UNIVERSITY OF MINNESOTA

A Comprehensive System for Assessing Truck Parking Availability

Final Report

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16. Abstract (Limit: 250 words)

Commercial heavy vehicle (CHV) drivers are required under federal Hours of Services (HOS) rules to rest and take breaks to reduce driving while fatigued. CHV drivers and operators must balance compliance to the HOS rules against on-time delivery requirements as well as shorter lead times to plan their trips, thereby making location and parking availability of rest area facilities more critical. Without timely, accurate parking availability information, drivers are left with the dilemma of continuing to drive fatigued, drive beyond HOS CHV operation limits, or park illegally on highway shoulders or ramps—all potential safety hazards. In this study, a multi-view camera system was designed and evaluated to detect truck parking space occupancy in real-time through extensive field operational testing. A system architecture was then developed to disseminate up-to-the-minute truck parking information through three separate information delivery systems: 1) Roadside Changeable Message Signs (CMS), 2) Internet/Website information portal, and 3) an onboard geolocation application. The latter application informs the driver of parking availability of one or more parking facilities that are downstream from their current direction of travel. All three notification mechanisms were evaluated during the field test. Survey studies were conducted to provide feedback from commercial heavy vehicle drivers and operators to better understand their perceptions of parking shortages and utility of the parking information delivery mechanisms. Overall, the system has proven to provide 24/7 around-the-clock per-space parking status with no need for manual interventions to correct detection errors, with per parking space accuracy typically equal to or exceeding 95 percent. The concept of operations field tests demonstrated the feasibility of the technical approach and the potential to alter freight borne trip behaviors by allowing drivers and carriers to plan stops and improve trip efficiency.

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EXECUTIVE SUMMARY

Truck parking can become a major safety concern when the driver lacks timely information on where there is available parking. The driver must then decide between either continuing to drive fatigued to search for available parking or to park illegally, for example, on highway shoulders and ramps. Either situation poses a serious safety concern. Under such circumstances when law enforcement officers encounter trucks parked illegally under this scenario, they may feel obligated to wake up the drivers to move their vehicles, thus forcing them to continue driving (perhaps beyond the legal HOS limit) to again search for legal parking. There is also a loss of productivity and increased fuel emissions as a result of the additional time drivers spend finding available parking.

Many previous studies that have pointed out capacity shortages on specific freight corridors contend that reliable parking notification is also needed to utilize the capacity effectively, preferably by using Intelligent Transportation Systems (ITS) approaches; there were many cases documented that indicate a mismatch between actual truck parking space availability and a driver's perception of the availability. This study focused on developing and testing a novel comprehensive Truck Parking Availability System (TPAS) along the Interstate-94 corridor in Minnesota.

There were a few important requirements that needed to be met in designing such a system. First, the system could not infiltrate or disturb the pavement surfaces or substructures. Second, the system must be operational 24/7 and perform any recalibrations without any human intervention. Such requirements led naturally to camera-based approaches for parking detection. A novel multi-camera approach was developed to directly detect designed truck parking stall occupancy for three state-sponsored truck parking facilities, accessible from the eastbound direction along the corridor, all within 100 miles west of Minneapolis-Saint Paul.

Three information delivery mechanisms were tested extensively through a concept of operations field test: 1) a commercial operator accessible web parking information portal, 2) an in-cab geolocation application that integrated within an existing on-board logistics device to support driver and carrier trip operations, and 3) roadside electronic message signs. Second, the detection performance was evaluated through extensive observations of historical data harvested under a variety of parking and environmental scenarios. Per space detection performance is typically better than 95 percent, which correlated with overall space occupancy count discrepancies between ±1 to ±3 counts. Generally the system is robust to various sources of observable factors recorded during the evaluation. A detailed analysis of detection performance and the sources of detection errors are provided within the report.

As part of the study user evaluations from commercial drivers and operators before and during the field tests were conducted. In short, there was a clear impact in driver and carrier attitudes and perceptions for utilizing TPAS notifications to more efficiently plan and complete long-haul trips. More than half of all users traveling along the corridor (drivers and operators) indicated “positive” or “very positive” impacts of TPAS on their productivity. The results also provided several important insights that can serve as a guide to design region-wide parking notification systems to best meet their needs. For example, the evaluations quantified preferable locations of roadside changeable message boards, and their perceived importance when compared to other information delivery mechanisms, as well as the desired reliability and accuracy of the parking availability notifications that would be displayed.

The system has continuously monitored parking availability between one year and four months and more than two and a half years, starting in early 2013, demonstrating that reliable operation and detection is feasible with this approach. The current architecture was integrated to test the aforementioned delivery mechanisms using a mid-tier platform to archive historical parking status data as well as disseminate truck parking notifications. It is possible to build in other information delivery protocols to fit other architectures suited for region-wide, interstate truck parking availability standards and delivery mechanisms, should the TPAS approach be adapted to a larger regional truck parking notification system.

CHAPTER 1: INTRODUCTION

The reliance on domestic truck-borne freight is unquestionable. In year 2012 sixty seven percent of all goods and materials by weight were shipped by Commercial Heavy Vehicles (CHVs). By year 2040, the Federal Highway Administration projects an increase of over five billion tons will be shipped by CHVs, representing sixty six percent of all goods and materials, which implies that there will be an increase of CHV trips completed on our roadways for the foreseeable future [1]. Furthermore, it is not unusual for long haul drivers to receive relatively short lead trip and delivery times. Such logistical constraints must also be balanced with ensuring CHV drivers obtain appropriate rest periods to avoid driving fatigued. Accordingly, the Federal Commercial Motor Vehicle Safety Administration (FMCSA) continues to mandate federal Hours of Service (HOS) regulations as a tool to reduce the risk of CHV crashes due to driver fatigue[1].

Compliance with the current FMCSA HOS regulations, commonly referred to as the "11-14-10 rule", requires that drivers can drive no more than 11 hours in a single day (with up to 3 additional hours of non-driving on-duty time) after which a period of 10 hours of rest is then required before going back on-duty to operate their vehicle again. During their trips drivers are also required to take a minimum of 30 minutes of rest for every 8 hours of driving. Currently, in addition to daily trip HOS rules, there is also a consecutive maximum on-duty period of either 70 hours in 8 days or 60 hours in 7 days, after which the driver must be off duty for 34 hours to 'reset' the clock. Any of these situations require that the driver finds available legal parking to stop and rest.

Truck parking can become a major safety concern when the driver lacks timely information on where there is available parking. The driver must then decide between either continuing to drive fatigued to search for available parking, or to park illegally, for example on highway shoulders and ramps. The latter is a significant traffic safety hazard especially at night or next to high speed traffic [2, 3]. Without adequate information for actual parking space availability, the driver may infer that nearby parking facilities have no available spaces after observing trucks parked on exit ramps or shoulders—when in fact nearby parking is available [4]. Furthermore when law enforcement officers encounter trucks parked illegally under this scenario, they may feel obligated to wake up the drivers to move their vehicles, thus forcing them to continue driving (perhaps beyond the legal HOS limit) to again search for legal parking. The added driving to search for available parking also wastes fuel and increases diesel emissions.

Several national and state sponsored studies that have pointed to capacity shortages also support the contention that existing truck parking capacity along many regional corridors has not always been efficiently utilized; some facilities between adjacent road segments were under capacity while others are near, or over, capacity [5-9]. A driver's perception of a shortage does not match consistently with

[1] Code of Federal Regulations 49 part 395; see www.ecfr.gov for full provisions

capacity utilization data in a given corridor. For example, a study Michigan reported on one corridor where 80 percent of the parking facilities were over their capacity 2.4 nights per week, 40 percent of the drivers believed more spaces need to be added. Yet, along another corridor 40 percent of the parking facilities were over capacity 1.6 nights per week, 67 of the drivers surveyed believed that more spaces were needed. Furthermore, increasing the number of truck stops and rest areas, or adding capacity to existing ones to alleviate parking shortages, may be either financially intractable, or incompatible with local restrictions [8, 10]. High occupancy levels at rest areas during night time hours have also been correlated with an increase in truck crash frequency on adjacent highway segments [11]. Intelligent Transportation System (ITS) technologies can be used to provide real-time information that would redirect drivers to nearby facilities with available parking, thereby utilizing the existing and future added capacity more effectively [6].

The Interstate 94 corridor within the state of Minnesota is a major national freight corridor that could benefit from providing parking information to truck drivers. Truck volumes average between 10 to 15 percent of all traffic along the corridor (averaged annual daily total traffic volumes between 20,000 and 180,000), and many drivers must also contend with urban congestion during peak hours as they approach the Minneapolis-Saint Paul metropolitan area. This is another logistical constraint that can affect how drivers plan their trips and when to take required breaks. Previous state-sponsored studies have shown frequent over capacity problems for the truck parking rest areas along the corridor, including the eastbound direction between the North Dakota boarder and the Twin Cities metropolitan area [7, 8, 12]. The problems experienced in the I-94 corridor in Minnesota are not unique to other aforementioned corridors, and therefore the development and testing of a comprehensive truck parking availability system is applicable to other corridors as well.

1.1 PROJECT RESEARCH SCOPE AND OBJECTIVES

The main objective of this proposal was to design and evaluate a comprehensive real-time truck parking availability system along the I-94 corridor passing through Minnesota. The parking detection system was to satisfy the following system implementation requirements:

1. The system could not infiltrate or disturb pavement substructure and surfaces.
2. The system could not interfere with parking facilities operations during the installation, maintenance, or its operation.
3. The system would automate real-time parking space occupancy information “24/7”.
4. The system would provide an architecture capable of aggregating, archiving, and broadcasting parking space information.
5. Test system would provide truck parking information dissemination over three mechanisms: 1) fixed location roadside parking availability notifications, 2) commercial operator accessible web portal, and 3) commercial driver in-cab mechanisms.

The team proposed a novel multiple camera sensor-based detection system to meet the aforementioned objectives. System parking space information accuracy and performance were quantified by comparing human ground-truth observations during continuous periods of operation as well as quantifying other reliability measures during the monitoring process and field operational tests.

A system usability assessment was performed by designing survey tool to collect data from drivers and operators who utilize the I-94 corridor. The before-installation and operation assessment was used as a guide for information dissemination and accuracy, while a second, follow-up evaluative survey was completed to gain feedback of the system in operation and validate pre-operations usability assessments.

The project scope originally included developing and integrating the system at three public sponsored rest areas in addition to a private commercial truck stop along the I-94 eastbound direction of the corridor, west of Minneapolis/Saint Paul. During the course of the project, the original private facilities operator could not participate and a similar agreement by another alternative private operator could not be reached. However, three state sponsored sites were implemented and extensively tested; they have been continually operational starting in early 2013.

1.2 REPORT ORGANIZATION

The report is organized as follows. Chapter 2 summarizes ITS approaches and technologies for estimating truck and vehicle parking availability published in literature. Chapter 3 provides an overview of the technological approach for truck parking detection. Chapter 4 then summarizes the results of a usability study using survey data collected from CMV drivers and operators who use the Interstate 94 corridor (within the Midwest region) prior to system deployments and field operational testing. Chapter 5 describes the truck parking facilities and supporting architecture to provide real-time truck parking information dissemination and system monitoring. Truck parking detection performance (accuracy and around-the-clock reliability) is provided in chapter 6. Chapter 7 summarizes a full operational field test and a subsequent user evaluation study conducted by the ATRI team members. Conclusions and future recommendations are provided in chapter 8.

CHAPTER 2: BACKGROUND

Intelligent parking systems has been an active area of research and development for several years. This chapter provides a broad overview of parking detection technologies and the existing challenges which such technologies must address.

Real-time parking monitoring methodologies can be categorized as *indirect* and *direct.* Indirect methodologies are based on detecting and classifying vehicles at all ingress and egress points of the parking facility and summing the difference over accumulated counts at specified time intervals [4, 13, 14]. Fallon & Howard [15] developed a system based on embedding small battery powered magnetometers (75mm x 140mm) in the pavement at the egress and ingress locations of the parking facility to estimate occupancy by subtracting the two counts in real-time. Manually observed vehicle counts over a 30 day period found that there was a small non-stationary bias in the detector over time which resulted in a false detection rate averaging about one vehicle per day. The magnetometers operate with a similar principle to in-pavement loop detectors but with reportedly much less disruption to pavement surfaces. As the test facilities had between 27 and 35 spaces, the accumulated error produced unacceptably high occupancy estimations within just two weeks of operation.

Another indirect approach suggested by Gertler & James [13] utilized available commercial off-the-shelf computer vision camera sensors at the entrance and exit of a 30 space private parking facility. The camera sensors utilized "trip-wire" presence detectors in order to sense vehicle presence and motion, and classify vehicle type based on estimating their length. The reported detection accuracy analyzed from 1044 outbound, and 841 inbound vehicles, observed during 3 mid-day periods and one night period, was 86 percent to 96 percent during the day, and 27 percent to 55.3 percent at night. The authors reported that poor lighting at night, different intensity/color profiles of the tractor and trailer, shadows, birds flying in front of the camera sensors, and nearby vehicle headlights, were the cause of the false detections. A recent effort sponsored by the Federal Motor Carrier Safety Administration demonstrated a system integrating either road-side or overhead laser scanners with a Doppler radar sensor detection system. Their study also focused on assessing vehicle classification accuracy, because it would improve the estimate the actual number of parking spaces used due to different vehicle lengths entering and exiting the facility. There are many challenging real-world scenarios that were identified that can confound this type of approach– for example, a bob-tail exits without its semi-trailer (trailer drop), or two small vehicles ‘double-up’ in one space. Vehicle class identification error out of 6 classes was within 5 percent, with entrance count errors typically 0.1 percent. Vehicle parking count errors drifted between 3 (93.1 percent) to 11 counts (75 percent) accurate, over the course of three days without re-zeroing. [14]. Note that the test facilities had a capacity of 44 parking stalls. To conclude, although the latter approaches based on ingress-egress count detection are intuitively obvious, the general problem is that small counting and vehicle classification errors accumulated over time can lead to unacceptably large errors in the parking space occupancy estimates.

