



Gregory L. Brinster \*🖻, Jairaj Desai 🔍, Rahul Suryakant Sakhare 🔍, Jijo K. Mathew ២ and Darcy M. Bullock ២

Joint Transportation Research Program, Lyles School of Civil and Construction Engineering, College of Engineering, Purdue University, West Lafayette, IN 47907, USA; desaij@purdue.edu (J.D.); rsakhare@purdue.edu (R.S.S.); kjijo@purdue.edu (J.K.M.); darcy@purdue.edu (D.M.B.) \* Correspondence: gbrinste@purdue.edu

Abstract: The Federal Motor Carrier Safety Administration (FMCSA) and National Highway Traffic Safety Administration (NHTSA) reported that in 2020, 7.3% of large truck driver fatalities had speed as a contributing factor. Several states have implemented truck differential speed limits (DSLs) with the objective of improving safety. This study compares truck speeds in 16 states, 8 of which have implemented DSLs (Arkansas, California, Idaho, Indiana, Michigan, Montana, Oregon, and Washington) and 8 of which have not (Illinois, Kentucky, Minnesota, Oklahoma, South Dakota, Tennessee, Wisconsin, and Wyoming). The DSLs ranged from 55 MPH in California (CA) to 70 MPH in Montana (MT). Over 240,000 speed samples from connected trucks were analyzed during a oneweek period from 15–22 April 2024. The 50th percentile truck speeds ranged from 60 MPH in Oregon to 69 MPH in Wyoming. The 85th percentile truck speeds ranged from 65 MPH in Washington, Oregon, and California to 74 MPH in Wyoming. The 85th percentile speeds across all segments were greater than the posted truck speed limit in 90% of segments with DSLs, but only 12.5% of segments without DSLs. The average interquartile range (IQR) of truck speeds for the eight states with DSLs was 19% smaller than the average IQR of the eight states without DSLs. The methodologies and visuals presented by this study are easily scalable to any route and location provided the availability of a representative connected truck dataset.

Keywords: differential speed limits; connected truck data; truck speeds; safety

# 1. Introduction

The Federal Motor Carrier Safety Administration (FMCSA) [1] and National Highway Traffic Safety Administration (NHTSA) [2] observed that in 2020, 7.3% of large truck crashes (Gross Vehicle Weight Rating (GVWR) > 10,000 lb.) identified speed as a factor in driver fatalities. The Surface Transportation and Uniform Relocation Assistance Act of 1987 and the National Highway Designation Act of 1995 gave U.S. states the ability to set their own speed limits, removing a federal limit of 55 miles per hour (MPH) [3]. Subsequentially, in the mid-1990s, multiple states [4] began implementing differential speed limits (DSLs) that reduced the speed limit for trucks. In doing so, agencies intended to reduce both the frequency and severity of speeding-related truck crashes. Previous research in this domain has focused on evaluating the safety benefit/cost of deploying DSLs [4–8]. Multiple studies concluded that crash rates increased for analyzed segments, regardless of their speed limits being uniform, having a differential, changing from one to another, etc. [4–6]. Other studies concluded that DSLs increase the number of car-truck overtaking maneuvers [7,9], inferring a reduction in overall safety. Aside from differential truck speed limits, other interventional measures have been implemented to improve truck safety by optimizing roadway geometric design, curve radius, and roundabout clearance [10-13]. A 2022 study by Desai et al. [14] utilized connected truck data to analyze the effectiveness of DSLs across Illinois, Indiana, Ohio, and Pennsylvania. This study found that in Indiana, a 5 MPH truck



Citation: Brinster, G.L.; Desai, J.; Sakhare, R.S.; Mathew, J.K.; Bullock, D.M. Expanding on Methodologies for Analyzing Truck Speeds in States with Differential Speed Limits. *Safety* 2024, *10*, 99. https://doi.org/ 10.3390/safety10040099

Academic Editor: Raphael Grzebieta

Received: 26 August 2024 Revised: 18 November 2024 Accepted: 22 November 2024 Published: 26 November 2024



**Copyright:** © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https:// creativecommons.org/licenses/by/ 4.0/). DSL reduction from 70 MPH to 65 MPH resulted in only a 1–2 MPH reduction in truck speeds when compared with control group segments in the neighboring states.

