Effects of Fare Payment Types and Crowding on Dwell Time

Fine-Grained Analysis

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Dwell time, the time a transit vehicle spends stopped to serve passengers, contributes to the total reliability of transit service. Dwell time is affected by factors such as passenger activity, bus crowding, fare collection method, driver experience, and time of day. The types of effects crowding can have on dwell time are debatable because of its interaction with passenger activity and inaccuracies in its calculation. Different payment methods also have an effect on dwell time. This debate can be linked to the absence of appropriate data that can actually capture the real effects of these variables. This research attempts to determine the influence of crowding and fare payment on dwell time through manual data collection. The study was conducted along three heavily used bus routes in the TransLink system in Vancouver, British Columbia, Canada. Multiple regression dwell time models are performed by using a traditional model and a new expanded model with the additional details that manually collected data provide. The traditional model overestimated dwell times because of a lack of detail in fare payment and crowding, while the expanded model showed that crowding significantly increased dwell time after approximately 60% of bus capacity was surpassed. Fare payment methods had various positive effects on dwell time, with different magnitudes. This research can help public transit planners and operators develop better guidelines for fare payment methods as well as policies associated with crowding.

As ridership grows and budgets shrink at public transit agencies across North America, crowding on public transit vehicles is likely to increase. Dwell time consumes approximately 26% of the total trip time and as such, longer and shorter dwells can have significant effects on run time variation (*1*). Understanding the relationship between fare payment, in-vehicle crowding, and dwell times will help agencies deliver quality public transit by improving service planning and scheduling. While a full bus may appear to be the epitome of efficiency, the additional load may cause dwell and run times to increase significantly (*2*). This research paper tries to understand how a variety of fare payment methods, crowding, and the interaction between these variables affect dwell times.

Crowding on buses is a challenge that many transit agencies are facing. TransLink, the local transit provider in Vancouver, British Columbia, Canada, is not an exception. Three urban, high-frequency, heavily used routes are studied to determine the effects of crowding and fare payment on dwell time. Manual counts were performed detailing passenger movements, fare types used, dwell service times, and levels of crowding.

This paper begins with a review of the current literature on dwell times and the factors that can affect them. The following sections explain the methods used to gather, clean, and interpret the data. The final sections analyze the dwell time model, present a sensitivity analysis, and provide recommendations and conclusions.

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LITERATURE REVIEW

"Dwell time" is defined as "the amount of time a bus spends while stopped to serve passengers" (*3*). As dwell time can consume up to 26% of the total travel time of buses, it is vitally important to understand the factors that affect it in detail. By better understanding these factors, transit agencies can introduce changes that can help to reduce dwell times (*1*).

To truly understand the factors influencing dwell time, a more refined formulaic definition is needed. The following formula is widely used for dwell time models (*3, 4*).

$$t_d = P_a * t_a + P_b * t_b + t_{oc} + t_{unexp} + f_{rl}$$

where

- t_d = average dwell time (s),
- P_a = number of alighting passengers at stop,
- t_a = average passenger alighting time,
- P_b = number of boarding passengers at stop,
- t_b = average passenger boarding time,
- t_{oc} = door opening and closing time,
- f_{rl} = friction factor accounting for additional delay caused by interaction between number of passengers on board and number of passengers boarding and alighting (captures effect of crowding), and
- t_{unexp} = time of unexpected activities (e.g., wheelchair lift use).

The first five variables in the equation are defined in the *Transit Capacity and Quality of Service Manual* (TCQSM) and quantify how many passengers board and alight, the time it takes for this exchange per passenger, and the time it takes to open and close the door (*5*). This equation is presented in the TCQSM with the assumption that no fare payment is made at any door. Yet the TCQSM includes a section on fare payments and their effects on dwell time variations. Accordingly, several $P_b * t_b$ can be incorporated into this equation as needed depending on the number of fare payment types. The final two variables, f_{rl} and t_{unexp}, have been added, on the basis of the literature, to create a more realistic model (*4*). The variable f_{rl} captures the effect that the load of the bus has on boarding and alighting passengers. Unexpected delays caused by wheelchair ramp use, waiting for passengers to board, or other delays are captured in the variable t_{unexp}.

Electronic Data Collection

Automatic passenger counters (APCs) have been used to gather data remotely and inexpensively since their introduction in the mid-1970s (*6*). APCs are generally integrated with an automatic vehicle location (AVL) system. An AVL system is part of a larger integrated communications system. The combined use of these systems provides a breadth of data that is unattainable with standard manual counting techniques. While the aggregate of these data is useful for dwell time analysis, there are concerns about data validity and reliability and loss of detail.

As of 2002, Moore et al. concluded that "there is no fully objective evidence that APCs can provide adequate data for section 15 reports" (*6,* p. 145). In addition, Dueker et al. mention that wheelchairs, walkers, and strollers can confound APCs (*4*). In their study of two bus routes containing different APC equipment, Kimpel et al. found that estimates of boardings were accurate at the system level (*7*). However, one type of equipment overestimated boardings by a statistically significant margin, while APCs of both types overestimated passenger loads by a statistically significant margin (*7*). These contradictory findings indicate that APC and AVL data can be good for certain types of analysis—such as running time models or dwell time models—that do not require detailed load information. In studies concentrating on passenger load effects, other methods such as manual counts might be appropriate to increase the accuracy and provide the required detail for developing a better model.

