Understanding the Factors that Influence the Probability and Time to Streetcar Bunching Incidents

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UNDERSTANDING THE FACTORS THAT INFLUENCE THE PROBABILITY AND TIME TO STREETCAR BUNCHING INCIDENTS

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ABSTRACT

Bunching is a well known operational problem for transit agencies and it has negative impacts on service quality and users' perception. While there has been a substantial amount of literature on understanding the causes of bus bunching and strategies used to mitigate the effects of this problem, there has been little research on streetcar bunching. Although bus and streetcar systems share many similarities, one major difference between the two is that streetcars cannot overtake each other. This makes bunching in streetcar networks more critical to the reliability of the system and an important topic that requires more in-depth understanding. This research aims at understanding the factors that impact the likelihood of streetcar bunching and to investigate in more detail the external and internal factors that impact the time to bunching since the departure of a streetcar from its route's terminal. To achieve the first goal, the study uses a binary logistic regression model, while it uses survival analysis - accelerated failure time (AFT) model to address the second goal. The study utilizes automatic vehicle location (AVL) system data acquired from the Toronto Transit Commission (TTC), the transit provider for the City of Toronto. The models' results show that headway deviations at terminals both increase the probability of bunching and accelerate the time to bunching. The discrepancy in vehicle types between two successive streetcars also increases the likelihood of bunching and accelerates the time to bunching. This study offers a better understanding of the factors that impact streetcar service bunching, which is an important component of transit service reliability.

Keywords: Streetcar, bunching, reliability, accelerated failure time (AFT) model, survival analysis

INTRODUCTION

Public transit systems face many different operational problems and disruptions that can degrade the quality and reliability of service. One of the most common disruptions is vehicle bunching. Bunching occurs when two or more consecutive vehicles on the same route are unable to maintain their scheduled headways and end up following each other too closely. Bunching causes serious challenges to both the passengers and operators. For the passengers, bunching causes longer or variable wait times and vehicle overcrowding, which both contribute to reducing users' satisfaction. For the transit agencies, bunching leads to increased costs due to the inefficient use of resources since overcrowded vehicles at the front of a bunch would be followed closely by near-empty ones. Bunching also impacts the overall image of transit agencies, making it harder to attract new transit riders and retain the existing ones (1, 2). For all these reasons, bunching has been a popular topic in the literature over the past two decades.

Bunching is a well known problem that is frequently experienced in the City of Toronto, not only along bus routes but even worse along streetcar routes (*3*). Although buses and streetcars share many similarities, one major difference between the two is that streetcars cannot overtake each other since they are limited to the path of their track infrastructure. This subtle difference makes bunching incidents more critical to the streetcar system quality than buses, which can overtake each other. The problem is exasperated in Toronto by the very high frequency of streetcar services relative to bus services. Yet, there is very little literature found on streetcar bunching. This is likely due to the fact that streetcars are an uncommon transit vehicle mode and are utilized in very few cities around the world. However, many cities are now planning or in the construction stage of building new light rail or streetcar systems including Minneapolis, Kansas City, and Montreal (*4*). For example, in 2016, Kansas City introduced a new streetcar line, with further plans of expansion (*5*). Streetcar technology may be mature, but streetcar bunching is a topic that needs a more comprehensive study as streetcar and light rail systems become more popular.

The TTC streetcar system is one of the largest in North America. In 2016, the TTC operated 11 streetcar routes, covering 338 km (*6*). Approximately 300,000 passengers ride the streetcars on a typical weekday. Headways range from 2 to 10 minutes on the streetcar network with the average being approximately 4 minutes on weekdays during the morning and afternoon peak periods. The TTC has a fleet of 250 streetcar vehicles using a combination of three different types which are listed in order of increasing capacity: a standard vehicle (Canadian Light Rail Vehicles - CLRV), an articulated vehicle (Articulated Light Rail Vehicles- ALRV), and a new low-floor articulated vehicle (Flexity Outlook) that was just introduced in 2014. The majority of streetcar routes operate on a shared right of way. However, there are a few that operate on a dedicated right of way and some on a hybrid right of way with portions that are dedicated and others shared.

