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Technical Report Documentation Page

1. Report No. RES2013-45	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle *Empirical Evaluation of the Accuracy of Technologies for Measuring Average Speed in Real Time*		5. Report Date August 2017 6. Performing Organization Code
7. Author(s) Hargrove, S., Lim, H., Han, L., Freeze, P.B.		8. Performing Organization Report No.
9. Performing Organization Name and Address University of Tennessee 525 John Tickle Engineering Building 851 Neyland Dr Knoxville, TN 37996		10. Work Unit No. (TRAIS) 11. Contract or Grant No. 42B268 (FHWA)
12. Sponsoring Agency Name and Address Tennessee Department of Transportation Research Office 505 Deaderick Street, Suite 900 Nashville, TN 37243		13. Type of Report and Period Covered Research Report August 2013 to June 2016 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

The determination of travel time conditions for traveler information plays an important role in setting driver trip expectation and informed route selection decisions. The Tennessee Department of Transportation (TDOT) has the ability to compute expected travel time within the four (4) urban areas where corridors have been fully instrumented with SmartWay ITS field devices and associated communication. However, TDOT currently lacks the ability to effectively provide this travel time information to travelers in corridors beyond the SmartWay program in many suburban corridors outside the urban areas. Federal regulations require all state DOT's to develop means to measure traffic speeds and calculate travel times for all maintained road networks by 2014. This study acquired and examined probe vehicle based real-time travel data and strategize a sustainable implementation plan to provide comprehensive travel time information to motorists in the years to come.

This is a continuation from a Tennessee Technical Assistance Program (TTAP) contract where a probe-vehicle database from INRIX as well as ground truthing equipment from 3M had previously been acquired. A significant amount of the effort went to the analysis of the quality of the field data from sources including INRIX, ALPR, NAVTEQ, Bluetooth, Google Maps and TELVENT.

17. Key Words **TRAVEL TIME INFORMATION, TRAVEL TIME MEASUREMENT, ITS, INTELLIGENT TRANSPORTATION SYSTEMS**		18. Distribution Statement .	
19. Security Classif. (of this report) Unclassified	20. Security Classif. (of this page) Unclassified	21. No. of Pages 10	22. Price $110,237.36

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorized**

Executive Summary

This is the final report of the project, which is a continuation from a TTAP contract where we had already acquired probe-vehicle database from INRIX as well as ground truthing equipment from 3M. The final quarter saw continued activities on field data analysis. Significant amount of the effort went to the analysis of the quality of the field data from sources including INRIX, ALPR, NAVTEQ, Bluetooth, Google Map, and TELVENT. We were able to isolate the "time drifting" problem on some of the computers used in this study and corrected the problems with post-processing of the data. A presentation was made to TDOT in July to report on the analysis results of the field sensor data. The slides from the presentation are provided as an attachment to this report.

Synopsis of the Problem Being Researched

The determination of travel time conditions for traveler information plays an important role in setting driver trip expectation and informed route selection decisions. The Tennessee Department of Transportation (TDOT) has the ability to compute expected travel time within the four (4) urban areas where corridors have been fully instrumented with SmartWay ITS field devices and associated communication. However, TDOT currently lacks the ability to effectively provide this travel time information to travelers in corridors beyond the SmartWay program in many suburban corridors outside the urban areas. Federal regulations requires all state DOT's to develop means to measure traffic speeds and calculate travel times for all maintained road networks by 2014. This study will acquire and examine probe vehicle based real-time travel data and strategize a sustainable implementation plan to provide comprehensive travel time information to motorists in the years to come.

Project Objectives

- Acquire and examine probe vehicle based real-time travel data;
- Strategize a sustainable plan for TDOT to acquire travel time information; and
- Strategize a sustainable implementation plan for TDOT to provide comprehensive travel time information to motorists in years to come.

Activities this Quarter

- Project completed.

Schedule and Budget

Task 1. Travel Time Database Acquisition
Task 2. Alternative Database Assessment
Task 3. Exploration of On-Line Database Extraction
Task 4. Travel Time Ground Truthing
Task 5. Preliminary Data Quality Assessment
Task 6. Reports and Recommendations

We are 100% done with the tasks with the expenditures is also at 100% for Phase I.

Empirical Evaluation of the Accuracy of Technologies for Measuring Average Speed in Real Time

Stephanie R. Hargrove, Hyeonsup Lim, Lee D. Han, and Phillip Bradley Freeze

A federal mandate challenges states to acquire and to disseminate reliable travel time–speed information with limited sensor infrastructure and resources; the mandate also opens the opportunity to look beyond traditional sensor technologies. Some of these new and promising travel data technologies include various deployments and combinations of GPS, probe vehicles, cellular devices, Bluetooth devices, radio frequency identification, automated license plate recognition (LPR), and even social media. To take on this challenge, the objective of this study was to provide several key considerations for evaluation of travel speed data for general cases. The key items included obtaining reliable ground truth data, transforming and comparing data sets, and evaluating data accuracy. Along with the explanation of these considerations, the results of a case study are provided to help illuminate the issues. The case study, which was performed in the vicinity of downtown Nashville, Tennessee, along Interstate 40 and Interstate 65 evaluated real-time travel time–speed data from Bluetooth sensors, from probes supplied by two major vendors, and from remote traffic microwave sensors. These data were compared with ground truth data from an LPR-based vehicle tracking system as well as video footage collected simultaneously. The paper discusses the reliability of ground truth, the advantages and shortcomings of different technologies, the evaluation of data accuracy methodologies, and future research directions.

Recognizing the need to provide better travel time information to the general public, FHWA ruled that all states must have an established real-time information program for traffic and travel conditions to cover all Interstate system highways in the Safe, Accountable, Flexible, Efficient Transportation Equity Act: A Legacy for Users under the heading congestion relief that requires the secretary of transportation to implement a real-time management information program (*1*). This federal mandate challenges the states to acquire and to disseminate reliable travel time–speed information with limited sensor infrastructure and resources; it also opens up the opportunity to look beyond the traditional sensor technologies. Some of these new and promising travel data technologies include various deployments and combinations of GPS, probe vehicles, cellular devices, Bluetooth devices, radio frequency identification, automated license plate recognition (LPR), and even social media.

