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After Study of The Bus Rapid Transit A Line Impacts

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AFTER STUDY OF THE BUS RAPID TRANSIT A LINE IMPACTS

FINAL REPORT

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EXECUTIVE SUMMARY

The A Line, Minneapolis-St. Paul's first arterial Bus Rapid Transit (BRT) line, serves both as an immediate response to high levels of transit demand along the Snelling Avenue corridor and as a blueprint for future BRT implementation in the Twin Cities as transit users desire faster, more reliable, and safer transit options when they navigate the metropolitan region. Following its implementation in the summer of 2016, the A Line has had an overwhelmingly positive response and rapid increases in ridership. Given the newness of this system, however, proportionally little is known regarding the operations and potential impact of BRT when compared to Light Rail Transit (LRT) and local bus service.

In response to the limited awareness surrounding BRT and the A Line, this study aims at providing answers to several main questions:

1. What impact does the A Line have on surrounding traffic?
2. What are the effects of A Line implementation on the corridor's transit capacity?
3. How do riders' perceptions of the A Line differ from rail service, express service, and local service?
4. What factors are most important in affecting rider satisfaction?
5. What elements of the A Line should be prioritized for service quality improvements?

To answer question one, video cameras were installed on two of the busiest stations located on either side of I-94 (Northbound Snelling and University and Northbound Snelling and Dayton) to record and measure several traffic conditions such as the queue length and flow rate of the surrounding traffic. The average traffic conditions for four signal cycles before the arrival of an A Line bus were compared with the average conditions for the four cycles after bus arrival to determine if dwelling A Line buses had statistically significant impacts on surrounding traffic. To ensure completeness of the analysis, two periods of time were analyzed: one period during high-volume traffic, which occurred during the twelve-day 2017 Minnesota State Fair, and a second period of regular (non-holiday) traffic during the month of August up until the 2017 State Fair. After performing this analysis, it was found that in both time periods (Fair and non-Fair), bus dwelling did not have a statistically significant impact on intersection queue length or traffic-flow rate at either of the two researched stations. What minimal impact A Line buses did have on surrounding traffic was dissipated within (or one signal cycle removed from) the traffic cycle in which the bus arrived. The limited extent of this impact may largely be a result of BRT features present on the A Line intended to increase the speed of boarding and alighting (and thus minimize bus dwelling) such as off-board payment, wider doors, and the allowance of boarding and alighting from both front and rear doors.

In addressing question two, it was first noted that because of the new service combination along Snelling Avenue of a reduced headway Route 84 and the high frequency A Line service that the combined maximum seated capacity per hour along the corridor increased given that there were more buses per hour serving the corridor. In addition to this increase as a result of the combined service, Automatic Passenger Count (APC) data as well as General Transit Feed Specification (GTFS) data was used to calculate load factors indicating the average weekday bus occupancy at the major stops along Snelling Avenue for all operating hours. This approach provided a more detailed comparison between the previous Route 84 service in 2016 along the Snelling Avenue corridor with the new service combination in 2017 of a reduced headway Route 84 and the high frequency A Line service. For example, it was determined that the hourly load for 7 a.m. carried past University and Dayton increased

from 79.6 people in 2016 to 117.4 in 2017. Overall, it was found that bus loads were larger for the A Line for almost all stop locations and hours of the day, with a particularly large increase in the afternoon hours.

In terms of overall satisfaction, the A Line performs better than local buses and does not differ significantly from express buses, light rail and commuter rail. For individual service attributes, most attributes of the A Line perform better than local buses, but worse than the commuter rail and equivalently to light rail. The top three important service attributes to overall satisfaction are “paying my fare is easy,” “hours of operation,” and “handling of concerns/complaints.” Despite the fact that many commuter rail attributes perform better than the same factors for the A Line, the most important attributes for each mode are similar or offset each other leading to a similar overall satisfaction rating. It is recommended that the transit agency improve the attributes that have higher relative influences and lower mean performances. Based on this criterion, the attributes that should be given priority are “shelter/station conditions and cleanliness” and “behaviors of other passengers and atmosphere on board.”

CHAPTER 1: INTRODUCTION

Over the past two decades, public transportation has increased in popularity in the United States with transit usage expanding by 30% compared to 1996 (1). In response, transit agencies have increased capacity to meet the rising demand by, among other methods, increasing bus frequency, adding Traffic Signal Priority (TSP), and/or adding additional routes to serve the areas of highest demand (2, 3). One form of public transit that has seen increased implementation around the world is bus rapid transit (BRT). Compared with traditional buses, a typical BRT service has more advanced features, including dedicated right-of-ways, off-board fare collection, more equipped stations, and other features intended to improve user experience and reduce travel time (4). In addition to full-service BRTs, arterial or BRT-Lite, which possess many “full service” BRT features but operate in mixed traffic, have also gained popularity in select cities across the United States, such as the select bus service (SBS) in New York, BRT-Lite in Nashville and Los Angeles, RapidRide in Seattle, and the A Line in the Twin Cities.

Since the introduction of the A Line, Snelling Avenue corridor ridership has increased by nearly one third, and in 2017 alone, nearly 1.6 million rides were provided (5). As of 2017, the three top ridership stations along this 10-mile route, excluding the two transit centers, were Snelling and University, Snelling and County Road B, and Snelling and Grand (5). One reason behind this growth in ridership could be the A Line’s 20-25% increase in service speed when compared to the previous route servicing this corridor (Route 84) or its 94% on-time performance (5).

A Line stations are located curbside, and thus buses consequently dwell on-line rather than pulling off the thru-lanes and into a dedicated bus bay. The majority of A Line buses (69% of buses during non-State Fair periods and 37% of buses during the Fair period), however, dwell for less than 20% of the green time length. Furthermore, during normal weekday operating conditions, average green dwell time (the time in which a bus is dwelling during a green cycle) peaks at 7 a.m. with a value of 41 seconds but otherwise remains within a range of approximately 10-20 seconds until 6 p.m. at which point green dwell time decreases below 10 seconds. One potential reason why there is not a peak in dwell time at the end of the work day—as there was at 7am—is that signal timing plans along Snelling Avenue are different for morning and evening peak rush periods.

Riders’ satisfaction can inform transit agencies of their service qualities. Several statistical methods have been applied to explore user satisfaction toward BRT services, including an ordinary least squares linear regression (6), stepwise regression (7), and others. However, certain limitations exist among those methods. For example, they require the study sample to follow specific distribution patterns, cannot solve the problem of potential multicollinearity, and cannot adequately visualize the possible non-linear relationship between dependent and independent variables. In addition, although plenty of research focuses on riders’ satisfaction of traditional BRT, there are a limited number of studies concerned with perceptions toward arterial BRT. Due to the increasing popularity of the arterial BRT, understanding performance and features different from local buses takes higher priority.

Given that the A Line is the first arterial BRT line in the Twin Cities metropolitan area, this study aims to provide insight into the benefits, shortcomings and avenues for future improvement and implementation of BRT service in the Twin Cities. A literature review on similar studies will first be presented followed by an analysis of the effect A Line BRT operation has on the surrounding general traffic and road capacity. Transit capacity will then be analyzed to ascertain whether the passenger capacity per hour along the transit corridor has improved since A Line implementation. From these two analyses, one can determine whether the benefits of BRT outweigh any potential costs to the general traffic. Finally, the 2016 transit rider survey data from Metro Transit is used to assess the perception

both users and non-users have toward the A Line, and from this data, priorities of service attributes are suggested.

CHAPTER 2: LITERATURE REVIEW

The first ideas that will be discussed concerning the impact of bus systems on surrounding traffic, focus on how the location and type of bus stop affects traffic capacity and how buses and bus stops affect adjacent traffic's speed. Following the review of these studies, previous research focused on the use of traffic signal timing adjustments as an approach to mitigating the potential negative impacts buses impart on general traffic are reviewed. Lastly, several studies that provide better estimation methods for traffic parameters are presented to provide a better understanding of how their methods could be utilized for this study. These topics consider methods to better estimate parameters like signal timing, dwell time, lost time, and capacity, as well as how to better calculate the capacity and flow for signalized intersections. The aforementioned aspects in the literature are summarized in Section 2.1.

In addition to the previously mentioned research, literature concerning BRT quality of service is reviewed in Section 2.2. The basics of BRT systems will first be outlined to establish an overall understanding of a BRT system's functionality. Then, previous studies exploring how BRT affects rider satisfaction are discussed. It is also important to compare the satisfaction of BRT to other types of transit services in order to evaluate and compare BRT with other services. Different determinants of satisfaction for different transit types will also be compared, as this can vary from one service to another. Additionally, a study focusing on rider perception of BRT in mixed traffic in New York City is examined due to this system's similarity to the A Line. Lastly, several statistical approaches to examine rider satisfaction are discussed.

2.1 LITERATURE ON CAPACITY IMPACTS OF BRT AND ARTERIAL BRT

Several studies exist that examine how bus stop location – both location relative to a nearby intersection (near-side, mid-block, and far-side) and absolute location (curbside and bus-bay)—affects road capacity. A near-side bus stop is a stop that is located upstream from an intersection on an approach/incoming link. A far-side bus stop is located downstream from an intersection on a departing/outgoing link. A mid-block bus stop, however, is located at a significant distance from any intersection.

When considering various parameters like traffic flow rate, capacity, and average bus speed near a bus stop, near-side stops were found to have a more negative impact when compared to far-side and mid-block stops (8). Furthermore, road capacity increases as the distance between a bus stop and an intersection increases until reaching a maximum at a particular point that is dependent on the intersection's signal timing and the bus dwell time, according to a study from Zhao et al (2). Consequently, Zhao et al, recommended that far-side bus stops replace near-side stops.

The speed reduction of vehicles near buses and bus stops has been discussed in many past studies (9, 10). Wang et al. considered several different factors when evaluating vehicular speed reduction, including peak vs. non-peak hour, whether a bus was present at a given bus stop, and the number of berths at each stop (10). This study ultimately concluded that a reduction in speed was observed for both peak and non-peak hours only at near-side stops. In addition, Wang et al. noted that an increase in the number of bus stop berths decreases vehicular capacity (10). The presence of a bus at a bus stop, however, had the most apparent impact on speed reduction in comparison with all other factors. For far-side and mid-block stops, vehicular speed began decreasing between five and ten meters before the bus stop, while vehicular speed began increasing about 45 meters past the location of the bus stop (10).

Vehicular speed reduction can be correlated to different types of bus stops in addition to the locations of bus stops (11–13). For example, there are certain thresholds at which the average speed of traffic begins to rapidly decrease in the presence of curbside bus stops. A threshold of a 25% reduction in speed can be utilized as a marker to determine when curbside stops should be replaced with bus bays (6). This study's model could also be extended to determine different threshold points for bus bays with different capacities, dwell times, and traffic compositions. Different bus stop types also affect capacity in other ways, however. A study found that a separate stop lane should be implemented for cases where a bus stop is located close to an intersection in order to have the smallest impact on the road capacity (11). Fitzpatrick et al. related traffic volumes of roadways to bus stop types by utilizing a traffic simulation model to determine what types of bus stops could provide the greatest benefit considering curbside stops, bus bays, open bus bays, and queue jumpers (13). For mid-block and far-side stops, bus bays were found to be most beneficial for volumes of 350 or more vehicles per hour per lane. In addition, it was determined that the queue jumper design is best utilized when the traffic volumes are above and around 250 vehicles per hour per lane.

In considering these negative impacts on capacity, it is important to discuss potential mitigations and solutions. A study from Truong et al. considered how traffic signals along an arterial could optimize signal timing for Transit Signal Priority (TSP) (14). In this study, the authors found that there is a multiplier effect that minimizes bus delay on an arterial when TSP is employed and that TSP has negligible effects on traffic delay. Positive results suggested that TSP strategies could be scaled to a network level. Another study developed a model to design signal plans that better control traffic based on the delay experienced by vehicle drivers (15). For near-side bus stops in particular, increasing the green time ratio or decreasing the cycle length can successfully help mitigate the impacts of bus stops on adjacent vehicles (16). In addition, holding buses upstream from stops or locating bus stops further upstream past where the queue at a signalized intersection normally ends could help mitigate any negative impacts resulting from the bus stop. These solutions offer promising recommendations to minimize the potential effects that BRT has on surrounding traffic.

To fully understand the impacts that transit has on vehicular traffic, it is also important to consider how different methods and models can be applied to estimate relevant parameters. Previous studies have developed models to better estimate signal timing, dwell time, time lost serving the stop, and road capacity (8, 15, 17). Along Snelling Avenue, there are several BRT stops that are located upstream of signalized intersections. Accordingly, the impact of these stops on the intersection delay can be important to consider when determining how the A Line affects traffic. A microscopic simulation model was developed which utilized the computer simulation language MODSIM which can be used to approximate the delay for cases like the A Line (15). Similarly, a dwell time and lost time estimation model based on data from cities in China was created and verified (8). Another potential model that is found in the literature investigated how vehicle capacity can be determined based on gap acceptance and queueing theories as the capacity of vehicles on the roadway is affected by the presence of buses (17).

While the aforementioned methods and models have the potential to be applied to the A Line after study, saturation flow and capacity at signalized intersections are two extremely important parameters that should be given increased attention. While several manuals exist to calculate the capacity of bus stops, bus facilities, and the capacity for vehicles at intersections individually, they do not consider the interactions between these two modes (18, 19). Consequently, for this study, it is important to consider how capacity can be calculated using other methods. Although some microsimulation traffic models may have capabilities to determine the interaction between the buses and intersections, clear guidelines do not exist regarding how to directly calculate and evaluate the impact of buses on intersections. For

example, a study from Shao et al. found that the traditional approximation of headway overestimated the actual value, and accordingly, saturation flow rate was underestimated (20). Thus, a new estimation model was developed for the calculation of saturation flow rate to determine an intersection's capacity. A saturation flow adjustment factor for population may also be needed to determine the capacity of an intersection (21). Other factors to consider when estimating the capacity are saturation flow rate differences between multiple through lanes as well as the pavement conditions. The right lane may have lower saturation flow rates than the left lane due to aggressive drivers (21). Calculating intersection capacity will be essential for this study as capacity along the A Line route is estimated.

2.2 LITERATURE ON BRT QUALITY OF SERVICE

In order to obtain avenues of analysis when studying general perception users and non-users have regarding the A Line quality of service, previous studies examining the impact of BRT systems on rider satisfaction were analyzed. To determine the most effective features offered by BRT systems, Baltes (2003) analyzed the data from two onboard surveys conducted in 2001 along the BRT lines in Miami and Orlando, Florida (7). Baltes used a stepwise regression to estimate the importance of each attribute to the overall satisfaction and found that some BRT features such as high service frequency, reliability, comfort, and travel time were most valued by passengers. Based on the results, it is recommended that many features of BRT could be added to other bus systems to improve their quality of service. By discussing the main attractions of BRT to the riders, this paper offered valuable insights for research and implementations regarding future BRT systems. Several similar studies also explored rider satisfaction with BRT features (22–24). Nevertheless, although these studies identified service attributes that are important to BRT riders, their analyses only focused on BRT services. To better understand the improvements that BRT could provide, the comparison between BRT and conventional bus services is necessary.

Cao et al. contributed to the BRT research by exploring and comparing rider satisfaction with BRT and other types of transit services (25). This study used the BRT service in Guangzhou, China as an example and distributed surveys at 20 stations along a transit corridor in the city. Three types of transit services were surveyed: BRT, conventional buses, and the metro rail service. The final data included around 500 observations for each type of service. Using bivariate ordered probit models and multivariate analyses, this study showed that, although the overall satisfaction of BRT was lower than the metro, BRT still offered a better quality of service than conventional buses. The three attributes that contributed most to this difference between BRT and conventional buses were ease of use, safety while riding, and convenience of service.

Aside from BRT services that are fully equipped with major BRT features, arterial BRT, which operates in mixed traffic with only select BRT features, has also begun to launch in many cities, including the A Line in the Twin Cities, the Metro Rapid in Los Angeles and the Select Bus Service (SBS) in New York. Cain and Flynn (2013) categorized this type of BRT service as “BRT-Lite”, whereas the services with all major BRT features are categorized as “full service BRT”(26). “BRT-Lite” often does not have dedicated right-of-ways and operate in mixed traffic, but they have some of the low-cost BRT features such as signal priorities, far-side stops, online boarding, and enhanced stations. With the development of this type of rapid transit, some researchers have also begun to study its quality of service from the perspective of passengers.

Cain and Flynn explored the difference in the determinants of overall satisfaction with five different types of transit in the Los Angeles metro area: the Metro Rapid (“BRT-Lite”), Metro Orange Line (“full service” BRT), light rail, heavy rail, and local bus services (26). The study used a combination of focus

groups and attitudinal surveys to explore the differences in rider satisfaction among these various types of transit services and the causes of these differences. The survey data contained approximately 400 observations of transit riders for each type of the six transit services through on-board surveys, as well as 400 observations of non-transit riders through telephone surveys. The results showed that the level of overall satisfaction for full-service BRT was higher than conventional buses' and similar to light rail transit. This difference in overall satisfaction across transit modes resulted from various tangible service attributes such as reliability and service span, as well as intangible attributes such as safety and comfort. The results also indicate that "BRT-Lite" achieved particularly high overall satisfaction per dollar invested, thus making "BRT-Lite" a highly cost-effective transit investment option.

Wan et al. (2016) also explored riders' perception of a BRT-Lite service that operates in mixed traffic (6). They interviewed 1,700 New York City Select Bus Service (SBS) riders and analyzed the data with ordinary least squares (OLS) linear regression models. The results showed that service frequency, reliability, and speed were influential on the overall satisfaction of all the routes, which is consistent with previous transit studies. The information provided at stations where there were more riders who were relatively unfamiliar with the service also had a significant impact on the overall satisfaction of SBS. This study offered valuable insights regarding BRT that operates in mixed traffic. Nevertheless, the OLS linear regression used in this study was not capable of addressing the potential multi-collinearity among service attributes.

As shown above, various statistical approaches have been used to examine the rider satisfaction with BRT services, including OLS linear regression (6), stepwise regression (7), and ordered probit models (25). Nevertheless, statistical regression has certain limitations. First, a valid statistical model requires that the dependent variables follow a particular distribution, which the overall satisfaction usually does not meet. Second, because independent variables are sometimes highly correlated with each other, the potential multi-collinearity decreases the salience of the model and the results. Third, it is difficult to visualize the potential non-linear relationships between satisfaction with individual service attributes and with the service as a whole. As a result, the following study of the A Line employed a machine-learning method and a gradient boosting algorithm in order to overcome the limitations of traditional regression and increase the salience of the modeling results.

