Simulating Service Reliability of a High Frequency Bus Route Using Automatically Collected Data

by

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Abstract

High frequency bus routes are subject to a variety of influences that can affect the quality of service provided to passengers. Since they have short headways and high passenger demand interaction between buses can easily develop, causing degradation in service reliability. This, in turn, can prompt service interventions to correct service reliability. Transit agencies are implementing new technology that provide rich data sets for analysis and are also experimenting with a variety of operating policies to improve service reliability.

This research develops a simulation model of high frequency bus service in order to study the causes of service unreliability and strategies to alleviate it. The model is designed to be used in conjunction with data recorded by the Automatic Voice Annunciation System (AVAS), Automatic Passenger Counting (APC), and Automatic Fare Collection (AFC) systems and is calibrated to represent route 63, a key bus route in the Chicago Transit Authority (CTA) network

The simulation model is first used to conduct a sensitivity analysis of the factors influencing reliability, such as passenger demand, terminal departure behavior, and unfilled trips. Next, several operating strategies, including terminal departure and timepoint holding for schedule or headway, are modeled and evaluated for their potential to improve reliability.

The sensitivity analysis and application testing support the use of passenger-centric metrics such as passenger-experienced waiting time and crowding over more aggregate headway measures such as large headways and bunching. Model results show that headway management strategies implemented at the terminal can significantly improve bus service reliability and ameliorate the impacts of unfilled trips on route 63, as measured by passenger waiting time, crowding, and big-gaps / bunches.

The simulation model is a valuable research tool for applications beyond those tested in this thesis. The model developed can be applied with from data collected by automatic collection systems which is a particularly useful feature for transit agencies.

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

To My Family

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1 Introduction

This thesis presents the design, calibration/validation, and application of a micro-simulation model to test strategies for improving service reliability on high frequency bus routes.

The simulation model is designed to allow the user to gain insight into the factors influencing bus service reliability and to test new strategies to improve reliability. The bus route is represented at the "key stop" / route segment level of detail and the individual buses are simulated to be operating on schedules that include the detail of normal operations in a typical public transportation network. The variable aspects of a bus route represented within the simulation model include: bus running time; stop dwell time; terminal and timepoint operator departure behavior; and passenger demand. Within this framework, operating strategies may be implemented that, for example, adjust the schedule, manage terminal departures, or apply time point holding.

The simulation model is calibrated to represent a key bus route in the Chicago Transit Authority (CTA) network. Once calibrated, the model is validated to confirm accurate representation of the route. The calibration and validation parameters for the key bus route are derived from data captured by the Automatic Voice Annunciation System (AVAS) and procedures are outlined to adapt the model to other bus routes.

The simulation model is used first to conduct a sensitivity analysis of bus service to the factors influencing reliability, such as passenger demand, terminal departure behavior, and unfilled trips. Next, several operating strategies, including terminal departure and timepoint holding for schedule or headway, are implemented in the model and are evaluated for their potential to improve reliability. The sensitivity tests and operating strategies are evaluated using the passenger-centric metrics of crowding and waiting time as well as the current CTA metrics of "big-gaps" and "bunching".

1.1 Motivation

The operations of high frequency bus routes (typically defined as operating every 10 minutes or less) are subject to a variety of influences that can greatly impact the level of service provided to passengers. High frequency bus routes have short headways (i.e. the time between successive buses) and high passenger demand which leads to interaction between buses. Bus interactions cause a degradation of service reliability, but service interventions to correct service reliability may have complex ramifications. Transit agencies are implementing new technology that provide a rich data set for analysis and are experimenting with a variety of operating policies to improve service reliability. A simulation model would be an appropriate tool to represent the complexity of a bus route and could be configured with the recently available data.

1.1.1 High-Frequency Bus Route Service Reliability

On high frequency bus routes, passengers may be assumed to arrive randomly, so constant headways will best distribute the passenger load across buses and minimize the passenger waiting time (Furth et al., 2006). Constant headways, however, are unstable. The real world variability in traffic, passenger demand, and across operators quickly pushes the bus service toward the stable but undesirable state of "bus bunching". Bus bunching is the popular term for two or more buses serving a route in close proximity, usually within a minute of each other. Bus bunching is most common on high frequency routes because high passenger demand creates strong interactions between successive trips. With high passenger demand, small variations in headway may lead to a feedback cycle that increases the variation. For example, a bus traveling with a shorter leading headway will pick up fewer passengers than usual; therefore the dwell time will be shorter than usual and the headway will be reduced. This continues until the bus catches up with its leader along the route. (Turnquist and Bowman, 1980)

As opposed to constant headways, bunching of buses is generally the least effective service configuration on a high frequency route. Bunched buses will create long passenger wait times by creating long service gaps and an uneven distribution of passengers across buses, unless the drivers informally begin to cooperate by each picking up passengers at alternating stops. Bus bunching is a major type of service unreliability that increases the operations cost for the transit agencies through inefficient use of fleet capacity. When bus bunching occurs, more buses are required to serve a route at the established crowding standards. The passenger travel cost is also increased through the need to budget more time to account for the unreliability. Furthermore, if trips on the route require a greater time budget due to unreliable service, fewer passengers may use the service and the transit agency will collect less revenue. (Abkowitz et al., 1978)

In order to separate bunched buses, and prevent bunches from occurring in the first place, a variety of operations control strategies may be implemented on a bus route. The effectiveness of any strategy, or combination of strategies, depends on the route characteristics and implementation method. General route characteristics will determine which strategies are most effective, for example, reliability on a route with a lot of passenger crowding may not necessarily benefit from an improvement in fare media technology (Milkovits, 2008). The implementation method determines when, where, and how a strategy is implemented and enforced. If a strategy is implemented without consideration of the current state of the route, it may do more harm than good. For example, one way to separate a pair of bunched buses is to hold one bus. If the decision on which bus to hold does not include the passenger load, the holding strategy may increase the passenger in-vehicle time unnecessarily on an already crowded bus. Furthermore, there may be a large gap in service preceding this bunch, and holding will only exacerbate the situation. Conversely, if the gap in service is following the bunch and a bus is lightly loaded with passengers, it would be better to hold that bus to even out the headway. Successfully enacting strategies is restricted by data availability and a good understanding on the interaction of these strategies with the route characteristics. (Levinson, 1991)

1.1.2 Agency Efforts to Improve Bus Reliability

CTA is one of many transit agencies that are making the multi-million dollar investment to equip their fleet with real-time AVL reporting systems to improve bus service reliability (CTA Press Release, 2006). These systems promise to fundamentally change the lives of both passengers and bus supervisors. For passengers, the real time location data is used to generate stop arrival time predictions so that passengers will have a good estimate on the next bus arrival and can change their waiting behavior. For bus supervisors, real time data means that the supervisor no longer needs to be on the street to get a picture of the service on a bus route. Moreover, the picture of service that a supervisor will have is of the entire route, rather than just what have recently passed their location. With operations control strategy decisions not restricted to what is seen on the street, service restoration could be much more effective. It is not clear, however, how much more effectively service restoration may be implemented or what condition displayed in the real time data should initiate a service restoration action.

Every bus in the CTA fleet has an Automatic Vehicle Location (AVL) and Automatic Fare Collection (AFC) system installed. An increasing percentage of buses also have an Automatic Passenger Counting (APC) system installed. The AVL system records the current vehicle location and time. The APC system records the passenger boardings and alightings at each stop and calculates the onboard passenger load. The AFC system records all electronic fare transactions. All of this data is saved on the bus and later downloaded to the bus data archive for reporting and analysis. From this data, information about the running time, dwell time, terminal recovery behavior, and passenger demand may be gleaned.

In an effort to understand the effectiveness of various operations control strategies, CTA has historically (CTA Press Release, 2000) and is currently (CTA Press Release, 2008) experimenting with bus bunching reduction pilot programs. In these programs, a few routes are chosen and a different operations control strategy is applied to each. This approach has limited conclusions due to the differences in the characteristics of the selected routes that cannot be controlled. To properly analyze the various strategies, it is necessary to compare the service impacts holding everything else constant. Unfortunately, this is practically impossible in a working public transit system. Even if the same route were to be used, passenger demand changes from season to season as do the operators serving the route. All of these concerns do not even consider that each of these pilot programs risks a potentially negative impact on the passenger experience. These issues can be avoided by developing a simulation model of the bus route to test operations control strategies.

1.1.3 Simulation Models as Tools to Study Bus Reliability

A simulation model is a tool that can be developed and calibrated to represent the important characteristics of a particular route. Furthermore, a simulation model can represent a route generically which will allow development and testing of operations control strategies for many routes with the same characteristics. Any number of different strategies may be evaluated with the model, provided that the appropriate input data is available. This approach to evaluating operations control strategies avoids negatively impacting passengers and controls for variables that may change between routes or on the same route over time. Furthermore, a simulation model allows the user to visualize the impacts of many factors on bus operations. This visualization is similar to that provided by the real time AVL system and therefore can also help train supervisors to use real time data effectively for service restoration.

1.2 Objectives

The objectives of this thesis are as follows:

- To develop a micro-simulation model of a major bus route that represents the variability of movement, dwell, operator reliefs, and terminal recovery and can simulate and evaluate configurable service restoration strategies.
- To calibrate and validate this model using automatically collected data from CTA bus route 63.
- To conduct sensitivity testing on the factors influencing reliability to gain insight into the impact of each on passenger perceived reliability.
- To evaluate real time data driven bus supervisor operations control strategies.
- To provide an interface for convenient application of the simulation model to other bus routes.
- To provide a visual element of the simulation that can be used for training.

1.3 Research Approach

In developing a bus route model, it is important to keep the basic tenets of simulation modeling in mind. A simulation model must be developed with its specific application(s) in mind. A simulation model cannot include every detail of the system and is unlikely to represent the actual system perfectly. Rather, the model results are intended to give the modeler insight into the system. This concept is best summed up in a quote by George Box: "All models are wrong, some models are useful" (Box, 1979). Furthermore, any simulation model is only as good as the input data (Law, 2003). Sub-models generate input data that are used in the simulation model. The limitations of the input data will constrain the model applications.

The simulation model developed in this thesis is designed to test the impact of operations control strategies on bus service reliability. These strategies include preventative strategies, such as schedule improvements, and corrective strategies, such as holding vehicles. Therefore, the simulation model must be of sufficient detail to represent bus service reliability accurately, implement simulated operations control strategies, and reflect their impacts. While the model will be validated on a single route, the intention is to build a simulation model that could be applied to a variety of bus routes for more comprehensive testing of operations control strategies.

The simulation model is developed at the "key stop" level of detail with full representation of the dwell time and holding at all scheduled timepoints, terminals, and stops with high levels of passenger activity. This level of detail requires input data describing segment running time, stop dwell time, timepoint/terminal operator departure behavior, and passenger demand.

This implementation has advantages over previous bus route simulation models because it does not rely on detailed traffic data, it includes a visual component, and makes use of the automatically collected data from bus systems.

Prior research into bus service reliability is used to identify the key components that determine the input data for the simulation model. The parameters for sub-models are estimated from the archived AVAS data on CTA route 63. Where the available data is insufficient to set parameters of the key characteristics, the models are either simplified or the user can set the required values.

CTA route 63 was chosen for validation and initial application of the model because of its sustained high frequency service and potential for service reliability improvement. Conclusions are drawn based on the potential improvement in bus service reliability based on the implementation of operations control strategies using various thresholds.

1.4 Thesis Organization

Chapter 2 reviews the previous research in two areas: bus service reliability and transportation simulation modeling. Previous research on bus service reliability identifies the important aspects of bus service that need to be represented in a bus route simulation model. Previous simulation model research is examined with respect to the purpose and use of such models and the availability of data required to configure a realistic model in each case.

Chapter 3 presents the detailed simulation model design. This chapter describes the program design and the methods used to simulate bus movement, dwell, and terminal behavior. User interfaces, including the configuration utility, run parameters, and visual component of the simulation model are also discussed in this chapter.

Chapters 4-6 describe the particulars of the route 63 case study. Chapter 4 presents an overview of the CTA bus network, route 63, and the bus operations control strategies that are currently used. Chapter 5 presents the data analysis of route 63 and the development of the running, dwell, terminal departure, and passenger demand model functions and parameter estimation. Chapter 6 describes the validation procedure and compares the simulation model results with data from route 63.

Chapter 7 presents the applications of this simulation model and discusses their implications.

In conclusion, Chapter 8 discusses the limitations and potential future applications of the simulation model.

2 Literature Review

A simulation model to reproduce bus service reliability and test operating strategies must be sensitive to the factors influencing reliability and the various operating strategies which may be deployed to improve service. Section 2.1 reviews the prior research related to bus service reliability focusing on the measures, causes, and strategies to improve reliability. Section 2.2 reviews previous bus simulation models.

2.1 Reliability

This section reviews the prior research into bus service reliability and discusses the primary factors influencing reliability, the metrics used to measure reliability on a high frequency bus route, and the operating strategies to manage reliability.

2.1.1 Bus Reliability Metrics

Abkowitz et al. (1978) found that most transit agencies were using reliability metrics based on schedule adherence, which is not necessarily the most important aspect to passengers, especially on high frequency routes. Furthermore, a faulty schedule will affect these metrics. The study emphasized the importance of having good measures of reliability to accurately identify problems and measure improvements. The authors proposed a series of passenger-centric reliability metrics that capture the distribution of travel time, schedule adherence and headway distribution. The distributions are characterized by the mean, coefficient of variation (mean divided by the standard deviation), and the percentage of observations beyond a certain value.

Cham (2006) extended this framework to take advantage of the new information available through AVL/APC and other automatic data collection systems. Cham proposed measuring reliability using three primary metrics: passenger waiting time, crowding, and schedule adherence.

The new level of data available from AVL/ APC systems permits a refinement of the metrics originally proposed in Abkowitz et al. (1978). Furth et al. (2006) conducted a survey of the implementation and use of automatic data collection systems in transit authorities. This research went on to propose guidelines for system design and data analysis and developed prototype tools to assist in the data analysis.

In this section, Cham's extension of Abkowitz et al.'s reliability metrics and Furth et al.'s data analysis tools are discussed.

Passenger Waiting Time

To measure passenger waiting time on a high frequency bus route, the passenger arrival behavior and headway distributions have to be studied. Passengers on a high frequency bus service are assumed to arrive randomly because the expected wait time until the next bus in the worst case scenario of just missing the bus, should not be long due to the short scheduled headway and the variability in bus arrival times may be of the same order of magnitude as the headway. Therefore, service reliability from the passenger perspective depends on the headway regularity, rather than schedule adherence. The Transit Capacity and Quality of Service Manual (TCQSM) categorize the headway coefficient of variation according to the level of service classes listed in Table 2-1 (Kittleson and Associates et al., 2003).

Table 2-1: Categorization of Headway Coefficient of Variation*

LOS	c_{vh}	$P(h_i > 0.5\ h)$	Comments
A	0.00-0.21	≤1%	Service provided like clockwork
B	0.22-0.30	≤10%	Vehicles slightly off headway
C	0.31-0.39	≤20%	Vehicles often off headway
D	0.40-0.52	≤33%	Irregular headways, with some bunching
E	0.53-0.74	≤50%	Frequent bunching
F	≥0.75	>50%	Most vehicles bunched

NOTE: Applies to routes with headways of 10 minutes or less.

*Source: TCQSM - 2nd Edition

Furth et al. (2006) developed the concept of the "budgeted" waiting time as an important factor to consider as well as the actual waiting time. When planning a trip, passengers will budget waiting time. To make sure they are not late at their destination some passengers may budget their waiting time at the 95th percentile of the actual waiting time distribution. The difference between the 95th percentile of waiting time during perfect and actual operations is the excess budgeted waiting time.

Crowding Levels

Crowding levels on the bus will reduce the quality of service for onboard passengers. In the limit, severely crowded buses may extend the waiting time beyond one headway due to the waiting passengers being unable to board the first bus to arrive.

Furth et al. (2006) argue that crowding should be measured based on the average crowding experienced by the passenger, rather than the average crowding per vehicle on the route (e.g. twice as many customers will experience crowding on a packed bus than will experience comfortable conditions on a half-full bus trip). This metric gives a better idea of the crowding as experienced by the average passenger, which is more important than the average crowding on the route. The authors extend the TCQSM defined crowding impact on comfort for different passenger loads on a 42 seat bus as shown in Table 2-2. The level of service (LOS) is associated with a passenger load up to the number in the first column. So LOS F2, although not listed explicitly in the table, accounts for passenger loads above 69.

Table 2-2: Crowding Level Categories*

Load (pax)	Basis	Passenger Comfort	*TCQSM* LOS
21	0.5 * (no. of seats)	Can sit next to unoccupied seat	A
32	0.75 * (no. of seats)	Can choose seat	B
42	no. of seats	Seated	C
53	3.85 sq. ft. per standee	Standing but not crowded	D
62	2.2 sq. ft. per standee	Full	E
69	1.6 sq. ft. per standee	Borderline of crowded and overcrowded	F1†

†LOS F from the *TCQSM* has been subdivided into levels F1 and F2.

***Source: Furth et al. (2006)**

The authors apply these categories as follows: If a 42 seat bus has 60 passengers on board, 42 will be counted as seated (TCQSM LOS C), and the remaining 18 will be counted as standing and crowded, but not overcrowded (TCQSM LOS E).

Schedule Adherence

The TCQSM surveys the schedule adherence metrics implemented by transit agencies and discusses the sensitivity of passengers to early departures on low-frequency bus routes (ten minute headways are used as a delimiter between high and low frequency routes). The manual explains that on high frequency routes headway regularity is more important than schedule adherence due to the passenger arrival behavior and propensity for bus bunching.

There are situations however, where poor schedule adherence will indirectly impact headway regularity. For example, during an operator relief, a trip running ahead of schedule may have to wait until the relief operator arrives. Also a late trip that arrives at the terminal with no recovery time available cannot be deployed early to maintain headway. Thus, although the schedule adherence may not be a primary metric of reliability on high frequency routes, it is important to pay attention to schedule adherence on these routes at the terminal and relief points.

2.1.2 Causes of Unreliability

Building upon the research of Abkowitz et al. (1978), Cham (2006) identified 5 categories in which to group the causes of bus service unreliability: schedule deviations at terminals, running time variations, passenger loads, environmental factors, and operator behavior. These categories are used to guide our discussion of the causes of bus service unreliability.

Schedule Deviations at Terminals

The terminal departure time for each bus depends on the terminal departure policy. Terminal departure times can be set to maintain a trip schedule or headway (terminal departure policies are discussed in more detail in Section 2.1.3). Cham's schedule deviations at terminals category is interpreted here to include both types of terminal departure policies. Under either policy, schedule deviations at terminals can result from bus or operator unavailability, late completion of the previous trip, inadequate scheduled recovery time, and poor operator discipline.

Abkowitz et al. (1978) identify schedule deviations at terminals as a primary cause of service unreliability because the deviations can compound over the entire course of the route. For example, a slightly longer headway at the terminal may compound with higher passenger boardings so that dwell times become longer and longer over the entire route.

Deviations at terminals are an important cause of unreliability and it should be relatively easy to address the problem. After departing the terminal some passengers will always be onboard the buses so that en route operations control strategies often have some negative effects. Furthermore, if the terminal departure policy is to maintain schedule, bus schedules typically have recovery time scheduled at the terminal and setting the correct amount of recovery time is critical.

Running Time Variations

Variability in running time impacts bus service reliability both in the course of the trip and, if the variability in running time causes trips to take longer than the scheduled running and recovery time, on subsequent trips. Variability of running times between trips will affect the headway distribution which contributes to excess passenger waiting times. A path choice model developed by Hickman (1993) estimated waiting time variation as a function of running time (and terminal departure) variation.

Abkowitz and Tozzi (1987) and Strathman et al. (2000)* identified the determinants of bus running time including route length, lane geometry and parking characteristics, signalized intersection prevalence and timing, stops served, passenger demand, time of day, and seasonal effects. Strathman et al. (2002) estimated a run time model using regression methods on automatically collected data and obtained significant estimators for the determinants listed above. This model was then extended to study the impact of operator experience on running time.

Passenger Load

Passenger loads are sensitive to headway regularity, arrival behavior of the passengers, and the scheduled frequency. Even headways are most likely to produce even passenger loads, assuming random passenger arrivals which are typical of high frequency services.

Milkovits (2008) examined the impact of overcrowded buses on dwell time and estimated an ordinary least squares model (OLS) of bus dwell time model to capture this effect. This work concluded that, in crowded situations, the advantage of smart media fare cards is lost and there is an overall penalty based on the number of passengers onboard and boarding / alighting.

In the running time model developed by Strathman et al. (2002), the number of stops served had a significant positive impact on the total running time. The more passengers on the bus means more stops will be served, at least to let onboard passengers alight the bus. If the passenger load variability is high, the variability of running times will also be increased.

Environmental Factors

Environmental factors include variations in traffic, weather, and other exogenous aspects affecting bus service. Environmental factors mainly impact bus service reliability through the running time. Mixed-use right of ways include interference with bus service from double-parked cars, traffic accidents, turning traffic, or just heavy traffic. Some of these causes, such as double-parked cars and traffic accidents are random and will have a relatively short impact on bus service reliability, maybe only affecting a few trips. Weather impacts are also random, but may impact an entire day's operation. Other environmental causes, such as turning or heavy traffic have a more systematic impact on bus service.

* Referenced through Strathman (2002)

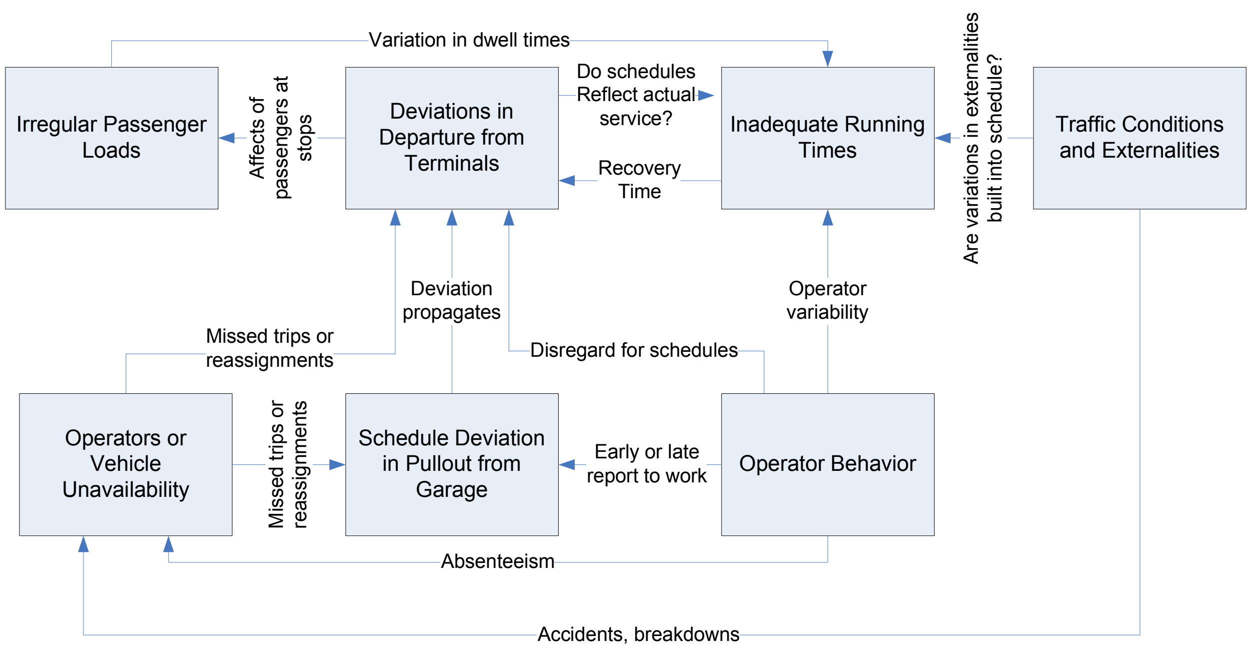
Operator Behavior

Operator behavior in general and differences in behavior among operators may cause unreliability in bus service through running times, terminal departure and relief processes, and schedule deviations. Strathman et al. (2002) found operator experience to be negatively correlated with the running time. More experienced operators are more comfortable with the bus, route, and even handling of passengers. Operators who are not self disciplined might arrive late for reliefs and take extended breaks at the terminal. In the worst case, operators will not show up at all for the trip, causing the headway to be twice as long as scheduled.

Interactions of Causes

Each of the causes of unreliability will be present to some extent on every bus route. The causes interact and make it difficult to isolate and address each, or even to understand the effectiveness of a strategy addressing one cause. For example, a schedule deviation may lead to a larger passenger load, which will extend the dwell time. Cham (2006) presents the variety of interactions between these causes in the flow chart shown here as Figure 2-1.

Figure 2-1: Interactions of the Causes of Bus Unreliability*



***Source: Cham (2006)**

Depending on the existence and severity of the causes on a particular route, it may not be sufficient to manage service reliability by addressing just one cause. The best place to implement operations control strategies is at terminals both because there are no passengers onboard and it prevents propagating headway variability from the beginning of the route, however, there are 4 different causes identified in Cham's figure that contribute to terminal departure deviation: inadequate running times, operator behavior, garage pullout deviation, and operator or vehicle unavailability.

2.1.3 Strategies to Improve Reliability

A review of prior research reveals a plethora of theoretical and applied operations control strategies to address the causes of unreliability discussed in Section 2.1.2. Abkowitz et al. (1978) categorized strategies to improve service reliability into two major categories: preventative and corrective. Preventative strategies are meant to prevent unreliability from developing in the first place, while corrective strategies are implemented when unreliability is present. Each strategy is targeted at addressing a certain aspect of service unreliability and is dependent on data availability to determine when the condition is right to implement and to what degree the strategy should be enforced. Wilson et al. (1992) found that the implementation of holding on the MBTA's Green Line LRT on occasion created more passenger delays due to insufficient data on headways. Cham (2006) compiled the strategies identified in previous research. Preventative and corrective strategies are summarized in Table 2-3 and Table 2-4 respectively.

It is important to realize that a mix of these strategies is often implemented on the street, to reflect the multiple and interacting causes of unreliability discussed in Section 2.1.2. Depending on the practice in the transit agency, some strategies may be implemented more effectively than others and this clouds the potential effectiveness of each strategy. For example, there could be an excellent terminal departure policy, but if the schedule does not have adequate time, this will not improve the reliability. Levinson (1991) reported that long routes or poorly managed schedules are main reasons cited by transit authorities for poor performance or difficulty in supervising a route.

The limited data available about the route conditions restricts our ability to evaluate the effectiveness of some strategies listed above (e.g. evaluation of the effectiveness of lane or signal priority requires detailed traffic data). This research is focused on, but not limited to, evaluating service supervision leveraging the newly available real time AVL data. The terminal and timepoint holding control strategy that will be evaluated in this research is now described in detail.

Table 2-3: Strategies to Prevent Bus Route Unreliability

Strategy	Description
Route Design and Lane Priority	Changing route characteristics such as the length and number of stops as well as lane access restrictions (temporary or permanent).
Signal Priority	Vehicle and signal communication to facilitate bus access to stops and movement through intersections. Priority may be conditional based on performance relative to the bus schedule.
Stand-by Operators and Buses	Make operators and vehicles available in case of a breakdown or no-show on the route. May also be used if extra capacity is required on a route.
Operator Training / Discipline	Minimize the impact of operator behavior on the variability of running time and terminal departures. Discipline measures reduce absenteeism.
Schedule Adjustment	Increase running time and/or terminal recovery time in the schedule so more trips will complete within the scheduled time and be able to begin the next trip on-time.
Dwell Time Mitigation	Reduce dwell time through encouraging fare media with faster processing times, improved vehicle technology, and parallel boarding/alightings.
Service Supervision	Real time monitoring and active management of schedule and headways at terminals and along the route. If a service issue is identified, the supervisor may implement the corrective strategies, such as holding, expressing, short turning, or dead heading vehicles as necessary.

Table 2-4: Corrective Bus Route Operations Control Strategies

Strategy	Description
Holding	The vehicle is instructed to stand for a specified period of time to correct either the schedule or the headway. Holding for schedule correction is typically implemented when the vehicle is running ahead of schedule. Holding for headway is done when buses are bunched and/or the following headway is long.
Expressing	The vehicle is instructed to progress down the route faster than in normal operations. This is achieved by either going full express (no intermediate stops are served), limited stops (only a limited number of intermediate stops are served), or alighting-only (no additional passengers may board, but onboard passengers may alight).
Short Turning / Deadheading	The vehicle is taken out of service and advanced to another part of the route to get a bus back on schedule or close a large headway gap. Short turning involves ending a trip before the terminal and beginning the next trip at that point. Deadheading involves advancing the bus to some other point on the route before reentering service.

Terminal and Timepoint Holding

As discussed earlier, headway adherence is more important than schedule adherence on high frequency bus service. Holding for headway may be implemented using information about the preceding headway or both the preceding and following headway (Turnquist, 1981). Turnquist explains that the optimal headway strategy depends on the correlation between the headways. If headways are strongly correlated (i.e. short headways are often followed by long headways), holding based on the leading headway will be sufficient to even out the headways. If the headways are not correlated (e.g. bunches of more than two buses), then holding to even the preceding and following headway will have the greatest effect on bus service reliability; this strategy is referred to as "prefol", for previous and following headway. Without real time AVL data, the only holding strategy that may be implemented is based on the preceding headway.

Turnquist and Blume (1980) explore the importance of the control point location. The purpose of the holding strategy is to reduce the passenger waiting while accepting some negative impact on passenger in-vehicle time. Therefore, it is best to hold at points that maximize the reduction in passenger waiting time and minimize the increase in passenger in-vehicle time. For this reason, holding at terminals is advantageous because there are no passengers on board and an entire route of waiting passengers can benefit.

Pangilinan et al. (2008) evaluated the effectiveness of holding on CTA bus route 20 by first constructing a Monte Carlo simulation model and then conducting a week long experiment involving a supervisor in the control center monitoring the real time AVL data and communicating service adjustments to supervisors located at terminals and timepoints. The holding strategy was implemented based on the findings of the research discussed above (prefol at timepoints with more passengers waiting than onboard) and a dramatic improvement in bus service reliability was found. This work demonstrated the effectiveness of the holding strategy on a particular route, albeit with intensive personnel involvement. The research also focused on a limited set of trips in a single direction, and therefore did not capture the impact of holding on operator reliefs or even the successive terminal recovery time. The focus on the inbound direction is appropriate for a route with strongly directional demand such as CTA route 20, but less so on a cross town route with constantly high passenger demand in both directions, such as CTA route 63. This research will extend Pangilinan et al.'s work by building a simulation model to be used on other routes in more detail, by including recovery time at both terminals and by eliminating the assumption that successive trips are independent.

2.2 Previous Bus Simulation Models

Much of the prior research into the factors influencing bus reliability acknowledges the difficulty in determining the appropriate operations control strategy. This difficulty is due to the complex interactions that cause unreliability. These works often recommend and/or implement simulation models to gain understanding of how the causes of unreliability interact and to test different implementations of operations control strategies. The prior models developed vary based on the application of the model and data availability. A main difference in bus route simulation models is whether the general traffic is represented explicitly or implicitly.

2.2.1 Explicit Traffic Representation

Representing transit operations in a microscopic traffic model is very useful in evaluating lane and signal priority operations control strategies, as shown by Khan and Hoeschen (2000), Morgan (2002), and Chandrasekar et al. (2002), among others using commercial modeling packages.

There are several commercial traffic simulation packages available that explicitly represent transit (VISSIM), may be extended to do so (MITSIM), or that may represent transit indirectly (for example Khan and Hoeschen, 2000 in CORSIM). The convenience of using a pre-existing traffic modeling package is countered by the restricted access to the source code (with the exception of Morgan's use of MITSIM). Development of a model "from scratch" with complete access to the source code enables the user to adapt the model to new operations control strategies and inputs more easily.

However, representing traffic is beyond the goals of this research, which is to evaluate operations control strategies available through real time AVL data. Furthermore, requiring the simulation model to gather or generate data on car O/D, lane geometry, and traffic signal location and timing will make it difficult to apply the model to other routes in the CTA bus system. Several other researchers have developed simulation models "from scratch" that do not rely on traffic data but incorporate the traffic impact implicitly through the travel time distributions.

2.2.2 Implicit Traffic Representation

Prior to the widespread implementation of onboard automatic data collection systems, early models were developed with data from surveys (Senevirante, 1990) or radio signposts (Andersson et al., 1979). Bus route simulation models based on onboard automatically collected data range from relatively simple Monte Carlo simulation models implemented in Excel (Pangilinan et al., 2008; and Fattouche, 2007) to highly detailed models implemented in MATLAB (Moses, 2006).

The Monte Carlo simulation models implemented by Fattouche and Pangilinan et al. have narrow application foci and require the assumption that successive transit trips are independent. Fattouche (2007) demonstrated this assumption to be valid on CTA route 95E and route 47, but admits that this assumption may be violated on routes with greater passenger demand. Pangilinan et al. (2008) fortified their research conclusions with a week long pilot program on the actual route. This research will capture more aspects of the route and does not rely on the assumption of independence between successive trips. Thus, the model developed in this research may be applied to high frequency routes with more confidence and test operations control strategies, including, but not limited to those tested in Fattouche and Pangilinan et al.

Senevirante (1990) also developed a Monte Carlo simulation model (Bus-Monitor) and did connect successive bus trips into blocks of up to 3 cycles. The model was developed at the stop level of detail so reconfiguration of the model to another route could be very labor-intensive as travel time and passenger demand for each segment and stop need to be estimated. Moreover, only schedules with a constant headway could be represented. The simulation model developed in this research is developed at the key stop (schedule timepoints and stops with high passenger demand) level of detail to simplify the configuration. As discussed in Chapter 3, the simulator schedule is configured by trips and blocks to support any headway and running time changes.

In work very similar to this research, Moses (2005) developed a micro-simulation bus model using AVL/APC data for CTA route 9. Moses developed his model using MATLAB at the stop level of detail. Unfortunately, Moses was unable to validate the model in terms of route travel time and headway variation. The failure to validate was attributed to the insufficient representation of operator behavior, dwell times, and route specific attributes. The model created in this research is developed at the key stop level of detail. This allows for more information about dwell time to be included at the stops where dwell time has a significant impact on running time. The operator behavior is represented using agent based modeling techniques. A more robust dwell time model is developed and the residuals per key stop are included. Finally, the route used for validation (route 63) is a shorter route than route 9 (~ 1 hour each direction vs. 1.75 hours each direction) with only one pattern. This avoids the need to model the complex passenger demand across multiple patterns.

Unlike the commercial packages, models with implicit traffic representation often do not include a visual component, with the exception of the TRAMS simulation package developed by Vandebona and Richardson (1985). This work developed a simulation model of an on-street LRT route using the TRAMS: Transit Route Animation and Modeling by Simulation package. The TRAMS program was one of the first simulation programs to include a visual display of the model operation. This display is used to verify simulation operation, form qualitative conclusions about service performance, and to allow for real-time interaction with the model. The simulation model developed in this thesis includes a visual interface for these reasons.

3 Bus Route Simulator Model Design

The previous chapter outlined the advantages and shortcomings of past models. This chapter explains in detail how the advantages of previous models are incorporated into this simulation model, as well as how this model compensates for the shortcomings found in previous models.

The input and output parameters of the model are discussed in the first half of this chapter. The input requirements will shape the exploratory data analysis and model specification presented in Chapter 5. The output specification reflects the purpose of this research, which is to understand and evaluate bus service reliability. The second half of this chapter delves into the inner workings of the simulation model. The decision to implement the model in an agent-based modeling environment is discussed, followed by a review of the model architecture and a walk through of the simulated bus route operation.

3.1 Inputs

This section discusses the inputs to the simulation model necessary to represent a bus route. The inputs represent three different aspects of the route: constant, variable, and configurable. To build the model, constant aspects, or basic route information, such as number of stops, schedule, bus type, etc. are needed. Chapter 4 discusses basic route information for CTA route 63 for which this model is validated in detail. The variable aspects of a bus route not explicitly simulated in the model (passenger demand, dwell time, travel time, terminal departure behavior) are represented through sub-models developed in Chapter 5. Finally, the parameters of the configurable aspects, such as operations control strategies are proposed in Chapter 7.

3.1.1 Constant Inputs

Schedule information and route data at the key stop level of detail are necessary to represent the route accurately and simulate buses operating on the street.

Schedule

To represent the assignment of a vehicle and operator to a sequence of trips, the scheduled trip blocks, start time information and list of trips and recovery time for each trip are required. For each trip, information on the pattern, scheduled running time, and reliefs are necessary to start and end the trip in the correct location, set the schedule adherence, and change operators as scheduled in the real world.

Route Layout

The layout of the route is used to create a framework within the simulation model to accept the key stop (schedule timepoints and stops with high passenger demand) and segment specific parameters. The number of minor stops per segment is necessary to build a visual representation of the bus route with the key stops appropriately spaced.

3.1.2 Variable Inputs

Passenger demand, dwell time, running time, and terminal departure behavior are each a significant part of bus operations and include a large amount of complexity. The delineation between the complexity represented in the simulation model and what is expected to be represented through the input models are discussed in this section. The level of complexity represented in the simulation model is defined so that the input models may be developed using the AVAS and AFC data.

Passenger Demand

Passenger demand is a critical input to evaluate route performance from the passenger perspective. Passenger demand is realized in the model as boarding and alighting passengers at each key stop and segment. The number of passengers that can actually board the bus depends on the bus capacity after the passengers have alighted.