Direct methods, on the other hand, will not be subject to any accumulation error over time and therefore in theory should provide more reliable information without any manual intervention to correct errors. Furthermore, 'trip-wire' counting cannot determine actual occupancy for undisciplined parking which occurs when drivers do not respect parking lane line designations, differ in their maneuvering skills, or where lanes are not delineated [13]. Instead of utilizing the aforementioned in-pavement magnetometer sensors as a 'trip-wire', Fallon and Howard [15] created a detection 'grid' within the parking facility. In each parking stall two pucks were embedded within the pavement surface longitudinally 6.1m apart with the objective to sense different length vehicles. The detection signals were transmitted wirelessly to nearby receiving stations. The approach did not prove to be successful because aberrant driving and parking behaviors confounded the occupancy detection. For example, they were not able to reconcile incorrect detections when drivers did not respect the actual space delineations when parking or maneuvering their vehicles, or after semi-trailer drops. A recent study in Florida by [16] deployed a multiplicity of commercial wireless in-pavement 'puck' sensors each containing a magnetometer plus a skyward pointing IR beam to improve presence detection reliability. Two 13 stall state sponsored truck rest areas were instrumented, by embedding three such sensors longitudinally per stall. They then used the system to evaluate a truck parking forecasting algorithm based on a scalar Kalman Filter, updated every eight hours, to predict hourly occupancy levels typically to within ±3 counts of the sensor detection occupancy measurement.

Direct parking space occupancy detection based on using camera 2D image sensors has received considerable due to their ease of maintenance and surveillance capabilities. Modi et al. [17] demonstrated a computer vision-based approach to directly detect space occupancy of vehicles utilizing a foreground/background blob segmentation algorithm based on time-variant mixture of Gaussians combined with shadow removal. Wu et al. [18] ortho-rectified a 2D camera view of vehicle parking spaces into a top-down viewpoint before segmenting each parking space. A sliding window of 3 parking spaces, moved one space at a time, encoded the detection result based on calculating probabilities of occupancy using mean color of the space compared to a color feature prior of the empty space. A Markov Random Field model was then used to impose a penalty cost to disambiguate overlapping probabilities that lead to conflicting conclusions of occupancy. They reported an accuracy range from 76 percent to 94 percent. True [19] computed a color (in YCbCr space) histograms of parking space regions defined *a priori*. The luminance component is discarded to mitigate intensity changes in the scene. The histograms are compared with a training set of histograms to classify the space as occupied or empty with classification accuracy between 68 percent and 94 percent. Seo and Urmson [20] utilized fly-over aerial images to train an SVM linear classifier. A classification accuracy of 91.5 percent was achieved in one non-training Google aerial photo. They noted, even for aerial imagery, it was important to train with cases where occlusions were evident. Bong et al. [21] used color subtraction from an a-priori vacant background image to obtain large difference binary blobs which were ANDed with Sobel edge detection of the difference image. Shadow removal was obtained by discriminating the density of edges in a shadow vs. a vehicle. The system was tested under various lighting and weather conditions with accuracies no worse than 93.8 percent for eight private vehicle parking spots across 191 samples, but the system cannot tolerate occlusions. Deng et al. [22], designed a Bayesian discriminator from Principal Component Analysis (PCA) using Canny edge density, variance of intensity, and pixel correlation with a background image, for one private vehicle parking space. 1,687 camera images collected over 14 days were analyzed with a detection rate of 99 percent. Occlusions from adjacent vehicles and multiple parking space detection were not addressed with this approach.

Researchers in [23] computed Harr-like features within 24x24 pixel patches to discriminate between empty, and occupied spaces (from background empty spot model). Thirty samples were analyzed for a region of interest encompassing four parking spaces, with classification accuracy between 100 percent and 90 percent. There were more false positives as the number of vehicles occupying the parking spaces increased. Very recently, researchers developed a multi-camera system to monitor on-street car parking. Observed 'Vacant' vs. 'Occupied' parking space training data were constructed to train an SVM (Support Vector Machine) for parking status classification. Feature vectors were derived from Histogram of Orient Gradient cells lying within a user-defined region of interest (ROI) that defined a boundary around parking spaces. They reported a detection accuracy between 91.9 percent and 94.8 percent across 5 days of recorded video [24]. A limitation to the approach was that it required a very large training set of scenes representing occupied and vacant parking scenarios under all possible lighting, weather, and parking conditions. Training sets had to be generated that was specific to a given camera viewpoint of the spaces.

In all the aforementioned 2D computer vision methods, rapid changes in background illumination, glare, shadows, and partial occlusion from overlapping vehicles present numerous challenges. The methods were evaluated primarily with private vehicles, where such challenges become even more notable with tractor-trailer trucks because of their larger size and height compared to private vehicles. A multi-camera view approach was developed by the team to specifically address these challenges.

CHAPTER 3: TRUCK SPACE PARKING DETECTION

The advantage of the multi-view approach is that it affords the ability to reconstruct the scene observed by the cameras in three dimensions (Figure 3.2). In this approach, Structure from Motion (SfM) techniques are used to build a 3D representation of the scene [25, 26]. The advantage of obtaining the 3D structure of scenes with multi-view stereo reconstruction techniques over aforementioned 2D image processing techniques is that the multiplicity of views are used to perform photo redundancy checks to filter out artifacts arising from signal noise, camera optics, and object motions that displace differently between the images, thereby improving the robustness and accuracy of the reconstructed 3D features [25]. Results of such an approach reported in the literature are impressive; 'photorealistic' highly detailed accurate 3D geometric surface and point representations of complex urban cityscapes and objects were demonstrated. Robust segmentation of overlapping, complex objects, under varied lighting can be achieved that typically confound 2D techniques from a single camera [26]. The SfM-based vehicle detection algorithm first integrates an implementation of the Bundler from [27, 28] to solve for unknown camera intrinsic and extrinsic parameters, with the Patched-based Multi-View Stereo 3D dense point reconstruction technique (PMVS) [25]. The theory for the truck parking occupancy detection algorithm is described below, with a cursory overview of the SfM-3D reconstruction process (Figure 3.1).

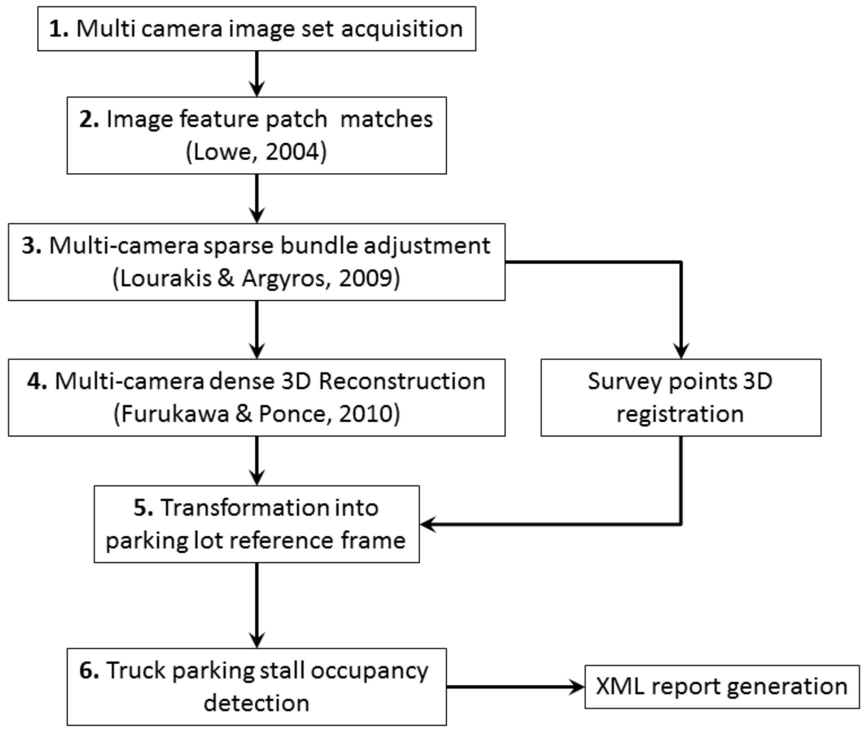


Figure 3.1. Algorithm steps for truck parking space occupancy detection.

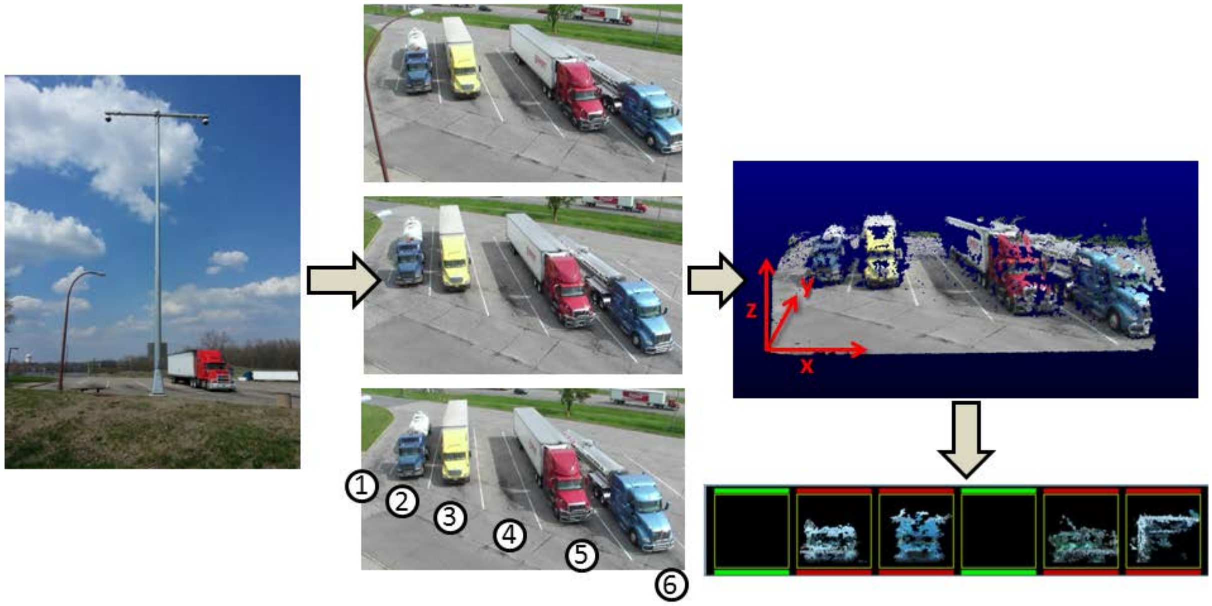


Figure 3.2. Truck 3D occupancy vehicle detection for a group of parking spaces.

3.1 3D VEHICLE OBJECT RECONSTRUCTION

After acquisition of multiple images, the first step builds a set of putative matching image point coordinates, $\boldsymbol{x}_{i,j}$ across $j = 1 \dots m$ separate camera views using SIFT features [29, 30]. Concretely, the assumption is given that the transformation from the *unknown* 3D (*4x1*) homogeneous world coordinate $\boldsymbol{X}_i$ to the corresponding (*3x1*) homogeneous image point $\boldsymbol{x}_{i,j}$ can be described by the common perspective transform representation:

$$\lambda \cdot \boldsymbol{x}_{i,j} = [\boldsymbol{K}][\boldsymbol{R} \mid \boldsymbol{t}\,]\,\boldsymbol{X_i} \tag{3.1}$$

where the $\boldsymbol{K}$ is the (*3x3) intrinsic* camera parameter matrix, which projects the 3D coordinate onto the image plane, and the upper (*3x3*) direction cosine matrix $\boldsymbol{R}$, and the upper (*3x1*) vector $\boldsymbol{t}$ compose the (*3x4*) *extrinsic* matrix, which transposes the world coordinate $\boldsymbol{X}_i$ into the camera frame. The coefficient λ represents an arbitrary scale factor. The Bundler efficiently seeks to minimize the following cost objective function, *C*, across all camera pairs and given image points, as presented in [31]:

$$C = \sum_{j=1}^{m}\sum_{i=1}^{n}\left\|Q(\boldsymbol{a_j}, \boldsymbol{b_i}) - \boldsymbol{x}_{i,j}\right\|^2 \tag{3.2}$$

where $||\cdot||^2$ is the L2 norm distance between the estimated image point, $\hat{\boldsymbol{x}}_{i,j} = Q(\boldsymbol{a_j}, \boldsymbol{b_i})$, and a corresponding actual image point $\boldsymbol{x}_{i,j}$ in (3.11). The parameter vector $\boldsymbol{a_j}$ represents each of the 12 extrinsic parameters on the right-hand side of (3.11), and the parameter vector $\boldsymbol{b_i}$ the scaling parameters on the left hand side of (3.11).