2.3 LITERATURE REVIEW CONCLUSION

In summary, the reviewed literature are from two areas—one on how transit system configurations affect the capacity of road/intersection and a second area regarding how users' perceive the transit service quality. For the former aspect, several key questions were answered in the literature review, including how different parameters affect capacity, how negative impacts on traffic from bus lines can be mitigated, and how different methods and models can be utilized to best conduct the research for the study. Lacking from the current literature are specific guidelines and best practices on how to most accurately calculate vehicle capacity in the presence of bus stops and buses, especially for settings in the United States. This is the topic that will be explored further. Although, there are many suggestions on how individual parameters can be measured, it will be important to amalgamate the information from these various studies to find an accurate method to determine the impact of the A Line BRT on surrounding traffic.

For the latter aspect, articles were explored concerning BRT basics, how BRT affects satisfaction compared to other transit types, arterial BRT systems, different determinants of rider satisfaction, rider perception of BRT in mixed traffic, and several statistical methods to examine satisfaction. Despite many studies on rider satisfaction of conventional BRT, the number of studies focusing on arterial BRT is

relatively limited. As arterial BRT services become popular, it is important to understand their performances, influential attributes, and their differences from local buses. Using the A Line in Twin Cities, Minnesota as an example of arterial BRT, this project aims to explore riders' perceptions and satisfaction of the A line, provide policy implications, and contributes to the existing knowledge regarding the arterial BRT.

CHAPTER 3: CAPACITY DATA DESCRIPTION & OVERVIEW

In order to analyze the potential impacts of the A Line, several datasets were employed. The datasets include both existing data that was acquired from different transportation agencies and new data that was collected specifically for this project. The major sources of data that are utilized in the traffic and capacity portion of this research are existing Automatic Passenger Counting (APC) information and new video-based data.

3.1 CAPACITY DATASET

Prior to the selection of the sites at which video data was collected, a tour of the A Line route was conducted via car to assess current conditions at each bus stop. The main factors recorded for each A Line stop were the positioning of the stop (near-side, far-side, or midblock), the number of lanes in front of the stop, whether the intersection nearest the stop was signalized, and the availability of light poles or signal arms for camera installation.

Using the data collected during the preliminary site visits, and after consulting with the project's technical liaison, four sites (two intersections with both a northbound and southbound station) were selected (Figure 1). The first pair of stops, located at the intersection of Snelling and Dayton (also referred to as "Dayton"), was characterized as a far-side stop in the northbound direction (Figure 2) and a near-side stop for the southbound direction where both locations were relative to Selby Avenue. In addition, both northbound and southbound stations were located on-line and had two thru-lanes and one left turn lane. The second pair of stops, located at the intersection of Snelling & University (also referred to as "University"), was denoted as a near-side stop (Figure 3) and far-side stop relative to University Ave for the northbound and southbound directions respectively. These stations were again located on-line and had three lanes in the southbound direction (two thru and one left) and four lanes in the northbound direction (two thru, one left, and one right). The University station was primarily chosen given that it is the busiest station along the A Line route. Thus, if it were shown that the A Line had no effect on surrounding traffic in these high-volume conditions, it could be inferred that the buses would not impact the other, less busy, stations.

At each of the studied intersections, two battery-powered video recording stations were affixed to signal arms and light poles, one facing the northbound station and the second pointed in the direction of the southbound station. These cameras were attached to tall structures such as light poles to provide a wide and long-range view. Care was taken to include at least one signal head for the relevant signal and, in the case of the University stops, the light rail tracks, in the view for each camera. At Snelling and University, the southbound camera began recording on August 2, 2017 and ran until August 31, 2017 while the northbound camera started on August 2, 2017 and ran until September 5, 2017. For the Dayton station, both the southbound and northbound cameras began on August 10, 2017. The southbound camera recorded up until September 15, 2017 while the northbound camera recorded until September 9, 2017. Video was collected between the hours of 6:00 am and 9:00 pm. The video collection thus provides approximately one month's worth of data for each camera including both peak and off-peak times as well as encompassing the two week period of the Minnesota State Fair so as to include both normal and extremely high-volume traffic. In total, over 1,000 hours of video footage were collected at the two station pairs mentioned above. Given this large amount of video data, the analysis below focuses only on the two northbound stations.

In addition to the aforementioned video data, APC data also provides essential information by assigning a unique trip identification number to each bus. Some of the most important and relevant information from the APC dataset includes the number of passengers boarding and alighting, the date and time, and the travel direction at each individual stop for each A Line bus.

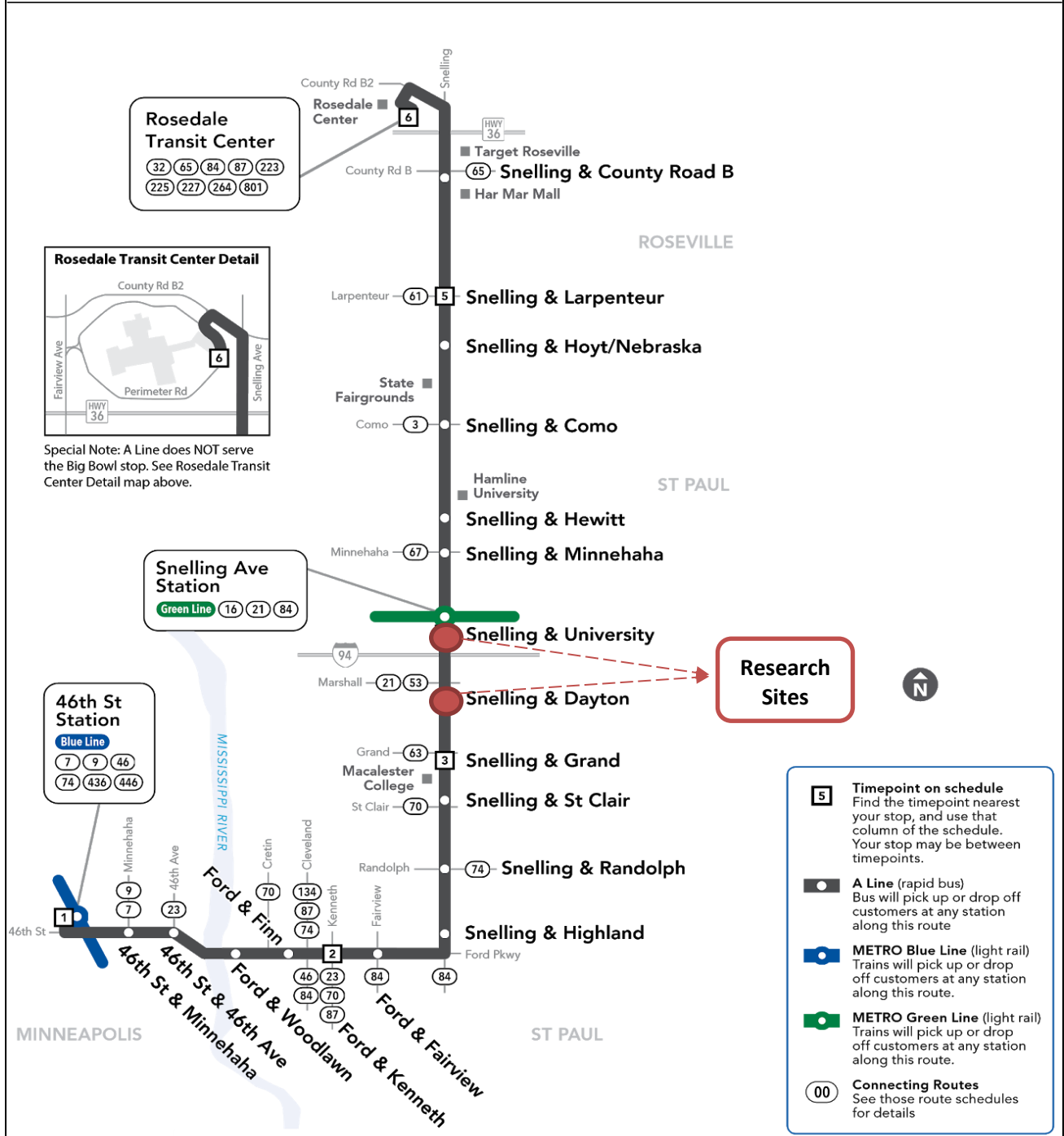


Figure 1: A Line BRT route with denoted research stops in red



Figure 2: Camera View-Snelling and Dayton (northbound stop)

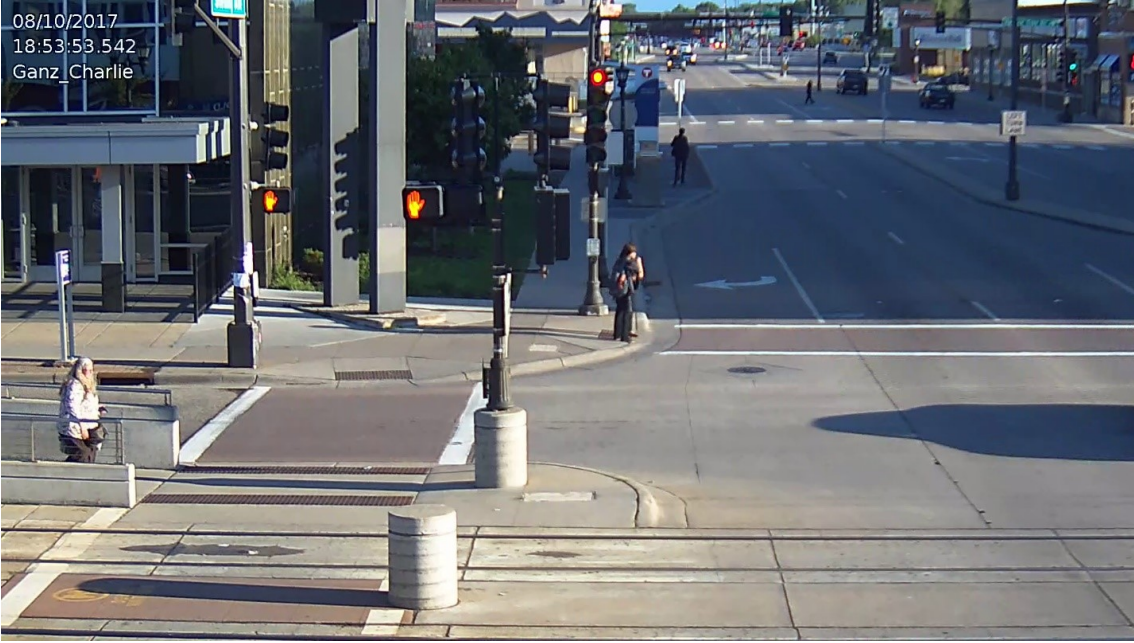


Figure 3: Camera View-Snelling and University (northbound stop)

3.1.1 Video Data Reduction & Filtering

In order to reliably and consistently interpret the video data, two data filtering passes were conducted.

The first data reduction pass consisted of finding all BRT buses that were filmed at both of the researched stations. The buses at the selected sites were found by scanning the video at high speed to find every instance where a bus stopped at the BRT stop being filmed. For each A Line bus that was identified, the time of arrival was noted and a screenshot was made of the beginning of the most recent red light before the bus arrived that was not influenced by a LRT or emergency vehicle. While observing the Snelling and University stops, the time that a light rail train crossed Snelling was noted so that it could be avoided. Instances that light rail trains or emergency vehicles were present were recorded and avoided because of their influence on cycle length as a result of signal priority or preemption.

The arrival screenshots were then examined to roughly determine the type of traffic flow. If a queue was present at the stop-line of the relevant intersection at the beginning of the red light, conditions were considered to be over-saturated because the demand was higher than the capacity for the green phase. If a queue was not present but the traffic on the road downstream of the relevant intersection was approximately as dense as the traffic on the road upstream of the relevant intersection, conditions were considered to be approximately saturated because the queue from the previous red phase had likely taken most—if not all—of the previous green phase to clear. If no queue was present at the stop-line of the relevant intersection and the traffic was sparse both upstream and downstream of the relevant intersection, conditions were considered to be unsaturated.

Following the sorting of the screenshots, 200 bus arrivals at each site were selected. The collection of arrivals contained data from each of the three conditions but particular emphasis was placed on the arrivals during approximately saturated conditions as this condition represents the situation in which bus arrivals have the highest potential to impact surrounding traffic.

Once the bus arrivals of interest had been identified for each site, a second pass of the data was performed in which information was collected for each traffic signal cycle for four cycles before the bus arrived and for four cycles after the bus arrived.

Figure 4 shows the numbering of traffic cycles and their relationship to cycle zero, which is defined as the cycle in which the bus arrived at the station.

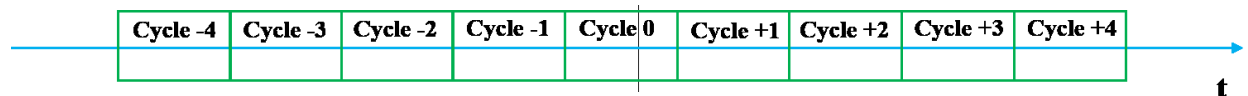


Figure 4: Traffic measure counting periods before and after bus arrival

For the red phase of each cycle, the collected data consisted of the time of day the last car went through after the yellow phase began, the number of passenger cars in the queue at the end of the red phase, the number of large vehicles in the queue at the end of the red phase, whether there was a gap in front of the bus, and, where applicable, whether a queue in the left turn lane was blocking any of the thru-lanes. For each of the green phases, the collected data consisted of the time of day that the green phase began and the number of passenger cars and large vehicles entering the intersection from the direction of the bus stop. The time of day that the bus arrived and departed from the stop were also recorded.

Using the data from the second pass of the data reduction process, several pieces of information were calculated. For each cycle, the length of the queue (in passenger car equivalents) at the end of the red phase, the effective green time, and the average flow rate (in passenger car equivalents per lane per hour of effective green) were calculated. Passenger car equivalents were calculated using the Highway Capacity Manual (HCM) standard values for relevant conditions. Additionally, for each bus, the dwell time and the portion of the dwell time that overlapped with the effective green phase (denoted as green dwell time) were calculated. Bus dwell time was recorded during Cycle 0 while all other measures were recorded during cycles $\pm 1, 2, 3, 4$.

Four cycles, rather than a smaller number, were chosen on either side of cycle zero in order to minimize random fluctuations in traffic conditions and so that aggregate effects could be observed. On average, one signal cycle phase for Snelling & University was 2 minutes long while the average cycle phase for Snelling & Dayton was 1 minute 59 seconds long. Thus, data collection extended 8 minutes on either side of a bus arrival. Due to the A Line’s high frequency headway of only 10 minutes for the majority of the day, one potential concern of this approach was that the traffic conditions would be double counted as the four cycles after the arrival of one bus correspond to the four cycles preceding the next bus. In order to address this feature, autocorrelation and partial autocorrelation tests were conducted on the queue length and flow data in the four before cycles together with the cycle during which the bus arrives.

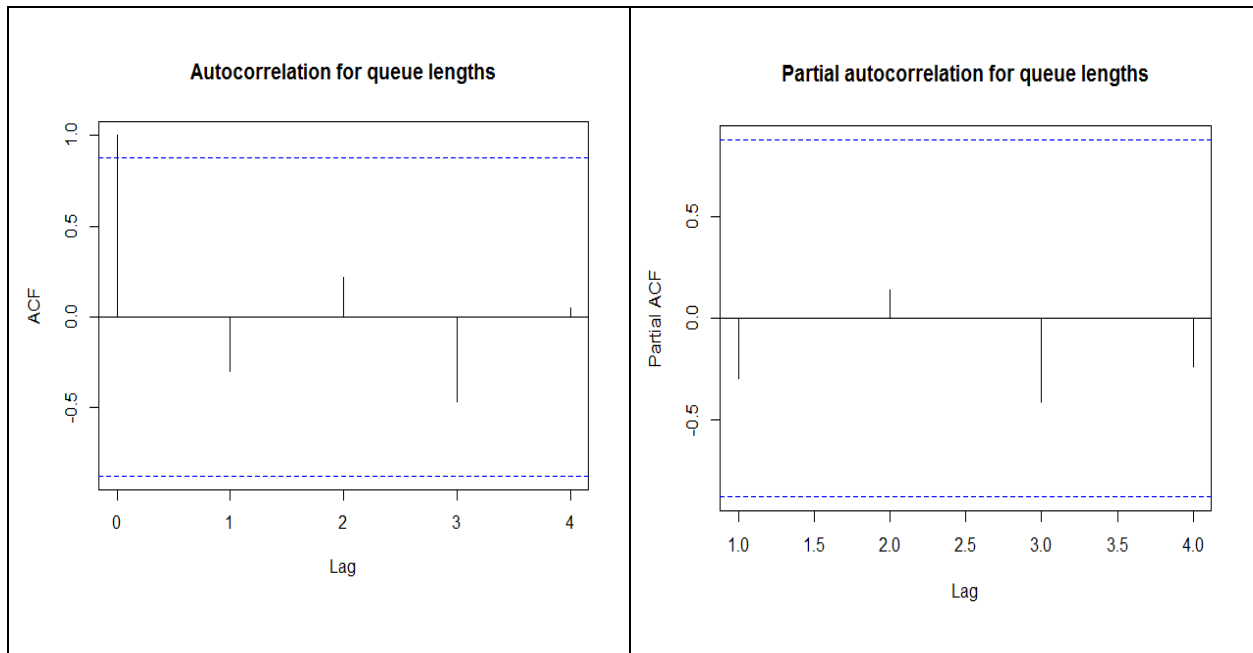


Figure 5: Autocorrelation and partial autocorrelations for “before arrival” queue lengths

Figure 5 shows the autocorrelation and partial autocorrelation results for queue lengths of one randomly selected bus record which is indicative of other randomly sampled points. In the autocorrelation plots, “lag” represents the distance (as given in number of cycles) between the two queue lengths being compared. Thus a lag of 2 indicates that two cycles separate the values being compared. Lag 0 is excluded from this analysis because this quantifier indicates a cycle that is correlated with itself and will thus, always have an absolute value equal to 1. From the autocorrelation plot, it is apparent that none of the correlations, aside from this lag 0 value, cross the threshold for being

statistically different from zero (as indicated by the two dashed horizontal lines). In addition, the results of the correlation are both positive and negative indicating differences among the cycles. Had a bus impacted the before arrival queue lengths of the preceding bus's before-arrival queue lengths, there would have been correlations among the four conditions. Therefore, the autocorrelation shows that there are no significant correlations among the four before-arrival queue lengths and that four cycles is not only a valid approach but that four cycles are needed to minimize the fluctuations in the average before and after traffic conditions. Partial autocorrelations reflect the correlations after removing the linear dependence from the data. In this test, it is again shown that none of the correlations are significantly different from zero.

