USING ARCHIVED TRANSIT DATA TO ANALYZE THE EFFECT OF RAINFALL ON TRANSIT PERFORMANCE MEASURES AT THE ROUTE LEVEL

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ABSTRACT

Using Archived Transit Data to Analyze the Effect of Rainfall on Transit Performance Measures at the Route Level

Nicholas F. Bleich

This study investigates the effect of rainfall on transit performance measures at the route level in the Puget Sound region of Washington State. Transit agencies are required to report certain performance metrics to the Federal Transit Administration (FTA), but performance measures can also be used to evaluate service and provide customers with information regarding the transit system. Using a three-year sample of archived automatic vehicle location (AVL) and hydrologic data the relationships between ridership, travel time, delay, and rainfall were investigated. The analysis of daily ridership and rainfall resulted in no statistically significant results, however, the results are supported by the existing research in this field. There was a generally negative trend in ridership with respect to rainfall. The analysis of travel time and rainfall did not result in the expected outcome. It was hypothesized that travel time would vary with rainfall, but that was not always the case. During many rainfall events the travel time remained average. The analysis of delay and rainfall shows that the impact of rainfall on delay is more complex than assumed. The delay during dry trips was different than the delay during light and moderate rain, but during heavy rain the statistical different disappeared. These results, implications for transit operators, and future research opportunities are discussed.

Keywords: Public Transit, Weather, Performance Measures

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1. INTRODUCTION

Moving Ahead for Progress in the 21st Century (MAP-21) transportation authorization, signed into law by President Obama in 2012, provided $10.6 billion for public transportation in the 2013 fiscal year (FY) and $10.7 billion in FY 2014 (FTA, 2012). MAP-21 also established performance-based planning and operations requirements to qualify for Federal funding administered by the Federal Transit Administration (FTA) furthering the goals of the Act, including safety, state of good repair, performance, and program efficiency (FTA, 2012). Public transportation operating agencies report performance measures to the National Transit Database (NTD) operated by FTA. The data submitted to NTD is standardized so that comparisons can be made between transit systems around the country. Transit agencies report basic descriptive statistics, financial information, service performance measures, ridership information, and safety and security reports (FTA NTD, 2012). Beyond the Federal requirements, agencies assess performance measures to provide transparency to riders and constituents.

The data reported to the NTD is collected onboard transit vehicles. These systems track what is happening on board the vehicle, but they do not provide data for the environment around the transit vehicle. Vehicular traffic in mixed-flow lanes creates uncontrollable external delays affecting transit performance measures. This information is currently not recorded by automatic vehicle location (AVL) systems. Weather can also have an effect on transit performance measures. Adverse weather conditions impact transit performance (Singhal et al., 2014). This thesis explores the effects rainfall has on transit performance measures by evaluating ridership, travel time, and delay for Sound Transit Route 545 in the Puget Sound region.

1.1. Background

Sound Transit was created in 1993 to serve as the regional public transportation agency in the greater Puget Sound region in Washington State. The agency is tasked with planning, constructing, and operating regional public transportation systems. Currently, Sound Transit operates regional buses, commuter rail, light rail, and a streetcar system providing high-capacity transit options for people to travel between regional growth centers. The regional bus system is operating in conjunction with King County Metro, Pierce Transit, and Community Transit, the three local transit agencies in the Puget Sound region. Sound Transit ridership has been increasing annually, with approximately 17.6 million boardings in 2014 (Sound Transit, 2014). All of the Sound Transit regional buses are outfitted with AVL systems which are used for real time management of transit operations. These systems are maintained and operated by King County Metro.

The first widespread implementation of an automated passenger counter (APC) system in the United States began in 1982 at King County Metro. At that time, about 15 percent of the fleet was equipped with passenger counters, and they used signposts and odometer readings to track the vehicle location (Furth et al., 2003). Ten years later in 1992, Metro acquired its first AVL and computer aided dispatch (CAD) system. This system also utilized signposts and odometer readings to track the vehicle location. As a vehicle passed a roadside signpost, they would receive the transmitted signpost identification number and store that along with the current odometer reading in the on-board computer system. The system would then send the signpost identification along with the odometer reading to the operations center every 90 seconds by radio (TCRP Synthesis 73, 2008, pg. 47). In 2007, it was announced that a “smart” bus technology would be installed on the entire fleet; this included Sound Transit vehicles. The new Communications Center System (CCS) would replace the existing AVL/CAD and APC systems and use GPS satellites to track vehicles instead of the roadside signposts (King County Metro).

The upgraded AVL system is part of the CCS, and includes mobile data terminals where the drivers can login to the system, automated stop announcements and dynamic message signs (DMS) displaying the next stop, automatic passenger counters (APC) on select buses, and transit signal priority (TSP) capabilities on all buses (TCRP Synthesis 73, 2008, pg. 49). This system is global positioning satellite (GPS) based, transmitting data much more frequently than the previous fixed-route AVL system. The data is archived at the stop-level, providing a rich source of accurate time and location information supplemented by passenger information on APC equipped vehicles randomly assigned to each route.

1.2. Objective

While many transit performance measures are only reported on an annual basis, performance measures can be analyzed for any timeframe and scale of transit operation. The objective of this study is to investigate the relationship between bus transit and localized rainfall data. This study focuses on examining the relationship between rainfall intensity and trip level performance measures on a busy regional bus route. First, daily ridership is analyzed on rainy and dry days to understand how riders utilize the route in adverse weather. Looking at three test days of varying amounts of precipitation, trip travel time is graphically explored for all transit trips on those days. One morning of one test day is then examined to attempt to diagnose a breakdown in transit performance. This study aims to build off of the existing research studying the link between adverse weather conditions and transit performance. This study looks at the effect on one transit route and specific transit trip performance, complementing previous studies which looked at network level analysis for transit systems on rainy days.

1.3. Literature Review

Previous research investigated the impact of weather factors on vehicle safety, speed, and traffic volume (Ibrahim & Hall, 1994; Edwards, 1998; Edwards, 1999; Kyte et al., 2001; Eisenberg, 2004; Golob & Recker, 2004; Maze et al., 2006; Qiu & Nixon, 2008; Strong et al., 2010). The impact of weather factors on transit ridership has been a subject of limited study. Most studies focus on analyzing and estimating changes to ridership due to weather. A negative correlation between weather factors and ridership has been revealed by a majority of the research (Guo et al., 2007; Cravo & Cohen, 2009; Kashfi et al., 2013; Stover & McCormack, 2013; Arana et al., 2014; Singal et al., 2014; Li et al., 2015). However, some studies have found an increase in transit ridership during the worst weather events (Khattak, 1991; Khattak, 1995; Khattak & de Palma, 1997). The relationship between weather and transit is geographically dependent. This literature review summarizes some of these previous studies.

The study of Guo et al. (2007) was the first widespread study investigating the impact of five weather elements (temperature, rain, snow, wind, and fog) on daily bus and rail ridership. The study looked at the variation across modes, day types, and season. Ridership was the focus of the study, because it is an important dimension of system performance. The system level of the transit network was chosen because a relationship is more likely to be evident on the system level than the route level. Individual route level analysis was recommended as a logical follow-up topic. The analysis used a linear regression model to analyze the Chicago Transit Authority ridership. Rain events, snow, and wind were found to negatively impact ridership. Temperature and fog attributed to an increase in transit ridership. Extreme weather events were found to have a negligible impact on transit ridership.

Stover and McCormack (2013) studied the impacts of weather factors on transit ridership in Pierce County, Washington over three years. The study looked at four weather factors: wind, temperature, rainfall, and snowfall. All four factors had significant effects on transit ridership in at least one of the seasons. Wind had a small effect during all seasons, except for summer. Temperature was found to have an effect only during the winter months. Temperatures which were 7ºF warmer than average in winter resulted in a 5.66 percent increase in transit ridership, while temperatures which were 7ºF colder than the average resulted in a 11.23 percent decrease in ridership. Rainfall was the only factor found to affect ridership in all four seasons. One inch of rain resulted in decreases of 5.05 percent in winter, 9.73 percent for spring, 7.36 percent for summer, and 5.97 percent for fall. The final weather factor, snow, had a significant effect on ridership only during the winter. Snow led to an 11.12 percent decrease in ridership. Further research was recommended to investigate the effect of weather on different types of bus-routes, i.e. commuter routes.

Cravo and Cohen (2009) employed a cross-sectional regression model to assess the impacts of temperature, rain and snow on transit ridership and revenue in New York City. The study included 15 years of ridership and weather data. The magnitude of weather's impact differed by mode, day of the week, and by season. A majority of the variables were found to have statistically significant impacts on ridership and subsequently revenue. Rain and snow were found to negatively impact the ridership for all modes, including bus ridership. Cooler-than-normal temperatures increased subway revenue in the spring and fall and increased bus revenue in all seasons.

Arana et al. (2014) analyzed the influence of weather conditions on the number of discretionary bus trips made in Gipuzkoa, Spain. The data was collected from a CAD/AVL system which was not disaggregated for riders, and only provided daily ridership. The study looked at trips made on Saturdays and Sundays in 2010 and 2011. Multiple linear regression model results showed that wind and rain resulted in a decreased number of trips and that a temperature increase resulted in an increase in the number of trips. This pattern was shared by both the regular and the occasional transit passengers.

Kashfi et al. (2013) explored the relationship between daily bus ridership and daily precipitation for a three-year period in Brisbane, Australia. The study looked at rainfall's effect on daily ridership and ridership during the AM peak period separately. It was hypothesized that rainfall occurring during the AM peak period (6:00 am to 10:00am) would greatly affect mode choice. It was observed that rain events have varying impacts on daily bus ridership. The ridership during the AM peak period was more sensitive to rain. Overall, rainfall negatively affected bus ridership in Brisbane. A negative correlation between AM peak period precipitation and daily ridership was discovered. This suggests that rainfall in the morning significantly reduces ridership throughout the rest of the day.

Singal et al. (2014) built upon previous research studies by utilizing a more refined data set. The study used two years of hourly and daily subway ridership from New York City Transit. The analysis compared the weather impacts on ridership based on day of week, time of day, combinations of both day of week and time of day, and by location. The time of day models indicated that under any given weather condition, for any day of the week, the ridership during the PM peak period is most affected and the AM peak period is the least affected. Hourly ridership models better take into account individual weather conditions when compared to the daily ridership models utilized in previous studies. The study endorses previous research studies which recognized the adverse impact of weather conditions on transit ridership.

McCormack (2015) suggests that the effect of weather on ridership can be characterized by two behavioral responses. People may substitute one form of transportation for another in adverse weather or weather may affect ridership by changing the type, frequency, and timing of discretionary trips. The author considers how income affects the relationship between ridership and weather conditions. The study focuses on ridership for the Chicago Transit Authority rail system for 13 years. The general model results from this study are consistent with the majority of literature. An increase in temperature resulted in increased ridership. Rain, snow, fog, and wind during the day resulted in decreased ridership. Extreme weather events are associated with a decrease in ridership. The exception is extreme snow events, during which transit ridership increases. When income is considered in the ridership models, lower income groups may be more responsive than higher-income groups to weather conditions. A number of factors could explain this result including: deteriorating infrastructure in poor neighborhoods prohibiting access to rail stations, longer trips necessary to access rail stations, or a lack of public services in poor neighborhoods and at rail stations.

Li et al. (2015) used smart card data to analyze the impact of weather on bus ridership in Fengzian, Shanghai. A cluster analysis was used; similar bus routes were classified into representative groups. Five clustering variables segmented the routes: the average departure interval, length of the route, the number of bus stops, the route type, and the level of crowdedness on the bus line. The multiple linear regression model was used to analyze the effects of weather on bus ridership and took into account temperature, humidity, wind speed, and rainfall. All four weather variables had negative impacts on bus ridership and their specific impacts varied depending on season and cluster. The analysis concluded that there is no one-sized-fits-all conclusion about the relationships between weather attributes and bus ridership. It is paramount that the relationships between weather attributes and ridership be investigated in different geographical contexts.

Creative approaches have been tested to explore how to better classify weather factors. The study of Kalkstein et al. (2009) examined whether daily weather affects ridership in urban transportation systems. The study compared daily ridership to air masses, which take into account the entire section of air over a region. The ridership data was compared to a daily air mass calendar based on spatial synoptic classification. This classification characterizes air masses based on many meteorological variables. This method compares ridership to a single variable which encompasses the standard weather factors. ANOVA was used to compare the mean ridership residuals among the different air mass types. Air masses were found to have a significant impact on daily rail ridership. Three urban systems were used in the study: Chicago Transit Authority, Bay Area Rapid Transit, and the Hudson-Bergen light rail line. Ridership increased on dry, comfortable days and decreased on moist, cool days. Seasonality was not a significant factor with respect to the air mass – ridership relationship.

Some early research into weather factors and transit ridership attempted to quantify the monetary effects of a change in relationship. Changon (1996) used a three-year dataset to assess the effect of summer precipitation on a number of transportation factors; collisions, traffic volume, transit ridership, and air travel delays were independently investigated. Summer rain events were found to result in a small decrease, between 3 and 5 percent, in daily ridership. The decreases in bus ridership due to rain were significant using a matched pair t-test at the 0.05 level. These decreases in ridership resulted in approximately $13,000 (1979 dollars) in lost bus revenue. It was estimated that the total loss for the summer from 40 rain days was in excess of $0.6 million (1979 dollars). Rain events had a larger impact on midday transit riders, presumably influencing discretionary passengers more than commuters. Rainfall occurring in the afternoon and evening had the smallest effect on ridership. The authors hypothesized that passengers had already committed to the day's activities and travel mode by the time rainfall occurred.

There has been very little research into the relationship between weather and transit travel time. Hofmann and O'Mahony (2005) investigated the impact of adverse weather on bus performance measures including: ridership, frequency, headway regularity, bunching, and travel time variability. A slight decrease in ridership was reported for rainy days. Travel time was also reported to be affected by rainfall, leading to longer average trip time on rainy days. However, the conclusion was based on simple comparisons of travel time. Whether the difference is statistically significant is not clear. This study utilized a small sample size of transit data.

Contrary to the previous research, a number of studies have associated severe weather events with an increase in transit ridership. Khattak (1991) administered a behavioral travel survey in Chicago which identified that commuters divert from automobile to transit during extreme weather. Bicyclists and pedestrians also shifted to transit during extreme weather. The same was found to be true for commuters in the San Francisco Bay Area (Khattak, 1995).

The results of these studies have been confirmed in different locations. Khattak and de Palma (1997) administered a travel survey in Brussels, Belgium and achieved a response rate of 50 percent. This resulted in a sample size of 1218 responses. The survey was administered as to ensure randomness and that a sufficiently large dataset would be available for the analysis. A large fraction of automobile users, 54 percent, stated that they would change their mode, departure time, and/or route choices in response to the weather conditions. Of the respondents who stated they would change their mode because of adverse weather, 27 percent stated that mode change was important or very important. These drivers would be switching from a single occupancy vehicle to a carpool or to public transit, it was not stated what percentage of drivers would choose which alternative mode.

1.4. Experimental Design

In order to understand the relationship between rainfall intensity and transit vehicle performance in the Puget Sound, we raise the question whether transit ridership is affected by rainfall occurring at any point throughout the day. This analysis can provide an understanding of route level ridership choices.

To analyze the effect rainfall has on transit ridership, comparable data is necessary to represent both ridership and rainfall. This comparison is made at the daily level, utilizing daily transit ridership and 24-hour rainfall data. A day is considered to be a rainy day if more than five one-hundredths (0.05) inches of precipitation fell during the 24-hour period. In order to examine the impact of rainfall on daily ridership across the year, an adjustment was made for seasonality effects. Using the adjusted ridership, the effect of rainfall on ridership could be investigated using standard statistical methods.

Using the ridership analysis, the effect rainfall intensity has on transit travel time and what factors could lead to this increase in travel time is evaluated. After preliminary investigation, it is hypothesized that transit travel time can be affected by rainfall. Through visual interpretation and standard statistical analysis, inferences can be made between rainfall and transit performance.

In order to test this hypothesis, we must understand the typical performance of this transit route. To understand the typical performance of the transit route, a dry midweek day was selected as a baseline test day and an annual average performance was calculated. Understanding this typical performance will allow for the performance on the rainy days to be compared to the typical day and the annual average performance. Two rainy days were also selected as test days for this analysis.

The extent to which transit travel time is related to rainfall intensity is not well understood. Therefore, to examine the relationships between rainfall and transit travel time, a graphical comparison of the transit performance was used in this study. The travel times of each transit trip on the test days were plotted against the annual average travel time for that same transit trip, based on trip start time, with plus and minus one standard deviation of the annual average travel time. Additionally, the measured rainfall intensity from that day was plotted to provide inferences into the difference in travel time. Speed contour plots were also generated for the test days to observe the precise differences in speed along the transit route. These speed contour plots show if changes in speed are occurring at expected locations.

Further exploration into the relationship between rainfall and transit performance measures utilizing archived CCS data conclude this study. An attempt is made to understand the causes of travel time increases over five consecutive bus trips. Time space diagrams highlight different points at which excessive delays occur. Managing these delays could help reduce travel time during rainfall events. A preliminary investigation into the connection between average daily trip delay and daily rainfall attempts to predict the delay during rainfall events.

1.5. Thesis Organization

This thesis is divided into the following six chapters:

- Chapter 1 – Introduction: This chapter provides background including: an overview of the objective, the literature review, and the experimental design.
- Chapter 2 – Data: This chapter explains the two data sets used for this study. An overview of AVL systems is also included in this chapter.
- Chapter 3 – Impact of Rainfall on Daily Ridership: This chapter analyzes rainfall's effect on daily ridership using three years of transit and rainfall data. Comparisons are made using all days, broken down by the day of the week, and by season.
- Chapter 4 – Transit Travel Time and Rainfall: This chapter develops graphical representations of travel time and rainfall for three test days. Speed contour plots accompany the graphics. The effects of rainfall on travel time are hypothesized.
- Chapter 5 – Rainfall and Transit Performance Measures: This chapter explores additional uses for archived CCS data. The data is used to explore the development of delay during adverse weather and a relationship between rainfall and delay is explored.

2. DATA

The route chosen for this study is Sound Transit Route 545 in the Puget Sound region of Washington State. It is a 19 mile route connecting Seattle to Redmond. This corridor begins in the SODO neighborhood of Seattle and runs through downtown along 5th Avenue in the eastbound direction and 4th Avenue in the westbound direction. The corridor then continues onto Interstate 5 and travels across the State Route (SR) 520 Floating Bridge and along SR 520 to downtown Redmond ending at the Bear Creek Park-and-Ride, as illustrated in Figure 1. This route served approximately 2.6 million riders in 2014 (Sound Transit, 2014). This route makes stops near major employer headquarters in the Puget Sound region including Microsoft and Amazon. Peak travel occurs in the westbound direction in the A.M., traveling from the suburbs to the downtown core, and in the eastbound direction in the P.M. This study focuses on both the eastbound and westbound directions using AVL and APC data and hydrologic data obtained from January 2012 to December 2014.

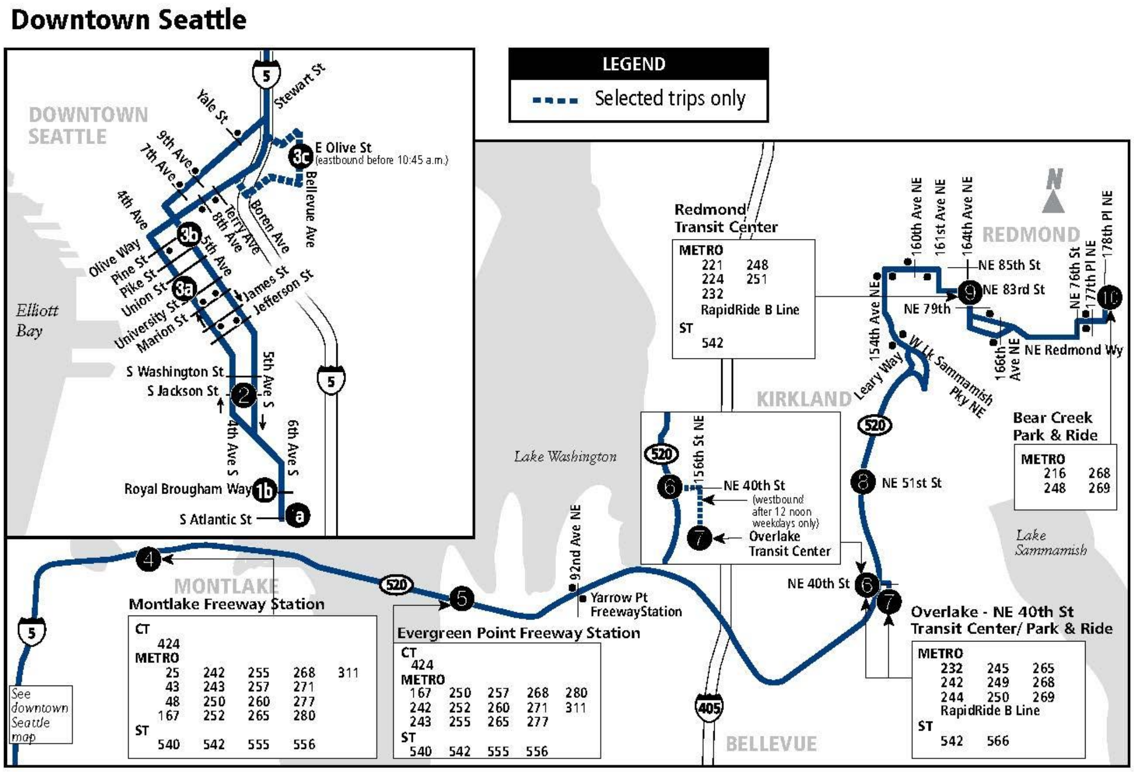

Figure 1 Sound Transit Route 545 Map

2.1. Communications Center System (CCS) Data

The purpose of an AVL system is to support operators, supervisors, and dispatchers during real-time fleet operations management (TCRP Synthesis 73, 2008). The AVL system is a major component of the CCS. Additional components include: real time traffic information systems, an integrated APC system, and wireless local area network (WLAN) and radio connections. Figure 2 outlines the onboard components of the CCS. GPS satellites provide vehicle location information to the AVL system through an onboard antenna. This data is then processed by the onboard computer, and the real time location of the vehicle is transmitted to the dispatch center using radio communications. The real time location data is also used to trigger the automated announcements and provide real time schedule information to the driver, passengers, and dispatcher. Information is transmitted from the vehicle to the dispatcher at regular intervals or in response to a real time action. The APC system utilizes doorway sensors to track the number of boardings and alightings. All of the data collected by the onboard system is then stored on an internal memory drive, which can be downloaded at the garage through a physical interface or over WLAN connections at the end of each day. King County Metro currently archives AVL data from the majority of its fleet with the exception of the few legacy system equipped vehicles still operating. This archive is accessible through a data request, but it is not currently published online for download. The data is a rich resource for planning and operational analysis as well as research. This study uses archived data to investigate transit performance during rainfall events.

