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Truck and Passenger Car Connected Vehicle Penetration on Indiana Roadways

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Abstract

Commercially available connected vehicle (CV) probe data has been demonstrated to provide scalable and near-real-time methodologies to evaluate the performance of road networks for various applications. However, one of the major concerns of probe data for agencies is data sampling, particularly during low-volume overnight hours. This paper reports on an evaluation that looked at both connected passenger cars and connected trucks. This study analyzed 40 continuous count stations in Indiana that recorded more than 10.8 million vehicles and more than 13 million trips (3 billion records) from CV data over a 1-week period from May 9th to 15th in 2022. The average truck penetration was observed to be 3.4% during overnight hours from 1 AM to 5 AM when the connected passenger car penetration was at the lowest. When both connected trucks and connected car penetration were analyzed, the overall CV penetration was 6.32% on interstates and 5.30% on non-interstate roadways. The paper concludes by recommending that both connected car and connected truck data be used by agencies to increase penetration and reduce the hourly variation in CV penetration. This is particularly important during overnight hours.

Keywords

Connected Vehicle Data, Trucks, Penetration, Big Data

1. Introduction

The Federal Highway Administration reported 3.26 trillion vehicle-miles travelled (VMT) on United States roadways in 2019 [1]. One fourth of the VMT were on Interstates. Of the total, 0.3 trillion (around 10%) VMT were accumulated from single-unit or combination trucks. On Indiana roadways, trucks accumulated 9.7 billion VMT out of 82.7 billion total VMT [1] [2]. Trucks are important contributor to the traffic conditions on roadways. It becomes critical part of traffic data that is used to assess the transportation system performance.

In recent years, connected vehicle (CV) probe data has emerged as an important and scalable data set. In August 2020, more than 167 billion passenger car trajectory waypoints were collected across 11 states [3]. Granular information received from individual vehicles have been curated for a variety of applications such as work zone monitoring [4] [5] [6], assessment of winter operations [7] [8], performance at intersections [9] [10] [11] and assessment of roadways in general [3] [12] [13] [14].

One of the major concerns for agencies is representativeness of the CV data from two aspects: sample size for accurately providing information about traffic conditions and mix of different vehicle classes. A past study has shown that penetration of CV data was around 4.3% on interstates [15] suggesting acceptable penetration levels for developing scalable roadway performance measures. However, it consisted of majority passenger cars. Inclusion of trucks as part of the CV data is important for measuring the entire traffic stream, especially in Indiana where trucks can comprise over 40% of traffic on some interstate routes [2]. Providers of commercially available CV data have recently incorporated truck data as part of the total CV data set. This study reports on the penetration of CV data for both truck and passenger cars.

2. Literature Review

Transportation agencies need timely and representative traffic data to assess transportation needs, evaluate system performance and to develop highway planning and programming recommendations. It also plays a very important role in route planning and in the design of highway projects. The state-of-the- practice infrastructure-based traffic monitoring mainly consists of loop detectors [16] [17] [18] [19] [20], cameras [21] [22] [23] and radar [24] [25] [26]. Installation and maintenance for such technologies incur substantial costs and may be prohibitive for scalable systemwide deployment [27] [28] [29] [30]. In the past two decades, probe-based, non-intrusive methods to collect traffic data were developed to monitor performance without infrastructure.

As early as 1999, collecting traffic data from tracking cellular phone or GPS was a technologically feasible and cost-effective alternative. GPS based travel time data was used to evaluate agency infrastructure in Louisiana [31]. By the early 2010s, crowdsourced probe vehicle data became available to both drivers and agencies through many providers and smartphone applications [32] [33] [34]. While data gathered from smartphones was the main component to this crowdsourced data, some providers incorporated GPS-enabled vehicles as well [35] [36]. In the following years, many studies have been conducted to understand the accuracy of these datasets. A study conducted on 2500 miles of roadway on and around I-95 evaluated commercially provided probe travel time and speed data [37]. A two-month study compared probe data speeds to speeds obtained from loop detectors [36]. Studies have compared probe data to Bluetooth sensors with a focus on arterials and surface streets [35] [38] [39]. A multi-year study compared probe data to radar sensors [40]. Several CV data providers emerged in recent years that directly collected data from original equipment manufacturers (OEMs) or provided aggregate data from combination of several sources.

CV trajectory data, which contains individual vehicle locations, timestamp, speed, heading, and anonymized trip identifiers from onboard sensors is gaining in popularity as agencies and practitioners are starting to incorporate the data into their business processes. Over the past several years, many studies focused on creating methodologies for evaluating road networks at low penetration. A study conducted by Zhang *et al.* found that a 4% penetration was sufficient to improve ramp metering performance [41]. However, studies by Day *et al.* found that aggregated data at penetration levels as low as 0.09% - 0.8% would provide acceptable levels of representation for corridor retiming given a large enough aggregation period [42] [43].

While connected vehicle data has led to the creation of several new techniques to evaluate road networks [3] [4] [5] [6] [7] [9] [10] [11] [14] [44] [45] [46] [47], few studies have looked at CV penetration rates. In 2016, Li *et al.* compared loop detectors counts to vehicle trajectory counts and found an average percent penetration of 1.1% with a range of 0.2% to 2.0% depending on the time of day [48]. A past study also observed the passenger car penetration in August 2020 ranged from 3.9% in Pennsylvania to 4.6% in Indiana [15] [49].

Ease of scalability and widespread application makes CV data very useful and critical for timely assessment of roadway performance. However, many agencies are concerned about the representativeness of the CV data. Previous study by Hunter [50] calculated penetration of CV data for passenger cars. Penetration rate was observed adjacent to selected count stations in the states of California, Connecticut, Georgia, Indiana, Minnesota, North Carolina, Ohio, Pennsylvania, Texas, Utah, and Wisconsin. For this study, 381 continuous count stations were selected to be geographically distributed, represent both interstate and non-interstate roadways, have a variety of traffic volumes, and to be in both rural and urban environments as shown in **Figure 1**.

The traffic counts for the 381 count stations were obtained from their respective state DOTs. These were compared against the regional CV data of passenger cars. **Figure 2** shows the penetration rate for interstates and non-interstate roadways across eleven states in August 2021. In general, penetration rates were higher for non-interstate roadways compared to interstates with exception of Georgia, and Ohio. For interstate stations, the lowest percent penetration was a California station with a percent penetration of 2.1%. Meanwhile, for non-interstate stations, an Indiana station had the lowest percent penetration at 1.6%. For both interstate and non-interstate categories, Wisconsin had the stations with the highest percent penetration, 18% for an interstate station and 10% for a non-interstate station. The median values across all eleven states were 4.1% and 4.3% for interstate and non-interstates, respectively. Penetration was observed to

