Bus dwell time analysis using on-board video

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ABSTRACT

When a dwell time equation was needed to plan a proposed campus shuttle route, no recent equations for buses could be found. However, the buses in the local system were equipped with video cameras that permitted counts of variables that might affect dwell time. Conversion of data from video to worksheets was surprisingly easy. Viewing the videos was also instructive, in terms of how passenger numbers and behavior affect dwell time, and how unusual events should be dealt with in the database. The dwell time equations that were developed from the local video data were compared with equations found in the literature. There was a distinct difference. This paper describes the video system, how the local data were transcribed, how the dwell time equations were specified and tested, and how alternate equations were applied to the proposed route. The advantages of using video as a data source are recounted.

INTRODUCTION

The Master Plan for Purdue University's campus contains a provision for a 2.27-mile "shuttle loop" on which bus service would be provided. When a detailed design of a Bus Rapid Transit service on this route was attempted as a class project in a Public Mass Transportation course, the students had reasonable information about certain elements of the shuttle loop's operation:

- Bus acceleration and deceleration rates
- Maximum speed on each segment between stops
- Estimated number of passengers boarding and alighting at each stop by time of day.

It quickly became apparent that a key element was dwell time -- the time a vehicle would spend discharging and taking on passengers at each proposed stop. A good estimate of dwell time was needed to determine the time needed for a bus to complete the loop at any given time of day. This information, coupled with a desired headway, would determine the number vehicles needed to meet service requirements.

When a method for converting passenger boardings and alightings into dwell times was sought, only a few studies of possible use were found.

DWELL TIME STUDIES IN THE LITERATURE

Feder (*1*) developed the following equation to predict dwell time: DT = 1.31 + 2.573*BA, where BA = number of boardings and alighting at a bus stop.

Levinson (*2*) reported that bus dwell time (DT) was DT = 5.0 + 2.75*BA, where BA = number of "interchanging" (boarding or alighting) passengers.

Guenthner and Sinha (*3*) found DT/passenger = 5.0 – 1.2*ln(BA), where BA = number of boardings and alighting at a bus stop.

Guenthner and Hamat (*4*) computed dwell time separately for boarding and alighting bus passengers: DT = 2.25 + 1.81*A and DT = -0.27 + 5.66*B, where A = number of alighting passengers and B = number of boarding passengers.

Work by Lin and Wilson (*5*) for light rail transit determined that the number of standees could affect dwell times by "up to half a minute, or more":

$$DT = 9.24 + 0.71*B + 0.52*A + 0.16*LS$$

where B = number of passengers boarding the train
A = number of passengers alighting from the train
LS = number of departing standees

Based on observations made at light rail stations, Puong (*6*) developed models "showing linear effects in passenger boardings and alightings but nonlinear effects in the on-vehicle crowding level":

$$DT = 12.22 + 2.27*B_d + 1.82*A_d + 6.2*10^{-4}*TS_d^{3}*B_d$$

where

A_d = alighting passengers per door,
B_d = boarding passengers per door, and
TS_d = through standees per door, i.e., total through standees divided by the number of doors

Bertini and El-Geneidy (*7*) observed dwell times at bus stops along Portland OR TriMet Route 14. The mean of 459 dwell times was 12.42 seconds, with a standard deviation of 9.23 seconds. No equation was developed.

Dueker et al. (*8*) analyzed nearly 400,000 bus dwell observations in Portland OR that were collected using automated vehicle location (AVL) and automated passenger count (APC) technology. The resulting equation was

$$DT = 5.136 + 3.481*B - 0.04*B^2 + 1.701*A - 0.031*A^2 - 0.144*ONTIME + 1.364*TOD2$$

where

- DT is the duration in seconds the front door is open at a bus stop where passenger activity occurs.
- B is the number of boarding passengers.
- A is the number of alighting passengers.
- ONTIME indicates whether the bus is “ahead or behind schedule”.
- TOD2 is the effect (1.364 seconds) on dwells of mid-day operation, referenced to dwells during the morning peak period.

UPDATED DATA ON DWELL TIME

Many of the dwell time equations found in the literature were old or dealt with rail transit. Since the 1980s, low-floor buses have become more prevalent and fare collection has become more efficient. Furthermore, a route on campus may have passenger characteristics different from the routes used in the earlier studies. For the class project, a plausible hypothetical equation was used, just to demonstrate how dwell time can affect a route design. Clearly, there was a need for a more extensive study, but there was not sufficient time to conduct an appropriate study before the semester ended.

Greater Lafayette Public Transportation Corporation (GLPTC aka CityBus) is the local bus operator that also serves the campus. CityBus had an automatic passenger count (APC) system that provided a data base with the format shown in Table 1. Note that it has almost enough data to permit a statistical analysis of dwell time without a field study. However, one data item is missing. In order to compute dwell time, the times at which the front door opens and closes are needed. The APC data in Table 1 include only the door closing time, i.e., the Actual departure time.

