Impact of Arterial BRT-Lite Green Dwell Time on General Traffic and Intersection Capacity

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Abstract: This paper studies the effect dwelling mixed-traffic arterial Bus Rapid Transit (BRT-"Lite") buses have on general traffic conditions and intersection capacity. Queue length and flow rate data collected from the busiest intersection along the bus route were used as proxies for quantifying traffic impacts. Two traffic scenarios were examined: (1) high volume oversaturated traffic; and (2) normal intersection conditions that were at or below saturation levels. Through use of linear regression models and a *k*-means clustering analysis—comparing traffic conditions before and after bus arrival as a function of green dwell time—it was found that BRT-Lite buses have no statistically significant impact on intersection performance or traffic capacity. This conclusion was further complemented by paired *t*-test results in which bus dwelling was found to result in an approximate change in both the average queue length and flow rate of only 1%. As a pilot study for the new BRT-Lite system, this research provides additional insights into the practical applicability of mixed traffic BRT systems and enriches the body of literature on related subjects. **DOI: 10.1061/JTEPBS.0000328.**

Introduction

Over the last two decades, public transportation has increased in popularity in the United States with transit usage up 30% compared with 1996 (Hughes-Cromwick et al. 2018). In response, transit agencies have increased bus capacity to meet the rising demand by using a variety of methods which include increasing bus frequency, adding traffic signal priority (TSP) for transit vehicles, changing existing services to Bus Rapid Transit (BRT), and adding additional routes to serve the areas of highest demand (Metropolitan Council 2015; Transportation Management and Design 2002). While these actions address the increasing bus ridership, they also have the potential to negatively affect surrounding traffic capacity.

Much research has been done on mixed-traffic local buses' impact on surrounding traffic flow when stations are located on-line at curbside locations. For example, Wang et al. (2018) found that dwelling buses operating in mixed traffic at curbside stops may act as traffic bottlenecks owing to the frequent occurrence of lane-changing behaviors as a result of the bus in addition to creating traffic conflicts between buses and motorized vehicles and bicycles. This bottleneck behavior was found to reduce vehicle capacity owing to a reduction in motorized vehicle speeds for both peak and nonpeak hours (Wang et al. 2017), as well as having a negative effect on the speed of nonmotorized vehicles when at far and mid-block stops (Wang et al. 2018). In response to the decrease in motor-vehicle speed as a result of on-line local buses, many studies have examined alternative stop locations (Wang et al. 2018; Gu et al. 2013; Koshy and Arasan 2005).

Various methods have been adopted to better understand the relationship between road capacity reduction and the operation of buses. Yang et al. (2011) applied additive-conflict-flow procedures to study the impact of curbside stops under mixed traffic conditions. By modeling the bus stream using queuing theory, a car capacity relationship between bus flow and nonmotorized traffic flow was subsequently derived. It was concluded that the capacity reduction monotonically decreased with respect to bus flow rate with fixed nonmotorized traffic flow. A gap acceptance model was also used to model capacity reduction under the same problem setting and similar results were obtained (Yang et al. 2009). Using cellular automaton (CA) to model intersection and bus stop layout, Zhao et al. (2007) found that roadway capacity is reduced as a function of the distance between the stop and intersection as well as the intersection cycle length and bus dwell time for near-side stops. Capacity impacts due to different bus stop locations, such as near-side, far-side, and midblock, have also been investigated by researchers using nonsimulated observed data. For near-side bus stops with one berth, researchers found roadway capacity to be reduced by 2% (Wang et al. 2017). Simulation models were used to explore related problems as well. For example, Koshy and Arasan (2005) determined that increasing bus dwell time negatively impacted general traffic speeds, but that the impact on road capacity was unclear.

The impact of removing a general purpose lane for use as an exclusive bus lane for "full service BRT" has also been examined in detail because dedicated bus lanes are a key feature of BRT's claim to fast and reliable service. While the vast majority of the literature focuses on the benefits BRT systems bring to transit

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Note. This manuscript was submitted on January 18, 2019; approved on September 4, 2019; published online on January 29, 2020. Discussion period open until June 29, 2020; separate discussions must be submitted for individual papers. This paper is part of the ***Journal of Transportation Engineering, Part A: Systems***, © ASCE, ISSN 2473-2907.

users, some studies also discuss the impacts on surrounding traffic. Of the studies that focus on the impacts BRT systems have on the surrounding general traffic, Currie and Lai (2008) found that in Melbourne, road users' disadvantage, as a result of exclusive bus lanes, increases with traffic volume and that at a traffic volume of 1,000 vph or greater, the disadvantage to road users exceeds the benefit to transit users. In order for an exclusive BRT lane to be viable for inner suburban circumstances, Currie and Lai (2008) concluded that short-length bus headways must be less than 5 min and traffic conditions in the remaining traffic lanes must be less than 500 vph. Through use of the TRANSYT-7F simulator, Shalaby (1999) found that following the implementation of reserved/exclusive bus lanes in an arterial of downtown Toronto, average transit delay reduction was outweighed by the deterioration of the average vehicular traffic performance, which had an increase in delay of up to 28% during morning northbound trips. Thus, the literature is in agreement that exclusive bus lanes are only suitable for low traffic flows when the impact of removing a general-purpose lane does not cause flow rates in the remaining lane(s) to exceed saturation levels.

While the impacts of bus operation on the surrounding traffic have been extensively studied for mixed-traffic local buses and exclusive lane configurations present in full service BRT systems, proportionately few studies have been devoted to transit arrangements between these two extremes. One system that has been studied and can be classified as an intermediary between these two systems, however, is the bus lane with intermittent priority system (BLIP) in which general traffic is allowed to use the bus lane only when a bus is not present. Eichler and Daganzo (2006) developed an analysis of traffic capacity reduction based on kinematic wave theory, and showed that when BLIP headways are much longer than signal cycle length and when the street in question has three or more lanes, then there is no significant road capacity reduction resulting from BLIPs. The results of this research also suggest avoiding implementation of this system for roadways that are already near or exceed capacity. Another study on BLIPs showed that traffic capacity drops owing to vehicles merging from the bus lane to general traffic lanes, as illustrated by the fundamental diagram parameters vehicle acceleration and merging section length (Chiabaut et al. 2012). A comparison study of BLIPs in Melbourne and Lisbon focused on BLIP systems from a practical perspective noting that the system has a limited impact on traffic operations but does not work in saturated traffic conditions (Currie and Lai 2008).

