Evaluation of Iowa Truck Parking Information and Management System Phase 2: Performance Measures and Data Analysis

Final Report
December 2023

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16. Abstract

This report presents a comprehensive analysis of the performance of the Iowa Truck Parking Information and Management System (TPIMS) during the proposed grant year that spanned 2019 to 2021. The evaluation is based primarily on fine-grained parking flow data, images, hour-of-service violations, American Transportation Research Institute (ATRI) surveys, and a truck driver survey. The key aspects examined include system utilization, reliability, and impact on safety. Furthermore, the report delves into several additional discussions, such as comparing TPIMS performance with other Mid America Association of State Transportation Officials (MAASTO) states, conducting predictive analysis, and performing anomaly detection. The analysis provides valuable information on the effectiveness and efficiency of the Iowa TPIMS and contributes to a comprehensive understanding of its impact on truck parking planning and safety.

This research finds that the shortage of truck parking is a pressing issue in Iowa and the MAASTO region. Providing real-time truck parking information helps truck drivers better plan for parking and thus improves parking utilization and safety. However, the accuracy of the information largely depends on the performance of the sensor. The sensor pucks used in the Iowa TPIMS started to fail after one and a half years at some sites, but the failures were not discovered until about a year later. Therefore, continuous monitoring of sensor health and independent verification of parking data are recommended for future TPIMS deployment.

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EVALUATION OF IOWA TRUCK PARKING INFORMATION AND MANAGEMENT SYSTEM PHASE 2: PERFORMANCE MEASURES AND DATA ANALYSIS

Final Report
December 2023

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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EXECUTIVE SUMMARY

This report presents a comprehensive analysis of the performance of the Iowa Truck Parking Information and Management System (TPIMS) during the grant period that spanned 2019 to 2021. The evaluation is based primarily on fine-grained parking flow data, images, hour-of-service violations, American Transportation Research Institute (ATRI) surveys, and a truck driver survey. The key aspects examined include driver use of the system, reliability, and impact on safety. Through quantifying various performance measures and developing visualization tools, we found the following:

1. After deploying TPIMS, the average utilization increases and standard deviation decreases, indicating a more even distribution of use of parking sites along I-80.
2. During the three-year grant period, most TPIMS sites experienced system downtime of less than 5%, indicating high system reliability.
3. Based on the predefined accuracy standard (i.e., 85% accurate for small sites and 90% accurate for large site), only 60% of the time the flow data are considered accurate for small sites and 30% for large sites, which is consistent with driver perceptions.
4. After TPIMS deployment, hours of service (HOS) violations by section had steadily reduced over years, indicating improved safety.

Iowa is the only participating state in the Mid America Association of State Transportation Officials (MAASTO) TPIMS project that does not use roadside variable message signs (VMS). Instead, the Iowa Department of Transportation (DOT) chose to disseminate truck parking availability information only through applications, Iowa 511, and in-cab information systems. By eliminating the cost of installing and maintaining the VMS, Iowa DOT deployed TPIMS at more sites than other participating states. Note that the other seven states that installed VMS also provide real-time data feeds for apps, websites, and in-cab systems. By comparing the performance of the system in terms of system accuracy, parking lot use at night, and HOS violations, the Iowa TPIMS performs similarly to other states. This could be because most drivers plan for overnight parking more than an hour in advance using smartphone apps. Therefore, the benefit of providing parking information on VMS could be limited.

Furthermore, since truck drivers need to be informed about the expected availability of parking spaces at their planned time of arrival, a popular time feature was developed using hybrid horizon prediction models for pre-trip planning and en route decision making. These predictive analytics have the potential to help truck drivers plan for parking day ahead and on the road. To better monitor sensor failures, a real-time alert system based on visual sensing was also developed. By automatically detecting significant discrepancies between truck count from surveillance camera images and parking flow data, this low-cost solution improves the accuracy of the TPIMS.

In summary, the shortage of truck parking is a pressing issue in Iowa and the MAASTO region. Providing real-time truck parking information helps truck drivers better plan for parking and thus improves parking utilization and safety. However, the accuracy of the information largely depends on the performance of the sensors. The sensor pucks used in the Iowa TPIMS started to

fail after one and a half years at some sites, but these failures were not discovered until about a year later. Therefore, continuous monitoring of sensor health and independent verification of parking data are recommended for future TPIMS deployment.

1. INTRODUCTION

During the past few decades, the growth of international and interstate trade has exerted significant pressure on the domestic transportation network in the United States. Among all modes of transportation for domestic freight delivery, trucks are the most used in terms of weight and value carried (BTS 2017). The Freight Analysis Framework (FAF) projects a substantial increase in truck traffic, especially along the major interstates (FHWA 2018).

Various public, private, and non-profit entities have extensively discussed truck parking issues. Common findings include expected growth in truck activity, severe shortages of truck parking spaces, limited information on parking opportunities, and challenges arising from tight delivery schedules and specific rest requirements (FHWA 2015). Studies, such as the one conducted by the Federal Highway Administration (FHWA) Office of Safety Research and Development, have highlighted the undersupply of truck parking spaces compared with the demand (Fleger et al. 2002).

The investigation of the National Cooperative Highway Research Program further confirmed the severe shortages of truck parking (Trombly 2003). The report also described challenges related to legislative authority and regulatory issues in developing truck parking locations and highlighted a number of state transportation department practices and potential solutions to truck parking challenges, including intelligent transportation systems (ITS) strategies to improve the accessibility of real-time information about available parking spaces for truck drivers. Using volume and congestion data in 2012, FHWA assessed the demand for truck parking and the availability needs. They determined that there was a widespread shortage of truck parking facilities and that in certain areas the shortage was acute (FHWA 2015).

In 2016, the American Transportation Research Institute (ATRI), on behalf of the Mid America Association for State Transportation Officials (MAASTO), developed and pre-tested a truck driver survey that contained 28 questions relating to truck parking issues in the MAASTO region (ATRI 2016). The survey was distributed online to carriers operating in the MAASTO region and through state trucking associations in the Midwest. From the 2,659 responses, ATRI concluded that truck parking issues result in significant amounts of lost productivity in the MAASTO region. Furthermore, truck parking issues in the MAASTO region are similar to or worse than those in other regions.

Another face-to-face survey with truck drivers on truck parking was also conducted by ATRI at the Mid-America Trucking Show in Louisville, Kentucky, on March 23–25, 2018. “Truck parking” and “driver shortage” were the top priority issues in the freight industry according to the responses of commercial drivers and executives from motor carriers (ATRI 2018).

The Truck Parking Information and Management Systems (TPIMS) project is an innovative multistate effort undertaken by MAASTO to address critical truck parking issues affecting regional economic competitiveness. The system monitors and detects available truck parking spaces at public and private parking facilities on designated, major interstate, and highway corridors throughout the region, helping commercial truck drivers make safer and more efficient parking decisions through a user-focused information service that consistently provides reliable and timely parking information.

Iowa is one of eight participating states in this project, along with Indiana, Kansas, Kentucky, Michigan, Minnesota, Ohio, and Wisconsin. The MAASTO TPIMS went live in January 2019 and has been in operation for three years or more. To eliminate the cost of installing and maintaining variable message signs (VMS), Iowa Department of Transportation (DOT) chose to disseminate truck parking availability information only through apps, Iowa 511, and in-cab information systems. The seven other states installed VMS to broadcast parking information, in addition to providing real-time data feeds for apps, websites, and in-cab systems.

This report presents a comprehensive analysis of the performance of the Iowa TPIMS during the proposed grant year that spanned 2019 to 2021. The evaluation is based primarily on fine-grained parking flow data, images, hours of service (HOS) violations, ATRI surveys, and a truck driver survey. The key aspects examined include system utilization, reliability, and impact on safety. Furthermore, the report delves into several additional discussions, such as comparing TPIMS performance with other MAASTO states, conducting predictive analysis, and detecting anomalies in parking data. The analysis provides valuable information on the effectiveness and efficiency of the Iowa TPIMS and contributes to a comprehensive understanding of its impact on truck parking planning and safety.

2. DATA COLLECTION

2.1 TPIMS Parking Flow Data

The TPIMS has operated in Iowa since January 2019. The system uses various vehicle detection methods, such as in-ground pucks and in-and-out sensors, to monitor and measure the availability of parking spaces at different sites. The collected parking data is then transmitted to the state database. Subsequently, real-time parking availability information is stored and disseminated to the public through a standard JSON file-based web service.

This data serves as a valuable resource for Iowa 511 traveler information systems, as well as third-party applications and in-cab systems accessible to truck drivers. Iowa 511, an official traveler information website managed by the Iowa DOT, provides up-to-date information on road conditions, helping travelers make well-informed decisions about their routes and travel plans. The TPIMS rest area information is integrated as one of the layers within the Iowa 511 platform.

Figure 1 shows the architecture of the system. Additionally, the Mid-America Freight Coalition (MAFC) archived parking flow data and the Iowa State University (ISU) Large Scale Storage (LSS) service archived the image data.

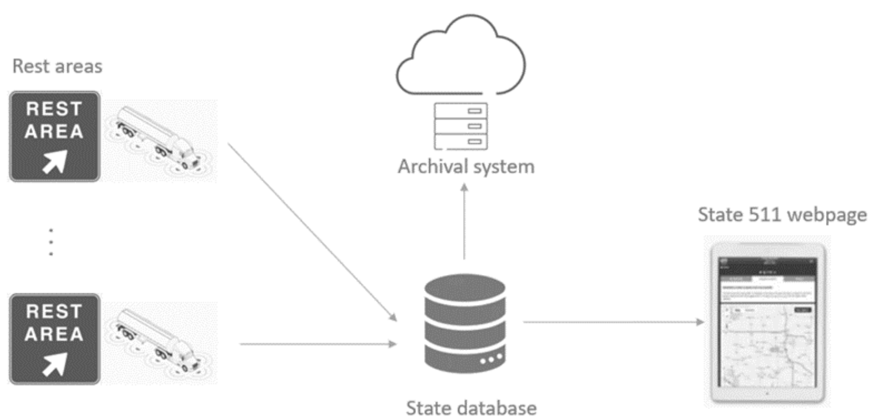

Figure 1. TPIMS data flow

Figure 2 is the TPIMS user interface on the Iowa 511 website. By selecting the “Rest Areas” layer, real-time parking availability and the corresponding images can be viewed for the TPIMS sites. In addition to Iowa 511, the TPIMS data feed is also consumed by application developers, logistics service providers, and so on. By April 25, 2023, 35 users from 23 different companies and organizations were registered to receive the Iowa TPIMS data feed.

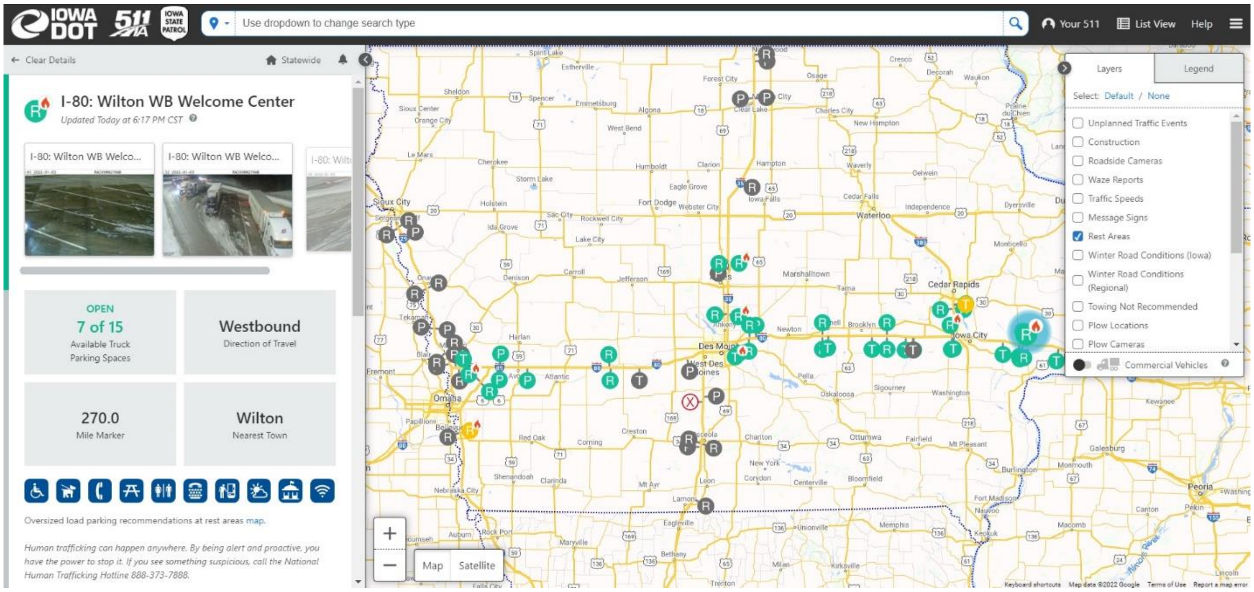

Figure 2. TPIMS user interface on Iowa511

The east-west freight corridor, I-80, spans Iowa and comprises 33 parking sites that are involved in the TPIMS project. Among those, 12 are eastbound public rest areas, 11 are westbound public rest areas, and 10 are private truck stops that serve traffic from both directions. There are 10 additional sites on I-29, I-35, I-380 and I-235 with a north-south direction that are close to the I-80 corridor. Capacities range from 5 to 850. At most sites, sensor pucks are installed in each parking space to monitor occupancy. At a few private sites, radar sensors are installed at the entrance and exit to count the number of trucks that enter and exit the parking lot. Table 1 lists the site information.

Table 1. TPIMS parking sites

Site	Interstate Highway	Capacity	Facility Type	Mile Marker	Sensor Type
RA19E	I-80	15	Public	19.6	Puck
RA19W	I-80	16	Public	19.6	Puck
RA32E	I-80	5	Public	32	Puck
RA32W	I-80	5	Public	32.2	Puck
DALLSCAL115E	I-80	23	Public	115	Puck
RA148E	I-80	24	Public	147.5	Puck
RA148W	I-80	22	Public	147.7	Puck
JASPSCAL151W	I-80	24	Public	150.75	Puck
RA237E	I-80	23	Public	236.8	Puck
RA237W	I-80	23	Public	237	Puck
RA44E	I-80	10	Public	44.2	Puck
RA80W	I-80	12	Public	80	Puck
RA80E	I-80	12	Public	80.6	Puck
RA180E	I-80	23	Public	180.3	Puck
RA180W	I-80	10	Public	180.3	Puck
RA208E	I-80	22	Public	208.3	Puck
RA208W	I-80	19	Public	208.3	Puck
RA268E	I-80	8	Public	268.3	Puck
RA268W	I-80	8	Public	268.3	Puck
RA270E	I-80	12	Public	270	Puck
RA270W	I-80	15	Public	270	Puck
RA300E	I-80	14	Public	299.6	Puck
RA300W	I-80	20	Public	300.3	Puck
PRAIRIEM144	I-80	48	Private	142	Puck
KG182	I-80	11	Private	182	Puck
KG216	I-80	9	Private	216	Puck
MD220	I-80	28	Private	220	Puck
KG237	I-80	14	Private	237	Puck
KG267	I-80	12	Private	267	Puck
KWIKSTAR202	I-80	110	Private	201.8	In-and-out
CASEYS220	I-80	20	Private	220	In-and-out
BP259	I-80	46	Private	259	In-and-out
TS284	I-80	850	Private	284.3	In-and-out
RA120N	I-35	16	Public	120	Puck
RA120S	I-35	17	Public	119	Puck
RA98N	I-35	20	Public	98.6	Puck
RA98S	I-35	21	Public	98.6	Puck
KGI23511	I-235	11	Private	11	Puck
CASI38013	I-380	92	Private	13	In-and-out
RA11SB	I-380	17	Public	11.4	Puck
RA11NB	I-380	17	Public	11.5	Puck
KSI38013	I-380	11	Private	13	Puck
TQPI2975	I-29	50	Private	75	In-and-out

All member states of MAASTO are required to provide three standard data feeds (a dynamic public feed, a static public feed, and a dynamic archive-only feed) for their publicly and privately owned truck parking sites. Dynamic and static public feeds facilitate the sharing of truck parking availability information with third-party application developers and other relevant agencies. This enables these entities to disseminate the information through their respective applications and platforms. On the other hand, the dynamic archive-only feed is intended for internal system monitoring and measuring performance. This report primarily uses the data obtained from the dynamic archive-only feed. Three different data feeds and their respective fields are shown in Figures 3 through 5 (Iowa DOT 2019).

Element	Type	Description
siteId	string	Unique fixed-length identifier including state, route number, route type, reference post, side of road and unique location number or name abbreviation. See more detailed description in appendix.
timeStamp	string	Provides the date and time that the site record was last updated. See more detailed date and time representation description in appendix.
timeStampStatic	string	Provides the date and time that the site static record was last updated. See more detailed date and time representation description in appendix.
reportedAvailable	string	Number of available spots shared through the data feed. The number is capped at the total number of parking spots at the site and "Low" is reported if the low threshold is reached.
trend	string	Optional. Reports whether the site is emptying, steady or filling. Accepted values: **"CLEARING"** / **"STEADY"** / **"FILLING"** / **null**. See more detailed description in appendix.
open	boolean	Will report open unless the parking site is closed to parking for maintenance or another situation. Possible values: **true** / **false** / **null**
trustData	boolean	This flag will report that the site is operating normally. Possible reasons for a "false" value include periods where the site is under construction while open to traffic, IT maintenance windows, or equipment failures. Possible values: **true** / **false** / **null**
capacity	number	Total number of parking spots within the site.

Figure 3. Fields in dynamic public feed

Element	Type	Description
siteId	string	Unique fixed-length identifier including state, route number, route type, reference post, side of road and unique location number or name abbreviation. See more detailed description in appendix.
timeStamp	string	Provides the date and time that the site record was last updated. See more detailed date and time representation description in appendix.
relevantHighway	string	Provides the highway from which the truck parking area can be accessed. See highway nomenclature in appendix.
referencePost	string	Provides the Reference Post (mile marker) for the center of the rest area or interchange.
exitID	string	At interchanges, the designated interchange number is provided. For rest areas and weigh stations that do not have an exit identification the value will be set to null.
directionOfTravel	string	Text indicating the direction(s) of travel that can access the site (Eastbound – E, Westbound – W, Northbound – N and Southbound – S). For sites that can be accessed by either direction of travel, a bidirectional identifier such as "NS" or "EW" can be used.
name	string	Name of facility as text (e.g., Rest Area or Flying J Truck Stop).
location	array	This array contains the seven following data elements about the site's physical location:
latitude	number	The latitude in a float format.
longitude	number	The longitude in a float format.
streetAdr	string	Text based address number and street name.
city	string	Name of city in which the parking area is located. If not in a city, the county name can be used (e.g., **Johnson County**).
state	string	Abbreviation for state in which the parking area is located.
zip	string	ZIP code of the location
timeZone	string	Time zone in which parking is located. Accepted values: **"Eastern"** / **"Central"** / **"Mountain"** / **"Pacific"** / **"Alaska"**
ownership	string	Text used to indicate whether a parking site is privately owned or publicly owned. Accepted values: **"PR"** / **"PU"**
capacity	number	Total number of parking spots within the site.
amenities	array of strings	Optional. List of text based amenities descriptions. Data structure would allow a varying number of amenities to be listed.
images	array of strings	Optional. Provides a link to an image file on a server that shows the lot status visually. This is only used if images are being captured and shared from a surveillance camera, otherwise it will be null.
logos	array of strings	Optional. Provides a link to an image file on a server that shows the private truck stop logo or TPIMS logo.

Figure 4. Fields in static public feed

Element	Type	Description
siteId	string	Unique fixed-length identifier including state, route number, route type, reference post, side of road and unique location number or name abbreviation. See more detailed description in appendix.
timeStamp	string	Provides the date and time that the site record was last updated. See more detailed date and time representation description in appendix.
timeStampStatic	string	Provides the date and time that the site static record was last updated. See more detailed date and time representation description in appendix.
reportedAvailable	string	Number of available spots shared through the data feed. The number is capped at the total number of parking spots at the site and "Low" is reported if the low threshold is reached.
trend	string	Optional. Reports whether the site is emptying, steady or filling. Accepted values: **"CLEARING"** / **"STEADY"** / **"FILLING"** / **null**. See more detailed description in appendix.
open	boolean	Will report open unless the parking site is closed to parking for maintenance or another situation. Possible values: **true** / **false** / **null**
trustData	boolean	This flag will report that the site is operating normally. Possible reasons for a "false" value include periods where the site is under construction while open to traffic, IT maintenance windows, or equipment failures. Possible values: **true** / **false** / **null**
capacity	number	Total number of parking spots within the site.
lastVerificationCheck	string	Date and time of the last manual reset/verification check. Used for performance measures and system monitoring, not for public consumption. Possible values: **date and time** / **null**. Null is input if a state is manually providing verification check data to MAFC. See more detailed date and time representation description in appendix.
verificationCheckAmplitude	number	Amplitude of the last manual reset/verification check adjustment. Can be negative, positive or zero.
lowThreshold	number	If the parking spot availability in the lot drops below this value, the data feed will report "Low" instead of a number.
trueAvailable	number	This will be the actual number of spots the detection system is reporting is available. This number can exceed the maximum number of spots and will report actual values under the "Low" threshold or even negative values. Used for performance measures and system monitoring, not for public consumption.

Figure 5. Fields in dynamic archive only feed

2.2 Truck Volume Data

More than 200 automatic traffic recorders (ATR) are located throughout the Iowa roadway network to continuously count classified traffic volume and record the distribution and variation of traffic flow. There are 11 ATR sensors along the I-80 corridor, and 7 of them provided stable data during the study period. The annual average daily truck traffic (AADTT) and the monthly average daily truck traffic on the roads can be derived from the ATR data. Figure 6 shows the location of the ATR sites and the TPIMS sites on I-80.

Figure 6. ATR sites and TPIMS sites location

The classified traffic volume is collected through ATR sensors. Among those 7 sites, 1483802, 1483810, 1483811 and 1483812 have length-based detectors with three bins (Bin 1: 1 to 21.5 ft, Bin 2: 21.5 to 49 ft, Bin 3: 49+ ft). Trucks are classified in Bin 3 (Iowa DOT 2014). Other sites have axle-based detections according to FHWA's 13-category classification. Groups 5 to 13 are trucks with different numbers of axles (FHWA 2014).

2.3 HOS Data

HOS violations were used to quantitatively measure corridor safety improvement by comparing the number of violations before TPIMS deployment (2018) and after deployment (2019–2021) (HNTB 2019). This involved the use of the Federal Motor Carrier Safety Administration (FMCSA) database known as the Motor Carrier Management Information System (MCMIS), which contains inspection data from state and federal inspections of motor carriers, shippers of hazardous materials, and transporters of hazardous materials operating in the US. These inspections were carried out on the road by personnel under the Motor Carrier Safety Assistance Program (MCSAP). Table 2 shows a typical structure of the inspection file that contains eight tables.

Table 2. FMCSA inspection file contents

Table	Name	File
1	Inspection Table	Insp_Pub_01012018_12312018HDR.txt
2	Carrier Table	Insp_Carrier_Pub_01012018_12312018HDR.txt
3	Part Section Table	Insp_Part_Section2018HDR.txt
4	Unit Table	Insp_Unit_Pub_01012018_12312018HDR.txt
5	Violation Table	Insp_Viol_Pub_01012018_12312018HDR.txt
6	Shipper Violation Table	Insp_ViolShip_Pub_01012018_12312018HDR.txt
7	Violation Description	Insp_Supp_Violation2018HDR.txt
8	Special Studies Table	Insp_Study_Pub_01012018_12312018HDR.txt

Each table in the inspection file is a tab-delimited flat file with its own distinct layout. A common and consistent field (a key) connects the records across the tables. For this analysis, the Inspection and Violation tables were merged into "INSPECTION_ID" (the common key) to determine the number of HOS violations. It was observed that the Violation Description table contained an incomplete and unformatted description, and therefore it was excluded from this analysis. Table 3 shows the nine fields of the Inspection and Violation tables selected for evaluation.

Table 3. Selected fields in inspection table and violation table

Table	Field	Content	Example
Inspection Table	INSPECTION_ID	Inspection ID	
	REPORT_STATE	State where the inspection occurred	IA, KS
	COUNTY_CODE	County where the inspection occurred	209, 197
	INSP_DATE	Date when the inspection occurred	
	LOCATION_DESC	Location briefly described	80MM EB I80, WB WATERLOO
Violation Table	INSPECTION_ID	Inspection ID	
	INSP_VIOLATION_ID	Violation ID	
	INSP_VIOLATION_CATEGORY_ID	MCMIS violation categories (FMCSA 2014)	06 – 60/70-hour rule violation, 11 – seat belt
	PART_SECTION_ID	FMCSA regulations violation code (FMCSA 2019)	3576 – 395.3B/R, 60/70-hour rule violation (property)

The Inspection Table contains a record of all inspections, including those without violation, with single violations, and with multiple violations. In the violation table, there is a record of all violations. During the analysis, it was not feasible to geocode or directly associate a violation record with a specific roadway because the field "LOCATION_DESC" is an inconsistent freeform text. For example, the field contains texts like “I80”, “I-80,” and “80,” which could mean an inspection occurred along I-80. However, it is unclear whether other text tags are associated with the same corridor. Therefore, the number of HOS violations was calculated by counties along the TPIMS corridors.

2.4 TPIMS Image Data

All TPIMS projects are required to provide manual check results to monitor the accuracy of parking flow data. Manual sensor accuracy check results are stored in two fields: “LASTVERIFICATIONCHECK” and “VERIFICATIONCHECKAMPLITUDE.” The time of the latest availability verification is in “LASTVERIFICATIONCHECK,” and the adjustment amplitude (can be negative, positive, and zero) from the last verification is in “VERIFICATIONCHECKAMPLITUDE.” These fields are meant to be used to monitor the accuracy of the TPIMS system, but for the puck sites, a problem in the software program caused overwriting, rendering these fields incapable of providing valid accuracy check information. Therefore, the TPIMS image data is used as a supplement for checking the system accuracy.

Each Iowa TPIMS site is equipped with surveillance cameras. At public rest areas, one camera will take pictures with a 13-second rotating lens from three angles (entry, center, and exit) every five minutes. Private truck parking sites have a varied number of cameras, and the images are not for public use. Live images are displayed on the Iowa 511 website together with parking flow data, and the ISU LSS service archives TPIMS images displayed on the Iowa 511 website every five minutes.

Figure 7 shows an example of live images from three different angles displayed on the Iowa 511 website of the 208WB rest area at 1:25 p.m. (CDT) on April 10, 2023. We can see that three trucks and one truck head were at this site. RA208WB is equipped with a camera oriented toward the head of trucks, offering a favorable camera angle that encompasses the entire parking area. However, image quality varies and does not always meet this ideal condition. Figure 8 shows some examples of poor camera angles. For these sites, it is hard to identify the number of trucks.

Figure 7. Images from RA208W

Figure 8. Examples of uncountable cases: from left to right, tail view, incomplete view of parking lot, view with unspecified spaces

Table 4 provides the image quality of the TPIMS sites with pucks in the pavement. Image quality was rated based on what was visible in the image:

- A: clear truck head view
- B: tail view
- C: incomplete view of the parking site
- D: cannot specify all parking spaces

Only quality A sites were chosen for manual accuracy check. In this report, seven rest areas with relatively good image quality were selected (RA180E, RA208W, RA237W, RA270E, RA270W, RA300E, and RA300W) to check the accuracy of the TPIMS.

Table 4. Image quality summary of puck sites

	Site ID	Short Site Name	Image Quality
1	IA00080IS0001900ERA19E000	RA19E	B
2	IA00080IS0001900WRA19W000	RA19W	B
3	IA00080IS0003200ERA32E000	RA32E	D
4	IA00080IS0003200WRA32W000	RA32W	D
5	IA00080IS0014800ERA148E00	RA148E	C
6	IA00080IS0014800WRA148W00	RA148W	C
7	IA00080IS0023700ERA237E00	RA237E	C
8	IA00080IS0023700WRA237W00	RA237W	**A**
9	IA00080IS0004400ERA44E000	RA44E	D
10	IA00080IS0008000WRA80W000	RA80W	D
11	IA00080IS0008000ERA80E000	RA80E	D
12	IA00080IS0018000ERA180E00	RA180E	**A**
13	IA00080IS0018000WRA180W00	RA180W	C
14	IA00080IS0020800WRA208W00	RA208W	**A**
15	IA00080IS0026800ERA268E00	RA268E	B
16	IA00080IS0026800WRA268W00	RA268W	B
17	IA00080IS0027000ERA270E00	RA270E	**A**
18	IA00080IS0027000WRA270W00	RA270W	**A**
19	IA00080IS0030000ERA300E00	RA300E	**A**
20	IA00080IS0030000WRA300W00	RA300W	**A**
21	IA00035IS0009870NRA98N000	RA98N	C
22	IA00035IS0009870SRA98S000	RA98S	C
23	IA00080IS001150OEDALLSCAL	DALLSCAL115E	C
24	IA00080IS001510OEJASPSCAL	JASPSCAL151W	C
25	IA00080IS0020800ERA208E00	RA208E	C
26	IA00380IS0001140SRA11S000	RA11S	C
27	IA00380IS0001150NRA11N000	RA11N	C
28	IA00035IS0012000NRA120N00	RA120N	C
29	IA00035IS0012000SRA120S00	RA120S	C
30	IA00080IS0014400WPRAIRIEM	PRAIRIEM144	C
31	IA00080IS0018200WKUMandGO	KG182	D
32	IA00080IS0021600WKUMandGO	KG216	D
33	IA00080IS0022000WMCDONALD	MD220	C
34	IA00080IS0023700WKUMandGO	KG237	D
35	IA00080IS0026700WKUMandGO	KG267	D
36	IA00235IS0001100WKUMandGO	KGI23511	C
37	IA00380IS0001300WKWIKSTAR	KSI38013	C

The designed accuracy manual check (HNTB 2017) is performed at least once a week for the puck sensor sites and once or twice a day for the in-and-out sensor sites. TPIMS was first planned to run for 3 years per grant requirements, so the designed number of manual checks is about 160 per puck site. To replicate the designed manual checks, images of seven parking sites are sampled from the archived image data set. Some unexpected situations made the image not available for manual count. For example, the image of one or more angles is missing, snow/ice is covering the lenses, or images were duplicated when archived.