Mining and extracting useful travel time–speed data from these newly repurposed data sources, which were not originally created for travel time–speed measurement originally, are not simple tasks (*2–6*). In addition, private vendors who market these data are unwilling to disclose the algorithms used in the processing, filtering, aggregation, imputation, and other data-smoothing processes. This unwillingness makes evaluating the myriad of evolving and maturing travel time–speed technologies a real challenge.

To take on this challenge, this study aimed to provide several key considerations for evaluation of travel speed data for general cases. The key items included obtaining reliable ground truth data, transforming and comparing data sets, and evaluating data accuracy. Along with an explanation of these considerations, the paper provides the results of a case study to help illuminate the issues.

STUDY SITES AND DATA COLLECTION

The primary consideration for study site selection is the availability of all data sources within a roadway segment of a traffic management center (TMC) where significant variance in traffic speeds–travel times is commonly observed. To this end, a stretch of I-40E–I-65S near downtown Nashville, Tennessee, from Demonbreun Street to 12th Avenue was selected (Figure 1). Data collection stations (A, B, and C) were deployed on the overpasses above the Interstate, which has three lanes until the addition of a fourth lane from the second on-ramp. Just beyond Station C, the Interstate splits into I-40 and I-65, with two lanes going to each. During the data collection period, the segment from A to C saw the deployment of six LPR cameras (two for each station), three Bluetooth sensors mounted on light poles near each overpass, two remote traffic microwave sensors (RTMSs), and probe vehicles from two data providers, each covering two TMC sections.

Traffic Data Sources for Comparison

Although previous studies have evaluated some private data providers, reassessment of those providers is still critical, largely because the performance of these types of data can vary significantly in relation to factors connected to deployment of local technology (*7–11*). Two prominent private data providers (DP1 and DP2) were subsequently selected to supply aggregated real-time minute-by-minute travel time–speed data. (The authors were concerned about the quality of

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Transportation Research Record: Journal of the Transportation Research Board, No. 2594, Transportation Research Board, Washington, D.C., 2016, pp. 73–82.
DOI: 10.3141/2594-11

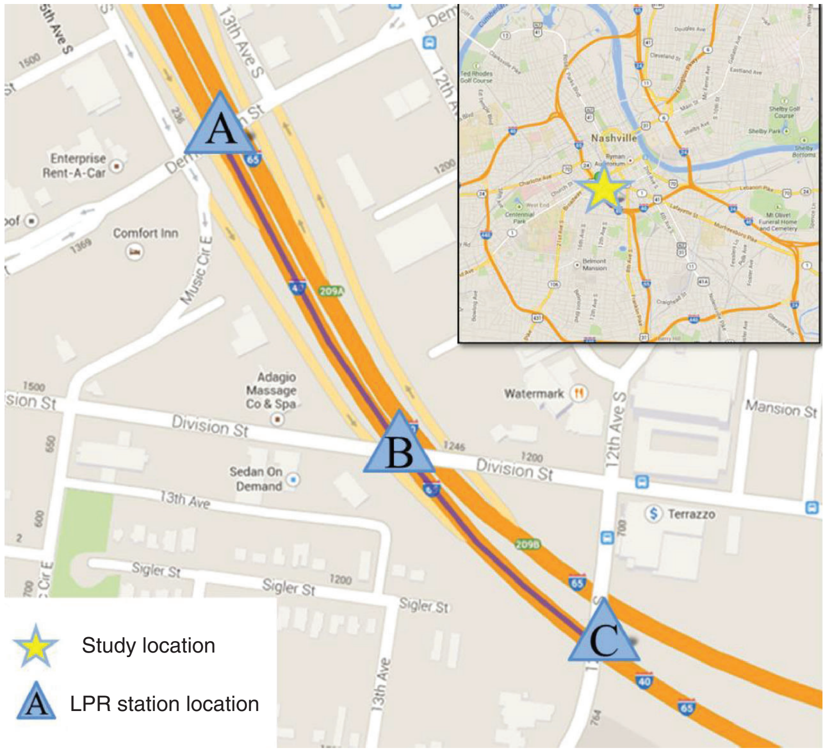


FIGURE 1 Study site.

these data because neither provider was willing to disclose the data aggregation process or to provide the raw data.)

In addition to the data from private providers, Bluetooth technology and the Tennessee Department of Transportation's existing RTMS sensors were also evaluated. Bluetooth sensors have become a common tool for collecting traffic data for their cost-effectiveness, ease of setup, and the minimal knowledge of the technology required for operation (*7, 12–15*). By matching media access control addresses captured at two locations by using postprocessing software, road speeds and travel times were derived.

RTMS sensors provide lane-by-lane volume, occupancy, speed, and vehicle classification for a cross section of a roadway. Over time, an RTMS sensor may become less accurate at capturing traffic data because of any or all of the following reasons: moving of the sensors, damage from natural elements, and inconsistent maintenance. Table 1 compares the data providers and the roadside technologies.

GROUND TRUTH

To assess the accuracy of the aforementioned travel time–speed data, the ideal would be to track every vehicle in the study area during the entire duration of data collection without subsampling, subaggregation, or any kind of omission. This ideal, however, is not attainable in an automated and sustained manner over time. The literature on methodologies of collecting ground truth data (*16–19*) identified probe vehicles (*20, 21*), Bluetooth (*7, 13–15, 22, 23*), LPR technology (*24–28*), and radio frequency identification (*29, 30*). Some desirable features of a ground-truthing methodology include

- Individual data points;
- Large enough sample size;
- Backup data to validate ground truth data, such as video records;
- High accuracy of time measurements;

TABLE 1 Summary of Selected Traffic Data Technologies and Providers

	Traffic Data Technologies			
Variable	Bluetooth	DP1	DP2	RTMS
Data type	Time, signal strength	Speed, travel time	Speed, travel time	Volume, occupancy, speed, vehicle classification
Aggregation and time resolution	Each MAC address, all lanes	60 s, all lanes	60 s, all lanes	30 s, per lane
Data source	Cellular and in-vehicle Bluetooth devices	State installed sensors, probe vehicles, GPS, cell phone	State installed sensors, probe vehicles, GPS	Roadside detectors
Accuracy checks performed	Postcollection processing with filters	Independently verified in large-scale testing	Data checks prior to map matching	Postcollection processing with filters

NOTE: MAC = media access control.