Crowding

Passenger crowding in public transit vehicles is difficult to define. Stated simply, a vehicle is in a crowded state when people on the vehicle impede the flow of individuals boarding and alighting. Dueker et al. define a crowded vehicle as such when its load is greater than 85% of total capacity (*4*). Milkovits asserts that crowding occurs when the number of passengers on board is greater than the number of seats (*8*). A study concentrating on dwell times for the Massachusetts Bay Transportation Authority's Green Line light rail system found that dwell time is affected by the number of passengers boarding and alighting and the number of people on board the vehicle (*2*). To account for the effect of crowding some studies included a friction variable. Friction is a compound variable that attempts to incorporate the effects of crowding and the number of passengers boarding and alighting. Friction was included in studies by Dueker et al. (*4*) and Tirachini (9).

Fare Payment

The method and location of fare payment can have a significant effect on dwell time. Different fare media types also have different effects. Passengers that pay with cash when change is given have the largest effect on dwell time, while fare that is merely shown to operators (not swiped or tapped) has the smallest effect (*8*). A passenger that pays with a magnetic stripe ticket adds less time to the dwell compared with passengers using cash when no change is given (*9*). Electronic smart media cards were reported to be faster than magnetic stripe tickets. However, the difference was negligible with the presence of crowding. More detailed analysis is needed to better understand the effects of these fare payment methods on dwell time, especially when combined with crowding information.

METHODOLOGIES

In collaboration with TransLink, the local transit authority serving the Vancouver region, three urban, high-patronage routes that experience crowding on a regular and sustained basis were chosen for study. The routes were the Number (No.) 5, No. 9, and No. 99 (Figure 1). All three traverse dense residential and commercial areas and intersect with rapid transit lines. The No. 5 and No. 9 are local service routes and operate identical low-floor trolley buses. The No. 99 B-line is an express bus with more than 50,000 boardings per day and operates articulated low-floor buses. Table 1 includes a summary of the characteristics of the studied routes.

Data Collection

Manual observations of passenger movement, fare payment methods, and crowding were collected with permission from TransLink and its subsidiary bus operations company, Coast Mountain Bus Company. The data were collected from April 12 through May 12, 2012. To best capture the effects of crowding, data were collected predominantly during the morning (7 to 10 a.m.) and afternoon (3 to 6 p.m.) peak hour periods and a random sample of runs was surveyed during those times. This study relies on manual counts that collect detailed observations at each stop. Each bus had one person recording the passenger activity at every door. For example, an articulated bus had three volunteers recording the passenger movement and fare payment method as well as the status of crowding on the bus.

Before the recorders boarded the bus, the weather, temperature, date, and recorder's name were documented. In addition, the recorders collected information from the driver concerning the driver's number of years of experience and gender. Terminus stops are defined as the first and last stops that data collection occurred. As such, dwell times are not accurate because operators are required to wait for extended periods for scheduled departure times. Accordingly, passenger counts will not correspond to the dwell time. An additional variable, PassServiceTime, was recorded to capture the difference between the time taken to serve passengers and the non-passenger-related delays during dwell time (changing operators, waiting at time points, or waiting for red lights, all with the doors open). Data from the collection sheets were then entered into a spreadsheet for analysis.

To better understand the effects of fare payments and crowding on dwell time two statistical models are generated. The first is a traditional model that uses data similar to what is being collected by an APC-equipped bus. The second model is the extended one, which includes more detailed variables that were collected in the study. The extended model allows a better understanding of the different effects of fare policies and crowding on dwell time.

