Arterial performance measurement is a critical issue for transportation system management, traveler information, and real-time situation-aware routing. In many urban areas current information on freeway conditions is available, appropriately given the large amount of travel that occurs on these facilities. However, because nearly 40% of the vehicle miles traveled in the United States occur on arterials, there is a need to provide similar information that can be used not only by travelers but also by traffic engineers and managers. Because many arterials are equipped with actuated traffic signals, the use of already installed sensors has been explored as one source of traffic volume, occupancy, or speed data to inform an arterial performance system. Coupled with this, there is a potential to exploit the availability of mobile probe geolocation data from sources such as automatic vehicle location systems for fleets of buses or taxis, or from cellular phone or other Global Positioning System–type devices. To demonstrate the potential value of fusing data from fixed and mobile surveillance systems toward improved arterial performance reporting, this paper describes the results of a case study from Portland, Oregon, that extracted improved arterial performance measures by combining data from traffic signal system detectors and from buses acting as probe vehicles. In particular, graphical techniques are developed that trace the boundaries of the congested regime in time and space along an arterial corridor. The paper includes recommendations for expanding the techniques to other corridors, using higher resolution, real-time transit location data, and online implementation of an arterial travel time information system.

Most urban areas in the United States offer real-time freeway speed, travel time, and incident information, but there is a need to expand traffic management and traveler information to the arterial system because it handles nearly 40% of the nation’s vehicle miles traveled. It is clear that for many travelers an arterial performance measurement system would be useful for trip planning, en route information, and dynamic routing. In addition, traffic engineers and transportation system managers would benefit by being able to continuously evaluate the effectiveness of signal timing plans and other operational improvements in real time and in retrospect. At a broader level, archiving arterial performance data over time would allow planners to monitor more than just the freeway portions of the network, which is useful for congestion monitoring and regional transportation planning.

One reason that arterial performance systems are not as mature as those for freeways is that interrupted flow facilities are more difficult to monitor. Travel time along an arterial can be broken into two distinct components: the time to traverse the links between traffic signal influence areas and the time to traverse the signalized intersection itself. When unaffected by queues, traffic between nodes can be treated like that on an uninterrupted flow facility and point-based speed measurements can be extrapolated over segments of influence (e.g., from loop detectors). Travel time measurements through intersections require more detailed measurements about queue formation and dissipation, as well as the status of the traffic signal settings.

Given these challenges, recent research has been directed toward improving techniques to monitor arterial performance (1–11). Some research has measured each component directly (3–5), and some has modeled relationships between traffic flow and signal control settings (6, 7). Another approach addresses the data collection problem by predicting arterial corridor travel time based on count and lane occupancy data from corridor signal loop detectors, green times, cycle lengths, and offsets (9). The use of individual vehicle actuation data rather than arbitrary temporally aggregated data (e.g., 30-s data) for performance measurement at isolated signals was examined (10), and the effect of fusing these data with signal timing data was tested (11). Although these approaches are very promising, high-resolution data are not currently available from most signal systems.

This paper builds on past research in arterial performance based on signal detection as well as past research of transit vehicle geolocation systems as a source of probe data for real-time arterial monitoring and travel time reporting (12–14). Transit and other fleet vehicles are increasingly equipped with automatic vehicle location (AVL) systems and other Global Positioning System–like devices. In Portland the 700 buses in TriMet’s system are “smart,” in that their bus dispatch system (BDS) monitors and archives their exact location, schedule status (on-time, late, or early), passenger load and individual passenger movements, and other important performance parameters. From a historical perspective, these data can be processed to provide a comprehensive picture of current arterial speed across all arterials that contain bus routes. As an illustration of this, Figure 1 shows a map of the Portland metro area with bus speeds (indicated by the color code shown on the figure).
FIGURE 1 Arterial speed maps generated from transit geolocation data, Portland.
recorded at 7:30 a.m. on May 7, 2007. The figure shows two possible backgrounds—an aerial photo and a map. Archived data were used to compute average bus speeds (during 15-min intervals) for every arterial link for each day in 2007.

There are well-known limitations to using fleet vehicle geolocation data (including buses or taxis) because the operational characteristics of those vehicles are different from “normal” traffic. For example, when buses stop to serve passengers, their travel time will include the dwell time and deceleration and acceleration delay. Even when not stopping to serve passengers, buses have different performance characteristics because of their large size, and they generally travel slower than standard passenger vehicles. Also, although many buses archive detailed stop-level performance data, limitations in communication systems currently limit the quantity and frequency of real-time location reporting, which would constrain its utility for providing real-time arterial condition information.

