Transit Buses as Traffic Probes

Use of Geolocation Data for Empirical Evaluation

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With the growing availability of data because of the deployment of intelligent transportation systems, methods for assessing and reporting traffic characteristics and conditions have begun to shift. Although previous level-of-service methods were developed for use with limited data, actual performance measures can now be developed and tested. On freeways, performance measures often are estimated directly by using data from inductive loop detectors (e.g., speed, occupancy, vehicle counts). For arterials with numerous signalized intersections, performance measures are more challenging because of more complicated traffic control and many origins and destinations. However, within signalized networks, travel time, speed, and other key performance measures can be obtained both directly and indirectly from sources such as automatic vehicle location (AVL) data. The use of AVL data for characterizing the performance of an arterial is demonstrated. First, data are extracted from the bus dispatch system of the Tri-County Metropolitan Transit District (TriMet), the transit provider for Portland, Oregon. Then, the performance characteristics as described by bus travel on an arterial are compared to ground truth data collected by probe vehicles equipped with Global Positioning System sensors traveling with normal (nontransit) traffic on the same arterial on the same days. Comparisons are made between the two methods, and some conclusions are drawn regarding the utility of the transit AVL data.

Freeway performance characteristics are relatively well understood. However, arterials are characterized by complicated traffic behavior and many more variables than are associated with freeways. For arterial performance measurement, traffic conditions often are evaluated by using test vehicles to collect travel time and delay data (*1*). However, these travel time and delay studies are limited temporally and spatially and are time-consuming and expensive. Test vehicles and personnel may be dispatched to collect travel time data for one peak period on only 1 day.

With increasing deployment of intelligent transportation systems (ITS), the floating probe vehicle technique can play an important role for collecting data in real time. Probe vehicles respond to changes in traffic flow as they traverse the network and can transmit location and travel time data to a traffic management center at frequent time intervals (*2*). As in the case of a transit fleet, these floating probes may already be in the traffic stream.

Most transit automatic vehicle location (AVL) systems are used primarily for managing operations in real time. Previous research used transit AVL data to test possible congestion monitoring and transit information uses (*3;* T. Williams, unpublished paper).

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BACKGROUND

There is growing interest in providing performance measures along arterials, in the context of advanced traffic management systems (ATMSs) and advanced traveler information systems (ATISs). In Portland, Oregon, the Tri-County Metropolitan Transit District of Oregon (TriMet) provides transit service in the metropolitan area. On weekdays, more than 600 TriMet buses traverse most major arterials during peak periods (*4*). These vehicles are equipped with a bus dispatch system (BDS), which includes AVL, comprising differential Global Positioning Systems (GPS), automatic passenger counters, wireless communications, and stop-level data archiving capabilities. BDS provides a rich source of accurate time and location information. Because the buses are already in the traffic stream, they can be used as probe vehicles for collecting travel time data. BDS records bus arrival and departure times at each geocoded stop and records the maximum instantaneous speed achieved between stops. As a result, TriMet, the Oregon Department of Transportation, and the city of Portland are developing plans to use BDS data for ATMS and ATIS purposes.

The extent to which the travel characteristics of buses are related to those of general traffic is not well understood. Therefore, a comparison of the transit bus data and ground truth data collected by GPS-instrumented passenger vehicles was conducted. Vehicle trajectories—graphs of vehicle location versus time—of both buses and nontransit test vehicles were produced to measure the differences in travel time and speed. For a better understanding of this relationship, hypothetical and pseudo bus analyses were also investigated. Hypothetical buses are defined as buses traveling nonstop, and pseudo buses are buses traveling at the maximum speed recorded for each link.

Speed contour plots were used to observe the precise differences in speed for both types of vehicle traveling along a study corridor. By estimating speeds throughout a road segment at any particular time, speed contours were plotted on a three-dimensional graph by using time and location as the *x*-axis and the *y*-axis, respectively.

DATA

The study location is a 2.5-mi corridor on SE Powell Boulevard in Portland. The corridor begins in downtown Portland at SW First Avenue and continues across the Willamette River on the Ross Island Bridge to SE 39th Avenue, illustrated in Figure 1. The corridor serves approximately 50,000 vehicles per day (*5*); peak travel is westbound during the morning peak and eastbound during the evening peak. This paper focuses on that part of the study in the eastbound

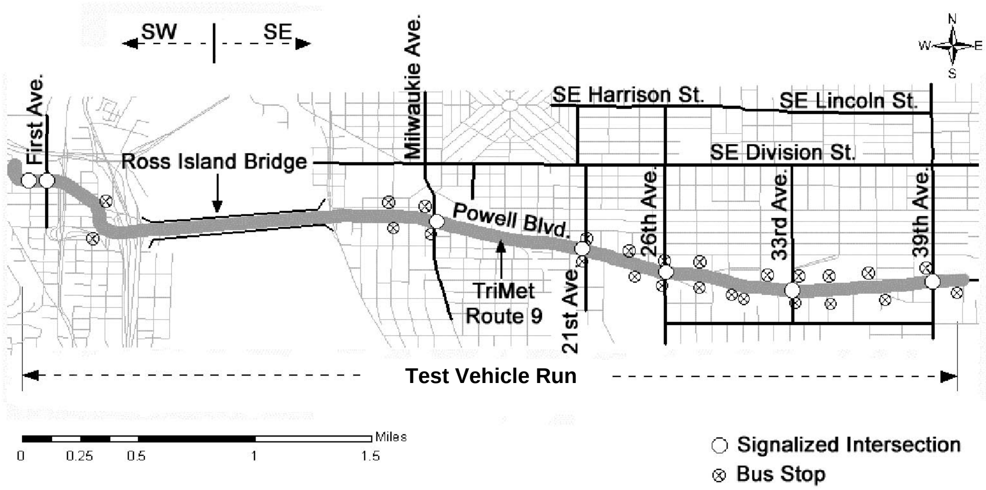

FIGURE 1 Study corridor.

direction that used BDS and test vehicle data obtained on Thursday, November 1, 2001, and Wednesday, November 7, 2001.

BDS provides rich transit monitoring data in both real-time and archived formats. For each bus trip and for each geocoded stop, BDS records arrival time, departure time, number of boardings and alightings, and location (in NAD83 state plane *X-Y* coordinates). In addition, the system stores the maximum instantaneous speed achieved between stops. As shown in Figure 2, each stop has an imaginary 100-ft-diameter circle inscribed around it. If the bus stops at Stop *i*, then BDS records the time that the door opens as the arrive time, records the dwell time as the difference between door-open time and door-close time, and records the leave time as the time the bus recrosses the stop circle. Where passengers are served, BDS records the number of boardings and alightings through both doors (*6*) by using automatic passenger counters. If the bus does not stop at Stop *j*, the BDS records the times at which the bus crosses the circle as the arrive time and the leave time.

Test vehicles equipped with GPS devices were dispatched during the study period to collect simultaneous corridor time, location, and travel time information. The GPS devices were programmed to record each test vehicle's precise location (latitude and longitude) with a time stamp every 3 s. Travel time data thus were available for a minimum of 15 runs in each direction (eastbound and westbound) for each study day. Transit AVL data were also obtained for the same days and times. Note that the transit data are location based, because the BDS system recorded data at preprogrammed stop locations, whereas the test vehicle GPS data are time based, recorded at specific times. This study demonstrates how fusing the location-based data with the time-based data can reveal important relations between the two sources.

