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Introduction

Prior TransNow funded research by Portland State University (PSU) and the University of Washington (UW) in cooperation with Tri-Met, the transit provider for the Portland metropolitan area, has utilized a rich set of archived data from the Automatic Vehicle Location (AVL)-based Bus Dispatch System (BDS). Tri-Met is one of the few transit agencies that archive AVL data for analysis and research.

The literature on predicting bus transit arrival times for customers has focused on normal operating conditions. Yet, customers are also interested in knowing transit vehicle arrival time when operating conditions are not normal. This research focuses on arrival time predictions under abnormal conditions.

Part of this research relies on an "algorithmic approach" that employs a synthetic "time to arrival" function, or average speed from the current location to the location of interest. This function can be modified for abnormal conditions. This approach is employed by the University of Washington and is described in a separate technical report (Cathey and Dailey, Forthcoming). In addition, a "statistical approach" focuses on delays that occur at unexpected times, such as traffic delays resulting from drawbridge interruptions and excess dwell time resulting from bus-lift operations. The statistical approach provides an estimate of delay at the time of occurrence, which is updated with the actual time of delay at the ending time of the occurrence. The statistical approach is described in this report.

Algorithmic Approach

The UW received one month, November 2000, of archived status and exception reports to calibrate the model for normal conditions. Status reports of time and position of all buses at regular time intervals were augmented with exception reports for buses that were not running on schedule. The data were analyzed to model operations for baseline conditions. Traffic delay data for Hawthorne Bridge draw bridge operation for November 2000 have been forwarded to the UW for calibration under abnormal conditions. Bridge closure data for November 2001 will provide for validation.

The UW part of the project expanded on a previous project that created a new algorithm to predict the arrival/departure time for transit vehicles. In the previous project, a prediction algorithm appropriate for use with Tri-Met's scheduling and AVL system was documented (Cathey and Dailey, 2001). This algorithm provides a clearly defined open and independent mechanism to assign vehicles to trips and predict arrival/departure. This work documents a methodology for performing data fusion in making predictions. Data fusion may incorporate information existing outside of transit schedules and include traffic, weather or historical information.

Three assumptions are made in solving this general problem: (1) there is a fleet of transit vehicles that travel along prescribed routes; (2) there is a transit database that defines the schedule times and the geographical layout of every route and time point; and (3) there is an automatic vehicle location (AVL) system, where each vehicle in the fleet is equipped with a transmitter and periodically reports its progress back to a transit management center.

The predictive algorithm employs a Kalman filter approach. A central tenant of the algorithm is that a synthetic "time to arrival" function for every destination can be created. This time to arrival function can be evaluated at each position along a linear route to estimate the time remaining until arrival. This function is analogous to the speed the vehicle would have to travel if it were to travel at a constant speed from location x to the goal. (This is not to be confused with the actual speed of the vehicle, which is not used in this approach.) This arrival function is used in the time update equations for the linear Kalman filter, as well as the data update equations. This time to arrival function represents the best estimate of the progress of a vehicle on a particular route at a specific time of day. As such, changes in the environment such as snow or traffic incidents can be factored into the arrival prediction algorithm by substituting a modified arrival function that reflects the adverse conditions. This new arrival function is created by first identifying a "normal" arrival function using a set of recorded data, then data from abnormal conditions are used to determine the transformation necessary to reflect the new conditions.

The normal arrival function was created by: (1) estimating a set of discrete arrival function values for a route, and (2) approximate this set using a continuous polynomial. This function is used to make estimates of the prediction errors in the normal case that will be characterized statistically so that a threshold for deviation from normal can be identified. The new arrival function is created by optimally weighting the original arrival function to replicate the travel times under the adverse conditions. Creating the transformation and identifying the threshold for deviation from normal are the principal contributions of the research effort. With these two tools the previously developed optimal filter techniques can be used directly to estimate arrival times under adverse conditions.