Given that signal system and transit geolocation data each have separate limitations, the two sources combined may have an ability to be more complete and accurately characterize the performance of an arterial. Therefore, the objective of this paper is to examine the potential of using bus geolocation data to improve arterial monitoring as compared with what can be achieved by using signal system data alone. It is envisioned that the techniques developed here can be extended to real-time traffic management and traffic information applications. The paper first describes the data available for a case study corridor, and then a prototype graphical method for combining these data sources is presented. Next, an algorithm is described that is based on the success of the prototype exploration. Finally, a summary and recommendations for future work conclude the paper.

**DATA SOURCES**

A case study has been conducted along a 4.5-mi section of the four-lane arterial Barbur Boulevard in Portland, Oregon, between Sheridan Street and the Barbur Boulevard Transit Center (a regional park-and-ride facility). This has been the test bed for exploring the fusion of bus geolocation data with traffic signal system data with the objective of developing an improved estimate of arterial performance. Figure 2 shows a schematic of the corridor, including locations of the signalized intersections and location of system detectors. Data were collected from the City of Portland’s traffic signal system and TriMet bus dispatch system for the week of February 12, 2007. The data and their analyses are described in the following sections.

**Archived Bus Dispatch System Data**

TriMet Route 12 traverses Barbur Boulevard. Each bus contains a Global Positioning System–based AVL system that archives performance metrics concerning each vehicle’s daily activities. The BDS records 26 data elements at each bus stop (whether the vehicle stops or not), including the arrive time, leave time, number of passengers boarding and alighting, and the dwell time. The BDS also records the maximum speed that the bus achieved between stops. Previous research developed a statistically valid relationship linking the bus trajectory data to passenger vehicle speeds and travel times along one particular corridor. As an extension of that work, this research uses BDS data to estimate arterial travel times for nontransit vehicles. This was done by using TriMet BDS data collected for the same days as City of Portland traffic signal system data along Barbur Boulevard.

**Traffic Signal System Data**

The Barbur Boulevard corridor is equipped with five detector stations configured as system detectors (count stations) in the City of Portland’s central traffic signal control system. The detectors are located between 100 and 780 ft upstream of each traffic signal stop bar. Each count station recorded average values from its detectors located in each lane. In addition to the average values recorded by the bank of detectors, the detector that saw the most activity for a given 5-min period was designated the “critical” detector, and values were recorded for that lane specifically. The critical lane, critical lane volume, critical lane occupancy, critical lane stops, critical lane speed, total volume, average occupancy, total stops, and average speed were collected for each 5-min period during the 9-day sample, from February 12 to February 20, 2007. It would be desirable to have high-resolution vehicle actuation data (or even measurements on a cycle-by-cycle basis with cycle status), but because of data management and communications issues 5-min intervals were the highest resolution available.

**DATA ANALYSIS**

To characterize traffic flow dynamics on northbound Barbur Boulevard during the study period, and given that the system detector and bus AVL data are available for simultaneous days and locations, it is possible to reconstruct a “map” of traffic conditions by producing a color contour plot of speed as measured by the detectors, overlaid with trajectories of the buses as constructed from the archived AVL data. When a time–space plane is used, a trajectory is a convenient way to view any vehicle’s progress over time and space, such that
the slope of the trajectory is the speed at any point. Figure 3 shows a preliminary analysis for viewing the bus and loop detector data on a combined time–space plane, in which the x-axis is time and the y-axis is the distance along Barbur Boulevard. The detector location names are labeled on the left-hand y-axis, and mileposts are labeled along the right-hand y-axis. As shown in the figure the loop detector measurements are color coded to indicate levels of congestion. Green represents free-flow conditions (0%–7.5% occupancy) and yellow (7.5%–22.5%), orange (22.5%–45%), and red (45%–100%) represent increasing levels of congestion. The selection of these thresholds was made experimentally based on an analysis of speed, flow, and occupancy data along the corridor. The corresponding speed ranges are also shown in the legend of Figure 3. These speeds are not necessarily linked to current Highway Capacity Manual arterial level-of-service speed thresholds, but future research or implementations could provide such a link.