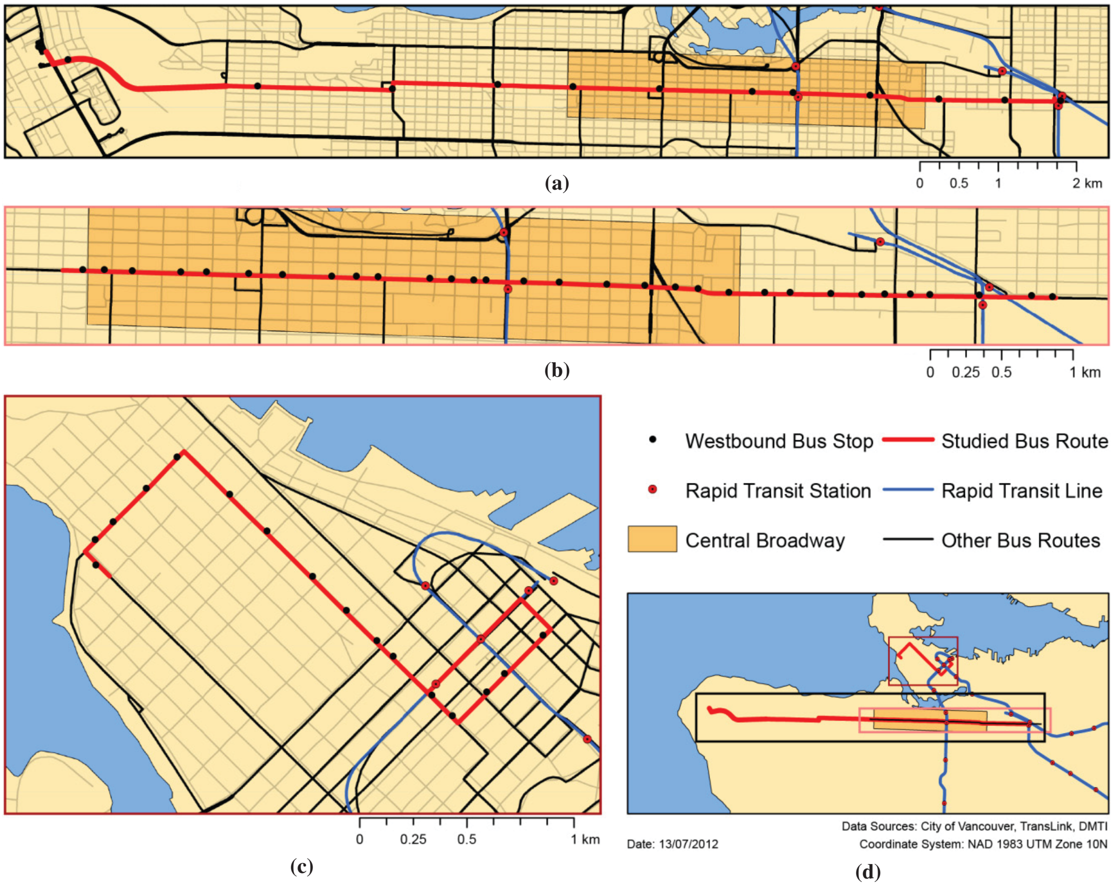

FIGURE 1 (*a* to *c*) Studied bus lines and (*d*) Vancouver context.

Variable Definition

Table 2 includes a list of variables used in the statistical models. Most of these variables follow the traditional dwell time model known in the literature (*10*). Yet some of the variables used merit further explanation. PassServiceTime captures the portion of the dwell that is used by passengers to board or alight. Dwell_Longest captures the time between door open and door close. The difference between Dwell_Longest and PassServiceTime is Dwell_Difference. Dwell_Difference represents the extra dwell time spent at stops that is not the result of passenger movements (time points, driver changes in the middle of the route, etc.). As buses in this study have different maximum capacities, load (occupied capacity) was translated into percentage of occupied capacity, as represented by the variable Load_%ofBusCapacity. Standee_PAX_Interaction was created on the basis of previous research and measures the interaction between boarding and alighting passengers (PAX) and the number of standees [(Standees^2) ∗ Total_PAX] (*8*). The number of standees was determined by subtracting the total number of people on board from the number of seats on the bus.

TABLE 1 Physical Characteristics of Routes 5, 9, and 99

Statistic	Route (westbound) No. 5 Robson	No. 9 Broadway	No. 99 B-Line
Length (km)	3.4	6.9[a]	16.2
Number of stops	15	31[a]	13
Headway peak (min)	5–7	4–5	2–4
Headway off peak (min)	7–8	11–12	4–5
Daily boardings (Monday–Friday)	9,400	25,300	54,350
Annual boardings	3,167,000	8,298,000	16,642,000
Service type	Local	Local	Express
Population (within 400 m of route)	42,000	79,000	68,000
Employment (within 400 m of route)	105,000	68,000	58,000

NOTE: Based on 2011 data.
[a]Section of route under study.

Data Cleaning

Data from the collection sheets were entered in their entirety, regardless of whether dwells or passenger movements had occurred. As such, data for the dwell time model required extensive cleaning. Stop level data entries were removed in instances in which Total_PAX = 0 or Dwell_Longest = 0. These removed data did not contain passenger movements or dwell time information. Terminus stops were also removed in this step as they generally have extra time. Entries were also removed in instances in which the recorder labeled the entry as inaccurate. Total boardings and alightings were checked for entire runs. If passenger activity did not balance (number of boardings in