The specific input data is the passenger arrival rate (per second) for each key stop and segment, the capacity of the bus (seated and standing capacity for level of service calculations), and the fraction of onboard passengers who will alight at each key stop and segment.

Dwell Time

Dwell time at key stops is represented explicitly in the simulation model to capture the interaction between successive bus trips and to allow for mid-route control strategies. Holding time at a key stop in response to a service intervention will be determined within the simulation model, but the dwell time due to passenger activity and/or operator reliefs is also needed. Dwell time at minor stops is not represented explicitly in the model; instead the dwell time and segment movement time are aggregated into the segment running time.

Segment Running Time
The dwell and movement time of a segment between successive key stops are aggregated together in the model as running time. When the bus departs a key stop the time until arrival at the next key stop is needed. The segment running time input is expected to account for traffic interference, traffic signal delays, minor stop dwells, and other segment specific travel delays which are not represented explicitly in the simulation model. Segment running time may be input into the simulation model as a distribution or as a set of observations, from which the simulation model will randomly sample.

Terminal Departure Behavior
At the completion of each trip the bus may recover at the terminal before beginning the next trip. The amount of recovery time taken depends on the minimum recovery time needed by the operator for a personal break, dwell time for passenger activity, recovery time available within the terminal departure policy (e.g. hold for schedule or headway), and the departure accuracy (when there is sufficient recovery time).

The schedule adherence at the terminal will be determined within the simulation model and used with the scheduled recovery time and the terminal departure policy to calculate the recovery time available. In an ideal world, the bus would take exactly the available recovery time and begin the next trip on-time. To capture the variability of the real world, inputs of the minimum recovery time for operator personal breaks and an error term to represent operator deviation around the available recovery time are included in the model.

3.1.3 Configurable Inputs
While all inputs are configurable, some are specially categorized as configurable because they are used in the application of the simulation model to evaluate control strategies. The control strategies evaluated with the simulation model are discussed in Chapter 7. As discussed in Chapter 2, there are two types of control strategies: preventative and corrective.

Preventative Strategies
Preventative strategies would be implemented through a modification to the constant or variable inputs. For example, to test the effectiveness of a new scheduling procedure, a previously modified route schedule would be input into the simulation model. The impact of preventative strategies on the input parameters would be determined outside the simulation model. A

simulation model is still a useful tool to test the impact of the strategies on bus reliability, but the actual implementation of the strategy is outside of the scope of the simulation model.

Corrective Strategies

Corrective, or operations control, strategy inputs must specify when and where and the thresholds to trigger the application of the service intervention. For example, the implementation of a holding strategy must define the route locations where holding may take place, and under what circumstances it would occur (e.g. hold for headway at terminals).

3.2 Outputs

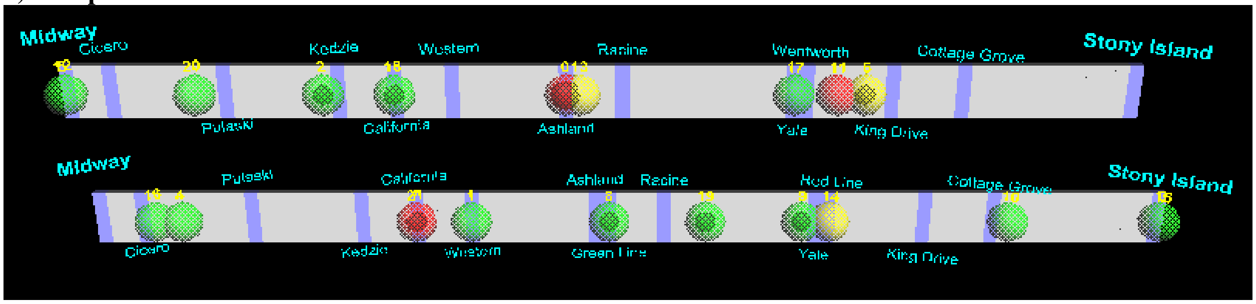
The necessary model outputs are determined by the metrics of bus service reliability defined in Section 2.1.1 as well as the goal to represent the route operations visually. To accomplish this, the simulation model has two primary output modes. When executing a single run, the simulation uses a graphical user interface (GUI) that shows the bus route from a bird's eye view. The simulation may also run in batch mode producing output data files. The details of each output method are discussed below.

3.2.1 Visual Display

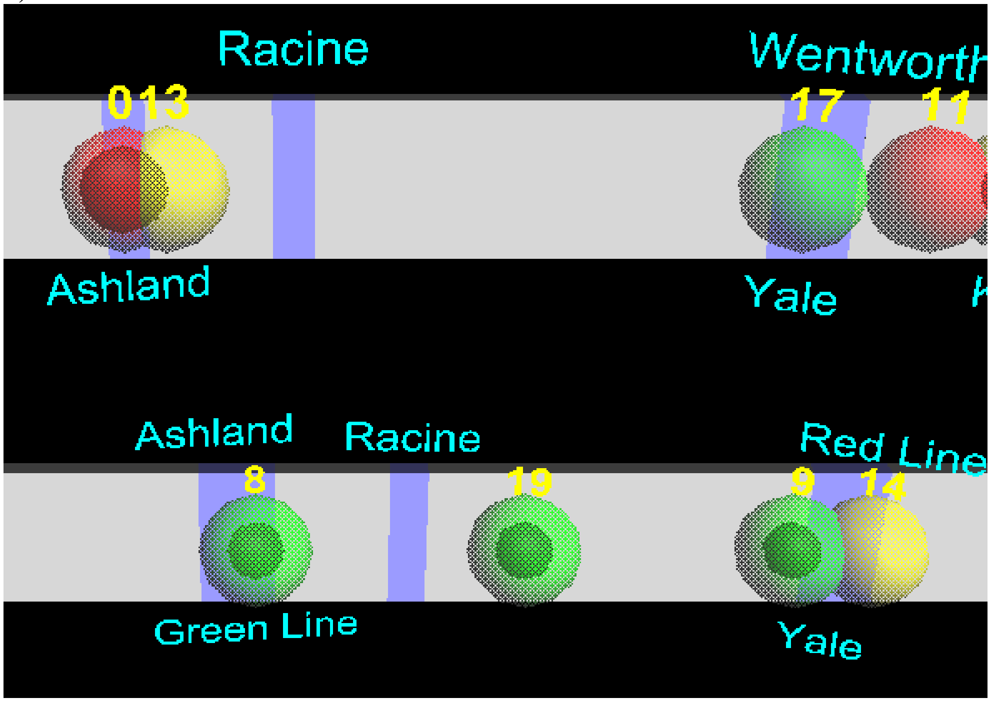
The visual display is useful both for debugging the simulation model, and to inform the user of the effect of the factors influencing reliability. The visual display is designed to be similar to a real-time AVL interface. Clever Devices' CleverCAD™ software displays the vehicles on a city map with the schedule adherence color-coded (Clever Devices, 2006). The screen shot of the simulation model in Figure 3-1 shows how route configuration, vehicle location, block id, schedule adherence, and passenger loading are all displayed. Key stops are identified on the route in blue. Vehicles in the screen shot below traverse the route clockwise. The vehicle location is represented by a semi-translucent sphere with the block id above. Similar to CleverCAD™ the schedule adherence is color-coded (green for on-time, red for late, yellow for early). The onboard passenger information is shown through a solid inner sphere with a radius relative to the fill ratio. For example, the inner spheres of the detail screen shot in Figure 3-1 show that all seats are taken on bus 0, half are taken on buses 8, 9, and 19 and less than half of the seats are taken on the remaining buses.

Figure 3-1: Simulation Model GUI

a) Complete Route



b) Detail



3.2.2 Metric Collection

Along with the bus service reliability metrics of passenger-experienced waiting time and crowding, other route operation details are necessary to capture, verify and validate route operation. This data will be used to validate the model and evaluate all applications, so it is important that the collection method is sound.

Passenger Waiting Time

The passenger waiting time is captured per passenger at each key stop and on each segment. On high frequency routes, passengers may be assumed to arrive randomly according to a uniform distribution. In these cases the average waiting time for passengers arriving since the previous bus is half the headway. The waiting time of passengers who are unable to board the first bus is calculated as half of the first headway plus the full headway of any succeeding bus until they are able to board. The key stop departure headway is used to calculate the waiting time of passengers arriving on the subsequent segment.

Crowding

Crowding is measured at each point where the onboard passenger count may change, i.e. at each key stop and mid-segment. The passenger load is measured as the number of passengers at each crowding level of service (LOS), defined in Table 2-2, and the time since the last observation. The crowding measure is weighted by passenger and time.

Verification and Validation Data

To verify and validate the model, it is necessary to capture many details of the simulated bus operations. At key stops and on each segment, the headway, passenger demand, recovery time, and dwell time are recorded. The simulated buses log data on the passenger load, schedule adherence, and travel time at each key stop and mid-segment.

3.3 Implementation

The input section above described the data needed to configure the simulation model. This data then needs to be organized in a clear manner to support parameter or configuration changes. A configuration utility is developed in Excel to organize this data and pass it to the simulation model.

The simulation model itself is developed in Java using the Repast Simphony agent-based modeling toolkit. The Repast toolkit is free and open source and includes a 3D GUI environment, scheduler, and random number generators, amongst other useful features. Repast is designed to support agent based modeling, a technique that is particularly useful when the elements of the model may be represented as interacting agents. This model was developed in Repast to provide the opportunity to extend the modeled representation of operators and supervisors. More information and downloads are available at repast.sourceforge.net.

3.4 Architecture

In an agent-based model, a system is represented through the interactions of individual agents in a common environment. This model is based on 3 major agent types (bus, ground, and scheduler) and an operating environment. All agents created in the simulation environment can access common variables through this environment. The ground agent represents segments, key stops, and terminals. The scheduler agent drives the simulation model by creating the buses at their scheduled start time, loading the bus schedule and other information into the bus agent, and starting the bus on its first trip. The bus agent represents a vehicle. Note that there is no separate agent representing a bus supervisor; instead, as will be explained in detail in the following section, control strategies are implemented within the ground, bus, or scheduler agent as appropriate. The following table relates the inputs and outputs discussed above to the agents in the model.

Table 3-1: Agent Inputs and Outputs

	Inputs	Outputs
Bus	scheduled trips capacity	trip running time passenger crowding schedule adherence
Ground	passenger demand per stop & segment dwell time parameters running time parameters minimum recovery time recovery time accuracy	headway passenger waiting time
Scheduler	scheduled blocks	filled trips

3.5 *Operation*

This section steps through the process of the agents' interactions to simulate operations on a bus route. The process is discussed from the initial model setup, garage pull-out, serving stops, traveling on the segments, and recovering at the terminal. The location of control strategy implementation is identified in this process description. In addition, Chapter 7 has full details of the implementation of the control strategies.

3.5.1 Model Setup

When the simulation model is loaded, the key stop and segment information are read from the configuration utility and the road, key stops, and terminals are created and loaded into the simulation environment. No bus agents are created at the beginning of the model run; only the list of schedule blocks is loaded into the scheduler agent.

3.5.2 Garage Pull-Out / Pull-In

The garage pull-out is instigated by the start time of the schedule block. At this time, the scheduler agent creates a bus agent and loads it at the beginning stop of the first trip in the block. Operator specific attributes may be set in the bus agent at this time. If operator specific attributes are used, they may be updated at each relief point in the bus block to reflect the change in operator. When the bus has reached the last stop of the final trip in the schedule block, it is removed from the simulation environment. If the run requires that a block not be filled, the scheduler agent will skip this step.

3.5.3 Serving a Key Stop

When a bus agent arrives at a key stop, the bus sends a request to the ground agent to get the dwell/holding time and initiate passenger activity. The ground agent calculates the number of passengers waiting to board and determines, based on the alighting passengers and bus capacity, the actual number of boarding passengers. If more passengers are waiting than the bus capacity, the latest passengers to arrive at the stop (in case of passengers bypassed by multiple buses) are saved in a queue. The passenger values are used to calculate the dwell time.

If this stop involves an operator relief, trip recovery, or a service intervention then there may be a hold time that is longer than the passenger dwell time. If the dwell time is longer than the hold time, the alighting passenger count is subtracted and the waiting passenger count is added to the onboard passengers. Conversely, if the hold time is longer than the dwell time, the alighting passengers are subtracted but the waiting passengers are not added at this time. Instead, the waiting passengers are only added when the hold time has expired and the bus is ready to depart. This method ensures that passengers will board the first bus to depart from, rather than arrive at, the stop.

The maximum of dwell and hold time is returned to the bus. The bus then remains at the stop until the (dwell/hold) time has expired. Before departing the stop, any passengers that arrived during the dwell time board the bus, if there is excess capacity.

The functional form and parameters of the boarding and alighting passenger rates as well as the dwell time and relief calculations are developed in Chapter 5.

3.5.4 Traveling on a Segment

When the dwell time at the key stop is complete, the bus updates the schedule adherence and sends a request for the segment parameters (distance, running time, and passenger activity). The ground agent calculates the passengers on the segment in exactly the same manner as at a key stop (using the parameters specific to the segment). To simulate smooth travel visually on the segment and distribute the passenger activity, the segment running time is divided by the segment length (determined by the number of minor stops). To travel across the segment, the bus counts down the divided running time and then moves one step forward. When the bus is halfway through the segment, the passenger activity is applied to the onboard passenger load. The passenger crowding data recorded at the midpoint is equivalent to evenly distributing the activity across the segment.

The functional form and parameters of the boarding and alighting segment passenger rates and the segment running time calculation are developed in Chapter 5.

3.5.5 Terminal Recovery

If the key stop is the last stop of the trip, the process will be the same as when serving any other key stop, with the exception that there will be no boarding passengers and all the passengers will alight the bus. After serving the stop, the bus moves to the starting point of the next trip, or pulls back to the garage if this is the final trip of the block. The bus will take its recovery time, if any, at the starting point of the next trip. The default recovery time calculation is based on a scheduled departure policy. In this case, the available recovery time is calculated as the scheduled recovery time minus the schedule deviation.

4 CTA / Route 63 Overview

The previous chapter described the inputs, outputs, and operation of a bus route simulation model to evaluate control strategies of bus service reliability. To develop recommendations, it is necessary to review the route of interest in terms of service standards, operating policies (including new pilot programs to improve service reliability), and personnel responsibilities and deployment. The simulation model is designed to be calibrated by data automatically collected from buses necessitating a review of the data availability and issues with automatic data collection systems. Finally, the model must be calibrated to an individual bus route as a proof of concept.

After a brief introduction to the Chicago Transit Authority (CTA) in Section 4.1, the CTA bus service management policies and procedures are discussed in Section 4.2. Section 4.3 reviews the automatically collected data availability and issues. The relevant details of route 63, the bus route to be modeled, are presented in Section 4.4.

4.1 Agency Overview

CTA is the second largest transit agency in the United States. The backbone of the CTA transit network consists of eight rapid transit lines and 46 key bus routes with 16 hours a day, 7 days a week minimum service levels. Key bus routes alone serve almost 50% of all passenger trips on the CTA system. More than 100 "support" bus routes and the Skokie Swift rapid transit line flesh out the network to provide service to the City of Chicago and 40 surrounding suburbs (CTA Service Standards, 2001; CTA Overview, 2008).

Bus routes typically follow the grid network of Chicago's streets running either north-south or east-west (besides several "express" routes which focus on the downtown). This grid network requires bus-to-bus and bus-to-rail transfers for trips between many origin-destination pairs in the network.

4.2 Management of Bus Service Reliability

This section describes CTA's approach to maintaining reliable bus service. Bus service reliability management depends on service standards and metrics for monitoring and evaluation of route performance. To achieve the service standards, CTA has developed a set of operations policies. The implementation of these policies is managed by a hierarchy of controllers, supervisors, and operators. CTA is constantly experimenting with new approaches to maintain service reliability; the design and initial results from bus reliability pilot programs are included at the end of this section.

4.2.1 Service Standards

The only reliability metric included in the current service standards is for passenger crowding (CTA Service Standards, 2001). Since the adoption of these service standards, however, CTA has developed new metrics to monitor the level of "bunching" (headways less than 60 seconds) and "big-gaps" (headways that are the greater of twice the headway, or 15 minutes) on a bus route. These new metrics are aggregated at the route level (Stubbe, 2008).

The CTA crowding standard defines 60 passengers as the maximum load for 40' buses. For key bus routes during the peak period, between 45 and 60 passengers onboard are deemed acceptable. A query of the automatically collected passenger data on 40' buses serving CTA routes, however, reveals that actual passenger loading occasionally approaches 70 passengers onboard.

4.2.2 Operating Policies

The simulation model calibration is sensitive to the current route operating policies. The relevant policies to be included in the simulation model are those concerning schedule and headway adherence, terminal departures, and overtaking.

Currently CTA manages all routes through schedule, rather than headway, adherence. Schedules are published at the timepoint level of detail for both operators and supervisors. Operators are expected to follow this schedule throughout the route and, if necessary, hold at timepoints if they are running ahead of schedule.

As with timepoints, operators are expected to hold at terminals and begin the next trip on-time. CTA policy is more stringent about early departures from the terminal than late departures. The current policy mandates that operators who arrive at the terminal with full recovery time must leave within 1 minute early and 5 minutes late to avoid disciplinary action.

Allowing buses to overtake prevents an inexperienced driver from slowing the route down. But overtaking also enables fast drivers to get well ahead of schedule. The CTA overtaking policy is sensitive to the service frequency: on high frequency routes, operators may overtake where they deem it to be safe.

4.2.3 Management Personnel

Bus service reliability at CTA is managed through a network of point supervisors, mobile supervisors, and controllers. Controllers are based at the control center and receive text messages and alarms from the operators. Controllers are responsible for dispatching mobile supervisors to disabled buses and incidents. Mobile supervisors are responsible for a geographical area of the city that includes sections of multiple routes and primarily respond to emergency situations identified by the controllers. If there are no incidents currently active, mobile supervisors perform service checks at terminals, timepoints, and relief points to ensure operators are maintaining the schedule. Point supervisors are typically located at high-traffic points of the system, e.g. pull-out points, terminals, and/or intersections of multiple/major bus routes with heavy transfer traffic. Point supervisors perform service checks and assist passengers (Moore, 2003; Pangilinan, 2006).

Supervisors and controllers communicate through two-way radio. Bus operators may send text messages, signal a request-to-talk, or engage the silent alarm on the bus to communicate with the control center. Supervisors and operators do not have the capability to communicate via radio; they can communicate only face-to-face (Barker, 2002).

4.2.4 New Efforts to Manage Bus Service

CTA has begun a four-pronged effort to target bus bunching through a focus on operations, supervision, schedules, and street conditions (Partridge, 2008).

The operations effort is a monitoring program of garage and terminal departures and running times to identify operators that run "hot" (drive too fast) or "drag" (drive too slow) on the street. The identified operators are trained and/or disciplined.

The responsibility of supervisors to manage service reliability is reinforced through reports of bunching and big gaps on each route. CTA is also in the process of equipping all supervisors with laptops or handheld devices to use the real-time AVL system (Bus Tracker) for service management.

Route schedules are evaluated to ensure that adequate running and recovery time is included in each route. In contrast to the existing policy on schedule adherence, an interval-based operation is being developed with less scheduled bunching and a goal of communicating headway to operators.

Street conditions can foil the best made schedule. In response, CTA is working to identify areas of the street network with high running time variability and is also developing aggressive policies to deal with double-parked cars blocking the right-of-way.

Individual routes are identified across the system and different combinations of the target areas are addressed to determine the most effective strategy. The most effective strategies to date have been to ensure that all trips are filled (~30% decrease in big gaps) and to increase running and recovery time in the schedule. Other strategies, such as removing mid-route timepoints, have been inconclusive.

4.3 Data Availability and Issues

This section describes the CTA-estimated, archived, and real time data sources available to examine route performance, service reliability, and simulation model calibration and the issues with collecting and processing the data.

4.3.1 CTA Estimated Data

For reporting and analysis purposes, CTA uses the automatically collected data to estimate the route ridership per hour. This data can be used to predict the total route ridership to be distributed to each key stop (schedule timepoints and stops with high passenger demand) and segment in the simulation model.

4.3.2 Archived Data

The primary data source for model calibration is the raw automatically collected data from Automatic Vehicle Location (AVL), Automatic Passenger Counting (APC), and Automatic Fare Collection (AFC) systems. The data from these systems is saved on the bus and transferred to the CTA database when the bus refuels.

Automatic Vehicle Location (AVL)

An AVL record is composed of the following: nearest stop location; bus, operator, trip, run and route identifiers; event, dwell and schedule adherence time information; and, if equipped with APC counters, passenger boarding and alighting per door and the number of onboard passengers. The measurement function and common issues with each of the AVL components are discussed below.

When starting a run, the operator must login and enter the run id. The AVL system then uses the schedule to determine the trip id from the time and run id. If the operator does not log-in correctly at either the garage pull-out or relief point, the AVL system may log the wrong or no trip id in the record.

The bus location mechanism uses a combination of GPS and dead-reckoning technology to locate the bus on the route. The location of each stop on the route is also saved in the AVL system so that a bus can identify each stop as it serves the route. The AVL system generates a stop record at every configured stop, served or unserved, as well as every time the bus doors open at a location not identified as a stop. A location record is generated every 200'. Occasionally the actual stop location is not recognized by the AVL system correctly. This may be due to a change in bus stop location in response to a road reconfiguration.

Dwell time is measured from the first door open, or handle signal, to last door close within 100' of bus travel (Scanlon, 2006). This may cause an over-allocation of dwell time, particularly for near-side stops. For example, at a near-side bus stop, the operator opens the doors to allow passengers to board and alight, but when the passenger activity is finished and the operator closes the door, the traffic signal is red so the bus remains at the stop. While the operator is waiting for the signal to change, more passengers arrive at the stop and the door is re-opened. In this case, the dwell time can include a significant amount of traffic signal delay time, not passenger delay time, which should be categorized as movement time.

The data from the AVL system can be used to identify running times and terminal departure behavior (in response to schedule deviation). If an APC is installed, the passenger impact on dwell time can be estimated. The APC system operation and issues are discussed in the next section.

Automatic Passenger Counter (APC)

Where installed, APCs are located on each door to count boarding and alighting passengers. Passengers are counted as they pass the APC sensors within the door-open, door-close time period including some grace period after the last door closes. To verify the accuracy of the APC system occasional, manual passenger counts are conducted. Common errors in the APC data are overcounts or undercounts of one passenger per stop. These errors may compound over the course of multiple trips, however, leading to erroneous onboard passenger counts.

Besides the passenger impact on dwell time, the APC data can also be used to estimate the passenger demand along the route. Where the APC data is inadequate, AFC data can be used to generate more reliable estimates of overall passenger demand as discussed in the next section.

Automatic Fare Collection (AFC)

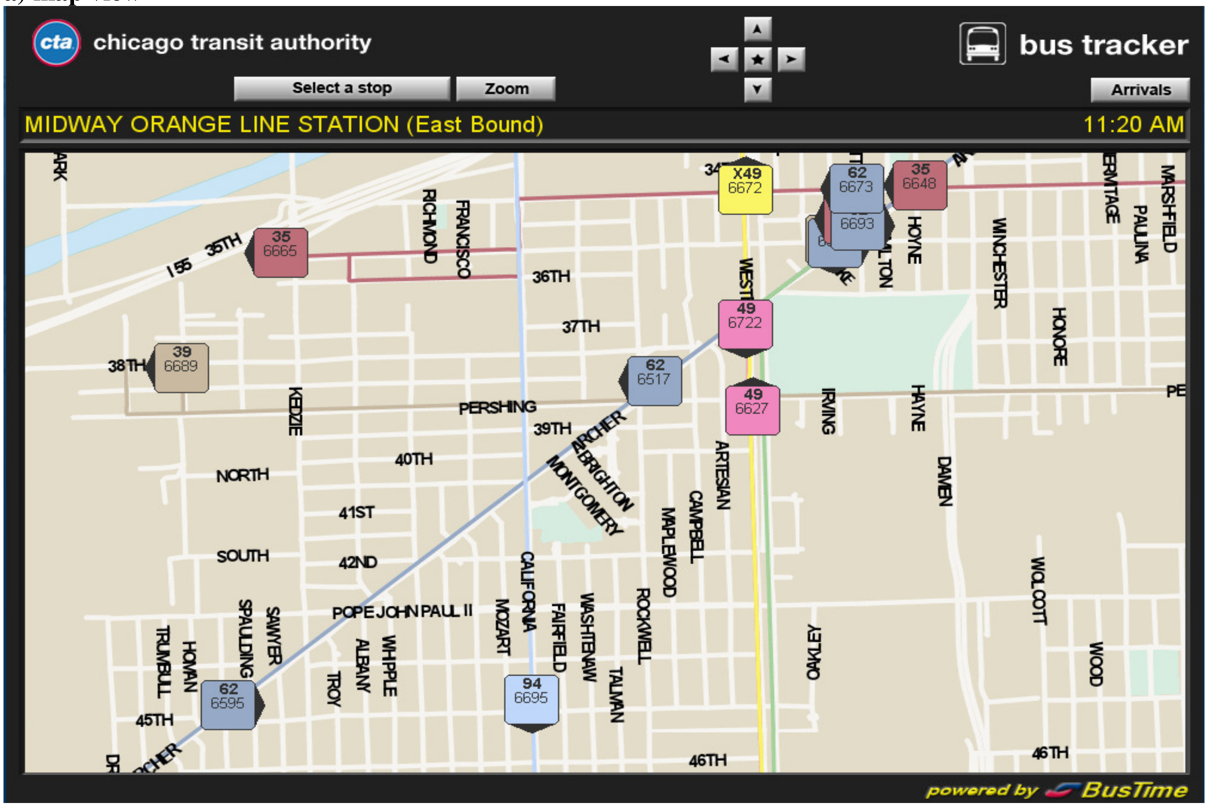
The AFC system creates a record for each fare transaction involving the smart media or magnetic stripe fare media: passengers paying with cash and non-paying passengers (e.g. children) are not recorded. Each record contains the event time, transaction type, farebox number and route number. The AFC data is a separate data collection system so the fare record is not automatically associated with an AVL record, although the system times are synchronized. The AFC data can be used in aggregate to estimate the total passenger demand at a finer time granularity than the hour interval of the CTA ridership estimates.

4.3.3 Real Time Data

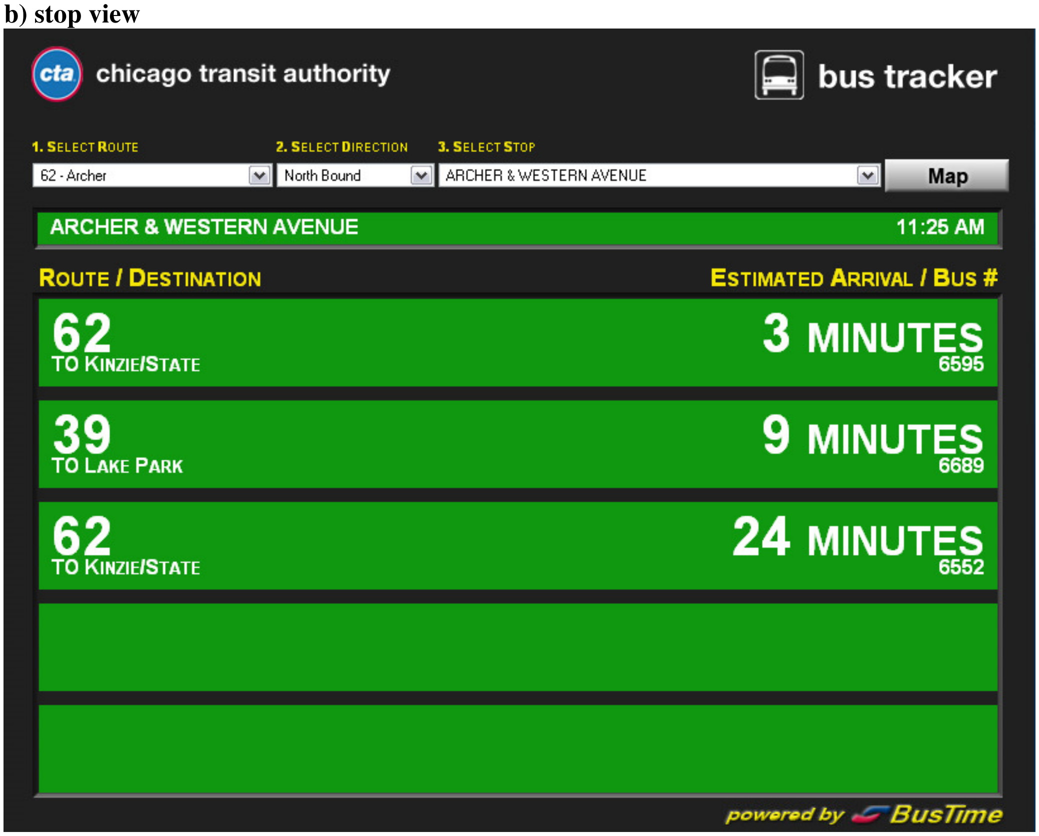
Bus Tracker is a real time AVL system that is currently being rolled out across the CTA bus network and will complement the efforts at all service management levels. Bus Tracker has two interfaces: a map interface that shows the current location, direction, and run number of each bus and a stop interface that shows the predicted arrival times of buses projected to arrive within the next half-hour. The Bus Tracker map and stop interfaces are shown in Figure 4-1. Buses serving different routes are shown together on the map but can be distinguished because the route id is displayed on the bus and each route uses a different bus icon color. A supervisor may use these interfaces to identify big gaps or bunches on the route in real time. Bus Tracker is publicly accessible online at ctabustracker.com.

Figure 4-1: CTA Bus Tracker

a) map view



b) stop view



4.4 Route 63 Summary Description

This section summarizes the relevant aspects of route 63, which is the validation route for the simulation model. Route 63 is an east-west cross-town (does not serve the downtown) route serving Chicago's 63rd street on the south side. Daily weekday passengers exceed 22,000 which ranks it fifth of all CTA bus routes. The route length is ~8 miles and half-cycle time is ~1 hour. There are transfers from route 63 to three rapid transit lines and multiple north-south key bus routes. Service is managed by a point supervisor stationed at Stony Island, the eastern terminal. During the AM and PM peak periods, a second supervisor is deployed at Midway, the western terminal.

4.4.1 Route 63 Layout

Route 63 has almost 80 stops in each direction. The key stops for route 63 are the union of timepoints and stops with the highest passenger demand with the exceptions of two timepoints: 63rd Street and Stewart and 63rd Street and Halsted (located between Racine and Yale). These timepoint stops are not represented explicitly in the model because they are rarely used pull-in timepoints in the schedule with low passenger demand. Table 4-1 shows the key stops in each direction and the number of stops on each segment. As noted earlier, transfers are necessary in many CTA trips, so the intersecting routes and/or rapid transit lines are identified at each key stop as a source of transferring passenger activity. The key stop segments range from 11 stops (roughly equivalent to 1 mile based on CTA average bus stop spacing of 400') to no stops (Yale (eastbound), Red Line and Green Line, (westbound)). The segments with no stops are cases where the transferring rapid transit passengers use either stop.

The key stops and segment lengths will determine the layout of the route in the simulation model. If a key stop is also a timepoint, then operator holding at that stop may occur in the simulation model.

Table 4-1: Route 63 Key Stops and Segments

a) Eastbound

STOP SEQ	LOCATION	SEGMENT STOPS	SCHEDULE TIMEPOINT	RANK (BY DIR)	TRANSFERS
1	MIDWAY	2	Y	6	Orange Line
4	CICERO	7	Y	12	63W, 54B, PACE
12	PULASKI	7	Y	13	53A
20	KEDZIE	3	Y	10	52
24	CALIFORNIA	3	N	9	94
28	WESTERN	7	Y	3	49, X49
37	ASHLAND	3	Y	1	9, X9, Green Line
41	RACINE	11	N	11	44
53	YALE	0	Y	2	24, Red Line
54	WENTWORTH	5	N	8	24, Red Line
60	KING DRIVE	4	N	7	3, Green Line
65	COTTAGE GROVE	11	Y	5	4, Green Line
77	STONY ISLAND	0	Y	4	6, 15, 28, X28

b) Westbound

STOP SEQ	LOCATION	SEGMENT STOPS	SCHEDULE TIMEPOINT	RANK (BY DIR)	TRANSFERS
1	STONY ISLAND	11	Y	7	6, 15, 28, X28
13	COTTAGE GROVE	4	Y	4	4, Green Line
18	KING DRIVE	6	N	6	3, Green Line
25	RED LINE	0	N	1	Red Line
26	YALE	10	Y	15	24, Red Line
37	RACINE	3	N	10	44
41	GREEN LINE	0	N	5	Green Line
42	ASHLAND	8	Y	9	9, X9
51	WESTERN	3	Y	2	49, X49
55	CALIFORNIA	3	N	8	94
59	KEDZIE	7	Y	11	52
67	PULASKI	7	Y	14	53A
75	CICERO	2	Y	13	63W, 54B, PACE
78	MIDWAY	0	Y	3	Orange Line

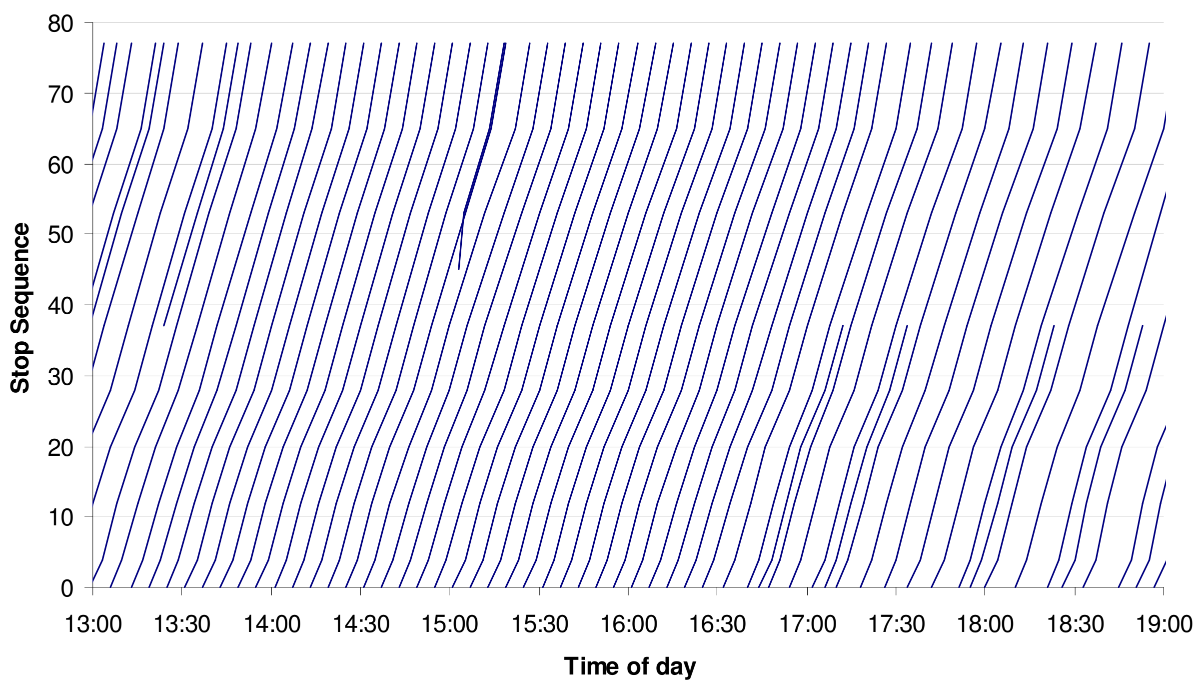
4.4.2 Schedule

Route 63 has a generally consistent headway of 6 minutes or less for more than 2 hours in the PM peak with little variation in the trip pattern as shown in the string charts in Figure 4-2. The spacing between the lines is the headway, a change in the slope of the line indicates a change in running time, and the length of line indicates the trip pattern. From 13:30 to 16:25 there is a constant 6 minute headway departing Midway (eastbound). The westbound headway departing Stony Island is a constant 6 minutes from 13:00 to 16:15. The scheduled one-way running time changes by only 2 minutes across this period and there are only 3 trips that do not run the full length of the route. The trip pattern is important because passenger demand may be sensitive to the final destination of the bus. Only one trip (westbound beginning at 15:25) does not terminate at the last stop.

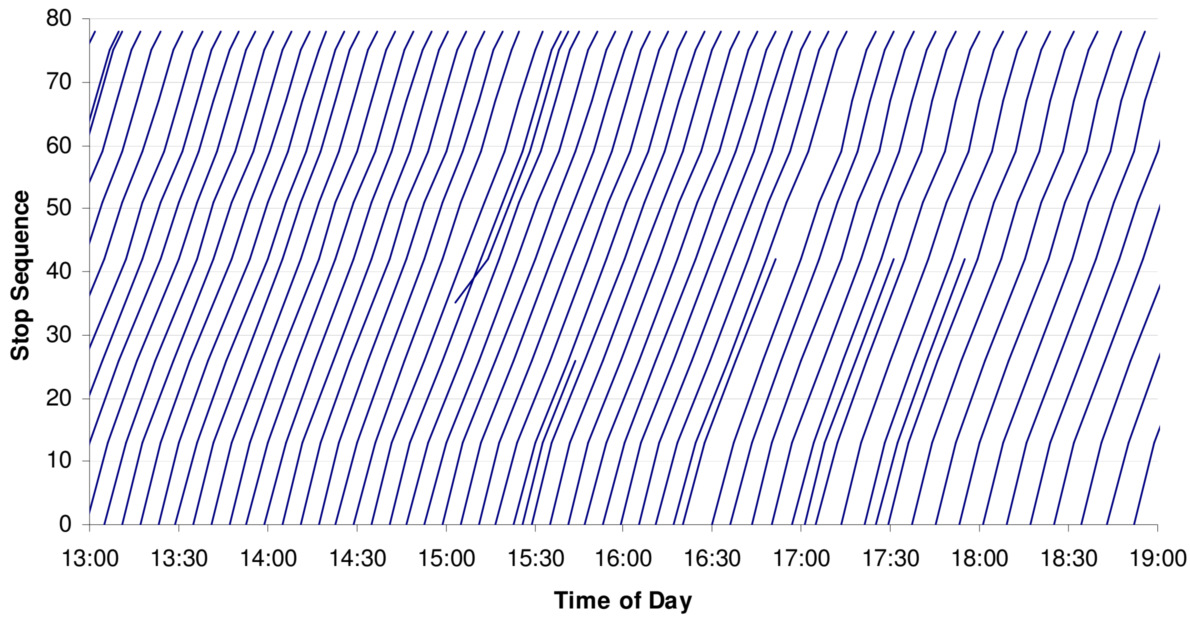
The schedule trips are chained together into blocks, including information about operator reliefs and recovery times, and are entered into the simulation model.