The duplication issue occurs when the Iowa511 images on Iowa511 are not updated and the Institute for Transportation (InTrans) image archiving system continues to download the same image with different file names (file name is timestamp.jpg). Figure 9 shows two of the unexpected situations (missing angle and blurry lens). With oversampling and removing unusable images, about 1,400 images are valid for manual counting for the three-year period and these seven selected sites.

Figure 9. Examples of uncountable cases: missing angle (top), blurry lenses (bottom)

2.6 ATRI Survey Data

ATRI, established as the research arm of the American Trucking Associations (ATA), is a renowned research organization dedicated to advancing the trucking industry. Through data-driven research and analysis, ATRI addresses the critical challenges faced by trucking companies, drivers, and other stakeholders. As part of its efforts, ATRI conducted four truck parking surveys in the MAASTO region in October 2016, May 2018, February 2020, and June 2021. These surveys collected vital information on demographics, truck parking demand in the MAASTO region, drivers’ methods to find parking, and the frequency and severity of parking-related issues. In particular, the survey in June 2021 focused on driver usage and perception of the TPIMS rather than parking demand and behavior. This report summarizes and compares survey responses on parking utilization, system reliability, and safety to obtain valuable information on truck parking patterns and TPIMS perceptions.

3. ANOMALY DETECTION

Before using the parking flow data from the archive feed to evaluate performance, the reliability of the data needs to be determined. Inadequate baselining and unstable transmission of the pucks influence the accuracy of flow data, and anomaly detection was performed based on historical flow records. An assumption is that the daily parking pattern should not change drastically over a short period of time. For example, Figure 10 shows the time series of the average availability at night (e.g., weekly availability at 2 a.m.) in a rest area RA180W. The choice of using average availability during nighttime hours for anomaly detection was made due to the reduced likelihood of external interference during this period. This is because most truck drivers are resting, resulting in fewer vehicles entering and leaving the parking lot. From January 2019 to May 2020, the average availability is less than 1 with small fluctuations, until there was a sudden rise in June 2020.

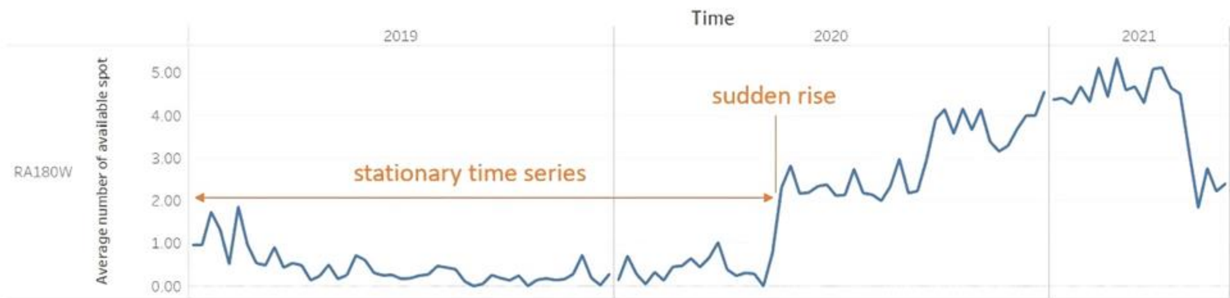

Figure 10. Time series trend of average availability at night

To check if this sudden increase was due to COVID-19 lockdowns, an analysis was performed on the volume of trucks in the I-80 corridor. The AADTT data for 2019 and 2020 were collected from seven ATRs along I-80 to investigate truck volume. Figure 11 shows the AADTT of eastbound and westbound truck traffic at these ATR locations. Westbound truck traffic was slightly heavier than eastbound. Truck traffic is heavier on the east side than on the west side along I-80. Furthermore, there are no significant differences in AADTT between 2019 and 2020.

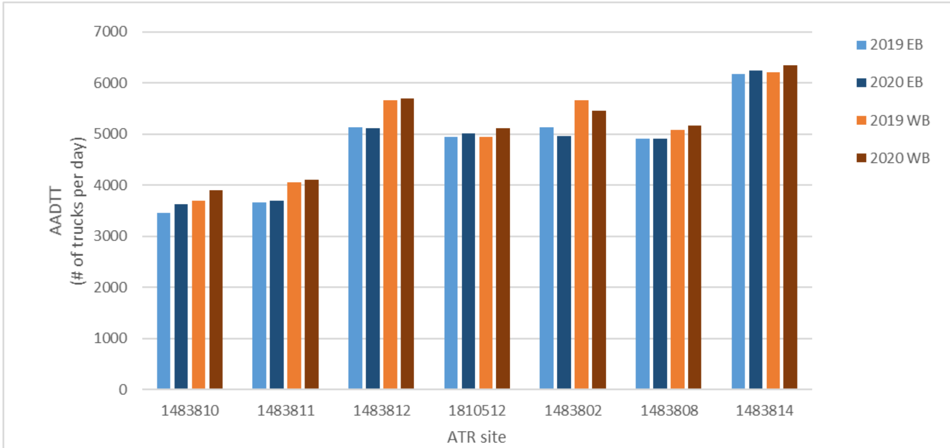

Figure 11. AADTT of selected ATR sites

Furthermore, the average daily truck traffic (ADTT) varies by season. Figure 12 shows the monthly average of daily truck traffic from eastbound traffic at the ATR site 1483814 (i.e., the east most ATR location). Truck traffic is generally higher in the summer months and lower in the winter months. Furthermore, truck flow was reduced by 10% in April and 8% in May in 2020 due to the COVID-19 lockdown. However, truck traffic recovered quickly in June. In general, the COVID-19 pandemic had a minimal impact on truck traffic on I-80 in Iowa.

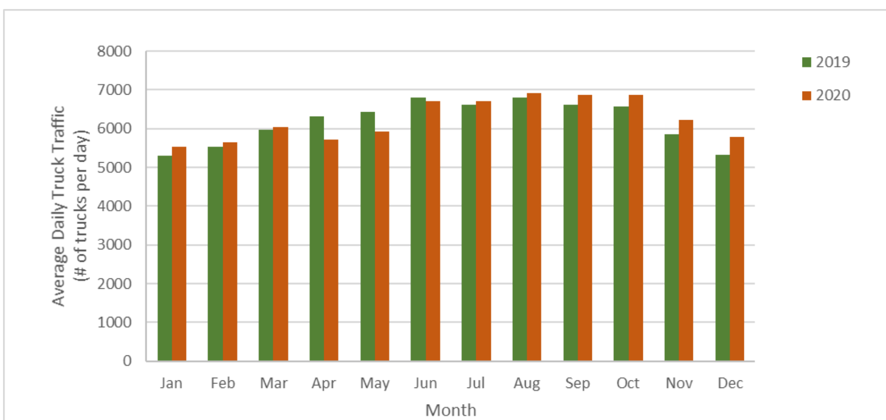

Figure 12. Monthly Average Daily Truck Traffic of ATR Site 1483814, Eastbound

After excluding the impact of COVID-19, the sudden increase in availability at night in Figure 10 may indicate sensor failure. This anomaly can be detected using some statistical methods. In particular, the pruned exact linear time (PELT) algorithm (Truong et al. 2018) is used to identify the change point caused by sensor failures.

More formally, let us assume that we have an ordered sequence of data, $y_{1:n} = (y_1, \dots, y_n)$. The number of changepoints, m, are with their positions $\tau_{1:m} = (\tau_1, \dots, \tau_m)$. Each change point position is an integer between 1 and $n - 1$ inclusive. $\tau_0 = 0$ and $\tau_{m+1} = n$ are defined and the change points are ordered such that $\tau_i < \tau_j$ if and only if $i < j$ is assumed. Consequently, the m

changepoints will split the data into $m+1$ segments, with the i^{th} segment containing $y_{(\tau_{i-1}+1):\tau_i}$ (Killick et al. 2012). PELT optimally partitions the data into an interval and uses an iterative pruning step to achieve an efficient computational cost. In particular, Truong et al. (2018) implemented a search method by minimizing, as shown in Equation 1:

$$\sum_{i=1}^{m+1}\left[C\left(y_{\tau_{i-1}+1},\dots,y_{\tau_i}\right)+\beta\right] \tag{1}$$

where

C is the cost function for a given segment,

y_{τ_i} is the datapoint,

τ_i is the position of segment *I*,

m+1 is the number of segments,

β is the penalty term for overfitting.

In the literature, a common cost function used for change point detection is twice the negative log-likelihood (Chen and Gupta 2012). However, quadratic loss, cumulative sums, and a combination of segment log-likelihood and segment length have also been used (Rigaill 2010). Regarding the penalty term, the Akaike Information Criterion (AIC) (i.e., $\beta = 2p$), the Schwarz Information Criterion (SIC), and the Bayesian Information Criterion (BIC) (i.e., $\beta = plog_n$) can be used, where p represents the number of additional parameters introduced by incorporating a change point. In this paper, kernelized mean change with radial basis function is used as the cost function and the BIC is used as the penalty term.

The PELT method adds pruning to the partitioning process. The optimal segmentation is $F(n)$, where

$$F(n) = \min_{\tau}\left\{\sum_{i=1}^{m+1}\left[C\left(y_{\tau_{i-1}+1},\dots,y_{\tau_i}\right)+\beta\right]\right\} \tag{2}$$

where *n* is the length of the data set.

By taking the last change point as a reference and determining the optimal segmentation of the data prior to that change point, the following form can be obtained:

$$F(n) = \min_{\tau_m}\left\{\min_{\tau|\tau_m}\sum_{i=1}^{m}\left[C\left(y_{\tau_{i-1}+1},\dots,y_{\tau_i}\right)+\beta\right]+\ C\left(y_{\tau_m+1},\dots,y_n\right)\right\} \tag{3}$$

The process can be repeated for the second to the last change point, the third to the last change point, and so on. Because conditioning is recursive and inner minimization is equivalent to $F(\tau_m)$, Equation 3 can be reformulated as follows.

$$F(n) = \min_{\tau_m}\{F(\tau_m) + C(y_{\tau_m+1}, \ldots, y_n)\} \quad (4)$$

The PELT algorithm starts by calculating $F(1)$ and then recursively calculates $F(2)$,…, $F(n)$. At each iteration, the optimal segmentation up to τ_{m+1} is stored. When $F(n)$ is reached, the optimal segmentation for the entire time series is determined and the number and location of change points are recorded. Minimizing over the previous values is performed at each step. The computational efficiency is achieved by removing candidate values of τ_m from the minimization. The essence of pruning in this scenario is to remove those change points that cannot possibly be minimum values from the minimization performed at each step.

The anomaly detection results are shown in Figure 13. The bars indicate that the parking flow data at the parking sites are stationary from the establishment of the Iowa TPIMS at different daytimes. Among the 43 parking sites, time series in 30 sites show strong nonstationarity before the end of the grant period (3 years). Most of them show that data of the first one and a half years are reliable (from establishment to Q2 2020).

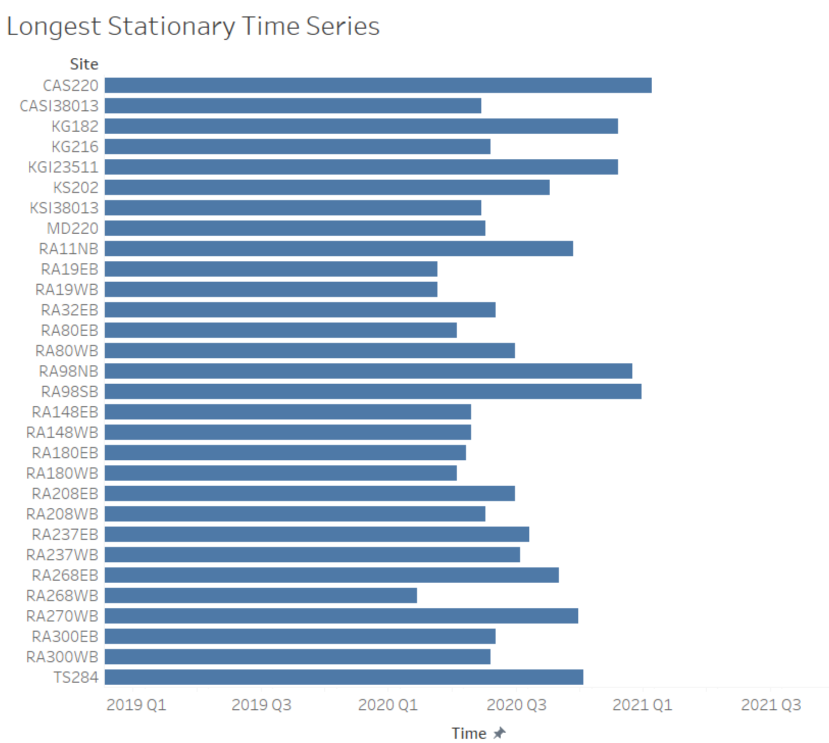

Figure 13. PELT stationary test result

To validate the effectiveness of the change point detection method, the PELT detection result is compared with the puck transmission log. The operational status of the puck sensors is recorded in the sensor transmission log, which is provided by a third-party company. The log records the last successful transmission from each puck to all participating TPIMS sites, providing information about the reliability of the puck sensors. Two pucks are installed at each parking spot, and each of them presents the date of its last successful communication. When any of the pucks stops communicating, the data of this parking space will be considered unreliable and, correspondingly, the number of reliable parking spots in this parking lot will be reduced by one. The puck transmission log is used to verify when the data collected by the pucks become unreliable, as a means of providing ground truth for the anomaly detection analysis.

Figure 14 shows an example of the parking flow data, PELT detected change points, and puck transmission log records at site RA180W. The top graph shows the weekly average of available parking spots at 2 a.m., where there was a sudden increase on Week 23 of 2020 (i.e., May 31–June 6, 2020). The middle graph shows that the PELT method detected a change point on week 24 of 2020. The bottom graph shows the number of reliable parking spots which are extracted from the puck transmission log data. Based on the log data, one parking spot became offline (i.e., both puck sensors failed) on May 28, 2020, resulting in the number of reliable spots dropping by one.

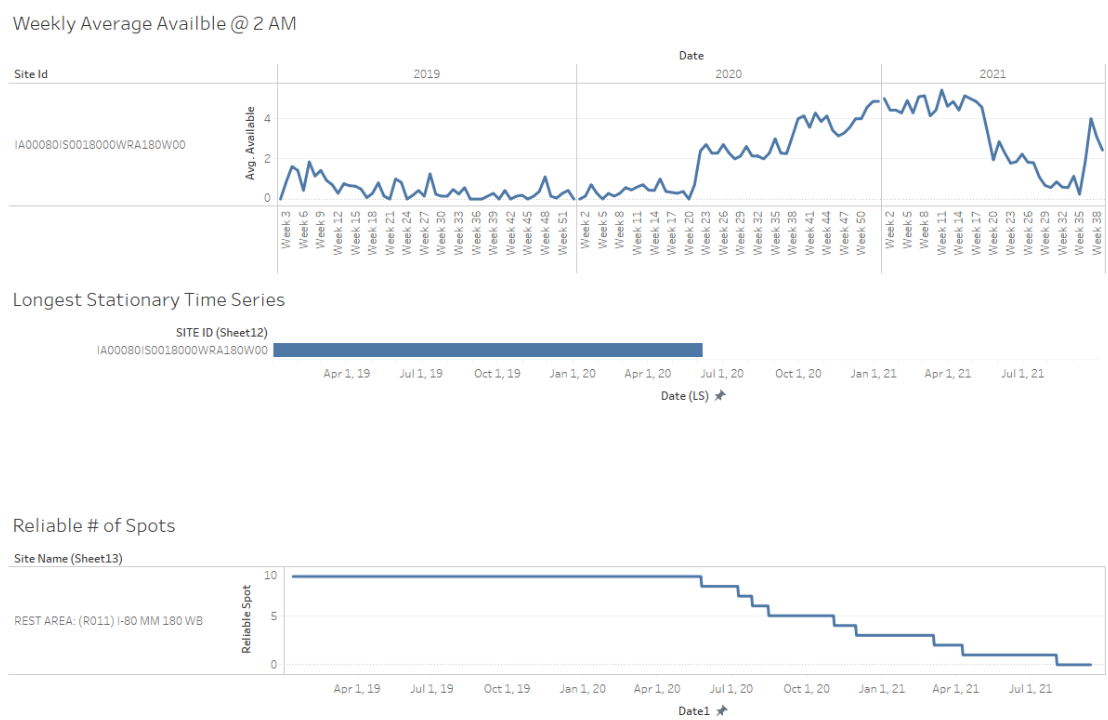

Figure 14. Stationary time series comparison

The reasons why the PELT method might not work well for some sites are two-fold. First, at the sites where the parking flow data did not follow an obvious trend, it is difficult to detect the change points. For example, the availability at night at DALLSCAL115E fluctuated significantly, as the weigh station is not a common place for truck drivers to rest overnight. The puck transmission log data indicated sensor failure on October 12, 2020, but the PELT algorithm was unable to detect the change point. Second, when a puck fails, the status is stuck in "occupied" or "unoccupied" according to its last status. If the failed sensor is stuck as "occupied" and the parking spot is usually occupied at night, the parking availability data will remain accurate despite sensor failure. For example, in RA300W, the puck transmission log indicated sensor failure at two parking spaces on July 3 of 2020, but the PELT algorithm did not detect a change point until August 3 of 2020 when 4 parking spaces became unreliable. This is confirmed by the flow data, in which the sudden increase of parking availability at 2 a.m. was observed on week 32 of 2020 (i.e., August 2–8, 2020). In general, the PELT method performed satisfactorily in detecting sensor failure based on flow data.

Figure 15 summarizes the detection results obtained using the PELT method. The figure comprises a frequency histogram that illustrates the sensitivity of the method at 27 TPIMS sites equipped with underground pucks. Two sites, RA32E and RA32W, were excluded from the analysis due to the inaccessibility of the puck transmission log data. The horizontal axis of the histogram represents the instances in which the PELT method detects a change point and reports the corresponding time. This axis also indicates the number of unreliable parking spots present at that specific parking site during that time, and the data regarding the number of unreliable parking spots are extracted from the puck transmission log. The symbol "x" represents instances where the PELT method failed to detect any change point in the available data series. On the vertical axis, the percentage of parking sites is represented. For example, within 26% of parking sites, only one unreliable parking spot is present when the PELT method reports a detected anomaly time. In general, the PELT method demonstrates its ability to respond before four parking spots become unreliable in 70% of the TPIMS sites. This finding indicates a satisfactory level of effectiveness in the context of our study.

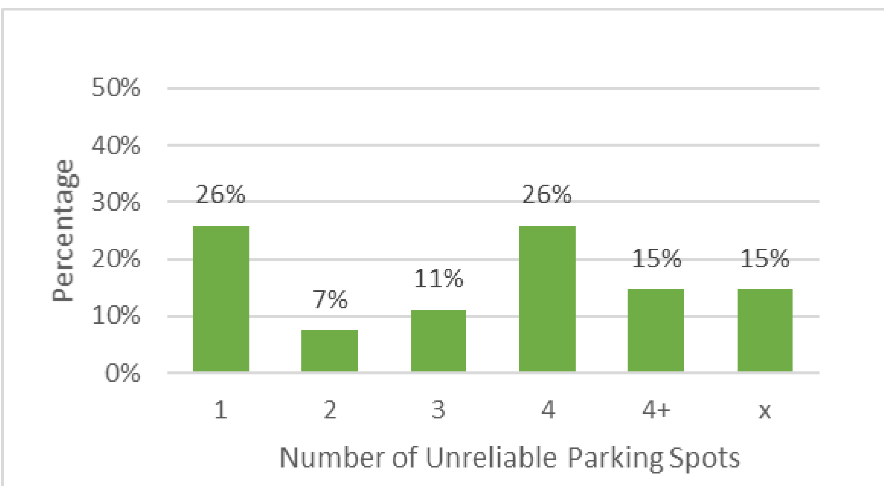

Figure 15. Summary of the PELT detection results

Based on the anomaly detection results, the study period of the evaluation analysis in this report is set at one and a half years from the deployment of TPIMS in Iowa (Q1 2019 to Q2 2020).

4. PERFORMANCE MEASURES

4.1 Utilization and Demand Cycle

4.1.1 Low Duration

When the number of available spots is below a certain threshold (i.e., 10% of the site capacity), "LOW" will be displayed instead of the actual available spaces. Figure 16 shows the 24-hour demand cycle of RA19E and DALLSCAL115E on April 11, 2019. The low duration is calculated as the sum of time periods when the number of available spots drops below the low threshold. In this example, "LOW" was displayed to truck drivers from 12 a.m. to approximately 5 a.m. and from 10 p.m. to midnight in RA19E. The daily low duration (DLD) was 420 minutes. The availability in DALLSCAL115E never dropped below the threshold, so the DLD is 0. A site with a DLD below 10% (i.e., 144 minutes) is considered as a non-busy site.

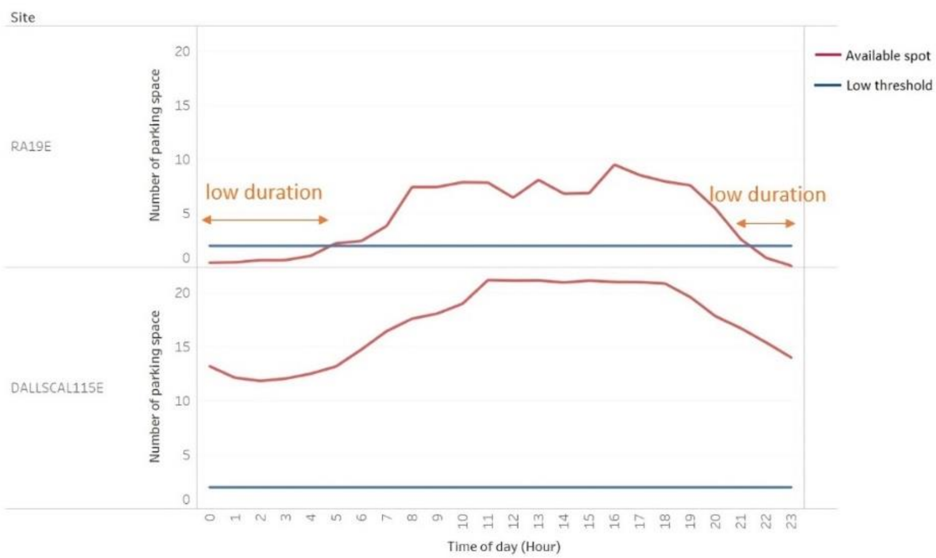

Figure 16. 24-hour demand cycle of site RA19E and DALLSCAL115E on April 11, 2019

The double-pointer method is applied to detect the time intervals when the availability is "LOW." The double-pointer method is a technique to search for a specific pair of values in a given data set, and the condition used to move the pointers is determined by the specific problem. Let A be a data set with n elements, $A = [a_1, a_2, a_3, \dots, a_n]$. The two pointers, i and j, are initialized at the beginning of the data series, respectively, $i = 1$ and $j = 1$. At each iteration, the condition that a_j is greater than the threshold is evaluated. If it is met, the solution is returned. If not, pointer j moves forward. The process is repeated until a solution is found for the current interval. Then, pointer i is set to where pointer j is located. All low availability intervals can be identified with the time complexity of $O(n)$. Then those intervals are aggregated daily as a metric, defined as DLD, to measure how busy a parking site is.

Figure 17 shows an example of how the double-pointer method works when scanning the parking flow data to find the low duration intervals. For a one-day scope, the start and end timestamps are inserted; one is exactly 12 a.m. and the other is 23:59:59. Then the rows of flow records are scanned; when the availability drops below the threshold (i.e., 65), we put two pointers and move the second one, until the availability goes back; we update the location of the pointers. The movements of the pointers are recorded, and then the intervals are added. In this case, the daily low duration is 403.2 minutes, as shown in Table 5.

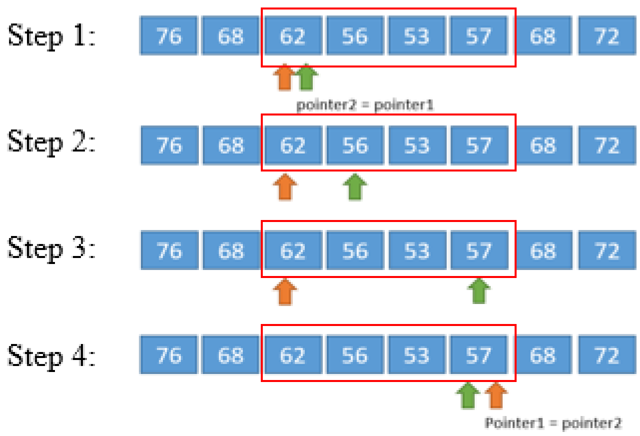

Figure 17. Example of the double-pointer method

Table 5. Example of low intervals and daily low duration

Start time	End time	Low(min)
2019-05-21 00:14:26	2019-05-21 05:44:12	329.77
2019-05-21 06:13:09	2019-05-21 06:24:12	11.05
…	…	…
2019-05-21 23:01:18	2019-05-21 23:54:12	52.9
		403.2

The DLD of each site is averaged over the study period as an indicator of use. A site is considered busy when the average DLD is above 10%, indicating that the site is full or close to full for more than 2.4 hours on an average day. Figure 18 shows the average DLD of the busy sites listed in order from west to east along I-80. As the TPIMS sites are more densely distributed on the east section of I-80 than on the west side, the averaged DLDs of the east sites tend to be smaller than the averaged DLDs of the west sites. Clearly, more parking facilities can alleviate parking difficulties.

Furthermore, two east TPIMS sites, RA270W and RA300W, had relatively high DLD. This could be due to the difficulty in finding parking for trucks in Illinois. Respondents to the ATRI survey reported that, among all MAASTO states, truck parking was the most difficult to find in Illinois (ATRI 2016). Note that TS284 is a private truck stop near Walcott and has a capacity of 850 parking spots, so the DLD is not particularly high.

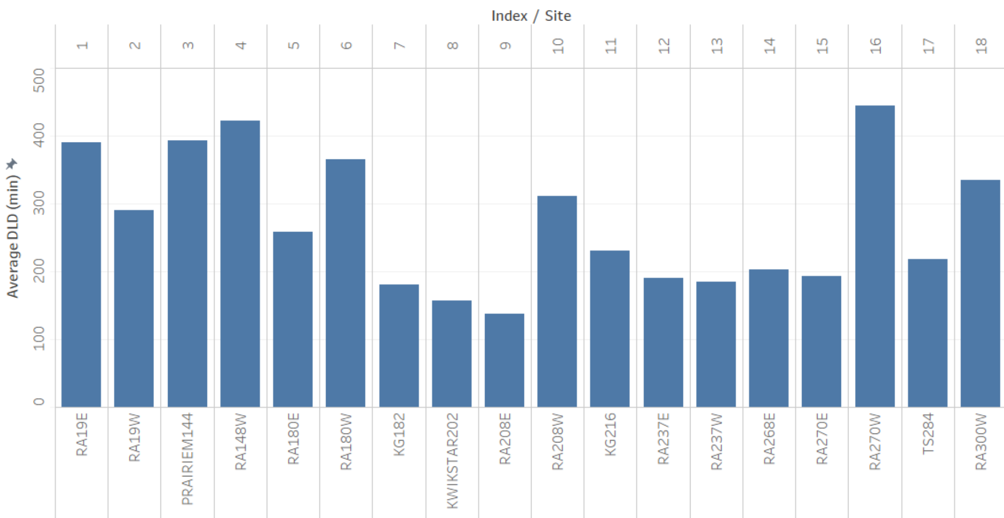

Figure 18. Average DLD of busy sites

Figure 19 shows the quarterly summary of the averaged DLD at RA300W. The drastic drop in DLD in the third and fourth quarters of 2020 was due to puck sensor failure, which is consistent with the anomaly detection result. This bar graph summary can be retrieved for all sites in a data visualization dashboard, introduced in Section 4.4.

Figure 19. Quarterly average daily low duration of RA300W

4.1.2 Utilization

Figure 16 also shows a typical demand cycle for a truck parking site. It shows that when truck drivers begin work every morning, availability starts increasing around 5 a.m. The site will then become crowded at around 10 p.m. when truck drivers start looking for a place to rest. To find the busiest hour of the day, a 24-hour demand cycle of the overall parking utilization distribution was analyzed. Overall utilization is defined as follows:

$$U_E = \frac{\sum Availability_i}{\sum Capacity_i}, i \in E \quad (5)$$

$$U_W = \frac{\sum Availability_j}{\sum Capacity_j}, j \in W \quad (6)$$

where E is a set of all eastbound sites and W is a set of all westbound sites.

Private sites are labeled as two-direction sites and provide parking spots for truck drivers in either direction; therefore, they were counted in both directions. Overall utilization reached its maximum at 2:00 a.m. in both directions (81.1% of the westbound sites and 81.6% of the eastbound sites), and the corresponding 24-hour demand cycle is shown in Figure 20.

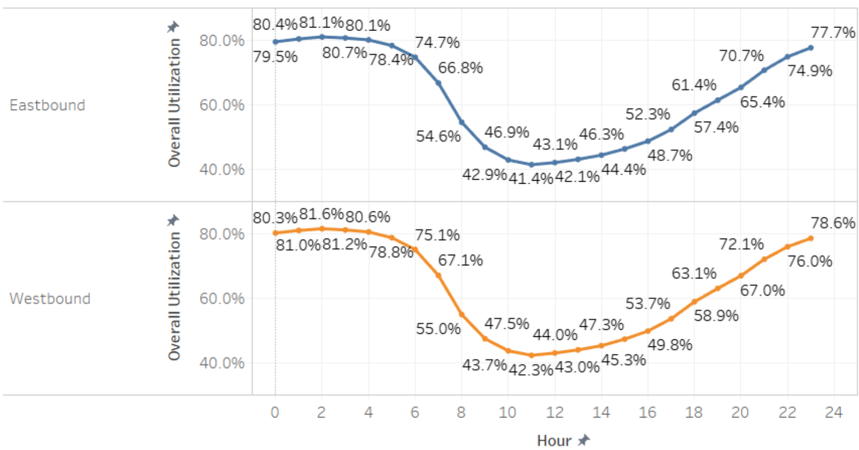

Figure 20. Overall utilization

Therefore, utilization at 2:00 am was selected as another metric to measure the busyness of a specific site. This metric is then analyzed across the sites to show spatial distributions. The temporal distribution shows the utilization demand cycle in a 24-hour scope at each site as another way to evaluate utilization.