TABLE 1 Excerpt of Automatic Passenger Count Data Report

Stop	Actual dep	Sched dep	Boardings	Alightings	Load
Route 0, Block 1503	8:00:17	7:40:00	0	0	0
CIRCLE PINES,3	8:00:17	8:00:00	0	5	0
Route 15, Block 1503	8:00:17	8:00:00	12	11	0
CIRCLE PINES,3	8:00:17	8:00:00	3	0	3
ALPHA CHI,3	8:00:41	8:00:30	3	0	6
ALPHA PHI,3	8:01:05	8:01:00	0	0	6
SIGMA NU,7	8:02:12	8:02:00	1	0	7
Hilltop & Tower,1	8:03:19	8:03:00	3	0	10
Russell & Tower,2	8:04:32	8:05:00	0	0	10
Waldron & Stadium,2	8:06:00	8:06:00	1	0	11

Fortunately, most buses operated by CityBus are equipped with as many as eight cameras (see Figure 1):

1. Through the front windshield
2. Along the right side of the bus (exterior)
3. Along the left side of the bus (exterior)
4. Looking out through the front door
5. Looking out through the side door
6. Looking forward from the back interior of the bus
7. Looking toward the back of the bus from the front interior of the bus
8. Looking down the rear exterior of the bus to the pavement (not shown in Figure 1)

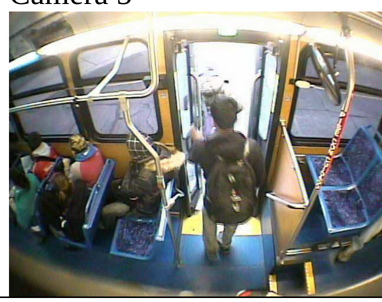
Camera 1

Camera 2

Camera 3

Camera 4

Camera 5



Camera 6

Camera 7

FIGURE 1 Camera views.

A sample video was obtained from CityBus. This video, and all subsequent videos used in this study, were for 40-foot buses with two side doors. Most passengers used a Purdue University pass; a few paid the cash fare. It was quickly determined that good dwell time information could be obtained from the video. Guided by the studies in the literature, the following data were extracted from the video.

1. Number of passengers standing in the aisle or in front of the side door after passengers have had the opportunity to find and take seats as the bus is proceeding to the next stop
2. Time at which front door opens
3. Number of passengers leaving by front door

4. Number of passengers leaving by side door
5. Number of passengers entering by front door
6. Time at which front door closes
7. Any special circumstances

These data were converted into the entries for each stop that are shown in Table 2. Table 2 contains dwell time data for 19 stops made by a bus between 10:32AM and 11:02AM on Wednesday 2 December 2009. In Table 2, “dwell time” = “Time front door closes” – “Time front door opens“, with exceptions that are explained below. Using Cameras 4 and 5 (and sometimes Camera 2), the numbers of passengers alighting and boarding were easily counted. Using Cameras 6 and 7 (and sometimes repeat viewing), the number of standees could be accurately determined.

The advantages of using video for data collection are (a) event times can be reviewed and corrected, (b) counts (especially of standing passengers) can be verified, (c) special circumstances can be noted and discussed by other members of the research team. Examples of “special circumstances” found in the first 30 minutes of video were:

A. A stop at which no passengers alighted or boarded while the bus doors were open. This stop was included in the database, because it helped establish the constant term in the dwell time equation to be estimated.
B. A stop at which the bus operator waited for a passenger to run to catch that bus. In this case, the time at which the door would have closed under normal circumstances was estimated.
C. A stop that had an artificially long dwell time, because it was a time check point. Again, the time at which the door would have closed under normal circumstances was estimated.

TABLE 2 Sample Dwell Time Data, 10:32-11:02AM

dwell		pax alighting		pax
time	standees	front	side	boarding
30	4	7	3	10
11	3	0	1	0
4	3	0	1	0
32	3	10	19	4
10	0	1	3	0
11	0	2	0	1
8	0	0	1	2
7	0	2	0	0
9	0	1	1	1
4	0	0	0	0
8	0	0	1	1
22	0	0	3	1
5	0	0	0	1
5	0	0	1	0
18	0	4	2	6
4	0	0	0	1
6	0	0	0	2
7	0	0	0	3
21	1	0	1	3

Another circumstance is possible: What if the side door closes after front door? In that case, the dwell time would be defined as “Time side door closes” – “Time front door opens”. Other unusual events can be handled in a similar way – in a way that explains dwell time in a reasonable way.

DWELL TIME DATA ANALYSIS

Five additional videos (in DVD format) were obtained from CityBus, increasing the number of stops in the analysis to 100. To investigate whether any non-linear relationships might exist, the following plots were created:

- Dwell Time (DT) vs. passengers leaving by front door (Figure 2a)
- DT vs. passengers leaving by side door (Figure 2b)

- DT vs. Total passengers alighting (Figure 2c)
- DT vs. Total passengers boarding (Figure 2d)
- DT vs. standees (Figure 2e)

With the exception of two points with extremely high dwell times, the plots in Figures 2a-2c do not exhibit non-linear behavior. The point with DT=143 occurred when 35 passengers boarded at one stop. The point with DT=160 was the result of 5 passengers leaving by the front door, 8 by the side door, followed by 55 boardings. These extreme cases may actually help develop a dwell time model that better represents a wide range of possible bus service conditions.