TABLE 2 Variable Definition

Variable Name	Description
Route5	Dummy equal to 1 if the trip was on the No. 5 Robson
Route99	Dummy equal to 1 if the trip was on the No. 99 B-line
Westbound	Dummy equal to 1 if the trip was in the westbound direction
Driver_Experience	The number of years of experience the driver has been operating the bus for TransLink
Driver_Gender	Dummy equal to 1 if the drivers gender is female
AM_Peak	Dummy equal to 1 if the trip began during the a.m. peak (6-9 a.m.)
PM_Peak	Dummy equal to 1 if the trip began during the p.m. peak (3-6 p.m.)
Dwell_Difference	Difference between Dwell_Longest and PassServiceTime
Wheelchair_Dummy	Dummy equal to 1 if there was a wheelchair ramp event
Bike_Dummy	Dummy equal to 1 if the bike rack was used
Stroller_Dummy	Dummy equal to 1 if during the dwell, a passenger boarded with a stroller, luggage, or other large bags that prolonged the boarding process
D1_Prepay	Front door, number of passengers that use a pass that is shown directly to driver
D1_MagneticSwipe	Front door, number of passengers that use a magnetic pass, verified by fare box
D1_Cash	Front door, number of passengers that pay cash at fare box, receive magnetic pass
D1_NoFarePresented	Front door, number of passengers that enter without presenting fare
D1_ Boarding	Front door, number of people entering at stop
D1_Alighting	Front door, number of people exiting at stop
D2_Boarding	Middle door, number of people entering at stop
D2_Alighting	Middle door, number of people exiting at stop
D3_Boarding	Rear door, number of people entering at stop
D3_Alighting	Rear door, number of people exiting at stop
Total_PAX2	Total boardings and alightings at all doors, squared
Load_%ofBusCapacity	Load expressed as a percentage of bus capacity
Load_%ofBusCapacity2	Interaction variable, load expressed as a percentage of bus capacity, squared
Standee_PAX_Interaction	Interaction variable, standees squared multiplied by total PAX
PassServiceTime	Dwell variable, only records the portion of the dwell that is used to serve passengers

NOTE: Dependent variable, Dwell_Longest is longest dwell at any door.

a run equals number of alightings), then all dwells during this trip are removed from the analysis. The final data set used in the analysis contained a total of 1,764 dwells.

ANALYSIS

Assessing dwell times on the basis of the average time required for a passenger to board or alight shows that there is a distinct difference between crowded and noncrowded conditions and between the different routes analyzed. Dwell time per passenger movement (Dwell_Time/PAX) was determined by dividing PassServiceTime time by the maximum passenger movements, boardings and alightings, at any door. As can be seen in Table 3, crowded conditions, defined as loads exceeding 70% of bus capacity, show an increase in service time per passenger of from 3.69 to 5.35 s on the No. 5 (a 1.66 s increase) and from 3.58 to 4.06 s on the No. 9 (a 0.48 s increase). This result is indicative of a reduction in the efficiency of dwell times during crowded conditions. Conversely, the No. 99 actually shows a decrease in passenger service time of 0.41 when buses are crowded. This gain in efficiency is likely attributed to an all-door boarding policy that drastically reduces the time required to serve passengers, especially when there are large passenger flows. Since the study was conducted during the peak period it was not surprising to have a low percentage of uncrowded conditions in the sample. Yet keeping them in the analysis is important to help control for any unobserved variations that the models could have missed and can affect the dwell time.

DWELL TIME MODELS

By using the longest dwell at any door (Dwell_Longest) in seconds as the dependent variable, two linear regression models were developed (traditional and expanded model). The variables and associated coefficient, *t*-statistic, and statistical significance are shown in Table 4. The traditional model uses the nondetailed variables to simulate APC-collected information, while the expanded model uses all the collected variables. Comparing these two models will enable one to show the value of obtaining such detailed information about every dwell and the effect of these variables on dwell time. The expanded model explains 86% of the variation in Dwell_Longest by using a sample size of 1,764 dwells, compared with the traditional model, which explains only 58% of the variation. The coefficients in the traditional model follow the expected signs, statistical significance, and magnitude. In general the model is comparable with previous research (*4, 11*). This increases the trust in the collected data in regard to their accuracy in predicting dwell time.

Moving to the expanded model, dwell times on the No. 5 Robson and the No. 99 B-line are 0.8 and 3.3 s longer, respectively, than those of the No. 9. The doors on the No. 99 B-line are controlled by

TABLE 3 Summary Statistics at Stop Level

	No. 5 Robson				No. 9 Broadway				No. 99 B-Line			
	Noncrowded		Crowded		Noncrowded		Crowded		Noncrowded		Crowded	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
D1_Prepay	1.82	2.84	5.38	9.70	2.43	3.92	5.57	9.53	0.85	1.26	1.53	1.93
D1_MagneticSwipe	0.57	1.25	1.23	2.13	0.58	1.22	0.90	1.69	0.36	0.80	0.38	0.74
D1_Cash	0.22	0.56	0.38	0.96	0.15	0.46	0.07	0.25	0.17	0.48	0.23	0.52
D1_NoFarePresented	0.02	0.16	0.00	0.00	0.02	0.15	0.00	0.00	0.01	0.13	0.02	0.15
D1_Alighting	0.57	1.07	0.31	0.63	0.66	1.28	0.90	1.32	0.75	1.33	1.26	1.79
D2_Boarding	0.00	0.04	0.00	0.00	0.03	0.50	0.10	0.40	2.00	2.30	5.11	3.21
D2_Alighting	2.54	3.25	1.62	2.06	2.86	3.83	2.40	3.64	2.93	3.14	4.79	4.76
D3_Boarding	na	na	na	na	na	na	na	na	2.90	3.08	7.45	4.67
D3_Alighting	na	na	na	na	na	na	na	na	3.72	3.76	5.98	5.60
Load_%ofbusCapacity	24.72	16.25	77.31	4.79	37.81	15.20	74.53	2.70	35.71	16.74	79.17	5.81
Dwell_time/PAX	3.69	2.31	5.35	2.65	3.58	2.25	4.06	2.21	2.18	1.78	1.77	1.95
Number of dwells	562		13		689		30		423		47	

NOTE: Crowded condition is load > 70% of capacity; SD = standard deviation; na = not applicable.

