Applications of Automatic Vehicle Location Systems Towards Improving Service Reliability and Operations Planning in London

by

Joseph Emanuel Ehrlich

Bachelor of Engineering, Civil Engineering,
McGill University, 2008

Submitted to the Department of Civil and Environmental Engineering
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ABSTRACT

Technological advances in the transit industry, such as the introduction of Automatic Vehicle Location (AVL) systems, have provided agencies with robust data collection and measurement systems and enabled the development of comprehensive planning and operations tools. This thesis reviews the impact of an AVL installation in London, and demonstrates how data recorded by this system may be used to improve service reliability and operations planning on the London bus network. In particular, this thesis focuses on capabilities which would have been impossible prior to the installation of AVL.

Service reliability has traditionally been measured from an operations perspective despite a major objective of the transit agency being to provide high quality service to passengers. A framework for a service reliability analysis is developed which explores new passenger-centric measures used to describe the quality of transit service, which are measured with AVL data. First, an analysis of trends in service reliability and factors that contribute to service reliability is performed in order to gain a better understanding of the environment in which transit services are operated. Three new passenger-centric measures of reliability are then introduced which describe the entire bus passenger experience. These measures are evaluated for a set of origin/destination pairs on six bus routes, and the differences in the perception of reliability between the new measures and the traditional measures are identified. The analysis demonstrates that while the traditional measures of reliability are relevant, the new measures provide additional insight. Recommendations are made with regard to implementing these new measures, providing better passenger journey information by applying these measures, and improving service control practices by monitoring these measures.

AVL data provides for the development of more robust operations plans since these data allow for a greater degree of accuracy when measuring point to point running times. A framework is presented for how running times measured with AVL may be used to assess the efficacy of current operations plans and aid operations planners in vehicle scheduling. Recommendations are made with regards to how AVL data should be used to evaluate the effectiveness of existing schedules and develop more robust schedules.

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Any errors or omissions are entirely my own.

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1 Introduction

This thesis will provide a systematic review of the impact of a large scale AVL (Automatic Vehicle Location) system implementation on a bus network in a major urban area using London as the case study. It will assess whether a recent AVL implementation has improved network operations and service reliability and provide guidance for other transit operators with regard to potential planning and operations benefits that may not necessarily have been defined and quantified when such systems were procured.

Transit agencies often focus initially on making sure the technology implementation proceeds as smoothly as possible. What is sometimes overlooked during implementation is that technology enables application of better planning and operations analysis methods. Specific areas of planning and operations analysis for which AVL data may be of particular use will be identified, and their potential benefits discussed.

This thesis will summarize how a bus operator may maximize the benefits of AVL focusing on selected planning and operations functions. It will combine a literature review on bus service reliability metrics, methods for analyzing AVL data, and lessons learned from the service reliability exercise and apply them towards developing new metrics to assess service reliability in the context of performance measurement, service control, and operations planning. This will all be presented in the context of London Buses, which introduced a new AVL system called iBus in 2009.

1.1 Motivation

The transit industry is constantly evolving to take advantage of technological advances. While a transit agency would ideally upgrade their operations technologies at will to reflect the latest, most sophisticated products available on the market, fiscal and capital constraints prevent the agency from doing this. Therefore, when it is faced with an opportunity to make a capital investment, the agency has an obligation to ensure that the benefits of the investment are maximized. In the context of an upgrade in technology, this involves ensuring that the status quo is maintained or improved, as well as investigating possible new functionalities the technology improvements may provide.

More sophisticated data collection systems enable transit agencies to analyze a wider range of performance measures with substantially higher accuracy. Before the implementation of automated data collection systems, collecting data was very labor intensive and costly. Manual surveyors had to be placed at key points along routes to collect data such as run times, bus frequency, and passenger loads, and even the best observers made errors (Multisystems, Inc., 1985). Obtaining a large sample of any data was difficult and costly. Automated data eliminates this need by providing data on the great majority of the population (Furth, 2000). In addition, data that were virtually impossible to collect before, such as bus arrival and departure times at *every* stop along a route, are now feasible. It is therefore important to determine what uses these additional data may have in aiding transit agencies to achieve their mission as efficiently as possible. If an agency simply continues to use old measures developed in a different environment, the only possible improvement is through better estimates of these old measures.

The transit industry, like any other industry, strives to maximize efficiency and resource utilization in order to avoid redundancy and to control costs. AVL data, which enables operators to more accurately monitor vehicles and to analyze data at a finer level of granularity than was previously possible, should aid in minimizing operating costs. AVL data also enables new measures, such as reliability of service, to be specified, measured, and used in financial analyses with the aim of more accurately measuring project benefits (Hollander and Buckmaster, 2009).

AVL implementation also provides agencies with an opportunity to step back and assess whether they are meeting their service delivery objectives. While the primary aim of the agency should be customer service, an agency may mistakenly focus only on operations to try to achieve better service. For example, when making real-time service control decisions, one rarely hears a controller ask how many passengers will be affected by an intervention. Instead, the controller makes the decision from an operations perspective, such as attempting to get all buses back "on schedule" by short-turning numerous trips. Even though agencies strive to be customer oriented, they may mistakenly focus heavily on the bottom line, which leads to a more operations oriented response to service disruptions.

In addition to providing new data analysis capabilities, the role of the transit agency is also changing. New technological sophistication shifts the emphasis from hands-on operations monitoring to more of a technical support and advisory role. Some systems, such as most British bus services and York Region Transit near Toronto, do not engage in operations at all but focus on network planning and performance monitoring (York Region Transit, 2010). With a continuing shift in the industry towards contracted bus services, the number of agencies shifting their focus is likely to keep increasing.

An improved transit system equates to improved operations and customer satisfaction. This in turn leads to improved efficiency, which saves the agency – and the taxpayer in the case of publicly-supported systems – money in the long run (Callas et al, 2004). Studies have been conducted evaluating the effects of these new automated systems for medium sized bus properties, such as Portland, OR (Callas et al.1999, 2001, 2003, and 2004). However, this thesis presents an opportunity to analyze a large-scale AVL implementation in London, UK, which may have implications for other megacities around the world.

1.2 Objectives

The overarching objective of this thesis is to demonstrate how transit agencies can get the most value out of their AVL systems. It will be especially important to show that AVL data does not just provide better means of *calculating* metrics and service standards that agencies had previously estimated using less accurate methods; rather, due to the windfall of data it is possible to extract from this technology, AVL data also enable agencies to *develop* more robust and sophisticated metrics and analysis methods. The benefits of AVL will be evaluated for the service reliability measurement and operations planning functions.

This objective will be achieved by examining the following issues in detail:

- Factors that affect service reliability will be analyzed to determine whether introducing an AVL system in London can be shown to improve reliability. This analysis addresses two topics: the first is determining whether the implementation of AVL results in measurable improvement. The second is that it will enable a more complete picture to be painted of the many factors that may potentially affect service reliability, and their relative importance.
- New, more robust measures of service reliability will be developed that better describe the operating environment, both from an operational perspective and from the passenger's perspective. As has already been discussed, agencies generally focus on operations performance, which may not be the best way to understand the passenger perspective. This will reveal the relative differences between the passenger's perception and the operator's perception of good service.
- It will be demonstrated how archived AVL data may be used to create more accurate operations plans, increasing system efficiency and reducing operating costs. The finer data provided by archived AVL data will allow for more accurate measurement of running time, providing more reliable information on which to build the operations plan.

1.3 Research Approach

The objectives outlined above will be pursued in the context of the bus network in London, UK, which recently completed a system-wide AVL implementation, called iBus. Methods already developed and used elsewhere in the industry will be synthesized and applied in this new context.

While London is used as the case study in this research, many of the conclusions developed may be applied universally to other large transit systems. However, there are some important differences between the London system and the typical North American transit system that should be recognized at the outset.

In contrast to most North American transit agencies, where service planning, operations, and monitoring are all performed by a public agency, London's bus network is privately operated via a tendering and contracting process (London Assembly, 2006). The public agency, Transport for London (TfL), through its London Buses subsidiary, is responsible for setting routes, tendering operations contracts, and monitoring operations (TfL, 2008). A consequence of this organization is that TfL has developed a comprehensive bus monitoring performance system that includes extensive data collection and analysis. The specific nature of the London bus network is described in detail in Chapter 3. However, it suffices here to say that there are some fundamental differences between the operations of the London bus network and the typical North American transit operation which arise from the fact that bus operations are contracted to the private sector. The thesis will look at how London is measuring the benefits of AVL, identify work they have produced thus far to make use of new data, and suggest ways they may further take advantage of the data analysis potential presented by AVL.

Before demonstrating the benefits of AVL, it is essential that the analyst has an understanding of factors affecting service reliability. With this understanding, the analyst will be more informed about what he/she may control in order to improve service reliability. This will be performed by creating a comprehensive set of factors that affect service reliability and assessing their relative importance. Those factors that are found to be significant will then be included in a regression model, which will provide a rough picture of how these factors affect service reliability.

This thesis will apply accepted methods already developed for the industry towards new uses. It intends to present a synthesis of two areas of recent research. The first area, developed by Chan (2007) and Uniman (2009), challenges the classical conceptions of service reliability. For the most part, work on service reliability has focused on providing smooth operations, which is desirable from an operations standpoint. However, the transit agency should also focus on providing the best travel experience for the passenger, as the passenger is one of the most important stakeholders in the system. It is therefore essential that service reliability be analyzed also from the passenger's perspective. This objective will be met by analyzing the parts that make up the passenger travel experience, and developing measures that accurately reflect these parts.

Passenger-centric service reliability measures also aid in the service control process as analyzed by Carrel (2009) and Froloff et. al. (1989). A major impetus for installing AVL systems is that it improves service controllers' ability to make informed service control decisions. However, formal analyses of which decisions should be taken in specific situations have generally been lacking with bus AVL installations. A comprehensive survey of industry research pertaining to formalizing the service control process will be included in order to provide guidance for analysts wishing to apply passenger-centric service reliability measures towards the improvement of service control.

The second area, developed by, among others, Furth and Muller (2006), provides a framework for using AVL data to provide more robust measurements of service reliability and to aid in the operations planning process. AVL data will be used to compare observed operations to scheduled operations, in order to demonstrate how these data enable schedulers to make more informed decisions resulting in more robust schedules. This will also demonstrate how using AVL data, which is more accurate and efficient than manual data collection methods, also enables schedulers to more efficiently use resources by reducing uncertainty (and therefore slack time) on bus runs where a bus is waiting between trips. Numerous studies to the same effect have been produced in Portland, OR, which will be presented in the literature review in Chapter 2 (Callas et al. 1999, 2001, 2003, and 2004).

1.4 Thesis Organization

Chapter 2 will present a literature review of research focusing on applications of AVL data with regard to performance measurement, operations planning, and service control. Chapter 3 will describe the bus network in London, focusing on organizational structure, the contract tendering process, and the history of AVL technology deployment in London. Chapter 4 will introduce reliability measures currently used by London Buses, describing them and evaluating their benefits and limitations. This chapter will also discuss factors that affect service reliability on the London bus network, and will present a regression model that relates service reliability to a number of factors identified by London Buses staff. Chapter 5 will look at new, robust service reliability measures that may be estimated from AVL data. In particular, it will focus on measuring reliability from the passenger's perspective as opposed to just the operator's perspective, and recommendations will include how these measures may aid in making more educated service control decisions. Chapter 6 will present applications of AVL towards developing more accurate operating plans and analysis of run time distributions for various bus routes, comparing current practice with those developed using AVL data. Finally, the work will be summarized in Chapter 7, which will also discuss opportunities for future research in this field of study.

2 Literature Review

This chapter introduces the essential theories pertaining to service reliability, operations planning, and service control required for the subsequent analyses presented in this thesis. A summary of a comprehensive analysis of an urban AVL installation in Portland, Oregon, USA is also provided to demonstrate how an AVL system may be used to provide a multitude of benefits in all areas discussed.

Section 2.1 presents a brief overview of studies that have summarized the benefits of AVL. Section 2.2 introduces service reliability measures of relevance to this thesis, focusing on recent developments of customer-oriented measures. Section 2.3 describes operations planning, focusing specifically on the scheduling process. Section 2.4 presents an overview of research performed on service control. Section 2.5 presents a summary of work conducted in Portland, Oregon, USA, a medium sized property which has been analyzing AVL for the past decade. The chapter is summarized in Section 2.6, describing how the concepts presented in this chapter apply to this thesis.

2.1 Using AVL Data for Analysis

An advantage of AVL is that it allows transit agencies to improve the accuracy and extend analyses aimed at improving operations and performance monitoring. A brief survey of the benefits of AVL identified in literature is presented below.

Parker (2008) takes stock of current agency practices by presenting a survey of how AVL systems have been used in bus systems in North America. A noted challenge of implementing AVL is adapting agency business practices and operating procedures to accommodate the new capabilities available with AVL. While all agencies surveyed indicated that practices in their operations units were being adapted for AVL, only 62% of agencies' information technology departments and only 42% of their planning departments were modifying practices to accommodate AVL. Parker foresees a challenge in convincing agencies of the importance of these data sources.

Furth et al. (2006) present a comprehensive survey of the attributes of modern AVL systems and how these systems may be used to improve transit service. One of the major benefits identified is linking AVL data to APC (Automatic Passenger Counters) data installed on many transit vehicles. APC systems are capable of estimating passenger loads on buses via sensors installed at every door on a bus. APC records with timestamps may easily be linked to AVL bus location data and the analyst is then able to estimate loadings on vehicles and passenger volumes at stops, enabling the development of service metrics which reflect passenger volumes. The result provides a more accurate picture of the effects of certain attributes of service (such as headway variability) on the customers, more accurately linking the supply side of transit – the vehicles and their operating schedules – with the demand side. Of particular interest to this thesis, methodologies are presented for using archived AVL and APC data to set running times and measure wait time, which will be discussed in subsequent sections of this chapter.

Furth et al. point out that as a result of the new potential for analysis provided by AVL systems, transit agencies, which used to be "data poor," are now "data rich". This has enabled transit systems to focus their planning and operations analyses in the five following areas:

1. Extreme values – In the past, manual surveys, which result in small samples, were not able to provide accurate distributions of running times or headways. Thus, agencies generally focused their analyses on mean values. Now, with AVL and its potential to produce very large sample sizes, accurate distributions of these attributes can be produced. This enables the service providers to produce more accurate schedules, as bus cycle times are generally governed by the 90th or 95th percentile running time. In addition, more accurate headway distributions will provide better measures of the passenger experience on high frequency routes as passengers may schedule their trips based on a value closer to the 95th percentile wait time rather than the mean wait time (Furth and Muller, 2006).
2. Customer-oriented service standards and scheduling – Matching AVL data with APC data enables the transit provider to more easily estimate reliability metrics that are more passenger focused, such as the percentage of passengers waiting more than a given number of minutes for a bus to arrive. Previously, agencies were not capable of calculating the passenger costs of alternative strategies.
3. Planning for operational control – The effects of real-time control decisions may now be measured. For instance, AVL data can indicate the effect on wait time of short-turning a bus.
4. Road congestion –AVL data records can be used to measure how the introduction of transit signal priority schemes or dedicated bus lanes have affected running times.
5. Other hidden trends – It is possible to find new trends in what was previously treated as random variation in the data, such as explaining run-time variability across vehicle operators.

While all the above points merit analysis, points 1-3 are of particular relevance to this thesis, as they may be applied in the methodologies used in subsequent analyses.

2.2 Measures of Service Reliability

Service reliability measures analyze the consistency of the service provided. In an ideal world, transit services will operate exactly according to the operations plan. However, a number of factors, such as weather, traffic congestion, driver behavior, passenger demand, and controller actions, will cause the transit service to deviate from the operations plan and introduce randomness into these operations. The goal of the agency is to minimize these deviations. This may be achieved by developing absolute measures to describe an operations plan, developing relative measures to describe the deviations from the plan, and monitoring the service regularly. A survey of measures relevant to this research is presented in this section.

Abkowitz et al. (1978) define service reliability as "the invariability of service attributes which influence the decisions of travelers and transportation providers." They demonstrate how reliability is important to both passengers, whose travel behavior is correlated with the perceived reliability of certain services, and operators, who equate reliability with cost effectiveness. Measures accounting for the variability in the day-to-day experiences of passengers and operators are proposed; it is using this framework that most modern measures of reliability were developed.

2.2.1 Wait Time

Passengers place a high value on minimizing the amount of time they have to wait for a vehicle at a stop. For low frequency routes, this typically involves consulting the timetable and factoring in prior experience selecting a departure time. In this case, a service is reliable if buses arrive consistently according to the timetable. However, on high frequency routes, vehicles are assumed to depart frequently enough that passengers do not necessarily consult a timetable. Passengers are assumed to arrive at stops randomly. In this case a reliable service would be one where a passenger would never have to wait longer than the scheduled headway.

The classic equation for average wait time, as shown in Equation 2-1, takes into account the variability of headways via the coefficient of variation (Odoni, 2008). This is an absolute measure which may be applied towards developing relative measures describing the wait time experience. The lower limit of this equation represents an ideal situation where headways are perfectly uniform; the expected wait time would simply be half the scheduled headway. However, when headways are not uniform, a randomly arriving passenger is more likely to arrive during a long headway than a short headway, resulting in the expected wait time being greater than the average headway. This is also true for scheduled services with uneven headways.

$$Average\ Wait\ Time = 0.5 * E[Headway] * (1 + COV_{Headway}^2) \qquad \text{(Equation 2-1)}$$

It is interesting to note, however, that Jolliffe and Hutchinson (1975) demonstrated that passenger arrivals are not necessarily random for a reliable, headway-based service. If the day-to-day variation in bus arrival times is small, regular passengers get a feel for when the bus they need is likely to arrive, and may time their arrivals at the stop accordingly. The average passenger wait time is therefore less than predicted in Equation 2-1. This is true even for passengers who do not time their arrivals at bus stops, as they may wait at a local coffee shop and only head to the bus stop once they see a bus coming. This trend is quite difficult to quantify, however, without performing large surveys, so the classic methodology (i.e. Equation 2-1) is widely accepted in the industry.

It is possible to build a wait time distribution from AVL-based headway data (Furth and Muller, 2006). By combining a distribution of the headways with the frequency of occurrence of each value of the headway, it can be shown that the fraction of headways greater than a length determine the probability of waiting the given amount of time. The probability density function of passenger wait time is expressed in Equation 2-2.

$$f_W(W) = [1 - F_H(W)]/E[Headway] \qquad \text{(Equation 2-2)}$$

Where:
W is the amount of time a passenger spends waiting for a vehicle;
$f_W(W)$ is the probability density function of passenger wait time; and
$F_H(W)$ is the cumulative distribution function of headways.

Furth and Muller (2006) developed the concept of hidden waiting time. They note that in order for passengers to arrive at their destinations on-time most of the time, they need to budget more than the expected wait time, as budgeting only the expected wait time will ensure they arrive on-time only 50% of the time. They assume that a passenger will budget to arrive on-time 95% of the time, so the passenger will use the 95th percentile of wait time. The 95th percentile wait time is based on a distribution of the headways as well as the frequency of each headway, as shown in Equation 2-2. The difference between the 95th percentile wait time and the expected wait time, potential waiting time, is either realized at the beginning or end of the trip. When the potential waiting time occurs at the end of the trip, it can be "redeemed" by additional time gained at the destination. However, the value of this redeemed time is not as high as if it was not needed in the first place, as the passenger is constrained by what he/she is able to do at the destination.

2.2.2 Excess Waiting Time

Excess Waiting Time (EWT) is a relative measure that has been used in the industry to measure the variability of bus arrivals. It represents the *extra* amount of time a passenger waits on average above the scheduled wait time. As shown in Equation 2-3, it is the mathematical difference between the observed average wait time and the scheduled average wait time.

$$EWT = Observed\ Wait\ Time - Scheduled\ Wait\ Time \qquad \text{(Equation 2-3)}$$

Note that both the observed wait time and the scheduled wait time are calculated using Equation 2-1.

2.2.3 In-vehicle Travel Time

In-vehicle travel time is an absolute measure defined as the amount of time a passenger spends in a given transit vehicle between the origin and destination stops. While the monetary value of a unit of in-vehicle travel time is generally perceived to be lower than the monetary value of a unit of wait time, any uncertainty introduced into in-vehicle travel time will result in disutility to the passenger (Small and Verhoef, 2007). Passengers on severely delayed vehicles (e.g. a bus stuck in congestion or a train stopped between stations) will realize that service is not operating as planned and will therefore perceive the service negatively. These passengers may budget their time accordingly for their subsequent trips.

2.2.4 Journey Time

Journey Time is an absolute measure which reflects the total passenger journey experience. Ideally it would describe the passenger experience from leaving the origin location (e.g. home) to arriving at the destination location (e.g. work). However, in most cases it is infeasible to monitor the travel patterns of every passenger at this level of detail in order to gain a full sample of origins and destinations.

Uniman (2009) described how the London Underground measures a passenger journey. It is broken down into five components: Ticket Purchase Time; Access, Egress and Interchange Time; Platform Wait Time; On-train Time; and Closures. Each component has an associated unit value of time[1], as passengers perceive each part of their trip differently.

This framework may be applied to the London bus network if certain changes are made to reflect the different characteristics of each mode. While it is common for Underground riders without valid tickets to purchase a ticket as part of their overall trip, this is less common for bus riders since many buses in Central London do not accept cash payment. Ticket machines are available at select bus stops, interchanges with the Underground, and at private retailers outside the system.

Access, Egress and Interchange times are also less well-defined for buses. Rail stations have clearly defined distances from the point of access to the platform. With a few exceptions (major bus terminals such as bus-only platforms within Underground stations), bus stops have no access or egress distance. However, when interchanging between bus routes, a passenger must walk between bus platforms, even though the interchange may not take place within the defined structure of a station, there is still a time penalty for the interchange.

[1] For information about the concept of value of time, see Small and Verhoef (2007) and Wardman (2001).

Chapter 5 will present the derivation for Journey Time used in this thesis, which is an indeterminate measure when applied to an un-gated transit network. It will be defined as the sum of wait time and in-vehicle travel time.

2.2.5 Excess Journey Time and Reliability Buffer Time

Excess Journey Time (EJT) and Reliability Buffer Time (RBT) are two relative measures of reliability that may be calculated from Journey Time. Chan (2007) presents a survey of possible applications of AFC data, including two metrics of particular relevance to this thesis: the Excess Journey Time Metric and the Reliability Factor, which Uniman (2009) renamed Reliability Buffer Time. There metrics were developed for the London Underground which uses smartcards (i.e. Oyster Cards) for a tap in/tap out fare payment system, resulting in measurable, determinate journey times. Most bus networks do not require users to both tap in and tap out, resulting in indeterminate journey times. However, the underlying theory behind these metrics can easily be applied to buses.

Excess Journey Time is defined as the difference between the observed journey time and the scheduled journey time, as expressed in Equation 2-4. It therefore represents the amount of time a passenger had to spend in transit over and above the expected, or scheduled, Journey Time. An aggregate EJT metric was also developed by Chan, as AFC data were used to scale up the individual EJTs for a given origin/destination pair.

EJT = Observed Journey Time – Scheduled Journey Time (Equation 2-4)

Reliability Buffer Time is defined as the difference between the 95th percentile Journey time and the median Journey Time for a given origin/destination pair, as shown in Figure 2-1 (Uniman, 2009) and defined in Equation 2-5. This represents the extra time passengers must budget to reach their destination on-time with 95% predictability (Chan, 2007). Using the median Journey Time to time one's expected arrival at a destination would result in arriving late 50% of the time. This factor is independent of the schedule, and it describes the true variability of operations, as opposed to EJT which describes the deviation of operations from the schedule, even for cases when the operations are consistent.

RBT = 95th Percentile Journey Time – Median Journey Time (Equation 2-5)

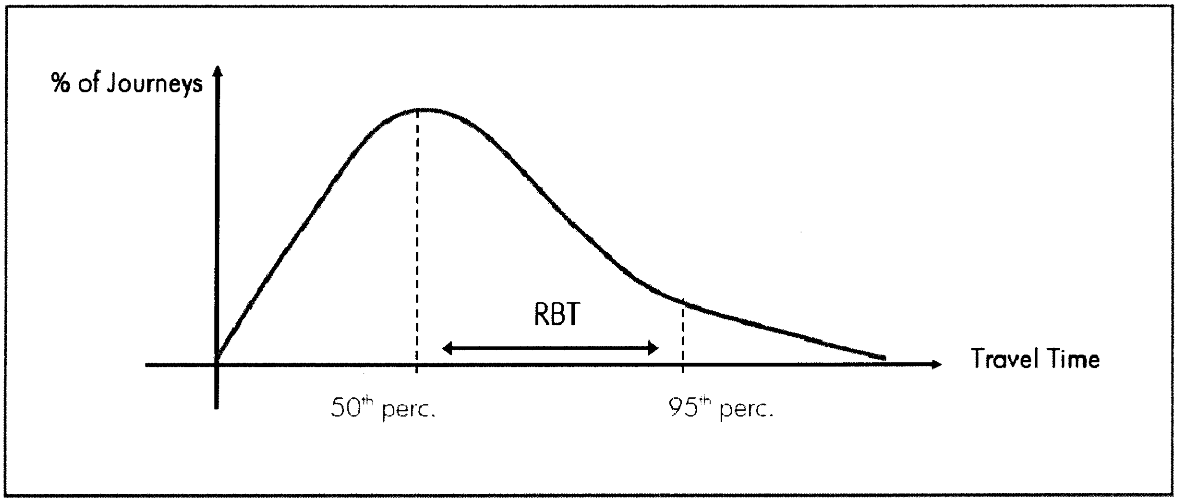

Figure 2-1 - Reliability Buffer Time

Uniman et al. (2009) develop RBT further by introducing a metric called Excess Reliability Buffer Time (ERBT) to compare reliability with a baseline reliability measurement (see Figure 2-1). ERBT captures the excess amount of time passengers are required to budget to arrive at their destination on-time over and above the excess amount of time that would have been required under normal operating conditions. This measure acknowledges that transit services experience unavoidable variability in operations. However, services also experience many avoidable or preventable disruptions. ERBT captures the difference between these two types of performance by comparing a given RBT to a baseline formed from "typical" RBT values, as shown in Equation 2-6. This measure allows agencies to define a desired level of unreliability, and measure their operations against this baseline.

$$ERBT = RBT_{Overall} - RBT_{Typical} \qquad \text{(Equation 2-6)}$$

This procedure also enables the number of trips experiencing an unacceptable level of unreliability to be quantified, expressed as the Percent of Unreliable Journeys (Uniman et al, 2009). This measure is simply the number of journeys with a positive ERBT (i.e. the number of journeys where RBT was found to be greater than the baseline).

2.3 Operations Planning

Operations planning is a crucial element of bus network design. Ceder and Wilson (1986) characterize the bus planning process as a sequential process with 5 levels, as shown in Figure 2-2; the outputs from one level are inputs at the next level. This research focuses on the third and fourth levels, timetable development and bus scheduling.

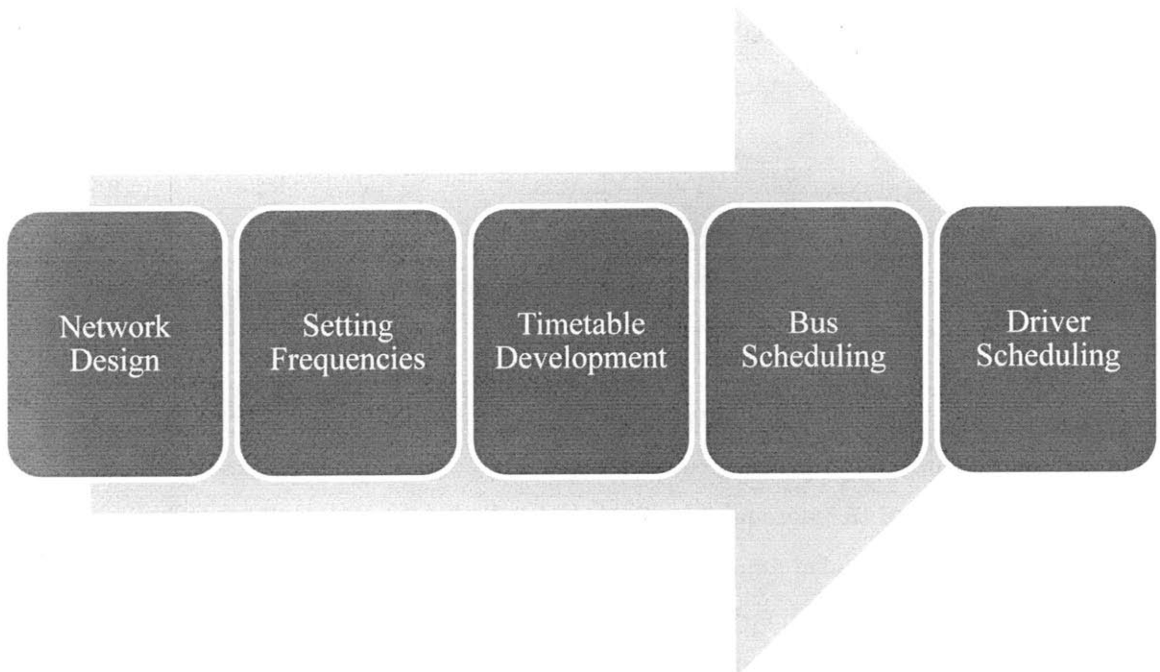

Figure 2-2 - The Bus Planning Process

Timetable development involves using three inputs, passenger demand, service hours, and running times, to develop departure and arrival times for every trip. Once departure and arrival times for every trip have been defined, individual buses may be assigned to each trip.

Bus schedules are developed from the timetable and requires four inputs, deadhead times, recovery times, schedule constraints (the timetable), and cost structures. This research focuses on running times and recovery times, for which AVL data may contribute more comprehensive and reliable inputs.

The amount of time a vehicle is allocated to operate a round trip is referred to as *cycle time* with the time for a one-way trip called *half cycle time*. This may be broken down into two components: *running time* and *recovery time*. Running time is the amount of time the vehicle spends in transit from the origin to the destination. Recovery time is recovery time and/or layover time allocated at the end of the trip which has the purpose of ensuring that the next departure leaves on time and the driver has a break between trips. It is intended to capture the variability in running times.

Transit services, in particular buses operating in mixed traffic, are susceptible to high running time variability if left uncontrolled. This variability is caused by numerous factors, including weather and traffic variability, differences in driver behavior, dispatching practices, and variability in dwell times (Abkowitz et al., 1978). Thus, schedulers have to strike a balance between service reliability and travel speed, as a slow service may be reliable but will still deter passengers from using transit.

In the past, measuring running time required manual surveyors and was therefore labor intensive. Setting running times also depended heavily on input from passengers and operators (especially when new field surveys were impossible), and was therefore most sensitive to exceptional incidents as opposed to being indicative of typical operations (Furth, 2000). With AVL, it is possible to measure terminal to terminal running times quite easily, and trends in running time can be analyzed over time. Some formal analyses performed on determining running time, recovery time, and cycle time are presented here, and mainly reflect the work of Furth and Muller (2006) and Fattouche (2007).

Defining scheduled running time and cycle time is a function of the agency's policy as well as the operational goals for the route. High frequency routes have different operating objectives than low frequency routes, and therefore different requirements when developing a schedule. Using a low percentile running time as the scheduled running time may make sense on a high frequency route where the published timetable is irrelevant from the passenger's perspective. However, this would result in many late trips on low frequency routes, which passengers will perceive as unpunctual operations.

It is important to note that while buses being late on low frequency services is undesirable, being early is even less desirable. Since passenger arrivals at stops on low frequency routes are often based on a timetable, a bus that leaves a stop before the published time may result in a missed trip and a long wait for the next bus arrival. Thus, run times on low frequency routes are generally set to low to mid range percentile values of observed run times, and early buses en route are held at a stop until the appropriate scheduled departure time.

A common North American practice is to set scheduled running time equal to the mean or median observed running time. This alone provides too little slack, and results in a high probability of lateness on the trip (Furth and Muller, 2006) as well as on subsequent trips unless sufficient recovery time is provided. Scheduling running times at the 85th percentile of running time, which some agencies use, will result in numerous early trips on low frequency services requiring holding, but may result in better schedule adherence from the passenger's perspective (Furth, 2000). On high frequency services, the tradeoff between long holding times (and therefore longer running times) and the evenness of headways must be considered (Fattouche, 2007).

Furth and Muller (2006) looked at the tradeoff between service reliability and optimal running time schedules for low frequency routes. They note that while adding holding points en route is used to create a more reliable schedule, it also results in a higher user cost since travel times become longer on average. However, time spent at holding points merely results in a redistribution of the slack time over the entire journey, as opposed to concentrating it at the end of the trip, and therefore does not increase the operating costs of the route. By performing simulations to optimize the tradeoff between user costs and operational reliability, they found that the optimal scheduled run time for low frequency routes should be set to the mean plus one standard deviation of the observed run times (approximated by the 85th percentile), and the optimal half cycle time should be set to the mean plus 2 to 3 standard deviations of the route running time.

Furth et al. (2006) compare scheduled and observed running times by plotting chronological distributions of running time. By grouping the distributions into timebands of homogenous running times, it is possible to calculate percentile values of running time for certain times of the day, in order to create more accurate and efficient schedules. It is important to note, however, that the timebands used for setting running times may not be the same as those used for setting route frequencies. Route frequencies are set based on passenger demand; more frequent service will be operated during peak periods. Running times are based on observed operating conditions, which may not correspond directly to the periods used to define passenger demand.

Fattouche (2007) proposes a method to use AVL data to set running times for high frequency services in Chicago. She presents a methodology for modeling how a new schedule may affect bus reliability. When determining the effectiveness of a schedule, Fattouche notes that passengers face a tradeoff between travel time and wait time, both of which may be expressed as cost. Excessive use of schedule based holding strategies may result in a slow travel experience for passengers on the bus, while focusing solely on ensuring each trip is completed as quickly as possible may result in uneven headways, and therefore increases the variability in wait times. Additionally, agency costs must be considered to ensure that sufficient resources are available for implementing the schedule.

By formulating this as a generalized cost minimization problem, Fattouche is able to determine optimal practices for scheduling. She employs historical AVL data to develop running time and headway distributions and predict the costs of implementing different scheduling policies, including schedule based holding, setting scheduled running times to different percentile values, and comparing these to the existing schedule. Fattouche found that the optimal solution results in total user costs that are similar to those for the original schedule. She concludes that generalized cost minimization is capable of improving reliability and the passenger experience, although each solution provided by her method is based on an individual route's operating constraints, and is therefore applicable only to the given route.

2.4 Service Control

Far less effort has been put into formally defining the bus service control process and developing a best practices guideline for it. The works presented in this section, notably those from the RATP and various research projects at MIT, provide a framework for creating a formal process while acknowledging that every disturbance to a network presents a unique situation that cannot be remedied via an off-the-shelf solution. The majority of research performed thus far has been for rail-based systems which operate in a protected environment, but the RATP's (Régie Autonome des Transports Parisiens) report is one which has focused specifically on bus operations.

This thesis will not recommend specific best practices for service control using AVL data, as best practices are highly dependent on operational philosophies and on the individual route operating environment. However, it is important for the reader interested in using AVL data to formalize service control methods to have a comprehensive understanding of the underlying theory behind service control and the range of control interventions available.

Ensuring service controllers are trained properly in using the AVL system to its full capabilities is crucial in meeting the objectives of service control, as Parker (2008) points out. Service controllers have a high turnover, so management must constantly monitor the staff to ensure that they are taking full advantage of the equipment and technology at their disposal.

Froloff et al. (1989) at the RATP in Paris endeavored to characterize the service control process systematically and develop a theoretical framework for service management. They believed there was a lack of "formalized knowledge" with regard to service management, which proved problematic because it was impossible to train controllers based on sound theory, so all training was based on anecdotal experience. This lack of knowledge also prevented future route design and operations plans from being designed to their potential.

Froloff et al. considered the operation of a bus route to have 2 main components, as presented in Figure 2-3:

1. The Functioning of the Route – The condition of the route at a given time. This may be described by a set of variables such as the vehicles' positions in time and space, their loads, etc.
2. Service Management – Adapting the service plan as operations unfold. This focuses on analyzing the gaps between the planned and existing operations, and methods to resolve these disparities.

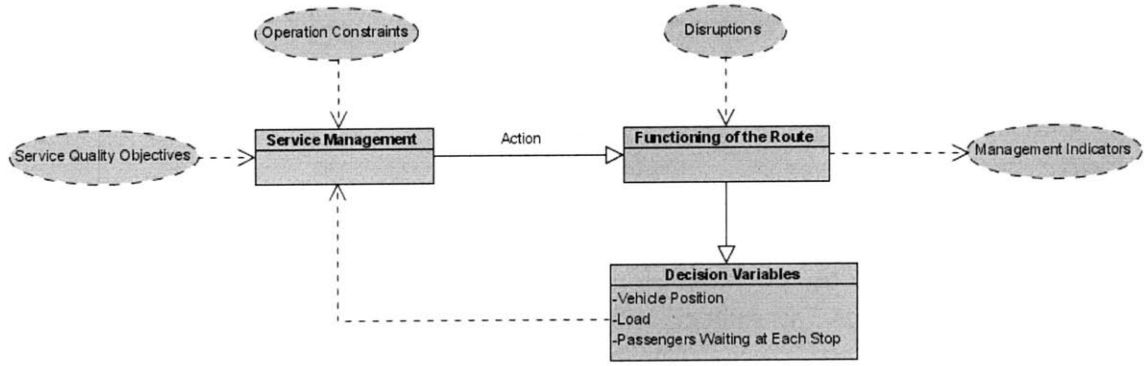

Figure 2-3 - A Schematic of Bus Route Operations

While the operating schedule is static for a given day and time, service management is significantly more dynamic. As shown in Figure 2-4, it may be represented as a set of conditions (starting with the ideal condition) which are subject to disruption. Actions are carried out to counteract the disruption, and the system moves to a new condition.

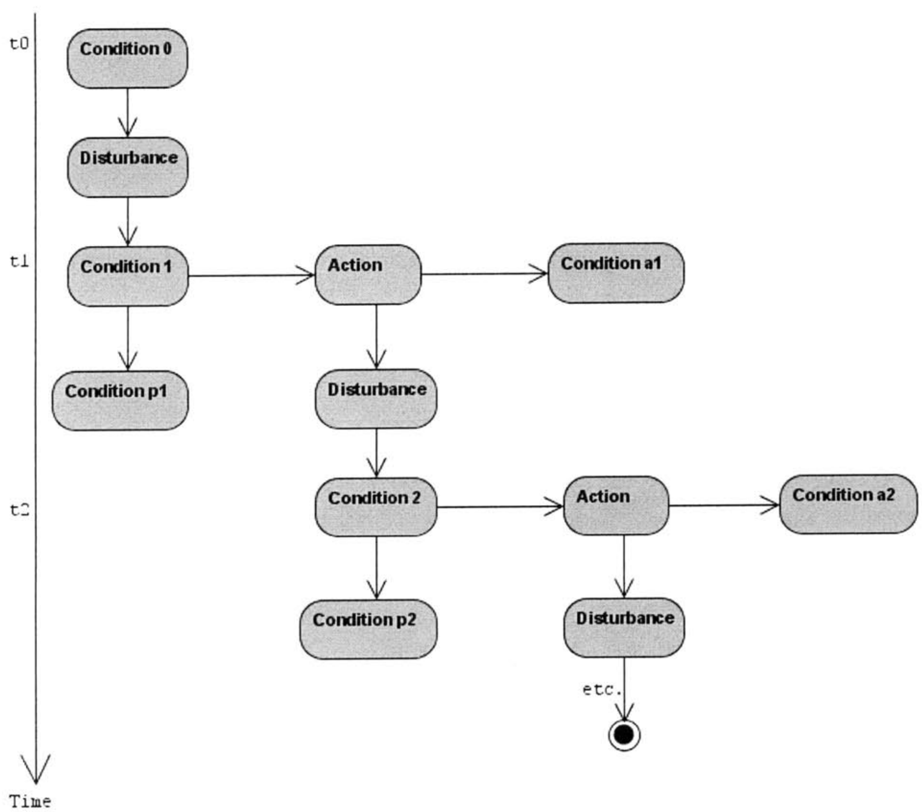

Figure 2-4 - Evolution of the System over Time

The authors endeavored to categorize and provide comprehensive lists of both service management strategies and restoration actions within the context of the RATP's bus network. Four main operating philosophies were identified, each deemed appropriate depending on the type of route, time of day, and other operating conditions:

1. Meeting Passenger Demand – This strategy, which dominates during peaks, places priority on ensuring no passengers are left behind at any stop.
2. Providing a Consistent Service – This strategy, which dominates during the off-peak, minimizes wait time by striving for even headways.
3. Ensuring Punctuality – This strategy dominates for low frequency routes, where passengers consult published timetables to time their arrivals at stops.
4. Meeting Staffing Requirements – This strategy takes staffing constraints into account, respecting driver scheduling and minimizing overtime.

Froloff et al. developed a set of fairly crude metrics using the data at their disposal at that time to assess service reliability and to determine which service management strategy controllers should focus on. With the introduction of AFC and AVL data sources, additional metrics, such as those to be presented in Chapter 5, have been developed and implemented to more accurately reflect operating conditions.

Fifteen main service restoration (intervention) actions were identified, which may be carried out at the beginning of the route and/or en route (see Table 2-1). These interventions can only be applied if there is both a staff member and a vehicle available. In cases where one is available and not the other, the controller is required to ensure the missing component is added as soon as possible in order to avoid further service disruptions.

Table 2-1 - Summary of Service Restoration Actions

Location	Service Restoration Action	Description
Beginning of Route	Jumping	If the scheduled vehicle is not available, the controller may substitute another vehicle for the scheduled vehicle.
	Reassigning	A scheduled block is reassigned to an earlier time.
	Shift schedule timeframe	When the controller is able to anticipate a delay, he/she may shift the entire schedule over by a certain amount of time to try and preemptively fill in the anticipated gaps in service.
	Eliminate trip	Trips may need to be dropped if no staff or vehicles are available, or if the terminal cannot be reached due to other issues such as severe congestion.
	Add trip	This action is generally used in cases of unusually high demand, such as special

Location	Service Restoration Action	Description
		events, where the scheduled service will not be able to meet the passenger demand.
	Modify headways	A trip cancellation may result in a longer than usual gap of service. In order to make sure service is spaced as evenly as possible, the entire route's headway may need to be lengthened.
En Route	Modify scheduled running times	This intervention enables running times to better reflect reality, and was already discussed in Section 2.3 as part of operations planning.
	Hold at bus stop	Holding can be used to absorb large point loads (i.e. schools) or be used to even out service.
	Change bus	Changing the vehicle used to run the trip may be used when dealing with breakdowns and other service interventions such as short-turning. Passengers will need to transfer from one vehicle to another.
	Pass on route	This intervention can be used during incidents of bus bunching. The less crowded vehicle is sent ahead of the crowded vehicle to pick up the next passengers in order to even out the loads on the two buses. This is referred to as "leapfrogging" when done more than once.
	Change drivers	This intervention involves switching drivers at a point where buses in opposite directions meet, which is equivalent to two short turns. This can enable work rule requirements to be met (e.g. minimizing overtime).
	Detour	Detours are used to avoid an area of congestion or, in cases of deadheading/expressing, they are used to minimize travel time.
Any point of the Route	Short-turning	This is used to fill in gaps or relieve heavy loads in the opposite direction, to restore ideal conditions when a previous service intervention had been used on a bus, or to adjust the schedule of a late driver.