Also in Figure 3 the bus trajectories are added to the loop detector readings, with each point on the trajectory indicating the time that the bus passed (or served) a particular stop. Each point on the bus trajectory is also color coded; the color of the circle indicates the maximum speed achieved on the upstream segment. Examining the data shown in the figure near the Bertha detectors (approximately Mile 2) between 5:00 and 6:00 p.m., slower bus speeds (which appear in red) confirm the slower conditions reported by the signal detectors. However, examining the data just beyond the signalized intersection, mostly freely flowing (green) bus velocities suggest (as expected) that the slower conditions do not persist beyond the intersection. Further refinements on this concept will be described later.

An analysis of measured traffic signal detector occupancy data revealed that free-flow conditions break down at about 7% to 10% occupancy at the system detector. Peak flow appears to be reached at about 23% occupancy. After remaining constant from 23% to 50%, flow begins to decline at occupancies above about 50% (although data are understandably sparse for regimes above 35% occupancy; more data should be collected to robustly model the precise shape of the curve). These occupancy values are typical for the system detectors in the corridor.

Route 12 bus travel times were also analyzed for the Barbur Boulevard corridor using the BDS data. Bus travel times ranged between 12 and 16 min, with shorter travel times in the early morning and late evening periods. Most important for the purposes of this study are the 7:00 to 9:00 a.m. peak and the 4:00 to 6:00 p.m. peak period. Travel time estimation and condition reporting during free-flow conditions are important but relatively straightforward if conditions are homogeneous. Because estimating travel times is most difficult and most critical during transitions to and from congested periods, it was important to identify the congested periods that occurred during this week.

**Bus Geolocation Data and Ground Truth**

Past research has investigated the prospect of using data from buses to generate travel time estimates for passenger vehicles (12–14). In one comprehensive case study using data from a Portland arterial, several statistically valid methods were explored in depth for generating travel time estimates using TriMet BDS geolocation data (14). Several algorithms for computing arterial travel time from the AVL data were compared with actual probe vehicle travel times along Powell Boulevard. The first method tested was one in which the dwell time was subtracted from the bus trajectories to reduce the travel time by the total amount of time that the bus is stopped serving passengers. Because TriMet’s measurement of dwell time is from the time the door opens until the time the door closes, this method does not account for lost time due to deceleration and acceleration. Another method tested in Bertini and Tantiyanugulchai was the “max speed” method (described above) (14). As a proxy for knowing the speed of other adjacent vehicular traffic, this method extrapolates the bus’s maximum speed over the entire segment between two stops to estimate the vehicular travel time for each segment. These estimates are summed to create a travel time estimate for the travel area in question. This method effectively excludes stops as well as time lost accelerating and decelerating. Because passenger cars do stop, accelerate, and decelerate as a part of normal travel, this method underestimates...
travel times. The extrapolation of this trajectory underpredicted the nontransit vehicle travel time by 20%. After adjustment by this value, the underprediction was confirmed to most reliably approximate actual vehicle travel times, which were found to be 125% of the travel times determined using the maximum segment speed. A statistically valid model for arterial speed and travel time was developed using this relation. The “max speed” method will be applied in this paper to serve as the ground truth for comparison using other available data.

**Limitations of Bus Geolocation Data**

Although the “max speed” method proved a valid method for predicting vehicle travel times, the ability to use buses as probes is limited by headway, which determines the frequency with which a bus can report arterial conditions. This is an issue with any probe-based surveillance system, whether from buses, taxis, or personal vehicles. Figure 4 demonstrates a situation in which conditions change for the worse in between the passing of two buses. Signal system detector measurements indicate very slow speeds from 8:00 to 8:30 a.m. at the Hamilton traffic signal. Consistent with this, the slope of the first bus trajectory in Figure 4 reveals that the bus did experience a reduction in speed. Judging by the red on the figure, the congestion appears to have built further at 8:10 a.m. However, no bus passed through the corridor until 8:20 a.m. at which point the detectors suggest conditions had improved.

Figure 4 demonstrates that travel times estimated based on bus probe reporting would predict that a vehicle departing at 8:10 a.m. would traverse the corridor faster than it would actually experience, a situation that traveler information providers strive to avoid (underprediction). In this case study the bus probe data offer the benefit of spatial coverage because they traverse the entire corridor, but are limited in their temporal coverage because of headway limitations. Conversely, the traffic signal system data are limited in their spatial coverage because data are collected only at fixed locations. The signal system data are available at higher temporal resolution, in this case every 5 min. These two data sources thus appear to have the potential to complement one another, which is the focus of this research.