TABLE 4 Dwell Time Model

	Traditional Model			Expanded Model		
Variable Name	Coefficient	*t*-Statistic	Statistical Significance	Coefficient	*t*-Statistic	Statistical Significance
Constant	9.417	7.607	.000	6.869	9.102	.000
Route5	–0.097	–0.148	.882	0.773	1.888	.059
Route99	0.682	0.693	.488	3.301	5.604	.000
Westbound	–0.522	–0.999	.318	0.075	0.244	.807
Driver_Experience	na	na	na	–0.004	–0.193	.847
Driver_Gender	na	na	na	–0.342	–0.651	.515
AM_Peak	–0.404	–0.526	.599	–0.203	–0.450	.653
PM_Peak	0.874	1.524	.128	–0.116	–0.341	.733
Dwell_Difference	na	na	na	0.909	55.170	.000
Wheelchair_Dummy	na	na	na	38.475	18.115	.000
Bike_Dummy	na	na	na	3.849	2.821	.005
Stroller_Dummy	na	na	na	5.511	4.915	.000
D1_Prepay	na	na	na	2.226	29.245	.000
D1_MagneticSwipe	na	na	na	3.033	19.330	.000
D1_Cash	na	na	na	4.209	13.504	.000
D1_NoFarePresented	na	na	na	1.568	1.526	.127
D1_Boarding	3.105	32.806	.000	na	na	na
D1_Alighting	1.858	7.784	.000	1.309	9.176	.000
D2_Boarding	0.598	2.189	.029	0.240	1.487	.137
D2_Alighting	0.974	8.998	.000	0.636	9.983	.000
D3_Boarding	1.456	6.722	.000	0.835	6.513	.000
D3_Alighting	0.965	5.600	.000	0.517	5.093	.000
Total_PAX2	–0.013	–6.931	.000	–0.005	–4.663	.000
Load_%ofbusCapacity	–0.181	–3.004	.003	–0.062	–1.764	.078
Load_%ofbusCapacity2	0.002	2.346	.019	0.001	2.341	.019
Standee_PAX_Interaction	0.001	2.052	.040	0.001	3.694	.000

NOTE: For traditional model, N is 1,764 and R^2 is .580; for expanded model, N is 1,764 and R^2 is .860. na = not applicable.

the driver to facilitate all-door boarding; operators waiting for passengers to clear the rear doors before closing them could contribute to the longer dwells on the No. 99. The direction of travel, years of driver experience, and driver gender did not show a statistically significant effect on dwell time in the sample. Dwell times are marginally faster during the a.m. and p.m. peak than during nonpeak times. This effect has been attributed to more regular riders using prepaid fare and more directional passenger traffic reducing the mix of boardings and alightings at the same stop (*4, 11*). Delay-related variables, wheelchair ramp events, bike rack events, and passengers with strollers or other bulky items, show statistically significant increases in dwell time. A wheelchair event adds 38.4 s to dwell time, which is 24.0 s faster than has previously been found (*4*). This reduction in dwell time is likely attributable to the age of the bus fleet. The majority of the buses in the fleet are less than 10 years old and all have low floors, fast ramp actuations, and efficient tie-down systems, which reduce the time needed to serve passengers in wheelchairs.

As would be expected, boardings and alightings at all doors are associated with an increase in dwell time, while certain fare types have larger impacts on dwell time. All passenger movement variables are significant except boardings with no fare at Door 1 and boardings at Door 2. Passengers boarding with prepaid fare are the fastest to board (of paying passengers) as they have no interaction with the fare box and only need to show their pass to the driver (2.2 s per passenger). Each passenger using a magnetic swipe ticket adds 3.0 s to dwell time, while those using cash add 4.2 s while keeping all other variables constant at their mean value. Finally, each passenger who boards through the front door and does not pay the fare, even though the passenger does not interact with the fare box or show a pass to the driver, adds 1.6 s. This finding is attributed to these passengers offering an explanation to the operator as to why they cannot pay. It is important to note that throughout this study, less than 0.5% of passengers boarded through the front door without paying a fare.

Passengers alighting at the front door take longer than those alighting through rear doors. A passenger alighting at the front door will extend the dwell by 0.7 s more than one alighting through the rear door. Crowding and friction around the front door likely create this difference as passengers tend to resist moving to the back of the bus. It could also be attributed to the time needed to access the front door. Unlike the rear where passengers can wait directly adjacent to the doors, passengers alighting at the front door are required to wait behind the driver's seat to ensure that the driver's sight lines are not obstructed and until other passengers board the bus. A passenger boarding at Door 2 adds 0.24 s and 0.84 s boarding at Door 3. Boarding events at the second door occurred in less than 0.5% of all dwells on the No. 5 and No. 9 as boarding through the rear door is normally not allowed on either of these routes. Therefore, the effects of this variable can be attributed almost entirely to the No. 99 B-line. The effects of boarding and alighting through Door 3 are entirely attributed to the B-line as it is the only route that uses articulated buses.

