# A Transit Route Simulator for the Evaluation of Control Strategies Using Automatically Collected Data

by

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## Abstract

This thesis develops and tests an extensible simulation model that uses automatically collected transit data to simulate transit route operations, demand, and control mechanisms. This model is motivated by the increasing availability of automatically collected transit data, which enables more detailed simulation and validation and also allows for advanced control strategies that can be evaluated using simulation. A framework is presented for using simulation to evaluate the improvement in service quality enabled by data.

Most previous transit route simulation models included an explicit representation of traffic flow, which requires extra input data and introduces extra complexity. A detailed simulator design is presented that uses only transit-derived data to simulate vehicle and passenger movements and outputs a detailed log for flexibility of performance measurement.

A case study of operations on the CTA's Route 9 Ashland was used to demonstrate and test the simulator. The simulator could be used to test alternative operator and supervisor behavior strategies and supervisor deployment schemes, as well as potential technological advances involving real-time data. Schedule, vehicle movement, terminal departure punctuality, passenger demand, and dwell time inputs for the simulator were derived from Route 9's schedule, AVL data, and APC data.

The case study simulation was subjected to validation tests that compare simulated and real headway regularity, trip travel time, and maximum load statistics. Significant differences were found in all three tests. Adjustments were employed in attempt to make the simulation match reality. The results of adjustments to input parameters show that dwell times are an important source of headway variability. The results of adjustments to operator and passenger behavior and of controls indicate that effects that apply only to bunched vehicles have limited impact on service.

After each of these adjustments, the simulation still did not pass validation tests. A prime cause for this result may be the intelligent behavior of transit agency personnel, particularly operators, a potentially fruitful area for future research.

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

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B"H.

Professor Nigel Wilson has been my advisor in the best senses of the word for five years, from bringing me into the exciting world of transit research through my freshman UROP to helping me make the right academic choices in undergraduate and graduate school to coaching me through the final throes of this thesis. No one, including me, could ever see as quickly where my ideas were going as Nigel could, and my meetings with him were very often the most enjoyable and stimulating part of doing research.

You name it, and Ginny Siggia takes care of it, including if "it" is an insufficiently-organized student. She and the rest of the administration of the Department of Civil and Environmental Engineering and of MIT in general deserve great thanks for keeping everything running.

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My life at MIT was made whole by the community surrounding the MIT Orthodox Minyan. It gave me unique experiences, great friends, and my wonderful wife (see below).

My parents, Mr. Solomon Moses and Mrs. Susan Moses, brought me up to be

[1]This thesis would not have been nearly as pretty, and the processing not nearly as fun, without Athena's LaTeXfor MIT Theses.

a "mench," to be interested in the world, to rise to challenges, to communicate in correct English, and to know how to get around on transit, among other virtues, and then they sent me to the best Institute in the world. They have been a great source of advice, comfort, support, and love to this graduate student, as have my grandparents, Mr. Henry Jellinek and Mrs. Clara Jellinek, and my in-laws, Dr. Walter Lemann and Mrs. Susan Lemann. My thanks and apologies go to all of them and to my siblings, Rebecca and Jonathan, for being patient while I tried to get this work done.

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# Contents

# List of Acronyms

**AFC** Automatic Fare Collection

**APC** Automatic Passenger Counter

**AVAS** Automatic Voice Annunciation System

**AVL** Automatic Vehicle Location

**CTA** Chicago Transit Authority

**GPS** Global Positioning System

**MDT** Mobile Data Terminal

**OCC** Operations Control Center

**WLAN** Wireless Local Area Network

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# Chapter 1

# Introduction

## 1.1 Motivation

### 1.1.1 Questions Raised by New Technologies

Technologies are rapidly becoming available in the transit industry that allow service management staff to gather and use information about the real-time status of their vehicles. Automatic Vehicle Location (AVL) systems use Global Positioning System (GPS), signpost-based, or odometer-based tracking to keep vehicles constantly updated about their own positions. Automatic Passenger Counters (APCs) use infrared sensors (or other technologies) to keep track of how many people get on and off a vehicle at each stop, and Automatic Fare Collection (AFC) systems count fares and in some cases record the entries, and even the exits, of individual farecards. Communications systems using digital radio or cell-based networks allow data to be exchanged between vehicles, control centers, and supervisors. Operations Control Centers (OCCs), Mobile Data Terminals (MDTs) on vehicles, and wireless-enabled handheld or laptop computers allow people across a transit system to display and manipulate digital information and messages.

Currently, the state of service management practice in most transit agencies is that each service manager makes decisions based on what he has observed directly and what his experience tells him to assume. Used together, the suite of technologies described above could dramatically increase the amount of information available to support service management. Service managers could have instant knowledge of where all of their vehicles are and how many passengers each one is carrying. More importantly, service managers could use this information in real-time to improve their ability to correct problems that arise in service and maintain smooth operations.

This potential raises some important questions. What would service managers do differently if they had this kind of real-time information? What good would the newly enabled strategies do for the transit authority and for its passengers? Which components of the real-time technology are most important, and which parts of the information have to be most precise to be useful?

### 1.1.2 The Difficulty of Direct Experimentation

Like many questions about the value of different practices in transit operations, the most direct way to answer these questions is to do a series of experiments in which different practices are used in real service for a significant duration and the effects are measured. For many questions, however, this technique would be totally impractical. Firstly, because any given transit authority's service has a direct effect on the daily lives (and livelihoods) of thousands (or millions) of people, intrusive experimentation that could negatively impact service quality or efficiency is tolerable on, at most, a very limited scale, and must be preceded by careful investigation.

Another reason that extensive experimentation using "live" transit service is impractical, particularly when dealing with questions of technology procurement, is cost. Experimentation with alternative sets of service management rules, or even with alternative schedules, for example, would require essentially a one-time investment of labor time for retraining of employees and/or communication to the public. The cost of this investment would not be trivial, but pales in comparison to the cost of procuring and deploying a new technology system. In most cases, because of the important role of the central computer infrastructure in such systems, it is expensive to even do a limited deployment. As a result, experimenting with a range of alternative deployments would be extremely expensive.

Finally, a related reason for the impracticality of experimentation with technology deployments is time. It takes a great deal of time to procure and deploy a new technology system, and additional time to train transit personnel in its use. Even after the new system is deployed and in use, it can still take a long time for transit personnel to get used to incorporating it into their operations. After all of this initial time has elapsed, each experiment requires a significant enough amount of time to measure the impacts reliably. All of these requirements add up to make any experiment take much more time than would be practical.

### 1.1.3 Simulation

A way to experiment with different technology deployments and service management policies without potentially inconveniencing thousands of people, incurring prohibitive costs, or taking large amounts of time is simulation. Using a simulation model that captures the operations of a transit route (or network) and various alternative forms of technology-enabled service management, it is possible to predict the impacts of these alternatives without actually implementing them.

For example, to predict the effects of making automatically colleceted, real-time data available to service management personnel, a set of service management strategies that use the data should be designed. The benefit of these strategies over strategies that do not use real-time data can be compared by running simuations that implement each set of strategies, extracting performance measurements from the alternative simulations, and comparing the performance measurements.

An additional benefit of the proliferation of the automatic data collection systems described above is that they generate large amounts of archival data that can be used for close analysis of many aspects of transit operations. In particular, this data can be used both for the initial calibration of a simulation model to behave like the real service and as a basis for comparison for validation testing. Until the relatively recent proliferation of some of these technologies, it was practically impossible to collect sets of data for these tasks that covered enough of a transit system, for enough time, with enough detail, using the manual data collection techniques available. Consequently, there is a new opportunity now to create and test simulation models with a more detailed relationship to the transit systems they model than before.

## 1.2 Objectives

The objectives of this research are:

- To develop a simulation model that uses automatically collected transit data to simulate transit route operations, demand, and control mechanisms. This model must be extensible so that additional control mechanisms and strategies for their use can be implemented within its basic framework.

- To use this model to simulate a real transit route using data collected from that route.

- To test the validitity of the resulting simulation (and of the underlying model framework) by comparing its measured behavior with that of the real service, and to make adjustments to the model, as indicated by the results of these tests.

## 1.3 Thesis Organization

Chapter 2 discusses the design of the simulator, including the prior work that serves as its context; its goals, data needs, and specifications; and notes about its implementation.

The next four chapters describe the case study that was used to demonstrate, test, and adjust the simulator. Chapter 3 introduces the context of the case study: Route 9 Ashland at the Chicago Transit Authority (CTA), and the control structures and technologies available and in consideration for that route. Chapter 4 discusses the data processing that went into creating appropriate inputs for the simulation of Route 9. Chapter 5 defines the validation tests of the simulation and presents their initial results. Chapter 6 goes through the set of adjustments and additional tests that were conducted in an attempt to make the simulation conform to reality.

Finally, Chapter 7 explores the conclusions that can be drawn from the results of the adjustments and tests in the previous two chapters and suggests avenues of future research.

# Chapter 2

# Simulator Design

This chapter describes the design of the simulation model. The first section discusses prior work in bus transit simulation as a context for this design. In the next section, general goals for the design of this model, informed by the prior work, are specified. Next, the inputs required by the simulator are listed and explained. The following section details the behavior of the simulator. The final section of this chapter discusses how this desgin was implemented.

## 2.1 Prior Work

### 2.1.1 Bus Route Macrosimulation Models

Some of the earliest bus route simulation models used macrosimulation. One example of this is (Abkowitz and Engelstein, 1983), which used a regression-based model to simulated trip running times based on aggregate statistical inputs such as trip length and total boardings and alightings.

### 2.1.2 Bus Route Microsimulation Models

A review of the transit simulation literature indicates that the past few decades have seen many different implementations of bus route microsimulation, representative examples of which are cited in this section. Some of them had similar objectives to those of this reasearch, including (Andersson et al., 1979), (Goldblatt and Yedlin, 1981), (Victor and Santhakumar, 1986), and (Chandrasekar et al., 2002), all of which evaluated control measures such as holding and short-turning; and (Khan and Hoeschen, 2000), which included a simulated AVL system.

One past bus transit microsimulation study that had much in common with this one was (Andersson et al., 1979), which used automatically collected bus movement and demand data to inform a detailed microsimulation model of a bus route. The simulation was designed to test the effects of individual control measures, so instead of including an automated decision-making process and showing the results of implementing general policies as the simulator described in this thesis does, its control interventions were triggered manually by a human who was monitoring the simulation, and the results of each individual action were reported. In addition, the vehicle movement data used to inform the simulation came from a system that used radio signposts placed periodically along the route and was therefore substantially less detailed than contemporary AVL data, which can provide the precise location of the vehicle at any point.

### 2.1.3 Traffic Representation

One characteristic that most past bus route microsimulation models share is an explicit representation of the traffic environment, either through macrosimulation (mostly in earlier models such as (Goldblatt and Yedlin, 1981) and (Jain et al., 1991)) or microsimulation (used in more recent work such as (Bauer et al., 1995)[1], (Khan and Hoeschen, 2000), (Chandrasekar et al., 2002), (Morgan, 2002), and (Balvanyos et al., 2003)). Such a representation allows the model to make predictions about traffic signal priority schemes (a major focus of many of these studies), exclusive lanes, and the effects of transit on traffic, and these elements were studied in almost all of the works cited.

However, modeling the traffic environment presents a number of costs to the mod-

[1]Bauer's research was actually on light rail, but the issues faced in the simulation were very similar to those raised by bus simulation.

eler:

- It is necessary to collect data about the flows on the traffic network and use them to calibrate corresponding simulator inputs. Where there is insufficient traffic data, assumptions must be made.

- The model must incorporate definitions of vehicle behavior, such as car-following and lane-changing behaviors. These, too, must be calibrated from available data and depend on simplifying assumptions of the decisions drivers make. They also add complexity to the simulation.

- Definitions of traffic signal timings are also required, adding yet more complexity and requirements for external data.

In addition, in most cases, the transit simulation tool is developed as an adaptation or extension of a traffic simulator, such as NETSIM/CORSIM ((Bauer et al., 1995) and (Khan and Hoeschen, 2000)), PARAMICS ((Chandrasekar et al., 2002) and (Balvanyos et al., 2003)), or MITSIM (Morgan, 2002). This approach leads to the following problems for transit simulation:

- The assumptions about vehicle behavior in the base model are geared toward private automobiles, rather than transit vehicles, so where the behaviors of these two types of vehicles differ, the original set of assumptions has to be overcome.

- These tools vary in flexibility, ranging from a program whose source code is entirely available for modification by the researcher (MITSIM, in Morgan's case) to a piece of proprietary commercial software whose outputs cannot be modified (CORSIM, which forced Khan to use a clever trick to extract data that could be used to calculate bus travel times). In all cases, there are elements of the base traffic model that cannot be changed[2], and in most cases, it would be ideal to change these elements in order to simulate transit. These inflexibilities force researchers to devise workarounds to model various aspects of transit and often

[2] Even if the source code is available, some assumptions cannot be undone without reengineering the whole program.

result in making compromising assumptions about the transit representation to be able to use the traffic simulator.

One example of this problem is that the NETSIM/CORSIM model does not deal explicitly with passengers, so the studies that used it had to model them indirectly by their effects, such as dwell time.

## 2.2 Goals

This section describes the general goals and defining features of the simulator. In particular, the following important features (discussed in detail below) were absent in most of the simulations found in the literature review described in 2.1, and none of those simulations include all of them.

- Explicit representations of transit-specific features like passengers and vehicle schedules.
- Flexibility in defining control interventions and outputs.
- The ability to implement control interventions automatically based on simulated policies, without intervention from a user.
- Reliance entirely on automatically-collected transit data and no exogenous data.

### 2.2.1 General Operations and Features

As was described in the first objective listed in Section 1.2, the goal of this simulator is to simulate transit route operations, demand, and control interventions. Particular features of the simulator operations should include:

- The simulator should simulate vehicles moving along a route, stopping at stops and allowing passengers to board and alight at those stops.
- The number of passengers at each stop and on each vehicle should be tracked, so that collections of passengers can have the appropriate effect on dwell times, and

so that it is possible to produce performance measurements related to passenger movements. However, because of the great increase in complexity it would require, the simulator need not track individual passengers moving through the system.

- Vehicles should serve trips according to a schedule, rather than simply a generalized scheduled departure headway. In addition, vehicles should be assigned to blocks (vehicle work assignments) that have them proceeding from one trip to the next, allowing for the possibility of extreme lateness on one trip affecting the start time of that vehicle's next trip. These characteristics are absent from many prior traffic-based simulation studies, which model bus departures, like other vehicle entries to the network, as a frequency-specified flow rather than as individually scheduled departures.

- A flexible framework should be provided for defining different kinds of control interventions and for setting them to be triggered by vehicles arriving at particular locations. At any time, it should be possible for control interventions to access the instantaneous locations and passenger loads of all vehicles, as well as relevant schedule data. This type of flexibility would be difficult or impossible to achieve with many prior models, as discussed in Section 2.1.

  For the purpose of this study, two control interventions were implemented: Hold for Schedule and Hold for Headway. They are defined in Section 2.4.7.

The specifications for the operations of the simulator are discussed in detail in Section 2.4.

### 2.2.2 Input Sources

An additional defining characteristic of the simulator is that it should be possible to calibrate the model to simulate a real transit route, using a collection of inputs derived from automatically collected performance and demand data from that route. This transit data (principally schedule, AVL, and APC data, in most cases) should be sufficient to inform the simulation without any non-transit data, such as general traffic flow data or socioeconomic ridership indicators, unlike many of the models used in the literature discussed in Section 2.1.

Provided that the necessary transit data is available, which relatively recent technological developments enable, this characteristic simplifies the data collection effort by making appeals to external sources of data unnecessary. In addition, basing the simulation directly on data collected from the route that it simulates allows for a very clear understanding of the relationship between the inputs and the resulting behavior. The specifications for the inputs to the simulator are discussed in detail in Section 2.3.

### 2.2.3 Outputs

Finally, at the end of each simulation run (or set of runs), the simulator should output a complete picture of what happened during the entire run, including

- A record for every time a vehicle block or trip starts and for every operator relief.
- The arrival and departure times of each vehicle at each stop, and the amount of time spent dwelling while passengers boarded and alighted.
- The number of passengers boarding and alighting each vehicle at each stop.
- A record of each time a control intervention is employed, including any relevant immediate results of that intervention (for example, the number of seconds a vehicle was held).

Using these outputs, it is possible to calculate a wide range of performance measures.

## 2.3 Input Specifications

The simulation requires four sets of inputs: route description, passenger demand, vehicle movement, terminal behavior, and control strategy. In accordance with the goal set in Section 2.2.2, all of these inputs can be derived from endogenous transit data. An example of how they were derived from data belonging to a particular transit system is presented in Chapter 4.

### 2.3.1 Route Description

A basic understanding of the building blocks of a transit schedule is necessary to understand the Route Description inputs.

- **Pattern** — One pattern is defined for each possible path that a vehicle could take in one direction along a route. For example, a simple route with no variants is described by two patterns — one for each direction (or, in the case of a circle route, just one pattern); an owl variant that does not go as far would require two more patterns.

- **Trip** — A trip is an assignment to traverse a given pattern, starting at a given scheduled start time.

- **Block** — A block is a string of sequential trips to be served by one vehicle over the course of a day.

- **Run** — A run describes a piece of work assigned to an operator. Usually composed of a string of sequential trips like a block, a run, unlike a block, can start or end in the middle of a trip, when one operator relieves another at a relief point.

- **Timepoint** — A timepoint is a point along the route where a scheduled passing time is defined for each trip.

#### Route Patterns

Each pattern is an ordered list of the stops used by one variant of the route, in one direction.

In addition to the basic list of stops, each pattern in which operator reliefs take place is assigned a stop as a relief point, where vehicles stop to fulfill a scheduled relief.

#### Vehicle Schedule

The vehicle schedule defines the list of trips that are scheduled to take place and assigns the trips to vehicle blocks. Each trip is defined by a pattern and a start time, and each block is defined by a list of trips.

Operator reliefs scheduled to take place within a vehicle block (where the need to switch operators forces a vehicle to wait until the relief operator appears) also belong in the vehicle schedule. Also, if scheduled passing times at time points are used in any control strategies (including a standard behavior of waiting at timepoints), those scheduled passing times should be in the schedule.

### 2.3.2 Passenger Demand

Given that demand rates vary by time of day, both $PAR_i$ and $PAF_i$ (defined below) should be estimated separately for each of a set of time periods that cover the period to be simulated.

#### Passenger Arrival Rates ($PAR_i$)

For each stop (in each direction) $i$, $PAR_i$ is the average number of passengers arriving per hour.

This specification, like the one in Section 2.4.1, requires an assumption that within a time period, the passenger arrival process is independent of time. This assumption breaks down on low-frequency routes (with headways generally greater than 10 minutes), so if this simulator is to be used on a low headway route, the treatment of passenger demand will have to be extended to include other demand processes.

### Passenger Alighting Fractions ($PAF_i$)

For each stop (in each direction) $i$, $PAF_i$ is the average fraction of passengers on an arriving vehicle that alight at $i$.

This specification assumes that this fraction is independent of what pattern is being run, and ignores any correlation between boardings at one stop and alightings at another. If these assumptions prove to be unsupportable, the model should be extended to allow pattern and locations of boardings to alter instantaneous values of $PAF_i$.

### Vehicle Capacity ($VC$)

$VC$ is the maximum number of passengers that can be on board a vehicle at any time.

## 2.3.3 Vehicle Movement

The Vehicle Movement inputs are designed to capture everything that affects a vehicle's movement along a route, such as traffic conditions, traffic signals, acceleration, deceleration, and passenger demand, either explicitly (as with the effect of passenger demand) or implicitly. This approach removes the need for a great deal of the input data required by almost all of the models surveyed in Section 2.1.

An underlying assumption for this set of inputs is that all of the time that a vehicle spends over the course of a trip (besides time spent waiting for a relief or to obey a control intervention) can be divided into three categories: a) time spent servicing a stop (that is, with the doors open to allow passengers to board and alight), b) time spent traveling from one stop area to another, and c) time spent traveling through a stop area (See Figure 2-1 for an explanation of what "stop area" means in this context.)

The last of these represents the part of the trip in which a bus's behavior depends on whether it services a stop, excluding the time spent actually servicing the stop (with the doors open). It therefore captures the difference between the time a vehicle

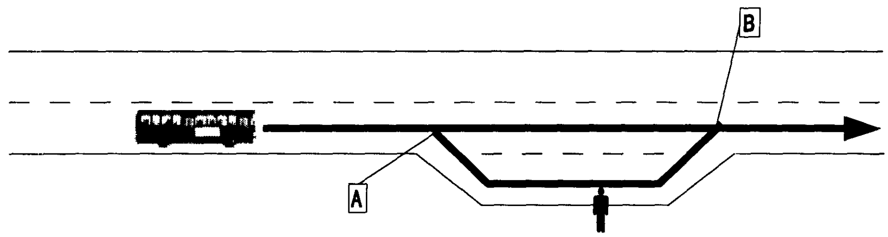


Figure 2-1: For the purpose of this work, a "stop area" is defined as the area around a stop in which a vehicle's movements depend on whether, or not, it services that stop. Typically, the "stop area" would extend from the point where a vehicle starts decelerating or leaving the travel lane (point A) if it plans to service the stop to the point where it finishes accelerating or re-entering the travel lane (point B) after servicing it.

takes to drive by a stop and the time it takes to decelerate, pull into the stop, accelerate, and pull back into traffic.

These three categories of travel time are expressed to the simulator in the form of the following three inputs. Like the demand inputs, these inputs (except the dwell time function) should be estimated by time period, given that traffic conditions vary over the course of the day.

### Inter-Stop Movement Times ($MT_{i,j}$)

For each pair of stops $(i, j)$ that are sequential in any pattern, $MT_{i,j}$ is the mean movement time between $i$ and $j$. Additionally, movement time inputs could include: $StdMT_{i,j}$, the standard deviation of the movement time, representing variability between the movement times of different vehicles, and $MinMT_{i,j}$ and $MaxMT_{i,j}$, the minimum and maximum movement time.

These inputs are intended to capture all of the effects of traffic, traffic signals, and operator behavior through their impact on the mean and standard deviation of inter-stop movement times. This simplification rests on the assumption that these effects are not significantly correlated with any elements that are variable over the course of a time period, such as the positions of vehicles with respect to each other.

#### Stopping Penalties ($SPO_{i,j}$, $SPD_{i,j}$) (optional)

For each link connecting two adjacent stops $i$ and $j$, $SPO_{i,j}$ and $SPD_{i,j}$ are the average extra travel time (excluding time with the doors open) that a vehicle experiences along $(i, j)$ as a result of stopping at the origin, $i$, and as a result of stopping at the destination, $j$, respectively. $StdSPO_{i,j}$ and $StdSPD_{i,j}$, the standard deviations of these terms, may be input as well; if so, $MinMT_{i,j}$ and $MaxMT_{i,j}$ should also be included.

#### Dwell Time Function ($DT(B, A, O)$)

$DT(B, A, O)$ is a function that determines how long the vehicle sits with its doors open, given $B$ and $A$, the number of passengers boarding and alighting (and possibly $O$, other factors).

### 2.3.4 Terminal Behavior

#### Terminal Departure Punctuality ($TDP_\tau$)

For each terminal $\tau$, $TDP_\tau$ and $StdTDP_\tau$ are the mean and standard deviation of the number of minutes late (or early) that vehicles leave $\tau$ to start a trip.[3] $MinTDP_\tau$ and $MaxTDP_\tau$, the minimum and maximum of this value, should be included as well.

It is assumed that these statistics represent punctuality that is unaffected by a vehicle's lateness arriving at the terminal. (In other words, if a vehicle arrives at the terminal late and leaves late as a result, it should not impact these statistics.)