**Traffic Signal System Data**

The use of traffic signal system detector measurements to report arterial traffic conditions and estimate travel times on Barbur Boulevard is illustrated in Figure 5. Figure 5a shows a time–space diagram (in which the x-axis is time and the y-axis shows the distance along the arterial) for Thursday, February 15, 2007, during a sample 2-h period between 4:30 and 6:30 p.m. On this time–space diagram, the 24 vertical lines indicate the 5-min intervals at which the detectors report congestion information. Each small square represents a loop detector data point, with one data point per detector at each 5-min interval. Each detector speed measurement has been extrapolated in time during the subsequent 5-min interval, and in space halfway to the upstream detector and halfway to the downstream detector (this is referred to as the midpoint method, which is commonly used in freeway travel time estimation). On freeways, other researchers have proposed many other algorithms to obtain travel time estimates, for example van Lint (17). Green sections indicate periods with free-flow conditions (0%–7.5% occupancy), yellow represents higher occupancies and slower speeds (7.5%–22.5% occupancy), followed by orange for congested conditions (22.5%–45% occupancy). Red would be very congested (>45% occupancy). Bus trajectories are superimposed as dashed lines.

Using the technique of interpolating the traffic signal system–measured occupancy or speed at each signalized intersection as a representation of conditions along the entire link conditions will not necessarily be reliable. For example, use of the midpoint method results in congested conditions being reported between Mileposts 1 and 3. If in reality the congested conditions are present only over a ½-mi segment (rather than the entire 2-mi segment), the conditions would be misreported and travel time estimates would be substantially overpredicted. This situation is demonstrated in Figure 5b, in
which the solid trajectory is based on the loop detector readings. In this example, the detector prediction overestimates travel times as compared with the dashed bus trajectory for the reason highlighted above. More troublesome for travel time information would be an analogous situation in which the congested regime is underestimated, resulting in an underprediction of travel times.

### Fusing Data from Fixed Sensors and Mobile Probes

The use of two simultaneous data sources from the same location and the same time period makes this research somewhat novel. Figure 6 reveals corridor traffic conditions during 4 days of analysis: Monday, February 12 through Thursday, February 15, 2007. Figure 6a contains the traffic signal measurements extrapolated over the corridor using the midpoint method for each day, as well as the bus trajectories with the maximum speed color coded at each stop location. To improve the accuracy of traffic condition description, an algorithm was developed that identifies regions in time and space that fall into the congested regime. In Figure 6 those regions are shown as black diamonds. The congestion identification algorithm is described in detail below.

The algorithm enhances the ability to characterize arterial conditions using data from the signal system and the mobile probes. In Figure 6a, for example, the algorithm identifies points that match with the most congested signal system detector readings. The bus probe data supplement the detector data by characterizing the spatial extent of the congestion. Conditions shown in Figure 6b exhibit a region where the detectors measure occupancy between 22.5% and 45% (orange), but the bus probe trajectories suggest that the buses were affected by congestion at two particular times and locations. The congestion upstream of the Bertha detectors matches well with the detector data. The second event is at SW 24th Avenue, a location where there is a traffic signal, but no system detector. Conditions shown in Figure 6c reveal that the probe data corroborate and inform the detector measurements. The bus probe data in Figure 6d reveal that congestion was present beginning at 7:30 a.m., with a queue apparently growing in magnitude to a maximum at approximately 8:30 a.m. before ultimately clearing just after 9:00 a.m.

### Extracting Arterial Traffic State Information from Geolocation Data

As noted, buses behave differently from passenger vehicles. The flatter slope of a bus trajectory might indicate the presence of congestion, but may also result from the bus stopping to serve passengers or from a layover. To overcome that difficulty, an algorithm was developed to distinguish “bus” behavior from the presence of an actually congested region in time and space. Toward that end, the first step was to calculate the slope of each bus segment, which is the average bus speed over that segment. The dwell time (time that the bus door is open) was subtracted from the total travel time between two stops. This subtraction does not include time lost to acceleration or deceleration.

The second step was to identify a threshold speed below which traffic could be characterized as “congested.” Note that with further research on different corridors, it may be possible to relate this threshold speed to the speed limit to make this technique transferable to other sites. The speed threshold is a variable that can be adjusted based on site-specific conditions. For the corridor in this study, the value of 11 mph was found to be a threshold speed that yielded good results. Finally, a condition was added that requires consecutive segments to experience average travel speeds below the threshold speed before both segments are identified as experiencing “congestion.” This proved an effective method for eliminating false positives. The exact algorithm is