Historically, studies have been completed using Bluetooth probe data to measure travel times [15–20], spatial and temporal performance measures in work zones [21,22], truck identification [23], estimate vehicle count [24], and queueing times near international border crossings [25]. Eliminating the need for individual Bluetooth data scanners, recent research in the connected vehicle (CV) and connected truck (CT) space has been conducted to complete similar studies [26–28]. The CV penetration rate along Indiana roadways increased from approximately 4.3% to 6.3% between 2021 and 2022, while CT penetration was estimated at 3.4% in 2022 [29]. These CV data have been effectively applied to other research topics such as predicting traffic conflicts [30,31], estimating traffic stream density [32], developing adaptive signal control [33], and analyzing the impact of various speed reduction tactics [34]. Similarly, CT data have been leveraged to perform winter-weather after action reports [35], identify long-haul truck parking [36], and estimate truck traffic flow [37]. Both CV and CT data have been critical to recent visualizations of freeway traffic conditions [38].

## 1.1. Research Objective, and Scope

The objective of this research is to expand the sample of both the states with DSLs and the control group states to assess the impact of truck DSLs on truck speeds across a diverse set of states and interstate routes. This study identified 16 states; truck DSLs were implemented in 8 states (Arkansas, California, Idaho, Indiana, Michigan, Montana, Oregon, and Washington), and 8 adjacent states without truck DSLs served as the control group (Illinois, Kentucky, Minnesota, Oklahoma, South Dakota, Tennessee, Wisconsin, and Wyoming). The DSLs ranged from 55 MPH in California (CA) (reduced from 70 MPH) to 70 MPH in Montana (MT) (reduced from 80 MPH).

### 1.2. Study Locations

Figure 1 shows the 18 segments along four interstates across 16 states studied for this analysis. The callouts to the blue dots indicate segment locations used for sampling truck speeds. The first line of the callout shows the abbreviated state name, interstate (I-90/I-69/I-5/I-40), and whether it was a DSL or a control group with a uniform speed limit (USL). The second line indicates the truck speed limit along the segment studied in that state. All segments were approximately 5 miles in length and avoided interchanges, rest areas, and weigh stations to remove potential biases and externalities in the connected truck data.

In order to obtain a better understanding of how differential speed limits impact trucks speeds, it was important to consider all eight states that, as of July 2024, had posted differential speed limits. Including all eight states ensured the most accurate statistical representations and reduced any chance for bias introduced from state selection. Figure 2 shows independently collected commercial vehicle dash camera images showing four DSL values analyzed in the study, ranging from 55 MPH in California (Figure 2a) to 70 MPH in Arkansas (Figure 2d). Strategically selecting states with USLs adjacent to or in between the DSL states allowed for control points along common interstate routes. For example, a section of I-69 in Kentucky (USL) was selected as a control for corresponding sections of I-69 that were selected in Indiana (DSL) and Michigan (DSL).

In all 18 segments, emphasis was placed on avoiding any interchanges, rest areas, and weigh stations, referred to as interruptions in following text, along the five-mile segments. This intentional exclusion was meant to reduce the inconsistencies in truck speed data potentially caused by these features and associated externalities (merging or exiting traffic, for example). In addition, the travel direction was kept consistent across all segments for each of the four interstates (either eastbound or northbound). The geographic environment was also kept very similar, avoiding any major urban areas or extreme curves/grades. In



some cases, it was not possible to completely avoid grade changes, but efforts were made during segment selection to minimize the severity.



**Figure 1.** Map of the United States with DSL states highlighted in yellow, red lines indicating routes chosen for analysis, and blue lines indicating individual 5-mile segments analyzed.









(**d**)

**Figure 2.** Truck dashcam images showing DSL signs for different speeds: (**a**) California DSL on I-5 NB from 70 MPH to 55 MPH; (**b**) Oregon DSL on I-5 NB from 65 MPH to 60 MPH; (**c**) Idaho DSL on I-90 EB from 75 MPH to 65 MPH; (**d**) Arkansas DSL on I-40 EB from 75 MPH to 70.