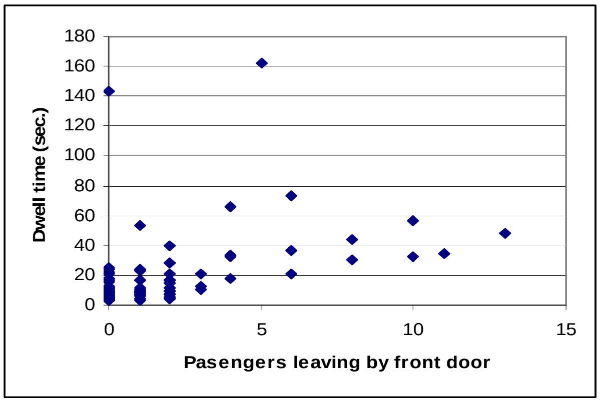


FIGURE 2a DT vs. passengers leaving by front door.

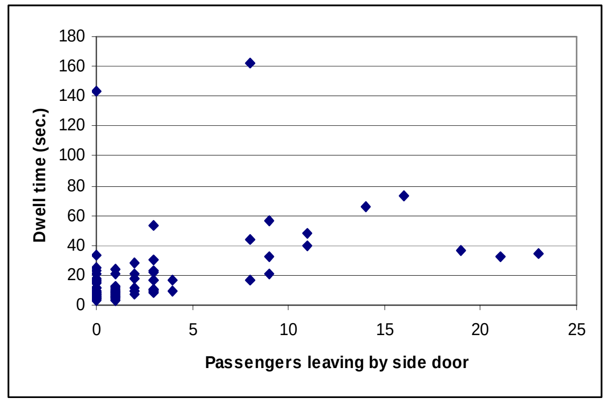


FIGURE 2b DT vs. passengers leaving by side door.

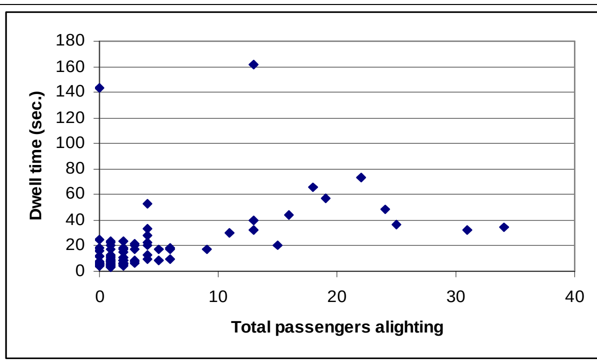


FIGURE 2c DT vs. Total pax alighting.

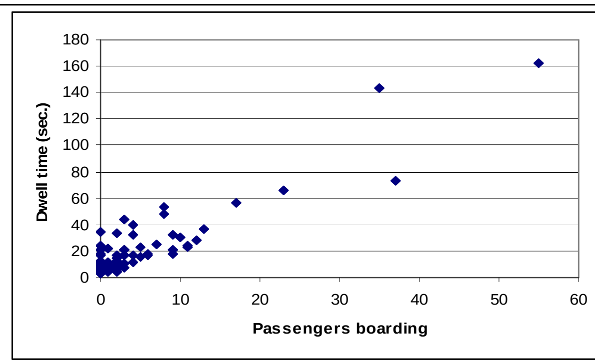


FIGURE 2d DT vs. Total pax boarding.

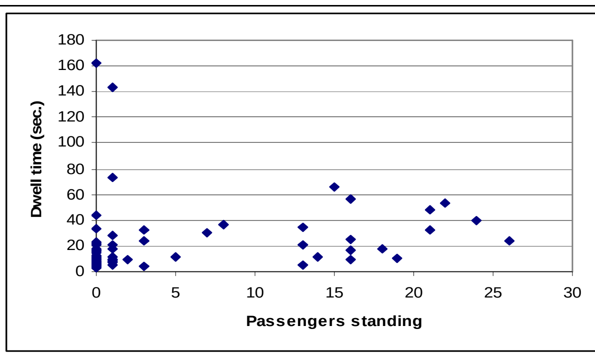


FIGURE 2e DT vs. Standees.

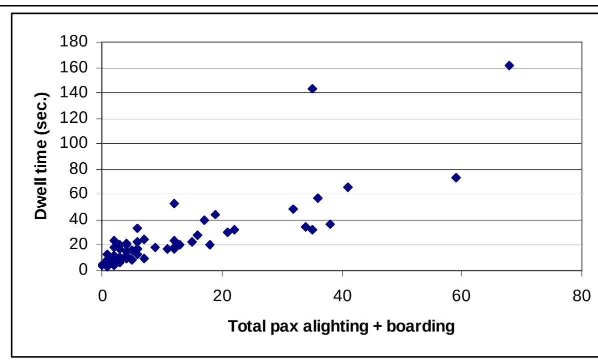


FIGURE 2f DT vs. Total Alightings + Boardings.