The analysis of flow rates resulted in the same conclusion that there were no significant correlations among the four cycles prior to the arrival of a bus. Thus, the results for the randomly selected records of data, though not the complete data set, indicate that all four cycles can be used for the "before arrival" traffic condition without fear of double counting data in the following analysis. Thus, in future studies, fewer signal cycles could likely be observed. The drawback of using future cycles in the future, however, is that there would be more variation in the data points leading to a less statistically robust conclusion.

This a time-series analysis where a series of queue lengths (flow rates) before and after an A Line bus arrival forms one piece of sample data. Instead of averaging all sample data that may lead to the loss of potential information indicating negative capacity impacts of bus arrivals, autocorrelation and partial autocorrelation analyses were carried out for each sample. For queue length, 18 samples of the State Fair period and 140 samples outside the State Fair period were checked, none of which had correlations greater than the critical value 0.877. For flow rates, 38 and 162 samples for the State Fair period and non-State Fair period were checked, the outcomes were the same – none showed significant correlations. Thus, we can safely use the data four cycles before and after without being worried about the double-counting problems.

Even after this careful setup and filtering of the data, however, one limitation of the video data remained. The limitation was that because of the roadway configurations leading up to the station and the limited field of view for the video camera, queue length could not be accurately counted when the queue extended beyond the scope of the video frame. These "invisible queues" were denoted in the dataset with a queue length place-holder value of 100. As this value did not represent the actual queue length, however, it could not be included in the analysis and was thus filtered out. In order to determine if this filtering would skew the results from the rest of the dataset, the number of cycles that contained an "invisible queue" after the arrival of a bus were counted and compared to the number before the given bus arrived for the non-State Fair Snelling & University northbound stop (Figure 6). From the results of this analysis, it is clear that the impact of these "invisible queues" is normally distributed and that the vast majority of invisible queues occur at the same rate before and after a bus arrival. This observation thus justifies the decision to exclude these invisible queue lengths. While not included as a figure, the conclusion from the invisible queue analysis of the State-Fair Snelling & University data and the non-State Fair Snelling & Dayton are identical to that from the non-State Fair Snelling & University station shown above. After this filtering, and removing data points in which the green dwell time was a statistically significant outlier, the remaining number of data points used in the following analysis is shown in Table 1. No data points were present for the Dayton northbound station during the State Fair period due to time limitations.

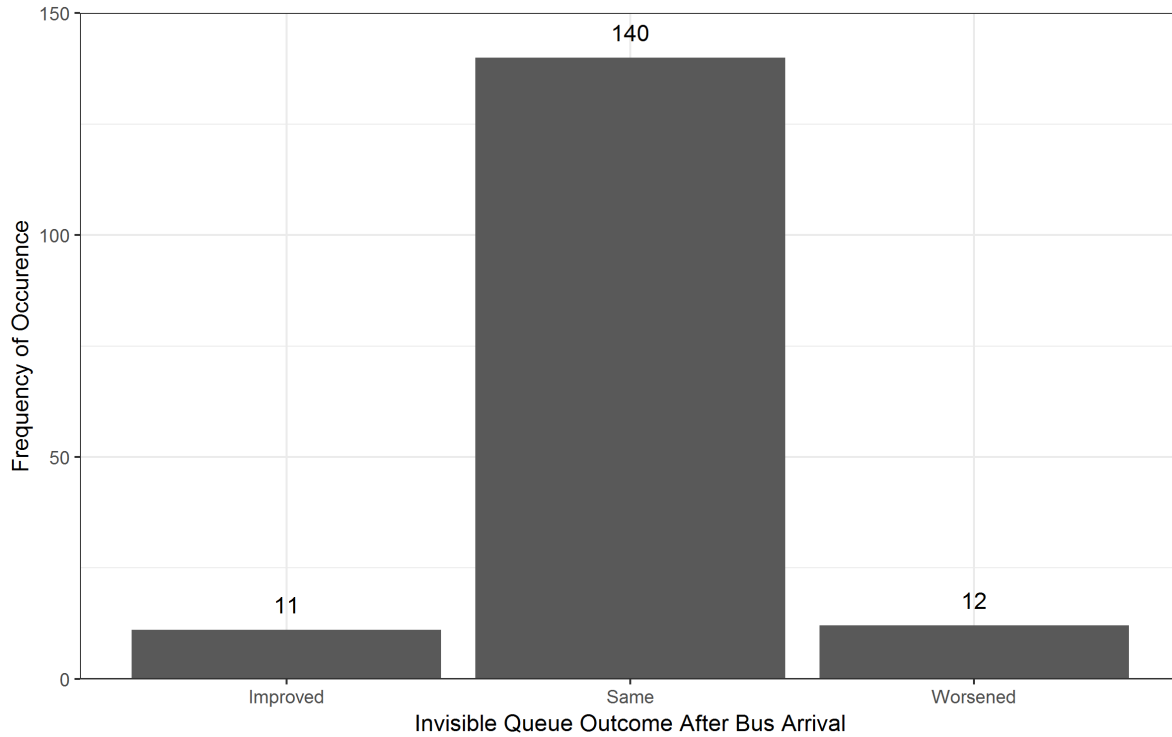


Figure 6: Invisible queue behavior during non-State Fair period at Snelling & University

Table 1: Remaining observations used in the capacity analysis for each location and period

	State Fair	No Fair
University NB	38	163
Dayton NB	N/A	68

CHAPTER 4: CAPACITY ANALYSIS

4.1 STATE FAIR IMPACTS

As described in Chapter 3, two sets of video-based data were employed in this research, one in which traffic was heavily oversaturated during the Minnesota State Fair and one dataset from normal traffic conditions during which traffic was at, or slightly above, saturation. Figure 7, below, displays a sampling of the variables used in both datasets plotted against the traffic cycle number (as described in Figure 4) to highlight the differences and similarities between the data before and after bus arrival. The primary similarity between the two periods is the relative traffic condition stability from four cycles before bus arrival in Cycle 0 to the four cycles after the arrival. While there is greater variability for State Fair data in the cycles immediately adjacent to the bus arrival, this is likely due to the oversaturated nature of traffic during this period. It is also important to note that even this variability is on the scale of less than 5 PCE and again is approximately constant when at a distance one or more cycles removed from the bus arrival. This stability is a first indication that A Line bus arrivals may not affect traffic conditions as will be discussed later in this report. From Figure 7, it can be seen that the volume of traffic at the intersection of Snelling & University during the State Fair was approximately 1.75 times the volume during normal conditions. Additionally, under normal conditions, it can be further observed that the intersection is slightly saturated, as evidenced by a residual queue of only approximately three passenger car equivalent (PCE) lengths after each green cycle, as compared with the oversaturated State Fair queue that was, on average, approximately 35 PCE.

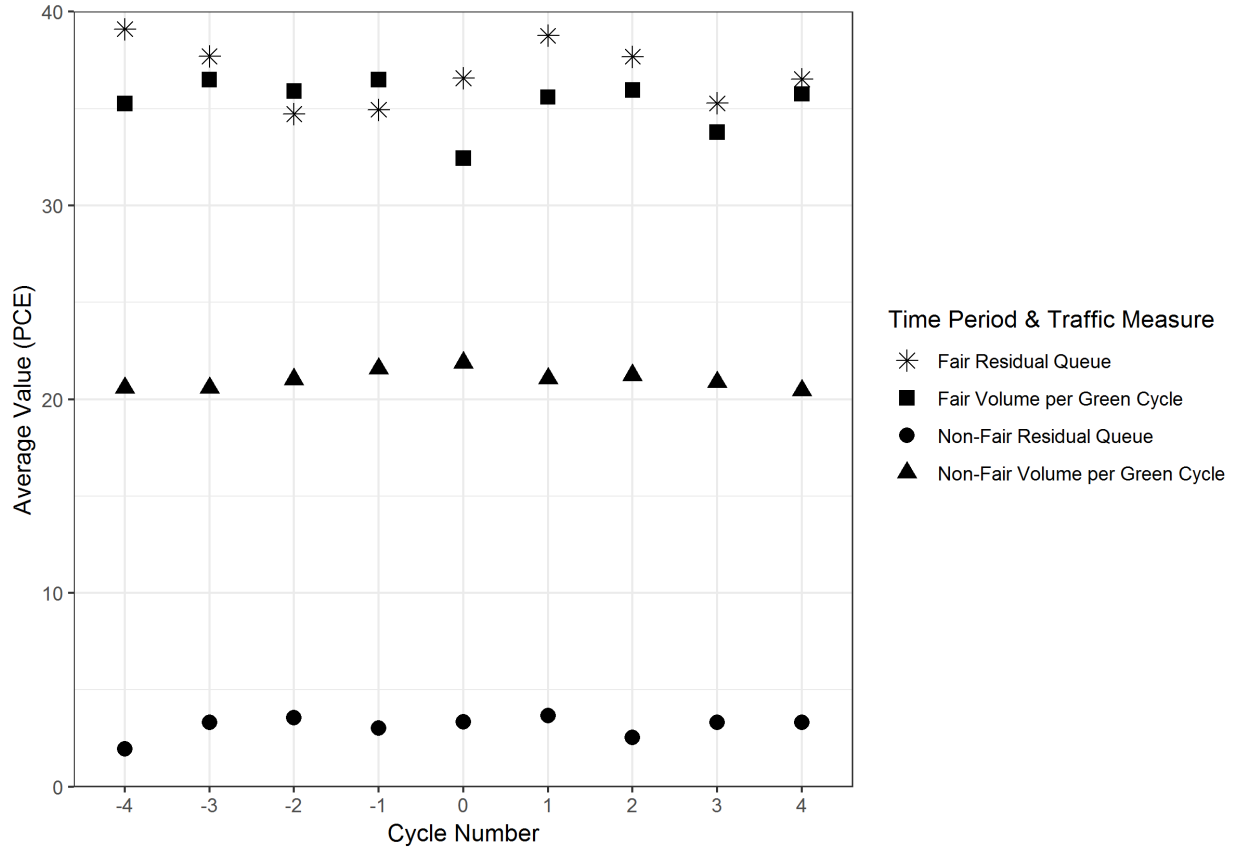


Figure 7: Traffic conditions as a function of cycle number (Snelling and University)

Furthermore, when comparing the average bus dwell time at each stop using APC and AVL data from the non-Fair period (Figure 8a) and the period during the State Fair (Figure 8b), it is apparent that both periods have long average dwell time at stop number 13 (Snelling & University) as expected given that this is the stop at which passengers can transfer to the Green Line Light Rail. Of more significance, however, is that for the State Fair period, dwell time greatly increases by approximately 40 seconds at stop number 16. This makes intuitive sense as stop number 16 is the primary stop serving the state fair. Outside of the State Fair period this stop is located at the corner of Snelling & Como but during the state fair the stop was temporarily moved to Snelling & Midway to better serve the State Fair entrance (27). Thus, it is clear from Figure 7 and Figure 8 that the two periods represent very different traffic conditions and as such, the following analysis treats each period separately.

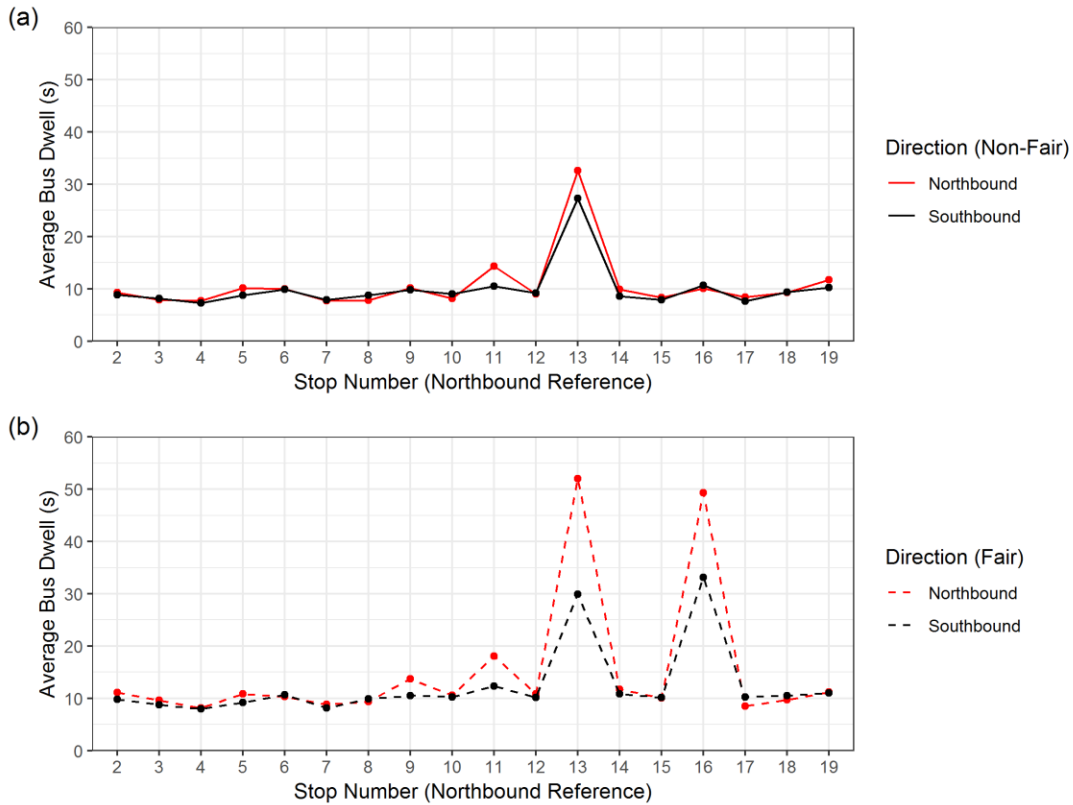


Figure 8: Dwell time along A Line route outside (a) and during (b) 2016 State Fair period

In summary, before proceeding with the bulk of the capacity analysis, data was filtered into State Fair and non-State fair datasets in which invisible queues were removed and four cycles were used both before and after arrival for the relevant traffic conditions.

4.2 CLUSTERING ANALYSIS METHODOLOGY & RESULTS

Average queue lengths and flow rates for the four signal cycles before and after the arrival of a bus were calculated and used together with bus dwell times during a green signal as attributes used in clustering the data into distinct subsets. Each group was averaged rather than taken as four distinct data points, in order to obtain a stable state from which traffic measures could easily be compared. As detailed above, if these cycles were not averaged, the random variation of these measures would negatively affect the ability to assess the potential impact A Line buses impart on surrounding traffic.

The clustering method applied in this research is “K-Means Clustering”, which partitions the complete sample of data points into k number of subsets in which each data point is closer to its own cluster center than other cluster centers. After analyzing the data for use in the “K-Means Clustering Method” across thirty different indices, which calculate the fit of a given cluster, it was determined that the use of k=2 clusters would best fit the data used in this report as two clusters were most effective in minimizing intra-cluster deviation of points and the within-cluster sum of squares.

Prior to analyzing the data with the clustering method, all data were normalized on a scale from 0-1, using Equation 1, to avoid a domination problem of any one attribute.

$$X_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

In particular, if this normalization approach had not been taken, dwell time would have dominated the clustering process because these values are usually larger than the other traffic measure. Thus, by normalizing the data, single attribute domination was avoided while still preserving the relative relationship between traffic measures. Following the clustering analysis, normalized values were converted back to their respective averages in order to preserve the cluster distributions while at the same time using physical values for ease of interpretation in all following figures.

If bus dwell time has a significant negative impact on the road capacity or traffic flow, it is expected to see cluster(s) with highly different traffic conditions (i.e. queue length or flow rate) when comparing the measures from before and after the bus arrival. Thus, by observing the cluster positioning, one can qualitatively determine if a correlation exists between bus dwell time and traffic measure changes.

4.2.1 Clustering Results

Figure 9a and Figure 9b illustrate the relationships between the average traffic conditions (queue length and traffic flow rate respectively) before (x-axis) and after (y-axis) the arrival of a bus for the non-State Fair period at the intersection of Snelling & University. This plot is the two-dimensional projection of the original 3-D point cloud which is comprised of green dwell time, before bus arrival traffic condition, and after-arrival traffic condition. The k-means cluster centers are denoted by black squares labeled with the centers' average green dwell times to give perspective on the three-dimensional aspect of the data. Cluster 1 (circular points) corresponds to short green dwell times of less than 15 seconds and Cluster 2 (triangular points) represents longer green dwell times ranging from 15-45 seconds. Due to the fact that the dwell times are markedly different, the 2-D projection of data shown below appears to portray only one cluster rather than two. However, the clusters are in fact different because of their different three dimensional depth (green dwell time) that is indicated in the clusters' parenthetical label. Additionally, both plots in Figure 9 have a dashed "line of equality" which represents where traffic measure values are the same before and after bus arrival. Thus, if the data lie primarily below this line, it can be concluded that the bus positively impacts the relevant traffic conditions. If the majority of the data points are above the line, the bus negatively impacts the conditions, and if the points lie along the dashed line it can be inferred that bus arrivals have no significant impact. In Figure 9a and Figure 9b, the majority of the data points, as well as the two cluster centers, are closely distributed along the equality line. In addition, a two-sample Kolmogorov-Smirnov (K-S) test was performed in order to compare the similarity in the distribution of the traffic conditions before the arrival of a bus with the same traffic condition after the bus arrival. From the K-S test, it was found that the p-values for queue length and flow rate were 0.8492 and 0.7658 respectively. Thus, in

both instances, the p-values were much greater than 0.05 and as such, the null hypothesis—that the traffic conditions before bus arrival had the same distribution as the values of the traffic condition after bus arrival—was unable to be rejected for both queue length and traffic flow. Thus, when taking this result in tandem with the clustering of data points along the equality line, it can be inferred that the arrival of an A Line bus does not affect aggregate traffic queue length or flow rate at Snelling & University despite the fact that data points in the second cluster have an average green dwell time of 26 seconds, or roughly 28% of the average green time signal length. Additionally, the presence of the cluster centers near or on the equality line further indicates that the data points which do occur further away from the line are more of a random effect, as the cluster center represents the mean of the data points within the cluster.

