created by the author based on model estimation results

Figure 5-18 Interchange Penalty at Selected Underground Stations



Note: unit= hours of entry/exit walking time /weekday

Source: created by the author based on model estimation results

Figure 5-19 Daily Time Penalty due to Interchanges

5.7.3 Interchange Movement Models: C1/C2 and D1/D2

Model C1 captures the effect of interchange time explicitly by including interchange walking and interchange waiting times. Both are significant with the expected signs. The more time spent on executing an interchange along a path, the less likely that path is to be chosen. Interchange waiting is viewed less negatively than the initial waiting, while interchange walking is more onerous than entry/exit walking. These two variables capture part of the interchange influence from the station dummy variable. Leicester Sq is the most heavily affected station. Its coefficient is rendered insignificant at the five percent level by the interchange time variables, which suggest that most of the interchange penalty at these two stations is caused by interchange time. For other stations, there are still factors other than interchange time which affect the interchange decision.

Model D1 adds the five design attributes to capture the influence of the non-time factors. Four are significant at the five percent level, while the horizontal distance is significant at the 10 percent level. After the interchange walking time is controlled for, the total number of stairs adds an additional burden to interchange experience, while all other attributes reduce that burden. The presence of an escalator, the longer ramp, and being a same-level interchange will mitigate interchange penalty. Ramp is favored probably because it often replaces stairs which are usually viewed as a barrier to walking.

I do not have a good explanation for the horizontal distance sign which is counter intuitive. One possibility is that given the total interchange time, longer horizontal walking is better because it indicate less vertical movement. The Holborn variable has the most dramatic change from model C1 to D1. Its coefficient is rendered insignificant by the interchange time and design attributes, which suggest that most of the interchange experience can be explained by the seven interchange variables in Model D1. Both C1 and D1 are significant improvements over the previous model with a higher goodness-of-fit (see Table 5-29).

Including map attributes also improve model explanatory power significantly (Table 5-30). Specifically, model D2 has the highest goodness-of-fit of all eight models, and is used test the validity of the developed models and policy simulation in latter applications. A prediction test is performed based on the estimation result. The dataset is split into two parts, each having half the observations from the original dataset. The split is based on odd and even number of the access station code, so it is a random process. Next, one half dataset is used for estimation using the D2 specification. Then, the results are used to predict the path choice in the other half dataset. The prediction rate is calculated based on the following equation:

$$Predict = \frac{\sum_n \sum_i P_n(i) * C_n(i)}{N} \tag{9}$$

where

$P_n(i)$ = the calculated probability of observation *n* choosing path *i*,
$C_n(i)$ = 1 if path *i* is chosen by observation *n*, 0 otherwise
N = number of observations

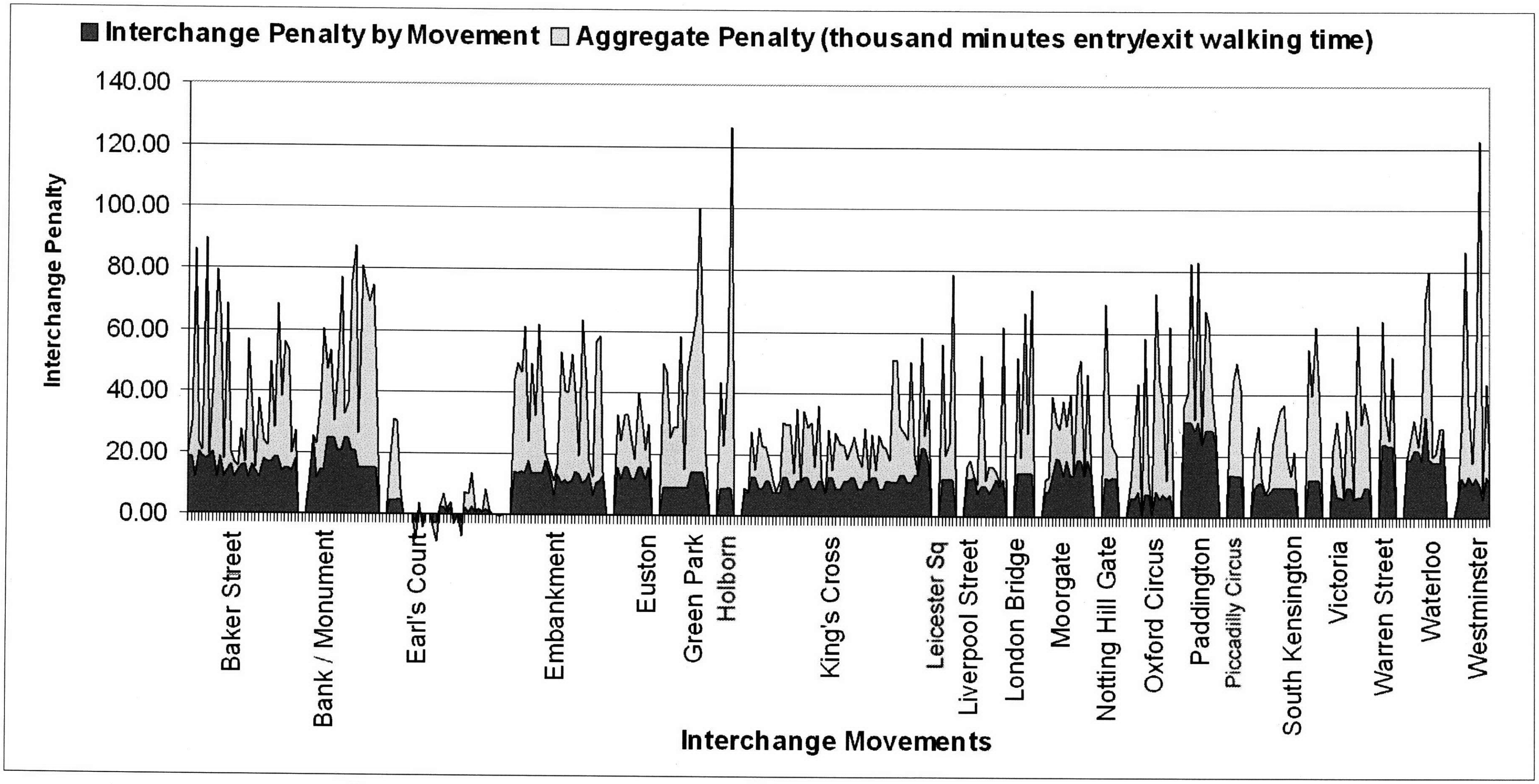
The average probability of correct prediction is 80 percent, suggesting that the final model specification works well in predicting travelers' path choice in the Underground.

I calculate the interchange penalty using the same method as for the station specific model. Results suggest there is a big variation of interchange environments across movements within the same station. For example, at Green Park, the value is only 5.5 minutes between the Jubilee Line southbound and the Victoria Line, but increases to 8.5 minutes between the Piccadilly Line eastbound and the Victoria Line. Data show that the former movement has a short walking distance (2.6 vs. 4.7 minutes), is assisted by escalators, and involves fewer stairs (19 vs. 44), than the latter movement. The variation is even greater in terms of aggregate impact. For example, at Green Park station, the ratio of interchange penalty between the worst and best movement is 1.55, but the ratio of aggregate interchanges impact between the worst and best movement jumps to 13.4. Figure 5-20 shows the variation of interchange penalty and aggregate interchange impact for 303 interchange movements in the Underground.

The four worst movements, in terms of the interchange penalty, are at Waterloo between the Bakerloo southbound and the Northern Line and at Paddington between the Bakerloo Line and the Circle/District Line. The worst four movements, in terms of aggregate interchange loss, are at Holborn between the Central and Piccadilly Lines westbound, at Westminster between the District and Jubilee Lines eastbound, at Green Park between the Piccadilly Line westbound and the Victoria Line southbound, and at Baker St between the Bakerloo Line northbound and the Metropolitan Line westbound.

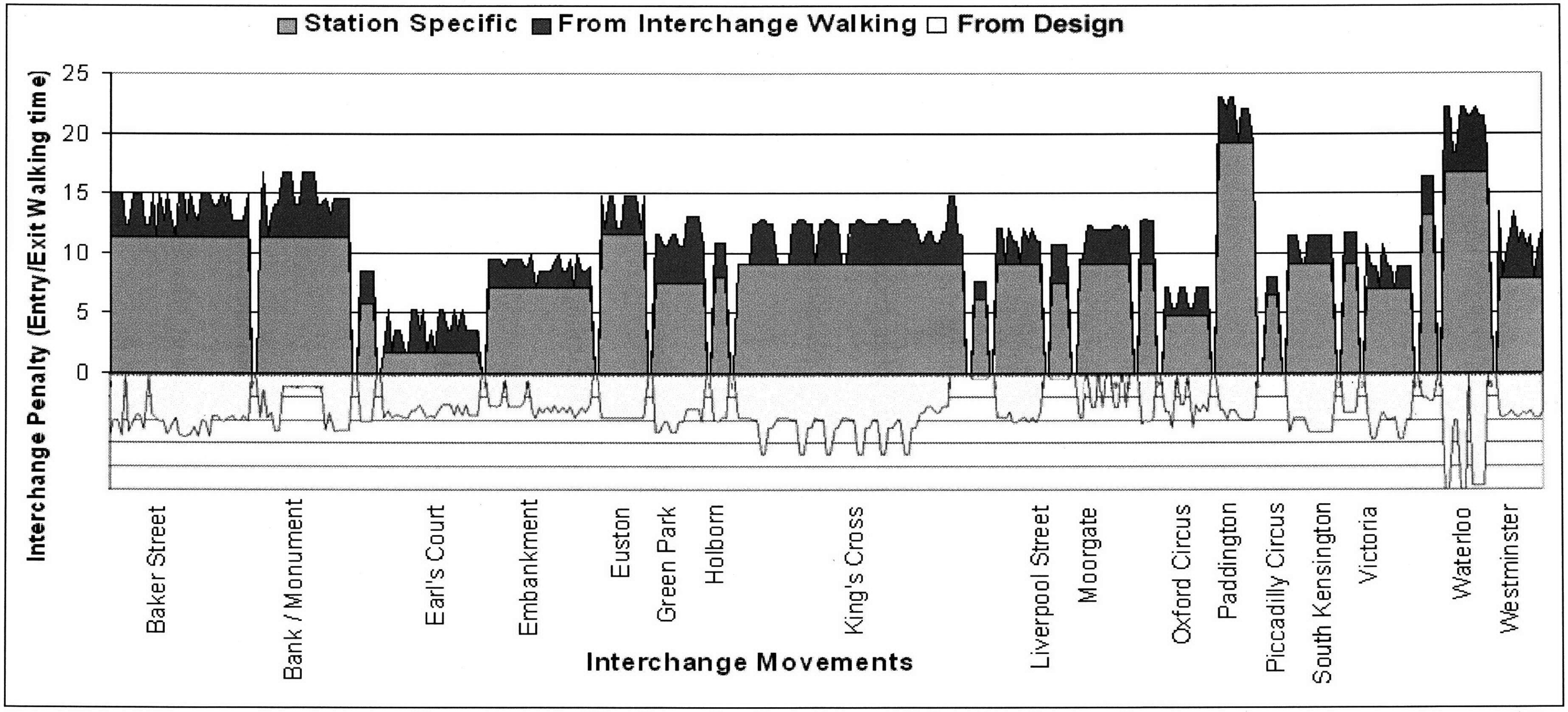
In order to examine the contribution of the physical environment to the interchange experience, I calculate the same value for three groups of variables: (1) interchange walking that captures the connection time between platforms, (2) design variables that capture the connection type, and (3) the residual interchange penalty not including these factors. The computation is based on a new model excluding interchange waiting time because it does not belong to the physical interchange environment (Appendix E). This analysis provides more information to understand the interchange environment.