BUS PROBE ANALYSIS

For the transit probe investigation, TriMet Route 9 was selected for analysis on Powell Boulevard. Route 9 provides service between downtown Portland and the Gresham Transit Center with approximately 80 trips per direction per day. The study corridor (between a time point at SW 1st Avenue and a time point at SE 39th Avenue)

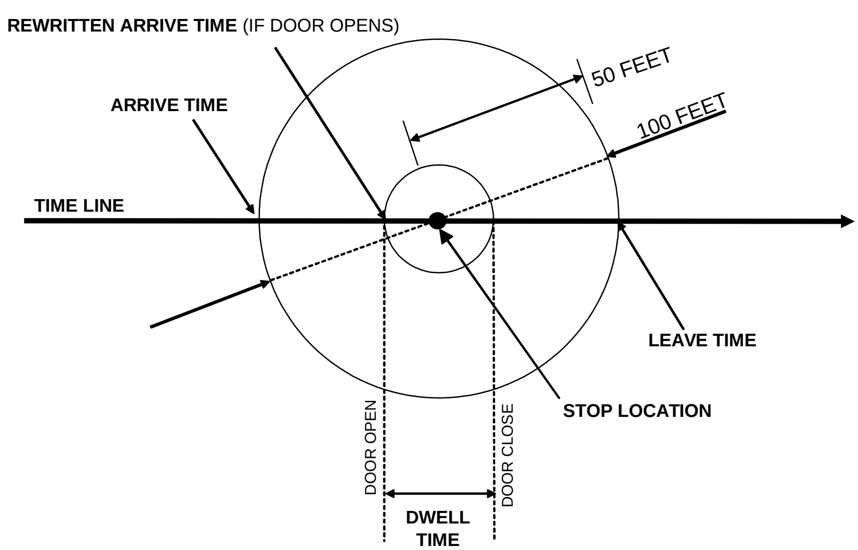

FIGURE 2 A 100-ft stop circle at which BDS recorded times and locations.

has 13 eastbound and 12 westbound stops. In the study corridor, TriMet provides a scheduled mean trip time of 10.65 min, with trip times ranging between 8 min during the off-peak period and 13 min during the peak period. On November 1, 2001, the mean observed dwell time was 12.1 s with an average of three passengers boarding and alighting per stop served in the corridor. The buses stopped at an average of six stops to serve passengers. Bus data on November 7, 2001, indicated similar results for all previously observed elements (mean observed dwell time of 13 s, average of three passenger boardings and alightings, and seven stops served). Because the data collected on these 2 days represent bus travel on the corridor during the morning peak period, for easy demonstration purposes the rest of the paper focuses on 1 day's results, November 1, 2001.

Figure 3 illustrates a preliminary investigation of the BDS data by using vehicle trajectories, constructed by plotting the cumulative distance each bus traveled on the *y*-axis and time on the *x*-axis. A trajectory's slope at any time *t* is the bus speed at that time on that route segment. Each trajectory shown in Figure 3 describes an individual bus traveling eastbound (outbound), and the Ross Island Bridge is illustrated with two stripes, between 0.3 and 0.7 mi from the beginning of the corridor. On the secondary (right-hand) *y*-axis, Figure 3 shows the stop locations along the route, from Stop 4964 between SW Naito Parkway and the Ross Island Bridge to Stop 4651 at the corner of Powell Boulevard and SE 39th Avenue.

The bus trajectories illustrated in Figure 3 are sample eastbound trips (total of 15 trips). As shown in Figure 3, the small horizontal segments reflect bus movement within the stop circles, matching stop locations on the secondary *y*-axis. The difference between the first location and last location projected on the *x*-axis is the total trip time (run time). The mean run time was 7:46 min and varied (in the study period) between 5:12 and 10:24 min. In Figure 3, passenger activity can be observed to be high at particular stop locations. Specifically, Bus Trips 1, 2, 4, 5, and 6 had long dwell times at Stop 4627, located at the corner of Powell Boulevard and SE 26th Avenue. The mean dwell time for all stops throughout the corridor was 73 s.

In Figure 3, the trajectories show that the buses were traveling at a mean speed of 40 mph at the beginning of the corridor. However, at the end of the trip, the trajectories show variations in corridor travel time for all buses, and trajectories show that the buses were traveling with similar patterns between each stop pair. Because these buses traveled through the study corridor in the eastbound direction, which had lower traffic volumes in the morning peak, the bus corridor travel time varied more directly with passenger activities or dwell time. As can be seen in Figure 3, high passenger activity levels appeared to cause increased bus delay. For example, Bus Trip 2 experienced the longest travel time (9:06 min) because of the long activity at Stop 4537.

A benefit of the use of vehicle trajectories is the ability to pinpoint specific locations and times at which vehicle behavior changes. An example of this benefit is in the case of Bus Trip 2, where a change in bus performance can be easily observed. As shown in Figure 3, at distance 1 mi, Bus Trip 2 was traveling at 22 mph after the bridge and stopped for 2:30 min at Stop 4537. The bus data indicate a dwell time of 54 s, with five passenger boardings and three alightings.

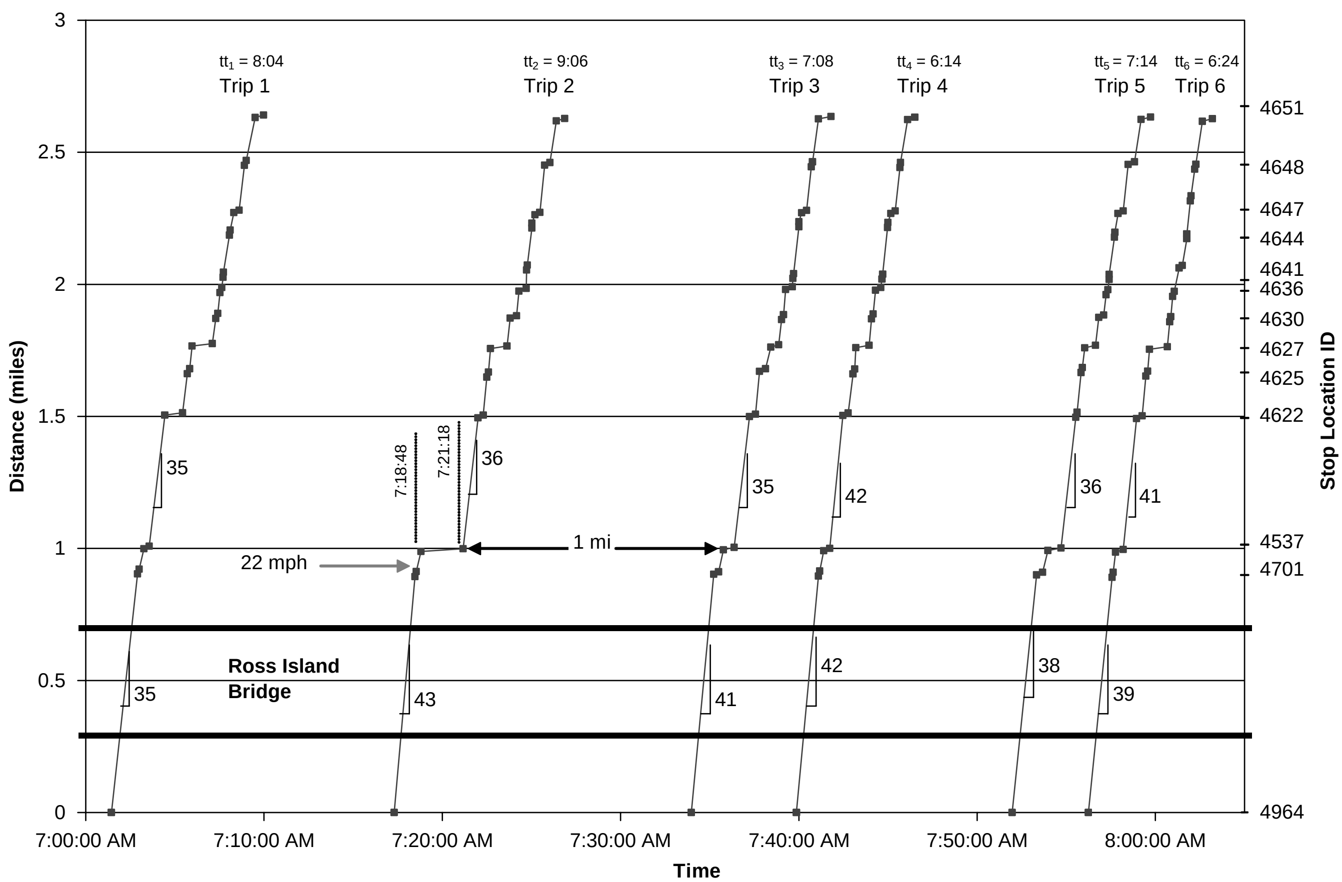

FIGURE 3 Bus trajectories.