The expectation was that DT would have a linear relationship with Total Passengers Alighting (A) and with Total Passengers Boarding (B) for small and moderate values of A and B, then increase more rapidly as standing passengers associated with high A and B values began to affect passenger movements within the bus. Figures 2c-2e do not show that behavior, however.

Several multiple linear regression equations were proposed and estimated. The results are summarized in Table 3.

TABLE 3 Multiple Linear Regression Results (n=100, t_{crit}=1.66)

Model Nr.		CONSTANT	S	A(front)	A(side)	B	Adjusted R^2
1	*Coefficients*	5.034	0.475	1.259	-0.206	2.571	0.865
	T Stat	4.606	3.352	2.435	-0.662	21.589	
2	*Coefficients*	5.044	0.455	1.022	XXX	2.553	0.865
	t Stat	4.629	3.296	2.746	XXX	22.093	
3	*Coefficients*	6.237	XXX	0.484		2.542	0.847
	t Stat	5.621	XXX	3.215		20.158	
4	*Coefficients*	4.978	XXX	1.644			0.726
	t Stat	3.373	XXX	16.215			

Model 1 included all proposed independent variables.

- DT = dwell time
- S = number of standing passengers
- A(front) = the number of passengers alighting by the front door
- A(side) = the number of passengers alighting by the side door
- B is the number of boarding passengers.

The results (adjusted R^2 = 0.865) were good, but the A(side) variable was not significant. This was consistent with what was observed in the video -- "passengers alighting by side door" never controlled the dwell time. The variable A(side) was removed and Model 2 was estimated. The linear fit remained at Adjusted R^2 = 0.865, but all independent variables were significant.

To permit comparisons with dwell time equations found in the literature, Models 3 and 4 with the following variables were estimated from the CityBus video data:

- A = total passengers alighting = A(front) + A(side)
- AB = BA = number of boardings and alightings at a bus stop = A+B

Model 3 is a linear equation with two independent variables that have strong explanatory power and make sense: The lower Adjusted R^2 for Model 3, however, indicates that combining the A(front) and A(side) variables reduces the explanatory power of the Dwell Time equation for the CityBus video data. Model 4 was added to permit comparison with the Feder and Levinson equations, each of which uses BA as the only independent variable. The Feder and Levinson equations had coefficients for BA of 2.573 and 2.75, respectively. Their constant terms were 1.31 and 5.0, respectively. In Model 4, the constant is larger and the coefficient is smaller: DT = 4.978 + 1.644BA. Despite the promising appearance in Figure 2f, Adjusted R^2 for Model 4 was only 0.726.

MODEL COMPARISON AND EVALUATION

To evaluate the model found from on-board video in this study, the bus equations cited in the "Dwell Time Studies in the Literature" section of this paper were plotted for N passengers (alighting + boarding) at a stop, $1 \leq N \leq 20$. (See Figure 3.) When an equation includes a BA term, BA = N. When an equation includes both B and A terms, B = A = N/2.