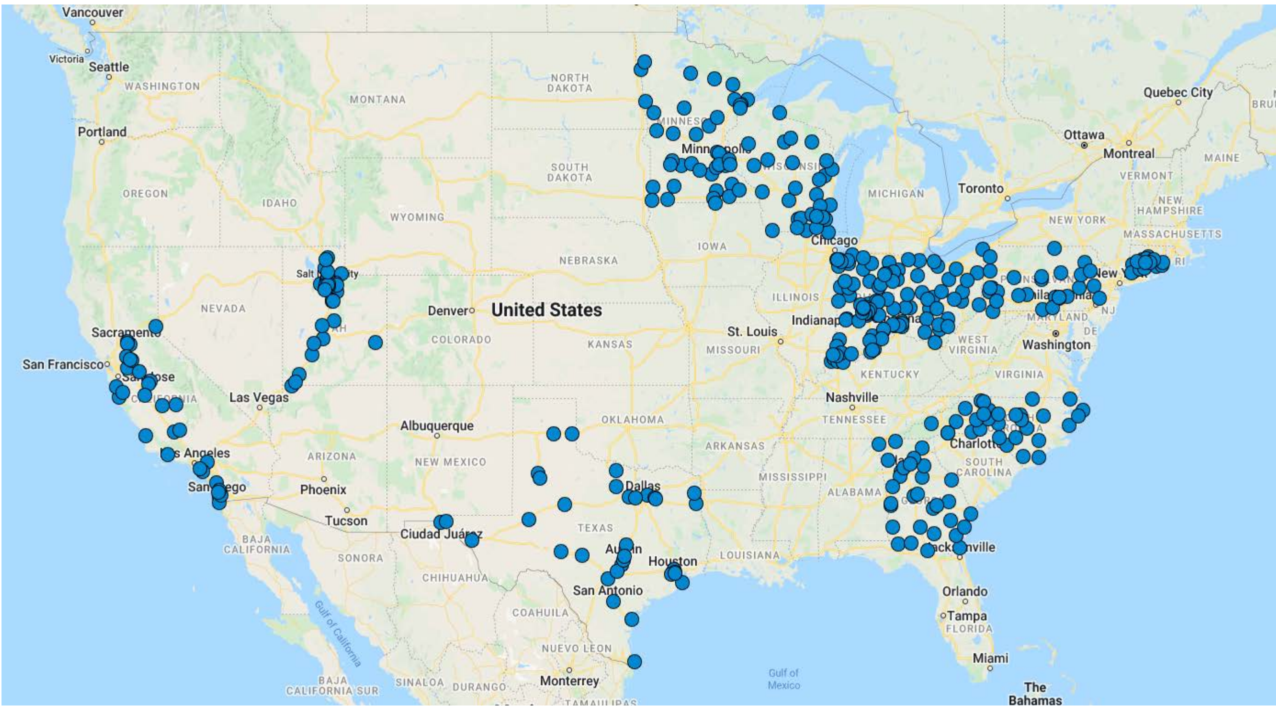


Figure 1. Locations of 386 count station across eleven states analyzed for passenger car penetration [50].

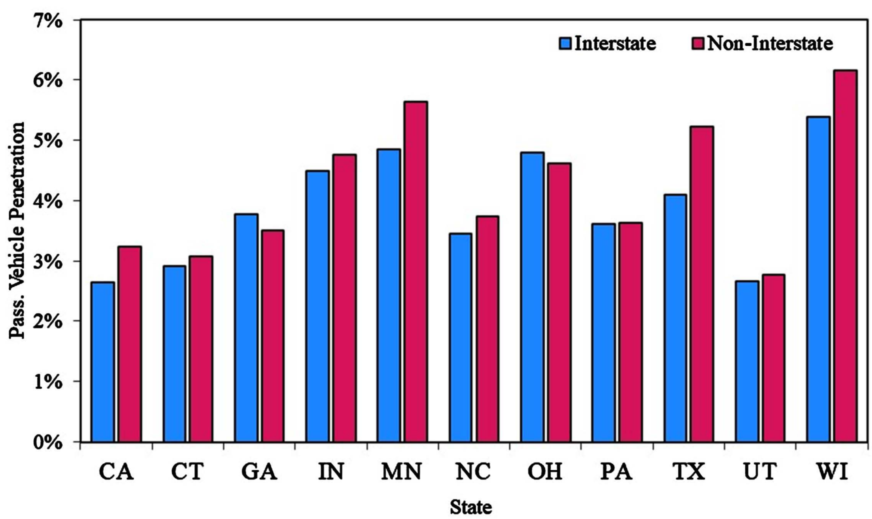


Figure 2. Passenger car penetration on interstates and non-interstate roadways across eleven states in August 2021 [50].

be highest in Wisconsin and lowest in Utah [50]. However, the previous studies consisted of only passenger cars and did not have CV data for trucks as part of the study. Trucks are one of the key parts of the traffic stream. This study reports on the penetration of CV data for both trucks and passenger cars.

3. Data Description

1) Traffic Count Data

The traffic counts were obtained from Indiana Department of Transportation's

(DOT's) traffic count database system [2] and are considered the ground truth vehicle counts. Many different technologies are utilized at continuous count stations, such as inductive loops, piezoelectric sensors, and magnetic sensors [51]. Indiana DOT's Statewide Traffic Monitoring System consists of permanent continuous count stations that can collect volume, speed, and vehicle classification data 24 hours per day throughout the year [52].

For the purposes of this study, data from 40 such count stations (**Figure 3**) was obtained for the period of 1 week between Monday, May 9th and Sunday, May 15th, 2022. An example count station located on I-65 mile marker (MM) 47, utilizes inductive loops shown by callout i in **Figure 3**. Out of the 40 count stations, 19 were along interstates (shown by red circles in **Figure 3**) and remaining 21 were along non-interstate roadways (shown by blue circles in **Figure 3**) covering different geographical areas of the state. **Table 1** provides summary of these count stations along with Annual Average Daily Traffic (AADT) for 2021. The traffic count data was grouped hourly at each of the location along with vehicle classification information for further analysis.

A total of 10.88 million vehicles were recorded across 40 stations over the 7-day analysis period. Of which, 9.03 million were at interstate stations and 1.85 million at non-interstate stations. **Figure 4** shows the hourly total vehicle volume