According to TriMet's Route 9 schedule, Stop 4537 is a time point with a scheduled stop time. The operator who arrives at this stop early must depart on schedule. However, in this case, the bus arrived at Stop 4537 at 7:18:48 a.m., which was 2:48 min after the scheduled stop time of 7:16 a.m. There would be no means of waiting; rather, the operator needed to rush to catch up with the schedule. This long dwell time can be explained by the stop location near a signalized intersection (a nearside stop located east of SE Milwaukie Avenue). After Bus Trip 2 closed the door and departed from Stop 4537, it reached a signalized intersection at the same time the signal phase changed to red, and the bus had to wait until the next cycle before it could leave the stop circle. This resulted in the additional recorded stop time of approximately 1 min.

Toward developing an algorithm to relate bus data to actual traffic conditions, experiments that used bus data were conducted, including hypothetical, pseudo, and modified pseudo bus scenarios. Nontransit vehicles do not decelerate and accelerate to serve passengers, so the hypothetical bus concept considers a potential nonstop bus trajectory by subtracting the dwell times. The resulting nonstop trajectory is an approximation of how a bus would travel if it did not stop to serve passengers. Buses are large vehicles, and their operations often are motivated by schedule adherence and are affected by individual driver characteristics (*7*). Thus, even without stops, their travel characteristics will be different from those of passenger cars.

The BDS system recorded the maximum instantaneous speed achieved between pairs of stops (*6*). A pseudo bus trajectory was created by stringing together segments of a trip where the pseudo bus traveled at its maximum recorded speed between each pair of stops. This was based on the hypothesis that the maximum speed could approximately reflect the speeds of nontransit vehicles along the route. Further, a modified pseudo bus was created by taking into consideration the dwell times of the actual bus. A modified pseudo bus would hypothesize behavior of an actual bus but traverse the corridor at a faster speed.

Figure 4 shows the combination of the bus trajectories with these three conceptual bus trajectories. As shown, the four trajectories began at the same departure time. For example, on Trip 2, all four trajectories began at 7:17:18 a.m. Pseudo bus trajectories reflect the shortest travel times; for example, Pseudo Bus Trip 2 finished at 7:21:20 a.m., faster than modified Pseudo Bus Trip 2, Hypothetical Bus Trip 2, and Bus Trip 2 by 1:43, 3:49, and 5:32 min, respectively. The mean pseudo bus speed was 36.6 mph, 1.5 times the actual mean bus speed (21 mph). The mean hypothetical bus speed was 22.4 mph, which is about the same as the mean actual bus speed, whereas the modified pseudo bus mean speed was 28.9 mph, about 1.4 times the mean actual bus speed. Because all three conceptual buses, the hypothetical, pseudo, and modified pseudo, were created to reflect potential nontransit travel, pseudo buses maintain more stable speeds along the route. The comparison of the pseudo buses

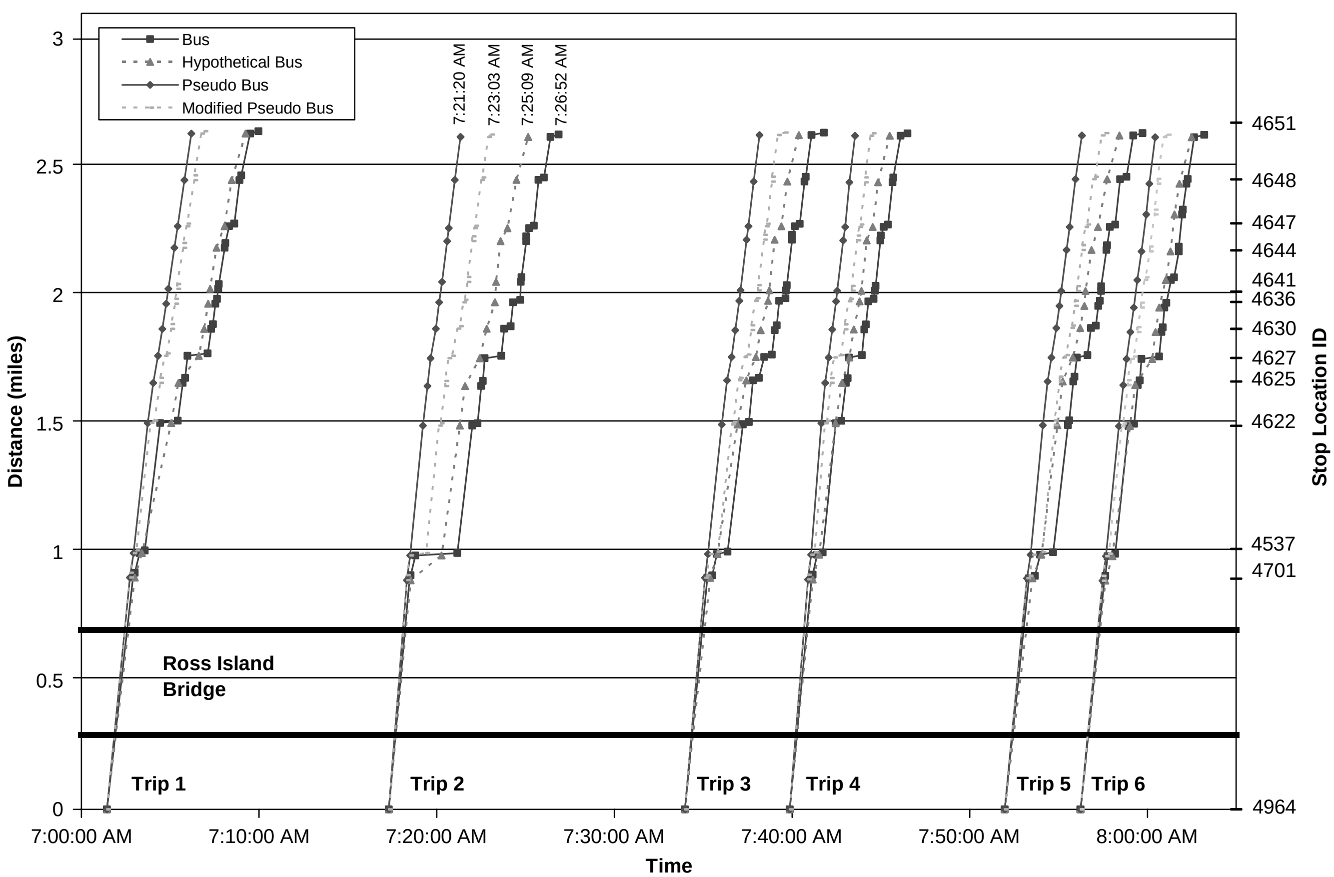

FIGURE 4 Comparison of actual bus and conceptual bus trajectories.

and the test vehicles will be most relevant and will be described further.