#### 2. Materials and Methods

#### 2.1. Connected Truck Data

Connected truck trajectory data are currently available from several third-party vendors at a market penetration rate between 1% and 4% [29]. These data contain anonymized speed, heading, timestamp, geopositional coordinates, and a unique vehicle ID with an approximate 10 s reporting frequency. Data are collected through either a direct connection, a third-party telematics device, or a smartphone app.

Connected truck data in this study were reported at a frequency of approximately 10 s for 140,000 unique trucks on average every day. This totaled approximately 225 million records of nationwide truck data every day of the week. These data were then linearly referenced to 0.1-mile spatial polygons along selected interstate routes using existing methodologies (Figure 2.5 from [38]), which could be visualized by spatiotemporal heatmaps [38]. These heatmaps were color-coded based on speeds from the CT data, visualizing the traffic conditions for a specified corridor over a given time. Figure 3 contains three heatmaps along I-5 in Washington (Figure 3a), Oregon (Figure 3b), and California (Figure 3c). These heatmaps aid in detecting instances of recurring or nonrecurring congestion along a route, a vital step in segment selection as well as study period selection for this study.



Figure 3. Cont.



**Figure 3.** Connected truck heatmaps for I-5 northbound segments (15–22 April 2024): (**a**) I-5 segment in Washington (WA-5-DSL); (**b**) I-5 segment in Oregon (OR-5-DSL); (**c**) I-5 segment in California (CA-5-DSL).

#### 2.2. Study Period Selection

Once generated, the 5-mile segment heatmaps were then examined closely to determine a one-week timeframe for the study to take place. Efforts were made to avoid any significant traffic events that may have taken place during the 7-day period. Figure 3b shows a moderate reduction in speeds between mile markers (MMs) 90 and 91 on I-5 northbound (N) in Oregon, but this reduction in speeds was consistent throughout the week and even across multiple weeks. This consistency indicated that roadway geometry may have played a factor in this systematic reduction of truck speeds for that given corridor. Because of the frequently spaced interchanges along I-5 in Oregon, this was the only segment possible for a 5-mile analysis and hence was considered for this study.

### 2.3. Truck Speeds

Summary statistics of connected truck speeds observed on the 18 selected segments for the week of 15–22 April 2024 were computed and tabulated. These truck speeds were separated into 25th, 50th, 75th, and 85th percentiles. Data for the segments with differential speed limits can be found in Table 1(a), and those for the segments with uniform speed limits can be found in Table 1(b). Cells shaded in red indicate speeds that were greater than the posted truck speed limits. The final column shows the difference between the observed 85th percentile speeds and the posted truck speed limit, especially because of the 85th percentile speed being the widely considered threshold to determine vehicles exceeding the safe speed limits designated for a particular roadway and its traffic conditions [39]. Only speed records between 0 MPH and 100 MPH were considered for the analysis in order to exclude outliers and account for data reporting issues.

ID	MM Range	Speed Limit	Truck Speed Limit	# of Trips	25th Percentile Speed (MPH)	50th Percentile Speed (MPH)	75th Percentile Speed (MPH)	85th Percentile Speed (MPH)	+/— of 85th Percentile from Truck Speed Limit
					(a)				
MI-69-DSL	170–175	75	65	183	64.62	65.23	66.93	67.73	2.73
IN-69-DSL	290–295	70	65	2495	64	65.24	67.73	69	4
WA-5-DSL	83.1-88.1	70	60	2365	60.27	62.76	64.62	64.62	4.62
OR-5-DSL	90–95	65	60	1513	55.3	59.65	63	64.62	4.62
CA-5-DSL	359–364	70	55	2959	59.02	61	63.38	64.62	9.62
WA-90-DSL	256-261	70	60	1148	62	64	64.94	65.87	5.87
ID-90-DSL	33.5–38.5	75	65	418	60.89	64	66	67.94	2.94
MT-90-DSL	383.5–388.5	80	70	605	64.62	68	70	70.21	0.21
IN-90-DSL	32–37	70	65	2368	63.38	65	67.11	68.35	3.35
AR-40-DSL	48–53	75	70	2505	63.38	65	67.73	69.59	-0.41
					(b)				
ID	MM Range	Speed Limit	Truck Speed Limit	# of Trips	25th Percentile Speed (MPH)	50th Percentile Speed (MPH)	75th Percentile Speed (MPH)	85th Percentile Speed (MPH)	+/— of 85th Percentile from Truck Speed Limit
KY-69-USL	95-100	70	70	615	64	65.87	68.97	70	0
WY-90-USL	194–199	80	80	115	65.06	68.97	72	74	-6
SD-90-USL	195–200	80	80	244	64.62	68.35	72	73	-7
MN-90-USL	52–57	70	70	282	65	67	71	72.08	2.08
WI-90-USL	56-61	70	70	1955	64	65.24	68	69.59	-0.41
IL-90-USL	30–35	70	70	2336	62.76	64.62	65.87	67.11	-2.89
OK-40-USL	241-246	75	75	1288	64.62	67	70	71.03	-3.97
TN-40-USL	33.5-38.5	70	70	4585	64	65.24	68	69.59	-0.41