- High accuracy of distance measurements;
- Lane-by-lane travel speeds; and
- Exact length (start and end locations) of the target segment.

For this study, LPR technology was employed to track individual vehicles at the three stations (A, B, and C) to provide a surrogate of ground truth. LPR was chosen over other vehicle tracking technologies because the technology's small detection window results in a relatively small travel time error, especially at higher speeds (*31*). LPR technology also affords a more comprehensive appreciation of the traffic flow by tracking vehicles within the road lanes, allowing discernment of the speed gradient of subflows in fast and slow lanes that is associated with lane-changing activities.

The LPR-based vehicle-tracking functionality required for ground truth employs a pair of mobile LPR units to cover all lanes at each station (six cameras total). License plate information is acquired by each LPR unit and then matched automatically by means of a self-learning text-mining algorithm developed by Oliveira-Neto et al. (*32–34*). The algorithm uses a moving time window and weighted edit distance technique to achieve significant matching performance (98% matching rate with less than 1% false positives). The segment travel time for each matched plate, and hence vehicle, is then evident.

Sensitivity of Measurement Accuracy

By definition, "speed" is the change in distance over time. To evaluate speed data, being able to measure both time and distance accurately is desirable. Figure 2 shows the contour plots of the range of speed errors of ±15 mph to illustrate how errors in time and distance measurement affect the error in speed, for different true speed, time, and distance. The densities of these contour lines of speed errors indicate the sensitivity of the resultant speed to the measurement errors in time and distance. Denser contours indicate a greater error in speed with the same amount of error in space–time measurement. For instance, to result in an average speed of 30 ± 5 mph when the true distance is 2,640 ft, the errors in time and distance measurements must be within Range *a* in Figure 2.

Sample Size of Ground Truth Data

Suppose two technologies, *x* and *y,* for which the standard errors of measurements are σ_x and σ_y, and their sample sizes at each time period are $n_{\bar{X}}$ and $n_{\bar{Y}}$, respectively. For calculation of the standard errors of average of samples at each period, $\sigma_{\bar{X}}$ and $\sigma_{\bar{Y}}$, Equation 1 is well known:

$$\sigma_{\bar{X}} = \frac{\sigma_x}{\sqrt{n_{\bar{X}}}} \qquad \sigma_{\bar{Y}} = \frac{\sigma_y}{\sqrt{n_{\bar{Y}}}} = \frac{\alpha \times \sigma_x}{\sqrt{n_{\bar{Y}}}} \tag{1}$$

To get $\sigma_{\bar{X}} \geq \sigma_{\bar{Y}}$

$$\frac{\sigma_x}{\sqrt{n_{\bar{X}}}} \geq \frac{\alpha \times \sigma_x}{\sqrt{n_{\bar{Y}}}} \tag{2}$$