TEST VEHICLE ANALYSIS

From the test vehicle data obtained from the GPS devices, the distance between two reported locations was estimated by using the spherical geometry method (*8*). Test vehicle trajectories were plotted, as shown in Figure 5. The mean test vehicle corridor speed was 27.1 mph, ranging between 20.3 and 40.2 mph. The mean test vehicle travel time was 5:54 min, varying between 3:52 and 7:35 min.

From the trajectory slopes, it is shown that the test vehicles experienced stop-and-go traffic conditions along the corridor. For example, the inset for Vehicle Trip 3 shows that the test vehicle decelerated at distance 0.99 mi, stopped for a short period, and then accelerated to the vehicle's desired speed of 36 mph. The inset in Figure 5 also shows that between distance 0.99 mi at 7:18:45 a.m. and distance 1.03 mi at 7:19:33 a.m., Vehicle 3 traveled at 3 mph. This was observed where the vehicle arrived at a signalized intersection. As detailed in Figure 6, at 7:18:45 a.m., the test vehicle arrived at a signalized intersection between Powell Boulevard and SE Milwaukie Avenue at the end of a queue. The vehicle waited for approximately 0:42 min, appeared at the next location, 0.01 mi downstream, at 7:19:27 a.m., and then accelerated toward the intersection at 7:19:30 a.m. From Figure 6, it is clear that the vehicle accelerated after the signal phase turned green and the queue diminished by noting the increasing gap between vehicle locations over time. This behavior was observed at the same location for Trips 1, 2, 4, and 5. However, test vehicle decelerations occurred at slightly different locations, because each vehicle reached the end of the queue at a slightly different location.

SAMPLE SIZE ANALYSIS

For a travel time study, a minimum sample size is desired to minimize the data collection cost to fit within budgetary constraints. However, output from this sample size determination is also a valuable resource to ensure a high level of statistical confidence and reliability of the data. Therefore, it is important to execute a number of travel time collection runs to determine a statistically permitted level of error from the sample size.

The statistical estimation for the sample size *n* is based on specifying probability statements about the level of confidence in the error that is most acceptable. Often the estimation is performed on the

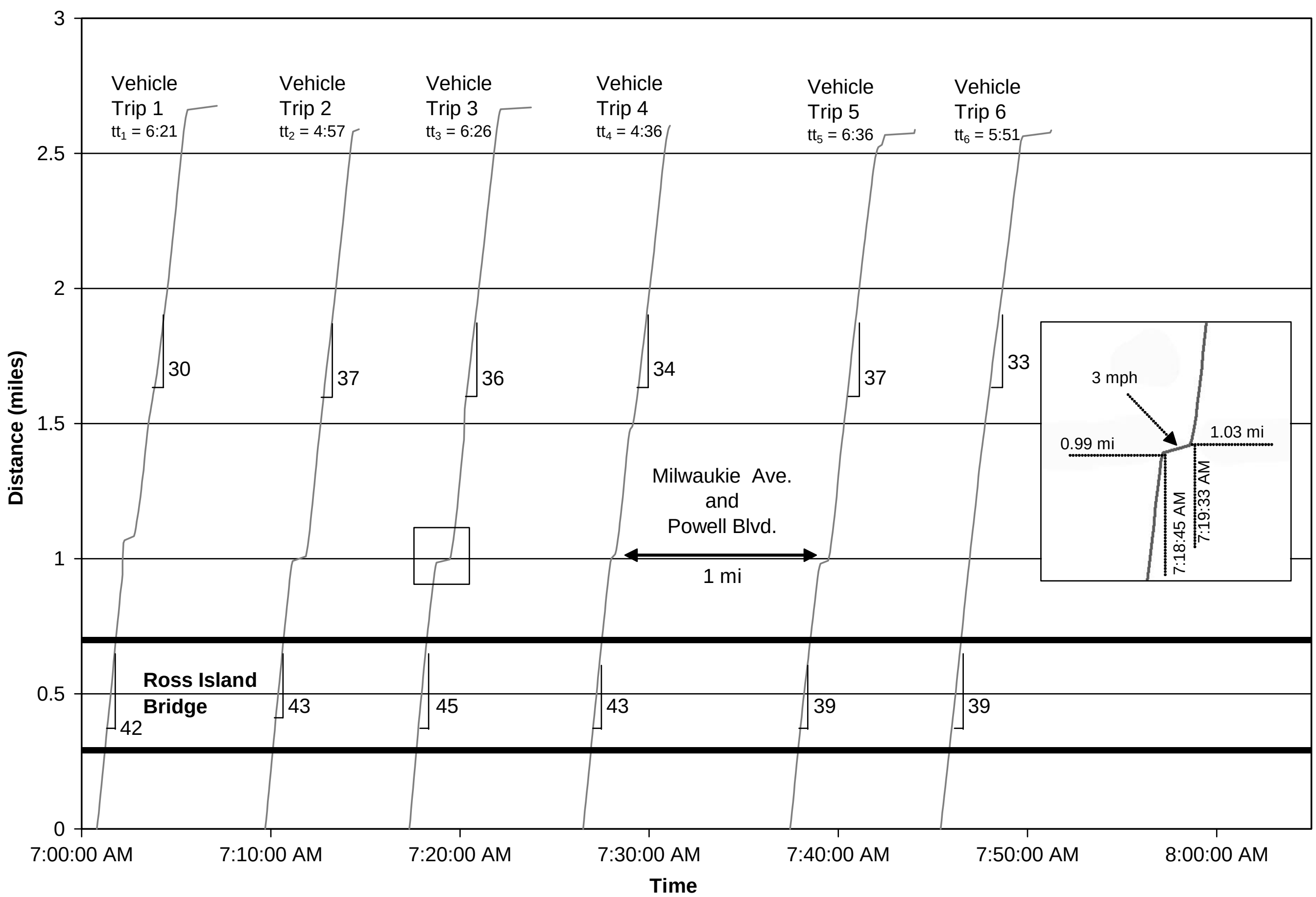

FIGURE 5 Test vehicle trajectories.