**Table 1.** Summary of connected truck speed statistics for 18 selected segments: (a) segments with differential speed limits; (b) segments with uniform speed limits. Speeds above posted truck speed limit are shaded in red.

Cells shaded in red indicate speeds that were greater than the posted truck speed limits.

### 3. Results

#### 3.1. Cumulative Frequency Diagrams

To better visualize the truck speeds, cumulative frequency diagrams (CFD) were used. Figure 4a plots CFDs for all 18 segments analyzed in this study, while Figure 4b,c plot only segments with DSLs and USLs, respectively. These diagrams represent truck speed on the horizontal axis and cumulative distribution on the vertical axis. Circle and rhombus indicators are placed along each of the colored traces to identify the truck speed limit for that specific segment. DSL segments are marked with a colored circle and thick line, while USL segments are marked with a rhombus and a thin line. Figure 4a presents readers the opportunity to visually compare the trends between segments with and without DSLs.

From the plots in Figure 4, it is apparent that the DSL states generally observed lower truck speeds. This reduction, however, was marginal compared with the reduction in speed limit. The speed limit indicators in Figure 4b were scattered, with most at or below the 50th percentile, while all but one of the USL segments were at or above the 85th percentile. Nearly all the USL segments experienced more than 85% of trucks traveling below the posted speed limit, while only about 50% of trucks did so along DSL segments. A similar trend can be seen in Table 1, where 5 of the 10 DSL segments were above the speed limit (shaded red) in the 50th percentile column, but only one of the USL segments experience 85th percentile speeds above the posted limit.

Another valuable metric when comparing CFDs is the interquartile range (IQR). Each segment's IQR was calculated by subtracting the 25th percentile speed from the 75th percentile speed. This IQR value quantifies the spread among the data, where higher numbers indicate a greater spread. One way to visualize the IQR is by looking at the

slope of the CFDs between the 25th and 75th percentiles. Thick black horizontal lines were added at these intervals for better viewing in Figure 4. Looking at Figure 4a, the thick lines, representing DSLs, had a "steeper" or greater slope than the thin lines, representing USLs. This same trend can be seen when the graphs are split by speed limit type in Figure 4b,c.



**Figure 4.** Cumulative distribution of truck speeds for all selected segments: (**a**) all segments; (**b**) only DSL segments; (**c**) only USL segments.

These steeper slopes correlate to a smaller average IQR value. It was found that the average IQR for DSL segments was 19% lower than the average IQR for USL segments. The IQR values found in this study were 4.4 MPH and 5.2 MPH for DSL and USL segments, respectively. This suggests that trucks traveled at a more consistent speed through DSL segments than through USL segments.

In order to remove the difference in speed limits, a relative CFD can be plotted, as found in Figure 5. These plots take the same data as Figure 4 but center them about the individual speed limits. Marked by the single black vertical line, the "0" value represents the relative speed limit for each individual segment. Each segment is colored based on its posted truck speed limit, such as California at 55 MPH, see trucks following a greater speed relative to the posted limit. Segments with higher truck speed limits, such as Wyoming at 80 MPH, see the vast majority of trucks traveling at a lower speed relative to the posted limit. Figure 5a demonstrates an interesting trend, as the colors follow a similar trend, aside from a couple of outliers, from red to purple. This trend is independent from the speed limit type; USL and DSL segments both follow this same trend. Figure 5b,c show the same plotting scheme, but for only the DSL and USL segments, respectively.