Much like BLIPs, BRT-Lite serves as an intermediary system between full service BRT and mixed traffic local buses. BRT-Lite, also known as arterial-BRT, buses do not operate in exclusive bus lanes but still maintain many other typical BRT features such as off-board fare collection, high-capacity bus design, curbside stops, and traffic signal priority (SRF Consulting Groups 2012). Because transit agencies are faced with rising demand for more reliable and frequent service in the face of limited operating budgets, arterial BRT-Lite systems may become more frequently implemented. Yet, at the moment, research on the potential impacts of implementing such systems is relatively scarce. Furthermore, of the research that does exist on this select form of BRT system, the vast majority analyzes the benefits to the transit user without focusing on the potential costs placed on the surrounding general traffic. As a result, the current literature is split into somewhat of a dichotomy with many studies focusing primarily on either general auto traffic and traffic signal control systems (Ma et al. 2018; Yao et al. 2019), or analyzing the benefits transit riders receive from BRT and BRT-Lite systems with little or no research addressing the interaction between BRT-Lite and general auto traffic. Thus, the research presented here complements existing work and addresses the perceived void in the literature by answering the question, how does the dwell time of BRT-Lite buses affect intersection capacity and operation? In order to answer this question, the following report provides an overview of the studied BRT-Lite system and data involved in the study, followed by the relevant methodology and analysis, before concluding with the key findings and generalizations on the effect BRT-Lite systems have on the surrounding traffic.

Data Collection and System Overview

Line Overview

For the purpose of this research, the studied arterial BRT-Lite route was the A Line, located in the Minneapolis–Saint Paul metropolitan area. The A Line is a 16.1-km (10-mi) route operating in mixed traffic serving four cities in the greater Twin Cities region. For the majority of the route, the A Line runs along Snelling avenue, an urban arterial with 2–3 signalized intersections per kilometer (3–4 signalized intersections per mile) and average free-flow speeds of between 40 and 56 km/h (25 and 35 mi/h). The purpose of this route was to supplement, and largely replace, an existing local bus route with a goal of providing a faster and more reliable service between the two light rail lines that serve the area (Metro Transit 2018). Given its designation as a BRT-Lite service, the A Line includes many traditional BRT features such as off-board fare collection, wider bus doors and higher capacity vehicles, on-line curbside stations, as well as active traffic signal priority at many intersections. As discussed previously, the key feature that classifies the A Line as an arterial BRT (BRT-Lite) is that it does not operate in an exclusive lane. In a previous study (Metro Transit 2018), it was determined that after the first year of A Line operations, corridor ridership grew by 32% and that A Line buses operate at speeds 20%–25% faster than the previous local buses. At the busiest station, northbound Snelling avenue and University avenue, the average bus dwell time that overlapped with a green traffic signal (referred to as green dwell time hereafter) was 17.3 s, or just 18.6% of the average signal green time of 93 s. Furthermore, at the Snelling and University station, which will be the station analyzed for the remainder of the paper, the green time to cycle length ratio $[g/C]$ was 0.715. The primary street that the A Line operates on, Snelling avenue, carries an annual average daily traffic (AADT) ranging from 25,500 to 43,000 passenger car equivalents (PCE) (MnDOT 2018).

Data Collection

In order to assess the impact A Line buses have on the surrounding traffic conditions and capacity, the Minnesota Traffic Observatory (MTO) collected over 1,000 h of video data at the busiest A Line station (northbound Snelling and University) from 6:00 a.m.–10:00 p.m. every day for 26 days, including weekends. The studied station was a near-side on-line stop in mixed traffic located immediately upstream of the controlled Snelling and University intersection (Fig. 1). The northbound stream was composed of one right and one left turn lane as well as two through-lanes. The data collection period encompassed the week of the Minnesota State Fair so as to include both normal and extremely high volume traffic. The busiest station was chosen because if it could be determined that the BRT-Lite service did not negatively impact traffic conditions and capacity at the station with the highest traffic and transit volume levels, then it could be concluded that the BRT-Lite service along the entire route did not have a negative impact on traffic conditions. This assumption was justified by the observation that at all other stations, bus dwelling was a smaller percentage of the

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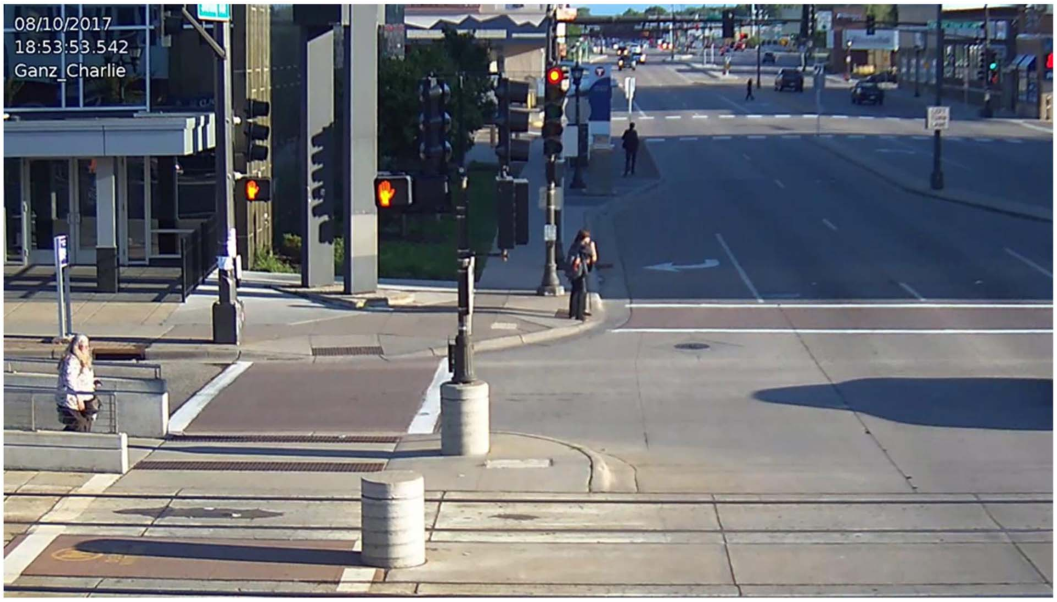

Fig. 1. The A Line Snelling avenue and University avenue (northbound stop). (Image by authors.)