Location	Service Restoration Action	Description
	Extending trip	This intervention may be used on routes with scheduled short turns. Extending a scheduled short turn fills in a gap on the outer segment of the route.
	Modifying trip	This intervention is used to change the destination of a trip on a route with branches or to switch deadheads to revenue service.

With the strategies and intervention methods identified, the report attempts to formalize how the service controller should choose the appropriate service management strategy and interventions appropriate to the route condition in question. Four guiding constraints are considered:

1. Demand – The controller should ensure that the service provided (i.e. the supply) matches the demand for that route. This is performed by producing loading diagrams for the time of day in question. When high peak loads exist at certain points, the controller may need to short-turn buses to meet these peaks.
2. Running Times – Congestion causes significant delays to buses and can cause severe service disruptions. However, controllers can use historical data to modify the scheduled run times to reflect reality. Routes which have congestion in spots may have irregular headways over the congested section; however, these sometimes correct themselves (what the authors term the "accordion effect"). The service controller must know how each individual route responds to congestion in order to make the most informed decision possible.
3. Topography – The controller must be aware of possible points for short-turns. If none exist, it is impossible to short-turn a route. Possible detours for deadheads and expresses should also be investigated in order to react to adverse situations. If the route shares a trunk section with other routes it may be possible to take advantage of the other common routes during service interventions. The trunk section becomes less important for the route with the delay as the other routes could pick up the load. Short-turns are likely to be more effective on longer routes than shorter routes since they may not make up much time on short routes.
4. Route Attributes – The controller must always keep in mind the constraints present on each route, such as: garage location(s), the number of buses run on the route (fewer buses mean less possibility of performing service interventions), the location of relief points, and staffing attributes.

Froloff et al. concluded that best practices for service management cannot be simplified to an off-the-shelf solution. Each situation has unique constraints and sometimes conflicting objectives that need to be met.

It is up to the controller to act according to his or her best knowledge when planning service interventions. They anticipated that the job of the controller would evolve into the role of a technician, as the technology at his or her disposal continues to improve.

Koffman (1978) ran computer simulations to assess effective control interventions for dealing with bus bunching, including holding, expressing (using various thresholds to determine when expressing was necessary), and using signal priority for buses trying to close large gaps. Holding was found to increase both passenger travel times and bus travel times, while expressing was found to reduce them, at the expense of increased overall passenger wait times. As econometric demand analyses (Small and Verhoef, 2007) have shown that wait time is valued more highly than in-vehicle time, the reader was led to conclude that a high threshold for expressing or a conservative use of holding would be the most effective way of balancing speed with wait time.

Rahbee (2001) analyzed high frequency rail line performance and control in the context of the MBTA's (Massachusetts Bay Transportation Authority) Red Line in Boston. He grouped service delivery problems into three categories, and proposed ways of dealing with them. The service delivery problems are:

1. The customer's needs are not met;
2. The service provider's needs are not met; and
3. A lack of clearly defined objectives and constraints for service controllers.

By analyzing a combination of passenger loads, observed headways, and the way controllers dealt with common issues on the line, Rahbee was able to make recommendations as to how to improve service for passengers, make improvements to the operations plan, and suggest new intervention methods for service controllers to make the service more reliable. It is important to note that his suggestions were specific to the Red Line, but while they may not be directly applicable elsewhere, lessons can definitely be gleaned from the methodology he used to arrive at his recommendations.

Carrel (2009) analyzed the service control decision environment for the Central Line on the London Underground. While the rail operational environment has significant differences from the bus operational environment (rail systems are relatively isolated), Carrel makes many points that are applicable to both. He expanded the service delivery environment developed by the RATP and makes it analogous to a business process, as shown in Figure 2-5, where a set of inputs at each level leads to the development of a plan. The plan is then implemented at a lower level, and feedback from the lower levels (such as passenger surveys and service metrics) provides information to the higher level decision makers on how to modify the service delivery plan to optimize the service provided.

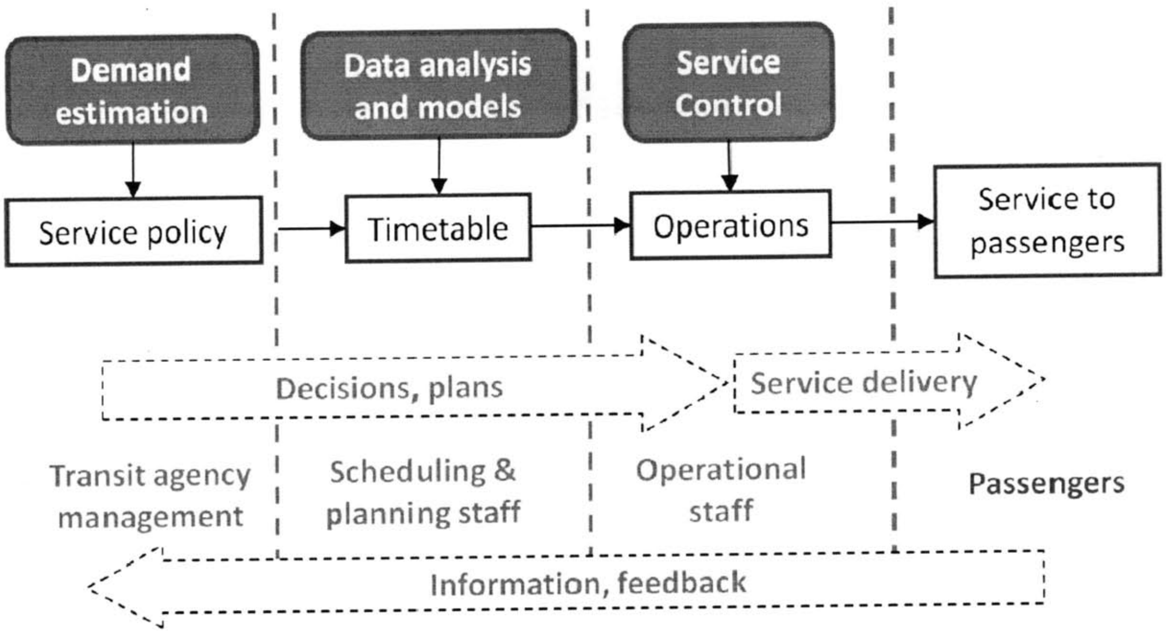

Figure 2-5 - Service Delivery as a Business Process

Carrel developed a formalized service control decision environment, and tested his assumptions by simulating the effect of certain control interventions on the Central Line. This would be very difficult to do for a bus network, since bus operations are considerably more dependent on the environment in which the route operates (background traffic/congestion, weather, etc.).

Controllers are required to respond to disruptions in real-time. This puts a lot of pressure on them during peak hours, or during severe disruptions. They therefore may not have the time to think through all possible interventions and their respective consequences. During off-peak hours, and for minor, isolated incidents, their thought process may be easier and more measured. Additionally, since there is no formalized method of dealing with each unique problem, there is no "right" solution. However, Carrel noted that service controllers make decisions based on several primary objectives, which assume that the scheduled timetable represents the optimal operating environment:

- Maximizing the number of scheduled trips operated; and
- Minimizing the overall lateness of the network.

He identifies additional constraints that controllers are faced with, the most notable being the interaction between crew scheduling and operations. Train operators are only allowed to work a certain number of hours per day and are entitled to mid-shift meal breaks (similar to bus drivers in London). This poses challenges when dealing with service interventions, as the preferred intervention may break some of the work rules of train operators. If this is the case, an alternate solution will need to be developed. Carrel proceeds to develop methods of quantifying service control interventions. The first method is purely analyzing them at an aggregate level, such as enumerating the number and type of interventions on a daily basis. This can be broken down into timebands, which is useful since it can test the RATP's assumption that controllers use different interventions based on the most pressing concerns at the time of day the disruption takes place. The route under analysis may also be broken down into sections, and a comparison of the scheduled number of trips versus the observed number of trips carried out, and expressed as a percentage similar to the Lost Mileage metric used in London Buses[2].

He also attempts to quantify the effects of specific service control interventions on passengers. To do this, he matches train locations with Oyster transactions to determine the Reliability Buffer Time (RBT) proposed by Uniman (2009) and Chan (2007), which was discussed previously. This framework for measuring the impacts of interventions on passengers may also be applied on the bus network, since methods for linking Oyster data with iBus data to determine passenger origins and destinations have recently been developed.

He concludes by recommending ways that the Underground could better monitor service quality and make the service controller's job more effective. These include improvements in the way data are collected and stored (moving away from manual data collection and manually matching different data sources), integrating the crew schedule with the operations schedule, and improving the interface of the service controller's workstation.

In the context of the bus network, the author has observed all of the issues and constraints mentioned by Carrel when visiting control centers and analyzing data. While performing an accurate simulation for a bus route may be impossible without collecting traffic flows, pedestrian flows, signal timings, and reconstructing the entire route, it may still be possible to identify and reconstruct service interventions on the bus network. London Buses is currently running a trial where reasons for trip cancellations are identified in their AVL database. Combining this information (the reason why a scheduled trip does not appear in the observed data) with knowledge about each vehicle's physical location in time and space will enable the analyst to identify short turns, expresses, and buses taken out of service, from which the relative effects of each kind of service intervention can be measured. This would aid in developing best practices guidelines for bus service control.

[2] Lost Mileage is defined in Chapter 4.

2.5 AVL Case Study: Portland, Oregon, USA

Tri-Met in Portland, Oregon, USA, has performed a considerable amount of research into using their bus AVL system to improve scheduling, operations, and service reliability. To give a sense of the totality of benefits provided by automated data sources, this section summarizes studies performed using this system of relevance to the three main areas of focus of this thesis.

The Bus Dispatching System (BDS), which includes Tri-Met's AVL, also has radio capabilities, on-board displays for operators indicating schedule adherence, text messaging between operators and dispatchers, APC equipment, and a dispatching center. The BDS system has been adept at better informing managers about current route operations. Decision makers and analysts now have actual data to support claims about service and performance as opposed to relying on hearsay. Prior to the implementation of AVL, Tri-Met only used on-time performance to evaluate service delivery. With new data available as a result of AVL, they have been able to analyze a range of new metrics, including headway variance, travel time variance, skipped stops due to crowding, and EWT (Callas et al., 1999).

Service Reliability

Tri-Met compared service reliability pre-AVL with service reliability after the AVL rollout (Callas et al., 1999). Special attention was paid to changes in on-time performance, headway distributions, and run time distributions. In order to compare reliability across routes in the network, two metrics were developed, the Headway Ratio and the Run Time Ratio, as shown in Equations 2-7 and 2-8, respectively. These metrics provide an easy-to-understand indication of how observed performance compares to scheduled performance. Values that are closest to 1 indicate good performance.

Headway Ratio (HR) = (Observed Headway / Scheduled Headway) (Equation 2-7)

Run Time Ratio (RTR) = (Observed Run Time / Scheduled Run Time) (Equation 2-8)

A sample of 8 routes was selected for analysis. When compared to the pre-AVL operating environment, on-time performance increased by 9.4%. It was observed that service generally deteriorates during the AM peak, which has residual effects on reliability during the midday and the PM peak. Service is generally restored to normal by the evening. This indicates that additional steps need to be taken to ensure controller interventions occur as early as possible. The COV (coefficient of variation) of headways was reduced by 5%, with the largest reduction in the PM peak. There were no changes in run times; however the COV of run times decreased significantly, indicating more consistent service. Bus bunching was also declined significantly, due to the ability of service controllers to better manage headways.

Scheduling

Tri-Met designed their AVL system to be able to collect stop-level information about bus service. One application of this capability is using AVL data to improve scheduling. In the past, bus monitoring was conducted manually, with surveyors monitoring buses at key points along a line. AVL enabled Tri-Met to collect run-time data for virtually all bus trips. A distribution of run times was built, and compared to the operations plan. Portland's accepted method of scheduling is setting the scheduled run time to be the mean or median travel time, and the recovery time to be the difference between the 95th percentile run time and the scheduled run time. Results employing this method by using AVL data were compared to the current schedule, and results showed that system efficiency could be improved using AVL data to set more realistic run times, saving the system about $6-8 million annually. For Portland, recovery time could be reduced using this method, resulting in these substantial one-time savings. However, a system may not always select the optimal recovery time as it prevents the running of "clean" (or "clockface") schedules, where all trips start on at least a 5-minute mark (Callas et al., 2004).

The authors conclude that these new data sources are improving system efficiency and on-time performance. On-time performance in January of 2004, typically a poor month for reliability due to weather, was 82.4%, considerably higher than the system standard of 75%.

Service Control

The BDS system has provided service controllers with additional data to make more informed decisions. Bus drivers are now also aware of their individual schedule adherence via displays mounted in the driving console of each bus. Since both drivers and service controllers are aware of bus performance in real time, it is generally expected that service disruptions have been resolved faster, resulting in smoother operations (Callas et al., 2001).

A least squares model was developed to model the relationship between headway variation and bus passenger loading using Tri-Met's AVL/APC data (Callas et al., 2003). Results indicated that variability in headways cause cases of extreme passenger loading. Therefore, controllers need to be aware of methods to ensure that headways are maintained as evenly as possible. In particular, it was noted that even headways leaving the route origin will create the most even loads downstream.

Summary

Portland has been able to use their AVL system to develop more robust measures of service reliability, improved methods of operations planning, and improved ways of disseminating real time information to service controllers. These improved capabilities have resulted in measurable benefits for the bus network, providing an impetus for other transit properties with AVL installations to perform similar analyses. This thesis will, in part, analyze the AVL system used on the London bus network in a similar fashion.

2.6 Summary of Prior Work/Applicability to Current Study

This chapter has introduced the main concepts of relevance to this thesis. In particular, concepts presented were categorized into three main subject areas: service reliability, operations planning, and service control.

The first subject area pertains to service reliability. Classical measures of service reliability, such as wait time and Excess Wait Time, were defined, as well as more recent measures of service reliability, such as Journey Time, Excess Journey Time, and Reliability Buffer Time, which are the product of recent trends focusing on passenger-centric measures of reliability based on large datasets. These new measures attempt to capture the overall passenger experience (from origin to destination), as well as the range of passenger experiences (as opposed to the mean value).

Both EJT and RBT were developed in the context of a fully gated rail system, where Journey Time could easily be measured from AFC data. This is less trivial for bus networks, as precise passenger arrivals at bus stops cannot be measured, and must be estimated based on observed headways and assumptions about passenger arrival distributions. Research pertaining to service reliability in this thesis will employ similar measures to the ones presented in this section; however, different data sources will be used to develop these measures, reflecting the different environment in which buses operate.

The second subject area pertains to operations planning, with a specific focus on schedule development. Scheduling methods for both high frequency and low frequency services were discussed. Regardless of route characteristics, this literature survey has shown that an accepted method for scheduling running time is to analyze the observed running time distributions, taking into account the individual operating constraints of each route, and perform an optimization to maximize the use of operator resources. Research in this thesis will analyze observed running time distributions from AVL data. The references in this review, along with the analysis presented in Chapter 6, should provide a comprehensive framework for an agency looking to define scheduling best practices.

The third subject area discussed pertains to service control. The objective of presenting this subject area was slightly different than the previous two subject areas, as this thesis will not focus on analyzing current service control practices and developing recommendations for service control best practices. Instead, this section was meant to provide the reader with sufficient background information to apply best practices observed in the industry towards developing their own best practices with the improved capabilities of AVL systems. Measures introduced in the previous two subject areas may be employed towards monitoring and assessing the current state of an agency's service control practices.

A summary of studies performed using the AVL system installed on the Portland (Oregon) bus network was provided as an example of comprehensive analyses that may be performed on any AVL installation. These studies showed the wide range of practical implications such installations provide, and presented an impetus for analyzing even larger scale AVL installations, as is the intent of this thesis, to see whether a similar level of data analysis is possible.

3 Bus Service in London

This chapter introduces the organizations responsible for and arrangements for delivering bus service in London. Section 3.1 describes Transport for London (TfL), the agency responsible for planning and monitoring all public transport services in London, and London Buses, its subsidiary. Section 3.2 describes the iBus AVL system, including London Buses' motivation to deploy this new AVL system.

3.1 Transport for London and London Buses

Transport for London is responsible for managing numerous modes of transportation in London, including the bus network, the London Underground, Docklands Light Railway, London Overground, London Trams, London River Services, Victoria Coach Station, and Taxis. In addition, TfL manages 580 km of roads within London, as well as 6000 traffic lights (TfL, 2009d). TfL is also responsible for the Oyster smartcard, which is used for the great majority of fare payments on the network.

TfL is run by the Greater London Authority, a body whose responsibilities include setting the transportation strategy for metropolitan London. The Authority consists of the Mayor and the 25 member Assembly. The Mayor is responsible for developing a transportation strategy for London as well as setting TfL's budget, subject to approval by the Assembly. He is also responsible for developing the fare structure, for having a say in how commuter rail operations are handled, and for allocating funds for system expansion. The Assembly acts as a watchdog over the Mayor's activities to ensure that they are meeting the best interest of Londoners (Greater London Authority, 2010).

3.1.1 Congestion Charging

One of the major policies that has shaped the London transportation network over the past decade was the introduction of congestion charging in 2003. At the beginning of the decade, central London was experiencing some of the worst congestion in Europe, causing major disruptions to the area. Ken Livingstone, the Mayor at the time, proposed introducing a congestion charge for any vehicle entering central London during business hours as a way of mitigating traffic in the area. The congestion charging zone was introduced in 2003, expanded to the west in 2007, but that expansion will be withdrawn by 2010 (TfL, 2009a). Figure 3-1 shows the current setup of the congestion charging zone, including the western extension (TfL, 2010b).

Any vehicle entering the Congestion Charging Zone (CCZ) on weekdays between 7 AM and 6 PM is required to pay £8. Vehicles are monitored by cameras at every entrance and exit to the zone. The revenue from this project is required to be reinvested towards improving the London transportation network (TfL, 2009a).

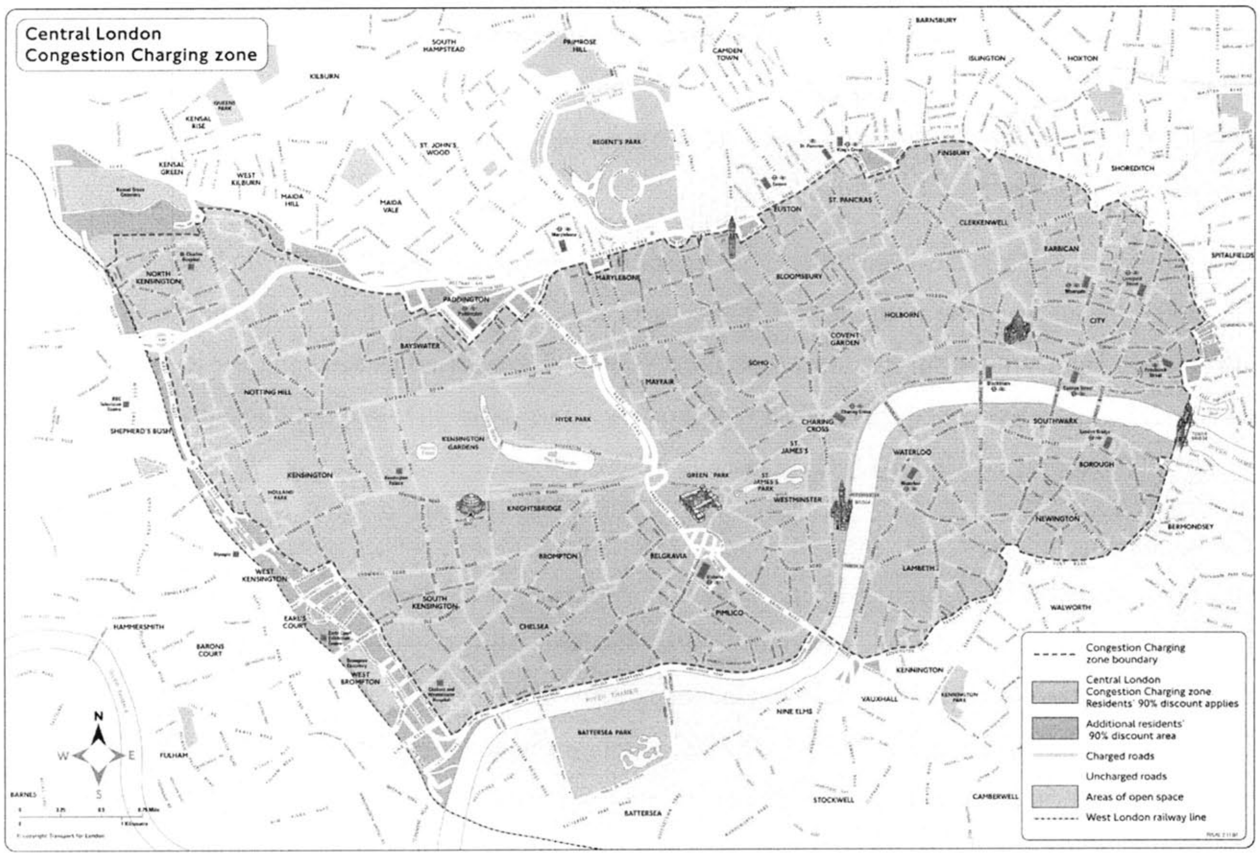

Figure 3-1 - Central London Congestion Charging Zone

Since a significant mode shift from automobiles to public transit was anticipated due to the implementation of this scheme, it was crucial to ensure that the new arrangement could still provide sufficient capacity for the demand entering and exiting the zone. With the Underground network at capacity, TfL focused its efforts on expanding the capacity of the bus network, since buses would be driving on less congested streets than before. Significant bus fleet expansions, as well as increased bus priority measures, were therefore introduced simultaneously with the opening of the CCZ.

The net result has been a 21% decrease (70,000 vehicles) in the daily number of vehicles entering the zone, while the bus network has experienced a 6% increase in ridership during congestion charging hours (TfL, 2009a).

3.1.2 Oyster Card

The Oyster Card is a contactless smartcard used to pay fares on TfL's network, including the National Rail network as of 2010. Introduced in 2003, it has greatly simplified fare payments from the passenger's perspective. Passengers without travelcards (annual, monthly, or weekly unlimited use passes) used to have to pay the exact point-to-point cash fare before entering the system. With the Oyster Card, it is possible to load the card with a cash value and have the system automatically calculate and deduct the appropriate fare. Oyster cards also have daily price capping mechanisms, meaning a rider who uses the system frequently on one day will effectively be charged slightly less than the previously available one-day pass (TfL, 2009c).

The Oyster penetration rate exceeds 80% of all transactions on the network and 86% of all bus journeys (TfL, 2009b), with the majority of the non-Oyster users being National Rail travelcard holders. However, with the introduction of Oyster Pay As You Go (PAYG) on National Rail in 2010, the Oyster penetration rate is anticipated to rise even further. Over 6 million Oyster cards are in use in London and on an average weekday, TfL records 10 million Oyster transactions (TfL, 2009c).

In addition to the passenger benefits provided by Oyster, the card has greatly expanded TfL's data collection and analysis capabilities. Every Oyster tap on the network, whether it is at a rail station gateline or at a bus farebox, is recorded and saved in a central database. This provides analysts with invaluable information such as ridership and origin/destination patterns on the various modes in TfL's network. Since most rail stations are gated, and since PAYG users are required to tap in and out of the system to ensure the proper fare is deducted, Underground origin/destination patterns are directly measurable from the Oyster database. On buses, the passenger only taps into the system, requiring Oyster transactions to be chained and matched with iBus AVL data to infer origins and destinations for each passenger. For an explanation of this procedure, the reader is referred to Wang (2010).

3.1.3 London Buses

The red Routemaster double decker bus is an instantly recognizable icon of London, and has been the face of London Buses for the last half of the 20th century. While the majority of the Routemaster fleet has been retired, buses still form an essential component of London's transit network. This section will present an overview of the history of the London bus network, including a description of the evolution of the public agency's responsibilities and the evolution of the bus contracting process in London.

The London bus network consists of over 700 routes run by about 20 different private operators and managed by London Buses. 100 of these routes run 24 hours a day (TfL, 2009b). There are approximately 8000 buses serving the London area, assigned to one of approximately 90 garages run by the private operators. The network is quite complex, with many corridors being served by multiple routes. As an example, a spider map of bus routes serving Oxford Circus, a major destination in Central London, is shown in Figure 3-2 (TfL, 2010a).

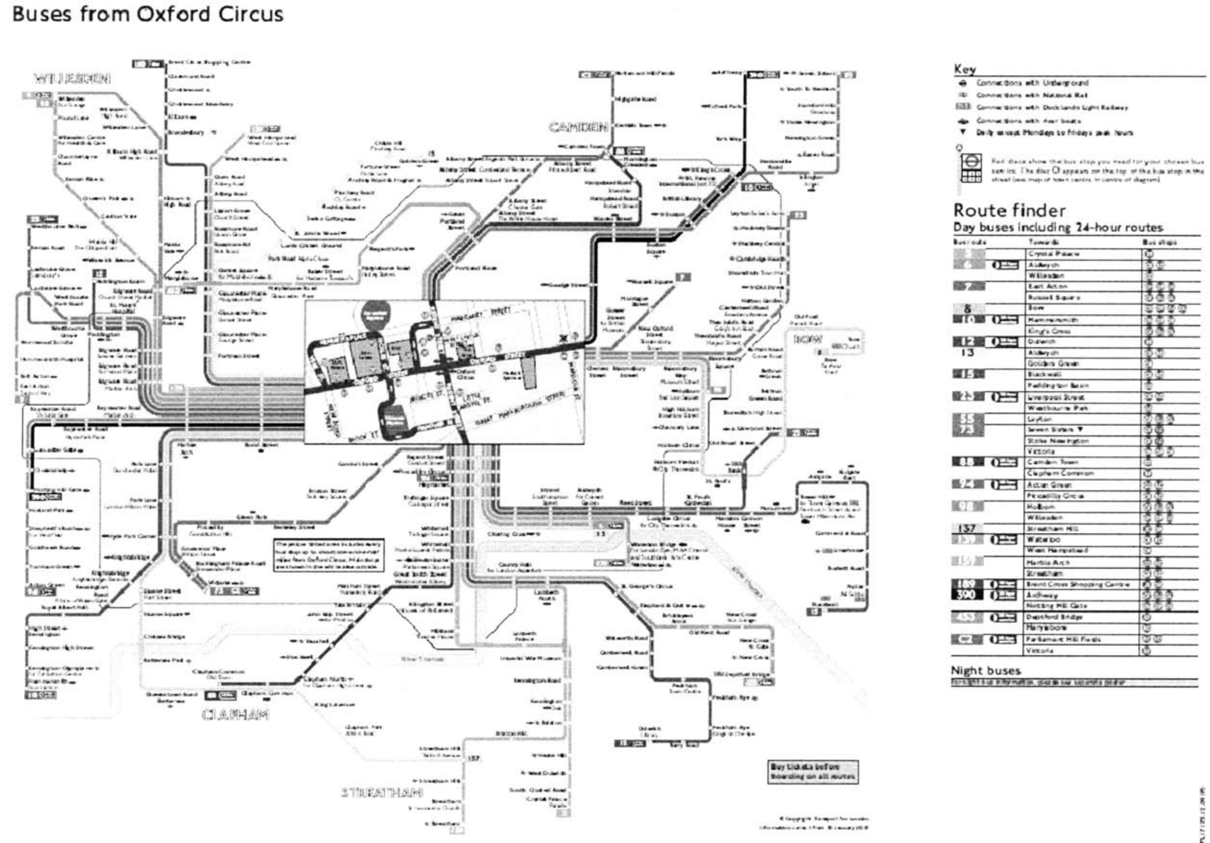

Figure 3-2 - Oxford Circus Bus Routes

London Buses were publicly run from the 1930s to 1986. London Transport, which was controlled by the Greater London Council from 1970 to 1984, was responsible for bus operations, which were provided via government subsidies. London Transport was broken up in 1985 in anticipation of deregulation. Bus operations were controlled by London Buses Limited, and contract tendering was carried out by the Tendered Bus Division. This structure remained in place until there were no longer any publicly run routes, at which point operations was dissolved.

When TfL was created in 2001, the bus division, now called London Bus Services Limited (London Buses) was assigned to the Surface Transport division of TfL. London Buses current responsibilities include route planning, contract tendering, service quality monitoring, and support services such as providing bus stations and shelters. An organizational chart of London Buses is shown in Figure 3-3, adapted from the Surface Transport Organization Chart (TfL, 2009e).

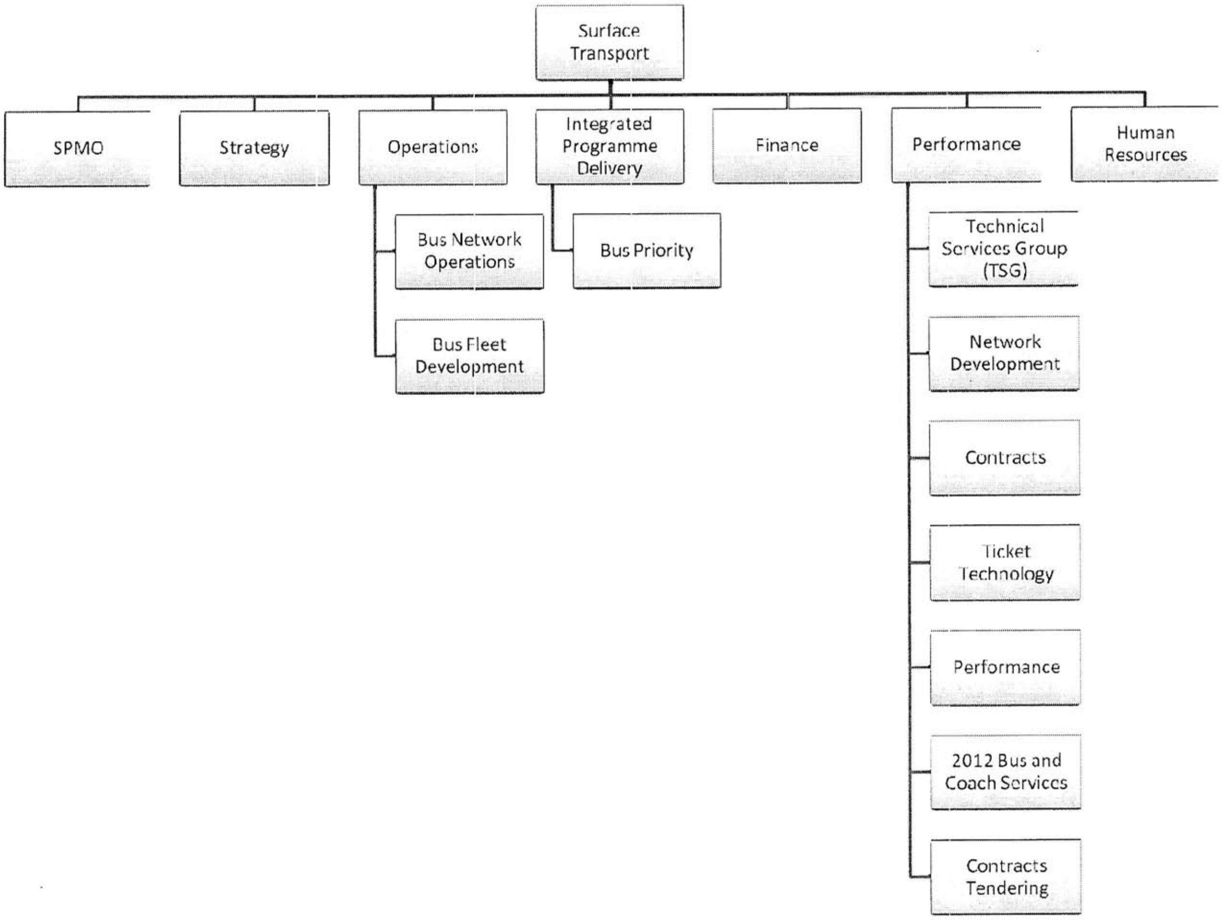

Figure 3-3 - London Buses Organizational Chart

When London's bus operations were privatized in 1986, at approximately the same time that bus operations in the rest of the United Kingdom were deregulated, London was exempted from complete deregulation. London was subsequently able to maintain control over the planning and tendering of bus routes (TfL, 2008).

Prior to privatization, London Transport split its bus operations into 13 geographically distinct subsidiary operators, which had to compete with private operators for the right to run bus services. Initially, 40% of contracts were awarded to private operators, with that number increasing over time. Currently, with the sale of East Thames Buses in 2009, no bus operations in London are publicly operated.

The first type of contract structure introduced, Gross Cost Contracts, lasted from the beginning of privatization in 1985 to 2000. Operators submitted bids to London Transport which took into account all aspects of service operations, such as vehicle and staffing costs. Contracts tendered were for variable lengths, in order to ensure that the entire network did not have to be retendered simultaneously. With this contract structure, operators were paid a lump sum for the operations and revenues were kept by London Transport (TfL, 2008).

Since the initial goal of privatization was to transfer risk from the public sector to the private sector, contracts were refined in 1995 with the introduction of Net Cost Contracts. With these contracts, operators kept the revenue generated by their own operations and bid the projected net cost (total cost minus projected revenues). Besides the transfer of risk, an initial perceived benefit of these contracts would be that services would improve, as operators would have an incentive to run more frequent and reliable services in order to earn additional revenue.

Net cost and gross cost contracts were not set up to penalize operators directly for not running scheduled services nor were they able to reward or penalize operators for running a reliable service. Operators therefore had few financial incentives to improve services, to the detriment of the riding public. It was in this context that Quality Incentive Contracts (QIC) were introduced in 2001, by what by this point had become TfL. QICs, which are still in use today, provide financial incentives related to the quality of service an operator runs. Quality of service is measured by two main metrics, Excess Waiting Time (EWT) and Percent Lost Mileage, both of which will be explained in subsequent sections. Each route has a benchmark metric that operators are required to meet, and they are further rewarded for going above and beyond the minimum benchmark. TfL once again is responsible for collecting all fares via fare machines installed on all buses, and they still keep all the revenue. These have historically been high incentive/penalty payments that clearly influence the management of the contracts (London Assembly, 2006).

Performance is measured on a TfL-defined period basis. The fiscal year, which starts in April, is comprised of 13 (approximately) 4 week long periods. At the end of each period, each operator is ranked based on a number of performance metrics. Bonus and penalty payments are based on an incremental scale (0.10 minute change in EWT for high frequency routes). The maximum bonus is 15% of the contract price while the maximum penalty is 10% of the contract price. Operators are paid 75% of the contract during each period, and incentives and deductions are paid annually (TfL, 2008).

QICs are tendered for a period of 5 years, with an automatic extension for another 2 years if the operator has met an "Extension Threshold" as defined in the contract. The contracts tendered are staggered, resulting in about 20% of the network being retendered each year. Within the QIC framework, London Buses maintains responsibility for planning, tendering, and monitoring bus services, although due to the nature of QICs, this has become a more complex and "high stakes" process (TfL, 2008).

As of 2008, QICs have been expanded to account for more than just service reliability. The next generation, called QIC2, also looks at the quality of the service, in terms of operator behavior and bus cleanliness measured through mystery traveler surveys and periodic inspections of vehicles at terminals.

When a route is tendered, London Buses specifies the following (TfL, 2008):

- The physical route;
- The bus frequency;
- The type and capacity of vehicle operated; and
- The minimum performance standards, expressed via EWT and Percent Lost Mileage.

Operators are then asked to submit bids to operate each route. London Buses evaluates each bid based on, but not limited to, the price, the operator's track record, the feasibility of the schedule, the equipment operators have or may potentially be able to acquire, and health and safety concerns. Operators are responsible for setting the actual vehicle and crew schedules (with the timetable subject to TfL's approval), buying and maintaining the buses, and providing controllers to manage the routes.

3.2 iBus and AVL on London Buses

iBus, an AVL system owned by Trapeze Software Incorporated, has recently been installed on all buses in London, replacing the legacy AVL system, a Band III radio system, which had been used on the majority of the network since 1996. The history of AVL on London Buses, including the reasons why the Band III system had to be replaced and the expanded capabilities of iBus, is summarized in this section.

When conceived of and installed in the 1980's, the Band III radio system was meant to provide voice and emergency communications on what was then a network of 5000 buses. Controllers were able to contact drivers and initiate responses to emergencies, known as code red. At the time, there was no way to visually track the locations of all vehicles in real time. Once AVL technology started being developed, London Buses became interested in seeing if it could be installed on a network of its size. However, at the time, no AVL system had been implemented on a network as large as the London Bus network, so in 1996 London Buses decided to use an ad hoc implementation by adapting the existing radio system for an anticipated fleet size of 6500 buses (TfL Surface Transport, 2009a).

The requirements for this system were constantly evolving as new uses for AVL were found. For example, it was found that it was possible to link the system with the ticket machines on board the buses. New uses for AVL were also found during system roll out as London Buses gained a greater understanding of how AVL works. Examples included finding ways of linking AVL to bus priority signals and traffic enforcement cameras. Optical sensors and odometer readings were used to determine vehicle location, and this information was transmitted to service controllers and to the real time bus arrival passenger information system signs known as Countdown. As this was a new technology being applied to a system not designed to handle it, London Buses had no way of knowing what the capacity of the system was or how long it would remain operational.

This system was replaced because it was determined that it was no longer suitable for the requirements of London Buses. When the legacy system was installed, the London bus network was significantly smaller than it is now. The introduction of the Central Congestion Charging Zone (CCZ) in 2003 and associated transit improvements greatly strained the capabilities of the legacy system since the expanded system (8000 buses) was larger than the design capacity of the AVL system. This strain increased the risk of a system-wide failure, which would have compromised the safety and operational capability of the bus network. A failure would have prevented emergency calls from being transmitted, prevented service controllers from carrying out their duties, and shut down the Countdown signs. London Buses had no choice but to conclude that the legacy system had reached the end of its useful life.

A business case for a new AVL system was developed by London Buses in 2003 to meet the following requirements (TfL Surface Transport, 2009a):

- A "Code Red" emergency system;
- Service control workstations;
- Performance monitoring capabilities;
- Data storage capabilities;
- Real time passenger information technology; and
- The ability for the new technology to be integrated with other systems used by TfL.

Anticipated benefits of the system included a reduction in system wide EWT and an increase in passenger willingness to pay due to improved passenger information. A discussion of whether a reduction of EWT was realized is discussed in Chapter 4.

Realized benefits from the system included (TfL Surface Transport, 2009a):

- An increase in observed call volumes on the radio system;
- More accurate Countdown sign predictions;
- Improved customer satisfaction due to better passenger information (such as on-board audiovisual stop announcements);
- A higher percentage of buses displayed on service controller workstations; and

- More accurate data available for analysis since data collection has shifted from manual surveyors to automated data collection.

Network-wide installation of iBus commenced in 2007 with tests on a trial operator and was completed in spring of 2009. A total of 8260 vehicles were fitted with iBus and 22,992 drivers and 1213 service controllers were trained to use the new system. The system cost £117 million to implement (TfL, 2009b).

iBus uses GPS to monitor the locations of buses on the network, in contrast to the legacy system which used optical sensors combined with odometer readings. This enables iBus to more precisely pinpoint the locations of buses, as a bus on the legacy system that was diverted off the normal route path may have been erroneously displayed as being en route on a service controller's workstation.

Along with enough capacity to handle the current fleet size, iBus has additional functionality compared with the legacy AVL system. Whereas the legacy system was incapable of handling data transmission, data indicating bus location is now stored on bus and is transferred to a central database with iBus. This enables London Buses to keep track of all buses in the system at all times, to save these data, and to develop reports based on historical performance.

The iBus system makes a record for every bus entering and leaving a stop, known respectively as the observed arrival time and the observed departure time. A bus enters a stop 50 m upstream of the signpost indicating the stop and leaves the stop 30 m downstream of the signpost. A record is also made when a bus opens and closes its doors at the stop. As a driver may open and close doors multiple times a stop, what is actually recorded in these timestamps is somewhat unclear. The timestamps do not specify whether a bus has actually stopped at the stop or has just passed through.

The most visible impacts of iBus are those that relate to passenger amenities. All buses are now fitted with an automated audiovisual stop announcement system. Announcements are triggered based on the location of the bus as determined by iBus. Predictions at Countdown signs, installed at key bus stops to provide real-time bus arrival information indicating when the next bus for routes stopping at any given stop will arrive, have also improved (TfL Surface Transport, 2009a).

Service controllers have been provided with improved functionality. The iBus system enables them to keep track of every bus on a route or corridor, and to make the appropriate service control interventions using Windows-based software integrated with GIS and radio management tools. This includes, but is not limited to, modifying vehicle run numbers, maintaining direct contact with drivers, setting up curtailments and diversions, and ensuring that buses on a route are evenly spaced to maintain consistent headways. The availability of buses on the garage workstations is now 95% network-wide, compared with ~90% for the legacy system.

Numerous roadside controllers were required to supplement the old AVL system. Some routes were dispatched primarily with roadside controllers, while others were controlled from a central location. While roadside controllers are still necessary with the iBus system to monitor and dispatch drivers (e.g. making sure they are wearing uniforms), dispatching may be performed via the controller interface at the control center.

The service controller's workstation interface, called Vicos-Lio, is installed on every computer used for service control on the network, at all private operators' bus garages (approximately 90), and at London Buses' office at Trinity Park. Bus routes may be visualized using this interface either as line diagrams, not to scale, or on a scaled, GPS-based network map. A single workstation may handle multiple bus routes, and controllers generally monitor 3-5 routes. Each route is shown on a separate display with buses color coded based on their schedule adherence.

4 Factors Affecting Service Reliability

Before new measures of service reliability are introduced, it is necessary to gain an understanding of what causes service to be reliable or unreliable. Service providers generally have notions of why service is reliable or unreliable; however, they rarely include a formal analysis that validates their suspicions. This chapter will identify the major factors affecting service reliability, and provide a framework for an analysis of their influence on reliability. The objective is to model reliability as a function of the various factors believed to influence it. While the data available are not extensive enough to develop the ideal model, this analysis will at the very least produce a better understanding of the environment in which transit services are operated and its influence on reliability.