#### Minimum Recovery Times ($MRT_\tau$)

$MRT_\tau$ is the minimum time a vehicle must spend at each terminal $\tau$ between arriving there at the end of a trip and departing to start the next trip. $StdMRT_\tau$, the

[3] For example, if $TDP_\tau = -3$, the average vehicle will leave $\tau$ three minutes early. If, in addition, $StdTDP_\tau = 0$, every vehicle will leave $\tau$ exactly three minutes early.

standard deviation of this term, may be input as well, in which case $MinMRT_\tau$ and $MaxMRT_\tau$, a minimum and maximum, should also be included.

This specification ignores any effects (other than arrival time at the terminal, of course) of previous trips on required recovery time. For example, if the operator did not have enough recovery time for a substantial break at the end of the last trip, the minimum recovery time at the end of this trip may be higher in real life than the input value of minimum recovery time.

### 2.3.5 Control Strategy Inputs

#### Control Intervention Variations

A table must be input that defines each control intervention variation that may be used in the simulation. Some control interventions require one or more parameters to be defined. (For example, both Hold for Schedule and Hold for Headway have a Maximum Hold parameter that allows them to be limited to a given maximum hold time.) Any value of a parameter for a particular intervention that could be used in the simulation defines a variation of that intervention. The variations table defines each variation in terms of the basic control intervention and the parameter[s]. (For example, separate variations can be defined for Hold for Schedule with no maximum hold time, with a maximum hold time of 60 seconds, and with a maximum hold time of 120 seconds.)

#### Control Intervention Triggers

An additional table must be input that determines which control interventions are triggered at which stops. This table should have a record for each control variation to be triggered at each stop at which control interventions may be triggered. For example, this table may include six entries indicating that Hold for Schedule with a maximum hold time of 60 seconds is to be triggered at stops 5, 10, and 15, and Hold for Headway with no maximum hold time is to be triggered at stops 3, 10, and 20.

## 2.4 Simulator Operation

This section describes the basic operations of the simulator: how it uses the inputs described above to simulate vehicle and passenger movements. Seven major activities are included: the generation of passenger demand; a vehicle's pulling out into service, arriving at a stop, servicing a stop, departing from a stop, and ending a trip; and control interventions.

### 2.4.1 Passenger Demand

The number of passengers waiting at each stop $i$ at time $t$, $PW_i^t$, is initialized to 0. This initialization should happen shortly before the first time a vehicle arrives at that stop, and the beginning of the simulation should be discarded as "warm-up" time to minimize the effects of this arbitrary initialization.

Whenever needed, the simulator updates $PW_i^t$ based on

$$PW_i^t = PW_i^{LQP_i} + Prand((t - LQP_i) \cdot PAR_i) \tag{2.1}$$

where $LQP_i$ is the time of the last query of the number of passengers at $i$ and $Prand$ is a function that returns a random number of arrivals based on a Poisson process with the given parameter[4].

### 2.4.2 Pulling out

When a block is scheduled to start (according to the vehicle schedule), a vehicle $v$ is assigned to that block and pulls out (arrives at the first stop on the pattern assigned by the first trip of the block). Its pullout time is defined as

$$POT_v = BST_v + InBounds(Nrand(TDP_{BOT_v}, StdTDP_{BOT_v}), \\ MinTDP_{BOT_v}, MaxTDP_{BOT_v}) \tag{2.2}$$

[4]See the footnote to Section 2.3.2

where $BST_v$ is that vehicle block's scheduled starting time, $BOT_v$ is its scheduled origin terminal, $Nrand$ is a function that returns a normally distributed random variable with the given mean and standard deviation, and InBounds is a function that repeats drawings from the given random function until the result is within the given bounds, ensuring that the vehicle does not leave unreasonably early or late.

### 2.4.3 Arriving at a Stop

When a vehicle $v$ arrives at a stop $i$, a decision is made whether (or not) it will service (stop at) $i$. Stop $i$ is serviced by vehicle $v$ if any of the following conditions are true:

- There are passengers waiting at $i$, and $v$ has a passenger load which is less than capacity.
- There are passengers on $v$ who will alight at $i$. The number of passengers who will alight at time $t$ is given by

$$PA_{v,i}^t = Brand(PL_v^t \cdot PAF_i) \tag{2.3}$$

  where $PL_v^t$ is the passenger load on $v$ at time $t$ and $Brand$ is a function that returns a binomially distributed random variable with the given mean.

- $v$ is scheduled for an operator relief at $i$.
- Some control intervention forces $v$ to stop at $i$. (See Section 2.4.7.)

Otherwise, $v$ departs from $i$ immediately upon arrival.

### 2.4.4 Servicing a Stop

When a vehicle $v$ services a stop $i$ at time $t$, the following events happen, in order.

1. $PA_{v,i}^t$ (see Equation 2.3) passengers alight and are subtracted from $PL_v^t$.
2. As many of the passengers waiting at $i$ as remaining space on $v$ will permit (in particular, $min(PW_i^t, (VC - PL_v^t))$) board; they are subtracted from $PW_i^t$ and added to $PL_v^t$.

3. The appropriate dwell time for the numbers of passengers alighting and boarding, as given by $DT$, elapses.

4. If $v$ is scheduled for an operator relief at $i$, time elapses until the scheduled relief time, if it has not yet arrived.

5. If a control intervention forces $v$ to wait until an appointed time or for a certain duration, it does.

6. $PW_i^t$ is updated to account for the time that has elapsed since $v$'s arrival at $i$. If $PW_i^t > 0$, meaning that more passengers have arrived at $i$ in that time, as many of the new passengers as space will permit (defined as above) board. The appropriate dwell time for these new boardings, as given by the dwell time function $DT$, elapses.

After it has serviced the stop, $v$ departs.

### 2.4.5 Departing from a Stop

When a vehicle $v$ departs from a stop $i$ at a time $t$, it first determines if $i$ is the last stop on the route pattern that $v$ is currently traversing. If so, $v$ ends its trip (see Section 2.4.6).

If $i$ is not the last stop on $v$'s current pattern, $v$ continues toward the next stop, which we will call stop $j$. The arrival of $v$ at $j$ is set to occur at time $t + TMT_{v;i,j}$, where $TMT_{v;i,j}$, the total movement time of $v$ from stop $i$ to stop $j$, is given by one of two expressions, depending on whether stochastic elements of the vehicle movement inputs were included:

$$TMT_{v;i,j} = MT_{i,j} + (SS_{v,i} \cdot SPOi, j) + (WSS_{v,j} \cdot SPDi, j) \tag{2.4}$$

or

$$TMT_{v;i,j} = InBounds(Nrand(MT_{i,j}, StdMT_{i,j}) + SS_{v,i} \cdot Nrand(SPO_{i,j}, StdSPO_{i,j}) + WSS_{v,j} \cdot Nrand(SPD_{i,j}, StdSPD_{i,j}), MinMT_{i,j}, MaxMT_{i,j}) \quad (2.5)$$

where $SS_{v,i}$ and $WSS_{v,j}$ are dummy variables indicating whether vehicle $v$ serviced stop $i$ and will serve stop $j$, respectively, and the *InBounds* function is used (like in Equation 2.2) to keep the stochastically determined movement time within a reasonable range.[5] The $SS$ and $WSS$ terms are only included if the optional stopping penalty inputs were included.

### 2.4.6 Ending a Trip

When $v$ ends its current trip at time $t$ and terminal $\tau$, it first determines if the trip it is ending is the last one in the block that it is assigned to. If so, $v$ is removed from the simulator (that is, it pulls in to the garage).

If not, $v$ is scheduled to start its next trip. Its trip start time can be calculated in one of two ways, depending on whether the stochastic elements of the minimum recovery times were included:

$$TST_{v,\tau} = max(SST_{v,\tau}, (t + MRT_\tau)) + InBounds(Nrand(TDP_\tau, StdTDP_\tau), MinTDP_\tau, MaxTDP_\tau) \quad (2.6)$$

[5]It is readily apparent, by the time $v$ departs $i$, whether $v$ serviced $i$. While $WSS_{v,j}$ isn't deterministically known as $v$ departs $i$, enough information is known for a very good guess. $PA^t_{v,j}$ is calculated and fixed at this point, since it is dependent only on $PL^t_v$, which will not change before $v$ arrives at $j$ (assuming that passengers do not board and alight the vehicle while it is moving with the doors closed). In addition, it is known at this point whether $v$ has a scheduled relief at $j$. If either $PA^t_{v,j} > 0$ or a relief is scheduled, then $WSS_{v,j} = 1$. If not, whether $v$ will stop at $j$ is dependent on whether there will be passengers waiting to board there (and space on $v$ to accomodate them). In that case, the number of passengers that will be waiting at $j$ when $v$ arrives there is estimated to be $PW^t_{v,j}$ the number of passengers there now. This will only lead to an incorrect value of $WSS_{v,j}$ if $PW^t_{v,j} = 0$, there is space on $v$, and one or more passengers arrive at $j$ during $TMT_{v;i,j}$, which add up to a failure circumstance infrequent enough to be allowable for this purpose. Similarly, unforeseen control interventions at $j$ could cause $v$ to stop there even if it is not expected to when it leaves $i$.

or

$$TST_{v,\tau} =$$

$$max(SST_{v,\tau}, t + Inbounds(Nrand(MRT_\tau, StdMRT_\tau), MinMRT_\tau, MaxMRT_\tau) + Inbounds(Nrand(TDP_\tau, StdTDP_\tau), MinTDP_\tau, MaxTDP_\tau)) \quad (2.7)$$

where $SST_{v,\tau}$ is vehicle $v$'s scheduled start time on trip $\tau$. These expressions start with the scheduled start time or after the minimum recovery time elapses, whichever is later, and add a random punctuality term. Once again, the *InBounds* function is used to keep this random term within a reasonable range.

### 2.4.7 Control Interventions

#### Triggering an Intervention

When a vehicle arrives at a stop, the control interventions triggers table is checked to see if there are any control interventions that are triggered at that stop. If there are, then each control intervention variation listed for that stop is applied to the arriving vehicle.

The particular control intervention definitions, including information about when they take effect (other than the stop trigger) must be programmed in as parts of the simulator. For the purpose of this study, two control interventions were implemented: Hold for Schedule and Hold for Headway.

#### Hold for Schedule

When a vehicle $v$ arrives at time $t$ a stop $i$ at which Hold for Schedule is set to be triggered with maximum hold time $MHT_i$, $v$ is held at $i$ for an amount of time given by

$$SHT^t_{v;i} = min(MHT_i, max(0, SDT_{v;i} - t)) \quad (2.8)$$

where $SDT_{v;i}$ is the scheduled departure time of $v$ from $i$.

### Hold for Headway

When a vehicle $v$ arrives at time $t$ a stop $i$ at which Hold for Headway is set to be triggered with maximum hold time $MHT_i$, $v$ is held at $i$ for an amount of time given by

$$HHT_{v;i}^{t} = min(MHT_i, max(0, ASH_i - (t - LVD_i^t))) \tag{2.9}$$

where $ASH_i$ is the average scheduled headway at stop $i$ during the current time period and $LVD_i^t$ is the time of the last vehicle departure before $t$ from $i$. The expression $(t - LVD_i^t)$ is the preceding headway.

## 2.5 Implementation

The simulator was implemented using the MATLAB scripting language and functions from MATLAB's standard Toolboxes as well as its Statistics Toolbox. MATLAB was chosen as the platform for this effort because:

- Since it offers a high-level, interpreted language, MATLAB lends itself to relatively rapid and easy development and testing of scripts.
- MATLAB offers a powerful suite of mathematical and statistical functions which are useful for simulation.
- One of MATLAB's specialties is data processing, so it was also used both for preprocessing the simulator inputs and for post processing the outputs. In this way, the data flowed seemlessly through both of these processes and the simulator without having to be translated from one format to another.

The basic form of the simulator program is an event-based simulation, in which each of the events described in Section 2.4 concludes by scheduling another event on a queue. After each event concludes, an event handler executes the event on the queue with the next scheduled time.

# Chapter 3

# Chicago Transit Authority Case Study

A case study was conducted of an application of the simulator described in Chapter 2 using the CTA's Route 9 Ashland. The intended purpose of this case study was twofold:

- To test the effectiveness of the simulator for making determinations about a real case.
- To provide a practical demonstration of the simulator.

This chapter describes the context of this case study, the technologies and control structures that the simulator can be used to evaluate, and the preparation of the data used to create a simulation for this case study.

## 3.1 Context Overview

### 3.1.1 CTA System

The CTA operates the second largest transit system in the United States, covering the city of Chicago and its closest suburbs. The system includes an extensive heavy rail network and one of the largest bus systems in the country, with about 2,000 buses, approximately 1,700 in the peak period, operating on about 145 bus routes (Chicago Transit Authority, 2004a), (Federal Transit Administration, 2003).

The Chicago street network that CTA buses operate on is, in general, a well-ordered rectilinear grid, with major streets every half-mile and smaller streets at quarter-mile and eighth-mile intervals between the major streets (Chicago Transit Authority, 2004b). The numbering system counts 100 addresses to each eighth-mile block, starting at a particular downtown intersection. For example, the downtown area known as "the Loop" goes from 200N, one quarter-mile north of the reference intersection, to 400S, one half-mile south of it. The other borders of the Loop are at 200W and 100E. In most of the South Side, the East–West streets are numbered in accordance with their coordinates, so that, for example, $74^{\text{th}}$ Street is at 7400S, about nine miles south of the Loop.

### 3.1.2 Route 9 Ashland

#### Location

A schematic of Route 9 Ashland, including timepoints, rail connections, and major bus connections, is presented in Figure 3-1, and an annotated list of timepoints is presented in Table 3.1. Route 9 Ashland is one of CTA's longest bus routes, running approximately 18 miles North–South between 103rd Street and Belle Plaine Avenue (4100N) (Chicago Transit Authority, 2003). Route 9 is so long that the scheduled one-way running time during peak periods is over 1.75 hours. Running principally on Ashland Avenue (1600W), about 1.75 miles west of the Loop, it connects with four of the six CTA rail lines that serve the Loop and the Metra commuter rail system, as well as with many high-demand East–West bus routes. Route 9 is operated from the $74^{\text{th}}$ Street Garage, located nearby at 1815 W $74^{\text{th}}$ Street. Consequently, the point on the route at which vehicles begin and end their blocks and operators begin and end their runs is at $74^{\text{th}}$ Street.

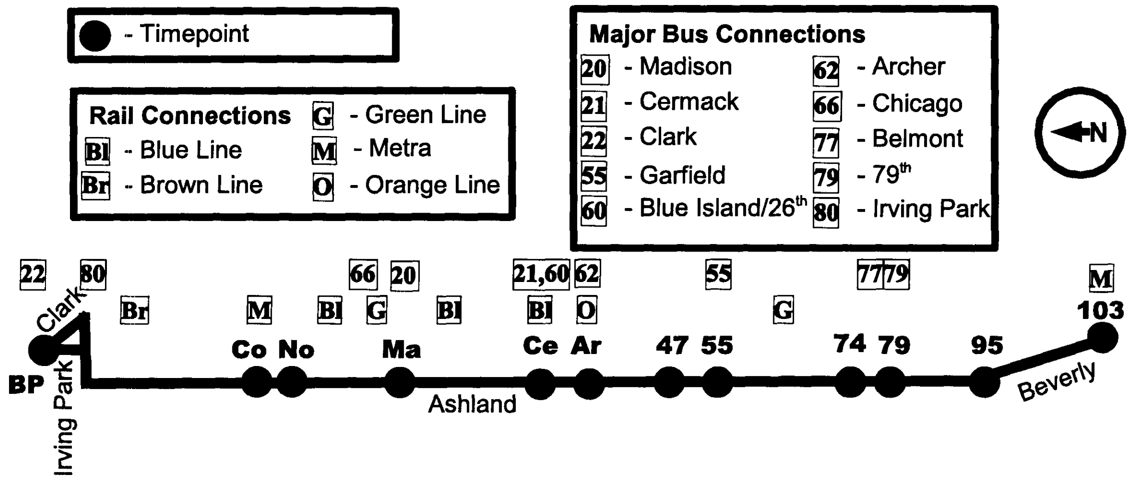


Figure 3-1: Route 9 Ashland Schematic. Not to scale. Timepoints are identified by codes, which are expanded in Table 3.1.

| Code # | Timepoint | N-S Coordinate | Comments |
|---|---|---|---|
| 103 | $103^{rd}$ & Vincennes | 10300S | Peak southern terminal |
| 95 | $95^{th}$ & Ashland | 9500S | Non-peak southern terminal |
| 79 | $79^{th}$ & Ashland | 7900S | |
| 74 | $74^{th}$ & Ashland | 7400S | Pull-outs, pull-ins, and reliefs |
| 55 | $55^{th}$ & Ashland | 5500S | |
| 47 | $47^{th}$ & Ashland | 4700S | |
| Ar | Archer & Ashland | 3000S | Detour in effect between Archer |
| Ce | Cermack & Ashland | 2300S | and Cermack during study period. |
| Ma | Madison & Ashland | 0N/S | |
| No | North & Ashland | 1600N | Only for Owl trips (terminal) |
| Co | Cortland & Ashland | 1900N | |
| BP | Clark & Belle Plaine | 4100N | Northern terminal |

Table 3.1: Route 9 Ashland Timepoints. Codes are used to identify timepoints in Figures 3-1 and 3-3.

### Demand

The Bus Operations Service Restoration Guide (1996) described Route 9 as "the heaviest route in the system" (Chicago Transit Authority, 1996). It serves residential areas, schools, hospitals, the Sun-Times complex, and other places of work. The demand has a bimodal character, with many South Side-based passengers connecting to the Green Line terminal at 63$^{rd}$ Street or to other rail lines or East–West bus routes on the South Side, and many North Side-based passengers similarly connecting to North Side services (Moses, 2003).

## 3.2 Control Structure

This section describes the methods that the CTA currently uses to manage its bus routes in general, and Route 9 in particular, as well as the possible areas in which these methods could be modified in an attempt to improve service quality. The control structure for the CTA bus system, like that of many transit systems, is accomplished by four groups of people: operators, point supervisors, mobile supervisors (and transportation managers), and dispatchers. A schematic of the communications links available between and within these groups is presented in Figure 3-2.

### 3.2.1 Operators

#### General CTA role

Operators directly control the movement of the vehicles, the operation of vehicle doors, and interactions with passengers. They know firsthand exactly where the vehicle is and roughly how many passengers are on board. However, their only knowledge about the status of other vehicles comes from whatever is in visible range and whatever they learn by communicating with the dispatch center.

Officially, operators have limited discretion regarding how they should operate. They are expected to progress up the route and attempt to hit each time point on time. Realistically, operators, particularly the more experienced ones, routinely

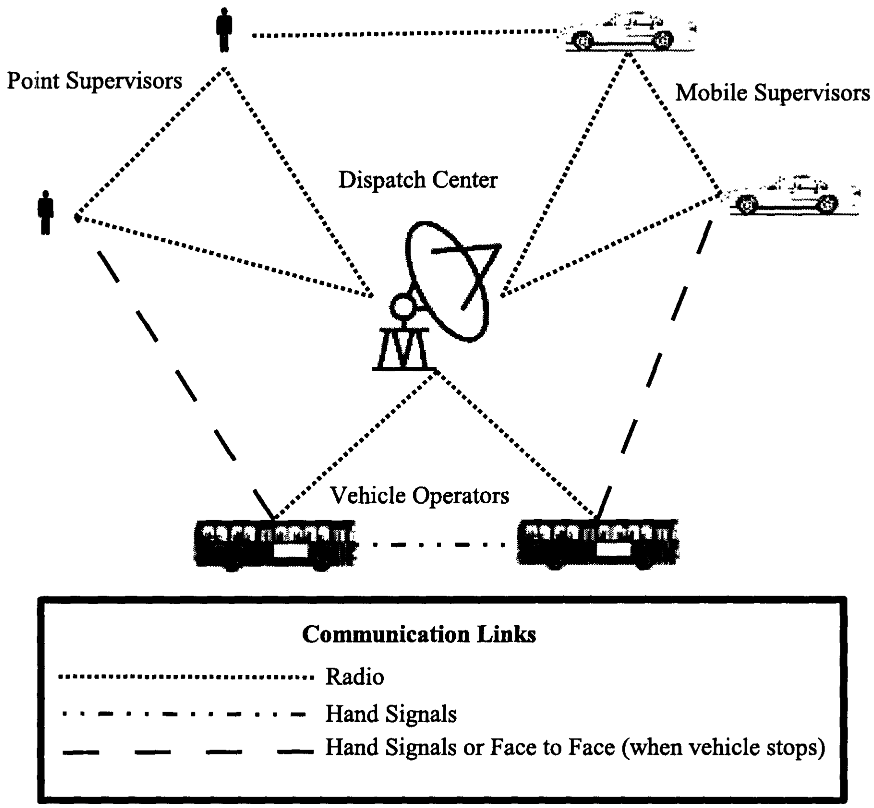


Figure 3-2: CTA Bus System Communications Links

adjust their own speed and the time spent at stops, at least within some range. They exercise these abilities for various reasons, including slowing down to avoid arriving at timepoints early, speeding up to avoid being late, and either distancing themselves from nearby vehicles to restore regularity or intentionally getting close to their leader to reduce their own passenger load (which is against the rules, but happens anyway). In addition, operators have the discretion to collaborate (typically via hand signals) on passing each other when their vehicles get bunched, in order to even out their of passenger loads and to improve overall performance.

### Route 9 Behavior

On Route 9, because of the lack of constant supervision above 55$^{\text{th}}$ Street (described below), operators sometimes behave erratically on the rest of the route (Moses, 2003). Sometimes, they run ahead of schedule northbound (north of 55$^{\text{th}}$ Street) knowing that they will not get caught. Additionally, they sometimes start southbound trips late, either because of insufficient recovery time at the Belle Plaine terminal or because of the lack of oversight there.

### Control Alternatives

There are a number of possible alternative control sets of rules for operator behavior that the CTA could consider adopting and that a simulation could test.

First, the rules for the behavior of operators that encounter each other along the route could be adjusted. Rules could be instituted that take into account the crowding levels of both vehicles, their schedule adherence, and the operator's perceptions (or AVL-provided information, if made available) about the space in front of the leader and behind the follower. These rules could help the two operators decide whether to pass, speed up and allow drop-offs only, or slow down and hold for a minute or two.

Another set of rules that could be adjusted is the one dealing with timepoint approaches. The rules against operators arriving at timepoints early could be loosened in case of bunching, particularly when operators have the ability to ease service irregularity by arriving at timepoints or terminals early.

### 3.2.2 Point and Mobile Supervisors

#### General CTA role

Point supervisors are posted at strategically located timepoints throughout the CTA system. In practice, the main duty that most of them fulfill is carrying out service checks, in which they record the time that each vehicle passes their points. In addition, those that are located at relief points — where operators end their runs and pass their vehicles off to other operators — are responsible for managing reliefs and taking action when operators are late for, or miss, their reliefs. In theory, all point supervisors are also responsible for a broader service management mission that includes taking action to preserve service quality when they detect it degrading. In practice, they tend to intervene only when operators are particularly late and require interventions in order to make their reliefs on time. They also initiate disciplinary actions against operators who arrive at their time points particularly early, causing operators to make an extra effort not to be early when approaching staffed timepoints.

Mobile supervisors (and sometimes transportation managers) drive around in defined zones and manage service disruptions within their areas. For the most part, they are directed by dispatchers to incidents that need particular attention. In addition, during peak periods, some of them station themselves temporarily at strategic locations where service irregularities often develop.

#### Route 9 Deployment

The CTA Bus Operations Service Map (CTA Facilities Development, 1998) displays the planned locations of point supervisors throughout the system. In particular, it includes seven planned locations for point supervisors along Route 9, ranging along the route from $74^{\text{th}}$ Street in the south to Belmont (3200N) in the north. In practice, budget cuts have forced the CTA to deploy supervisors at only a fraction of the listed locations.