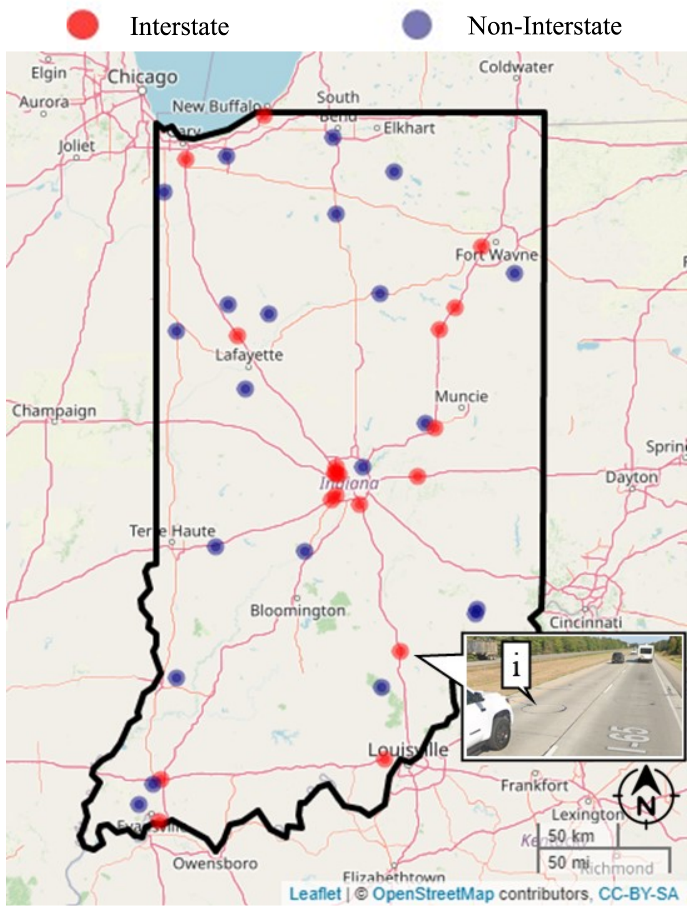


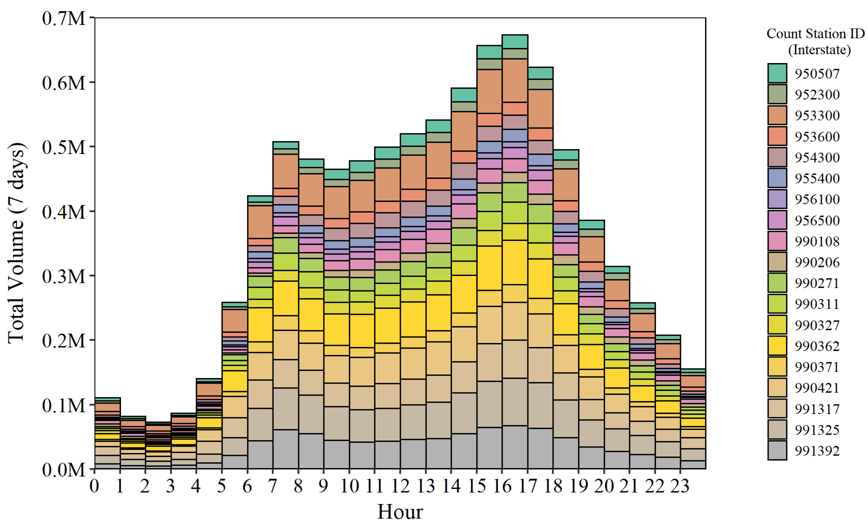
Figure 3. Locations of 40 count stations on Indiana roadways.

Table 1. Summary of 40 count stations in Indiana.

#	Count Station ID	Interstate or Non-Interstate	Location Description	County	AADT (year 2021)	Passenger car %	Commercial vehicle %
1	950102	N	US-231 (CR 800 S)	TIPPECANOE	8209	73%	27%
2	950507	I	I-65 SB MM 47.0	JACKSON	40,730	55%	45%
3	951000	N	US-41 (SR 18)	BENTON	3560	61%	39%
4	952100	N	US-24 (SR 19)	MIAMI	10,599	73%	27%
5	952200	N	US-27 (CR 350 W)	ADAMS	11,034	79%	21%
6	952300	I	I-69 RM 268.2	GRANT	29,844	61%	39%
7	953300	I	I-465 SB MM 10.0	MARION	121,469	79%	21%
8	953600	I	I-70 EB MM 108.0	HANCOCK	36,017	51%	49%
9	954300	I	I-94 MM 44.5	LAPORTE	47,641	69%	31%
10	954600	N	US-31 (SR 10)	MARSHALL	190,622	73%	27%
11	954700	N	SR-49 (N E. 600 N)	PORTER	31,304	81%	19%
12	955200	N	US-50 (RD 175W)	RIPLEY	3842	75%	25%
13	955400	I	I-64 MM 117.0	FLOYD	31,841	75%	25%
14	956100	I	I-64 MM 28	GIBSON	17,545	46%	54%
15	956400	N	SR-66 (POSEY C/L)	VANDERBURGH	8560	83%	17%
16	956500	I	I-69 WB MM 2.2	VANDERBURGH	26,175	87%	13%
17	990107	N	SR-42 EB RM 12.2	CLAY	1784	97%	3%
18	990108	I	I-65 NB MM 186.0	WHITE	42,476	66%	34%
19	990202	N	US-6 EB RM 93.6	ELKHART	5320	87%	13%
20	990206	I	I-69 NB MM 78.2	HUNTINGTON	29,237	70%	30%
21	990271	I	I-69 MM 303.8	ALLEN	51,260	88%	12%
22	990302	N	SR-32 EB RM 107.7	MADISON	7695	98%	2%
23	990305	N	BINFORD BLVD	MARION	35,894	99%	1%
24	990311	I	I-65 SB MM 119.7	MARION	55,261	90%	10%
25	990327	I	I-69 (N. OF SR 9)	DELAWARE	43,996	76%	24%
26	990362	I	I-65 MM 104.0	MARION	127,676	87%	13%
27	990371	I	I-65 MM 121.5	MARION	45,243	92%	8%
28	990403	N	US-20 WB RM 77.1	ST JOSEPH	37,896	86%	14%
29	990404	N	US-41 SB RM 253.3	LAKE	14,483	93%	7%
30	990407	N	US-24 EB RM 27.3	WHITE	3113	83%	17%
31	990408	N	US-421 RM 157.9	CARROLL	5346	97%	3%

Continued

32	990421	I	I-65 MM 256	LAKE	112,183	82%	18%
33	990502	N	SR-67 SB RM 80.6	MORGAN	7749	96%	4%
34	990505	N	US-421 SB RM 29.2	RIPLEY	4653	93%	7%
35	990509	N	SR-56 EB RM 109.2	WASHINGTON	4337	91%	9%
36	990601	N	SR-550 EB RM 7.1	KNOX	1211	100%	0%
37	990607	N	US-41 NB RM 15.3	VANDERBURGH	21,261	90%	10%
38	991317	I	I-70 MM 70	MARION	102,642	82%	18%
39	991325	I	I-465 MM 18.45	MARION	132,613	88%	12%
40	991392	I	I-465 MM 20	MARION	109,875	92%	8%



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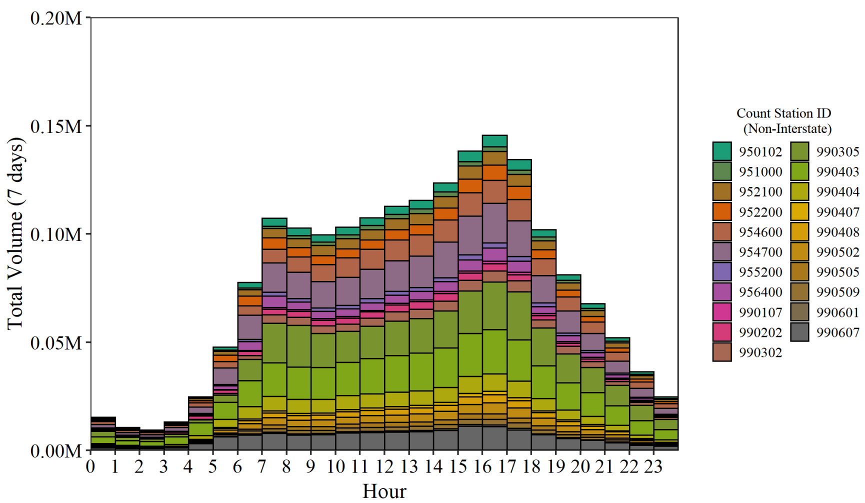


(b)

Figure 4. Total vehicle volume for 7 days by count stations in Indiana. (a) 19 interstate count stations; (b) 21 non-interstate count stations.

for the seven days at each of these stations. Vehicle volumes were highest during the evening peak hour between 4:00 PM and 5:00 PM and lowest during night hour of 2:00 AM to 3:00 AM. Morning peak was observed between 7:00 AM to 8:00 AM period.