This chapter will use the London bus network as a case study to investigate factors affecting service reliability. Section 4.1 will present the service reliability measures currently employed by London Buses. Section 4.2 analyzes the trends in service reliability observed in London over the past decade. A discussion of what are believed to be major factors affecting service reliability will be presented in Section 4.3. A statistical analysis of these trends with respect to measures of service reliability, and a regression analysis where service reliability is modeled as a function of the factors believed to influence it is developed in Section 4.4. Finally, Section 4.5 will summarize the results of this chapter.

4.1 Reliability Measures Used by London Buses

This section summarizes the service reliability measures that London Buses uses to monitor route and operator performance. Some of these measures were introduced in the literature review in Chapter 2, as they have been applied elsewhere. The focus of this section, however, is to discuss specifically how London Buses calculates these measures, and what the benefits and limitations of these measures are from London's perspective. The measures include Excess Waiting Time (EWT) for high frequency[3] routes, Percent On-Time for low frequency[4] routes, and Percent Lost Mileage. While Percent On-Time will be discussed in order to provide a comprehensive picture of the London bus network, most of the analysis in this thesis will focus on high frequency routes, as they make up over 80% of operations on the London bus network.

Quality of Service Indicators (QSI) are standards used by London Buses to measure the performance and reliability of its bus operators using field data observations. There are approximately 200 "QSI points" on

[3] High frequency routes have headways of 12 minutes or less (5 or more buses per hour). Passengers on high frequency routes are assumed to arrive randomly, as the service arrives often enough that passengers do not need to consult a schedule before heading to the bus stop.
[4] Low frequency routes have headways of 15 minutes or more (4 or fewer buses per hour). Passenger arrivals are not assumed to be random, as passengers are assumed to use schedules to decide when to arrive at the bus stop, in order to minimize wait time.

the bus network, each of which is surveyed 16 times over a 12 week period, providing a 6% sample of bus trips. A major issue with such a small sample size is that many incidents that would have detrimental effects on the QSIs are not captured, and those that are captured have a disproportionate influence. As soon as TfL has full confidence in the accuracy of its new AVL iBus data, it is expected that QSI data will be extracted from the iBus system, enabling nearly a 100% sample of data to be collected. The two QSIs of concern to this research are Excess Waiting Time, the main measure currently used to gauge service reliability, and Percent Lost Mileage.

4.1.1 Excess Waiting Time

EWT is used to assess the service reliability of high frequency routes, on which passengers are assumed to arrive randomly at stops, as these routes run frequently enough that passengers do not need to check the schedule. Passengers on these routes are most concerned with the regularity of service; they do not expect to wait longer than the scheduled headway of the route. EWT therefore measures the regularity of service for high frequency routes and is calculated as follows:

$$EWT = AWT - SWT \qquad \text{(Equation 4-1)}$$

AWT is the Actual (observed) Waiting Time and SWT is the Scheduled Waiting Time. SWT is based on the scheduled headway, while AWT is based on observed bus arrivals (departures). As shown in Chapter 2, waiting time is computed as follows:

$$WT = 0.5 * E[Headway] * (1 + COV_{Headway}^2) \qquad \text{(Equation 4-2)}$$

COV is the coefficient of variation of the headway (a measure of variability) and E[Headway] is the expected value, or average, of the headways. Note that the lower limit of waiting time is half the average headway, which occurs if the scheduled headways are perfectly even. The actual waiting time is generally higher than the average scheduled waiting time due to normal headway variation and the fact that a randomly arriving passenger is more likely to arrive during a long headway than during a short headway.

At London Buses, AWT and SWT, and by extension EWT, are calculated for every hour of service during the day. All headways completely contained by a clock hour, and the headway that straddles the end of the hour under analysis and the beginning of the next hour, are counted in the calculation. Each hourly datum used in the aggregate EWT measure is then scaled by a Passenger Journey (PJ) factor, representing the approximate system-wide ridership for that hour. PJ factors for FY 2005/2006 are listed below in Table 4-1 (TfL Surface Transport, 2009b). London Buses applies the same PJ ridership proportion factors for every route on the bus network.

Table 4-1 - Passenger Journey Factors for FY 2005/2006

	PJ Factor		
HOUR	**Mon-Fri**	**Sat**	**Sun**
00:00 - 01:00	0.0072	0.0185	0.0261
01:00 - 02:00	0.0028	0.0090	0.0144
02:00 - 03:00	0.0017	0.0089	0.0091
03:00 - 04:00	0.0016	0.0048	0.0099
04:00 - 05:00	0.0036	0.0040	0.0027
05:00 - 06:00	0.0080	0.0081	0.0062
06:00 - 07:00	0.0225	0.0165	0.0107
07:00 - 08:00	0.0575	0.0272	0.0213
08:00 - 09:00	0.0811	0.0378	0.0253
09:00 - 10:00	0.0622	0.0551	0.0408
10:00 - 11:00	0.0503	0.0635	0.0627
11:00 - 12:00	0.0520	0.0800	0.0569
12:00 - 13:00	0.0556	0.0724	0.0744
13:00 - 14:00	0.0574	0.0919	0.0787
14:00 - 15:00	0.0634	0.0786	0.0712
15:00 - 16:00	0.0815	0.0732	0.0711
16:00 - 17:00	0.0827	0.0689	0.0755
17:00 - 18:00	0.0827	0.0679	0.0771
18:00 - 19:00	0.0710	0.0574	0.0716
19:00 - 20:00	0.0504	0.0489	0.0514
20:00 - 21:00	0.0368	0.0400	0.0455
21:00 - 22:00	0.0277	0.0251	0.0371
22:00 - 23:00	0.0228	0.0229	0.0327
23:00 - 00:00	0.0174	0.0195	0.0276
Total	1.0000	1.0000	1.0000

Once hourly AWT and SWT are calculated, they are aggregated for higher level analyses. AWT is weighted by observed buses per hour (OBPH) and SWT is weighted by scheduled buses per hour (SBPH) to provide Weighted EWT, as shown in the following equation:

$$EWT_{Weighted} = \frac{\sum AWT_{Hourly} * OBPH}{\sum OBPH} - \frac{\sum SWT_{Hourly} * SBPH}{\sum SBPH}$$

(Equation 4-3)

Weighted EWT (hereafter referred to as EWT) is used to report aggregate data by route. Raw data is generally aggregated by route, garage, operator, period, quarter, and network. Performance incentives are calculated based on an operator's EWT performance, as described in Section 3.1.3.

EWT is currently measured manually by surveyors in the field at QSI points. Surveyor observations are uploaded to the Stabs database, a Microsoft Access based interface which is used to generate service reliability reports based on these data. With the introduction of iBus, however, London Buses aims to move to a fully automated system for measuring EWT. Since the intent of iBus is to measure nearly a 100% sample of observed trips, London Buses is expecting a more robust measurement of EWT in the near future.

It is unclear whether London Buses plans to continue measuring these data exclusively at QSI points, or whether they will realign the measurements based on the observed ridership patterns on these routes to more accurately reflect passenger demand. The merits of measuring EWT for major OD pairs versus the fixed QSI locations will be discussed in Chapter 5. An opinion shared by staff members at TfL is that bus controllers currently tailor their operations around QSI points as opposed to the actual passenger ridership patterns on the route, since performance incentives are awarded at QSI points. This is a concern when a major destination occurs following the last measured QSI point on a route. Buses may be short-turned or deadheaded before they reach this destination in order to improve performance at the earlier point, to the detriment of passengers later on the route.

4.1.2 Percent On-Time

Percent On-Time is a measure used to assess the service reliability of low frequency routes with non-random arrivals. Passengers on low frequency routes are concerned with the punctuality of the bus service. If the bus departs from a stop early, the passenger may not yet have arrived at the stop, and will miss the bus. As a consequence, bus operators in London face steep fines for early departures. If the bus arrives at the stop late, the passenger may be waiting a long time and perceive the service negatively. Bus departure times are therefore compared with their scheduled departure times to assess the punctuality of the route. The measure itself is the ratio of observed on-time buses to scheduled buses over the time period in question. In order to scale the sample for aggregate comparison across routes, data are weighted by scheduled buses per hour. Table 4-2 presents the various definitions of service reliability used for low frequency routes.

Table 4-2 - Definitions of Service Reliability on Low Frequency Bus Routes

On Time	Between 2 minutes early and 5 minutes late
Early	2.5 to 9 minutes early
Late	5 to 15 minutes late
Non-arrival	Greater than 9 minutes early or 15 minutes late

Since low frequency routes account for only 20% of scheduled mileage on the network, this thesis will concentrate on measures applicable to high frequency routes. However, some of the research, such as the run time analysis presented in Chapter 6, may also be applied to low frequency routes.

4.1.3 Percent Lost Mileage

Percent Lost Mileage is defined as the percent of scheduled route miles that were not run over the time period in question. When route miles are not run, operators are required to provide the reason, referred to as the cause code, for why they were not run. A listing of all cause codes currently used is shown in Table 4-3 including traffic, crew shortages, and maintenance issues (TfL Surface Transport, 2009b). These data are susceptible to reporting errors since operators are penalized for certain faults (such as staffing and maintenance issues) and not for others (such as traffic) and may therefore not be totally accurate about assigning cause codes for Lost Mileage.

Lost Mileage is currently recorded manually by the operators and manually inserted into a database at TfL. London Buses is currently testing a system whereby cause codes for missing data in the iBus database will be entered electronically by the operators in real-time, thereby minimizing the risk of human error in the current data collection methodology.

Lost Mileage is divided into two categories: Deductible and Non-Deductible. Deductible Lost Mileage involves situations where the operator was responsible for the cancellation of a whole or part trip, such as a mechanical breakdown or staffing shortage. Operators are penalized for the mileage lost in these situations. Non-Deductible Lost Mileage accounts for whole or part trip cancellations that are beyond the operator's control for which they are not penalized. The most common cause of non-deductible Lost Mileage is traffic congestion. Other non-deductible Lost Mileage causes relevant to this thesis include malfunctioning iBus units and driver error. Since TfL is responsible for the installation and upkeep of each iBus unit installed on the bus network, operators are not penalized for missing data when the iBus unit is malfunctioning. Driver error includes situations where the driver neglects to enter the proper trip information into the system (i.e. a login error), which results in null data entries in the iBus database for trips that were run.

Table 4-3 - Lost Mileage Cause Codes

Category	Cause		Detailed Cause	
Lost Deductible	ST	Staff	ST01	Absence / late / sickness
			ST02	Shortage of establishment
			ST03	Staff dispute
			ST04	Other
	MC	Mechanical	MC01	On-road breakdown
			MC02	No serviceable bus
			MC03	Defective wheelchair ramp
			MC04	Other
	OD	Other Deductible	OD00	iBus missing trip AUTOMATIC DEFAULT
			OD01	Staff error
			OD02	Defective radio
			OD03	Bus blocked in garage
			OD04	Other – incl reason unknown / in doubt
Lost Non-deductible	TR	Traffic	TR01	Traffic congestion
	ON	Other Non-deductible	ON01	Incident – reportable under LBSL incident reporting system
			ON02	Disaster – fundamental change to operation
			ON03	Road closed / blocked – bus diverted / turned
			ON04	Anti-social behaviour – service withdrawn
			ON05	LBSL agreed curtailed miles
			ON06	Other
Operated	OP	Operated	OP00	iBus validated trip AUTOMATIC DEFAULT
			OP01	Bus on in-service diversion
			OP02	Recovered mileage
			OP03	Driver error
			OP04	Bus data not downloaded
			OP05	iBus technical errors
Non-validated	NV	Non-validated	NV00	iBus non-validated trip AUTOMATIC DEFAULT

4.1.4 Other Measures of Reliability

TfL monitors and publishes additional measures of service reliability which are not used when assessing operator performance for contractual purposes. Additional measures calculated for high frequency routes include the Chance of Waiting Longer than 10 minutes and the percentage of Long Gaps (headways greater than 4 times the scheduled wait time).

Unlike EWT or Lost Mileage, these measures are for informational purposes only and have no bearing on incentive payments. TfL's rationale for measuring and publishing these measures is that they perceive them to be more easily understood by the public than EWT or Percent Lost Mileage. Reports ranking operators by these measures are regularly published on the public section of TfL's website, but besides the positive or negative press an operator receives from these reports, they have no financial bearing for TfL and the operators.

4.2 Trends in EWT over the Past Decade

An analysis of how EWT has fluctuated in recent years provides a starting point for determining which factors have affected service reliability, and how service reliability may respond to similar situations in the future. This section looks at trends in EWT from 1998 to 2009, endeavoring to explain major shifts in EWT as well as elucidating other trends, such as seasonality.

A long-held belief at London Buses has been that the introduction of Congestion Charging in 2003 resulted in a significant decrease in EWT, and therefore an improvement in service reliability. While the figures that will be presented in this section indicate a decrease during that time period, it may not be due to congestion charging alone. Concurrent with Congestion Charging, Quality Incentive Contracts were introduced, which may also have resulted in improved reliability.

Another motivation in analyzing EWT trends is determining whether the introduction of iBus from 2007 to 2009 resulted in an immediate, measurable improvement in service reliability. When presenting the business case for acquiring the iBus system, TfL believed that iBus would improve reliability, and the resultant time savings would be a windfall for passengers. As the results below indicate, this cannot be clearly demonstrated.

Figure 4-1 shows EWT by operator from 1998 to 2009. A clear downward (i.e. positive) trend in EWT has been observed over the past decade, as well as a significant decrease in the variance in EWT between operators. EWT has decreased from about 2 minutes in 1998 to about 1 minute in 2005, and has been stable since then, indicating a significant increase in service reliability in the first half of the decade. The most significant decrease was observed between 2002 and 2003. This may be attributed to two interlinked factors: the introduction of the Central London Congestion Charging zone and the introduction of Quality Incentive Contracts in the preceding year, which provided incentives for operators to improve service. Since then, however, EWT has remained relatively stable. This demonstrates that despite additional network or service control improvements, such as a new AVL system, EWT may have reached a lower limit in the current operating environment.

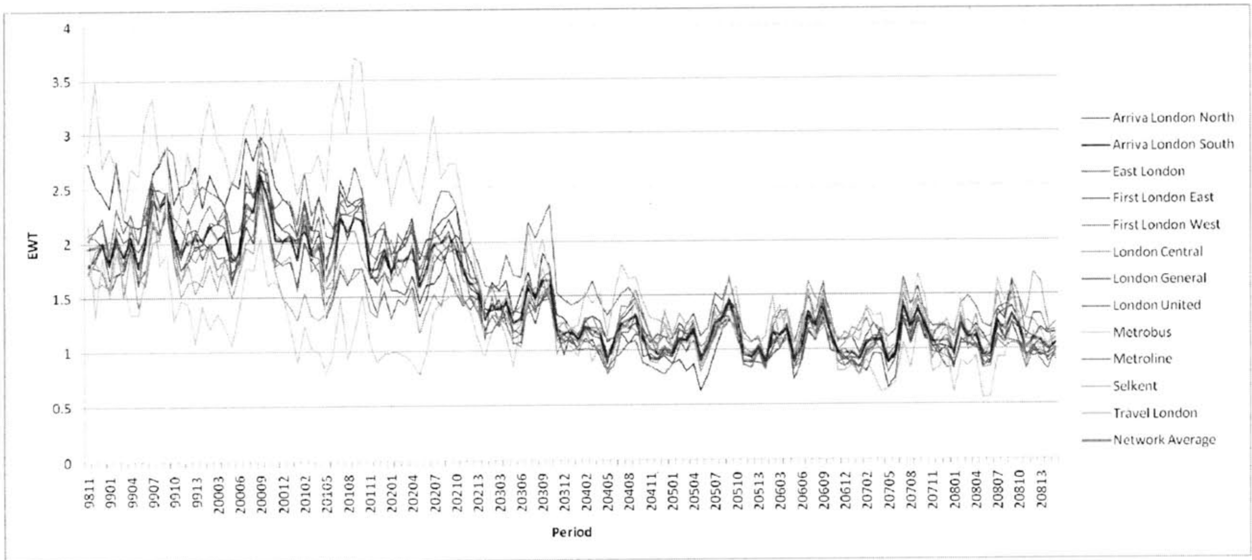

Figure 4-1 - EWT by Operator, 1998 - 2009[5]

Another trend of note is that the variability of EWT reduced from the first half of the decade to the second half. From 1998 to 2002, the most reliable operators had EWT values below 1.5 minutes, while the least reliable operators had EWT above 2.5 minutes. After 2002, the distribution of EWT values across operators tightened significantly. This may be due to the introduction of more incentive based contracts around this time, motivating poorly performing operators to improve their service reliability to be in line with their competitors.

Figure 4-2 shows the EWT by operator magnified from 2003-2009. A pattern resulting from seasonality effects is evident in this diagram, as peaks and valleys tend to occur during the same periods on an annual basis. Peaks tend to occur during high traffic periods (such as the beginning of the school year and the buildup to Christmas) and during months with poor weather conditions (such as the middle of the winter). Valleys occur during low traffic periods and seasons with milder weather conditions (such as during the summer or during school holidays). The yearly peak is generally around Periods 6 to 9 (September to December) due to the build-up of economic activity during the Christmas shopping season, and the lowest value is in Period 5 (August) when traffic is lightest due to summer holidays.

Another item of interest in this figure is that while the variability in EWT across operators tightened from 2003-2007, it once again increased as of 2007, approximately the same time iBus installation started. This may indicate that it took operators some time to become familiar with the new technology, and to cope

[5] The x-axis in all figures in this section show TfL fiscal periods. The fiscal year, starting in April, is broken down into 13 4-week periods. Each period as of 2000 is expressed as a 5-digit number (periods in the 1990's are 4 digits). The first 3 (2) digits identify the year (i.e. 203 is 2003) and the last 2 digits identify the period (i.e. 02 is Period 2).

with teething problems. Whether the distribution of EWT tightens again as the operators' comfort level with the iBus system increases remains to be seen, and will be interesting to observe in the future.

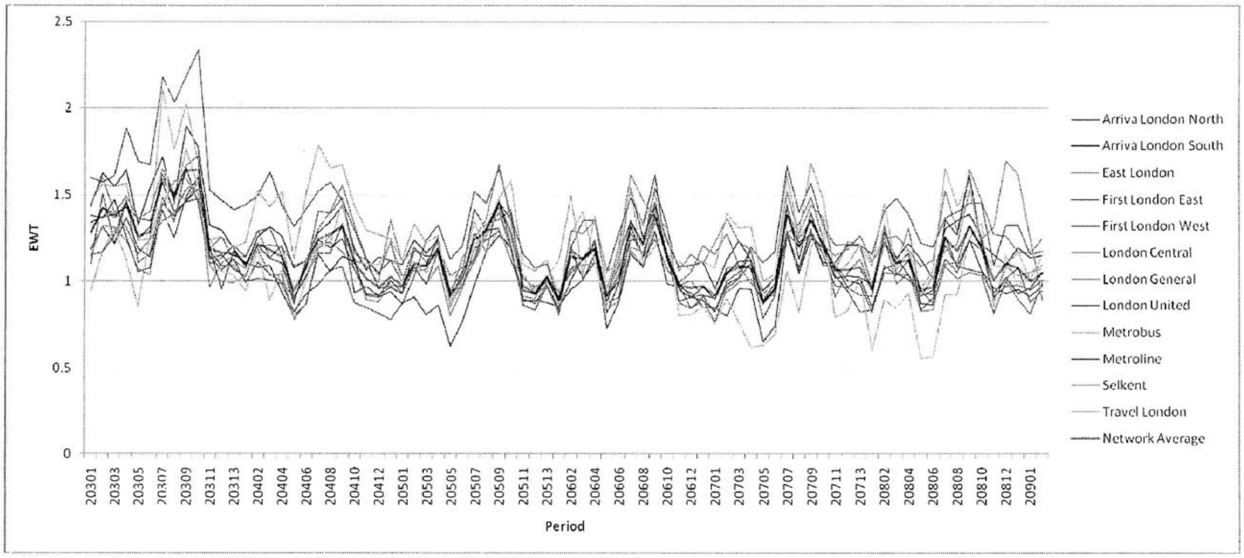

Figure 4-2 - EWT by Operator, 2003-2009

To gain a better understanding of how service reliability was affected by iBus installation, Figure 4-3 compares the standard deviation of EWT across operators the year before iBus installation started with the standard deviation of EWT during iBus installation, which is shaded. After taking into account seasonality effects, it is evident that the standard deviation of EWT among operators increased during iBus installation. This may be explained by the fact that the installation proved to be disruptive for the operators, as different buses run by the same operator were running on different AVL systems.

A subsequent analysis evaluating the variance of EWT within each operator during iBus installation would have been ideal. This would have involved analyzing the set of each operator's routes, both before and during iBus installation, to determine whether the variance in EWT within operators increased during installation. However, these data are not easily accessible in a form that would have made this analysis possible. While EWT values for each route/period combination are available, the factors used to scale these values when aggregating EWT or comparing EWT across routes are not easily accessible. This also proved to be an issue in the regression analysis presented later in this chapter. For that analysis, AWT/SWT, a measure which normalizes actual waiting time by the scheduled waiting time, was used, as described in Section 4.3.1.

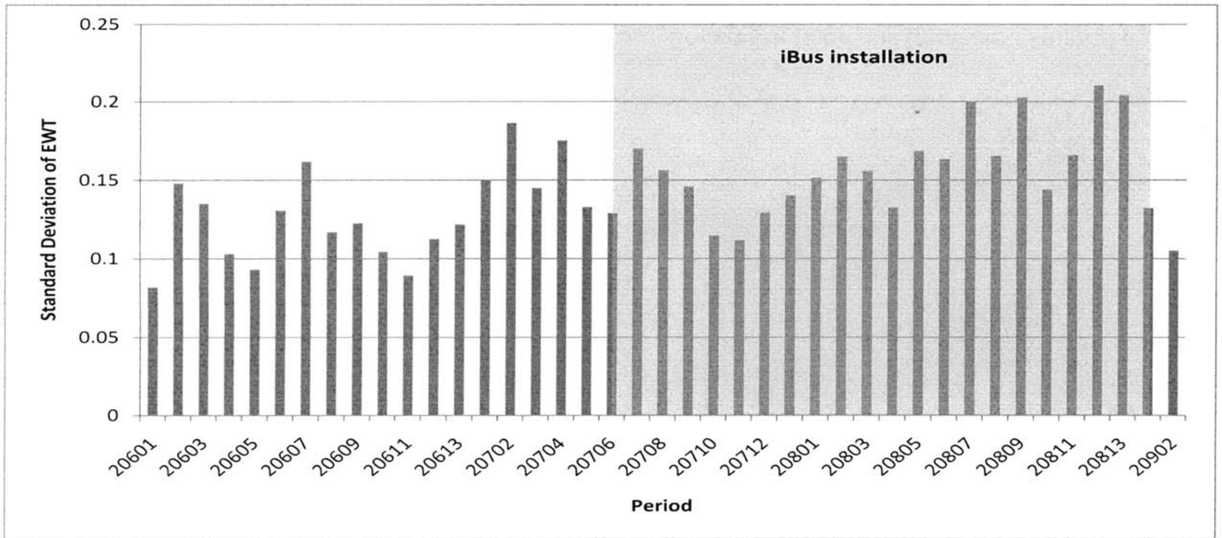

Figure 4-3 - Standard Deviation of EWT among Operators, 2006-2009

This section summarized the major trends in EWT over the past decade. However, this level of analysis fails to clarify which factors were responsible for the observed trends. In order to achieve that objective, the data need to be analyzed at a finer level of detail, as described in the next two sections.

4.3 Factors affecting Reliability

The greatest challenge in this exercise is identifying the factors affecting service reliability. A formal study to identify factors affecting service reliability and quantifying their effects has never been performed on the London bus network. The list of potential factors affecting service reliability may be extensive; the hypothesis presented in this section represents a range based on discussions with various stakeholders familiar with bus operations in London, and based on observations by the author.

As shown in the previous section, EWT has remained relatively stable since 2003, although there is no consensus on the reasons why. Staff at TfL have speculated that worsening traffic conditions throughout London were offset by the increase in bus priority lanes and bus priority signals being installed throughout the region, as well as being offset by the added features for service control made possible by the iBus system. The recent economic recession has complicated matters, as ridership on the bus network has decreased due to the decreased employment in Greater London, reducing vehicle dwell times and potentially increasing service reliability. It is therefore very difficult to identify why EWT has followed the pattern currently observed.

Many potential factors that were believed to affect service reliability were identified, and data describing these factors for subsequent use as inputs into a regression model. However, as shown in subsequent sections, not all that were assumed to be important were shown to be statistically significant. In order to simplify and organize the analysis, potential factors are grouped into one of the categories summarized in Figure 4-4.

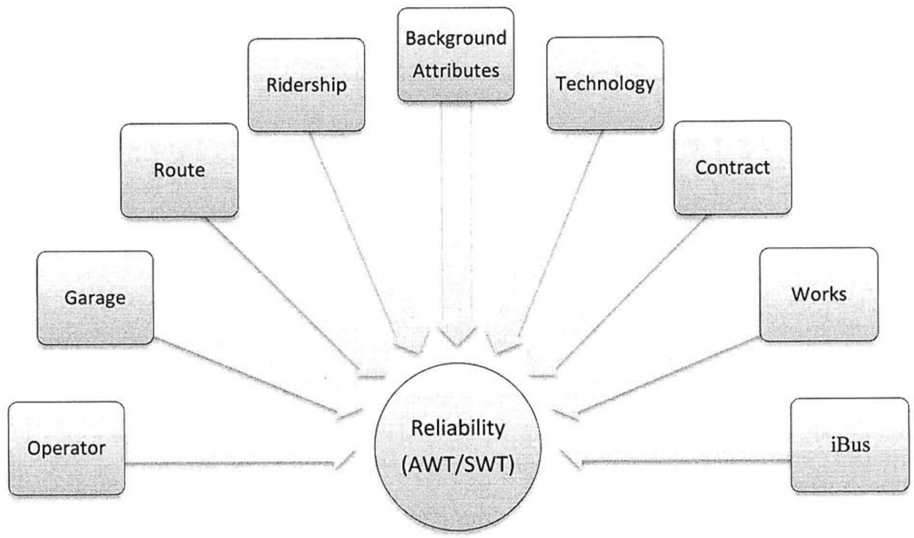

Figure 4-4 - Categories of Factors Believed to Affect Reliability

Various potential variables which provided a good description of some or all of the data in each category of potential factors were assigned to the relevant category. The result of this process is shown in Table 4-4. Each category, along with the data that were collected to describe it in the subsequent regression analysis, is discussed in the following sections.

Measurable variables were categorized based on whether they were binary, continuous, or discrete. Binary variables are those that have two potential values, modeled as 1 or 0. These include dummy variables that are used as proxies for non-quantifiable attributes when used in a regression model. Since measuring specific operator and garage attributes was difficult, each individual garage and operator was modeled as a dummy variable. Discrete variables take only integer values. Continuous variables may take on integer or non-integer values, thereby being a smooth function.

The availability of certain data was limited, and not all data desired for the analysis were attainable. The following analysis therefore is not based on an exhaustive list of all factors that affect service reliability – it is doubtful such a list could ever be developed – but should give a good indication of whether the identified factors were, in fact, significant, since the factors that were considered to be the most important (traffic congestion, route attributes, weather, iBus installation, etc.) were included in the analysis.

Table 4-4 - Potential Measures for Analysis

Attribute	Potential Measure	Variable
Dependent	AWT/SWT	C
Operator	Driver/Controller Ratio	C
	Lost Mileage	C
Garage	Frequency of Breakdowns	C
Route	Vehicle Attributes	D/C
	Location of Route (central/suburban)	D
	Bus Priority Measures	D
	Length of Route	C
	Scheduled Peak Headway	C
Ridership	Fluctuations/Variability in Passenger Volumes	C
Background	Traffic/Congestion	C
	Weather	C
	Congestion Charging	D
	Recession	B
	Period	B
	Socio-economic Measure	C
Technology	AVL Installed	B
Contract	Contract Changes	B
	New Operator	B
Works	Crossrail Construction	B
iBus	iBus Installed	B

B=Binary *C=Continuous* *D=Discrete*

4.3.1 Reliability – Dependent Variable

While EWT is the measure generally used to assess the performance of high frequency routes, it is not particularly well-suited to the needs of a regression analysis. EWT is a relative measure, which captures the difference between a route's observed wait time and its scheduled wait time. However, the relative magnitudes of this difference are not equal across all routes. For example, an EWT of 2 minutes indicates considerably poorer service on a route with a 4-minute headway than it does on a route with a 12-minute headway. On the 4-minute headway route, it means passengers on average are waiting an extra half headway over and above the scheduled wait time, while on the 12-minute headway route passengers are only waiting an extra 1/6 headway over and above the scheduled wait time. Passengers on the 4-minute headway route will perceive this deviation from service to be more severe than the passengers on the 12-minute headway route.

An alternative measure, which normalizes each route's wait time, was deemed to be more appropriate for this analysis. This measure, AWT/SWT, is the route's actual wait time divided by its scheduled wait time. In essence, each route's actual wait time is normalized by its scheduled wait time, providing an indication of how large the actual wait time is compared with the scheduled wait time. This is similar to the Headway Ratio used on the Tri-Met system in Portland, described in Chapter 2. This was found to provide a significantly better fit with the data collected for this analysis, and resulted in the development of more robust models. It is therefore used as the dependent variable (i.e. the measure of reliability) in the regression analysis.

Values for AWT/SWT were extracted from TfL's MS Access-based Stabs 1.0 database, which contains information on the manual QSI point field surveys. Data from each survey for every QSI point are stored in this database, and queries are run on the data to manipulate it as desired. Each datum contained a singular EWT and AWT/SWT measurement for every route/period/operator/contract combination from Period 1, 2006 to Period 2, 2009. A total of 15,007 data points were extracted for high frequency routes.

4.3.2 Operator Attributes

Factors falling into this category describe each operator's individual operating philosophy and operating culture, which may vary due to differing management styles and service delivery objectives. Measureable factors identified for analysis included the Driver to Controller Ratio, an indication of the scope of the service controller's responsibilities, and Percent Lost Mileage.

Percent Lost Mileage is defined as the percent of scheduled route miles that were not run over the time period in question, as explained at the beginning of the chapter. When a scheduled bus run was not operated, the operator in question must provide TfL with a reason why the bus was not operated. Possible reasons include traffic congestion, crew shortages, and maintenance issues. Percent Lost Mileage data were categorized by route/period, and lost mileage was reported for numerous deductible and non-deductible causes (including traffic), as explained in Section 4.1.3.

During the time period under analysis, 97.4% of the scheduled mileage on high frequency routes was operated (i.e. Lost Mileage was 2.6%). The majority of Lost Mileage, 1.6%, was attributed to traffic. Of the remaining 1%, 0.4% was due to mechanical malfunctions, 0.1% was due to staffing, and 0.5% was due to other causes.

4.3.3 Garage Attributes

Factors falling into this category describe each bus garage's individual attributes. Observations on-site at bus garages have shown that each garage's workforce has a unique work environment. It was therefore hypothesized that some garages may be more effective at delivering a reliable service than others. Measures identified to describe garage attributes included the frequency of bus breakdowns by garage, and some other descriptors for maintenance carried out at each garage. However, the frequency of breakdowns by garage did not yield any significant results and was not used in subsequent analyses. Instead, a binary variable representing each garage was used as a proxy for all non-measurable garage attributes.

4.3.4 Route Attributes

Each route has characteristics which may affect its service reliability relative to other routes. Measurable route attributes which were used in this analysis include:

- Vehicle Attributes – These set of attributes define the type of vehicle operated on the route. They include the number of floors of the vehicle (both single- and double-decker buses are operated in London), the length of each vehicle, and the number of doors on each vehicle (more doors improve passenger flow and should result in shorter dwell times).

  Queries to identify vehicle attributes were run on TfL's Busnet database, which contains records of various route and vehicle attributes, such as garage assignments and vehicle assignments. From this database, it was possible to determine which routes were assigned to which garage(s) over the period of analysis, and attributes of the vehicles – such as the number of doors on each vehicle, the number of decks on the vehicle, and the length of the vehicle –assigned to each route over the period of analysis.

- Location of Route (central/suburban) – Routes in Central London may be more susceptible to the effects of road congestion than those operating on the periphery of the metropolitan area.

Therefore, it was hypothesized that Central London routes are less likely to be reliable than Outer London routes. Locations of routes were determined by GIS.

- Bus Priority Measures – The extent to which the route operates with one or more bus priority measures may have an effect on its reliability. Routes with extensive use of bus priority lanes or bus signals were hypothesized as likely to be more reliable than those operating in mixed traffic for the majority of their route.

- Length of Route – Long routes may be more difficult to control than short routes, as the random variability in running times may be correlated with route length. Geographic data, such as route length and urban boundaries, were taken from TfL GIS (Geographic Information System) data, extracted in January 2009. These data provide a snapshot of the bus network at the time the data were supplied; they do not show service changes that took place over the period of analysis. The data are therefore not necessarily accurate for every route/time period combination. However, even if a routing was changed, it was probably not significant enough to have a drastic effect on the model. Bus routes may be extended or diverted, but they will not suddenly be reassigned to another routing.

- Scheduled Peak Headway – The peak headway provides an indication of the demand served by a route. These data were extracted from Busnet in the form of the buses per hour during the AM peak.

4.3.5 Ridership Attributes

Ridership, while related to the headway operated on a route, may also have a direct effect on service reliability. High ridership, combined with uneven bus spacing, results in long dwell times, and if service controllers do not monitor dwell times closely, this may result in unreliable service.

Ridership for each route was used as input into the regression analysis. Ridership by route by period was based on data recorded in the ETM (Electronic Ticket Machine) database by TfL's Fares and Ticketing department. The data used as input to the model were the aggregate ridership numbers on each route for each period. Another factor, a measure describing a level of crowding on each route, was desired as well, but could not be obtained.

4.3.6 Background Attributes

Background conditions, such as traffic, weather (seasonality), and socio-economic factors, should have significant effects on reliability. As already demonstrated in the previous section, seasonality trends are evident when analyzing the reliability of the London bus network. Seasons with high traffic volumes and/or poor weather cause the network to perform less reliably than low traffic/good weather seasons.

Numerous background attributes were identified, and data were collected for those attributes deemed to be most important, including:

- Traffic/Congestion – Road congestion was hypothesized to have a significant effect on service reliability, since buses operating in mixed traffic must contend with congestion. It was challenging, however, to find a measure for congestion that could easily be applied across the whole network.

  ITIS (Integrated Transport Information Services) data is a GPS based system used by London Streets (another subdivision of Surface Transport at TfL) that tracked the location of registered vehicles (cars, trucks, and buses) every minute from 2004-2006. These data are used to determine traffic speeds throughout London. Approximately 75,000 observations per hour are recorded between 7:00 and 19:00 for over 5600 km of road in the London area. The ITIS network is made up of over 22,500 links in the London region. Data are received in 15 minute increments within each day for each link.

  A key output from this ITIS data is the Delay Measure, which is an indicator of the level of congestion (lost minutes per km travelled) when compared with the free flow speed. All data are weighted by flow in order to provide aggregate measures. The data are available in both GIS and tabular formats.

  While the Delay Measure would be an ideal measure to use for congestion, the data are not recent data, nor are they easily matched with bus routes. Each bus route would have to be divided into links corresponding to the ITIS network, and the measurements from ITIS would have to be aggregated somehow. This matching and aggregation process would be extremely cumbersome, and prone to error. It was therefore decided to use Percent Lost Mileage Due to Traffic (1.6% for the time period analyzed) as a proxy for congestion, with the caveat that these data are reported by the operators and may therefore contain faults. Since operators are not penalized for Lost Mileage attributed to traffic, operators may attribute other causes of lost mileage for which they would be penalized, such as staffing shortages and mechanical breakdowns, to traffic. Thus, this data source should not be considered to be entirely accurate. Should better data describing traffic be available in the future, these data should be used instead of Lost Mileage.

- Weather – Applying measures of weather were anticipated to more accurately represent the seasonality effects described earlier. Staff at London Buses had studied the correlation between reliability and measures of weather, such as precipitation. The historical weather data provided by the Met Office, the national weather service in the United Kingdom, were not tailored to the needs of the project, since during the period in question, there was no Met Office weather station in London with sufficient data for the analysis. Data from the website www.wunderground.com were used instead. With one exception, precipitation data by period from the Crouch End weather station were used. There was a 1-month interval where these data were faulty, so data from the Hounslow weather station in southwest London were used as a proxy.

- Congestion Charging – The introduction of Congestion Charging in 2003 was expected to have improved bus reliability. The Western Extension Zone was introduced later, and its effects are measured by this variable.

- Recession – The global recession which started in September, 2008 was thought to cause a decrease in ridership on the bus network as well as a decrease in overall traffic. A dummy variable was used to differentiate between observations pre-recession and during the recession.

- Period – These are a set of dummy variables meant to represent seasonality effects not captured by the weather or other variables.

- Socio-economic – Since ridership and congestion were hypothesized to be highly correlated with economic conditions, a socio-economic metric to use in the model was needed. Percent unemployment was selected for this measure, as the level of employment was believed to directly affect the volume of traffic, both transit and non-transit. The GNP was also considered; however the effect of any recession generally lags the GNP by 2 or 3 months.

  Percent unemployment data for Greater London in 3-month increments for the period of study were extracted from the Office for National Statistics (www.statistics.gov.uk). The data, which are based on unemployment percentages of all members of the workforce over 16, were reported until April 2009, so employment data for subsequent dates were assumed to be equal to April 2009.

4.3.7 Technological Attributes

This factor describes whether AVL is available and running on the buses. If AVL is not available on a given bus route for an extended period of time, service controllers on this route may not be able to perform their duties as well as their peers on routes equipped with a working AVL system. This may be especially true for the network pre-iBus, since not all routes were equipped with the legacy AVL system. At the completion of iBus installation, all buses run on the network were equipped with AVL units. However, the degree to which each operator uses the new tools provided by AVL to make more informed service control decisions may vary. A binary variable indicating whether a route had AVL (legacy or iBus) installed is used to measure this technological effect.

4.3.8 Contract Attributes

All new contracts on the London bus network are Quality Incentive Contracts (QIC), as discussed in Chapter 3. However, some legacy gross/net cost contracts remain, and due to the different incentive structure of these contracts, performance on these sets of routes may be different. This set of attributes is also intended to capture the teething effects when a new contract is signed and an operator modifies their operations to meet the new contract requirements. Two binary measures are used. The first indicates a period where a route's contract structure was modified. The second indicates a period where a route's operator changed.

4.3.9 Works

Construction projects are essential disruptions to the road network to ensure it remains in good condition, but may have an adverse effect on operations when work is being carried out. While it was not possible to acquire information on all the road works performed in London during the period under analysis, the start of Crossrail construction at Tottenham Court Road resulted in numerous bus diversions in Central London, and could therefore be used as a test to see what effect a major project has on reliability. A dummy variable indicating the routes and periods affected by Crossrail construction was included in the model to test whether these projects have a significant effect on service reliability.

4.3.10 iBus

The introduction of iBus was assumed to increase service reliability on the London bus network. While the analysis in previous sections showed no visible improvement in reliability before and after iBus installation, it may show an effect once all the other factors accounted for. A binary variable is used to represent whether a given route/period combination had iBus installed. This does result in an overlap between this variable and the technological variable. However, in order to avoid multicollinearity, the two variables are never used in the same model.

4.3.11 Data Specifications and Limitations

Data by period were collected from Period 1, 2006 to Period 2, 2009, corresponding to April 1, 2006 to May 29, 2009. When data were not readily available by period, they were manipulated in order to be expressed by period. Stabs AWT/SWT data were used as the baseline data, and all other data were manipulated in order to match the Stabs data.

Including binary (dummy) variables for the 13 periods in a year, the 93 garages observed on the network during the period of analysis, and the 26 operators that operated at least one high frequency route during the period of analysis, a total of 188 potential binary, discrete, or continuous variables were assembled for the analysis. A table of all variables is provided in Appendix 1.

The data used for this analysis were not created specifically for this exercise. The data contain many imperfections, such as some data being broken up by month as opposed to period, and are of variable quality. Therefore, some degree of error should be expected in the regression modeling.

4.4 Quantifying the Influence of Service Reliability Factors

Determining which of the factors identified in the previous section are the most important contributors to service reliability involves a two step procedure. The first step, described in Section 4.4.1, involves analyzing the interaction between the dependent variable (AWT/SWT) and all potential independent variables, to see the one-on-one interaction. This is performed via a correlation analysis, which can be displayed as a scatter plot. Variables which are linearly related to each other are highly correlated, and the independent variable is perceived to be a potentially significant contributor to the dependent variable. When no discernible pattern is evident, the independent variable is assumed to have little or no effect on the dependent variable. It is also necessary to analyze those independent variables that are highly correlated with each other, as they may display multicollinearity if both are included in the regression model.

The second step of the analysis, introduced in Section 4.4.2 with results summarized in Sections 4.4.3-4.4.5, is to build the regression models and to determine which model has the best fit. This involves modeling the dependent variable as a function of the independent variables expected to be influential, as well as other independent variables that may not have been shown to be correlated with the dependent variable, but are nonetheless believed to be important based on a priori reasoning.

4.4.1 Correlation Analysis

A correlation matrix was developed for all factors that were believed to likely affect high frequency route reliability. This was performed in order to understand the general relationship between the independent and dependent variables, and to determine which of the potential variables should be included in the regression models. Variables with a correlation of 1 are perfectly correlated with each other; those with a correlation of 0 have no correlation with each other.

Table 4-5 shows the variables with the highest correlations with AWT/SWT. The consensus among staff at TfL was that traffic congestion was an important – if not the most important – factor affecting service reliability. This was validated by the correlation analysis: Percent Lost Mileage due to Traffic had a correlation of 0.64 with AWT/SWT, the highest correlation with AWT/SWT in this analysis. It should be noted, however, that Percent Lost Mileage is not a reliable traffic index, as these data are reported by the operators, who may not always identify the correct cause for lost trips. Actual traffic would probably not be as highly correlated with AWT/SWT as this measure is.

Table 4-5 - Factors Highly Correlated with AWT/SWT

Measure	**Correlation with AWT/SWT**
Percent Lost Traffic	0.64
AM Peak Buses per Hour	0.56
Ridership	0.56
Ridership/km	0.51
Central London Route Length	0.43
CCZ Route Length	0.42
Vehicle Length	0.28
Routes/Workstation	-0.28
Bus Priority Measures in Place	0.28

With the exception of Routes/Workstation and "Bus Priority Measures in Place," the correlations between the variables presented in Table 4-5 with AWT/SWT reflect a priori assumptions. Two ridership measures, Ridership and Ridership/km, and one measure describing passenger demand, "AM Peak Buses per Hour," have a positive correlation with AWT/SWT. This is expected for two reasons. First, higher ridership causes dwell times to increase, and therefore introduces additional variability into service. Second, routes with higher ridership generally serve areas of higher traffic, and so may also be affected by road congestion.