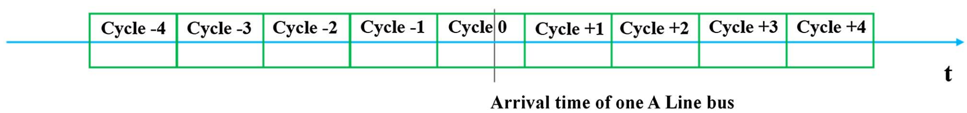

Fig. 2. Traffic measure counting periods with increasing time along the axis.

green traffic signal cycle and vehicles could more easily manipulate around the bus, owing to lower traffic volumes, minimizing any potential negative impact from the BRT-Lite service.

The Minnesota Traffic Observatory parsed all video data into nine intersection traffic signal cycles (Fig. 2) in which each cycle was composed of a "red time" and a "green time" portion based on the traffic signal controlling traffic in the direction in which the bus was traveling. Cycle 0 is defined as the cycle in which an A Line bus arrived, and negative and positively indexed cycles represent cycles before and after bus arrival, respectively. For each cycle, the length of the queue in PCE at the end of a red phase, the effective green time, and the flow rate (in PCE per lane per hour of effective green) were calculated for each cycle. Passenger car equivalents were calculated using the *Highway Capacity Manual* (HCM) standard values for relevant conditions. Additionally, the dwell time and the green dwell time were calculated for each bus arrival [National Research Council (US) 2010]. For this study, green dwell time was used rather than dwell time because green dwell time more effectively captures the potential negative effect BRT-Lite buses may have on surrounding traffic given that surrounding traffic is already stopped during the portion of the dwell time that occurs during a red signal. Bus dwell time and green dwell time were recorded during Cycle 0, while all other measures were recorded during cycles ± 1, 2, 3, and 4. After this data filtering, 162 bus arrival records (hereafter referred to as data points) containing the information described were used for the non-State Fair analysis and 38 data points were used for the State Fair data set.

State Fair Comparison

As described previously, two sets of video-based data were employed in this research, one in which traffic was oversaturated during the Minnesota State Fair, and one data set from normal traffic conditions during which traffic was at or below saturation. Fig. 3 displays a sampling of the variables used in both data sets plotted against the traffic cycle number (as described in Fig. 2) to highlight the differences and similarities between the two time periods. The primary similarity between the two periods is the relative traffic condition stability from four cycles before bus arrival to four cycles after the arrival where bus arrival is defined as Cycle 0. While there is greater variability for the 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 temporal distance of two signal cycles or more from the bus arrival. This stability is a first indication that BRT-Lite bus arrival may not affect traffic conditions, as discussed subsequently in this paper. From Fig. 3, it is clear that the volume of traffic during the State Fair was approximately 1.75 times the volume during normal conditions. Additionally, under normal conditions, it can be seen that the intersection is slightly saturated, as evidenced by a residual queue of only approximately 3 PCEs after each green cycle in comparison with the oversaturated State Fair residual queue that was, on average, approximately 35 PCE long. Thus, it is clear that the two periods represent very different traffic conditions and as such, the following analysis treats each period separately.

Methodology

A summary of the proposed framework including data preprocessing steps is provided in Fig. 4 with method and model specifics presented subsequently.

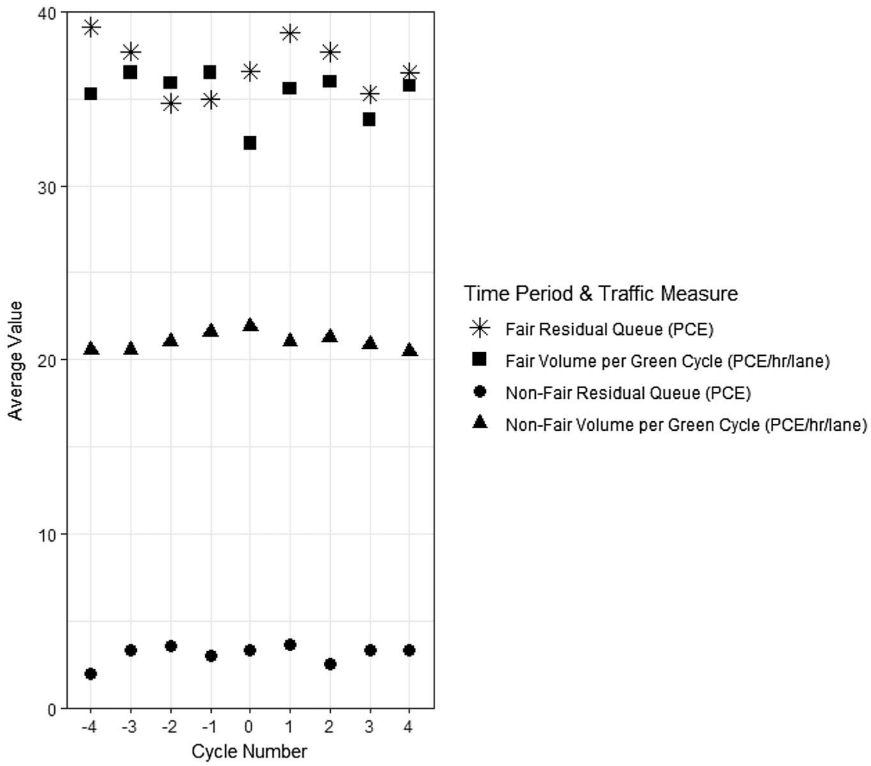

Fig. 3. Traffic conditions as a function of cycle number during and outside of the State Fair period.