Figure 21 shows an example of the spatial distribution of utilization at night to demonstrate the variation in utilization between multiple sites. The average utilization and standard deviation of utilization among sites at 2 a.m. are computed by direction and compared by quarters.

Since TPIMS went into operation in January 2019, truck drivers have had access to real-time parking availability information through Iowa 511 and other apps that consume the data feed. An increase in average utilization and decrease in standard deviation indicate a more even distribution of utilization in the next two quarters. Furthermore, seasonal changes can affect utilization. During the winter months, average utilization decreases due to reduced truck traffic. In addition, variations in utilization between sites can increase due to winter weather.

Figure 21. Comparison of utilization at 2 a.m.: average utilization and standard deviation across multiple sites

The daily trend is influenced by the day of the week and the type of site. Figure 22 compares the trend of daily utilization for the first two quarters in 2019 and 2020. In 2020, the use of public sites increased slightly during the night and increased significantly during the day compared to 2019. This could be due to increasing awareness of the TPIMS by drivers over time. However, the utilization of private sites did not show significant changes. On weekends, private site utilization exhibited a decline, particularly at night in 2020 compared with 2019.

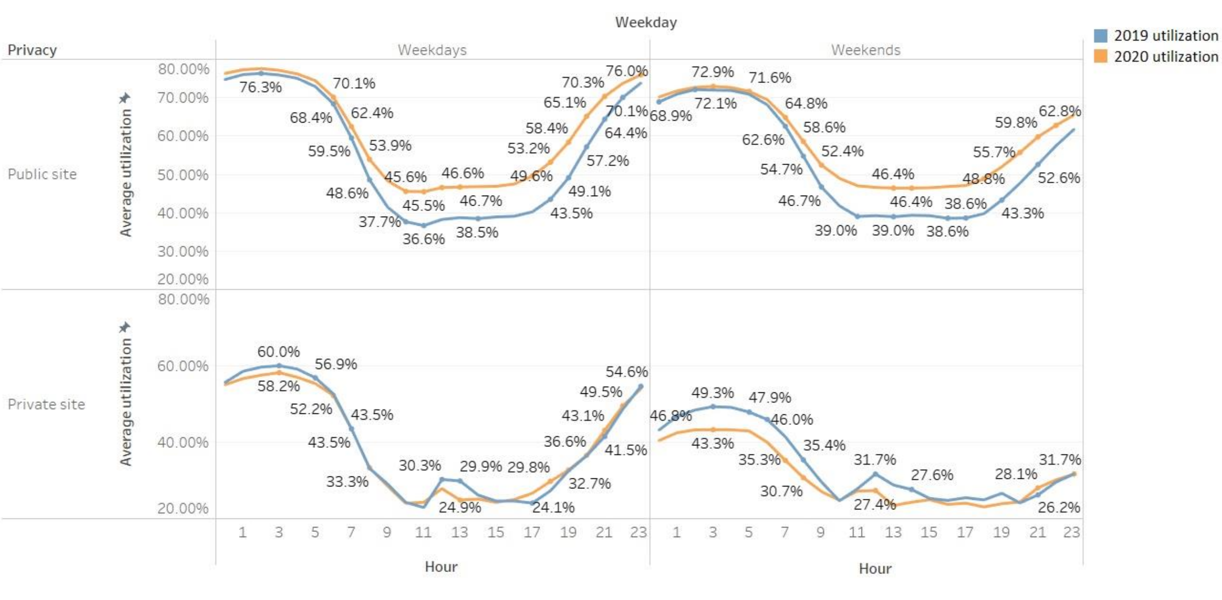

Figure 22. Comparison of utilization on weekdays and weekends

The increase in daytime parking at public sites and the decrease in nighttime parking at private sites in 2020 could be due to the increase in regional freight transport and the changes in HOS regulation made during the pandemic (FMCSA 2020). In particular, on March 13, 2020, the FMCSA issued an emergency declaration that suspended HOS regulations. Initially, the HOS suspension applied to deliveries of COVID-19-related medical supplies, food for grocery stores, supplies to build quarantine facilities and emergency housing, and emergency service personnel. Later, on March 18, 2020, FMCSA expanded the suspension to include drivers who deliver fuel, non-food groceries, and raw materials needed for essential goods. Under typical HOS regulations, truckers can drive for no more than 11 consecutive hours on a 14-hour workday. Until the COVID outbreak, drivers also had to take 30-minute breaks every 8 hours and 10 full hours off duty at the end of a workday. Furthermore, within a 7 or 8-day working period, drivers could drive no more than 60 or 70 hours. These regulations were temporarily lifted, which allowed truckers more flexibility in parking choices.

In examining the demand cycle, a noteworthy aspect to consider is the slope of the trend line, which reflects the rate of change in utilization. The investigation reveals an interesting observation concerning the different working patterns of truck drivers during summer (Q2 and Q3) and winter (Q1 and Q4). The data illustrate that the most substantial decrease in utilization occurs between 7:00 and 8:00 a.m. for both seasons. However, the second most significant drop occurs between 6:00 and 7:00 a.m. in summer, whereas during winter it shifts to 8:00 and 9:00 a.m. Evidently, truck drivers tend to begin their work earlier in the summer months. Additionally, the analysis highlights that truck drivers end their work approximately one to two hours later in the evening during summer compared with winter. This disparity can be rationalized by the substantial discrepancy in daylight hours between the two seasons, prompting truck drivers to allocate more time to travel on the road during summer. Note that the original data are in Coordinated Universal Time, but in the whole analysis process they are transformed into Central Daylight Time.

Table 6. Change rate of utilization

Hour	Summer	Winter
6 to 7	-14%	-13%
7 to 8	-18%	-20%
8 to 9	-13%	-20%
…	…	…
18 to 19	12%	18%
19 to 20	14%	17%
20 to 21	13%	14%

The spatial and temporal distribution of utilizations and low durations can be further explored using the data dashboard presented in Section 4.4.

4.1.3 ATRI Parking Surveys

Regarding utilization, we analyzed survey results extracted from ATRI's analyses of its MAASTO truck parking survey. These results pertain to questions that appeared in multiple surveys, providing valuable information on the utilization patterns and trends related to truck parking in the MAASTO region. First, truck drivers were asked to describe their time to find parking in the MAASTO region. Table 7 shows the results. The study examined driver-reported search times for truck parking in 2016, 2018, and 2020. In 2018, drivers were less likely to report search times exceeding an hour (10.9% compared with 18.0% in 2016), and more likely to report search times of under 15 minutes (20.6% compared with 9.9% in 2016). Most responses in 2018 fell within the search time range of 15 minutes to 1 hour (68.5%), similar to the pattern observed in 2016. Despite the growing economy, drivers' proficiency in finding parking seemed to improve, possibly attributed to the availability of parking resources, such as parking applications. However, in 2020, there was an increase in the likelihood that drivers report search times greater than 30 minutes (44.4% compared with 31.8%), indicating a potential increase in utilization and a potential challenge in finding available truck (ATRI 2016, 2018, 2020).

Table 7. Average search time

Search Time	Oct. 2016	May 2018	Feb. 2020
Less than 15 min	9.9%	20.6%	13.3%
15-30 min	30.0%	36.7%	24.4%
30-60 min	42.1%	31.8%	44.4%
More than 60 min	18.0%	10.9%	17.8%

Second, truck drivers were asked to describe the frequency of parking in the MAASTO region. The findings, presented in Table 8, demonstrated a considerable demand for parking. Almost all truck drivers surveyed required parking in the MAASTO region at least once a week, with more than 70% of drivers needing parking two to seven times each week in 2016, more than 60% in 2018 and more than 80% in 2020.

Table 8. Frequency of parking in the MAASTO region

Frequency	Oct. 2016	May 2018	Feb. 2020
Every day	9.9%	14.0%	18.6%
5-6 times a week	15.3%	11.6%	18.1%
2-4 times a week	47.7%	36.2%	44.2%
Once a week	14.3%	16.9%	11.1%
Less than once a week	12.7%	21.2%	8.0%

The final focus of this research was truck drivers' assessments of parking lot occupancy in facilities with designated parking areas, with data collected from the 2018 and 2020 surveys. The results highlight the challenge of finding available parking at existing facilities in the MAASTO region, which worsened in 2020. In 2018, more than 70% of drivers reported that parking facilities were occupied at or above 75% capacity, while in 2020, this figure increased to more than 85% (Table 9).

Table 9. Assessment of parking lot occupancy by drivers

Occupancy	May 2018	Feb. 2020
Empty	4.3%	0.0%
25% full	8.3%	1.3%
50% full	12.0%	11.2%
75% full	39.3%	32.3%
Completely full	17.9%	12.1%
Overcapacity	18.2%	43.0%

In particular, a facility was defined as overcapacity if trucks were parked in unauthorized spaces, including unmarked areas, entrance/exit ramps, and road shoulders. This type of unauthorized parking poses safety risks for truck drivers and the general public. Parking on shoulders and ramps creates a driving hazard, while parking outside designated spaces may increase the likelihood of property damage due to limited maneuver space for drivers.

4.2 System Reliability

4.2.1 System Downtime

The system downtime measure evaluates the percentage of time that the system is not working as intended. Data for each site are analyzed to determine whether there are data records for at least each 5-minute period. If records are missing, the amount of time the site is considered down will be determined by subtracting the time stamp field of the last record before the gap from the first record after the gap in data less than five minutes. Gap intervals were detected by the double-point method and then aggregated. To evaluate the long-term reliability of the system, downtime was aggregated at monthly and quarterly levels in the data visualization dashboard, as discussed in Section 4.4.

During the three-year grant period, 36 of 43 TPIMS sites experienced a system downtime of less than 5%. Figure 23 presents a summary of the overall percentage of system downtime at all sites. It is important to note that RA32E encountered prolonged system downtime due to a resurfacing project initiated in October 2020. The quarterly downtime pattern for RA32E is shown in Figure 24, revealing a complete site outage for the subsequent two quarters starting in Q4 2020.

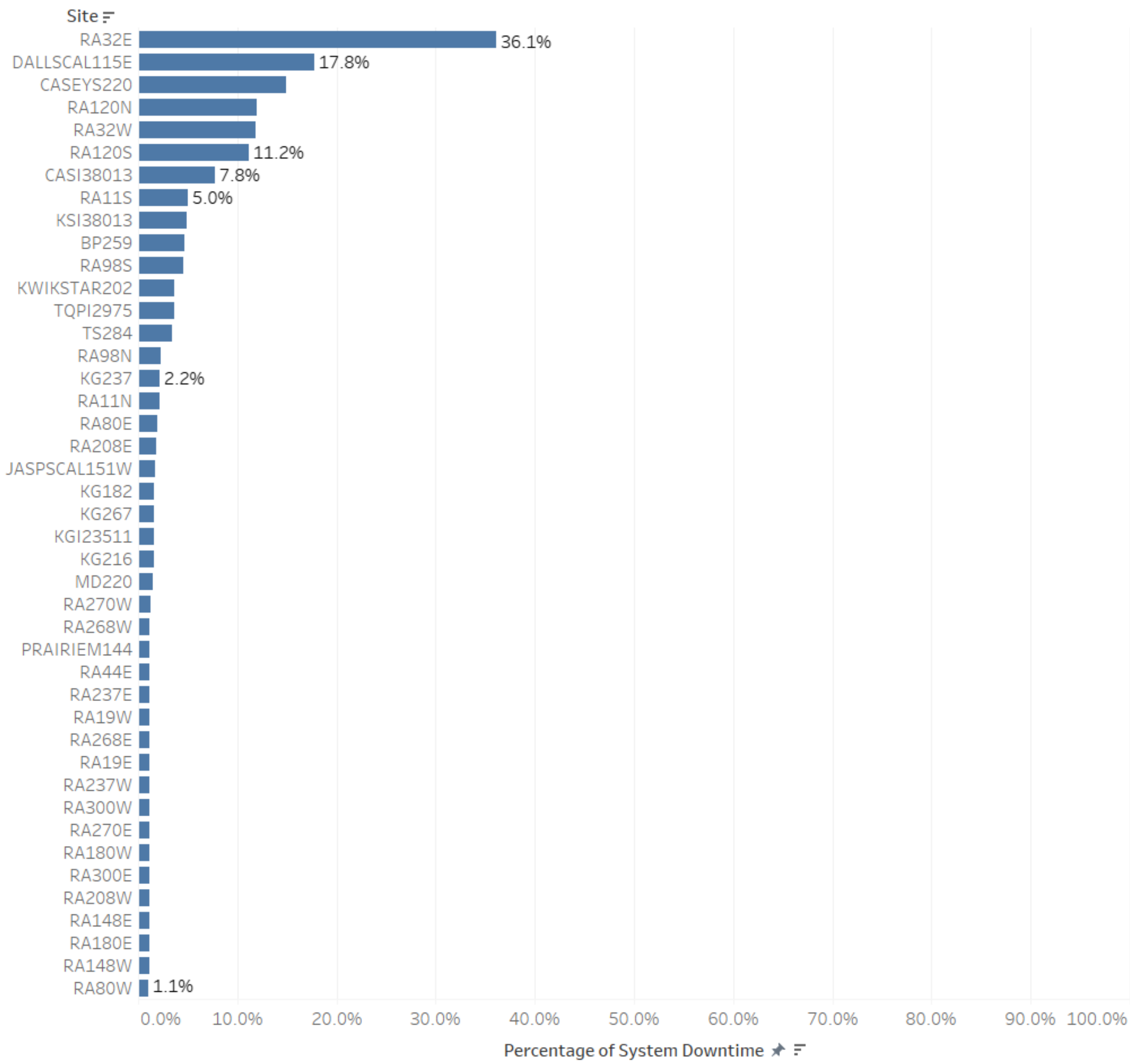

Figure 23. Percentage of system downtime

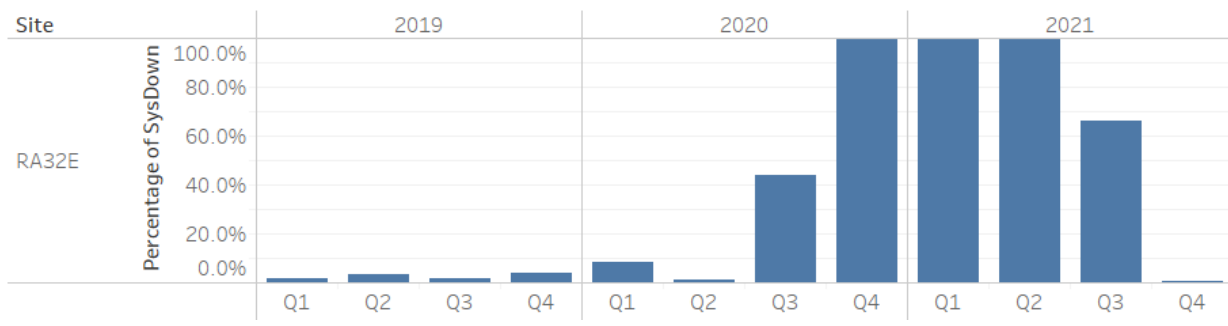

Figure 24. Quarterly summary of system downtime for RA32E

To prevent prolonged system downtime, we have also implemented a daily alert system that uses AWS bucket-specific email sending functionality. This system operates on a daily basis. From the 24-hour parking flow data for the previous day, the system downtime for each site is calculated. When system downtime lasts more than 15 minutes at one or more TPIMS sites, the system will automatically generate and send email reports to investigators.

4.2.2 User Complaints

The user perception of system reliability is included in the 2020 ATRI survey. Figure 25 (ATRI 2020) shows that about 44% of drivers reported that the information was "accurate" or "reasonably accurate." A similar percentage of drivers consider the system "unpredictable" or "inaccurate."

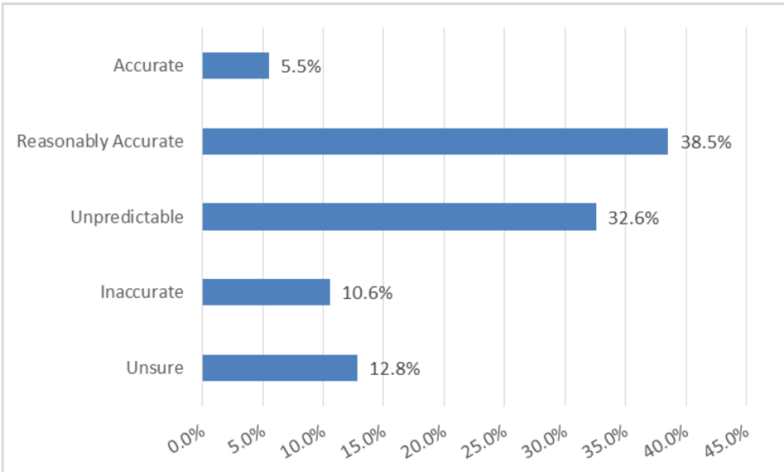

Figure 25. TPIMS accuracy rating

4.2.3 Accuracy

In evaluating the system's ability to report accurate information to drivers in real time, data in the archived feed was used. This database contains a record of the reported number of parking spaces available at each site with a 5-minute interval since the implementation of TPIMS. Routine visual inspection is performed at each site to validate the output reported by the system, wherein the actual number (from inspection) of available parking is stored in the database and used to correct the reported parking availability in the system. By comparing the reported and actual available parking spaces, the accuracy of the system can be quantified.

Figure 26 elaborates using two examples of how the manual check is flagged in the archived data. Note that only related columns are displayed for concision.

SITE_ID	TIME_STAMP	AVAILABLE	LASTVERIFICATIONCHECK	VERIFICATIONCHECKAMPLITUDE
IA00080IS002840OEI80TRSTO	01-JUN-20 12.26.47 PM	294	01-JUN-20 12.03.02 AM	0
IA00080IS002840OEI80TRSTO	01-JUN-20 12.31.49 PM	293	01-JUN-20 12.03.02 AM	0
IA00080IS002840OEI80TRSTO	01-JUN-20 12.36.49 PM	299	01-JUN-20 12.03.02 AM	0
IA00080IS002840OEI80TRSTO	01-JUN-20 12.39.55 PM	285	01-JUN-20 12.39.55 PM	14
IA00080IS002840OEI80TRSTO	01-JUN-20 12.41.47 PM	289	01-JUN-20 12.39.55 PM	14
IA00080IS002840OEI80TRSTO	01-JUN-20 12.46.14 PM	289	01-JUN-20 12.39.55 PM	14
IA00080IS002840OEI80TRSTO	02-JUN-20 12.11.15 AM	135	01-JUN-20 12.39.55 PM	14
IA00080IS002840OEI80TRSTO	02-JUN-20 12.12.32 AM	130	01-JUN-20 12.39.55 PM	14
IA00080IS002840OEI80TRSTO	02-JUN-20 12.16.15 AM	130	01-JUN-20 12.39.55 PM	14
IA00080IS002840OEI80TRSTO	02-JUN-20 12.16.38 AM	185	02-JUN-20 12.16.38 AM	-55
IA00080IS002840OEI80TRSTO	02-JUN-20 12.17.31 AM	180	02-JUN-20 12.16.38 AM	-55
IA00080IS002840OEI80TRSTO	02-JUN-20 12.21.18 AM	180	02-JUN-20 12.16.38 AM	-55

Figure 26. Manual check records in parking flow data

On June 1, 2020, at 12:39:55 p.m. (UTC), a manual check on the actual number of available slots was conducted, and this time flag is stored in column "LASTVERIFICATIONCHECK." The value obtained from visual inspection was stored in column "AVAILABLE," and then an amplitude is stored in column "VERIFICATIONCHECKAMPLITUDE." This means that the system had reported the number of slots available to be 299, whereas visual inspection reported the actual number of slots to be 285, thus producing an amplitude of 14. The cells in columns "LASTVERIFICATIONCHECK" and "VERIFICATIONCHECKAMPLITUDE" were automatically forward filled until the next manual check that occurred on June 2, 2020, at 12:16:38 a.m. (UTC). At the next inspection, the system reported that 130 slots were available, but the manual check revealed that the actual number of slots was 185. This resulted in an amplitude of -55.

According to HNTB (2017), the accuracy should be calculated as a percentage of actual available spaces at the rest point in time by

$$\text{Accuracy} = 1 - \left|\frac{Reporting - Actual}{Actual}\right| \tag{7}$$

Since the actual availability is nonnegative, we can separate the accuracy into two cases: when the actual availability is zero and when the accuracy is not calculable. When the actual availability is positive, the equation can be rewritten as follows:

$$\text{Accuracy} = 1 - \frac{|Reporting - Actual|}{Actual} = 1 - \frac{|Amplitude|}{Actual} \tag{8}$$

According to HNTB (2017), the target level of accuracy is 85% for small lots (<15 spaces) and 90% for other lots.

Two detection technologies are used at Iowa parking sites. Table 10 shows the six private truck stops that use in-and-out detection, and their target level of accuracy is 90%.

Table 10. Truck stops using in-and-out detection

Site Code	Capacity
IA00380IS0001300WCASEYS00	92
IA00080IS0022000WCASEYS00	20
IA00080IS0020200WKWIKSTAR	110
IA00080IS0025900WBP000000	46
IA00029IS0007500WTQUICPIC	50
IA00080IS002840OEI80TRSTO	850

All other sites are equipped with sensing pucks. Based on the result of the anomaly detection of the parking flow data and the banner puck record provided by eX^2, pucks had failed since summer 2020 at most TPIMS sites in Iowa. Therefore, the study scope of the manual check analysis below is from January 2019 to June 2020. Table 11 shows the summary of the manual check cases in Iowa parking lots.

Table 11. Manual check cases

State	Lots	Total Number of Manual Check Cases	Number of Actuals = 0 cases	Accuracy Calculable Cases	Accuracy 85%+ or 90%+ Cases	Accuracy 85%+ or 90% + cases (percentage)
IA	Small	1127	61	1066	1023	95.97%
IA	Large Puck	1427	18	1409	1348	95.67%
IA	Large In-and-Out	7014	7	7007	1673	23.88%

Some visual checks were also made based on the archived images of the parking sites in Iowa, as mentioned in Chapter 2, after checking the images and angles of all TPIMS sites, images from seven sites (RA180E, RA208W, RA237W, RA270E, RA270W, RA300E, and RA300W) were used for checking accuracy because of their relatively higher quality views of truck heads. At each parking site, images from three angles were archived every five minutes and then concatenated to obtain an overall view of the site. Among these sites, RA270E (capacity = 12) and RA300E (capacity=14) are small sites.

According to the anomaly detection results, the study range is set from January 2019 to June 2020. That leaves us with about 700 valid images for truck counting. Although the results might be influenced by the resolution of the image, angle of the camera, and time mismatch between flow records and archived images, it can be considered as an auxiliary investigation of accuracy of TPIMS. Table 12 shows the comparison of manual checks in parking flow data and visual check results. As mentioned in Section 4.2.3, the target accuracy level of small sites is 85% during each manual check. The manual check record in the parking flow data indicates that

97.39% of the manual check cases reach the target, while the image comparison shows that only 61.86% cases reach the target.

Table 12. Manual check in parking flow data and visual check

Lot Size	Data Source	Total Number of Manual Check Cases	Number of Actuals = 0 cases	Accuracy Calculable Cases	Accuracy 85%+ or 90%+ Cases	Accuracy 85%+ or 90% + cases (percentage)
Small	Flow data	118	3	115	112	97.39%
	Image	195	1	194	120	61.86%
Large	Flow data	303	8	295	275	93.22%
	Image	534	1	533	164	30.77%

4.3 Corridor Safety

4.3.1 HOS Violation

Fourteen counties were selected to investigate whether the Iowa TPIMS had improved corridor safety, as shown in Figure 27. The study period is from 2018 to 2021. Table 13 shows a summary of the number of inspections and violations compared year by year.

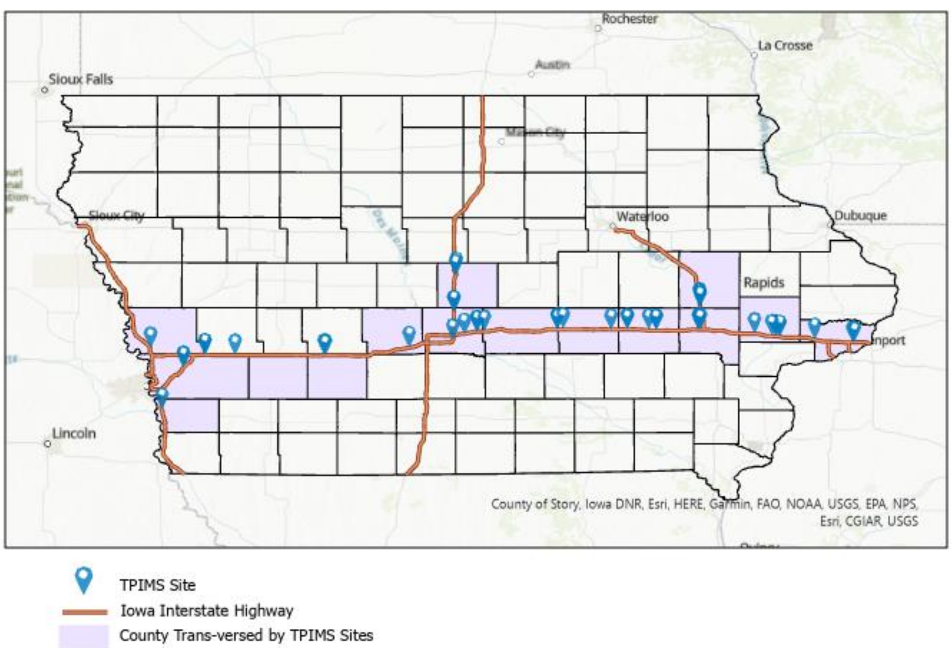

Figure 27. Counties traversed by the TPIMS corridors in Iowa

Table 13. Inspections and violations

Year	Number of Inspections	Number of inspections without violation	Number of inspections with violation	Number of Violations
2018	19567	4317	15250	41523
2019	19454	3893	15561	42181
2020	12400	2406	9994	26776
2021	16989	2925	14064	37409

The selection of the kind of violation to be analyzed was guided by the MCMIS Inspection File Catalog Documentation (FMCSA 2014) and the proposed HOS Violation Measures by HNTB (2019), which led to the emergence of two grouping systems. HNTB (2019) identified the criteria fields as "INSP_VIOLATION_CATEGORY_ID" and "PART_SECTION_ID," respectively. Table 14 provides more details on the selection criteria for quantifying HOS violations.

Table 14. HOS violations

Identification system	Field Value	Data Element	Description
INSP_VIOLATION_CATEGORY_ID	04	10/15	10/15 hour rule violation
	05	15/20	15/20 hour rule violation
	06	60/70	60/70 hour rule violation
	07	OTTHOS	All other HOS violations
PART_SECTION_ID	3570	395.1O	16-hour rule violation (property-carrying vehicle)
	3572	395.3A1/R	11-hour rule violation (property-carrying vehicle)
	393840	395.3A2-PROP	Driving beyond 14-hour duty period (property-carrying vehicle)
	3574	395.3A2/R	14-hour rule violation (property-carrying vehicle)
	395654	395.3A3II	Driving beyond the 8-hour limit since the end of the last off-duty or sleeper period of at least 30 minutes
	393841	395.3A3-PROP	Driving beyond the 11-hour driving limit in a 14-hour period (property-carrying vehicle)
	396340	395.3A3-PROPN	Nominal violation: Driving beyond the 11-hour driving limit in a 14-hour period (property-carrying vehicle)
	393842	395.3B1-PROP	Driving after 60 hours on duty in a 7-day period (property-carrying vehicle)
	396341	395.3B1-PROPN	Nominal violation: Driving after 60 hours on duty in a 7-day period (property-carrying vehicle)
	393843	395.3B2	Driving after 70 hours on duty in an 8-day period (property-carrying vehicle)
	396342	395.3B2-NOM	Nominal violation: Driving after 70 hours on duty in an 8-day period (property-carrying vehicle)
	3576	395.3B/R	60/70-hour rule violation (property-carrying vehicle)

The results were classified into “HOS violations” and “Other violations” for each year and for each grouping system. Subsequently, a year-by-year comparison with the result shown in Figure 28. The main findings are as follows:

1. The number of violations was significantly reduced in 2020, which could be due to the reduced number of roadside inspections during the pandemic.

2. The percentage on the bars indicates the proportion of HOS violations and other violations in that year. After the TPIMS was deployed in January 2019, HOS violations by section had decreased from 1.82% to 1.08%, which was a 40.7% percent reduction.

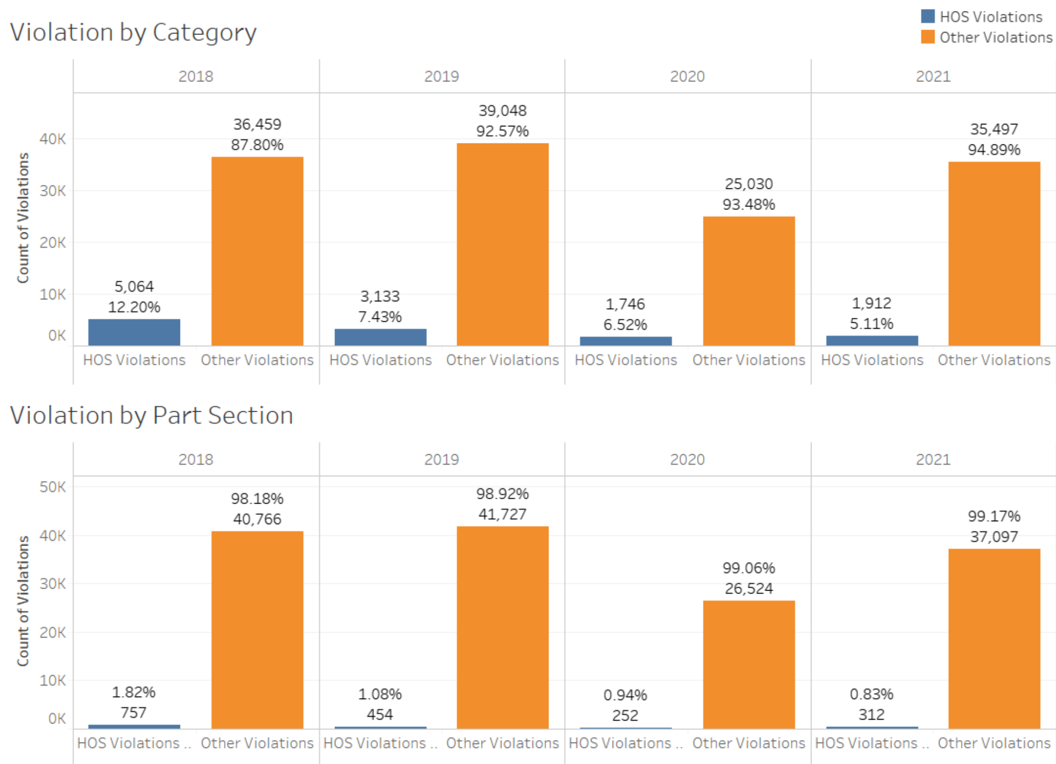

Figure 28. Comparison year by year of HOS violations

4.3.2 ATRI Truck Parking Survey

The ATRI surveys include some questions about safety. The survey included various questions, and, for some, consistent responses were observed, enabling the identification of continuous trends. However, questions were asked differently regarding some aspects, making it difficult for longitudinal comparison.