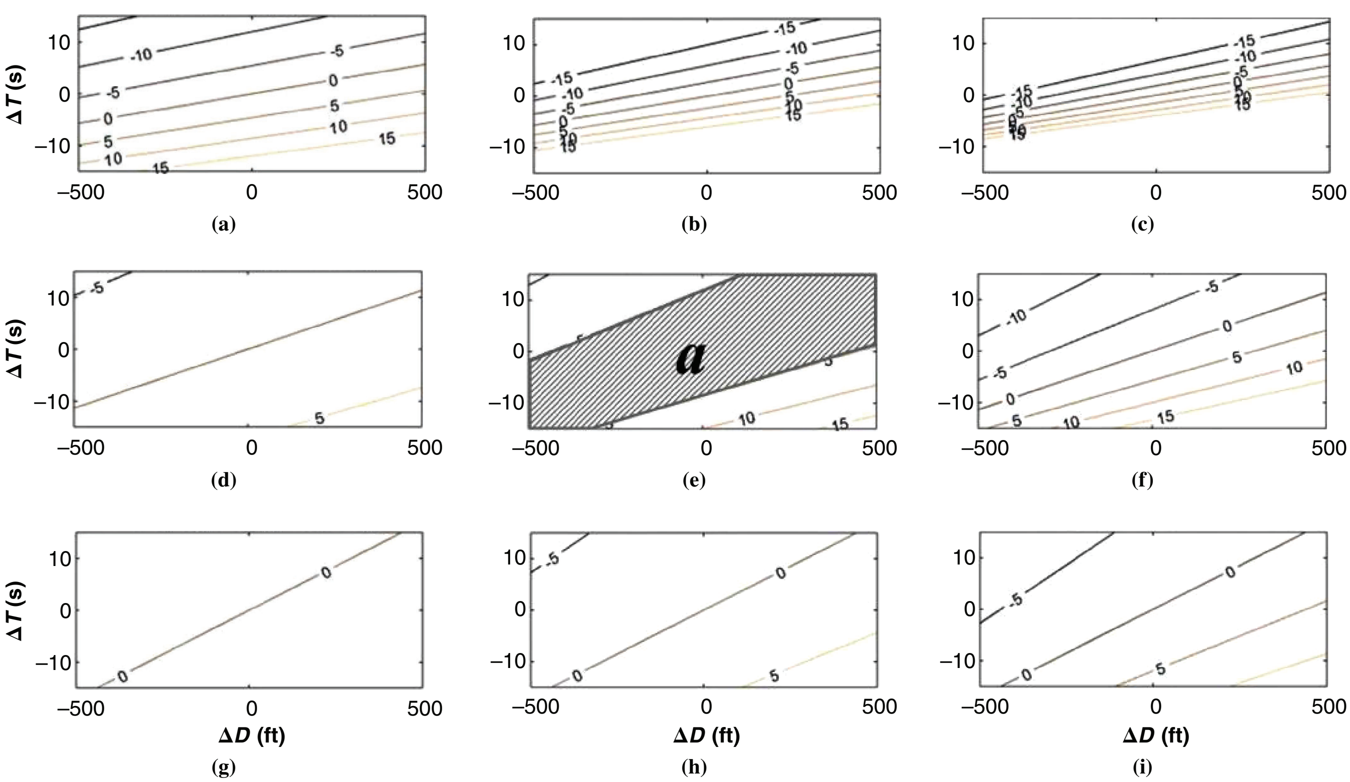


FIGURE 2 Contour plots of measurement error in speed for various distances, speeds, and periods: (*a*) 5,280 ft at 60 mph for 60 s, (*b*) 2,640 ft at 60 mph for 30 s, (*c*) 1,760 mph at 60 mph for 20 s, (*d*) 5,280 ft at 30 mph for 120 s, (*e*) 2,640 ft at 30 mph for 60 s (with Range *a* showing average speed of 30 ± 5 mph), (*f*) 1,760 ft at 30 mph for 40 s, (*g*) 5,280 ft at 20 mph for 180 s, (*h*) 2,640 ft at 20 mph for 90 s, and (*i*) 1,760 ft at 20 mph for 60 s.

TABLE 2 Summary of Sample Size and Percentage of RTMS for Roadside Technology Data Set

Roadway Section	Data Source Sample Size				Percentage of RTMS		
	LPR[a]	LPR[b]	Bluetooth	RTMS	LPR[a]/RTMS	LPR[b]/RTMS	Bluetooth/RTMS[c]
A to C	2,758	4,811	1,958	—	[d]	[d]	[d]
A to B	3,431	6,835	—	43,980	8%	15.5%	4.5%
B to C	4,885	8,671	—	43,208	11%	20.1%	4.5%

NOTE: Cells with dashes are the segments in which speed data were not collected for the designated data source.
[a]LPR data that match perfectly at each station.
[b]LPR data after self-learning matching algorithm applied.
[c]Bluetooth/RTMS was calculated using the total sample size for Sections A to C.
[d]RTMS data were not available.

$$\sqrt{n_{\bar{Y}}} \geq \alpha \times \sqrt{n_{\bar{X}}} \tag{3}$$

Now a condition to use y is obtained, as follows:

$$n_{\bar{Y}} \geq \alpha^2 \times n_{\bar{X}} \tag{4}$$

$$\frac{n_{\bar{Y}}}{n_{\bar{X}}} \geq \left(\frac{\sigma_y}{\sigma_x}\right)^2 \tag{5}$$

Equation 5 means that the condition of using technology y as ground truth data, in relation to measurement error and sample size, requires the proportion of the sample size for the technology y over that for technology x to be larger than the square of the proportion of standard error of technology y over the standard error of technology x when the data are evaluated at the aggregated level (i.e., average of each period). For instance, if the standard error of technology y is twice that of x ($\alpha = 2$), then the required sample size of y is, at least, four times that of x. However, as discussed earlier, the decision on which technology to use for the ground truth data is much more complex. Furthermore, if one wants to evaluate travel speed data at the individual data point level, then the measurement error might be much more important than the sample size.

Although Equation 5 might be more appropriate for evaluating aggregated data, the relationship can also be used to reduce the measurement error of individual data points by employing multiple devices at the same location.

To get the sample size of a population, a technology with a high accuracy of collecting traffic counts, besides the ground truth data for travel speed, can be used. In this study, RTMS was used to compare count data with LPR and Bluetooth. RTMS had high accuracy predominantly in traffic counts (*35*), while RTMS speed results varied in relation to the mounting location (*36*).

Table 2 contains a brief overview of the sizes of the samples taken during field data collection, October 18, 2013, from approximately 7:00 a.m. to 6:00 p.m. As Table 2 shows, LPR technology, with the advanced algorithm introduced by Oliveira-Neto et al., was able to capture 15% to 20% of the RTMS volume, while Bluetooth captured less than 5% (*32, 33*).

Importance of Lane-by-Lane Speed Data

With two LPR cameras installed in each location, four flows were captured for one segment. In Figure 3, Lanes 2 and 3 mainly represent the faster traffic flow compared with Lane 1. LPR permits a thorough investigation of the traffic flow by tracking vehicles within the road lanes.

The afternoon peak has two clearly separate flows along the same roadway. The first flow, Lanes 2, 3 → Lanes 2, 3 and Lanes 2, 3 → Lane 2, is recovering to uncongested flow conditions, while the other traffic flow remains congested.

TRANSFORMATION OF DATA

Before the evaluation process, several data composition and quality control techniques were implemented to verify the validity of the ground truth data collected and of all the other data sources. This step was completed by determining a procedure for comparing the ground truth data to the collected-data source, establishing appropriate periods, and eliminating outliers.

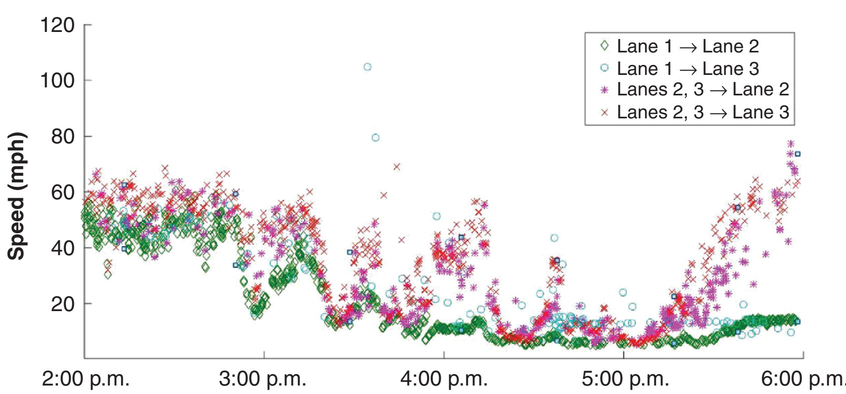


FIGURE 3 Example of lane-by-lane travel speed data.