Computing the derivative of the above cost function and rearrangement of Jacobian derivative matrix terms, results in a sparse block matrix which is then solved very efficiently using gradient based optimization methods. It should be apparent that (3.1) and (3.2) can be generalized to any number of camera views, without the requirement that each image coordinate should match in all *m* camera views. Also, one can implement different image point scaling models for the original image points on the left hand side of (3.1) to compensate for systematic image projection errors; the Bundler utilized a 4th order radial lens scale distortion correction model. RANSAC is used to remove outlier putative matches $\boldsymbol{x}_{i,j}$ as determined by the computed L2 norm difference between $\hat{\boldsymbol{x}}_{i,j}$ and $\boldsymbol{x}_{i,j}$ after each iterative minimization step of the cost objective function. After each solution, additional optimizations are performed with a RANSAC procedure to remove image re-projection outliers to further refine the parameter estimation. Note that before the aforementioned iterative adjustment procedure is carried out, the initial putative SIFT point matches between successive camera pairs are refined with initial camera poses and focal length estimates by a separate iterative procedure based on homography constraint violations. The aforementioned steps are done to reduce the chances of finding a local poor local minimum [27]. For the deployed truck parking system, an initial focal length estimate based on the manufacturer specifications for each PTZ camera is input into the Bundler.

The bundled camera transform and intrinsic solutions also contain a sparse set of 3D coordinate point correspondences for the complete scene [27, 28]. However the sparse structure of points were insufficient for discriminating vehicles and subsequent space occupancy detection. Semi-dense 3D reconstruction is then achieved with Patch-based Multi-view Stereo reconstruction (PMVS) [25, 26]. The essence of PMVS, which uses the estimated intrinsic and extrinsic parameters for each camera, is that a localized surface patch model is used to perform putative matches of associated image points falling on the epipolar lines between each set of camera pairs (in this case, 3 cameras are used and therefore there are $n\cdot(n-1)/2$ = 3 such pairs). A small image patch is projected onto a square surface patch which is then rotated (pitch and yaw) with respect to the camera image planes. The reconstruction algorithm performs an iterative process of matching, expanding, and filtering. The matching process consists of matching patches, $p\ in\ \mathbb{R}^2$ along epipolar lines using normalized cross-correlation based on either Harris corner point or Difference of Gaussian features starting at the closest point candidate to the image plane (a patch size of 5x5 pixels provided the best results for this system). In each putative match, an initial 3D center position for each patch, $\boldsymbol{c}(p)\ in\ \mathbb{R}^3$ and its surface normal $\boldsymbol{n}(p)\ in\ \mathbb{R}^3$ are used to compute a normalized cross-correlation score. $\boldsymbol{c}(p)$ and $\boldsymbol{n}(p)$ are obtained by iteratively rotating the surface patch until the highest normalized cross-correlation score is obtained between the projected image pixels on the patch. The correlation score and location surface patch data are associated with 2x2 pixel cells containing the image coordinates. The expansion step consists of marching through remaining empty cells with a similar process; the filtering step performs photo-consistency checks, using the surface patch parameters and depth information to resolve surface discontinuities; for example, a person or part of a vehicle enters one camera view but is not present in the others, or water droplets form on the protective lens cover of the enclosure during snow or rain precipitation, or sunlight glare interferes with the image, and so on, all of which will similarly affect photo-consistency between each of the camera views. The above 3 steps are repeated until all the cells have been tested amongst the camera pairs. A more complete discussion of the algorithm is described in [25, 26].

The aforementioned optimization procedure for intrinsic and extrinsic multi-camera parameters are expressed in an arbitrary scale and world coordinate system and will be affected by the initial putative matches between the feature points contained within the captured image sets. Thus in order to align the 3D point cloud representation of the parking facilities scene, a similarity transformation must be determined to transform the point cloud into a desired metric coordinate frame. Snavely et al. [27] created interactive tools that allowed the user to 'fit' a similarity transformation, composed of a rigid body 3D transformation and a uniform scale factor, to a scene or 2D map. An example of an automated approach to transform one 3D point cloud into another was demonstrated in [32] by creating, and then matching, viewpoint invariant image texture patches oriented along the estimated surface normal of each XYZ point within the 3D point clouds (the projected patch features were described by SIFT descriptors). Such approaches are not suitable for the parking detection system because both the scene foreground and background change throughout time. A procedure to automate the estimation a similarity transformation to align the SfM 3D data with the parking lot surface was therefore developed, and is described below.

First the end points and mid-points of each parking space lane line, $\boldsymbol{L_i}, i = 1 \ldots m$, were surveyed using a dual channel Trimble MS750 DGPS survey instrument that obtained the RTK corrections from the MNCORS Virtual Reference Station network over a cellular internet connection. The relative distance between survey points, and deviation from a fitted flat plane, were both within approximately 4 inches (10cm) at two standard deviations (NAD83 Minnesota State Plane). For each overlapping image set $\boldsymbol{I_n}, n = 1 \ldots 3$ camera views acquired at sample time s, where by the extrinsic and intrinsic parameters for each camera are obtained by the Bundler described in section 3.1 . A set of image points $\boldsymbol{p_{i,n}}$ corresponding to $i = 1 \ldots c, c < m$ survey points $\boldsymbol{L_i}, i = 1 \ldots c$ that can be projected into all n camera views. The intrinsic and extrinsic parameters are used to back project the undistorted 2D image point $\boldsymbol{p'_{i,n}}$ into its equivalent world coordinate $\boldsymbol{\hat{L}_i}$, using each camera pair (j, k). With three cameras, there will then be $3 \times (3-1) \div 2 = 3$ back projection solutions for $\boldsymbol{\hat{L}_i}$ with $j, k = \{\{1,2\},\{2,3\},\{1,3\}\}$. For each solution, a back projection error vector, $\boldsymbol{\epsilon_{i,(k,j)}}$, is computed as the difference vector orthogonal to the two closest 3D points, $\boldsymbol{\alpha_j}, \boldsymbol{\beta_k}$ lying on each of two normal direction rays, $\boldsymbol{u_j} = \boldsymbol{p'_{i,j}}/f_j$, $\boldsymbol{u_k} = \boldsymbol{p'_{i,k}}/f_k$ emanating from the camera pair (j, k) focal centers, $\boldsymbol{c_j}, \boldsymbol{c_k}$. This relationship is mathematically described as:

$$\boldsymbol{\epsilon_{i,(k,j)}} = \boldsymbol{\alpha_j} - \boldsymbol{\beta_k} \tag{3.3}$$

$$\widehat{\boldsymbol{L}}_{\boldsymbol{i}} = \boldsymbol{\epsilon}_{\boldsymbol{i},(\boldsymbol{k},\boldsymbol{j})}/2 + \boldsymbol{\alpha}_{\boldsymbol{j}} \tag{3.4}$$

$$\text{where} \quad \boldsymbol{\alpha}_{\boldsymbol{j}} = \boldsymbol{c}_{\boldsymbol{j}} + a_j \cdot (\boldsymbol{u}_{\boldsymbol{j}} - \boldsymbol{c}_{\boldsymbol{j}})/d \tag{3.5}$$

$$\boldsymbol{\beta}_{\boldsymbol{k}} = \boldsymbol{c}_{\boldsymbol{k}} + a_k \cdot (\boldsymbol{u}_{\boldsymbol{k}} - \boldsymbol{c}_{\boldsymbol{k}})/d \tag{3.6}$$

The scalars a_j, a_k, and d computed by:

$$a_j = (\boldsymbol{u}_{\boldsymbol{k}} - \boldsymbol{c}_{\boldsymbol{k}}) \times (\boldsymbol{c}_{\boldsymbol{j}} - \boldsymbol{c}_{\boldsymbol{k}}) \circ (\boldsymbol{u}_{\boldsymbol{j}} - \boldsymbol{c}_{\boldsymbol{j}}) \times (\boldsymbol{u}_{\boldsymbol{k}} - \boldsymbol{c}_{\boldsymbol{k}})$$

$$a_k = (\boldsymbol{u}_{\boldsymbol{j}} - \boldsymbol{c}_{\boldsymbol{j}}) \times (\boldsymbol{c}_{\boldsymbol{j}} - \boldsymbol{c}_{\boldsymbol{k}}) \circ (\boldsymbol{u}_{\boldsymbol{j}} - \boldsymbol{c}_{\boldsymbol{j}}) \times (\boldsymbol{u}_{\boldsymbol{k}} - \boldsymbol{c}_{\boldsymbol{k}})$$

$$d = (\boldsymbol{c}_{\boldsymbol{j}} - \boldsymbol{c}_{\boldsymbol{k}}) \times (\boldsymbol{u}_{\boldsymbol{k}} - \boldsymbol{c}_{\boldsymbol{k}}) \circ (\boldsymbol{u}_{\boldsymbol{j}} - \boldsymbol{c}_{\boldsymbol{j}}) \times (\boldsymbol{u}_{\boldsymbol{k}} - \boldsymbol{c}_{\boldsymbol{k}})$$

Three estimates of $\widehat{\boldsymbol{L}}_{\boldsymbol{i}}$ are computed and retained: 1) the mean value between all camera pairs, 2) the minimum error $\boldsymbol{\epsilon}_{\boldsymbol{i},(\boldsymbol{k},\boldsymbol{j})}$ estimate of $\widehat{\boldsymbol{L}}_{\boldsymbol{i}}$, and 3) the estimate associated with the largest projection angle between $\boldsymbol{u}_{\boldsymbol{j}}$ and $\boldsymbol{u}_{\boldsymbol{k}}$. For each set of estimates, a least-squares fit of the parking lot plane is computed, with outlier removal. The remaining set of r back projected coordinates in the acquired time sample s are then used to estimate the initial similarity transformation composed of a uniform scale, S_s, a rigid body rotation matrix, $\boldsymbol{R}_{\boldsymbol{s}}$, and translation vector, $\boldsymbol{t}_{\boldsymbol{s}}$. Such an estimate follows from the procedure in [33] by first normalizing each $\widehat{\boldsymbol{L}}_{\boldsymbol{i}}$, and $\boldsymbol{L}_{\boldsymbol{i}}$ relative to their respective point centroids, thereby providing an estimate $\hat{S}_s$ for the uniform scale factor e.g.:

$$\hat{\boldsymbol{l}}_{\boldsymbol{s},\boldsymbol{i}} = \frac{(\widehat{\boldsymbol{L}}_{\boldsymbol{s},\boldsymbol{i}} - \widehat{\boldsymbol{\rho}}_{\boldsymbol{s}})}{\|\widehat{\boldsymbol{L}}_{\boldsymbol{s},\boldsymbol{i}} - \widehat{\boldsymbol{\rho}}_{\boldsymbol{s}}\|} \tag{3.7}$$

$$\boldsymbol{l}_{\boldsymbol{i}} = \frac{(\boldsymbol{L}_{\boldsymbol{i}} - \boldsymbol{\rho})}{\|\boldsymbol{L}_{\boldsymbol{i}} - \boldsymbol{\rho}\|} \tag{3.8}$$

$$\hat{S}_s = \frac{\|\boldsymbol{L}_{\boldsymbol{i}} - \boldsymbol{\rho}\|}{\|\widehat{\boldsymbol{L}}_{\boldsymbol{s},\boldsymbol{i}} - \widehat{\boldsymbol{\rho}}_{\boldsymbol{s}}\|} \tag{3.9}$$

where

$$\widehat{\boldsymbol{\rho}}_{\boldsymbol{s}} = \frac{1}{r} \cdot \sum_{\boldsymbol{i=1}}^{\boldsymbol{r}} \widehat{\boldsymbol{L}}_{\boldsymbol{s,i}}\,, \qquad \boldsymbol{\rho} = \frac{1}{r} \cdot \sum_{\boldsymbol{i=1}}^{\boldsymbol{r}} \boldsymbol{L}_{\boldsymbol{i}} \tag{3.10}$$

The uniform scalar follows from the normalized representations in (3.7) and (3.8), can be expressed as quaternion vectors, with the real component, q_0 set to zero. The unknown rotation, $\boldsymbol{R}_{\boldsymbol{s}}$, to transform each normalized back projected 3D coordinate $\hat{\boldsymbol{l}}_{\boldsymbol{s,i}}$ into the reference coordinate $\boldsymbol{l}_{\boldsymbol{i}}$ can also be expressed as a quaternion, $\widehat{\boldsymbol{q}}_{\boldsymbol{R}_{\boldsymbol{s}}}$ through Euler's formula, which then can be estimated with least squares by constraining $\left\|\widehat{\boldsymbol{q}}_{\boldsymbol{R}_{\boldsymbol{s}}}\right\|$ = 1, and row-wise augmentation of all $\hat{\boldsymbol{l}}_{\boldsymbol{s,i}}$, and $\boldsymbol{l}_{\boldsymbol{i}}$ [34] of the following quaternion equation:

$$\widehat{\boldsymbol{q}}_{\boldsymbol{l,s}} \times \widehat{\boldsymbol{q}}_{\boldsymbol{R}_{\boldsymbol{s}}} - \widehat{\boldsymbol{q}}_{\boldsymbol{R}_{\boldsymbol{s}}} \times \boldsymbol{q}_{\boldsymbol{l}} = 0 \tag{3.11}$$

The estimate of the 3D translation is computed directly from equations (3.7) through (3.9):

$$\hat{t}_s = \boldsymbol{\rho} - \widehat{\boldsymbol{\rho}}_{\boldsymbol{s}} \cdot \hat{S}_s \tag{3.12}$$

Recall that from the time sample s three separate sets of the remaining r matched points $\left(\widehat{\boldsymbol{L}}_{\boldsymbol{s,i}}, \boldsymbol{L}_{\boldsymbol{i}}\right), i = 1 \dots r$, are used to compute their representative rotation, translation and uniform scale parameters defined respectively in (3.11), (3.12), and (3.9). A final representative set of back projected coordinates, $\{\widehat{\boldsymbol{L}}'_{\boldsymbol{i,s}}\}$ is selected based on the aforementioned similarity transformation parameters which produce the smallest RMS error from $\boldsymbol{L}_{\boldsymbol{i}}$.