Until recently, each garage decided which locations to staff within its assigned area. Consequently, of the seven planned points, only the three within the district assigned to 74th Street Garage were staffed, resulting in Route 9 having no fixed supervision north of 55th Street. More recently, the CTA centralized its bus service management function, allowing central administration to redeploy all of the system's available supervisory manpower to serve the system better. For Route 9, this resulted in three supervisors stationed at 74th Street, 55th Street, and Fullerton Street (2400N). The original and new supervisor deployments are shown in Figure 3-3. In addition, the CTA is considering alternative supervisor deployments that use fewer point supervisors and more mobile supervisors.

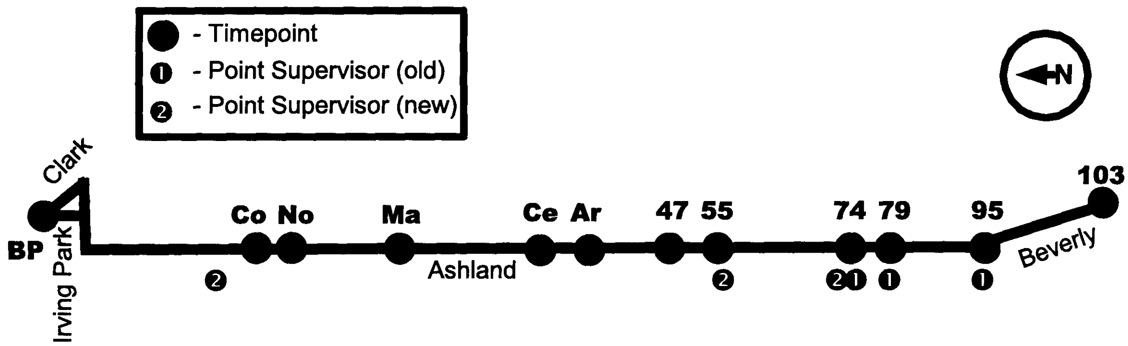


Figure 3-3: Route 9 Ashland Schematic with Supervisor Locations. Not to scale. Timepoints are identified by codes, which are expanded in Table 3.1.

### 3.2.3 Dispatchers

Dispatchers are able to communicate, via the radio system, with both operators and supervisors. As a result, one of their major responsibilities is to relay messages back and forth between these two groups. In addition, dispatchers are responsible for directing mobile supervisors to the locations of incidents that need their attention.

## 3.3 Technology Available and in Consideration

### 3.3.1 Automatic Voice Annunciation System

The CTA completed initial deployment of the Automatic Voice Annunciation System (AVAS) on most of its buses in 2004. Its main purpose is to announce upcoming stops automatically to passengers on CTA buses. To accomplish this, the system uses GPS technology along with schedule information to determine exactly where it is, both geographically and in relation to the schedule. The same location information is exported to a database and is available for off-line analysis. In addition, a portion of the bus fleet (about 12%) is equipped with an APC module, which adds passenger count information to the location data. Currently, AVAS is not connected to a real-time radio system, and all of its data is downloaded via Wireless Local Area Network Wireless Local Area Network (WLAN) when a bus returns to its garage.

### 3.3.2 Radio Communication

CTA buses are also equipped with radios that allow for real-time voice and data message communications between dispatchers and operators. These radios are also used to poll each bus periodically for its location for use in a seperate AVL system. This location information is currently used only for identification of the location of vehicles whose operators report problems or trigger the emergency alarm, but not directly for monitoring and managing service quality. Part of the reason for this is that the location information provided by this system comes in the form of raw GPS coordinates and is not related to stop locations, unlike the AVAS information.

However, the CTA is considering procuring its next upgrade of the radio system either as a module to AVAS or with a tie-in to AVAS. This addition would allow the stop-matched AVL data and possibly also the APC data that are collected by AVAS to be transmitted and used in real-time.

### 3.3.3 Operator Displays

As part of the radio system, every bus in the CTA fleet is equipped with an MDT. An MDT is a computer that handles the vehicle's communications with the dispatch center over the radio channels and also provides an interface between the operator and the system. It allows the operator to select text messages (including "Request to Talk") from a menu to send to the dispatch center, and displays messages received from the dispatch center. It is also capable of automatically displaying real-time schedule adherence information, such as a notification that the vehicle was five minutes late at its last time point, but this capability is not currently activated on the CTA's MDTs because the system they are part of is not tied in to schedule data.

Besides the current uses of the MDTs, they could potentially be used to handle communications with parties besides the dispatch center, such as supervisors and other operators. They could also be used to monitor schedule adherence information, headway adherence information, and the status of service restoration measures in place.

### 3.3.4 Supervisor Wireless Units

The CTA is currently considering deployment of wireless computer units for supervisors, and has begun designing the software for these units. Currently, the focus of the development process has been on the use of these units for exchanging of data messages between supervisors, between supervisors and the dispatch center, and possibly even between supervisors and operators. Such capability would allow for greater communications and coordination between all members of the service management staff and would decrease the load on the voice radio channels.

Once wireless computer units are in the hands of supervisors, additional capabilities could be added (depending on the architecture of the units). The units could be used to provide the supervisors with real-time vehicle location and possibly passenger load information to help them make service restoration decisions. They could also be used to help them implement those decisions by facilitating communication of the decisions to the appropriate operators and the dispatch center and possibly by offering some calculations and analyses to support the decision making process.

# Chapter 4

# Input Data

This chapter discusses the estimation of input parameters for the Route 9 simulation case study. The first section explains where and when all of the raw sources of input data came from, and the following sections describe the processing of the three types of data used: Schedule, AVL, and APC.

## 4.1 Source

To produce the simulator inputs described in Section 2.3, a data set was collected from Route 9 for the mornings of the five weekdays starting Monday, January $12^{\text{th}}$, 2004, exported from the CTA's AVAS, which was described in Section 3.3.1. For the purposes of this study, the morning period was defined as 0500 to 1100, but data from a period starting at 0330 was included to provide a "warm-up" period for the simulator.

All of the AVAS data was initially processed into plain text files from its original database format using Microsoft Access. The data in these text files were manipulated into the formats used in the simulator using a series of custom MATLAB scripts.

## 4.2 Schedule information

The information listed under "Route Description" in Section 2.3 was derived from a collection of schedule tables exported from AVAS. The pattern table, trip table, and block table all came nearly directly from corresponding tables in the schedule export. In addition, because control strategies were implemented in which any stop could be used as a time point (See Section 6.3.), a table from the AVAS data that assigns a scheduled passing time to every stop[1] was incorporated as the input for scheduled passing times in the simulator.

In the pattern table, the relief point for each pattern was set manually to the 74$^{\text{th}}$ Street stop, the relief point for all runs on the actual route. Correspondingly, one of the data processing scripts set the relief time for each trip with a scheduled relief (as determined from the trip schedule data) to the scheduled passing time of that trip at 74$^{\text{th}}$ Street.

## 4.3 AVL

### 4.3.1 Availability

AVAS equipment, including the technology necessary to collect AVL data, is installed on all of the vehicles that serve Route 9. In some cases, the AVAS equipment on a particular vehicle was malfunctioning during all, or part of, the study period, resulting in a gap in the available AVL data. Of approximately 850 trips scheduled to start during the main morning period over the five days, AVL data was reported from 598, or about 70% of them. Because the incidence of scheduled trips that are not served is generally low, and is certainly lower than 30%, it is assumed that the trips missing in the data were served but were not covered by functioning AVL equipment.

In essence, the AVL data that was used consists of a series of stop passing records, with one record for each time a vehicle passed a stop. Each record identifies the

[1]The scheduled passing times for stops that are not used by the CTA as timepoints were derived by the AVAS by interpolating between the scheduled timepoints.

vehicle; the scheduled route, pattern, block, run, and trip that it was operating; the stop it passed and the time it passed it; and if it serviced that stop, the amount of time spent there with the doors open.

### 4.3.2 Vehicle Movement Inputs

The AVL data was used to generate the simulator inputs described under "Vehicle Movement" and "Terminal Behavior" in Section 2.3 (with the exception of the Dwell Time Function, which was derived from APC data).

Two different processes were used to extract vehicle movement times from the AVL data, a simpler one that did not calculate stopping penalties and a more complicated one that did.

#### Beginning of Both Processes

Both processes started with a list of pairs of adjacent stops in any Route 9 pattern, derived from the pattern table in the Route Description data. Next, for each pair of stops, both processes collected a list of instances in the AVL data of a vehicle passing the two stops in sequence and calculated the difference between the arrival times at the two stops (minus any door-open time at the first stop). Finally, both processes calculated $MinMT_{i,j}$ and $MaxMT_{i,j}$, the minimum and maximum of these differences, for each time period.

#### First Process: No Stopping Penalties

The first process then simply took the mean and standard deviation of these differences for each time period to generate $MT_{i,j}$ and $StdMT_{i,j}$.

### Second Process: Stopping Penalties Included

The second process used linear regression to derive the vehicle movement and stopping penalty statistics all together, using the following regression function:

$$ATD_{i,j} = \alpha + \beta_1 \cdot SO_{i,j} + \beta_2 \cdot SD_{i,j} \tag{4.1}$$

$$MT_{i,j} = \alpha \tag{4.2}$$

$$SPO_{i,j} = \beta_1 \tag{4.3}$$

$$SPD_{i,j} = \beta_2 \tag{4.4}$$

where $ATD_{i,j}$ is the vector of observed differences of arrival times at stops $i$ and $j$, and $SO_{i,j}$ and $SD_{i,j}$ are vectors of dummy variables that indicate whether the vehicle serviced $i$ and $j$, respectively. These regression results were calculated for all of the vehicle movements in each time period. In addition, the variability inputs $StdMT_{i,j}$, $StdSPO_{i,j}$ and $StdSPD_{i,j}$ were calculated as the standard errors associated with the terms $\alpha$, $\beta_1$, and $\beta_2$.

### Descriptive Statistics

The minimum, median, and maximum values (over all time period, link pairs) of each of the the movement time input parameters derived using the processes described above are presented in Table 4.1. The following features can be observed in these statistics:

- The medians of all input parameters are much closer to the minimums than they are to the maximum. This is because during most of the day, the movement time over most links was less than 60 seconds, while a few instancces of much greater movement times were measured at some times, over some links.

- The values of $MT_{i,j}$ and $StdMT_{i,j}$ measured by the second process were lower than those measured by the first process, because some of the mean and variability of the movement times were absorbed in the second process by the stopping penalties.

- The estimated values of $SPO_{i,j}$ and $SPD_{i,j}$ included both highly negative and highly positive values, indicating that at some stops, whether a vehicle stopped at a stop or not had a strong effect on its movement time.

### 4.3.3 Terminal Behavior Inputs

Two classes of terminal behavior inputs were described in Section 2.3: terminal departure punctuality statistics and minimum recovery time statistics.

#### Terminal Departure Punctuality

To calculate terminal departure punctuality statistics, first, the set of all trips that arrived at their destination terminal within the first half of their scheduled recovery time[2] was collected. The basis for this selection was the assumption that the remaining half (or more) of the scheduled recovery time available to these vehicles was enough to allow a punctual start on the next trip independent of their punctuality ending their previous trip. Next, for each of these trips that was not a pull-in, the difference between the start time and scheduled start time of the vehicle's next trip was calculated . Then, it was possible to calculate $TDP_\tau$, $StdTDP_\tau$, $MinTDP_\tau$, $MaxTDP_\tau$, as the mean, standard deviation, minimum, and maximum of these differences at each terminal $\tau$.

#### Descriptive Statistics

Descriptive statistics of the terminal departure input parameters derived using the process described above are presented in Table 4.2. The positive statistics for $TDP_\tau$ indicate that more vehicles started their trips late than early or that vehicles that vehicles' lateness had a greater magnitude than their earliness. The latter of these notions, in particular, is supported by the fact that the absolute values of the median and maximum of $MaxTDP_\tau$ are significantly higher than those for $MinTDP_\tau$.

[2]This set made up about 90% of the 407 trips that were observed turning around at a terminal.

### Minimum Recovery Time

Because the minimum recovery time is detectable only in vehicles that arrive at the terminal late enough to affect the start of their next trip, and because it is impossible to tell if a vehicle started its next trip late because of its arrival time at the terminal or because of other punctuality issues, it was difficult to determine which vehicles experienced minimum recovery times. There were many instances of vehicles turning around and starting their next trip essentially immediately, indicating that $MinMRT_\tau$, at least, is 0 for all terminals $\tau$. However, a process for determining what the other minimum recovery time inputs should be was not found. In the simulation, values of 0 and 60 seconds were tested, with very little impact on operations, since the incidence of vehicles arriving at a terminal after most of their scheduled recovery time has elapsed is low.

## 4.4 APC

### 4.4.1 Availability

Because only about 12% of CTA vehicles with AVAS equipment also include an APC module, only about that proportion of the trips in the study period contributed to available APC data. In particular, APC data was reported from 71 trips during the study period, constituting about 12% of the AVL trips and about 8% of all scheduled trips. The APC data is an extension of the AVL data that adds counts of passengers boarding and alighting at each door to each AVL record corresponding to a serviced stop.

### 4.4.2 Dwell Time Function

#### Model Selection

A project associated with this research was conducted by Jose Soltren to determine what would be an appropriate form for a dwell time function using the CTA's AVAS data (see (Soltren, 2004)). He started with a simple, "sequential" dwell time model that includes only a constant term and linear boardings and alightings terms, and tested various modified forms. Modifications that he tested included:

- The inclusion of a term that is linear in passenger load. This modification was rejected because the load term did not have a significant enough t-statistic and because of problems (discussed in Section 4.4.3) with using load from the AVAS data.

- The separation of the alightings term into two terms: one for front alightings, and one for rear alightings. This modification was rejected for the purposes of this study because in a simulation context, it would be necessary to estimate each passenger's likelihood of alighting through one door or the other. Because passengers' decisions of whoch door to alight through are based on a large variety of factors, some of which[3] are difficult to measure, this estimation would be likely to contribute more error to the dwell time estimation.

- The separation of the boardings term into two terms: one for the last $n$ passengers to board, where $n$ is configurable, and one for all previous passengers. This form is based on the observation that an operator will sometimes close the doors and depart from a stop while the last one (or more) passengers are still in the process of boarding. Soltren tested models in which $n$ was set at 1, 2, and 3. He found that in models in which $n$ was set to 2 or 3, the estimated coefficients corresponding to the two boardings terms were statistically indistiguishable, but when $n$ was set to 1, the two boardings terms were significantly different.

Soltren selected a dwell time model using only the last modification mentioned above, and with $n$ set to 1:

$$DT(B, A) = \alpha + \beta_1 \cdot min(B, 1) + \beta_2 \cdot min(B - 1, 0) + \beta_3 \cdot A \tag{4.5}$$

[3]For example, the position of the passenger on the vehicle, the number of passengers who are standing, and the location of the passenger's destination with respect to the stop.

in which $B$ is the number of passengers boarding, $A$ is the number of passengers alighting, $min(B, 1)$ represents the last passenger to board, and $min(B-1, 0)$ represents all previous passengers.

### Parameter Estimation

Linear regression was used to derive the terms of this function from all the records of serviced stops in the Route 9 APC data. Descriptive statistics of this dataset are presented in Table 4.3. The resulting parameters are presented in Table 4.4. The t-statistics for the parameters and the $R^2$ statistic for the regression, which indicate that all of the parameters are statistically significant, are also presented.

## 4.4.3 Passenger Demand Rates

The passenger demand inputs described in Section 2.3 were derived from the available APC data, with the exception of vehicle capacity, which was set initially to 80 and later tested at alternative values, as discussed in Section 6.2.

### Adjusting APC Observations

However, before these inputs, particularly passenger alighting fractions, could be derived, it was necessary to adjust the APC data to make the instantaneous passenger load observations more meaningful. Because of errors in individual boarding and alighting counts along the route, a running total of the number of passengers on board at any time occasionally dips below zero, which is clearly infeasible, and makes it impossible to calculate the fraction of arriving passengers who alight.

To correct this, a process was used that made three types of corrections:

- At the first stop of each trip, all alightings were removed, based on the assumption that passengers never alight at the first stop. One boarding at that stop, if available, was removed for each removed alighting, based on the assumption that the alightings and boardings are explained by the operator getting on and off repeatedly at the terminal.

| | First Process | | Both Processes | |
|---|---|---|---|---|
| | $MT_{i,j}$ | $StdMT_{i,j}$ | $MinMT_{i,j}$ | $MaxMT_{i,j}$ |
| minimum | 6 | 0 | 2 | 7 |
| median | 29 | 10 | 16 | 56 |
| maximum | 636 | 247 | 413 | 907 |

| | Second Process | | | | | |
|---|---|---|---|---|---|---|
| | $MT_{i,j}$ | $StdMT_{i,j}$ | $SPO_{i,j}$ | $SPD_{i,j}$ | $StdSPO_{i,j}$ | $StdSPD_{i,j}$ |
| minimum | 5 | 0 | -99 | -195 | 0 | 0 |
| median | 26 | 3 | 5 | 0 | 4 | 2 |
| maximum | 405 | 133 | 300 | 144 | 188 | 120 |

Table 4.1: Descriptive Statistics of Movement Time Input Parameters. All quantities are in seconds. All statistics were taken from the set of all time period, link pairs in which a value of $MT_{i,j}$ was measured.

| | $TDP_\tau$ | $StdTDP_\tau$ | $MinTDP_\tau$ | $MaxTDP_\tau$ |
|---|---|---|---|---|
| minimum | 13 | 48 | -275 | 131 |
| median | 45 | 94 | -96 | 232 |
| maximum | 111 | 134 | 45 | 371 |

Table 4.2: Descriptive Statistics of Terminal Departure Punctualities Input Parameters. All quantities are in seconds. All statistics were taken from the set of all time period, terminal pairs in which a value of $TDP_\tau$ was measured.

| | Dwell Time (sec) | Boardings | Alightings |
|---|---|---|---|
| minimum | 1 | 0 | 0 |
| median | 7 | 1 | 1 |
| maximum | 232 | 27 | 34 |

Table 4.3: Descriptive Statistics of Dataset Used for Estimation of Dwell Time Parameters. 3962 observations were used.

| Parameter | Interpretation | Value | t-statistic |
|---|---|---|---|
| $\alpha$ | Constant term per dwell | 5.94 | 10.6 |
| $\beta_1$ | Time for last boarding | 4.16 | 11.5 |
| $\beta_2$ | Time for each additional boarding | 5.49 | 6.5 |
| $\beta_3$ | Time for each alighting | 1.66 | 28.2 |

Table 4.4: Estimated Dwell Time Parameters. The value of the $R^2$ statistic was 0.24.

- Similarly, at the last stop of each trip, all boardings were removed, based on the assumption that passengers never board at the last stop. One alighting at that stop, if available, was removed for each removed boarding, based on the assumption that the boardings and alightings are explained by the operator getting on and off repeatedly at the terminal.

- For each instance in which the number of alighting passengers at a stop was greater than the arriving passenger load there, extra boardings upstream of the stop to make the arriving passenger load match the number of alightings. The following criteria were used to distribute extra boardings to the upstream stops:

  - Boardings were only added at stops where passenger activity was observed.
  - The number of boardings added per stop was minimized, based on the assumption that most errors in the APC counts were off by one.
  - Upstream stops with high dwell times and low passenger activity were prioritized for receiving extra boardings.

The numbers of stops (and fraction of total stops with observed passenger activity) at which passengers were removed or added are presented in Table 4.5 along with descriptive statistics of the number of passengers removed or added. A small minority of stops were affected, and most of these had only one passenger added or removed.

### Passenger Arrival Rates

To calculate the passenger arrival rates using the [corrected] APC data, each APC observation of boardings was interpreted to represent an instantaneous observation

| | Passenger Activity | Boardings Removed | Alightings Removed | Boardings Added |
|---|---|---|---|---|
| number of stops | 4139 (100%) | 14 (0.3%) | 16 (0.4%) | 138 (3.4%) |
| minimum | | 1 | 1 | 1 |
| median | | 2 | 1 | 1 |
| maximum | | 127 | 137 | 5 |

Table 4.5: Descriptive Statistics of Instances of Adjusted APC Counts

of a passenger arrival rate — the number of passengers who boarded divided by the amount of time in which they all arrived, the elapsed time since the last vehicle departed from that stop. This leads to the following formula for aggregate passenger arrival rate at stop $i$:

$$PAR_i = \frac{\sum_{v \in V} PB_{v,i}}{\sum_{v \in V} PHW_{v,i}} \tag{4.6}$$

where $V$ is the set of all [APC-equipped] vehicles that arrived at $i$, $PB_{v,i}$ is the number of passengers boarding $v$ at $i$, and $PHW_{v,i}$ is the preceding headway of $v$ at $i$.

### Passenger Alighting Fractions

Similarly, each APC observation of a vehicle with passengers on it arriving at a stop was interpreted as an instantaneous observation of a passenger alighting fraction — the number of passengers who alighted divided by the number who arrived on the vehicle. This leads to the following formula for an aggregate passenger alighting fraction at stop $i$:

$$PAF_i = \frac{\sum_{v \in V_p} PA_{v,i}}{\sum_{v \in V_p} APL_{v,i}} \tag{4.7}$$

where $V_p$ is the set of all [APC-equipped] vehicles that arrived at $i$ with passengers on board, $PA_{v,i}$ is the number of passengers alighting from $v$ at $i$, and $APL_{v,i}$ is the arriving passenger load on $v$ at $i$.

| | $PAR_i$ (Passengers / Hour) | $PAF_i$ |
|---|---|---|
| minimum | 0 | 0 |
| mean | 4.5 | 3.7% |
| maximum | 66.5 | 100% |

Table 4.6: Descriptive Statistics of Passenger Demand Input Parameters. All statistics taken over the set of all time period, stop pairs at which passenger demand rates could be measured. A value of 100% for $PAF_i$ indicates a stop at which all passengers alight, usually a terminal.

### Descriptive Statistics of Passenger Demand Rates

Descriptive statistics of the passenger demand input parameters derived using the processes described above are presented in Table 4.6.

# Chapter 5

# Validation Tests

Before any simulation experiments can be performed with confidence, it is necessary to ensure that the simulator, using inputs that represent current operations, exhibits behavior similar to actual operations. This validation is accomplished by comparing certain statistics that describe the aggregate behavior of both the simulated and real operations of the route and that can be derived from both the outputs of the simulator and archived data from the actual route. To ensure that the validation results apply similarly to different parts of the day, the validation measures should be aggregated into a set of time periods that cover different times of day. If the differences between the measures from the simulator and from the real route are statistically significant, then it is difficult to be confident in the results of further experimentation, and this may indicate a need to alter simulation inputs or the workings of the simulator itself.

For this study, three validation measures are used: observed headways, trip travel time, and maximum load. The validation requirements are described in Section 5.1, and the results of the initial validation tests are presented in Section 5.2.

## 5.1 Validation Requirements

### 5.1.1 Observed headways

Observed headways should be compared with the simulated values at each of a set of stops spread along the route in each direction (these may be scheduled timepoints), to demonstrate the validity of the simulation over the entire length of the route.

The headway between each bus and its leader when it arrives at a particular stop is recorded, and the primary validation measure is the standard deviation of all headways at that stop. While the mean headway is also computed, it is less useful. For every extra minute in a long headway, there is a minute missing from a short headway. Consequently, barring certain boundary effects[1], the simulated mean headway should always be the same as the scheduled mean headway. It should only be significantly different (again, barring boundary conditions) if there is something seriously wrong (such as a missing trip) with the service or the simulator.

On the other hand, the headway standard deviation is a very powerful validation measure. Unlike the mean, it is positively affected by both above-average and below-average headways, so it is a good measure of service irregularity. Consequently, it is also a very good indicator of the basic quality of service produced on a real (or simulated) route. In addition, it represents a useful aggregation of the effects of all of the elements that determine the vehicles' progress along the route, and therefore a good indicator of the degree to which these effects are accurately represented in the simulator.