Two measures of route length were shown to be positively correlated with AWT/SWT. It was assumed that by their nature, long routes, if left uncontrolled, are more likely to be subject to variability in service than short routes. Each trip on a long route spends more time in traffic, has more stops (which introduces dwell time uncertainty), and most likely has to pass through more traffic signals than a short route. This assumption was validated by the correlation analysis.

Routes/Workstation is a measure of the service controller's workload. It was assumed that a controller responsible for fewer routes would be able to give greater focus to each route, resulting in better service. This is not supported by the correlation analysis, as Routes/Workstation has a negative correlation with AWT/SWT, indicating that as the number of routes a controller is responsible for increases, the quality of the service offered increases. Since this is contrary to the a priori expectations, further study is required to analyze the operators' service control practices in order to determine why this relationship is observed.

Another measure that did not correspond with a priori assumptions was "Bus Priority Measures in Place." It was assumed that bus routes with priority measures in place, such as bus signal priority or reserved bus lanes, would experience better service. The route would be subject to less variability due to a lesser influence of traffic. However, the correlation analysis indicated that bus priority measures are positively correlated with AWT/SWT, indicating that priority measures result in worse service. It may be concluded that better data describing bus priority should be collected, or that these measures have less of an effect on service reliability than originally thought.

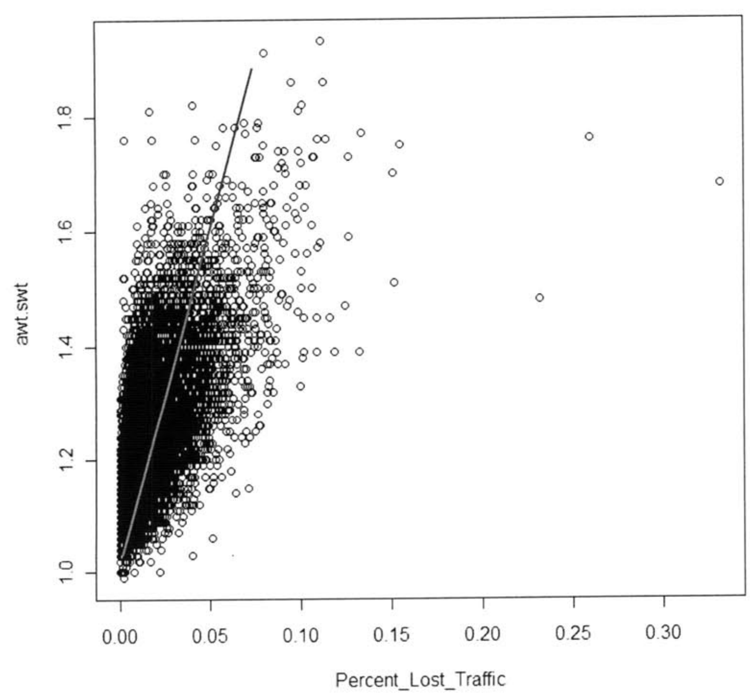

Figure 4-5 - Scatter Plot of AWT/SWT versus Percent Lost Mileage Due to Traffic

Figure 4-5 shows a scatter plot of AWT/SWT versus Percent Lost Mileage Due to Traffic illustrating two sets of data which are highly correlated. The data in this figure are clustered closely around an upwards trend line, and the relationship between the two sets of data could be approximated by a function. Data not highly correlated with each other would be considerably more scattered, and a trend line would be less apparent.

4.4.2 Regression Models

The models presented in this analysis were developed using least squares regression to fit a function to data by minimizing the squared error between each datum and its corresponding value on the estimated function (Pindyck and Rubinfield, 1998). The resultant equation is of the following form:

$$Dependent\ Variable = \beta_0 + \beta_1 * Var_1 + \cdots + \beta_n * Var_n + \varepsilon \qquad \text{(Equation 4-4)}$$

Where β_0 represents the estimated intercept term, $\beta_1,\ldots,\beta_n$ are estimated coefficients of independent variables 1 to n, and ε is the error term. A positive coefficient indicates a positive influence of the independent variable on the dependent variable, and a negative coefficient indicates the opposite. For dummy variables, the estimated coefficient represents the direct effect of the dummy variable on the dependent variable in units of the dependent variable. For example, if a regression with AWT/SWT as the dependent variable shows Garage X with an estimated coefficient of 0.20, this indicates that a route which operates out of Garage X will cause AWT/SWT to be 20% greater than the baseline AWT/SWT value, all else being equal.

Two statistics are widely used to assess the efficacy of an estimated model. The first statistic is the t-statistic, which indicates whether an estimated coefficient is statistically significant at a specific confidence level. By using the Student's t-distribution, the t-statistic indicates the probability of the estimated coefficient being different from 0. A t-statistic with a magnitude greater than 1.96 indicates that the estimated coefficient is not 0 with 95% confidence.

The second statistic of note is the adjusted R-squared value. This indicates how well the observed data fit the estimated model, and is therefore used to compare models developed from the same data. An R-squared value of 1 indicates a perfect fit, while an R-squared value of 0 indicates no fit (Pindyck and Rubinfield, 1998). While this statistic provides an indication of how well the model fits the data, it does not provide the sole indication when assessing whether a model should be used. R-squared values, t-statistics, and validations of a priori hypotheses must all be assessed in order to reach a final decision concerning the merits of the developed models.

Some 15 models were developed and compared with each other. Since some attributes' data were easier to obtain than others, not all attributes or categories of attributes were included in every model. The two models that provided the best fit with the data and made the most intuitive sense are presented in this section.

A priori hypotheses are required before testing and developing models. These relate to the factors that are expected to be significant, and how various independent variables relate to each other. The regression was proposed to resemble the following function, modeling service reliability as a function of one or more of the variables belonging to each of the nine categories of factors believed to affect service reliability:

AWT/SWT *= f(Operator, Garage, Route, Ridership, Background Attributes, Technology, Contract, Works, iBus)* (Equation 4-5)

Dummy variables were created for every bus garage, every operator, and every period. These were intended to capture conditions in each garage/operator/period that were not quantified in other variables. Since a set of X alternatives can have only X-1 dummy variables, the following were assumed to be the "base case":

- Garage – AN (Acton Tram)
- Period – P1 (April)
- Operator – TG (Travel London)

4.4.3 Model 1: Variables with High Correlation with AWT/SWT and Other Variables Deemed Important

The first model presented, specified in Equation 4-6, shows how effective a few variables with high correlations with AWT/SWT and others deemed important based on a priori reasoning are at predicting service reliability. It is used to determine the magnitudes of each factor's effect on reliability. Additionally, this model could be used as a rough forecaster of service reliability, owing to the small number of variables that would need to be estimated as input. It was selected as the best model from a set of models developed from these important factors. As the results in Table 4-6 indicate, the model has a surprisingly high adjusted R-squared value considering the low number of independent variables used as inputs. In addition, all coefficients are significant at the 95% confidence level.

AWT/SWT *= f(iBus, Precipitation, Ridership, Length, Percent Lost Traffic)* (Equation 4-6)

Most of the estimated coefficients make intuitive sense. Increased precipitation should result in a worsening of service reliability, as should higher ridership and greater congestion. iBus installation is also shown to have resulted in a very slight reduction in AWT/SWT of -0.00393 or 0.4%. However, the estimated coefficient for the route length indicates that longer routes have a lower AWT/SWT, and so are more reliable. While this may be true assuming excellent service control, longer routes are prone to more bus bunching than shorter routes and should therefore have greater variability in headways. This does not correspond to the a-priori expectations, and may point to another factor which has a high correlation with route length but is not included in this model.

Table 4-6 - Model 1 Results

Variable (see Appendix 1)	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.09E+00	3.08E-03	354.55	< 2E-16
iBus	-3.93E-03	1.53E-03	-2.563	0.0104
Precipitation_.mm.	8.74E-05	2.18E-05	4.01	6.11E-05
Ridership	2.69E-07	3.81E-09	70.7	< 2E-16
Length	-1.62E-03	1.92E-04	-8.472	< 2E-16
Percent_Lost_Traffic	3.88E+00	4.46E-02	87.04	< 2E-16

Adjusted R-squared: 0.586

Percent Lost Mileage due to Traffic (Percent Lost Traffic) was shown to be the variable most highly correlated with AWT/SWT, and was therefore included in this model. While this variable represents the best estimate of traffic conditions currently available, it should be noted that since Percent Lost Traffic is reported by operators, it is closely linked with AWT/SWT and is not truly an independent variable. When this variable is not included in the model, as specified in Equation 4-7 with the results shown in Table 4-7, the adjusted R-squared decreases by 44%, from 0.586 to 0.323. Thus, the fit of the model decreases significantly when this measure of traffic is not included. Additionally, in this model, the impact of iBus on AWT/SWT is no longer significant. Future analyses relating to service reliability should attempt to include a more independent measure of traffic.

AWT/SWT = f(iBus, Precipitation, Ridership, Length) (Equation 4-7)

Table 4-7 - Model 1 Without Percent Lost Traffic

Variable (see Appendix 1)	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.12E+00	3.91E-03	287.47	< 2e-16
iBus	-3.02E-03	1.96E-03	-1.543	0.123
Precipitation_.mm.	2.04E-04	2.78E-05	7.327	2.50E-13
Ridership	3.50E-07	4.73E-09	74.117	< 2e-16
Length	-1.90E-03	2.45E-04	-7.749	1.00E-14

Adjusted R-squared: 0.323

4.4.4 Model 2: Accounting for Seasonality and Operator Behavior

The second model presented, expressed in Equation 4-8, demonstrates how regression may be used to rank various factors' effects on service reliability, specifically rankings for seasonality and operator behavior. Dummy variables have been included for each season and operator (except for the base case, as discussed above), and their relative effects on AWT/SWT are measured. The model results are presented in Table 4-8.

AWT/SWT = f(iBus, Precipitation, Ridership, Length (Inner London, Central London, Outer London), Ridership/km, Percent Lost Traffic, Operators, Periods) (Equation 4-8)

Table 4-8 - Model 2 Results

Variable (see Appendix 1)	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.08E+00	7.92E-03	136.883	< 2e-16
Contract_Change	4.70E-02	1.09E-02	4.299	1.73E-05
Precipitation_.mm.	2.64E-05	2.67E-05	0.988	0.323201
Ridership	1.64E-07	1.20E-08	13.633	< 2e-16
Rider/km	1.24E-06	1.50E-07	8.219	2.27E-16
iBus	-5.83E-04	1.51E-03	-0.387	0.698611
Central_Length	7.24E-03	5.10E-04	14.201	< 2e-16
Inner_Length	5.61E-04	4.04E-04	1.387	0.165552
Outer_Length	7.99E-04	3.43E-04	2.331	0.019795
Percent_Lost_Traffic	3.66E+00	4.50E-02	81.297	< 2e-16
AR	-9.28E-03	5.44E-03	-1.705	0.08831
BU	-1.23E-03	8.83E-03	-0.14	0.888836
CC	-4.51E-02	6.42E-03	-7.023	2.30E-12
CW	-4.00E-02	6.32E-03	-6.33	2.54E-10
CX	-2.99E-02	6.49E-03	-4.599	4.28E-06
DK	-7.12E-02	1.18E-02	-6.056	1.43E-09
EL	-4.72E-02	6.18E-03	-7.649	2.18E-14
ET	1.41E-02	8.66E-03	1.626	0.10396

Variable (see Appendix 1)	Estimate	Std. Error	t value	Pr(>|t|)
FE	-3.12E-02	1.23E-02	-2.54	0.011094
HK	-2.22E-02	9.38E-03	-2.37	0.017817
KB	-2.93E-02	8.77E-03	-3.338	0.000847
LC	-8.02E-02	6.79E-03	-11.811	< 2e-16
LD	-7.08E-02	8.39E-03	-8.443	< 2e-16
LE	-5.55E-02	6.60E-03	-8.406	< 2e-16
LG	-7.72E-02	6.35E-03	-12.157	< 2e-16
LU	-3.11E-02	6.24E-03	-4.976	6.58E-07
MB	-5.07E-02	7.41E-03	-6.841	8.23E-12
ML	-6.22E-02	6.11E-03	-10.173	< 2e-16
NC	2.62E-03	1.06E-02	0.248	0.803942
OL	-7.08E-02	1.27E-02	-5.562	2.73E-08
SE	-2.17E-02	6.41E-03	-3.383	0.00072
SL	-4.68E-02	6.33E-03	-7.404	1.41E-13
SV	-7.84E-02	7.44E-03	-10.548	< 2e-16
P2	2.72E-02	3.32E-03	8.192	2.83E-16
P3	3.06E-02	4.18E-03	7.324	2.56E-13
P4	2.70E-02	3.74E-03	7.216	5.68E-13
P5	6.64E-03	3.87E-03	1.714	0.08662
P6	1.43E-02	3.67E-03	3.907	9.38E-05
P7	4.13E-02	3.73E-03	11.071	< 2e-16
P8	3.11E-02	3.64E-03	8.563	< 2e-16
P9	4.61E-02	4.00E-03	11.521	< 2e-16
P10	6.95E-02	3.53E-03	19.665	< 2e-16
P11	1.58E-02	3.71E-03	4.267	2.00E-05
P12	1.68E-02	3.83E-03	4.395	1.12E-05

Variable (see Appendix 1)	Estimate	Std. Error	t value	Pr(>|t|)
P13	1.11E-02	3.68E-03	3.007	0.002645

Adjusted R-squared: 0.646

As opposed to the first model presented, the signs of the coefficients of the length variables are correct – the longer the route, the higher the likelihood of delay, especially in Central London. The adjusted R-squared value improved over those presented in the first model, to 0.65 for AWT/SWT, indicating this model is a better predictor of service reliability.

With one exception, the seasonality coefficients are significant. Period 5, during the middle of the summer, may not be significant because it bears a high resemblance to Period 1 (April), which is the base case. In addition, Period 10, December, is the worst consistent with the views of TfL staff that the worst time of the year is the build-up to Christmas. The most reliable periods identified by the model, Periods 1 and 5, are sensible since they occur during the middle of the summer when passenger volumes are light and the weather is calm, and in April, which also has calm weather. However, precipitation is no longer significant once seasonality is included in the models, demonstrating that these seasonality variables better describe the effects of weather than precipitation. This is assumed to occur because seasonality accounts for facets of weather that precipitation does not account for, such as temperature.

The magnitudes of the operator dummy variables provide a "ranking" of the operators based on historical data. In essence, all else being equal, this captures which operators are more or less reliable than others. This may be due to the unique behavior and working culture that each operating company fosters. According to this analysis, ET (East Thames) is the worst performing operator while LC (London Central) is the best performing operator. The difference in AWT/SWT between these two operators is approximately 0.0943 or 9.4%, indicating that operator differences are a major contributor to service reliability.

Even though considerably more factors are accounted for in this model than in the previous model, iBus installation is not shown to be significant in this model. Other models tested and not presented here produced similar results, indicating that merely installing iBus did not directly lead to improved service reliability. The users of the AVL system, including the agency, the operators, and the drivers, must adapt their operating and planning strategies in order to take advantage of the AVL capabilities in order to produce a measurable impact on reliability.

4.4.5 Summary of Regression Analysis

The two regression models presented in this section demonstrated how service reliability can be described by factors believed to affect it. The first model showed the influence highly correlated factors with AWT/SWT and others believed to play a significant role have on service reliability, and had an adjusted R-squared value of 0.586. The most highly correlated factors with reliability were Lost Mileage due to Traffic, precipitation, ridership, and route length, which were also included in the second model. iBus was also found to have a small effect on improving reliability.

The second model presented accounted for seasonality and operator attributes and showed that these attributes are important contributors to reliability; this model had an adjusted R-squared value of 0.646, indicating it fits the data better than the first model. However, this second model employed considerably more variables than the first model, for a 10% overall improvement in the adjusted R-squared value.

A benefit of the second model when compared with the first model is that it enables the analyst to account for variability in reliability due to seasonal variation and operator attributes. The analyst is therefore able to identify which periods of the year display poor reliability, and make more accurate predictions about reliability in future years. The second model also makes it possible to rank operators by their contribution to reliability. By identifying operators that in general have good (or poor) reliability, controlling for other variables, the analyst can focus on what causes these operators to perform better (or worse).

4.5 Summary

This chapter introduced the measures currently used by TfL to assess service reliability, and endeavored to account for major factors contributing to service reliability. By analyzing trends in service reliability over time, patterns such as seasonality, and responses to major events such as the restructuring of contracts and the increase of bus services in 2003, were identified. However, the contributions of other factors expected to be important were not evident at this high level, which is why the data were investigated further via statistical analysis and regression modeling.

This analysis has some practical applications in spite of the fact that it may be difficult to extend this work to ascertain each factor's contribution to service reliability. First and foremost, the fact that identifying factors affecting service reliability is such a complex procedure helps explain why it is so difficult to achieve highly reliable service in an operating environment like London. There will always be factors, such as variability in operator/driver behavior, weather, and traffic, that lead to unreliability. The more complex the network, the more numerous the factors at play become.

Service will never be perfectly reliable and therefore an AWT/SWT approaching 1 is infeasible. External factors that agencies and operators have no control over, such as weather and other seasonal factors, were shown to be significant, meaning that in spite of the service control mechanisms available, service interruptions are inevitable.

Differences in operators appear to have a significant effect on service reliability. The second set of models presented included dummy variables for each operator, and the differences in coefficients in these variables were striking. The operator alone is responsible for a 0.0943 unit or 9.4% range in AWT/SWT, meaning some operators have considerably better service control management systems and practices in place than others. This provides an impetus to analyze why some operators and routes exhibit better performance than others, which is one of the major motivations behind the next chapter.

One intended benefit of this analysis was not realized. The effects of the recent iBus AVL installation were not proven to be significant once all other variables were accounted for. The first model estimated that iBus has a very small but statistically significant effect in improving reliability. However, when Percent Lost Traffic was dropped from this model the impact of iBus on reliability was no longer significant. The second model, which accounted for a greater number of factors than the first model, showed the effects of iBus installation to be insignificant. The author is led to believe that merely installing an AVL system will not produce a measurable improvement in service reliability. Service reliability will only be improved if the agency and operators use its capabilities to improve their operating and planning practices.

5 Service Reliability Measurements using AVL Data

When evaluating the quality of a transit service, the industry is increasingly focused on developing passenger-centric measures of service reliability. While such measures were always desirable, previously agencies were constrained by the type and amount of data they could cost-effectively collect. With the introduction of automated data systems, notably AVL and AFC, agencies now find themselves with a plethora of data for analysis. This chapter will investigate how these data, concentrating specifically on AVL data, may be used to develop more robust measures of service reliability that better reflect the passenger experience.

This chapter will provide a framework for developing service reliability measures that focus on the bus passenger experience. It will build upon the work developed by Uniman (2009), Chan (2007), and Furth and Muller (2006a) described in Chapter 2. Three "new" measures of bus service reliability will be introduced in Section 5.1: Journey Time, Excess Journey Time (EJT), and Reliability Buffer Time (RBT). Journey time, an absolute measure of reliability, facilitates the calculation of EJT and RBT, two relative measures of reliability. These measures account for the totality of the passenger experience by including both wait time at the origin stop and in-vehicle travel time between the origin and destination stops, as opposed to more traditional measures such as EWT which account only for wait time. Since London Buses will be used as the case study for analysis, iBus data will be introduced in Section 5.2, including how accurate the data are currently perceived to be, and the implications of any inaccuracies. The methodology for the analysis will be described in Section 5.3, and Section 5.4 will present examples of EJT and RBT analyses performed for a set of six routes in London. Results for these routes will be compared with the measures TfL currently uses to assess performance to show the differences between the operations of the route, as currently perceived, and the passenger experience, as approximated by the new measures. Section 5.5 will present a summary of the chapter and a set of recommendations for how the work developed in this chapter may be applied in the transit industry.

One benefit of focusing on the passenger experience is that agencies can gain a better appreciation of how common service control interventions affect passengers. The analysis presented in this chapter will include routes that are perceived to have very good operations (i.e. virtually all scheduled trips are run and headways are not highly variable) as well as routes that operate poorly. By comparing reliability on these routes, it is anticipated that trends contributing to better (or worse) operation of the route will be revealed.

5.1 Passenger Focused Measures of Reliability

EWT, the main measure of service reliability used by London Buses and other transit systems for high frequency services, focuses on an important aspect of the passenger experience: wait time. This provides a robust indicator of how well an operator manages to provide service with consistent bus arrivals and departures. However, it does not provide an indication of what happens to passengers after they board a bus: do they reach their destination in a reasonable time? How variable is the in-vehicle experience? How much total time do they spend within the bus network?

While EWT is a necessary measure of reliability, the passenger experience consists of more than just wait time. This section will propose new measures of reliability that represent an incremental improvement over EWT, and will describe additional aspects of the passenger journey experience leading to more comprehensive measures of reliability. Short of manually going through AVL data, these measures should help identify routes whose operations would merit a more in-depth analysis. This study is particularly relevant now, as using AVL data enables these additional measures to be computed, which would previously have been difficult or impossible. To gain a fuller picture of the passenger experience, the complete passenger journey will be analyzed, and those components of the passenger journey which can be measured with automated data sources will be identified.

As discussed in Chapter 4, bus journey times are very susceptible to external factors, such as congestion and weather. This results in greater variability in in-vehicle times than for rail journeys. The formulation of journey times developed in Uniman (2009), and discussed in Chapter 2, was based on AFC data from the London Underground rail system, which uses tap in/tap out fare control. This provides the analyst with a known total trip length, the value of which is the difference between the time the passenger tapped out and the time he (she) tapped in to the system. This results in a set of known journey times, from which it is easy to compute the cumulative distribution function (CDF) for journey times. With most bus networks, including London, obtaining the CDF for journey times is more complicated for two reasons:

1. AFC users still tap into the system but are not required to tap out when exiting the vehicle.
2. Since tap in occurs when boarding the bus, the recorded journey time excludes the wait time before the bus arrives. In the Underground case, since tap in occurs when entering a station, the journey time includes wait time for a train.

For these reasons, AVL data are used to calculate percentile journey times for bus passengers, although the process is not as deterministic as with a fully gated rail system with entry and exit-controlled AFC. With AVL data, it is possible to determine both the headway preceding a given bus trip and the in-vehicle travel time between a given origin stop and destination stop. This is done by performing simple arithmetic operations on timestamps extracted from the AVL system, once the origin/destination (OD) pair has been identified.

Section 5.1.1 will define the various components of the bus journey, focusing specifically on two components over which operators have control: wait time and travel time. Journey Time, an absolute measure of reliability used to describe the passenger experience, will be formally defined in Section 5.1.2. Two relative measures of reliability, Excess Journey Time and Reliability Buffer Time, will then be defined in Section 5.1.3, based on the definition of Journey Time derived for buses.

5.1.1 Components of Bus Journey Time

The bus journey time has several components:

1. **Access Time** – This represents the amount of time for the passenger to walk from his (her) origin to the bus stop. While this time is not measurable with AVL data, the distance from the origin to a bus stop may be calculated from AFC data for home-based trips for smart cards with a registered home address.
2. **Wait Time** – This is the time the passenger spends at the bus stop waiting for the bus to arrive. Neither AVL data nor AFC data indicate the arrival time of the passenger at the stop; however, if the assumption is made that a randomly arriving passenger (for a high frequency service) is equally likely to arrive at any point during the preceding headway, the mean wait time may be inferred (see further discussions of this below).
3. **(In Vehicle) Travel Time** – This is the time the passenger spends on the bus between their origin stop and their destination stop. It may be calculated from AVL data, by finding the difference in timestamps between the origin and destination stop for a given trip.
4. **Egress Time** – This represents the time it takes the passenger to walk from the destination stop to the final destination of the trip. Similar to access time, the egress distance may be calculated from AFC data in certain instances.
5. **Transfer Time** – For multi-leg trips, this represents the amount of time the passenger takes to go from the stop/platform of the alighting vehicle to the stop/platform where he or she will board a vehicle for the next leg of the trip.

The analysis presented in this chapter will focus on journey components that may be measured or inferred exclusively with AVL data: *wait time* and *travel time* for a given OD pair at the bus stop level. The sum of wait time and travel time will be referred to as *Journey Time*.

While travel time is directly measurable from automated data sources, wait time is not. On bus networks with AFC systems, the time a passenger boards a bus is directly measurable. However, the time the passenger arrives at the bus stop remains unknown, making a precise estimate of each passenger's wait time impossible.

An assumption is therefore required in order to estimate wait time. For high frequency routes, it is reasonable to assume that passenger arrivals are random, so they have a uniform probability density function (PDF) during small, homogenous time periods. A passenger is equally likely to arrive at any time during a given headway, as illustrated by the PDF shown in Figure 5-1. For any given trip i, the PDF extends from time 0 to the length of the headway preceding i, H_i.

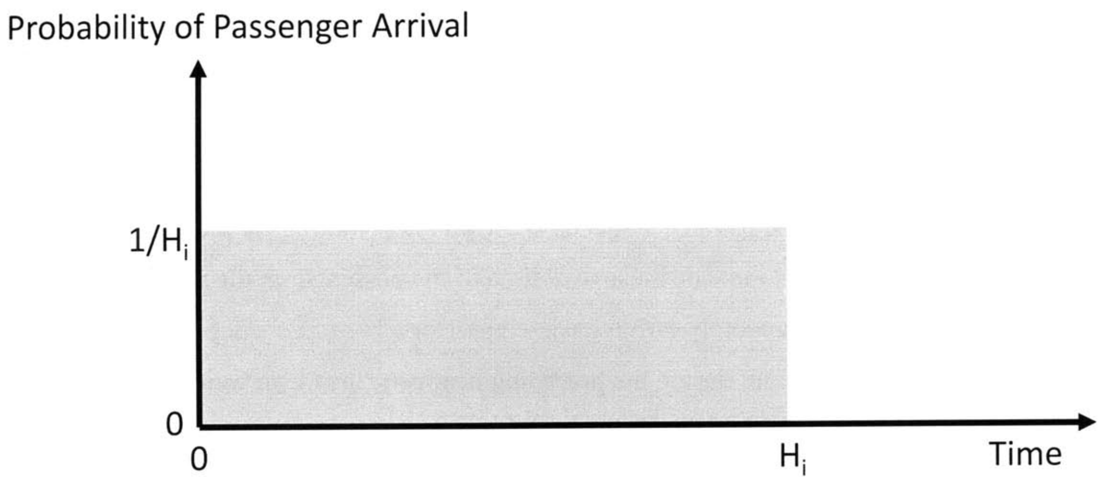

Figure 5-1 - Passenger Arrival PDF

A wait time distribution is estimated by computing the probability that a passenger on a given bus trip at a given origin stop, i, has a wait time, W_i, less than a given time, x. This probability is computed by integrating the PDF from 0 to x. If the given time is greater than the observed headway for bus i, a passenger has a 100% chance of waiting less than the given time. If the given time is less than the observed headway, H_i, the probability of waiting less than the given time is x/H_i, the integral of the PDF between 0 and x, as expressed in Equation 5-1.

$$P(W_i \leq x) = \begin{cases} 0, & 0 \leq x \\ \frac{x}{H_i}, & 0 \leq x < H_i \\ 1, & x \geq H_i \end{cases}$$

(Equation 5-1)

This is not a precise method for estimating wait time; it is a distribution which most likely resembles passenger arrival patterns for high frequency services.

One critical assumption when calculating a wait time distribution is that a passenger boards the first bus that arrives at a given stop. This implies that each arriving bus has sufficient capacity to pick up all passengers waiting at a given stop, which is not always true, especially during periods of high demand and with uneven service.

If a randomly arriving passenger during a given, homogenous timeband is assumed to board the first arriving bus, the probability of the passenger being found on a given bus out of the set of buses observed during the timeband can be computed. Consider the example shown in Figure 5-2. Four headways are shown during a homogenous time period in which the passenger arrival PDF is assumed to be uniform. The passenger is most likely to arrive during H3, the longest headway in this time period, and is least likely to arrive during H2, the shortest headway. Since the passenger arrival distribution is uniform throughout the period, the probability of a passenger arriving during H1 is computed by dividing H1 by the period length. Equation 5-2 shows a generalized form of this equation for a set of N trips, where the probability of a passenger arriving during a headway H_i, and therefore the probability of the passenger being on bus i, is shown.

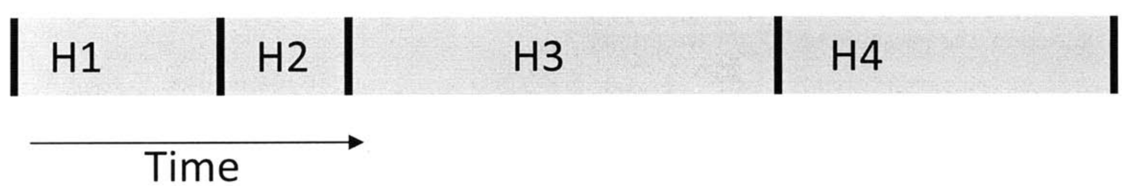

Figure 5-2 - Passenger Arrival Distribution across Four Headways

$$P(Passenger\ on\ bus\ i) = \frac{H_i}{\sum_{i=1}^{N} H_i} \qquad \text{(Equation 5-2)}$$

Now that wait time for a passenger on an individual bus and the probability of a passenger being observed on a given bus out of a set of buses have been defined, these definitions are applied towards computing Journey Time.

5.1.2 Journey Time

Journey Time is an absolute measure of reliability accounting for the components of the passenger experience over which the bus operator has control: wait time and travel time. As expressed in Equation 5-3, Journey Time, J_i, is the sum of wait time (non-deterministic and represented by a PDF), W_i, and travel time (deterministic and computed as a single, known value), T_i. To differentiate this measure from the journey time discussed in Section 5.1.1, which includes access time, wait time, travel time, egress time, and transfer time, the measure introduced here will be capitalized and referred to as Journey Time.

$$J_i = W_i + T_i \qquad \text{(Equation 5-3)}$$

Since wait time is not measurable, Journey Time is also not measurable. It is only possible to calculate a distribution of Journey Times based on information known about travel time and the assumptions made about wait time.

For a given bus trip between a given OD pair, the real, non-measurable Journey Time falls between two values, reflecting the range of possible wait times (travel time is known and therefore constant for the given trip). The minimum value of Journey Time is realized when a passenger arrives at the origin stop as the bus is about to depart. In this case, the wait time is zero and the Journey Time is equivalent to the travel time, T_i. The maximum value of Journey Time is realized when a passenger arrives at the origin stop just after a bus departure. The passenger must wait the entire length of the next headway before boarding the first arriving bus. In this case, the Journey Time is the sum of the headway preceding the given bus trip, H_i, and the given bus trip's travel time, T_i. In all other cases, Journey Time falls between these minimum and maximum values, and the probability of the Journey Time being less than or equal to a given time is based on the passenger PDF for wait time.

Figure 5-3 provides an example of how Journey Time is computed for single journeys. Each trip shown consists of a measured travel time and a PDF of wait time based on measured headways. The set of journeys is being compared to a given time, j, to find the probability that a Journey Time represented by the set of journeys is less than or equal to j. In the case of Trip 2, the travel time is greater than j. Therefore, the minimum Journey Time for a passenger on Trip 2 is greater than j, resulting in a 0% probability that a passenger with a Journey Time less than or equal to j is on Trip 2. Trip 3 has a maximum Journey Time less than j. Therefore, 100% of passengers on Trip 3 have a Journey Time less than j. On Trip 1, j falls between the maximum Journey Time and the minimum Journey Time. Therefore, the probability of a passenger journey being less than or equal to j is expressed as (j-Ti)/Hi, the integral of the wait time PDF to the left of j (i.e. Journey Times less than j).

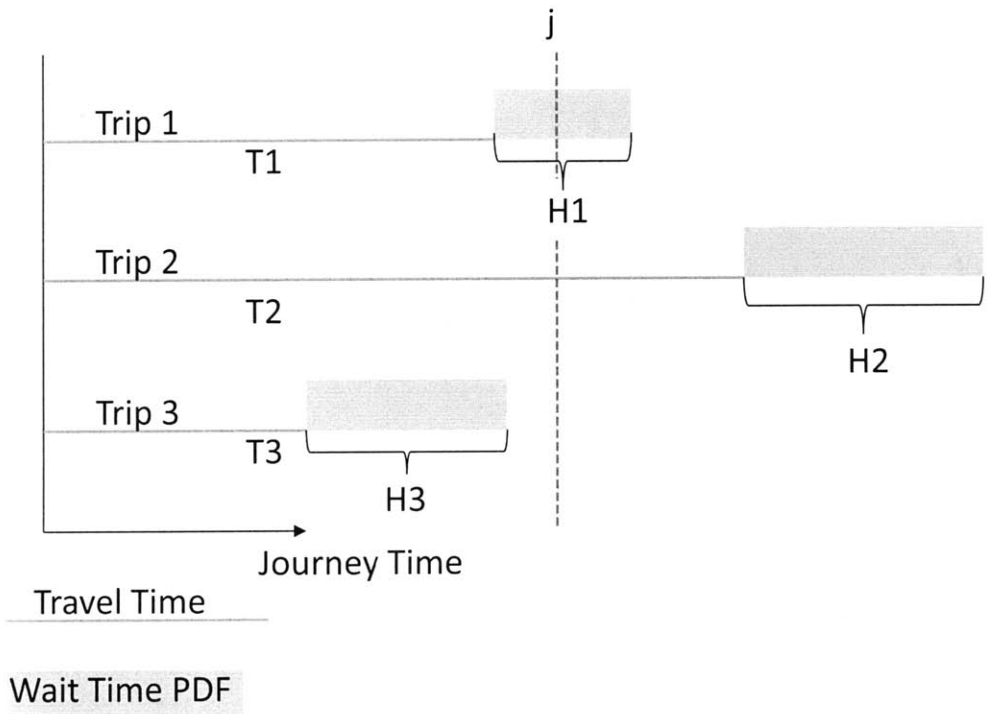

Figure 5-3 - A Set of Journey Times for 3 Bus Trips

The Journey Time cumulative distribution for an individual trip is shown in Equation 5-4. As demonstrated by each of the three trips shown in Figure 5-3, j may either be less than T_i, between T_i and T_i+H_i, or greater than T_i+H_i.

$$P(J_i \leq j) = \begin{cases} 0, & j < T_i \\ \dfrac{j - T_i}{H_i}, & T_i \leq j < T_i + H_i \\ 1, & j \geq T_i + H_i \end{cases} \qquad \text{(Equation 5-4)}$$

For a set of journeys, it is difficult to directly compute the Journey Time corresponding to a given percentile value. Therefore, for a range of bus journeys (including known travel times and wait time PDFs) between a given OD pair, the probability of a passenger having a Journey Time less than or equal to j, a given time, is used to calculate the Journey Time cumulative distribution, with desired percentile values inferred by interpolation.

Observed travel times and headways have different distributions, as shown in Figure 5-4, and are therefore statistically independent. Thus, when calculating the percentile Journey Times over more than one observed trip, the corresponding percentile travel time and wait time cannot simply be added, as this produces an inaccurate estimate of Journey Time.

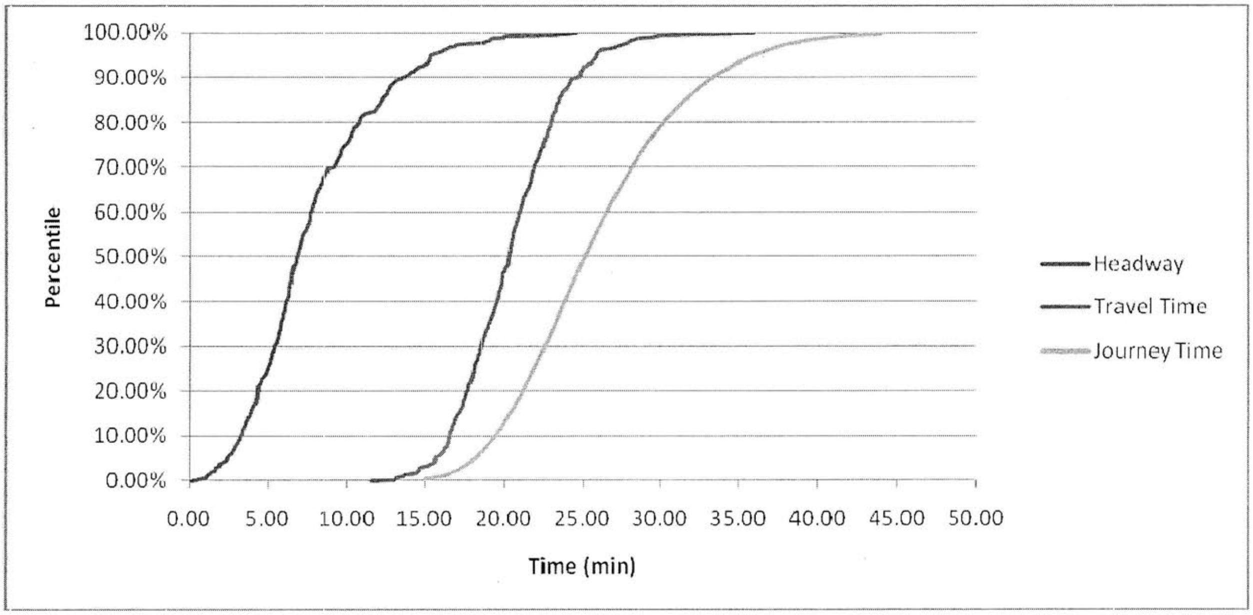

Figure 5-4 - Headway, Travel Time, and Journey Time CDF for Route 259 between Edmonton and Seven Sisters

Figure 5-3 also shows how a Journey Time distribution may be derived for this set of bus trips. To compute the probability of Journey Time being less than a given time j for this set of trips, the integral of the wait time PDFs that fall to the left of j are computed (a modification of Equation 5-4). This represents the total amount of potential wait time on the given trips that would have resulted in a Journey Time less than or equal to j (i.e. j – Ti for those trips where j falls between the minimum and maximum Journey Time, H_i for trips where x is greater than the maximum Journey Time, and 0 for all other trips). The potential wait time is then divided by the total amount of wait time during this time period (i.e. the sum of all headways) to create the Journey Time distribution.

This aggregate result is computed by multiplying Equation 5-2 and Equation 5-4. In essence, what is calculated is the product of the probability of a passenger being on trip i and the probability of a journey on trip i being less than or equal to the given time j. This is expressed in Equation 5-5 and 5-6 for a set of N trips, and these equations are subsequently used to compute the Journey Time distributions presented later in this chapter.

$$P(J \leq j) = \frac{\sum_{i=1}^{N}(P(J_i \leq j) * H_i)}{\sum_{i=1}^{N} H_i} \qquad \text{(Equation 5-5)}$$

Where:

$$(P(J_i \leq j) * H_i) = \begin{cases} 0, & j < T_i \\ j - T_i, & T_i \leq j < T_i + H_i \\ H_i, & j \geq T_i + H_i \end{cases} \qquad \text{(Equation 5-6)}$$

A Journey Time distribution is produced from AVL data using this result, and the desired percentile values are found via linear interpolation.

5.1.3 Excess Journey Time and Reliability Buffer Time

The derivation above makes it possible to determine the entire CDF of passenger Journey Times. This enables the analyst to calculate relative measures of reliability. Of particular interest to the analysis presented in this chapter are the following three Journey Times, which may be specified for any given OD pair:

1. **Scheduled Journey Time** – This represents the Journey Time experienced by a randomly arriving passenger if the service is delivered exactly according to the schedule. It is calculated by computing a CDF based on the scheduled Journey Time between the given OD pair.

2. **Median Journey Time** – This represents the typical trip length experienced by a randomly arriving passenger. It is computed as the 50^{th} percentile CDF for Journey Time based on AVL data.

3. **95^{th} Percentile Journey Time** – This represents "poor service" for a passenger, which would be expected to occur 1 in every 20 journeys, or approximately once a month for a commuter. It is computed as the 95^{th} percentile CDF for Journey Time based on AVL data.

These Journey Times enable two relative measures of service quality to be calculated, Excess Journey Time and Reliability Buffer Time:

1. **Excess Journey Time (EJT)** is the difference between the median journey time and the scheduled journey time, as shown in Equation 5-7. This metric compares the average performance of a route with its advertised performance. In essence, this extends EWT to include in-vehicle travel time.

   EJT = Median Journey Time – Scheduled Journey Time (Equation 5-7)

2. **Reliability Buffer Time (RBT)** is the difference between the 95^{th} percentile journey time and the median journey time, as shown in Equation 5-8. This represents the extra time a passenger needs to budget above and beyond the median Journey Time to be confident of arriving at the destination on time 19 times out of 20. RBT allows the analyst to focus on variability of service as it affects the passenger experience.

$$\text{RBT} = 95^{\text{th}} \text{ Percentile Journey Time} - \text{Median Journey Time} \qquad \text{(Equation 5-8)}$$

The motivations for using these measures are similar to their counterparts developed by Uniman (2009) and Chan (2007). As Uniman (2009) has shown for the Underground, in order for a passenger to arrive at his/her destination on time 95% of the time, he/she needs to budget enough time to match the 95th percentile of the cumulative density function of *total* journey time. A trip taking less than the 95th percentile travel time results in extra time being available at the end of the trip as well as providing an on-time arrival (Furth and Muller, 2006). An advantage of RBT is that it accounts for variation in total Journey Time including both passenger wait time and in-vehicle travel time, reflecting their combined effect.

While passengers are concerned with their journeys being reliable, they also appreciate a service that is consistent with the schedule. This is true of a schedule that only displays headways and estimated travel times, as is the case with many high-frequency urban bus lines. In order to see how accurate the schedule is compared to observed operations, Excess Journey Time (EJT), which compares the median Journey Time with the scheduled Journey Time, is used.

5.2 iBus Data

This section introduces iBus data, on which the analysis in this chapter is based. TfL's intention is to use these data to produce reports describing the operations and performance of the bus network. As will be discussed, some ambiguities currently exist in the data, presenting challenges in producing a full and accurate picture of operations. Methods must therefore be developed to resolve the ambiguities in the data, and in cases where the ambiguities cannot be resolved, the accuracy of the data must be verified.