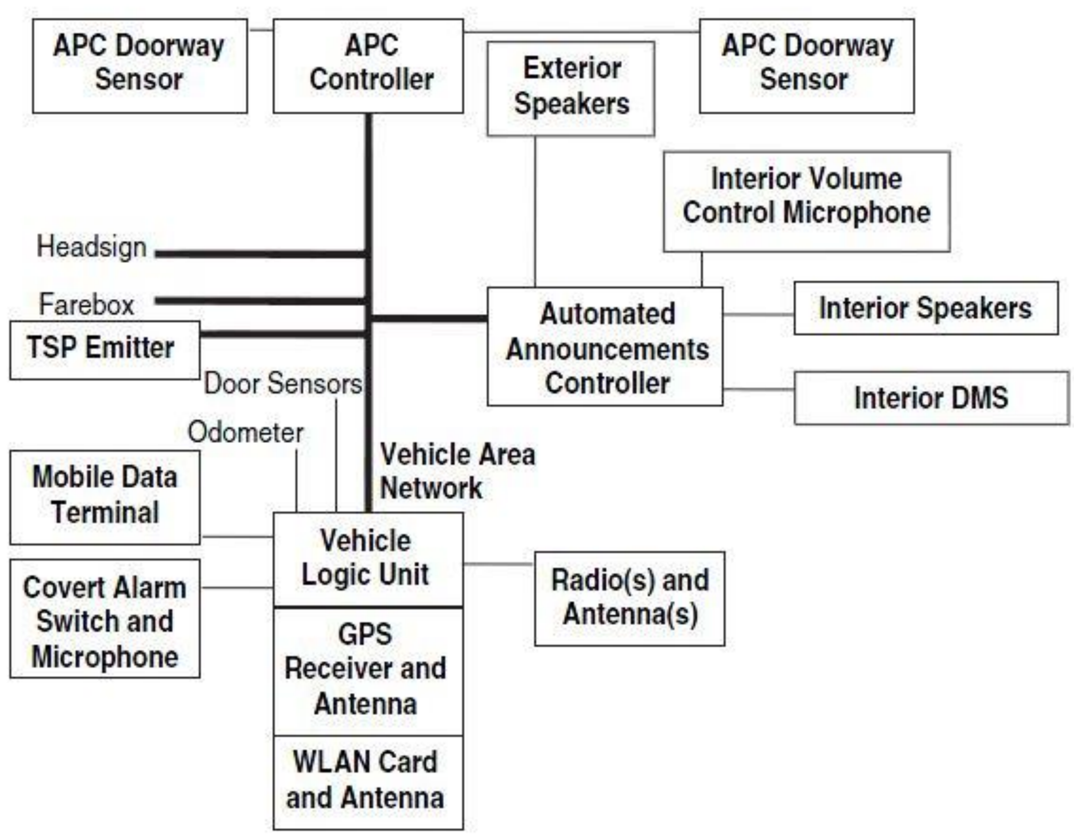

Figure 2 Sample Schematic of the CCS on a Transit Vehicle (TCRP Synthesis 73, 2008)

2.2. Archived Component of CCS

The data is stored for each bus trip and for each geo-coded stop. The system records the actual stop time (compared to the scheduled time), dwell time, and the number of boardings and alightings (when APC equipped) at every stop. Table 1 includes a sample list of archived CCS data.

As shown in Table 1, the Trip ID is indicated in the first field. This ID is a unique identifier for each trip, however, it repeats and/or changes from day to day. The Pattern ID, located in the second field, represents a unique ordered set of stops served by a variant of the route. This route has many Pattern IDs for each direction, and many trips deviate to serve park-and-ride locations only during peak hours. The Block number is assigned to a vehicle from the time it leaves the garage to the time it returns. The Route Number and prominent Direction are also included as part of the data. All stops along a trip are grouped together by the Scheduled Start Minute; this is the number of minutes after midnight the trip was scheduled to start. The Operation Date is also used to group and sort transit trips. The Vehicle ID identifies the unique transit vehicle for each trip. The stops are geo-coded and identified by Stop ID. The Stop Sequence is the order in which the route pattern is executed. There are gaps in the Stop Sequence, because other events are included as part of the route pattern. The Stop Name also identifies the unique stops and can be linked to a map database.

Table 1 Sample Transit Trip from Archived CCS Dataset

TRIP_ID	PATTERN _ID	BLK	RTE	DIR	SCH_ST _MIN	OPD_DATE	VEHICLE _ID	STOP _ID	STOP _SEQ	STOP_NAME	SCH_STOP _SEC	ACT_STOP _ARR	SCH_STOP _TM	ACT_STOP _TM	OFF_SCH _SEC	DWELL _SEC	DOORS _OPEN	DOOR_OPEN _SEC	ONS	OFFS	LOAD
18159785	41545539	54502	545	E	301	5/1/2012	9631	620	3	4TH AVE S & S JACKSON ST (620)	18417	18428	5:06:57	5:07:08	-11	0	Y	0	5	2	3
18159785	41545539	54502	545	E	301	5/1/2012	9631	640	5	4TH AVE & JAMES ST (640)		18505		5:08:25		20	Y	6	2	0	5
18159785	41545539	54502	545	E	301	5/1/2012	9631	660	6	4TH AVE & MADISON ST (660)		18603		5:10:03		0	N	0	0	0	5
18159785	41545539	54502	545	E	301	5/1/2012	9631	682	8	4TH AVE & UNIVERSITY ST (682)	18620	18673	5:10:20	5:11:13	-53	0	N	0	0	0	5
18159785	41545539	54502	545	E	301	5/1/2012	9631	700	9	4TH AVE & PIKE ST (700)		18700		5:11:40		18	Y	14	6	0	11
18159785	41545539	54502	545	E	301	5/1/2012	9631	1050	10	OLIVE WAY & 8TH AVE (1050)		18863		5:14:23		9	Y	4	0	1	10
18159785	41545539	54502	545	E	301	5/1/2012	9631	1070	11	OLIVE WAY & TERRY AVE (1070)		18894		5:14:54		26	Y	5	1	0	11
18159785	41545539	54502	545	E	301	5/1/2012	9631	13460	13	BELLEVUE AVE & E OLIVE ST (13460)	19081	19056	5:18:01	5:17:36	25	0	N	0	0	0	11
18159785	41545539	54502	545	E	301	5/1/2012	9631	71350	14	SR 520 RAMP & MONTLAKE FREEWAY STATION (71350)	19379	19329	5:22:59	5:22:09	50	13	Y	7	2	0	13
18159785	41545539	54502	545	E	301	5/1/2012	9631	71351	17	SR 520 & EVERGREEN POINT RD (71351)	19621	19591	5:27:01	5:26:31	30	0	N	0	0	0	13
18159785	41545539	54502	545	E	301	5/1/2012	9631	71352	18	SR 520 & 92ND AVE NE (71352)		19667		5:27:47		0	N	0	0	0	13
18159785	41545539	54502	545	E	301	5/1/2012	9631	71336	20	SR 520 RAMP & NE 40TH ST (71336)	20043	19990	5:34:03	5:33:10	53	16	Y	6	0	3	10
18159785	41545539	54502	545	E	301	5/1/2012	9631	71353	22	SR 520 & NE 51ST ST (71353)	20168	20121	5:36:08	5:35:21	47	10	Y	5	0	2	8
18159785	41545539	54502	545	E	301	5/1/2012	9631	72458	23	WEST LAKE SAMMAMISH PKWY NE & LEARY WAY (72458)		20327		5:38:47		0	N	0	0	0	8
18159785	41545539	54502	545	E	301	5/1/2012	9631	73848	24	NE 85TH ST & 154TH AVE NE (73848)		20409		5:40:09		10	Y	3	0	2	6
18159785	41545539	54502	545	E	301	5/1/2012	9631	73757	25	NE 85TH ST & 161ST AVE NE (73757)		20500		5:41:40		16	Y	12	0	2	4
18159785	41545539	54502	545	E	301	5/1/2012	9631	71951	26	NE 83RD ST & 164TH AVE NE (71951)	20636	20572	5:43:56	5:42:52	64	9	Y	5	1	0	5
18159785	41545539	54502	545	E	301	5/1/2012	9631	72489	28	SR 202 & 166TH AVE NE (72489)		20707		5:45:07		0	N	0	0	0	5
18159785	41545539	54502	545	E	301	5/1/2012	9631	72306	29	NE 76TH ST & 177TH PL NE (72306)		20820		5:47:00		24	Y	11	0	4	1
18159785	41545539	54502	545	E	301	5/1/2012	9631	81755	31	BEAR CREEK PARK AND RIDE (81755)	21061	20922	5:51:01	5:48:42	139	0	N	0	0	0	0

There are several fields related to the time the vehicle reaches the stop. The system records the Actual Stop Second, which is the time in the number of seconds after midnight the vehicle actually reaches the geo-coded stop location. The Scheduled Stop Second is the time in seconds after midnight when the vehicle is scheduled to arrive at the geo-coded stop location. These values are also converted into a time variable, as hh:mm:ss using a 24-hour clock. The Off Schedule Seconds is the difference between the Scheduled Stop Second and the Actual Stop Second. A negative value indicates that the vehicle arrived later than scheduled. If the door opens to serve passengers, a Dwell Seconds and a Door Open Seconds are recorded. The Dwell Time is the number of seconds at which the vehicle was stationary, or dwelled, at a stop. A Dwell Time of zero indicates that the vehicle did not stop. The Door Open Seconds is the amount of time which the doors remains open, presumably to allow for boardings and alightings.

On transit vehicles which have APC systems installed, the APC records the total number of boarding and alighting passengers stored in two separate fields, Ons and Offs. The APCs are installed at both the front and rear doors and use infrared beams to detect passenger movement. The APCs are only activated if the door opens. The passenger Load is calculated for each stop, and is the difference between the sum of Ons for all previous stops and the sum of Offs for all previous stops.

2.3. Hydrologic Data

The rainfall data was obtained from the King County Hydrologic Information Center which maintains over 500 sites in King County. The rainfall data used in this study comes from the Mercer Island Rain Gage, shown in Figure 3. This rain gage was chosen because of its proximity to the entire transit route. A single rain gage was chosen to allow for consistency along the route. The rain gage uses a tipping bucket to measure rainfall, and the rainfall totals are stored by data loggers. The gages are calibrated approximately 10 times per year. They record rainfall every 15 minutes in 0.01 inch increments. The accuracy is checked by comparing nearby gage data (King County Hydrologic). Data from all of the sites is available for download through a portal.

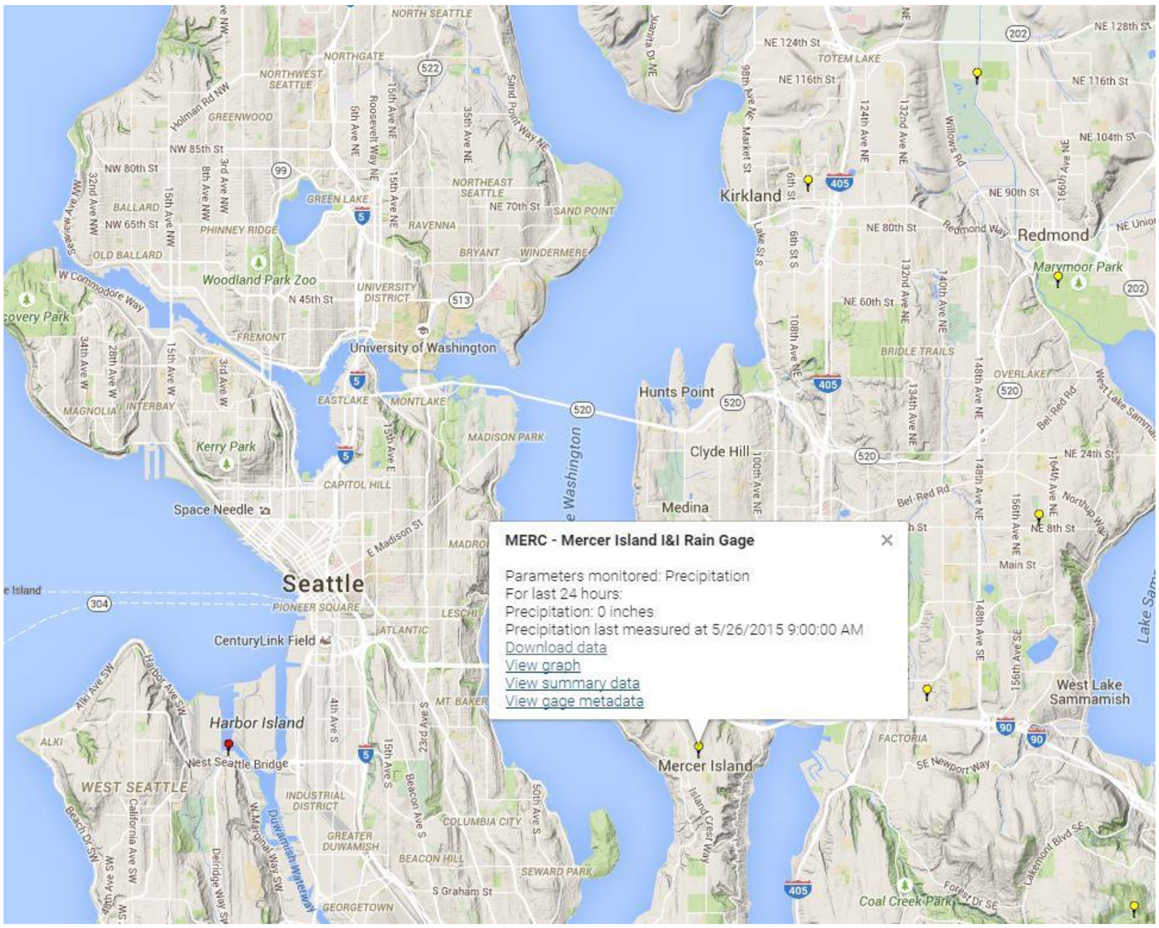

Figure 3 Location of Mercer Island Precipitation Gage

3. IMPACT OF RAINFALL ON DAILY RIDERSHIP

A number of studies (Hoffman & O'Mahony, 2005; Guo et al., 2007; Stover & McCormack, 2012; Kashfi et al., 2013; Arana et al., 2014) have investigated the impacts of weather variables on transit ridership. The goal of this chapter is to utilize previous methodologies to investigate whether the daily ridership of Sound Transit Route 545 is affected by rainfall events. A negative correlation between weather factors and ridership has been revealed by a majority of the research (Guo et al., 2007; Cravo & Cohen, 2009; Kashfi et al., 2013; Stover & McCormack, 2013; Arana et al., 2014; Singal et al., 2014; Li et al., 2015). However, some studies have found an increase in transit ridership during the worst weather events (Khattak, 1991; Khattak, 1995; Khattak & de Palma, 1997). Kashfi et al. (2013), developed a methodology to analyze the daily ridership of a transit network on rainy and dry days. Using their methodology as the basis, an analysis of daily ridership was conducted. The analysis will direct further investigation into transit travel time on a select number of case study rainy days for Sound Transit Route 545.

The weather pattern of the Puget Sound region is predictable by season due to marine climate. Temperatures remain mild year-round with very few days below freezing (32ºF) or above 90ºF. The winters are wet and summers are dry (U.S. EPA, 2013). The average annual rainfall for the region is approximately 39 inches over 154 days (City of Seattle).

3.1. Data

Two data sets were used for this analysis, archived CCS data provided by Sound Transit and daily precipitation data from King County. Both datasets covered a three-year period from January 1, 2012 to December 31, 2014.

The archived CCS data was manipulated to become compatible with the daily precipitation data. The CCS data contains information collected by vehicles equipped with APC systems for boardings and alightings. APC systems are not installed on all Sound Transit vehicles. At least 10 percent of vehicles on each route are equipped with APC systems as recommended, by The *Transit Cooperative Research Program Report 113, Using Archived AVL-APC Data to Improve Transit Performance and Management*, in order to analyze mean demand on a transit route. Since the data being analyzed is being compared to itself, the lower percentage of APC equipped vehicles will not affect this analysis. It was assumed that the same number of passengers boarded and alighted. The daily ridership dataset is the sum of all boardings from APC equipped transit trips. The compiled dataset included 727 working day ridership data points, the working day ridership represented the total ridership for both directions of Route 545. During the three years there were 752 working days. Working days exclude public holidays and weekends. When Sound Transit installed the upgraded CCS the roll out happened over the course of a couple of months. This resulted in the loss of 25 weekday data points.

Daily precipitation data was collected from the King County Hydrologic Information Center. The weather station measures weather variables, precipitation, from 12:00 AM to 11:59 PM local time, and records the time using Coordinated Universal Time (UTC). The dataset was supplied containing both time codes, and the local time was used for this analysis. A day was considered a rainy day if more than five one-hundredths (0.05) inches of rain fell during the 24 hour period. This threshold was taken from the prevous study (Kashfi et al., 2013). Using the collected daily rainfall totals for the three years, the average monthly rainfall was calculated. Figure 4 presents the average monthly precipitation from the three year period from the Mercer Island precipitation gage, the most representative gage to the entire transit route.

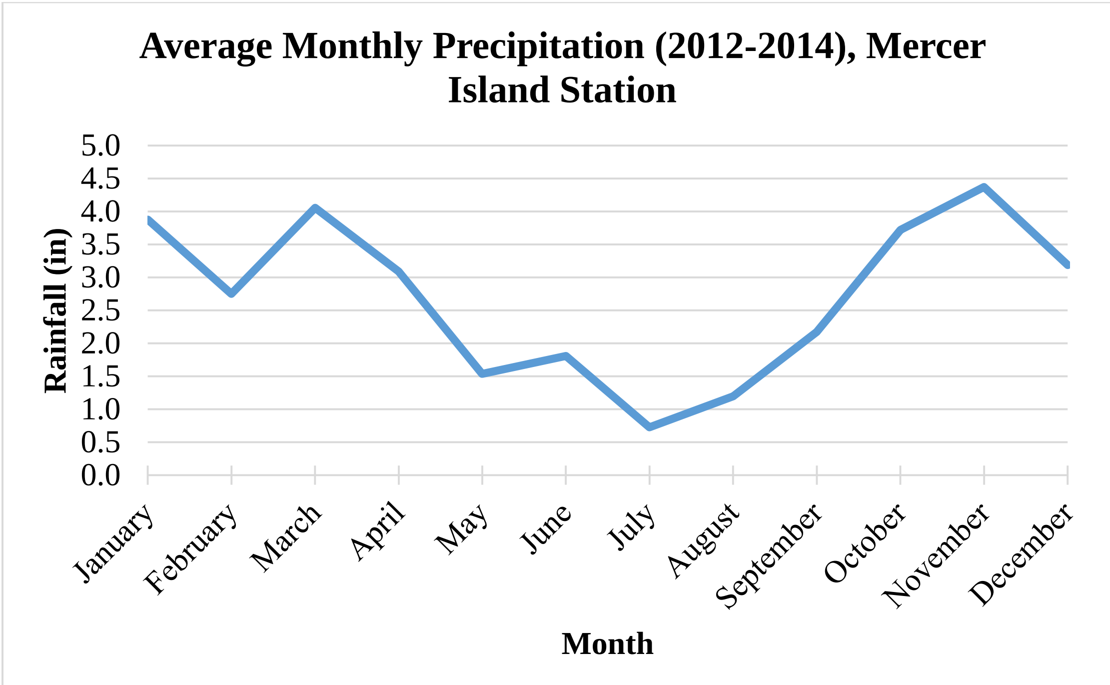

Figure 4 Average Monthly Precipitation, Mercer Island Station

3.2. Seasonality Analysis and Adjustment

In order to examine the impact of rainfall on daily transit ridership, Kashfi et al. (2013) applied a seasonality index to adjust the daily ridership values to account for the temporal fluctuations in ridership. To apply a seasonality index, daily ridership was segmented by weekday. Figure 5 shows a boxplot for the daily ridership by day of week for the three-year analysis period. A similar method was adopted for each month of the year. Figure 6 shows the boxplot for the daily ridership by month for the three-year period.

The mean and standard deviation of daily ridership by day of the week and by month of the year are presented in Table 2 and Table 3, respectively. The variation in the daily ridership is more pronounced throughout the months of the year than the days of the week.