The TTC publishes a daily customer service score card that shows how well it meets its target goals (*7*). Its goal for the streetcar service is to provide on-time departures from end terminals at least 90% of the time. However, the streetcar service performance continues to hover around the 50-60% range, falling well short of its 90% goal. Therefore, in an effort to improve service, the TTC plans to replace its old fleet with over 200 Flexity vehicles on a gradual basis. The TTC believes that the higher capacity vehicle will reduce bunching on its network (*7*). This is because the new vehicles will be operated with longer headways compared to the ones currently in effect, while maintaining the same route capacity. The City of Toronto is also currently in the process of constructing the Eglinton Crosstown, a new high-end light rail line, and it is planning the addition of more light rail routes (Finch West LRT and Sheppard East

LRT). Therefore, with the expected growth of the network and the city population, it is more critical now than ever to have a clear understanding of the factors that influence streetcar bunching to ensure a better service operation overall. This will help transit agencies, including the TTC, minimize the occurrence of bus bunching, which will likely lead to better service efficiency and higher rider satisfaction.

This research aims at understanding the factors that impact the likelihood of streetcar bunching within the City of Toronto. It also explores in more detail the external and internal factors that impact the time to the initial bunching incident. The first model explores the odds of a headway becoming a bunching incident, irrespective of the location of the incident. The knowledge gained from this model could help transit operators formulate policies and strategies to reduce the occurrence of bunching incidents. The second model estimates the time to the initial bunching incident, given that one occurs. The later a bunching incident occurs, the better it is for the operator; in other words, it is extremely useful to formulate policies that delay the onset of bunching and its detrimental effects as far down the line as possible knowing that bunching cannot be eliminated completely. The second model can help inform and guide such strategies. The combined results of the two models can help inform policies that minimize the occurrence of bunching and delay their onset if they do occur.

LITERATURE REVIEW

A sizable body of the transit literature has focused on bus bunching in terms of generating and proposing several holding strategies to reduce bunching once it has occurred. For example, Daganzo has developed several studies that provide theoretical holding techniques and other corrective actions to deal with bus service bunching (*8*, *9*). Daganzo and Pilachowski proposed a control strategy whereby bus speeds are adjusted to maintain headways and consequently, reduce bus bunching (*10*). Similarly, Moreira-Matias et al. and Liang et al. have developed different theoretical methods to handle bunching once it has occurred (*11*, *12*). Other researchers have focused on exploring the factors that affect bus service travel, running time and dwell time (*13*, *14*).

Despite these previous efforts, there is little that has been done on understanding the causes and factors that impact bus bunching. There is also an absence of research on estimating the time until a bunching incident occurs and the factors that impact this. In fact, only a few studies can be found in the literature that investigated bus bunching using statistical analyses. One of them is done by Mandelzys & Hellinga (*15*), where they attributed bus bunching to fluctuating travel times between stops and dwell times. These characteristics were also attributed to bus bunching in (*16*, *17*). Diab et al. (*1*) developed a bus bunching model that was used to investigate several factors such as passenger volume, delay at start, and their impact on the probability of bunching. In contrast to work that has been done regarding bus bunching, it is rare to find articles on streetcar bunching.

Other researchers have focused on understanding the impacts of several factors on streetcar service performance, but not specifically on streetcar bunching. For example, Currie has generated multiple articles regarding the impacts of different factors on streetcar service performance. He explored streetcar safety (*18*), weather impacts (*19*), and dwell times (*20*, *21*) and compared streetcar performance in different countries (*22*, *23*). He also discussed how transit signal priority (TSP) handles bunched streetcar vehicles (*24*). Ling and Shalaby developed a reinforcement learning approach to control streetcar bunching (*25*). With this very little research on streetcar service operations, and even lesser on streetcar bunching, a better understanding of the streetcar service bunching is needed. With the availability and the accuracy of AVL data, we are now able to investigate streetcar bunching, while isolating the effects of different influential variables on the service.

Similar to streetcar bunching, the application of survival analysis in bunching incidents has not been explored before. Survival analysis was applied to the disruption duration in the TTC's subway system (*26*) and provided a satisfactory model to predict the effects of different factors on disruption durations. In Yu et al.'s (*27*) work, bus travel time predictions and associated uncertainties were generated from survival analysis. Survival analysis seemed to provide promising results in both studies and has much potential for its application in our study to investigate the time it would take for two vehicles to bunch.

METHODOLOGY

The objectives of this analysis is to understand the general factors that impact the likelihood of streetcar bunching as well as to investigate in more detail the external and internal factors that impact the time to bunching. The data used in the analysis come from the TTC's AVL system for eight streetcar routes within the City of Toronto for the last week of January 2016. The routes are 501, 504, 505, 506, 509, 510, 511 and 512; they are highlighted in Figure 1. The other three routes that were removed from the analysis (i.e., routes 502 and 503) were operated only by buses due to a shortage of streetcar vehicles at that time or was completely new (i.e., Route 514). The TTC's AVL system records each vehicle's location every 20 seconds. The acquired data included both weekends and weekdays, with a total of six million observations. The week chosen for data collection had mild and clear weather with minimal track construction, closures, or diversions. The eight routes included in the analysis are all high frequency routes, operated every 10 minutes or better anytime of the day every day of the week (*28*). Each streetcar route operates using one or a combination of the three different vehicle types mentioned in the introduction.