Individual Data Points Versus Aggregated Level of Data

The resolution of traffic affects calculation of measurements and even decision making (*6*). Figure 4 illustrates the two considered methods assessed to evaluate the travel speeds of collected-data sources against the ground truth. The first method assigns all data to a specific period (e.g., 1 or 5 min) and calculates average speed for each period. The second method keeps their original resolutions. In Figure 4, all ground truth is represented in black, and the data source being compared is in red.

Averaging data by Method 1 establishes a simpler way to calculate deviations between more than two data sources because the paired comparison analysis will be based on single values for each period of each data source. However, this method may produce incorrect results, which could be significantly different from the original data set. These differences would be severe issues if clearly different traffic flows exist in the largely defined period.

Because LPR technology can observe individual vehicles, this study chose Method 2 to compare travel speeds of each vehicle captured with LPR with all other data sources. For data sources with accessible raw data, such as Bluetooth and RTMS, the 5-min moving

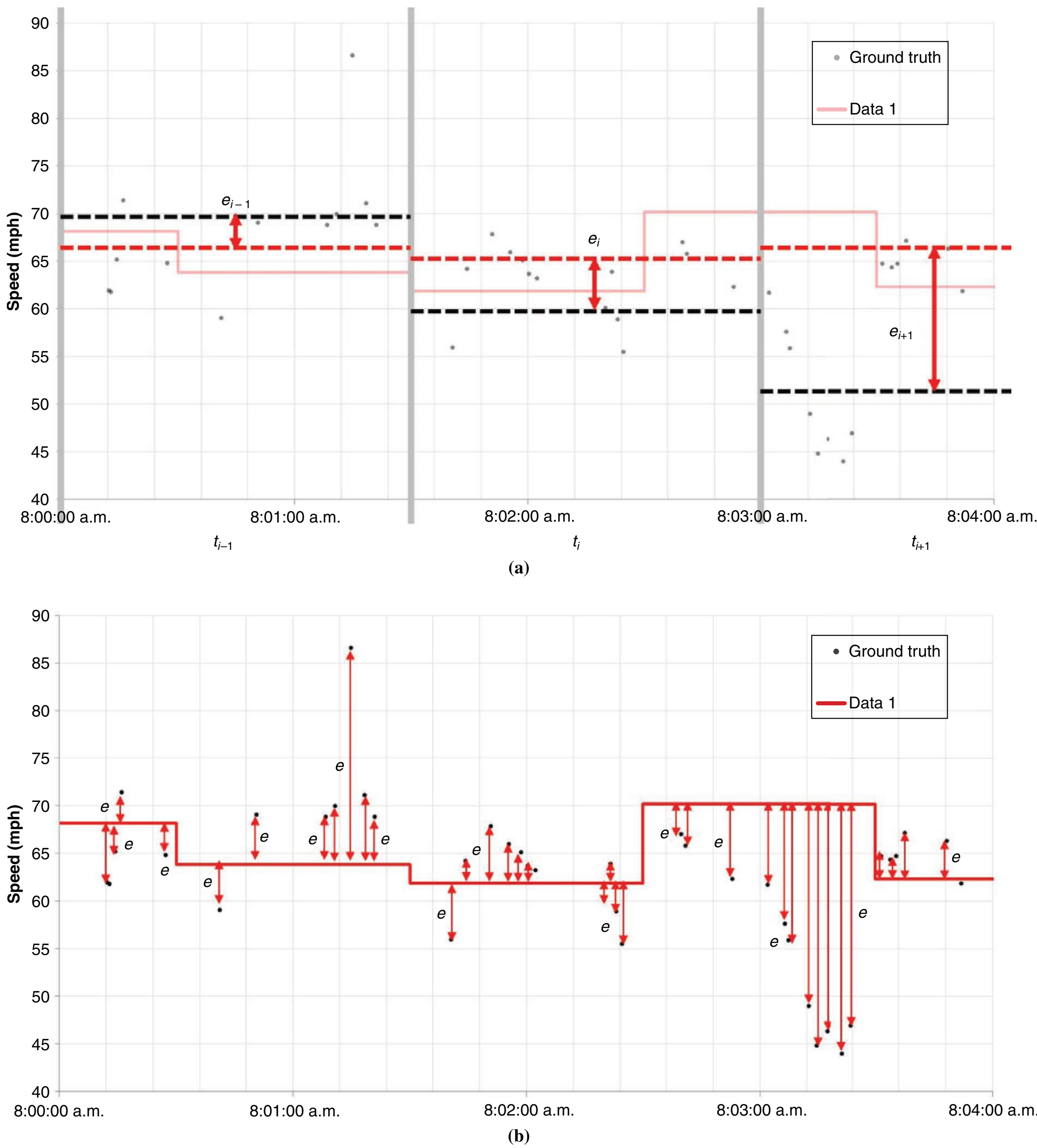


FIGURE 4 Two methods for comparing speed data: (*a*) setting all data to a specific period and (*b*) keeping all data in original format.

average was calculated on the basis of the time at which each data point was identified.

Moving Average of Travel Speeds

Moving average of traffic data captured by the roadside technology was calculated to compare with the travel speeds of the ground truth's individual vehicles. The term "moving" is used because every time a new observation becomes available for the time series, it replaces the oldest observation in the equation, and a new average is computed. As a result, the average changes or moves as new observations become available.

To represent the moving average of travel speed, the first question to be answered is how to group them, in other words, whether the moving average should be calculated on a fixed number of vehicles (i.e., fixing n_i in Equation 6), fixed periods, or some other ways. Fixing the number of vehicles may involve data points far from the time that one wants to calculate the moving average, which, in the case of traffic conditions, can also be significantly different.

To group the data points properly, they are assumed to be in almost the same traffic condition. For this grouping issue, by considering the changes of traffic conditions, a better way, such as a moving average based on flexible periods, may be possible; however, defining the boundary of changes to traffic conditions is quite difficult. Thus, in this study, the discussion is focused on a moving average of fixed periods.