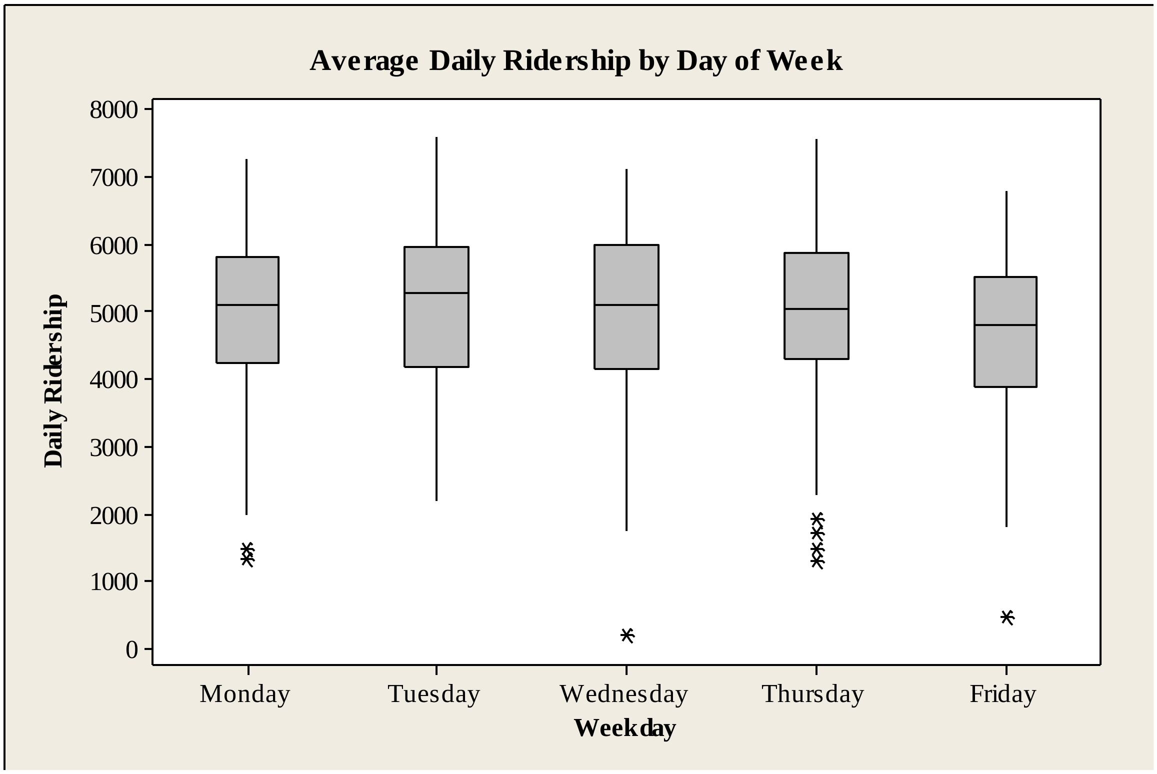

Figure 5 Average Daily Ridership by Day of Week for Three-year Analysis Period

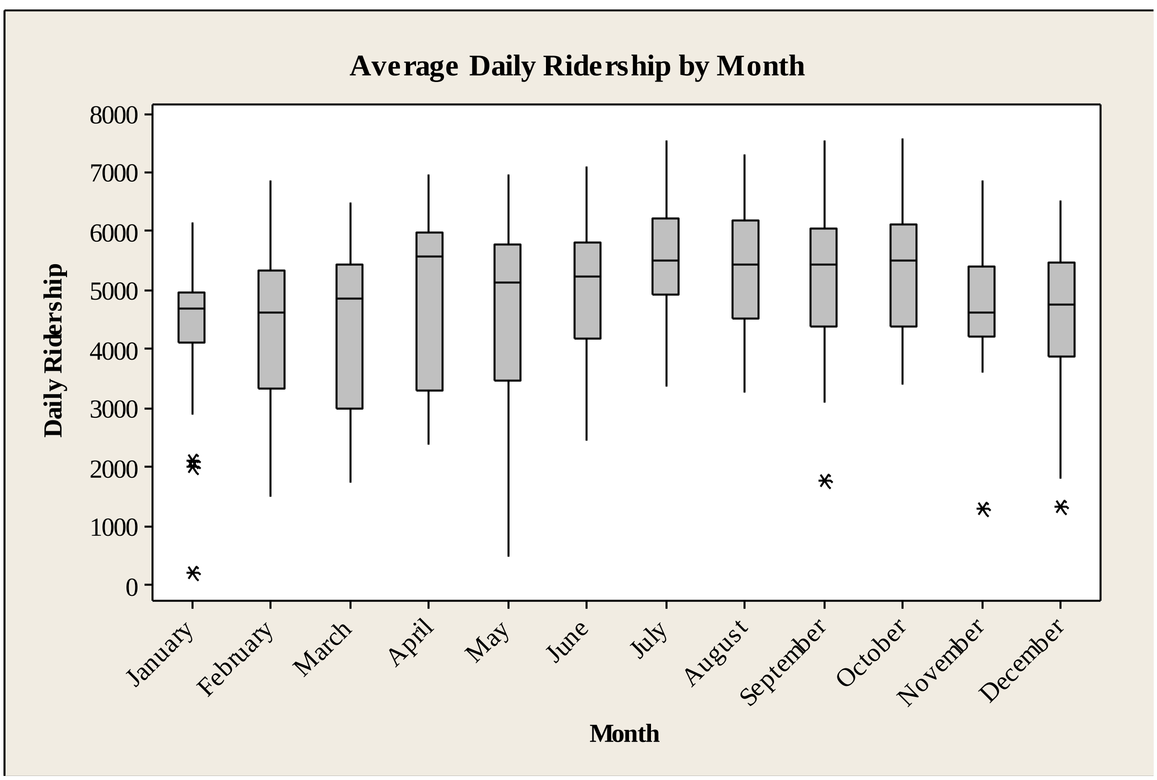

Figure 6 Average Daily Ridership by Month for Three-year Analysis Period

Table 2 Mean Daily Ridership by Day of the Week

Day of Week	Total Observations	Mean	Standard Deviation
Monday	138	4,930	1,212
Tuesday	148	5,100	1,176
Wednesday	149	4,898	1,297
Thursday	145	4,934	1,261
Friday	147	4,615	1,151

Table 3 Mean daily ridership by Month of the Year

Month	Total Observations	Mean	Standard Deviation
January	44	4,420	1,070
February	52	4,372	1,421
March	64	4,361	1,337
April	65	4,882	1,366
May	65	4,664	1,373
June	61	5,034	1,155
July	65	5,494	968
August	66	5,321	966
September	60	5,230	1,028
October	69	5,341	1,069
November	53	4,767	942
December	63	4,546	1,209

The monthly mean daily ridership variation is significant. The lowest monthly ridership is found in March and the highest ridership is found in July. The difference in ridership between these two months is more than 1,000 passengers per day. This difference accounts for approximately 26 percent and 21 percent of the monthly ridership in March and July, respectively.

An Analysis of Means (ANOM) was conducted to determine which, if any, of the analysis group has a mean significantly different from the overall average of all the group means combined. The two analysis groups were day of the week and month of the year.

This analysis utilizes a lower decision line and an upper decision line. Any of the individual group means not contained between the decision lines is deemed significantly higher or lower than the overall average of all the groups. Figure 7 shows that Friday is statistically different (alpha = 0.05) from other days of the week.

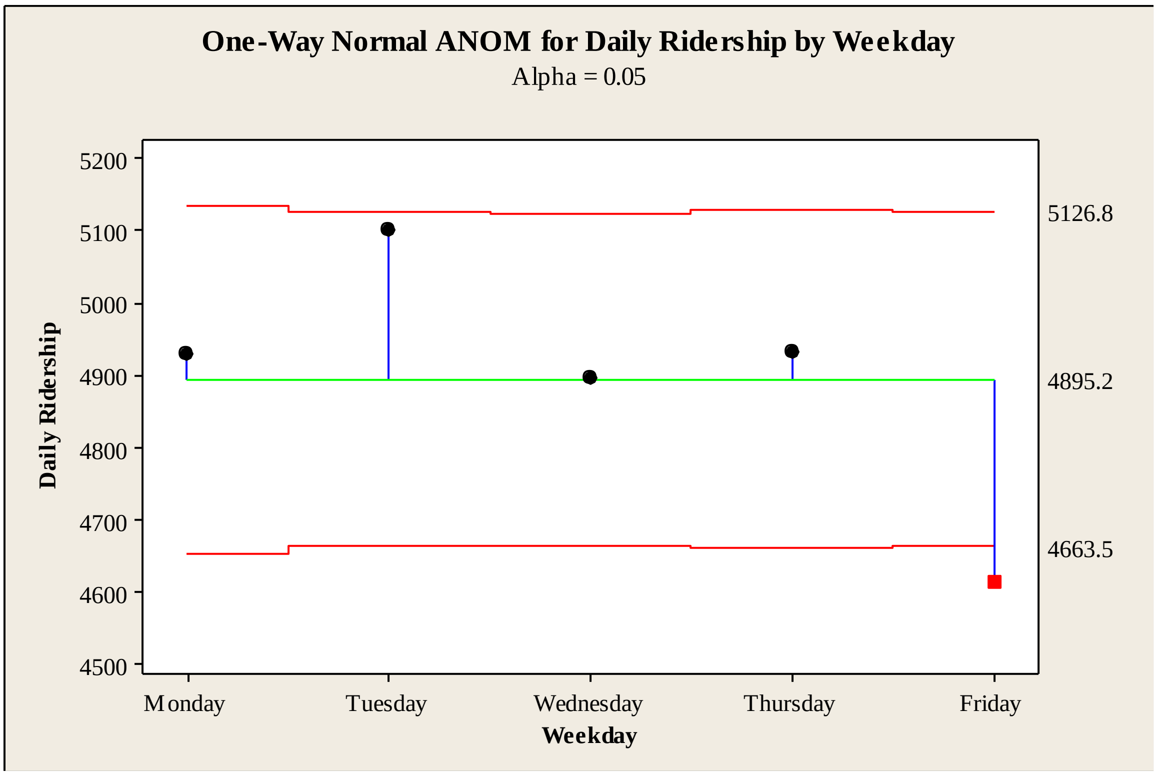

Figure 7 ANOM for Daily Ridership by Weekday.

More variation is observed between the monthly ridership volumes. Figure 8 shows the ANOM analysis for daily ridership by month. January, April, May, June, September, November, and December are statistically the same as the overall annual mean daily ridership. However, February, March, July, August, and October are statistically different (alpha = 0.05) from the other months. The outcomes of this analysis confirm the existence of seasonality in the monthly ridership patterns.

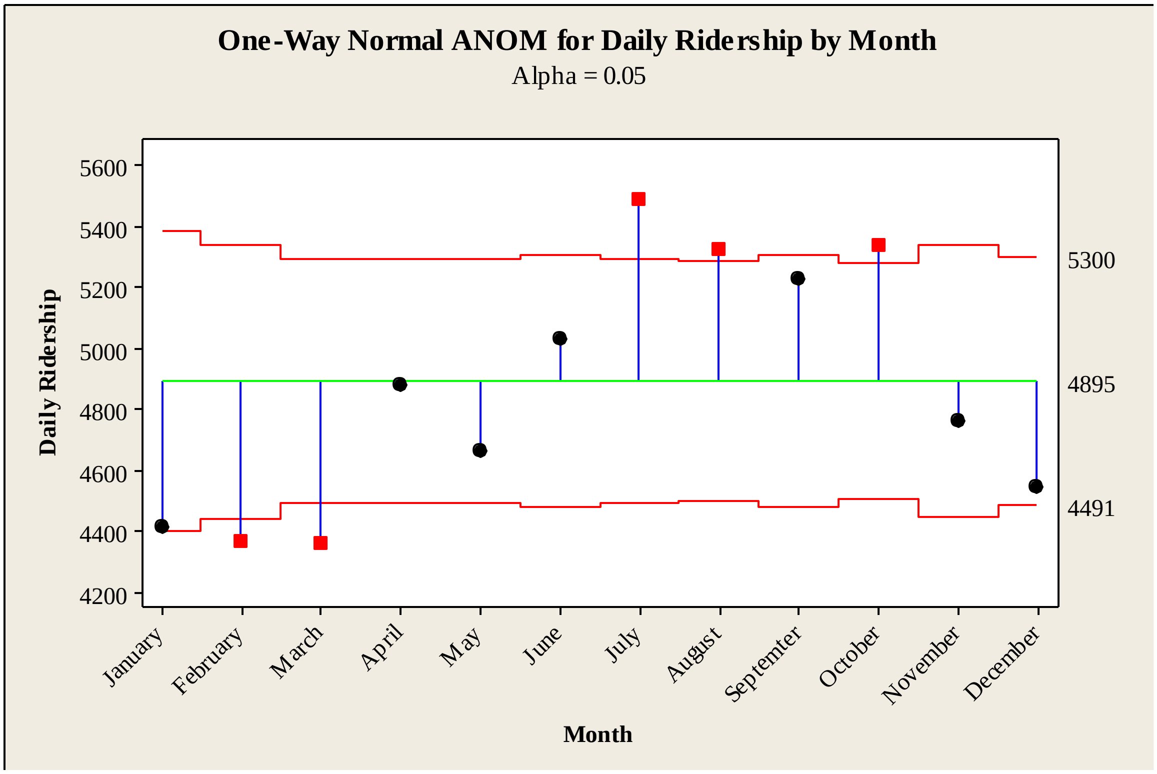

Figure 8 ANOM for Daily Ridership by Month

As revealed from the ANOM, it is essential to eliminate the monthly seasonality from the ridership data, in order to compare rainfall events that occur in different months. Equation 1 was used to adjust the daily ridership to account for seasonality.

$$Adjusted\ Ridership\ (By\ Month) = \frac{Ridership\ Data\ for\ Each\ Day\ of\ Month}{SI\ (Seasonal\ Index)} \quad (1)$$

The seasonal index (SI) is a measure of the degree of seasonality. The SI is determined by dividing the average ridership from each month by the sum of the average ridership from all months during that year. Monthly SI values were calculated for each year of the analysis period. An average of the three monthly SI values was calculated and used to adjust all daily ridership data points from that month over the three-year period. For example, a SI value above 1.0 indicates that the ridership volume of that particular month is higher than the mean of the ridership volume over the entire year. Figure 9 compares the original daily ridership and the seasonally adjusted daily ridership volumes by month of the year.

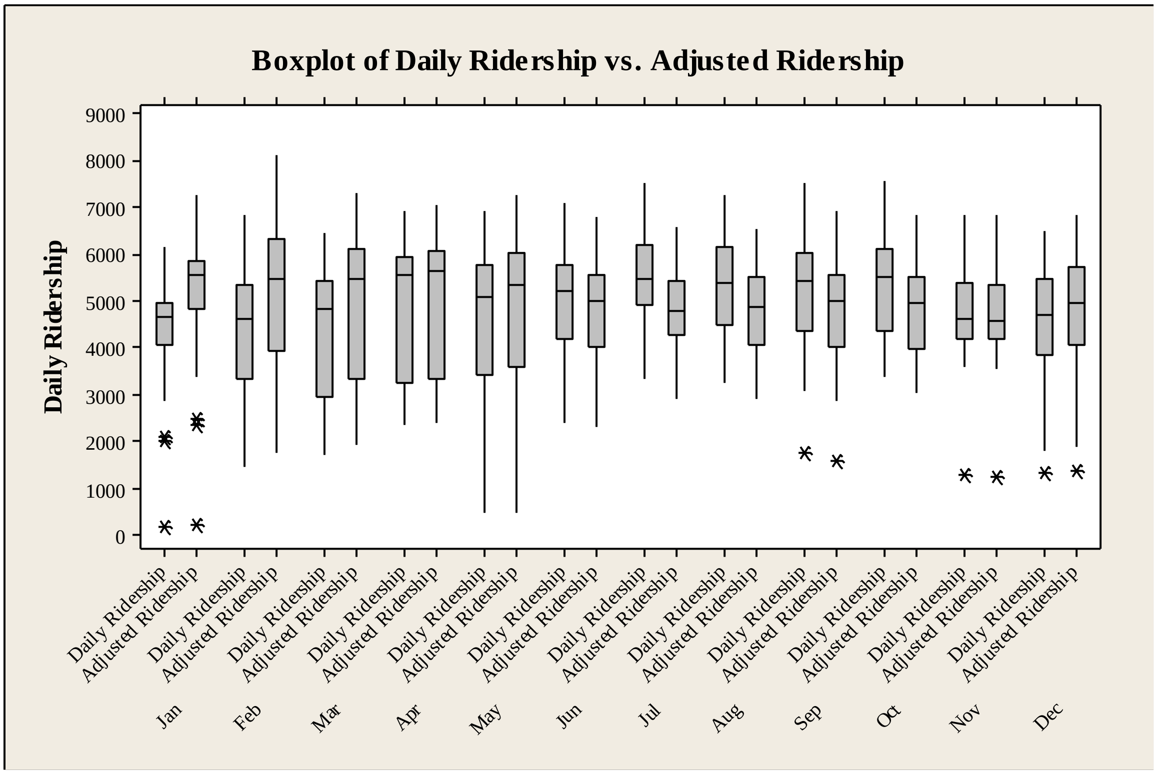

Figure 9 Average Daily Ridership by Month Before and After Adjustment

Figure 10 presents the ANOM for daily ridership by month using the seasonally adjusted ridership values. All of the months are now statistically the same as the annual average daily ridership.

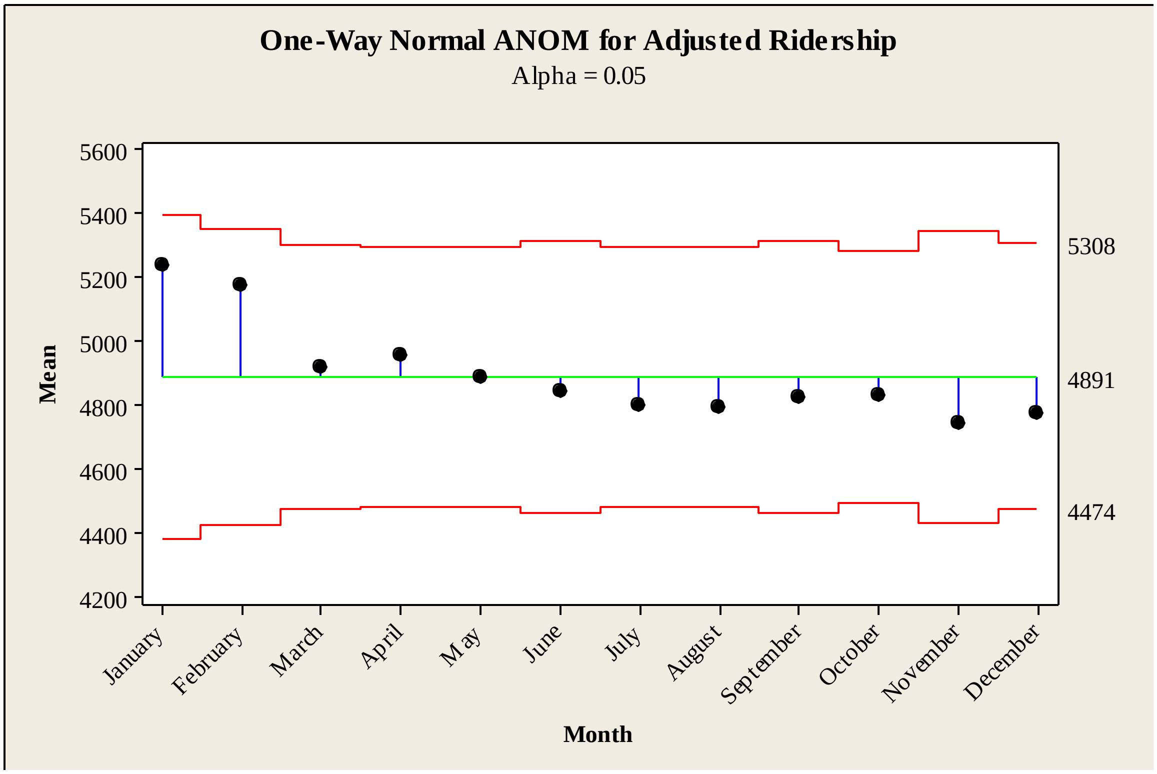

Figure 10 ANOM for Daily Ridership by Month with Adjusted Ridership

3.3. Ridership Analysis

A precipitation threshold was determined in order to distinguish between rainy and dry days. A threshold of five one-hundredths (0.05) inches of precipitation over the course of any day was considered to be a "rain" day. Similarly, the "non-rain" day is when there was less than 0.05 inches of precipitation over the course of any day. The analysis looks at the effect of rain on three different levels: the effect on daily ridership using all days, the effect on daily ridership by day of the week, and the effect on daily ridership by season.

3.3.1. Effects of Rain on Daily Ridership

Table 4 shows the analysis result comparing the adjusted ridership on non-rain and rain days. There were 259 rainy weekdays during the three-year period.

Table 4 Average Daily Ridership on Rain and Non-Rain Days

Year	Rainy Days	Ridership Mean		Ridership Change	t-test Significance
		Non - Rain	Rain		
2012 2013 2014	87 89 83	4,930	4,820	-2.23%	0.252 (non-sig)

The analysis shows that rain has no statistical impact on the daily ridership of Sound Transit Route 545. Any rainfall occurring during the day resulted in a 2.23 percent reduction in ridership. An independent t-test was done to determine whether the mean differences between two groups are statistically significant. The results of this t-test concluded that the mean difference between non-rain and rain days are not statistically significant with a 95% confidence interval. Figure 11 displays the variability in the data points for non-rain and rain days using a boxplot.

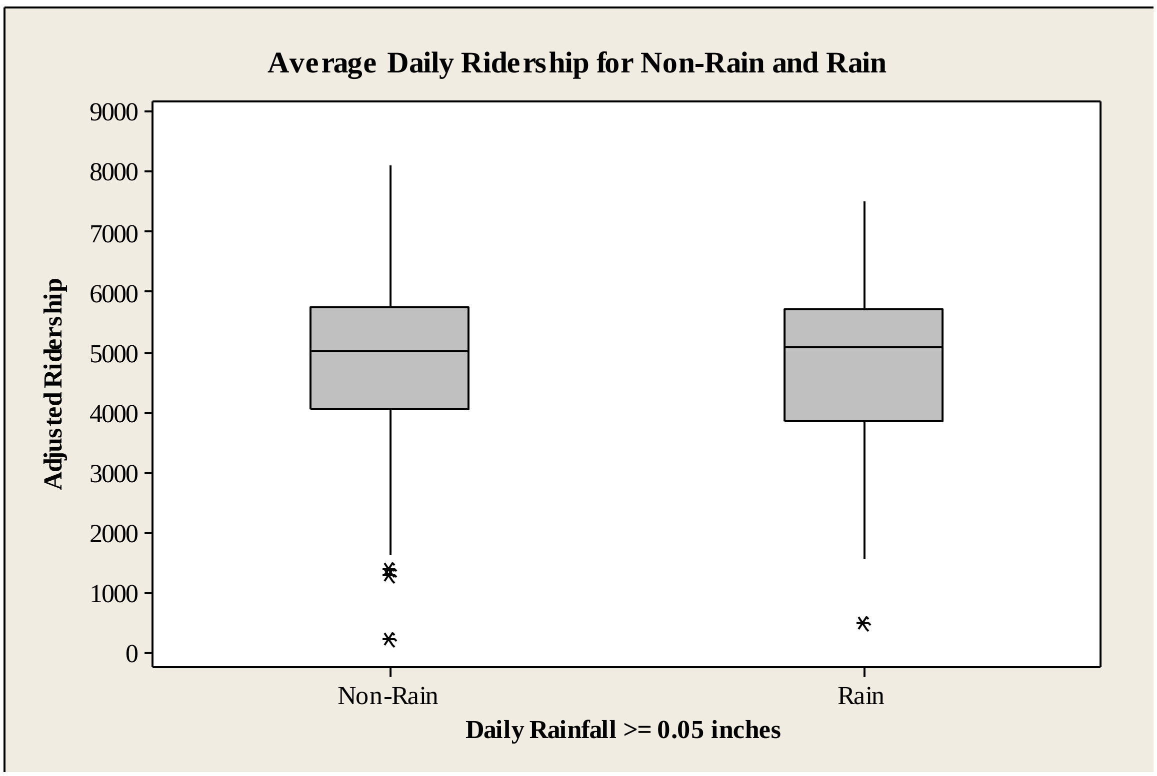

Figure 11 Average Daily Ridership for Non-Rain and Rain Days

3.3.2. Effects of Rain on Daily Ridership by Day of Week

It could be hypothesized that daily ridership would fluctuate during the week. Table 5 shows the analysis result comparing the adjusted daily ridership for non-rain and rain days by the day of the week.

Table 5 Effect of Rain on Daily Ridership by Day of the Week

Day of Week	Ridership Mean		Ridership Change	t-test Significance
	Non-Rain	Rain		
Monday	4,892	4,907	0.31%	0.945 (non-sig)
Tuesday	5,130	5,005	-2.44%	0.535 (non-sig)
Wednesday	4,905	4,881	-0.49%	0.916 (non-sig)
Thursday	4,979	4,894	-1.71%	0.693 (non-sig)
Friday	4,739	4,455	-5.99%	0.167 (non-sig)

The analysis shows that rainfall has a mixed effect on daily ridership. For rainfall occurring on Mondays, the results show a 0.31 percent increase in ridership. While the other days of the week result in a decrease in ridership on rainy days. The largest change occurs on Fridays, when 5.99 percent fewer people ride when it is raining. On Fridays, the transit riders may have plans for after-work which involve an alternate mode of transportation and the rainfall only compounds their desire to not travel by transit. Five individual independent t-tests were conducted to determine the significance of the change in ridership. All five concluded the change in ridership was not statistically significant. It was concluded that Monday and Wednesday have almost identical ridership on non-rain and rain days. Figure 12 displays the variability in the data points for non-rain and rain days by weekday. This boxplot shows that on rainy days there is a greater amount of change between the 25th and 75th percentile daily ridership numbers for all weekdays except Thursday.