Figure 4-2: Route 63 Schedule Time-Space Plots

a) Eastbound



b) Westbound



4.4.3 Vehicles

Route 63 is served by two different models of 40’ buses: 25% of the trips are provided by the 4400-series TMC and the remaining 75% by the 6000-series Flxible Metro. The TMCs entered service in 1991 and are among the oldest buses in the CTA fleet. The Flxible Metro is only slightly newer than the TMC buses with an original service date of 1995. Both buses are high-floor with a lift in the front door and 39 and 45 seats respectively. As mentioned earlier, 70 passengers is an appropriate maximum capacity level to use for a 40’ bus (from a query of the APC data). Although the buses have different numbers of seats, it is assumed that any extra seats reduce the room for standees, so the maximum capacity is unchanged.

Table 4-2 applies the crowding levels defined in Table 2-2 with the exception of the level of service (LOS) categories F1 and F2. These two categories are combined into a single category because, with a bus capacity of 70 passengers, only 1 passenger would ever be at level F2.

Table 4-2: Crowding Level of Service (LOS)

		4400-Series TMC	5500-Series Flxible Metro
Seats		39	45
LOS (onboard passengers)	A	19	22
	B	29	33
	C	39	45
	D	53	53
	E	62	62
	F	70	70

When a bus block is started in the simulation model, a uniform distribution is used to determine the type of bus that is serving that block. This bus can then report the number of passengers at each crowding LOS directly.

5 Exploratory Data Analysis and Model Specification

This chapter presents the data exploration, model development and parameter estimation for route 63. Section 5.1 describes the inputs to the simulation model and discusses the factors influencing bus service reliability. Section 5.2 reviews the data sources and the data processing. Sections 5.3-5.6 present the data analysis for each of the input models, including:

1. The relevant data sources, mining techniques, and summary statistics.
2. The impact of each component on reliability.
3. The selection of the most appropriate components and the definition of the model functional form.

This effort is guided by the discussions in previous chapters, which are summarized below.

In Chapter 2, several research studies are discussed which define and investigate the important factors influencing bus service reliability. Bus service reliability depends on a series of travel time components, including, but not limited to the variability of vehicle movement time, dwell time at stops, and recovery time at the end of each trip. These travel time components all contribute to the variability in service that is observed on the street. The distribution of passenger activity along a route and across time is also an important factor influencing service reliability. For example, bunched buses and large gaps in service are more important on route segments where more passengers are waiting to board than on segments where more passengers are alighting.

Chapter 3 described the appropriate level of detail and key components of the simulation model, given the goals of this research. The simulation model is designed to gain further insight into the importance of the factors influencing bus service reliability, test operations control strategies, and serve as a training tool for bus supervisors. To support these goals, the model is developed at the key stop (schedule timepoints and stops with high passenger demand) level of detail and includes detailed passenger activity inputs and resulting impacts.

Chapter 4 described CTA bus route 63, to which the model is initially applied, including timepoints, key stops, schedule, overall passenger demand, and supervisor locations

5.1 Inputs and Factors Influencing Variability

This section defines the four primary inputs to the simulation model and lists the factors that influence their variability. Each of the factors must be accounted for in the data analysis and model development.

Segment Running Time

The segment running time is the total time (movement plus dwell) from a key stop departure to the next key stop arrival. Chapter 3 defined the key stop as the appropriate simulation model level of detail, so time spent serving minor stops within a segment is not represented explicitly in the model. Instead, the movement and minor stop dwell time for a segment are aggregated into a single time value. Therefore, a model is required that predicts the elapsed time from each key stop departure to the following key stop arrival based on the significant factors affecting movement and cumulative minor stop dwell time. The significant factors affecting segment movement and dwell time, as discussed in detail in Section 2.1.2, are listed below:

1. Number of Stops
2. Traffic Signals (number and timing)
3. Traffic Interference
4. Passenger Activity
5. Weather
6. Operator Behavior

Key Stop Dwell Time

The dwell time at each key stop is represented explicitly in the simulation model. A model for each key stop is required that estimates dwell time based on the significant influences, such as passenger activity and operator reliefs. The significant factors affecting key stop dwell time, as discussed in detail in Section 2.1.2, are listed below:

1. Passengers Activity
2. Holding
3. Operator Reliefs
4. Stop Location

Terminal Recovery Time
Terminals are included as key stops and are modeled explicitly. Since terminal departure behavior is an important operations control strategy to be tested within the simulation model, a model of terminal departure behavior is required. The significant factors affecting terminal recovery time, as discussed in detail in Section 2.1.2, are listed below:

1. Departure Policy
2. Minimum Time
3. Available Recovery Time
4. Operator Behavior, Training, and Policy Enforcement

Passenger Demand
The passenger demand distribution and rate is necessary to represent bus loading, which is a key metric as defined in the model definition chapter. To represent and calculate these metrics accurately, a model is required for passenger demand by time and location. Moreover, a good measure of bus service reliability should consider the passenger perspective which means weighing the headway variation by the passengers impacted. Besides calculating the passenger demand by time and location, there is a variability to passenger demand influenced by the factors discussed in detail in Section 2.1.2, are listed below:

1. Weather
2. Time of Day
3. Transfers

5.2 Data Sources and Processing

Three data sets are used: CTA AVAS, AFC, and CTA official ridership counts. The AVAS data provide stop level vehicle location and passenger count data as well as timepoint schedule information for each trip. AFC data provide individual fare transaction records. The official ridership counts provide total route boardings per hour. Data between 14:00 and 18:00 are collected from 15 weekdays in November 2006 (excluding the Wednesday through Friday of Thanksgiving week).

5.3 *Segment Running Time Model*

The segment running time is defined to include movement time and minor stop dwell time on each segment and so the factors influencing both movement time and dwell time will impact the variability of the segment running time.

This section examines the relevant data for several of the factors influencing running time discussed in Section 5.1. The data is partitioned based on the route segment to control for differences in the number and timing of traffic signals, the number and location of minor stops, and other street characteristics unique to each segment. As discussed in Section 2.2, a microscopic traffic simulation model would be required to fully understand and test changes in factors such as traffic signals and stop location, but data to construct such a model is not readily available. Partitioning the data by segment to test the impact of the other factors (passenger demand, etc.) avoids this issue. Once the impact of the other factors has been examined, a distinct running time model is built for each route segment. The segment models implicitly capture the impact of traffic signals and stop locations on running time on each segment.

To develop a segment running time model, the cleaned data set is first examined for systematic variation. Once a homogenous time period is identified, the movement time and dwell time components of running time are tested for significance. After identifying the important components of running time (movement or dwell time), factors that influence running time through time-varying characteristics (weather, traffic incidents) and operator behavior are examined. Finally, the functional form of the running time model is developed and parameters are estimated for each component.

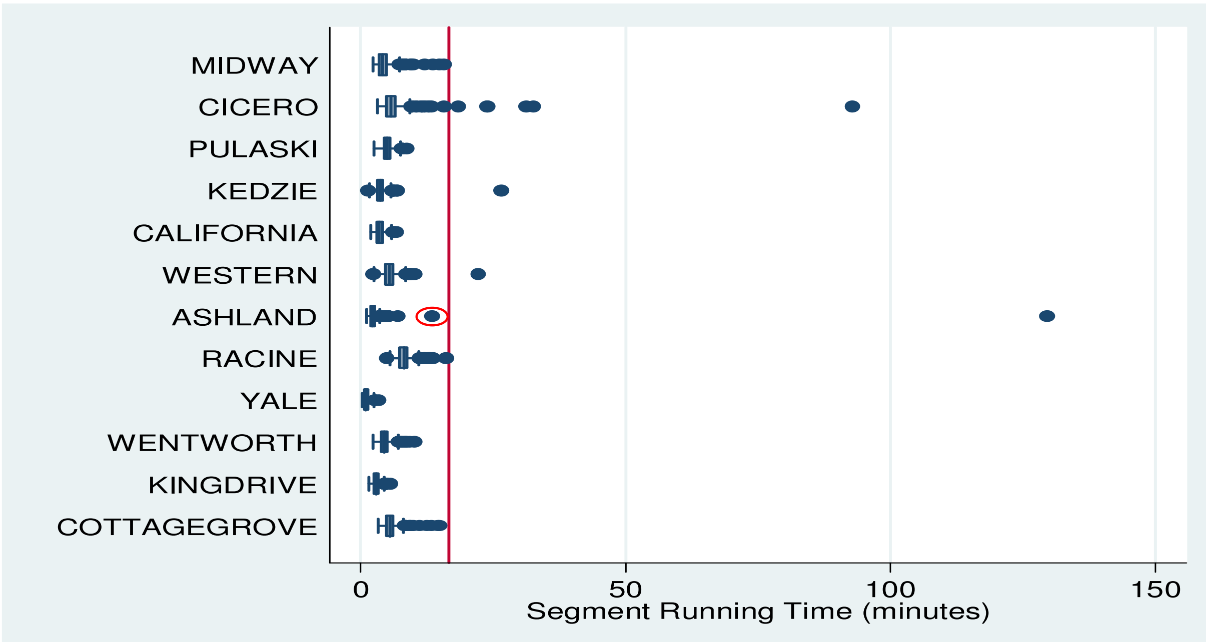
5.3.1 Data Analysis

The AVAS data set is examined for outliers caused by either passenger incidents (medical, non-payment, etc.) or vehicle incidents (minor break-down, accident) on each segment of route 63. Box-plots[*] are used to identify outliers in the running time data in Figure 5-1. With the exception of one observation on the Ashland (eastbound) segment (highlighted with a red circle), running times of greater than 17 minutes were determined to be outliers (shown by red vertical line).

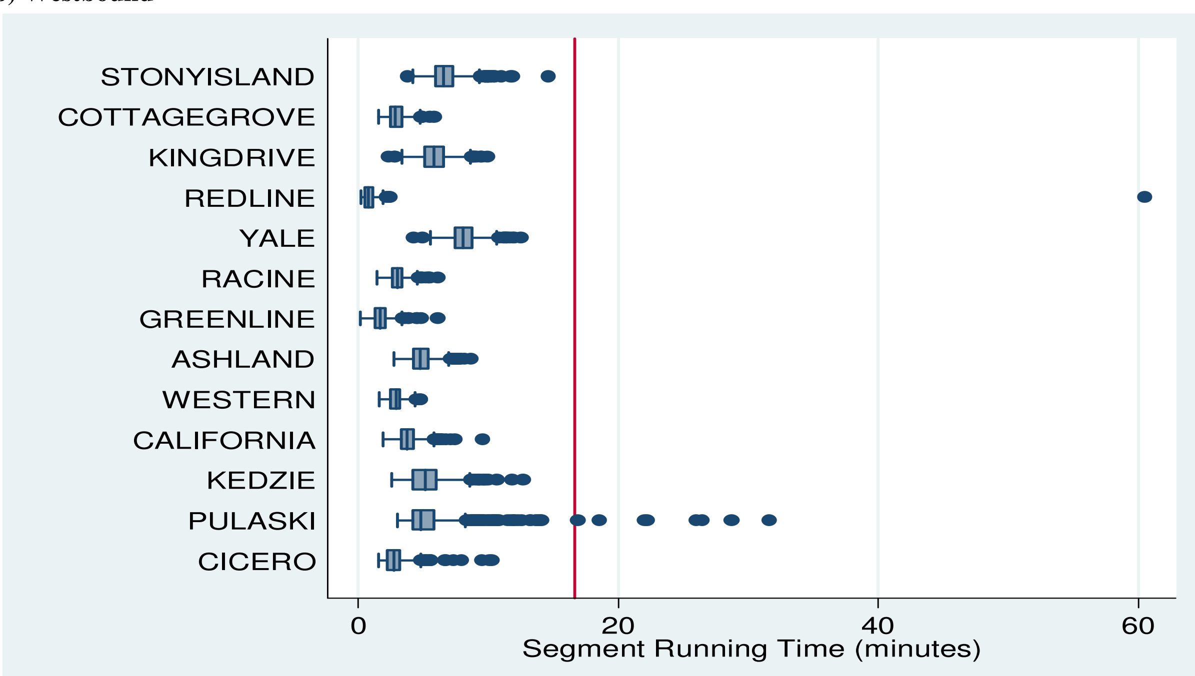
[*] See Appendix A for a description of box plot characteristics

Figure 5-1: Route 63 Running Time Analysis

a) Eastbound



b) Westbound



Note that the Cicero (eastbound) and Pulaski (westbound) segments have particularly long tails. These segments have an at-grade rail crossing, which is the likely cause of these long running time observations. These observations are removed from the following analysis because this is a unique characteristic of one segment of the route and the correlation between successive trips that are impacted by the rail crossing may skew the analysis. Excluding these observations limits the model applicability to cases where the freight rail crossing does not causes long delays. Less than 10 trips are observed with long delays likely due to the freight rail crossing, so the model findings will be relevant in the great majority of cases on route 63.

The summary statistics for the remaining data are shown in Table 5-1. The mean running times range from 1 minute on short segments with no minor stops to 8 minutes on the Racine-Yale segment. The standard deviation is less than 2 minutes in all cases except for Pulaski (westbound). Except for this segment, and the short segments with no minor stops, the standard deviation is less than 30% of the mean. Note the very short minimum running time statistics for the segments with no minor stops. These short running time observations arise where one (or both) of the key stops are not served. When a stop is not served, the AVL system records the event when the bus is estimated to be at the stop location which may not be at the true time. This does not affect the overall route running time, because any underestimation of running time on one segment will be coupled with overestimation of the running time on the adjacent segment. Furthermore, analysis of the running time revealed no significant difference between the running times when the key stop is served or not. Therefore, all these observations are included in the data set.

The summary statistics show that there is a large amount of variability in segment running time, which may be caused by either systematic or random factors. The following section examines the running time for systematic variation. Once any systematic variation is identified and controlled for, the other factors influencing running time variability include passenger activity, weather/traffic incidents, and operator characteristics, can be examined.

Table 5-1: Route 63 Segment Running Time Statistics

a) Eastbound

Key Stop Segment	obs	Running Time (minutes) mean	stdev	min	max
MIDWAY TERMINAL	275	4.1	1.2	2.4	12.1
CICERO	278	5.8	1.6	3.3	13.3
PULASKI	279	5.2	1.0	2.8	8.7
KEDZIE	279	3.7	0.8	1.4	6.9
CALIFORNIA	279	3.7	0.8	1.9	6.3
WESTERN	280	5.5	1.2	2.4	10.1
ASHLAND	273	2.3	0.6	1.1	7.1
RACINE	278	8.4	1.4	4.9	16.1
YALE*	289	1.0	0.5	0.3	3.4
WENTWORTH	287	4.7	1.0	2.7	9.3
KING DRIVE	287	3.0	0.6	1.5	5.6
COTTAGE GROVE	286	5.7	1.1	3.4	11.1

b) Westbound

Key Stop Segment	obs	Running Time (minutes) mean	stdev	min	max
STONY ISLAND	260	7.0	1.4	4.2	14.7
COTTAGE GROVE	275	3.0	0.6	1.5	5.5
KING DRIVE	266	6.0	1.1	3.7	9.5
RED LINE STATION*	267	0.8	0.4	0.2	2.5
YALE	263	8.3	1.1	5.8	12.5
RACINE	272	3.0	0.6	1.5	5.5
GREEN LINE STATION*	279	1.9	0.7	0.7	6.1
ASHLAND	279	4.9	0.9	2.9	7.9
WESTERN	276	2.9	0.5	1.6	4.8
CALIFORNIA	277	3.9	0.9	2.2	9.6
KEDZIE	278	5.6	1.5	2.6	12.7
PULASKI	277	5.6	2.3	3.0	15.0
CICERO	277	2.9	0.9	1.7	9.5

* No intermediate minor stops on segment

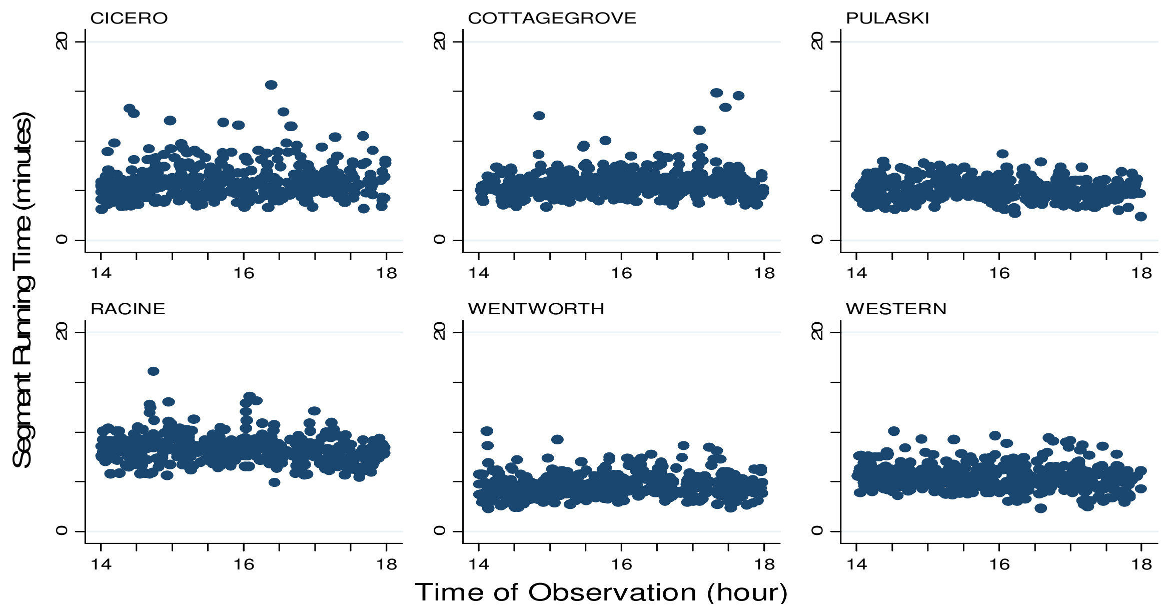
5.3.2 Systematic Variation by Time of Day

Any systematic variation in running time due to time of day variation in traffic and/or passenger demand should be most obvious on the longer key stop segments. Figure 2-1 shows observed running times by time of day for segments having at least 5 minor stops.

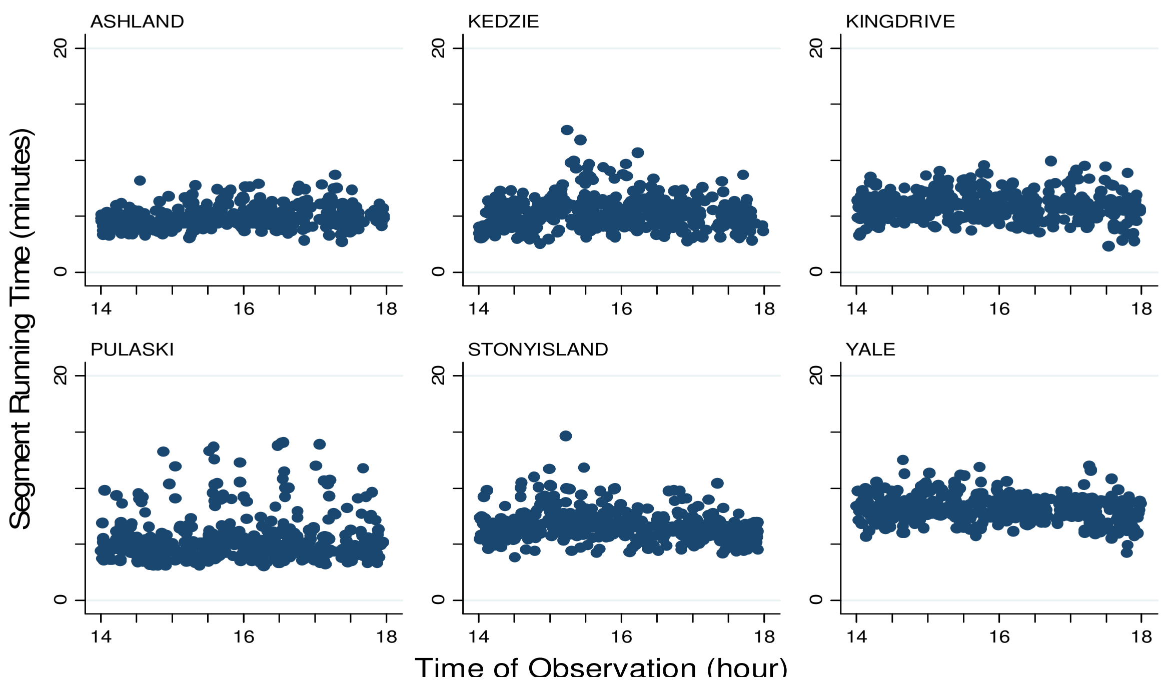
Note that there is no clear systematic variation in the running times over the 14:00-18:00 time period in any of these plots. The lack of systematic variation in running times means that further analysis into running time variability may be conducted on observations from any time between 14:00 to 18:00.

Figure 5-2: Route 63 Segment Running Time by Time of Day

a) Eastbound



b) Westbound



The lack of systematic variation due to traffic is reasonable in this case as route 63 is a cross-town route far from downtown, thus there is not necessarily a strongly time-dependent traffic pattern. As will be shown later there is systematic variation in passenger demand on route 63 across this period and a positive correlation between passenger activity and dwell time is expected. The lack of systematic variation in segment running time corresponding to the systematic variation in passenger demand suggests that dwell time is not a dominant factor in running time on these route segments. The next section examines the individual contribution of dwell time and movement time variability to total running time variability.

5.3.3 Components of Running Time Variability

This section examines the contribution of both movement and dwell time variability to running time variability. The results of this analysis will determine which factors influencing variability should be included in the segment running time model. For example, if dwell time is demonstrated to be an important factor in running time, then the factors influencing dwell time variability such as passenger activity must be included in the segment running time model. If a segment does not contain any minor stops, then the movement time variability is responsible for the entire running time variability. Thus, the three segments that do not contain minor stops (Ashland (eastbound); Red Line Station, Green Line Station (westbound)) are excluded from this analysis.

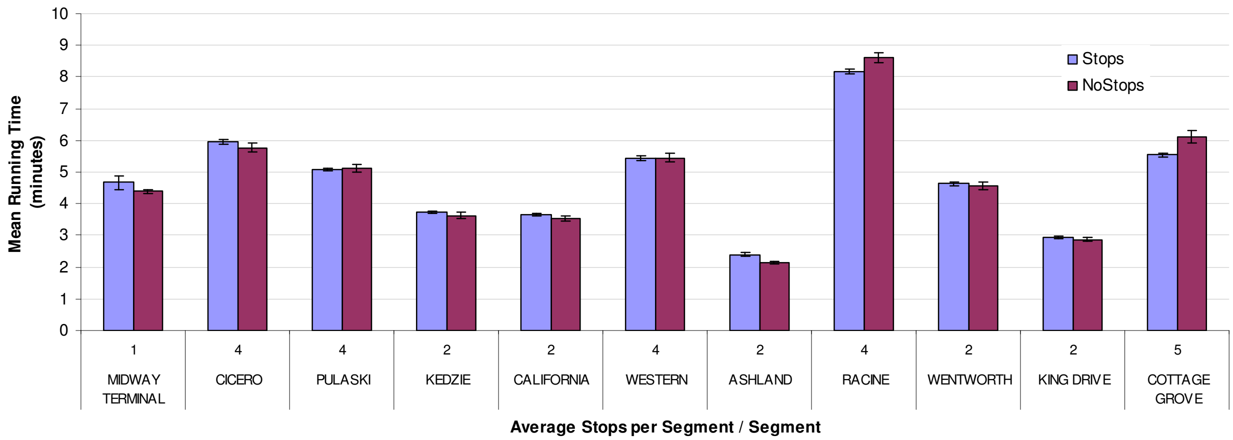
First, the data is segmented by whether any minor stops are served to compare the running time with passenger activity to the running time with no passenger activity. If the dwell time is an important factor in running time for a particular segment, the average running time with minor stops served will be significantly higher than the running time without any minor stops served. Besides dwell time, serving stops requires a bus to slow down, pull out of traffic, and pull back into traffic which takes more time than without stopping. The difference between running time with stops served and running time without stops served should be largest on the segments where the most minor stops are served on average.

On the other hand, if the movement time is the dominant factor, then there should be no significant difference in the average running time per segment between the set of observations with minor stops served and not served. This will be the case if there is not much passenger demand and if the bus is stopping for traffic signals as often or more than it is stopping for passengers.

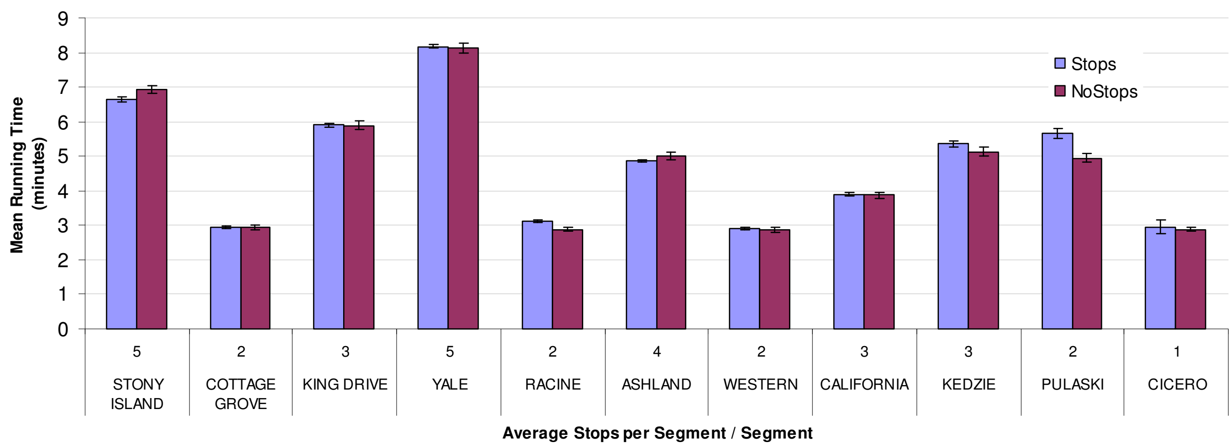
The average and standard error of the running times per segment displayed in Figure 5-3 show an apparent (as determined by no overlap in the range of standard error) difference in the running times on the Ashland, Racine, and Cottage Grove segments (eastbound) and the Racine and Pulaski segments (westbound). There are at least 80 running time observations with stops served and no stops served for each segment.

Figure 5-3: Route 63 Segment Running Time Comparison by Stops Served

a) Eastbound



b) Westbound



Ashland (eastbound) and Pulaski and Racine (westbound) are the only segments where the minor stops served observations have longer running times than the no minor stops served observations. These segments have small numbers of served minor stops on average (displayed along the x-axis above the key stop segment name). On the Pulaski segment the at-grade rail crossing may again be coming into play. It is possible that, when delayed by a train, the operators are "jacking the brake", thus registering a false stop. In this case, there would be a strong correlation between minor stops served and longer movement times, independent of the passenger demand.

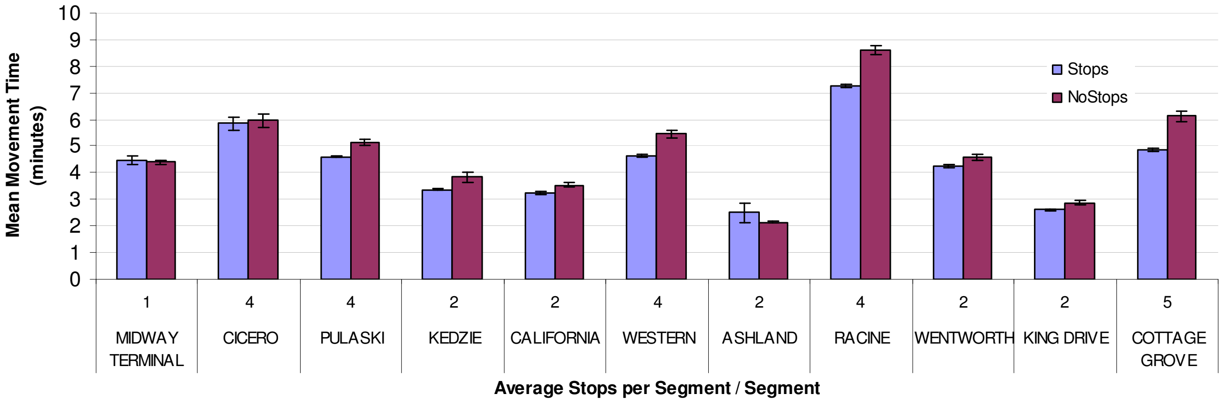
The Racine and Cottage Grove (eastbound) segments are interesting because they show an apparently longer running time when no minor stops are served. These segments are the longest on the route, with 11 stops each and have a high average number of served minor stops. Therefore, these are segments where the running time with minor stops served should be longer than the running time with no minor stops served. The longer running times with no minor stops served may be the result of interactions between bunched buses. A following bus may avoid making any minor stops because the leader is handling all the passengers, but if the follower does not overtake the leader, the running time will be the same for both. Headway data is limited on the observations with no minor stops served, and this reasoning only explains equal, not longer, running times when no minor stops are served. The review of CTA operating policies in Section 4.2.2, found that overtaking is permitted if the operator deems it to be safe.

The counter-intuitive results of the running time comparison with minor stops served and not served implies that movement time variability is dominant in the segment running time variability. To further test this relationship between dwell and movement time, the observed dwell time is subtracted from the running time in observations where minor stops are served. As discussed in the Section 4.3.2, the observed dwell time may include movement time at near-side stops. If movement time is captured as dwell time, subtracting the dwell time from the running time will result in something less than the actual movement time. Observations with no dwell time should represent the actual movement time, and may be greater than the running time minus the dwell time.

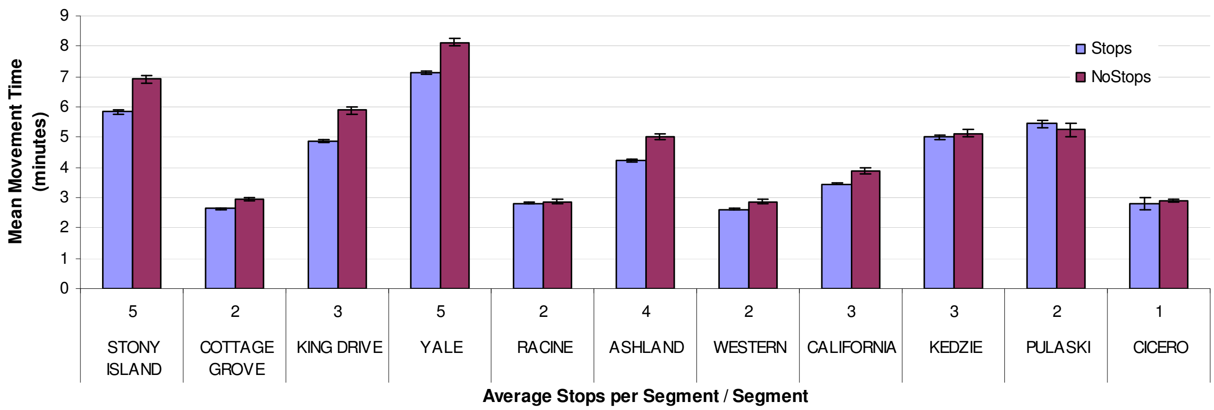
The average and standard error of the movement times per segment displayed in Figure 5-4 shows no longer movement times where minor stops are served as determined by no overlap in the range of standard error. Several segments (Western, Racine, Cottage Grove (eastbound); and Stony Island, King Drive, Yale, Ashland (westbound)) have large differences in the movement time between observations with minor stops served and no minor stops served, with the movement times for observations with no stops served being much higher. These segments also have a higher average number of minor stops served. Of course, serving minor stops is a necessary condition for a part of the movement time to be included in the observed dwell time, so it is expected that the higher the number of minor stops served, the more movement time will be recorded as dwell time.

Figure 5-4: Route 63 Segment Movement Time Comparison (stops served vs. no stops served)

a) Eastbound



b) Westbound



Collectively, Figure 5-3 and Figure 5-4 demonstrate that dwell time is not a significant influence on segment running time. Therefore, the data does not justify including the additional complexity of passenger demand for minor stops in the model. Moreover, if a dwell time component were to be included in the running time model, the running time would be overestimated. This is shown in Figure 5-3 where the average running time is not significantly different across most segments between trips that serve minor stops and those that do not.

The approach of combining movement and dwell time into a single distribution is not so radical given that the top ten stops with respect to passenger activity are removed from the segments, so that the running time variability should be dominated by the variability in movement time.

5.3.4 Testing the Factors Influencing Movement Time Variability

Section 5.3.2 found that there was no systematic time of day variation in segment running time, not unexpected on a cross-town route. Section 5.3.3 found that the dwell time due to passenger activity is not a significant component of the segment running time. This section examines the segment running time data for influence of other factors, specifically traffic, weather, and operator behavior.

Previous Running Time

Weather and random traffic impacts on running time may be tested using the proxy variable of the running time of the previous bus on the same segment. If there is a significant difference between the running time of the previous bus and the average running time on the same segment due to, for example, weather or traffic incidents, then the following trip might also be impacted, if the incident persists long enough to affect both trips. Any effects that do not impact (at least) two successive trips are assumed to be best represented through a random error term in the running time model.

To explore this effect, a subset of the data with a previous running time that is significantly different from average is examined for correlation between the previously completed trip running time on a segment and the next trip running time on the same segment. A significant difference in running time is defined as greater than the mean plus one standard deviation of the running time. Results of an ordinary least squares regression are displayed in Table 5-2. The segments where the coefficient of the previous travel time variable is not statistically significant are greyed out.

No strong or consistent correlation with previous running time was found across the segments. Not even the constant term was statistically significant across all segments, due to the previous running time term. The inconsistency and weakness of the regression test results does not warrant including this variable in the running time model. So weather and traffic incidents do not appear to impact bus running times consistently, perhaps differences in operator behavior are overriding the correlation of the travel time on successive trips by different operators.

Table 5-2: Route 63 Previous Running Time Correlation

a) Eastbound

Key Stop	Previous Running Time	t-stat	constant	t-stat	AdjR2	obs
MIDWAY	0.01	0.09	297	5.42	-0.03	37
CICERO	-0.74	-1.32	884	2.91	0.02	47
PULASKI	0.00	0.13	307	29.98	-0.02	59
KEDZIE	0.00	0.09	218	15.12	-0.02	67
CALIFORNIA	0.25	1.11	155	2.27	0.00	79
WESTERN	0.03	0.17	314	3.58	-0.01	72
ASHLAND	0.00	-0.65	139	17.66	-0.02	32
RACINE	0.24	1.43	357	3.30	0.02	46
YALE	-0.20	-1.38	79	5.11	0.01	82
WENTWORTH	0.81	4.21	-21	-0.27	0.25	52
KING DRIVE	-0.25	-1.22	239	4.92	0.01	61
COTTAGE GROVE	-0.06	-0.87	368	10.66	-0.01	51

b) Westbound

Key Stop	Previous Running Time	t-stat	constant	t-stat	AdjR2	obs
STONY ISLAND	-0.09	-0.51	467	4.87	-0.02	51
COTTAGE GROVE	-0.19	-1.15	226	5.52	0.00	68
KING DRIVE	0.61	1.72	98	0.6	0.04	45
RED LINE	0.00	0.47	42	21.87	-0.01	102
YALE	0.46	1.81	231	1.49	0.04	55
RACINE	0.06	0.4	165	4.22	-0.02	56
GREEN LINE	0.43	2.99	35	1.36	0.12	60
ASHLAND	0.22	0.91	223	2.33	0.00	47
WESTERN	-0.46	-2.26	277	5.89	0.07	57
CALIFORNIA	-0.16	-1.13	293	6.08	0.01	51
KEDZIE	0.18	1.17	290	3.97	0.01	71
PULASKI	0.37	4.85	132	2.39	0.28	58
CICERO	0.23	2.11	130	3.88	0.07	44

Operator Behavior

The last factor potentially influencing segment running time variability to be tested is operator behavior. An operator's behavior and ability is the result of experience, training, and personality. Parallel research conducted by Yuan Yuan (2008) using this dataset investigated the correlation between operators and running time. Yuan conducted a difference of means test to check if the running time of any operator is significantly different from the running times of the remaining set of operators. Few operators were found to have significant differences and even when a significant difference in running time per operator was found, it was not consistent; operators that were slow in one direction were often fast in the opposite direction.