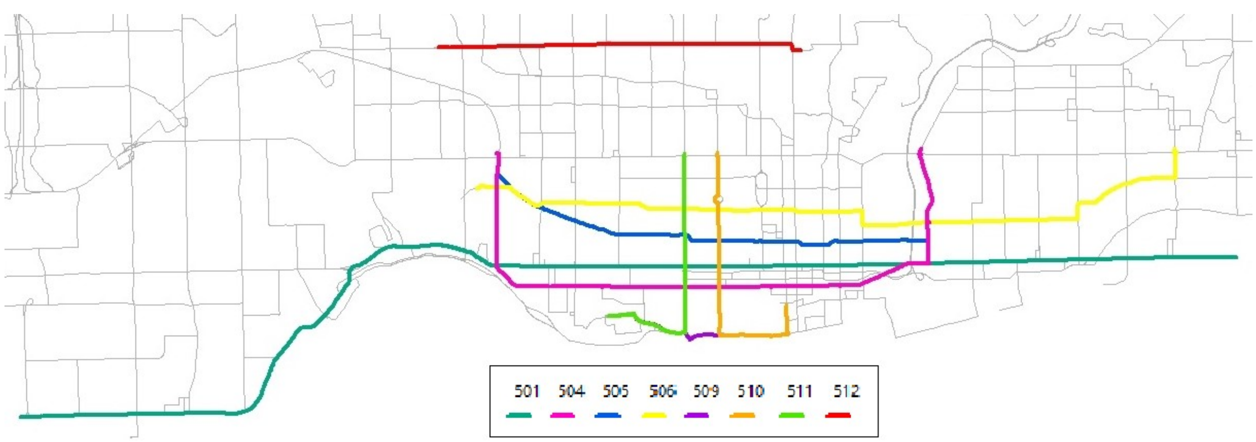

FIGURE 1 Map of TTC Streetcar Routes Included in the Study

The unit of analysis in this paper is the headway between consecutive vehicles. Since streetcars cannot overtake one another, the study focuses on the location when any pair of consecutive streetcars first form a bunch on the route. Bunching incidents were isolated at the segment level. A bunching incident is defined to be when the actual headway between two vehicles is less than half of the scheduled headway. To assist in understanding the dynamic factors that influence the streetcar bunching phenomenon, information about the previous headway of a bunching occurrence is also used. The headway (or vehicles) is labelled as shown in Figure 2 to better understand the methodology. The vehicle in question is labelled as Following (F), vehicle in front of it is labelled Leading (L), and vehicle prior to the Leading is labelled as Leading+1 (L+1). If a bunching incident was observed between F and L, the headway between L and L+1 was considered as a predictor in the models. The underlying rationale is that if the Leading+1 vehicle is leaving the terminal early and the Leading vehicle is slightly late, the latter will likely pick up more passengers in addition to its normal load, leading to more delays for itself. Meanwhile, the Following vehicle (vehicle in question) will find fewer passengers to serve along the route even if it is leaving the terminal on time, increasing the odds of bunching with the Leading vehicle at a point down the line. Furthermore, the time to the initial bunching incident is defined to be the time it takes for the first bunching incident (as opposed to subsequent bunching incidents) in a trip to occur. The time is measured from the instant the Following streetcar leaves its route terminal to the instant it first catches up with the Leading streetcar.