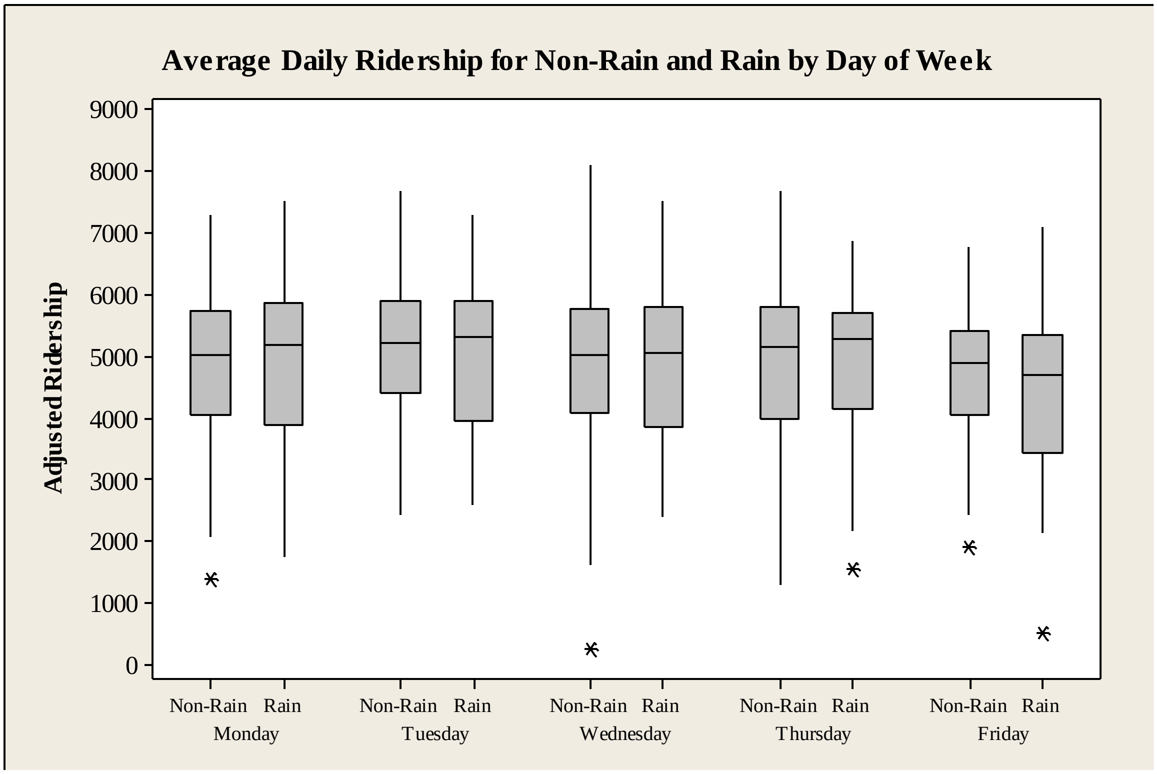

Figure 12 Average Daily Ridership for Non-Rain and Rain Days by Day of Week

3.3.3. Effects of Rain on Daily Ridership by Season

Since there is seasonal variability in precipitation, it is expected that the effect of rain on daily ridership will be different by season. Table 6 shows the analysis result comparing the adjusted daily ridership for non-rain and rain days by the season.

Table 6 Effect of Rain on Daily Ridership by Season

Season	Ridership Mean		Ridership Change	t-test Significance
	Non-Rain	Rain		
Winter (Dec to Feb)	5,121	4,954	-3.26%	0.462 (non-sig)
Spring (Mar to May)	5,064	4,724	-6.71%	0.115 (non-sig)
Summer (Jun to Aug)	4,853	4,607	-5.07%	0.192 (non-sig)
Fall (Sep to Nov)	4,766	4,874	2.27%	0.449 (non-sig)

The analysis shows that rainfall has a mixed effect on ridership when broken down by season. During the fall, rainfall actually increases daily ridership by 2.27 percent. During the other three seasons, the rainfall continues to have a negative impact on ridership. The largest change in ridership comes during the spring months, when ridership is 6.71 percent lower on rainy days. Four individual independent t-tests were conducted to determine the significance of the change in ridership by season. All four tests concluded the change in ridership was not statistically significant. Figure 13 displays the variability in the data points for non-rain and rain days by season. This boxplot shows that for rain days, there is a greater amount of change between the 25th and 75th percentile daily ridership numbers for all seasons except fall and summer. Transit riders may have more flexible schedules during the summer months when school is not in session. Further investigation is necessary to understand the increase in transit ridership during the fall months on rainy days.

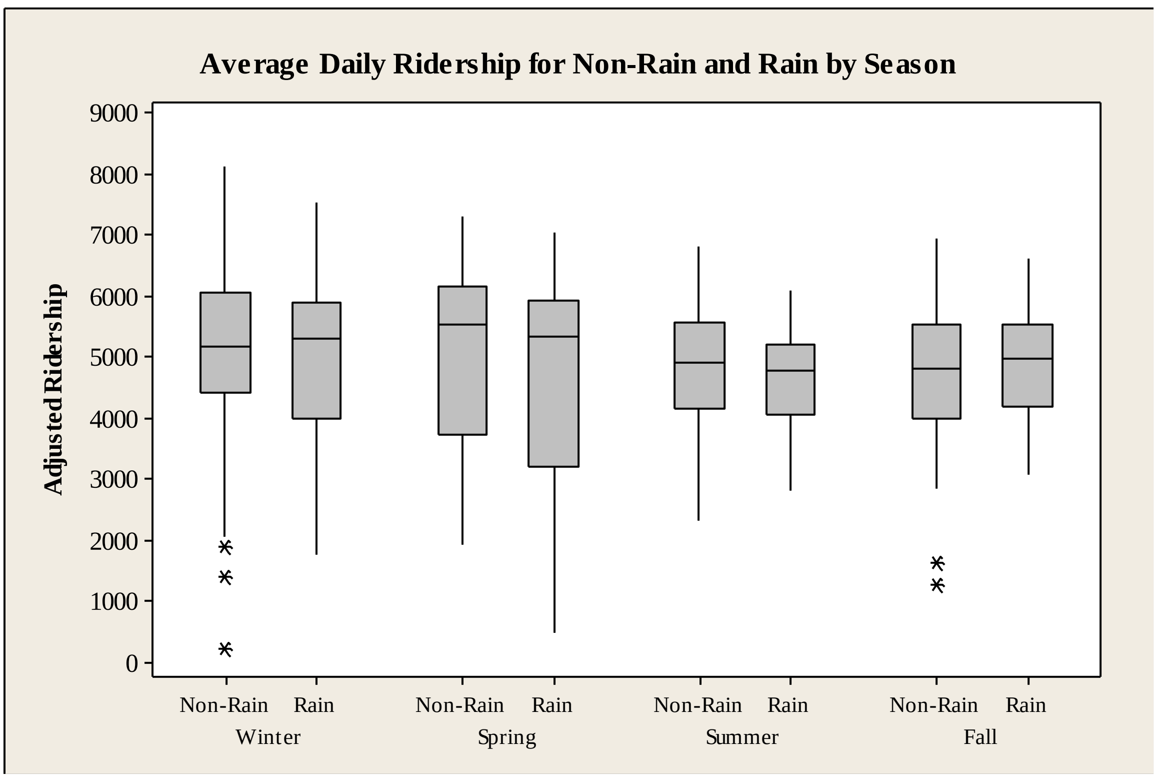

Figure 13 Average Daily Ridership for Non-Rain and Rain Days by Season

3.4. Summary

Daily ridership fluctuated on rainy days, but this fluctuation was not definitively positive or negative. The changes in ridership varied by day of the week and season, however, there was a negative overall trend in transit ridership when looking at all of the days over the three-year period. The ridership was 2.23 percent lower on rainy days; this decrease was not statistically significant at a 95 percent confidence interval. The negative trend in transit ridership continued through much of the analysis. The only positive increase in transit ridership occurred when looking at ridership on Monday during the day of the week analysis and in the fall during the seasonal analysis. None of the analyses returned statistical significance, meaning that daily ridership on rainy and non-rain days are not different at a 95 percent confidence interval using independent t-tests. In general, rainfall does decrease daily ridership, but further analysis utilizing a more robust data set could lead to definitive results.

There are a number of limitations to this analysis. The precipitation data was collected from only one site, the precipitation may vary across the entire length of the transit route. Additionally, the analysis only focused on one weather factor, precipitation, and the combination of additional factors could affect daily ridership differently.

4. TRANSIT TRAVEL TIME AND RAINFALL

Travel time is the duration of a passenger trip from the origin to the destination of the transit trip over a specified route (TCRP Report 88, 2003). The travel time was calculated from layover stop at the beginning of the route to layover stop at the end of the route in each direction, westbound and eastbound. Travel time, reported as a time value, is closely tied to travel speed, reported as a travel rate. The conversion between travel time and travel rate is the distance between stops along the route (TCRP Report 88, 2003). Travel Time is of interest to the public, decision-makers, transit managers and transportation planners, as it is a performance measure understood by all. It is used to monitor service and measure passenger comfort (TCRP Report 88, 2003). From the previous chapter, it has been shown that passengers will still ride the bus in the rain, but understanding the effect of rain on travel time will allow for better customer information.

Hofmann and O'Mahony (2005) investigated the effect of adverse weather conditions on transit travel time for three transit routes over five test days. Their analysis showed that the average travel time increased on rainy days compared to non-rainy days. The analysis, however, does not provide any representation beyond a table summarizing the travel times on rainy and non-rainy days. In this chapter, a methodology is described and utilized to graphically represent the fluctuation in travel time on three test days.

This analysis utilizes the same datasets as described in the previous chapter. The same three-year period from January 2012 through December 2014 was available for the analysis. There were specific test dates during 2012 which experienced rainfall throughout the entire day, spanning the time in which the transit route was operated. Because of this, the three test days were selected from 2012. By using dates from the same year, a direct comparison could be made using annual average travel time. The collision records were checked to ensure that external delays were not caused by incidents along the route. The first test day will serve as the non-rainy day, May 15, 2012. The second day, March 15, 2012, experienced a moderate amount of rainfall, 1.24 inches. The rainfall on March 15, 2012 occurred at a low intensity over the course of the day with periods of high intensity rainfall. The third test day, November 19, 2012, experienced a large amount of rainfall, 2.44 inches. On this date, most rainfall occurred during the 24-hour period of precipitation monitoring. This day represents a 5-year, 24-hour rainfall event, meaning that there is a one in five chance that one 24-hour period will experience this amount of rainfall each year (NOAA, 1973).

4.1. Methodology for Travel Time Analysis

The purpose of this analysis is to explore the effects rainfall have on individual transit trips and build off of the previous studies in which the average daily travel times are presented for rainy and non-rainy days. The outcome is a graphical representation of travel time throughout the day by bus trip starting time. The bus trip starting time is the one variable in the archived CCS data which is unique to all data lines for each transit trip on any particular day. This variable is used for the comparison between the actual travel times on the test day, the annual average travel time, and the annual average scheduled travel time. The data points describe the travel time and do not explore travel time variations along the route.

4.1.1. Graphic Representation of Travel Time

The data for the entire year of 2012 was extracted from the database containing the three-year period of CCS data to create the graphical representations. The first step in manipulating the new data set was to attach the distance along the route in feet and miles corresponding to the stop and direction to each data line. The array lookup function in Excel was used to query a table of Stop ID numbers and their corresponding distances along the route in feet. The distance of each stop along the route was determined using ArcMap and the transit shape files provided by King County. By direction, the stops were attached to the transit line shape file and the linear distance along that line to the stop was determined using the ArcMap Toolbox. The distances along the route in feet were converted to miles.

The annual average travel time for each bus trip starting time was then determined. A pivot table was used in Excel to extract the necessary information from the data set. For each bus trip starting time, a yearly average arrival time for each stop along the route was calculated. There were 85 unique bus trip starting times for the eastbound direction and 84 unique bus trip starting times for the westbound direction over the course of the year. Due to the scheduling and patterns of certain bus starting time trips, not every trip started and ended at the same stop. To alleviate this change in schedule and make each travel time comparable to each other, stops were chosen for both the eastbound and westbound directions to represent the beginning and end of the trip. In the eastbound direction, the beginning of the trip was 6th and Atlantic, at mile zero, and the end of the trip was Bear Creek Park-and-Ride, at mile 19.3. Some trips in the eastbound direction continue past this point for one additional stop, but this stop was ignored since all trips stop at Bear Creek. Not every bus trip starting point in the eastbound direction is 6th and Atlantic; some trips begin at the second stop on the route, 4th and Jackson. The travel time to the beginning of the route was back-calculated to provide an even set of data to calculate the total travel time for each bus trip starting time. To do this, the difference between the first and second stop in the eastbound direction was determined for those bus trips starting times which began at the first stop. It took on average 4 minutes and 23 seconds to travel from stop one to stop two. This was then subtracted from the arrival time at stop two for those trips which did not begin at stop one. This estimated arrival time at stop one was used in the travel time calculations. All westbound trips begin at Bear Creek Park-and-Ride, at mile zero, and travel to 6th and Royal Brougham Way, at mile 18.7. Every westbound trip starts and ends at these stops. It was not necessary to back calculate arrival times as was done for the eastbound direction. The travel time for each trip was then calculated by taking the difference between the arrival time at the last stop and the arrival time at the first stop for each bus trip starting minute.

Since the travel times for each bus trip starting time end at a specific stop, the standard deviation in the travel time is the standard deviation in the arrival time at the final stop. The standard deviation of the arrival time for the last stop in both the eastbound and westbound directions were extracted using a pivot table in Excel. Standard deviation is a built in function of the pivot table summary options. The standard deviation for each bus trip starting time was added and subtracted from the average trip time to develop a one standard deviation confidence interval. This interval is used to understand the variability in the travel time from the annual average for each bus trip starting time.

The scheduled travel time for each bus trip starting time was determined using the same methodology as the annual average travel time. By extracting the average scheduled arrival time for each stop by bus trip starting time, the seasonality of the scheduled travel time will be removed. The same first and last stops were used for the scheduled travel time calculation for both directions. The westbound direction could be calculated using the extracted data, because, like the average travel time, all westbound trips started and ended at the same stops. For the eastbound direction, the scheduled travel time for the first stop was back-calculated for those trips beginning at the second stop. The final product was the scheduled travel time for each bus trip starting time with the seasonality of schedule variation removed.

The actual travel time for the test days was calculated using much of the same methodology as the other travel times. To extract the data for each test day, an additional criteria was added to the pivot table in Excel to select only one day and one direction of arrival times by bus trip starting time. Due to schedule changes throughout the year, not every test day has the same number of bus trip starting times. These missing bus starting trips were left blank in the dataset. Since the actual travel times are being compared to the average travel time and scheduled travel time for the same bus trip starting minute, these missing starting times will not affect the comparison. The same back calculations were necessary for eastbound travel time calculations. The consistency of the first and last stops was maintained in the actual travel time calculations.

The rainfall for each test day was downloaded from the King County Hydrologic Information Center for 15 minute intervals. The rainfall was then converted from the number of inches of rain which fell during the 15 minute period to the rainfall intensity during the 15 minute period, in the units of inches per hour.

For each test day and direction of travel, all of the data sets were compiled into a single Excel spreadsheet. The data sets included the annual average travel time, plus and minus one standard deviation of the annual average travel time, the scheduled travel time, the actual travel time, and the rainfall intensity for the test day. Using the multiple chart feature in Excel, which allows different chart types on the same chart, all of the data sets were plotted on the same figure. The annual average travel time, standard deviation, and the scheduled travel time were plotted as line charts. The actual travel time for the test day and direction was plotted as an xy scatter plot. The rainfall intensity was plotted using the secondary x and y axis, because the rainfall data are in different units than the travel time data. The scaling of the secondary y axis separated the datasets so that all are visible in one figure. These figures display the variability in travel time in each direction on the test days compared to rainfall intensity.

4.1.2. Speed-Contour Plots

Speed contour plots can be used to visualize precise changes in speed along a route and over a time period. Speed contour plots accompany the graphical representations of travel time for each direction of each test day. To create these plots, the speeds of the buses between each stop were calculated. The moving speed was calculated using the distance between stops, the arrival time at each stop, and the dwell time at each stop. The data already contains an arrival time for every stop record, but the data does not include the time at which the bus departed each stop. The departure time for each stop was calculated by adding the dwell time at each stop to the arrival time at the same stop. By calculating this variable, a moving speed was calculated by removing the time from the trip where the bus is stationary.

The speed at which the vehicle travelled before arriving at a stop was calculated and stored on the stop the vehicle was approaching. The first stop on a route would have a speed of zero. The speed for the second stop was calculated by dividing the distance between the first and second stop by the difference in time from the arrival at the second stop and the departure of the first stop. This process was repeated for all of the test data. The final result was an Excel spreadsheet with all of the speed values attached to each stop entry.

Using Minitab 16's contour plot feature, the distance along the route, calculated using ArcMap, was plotted against the time of day showing the speed at which a vehicle was traveling at that point. Not every point in the plot has a related speed value. Minitab interpolates between all known points to complete the plot. The Distance Method, an interpolation function within Minitab, was used with a distance power of 6 to produce smooth changes in speed along the route and through time.

4.2. Travel Time Analysis – May 15, 2012

The first test day chosen from 2012 was Tuesday May 15. This was a day during a dry period making it a representative baseline day for comparison to the other dates selected. For a comparison to the other test days, they all must share similar characteristics. School was still in session during this date, making it an ideal comparison to the other test days, which also fell on school days. The dry months in the Puget Sound occur during the summer when the majority of schools are not in session.

4.2.1. Westbound Directional Analysis

Figure 14 illustrates the graphical representation of travel time for the westbound (inbound) direction of Route 545. On May 15th, there were 75 trips with the first trip leaving the Bear Creek Park-and-Ride at 4:26 am. The last trip departed at 10:22 pm. The average headway was 14 minutes and 30 seconds with the peak hour headway less than 10 minutes.

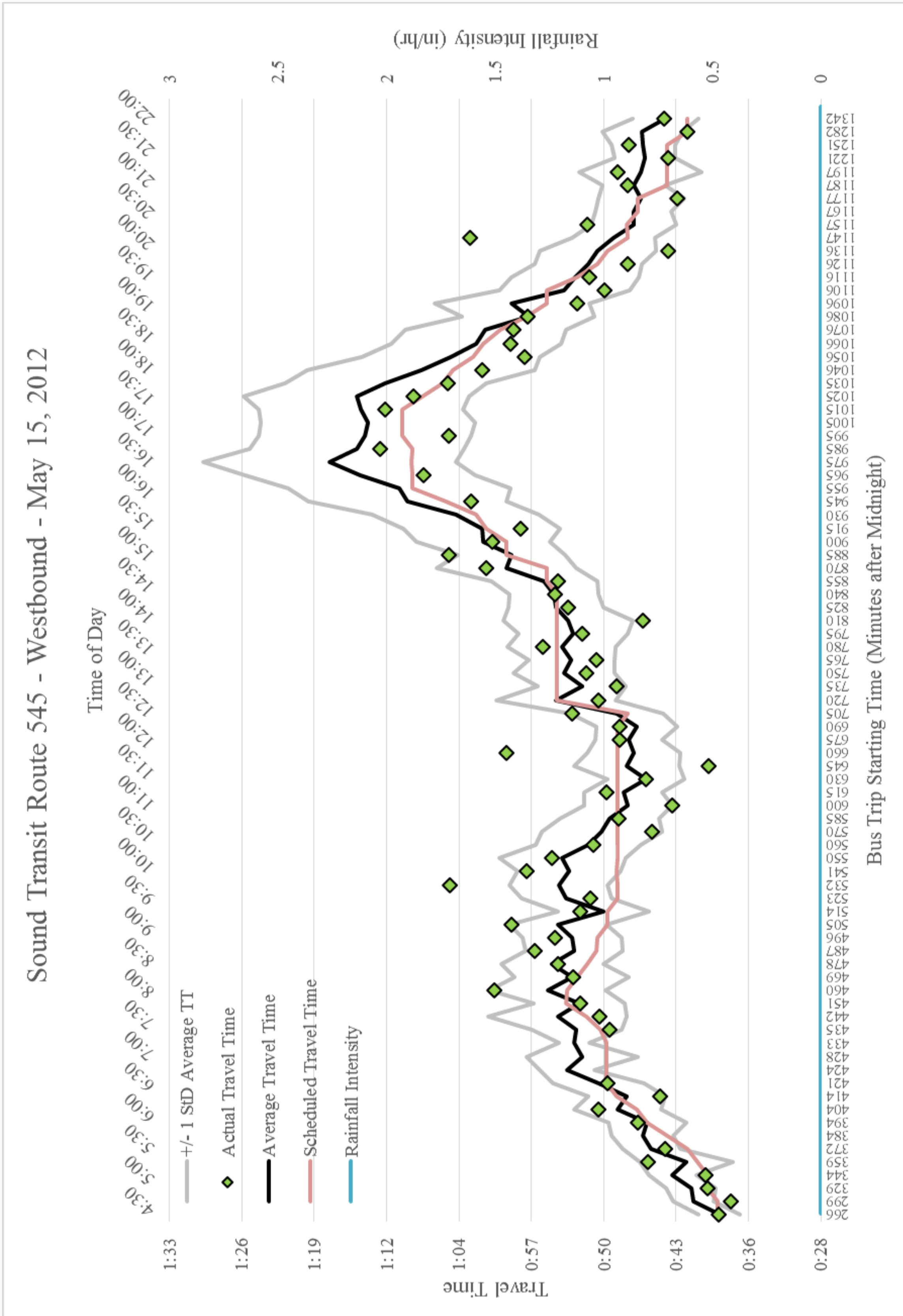

Figure 14 Travel Time for May 15, 2012 Westbound

The average travel time to make the 18.9 mile trip was 53 minutes and 8 seconds. This was faster than the average trip travel time from the annual travel time of 54 minutes and 41 seconds. Over the entire length of the route, the average trip on May 15th in the westbound direction was 71 seconds off schedule. The trips were on average approximately a minute late when compared to the scheduled travel time for that date. These performance measures are used as a baseline for comparison to the two rainy test days.

It appears that more variability occurred in the travel time during the off peak hours. Between 10 am and 2 pm, the travel times fluctuated from exceeding one standard deviation to being faster than the average travel time. This variability is not ideal for transit operators or customers. During the off peak hours, many riders are making discretionary trips, and this variability could cause them to change their travel habits in the future. A majority of these off peak trips were also faster than the scheduled travel time. Near the end of the route the scheduled time point stops are estimated arrival times, which means that the buses do not have to remain at the time point.