### 5.1.2 Trip travel time

For each direction, a segment of the route that is part of every route pattern involved in the study[2] should be selected, the travel time from end to end of that segment

[1]For example, a vehicle that is scheduled to arrive at the end of one time period but sometimes arrives at the beginning of the next, contributing its headway to the latter's statistics instead of the former's.

[2]Usually the main variant of the route, excluding late night or peak period spurs.

should be calculated for every trip in its direction, and the mean and standard deviation of these travel times should be computed.

Mean travel time for a whole trip is a gross aggregation of everything that a vehicle takes time to do over the course of a trip. Therefore, it can serve as a good indicator of whether the simulated magnitudes of vehicles' movement times and dwell times are consistent with reality. In addition, the trip travel time is an important measure of quality of service, both to the passengers and to the operating agency. The standard deviation gives an idea of whether the simulated movement times and dwell times, in the aggregate, are as variable as they are in reality, but this is a less useful measure, especially since the headway variability measurements capture travel time variability in a more targeted way.

### 5.1.3 Maximum load

The maximum passenger load on each trip should be determined. Then, the mean and standard deviation of the maximum load over all trips in each direction should be calculated. The primary value of these statistics is to provide an aggregate indication of the validity of the demand processes in the simulator and the demand inputs. Additionally, since service irregularity leads to irregular distribution of passengers between vehicles, both the mean and standard deviation of maximum load provide a secondary indication of the regularity of service.

## 5.2 Initial Validation Results

The validation tests described in Section 5.1 were run with the specifications presented in this section. The initial results obtained are also presented in this section.

For each set of validation tests, five simulation runs were run, simulating five morning peak periods, so that the set of results would be comparable to the data from five morning peak periods of service. The time period that was used for comparison was 0500 to 1100, so baseline real data was only used for comparison from that period. In order to generate simulator results for that period, each simulator run went from

0330 to 1100, providing a 1.5-hour "warm-up period" to avoid any boundary effects during the six primary hours of simulated service.

### 5.2.1 Observed Headways

#### Specifications

The headways experienced in the simulator and in real life during the study period, were measured at or near each of the eleven scheduled time points (listed in Table 3.1) in each direction, for each of the six hours between 0500 and 1100.

The observed headway calculations for the real data ignore all vehicles whose scheduled leaders do not appear in the data, since this would most likely be a result of missing or malfunctioning data collection devices on leaders that actually did serve their scheduled trips. As was noted in Section 4.3.1, approximately 30% of scheduled trips that started in the study period did not report AVL data.

The simulated and observed mean headways for each hour/timepoint pair were compared using a two-tailed t-test at a 95% confidence level. The difference between the two means was considered to be to be statistically insignificant if this t-test was unable to reject the hypothesis that the two means are equal.

Similarly, the standard deviations of the simulated and observed headways for each hour/timepoint pair were compared using a two-tailed F-test at a 95% confidence level.[3] The difference between the two standard deviations was considered to be statistically insignificant if this F-test was unable to reject the hypothesis that the two standard deviations are equal.

#### Results

The initial headway validation results are presented in Tables 5.1 and 5.2, both of which compare simulated headway statistics with observed headway statistics. Both tables (and all other headway comparison tables) use the following conventions:

[3]The F-test actually compares variances, which are the squares of standard deviations, but standard deviations are presented in this study because they are in the same units as the means.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 8 | 7 | 7 | 9 | 9 | 10 | 14 | 16 | 35 | 7 | 0 |
| 6 — 7 | 14 | 5 | 6 | 7 | 6 | 6 | 8 | 8 | 9 | 9 | 4 | 11 |
| 7 — 8 | 8 | 5 | 5 | 5 | 6 | 7 | 7 | 8 | 8 | 10 | 5 | 7 |
| 8 — 9 | 7 | 7 | 6 | 6 | 5 | 6 | 6 | 8 | 8 | 8 | 9 | 9 |
| 9 — 10 | 0 | 7 | 8 | 7 | 7 | 6 | 6 | 5 | 5 | 6 | 6 | 0 |
| 10 — 11 | 0 | 7 | 8 | 9 | 8 | 8 | 7 | 6 | 6 | 6 | 6 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 8 | 6 | 7 | 6 | 10 | 11 | 14 | 17 | 36 | 7 | 0 |
| 6 — 7 | 14 | 5 | 6 | 7 | 8 | 6 | 8 | 8 | 9 | 9 | 4 | 11 |
| 7 — 8 | 7 | 5 | 5 | 5 | 6 | 7 | 7 | 7 | 9 | 10 | 5 | 6 |
| 8 — 9 | 7 | 6 | 7 | 6 | 5 | 5 | 6 | 8 | 6 | 7 | 7 | 9 |
| 9 — 10 | 0 | 6 | 8 | 7 | 7 | 6 | 5 | 5 | 5 | 6 | 7 | 0 |
| 10 — 11 | 0 | 6 | 8 | 9 | 8 | 6 | 7 | 6 | 6 | 6 | 6 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 — 7 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 7 — 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 — 9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 — 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 10 — 11 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 5.1: Initial Headway Means Comparison

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 5 | 4 | 6 | 6 | 7 | 3 | 10 | 12 | 5 | 6 | 0 |
| 6 — 7 | 3 | 3 | 4 | 7 | 7 | 7 | 2 | 3 | 5 | 6 | 3 | 5 |
| 7 — 8 | 5 | 3 | 4 | 7 | 7 | 9 | 3 | 5 | 6 | 10 | 5 | 6 |
| 8 — 9 | 2 | 3 | 4 | 7 | 7 | 7 | 3 | 7 | 7 | 8 | 7 | 8 |
| 9 — 10 | 0 | 3 | 4 | 6 | 7 | 7 | 3 | 5 | 6 | 8 | 7 | 0 |
| 10 — 11 | 0 | 3 | 4 | 6 | 6 | 7 | 3 | 5 | 6 | 8 | 5 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 6 — 7 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| 7 — 8 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 8 — 9 | -1 | -1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 5.2: Initial Headway Standard Deviations Comparison

- All measurements are rounded to the nearest minute.
- Reported means or standard deviations of 0 minutes correspond to times and locations in which there were no observations[4].
- To conserve space, only data from selected timepoints is presented.
- The Comparison section of the table contains:
  - A value of 1 for every cell in which the simulated value is statistically significantly higher than the observed value.
  - A value of $-1$ for every cell in which the simulated value is statistically significantly lower than the observed value.
  - A value of 0 for every cell in which either the observed and simulated values were not statistically significantly different or there were not enough observations to determine their statistical similarity or difference

  This section highlights general trends in the similarities and differences between the two sets of data. For example, in a part of the day, or of the route, in which there is a preponderance of values of 1, the data indicate that the simulated values are, in general, significantly higher than the actual values.

As expected, Table 5.1 indicates that, allowing for boundary conditions between time periods, the simulated and observed mean headways are statistically similar.

The comparison of the simulated and observed headway standard deviations presented in Table 5.2, on the other hand, indicates significant differences. In particular, the simulated standard deviations are consistently higher than those observed, especially later in the route. In other words, the simulated service is much less reliable than the real service, and the additional irregularity in service seems to propagate over the course of the route. This inconsistency is sufficiently high to keep the simulator from being validated as is, indicating that adjustments to the simulation are required.

[4]For example, at 10 am, Route 9 does not serve $103^{rd}$ Street.

| Timepoint | Sequence # | Comments |
|---|---|---|
| $103^{rd}$ & Vincennes | 1 | Peak southern terminal |
| $95^{th}$ & Ashland | 9 | Non-peak southern terminal |
| $79^{th}$ & Ashland | 25 | |
| $74^{th}$ & Ashland | 31 | Pull-outs, pull-ins, and reliefs |
| $55^{th}$ & Ashland | 51 | |
| $47^{th}$ & Ashland | 60 | |
| Archer & Ashland | 77 | Orange Line; Detour in effect to Cermack |
| Cermack & Ashland | 83 | Blue Line |
| Madison & Ashland | 102 | |
| North & Ashland | 122 | End of northbound Owl trips |
| Cortland & Ashland | 125 | |
| Clark & Belle Plaine | 151 | Northern terminal |

Table 5.3: Timepoint Sequence Numbers in Space-Time Diagrams

Another way to see the propagation of headway irregularity is by looking at "space-time diagrams." These diagrams display the movements of vehicles along the route by plotting the time that each vehicle arrives at each stop as a point on the space-time continuum. The x-axis refers to the sequence of stops along the route, and the y-axis refers to time. So, a vehicle going from one terminal to the other results in a string of points from the left end of the diagram to the right, and the time it takes to make the trip is represented by the vertical distance between the points representing the beginning and end of its trip. The headway between two vehicles at a stop is the vertical distance between their points at the horizontal location corresponding to that stop.

The space-time diagram corresponding to the schedule for all of Route 9's northbound trips during the study period is presented in Figure 5-1. In this diagram (and all space-time diagrams that follow), the y-axis is in hours (all AM), and the x-axis is the sequence of stops along the route from $103^{rd}$ Street to Clark and Belle Plaine. Table 5.3 lists the timepoints along the route and the corresponding sequence numbers.

Some features to note on this diagram include:

- Peak trips begin at $103^{rd}$ Street, and off-peak trips begin at $95^{th}$ Street.
- Pull-in trips end at $74^{th}$ Street, and Pull-out trips begin there. Some pull-in

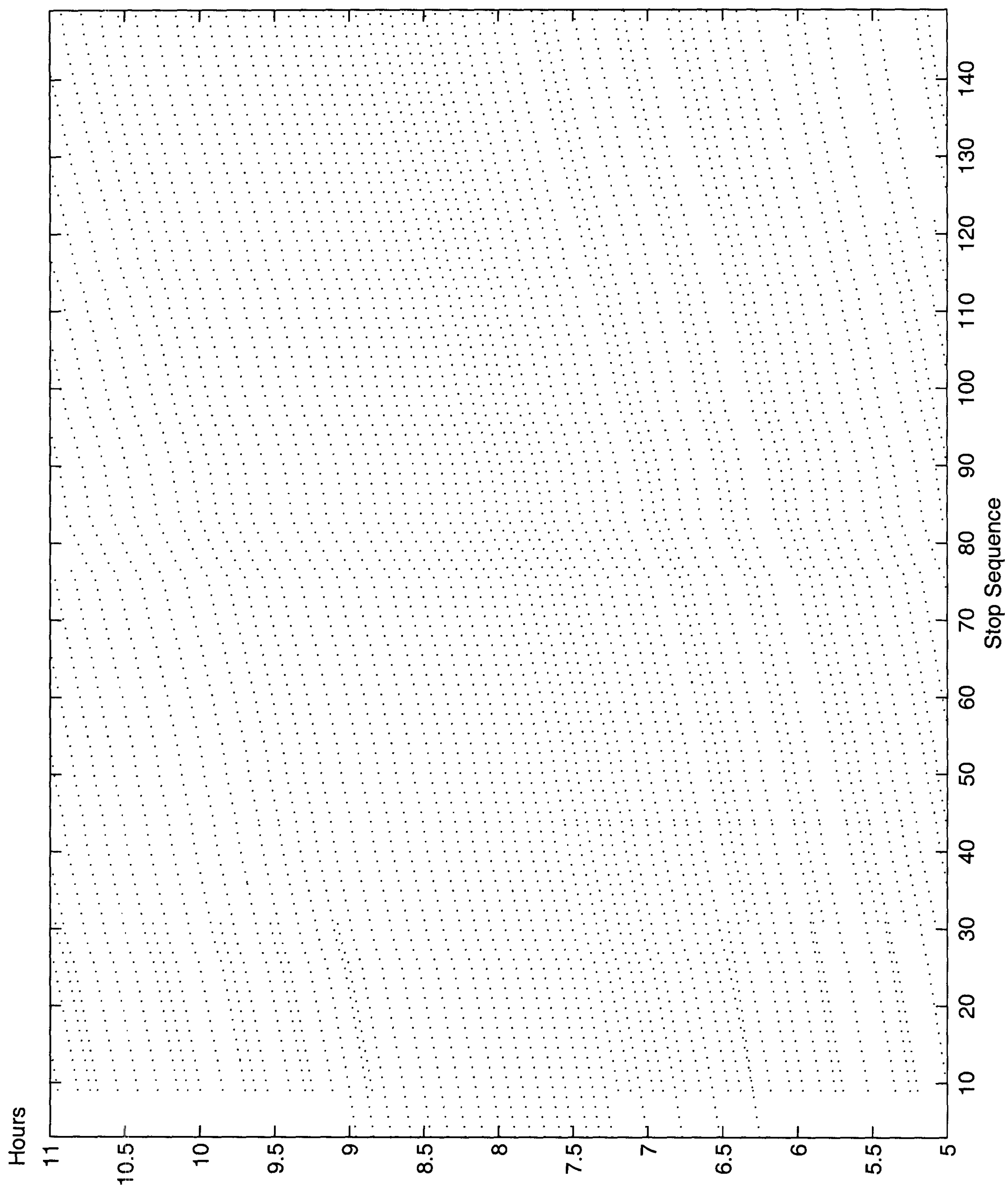


Figure 5-1: Space-Time Diagram of Route 9's Northbound Schedule

trips are clearly not meant to be part of an even schedule.

- There is a discontinuity between the Archer and Cermack timepoints corresponding to a detour there during the study period that resulted in a gap in the data. (This is more pronounced in the diagrams that include AVL data.)

- The strongly parallel nature of the lines indicates that adjacent vehicles are scheduled to travel at the same (or similar) speeds.

The space-time diagram representing northbound service on Route 9 on the morning of Wednesday, January 14, 2004 is shown in Figure 5-2 as a representative sample of what real service looks like on such a diagram. Some features to note in this diagram include:

- The fine dotted lines representing the schedule (as in Figure 5-1) are included for reference.

- AVL observations of vehicles arriving at stops are represented by heavy dots. Line segments connect dots from the same trip.

- Some errant AVL observations that indicate vehicles moving in unnatural ways are easily identifiable. These are a result of some individual AVL observations that were erroniously assigned to the wrong stops and should be ignored.

- Trips that appear in the schedule but not the AVL data were either actually not served, or more likely, were served by vehicles with malfunctioning AVL units (see Section 4.3.1).

- The first two stops and last two stops of some trips were removed from the data due to issues with terminal-area data.

- Vertical or near-vertical line segments around Stop 31 (74$^{\text{th}}$ Street) represent vehicles waiting there for their reliefs. (This phenomenon is also evident in space-time diagrams of simulated service.

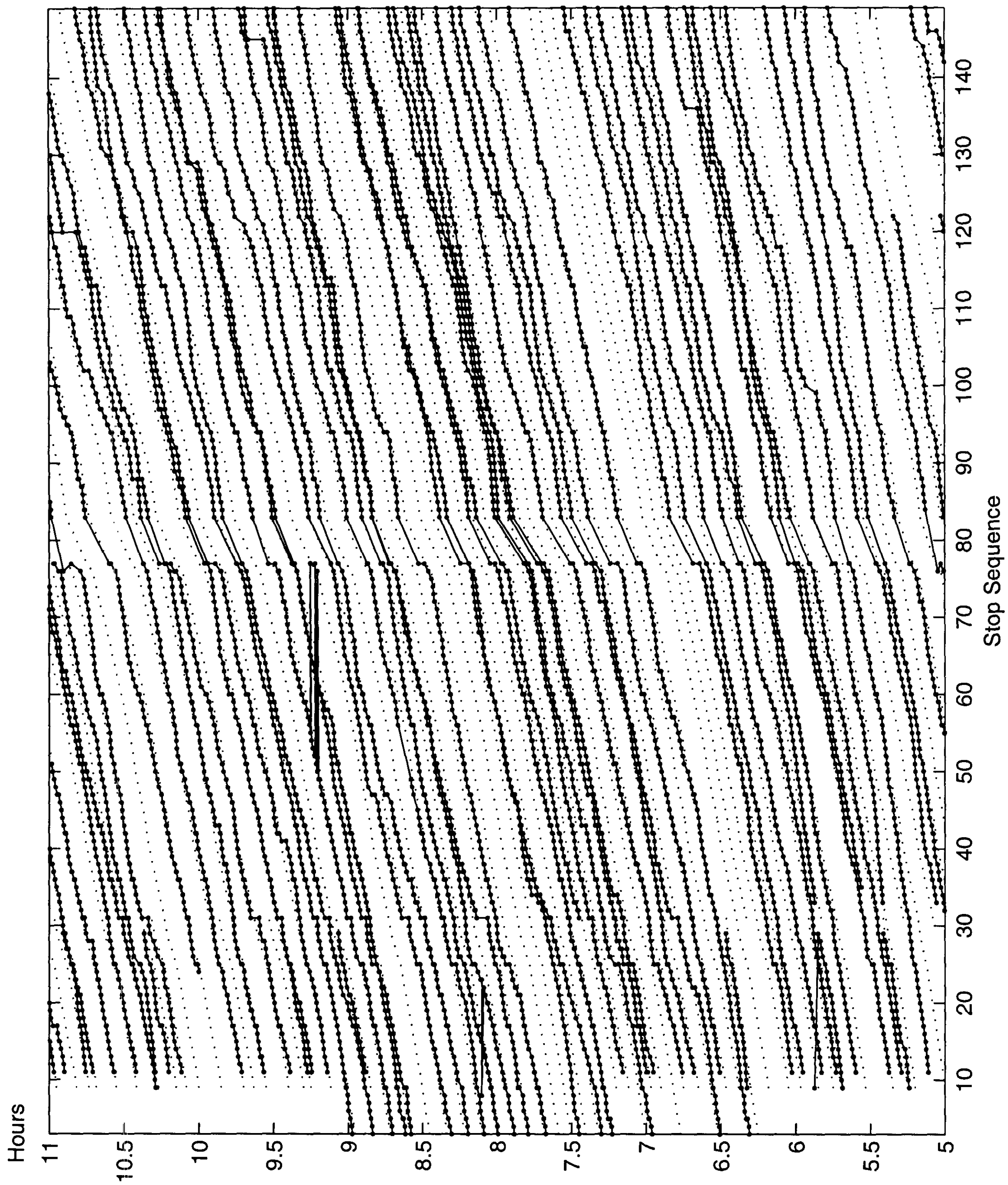


Figure 5-2: Space-Time Diagram of Route 9 Northbound Service on Wednesday, January 14, 2004

- There is some evidence of significant bunching. A particularly clear example is around Stop 100 at around 0745.

For comparison, the space-time diagram from a representative sample of one of the initial simulator runs is shown in Figure 5-3. The most important feature to note on this diagram is that it seems that the simulated vehicles are drawn to each other like magnets. They rapidly form very tight bunches of many vehicles each that persist until the end of the trip, resulting in much more pronounced bunching and gapping than is seen in Figure 5-2. This qualitative discrepancy of behavior constitutes further confirmation that the simulator and/or its input data require adjustment.

In fact, this discrepancy was the primary focus of most if not all of the adjustment efforts discussed in Chapter 6. One reason for this choice is that the three validation measures are strongly interrelated, as is discussed below, in Sections 5.2.2 and 5.2.3, and in some ways, inflated irregularity of service drives discrepancies in the other two measures, so it seems reasonable to expect that solving the first discrepancy is likely to go a long way toward solving the other two. Additionally, since regularity of service is a primary determinant of service quality, it follows that it deserves primary consideration in an attempt to simulate service and predict changes in service quality.

### 5.2.2 Trip Travel Time

#### Specifications

The time it took each trip in the simulator and in real life to traverse the part of the route between 95$^{\text{th}}$ Street and Clark and Belle Plaine (the largest segment that is served by all non-owl trips), in each direction was measured. These measurements were aggregated by trip start time into the same six one-hour periods used for the headway measurements, and the same statistical tests were used to compare the means and standard deviations.

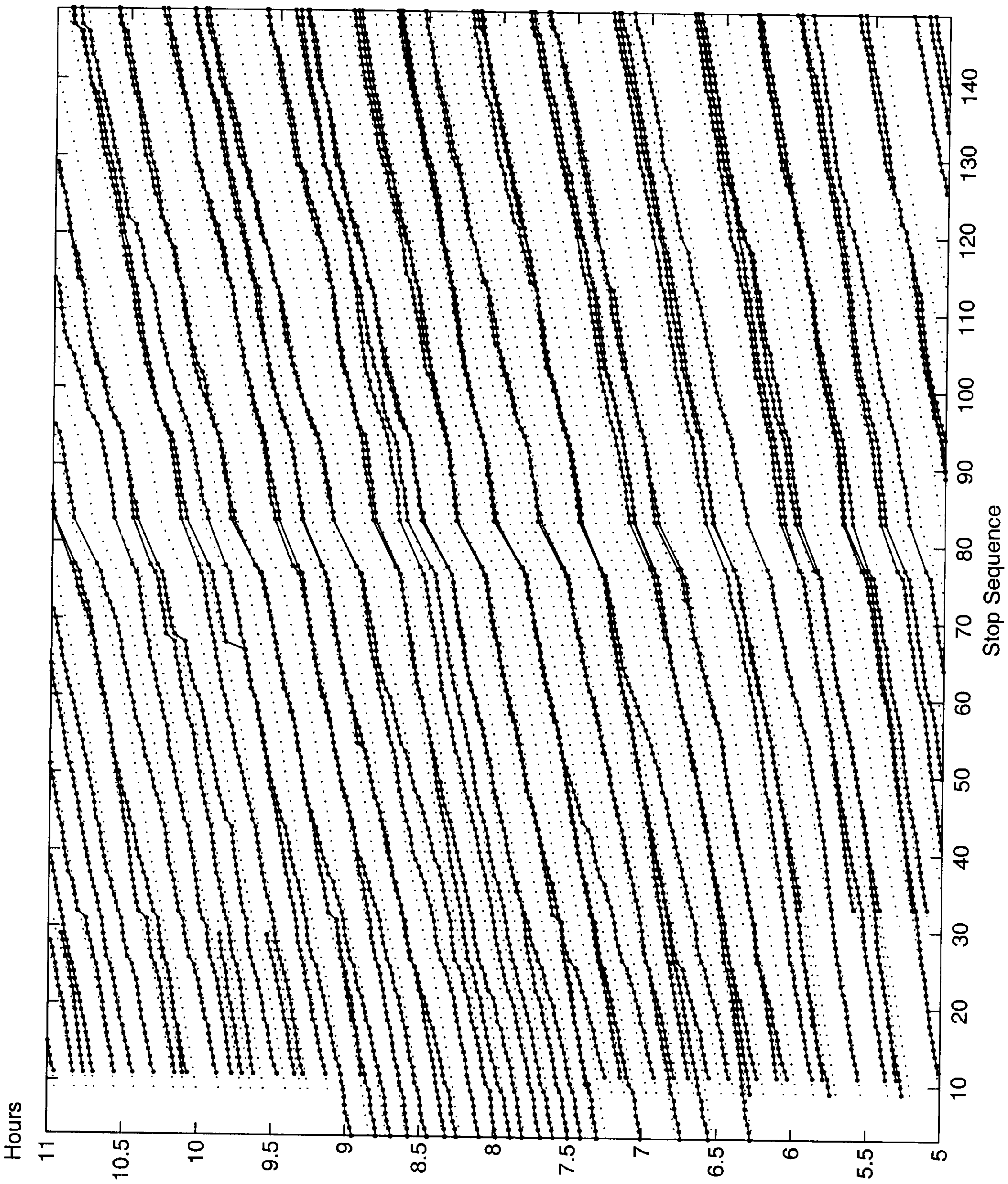


Figure 5-3: Space-Time Diagram of Route 9 Northbound Service from Initial Simulation

### Results

The means and standard deviations of the observed and simulated trip travel times are presented and compared in Tables 5.4 and 5.5. The Comparison section in these tables follows the same convention as the corresponding sections in the headway comparison tables.