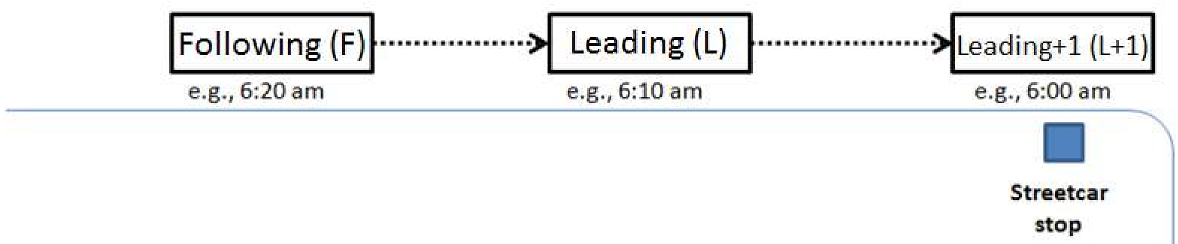

FIGURE 2 Streetcar Vehicle Labelling System

The first model is a binary logistic regression model that investigates the effects of different factors on the likelihood of a streetcar bunching. Headways that experienced bunching and those that did not experience bunching were included in this model. Many variables were tested but were eliminated from the model due to insignificance such as schedule deviation for both the following and leading vehicle as well as headway ratios. Squared terms of some independent variables were used to account for a possible non-linear relationship between each variable and the dependent variable, if such a relationship existed. In addition to the route number, direction, day of the week and time of day variables, other variables were utilized in the models.

A set of headway deviation dummy variables were used in the model to reveal the impact of different combinations of headway deviations on bunching. Headway deviation is measured at the terminal and is categorized into three classes: shorter than scheduled headway, same as scheduled headway, or longer than scheduled headway. Headways that fall between 80-120% of the scheduled headway are defined to be the same as scheduled headway or on time. Headways that are less than 80% are defined to be shorter than scheduled headway and those greater than 120% are longer than scheduled headway. These values were arbitrarily chosen, but seemed logical as some tolerance is required in defining on-time performance.

The second model, an AFT model, was used to explore the impact of both internal and external factors on the time to the first bunching incident for pairs of successive streetcars. The time is calculated from the terminal to the following vehicle it first bunched with the leading vehicle. Therefore, the model only focuses on the first location where bunching began to occur. In this model, only bunched trips were used. The AFT models are typically used in medicine to analyze the time to an event, which is usually death or failure. In our case, a bunching incident can be considered as a failure event. External factors such as traffic volume, existence of transit signal priority, and the number of signalized intersections were included in this model. The internal factors discussed above were also included in the model. A detailed description of the variables used in both models can be found in Table 1.

TABLE 1 Description of the Independent Variables Used in the Models

Variable Name	**Variable Type**	**Description**
Weekday/Weekend	Dummy	Weekend (0) or weekday (1)
Trip Direction	Dummy	Eastbound/Southbound (0) or Westbound/Northbound (1)
Vehicle Combination	Categorical	Following & leading are same vehicle type = 0 Following vehicle capacity is larger than leading vehicle capacity = 1 Following vehicle capacity is smaller than leading vehicle capacity = 2
Time Period	Categorical	AM Peak=1, Midday=2, PM Peak=3, Evening = 4
Route #	Categorical	Streetcar route number; it captures route characteristics such as route length, right of way and average stop distance
Following & Lead Headway Ratio	Continuous	Ratio of actual F, L vehicle headway to the scheduled headway
Lead & Lead+1 Headway Ratio	Continuous	Ratio of actual L, L+1 vehicle headway to the scheduled headway
Scheduled Headway	Continuous	Scheduled headway between vehicles
Scheduled Headway^2	Continuous	Squared value of scheduled headway
Cumulative TSP	Continuous	Number of intersections equipped with transit signal priority between the terminal and bunching location
Stop Combination	Continuous	Stop placement at route level: if same stop (all near or all far side) placement (0), Combination of near and far side stops (1)
Cumulative Pedestrian Crossing	Continuous	Number of pedestrian crossings between the terminal and the bunching location
Cumulative Signalized Approaches	Continuous	Number of signalized intersections between the terminal and the bunching location
Traffic Volume	Categorical	Traffic volume is define to be a proportion of the highest volume. Low volume (0-33% of highest volume) (0), medium volume (34-66%) (1), high volume (67-100%) (2)

Lshort	Dummy	Leading vehicle is not short turned from the opposite direction (0), leading vehicle is short turned (1)
Short/Short	Dummy	Actual headway between F, L is shorter than scheduled headway and actual headway between L, L+1 is shorter than scheduled headway at terminal
Short/On Time	Dummy	Actual headway between F, L is shorter than scheduled headway and actual headway between L, L+1 is the same as scheduled headway at terminal
Short/Long	Dummy	Actual headway between F, L is shorter than scheduled headway and actual headway between L, L+1 is longer than scheduled headway
On Time/Short	Dummy	Actual headway between F, L is the same as scheduled headway and actual headway between L, L+1 is shorter than scheduled headway at terminal
On Time/ On Time	Dummy	Actual headway between F, L is the same as scheduled headway and actual headway between L, L+1 is the same as scheduled headway at terminal
On Time/Long	Dummy	Actual headway between F, L is the same as scheduled headway and actual headway between L, L+1 is longer than scheduled headway at terminal
Long/Short	Dummy	Actual headway between F, L is longer than scheduled headway and actual headway between L, L+1 is shorter than scheduled headway at terminal
Long/On Time	Dummy	Actual headway between F, L is longer than scheduled headway and actual headway between L, L+1 is the same as scheduled headway at terminal
Long/Long	Dummy	Actual headway between F, L is longer than scheduled headway and actual headway between L, L+1 is longer than scheduled headway at terminal
Route 501 x Short/Short	Dummy	An interaction variable between trips that belong to Route 501 and also experience shorter than scheduled headways