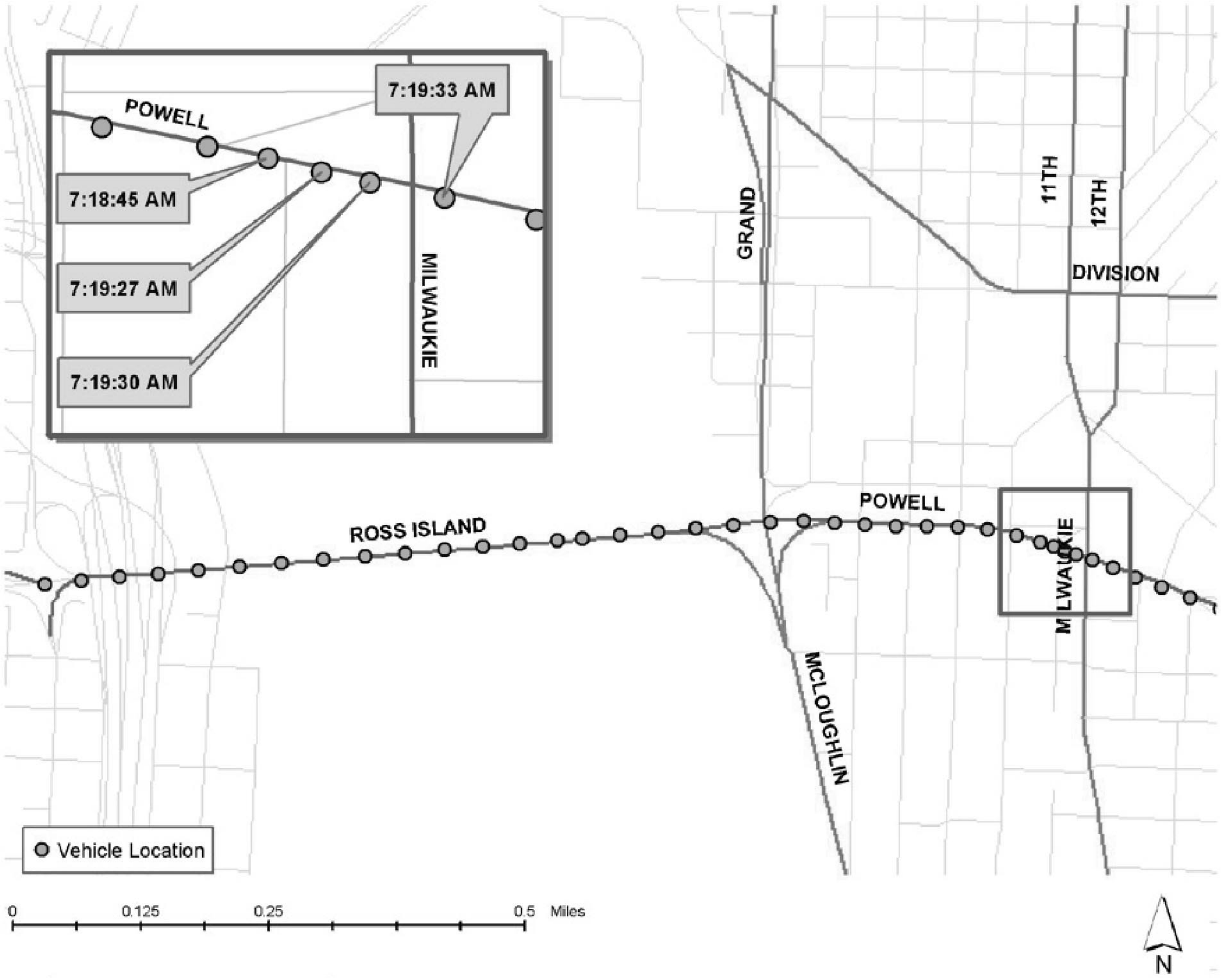

FIGURE 6 Geocoded vehicle locations (Projection: NAD 1983 HARN StatePlane Oregon North FIPS 3601).

basis of prior information or an initial presample, which leads to a random variable having a *t*-distribution with $n - 1$ degrees of freedom. At a level of confidence of $(1 - \alpha)100\%$, the minimum sample size is expressed as

$$n = \left[\frac{t_\alpha \cdot s}{E}\right]^2$$

where

n = minimum sample size,
s = estimated standard deviation of random samples,
t_α = *t*-distribution statistic for a confidence level of $1 - \alpha$ (*9*), and
E = maximum error of estimation.

For this study, both bus data and test vehicle data were used to determine the minimum number of runs:

- Bus mean speed, 21 mph;
- Standard deviation, 4.07 mph;
- $\alpha = 0.05$ (corresponds to 95% level of confidence);
- $E = \pm 3$ mph (*1*); and
- Number of bus trips, 15 runs.

Since the statistic t_α is a function of *n*, an iterative procedure is required to solve for *n*, and, as a result, $n \approx 10$ runs.

- Test vehicle mean speed, 27.1 mph;
- Standard deviation, 5 mph;
- $\alpha = 0.05$;
- $E = \pm 3$ mph; and
- Number of test vehicle trips, 15 runs.

With the same iterative procedure, *n* was estimated to be ≈13 runs. This ensures that the availability of data exceeds the minimum level of confidence of 95%.

COMPARISON

Eastbound bus run times were estimated by using the difference between leave time from the first stop (Stop 4964) and arrive time at the last stop (Stop 4651) on the corridor. Test vehicle travel times were estimated by subtracting the time recorded at the end of the route from the time at the beginning. Both include the time when vehicles stopped because of traffic control and congestion.

To use the bus data to represent actual traffic conditions, experiments that used the bus data were conducted, including the pseudo, modified pseudo, and hypothetical bus scenarios. Figure 7 shows hypothetical, pseudo, and modified pseudo trajectories and test vehicle trajectories for two trips. As shown, the actual bus and test vehicle trajectories had similar shapes. By subtracting the effects of the stop-and-go conditions that created the horizontal offsets on the test vehicle trajectory, it is clear that the test vehicle link speeds were substantially higher than those of the actual bus. Instead, the test vehicle's speed appeared similar to the speed of the pseudo bus.

To verify this, test vehicle and pseudo bus travel times were plotted versus departure time in Figure 8*a*. Travel time trend lines indicate that all vehicles spent more time traversing the study corridor during the morning peak period (7:00–9:00). The speeds of the test vehicles and pseudo buses were also plotted against the departure time, as shown in Figure 8*b*. The speed scatter plots show that vehicles traveled at lower speeds during the morning peak period as well. Traffic conditions became worse through time as trend lines on both vehicle speed and pseudo speed declined. The mean travel times for all four scenarios are shown in Figure 9*a*, along with travel time variation using the box plot technique in Figure 9*b*. From this box plot, pseudo bus travel times show the least variation, ranging between 3:40 and 5:07 min with a median travel time of 4:12 min.

The relationships between travel time and speed of the test vehicles and the three bus scenarios were analyzed. It was determined that the mean test vehicle corridor travel time was 1.36 times the pseudo bus travel time. However, the test vehicle and pseudo bus travel times were found to be closer on the Ross Island Bridge. This bridge has no shoulders and its approaches are bottlenecks, so traffic usually flows freely on the bridge. As shown in Figure 9*a*, the test vehicle mean travel time on the bridge was lower but close to the actual bus mean travel time and also to all three conceptual bus mean travel times on the bridge. This indicates that free-flow traffic conditions prevailed on the bridge, allowing the buses and test vehicles to achieve similar speeds.

Corridor speeds were determined by dividing the total travel distance, approximately 2.6 mi, by the net travel time. Figure 8*b* shows the comparison between test vehicle speeds and pseudo bus speeds. Figures 10*a* and 10*b* show a comparison between bridge travel time and speed in detail. Both test vehicle and pseudo bus travel times and speeds were scattered close to one another, and their trend lines were close and appeared to be parallel.

Average U.S. bus travel times were reported as 4.2 min/mi in suburbs, 6 min/mi in the city, and 11.5 min/mi in the central business district (*10*). Figure 9*a* shows a mean travel time of 7:46 min, or 3 min/mi, which is faster than the national study reported. From this study, a comparison of test vehicle and bus speeds shows that test vehicle speeds were 1.3 times greater. The national average shows that vehicles usually travel 1.4 to 1.6 times faster than buses (*10*), and the U.S. Department of Transportation reports an average bus speed of 10 mph in the city and 14.3 mph in the suburbs (*11*).