The comparison of the means in Table 5.4 indicates that on average, simulated trips tended to take the same amount of total time as their real counterparts. While there are some statistically significant discrepancies, they do not show a general bias toward longer (or shorter) trips.

However, the comparison of the standard deviations shown in Table 5.5 indicates a trend toward greater variability in the simulated trip lengths. The standard deviations of the travel times of the simulated trips were consistently higher than their counterparts in the real data. This discrepancy indicates that there were many more instances of extremely long or extremely short trips in the simulation than there were in real life. This finding is consistent with the discrepancies in the headway standard deviations discussed in Section 5.2.1 because when vehicles bunch, the leader is usually behind schedule and will therefore take more time than average to complete its trip, while the follower is usually ahead of schedule and will therefore take less time.

| | Observed | | Simulated | | Comparison | |
|---|---|---|---|---|---|---|
| Period | North | South | North | South | North | South |
| 5 — 6 | 85 | 83 | 87 | 82 | 0 | 0 |
| 6 — 7 | 97 | 98 | 98 | 96 | 0 | 0 |
| 7 — 8 | 98 | 97 | 99 | 93 | 0 | -1 |
| 8 — 9 | 97 | 91 | 105 | 92 | 1 | 0 |
| 9 — 10 | 97 | 93 | 100 | 88 | 0 | -1 |
| 10 — 11 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 5.4: Initial Trip Travel Time Means Comparison

| | Observed | | Simulated | | Comparison | |
|---|---|---|---|---|---|---|
| Period | North | South | North | South | North | South |
| 5 — 6 | 3 | 6 | 8 | 6 | 1 | 0 |
| 6 — 7 | 4 | 4 | 6 | 7 | 1 | 1 |
| 7 — 8 | 4 | 3 | 5 | 5 | 0 | 1 |
| 8 — 9 | 3 | 3 | 6 | 4 | 1 | 0 |
| 9 — 10 | 3 | 3 | 7 | 5 | 1 | 1 |
| 10 — 11 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 5.5: Initial Trip Travel Time Standard Deviations Comparison

### 5.2.3 Maximum Load

#### Specifications

The maximum passenger load experienced by each trip in the simulator and each of the 71 trips (see Section 4.4.1) that contributed APC data to the real-life dataset were measured. These statistics were aggregated using the same scheme that was used for trip travel time, by direction and by time period.

#### Results

The means and standard deviations of the observed and simulated maximum loads are presented and compared in Tables 5.6 and 5.7. The Comparison section in these tables follows the same convention as the corresponding sections in the other comparison tables.

The comparison of the means in Table 5.6 shows that in general, the average maximum load on simulated trips was similar to that of real trips. This finding is

| | Observed | | Simulated | | Comparison | |
|---|---|---|---|---|---|---|
| Period | North | South | North | South | North | South |
| 5 — 6 | 14 | 20 | 17 | 11 | 0 | -1 |
| 6 — 7 | 24 | 22 | 27 | 19 | 0 | 0 |
| 7 — 8 | 35 | 26 | 35 | 26 | 0 | 0 |
| 8 — 9 | 37 | 21 | 35 | 29 | 0 | 0 |
| 9 — 10 | 34 | 20 | 31 | 24 | 0 | 0 |
| 10 — 11 | 21 | 17 | 26 | 19 | 0 | 0 |

Table 5.6: Initial Maximum Load Means Comparison

| | Observed | | Simulated | | Comparison | |
|---|---|---|---|---|---|---|
| Period | North | South | North | South | North | South |
| 5 — 6 | 8 | 10 | 13 | 9 | 1 | 0 |
| 6 — 7 | 14 | 12 | 16 | 16 | 0 | 0 |
| 7 — 8 | 9 | 11 | 13 | 16 | 0 | 0 |
| 8 — 9 | 8 | 13 | 13 | 15 | 1 | 0 |
| 9 — 10 | 12 | 7 | 14 | 12 | 0 | 1 |
| 10 — 11 | 13 | 7 | 14 | 10 | 0 | 0 |

Table 5.7: Initial Maximum Load Standard Deviations Comparison

consistent with the idea that if the same number of total passengers are served by the same number of trips, the average trip will handle approximately the same number of passengers, since every trip with fewer passengers than average is compensated for one with more. Maximum load is closely correlated with total passengers served by a trip, assuming a roughly constant load profile.

The comparison of the standard deviations in Table 5.7 has similar implications to the comparison of trip travel time standard deviations presented above. In general, the maximum load on simulated trips was more variable than the maximum load on their real counterparts. Like the similar discrepancy in the case of trip travel times, this discrepancy is related to the higher prevalence of bunching in the simulator. When two vehicles bunch, the leader tends to pick up passengers that would have boarded the follower if the two vehicles had maintained space between themselves, resulting in a higher maximum load on the leader and a lower one on the follower.

# Chapter 6

# Model Adjustments

As was described in Chapter 5, validation is a prerequisite for experimentation using the simulator along with the particular set of inputs generated from the CTA's Route 9 data. Because the initial results of the validation were not satisfactory, adjustments to the simulation became necessary. The goal of these adjustments was to change simulation conditions in ways that bring the simulation in line with reality, as measured by the validation tests.

This chapter presents the extensive set of adjustments that were employed while attempting to bring the validation tests into line and to make the simulation a closer reflection of reality. The implications of the results of these adjustments on the mechanics of the simulation, on Route 9, and on transit operations in general are also presented.

To attempt to get the simulation to generate statistics that are more in line with those derived from the real-life data, three different types of adjustments of the simulation were employed:

- Adjustments of the input paramters to the simulator (and selection of which input parameters to use).
- Changes in the behavior of the vehicles and passengers in the simulator and adjustments to parameters used to define this behavior.
- Changes to the simulated deployment of control personnel and to the behavior

of those personnel.

In general, unless otherwise noted, each adjustment was employed independently of other adjustments, so that the isolated effects of each could be tested.

## 6.1 Input Parameters

One intutive way to attempt to change the data that comes out of a simulation is to change the data that goes into it. Variations of each of the principle types of input data for the simulation were tested: trip start time punctuality, movement times, demand, and the dwell time function.

### 6.1.1 Trip Start Punctuality

Since bunching is a phenomenon that feeds on itself, headway irregularities that start at the beginning of a trip are likely to have a strong impact on the rest of the trip, since they provide a basis for bunching propagation along the route. So, changing trip start punctuality and recovery time simulator inputs or the way the simulator deals with them could have a strong impact on the headway regularity statistics over the whole route.

Given a fixed schedule, the element that determines how much space there is between vehicles leaving a terminal is the variation between vehicles' punctuality — how early or late they depart. Assuming that the scheduled departures from a terminal are fairly regular to begin with (which is true, at least, of peak-period departures from Route 9's southern terminal, as seen in Figure 5-1), the actual departures will remain fairly regular if all trips in a time period depart either late or early by a similar amount of time. However, if the trips do not share a common offset, but instead depart with varying degrees of lateness or earliness, the set of departures will become much less regular. An extreme example of this effect is that if vehicles alternate departing one half-headway late and one half-headway early, they will begin the trip in bunches of two with double-headway gaps between them.

Consequently, the input trip start punctuality standard deviation in a given time period has an important effect on the initial service regularity at the beginning of the route. If this input is too high, simulated service at the terminal will be less regular than real service there, which is also likely to make simulated service over the rest of the route less regular.

### Adjustments Based on Headway Variabilities

An experiment was conducted in which the trip start punctuality standard deviation inputs were adjusted based on the observed headway variability at the terminals. Where simulated terminal headway variability was higher than their real counterparts, trip start punctuality standard deviation inputs were lowered. Where the simulated variability was too high, the punctuality inputs were raised. In particular, the following formula was used:

$$StdTDP_{\tau}^{P'} = StdTDP_{\tau}^{P} \cdot \frac{StdHWO_{\tau}^{P}}{StdHWS_{\tau}^{P}} \forall \tau \tag{6.1}$$

where $StdTDP_{\tau}^{P}$ is the "original" input trip start punctuality standard deviation at terminal $\tau$ during time period $P$, $StdTDP_{\tau}^{P'}$ is the adjusted input, $StdHWO_{\tau}^{P}$ is the standard deviation of the headways observed at terminal $\tau$ during time period $P$ in real service, and $StdHWS_{\tau}^{P}$ is the simulated measure.

The effect of this adjustment on the inputs is presented in Table 6.1, along with the headway standard deviations that were used to calculate the adjustment and the simulated headway standard deviations using the adjusted inputs. Examination of the headway standard deviations in the original simulation and in the simulation that resulted from the adjustment indicates that the effect of this adjustment on service regularity was inconsistent:

- In some cases, such as at 103$^{\text{rd}}$ between 0600 and 0700, the adjustment brought the simulated service regularity very close to the observed value.

- In some cases, such as at Belle Plaine between 0800 and 0900, the change

| Trip Start Puntuality Standard Deviation Input | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Initial | | | Adjusted | | |
| Period | | | | B.P. | 103rd | 95th | B.P. | 103rd | 95th |
| 5 — 6 | | | | 0.8 | | 2.2 | 0.6 | | 3 |
| 6 — 7 | | | | 1.5 | 1.5 | 1.1 | 1.3 | 1 | 1.1 |
| 7 — 8 | | | | 2.2 | 0.8 | 1 | 1.9 | 0.8 | 0.7 |
| 8 — 9 | | | | 2.1 | 1.3 | 1.6 | 2.3 | 2.1 | 2.2 |
| 9 — 10 | | | | 1.7 | | 1.9 | 1.7 | | 2.1 |
| 10 — 11 | | | | 1 | | 1.6 | 0.6 | | 2.4 |
| Headway Standard Deviation | | | | | | | | | |
| | Observed | | | Simulated (Before) | | | Simulated (After) | | |
| Period | B.P. | 103rd | 95th | B.P. | 103rd | 95th | B.P. | 103rd | 95th |
| 5 — 6 | 2.4 | | 6.2 | 3.1 | | 4.6 | 3.0 | | 5.0 |
| 6 — 7 | 2.0 | 1.8 | 2.7 | 2.2 | 2.5 | 2.6 | 1.7 | 1.9 | 2.9 |
| 7 — 8 | 2.7 | 4.9 | 1.9 | 3.3 | 4.8 | 2.7 | 3.4 | 5.0 | 2.7 |
| 8 — 9 | 2.8 | 2.6 | 3.6 | 2.5 | 1.7 | 2.6 | 3.2 | 2.1 | 2.8 |
| 9 — 10 | 2.7 | | 2.9 | 2.8 | | 2.6 | 2.6 | | 2.9 |
| 10 — 11 | 1.7 | | 4.1 | 2.8 | | 2.7 | 3.1 | | 3.3 |

Table 6.1: Adjusting the Trip Start Punctuality Standard Deviation Inputs Based on Headway Variability at the Terminals (All statistics are rounded to the nearest tenth of a minute.)

in simulated service regularity overshot its initial difference from the observed value, so that if it was too low before, it was now too high.

- In some cases, such as at 95$^{\text{th}}$ betwen 0500 and 0600, the adjustment brought the simulated service regularity closer to the observed value, but still left a significant difference.

- In some cases, such as at Belle Plaine between 1000 and 1100, the adjustment actually caused the simulated service regularity to be further from the observed value than it was before.

These mixed results indicate that the chosen method for adjusting the trip start punctuality standard deviation inputs was not a reliable way to improve the realism of the simulation. Furthermore, they indicate that these inputs do not have as strong an effect on vehicle spacing at the terminals as was expected, since the chosen method of adjustment depended on the assumption that this effect was significant.

### Deterministic Terminal Departures

Two additional experiments were conducted to determine the effect of trip start punctuality on simulated headway variabilities. In the first experiment, the input standard deviations of trip start punctualities were all set to zero, forcing all trips within a time period to start the same number of minutes early or late. The second experiment went even further by eliminating the trip start punctuality inputs altogether and forcing all trips to start on schedule.[1]

The results of the two experiments were very similar, so only those of the more extreme second case are presented here. Table 6.2 compares the simulated headway standard deviations with on-time terminal departures with those observed in the real service. It shows that forcing trips to start on schedule made simulated headways near the beginning of the route (in both directions) much more regular than real headways, in contrast to the initial simulation (Table 5.2), in which the simulated and real headway variabilities near the terminals were more similar. Not surprisingly, starting strictly on time also meant starting with better regularity.

What was more surprising was that most of the gain in regularity only lasted through approximately half of the route. By the time simulated vehicles had traveled that far, their spacing became less regular than that of their real counterparts, very similarly to the behavior of the vehicles in the initial simulation. Although the vehicles started with regular spacing, their regularity deteriorated severely over the route, much more so than that of real vehicles.

Qualitative confirmation of this phenomenon can be seen in a representative space-time diagram of northbound service in this simulation (Figure 6-1). In this diagram, it is possible to see that vehicles started on time, but then formed tight, persistent bunches like they did in the initial simulation (see Figure 5-3), but a little bit later in the trip.

The deterioration of service regularity in this simulation indicates that it is un-

[1]In both cases, vehicles' terminal departure times were only deterministic when the vehicles finished their previous trip before their scheduled departure time. This was true, however, in almost all cases.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 4 | 3 | 4 | 4 | 6 | 2 | 10 | 12 | 13 | 4 | 0 |
| 6 — 7 | 1 | 2 | 3 | 8 | 9 | 4 | 1 | 2 | 3 | 4 | 3 | 8 |
| 7 — 8 | 4 | 2 | 3 | 6 | 8 | 9 | 1 | 3 | 5 | 8 | 5 | 7 |
| 8 — 9 | 1 | 2 | 3 | 6 | 6 | 8 | 2 | 4 | 5 | 7 | 8 | 9 |
| 9 — 10 | 0 | 2 | 2 | 7 | 7 | 7 | 1 | 4 | 4 | 6 | 5 | 0 |
| 10 — 11 | 0 | 2 | 2 | 7 | 7 | 7 | 2 | 3 | 5 | 7 | 5 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | -1 | -1 | -1 | -1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 6 — 7 | -1 | -1 | 0 | 0 | 1 | 0 | -1 | 0 | 0 | 1 | 0 | 1 |
| 7 — 8 | 0 | 0 | 0 | 1 | 1 | 1 | -1 | 0 | 0 | 1 | 0 | 0 |
| 8 — 9 | -1 | -1 | 0 | 0 | 0 | 1 | -1 | 0 | 0 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 0 | 1 | 1 | 1 | -1 | 0 | 1 | 1 | 0 | 0 |
| 10 — 11 | 0 | -1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |

Table 6.2: Headway Standard Deviations Comparison — On-time Terminal Departures

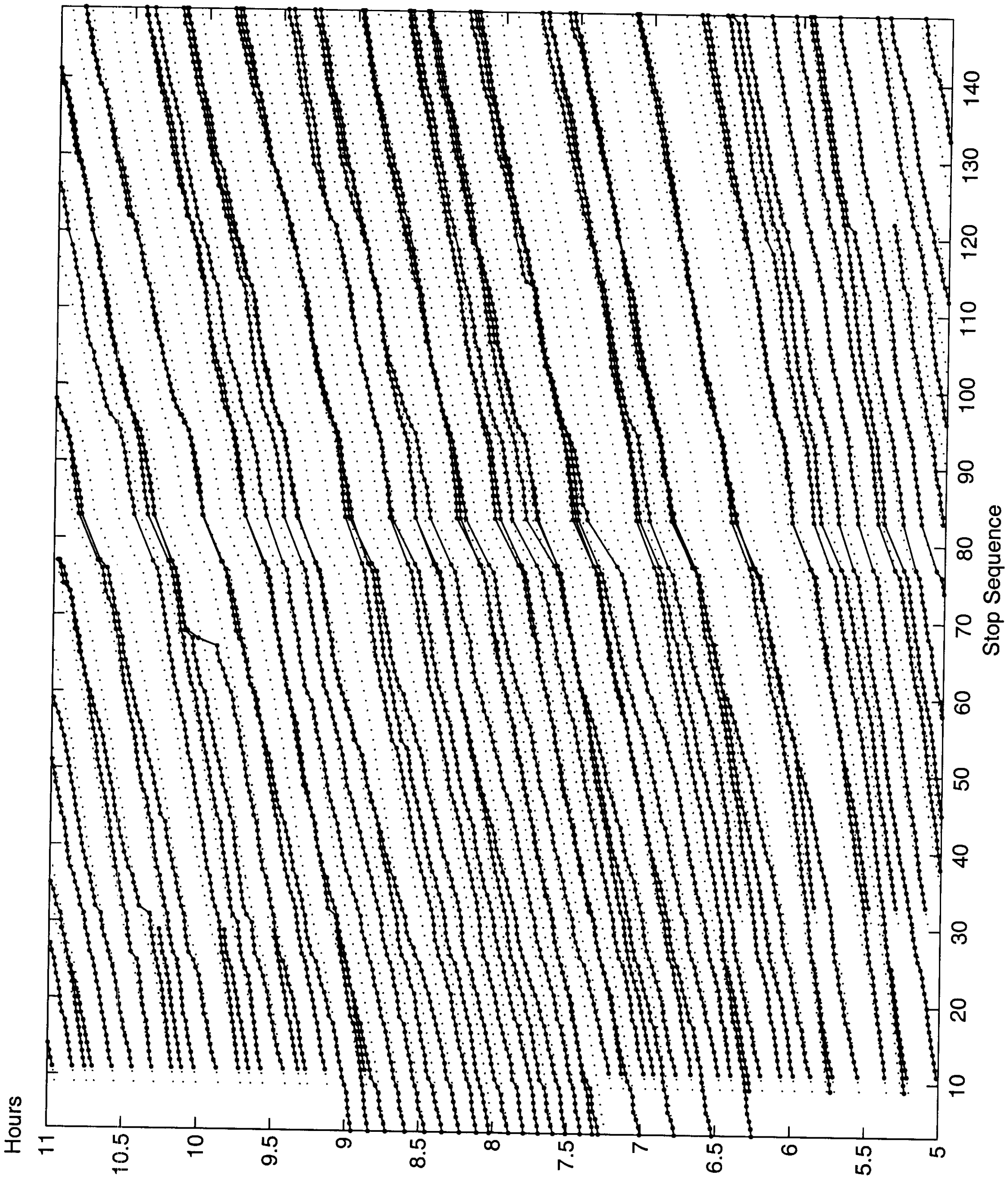


Figure 6-1: Space-Time Diagram of Route 9 Northbound Service from Simulation with On-Time Terminal Departures

likely that changes to trip start punctuality statistics are the appropriate measure for correcting the simulation's tendency toward excessive service irregularity. While a drastic change in terminal departure punctuality behavior had a strong impact on headways near the beginning of the route, strong enough to make them significantly more regular than would be realistic, it left simulated headways in the second half of the route significantly less regular than real headways. Instead, it seems that elements of the simulation that affect headway regularity deterioration along the entire route are better targets for experimentation.

### 6.1.2 Movement times

One potential contributor to deterioration of service regularity is the basic stop-to-stop movement time statistics that are input to the simulator. Most directly, if the movement time standard deviations going into the simulator are too high, that would clearly inflate the variability of vehicles' overall running times, increasing the frequency with which vehicles converge upon one another, and thereby increasing headway irregularity.

#### Less Variable Movement Times

To test the influence of input movement time standard deviations on the deterioration of headway regularity, an experiment was conducted in which these inputs were all decreased by 50%. The results of this experiment are presented in Table 6.3. In general, headway standard deviations along the route were very similar to those in the initial simulation (see Table 5.2); they were slightly better in some parts of the route (particularly on the southbound side) and times of day, and slightly worse in others. The prevalence of severe bunching in a representative space-time diagram (Figure 6-2) confirms the finding that a drastic decrease in the input standard deviations of movement times did not bring about a commensurate effect on service regularity.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 5 | 5 | 6 | 6 | 8 | 2 | 10 | 12 | 11 | 5 | 0 |
| 6 — 7 | 2 | 2 | 4 | 8 | 8 | 7 | 2 | 3 | 3 | 4 | 4 | 6 |
| 7 — 8 | 4 | 2 | 4 | 6 | 8 | 9 | 2 | 4 | 5 | 7 | 5 | 6 |
| 8 — 9 | 2 | 3 | 4 | 6 | 6 | 8 | 3 | 7 | 6 | 7 | 8 | 8 |
| 9 — 10 | 0 | 3 | 4 | 7 | 7 | 8 | 2 | 4 | 7 | 9 | 8 | 0 |
| 10 — 11 | 0 | 3 | 4 | 7 | 7 | 8 | 2 | 5 | 6 | 6 | 5 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 — 7 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| 7 — 8 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 — 9 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |

Table 6.3: Headway Standard Deviations Comparison — Movement Time Standard Deviations Decreased by 50%

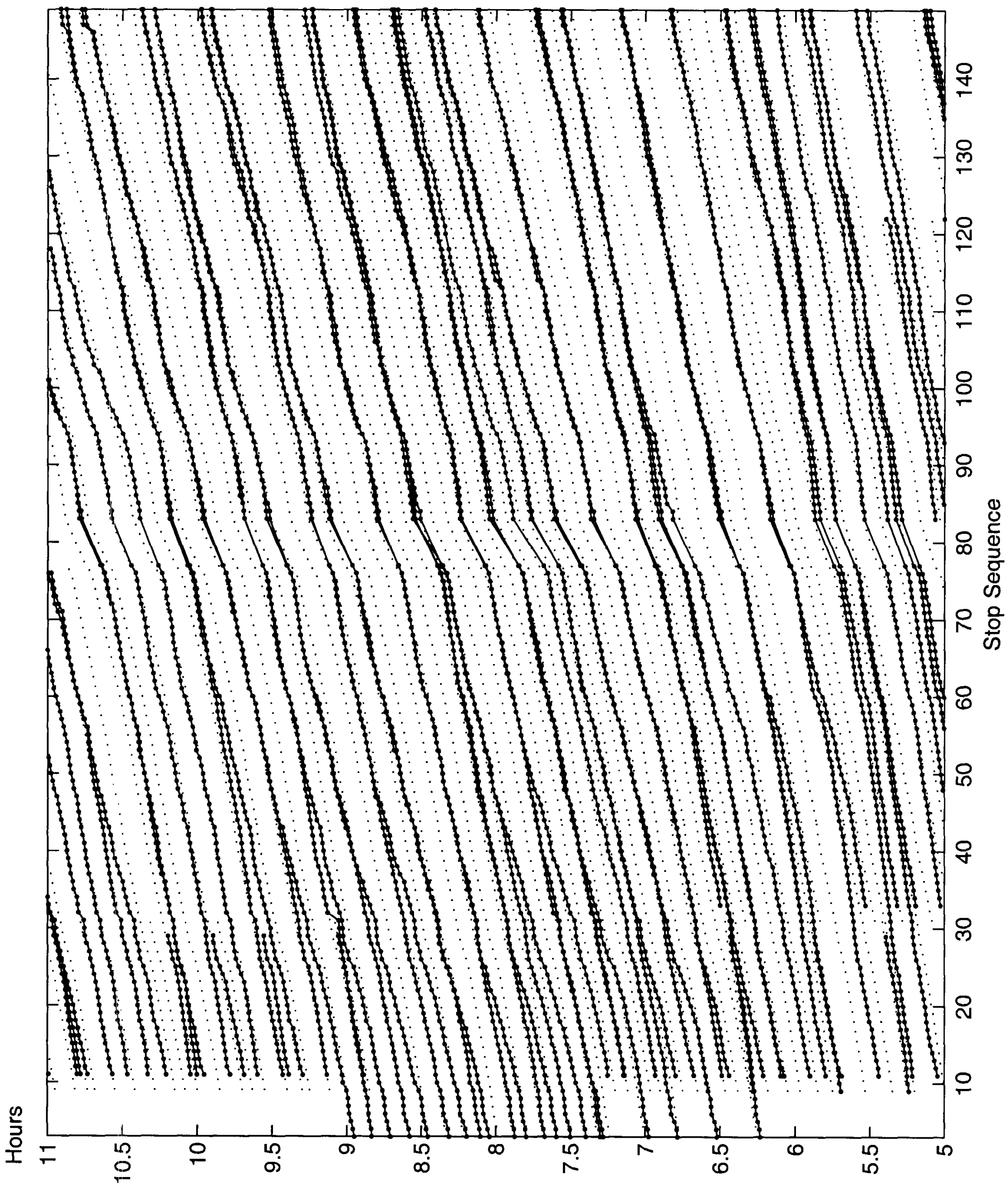


Figure 6-2: Space-Time Diagram of Route 9 Northbound Service from Simulation with Movement Time Standard Deviations Decreased by 50%

### Deterministic Movement Times

Another experiment was conducted that employed more far-reaching changes to the the simulator's movement time inputs. The standard deviations associated with the movement time inputs, $StdMT_{i,j}$, did not take into account the correlation between the movement times of two vehicles that traversed the same link on the same day at similar times. Nor did they take into account the correlation between the movement times of one vehicle over two links near each other. These correlations could play a role in determining whether vehicles bunch since adjacent vehicles experiencing highly varying movement times are more likely to move toward, or away from, each other. Because of this, in this experiment, the simulator was changed to ignore the $StdMT_{i,j}$ terms and just assign each vehicle's movement time at each stop based on the appropriate value of $MT_{i,j}$.