2) Connected Vehicle (CV) Data

CV data was obtained through a third-party data provider. This provider receives its data directly from the original equipment manufacturers (OEMs). Previous studies using CV trajectory data consisted of passenger cars, hereafter referred as *connected passenger cars*. However recent development from these data providers has made similar data available for the commercial trucks, hereafter referred as *connected trucks*. The CV data used consists of anonymized individual trajectory waypoints that are collected every 1 - 3 seconds for connected passenger cars and 3 - 60 seconds for connected trucks along with an anonymized trajectory identifier and GPS, timestamp, and heading information.

Figure 5 shows comparison of connected passenger car and truck records for one-hour period during the evening peak hour from 4:00 PM to 5:00 PM and early morning hour from 2:00 AM to 3:00 AM in Indiana. More than 37 million connected passenger car records during the evening peak hour covers entire roadway system in Indiana (**Figure 5(a)**) whereas 0.46 million truck records cover major highways during the same hour (**Figure 5(b)**). However, during the night hour the coverage is sparse. There are only 0.93 million records from passenger cars (**Figure 5(c)**), 1/40 times compared to the evening peak hour. During the same night hour, trucks had 0.22 million records, 1/2 times compared to the evening peak hour. The statewide coverage of entire roadway system without any major infrastructure deployment is one of the key advantages of CV data.

The counts were obtained separately for passenger cars and trucks by identifying quarter to one-mile geofence regions near the count station that spanned the entire width of the road. In some cases, due to intersections, driveways, or curves in the road, the geofence region was shortened to avoid these features. The trajectory waypoints located inside the geofence region were selected, and the number of unique trajectories was counted.

4. Methodology

Data for 1 week period from Monday, May 9th to Sunday, May 15th was analyzed. Traffic count data provided information about vehicle volumes and its classification. Indiana DOT uses Federal Highway Administration's (FHWA's) 13 vehicle category classification system [53] from C1 to C13 with additional two categories as unclassified vehicles (C14) and error vehicle (C15). Vehicles from class C1 to C3 are referred as passenger vehicles, C4 to C7 as single unit trucks, C8 to C13 as combination trucks and C14 or C15 as other vehicle type. Average hourly vehicle volume is computed by taking average across all the stations (interstate and non-interstate separately) for each of the vehicle class as shown in Equation (1).

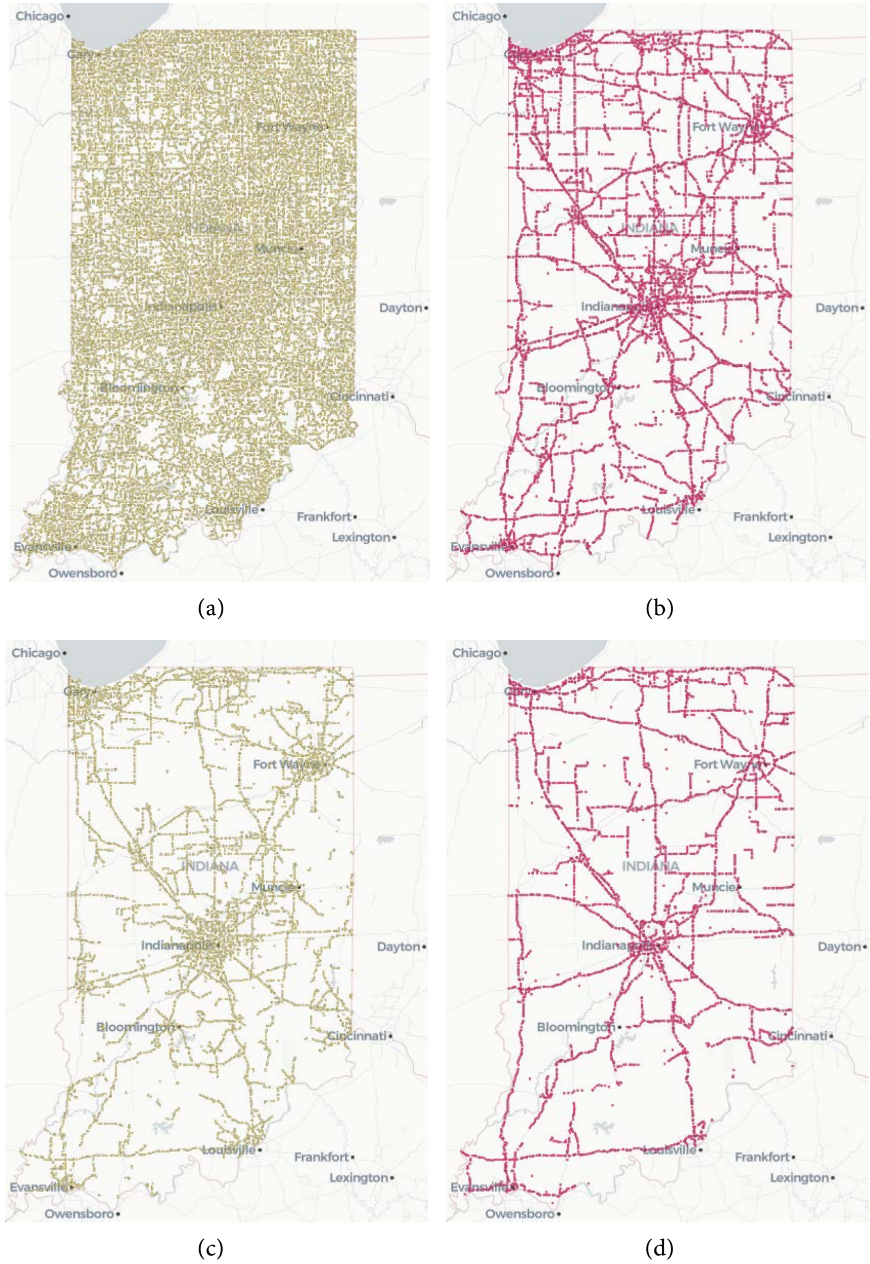


Figure 5. CV records, evening peak and early morning hour, Wednesday, May 11th, 2022. (a) Connected passenger cars from 4 PM to 5 PM (37,244,649 records); (b) connected trucks from 4 PM to 5 PM (463,534 records); (c) connected passenger cars from 2 AM to 3 AM (932,019 records); (d) connected trucks from 2 AM to 3 AM (218,789 records).