Figure 15 shows the speed at which buses were traveling throughout the day in the westbound direction on May 15th. Three clear regimes can be seen from this graphic. The beginning of the route, before mile 4, the vehicles are travelling on local and arterial streets. Between miles 4 and 16 the vehicles are traveling in mixed-flow lanes on the freeway. After mile 16, the vehicles are traveling through Seattle’s downtown core. The average speed for the trip was 18.1 miles per hour (mph). The box represents the average trajectory of a transit vehicle. The speed-contour plots also illustrate the congestion on the freeway section of the route. After 12 pm (noon) each transit trip makes an additional stop where they exit the freeway, as illustrated between miles 4 and 6. This stop causes the prolonged section of low speed. Congestion develops on the freeway between miles 10 and 14 during the PM peak period. The characteristics of this speed-contour plot are used as a baseline for comparison to the two rainy test days.

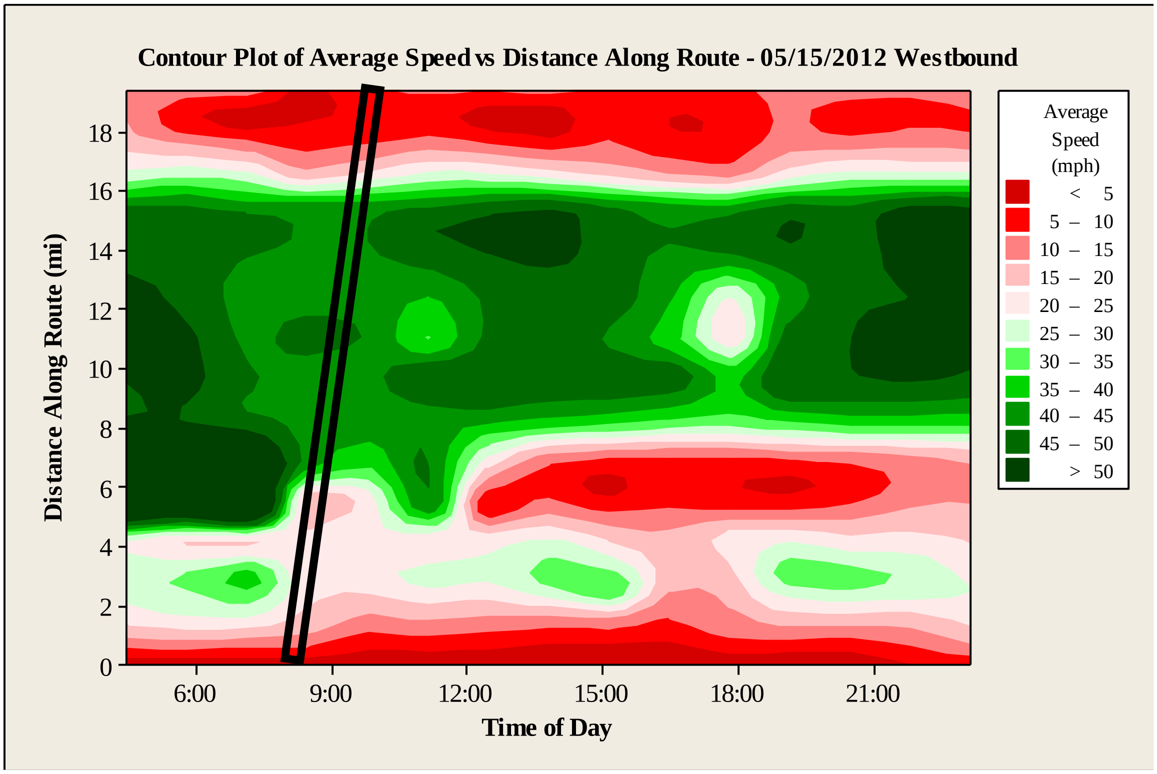

Figure 15 Speed-Contour Plot for May 15, 2012 Westbound

4.2.2. Eastbound Directional Analysis

Figure 16 illustrates the graphical representation of travel time for the eastbound (outbound) direction for Route 545. There were 75 trips eastbound on May 15th with an average travel time of 55 minutes and 19 seconds. The average per trip travel time from the annual average travel time data was 56 minutes and 26 seconds to travel 19.3 miles. The first eastbound trip departed 6th and Atlantic at 5:01 am. The last trip departed at 10:52 pm. The average headway was 14 minutes and 28 seconds with some peak hour headways less than 5 minutes.

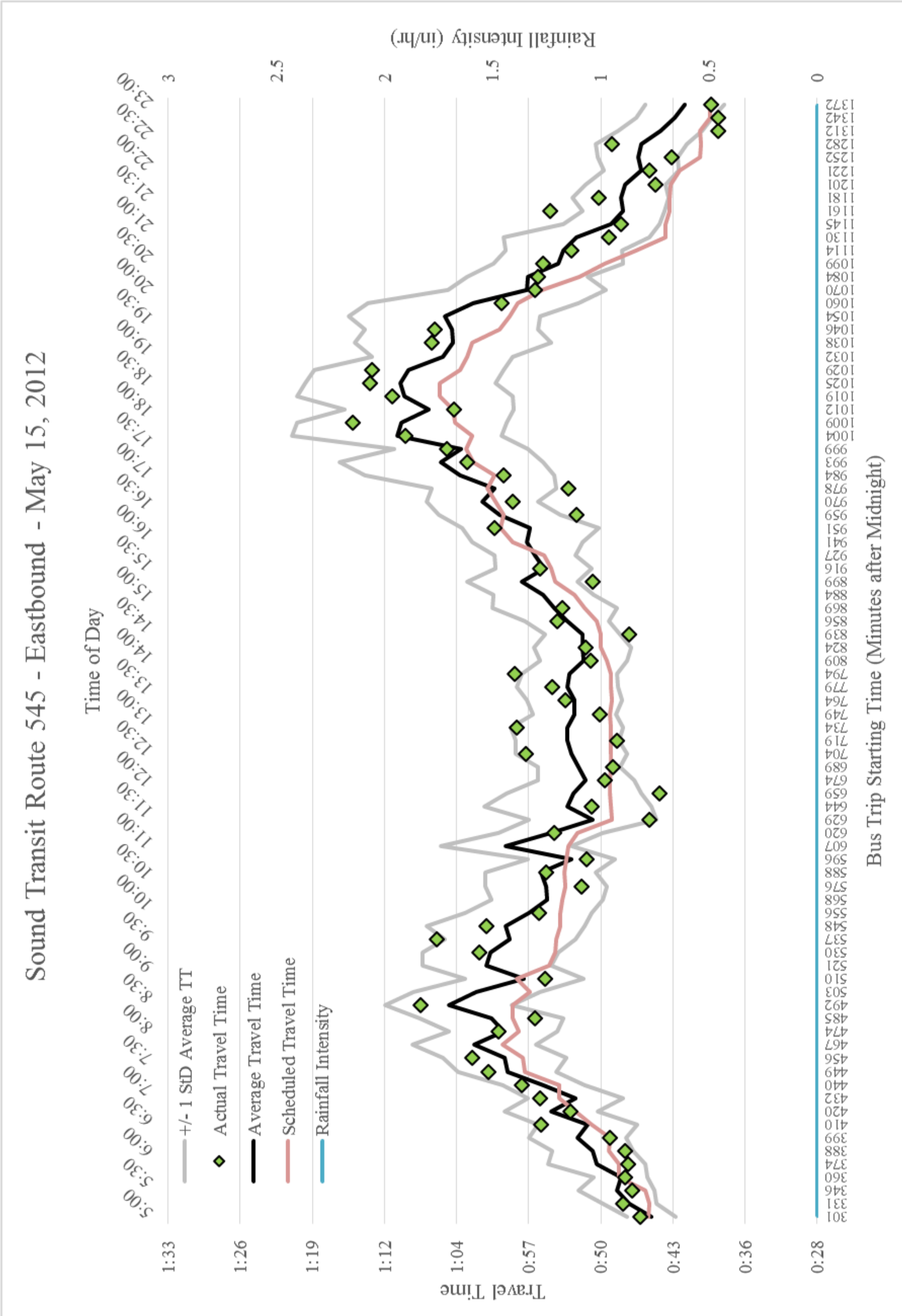

Figure 16 Travel Time for May 15, 2012 Eastbound

Over the course of the day the average eastbound trip was 25 seconds off schedule at the end of the route. Each trip was on average less than half a minute off of the scheduled arrival time at the last stop of the route. These performance measures are compared to the two test rainy days for the eastbound direction.

Similar to the westbound direction, the eastbound direction experienced greater variability in the travel time during the off peak hours. The AM and PM peak hours remained within one standard deviation of the average travel time for each bus trip starting time. The consistency in travel time of the route makes it convenient for commuters who make the same trip every day. The off peak hours are utilized by a different subset of riders. These riders could be more affected by the travel time variability.

Figure 17 shows the average speed of buses throughout the day on May 15th compared to the distance along the route. Three clear regimes can be seen in the figure, similar to Figure 15. Before mile 2.5 the buses are traveling through Seattle’s downtown core on city streets. The buses are not able to achieve a high average speed throughout the entire course of the day through this section. Between miles 2.5 and 14.5, the buses are traveling on the freeway on mixed flow lanes. This section can represent the congestion and speed on the freeway throughout the day. The average speeds are higher during the off peak hours. A small amount of congestion develops during the PM peak at mile 10. After mile 14.5 the buses are traveling on local and arterial streets. There are pockets of higher speeds when the arterials are not congested during off peak hours. The average speed for each trip during the day was 18.5 mph. This speed-contour plot is used for comparison to the two rainy day speed-contour plots for the eastbound direction.

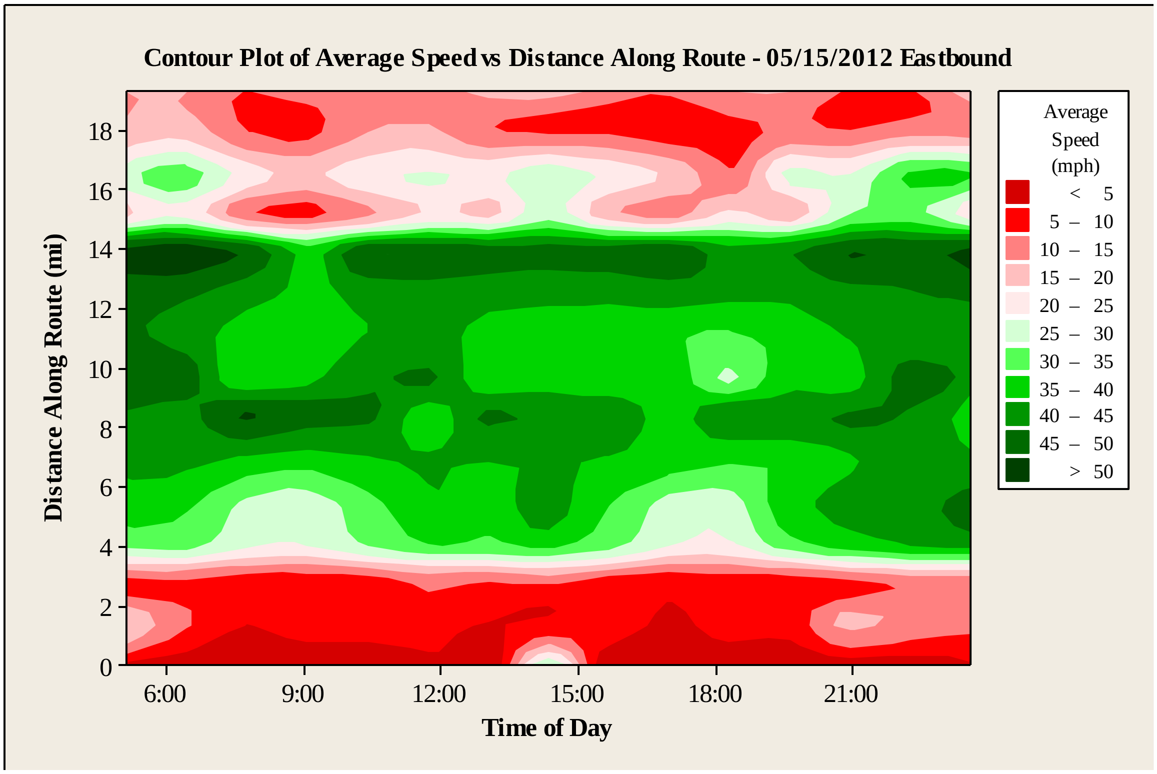

Figure 17 Speed-Contour Plot for May 15, 2012 Eastbound

4.3. Travel Time Analysis – March 15, 2012

The second test day selected was March 15, 2012. Moderate rainfall was experienced throughout the day, with light rainfall occurring steadily. Two high intensity, short rainfall events occurred during the day. During the 24 hour period, 1.24 inches of rain accumulated at the Mercer Island precipitation gage. The short, high intensity rainfall events which occurred on March 15th had varying effects on travel time. The performance measures are compared to the dry test day and to the annual averages.

4.3.1. Westbound Directional Analysis

Figure 18 illustrates the graphical representation of travel time for the westbound direction of Route 545 on March 15, 2012. There were 72 westbound trips on March 15, 2012. The first trip departed at 4:26 am and the last trip departed at 10:22 pm. These are the same first and last trip as the baseline test day. There were three additional trips westbound on May 15th. The average headway was 21 minutes and 11 seconds. This is much larger than the average headway from the baseline test day. The average headway on March 15th was nearly seven minutes longer than the average headway on May 15th. The average travel time on March 15th was also longer than both the baseline test day and the annual average. The average travel time on March 15th was 54 minutes and 52 seconds compared to 53 minutes and 8 seconds on May 15th and the annual average of 54 minutes and 41 seconds.

During periods of light or no rainfall on March 15th the westbound travel times followed the pattern of the average travel time. At the beginning of the PM peak period, a short high intensity rainfall event occurred which caused travel times to spike. After another short high intensity rainfall event during the off peak period travel times remained average. It appears that rainfall events affect transit travel times differently during the peak and off peak periods. Additional compounding factors could have affected travel time during the peak periods. An analysis combining these factors could provide a more definitive link between travel time and rainfall.

The average trip on March 15th was approximately 144 seconds off schedule at the end of the westbound route. These trips were on average twice as delayed as the baseline test day. However, there were a number of trips during the PM peak period which were more than 10 minutes late. One trip, the westbound trip departing at 3:45 pm, was 16 minutes off schedule by the end of the route. This trip occurred during a short high intensity rainfall event. The other short high intensity rainfall event which occurred around 10:30 am after the AM peak period appeared to have no noticeable increase in travel time.

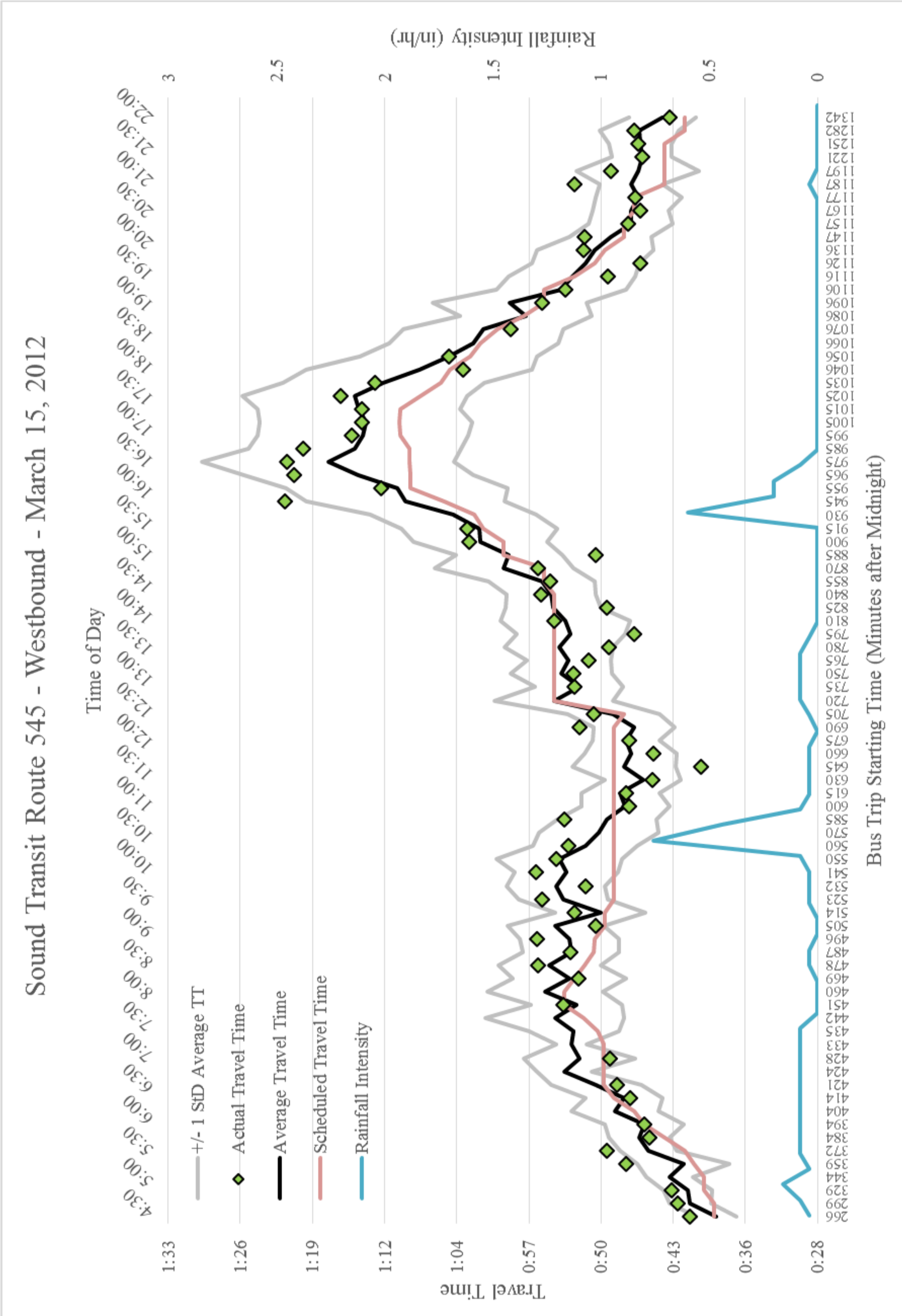

Figure 18 Travel Time for March 15, 2012 Westbound

Figure 19 shows the average bus speed along the route on March 15th, the second test day, in the westbound direction. When compared to Figure 15, the speed-contour plot for the baseline test day, a number of distinct differences appear. The average speed through the day is lower on March 15th. During the AM peak period, a slowdown occurs where one did not occur before. Between miles 11 and 13, between the hours of 5 am and 10 am, the average speed is between 30 and 35 mph. On the baseline day, the speeds in this section were upwards of 35 mph and even exceed 45 mph prior to 7 am. Steady rain occurred during this time period. The area of congestion found during the PM peak period spans a longer time frame on March 15th; it also affected a longer segment of the route. Outside of the freeway section (between miles 4 and 16), the average speeds appear to be higher on the rainy day than on the baseline day.

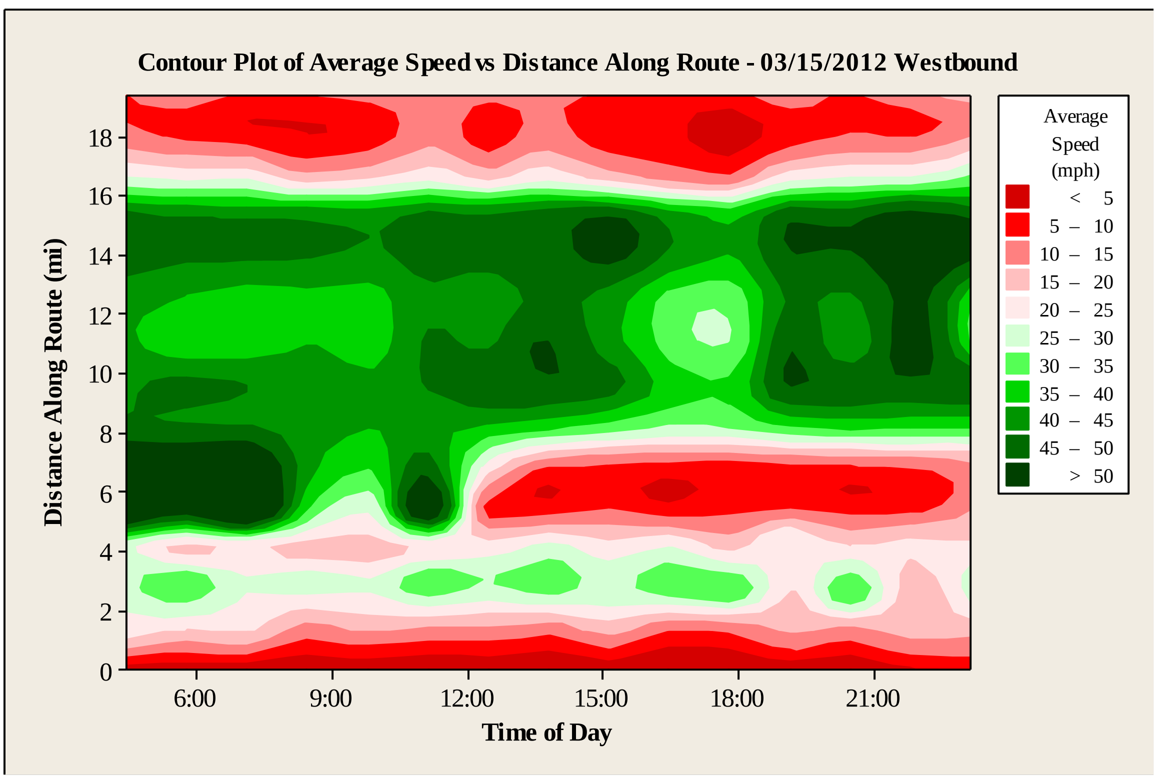

Figure 19 Speed-Contour Plot for March 15, 2012 Westbound

4.3.2. Eastbound Directional Analysis

Figure 20 illustrates the graphical representation of the travel time for the eastbound direction on the second test day, March 15th. There were 64 eastbound trips on the test day. The first trip departed 6th and Atlantic at 5:01 am and the last trip of the day departed at 10:52 pm. The average headway was 17 minutes with some headways less than 5 minutes during peak periods. The headway on March 15th was two and a half minutes longer than the baseline test day, May 15th. This difference in headway could stem from a difference in daily schedules. The average delay for the trips on March 15th was 24 seconds. Less delay occurred on this rainy test day than the baseline dry day. There are many factors which affect delay, rainfall is just one factor that may or may not have a significant effect. A detailed analysis of overall trip delay was not part of this study.