The Portland State research discussed in Section 2.1.2 found that running times improve with seniority (Strathman et al., 2002). The experience level of the operators serving this route is shown in Figure 5-5. Operators with 3 years experience or less are part time. About half of this route is served with part time operators, although most of those operators have 3 years of experience.

Figure 5-5: Route 63 Operator Experience

Due to the lack of conclusive evidence of operator behavior in Yuan's research, a distribution of operator behavior is not included in the route 63 segment running time model. However, results of the Portland State research and the interest in understanding the impact of operator behavior variability, as discussed in Chapter 2, do justify including an operator behavior input in the final model.

5.3.5 Model Functional Form

The previous analysis concludes that the best method to simulate segment running time is to sample from the set of observations.

The influence of minor stop dwell time or the factors influencing variability of movement time on segment running time can not be estimated given the available data. There are significant differences in segment running time based on the segment characteristics, including length, signals, and street design. Attempts to fit a distribution to the sample were not successful due to poor fits on several segments. Therefore, the best representation of segment running time on route 63 is a random sample from the set of running time observations. Using the sample of observations will facilitate adapting the simulation model to represent other routes.

In this functional form, the operator impact on segment travel time may be represented by segmenting the observations into "fast" and "slow" groups or by simply multiplying the estimated value by an operator-specific parameter.

The input model depends on the following assumptions in conjunction with other schedule and passenger demand inputs:

- The scheduled travel time does not have a significant impact on operator behavior, i.e. a schedule with excessive travel time will not cause operators to drive more slowly.
- Within the typical ranges of passenger demand, the dwell time at minor stops has no significant influence on segment running time variability.

5.4 Key Stop Dwell Time Model

The analysis in this section investigates passenger activity and holding at mid-route key stops (including timepoints). Passenger activity and holding at terminals is represented through a different model that is discussed in the terminal departure section. The factors influencing dwell time at key stops include passenger activity, stop location, holding, and operator reliefs. The model will estimate the dwell time at each key stop on the route.

To develop the dwell time model, an initial model of dwell time due to passenger activity is first reviewed. Using the estimate of dwell time due to passenger activity, the unexplained dwell time is examined for holding and operator relief impacts, where relevant. The remaining unexplained dwell time is segmented by key stop and examined for differences.

5.4.1 Data Analysis

The dwell time is recorded by the AVL system and is automatically joined to the passenger counts recorded by the APC system with the analysis restricted to trips on buses with functioning APC units. To be included, the observation must have a non-zero dwell time and passenger activity.

Section 4.3.2 discussed the APC issue of passenger activity being over or undercounted by one on occasion. Assuming that the miscounts are evenly distributed across observations, this issue will not adversely affect the analysis. Another issue is that the APC system recorded count of passengers onboard is often wrong due to compounding off-by-one errors and not resetting the count at the beginning of each trip. To correct the count of passengers onboard, trip records are arranged in order and the passengers onboard when the bus arrives at the key stop are calculated from the door passenger activity counts.

The summary statistics are listed in Table 5-3. Note the high mean and maximum dwell times at the stops with operator reliefs (Ashland (eastbound) and Green Line Station (westbound)). Unfortunately, the low deployment of APC counters on route 63 limits the number of good observations of passenger activity. Key stops that do not have high passenger demand, e.g. Pulaski (eastbound), have less than 20 observations and the most observations at any stop is 72. The high dwell time coefficient of variation of 0.5 or greater is due, in part, to the high variability in passenger activity. Controlling for passenger activity through a dwell time model will reveal the impact of the other factors influencing dwell time variability.

5.4.2 Passenger Activity

Unless a bus is holding or an operator relief is taking place, each dwell is primarily due to passenger activity. Although the observed dwell time varies from stop to stop depending on the stop location and holding and operator reliefs; the impact of passenger activity on dwell time should not change along the route. To best estimate the impact of passenger activity on dwell time, it is necessary to control for holding and operator reliefs, as well as manage the influence of the stop location. Prior research into dwell time accomplished this by gathering records from far-side, non-timepoint stops across the CTA bus network. A highly detailed model of dwell time was developed in this research (Milkovits, 2008), which is described in Appendix C. The application of this dwell time model involved taking the maximum dwell time of the front and rear door and included special treatment for "atypical" passengers.

The dwell time model used here is a simplified version of the model developed in the previous work. Unlike the detailed dwell time model, the model implemented here does not include estimators for fare media type or bus type specific differences and the front alightings are simplified from piecewise linear to a single linear variable. The fare media information may be reintroduced to the model to test the impact of fare media bus service reliability. The model assumes that the distribution of fare media use is the same at each key stop. The bus type specific parameters are eliminated because route 63 is served by high-floor buses, types 4400-Series TMC buses and 6000-series Flxible Metro, that were not included in the dwell time model analysis due to their age and lack of APC counters.

Table 5-3: Route 63 Key Stop Dwell Time Summary Statistics

a) Eastbound

Key Stop & Location[*]		obs	Dwell Time (sec) mean	stdev	min	max	Ons mean	stdev	max	Offs mean	stdev	max	Passenger Load mean	stdev	max
CICERO	FS	58	27	26	2	141	4.9	4.5	18	0.9	1.1	4	14	11	54
PULASKI	FS	13	15	14	4	53	0.9	2.0	7	1.0	0.9	3	10	7	28
KEDZIE	NS	23	43	37	3	143	3.1	2.7	10	2.7	2.7	10	10	9	34
CALIFORNIA	FS	31	22	18	2	69	3.1	2.4	8	1.8	1.8	6	13	9	34
WESTERN	FS	57	37	27	3	115	5.4	4.7	19	2.5	2.2	9	15	11	38
ASHLAND	FS	49	112	77	16	437	5.4	3.9	15	7.1	6.6	38	19	13	48
RACINE	NS	53	22	15	4	85	2.0	2.2	11	2.9	2.7	12	19	13	44
YALE	NS	72	34	21	3	90	2.2	2.2	8	7.7	4.8	22	18	13	58
WENTWORTH	FS	62	31	24	2	112	6.0	4.4	20	0.5	0.9	4	14	11	40
KING DRIVE	FS	71	38	25	3	113	2.8	2.2	8	6.9	5.2	21	18	13	56
COTTAGE GROVE	NS	65	47	35	4	216	3.9	3.4	13	6.4	3.8	14	13	11	45

b) Westbound

Key Stop & Location*		obs	Dwell Time (sec) mean	stdev	min	max	Ons mean	stdev	max	Offs mean	stdev	max	Passenger Load mean	stdev	max
COTTAGE GROVE	NS	68	61	38	8	180	6.7	4.8	18	4.0	3.4	15	10	13	52
KING DRIVE	NS	63	58	34	6	206	6.5	4.6	23	4.0	3.0	11	14	13	58
RED LINE	MB	58	64	35	4	168	11.1	6.6	29	5.1	3.1	15	18	13	56
YALE	FS	39	20	30	1	183	5.0	6.9	24	1.9	2.8	12	23	14	65
RACINE	NS	63	25	16	4	82	2.7	3.6	22	4.2	3.3	14	24	15	61
GREEN LINE	TERM	63	74	59	2	223	6.0	5.5	22	6.7	4.1	17	22	15	57
ASHLAND	FS	47	31	21	1	81	5.0	3.9	14	1.6	3.1	13	19	15	61
WESTERN	NS	68	40	25	5	117	3.5	3.4	16	7.2	4.2	19	22	17	69
CALIFORNIA	FS	13	12	10	3	38	0.3	1.1	4	4.5	4.3	16	24	25	77
KEDZIE	FS	61	22	18	1	82	2.5	2.8	12	3.3	3.0	12	13	16	65
PULASKI	NS	59	35	27	1	128	1.9	2.6	10	2.5	2.5	15	14	17	68
CICERO	NS	57	18	17	1	77	0.3	0.6	2	4.4	2.7	12	13	16	68

[*] FS = Far Side, NS = Near Side, MB = Mid-Block, TERM = Terminal

The dwell time model used data from low-floor buses where a significant difference in time per passenger alighting between the first two passengers and successive passengers was found. The theory behind this difference is that all passengers need to stay back from the door, but once the alighting has begun, there is no overhead. On a high floor bus, the stairs will cause a constant delay for all alighting passengers. Thus it is more appropriate to represent the dwell time per alighting passenger as a single variable. The single variable estimator for all passengers alighting is closer to the estimator for 1 or 2 passengers alighting than to the estimator for 3 or more passengers alighting.

The estimated dwell time model with the simplified variables is summarized in Table 5-4 and the model functional form is shown in Equation 1.

Table 5-4: Passenger Activity Dwell Time Model Parameters

		coefficient	t-statistic
Obs		169479	
Adj. R2		0.6978	
Constant		-0.48	-27.03
Boardings		3.66	610.98
Alightings	Front	2.26	183.16
	Rear	2.70	182.97
Crowding		0.0013	16.89

Equation 1: Passenger Activity Dwell Time Model Functional Form

$$P(ons, frontoffs, rearoffs, crowding) =$$
$$-.48 + Max(3.66 \times ons + 2.26 \times frontoffs, 2.70 \times rearoffs) + 0.0013 \times crowding + \varepsilon$$
$$crowding = (throughPassengers)^2 \times (ons + totalOffs)$$

To implement this model, the alighting door choice and error term ε must be defined.

Alighting Door Choice

To calculate the assignment between front and rear door alightings, a binary choice model is used to first calculate the front door alighting percentage, then a binomial distribution is used to calculate the number of front and rear door alighting passengers (Equation 2).

Li et al. (2006) found that the most significant indicators of passenger alighting door choice are the total number of passengers alighting and the total onboard. Using the same dwell time data as above, a binary logit choice model is estimated with the results summarized in Table 5-5. The low rho square value shows that much of the variation in alighting door choice is not explained, but the z-statistics show that all of the coefficients are statistically significant. A low rho square value is not surprising given the large number of observations.

Equation 2: Alighting Door Choice Model

$$x_2 = passengersAlighting, x_3 = passengersOnboard$$

$$P_n(i) = \frac{1}{1+e^{-\beta x_n}}, \beta x_n = \beta_1 + \beta_2 x_2 + \beta_3 x_3$$

$$FrontDoorAlightings = Binomial(P_n(i), x_2)$$

Table 5-5: Alighting Door Choice Estimates

Obs		230567	
ρ^2		0.01	
		coefficient	z
Constant (front)	β_1	0.525	62.02
Total Alightings	β_2	-0.017	-13.06
Onboard	β_3	-0.014	-45.93

The model results show an initial preference for front door alightings (indicated by the positive constant term), but the utility of front door alightings decreases as onboard passengers and alightings increase. This makes sense because, with more onboard passengers, it is more difficult to access the front door so rear door alightings increase. Also, when more passengers are alighting, they are more likely to use both doors to hasten the process.

Atypical Passengers

The previous research in the factors influencing dwell time separated atypical passengers in the model estimation to be included in dwell time prediction. Dwell time observations with more than 8 seconds dwell time per passenger are deemed to include atypical passengers. To include the atypical passenger impact, the error term of the dwell time (sampled from observations with typical passengers) is overridden with an error term sampled from observations with atypical passengers. To facilitate dwell time prediction with atypical passengers, a distribution is fitted to the unexplained variation of the atypical passenger observations. The statistics and gamma distribution of the unexplained variation are shown in Table 5-6 and Table 5-7 respectively. The density of the observed data and the gamma distribution are shown in Figure 5-6.

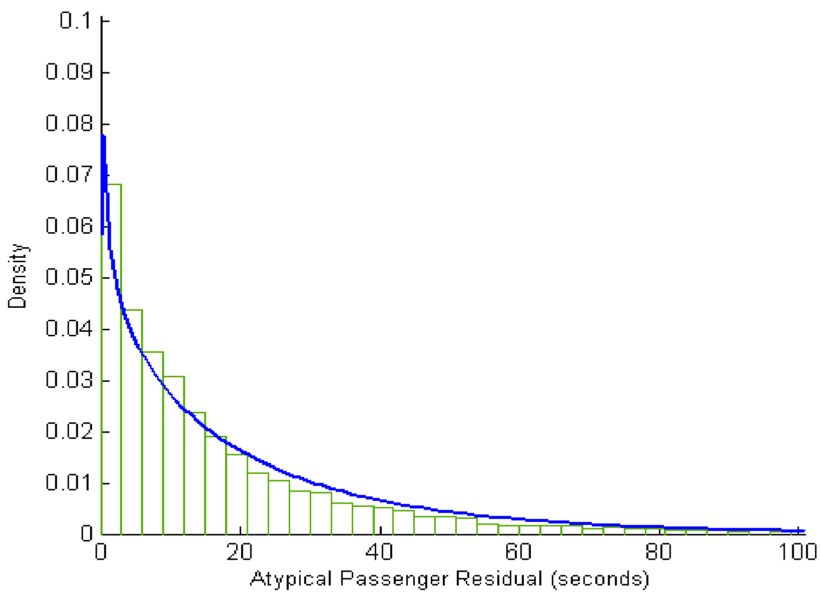
Table 5-6: Unexplained Dwell Time Variation for Atypical Passengers

obs	mean	stdev	min	max
10285	25	32	5	290

Table 5-7: Atypical Passenger Unexplained Variation Gamma Distribution Parameters

Obs	10285
Log Likelihood	-41465
Intercept	4
alpha	0.82
lambda	25.81

Figure 5-6: Atypical Passenger Residual Distribution



5% of the original dwell time observations are identified as including atypical passengers, so in 5% of the dwell time predictions, the error term ε is sampled from the atypical gamma distribution.

Using this dwell time model, the dwell time due to passenger activity is predicted for each stop record. The following sections examine the unexplained variation in dwell time for holding and operator relief impacts.

5.4.3 Schedule Holding

An operator may hold at a scheduled timepoint if the trip is running ahead of schedule. Holding on CTA bus routes is expected to occur only at timepoints because the supervisor guides are published with a schedule at this level of detail. Thus, key stops that are not scheduled timepoints are excluded from this portion of the analysis. This research also assumes that operators hold only at timepoints and that the holding is recorded as part of the dwell time. Therefore, holding will be evident as dwell time that is above the predicted time due to passenger activity and only when the bus is ahead of schedule. Holding is expected to occur later in the route because operators ahead of schedule early in the route may be concerned that some unexpected event may cause a delay later on the route. In theory, as an operator moves along the route, the likelihood of a delay decreases, so they are more likely to hold to maintain the schedule.

To look for evidence of holding at timepoints, the dwell time is first predicted based on passenger activity. The remaining unexplained dwell time is then tested for correlation with the schedule deviation. A minimum schedule deviation of 1 minute early is used because operators track their schedule with a watch, and therefore are not sensitive to schedule deviations of less than 1 minute. The correlation test results are shown in Table 5-8. Trips on route 63 are seldom early, so the observation counts are less than 10 at any timepoint, and most timepoints do not have any observations.

A negative correlation means that the greater the (early) schedule deviation, (a negative value means the operator is early), the greater the unexplained dwell time which is the expected result. However, only two timepoints, Western (eastbound) and Cottage Grove (westbound) show a negative correlation with a reasonable number of observations.

Table 5-8: 63 Correlation between Dwell Time Residual and Schedule Deviation

a) Eastbound

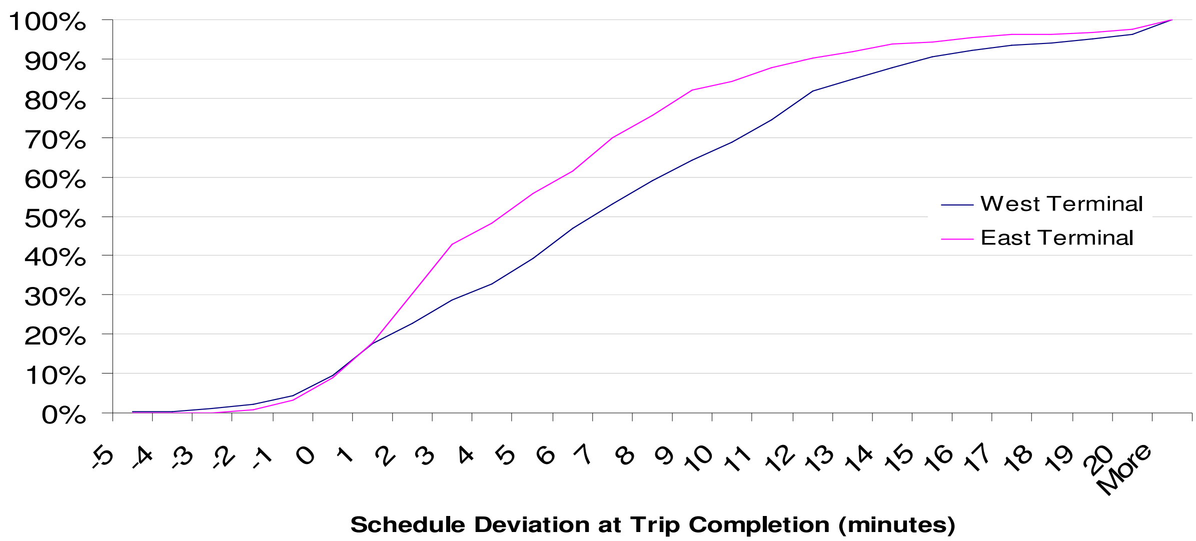
Timepoint	obs	correlation
CICERO	0	N/A
PULASKI	2	1.00
KEDZIE	0	N/A
WESTERN	9	-0.72
ASHLAND	0	N/A
YALE	4	0.09
COTTAGE GROVE	2	1.00

b) Westbound

Timepoint	obs	correlation
COTTAGE GROVE	5	-0.91
YALE	3	-1.00
ASHLAND	0	N/A
WESTERN	0	N/A
KEDZIE	6	0.21
PULASKI	2	1.00
CICERO	2	-1.00

Figure 5-7 shows the cumulative distribution of schedule deviation at each terminal. Across all records, not just those with APC counters installed, fewer than 20% of trips in the either direction are completed early or less than 2 minutes late. Furthermore, more than 50% of the trips are completed more than 5 minutes late.

Figure 5-7: Route 63 Cumulative Distribution of Trip Completion Schedule Deviation



This limited data is inconsistent and inconclusive, which does not preclude the existence of holding on route 63, but does not provide guidance for parameter development to describe it. Therefore this component of the input model is not active during validation, but the functional form described in Equation 3 is developed for sensitivity and operations control strategy testing.

Equation 3: Schedule Holding Dwell Time Model

$$H(i, schDeviation, op) = \{schDeviation < -60 \mid PHold(i \mid op) \times -schDeviation, 0\}$$

$PHold(i \mid op) =$ Probability of holding at timepoint i, given operator op

Although there is no evidence of dwell times being extending by holding, scheduled operator reliefs may have an impact, as discussed below.

5.4.4 Operator Relief Behavior

Operator reliefs depend both on the relieving operator not arriving late and the operator to be relieved not arriving early. If either happens, the dwell time is extended until the relieving operator is available to continue the trip. When the vehicle and relieving operator are both present, there is still a time penalty for the operators to switch. Relief times of 1 to 2 minutes are expected if the relieving operator is present when the vehicle arrives.

There may also be passenger activity occurring during an operator relief; therefore to analyze the dwell time penalty due to operator reliefs, the dwell time due to passenger activity must be removed. Using the dwell time model in Table 5-4, the unexplained variation is examined at both relief stops. Table 5-9 presents the summary statistics of the dwell time recorded during reliefs minus the predicted dwell time due to passenger activity.

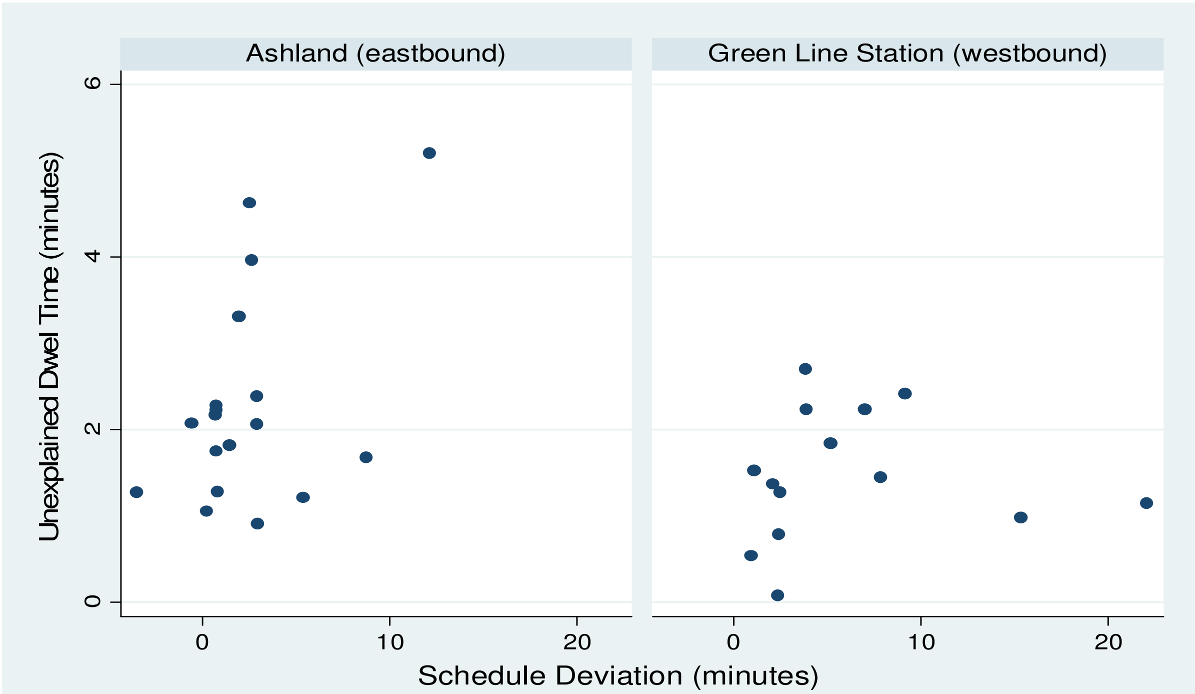
Table 5-9: Summary Statistics of Unexplained Dwell Time during Operator Relief (seconds)

	obs	mean	stdev	min	max
Ashland (eastbound)	18	138	73	55	312
Green Line (westbound)	14	88	45	5	162

The observations at the westbound relief point have a mean excess dwell time almost 60 seconds less than the eastbound relief point even though the relief points are at the same location. Ashland (eastbound) is a far-side stop; therefore the dwell time cannot be extended by a traffic signal.

Operator reliefs are sensitive to schedule adherence, specifically if the vehicle is early additional delays may occur. Figure 5-8 graphs the unexplained dwell time as a function of the schedule deviation. As noted above, there are very few instances of the bus arriving early. The few records with an early vehicle arrival and majority of unexplained dwell times of 1-2 minutes suggest that the relieving operator is present in the observations. The range of operator relief times may be due to differences in the inclination of the operators to chat with each other or the time for the relieving operator to adjust the mirrors and log-in to the onboard systems.

Figure 5-8: Route 63 Unexplained Dwell Time at Operator Relief Points



Operator reliefs have a significant impact on dwell time; therefore the potential penalty of operator reliefs should be included in the dwell time predictions. Equation 4 shows how the schedule adherence and relief overhead are combined into a model to calculate the operator relief dwell time. The variables *i, t* represent the key stop and trip id. If there is a scheduled operator relief at the current key stop, the schedule deviation of more than 3 minutes early plus the relief penalty are returned. Therefore, this model assumes that the relieving operator is present 3 minutes early. The data in Table 5-9 provide a distribution of the relief penalty in situations where the relieving operator is present when the vehicle arrives.

Equation 4: Operator Relief Dwell Time Model

$$R(i,t,schDeviation) = \{(i,t) = relief \mid Max(-schDeviation - 180,0) + \delta_i, 0\}$$

δ_i =Normal distribution of relief penalty (parameters for validation in Table 5-9)

5.4.5 Stop Specific Characteristics

The observed dwell time depends on the stop location (near-side, far-side, or terminal) so that the distribution of the unexplained variation in dwell time is unique for each stop. It is important to predict the observed dwell time accurately in the model so that the movement time is reintroduced to the simulation model. It is not appropriate to develop an independent distribution of unexplained variation in dwell time for each stop because there is not enough data with valid passenger counts. Furthermore, this approach will create an additional step when adapting the simulation model for other routes. Instead, the stop specific characteristics will be derived by comparing the predicted dwell time in the simulation model with the recorded dwell time (with no constraints on valid passenger counts). The details of the development of the stop specific parameters are explained in Section 6.3.1.

5.4.6 Model Functional Form

Models have been developed to estimate the dwell time due to passenger activity, holding, and operator reliefs. The combination of these models to calculate the dwell time at each stop is shown in Equation 5.

Equation 5: Overall Dwell Time Model

$$DT_{i,t} = MAX(H_i(schedule, operator), P(ons, offs, crowding)) + MAX(\varepsilon_i, R(i, t, schDeviation))$$
$$i \in KS, t \in Trips$$

DT_i is the predicted dwell time at key stop i. The predicted dwell time is composed of the maximum of a systematic component and the maximum of a random component. The systematic component is a function of holding H_i and passenger activity P. The random component is composed of the regular and atypical passenger distribution ε_i and the operator relief distribution δ. *KS* is the set of all key stops.

5.5 Terminal Departure Behavior Model

This section focuses on the special case of key stops that are also terminals. Terminals are located at either end of the route and, except for loop routes, all passengers still onboard from the previous trip alight at the terminal. Typically, a bus schedule has recovery time scheduled at the terminals to allow runs to get back on schedule before the next trip start and for operators to have a personal break. Terminals are also ideal locations to implement service operations control strategies because there are few passengers onboard the bus and often ample curb space for the bus to stand. The minimum recovery time taken at the terminal is determined by the personal break required (or desired) by the operator. As reviewed in Chapter 4, CTA policy places no restriction on operator use of the washroom regardless of the schedule adherence, as long as the time is not abused. Recovery time available above the minimum required for a personal break depends on the recovery policy, e.g. hold for headway or schedule. The accuracy of the next trip departure, given sufficient recovery time, is dependent on operator behavior, training, and discipline.

The terminal departure behavior analysis first estimates the minimum recovery time required for typical operator personal breaks. The CTA terminal departure policy is reviewed to determine the available recovery time, then the estimated minimum recovery time is used to select observations with sufficient recovery time. This data set is analyzed for evidence of departure discipline. A model of terminal departure behavior based on the minimum recovery time and departure accuracy is developed.

5.5.1 Data Analysis

Recovery time is calculated from the previous trip arrival at the terminal to the next trip departure, as recorded in the AVL data. Available recovery time is calculated as the arrival time subtracted from the next departure time as determined by the agency policy. This analysis includes only observations with a recovery time of less than 20 minutes to eliminate cases where trips are re-ordered or other abnormal behavior occurs.

The CTA policy is to maintain schedule and operators should not depart a terminal early unless instructed by a supervisor. There is a supervisor located at both terminals in the PM peak period and the Midway terminal has a break room with restroom facilities and snack machines.

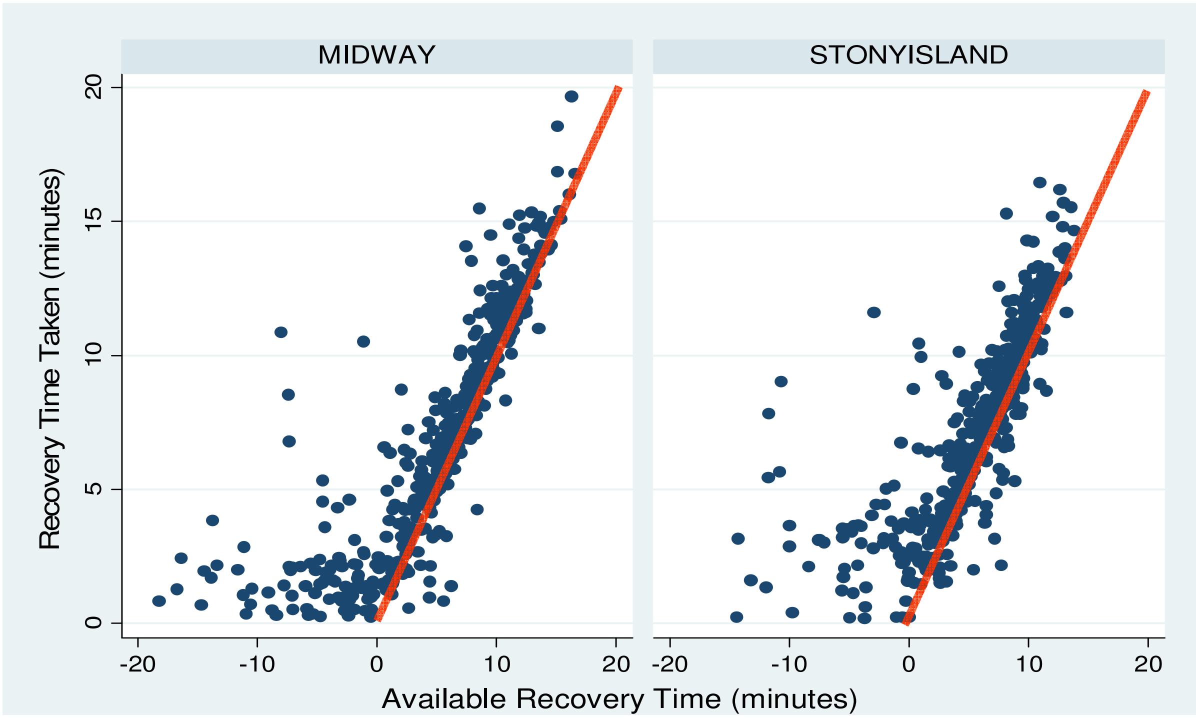
Table 5-10 shows the summary statistics for the recovery time taken and the departure schedule deviation. Overall there is little difference in the average recovery time taken at either terminal.

Table 5-10: Recovery Time and Deviation from Scheduled Departure (minutes)

	Recovery Time					Scheduled Departure Deviation			
	obs	mean	stdev	min	max	mean	stdev	min	max
Midway	466	7.2	4.3	0.2	19.7	2.0	3.5	-4.8	19.0
Stony Island	448	7.2	3.5	0.2	16.5	2.0	3.2	-5.6	19.7

The comparison of the available recovery time and the actual time taken in Figure 5-9 shows that operators generally do not leave the terminal early. The solid line demarcates on-time terminal departures and the observations to the right of this line have a higher available recovery time than the time taken, meaning the trip started early. Most of the observations departed on-time or late.

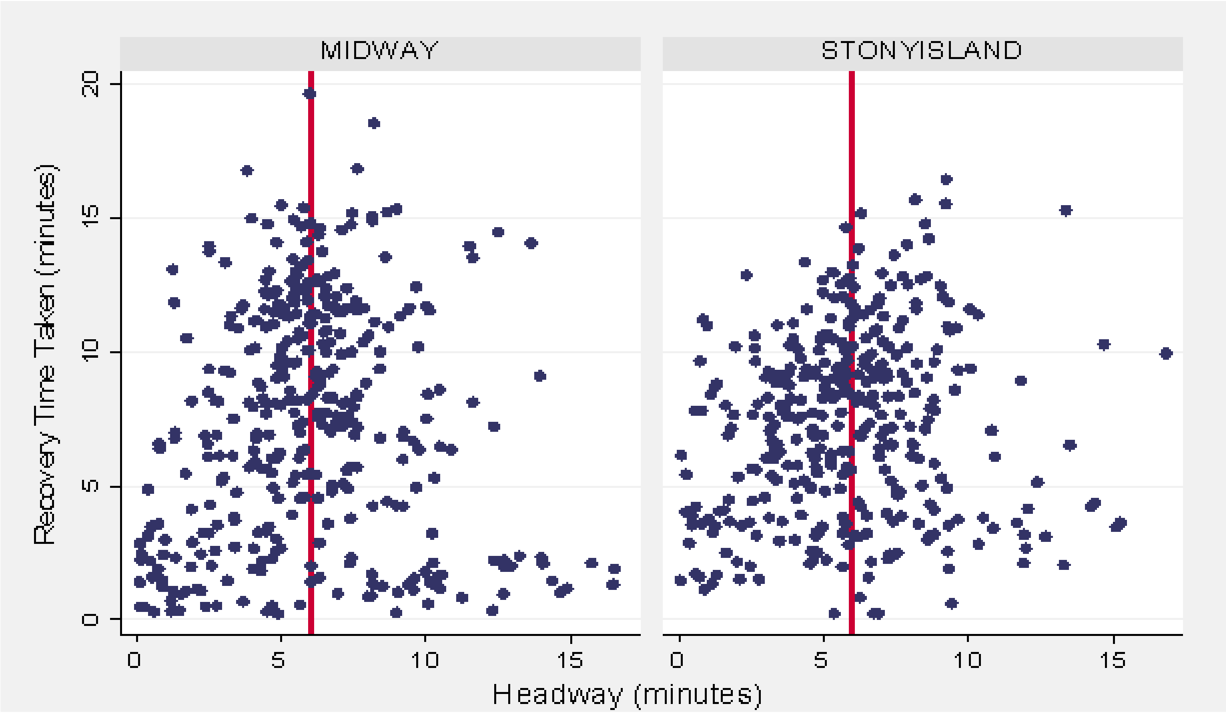
Figure 5-9: Comparison of Available Recovery Time and Recovery Time Taken



Behavior is different when inadequate recovery time is available (observations with a negative available recovery time). Segmenting the data according to whether or not there is sufficient recovery time will provide insight into the minimum time at the terminal and the tendency of operators to leave on schedule.

The strength of the CTA policy to respect schedule departure, and the lack of headway information is apparent in Figure 5-10 which compares the headway with the recovery time. If there were sensitivity to headway, the observations would be concentrated along the 6 minute scheduled headway (shown by the solid line). The observations to the left of the headway line are of particular interest because, in these cases, headways could have been improved by extending the recovery time.

Figure 5-10: Relationship between Recovery Time taken and Departing Headway



5.5.2 Minimum Recovery Time

The CTA terminal departure policy is sensitive to schedule, as opposed to headway, so operators that arrive without any time before their next scheduled departure should depart as soon as possible. Therefore, recovery time taken when there is none available can be viewed as the minimum recovery time required for operator personal breaks. The summary statistics for minimum recovery time defined in this manner are shown in Table 5-11.

Table 5-11: Minimum Recovery Time

	obs	mean	stdev	min	max
Midway	88	1.9	1.9	0.2	10.9
Stony Island	61	3.0	2.1	0.2	11.6

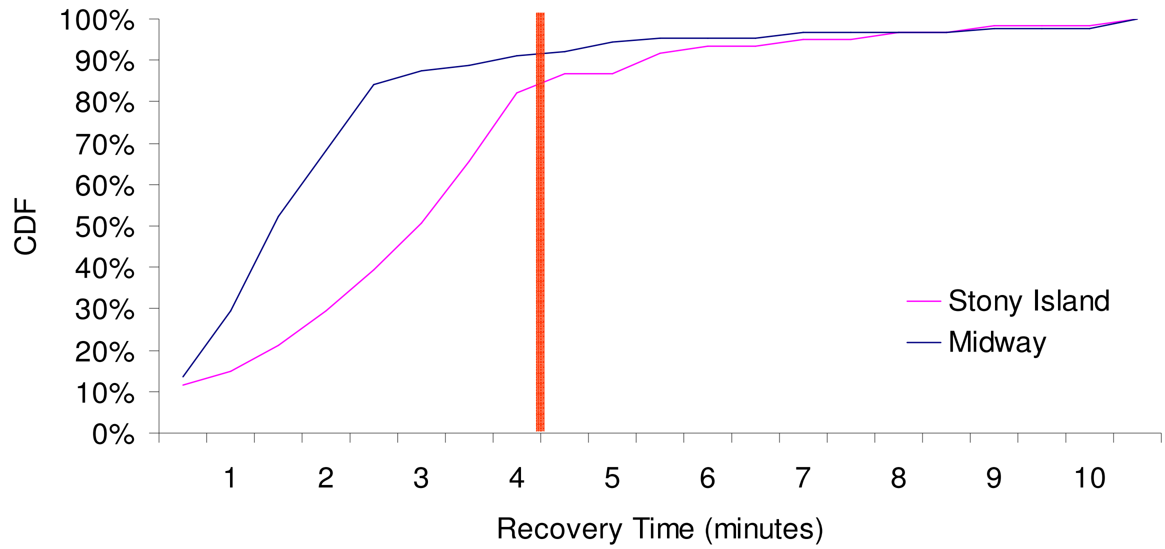
On average, about 1 minute more recovery time is required at the Stony Island terminal, although the standard deviation at each terminal is similar.

To calculate the minimum recovery time required by each operator in the simulation model, a normal distribution is fitted to the data summarized in Table 5-11. This distribution is sampled to determine the minimum recovery time constraint.

5.5.3 Departure Schedule Deviation

An estimate of the minimum recovery time is necessary to segment the data and analyze the accuracy of departures with sufficient recovery time. The CDF of the recovery time, (see Figure 5-11), is useful to determine what value of minimum recovery time will account for the majority of situations. Note that the recovery time CDF increases sharply at first and has a long tail. To capture the majority of observations, it is sufficient to set the value at the top of the sharp increase in the CDF. Observations beyond this are likely due to noise.

Figure 5-11: CDF of Recovery Time



The cutoff value is set at 4 minutes, marked by the red line; this includes more than 80% of observations at each terminal. The cutoff value is used to identify observations with sufficient recovery time. Statistics for observations with at least 4 minutes of available recovery time are shown in Table 5-12. The mean value of the schedule deviation in this table shows that, on average and given sufficient recovery time, operators depart within 1 minute of the scheduled departure time from each terminal, albeit with significant variations.