Typically, with uniform scale corrections an RMS error of about two feet (0.5 meters) along any axis was observed which resulted in significant detection errors. A second alignment refinement step was therefore developed to correct for non-linear scale effects in the real-world 3D space. A first order correction in the horizontal *x,y* plane is estimated using the matching set $\widehat{\boldsymbol{L}}'_{\boldsymbol{i,s}}$ and $\boldsymbol{L}_{\boldsymbol{i}}$, while a second order correction model to correct elevation, ΔZ , was estimated using the dense *transformed* 3D PMVS reconstruction data:

$$\Delta X = a_0 + a_1 \cdot g_x + a_2 \cdot g_y \tag{3.13}$$

$$\Delta Y = b_0 + b_1 \cdot g_x + b_2 \cdot g_y \tag{3.14}$$

$$\Delta Z = c_0 + c_1 \cdot g_x + c_2 \cdot g_y + c_3 \cdot g_x \cdot g_y + c_4 \cdot g_x^2 + c_5 \cdot g_y^2 \tag{3.15}$$

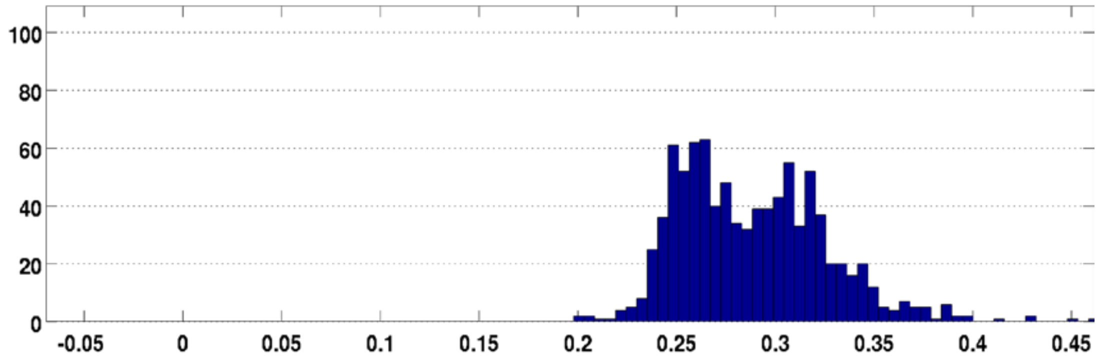
Note $g_{()}$ in (3.13) through (3.15) refer to the *x*,*y*,*z* components of the *transformed* quasi-dense PMVS reconstruction points, $\boldsymbol{g}_i'$.

The elevation correction procedure searches for good candidate dense points that are representative of the parking lot surface using the following 2-step filtering method. First, an elevation boundary is placed above, and below, the plane based on the aforementioned RMS error along the vertical axis relative to the reference survey points, $\boldsymbol{L}_i$. The second step filters the remaining dense reconstruction points by applying a threshold of the directional difference of the computed PMVS patch surface normal from the estimated parking lot surface normal. A threshold value of |20°| was determined experimentally. This procedure reduced the RMS error between $\hat{\boldsymbol{L}}_{i,s}'$ and $\boldsymbol{L}_i$ to within one foot (0.3m) under most cases (Figure 3.3), which has provided sufficient alignment thus far for robust parking occupancy classification.

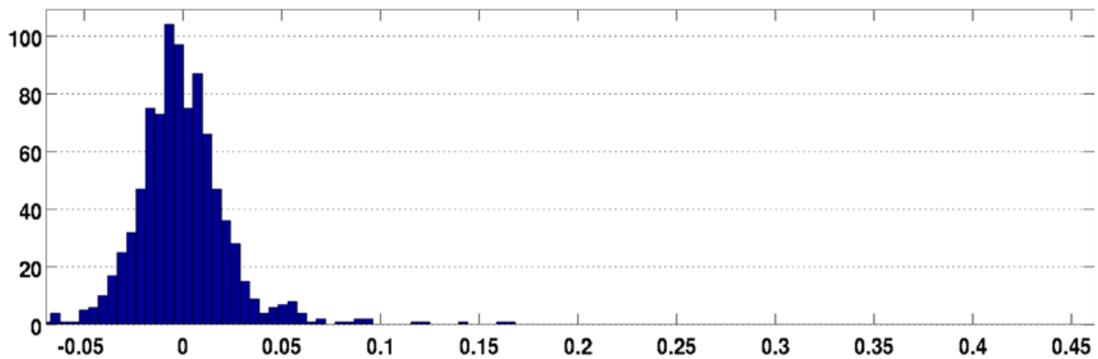
3.3 OCCUPANCY CLASSIFICATION

A classifier was then designed based on estimating the above-plane 3D point probabilities within each parking space with respect to the total number of reconstructed 3D points. The estimate is computed by segmenting and summing the above-plane points which lie within a 6-sided convex 3D polyhedron, defined by intersecting 4 vertical planes aligned with the vertical elevation Z-axis and coincident with the parking lanes and their front/back end points, and a horizontal plane elevated 16.4 ft. (5 meters) above the surface which is greater than the USDOT FHWA regulation height of 13.5 ft. (4.1m). Based on empirical observations, an above-surface threshold of 0.3 meters has been used to segment vehicle objects from the parking lot plane (Figure 3.3). The 3D point probabilities can then be used be used to determine an optimal decision boundary for occupancy to minimize type I (False Positives) and type II (False Negatives) errors. The decision boundary selection procedure is further described in chapter CHAPTER 6: .

a.



b.



c.

Figure 3.3. Elevation re-alignment of extracted 3D parking lot planar points;

a) night-time camera view of 6 parking spaces; b) Distribution of Z-elevation component of extracted parking lot surface points before alignment model in (3.13) through (3.15); c) Z-elevation distribution after alignment model correction.

CHAPTER 4: PRE-IMPLEMENTATION USABILITY STUDY

As part of the Minnesota truck parking availability system (TPAS), a survey was designed for motor carriers and commercial drivers to examine the specific needs and preferences for disseminating real-time parking space availability information to truck drivers. The objectives of the survey were to: 1) characterize the general nature and driving behavior of the freight borne trips along the corridor, as well as driver demographics, 2) understand perceptions concerning truck parking availability, 3) determine preferences for information dissemination and the level accuracy, and 4) determine the perceived value of such parking information along the corridor. The information was used to guide engineering performance and operational testing decisions for TPAS (chapters CHAPTER 6: and CHAPTER 7:).

4.1 PRE-IMPLEMENTATION USABILITY SURVEY METHODOLOGY

ATRI team members developed an online survey instrument to obtain driver and carrier needs and preferences for TPAS. The survey request information related to truck parking availability notification mechanisms and format, as well as system capabilities and reliability. The survey was relatively brief in length (18 questions for drivers and 15 for carriers) and primarily consisted of multiple choice (close-ended) questions. This format was chosen to maximize participation by requiring minimal time to complete, and to limit potential data quality issues associated with open-ended responses. Survey questions were also tailored to the two specific target groups based on the response provided to the first question (i.e. drivers received one set of questions while carriers received a slightly modified set of questions).

Prior to distribution, the survey was reviewed by several industry stakeholders, as well as the TPAS and Michigan Truck Parking management research teams, and several questions were modified based on the evaluator's recommendations[2]. ATRI promoted the survey through several media outlets, including industry news alerts and coverage through major industry news organizations. To augment the data collection efforts, ATRI also worked with the state truck associations located along the I-94 corridor (Michigan, Indiana, Illinois, Wisconsin, Minnesota, and North and South Dakota) to distribute additional announcements to their memberships.

The survey was distributed online for one month from September 17th to October 24th 2012 and a total of 465 surveys were completed. All responses were then reviewed by the research team and 130 surveys were ultimately removed from the database due to incompleteness, duplication or other abnormalities, resulting in a cleansed dataset of 335 surveys. Of these surveys, 242 (72.2 percent) of the respondents identified themselves as drivers while 93 (27.8 percent) reported that they worked in other

[2] The Michigan Department of Transportation was also studying and developing a truck parking information system along the I-94 corridor within that state, through the FHWA at the time of the survey study.

occupations in the trucking industry (such as dispatchers, or operations, business/accounting, or as a senior executives). A copy of the full survey is listed in Appendix A.

In short, the survey analyses suggest that there was a perceived lack of safe, legal available parking from both the carriers and drivers. Furthermore, majority of those surveyed (86.6 percent of carriers, and 89.2 percent of drivers) indicated that the parking information must be at least 85 percent reliable for it to be useful to their operations. By and large, attitudes and perceptions on truck parking availability and information were consistent between the carriers and drivers. The relevant findings are discussed below.

4.2.1 Driver and Carrier Demographics

Of the drivers surveyed, the respondents were primarily male (85.8 percent) and approximately two thirds (67.1 percent) were employee/company drivers while one third (32.9 percent) were owner-operators. The majority (69.5 percent) of the drivers surveyed were between the ages of 45 and 64, followed by 25 to 44 years old (27.2 percent), younger than 25 (2.1 percent) and older than 65 years (1.3 percent).

The majority of the surveyed drivers operated in the for-hire truckload (TL) sector (70.6 percent), followed by private fleets (15.1 percent). The remaining drivers (between 1.7 and 3.8 percent) operated for other businesses such Less-than-truckload, tanker, flatbed hauling, express/parcel service. Nearly three quarters (73.6 percent) of the driver respondents reported working for a motor carrier operating more than 50 trucks. While the majority of carriers at the national level operate fleets of 20 or fewer power units, medium to large carriers are responsible for the majority of truck registrations and driver employment; the driver sample population from the survey were therefore indicative of the national fleet trends.

Respondents who identified themselves as motor carriers (i.e. non-drivers) a majority of respondents identified themselves as working in safety-related occupations (36.8 percent), followed by dispatching (26.4 percent), operations (21.8 percent), senior-level positions (13.8 percent) and business/accounting (1.1 percent). Similar to the distribution of driver respondents, the majority of carriers operated in the for-hire Truck Load sector (66.7 percent), followed by private fleets (10.3 percent).

4.2.2 General Travel Characteristics

None of the driver respondents reported being a local delivery driver, while nearly three quarters (74.2 percent) were long haul drivers (500+ miles per trip) and 28.5 percent were regional drivers (100-499 miles per trip). Regarding the usage of the corridor, approximately half (55.4 percent) of the drivers indicated that between 1 and 25 percent of their loads require travel on I-94 while another 18.8 percent reported that they utilize the corridor for between 26 and 100 percent of their loads (Figure 3). One quarter (25.8 percent) of the drivers indicated that they did not use the I-94 corridor for commercial trips. Therefore, a significant number of freight borne trips utilize the corridor, with most requiring significant travel time.

4.2.3 Truck Parking Issues and Concerns

Lead times for the trips tend to be small (under 24 hours); however there is some discrepancy reported between drivers and carrier personnel with the operational or management functions. Over two thirds (69.9 percent) of the drivers surveyed typically receive less than 24-hours of notice prior to a long-distance trip followed by a 1 to 4 day notice at 28.5 percent (Figure 4). Therefore, nearly all driver respondents (98.4 percent) indicated they receive four days or less advance notice of freight delivery information. On the other hand, carriers reported giving drivers slightly more notice of long-distance trips compared to the driver respondents. Over half (53.6 percent) of the carrier respondents reported that drivers receive less than 24-hours of notice, followed by 1 to 4 days (40.5 percent), 5 to 9 days (3.6 percent), or more than 10 days (2.4 percent).

Lastly, employee drivers reported less notification time for long trips than owner-operators. In particular, a larger number of owner-operators (44.9 percent) report receiving more than one day advance notice compared to employee drivers (22.9 percent). A majority of both types of drivers still receives less than 24 hours of notice (55.1 percent of owner-operators and 77.0 percent of employee drivers). The remaining 1.2 percent of employee drivers and 2.6 percent of owner-operators receiving five, or more days, advance notification.

Drivers rank-ordered a list of five truck parking issues on a scale ranging from “never experience” to “always experience (Figure 4.1).” The two most frequently experienced parking issues were “parking only available in unsafe locations” along with “parking available on ramps or shoulders.” 43.1 percent of drivers “always” or “often” experienced parking available in unsafe locations, while 44.7 percent reported “always” or “often” finding parking locations only on ramps or shoulders. As for the remaining parking issues, rest time area limits were “always” or “often” experienced by only 28.9 percent of drivers. Truck vandalism and cargo theft were the least common occurrences, with 79.0 percent of drivers reporting that they “rarely” or “never” experienced vandalism and 87.7 percent of drivers indicated they “rarely” or “never” encountered cargo theft.

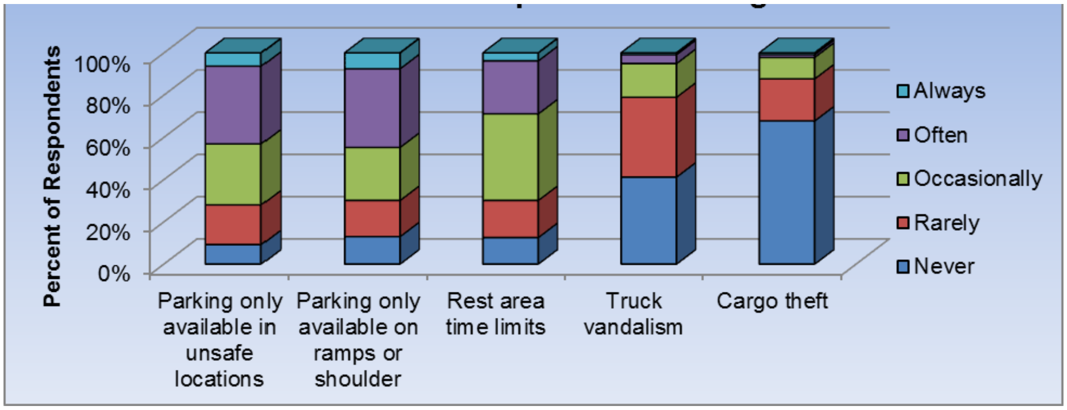


Figure 4.1. Driver distribution by rate of experiencing parking issues.