Some stations, such as Waterloo, have a large pure interchange penalty, but also perform well in mitigating that inconvenience by providing better design features. For some interchange movements, such as those at Green Park, both the pure interchange penalty and the design



Source: created by the author based on model estimation results

Figure 5-20 Interchange penalty by Interchange Movement



Source: created by the author based on model estimation results

Figure 5-21 Contributions of Physical Environment to Interchange penalty

features are reasonable, but the long interchange walk required makes them less acceptable. Such a difference implies distinct investment strategies at the two stations in order to improve the interchange experience. The contributions of the three components across movements are summarized in Figure 5-21.

The model estimation results further validates the research design, path choice generation, and attributes computation presented in previous sections. The sequential improvement of models also supports the argument that interchange analysis should go beyond the system average, the current state of practice, and be calibrated at the station and movement levels. Path-choice-based interchange modeling not only identifies the great variation of interchange experience even within the same station, but also reveals the different roots of the interchange penalty. It not only helps explain passengers' interchange decisions, but also facilitates project selection and evaluation with respect to interchange planning and operation in the Underground.

5.8 Applications in Planning and Operation

This research can be of value in the Underground planning and operation in multiple areas: ridership forecasting, network design, service design, service management, and marketing strategy. This section focuses on two specific examples to explore the potential impact of this research: Underground system-wide passenger flow assessment, and the impact evaluation of the Bank/Monument Interchange project.

Passenger-flow prediction is critical for operation and planning of public transport, especially for a congested system like the Underground. However, tracking how passengers travel inside the system after they enter is extremely difficult. The Underground currently relies on the RODS survey to identify people's travel paths in the system, but RODS covers less than

10 percent of daily Underground trips and seriously under-represents certain trip groups such as the early-morning trips. Furthermore, based on conversations with managerial staff in the Underground, I determined that no accurate volume count has been possible on critical line segments in the system. The path choice model developed here might offer improved forecasts of passenger flow in the Underground, and help predict changes in system usage in response to planed or unexpected events, such as service disruptions, planned station closures, accidents, or terrorist attacks.

5.8.1 Interchange Impact on Passenger-Flow Prediction

Interchanges affect passengers' path choice decisions and hence passenger flows on links in the network. In the Underground RailPlan network, the interchange attributes included are interchange walking and waiting times, and an additional penalty. However, this penalty is a uniform value, 3.5 minutes, for all interchange stations in the network, which is a relatively simple treatment. This simplification might lead to the under- or over-estimation of passenger link flows on certain Underground segments. This example illustrates such a possibility by defining the interchange penalty at the station and movement levels as described in prior sections of this chapter.

I develop three scenarios: (1) base scenario uses the default network in RailPlan assuming a system-average interchange penalty of 3.5 minutes; (2) station scenario specifies the interchange penalty at the station level with major interchange stations having different values; (3) movement scenario further defines the interchange penalty at the movement level, which represents the actual interchange situation. I use the demand from the one hour (7:30 to 8:30AM) of the morning peak period to simulate the link flows.

The OD matrix used is based on the smart card system, Oyster Card, and was developed by Gordillo (2006) and Chen (2007) as an alternative to the current OD matrix which is based on RODS.

Three comparisons are performed based on the three scenarios: station scenario versus the base, movement scenario versus the base, and station scenario versus movement scenario, on two sets of measures: aggregate flows on each (physical) link (not service route), and boardings and alightings at each platform (not station). Boardings (alightings) include original entries (exits) as well as interchange boardings (alightings), and so are affected by the different interchange attributes assigned to the network even though the OD matrix is fixed. The assignment is conducted using TransCAD 5.0. [27]

Boardings and Alightings

The three scenarios are compared at two levels: system as a whole versus individual platforms or links, and the average versus the variation of change.

Table 5-31 summarizes the results for boardings and alightings for each scenario at the system level. The average boardings and alightings among the scenarios change slightly from 815 in the base to 810 and 811 in the station and movement scenario, respectively. The reduction is likely due to the higher interchange penalties defined in the two alternative scenarios. Passengers are more likely to avoid interchanges in the station and movement scenarios. The variation of boardings and alightings is relatively large in all three scenarios. For example, the coefficient of variation is around 1.42 and 1.46 for boardings and alightings,

[27] TransCAD 5.0 does not allow a definition of the transfer penalty by station and direction. A transfer wait time table was used, which assigned a fixed value to line-to-line transfers at particular stops. It will override the transfer waiting time calculated from headways. This transfer wait time table acts like a penalty table. Accordingly, the penalty should be recalculated without the transfer waiting time in model estimation in order to avoid double counting. For details, please see TransCAD Demand Modeling Manual (version 4.8) page 276-277.

respectively, in the three scenarios. The top five platforms remain almost the same, except the northbound Bakerloo Line at Waterloo station, while their rank changes slightly. The slight difference among the scenarios indicate that better defining the interchange penalty does not reveal dramatic changes in the boarding and alighting pattern in the Underground as a whole. This is reasonable because the origin and destination pattern is fixed for all scenarios, and the interchange penalty affects only a portion of trips in the Underground. However, the improved penalties can have a significant impact on certain platforms especially those operating close to capacity.

Table 5-31 summarizes the comparison results at the individual platform level from the three scenarios. The difference of boardings and alightings are calculated based both on their true and absolute values. In the true value case, the difference is small, only three to five passengers per platform, because increases and decreases can be cancelled each other out. In the absolute value case, the difference is around 40 passengers, either more or less than the base scenario. Such a difference represents a four percent change of boardings, and a three percent change of alightings across all platforms. The one percent difference is caused by the fact that alightings are more concentrated than boardings at stations in the Underground.

The difference is much larger for some platforms. For example, the maximum change of boardings is between 879 and 931 passengers in the station and movement scenarios, representing 22 to 18 percent of difference from the base scenario (second row in Table 5-32). In the station scenario, most boarding reductions are concentrated at four Victoria Line stations: King's Cross, Euston, Oxford Circus, and Green Park, with increased boardings scattered among Earl's Court, King's Cross, Embankment, Leicester Sq, Victoria, and Piccadilly Circus,

Table 5-31 Estimated Boardings and Alightings from Three Scenarios

Scenarios	**Base Scenario**		**Station Scenario**		**Movement Scenario**	
	Boardings	Alightings	Boardings	Alightings	Boardings	Alightings
Average	815	815	810	810	811	811
Max	8416	8686	8101	8269	8277	9024
Stdev	1156	1192	1146	1178	1160	1188
Top Five Platforms	V(S) Finsbury, 8416 V(N)Victoria, 7743 V(N) Brixton, 7743 B(N) Waterloo, 5962 M(S) King's, 5874	V(S) Oxford, 8686 V(N) Oxford, 8144 V(S) Victoria, 6215 D(E)Monument, 5673 B(S) Oxford, 5336	V(S) Finsbury, 8101 V(N) Victoria, 6979 M(S) King's, 6592 D(W) Victoria, 6182 V(N) Brixton, 6049	V(S) Oxford, 8269 V(N) Oxford, 7744 D(E) Earl's, 5869 V(S) Victoria, 5693 D(W) Victoria, 5632	V(S) Finsbury, 8277 V(N)Victoria, 7400 D(W) Victoria, 6498 M(S) King's, 6482 V(N) Brixton, 6049	V(S) Oxford, 9204 V(N) Oxford, 7964 D(W) Victoria, 5833 V(S) Victoria, 5757 D(E) Earl's, 5560

Note: V=Victoria Line, B = Bakerloo Line, N =Northern Line, M = Metropolitan Line, D = District Line, P = Piccadilly Line, (N) = Northbound, (S) = Southbound, (E) = Eastbound, (W) = Westbound

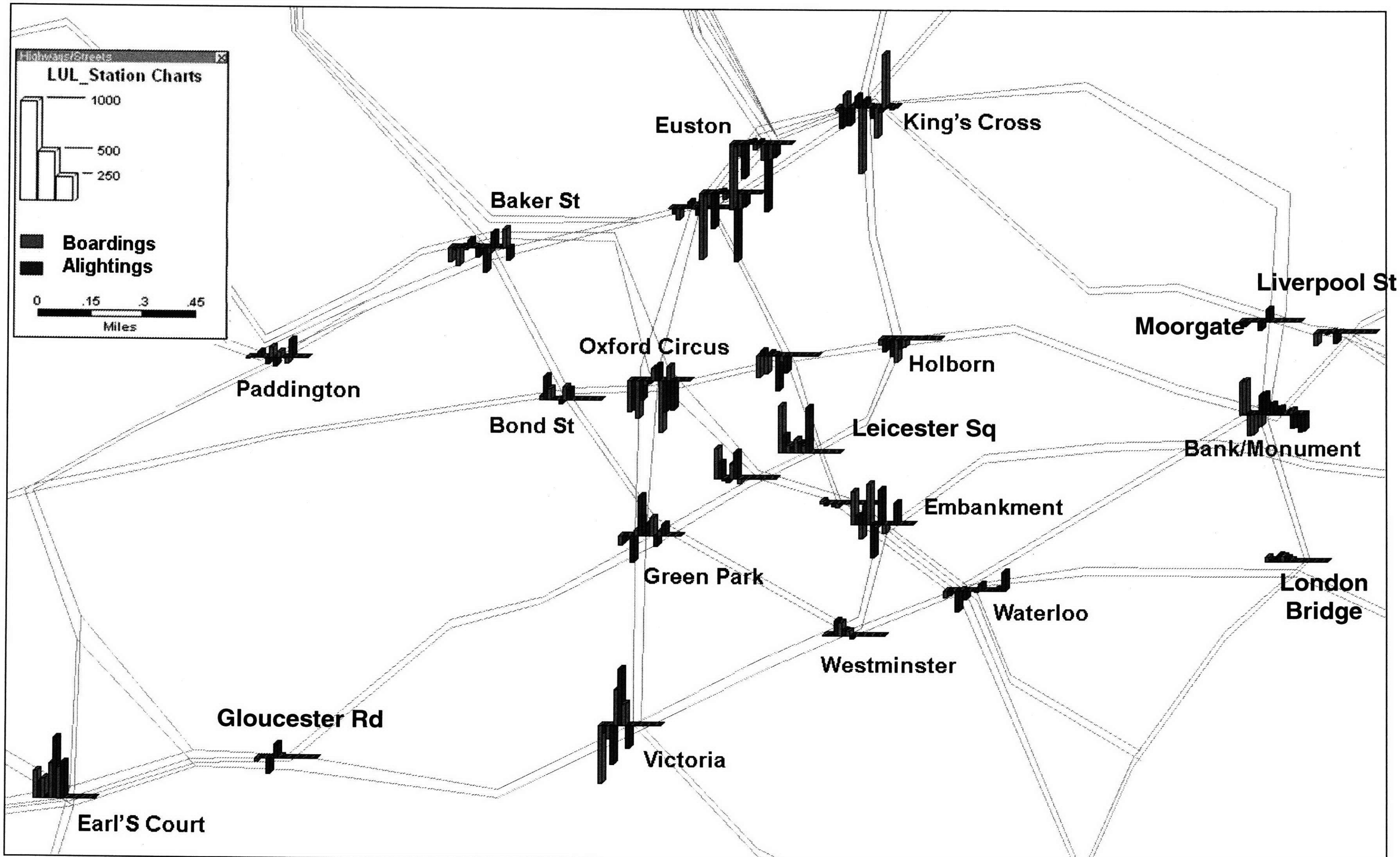
Table 5-32 Differences of Boardings and Alightings between Scenarios