Specifically, drivers were first asked to share their experiences with respect to various truck parking problems. Their responses are consolidated in Table 15. In particular, two parking-related concerns, namely the availability of parking solely on shoulders/ramps and the presence of parking in unsafe locations, demonstrated an upward trend in prevalence over the years 2016 to 2020. For instance, in 2020, a substantial 85.3% of respondents indicated that parking was “always” or “sometimes” available on ramps/shoulders, whereas in 2016 and 2018 the corresponding percentages were 62.7% and 70.8%, respectively. These findings show growing safety concerns expressed by respondents and underscore the importance of addressing truck parking challenges and their potential safety implications (ATRI 2016, 2018, 2020).

Table 15. Parking issues in the MAASTO region

Issue	Oct. 2016			May 2018			Feb. 2020		
	Always/ Often	Somet imes	Rarely/ Never	Always/ Often	Some times	Rarely/ Never	Always/ Often	Some times	Rarely/ Never
Rest area time limit	15.6%	38.4%	46.0%	15.1%	36.9%	48.0%	14.2%	37.6%	48.2%
Parking is available only on ramps or shoulder	30.1%	32.6%	37.3%	33.1%	37.7%	29.2%	49.4%	35.9%	14.8%
Parking is available only in unsafe locations	29.8%	38.4%	31.7%	27.7%	39.3%	33.0%	32.1%	43.0%	24.9%
Truck damage while parked	3.1%	16.3%	80.6%	4.5%	19.9%	75.6%	6.4%	18.6%	75.0%
No parking available for oversize vehicle	27.8%	20.3%	51.9% %	31.5%	23.2%	45.2%	45.9%	20.9%	33.1%

ATRI also delved into the issue of truck drivers parking in unauthorized locations. In the 2018 survey, participants were questioned about their unsafe parking behavior. Approximately 22.8% of the respondents admitted to parking "often" or "always" in unauthorized locations (Figure 29). However, in the subsequent 2020 survey, the approach to questions and responses changed. Participants were instead asked to describe their parking frequency in unauthorized locations "since the installation of the MAASTO truck parking information system" (TPIMS). The findings, as shown in Figure 30 (ATRI 2020), revealed that the majority of survey participants (58.2%) reported no significant change in their parking frequency compared to before MAASTO TPIMS implementation. This consistency in behavior can be attributed to the persistent lack of parking capacity in areas where parking is most urgently needed.

Never	Rarely	Sometimes	Often	Always
20.4%	22.0%	34.9%	19.6%	3.2%

Figure 29. Frequency of drivers parking in an unauthorized location (2018)

Parking Frequency in Unauthorized Location	Percent
More Often	7.7%
Less Often	34.1%
About the Same	58.2%

Figure 30. Frequency of drivers parking in an unauthorized location (2020)

Participants were asked to assess whether they perceived an improvement in their safety and/or compliance with HOS requirements regarding the availability of the MAASTO truck parking system. Figure 31 (ATRI 2020) illustrates the responses to this question. Among the respondents, 21.5% reported that the MAASTO system had indeed contributed to improved safety or compliance with HOS regulations. However, a higher proportion responded negatively, 35.4% indicating that their safety was not perceived as beneficial and 43.0% stating that their safety remained relatively unchanged. ATRI also stresses that while many participants did not perceive a safety benefit or a change in their safety levels, it is essential to note that this does not imply that these drivers are less safe. An alternative explanation is that they may already be safe drivers and, therefore, the MAASTO truck parking system may not significantly impact their safety practices.

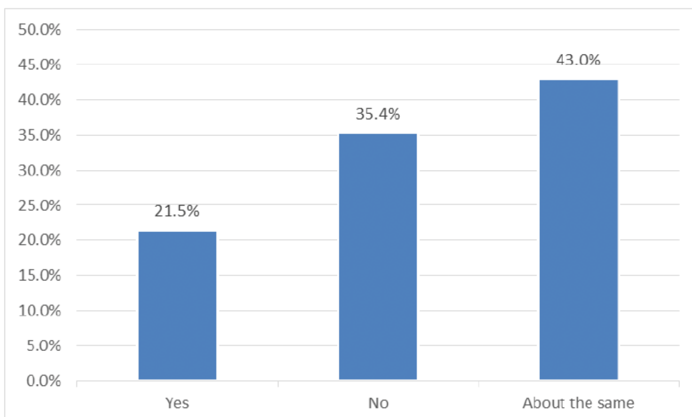

Figure 31. TPIMS improve safety and/or HOS compliance

4.4 Visualization Tool

A dashboard was developed to evaluate and monitor the performance of TPIMS. Since commercial truck activities can be influenced by seasons and days of the week, quarter and weekday filters can be used for various temporal analyses. In addition, the "Map Selector" panel allows users to select a specific site or a group of sites on the map and view the corresponding performance measures. The "Select Direction" filter can select sites based on travel direction for spatial analysis.

Figure 32 demonstrates the use of the visualization tool. By selecting sites in the "Map Selector" in the upper left panel, the average DLD (in minutes) and system downtime (in percentage) are shown in the upper right panel of the dashboard. The measures are summarized by quarter, with a monthly summary also available when hovering the cursor on a specific quarter summary result.

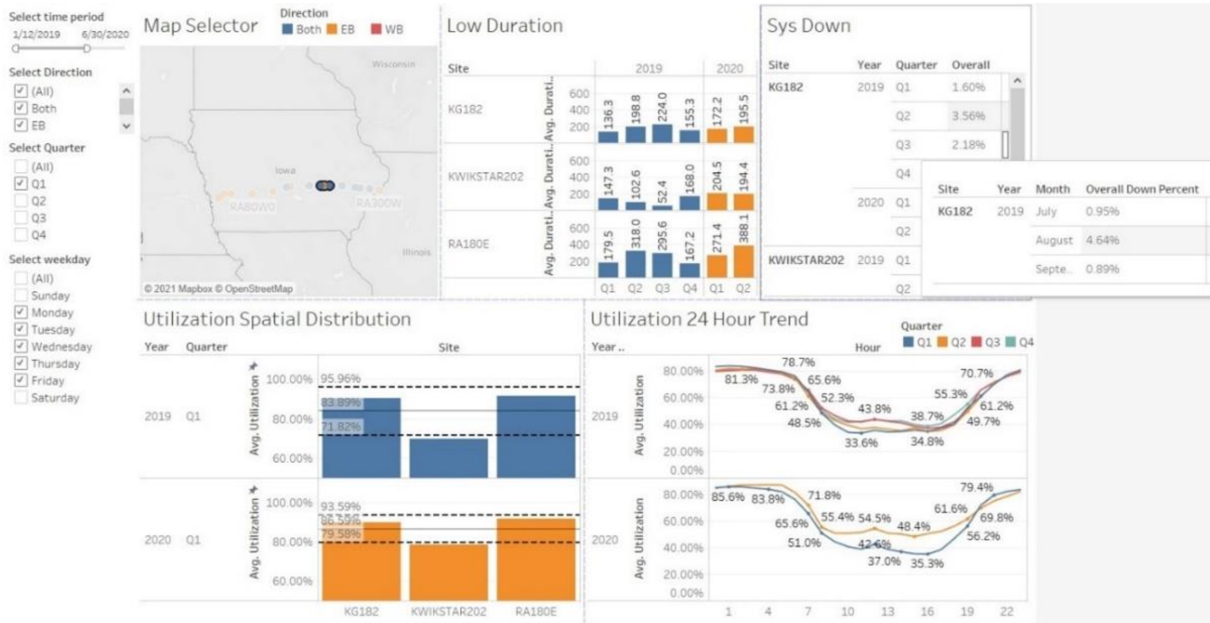

Figure 32. Overview of the data dashboard

The spatial distribution of utilization can be investigated when a set of adjacent sites are selected in the "Map Selector." For example, the spatial utilization distribution is shown in the lower left panel that compares three eastbound sites. The average utilization at 2 a.m. in the first quarter of 2019 was 83.89%, with a standard deviation of 12.07%. However, in 2020, the average utilization increased to 86.59%, and the standard deviation decreased to 7.01%. A higher mean and a lower standard deviation of utilization across multiple sites indicate a more evenly distributed parking demand.

Similarly, the temporal distribution can be observed in the "Utilization 24-Hour Trend" panel. By selecting the sites and days of the week, the averaged 24-hour trend of each quarter is plotted in the lower right panel.

5. COMPARISON WITH OTHER STATES

Eight states participated in the MAASTO TPIMS project. All states besides Iowa have implemented variable message signs to display parking spaces available on the roadside. Therefore, sensing technology, data availability, and performance are compared.

5.1 Sensing Method

Different states adopted different sensing technologies in their TPIMS. In the Iowa TPIMS, both space-by-space underground pucks and in-and-out sensors are used to collect occupancy data. Table 16 summarizes the different sensing methods in the MAASTO states.

Table 16. Sensing method

State	Detection
IA	In-and-out, space-by-space detection by Banner pucks
IN	Space-by-space detection using magnetometers by Sensys
KS	Space-by-space detection by University of Minnesota computer vision
KY	In-and-out radar-based detection
MI	Video analytics software (Quantum Signal)
MN	Space-by-space detection by Banner pucks
OH	In-and-out detection, space-by-space puck detection
WI	In-and-out detection

5.2 Performance Comparison

5.2.1 Utilization

This section assesses the utilization of parking before and after the deployment of the TPIMS. To begin this evaluation, the availability of data across all states is examined. Table 17 presents a list of all data stored in the MAFC data warehouse. It is observed that the flow data before the implementation of the TPIMS is notably scarce.

Table 17. Flow data availability

State	Before	After	Comment
IA	12/1/2018–12/31/2018	Since 1/11/2019	
IN	—	Since 1/11/2019	Cannot compare before and after difference
KS	12/7/2018–12/27/2018	Since 1/11/2019	No before data in 2 sites (Total 13 sites)
KY	12/21/2018–12/28/2018	Since 1/11/2019	Limited before data
MI	12/7/2018–12/28/2018	Since 1/11/2019	
MN	—	Since 1/14/2019	Cannot compare before and after difference
OH	—	Since 3/24/2019	Started recording since 12/7/2018, but the data is invalid (recorded capacity as availability). Valid data after 3/24/2019.
WI	12/7/2018–12/27/2018	Since 1/11/2019	No data before in 7 sites (Total 11 sites)

As mentioned in the previous section, occupancy at night can be a good indicator of utilization. Table 18 is a summary of the average utilization of all sites in each of the eight TPIMS states before and after the launch of the TPIMS. Data from before the deployment of the TPIMS were available from December 7–27, 2018, for most states. For Kentucky, pre-TPIMS data were only available from December 21–28, 2018 (Christmas week). Q2 utilization in 2019 was compared to data from before the TPIMS was implemented to account for gradual adoption by apps and Iowa511. In general, the growth in utilization during the night can be found in all comparable states.

Table 18. Average utilization at 2 a.m.

	Before*	After (2019 Q1)	After (2019 Q2)	Before vs. 2019 Q2 Growth***
IA	71.8%	72.6%	78.3%	6.5%
IN	—	54.1%	48.7%	—
KS	66.3%	72.1%	72.7%	6.4%
KY	49.2%**	77.3%	81.2%	32% (limited before data)
MI	50.4%	57.1%	61.0%	10.6%
MN	—	68.3%	73.1%	—
OH	—	—	82.9%	—
WI	67.2%	74.5%	74.8%	7.6%

* Before data were collected 12/7/2018-12/27/2018.
** Before data were only available from 12/21/2018 to 12/28/2018 (Christmas week) for KY.
*** 2019 Q2 utilization is compared with Before to account for gradual adoption of TPIMS.

5.2.2 Accuracy

Based on the parking flow data collected from the dynamic archive-only feed, the manual check accuracy in other states is also analyzed. The background of how accuracy is calculated can be found in the section Accuracy under System Reliability. Table 19 is the summary of manual checks in all MAASTO states. Note that only Iowa, Indiana, Kentucky, Ohio, and Wisconsin recorded their manual check details in the parking flow data. The lots are separated into small- and large-capacity lots as required. Lots in Kentucky and Wisconsin all have more than 15 spaces.

Table 19. Manual check cases in MAASTO states

State	Lot Size	Total Number of Manual Check Cases	Number of Actual = 0 cases	Accuracy Calculable Cases	Accuracy 85%+ or 90%+ Cases	Accuracy 85%+ or 90%+ Cases (percentage)
IA	Small	1127	61	1066	1023	95.97%*
IA	Large	8441	25	8416	3021	35.90%
IN	Small	800	37	763	59	7.73%
IN	Large	10129	217	9912	1856	18.72%
KY	Large	17155	6503	10652	2428	22.79%
OH	Small	926	11	915	641	70.05%
OH	Large	7143	26	7117	2523	35.45%
WI	Large	18296	268	18028	7718	42.81%

*To be consistent with other states, we used manual data checking to assess the accuracy of the Iowa TPIMS. The more reliable estimates based on images are presented in Table 12.

5.2.3 Safety

An investigation of HOS violations was conducted in other MAASTO states using FMCSA roadway inspection data. Detailed descriptions of the data can be found in Section 4.3.1. Only data for the grouping system that used “PART_SECTION_ID” were included in this analysis. This is because from the previous results obtained, the part section group produced a more accurate data set, which could be linked to the clear description it has for all violation records. Figure 33 shows a map of the counties through which the TPIMS corridor traversed other MAASTO states, and Figure 34 shows the proportion of HOS violations in each year in each MAASTO state. Among the eight states, seven states experienced a reduction in the proportion of HOS violations after TPIMS was deployed in January 2019, except Minnesota.

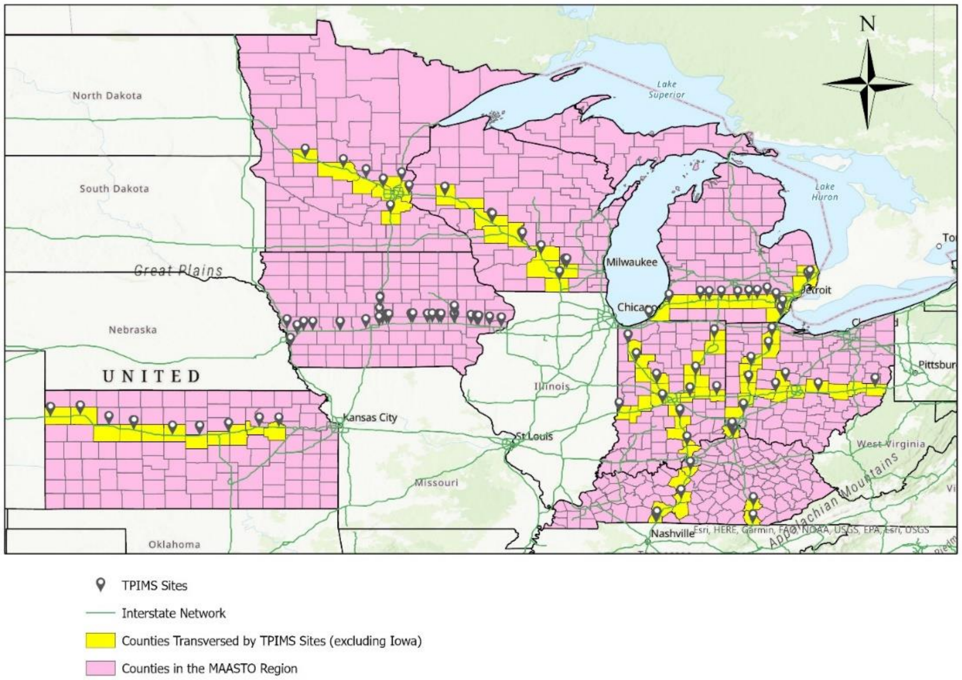

Figure 33. Counties traversed by the TPIMS corridors in other MAASTO states

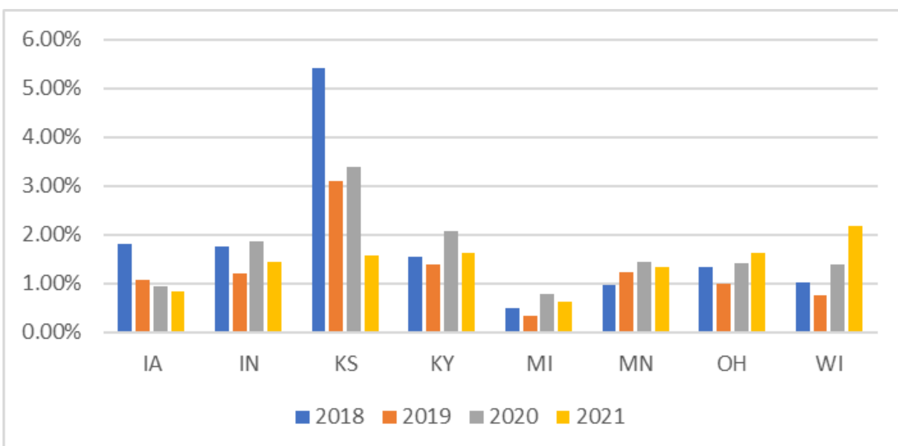

Figure 34. Percentage of HOS violations as a percentage of total violations each year in each MAASTO state

6. TRUCK DRIVER SURVEY

A questionnaire was developed to understand the parking experience of truck drivers and their opinions on TPIMS. The questionnaire asked about parking experience in general, parking experience outside Iowa, and parking experience in Iowa, as well as some general information about the drivers and their employers. The detailed questions are provided in Appendix A.

ISU's Center for Survey Statistics and Methodology-Survey Research Services (CSSM-SRS) conducted intercept surveys of truck drivers in Iowa. The purpose of the surveys was to gain information to improve the experience of parking trucks in Iowa.

The principal investigator (PI) submitted an application to ISU's Institutional Review Board (IRB) for approval to collect human subjects' data. At the direction of the IRB, CSSM-SRS contacted the ISU Office of Risk Management (ORM) to obtain approval from that office prior to IRB approval. ORM required CSSM-SRS staff to meet with an officer of ISU's Police Department to develop procedures for data collection that would be followed to ensure the safety of CSSM-SRS field staff. After completion of the approved procedures, IRB approval was granted. Safety procedures included sending teams of at least two field personnel to each location, setting up outdoors in areas covered by video cameras where available, and only surveying truck drivers during daylight hours.

The research team worked with Iowa DOT contacts to identify truck stops and rest areas along interstate highways that use TPIMS. Additional sites without the system were also selected due to the high volume of truck drivers at these sites.

6.1 Data Collection Procedures

CSSM-SRS sent teams to seven different sites to collect data. Two sites with higher volume truck driver traffic were visited twice. A short survey of 31 questions was printed on the front and back of a single sheet of paper. Field staff intercepted truck drivers as they approached the truck stop or rest area building to ask them to complete the survey. The surveys were distributed on clipboards for ease of completion. A short summary of the study was provided. Study participants were thanked for their participation with a $5 gift card that could be used at the survey location.

At each site, field staff set up a table covered by an ISU Survey Research Services tablecloth (see Figure 35a) and additional signage alerting participants to the truck parking survey and the $5 incentive (Figure 35b).

(a) Tablecloth from ISU Survey Research Services

(b) Additional signage

Figure 35. Setup of survey location

The initial plan was to visit four Kum and Go truck stops and two rest areas for a total of six sites, with the expectation to stay at each site for six hours in the afternoon and early evening hours.

Kum and Go corporate management granted permission to survey truck drivers at their locations. After the first two attempts at data collection, the plan was revised due to the low number of truck drivers available for survey participation. Higher traffic volume truck stops were then contacted to obtain approval to survey truck drivers at their locations. The following companies were contacted: Casey’s, Kwik Star, Taylor’s QuikPick, and Walcott’s I-80 Truck Stop. Only Casey’s corporate management allowed survey data collection at their sites. Based on feedback from truck stop employees, data collection was performed earlier in the day to catch drivers in the morning and during lunch hour.

A total of nine site visits were made to achieve the data collection goal of 200 completed surveys. Field staff visited two sites in one day to maximize time.

Table 20. Site visit locations, dates, and survey completion

Site	Date	Completed Surveys
Grinnell Kum and Go I-80	6/5/23	6
MM80 Rest Area I-80	6/6/23	14
Cedar Rapids Casey's I-380	6/8/23	44
Des Moines Kum and Go I-235	6/13/23	4
MM99 Rest Area I-235	6/13/23	5
Cedar Rapids Casey's I-380	6/14/23	37
Newton Casey's I-80	6/15/23	15
Ankeny Casey's I-235	6/20/23	38
Ankeny Casey's I-235	6/22/23	46
Total Completed Surveys		**209**

Field staff intercepted all truck drivers, but about 50% declined to participate in data collection due to a number of factors, including language barriers, tight timelines, and lack of interest in the survey. Anecdotally, field staff were told by truck drivers that the subject of the survey was important and necessary due to the lack of truck parking spaces available in Iowa.

6.2 Survey Results

This section presents some key findings of the survey. The summaries of the responses to all the questions are provided in Appendix B.

First, most drivers plan to park 30 minutes or more in advance. In particular, when parking overnight, two-thirds of drivers start planning more than an hour in advance (Figure 36).

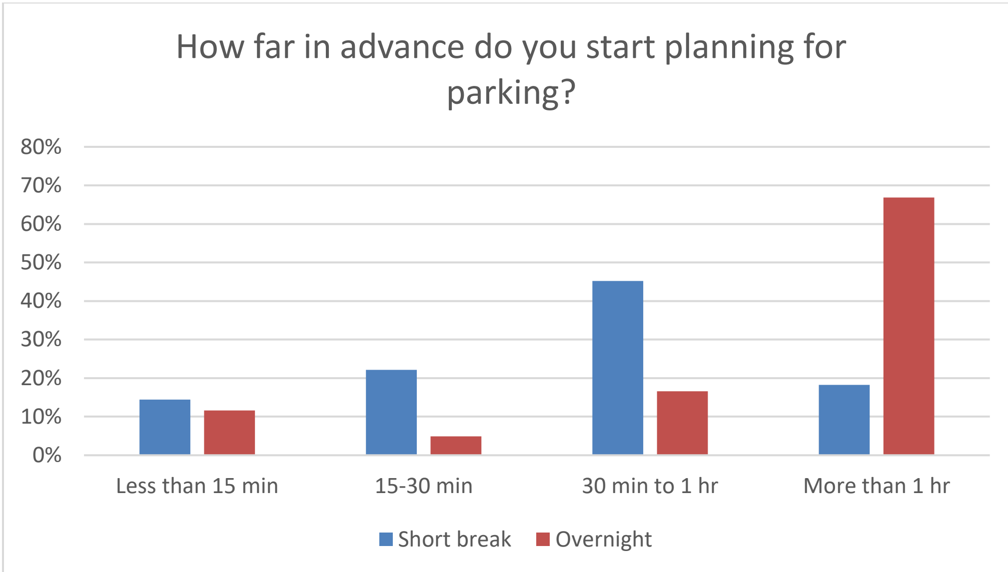

Figure 36. How far in advance do you plan to park?

Second, most drivers (78%) use smartphone apps, in-cab applications, or websites to access parking information (Figure 37).

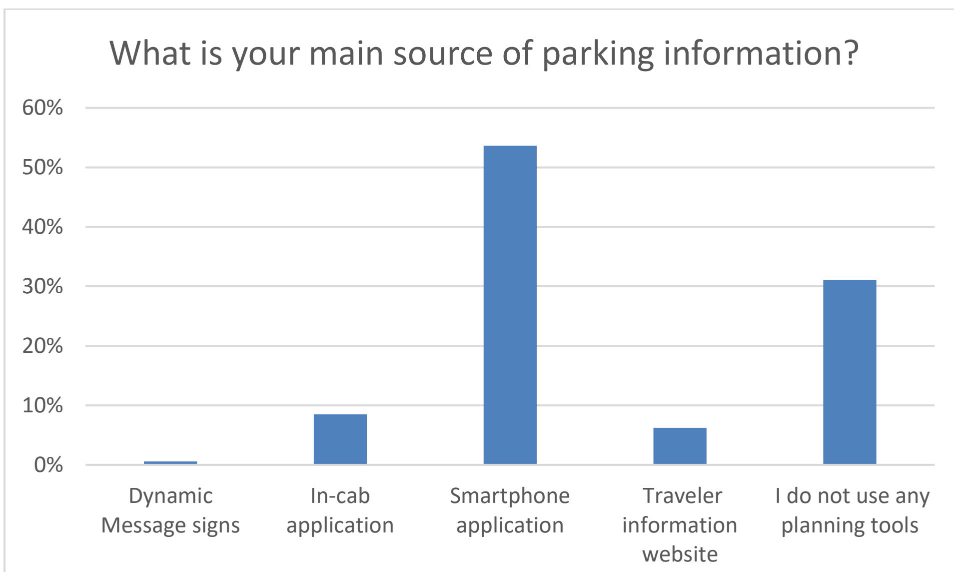

Figure 37. Main source of parking information

Third, finding parking takes less time in Iowa compared with other states but could take more than 30 minutes in 40% of cases (Figure 38).

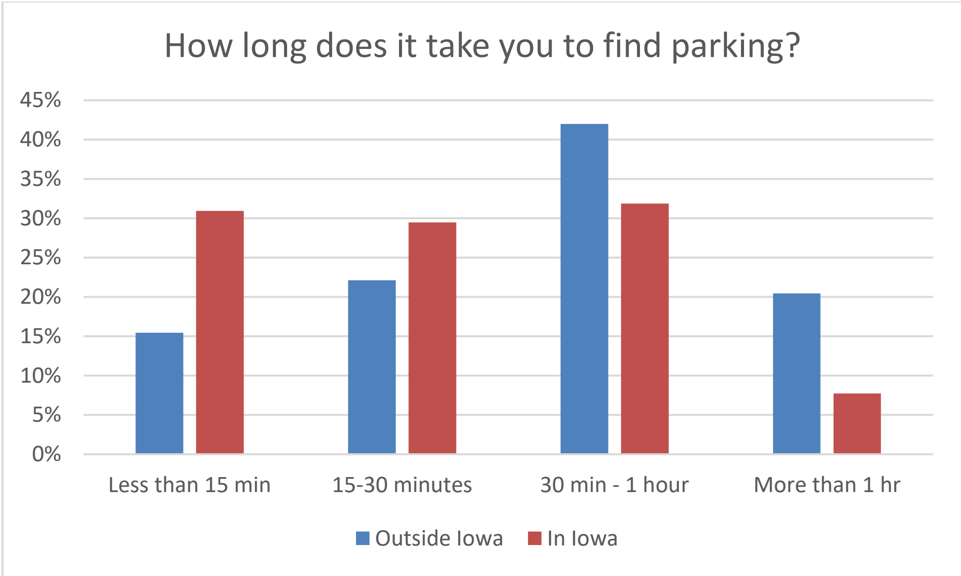

Figure 38. How long does it take to find parking?

Fourth, most drivers (57%) use real-time information to find parking in Iowa (Figure 39). Additionally, about two-thirds of drivers view images of the parking lot, indicating the importance of providing visual information (Figure 40).

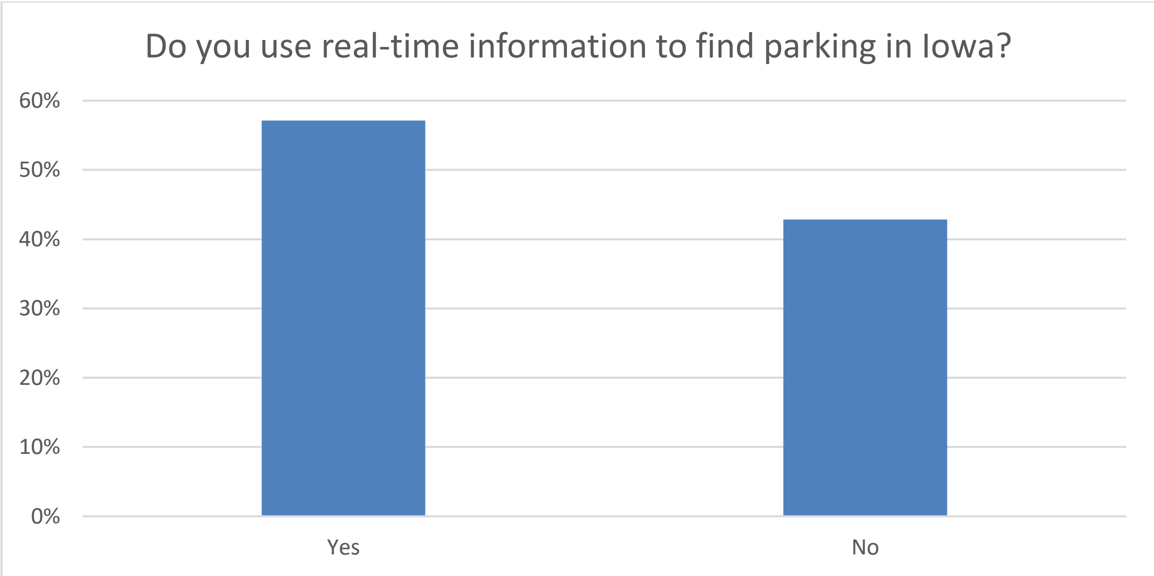

Figure 39. Use of real-time information to find parking in Iowa

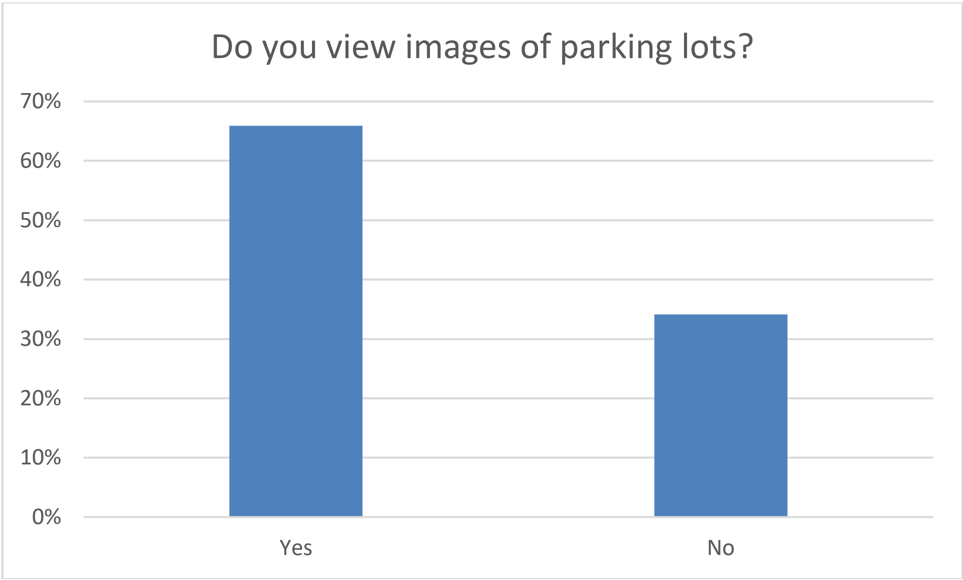

Figure 40. View images of parking lots

Finally, a total of 38% of drivers find parking information accurate, which is consistent with the ATRI survey results (Figure 41). This highlights the importance of improving sensor technologies and continuous monitoring of sensor health.