ANALYSIS

Descriptive Statistics

Table 2 shows the summary statistics of the trips used in the study and the % of bunched headways per route. If a headway experiences bunching in any segment (i.e. less than half the scheduled headway), it is considered a bunched headway. In total, about 30,500 headways were included in the analysis. The majority of the analyzed headways occurred on weekdays. Out of the total number of headways, approximately a quarter of them were involved in a bunching incident. Route 504, with the highest ridership in Toronto (65,000 riders per day), experiences the highest number of bunched headways (38.9%).

TABLE 2 Descriptive Statistics of Headways Used in Models

	Direction		Day		Time Period						
Route	EB/ SB	WB/ NB	Week end	Week day	AM Peak	Mid day	PM Peak	Even- ing	Grand Total	Bunching Events	% bunch
501	3894	3880	1006	6768	1282	2242	1602	2648	7774	2141	27.5%
504	2918	2662	543	5037	1156	1367	1284	1773	5580	2171	38.9%
505	1313	1279	399	2193	423	791	505	873	2592	508	19.6%
506	1154	1080	260	1974	482	750	470	532	2234	839	37.6%
509	1212	1210	409	2013	331	732	610	749	2422	877	36.2%
510	1711	1715	554	2872	430	1213	779	1004	3426	741	21.6%
511	1242	1197	354	2085	432	724	483	800	2439	415	17.0%
512	2034	2004	468	3570	742	1183	864	1249	4038	65	1.6%
Total	15478	15027	3993	26512	5278	9002	6597	9628	30505	7757	25.4%
%	50.7%	49.3%	13.1%	86.9%	17.3%	29.5%	21.6%	31.6%	na	na	na

Bunching Probability Model

In this model, headways that have experienced bunching are coded as "1" and those that have not experienced bunching are coded as "0". The results of this model are reported in Table 3. Variables that are found to be statistically significant of at least 90% are bolded in the table. This model has a Nagelkerke R Square value of 0.59, which indicates that 59% of the variance has been explained by the model. This R square value is comparable to other binary logistic models that investigate on-time performance (*1*, *29*).

The route number variables, which have been included in the model as control variables, show a significant coefficient. This is expected since each route has different right of way characteristics, length, as well as the average stop distance. As shown in the descriptive statistics, Route 512 experienced the least amount of bunching, and therefore this model shows that all other routes have higher odds of bunching compared to this route. The model also indicates that the odds of bunching are higher on weekdays compared to the weekend. This is expected as there is an increase in ridership, frequency and traffic congestion during the week than the weekend. In addition, the midday, PM peak, and evening time periods were found to increase the odds of bunching compared to the AM peak. The increased chances of bunching frequency in the midday and evening peaks are likely due to the combined effect of the relatively high streetcar frequencies with lower volumes of the general traffic. .

Interestingly, the model shows that when the following vehicle has a greater capacity than the leading vehicle, this reduced the odds of bunching by 24%. This can be explained by the fact that since the following vehicle has a higher capacity, it will be able to hold more passengers and thus have a longer dwell time as well as total travel time. These longer times will prevent it from catching up with the leading vehicle. However, when the following vehicle has a lower capacity than the leading vehicle, the odds of bunching are increased by 124%. This is due to the fact that the leading vehicle will likely have longer dwell times, making it easier for the following vehicle to catch up and bunch with it. To summarize, both of the previous cases indicate that vehicles with higher capacity are slower, and therefore they bunch with the following ones while increasing the headway gap with the leading ones.