As buses in this study have different maximum capacities, the effect of passenger load was determined by using the percent of occupied capacity. A 1% increase in the passenger load of the bus generated a 0.06-s reduction in the dwell time. While this may seem counterintuitive, the coefficient of this variable must be interpreted together with the square term of this variable, which is Load_%ofBusCapacity2, as they work in tandem to affect the independent variable. The interaction variable, Load_%ofBusCapacity2, has a statistically significant positive effect. The effect of the variables Load_%ofBusCapacity and Load_%ofBusCapacity2 together indicates that dwell times will decrease as load increases because of the effect of Load_%ofBusCapacity. Once a certain threshold is reached, the effect of the square term variable, Load_%ofBusCapacity2, will cause dwell times to increase.

DISCUSSION OF RESULTS

Traditional and Expanded Dwell Time Models

By using coefficients derived from Table 4 a sensitivity analysis is conducted for the extended and the traditional model. The coefficients are multiplied by the mean values of each independent variable in the model. The first sensitivity analysis used 11 and five passengers at a stop to estimate the dwell time at different levels of bus occupancy. Figure 2 shows the output from the first sensitivity analysis for traditional and expanded models while the occupancy of the bus is varied and the passenger activity is fixed at five and 11 passengers per dwell.

As shown in Figure 2, the effect of PAX is apparent in the relationship between the two sets of curves. At both levels of PAX, the traditional model tends to overestimate dwell times at the lowest levels of bus occupancy. With low PAX, the dwell times predicted by the two models are similar. However, as passenger movements increase, the traditional model begins to overestimate dwell times. This effect results from the lack of additional passenger boarding detail, as provided in the expanded model. The traditional model uses the average boarding time for all fare types, adding 3.1 s to the dwell for a passenger boarding at the front door, regardless of payment method, while keeping all other variables constant at their mean value. A passenger boarding with a pass that only needed to be shown to the driver adds only 2.2 s to the dwell as seen in the expanded model. With the majority of passengers using this type of fare media, as PAX increases, the error in the traditional model increases as well.

Dwell times produced by using the traditional model are similar at both ends of the curve. The expanded model is different in that the curve is much flatter through to about 50% of capacity. This difference is expected as the variable Dwell_Difference is not included in the traditional model. This variable measures the difference between the time required to serve passengers and total dwell time inclusive of non-passenger-related delays. Including this variable changes how the variables Load_%ofBusCapacity, Load_%ofBusCapacity2, and Standee_PAX_Interaction affect the curve. The majority of these non-passenger-related delays occurred in instances in which occupied capacity was less than 30%. This finding helps to explain the difference between the two curves at lower bus occupancy. Non-passenger-related service delays are clearly an important component of dwell time that is difficult if not impossible to capture with only APC data.

As bus occupancy increases above 50%, both models show an increase in dwell time. Previous research has attempted to define a bus occupancy threshold above which crowding begins to affect dwell time (*2, 4, 8*). The results of this research suggest that crowding, as it relates to its effect on dwell time, occurs after the bus passes 60% capacity. As can be seen in Figure 2, dwell time begins to increase more sharply after that point. A typical Vancouver trolley bus at 60% occupancy would have all seats occupied, and approximately 15 standees, which corroborates observations made during data collection.

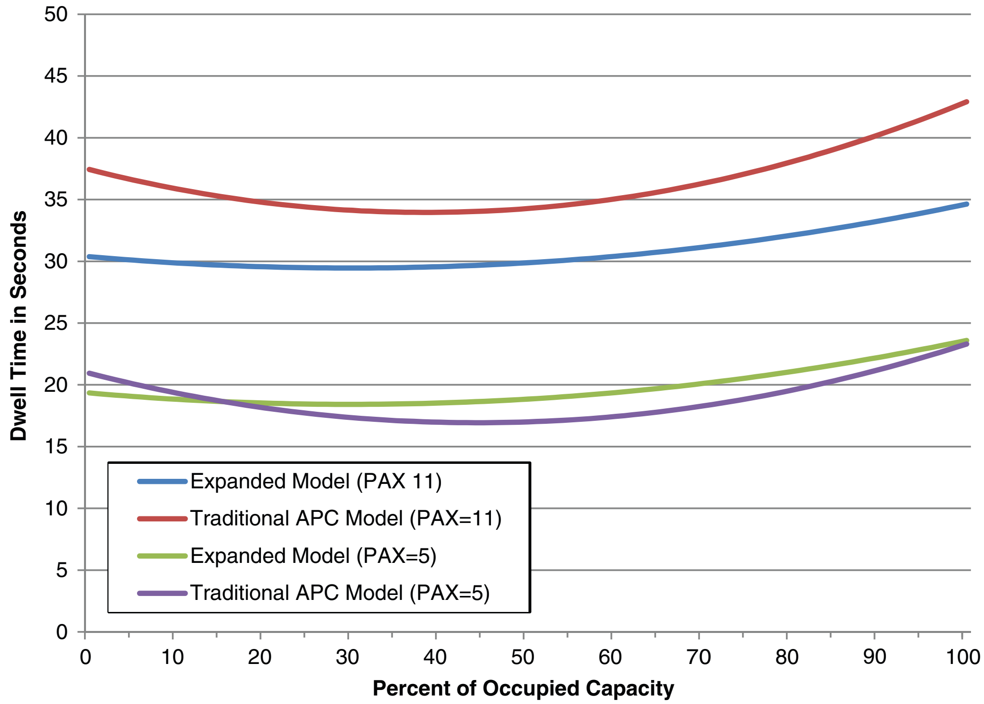

FIGURE 2 Comparison of two dwell time models: traditional and expanded at PAX = 11 and PAX = 5.