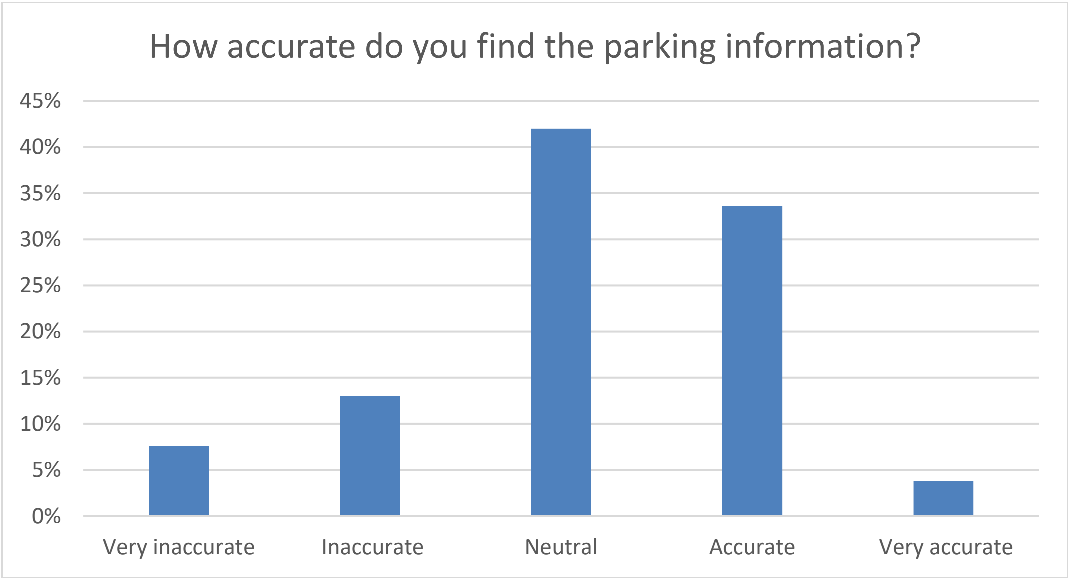

Figure 41. Perception by drivers of the accuracy of parking information

7. PREDICTIVE ANALYSIS

The Iowa TPIMS offers real-time utilization data, but truck drivers also want to know the expected availability of parking spaces at their planned arrival time. This section aims to introduce hybrid horizon prediction models for pre-trip planning and en route decision making for truck drivers, and the model is used in a user-friendly “Popular Time” panel.

7.1 Prediction Models

7.1.1 Pre-trip Model

In this study, it is hypothesized that truck drivers plan where they will spend the night while traveling prior to departure. We assume that truck drivers follow a two-step procedure when planning their parking arrangements, requiring the development of two different types of pre-trip prediction model. First, truck drivers estimate their workload for the upcoming day and then look for a possible parking site based on this estimate. Second, while on the road the following day, truck drivers recheck the availability of the initially chosen parking site when approaching and make a final decision on the most suitable place to park.

First, the historical use of the parking sites obtained from the TPIMS dynamic archive-only feed is organized into the “previous day” and “previous week” levels. Second, referring to the experience of past research and the analysis results in the data dashboard, parking behavior is greatly influenced by attributes like location, time, traffic, and weather condition. Therefore, the TPIMS sites are organized into a network, and each site is mapped to adjacent TPIMS parking sites upstream and downstream to obtain the utilizations in the adjacent sites. Note that there may be other parking lots outside the scope of the Iowa TPIMS.

Truck volume is also collected from 7 ATR and 20 Wavetronix sensors based on data availability to cover more TPIMS sites. In consideration of resolution unity (ATR volume is in 15 minutes and the Wavetronix volume is in 20 second) and the fact that the truck volume can be very low in some sparsely populated areas, the truck volume is aggregated into an hour-level scope.

Third, weather information is collected from the Iowa Environmental Mesonet (IEM) developed by the Department of Agronomy at ISU. The IEM collects environmental data, such as road temperature, weather watches and warnings, and wind direction from cooperating members. The IEM Gridded Analysis is an integrated system where all weather information is aggregated every five minutes into a small rectangular longitude and latitude grid at a resolution of 0.01 degrees in both directions. It is assumed that the weather in the grid is the same as it is in the TPIMS sites and that the TPIMS sites are mapped into the grid to provide weather information for each site.

Those attributes are integrated together and analyzed in various tree-based machine learning methods to accurately predict parking before a trip, and the performances of the models are described by root mean square error (RMSE) (Equation 9). Furthermore, to reduce the running time of the model, the experiment covers the period from January 2019 to December 2019, with a training set comprising 70% of the data. u_i is the utilization of a parking site.

$$RMSE = \sqrt{\frac{1}{N}\sum_{1}^{N}(u_i - \hat{u}_i)^2} \tag{9}$$

The pre-trip models were built on two different scopes: more specific models that predicted parking for each site and overall models that predicted parking for all sites. Table 21 shows that the overall models that used the historical utilization of the previous week gave slightly more accurate predictions than the models that used data from the previous day. This reveals a weekly pattern in parking demand, which is consistent with the results of previous analysis of truck parking patterns (Sadek et al. 2020). The best model is XGB because of its mechanism for better generalizing the large data set (in which all sites are evaluated together).

Table 21. Prediction results for overall models

	Decision Tree	**Random Forest**	**Gradient Boosting**	**XGB**
Previous Day	0.241	0.178	0.174	0.170
Previous Week	0.236	0.174	0.170	0.166

Site-specific models were then built to compare with the overall model, and the gradient boost regressor was selected as the best performance model in all test parking sites. Again, we found that models using the historical utilization of the previous week performed slightly better than the models using the historical utilization of the previous day. We also found that the models that included all constructed attributes (spatial relation, weather condition, and truck traffic volume) performed better than the models that only included historical utilization itself. Table 22 shows the test results of the average RMSE.

Table 22. Prediction results for site specific models

	Gradient Boosting	**Gradient Boosting with only utilization attribute**
Previous Day	0.157	0.166
Previous Week	0.154	0.162

Overall, the recommended pre-trip prediction model is a site-specific machine learning ensemble model with a gradient boost regressor that uses the historical utilization of the previous week, spatial relation, weather conditions, and truck traffic volume.

7.1.2 En Route Model

Although ensemble tree-based methods demonstrate favorable prediction results, their implementation requires additional efforts in collecting and manipulating weather data from the Iowa IEM gridded system, as well as traffic volume data from the Iowa ATR traffic planning system and the Iowa Wavetronix traffic operation system. These two data sets are highly localized, and the processes of verifying the availability, quality, and mapping of these data sources is time-consuming relative to the process of manipulating the parking flow data.

Therefore, to predict utilization for en route decision-making, some black-box deep learning models that do not depend on these additional data sources can be considered. In this report, we introduce a sequence-to-sequence neural network architecture to develop a truck parking site utilization prediction (TPSUP) model that only uses historical utilization information, where the spatial and temporal characteristics are extracted and represented by transforming the utilization data (Yang et al. 2021).

The input attributes are organized differently to adapt to the architecture of the neural network. The historical utilization sequence of the current site (C_i) is a sequence based on continuous temporal utilization records from the recorded farking flow data. The time interval t_i and window sized ws_i are fixed. The flow data are used as inputs for the TPSUP, including the records of $c_1, c_2, \dots, c_i$.

The spatial and temporal dependency sequence D_i contains encoded location and time information belonging to each utilization record for the current site. D_i includes the utilization in adjacent sites and the temporal dependency extracted from timestamps. A model would need to reflect periodicity so that the parking behavior of hour 23 is closer to that of hour 0 instead of hour 20. The day and month attributes cannot be used in their raw forms because, for example, the raw format of the last hour of the day will have 24 times the weight of the first. To achieve this, the time information is encoded with sine and cosine as follows, where s_i represents the accumulated second of the current record:

$$x_i^{sin} = \sin\left(s_i \times \frac{2\pi}{\sum s}\right) \tag{10}$$

$$x_i^{cos} = \cos\left(s_i \times \frac{2\pi}{\sum s}\right) \tag{11}$$

After the encoding process, a long short-term memory (LSTM) cell-based neural network is constructed to memorize the historical utilization in the processed sequence. Figure 42 shows the sequential logic structure of the TPSUP network.

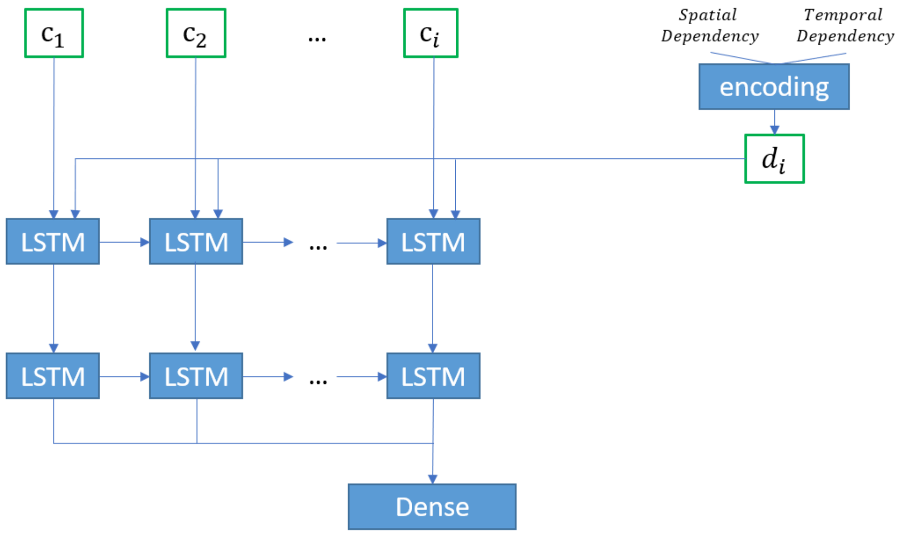

Figure 42. Structure of TPSUP model

Our proposed TPSUP architecture was tested on a specific site, PRAIRIEM144, which has a capacity of 48 spots. The number of units is fixed at 64 in two hidden layers, and the activation function is a hyperbolic tangent. The prediction scope is set to one hour because, based on the results of the ATRI survey (ATRI 2018), 42.1% of the test respondents spent 30 minutes to 1 hour searching for safe parking. The prediction results are compared with the basic recurrent neural network (RNN) model in Table 23.

Table 23. TPSUP model performance and comparison

	RNN	**TPSUP**
Test RMSE	0.0759	0.0429
Training Time	855s	650s

Our proposed TPSUP performs better than a basic RNN in terms of RMSE and training time. Therefore, our study recommends the proposed TPSUP architecture as an effective en route prediction model for truck drivers looking for up-to-date information on safe parking areas. Figure 43 shows an example of the predictive results of the data for one week from December 15, 2019.

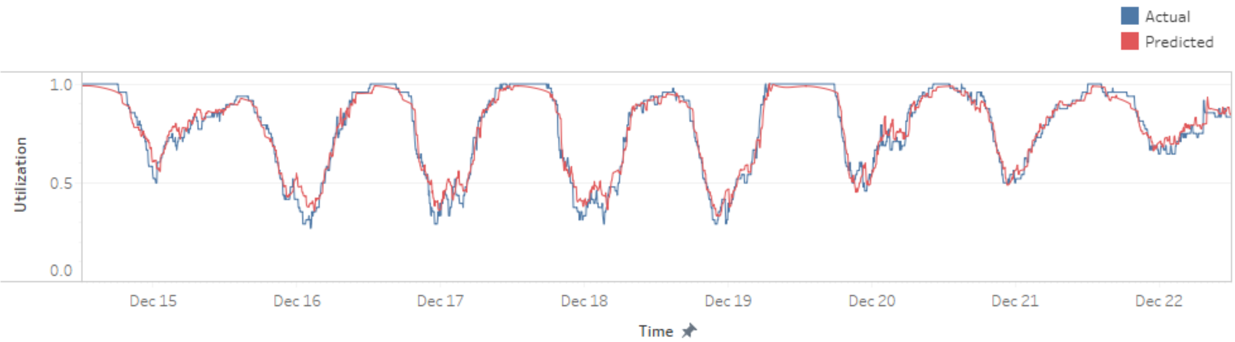

Figure 43. Actual and predicted utilization

7.2 Design of "Popular Times" Feature

The "Popular Times" feature in the map application is a valuable tool that provides users with information about how busy a particular location is at different times of the day and week. It helps users plan visits more effectively by providing information on crowd levels in various establishments, such as restaurants, cafes, shopping malls, and other popular destinations. The focus of this section is to investigate the possibility of integrating this feature into the TPIMS user interface to improve the travel planning capabilities of truck drivers.

As described in Section 7.1.1, the prediction models are designed in two scopes (an ensemble machine learning model using data from the previous week for pre-trip use and a deep learning long-short-term memory model using data from the previous hour for en route use).

An experiment was carried out at site PRAIRIEM144. Figure 44 presents an example of the estimated popular times derived from the application of the gradient boost model, using data from the previous week. Using this feature, truck drivers can select the desired time of day and day of the week to assess the level of crowding and plan their workload accordingly. As an example, consider a scenario where a truck driver intends to rest at site PRAIRIEM144 on a Thursday at 7:00 p.m., where the estimated utilization rate reflects approximately 0.85, indicating the availability of 7 vacant spots.

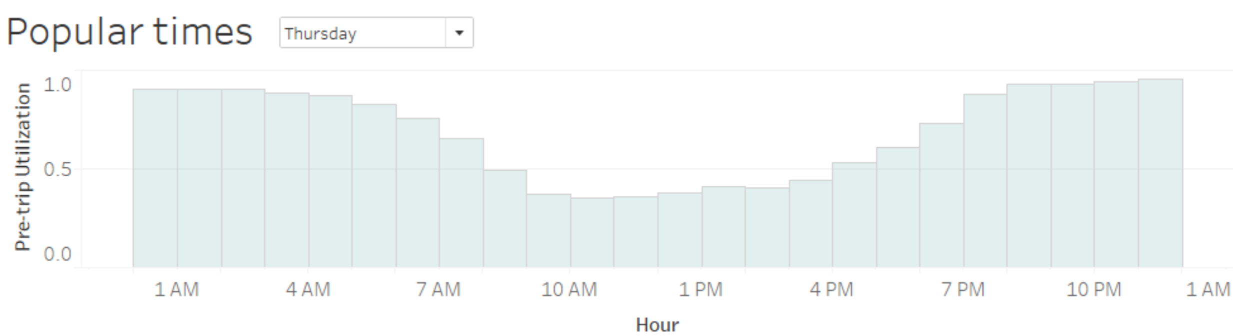

Figure 44. Pre-trip popular times

Then on the following Thursday, while actively driving towards the designated site, the most recent estimation of utilization obtained from the LSTM model indicates that the parking site will be nearing maximum capacity by the driver's anticipated arrival time. Consequently, the driver can choose to explore alternative secure parking options. Note that the ground truth utilization value at 7 p.m. corresponds to a utilization rate of 1, indicating that the parking site is indeed fully occupied at this specified time.

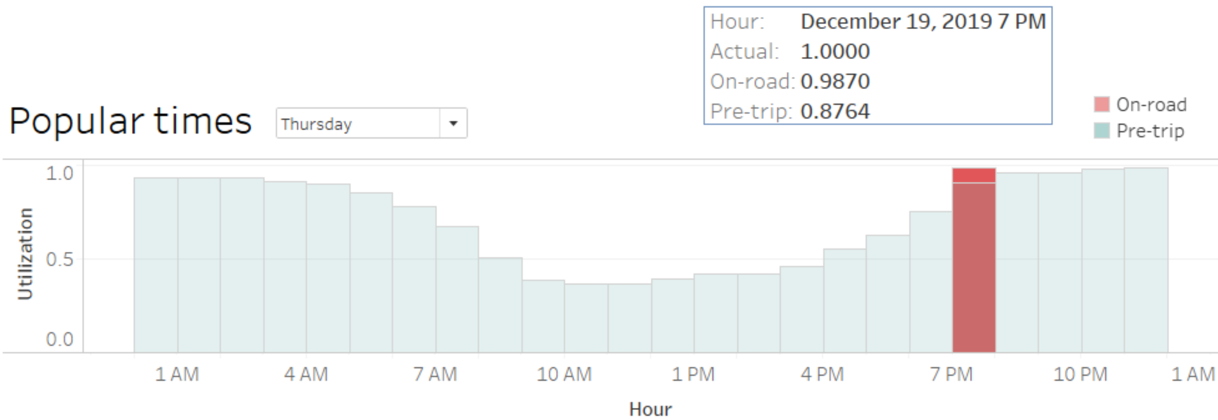

Figure 45. En route popular times

This popular dual-level time estimation offers several benefits to users. It helps truck drivers plan their activities by providing them with a better understanding of when a location is expected to be more or less busy. Additionally, it allows truck drivers to avoid peak times and choose less crowded periods or areas to park, reducing illegal parking and ensuring a more pleasant rest.

It is worth noting that while popular times provides estimates based on historical data, it may not be 100% accurate in real time. Factors such as unexpected events or changes in local circumstances can affect crowd levels (e.g., parking site closures). Nevertheless, this feature remains a valuable tool for gaining general insights into a location's popularity patterns.

While truck drivers are using this tool, especially when they are en route, it is important to know how often the en route model is wrong to the extent that drivers notice the difference. For example, the tool may tell a driver that the site ahead is almost full (e.g., that the number of available spots is less than 10% of the site capacity, causing "LOW" to be displayed on Iowa511 as described in Section 4.1.1). However, upon reaching the site, the driver finds that it is not as occupied as the tool suggested. Alternatively, the tool may indicate that a site has significant availability, implying a relatively empty condition. However, on arrival, the driver has difficulty finding an unoccupied parking space.

Therefore, in this experiment, the en route results are transformed into a "frustration" matrix. In Table 24, "low" indicates that the availability is below 10% of the site capacity (i.e., 5 in the case of site PRAIRIEM144). In this particular scenario, the calculated frustration index amounts to

4.49%, which signifies the magnitude of frustration experienced by drivers who may perceive the notable disparity between anticipated and actual parking conditions.

Table 24. Frustration matrix

	Actual Not Low	**Actual Low**
Predicted Not Low	66.41%	1.49%
Predicted Low	3.00%	29.11%

8. VISUAL SENSING

Previous studies on the reliability of the Iowa TPIMS have identified various functional failures that significantly impact the system's efficiency. This chapter presents a system architecture for the data archiving and retrieval system, as well as reliability measures and an image processing-based failure detection method to monitor the system's operation and prevent prolonged system failures using the dynamic archive-only feed. The proposed fault detection and reporting system aims to improve the accuracy of TPIMS, consequently improving the safety and competitiveness of freight transportation in Iowa and providing valuable information for the prospective implementation of smart truck parking systems.

Advancements in sensing, data storage, and transmission technologies have allowed information management systems to be rapidly developed and implemented in various fields in recent years. However, most of the research on detection and warning of abnormal behaviors of intelligent transportation systems has investigated the reasons behind abnormal data trends. For example, Chen et al. (2015) used color-coded charts and a semantic zooming method to investigate anomalies in speed, flow, and lane occupancy information from sensing sites along a freeway in Taiwan. Those anomalies did reflect traffic events such as bottlenecks, human mobility during a traditional holiday, and typhoon strikes, during the three-year study period.

However, it is worth noting that abnormal data may not always indicate changes in travel behavior, but rather instability in the system itself. Less research has focused on monitoring sensor failure and life span to detect these problems. Abnormal parking behaviors in highway truck rest areas were found in the summer of 2020. However, the investigation of truck activities (volume) during 2019 and 2020 showed that the anomaly was caused by large-scale sensor failure, not by the change in the travel pattern due to the COVID-19 pandemic.

Surveillance cameras installed at parking sites along Iowa corridors make image-based detection possible. The field of vehicle detection has achieved remarkable success through the use of convolutional neural networks. Since its introduction in 2018, the You Only Look Once (YOLO) architecture has been used for vehicle detection in many experiments conducted on different road scenarios throughout the world. Lin and Sun (2018) developed a system for counting vehicles on roadways and conducted an experiment at certain entrances and exits on the campus of National Central University in Taiwan. In that study, the image recognition block of YOLO was employed for object detection.

After YOLO was used to identify objects in each frame, the counting block subsequently determined whether detected objects in successive frames were indeed the same entity. A checkpoint was defined in the counting block, at which the counter would check if a vehicle was passing that checkpoint frame by frame. For each vehicle coordinate in the current frame, the counter would find the pair that had the shortest distance between this coordinate and all vehicle coordinates in the previous frame. By comparing the ground truth and the counting results, the accuracy could reach 100% in the morning and afternoon periods.

Song et al. (2019) introduced a detection and counting system by transforming the highway road surface into effective areas (remote and primary areas) and applying the processed images into YOLOv3 networks to detect the type and location of vehicles. The experimental result of about 60,000 annotated instances verified that the proposed method achieved an 87% mean average precision (mAP) for highway scenes.

For parking scenarios, Ding and Yang (2019) used YOLOv3 with a self-designed feature extraction residual block and conducted an experiment of their deeper structure in the Kaggle PKLot data set. Precision increased from 91.6% for YOLOv3 to 93.3% for their improved model, while recall increased from 87.2% to 90.9%. Dixit et al. (2020) proposed a smart parking system for urban parking lots using mobile applications, internet of things (IoT) technologies, and computer vision. Besides the proposed architecture of driver-side data upload through NodeMCU data transmission, CCTV cameras and the YOLO algorithm were also included in the structure to verify the occupancy of parking spaces. The authors claimed that this "belt and braces" architecture would report parking lot occupancy in a timely and robust manner and that it reduced deployment and operating costs compared to the existing sensor-based smart parking system.

In the context of urban street parking, Chen et al. (2020) proposed a system based on the YOLOv3 algorithm and deployed it on a Jetson TX2 platform. The system was designed to accurately detect parking occupancy by integrating controlled streetlights that could detect whether a spot was occupied, with the goal of reducing costs while maintaining robustness under various weather conditions. The proposed solution was evaluated using the CNRPark+EXT data set (a simulated model) and real-world scenes captured by a camera. The system achieved high test accuracies of 98% and 93% in CNRPark+EXT images and real scenes, respectively, validating the effectiveness of the proposed approach.

Xie and Wei (2021) developed an advanced YOLOv3 algorithm to detect parking occupancy. The new network improved on the original by six different measures, including changing the resolution of network input, increasing momentum, increasing the weight attenuation value, increasing the batch size, and reducing jitter. Furthermore, a novel item-based attention mechanism was incorporated, featuring both channel and spatial attention in the feature extraction network. In particular, the selected feature vector replaced the original feature vector, and residual fusion and second-order terms were used to accelerate convergence while minimizing information loss in the fusion process. Experiments on 493 parking lot images showed that the algorithm effectively reduces the positioning error of the bounding box and improves the detection accuracy of unoccupied spots.

8.1 Methodology Behind the Sensor Fault Detection System

As illustrated in Figure 46, the proposed architecture entails seven modules.

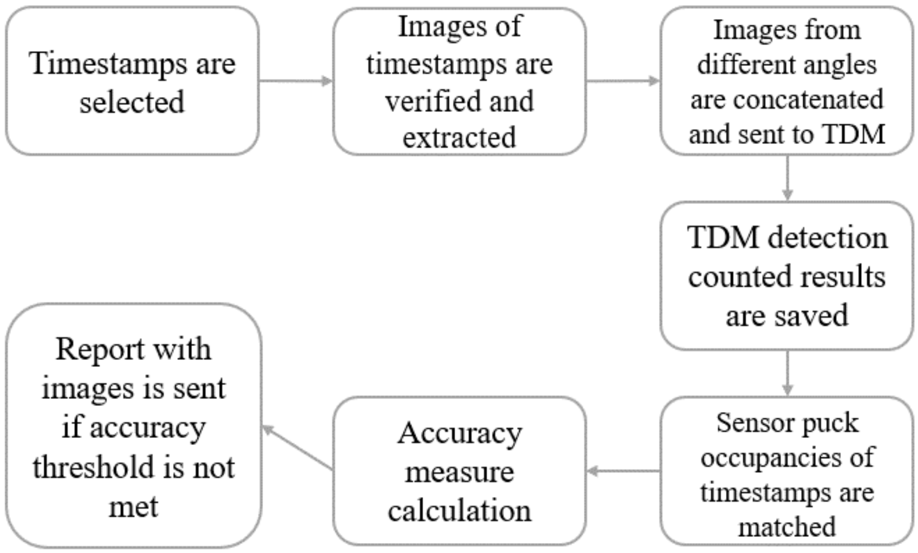

Figure 46. System overview

First, a set of timestamps within the study period (e.g., one week) is selected to be checked for accuracy, including peak and off-peak hours. Second, the images are verified to be up to date. The filename of each image is the date and time that the image was archived, and the exchangeable image file format (Exif) metadata contains the date and time when the image was taken. If the timestamp information in the metadata does not match the filename, it means that the images on Iowa511 have stopped updating and that the archiving system is saving the same image with different filenames. In such cases, the sites and timestamps will be labeled incomparable in the report and skipped in the YOLO detection steps. Third, the images from different angles are concatenated and sent to the truck detection model (TDM). Fourth, the TDM detects trucks from the concatenated image. The annotated results with coordinates are translated into truck counts. The fifth step is to extract the number of occupied spaces from the flow data collected by the sensor pucks. Sixth, the accuracy metric is calculated by comparing the sensor data with the TDM results. Finally, a report is generated if the accuracy rate falls below a predefined threshold, such as 90%, over a period of one week. The corresponding images are sent along with the result to the operator for further inspection to determine whether further action is necessary.

The TDM was implemented using the YOLOv5s network (Jocher 2022). The YOLO algorithm first divides the input image into a grid of size $S * S$, and each grid cell is responsible for detecting the object centered in it. The B bounding boxes and their corresponding confidence scores are predicted by each grid cell, and the final predictions are made based on a combination of the bounding box coordinates and confidence scores. This approach allows for fast and accurate object detection and has become widely used in various computer vision applications.

The confidence score $Pr\ (Object) * IOU_{predict}^{truth}$ represents the probability that an object exists ($Pr(Object) > 0$) and the confidence of the prediction ($IOU_{predict}^{truth}$). Intersection over union (IOU) is an important measure of the degree of overlap between a prediction box and a ground truth box. The higher the IOU score, the more accurate the position of the predicted box.

Equation 12 shows the calculation of the IOU score, where $B_{predict}$ represents the predicted bounding box and B_{gt} is the ground truth box. The score can be further improved with more advanced algorithms, such as generalized IOU (GIOU), which considers the size of the boxes and no-intersection situations, and complete IOU (CIOU), which considers the non-coincident border and width height ratio.

$$IOU = \frac{area\ (B_{predict} \cap B_{gt})}{area\ (B_{predict} \cup B_{gt})} \tag{12}$$

The conditional class probability $Pr(= Class|Object)$ is also predicted in each grid cell regardless of the number of boxes, and only the contribution of the grid cell containing an object is calculated. A class-specific confidence score C_i^j for each box is obtained by multiplying the individual box's confidence prediction with the conditional class probability (Equation 13). This process takes into account both the existing probability of class-specific objects in the box and the fitness between the predicted box and the object.

$$C_i^j = Pr(Object) * IOU_{predict}^{truth} * Pr(Class|Object) = Pr\ (Class)_j^i * IOU_{predict}^{truth} \tag{13}$$

For the i^{th} grid, j represents the bounding box and C_i^j represents the confidence score of the j^{th} bounding box of the i^{th} grid. $P_i^j = 1$ means that a target exists. During the training process, the following loss function is optimized:

$$\begin{aligned} L = {} & loss_{box} + loss_{class} + loss_{object} \\ & = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathrm{I}_{ij}^{object} [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2] \\ & + \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathrm{I}_{ij}^{object} \left[\left(\sqrt{w_i} - \sqrt{\widehat{w}_i}\right)^2 + \left(\sqrt{h_i} - \sqrt{\hat{h}_i}\right)^2 \right] \\ & + \lambda_{class} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathrm{I}_{ij}^{object} \sum_{c \in Class} \left(p_i(c) - \hat{p}_i(c)\right)^2 \\ & + \lambda_{object} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathrm{I}_{ij}^{object} (C_i - \hat{C}_i)^2 \\ & + \lambda_{noobject} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \mathrm{I}_{ij}^{noobject} (C_i - \hat{C}_i)^2 \end{aligned} \tag{14}$$

where λ is the coefficient of each component, (x_i, y_i) denote the center of the box relative to the bounds of the grid cell for the i^{th} grid, (w_i, h_i) are the normalized width and height relative to the image size, $\mathrm{I}_{ij}^{object} = 1$ indicates the existence of objects, and $p_i(c)$ represents the category probability of the target. Note that the loss function penalizes classification errors only when an object is present in the corresponding grid cell. Similarly, the loss function penalizes bounding box coordinate errors only when the predictor is "responsible" for the ground truth box (i.e., the highest IOU of any predictor in that grid cell is achieved) (Xu et al. 2021, Zhao et al. 2019).