The average travel time was 54 minutes and 2 seconds on March 15th. This travel time was faster than the baseline test day, May 15th. The travel time was also faster than the annual average travel time of 56 minutes and 26 seconds. The rainfall does not appear to have had an effect on the eastbound travel time. The westbound travel time was affected by the short high intensity rainfall events, but the eastbound direction did not show as drastic changes in travel time. The afternoon rainfall event appears to have caused some variability in the travel time in the eastbound direction, but they are all within one standard deviation of the average. The connection between rainfall and travel time is difficult to diagnose with a graphical representation of travel time. The morning rainfall event appears to have an effect on travel time. The spike in travel time did not exceed plus one standard deviation. Trips prior to the rainfall were travelling ahead of schedule, during the rainfall the travel time returned to the average.

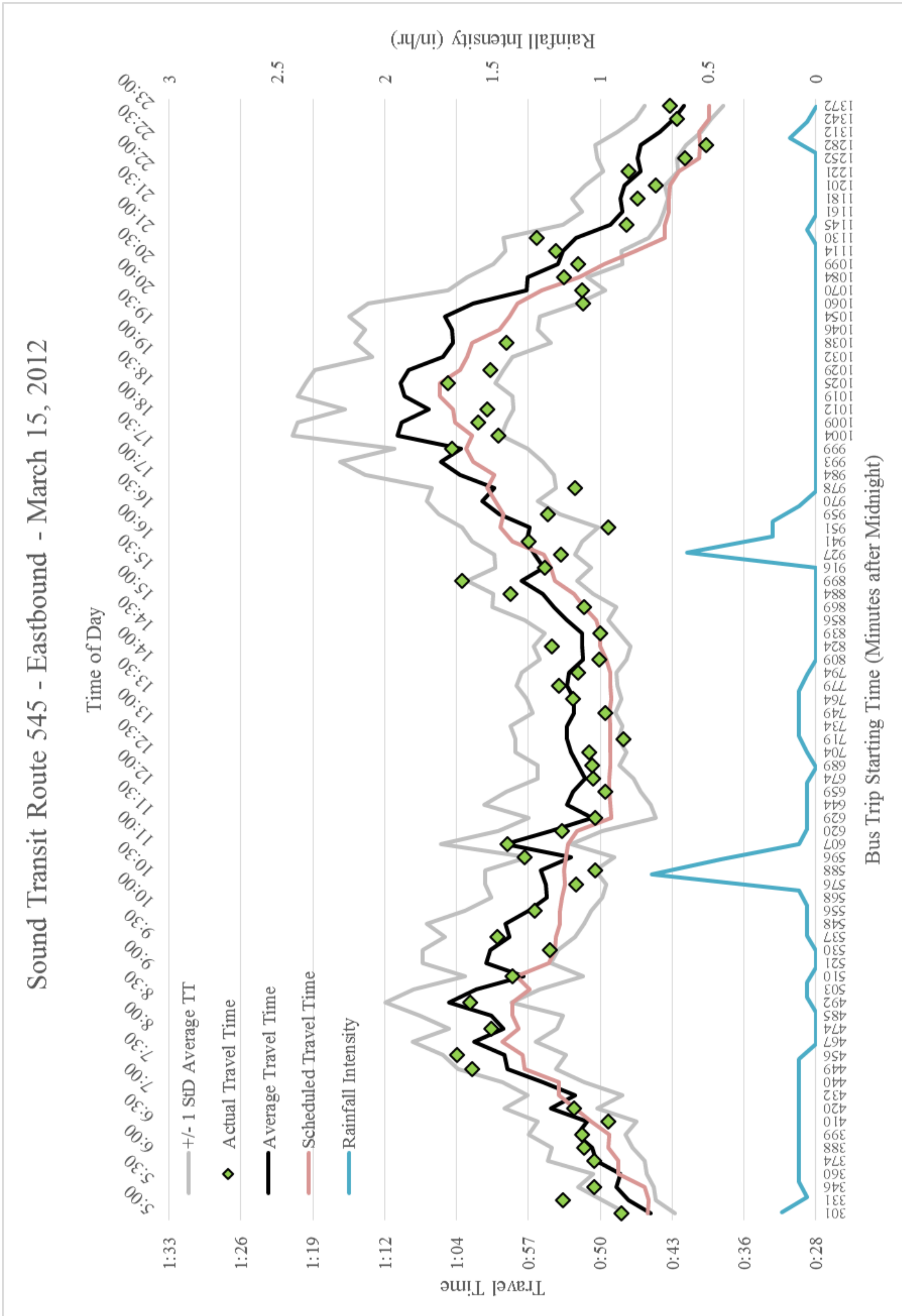

Figure 20 Travel Time for March 15, 2012 Eastbound

Figure 21 is the speed-contour plot for eastbound travel on March 15th. The average speed is shown along the route and throughout the day. The average speed per trip throughout the day was 18.3 mph. The increased average speed corresponds to the decreased travel time. The average speed on March 15th was 0.2 mph faster than on May 15th. The speeds on March 15th appear consistent throughout the day by regime. The first regime, before mile 2.5, was consistent throughout the day. This travel occurred in Seattle's downtown core. The speeds in the second regime, between miles 2.5 and 14.5, appear to be lower than on May 15th. There are no points throughout the day where the average speed in this section fell below 30 mph. In the third section, beyond mile 14.5, the average speeds appear to be higher than on May 15th. This section could be where the travel time increases occurred. As confirmed by the speed-contour plot, the eastbound directions of March 15th and May 15th appear to be very similar despite the rainfall on March 15th.

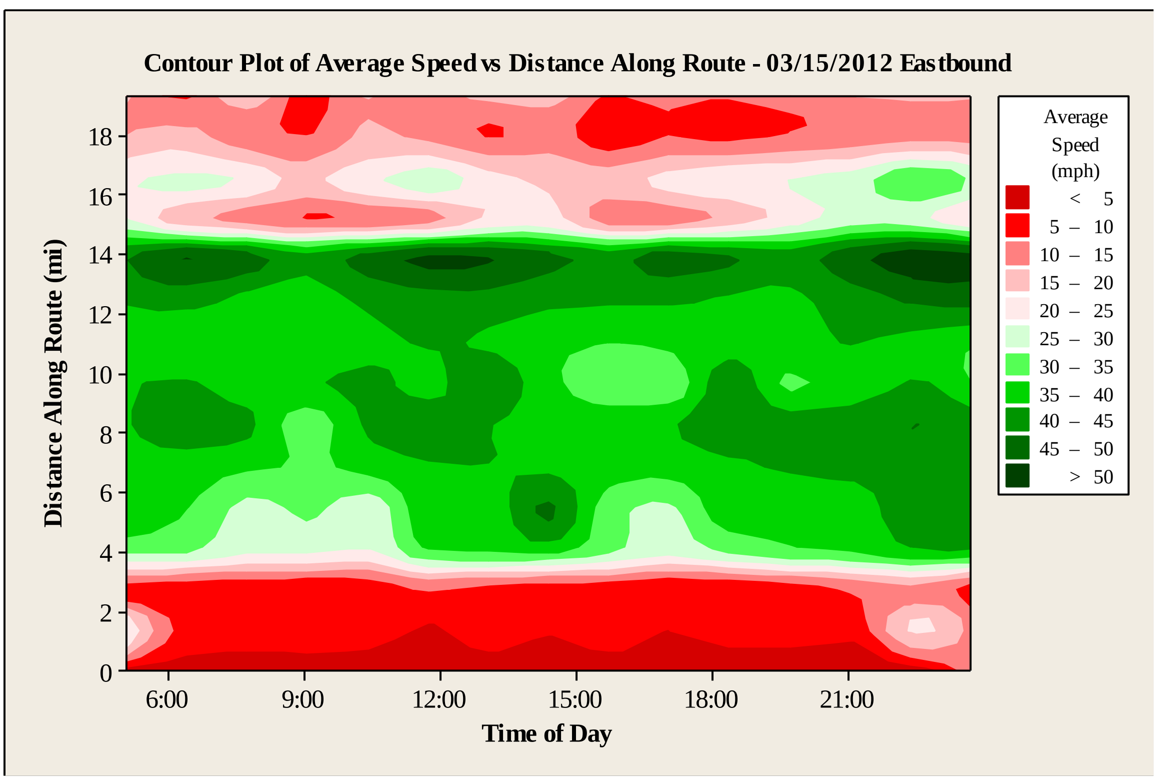

Figure 21 Speed-Contour Plot for March 15, 2012 Eastbound

4.4. Travel Time Analysis – November 19, 2012

The third test day selected was November 19, 2012. This day was selected because it received the most rainfall during a 24-hour period in 2012. The total rainfall was 2.44 inches over 24 hours. Much of the rainfall fell during the operating hours of Route 545. Not only did steady moderate rain fall throughout the majority of the day, there was a period of high intensity rainfall in the early afternoon. The 5-year 24-hour storm event in the Puget Sound region is 2.5 inches (NOAA, 1973). Statistically, the storm which occurred on November 19^{th} will occur once every five years. The performance measures from this test day are compared to the baseline test day and annual averages.

4.4.1. Westbound Directional Analysis

Figure 22 is the graphical representation of travel time for the westbound direction on November 19^{th}. There were 69 westbound trips on this day, which is the fewest number of trips during any of the test days for the westbound direction. There could have been older buses operating on the route or buses whose AVL systems were not working. The average headway for the day was 14 minutes and 41 seconds. The headway on November 19^{th} was similar to the baseline test day, but smaller than on March 15^{th}.

The average travel time was 56 minutes and 23 seconds. This is the longest average travel time of the three test days and longer than the average travel time. This travel time value does not accurately describe the change in travel time throughout the day. Of the trips departing before 10:00 am, only five trips out of 22 trips had travel times near or below the average travel time for the same bus trip starting time. Out of the 22 trips 16 trips exceeded one standard deviation beyond the average travel time for the same bus starting trip time. Steady moderate rainfall occurred throughout these 22 trips.

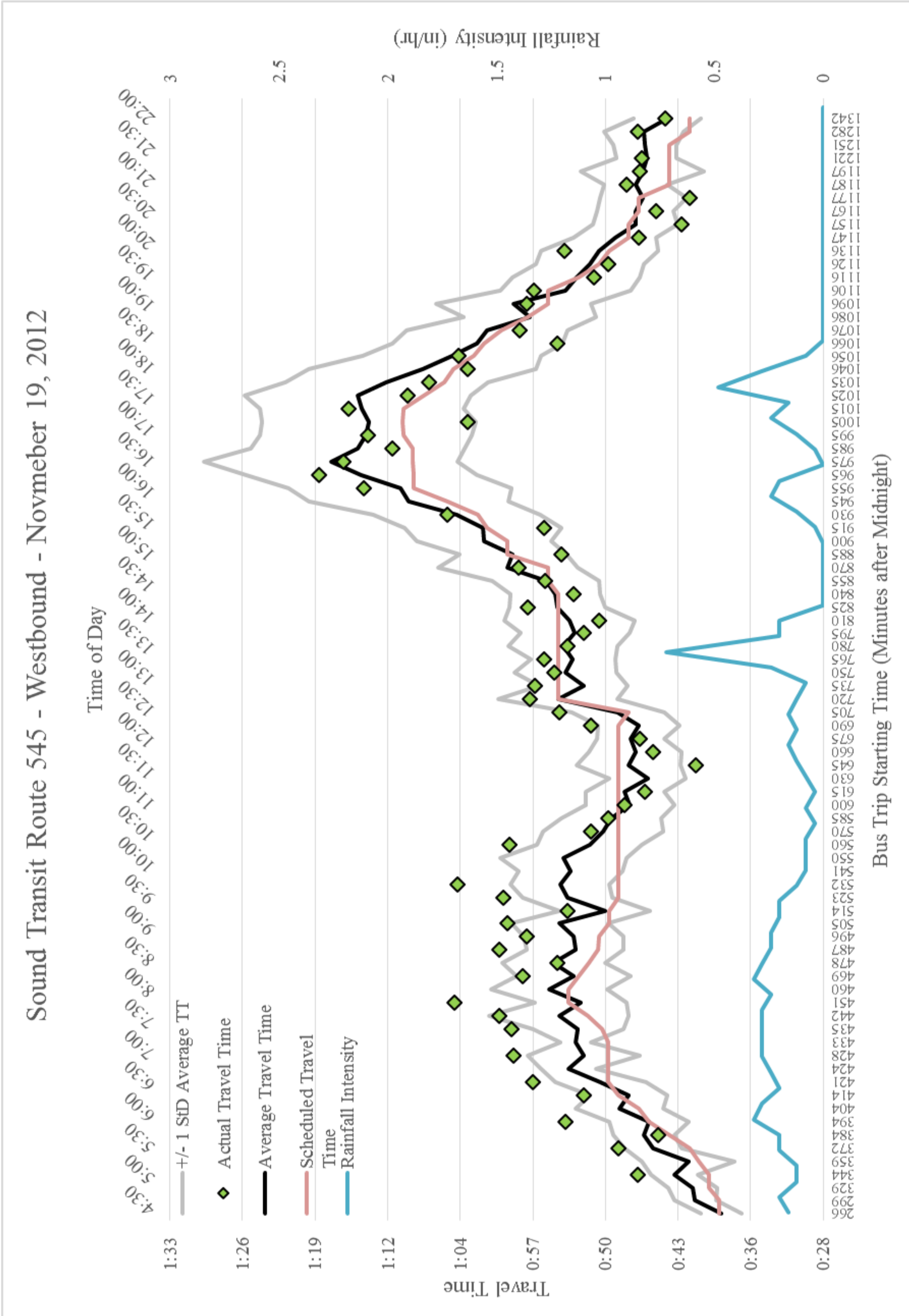

Figure 22 Travel Time for November 19, 2012 Westbound

The average delay for each trip throughout the day was 200 seconds, 3 minutes and 20 seconds. During the 22 trips in the morning, which experienced steady rainfall, the average delay was 7 minutes and 47 seconds. Three trips were over 10 minutes late, one of those trips was nearly 16 minutes late. After the morning of large delays, the rest of the day followed the average travel time pattern.

During the afternoon, a few high intensity rainfall events occurred for short intervals. These events did not appear to have a significant impact on the travel time like the consistent prolonged rainfall did during the morning period. Similar to the second test day, rainfall events during the off peak hours caused a pattern of travel times which was near or below the average travel time to spike above the average travel time. This spike did not exceed the standard deviation of the travel time.

The connection between rainfall and travel time appears to be mixed based on the westbound analysis of the three test days. There appears to be a connection between rainfall and travel time during prolonged periods of moderate intensity rainfall. This connection could be caused by any number of other factors as well.

Figure 23 shows the average speed along the route for the third test day. The average speeds appear to be lower over the course of the day, which would lead to the increased travel times. Previous sections of lower speeds are exacerbated on this test day. The section of lower speed which appeared on the second test day during the morning between miles 11 and 13 is more pronounced on November 19th. The speeds drop below 30 mph and the time at which the speeds remain lower between these miles is longer. The slowdown extends into the early afternoon. In the PM peak period the congestion, which has always developed at the same point, is worse. The average speeds in this section drop below 20 mph. During the afternoon when the route diverts off of the freeway to stop at mile 6, the speeds appear to be on average slower than the other test days. Understanding the rainfall patterns along the route and throughout the day could provide a connection between rainfall and average speed.

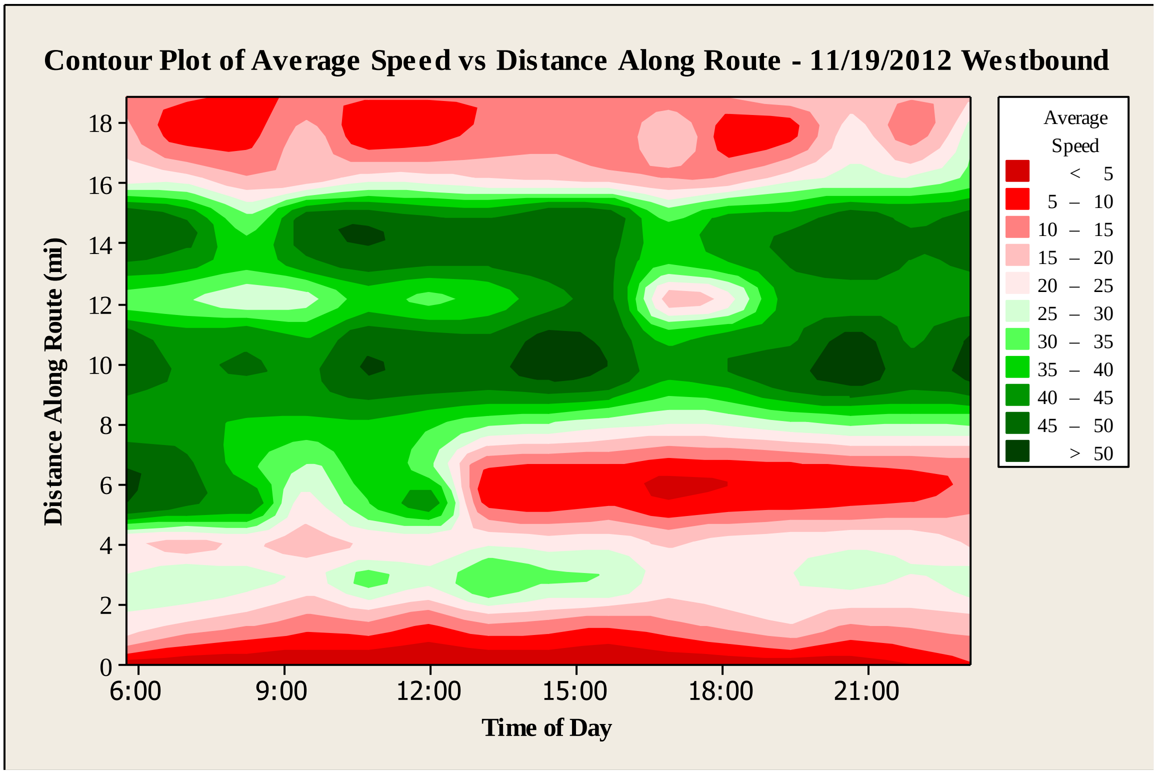

Figure 23 Speed-Contour Plot for November 19, 2012 Westbound

4.4.2. Eastbound Directional Analysis

Figure 24 is the graphical representation of travel time in the eastbound direction for the third test day, November 19th. There were 79 eastbound trips made on this day. The first trip departed at 5:01 am and the last trip departed at 10:52 pm. The average headway was 13 minutes and 21 seconds which was the shortest of the three test days. The average travel time for the day was 58 minutes and 2 seconds. This travel time was the longest out of the three test days and nearly 2 minutes longer than the annual average travel time.

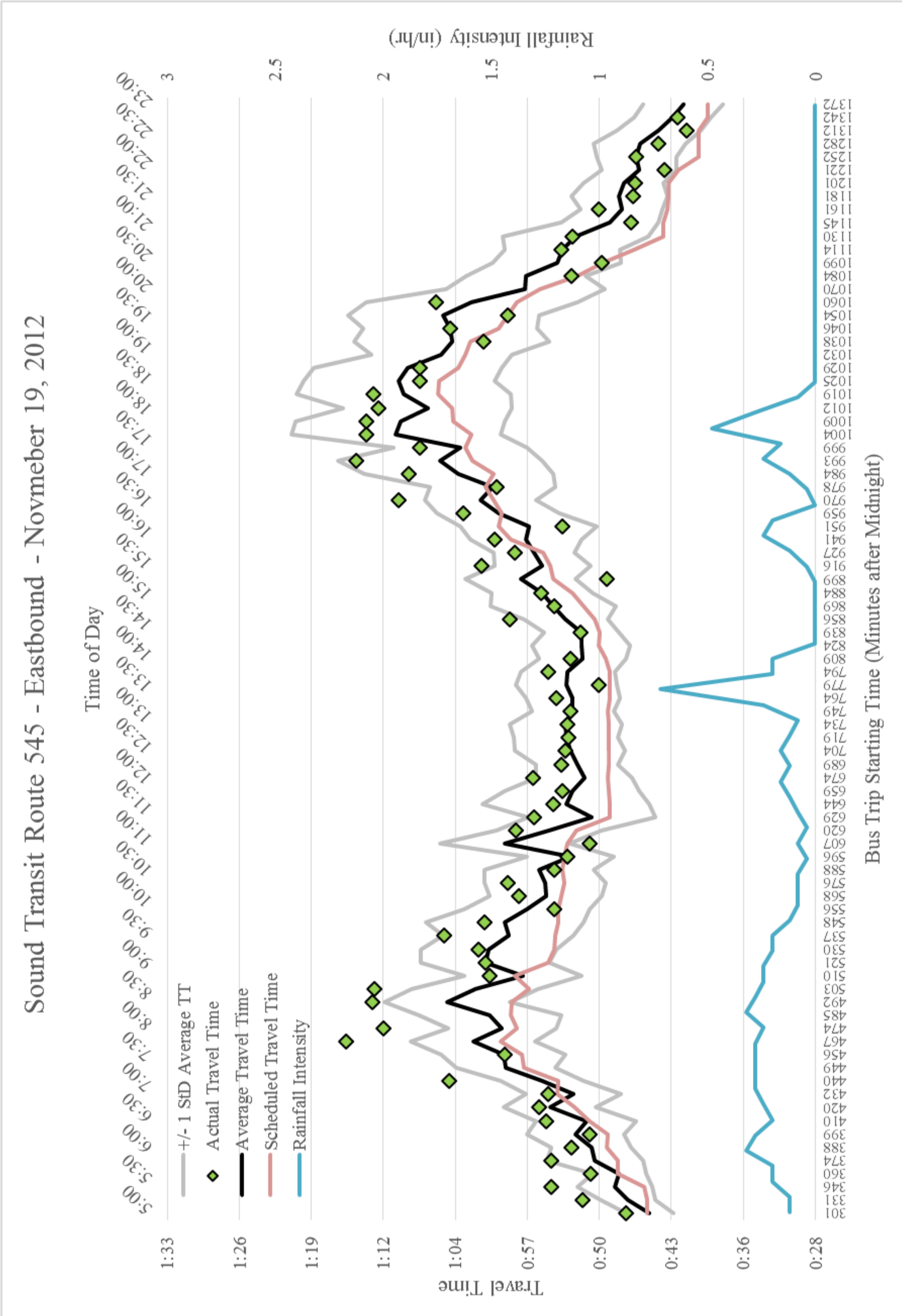

Figure 24 Travel Time for November 19, 2012 Eastbound

Throughout the majority of the day the travel times are within one standard deviation of the average travel time with the exception of eight trips in the morning and three trips in the afternoon. The average delay per trip was 260 seconds, 4 minutes and 20 seconds. Four of the eight trips in the morning to exceed the standard deviation of the average travel time experienced delays of approximately 15 minutes each.

Figure 25 shows the average speed along the route for November 19th. The speed-contour plot highlights areas of much lower speeds when compared to the previous plots. During the AM peak, when the vehicles experienced long delays, the average speed of the freeway section was less than 35 mph. The speed differential during this slowdown in the morning is as large as 20 mph in spots when compared to the baseline test day. The average speeds in the first section, in the city, are higher on this day compared to the other test days. Speeds remained lower throughout the day until the rainfall subsided in the evening.