5.2.1 Data Format

All data used for iBus analysis were queried from the LRD Test database via a Hyperion-based interface. The LRD Test database contains records of all bus schedules and all buses observed in iBus. When a scheduled bus is not observed, the fields corresponding to observed times are null. The following data columns were extracted from the LRD database:

- "Shortdesc" – Route number
- "Direction" – Direction of the trip, which takes on a value of 1 or 2
- "Tripnr" – Trip number
- "Scheduleddeparturetime" – A timestamp indicating the date and time the bus is scheduled to leave the stop

- "Observed Arrival Time" – A timestamp indicating the time the bus was observed to arrive at the stop (date and time). Note that there is ambiguity on what exactly is recorded[6].
- "Observed Departure Time" – A timestamp indicating the time the bus departed the stop. As with the Observed Arrival Time, there is ambiguity on what is actually recorded.
- "Shortdesc2" – A unique identifier for the bus stop, which may be joined to the set of bus stops in the GIS database.
- "Longdesc" – The name of the bus stop, which is either an intersecting street or a local landmark.
- "Stopsequence" – The sequence number for the in the trip. 1 would be the first stop (origin), 2 would be the second stop, etc. For routes with regularly scheduled short-turn service, the sequence starts at 1 at the first stop of the trip in question, even if the trip starts midway along the full route.
- "Scheduleddistance" – An integer value representing the distance, in meters, between the stop in question and the previous stop
- "Sched Dist In Trip" – An integer value representing the cumulative distance of the trip from the origin stop to the stop in question. It is the sum of all the "Scheduleddistance" entries for the trip in question up to and including the stop in question.

5.2.2 Missing Data

There are numerous instances of null, or potentially missing, data in the iBus database. In order to validate whether this was due to systematic error, or due to a trip not being operated, a comparison of iBus data with manual survey data, extracted from the Stabs database for QSI points on the routes under analysis was performed. Table 5-1 lists the scenarios for possible data issues in both the Stabs and iBus databases.

As shown in Table 5-1, a common concern when analyzing missing trips is determining whether a driver has simply neglected to log in before starting each trip. Drivers may not log in to the system before pulling into the first stop, and may log out before pulling out of the last stop. While it is possible for service controllers to log drivers in, they may not notice a missing trip immediately. This can result in a significant number of missing trip observations at both termini of the route. In this analysis, when a missing origin (destination) stop is involved in subsequent analyses, the following (previous) stop record will be used as a proxy if it exists.

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[6] The timestamp represents one of the four following occurrences: the time the bus enters a radius around the stop, the time it leaves the radius around the stop, the time the doors open, or the time the doors close. The event recorded varies according to established sequential event patterns coded into the iBus system and TfL does not have records of which event specifically is being recorded.

Table 5-1 - Missing Data Issues

Issue	Stabs (Manual Survey)	iBus
Trip not run, bus not deadheaded	Not included	Null
Trip not run, bus deadheaded with signs indicating route	Possibly included (due to signage)	Possibly included if driver remained logged in, otherwise null
Trip not run, bus deadheaded not indicating route	Not included	Possibly included if driver remained logged in, otherwise null
Trip run, driver not logged in	Included, unless missed by surveyor due to human error	Null
Trip Run, iBus not working	Included, unless missed by surveyor due to human error	Null
Trip Run, iBus working, driver logged in	Included, unless missed by surveyor due to human error	Included

While comparing each observed trip in iBus with each trip observed by the manual surveyor, raw survey data from Stabs are not readily accessible; formatted reports are more common. Each report from Stabs contains a summary of observations for one 2.5 to 3 hour shift at a specific QSI point. Data in this report include:

- The location of the survey;
- The time and date of the shift;
- The length of the shift;
- The maximum observed gap between buses;
- The number of expected buses;
- The number of observed buses;
- AWT;
- SWT; and
- EWT.

An SQL query of the iBus data and a subsequent spreadsheet analysis enable similar data from AVL to be generated in order to make a comparison with the manual survey data. The query selects all buses at the given stop which were observed during the period of the manual survey; records of scheduled trips that had null observed departure times were excluded, as these trips were assumed to have not been run. These data were ordered by observed departure time, from which the headways between successive observed buses were computed, as well as the number of observed buses. The set of headways from all surveys were combined in one spreadsheet, from which aggregate AWT and SWT values were computed for the entire period. Results could then be compared with the manual surveys. Table 5-2 presents the comparison for Routes 38, 98, 148, 211, and 259 for all manual surveys conducted during the AM peak between November 14 and December 11, 2009.

Table 5-2 - AM Peak Stabs/iBus Comparison for 5 Routes

	Route 38		Route 98		Route 148		Route 211		Route 259	
	Stabs	iBus	Stabs	iBus	Stabs	iBus	Stabs	iBus	Stabs	iBus
AWT (min)	2.36	2.57	3.29	3.96	5.80	6.70	6.57	7.07	5.02	5.07
SWT (min)	1.42	1.52	2.52	2.53	3.62	3.63	3.85	3.87	3.71	3.71
EWT (min)	0.94	1.04	0.77	1.43	2.18	3.06	2.72	3.20	1.30	1.36
Max Gap (min)	14.93	15.35	19.62	21.03	28.18	37.15	27.90	27.02	24.78	18.23
Observed Buses	444	440	172	157	134	122	45	43	118	113

Two important differences are observed in Table 5-2. The first is that the number of buses observed in Stabs is always greater than the number of buses observed in iBus. The second trend is that EWT calculated with iBus data is always greater than EWT calculated with Stabs data. While this may suggest that iBus is not an accurate means of estimating EWT, a closer look at the relative differences between similar computation in iBus and Stabs is warranted.

Large sample sizes mitigate the effect of missing buses, as seen with Route 38. Route 259, which has a smaller sample size, still displays a good EWT match because it has a relatively low number of missing trips (about 4% of the manually observed trips). Routes 98 and 148 have about 9% of manually observed trips not recorded by iBus; these trips do not match up as well with the manual data. This is because there are too many large headways created due to missing trips to render the sample unbiased.

With very small sample sizes, even if the percentage difference in the number of observed buses with iBus and Stabs is not great (about 4% for route 211), the missing buses have a much greater effect on EWT, as the large gaps produced by missing buses are squared in this calculation.

While the above comparisons represent the entirety of manual surveys carried out on the respective routes during the AM peak for the period in question, they represent only a very small sample of the iBus data available for analysis. It was assumed that as the sample size grows beyond the sizes indicated above, the errors should decrease. This was tested by analyzing two of the poorer matching routes, Route 148 and 211, over all weekday timebands, as shown in Table 5-3. However, the results indicate that matching remains poor for these two routes.

Table 5-3 - Route 148 and Route 211 Weekday Stabs/iBus Comparison

	Route 148		Route 211	
	Stabs	iBus	Stabs	iBus
AWT (min)	5.42	6.07	6.14	6.91
SWT (min)	3.77	3.80	4.22	4.36
EWT (min)	1.65	2.27	1.92	2.55
Max Gap (min)	29.03	37.15	30.32	39.78
Observed Buses	494	465	274	266

It is still in the best interest of both TfL and the operators to minimize the amount of missing data in order to provide more accurate estimates, as it will have implications for performance evaluation once performance measurement is automated via iBus. The implications of missing data from the operations perspective are discussed below.

5.2.3 Imputation

TfL has developed a methodology called Imputation to address missing iBus data issues caused by malfunctioning AVL units. By identifying data with Lost Mileage attributed to technological faults, TfL uses historical AVL data to provide a best estimate of the headways before and after the missing bus. This methodology is needed to provide as accurate an estimate of the QSI measures as possible.

This methodology was developed based on an artificial (i.e. generated) set of iBus data: A virtual route with 5 QSI points was created, and a range of headway/standard deviation distributions was generated and compared with real data from 2 routes. If the calculated EWT for the generated route was similar to the observed EWT, the headway/standard deviation distribution was used in subsequent analyses. A range of headways (between 3 and 12 minutes) was tested, reflecting the range of headways operated on the bus network. Factors for schedule adherence, bus bunching, journey time, and randomness (singular incidents/delays) were introduced into the generated data to resemble real-life operating conditions. Up to 25% of the generated iBus data were removed on a random basis with the intent of filling in missing data by inserting the mean headway based on an observed headway distribution, excluding all headways from the distribution above a certain percentile. Percentiles tested ranged from 70% to 100% in increments of 10%. Using the mean headway based on a distribution of headways with values less than or equal to the 90th percentile headway was found to best match to the full data set results.

Imputation lowered the AWT in the dataset compared to a base case not requiring imputation. However, a sharp increase in AWT was noted when more than 20% of the data are missing. It was therefore proposed that imputation only be run when less than 20% of the data are missing. Lower headway means and standard deviations produced more accurate results due to the tighter headway distributions in these cases.

While this is a reasonable way to deal with missing data, imputation will not be used in this research. Using historical data involves an inherit risk of bias, because those data reflect the historical conditions in which the route operated, which may not be similar to current conditions. Additionally, the data provided for the analysis in this thesis do not include Lost Mileage causes, so it would be impossible to identify which bus trips should be imputed and which should not. Finally, since buses may overtake each other on the road, there is no way of being sure which gap the imputed bus should be filling. To avoid these difficulties, the iBus data will be used as is with the caveat that a close monitoring of the iBus system is required to minimize these types of errors.

5.2.4 Implications for London Bus Operations

While operators are not directly penalized for driver errors using iBus, it is to their advantage to ensure that the data reported are as accurate and complete as possible. The operators are paid for trips that do not appear in iBus but were known to have been run. However, the missing data in the iBus database for these trips are not imputed; the artificially large gaps are used in subsequent QSI calculations to the detriment of the operator. While it may be possible to identify missing trips in iBus that were in fact run, it is a time consuming process.

The imputation procedure is only run in instances where a malfunctioning iBus unit is the cause of missing data; in all other cases, missing data will be ignored, meaning that missing trips were assumed not to have been run. TfL imputes missing trips due to malfunctioning iBus units because upkeep of iBus units is their responsibility; thus operators should not be penalized for these missing data. This has severe implications for operators that do not closely monitor driver behavior, especially those not ensuring that drivers log into the correct run before starting their trips. If the driver fails to log in or is logged in incorrectly as the bus passes a QSI point, that trip will not be counted towards that route's QSI measures. The bus missing from the iBus data results in an observed "headway" that was in fact two headways. This becomes particularly severe if consecutive buses are not counted, as EWT is a function of the square of the headway. It is therefore in the operator's best interest to ensure that all operators log in at the beginning of each trip, as their QSI performance will be more accurate once measurement becomes fully automated.

It may be advisable for TfL to rethink how maintenance of iBus units is carried out, or to set additional rules concerning operators with malfunctioning iBus units. One possibility would be to transfer maintenance responsibility of iBus units from TfL to the private operator. The risks and penalties associated with malfunctioning units would therefore be borne by the operators. A less drastic possibility would be ensuring that all buses have a functioning iBus unit at the start of each duty. In a situation where a bus that has yet to be dispatched from the garage has a malfunctioning iBus unit, operators would be required to ground that bus until the unit is fixed. Malfunctions en route would be treated as they currently are. While these are merely suggestions, they reflect the concerns evident with the way missing data is currently handled, and may lead towards a solution that is more in line with TfL's service delivery objectives.

5.3 Methodology

This section describes the procedure for calculating the service reliability measures introduced at the beginning of the chapter using the data sources introduced in the previous section. The objectives of the analysis are to develop headway, travel time, and Journey Time distributions from a database of iBus timestamps. The main tools used for the data analysis were Microsoft SQL Server to query the extracted iBus data and Microsoft Excel to post-process the data.

Each route's iBus extract is essentially a list of every scheduled trip, stop and day combination for that route. In order to filter and order the data for the proposed analysis, the data were uploaded into an SQL database and queried. For a given OD pair, the SQL query was able to order all observed bus trips[7] chronologically, and calculate scheduled and observed in-vehicle travel times. By joining the list of all records for the given route to itself to match the given origin stop with the given destination stop for each trip, ensuring that records matched contain the same trip number and date, the in-vehicle travel time is calculated by taking the difference in timestamps between the given origin and destination stops.

These ordered data were then exported into a spreadsheet where the headways were calculated as the difference in Observed Departure Time timestamps at the origin stop between two successive, chronological records. Once the headway distribution is known, AWT is calculated. SWT is calculated in a similar fashion, but by using the scheduled departure timestamps instead of the observed times. Once AWT and SWT are known, EWT is calculated as the difference between the two values.

In-vehicle travel time distributions, which will be analyzed further in Chapter 6, are calculated from the set of observed travel times generated between a given OD pair. Each observed trip during the period

[7] Observed bus trips have non-null Observed Departure Time timestamps at both the origin stop and the destination stop.

being analyzed results in one in-vehicle travel time. These data are sorted and ranked as required to produce percentile values.

Journey Time distributions and percentile values are found using the methodology presented earlier in this chapter. Inputs into the analysis are the observed in-vehicle travel time and the headway[8]. For a randomly arriving passenger, the headway represents the maximum wait time a passenger boarding the bus arriving at the end of the headway would experience. The sum of this headway and the in-vehicle travel time on the given bus would therefore represent the maximum Journey Time a passenger on that bus can experience.

To generate percentile values, a spreadsheet with a set of bins representing potential Journey Times is created, as shown in Table 5-4. Each trip is then allocated across the bins. If the in-vehicle travel time is greater than the bin value, it is impossible for any passenger on this trip to have experienced a Journey Time equal to or less than the bin value. If the maximum possible Journey Time is less than the bin value, all passengers on this trip experienced a Journey Time less than or equal to the bin value. If the bin value falls between the in-vehicle travel time and the maximum Journey Time, some passengers may have experienced a shorter Journey Time than the bin value, while others experienced a longer Journey Time. Equation 5-6, a sample of the formula based on Equation 5-5, was used to calculate Cell E3 in Table 5-4:

$$= \mathrm{IF}(\mathrm{E\$2} < \$C3{,}0{,}IF(E\$2 >= (\$C3 + \$B3){,}\$B3{,}E\$2 - \mathrm{\$C3})) \qquad \text{(Equation 5-9)}$$

In the first case, a 0 is recorded in the cell for the given bin/trip pair, as shown in Cell E3. In the second case, the value of the headway preceding the given trip is recorded, as shown in Cell K3. In the third case, the difference between the bin value and the observed in-vehicle travel time is recorded, as seen in Cell J3. For each bin, these values are summed across all trips, as shown in Row 13, then divided by the sum of the headways to produce the percentile Journey Time represented by the bin value in Row 14.

When a certain percentile value is required (e.g. 95th percentile) not corresponding exactly with any given bin value, linear interpolation is used with the two surrounding bin/percentile combinations as inputs. For example, to find the 95th percentile Journey Time, bin/percentile pairs (24, 0.92) and (25, 0.96) are used as inputs to the interpolation, resulting in a 95th percentile Journey Time of 24.75 minutes. The desired Journey Times are then found, and EJT and RBT calculated.

[8] The average measured headway is also presented as an indicator of how many buses were observed. If the average headway is greater than the scheduled headway (or greater than twice SWT), there is evidence of missing buses.

Table 5-4 - Sample Journey Time Calculation Spreadsheet

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P
1		**Headway (min)**	**IVTT (min)**	**Max Journey (min)**	**Bins (min)**											
2					**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
3	**Trip 1**	2.27	18.77	21.04	0.00	0.00	0.00	0.23	1.23	2.23	2.27	2.27	2.27	2.27	2.27	2.27
4	**Trip 2**	7.38	19.25	26.62	0.00	0.00	0.00	0.00	0.75	1.75	2.75	3.75	4.75	5.75	6.75	7.38
5	**Trip 3**	2.07	19.61	21.68	0.00	0.00	0.00	0.00	0.39	1.39	2.07	2.07	2.07	2.07	2.07	2.07
6	**Trip 4**	4.95	16.09	21.04	0.00	0.91	1.91	2.91	3.91	4.91	4.95	4.95	4.95	4.95	4.95	4.95
7	**Trip 5**	3.72	16.68	20.40	0.00	0.32	1.32	2.32	3.32	3.72	3.72	3.72	3.72	3.72	3.72	3.72
8	**Trip 6**	6.42	18.19	24.61	0.00	0.00	0.00	0.81	1.81	2.81	3.81	4.81	5.81	6.42	6.42	6.42
9	**Trip 7**	3.68	15.50	19.17	0.50	1.50	2.50	3.50	3.68	3.68	3.68	3.68	3.68	3.68	3.68	3.68
10	**Trip 8**	1.16	19.33	20.49	0.00	0.00	0.00	0.00	0.67	1.16	1.16	1.16	1.16	1.16	1.16	1.16
11	**Trip 9**	4.96	15.80	20.76	0.20	1.20	2.20	3.20	4.20	4.96	4.96	4.96	4.96	4.96	4.96	4.96
12	**Trip 10**	2.70	20.80	23.50	0.00	0.00	0.00	0.00	0.00	0.20	1.20	2.20	2.70	2.70	2.70	2.70
13	***Sum***	*39.30*			*0.70*	*3.92*	*7.92*	*12.97*	*19.95*	*26.80*	*30.57*	*33.57*	*36.07*	*37.68*	*38.68*	*39.30*
14	***Percentile***				***0.02***	***0.10***	***0.20***	***0.33***	***0.51***	***0.68***	***0.78***	***0.85***	***0.92***	***0.96***	***0.98***	***1.00***

5.4 Analysis

This analysis focuses on demonstrating the value of the three passenger-centric measures developed earlier in this chapter. However, when considering recommendations and policy implications based on this research, there are numerous dimensions that need to be considered. In many cases, TfL will need to consider the tradeoffs between these dimensions when deciding on service delivery objectives and policy. The dimensions are as follows:

- The customer experience – This dimension focuses on ensuring that the needs of the riding public are adequately met. A good service from the perspective of the public ensures that ridership will remain strong, and may induce more riders to take transit. Negative performance has an adverse affect on ridership, and may cause long-term harm to the perception of the system.
- Equity – This dimension reflects the need for good service, regardless of the demand pattern on an individual route. This includes ensuring that a good service is run on all parts of the network, even if incidents require a reallocation of resources from smoothly running services to fill in service on another part of the network. In day-to-day operations, this means ensuring that the off-peak direction receives its fair share of service so that passengers taking the bus in this direction are not greatly inconvenienced.
- Efficiency – This dimension reflects the need for operators to provide as good a service as possible without creating too much redundancy in the network. It would be ideal to have buses and drivers on standby should large gaps occur; however, this may not be feasible. The operator, and by extension TfL, are interested in providing the best possible service for the lowest cost.
- The service TfL is paying for versus the service TfL would like to have provided – Operator performance is judged based on clearly-defined measures set by TfL. Operators therefore tailor their operations to satisfy these measures to the best of their abilities. However, the question arises as to whether these measures best reflect the goals and objectives TfL sets when it defines good service. Do the current measures enable TfL to meet their service delivery objectives, or are some targets not being met?

The analysis also requires a set of assumptions:

- When analyzing a time period (e.g. AM peak), the headway is assumed to be constant across the period. Aggregate results, therefore, are not weighted by scheduled or observed buses per hour.
- Each example in this analysis focuses on the experience of a randomly arriving passenger on one OD pair. Potential ways to aggregate the measures presented in order to generate a route or network measure of reliability are discussed later in this chapter.

One of the objectives of this analysis was to determine how operations differed across routes with satisfactory EWT values (via manual surveys) and low Percent Lost Mileage due to traffic, and routes with satisfactory EWT but high Percent Lost Mileage due to traffic. The routes with the low Percent Lost Mileage (about 3-5%) will be referred to as "Good" routes, and the routes with high Percent Lost Mileage (8-9%) will be referred to as "Poor" routes. Key attributes of the 6 routes chosen are shown in Table 5-5. For each route, Wait Time, Percentile Run Times, Percentile Journey Times, EJT, and RBT will be analyzed for 2-4 major OD pairs. The procedure for selecting OD pairs is described in the following section. All analyses were performed based on 4 weeks of observations, from November 14, 2009 to December 11, 2009, and results shown are for the AM peak, between 7:00 and 9:30.

Table 5-5 - Panel of Routes for Analysis

Route	Headway (min)	EWT	Target EWT[9]	EWT Var[10]	% Lost Traffic
"Good"					
38	3-7	1.07	1.30	0.23	4.71%
98	4-6	1.24	1.70	0.46	3.45%
148	7-10	1.87	1.20	-0.67	3.04%
"Poor"					
88	5-8	1.74	1.70	-0.04	8.58%
211	6-10	1.73	1.30	-0.43	8.95%
259	6-10	1.54	1.70	0.16	8.38%

5.4.1 Selection of OD Pairs

High volume origin/destination (OD) pairs were identified for each route under analysis by using ridership numbers from the Bus Origin Destination Survey (BODS). BODS is a manual survey performed one day every 5 years for each bus route, providing a snapshot origin/destination matrix for the given route. For each route, 3 or 4 high volume origin/destination pairs based on AM peak ridership were chosen for subsequent analysis. However, in instances where major OD pairs were similar (i.e. two pairs sharing an origin and with neighboring destination stops), another pair was selected for analysis in order to provide a broader sampling of operations along the route.

[9] Target EWT is the baseline EWT value to which operator performance is evaluated. EWT values less than Target EWT indicate the operator is doing better than the expected performance, and may be eligible for bonus payments. In the opposite case, when EWT is greater than Target EWT, the operator may be subject to penalties.
[10] EWT Variance is the difference between Target EWT and EWT.

The ridership numbers used in the BODS survey were used only to select these origin/destination pairs; they were not used in the reliability analysis itself. Some of the BODS surveys used were several years old, and therefore may not accurately reflect current route ridership patterns. The OD pairs selected for analysis represent between 4-13% of the total AM peak ridership for the selected routes.

Results presented below include both the peak direction and the off-peak direction for each OD pair. While the peak direction may be of primary importance in ensuring reliable service, the off-peak direction was analyzed in order to see whether the operators were providing the service TfL paid for in this direction, or whether they were compromising service in this direction by short-turning or deadheading buses in order to better serve the peak direction. Short-turning will result in Lost Mileage; however it may improve EWT in the peak direction by filling in large gaps in service. Comparing operations among different routes will provide an indication of how the operators trade off the equity and efficiency dimensions of providing service discussed above.

It is suspected that the off-peak direction experiences the bulk of Lost Mileage. It will be possible to verify this hypothesis by comparing the average measured headway in the peak and off-peak direction, providing an indication of the average number of buses operated in each direction, and accounting for discrepancies in wait and travel times. If wait times are considerably larger in the off-peak direction, and the average headway indicates that missing buses are common on this segment, fewer buses are being used to serve this direction, indicating deadheading or short-turning is being used. The challenge for the operator is to find the right balance between the focus on peak service and providing a reasonable service overall, while the challenge for TfL is to define what requirements should be met in these situations.

5.4.2 Route 38

Route 38 is one of the busiest bus routes in London. It is a radial route which runs from Clapton, northeast of Central London, through Hackney and Islington to Victoria Station in the southwest corner of Central London. During peak hours, the central section of the route has 2-minute headways, while the outer section, in Hackney and Clapton, has 4-minute headways. This route therefore has regularly scheduled short-turn services recognizing the difference in passenger demand between the outer and central sections of the route. As shown in Figure 5-5, there are six QSI points[11] along this route. Due to a lack of available road space around Victoria Station, terminating buses are not allowed layover at Victoria, which makes operations in the outbound direction originating in Central London more difficult to control.

[11] QSIs are measured at the first stop and intermediate stops in the given direction, but never at the last stop. Therefore, QSI points shown at a terminal in the figures presented are only measured for buses departing the given terminal.

Four OD pairs were analyzed for Route 38. The ridership of the high volume direction of the OD pairs accounted for 9.5% of the AM peak ridership on this route. While the peak direction during the AM peak is southbound towards Central London, the three highest point to point loads were recorded in the off-peak direction departing northbound from Victoria towards points in Central London around Green Park and Piccadilly Circus. These OD pairs account for 7% of the total AM peak ridership. Thus, in addition to serving as a radial route from outer London to Central London, this route distributes National Rail passengers arriving at Victoria to major destinations in Central London, where it acts as a parallel service to the busy Victoria Line on the Underground. Since these point to point loads originating at Victoria were bound for three neighboring stops, only one of the three OD pairs, from Victoria to Green Park, was selected for analysis, and the other two pairs were assumed to yield similar results.

Loads for major ODs in the peak direction were more evenly distributed than those in the off-peak direction. Three high volume OD pairs were selected in this direction, although they only account for 2% of the total AM peak ridership. Two of these pairs are feeders to Angel and the surrounding neighborhood northwest of Central London. One of these OD pairs (Northchurch to Angel) is on the segment of the route with 2-minute headways and the other (Hackney Central to Angel) is on the segment of the route with 4-minute headways. The other OD pair chosen in this direction, from Clapton to Tottenham Court Road, is representative of passengers using this route as a commuter service from northwest London to Central London, a corridor not served by the Underground.

Table 5-6 presents the results of the service reliability analysis for Route 38. The average (measured) headways on this route indicate that most scheduled buses are run (scheduled headways range from 2-6 minutes). Therefore, large EWT values would indicate highly variable headways, which is not surprising considering the challenge of maintaining bus spacing for 2-minute headways.

Average headways on the Green Park/Victoria OD pair show fewer observed buses southbound than on the Northchurch to Angel segment, indicating missing buses on this segment. Since few missing buses are observed further upstream, buses may be curtailed in Central London before they reach the southern destination at Victoria. This intervention may be used in part to offset the fact that there is insufficient space at Victoria for layovers, so curtailments are used instead to manage gaps in service.

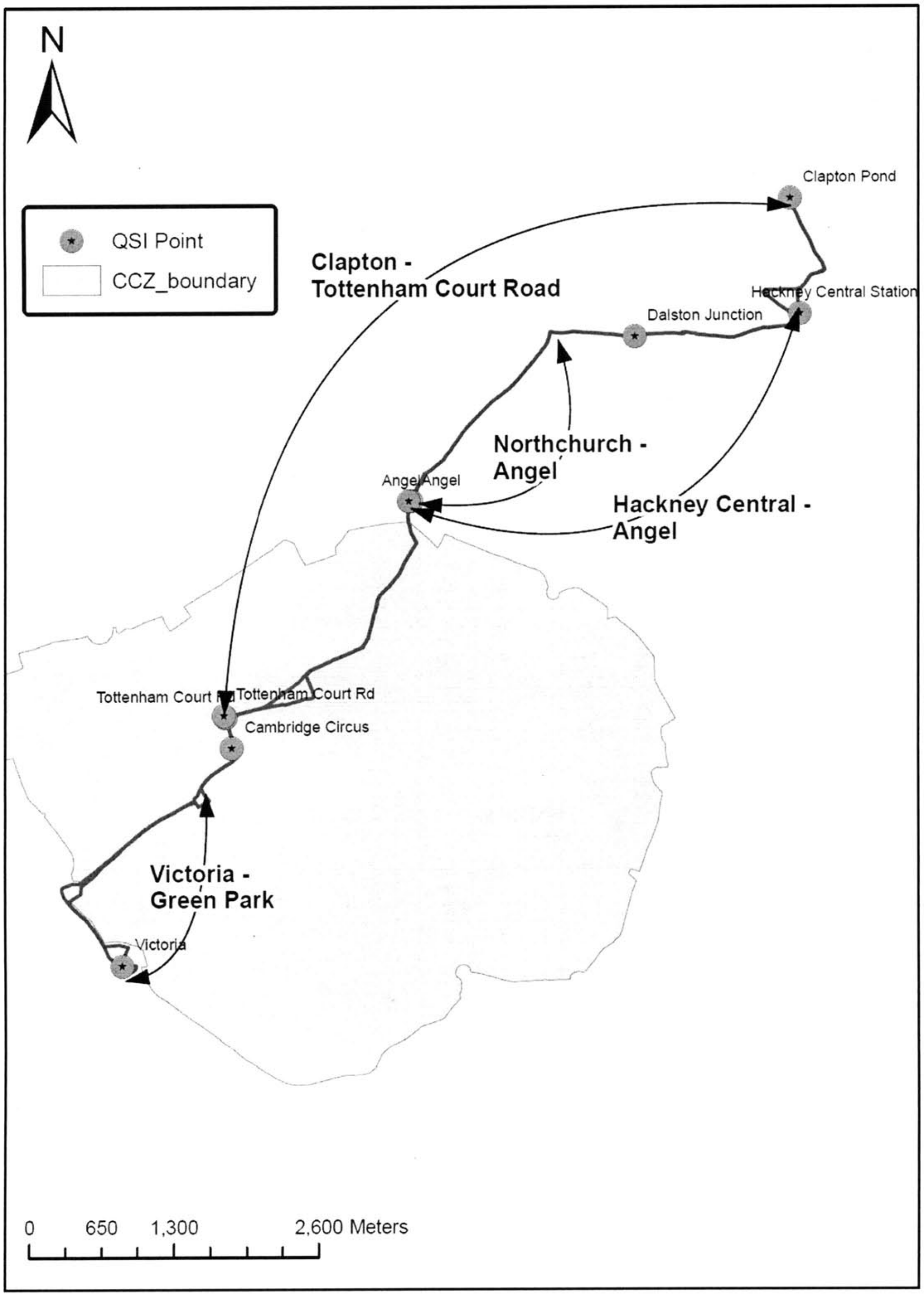

Figure 5-5 - Route 38 QSI Points and OD Pairs[12]

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[12] CCZ_boundary is the boundary of the Central Congestion Zone, representing the area of Central London. The arcs denote the OD pairs under analysis.

Table 5-6 - Route 38 Reliability Analysis[13]

Origin	Destination	Direction	Avg. Headway (min)	Wait Time (min)			Travel Time (min)			Journey Time (min)				
				AWT	SWT	EWT	95th	50th	Scheduled	95th	50th	Scheduled	RBT	EJT
Victoria	**Green Park**	**NB**	**3.06**	**2.06**	**1.33**	**0.73**	**9.75**	**6.66**	**8.2**	**13.5**	**8.5**	**9.3**	**5.0**	**-0.8**
Green Park	Victoria	SB	2.93	2.80	1.22	1.58	10.98	6.45	5.7	16	8.9	6.9	7.1	2.0
Northchurch	**Angel**	**SB**	**2.22**	**2.31**	**1.13**	**1.18**	**12.13**	**8.2**	**8.4**	**17.0**	**10.6**	**9.8**	**6.4**	**0.8**
Angel	Northchurch	NB	3.22	2.95	1.68	1.27	7.62	5.9	5.9	14.5	8.1	7.4	6.4	0.7
Hackney Central	**Angel**	**SB**	**4.69**	**3.77**	**2.28**	**1.49**	**44.25**	**27.52**	**24**	**51.0**	**31.5**	**27.5**	**19.5**	**4.0**
Angel	Hackney Central	NB	5.17	4.06	2.38	1.67	27.95	21.55	18.3	35.0	25.2	20.9	9.8	4.3
Clapton	**Tottenham Court Rd**	**SB**	**4.91**	**3.46**	**2.33**	**1.14**	**77.85**	**52.07**	**45**	**81.5**	**56.2**	**48.4**	**25.3**	**7.8**
Tottenham Court Rd	Clapton	NB	5.19	4.04	2.39	1.65	52.19	43.26	38.9	59.0	47.4	42.1	11.6	5.3

[13] The high volume direction for each OD pair is indicated in bold in this table and in all subsequent tables in this analysis.

One item that becomes evident when analyzing this route is that operations are very different between the inner half and the outer half. In particular, even though the magnitudes of EWT are consistent across all OD pairs, when wait times are normalized by SWT, a different trend is noticed. AWT/SWT approaches 2 on the inner half and is closer to 1.5 on the outer half, indicating that headways are more variable on the inner half of the route. This is not surprising, as it is difficult to maintain 2-minute headways on congested streets. With such short headways, a bus that arrives at a traffic signal at the end of a red phase could easily catch up with a bus that had stopped at the signal at the beginning of the red phase.

EJTs are quite low for this route. Those on the inner half indicate that the median Journey Time is a fairly accurate representation of the schedule. While EJTs on the outer half of the route appear to be large at first glance, when the scheduled Journey Time is used as a baseline for normalizing these values, they represent quite a low proportion of the scheduled Journey Time, and therefore indicate that the median passenger experience on this route is accurately described by the schedule.

The magnitudes of RBT are quite high for OD pairs originating in the outer half (Hackney and Clapton) in the southbound direction. For example, on the Clapton/Tottenham Court Road OD pair, a passenger must allow a buffer of 25 minutes in order to arrive on time with 95% certainty. Two factors account for this. First, there is very high variability in travel times indicating a high sensitivity to traffic conditions. Secondly, this is exacerbated by extremes in wait time, possibly due to uneven passenger loading as a result of the travel time variability. However, when the median Journey Time is used as a baseline for assessing RBT, these RBT values range between 45% and 62% of the median Journey Time, which is a lower percentage than is found on most other routes analyzed.

Another interesting difference between OD pairs on the inner half and the outer half of the route is that while the peak and off-peak directions have similar reliability on the inner half, on the outer half the RBT values in the peak direction are at least twice as large as in the off-peak direction. This is due to the variability of observed travel times between the two directions; the variability is much larger in the peak direction, indicating that the peak direction suffers variability caused by congestion. These new measures therefore show that this route is experiencing more variable service than suggested by EWT values alone, and may indicate a need for bus priority measures as a potential method for reducing travel time variability on the outer half, and a need for better headway management on the inner half.

5.4.3 Route 98

Route 98 is a radial route which runs from Willesden, northwest of Central London, to Tottenham Court Road via Marble Arch. There are three QSI points per direction at roughly equal intervals, as shown in

Figure 5-6. Being a radial route, the AM peak direction is from Willesden towards Central London. This direction has twice as many passenger trips during the AM peak as the lighter direction.

Owing to the difference in loads between the inbound and outbound directions, all the high volume AM peak OD pairs on this route are in the inbound (southbound) direction, and the ridership on these pairs in the peak direction represents about 4% of the overall AM peak ridership, evenly split among the four pairs. None of the high volume OD pairs are found on the portion of the route that runs through Central London. The Central London segment, from Marble Arch to Tottenham Court Road, is along Oxford Street, one of the busiest bus corridors in the city with numerous parallel services. Therefore, ridership between origins and destinations on this segment may be split among numerous parallel routes. Additionally, this route roughly parallels the Bakerloo Line, which may provide a faster journey time into Central London with greater connectivity than the bus.

A large number of passengers are using this route as a feeder/distributor service to connect with the various rail/Underground stations it serves, such as Kilburn High Road (Overground), Kilburn Park (Bakerloo), and Willesden Green (Jubilee), as opposed to using it to access Central London. The longest journey was from Willesden Green (the neighborhood, not the Underground station) to Orchardson Street in the St. John's Wood neighborhood. The shortest, from Walm Lane to Deerhurst Road, distributes passengers from the Willesden Green Underground station to destinations in the local neighborhood. The two other pairs account for passengers transferring to and from the London Overground at Kilburn High Road. Those passengers originating at Willesden Green may be using the Overground to connect to Euston Station; passengers boarding Route 98 at Kilburn High Road are transferring from the Overground to destinations in St. John's Wood.

Table 5-7 shows that Route 98 provides good overall service. Measured headways are consistent with scheduled headways (4-6 minutes), indicating few missing buses on the route. In the northbound direction, measured headways are slightly higher on the outer portion, indicating that there may be some deadheading to ensure demand in the peak (southbound) direction is adequately served. However, relatively low EWT values for all OD pairs indicate that when curtailments do occur, buses are being evenly spaced to minimize the impact.

EJTs are among the lowest of all the routes analyzed. The schedule therefore provides an accurate estimate of the median passenger experience. Additionally, scheduled travel times are close to the 50th percentile travel times, indicating that schedulers have a good grasp of the operations of the route. Accurate travel time estimates are possible because it is subject to a low degree of variability (except for Kilburn High Road to Orchardson Street); traffic has little effect on the reliability of this route.

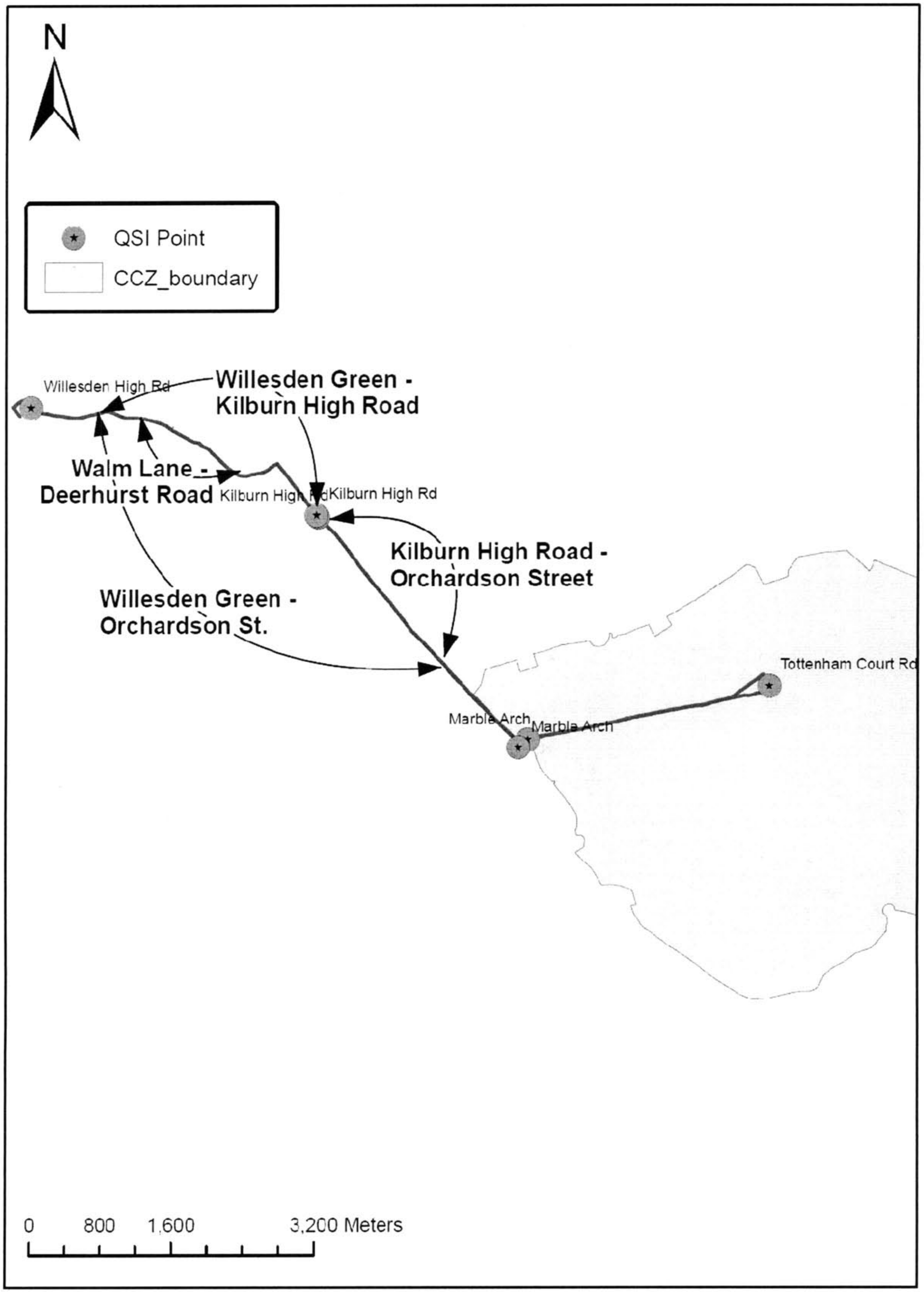

Figure 5-6 - Route 98 QSI Points and OD Pairs

Table 5-7 - Route 98 Reliability Analysis

Origin	Destination	Dir.	Avg. Headway (min)	Wait Time (min)			Travel Time (min)			Journey Time (min)				
				AWT	SWT	EWT	95th	50th	Scheduled	95th	50th	Scheduled	RBT	EJT
Willesden Green	**Orchardson St**	**SB**	**5.08**	**3.14**	**2.38**	**0.76**	**32.47**	**23.7**	**24.94**	**37.0**	**27.0**	**27.9**	**10.0**	**-0.9**
Orchardson St	Willesden Green	NB	6.06	4.10	3.06	1.04	22.99	19.2	18.78	30.7	22.8	21.7	7.9	1.1
Kilburn High Rd	**Orchardson St**	**SB**	**5.03**	**3.60**	**2.40**	**1.20**	**16.68**	**8.10**	**8.76**	**22.0**	**11.7**	**11.2**	**10.3**	**0.5**
Orchardson St	Kilburn High Rd	NB	6.07	4.10	3.06	1.04	8.32	6.52	6.81	17.0	10.0	9.7	7.0	0,3
Walm Ln	**Deerhurst Rd**	**SB**	**5.06**	**3.25**	**2.40**	**0.85**	**3.40**	**2.67**	**3.00**	**10.8**	**5.5**	**5.4**	**5.3**	**0.1**
Deerhurst Rd	Walm Ln	NB	6.63	5.10	3.50	1.59	2.79	1.91	2.96	15.0	6.2	6.1	8.8	0.1
Willesden Green	**Kilburn High Rd**	**SB**	**5.06**	**3.13**	**2.39**	**0.75**	**19.3**	**15.19**	**16.12**	**25**	**18.3**	**18.7**	**6.7**	**-0.4**
Kilburn High Rd	Willesden Green	NB	6.43	4.62	3.42	1.21	15.63	12.43	11.88	25	16.5	15	8.5	1.5

Both the Kilburn High Road/Orchardson Street and the Walm Lane/Deerhurst Road OD pairs have high RBTs when compared with the median Journey Time, indicating unreliable service. The RBTs on these segments are nearly equivalent to the median Journey Time; Journey Times between these pairs are therefore subjected to a high degree of variability. This is a trend observed for short trips across all routes, since a unit time of variability has a much larger effect on a short trip than on a large trip. Reducing variability on such a small scale may be a challenging goal for operators.

The other two OD pairs represent longer trips typically taken on this route. For these two pairs, the RBT is 1/3 of the median Journey Time, quite low when compared with the other routes. This indicates that the route is reliable for passengers between these OD pairs.

5.4.4 Route 148

Route 148 is a radial route running from Camberwell in South London to White City in West London via Central London. Since both ends of the route are outside Central London, aggregate loads in both directions are fairly even. This route operates with 7-8 minute headways during the AM peak. As shown in Figure 5-7, the westbound direction has four evenly-spaced QSI points, while the eastbound direction has three QSI points (Victoria not being measured in the eastbound direction), with a large gap along the central portion of the route between Notting Hill Gate and Elephant and Castle.

Four high volume OD pairs were identified for analysis on this route, and the high volume direction ridership on these OD pairs represents 7% of the AM peak ridership. In particular, Shepherd's Bush, a major interchange and shopping area in West London, was identified as a major origin and destination on this route. 12% of AM peak eastbound passengers were observed to travel between Shepherd's Bush and destinations between Notting Hill Gate and Marble Arch.