1. Calculate the slope of each bus segment (less dwell time) that is equal to the average bus speed.
2. Identify a threshold speed that will be considered “congested.”
3. Find consecutive segments that experience travel speeds below the threshold “congested” speed:
   - if slope of Segment $1 < \text{speed\_threshold}$
     - if slope of Segment $2 < \text{speed\_threshold}$
       - location\_congested ($x-1$) = true
       - location\_congested ($x$) = true
       - location\_congested ($x+1$) = true
     - end
   - end

FIGURE 5 Time–space diagrams showing trajectories based on signal system measurements: (a) sample 2-h period between 4:30 and 6:30 p.m. and (b) sample half-hour period between 5:30 p.m. and 6:00 p.m.
FIGURE 6  Barbur Boulevard time–space diagrams illustrating the method for combining probe and signal system data: (a) February 12, 2007; (b) February 13, 2007; (c) February 14, 2007; and (d) February 15, 2007.
Characterizing the Congested Regime

As noted, the bus probe data can inform and improve the detector condition and travel time estimates by determining the shape of the congested regime around each signal. Returning to Figure 5a, the dashed lines are the actual bus trajectories for the same day and time period as the detector readings. A close inspection of the slope of the bus trajectories reveals that the buses experienced a speed reduction inside the congested regime, with travel time predictions then being adjusted accordingly. The second way is an archival use of the data, which introduces another parameter that can be adjusted. It is possible to count the number of times that a particular stop location is flagged as being part of a congested regime in a given day, week, month, or year. It would then be possible to examine locations that were part of a congested regime for a percentage of time, say 10% of all runs. In this analysis it was found that congestion occurred most frequently upstream of the Bertha detectors. The ability to identify regions that experience congestion most often can help a city to strategically locate additional detection or implement other measures.

Summary

For the data analyzed in this project, hypothetical vehicle (non-bus) travel time estimates were calculated from the signal system data as well as estimates based on the maximum speed method, which are used as a proxy for passenger vehicle ground truth. Estimates based on extrapolated point-based speed measurements do not correspond well with the bus probe measurements. This is true particularly during a congested period, when estimates result in significant overprediction. The reason for this, discussed previously, is that the detector travel time estimates are based on the midpoint method and as a result, the very slow speed estimates reported by the sensors at Bertha are being extrapolated during the 2-mi segment between Mileposts 1 and 3. Also computed were the revised loop detector travel estimates that incorporate the bus probe data to redefine the congested regime around the Bertha signals as well as employ the maximum speed from the bus data to estimate the unknown intervals.

The relationship, however, is less effective during the earlier off-peak periods. The reason is that this research demonstrates a method for modeling the shape of congestion around a traffic signal by focusing only on the two traffic signals at Bertha. However, although it was found that congestion occurred most often upstream of the traffic signals at Bertha, Figure 8 suggests that congestion occurs at other...
FIGURE 8  Time–space diagram plots illustrating the method for combining bus probe and signal system data: (a) manual revised estimate of congested regime on northbound Barbur Boulevard, February 15, 2007; (b) identification of segments of study area where loop detector readings do provide useful information; (c) maximum speed readings from buses, representing a complementary source of data; and (d) color contour plot derived from a combination of signal system and archived AVL bus data.
signals as well. Furthermore, Figure 8d suggests that the shape of the congestion regime can vary throughout the day. Thus, Figure 8b is satisfactory for the p.m. peak period because conditions were accurately described for that particular period. Accurate travel time predictions for other travel times will require that congestion intervals be defined around additional traffic signals. Further research can also refine this method to allow the shape of the congestion interval around each signal to be defined throughout the day on the basis of the congestion algorithm derived from the bus probe data. This paper has developed a theoretical model for using signal system data in conjunction with bus data to evaluate arterial performance. Refinement of the model to include other traffic signals and perhaps dynamic definition of congestion intervals is needed before accurate travel time estimations can be made. That is planned as part of ongoing research.

Table 1 contains travel time estimates for the entire week based on the various methods that have been described in this paper. Although the theoretical combined signal–bus method is not applicable to the entire week for the reasons mentioned above, analyzing even these preliminary travel time predictions is instructive. The accuracy of congested travel time predictions is instructive. The Signal + Bus method is much closer to the modified Max Speed estimates, although as expected they are not perfect. By narrowing the region of influence of the Bertha detectors, the travel time estimate deviations were successfully reduced to more closely match those suggested by the modified Max Speed estimates.