To account for the correlation between movement times on the same day (and the lack of correlation between movement times on different days), the AVL data was separated into five portions, one for each day of observations, and a separate set of movement time statistics was calculated from each portion. Then, the simulator was changed so that it would choose one set of movement time statistics for each simulator run, effectively making each run simulate the traffic conditions of one of the days of observations. In addition, in this experiment, the simulator was set to ignore stopping penalties because the number of observations available for regression in each portion of AVL data was too low to produce a significant number of reliable stopping penalties.

These measures made movement times deterministic, given the simulator run ("day"), time, and pair of stops. As a result, in this experiment, only two factors could change the headway between two successive vehicles (in most cases[2]): differing dwell times and slightly differing movement times in the case that the two vehicles arrived at a stop on either side of the boundary between time periods.

The impacts of these adjustments on headway irregularity are presented in Table 6.4. The results are not substantially different from those of the previous experiment

[2]One exception would be when a vehicle holds for its scheduled relief.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 5 | 5 | 5 | 6 | 8 | 3 | 10 | 13 | 14 | 5 | 0 |
| 6 — 7 | 3 | 3 | 4 | 8 | 9 | 6 | 2 | 3 | 3 | 5 | 4 | 7 |
| 7 — 8 | 5 | 2 | 3 | 6 | 8 | 11 | 3 | 5 | 5 | 8 | 5 | 6 |
| 8 — 9 | 2 | 3 | 3 | 6 | 7 | 8 | 3 | 5 | 5 | 8 | 9 | 10 |
| 9 — 10 | 0 | 4 | 4 | 6 | 6 | 8 | 3 | 4 | 5 | 6 | 6 | 0 |
| 10 — 11 | 0 | 3 | 4 | 6 | 7 | 8 | 2 | 5 | 6 | 7 | 5 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 6 — 7 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 7 — 8 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 8 — 9 | -1 | -1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |

Table 6.4: Headway Standard Deviations Comparison — Deterministic Movement Times

that simply reduced the movement time standard deviations (see Table 6.3). There are some minor improvements in service regularity over the initial simulation (see Table 5.2), but there are also some places where service became less regular.

The results of this experiement and the previous one indicate that the movement time input parameters are not a primary contributor to the deterioration of headway regularity. This finding suggests that the parameters and behaviors that address passenger dwell times and related passenger demand, the other major contributor to vehicle travel time, may comprise a more promising target for successful adjustment of the simulator. In addition, this finding suggests that in the real world, instantaneous variability in traffic conditions does not make the most significant contribution to service irregularity.

### 6.1.3 Demand Characteristics

Besides inter-stop movement times, the other thing that vehicles spend most of their time on in the course of a trip is dwell times at stops. In addition, since the amount of time spent dwelling is dependent on an element that is highly variable, namely passenger activity, it seems likely that variability in passenger activity, through its effect on dwell times, contributes strongly to variability in vehicle positions and therefore in headways. This section discusses experiments that altered the basic passenger demand inputs, and Section 6.1.4 discusses experiments in which the dwell time function parameters were altered.

#### No Passengers

The first experiment that altered the passenger demand parameters was intended not to produce a more realistic simulation, but to demonstrate the central role of passenger demand in both simulated and real service. In this experiment, all passenger demand was removed by setting all passenger arrival rates ($PAR_i$) to zero.

Two important results of this experiment can be seen clearly in a representative space-time diagram (Figure 6-3):

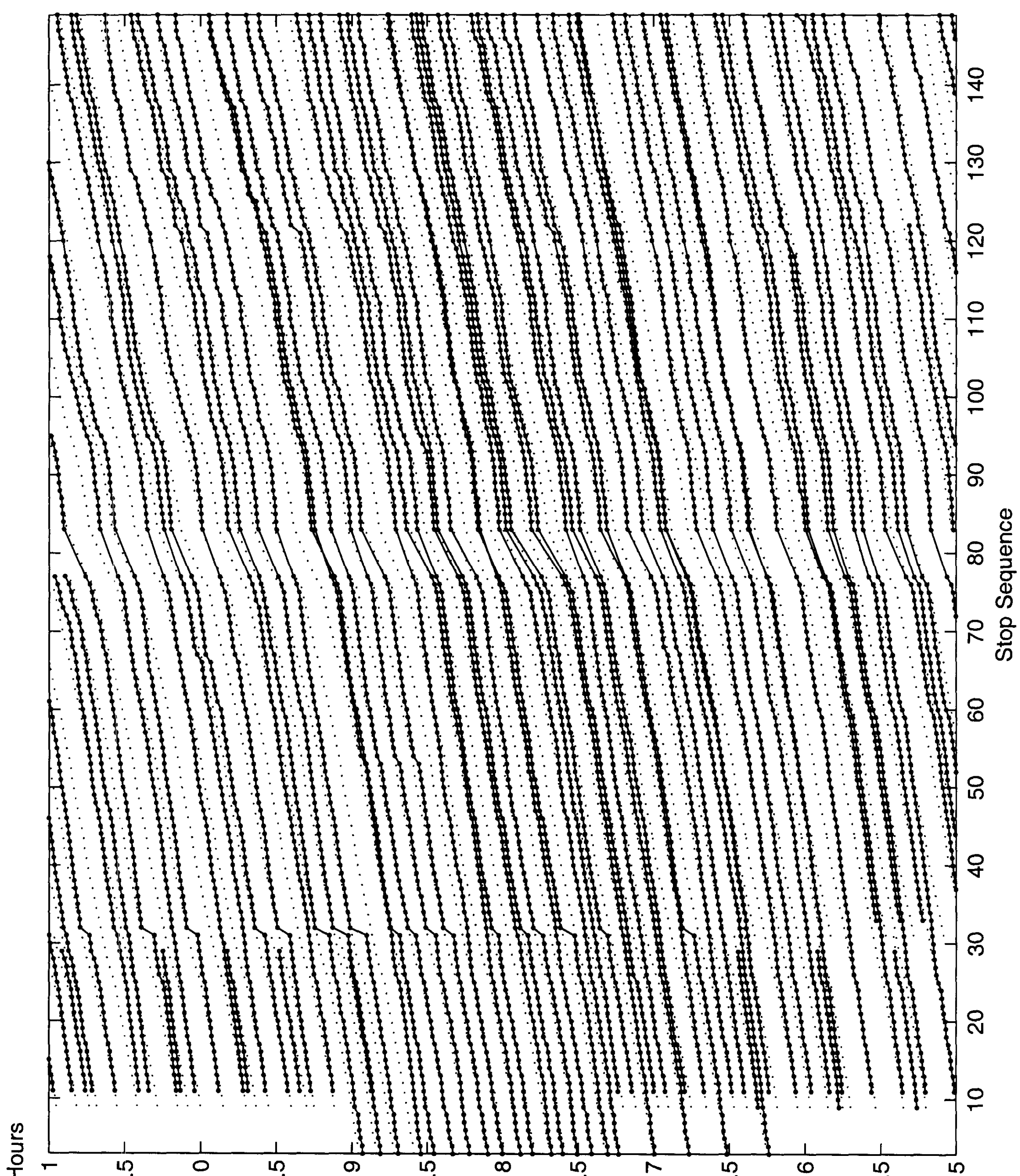


Figure 6-3: Space-Time Diagram of Route 9 Northbound Service from Simulation with No Passengers

- The lines representing the simulated trips are mostly parallel to each other and do not converge.

- These lines are noticably flatter than the corresponding lines representing the trips' schedules. Each trip's simulated line ends significantly lower than the corresponding scheduled line, meaning that each simulated trip ended significantly earlier than scheduled.

The first feature indicates that without passengers, the simulated vehicles have very little tendency to bunch and gap (if any), resulting in much more regular service along the entire route than when passengers were included in the simulation. This finding is confirmed by the corresponding headway variability results, presented in Table 6.5.

In this experiment, all of the movement variability experienced by vehicles had to come from inter-stop movement times, trip start delays, and (occasionally) reliefs. The resulting low headway variability suggests that these factors by themselves do not make a great contribution to variability in service regularity (with the exceptions of reliefs, which forced many too-early vehicles to wait at the relief point until their relief times). Instead, it seems that the main cause of the bunching phenomenon in the simulation (and, presumably, in real service as well), is the dwell times caused by passenger demand.

This finding is consistent with the premise that dwell times cause bunching to propogate by making late vehicles more loaded and therefore later and early vehicles less loaded and therefore earlier. In addition, this finding confirms the major finding at the end of Section 6.1.2, that parameters and behaviors related to passenger demand and dwell time seem to make the best targets for adjustments to the simulator (and possibly even for adjustments to real service) to control the propogation of bunching.

The second feature shown in the space time diagram indicates that dwell times contribute a good deal to vehicles' travel time. This is confirmed by the trip travel time results presented in Table 6.6 (as compared with the results of the initial simulation in Table 5.4). In addition, the trip travel time variability results (in northbound

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103$^{rd}$ | 95$^{th}$ | 74$^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | 74$^{th}$ | 95$^{th}$ | 103$^{rd}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103$^{rd}$ | 95$^{th}$ | 74$^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | 74$^{th}$ | 95$^{th}$ | 103$^{rd}$ |
| 5 — 6 | 0 | 4 | 4 | 4 | 4 | 5 | 3 | 9 | 10 | 8 | 5 | 0 |
| 6 — 7 | 3 | 2 | 3 | 4 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 8 |
| 7 — 8 | 3 | 2 | 3 | 3 | 3 | 3 | 2 | 2 | 3 | 4 | 3 | 4 |
| 8 — 9 | 1 | 2 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 3 | 5 | 6 |
| 9 — 10 | 0 | 3 | 3 | 4 | 4 | 3 | 2 | 2 | 2 | 3 | 7 | 0 |
| 10 — 11 | 0 | 3 | 4 | 4 | 4 | 4 | 2 | 2 | 2 | 3 | 4 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103$^{rd}$ | 95$^{th}$ | 74$^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | 74$^{th}$ | 95$^{th}$ | 103$^{rd}$ |
| 5 — 6 | 0 | 0 | -1 | -1 | -1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 — 7 | 0 | 0 | 0 | -1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 7 — 8 | -1 | 0 | 0 | -1 | 0 | 0 | 0 | -1 | -1 | 0 | 0 | -1 |
| 8 — 9 | -1 | -1 | 0 | -1 | -1 | -1 | 0 | -1 | 0 | -1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 1 | 0 | 0 | -1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 |

Table 6.5: Headway Standard Deviations Comparison — No Passengers

| | Observed | | Simulated | | Comparison | |
|---|---|---|---|---|---|---|
| Period | North | South | North | South | North | South |
| 5 — 6 | 85 | 83 | 72 | 71 | -1 | -1 |
| 6 — 7 | 97 | 98 | 78 | 77 | -1 | -1 |
| 7 — 8 | 98 | 97 | 81 | 82 | -1 | -1 |
| 8 — 9 | 97 | 91 | 84 | 83 | -1 | -1 |
| 9 — 10 | 97 | 93 | 80 | 76 | -1 | -1 |
| 10 — 11 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 6.6: Trip Travel Time Means Comparison — No Passengers

| | Observed | | Simulated | | Comparison | |
|---|---|---|---|---|---|---|
| Period | North | South | North | South | North | South |
| 5 — 6 | 3 | 6 | 2 | 4 | -1 | 0 |
| 6 — 7 | 4 | 4 | 3 | 7 | -1 | 1 |
| 7 — 8 | 4 | 3 | 2 | 8 | -1 | 1 |
| 8 — 9 | 3 | 3 | 3 | 7 | 0 | 1 |
| 9 — 10 | 3 | 3 | 3 | 6 | 0 | 1 |
| 10 — 11 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 6.7: Trip Travel Time Standard Deviations Comparison — No Passengers

direction[3]) presented in Table 6.7 (as compared with Table 5.5) show that removing passenger demand also leads to a significant decrease in the variability of trip travel times, which fits with their impact on headway variability.

### Reduced Passenger Demand

Since a simulation with the original demand input parameters exhibited too much headway irregularity and a simulation with no demand inputs exhibited almost no headway irregularity, a series of experiments was conducted to test whether the discrepancy in headway irregularity was a result of some inflation in the input passenger arrival rates. Experiments were conducted in which all input passenger arrival rates were reduced first by 50% , and then by 75%. In both experiments, the resulting headway irregularity statistics were still significantly greater in many cases (particu-

[3]The southbound results are skewed by the fact that in the southbound direction, the relief point is near the end of the route, so passenger-free vehicles arrive extremely early and are held for very long times for their scheduled reliefs, resulting in trips that include reliefs taking much longer than trips that do not. This effect also caused the northbound trip travel time standard deviations to be slightly inflated.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 5 | 4 | 4 | 5 | 6 | 3 | 10 | 12 | 11 | 6 | 0 |
| 6 — 7 | 2 | 2 | 3 | 7 | 8 | 5 | 2 | 3 | 3 | 4 | 4 | 7 |
| 7 — 8 | 4 | 2 | 3 | 5 | 5 | 8 | 3 | 4 | 4 | 7 | 4 | 5 |
| 8 — 9 | 2 | 3 | 3 | 5 | 5 | 6 | 3 | 5 | 5 | 7 | 8 | 8 |
| 9 — 10 | 0 | 3 | 3 | 6 | 7 | 6 | 2 | 4 | 5 | 7 | 8 | 0 |
| 10 — 11 | 0 | 3 | 4 | 6 | 7 | 6 | 2 | 4 | 5 | 6 | 5 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 0 | 0 | -1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 6 — 7 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| 7 — 8 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 — 9 | -1 | -1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 — 10 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |

Table 6.8: Headway Standard Deviations Comparison — Passenger Demand Reduced by 50%

larly later in the route and later in the morning) than their observed counterparts, as shown in Tables 6.8 and 6.9. These results indicate that the discrepancies are not a result of a simple, across-the-board inflation of passenger demand statistics.

### Deterministic Passenger Demand Rates

If the simulator's failure to pass validation tests was not [primarily, at least] a result of generally inflated mean demand rates, perhaps it was a result of some discrepancy in the input standard deviations of these rates. Because the principle discrepancy between the initial simulation and real service was one of excessively irregular service

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 5 | 4 | 5 | 6 | 9 | 2 | 10 | 11 | 9 | 5 | 0 |
| 6 — 7 | 2 | 3 | 4 | 6 | 6 | 5 | 2 | 3 | 4 | 4 | 4 | 8 |
| 7 — 8 | 4 | 2 | 2 | 4 | 5 | 7 | 2 | 4 | 4 | 6 | 4 | 5 |
| 8 — 9 | 1 | 2 | 2 | 4 | 4 | 5 | 3 | 5 | 4 | 5 | 6 | 8 |
| 9 — 10 | 0 | 3 | 2 | 4 | 5 | 5 | 3 | 4 | 5 | 5 | 8 | 0 |
| 10 — 11 | 0 | 3 | 3 | 4 | 6 | 6 | 2 | 4 | 4 | 5 | 4 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 0 | 0 | -1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 — 7 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 7 — 8 | -1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 8 — 9 | -1 | -1 | 0 | -1 | -1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 9 — 10 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |

Table 6.9: Headway Standard Deviations Comparison — Passenger Demand Reduced by 75%

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 5 | 4 | 6 | 6 | 8 | 3 | 11 | 13 | 16 | 6 | 0 |
| 6 — 7 | 2 | 3 | 5 | 7 | 8 | 7 | 2 | 4 | 4 | 5 | 4 | 7 |
| 7 — 8 | 4 | 3 | 4 | 7 | 8 | 10 | 3 | 5 | 6 | 11 | 6 | 8 |
| 8 — 9 | 2 | 3 | 4 | 7 | 8 | 9 | 3 | 6 | 7 | 8 | 9 | 9 |
| 9 — 10 | 0 | 3 | 3 | 7 | 7 | 9 | 3 | 5 | 6 | 8 | 7 | 0 |
| 10 — 11 | 0 | 3 | 4 | 8 | 7 | 9 | 3 | 5 | 6 | 8 | 5 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 0 | -1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 6 — 7 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 7 — 8 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 0 |
| 8 — 9 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.10: Headway Standard Deviations Comparison — Deterministic Passenger Demand Rates

in the simulation, the cause could be excessively high demand irregularity. Consequently, an experiment was conducted in which the passenger demand standard deviation input parameters were ignored, and passengers arrived at stops and alighted from vehicles based on deterministic arrival rates, rather than Poisson and Binomial processes.

The headway variability results of this experiment are presented in Table 6.10. These results show that deterministic passenger demand rates did not lead to a significant improvement in simulated headway variability. This finding is confirmed qualitatively by the representative space-time diagram shown in Figure 6-4, which displays the same strong tendency toward persistent bunching found in the initial simulation.

These results and those of the previous experiments in this section indicate that problems in the passenger demand input parameters are not likely to be the main source of the extra headway variability in the simulation.

### 6.1.4 Dwell Time Function Parameters

The last simulator inputs that were adjusted were the parameters of the dwell time function. Because the dwell time function translates passenger activity into vehicle delay, its parameters can have a great impact on the overall movement of vehicles, since, as was discussed above, this aspect of vehicle delay makes important contributions to headway variability. In addition, because dwell time functions tend to leave a great deal of dwell time variability unexplained[4], even the best estimates of their parameters are subject to uncertainty.

A series of experiments was conducted that included a number of different sets of dwell time function parameters. These sets of parameters were designed to test the effects of three general types of changes to the parameters: decreasing all of the parameters, increasing the ratio of the constant term to the boarding and alighting terms, and increasing the ratio of the boarding and alighting terms with respect to the constant term.

#### No Dwell Times

Before experiments with alternative dwell time parameters were conducted, an experiment was conducted in which all parameters were set to 0, producing an experiment effectively very similar (as far as vehicle progress is concerned) to the previous experiment in which there were no passengers[5] (see Section 6.1.3). As expected, the results

[4]For example, see (Dueker et al., 2004), in which one of the most sophisticated and data-rich dwell time studies to date resulted in a best model whose "explanatory power [is] low" with an $R^2$ value of 0.35.

[5]The main difference in vehicle progress between the experiment with no passengers and the one with no dwell times is that the latter included stopping penalties at stops where passengers boarded or alighted.

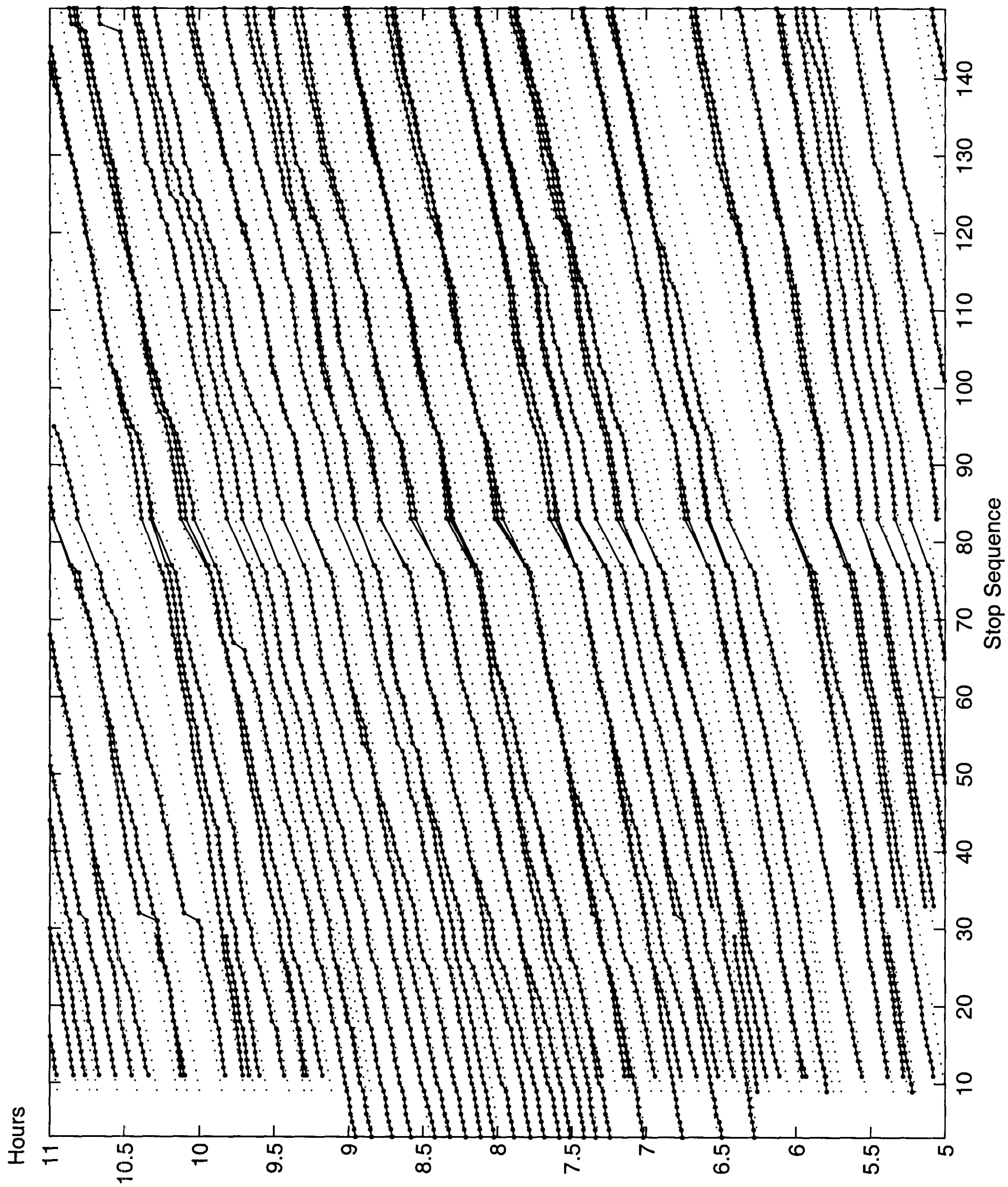


Figure 6-4: Space-Time Diagram of Route 9 Northbound Service from Simulation with Deterministic Passenger Demand Rates

of this experiment were also similar to those of the previous one, with vehicles tracing largely parallel lines through the space-time diagram and not bunching (see Figure 6-5). This experiment serves as a dramatic demonstration of the impact of the dwell time parameters.

### Reduced Dwell Times

Because passenger demand, as expressed through dwell times, is a primary driver of the bunching phenomenon, as was discussed above, an experiments was conducted to investigate the effect of decreasing the general influence of passenger demand on vehicle movements by decreasing all of the dwell time parameters. In particular, all four dwell time parameters were decreased by 50%.