Many trips also terminate at Shepherd's Bush and one OD pair, from Victoria Station to Shepherd's Bush, was included to represent this segment of ridership. This OD pair likely contains passengers from National Rail services at Victoria travelling to the employment and shopping district at Shepherd's Bush. The other OD pair, from Walworth Road to Elephant and Castle, was included to represent ridership on the segment of the route serving Walworth and Camberwell in South London. This OD pair accounts for passengers travelling from this neighborhood to the major interchange (bus, Underground, and National Rail) at Elephant and Castle, where connections to numerous destinations in the region are possible. Thus, a fairly broad snapshot of possible origins and destinations were covered on this route.

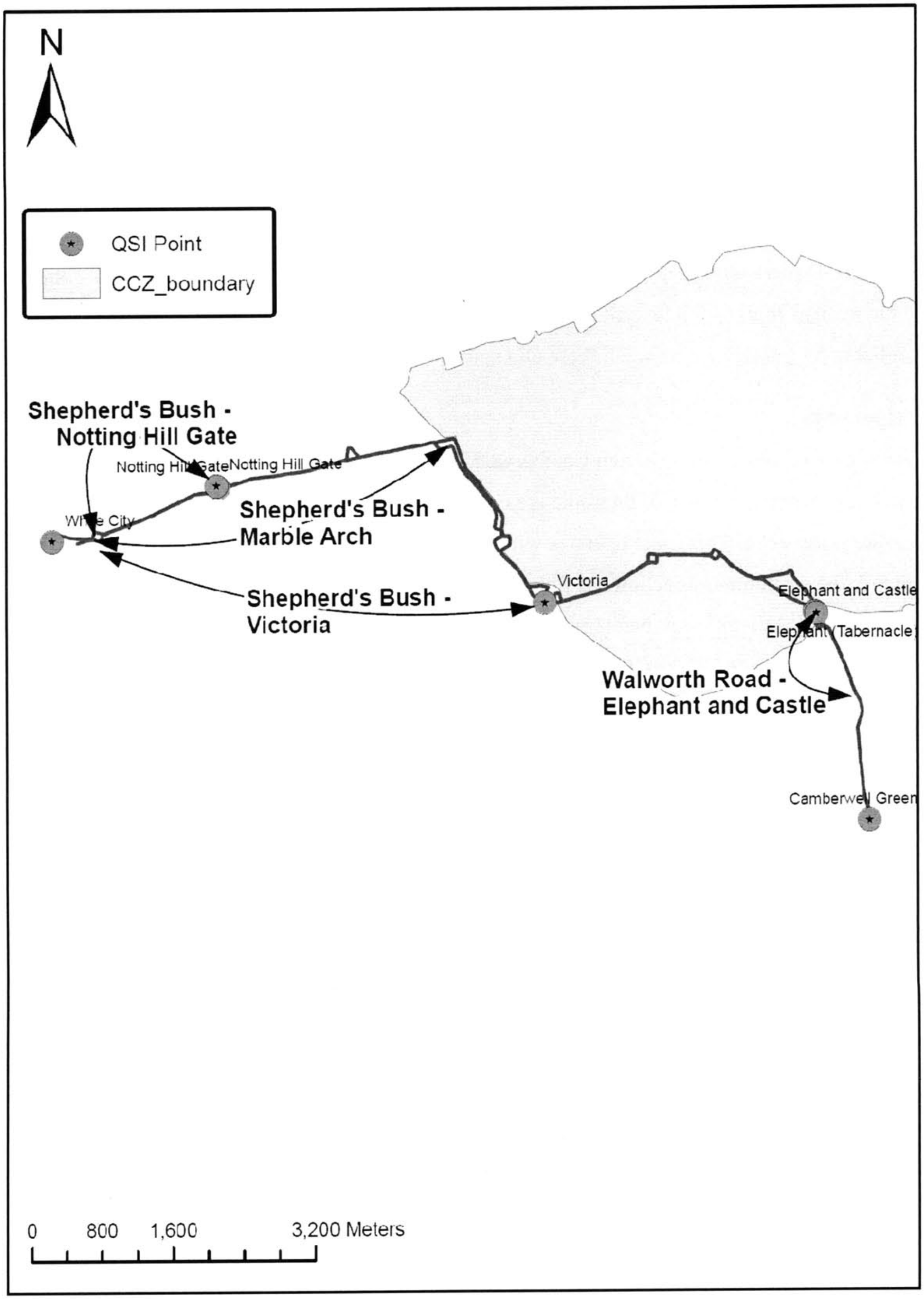

Figure 5-7 - Route 148 QSI Points and OD Pairs

Table 5-8 - Route 148 Reliability Analysis

Origin	Destination	Direction	Avg. Headway (min)	Wait Time (min)			Travel Time (min)			Journey Time (min)				
				AWT	SWT	EWT	95th	50th	Scheduled	95th	50th	Scheduled	RBT	EJT
Shepherd's Bush	**Marble Arch**	**EB**	**8.27**	**5.65**	**3.53**	**2.12**	**29.79**	**22.78**	**19.22**	**42.0**	**28.0**	**22.8**	**14.0**	**5.2**
Marble Arch	Shepherd's Bush	WB	10.79	8.86	4.02	4.84	22.17	17.97	20.15	45.5	24.8	24.2	20.7	0.6
Shepherd's Bush	**Notting Hill Gate**	**EB**	**8.27**	**5.65**	**3.53**	**2.12**	**15.35**	**10.88**	**8.96**	**28.5**	**15.9**	**12.5**	**12.6**	**3.4**
Notting Hill Gate	Shepherd's Bush	WB	10.78	8.60	4.22	4.37	13.83	10.98	12.45	37.0	17.7	16.5	19.3	1.2
Victoria	**Shepherd's Bush**	**WB**	**10.67**	**8.67**	**3.75**	**4.91**	**32.82**	**28.02**	**30.19**	**55.5**	**34.8**	**34.1**	**20.7**	**0.7**
Shepherd's Bush	Victoria	EB	8.21	5.34	3.53	1.81	44.77	36.06	31.35	56.0	41.6	35.2	14.4	6.4
Walworth Road	**Elephant and Castle**	**WB**	**7.85**	**5.66**	**3.60**	**2.06**	**9.86**	**5.59**	**5.00**	**23.0**	**10.6**	**8.5**	**12.4**	**2.1**
Elephant and Castle	Walworth Road	EB	9.13	6.85	3.87	2.98	4.87	3.52	4.00	21.0	9.1	7.9	11.9	1.2

Measured headways on this route, as shown in Table 5-8, indicate numerous missing buses, since headways are often more than twice the SWT. This also accounts for the high estimated EWT values. The error analysis presented earlier in the chapter already indicated that this route is missing data, to the detriment of its estimated performance. That said, this analysis provides an indicator of how operators could be adversely affected if all iBus units are not working properly or if some drivers are not properly logged in to the iBus system.

Average headways on the OD pair on the southeastern end of the route are lower in both directions than they are for the other OD pairs. In spite of the missing data (assumed to be random), more buses may be run on this end of the route, indicating the possibility of curtailments in Central London. Further analysis into the operations of this route is required to support this assertion.

Travel time variability is relatively low on this route (except for Walworth Road to Elephant and Castle), indicating that reliability is not severely affected by congestion. Were more accurate measurements of headways available for this route, it would be interesting to see whether overall reliability, as expressed by Journey Time, would decrease.

EJTs in the eastbound direction are large across all OD pairs. When normalized by scheduled Journey Time, the magnitude of EJT is approximately 25% the magnitude of the scheduled Journey Time, a higher ratio than observed on most other routes. The schedule on this route therefore does not provide a good estimate of the median passenger experience.

RBT values are large in both directions, although those in the westbound direction are particularly severe, with magnitudes ranging from 60% to over 100% of the median Journey Time. Service on this route is therefore unreliable, and passengers are not able to estimate Journey Times with a high degree of certainty. For instance, passengers travelling westbound beyond Central London (i.e. towards Shepherd's Bush) may need to budget an extra 20 minutes over the median Journey Time to be assured of getting to their destination on time.

As has been observed on other routes, short distance OD pairs are subject to greater unreliability than longer trips. This is observed for both Shepherd's Bush/Notting Hill Gate and Walworth Road/Elephant and Castle, where RBTs are larger than the median Journey Time (i.e. the 95^{th} percentile Journey Time is more than twice the median Journey Time). Service may be difficult to control over short distances, especially if holding points are not located around or within the segment under analysis.

5.4.5 Route 88

Route 88 runs north/south from Camden Town to Clapham Common through Central London. Loads in the AM peak are higher in the northbound direction than the southbound direction, as the bus serves as a feeder to the southern sections of the Northern Line and Victoria Line. The southbound direction has four evenly-spaced QSI points, while the northbound direction has three evenly-spaced QSI points, as shown in Figure 5-8.

Four high volume OD pairs were analyzed on Route 88, reflecting high volume travel patterns in both the northbound and the southbound directions. The high volume direction ridership for the four pairs analyzed accounts for 6% of the AM peak ridership. Two pairs with high volumes identified in the northbound direction, Stockwell to Vauxhall and Clapham North to Stockwell, are south of Central London, and are parallel to the Victoria Line and the Northern Line, respectively. They each account for about 1.5% of the route's ridership. Passengers on these segments may be using the bus to avoid crowded segments of the Underground network. The other pair in the northbound direction, Vauxhall to Westminster, most likely represents passengers using the bus to cross the Thames River and commute to Central London, and accounts for about 1% of the route's ridership.

The high volume OD pair identified in the southbound direction, Camden Town to Oxford Circus, represents riders travelling from the high density neighborhood of Camden to employment and shopping destinations in Central London. This segment approximately parallels the Northern Line, which may indicate that passengers are taking the bus to avoid another crowded segment of the Underground.

The results of the reliability analysis for Route 88, in Table 5-9, demonstrate that many riders are experiencing unreliable service. All measured headways were more than twice the SWT, signifying numerous missing buses, and possibly a high number of curtailments. The high EWT values computed are therefore explained by missing buses.

This route is sensitive to traffic conditions in Central London, as travel times for both the Camden Town/Oxford Circus and Vauxhall/Westminster OD pairs were highly variable. Travel times in South London were less variable. While the scheduled travel time for all OD pairs approximated the median travel time, indicating that schedulers are making accurate travel time estimates, EJT values normalized by scheduled Journey Time for short trips (Clapham North/Stockwell and Vauxhall/Stockwell) were higher than most other routes analyzed.

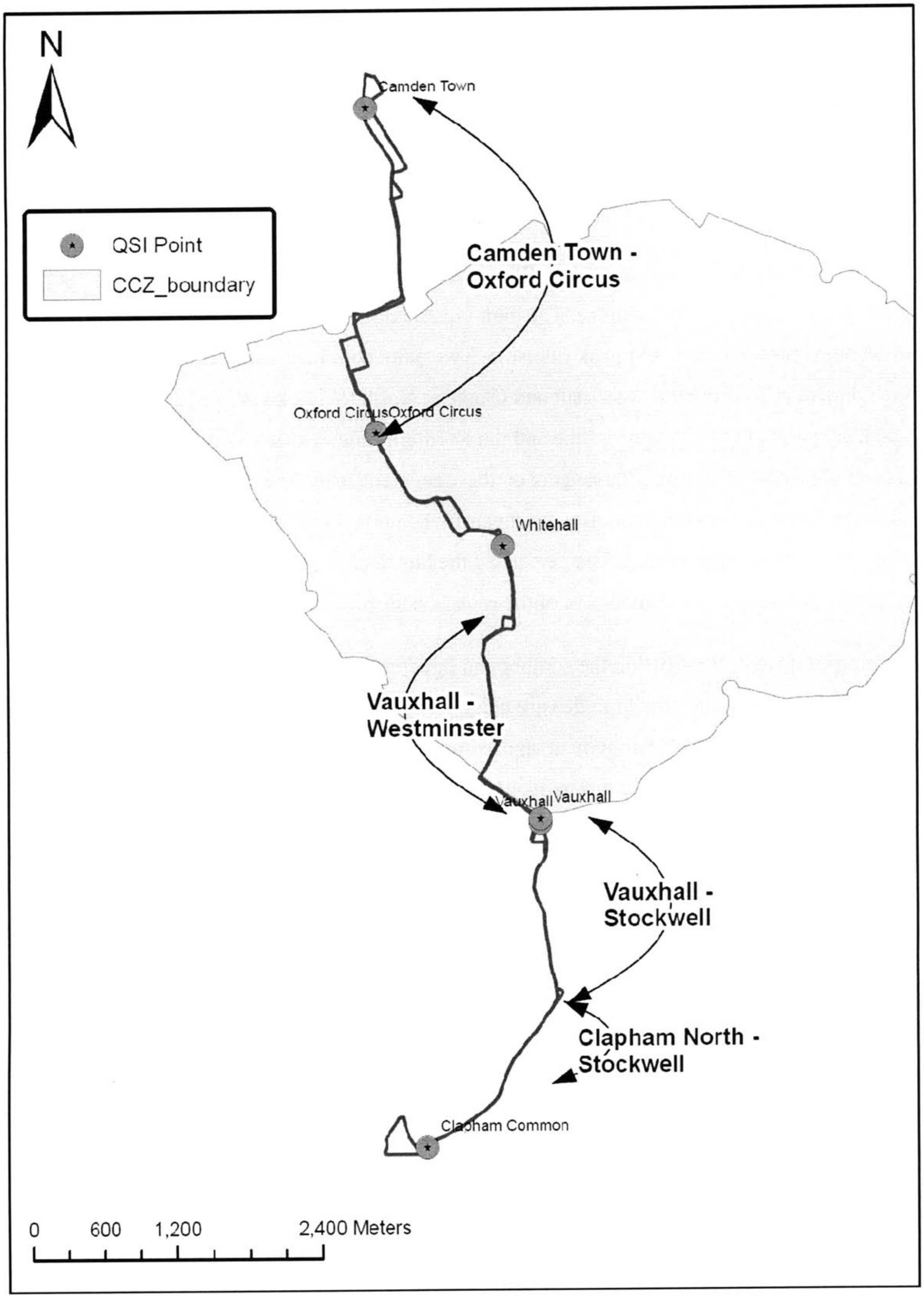

Figure 5-8 - Route 88 QSI Points and OD Pairs

Table 5-9 - Route 88 Reliability Analysis

Origin	Destination	Direction	Avg. Headway (min)	Wait Time (min)			Travel Time (min)			Journey Time (min)				
				AWT	SWT	EWT	95th	50th	Scheduled	95th	50th	Scheduled	RBT	EJT
Camden Town	**Oxford Circus**	**SB**	**7.84**	**5.13**	**3.52**	**1.61**	**29.05**	**16.80**	**17.18**	**38.5**	**21.6**	**20.9**	**16.9**	**0.7**
Oxford Circus	Camden Town	NB	8.61	6.61	3.52	3.08	18.00	14.23	13.91	33.5	19.8	17.4	13.7	2.4
Stockwell	**Vauxhall**	**NB**	**6.88**	**4.73**	**3.31**	**1.42**	**11.36**	**8.48**	**8.72**	**24.0**	**12.6**	**12.0**	**11.4**	**0.6**
Vauxhall	Stockwell	SB	9.35	6.41	4.07	2.34	7.46	5.64	5.68	24.0	10.9	9.8	13.1	1.1
Clapham North	**Stockwell**	**NB**	**7.18**	**5.13**	**3.27**	**1.86**	**8.24**	**5.12**	**6.43**	**19.5**	**9.3**	**7.8**	**10.2**	**1.5**
Stockwell	Clapham North	SB	9.71	7.05	4.37	2.68	8.46	5.25	4.00	28.0	11.0	8.2	17.0	2.8
Vauxhall	**Westminster**	**NB**	**7.01**	**4.99**	**3.30**	**1.69**	**18.91**	**10.28**	**10.25**	**27.0**	**15.0**	**13.6**	**12.0**	**1.4**
Westminster	Vauxhall	SB	8.56	5.78	4.02	1.77	16.97	10.23	10.85	28.0	15.6	14.8	12.4	0.8

All RBT values are greater than 10 minutes, and some passengers, especially those on shorter segments, experience 95th percentile Journey Times that are twice the length of the median Journey Time. On longer segments, RBT still indicates a high level of unreliability, as its magnitude is at least 69% of the magnitude of the median Journey Time.

There are no large differences in reliability between the service provided in the peak and the off-peak directions. However, the southbound direction generally performs slightly worse than the northbound direction, with the exception of the OD pair between Clapham North and Stockwell, where the southbound direction is considerably poorer than the northbound direction. While worse southbound performance may be due to the residual effects of congestion in Central London, this OD pair is after the last southbound QSI point, suggesting management may be focused on QSI performance as opposed to being focused on serving passenger demand.

5.4.6 Route 211

Route 211 runs east/west between Hammersmith and Waterloo via Victoria. This route has three QSI points in the westbound direction and two in the eastbound direction (Sloane Square is not measured eastbound), as shown in Figure 5-9. Loads are fairly high leaving Waterloo and approaching and departing Hammersmith going to and from the neighborhood around Charing Cross Hospital, but relatively low on the rest of the route. Consequently, the OD pairs analyzed do not account for operations on the middle of the route. Two OD pairs, representing three high volume movements were identified for this route. The high volume movements represented 13% of the route's AM peak ridership.

Hammersmith to Greyhound Rd., one of the two OD pairs analyzed, was identified as a high volume pair in both directions during the AM peak, accounting for 3.6% of the total ridership. When combined with high passenger volumes at surrounding stops at Charing Cross Hospital and Munster Road, this short segment from Hammersmith accounted for 9% of AM peak ridership.

The other OD pair analyzed on this route, between Waterloo and Great Smith Street across the river, has high volumes in the westbound direction during the AM peak. When Great Smith Street is combined with an adjoining stop, this OD pair accounts for 5% of AM peak ridership. It is interesting to note, however, that this OD pair occurs after the last QSI point in the eastbound direction. It would be interesting to see whether service is less reliable on this segment, as that may provide an indication of service controllers tailoring operations around QSI points.

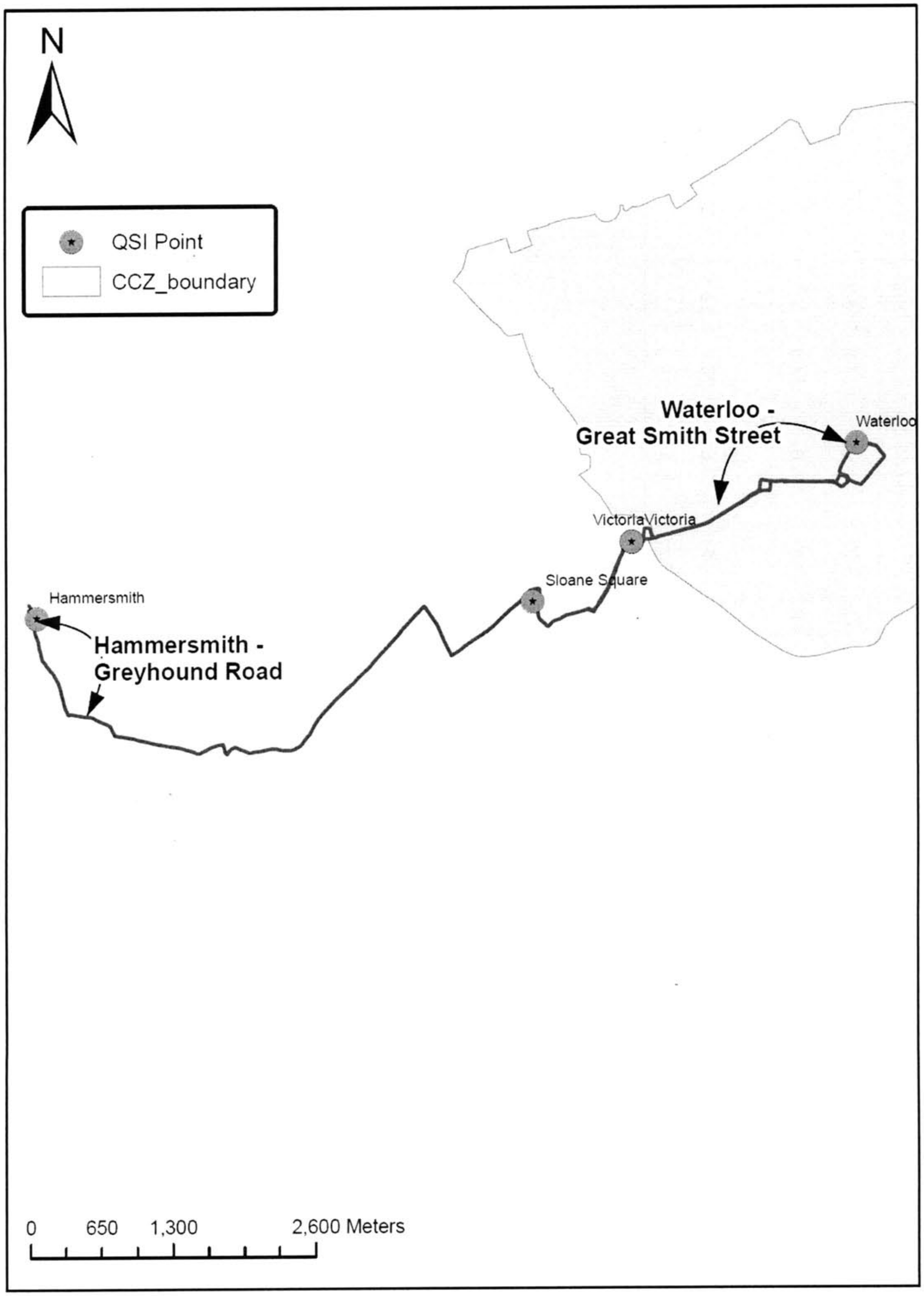

Figure 5-9 - Route 211 QSI Points and OD Pairs

Table 5-10 - Route 211 Reliability Analysis

Origin	Destination	Direction	Avg. Headway (min)	Wait Time (min)			Travel Time (min)			Journey Time (min)				
				AWT	SWT	EWT	95th	50th	Scheduled	95th	50th	Scheduled	RBT	EJT
Greyhound Rd	**Hammersmith**	**WB**	**10.37**	**7.29**	**3.90**	**3.39**	**7.33**	**3.57**	**6.6**	**24.0**	**9.9**	**10.5**	**14.1**	**-0.6**
Hammersmith	**Greyhound Rd**	**EB**	**9.88**	**6.44**	**3.74**	**2.70**	**7.80**	**3.37**	**6.0**	**23.0**	**9.1**	**9.4**	**13.9**	**-0.3**
Waterloo	**Great Smith St**	**WB**	8.15	**4.98**	**3.63**	**1.35**	**12.76**	**7.73**	**7.6**	**22.0**	**12.5**	**11.2**	**9.5**	**1.3**
Great Smith St	Waterloo	EB	11.77	8.17	4.45	3.72	8.25	6.42	6.8	28.5	13.2	11.2	15.3	2.0

Results of the service reliability analysis for Route 211 are summarized in Table 5-10. Average headways are quite large when compared with the schedule (6-10 minutes and more than twice SWT), indicating that many buses are missing. This is verified by the large EWT values, indicating passengers are not being served by as many buses as they should be. It is unclear whether missing buses are due to data issues or poor service control.

Both OD pairs analyzed on this route are short trips, with scheduled travel times in the 6-7 minute range. Observed travel times indicate that these scheduled travel times are fairly conservative when compared to median observed travel times; however 95th percentile travel times suggest that there is a high level of variability in these travel times, possibly due to traffic.

EJT values are quite low on the western end of the route even though EWT values are high. Again, this is due to the conservative scheduling practices used, giving the operators buffer time built in to the schedule. The eastern end of the route shows higher EJT values, which are still not very high compared with the scheduled Journey Time. However, the observed RBT values for this route indicate that the service is unreliable, since all RBTs except for the Waterloo to Great Smith Street RBT are greater than the median Journey Time, and even this one approaches the median Journey Time. The 95th percentile journey is therefore more than twice as long as the median journey. While it is true that both of these OD pairs are short trips, which have already been shown to be unreliable on other routes, it is particularly concerning on this route due to the number of riders using these segments and experiencing unreliable service. It is especially important for managers on this route to investigate what is causing this unreliability, and to find ways to mitigate it.

Another interesting result for this route is the comparison of both directions for the Waterloo/Great Smith St. OD pair. The peak direction (WB) has an RBT nearly 6 minutes lower than the off-peak direction (the 95th percentile Journey Time nearly twice the median Journey Time), an EWT almost a third as large, an average headway 3.5 minutes less, and an observed headway more than 3.5 minutes lower than the off-peak direction, in spite of similar observed travel times. This means that buses are not being run in the off-peak direction as frequently as in the peak direction, suggesting that deadheads are occurring in order to ensure smooth operations at Waterloo. Managers may want to investigate whether service on this route is being curtailed after the last QSI point eastbound.

5.4.7 Route 259

Route 259 is a radial route running from Edmonton, north of Central London, to King's Cross, at the northern edge of Central London. Since this route serves numerous residential neighborhoods north of Central London, AM peak flows are predominantly southbound. The northern half of the route, from

Edmonton to Finsbury, serves as a feeder to Underground stations on the Piccadilly and Victoria Lines in Tottenham and Finsbury. This route has three evenly spaced QSI points in each direction, as shown in Figure 5-10.

Three high volume OD pairs were analyzed for this route, all of which were based on southbound passenger volumes, and represent 5% of the AM peak ridership. Unlike the other routes analyzed, no OD pairs on this route had particularly high ridership. The first pair, from Bruce Grove to Seven Sisters, connects a National Rail station with an Underground Station, and is used to account for numerous trips observed to originate within Tottenham destined for Seven Sisters. The second pair connects Edmonton Green at the northern end of the route with Holloway, a major destination north of Central London, and is used to represent riders with longer trips. The third pair connects Edmonton Green with Seven Sisters, reflecting the route serving as a feeder to the Victoria Line from outer segments of the route.

No major OD pairs were identified along the southern segment of the route into Kings Cross. As both the Piccadilly and Victoria Lines connect with this route around Finsbury Park, passengers heading into Central London may be taking advantage of faster journey times to Central London on the Underground.

The results, as shown in Table 5-11, indicate that the published schedule does not provide an accurate indicator of normal operations. While the measured headways for the Bruce Grove/Seven Sisters and the Edmonton Green/Seven Sisters (southbound) OD pairs indicate that approximately the proper number of buses is being run, the Edmonton Green/Holloway pair indicates that fewer buses are observed between these stops, especially southbound. Buses may be curtailed at the southern end of the route in order to provide additional feeder traffic to passengers transferring to the Underground in Tottenham (Seven Sisters). EWT values are fairly high, although this may be due to both headway variability and missing buses, since some of the measured headways were reasonable.

When compared with the other routes analyzed, the variability in travel time is quite low, demonstrating that this route is not heavily affected by road congestion. This is explained in part by the fact that the route terminates at the northern edge of Central London, containing no mileage within Central London, and may be less susceptible to traffic variability. However, the scheduled travel time is always less than the median travel time, and EJTs, when compared with scheduled Journey Time, are also relatively high. Schedulers may either be deliberately assigning short travel times to speed service, or they may be underestimating travel times.

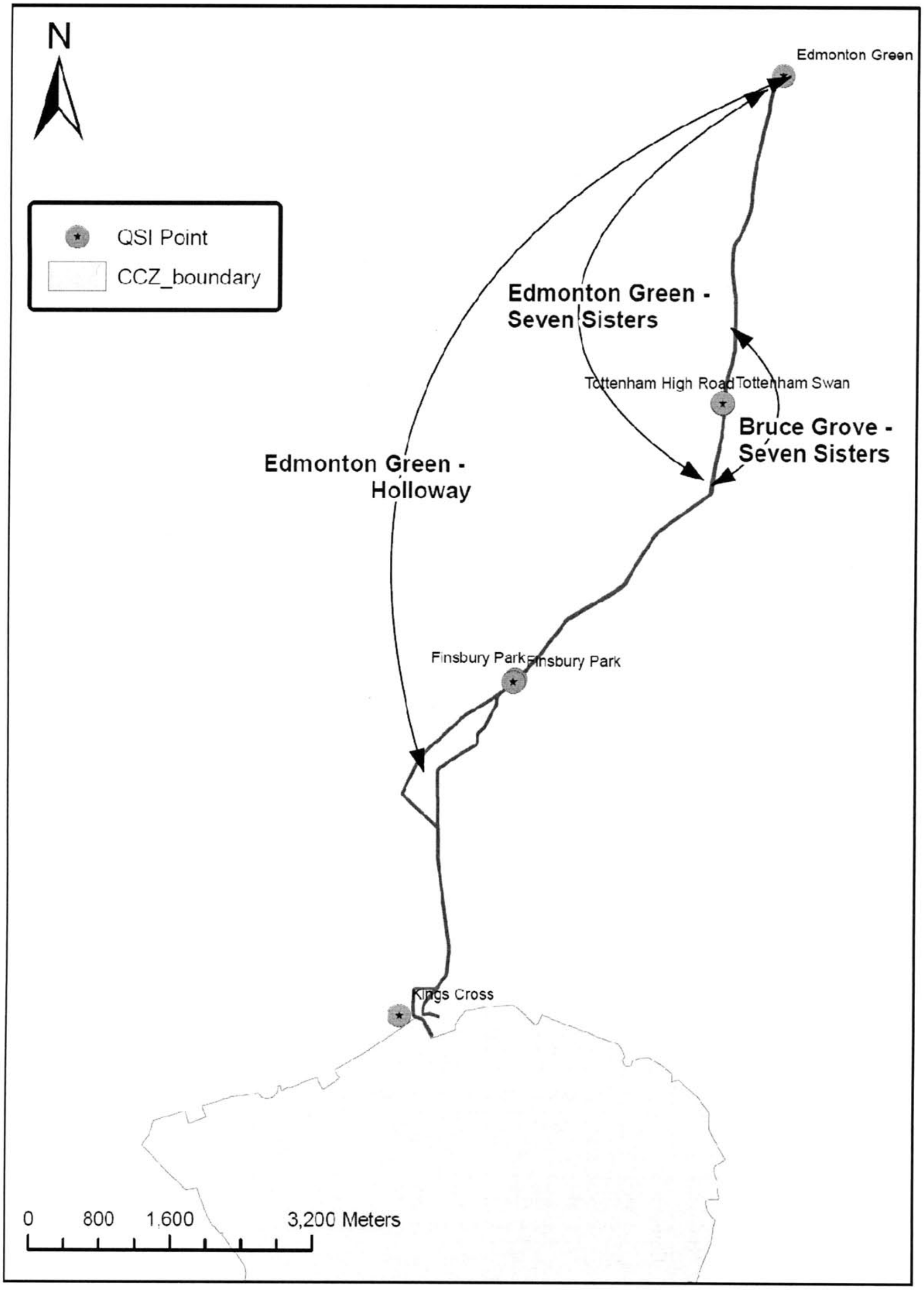

Figure 5-10 - Route 259 QSI Points and OD Pairs

Table 5-11 - Route 259 Reliability Analysis

Origin	Destination	Direction	Avg. Headway (min)	Wait Time (min)			Travel Time (min)			Journey Time (min)				
				AWT	SWT	EWT	95th	50th	Scheduled	95th	50^{th}	Scheduled	RBT	EJT
Bruce Grove	**Seven Sisters**	**SB**	**7.32**	**5.06**	**3.53**	**1.53**	**6.59**	**4.9**	**3**	**18.5**	**9.3**	**6.4**	**9.2**	**2.9**
Seven Sisters	Bruce Grove	NB	8.77	6.18	4.11	2.07	5.97	4.38	3.5	20.5	9.6	7.5	10.9	2.1
Edmonton Green	**Holloway**	**SB**	**8.65**	**5.87**	**3.58**	**2.29**	**52.42**	**43.70**	**37**	**65.0**	**49.5**	**41.5**	**15.5**	**8.0**
Holloway	Edmonton Green	NB	8.95	5.86	3.86	2.00	41.47	35.59	31.7	53.0	40.7	35.9	12.3	4.8
Edmonton Green	**Seven Sisters**	**SB**	**7.76**	**4.99**	**3.58**	**1.41**	**25.55**	**20.28**	**16**	**36.0**	**25.1**	**19.4**	**10.9**	**5.7**
Seven Sisters	Edmonton Green	NB	9.20	6.35	4.11	2.24	20.97	16.72	13.6	34.0	22.4	17.8	11.6	4.6

The phenomenon concerning short trip distances is observed on this route as well. 95th percentile Journey Times on the Bruce Grove/Seven Sisters OD pair are twice the median Journey Times, meaning unreliable service. To reach his (her) destination with 95% certainty, a passenger needs to budget twice the median Journey Time.

However, when RBT values are compared with the median Journey Time for the longer OD pairs, they are observed to be quite low compared with the other routes analyzed. In all cases the magnitude of RBT is less than 50% of the median Journey Time, in contrast to the other routes, where the RBT ranged from 50% to more than 100% of the median Journey Time. Route 259 is more reliable than these other routes, in spite of a higher rate of missing bus trips.

5.4.8 Observations on the Reliability Analysis

This analysis has shown variation in service reliability that does not always correspond to general perceptions of good and bad routes. As summarized in Table 5-12, when richer measures of service reliability are used, the perception of service quality can change. For example, Route 259, which was initially perceived to have poor reliability, was found to have the most consistent Journey Times; the magnitude of RBTs measured on Route 259 was lowest when RBT was normalized by Journey Time. Other routes, such as Route 148, were shown to have inaccurate schedules; the median journey experience on this route does not reflect the information provided to the passenger.

Distributions were created for travel time and Journey Time, two absolute measures analyzed. By analyzing a distribution as opposed to just a mean value, a range of passenger experiences are accounted for. Without analyzing these distributions, it would have been very difficult to gauge the magnitude of variability of passenger experiences. This type of analysis therefore provides the agency with valuable information concerning the consistency of service provided, as well as providing an impetus for reducing the variability of service.

The analysis shows that a good (or poor) EWT does not necessarily correlate with a good (or poor) RBT and EJT. These two new measures reflect something not captured by EWT and Percent Lost Mileage, and enable the analyst to quantify the variability in passenger experience. Therefore, while EWT may be a good indicator of one aspect of network performance (i.e. bus spacing), it alone does not provide a comprehensive indicator of the entire passenger experience. By accounting for both wait time and travel time, Journey Time, EJT and RBT describe the entirety of the passenger journey and account for the variation experienced between the scheduled Journey Time, the median Journey Time, and the 95th percentile journey time. They describe different but important aspects of the service, and facilitate the quantification of unreliability.

Table 5-12 - Summary of Reliability Analysis

Route	Headways	EWT	Travel Time	Schedule Effectiveness (EJT)	Reliability (RBT)
38	Few missing buses	Variability due to bus spacing, especially on the inner part of route with 2-minute headways	Variable - high sensitivity to traffic	Median journeys reflective of schedule	Average level of unreliability - RBT/50th percentile Journey Times range from 45%-62%
98	Few missing buses	Low - buses are being spaced evenly	Consistent - traffic has little effect	Median journeys reflective of schedule	Long trips reliable, short trips unreliable
148	Many missing buses, due to missing data issues	Variable due to missing buses	Consistent west of Central London, variable south of Central London	Schedule does not provide an accurate estimate of median Journey Time	Unreliable - 95th percentile Journey Times nearly twice median Journey Times (for both short and long trips)
88	Many missing buses	Variable due to missing buses	Variable - high sensitivity to traffic	Schedule reliable for long trips, unreliable for short trips	Unreliable - RBT/50th percentile Journey Times at least 69%, and especially poor for short trips
211	Many missing buses	Variable due to missing buses	Highly variable	Median journeys reflective of schedule	Unreliable - not ensuring short trips, accounting for a significant proportion of ridership, have consistent Journey Times
259	Few missing buses on some segments, more missing buses on other segments	Variable due to both missing buses and uneven bus spacing	Consistent - traffic has little effect	Schedule does not provide an accurate estimate of median Journey Time	Reliable - lowest RBT/50th percentile Journey Times observed (all less than 50%), except for short trips

One notable trend observed was that short trips (i.e. less than 10 minutes) were always found to be very unreliable. In order to be sure of arriving at his (her) destination on-time 95% of the time, a passenger on a short trip must budget about twice the median Journey Time. This was of special concern on Route 211, since a large number of riders make short trips on this service, and the route is therefore not adequately serving its ridership.

5.4.9 Service Control

Service control interventions are an important element in the day-to-day operations of a bus network. Controllers make decisions that may have significant ramifications for the ridership on any given route. The results of this analysis may better inform service controllers as to how their decisions affect operations and be a step towards improving service control.

The route-by-route reliability analysis provides another tool in identifying whether a route's service delivery objectives are being met. If they are not, such as on Route 88, unreliable service is provided, and the service control practices used on this route may not be effective. This analysis therefore enables managers to identify routes with both good and poor operations that merit further analysis.

The service patterns on certain routes indicate the control function focuses on maximizing QSI performance as opposed to providing good service on the entire route. The controller may be using this strategy because operators are more concerned with maximizing their performance incentives than they are with best serving the riders. Observations on Route 211 and Route 88 indicate that frequent curtailments are occurring after the last QSI point in a given direction, in spite of demand further downstream, albeit in the low-volume direction. Operators are currently not penalized for failing to serve points not measured in QSI surveys, and therefore have little incentive to service the entire route when delays require a reallocation of buses. This analysis showed the detrimental impact to passengers on the segments downstream from the last QSI point as a result of this service delivery philosophy.

The reliability measures developed provide insight into the impacts of service control decisions on ridership. Before, controllers may have had a sense of how these decisions affected operations, but they may not have been able to measure the passenger impact of their decisions. Were the data readily available, it would be interesting to compare the frequency of curtailments at certain points on the routes analyzed with the measures developed to see if any correlation exists between the two. If these interventions are highly correlated with EJT and/or RBT, they may not be the most appropriate to use in these situations, and other possible service control strategies should be developed.

5.5 Summary and Recommendations

This chapter introduced and demonstrated the effectiveness of using AVL data to support passenger-centric measures of service reliability. By analyzing a set of routes on the London bus network, it was found that these new measures complement the existing measures by providing additional information about the quality of service provided and the passenger experience on the bus network. If this information was generally available, it would enable passengers to make more informed decisions about their journeys.

Missing iBus data remains an issue. While TfL has developed the imputation methodology to address data missing due to malfunctioning iBus units, other errors, such as operators not logging in properly, remain the responsibility of the operators. It is therefore in the operators' best interest to rigorously monitor their drivers to ensure they log in at the beginning of each run so that they will not be penalized for missing trips that were in fact run. They should also be aware that once performance monitoring is automated, missing data can have a significant effect on route performance. TfL could also mitigate the amount of data lost due to malfunctioning iBus units by transferring maintenance responsibility for these units to the operators, or at least ensuring operators only dispatch buses with working units. The results of this analysis, in particular for Route 148, indicate that missing data may have a negative effect on how an operator's service is evaluated.

The analysis was performed on a set of six routes with good EWT performance but varying Lost Mileage performance for a 4-week period in November/December, 2009. Results did not always confirm the a priori expectation that low Lost Mileage results in good overall operations and vice versa, as Route 259, a route with high Lost Mileage, was shown to have the most consistent service. Conversely, Route 148, a route with low Lost Mileage, was found to be unreliable, although this may also be due to missing data. While the average case may be acceptable for this route, the extreme case, occurring about once a month, results in severe delays to the passengers. Journey Time, EJT, and RBT therefore provide additional detail above and beyond EWT.

Implications of this analysis may be that TfL should reevaluate its service delivery objectives in order to define more clearly what good service is and how to prioritize who should receive good service. The agency will need to think hard about prioritizing good service in the peak direction while at the same time providing acceptable service in the non-peak direction. Due to varying passenger loading patterns, one solution will not necessarily work for the whole network, as certain routes serve as high volume commuter routes into and out of the city center while others have fairly even loads in both directions. Analyzing the service provided across different routes also enables managers to identify routes with good service and compare their operations and service control practices to routes with poor service. This will facilitate the development of best practices guidelines.

Specific recommendations relating to changes in policy are beyond the scope of this thesis. However, numerous points and observations brought up in this analysis may be relevant for future consideration by TfL and other transit authorities. In order to make informed policy choices, the decision makers will need to consider the four dimensions listed at the beginning of the analysis and determine within the context of the agency how important their various service delivery objectives are.

The following proposals for TfL to consider emerge from this work:

- **Measuring reliability based on OD patterns -** Since reliability will no longer be measured manually once iBus data has been fully accepted, TfL should also rethink whether it is appropriate to use data only at QSI points. Should the agency be rewarding operators that meet EWT standards at QSI points, or should their incentive structure reflect actual passenger travel patterns? Generally, the QSI points are at high passenger volume locations, but this is not true in all cases. To better gauge how the service affects passengers, it may be worthwhile to measure service reliability at high volume locations as determined by OD patterns, and to weight the measurements at each OD pair by the passenger volume on the given OD pair.

- **Developing aggregate measures for Journey Time, EJT, and RBT –** The research presented in this chapter focused on deriving Journey Time, EJT and RBT measures for a given OD pair and timeband, in which the passenger arrival distribution was assumed to be uniform. However, the passenger arrival distribution varies over the course of a day, and across days. Additionally, different OD pairs have different levels of ridership. One Journey Time/EJT/RBT observation therefore may not be as representative of the overall rider experience as another observation, so a method for weighting and aggregating Journey Time, EJT, and RBT needs to be developed. As opposed to EWT, which is aggregated based on bus frequencies and network-wide ridership, Journey Time, EJT, and RBT should be aggregated based on the observed ridership for each OD pair and timeband combination, since the intent of these measures is to capture the impact of service reliability on passengers. Accurate ridership for each OD pair is needed in order to weight each observation appropriately.

  Wang (2010) has developed a methodology for estimating a stop-level OD matrix for a given bus route by using AFC and AVL data. Passenger boardings on buses are inferred by matching the transaction timestamp recorded in the AFC system with the closest stop timestamp in the AVL system. Destinations are inferred by finding the closest stop on the originating route to the passenger's subsequent boarding stop, if possible. The result of this procedure is that it is possible to estimate ridership for a given OD pair and timeband combination.

By applying Wang's methodology, it should be possible to develop an aggregate service reliability measure representing the aggregate passenger experience, since ridership numbers may be calculated for every timeband/OD pair combination. A possible aggregation is the aggregate EJT value found by weighting all EJT observations by the observed passenger volumes for each timeband (i) and OD pair (j):

$$EJT_{Aggregate} = \frac{\sum(EJT_{i,j} * Ridership_{i,j})}{\sum EJT_{i,j}} \qquad \text{(Equation 5-10)}$$

To calculate EJT by timeband, a single i would be used in each calculation; to calculate EJT by OD pair across all timebands, j would be held constant. The same procedure could also be used for Journey Time and RBT.