Comparisons	Station - Base		Movement - Base	
	Boardings	Alightings	Boardings	Alightings
True Value				
Average	-5.0	-5.1	-3.4	-3.4
Max	718	792	931	954
Min	-879	-895	-889	-859
Stdev	109.6	107.8	111.8	119.6
ABS Value*				
Average	36 (4.2%)	39 (3%)	35 (4.1%)	41 (3.3%)
Max	879 (22.3%)	895 (23.1%)	931 (18.3%)	954 (19.6%)
Stdev	104 (43.9%)	101 (7.1%)	106 (43.8%)	113 (8.7%)
Top Five Platforms	V (S) at Euston, - 879 (3878**)	N (N) at Euston, – 895 (3867)	D (E) at Victoria, + 931 (5083)	D (W) at Victoria, + 954 (4879)
	N (N) at King's, - 876 (3329)	D (E) at Earl's, + 792 (5077)	N (N) at King's, – 889 (3329)	D (E) at Victoria, + 865 (3616)
	V (N) at Victoria, - 764 (7743)	D (W) at Victoria, + 753 (5632)	V (S) at Euston, – 879 (3878)	N (N) at Euston, - 859 (3867)
	M (S) at King's, + 718 (5874)	N (S) at Leicester, + 606 (2293)	D (W) at Victoria, + 794 (5704)	N (S) at Leicester, + 854 (1687)
	V (S) at Oxford, - 688 (2942)	P (W) at Green PK, + 526 (1927)	V (S) at Oxford, - 652 (2942)	D (W) at Embankment, + 711 (3284)

Note:
1 N =662; Percent is compared to the base scenario
2 V=Victoria Line, N =Northern Line, M = Metropolitan Line, D = District Line, P = Piccadilly Line, (N) = Northbound, (S) = Southbound, (E) = Eastbound, (W) = Westbound
3 * Differences are calculated based on absolute values; ** boardings in the base scenario

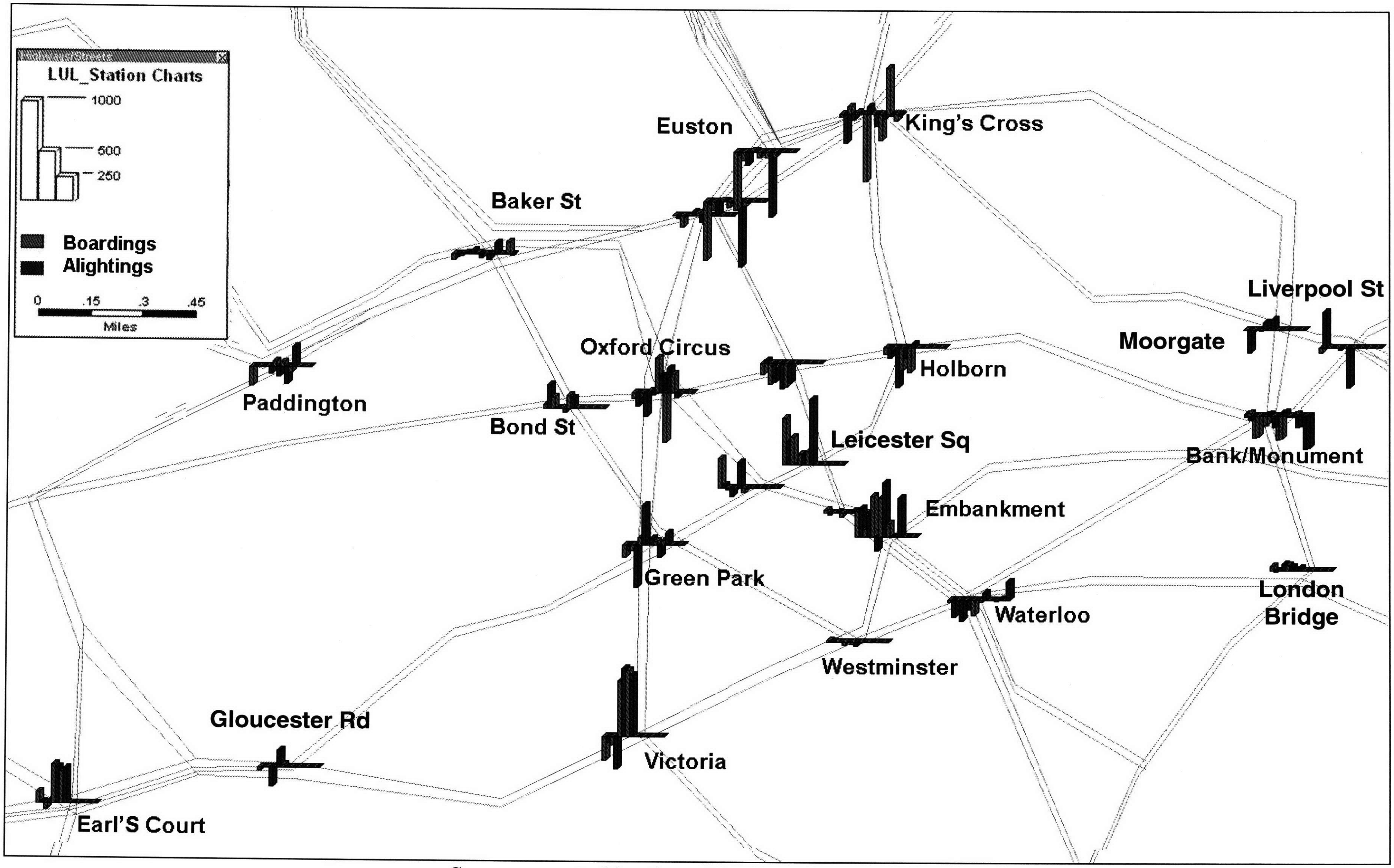
Corresponding interchange penalty (multiple number corresponds to multiple movements)

Euston V (SB): 11 and 8.3 minutes;
Euston V (NB): 8.3 minutes;
Euston N (NB): 11, 8.3, 11, 11, 11, 11 minutes;
King's Cross N (NB): 8.5 minutes;
Oxford Circus V (SB): 4.6, 5.4, 0.7, 4.6 minutes;
Victoria V (NB): 5.0, 3.3 minutes;
Victoria D (EB): 7.4 minutes
Victoria D (WB): 3.2 minutes
Earl's Court D (EB): 0.8, 2.2 minutes



Note: a bar below the zero level indicates a decrease of boardings or alightings from the base to the station scenario
Source: created by the author based on model estimation results

Figure 5-22 Change of Boardings and Alightings between Station and Base Scenarios



Source: created by the author based on model estimation results

Figure 5-23 Change of Boardings and Alightings between Movement and Base Scenarios

etc. For example, at the Metropolitan Line southbound platform, the station scenario predicts 718 more passengers than the base scenario's 5,874 (last row in Table 5-32). The movement scenario produces similar results. Figure 5-22 and 23 illustrate the change of boardings and alightings between the alternative and the base scenarios by platform.

The results are consistent with the estimated interchange penalties at these platforms. For example, the District Line eastbound at Earl's Court and the District Line westbound at Victoria have smaller interchange penalties than the current value in RailPlan (0.8 to 3.2 minutes vs. 3.5 minutes). Both have among the highest boarding or alighting increases in the alternative scenarios (792 and 794 passengers) (Table 5-32). Other platforms such as the Victoria Line southbound at Euston and the Northern Line northbound at King's Cross have relatively large interchange penalties as well as large reduction of boardings and alightings in the two scenarios. At many of these stations, crowding has been a major concern to passengers as well as to the operator. Therefore, how accurately the interchange penalty is defined could have a significant impact on planning and operation at these platforms.

The two alternative scenarios appear to differ more on the variation than on the average value of changes compared to the base scenario, especially on alightings (Table 5-32). The observation is not counter-intuitive since we expect a larger variation of difference when the interchange penalty is defined for each movement rather than for each station.

Passenger Flows

Passenger flows here refer to the total number of passengers on a physical link. In most cases, a link is the segment between two Underground stations in a specific direction. There are

Table 5-33 Estimated Passenger Flows from Three Scenarios

Scenarios	Base Scenario	Station Scenario	Movement Scenario
Average	9862	9911	9929
Max	47114	46336	46070
Stdev	9725	9759	9825
Top Five Link Sets *	CT(W): Stratford -St Paul (42140 -47114)** V(S): Finsbury Park--Warren St (38536 – 39374) CT(W): Chancery Lane- St Paul (37232-38340) CC/D(I/E): Sloane Sq – St James Park (35732-35970) D(E): Victoria-St James Park (35732)***	CT(W): Stratford -St Paul (41294-46336) V(S): Finsbury Park- King's (38773-39394) CT(W): Leyton-Stratford (38070)*** V(S): King's- Warren (36934-38005) CT(W): Chancery Lane- St Paul (36367)***	CT(W): Stratford -St Paul (41344-46070) V(S): Finsbury Park- Warren St (38106-40340) CT(W): Leyton-Stratford (38070) CC/D(I/E): Sloane Sq – St James Park (36966-37015) CT(W): Chancery Lane- St Paul (36423)

Note:
1 * in most case refer to consecutive links with similar passenger flow; ** range of passenger flows on the link set; *** only one link between the two stations
2 V=Victoria Line, CC =Circle Line, CT = Central Line, D = District Line, (I) = Circle Line inner bound, (S) = Southbound, (E) = Eastbound, (W) = Westbound

Table 5-34 Difference of Passenger Flows by Link between Scenarios

	Station - Base	Movement - Base
True Value		
Average	49 (0.55%)	67 (0.61%)
Max	2393 (7.8%)	2826 (9.2%)
Stdev	438 (6.6%)	516 (7.0%)
Absolute Number		
Average	209 (2.2%)	253 (2.5%)
Max	2393 (7.8%*)	2826 (9.2%)
Stdev	389 (6.2%)	454 (6.5%)
Top Five Link Sets**	D (W): Monument -Temple + 2393*** (30717)	D (W): Monument –St James Park + 2825 (30717)
	CC/M (O/S): Liverpool-Tower Hill + 1949 (6885)	D (W): Embankment-Temple + 2574 (29182)
	V (S): Warren St - Green Park – 1998 (31426)	D (W): Gloucester Rd –Sloane Sq + 2367 (19237)
	D (W): Embankment-Temple + 1812 (29182)	V (S): Oxford – Green Park – 2059 (23721)
	V (N): Victoria-Warren St - 1740 (26974)	CC/M (O/S): Liverpool-Tower Hill + 1969 (6885)