The headway variability results of this experiment (presented in Table 6.11 were similar to those of the 50% demand experiment discussed in Section 6.1.3 and presented in Table 6.8. In particular, the simulated headway variability statistics were brought closer to their real equivalents, but they were still higher than their real equivalents in many cases.

In addition, this adjustment to the dwell time parameters caused, as expected, a significant decrease in trip travel times. Table 6.12 shows that the result was that after this adjustment, simulated trips took consistently less time than real trips, demonstrating that this level of dwell time parameter reduction is unrealistic.

These results indicate that while the dwell time parameters have a strong effect on headway variability, even a drastic reduction of all dwell time parameters does not make the simulation conform to reality.

### Increased Weight of Constant Term

The next two experiments attempted to decrease the variability in the movement of vehicles that serve more (or fewer) passengers while holding the total contribution of dwell times to vehicle travel times more or less constant. In the first of these experiments, the ratio of the constant term of the dwell time function to the coefficients of the boarding and alighting terms was increased by doubling the constant term

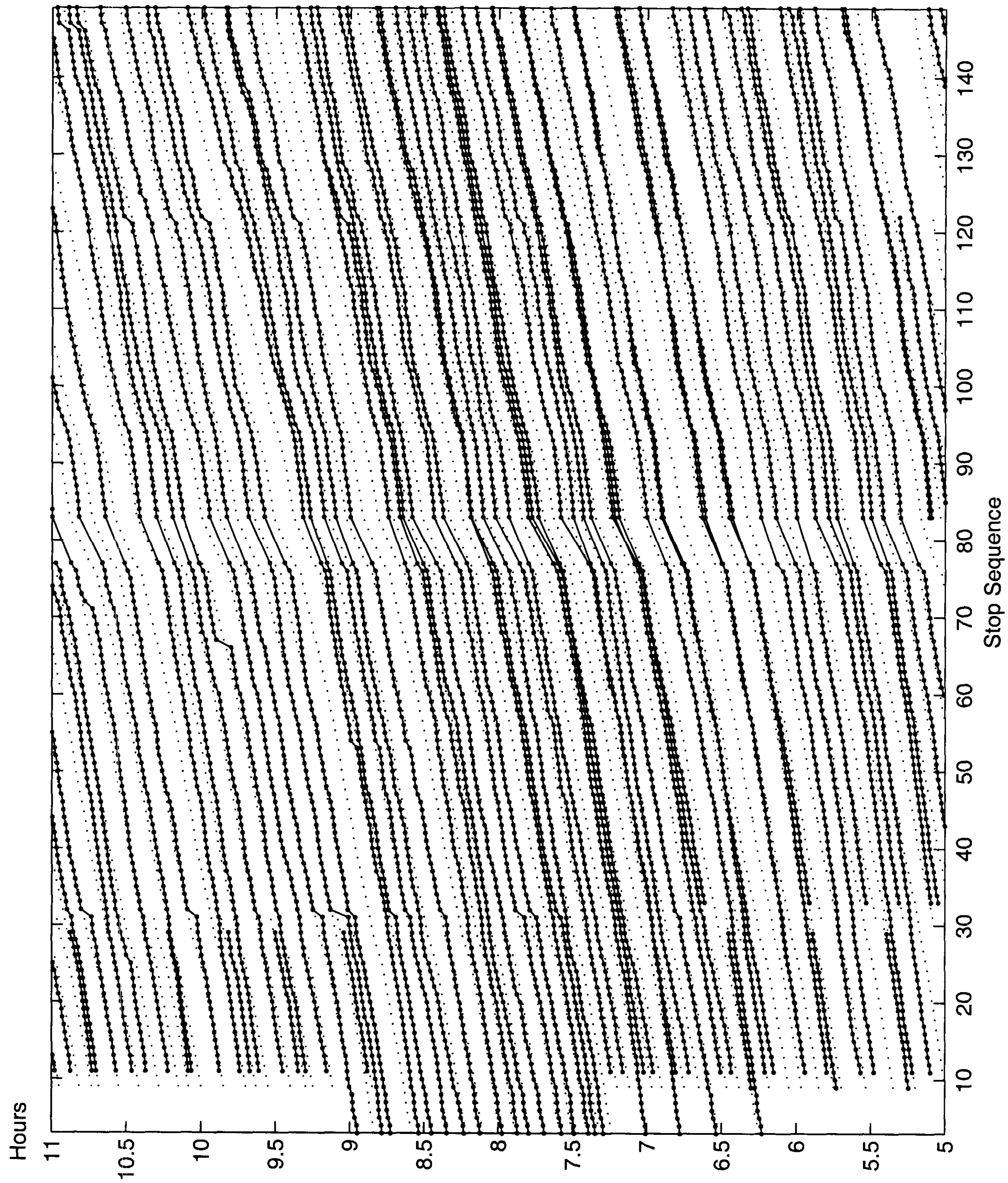


Figure 6-5: Space-Time Diagram of Route 9 Northbound Service from Simulation with No Dwell Times

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103$^{rd}$ | 95$^{th}$ | 74$^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | 74$^{th}$ | 95$^{th}$ | 103$^{rd}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103$^{rd}$ | 95$^{th}$ | 74$^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | 74$^{th}$ | 95$^{th}$ | 103$^{rd}$ |
| 5 — 6 | 0 | 5 | 4 | 5 | 6 | 9 | 3 | 10 | 12 | 12 | 5 | 0 |
| 6 — 7 | 2 | 2 | 3 | 6 | 6 | 5 | 2 | 2 | 3 | 4 | 4 | 8 |
| 7 — 8 | 4 | 2 | 3 | 5 | 5 | 7 | 3 | 3 | 4 | 6 | 4 | 5 |
| 8 — 9 | 2 | 3 | 3 | 5 | 4 | 5 | 3 | 6 | 6 | 6 | 5 | 5 |
| 9 — 10 | 0 | 3 | 3 | 5 | 5 | 6 | 3 | 5 | 5 | 7 | 6 | 0 |
| 10 — 11 | 0 | 3 | 3 | 6 | 6 | 6 | 2 | 4 | 5 | 6 | 5 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103$^{rd}$ | 95$^{th}$ | 74$^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | 74$^{th}$ | 95$^{th}$ | 103$^{rd}$ |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 6 — 7 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 7 — 8 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| 8 — 9 | -1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| 9 — 10 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.11: Headway Standard Deviations Comparison — Dwell Time Function Parameters Reduced by 50%

| | Observed | | Simulated | | Comparison | |
|---|---|---|---|---|---|---|
| Period | North | South | North | South | North | South |
| 5 — 6 | 85 | 83 | 81 | 77 | -1 | -1 |
| 6 — 7 | 97 | 98 | 90 | 88 | -1 | -1 |
| 7 — 8 | 98 | 97 | 92 | 90 | -1 | -1 |
| 8 — 9 | 97 | 91 | 96 | 88 | 0 | -1 |
| 9 — 10 | 97 | 93 | 94 | 83 | -1 | -1 |
| 10 — 11 | 0 | 0 | 0 | 0 | 0 | 0 |

Table 6.12: Trip Travel Time Means Comparison — Dwell Time Function Parameters Reduced by 50%

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 5 | 6 | 7 | 8 | 9 | 3 | 11 | 13 | 8 | 6 | 0 |
| 6 — 7 | 1 | 3 | 4 | 8 | 8 | 7 | 3 | 4 | 5 | 6 | 4 | 6 |
| 7 — 8 | 5 | 2 | 4 | 6 | 8 | 9 | 3 | 4 | 5 | 8 | 5 | 7 |
| 8 — 9 | 2 | 2 | 4 | 7 | 6 | 7 | 4 | 7 | 6 | 8 | 9 | 10 |
| 9 — 10 | 0 | 3 | 3 | 7 | 7 | 8 | 2 | 5 | 6 | 8 | 7 | 0 |
| 10 — 11 | 0 | 3 | 4 | 7 | 8 | 8 | 3 | 5 | 6 | 7 | 7 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 6 — 7 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| 7 — 8 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 8 — 9 | -1 | -1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 1 | 1 | 1 | 1 | -1 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.13: Headway Standard Deviations Comparison — Weight of Dwell Time Function Constant Term Increased

coefficient and halving each variable term coefficient.

The reasoning behind this tactic is that the latter terms express more variability between vehicles with heavier and lighter passengers loads because the vehicles with heavier loads will tend to have more passengers getting on and off at each stop. The effectiveness of this reasoning is limited, of course, by the fact that more heavily-loaded vehicles will also tend to make more stops, thus experiencing greater impact from the constant term as well.

In fact, the headway regularity results of this experiment (see Table 6.13) were, for the most part, similar to those of the initial simulation (Table 5.2) or slightly

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 5 | 4 | 5 | 6 | 10 | 4 | 11 | 13 | 13 | 6 | 0 |
| 6 — 7 | 3 | 3 | 6 | 9 | 8 | 6 | 3 | 5 | 6 | 6 | 5 | 9 |
| 7 — 8 | 6 | 4 | 6 | 8 | 10 | 10 | 4 | 6 | 7 | 11 | 6 | 8 |
| 8 — 9 | 6 | 6 | 6 | 9 | 8 | 9 | 6 | 8 | 7 | 10 | 10 | 12 |
| 9 — 10 | 0 | 3 | 7 | 8 | 9 | 11 | 6 | 7 | 8 | 10 | 9 | 0 |
| 10 — 11 | 0 | 5 | 7 | 9 | 10 | 10 | 8 | 8 | 9 | 10 | 9 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 0 | -1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 |
| 6 — 7 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 1 |
| 7 — 8 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| 8 — 9 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 9 — 10 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.14: Headway Standard Deviations Comparison — Weight of Dwell Time Function Constant Term Decreased

worse.

### Decreased Weight of Constant Term

An alternative line of reasoning is that slow, heavily loaded, vehicles are slowed down more by the large number of stops they have to make than they are by the number of passengers getting on and off. If so, decreasing the ratio of the constant term of the dwell time function to the other terms could be a solution that lowers the tendency of vehicles to form bunches without making vehicles' progress along the route unrealistically fast.

The next experiment tested this reasoning by halving the constant term coefficient and doubling the variable term coefficients. In this case, the headway regularity results, shown in Table 6.14 were significantly worse than those of the initial simulation, indicating that the amount of time it takes individual passengers to board and alight has a very strong effect on the regularity of service.

## 6.2 Behavior Changes

A series of adjustments were made to various aspects of the simulator's behavior in order to make the simulation better match reality. These adjustments were driven by the need to improve the results of validation tests, but they also reflected refinements in the conceptual realism of the simulator. This section discusses three general categories of behavior modifications:

- Modification of the behavior of vehicles and operators that come near each other.
- Modification of the decisions made by passengers with a choice of vehicles to board.
- Modification of the behavior of vehicles and passengers when vehicles get crowded.

### 6.2.1 Passing Behavior

The behavior exhibited by two vehicles that encounter each other at a point along the route can have a strong impact on the evolution of service quality in the face of bunching. Typically, when two vehicles bunch, the leader is carrying more passengers than the follower, since the discrepancy in time spent serving those passengers already is what helped make the leader fall behind and the follower become early. This difference in passenger loads can likewise affect the relationship between the future movements of the vehicles and therefore the spacing between them. Consequently, the ways in which these vehicles interact could have an important impact on their future bunching.

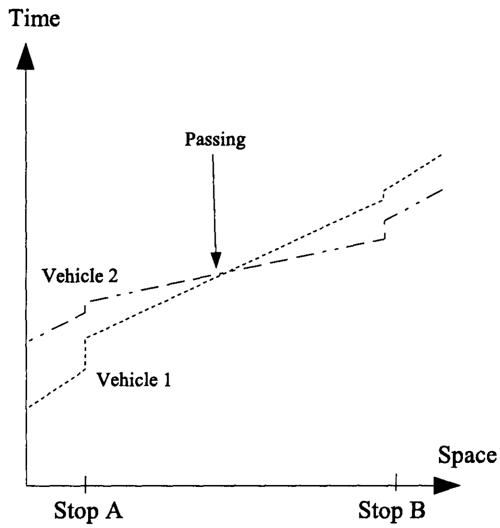


Figure 6-6: Vehicle 2 passes Vehicle 1 on the way from Stop A to Stop B because Vehicle 2's movement time is significantly lower.

Initially, the simulator took a "hands-off" approach to vehicle passing behavior. If two vehicles departed from a stop A at different times, heading for the next stop B, and the follower's randomly-selected movement time was lower than the leader's by a great enough margin for the follower to reach stop B first, then it would reach stop B first, effectively passing the leader. (See Figure 6-6.) Similarly, if two vehicles both arrived at a stop, and the follower had a dwell time sufficiently shorter than the leader's to allow it to leave before the leader, it would leave for the next stop before the leader, again effectively passing it. (See Figure 6-7.) (The distribution of passengers between two vehicles that arrive at the same stop at similar times is discussed below.)

This passing behavior tends to promote "leap-frogging," in which two vehicles that encounter each other continually take turns passing each other. The leap-frogging comes as a result of the leader tending to pick up most or all of the passengers at each stop and therefore experiencing a longer dwell time. This allows the follower to pass the leader and become the leader at the next stop with waiting passengers, where the two vehicles are likely to switch their order again. The leap-frogging has the effect of keeping the two vehicles moving together for the rest of the trip at a

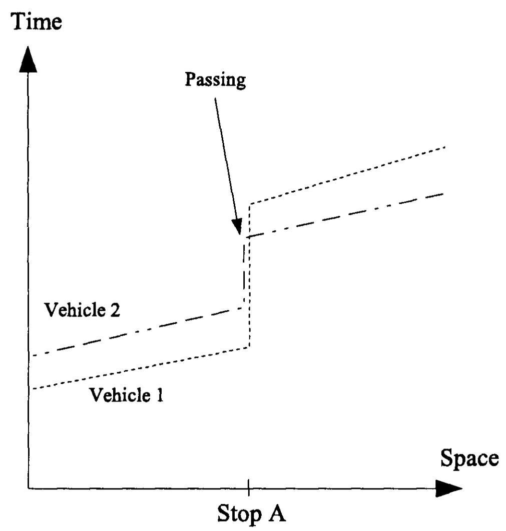


Figure 6-7: Vehicle 2 passes Vehicle 1 at Stop A because Vehicle 2's dwell time is significantly lower.

speed slightly faster than the (original) leader would have experienced without the help of the (original) follower. (See Figure 6-8.) Consequently, some other effect would be necessary to cause two bunched vehicles to diverge, as sometimes happens in real service.

### No Passing

The simulator was modified to implement a strict "no passing" policy, in which each follower maintains a separation of at least 45 seconds[6] behind its leader. An experiment that used this modification to the simulator resulted in even more severe bunching, as seen in Figure 6-9. While the vehicles did maintain the required separations, bunched followers always stayed exactly that distance from their leaders, forcing the leaders to pick up all of the passengers along the rest of the route and therefore move very slowly, trapping more and more vehicles backed up behind them. This unrealistic result indicates that a strict "no passing" rule does not describe real operator behavior, nor would it be more effective behavior.

[6]Different values for this threshold were tested, but they all yielded similar results.

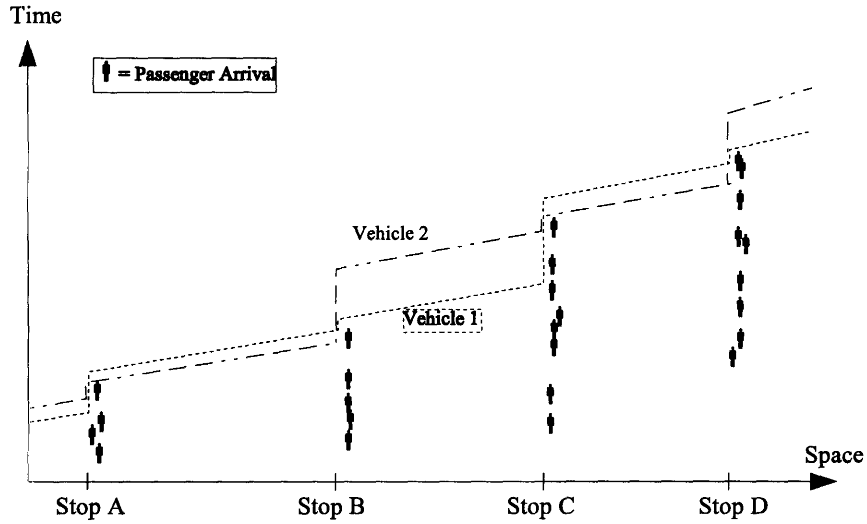


Figure 6-8: Vehicle 1 and Vehicle 2 "leap-frog," continually pass each other, as they take turns picking up the larger load of passengers at each stop.

### Passing Only When Early

To mitigate the extreme effects of the modification used in the previous experiment, which did not result in an improvement of the simulation's conformance with reality, an alternative policy was implemented in which a follower maintains space behind its leader until the follower falls behind schedule, at which point it is allowed to pass. The headway regularity results of this policy (see Table 6.15) were similar to those of the original "hands-off" policy because two vehicles would start leap-frogging as soon as the follower fell behind schedule.

The results of these two experiments indicate that if a significant difference in the behavior of vehicles that encounter each other in the simulator and in reality caused the discrepancy in performance between them, then it is likely that the real behavior is more complex than a simple rule that dictates when vehicles pass each other. Neither of these modifications were included in later simulations.

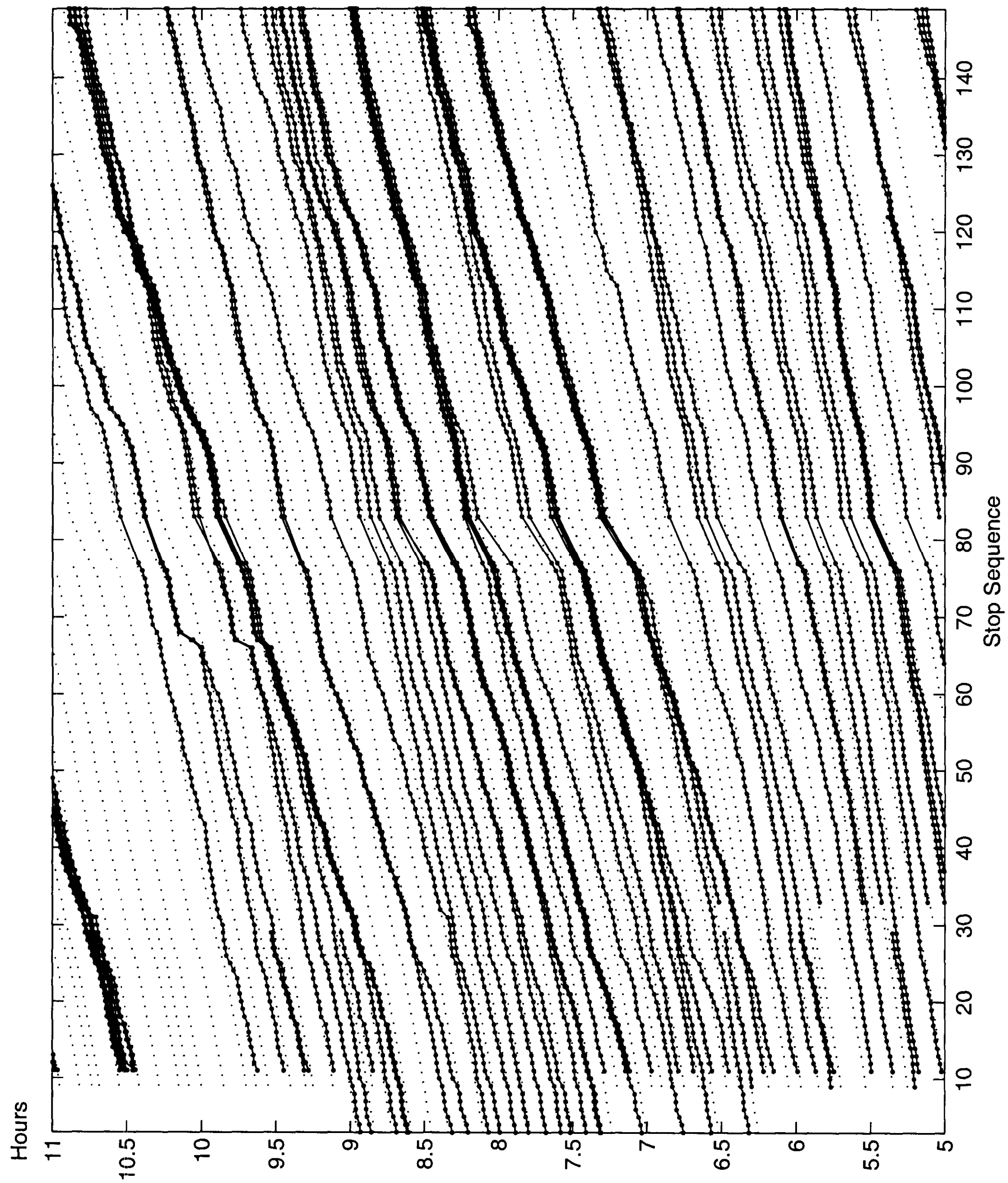


Figure 6-9: Space-Time Diagram of Route 9 Northbound Service from Simulation with No Passing. The large gap in service at the beginning of the route at around 10 AM is a result of vehicles ending their Southbound trip extremely late and in a large bunch.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103$^{rd}$ | 95$^{th}$ | 74$^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | 74$^{th}$ | 95$^{th}$ | 103$^{rd}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103$^{rd}$ | 95$^{th}$ | 74$^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | 74$^{th}$ | 95$^{th}$ | 103$^{rd}$ |
| 5 — 6 | 0 | 5 | 4 | 6 | 7 | 7 | 3 | 11 | 13 | 13 | 6 | 0 |
| 6 — 7 | 3 | 3 | 5 | 8 | 9 | 8 | 2 | 4 | 6 | 6 | 4 | 6 |
| 7 — 8 | 5 | 3 | 4 | 7 | 8 | 10 | 4 | 5 | 6 | 10 | 5 | 7 |
| 8 — 9 | 2 | 3 | 4 | 8 | 7 | 8 | 4 | 7 | 7 | 7 | 8 | 9 |
| 9 — 10 | 0 | 3 | 4 | 6 | 7 | 8 | 2 | 5 | 7 | 8 | 8 | 0 |
| 10 — 11 | 0 | 3 | 4 | 7 | 7 | 9 | 3 | 5 | 6 | 8 | 6 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103$^{rd}$ | 95$^{th}$ | 74$^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | 74$^{th}$ | 95$^{th}$ | 103$^{rd}$ |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 |
| 6 — 7 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 | 1 |
| 7 — 8 | 0 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 8 — 9 | 0 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.15: Headway Standard Deviations Comparison — Passing Restricted to Early Vehicles

### 6.2.2 Passenger Distribution Decisions

In addition to the behavior of vehicles that encounter each other at a stop or between stops, the behavior of passengers waiting at a stop who see two vehicles near each other at, or approaching, that stop can also affect the evolution of bunching. When passengers are waiting at a stop and either two vehicles arrive at once or one vehicle arrives with a second close behind, some of the passengers may choose to board the second vehicle instead of the first. This choice may be affected by a number of factors:

- If the leader runs out of capacity, the remaining passengers are forced to board the follower. This is true regardless of whether the follower is nearby or not.
- If passengers see that the leader is crowded, even if it is not crowded to capacity, and the follower has arrived or is approaching, some may choose to board the follower in order to avoid the crowd on the leader.
- If the two vehicles arrive at once or if the follower arrives while passengers are still boarding the leader, some passengers who have not yet boarded may choose to board the follower in order to board more quickly.