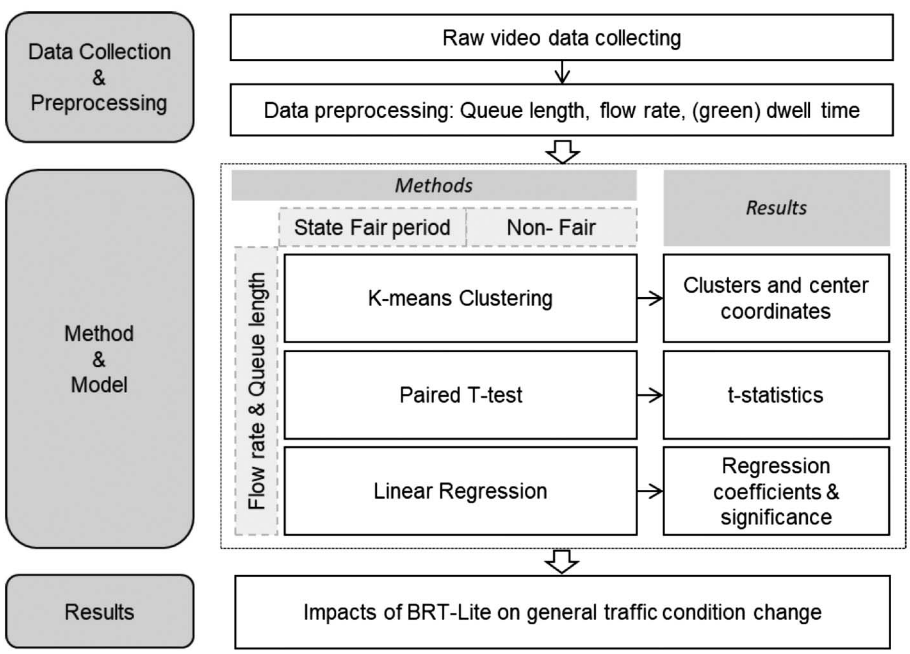

Fig. 4. The proposed methodology framework.

k-Means Clustering of Traffic Measures

Average queue lengths and flow rates in the four signal cycles before and four signal cycles after the arrival of a bus, as depicted in Fig. 2, were calculated and used together with green dwell time as the three attributes employed in data clustering. The queue and flow rate values for each of the four cycles before and after a bus arrival were averaged rather than taken as four distinct data points in order to obtain a stable state from which traffic measures could be easily compared. It was determined that if these cycles had not been averaged, the random variation of these measures would negatively affect the ability to assess the impact of the bus on traffic conditions.

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 clusters' centers. After analyzing the data for use in the k-means clustering method across 30 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 because two clusters was most effective in minimizing intercluster deviation and within-cluster sum of squares. Prior to analyzing the data with the clustering method, all of the data were normalized, using Eq. (1), on a scale from 0–1 to avoid a domination problem of any one attribute while still preserving the relative relationship between the traffic measures. After clustering assignments were performed, normalized values were converted back to their respective averages in order to preserve the clusters while using physical values in all figures in order to ensure an easier interpretation of the results

$$X_{\text{normalized}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

If bus dwell time has a significant negative impact on 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 determine if a correlation exists between bus green dwell time and traffic measure changes.

To further support these qualitative results, a paired samples t-test is employed to compare the mean difference between the before and after bus arrival traffic measures to see if the difference in means is statistically different from zero. Given that paired t-tests can only be utilized when the difference between each pair of values is normally distributed, sample size is ensured to be larger than 30 and a Shapiro–Wilk normality test is conducted. Following this check, the mean difference (m) and standard deviation of difference(s) between each pair of values is calculated with the null (H_0) and alternative hypotheses (H_a) shown in Eq. (2)

$$\begin{aligned} &H_0{:}m = 0 \\ &H_a{:}m \neq 0 \end{aligned} \tag{2}$$

Linear Regression Model

Two types of linear regression models were used to fit the traffic data and determine if there was a significant correlation between bus green dwell time and traffic measure changes before and after the arrival of an A Line bus.

The first linear regression model [Eq. (3)] assigns 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

$$y = \beta_0 + \beta_1 x \tag{3}$$

The primary interest is in testing if the coefficient β_1 is nonzero in a statistically significant way. If β_1 is nonzero, it is evidence that bus green 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 green 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 Eqs. (4) and (5), respectively

$$H_0{:}\beta_1 = 0 \tag{4}$$

$$H_a{:}\beta_1 \neq 0 \tag{5}$$

The second linear regression model, in contrast, takes the bus green 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:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \tag{6}$$

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

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

Analysis Results and Discussion

k-Means Clustering and Paired t-Test Results

Fig. 5 displays the non-State Fair relationship between queue length and green dwell time before the data was parsed into the discrete clusters. Average before and after queue lengths are located along the x-axis and y-axis, respectively, while the green dwell time is located on the z-axis. In this three-dimensional (3D) visualization, it is apparent that a large number of bus records/data points have a green dwell time of 0 s. For the non-State Fair data, approximately 42% of arrivals have a green dwell time of 0 s while only 21% of arrivals during the State Fair have a green dwell of 0 s. The second trend visible in the 3D data cloud is that the vast majority of data points (both with a green dwell time of 0 s and nonzero green dwell times) fall along a diagonal line in which the queue length before and after bus arrival is approximately equal. For a more complete and precise analysis of the data, the 3D point cloud was clustered and displayed in various 2D projections to more closely observe the impact green dwell time had on both queue length and traffic flow.

Figs. 6(a and b) 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 BRT-Lite bus outside the dates of the State Fair. The k-means cluster centers are marked by solid symbols labeled with the cluster's average

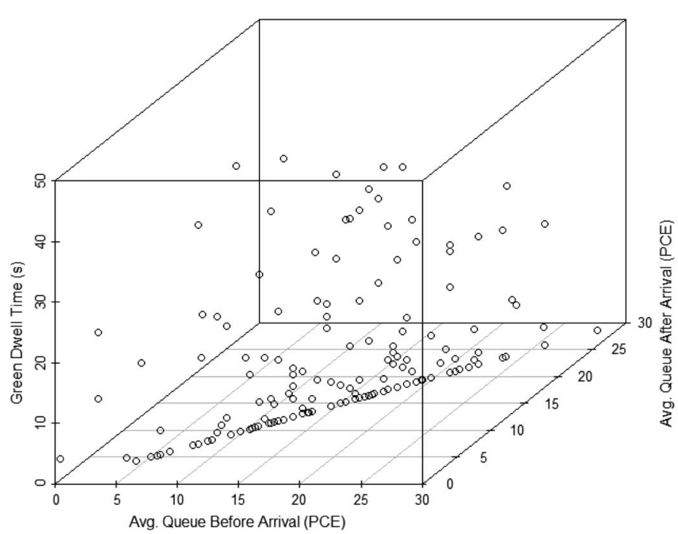

Fig. 5. Three-dimensional point cloud of non-State Fair data used in the clustering analysis.