$$V_i^C = \frac{\sum_{n=1}^{r} V_{i,n}^C}{r} \tag{1}$$

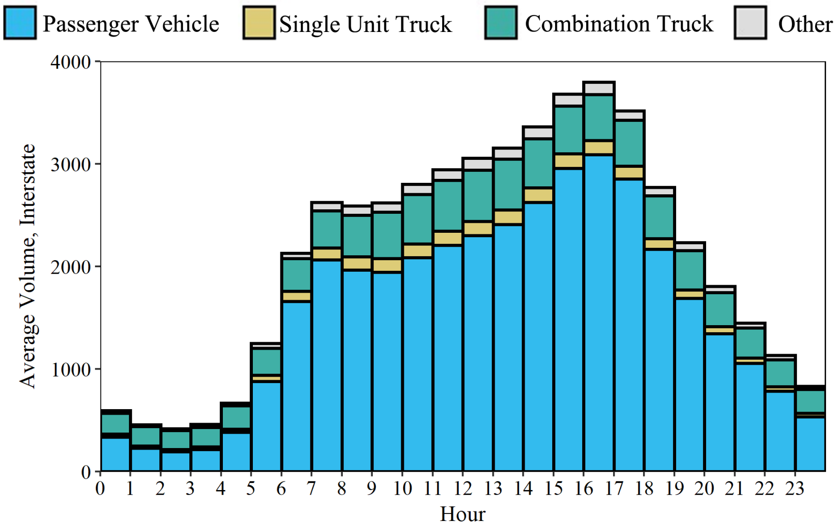
where V_i^C is the average volume during the i^{th} hour for vehicle class C, $V_{i,n}^C$ is the average volume during i^{th} hour for vehicle class C at count station location n over the 7 days and r is the number of count stations for each station type *i.e.*, 19 for interstates and 21 for non-interstates. Vehicle class C refers to either passenger vehicles, single unit trucks, combination trucks or others.

Hourly percentage of vehicle class is given by Equation (2).

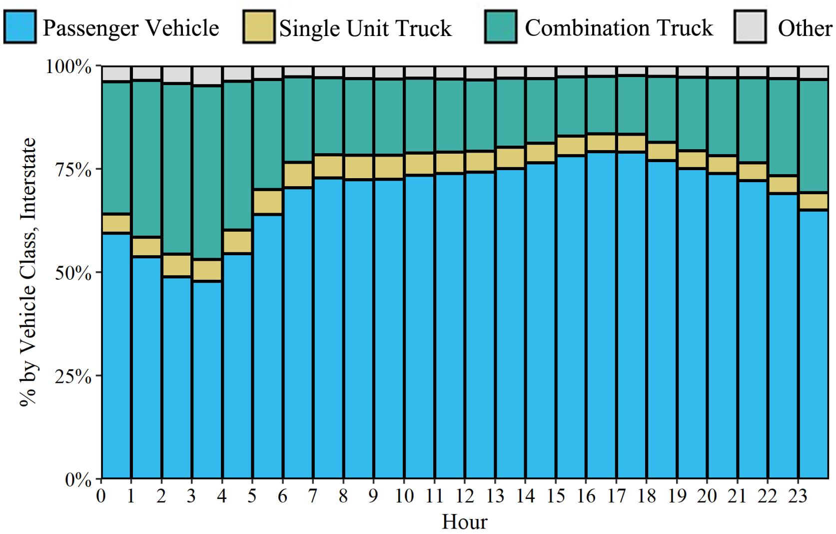
$$v_i^C = \frac{V_i^C}{\sum_{C=1}^{4} V_i^C} \tag{2}$$

where v_i^C is the percentage of vehicle class C during i^{th} hour, V_i^C is the average vehicle volume during i^{th} hour for vehicle class C (as computed from Equation (1)). There are a total of four vehicle classes, hence C value ranges from 1 to 4.

Hourly average vehicle volume (V_i^C) and hourly percentage of vehicle class (v_i^C) is shown in Figure 6 and Figure 7 for interstates and non-interstate roadways respectively. Total hourly average volume for interstates ranged from 419



(a)



(b)

Figure 6. Vehicle volume summary across 19 count stations along interstates. (a) Hourly average vehicle volume stacked by vehicle class; (b) hourly vehicle volume percentage by vehicle class.

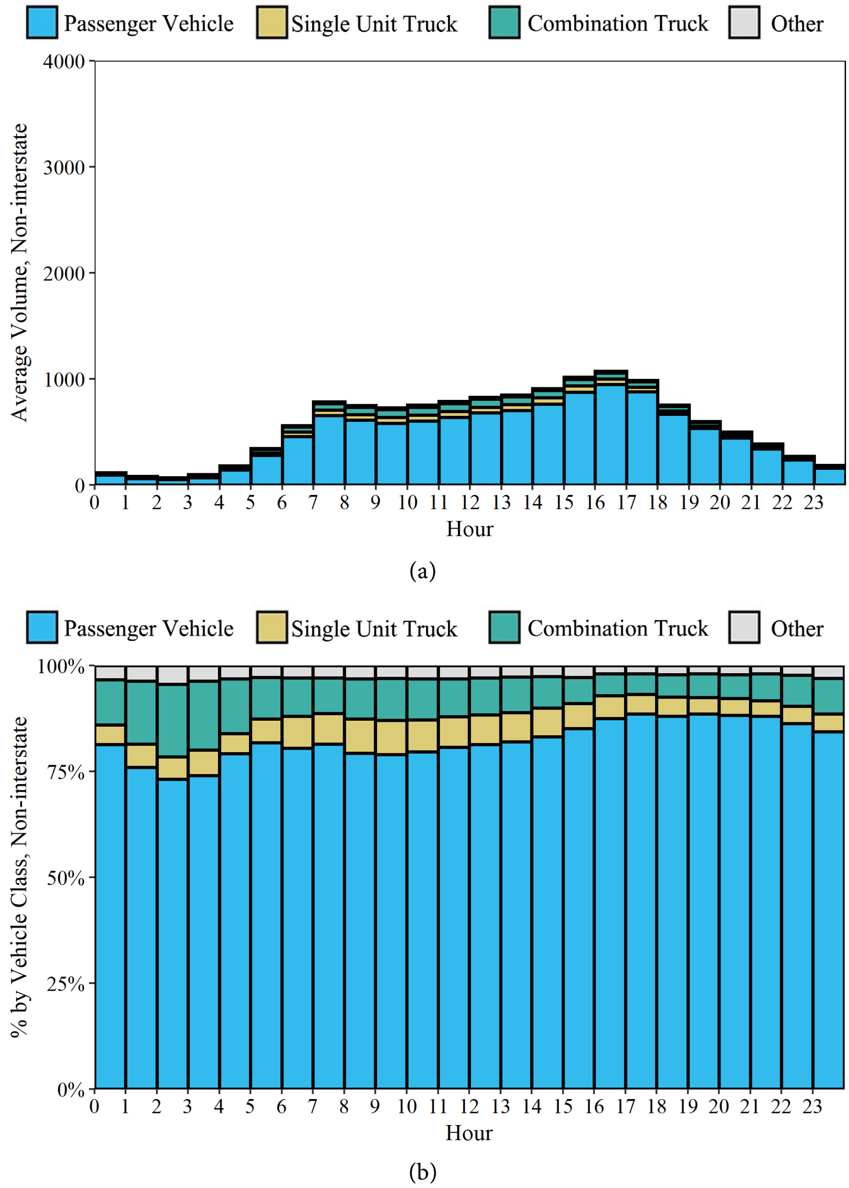


Figure 7. Vehicle volume summary across 21 count stations along non-interstate roadways. (a) Hourly average vehicle volume stacked by vehicle class; (b) hourly vehicle volume percentage by vehicle class.