The model indicates that for every minute that scheduled headway is increased, the odds of bunching is reduced by 44%, which is expected and was found in the bus literature (*1*). Therefore, schedule design plays a big role in bunching for streetcar service, and transit agencies should address this problem. This can be done by providing higher volume vehicles with longer headways, which is currently the TTC's plan (*7*). The dummy variable Lshort was added to the model to understand the effects of short-turning on bunching incidents. On routes 504 and 510, up to 20% of the vehicles are short-turned. The strategy of short-turning is used in streetcar operations to address a serious effect of bunching occurrence, namely the long gaps in service downstream of bunched vehicles. It is assumed that the TTC short-turning procedure is only implemented when there is a long gap ahead of a streetcar bunch extending into the opposite direction. The model indicates here that when the leading vehicle is short-turned, it decreases the odds of bunching by 64%. This is logical since the following vehicle will still have to go to the terminal and run back in the opposite direction, which will create a gap between originally bunched trips.

With respect to headway deviation at terminals, only five of the nine combinatory dummy variables were found to be significant. A pattern can be noted with the significant combinatory headway deviation variables: when the following vehicle has an actual headway that is shorter than the scheduled headway, the odds of bunching is increased and when the following vehicle has an actual headway that is longer than the scheduled headway, the odds of bunching is reduced. The headway deviation combination that increases the odds of bunching the most is when the following vehicle has a shorter headway and the leading vehicle has a longer headway at the terminal, increasing the odds of bunching by 146%. This scenario essentially represents when the leading vehicle is delayed at start and the following vehicle leaves early at start. When the leading vehicle is delayed, it is likely to pick up more passengers, thus experiencing longer dwell times. When the following vehicle leaves the terminal early, it has very fewer passengers to pick up and therefore can easily catch up to the leading vehicle. In contrast, when the following vehicle has a longer headway and the leading vehicle has a shorter headway, this situation provides the greatest reduction in the odds of bunching out of all the cases where the following vehicle has a longer headway. An interaction variable between route 501 and short/short headway deviation combination is included in the model due to the fact that route 501 experiences a lot of short/short headway deviations and skews the results of the short/short variable.

TABLE 3 Streetcar Bunching Probability Model Results

	Coefficient	**Wald**	**Significance**	**Odds Ratio**	**95% Confidence Interval**	
					Lower	**Upper**
Wkday	**2.15**	**2450.65**	**0.00**	**8.62**	**7.92**	**9.39**
Trip direction	**0.32**	**72.73**	**0.00**	**1.37**	**1.28**	**1.47**
Lshort	**-1.02**	**253.45**	**0.00**	**0.36**	**0.32**	**0.41**
Vehicle Combination	(Reference to same vehicle type for both following and leading vehicles)					
FVehCap > LVehCap	**-0.27**	**18.60**	**0.00**	**0.76**	**0.67**	**0.86**

FVehCap < LVehCap	**0.33**	**32.36**	**0.00**	**1.39**	**1.24**	**1.56**
Time Period	(Reference to AM Peak					
Mid Day	**0.78**	**183.44**	**0.00**	**2.19**	**1.95**	**2.45**
PM Peak	**0.18**	**10.17**	**0.00**	**1.20**	**1.07**	**1.34**
Evening	**0.94**	**145.62**	**0.00**	**2.56**	**2.19**	**2.98**
Route Number	(Reference to Route 512)					
Route 501	**8.16**	**2121.09**	**0.00**	**3494.14**	**2469.15**	**4944.62**
Route 504	**3.12**	**547.37**	**0.00**	**22.62**	**17.42**	**29.37**
Route 505	**3.88**	**696.07**	**0.00**	**48.58**	**36.40**	**64.82**
Route 506	**4.94**	**1190.14**	**0.00**	**139.23**	**105.19**	**184.31**
Route 509	**3.88**	**747.04**	**0.00**	**48.53**	**36.73**	**64.10**
Route 510	**2.03**	**212.45**	**0.00**	**7.61**	**5.79**	**9.99**
Route 511	**2.49**	**305.49**	**0.00**	**12.05**	**9.11**	**15.92**
Scheduled Headway	**-0.59**	**938.62**	**0.00**	**0.56**	**0.53**	**0.58**
Headway Deviation Combination	(Reference to On Time/On Time)					
Short/Short	0.00	0.00	0.96	1.00	0.83	1.22
Short/On Time	**0.18**	**2.68**	**0.10**	**1.20**	**0.97**	**1.48**
Short/Long	**0.38**	**14.26**	**0.00**	**1.46**	**1.20**	**1.77**
On Time/Short	-0.04	0.11	0.74	0.96	0.78	1.20
On Time/Long	0.05	0.18	0.67	1.05	0.84	1.32
Long/Short	**-0.68**	**40.58**	**0.00**	**0.51**	**0.41**	**0.63**
Long/On Time	**-0.51**	**16.88**	**0.00**	**0.60**	**0.47**	**0.77**
Long/Long	**-0.27**	**6.26**	**0.01**	**0.76**	**0.62**	**0.94**
Route 501 x Short/Short	-24.59	0.00	0.96	0.00	0.00	na
Constant	-0.45	6.29	0.01	0.64	na	na