These aggregate measures could be used to evaluate operators the same way EWT is used currently. However, further study is required to validate and test these measures before they can be deployed.

- **Using Journey Time, EJT, and RBT as measures to complement EWT** - In order to gain a more robust understanding of service quality relative to the passengers' expectations, Journey Time, EJT, and RBT should be used as complements to EWT. Performance monitors will be able to measure both the regularity of service and the effectiveness of service control interventions on that route. Some passenger-oriented measures should be adopted by TfL, as EWT does not fully describe service reliability, meaning the needs of the agency's most important stakeholder, the riding public, are not being comprehensively measured. Results show that services with good EWT can have quite variable Journey Times, indicating that the service provided by London Buses is not always reflected by EWT. Measures that encourage operators to deliver service more consistently should be adopted.

The analysis has shown that Journey Time, and by extension EJT and RBT, enables operators to quantify how reliable the service provided really is by analyzing the distribution of trip times as opposed to relying on the mean value. Operators are more likely to receive negative feedback from passengers experiencing some of the poorer service than the average service. If services are consistent, passengers are less likely to complain. A possible performance monitoring scheme employing EWT, Journey Time, EJT, and RBT could be as follows:

- EWT is used to ensure that the minimum level of service is being met;
- Scheduled Journey Time and the 50th percentile Journey Time are used as baselines with which to normalize the magnitudes of EJT and RBT across the bus network in a fashion similar to the Headway Ratio (Chapter 2);
- EJT is used to ensure that the passengers are receiving a similar service to that promised; and
- RBT is used to ensure that operators endeavor to minimize the variability in ridership experience as much as possible.

Measures taken at high ridership locations (not necessarily current QSI points) will better reflect the service as experienced by many users. Operators would then be evaluated on all these aspects of the service, and would be rewarded (or penalized) for meeting (or failing to meet) certain benchmarks, as is currently done with EWT.

- **Providing passengers with more accurate journey information** – Journey Time, EJT, and RBT may provide passengers with more meaningful information before they embark on a journey. Possible uses for these data would be on schedules posted at stops as well as on online journey planners. In both instances, an estimated journey time, based on the 50th percentile Journey Time would provide a more reliable estimate than the published schedule, and would also provide an impetus for operators to set their schedules to be more consistent with observed operations. Estimated journey times could also be set by timeband to provide passengers with more accurate estimates of journey times by time of day, compared to current published schedules in London which only provide an estimate of off-peak travel times.

  Estimated journey times alone do not provide passengers with enough information to make informed travel decisions. Now that agencies have the ability to estimate travel time distributions, some indication of a range of times should be provided to passengers in order to prepare them for a chance of a longer trip than the median trip length. The most evident application in this regard would be to include RBT in schedules and journey planner applications, giving passengers a sense of the normal range of trip times experienced on the given journey, as opposed to one average value that may turn out to be a gross underestimate of the trip time. By providing an estimate of a buffer time required to get to the destination with 95% certainty (RBT) on journey planners and published timetables, passengers would be better informed about potential journey times and be able to plan their journey based on how important being on time is to them. Publishing the RBT would also be a show of good faith on the agency's part, as they will acknowledge the fact that the service does not always run as scheduled, and provide some indication to passengers of the network reliability.

- **Using observations from this analysis towards developing best practices for service control -** The analysis presented in this chapter develops new passenger-centric measures of effectiveness that can be used to identify service with good (poor) operations. By further analyzing good (poor) routes, managers may be able to identify service control practices that are beneficial (detrimental) to the route's reliability. This would aid in the development of best practices.

  Developing best practices for service control would involve a shift in the division of responsibilities between TfL and the operators, as TfL currently does not monitor the service control practices of each operator. iBus enables TfL to more closely monitor each vehicle's location, and flag situations where TfL believes poor service control practices are being used. TfL would be able to support these assertions by applying the new measures introduced in this chapter to areas of concern in order to gauge the practice's effect on passengers.

  For example, TfL would be able to identify stops with unusually high EWTs compared with the rest of the route and flag them for further analysis. OD pairs with unusually poor reliability, as expressed by RBT, enable TfL to identify unreliable segments and study whether appropriate service control interventions are being used. By identifying sets of routes with similar operating environments, it will be possible to compare the operations of poorly performing routes with better-performing routes. Should TfL develop these guidelines, they would have to more closely monitor service control practices via iBus in order to penalize operators who do not follow them.

- **Using historical run time data to develop more robust schedules –** As this is the topic of the next chapter, it will not be discussed further here. It suffices to mention that having a better grasp of congestion at points along a route and run times by time of day will produce better schedules and enable operators to allocate their resources more efficiently.

6 Applications of AVL Data for Operations Planning

Transit operations planning has evolved considerably over the past few decades. Technology improvements and a resulting better understanding of the variability in day-to-day operations have provided planners with additional tools to refine operating plans. Automated scheduling software capable of optimizing crew and vehicle assignments are now widely used incorporating algorithms that clearly outperform earlier manual methods. However, these programs still rely on certain estimated inputs, such as vehicle running times, that are often highly variable and not easily represented by fixed values for a given time period.

With the advent of AVL data it is now possible to measure running times more accurately. AVL makes it possible to collect nearly complete location data pertaining to observed bus journeys, providing operations planners with a rich picture of running times with which to develop a schedule. Using these more accurate running time data as inputs into the scheduling process should result in more robust operating plans, and therefore a more reliable service.

A robust operating plan is beneficial to both the transit agency and the passenger. For the agency (or operator), resource utilization is maximized and operating costs are minimized. Operations will better reflect the published timetable and reliability will improve. The result is better passenger perception of the service, as measured by a decrease in the relative measures of reliability introduced in Chapter 5. Operators will also benefit from a better public perception of their service and, hopefully, increased demand for the service.

Vehicle scheduling inputs typically consist of estimates of four time-based measures:

- **Running time** is the time a vehicle takes to travel between a given origin and destination. In this chapter, it will generally refer to the length of time required to complete a one way trip between the first and last stop of a given route. This is analogous to the travel time measure used in Chapter 5. It is referred to as running time in this chapter to emphasize the fact that this chapter focuses on analyzing operations from the operator's perspective as opposed to the passenger's perspective.
- **Recovery time** is a buffer time provided at the end of each trip to account for running time variability. It reduces the probability that delays will propagate further downstream, as drivers will normally have a buffer before starting their next trip.
- **Cycle time** is the amount of time allotted to complete a round trip on a given route. It is the sum of running time and recovery time for each of the two directions on a route.

- **Half cycle time** is the amount of time allotted to complete a trip in one direction on a given route. It is the sum of running time and recovery time for a given one-way trip.

This chapter will demonstrate how a more robust operating plan can be developed by using AVL data, using the London bus network as a case study. It will start by reviewing operations planning in Section 6.1, introducing important issues that will be discussed subsequently. This will include issues unique to the Transport for London bus network. Section 6.2 will introduce iBus and Caesar data, used as inputs for the analysis. In Section 6.3 the methodology used for the analysis is presented, with the results and observations discussed in Section 6.4. Section 6.5 summarizes the analysis, and discusses applications of this work to improve operations planning.

6.1 Operations Planning

Operations planning has already been introduced and defined in Chapter 2. It is a critical part of the bus planning process and includes, among other things, developing vehicle schedules (Ceder and Wilson, 1986). The analysis in this chapter focuses on vehicle scheduling, including how to develop a vehicle schedule and how to evaluate its effectiveness. Schedule development requires numerous inputs including expected passenger demand, fleet and crew availability, and running times. Passenger demand and vehicle capacities are used to define the frequency of the service required. The frequency is combined with running times to determine the route's fleet and staffing needs. This process is subject to various constraints, such as the number of available vehicles and staff, and may require numerous iterations before a result satisfying all constraints is produced.

A good operating plan is one where the scheduled service has a high probability of being achieved in daily operations, while at the same time ensuring that the operator's resources are allocated rationally. EJT, introduced in Chapter 5, is a relative measure of service reliability which assesses how well daily operations reflect the operations plan by comparing the median journey time with the scheduled journey time. If an operator is able to achieve consistently low EJT values, the operator has developed a robust operating plan with scheduled services reflecting reality. If this is combined with low journey time variability, expressed by RBT, the operator can shift the focus from relative measures of reliability towards reducing overall journey times.

The intent of this section is to introduce the issues relating to the operating plan that will be discussed and analyzed in this chapter. Section 6.1.1 will discuss factors related to timetable development. Specifically, the issue of setting scheduled running and cycle times based on observed running times will be discussed, including differing philosophies on how the observed running time data should be treated. Section 6.1.2 will discuss operations planning in London, noting specific issues unique to the London bus network.

6.1.1 Estimating Running and Cycle Times

An important concern in operations planning is to document running times. Actual running times will never perfectly match scheduled running times due to trip-to-trip running time variability. Nevertheless, the greater the understanding the operations planner has of running times on a given route, the more robust the estimate of the scheduled running time will be. Using historical observed running times will provide the planner with the most data from which to make an estimate. A simple way of making such an estimate is to schedule running and cycle times based on observed running time percentiles. The decision making framework for developing this estimate depends on the service delivery objective of the given bus route.

A major objective when scheduling low frequency bus service is to maximize the number of on time departures. Since passengers on these services typically time their arrivals based on the schedule, buses should not depart early, nor should they arrive very late. However, a greater disbenefit is experienced by passengers for a bus that departs early than for a bus that departs slightly late, as a passenger arrival timed for the given bus may miss the early departure. When an operations planner uses observed running time data to set scheduled running times, setting a low percentile observed running time value as the scheduled running time is most feasible since buses will have a low probability of arriving early. This will minimize the potential of an early departure[14].

A major service delivery objective of high frequency routes is transporting passengers from their origins to their destinations as quickly as possible. Since buses arrive frequently, passengers do not consult the schedule before departing for their journey and are therefore not concerned with precise departure times. To ensure as speedy a service as possible, some operators set scheduled running times corresponding to low percentile values of observed running times, leaving it to service controllers to ensure buses are evenly spaced. As a result, the majority of bus trips run on the route are "late," with the expectation that late drivers will operate their service as quickly as possible to make up time.

When scheduling recovery time and cycle time for both high and low frequency routes, the operations planner needs to strike a balance between ensuring as many buses as possible have sufficient time to complete their trips and minimizing the amount of time buses and drivers spend idling at the terminals. A bus that cannot complete a trip in the time allotted not only affects that run, it also delays subsequent trips scheduled for that bus. Conversely, the operator wants to minimize idling at a terminal and maximize the time buses are in revenue service in order to maximize revenue. Generally, setting cycle time to a high percentile observed running time value (e.g. the 90^{th} or 95^{th}) is recommended, as this will minimize the

[14] In these situations, service controllers should hold buses at stops instead of letting them departing early.

probability of a delayed trip propagating throughout the course of the day. The specific percentile value to be used as the input is a matter of agency policy, and must be decided upon in the context of the agency's operating objectives, in particular the relative priorities on speed and productivity, and reliability.

AVL data provides the operations planner with an additional tool when developing and evaluating operating plans. In particular, it represents the first time the operations planner has access to a complete set of running time observations. Previously, operations planners relied on a combination of manual surveys, other automated data sources, and passenger or driver observations to estimate running times. While manual surveys are feasible when a small sample of data is required, a complete sample would have been prohibitively expensive. Manual surveys are also prone to human error, something eliminated when a fully automated process is employed.

With AVL data, it is possible to create a distribution of running times, from which periods of homogenous running times used are identified and defined as timebands as input to scheduling (Furth et al., 2006). These timebands may not necessarily correspond with the passenger demand distribution (and therefore the timebands used to set bus frequencies), as these are based on other factors. Scheduled running and cycle times may then be assigned to each timeband, based on observed percentile values from the running time distribution. The analysis presented in this chapter will illustrate how these timebands can be developed.

AVL data also enables the operations planner to identify areas of concern in an existing schedule and propose the necessary modifications required for a more reliable service. This comparison can be performed post-implementation to review the effectiveness of a new schedule. When comparing a schedule to observed performance, the operations planner focuses on two specific areas:

- **Identifying when insufficient time is allotted for service** – This is an indication of a poor operating plan. When observed running times are greater than scheduled cycle times, buses will not finish their given trip on time, nor will they be able to start their next trip on time. These delays propagate throughout the day, and may result in trip cancellations and curtailments.
- **Identifying when excess time is allotted for service** – When observed running times are significantly less than scheduled cycle times, vehicles and drivers are left idling at terminals for an excessive amount of time. This is a waste of operator resources, as idling vehicles do not perform any useful work.

6.1.2 Operations Planning and London Buses

The operations planning process at TfL is somewhat different than that typically used in the US transit industry. As already discussed in Chapter 3, London Buses is responsible for setting route frequencies for all bus routes based on passenger demand and vehicle capacities. However, they are not responsible for developing timetables for these bus routes. This aspect of the operations planning process is performed by private operators bidding to operate a service. After an operator proposes a schedule, London Buses' responsibility is to review and approve it. In contrast, scheduling is performed in-house by most North American authorities.

Since the legacy AVL system in London was not capable of recording and storing data, it is unclear how much a priori knowledge both London Buses and the private operators had when developing and reviewing schedules. Regardless of whether formal (manual) running time surveys were carried out, or whether running times were determined in other ways, the fact that AVL data records the running time for virtually all trips operated between two given stops should lead to a more robust set of running times and resulting schedules.

Within the context of the London bus network, one focus of this analysis is to evaluate whether bus operators in London are developing schedules that accurately reflect observed running times. TfL does not currently provide operators with historical AVL data, although this is expected to change once TfL has completed the acceptance phase of the iBus system implementation. Operators, responsible for developing schedules, are consequently also responsible for measuring their own running times without the aid of the AVL system provided by TfL. These measurements may be performed manually, resulting in a lower level of accuracy, or via an alternate automated source.

Additionally, TfL does not currently use iBus to measure running times, meaning the agency does not necessarily have accurate estimates of running time distributions for London's bus routes. They may not be able to assess schedules produced by operators as rigorously as they would like to. The results of this analysis will enable TfL to assess schedules developed by operators more rigorously, thereby reducing the probability of major schedule modifications, with its associated costs, mid-contract.

The other focus of this analysis of interest to London, and of relevance to the broader industry, is to demonstrate how AVL data may be used to develop even more robust estimates of running times, and therefore produce stronger schedules. This will enable operators to use their resources more efficiently in some instances by saving on operating costs, reducing unproductive time. TfL will benefit by being able to collect historical running time data. These data can be supplied to prospective operators when tendering new bus route contracts and used internally to gain a better sense of the schedules these operators produce when TfL reviews them.

6.2 Data

The operations planning analysis requires two data sources as inputs: AVL data extracted from the iBus database and vehicle scheduling data extracted from the Caesar database. While running times are easily calculated from iBus data alone, cycle times require querying the Caesar database in order to match a one-way trip in iBus with the following trip on which the same bus was operated. This section will briefly introduce both these data sources, describing how they are of use to this work.

6.2.1 iBus

iBus data have already been described in detail in Chapter 5. The extracted iBus data contain the stop by stop records of observations for every bus trip run on a given route for which the AVL system was operational. Among other things, each datum identifies a route, direction, trip number, stop, scheduled departure time, and observed departure time.

Missing trips from the iBus database may or may not have been operated, but in any case, are assumed to occur at random. Thus, the data extracted from iBus solely for the purpose of calculating running times are assumed to be unbiased. Of particular concern to this analysis, however, is the large amount of missing data at terminal stops. If timestamps at these stops had been used for the following calculations, the sample size would have significantly decreased. Therefore, the second and penultimate stops will be used as proxies for the origin and destinations stops, respectively, when calculating observed running times. A correction factor will be added to these running times representing the scheduled running time between the first two stops and the last two stops on every trip. Scheduled running times will be calculated using the scheduled departure time at the first stop and the scheduled arrival time at the last stop, and will not require the use of a correction factor.

6.2.2 Caesar

Caesar is an interface used by London Buses to record each route's schedule. In addition to providing scheduled departure times from major stops, it also provides the vehicle schedule for a given route, which is vital to this analysis. The vehicle schedule is displayed in a form similar to that presented in Table 6-1, where a next trip is identified for each given bus trip. For example, once the bus assigned to Trip 1 completes Trip 1, it then operates Trip 26. Caesar data are used to determine scheduled cycle and half cycle times, by matching a given bus trip to the next trip on which the bus was operated.

Table 6-1 - Sample Caesar Data

Trip No.	Next Trip
1	26
3	38
5	48
7	50
9	54

6.3 Methodology

Two measures are calculated and subsequently plotted in this analysis: running time and (half) cycle time. Running time is defined as the difference between the arrival time at a given destination stop and the departure time from a given origin stop, as shown in Equation 6-1. Running times are calculated for both scheduled trips and observed trips. In Sections 6.4.1 and 6.4.2, the running times will be calculated from terminal to terminal[15]. In Section 6.4.3 the origin and destination may be a combination of the terminal stops of the given bus route or a QSI point along the route.

$$\text{Running time} = (\text{Arrival Time})_{\text{Destination}} - (\text{Departure Time})_{\text{Origin}} \qquad \text{(Equation 6-1)}$$

Half cycle time for a given bus trip is defined as the difference in scheduled origin terminal departure times between the given trip and the next trip (in the opposite direction) on which the vehicle is assigned to run, as shown in Equation 6-2. Similarly, cycle time for a given bus trip is defined as the difference in scheduled origin terminal departure times between the given trip and the next trip in the same direction on which the vehicle operates, as shown in Equation 6-3. Caesar data are queried in order to identify the next trip of a given bus.

$$\text{Half Cycle Time}_{\text{Trip } i} = (\text{Departure Time})_{\text{Origin Trip } i+1} - (\text{Departure Time})_{\text{Origin Trip } i} \qquad \text{(Equation 6-2)}$$

$$\text{Cycle Time}_{\text{Trip } i} = (\text{Departure Time})_{\text{Origin Trip } i+2} - (\text{Departure Time})_{\text{Origin Trip } i} \qquad \text{(Equation 6-3)}$$

Recovery time for a given trip is the difference between its (half) cycle time and its running time. While not explicitly calculated in this analysis, it is easy to discern from analyzing a graph in which both (half) cycle time and running time are plotted. Recovery time for a given trip is assumed to occur after the bus

[15] Observed running times are calculated between the second and next to last stops using iBus data, and a correction factor representing the scheduled running time between the first two stops and the last two stops is added. What is subsequently referred to as "observed running time" includes these correction factors.

has arrived at the destination stop and is assumed to end when the bus is observed to depart the next trip's origin stop.

Computed running times and (half) cycle times are plotted versus the observed or scheduled departure time from the origin stop. Additionally, hourly percentile values are calculated for the observed running times, with the 50th, 85th, and 95th percentile running times plotted as step functions. The 85th and 95th percentiles are shown because they represent a range of acceptable cycle times, while the 50th percentile is often used to determine scheduled running times. Since running times are plotted chronologically (by time of day), clusters of homogenous running times may be grouped into timebands.

Once observed running times are plotted, the given schedule may be compared to the observed operations, enabling the operations planner to assess the feasibility of the given schedule. A new schedule may be drawn up, based on identified timebands, and vehicles and crews assigned accordingly. For example, suppose a cluster of 3 hours was found to have a 50th percentile running time of 40 minutes, an 85th percentile running time of 45 minutes, and a 95th percentile running time of 50 minutes. The operations planner may set the scheduled running time for these 3 hours to be 40 minutes and the scheduled half cycle time to be 50 minutes, resulting in a scheduled recovery time of 10 minutes. In this case, 95% of all bus trips should be able to be completed on-time without affecting any subsequent trips. Precisely which percentiles are used to set running cycle times varies and is a matter of agency policy.

In addition to analyzing terminal-to-terminal running times, it is also possible to break the route into segments and analyze running times on each segment individually in a manner similar to the terminal to terminal analysis. An example of this will presented later in this chapter.

Optimizing vehicle/crew assignments, the next step in operations planning, is beyond the scope of this research, since it does not involve the use AVL data beyond what is discussed here. However, vehicle and crew scheduling involves its own set of constraints which may force the first iteration of the timetable to be modified subsequently.

6.4 Analysis

This analysis focuses on demonstrating the benefits of using AVL data for revising existing operations plans and developing new operations plans. It applies the methodology presented above and shows results for two routes of the London bus network. These two routes, Route 98 and Route 259, were analyzed in the service reliability study presented in Chapter 5, and were chosen for this analysis based on the observations presented in that chapter. In particular, observed running times between the OD pairs presented in Chapter 5 for Route 98 closely matched the scheduled running times, while results presented for Route 259 showed a poor match between the scheduled and median running times. Maps of Routes 98 and 259 are shown in Figures 5-6 and 5-10, respectively.

Data for each route, comparing the operations plan with observed operations, will be presented graphically. Three graphs will be presented for each route: one for each direction and another for a full cycle (i.e. a round trip). Each graph will display the scheduled running times, the scheduled (half) cycle times, a plot of all observed terminal-to-terminal running times, and hourly observed running times for the 50th, 85th, and 95th percentile values of the observed running time distribution. Observations are presented by time of day, and represent the totality trips between the given stops recorded in the AVL system on weekdays between November 14 and December 11, 2009. When interpreting the graphs, the following questions will be addressed:

- **What do observed running times say about operating conditions along the route?** Highly variable running times may be indicative of inconsistent driver behavior or significant impacts of traffic and other incidents on the road.
- **What is the operator's scheduling philosophy?** Routes with scheduled running times that are mainly lower than observed running times may indicate a desire by the operator to encourage bus driver to complete each run as quickly as possible. Routes where the scheduled running times closely matches the median observed running time may indicate a desire on the operator's part for drivers to drive according to the schedule.
- **Is the given schedule feasible?** Comparing the scheduled cycle time to the set of observed running times will provide an indication of the current schedule feasibility. If a significant number of trips (e.g. more than 5 or 10%) take longer than the scheduled cycle time, insufficient time is allotted to enable buses to operate the schedule reliably.
- **Is the operator maximizing resources?** Sometimes the recovery time provided may be overly generous. If there are instances where the maximum observed running times are significantly lower than the scheduled cycle time, an excess amount of recovery time is provided. Resources may be allocated more efficiently by lowering the recovery time and either reassigning vehicles and drivers to other routes, or by operating a more frequent service on the given route with the same number of vehicles.
- **How may the running times be broken up into timebands?** Furth et al. (2006) demonstrated that the distribution of observed running times is statistically independent from the distribution of passenger demand. While route capacity should be allocated based on passenger demand, scheduled running times may not necessarily fall into the same timebands. Separate timebands should be determined from observed running time data, based on natural groupings of subsequent

trips with similar running times. The graphs presented will enable the operations planner to define timebands of trips with similar running times.

In certain instances running times may not remain constant for extended periods of time, making timeband identification difficult. It may not be feasible to use this methodology in these situations, and alternate methods of assigning running times should be investigated.

- **What modifications may be implemented to create a more robust schedule?** This summarizes the observations for the given route. Based on the answers to the questions above, a modification, such as an extension or reduction of scheduled running or cycle times, may result in a more accurate schedule. Such decisions must also take into account constraints not considered in this analysis, such as vehicle and staffing constraints, when the final operating plan is developed.

Additionally, the analysis will present a breakdown of the southbound direction of Route 98 into three segments, each of which has a unique running time distribution. This will demonstrate the possibility of performing a similar analysis to the one presented for the entire one-way trip at a finer level of detail, resulting in a tighter estimate of running times for route segments. Such a procedure would be especially useful for low frequency routes, since more robust estimates of departure times at each stop would be attainable.

Results for Route 98 will be presented in Section 6.4.1 while results for Route 259 will be presented in Section 6.4.2. Section 6.4.3 will present an additional analysis of the northbound direction of Route 98, where the route will be broken down by QSI points into 3 segments.

6.4.1 Route 98

The analysis presented in Chapter 5 showed Route 98's median running times to be generally lower than its scheduled running times. Its 95th percentile running times were not much higher than the scheduled running times. This preliminary analysis indicated that schedulers provide ample time for drivers on Route 98 to complete their trips. Whether this is, in fact, true is investigated here.

Southbound running and half cycle times for Route 98 are presented in Figure 6-1, northbound running and half cycle times are presented in Figure 6-2, and round trip running and cycle times are presented in Figure 6-3. The southbound direction of this route terminates in a small, on-street loop around Holborn Station. As this is an on-street terminal in Central London, insufficient road space may be available for extended layovers. Drivers may have to start the northbound trip as soon as possible, or service controllers may need to curtail buses before they reach this point should gaps in service develop. An analysis of Figure 6-1, Figure 6-2, and Figure 6-3 is presented below.

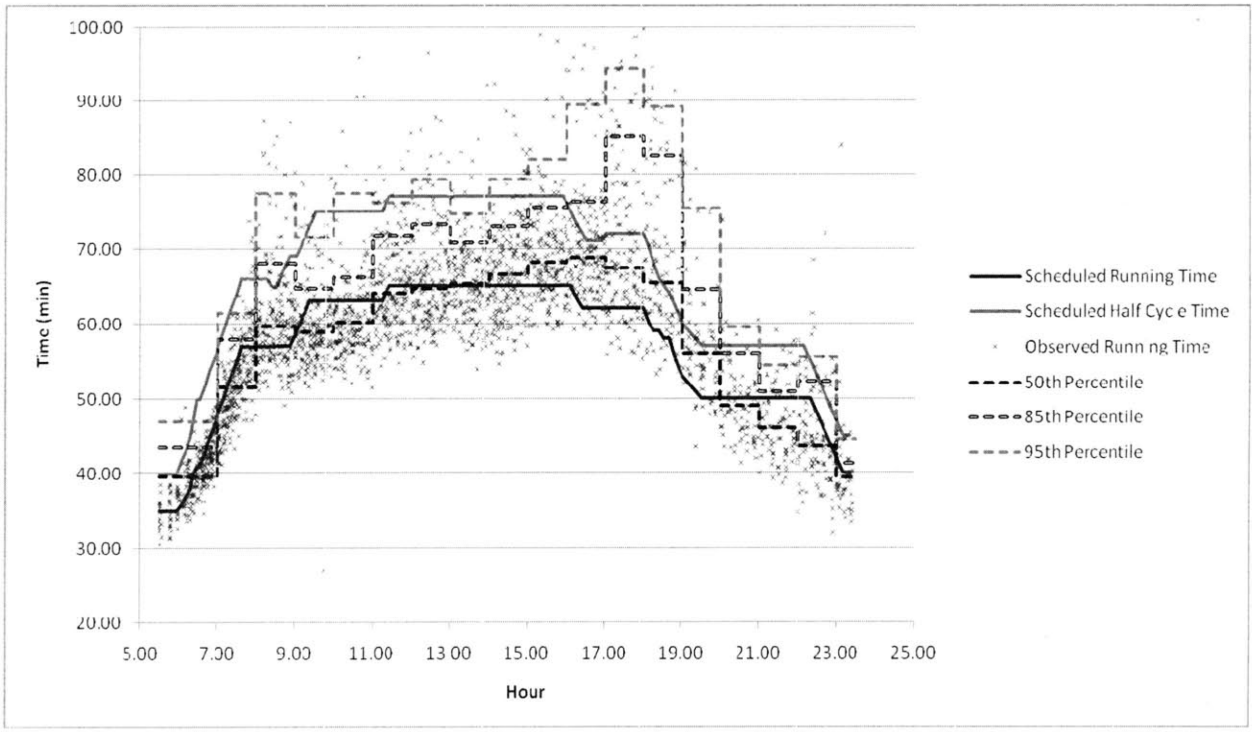

Figure 6-1 - Route 98 Southbound Running and Half Cycle Times

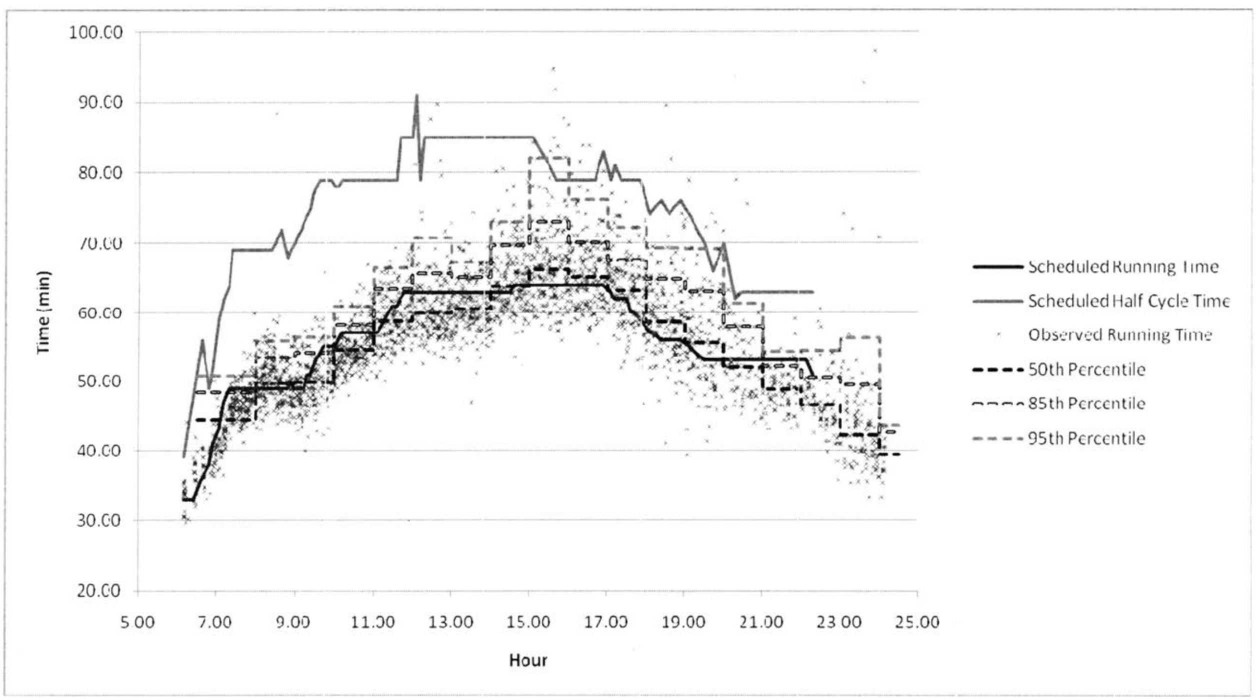

Figure 6-2 - Route 98 Northbound Running and Half Cycle Times

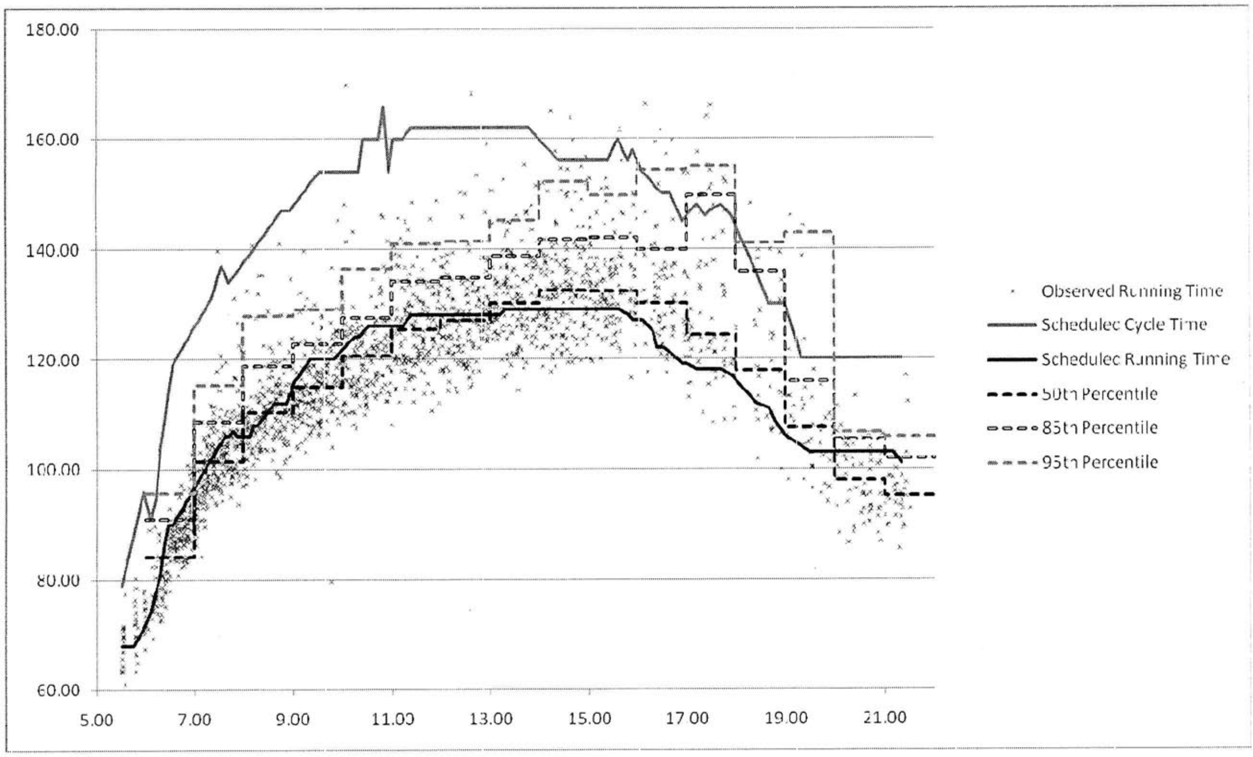

Figure 6-3 - Route 98 Running and Cycle Times

What do observed running times say about operating conditions along the route?

The distributions of observed round trip running times for Route 98 indicate that running times become increasingly variable as the day progresses. The distribution is fairly tight from the start of service until the early afternoon, as the majority of observed running times are clustered around the scheduled running time. However, in the early afternoon the distribution diverges - the median running time starts to decrease while the upper percentile running times continue to increase. The variability in running time is principally in the southbound direction. Northbound running times are consistent throughout the day, while the southbound direction experiences disruptions between 16:00 and 20:00.

This implies that operations are quite predictable on the route until the early afternoon, and traffic is therefore not assumed to play a significant factor in the route's operations during this time period. However, the increased running time variability during the PM peak and early evening suggest that traffic plays a significant factor in this route's operations during these times.

What is the operator's scheduling philosophy?

Operations planners on this route set scheduled running times to the median observed running times, as evidenced in all three graphs. Drivers are likely required to pay attention to the schedule, and ensure they meet the schedule as closely as possible. If drivers are on time, buses are evenly spaced.

However, cycle times are quite generous in the mornings and early afternoons. Scheduled cycle times are about 10 minutes greater than 95th percentile running times from the beginning of service until 14:00. Southbound recovery time is insufficient in many cases, while recovery time provided in the northbound direction is quite generous to even out this discrepancy. Since the southern terminal is in Central London, buses may not be allowed to idle between runs, and drivers may have to start their return trips immediately. This provides a constraint in the schedule, and therefore scheduled recovery times southbound are low.

Is the given schedule feasible?

The given schedule is feasible for trips scheduled during the morning and midday but deteriorates during the PM peak. In the afternoon, numerous southbound trips have observed running times greater than the scheduled half cycle time, and between 16:00 and 20:00 a significant number (30-35%) of trips are longer than the scheduled half cycle time. Insufficient recovery time is provided in the northbound direction to compensate for the southbound direction, indicating that trips during the PM peak have a high probability of being late or cancelled. As shown in Figure 6-3, the hour between 17:00-18:00 displays the worst operations, as the 85th percentile running time is greater than the scheduled cycle time.

Is the operator maximizing resources?

This operator is not maximizing its resources during the morning, midday, and evenings after 21:00. By scheduling generous recovery times, almost all journeys are assured of starting on time, and this may be reflected by this route's exceptional QSI performance. However, this also indicates that many drivers and vehicles have long layovers between trips (at least 20 minutes per round trip midday), resulting in wasted resources. This operator may be better served by reducing recovery time during the morning and midday and reassigning the extra vehicles and crew to a route that requires additional resources or by operating more frequent service during this time.

Conversely, during the PM peak, additional vehicles are required to meet the schedule between 16:00 and 20:00. Insufficient cycle time is allotted, especially between 17:00 and 18:00, as evidenced by an 85th percentile running time greater than the scheduled cycle time. Additionally, 95th percentile running times exceed cycle times for the entire 4 hour period. Service suffers as a result.

How may the running times be broken up into timebands?

Since running times on this route are rarely constant for a long period of time, grouping them into timebands larger than 1 or 2 hours may not be feasible, and therefore schedulers should use timebands no greater than 1 hour when setting running and cycle times. This approximates the method currently used to set schedules on this route; however, schedulers are currently using a linear function to set running and cycle times during certain parts of the day. Since this linear function approximate the 50th percentile running times, using a linear function to set running times during these periods may be more effective than defining timebands.

Additionally, the scheduled cycle time, which is also linear in parts, bears no resemblance to the higher percentile running time distributions. The midday timeband starts with trips with sufficient recovery time, but recovery time is insufficient by the end of this timeband. The scheduled cycle time should still resemble a linear function in the morning and evening; however, it should be modified to resemble the 85th or 95th percentile running time distributions.

What modifications may be implemented to create a more robust schedule?

The observations for Route 98 indicate that operations planners are not developing schedules that reflect actual route operations. While the scheduled running times resemble observed running times, the scheduled cycle times indicate that the operations planners do not fully appreciate the variability in running times on this route. Consequently, the following modifications to the given schedule are recommended:

- Scheduled running times should gradually increase in hourly increments until 17:00, with additional recovery time allotted from 16:00 to 20:00. Running times are currently scheduled to be constant during the midday, but the data indicate an upward trend in running times until 17:00. Service during the PM peak is suffering from scheduled cycle times lower than many observed running times. This modification will require additional crew and vehicles to maintain the given service frequencies.
- Cycle times should be reduced from the start of service to 15:00 and after 20:00. The amount of round trip recovery time currently scheduled during these time periods is nearly 20 minutes greater than 95th percentile running time in some instances; resources will be saved by reducing recovery time and having fewer buses deliver the same service.

6.4.2 Route 259

The analysis of Route 259 in Chapter 5 indicated that median running times exceeded scheduled running times for the OD pairs analyzed. The 95th percentile running times were also considerably higher than median running times. This preliminary analysis suggested that there may be a large variability in running times for this route, and that the schedule provided may not be accurate. In this section, this route is analyzed in more detail to determine whether these preliminary results are in fact indicative of poor operations planning, or whether they reflect a different operational philosophy.

Southbound running and half cycle times for Route 259 are presented in Figure 6-4, northbound running and half cycle times are presented in Figure 6-5, and round trip running and cycle times are presented in Figure 6-6. Since the southern terminal of this route is at Kings Cross in Central London, there may not be sufficient space at this end of the route for long layovers, giving service controllers less flexibility in evening out gaps in service. Drivers may have to start their return trip as soon as possible. Answers to the specific questions of relevance to this analysis are presented below.

What do observed running times say about operating conditions along the route?

The observed running time distribution for Route 259 is wider than the distribution for Route 98. The coefficient of variation for all round trip running times on Route 259 is 0.38, which is greater than on Route 98, where it is 0.16, indicating greater running time variability on Route 259. Observed running times are less concentrated (i.e. more scattered), although they generally fall between the scheduled running time and the scheduled cycle time. Due to the wider distribution of running times, this route may be sensitive to a variety of environmental factors, including traffic congestion.

What is the operator's scheduling philosophy?

All three figures show the scheduled running time to be less than the vast majority of observed running times, except southbound between 16:00 and 20:00. This indicates that operator may be focused on providing as fast a travel time as possible for its passengers by encouraging drivers to complete runs as quickly as possible. Drivers on this route have a schedule that is near-impossible to achieve, resulting in late arrivals at the last stop on almost all trips. Since they are always running late, drivers may have the impetus to drive fast, although it could also be hypothesized that some drivers may ignore this impetus if they surmise that they can never be "on-time."