Finally, there are a number of questions that were encountered with regard to interpolating detector speed readings that are worth noting. The first is that the detectors sometimes reported speeds less than 5 mph. Applying a low reading such as 2 mph to a half-mile segment adds 15 min to a travel time estimate, which can result in a substantial travel time overprediction. To remedy this problem, it might be necessary to establish a minimum or “floor” speed. This leads to a second question. If, as in Figure 8d, the congestion backs up for more than a mile, what adjustment would need to be made to the speed recorded at the signal? In other words, speeds would be expected to drop the closer a vehicle gets to the traffic signal. Thus, it might be necessary to apply a multiplier factor to the detector speeds by some amount based on the distance from the signal.

### CONCLUSIONS

By using graphical tools, statistically valid algorithms, and a rich source of archived data from two sources, this paper has demonstrated the potential for using bus AVL data to construct the shape of the congested regime on an arterial in Portland, Oregon. It has been shown that it is possible to compare the evolution of bus trajectories over an arterial segment with hypothetical trajectories generated from loop detector data. An algorithm for identifying congestion intervals has also been demonstrated.

These results are promising, especially in light of the fact that neither of these two data sources was designed for measuring arterial performance. The detector data are particularly limiting because they were aggregated at the 5-min level and not related to signal cycles or phase operation. Furthermore, some of the detectors are not well calibrated, which affects the accuracy of the reported travel speeds. Despite these challenges, by combining the two data sources, this project has significantly improved the understanding of how traffic was operating on Barbur Boulevard and has made strides toward achieving accurate travel time predictions.

This analysis has focused on the uses of archived TriMet AVL data. However, some AVL data are available in real time. The authors have recently begun working with data from C-TRAN, the transit provider for Clark County, Washington (part of the Portland–Vancouver metropolitan region). C-TRAN has installed an AVL system more recently than TriMet, and C-TRAN buses report their position back to central dispatch every 10 s. TriMet’s communication interval is closer to a 60- to 90-s time frame and does not include the maximum speed parameter. One of the next extensions of the analysis presented in this paper will be the use of real-time bus data to identify the time–space dimensions of congested regimes on key regional arterials. Although the loop detectors used in this study provide data only every 5 min, a bus that passes through the arterial corridor at a relatively high speed could signal that the congestion has ended minutes before the

### Table 1 Travel Time Comparison

<table>
<thead>
<tr>
<th></th>
<th>Actual Bus</th>
<th>Max Speed Method</th>
<th>Signal</th>
<th>Max Speed × 1.25</th>
<th>Signal + Bus</th>
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<tr>
<td><strong>Northbound—Mean Travel Time</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weekday morning peak (n = 38)</td>
<td>15.3</td>
<td>7.7</td>
<td>14.9</td>
<td>9.6</td>
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<tr>
<td>Weekday midday off-peak (n = 132)</td>
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<td>11.1</td>
<td>9.1</td>
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<tr>
<td>Weekday evening peak (n = 46)</td>
<td>13.8</td>
<td>7.8</td>
<td>13.1</td>
<td>9.8</td>
<td>8.4</td>
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<td><strong>Northbound—Standard Deviation</strong></td>
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<td></td>
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<tr>
<td>Weekday morning peak (n = 38)</td>
<td>2.0</td>
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<td>4.4</td>
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<td>2.0</td>
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<tr>
<td>Weekday evening peak (n = 46)</td>
<td>1.5</td>
<td>1.2</td>
<td>1.5</td>
<td>1.2</td>
<td>0.8</td>
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<tr>
<td><strong>Northbound—Mean Speed</strong></td>
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<tr>
<td>Weekday morning peak (n = 38)</td>
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<td>18.1</td>
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<td>Weekday midday off-peak (n = 132)</td>
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<td>37.0</td>
<td>24.3</td>
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<tr>
<td>Weekday evening peak (n = 46)</td>
<td>19.5</td>
<td>34.6</td>
<td>20.6</td>
<td>27.7</td>
<td>32.3</td>
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next detector measurement. A threshold speed could be set, and once
a bus that reports passing through the arterial exceeds that speed, the
travel time estimates can be adjusted accordingly to indicate shorter
travel times.

ACKNOWLEDGMENTS

Funding and support for this project were provided by the National
Science Foundation, Oregon Department of Transportation, FHWA,
City of Portland, and TriMet. The authors particularly thank David
Crout and Steve Callas of TriMet and David Daily of C-TRAN for
providing transit data for the project. Bill Kloos and Willie Rotich
of the City of Portland and Fred Liang of the City of Bellevue also
provided valuable advice and input to the project.

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The Regional Transportation Systems Management and Operations Committee sponsored publication of this paper.