**Figure 5.** Difference between posted speed and observed truck speeds for all selected segments: (a) all segments; (b) only DSL segments; (c) only USL segments.

Combining the concepts of Figures 4 and 5, it is possible to separate the segments into groups based on the passenger car speed limit. In one case, Figure 6 looks at the three segments with an 80 MPH passenger car limit. Two of the segments, along I-90 in South Dakota and Wyoming, were USL segments, while the lone DSL segment was along I-90 in Montana. This DSL segment in Montana had a truck speed limit of 70 MPH, a reduction of 10 MPH. This truck speed limit began reducing the observed truck speeds around the 50th percentile, pointed out by callout i in Figure 6. By the 75th percentile (Figure 6 callout ii), observed truck speeds were reduced by approximately 2 MPH compared with the two other USL routes.



Figure 6. Absolute truck speeds for all segments with 80 MPH passenger car speed limits.

#### 3.2. Statistical Analysis

In order to determine the statistical significance of implementing differential speed limits, a hypothesis test was created. This hypothesis test aimed to determine if the mean speeds along two corridors, one with differential speed limits and another with uniform speed limits, were significantly different from one another. In order to ensure the integrity of this test, segments along the same route in two states were selected. The segments both had the same passenger car speed; one segment had a USL, and the other had a DSL. The results for the *t*-tests, at a 95% confidence interval, can be seen in Table 2.

Table 2. *t*-test results for three sample comparisons.

Comparison Segments		Speed Difference Threshold (MPH)	Sample Size		Mean Speed (MPH)		Standard Deviation (MPH)		<i>p</i> -Value	Statistically Significant?	
Route	State 1 (USL)	State 2 (DSL)		State 1	State 2	State 1	State 2	State 1	State 2		
I-69	KY (70)	IN (70–65)	0	4309	21,362	65.317	65.197	8.762	5.778	0.194	No
I-40	OK (75)	AR (75–70)	2	8969	14,807	66.895	64.677	7.350	7.673	0.015	Yes
I-90	WY (80)	MT (80–70)	1	742	3655	68.848	67.068	5.280	6.251	< 0.001	Yes

Looking at the above results, it can be concluded that some DSLs did not lead to a statistically significant reduction in mean truck speeds, while others did. Along I-69 in Kentucky and Indiana, a 5 MPH reduction in Indiana, from 70 to 65 MPH, did not correlate with a statistically significant reduction in mean truck speeds. Conversely, along I-40 in

Oklahoma and Arkansas, a 5 MPH reduction in Arkansas significantly correlated to a 2 MPH reduction in mean truck speeds.

## 4. Conclusions

With the increasing frequency and widespread availability of connected truck data, the methodology and visuals outlined in this paper provide a framework to scale a small-focus case study to a nationwide analysis over any given period of time and corridor of choice. It can similarly be scaled to any route, not just interstates, as long as the penetration rate is sufficient to aid in data-driven decision-making processes for roadway infrastructure as it relates to truck traffic (freight priority corridors, dedicated truck lanes, setting speed limits, and weigh station and rest area placement to name a few).

This study applied methodologies previously outlined to analyze the statistical relationship between reduced differential truck speed limits and observed truck speeds. Eighteen unique five-mile segments across four interstates, independent of interchanges, rest areas and weigh stations, were identified and analyzed. These segments covered all eight states that deploy DSLs and eight adjacent states that follow USLs (Figure 1). Aggregating over 240,000 speed samples showed very little statistical reduction in speeds due to DSLs. Along I-40, Arkansas experienced a 1–2 MPH decrease in 85th percentile speeds when a DSL reduced the limit from 75 MPH in Oklahoma to 70 MPH in Arkansas. Conversely, when the truck speed limit was reduced from 70 MPH in Illinois to 65 MPH in Indiana along I-69, 85th percentile truck speeds increased by 1–2 MPH. A segment of I-5 in California with 55 MPH reduced speeds experienced identical 85th percentile truck speeds as a segment in Oregon with 60 MPH reduced speeds (Figures 4 and 5). It was concluded that the IQR for DSL segments was, on average, 19% less than that for USL segments, a reduction of 0.8 MPH. This correlates to a more consistent observed truck speed through DSL segments than through USL segments.