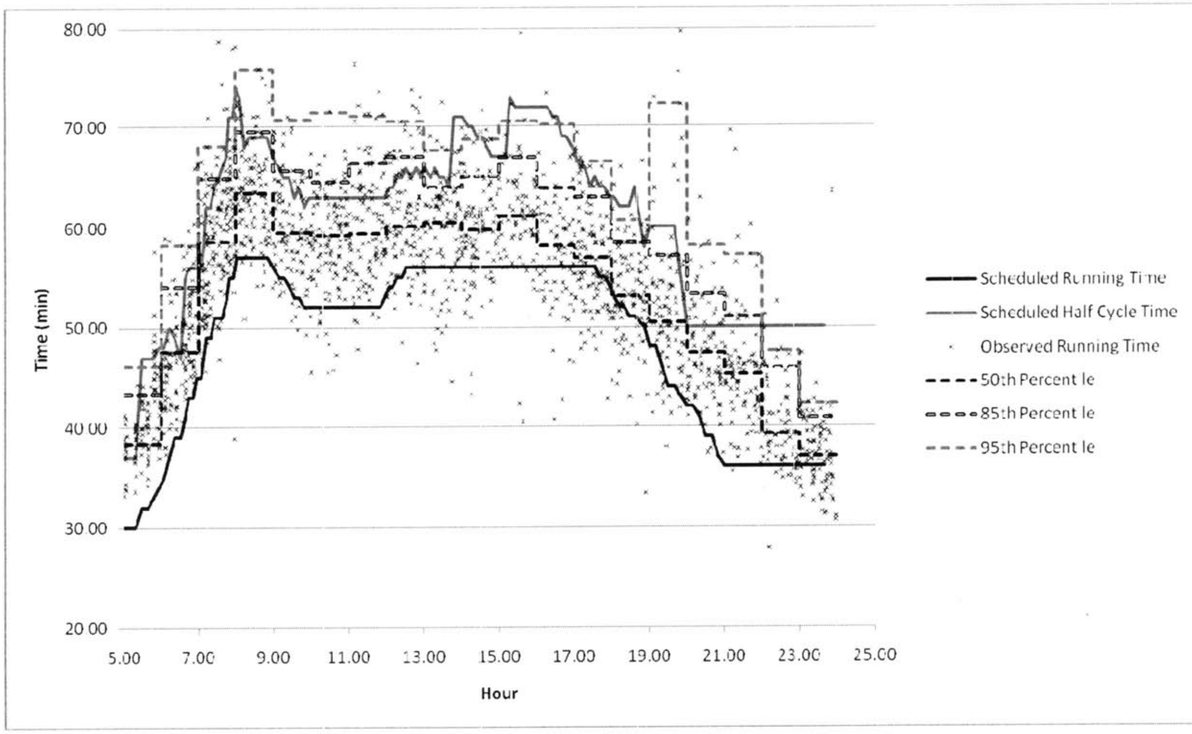

Figure 6-4 - Route 259 Southbound Running and Half Cycle Times

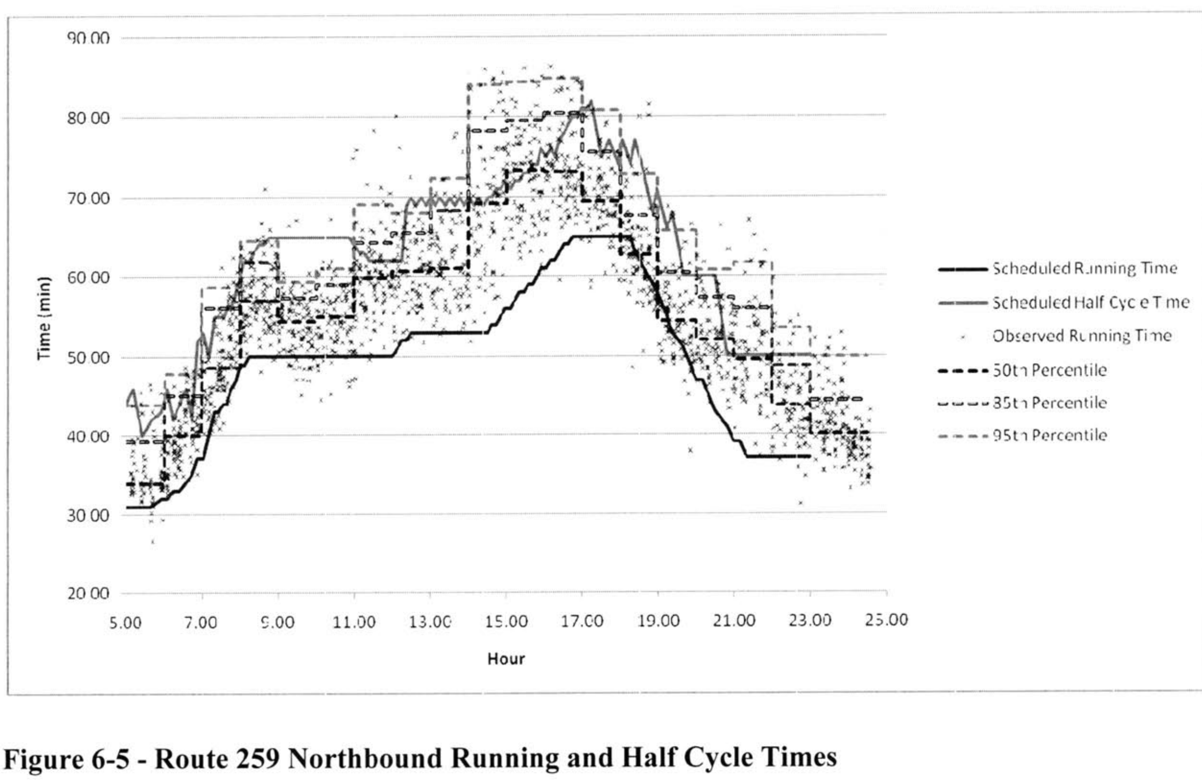

Figure 6-5 - Route 259 Northbound Running and Half Cycle Times

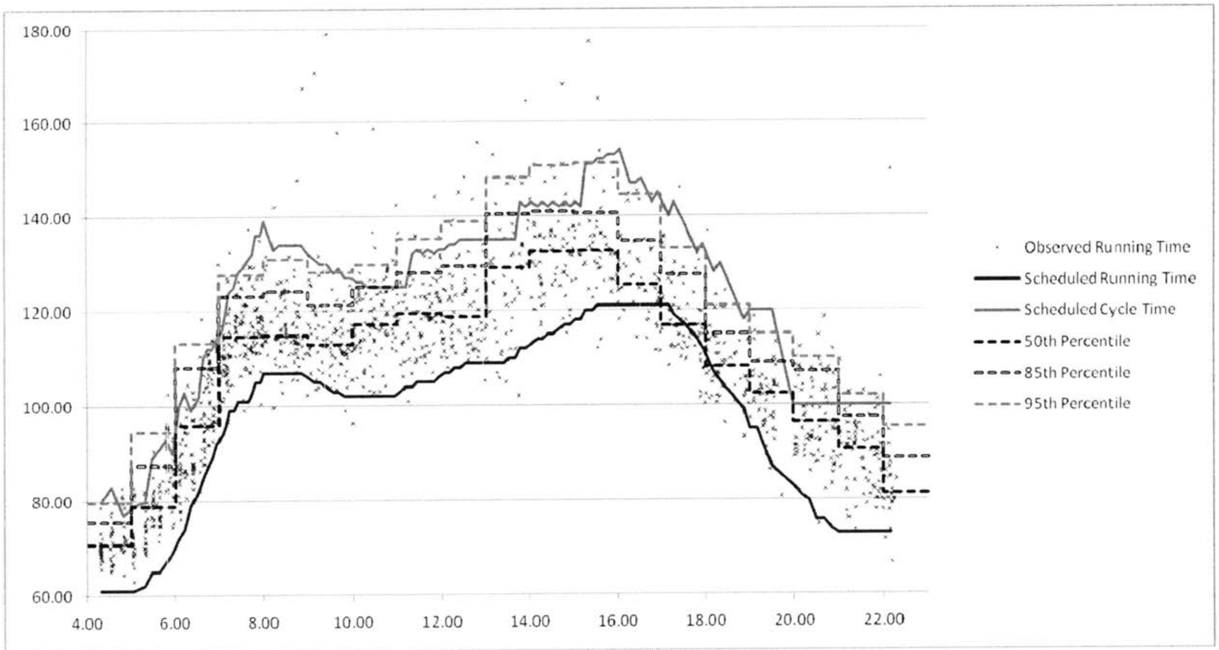

Figure 6-6 - Route 259 Running and Cycle Times

With such a scheduling philosophy, the operator needs to ensure that the public does not perceive the service to be poor. If the schedule provided to the public has running times reflecting the schedules, the public may perceive that the buses on this route are slower than they should be, and will therefore view the route to be unreliable. A measure of this unreliability, EJT, was already discussed for this route in Chapter 5, where this route was demonstrated to have poor EJT. It would therefore be worthwhile for the public schedule to show running times based on observed running times as opposed to the scheduled running times currently used internally, as these underestimate the length of most trips.

Is the given schedule feasible?

The current schedule on Route 259 appears to be feasible from the start of service through the AM peak and from the PM peak through the early evening. The schedulers on this route have a good grasp of the overall operating environment (see Figure 6-6), as cycle times are sufficient to accommodate most round-trip running times, except between 11:00 and 16:00 and between 20:00 and 21:00. The current schedule may not be feasible during the midday – the 95th percentile running times are greater than the scheduled cycle time, while the 85th percentile running time exceeds the scheduled cycle time in some instances. It may be worthwhile to increase the scheduled cycle time during the midday by about 5 minutes to mitigate the risk of delays.

The 85th and 95th percentile running times on the northbound direction between 14:00 and 17:00 are greater than the scheduled half cycle times in this direction. However, starting at 14:00, the southbound direction has additional recovery time allocated during this time period to accommodate up to the 85th percentile round trip running times, approximately corresponding to the jump in the northbound travel time distribution. The schedule is most likely built this way because insufficient space exists in Central London for extended layovers. Schedulers therefore reassign this layover time to the northern end of the route, as shown in Figure 6-6, thereby balancing the need to ensure a feasible schedule with the constraints of the operating environment.

In the evening, between 20:00 and 21:00, the scheduled cycle and running times decrease, while observed running times indicate that the decrease should not be as large as reflected in the schedule, since about 60% of observed trips had running times greater than the scheduled cycle time. Schedulers should therefore increase the cycle time for this period, which will require adding additional vehicles and crew.

Is the operator maximizing resources?

The schedulers for Route 259 are maximizing vehicle use. With the exceptions noted between 11:00 and 16:00 and between 20:00 and 21:00, scheduled cycle times very closely follow the 95th percentile observed running time distribution. However, if cycle times are increased slightly during the exceptional time periods, the same level of resource efficiency will be realized for these time periods.

How may the running times be broken up into timebands?

The hourly running time distributions presented for this route indicate large differences in running times between consecutive hours, especially from the start of service to 7:00 and from 15:00 to the end of service. During the midday, 50th percentile round trip running times are homogenous in three 3-hour blocks: from 7:00 to 10:00, from 10:00 to 13:00, and from 13:00 to 16:00, and therefore lend themselves to be grouped to set running times. A similar trend is observed for higher percentile running times between 7:00 and 10:00 and between 13:00 and 16:00, indicating these periods may be grouped to set scheduled cycle times. However, the upper percentiles increase in hourly increments between 10:00 and 13:00, and therefore cycle times should be grouped into timebands of no greater than 1 hour for this period. During the rest of the day, timebands no greater than 1 hour should be used (or the linear function currently employed on this route may be kept), as running times change significantly on an hourly basis.

What modifications may be implemented to create a more robust schedule?

The observations described above indicate that while schedulers have a solid understanding of running times, analyzing AVL data for Route 259 provides additional guidance in developing a more robust schedule for this route. In particular, the analysis suggests the following:

- Round trip cycle times should be increased by about 5-10 minutes between 11:00 and 17:00. Currently, nearly 15% of buses cannot finish their runs in the time allotted. This small increase will ensure more trips will be completed on time, and reduce the risk of delays propagating throughout the day.
- Additional running and recovery time (about 10 minutes) should be scheduled between 20:00 and 21:00 since running time does not decrease as quickly during this time period as the schedule currently indicates.
- From 7:00 to 16:00, scheduled running times should be grouped into three 3-hour timebands. Cycle times may be grouped into two 3-hour timebands between 7:00 and 10:00 and 13:00 and 16:00. During the rest of the day, timebands used to set running and cycle times should be no greater than 1 hour, or should resemble a linear function.

6.4.3 Segment Analysis

The analyses presented for Routes 98 and 259 above may also be performed at a finer level of detail. Figure 6-7 through Figure 6-9 present an example of this for the southbound direction of Route 98. This direction has been divided into 3 segments, with the divisions between segments representing a QSI point. As the figures show, the running time distribution for each segment differs over the course of the day:

- The first segment, between Willesden and Kilburn High Road, has a relatively tight distribution with a midday peak.
- The second segment, between Kilburn High Road and Marble Arch, has two very distinct peaks at 8:00 and at 16:00 where running times are highly variable. This segment appears to be especially susceptible to disruptions during peak periods.
- The third segment, between Marble Arch and Tottenham Court Road, has a running time distribution that becomes wider as the day progresses.

The fact that each segment has a different distribution provides additional insights to operations planners with regards to how they should expect the route to perform. For example, they should anticipate that delays during peak periods will frequently occur between Kilburn High Road and Marble Arch. Knowing when to expect delays is especially important when evaluating low frequency routes, as there is a greater need for these routes to be on time (or a little late) as frequently as possible.

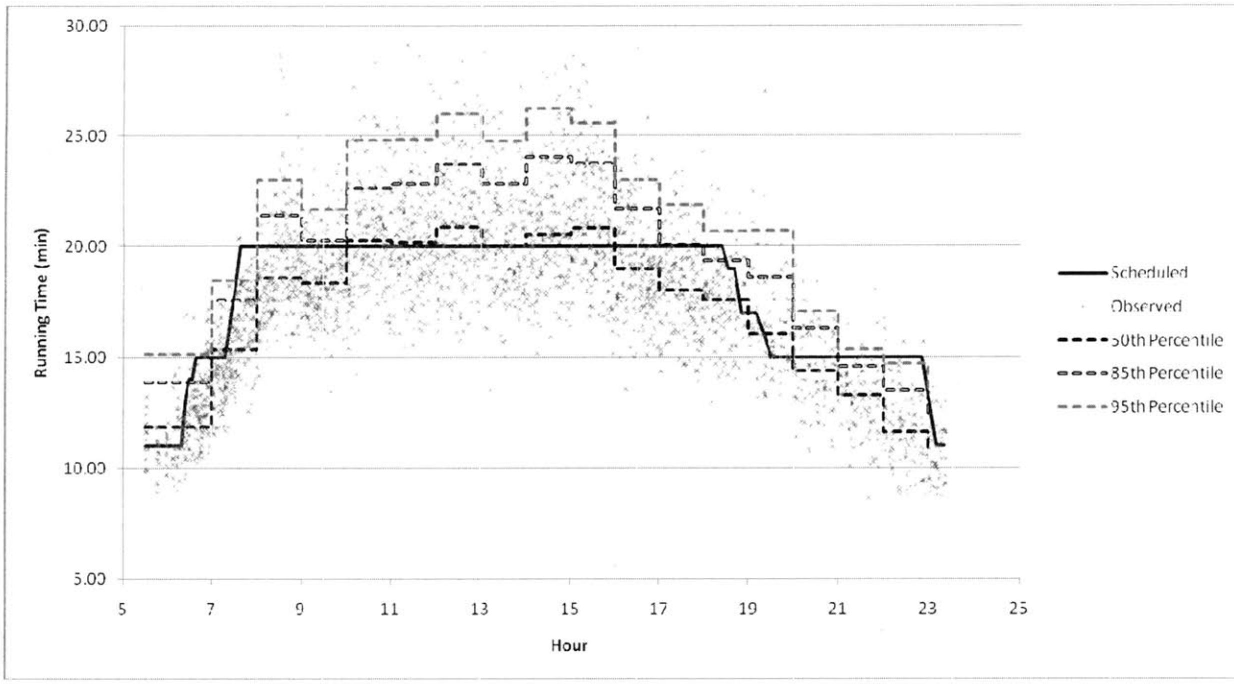

Figure 6-7 - Route 98 Southbound Running Times between Willesden and Kilburn High Road

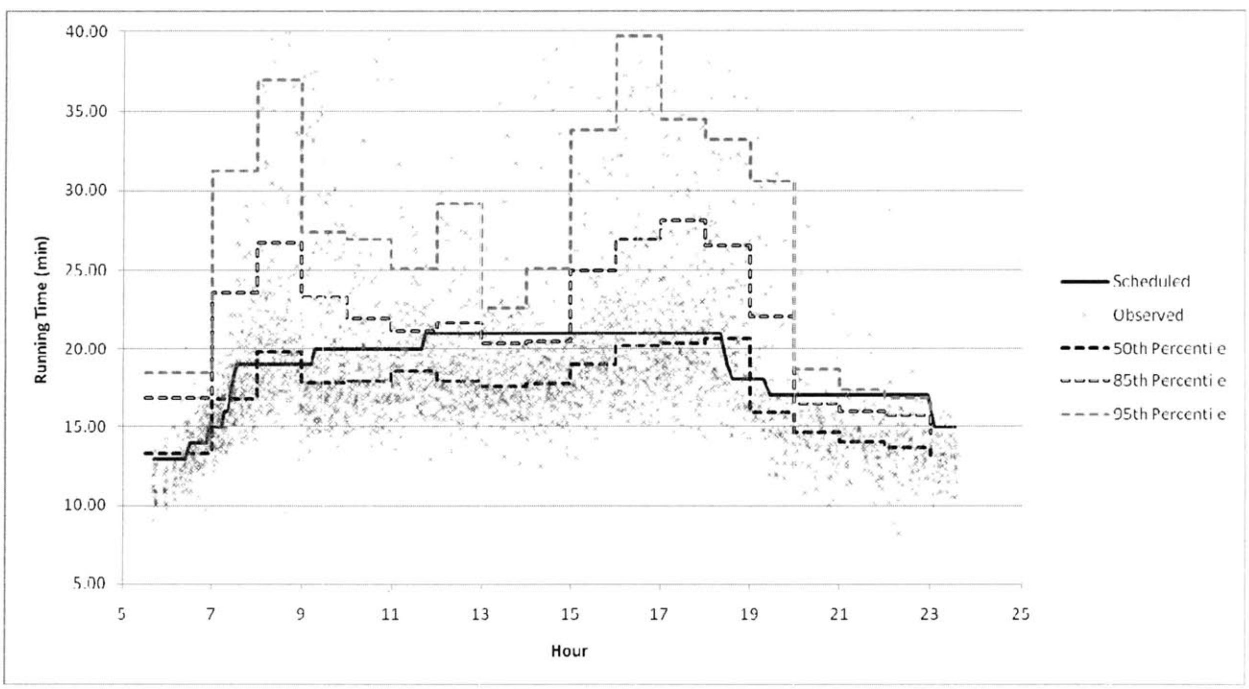

Figure 6-8 - Route 98 Southbound Running Times between Kilburn High Road and Marble Arch

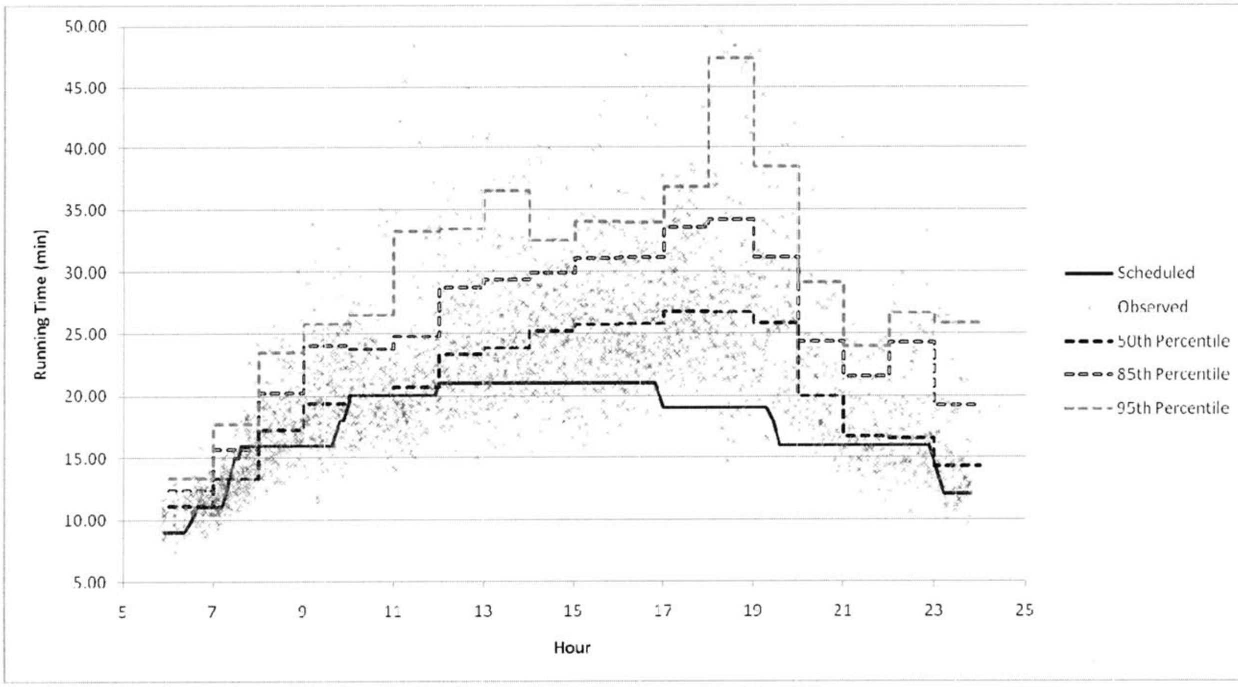

Figure 6-9 - Route 98 Southbound Running Times between Marble Arch and Tottenham Court Road

Planners may analyze these segments in a similar fashion as the analysis presented for the entire route/direction in order to set running times for each segment individually. They may then sum the individual run/recovery times determined for each segment (subject to the limits of the full trip analysis) to create an aggregate running time and recovery time for the given direction.

6.5 Summary

This chapter has demonstrated how AVL data may be used to aid in the operations planning process by enabling the development of more robust schedules. AVL data has the capability of providing additional insight into operations planning by providing the operations planner with a better estimate of expected running times, increasing the accuracy of the schedule. These data have the capability of providing a nearly 100% sample of trip observations; replicating this with a manual survey would be prohibitively costly. In addition, AVL data are recorded for every stop, enabling planners to estimate running times for smaller segments of any route.

Various aspects of the operating plan were discussed, including what constitutes a good operating plan and how operations planners estimate running times when developing schedules. Achieving a good operating plan, which involves developing a policy on how to use observed data when scheduling running times, is of benefit to both passengers and operators. Improved service reliability and more efficient resource utilization are just some of the potential benefits from implementing a robust operating plan.

The operating plans of two routes in the London bus network were analyzed by comparing observed running times with scheduled running and cycle times, and modifications to the given operating plans were recommended. The observations on these two routes indicate that operators have a reasonable idea of the route running times; however, AVL data would enable them to adjust their operations plans further, creating more precise schedules. This analysis was intended to be an example of how much information may be gleaned from a relatively simple analysis.

These results are of particular interest to London Buses because it demonstrates how AVL provides the agency with additional information when reviewing potential schedules developed by operators. It will allow TfL to more easily identify infeasible schedules, and inform operators of the necessary modifications to a new schedule before it is put into service.

TfL should also provide archived AVL data to operators to assist them in developing schedules. This will provide the operators with more information at the beginning of the operations planning process, and reduce the probability of a suboptimal schedule being developed and implemented. It should also help both parties optimize the use of available vehicle resources. It will reduce the overall workload for TfL, as this will lessen the need to renegotiate contracts due to infeasible schedules being approved and implemented.

Overall, it is recommended that transit agencies view AVL as an important tool in developing and assessing schedules. Agencies will gain better estimates of running times, and be able to develop more robust operating plans. Once agencies realize how AVL improves running time measurements, they will be able to develop specific running and cycle time policies in with their service delivery objectives. This results in a more effective utilization of resources, which maximizes fleet and crew efficiency while minimizing overall cost to the agency, and also achieving more reliable service.

7 Conclusions and Recommendations

This thesis demonstrated how AVL data may aid in two facets of bus service delivery: service reliability and operations planning. In particular, this research investigated new uses of AVL data which transit agencies may not have considered and which could easily be adopted and implemented by these agencies to improve their service. The recent implementation of the iBus AVL system in London, UK served as an example to demonstrate the range of new capabilities and applications provided by AVL data.

Service reliability and operations planning were chosen as areas of focus due to their relationship with the archived data provided by AVL systems (namely ubiquitous time and location information for all operating vehicles), and the extensive amount of research performed in these areas of transit operations, as shown in the literature review in Chapter 2. Major theories and developments in both of these areas were used as inputs for developing a framework to demonstrate how a transit agency may take full advantage of AVL's automated data collection capabilities.

The London, UK bus network, managed by Transport for London, was used as the case study throughout the analysis. While many of the results are applicable to agencies throughout the industry, the reader must bear in mind that the London bus network has a unique operating structure that may have ramifications for how the measures and methodologies introduced in this analysis are applied elsewhere. Most significantly, TfL is responsible for planning and monitoring bus service, but not for operating service. Contracts for bus routes are tendered to private operators, and contracts are rebid every 5-7 years. Due to this unique arrangement, the agency is structured differently than most other agencies in the industry, which are either entirely public (i.e. a public agency responsible for both service planning and operations) or private, as is the case with most other bus properties in the United Kingdom. However, recent trends in the industry indicate that an increasing number of public agencies are tendering operations to the private sector; it is anticipated that the results of this analysis will be increasingly relevant in the future as agencies shift from focusing on operations towards service planning and performance monitoring.

This chapter will summarize the work presented in this thesis, propose a set of recommendations, and explore possibilities for future work. Each area of focus will be summarized in its own section: service reliability in Section 7.1 and operations planning in Section 7.2.

7.1 Service Reliability

Service reliability was evaluated within the context of AVL implementation in London. The motivation behind this was twofold: first, to gauge whether the introduction of the AVL system resulted in a measurable impact on service reliability, and second, to demonstrate how additional data collection capabilities possible with AVL systems enable the development and estimation of new, robust measures of service reliability.

The effect of an AVL system implementation on service reliability was evaluated within the framework of identifying a comprehensive set of factors that affect service reliability in London. First, trends in service reliability, as measured by passenger Excess Waiting Time, were analyzed over a 10-year period. This showed that reliability has been fairly consistent since 2003, in spite of the iBus AVL installation from 2007-2009, and may therefore have reached a natural lower limit. A regression analysis, accounting for many more factors believed to influence reliability, computed the relative magnitudes of these factors' effects on service reliability, but was unable to comprehensively explain reliability. Thus, it was concluded that reliability is a complex phenomenon which is not easily explained, as many factors, both measurable and non-measurable, affect it in significant ways. Additionally, it was determined that merely installing an AVL system does not produce noticeable improvements in reliability; the agency must adapt its operating and monitoring practices to reflect the new capabilities of AVL in order to realize these potential benefits, examples of which were provided in the rest of the thesis.

The second motivation behind the reliability analysis was to introduce new measures of reliability that better reflect the passenger experience, which were meant to complement existing measures of reliability used by agencies for performance monitoring, such as EWT in London. These measures follow two recent trends in the transit industry. First, more accurate and comprehensive data sources enable agencies to measure aspects of service, such as the passenger experience, that would have been nearly impossible prior to the availability of these automated data sources. Second, automated data sources also enable agencies to compute distributions of measures of reliability as opposed to single, mean values. Agencies are able to focus on extreme values, and to find ways to reduce the variability in order to produce a more consistent ridership experience. In particular, the new measures of reliability presented in this analysis endeavored to account for the entirety of the passenger experience over which the operator has control: the total amount of time a passenger spends on the bus network. This includes the time a passenger spends waiting at a bus stop for a bus arrival, as well as the amount of time on the bus between an origin stop and a destination stop, measured via timestamps extracted from AVL at given stops.

Three measures of reliability were introduced. The first, Journey Time, is an absolute measure which enables the calculation of the other two measures, Excess Journey Time and Reliability Buffer Time. Journey Time accounts for the wait time and travel time of a passenger between a given origin stop and destination stop. EJT and RBT provide specific measures of the variability of the passenger experience by comparing the median Journey Time provided with the scheduled Journey Time, and the 95th percentile

Journey Time with the median Journey Time, respectively. The effectiveness of these measures was demonstrated by assessing major origin/destination pairs on a set of six bus routes in London, and comparing a priori assumptions about their perceived reliability with the results computed in this analysis. Instances were observed where routes which were initially perceived to have good operations were found to be unreliable, and vice versa. The conclusion was reached that the current measures used to assess reliability, while important, are not able to fully describe the passenger experience on the bus network. However, when the new measures are used to supplement the current measures, a greater understanding of the passenger experience on the bus network is realized.

Applications of AVL relating to service control were discussed as a consequence of the service reliability analysis. While the new iBus AVL system provides service controllers with a range of new capabilities, this study did not propose best practices for enabling service controllers to make the most informed decisions based on these new capabilities, as this should be determined by monitoring control practices and their effects over time. Instead, this research proposed how the proposed new measures of service reliability developed may aid in diagnosing the service control process.

7.1.1 Recommendations and Future Work

The following actions are recommended based on the results of the service reliability analysis:

- **Reliability should be measured based on passenger origin/destination patterns**. Reliability on the TfL bus network is currently measured at approximately 3-4 evenly spaced points along a bus route. These points do not necessarily correspond with major origins or destinations, and therefore reliability is not being measured in a way which fully reflects passenger travel patterns. With AVL data, it is possible to compute these measures of reliability at any given stop along a route. Therefore, now is an opportune time for the agency to rethink how to most appropriately measure reliability, which should include placing more emphasis on passenger travel patterns.
- **The three new measures of reliability introduced – Journey Time, EJT, and RBT – should be added to TfL's contracting scheme as complements to EWT**. TfL currently provides incentives to operators based on EWT measurements, by comparing measured EWT with a target EWT value. As demonstrated, EWT is an important descriptor of reliability but does not reflect the full passenger experience on the bus network. However, if the measures developed in this thesis are used as complements to EWT, TfL will be able to monitor additional aspects of reliability and provide incentives to operators to improve their operations to reflect these additional measures of reliability.

Journey Time should be used as a baseline by which the magnitudes of individual EJT and RBT measurements can be assessed and compared across the network. By doing so, TfL will be able to monitor the effectiveness of bus operations, while ensuring that passengers receive appropriate levels of service. For examples of how to develop a framework for incorporating passenger focused measures of reliability into the overall performance evaluation process, the reader is referred to Fijalkowski (2010).

- **More accurate journey information should be provided to passengers**. Schedules currently posted at stops for high frequency routes in London display a range of possible headways and an estimated off-peak travel time. By applying AVL data and the new measures of reliability developed, more accurate and reliable information can be provided to passengers. By using the Journey Time measure, TfL can provide passengers with estimated Journey Times broken down by time of day (including peak and off-peak periods). Additionally, TfL should consider providing passengers with an estimate of the possible range of Journey Times they may experience, which will allow passengers to schedule a buffer time should they need to reach their destination on-time with a high degree of certainty. This can be provided via the RBT measure.
- **TfL should use the new measures of reliability developed to aid in monitoring service control practices on its bus network**. When developing best practice guidelines for service control, TfL should have an understanding of how service control interventions affect reliability on the entire route. The measures developed in the service reliability analysis describe additional factors of reliability not captured by EWT, and will provide additional information with regards to the effects of different control interventions.
- **Future Work: Developing Aggregate Measures of Reliability.** The measures of reliability introduced were developed at a disaggregate level. The next logical step in expanding these measures would be to develop a means for aggregating each measure, in order to provide a descriptor of route, operator, and network performance across non-homogenous time periods. Since these are passenger-centric measures of reliability, the most sensible way of aggregating individual observations would be to weigh each measurement by observed ridership. To do so, it is recommended to combine these measures with the methodology developed by Wang (2010) for estimating a route-level OD matrix. A precise method for aggregation will then need to be developed.

7.2 Operations Planning

The second area of application for AVL data pertained to how these data may be used to improve operations planning. Specifically, methods for developing more robust vehicle schedules were investigated. AVL provides for more accurate and comprehensive measurement of historical running times which, in turn, provides operations planners with more robust inputs into the operations planning process. This is of special concern to the London bus network because TfL is not responsible for developing schedules, nor does it currently measure running times to assess the quality of schedules provided by the operators. AVL therefore is a tool with which TfL may assess schedules developed by operators.

This analysis demonstrated how observed running times from AVL may be used to estimate new schedules. Running times with similar magnitudes may be clustered into timebands and used as inputs into the scheduling process. These timebands reflect traffic conditions, which do not necessarily correspond to timebands of passenger demand used to set bus frequencies. It was observed, however, that running times in London rarely stay constant for a long period of time and even display linear increases (decreases) at the beginning (end) of the day, indicating large traffic fluctuations on the road network. Therefore, grouping running times into wide timebands is not always feasible.

The schedules of two routes were analyzed, and their effectiveness assessed by comparing certain percentiles of observed running times with scheduled running and cycle times. While schedulers on both routes had a solid understanding of how the route performs over the course of a day, each route had periods of the day in which excess cycle time was allotted, resulting in wasted resources, and periods which had insufficient cycle time allotted, resulting in a high probability of delays developing and perhaps propagating throughout the rest of the day. Thus, the analysis demonstrated that using AVL data enables the operations planners to refine their schedules, resulting in more robust schedules.

7.2.1 Recommendations and Future work

Based on the results of the operations planning analysis, the following actions are recommended:

- **Agencies with AVL data capabilities should include running time observations from AVL when developing and evaluating schedules**. This provides them with an additional tool with which to develop robust operating plans, and results in more reliable service. Passengers benefit from improved reliability and operators benefit from a more efficient utilization of their limited resources.
- **TfL should measure running times with AVL data and use these data to assess schedules developed by operators**. Additionally, these running time data should be made available to the operators for their use as inputs to new schedules. This is of mutual interest to both TfL and the operators, as it reduces the probability that contracts will have schedules based on inaccurate data, and therefore reduces the probability of having to renegotiate mid-contract.

- **Future Work: Developing Scheduling Policies and Best Practices.** Agencies will need to reevaluate their service delivery objectives in order to develop guidelines for setting schedules. Once agencies understand how AVL may be used to improve the operations planning process, they will be able to set policies with respect to setting optimal running and cycle times. Investigating optimal running and cycle times was beyond the scope of this thesis (see Fattouche (2007) and Furth and Muller (2006)), and is therefore recommended as future research for TfL.

Appendix 1 – Potential Variables Used in Regression Analysis

Variable	**Description**
AWT/SWT	Actual waiting time / Scheduled waiting time
EWT	Excess waiting time (AWT – SWT) from Stabs
Operator Change	1 if operator for previous period <> operator for current period, otherwise 0
Contract Change	1 if Route Group for previous period <> operator for current period, otherwise 0
Precipitation (mm)	Rainfall for period in mm. With 3 exceptions (Hounslow), rainfall taken from weather station in Crouch End. Hounslow used when Crouch End data found to be faulty.
Crossrail	1 if route was affected by construction around Tottenham Court Road as of Jan 2009, otherwise 0. Routes identified in "Changes to buses during Tottenham Court Road improvement works from January 2009" brochure.
G1	If given route operates from G1 during given period, 2 letter garage code, otherwise 0
G2	If given route operates from G2 during given period, 2 letter garage code, otherwise blank (also blank if G2 = G1)
G3	If given route operates from G3 during given period, 2 letter garage code, otherwise blank (also blank if G3 = G1 or G3 = G2)
Legacy AVL	=1 if G1, G2, or G3 is GR or EB (garages which did not have AVL installed before iBus), otherwise 0
iBus	= 1 after and including 1st period that 1st garage on route started installing iBus
iBus End	= 1 after and including 1st period that last garage on route finished installing iBus
Recession	=1 after September 2008 (current recession), otherwise 0
AN	Acton Tram 2 letter garage code dummy
ON	Alperton 2 letter garage code dummy
AE	Ash Grove 2 letter garage code dummy
HK	Ash Grove 2 letter garage code dummy
BK	Barking 2 letter garage code dummy
DX	Barking 2 letter garage code dummy
BA	Battersea 2 letter garage code dummy
QB	Battersea 2 letter garage code dummy
BC	Beddington 2 letter garage code dummy
CN	Beddington Farm 2 letter garage code dummy
BV	Belvedere 2 letter garage code dummy
BX	Bexleyheath 2 letter garage code dummy
BW	Bow 2 letter garage code dummy
AH	Brentford 2 letter garage code dummy
BN	Brixton 2 letter garage code dummy
ZR	Brixton II (Tram Shed) 2 letter garage code dummy
TB	Bromley 2 letter garage code dummy

Variable	Description
Q	Camberwell 2 letter garage code dummy
TL	Catford 2 letter garage code dummy
CT	Clapton 2 letter garage code dummy
MY	Crawley 2 letter garage code dummy
W	Cricklewood 2 letter garage code dummy
C	Croydon 2 letter garage code dummy
TC	Croydon 2 letter garage code dummy
RN	Dagenham 2 letter garage code dummy
DT	Dartford 2 letter garage code dummy
BT	Edgware 2 letter garage code dummy
EW	Edgware 2 letter garage code dummy
EC	Edmonton 2 letter garage code dummy
E	Enfield 2 letter garage code dummy
EB	Epsom 2 letter garage code dummy
FW	Fulwell 2 letter garage code dummy
GY	Grays 2 letter garage code dummy
EY	Greenford 2 letter garage code dummy
G	Greenford 2 letter garage code dummy
HO	Hackney 2 letter garage code dummy
SO	Harrow 2 letter garage code dummy
HD	Harrow Weald 2 letter garage code dummy
HZ	Hayes 2 letter garage code dummy
WS	Hayes 2 letter garage code dummy
HI	High Wycombe 2 letter garage code dummy
HT	Holloway 2 letter garage code dummy
HM	Horsham 2 letter garage code dummy
AV	Hounslow 2 letter garage code dummy
WK	Hounslow Heath 2 letter garage code dummy
KX	Kings Cross 2 letter garage code dummy
LV	Leeside Road 2 letter garage code dummy
T	Leyton 2 letter garage code dummy
ZL	Liverpool St 2 letter garage code dummy
MA	Mandela Way 2 letter garage code dummy
AL	Merton 2 letter garage code dummy
NX	New Cross 2 letter garage code dummy
NW	North Wembley 2 letter garage code dummy
NP	Northumberland Park 2 letter garage code dummy
N	Norwood 2 letter garage code dummy
MB	Orpington 2 letter garage code dummy
OR	Orpington 2 letter garage code dummy

Variable	Description
AD	Palmers Green 2 letter garage code dummy
PK	Park Royal 2 letter garage code dummy
PM	Peckham 2 letter garage code dummy
PA	Perivale 2 letter garage code dummy
PV	Perivale 2 letter garage code dummy
PD	Plumstead 2 letter garage code dummy
PB	Potters Bar 2 letter garage code dummy
AF	Putney 2 letter garage code dummy
BE	Rainham 2 letter garage code dummy
NS	Romford 2 letter garage code dummy
S	Shepherds Bush 2 letter garage code dummy
SI	Silvertown 2 letter garage code dummy
SN	South Mimms 2 letter garage code dummy
V	Stamford Brook 2 letter garage code dummy
SF	Stamford Hill 2 letter garage code dummy
SW	Stockwell 2 letter garage code dummy
A	Sutton 2 letter garage code dummy
TH	Thornton Heath 2 letter garage code dummy
TV	Tolworth 2 letter garage code dummy
AR	Tottenham 2 letter garage code dummy
NC	Twickenham 2 letter garage code dummy
TF	Twickenham 2 letter garage code dummy
U	Upton Park 2 letter garage code dummy
UX	Uxbridge 2 letter garage code dummy
WL	Walworth 2 letter garage code dummy
WD	Wandsworth 2 letter garage code dummy
WE	Ware 2 letter garage code dummy
RA	Waterloo 2 letter garage code dummy
PL	Waterside Way 2 letter garage code dummy
GR	Watford 2 letter garage code dummy
ZO	Metroline Wembley Park 2 letter garage code dummy
WH	West Ham 2 letter garage code dummy
X	Westbourne Park 2 letter garage code dummy
AC	Willesden 2 letter garage code dummy
WJ	Willesden Junction 2 letter garage code dummy
WN	Wood Green 2 letter garage code dummy
P1	Period 1 dummy
P2	Period 2 dummy
P3	Period 3 dummy
P4	Period 4 dummy

Variable	Description
P5	Period 5 dummy
P6	Period 6 dummy
P7	Period 7 dummy
P8	Period 8 dummy
P9	Period 9 dummy
P10	Period 10 dummy
P11	Period 11 dummy
P12	Period 12 dummy
P13	Period 13 dummy
Deck 1	# of decks on bus type 1 (of 5) running on given route for given period, or blank
Door Sets 1	# of doors on bus type 1 (of 5) running on given route for given period, or blank
Veh Length 1	Length of bus type 1 (of 5) running on given route for given period, or blank
Deck 2	# of decks on bus type 2 (of 5) running on given route for given period, or blank
Door Sets 2	# of doors on bus type 2 (of 5) running on given route for given period, or blank
Veh Length 2	Length of bus type 2 (of 5) running on given route for given period, or blank
Deck 3	# of decks on bus type 3 (of 5) running on given route for given period, or blank
Door Sets 3	# of doors on bus type 3 (of 5) running on given route for given period, or blank
Veh Length 3	Length of bus type 3 (of 5) running on given route for given period, or blank
Deck 4	# of decks on bus type 4 (of 5) running on given route for given period, or blank
Door Sets 4	# of doors on bus type 4 (of 5) running on given route for given period, or blank
Veh Length 4	Length of bus type 4 (of 5) running on given route for given period, or blank
Deck 5	# of decks on bus type 5 (of 5) running on given route for given period, or blank
Door Sets 5	# of doors on bus type 5 (of 5) running on given route for given period, or blank
Veh Length 5	Length of bus type 5 (of 5) running on given route for given period, or blank
AM Peak bph	Average of bph1, bph2 and bph3 for given route and period. From Busnet
Length	Length of bus route taken from GIS, Jan. 2009. All lengths are the average of the 2 directions.
CCZ Length	Length of bus route within Central Congestion Zone, taken from GIS, Jan. 2009
WCZ Length	Length of bus route within Western Congestion Zone, taken from GIS, Jan. 2009

Variable	Description
Central Length	Length of bus route within Central London, taken from GIS, Jan. 2009
Inner Length	Length of bus route within Inner London, taken from GIS, Jan. 2009
Outer Length	Length of bus route within Outer London (Total Length – Inner – Central), taken from GIS, Jan. 2009
CCZ %	% of route within CCZ
WCZ %	% of route within WCZ
Central %	% of route within Central London
Inner %	% of route within Inner London
Outer %	% of route within Outer London
AR	Armchair Passenger Transport 2 letter operator code dummy
BU	Blue Triangle 2 letter operator code dummy
CC	First London East 2 letter operator code dummy
CW	First London West 2 letter operator code dummy
CX	Travel London 2 letter operator code dummy
DK	Docklands Buses 2 letter operator code dummy
EL	East London 2 letter operator code dummy
ET	East Thames Buses 2 letter operator code dummy
EY	ECT Bus 2 letter operator code dummy
FE	F.E Thorpe 2 letter operator code dummy
HK	CT Plus 2 letter operator code dummy
KB	Arriva Kent Thameside 2 letter operator code dummy
LC	London Central 2 letter operator code dummy
LD	Arriva The Shires 2 letter operator code dummy
LE	Arriva London North 2 letter operator code dummy
LG	London General 2 letter operator code dummy
LU	London United 2 letter operator code dummy
MB	Metrobus 2 letter operator code dummy
MI	Centra London 2 letter operator code dummy
ML	Metroline 2 letter operator code dummy
NC	NCP Services 2 letter operator code dummy
OL	Arriva Wandsworth 2 letter operator code dummy
SE	Selkent 2 letter operator code dummy
SL	Arriva London South 2 letter operator code dummy
SV	London Sovereign 2 letter operator code dummy
TG	Travel London (West) 2 letter operator code dummy
Workstations	(Sum of) workstations at garage(s) if available, otherwise blank.
Percentage Operated	% Mileage data
Percentage Operated before Non Deductible	% Mileage data
Percent Lost Staff	% Mileage data

Variable	Description
Percent Lost Mech	% Mileage data
Percent Lost Other Deductible	% Mileage data
Percent Lost Traffic	% Mileage data
Percent Lost Other Non Deductible	% Mileage data
D/C	Driver/controller ratio - For routes with more than one garage, sum of drivers/sum of controllers. If blank, no data available for garage(s).
PVR/Wrkstn	(sum of) Peak Vehicle Requirement / (sum of) # of workstations. If blank, no data available for garage(s).
Route/Wrkstn	(sum of) Routes / (sum of) # of workstations. If blank, no data available for garage(s).
Ridership	Aggregate ridership for the given period based on ETM data
Ridership/km	Total ridership divided by route length
Unemploy	% unemployment in London
Priority	1 if bus priority measure listed in "Bus Priority" worksheet in place, 0 otherwise

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