Similar to driver responses (Figure 4.2) carriers reported that the issue most often experienced by their drivers was truck parking availability only on ramps or shoulders (82.3 percent occasionally, often or always), followed by rest area time limits (79.3 percent) and truck parking availability limited to unsafe locations (78.3 percent).

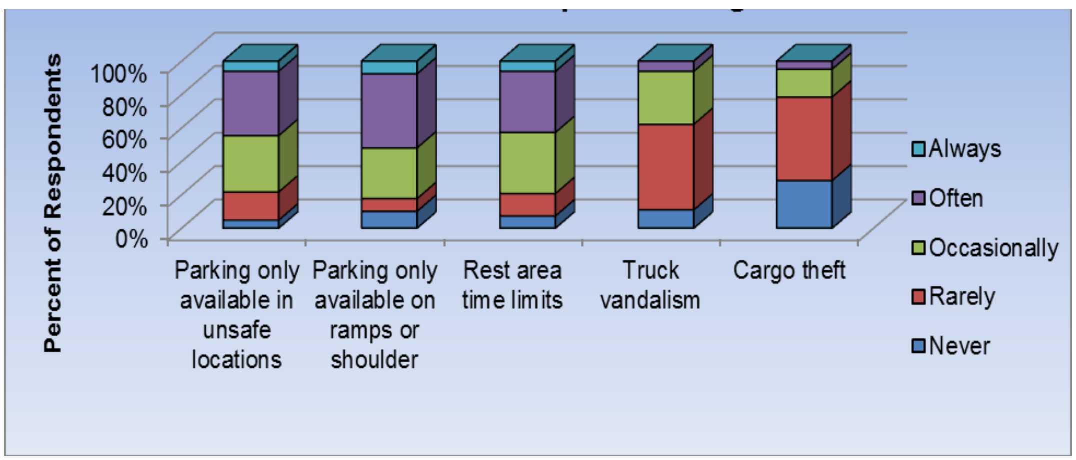


Figure 4.2. Carrier distribution by rate of experiencing parking issues.

Drivers were next asked to rank a predetermined list of reasons for seeking truck parking on a scale of 1 to 10 with "1" being the most important reason. Of these, hours-of-service (HOS) mandated rest was rated most important by the driver respondents by a wide margin, receiving an average ranking of 1.8. As Table 4.1 indicates, the second-most important reason was showering/restroom (4.4), followed by restaurant/eating (5.0), awaiting dispatch (5.9), staging/waiting for loads (6.1), weather-related (6.2), safety checks/load securement (6.4), mechanical issues/failures (6.4), avoiding congesting (6.8), obtaining directions (7.6) and personal communications (7.8). The same general trends were also evident when carriers were similarly asked to rank truck parking reasons (Table 4.2).

Table 4.1. Driver Distribution by Average Rankings of Reasons for Seeking Truck Parking

Reason for Seeking Truck Parking	Average Ranking
HOS Mandated Rest/Fatigue	1.8
Showering/Restroom	4.4
Restaurant/Eating	5.0
Awaiting Dispatch	5.9
Staging/Waiting for Loads	6.1
Weather-related	6.2
Safety Checks/Load Securement	6.4
Mechanical Issues/Failures	6.4
Avoiding Congestion	6.8
Obtaining Directions	7.6
Personal Communication	7.8

Table 4.2. Carrier Distribution by Average Rankings of Reasons for Seeking Truck Parking

Reason for Seeking Truck Parking	Average Ranking
HOS Mandated Rest/Fatigue	1.9
Showering/Restroom	5.0
Restaurant/Eating	5.2
Awaiting Dispatch	5.6
Staging/Waiting for Loads	5.7
Avoiding Congestion	6.0
Safety Checks/Load Securement	6.4
Mechanical Issues/Failures	6.4
Weather-related	6.5
Obtaining Directions	7.5
Personal Communication	7.8

4.2.4 Truck Parking Desired Amenities

Prioritizing amenities provided an understanding of other aspects of truck parking facilities that may further affect their choice to stop along their route, beyond the aforementioned results in section 4.2.3 . As before, in tables the most important ranking is a "1". Once again, the rankings mirrored the drivers' rakings, with restrooms and fueling services being the most important amenities, and retail stores, internet Access, and vending machines being the least essential. Note that adequate security was ranked within the top five amenities by both carriers and drivers, and lighting was ranked fifth by drivers. This would not be surprising as enhancing security, particularly at night can be achieved by improvements in lighting.

Table 4.3. Driver Distribution by Average Rankings of Truck Parking Amenities

Reason for Seeking Truck Parking	Average Ranking
Restrooms	2.7
Fueling Services	4.2
Showers	4.4
Adequate Security	4.7
Adequate Lighting	4.9
Restaurant	5.0
Access to the Interstate	5.2
Retail Stores	7.1
Internet Access/Wi-Fi	7.6
Vending Machines	8.3

Table 4.4. Carrier Distribution by Average Rankings of Truck Parking Amenities

Reason for Seeking Truck Parking	Average Ranking
Restrooms	2.7
Fueling Services	3.9
Adequate Security	4.4
Restaurant	4.5
Showers	4.7
Adequate Lighting	5.5
Access to the Interstate	5.7
Internet Access/Wi-Fi	7.5
Retail Stores	7.6
Vending Machines	8.0

4.2.5 Truck Parking Information Delivery

Insights to understand how information usage habits and desired information delivery methods for truck parking availability was assessed in order to understand which technology choices would provide the most benefit for carriers and their drivers. While on the road, drivers reported accessing the internet most often through a laptop (70.8 percent) in the truck or Smartphone.(63.1 percent). Figure 4.3 shows that these two methods predominates considerably over other technology choices, although interestingly carriers responded a much higher percentage of choice for Smartphones and Onboard devices.

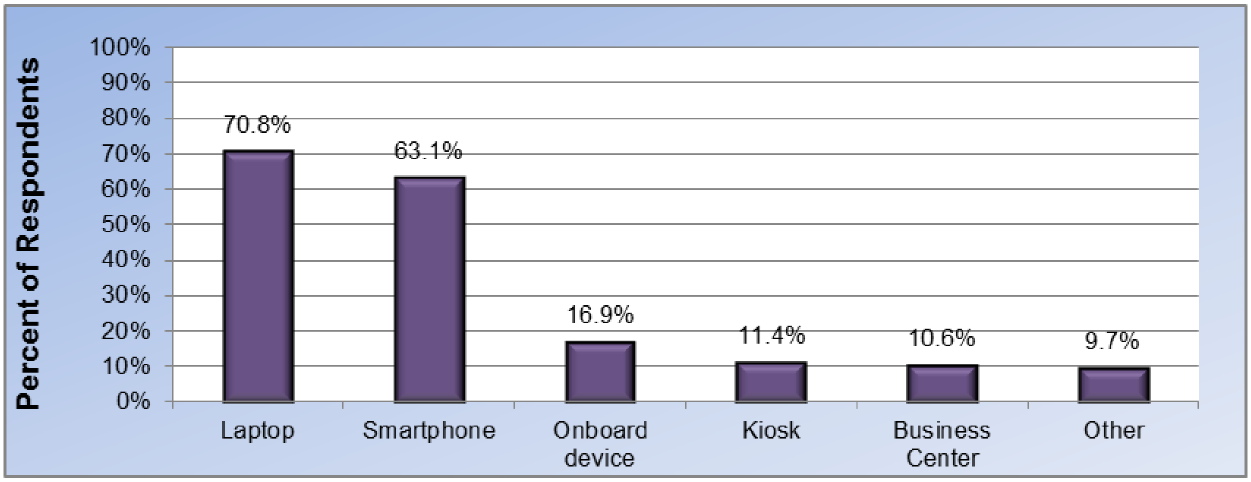


Figure 4.3. Driver distribution of preferred technologies for accessing Internet while on the road.

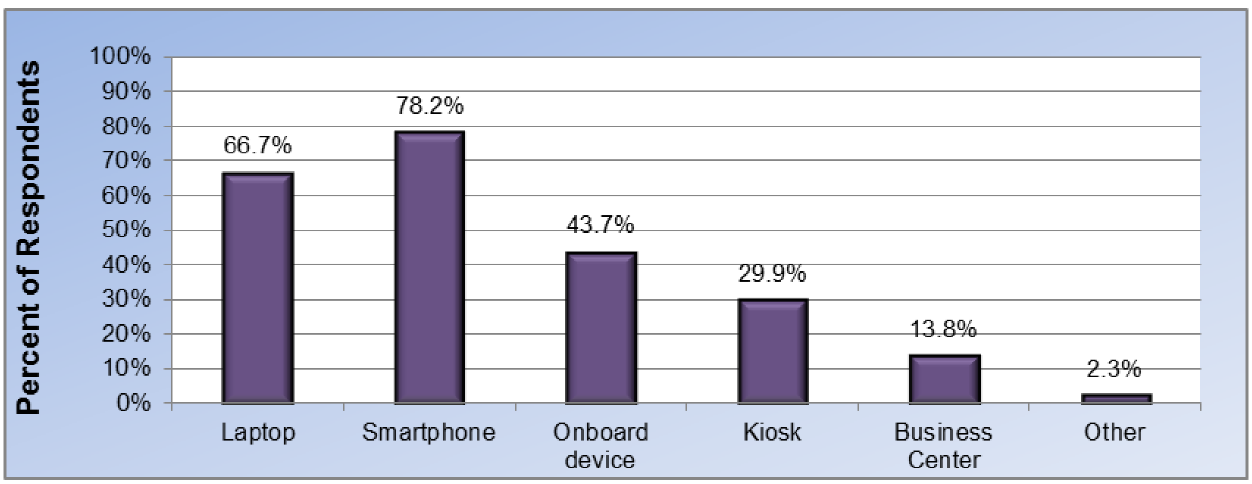


Figure 4.4. Carrier distribution of preferred technologies for accessing Internet while on the road.

Perhaps one of the more interesting results, from the perspective of a truck parking availability system along the corridor, was the desired notification method by either the drivers or the carriers. Survey participants were provided a list of potential truck parking availability notification methods and were asked to rank the methods on a scale of 1 to 6, with 1 being most preferred. As shown in Table 4.5, drivers were most interested in receiving truck parking availability information through roadside Changeable Message Signs (CMS) (average ranking of 2.3) followed by Smartphone applications (2.8), internet/websites (3.5) and onboard communication systems (3.6). Drivers were least interested in obtaining the information through a 511 system (3.8) or a dispatcher (5.0). The rankings from carriers were very similar, with a difference in ranking priority only between receiving parking information from the Onboard device and Internet/Website portal.

Table 4.5. Average Rankings of Truck Parking Notification Methods

Notification Method	Average Driver Ranking	Average Carrier Ranking
Changeable Message Sign	2.3	2.7
Smartphone Application	2.8	3.9
Internet/Website	3.5	4.4
Onboard device	3.6	4.5
511	3.8	4.7
Dispatcher	5.0	5.5

To gain insight as to the desired advanced notification distance of truck parking availability from the aforementioned delivery methods, respondents could select from a set of preferred desired upstream locations, independent of any other route-specific choices that could be made before reaching the parking facilities. Nearly half (47.6 percent) of the driver respondents indicated that they would prefer to receive truck parking availability information 20 miles away from the truck stop/rest area, followed by 5 miles (37.3 percent) and 10 miles (30.5 percent) (Figure 4.5). It should be noted, however, that 30.5 percent of the driver respondents would like more than one notification. A number of drivers noted that rest areas are typically spaced 30 to 50 miles apart and in rural regions, and privately run truck stop options can be limited. Adequate advance notice of truck parking availability would therefore assist drivers with scheduling their stopping location as well as ensure back-up options should their preferred location be full. To conclude, the distribution of preferred locations suggest that multiple advance notifications of truck parking availability would assist drivers with scheduling their stopping location as well as ensure back-up options should their preferred location be full.

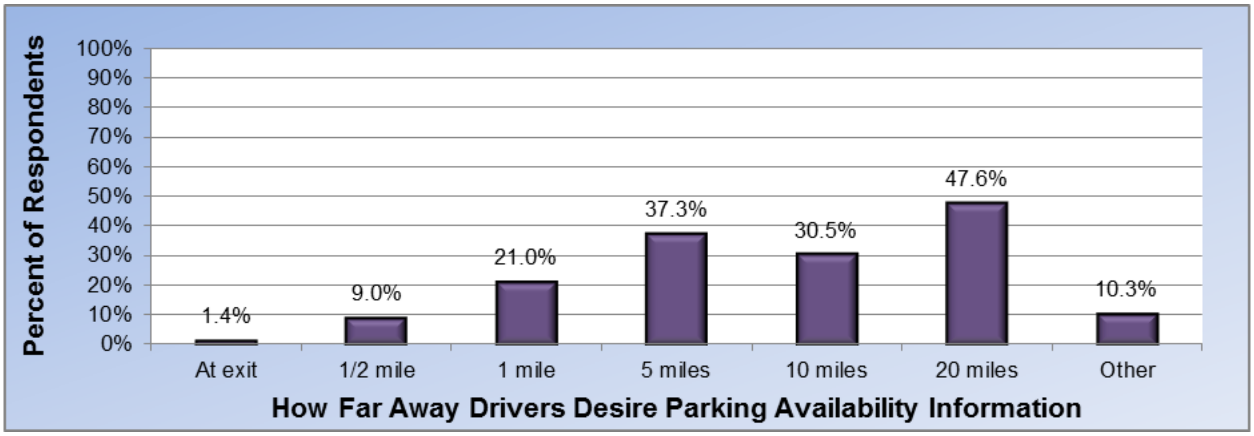


Figure 4.5. Driver distribution of preferred distances for receiving truck parking information.