Determining the appropriate time interval is very important; thus, having a realistic moving average is crucial. To achieve one, several trials examining different time intervals were implemented. In Figure 5, the moving average of speed data with different time intervals are compared with the raw data. As Figure 6, *a* through *f*, shows, the error increases as the time interval increases. However, the moving average speeds fluctuate considerably if the time interval used is too small. Thus, the decision on the time interval should be made with consideration of many factors, including the objectives of the evaluations.

In this case study, period i was selected on the basis of the time stamp of each vehicle identified in the ground truth data, including 2½-min intervals before and after the identified time stamp. After all vehicles within the 5-min range of period i were selected, the space mean speed was calculated. The moving average of time period i is defined as shown in Equation 6:

$$\bar{v}_i = \frac{n_i}{\sum_{k=1}^{n_i} \frac{1}{v_{ik}}} \tag{6}$$

where

$\bar{v}_i$ = space mean speed at period i,
n_i = number of vehicles at period i, and
v_{ik} = travel speed of kth vehicle at period i.

Conversion of Data from Travel Speed to Travel Time

Along with travel speed, travel time is a standard measure of freeway service quality (*37*). Travel time information is an indispensable part of travel information systems (*38*). If the travel data to be evaluated are mainly used for providing travel time information, the conversion of speed data to travel time, which is an inverse of speed, must be considered. Equations 7 through 10 explain how an error in speed can affect the error in travel time.

Let T be the true travel time and T^* be the observed travel time due to an error in speed ΔV.

$$T = \frac{D}{V} \qquad T^* = \frac{D}{V + \Delta V} \tag{7}$$

The error in travel time, ΔT, can be calculated as shown in Equation 8:

$$\Delta T = T^* - T = \frac{D}{V + \Delta V} - \frac{D}{V} \tag{8}$$

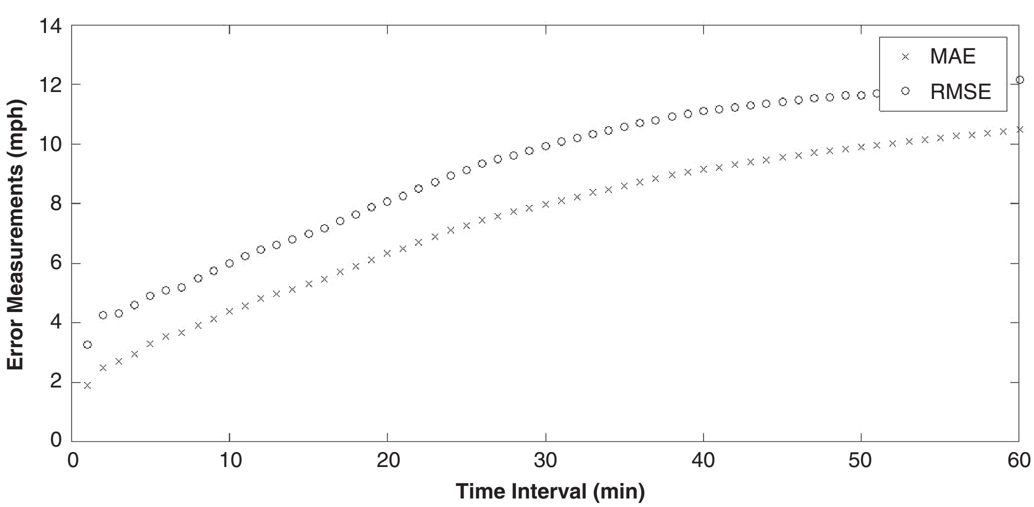


FIGURE 5 Impact of time interval on moving average speed: mean absolute error (MAE) and root mean square error (RMSE) of moving average compared with raw data.