In the YOLOv5 official code, four versions of the detection network are available, namely YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. Among them, YOLOv5s is the network with the smallest depth and width of the feature map. Unlike YOLOv4's significant improvements to YOLOv3, YOLOv5 does not have many algorithmic innovations for YOLOv4, and no research paper has explained the architecture and components. Therefore, to gain a comprehensive understanding of the algorithmic framework, we refer to the yolo5s.pt file and the network yaml file.

The architectures of YOLOv3, YOLOv4, and YOLOv5 all adopt the classic one-stage structure, which comprises four components: input, backbone, neck, and prediction. To understand the evolution from YOLOv3 to YOLOv4 and YOLOv5, it is imperative to review the structure of YOLOv3 and the enhancements made by YOLOv5.

The backbone consists of several convolutional neural network (CNN)–based blocks and is used to extract the features of the input image. By referencing residual learning in ResNet, the blocks enable the training of much deeper neural networks, which can lead to better performance. This backbone adopted by YOLOv3 is called Darknet-53. In YOLOv3, a grid unit is assigned to predict three bounding boxes with different scales for a particular object. During inference, the box with the highest IOU with the ground truth box is considered the final predicted result. YOLOv5 incorporates modifications to its structures that are based on both v3 and v4 (Jiang 2020). This process has the following advantages:

1. In the input, mosaic data augmentation enhances the network's ability to generalize to new data by providing it with a wide variety of augmented images and encourages the network to learn contextual relationships between objects and their surroundings. It also helps to mitigate the class imbalance problem that is often encountered in object detection data sets.
2. In the backbone, the focus module with slicing replaces the traditional pooling and stride operations with a convolutional operation that achieves spatial down-sampling. This module has the advantage of being computationally efficient and being able to reduce the number of parameters while maintaining high accuracy. It also helps increase the receptive field of the network, which improves the detection performance on smaller objects. The cross-stage-partial (CSP) structure (Wang et al. 2020) is adopted in both the backbone and neck to improve the performance of the model by reducing the number of computations required and improving information flow between layers. The feature map of the base layer is divided into two branches and then merges through a cross-stage hierarchy, which can ensure accuracy while reducing the amount of memory.
3. In the neck, the feature pyramid networks (FPN) and the path aggregate network (PAN) (Liu et al. 2018) are used for feature fusion and better feature representation. In this combination of operations, the FPN layer conveys strong semantic features from top to bottom, while the PAN conveys strong positioning features from bottom to top. Together, the parameters of

different detection layers are aggregated, providing a rich set of features that capture objects at different scales and resolutions.

The image data set presented in Section 2.4 was sent to the YOLOv5s structure for training, and after evaluating several different scenarios, the truck object detection model was obtained. Precision denotes the fraction of accurately predicted objects among all predicted objects, and recall measures the fraction of accurately predicted objects among all ground truth objects. The average precision is computed as the area under the precision-recall curve, and mAP is the mean of the average precision across all classes. mAP quantifies the average precision (AP) of the model across all classes and confidence levels and is a widely used evaluation metric in image-based object detection methods, including YOLO.

Comparing the mAP values of different object detection models is crucial in assessing their performance and overall detection accuracy. The corresponding equations are as follows. It should be noted that when multiple predicted boxes exist for a single ground truth box, only the predicted box with the highest IOU value will be labeled as true positive (TP). That is, a single ground truth box can only have one predicted box marked as TP. The precision-recall curve can then be drawn on the basis of the accumulated prediction labels. To find the area, the interpolation method is always used by setting 11 points [0, 0.1, 0.2…, 1].

$$Precision = \frac{TP}{TP+FP} = \frac{TP}{all\ detections} \quad (15)$$

$$Recall = \frac{TP}{TP+FN} = \frac{TP}{all\ ground\ truths} \quad (16)$$

$$Prediction\ Label = \begin{cases} TP & (max) IOU \geq 0.5 \\ FP & IOU < 0.5 \end{cases} \quad (17)$$

$$AP = \frac{1}{11} \sum_{r \in \{0,0.1,0.2,\ldots,1\}} p_{interp}(r) \quad (18)$$

$$mAP = \frac{\sum_{i=1}^{C} AP_i}{C} \quad (19)$$

The mAP of the validation set in the training process can be used to evaluate the model's performance. The images in the test set are then sent to the selected TDM. Although the mAP can also be calculated for these testing images, we define a different metric here using the number of counts since our task is to identify only trucks. When the manual annotated files are taken as the ground truth, a comparison of accuracy between this TDM and the sensor puck is also conducted. The accuracies can be represented in the following:

$$Accuracy_{image} = 1 - \left| \frac{n_{image} - n_{true}}{Capacity} \right| \quad (20)$$

$$Accuracy_{puck} = 1 - \left|\frac{n_{puck} - n_{true}}{Capacity}\right| \tag{21}$$

where n_{true} is the manual annotation count, n_{image} is the object detection result of existing truck/truck head, n_{puck} is the occupancy in puck flow data records, and $Capacity$ is the parking site capacity.

The detection and reporting system is designed under the assumption that the image-based TDM provides counts closer to the ground truth. As stated above, an alert will be sent when a certain accuracy threshold is reached. To measure the accuracy of the sensor puck in the detection procedure, we refer to the following metric:

$$Accuracy = 1 - \left|\frac{n_{image} - n_{puck}}{Capacity}\right| \tag{22}$$

where n_{image} is the object detection result of the number of trucks and n_{puck} is the occupancy in puck flow data.

To match the images and the flow records, a forward-fill method is used in the parking flow data, where the records are aligned with the next nearest five-minute interval.

8.2 Fault Detection System Test Results

In this section, the proposed error detection method and system design are tested with the real-world truck parking rest area image data mentioned in Section 2.4. TDMs were trained and tested in different scenarios, and the detection results are compared here. The experiments were carried out on both a local workstation with a CPU (Intel Xeon Gold 6230R) and a Google Colab cloud computing platform with a GPU (Nvidia Tesla T4). Torch version 1.13 was used.

8.2.1 TDM Training and Testing

In this research study, YOLOv5s was selected as the initial model due to its small size and fast processing speed. Compared with other YOLOv5 variants, v5s has a lower number of parameters (7.5 million) and requires less memory. The data set was split into three parts for training, validation, and testing, with ratios of 0.7, 0.2, and 0.1, respectively. Before using the established data set, we reviewed the recommended data sets from the official documentation of YOLOv5 for baseline training, including common objects in context (COCO), PASCAL VOC, and ImageNet.

Among the recommendations, the COCO data set (Lin et al. 2014) was selected because it was the most widely used. It consists of approximately 330,000 images with more than 2.5 million annotated object instances that span more than 80 object categories. The data set also features instance segmentation and key-point annotations. We first tried our test set on this multicategory model, and a half batch detection result (batch size = 16) is shown in Figure 47.

Figure 47. Testing result of YOLOv5s with default multi-category training set

COCO is a complete and high-precision database, and it might perform well in some balanced scenarios, such as when objects are about the same size with a clear front view. However, it is not suitable for our data set because a truck trailer might be detected as suitcase, bus, or train or a truck in the distance (usually from entry angle) might be detected as car. Noise is also high because COCO is so sensitive that the camera pole is detected as a traffic light and vehicles on the truck deck are also detected. Therefore, only annotating the truck head might help reduce these errors.

The annotated data set of a single pilot site (RA300) with about 150 images was first used to train the YOLOv5s architecture through a single CPU for speed estimation. For 300 epochs, the training time was about 663 minutes. Due to this long training time, cloud computing with GPU was used for subsequent training. The established training set consisted of approximately 1,000 concatenated images, with 15,000 annotated instances. The stochastic gradient descent (SGD) momentum was set to 0.937, with an initial learning rate and final one-cycle learning rate of 0.01. A batch size of 16 was used, resulting in a training time of approximately 201 minutes for 300 epochs. Subsequently, an entirely distinct test set was utilized to evaluate the model's performance. Table 25 presents a comparison between the model configurations and the results achieved. Analysis of the mAPs across epochs indicates convergence at around epoch 40 and that the test mAPs of Model 2 and Model 3 are the same. Therefore, Model 2 was selected as the final TDM. Figure 48 shows the loss and mAP at IOU = 0.5 of Model 2.

Table 25. Model summary

Index	Model	Epoch	Validation mAP	Test mAP
1	YOLOv5s + COCO	100	-	0.169
2	YOLOv5s + TPIMS	100	0.771	0.708
3	YOLOv5s + TPIMS	300	0.777	0.709

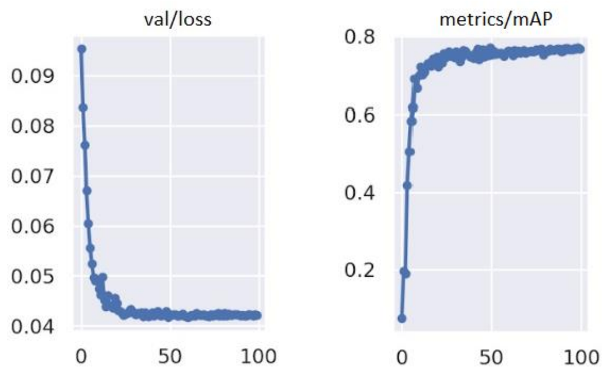

Figure 48. Loss and mAP of Model 2

8.2.2. Accuracy Comparison

The reliability of the sensor puck counts is determined by comparing with the image processing counts. Manual counts from the test set images are used as the basis for this analysis. Specifically, the accuracy of the image processing counts and the sensor puck counts are computed by comparing them with the ground truth.

Moreover, to determine the detection time of the proposed system, the test set is divided into two categories, truck parking during off-peak hours (i.e., 9:00 a.m. to 4 p.m.) and during peak hours (i.e., 5:00 p.m. to 8:00 a.m.). Table 26 compares the accuracy metrics for the different test scenarios.

Table 26. Summary of different test scenarios

Test time	**TDM mAP**	$Accuracy_{image}$	$Accuracy_{puck}$
All	0.709	0.940	0.844
Off-Peak Hours	0.824	0.973	0.829
Peak Hours	0.677	0.922	0.867

The results indicate that the proposed TDM performs better with images collected during the off-peak hours. This finding is expected as the lighting conditions during the day are better and the sparsely parked trucks have less overlap. In addition, image processing with the TDM is more accurate than the sensor pucks, though it is not intended to replace the puck system. Instead, the TDM is used to monitor and identify erroneous counts due to faulty sensors. Thus, the TDM is applied to images selected during off-peak hours to check the accuracy of sensor puck counts. This project was started in 2017, when the technology for image processing and deep learning was not as advanced as it is now, suggesting that current state-of-the-art techniques may provide even higher accuracy rates.

8.2.3. Detection and Reporting System

Real-time sensor fault detection and reporting was developed and demonstrated in the RA270W rest area. For example, on May 6, 2022, four detection times during off peak hours were selected (i.e., 9:00 a.m., 11 a.m., 1 p.m. and 3 p.m.). The images of these hours were concatenated and sent to the TDM. The TDM counts were compared with the sensor puck flow records to evaluate accuracy. The accuracy threshold was set to 0.9. At 3 p.m., the accuracy was below the predefined threshold, indicating possible sensor fault. Therefore, a report with the summary and the image taken at 3 p.m. was sent through the AWS S3 bucket to the operators for further investigation. The contents of this alert email are shown in Figure 49.

The proposed system can also be scheduled to run weekly to identify systematic errors in parking flow data. It is also a valuable tool to reduce the need for frequent manual checks at all TPIMS sites, allowing operators to focus on the sites that have been flagged by the image-based TDM.

Site	Day	Check Time	Capacity	Puck Count	TDM Count	Accuracy
RA270W	5/6/2022	9:00:00 AM	15	8	8	1.000
RA270W	5/6/2022	11:00:00 AM	15	11	10	0.933
RA270W	5/6/2022	1:00:00 PM	15	10	10	1.000
RA270W	5/6/2022	3:00:00 PM	15	7	4	0.800

Figure 49. Example of the contents in the email report

9. CONCLUSION AND RECOMMENDATIONS

This report presented a comprehensive analysis of Iowa's TPIMS performance during the grant year from 2019 to 2021. Since January 2019, the Iowa TPIMS has been providing real-time parking availability information to truck drivers through smartphone applications, in-cab technology, and traveler information websites. This report presented an evaluation of the system based on fine-grained parking flow data, HOS violations, images, ATRI surveys, and an intercept survey of truck drivers. The evaluation focuses on system utilization, reliability, and safety impact. In addition, anomaly detection methods and visualization tools were developed to help transportation agencies better monitor the performance of the TPIMS and make informed decisions based on large real-world data.

Specifically, the PELT-based anomaly detection method can detect sensor failures by identifying change points in the time series of parking flow data, allowing for quick response to detection failures without additional data collection effort. The data dashboard helps to monitor the TPIMS operations, identify spatial and temporal trends in parking site utilization, and support long-range planning decisions. The results of the data dashboard show that the Iowa TPIMS helped distribute the utilization more evenly between parking facilities along I-80 by providing real-time information about parking availability to truck drivers.

Iowa is the only participating state in the MAASTO TPIMS project that does not use roadside VMS. Instead, Iowa DOT chose to disseminate truck parking availability information only through apps, Iowa 511, and in-cab information systems. By eliminating the cost of installing and maintaining the VMS, the Iowa DOT was able to deploy TPIMS at more sites than other participating states. Note that the other seven states that installed VMS also provide real-time data feeds for apps, websites, and in-cab systems. By comparing the performance of the system in terms of system accuracy, parking lot utilization at night, and HOS violations, the Iowa TPIMS perform similarly to other states. This might be because most drivers plan for overnight parking more than an hour ahead using smartphone apps. Therefore, the benefit of providing parking information on VMS could be limited.

Furthermore, since there is a need for truck drivers to be informed about the expected availability of parking spaces at their planned time of arrival, a “Popular Time” feature was developed using hybrid horizon prediction models for pre-trip planning and en route decision making. These predictive analytics have the potential to help truck drivers plan for parking day ahead and on the road. To better monitor sensor failures, a real-time alert system based on visual sensing is also developed. By automatically detecting significant discrepancies between truck count from the surveillance camera images and the parking flow data, this low-cost solution improves the accuracy of the TPIMS.

In summary, the shortage of truck parking is a pressing issue in Iowa and the MAASTO region. Providing real-time truck parking information helps truck drivers better plan for parking, and thus improves parking utilization and safety. However, the accuracy of the information largely depends on the performance of the sensor. The sensor pucks used in the Iowa TPIMS started to fail after one and a half years at some sites, but the failures were not discovered until about a year later. Therefore, continuous monitoring of sensor health and independent verification of parking data are recommended for future TPIMS deployment.

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APPENDIX A. TRUCK DRIVER SURVEY QUESTIONNAIRE

Several rest areas and truck stops in Iowa are participating in a Truck Drivers' survey. Pleases circle one answer for each of the following questions. Your answers are voluntary and anonymous. Thank you!

Parking Experience

1. What is your main reason for needing parking?
   1 = Fatigue 3 = 10-hr Off-duty
   2 = 30 mins HOS break 4 = Other:_________

2. When do you plan for short parking times for breaks?
   1 = Less than 15 min 3 = 30 min to 1 hour
   2 = 15-30 min 4 = More than 1 hr.

3. How often do you need overnight parking?
   1 = Never *(skip to Q5)* 3 = 2-4 times/week
   2 = Once a week 4 = 5-6 times/week

4. How far in advance do you start planning for overnight parking?
   1 = Less than 15 min 3 = 30 min-1hour
   2 = 15-30 minutes 4 = More than 1 hr

5. Where do you prefer to park?
   1 = Public rest areas 3 = Highway ramps
   2 = Truck stops 4 = City streets

6. What is your main source of parking information?
   1 = Dynamic Message signs (DMS)
   2 = In-cab application
   3 = Smartphone application
   4 = Traveler information website
   5 = I do not use any planning tools
   6 = Other:____________________

Parking Experience Outside Iowa
(If you don't travel outside Iowa, skip to Q11)

7. How safe do you feel when you park when you are outside of Iowa?
   1 = Very unsafe 4 = Safe
   2 = Unsafe 5 = Very safe
   3 = Neutral

8. How long does it take you to find parking when you are outside of Iowa?
   1 = Less than 15 min 3 = 30 min - 1 hour
   2 = 15-30 minutes 4 = More than 1 hr

9. How often do you have difficulty finding parking when you are outside of Iowa?
   1 = Never 4 = Often
   2 = Rarely 5 = Always
   3 = Sometimes

10. How often do you park in undesignated locations (highway ramps, city streets, etc)?
    1 = Never 4 = Often
    2 = Rarely 5 = Always
    3 = Sometimes

Parking Experience IN Iowa

11. How often do you drive in or through Iowa?
    1 = Less than once/wk 3 = 2-4 times/week
    2 = Once a week 4 = 5-6 times/week

12. How often do you need parking in Iowa?
    1 = Less than once/wk 3 = 2-4 times/week
    2 = Once a week 4 = 5-6 times/week

13. How safe do you feel when you park in Iowa?
    1 = Very unsafe 4 = Safe
    2 = Unsafe 5 = Very safe
    3 = Neutral

14. How long does it take to find parking in Iowa?
    1 = Less than 15 min 3 = 30 min - 1 hour
    2 = 15-30 minutes 4 = More than 1 hr

15. How often do you get to a parking lot and find it full?
    1 = Never 4 = Often
    2 = Rarely 5 = Always
    3 = Sometimes

16. When it is full, what do you do?
    1 = Drive to the next stop/rest area
    2 = Park on highway ramps
    3 = Park on city streets
    4 = Other:_________________

Please continue to back

17. How often do you park in undesignated locations (highway ramps, city streets, etc)?
 1 = Never
 2 = Rarely
 3 = Sometimes
 4 = Often
 5 = Always

18. Do you use real-time information to find parking in Iowa? (smartphone, in-cab app, etc)
 1 = Yes
 2 = No *(skip to Q26)*

19. How important is real-time information to you in deciding where to park?
 1 = Very unimportant
 2 = Unimportant
 3 = Neutral
 4 = Important
 5 = Very Important

20. How to you get the real-time information?
 1 = In-cab app
 2 = 511 system
 3 = Smartphone app
 4 = Other:________

21. What kind of information do you get?
 1 = Static Information (amenities, capacity)
 2 = Dynamic Information (available slots, site images)
 3 = Both

22. How accurate do you find the parking information?
 1 = Very inaccurate
 2 = Inaccurate
 3 = Neutral
 4 = Accurate
 5 = Very accurate

23. Do you view images of parking lots on your preferred information source?
 1 = Yes
 2 = No *(skip to Q25)*

24. How helpful are these images to making your parking decisions?
 1 = Not at all helpful
 2 = Not very helpful
 3 = Neutral
 4 = Helpful
 5 = Very helpful

25. What other information should be included to help you make better parking decisions:

____

General Information

26. Which of the following best describes your employment?
 1 = Employee Driver
 2 = Owner-operator with own authority
 3 = O-O/Independent contractor leased to a motor carrier
 4 = Other:______________________

27. If you are an employee or leased driver, how many trucks does your fleet operate?
 1 = Less than 50
 2 = 51-250
 3 = 251-1000
 4 = Over 1000
 5 = Don't know

28. How long have you operated a Commercial Motor Vehicle?
 1 = Less than 1 year
 2 = 1-5 years
 3 = 6-10 years
 4 = 11+ years

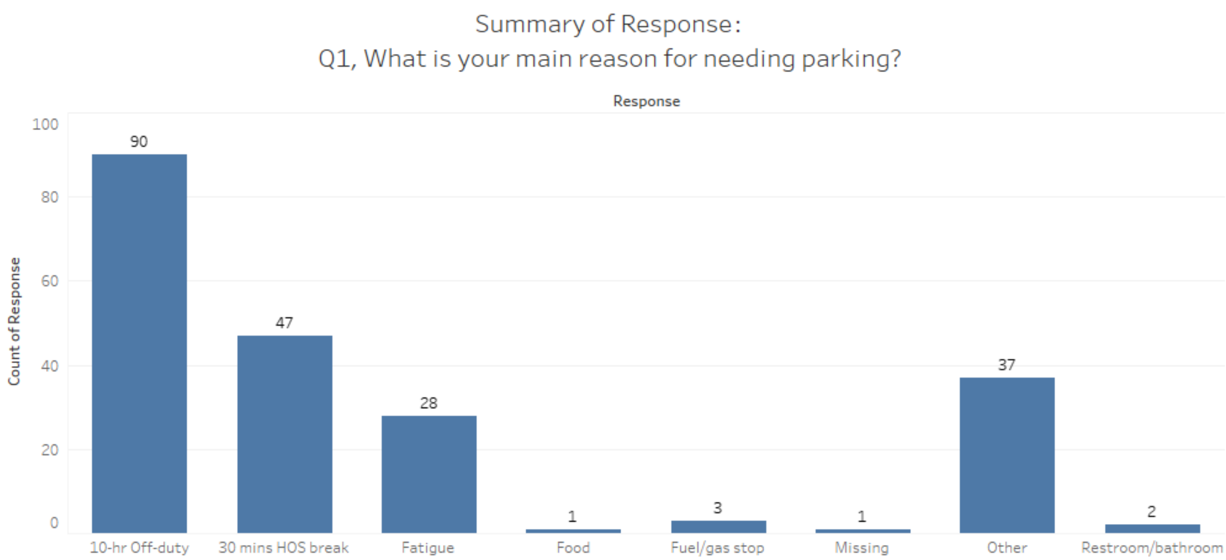
29. On average, how many days in a week do you drive a truck?
 1 = Once a week
 2 = 2-4 days/week
 3 = 5-6 days/ week
 4 = 7 days a week

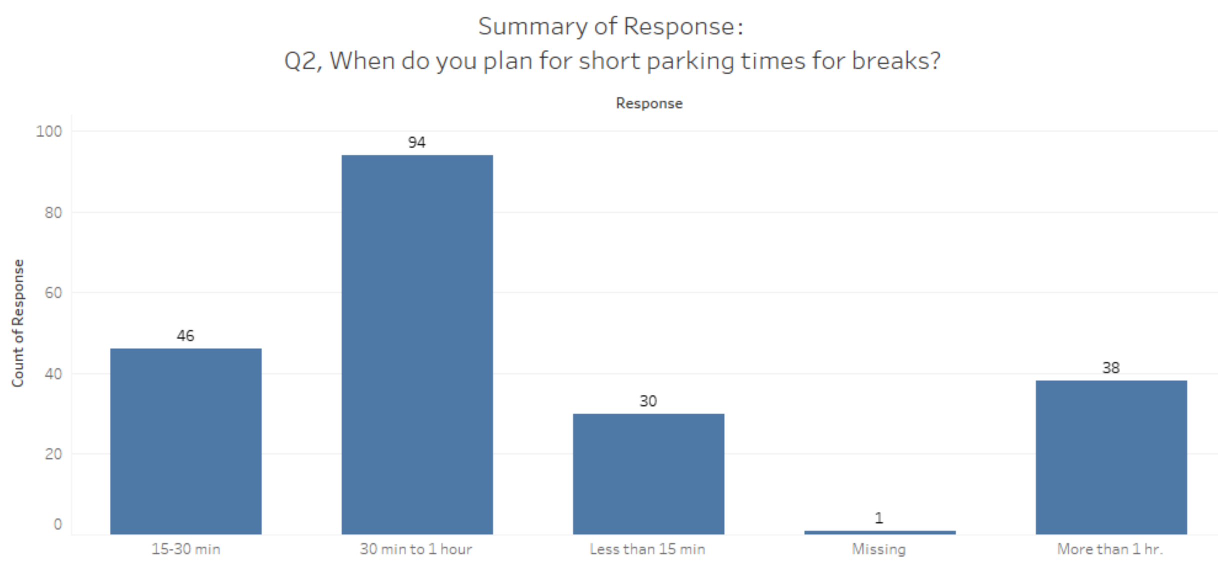
30. What is your usual length of haul?
 1 = Local, less than 100 miles per trip
 2 = Regional, 100-499 miles per trip
 3 = Inter-regional, 500-999 miles per trip
 4 = Long-haul, 1000+ miles per trip

31. What is your age category?
 1 = 25 or younger
 2 = 26-44
 3 = 45-64
 4 = 65 or older

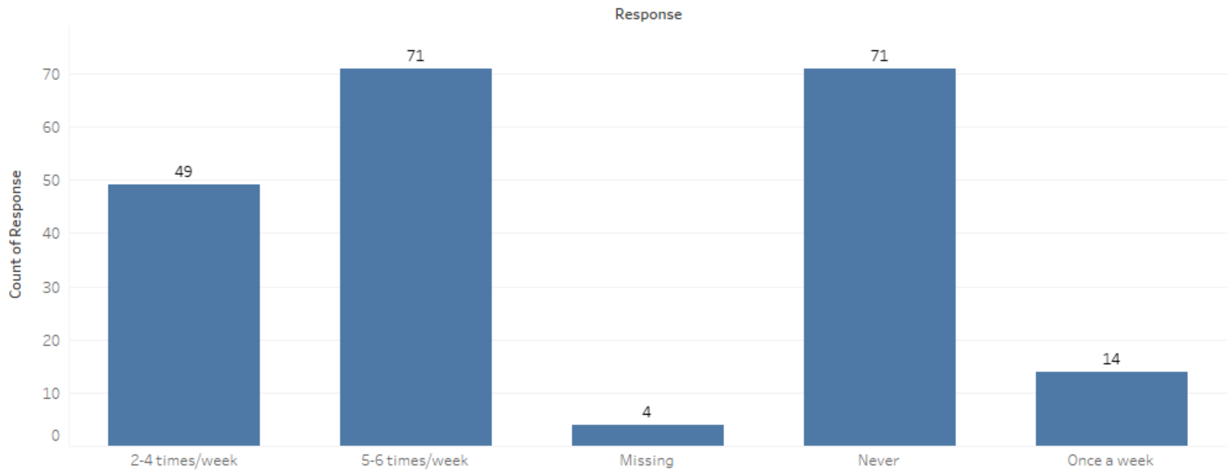
Thank You

APPENDIX B. TRUCK DRIVER SURVEY RESPONSES

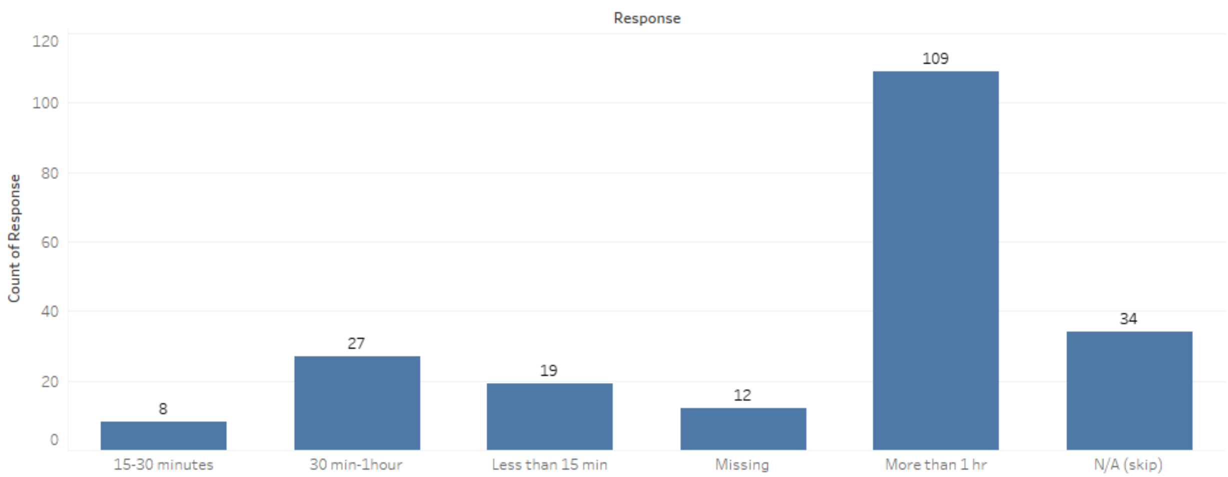




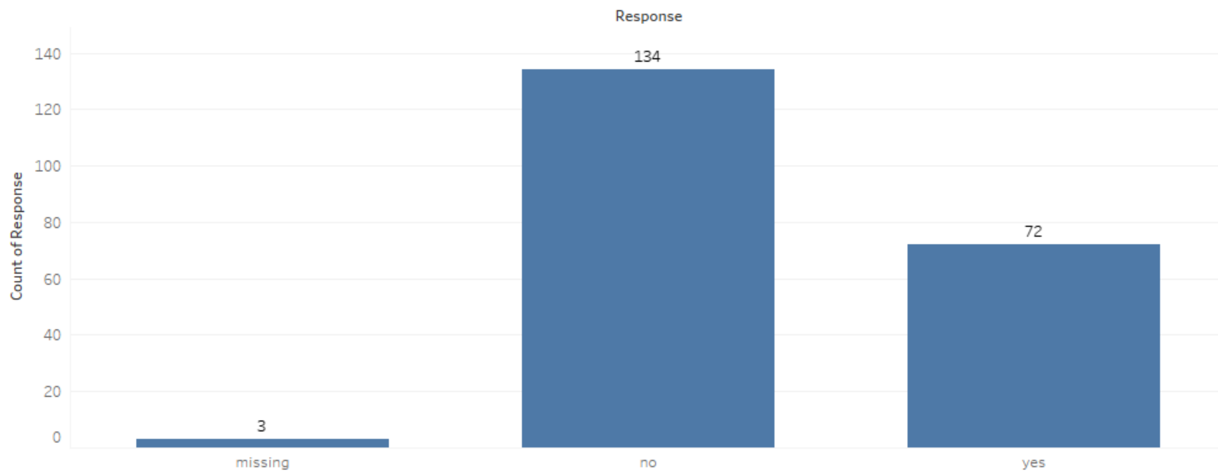
Summary of Response:
Q3, How often do you need overnight parking?