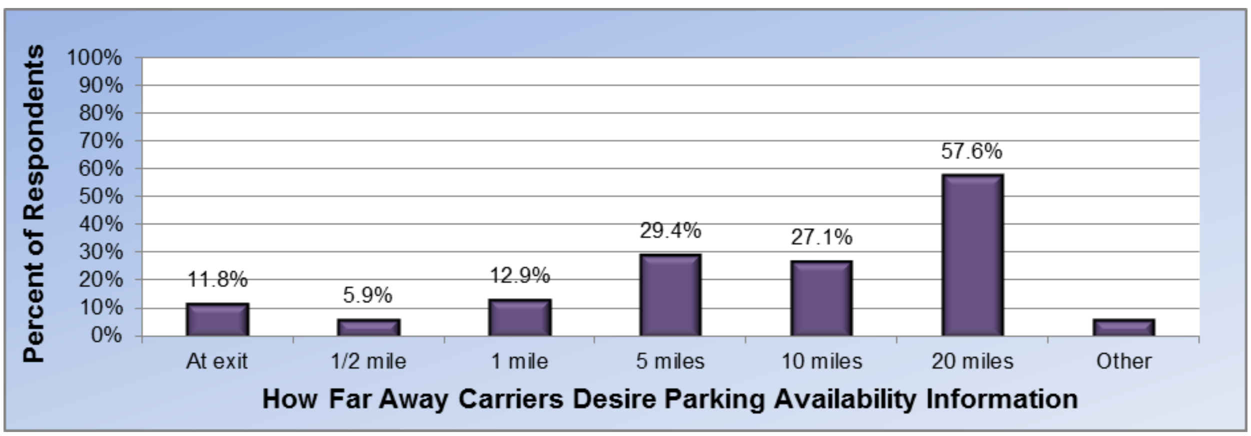


Figure 4.6. Carrier distribution of preferred distances for receiving truck parking information.

4.2.6 Acceptable Level of Truck Parking Information Reliability

The majority (89.2 percent) of drivers reported that the proposed truck parking availability system (TPAS) would have to be 85 percent or more reliable for it to be useful to them. Of those, 25.0 percent stated that TPAS would need to be 100 percent reliable. Similar to the driver responses, 86.6 percent of the carriers surveyed would need TPAS to be 85 percent or more reliable for it to be useful to their operations. A smaller portion of carriers (15.9 percent) would require the system to be 100 percent reliable compared to 25.0 percent of drivers (Figure 4.7 and Figure 4.8).

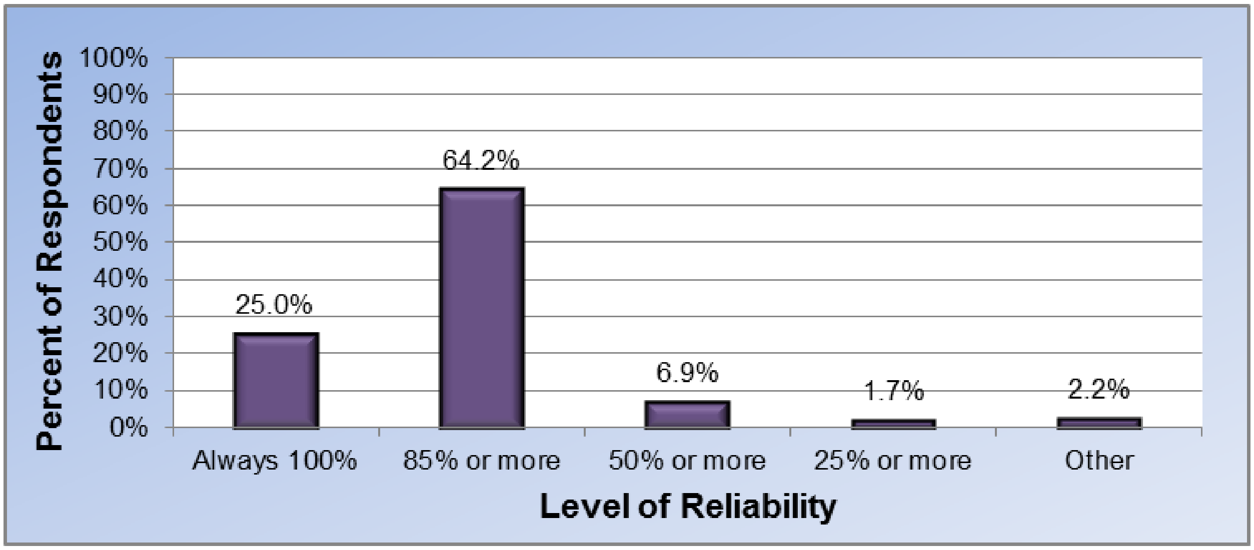


Figure 4.7. Driver distribution of acceptable level of reliability.

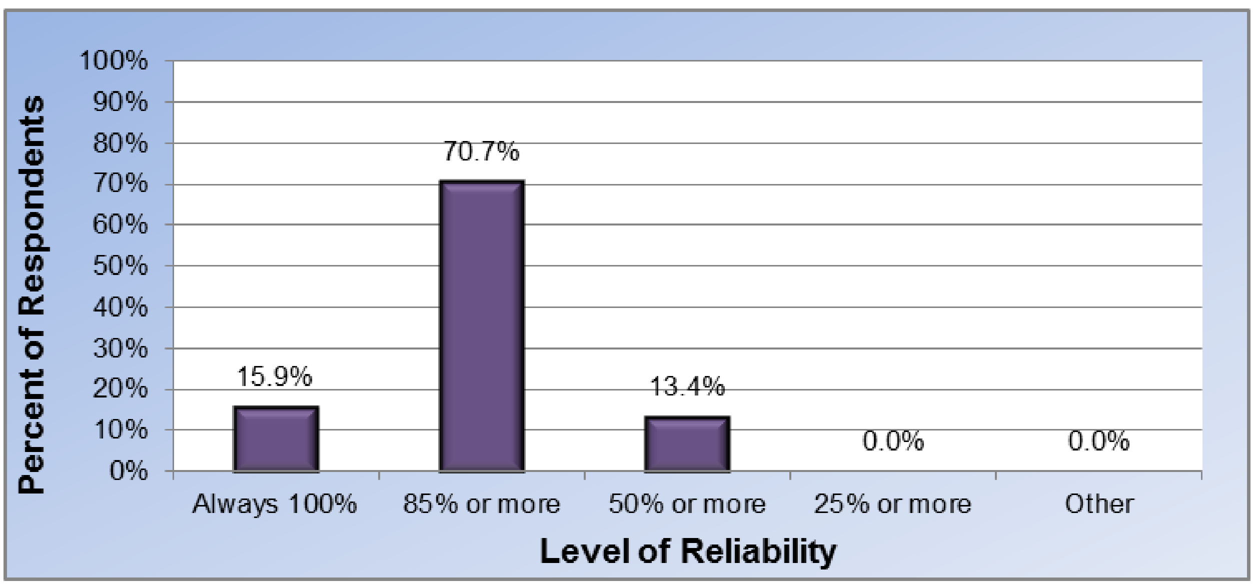


Figure 4.8. Carrier distribution of acceptable level of reliability.

4.2.7 Value of Truck Parking Availability Information

Lastly, the survey informed the team of the potential value of such information in terms of quantifying a perceived monitory value of reserving a truck parking space. While the same percentage of carriers reported that they would like the ability to reserve a truck parking spot as drivers (56.5 percent), carriers differed slightly on how much they would be willing to pay to reserve a parking spot (Figure 4.9 and Figure 4.10). Noticeably more carriers were unwilling to pay for a parking reservation than drivers (48.1 percent compared to 36.9 percent).

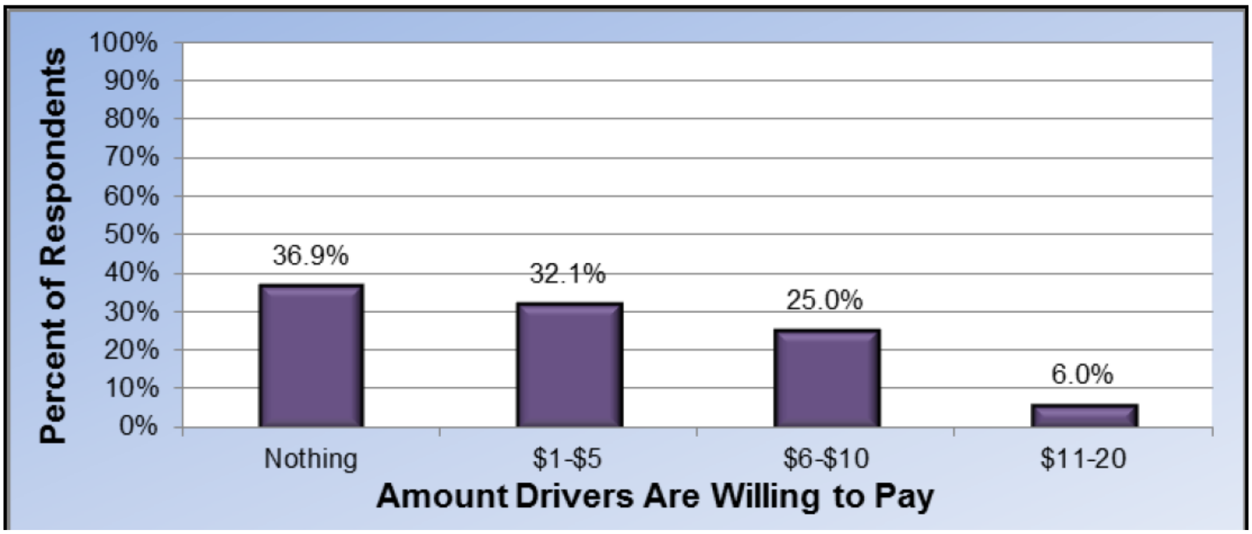


Figure 4.9. Distribution of drivers by amount willing to pay for truck parking reservation.

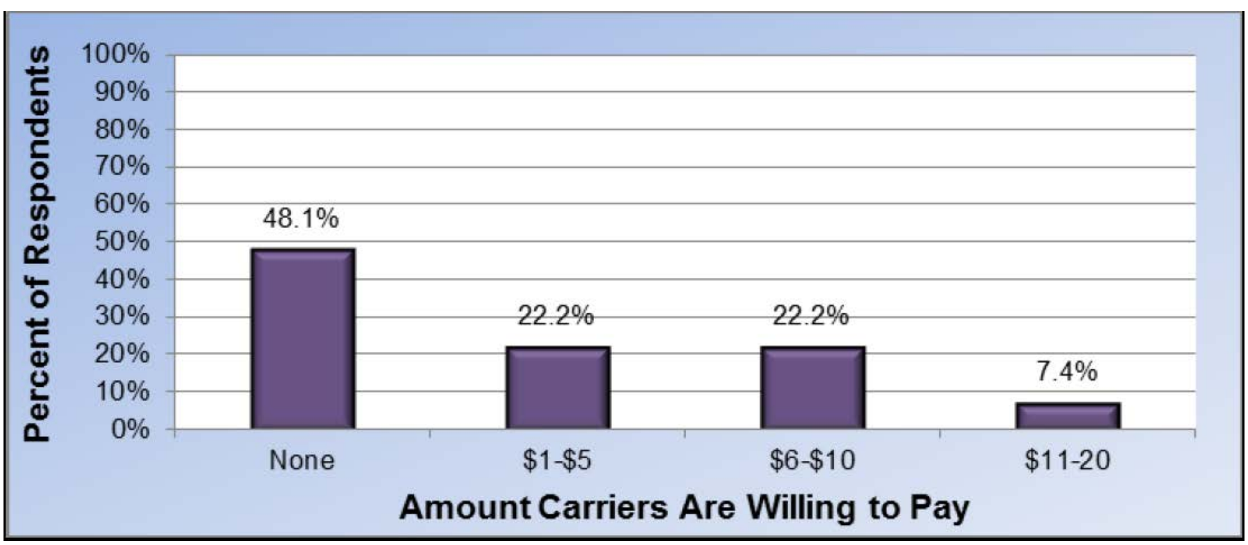


Figure 4.10. Carrier distribution by amount willing to pay for truck parking reservation.

4.3 USABILITY STUDY CONCLUSIONS

The survey results provided a foundation for steering engineering design decisions for corridor wide truck parking information decisions regarding desired accuracy, information delivery mechanisms, and potential deployment conditions to be of most benefit to drivers. By and large, attitudes and perceptions on truck parking availability and information were consistent between the carriers and drivers. The survey results suggest that there was a perceived lack of safe, legal available parking from both the carriers and drivers. Furthermore, a majority of the survey respondents indicated that the parking information must be at least 85 percent reliable for it to be useful to their operations (86.6 percent of carriers, and 89.2 percent of drivers).

A majority of drivers personally experienced three of the five critical truck parking issues listed in the survey at least occasionally, if not more frequently. These included parking availability on ramps or shoulders, rest area time limits and unsafe parking. In addition, both drivers and carriers ranked HOS mandated rest as the single most important reason for seeking parking. Although there were slight differences between employee drivers and owner-operators, the majority of drivers surveyed receive less than twenty-four hours of advanced notice for long haul trips, and are subject to change without much notice. Drivers therefore would favor a system that provides notifications of truck parking availability en route to their destination, and they apparently have the ability and capabilities to do so through multiple devices (onboard, smartphone, laptops).