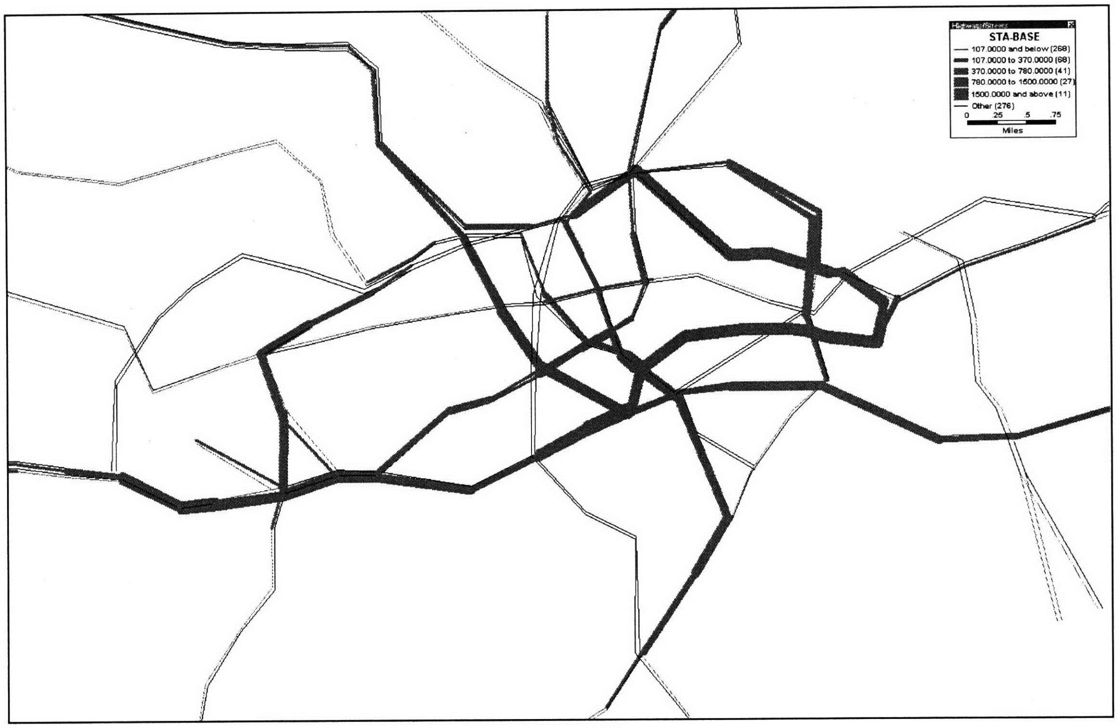
Note
1 * percent of the maximum flow difference, not the maximum percent; ** in most case refer to consecutive links with similar passenger flow; *** the largest change on that link set, number in parenthesis is the passenger flow in the base scenario on the link with the largest change
2 V=Victoria Line, D = District Line, CC = Circle Line, M = Metropolitan Line, (N) = Northbound, (S) = Southbound, (W) = Westbound, (O) = outer circle line

662 such links in the Underground network model. Different interchange penalties should result in different passenger flows since the penalty affects passengers' path choice.

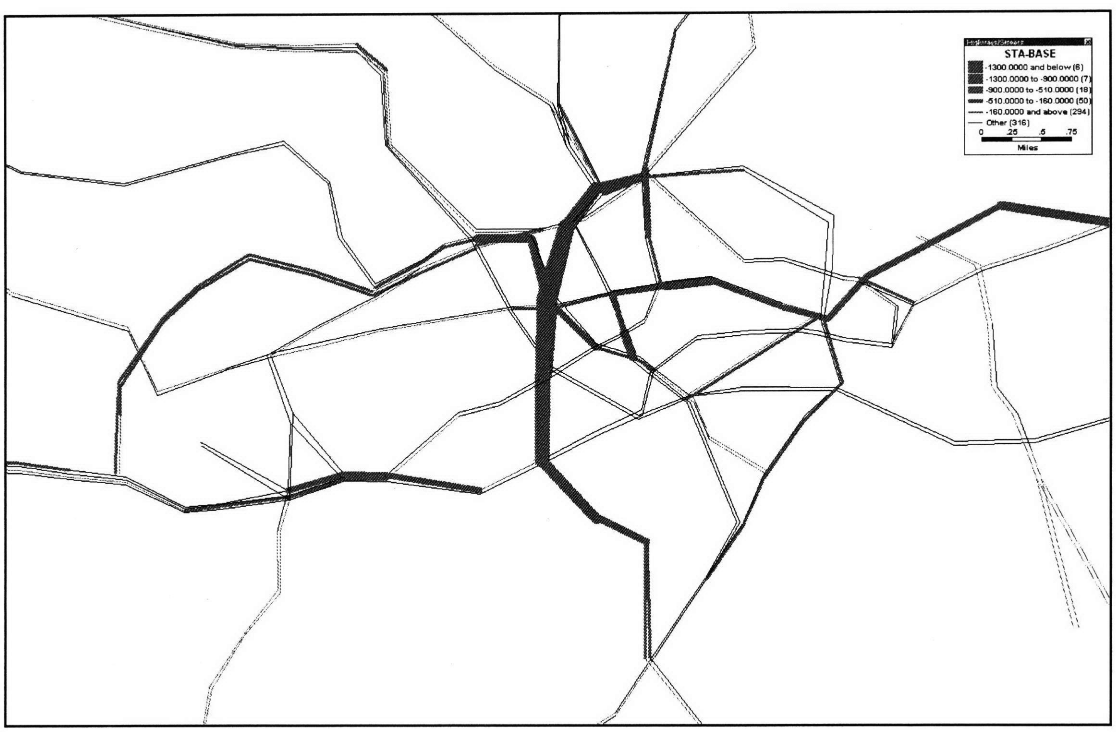
Tables 5-33 and 5-34 summarize the results of passenger flow from the three scenarios at the system as well as individual link level. Different from boardings and alightings, passenger flows increase in the alternative scenarios. This is because with higher interchange penalties, passengers are more likely to take longer path that involve less interchanges. Therefore, the average number of links per trip might increase at the system level, which increases the average passenger flows per link in the system in both scenarios.

At the individual link level, the average percentage change in passenger flow is also smaller than on boardings and alightings, about 0.6 percent when true values are calculated and 2.5 percent (209 to 253 passengers) when absolute numbers are used (Table 5-34). This result is reasonable because path changes might not always result in passenger flow change. For example, switching between direct and indirect services on the same line involves a different path choice, but does not affect the aggregate passenger flow on the links.

The difference is uneven across individual links with some links having relatively large flow increases or decreases in the alternative scenarios. For example, the largest difference occurs between Cannon St and Monument on the District line eastbound: the movement scenario predicts 2826 more passengers than the RailPlan model, representing 9.2 percent increase of passenger flow on that link. In general, both station and movement scenarios suggest the current RailPlan link assignment over-estimates the link flows on the Victoria, Piccadilly, and Central (east of Tottenham Court Road) lines but under-estimates the flows on the District and the southeast portion of the Circle lines in Central London (Figures 5-24 and 5-25). This is a reasonable result because in a network where the interchange penalty is high,



(a) Flow Increases



(b) Flow Decreases

Figure 5-24 Change of Aggregate Flows between Station and Base Scenarios

(a) Flow Increases

(a

(b) Flow Decreases

Figure 5-25 Change of Aggregate Flows between Movement and Base Scenarios

passengers will be less likely to take a path that involves interchanges. Paths that provide direct but slower connections will be more likely to be chosen, which might be what happens in the station and movement scenarios. This information is important to the Underground because some of these links are the most crowded in the system. Inaccurate estimates of the passenger flow will lead to less effective initiatives to mitigate the problem.

The difference between station and movement scenarios is small in terms of the average passenger flow change, but relatively large with respect to the variation of flow changes over individual links, consistent with the boarding and alighting results (Table 5-34). The difference is quite large on certain links. For example, as shown in Figure 5-26, the station scenario tends to over-estimate the flows on the Piccadilly and Northern lines, but under-estimate the flows on the Victoria and District/Circle lines in Central London. This result is probably caused by the over- estimated interchange penalties for some movements on the Piccadilly and Northern lines and under-estimated interchange penalties for certain movements on the District/Circle and Victoria lines in the station scenario (see Table 5-31 for relevant interchange penalties).

5.8.2 Interchange Closure between Bank and Monument

The interchange between the Bank and Monument stations is closed from the spring 2008 to summer 2009 due to escalator work, and so passengers are being advised to take alternative routes or stations to avoid delays. The model I developed can help understand passengers' response to this interchange closure and predict the resulting passenger flow changes in the Underground network. I examine two scenarios.

Scenario A uses the default RailPlan network but assigns an extremely large interchange penalty *only* to interchanges between the Central/Northern and the District/Circle lines at Bank

(a) Movement Scenario > Station Scenario

(b) Movement Scenario < Station Scenario

Figure 5-26 Change of Aggregate Flows between Movement and Station Scenarios

and Monument. The rest of the network remains unchanged. Scenario A is assumed to be the approach used by TfL to simulate the effect of the closure.

Scenario B assigns the same large interchange penalty to the closed interchanges, but also updates the RailPlan network with refined interchange penalties at the movement level. Scenario A is compared to the base scenario, while Scenario B is compared to the movement scenario specified earlier. The former is what the London Underground knows about the effect of this closure, based on their RailPlan model, while the latter is what this study suggests based on the path choice model developed by this research. In the movement scenario, the closed interchange links have a transfer penalty = 7minutes additional to transfer walking and waiting, twice the 3.5 minutes currently used in the base scenario by TfL.

The results from Scenario A and B are first presented, and the differences from the base with respect to boardings, alightings, and aggregate flows are analyzed and compared. Both scenarios A and B indicate an increase of boardings at surrounding stations: Embankment, Mile End, West Ham, Victoria, Oxford Circus, etc. and decreased boardings at Bank and Monument. Changes of alightings follow a broadly similar pattern. Table 5-35 lists the top five platforms in terms of decrease and increase of boardings and alightings. Figures 5-27 and 5-28 display the difference of predicted changes of boardings and passenger flow between the RailPlan method and the method proposed by this research. .

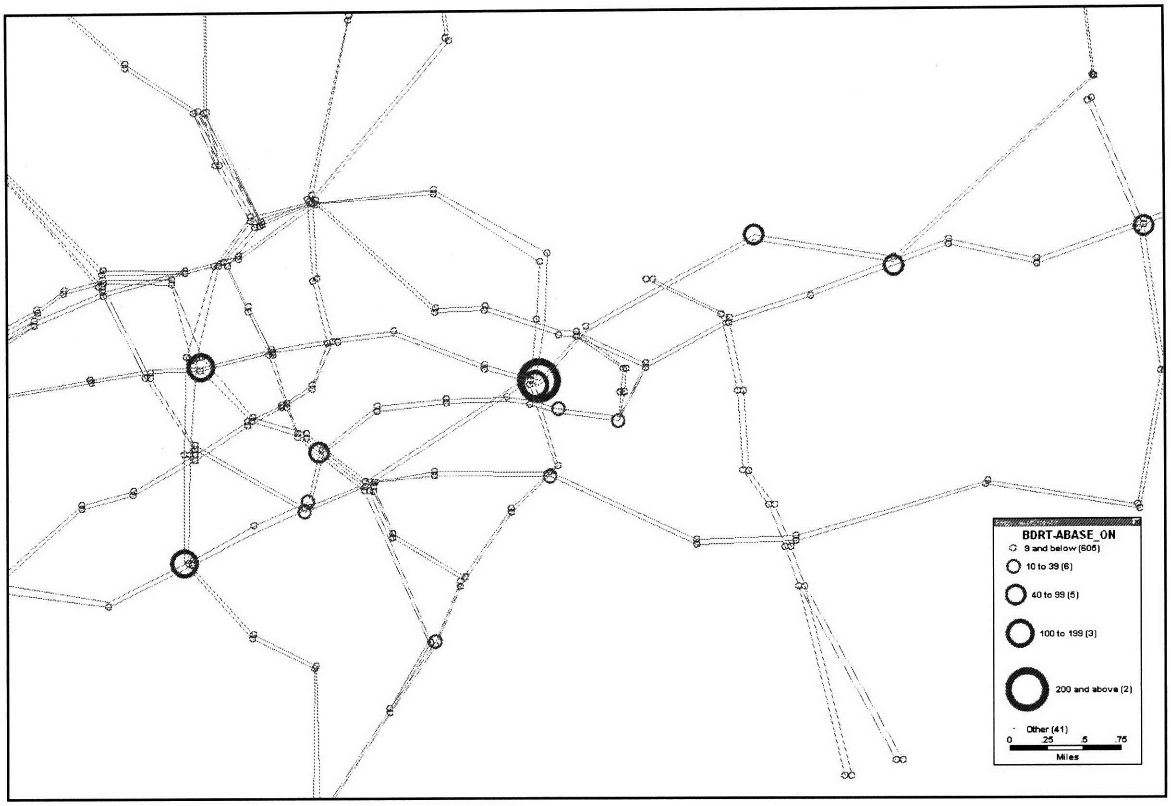
Compared to Scenario B, Scenario A tends to under-estimate the boarding increase at Bank and Monument, and over-estimate boarding increase at other stations such as Embankment and West Ham. The reason might be that the interchange between Bank and Monument is defined more negatively in the movement scenario than in the base scenario. Therefore, the interchange