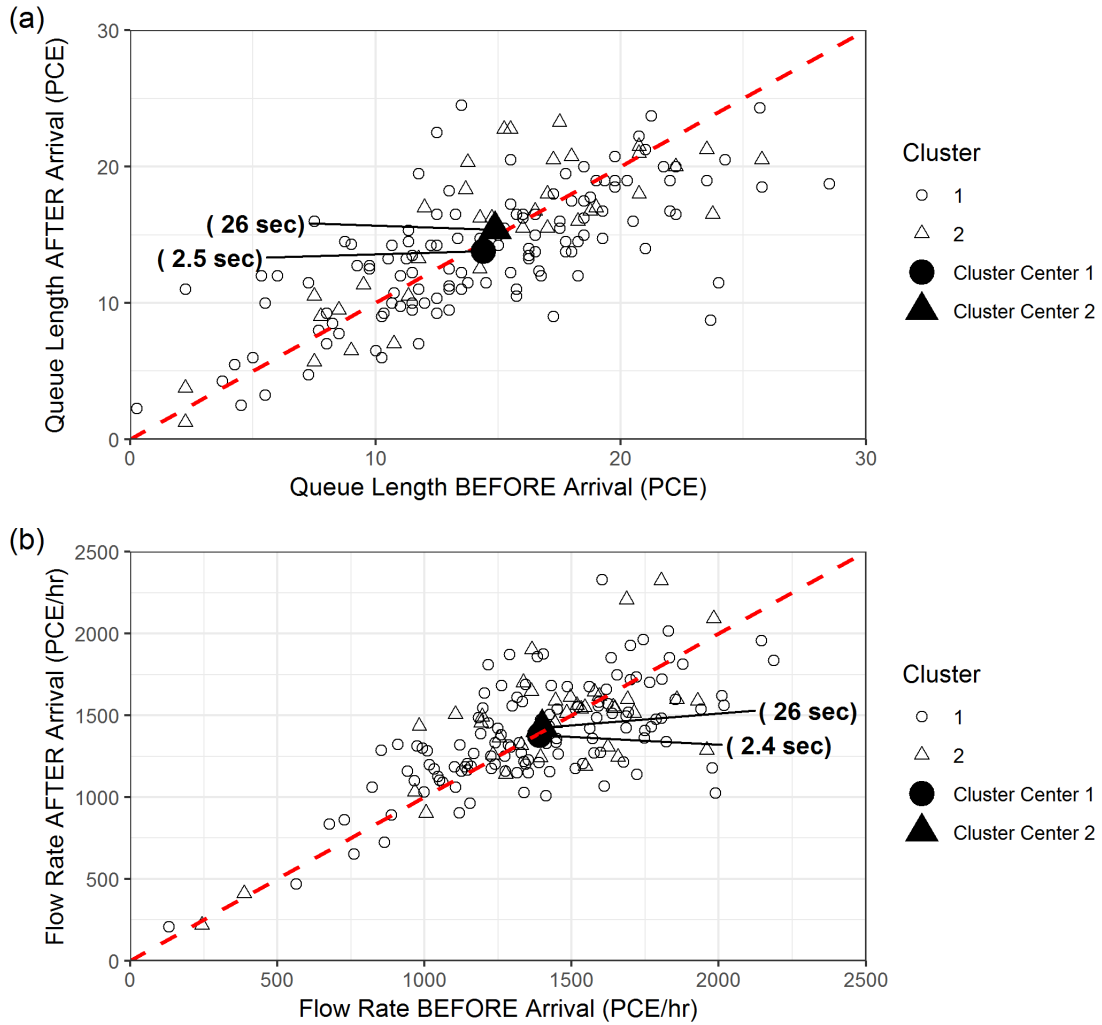


Figure 9: Snelling & University non-State Fair traffic condition clustering

Figure 10 contains two plots illustrating the same comparative relationships described in Figure 9 except that the data in Figure 10 is from the State Fair period of high volume traffic. When examining Figure 9 in comparison to Figure 10, it is important to note that there are fewer data points in the State Fair sample (Figure 10) due to a shorter time period represented by this data and because many bus records only contained invisible queues therefore removing the value of a queue length analysis. Additionally, both the queue length and flow rate are higher during the fair period as expected. Given the more limited number of State Fair data points, the dichotomous split between the green dwell times of the two clusters is less distinct than for the non-fair data. Instead, only the average green dwell times are distinct between the two clusters as Cluster 1 has an average green dwell time roughly double that of Cluster 2. Similar to the non-State Fair data, however, it can again be concluded that A Line BRT-Lite bus dwelling does not have a significant impact on traffic queue length (Figure 10a) or traffic flow rate (Figure 10b). This conclusion can be reached because the data are clustered around the equality lines and the K-S test p-values for queue length and flow rate traffic conditions were 0.9998 and 0.08973, respectively, indicating, again, that the null-hypothesis (stating before and after traffic condition distributions are statistically similar) cannot be rejected. Additionally, because the cluster centers fall

along the line, it can further be inferred that deviations away from the line are due to random variations.

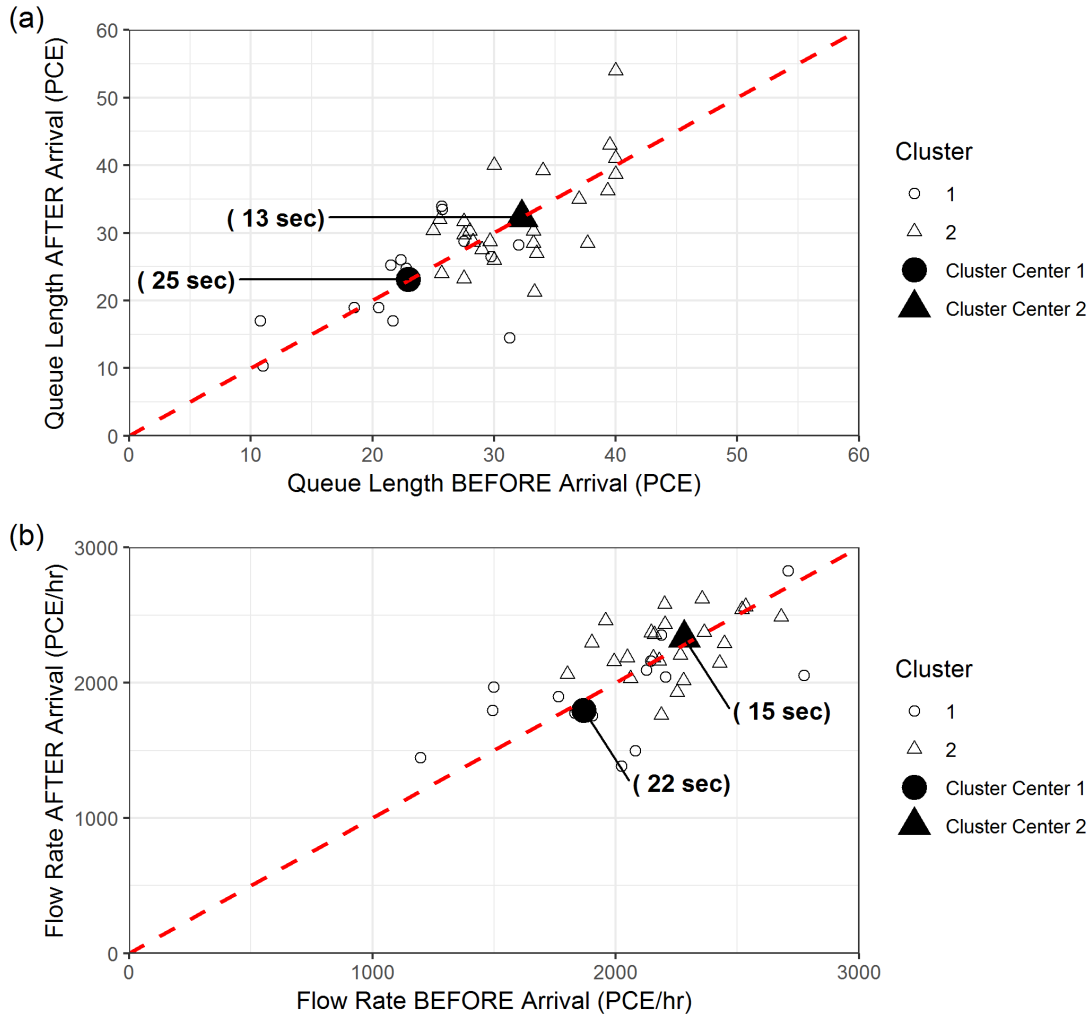


Figure 10: Snelling & University State Fair (high volume) traffic condition clustering

The same analysis described above for Snelling & University was performed for the intersection of Snelling & Dayton outside the State Fair time period with the results depicted in Figure 11. From the Dayton plot (Figure 11), one can observe the same aggregate behavior present at Snelling & University outside of the State Fair (Figure 9) and Snelling & University during the State fair (Figure 10). Namely, all cluster centers fall along the line of equality and the two flow rate cluster centers are almost identical—mirroring a similar behavior shown at Snelling & University during the same time period. As before, because the cluster centers fall along the equality line, the points which do diverge away from the equality line are primarily due to random variation not systematic behavior. In order to quantify the data point's adherence to the equality line a K-S test was performed, as in the Snelling & University data analysis, and p-values of 0.9359 and 0.7344 were obtained for the queue length and flow rate analyses. Therefore, because these p-values were much larger than 0.05, the null-hypothesis cannot be rejected further confirming that the before and after traffic condition distributions are not statistically different from each other.

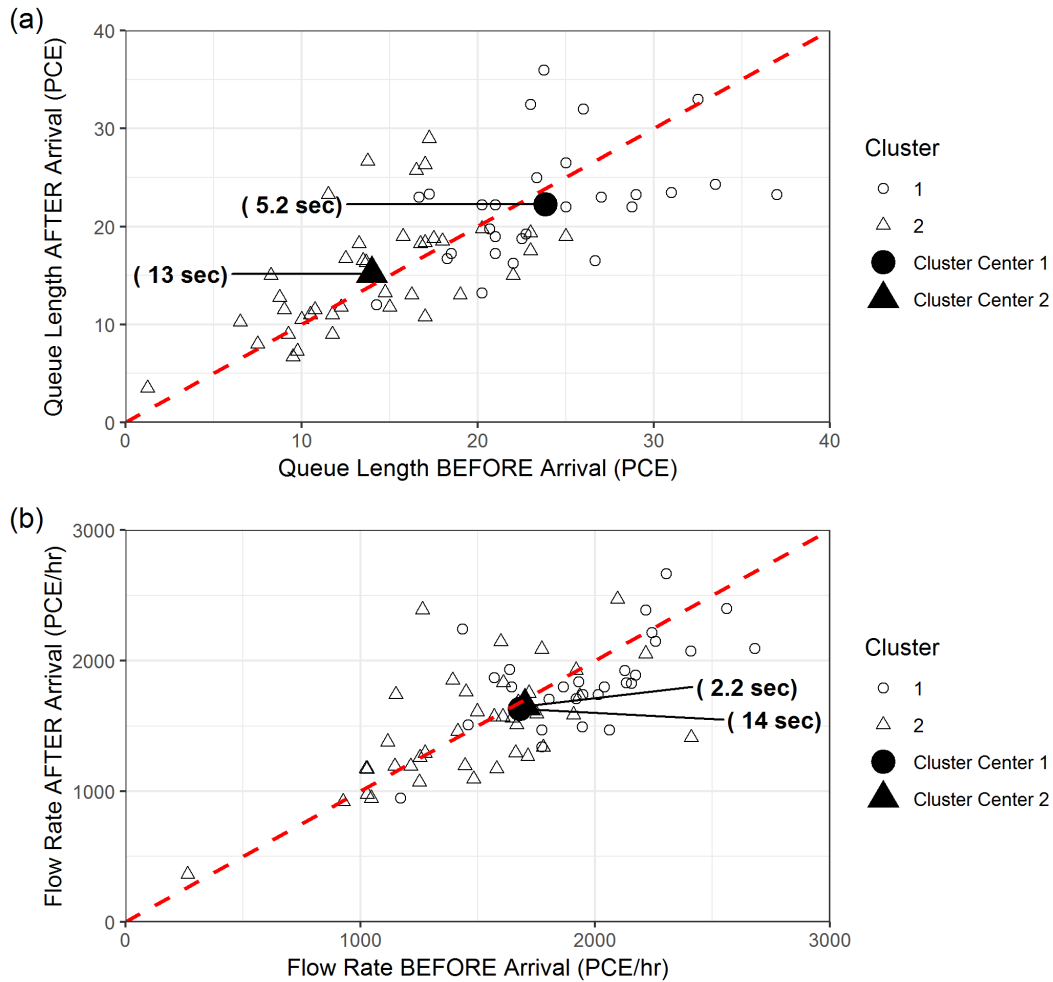


Figure 11: Snelling & Dayton State Fair traffic condition clustering

4.3 LINEAR REGRESSION METHODOLOGY & RESULTS

Two types of linear regression models were used to fit the traffic data in order to determine if there was a significant correlation between bus dwell time and queue length changes before and after the arrival of buses.

The first linear regression model takes the bus green dwell time as the independent variable and the change measurements, i.e. queue length changes and flow rate changes, as the response variables. The linear model is shown in equation 1, below, where the independent variable was chosen as the total time that bus dwell time overlapped with the green times of the downstream intersection:

$$y = \beta_0 + \beta_1 x. \quad (2)$$

The primary interest is in testing if the coefficient β_1 is statistically different from zero because if β_1 is non-zero, it is evidence showing that bus dwell time has an impact on the capacity of the road. To this end, a hypothesis test is carried out with a null hypothesis that the dwell time coefficient (β_1) is equal to 0 while the alternative hypothesis is that the dwell time coefficient is not equal to 0, as is shown in equations 3 and 4 respectively.

$$H_0: \beta_1 = 0 \quad (3)$$

$$H_a: \beta_1 \neq 0 \quad (4)$$

The second linear regression model, in contrast, takes the bus dwell time and average queue length (or average flow rate) before bus arrival as the explanatory variables, to determine if either variable significantly contributes to the traffic condition after a bus arrival. The model is as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2, \quad (5)$$

where, x_1 and x_2 represent the two explanatory variables—bus green dwell time and either queue length or flow rate before bus arrival—respectively.

As introduced in the previous section, traffic conditions during the State Fair period are dramatically different from normal operation conditions. Thus, the two linear regression models were fitted separately for both the State Fair period and non-State Fair period.

4.3.1 Linear Regression Results

The two linear regression models were fitted to State Fair and non-State Fair data separately with the regression results consolidated in Table 1. For all estimated coefficients, numbers in parentheses are the p-value followed by significance level denoted by the number of asterisks.

Given the p-values for coefficient β_1 in Model 1, as previously described, there is not enough evidence supporting the rejection of the null hypothesis that β_1 (bus green dwell time coefficient) equals zero. Thus, the results for Model 1 demonstrate that, regardless of which measurement was adopted to reflect general traffic capacity change (queue length or traffic flow), the impact of bus dwell time on the specific traffic condition change is not statistically significant.

While model 1 shows that green bus dwell time is not a factor that changes the traffic condition, Model 2 answers the question, which factor affects the traffic condition after the arrival of a bus? The fact that the coefficients for the before queue length and flow rate are strongly significant for all four regressions in Model 2, shows that the before queue length (or flow rate), rather than the bus dwell time, is the main driver in determining the traffic condition after the arrival of a bus. Thus, because the bus dwell time is again not significant, the results of Model 2 are consistent with Model 1. It is important to note that both estimated coefficients for queue length are positive, thereby confirming the intuitive results that a longer queue length before a bus arrival likely results in a longer queue length after arrival.

Table 2: Linear regression results with p-values listed in parentheses (Snelling & University)

Model	Period	Dependent Variable	β_0 (Intercept)	β_1 (Green dwell time)	β_2 (Before flow rate or queue length)
Model 1	State Fair period	Flow Rate Change	74.215 (0.270)	-3.878 (0.164)	-
		Queue Length Change	-0.749 (0.592)	0.048 (0.402)	-
	Non-State Fair period	Flow Rate Change	-12.215 (0.646)	1.232 (0.526)	-
		Queue Length Change	-0.718 (0.056) .	0.047 (0.088) .	-
Model 2	State Fair period	Flow Rate After	850.216 (0.005) **	-3.146 (0.220)	0.631 (3.56e-5) ***
		Queue Length After	4.100 (0.137)	0.059 (0.308)	0.825 (6.92e-7) ***
	Non-State Fair period	Flow Rate After	464.35 (5.98e-8) ***	1.213 (0.489)	0.657 (<2e-16) ***
		Queue Length After	4.323 (1.33e-7) ***	0.044 (0.065)	0.653 (2e-16) ***

Significance level: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ''

In order to determine if the deviations from the equality lines in Figure 9 and Figure 10 were truly random, the results of the linear regression (Table 2) and corresponding 95% confidence intervals (represented by the grey shaded band) were added to a plot displaying the difference in traffic condition as a function of green dwell time (Figure 12). From the four sub-plots in Figure 12, it is evident that, as demonstrated above, there is no significant trend between green dwell time and traffic conditions. This observation is shown by the trend lines for average queue length (Figure 12a & Figure 12c) and average flow rate (Figure 12b & Figure 12d). These fitted lines illustrate an increase in queue length over the range of green dwell times of less than five PCE for both State Fair and non-State Fair periods. Additionally, the fitted line for non-Fair flow remained approximately constant while State Fair flow decreased by up to only 100 PCE/hr, or 7.4% of the average flow during this period. Thus, any apparent relationship between the various traffic conditions and A Line green dwell time are so small as to be non-significant when compared to the average traffic conditions and aggregate behavior of the researched intersections.