In the original configuration of the simulator, only the first of these considerations had an effect in most situations. All passengers waiting at a stop when a vehicle arrived would board it, as long as it had enough remaining capacity. The only passengers that would "choose" the follower over the leader were those who arrived during the leader's initial dwell time; if another vehicle arrived before the leader's initial dwell time ended, those passengers would board the follower instead of extending the leader's dwell time and boarding it. (See Figure 6-10.)

Since this behavior did not take into account the reasons that passengers may choose to walk to or wait for the second bus, a new passenger decision-making process was implemented. In the new process, passengers took the vehicle in front of them into account as well as the next vehicle, if the follower was either already at the stop or about to arrive within a short amount of time[7]. Under the new rules, about two

[7]Experimentation with different reasonable values for this parameter indicated that it does not make a big difference. The value used was 45 seconds.

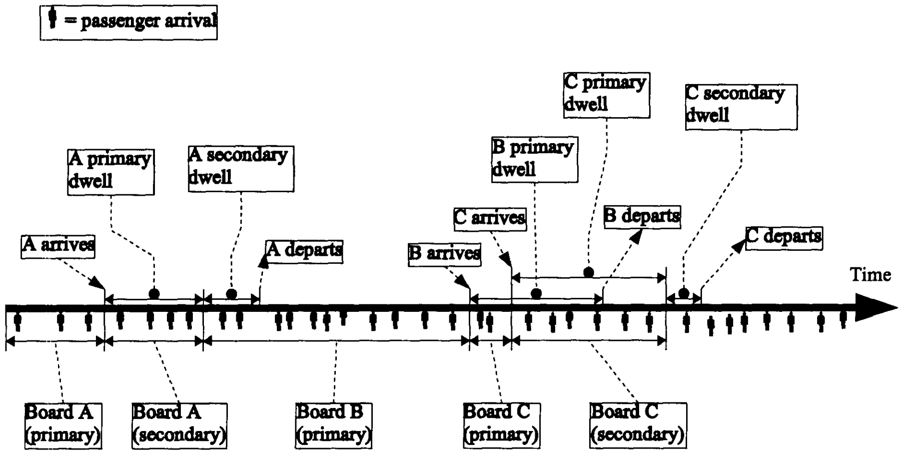


Figure 6-10: In the original configuration of the simulator, all of the passengers labeled as "Board B (primary)" boarded vehicle B, even though most of them were still waiting to board when vehicle C arrived.

thirds of waiting passengers who had not yet boarded the leader when the follower arrived would board the follower instead. In addition, if the follower was nearby (as defined above) when the leader arrived, then a fraction (between 10% and 75%) of all of the passengers waiting for the leader would wait for the follower, depending on how crowded the leader was.

Taken together, these rules transferred a large fraction of waiting passengers from a leader to a nearby follower. However, the general impact on service quality was marginal at best, as indicated by the results presented in Table 6.16, which display the same pattern of inflated headway irregularity seen in the results of the initial simulation (Table 5.2).

These results can be explained by the fact that the new rules only take effect when two vehicles are already bunched, and the most they do is move some passengers at some stops to the follower. The most that this movement of passengers can do is induce a momentary separation between the vehicles. This effect cannot cause a sustained and growing divergence between the two vehicles because it only applies to vehicles that are very near each other. However, because the new rule implements a

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 5 | 4 | 5 | 5 | 8 | 3 | 11 | 13 | 13 | 6 | 0 |
| 6 — 7 | 1 | 3 | 5 | 8 | 8 | 6 | 2 | 3 | 4 | 6 | 4 | 7 |
| 7 — 8 | 5 | 3 | 4 | 6 | 8 | 11 | 3 | 5 | 6 | 8 | 5 | 5 |
| 8 — 9 | 3 | 3 | 4 | 7 | 6 | 7 | 3 | 7 | 7 | 8 | 9 | 9 |
| 9 — 10 | 0 | 3 | 3 | 7 | 7 | 7 | 3 | 5 | 6 | 8 | 7 | 0 |
| 10 — 11 | 0 | 3 | 4 | 7 | 7 | 7 | 2 | 5 | 6 | 7 | 6 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 0 | -1 | -1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 6 — 7 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 7 — 8 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| 8 — 9 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.16: Headway Standard Deviations Comparison — New Passenger Distribution Rules

more refined understanding of passenger distribution decisions without harming the simulation results, it was preserved in later simulations.

### 6.2.3 Vehicle Crowding Behavior

Another decision that affects the distribution of passengers and the headway between vehicles is the decision by a vehicle whether, or not, to stop for waiting passengers. If a vehicle skips a stop that passengers are waiting at, it saves itself the entire dwell time delay and pushes the dwell time associated with those passengers onto its follower. In addition, if stopping penalties are in effect, the vehicle that skips a stop saves itself from the stopping penalty. As a result, a behavior that allows vehicles to skip some stops despite waiting passengers could potentially have a significant effect on vehicle movements.

#### Vehicle Capacity

In the original configuration of the simulator, the only reason a vehicle would not stop for waiting passengers was if it was already carrying a capacity passenger load. Therefore, the value chosen for vehicle capacity has an effect on the stopping decisions of the vehicles. A lower value for vehicle capacity puts a stronger control on the degree to which a vehicle can become crowded and therefore delayed by its passengers. A series of experiments were performed using reasonable values for vehicle capacity, ranging from the original value of 80 passengers , an estimate of the maximum crush loading capacity of a standard 40-foot bus, to 52, the maximum passenger load recorded in the real data.

The headway regularity results of the most extreme of these experiments, in which vehicle capacity was reduced to 52 passengers, are presented in Table 6.17. These results indicate that these adjustments did not produce significant changes in service quality, probably because their only direct effect is on the most heavily loaded vehicles. This finding indicates that through its direct effect as a strict limitation on boardings[8],

[8] As opposed to, for example, its effect on dwell times or on operator driving behavior.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 5 | 4 | 5 | 6 | 8 | 3 | 11 | 14 | 11 | 5 | 0 |
| 6 — 7 | 2 | 3 | 5 | 7 | 8 | 6 | 2 | 4 | 4 | 6 | 4 | 6 |
| 7 — 8 | 4 | 2 | 4 | 6 | 7 | 9 | 3 | 5 | 7 | 9 | 5 | 6 |
| 8 — 9 | 2 | 3 | 4 | 6 | 6 | 7 | 4 | 6 | 6 | 8 | 9 | 10 |
| 9 — 10 | 0 | 3 | 3 | 8 | 8 | 8 | 3 | 5 | 6 | 8 | 7 | 0 |
| 10 — 11 | 0 | 3 | 3 | 6 | 8 | 9 | 3 | 5 | 6 | 7 | 6 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 — 7 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| 7 — 8 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 8 — 9 | -1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.17: Headway Standard Deviations Comparison — Vehicle Capacity Set at 52 Passengers

vehicle capacity does not have an important role in service regularity, at least within the reasonable range that was tested.

### Drop-offs Only When Crowded

Occasionally in real service, when the operator of the leader of a bunched pair knows that her vehicle is bunched, she will choose to serve the next stop in a "drop-offs only" capacity, meaning that she will only stop there if there are passengers who want to alight there, but will leave passengers waiting to board for her follower. This tactic can bring about an immediate separation between the two vehicles by forcing extra dwell time onto the follower. It can also have a longer-term effect of making the passenger loads on the two vehicles more even, thereby taking away some of their tendency to converge.

This behavior was implemented in the simulator by having a vehicle with a nearby follower serve drop-offs only at the next stop if its passenger load was above a certain threshold. Experiments were run in which this threshold was set at 40 (approximately a seated load), 20, and 0 (removing the consideration of passenger load altogether). In each of these cases, the addition of this tactic did not have a strong impact on service quality metrics, probably because, as with previously-mentioned passenger distribution schemes, this one only affects vehicles that are already bunched and only has an ongoing effect on vehicles that stay bunched. The results of this collection of schemes indicate that policies and tactics with this characteristic of only effecting currently-bunched vehicles are unlikely to have strong effects on service quality.

Like the passenger distribution rules described in Section 6.2.2, this behavior did not impact service quality negatively and does constitute a refinement to the simulator's realism, so it was included in later simulations.

## 6.3 Control Mechanisms

An element of the behavior of real service that was intentionally absent from the original simulator base case configuration is intelligent real-time decisions by operators and supervisors to try to achieve, maintain, and restore regular service. However, if such decisions are actually implemented by the transit personnel managing Route 9, they could have a positive impact on service quality which is significant enough to explain some of the discrepancy between real service and the initial simulations. So, a series of experiments were conducted in which some of these decisions were introduced into the base case simulation.

### 6.3.1 Schedule-based holding

One of the simplest forms of service restoration control is timepoint-based holding. For this control mechanism, a set of stops are chosen to be timepoints, and a passing time is scheduled for each trip at each timepoint. If a vehicle arrives at a timepoint before its scheduled passing time there, the vehicle waits at that stop to bring it back on schedule. Besides the direct effect that this mechanism has on keeping vehicles on schedule and therefore headways even, holding early vehicles also reduces passenger-driven bunching by introducing space between the held vehicle and its leader and by making the held vehicle pick up passengers that would otherwise have slowed down its follower and caused it to bunch with *its* follower.

When implementing such a holding strategy, it is necessary to place reasonable limits on the amount of time that a vehicle can be held. If a vehicle arrives at a timepoint ten minutes early, it is unlikely to be held there until it gets back on schedule, because such a long hold would greatly annoy passengers on the vehicle (if, in fact, there are any). The simulator was modified to accept scheduled passing times at any stop and to designate stops as holding points, each with its own maximum holding time. These new capabilities were used to simulate two kinds of control that might be going on in the real service: vehicles holding at real timepoints when they arrive early, and early vehicles approaching timepoints more slowly than they otherwise would.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{\text{rd}}$ | $95^{\text{th}}$ | $74^{\text{th}}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{\text{th}}$ | $95^{\text{th}}$ | $103^{\text{rd}}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{\text{rd}}$ | $95^{\text{th}}$ | $74^{\text{th}}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{\text{th}}$ | $95^{\text{th}}$ | $103^{\text{rd}}$ |
| 5 — 6 | 0 | 4 | 3 | 5 | 6 | 10 | 3 | 11 | 13 | 14 | 5 | 0 |
| 6 — 7 | 2 | 3 | 5 | 7 | 7 | 6 | 2 | 3 | 5 | 6 | 4 | 8 |
| 7 — 8 | 5 | 2 | 4 | 7 | 8 | 8 | 3 | 5 | 5 | 8 | 6 | 6 |
| 8 — 9 | 2 | 3 | 4 | 7 | 6 | 8 | 4 | 7 | 7 | 8 | 7 | 7 |
| 9 — 10 | 0 | 3 | 3 | 8 | 8 | 8 | 3 | 6 | 7 | 9 | 8 | 0 |
| 10 — 11 | 0 | 3 | 4 | 7 | 7 | 9 | 3 | 6 | 7 | 7 | 6 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{\text{rd}}$ | $95^{\text{th}}$ | $74^{\text{th}}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{\text{th}}$ | $95^{\text{th}}$ | $103^{\text{rd}}$ |
| 5 — 6 | 0 | 0 | -1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 6 — 7 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| 7 — 8 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| 8 — 9 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.18: Headway Standard Deviations Comparison — Schedule Holding at Staffed Timepoints

### Holding at Timepoints

The first simulation of holding at timepoints selected the timepoints that were staffed with point supervisors at the time when the input data was collected: $74^{\text{th}}$, $63^{\text{rd}}$, and $55^{\text{th}}$ Streets. Each of these timepoints was assigned to be a hold-for-schedule point with a maximum hold time of 150 seconds.

The headway regularity results of this experiment are presented in Table 6.18. They show very few instances of improvement over the initial experiment (Table 5.2 in conformance of the simulation to reality. In fact, the addition of the timepoint controls made headway regularity worse in this experiment than in the original experiment over much of the route. This detriment to service regularity could be due to the fact that this implementation of timepoint holding ignores the distance from other vehicles of the vehicle being held. Consequently, holding early vehicles may have actually caused bunches in some cases by holding vehicles that were already far from their leaders and/or close to their followers. An alternative holding tactic that addresses this problem is discussed in Section 6.3.2.

### Dragging

Schedule holding was also used to simulate "dragging," the practice of operators of vehicles that are running early intentionally driving slowly in order to avoid arriving at timepoints early. This practice was simulated by assigning every stop from the beginning of the route to the last staffed timepoint (in each direction) to be a holding point with a maximum hold time of 30 seconds. This way, as long as a vehicle was ahead of schedule, it would pause briefly at each stop until it either got back on schedule or passed the last staffed timepoint.

Experiments were run that included this dragging effect both with and without the holding at staffed timepoints used in the previous experiment. The experiement that combined timepoint holding with dragging exhibited better headway regularity results; these results are presented in Table 6.19. The combination of control measures used in this experiment resulted in slightly better headway regularity statistics during some time periods, mostly in the parts of the route where the dragging was taking place. This finding offers some support for the idea that operators actually drag in response to their schedule adherence using tactics somewhat similar to the one simulated. However, this simulation also displayed worse headway regularity than the original simulation during many time periods, particularly in the later parts of the route, indicating that the behavior, as modeled, is not exactly what operators are actually doing.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 5 | 4 | 6 | 7 | 9 | 3 | 11 | 13 | 11 | 5 | 0 |
| 6 — 7 | 1 | 3 | 4 | 7 | 8 | 7 | 2 | 4 | 5 | 7 | 4 | 7 |
| 7 — 8 | 4 | 3 | 4 | 7 | 8 | 8 | 3 | 5 | 5 | 9 | 5 | 7 |
| 8 — 9 | 2 | 2 | 4 | 6 | 7 | 8 | 4 | 7 | 6 | 8 | 9 | 10 |
| 9 — 10 | 0 | 3 | 2 | 7 | 8 | 8 | 2 | 5 | 7 | 8 | 8 | 0 |
| 10 — 11 | 0 | 3 | 4 | 6 | 9 | 9 | 3 | 5 | 6 | 8 | 5 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | 103rd | 95th | 74th | Arch | Mad | B.P. | B.P. | Mad | Arch | 74th | 95th | 103rd |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 6 — 7 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| 7 — 8 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 8 — 9 | -1 | -1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 9 — 10 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.19: Headway Standard Deviations Comparison — Schedule Holding at Staffed Timepoints and Dragging

### 6.3.2 Headway-based holding

One other holding tactic, holding for headway, was simulated in other experiments. Sometimes, a supervisor or operator will hold a vehicle in place or slow a vehicle down even if it is on (or behind) schedule in order to create, maintain, or restore space between it and its leader. This tactic is intended to have a direct and positive effect on headway regularity.

The simulator was modified to allow experiments to use this tactic. A capability was added to assign stops as hold-for-headway points, with maximum hold times like those of the hold-for-schedule points. At hold-for-headway points, a vehicle is held if the time between it and its leader is less than the average scheduled headway in the current time period.

A series of experiments was run in which headway-based holding was deployed in ways analogous to the deployments of schedule-based holding discussed in Section 6.3.1:

- Simulating supervisors at staffed timepoints with maximum hold times of 150 seconds.
- Simulating dragging from the beginning of the route until the lasst staffed timepoint using headway-based holding at each stop with a maximum hold time of 30 seconds.
- Combining simulated supervisors with simulated dragging.

Of these three experiments, the one that produced the best headway regularity results was the second. These results are presented in Table 6.20. They show some instances of slight improvement in headway regularity over the initial experiment, but not many, and instances of decrease in headway regularity are included as well. (The results of the other two experiments showed even more evidence of decreased headway regularity.) These results indicate that like schedule-based holding, a strict policy of headway-based holding or dragging, at least as simulated, does not reflect real-life behavior of supervisors and operators.

| Observed | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Simulated | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 6 | 6 | 7 | 7 | 3 | 2 | 10 | 14 | 5 | 4 | 0 |
| 6 — 7 | 2 | 3 | 3 | 5 | 4 | 3 | 2 | 3 | 3 | 3 | 3 | 3 |
| 7 — 8 | 5 | 2 | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 5 | 4 | 6 |
| 8 — 9 | 3 | 4 | 3 | 6 | 5 | 6 | 3 | 4 | 4 | 5 | 6 | 7 |
| 9 — 10 | 0 | 3 | 2 | 4 | 4 | 5 | 3 | 3 | 3 | 3 | 4 | 0 |
| 10 — 11 | 0 | 4 | 3 | 4 | 4 | 4 | 2 | 2 | 3 | 3 | 3 | 0 |
| Comparison | | | | | | | | | | | | |
| | Northbound | | | | | | Southbound | | | | | |
| Period | $103^{rd}$ | $95^{th}$ | $74^{th}$ | Arch | Mad | B.P. | B.P. | Mad | Arch | $74^{th}$ | $95^{th}$ | $103^{rd}$ |
| 5 — 6 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 6 — 7 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| 7 — 8 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| 8 — 9 | -1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 1 |
| 9 — 10 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 1 | 1 | 0 |
| 10 — 11 | 0 | -1 | 0 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 |

Table 6.20: Headway Standard Deviations Comparison — Headway Holding at Staffed Timepoints and Headway-Based Dragging

# Chapter 7

# Conclusions

## 7.1 Summary of Findings

The process of validation testing (Chapter 5) and adjustments (Chapter 6) to the simulation generated the following results relating to the simulator. Where conclusions can be drawn about the nature of real service, they are noted.

- The transit route simulator described in Chapter 2 and adjusted in Chapter 6, without further adjustment, is unable to pass the validation tests described in Chapter 5, which compare characteristics of simulated service to those of real service on the same route.

- The major discrepancy between the simulation and real service is a stronger propagation of headway irregularities (bunching and gapping) in the simulation.

- This propagation is not a result of input parameters for the standard deviations of movement times and passenger demand rates being too high. In addition, it is unlikely to be a result of systematic errors in either movement time or passenger demand input parameters.

- Dwell times caused by passenger movements make a major contribution to the propagation of bunching and gapping in the simulation and presumably also in real service.

- The dwell time function parameters that define the relationship between the number of passengers boarding and alighting at a stop and the dwell time there have a strong impact on the propagation of headway irregularity, while the parameter that defines the constant term does not.

- Control measures that only affect vehicles while they are bunched seem to have little impact on the general propagation of headway irregularities in the simulator, and probably also in real service.

- The policies that were tested in this study for behavior of passengers, operators, and service managers did not have strong impacts on the general state of headway irregularity. Their impact on service in general is uncertain.

## 7.2 Reasons for Failure of Validation

As was noted above, none of the adjustments that were tested in this study succeeded in causing the simulation to pass the validation tests described in Chapter 5. Possible reasons for the discrepancies between the simulation and reality include:

- Systematic or localized errors in basic input parameters (such as movement times or passenger demand rates) or biased differences from the "true values" that they represent.

- Correlations between elements of the input parameters that are not taken into account by the input structure specified by the simulator. For example, correlation between the movement times of successive buses traversing the same link.

- Errors in the computer code that defines the simulator.

- Elements of complex behavior of passengers, operators, or service managers that serve to mitigate bunching propagation in real service but are absent from the simulator.

As was discussed above, it is unlikely that errors or biases in the basic input parameters constitute the major cause of the discrepancies between the simulation and real service. Likewise, errors in the simulator's computer code are not likely to be the cause, since the simulation, in general, behaves qualitatively the way that it would be expected to.

It is more likely that the other two potential problems listed, gaps in the simulator's understanding of correlations between input parameters and of elements of complex human decisions, are principal causes of the discrepancies between the simulation and real service.

### 7.2.1 Input Parameter Correlations

Possible correlations between the values represented by the simulator's input parameters include:

- Correlations between movement times of successive vehicles traversing the same link, between those of vehicles traversing successive links, and between those experienced by a particular operator over the course of the route.

- Correlations between passenger demand rates at successive stops and between the passenger demand rates at a stop experienced by successive buses.

### 7.2.2 Elements of Human Behavior

Elements of human behavior that are not included in the simulator and that may have an important impact on headway regularity include:

- Operator behavior intended to maintain service regularity and schedule adherence or to balance these goals. In particular, this behavior may include slowing down or speeding up between stops, shortening or extending dwell times, passing other vehicles, and shortening or extending terminal recovery time. In addition, this behavior may vary systematically betwen individual operators, with, for example, more experienced operators having a greater ability to control their speed.

- Decisions by service managers to hold a vehicle or authorize early arrivals of a vehicle at future timepoints in order to maintain service regularity or schedule adherence. Authorizing early timepoint arrivals depends on the ability of the operator to control his speed and could potentially have a greater impact on service regularity than holding, since it affects the progress of the vehicle along the rest of the route. As was discussed above, the results of simulation experiments indicate that this quality is important for making control interventions that have a significant effect on overall service regularity.

It seems likely that these behaviors, especially those of operators, are of prime importance in explaining the qualitative difference between simulated and real service. Many operators can exert a great deal of control on their speed and on how long they wait at stops. The results of this research underscore the fact that transit agency personnel, unlike this simulation, are intelligent decision makers who play an important part in maintaining reliable service.

## 7.3 Future Research

This research developed and tested a system for simulation of a transit route based solely on data collected from that route and the transit system that it is a part of. The major opportunities for future research that come out of this work involve potential revisions of, applications of, and extensions to the model.

### 7.3.1 Possible Revisions to the Model

The first step that will be necessary in future research that will use the simulator described in this work is revision of the model until it is able to pass basic validation tests. Revisions of the types described below could make the simulator do a better job of simulating real service, both conceptually and as expressed by the results of validation tests.

- A more complex dwell time function that includes elements such as passenger load, schedule and headway adherence, operator characteristics, and stop characteristics.
- A more complex passenger demand model that takes into account the route variant of the vehicle, correlations between boardings and alightings at different stops, and other characteristics that impact how many passengers attempt to board each vehicle at each stop.
- A more complex vehicle movement model that incorporates correlations between movement times of different vehicles and along different links and allows for operators to control their speed in response to schedule and headway adherence and passenger load levels. The more complex model could also include systematic differences in behavior between different operators.

Based on the conclusion at the end of Section 7.2.2, the aspect of the simulator whose improvement could bear the most fruit is that of operator behavior. A model that allows operators to control their speeds and dwell times and allows them to choose which stops to service under some circumstances could be developed based on a study of real operator behavior. This model could then play a central role in making the simulator more realistic. In addition, such a study could constitute an important contribution to the theoretical understanding of transit operations.

### 7.3.2 Possible Applications of the Model

When the simulator has been modified in a way that allows it to pass validation tests credibly, it will be possible to use it for its designed purpose, to evaluate the effects of alternative control structures on a transit route. Future research can apply the simulator to evaluating the benefits of real-time data, using the ideas in Section

1.1.3, or to examining the questions about alternative supervisor deployments or control policies raised in Chapter 3.

In addition, the simulator described in this research could be applied to bus routes with different characteristics than CTA's Route 9 Ashland. As was noted in Section 3.1.2, Route 9 is uncommonly long for a high-frequency urban bus route, even in Chicago. It is therefore subject to the effects of propagating headway unreliability more than most urban bus routes. Consequently, the discrepancies in headway variability statistics between the simulation of Route 9 and the real service, which were more evident in the second half of the route than in the first, may play a much weaker role in a shorter route.

### 7.3.3 Possible Extensions of the Model

The following ideas for extension of the capabilities of the simulator would allow it to be used for an expanded set of applications. The flexible and relatively simple nature of the simulator's MATLAB code makes these extensions and others possible.

- The capability to model a network of two or more transit routes rather than just one route. This capability would allow the simulator to model the interaction of transit operations with transfering passengers and to test service management strategies that take network effects into account.

- Additional service management techniques, such as authorizing early timepoint arrivals, short-turning and expressing.

- Modifications to allow the simulator to model rail service. These modifications would probably include a strict "no passing" rule, a dwell time function designed for rail service (such as the one developed in (Lin and Wilson, 1992) and (Puong, 2000)), and some consideration of train acceleration/deceleration behavior.

- Modification of the passenger demand process to allow for demand which is characteristic of a low frequency route (see Section 2.3.2).

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