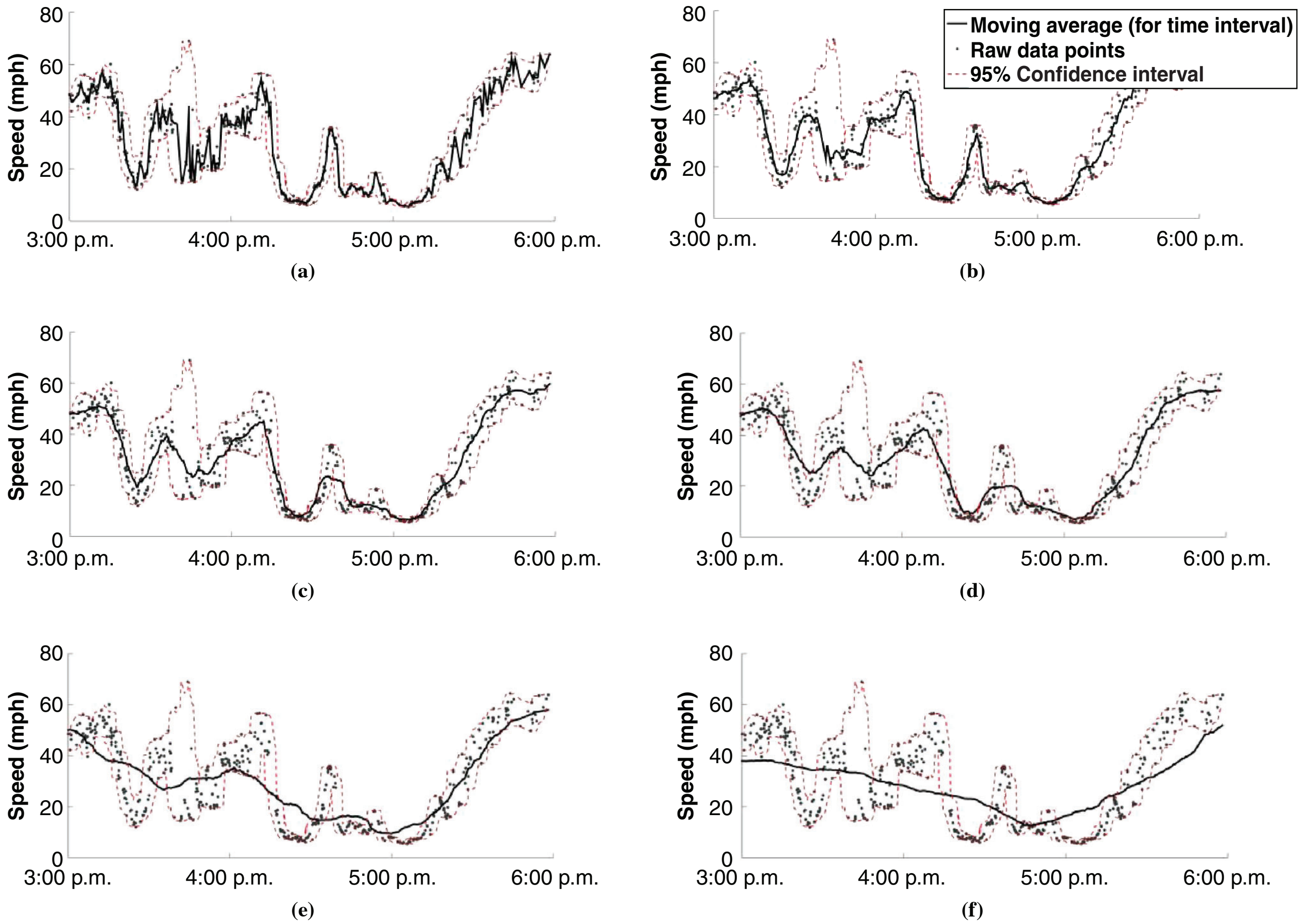


FIGURE 6 Visualization of impact on moving average speed for various time intervals: (*a*) 1 min, (*b*) 5 min, (*c*) 10 min, (*d*) 15 min, (*e*) 30 min, and (*f*) 60 min.

$$\Delta T = D \cdot \left(\frac{-\Delta V}{V(V + \Delta V)} \right) \tag{9}$$

In addition, $\Delta T/T$ is

$$\frac{\Delta T}{T} = \frac{-\Delta V}{V + \Delta V} \tag{10}$$

As Equations 9 and 10 show, the error in travel time (ΔT) gets larger as the true speed (V) gets smaller.

In Figure 7, this increase in the error in travel time becomes more severe as the speed decreases. For instance, when a speed of 15 mph is observed as 10 mph with a segment length of 1 mi, the travel time will be overestimated by 2 min (true travel time being 4 min).

Figure 8 illustrates the difference between using travel time and travel speed as an evaluation target. As the figure shows, the variations in travel times are much higher at low speeds. During the afternoon peak, the range of the 90% confidence interval for travel time is about 200 s, which is more than 10 times that during the off peak, while the difference of 90% confidence interval for travel speed between the afternoon peak and off peak is relatively much smaller. Because of this variation, the evaluation of travel speed data, which is also used for travel time information, may require additional scrutiny.

Elimination of Outliers

Elimination of outliers, like changing the length of a period, can affect the quality and integrity of a data set. Researchers would prefer to have all data, outliers or not, before any elimination decision is made. However, many technologies eliminate data deemed outliers by their own algorithms before researchers even receive the data. In the case of Bluetooth data, proprietary software determines the travel speed but, in the same process, also determines and eliminates all outliers. The basic concept is that any data point beyond three standard deviations from the mean is categorized as an outlier. These elimination algorithms should be studied so that the quality of the data is not inadvertently compromised under certain scenarios.

In the matching procedure of the LPR observations, a method selects certain candidates on the basis of a time window, which is defined by the mean and standard deviation of travel time at each period and thus eliminates outliers.

Often, determining the criteria of outlier elimination has no strong evidence. The common method is to set up the statistical boundary (i.e., confidence interval), with the extreme values outside of the boundaries being treated as outliers. However, those boundaries may be asymmetric, and some of those unusual data points may not be outliers.

One advantage of LPR is that the validation is available as long as the data are stored because the images of license plates are captured.

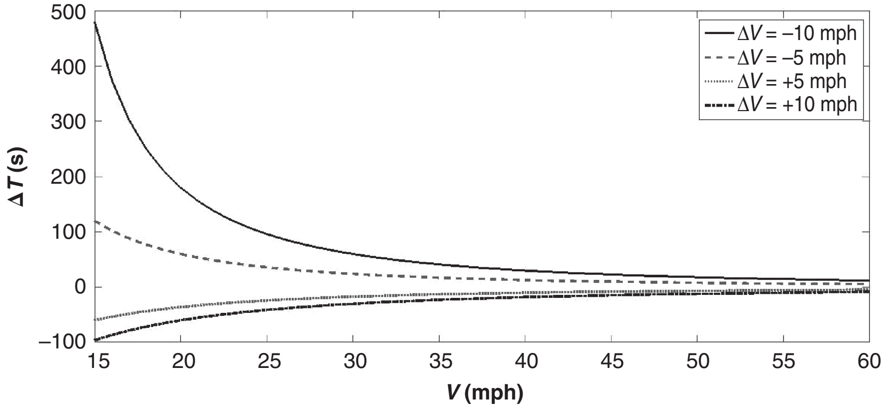
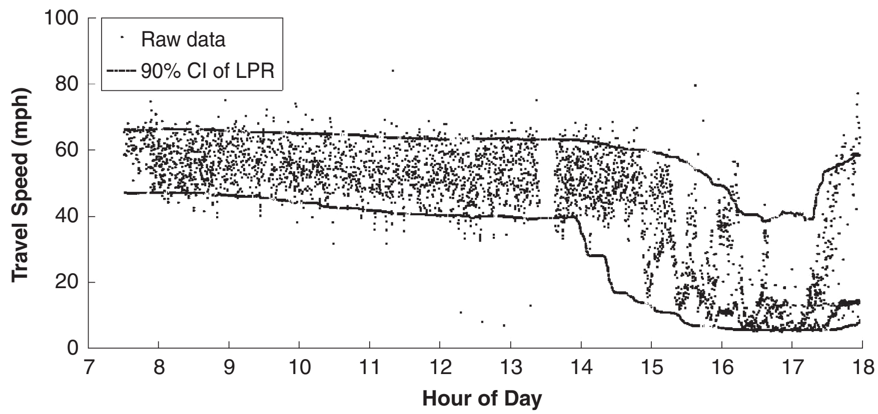
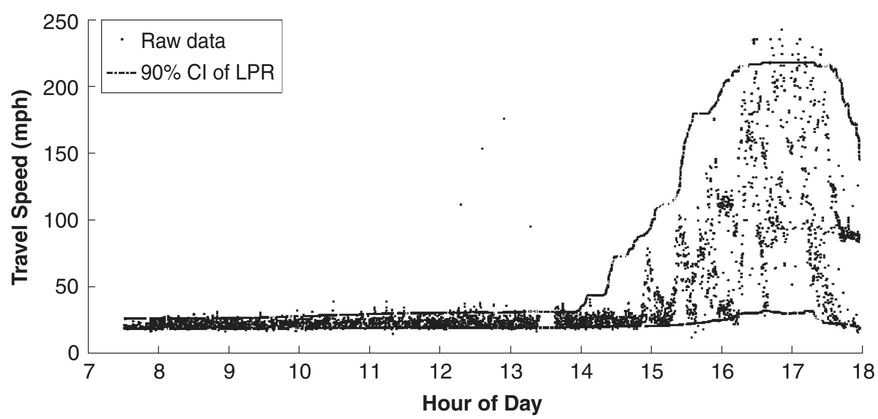