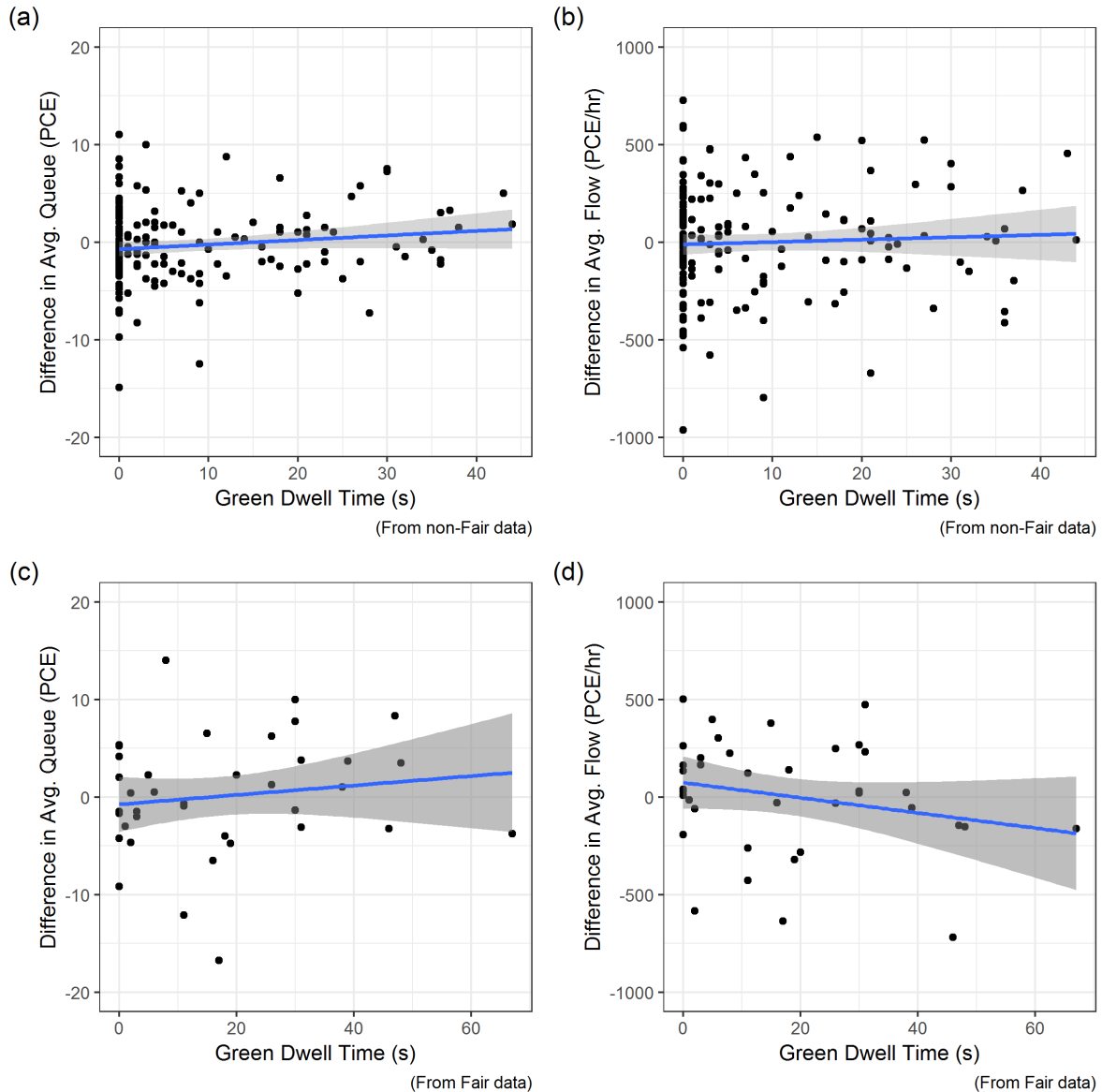


Figure 12: Snelling & University difference in traffic condition vs. green dwell time

The same process outlined above in Table 2 and Figure 12 for Snelling & University is followed below for the intersection of Snelling & Dayton with the only difference being that there was no State-Fair data. Similar to the Snelling & University regression results, given the p-values for coefficient β_1 in Model 1 for Snelling & Dayton, there is not enough evidence supporting the rejection of the null hypothesis that β_1 (bus green dwell time coefficient) equals zero when using flow rate change as the dependent variable. Thus, the results for Model 1 demonstrate that the impact of bus dwell time on traffic flow rate is not statistically significant. An additional similarity between the regression results for the two intersections is that before-arrival traffic conditions (β_2) are strongly significant as shown in Model 2. Unlike Snelling & University, however, green dwell time is a mildly significant factor in both queue length change (Model 1) and queue length after arrival (Model 2) at Snelling & Dayton. It is important to note that while these factors are marginally significant and positive, indicating that longer green dwell time leads to a longer queue length after an A Line bus arrival, the aggregate change in average queue length is

only approximately 5 PCE over the entire range of Green Dwell Times (Figure 13a). Thus, on the aggregate, it can be concluded that the overall impact of the A Line on surrounding traffic conditions is negligible at Snelling & Dayton as well as Snelling & University as previously detailed. Therefore, because these two stations, representing some of the busiest portions of the A Line route, show no significant impact, it can be further concluded that the A Line as a system does not impact intersection queue length or flow rate.

Table 3: Linear regression results with p-values listed in parentheses (Snelling & Dayton)

Model	Period	Dependent Variable	β_0 (Intercept)	β_1 (Green dwell time)	β_2 (Before flow rate or queue length)
Model 1	Non-State Fair period	Flow Rate Change	-115.077 (0.111)	6.809 (0.254)	-
		Queue Length Change	-2.022 (0.081)	0.210 (0.0304)*	-
Model 2	Non-State Fair period	Flow Rate After	413.997 (0.0111)*	6.447 (0.239)	0.689 (1.91e-11)***
		Queue Length After	4.436 (0.0314)*	0.149 (0.0961) .	0.676 (e.9e-11)***

Significance level: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.', 0.1 ''

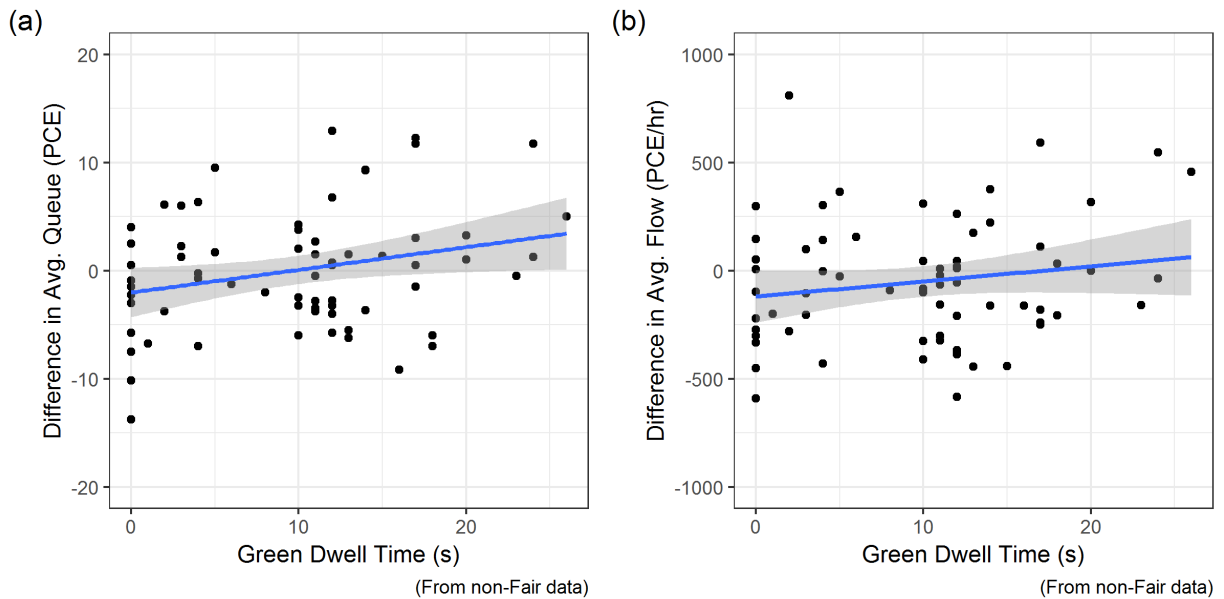


Figure 13: Snelling & Dayton non-Fair difference in traffic condition vs. green dwell time

4.4 TRANSIT CAPACITY METHODOLOGY & RESULTS

Transit capacity (the maximum number of passengers that can be carried past a certain point in a specific time period) was compared along the Snelling Avenue corridor before and after A Line implementation. Specifically, the load factor (the ratio of the number of passengers on a bus to the maximum number of seats on the bus) on the Route 84 sub-routes traveling along Snelling Avenue in 2016 was compared with the load factor of the A Line and Route 84 lines along Snelling Avenue in 2017. Load factors, were examined only along Snelling Avenue north of Ford Parkway because, as depicted in Figure 14, the headway and route geometry of Route 84 vehicles along this portion of the route was identical to current A Line service. For the 2016 Route 84 data, the sub-route 84x was excluded from the analysis as this route was a school extra making only a minimal amount of trips each day. Thus, this sub-route had a minimal impact on the corridor capacity and could be ignored.

In order to ensure consistency, weekday load factors were calculated over the same date range for both 2016 (prior to the Opening of the A Line in the summer) and 2017 routes. The date range chosen included only weekdays from the second Monday in March to the first Friday in June of both analyzed years.

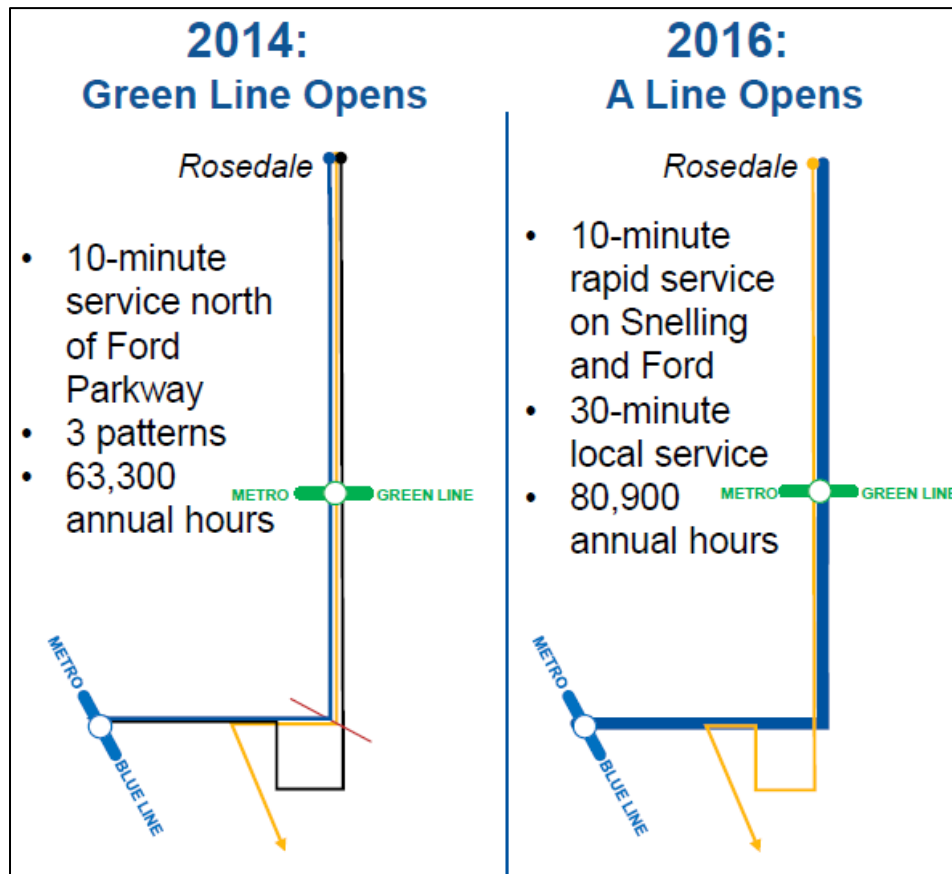


Figure 14: Transit service evolution along the A Line route before & after implementation [Source: (28)]

Figure 15 displays the average load factors between 4am and 11pm for each stop along the Route 84 configuration in 2016 that either coincided with, or were near, a location where an A Line station was built. This simplification was made to reduce the number of columns in the figures below and to

improve consistency when comparing the changes in bus loads as a result of the A Line. Below, and in each of the following load factor plots, darker colors represent a smaller load factor (more empty bus) while lighter shading depicts areas in which the bus load factor is higher. Additionally, by multiplying a load factor by 100%, one can obtain the average weekday occupancy percentage for buses at a particular stop and time of day. Thus, when studying Figure 15, it is apparent that the highest load factors occurred during the hours of 7am and 8am as well as between 2pm and 4pm. During these intervals, occupancy had peak values of 34% and 29% of the maximum bus capacity respectively. Additionally, for morning hours, the load was typically higher for the Snelling Avenue stops south of Minnehaha while in the afternoon, Northbound 84 buses were more full to the north of Snelling and Minnehaha.

4	0.02	0.03	0.03	0.03	0.04	0.04	0.03	0.04	0.04	0.04	0.03	0.02	0.01
5	0.04	0.07	0.09	0.08	0.11	0.10	0.12	0.12	0.11	0.11	0.09	0.08	0.02
6	0.09	0.12	0.15	0.14	0.19	0.19	0.15	0.16	0.16	0.14	0.14	0.11	0.04
7	0.17	0.23	0.28	0.28	0.32	0.34	0.21	0.27	0.26	0.22	0.19	0.12	0.06
8	0.19	0.25	0.29	0.28	0.33	0.33	0.23	0.26	0.24	0.19	0.18	0.11	0.03
9	0.18	0.21	0.23	0.23	0.25	0.27	0.21	0.23	0.22	0.21	0.20	0.12	0.04
10	0.13	0.16	0.17	0.17	0.19	0.20	0.18	0.20	0.20	0.19	0.19	0.12	0.08
11	0.12	0.15	0.16	0.17	0.19	0.20	0.18	0.21	0.19	0.18	0.18	0.12	0.06
12	0.15	0.19	0.20	0.19	0.23	0.23	0.23	0.25	0.24	0.20	0.20	0.12	0.05
13	0.14	0.16	0.17	0.18	0.20	0.21	0.22	0.22	0.21	0.20	0.19	0.12	0.11
14	0.24	0.25	0.22	0.21	0.23	0.24	0.23	0.29	0.29	0.27	0.26	0.17	0.17
15	0.19	0.24	0.21	0.21	0.24	0.25	0.26	0.28	0.27	0.28	0.29	0.18	0.07
16	0.14	0.20	0.21	0.20	0.23	0.23	0.23	0.25	0.25	0.24	0.25	0.15	0.05
17	0.17	0.20	0.20	0.21	0.24	0.24	0.26	0.26	0.25	0.20	0.19	0.11	0.04
18	0.13	0.14	0.14	0.14	0.16	0.15	0.15	0.16	0.16	0.14	0.14	0.09	0.08
19	0.11	0.13	0.13	0.13	0.13	0.13	0.14	0.15	0.14	0.12	0.12	0.07	0.03
20	0.12	0.15	0.15	0.15	0.18	0.18	0.17	0.17	0.17	0.14	0.13	0.06	0.04
21	0.07	0.10	0.11	0.09	0.10	0.10	0.13	0.15	0.14	0.11	0.10	0.06	0.03
22	0.12	0.13	0.13	0.12	0.11	0.11	0.15	0.14	0.14	0.12	0.11	0.06	0.02
23	0.06	0.10	0.10	0.10	0.10	0.10	0.11	0.12	0.11	0.09	0.07	0.03	0.01
	Highland	Randolph	St.Clair	Grand	Dayton	Spruce/Univ.	Minne.	Hewitt	Como	Nebraska	Larp.	Co.Rd. B	Rose

Figure 15: Northbound Route 84 Weekday Load Factor Plot Prior to A Line (3/13/2016--6/2/2016)

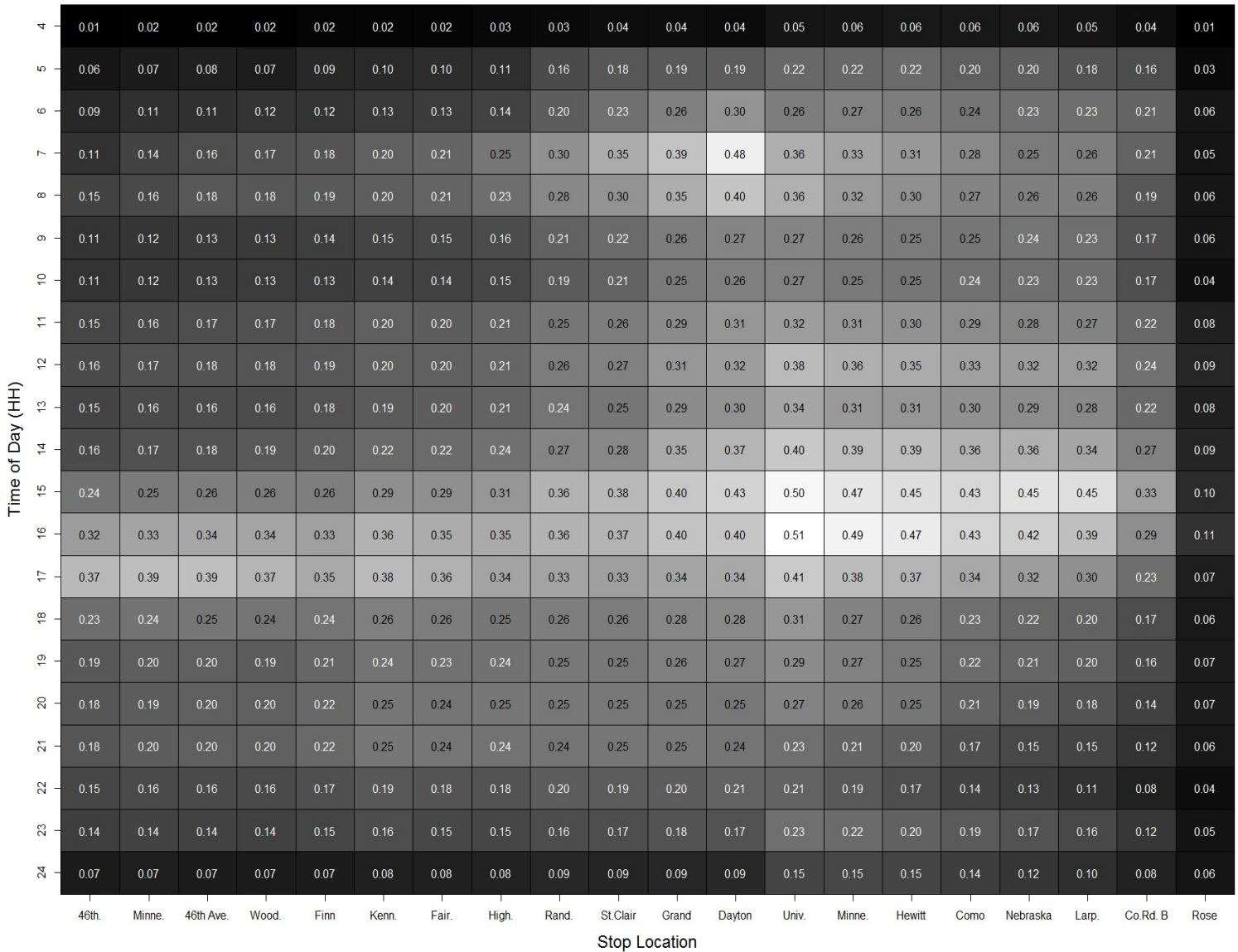


Figure 16: Northbound A Line Weekday Load Factor Plot (3/13/2017--6/2/2017)

Figure 16 displays the 2017 weekday A Line load factors for all stops along the route, not only along Snelling Avenue. By comparing the portion of this plot that lies along Snelling Avenue (Highland-Rosedale) with the 2016 Route 84 data in Figure 15, one can observe that the load factor for the majority of stops over the entire time period are higher for the A Line. For example, the peak load factor at Snelling & University at 4pm for the A Line is 0.51 while the value for Route 84 for this same time and location is 0.23 while the peak for Route 84 is 0.34 but occurs for Snelling & University at 7am. While these changes are due to both changing vehicle size and passenger flow, the number of passengers on an A Line bus is almost always greater than for Route 84, and thus this increase in load factor is primarily due to increased flow. Additionally, it can be noted that the load factors for each route is most similar in the morning hours while the greatest difference occurs in the afternoon.