Although these data are scalable to any market with CT data, various limitations exist. The largest limitation of this study is the usage of one commercial CT data provider. This narrows the scope of the analysis and could lead to possible bias. The data used in this study were also very large in nature and required a significant investment into both storage and management. Similar studies have been conducted in the CV space and found that approximately 500 billion records, covering all 50 U.S. states, occupied tens of TBs (terabytes) of data [40]. The CT data used in this study were reported at a 10–60 s frequency and took approximately 30 min for ingestion and storage.

**Author Contributions:** Conceptualization, D.M.B.; formal analysis, investigation, methodology, and validation, G.L.B., J.D., R.S.S., J.K.M. and D.M.B.; software, G.L.B., J.D., R.S.S. and J.K.M.; writing—original draft preparation, G.L.B., J.D. and D.M.B.; writing—review and editing, G.L.B., J.D., R.S.S., J.K.M. and D.M.B.; supervision, D.M.B. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the Joint Transportation Research Program. This work was funded through agreement between Purdue University and Indiana Department of Transportation.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

**Data Availability Statement:** The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author(s).

**Acknowledgments:** Connected truck data between 15 April and 22 April 2024 used in this study was provided by Omnitracs LLC (Westlake, TX, USA). Commercial vehicle dash camera images used by this study were provided by Vizzion Ltd. (North Vancouver, BC, Canada). This study is based on work supported by the Joint Transportation Research Program administered by the Indiana Department of Transportation and Purdue University. The contents of this paper reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein, and do

not necessarily reflect the official views or policies of the sponsoring organizations. These contents do not constitute a standard, specification, or regulation.

Conflicts of Interest: The authors declare no conflict of interest.