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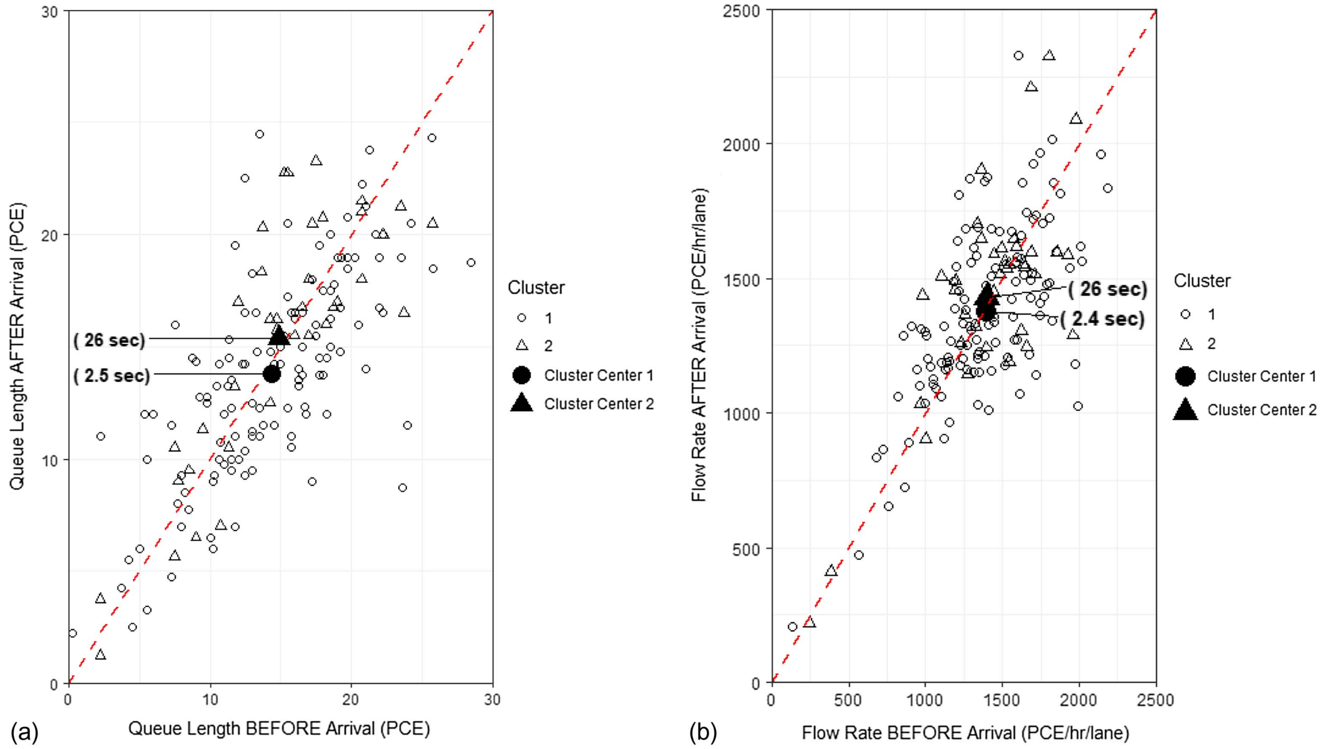

Fig. 6. Clustering results for non-State Fair (typical traffic volume) bus arrivals: (a) queue length before and after bus arrival; and (b) flow rate before and after bus arrival.

green dwell times for reference. Cluster 1 (circular points) corresponds with short green dwell times of less than 15 s and Cluster 2 (triangular points) represents longer green dwell times ranging from 15 to 45 s. Additionally, Figs. 6(a and b) have a dashed "line of equality" which represents where the traffic measures are the same before and after bus arrival. Thus, if the queue length data lie primarily below this line and the flow rate data lie above the line, it can be concluded that the bus positively impacts the relevant traffic conditions. This assumption is valid because in this scenario, queue length would be shortened and flow rate would be increased improving intersection performance. If the converse is true, then the bus negatively impacts the conditions, and if the points lie along the dashed line, then it can be inferred that bus arrivals have no significant impact on intersection capacity and performance. In Figs. 6(a and b), the majority of the data points, as well as the two cluster centers, are closely distributed along the equality line leading to the qualitative conclusion that BRT-Lite green dwelling does not appear to have a significant impact on intersection capacity performance.

To more completely comprehend the specific traffic measure changes as a result of each individual bus arrival, a box plot was created with line segments connecting each bus arrival data pair (before and after traffic measure). The ends of each box represent the upper and lower quartile values indicating the median of the upper and lower half of the data distribution, respectively. Thus, this plot allows for the visualization of both the distribution within and between the traffic measures both prior to and following the arrival of a BRT-Lite bus (Fig. 7). Despite the busyness of the plot, two significant conclusions can be drawn. First, the medians for both the queue before and after bus arrival are nearly identical. Second, the vast majority of queue pairs (before and after one bus arrival creates a pair) are relatively similar, as shown by the gradual slope of the lines connecting data pairs for all but a dozen records.

To complement this conclusion, the p-values from a paired t-test examining the difference in pair means for the non-State Fair before and after bus arrival queue data and before and after flow rates were 0.578 and 0.611, respectively (Table 1). Therefore, because the p-values are greater than the significance level of 0.05, the null hypothesis (that the difference in paired means is equal to zero:$m = 0$) cannot be rejected for neither the observed difference between the queue length mean before and after a bus arrival *nor* the observed difference of flow rate before and after the bus arrival. This conclusion is further illustrated by the fact that the mean difference in

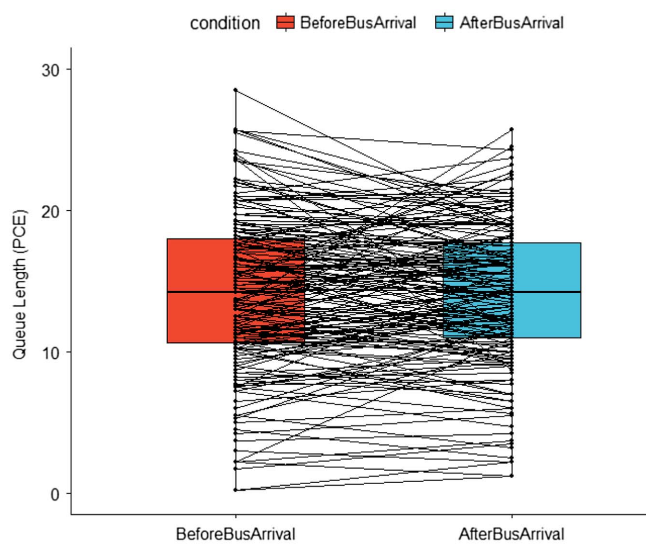

Fig. 7. Paired box plot for non-State Fair queue lengths before and after bus arrival with line segments connecting each data pair.