To verify the relationship between pseudo buses and test vehicles, a hypothesis test concerning the regression coefficient β (slope of regression line) was conducted. The null hypothesis of β = 0 was

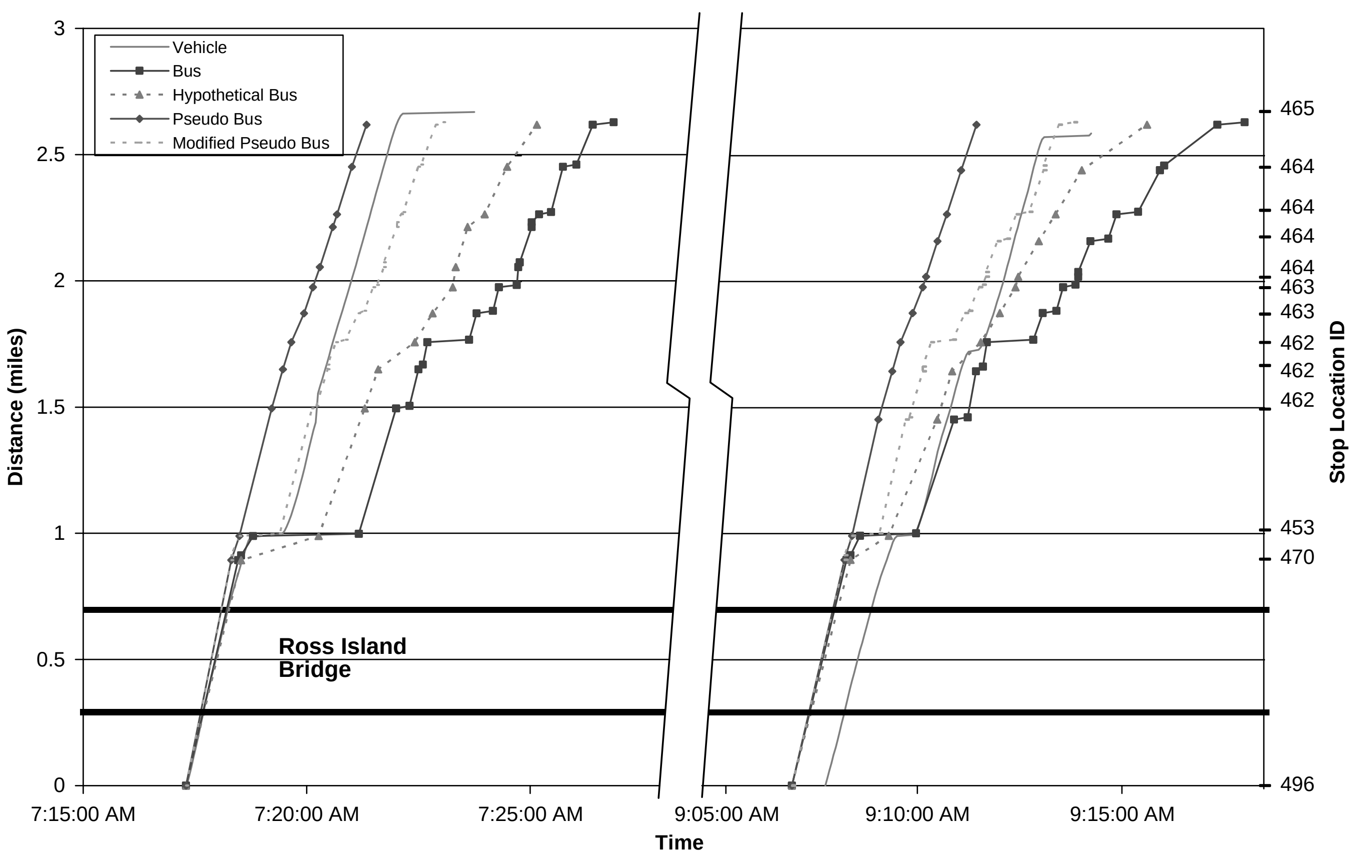

FIGURE 7 Comparison of test vehicle, actual bus, and conceptual bus trajectories.

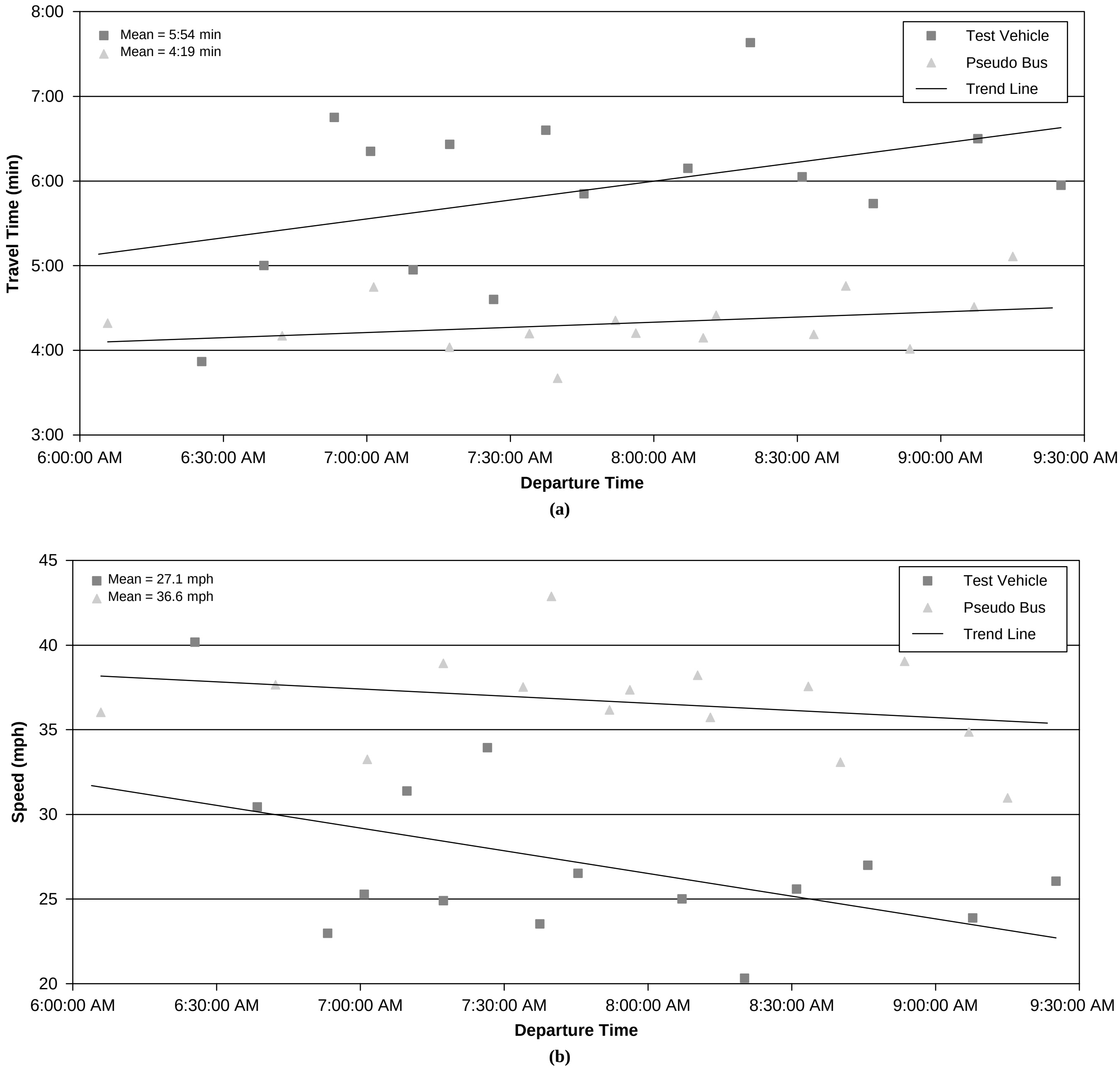

FIGURE 8 (*a*) Travel time and (*b*) speed of test vehicle and pseudo bus versus departure times.

formulated to prove an existing relationship between test vehicle speeds and pseudo bus speeds. This analysis was performed by using

- Alternative hypothesis, $\beta \neq 0$;
- Level of significance, $\alpha = 0.05$;
- Number of samples, $n = 20$; and
- T-critical, $t_{0.025}$ for 19 degrees of freedom $= \pm 2.093$.

Because the t-value was equal to 10.59, which is greater than +2.093, the null hypothesis must be rejected. It was concluded that there is a relationship between pseudo bus and test vehicle speeds.