Interaction Between Passenger Movements and Bus Occupancy

To assess the effects of different levels of passenger movement on dwell time, three passenger movement scenarios, based on high, medium, and low PAX averages, have been analyzed (Figure 3). The high scenario has PAX = 36 and is based on the average of dwells in which the percent of occupied capacity is greater than 85%. The medium scenario has PAX = 13 and is based on the average boarding and alighting activities of dwells that occurred when the bus was at less than 55% of occupied capacity. For comparison, an additional low PAX scenario in which only one passenger is boarding with prepaid fare has been added. These passenger movements are analyzed over all ranges of vehicle occupancy. The dwell times are presented as the percent change in dwell time over a baseline dwell of 31% of occupied capacity.

Figure 3 clearly illustrates that the effect of crowding on dwell time is most evident when PAX is low. The dwell time associated with each passenger movement is very high when the bus stops for few passengers. The reason is that the constant (door open and close time) and crowding penalty are distributed among very few passengers. Bus stops that serve few passengers are the least efficient and most affected by crowded conditions. With large numbers of passenger movements, people can easily move through to the exit. Conversely, with a static passenger load, one individual will have much more difficulty moving through the crowd toward the exit.

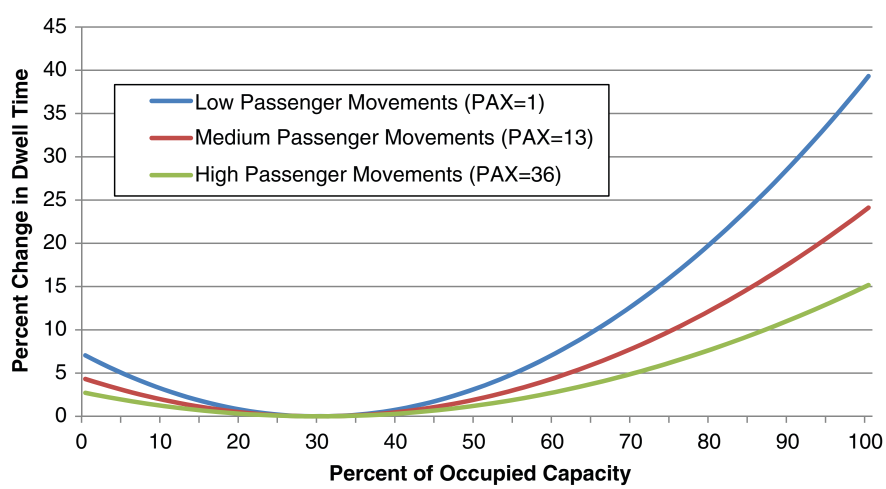

FIGURE 3 Percentage change in dwell times when 31% of occupied capacity is used as a baseline (No. 99 B-line).

Passenger Movements, Fare Payment, and Their Effects on Dwell Time

With the use of the coefficients derived from Table 4, a sensitivity analysis is conducted to predict dwell times for the No. 99 B-line traveling westbound with a male driver during the a.m. peak (Tables 5 and 6). The coefficients are multiplied by the mean values of each independent variable in the model. These estimates are based on two passenger boarding and alighting scenarios, 13 and 36. By using these two boarding and alighting scenarios while keeping all other variables constant at their mean, the effect on dwell time is examined at 30%, 60%, and 90% of occupied capacity.

The first increase in occupied capacity, from 30% to 60%, sees an increase in dwell time of 1.1 s for the medium PAX scenario and 1.5 s for the high PAX. This represents a 5% change in dwell times. This increase is minor considering that the dwell penalty is associated with a doubling of occupancy. However, adding the next 30% in occupied capacity increases dwell time by 4.4 s and 7 s. That result represents a 20% increase in dwell times regardless of the number of passengers boarding and alighting.

According to the results presented here, buses running above the 70% capacity threshold outlined in TransLink's *Transit Service Guidelines* will run much slower than those below this threshold. Two interrelated factors are the cause. Buses with heavier loads experience larger flows of people on and off than those with smaller loads. On the #5, dwells with passenger loads greater than 70% saw 40% more passenger movements than dwells below 70%. That rise is compounded by the increase in dwell time associated with crowding. These two factors serve to prolong dwells and slow the bus along its route. As Lin and Wilson found, overcrowding turns into a vicious cycle that only exacerbates the crowding problem, which can quickly lead to bunching and severely degraded service throughout the route (*2*). This is true especially on routes served by trolley buses where it is difficult to pass slow vehicles. On busy, high-frequency routes, focus should be on maintaining headways as opposed to adhering to schedules.