Statistical Approach

The PSU portion of the project focuses on statistical analysis of two types of abnormal delay: draw bridge interruptions of traffic and bus lift operations. These kinds of delay are regular occurrences, but the times at which they occur cannot be anticipated. Thus, they cannot be scheduled. The statistical approach generates estimates of delay that can be added using a "schedule deviation approach" for estimating downstream arrival times.

At the beginning of a delay event, an estimate of the time of delay should be incorporated into the time of arrival estimate. This statistical approach is intended to provide such an estimate of delay, which is used until the event is over, at which time the actual delay can be used in estimating time of arrival at a downstream location. For these types of events, delay-event reports would have to be generated and sent to the bus dispatch center at the beginning of the event to invoke the estimate of delay. At the conclusion of one of these events, another delay-event report would be needed to replace the estimate with actual amount of delay. Similarly, an "algorithmic approach" would utilize the beginning and ending delay-event reports into estimating a revised time of arrival function.

Data were obtained on the time and duration of closures for the Hawthorne Bridge and Tri-Met bus running time data between stop locations on either side of the bridge. These data are for trips that use the Hawthorne Bridge for a time period that includes one-half hour before and after each closure. For purposes of simplicity, we refer to these two locations as time points though they are not the same as “official” time point locations used in Tri-Met scheduling. Statistical analysis of these data yielded delay factors to add to time estimates used under normal conditions.

Also, a statistical model of dwell time to serve passengers at bus stops was estimated. This model accounts for effects associated with passenger boardings (ons) and alightings (offs), whether a lift operation occurs, type of bus (low floor or not), schedule deviation, and whether a bus is fully loaded. The lift operation parameter can be used to predict the additional dwell time associated with a lift operation, which can be added to the schedule deviation or can be included into the arrival function values for the algorithmic approach.

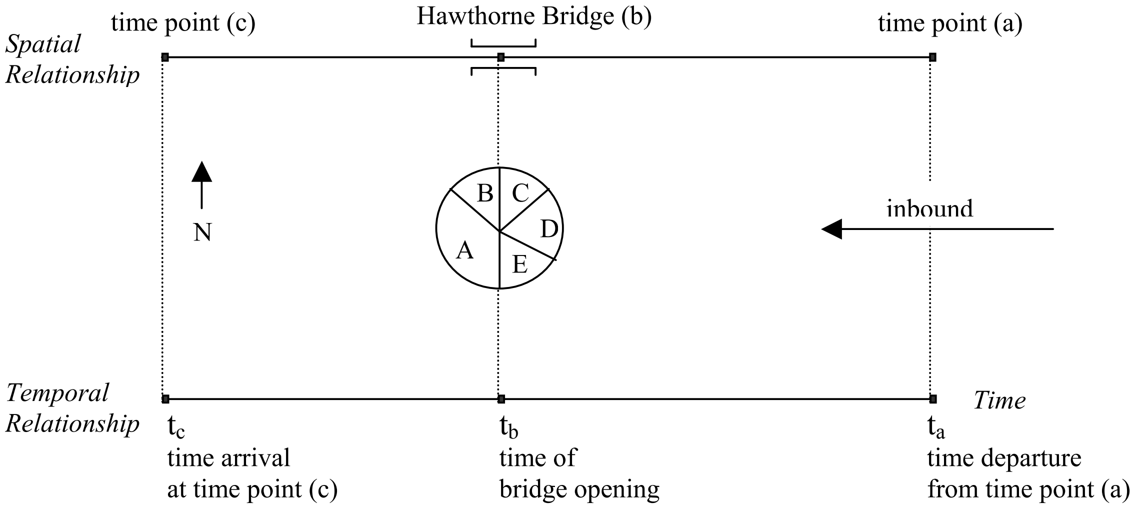
Statistical Analysis of Drawbridge Data

The historic Hawthorne Bridge in Portland is a low-level drawbridge serving boat and barge traffic. It is one of eight bridges that cross the Willamette River near downtown, effectively linking the east and west sides of Portland. Four of these bridges are draw bridges with the Hawthorne Bridge being the most active. It is commonly understood that draw bridge delay affects bus transit on-time performance (Guenthner & Hamat, 1983; Woodhull, 1987), though no empirical studies are known to exist. Transit schedulers attempt to account for recurring sources of delay when setting schedules. Schedulers also realize that random disturbances are likely to occur and compensate for this by adding recovery time into schedules. However, it is not cost effective for schedulers to accommodate delays resulting from non-recurring disturbances because this necessitates excessive layover times and reduces schedule efficiency.