To establish the relationship between test vehicle and pseudo bus speeds, reverse regression is used to test for the relative effects of measurement error and to obtain bounds on the true value of the coefficient β. Equations 1 and 2 show a switch between test vehicle speed and pseudo bus speed as dependent and independent variables before performing reverse regression. The two variables were converted to z scores before the regression was run and then were estimated without constant terms (*12*):

$$Y_{\text{pseudo}} = \alpha + \beta_{\text{veh}} X_{\text{veh}} + \epsilon \tag{1}$$

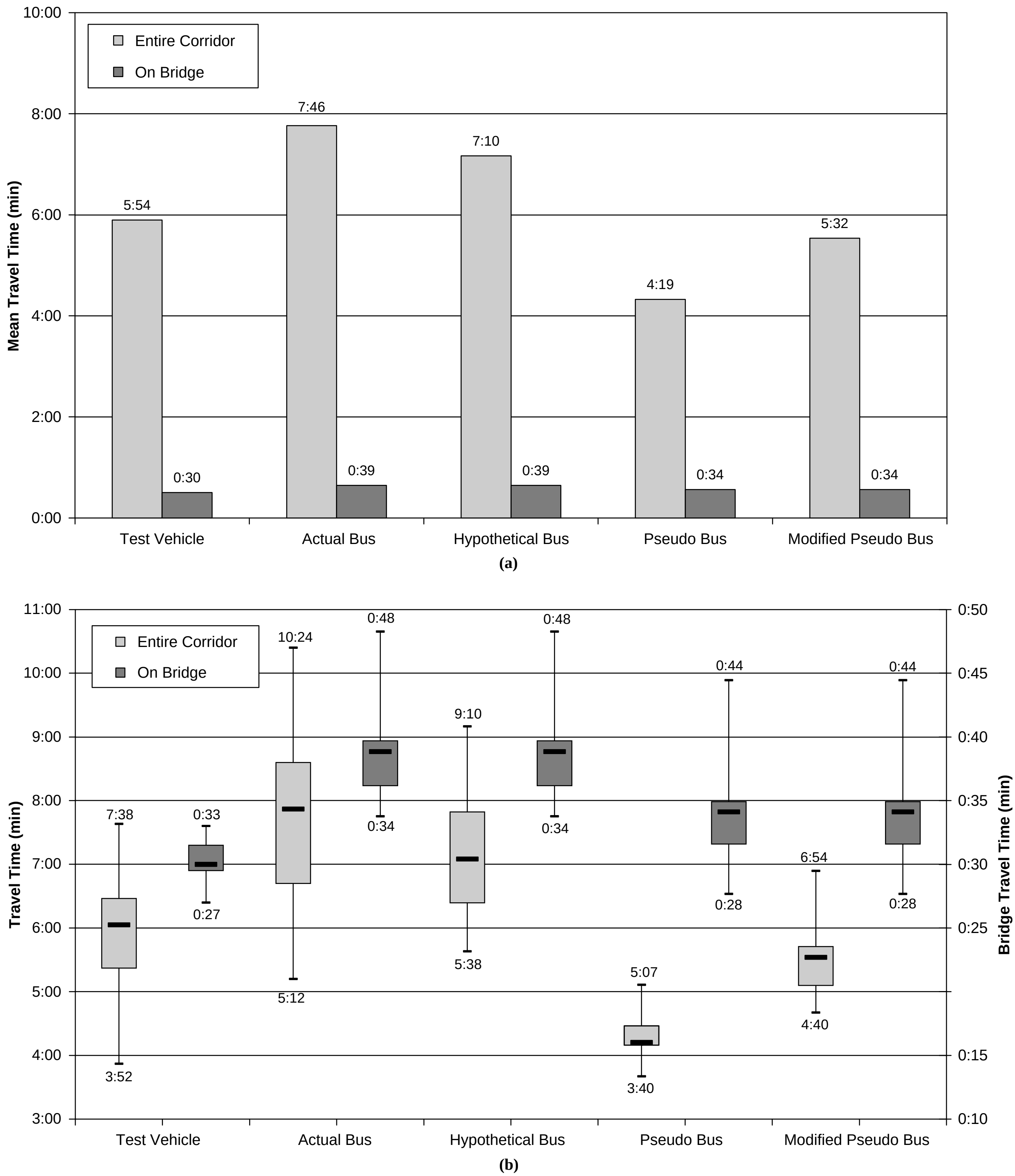

FIGURE 9 Mean travel time of four scenarios, both entire corridor and on bridge.

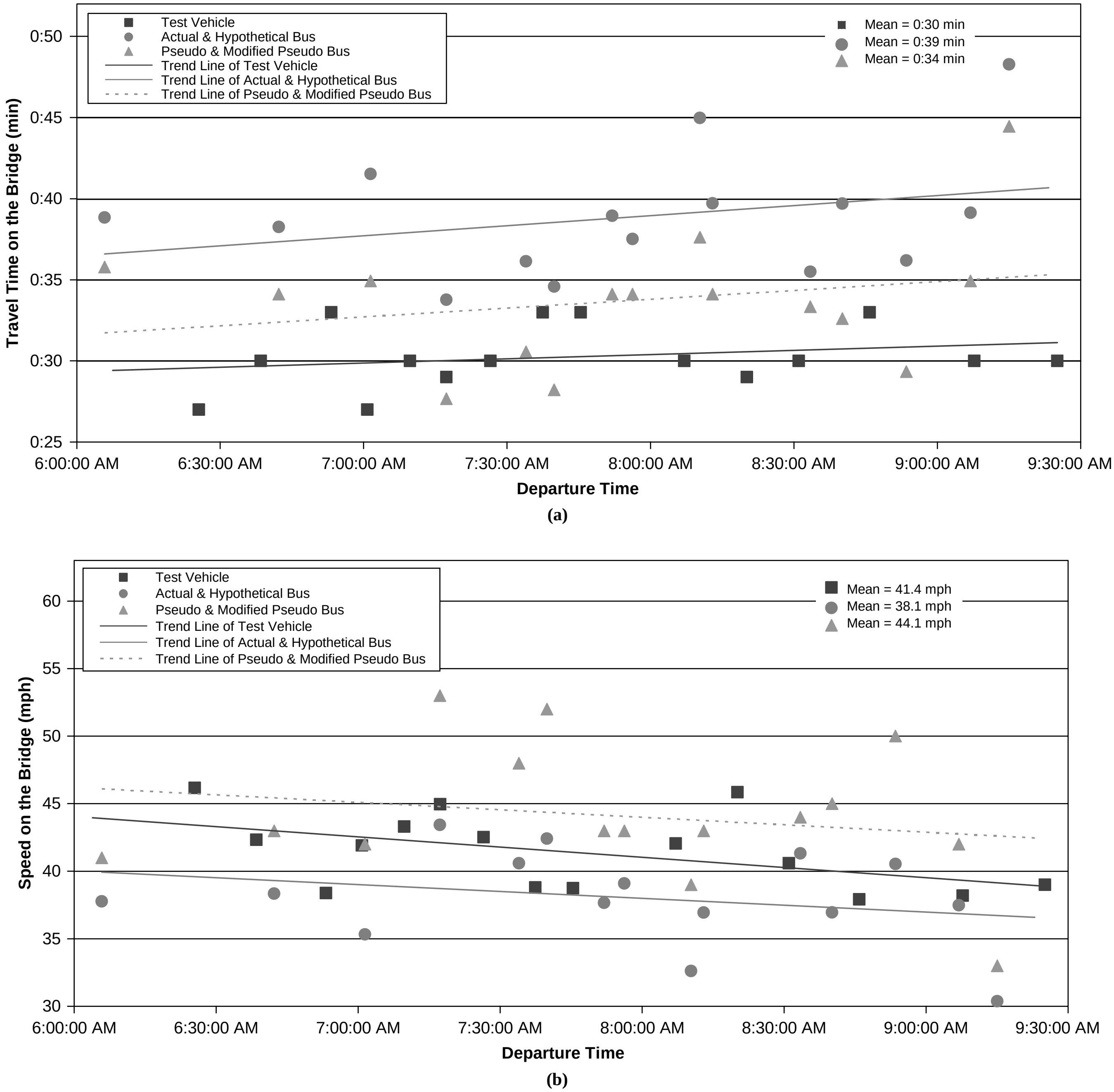

FIGURE 10 Test vehicle, actual bus, hypothetical bus, and pseudo bus comparison on (*a*) travel time on bridge and (*b*) speed on bridge.