(2 AM-3 AM) to 3801 (4 PM-5 PM). Passenger vehicles had most volumes during all hours compared to any of the other vehicle class. On average, 3% of vehicles were of other type. Percent of combination trucks were higher during night hours compared to during the day. It was the highest between 2 AM to 3 AM at 42% of all traffic counts. During the four-hour period from 1 AM to 5 AM, average unique counts for combination trucks was 790 compared to 1023 passenger vehicles. Trucks are major part of interstate traffic stream especially during the overnight hours. On the other hand, non-interstate traffic is mostly dominated by passenger vehicles. Combination trucks accounted most during the same early morning hour from 2 AM to 3 AM at 17% of all traffic counts.

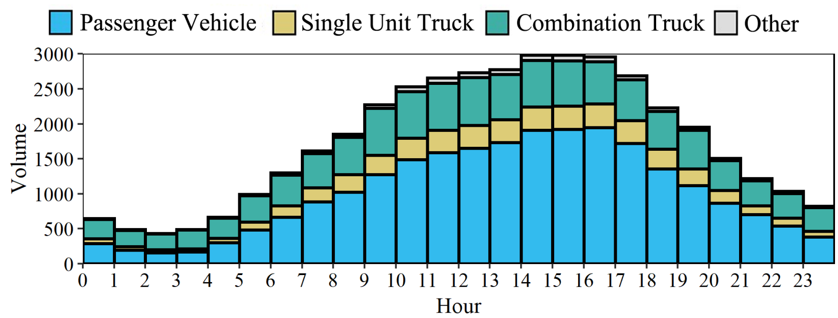
Hourly penetration of CV data is given by Equation (3).

$$P_{i,n}^{CV} = \left(\frac{T_{i,n}^{CV}}{V_{i,n}}\right)100 \tag{3}$$

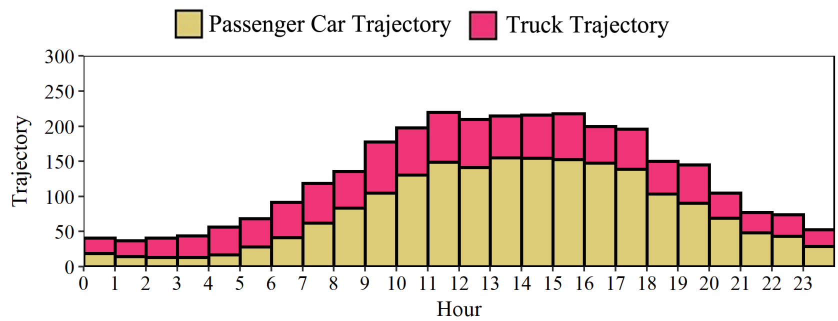
where $P_{i,n}^{CV}$ is penetration during i^{th} hour at count station n for connected vehicle CV *i.e.*, either connected passenger cars or connected trucks, $T_{i,n}^{CV}$ is trajectory count during i^{th} hour at count station n for connected vehicles (averaged for the entire week), $V_{i,n}$ is total volume during i^{th} hour at count station n given by Equation (4).

$$V_{i,n} = \sum_{C=1}^{4} V_{i,n}^{C} \tag{4}$$

Penetration is estimated separately for connected passenger cars and connected trucks at each of the count station locations. Figure 8 shows hourly traffic volume (Figure 8(a)), trajectory count (Figure 8(b)) and penetration for



(a)



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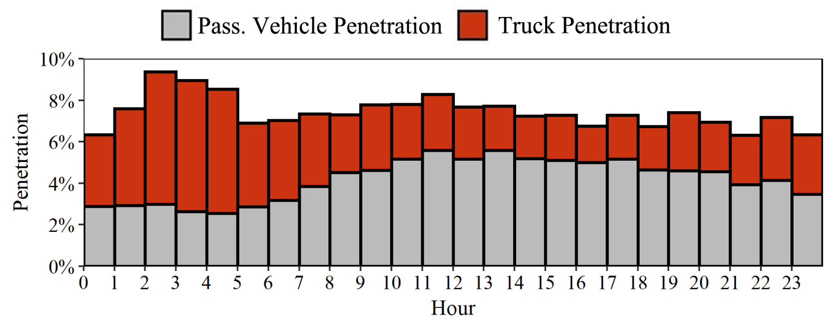

(c)

Figure 8. Interstate count station along I-65 MM 47, Count station ID 950507. (a) Vehicle volumes; (b) unique CV trajectory; (c) penetration of CVs.

CVs (Figure 8(c)) around an interstate count station at I-65 MM 47 (shown in Figure 3 callout i). For this interstate location, connected passenger car penetration was highest between 11 AM and 12 PM at 5.6% and lowest between 4 AM and 5 AM at 2.5%. Connected trucks penetration was highest between 2 AM and 3 AM at 6.4%, and overall was more than connected passenger cars from midnight until 7 AM. Inclusion of trucks increased the overall CV penetration over 6% during all hours of the day.

Similarly, Figure 9 shows hourly volume (Figure 9(a)), trajectory count (Figure 9(b)) and penetration for CVs (Figure 9(c)) around a non-interstate count station along US-31. For this non-interstate roadway section, connected passenger car penetration ranged from 1.9% (3 AM-4 AM) to 5.9% (4 PM-5 PM). Connected truck penetration ranged from 0.9% (3 PM-4 PM) to 4%