Although much of the river traffic that necessitates lifting the draw span occurs in off-peak periods, these unscheduled delays interrupt transit routes that traverse Hawthorne Bridge. The effect of these occurrences should be incorporated into estimates of arrival times that are provided to customers in real time.

This section describes a statistical procedure to account for delays in bus travel from lifting the draw span and interrupting street traffic. Travel time data for buses on routes using Hawthorne Bridge for periods just before, during, and just after lifting the draw span were used to estimate delay. Bus stop-level data between time points on either side of the bridge for a time period that includes one-half hour before and after each lift operation was selected from the Tri-Met archive of stop-level data. Statistical analysis of these data yielded delay factors to add to time estimates used under normal conditions. Only the inbound (westbound) direction was modeled. Figure 1 displays the spatial and temporal concepts of the model and the translation of the model’s results to running times under different bus arrival times in relation to time of bridge closures to traffic.

Figure 1: Spatial and Temporal Concepts



The variable DTB is the time between a bus departure and time point (a) at Grand and Hawthorne and it's arrival at time point (c) at 3rd and Main. The variable DTA refers to the time between the bridge closure (b) and the departure time of the bus from Grand and Hawthorne (a). This approaching time point to the bridge is far enough from the draw span to be largely unaffected by traffic queue build ups due to closure of the bridge. A positive value of DTA means the bus departed prior to the bridge closure, but a bus departing with a small positive value could still be caught by the closure. Values less than or equal to zero indicate that a bus will be delayed by the closure. A larger negative value indicates it may be caught in the traffic queue and a very large negative value indicates it will travel unaffected by the closure that occurred prior to its arrival on the bridge.

Table 1 provides definitions of the variables used in the analysis. The bridge delay effects are non-linear and are best estimated by two models. Model 1 is for buses arriving at the bridge approach time point during the period of 2 minutes before to 2 minutes after the bridge closure with the other model for buses arriving at the bridge approach time point 2 minutes after to 11 minutes after bridge closure. Table 2 provides descriptive statistics for the variables used in the opening and early- delay period bridge delay model and Table 3 describes the model. Model 1 estimates the delay for early arriving buses that may or may not be caught by the bridge closure. Model 2 estimates the delay for buses arriving at the bridge approach time point after the bridge is closed to traffic. In this model, delay dissipates for buses arriving as the time increases between the bridge closure to traffic and the departure of the bus from the bridge approach time point. Tables 4 and 5 describe the model for the latter period during which the traffic queue dissipates. Although the model controls for time of day and weekday and weekend effects, only the difference in time between the bridge opening and the departure from the approach time point (DTA) is used in the estimation of delay as shown in Figure 1.

Table 1: Description of Variables

Name	*Description*
DTB	Bus run time (seconds): Arrive time 3rd/Main - depart time Grand/Hawthorne
DTA	Bridge-bus time differential (seconds): Bridge open time - depart time Grand/Hawthorne
DTA2	DTA squared
DTA3	DTA cubed
SRT	Scheduled run time (seconds)
B_TOT	Bridge open time (seconds)
DAY_W	Day of week (1 = Weekday)
DAY_S	Day of week (1 = Saturday)
DAY_U	Day of week (1 = Sunday)
DAY_X	Day of week (1 = Holiday)
LOAD	Number of passengers on board
TOD_1	Time of day (1 = a.m. peak)
TOD_2	Time of day (1 = midday)
TOD_3	Time of day (1 = p.m. peak)
TOD_4	Time of day (1 = evening)
TOD_5	Time of day (1 = late night)
RTE_14	Route (1=Route 14)
RTE_104	Route (1=Route 104)
RTE_110	Route (1=Route 110)
DWELL	Dwell time (seconds)
ONS	Boardings (actual)
ONS2	Boardings squared (actual)
OFFS	Alightings (actual)
OFFS2	Alightings squared (actual)
DELAY	Departure delay (minutes)
LIFT	Lift operation (1 = true)
LOW	Low floor bus (1 = true)
ONOFFLD2	Passenger friction effect: ONS > 0 * OFFS > 0 * bus load >=30
RAD	Route typology (1 = radial)
FEED	Route typology (1 = feeder)
CTOWN	Route typology (1 = cross-town)