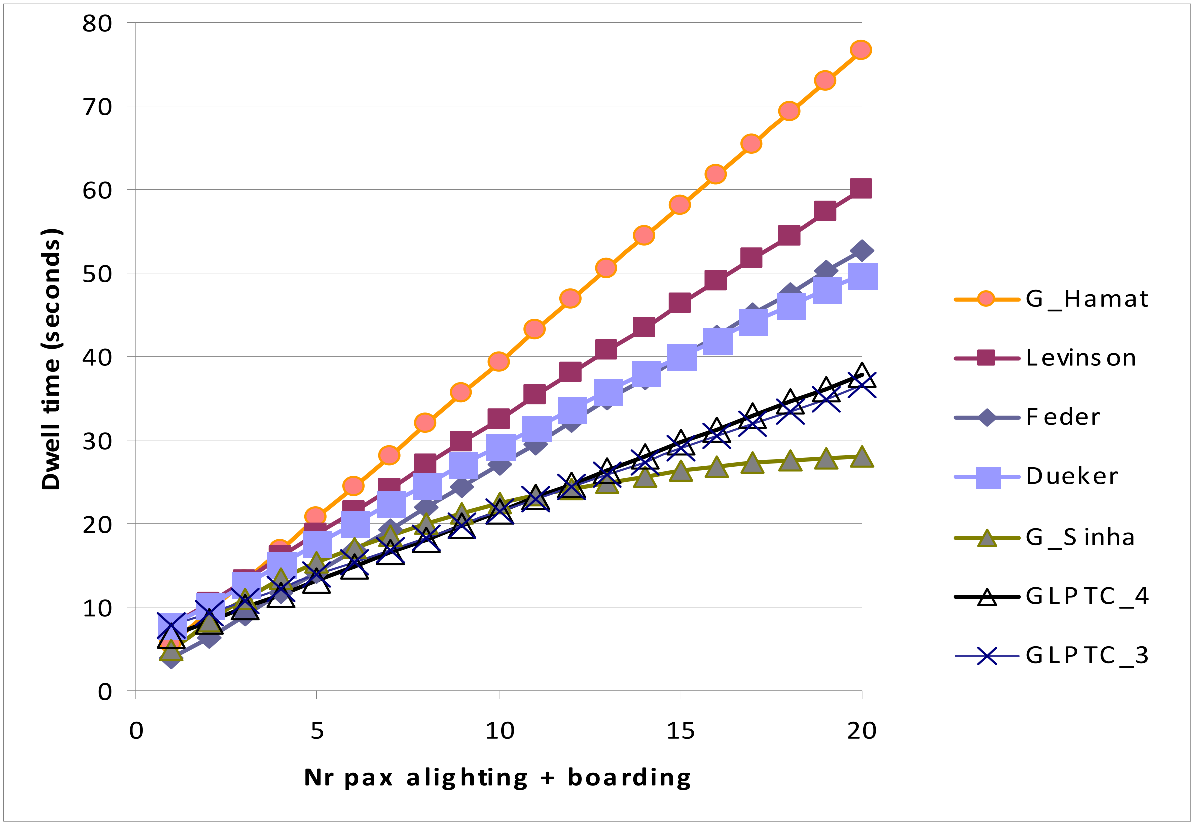


FIGURE 3 Plots of dwell time equations.

The spread in predicted dwell time as the number of passengers N increases from 1 to 20 is quite large. At N=20, the DT prediction from GLPTC video was 36.50 seconds for Model 3 and 37.86 seconds for Model 4. The Guenthner-Hamat prediction from 1988 data is 76.68 seconds. The GLPTC plot is clearly lower than any other plot except Guenthner-Sinha. There may be several reasons for this.

- The college students who make up most of the ridership in the video database have greater agility than the general population of bus riders in the other databases.
- Low-floor buses are the norm in today's bus fleet. They are more easily boarded and left than the buses in use in the 1980s.
- Most passengers boarding showed passes; few had to fumble for correct fare. If this seems to be a factor, Camera 4 in Figure 1 will make the inclusion of a *fare payment type* variable possible.
- Video data allow analysts the opportunity to look for unusual circumstances, review the video, and decide on the most reasonable way to include (or exclude) the events from the database. About 15 percent of the stops needed such decisions. Older studies relied on data

recorded using stopwatches and clipboards, so such review was not possible. Reasons for artificially long dwell times may have been missed.

- The newest study (*8*) used AVL/APC technology to increase the size of the database, but relied on rules such as deleting dwell times greater than 180 seconds. (In our database, no dwell times would have been deleted using this rule, even though several DT values were observed to be artificially high, and were corrected.) These and "other compromises to the conventional measurement of dwell time are offset by their ability to collect data on large numbers of dwells." (*8*) It is likely that the Dueker data overestimate dwell times, at least to some extent.

The spread in Figure 3 is a good reason for the video data in this study to be converted into an equation to use, at least for campus bus routes. Even for small values of N, differences in dwell time estimates on the order of 10-15 seconds are likely. When students are between classes, N>20 is not uncommon. These differences can accumulate, affecting the design of the route and the development of the schedule.

The Guenthner-Sinha equation DT/passenger = 5.0 – 1.2*ln(BA) is valid over a limited range of BA values. After, BA=24, DT/passenger begins to decline. When BA>64.5, DT/passenger is negative. The largest BA value in the GLPTC data was 68.

HOW MUCH VIDEO DATA DO YOU NEED?

Once in-vehicle cameras are installed, video data acquisition is primarily a matter of staff (or analyst) time. The digital video can be transferred to DVD media to facilitate data transcription into worksheet format. After a little practice, an analyst can convert an hour of video data into worksheet format in a little more than an hour. Fast-forwarding the DVD between stops makes this possible, even if some pausing or rewinds are necessary. The greatest time was spent trying to use Cameras 5-7 to accurately count the number of standees.

The author asked CityBus for videos that showed a variety of passenger load and (un)loading conditions. The resulting database had loads of 1-62 passengers, between 0 and 34 alightings, 0-55 boardings, and as many as 26 standees. The first set of DVDs came to us as four 30-minute DVDs for 8:00-9:30AM and 10:32-11:02AM, Wednesday 2 December 2009. We transcribed and analyzed the data for 10:32-11:02AM as a test. There were 19 stops shown on the DVD. At two stops, the bus operator waited well beyond the time the doors would ordinarily have been closed – once to wait for a late-arriving passenger and once to avoid leaving a time checkpoint too early. For these cases, we estimated the time at which the door would normally have been closed. This estimate is accurate to within one or two seconds. As part of our initial test on data for 10:32-11:02AM, we estimated the dwell time equation as DT = 5.91 + 0.97*side + 1.97*boarding, with adjusted $r^2 = 0.744$. Would this sample size have been adequate? After transcribing and analyzing the data for each new DVD, the cumulative data were used to estimate an updated dwell time model. A summary of these updates is given in Table 4.

This experiment revealed several lessons.