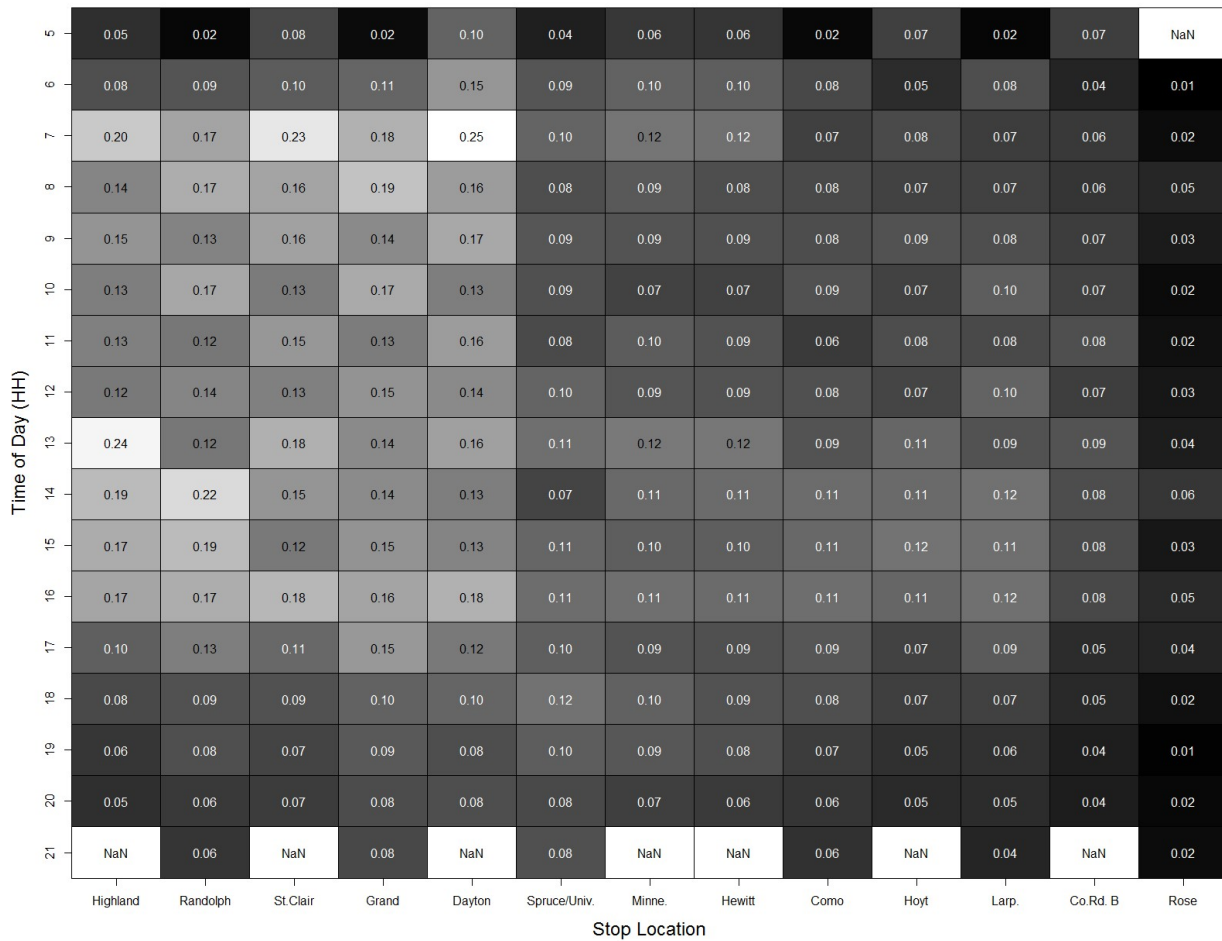


Figure 17: Northbound Route 84 Weekday Load Factor Plot After A Line Implementation (3/13/2017--6/2/2017)

As discussed previously, following the implementation of the A Line in the summer of 2016, transit service along Snelling Avenue was comprised of both the A Line, as well as a reduced frequency Route 84 Service. What can be seen in Figure 17, however, is that this reduced frequency Route 84 service has extremely low load factors north of the intersection of Snelling & Dayton and Snelling & University, indicating that users may primarily use the northbound Route 84 to travel to Green Line LRT service located at the intersection of Snelling & University while proportionately few continue further north.

Figure 18 is a visual depiction of the 7am data contained in all of the load factor plots above and can be used to more easily see the aggregate shifts in bus loads following the construction of the A Line. From this plot, it is evident that the average load factor for the 7am hour, in all cases, increased following the A Line implementation. Furthermore, despite the fact that the 2016 Route 84 had the same headway for the 7am hour as the A Line in 2017, the A Line still has a noticeably higher load factor, again primarily due to increased flow along the route. In addition, both of these northbound services had loads that peaked at the intersection of Snelling Avenue with University or Dayton, indicating that many riders may use the bus to connect with the Green Line LRT during this time period as expected.

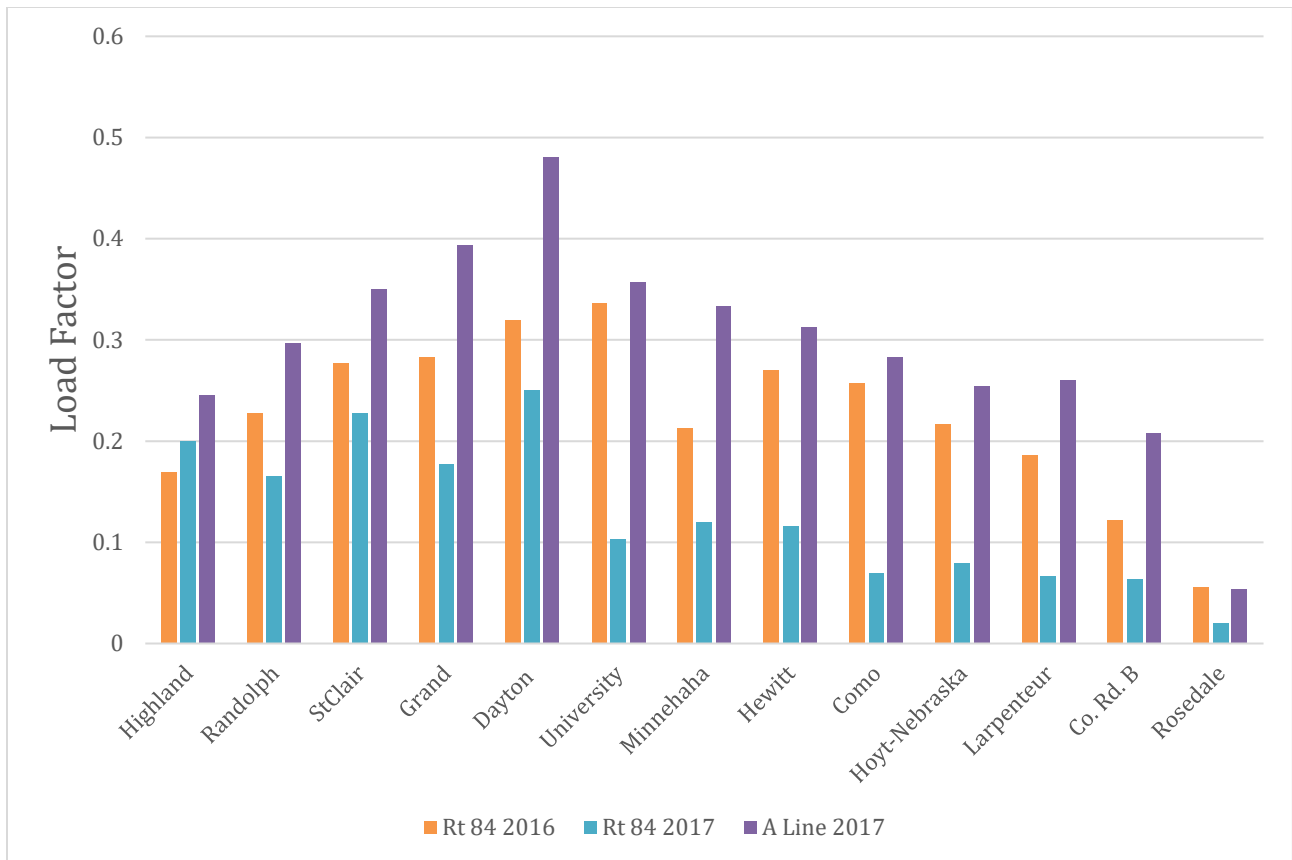


Figure 18: 7 a.m. average weekday load factor comparison for Snelling Avenue routes

After the summer of 2016, the Snelling Avenue corridor has been served by both the A Line as well as a reduced frequency Route 84 service shown above in teal. While the load factor, as shown in Figure 18, of the reduced Route 84 is significantly lower than that of the A Line, especially north of University, the combination of these two services allows for a much higher cumulative load to be carried along the corridor when compared with Route 84 prior to the summer of 2016. For example, for the 7am data displayed above, the average number of people carried northbound past University and Dayton increased from 79.6 in 2016 to 117.4 people in 2017. An additional example is that at 4pm, the northbound flow increased past University and Dayton increased from an average of 53.82 passengers in 2016 to 90.44 in 2017 representing a roughly 68% increase from the 4pm flow prior to the A Line.

CHAPTER 5: TRAVEL BEHAVIOR AND SERVICE PERCEPTIONS

Below the differences in demographic and trip characteristics between riders of the A Line and the parallel local bus routes are explored. Then, rider perception of transit services for the A line is compared with other transit modes, including local buses, express buses, light rail, and the Northstar commuter rail. In addition, the impact of A Line service features on user satisfaction is explored.

5.1 COMPARISON OF USER DEMOGRAPHIC AND TRIP CHARACTERISTICS

This section compares demographic and trip characteristics of riders of the A Line and the parallel bus routes. We used the 2016 Transit On-Board Survey, which was collected by Metro Transit, in the Twin Cities metro area. Passengers were recruited while they were traveling on transit vehicles, including local buses, express buses, Northstar commuter rail, light rail and the A Line. The demographic attributes include gender, the number of vehicles in the household, and so on. The trip features contain the number of transfers and trip destination. After data processing, 517 passengers of the A Line were kept for further analysis. We chose four local parallel bus routes: 65, 83, 84, and 87, with 802 passengers in total. Because the A Line and the four parallel routes serve adjacent areas in the city of St. Paul, we assume that riders should have been similar in terms of demographics and trip characteristics if the A Line were not deployed. Accordingly, any differences are attributable to the A Line. We used t-tests and chi-square tests to compare rider demographic and trip characteristics. The results are shown in Table 4. In general, if the p-value of a test is less than 0.05, passengers of the A Line have a significant difference from those of the parallel routes.

Questions 1 to 14 are related to passengers' demographic characteristics. Four variables significantly differ between the A Line and the parallel routes. In particular, passengers of the A Line have fewer vehicles in their household than those of the parallel bus routes. This is likely due to the difference in household size: A Line users have fewer household members than parallel bus route users. For the transit fare subsidy, 68.5% of A Line passengers do not get any financial support from their employers or schools. Yet, the share of parallel bus users is 49.2%. The difference is about 20%. These additional passengers without financial support are attracted to the A Line presumably because of its competitive advantages in quality of service. About three quarters of the passengers riding the A Line are White whereas White people accounts for 62% of parallel bus route users. A Line passengers are more affluent than parallel bus route users, with a p-value of 0.085. The latter two findings suggest that the A Line is more appealing to different riders, especially the White and higher income people.

Questions 15 to 16 are concerned with trip characteristics, and both of them show significant differences. A Line users transfer more than passengers of the parallel local bus routes. This is because the A Line has better connections than other routes. It connects with the Green Line and the Blue Line. As a major route in the region, the A line has its own feeder service. For trip destinations, 65.8% of the parallel bus route passengers are school or workplaces, larger than the share of the A Line. That is, the A line facilitates non-work travel by transit.

In summary, the A Line attracts additional choice riders, encourages transfers, and promotes transit use for non-work trips.

Table 4: Comparison of users' demographic characteristics between the A Line and parallel routes

Question	Answers	Parallel local bus	A Line	P-value	
Demographics					
1	The number of vehicles in the household	1.10	0.83	0.003*	
2	The number of household members in a respondent's house	3.11	2.69	0.004*	
3	The number of employed household members in a respondent's house	1.97	1.81	0.121	
4	Age ^a	5.39	5.67	0.057	
5	Total annual household income of a respondent ^b	4.64	5.03	0.085	
6	Gender	Male	47.5%	47.2%	0.942
		Female	52.5%	52.8%	
7	Whether a respondent was a visitor	Visitor	3.3%	2.4%	0.521
		Non-visitor	96.7%	97.6%	
8	Employment Status of a respondent	Employed Full-time	49.3%	46.3%	0.637
		Employed Part-time	26.9%	30.6%	
		Not employed	23.8%	23.1%	
9	Student status of a respondent	Yes	34.9%	32.8%	0.607
		No	65.1%	67.2%	
10	Does a respondent's employer or school subsidize (pay for) all or part of his or her transit fare?	Yes (all of the cost)	5.1%	6.1%	0.000*
		Yes (some of the cost)	45.7%	25.4%	
		None of the cost	49.2%	68.5%	
11	Whether a respondent has driver's license	Yes	60.0%	53.7%	0.145
		No	40.0%	46.3%	
12	Race/ethnicity	White	61.8%	74.0%	0.002*
		Non-white	38.2%	26.0%	
13	Does a respondent speak a language other than English in home	Yes	15.3%	11.2%	0.162
		No	84.7%	88.8%	
14	Whether a respondent is disabled	Yes	12.6%	10.8%	0.509
		No	87.4%	89.2%	
Trip Characteristics					
15	The number of transfers in a respondent's trip	0.64	0.76	0.037*	
16	Whether the destination is school/workplace	Yes	65.8%	57.2%	0.039*
		No	34.2%	42.8%	

* Significant at 95% confidence level.

a For age, we code eleven age intervals as eleven numbers, which are listed as followed: 1=Under 12, 2=13-15, 3=16-17, 4=18-24, 5=25-34, 6=35-44, 7=45-54, 8=55-64, 9=65-74, 10=75-84, 11=85 and Over.

b For household income, we code eight income intervals as eight numbers: 1=Less than \$15,000, 2=\$15,000-\$24,999, 3=\$25,000-\$34,999, 4=\$35,000-\$59,999, 5=\$60,000-\$99,999, 6=\$100,000-\$149,999, 7=\$150,000-\$199,999, 8=\$200,000 or more.

5.2 COMPARISON OF USER PERCEPTION

In this section, we compare user perception of the A Line and other transit modes. We used Metro Transit Rider Survey conducted in 2016 in the Twin Cities metro area. This survey covers all five modes, including the A Line, local buses, express buses, light rail (including the Green line and Blue line) and the Northstar commuter rail. In total, 8294 surveys were retrieved. After pre-processing of the data, 994 observations were deleted for missing values for transit modes. The final data include 7300 observations: 234 from the A Line, 945 from express buses, 2,256 from local buses, 3,296 from light rail and 569 from the commuter rail. The questionnaire for the A Line, express buses, and local buses contains 24 questions related to service satisfaction for all these transit modes. However, the questionnaires for light rail and the commuter rail only have 21 questions, because some questions in the bus survey are not applicable to rail transit. The respondents were asked to answer these questions on a five-point scale ranging from excellent to unacceptable. One-way ANOVA with a post-hoc test was used to compare passengers' responses to the survey as shown in Table 5. To facilitate reading, a green color indicates that the A Line service receives a better perception than other transit modes, and red indicates that the A Line service has a worse perception than other transit modes.

The first question in Table 5 is designed to evaluate the overall ratings of the service. The A Line performs better than local buses since the former is equipped with better facilities and service attributes, such service frequency and station amenities. The A Line is not different from other transit modes.

In terms of specific service attributes, the A Line performs better than local buses but worse than the Northstar commuter rail. As for the comparison between the A Line and express buses/light rail, passengers show different perceptions in different aspects of transit service.

The second question is about fare payment. A Line's rating is different from that of express buses and the commuter rail. Since almost all passengers of the latter two modes are commuters and they pay fare mainly using the Go-To card, their perception of payment is better than A Line riders, who pay fare using different ways including Go-To card, credit card, cashes, and so on.

The third and fourth questions are related to safety when people are waiting or riding. Passengers feel safer when they wait for or take express buses and the commuter rail than the A Line. Commuters are probably more familiar with each other since they all use the same service frequently. This makes them feel safer during the waiting or riding period. Further, commuters are more homogenous in terms of demographics than riders of the A Line.

The fifth question is designed to assess the behavior of other passengers and atmosphere among different transit modes. Since the A Line is equipped with better facilities and services than local buses, its passengers are more satisfied with the other passengers' behavior and the atmosphere. Express buses and the commuter rail perform better in these two aspects than the A Line. This is likely due to the reasons presented above.