Table 2: Descriptive Statistics for Bridge Delay Model 1

Sample Criterion: DTA >= -120 and <= 120 sec.						
Name	*N*	*Mean*	*Std. Dev.*	*Var.*	*Min.*	*Max.*
DTB	250	467.84	241.06	58,109.00	106.00	1,130.00
DTA	250	1.43	67.04	4,494.30	-120.00	120.00
DTA2	250	4.48E+03	4.15E+03	1.72E+07	0.00E+00	1.44E+04
DTA3	250	1.22E+04	6.13E+05	3.76E+11	-1.73E+06	1.73E+06
SRT	250	256.75	27.52	757.16	189.00	365.00
B_TOT	250	513.12	92.50	8,556.50	120.00	1,020.00
DAY_W	250	0.74	0.44	0.19	0.00	1.00
DAY_S	250	0.16	0.37	0.14	0.00	1.00
DAY_U	250	0.10	0.30	0.09	0.00	1.00
DAY_X	250	0.00	0.00	0.00	0.00	0.00
TOD_1	250	0.06	0.24	0.06	0.00	1.00
TOD_2	250	0.44	0.50	0.25	0.00	1.00
TOD_3	250	0.08	0.27	0.07	0.00	1.00
TOD_4	250	0.34	0.48	0.23	0.00	1.00
TOD_5	250	0.08	0.27	0.07	0.00	1.00
RTE_14	250	0.48	0.50	0.25	0.00	1.00
RTE_104	250	0.39	0.49	0.24	0.00	1.00
RTE_110	250	0.14	0.34	0.12	0.00	1.00

Table 3: Results of Bridge Delay Model 1

Sample Criterion: DTA >= -120 and <= 120 sec.			
Name	*Coef.*	*Std. Err.*	*T-Ratio*
DTA	-1.63	0.48	-3.40
DTA2	-0.01	0.00	-2.47
DTA3	0.00	0.00	0.34
SRT	-0.41	0.75	-0.55
B_TOT	0.33	0.15	2.25
DAY_S	-7.74	41.29	-0.19
DAY_U	-95.32	47.74	-2.00
TOD_2	-78.83	65.84	-1.20
TOD_3	-104.48	80.49	-1.30
TOD_4	-13.56	73.11	-0.19
TOD_5	-223.24	99.59	-2.24
RTE_104	28.81	30.98	0.93
RTE_110	59.42	45.26	1.31
CONST.	497.10	237.20	2.10
R2 ADJ.	0.25		

Table 4: Descriptive Statistics for Bridge Delay Model 2

Sample Criterion: DTA >= -600 and < -120 sec.						
Name	*N*	*Mean*	*Std. Dev.*	*Var.*	*Min.*	*Max.*
DTB	519	417.24	152.11	23,137.00	114.00	1,090.00