Table 5-35 Changes of Boardings and Alightings due to Bank/Monument Interchange Closure

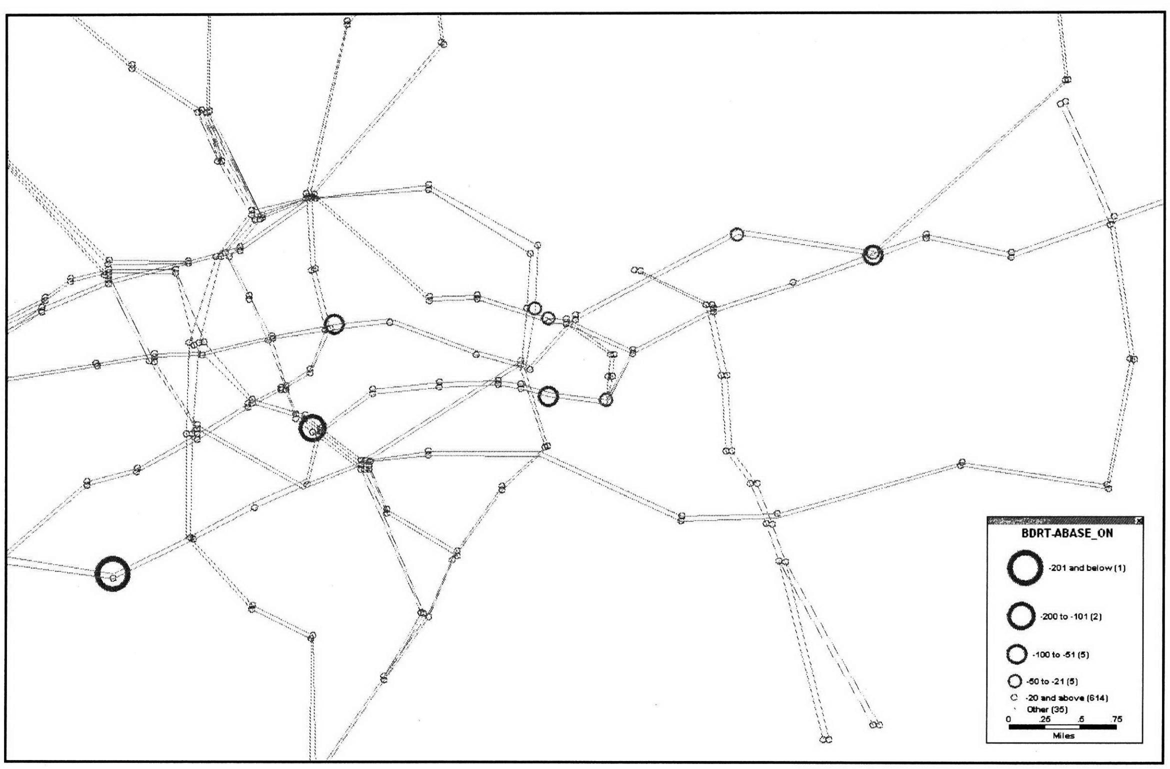
Top 5 Platforms	Scenario A – Base Scenario	Scenario B – Movement Scenario
Increased boardings	Embankment DS EB: 3765 + 621 Mile End CN WB: 5104 + 318 Sloane Sq DS EB: 1292 + 301 West Ham JB NB: 814 + 190 Embankment NT NB: 779 + 149	Embankment DS EB: 3873+ 681 Mile End CN WB: 4802 + 255 West Ham JB NB: 795 + 231 Victoria VTNB: 7400 + 110 Oxford Circus CN EB: 3991 + 110
Decreased Boardings	Monument DS EB: 1610 – 707 Bank NT SB: 1809 – 509 Monument DS WB: 1802 – 319 Bank CN EB: 2551 – 256 Bank CN WB: 3338 - 236	Monument DS EB: 1593 – 690 Bank NT SB: 1681 – 380 Monument DS WB: 1836 – 378 Bank CN WB: 3309 – 248 London Bridge NT NB: 4853 – 118
Increased Alightings	Embankment NT NB: 2681 + 479 Liverpool St MP NB: 1014 + 320 Sloane Sq DS EB: 808 + 300 Embankment DS EB: 3284 + 221 Blackfriars DS EB: 2995 + 220	Embankment NT NB: 3067 + 499 London Bridge JB NB: 1927 + 243 West Ham DS WB: 670 + 227 Blackfriars DS EB: 2959 + 220 Mile End DS WB: 4274 + 207
Decreased Alightings	Monument DS WB: 2692 – 866 Bank NT NB: 5222 – 701 Monument DS EB: 5673 – 467 Liverpool St CN EB: 4823 – 301 Bank NT SB: 2849 - 225	Bank NT NB: 5179 – 735 Monument DS WB: 2553 – 728 London Bridge NT SB: 3451 – 264 Bank NT SB: 2880 – 225 Blackfriars DS WB: 1547 - 220

closure will have a smaller influence on link flows in the movement scenario network than in the default RailPlan network.

With respect to aggregate flows, both approaches identify a similar pattern of flow reduction on the Northern Line (city branch) between Moorgate and Elephant and Castle, and on the District Line east of Tower Hill. The pattern of flow increase is also consistent between Scenario A and B: on the Northern Line (Charing Cross branch) between Charing Cross and Elephant and Castle, on the District Line between Westminster and Monument, and on the Central Line east of Liverpool St. However, Scenario A tends to over-estimate the flow

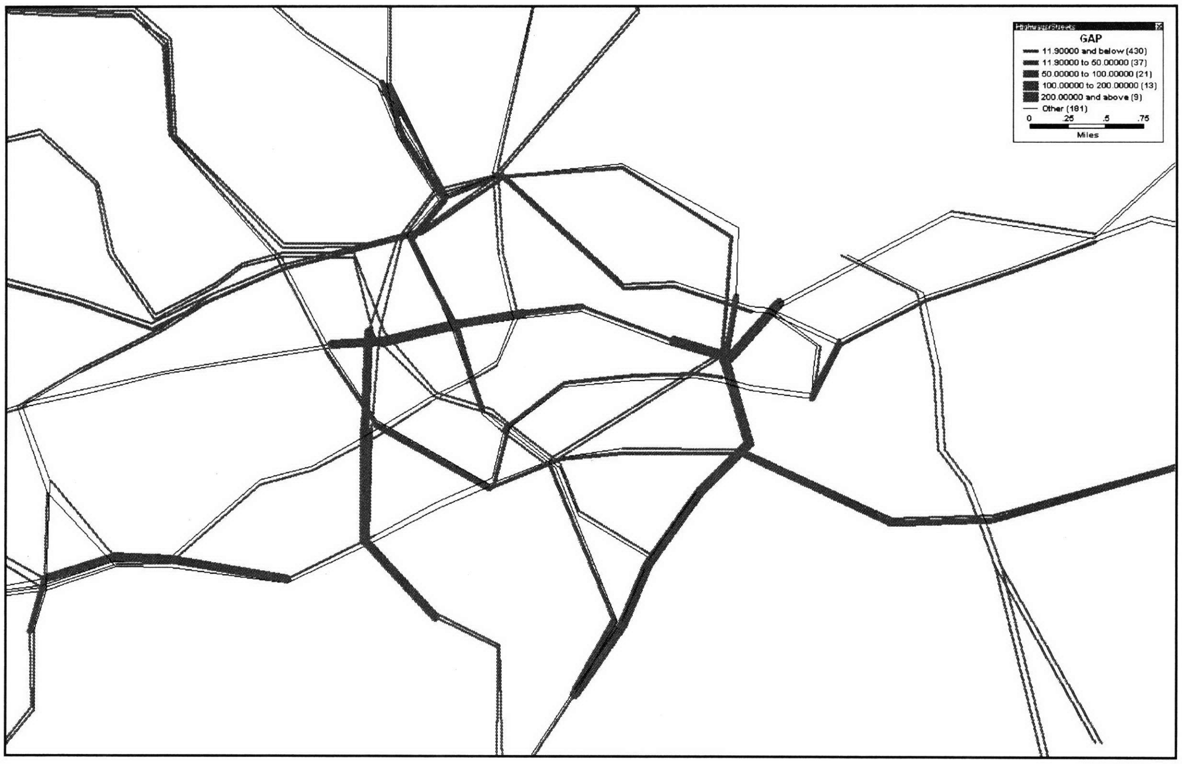


(a) (Scenario B – Movement) > (Scenario A – Base)



(b) (Scenario B – Movement) < (Scenario A – Base)

Figure 5-27 Boardings: Comparing Scenario A and Scenario B



(a) (Scenario B – Movement) > (Scenario A – Base)

(a) (Scenario B – Movement) < (Scenario A – Base)

Figure 5-28 Passenger Flows: Comparing Scenario B and Scenario A

reduction on the Northern Line City Branch as well as the flow increase on the Northern Line (Charing Cross branch), District Line, and Central Line. Such a difference is caused by the same problem as the default RailPlan network under-evaluates the interchange penalty between Bank and Monument.

In other words, the construction will not cause the level of congestion on the District Line east of Monument, on the Northern Line between Embankment and Kennington, and on the Central Line east of Liverpool Station. Such difference would certainly affect the evaluation of the Bank and Monument Interchange project as well as the effectiveness of corresponding efforts to mitigate the project impact in the Underground.

5.9 Conclusion of London Case Study

In this study, traditional path choice models are applied to the London Underground network, and two applications of the research findings in operation and planning are presented. The London study differs from the Boston study in that it deals with a much larger and more complex system, which has more specific and urgent needs for interchange planning. Therefore, in path generation, a traditional approach is used to cover the entire Underground network. The modeling focus is to define the interchange environment more accurately for the purpose of planning implications rather than to applying sophisticated models for the purpose of behavioral exploration.