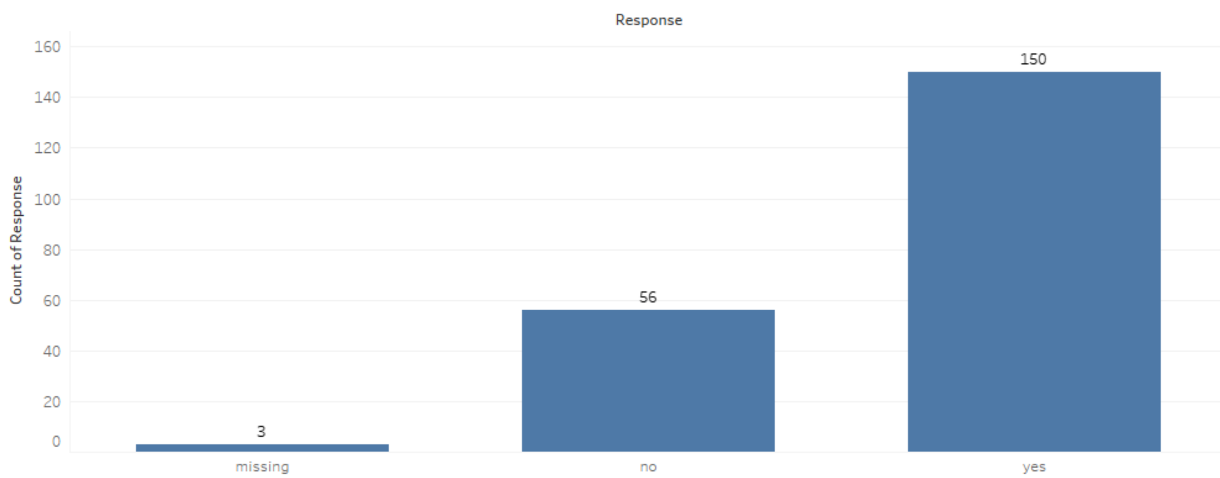
Summary of Response:
Q4, How far in advance do you start planning for overnight parking?



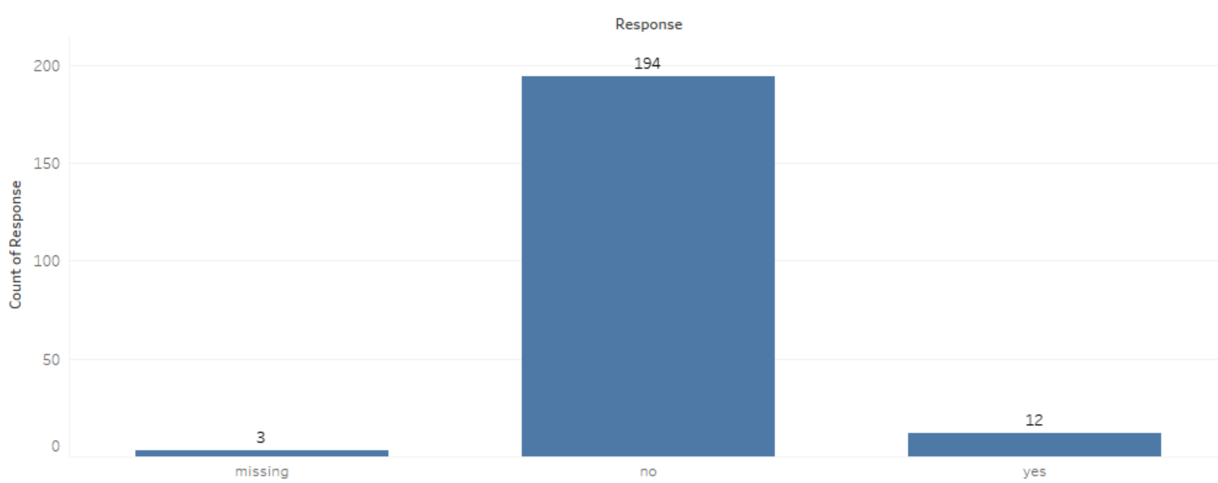
Summary of Response:
Q5a, Where do you prefer to park? Public rest areas

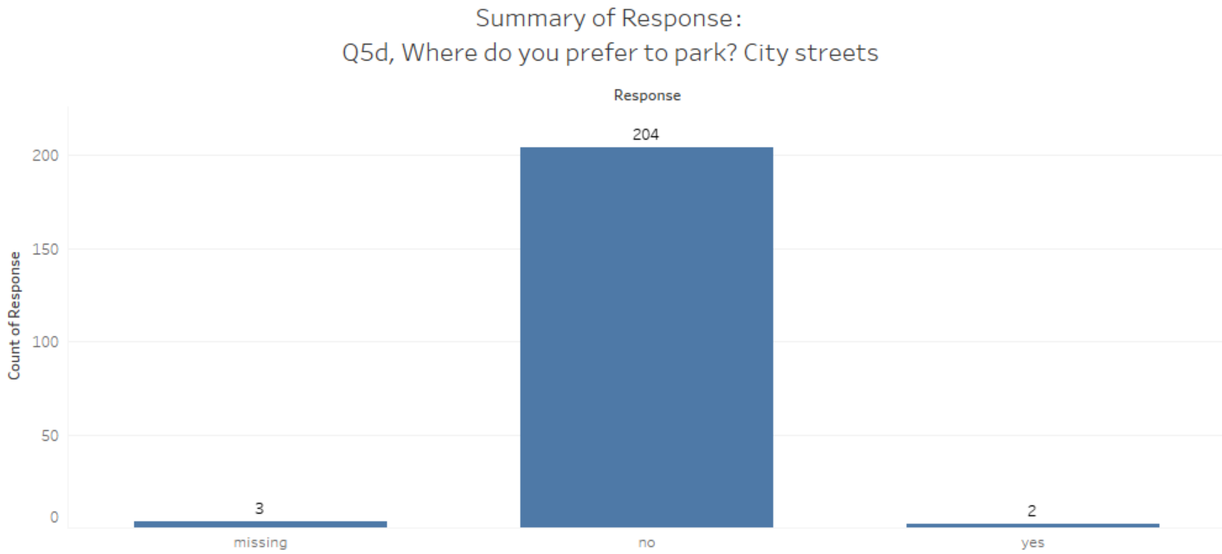


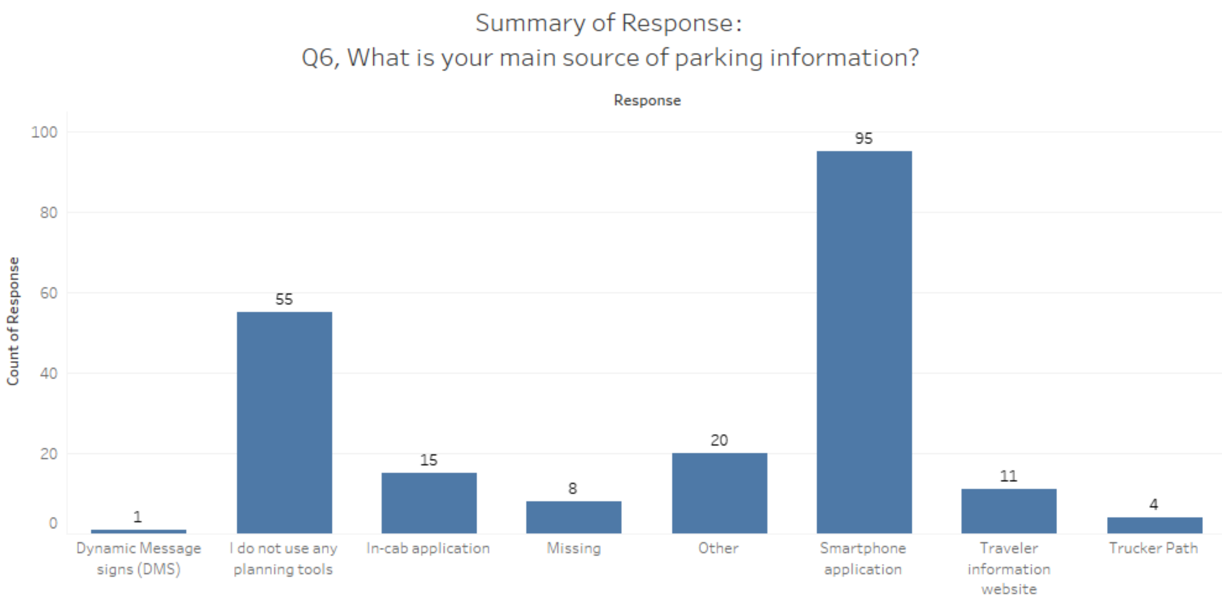
Summary of Response:
Q5b, Where do you prefer to park? Truck stops



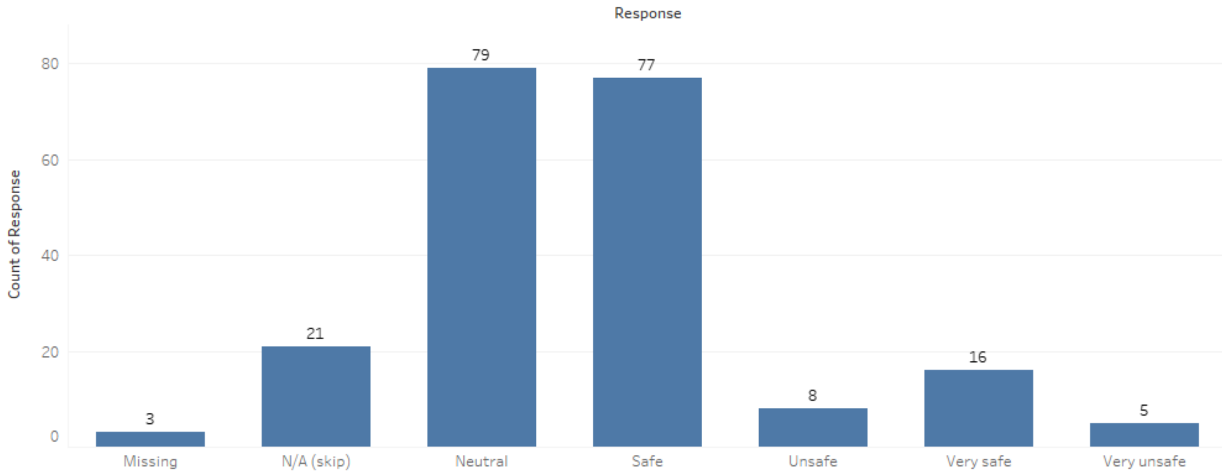
Summary of Response:
Q5c, Where do you prefer to park? Highway ramps



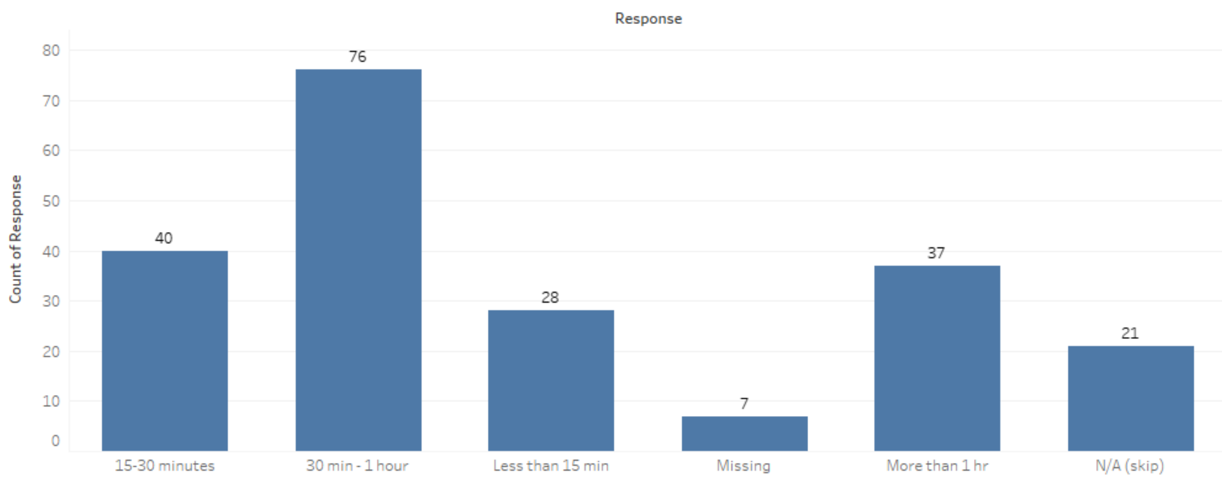

Summary of Response:
Q5d, Where do you prefer to park? City streets
Response
Count of Response
0
50
100
150
200
204
3
2
missing
no
yes

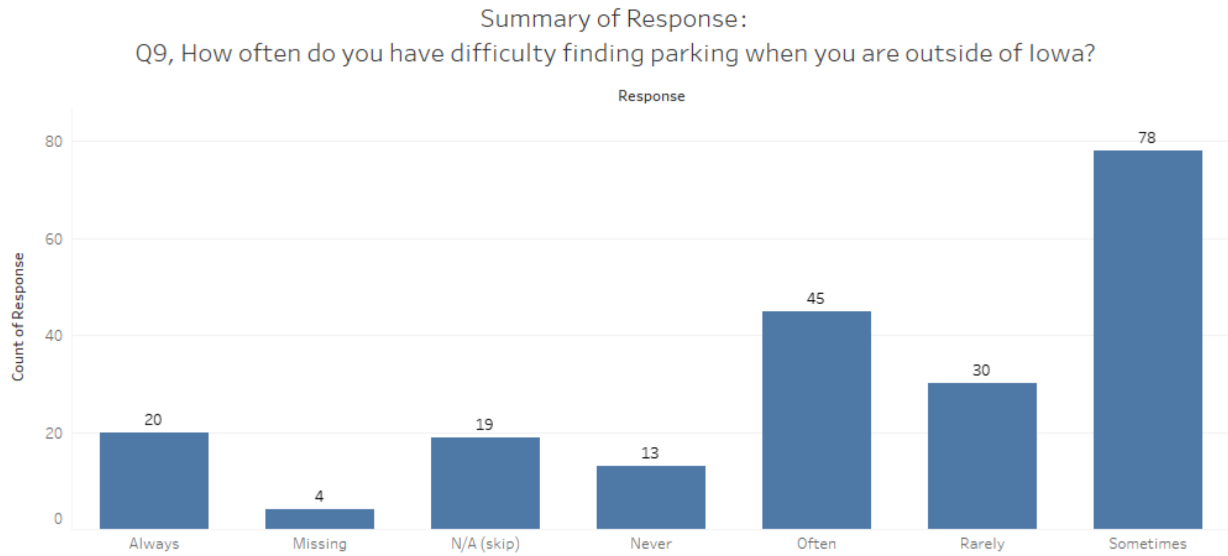

Summary of Response:
Q6, What is your main source of parking information?
Response
Count of Response
0
20
40
60
80
100
1
55
15
8
20
95
11
4
Dynamic Message signs (DMS)
I do not use any planning tools
In-cab application
Missing
Other
Smartphone application
Traveler information website
Trucker Path

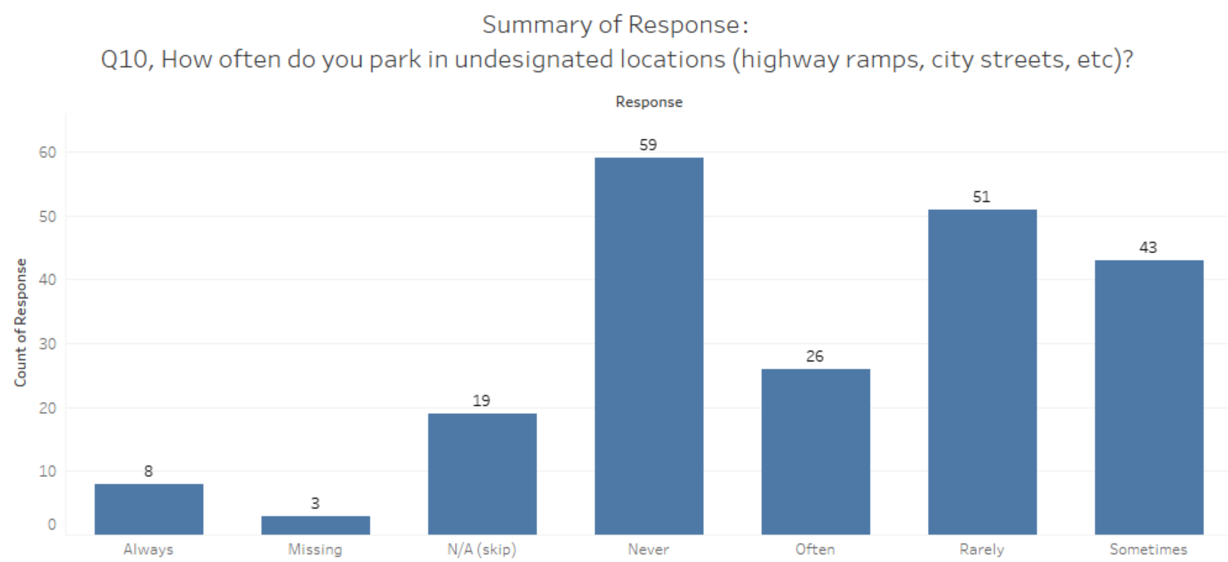
Summary of Response:
Q7, How safe do you feel when you park when you are outside of Iowa?



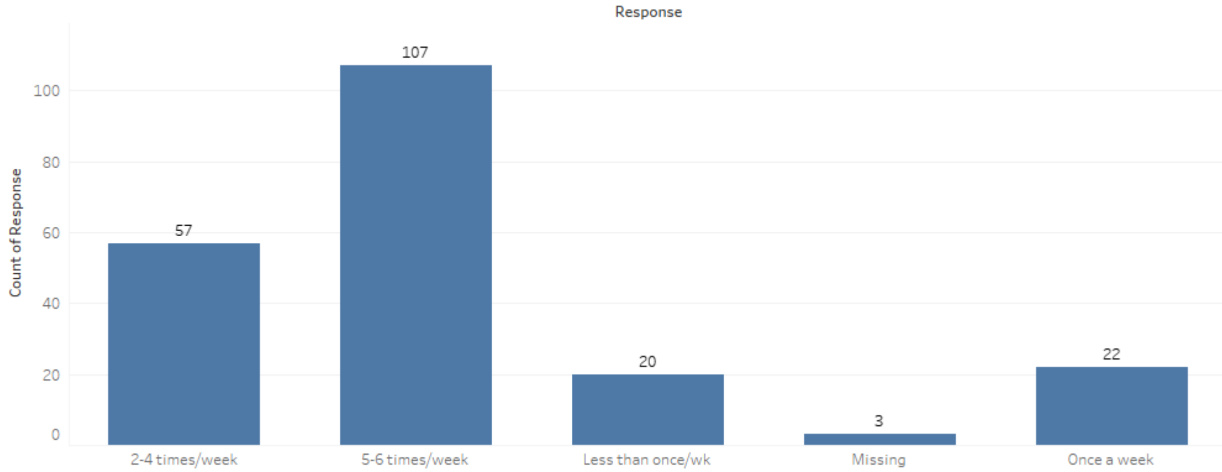
Summary of Response:
Q8, How long does it take you to find parking when you are outside of Iowa?



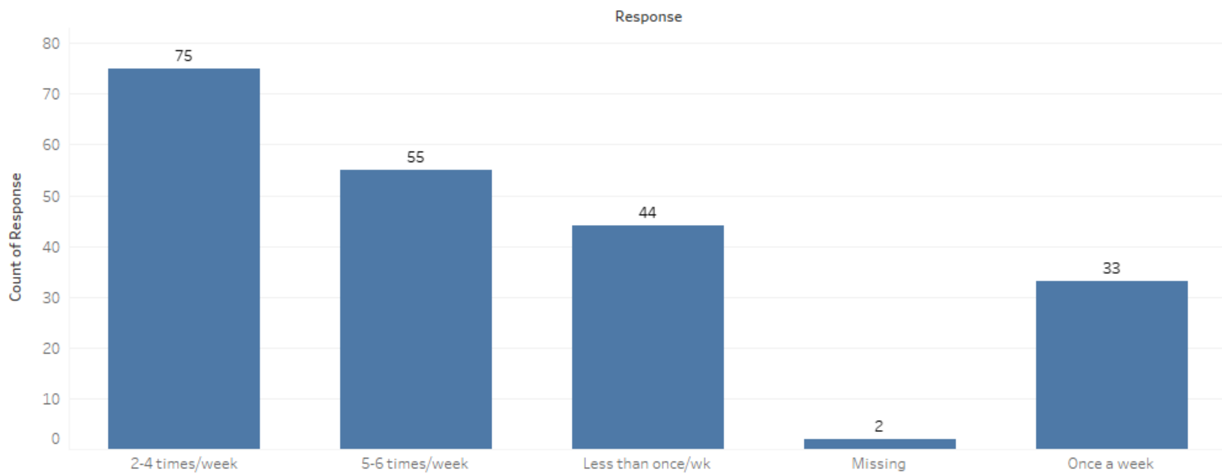

Summary of Response:
Q9, How often do you have difficulty finding parking when you are outside of Iowa?
Response
Count of Response
80
60
40
20
0
20
4
19
13
45
30
78
Always
Missing
N/A (skip)
Never
Often
Rarely
Sometimes


Summary of Response:
Q10, How often do you park in undesignated locations (highway ramps, city streets, etc)?
Response
Count of Response
60
50
40
30
20
10
0
8
3
19
59
26
51
43
Always
Missing
N/A (skip)
Never
Often
Rarely
Sometimes

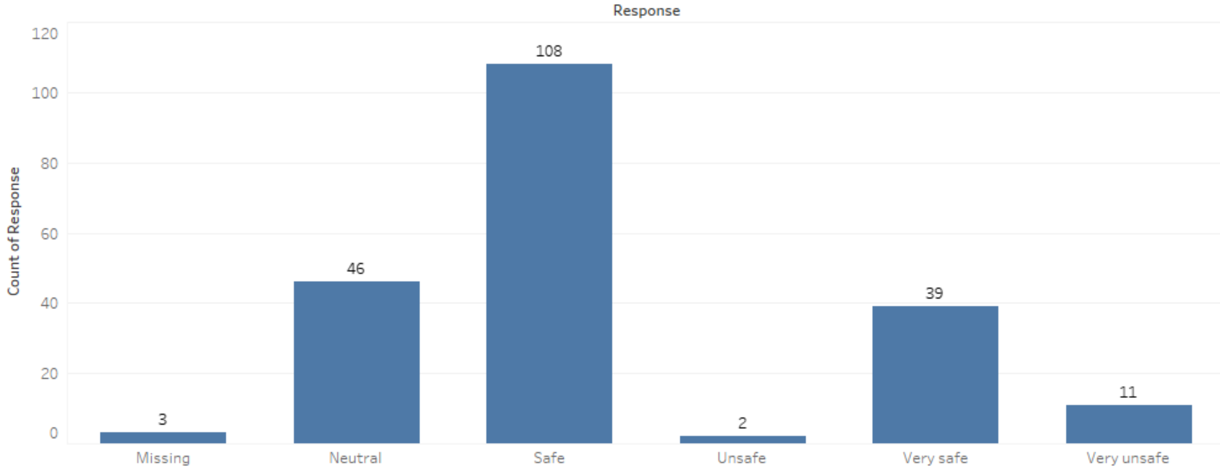
Summary of Response:
Q11, How often do you drive in or through Iowa?



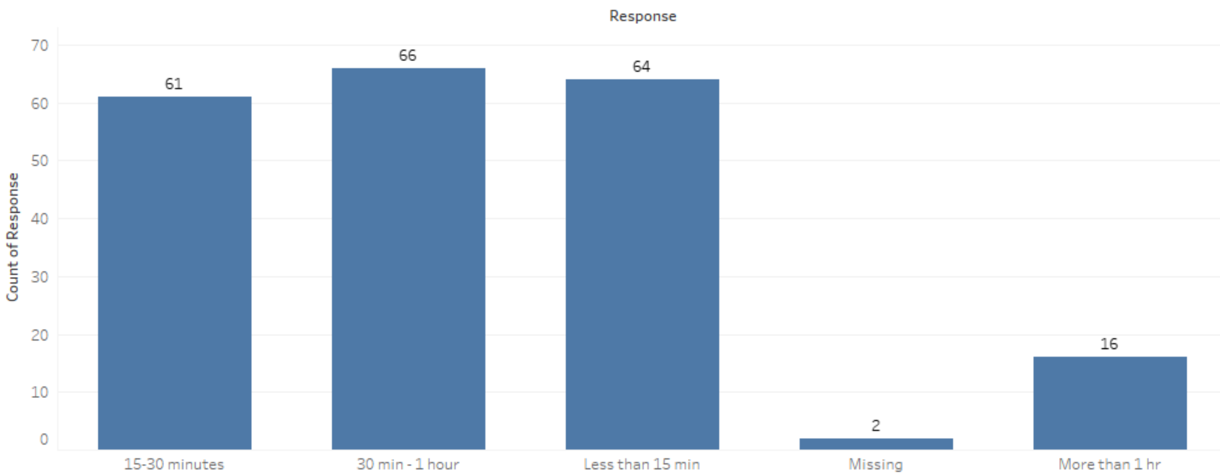
Summary of Response:
Q12, How often do you need parking in Iowa?

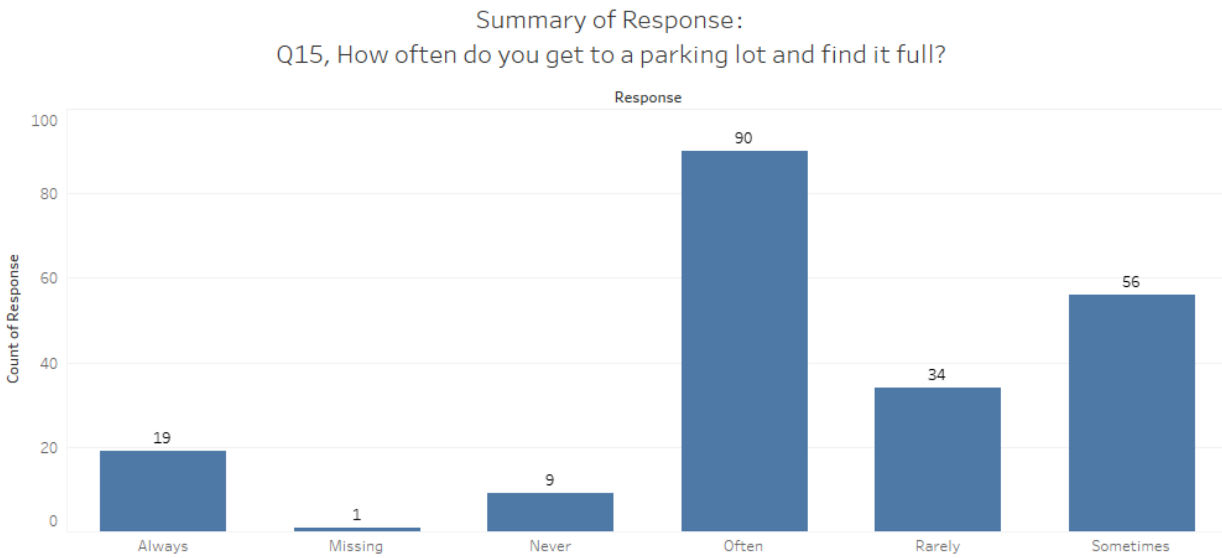


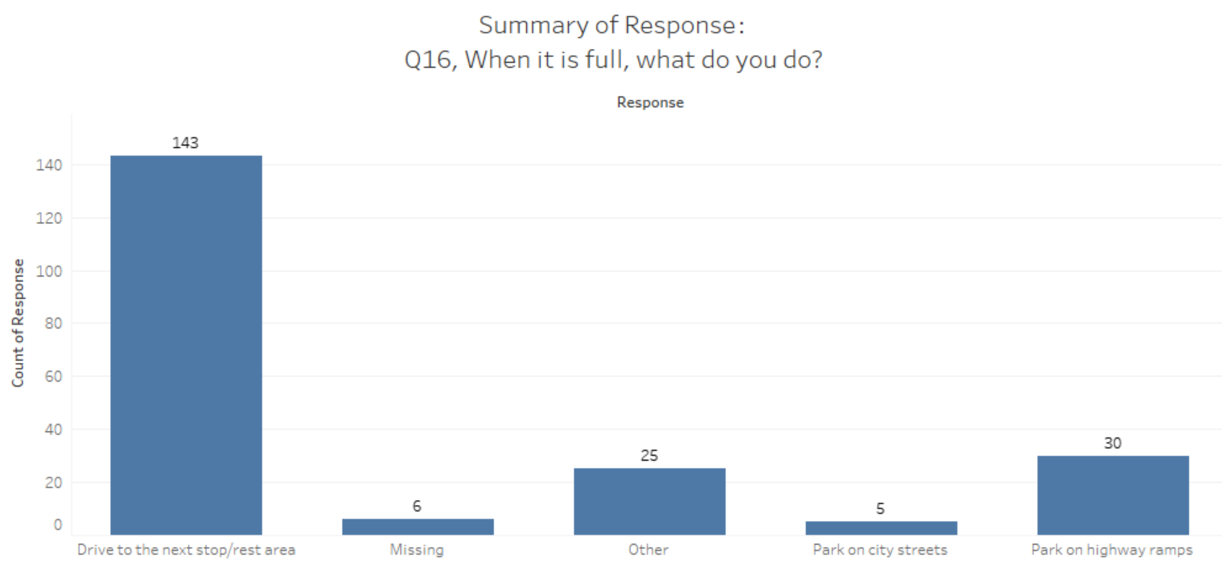
Summary of Response:
Q13, How safe do you feel when you park in Iowa?