An interesting finding regarding en route information however, is that even with a majority of drivers indicating they had Internet access, roadside Changeable Message Signs (CMS) were ranked the highest preferred method to receive truck parking availability notifications. While this may seem surprising to some, recent regulations relating to driver distraction and cell phone use may be a leading source for this preference. In addition, both drivers and carriers prefer to obtain the information 20 miles upstream of the parking facility (46.3 percent and 56.4 percent for drivers and carriers respectively). There was a secondary smaller peak for five miles upstream as well (37.3 percent and 29.4 percent for drivers and carriers respectively).

Finally, although a large majority of respondents would find parking information useful if at an acceptable level of accuracy, and slightly more than half (56.5 percent) would like the ability to reserve a spot, a large proportion of the respondents would be unwilling to pay for this service (48.1 percent of drivers and 36.9 percent of carriers). Of those willing to pay a low nominal fee (from $1 dollar to $5 dollars), there was a discrepancy between drivers (32.1 percent) and carriers (22.2 percent) which indicates an association between who would ultimately be responsible for the charge. The next chapter will provide an overview of the truck parking facilities utilized and the system architecture developed to deliver the truck parking availability information from the facilities.

CHAPTER 5: TRUCK PARKING SYSTEM IMPLEMENTATION AND ARCHITECTURE

Three public rest areas were deployed along eastbound Minnesota Interstate 94 heading into the twin cities. As mentioned earlier, historically these rest areas are known to frequently reach or exceed capacity, although the truck parking volumes were not necessarily distributed evenly for any given period of time. The following sections describe in detail the developed site plans that guided the deployments, the communication architecture for providing archival and data broadcasting capabilities, and a system monitoring tools for remote maintenance and performance evaluation.

5.1 TRUCK PARKING FACILITIES CONFIGURATION

All the implemented facilities follow an outward –oriented design standard, with a separate truck parking facility closest to the freeway using slanted parking stalls to remove right-turn angle maneuvers into and out of the parking space (thus forming a parallelogram shape for each stall) [35]. Table 5.1 summarizes the parking stall width, as measured by the orthogonal distance between the parking lane lines, vs. the front stall parallelogram width, as measured by the DGPS corrected survey instrument. Enfield and Big Spunk facilities separate private vehicle parking from truck and RV vehicle parking, while Elm Creek also contains larger spaces in the private parking facility to accommodate large RV parking.

Table 5.1. State Sponsored Truck Parking Stall Dimensions

	Stall Angle deg.	Stall Length ft. (m)	Stall Width ft.(m)	Stall Depth ft.(m)	Stall Front Width ft.(m)
Elm Creek	34.71±0.31°	84.24±0.24 (25.68±0.07)	14.12±0.75 (4.30±0.23)	59.83±0.19 (18.24±0.06)	19.88±1.19 (6.06±0.36)
Big Spunk	49.37±0.32°	88.63±0.74 (27.01±0.23)	14.51±0.57 (4.42±0.17)	57.71±0.37 (17.59±0.11)	22.37±0.71 (6.82±0.22)
Enfield	49.06±0.25°	86.57±0.90 (26.39±0.28)	14.13±0.24 (4.31±0.07)	56.39±0.67 (17.19±0.20)	21.70±0.37 (6.61±0.11)

A thirty-five-foot-tall (10.7 m) crank-down camera pole meeting roadside AASHTO standards, engineered and manufactured by Millerbernd Manufacturing (Windsted, MN), was deployed for all sites. The poles are designed to withstand a minimum wind speed of 90 MPH (145 KPH) and provide 20 years of service life. Each camera pole supports three network Power-over-Ethernet outdoor PTZ HD cameras (Axis Communications AB, Lund, Sweden). Below grade conduits were installed from a secured location within the visitor shelter to a camera pole, and then between each pole, to carry 110/120 VAC power and Ethernet network communication using steel-jacket single mode Ethernet fiber. A pole mounted NEMA weatherproof cabinet housed outdoor rated Ethernet switching hardware and fiber transceivers, Power-over-Ethernet (PoE) injectors for the cameras, and a remote controllable outdoor Nema-5 AC power control with surge protection used to allow remote maintenance tasks and provide additional lightening protection to the equipment. Three desktop Intel i7 3.5 GHz clock speed PCs running Linux were installed at each site to acquire and store image data from the cameras to use for analysis and detection, upload the detected parking space status, and execute of the detection module algorithm across the acquired image sets. Lastly, a 1500KV UPS was used to guard against short black-out periods (less than roughly 15 minutes), and brown-outs, as well as to perform a stable shutdown and power-up of the router and computing equipment in the advent of longer power outages [36]. There was no such power protection for the camera hardware.

5.1.1 Elm Creek

The first site to be built and brought online was Elm Creek (Figure 5.1). Before fixed infrastructure was installed at the site, several possible camera locations and heights were tested by positioning a camera instrumented trailer mast around the perimeter of the parking facilities and then processing the collected data using the 3D SfM reconstruction approach (section 3.1). Elm Creek had the smallest parallelogram tilt angle and a significantly larger amount of space behind the stall to the end-of-pavement or curb line than the other two truck parking areas (38.5 to 40 ft). The distance between the curb to the front of the stalls measured 32.12ft (9.79 m), and the distance from the back of stall =38.52ft (11.74m). The 3 front-of-stall facing poles were approximately 15 (4.5 m) to 30 feet (9.1 m) from the curb to cover all 15 parking spaces.

Installation by professional contractors was done in the fall of 2012, with power and internet service enabled in mid-January 2013. As with all sites in the study, before installation could commence, the plans went through the standard MnDOT Right-Of-Way permitting and approval process with the University of Minnesota and MnDOT.

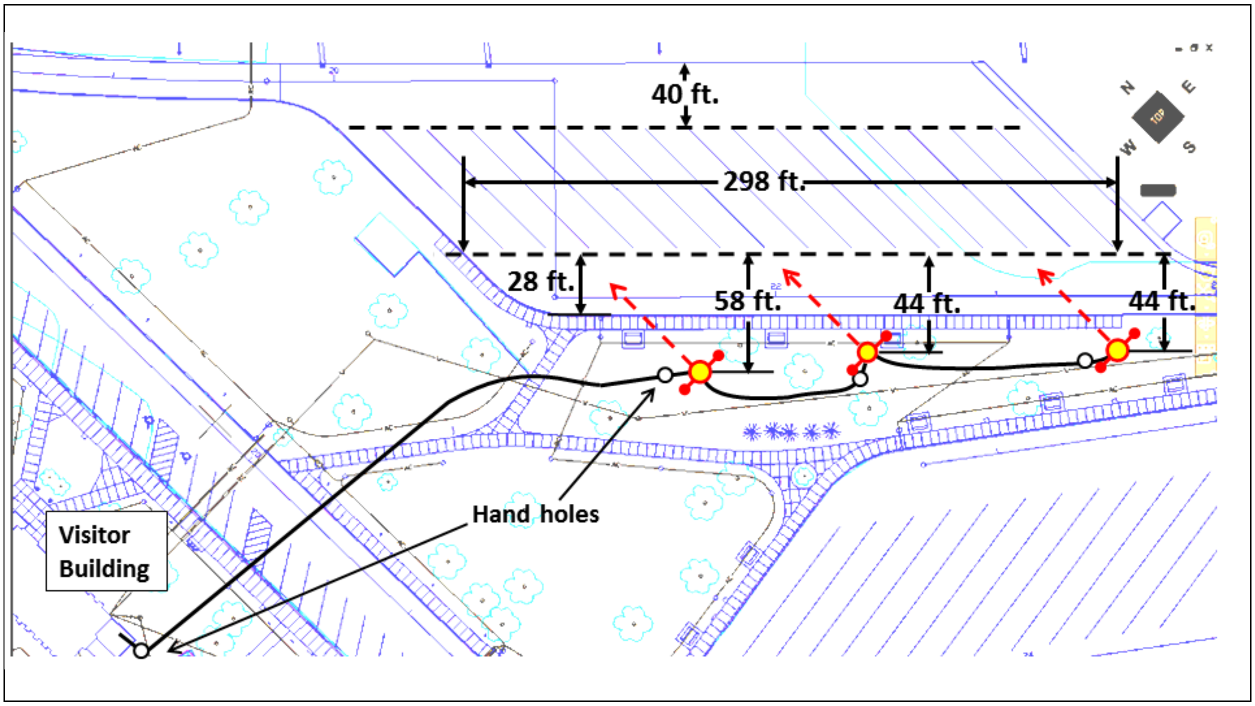


Figure 5.1. Elm Creek camera system site plan.

Figure 5.2. Elm Creek truck parking facility and camera poles deployment.

5.1.2 Big Spunk Lake

The system installation for Big Spunk Lake rest area was built starting in October of 2013, with wireless internet service enabled in late January 2014. The final deployment consists of three front-of-stall facing camera poles that were positioned between 15 to 30 feet from the curb. The site layout to cover the 16 parking spaces are illustrated in Figure 5.3. The curb-to-front of stall and curb-pavement edge-to-back-of-stall at Big Spunk measured 29.63 ft (9.03m), and 30.54(9.31 m) respectively.

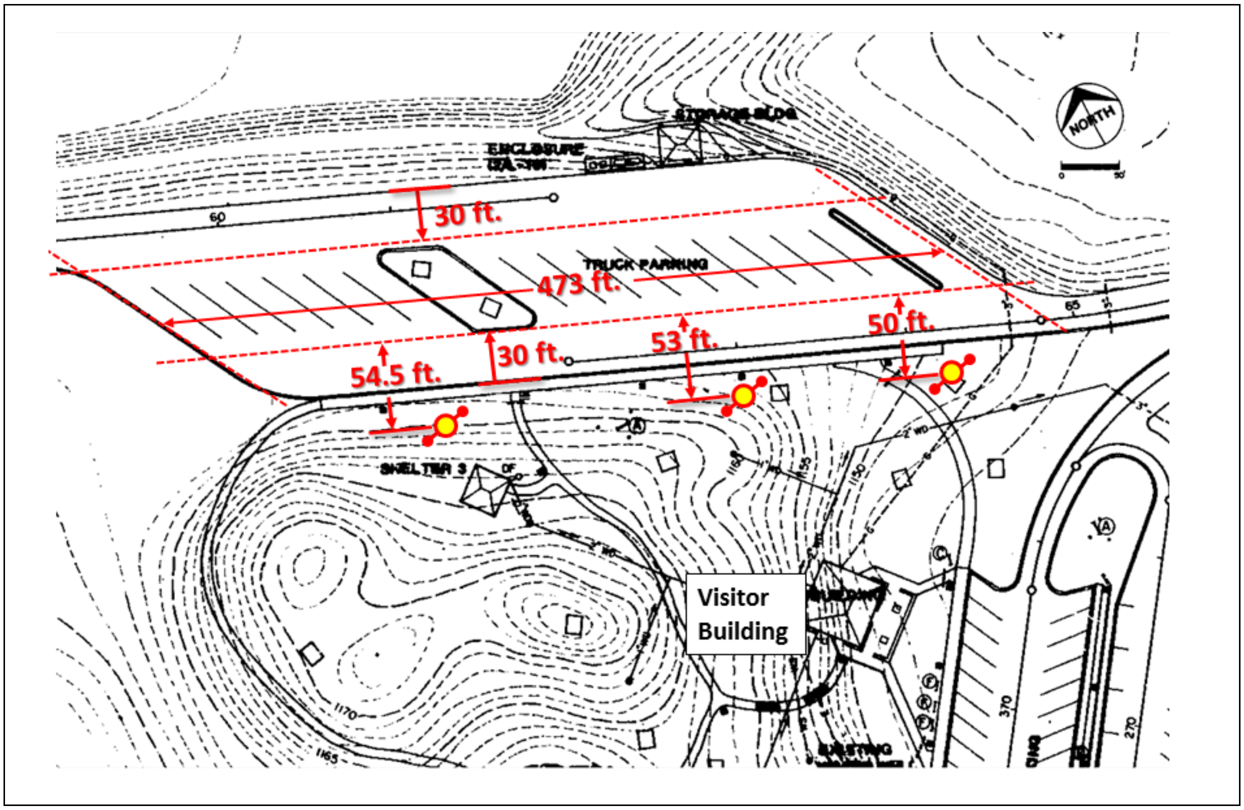


Figure 5.3. Big Spunk Lake camera system site plan.

(conduit paths from poles to shelter removed for clarity)

Figure 5.4. Big Spunk Lake truck parking facility and camera poles deployment.

5.1.3 Enfield

The system installation for Enfield rest area began in the late fall of 2013 and was completed in April of 2014, after spring ground thaw. Note that this sight is the most heavily wooded; due to tree branches that would have blocked camera views at the initial desired camera pole locations, a fourth camera pole was therefore placed at the rear of the parking lot facilities, affording back-of-the stall viewpoints. The site plans and installed pole locations to cover the 18 parking stalls are shown in Figure 5.5 and Figure 5.6.