The path generation process for the entire Underground network is extremely complex and time-consuming. I designed a conservative screening method to exclude "irrational" behavior, adopted the labeling approach and developed effectiveness and efficiency measures to guide the generation process, and recovered popular and credible revealed paths not generated in the process. This robust procedure works well producing a choice set covering 79 percent of revealed paths and 82 percent of trips, comparing nicely with path generation methods in prior studies.

Modified multinomial logit (MNL) models are applied, and 17 major interchange stations are specified as dummy variables in the utility function in order to control for the correlation between paths that share these stations. This approach partially overcomes the concern with path correlation, while avoiding the complexity of using more advanced models. The prediction test shows an average probability of correct prediction is 80 percent, suggesting that the simple MNL models work well in the path choice situation.

The system average value of the interchange penalty is 5.6 minutes of entry/exit walking time (4.9 minutes of in-vehicle time), including interchange walking and waiting, and reduce to 4.2 minutes of in-vehicle time if the effects of interchange walking and waiting are excluded. The value is little bit higher than the 3.5 minutes currently used by the Underground. However, the great variation of the interchange penalty across station and movement renders this average value meaningless. Some major interchange stations such as Paddington, Waterloo, Euston, and Bank /Monument have much higher penalties that exceed 10 minutes of in-vehicle time, while for Earl's Court that value is around 1 minute. The contrast is even bigger if examined at the movement level and if the penalty is aggregated to interchange trips. The results indicate that the prediction of path decisions in the Underground might be inaccurate due to the crude specification of transfer in its network model. The variation also suggests that there is a great potential for interchange planning in the system.

The results are then applied to the Underground network to update passenger flows and to evaluate the impact of interchange closure at Bank /Monument. They further illustrate that the developed models make different predictions of passenger flows in the Underground. With higher interchange penalties in the Underground, passengers interchange less, which reduces the total number of boardings and alightings at stations, but they are also more likely to take longer and probably more directly connected paths, which increases passenger flows on certain links. In other words, the current passenger flow prediction might over-estimate the platform crowding but under-evaluate link crowding in the Underground. In the case of Bank and Monument, because the interchange penalty estimated in this research is higher than the value currently used by the Underground, the current project evaluation might over-estimate the impact of the closure on boardings and alightings at Bank/Monument and surrounding stations, and passenger flows on related links. The applications demonstrate how well the interchange is modeled and measured affect our understanding of how a system performs, and how a project should be evaluated.

Chapter 6 CONCLUSIONS AND FUTURE RESEARCH

This research investigates transfer behavior based on passengers' travel path choice in public transport networks. It focuses on the relationship between individual travel demand and transfer-related transport supply at the path level, and the potential application of results to the operation and planning in public transport systems. The study demonstrates both the prevalence and complexity of transfer activities in public transport systems, and the lack of focus on transfer planning practice in public transport agencies. It introduces the theoretical basis of individual choice-making, describes the decision process with respect to path choice and the role of transfers, and adopts random utility models as the analysis approach.

The framework is applied to two empirical studies. The Boston case, with a simple and mid-sized public transport network, analyzes sub-path choices for subway and commuter rail trips destined for downtown. The London case, with a large and complex network, applies a traditional path choice analysis to the London Underground. Although both studies emphasize the average as well as the variation of transfer experience across space, time, trip, and individual, the Boston study puts more effort into understanding behavior, while the London study pays special attention to analyzing large and complex network problems.

Analysis results confirm that transfers indeed play a critical role in passengers' path choice in public transport networks. They also demonstrate that the path-based approach, though complex and time-consuming to develop, can shed new light on transfer behavior, and offers direct applications to operation and planning practice. Application examples show that how well transfers are considered in planning and operation practice can make a difference. This chapter summarizes these contributions (Section 6.1) and empirical findings (Section 6.2), and then discusses future research (Section 6.3).

6.1 Methodological Contributions

This study is one of the first comprehensive studies of transfer behavior in public transport systems. The main contribution to the current literature is the methodology developed for the transfer analysis: the path-based analysis approach, and the definition of the transfer penalty.

6.1.1 Path-based Analysis Approach

Path choice models have been widely used by transportation planners and researchers, but their application in the transfer analysis has not been well documented. The connection between transfer and path choice seems natural: path choice decisions respond to transfer experience, a key path attribute, and transfer decisions are "path-specific", corresponding to particular paths. Compared to mode choice analyses, the path-based approach developed by this study has at least two merits. First, it is able to provide the spatial location and the detailed movement information for transfers, while mode choice analyses often ignore or are unable to incorporate such information. Second, the path-based approach provides a decision situation closer to an experimental design. Origin, destination, and mode can all be treated as given. In a perfect situation, a path choice decision is made solely based on the transfer inconvenience; thus, external "noises" that may contaminate the transfer effect are excluded.

However, two features of the path-based approach limit its application to transfer analysis. First, the process of generating the choice set is extremely difficult and time-consuming because we often do not know what path attributes travelers consider and how they make trade-offs, and the generation results are often unjustifiable due to the lack of data (Section 3.3.1). Second, paths often overlap with each other, to different degrees and in different ways. In a public transport network, two travel paths can share a common link, the same service line, or the same transfer station (Section 3.2.2). Modeling techniques to control for these correlations are often sophisticated, and known by only a few analysts (Section 3.3.2). This research tackles these two issues in various ways. The Boston case study avoids both problems by constructing a special situation for path choice/transfer decisions, while the London case study focuses on the generation problem, and deals with the correlation issue rather simply.

In the Boston case study, I modify the path-based approach slightly. Because the public transport network is relatively small, passengers often do not have multiple travel paths. Instead, a sub-path choice situation is constructed to reflect passengers' decision between two egress paths from the public transport network to downtown Boston, one involving a transfer while the other does not (Section 4.2.1). Path choice generation is easier because (1) only a portion of the network is used, and (2) the feasible sub-paths are constrained by a few available service lines, which can be easily identified manually. Path correlation is also less of a problem because the two egress paths are unlikely to overlap with each other.

In the London study, I apply traditional path choice models. Choice set generation is conducted for a large and complex network, the London Underground, adopting conservative procedures to ensure the generated choice set has a sound theoretical basis and is consistent with observed behavior (Section 5.4.2). Only "rational" paths are selected through an extensive screening process. A large number of rules are applied to generate paths on two types of Underground networks: the first network uses the true link distance, and the second network uses the link distance on the system map. I examine non-generated revealed paths and recover some of them manually. The result is a credible choice set, covering 79 percent of revealed paths and 82 percent of surveyed trips.

The path-based approach successfully models transfer decisions at the travel path level. In the Boston case, it effectively captures passengers' trade-off between one (more) transfer and walk time savings. In the London case, the models I developed based on the approach correctly predict 80 percent of travelers' path choices, which is fairly high considering the complexity of the Underground network.

This approach is also able to add enriched spatial information to the transfer analysis. In the Boston subway case, I measure the transfer penalty for a total of 36 movements at four transfer stations, while in the London case, I investigate a total of 303 interchange movements across 17 major interchange stations. Movement-specific attributes such as facility design can thus be modeled. These movements could not be included in the analysis if it is not conducted at the path level.

Accordingly, research findings can be applied to predict travelers' reaction to proposed network changes: which alternative they will choose, and how that will affect congestion and travel time in the network. Such information can shed light on network and facility design, and service operation and planning. The approach can also efficiently evaluate and prioritize transfer-related investments because it enables a cost-benefit analysis incorporating not only time savings but also the residual transfer penalty. This issue is discussed later in this chapter.

6.1.2 Defining the Transfer Penalty

Another contribution of the research methodology is defining the concept of the transfer penalty. The transfer penalty describes the inconvenience perceived by a traveler making a transfer. I define it following a similar theory to the value of time (VOT), which is the marginal rate of substitution (MRS) of a transfer for time or money savings. The term was mentioned in a few studies, but has not been well defined. Because the transfer penalty may include different transfer components depending on the particular model specification, comparison between transfer penalties should be at the same level.

This concept covers both individual preferences and perceptions and the quality of transport supply (transfer environment), and can be quantified through path choice models. It incorporates all major factors that might affect the transfer experience into one framework, and enables comparison across systems, stations, movements, trips, and individuals. The value can also be easily converted into monetary values to allow cost-benefit analysis of transfer-related investments.

The usefulness of this concept partially relies on the revealed-preference (RP) data sources used in this research. Most prior studies used stated preference (SP) data to allow greater freedom in defining choice contexts, alternatives, and attributes; as well as the direct comparison of responses across individuals and over time. However, SP also suffers from the fact that the choice situation is usually uni or bi-dimensional, which is unable to evoke the realistic context for path choice in which alternatives are often perceived with multiple temporal and spatial constraints. RP has the advantage of increasing realism and richness of transfer decisions, but has the disadvantage of difficulty in controlling for the variety of choice contexts, choice sets, and attributes, which is dealt with through the path-based approach.

6.2 Empirical Findings

The developed methodology is applied to two empirical studies for the rail systems in Boston and the Underground in London. Both networks provide a large variability of transfer environments and a large volume of transfers.

6.2.1 Measuring the Transfer Penalty

The transfer penalties estimated in both studies are relatively high. The average transfer penalty for the Boston subway is equivalent to 7.3 minutes of walking time (10.6 minutes of in-vehicle time), including transfer walking and waiting. Considering the average waiting time for the subway is only between one to two minutes (see Table 4-2), and the average access time is between 6 and 10.5 minutes (CTPS 1994), this value is fairly high. The transfer penalty is even higher for most inter-modal transfers between commuter rail and subway. The average transfer penalty is about 17 minutes of walking at North Station, 14 minutes at South Station, and 8.5 minutes at Back Bay, which is slightly lower than the subway average. In the London Underground, the average transfer penalty is about 5.6 minutes of walking (4.9 minutes of in-vehicle time) including transfer walking and waiting, consistent with findings from two prior studies: 5.2 minutes from the 1985 London Transport report, and 3.7 minutes from the 1995 report, lower than the penalty (with the same specification) I got for the Boston subway system (10.6 minutes of in-vehicle time).

The lower transfer penalty in the London Underground than in the Boston subway and commuter rail is interesting because the former in general has a more complex transfer environment. Because the transfer penalty captures effects of both supply and demand sides of transfer, the surprising difference between Boston and London might be caused by the differences in both service quality and passengers. Several possible explanations exist. First, service frequency and reliability is better in the London Underground than in the Boston rail systems, which should reduce the transfer penalty. Second, Bostonians are probably more "picky" than Londoners with respect to public transport in general and to transfers in particular due to different culture and travel habits developed over years. The penalty should be probably higher for a Bostonian who traveled in the London Underground, or lower for a Londoner who interchanged in the Boston subway. Third, the density in London is much higher than in Boston, which affects the access and egress distance to and from the studied systems. This might influence the willingness to transfer within the system, though this assumption is yet to be proved empirically. Fourth, crowding in the Underground might affect model estimations. As illustrated in Section 5.5.4, crowding may result in additional transfers that appear to be unnecessary. Statistically, this will greatly reduce the value of the estimated transfer penalty because it seems that passengers "like" transfers as they do so even when not necessary. Such a crowding effect occurs in many stations and segments in the Underground, thus "mitigating" the negative impact of transfers.