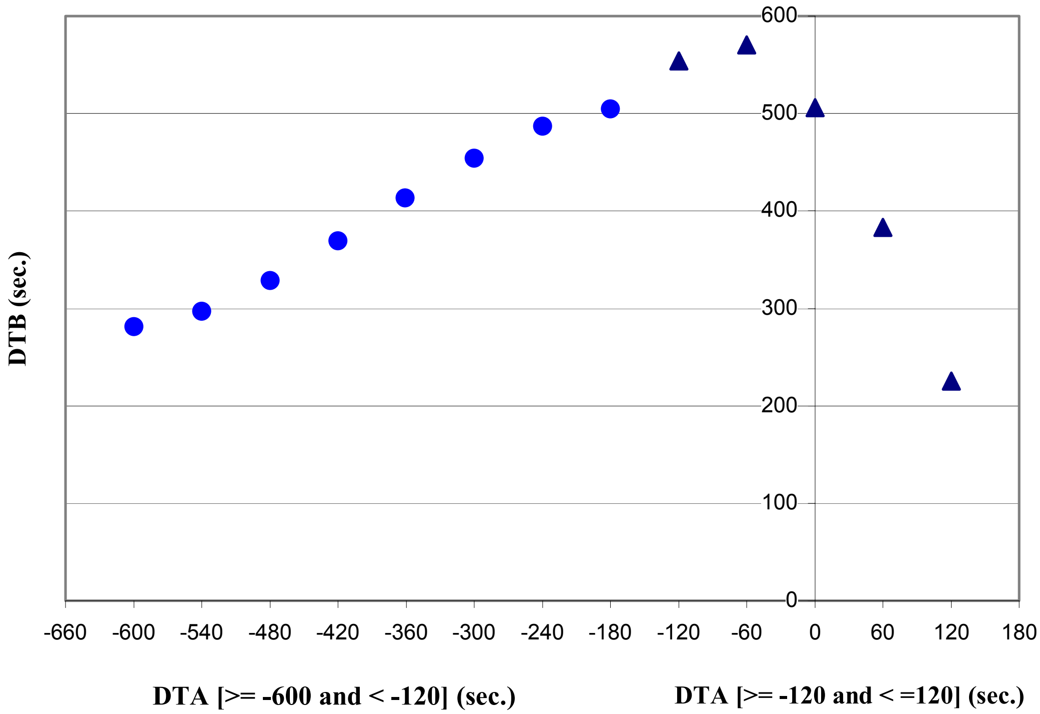
DTA	519	-355.92	139.83	19,552.00	-598.00	-122.00
DTA2	519	1.46E+05	1.03E+05	1.05E+10	1.49E+04	3.58E+05
DTA3	519	-6.61E+07	6.25E+07	3.90E+15	-2.14E+08	-1.82E+06
SRT	519	256.99	21.64	468.32	189.00	365.00
B_TOT	519	507.40	86.35	7,455.60	120.00	900.00
DAY_W	519	0.70	0.46	0.21	0.00	1.00
DAY_S	519	0.19	0.40	0.16	0.00	1.00
DAY_U	519	0.10	0.30	0.09	0.00	1.00
DAY_X	519	0.01	0.11	0.01	0.00	1.00
TOD_1	519	0.03	0.17	0.03	0.00	1.00
TOD_2	519	0.48	0.50	0.25	0.00	1.00
TOD_3	519	0.09	0.28	0.08	0.00	1.00
TOD_4	519	0.36	0.48	0.23	0.00	1.00
TOD_5	519	0.04	0.19	0.04	0.00	1.00
RTE_14	519	0.51	0.50	0.25	0.00	1.00
RTE_104	519	0.37	0.48	0.23	0.00	1.00
RTE_110	519	0.12	0.33	0.11	0.00	1.00

Table 5: Results of Bridge Delay Model 2

Sample Criterion: DTA >= -600 and < -120 sec.			
Name	*Coef.*	*Std. Err.*	*T-Ratio*
DTA	-1.36	0.80	-1.69
DTA2	-0.01	0.00	-2.27
DTA3	0.00	0.00	-2.13
SRT	0.34	0.29	1.16
B_TOT	0.74	0.05	13.99
DAY_S	-36.54	12.73	-2.87
DAY_U	-108.44	16.16	-6.71
DAY_X	-150.52	42.55	-3.54
TOD_2	91.71	26.81	3.42
TOD_3	67.81	30.48	2.23
TOD_4	10.12	27.96	0.36
TOD_5	24.02	38.77	0.62
RTE_104	15.19	10.16	1.50
RTE_110	-11.47	16.10	-0.71
CONST.	-85.29	125.10	-0.68
R2 ADJ.	0.53		

Figure 2 presents a generalization of the results of two models to calculate the estimate of delay for arrival time estimation using the schedule-deviation approach.