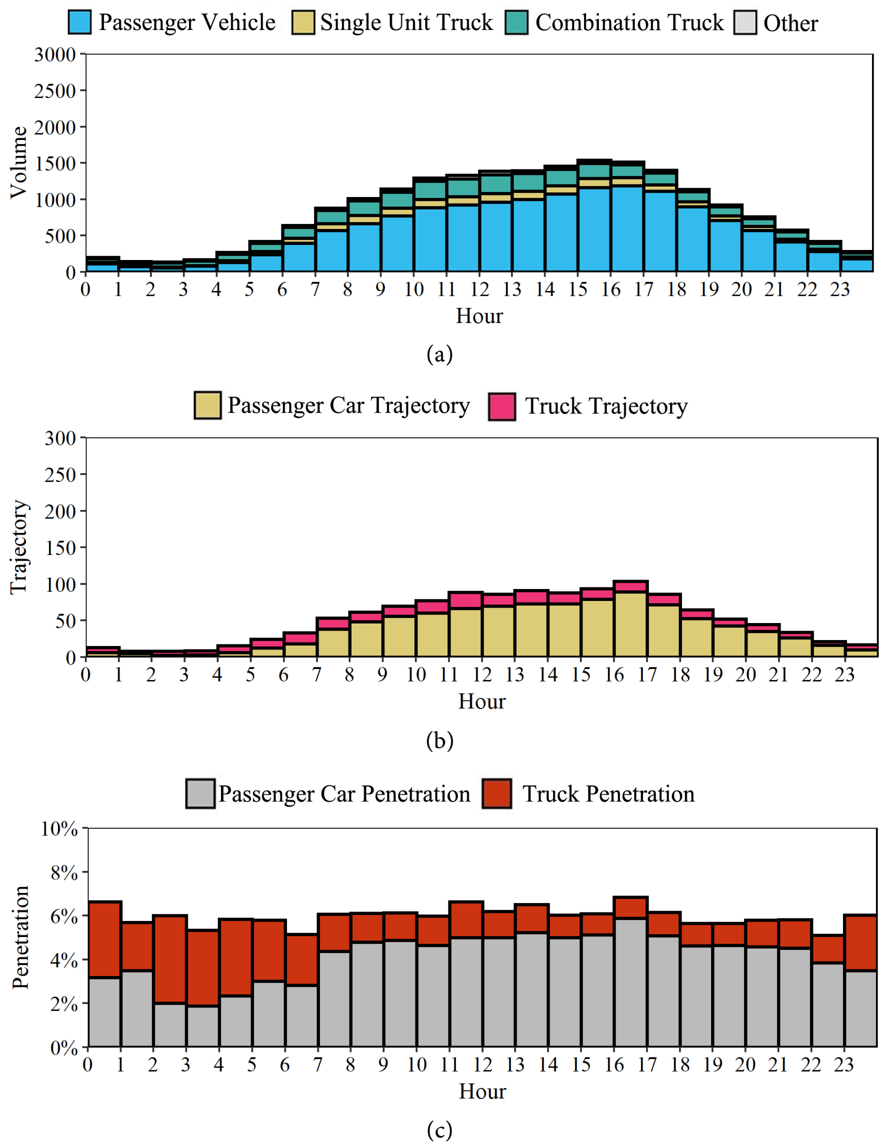

Figure 9. Non-Interstate count station along US-31, Count station ID 954600. (a) Vehicle volumes; (b) unique CV trajectory; (c) penetration of CVs.

(2 AM-3 AM). Similar to the interstate station, truck data improved the overall penetration especially during night hours.

5. Results

Hourly penetration across all interstate and non-interstate stations was aggregated. Figure 10 shows average hourly penetration for connected passenger cars and trucks on interstate (Figure 10(a)) and non-interstate stations (Figure 10(b)). On interstates, trucks improved the overall penetration of CV to over 6% throughout the day and significantly during night hours. Truck penetration was maximum between 2 AM to 3 AM at 3.72% when passenger car penetration was only 2.85%, thus making up 56.7% of the total sampled CV. However, trucks were not as significant on non-interstate roadways due to lower volumes of trucks on non-interstate roadways. Connected truck data also reduced the hourly variation of CV penetration.

Table 2 summarizes the hourly penetration values for both connected passenger cars and connected trucks at interstate and non-interstate station locations.

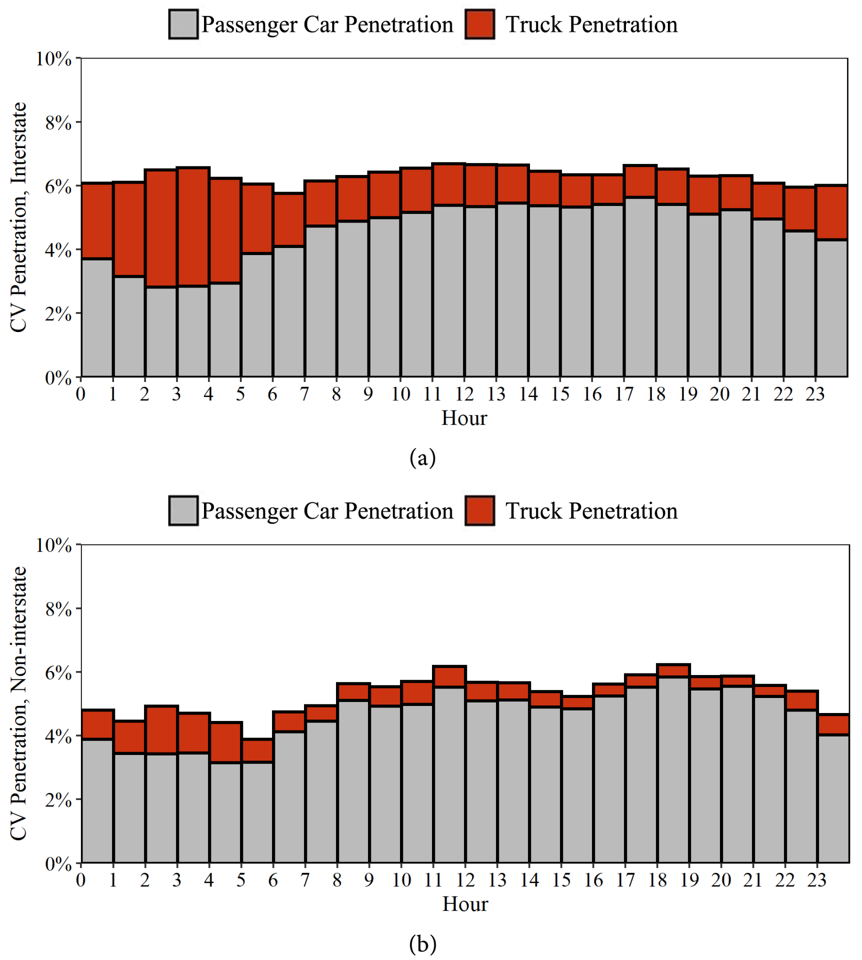

Figure 10. Hourly penetration of connected vehicles on interstate and non-interstate stations on Indiana roadways. (a) Interstate count stations; (b) non-interstate count stations.

Table 2. Hourly penetration of connected passenger cars and trucks on Interstate and non-interstate roadways in Indiana.

Hour	Interstate			Non-interstate		
	Connected Passenger Cars Penetration (%)	Connected Trucks Penetration (%)	Total Penetration (%)	Connected Passenger Cars Penetration (%)	Connected Trucks Penetration (%)	Total Penetration (%)
0	3.71	2.37	6.08	3.89	0.91	4.80
1	3.16	2.95	6.10	3.45	1.01	4.46
2	2.82	3.68	6.50	3.43	1.50	4.94
3	2.85	3.72	6.56	3.46	1.25	4.71
4	2.95	3.28	6.23	3.16	1.26	4.42
5	3.88	2.18	6.06	3.18	0.71	3.89
6	4.11	1.66	5.77	4.13	0.63	4.75
7	4.74	1.41	6.15	4.46	0.48	4.94
8	4.89	1.40	6.30	5.11	0.53	5.64
9	4.99	1.43	6.42	4.93	0.61	5.54
10	5.17	1.39	6.56	4.99	0.71	5.70
11	5.39	1.29	6.69	5.53	0.65	6.18
12	5.34	1.32	6.66	5.10	0.58	5.68
13	5.46	1.18	6.65	5.12	0.54	5.66
14	5.37	1.09	6.46	4.90	0.48	5.39
15	5.33	1.02	6.35	4.85	0.39	5.23
16	5.41	0.94	6.35	5.26	0.37	5.62
17	5.63	1.01	6.64	5.53	0.38	5.91
18	5.42	1.10	6.53	5.84	0.40	6.24
19	5.11	1.20	6.30	5.47	0.39	5.86
20	5.25	1.06	6.32	5.55	0.32	5.87
21	4.95	1.13	6.08	5.24	0.34	5.58
22	4.58	1.37	5.95	4.81	0.60	5.40
23	4.31	1.70	6.01	4.03	0.64	4.67
Average	4.62	1.70	6.32	4.64	0.65	5.30

Average overall penetration of CV data on interstate stations was 6.32% (trucks accounting for 1.7%) and on non-interstate stations was 5.30% (trucks accounting for 0.65%). The average truck penetration was observed to be 3.4% during overnight hours between 1 AM and 5 AM when the connected passenger car penetration was at the lowest.