1. An adequate range of values present in the dataset is more important than the number of bus stops (data points) in the dataset. For example, in the 0830-0900 and 1508-1542 time periods, there were no standees in the database. By themselves, the 34 data points for 0830-0900 and 1508-1542 will not produce a good DT equation, if it turns out that "standees" is an important independent variable in bus service at other times. At 34 of the 100 stops, there were passengers standing in the bus aisles – once as many as 26 standees. It was apparent in

the video that "standees" affected alighting and boarding time, which affects dwell time. After the first 30 minutes of data, *Standees* was always a significant variable.

TABLE 4 Comparing Model Results As More Video Data Are Added

	2-Dec-09	2-Dec-09	2-Dec-09	2-Dec-09	25-Jan-10	4-Feb-10
	1032-1102	0800-0830	0831-0900	0901-0931	1508-1542	1326-1346
cumul stops:	19	38	57	75	90	100
	Coefficients	*Coefficients*	*Coefficients*	*Coefficients*	*Coefficients*	*Coefficients*
Intercept	5.914	5.383	5.450	4.595	5.079	5.044
Standees, S	---	0.362	0.363	0.532	0.430	0.455
A(front)	---	0.969	0.974	0.761	1.321	1.022
A(side)	0.968	0.529	0.559	---	---	---
Boardings, B	1.970	1.437	1.393	2.337	2.255	2.553
Adjusted R^2	0.744	0.916	0.913	0.913	0.890	0.865

--- not significant at 95% Confidence Level

2. Even though the first four time periods in Table 4 are for the same morning, the cumulative model began to "settle down" after video data from <u>other</u> days and times of day were added. The 1508-1542 time frame had no standees and 1326-1346 had many, yet the behavior described by the cumulative models were being reinforced by those data.

APPLICATION TO CAMPUS SHUTTLE LOOP

This study was motivated by a need for a dwell time equation that could be applied to the design of a campus loop route. Model 2 in Table 3 is the best model to apply, because it has fewer variables than Model 1 and a higher R^2 than Model 3:

$$DT = 5.044 + 0.455*S + 1.022*A(front) + 2.553*B \qquad (1)$$

However, two practical matters arise:

1. We may have good forecasts of the number of students who will alight at any given bus stop, but to use Equation (1), we need to know how many passengers will use the front door. Our forecasts do not include values for A(front).
2. S is also a variable in the preferred DT equation, but S is also not available in our ridership forecasts.

We will attempt to address these issues later. For now, let us apply the simplest model, Model 3 in Table 3:

$$DT = 6.237 + 0.484*A + 2.542*B \qquad (2)$$

Equation 2 does not require values for A(front) or S.

In any case, the following preliminary analysis is needed.

Assumptions:

- Shuttle loop buses move clockwise along the loop.
- Bus acceleration rate is 3.0 mph/sec, deceleration rate is 2.5 mph/sec, and cruise speed is 20 mph.

Question: How much time is needed for a shuttle loop bus to complete the loop? Include driving time and dwell time.

Calculations:

- Driving time without stops = 2.28 mi/20 mph = 6.84 min.
- There are seven bus stops and 6 stop-sign-controlled intersections (3 of which are among the 7 bus stops) on the loop.
- Deceleration from 20 mph will take 20 mph/(2.5 mph/sec) = 8.0 sec over $(1/2)*(2.5*1.47)*(8.0)^2$ = 117.6 ft.
- Acceleration to 20 mph will take 98.1 ft over 6.67 sec.
- At 20 mph, driving 117.6 + 98.1 ft would take 7.34 sec.
- The deceleration/acceleration delay at each intersection or bus stop would be 8.0 + 6.67 - 7.34 = 7.33 sec., not including delay caused by other vehicles.
- Approximate delay from bus stops (without passengers) and stop-controlled intersections = (7+3)*7.33 sec = 73.3 sec = 1.22 minutes.
- Total time to complete a loop without discharging or picking up passengers would be 6.84 + 1.22 = 8.06 minutes.

Result: Continue the analysis to see if two shuttle loop buses can operate at 5-minute headways.

Forecasts of alighting and boardings at each loop stop were based on detailed data for existing campus routes. The hours beginning 11AM and 1PM have the highest ridership. Applying Equation 2 using the A and B values for alternating 5-minute time segments to the two loop buses had the following results:

- The first bus had 87 alightings and 85 boardings during the hour, and an average dwell time of 81 seconds per loop.
- The second bus had 135 alightings and 120 boardings during the hour, and an average dwell time of 104 seconds per loop.

This means that the loop can be traversed in ten minutes and a 5-minute headway can be maintained, if the dwell time estimates from Equation 2 are reliable. Having an equation based on more recent (and local) data was important, because A and B values can vary wildly during an hour, depending on whether classes have just let out or are about to start near a particular stop. The busiest stop for Bus #1 between 11 AM and 12 noon had 14 alightings and 30 boardings near some residence halls. Equation 2 estimated the dwell time at that stop as 56.4 seconds; the equation from Dueker et al. (*8*) estimated the dwell at 91.3 seconds. (Note: We used only the first five terms of the Dueker equation. We could not use the terms involving ONTIME and TOD2. This is another argument for estimating an equation that can be used as a forecasting tool.) The busiest stop for Bus #2 was 60 alightings and 18 boardings at the same residence hall stop a bit earlier. Equation 2 estimated the dwell time at that stop as 167.5 seconds; the Dueker equation estimate was 45.3 seconds. This also reinforces the impression in Figure 3 that higher values of A and/or B can amplify the differences in dwell time equations.