Figure 2: Plot of Estimated DTB



The plot of estimated running time between time points as shown in Figure 2 is generalized and used to determine the formulas as shown in Table 6. This time estimate from the formulae, less 220 seconds (bus running time under normal conditions) is the schedule deviation of a bus when it departs from the time point at the eastern approach to the Hawthorne Bridge. When that bus actually arrives at the first time point beyond the bridge, this estimate should be replaced by the actual travel time between time points, less 220 seconds. In this way customers are provided real-time arrival estimates that take into consideration the occurrence of an event, its estimated impact, and then its actual impact.

Table 6: Calculating the Bridge Delay

Scenario	*Criteria (in sec.)*	*Formula (in sec.)*
A: Bus traverses bridge before closure	when DTA > +120	DTB = 220
B: Bus is likely to be caught in early part of closure	when DTA < +120 and >= -30	DTB = 220 + (350/150) DTA (delay builds up)
C: Bus is definitely caught in closure	when DTA < -30 and >= -60	DTB = 570 (peak delay)
D: Bus is likely to be caught in the traffic queue	when DTA < -60 and >= -660	DTB = 220 - (350/600) DTA (delay diminishes)
E: Bus is far enough beyond closure and not impacted	when DTA < -660	DTB = 220

Statistical Analysis of Lift Data

Descriptive statistics for data used in the statistical analysis of the effect of lift operations on dwell times at bus stops are presented in Table 7. The data are from a two-week period in September, 2001 for all of Tri-Met's regular service bus routes. Dwell time is the duration in seconds the front door of the bus is open at a stop where passenger activity occurs. The data were purged of observations associated with the beginning and ending points of routes, layover points, and dwell times greater than five minutes (300 seconds). Observations with passenger loads (LOAD) greater than 70 were also excluded, indicating the automatic passenger counter data were suspect. Two weeks of stop-level records provided nearly 400,000 data points. Even though lift operations occur at only 0.7 of one percent of stops with passenger activity, the number of lift operations is large enough for a robust model.

Table 7: Descriptive Statistics for Bus Dwell Time

Dwell Time	*Mean*	*Std. Dev.*	*N*
With lift operation	87.93	47.38	2,603
Without lift operation	11.57	10.56	366,185
Both	12.60	16.01	369,870

Table 8 presents the descriptive statistics for the first bus dwell time model which uses all the observations and a dummy variable for lift operation (LIFT). The results of the model are presented in Table 9. Dwell time is explained by boarding passengers (ONS), alighting passengers (OFFS), whether the bus is ahead or behind schedule (DELAY), lift operation (LIFT), low floor bus (LOW), passenger friction (ONOFFLD2), time of day, and type of route. Square terms of the passenger activity variables are used to account for diminishing effects on dwell time. The passenger friction variable was developed to account for the effect of passenger activity on dwell times for buses that are near or fully loaded. It was posited that heavily loaded buses have greater dwell times due to this effect. The proxy variable was constructed by interacting ONS, OFFS, and LOAD greater than or equal to 30 passengers. The variable did not perform as expected[1].

The negative coefficient on DELAY indicates that dwell times tend to be less for late buses than for early buses. The negative coefficient may be due to drivers who limit dwells when buses are full to maintain schedules. Another possible explanation is that dwell times are minimal on fully loaded buses because alightings become the predominate passenger activity. Our analysis shows that alightings take considerably less time than boardings. The CONSTANT value of 5.17 seconds reflects the basic opening and closing door process, with the passenger activity, time of day, route type, and lift operation affecting that basic time by the amounts of the coefficients. The effect of a lift operation on dwell time in the first model is estimated to be 67.80 seconds. The lift operation effect is also examined more closely in a second model of dwell times where observations are limited to those with lift operations.

Table 8: Descriptive Statistics for Bus Dwell Time Model 1

Sample Criterion: DWELL =< 300 sec.

[1] The negative coefficient on the variable is counterintuitive. Other forms of this concept such as LOAD alone or LOAD greater than 30 in conjunction with ONS or OFFS did not perform very well either.