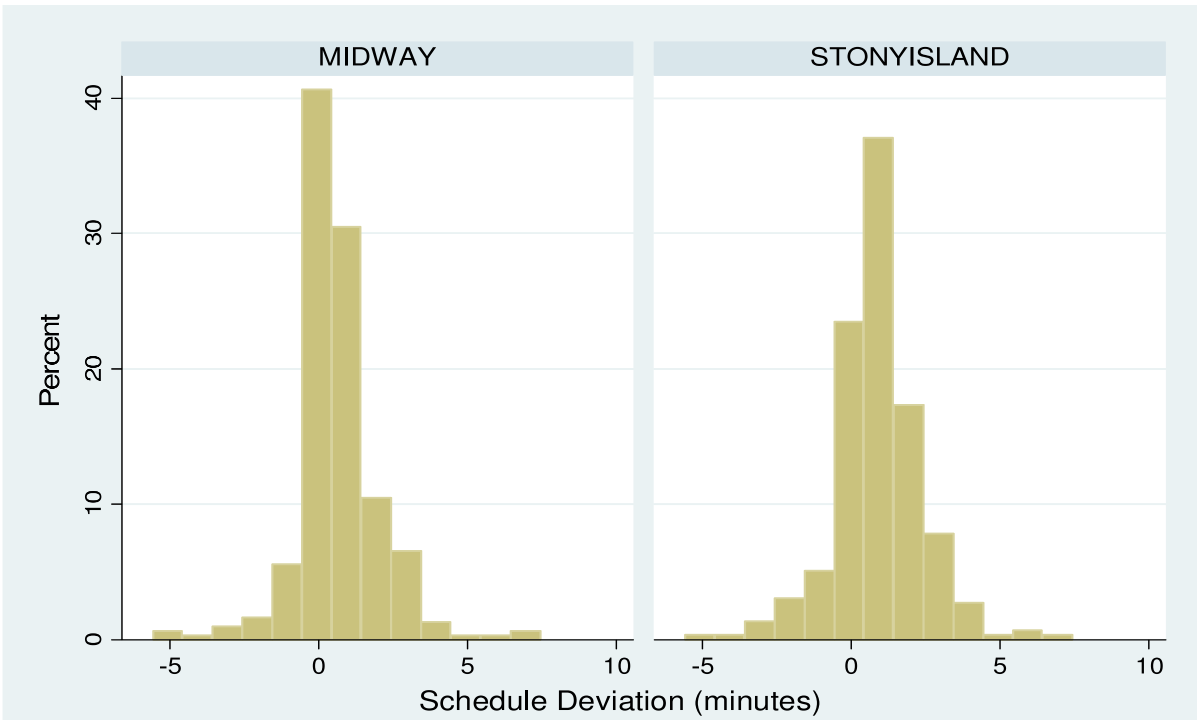
Table 5-12: Terminal Departure Schedule Adherence

	obs	mean	stdev	min	max
Midway	306	0.6	1.4	-4.8	6.9
Stony Island	295	0.9	1.5	-5.6	7.1

The CTA policy of no early terminal departures is evident when examining the histograms of the departure schedule adherence shown in Figure 5-12. The distribution of schedule deviation is similar at both terminals, with less than 10 percent of the trips departing early, and most of those within 2 minutes of the scheduled departure time. Late departures are more common, with a significant percentage of trips departing more than 2 minutes late.

The minimum recovery time analysis found the mean recovery time at Stony Island to be roughly one minute longer than the recovery time at Midway. The Stony Island penalty is also seen in situations with sufficient recovery time.

Figure 5-12: Schedule Deviation with Sufficient Recovery Time



To model the terminal departure accuracy, and allow for sensitivity testing of changes in the terminal departure policy, a two-stage distribution is developed. First, a uniform distribution is used to determine whether the operator departs early or late, then an exponential distribution is used to predict the actual schedule deviation. The parameters of these distributions are shown in Table 5-13. The small log likelihood magnitudes of the exponential distributions indicate a good fit of the distribution to the data.

Table 5-13: Route 63 Terminal Departure Accuracy

Terminal	deviation	exp - mu	exp – log likelihood	uniform - distribution
Midway	Early	35	-219	23%
	Late	63	-849	77%
Stony Island	Early	66	-239	25%
	Late	85	-762	75%

5.5.4 Model Functional Form

Segmenting the terminal departure recovery time according to the amount of recovery time (sufficient or insufficient) enables modeling terminal departure behavior for both situations. If there is insufficient time, the recovery time taken will be constrained by the minimum recovery time. If there is sufficient time, the recovery time will be determined by the operator tendency to depart on-time.

The amount of recovery time depends on the terminal departure policy. If the policy is to maintain schedule, the recovery time is calculated as the difference between the current time and the scheduled departure time. If the policy is to maintain headway, the recovery time is calculated as the balance of time before the next headway departure. The CTA terminal departure policy is to leave as close to the scheduled time as possible, regardless of the headway. The model in Equation 6 is used to calculate the recovery time as the maximum of the minimum recovery time and the available recovery time (including deviation).

Equation 6: Recovery Time Taken Model

$$RTime_i = Max(MinRTime_i, AvailTime(policy))$$
$$AvailTime(policy) = CalcTime(policy) + \delta_i$$

i = set of terminals, δ = available recovery time accuracy distribution

5.6 Passenger Demand Model

This section explains how passenger demand on a bus route is calculated across time and by location. Passenger demand is an important component in modeling bus service because it is a primary influence on the dwell time, as discussed in Section 5.4, and is necessary to evaluate the impact on passengers of service variability. Passenger demand is represented as a boarding rate for the entire route, which is then used to distribute boarding and alightings across the key stops and segments of the route in each direction.

The day to day variation in passenger boardings are analyzed first. Once these variations are controlled for, variations in passenger boardings across 15 minute time periods are analyzed. The passenger demand by location is then examined along the route in both directions. Finally, the passenger arrival behavior is analyzed. The result of this analysis is a model of the passenger demand by day, 15 minute time period, and key stop or segment.

5.6.1 Day to Day Variations in Passenger Demand

The CTA estimated hourly route ridership values are used to calculate the total boardings for the entire 14:00-18:00 time period. The summary statistics presented in Table 5-14 represent the day to day variation in passenger demand. There is a range of almost 2500 passengers between the maximum and minimum passenger boardings. Only passenger data from weekdays is analyzed so the overall trip patterns are similar and the variation in demand is likely due to weather and other exogenous factors.

Table 5-14: Route 63 Passenger Boardings (14:00 - 18:00)

	obs	mean	stdev	min	max
Boardings	15	7555	652	6269	8708

The dwell time model developed in Section 5.4 shows how passenger activity affects dwell time. Longer dwell times mean longer running times and less recovery time. Therefore, the variation in passenger demand will directly lead to variation in bus service reliability.

5.6.2 Passenger Demand by Time of Day

Besides day to day variations for the entire time period, the passenger demand is variable at a finer level of time granularity. The systematic component to this demand variability is due to repetitive scheduled activities such as work and school. Figure 5-16 shows the systematic variation in passenger demand by hour from the CTA estimated weekday boarding data in November 2006.

To get a finer level of detail on passenger demand, boarding counts from the AFC database are aggregated by 15 minute interval. As discussed in Section 4.3.2, the AFC database is not a complete record of all boardings; therefore it is necessary to scale each 15 minute boarding count by the ratio of the CTA estimated count of the hour over the AFC count. This process assumes that the ratio of AFC to total boardings is constant across the hour. This assumption was verified by examining the variation of the ratio hour to hour of the same day.

The day to day variation in passenger demand across the entire time period is controlled for by calculating the passenger demand per 15 minute time interval as a percentage of passenger demand across the entire time period. The scatter plots in Figure 5-14 show the percentage of the total time period passenger demand for each 15 minute time period. Note that there is little variation in the percentages within any time period. This implies that the passengers using this route have quite regular schedules. There may be some inverse correlation between adjacent 15 minute intervals, but this relationship results in small enough passenger counts that the overall effect in the model is negligible.

Figure 5-13: Route 63 PM Peak Ridership

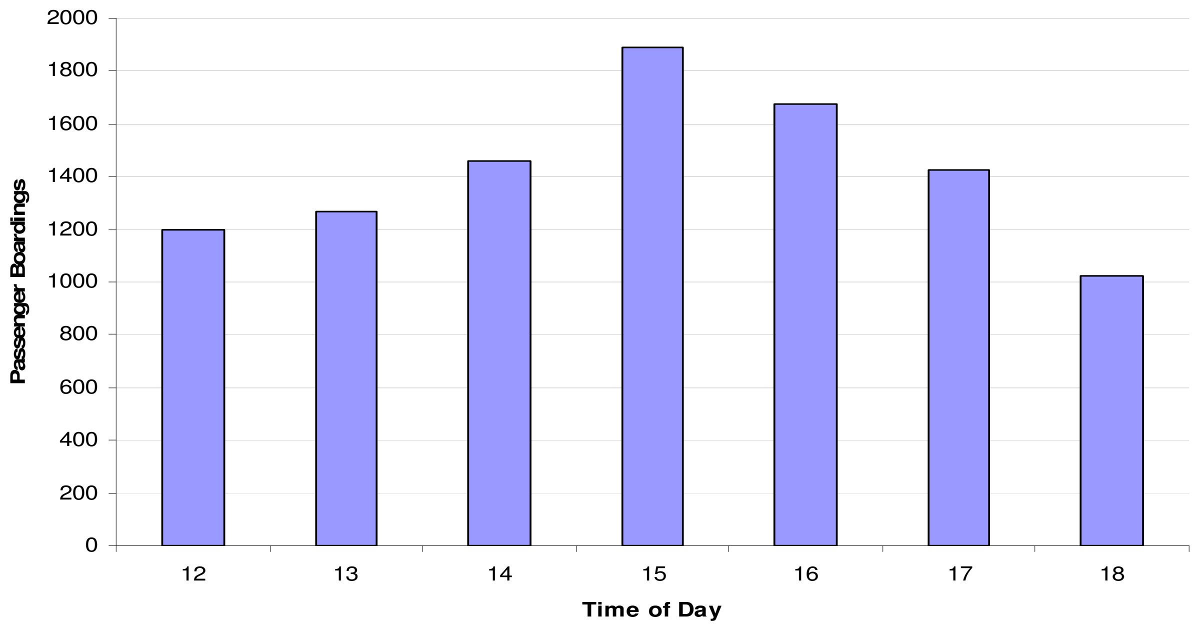
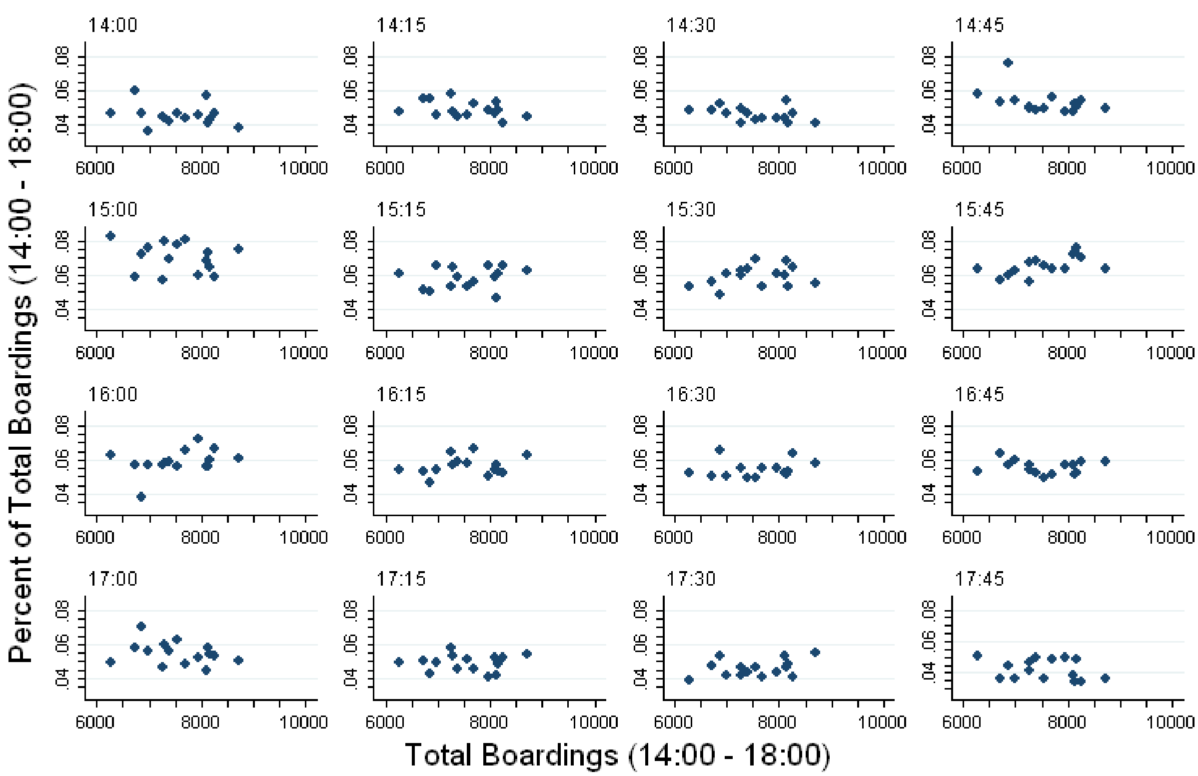
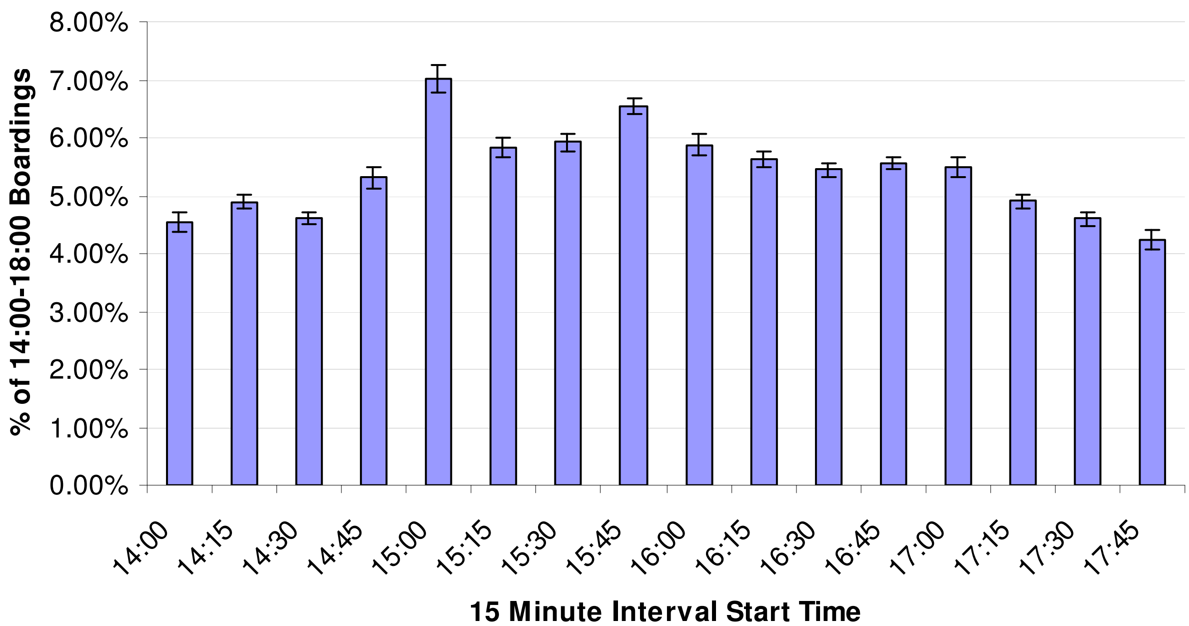


Figure 5-14: Percentage of Boardings per 15 Minute Time Interval



A few of the 15 minute intervals stand out as having clearly different percentages of the total boardings than the proximate intervals. The percentage of passengers on the 15 minute interval beginning at 15:00, for example, appears to be much higher than either the intervals at 14:45 or 15:15. This may represent the impact of children being released from school. The differences between the percentages of boardings across the 15 minute intervals are more obvious when comparing their means and standard errors as shown in Figure 5-15. For many of the time intervals, there does not appear to be a significant difference between the percentages of total boardings, for example 16:15 – 17:00 are all very similar. However, the sharp differences at 15:00, 15:45, and the decline after 17:00 all justify the development of the passenger demand model at the 15 minute level of granularity.

Figure 5-15: Mean and Standard Error of the Percentage of Boardings per 15 Minute Time Interval



5.6.3 Passenger Demand by Location

This section analyzes the allocation of demand across the key stops and segments of the route. The passenger demand allocation determines the passenger load profile and is a key component in evaluating reliability and operations control strategies, as discussed in Section 2.1.2.

The distribution of passengers across the route is determined by calculating the aggregate share of passengers served at each key stop and segment by direction from APC records. This method assumes that the distribution of passengers does not change over the time period selected and that the APC-equipped buses are representative of the entire population. These assumptions are necessary due to the issues in using APC data, as discussed in Section 4.3.2. Aggregation of the APC data avoids having to deal explicitly with the off-by-one errors that are common with this data collecting technology. The off-by-one errors are distributed across the entire route; therefore the ratio of passengers per stop to the total number of passengers is not significantly affected. Aggregation of APC data also makes best use of the limited available data. As shown in the summary statistics of Table 5-15, there are only 80 trips in each direction with working APC in this data set.

To analyze the passenger arrival rate characteristics, we assume that all passengers have arrived since the previous bus departed. Therefore, data to analyze the passenger arrival rate is collected only from trips where the preceding scheduled trip is recorded. This prevents an underestimation of the passenger arrival rate because an unrecorded trip may in fact be a bus serving passengers. Furthermore, it is necessary to enforce a minimum headway for this data set to avoid situations with bunched buses. If buses are bunched, some of the passengers waiting to board when the first bus arrives may board the second bus instead, especially if the first bus is crowded. A headway threshold of 100 seconds is used to avoid these situations. The summary statistics of the passenger arrival rate per minute are shown in Table 5-16. Note that the number of observations per key stop is sharply reduced from the 80 / 81 observations in the aggregate passenger demand data.

The APC data from all observations are summed to determine the total passengers boarding and alighting and the aggregate boarding and alighting counts per key stop and segment are then used to calculate the percentage of passenger activity at each stop and segment. The resulting percentages are displayed in Figure 5-16. Boarding passengers are shown as positive and alighting passengers are shown as a negative percentage of the boarding share on the left axis. Note also the passenger load profile plotted on the right axis is a sample passenger load assuming 120 passengers boarding the bus over the trip.

According to the passenger activity distribution, the peak load point is at Western (eastbound) and the Red Line Station (westbound). However there is a lot of passenger activity after the peak load point in both directions as indicated by the height of the column at each key stop.

Table 5-15: Route 63 Passenger Activity Summary Statistics

a) Eastbound

		Key Stop Ons			Key Stop Offs			Segment Ons			Segment Offs		
	obs	mean	stdev	max	mean	stdev	max	mean	stdev	max	mean	stdev	max
MIDWAY TERMINAL	80	8.8	8.2	30	0.0	0.0	0	1.4	4.6	27	0.0	0.0	0
CICERO	80	3.4	4.4	18	0.6	0.9	3	0.9	1.9	10	2.3	3.7	14
PULASKI	80	0.1	0.9	7	0.1	0.4	2	1.7	2.6	14	2.0	2.8	11
KEDZIE	80	0.9	2.1	10	0.7	1.8	10	1.3	2.3	11	1.4	2.3	11
CALIFORNIA	80	1.0	2.1	8	0.8	1.5	6	1.7	3.0	13	1.1	1.7	8
WESTERN	80	3.5	4.6	19	1.6	2.1	9	3.8	5.1	22	1.9	2.7	14
ASHLAND	80	4.0	4.1	15	5.8	6.6	38	0.8	2.0	11	1.2	2.4	14
RACINE	80	1.2	2.0	11	1.8	2.4	12	3.6	6.2	42	3.4	4.0	16
YALE	80	2.0	2.2	8	6.4	5.0	22	0.0	0.2	2	0.0	0.0	0
WENTWORTH	80	4.2	4.8	20	0.4	0.8	4	1.3	2.2	9	1.3	2.0	10
KING DRIVE	80	2.3	2.4	8	5.8	5.4	21	0.9	1.7	9	1.9	2.6	11
COTTAGE GROVE	80	2.9	3.4	13	5.0	4.2	14	1.4	2.5	11	4.3	6.0	39
STONY ISLAND	80	0.0	0.0	0	6.3	6.0	27	0.0	0.0	0	0.0	0.0	0

b) Westbound

		Key Stop Ons			Key Stop Offs			Segment Ons			Segment Offs		
	obs	mean	stdev	max	mean	stdev	max	mean	stdev	max	mean	stdev	max
STONY ISLAND	81	4.7	10.0	46	0.2	0.6	4	4.8	6.6	31	1.7	2.7	12
COTTAGE GROVE	81	5.3	5.1	18	3.4	3.4	15	1.5	2.3	9	1.4	1.9	7
KING DRIVE	81	5.0	4.9	23	3.2	3.0	11	4.4	5.6	19	2.5	3.0	15
RED LINE STATION	81	8.1	7.6	29	3.9	3.1	11	0.0	0.0	0	0.0	0.0	0
YALE	81	2.1	4.8	24	0.8	2.0	12	4.0	5.3	31	5.7	5.2	19
RACINE	81	1.9	3.2	22	3.3	3.3	14	0.4	1.0	5	1.3	1.6	6
GREEN LINE STATION	81	4.4	5.4	22	5.0	4.0	17	0.0	0.0	0	0.0	0.0	0
ASHLAND	81	2.6	3.9	14	0.4	1.0	5	3.0	4.5	24	5.0	5.9	29
WESTERN	81	2.5	3.3	16	5.5	4.4	19	0.7	1.3	6	3.1	3.4	12
CALIFORNIA	81	0.0	0.4	4	0.8	2.4	16	0.9	2.1	12	3.6	4.4	16
KEDZIE	81	1.6	2.5	12	2.4	2.9	12	0.8	1.5	6	1.3	1.7	6
PULASKI	81	1.0	2.3	10	1.4	2.2	15	0.5	1.0	4	1.2	2.3	15
CICERO	81	0.2	0.5	2	2.4	3.0	12	0.0	0.0	0	0.1	0.9	8
MIDWAY TERMINAL	81	0.0	0.0	0	2.9	3.1	16	0.0	0.0	0	0.0	0.0	0

Table 5-16: Route 63 Passenger Arrival Rates Summary Statistics

a) Eastbound

		Passengers Per Minute		
	obs	mean	stdev	max
MIDWAY TERMINAL	29	1.7	1.1	5.0
CICERO	25	0.5	0.4	1.7
PULASKI	24	1.0	0.9	4.0
KEDZIE	22	0.8	0.7	2.7
CALIFORNIA	25	0.7	0.7	3.0
WESTERN	24	1.1	0.8	3.2
ASHLAND	21	0.9	0.6	2.9
RACINE	26	0.3	0.4	1.7
YALE	17	0.4	0.4	1.7
WENTWORTH	21	1.0	0.6	2.4
KING DRIVE	26	0.5	0.6	3.1
COTTAGE GROVE	21	0.5	0.4	1.2

b) Westbound

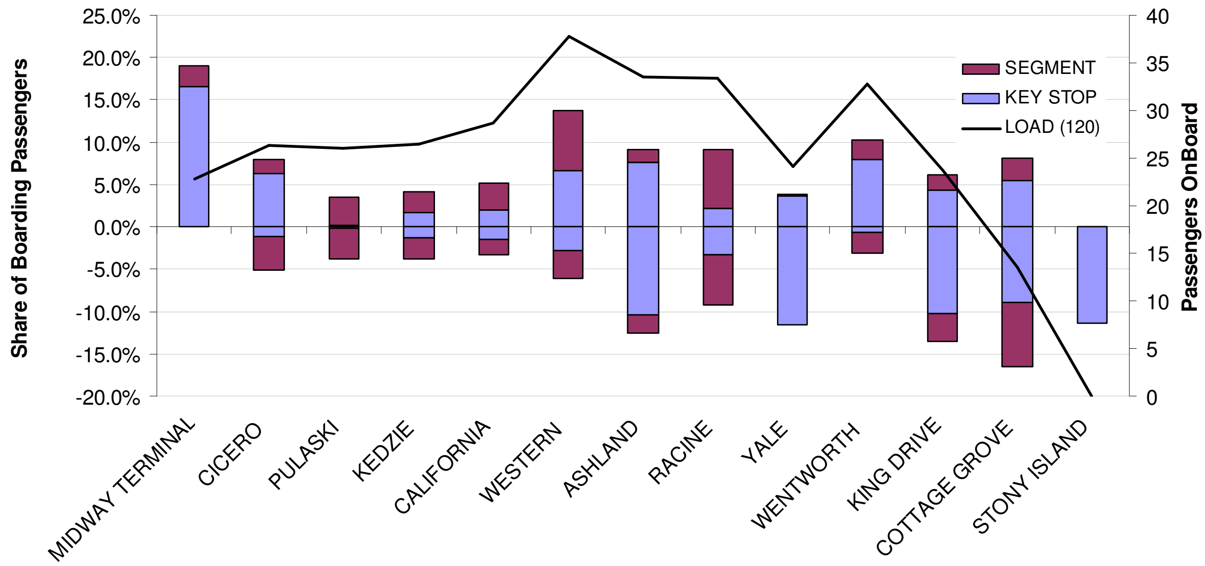
		Passengers Per Minute		
	obs	mean	stdev	max
STONY ISLAND	26	2.6	3.1	12.3
COTTAGE GROVE	24	1.0	0.7	2.0
KING DRIVE	27	1.1	1.1	6.1
RED LINE STATION	22	1.5	0.7	3.0
YALE	22	0.4	0.8	2.7
RACINE	19	0.4	0.5	1.7
GREEN LINE STATION	16	1.0	0.7	2.9
ASHLAND	15	0.4	0.6	2.2
WESTERN	14	0.4	0.4	1.1
CALIFORNIA	13	0.6	0.8	3.1
KEDZIE	15	0.3	0.2	0.8
PULASKI	14	0.2	0.3	1.0
CICERO	4	0.1	0.1	0.2

5.6.4 Passenger Arrival Process

Passenger arrivals may be conveniently represented by a Poisson process (Larson and Odoni, 1981) The prevalence of transfers in the CTA system, however, may cause lumpy arrivals of passengers as vehicles carrying multiple transferring passengers arrive on other bus or rail lines. The impact is seen through histograms of the passenger arrivals per second at the key stops with transfers to the rail line or other major bus routes in Figure 5-17. If there are a significant number of lumpy arrivals, there would be a second harmonic in the passengers per second distribution.

Figure 5-16: Route 63 Passenger Activity

a) Eastbound



b) Westbound

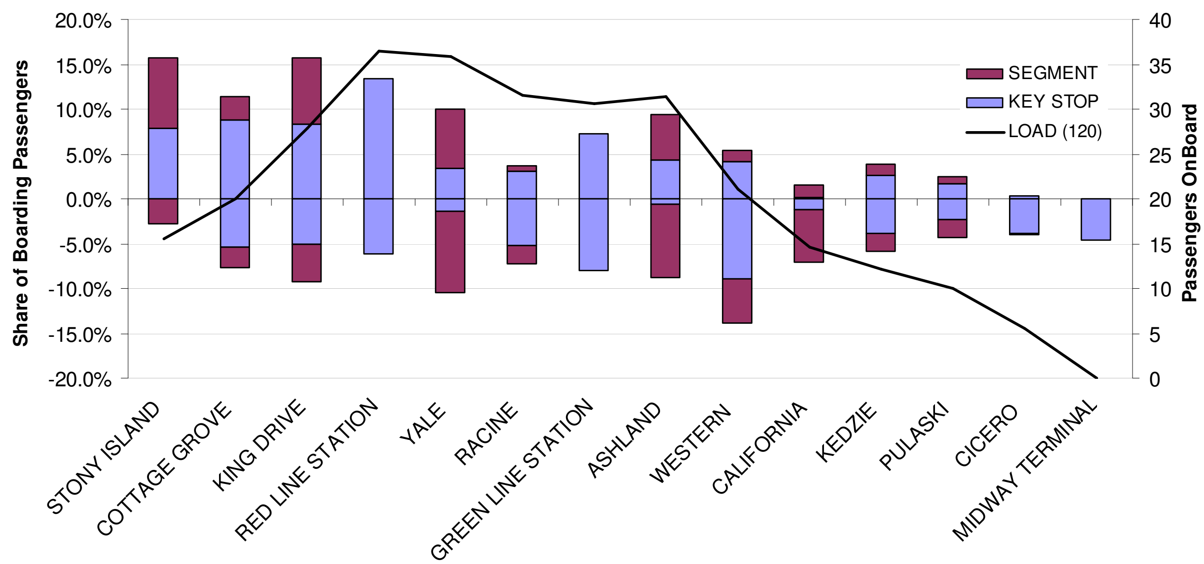
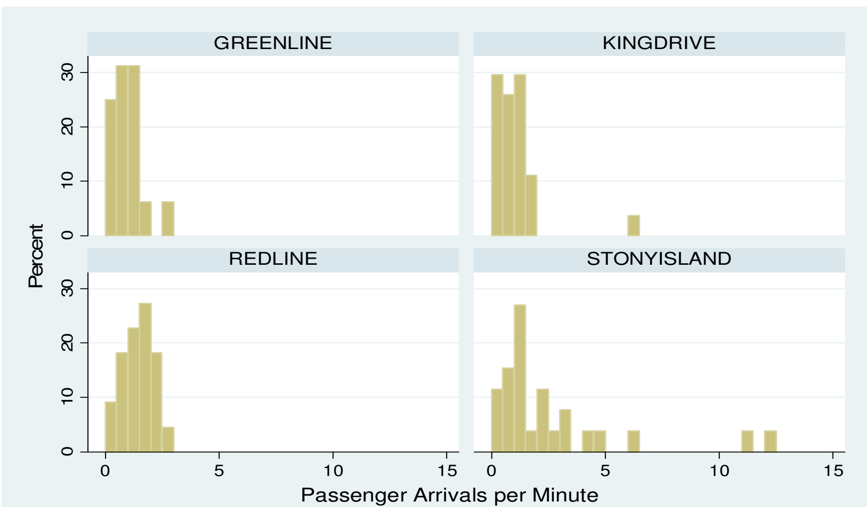


Figure 5-17: Route 63 Passenger Arrival Characteristics

a) Eastbound

b) Westbound



There are some observations of passenger arrivals per minute that are beyond the group at Midway (eastbound) and Stony Island and King Drive (westbound). Besides these cases, the boardings per second distributions do not show strong irregularity due to lumpy arrivals. This is likely due to the irregular transfer loads smoothing out the distribution.

5.6.5 Model Functional Form

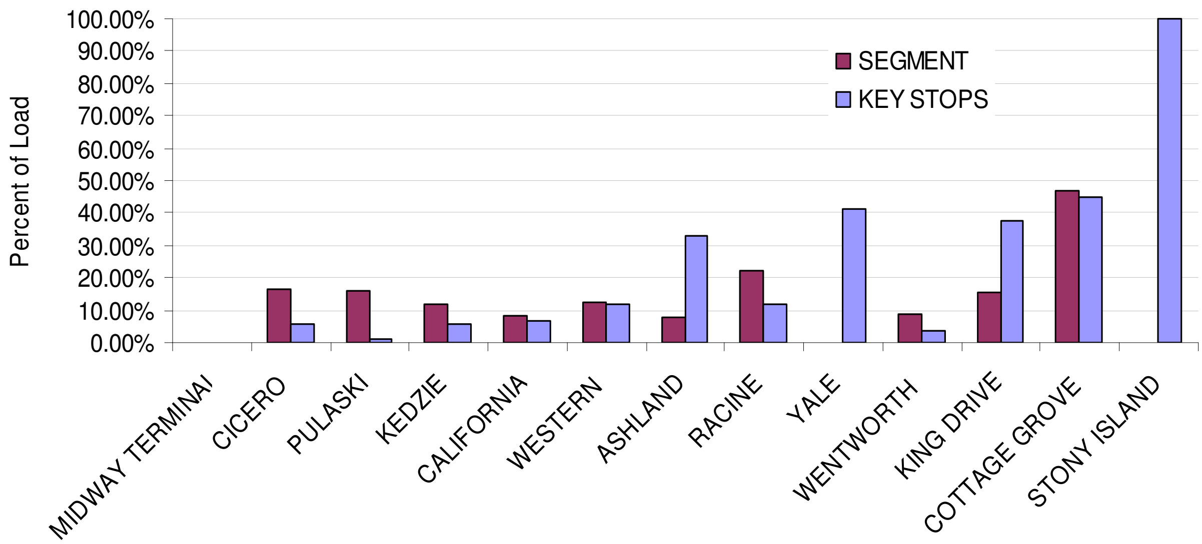
The passenger demand model is a sequence of steps that begins with the estimation of the overall passenger boardings for the entire time period and concludes with estimates of passenger arrivals per minute and percentage of passengers alighting at each key stop and segment. The passenger demand model sequence is described below:

1. Using the distribution of the official ridership in Table 5-14, estimate the passenger boardings for the entire time period.

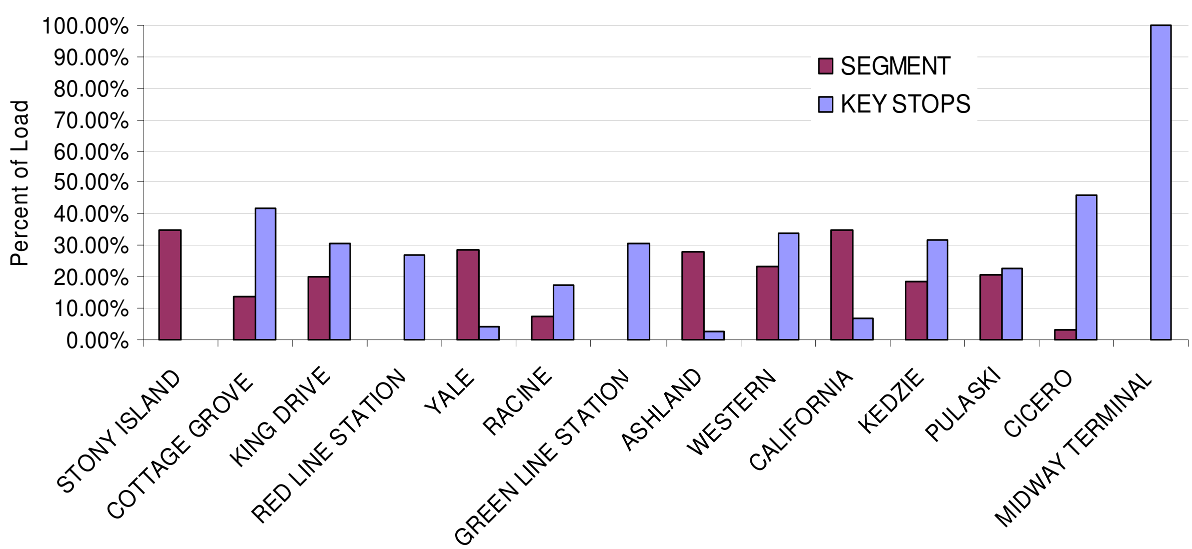
2. Apply the percentages in Figure 5-15 to calculate the passenger boardings for each 15 minute time period.
3. Apply the boarding percentages in Figure 5-16 to calculate the passenger boarding rate at each key stop and segment.
4. Use a Poisson distribution to calculate the passenger arrivals.
5. Calculate the alighting passengers from the percentages in Figure 5-18. These percentages are calculated from the alighting percentages shown in Figure 5-16.

Figure 5-18: Route 63 Passenger Alighting Percentages

a) Eastbound



b) Westbound



6 Model Validation

Model verification and validation is one of the most important steps in the modeling process. North and Macal (2007) put this step into context with the phrase: "Before verification and validation, models are toys; after verification and validation, models are tools." The authors go on to describe verification as the process of ensuring that the model inputs are correctly calculated and that the model itself is correctly programmed. Validation, on the other hand, is the process of confirming that the model actually reproduces the observed real-world behavior.

In Section 6.1, the parameters for the verification and validation testing are discussed, Section 6.2 briefly reviews the verification procedure and results, and Section 6.3 discusses the validation tests and results.

6.1 Verification and Validation Application

The simulation is validated at the period of peak demand on the route because this is the time when operations strategies will have the greatest impact on passengers and the variability of the running times and magnitude of the passenger demand will generally be greatest. In other words, the peak demand period is the most challenging to operate and has the greatest impact on passengers if service is poor.

Route 63 is scheduled to provide at most 6 minute headways for trips starting between 14:00 and 16:15. The CTA-estimated ridership per hour is shown in Figure 5-13 with the peak passenger demand occurring over the 15:00 hour.

However, it is not sufficient to simulate only trips during the peak period because the prior state of the route will impact the initial trips in the period of interest. It is necessary to simulate the trips immediately preceding the peak time period as well as those during this period and so trips that begin as early as 12:00 are included in the simulation. At the beginning of the simulation, headway cannot be used to estimate passenger arrivals because not all of the trips are populated, which makes the headway invalid. To compensate for this, the model operates in an initialization state from 12:00-13:00. In this state, passenger demand is calculated based on a constant scheduled - rather than actual - headway. By 13:00, all trips in the schedule are populated in the model and actual headways can be used to estimate passenger arrivals.