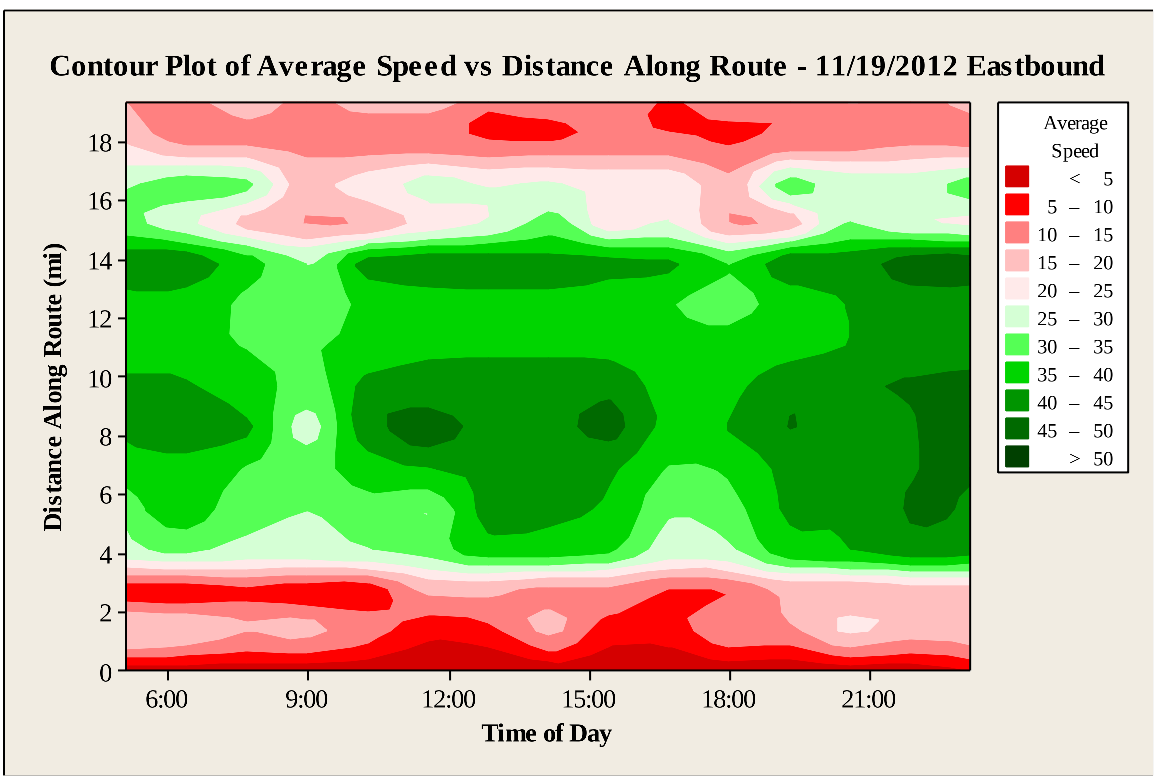

Figure 25 Speed-Contour Plot for November 19, 2012 Eastbound

5. RAINFALL AND TRANSIT PERFORMANCE MEASURES: ALTERNATIVE USES OF ARCHIVED CCS DATA

This chapter explores additional ways to utilize archived CCS data to investigate the relationship between rainfall and transit performance measures. The archived data can be manipulated to analyze variations in travel patterns and can also be combined with many years of data to attempt to understand larger trends. These two uses of archived CCS data are investigated in this chapter. Using the morning of the third test day, November 19, 2012, the spike in travel time in the eastbound direction is investigated. The results of this analysis could assist Sound Transit in actively managing their fleet in future extreme weather events. The full three-year dataset of CCS data is then used to attempt to relate the total daily rainfall to the average delay per trip using linear regression analysis. Weather forecasts could then allow Sound Transit to inform passengers about possible delays in inclement weather.

5.1. Diagnosis of Transit Breakdown on November 19, 2012

On the morning of the third test day, November 19th, travel times were around one standard deviation larger than the average travel time until 7:00 am. After 7:00 am, the travel time fluctuated between average and significantly slower for the trip starting time. The bus starting times investigated are 432, 440, 456, 467, and 474. All five of these trips are within the same hour. The travel times for starting time 432 and 456 are near the annual average. The other three trips experience travel times which exceed the standard deviation of the annual average travel time for the same starting time. The vehicle trajectories of the five trips were plotted on a time space diagram to understand their movement on the roadway compared to the scheduled trajectory.

Figure 26 illustrates the bus trajectories for the transit trips investigated from November 19th. The trajectories were constructed by plotting the cumulative distance the bus traveled on the y-axis and time on the x-axis. A trajectory's slope at any time is the average speed at that time. Performance measures like travel time, average speed, and delay can be derived from each trajectory. Travel time is visible as the time difference between the beginning and the end of the trajectories. The average speed for the trip is the slope of the line connecting the beginning of the route to the end of the route. Delay at any point is the horizontal distance between the actual trajectory and the scheduled trajectory. Three distinct sections are visible in the time space diagram, similar to the speed contour plots previously. Figure 27 illustrates these sections. The first section represents travel through Seattle's downtown core. Section two represents freeway travel. Section three represents travel on arterial and local streets in Redmond.

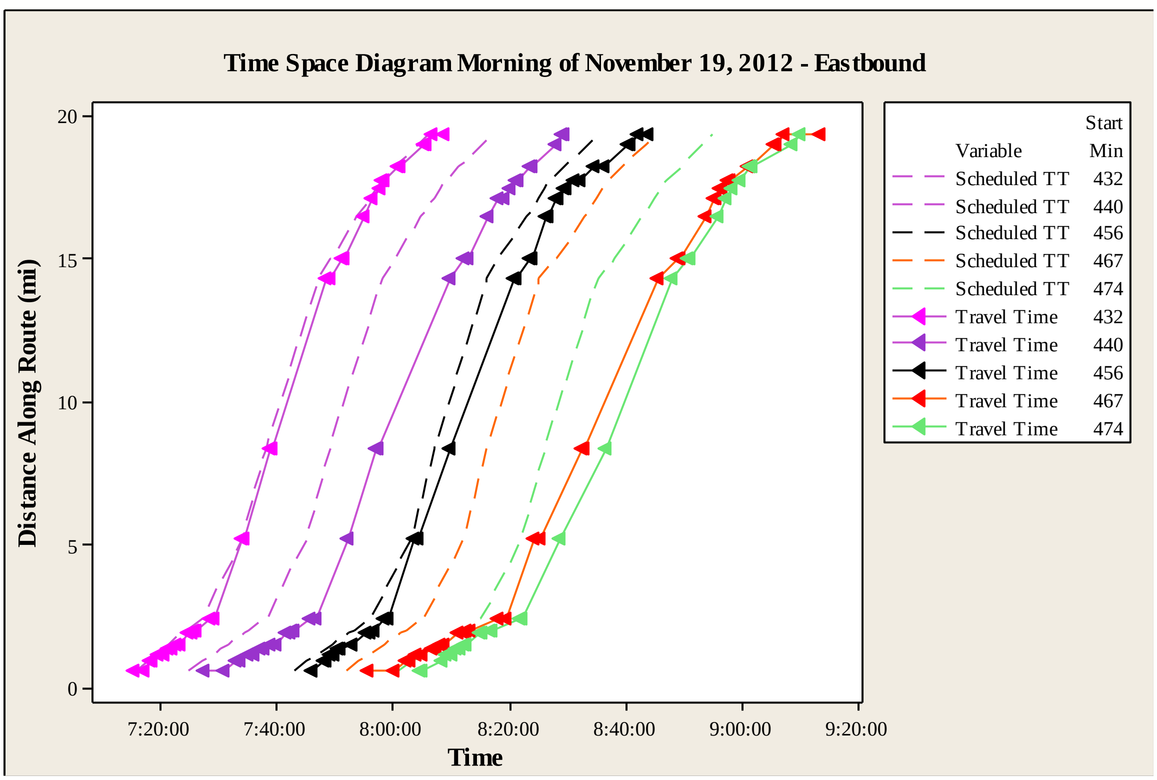

Figure 26 Eastbound Bus Trajectories on November 19, 2012

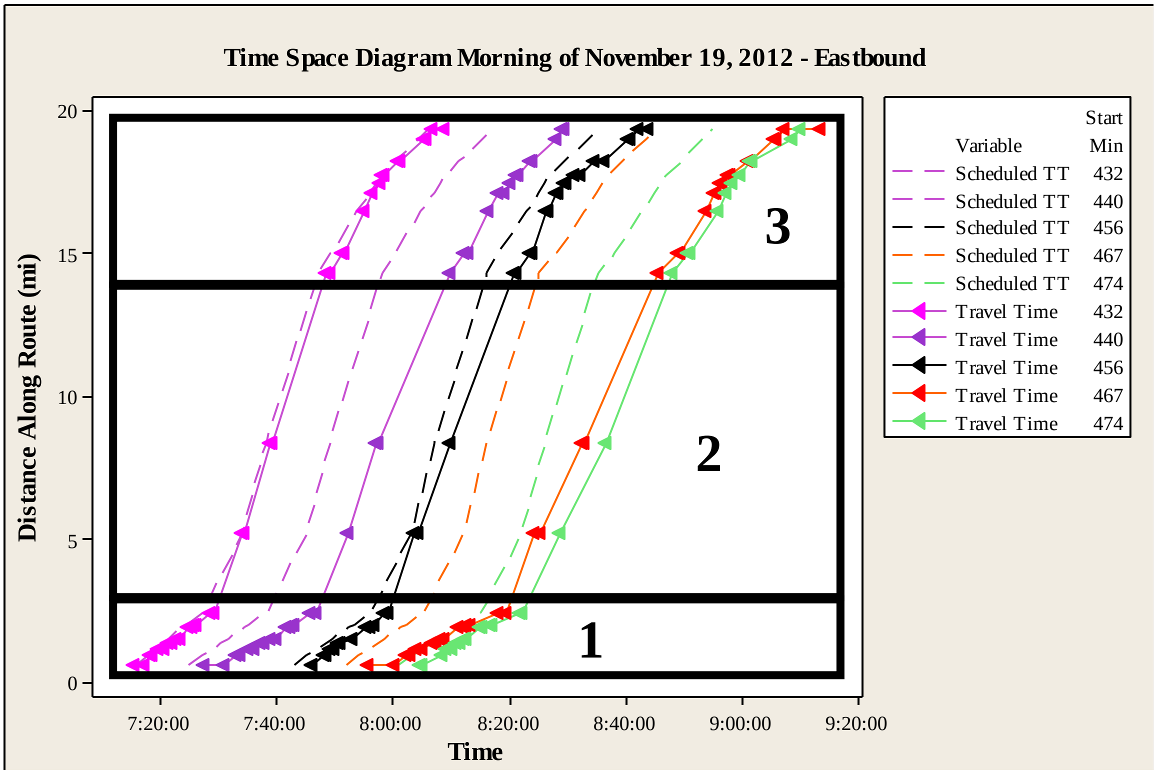

Figure 27 Sections of Eastbound Bus Trajectories on November 19, 2012

The average travel time for these five trips was 59 minutes and 10 seconds and varied between 49 minutes and 36 seconds and 1 hour 7 minutes and 20 seconds. The scheduled travel time for each trip was 50 minutes and 8 seconds. The average delay at each stop for the five trips was 456 seconds. Trip 432 operated ahead of schedule at points along the route and arrived within one minute of the scheduled arrival time at the end of the route. The average dwell time at each stop was 123 seconds, including all stops which were not serviced. All five trips experienced the same rainfall intensity of approximately one third of an inch per hour during their trips. By the time the fourth and fifth trips began their route, 0.96 inches of rain had fallen over the previous four hours. The effects of the rainfall could have compounded throughout the time frame of the five trajectories.

Separate time space diagrams for each of the three sections were created in order to understand the bus trajectories through each different section. Breaking the route into sections should illustrate the point of breakdown in the five trips. Figure 28 illustrates the five trajectories through Seattle's downtown core. Looking back at Figure 26, this section appears to be where the variation in trajectories occurs. An analysis of means for the delay at each stop in this section revealed that trips 432 and 456 arrived earlier than expected. Trips 440 and 467 arrived later than expected. Trip 474 was as late as expected. The two trips which arrived earlier than expected had the two fastest travel times and were able to avoid compounding delays along the route. The five trips averaged approximately the same speed; the variation in the average speed of 10.8 was not statistically significant. The very late arrival of trip 467 caused bunching to occur with trip 474 leading to an average headway through section one of four minutes.

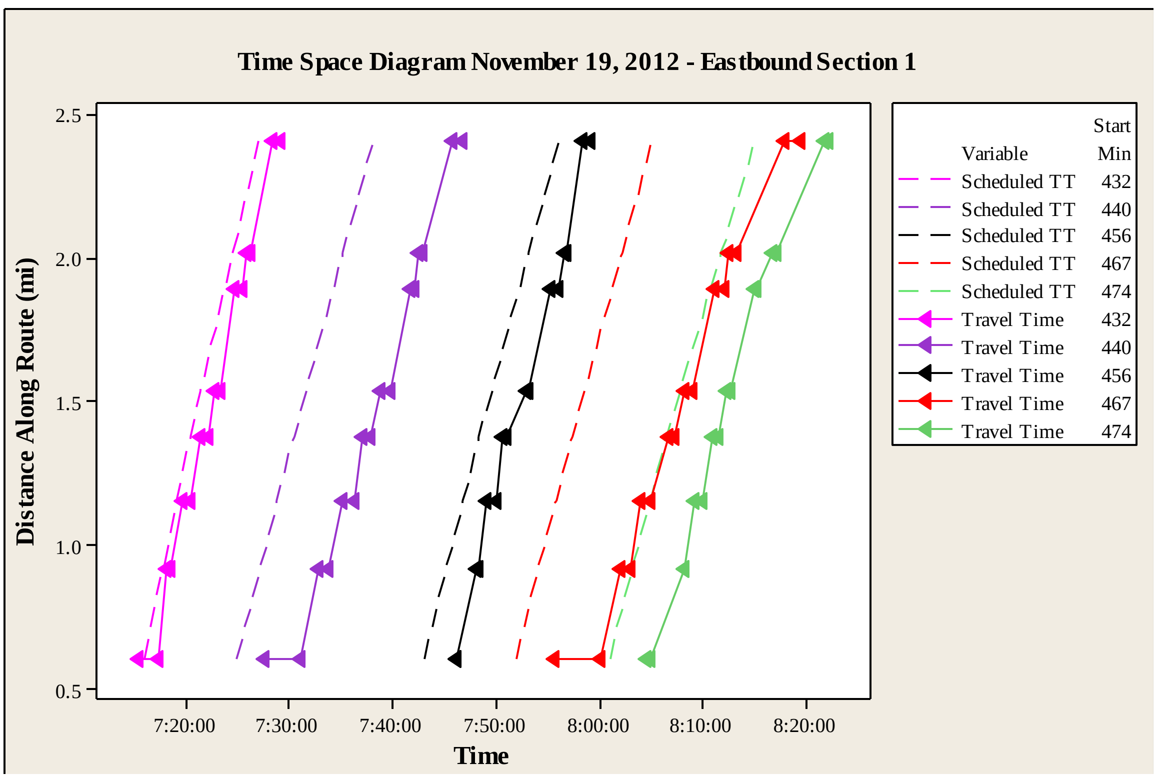

Figure 28 Section 1 of Eastbound Bus Trajectories on November 19, 2012

Bus bunching can affect the transit provider and the rider in significant ways. In bunching situations, the second bus often has lower or no ridership, because the leading bus has stopped and picked up all of the passengers waiting for the bus. Passengers are not aware that they are on a different bus than they were waiting for, as is the case with trip 467. This trip operated according to the schedule of the trip after it, trip 474. Trip 474 was then operating at a much higher per passenger cost and still emitting the same emissions. If this were to happen frequently it could reduce transit's benefit to the environment (Pilachowski, 2009). Riders waiting to catch the 467 trip were waiting on average over 10 minutes in section one. APC data is not available for trip 467, but trip 474 was made by an APC equipped vehicle. Through section one, a total of 20 riders had boarded the vehicle. The annual average ridership for trip 474 leaving section one was 38 riders. On this morning, trip 474 the vehicle was approximately half as full as an average trip leaving section one.

Figure 29 illustrates the five bus trajectories through section two of the route, the freeway segment. Few stops are made by any trip in this section as evident by the lack of flat lines at stop locations. The trajectories show that the average speed through this section decreases by trip. The average speed of trip 432 was just over 30 mph, while the average speeds for trips 467 and 474 were around 20 mph. This section comprises the majority of the route, so a 10 mph decrease results in a travel time difference of approximately 12 minutes between trip 432 and 467. Combined with the delay that occurred in the first section, a large difference in travel time is beginning to develop. Trip 432, the fastest trip, had a travel time 18 minutes faster than trip 467, the slowest trip.

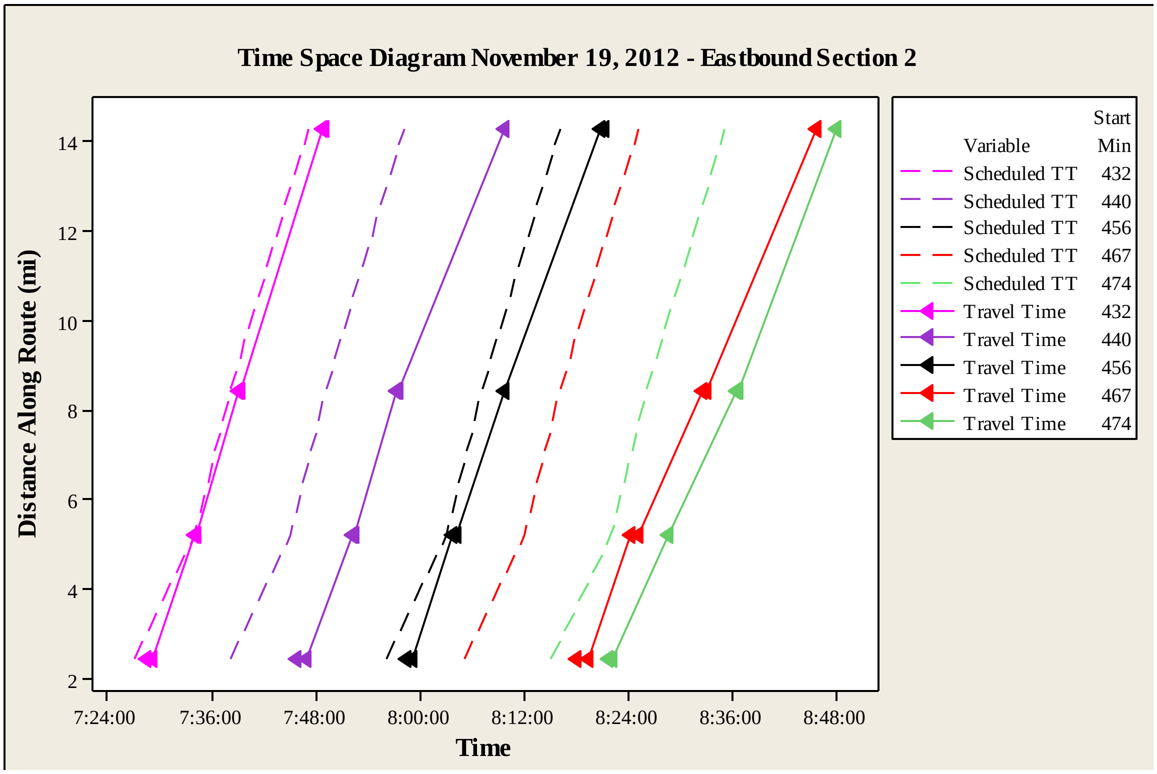

Figure 29 Section 2 of Eastbound Bus Trajectories on November 19, 2012

Figure 30 illustrates the five bus trajectories for section three of the route. This section travels along arterial streets and local streets in Redmond. All five trips have similar trajectories and have similar average speeds. This section does not appear to add to the difference in travel time between trip 432 and 467. The bunching of trips 467 and 474 got worse in this section of the route. At the third to last stop, SR 202 and 165th Avenue NE, the two buses were stationary at the same time at the same location. Active management of trip 467 and 474 could have avoided this bunching scenario. If the AVL data indicating the late arrival for trip 467 had been utilized in real-time, the trips could have been spread out to avoid long wait times for passengers at the stop location in inclement weather.

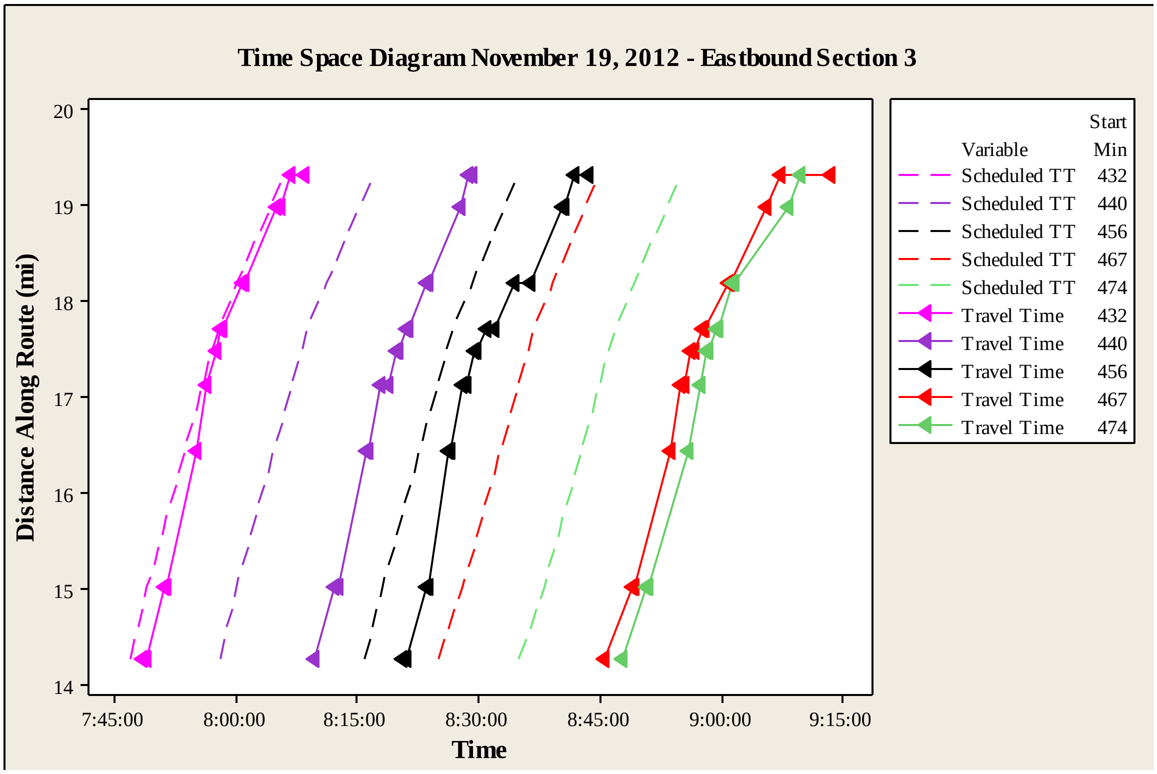

Figure 30 Section 3 of Eastbound Bus Trajectories on November 19, 2012

The majority of the delay occurred due to the late arrival of the transit vehicles at the beginning of the route. This could have occurred due to congestion on the way from the transit base to the beginning of the route or from previous trips made by the same transit vehicle that compounded the delay. Lower travel speeds through the second section also added to the higher travel times. The addition of 12 minutes of travel time to the freeway section is a large amount of additional delay. The mixed flow lanes in the freeway section added to this delay. High occupancy vehicle (HOV) lanes along this corridor could alleviate this difference in travel time.