Name	*N*	*Mean*	*Std. Dev.*	*Var.*	*Min.*	*Max.*
DWELL	369,870	12.50	16.01	256.36	2.00	300.00
ONS	369,870	1.22	1.99	3.94	0.00	45.00
ONS2	369,870	5.42	26.49	701.46	0.00	2,025.00
OFFS	369,870	1.27	1.90	3.60	0.00	47.00
OFFS2	369,870	5.21	25.14	631.94	0.00	2,209.00
DELAY	369,870	2.35	3.55	12.58	-29.66	57.50
LIFT	369,870	0.01	0.08	0.01	0.00	1.00
LOW	369,870	0.59	0.49	0.24	0.00	1.00
ONOFFLD2	369,870	0.12	0.33	0.11	0.00	1.00
TOD1	369,870	0.15	0.36	0.13	0.00	1.00
TOD2	369,870	0.41	0.49	0.24	0.00	1.00
TOD3	369,870	0.17	0.37	0.14	0.00	1.00
TOD4	369,870	0.20	0.40	0.16	0.00	1.00
TOD5	369,870	0.07	0.25	0.06	0.00	1.00
RAD	369,870	0.69	0.46	0.22	0.00	1.00
FEED	369,870	0.06	0.23	0.05	0.00	1.00
CTOWN	369,870	0.25	0.43	0.19	0.00	1.00

Table 9: Results of Bus Dwell Time Model 1

Sample Criterion: DWELL =< 300 sec.			
Name	*Coef.*	*Std. Err.*	*T-Ratio*
ONS	3.75	0.02	214.60
ONS2	-0.04	0.00	-27.10
OFFS	1.90	0.02	106.10
OFFS2	-0.03	0.00	-24.30
DELAY	-0.14	0.01	-22.48
LIFT	67.80	0.25	271.60
LOW	-0.21	0.04	-4.85
ONOFFLD2	-0.94	0.07	-14.24
TOD2	1.39	0.06	22.06
TOD3	0.93	0.08	12.45
TOD4	1.23	0.07	17.19
TOD5	-0.04	0.10	-0.43
FEED	0.58	0.09	6.19
CTOWN	-0.41	0.05	-8.30
CONSTANT	5.17	0.07	78.49
R2 ADJ.	0.38		

Table 10: Descriptive Statistics for Bus Dwell Time Model 2

Sample Criterion: DWELL <= 300 sec. and LIFT=1						
Name	*N*	*Mean*	*Std. Dev.*	*Var.*	*Min.*	*Max.*
DWELL	2,603	87.93	47.38	2,244.40	2.00	298.00
ONS	2,603	2.90	3.92	15.34	0.00	45.00
ONS2	2,603	23.75	75.89	5,759.40	0.00	2,025.00
OFFS	2,603	2.73	3.50	12.28	0.00	47.00
OFFS2	2,603	19.72	66.10	4,368.50	0.00	2,209.00
DELAY	2,603	3.08	3.87	14.96	-6.71	24.63
LOW	2,603	0.56	0.50	0.25	0.00	1.00
ONOFFLD2	2,603	0.15	0.36	0.13	0.00	1.00
TOD1	2,603	0.08	0.26	0.07	0.00	1.00
TOD2	2,603	0.56	0.50	0.25	0.00	1.00
TOD3	2,603	0.18	0.39	0.15	0.00	1.00
TOD4	2,603	0.15	0.36	0.13	0.00	1.00
TOD5	2,603	0.03	0.17	0.03	0.00	1.00
RAD	2,603	0.66	0.47	0.23	0.00	1.00
FEED	2,603	0.06	0.24	0.06	0.00	1.00
CTOWN	2,603	0.28	0.45	0.20	0.00	1.00