This study also shows a great variation of the transfer penalty across stations and platforms. In Boston, the best transfer station, Park St (4.8 minutes) has only half the transfer penalty of the worst station State (9.7 minutes). The difference is much larger at the movement level: the transfer penalty ranges from 2.3 to 21.4 minutes of walk time in peak hour, and from 4.4 to 19.4 minutes in off-peak. In London, among the 17 stations investigated in detail, the worst transfer station, Paddington, has a penalty of 11.7 minutes, while the best station, Earl's Court, has only 0.7 minutes. At the movement level, the transfer penalty ranges from 0.5 to 32.6 minutes of in-vehicle time among 303 movements at these stations. In both studies, models' explanatory power is significantly enhanced when the spatial unit is refined from the system average to the station and movement specifics.

In terms of trip and personal characteristics, I test many attributes, but only a few affect transfer decisions, most of which are trip features, such as trip frequency, trip purpose, fare media, and trip start time. Monthly pass users have a transfer penalty 3.8 minutes (walk time) less than the cash/ticket users in the Boston study. Frequent riders also have a smaller transfer penalty (2.7 minutes of walk time) compared with infrequent riders, probably due to their greater familiarity with the transit network. Peak period trips tend to have a smaller transfer penalty, probably due to the higher frequency of service at that time. Commuters tend to have lower transfer penalty values than non-commuters probably because they are more likely to be frequent users and monthly pass holders traveling in the peak. These findings are consistent with prior studies.

For the first time, I investigate the variation of the transfer penalty due to personal attitudes, preferences, and perceptions using the random parameter method. I do not find a significant variation of personal taste with respect to transfer decisions, and the goodness-of-fit is not improved significantly. The standard deviations of the transfer penalty are 1.95 and 3.15 minutes for the south and north sub-networks of the Boston commuter rail, respectively, which are much smaller than the differences of the average transfer penalties across transfer stations and movements. Both values indicate a relatively uniform perception among commuter rail riders of transfers to the subway. However, this result might be partially attributed to sampling: passengers included are current users of a particular public transport system. If both multimode passengers are selected, the difference should be larger, although we do not know to which extent. Personal attitudes, preferences, and perceptions might be important for transfers from cars to public transport (park-and-ride or kiss-and-ride). Car users are likely to have larger transfer penalties than current public transport passengers, probably due to the less inconvenient transfer environment as well as personal differences.

These findings have clear policy implications for the investigated systems in particular and public transport in general:

(1) The high value of the transfer penalty indicates that transfer inconvenience can significantly affect travelers' decisions: whether they view a particular mode as being acceptable; which path they will take; and how satisfied they are with their travel. Transfers should be one of the major concerns in service operation and planning.

(2) The difference of individual transfer experience is largely caused by the difference of transfer environment, not by their personal differences in terms of demographic characteristics, and attitudes, preferences, and perceptions. This suggests that improving the transfer environment, either through service quality or physical environment, should be a priority.

(3) The great variation of the transfer penalty across stations and movements indicates the potential as well as the urgency of transfer planning in major multimodal public transport networks. The severity is even more obvious if the transfer penalty is aggregated to total transfer trips. For example, in the London Underground, the coefficient of variation is 0.5 for the transfer penalty across movements, but increases to 1.03 for the aggregate transfer penalty across movements.

These leads to the third area of contribution of this study: application in planning and operation.

6.2.2 Applications in Planning and Operation

Findings of this research can be reflected in the transport network for service operation and planning because all findings correspond to specific links, nodes, or aspects of that network. Two types of applications are introduced: system monitoring, and project impact assessment.

Monitoring passenger link flows within a public transport network is always a challenge to an operating agency. Traditional methods rely on on-board surveys to collect OD information and point checks to collect passenger flows on critical links. The former is conducted infrequently, and results are often not representative of the total population, while the later usually does not provide accurate information, especially for a rail system. Automatic Fare Collection (AFC) systems greatly improve OD estimation, but they do not track passengers' travel path. Together with AFC data, this model can provide frequent, accurate, and detailed estimates of passenger flows on critical links and through critical interchange stations.

The London study illustrates the improved accuracy of passenger flows in the Underground. The transfer attribute in the RailPlan network currently used by the Underground is modified from a system-constant value to a station- and movement-specific variable. With higher interchange penalties in the Underground, passengers seem to interchange less, which reduces the total number of boardings and alightings at stations, but they are also more likely to take longer and probably more directly connected paths, which increases passenger flows on certain links. In other words, the current passenger flow prediction might over-estimate the platform crowding but under-estimate link crowding in the Underground. On average, the difference between the base and the alternative scenarios is four percent for boardings, three percent for alightings, and two percent for aggregate link flows.

The difference varies greatly across platforms or link especially for some of the most crowded stations or links: for example, more than 900 more passengers are predicted at Victoria on the District Line, representing an 18 percent increase of boardings. The largest difference of passenger flow occurs between Cannon St and Monument on the District Line eastbound with 2,826 more passengers predicted than the RailPlan value, representing a 9.2 percent higher link flow.

The general pattern is that the current RailPlan model tends to over-estimate the link flows on the Victoria, Piccadilly, and Central (east of Tottenham Court Road) Lines but under-estimate the flows on the District and the southeast portion of the Circle lines in Central London, probably because with higher transfer penalties, passengers are more likely to avoid transfers and take longer but directly-connected lines—in many cases, the Circle Line. Clearly, these differences have potentially serious implications for the operation and planning in the congested Underground network.

The second application is to predict passenger-flow changes in response to planned or unexpected events, such as service disruptions, planned station closures, facility maintenance, accidents, or terrorist attacks. Because of its detailed calibration of transfer attributes, the developed model is able to give a more accurate estimate than the current model used by the Underground. I apply it to a transfer-related project: the Bank-Monument interchange closure.

Both the current and the proposed models predict an increase of boardings at the surrounding stations: Embankment, Mile End, West Ham, Victoria, Oxford Circus, etc. and decreased boardings at Bank and Monument. However, the proposed model indicates that the current model tends to under-estimate the boarding decrease at Bank and Monument, and over-estimate the boarding increase at other stations such as Embankment and West Ham, because the latter tend to under-estimate the interchange penalty between Bank and Monument in the original network. In other words, the interchange is more unpleasant than planners thought, so closing it would not result in a change as high as they expected.

With respect to aggregate flows, both models identify a similar pattern of flow reduction on the Northern Line (between Moorgate and Elephant & Castle) and the District Line (east of Tower Hill), and flow increase on the Northern Line (between Charing Cross and Elephant & Castle), the District Line (between Westminster and Monument), and the Central Line (east of Liverpool St). However, the current model tends to over-estimate the flow reduction on the Northern Line City Branch as well as the flow increase on the Northern (Charing Cross branch), District, and Central Lines. Such a difference is caused by the same problem as mentioned earlier that the interchange penalty is under-evaluated by the Underground planners.

6.3 Future Research

The analysis results point to two potential fields of future research. First, given transfers can significantly affect the performance of public transport systems, how could we incorporate the transfer factor into the current transportation planning and policy decision-making process? Not paying sufficient attention to transfers in current practice is both a technical and an institutional problem. Emphasis on transfers would likely change the way business is done in public transport management, planning, and operation. It requires a paradigm shift and affects almost every aspect of the public transport industry. In this field, the focus should be on the institutional structure and decision-making process.

Second, this research only targets a particular public transport mode, rail, and demonstrates the application on a particular issue, passenger flow prediction. Natural extensions would be to cover more transfer types in a multimodal network, and explore other potential applications in public transport operation and planning. Two fields are explained in detail in this section: intermodal transfers and cost-benefit analysis of transfer improvement.

6.3.1 Intermodal Transfers

This study focuses on transfer behavior associated with public transport. As the first step, it covers transfers within the public transport network, and particularly within rail systems in the empirical analyses. Future work should include other types of transfers that are critical to the performance and competitiveness of public transport, such as transfers between bus and rail, and transfers between auto and public transport.

In most major multimodal systems, buses often act as the capillaries of the network providing feeder services to rail systems. In both Boston and New York, bus-to-rail transfer is the No. 1 transfer type in terms of total volume (see Table 2-2). However, compared to rail-to-rail transfers, bus-to-rail transfers are often less integrated in terms of service and station/stop design. They are also more likely to be subject to weather, traffic, neighborhood characteristics, safety concerns, etc. The method developed by this study can be directly applied to bus-to-rail transfers. On-board surveys are generally available from public transport agencies, but the path choice generation is more challenging than the urban rail case, because the process involves multimodal systems, and bus networks are typically more complicated than rail networks. A possible solution is to cover only major multimodal corridors rather than the entire network. However, a sufficient number of transfer points are required in order to retain a sufficient variation of transfer decisions.

Travelers can also access public transport by car either as a driver (park-and-ride) or as a passenger (kiss-and-ride). Auto-transfers deliver a large number of passengers to public transport, and for some systems, they are the dominant access mode. For example, auto-transfers usually take a high share of commuter rail trips: 75 percent in Chicago, 69 percent in Boston, and 87 percent in Washington DC [28] (TCRP 2004). However, these passengers are clearly choice riders, and can travel all the way to the destination if public transport becomes unavailable or unacceptable. Therefore, auto-transfers are especially important to public transport networks with the continuing pressure to increase ridership.

The method I developed needs to be modified in order to investigate auto-transfers. There are two methodological challenges. First, although on-board surveys of public transport systems document auto-transfers, these are travelers who already made their decisions--drive and transfer to public transport. Therefore, travelers who have both auto-transfer and auto-all-the-way options should be "generated". Here the process is more like generating *decision makers* rather than just the *choice set*. Second, auto users can access a large number of stations because of the mobility and flexibility of the car. This raises the issue of station choice—which station is considered by the auto user, which is a traditional choice set generation problem. Furthermore, data are not as supportive as in other transfer situations because household travel surveys, the only data source suitable for this investigation, normally record few revealed park-and-ride and kiss-and-ride decisions. An investigation might start with a single line in a busy corridor with many auto-transfer activities.

[28] Brunswick Commuter Rail, including stations in West Virginia

6.3.2 Cost-Benefit Analysis of Transfer Facility Design

Another potential field of exploration is to conduct more elaborate cost-benefit analysis for design improvement at transfer stations. The physical environment at large transfer stations can be very complex, and design features, such as escalators, ramps, and lifts discussed in this study, can significantly affect passengers' transfer experience. Improving physical design of a transfer station can be costly and time-consuming. For example, the project to renovate Victoria station, the busiest in the London Underground, will cost £500 million (about $ 1 billion) and five years to complete (VSU 2005).[29] The investment is guided largely by three principles: time savings to shorten travel time at the station, capacity expansion to reduce crowding and to solve safety concerns, and provide a more amenable environment to ease travel pressure at the station. All three aspects are covered by the current practice in the Underground but to a different extent with the first two being better incorporated into planning and operation than the last one.

For example, the Underground relies primarily on two tools to guide station improvement: Station Planning Standards and Guidelines (SPSG) and the Pedroute Strategic Model (PEDS). SPSG specifies standards on when and how a particular part of a station should be designed, for example, an escalator should be installed if a change of level exceeds five meters. The requirements, however, are seldom based on cost-benefit analyses. PEDS can assess the delay and congestion of all walk links at an Underground station; distinguishing between passageways, stairs, escalators, concourses, platforms, gate-lines and lifts. The model calculates social cost primarily based on time savings and crowding reduction. For example, regarding escalators, PEDS calculates the travel time savings and increased throughput due to the installation of an escalator, but does not account for the improved travel experience because of

[29] The project, Victoria Station Upgrade (VSU) will increase the station size by 50 per cent with a new ticket hall, lifts and escalators to ease congestion, step-free access from street level to the Victoria, Circle and District line platforms, and more convenient interchange connections.

reduced walking. The approach I used can be a useful complement to the current practice and has the potential to better tackle the third principle.