Table 1. Paired t-test p-values and mean difference between paired before and after traffic measures

Analysis period	Traffic measure	p-value	Mean difference (after–before)
Non-State	Queue length (PCE)	0.578	0.17
Fair	Flow rate ($PCE \times h^{-1} \times lane^{-1}$)	0.611	−10.87
State	Queue length (PCE)	0.929	−0.09
Fair	Flow rate ($PCE \times h^{-1} \times lane^{-1}$)	0.880	−7.16

queue length after a bus arrival, as compared with the value before arrival, was 0.17 PCE (approximately 1.2% of the average queue length) and the mean difference in flow rate was $-10.87\,PCE \times h^{-1} \times lane^{-1}$ or less than 1% of the average flow rates of approximately $1{,}400\,PCE \times h^{-1} \times lane^{-1}$.

Thus, when taking this result in tandem with the clustering of data points along the equality line, it can be inferred that BRT-Lite bus arrival and dwelling during a green traffic signal does not affect traffic queue length or flow rate despite the fact that data points in the second cluster have an average green dwell time of 26 s, or roughly 28% of the average green time signal length. This statistical independence of traffic conditions from bus green dwell time supports the results presented by Koshy and Arasan (2005). In their work, the authors demonstrated that for traditional buses dwelling for between 0 and 30 s at on-line curbside stops in traffic flows of between 0 and 2,000 vehicles per hour (closely mirroring the dwell time and traffic flows observed in this research), "the effects of dwell times of 10, 20, and 30 s duration, are nearly the same" as traffic speeds drop by less than 10 km/h (6 mi/h) (Koshy and Arasan 2005).

To further extend these conclusions, the same paired t-test was applied separately to non-State Fair peak and off-peak hours to investigate if bus dwelling had an impact on traffic during the periods of the day in which traffic was busiest. As summarized in Table 2, p-values for the difference in queue length and flow rates from before and after bus arrival data pairs were greater than the 0.05 significance level for both peak and nonpeak hours. Thus, these p-values indicate the null hypothesis—that no difference existed in the mean traffic measure before and after a bus arrival—was rejected for all four tests shown in Table 2. The results of these statistical tests therefore further indicate that BRT-Lite bus dwelling has no statistically significant affect on intersection performance, as measured through queue length and flow rate changes.

Fig. 8 contains two subplots illustrating the same comparative relationships described in the subplots of Fig. 6, except that the data in Fig. 8 is from the State Fair period of high volume traffic. When examining the State Fair data in comparison to non-State Fair results, it is important to note that there are fewer data points in the State Fair sample (Fig. 8) owing to a shorter time period represented by this data. Additionally, both the queue length [Fig. 8(a)] and flow rate [Fig. 8(b)] values 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-State Fair data. The State Fair data has higher deviation, when compared with non-State Fair data, owing to fluctuations in fair-goer arrivals as a result of fair hours and high attendance events such as concerts. As a result, for example, traffic volume is extremely high around the time the fair opens and is slightly less busy during the lunch hours. Despite these variations, it can again be concluded, as was the case in the non-State Fair data, that A Line BRT-Lite bus dwelling does not have a significant impact on traffic queue length [Fig. 8(a)] or traffic flow rate [Fig. 8(b)] during the high traffic volume conditions of the State Fair.

Table 2. Paired t-test p-values and mean difference between paired before and after traffic measures for peak and nonpeak hours during non-State Fair dates

Analysis time frame	Traffic measure	p-value	Mean difference (after–before)
Nonpeak	Queue length (PCE)	0.6363	+0.22
hours	Flow rate ($PCE \times h^{-1} \times lane^{-1}$)	0.230	+34.7
Peak	Queue length (PCE)	0.183	−0.55
hours	Flow rate ($PCE \times h^{-1} \times lane^{-1}$)	0.672	−13.49

This conclusion can be reached because the data are clustered around the equality lines and the State Fair paired t-test p-values for queue length and flow rate traffic conditions were 0.929 and 0.880, respectively. These results, again, indicate that the null-hypothesis—stating that the difference in traffic measure before and after bus arrival is equal to zero—cannot be rejected. A separate analysis for peak and nonpeak hours was not conducted for State Fair data owing to the limited sample size of data (Table 1).

Regression Results

The two linear regression models were fitted to State Fair and non-State Fair data separately. The regression results are consolidated in Table 3. For all estimated coefficients, numbers in parentheses are the p-value followed by significance level of the estimates 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) 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 green dwell time on the traffic condition change is not statistically significant.

Model 1 shows that bus green dwell time is not a factor that changes the traffic condition, and Model 2 answers the question of 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 queue length (or flow rate) 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 before bus arrival 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.

In order to determine if the deviations from the equality lines in all subplots of Figs. 6 and 8 were truly random, the results of the linear regression (Table 3) and corresponding 95% confidence intervals (represented by the shaded band) were added to a plot displaying the difference in traffic condition as a function of green dwell time (Fig. 9). From the four subplots in Fig. 9, it is evident that, as demonstrated previously, there is no significant trend between green dwell time and traffic conditions. This observation is shown by the trend lines for average queue length [Figs. 9(a and c)] and flow rate [Figs. 9(b and d)]. 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-State Fair flow remained