FIGURE 7 Impact of speed differences on travel time for distance of 1 mi.



(a)



(b)

FIGURE 8 Travel speed versus travel time for same data: (*a*) travel speed and (*b*) travel time.

Thus, if researchers visually investigate whether the extreme values are outliers, they might be able to construct a statistical model (such as a probit or logit model) to determine outliers.

EVALUATION OF DATA ACCURACY

With an increased demand for measuring travel data quality, multiple studies have been performed to examine the evaluation process (*11, 16, 18, 20, 39, 40*). One of the well-known comparisons of travel speed data technology was completed by the I-95 coalition by performing 5-min space mean speed validation across four states (*11*). While taking into account the past evaluation methods, the following section discusses the significance of the measurements chosen here, including visual investigation (using travel speed over time, confidence intervals, and histograms) and the calculation of RMSE for travel speeds and times.

Measurements of Errors

Makridakis and Hibon thoroughly examined the measurements of errors for evaluating data or methods with a statistical and practical view (*41*). They concluded that, for general cases, mean square error (MSE) is the most appropriate measurement for selecting a forecasting model, and mean absolute percentage error is most appropriate for evaluating the error of single series. Table 3 shows how the measurements are used for practitioners and academics from Makridakis and Hibon and includes a ranking of the importance for evaluation of travel speed data, which is the subjective views of the current authors (*41*).

MSE is "useful when we are concerned about large errors whose negative consequences are proportionately much bigger [sic] than equivalent smaller ones (e.g., a large error of 100 vs. two smaller ones of 50 each)" (*41*). Thus, using MSE rather than MAE means that larger errors of travel speed are accounted for more than an equivalent amount of smaller errors.

TABLE 3 Use and Importance of Error Measurements

Error Measurement	Type and Extent of Use[a]	Importance of Evaluation of Travel Speed Data[b]
To Report or Use Results of Forecasting Methods		
MSE (RMSE)	*****	+++
MAPE	*****	+++
MAE	***	+++
MdAPE	**	++
GMMSE	*	+
To Compare or Evaluate Methods		
RANKS	****	+
% better	****	++
dMAPE	***	+
Theil's U	**	+
Batting average	**	+
GMRAE	*	+
MdRAE	*	++
MAPE	****	+++
MdAPE	*	++

[a]***** = heaviest use; * = least use.
[b]+++ = high; + = low (subjective views of authors).
SOURCE: Makridakis and Hibon (*41*) (for second-column data).

RMSE is the square root of MSE yields and has the advantage of using the same units as the quantity being estimated. The RMSE is defined as shown in Equation 11:

$$\text{RMSE} = \sqrt{\frac{\sum (X_i - G_i)^2}{N}} = \sqrt{\frac{\sum e_i^2}{N}} \qquad (11)$$

where

X_i = obtained data from other sources at period i,
G_i = ground truth data at period i,
e_i = difference (error) at period i, and
N = number of observations used in computing RMSE.

CONCLUSION AND DISCUSSION

One of this study's goals was to establish an initial framework for determining LPR as a viable ground truth option aside from the key considerations that must be accounted for while evaluating travel speed data sets. To address practical issues along with theoretical aspects, the study investigated multiple data sources to evaluate data accuracy as compared to LPR (ground truth).

By using LPR technology, which admittedly may not be an ultimate solution for obtaining the ground truth, the user can obtain lane-by-lane speed data, relatively high accuracy of time and distance measurements, and identification of each vehicle traveling over the length of roadway. With LPR ground truth collected in accordance with other data sources—namely, RTMS, Bluetooth, and probe vehicle data from private providers—thorough and reliable evaluations become possible.

To proceed with future evaluations of real-time traffic data, a longer period of study at multiple sites involving more technologies would be desirable. The increase in data would allow a more substantial analysis of additional metrics that could be used to describe patterns and trends further. In addition, more investigation of ground truth, such as a required range of measurement error and sample size, should be a key part of future studies.

Additional research is required to evaluate the benefit and potential of fusing RTMS and Bluetooth types of roadside data with those from probe vehicles and cellular services. Because most state agencies have already invested in RTMS type technologies, some degree of fusion of RTMS with other technologies may be an economical option. If the difference between two data sources has a consistent pattern, those multiple data sources could possibly be calibrated to achieve higher accuracy and thereby become reliable data sources for evaluation.

ACKNOWLEDGMENTS

This research effort and associated findings were sponsored by the Tennessee Department of Transportation, the U.S. Department of Transportation's Southeastern Transportation Center, and the University of Tennessee's Chancellor Scholarship program.

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The Standing Committee on Urban Transportation Data and Information Systems peer-reviewed this paper.