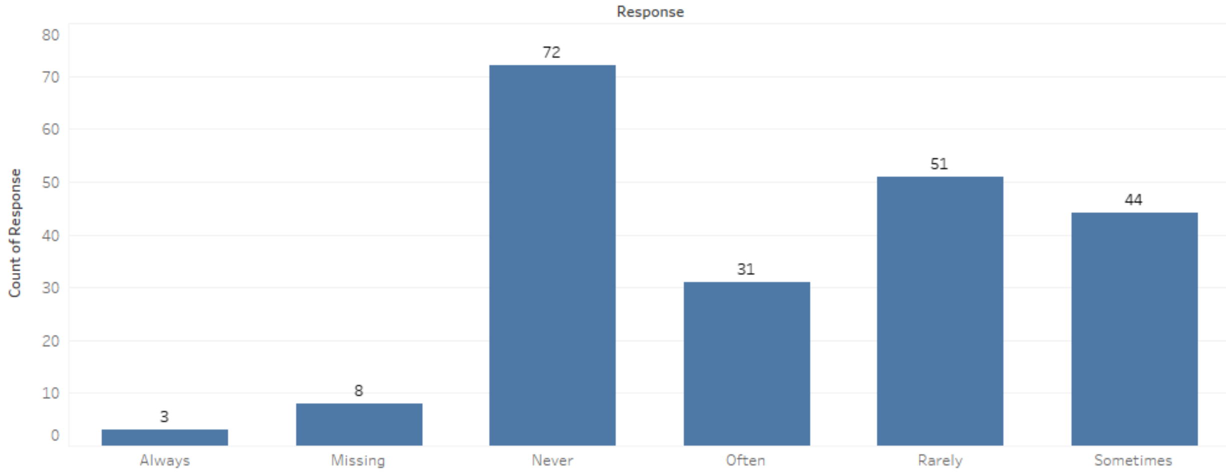
Summary of Response:
Q14, How long does it take to find parking in Iowa?



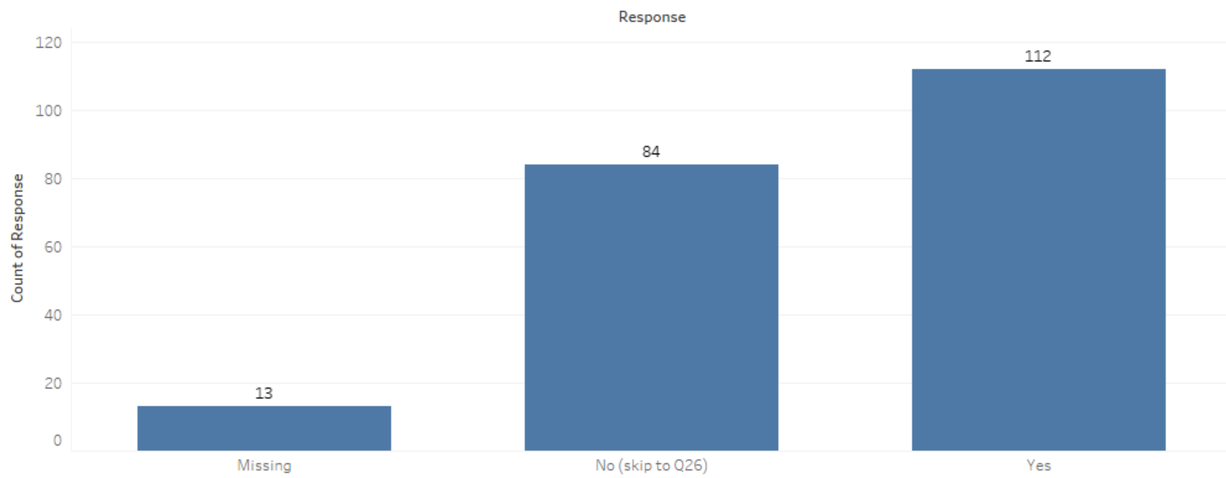

Summary of Response:
Q15, How often do you get to a parking lot and find it full?
Response
Count of Response
100
80
60
40
20
0
19
1
9
90
34
56
Always
Missing
Never
Often
Rarely
Sometimes

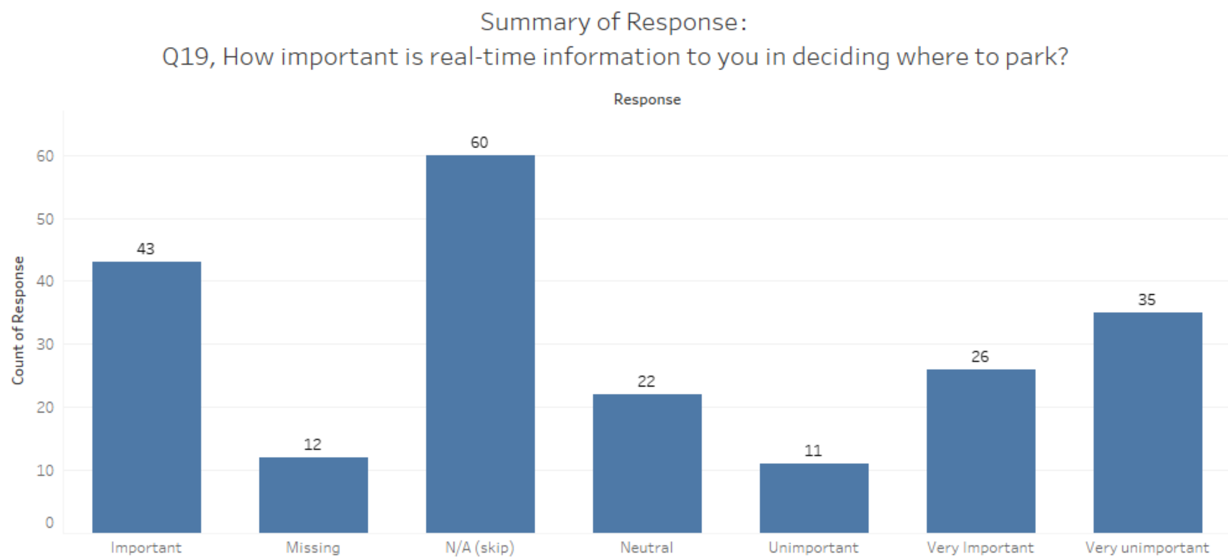

Summary of Response:
Q16, When it is full, what do you do?
Response
Count of Response
140
120
100
80
60
40
20
0
143
6
25
5
30
Drive to the next stop/rest area
Missing
Other
Park on city streets
Park on highway ramps

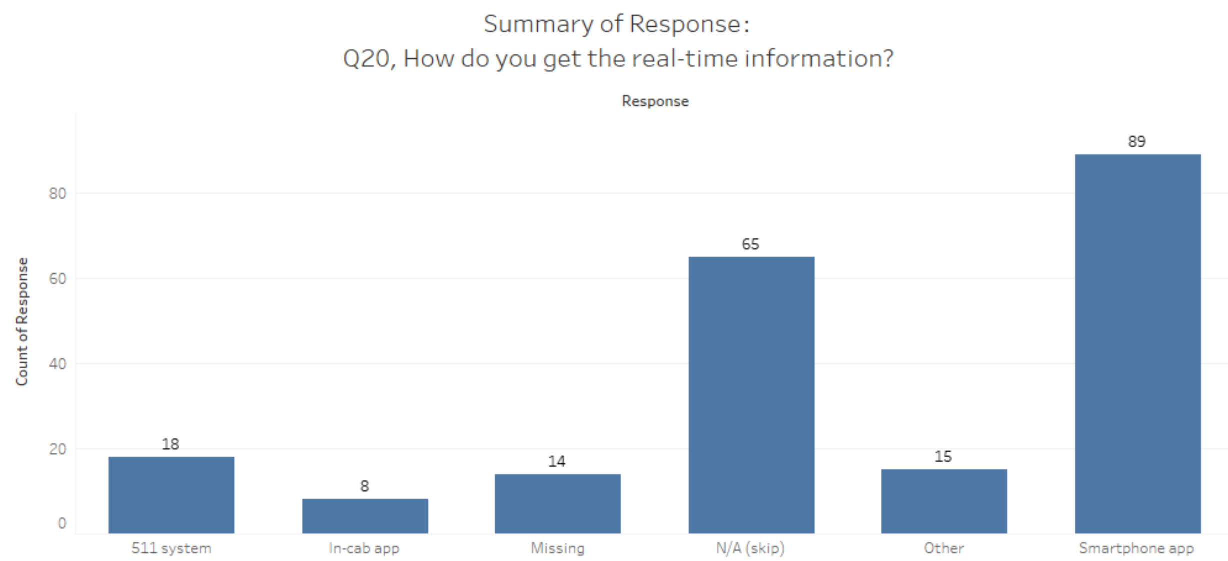
Summary of Response:
Q17, How often do you park in undesignated locations (highway ramps, city streets, etc)?

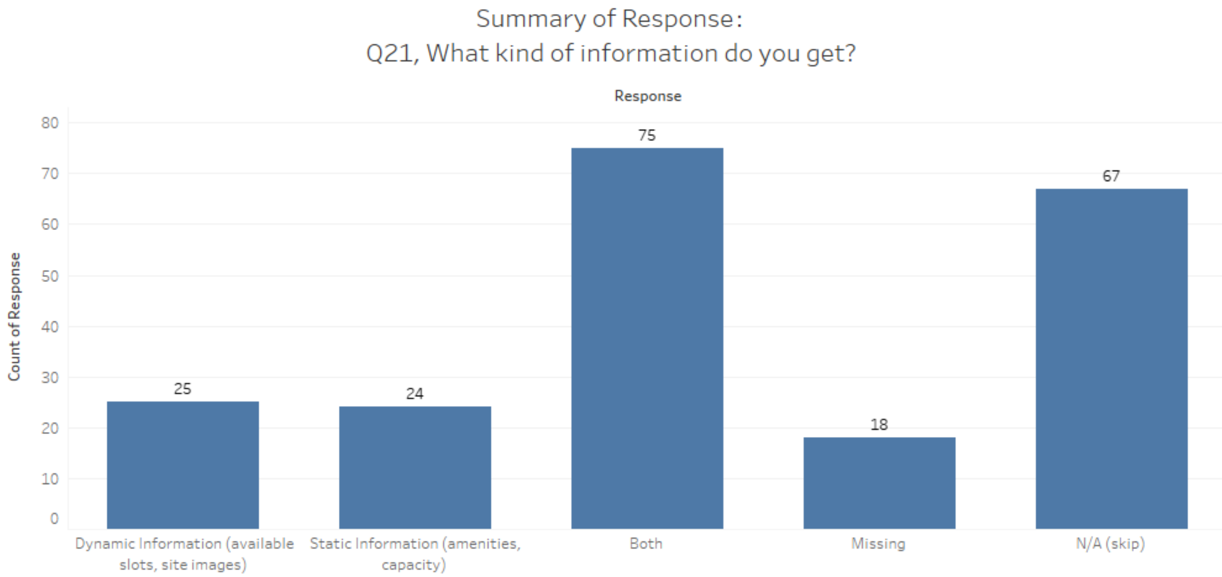


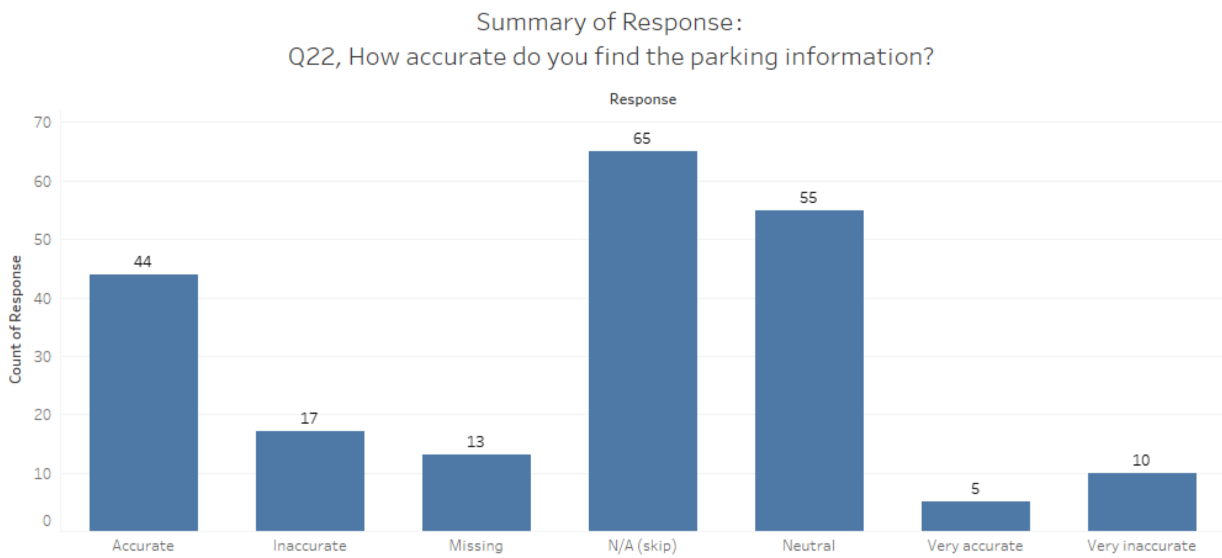
Summary of Response:
Q18, Do you use real-time information to find parking in Iowa? (smartphone, in-cab app, etc)



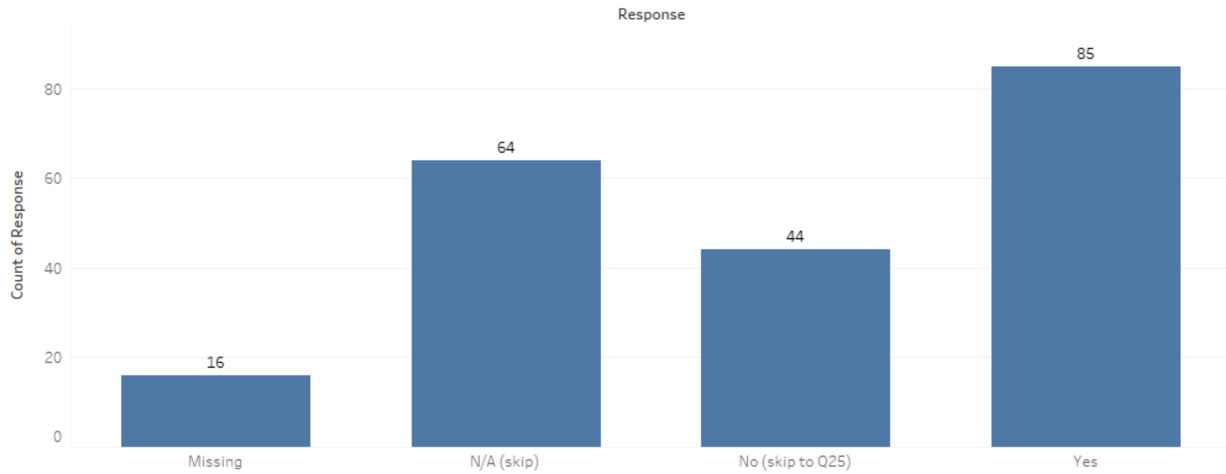

Summary of Response:
Q19, How important is real-time information to you in deciding where to park?
Response
Count of Response
0
10
20
30
40
50
60
43
12
60
22
11
26
35
Important
Missing
N/A (skip)
Neutral
Unimportant
Very Important
Very unimportant


Summary of Response:
Q20, How do you get the real-time information?
Response
Count of Response
0
20
40
60
80
18
8
14
65
15
89
511 system
In-cab app
Missing
N/A (skip)
Other
Smartphone app

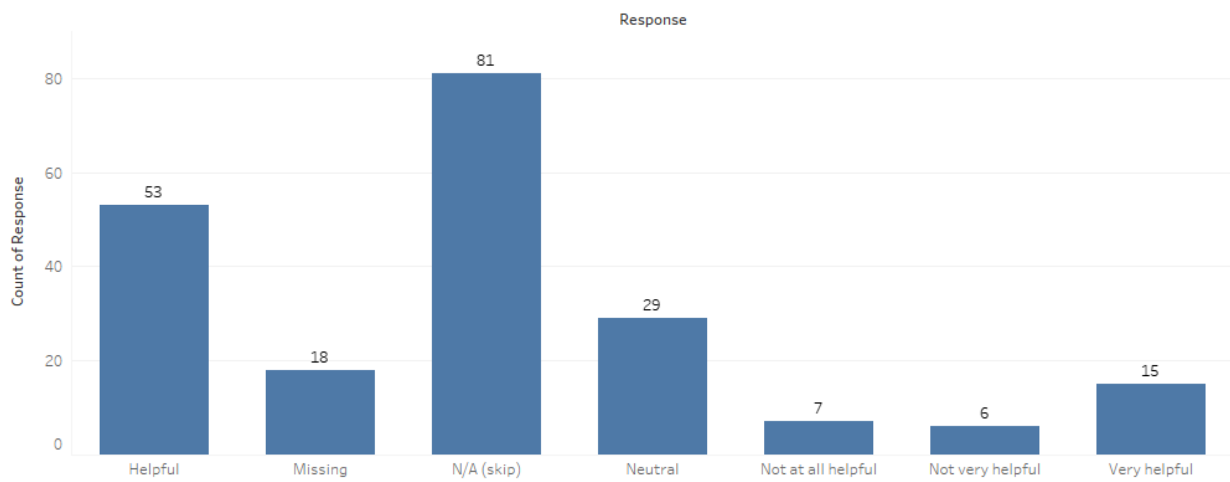

Summary of Response:
Q21, What kind of information do you get?
Response
Count of Response
80
70
60
50
40
30
20
10
0
25
24
75
18
67
Dynamic Information (available slots, site images)
Static Information (amenities, capacity)
Both
Missing
N/A (skip)

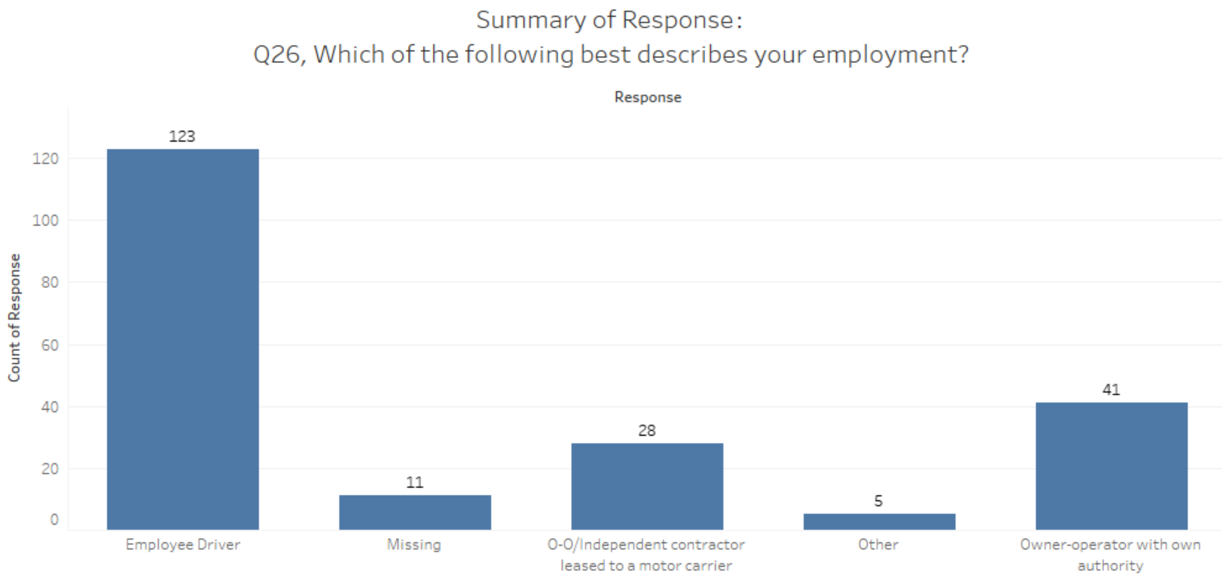

Summary of Response:
Q22, How accurate do you find the parking information?
Response
Count of Response
70
60
50
40
30
20
10
0
44
17
13
65
55
5
10
Accurate
Inaccurate
Missing
N/A (skip)
Neutral
Very accurate
Very inaccurate

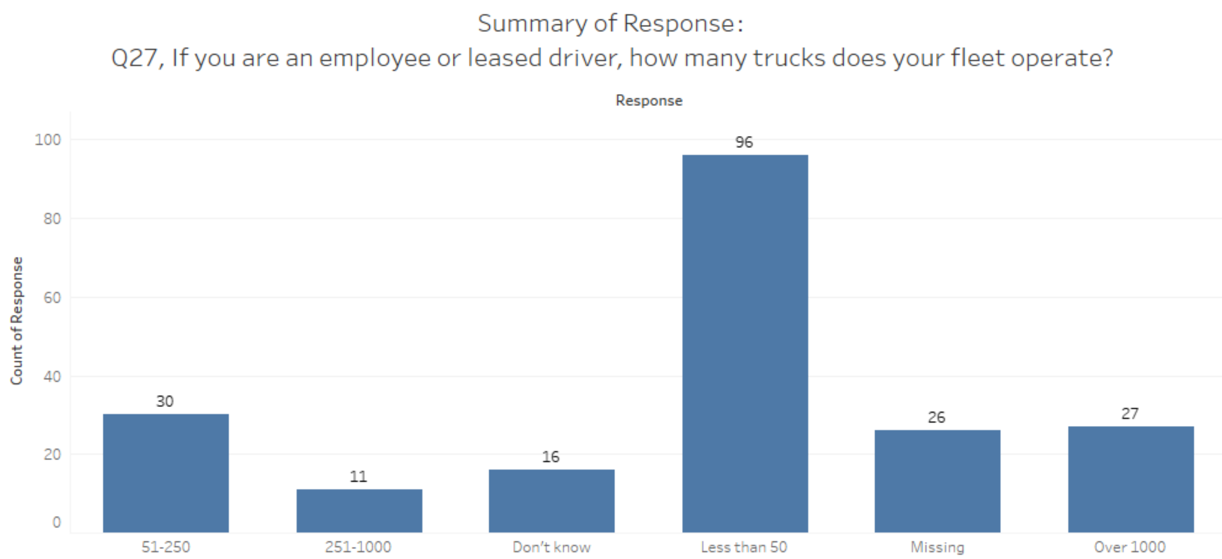
Summary of Response:
Q23, Do you view images of parking lots on your preferred information source?



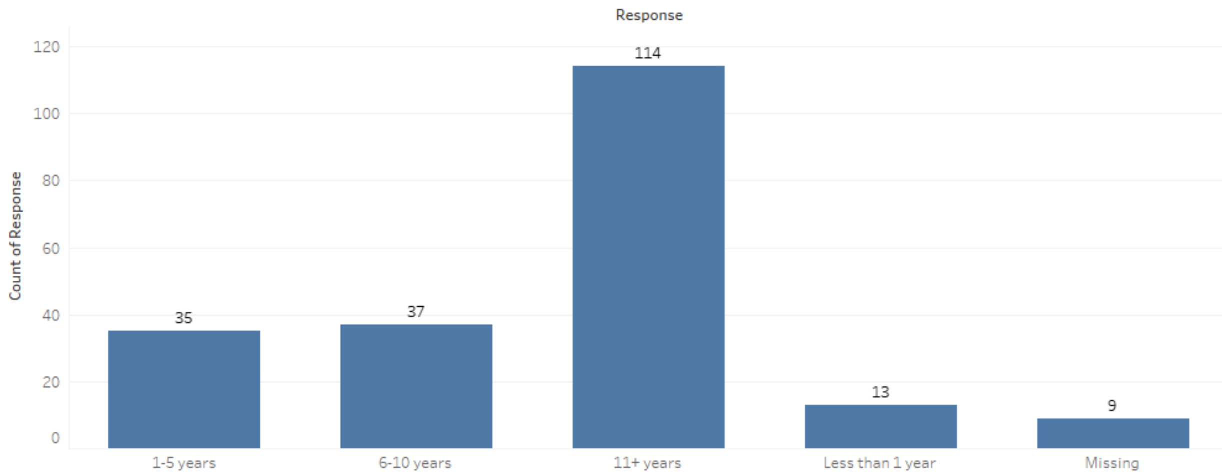
Summary of Response:
Q24, How helpful are these images to making your parking decisions?



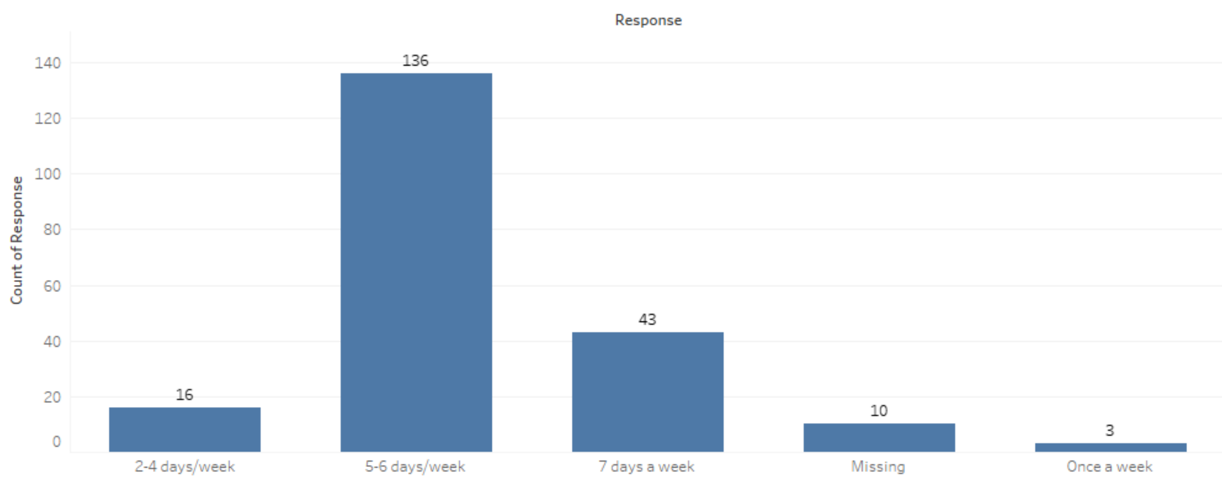

Summary of Response:
Q26, Which of the following best describes your employment?
Response
Count of Response
0
20
40
60
80
100
120
123
11
28
5
41
Employee Driver
Missing
O-O/Independent contractor leased to a motor carrier
Other
Owner-operator with own authority


Summary of Response:
Q27, If you are an employee or leased driver, how many trucks does your fleet operate?
Response
Count of Response
0
20
40
60
80
100
30
11
16
96
26
27
51-250
251-1000
Don't know
Less than 50
Missing
Over 1000

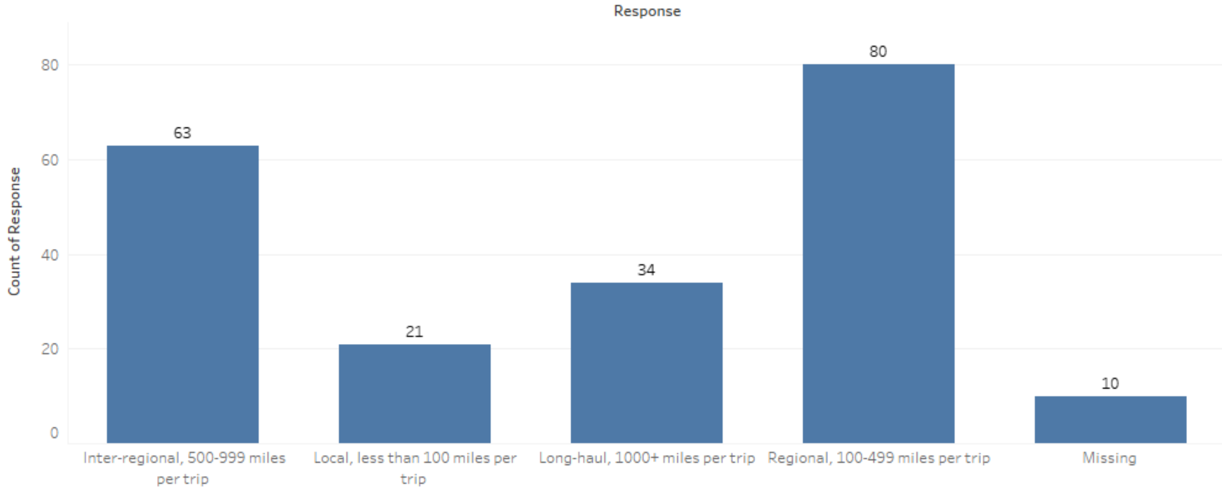
Summary of Response:
Q28, How long have you operated a Commercial Motor Vehicle?



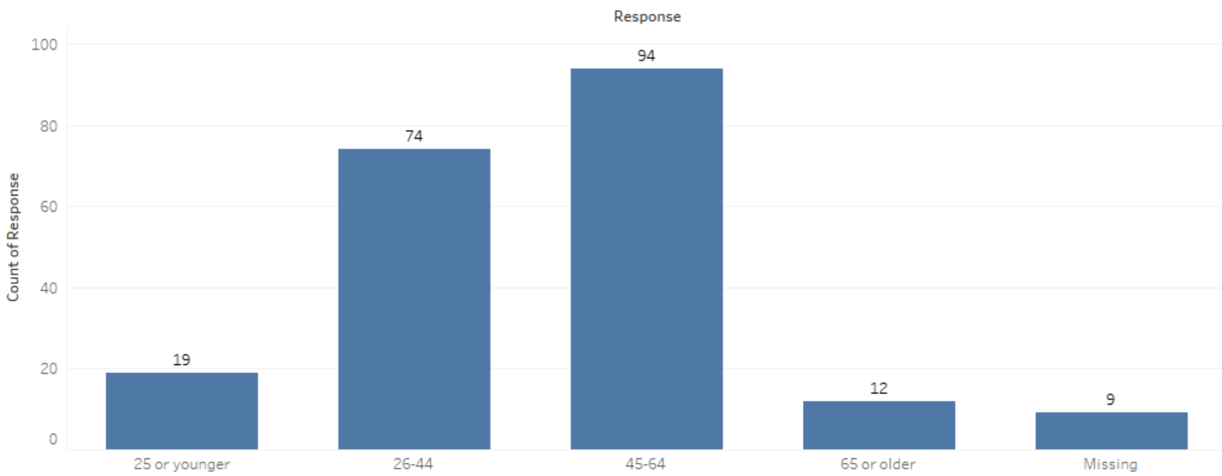
Summary of Response:
Q29, On average, how many days in a week do you drive a truck?



Summary of Response:
Q30, What is your usual length of haul?



Summary of Response:
Q31, What is your age category?



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