### References

- 1. Large Truck and Bus Crash Facts 2020–PFMCSA. Available online: https://www.fmcsa.dot.gov/safety/data-and-statistics/large-truck-and-bus-crash-facts-2020 (accessed on 9 July 2024).
- 2. Speeding-NHTSA. Available online: https://www.nhtsa.gov/risky-driving/speeding (accessed on 9 July 2024).
- Friedman, L.S.; Hedeker, D.; Richter, E.D. Long-Term Effects of Repealing the National Maximum Speed Limit in the United States. Am. J. Public Health 2009, 99, 1626–1631. [CrossRef]
- Sun, X.; Garber, N.J. "Determining the Safety Effects of Differential Speed Limits on Rural Interstate Highways Using Empirical Bayes Method", Art. no. UVACTS-14-5-36, May 2002. Available online: https://trid.trb.org/View/806239 (accessed on 9 July 2024).
- Garber, N.J.; Miller, J.S.; Yuan, B.; Sun, X. Virginia Transportation Research Council, "Safety Impacts of Differential Speed Limits on Rural Interstate Highways", FHWA-HRT-05-042, October 2005. Available online: https://rosap.ntl.bts.gov/view/dot/817 (accessed on 9 July 2024).
- 6. Garber, N.J.; Miller, J.S.; Sun, X.; Yuan, B. Safety Impacts of Differential Speed Limits for Trucks and Passenger Cars on Rural Interstate Highways: A Modified Empirical Bayes Approach. *J. Transp. Eng.* **2006**, *132*, 19–29. [CrossRef]
- Ghods, A.H.; Saccomanno, F.; Guido, G. Effect of Car/Truck Differential Speed Limits on Two-lane Highways Safety Operation Using Microscopic Simulation. *Procedia Soc. Behav. Sci.* 2012, 53, 833–840. [CrossRef]
- 8. Russo, B.J.; Rista, E.; Savolainen, P.T.; Gates, T.J.; Frazier, S. Vehicle Speed Characteristics in States with Uniform and Differential Speed Limit Policies. *Transp. Res. Res. J. Transp. Res. Board* **2015**, 2492, 1–9. [CrossRef]
- 9. Khondaker, B.; Kattan, L. Variable speed limit: An overview. Transp. Lett. 2015, 7, 264–278. [CrossRef]
- Alrejjal, A.; Ksaibati, K. Impact of mountainous interstate alignments and truck configurations on rollover propensity. J. Saf. Res. 2022, 80, 160–174. [CrossRef] [PubMed]
- 11. Godavarthy, R.P.; Russell, E.R. Low-Clearance Truck's Vertical Requirements at Roundabouts. J. Transp. Technol. 2015, 5, 214–222. [CrossRef]
- 12. Shin, J.; Lee, I. Reliability-Based Vehicle Safety Assessment and Design Optimization of Roadway Radius and Speed Limit in Windy Environments. *J. Mech. Des.* **2014**, *136*, 081006. [CrossRef]
- 13. Bucklew, K.J. Improving Freight Roadway Transportation with Dedicated Truck Lanes: Opportunities and Issues. *Transp. J.* **2011**, 50, 431–445. [CrossRef]
- 14. Desai, J.; Mathew, J.K.; Li, H.; Bullock, D.M. Using Connected Truck Trajectory Data to Compare Speeds in States with and without Differential Truck Speeds. *J. Transp. Technol.* **2022**, *12*, 681–695. [CrossRef]
- Aliari, Y.; Haghani, A. Bluetooth Sensor Data and Ground Truth Testing of Reported Travel Times. *Transp. Res. Rec.* 2012, 2308, 167–172. [CrossRef]
- Yuan, D.; Faghri, A.; Partridge, K. A Study on Applications and Case Studies Regarding Bluetooth Technology for Travel Time Measurement. J. Transp. Technol. 2019, 10, 65–87. [CrossRef]
- 17. Haghani, A.; Hamedi, M.; Sadabadi, K.F.; Young, S.; Tarnoff, P. Data Collection of Freeway Travel Time Ground Truth with Bluetooth Sensors. *Transp. Res. Rec.* 2010, 2160, 60–68. [CrossRef]
- Young, S.E. Bluetooth Traffic Detectors for Use as Permanently Installed Travel Time Instruments; MD-12-SP909B4D; University of Maryland Center for Advanced Transportation Technology: College Park, MD, USA, 2012. Available online: https://rosap.ntl.bts. gov/view/dot/23851 (accessed on 10 November 2024).
- 19. Wang, Y.; Malinovskiy, Y.; Wu, Y.J.; Lee, U.K.; Neeley, M. *Error Modeling and Analysis for Travel Time Data Obtained*; Washington State Department of Transportation: Washington, DC, USA, 2011.
- 20. Diaz, J.J.V.; Gonzalez, A.B.R.; Wilby, M.R. Bluetooth Traffic Monitoring Systems for Travel Time Estimation on Freeways. *IEEE Trans. Intell. Transp. Syst.* 2016, 17, 123–132. [CrossRef]
- 21. Wasson, J.S.; Boruff, G.W.; Hainen, A.M.; Remias, S.M.; Hulme, E.A.; Farnsworth, G.D.; Bullock, D.M. Evaluation of Spatial and Temporal Speed Limit Compliance in Highway Work Zones. *Transp. Res. Rec.* **2011**, 2258, 1–15. [CrossRef]
- Mudge, R.; Mahmassani, H.S.; Haas, R.; Talebpour, A.; Carroll, L. United States. Federal Highway Administration. Office of Operations, "Work Zone Performance Measurement Using Probe Data", FHWA-HOP-13-043, September 2013. Available online: https://rosap.ntl.bts.gov/view/dot/42244 (accessed on 10 November 2024).
- 23. Nadi, A.; Snelder, M.; Tavasszy, L.; Sharma, S. Truck identification on freeways using Bluetooth data analysis. In *Transportation Research Procedia*; Elsevier: Amsterdam, The Netherlands, 2018.
- 24. Gheorghiu, R.A.; Iordache, V.; Cormoș, A.C. Analysis of the Possibility to Detect Road Vehicles via Bluetooth Technology. *Sensors* 2021, 21, 7281. [CrossRef] [PubMed]
- Sell, N.L. "Empirical Investigations of Queuing and Surface Street Times Using Truck Probe Data Around International Border Crossings". The Ohio State University. 2014. Available online: https://etd.ohiolink.edu/acprod/odb\_etd/etd/r/1501/10?clear= 10&p10\_accession\_num=osu1405682680 (accessed on 10 November 2024).