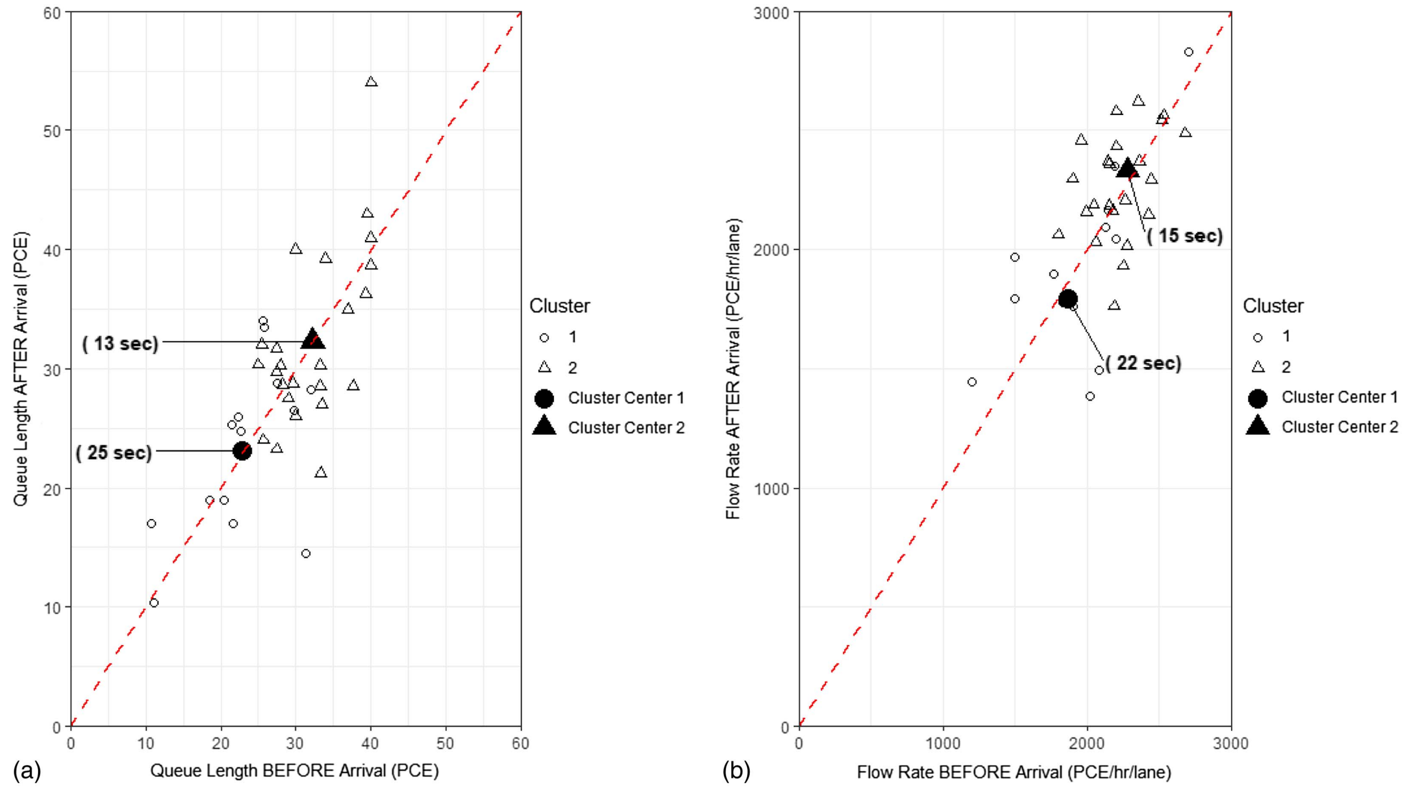

Fig. 8. Clustering results for State Fair (high traffic volume) bus arrivals: (a) queue length before and after bus arrival; and (b) flow rate before and after bus arrival.

Table 3. Results of linear regression models with p-values listed in parentheses

Model	Period	Dependent variable	β_0 (intercept)	β_1 (bus green dwell time)	β_2 (before arrival traffic measure)
Model 1	State Fair	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	Flow rate change	−12.215 (0.646)	1.232 (0.526)	—
		Queue length change	−0.718 (0.056)	0.046 (0.087)	—
Model 2	State Fair	Flow rate after	850.216 (0.005)**	−3.146 (0.220)	0.631 (3.56×10^{-5})***
		Queue length after	4.100 (0.137)	0.059 (0.308)	0.825 (6.92×10^{-7})***
	Non-State Fair	Flow rate after	464.35 (5.98×10^{-8})***	1.213 (0.489)	0.657 ($<2 \times 10^{-16}$)***
		Queue length after	4.323 (1.33×10^{-7})***	0.044 (0.065)	0.653 (2×10^{-16})***

Note: ***Significance level = 0; **Significance level = 0.001; *Significance level = 0.01; and Significance level = 0.05.

approximately constant while State Fair flow decreased by as much as 100 PCE/h, or 7.4% of the average flow during this period. Thus, any apparent relationships between the various traffic conditions and BRT-Lite green dwell time are so small as to be non-significant when compared with the average traffic conditions and aggregate behavior of the researched intersections.

Conclusion and Key Findings

BRT systems around the world have been acknowledged as an efficient infrastructure in carrying large volumes of passengers with faster and more reliable speeds than traditional local bus systems. Although a great deal of research has been conducted on BRT-related topics, the impact of BRT-Lite operations on general traffic conditions has not been given much attention. This study helps to fill that research gap by exploring if, and how, bus green dwell time affects road capacity by analyzing the A line mixed-traffic BRT-Lite system operating in the Minneapolis–Saint Paul metropolitan area.

Queue length and flow rate were selected as measures of traffic condition and road capacity. Two distinct traffic volume scenarios were compared, a period during the Minnesota State Fair representing high-volume traffic and a non-State Fair period comprised of normal volume conditions, to show the potentially different impacts of bus dwell time under varied general traffic volumes. The *k*-means clustering on three dimensions of the data (before traffic condition, after traffic condition, and bus green dwell time) was conducted and paired *t*-tests were implemented to ascertain the degree to which before and after bus arrival conditions were statistically different from one another. Results using either queue length or flow rate as a measure of traffic condition revealed that although clustered data points have distinct average bus green dwell times, the before and after traffic conditions are nearly identical.