Bunching Survival Model

A linear regression model as well as an ordinal logit model were developed to try to investigate the impact of the internal and external factors on the time to bunching. However, both of these models resulted in very low R squared and ρ squared values. Thus, a survival analysis was attempted next to model the time to the first bunch along the route. The model used the AFT specification rather than the Cox Proportional Hazard specification, because the study was interested in understanding the impact of the various factors on the survival time, not the hazard ratios.

Different distributions were tested to find the best fit. Comparing the Akaike Information Criterion (AIC) values for each distribution, the loglogistic distribution was found to have the best fit and was thus chosen for this model. The loglogistic distribution had the lowest AIC value at 14907 compared to the lognormal (15487), weibull (14975), and exponential (18461) distributions. The output of this model is reported in Table 4. Bolded variables indicate statistical significance of at least 90%. The reference variables are kept the same as in the first model to allow for comparison. A negative coefficient of a variable in this model indicates that as the magnitude of the associated variable increases the departing streetcar from the terminal will catch up with the leading streetcar (i.e. creating a bunching incident) sooner than later compared to the baseline scenario. In other words, a negative coefficient indicates an accelerated time to bunch (failure) or a reduction in the survival time. The acceleration factor is determined by exponentiating the coefficient, e^{β} (*30*).

Since the weekday variable has a negative coefficient, this means that on weekdays initial bunching incidents, when they happen, take place sooner (relative to the departure time of the following vehicle from the terminal) compared to weekends. The acceleration factor of $e^{-0.038} = 0.96$ indicates that the survival time or time to bunch on a weekday is 0.96 as large as on a weekend. However, this was not found to be statistically significant. This indicates that while the odds of bunching are higher during weekdays (according to the previous model), these weekday bunches also take a shorter time to occur (according to this model).

Compared to the time periods to the AM peak, the results show that during the midday, PM peak, and evening periods initial bunching incidents take longer to happen compared to the AM peak. The PM peak indicates that the time to bunching is increased by a factor of 1.67 compared to the AM peak. Again, the route numbers are included in the model as control variables. Regardless of the vehicle type combinations, when the vehicle capacities are different, the model indicates that the time to initial bunch will be accelerated compared to when they are the same vehicle type for both following and leading vehicles. This is expected because the differences in capacities will impact the dwell times and thus, time to bunching. Therefore, while the previous model indicates a difference in the impact of the size of vehicle on the probability of bunching, this model shows that when bunching occurs, it occurs quicker when combinations of different vehicle types are involved compared to the case of only one type of vehicles along the route.

Other internal variables such as scheduled headway, headway ratio between actual and scheduled headway for the following and leading vehicle, as well as the cumulative number of TSP-equipped intersections all indicated they would cause a longer time for the initial bunching incident to occur. For every additional minute of scheduled headway, the survival time is 1.11 times longer. Increasing the number of TSP-equipped intersections and headway ratio do not increase the time to initial bunching as much as increasing the scheduled headway, but they still do prolong the time to initial bunching. This is logical since increasing the headway ratio would imply an increase in the actual headway which is likely to prolong the time for two consecutive streetcars to meet in a bunching incident. However, the model shows that a combination of different stop placements will accelerate the time to initial bunching compared to when stops are placed all on the same side, whether it be far or near side. This could be because when stop placements are alternated, they can still be between two consecutive intersections (i.e. farside stop followed by a nearside stop) thus allowing the following vehicle to catch up more easily with the leading one.

In terms of the external factors, the cumulative number of pedestrian crossing and signalized approaches also accelerate the time to initial bunching. This is likely due to the effect of signalized approaches on interrupting streetcar movements. On routes that do not have dedicated right of way, streetcars must interact with vehicular traffic. High vehicular traffic actually increases the survival time by a factor of 1.30. This may sound counterintuitive but makes sense because the more traffic there is, the more vehicles there will likely be between the successive streetcars. A microsimulation model of streetcar operation in Toronto found similar results (*31*). This increased number of traffic vehicles between streetcars will increase the time it takes for a bunching incident to occur.