Using the escalator again as an example, the study I conducted suggests that the presence of escalator(s) is valued by passengers as equivalent to 3.7 minutes of in-vehicle time, even after the time saving is controlled for. Based on this value, a cost-benefit analysis can be conducted, in a fairly efficient way, to evaluate and prioritize all movements at Underground stations where escalator installation is possible. Together with SPSG and PEDS, such a cost-benefit analysis could provide a more comprehensive assessment of transfer-related investments. In order to do this, a detailed inventory of design features at each transfer stations is required, and the models presented in this research should be revised accordingly.

6.4 Concluding Remarks

This study represents one of the first comprehensive analyses of transfer activities in public transport networks. It demonstrates both the prevalence and complexity of transfer activities in public transport systems, and the lack of focus on transfer planning practice in public transport agencies. It introduces the theoretical basis of individual choice-making, describes the decision process with respect to path choice and the role of transfers, and adopts random utility models as the analysis approach. The methodology is applied to two empirical studies for the rail systems in Boston and London.

Results indicate that the path-based approach, based on revealed preference, is able to reflect the complexity of transfer behavior, and that transfers are perceived very negatively by public transport passengers and can significantly affect the performance and competitiveness of public transport. They also suggest that the system-average value of the transfer penalty has limited applications in planning and operation because the penalty varies greatly across station and movement. Such variation is largely caused by different transfer environments, not by different personal characteristics, attitudes, preferences, or perceptions, at least in this study.

Applications of the results to the London Underground network illustrate that the lack of careful consideration of the transfer effect can lead to inaccurate passenger-flow estimation as well as less credible project evaluation and investment justification. The results further confirm the potential, as well as the importance, of transfer planning in major multimodal public transport networks.

In summary, this research has made a significant contribution to both theory and practice related to transfers in public transport systems. With the completion of this research, more analysis avenues have been opened, and more attention might be paid to transfers by decision-makers and planners in the future, so that transfer behavior can be understood and overall practice improved.

APPENDIX

A: Selected Parcel Types Conducive to Pedestrian Activities

Number	Type
1	Auditorium/Sport Center
2	Bar/Tavern/Pub
3	Commercial / Residential Multi-Use
4	Department Store
5	Fast Food Restaurant
6	Medical Office
7	Mini-Storage Warehouse
8	Movie Theatre
9	Night Club
10	Other Exempt Buildings
11	Residential / Commercial Use
12	Restaurant/Lounge
13	Restaurant/Service
14	Retail Condo
15	Retail Condo: Exempt
16	Retail Store Detached
17	Retail/Warehouse/Service
18	Social Club
19	Stage Theater
20	Strip Center/Stores
21	Supermarket
22	Tennis/Racquet Club

Source: Boston Assessor Database 1996

B: Boston Subway Model: Transfer vs. Total Travel Time Savings

Software: Biogeme Version 1.3
Model: Multinomial Logit
Null log-likelihood: -2176.48
Init log-likelihood: -2176.48
Final log-likelihood: -1400.64
Likelihood ratio test: 1551.68
Adjusted rho-square: 0.355
Final gradient norm: 4.08714e-005
Variance-covariance: from finite difference hessian
Utility parameters:

Variables	Coefficient	t-test
Transfer Constant	-1.192	-24.2
Travel Time Savings due to Transfer	0.310	21.6

C: GISDK Script for TransCAD to Generate Path Choices

Note: This script finds the shortest path using Pathfinder algorithm given the weighting factor defined at the end of the script. It input ODs from table OD_TC50.dbf, and produces three output tables:

xxxattr.bin: reports each walk segment, and each in-vehicle segment (between interchanges), and their travel times
xxxstop.bin: reports all stops the path goes through

```
*****************************************************************************
Macro "Default"
   RunMacro("TCB Init")
// Define the working folder
   in_path = "D:\\TC_Path\\TC_50\\Model RailPlan Jul07 Zhan\\"

// Define the public transport network file
   net_file = in_path + "Only LUL Network rev 01.tnw"
   rs_file = in_path + "NatGridRoute.rts"
    Opts = null
    Opts.Input.[Transit RS] = rs_file
    Opts.Input.Network = net_file
    Opts.Input.[SP View] = {"D:\\TC_Path\\TC_50\\xxx.bin", "Transit Paths"}
    Opts.Global.[Path ID] = 1
    Opts.Global.[Skim Var] = {"In-Vehicle Time", "Initial Wait Time", "Transfer Wait Time",
"Transfer Penalty Time"}

// Define output tables
    Opts.Output.[Attribute Table]  = "D:\\TC_Path\\TC_50\\xxxattr.bin"
    Opts.Output.[Stop Table]       = "D:\\TC_Path\\TC_50\\xxxstop.bin"

// Define input OD table
   od_file = "D:\\TC_Path\\TC_50\\OD_TC50.dbf"
   od_vw = RunMacro("TCB OpenTable",,, {od_file})
   if od_vw = null then
      do ok = 0  goto quit  end
   rcd = GetFirstRecord(od_vw + "|",)
   V = GetRecordsValues(od_vw + "|", rcd, {"O", "D"},,,,)
   O_Vec = V[1]
   D_Vec = V[2]

   for i = 1 to O_Vec.length do
      Opts.Global.Origins = {-O_Vec[i]}
      Opts.Global.Destins = {-D_Vec[i]}

 // Call shortest path algorithm
```

```
      ok = RunMacro("TCB Run Procedure", 1,"Transit Shortest Path PF", Opts, &Ret)
      if Ret <> null then do
         msg = Ret[1][1]
         if msg = "No path found." |
           Position(msg, "None of the origin") > 0 |
           Position(msg, "None of the destination") > 0 then do
            Ret[1][1] = msg + "(" + String(O_Vec[i]) + "-" + String(D_Vec[i]) + ")"
            goto next_od
            end
         end
      if !ok then goto quit

      ok = RunMacro("TRSP Process Path Tables", &Opts, Ret)
      if !ok then goto quit

      next_od:
      end

   RunMacro("TRSP Display Path Tables", Opts)


   quit:
      Return( RunMacro("TCB Closing", ok, True ) )
endMacro



// Define weighting factors

Macro "set network 1" (net_file, rs_file, fare_weight)

   Opts = null
   Opts.Input.[Transit RS] = rs_file
   Opts.Input.[Transit Network] = net_file
   Opts.Field.[Link Impedance] = "IVTT"
   Opts.Field.[Route Fare] = "Excess Time"
   Opts.Field.[Route Xfer Fare] = "Excess Time"
   Opts.Field.[Route Headway] = "Headway"
   Opts.Global.[Global Fare Value] = 1
   Opts.Global.[Global Xfer Fare] = 0.4
   Opts.Global.[Global Fare Weight] = 2
   Opts.Global.[Global Imp Weight] = 1
   Opts.Global.[Global Xfer Weight] = 1
   Opts.Global.[Global IWait Weight] = 2
   Opts.Global.[Global XWait Weight] = 2
```

```
    Opts.Global.[Global Dwell Weight] = 0.01
    Opts.Global.[Global Dwell Time] = 0.01
    Opts.Global.[Global Headway] = 15
    Opts.Global.[Global Xfer Time] = 2
    Opts.Global.[Global Max IWait] = 60
    Opts.Global.[Global Min IWait] = 0.1
    Opts.Global.[Global Max XWait] = 60
    Opts.Global.[Global Min XWait] = 0.1
    Opts.Global.[Global Layover Time] = 5
    Opts.Global.[Global Max WACC Path] = 4
    Opts.Global.[Global Max Access] = 20
    Opts.Global.[Global Max Egress] = 20
    Opts.Global.[Global Max Transfer] = 20
    Opts.Global.[Global Max Imp] = 240
    Opts.Global.[Path Method] = 3
    Opts.Global.[Value of Time] = 0.2
    Opts.Global.[Max Xfer Number] = 5
    Opts.Global.[Max Trip Time] = 999
    Opts.Global.[Walk Weight] = 3
    Opts.Global.[Zonal Fare Method] = 1
    Opts.Global.[Interarrival Para] = 0.5
    Opts.Global.[Path Threshold] = 0
    Opts.Flag.[Use All Walk Path] = "Yes"
    Opts.Flag.[Use Stop Access] = "No"
    Opts.Flag.[Use Mode] = "No"
    Opts.Flag.[Use Mode Cost] = "No"
    Opts.Flag.[Combine By Mode] = "Yes"
    Opts.Flag.[Fare By Mode] = "No"
    Opts.Flag.[M2M Fare Method] = 2
    Opts.Flag.[Fare System] = 1
    Opts.Flag.[Use Park and Ride] = "No"
    Opts.Flag.[Use P&R Walk Access] = "No"

    ret_value = RunMacro("TCB Run Operation", 1,"Transit Network Setting PF", Opts, &Ret)

    if !ret_value then goto quit

   quit:
      Return( )
endMacro
```

D: London Underground System Average Model with Interchange Times

Software: Biogeme, Version 1.4
Model: Multinomial Logit
Number of estimated parameters: 6
Null log-likelihood: -16812.2
Init log-likelihood: -10343.7
Final log-likelihood: -7515.35
Likelihood ratio test: 18593.8
Adjusted rho-square: 0.553
Final gradient norm: 0.0539536
Variance-covariance: from finite difference hessian
Utility parameters:

Variables	Coefficient	t-test
Base Path Attributes		
Entry/exit walking	-0.274	-9.0
Actual in-vehicle time	-0.504	-21.5
Initial waiting	-0.438	-9.6
Number of interchanges	-2.095	-13.2
Interchange Times		
Interchange walking time	-0.285	-7.0
Interchange waiting time	-0.295	-10.1

E: Interchange Movement Model without Interchange Waiting Time

Software: Biogeme Version 1.4
Model: Modified Multinomial Logit
Number of estimated parameters: 29
Null log-likelihood: -16812.2
Init log-likelihood: -8499.54
Final log-likelihood: -6408.3
Likelihood ratio test: 20807.9
Adjusted rho-square: 0.617106
Final gradient norm: 0.0461621
Variance-covariance: from finite difference hessian
Utility parameters:

Variables \ Models	Coefficient	t-test
Base Path Attributes		
Entry/exit walking	-0.226	-6.2
Actual in-vehicle time	-0.164	-3.6
Initial waiting	-0.274	-5.9
Number of interchanges	-2.582	-10.5
Map Attributes		
Map distance	-1.165	-8.9
Number of stations	-0.314	-6.7
Station Variables		
Baker St	-0.422	-2.2
Bank/Monument	-0.468	-1.9
Bond St	1.016	3.4
Earl's Court	2.030	5.1
Embankment	0.583	1.8
Euston	-0.634	-2.2
Green Park	0.537	2.4
Holborn	0.374	1.6
Leicester Sq	0.748	2.1
London Bridge	0.533	1.3
Oxford Circus	1.233	5.7
Paddington	-2.932	-6.7
Piccadilly Circus	0.695	2.2
Victoria	0.583	2.5
Warren St	-1.015	-2.4
Waterloo	-1.906	-5.1
Westminster	0.427	1.5
Interchange Time		
Interchange walking time	-0.323	-8.3
Interchange Environment		
Total interchange stairs	-0.0039	-2.9
Total horizontal distance	0.0022	1.3
Presence of escalator	0.921	4.8
Ramp length	0.0097	5.7
Same level interchange	1.014	5.3

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