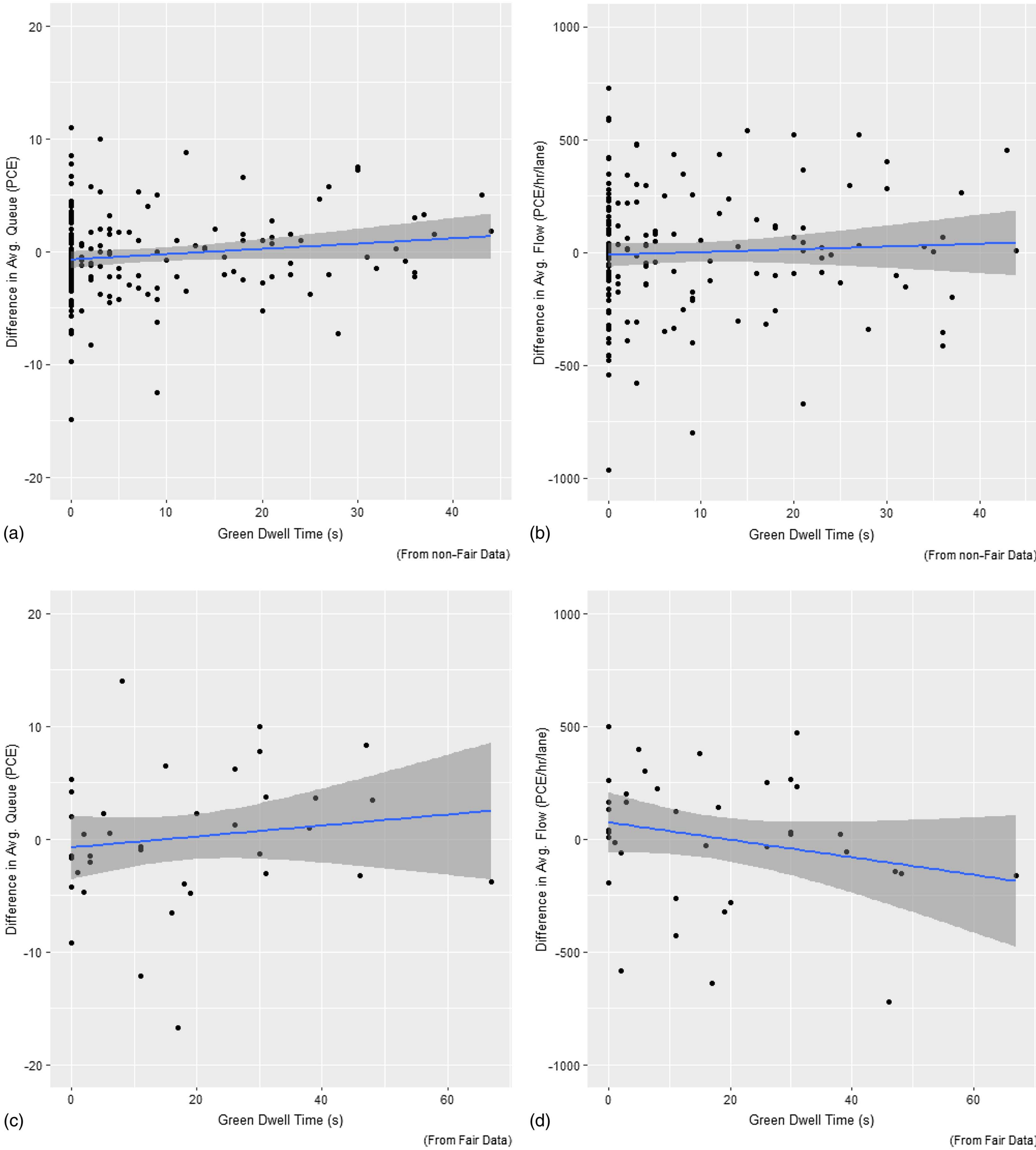

Fig. 9. Traffic condition change as a function of green dwell time and State Fair presence: (a) non-State Fair: queue length; (b) non-State Fair: flow rate; (c) State Fair: queue length; and (d) State Fair: flow rate.

In addition, comparisons between State Fair and non-State Fair period bus arrivals confirmed that in either case, the bus green dwell time does not have a significant impact on capacity reduction or the various traffic conditions studied in this research, as supported by the paired *t*-test results which failed to reject the null hypothesis that the difference in queue length and flow rate before and after bus arrival was zero. This failure to reject the null hypothesis is further illustrated by observing that the average queue length and flow rates after a BRT-Lite bus arrival changed by only 1%–3% when compared with the respective traffic measure before bus arrival for both the high and normal traffic volumes during and outside the 12 days of the State Fair as well as during nonpeak and peak hours.

In addition to analyzing the impact of bus dwell time on traffic conditions in high and low traffic volumes based on the presence of a special event (Minnesota State Fair), the impact of dwell time was also found to be statistically nonsignificant during high volume (peak hour) conditions *within* a given day because the null hypothesis—that the difference in traffic condition before and after a bus arrival was zero—failed to be rejected. Regression models were implemented to test the clustering analysis result that bus dwell time does not significantly alter the chosen traffic conditions. It was confirmed from the regression results that the hypothesis is valid and that traffic conditions after a bus arrival are strongly correlated with the traffic condition before the arrival of the bus rather than the bus green dwell time. Therefore, this research has shown that BRT-Lite systems have no statistically significant impact on surrounding traffic and intersection capacity and performance.

The main contribution of this research is that it stands as a first step in the analysis of BRT-Lite impacts on surrounding traffic environments. Thus, a more complete understanding of the relationship between bus service and surrounding vehicle flow and intersection capacity can now be formed by juxtaposing and comparing the results of this BRT-Lite research with existing literature on traffic impacts from local bus service and traditional "full-service" BRT. Further work and investigation can be conducted to expedite the time required to manually gather and process the video data as well as expanding the generalizability of this methodology to traffic conditions different from an annual average daily traffic of 25,500–43,000 PCE. Adopting other methods, such as time-series analysis, and an exploration considering downstream intersection signal timing are current avenues for future work.

Data Availability Statement

Queue length and flow rate data sets are available from the corresponding author by request.

Acknowledgments

The authors would like to thank Metro Transit and the Minnesota Traffic Observatory (MTO) for their assistance in providing the data necessary to make this research possible. This research is conducted at the University of Minnesota Transit Lab (http://umntransit.weebly.com/), currently supported by the following projects, in addition to others: National Science Foundation, award CMMI-1637548; Minnesota Department of Transportation, Contract No. 1003325 Work Order No. 15; Minnesota Department of Transportation, Contract No. 1003325 Work Order No. 44; and Transitways Research Impact Program (TIRP), Contract No. A100460 Work Order No. UM2917. Any limitation of this study remains the responsibility of the authors.

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