$$Y_{\text{veh}} = \alpha + \beta_{\text{pseudo}} X_{\text{pseudo}} + \epsilon \qquad (2)$$

where

Y_{pseudo} or X_{pseudo} = pseudo bus speeds,
Y_{veh} or X_{veh} = test vehicle speeds,
β_{veh} or β_{pseudo} = regression slope coefficient from Equations 1 and 2, and
ϵ = unknown error associated with vehicle–pseudo bus relationship.

$$\text{Bias} = 1 - \beta_{\text{veh}}\beta_{\text{pseudo}} \qquad (3)$$

Equation 3 shows the measurement of the bias attributed to the pseudo bus speed. Because the linear regression analyses result in $\beta_{\text{veh}} = 1.376$ and $\beta_{\text{pseudo}} = 0.712$, from Equation 3, this indicated the magnitude of the bias for the two variables of 2%. An average between β_{pseudo} and the inverse of β_{veh} equal to 0.72 is the regression coefficient in Equation 4:

$$\text{Vehicle speed} = 0.72(\text{pseudo speed}) + \epsilon \qquad (4)$$

With this method of calculation, the test vehicle speed was 0.72 and 0.94 times the pseudo bus speed for the entire corridor and on the bridge, respectively, at a 95% level of confidence.

A three-dimensional speed contour technique was used to assist in visualizing the speed differences between the buses and the test vehicles spatially and temporally. As shown in Figure 11, speed contour plots for buses and test vehicles were generated by using distance and time as the *x*- and *y*-axes, respectively, with speed plotted on the *z*-axis. The area between each pair of known data points was estimated by using a geographic information system statistical interpolation method called Kriging (*13*).

The speed contour diagram shows that the test vehicle speed changed smoothly on the surface because of the availability of data every 3 s, whereas changes in bus speeds were more coarse because the numbers of bus data points were limited. The concave surface reflects slower traffic conditions compared to other patterns on the surface. As vehicle *i* or bus *j* traverses through distance and time in a diagonal direction on the surface, concave and convex surface features describe the varying traffic conditions resulting from deceleration and acceleration. A concave surface feature, as an example, indicates that a vehicle faced queued traffic downstream and accordingly decelerated. A steep slope on the surface represents a faster change in speed of the vehicle. After the lowest point on the surface, traffic conditions began to return to unqueued conditions as the vehicle accelerated. By viewing the differences between the two speed surfaces, one can locate specific locations and times at which the test vehicles experienced conditions that were different from those experienced by the buses.

CONCLUSION

This preliminary study showed that actual arterial traffic conditions may be explained by using transit vehicle AVL information. From the set of transit data used here, bus movements generated from the maximum instantaneous speed achieved between each stop pair was found to most reliably depict the traffic movement of nontransit vehicles. Key performance measures like travel time and speed should be described by using the relationship established between the test vehicle and the pseudo bus. This study found that the test vehicle travel time was 1.37 times the pseudo bus travel time. Conversely, it was shown that the test vehicle speed was 0.72 times the maximum instantaneous speed achieved by the buses. Although this study focused on only one direction during the morning peak for 2 days, further analysis on both traffic directions on more days is ongoing. These results will provide a greater level of confidence to the study results. However, it is possible that this preliminary study is a helpful example toward developing any system that would help transit agencies and traffic engineers to better understand arterial performance assessment.

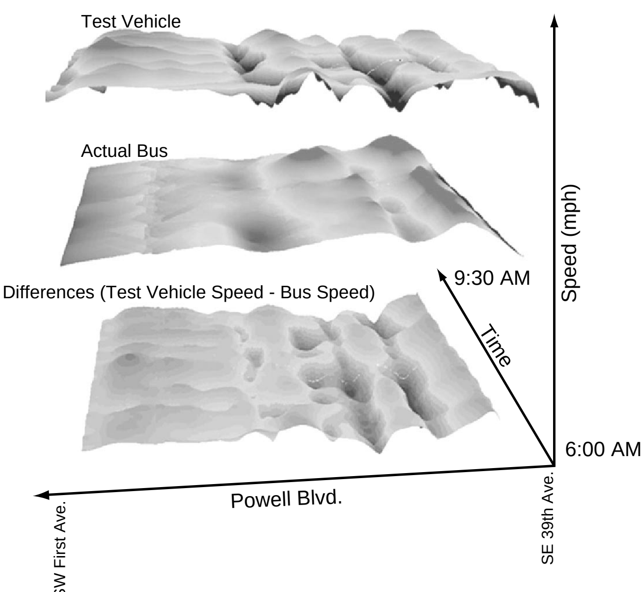

FIGURE 11 Speed contour plot.

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REFERENCES

1. Oppenlander, J. C. Sample Size Determination for Travel Time and Delay Studies. *ITE Journal,* Vol. 46, 1976, pp. 25–28.
2. Turner, S. M., W. L. Eisele, R. J. Benz, and D. J. Holdener. *Travel Time Data Collection Handbook.* Report FHWA-PL-98-035. FHWA, U.S. Department of Transportation, 1998.
3. Dailey, D. J. *The Use of Transit Vehicles as Speed for Traffic Management and Traveler Information in Addition to Performance Monitoring.* Transportation Northwest, University of Washington, Seattle, 2001.
4. Meet the Fleet. TriMet, Portland, Ore. 2002. www.trimet.org/factsandphotos/fleet.htm. Accessed Feb. 25, 2003.
5. *Oregon State Highway Transportation Volume Tables.* Oregon Department of Transportation, Salem, 2001.
6. El-Geneidy, A. Great Cities' University Coalition: Tri-Met Data Dictionary. www.gcu.pdx.edu/data/dictionary.htm. Accessed Jan. 20, 2002.
7. Strathman, J. G., T. J. Kimpel, K. J. Dueker, R. L. Gerhart, and S. Callas. *Evaluation of Transit Operations: Data Applications of Tri-Met's Automated Bus Dispatching System.* Center for Urban Studies, Portland State University, Ore., 2001.
8. Distance Calculation. Meridian World Data, Inc. www.meridianworlddata.com/Distance-Calculation.asp. Accessed Nov. 10, 2001.
9. Quiroga, C. A., and D. Bullock. Determination of Sample Sizes for Travel Time Studies. *ITE Journal,* Vol. 64, 1998, pp. 92–98.
10. Levinson, H. S. Analyzing Transit Travel Time Performance. In *Transportation Research Record 915,* TRB, National Research Council, Washington, D.C., 1983, pp. 1–6.
11. Characteristics of Urban Transportation Systems. Federal Transit Administration, U.S. Department of Transportation. 1992. www.fta.dot.gov/library/reference/CUTS/frchap3.htm. Accessed Oct. 17, 2002.
12. Crown, W. H. *Statistical Models for the Social and Behavioral Sciences: Multiple Regression and Limited-Dependent Variable Models.* Praeger Publishers, Westport, Conn., 1998, pp. 39–44.
13. Longley, P. A., M. F. Goodchild, D. J. Maguire, and D. W. Rhind. *Geographic Information Systems and Science.* John Wiley and Sons, West Sussex, England, 2001, pp. 297–301.

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