Table 11: Results of Bus Dwell Time Model 2

Sample Criterion: *DWELL <= 300 sec. and LIFT=1*			
Name	*Coef.*	*Std. Err.*	*T-Ratio*
ONS	9.11	0.40	22.75
ONS2	-0.17	0.02	-8.56
OFFS	0.42	0.41	1.04
OFFS2	-0.04	0.02	-1.70
DELAY	-0.25	0.21	-1.17
LOW	-7.95	1.65	-4.83
ONOFFLD2	-4.58	2.33	-1.97
TOD2	-3.89	3.05	-1.27
TOD3	-4.50	3.43	-1.31
TOD4	-5.16	3.51	-1.47
TOD5	-13.08	5.50	-2.38
FEED	11.23	3.35	3.35
CTOWN	-3.43	1.79	-1.91
CONST.	75.39	3.21	23.47
R2 ADJ.	0.29		

Table 10 presents the descriptive statistics for the second bus dwell time model where observations are limited to stops with lift activity. The results of the model are presented in Table 11. Dwell time for stops where the lift is operated is explained by the same variables as the overall dwell time model. An examination of the coefficients shows that dwell time is estimated to be 7.59 seconds less for low floor buses. The large CONSTANT value of 75.39 seconds indicates the majority of time is for the lift operation itself.

There are three estimates of delay time for lift operation. One is 67.80 seconds, the coefficient on LIFT from the model of all dwell times. Another is the difference between the mean of dwell time with lift operations (87.93 seconds) and without lift operations (11.57 seconds) which is 76.36 seconds. The third is the effect of a lift operation on running time from an earlier study of route running times (Strathman, Kimpel, Dueker, Gerhart, & Callas, Forthcoming). This third choice estimates the lift effect to be 59.80 seconds. This smaller value indicates drivers make up some of the time lost due to lift operations before the end of the route.

It is recommended that the second choice of 76.36 seconds be selected as the delay estimate at the outset of the lift event and that it be updated with the actual dwell time less the mean dwell time without lift operation as the bus departs that stop.

Findings and Conclusions

This analysis develops a statistical approach for estimating the amount of delay for events that are not predictable enough to build into time schedules. Two types of events were analyzed, drawbridge interruptions of traffic and bus lift operations. Other types of non-recurring events such as rail crossings could also be modeled.

Less systematic events, such as snow/ice events and traffic crash incidents, are more problematic. These kinds or events have greater variances. More data is needed on the type and duration of delays when the bus is stopped for non-passenger serving reasons.

There are three issues that need to be addressed before these research results can be implemented. First, the bridge delay model needs to be re-calibrated after installation of an automated time clock on the Hawthorne Bridge. The recording of bridge closure times by manual methods is too imprecise. Second, clocks on the bridges need to be linked to the Tri-Met Bus Dispatch Center. Third, data needs to be collected for unscheduled stops. Currently, the bridge delay model is not informed of the actual amount of time buses are caught in traffic queues. It can only be inferred by the travel time between bus stops, or if the driver opens the door when stopped between bus stops. The Bus Dispatch System needs modification to record and report unscheduled stops (with door closed). This type of stop needs definition, say moving less than 30 meters in one minute when outside of a bus stop circle. The duration of unscheduled stops would provide valuable information to provide better estimates of arrival times. Also, unscheduled stop data would be needed to address less systematic events, such as snow/ice events and traffic crash incident queues.

An alternative to creation of a new record type for unscheduled stops (with door closed) is to increase the frequency of status (or health) reports to a frequency of 30 to 90 seconds. This would enable the inference of unscheduled delays and stops. However, this is not feasible at this time, as it would generate too much radio traffic. Instead Tri-Met has introduced a report called Tracker Data that reports, time, vehicle, and schedule deviation every 80-90 seconds. Tracker data takes less space than health reports to transmit, because it contains schedule deviation in minutes rather than a longer record of lat/long position. In near normal operating conditions, the estimate of schedule deviation could be used to generate an estimate of location.

Nevertheless, the Tracker Data schedule deviation estimate is only valid during normal operating conditions. A major event, such as a snow or ice storm, may disrupt operations to the extent that the schedule deviation is not accurate, particularly if buses are out of sequence. Consequently, Tracker Data serve a useful function when buses are operating under normal or near normal conditions, but not when there is a major disruption to scheduled service. Then more frequent position reports are needed.

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