While pass-ups are not desirable, they occur throughout the system and may even be advisable when vehicles are heavily loaded and a stop request has not been made. Pass-ups would serve to reduce bunching, maintain headways, and improve reliability. With technological advances and integrated systems, the route number and destination signage on the front and side of the bus could be used to advise passengers of when the next bus will be coming and its approximate load. Other forms of social media could be implemented to alert passengers about crowding and possible pass-ups. Having certainty around the length of the delay and the likelihood of boarding the next bus would help reduce passenger frustration when pass-ups do occur.

TABLE 5 Boarding and Alighting Scenarios for Sensitivity Analysis: No. 99 B-Line

Variable	Scenario: 13 Passengers	Scenario: 36 Passengers
D1_Prepay	1	1
D1_MagneticSwipe	1	2
D1_Cash	0	1
D1_NoFarePresented	0	0
D1_Alighting	0	0
D2_Boarding	3	8
D2_Alighting	2	7
D3_Boarding	3	6
D3_Alighting	3	11

TABLE 6 Sensitivity Analysis: No. 99 B-Line

Scenario	Effect on Dwell Time: 30%	60%	90%
13 Passengers			
Dwell time (s)	21.5	22.6	27.0
Increase in dwell time (s) attributed to crowding	na	1.1	4.4
Increase (%)	na	5	19
36 Passengers			
Dwell time (s)	34.1	35.6	42.6
Increase in dwell time (s) attributed to crowding	na	1.5	7.0
Increase (%)	na	4	20

CONCLUSION AND RECOMMENDATIONS

The purpose of this research was to examine the effects of crowding and fare payment on dwell time. Remotely collected data allow for broad analysis; however, much of the detail during the dwell is lost. The manual data collection methods used in this study allowed for the delineation of dwell times that were passenger related and those that were caused by other events. The type of fare used was also recorded allowing for a more detailed and accurate model with respect to front door alightings. A traditional APC dwell time model and an expanded model were analyzed and compared. While both models showed that as the occupancy of the bus increases, dwell time also increases, the traditional APC model overestimated dwells, especially at high and low levels of bus occupancy. This difference is attributed to the detailed fare payment and dwell time data garnered through manual data collection.

When the sensitivity of dwell times to different levels of passenger movements are examined, a clear distinction between different levels of crowding is apparent. Dwell times clearly increase with the number of passenger movements occurring. However, under crowded conditions, the time taken to serve passengers at stops with low passenger movements is far greater than to serve those stops with high passenger movements, on a time per passenger basis. Consolidation of bus stops with low passenger movements on frequently crowded routes is recommended to reduce run time. Allowing passengers to board and alight through the rear doors at the busiest stops would also vastly improve dwell times.

Crowding begins to significantly affect dwell time after approximately 60% of occupied capacity. On the basis of that information, TransLink's *Transit Service Guidelines,* with its maximum desired occupancy of 70%, appears to strike a good balance between the efficiency of the service and passenger comfort especially on urban routes. It is recommended that the type of route (regular or express service), the context of the route (urban or suburban), and the boarding and alighting activities be considered when crowding is addressed.

As the level of crowding on the bus increases, so do the associated passenger movements during dwells. This effect serves to dramatically increase dwell times on heavily loaded buses. These crowded buses can affect the headways of vehicles following, especially on high-frequency routes served by trolley buses that are unable to easily pass a slow vehicle. During periods of crowding, focus should be on maintaining headways instead of adhering to a schedule. In several cases pass-ups are recommended to reduce the likelihood that an overcrowded bus is delayed. Additional recovery time would need to be added to schedules to account for the effects overcrowding has on heavily used routes. The added recovery time would thus make the buses less efficient from an operation standpoint.

Fare payment methods have a substantial effect on dwell time and accordingly on schedules. In other words, schedulers should account for fare payment type and add the adequate time for every route that can accommodate the fare payment methods implemented by the agency along every route. Different fare payment methods showed a statistically significant positive effect on dwell time. Cash payment had the highest effects followed by magnetic swipe. Preboarding payments are recommended to decrease time associated with cash transactions. Also flash card or tap-on technologies are recommended to replace the magnetic swipe to decrease the effect of monthly pass users on dwell time. Offboard fare collection is expected to lead to substantial time savings as the no fare presented variable showed the lowest effect on dwell time.

This study could be expanded by looking at other services and by examining how the characteristics of the built environment affect dwell time. Stop location (near side or far side), presence of an exclusive bus way or a high-occupancy lane that serves buses, and the location of stops in the street (whether it is in a travel lane or out of traffic) could be included.

With patronage on public transportation systems increasing across North America, continued investment is needed to accommodate this demand. Planners should work on finding ways to improve system efficiency, which will in turn reduce costs and improve service and so encourage more ridership. However, without investment, our transit systems will continue to be bogged down with crowding, experience reduced reliability, and provide poor customer satisfaction.

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