- Camargo, P.; Hong, S.; Livshits, V. Expanding the Uses of Truck GPS Data in Freight Modeling and Planning Activities. *Transp. Res. Rec.* 2017, 2646, 68–76. [CrossRef]
- Li, Y.; Zhao, L.; Rilett, L.R. Driving Performances Assessment Based on Speed Variation Using Dedicated Route Truck GPS Data. IEEE Access 2019, 7, 51002–51013. [CrossRef]
- Wang, Z.; Goodchild, A.; McCormack, E. Measuring Truck Travel Time Reliability Using Truck Probe GPS Data. J. Intell. Transp. Syst. 2016, 20, 103–112. [CrossRef]
- Sakhare, R.S.; Hunter, M.; Mukai, J.; Li, H.; Bullock, D.M. Truck and Passenger Car Connected Vehicle Penetration on Indiana Roadways. J. Transp. Technol. 2022, 12, 578–599. [CrossRef]
- Islam, Z.; Abdel-Aty, M. Traffic conflict prediction using connected vehicle data. Anal. Methods Accid. Res. 2023, 39, 100275. [CrossRef]
- 31. Anik, B.M.T.H.; Islam, Z.; Abdel-Aty, M. inTformer: A Time-Embedded Attention-Based Transformer for Crash Like-lihood Prediction at Intersections Using Connected Vehicle Data. *arXiv* 2023, arXiv:2307.03854. [CrossRef]
- 32. Aljamal, M.A.; Abdelghaffar, H.M.; Rakha, H.A. Estimation of Traffic Stream Density Using Connected Vehicle Data: Linear and Nonlinear Filtering Approaches. *Sensors* 2020, 20, 4066. [CrossRef]
- Yao, Z.; Jiang, Y.; Zhao, B.; Luo, X.; Peng, B. A dynamic optimization method for adaptive signal control in a connected vehicle environment. J. Intell. Transp. Syst. 2020, 24, 184–200. [CrossRef]
- Mathew, J.K.; Desai, J.; Li, H.; Bullock, D.M. Using Anonymous Connected Vehicle Data to Evaluate Impact of Speed Feedback Displays, Speed Limit Signs and Roadway Features on Interstate Work Zones Speeds. J. Transp. Technol. 2021, 11, 545–560. [CrossRef]
- 35. Desai, J.; Mahlberg, J.; Kim, W.; Sakhare, R.; Li, H.; McGuffey, J.; Bullock, D.M. Leveraging Telematics for Winter Operations Performance Measures and Tactical Adjustment. *J. Transp. Technol.* **2021**, *11*, 611–627. [CrossRef]
- Nevland, E.A.; Gingerich, K.; Park, P.Y. A data-driven systematic approach for identifying and classifying long-haul truck parking locations. *Transp. Policy* 2020, 96, 48–59. [CrossRef]
- 37. Wang, S.; Zhao, J.; Shao, C.; Dong, C.D.; Yin, C. Truck Traffic Flow Prediction Based on LSTM and GRU Methods with Sampled GPS Data. *IEEE Access* 2020, *8*, 208158–208169. [CrossRef]
- Sakhare, R.S.; Desai, J.; Mathew, J.; McGregor, J.; Kachler, M.; Bullock, D. Measuring and Visualizing Freeway Traffic Conditions: Using Connected Vehicle Data; JTRP Affiliated Reports; Purdue University: West Lafayette, IN, USA, 2024. [CrossRef]
- 39. FHWA Speed Information. Available online: https://safety.fhwa.dot.gov/uslimits/notes/speed\_info.htm (accessed on 26 July 2024).
- 40. Desai, J.; Mathew, J.; Li, H.; Sakhare, R.S.; Horton, D.; Bullock, D. *National Mobility Analysis for All Interstate Routes in the United States: December 2022*; Indiana Mobility Reports; Purdue University: West Lafayette, IN, USA, 2022. [CrossRef]

**Disclaimer/Publisher's Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.