6. Visualizng Impact of Combining Both Truck and Passenger Car CV Data

Spatiotemporal traffic speed heatmaps are utilized to visually analyze the traffic conditions and assess queues as shown by several previous studies [3] [4] [6]. CV trajectory data color coded by speed bins can be used to generate such heatmaps. One such example of traffic speed heatmap along I-65 northbound from MM 170 to 185 on Wednesday, May 11th and Thursday, May 12th, 2022, is shown in **Figure 11**. Horizontal axis represents the time of the day and vertical axis shows the location mile marker on the interstate. **Figure 11(a)** shows 0.53 million records from 3389 distinct trips of connected passenger cars. Callout i and ii points to the overnight hours with lower to no availability of connected passenger cars making it difficult to provide any information on traffic conditions

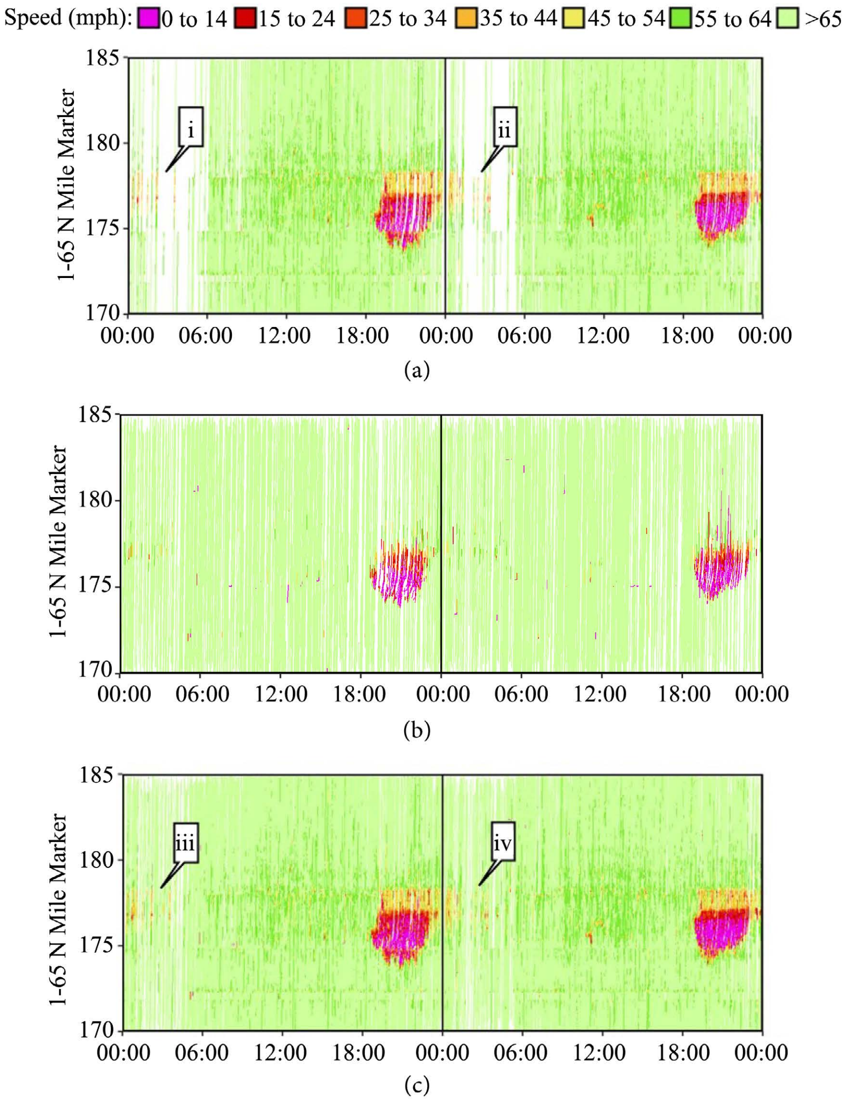

Figure 11. Comparison of connected truck and passenger car trajectories. (a) Connected passenger car (3389 trajectories); (b) connected truck (1866 trajectories); (c) combined CV data (5255 trajectories).

during these hours. Figure 11(b) shows 50,180 records from 1866 district trips of connected trucks. The additional data provides critical missing traffic condition information during the overnight hours. Combined connected passenger car and connected truck trajectories are shown in Figure 11(c). The combined heatmap depicts traffic condition information across all hours of the day especially during the night hours (callout iii and callout iv) that was missing from passenger cars alone (callout i and callout ii on Figure 11(a)). ITS camera images from MM 178.3 along I-65 are shown in Figure 12. Callout i and iii from Figure 11 corresponds to the image in Figure 12(a), and Callout ii and iv from Figure 11 corresponds to the image in Figure 12(b). It can be clearly seen from the camera images that truck traffic is moving through this section of the work zone during the overnight hours. Inclusion of truck data provides holistic view of the traffic condition and better represents the mix of vehicle classes in traffic steam.

(a)

(b)

Figure 12. ITS camera images at MM 178.3 along I-65 at night. (a) 2:28 AM on Wednesday, May 11th; (b) 2:34 AM on Thursday, May 12th.

7. Conclusion

Connected vehicle data has shown wide variety of applications in recent years. However, CV data consisted of majority passenger cars. This study evaluated the penetration of connected trucks at 40 count station locations in Indiana over a 1-week period from Monday, May 9th to Sunday, May 15th, 2022. Analysis of over 10.8 million vehicles captured during this period across all stations and more than 13 million trips (3 billion records) of CV data has shown that truck data significantly improved the penetration during overnight hours (**Figure 10**). On interstate locations, truck penetration was highest at 3.72% during the 3 AM to 4 AM period. The addition of truck data increased the overall CV penetration to over 6% throughout the day. Inclusion of truck data also provides a mix of vehicle classes that is more representative of the traffic stream. In addition to increasing penetration, including connected truck data also reduces the hourly variation in CV penetration (**Figure 11**) comprising up to 56.7% of the total sampled vehicles during the overnight hours, so an agency has a more consistent view of their network performance over the entire 24 hours of a day.

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Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: Bullock, Sakhare; data collection: Li, Sakhare, Mukai; analysis and interpretation of results: Sakhare, Hunter; draft manuscript preparation: Sakhare, Hunter, Li, Bullock. All authors reviewed the results and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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