The sixth question is about whether the operating hours meet passengers' needs. The A Line has frequent service in most time of a day, with a headway of 10 minutes. Local buses do worse than the A Line, probably because many services are infrequent. Express buses and the commuter rail also do worse than the A Line. Since the former two modes mainly serve commuters, their service is frequent during the morning and evening rush hours, but not during other periods. Light rail has a service frequency similar to the A Line, but light rail users tend to perceive better than the A Line users.

The seventh question is about whether the routes can meet passengers' need to get to their destinations. The commuter rail presents better scores than the A Line. Since the commuter rail mainly serve commuters and their destinations are relatively concentrated, it is relatively easier to meet their demands.

Table 5: Comparison of users' perception between the A line and other transit modes

Questions	The A Line's score	Local buses (N=2,256)		Express buses (N=945)		The commuter rail (N=569)		Light rail (N=3,296)	
		Diff	P-value	Diff	P-value	Diff	P-value	Diff	P-value
1 Overall rating of Metro Transit service	4.32	-0.187	0.001*	-0.048	1.000	0.132	0.156	0.030	1.000
2 Paying my fare is easy	4.47	-0.044	1.000	0.219	0.000*	0.198	0.004*	-0.017	1.000
3 Personal safety while waiting	3.97	-0.126	0.377	0.210	0.012*	0.471	0.000*	0.009	1.000
4 Personal safety while riding	4.21	-0.120	0.372	0.284	0.000*	0.411	0.000*	-0.099	0.829
5 Behavior of other passengers and atmosphere on bus/light rail/train	3.72	-0.201	0.021*	0.468	0.000*	0.453	0.000*	-0.077	1.000
6 Hours of operation for transit service meet my needs	4.08	-0.214	0.008*	-0.249	0.002*	-0.577	0.000*	0.212	0.007*
7 Routes go where I need to go	4.19	-0.124	0.381	0.016	1.000	0.192	0.045*	0.005	1.000
8 Total travel time is reasonable	4.22	-0.280	0.000*	-0.008	1.000	0.171	0.094	-0.024	1.000
9 Transferring is easy	4.22	-0.128	0.196	0.022	1.000	0.283	0.000*	0.074	1.000
10 Reliability - service is on schedule	3.99	-0.201	0.012*	-0.173	0.089	0.338	0.000*	0.197	0.013*
11 Drivers operate vehicles in a safe and responsible manner	4.36	-0.130	0.081	-0.024	1.000	0.201	0.003*	0.049	1.000
12 Vehicles are clean	4.16	-0.217	0.003*	0.076	1.000	0.392	0.000*	-0.142	0.167
13 Vehicles are comfortable	4.34	-0.299	0.000*	-0.238	0.001*	0.041	1.000	-0.192	0.005*
14 Routes and schedules are easy to understand	4.33	-0.181	0.006*	-0.100	0.718	0.131	0.261	0.016	1.000
15 Fares are easy to understand	4.41	-0.114	0.260	-0.030	1.000	0.030	1.000	-0.057	1.000
16 Availability of seating	4.22	-0.310	0.000*	-0.239	0.001*	-0.180	0.062	-0.117	0.418
17 Easy to identify the right bus	4.36	-0.183	0.001*	0.018	1.000				
18 Vehicles are environmentally friendly	4.12	-0.098	0.965	0.018	1.000	0.253	0.002*	0.129	0.262
19 Shelter/station conditions/cleanliness	3.90	-0.372	0.000*	-0.099	1.000	0.435	0.000*	0.029	1.000
20 Availability of the route map and schedule	4.17	-0.165	0.023*	0.036	1.000			0.051	1.000
21 Street/stop announcements	4.29	-0.344	0.000*	-0.246	0.001*				
22 Courteous [driver/conductors]	4.27	-0.102	0.367	0.147	0.066	0.472	0.000*		
23 Accessible for people with disabilities	4.38	-0.072	1.000	-0.008	1.000	0.160	0.150	-0.076	1.000
24 Handling of concerns/complaints	4.00	-0.118	1.000	-0.140	1.000	0.222	0.199	0.048	1.000

* Significant at 95% confidence level.

Green color: The A Line performs better than other transit modes.

Red color: The A Line performs worse than other transit modes.

The third column lists the average performance of A Line attributes. The average performance of other modes can be computed by adding the difference to the average performance of the A Line

The eighth question is related to whether the travel time is reasonable. The A Line performs better than local buses. The following attributes make travel time of the A Line shorter: online stops, signal priority, larger station spacing, and the proof-of-payment fare collection.

The ninth question is about transfers. Taking the commuter rail is easier than the A Line when it comes to transferring to other traveling modes. The commuter rail ends at the downtown transit terminal, which makes it easier to transfer.

The tenth question is about the reliability of transit service. Local buses are less reliable than the A Line. Online stops, signal priority, and the proof-of-payment fare collection help improve reliability. The commuter rail and light rail perform better than the A Line since the former two have dedicated right of way.

The eleventh question is about the drivers' manner when they are operating vehicles. The commuter rail performs better than the A Line because the former does not need to stop frequently during travel, hence making passengers feel more comfortable.

The twelfth question is related to the cleanliness of the vehicles. The A Line's vehicles are cleaner than those of local bus lines but dirtier than those of the commuter rail. These findings are consistent with the service level of different means of transit. Further, the ridership of local buses is higher and the riders are less homogenous, whereas the riders of the commuter rail are more homogenous than those the A Line.

The thirteenth question is designed to determine whether the vehicles are comfortable. The vehicles of local buses, express buses, and light rail are less comfortable than those of the A Line. The A Line is a new service and its facilities are newer and better, which make its passengers feel more comfortable.

The fourteenth question is about the understandability of the routes and schedules. The A Line's performance is better than local buses since it has fewer routes and schedule plans.

The sixteenth question is about the availability of seating. The A Line does better than local buses and express buses because its frequent service makes seats more likely to be available.

The seventeenth question is related to the easiness of identifying the right bus. The A Line does better than local buses since its bus is based on the design of light rail and easier to identify.

The eighteenth question is to ask whether the vehicles are environmentally friendly. The A Line does worse than the commuter rail. The commuter rail's vehicles use diesel-electronic power, which is perceived to be environment-friendly.

The nineteenth question is about the condition and cleanliness of the shelter or station. Local bus does worse the A Line, since its shelter, if any, is poorly constructed and less equipped. On the contrary, the commuter rail does better than the A Line since its station is better equipped and provide more amenities.

The twentieth question is related to the availability of the route map and schedule. The A line provides a better availability of this service than local buses because the A Line offers more information like the time need to wait for the next vehicle on the electrical information board in the station.

The twenty-first question is about the street and stop announcements. The A Line performs better than local buses and express buses. Since they all have street and announcement facilities in their vehicles, the reason for this significant difference is not clear.

The twenty-second question is designed to determine the manner of the driver or conductors. The commuter rail conductors are more courteous than the driver of the A Line. This is not surprising since the former serves passengers but the latter mainly operates vehicles.

As for the fifteenth, twenty-third and twenty-fourth questions, there are no significant differences between the A Line and other four transit mode.

In summary, for the first question of overall satisfaction, riders perceived that the A Line performs better than local buses because the result is statistically significant. Although the overall satisfaction with the commuter rail is higher than that with the A line, the difference is not statistically significant. Therefore, the performance of the A Line does not differ from that of the commuter rail, as well as express buses and LRT.

In terms of specific attributes, we do not observe many differences between the A Line and LRT. The A Line performs better for most attributes than local buses. By contrast, the commuter rail performs better for most attributes than the A Line. Express buses perform better in four attributes than the A Line. However, the former also perform worse in other four attributes than the A Line.

5.3 THE INFLUENCE OF SERVICE ATTRIBUTE ON RIDER SATISFACTION

This section explores how service features of the A Line affect user satisfaction using a combination of machine learning and impact-asymmetry analysis (IAA). We adopted the gradient boosting algorithm to analyze the survey data. Compared with traditional regression, gradient boosting, a machine-learning approach, better resolves the multicollinearity issue, increases the precision of results, and better handles the problems caused by missing values.

We built a prediction model with the 23 service attributes being independent variables while controlling for seven demographic variables: gender, income, race, age, auto ownership, household size, and disabilities. The model gives us the relative influence of these service attributes on overall satisfaction. These statistics measure their powers to predict the dependent variable (overall satisfaction) in percentages and are normalized to a sum of 100% (Column 3 in Table 6). We selected twelve attributes with a relative influence higher than 2% to conduct further analyses.

Using IAA, we classified service attributes into five categories based on their abilities to increase or decrease overall satisfaction (29). These five categories can be defined as follows:

- **Satisfiers** increase satisfaction if they are delivered. However, if not delivered, they do not decrease satisfaction. These attributes are usually viewed as advanced “add-on” features, which are not required but can significantly increase satisfaction if provided.
- **Delighters** are the extreme cases of satisfiers. They can highly satisfy users and increase satisfaction more significantly if delivered.
- **Hybrids** are the type of factors that have relatively linear and symmetric relationships with satisfaction. They can increase satisfaction if delivered and decrease satisfaction if not delivered.

- **Dissatisfiers** decrease satisfaction if not delivered. However, they have limited capacity to increase satisfaction if delivered. These attributes are usually “minimum requirements” that are expected but not enough to increase satisfaction.
- **Frustrators** are the extreme cases of dissatisfiers. They can highly decrease satisfaction if not delivered.

The IAA followed four steps:

- 1) **Recode variables.** The scale of overall rating was recoded as follows: “excellent” as 5, “good” as 4, “fair” as 3, “poor” as 2, and “unacceptable” as 1. Because Metro Transit stated that it has a high service quality standard, we set “good” as the reference level and recoded the five scales of independent variables into three numeric scales: **-1** (“unacceptable”, “poor” and “fair”), **0** (“good”) and **1** (“excellent”), indicating penalty, reference, and reward, respectively.
- 2) **Estimate penalty and reward indices of each service attribute.** We used gradient boosting decision trees to estimate the indices (see Section 3.3). When the performance of a service attribute increases from -1 to 0, we considered the corresponding change in overall satisfaction as the “penalty index (PI)”. When the performance increases from 0 to 1, we considered the corresponding change in overall satisfaction as the “reward index (RI)”.
- 3) **Compute the impact-asymmetry (IA) index.** We first estimated the overall range of impact on overall satisfaction (RIS) of each attribute ($RIS = RI + |PI|$) and its satisfaction-generating potential (SGP) and dissatisfaction-generating potential (DGP). The SGP and DGP were then used to generate the IA index based on the following equations:
 - a. $SGP = RI/RIS$
 - b. $DGP = |PI|/RIS$
 - c. The IA index = $SGP - DGP$
- 4) **Classify service attributes into five categories.** We used the thresholds used to define the categories: delighters ($IA \geq 0.7$), satisfiers ($0.2 \leq IA < 0.7$), hybrids ($-0.2 < IA < 0.2$), dissatisfiers ($-0.7 < IA \leq -0.2$), and frustrators ($IA \leq -0.7$)

Table 6 summarizes the mean performance, relative influences and factor classifications of the twelve attributes with a relative influence higher than 2%. The relative influence shows that the following five attributes have the greatest impact on overall satisfaction: “paying my fare is easy”, “hours of operation”, “handling of concerns/complaints”, “personal safety while riding”, and “courteous drivers/conductors”.

Table 6: Factor classifications and average performance of the A Line service attributes

	Mean Performance	Relative Influence (%)	Factor Classification
1 Paying my fare is easy	4.520	21.810	Delighter
2 Hours of operation	4.154	9.069	Satisfier
3 Handling of concerns/complaints	4.048	8.724	Frustrator
4 Personal safety while riding	4.167	5.771	Delighter
5 Courteous driver/conductors	4.324	5.246	Frustrator
6 Vehicles are comfortable	4.341	4.885	Delighter
7 Total travel time is reasonable	4.208	4.337	Hybrid
8 Reliability	4.040	3.858	Hybrid
9 Accessible for people with disabilities	4.418	2.171	Delighter

10 Transferring is easy	4.291	2.165	Dissatisfier
11 Behavior of other passengers and atmosphere on board	3.788	2.082	Satisfier
12 Shelter/station conditions/cleanliness	3.940	2.042	Frustrator

Note: The relative influence indicates the power of a variable to predict overall satisfaction. The larger the relative influence is, the more important the variable is.

In terms of factor classifications, four service attributes are delighters (“paying my fare is easy”, “personal safety while riding”, “vehicles are comfortable”, and “accessible for people with disabilities”) and two are satisfiers (“hours of operation” and “behavior of other passengers and atmosphere”). These delighters and satisfiers can increase satisfaction when delivered, and if not, they do not decrease satisfaction. On the other hand, three attributes are frustrators (“handling of concerns/complaints”, “courteous drivers/conductors”, and “shelter/station conditions/cleanliness”) and one is a dissatisfier (“transferring is easy”). These frustrators and dissatisfiers decrease overall satisfaction when they are not delivered, but they will not increase satisfaction if they are delivered. Finally, two attributes provide similar degrees of rewards and penalties on overall satisfaction (“total travel time is reasonable” and “reliability”). These two attributes are considered hybrids. They can both increase and decrease the satisfaction.

For improvement priorities, the mean performance of the top five important attributes is larger than 4 (“good”), the reference level. Therefore, none of them contributes to rider dissatisfaction. With that said, the transit agency can still improve rider satisfaction. “Hours of operation” and “personal safety while riding” are satisfiers/delighters. They have a substantial effect on rider satisfaction only when their performance is better the reference level. Therefore, improving these two attributes will further delight riders. By contrast, “handling of concerns/complaints” and “courteous driver/conductors” are frustrators. Frustrators/dissatisfiers are usually necessities to achieve qualified services but cannot delight riders once they are sufficiently delivered. As a result, the transit agency needs to improve them but only to the “good” level so that they do not create dissatisfaction. Because these two attributes are delivered, further improvement on these two attributes is unproductive.

Improving the remaining seven attributes may enhance rider satisfaction but the impact is not great. Among them, “transferring is easy” does not require additional attention because it is a dissatisfier and performs well. “Shelter/station conditions/cleanliness” is a frustrator and its mean performance is slightly below the reference level. Improving it seems to have a trivial effect on rider satisfaction. The mean performance of “behavior of other passengers and atmosphere” is also lower than the reference level. However, as a satisfier, it does not have a substantial detrimental impact on rider satisfaction. If the transit agency wants to improve it, its performance has to be enhanced beyond the reference level to be effective. “Vehicles are comfortable”, and “accessible for people with disabilities” are delighters and perform very well compared with other attributes. Therefore, they may not require further investment. “Reliability” and “total travel time is reasonable” are hybrids that can lead to both satisfaction and dissatisfaction. The transit agency could improve them as much as possible to enhance rider satisfaction.

In summary, when designing a future arterial BRT, the transit agency could refer to the list of attributes shown in Table 6. The following five service attributes require extra attention since they contribute the most to rider satisfaction: “paying my fare is easy”, “hours of operation”, “handling of concerns/complaints”, “personal safety while riding”, and “courteous drivers/conductors.”

In terms of the A Line, we recommend the transit agency to consider improving the following service attributes: “hours of operation”, “personal safety while riding”, “reliability”, and “total travel time is reasonable.”

CHAPTER 6: PERCEPTION OF NON-USERS

In this section, we carried out a field survey to different stakeholders along the corridor of the A Line BRT and analyzed their perceptions. We classified the stakeholders along the corridor into five categories: station area residents, business workers/owners, auto users, pedestrians/bicyclists, and real estate developers. For the perceptions of real estate developers, we refer to the results of Guthrie and Fan (30), which explored developers' perspectives on transit ways and transit-oriented development in the Twin Cities. For the remaining four types of stakeholders, we designed four survey instruments, respectively. The students of a Humphrey course (Networks and Places: Land Use, Transportation, and Design, Spring 2018) administered the surveys. They were trained on how to recruit respondents and how to ask questions. Students interviewed six to eight respondents for each type of stakeholders along the corridor (not necessarily at the stations) in March and April 2018. This report constitutes a qualitative analysis.

Most of the respondents spoke favorably towards the A Line. Some pedestrians and residents indicated that it is better than other transit routes. However, there is still skepticism: the A Line is "just a bus" and it has a limited influence on the image of the corridor. In general, respondents who have little experience with the A Line (such as auto users) are associated with neutral and negative perceptions. Although it is not easy to attract non-riders to ride the A Line, some residents felt that service improvements could be made, such as installing more cameras and lighting around the stations, improving the reliability of the NexTrip signs, charging less for the trips, and increasing service frequency.

Some respondents stated that the A Line has positively changed the image of the corridor, while others have not noticed any appreciable changes since the A Line opened. One pedestrian indicated that the A Line makes the neighborhood more urban and commuter-friendly. Some business workers predicted that the A Line can increase transit ridership and help reduce congestion in the corridor. They also mentioned that the distinctive bus stops of the A Line BRT are "nicer," which improves image and aesthetics along the corridor. Several residents expressed that the areas look cleaner, less depressed, more orderly and pleasant, and they appreciated the streetscape improvements as well as the roadway surface improvements that came with the A Line construction.

When it comes to the pedestrian and biking environment, the answers are mixed. Generally, the A Line has some positive impacts on the environment or at least has no negative impacts. On the other hand, nice stations of the A Line cannot help the lack of snow and ice removal on the sidewalks. Business workers and owners have not seen a significant change in the pedestrian and biking environment attributable to the A Line. One noted that there was a slight increase in pedestrian traffic right around the bus stations but did not specifically say that this has changed the overall environment around biking and walking in the neighborhood. Some residents appreciated improved lighting at the stations and the corridor. By contrast, one resident noted that it can still be dangerous for pedestrians in the corridor. Improvements in the general condition of the roadway and streetscape contribute to a better feeling of safety for drivers, however. According to Guthrie and Fan (30), developers think that walkability is very important for improving transit accessibility and discussed it frequently during their survey.

The A Line has somewhat improved the accessibility along the corridor. We asked business owners and workers whether the A Line has increased the accessibility to different destinations. They all felt that the A Line has a positive influence on providing access to another means of transport for both customers and employees. Some perceived that the A Line slightly increases the number of patrons to their

businesses because of increased traffic volume. One respondent stated that the A Line would change the demographic profile of his customers, bring in older people to his business. Another respondent stated that although the A Line does not increase the customer base, it provides employees a rapid, direct means of transport to work. Some respondents mentioned that their friends use the A Line as the primary means of commuting to work. Overall, the A Line would offer more people in the city opportunities to reach their employment. Some residents stated that the A Line should extend its route to serve more destinations and different connections. For developers, accessibility is important for them to choose the right location to carry out their projects. However, it is difficult for them to get permits in the central city and there are limited buildable sites around existing transitway lines (30). Between sites with similar conditions, transit access can make a difference in location choice. However, few developers will compromise other site-selection factors for a transit-oriented site (30). With that said, multifamily developers, redevelopers, and large office developers are interested transit-oriented sites. Proximity to transit is not a primary goal, but a characteristic which makes other goals, such as a lower parking supply, easier to achieve (30).