Data from the simulation model is aggregated across 10 independent model runs (representing 10 days of operation), each with a different random seed variable. This produced about the same number of observations as was collected over 15 days of real world AVL data. As discussed in Chapter 4, the disparity is due to unreported or unfilled trips; this means that only 60% of data from scheduled trips are captured and usable. Real world observations of segment running time or dwell time that were identified as outliers in Chapter 5 are excluded from this analysis representing approximately 1% of the real world trips.

Two statistical tests are used to compare model results with actual observations from the route. To compare means, the two-sample, two-tail t-test is used. To compare variances, the two-sample f-test for variances is used. These tests measure the level of statistical significance in differences between the samples. The 5% level of significance is used as the measure of success, i.e. if the means/variances are not statistically significantly different at a 95% confidence level, they are considered to be equivalent.

6.2 Verification

This section briefly describes the aspects of the model that are verified for correct behavior based on the functional form of the input models presented in Chapter 5 and the CTA bus operating procedures described in Chapter 4. Proper verification of the simulation model is key to ensure that the model results are a product of correct model function. The process of verification is described below:

Visual Inspection: The GUI component of the simulation model is particularly useful in the verification process. By simply looking at the initial model state, the route layout configuration can be verified. Visually monitoring the running model verifies that bus pull-outs/ins, route progress, and terminal layovers are programmed correctly.

Code Walkthroughs: To confirm that the bus travel time, dwell time, terminal behavior, and passenger demand are all calculated correctly, the model is run in “debug” mode and the associated methods are stepped through to confirm correct programming structure.

Simulated Data Comparison: Where a fitted distribution is used in the simulation model to represent an aspect of the real world, it is necessary to test that the mean and variance are not statistically significantly different between the observed data and the model output. The distributions verified are those for terminal departures (minimum recovery time and departure accuracy only), passenger arrival rates (mean only), and dwell time (reliefs and atypical passenger distributions only). Segment running time is determined by sampling from the real world observations (summarized in Table 5-1) so it is necessary only to confirm that the random sampling is programmed correctly.

6.3 Validation

Validation is an iterative process of model testing and improvement. While a model may be verified, it is never fully validated: there is always another validation test that may be conducted and each test that the model passes increases the user's confidence in the model results. The validation tests needed before using a model confidently will depend on the application of the model.

The aspects of the bus route operation that must be validated will depend on the reliability metrics that are used to measure performance of the route. The initial values of these metrics will be the baseline performance against which any new operations control strategy will be compared.

As discussed in Section 2.1.1, the purpose of this model is to study bus service reliability with performance reflected in the following metrics: passenger waiting time, crowding, and schedule adherence at the terminals and relief points. Due to limited data on the route (specifically passenger data), the passenger-centric metrics of waiting time and crowding from the model cannot be compared directly with the route functions, but may be inferred through a comparison of the trip time and headways of the real world and simulation observations. Passenger waiting time and crowding are functions of the headway deviation (by location) and the passenger demand. Once headway deviation is validated and passenger demand is verified, passenger waiting time and crowding in both the model and the real world are generated through the same computational process. Validating the components of these metrics and verifying the process to generate them are equivalent to validating the metrics directly.

A good approach to model validation is to start with the most basic aspects first, then progress to the more complex aspects that build on the basic ones. Trip time, headway, and schedule adherence all incorporate the impact of dwell time, so it is first necessary to validate the dwell time. The dwell time comparison is considered to be a validation step as opposed to verification because, unlike segment running time, dwell time is generated within the simulation model; it is not simply a model input.

With this in mind, the dwell times are analyzed first, and then trip times, followed by the schedule adherence at terminals and timepoints, and finally the headways are compared. Once validation has been completed on the metrics that can be compared to real world data, passenger waiting time and crowding can be examined.

6.3.1 Dwell Time

This section summarizes the normal (excluding holding and operator reliefs) dwell time validation tests and model adjustments. Dwell time is calculated in the model as a function of passenger demand, onboard crowding, and passenger alighting door choice and includes an error term to account for normal and "atypical" passenger variations. Observed dwell time clearly depends on passenger activity however the stop location may also be a significant factor.

Data Analysis

Table 6-1 shows the statistics and comparison test results for modeled and real world dwell times in seconds. The mean ratio is calculated as the mean of the real world observations divided by the mean of the model results. The statistical comparison results are presented as: 0 = no statistical difference; 1 = model results are statistically significantly larger than the real world results; -1 = model results are statistically significantly smaller than real world results. Terminals are not included in this comparison because it is impossible to determine what part of the recovery time is actually serving passenger demand from the AVL records at terminals.

All of the comparison test failures, which occur in 80% of the cases, are due to under-estimation of the dwell time in the model. The estimators for the dwell time model were calculated using a data set including only low-floor buses for "far-side" stops (i.e. stops located after an intersection). The TCQSM (Kittleson and Associates et al., 2000) default values of passenger boarding and alighting dwell time are about 20% higher for high-floor buses (the bus type serving route 63). The observed dwell time at "near-side" stops may also be longer and more variable than at far-side stops with similar passenger demand because the recorded dwell time may include some component of the travel time (e.g. waiting with the door open at a traffic light) as discussed in Section 4.3.2. Also, the actual data for the per-stop passenger arrival rates is limited and variable (see Table 5-13). With those caveats, it is no surprise that the real world and modeled dwell times do not match.

Table 6-1: Dwell Time Comparison

a) Eastbound

stop	location	Real World mean	Real World stdev	Model mean	Model stdev	Comparison mean	Comparison variance	mean ratio
CICERO	FS	26.3	21.9	17.6	12.8	-1	-1	1.49
PULASKI	FS	5.3	15.4	4.6	11.3	0	0	1.14
KEDZIE	NS	14.3	27.3	7.8	7.9	-1	-1	1.82
CALIFORNIA	FS	10.9	18.2	8.3	7.9	-1	-1	1.31
WESTERN	FS	29.8	30.6	24.7	19.0	-1	-1	1.21
ASHLAND	FS	82.7	38.3	36.6	22.2	-1	-1	2.26
RACINE	NS	21.4	20.3	10.1	10.4	-1	-1	2.11
YALE	NS	34.8	25.2	25.6	17.8	-1	0	1.36
WENTWORTH	FS	26.9	23.1	23.5	23.8	0	0	1.15
KINGDRIVE	FS	38.4	28.8	19.9	16.1	-1	-1	1.93
COTTAGEGROVE	NS	38.7	31.4	25.7	23.8	-1	0	1.50

b) Westbound

stop	location	Real World mean	Real World stdev	Model mean	Model stdev	Comparison mean	Comparison variance	mean ratio
COTTAGEGROVE	NS	54.5	36.7	30.9	23.5	-1	-1	1.77
KINGDRIVE	NS	50.9	35.5	27.6	21.3	-1	-1	1.84
REDLINE	MB	56.0	39.0	41.2	33.0	-1	0	1.36
YALE	FS	12.0	17.0	10.5	10.7	0	-1	1.14
RACINE	NS	26.2	22.7	14.5	12.9	-1	-1	1.81
GREENLINE	TERM	38.5	38.5	28.7	22.1	-1	-1	1.34
ASHLAND	FS	20.9	22.6	11.7	13.1	-1	-1	1.79
WESTERN	NS	40.5	30.2	21.3	15.1	-1	-1	1.90
CALIFORNIA	FS	3.8	7.3	1.5	4.0	-1	-1	2.46
KEDZIE	FS	14.5	16.7	13.6	11.6	0	0	1.07
PULASKI	NS	29.5	32.1	9.2	10.2	-1	-1	3.21
CICERO	NS	18.7	23.4	7.6	10.3	-1	-1	2.47

The consistently longer dwell times due to high floor buses on route 63 versus the predicted dwell time from the low-floor bus dwell time model are likely the cause of the systematic underestimation of dwell times at each stop in the simulation model. A 20% overhead for high floor buses in the dwell time will reduce the difference in the mean dwell time at all the stops, and may make several of the mean stop dwell time comparisons no longer statistically significantly different (e.g. California, Western, Yale (eastbound); and Red Line, Green Line (westbound)).

All of the near-side stops have a mean ratio of at least 1.5 (with the exception of Yale (eastbound)). Moreover, only near-side stops (with the exception of Ashland, King Drive (eastbound), and California (westbound)) have a mean ratio of greater than 1.75. Thus, stop location is also having a noticeable impact on dwell time. When predicting dwell time in the simulation model, detailed traffic and signal timing information would be required to calculate the degree to which the dwell time would be extended by a traffic signal. If the predicted dwell time at each far-side stop was scaled by a factor of 1.75, the mean modeled dwell time would be closer to the mean real world dwell time. Using such a scalar, however, assumes that the dwell time variation is well correlated with passenger activity, which may not always be true. For example, two passengers may cause a long dwell time at a near-side stop if they arrive 1 minute apart while the bus is waiting for the signal to change.

Although the estimate of overall passenger ridership is reliable, the allocation of passenger demand across key stops and segments is likely to have non-systematic errors due to the limited number of passenger counts. Errors in the passenger demand estimates (boarding and alighting) will effect the dwell time and may bias the model crowding and passenger waiting time. For example, the model may overestimate the level of crowding on the route if the alighting percentage is overestimated early in the route. More likely, there are negatively correlated errors in the estimated passenger demand between adjacent stops and segments. Overestimation of the passenger arrival rate on a segment correlated with underestimation on an adjacent key stop will cause the predicted stop dwell time to be too low, but not significantly impact the actual passenger loading and waiting time. It is tempting to use the dwell time comparison mismatches as a guide to adjust the passenger demand between stops and segments. But, any passenger demand redistribution must balance boardings and alightings and account for any near-side stop penalty, which will depend on the signal timing and traffic at the intersection.

To compensate for different bus types, stop locations, and potential passenger demand errors, the mean dwell ratio at each stop from Table 6-1 is implemented in the model as a scalar applied to the predicted dwell time. Use of a different scalar at each stop is appropriate because the passenger demand errors may not be systematic and the near-side stop impacts may not be consistent. Table 6-2 shows the model and real world dwell time comparisons with the mean ratio scalar applied. There is not a statistically significant difference in the mean dwell time at any stop, but the modeled dwell time at several stops in each direction has a greater variance than for the real world observations. The standard deviation of the dwell time per stop in Table 6-2 is not always an exact product of the mean ratio and standard deviation from Table 6-1 because the changes in dwell time impact other aspects of operations. When dwell times are increased, there is less terminal recovery time and hence more variable headways. Bunched buses will have a higher headway deviation than buses with an even headway because of the differences in passenger activity.

Table 6-2: Modified Dwell Time Comparison

a) Eastbound

		Real World		Model		Comparison	
stop	location	mean	stdev	mean	stdev	mean	variance
CICERO	FS	26.3	21.9	29.8	26.7	0	0
PULASKI	FS	5.3	15.4	5.0	8.8	0	-1
KEDZIE	NS	14.3	27.3	16.8	21.0	0	0
CALIFORNIA	FS	10.9	18.2	11.1	12.4	0	0
WESTERN	FS	29.8	30.6	29.2	22.3	0	0
ASHLAND	FS	82.7	38.3	75.3	45.7	0	0
RACINE	NS	21.4	20.3	22.7	23.3	0	0
YALE	NS	34.8	25.2	35.1	20.9	0	0
WENTWORTH	FS	26.9	23.1	25.7	25.8	0	0
KINGDRIVE	FS	38.4	28.8	38.0	30.8	0	0
COTTAGEGROVE	NS	38.7	31.4	38.9	34.1	0	0

b) Westbound

		Real World		Model		Comparison	
stop	location	mean	stdev	mean	stdev	mean	variance
COTTAGEGROVE	NS	54.5	36.7	57.3	42.1	0	0
KINGDRIVE	NS	50.9	35.5	50.1	42.5	0	0
REDLINE	MB	56.0	39.0	58.9	47.0	0	0
YALE	FS	12.0	17.0	11.1	12.4	0	0
RACINE	NS	26.2	22.7	28.1	27.0	0	0
GREENLINE	TERM	38.5	38.5	37.6	32.1	0	0
ASHLAND	FS	20.9	22.6	19.1	21.9	0	0
WESTERN	NS	40.5	30.2	38.7	29.3	0	0
CALIFORNIA	FS	3.8	7.3	5.7	13.9	0	1
KEDZIE	FS	14.5	16.7	13.1	11.8	0	0
PULASKI	NS	29.5	32.1	32.1	49.3	0	1
CICERO	NS	18.7	23.4	19.8	30.6	0	0

Using the mean ratio to scale the dwell time does not make the dwell time model superfluous. Successive bus trips should interact with each other through a dwell time that is sensitive to headway. Through the model, dwell time is calculated according to passenger activity, which is determined by headway, before it is scaled. Therefore, the assumptions necessary to adjust the dwell time at each stop are reasonable to validate the model.

The differences in standard deviation are small compared with the overall route running time and its standard deviation of about 1 hour and 4 minutes respectively. If the differences are significant, it will affect the comparison of trip times.

6.3.2 Trip Time

Simulating trip times accurately is important for all of the reliability metrics. The most obvious connection is with the schedule adherence metric at relief points and terminals. Through the terminal schedule adherence, trip times also influence the headway variability. Terminal recovery time affects the probability that a bus can begin its next trip on-time, and if the recovery time is exhausted by a long trip time, the headway on the following trip will probably be significantly different from the scheduled headway.

Trip times are calculated as the time from terminal departure to arrival at the next terminal and are independent of schedule deviation. The travel time is the sum of the segment travel time and key stop dwell times across the entire route.

Data Analysis

The trip time analysis compares actual and simulated running times of full length trips. Of the 48 total scheduled trips in the validation period (trips starting between 14:00-16:15), 3 trips are not full length and are excluded from this part of the validation.

Although there is a 2-minute increase in the scheduled running time between trips starting at 14:00 and trips starting at 15:00, there is no statistically significant difference in the observed mean trip times between these periods. Therefore, trip times are aggregated and compared across the entire period.

Table 6-3 compares the trip times (in minutes) between the real world and model observations. The standard deviation of the trip times is equal and the mean trip time is within half a minute so both are well within the 95% confidence interval.

Table 6-3: Trip Time Comparison

a) Eastbound

	obs	mean	stdev	min	max
Real World	267	58.9	4.4	48	79
Model	227	59.1	4.4	49	70

b) Westbound

	obs	mean	stdev	min	max
Real World	239	62.4	5.4	53	81
Model	221	62.1	5.4	50	81

Validated trip times confirm that the aggregation of the segment travel times and the dwell times accurately reproduce real world data. The next level of complexity in the reliability metrics to be validated is the schedule adherence at terminals and relief points.

6.3.3 Schedule Adherence

Schedule adherence is sensitive to the running and start time of the trip. The trip running times were validated above and the terminal departure behavior distributions have also been verified, but the actual start time of the trip is sensitive to the available recovery time. The available recovery time is determined by the scheduled recovery time, schedule adherence upon departure from the previous terminal, and the previous trip running time. Thus the schedule adherence of each trip depends on the schedule adherence of the previous trip, which depends on the schedule adherence of its previous trip, etc. This regression continues back to the point the bus pulled out of the garage. If the observed and modeled schedule adherences match, these functions and feedback loops are operating correctly.

Data Analysis

The schedule adherence upon arrival at terminals and relief points are collected from trips that begin between 14:00 and 16:15.

Table 6-4 displays the summary and test statistics in minutes. The variances are similar, but the mean value of schedule deviation on westbound trips at Midway is statistically significantly lower than the observed mean, as indicated by the t-statistic of -4.04 that has a greater magnitude than the critical value of -1.96.

Table 6-4: Schedule Adherence Comparison

a) Midway Station

	obs	mean	stdev	min	max	Test Statistic mean
Real World	277	7.7	5.8	-3.0	28.2	-4.04
Model	241	5.6	5.8	-9.5	31.3	

b) Stony Island

	obs	mean	stdev	min	max	Test Statistic mean
Real World	285	5.2	4.8	-2.9	24.4	-1.39
Model	240	4.7	4.8	-5.6	19.0	

The summary and test statistics in Table 6-5 show that the schedule adherence at the relief points is not statistically significantly different (mean t-test two tail critical value: 2.00, two sample f-test for variances critical value: 1.52 for Ashland (eastbound), 1.60 for Green Line (westbound)). This shows that, at least for trips with an operator relief, the model is accurately reproducing the schedule deviation at the relief point, which is about the mid-point of the route.

Table 6-5: Relief Point Schedule Adherence

a) Ashland (eastbound)

	obs	mean	stdev	min	max	Test Statistics mean	var
Real World	75	3.3	4.0	-3	15	-1.54	1.43
Model	60	2.6	3.4	-4	11		

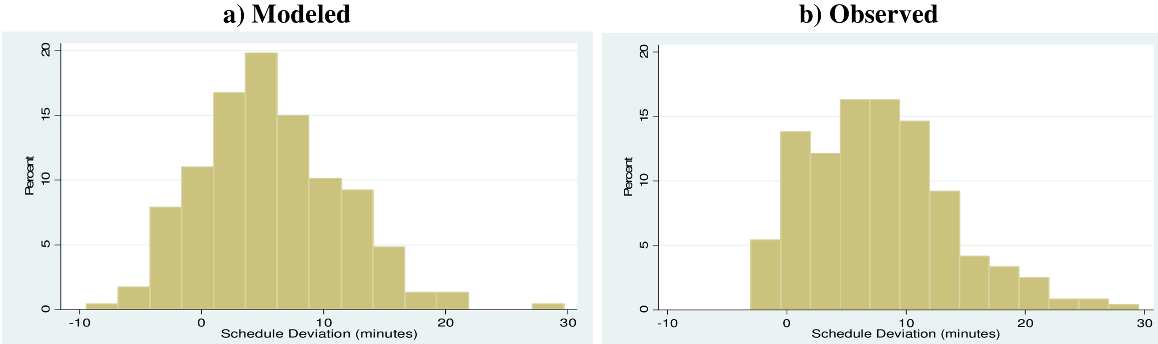
b) Green Line (westbound)

	obs	mean	stdev	min	max	Test Statistics mean	var
Real World	52	4.1	4.3	-2	22	0.22	1.37
Model	53	4.2	3.7	-3	14		

Figure 6-1 shows the distribution of modeled and observed schedule deviations for westbound trips arriving at the Midway terminal (positive schedule deviation means the bus arrived late). The real world observations show a greater number of trips arriving at Midway more than 15 minutes late and fewer trips more than 5 minutes early. Fewer early trips may be due to operators not wanting to arrive at the terminal ahead of schedule. More late trips may be due to a particular operator or group of operators that systematically take longer to serve the route and do not depart the terminal on-time. The interaction of consistent operator behavior and the regression loop of available recovery time, described above, may cause more late trips.

Figure 6-1: Schedule Deviation of Westbound Trips at Midway

a) Modeled **b) Observed**



The model implementation assumes that there is no significant difference in operator behavior because no consistent, significant behavior could be found in the running time analysis presented in Section 5.3.4. The difference in schedule deviation shown in Figure 6-1, however, suggests that there is an impact on route performance due to operator behavior that could be incorporated in a future version of the model. The lack of an operator-specific attribute in the simulation model requires the assumption that all operators behave consistently. If operators are consistently behind schedule, they may reduce the available recovery time. Therefore, the model may have more regular headways and be less sensitive to factors influencing reliability. A comparison of the headway variation will show how much the schedule deviation difference impacts the total route reliability.

6.3.4 Headways

Passenger waiting time is a function of headway deviation, passenger demand, and crowding (to capture cases where passengers are unable to board the first bus) which itself depends on passenger demand and headway. The passenger arrival rates in the model have been verified against the input values. Therefore, it is necessary to validate the modeled headway to have confidence in the passenger waiting time metric values. Because the key stops have the greatest passenger demand, headway statistics are compared at each of the key stops along the route.

Mean headways will only vary if the scheduled and actual trips are different or if the schedule in the model is incorrect. Barring these two situations, the same number of buses will be on the street therefore the average headway will be the same over the time period regardless of how the buses are distributed.

The variance of the headway, however, depends on the synthesis of all inputs to the route (trip times, passenger rates, terminal departure behavior, etc.). Validation of the headway variance signifies that the simulation model is giving appropriate weight to each factor influencing bus service reliability. Headway variance is also a good measure of route performance because short and long headways both increase the variance, instead of canceling each other out as in the case of the mean.

CTA has defined headway thresholds of "big gaps" and "bunching" as service quality metrics. Big gaps are defined as headways that are larger than the greater of twice the scheduled headway or fifteen minutes, bunching is defined as headways that are less than 1 minute. To present model results similar to the agency reliability metrics, the model is also validated against these measures of headways.

Data Analysis

The headways are calculated as the difference in departure time at each of the key stops on trips starting between 14:00 and 16:15. To avoid artificially high headways due to non-reporting buses, only headways where the preceding scheduled trip is recorded are included in the analysis (see Appendix B for more detail on this process). Through this process, non-reporting buses directly and indirectly make about 1/3 of the headways unusable.

The resulting means and standard deviation of the headway (in minutes) and the result of the t and f tests with 5% level of significance at key stops are shown in Table 6-6. The model reproduces the mean scheduled headway of ~6 minutes in each direction, but the real world mean headway is, in some cases, significantly shorter than scheduled. One potential cause of the shorter observed headways is that the unrecorded trips are actually unfilled trips. For example, if trip “A” is not filled, the next trip (trip “B”) is likely to be delayed due to the larger passenger demand. This reduces the headway between trip B and the following trip “C”. Headways following unfilled trips are excluded from the data analysis; but these may in fact be longer than average headways. Therefore, there may be a short headway bias in the data collection, which would cause a lower mean headway. The presence of a lower mean headway suggests that this route does sometimes operate with unfilled trips.

Unrecorded trips may also cause the observed variance to be less than it is in reality. This is evident in the comparison because the model has a higher variance in three out of the four cases where the modeled headway variance is statistically significantly different from the real world headway variance. The differences in the standard deviation between the model and the real world are all less than one minute, (with the exception of Cottage Grove (eastbound)). As expected due to increased variability, the standard deviation in the model headway increases along the course of the route.

Table 6-6: Headway Comparison

a) Eastbound

stop	Real World mean	Real World stdev	Model mean	Model stdev	Comparison mean	Comparison variance
Midway	6.0	2.4	6.1	2.3	0	0
Cicero	5.9	2.7	6.1	2.8	0	0
Pulaski	5.9	3.4	6.0	3.2	0	0
Kedzie	5.8	3.6	6.0	3.5	0	0
California	6.2	4.1	6.1	3.5	0	-1
Western	5.9	4.0	6.1	3.7	0	0
Ashland	5.8	4.2	6.1	4.2	0	0
Racine	5.8	4.3	6.1	4.5	0	0
Yale	5.3	4.5	5.8	4.8	1	0
Wentworth	5.4	4.7	5.9	5.2	0	0
KingDrive	5.8	5.2	6.0	5.5	0	0
CottageGrove	5.3	4.9	5.8	6.0	1	1

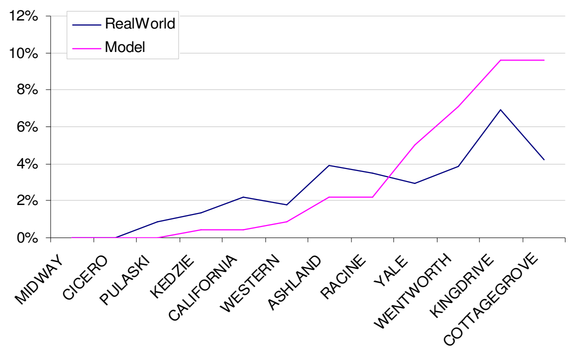
b) Westbound

stop	Real World mean	Real World stdev	Model mean	Model stdev	Comparison mean	Comparison variance
StonyIsland	5.7	3.0	5.8	3.1	0	0
CottageGrove	5.6	3.7	5.9	3.9	0	0
KingDrive	5.6	4.1	5.8	4.3	0	0
RedLine	6.0	4.8	5.8	4.5	0	0
Yale	5.5	4.5	5.8	4.6	0	0
Racine	6.1	5.0	5.8	4.9	0	0
GreenLine	5.9	5.2	5.9	5.1	0	0
Ashland	5.3	4.5	5.9	5.3	0	1
Western	5.3	5.0	6.0	5.8	1	1
California	5.3	5.1	5.9	5.6	1	0
Kedzie	5.4	5.3	5.9	5.6	1	0
Pulaski	5.3	5.3	5.9	5.8	0	0
Cicero	5.2	5.6	6.0	5.7	1	0

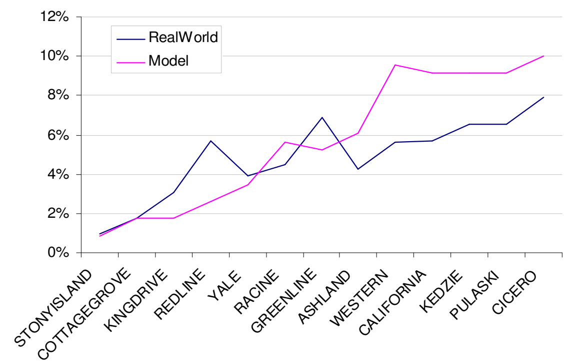
Figure 6-2 compares the percentage of big gaps and bunched headways in the model and the real world. The model results reproduce the expected upward trend of bunching and big gaps as buses progress along the route in each direction. Comparison of the overall trend is more important than the exact values because small changes in the headway may change the total count significantly, i.e. if headways are close to the threshold values of 60 seconds and 15 minutes respectively. The model appears to overestimate the number of big gaps towards the end of the route. However the observed mean headway shown in Table 6-6 towards the end of the route being less than the scheduled headway of 6 minutes suggests there may be longer headways that are not observed and these may be categorized as big gaps.

Figure 6-2: Big Gap and Bunching Comparison

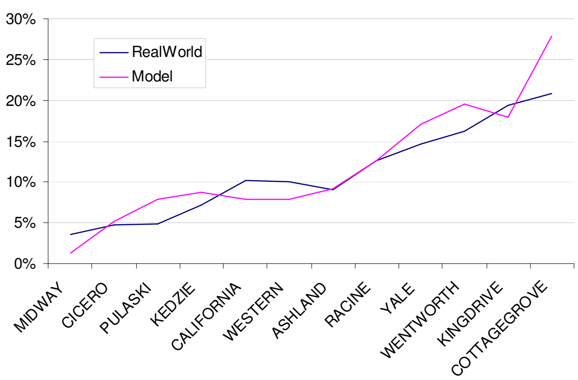
a) Big Gap - Eastbound



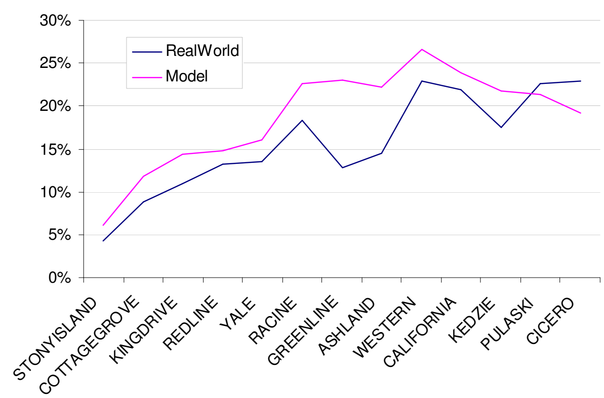
b) Big Gap - Westbound



c) Bunching - Eastbound



d) Bunching - Westbound



7 Sensitivity Analysis and Model Applications

The previous chapter verified and validated the simulation model output based on the trip times, headway variation, and schedule adherence. In this chapter, the simulation model is used in a series of sensitivity analyses and applications. The results of these tests are evaluated based on the passenger waiting time and passenger crowding reliability metrics identified as important in prior research discussed in Section 2.1.1 as well as the CTA big gap (>15 minutes) and bunching (<1 minute) metrics explained in Section 4.2.1.

Before beginning the sensitivity analysis, the passenger waiting time and crowding metrics are analyzed at the key stop level of detail in Section 7.1. Although the passenger waiting time and crowding metrics were not validated or compared with observed data due to the lack of such data, these metrics are a direct function of the headway and passenger demand, which have been validated, so they can be considered to be validated by proxy.

To facilitate the comparison of the sensitivity analysis and application results, the metrics are aggregated across the entire route. This is appropriate for the passenger waiting time and crowding metric, although not necessarily for the big gaps and bunching metrics, even though this is how the metric is implemented at the CTA. It is less informative to use the big gap / bunching metrics in aggregate form because, for example, a big gap on a route section with few passengers waiting is not as important as a big gap on a route section with many passengers waiting. Analyzing the big gap / bunching metrics alongside the waiting time and crowding metrics in aggregate has the added benefit of highlighting the limited information provided by looking only at the big gap / bunching metrics.

7.1 Passenger Metrics

This section reviews the passenger waiting time and passenger crowding metrics at each key stop and for each direction from the simulation model.

7.1.1 Passenger Waiting Time

Passenger waiting time is measured as average and budgeted waiting time at each key stop and segment. Assuming that passengers arrive randomly on this high-frequency route, *average waiting time* is calculated as half the headway plus the full headway of any successive buses if the waiting passenger is unable to board the first bus. Furth et al. (2006) introduce the concept of *budgeted waiting time* to capture the time a passenger must allow for their trip to avoid being late. Assuming that a passenger will tolerate being late no more than 5% of the time, the 95th percentile of waiting time is used as the budgeted passenger waiting time. The difference between budgeted and average waiting time is the *potential waiting time* and represents the "hidden" waiting time that is not always realized as time spent waiting at a stop (i.e. it could be realized as the time spent "being early" at their destination), but is still time that a passenger will typically include in their travel plans.

Under "ideal" conditions, average passenger waiting time is half the scheduled headway and budgeted time is 95% of the scheduled headway. For trips starting between 14:00 and 16:15 on route 63, the headway is constant at 6 minutes (with 1 exception where a short westbound trip halves the headway). Therefore, the ideal average and budgeted waiting times are 3 minutes and 5.7 minutes respectively. Under actual conditions, there is significant variation in the headways so the average and budgeted waiting times will be greater than the ideal conditions. In the average and budgeted waiting time calculation, the time is weighted by the number of waiting passengers. The passenger-weighted average waiting time for each key stop and segment is combined across 10 simulation model runs and displayed in the box plots[*] of Figure 7-1.

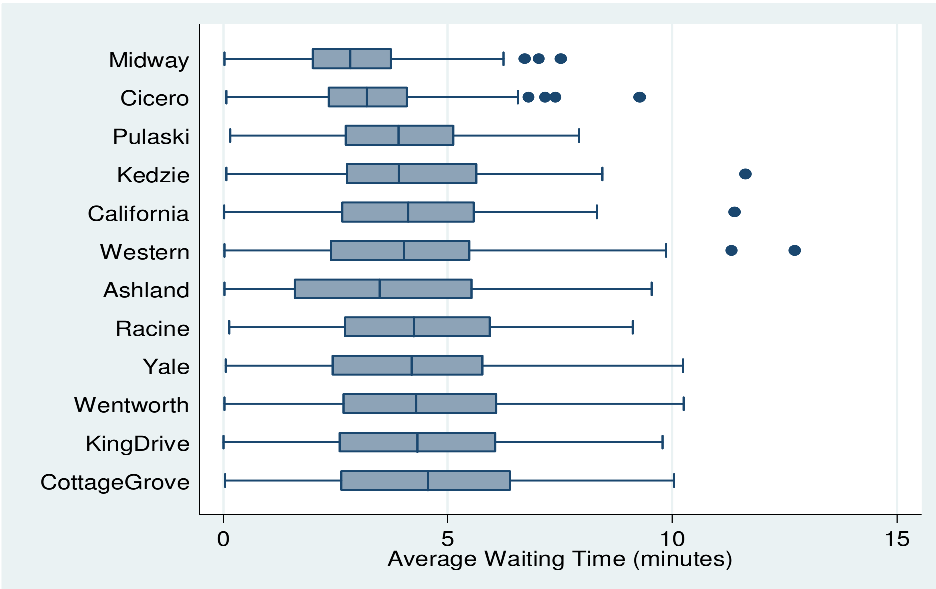
Passenger waiting time is related to the headway variation and similarly increases throughout the trip. The mean of the average waiting time (center line in the box) is close to 3 minutes (the scheduled average waiting time) at the beginning of the route. If the waiting time were not weighted by passengers, the mean of the average waiting time would be a constant 3 minutes along the route. But longer headways have more passengers waiting and shorter headways have fewer, so the weighted waiting time is at least 3 minutes. The tighter distribution at California (westbound) is due to the low passenger demand at this stop resulting in only a small number of observations.

The outlying values are indicators of the maximum headways, unless passengers are passed by the first bus. The incidence of passed-up passengers will be clearer in the crowding analysis of the following section.

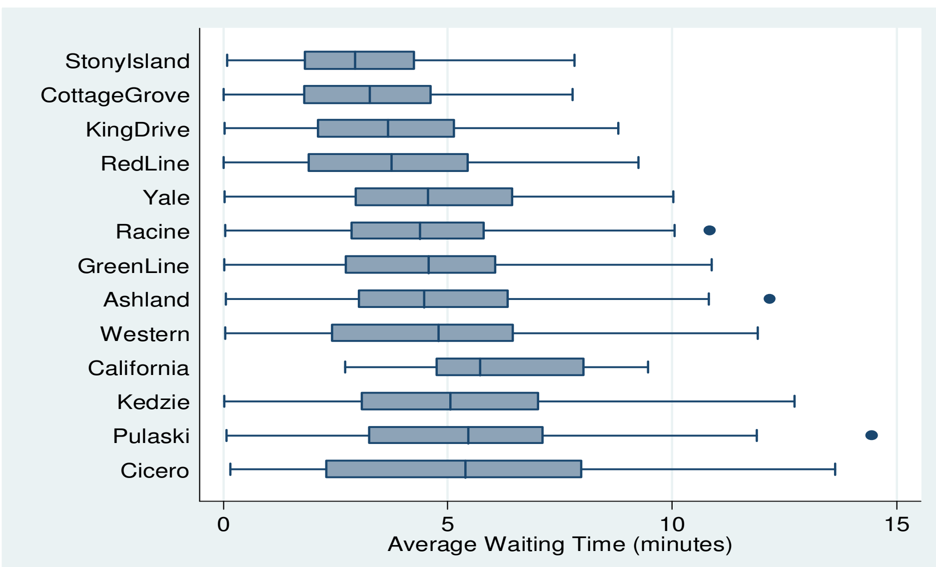
[*] See Appendix A for a description of box plot characteristics

Figure 7-1: Route 63 Passenger Weighted Average Waiting Time (simulated)

a) Eastbound



b) Westbound



7.1.2 Crowding

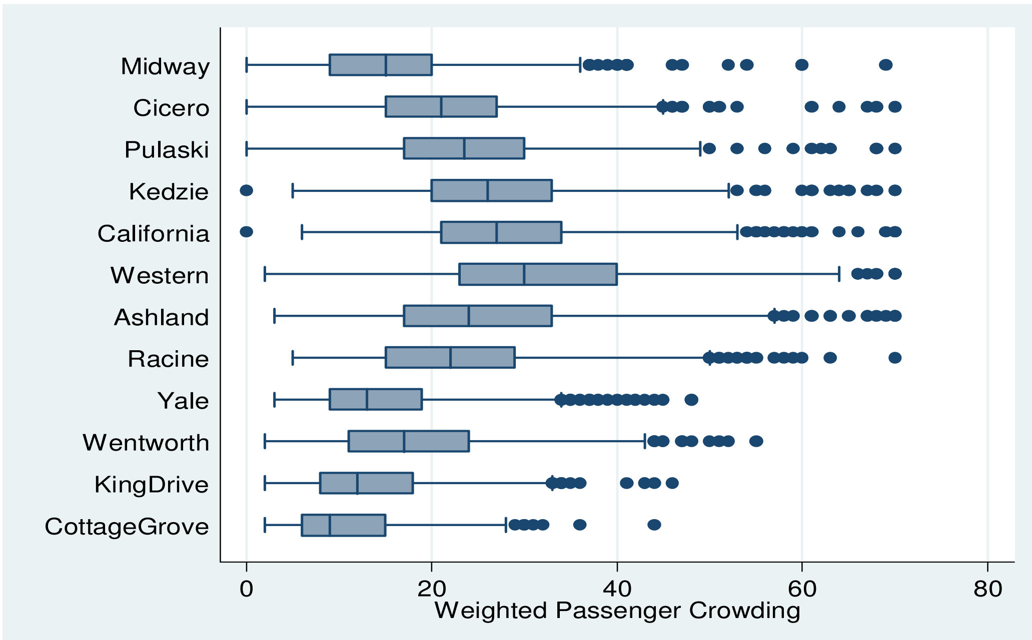
Onboard passengers are measured at each key stop and at the mid-point of each segment. Using this data, a crowding metric is created that captures the total number of passenger minutes at each crowding level, as defined in Table 4-2, across the entire route.

The onboard passenger values displayed in the box plots of Figure 7-2 aggregate the key stop and segment observations. The average passenger load follows the predicted passenger load in Figure 5-16 with the peak load points being Western (eastbound) and Red Line (westbound).