TABLE 4: AFT Model Results

Variable	Coefficient (β)	Standard Error	z	P>z	95% C.I.for Coefficient	
					Lower	Upper
Wkday	-0.038	0.02	-1.55	0.12	-0.09	0.01
Trip direction	**0.044**	**0.02**	**2.99**	**0.00**	**0.02**	**0.07**
TimePeriod	(Reference to AM Peak)					
Midday	**0.129**	**0.02**	**5.89**	**0.00**	**0.09**	**0.17**
PM Peak	**0.154**	**0.02**	**7.28**	**0.00**	**0.11**	**0.20**
Evening	**0.066**	**0.03**	**2.54**	**0.01**	**0.02**	**0.12**
Route	(Reference to Route 512)					
501	**-0.196**	**0.10**	**-1.97**	**0.05**	**-0.39**	**0.00**
504	**0.639**	**0.09**	**6.87**	**0.00**	**0.46**	**0.82**
505	**0.286**	**0.11**	**2.68**	**0.01**	**0.08**	**0.50**
506	0.109	0.11	1.04	0.30	-0.10	0.32
509	**-0.180**	**0.10**	**-1.84**	**0.07**	**-0.37**	**0.01**
510	**0.162**	**0.10**	**1.71**	**0.09**	**-0.02**	**0.35**
511	-0.078	0.10	-0.77	0.44	-0.28	0.12
VehCombination	(Reference to same vehicle type for both)					
FVehCap > LVehCap	**-0.079**	**0.02**	**-3.67**	**0.00**	**-0.12**	**-0.04**
FVehCap < LVehCap	**-0.084**	**0.02**	**-4.30**	**0.00**	**-0.12**	**-0.05**
SchedHead	**0.101**	**0.05**	**2.22**	**0.03**	**0.01**	**0.19**
SchedHead^2	**-0.011**	**0.00**	**-3.16**	**0.00**	**-0.02**	**0.00**
FLHeadRatio	**0.002**	**0.00**	**18.04**	**0.00**	**0.002**	**0.002**
LL1HeadRatio	0.000	0.00	-0.44	0.66	0.00	0.00
CumTSP	**0.077**	**0.00**	**23.79**	**0.00**	**0.07**	**0.08**
StopComb	**-0.373**	**0.13**	**-2.84**	**0.01**	**-0.63**	**-0.12**
CumPedCross	**-0.030**	**0.00**	**-7.09**	**0.00**	**-0.04**	**-0.02**
CumSigApp	**-0.006**	**0.00**	**-10.97**	**0.00**	**-0.01**	**-0.01**
Traffic Volume Cat	(Reference to low traffic volume category)					
Medium Volume	-0.012	0.02	-0.74	0.46	-0.04	0.02
High Volume	**0.267**	**0.04**	**6.84**	**0.00**	**0.19**	**0.34**
Constant	1.909	0.16	11.97	0.00	1.60	2.22

CONCLUSION

The overall results indicate that transit operators of streetcar systems should pay more attention to headway deviations at terminals particularly on weekdays. To reduce the likelihood of bunching occurrence, they should try to ensure that headways at terminal are not shorter than scheduled headway. Ensuring this will also lengthen the time to a bunching incident, if one occurs. During the planning process, stop locations should also be considered carefully, since different stop placements cause initial bunching incidents to occur sooner than later. Heavy traffic volume delays the onset of initial bunching, but this may also cause longer than anticipated travel times, which will also be a nuisance to passengers. In conclusion, it would be best if the TTC focused on the factors that could provide the most improvement (decreased odds of bunching and longer time to bunch) for both parties (operator and passenger) such as scheduled headway adherence and changes in fleet for consistency.

Since it is rare to find streetcar bunching models in the literature, this paper provides valuable insights into streetcar bunching. Nevertheless, with additional data such as passenger volume, which were not available for this paper, the models can be improved to provide more information to streetcar operators. The results from this study can be combined to build a real-time predictive model for bunching, which can allow transit operators to act proactively with expected bunching incidents. Such a model would be able to warn operators of potential and upcoming bunching incidents and the time it would take for the bunching incident to occur with a given accuracy.

The results and future work from this study provide great potential for streetcar operators. Armed with the knowledge gained from this study, operators can make informed decisions when trying to improve streetcar services or when planning and building new streetcar routes. This will allow operators to make evidence-based decisions instead of ad-hoc ones; and, therefore, they would be able to develop actual procedures or decision making processes to prevent and reduce bunching. Analogous to a screening procedure developed to give patients early treatment in an attempt to extend their life, a real-time predictive bunching model could "detect and cure" vehicles from bunching and extend its time away from the terminal to provide an efficient transit service to the public.

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