On the contrary, auto users stated that cars offer a better accessibility, which helps them reach multiple destinations conveniently, and the A Line cannot substitute for cars. This is one of the main reasons for auto users to keep using cars. The car privilege is also a factor as driving is always faster, more convenient and comfortable than taking the bus. So, some residents thought that it would be very difficult to induce drivers to switch to the A Line. Furthermore, almost all drivers have little or no knowledge of the A Line, even as they walked along the route of A Line or were just one block away. They have not taken the A Line in the past half a year, and did not understand the difference between the A Line and regular buses.

In summary, most respondents have a favorable view about the A Line, but those who use automobiles for their travel do not.

CHAPTER 7: CONCLUSION

The project conducted jointly by engineering and planning researchers was closely centered around two key questions: what impact does A Line operation have on the surrounding traffic and how do riders and the general public perceive A Line service? To answer these two primary questions, a capacity analysis on general traffic and transit as well as a study of the public perception of users and non-users was carried out.

The capacity analysis was comprised of the capacity of general traffic as well as transit capacity. Two traffic condition measures—queue length and traffic flow rate—were selected as indicators for general traffic capacity change. Data from the 4 traffic signal cycles prior to and 4 cycles after an A Line bus arrival were employed to determine if the traffic conditions significantly changed as a result of the arrival of an A Line bus. By creating 2-dimensional plots where the two axes represented the before and after-arrival conditions respectively, queue length and flow rate data were compared for each A Line bus arrival to determine if there was a clear trend present in which the conditions after the arrival of a bus were different than the conditions before the arrival. To make this assessment, bus records that shared similar green dwell times and occurred in similar traffic conditions were clustered together and the relative position of these clusters on the before and after plots were analyzed in comparison to a line of equality that indicated that traffic conditions were identical before and after arrival. Considering highly unbalanced traffic volumes inside and outside the State Fair period, the clustering and subsequent analysis of each type of data were carried out separately. Nevertheless, it was found that the cluster centers all fell along the equality line regardless of how long the bus was dwelling at the intersection, indicating that the impact bus dwell time had on surrounding traffic condition was negligible. Linear regression results further support this conclusion as the main determinant of traffic flow on Snelling Avenue was determined to be the traffic conditions present prior to the arrival of an A Line bus. In addition, these regressions found that traffic was statistically independent from the presence of an A Line bus, indicating that bus arrival, dwell, and departure had no measureable impacts on traffic operation.

From comparisons of the number of on-board passengers along Snelling Avenue, it was determined that the A Line carries larger loads than the previous Route 84 service for almost all operating hours and stop locations. Furthermore, it was also found that both the A Line and Route 84 service had the greatest passenger turnover at the Snelling and University Station, the connection station to the Green Line LRT, and that people tend to use the A Line for farther north destinations rather than Route 84, which likely signifies that individuals take the first bus that arrives.

The public perception analysis was carried out based on data from the on-board survey and a field survey. A comparison of riders of the A Line and parallel lines suggested that the A Line attracted additional choice riders, encouraged transfers, and promoted transit use for non-work trips. In terms of overall satisfaction, the A Line performed better than local buses and did not differ significantly from express buses, light rail and commuter rail. For individual service attributes, most attributes of the A Line performed better than local buses but worse than the commuter rail. The A Line performed equivalently to light rail. On the other hand, the A Line and express buses excelled in different attributes.

The top-five important service attributes to overall satisfaction are “paying my fare is easy,” “hours of operation,” “handling of concerns/complaints,” “personal safety while riding,” and “courteous drivers/conductors”. Future arterial BRTs should consider how to improve these attributes. To enhance

rider satisfaction of the A Line, the transit agency should consider the following service attributes: “hours of operation,” “personal safety while riding,” “reliability,” and “total travel time is reasonable.” Because rider satisfaction assesses quality of transit service from the perspective of riders, it does not consider the cost associated with the improvement. Therefore, transit agencies should use this recommendation as a starting point to choose cost-effective strategies.

Regarding the survey conducted among non-users along the A Line corridor, most respondents had positive perceptions of the A Line. Some believed that the A Line has changed the image of the corridor. Respondents’ perceptions of the A Line’s impact on the pedestrian and biking environment were mixed. The A Line increased the accessibility to different destination and offered some benefits to both businesses and employees although the improvement was limited when compared with cars. On the other hand, people who own cars and use cars for all their trips have not found the A Line to be a great enough improvement to change their preference for driving. Auto users have little experience with the A Line and cannot tell the difference between it and conventional buses.

In summary, the implementation of the A Line arterial BRT has been shown to have a negligible impact on surrounding traffic. Furthermore, A Line implementation simultaneously improved transit capacity, along with the Route 84 service, and both users’ and non-users’ perception of the service and general transit corridor.

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**APPENDIX A:
LITERATURE REVIEW SUMMARY**

Table 7: Literature Review Summary

(Author) Article	Location	Purpose	Parameters	Conclusions
<p>(Levinson et al 2003)</p> <p>Bus Rapid Transit: Synthesis of Case Studies</p>	<p>26 Case studies in the USA, Canada, Australia, Europe, and South America</p>	<p>Determine key features of BRT as well as costs and benefits</p>		<ul style="list-style-type: none"> • Number of BRT systems is growing • BRT can be a cost extension of rail transit lines • BRT can reduce saving times, attract new riders, and induce transit-oriented development • High speeds can best be achieved when operating in separate rights-of-way
<p>(Transportation Management & Design Inc 2002)</p> <p>Final Report: Los Angeles Metro <i>Rapid</i> Demonstration Program</p>	<p>Los Angeles, CA</p>	<p>Reevaluating performance of new Metro <i>Rapid</i> line based on select criteria</p>	<ul style="list-style-type: none"> • Reduce passenger travel times • Increase ridership & reliability • Attract new riders • Improve appearance & service effectiveness 	<ul style="list-style-type: none"> • Metro Rapid was deemed a success after meeting all of the program’s original objectives/parameters • Speeds increased by 20-30% • Ridership increased by 25-45%
<p>(Wang et al 2016)</p> <p>Modeling Bus Dwell time and Time Lost Serving Stop in China</p>	<p>Nanjing, Changzhou, and Guangzhou, China</p>	<p>Approximated dwell time and time lost serving stop</p>	<p>Bus stop type, length of bus stop, traffic conditions, traffic flow rate, capacity, average bus speed near bus stop</p>	<ul style="list-style-type: none"> • Bus stop location had a significant effect on bus dwell time and time lost serving stop when comparing near side stops to far side and mid-block stops • Near side stops may have more of a negative impact on the parameters

(Author) Article	Location	Purpose	Parameters	Conclusions
<p>(Chao et al 2018)</p> <p>Effect of Dwelling Buses on the Traffic Operations of Non-Motor Vehicles at Bus Stops in China</p>	<p>Nanjing China</p>	<p>Compared how speed of non-motor vehicles changed at different areas</p>	<p>Upstream vs at the bus stop vs downstream, bus arrival rate, bus average service time, flow rate of non-motor vehicles, number of conflicts, speed of non-motor vehicles</p>	<ul style="list-style-type: none"> • Bus presence significant for far side and mid-block stops • Bus presence significant for all locations in bus stop area, but not significant for any locations downstream
<p>(Wang et al 2017)</p> <p>The Impact of Dwelling Buses on Capacity of Motor Vehicles at Different Types of Bus Stops</p>	<p>Downtown Nanjing China</p>	<p>Measured vehicle speed reduction for various cases</p>	<p>Peak vs non-peak hour, with and without the presence of a bus at the stop, the number of berths at each stop</p>	<ul style="list-style-type: none"> • Near side stops reduce vehicle speed for both peak and non-peak hours • Decrease in vehicle capacity as number of berths increases • Presence of bus at stop has most apparent impact on speed reduction
<p>(Zhao et al 2007)</p> <p>The Capacity Drop Caused by the Combined Effect of the Intersection and the Bus Stop in a CA Model</p>	<p>China</p>	<p>Determined how a bus stop near a signalized intersection affects capacity</p>	<p>Distance between the stop and the intersection, the traffic light timing cycle, and bus dwell time Compared upstream and downstream bus stops both with and without a stop lane</p>	<ul style="list-style-type: none"> • Capacity grows as the distance between the bus stop and intersection increases Reaches maximum at certain point based on signal timing and dwell time • Separate stop lane should be implemented when bus stop is located close to an intersection Downstream stops could replace upstream stops for certain conditions

(Author) Article	Location	Purpose	Parameters	Conclusions
<p>(Wan et al 2016)</p> <p>Rider Perception of a “Light” Bus Rapid Transit System - The New York City Select Bus Service</p>	<p>New York City, USA</p>	<p>To understand rider’s perception of BRT services with limited space and funding.</p>	<p>Overall satisfaction, frequency, speed, on-time performance, bus-only lanes, ticket machine, shelters, comfort and cleanliness, route and schedules, bus stops, real-time information, limited stops</p>	<ul style="list-style-type: none"> • Most BRT riders used to be riders of replaced limited bus services; • BRT has higher rider satisfaction • The socio-demographic characteristics affect riders’ perception of BRT service • Riders tend to be less satisfied with the select bus service (SBS) in clear weather • Each BRT factors have different impacts on various routes.
<p>(Baltes 2003)</p> <p>The Importance Customers Place on Specific Service Elements of Bus Rapid Transit</p>	<p>Florida, USA</p>	<p>To evaluate the importance of each service attribute on overall satisfaction</p>	<p>Route structure, frequency of service and stops, schedule, boarding and alighting, color-coded buses and stops, signal, lanes, vehicle interiors, high-capacity buses, off-board payment, feeder network, coordinated land-use planning</p>	<ul style="list-style-type: none"> • BRT’s quality of service makes it a service different from standard local services • Customers place a high value on the BRT service characteristics frequency of service, comfort, travel time, and reliability of service

(Author) Article	Location	Purpose	Parameters	Conclusions
<p>(Koshy & Arasan 2005)</p> <p>Influence of Bus Stops on Flow Characteristics of Mixed Traffic</p>	<p>Chennai City, India</p>	<p>Determined how mixed traffic flow is affected by the presence of bus stops</p>	<p>Speed reduction vs dwell time</p>	<ul style="list-style-type: none"> • Average speed of traffic decreases rapidly at certain thresholds of flow when curbside bus stops are present • Threshold of 25% reduction in speed could be used as an appropriate marker of when curbside stops should be replaced with bus bays • Application could be extended for different conditions
<p>(Fitzpatrick & Nowlin 1997)</p> <p>Effects of Bus Stop Design on Suburban Arterial Operations</p>	<p>Texas, United States</p>	<p>Determined how to design bus stops based on location and traffic volume</p>	<p>Curbside stops, bus bays, open bus bays, queue jumpers</p>	<ul style="list-style-type: none"> • For midblock and far side bus stops, bus bay is best when traffic volumes are around 350 vehicles per hour per lane and greater • Queue jumper design is best when traffic volumes are approximately around and above 250 vehicles per hour per lane
<p>(Truong et al 2016)</p> <p>Investigating Multiplier Effects Created by Combinations of Transit Signal Priority Measures on Arterials</p>	<p>Melbourne, Australia</p>	<p>Determined if transit signal priority (TSP) on an arterial or network has multiplier effect on benefits for multiple scenarios</p>	<p>Various values for traffic volumes, signal offsets Specific values for turning proportions, single timing, headway</p>	<ul style="list-style-type: none"> • After optimizing signal offsets for TSP, there is a multiplier effect minimizing bus delay for an arterial • Negligible effect on arterial traffic delay • Bus delay savings far outweigh the increases in delay for side streets. • TSP strategies could be scaled and implemented on a network level.

(Author) Article	Location	Purpose	Parameters	Conclusions
(Wong et al 1998) Delay at Signal-Controlled Intersection with Bus Stop Upstream	Hong Kong, China	Estimated delay at a signalized intersection with bus stop upstream	N/A	<ul style="list-style-type: none"> • Model can be used to better design signal plans to control traffic based on the delay experienced by vehicle drivers
(Gu et al 2013) Mitigating Negative Impacts of Near-Side Bus Stops on Cars	California, United States	Made model to determine location for near-side stop to minimize negative effects on vehicles	N/A	<ul style="list-style-type: none"> • Lessen impacts by decreasing distance between bus stop and intersection by increasing green time ratio or decreasing cycle length • Employ idea that buses slow down or stop upstream of the bus stop • Locate bus stops further upstream past where the queue normally ends
(Yang et al 2009) Road Capacity at Bus Stops with Mixed Traffic Flow in China	Beijing, China	Made model to determine road capacity based on gap acceptance and queuing for mixed traffic flow	Bus presence vs no bus presence	<ul style="list-style-type: none"> • Vehicle capacity can be derived from gap acceptance theory based on the number of buses, cars, and bicycles present
(Shao & Liu 2012) Estimation of Saturation Flow Rates at Signalized Intersections	Beijing, China	Developed better method to approximate saturation headway and saturation flow rate	Headway and queue discharge Morning and evening peak hours	<ul style="list-style-type: none"> • Traditional approximation of headway overestimates the actual value, so saturation flow rate is underestimated • New estimation model for saturation flow rate developed to use for calculating an intersection's capacity

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<p>(Perez-Cartagena & Tarko 2005)</p> <p>Calibration of Capacity Parameters for Signalized Intersections in Indiana</p>	<p>Indiana, United States</p>	<p>Improved how to predict capacity of intersections considering other factors that may have an effect</p>	<p>Queue length, base conditions, town population, total green and yellow time, time when the saturation flow ends, time when the 4th vehicle's axles crosses stop bar, and the number of vehicle types in traffic composition</p>	<ul style="list-style-type: none"> • Size of the community that intersection is in plays a significant role in determining the capacity • Saturation flow adjustment factor population is needed • For multiple through lanes, the right lane may have lower saturation flow rates than the left lane • Pavement conditions could have an impact capacity as well
<p>(Somuyiwa & Adebayo 2005)</p> <p>Impact of Bus Rapid Transit System (Brt) on Passengers' Satisfaction in Lagos Metropolis, Nigeria</p>	<p>Lagos Metropolis, Nigeria</p>	<p>Examine the impact of BRT on passengers' satisfaction in Lagos metropolis</p>	<p>Speed, comfortability, reliability, safety, waiting time, fare, travel time, ease of use.</p>	<ul style="list-style-type: none"> • BRT has great impact on rider satisfaction. It also improve the quality of service of not only riders and residents • BRT can be a practical and technical alternative to highway reconstruction. • To improve the positive impact of BRT, greater land use coordination needs to be implemented.
<p>(Mahmoudi et al 2010)</p> <p>Analysis and Establishment of Bus Rapid Transit (BRT) on Customer Satisfaction in Tehran</p>	<p>Tehran City, Iran</p>	<p>To explore whether the operation and the features of BRT have significant relations with customer satisfaction</p>	<p>BRT service, BRT speed, driver behaviors, ergonomics. Customer satisfaction.</p>	<ul style="list-style-type: none"> • There are significant relationship between BRT operation, speed, driver behaviors, and ergonomics.

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<p>(Deng & Nelson 2012)</p> <p>The Perception of Bus Rapid Transit: A Passenger Survey from Beijing Southern Axis BRT Line 1</p>	<p>Beijing, China</p>	<p>Investigate the attitude of the public towards BRT, and the perceptions of residents who live close to BRT.</p>	<p>Speed, reliability, safety, convenience, frequency, comfort and cleanliness, overall satisfaction.</p>	<ul style="list-style-type: none"> • BRT passengers have high satisfaction regarding the service; • Transit-dependent riders have higher satisfaction in terms of reliability, comfort and cleanliness, and overall satisfaction; • BRT highly improve the attractiveness of adjacent residential areas.
<p>(Cao et al 2015)</p> <p>The Gaps in Satisfaction with Transit Services among BRT, Metro, and Bus Riders: Evidence from Guangzhou</p>	<p>Guangzhou, China</p>	<p>To explore rider satisfaction with BRT and compare it with the satisfaction with conventional buses and metro.</p>	<p>Ease of use, safety while riding, convenience of service, comfort while riding, comfort while waiting, other riders, door-to-door travel time, customer service, reliability, and frequency.</p>	<ul style="list-style-type: none"> • The top-three important BRT attributes are ease of use, safety while riding, and comfort while waiting. • The rider satisfaction of metro is the highest, followed by BRT and conventional buses.
<p>(Cain & Flynn 2013)</p> <p>Examining the Ridership Attraction Potential of Bus Rapid Transit Examining the Ridership Attraction Potential of Bus Rapid Transit: A Quantitative Analysis of Image and Perception</p>	<p>Los Angeles, USA</p>	<p>To investigate whether the BRT could capture the ridership attraction benefits related to rail.</p>	<p>Travel cost, door-to-door travel time, frequency of service, hours of service, convenience of service, reliability of service, safety while riding, comfort while riding, safety at stop, customer service, ease of use, other riders, avoid stress/cost of car use</p>	<ul style="list-style-type: none"> • Full- service BRT could replicate the standard and image quality of rails • “BRT-lite” services performs well and achieve high rider satisfaction per dollar investment.

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<p>(Mikulić & Prebežac 2008)</p> <p>Prioritizing Improvement of Service Attributes Using Impact Range-Performance Analysis and Impact-Asymmetry Analysis</p>	N/A	To propose a new three-step approach to prioritize service attributes	Impact range-performance analysis (IRPA), Impact asymmetry analysis(IAA)	<ul style="list-style-type: none"> • The method (IPA) that was popular has certain limitation; • The importance of each service attribute may vary according to its performance.
<p>(Guthrie & Fan 2016)</p> <p>Developers' Perspectives on Transit-Oriented Development</p>	Twin Cities, MN, the United States	To examine the perception of developers on transit-oriented development (TOD)	N/A	<ul style="list-style-type: none"> • To promote TOD, policy makers could consider reforming zoning, developing regulations, broadening the focus of TOD, including transit services and improvements; • To coordinate TOD with affordable housing, policy makers should pursue affordable-by-design solution and engage with affordable housing specialists.