5.2. Investigation of the Relationship between Rainfall and Delay

The final analysis performed attempted to correlate the delay per trip to the rainfall intensity during the trip. The delay for each trip was extracted using a Pivot Table in Excel from the archived CCS data. All three available years were used for this analysis. The delay was separated by eastbound and westbound since the trips have different characteristics. It could be assumed that rainfall would affect each direction differently. The statistically significant outliers were removed from the delay data using a box and whisker plot to identify the outliers. The remaining data was then joined with the rainfall intensity from the end of the trip using the array lookup function in Excel. The resulting dataset was then transferred to Minitab 16 for analysis. The analysis investigated the relationship between delay and rainfall intensity through scatter plots, histograms, and independent t-tests.

The rainfall intensity was divided into four categories in order to provide a comparison across magnitude of rainfall. The American Meteorological Society provides a clear delineation of rainfall in their glossary. When no rainfall occurred, zero (0.00) inches per hour, the trip was considered a “dry” trip. When between a trace (0.01) and a tenth (0.10) of an inch per hour of rainfall occurred during the trip it was considered to have experienced “light” rain. When between eleven tenths (0.11) and a third (0.30) of an inch per hour of rainfall occurred during the trip it was considered to have experienced “moderate” rain. When more than a third (0.31) of an inch per hour of rainfall occurred during the trip it was considered to have experienced “heavy” rain (American Meteorological Society, 2012).

The edited complete dataset, westbound and eastbound directions, included 103,188 trip delay data lines which included a corresponding rainfall intensity. The mean delay was -152.95 seconds. This translates to an average arrival two and a half minutes behind schedule. The standard deviation of the delay was 312.06 seconds. Figure 31 provides a complete statistical summary of the delay dataset.

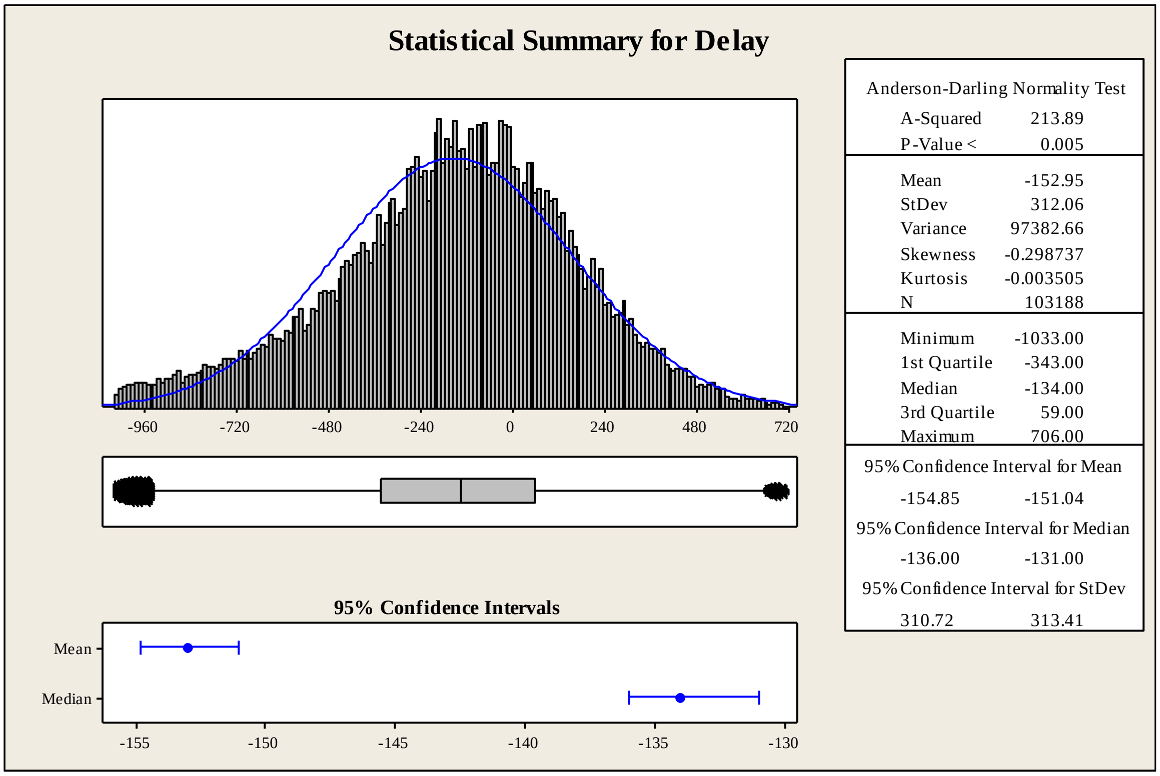

Figure 31 Statistical Summary for Complete Delay Dataset

The dataset can further be broken down by rainfall types. Figure 32 shows the histogram of delay by rainfall quantities as represented by density. The mean delay for dry trips is -149.0 seconds. The mean delay for light rain trips is -204.5 seconds. The mean delay for moderate rain trips is -253.8 seconds. The mean delay for heavy rain trips is -250.8 seconds. The delay grows as the rainfall intensifies. The statistical relationship between rainfall intensity and delay is evaluated by direction using independent t-tests. The t-tests compare the difference in the mean delay for each rainfall type. The tests were done with a 95 percent confidence interval (CI) to determine if the means from two rainfall types were different.

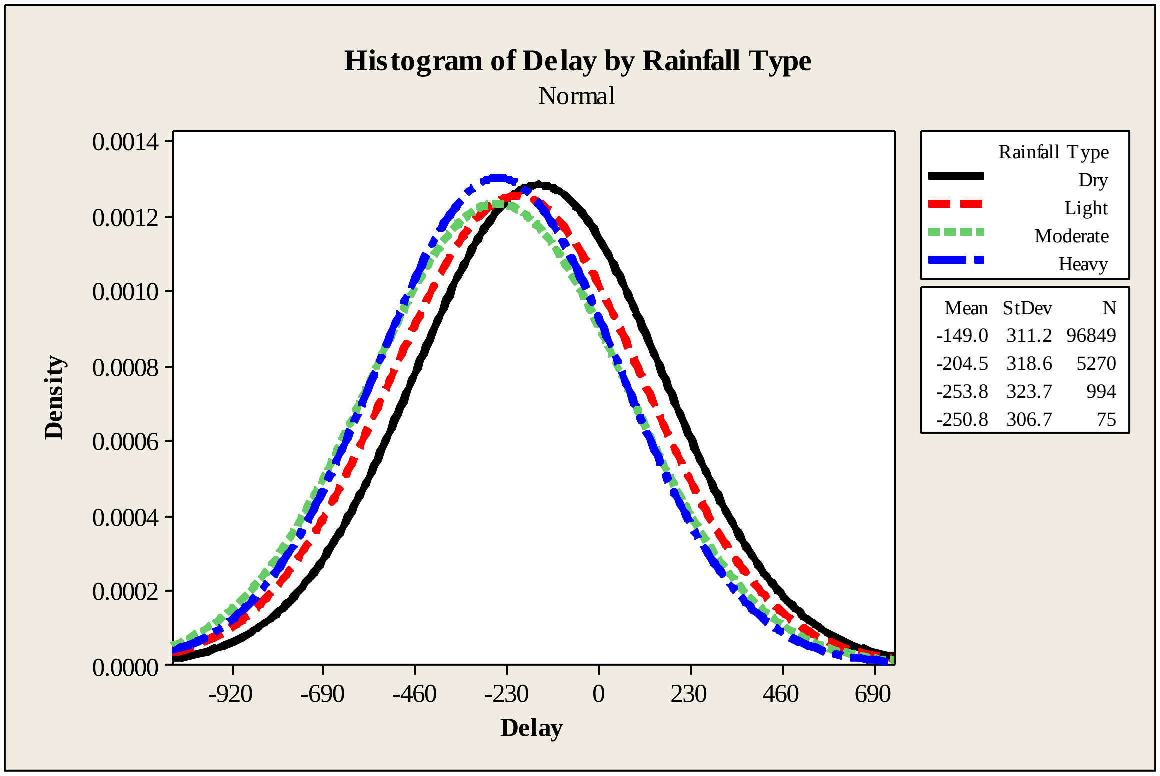

Figure 32 Histogram of Delay by Rainfall Type

Table 7 shows that delay during dry trips is statistically different from delay during light and moderate rainfall in the eastbound (outbound) direction. A p-value less than 0.05 represents significance. The delay during light rainfall events is also statistically different from the delay during moderate rainfall events. It was found that the delay during heavy rainfall events was not different than the delay experienced during any other type of rainfall. The non-significant results are highlight in the table. It appears that beyond the heavy rainfall threshold the relationship breaks down.

Table 7 Multiple Comparison Results of p-values for Rainfall Type EB (95% CI)

Rainfall Intensity		0 Dry	0.01-0.10 Light	0.11-0.30 Moderate	>0.30 Heavy
0	**Dry**	-	**0.000**	**0.000**	0.656
0.01-0.10	**Light**	**0.000**	-	**0.000**	0.650
0.11-0.30	**Moderate**	**0.000**	**0.000**	-	0.085
>0.30	**Heavy**	0.656	0.650	0.085	-

Table 8 shows similar results for the westbound (inbound) trips compared to the eastbound (outbound) trips. The delay during dry trips is statistically different from delay during all rainy trips. Unlike the eastbound direction, in the westbound direction the delay during heavy rainfall events is statistically different from the delay during dry trips. The delay during light rainfall events is also statistically different from the delay during moderate rainfall events. The non-significant results are highlighted in the table. The breakdown of the relationship continues between delay and heavy rainfall events.

Table 8 Multiple Comparison Results of p-values for Rainfall Type WB (95% CI)

Rainfall Intensity		0 Dry	0.01-0.10 Light	0.11-0.30 Moderate	>0.30 Heavy
0	**Dry**	-	**0.000**	**0.000**	**0.003**
0.01-0.10	**Light**	**0.000**	-	**0.010**	0.068
0.11-0.30	**Moderate**	**0.000**	**0.010**	-	0.287
>0.30	**Heavy**	**0.003**	0.068	0.287	-

Scatterplots were utilized in order to attempt to understand the trend in the change in delay with respect to rainfall intensity. Figure 33 shows the eastbound direction trip delay and rainfall intensity. Figure 34 shows the westbound direction trip delay and rainfall intensity. From looking at the figures, it does not appear that a regression model would produce any results. The variability in the data is large. The delay during dry trips spans from the minimum delay to the maximum delay. While rainfall and delay are connected, as shown with the t-test analysis, there are many additional factors which ultimately cause delay. The generally negative trend in delay with respect to rainfall intensity does not extend past the trips during moderate rainfall events. The heavy rainfall and extreme weather events should be a focus of a later study to understand why they are not following the identified patterns.

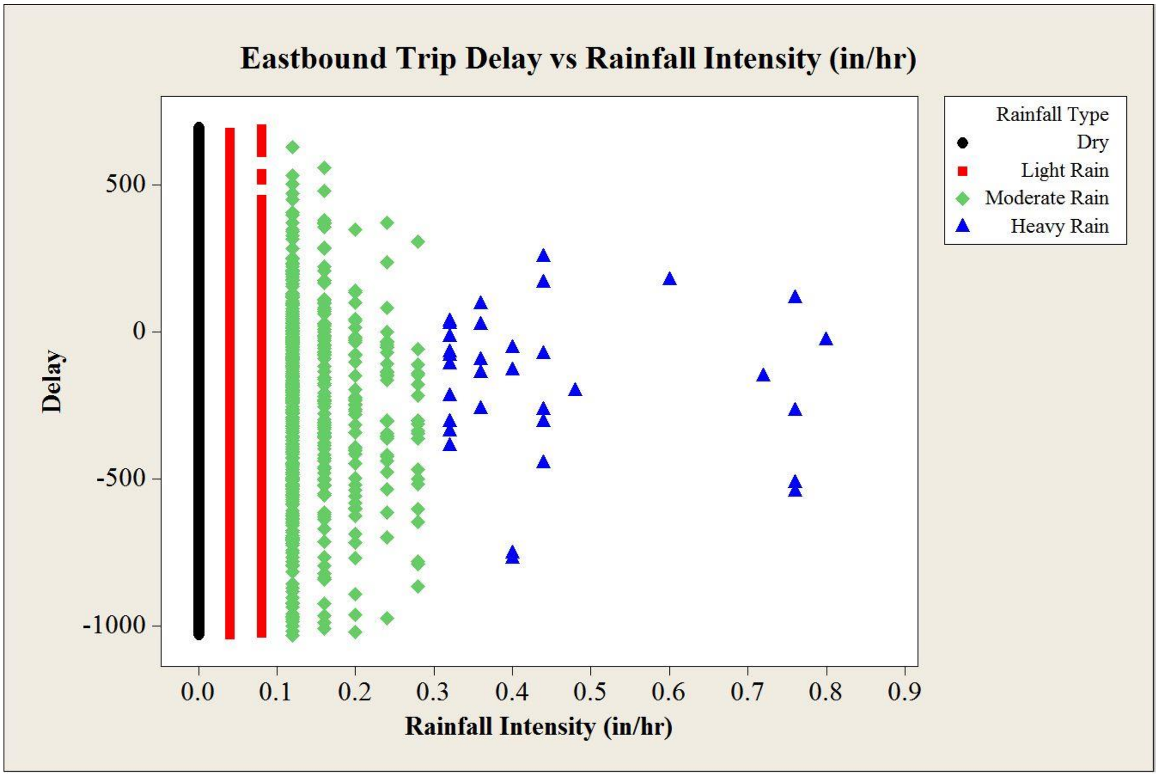

Figure 33 Scatterplot of Eastbound Trip Delay and Rainfall Intensity

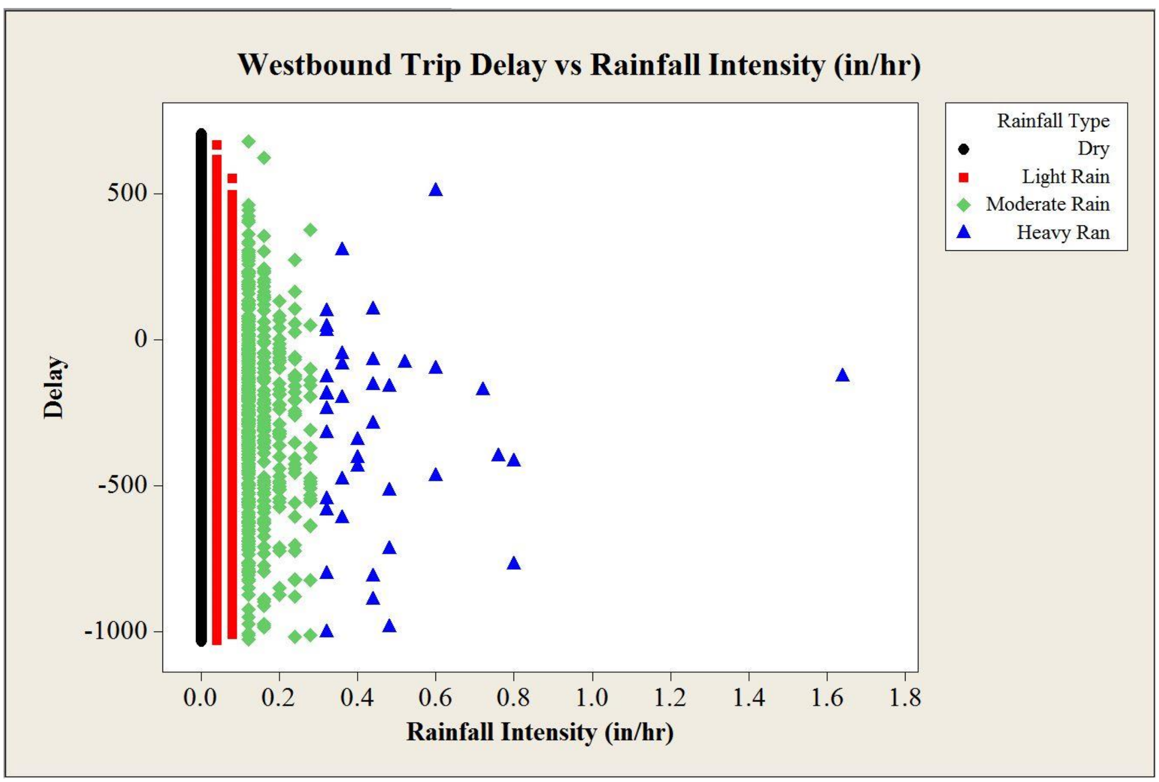

Figure 34 Scatterplot of Westbound Trip Delay and Rainfall Intensity

6. CONCLUSION

This study analyzed transit performance measures on one transit route over three years using two sets of data – hydrologic information and transit AVL data – in order to attempt to understand the relationship between weather factors and transit performance measures. Transit AVL systems are primarily used for managing real-time transit operations. For Sound Transit and King County Metro, the CCS was upgraded to provide better information to transit operators, riders, and local community members. The archived component of the CCS provides a valuable source of data for monitoring and analysis of service quality over time. This study has utilized the archived CCS data to investigate weather factors' relationship to transit performance measures in the Puget Sound region.

Daily ridership was extracted from the archived CCS data for dry and rainy days during a three-year period. Analyzing the raw daily ridership by month showed a large variation in daily ridership from month to month. In order to understand the true effect of rainfall on the daily ridership, each day during the three-year period had to be comparable. A seasonal index was applied to all of the daily ridership values to remove the seasonality in the data. The comparison between rainy and dry days revealed a decrease in daily ridership on rainy days. A rainy day was defined as more than five one-hundredths (0.05) of an inch of rain occurring over a 24-hour period. The average daily ridership on dry days for Sound Transit Route 545 was 4,930 riders. The average daily ridership on rainy days was 4,820 riders. There was a decrease of 2.23 percent in ridership on rainy days. Performing a t-test revealed a p-score of 0.252, which was not significant using a 95 percent confidence interval.

Since weather can be categorized by season the relationship between dry and rainy daily ridership was analyzed by season. The year was broken into winter, spring, summer, and fall. During the drier seasons, spring and summer, rain had a larger effect on daily ridership, causing a decrease of 6.71 percent and 5.07 percent, respectively. The rainfall during these seasons is less intense and it follows the trend of pervious research that rainfall has a negative effect on daily ridership. Ridership was also negatively affected during the winter months, a 3.26 percent decrease in daily ridership was observed. However, none of these changes were significant at a 95 percent confidence interval. Daily ridership in the fall actually increased on rainy days. The rainfall in the Puget Sound region is heaviest in the fall months. Existing research supports this finding, as transit ridership increases during extreme weather events (Khattak, 1991; Khattak et al., 1995; Khattak & de Palma, 1997). A 2.27 percent increase in daily ridership occurred on rainy days. This increase was not significant at a 95 percent confidence interval.

An attempt was made to connect travel time to rainfall intensity through a graphical representation of the data sets. The graphics included the annual average travel time, the average scheduled travel time, and plus and minus one standard deviation from the annual average travel time for each bus trip starting time observed throughout the year. Three test days were selected. The first day served as a baseline day, no rainfall was observed. The second test day saw moderate rainfall. The third test day was the rainiest day over the study period. The test days were analyzed for both inbound and outbound direction separately. Speed-contour plots were also created for each direction for the three test days. It was hypothesized that a connection could be observed between rainfall intensity and travel time by transit trip staring minute.

The six graphic representations provided mixed results when analyzed for a connection between rainfall intensity and travel time. Isolated high intensity rainfall events, which were short in length, appeared to have a direct effect on transit travel time. This phenomenon occurred on both of the rainy test days in both directions, though to varying degrees. Prolonged steady rainfall had mixed effects on travel time. On the second test day, which saw light prolonged rainfall, the travel times remained near the average travel time or within one standard deviation of the average for both directions. The third test day saw much heavier prolonged rainfall, averaging nearly one third of an inch per hour for five hours. During this time, the travel time for many of the trips exceeded the standard deviation of the average travel time. Some transit trips saw delays exceeding 15 minutes. Many factors could have affected these travel times, rainfall could be just one part of a larger equation. These graphical representations are intended to incite further investigation into rainfall's effect on transit performance measures on the trip level.

A preliminary trip level analysis for five trips on November 19, 2012 revealed that there are a number of factors which could lead to variations in travel time. Rainfall was not examined as a direct contributing factor, but it could be assumed that it had an effect on the factors investigated. The late arriving vehicles at the beginning of the route had an effect on the overall travel time of the trip. Of the five trips looked at, the two trips which experienced lower than expected delay due to vehicle arrival had the fastest travel times. The opposite is also true for the trips which had the largest delay at the beginning of the route; they had the longest travel times. Another noticeable location where delay occurred was on the freeway section of the route. Through this section a decrease of 10 mph was observed between the fastest and slowest trips. This 10 mph decrease translated to a 12 minute difference in travel time through the freeway section. The final section of the route produced nearly identical travel patterns. The increases in travel time and subsequent delay stemmed from the late arriving vehicle and the lower travel speeds through the freeway section of the route.

An attempt to develop a relationship between trip delay and the rainfall intensity occurring during that trip provided significant results. It was found that the delay occurring during dry trips was statistically different than the delay occurring during light and moderate rainfall events. This relationship was true for both directions of the route. In the westbound direction the delay occurring during heavy rainfall events was also statistically different than the delay occurring during dry trips. This part of the relationship did not hold true for the eastbound direction. When comparing the delay experienced during differing intensities of rainfall, the delay occurring during light rainfall was statistically different from the delay occurring during moderate rainfall. This relationship was true for both directions. The delay during heavy rainfall events was not statistically different from the delay occurring during light and moderate rainfall events.

From this study, it is suggested that further research should be conducted into rainfall's effect on transit performance measures in the Puget Sound region. Incorporating a larger amount of archived CCS data could allow for a more detailed study on extreme weather days. Tracking the same transit vehicle throughout the course of the day, on multiple routes, could allow for additional insights into the effect of late arriving vehicles. Additionally, this larger dataset could be used to analyze the daily ridership in the Puget Sound region to confirm the findings of this study. The final recommendation for research involves the prediction of average delay. Further factors should be included into a linear regression analysis to develop a model to predict delay on this route. Since this trip utilizes a long freeway segment where large delays could occur, this model could help passengers better plan their trips to arrive on time.

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