SYNTHESIZING DATA FOR THE PREFERRED DWELL EQUATION

The two issues raised at the start of the previous section are addressed here.

1. If we need to know how many passengers will alight by the front door, the two choices are (a) estimate the percent of alighting passengers who will use the front door, either as a fixed percentage or as a function of total A and standees, and (b) to use a dwell time equation that uses A = A(front) + A(side), such as Equation 2. We have already tried Option b in the previous section. To pursue Option a, we begin by computing

$$\%A(\text{front}) = \frac{A(\text{front})}{A(\text{front}) + A(\text{side})} = 0.38$$

from the video data. We can also plot of the proportion of alighting passengers who will use the front door, depending on the total number of alighting passengers (Figure 4a) and the number of standing passengers (Figure 4b). A reasonable expectation is that %A(front) would decrease as total A increases. Figure 4a does not support this. Likewise, Figure 4b dispels the notion that %A(front) would decrease as S increases.

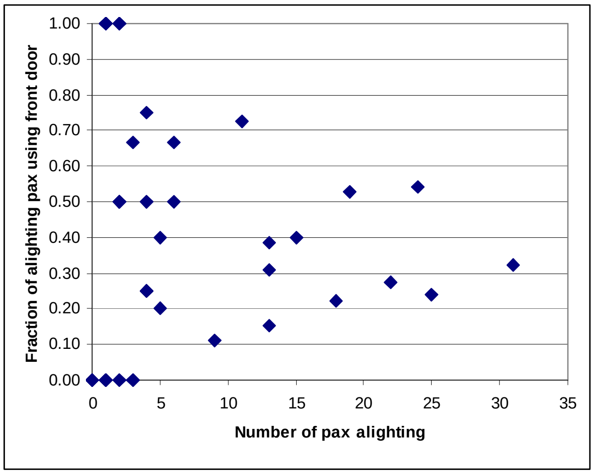


FIGURE 4a %A(front) vs. Total pax alighting.

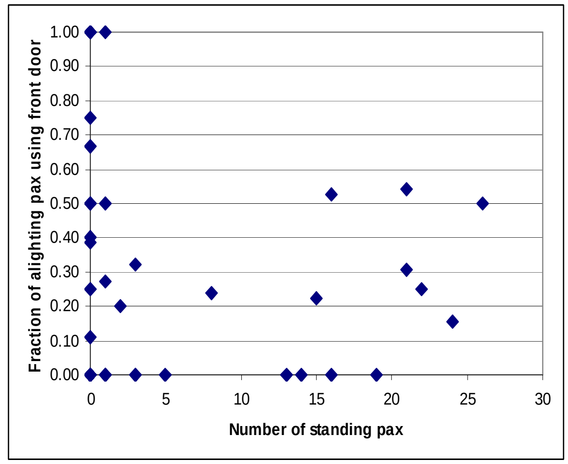


FIGURE 4b %A(front) vs. Total standing pax.

2. Our preferred Equation 1 indicates that dwell time is affected by the number of standing passengers. Watching the in-bus videos confirms the fact that some passengers stand, even when there are empty seats, but that there is a strong relationship between S and number of empty seats. The plot in Figure 5 is quite "well-behaved", viz.,

$$S = 0.0098*(NAS)^2 - 0.4795*NAS + 5.4836 \qquad (3)$$

with $R^2 = 0.9845$. NAS = "Number of available seats" = seats – passengers, which is negative when the passenger load exceeds the number of seats on the bus. If the initial passenger load on a bus is known or can be specified, the relationship in Figure 5 can be used to provide an estimated value for S to be applied at the next stop.

The calculations of average dwell time per loop for Buses 1 and 2 were repeated using Equation 1, with %A(front) = 0.38 and S estimated with Equation 3 when NAS<25.

- For Bus #1, average dwell time per loop went from 81 seconds to 77 seconds.
- For Bus #2, average dwell time per loop went from 104 seconds to 106 seconds.

The extra steps needed to synthesize data for the preferred Equation 1 does not lead to results for dwell time per loop that are much different from the simpler Equation 2. The A and B values in Equation 2 may be capturing much of the effects of A(front) and S in Equation 1. In either analysis, serving the campus loop with 2 buses on 5-minute headways appears practical. In fact, this service may be conservative. The calculations assumed that each bus would stop at each bus stop, incurring delays of 7.33 sec for deceleration/acceleration and 6.24 seconds for dwell time at stops where no passengers alighted or boarded.