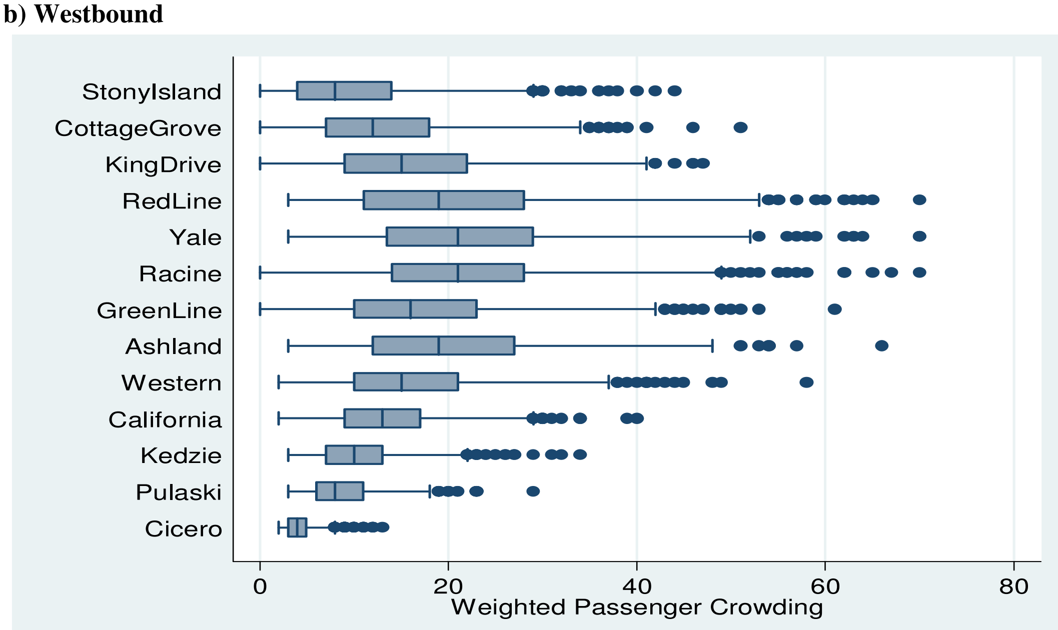
There are observations with 70 passengers onboard from Cicero through Racine (eastbound) and Red Line through Green Line (westbound). Passengers waiting at these stops on heavily loaded trips would be passed-up by these buses.

Figure 7-2: Modeled Onboard Passengers

a) Eastbound



b) Westbound



7.2 *Sensitivity Analysis*

The purpose of a sensitivity analysis is to gain insight into the significance of the factors influencing reliability. The sensitivity analysis selects one parameter in the model and sweeps through a range of reasonable values for this parameter. Twenty simulated runs are executed for each parameter value. The parameters varied in this analysis are the passenger demand, terminal departure behavior (accuracy and minimum recovery time), and percentage of filled trips.

In each parameter sweep, passenger waiting time, crowding, and the big gaps / bunching metrics are captured and compared. The average and budgeted passenger waiting time are presented along with a comparison of these observations to the scheduled average and budgeted values of 3 and 5.7 minutes, respectively. Crowding is displayed as the percentage of passenger-time spent at each of the crowding LOS categories (as defined in Table 4-2). Seated passengers are counted in crowding LOS A through C and standing passengers are counted in LOS D through F. For example, a fully loaded bus would have passengers counted at LOS C (all seated passengers) and LOS F (all standing passengers) only. The percentage of big gaps and bunching are also shown and compared with the baseline results. The schedule adherence metric is not used here because any schedule adherence issues (e.g. early arrivals at operator reliefs or late arrivals at the terminal) will be captured in the passenger centric metrics.

7.2.1 Passenger Demand

This section discusses the sensitivity of bus service reliability to changes in passenger demand. The passenger demand is varied from 25% of the actual value through 200% in increments of 25%. The results of this analysis are presented in Table 7-1. The first column indicates the percentage of passenger demand. The demand is minimal in the row with 25%, the base case is shown in the 100% row, and twice the demand is shown in the 200% row.

When only 25% of the base passenger demand occurs, the impact is so small that the waiting time values (Table 7-1a) may be used as a baseline of the bus service variability due to factors other than passenger activity (e.g. travel time or running time). The mean and budgeted waiting times are about 1 minute longer than the scheduled values of 3 and 5.7 minutes respectively. The reduction in passenger waiting time with 25% of passenger demand is due to the decreased dwell time and the decreased probability that a bus will be too crowded to pick up all the waiting passengers. So even when the passenger demand is minimal, the average and budgeted waiting times are still about 25% larger than the scheduled values.

Table 7-1: Passenger Demand Sensitivity Analysis

a) Passenger Waiting Time (minutes)

Pass Demand	Average	Budgeted	% of Sch. Average (3)	% of Sch. Budgeted (5.7)
25%	3.8	7.1	128%	125%
50%	3.9	7.3	129%	129%
75%	4.0	7.6	132%	133%
100%	4.2	8.1	138%	142%
125%	4.5	9.4	151%	165%
150%	4.7	9.8	157%	172%
175%	5.4	12.0	179%	210%
200%	6.0	13.7	199%	240%

b) Crowding

	LOS					
Pass Demand	A	B	C	D	E	F
25%	99.6%	0.4%	0.0%	0.0%	0.0%	0.0%
50%	86.6%	12.2%	1.2%	0.0%	0.0%	0.0%
75%	61.8%	27.6%	10.3%	0.2%	0.1%	0.0%
100%	40.6%	29.2%	27.9%	0.8%	0.8%	0.6%
125%	27.8%	25.1%	41.1%	1.3%	1.9%	2.7%
150%	19.2%	21.0%	50.2%	1.7%	2.8%	5.2%
175%	14.0%	16.2%	55.4%	2.0%	3.0%	9.4%
200%	10.1%	12.6%	59.8%	1.9%	3.1%	12.6%

c) Big Gaps / Bunching

Pass Demand	Big Gaps	Bunching	Big Gaps: % Change	Bunching: % Change
25%	1.6%	9.1%	-66%	-45%
50%	2.5%	11.5%	-46%	-31%
75%	3.1%	13.7%	-32%	-18%
100%	4.6%	16.7%	-	-
125%	7.4%	20.2%	63%	21%
150%	7.0%	21.6%	53%	30%
175%	9.2%	23.1%	101%	39%
200%	10.9%	24.4%	139%	47%

The budgeted waiting time metric is more sensitive than the average waiting time to changes in passenger demand, as shown by the comparison with the scheduled waiting time. The budgeted waiting time value increases at a faster rate when the passenger demand is increased above the base value (pass demand = 100%). This is likely due to the increased number of passengers who are unable to board the first bus due to crowding.

As expected, the change in passenger demand has a dramatic impact on the passenger crowding. As passenger demand increases, the largest increase is in the percentage of passengers seated with most seats taken (LOS C) or standing on an overcrowded bus (LOS F).

The change in percentage of big gaps and bunching follows the same trend as the passenger metrics. The relative change in big gaps however is much larger than the relative change in bunching when the passenger demand is increased to 200%. Increased passenger demand will potentially increase the total trip running time in excess of the half-cycle time and hence increase the average headway.

7.2.2 Terminal Departure Behavior

Terminal departure behavior is a function of the minimum recovery time required by an operator and the tendency of an operator to deviate from the specified departure time. To test the sensitivity of bus reliability to terminal departure behavior, these two aspects are studied independently.

Terminal Departure Deviation

This section tests the bus service reliability when the deviation of terminal departures, or tendency of operators to depart on-time, is changed. The output of the terminal departure deviation model (developed in Section 5.5.4) is adjusted to first simulate perfect departures (on-time departures with available recovery time) and then the deviation is increased until it is twice as great as observed in the real world. The deviation adjustment is increased in increments of 50%. So a terminal departure deviation of 0% represents perfect terminal departures, 100% represents the base case, and 200% represents deviations twice as great as observed. The minimum recovery time distribution is unchanged in this analysis. Table 7-2 shows the passenger waiting time, crowding, and big gaps / bunching results of the terminal departure accuracy sensitivity analysis.

Perfect terminal departures (terminal departure deviation = 0%) improve the budgeted waiting time by around 0.3 minutes. There is a more significant difference in the budgeted waiting time when the terminal departure deviation is increased. The budgeted time increases by 20% to nearly 10 minutes when the terminal departure deviation is 200% of the observed value. The range of the increased budgeted time over the schedule ranges from 36% to 72%, with the current operation at 42% over the schedule. This is a narrower range than shown in the passenger demand sweep, but passenger demand also directly impacts total running time so an increase in passenger demand should have a greater impact on service reliability.

Table 7-2: Terminal Departure Deviation Sensitivity Analysis

a) Passenger Waiting Time (minutes)

Term Dept Deviation	Average	Budgeted	% of Sch. Average (3)	% of Sch. Budgeted (5.7)
0%	4.0	7.8	132%	136%
50%	4.1	8.1	135%	142%
100%	4.2	8.1	138%	142%
150%	4.3	8.7	143%	152%
200%	4.7	9.8	157%	172%

b) Crowding

	LOS					
Term Dept Deviation	A	B	C	D	E	F
0%	42.6%	31.3%	24.6%	0.7%	0.4%	0.3%
50%	43.1%	30.1%	25.2%	0.7%	0.5%	0.4%
100%	40.6%	29.2%	27.9%	0.8%	0.8%	0.6%
150%	40.5%	28.6%	28.4%	0.9%	0.8%	0.7%
200%	38.5%	25.2%	32.9%	1.0%	1.2%	1.2%

c) Big Gaps / Bunching

Term Dept Deviation	Big Gaps	Bunching	Big Gaps: % Change	Bunching: % Change
0%	3.2%	15.0%	-31%	-10%
50%	3.9%	15.2%	-15%	-9%
100%	4.6%	16.7%	-	-
150%	4.9%	16.4%	7%	-2%
200%	7.0%	19.9%	54%	19%

The percentage of passengers on over-crowded buses (LOS F) doubles when the terminal departure deviation is increased to 200% of the base value, but is still only about 1%. Better accuracy leads to more even loading, as shown by the increased percentage of passenger time at LOS A and B and a decreased percentage at LOS C through F when the terminal departure accuracy is perfect.

Similar to the passenger demand sensitivity analysis results, the big gaps metric is more sensitive to changes in the terminal departure deviation than either the bunching metric or the passenger-centric metrics.

Service reliability improves by a smaller amount when the deviation is reduced than the amount that it degrades when the deviation increases. This implies that there is not much to be gained by further improving the behavior for on-time terminal departures on route 63, although there is much to lose if departure deviations increase.

Minimum Recovery Time

This section explores the service reliability when the minimum recovery time is changed. Specifically, the output of the minimum recovery time model (developed in Section 5.5.4) is adjusted to represent zero minimum recovery time (departure time is completely dependent on available recovery time and deviation) up to twice the observed minimum recovery time. The minimum recovery time adjustment is increased in increments of 50%. A minimum recovery time of 0% represents no minimum recovery time terminal departures, 100% represents the base case, and 200% represents a minimum recovery time that is twice as great as observed. The recovery time accuracy model is unchanged in this analysis. The results of the sensitivity analysis are displayed in Table 7-3.

Table 7-3: Minimum Recovery Time Sensitivity Analysis

a) Passenger Waiting Time (minutes)

Min Rec Time	Average	Budgeted	% of Sch. Average (3)	% of Sch. Budgeted (5.7)
0%	4.1	8.1	137%	143%
50%	4.1	8.0	135%	141%
100%	4.2	8.1	138%	142%
150%	4.1	8.0	137%	139%
200%	4.4	8.7	147%	153%

b) Crowding

	LOS					
Min Rec Time	A	B	C	D	E	F
0%	41.5%	29.8%	26.8%	0.8%	0.7%	0.4%
50%	41.6%	30.5%	25.9%	0.7%	0.6%	0.6%
100%	40.6%	29.2%	27.9%	0.8%	0.8%	0.6%
150%	41.5%	30.3%	26.3%	0.8%	0.5%	0.5%
200%	39.7%	28.5%	29.2%	1.0%	0.8%	0.8%

c) Big Gaps / Bunching

Min Rec Time	Big Gaps	Bunching	Big Gaps: % Change	Bunching: % Change
0%	4.4%	16.6%	-3%	-1%
50%	3.7%	14.9%	-18%	-11%
100%	4.6%	16.7%	-	-
150%	4.1%	16.1%	-9%	-3%
200%	5.9%	18.3%	30%	10%

The passenger waiting time metrics vary by less than one minute across all parameter values with essentially no change in either of the passenger-centric metrics until the minimum recovery time is doubled.

From this sensitivity analysis, it appears that the minimum recovery time at the current level is not a significant factor affecting bus service reliability of route 63.

7.2.3 Unfilled Trips

Unfortunately, unfilled trips due to breakdowns or insufficient equipment do occur, especially on a route served by 13 to 17 year old vehicles. In the route 63 headway analysis the mean observed headway was shorter than the schedule headway. As explained in Section 6.3.4, the shorter mean observed headway may be partially due to unfilled trips. The model, however, simulates every scheduled trip as filled. Unfilled trips will decrease bus service reliability however it is measured.

To test the sensitivity of route performance to unfilled trips, the probability of not filling a block of trips is increased from 0 to 20% in 5% increments. The decision to fill the block is made when loading the schedule into the model by sampling from a uniform distribution. There are 23 blocks and 124 trips in the model schedule and each block contains between 1 and 6 trips, with the majority of the blocks containing 5 or 6 trips. So the number of trips that will be unfilled will depend on the block selected. Successive model runs do not necessarily have the same blocks filled, which will cause greater variability in the results. Blocks from across the entire modeled time period (12:00-18:00) may be unfilled and the impact on the performance of trips scheduled between 14:00 and 16:15 is analyzed. The results shown in Table 7-4 are grouped by the percentage of unfilled trips.

As expected, the modeled passenger metrics increase dramatically in response to the reduction in service. The increased passenger demand per bus is seen mostly at LOS C and F as the buses become more crowded through increased demand per bus and the greater mean and variation in headway.

Increases in waiting time (shown in Table 7-4a) are due to longer headways and the reduced capacity causing more waiting passengers to be passed-up. Interestingly, the big gaps and bunching results in Table 7-4c show that the level of bunching does not consistently decrease as the unfilled trips increase. The inconsistent variation in the level of bunching is due to the random selection of unfilled trips. The lack of a decrease in the level of bunching, even though fewer buses are on the street, is due to relative increase in passenger demand per bus through reduced capacity causing buses to interact more strongly through the dwell time. If trip "A" is not filled, the following trip "B" will have more passengers to serve and will take longer to travel the route. If trip "C" is filled, the headway between B and C will decrease as B falls behind schedule thus leaving fewer passengers for C to serve. The fewer passengers that C has to serve, the faster it will run eventually catching up with B. Unless the unfilled trips are evenly distributed across the schedule or the headways are spaced, bunching is just as likely to occur, even with fewer buses on the route.

Table 7-4: Unfilled Trips Sensitivity Analysis

a) Passenger Waiting Time (minutes)

Unfilled Trips	Average	Budgeted	% of Sch. Average (3)	% of Sch. Budgeted (5.7)
0%	4.2	8.1	138%	142%
5%	4.7	10.3	157%	180%
10%	5.1	12.9	169%	226%
15%	5.3	11.7	178%	205%
20%	5.6	12.5	188%	219%

b) Crowding

	LOS					
Unfilled Trips	A	B	C	D	E	F
0%	40.6%	29.2%	27.9%	0.8%	0.8%	0.6%
5%	37.0%	29.4%	30.4%	1.0%	1.0%	1.2%
10%	31.1%	25.1%	37.8%	1.3%	1.2%	3.5%
15%	33.0%	24.0%	37.4%	1.2%	1.7%	2.7%
20%	31.3%	24.5%	38.1%	1.2%	1.7%	3.1%

c) Big Gaps / Bunching

Unfilled Trips	Big Gaps	Bunching	Big Gaps: % Change	Bunching: % Change
0%	5%	17%	-	-
5%	8%	18%	66%	8%
10%	7%	15%	59%	-8%
15%	11%	17%	135%	-1%
20%	12%	15%	161%	-12%

Section 8.2 summarizes the key findings of the sensitivity analysis and compares the effectiveness of the passenger-centric and the CTA big gap / bunching metrics.

7.3 Applications

This section presents the model results when a series of different operations control strategies are tested. The realm of possible model applications is discussed in Section 8.3.

7.3.1 Operating Strategy Implementation Details

Although route 63 is a high-frequency route, the current operations policy is to maintain schedule, regardless of headway. Control strategies to maintain headway, as discussed in Section 2.1.3, may be based on either the preceding headway or both the preceding and following headways (prefol).

In Section 2.1.3, terminals are identified as the best points on the route to implement a control strategy because few passengers will be onboard and any service improvements will affect the entire route. Implementing a strategy mid-route may also be advantageous if there are a significant number of passenger boardings in the latter part of the route. The passenger activity in Figure 5-16 shows that there is a majority of passenger boardings after the key stops Western (eastbound) and Red Line (westbound) and these stops are at least a third of the way into the route. Each strategy is implemented in the model initially at terminals only and then at terminals and these stops. Operators holding at these key stops should not be taking a personal break, so it is not necessary to calculate a minimum recovery time. It is also assumed in the implementation that the departure time at the key stops is clearly communicated to the operator and there is no deviation.

Implementing an operations control strategy mid-route means that passengers are likely to be onboard and will be delayed while the bus holds to maintain either headway or schedule. Half the scheduled headway (3 minutes) is used as the maximum holding time that onboard passengers will tolerate.

Schedule Management

With schedule management at key stops, buses will be held (up to the maximum value) if they are early at that point in the route. As discussed in Section 4.2.2, CTA policy mandates that operators do not depart a timepoint early. The exploratory data analysis in Section 5.4.3 was unable to determine actual operator response to the policy. Improvements in service reliability due to holding for schedule at this key stop may indicate a potential advantage from strict enforcement of the existing operations policy.

Headway Management

Both the preceding headway and prefol headway management strategies are implemented in the model. The details of the headway management strategy implementation include the trip selection, departure time calculation, and the expected operator deviation.

Headway management is most critical during the peak period with highest passenger demand. It is also easiest to implement a headway management control strategy when there is an even scheduled headway. Fortunately, route 63 has constant 6 minute headways in the afternoon peak period. So in the simulation model the headway management strategy is implemented on trips starting between 13:30 and 16:15. All other trips follow a schedule management policy.

With a management strategy based on previous headway, the terminal recovery time (time until departure) for each bus is calculated as the greater of the scheduled headway minus the previous headway and zero. The previous headway is the time since the last bus departed (or will depart) the terminal. In other words, the bus is instructed to depart the terminal as close to the scheduled headway as possible. The actual departure time of the bus, however, is still dependent on the minimum recovery time and deviation.

The prefol headway strategy is designed to improve on the previous headway strategy by reducing big gaps in service. The departure headway is calculated as the maximum of the scheduled headway and half the combined preceding and following headway. So if the preceding plus the following headway are greater than twice the scheduled headway, the departure headway will be longer than the scheduled headway. The preceding headway is calculated as described above and the following headway is determined by searching back up the route and using the current headway of the following bus.

To maintain the average scheduled headway, longer headways must be balanced with shorter headways. In the model, the headway deviation from each departure is recorded. When the net headway deviation is positive, indicating longer-than-average headways, the departure time of successive trips is reduced by up to 1 minute, where possible, until the net deviation is reduced to zero. For example: if the scheduled headway is 6 minutes, but a bus departs with an 8 minute headway, the next two trips will be instructed to depart with 5 minute headways so that the average headway is 6 minutes.

As discussed in Section 4.2.2, the CTA terminal departure policy is more averse to early than late departures. The operator behavioral response to this policy is seen in the terminal departure accuracy distributions of Figure 5-12. There are more occurrences of operators departing the terminal late and a wider dispersion of the schedule deviation for late departures. The policy to manage early departures is especially relevant on low-frequency routes where passenger arrivals are sensitive to the schedule. On high-frequency routes with a headway maintenance policy, however, there is no advantage to this policy. If the recovery time determination at the terminal is sensitive to headway, rather than schedule, a regular distribution of schedule deviation may be more desirable. For example, if operators are continually leaving late and the following bus is continuously held at the terminal, the actual headway in service will be longer. Therefore, when a headway management strategy is implemented, the deviation of terminal departures should be unbiased (no preference for early or late departures).

To implement the change in the terminal departure deviation, the probability of early or late departures is changed from 25/75 to 50/50. Furthermore, if a transit agency were to implement a headway management strategy, it is likely that the terminal departure accuracy could be improved as well. Thus, to predict the magnitude of departure deviation, the distribution for early departure deviations is used for both early and late departures (parameters defined in Table 5-13). This assumes that the behavior of operators in response to the existing stringent early departure management can be applied to both early and late departures when the departure is managed more closely in congruence with a headway control strategy implementation.

7.3.2 Results

The simulation model is configured with each strategy (schedule, previous headway, prefol headway) implemented at just the terminal and then at the terminal and designated point on the route. The resulting reliability metrics from 20 simulation model runs with each strategy and location are shown in Table 7-5. The results are grouped by location because there may be different resources required (e.g. a supervisor may be necessary at both the key stop and terminal).

Terminal Strategies

When the control strategy is implemented only at the terminal (first three rows of Table 7-5c), the headway strategies reduce the percentage of big gaps and bunched buses by more than 10%. These reductions, however, do not translate into significant reductions in either average or budgeted waiting times. The previous headway strategy budgeted waiting time actually increases slightly. It is surprising that the percentage of big gaps and bunched buses are reduced and yet the budgeted waiting time does not change accordingly. This reveals the limitation of aggregating the bunching / big gaps percentages without consideration of affected passenger demand because the big gaps in the previous headway model run are occurring in areas of high passenger demand.

Table 7-5: Operating Control Strategy Comparison

a) Passenger Waiting Time (minutes)

Location	Strategy	Average	Budgeted	% of Sch. Average (3)	% of Sch. Budgeted (5.7)
Terminal	Schedule	4.2	8.1	138%	142%
	Previous Headway	4.0	8.2	134%	145%
	Prefol Headway	4.0	7.9	132%	139%
Terminal & Key Stop	Schedule	4.1	8.2	138%	144%
	Previous Headway	3.8	7.7	127%	135%
	Prefol Headway	3.7	7.6	125%	133%

b) Crowding

Location	Strategy	LOS A	B	C	D	E	F
Terminal	Schedule	40.6%	29.2%	27.9%	0.8%	0.8%	0.6%
	Previous Headway	44.6%	30.2%	23.2%	0.6%	0.6%	0.7%
	Prefol Headway	45.4%	31.5%	21.7%	0.6%	0.5%	0.4%
Terminal & Key Stop	Schedule	42.7%	30.8%	24.8%	0.7%	0.5%	0.5%
	Previous Headway	45.7%	31.3%	21.4%	0.5%	0.6%	0.5%
	Prefol Headway	44.2%	32.5%	22.0%	0.5%	0.4%	0.5%

c) Big Gaps / Bunching

Location	Strategy	Big Gaps	Bunching	Big Gaps: % Change	Bunching: % Change
Terminal	Schedule	4.6%	16.7%	-	-
	Previous Headway	4.0%	13.7%	-12%	-18%
	Prefol Headway	3.4%	12.7%	-26%	-24%
Terminal & Key Stop	Schedule	4.3%	16.3%	-6%	-2%
	Previous Headway	2.8%	11.5%	-38%	-31%
	Prefol Headway	2.4%	10.5%	-46%	-37%

The effectiveness of the prefol strategy to reduce big gaps in service is apparent in the budgeted waiting time and percentage of big-gaps results. This strategy creates the greatest improvement in service as shown by the lowest average waiting time and percentage of standing (LOS D - F) passengers. The improvement of a prefol strategy over a schedule strategy, however, is not large. This suggests that there is sufficient recovery time currently scheduled for route 63. If the scheduled recovery time was insufficient, a terminal departure policy based on schedule would instruct buses to leave immediately and any bunched buses would not be spread.

Terminal and Key Stop Strategies

Overall, adding management of bus service at a key stop improves service reliability. Of the three, schedule management is the least beneficial, as expected because the majority of trips are behind schedule (see Table 6-4).

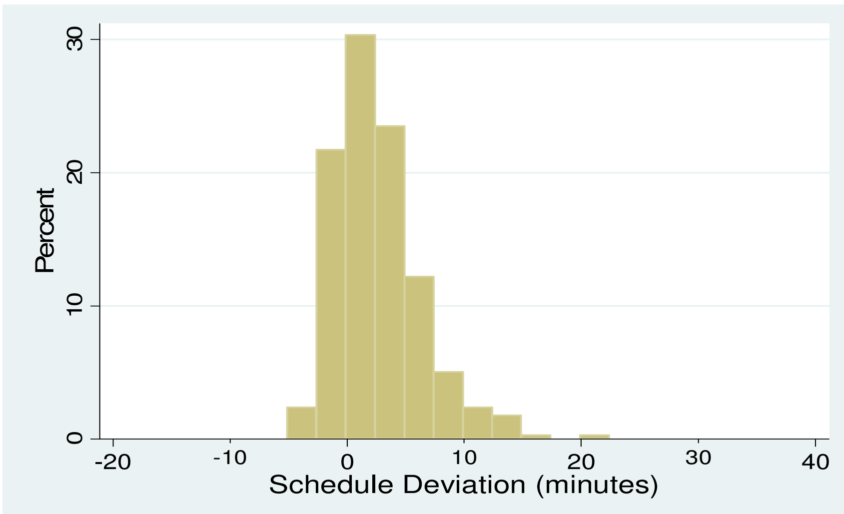
Both headway strategies decrease bunched buses by more than 30% and big gaps by around 40%, and the prefol strategy is generally more effective than the previous headway strategy. The reduction of bunched buses and big gaps is validated by an associated reduction in average and budgeted waiting times to 124% and 136% of the scheduled values respectively.

The improvement in service reliability measured by waiting time and crowding is at the expense of onboard passenger time. The onboard passenger delay time is limited to half the headway (3 minutes) in this experiment. A potential improvement of the headway strategy would be to include consideration of the onboard passenger level in the decision to hold a bus. In the extreme situation a completely full bus should never be held because many passengers onboard will be delayed and few downstream waiting passengers will be able to board due to the lack of room. In the current implementation of the prefol or previous headway management strategies, 60% of passengers do not experience any delay and all delays are limited to 3 minutes.

Another downside of managing service by headway is the potential for large schedule deviations at terminals and operator reliefs, which may lead to missed connections and excessive overtime pay. Figure 7-3 and Figure 7-4 show the schedule deviation at the relief points and terminals under the current schedule strategy and a prefol headway strategy at the terminal and one key stop.

Figure 7-3: Schedule Adherence at Relief Points

a) Schedule Management at Terminal



b) Prefol Headway Management at Terminal and Key Stop

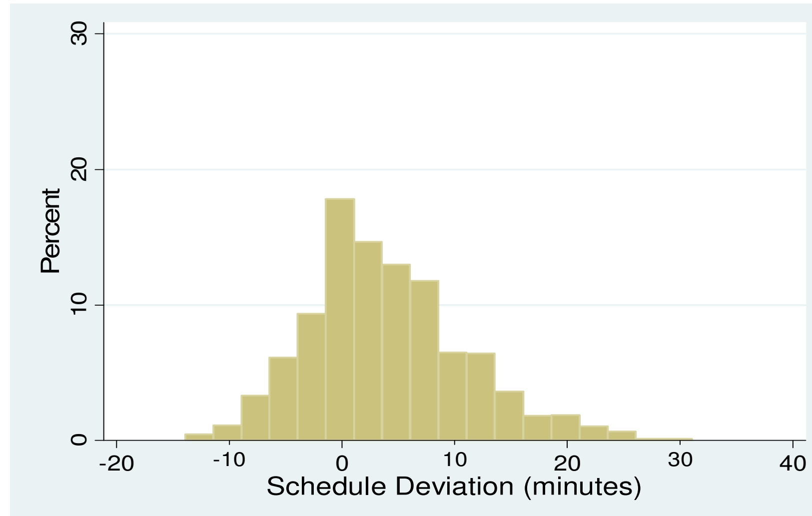
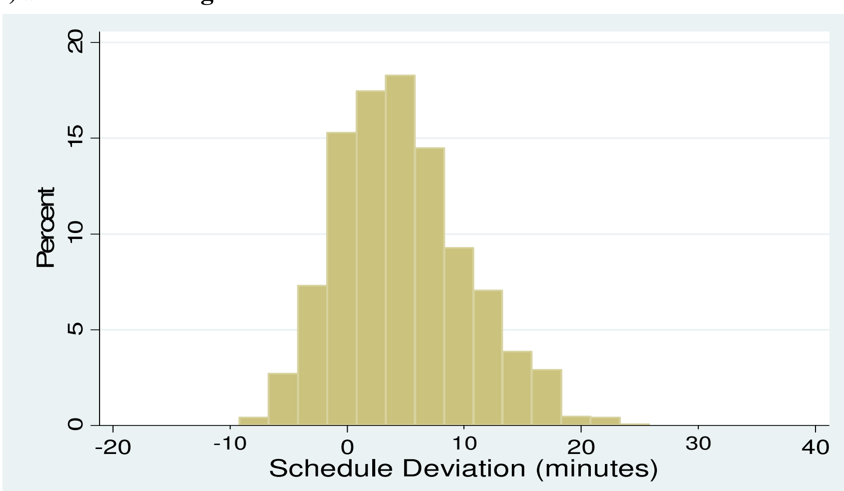
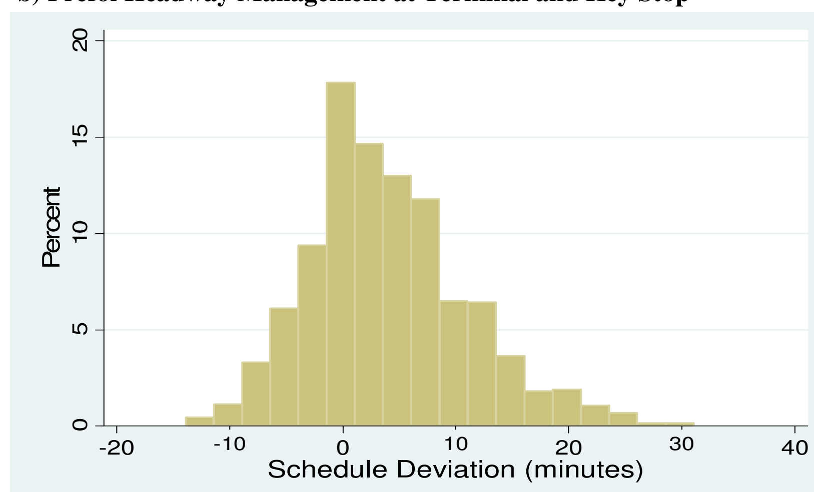


Figure 7-4: Schedule Adherence at Far Terminal

a) Schedule Management at Terminal



b) Prefol Headway Management at Terminal and Key Stop



The prefol headway strategy has a wider range of schedule deviations at both relief points and terminals. About 25% of the prefol headway managed trips will arrive at the relief point more than 3 minutes early (possibly before the relieving operator is ready) and a significant percentage of the trips will arrive at the relief point more than 5 minutes late. Early arrivals at the terminal are not problematic, but arrivals that are more than the scheduled recovery time late will lead to overtime pay or other route connections to be late. The percentage of trips arriving more than 10 minutes late (the average scheduled recovery time) is roughly equivalent between the two strategies, but the prefol headway management strategy does have a greater maximum. Including sensitivity to a schedule adherence in the decision to hold a bus would reduce operator relief delays due to early arrivals or missed connections and overtime due to late arrivals

Unfilled Trips

To evaluate the robustness of the control strategies tested above, an abridged version of the unfilled trips sensitivity test (see Section 7.2.3) is run with each control strategy. Reliability metrics from each of the operating control strategies with up to 5% of trips unfilled are compared in Table 7-6.

As expected, unfilled trips cause an increase in the passenger waiting time no matter what control strategy is implemented. The benefit of managing the headway at both a key stop and terminal over the terminal only is virtually eliminated. Previous headway management at key stop and terminal actually generates a longer budgeted waiting time. This is due to the previous headway strategy not accounting for big gaps in the following headway. Schedule management at the terminal and key stop appears to significantly improve service reliability over a terminal only implementation, although not as much as the terminal only headway strategies.

The minimal benefit of implementing the headway strategy at the key stop as well as the terminal suggests that most of the unfilled trip correction is done at the terminal and the key stop holding is not necessary. The small benefit may not justify the additional passenger delays (more than 50% of onboard passengers are delayed) to hold buses mid-route.

Table 7-6: Operating Control Strategy Comparison with up to 5% of trips unfilled

a) Passenger Waiting Time (minutes)

Location	Strategy	Average	Budgeted	% of Sch. Average (3)	% of Sch. Budgeted (5.7)
Terminal	Schedule	4.7	10.3	157%	180%
	Previous Headway	4.3	9.1	143%	159%
	Prefol Headway	4.3	9.2	145%	161%
Terminal & Key Stop	Schedule	4.5	9.4	149%	166%
	Previous Headway	4.4	10.1	145%	177%
	Prefol Headway	4.2	9.1	139%	160%

b) Crowding

Location	Strategy	LOS A	B	C	D	E	F
Terminal	Schedule	37.0%	29.4%	30.4%	1.0%	1.0%	1.2%
	Previous Headway	41.0%	31.4%	25.3%	0.7%	0.8%	0.8%
	Prefol Headway	40.8%	30.3%	26.5%	0.7%	0.7%	1.0%
Terminal & Key Stop	Schedule	38.5%	28.6%	29.4%	1.0%	0.9%	1.5%
	Previous Headway	40.7%	28.4%	27.6%	0.9%	0.8%	1.7%
	Prefol Headway	39.5%	29.9%	27.3%	1.1%	1.1%	1.1%

c) Big Gaps / Bunching

Location	Strategy	Big Gaps	Bunching	Big Gaps: % Change	Bunching: % Change
Terminal	Schedule	7.6%	18.0%	-	-
	Previous Headway	5.6%	14.0%	-26%	-22%
	Prefol Headway	5.5%	14.9%	-27%	-17%
Terminal & Key Stop	Schedule	5.9%	15.9%	-23%	-12%
	Previous Headway	5.5%	12.7%	-27%	-29%
	Prefol Headway	5.6%	11.6%	-26%	-36%

8 Summary and Conclusions

This chapter begins with an evaluation of the simulation model design, categorized by the configuration requirements and assumptions, outputs, and applicability. Section 8.2 summarizes the key findings of the simulation model validation, sensitivity analysis, and applications. Finally, Section 8.3 identifies future directions for continuation of this research.

8.1 Simulation Model Evaluation

This section summarizes the data and assumptions required to simulate bus route operations, the model outputs, and the scope of appropriate model applications.

8.1.1 Model Configuration and Assumptions

A goal of the simulation model is that it can be readily adapted to other routes. This section discusses the data and assumptions required to simulate operations of a bus route. To explain the data requirements, the model level of detail and operation are first reviewed.

The simulation model represents bus movement at the "key stop" (schedule timepoints and stops with high passenger activity) level of detail. Dwell time at key stops is represented explicitly, but dwell time at stops within a segment are aggregated within the segment running time distribution. Individual passenger trips are not represented explicitly, instead boarding rates and alighting percentages are established for each key stop and segment to estimate passenger load.

To adapt the model to a different route involves the following steps:

a) To construct the route in the model, information on the schedule and route layout are necessary
b) To calibrate the model, data is needed for the segment running time, key stop dwell time, terminal departure behavior, and passenger demand
c) To evaluate control strategies in the model, the impact of the strategy on the input data and the implementation of the strategy must be represented in the model.

The new data sources and processing for each of the route characteristics are summarized in Table 8-1.

Table 8-1: Simulation Model Data Requirements

	Data Source	Process
Schedule	timepoint-based schedule	• Create a trip record for each unique pattern, running time, and relief combination in the time period • Create bus blocks with a list of trips and recovery time between each defining each block
Route layout	maps and agency estimated data	• Determine the key stops according to the schedule, passenger demand, and transfers
Segment Running Time	AVL	• Collect running times between key stops
Key Stop Dwell Time	AVL	• Collect dwell time at key stops (segmented by operator reliefs, holding, and normal activity) • Use previously estimated dwell time model. • Apply scalar to compensate for bus type, key stop location, and passenger demand variation.
Terminal Departure Behavior	AVL	• Collect observed recovery time and available recovery time. • Estimate distributions of minimum recovery time and recovery time deviation
Passenger Demand	agency estimates, AFC, APC	• Use agency estimates for overall route demand and AFC data to break down the estimate for 15 minute intervals. • Collect aggregate passenger boarding and alighting counts per key stop and segment and estimate demand distribution by location
Control Strategy	agency policies and prior research	• Configure input data using Excel model configuration utility • Implement strategy in model by modifying Java code

The simulation model configuration described above depends upon the following assumptions:

- Dwell time on key stop segments does not cause a significant impact on segment running time (may be violated through changes in passenger demand or poor identification of key stops)
- Successive trips on the same segment are independent (may be violated if there is a temporary traffic condition that delays several trips – e.g. a freight train)
- Operators do not adjust their driving behavior in response to the schedule (may be violated if the schedule has too much running time and strict timepoint holding – i.e. the operators may slow down to avoid holding)
- The passenger demand patterns do not change across the time period (may be violated by an extended time period)
- Random arrival of passengers (may be violated on low-frequency routes)

8.1.2 Model Outputs

Data from each bus, key stop, and segment is output to a series of comma-delimited text files that can be processed by a spreadsheet, statistical, or database application.

The simulation model also includes a graphical user interface (GUI) that shows route operations from a "bird's-eye" view. The GUI displays the location, schedule adherence, and passenger load of each bus. The GUI also supports selecting individual buses to send specific instructions (e.g. speed-up, slow-down).