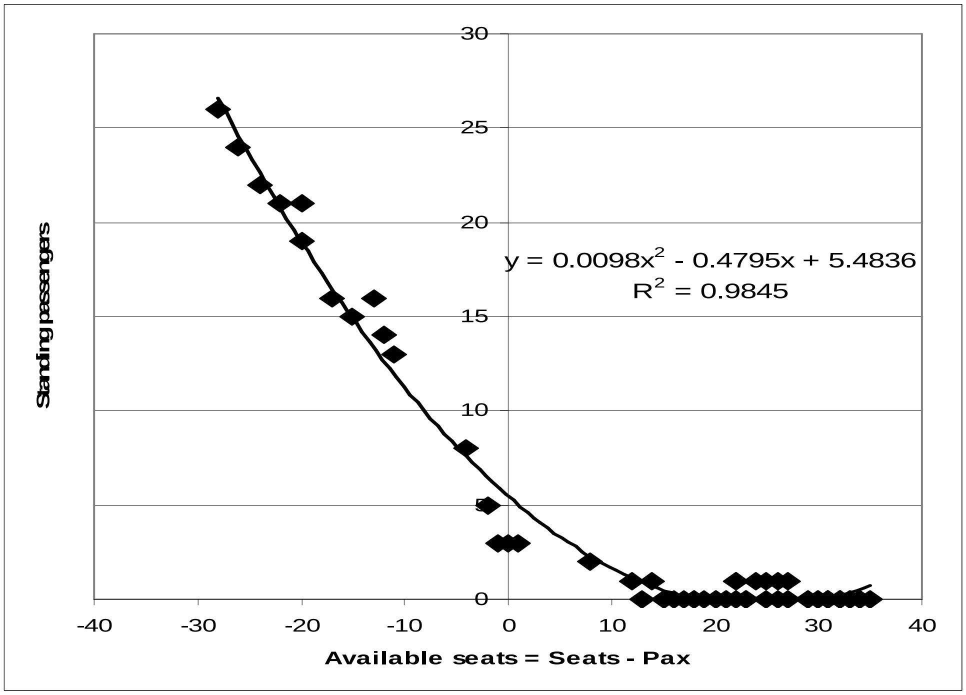


FIGURE 5 Standing passengers vs. available seats.

COLLECTING PRIMARY DATA USING VIDEO TECHNOLOGY

Surveillance cameras have been in use on transit buses for the last decade. The number of agencies of all sizes that are acquiring them is growing rapidly. The author asked CityBus to provide videos that showed a wide range of values for number of alighting passengers, boarding passengers, and standing passengers. As a result, the scenes in the videos are for busier-than-average time periods. However, this does not invalidate the analysis. In fact, it helps add data points in the higher ranges of the variable values. As new videos were received from CityBus, data were extracted and added to the cumulative database. Because of the range of values in the data, only 100 stops were needed to develop a reasonable and useful dwell time equation.

As this is written, CityBus is acquiring a new Automatic Passenger Counting (APC) system for its buses. Even if the new system will add "Time door opens" to the data previously collected (see Table 1), it may not be adequate to provide the basis for a dwell time equation that satisfactorily represents the operations being studied. The APC system will permit a lot more data to be processed, but it would not permit the analyst to directly "observe" values such as number of passengers standing. Video allows direct observation of unusual events. At nine of the 100 stops, we had to estimate the normal door closing time, when the driver waited for late passengers or held the bus at a time check point. At five other stops, we observed delays due to slow issuance of a transfer, a passenger fumbling for the fare or a pass, or unusually long gaps between passengers as they boarded. Looking at an automated database, these events might be discarded as outliers. However, these five events were included in this analysis, because they are a daily part of the passenger boarding process. If other events, such as a wheelchair boarding, were to take place, having a video record would help the analyst decide how to incorporate the event in the dwell time equation.

As is often the case, there is a tradeoff: borrow a dwell time equation from another place or collect your own data and build your own equation. Being able to develop good dwell time equations with a modest amount of video data can be of great value to a transit operator. The study described in this paper was motivated by the lack of an up-to-date dwell time equation in the literature that could be transferred to the analysis of a proposed campus shuttle loop route. Once we learned how to use the DVD playback software, it was easy to enter the data into a worksheet for analysis. The data analysis feature in the worksheet was sufficient to build several reasonable dwell time equations. One equation had stronger explanatory power but had independent variables that are not usually available in forecasts. Methods to synthesize values for *passengers alighting by the front door* and *number of standing passengers* were developed and applied to the proposed campus shuttle loop service. A simpler equation, which includes only *number of passengers alighting* and *number of passengers boarding*, produced similar dwell time estimates on the campus route.

Even if a dwell time equation has been developed from local transit video, it may be not applicable to all local cases. For example, the dwell time equations in this study were based on video created on standard 40-foot buses with two exit doors, only one of which was used for entry. If 60-foot articulated buses are to be used on a route, the "40-foot equations" may not be applicable. "Artics" tend to have three doors, not two, and carry more passengers, many of them standing. Also, Bus Rapid Transit (BRT) vehicles may have two or three doors, and often operate on routes where fares are paid before boarding. Fortunately, this paper has demonstrated that a modest amount of video data for operations covering a particular situation (doors per bus, fare payment policy, etc.) can be sufficient to develop a dwell time equation that will be useful in transit route planning.

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