8.1.3 Applicability

The simulation model is constructed to be a research tool for testing a variety of preventative and corrective control strategies. The strategies that may be tested are limited by the available input data and the simulation model level of detail. Because traffic is not explicitly represented, control strategies that aim to alleviate traffic impact on service reliability (e.g. lane or signal priority) may not be directly tested in the model. Control strategies that could be effectively tested with this simulation model are, for example, preventative strategies that adjust the schedule and terminal departure behavior as well as corrective strategies of holding, expressing, or short-turning buses.

8.2 Findings

This section summarizes the results of the validation, sensitivity analysis, and control strategy applications. The efficacy of the CTA metrics of big gaps (> 15 minutes) and bunching (< 60 seconds) is evaluated through comparison with the passenger centric metrics of waiting time and crowding.

8.2.1 Model Validation

The simulation model results were validated by a comparison to the observed headway, trip time, and schedule adherence on route 63. The model results were within a 95% confidence interval of the route observations, except for the schedule adherence of westbound trips at Midway terminal. Systematic variation in terminal departures and running times due to operator behavior are the probable cause of the schedule deviation. The effect of operator behavior on this route, however, is not strong enough to significantly impact more than one of the validation tests so the model results are still valid.

8.2.2 Sensitivity Testing

In the sensitivity tests, the amount of passenger demand, terminal departure deviation, minimum recovery time, and trips served is varied around the observed value to determine the influence of each factor on service reliability.

Even when passenger demand is reduced to a minimal value (25% of observed demand), the average and budgeted waiting time is still about 1 minute longer than the scheduled value. The longer waiting times are due to terminal departure deviations or running time variations.

With respect to terminal departure behavior, service reliability is more sensitive to changes in the departure deviation than changes in the minimum recovery time. For both sensitivity tests, there were smaller changes in service reliability when the parameter is reduced than when it is increased. So improvement of the current terminal departure management with the current policy will not translate into large changes in service reliability, but, degradation in terminal management will significantly affect service reliability.

When the percentage of unfilled trips is increased all of the service reliability metrics, except for the percentage of bunched buses, show a significant decrease in service reliability. When 15-20% of the trips are not filled, the budgeted waiting time and big gaps are twice the values when all trips are filled. The bunching metric does not decrease significantly; even though fewer buses are on the street because the schedule managed terminal departure policy is not redistributing the buses evenly.

8.2.3 Control Strategy Evaluation

A series of terminal and mid-route control strategies were evaluated with the model. The control strategies were tested first under normal operation (all trips are filled) and then with up to 5% of the trips unfilled.

Determining vehicle departure according to the previous and following headway (prefol) significantly improves service reliability from the current schedule management strategy. The results of the prefol strategy implemented at the terminal and key stop, however, are only slightly better than the results of the schedule management strategy implemented at the terminal only with no schedule deviation.

Only one key stop was selected for management in each direction and the determination of the particular key stop may be improved by a closer study of trip patterns and variability. This implementation did raise some important considerations when implementing an operations control strategy mid-route. Managing headway mid-route often requires holding a bus with passengers onboard. With the prefol strategy, about 40% of the passengers are delayed up to 3 minutes at the key stop. Determination of a maximum holding time threshold and policy for moving passengers up is an important aspect of a prefol strategy. Passenger tolerance to holding will depend in part on the length of the trip, i.e. passengers may tolerate a percentage of holding time as part of the overall trip time. Headway managed strategies also cause greater schedule deviations. A significant number of trips are more than 10 minutes late arriving at the terminal which may cause more overtime pay and late connections with other trips. An improvement of any mid-route holding strategy would be to include the number of passengers onboard and the schedule deviation of the trip in the holding time determination.

8.2.4 Evaluation of Big Gaps / Bunching Metrics

The control strategies were evaluated using passenger centric metrics of waiting time and crowding along with CTA's reliability metrics of big gaps and bunching.

Although bus bunching is a political issue, the big gaps metric better reflects the passenger experienced waiting time. Since, to quote Fred Salvucci, "passengers don't mind the bunches, they mind the gaps" (Salvucci, 2008). However, an aggregation of big gaps is not necessarily an accurate measure of the waiting time experienced by passengers. When evaluating the terminal departure strategies, service with previous headway management at terminals has a lower percentage of big gaps than a service managed by schedule, but the budgeted passenger waiting time is greater. So the big gaps in this scenario are in areas where more passengers are waiting to board.

The big gaps and bunching metrics were also correlated to the passenger-experienced crowding level. Changes in the percentage of bunched buses are correlated with the percentage of passengers at the lowest crowding level of service. This is because, when there are fewer bunched buses, bus service and passenger loads are better distributed along the route. Changes in big gaps are correlated to the percentage of passengers at the highest crowding level of service. Buses following a big gap are more likely to be heavily loaded as they pick up all passengers who have arrived since the previous bus.

8.3 Future Research

The simulation model is a valuable research tool for many applications beyond those tested in this thesis. The model in its current form may also be extended to include more complex bus operations and even be adapted to simulate rail operations.

8.3.1 Other Applications

This section proposes applications of the model that would not require any additional model development.

Supervisor Training

The model GUI interface could be used to train bus supervisors and operators. Observing a bus route from the model perspective will provide an improved understanding of the causes of service unreliability.

Adaptation to other bus routes

Any high-frequency bus route may be implemented in the model, as long as the assumptions described earlier in this chapter are not violated. The configurable inputs also allow simulation a of hypothetical route to test control strategies on generic types of routes – e.g. feeder, cross-town. Evaluating control strategies on hypothetical routes will inform service intervention guidelines that may be applied to multiple routes of the same type. This is more efficient than simulating each route individually to determine the optimal control strategy.

Preventative Control Strategies

Control strategies that result in a change of schedule, dwell time, or terminal departure behavior can be implemented in the model through the input parameters without changing the simulation model program.

8.3.2 Model Extensions

The bus route is simulated through interactions of three different types of agents (bus, ground, and scheduler). This architecture allows the model to be extended to simulate other control strategies, increase the sophistication of the agents, and simulate rail operations.

Control Strategies

As mentioned earlier, the prefol strategy may be enhanced to include passenger loading and schedule adherence in the holding calculation. Other corrective control strategies, such as expressing and short turning, may also be implemented in the model with input parameters to specify the location and threshold for enacting the intervention.

Increase Sophistication of Agents

The simulation model was developed using the Repast Simphony toolkit. Repast is specially designed to facilitate development of agent-based models. This modeling technique is particularly useful when representing independent decision-making elements within the system (North and Macal, 2007). The simulation model could be extended to allow for more sophisticated interactions between the operators. Furthermore, a supervisor agent may be added to the model to add subtlety to route management.

Simulate Rail Operations

The model could be adapted to simulate rail operations without significant changes. The segment travel time and dwell time can be reconfigured with estimates of rail operations and the key stops of the bus route would be equivalent to rail stations. To prevent overtaking, the ground agent can serve as a rail block and communicate the maximum speed to the vehicle agent. Terminal operations would require additional development to represent the track configuration constraints.

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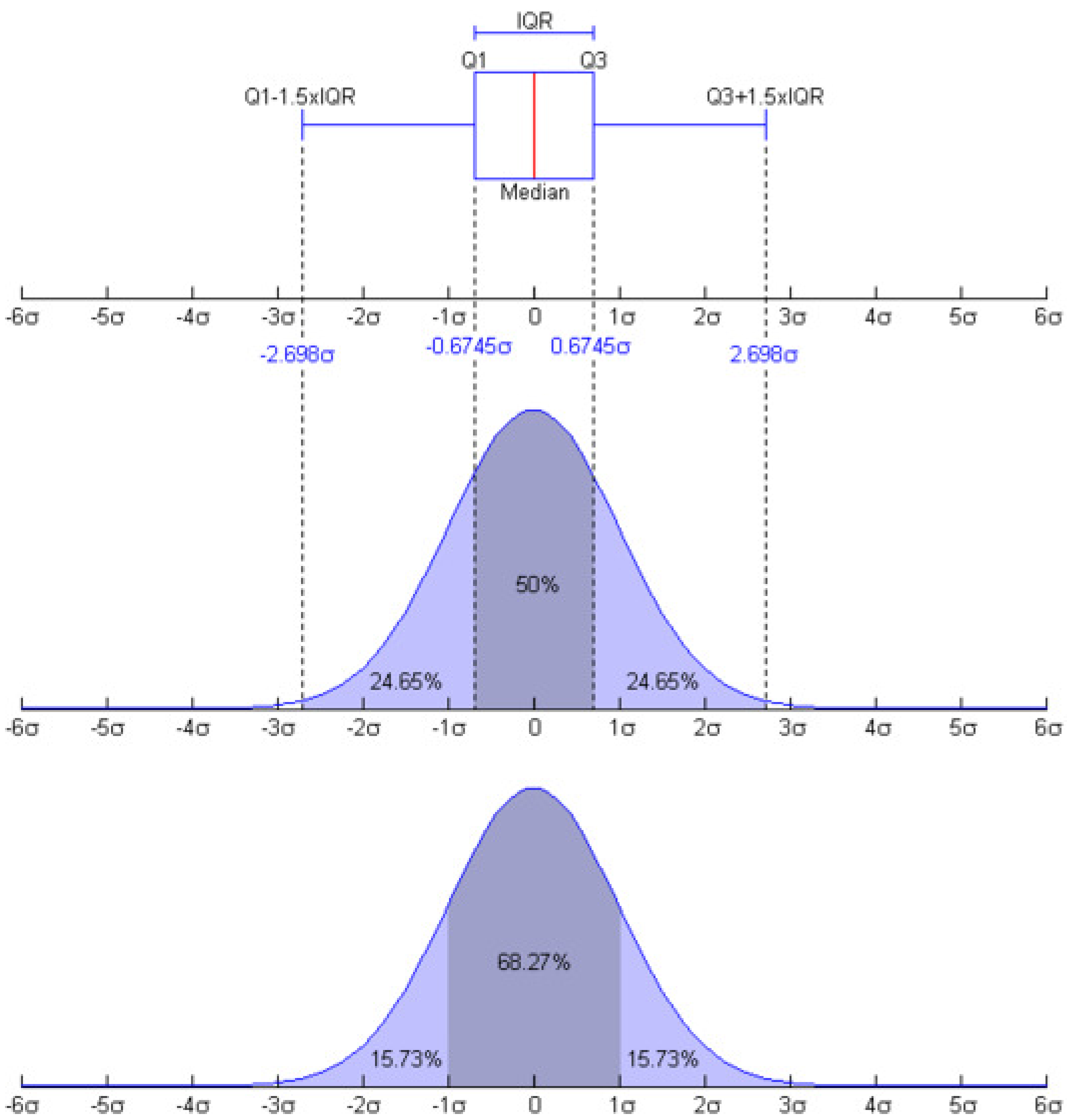
Appendix A: Box Plot Interpretation Guide



Source: en.wikipedia.org/wiki/Image:Boxplot_vs_PDF.png#filelinks

A box plot is based on "quartiles". The box consists of one quartile on either side of the median is the inter-quartile range (IQR) and includes 50% of the observations. The quartiles on either side of the box are referred to as the upper and lower quartile. There are also "whiskers" that extend from the upper and lower quartile. The full range of the box and whiskers covers about 99% of all observations. If the distribution is normal, the whiskers are 1.5 times the length of the IQR. Any observations outside of the box and whisker range are indicated by individual dots and may be identified as outliers.

Appendix B: Trips Master Table

The AVAS provides a plethora of data, but the data needs to be refined, processed, and organized to be useful. A sequence of manual and automated data processing steps select subsets of the data from CTA's archive ORACLE SQL tables and organize the data into a usable format in a new table: TRIPS_MASTER. The manual and automated data processing steps to create the TRIPS_MASTER are listed below:

1. Create the set of key stops as a union of the scheduled timepoints and stops ranked 10 or higher with respect to passenger activity.
2. Generate the TRIPS_MASTER table with schedule information inferred by interpolation for key stops.
3. Aggregate AVL/APC passenger and time information across key stops and key stop segments and join this data to the key stop schedule information in TRIPS_MASTER.

Once the data is in this format, it is more efficient to identify erroneous records such as two buses logged into the same trip number. Trips with no observations are easily identified in the TRIPS_MASTER table because the scheduled trip record creates a placeholder for each scheduled trip. The TRIPS_MASTER table also simplifies the data collection for model development by calculating metrics such as running time, headway, and passenger demand. Full details of the TRIPS_MASTER table are shown in Table B- 1.

Table B- 1: Trips Master Table

Populated for every scheduled trip for each day	
General Information	
ROUTE_ID	Route identifier
RUN_ID	Run identifier
TRIP_ID	Trip identifier
DIRECTION	Direction of trip
BT_VER	Schedule version
Scheduled Time per Trip	
TRIPSTART	Trip start time
TRIPEND	Trip end time
SCHTIME	Scheduled time of this location
DAY	Day of the month
Location	
TIMEPOINTID	Key stop location identifier
GEODESCRIPTION	Key stop name

Only populated if this trip is observed	
Serving Bus and Operator	
BUS_ID	Bus identifier
OP_ID	Operator identifier
Key Stop Observations	
ARRTIME	Arrival time at the key stop
ARR_SCH_DEV	Schedule deviation upon arrival
DEPTIME	Departure time from the key stop
DEP_SCH_DEV	Schedule deviation upon departure
DWELL_TIME	Dwell time at key stop
PASS	Passengers onboard at the key stop
TP_ONS	Boarding passengers at the key stop
TP_OFFS	Alighting passengers at the key stop
Relationship to Previous and Next Trip	
HEADWAY	Time since departure of preceding trip
NEXT_HDWY	Time until departure of following trip
Segment Data	
TTIME	Segment travel time
PREV_TTIME	Travel time of previous trip
SEG_ONS	Passenger boardings
SEG_OFFS	Passenger alightings
SEG_STOPS	Number of stops served
SEG_DWELL	Dwell Time

Appendix C: Dwell Time Research

Modeling the Factors Affecting Bus Stop Dwell Time
Using AFC, AVL, and APC Data

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ABSTRACT

Dwell time at bus stops represents a significant portion of bus operation time and its variance. While dwell time is highly correlated with the number of passengers boarding and alighting, there are also secondary factors, specifically crowding, fare type and bus design, that may have a significant impact on dwell time. These secondary factors may strongly influence the effectiveness of different strategies to improve service. Automatic data collection systems provide a plethora of data but require preprocessing to combine records from different collection systems, to control for measurement error, and to determine the significant factors influencing dwell time. Using data from the automatic passenger counting (APC), automatic fare counting (AFC), and automatic vehicle location (AVL) systems installed on Chicago Transit Authority (CTA) buses, the paper develops and implements preprocessing techniques, estimates a dwell time model, and analyzes the impact of the secondary factors. Smart media fare cards are estimated to have a 1.5 second faster transaction time than magnetic strip tickets, but only in un-crowded situations. When the number of on-board passengers exceeds the seating capacity, there is no statistically significant difference between the fare media types.

INTRODUCTION

Dwell time at stops is understood to be an important component of travel time in transit systems, particularly bus operations (1). Transit authorities manage the impact of dwell time through fare media, bus design, and service levels. However, these options cost money, so it is important to understand the potential benefit from each.

With the widespread implementation of AVL, APC, and AFC systems, we are able to analyze large amounts of data and can estimate the impact of dwell time management techniques. Moreover, we can use this data to gain insight into the incidence and distribution of the uncontrollable variability in the system. For example, a passenger who takes a long time to locate their smart media fare card may very well take longer to board the bus than one paying in cash that has two crisp dollar bills at the ready. Another example is that of the elderly passenger who is not able to stand while the bus is in motion, so the dwell time must be extended until this passenger has found a seat. In this model approach, the passengers who are out on the tail of the dwell time per passenger distribution are categorized as "atypical" and are separated from the data set so they can be analyzed separately. The advantage of a bifurcated analysis is to explicitly represent dwell time as a combination of recurrent, semi-controlled factors and uncontrolled variation.

PRIOR WORK

Earlier research into dwell time has explored a multitude of factors, but these studies either relied upon limited manually collected data sets and are now dated, or used automatically collected data without detail on fare media type.

Prior research into dwell time from manually collected data measures the impact of fare type, boarding and alighting passengers, crowding, and vehicle configuration. Zografos and Levinson (2) estimate the base service time as 2 seconds per passenger in a no fare bus system until passengers exceed the seating capacity at which point the service time increases. Marshall et al. (3) find that different fare media types and structures create an average passenger service time of up to 8 seconds, but this study predates the widespread implementation of smart cards or magnetic stripe fare media. Lin and Wilson (4) estimate a dwell time model for light rail vehicles. In this study, they develop a functional form that estimates the dwell time per door and find that the crowding effect is best captured nonlinearly. The cost of collecting data manually limits the number of observations in these data sets to a handful of stops, operators, and times of day. Furthermore, rare conditions such as the atypical passenger will not be well captured in a limited data set.

Automatically collected data avoids these problems, but with a loss of detail. Dueker et al's research (5) uses a much larger data set provided by APC systems. With 350K observations, the researchers explore time of day impacts (finding that AM peak is the shortest dwell time) and the impact of schedule adherence (as an operator falls behind schedule, the dwell time is shortened). However, this study does not include information about fare media type or separate passenger activity by door. Near-side stops (which may include longer dwell times due to traffic lights) are also included in this data set, which increases the variability of the dwell time. While the researchers do separate lift operations and estimate them separately, they do not pull out other outliers which may be categorized as atypical passengers and quantified separately. The fit of the regression model is .345, which suggests a lot of unexplained variability.

The Transit Capacity and Quality of Service Manual (TCQSM) (6) recognizes the importance of dwell time in capacity and service planning and suggests passenger service times of 3.5 seconds with Smart Cards and 4.2 seconds with Magnetic Stripe tickets. Crowded situations and bus type differences are accounted for by adding or subtracting .5 seconds to each service time respectively. This research aims to validate or refute the suggested values with automatically recorded data and leverage the wide availability of data at the Chicago Transit Authority (CTA) to better reflect the impacts of crowding.

DATA COLLECTION METHODS AND VARIABLES

The data used in the dwell time model is collected through the APC, AFC and AVL systems installed on CTA buses. Prior to estimating the model with this data, the AFC and AVL/APC records must be combined and erroneous or questionable records either corrected or removed. The cleaning and selection process is summarized below.

The dwell time is measured between "first door open" and "last door closed" within 100 feet of vehicle movement (the start and end time is signaled either from the door open sensor or the door control switch – see Table 1). Note that a dwell time signaled from the control switch will be longer than one signaled from the door open sensor since the control switch time includes the time for the door to fully open. (7) Passengers are counted as they pass the APC sensors within the door-open, door-close time period including some grace period after the last door close. Passenger boarding and alighting counts are captured for each door.

Data is used from the three most common and modern bus types at CTA as listed in Table 1.

Table 1 Bus Types and Characteristics

				Dwell Time Signal	
Bus	**First Delivered**	**Length (feet)**	**Seats**	**Front**	**Rear**
Nova	2000	40	37	Door Open	Control Switch
Nabi	2003	60	61	Control Switch	Control Switch
New Flyer	2006	40	39	Control Switch	Door Open

All buses are low floor, equipped with "Go Lane" smart media card readers, and have 2 doors. The front door is available for both boarding and alighting while the rear door is reserved for alighting only. The Nabi is unique in that the rear door is extra wide and allows for two lanes of alighting passengers. Note also that the Nova has door-mounted front APC sensors and may undercount passengers who board/alight before the doors are fully open.

AFC records are captured through a different system than the APC/AVL system. The records can be combined however by matching farebox to bus and matching fare transaction time to stop event time. The AFC events that impact dwell time will be those that occur while the bus doors are open. AFC events after the doors are closed will not impact the dwell time and therefore are not included in the data set. Furthermore, only trip transaction records are included in the data set (i.e. insufficient fare, add value, etc. events are excluded). This combination creates entries for each AVL stop record which contain the number of Chicago Card (smart media card) and Transit Card (magnetic stripe ticket) transactions within the dwell time. Once the AFC events are associated with the AVL/APC stop record, the FON count is checked against the total fare transactions to correct for small levels of APC undercounting.

Data Exclusions

This section discusses the AVL/APC records that are excluded from analysis.

CTA buses report through the AVL data when the APC sensors are blocked. This may occur when there is a high level of crowding on-board or when the sensors are misaligned. APC records from misaligned sensors will be incorrect; therefore observations from busses that reported a blocked sensor on every stop observation were excluded from the data set.

In order to estimate the dwell time as determined solely by passenger activity, both timepoint and near-side stops were eliminated from the data set. Timepoint stop observations may include schedule correction or “holding” time. The dwell time at near side stops may be extended by a red light where the driver either holds the door open through the light, or extra passengers are able to board (both situations will lengthen the dwell time beyond the actual passenger activity constrained value).

There are cases where the APC counter is obviously wrong; one specific case is 39 passenger boardings within 3 seconds. In order to eliminate these cases, a minimum dwell time per passenger is set at .5 seconds.

A maximum dwell time per passenger is also applied, but this data is excluded with the intention of building a different model estimate of the atypical passengers who have a per passenger dwell time of greater than 8 seconds. Separating the data by dwell time per passenger avoids having to cut off the dwell time at an arbitrary value and isolates those passengers/situations that are highly variable. A more detailed analysis of atypical passenger observations is included in the following section.

Wheelchair ramp operations are also excluded from the data set and will instead be included in the atypical passenger estimate due to the high variability of dwell time associated with ramp operation.

Variables

- DWELL_TIME – Dependent variable, measure of time in seconds between first door open to last door close.
- FON_EX – APC counted passengers that do not have an AFC record associated with them. This may be due to these passengers paying with cash, not needing to pay (children), or completing their fare transaction after the dwell time period has ended.
- CARDS – Variable for the number of passengers who pay with a Smart Media Card (Chicago Card) within the dwell time.
- TICKET – Variable for the number of passengers who pay with a magnetic stripe ticket (Transit Card) within the dwell time.
- AFC_TRANS – Sum of total CARDS and TICKET transactions within the dwell time.
- FOFF12; FOFF3UP – Variable for the number of passengers alighting through the front door grouped by the first two passengers (FOFF12) and the 3rd and higher (FOFF3UP).
- ROFF – Variable for the number of passengers alighting through the rear door.
- ST2_PASS – Variable of the total passenger activity (ONS + OFFS) from the door with the maximum dwell time multiplied by the square of the number of thru-passengers above the seating capacity (0 if seating capacity is greater than number of thru-passengers). Thru-passengers is defined as those passengers who are on-board before the observation and do not alight at the stop.
- F_SENSOR – Dummy variable to capture when the APC sensor is blocked in an un-crowded situation. The sensor is recorded as blocked if it is blocked when the door handle is first activated, or when the sensor is blocked for longer than 10 seconds. These cases may be baby carriages, many passengers boarding, crowded cases or faulty mechanisms. To eliminate cases with faulty mechanisms, buses that report blocked sensors in every observation of a day are excluded from the analysis.

Observations were collected from CTA buses running regular service during the entire month of November 2006 with a total of 173,750 observations across 85 routes, 927 stops, and 2,977 operators. The summary statistics of the data are presented in table 2.

Table 2 Summary Statistics

Nabi	Obs	21718		
Variable	Mean	Std. Dev.	Min	Max
dwell_time (secs)	6.41	6.72	1	122
fon_ex	1.15	1.87	0	39
cards	0.01	0.18	0	11
ticket	0.03	0.28	0	11
afc_trans	0.04	0.36	0	11
foff12	0.60	0.73	0	2
foff3up	0.07	0.40	0	18
roff	0.57	1.09	0	14
st2_pass	68.57	409.33	0	8379
f_sensor	0.01	0.10	0	1
dwellperpass	2.72	1.68	0.56	8
New Flyer	Obs	103902		
Variable	Mean	Std. Dev.	Min	Max
dwell_time (secs)	6.68	8.23	1	164
fon_ex	1.41	1.88	0	36
cards	0.00	0.07	0	7
ticket	0.04	0.39	0	28
afc_trans	0.04	0.42	0	29
foff12	0.52	0.71	0	2
foff3up	0.08	0.43	0	11
roff	0.47	0.92	0	19
st2_pass	10.79	112.69	0	5324
f_sensor	0.02	0.13	0	1
dwellperpass	2.51	1.57	0.52	8
Nova	Obs	39866		
Variable	Mean	Std. Dev.	Min	Max
dwell_time (secs)	8.12	9.82	1	160
fon_ex	1.72	2.02	0	29
cards	0.01	0.13	0	8
ticket	0.06	0.47	0	19
afc_trans	0.06	0.53	0	22
foff12	0.49	0.70	0	2
foff3up	0.08	0.48	0	14
roff	0.48	1.11	0	22
st2_pass	11.05	99.74	0	3042
f_sensor	n/a	n/a	n/a	n/a
dwellperpass	2.78	1.62	0.55	8

MODEL ORGANIZATION AND FORMULATION

This section discusses the functional form of the model and how the data is segmented by atypical passengers, door activity, crowding, and bus type.

To address the motivating questions of crowding impact and to understand the impact of dwell time on bus operations, it is advantageous to first define and separate the outlying per-passenger dwell times (attributed to atypical passengers).

It is assumed in the model formulation that passenger activity is independent between doors, but occurs serially at any door. Some bus types, especially the Nabi, have particularly wide front doors which allow simultaneous boardings and alightings. Field observations of actual passenger behavior, however, suggest that boarding passengers usually wait for the alighting passengers to clear before beginning to board. Therefore, the data is divided by bus type and the model is built by first predicting which door will have the longest dwell time to handle its activity. Finally, we can test for significant differences in crowded situations and combine the data to test explicitly for differences among the three bus types.

Atypical Passengers

Eight seconds per passenger was chosen as the cut off for dwell time per passenger for typical passengers because it is about twice the estimated time for passenger activity (see table 5 and table 6 for per passenger dwell time estimates) and excludes only 5% of all observations across all bus types. When representing the impact on dwell time due to atypical passengers it is best to have these records as a distribution, rather than just part of the residual.

It is important to note that 8 seconds per passenger as a cutoff of dwell time is not universal. This cutoff will depend greatly on the bus type, farebox, and fare (more expensive fares will take longer for cash transactions). After all, Marshall et al. estimated an 8 second average passenger service time in their 1990 study, twice that which was found in this data set. Besides the advances in fare media technology, the reduced dwell time per passenger may be due to improvements in the farebox ability to process cash transactions. (3)

Max Door Estimations

APC Data is collected on both doors, yet only one of the doors will be the controlling or governing factor in the dwell time. When there is activity through both doors, however, it is not possible to determine immediately from the data which one has the longer dwell time. Therefore, the regression model is first estimated using data with a single type of passenger activity and door (e.g. for the rear door – there were no FON, FOFFS or AFC transactions). Using these estimates for the remaining records that have passenger activity through both doors, the expected dwell time associated with the front and rear door was calculated. Whichever door has the longest expected dwell time is identified to be the governing door and the values of passenger activity for the other door are set to zero for the estimation process. This estimation and prediction process was done separately for each bus type.

Crowding

While the threshold for crowding is fuzzy, we use the number of seats on the bus as the value above which passengers on the bus begin to impact the boarding and alighting process; the "crowded" state. Some passengers will stand even when not all of the seats of the bus are taken. Even when there are passengers standing, however, they do not necessarily impede the flow of passenger activity. Using the number of seats as a threshold value results in a situation where there are enough standees that they are likely to impact passenger activity.

Most of the previous dwell time models include a variable to capture the effect of crowding. Lin and Wilson (4) developed models with different linear and non-linear combinations of the number of standees and boarding and alighting passengers. Lin and Wilson achieved a slightly improved fit with a non-linear crowding variable. In the development of this model, several different combinations of onboard and boarding/alighting passengers were investigated and the best fit was found using the square of the sum of boarding, alighting, and onboard passengers. An exponential variable should give a better representation than a linear variable because each additional standee or boarding/alighting passenger above a critical value will take longer than the previous average.

The standees that create a crowding impact are those who are on the bus through arrival and departure from the stop. In other words, the impact of crowding is only realized when there are standees impeding the alighting and boarding process. The APC data records passenger load after all passenger activity has taken place; therefore we need to subtract the number of boarding passengers to calculate the standees that will impact crowding. The crowding impact per stop is measured by the number of standees squared multiplied by the total passenger activity. To analyze the impacts of crowding on the other variables, the estimates of the entire data set are compared to the crowded and non-crowded situations for each bus type.

Model Estimates

To determine the impact of crowding, a single model is estimated with dummy variables to distinguish the crowded and non-crowded situations. These results are shown in table 3 for the New Flyer bus. Note that all t-statistics listed in this document are robust to correct for heteroskedasticity.

The F-Test was used to test for a statistically significant difference in the estimators between open and crowded. Estimators (besides the crowding term) that have a statistically significant difference of less than 0.5 seconds are not distinguished in the combined model. A minimum statistically significant difference of 0.5 seconds is used to simplify the dwell time prediction model and to highlight the estimator differences that will have a relatively strong impact on dwell time.

Table 3 New Flyer Front Door Estimates with Complete Crowded Separation

Adjusted R2: 0.72

Passenger Levels	**open**		**crowded**	
Variable	**est**	**t-stat**	**est**	**t-stat**
FON_EX	3.67	140.66	3.85	36.46
TICKETS	4.26	41.82	4.07	13.89
CARDS	3.10	6.86	5.47	4.38
FOFF12	2.84	85.52	2.76	19.14
FOFF3UP	1.52	20.13	1.20	3.80
F_SENSOR	4.75	20.45		
ST2_PASS			0.002	4.93

	Both	
	est	**t-stat**
intercept	-1.18	-23.63

The largest difference is between the estimates for CARDS in open versus crowded situations, with a difference that is significant at the 90% level of confidence. Interestingly, there is not a statistically significant difference between the crowded CARDS and TICKETS estimators, while there is a statistically significant difference between the open CARDS and TICKETS estimators. Therefore, the best model is to combine the fare media types into a single variable in crowded situations. This has significant implications because it means that there is no dwell time savings with the smart media technology if the bus is crowded. Table 4 lists the refined model estimate with all the appropriate variables combined across crowded and open situations.

Table 4 Simplified model of Front Door Dwell time on New Flyer Buses

Adjusted R2: 0.72

variable	est	t-stat	Passenger Levels
intercept	-1.19	-23.68	both
FON_EX	3.67	141.61	
FOFF12	2.83	86.16	
FOFF3UP	1.50	20.44	
CARDS	3.10	6.85	open
TICKET	4.26	41.79	
F_SENSOR	4.73	20.33	
AFC_TRANS	4.24	13.29	crowded
ST2_PASS	0.0027	6.82	

The same process was applied to the Nova and Nabi bus types to get the best functional form for each bus type as well as for the rear door of each bus. Once this was done, the data set of all three bus types was combined and dummy variables were used to delineate the common variables across buses. The model was then further refined to include only those dummy variables that are statistically significant. The result of this process is two regression models, one for the front door and one for the rear door. The front and rear door estimates are displayed in table 5 and 6 respectively.

Table 5 Dwell Time Estimates – Front Door

Adjusted R2: 0.73

Variable	DUMMY	est	t-stat	Passenger Levels
intercept		-1.22	-26.49	All
NABI		0.53	7.81	
FON_EX		3.68	154.17	
	NOVA	0.38	10.51	
	NABI	-0.59	-11.32	
FOFF3UP		1.52	26.22	
CARDS		2.62	10.15	Open
TICKET		4.88	39.55	
	NFLYER	-0.58	-3.62	
FOFF12		2.83	104.59	
F_SENSOR		4.60	21.55	
AFC_TRANS		4.35	15.54	Crowded
FOFF12		3.52	22.54	
	NFLYER	-0.74	-3.71	
ST2_PASS		0.0011	5.56	
	NFLYER	0.0017	3.53	

Table 6 Dwell Time Estimates – Rear Door

Adjusted R2: 0.37

Variable	DUMMY	est	t-stat	Passenger Levels
Intercept		1.42	22.49	All
	NABI	2.64	21.26	
ROFF		1.69	40.86	
	NOVA	0.42	7.47	
	NABI	-0.42	-5.37	
ST2_PASS		0.005	5.64	Crowded
	NOVA	0.004	2.11	
	NABI	-0.003	-3.36	

INTERPRETATION OF MODEL RESULTS

All primary (non-dummy) estimates are positive with the exception of the front dwell intercept. This negative value is likely due to a significant number of observations with less than 3 second dwell times. These observations involve the operator flipping the handle and the agile passenger leaping into, or off, the bus. All estimates are statistically significant at the 95% confidence level using robust t-statistics. The overall fit of the model, particularly the front door dwell time (.73) is very high.

Fare Media and Boarding Passengers

The New Flyer bus shows a faster processing time of magnetic stripe tickets. This may be due to the more accessible location of the ticket reader on the left side of the farebox. The ticket reader is located on the right side on both the Nova and Nabi buses. Across all bus types, the model estimates show that smart media cards are roughly 1.5-2 seconds faster to process than the magnetic stripe tickets. But, there is no statistically significant difference between the two fare types in crowded situations. Therefore, when the bus is crowded, simply moving onto the bus is the bottleneck and it does not matter what type of fare is used.

The value of the additional boardings (FON_EX) coefficient is between the CARDS and TICKET coefficient values. This is because additional boardings will represent mixed cases. Cash transactions should be longer than either smart media or magnetic stripe fare media, but passengers who have not paid their fare within the dwell time will be faster than any fare media transaction. These two cases are both included in the additional boardings variable and will tend to balance each other out. The difference in the additional boardings coefficient across bus types may be explained by the particulars of bus configuration. The wider front doors of the Nabi may allow faster boarding or less disruption in alighting leading to lower boarding times. The Nova bus, however, may be systematically undercounting the passengers that slip through before the doors are completely open and the APC sensors aligned.

Alighting Passengers

Multiple piecewise linear arrangements were attempted, but the only statistically significant division was on front alighting passengers (FOFF). The model estimates that the first two passengers to alight through the front door will take about 1 second longer to alight than the succeeding passengers or rear door alighters. This is reasonable because these passengers must stand away from the front doors, while other passengers may queue directly in front of the rear doors to alight. At the front door, this difference may also be due to the potential conflict with boarding passengers with the first two alighting passengers blazing the trail for any following alighting passengers. In crowded situations, the model shows that on average an additional second is needed for each of the first two passengers to alight on the Nova and Nabi.

For rear door alighting passengers, the Nabi has the shortest dwell time per passenger consistent with its double-width rear doors allowing faster alighting. However the overhead of the Nabi shown through the intercept is 2.64 seconds greater on average than the other two bus types. This may be due to the further distance of the rear door at the back of the articulated bus making it difficult for the operator to recognize when alighting is complete.

Crowding

The total passenger activity times the standees squared (ST2_PASS) coefficient is statistically significant but only has a real impact on the predicted dwell time at the maximum values of the data set. The mean values of ST2_PASS are around 100 – 400, which will be at most a few seconds of extra dwell time at the stop. This estimate allows a comparison across bus type and shows that the Nabi has the smallest crowding impact on front or rear door activity. This is surprising because the New Flyer and Nova buses have the same number of doors and are shorter than the Nabi. The difference may be in the passenger behavior. Articulated buses are typically used on the express routes, where passengers have longer travel times. The longer the travel time, the more likely a passenger will be to move well into the bus and away from the doors. Note that the crowding variable is squaring the standees; therefore additional onboard passengers are estimated to have a larger impact on crowding than additional boarding and alighting passengers.

Prediction

To use this model for prediction, the dwell time must be calculated for the front and rear door and the maximum of these calculations used for the overall dwell time. This model is particularly useful for predicting marginal change, such as a change in fare media type. This model may be further used to predict the increased dwell time and travel time caused by either a reduction in service or increased passenger demand. When predicting the total dwell time for an entire route, it is necessary to use the atypical passenger distribution as an input in 5% of instances. For an atypical passenger, the dwell time per passenger will be overridden by a sample from the fitted distribution of atypical passengers.

Sample Application

The significance of the crowded impact on fare media is demonstrated by predicting the change in dwell time if all customers used smart media cards on a crowded and non-crowded route. Table 7 shows running time, dwell time, and fare media transactions from a single peak period trip on CTA route 4 and route X49. Using the estimated model, the change in dwell time is predicted if all passengers currently using a magnetic stripe ticket switched to the smart media card. The prevalence of crowding on the X49 trip prevents the fare media from having any significant impact on dwell time.

Table 7 Change in Fare Media

							Savings if 100% Cards		
Route	Running Time	Dwell Time (sec)	Boardings	Tickets	Cards	Non-Crowded Ticket	total time (sec)	% dwell	% running
4	1:10:54	604	103	92	8	77	138	22.85%	3.24%
X49	1:46:55	755	112	77	4	12	18	2.38%	0.28%

CONCLUSION

Identifying and separating atypical passengers and excluding known or potential biases due to near-side and timepoint stops allows for the estimation of a dwell time model on a large set of data with a very good fit of .73 for the front door and .37 on the rear door. This practice is appropriate so long as the atypical passenger dwell times override the predicted dwell times with the same frequency that they occur in the data.

The remaining data is partitioned by bus type, door choice, and crowding levels. These partitions are leveraged to estimate first separate, then combined, models with a high level of detail on the differences in dwell time behavior depending on the bus type, door choice, and passenger demand. The resulting models provide more subtlety than previous dwell models based on automatically collected data. For example, the model estimates demonstrate the advantage of Smart Media fare cards over magnetic stripe fare tickets to be about 1.5-2 seconds. This advantage, however, is not observed when there are more passengers on board than the seating capacity of the bus. Therefore, the advantages of new fare media technology in improving bus operations occur principally when service levels avoid crowding.

The large data set provides the opportunity to compare the residuals across time of day, stop, operator and route to look for other significant relationships. It would also be interesting to extend the ordinary least squares regression model to include distributions to account for the impacts of operator, time of day, stop, etc.

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