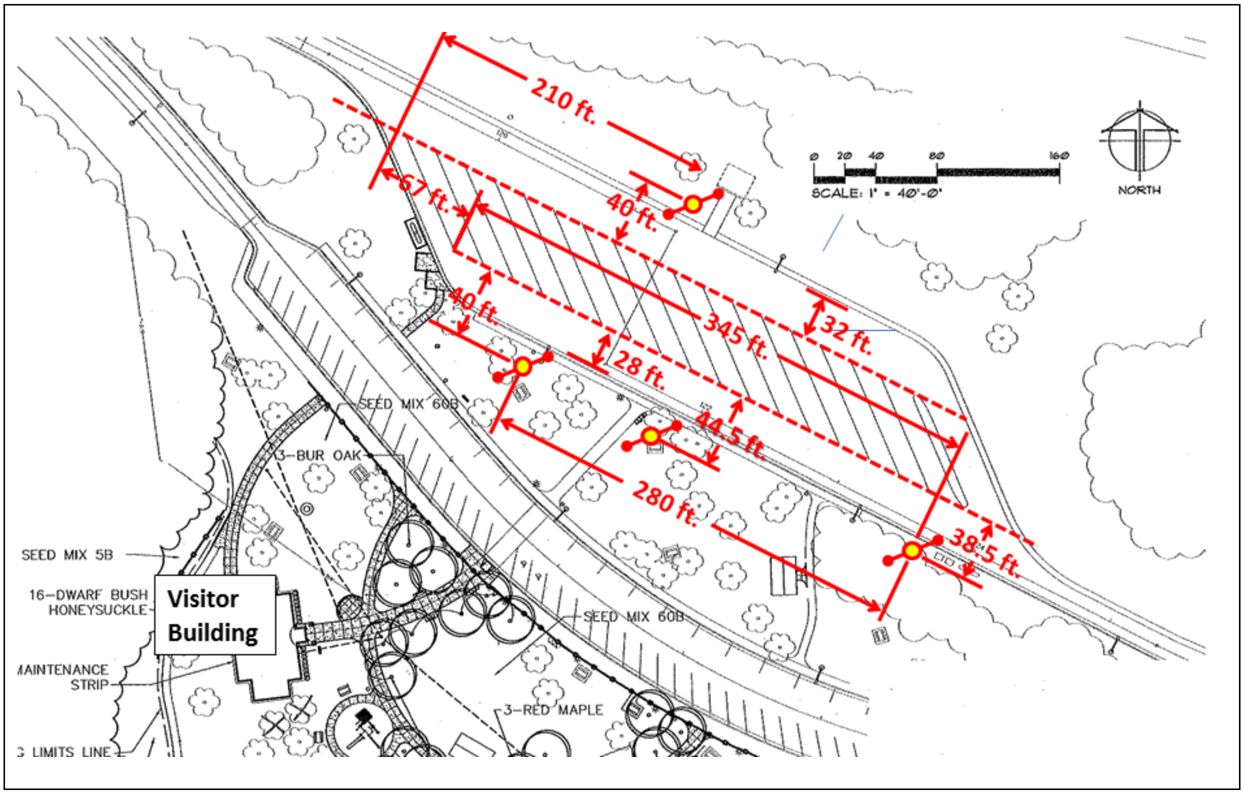


Figure 5.5. Enfield truck parking camera system site plan.

(conduit paths from poles to shelter removed for clarity)

Figure 5.6. Enfield truck parking facility and camera poles deployment. TOP: front parking stall view, BOTTOM: cameras view back end of parking stalls

The system installation for Enfield curb-to-front of stall and curb-pavement edge-to-back-of-stall measured 30.34 ft. (9.25m), and 32.8 ft. (10.00m) respectively.

5.2 DATA DISSEMINATION ARCHITECTURE

A software system architecture was developed to enable region-wide parking availability monitoring and dissemination. The occupancy detection data are packaged as XML reports containing the image acquisition UTC time, a site identification number, the parking occupancy status, and a unique user identifier (UUID) for each data set collected. The XML reports are then uploaded through user authentication over Secure Socket Layer (SSL) to the Data distribution and Database server (DDS) via a HTML RESTtful interface (Representational State Transfer via HTTP services on Windows Server 2012 .NET). Communication between the site and the DDS is achieved using 4G LTE cellular service (Figure 5.7).

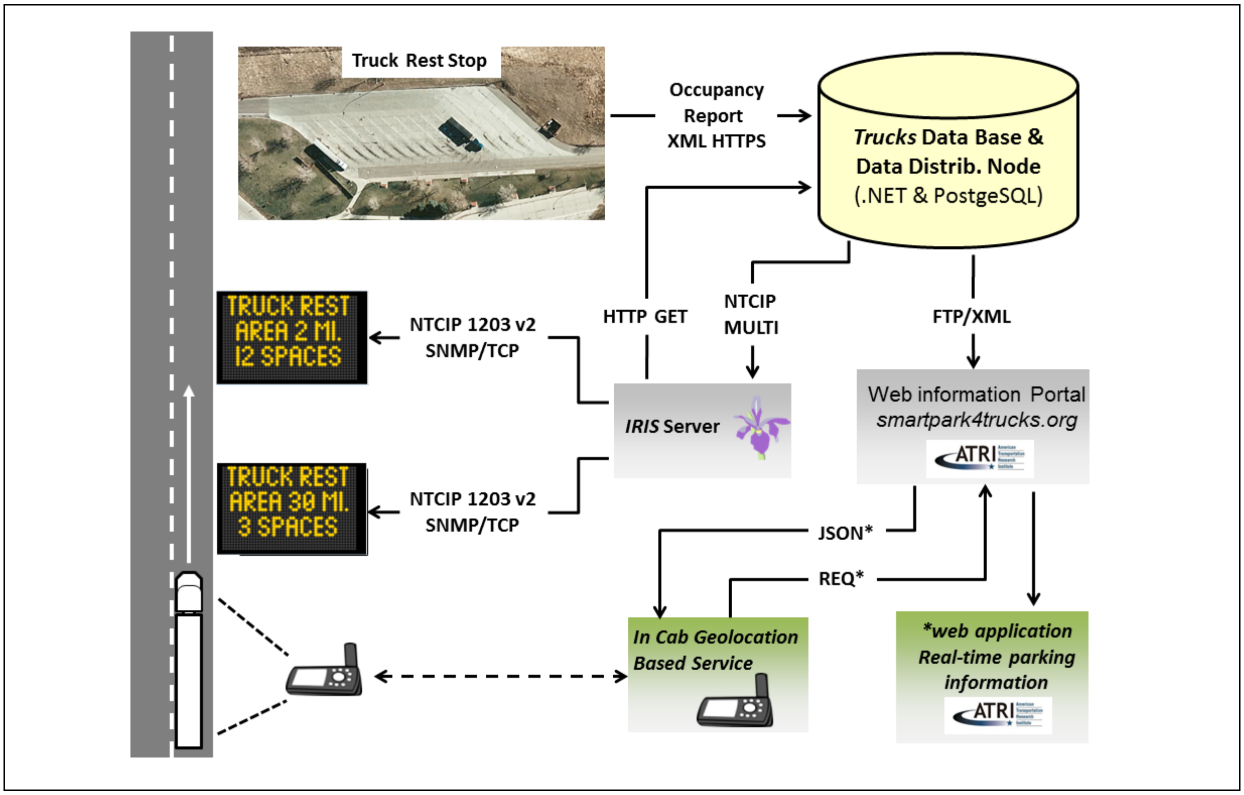


Figure 5.7. System architecture for archiving and disseminating truck parking information

Upon receipt of an XML occupancy report from a given site, the DDS recorded the reception time and archived the report in a relational PostgreSQL database. The database also stores meta-information for each site; their geographic locations, designed parking capacity, E-911 addresses and highway mile post descriptors. A front-end web interface on the DDS was used to inspect current occupancy counts in real-time as well as query the database over specified periods to obtain historical count reports. The data was also disseminated to three different information portal systems: 1. Web-based information dissemination portal for commercial freight operators, smarpark4trucks.org, 2. In-cab services and 3, Roadside Changeable Message Signs. An Intelligent Roadway Information System server (IRIS) [37]queries the DDS to communicate with roadside Variable Message Signs using the (NTCIP) communication protocol [38]. The query mechanism was achieved through a RESTful interface which returned a timestamped MULTI formatted text string. The IRIS query was set to pole the TPAS DDS every 30 seconds.

The web and in-cab information portals were managed and lead by ATRI. The web portal parking notifications were updated from the UMN DDS via an XML feed through an authenticated FTP upload client connection executed up to once every 30 seconds. Only the total occupancy count information was utilized. Other XML elements included the designed parking capacity of the facilities, the WGS84 Longitude, Latitude coordinates, the Mile Post, a unique facilities numeric identifier, a name description, and the UTC ISO 8601 date-timestamp with the local DST time zone correction at the facilities, all of which are processed and then displayed on the web user interface when the operator clicks on the parking icon located on the google map (Figure 5.8).

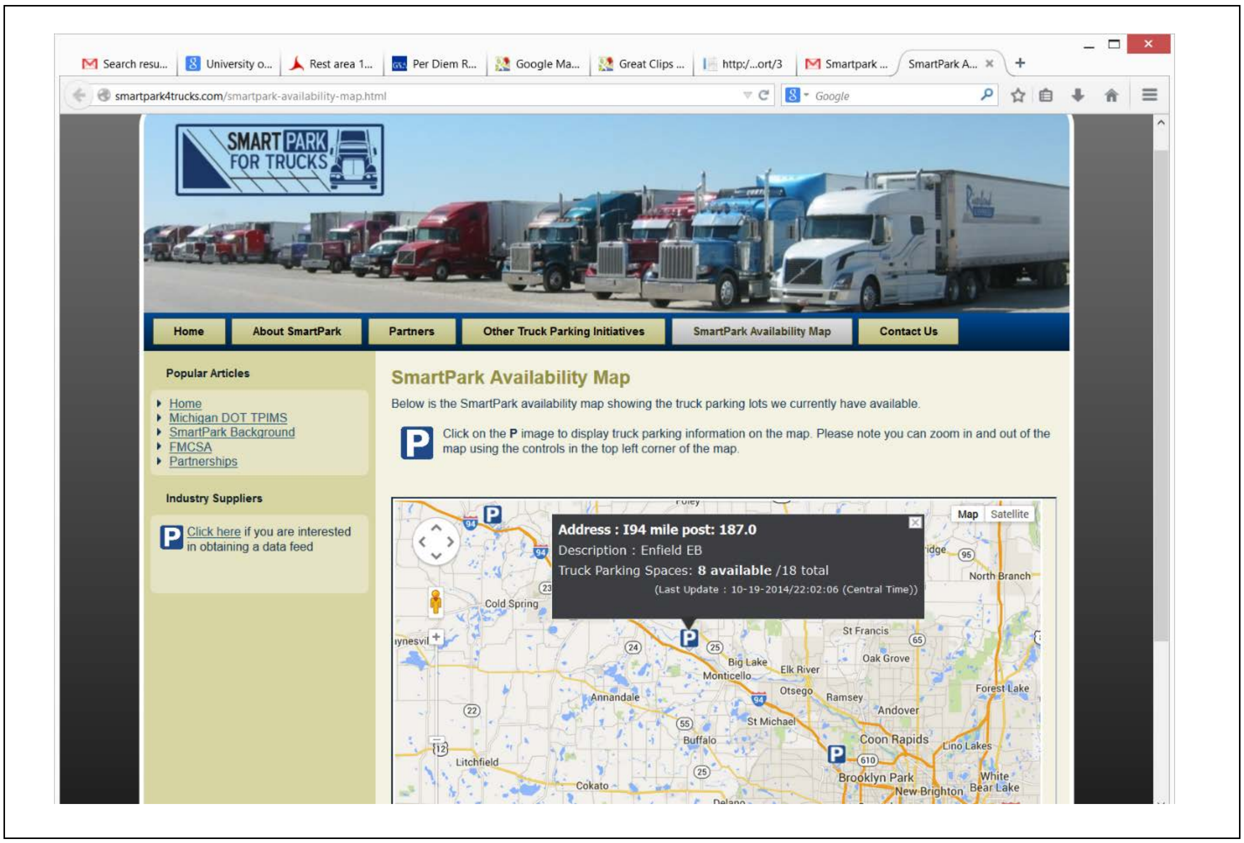


Figure 5.8. SmartParkforTrucks.org operator web portal

The in-cab embedded application, SmartPark, consisted of a driver graphical user interface, cellular modem internet connection, and embedded GPS receiver embedded into an in-cab device. The proprietary communication protocols between the in-cab device and the geolocation services platform were developed by PeopleNET, a division of Trimble, located in Minnesota. SmartPark implemented a 'hands-free' application interface that provided automated regular parking notification updates every five minutes, or through geo-fence triggered parking status notifications, of the truck parking facilities located downstream of the traveling vehicle. The geo-fences were spaced every five miles from twenty miles downstream of the closest oncoming truck parking facilities. Further interface details are described in the concepts of operation field tests described in 7.1 .

CHAPTER 6: TRUCK PARKING SPACE DETECTION PERFORMANCE

Sufficient capability for self-calibration and self-maintenance must be achieved to avoid human intervention to retain accuracy and operate 24/7. The system was evaluated by first collecting and quantifying detection performance from a validation dataset, and then subsequent detection performance capabilities over other varied periods of time across all the implemented sites. A detailed summary of the methodology used for quantifying detection performance and validation is presented next in sections 6.1 and 6.2 below. Several other collected data sets were further evaluated as discussed in section 6.3 .

6.1 DETECTION PERFORMANCE MEASUREMENT METHODOLOGY

A manual ground-truth process was developed to interactively label the parking status of several observed spaces which were processed by the vision module detection algorithm. General attributes pertaining to weather conditions, double-parking, private vehicles vs. trucks (SUTs, buses, and large RVs were also classified as trucks), visibility of parking stall lane lines, lens obstructions, or other anomalies that may contribute to detection or human observation errors, was also be annotated by the observer. A single camera view from each pole viewing the intended set of parking stalls to be detected was displayed to the user by the manual labeling software (Figure 6.1).

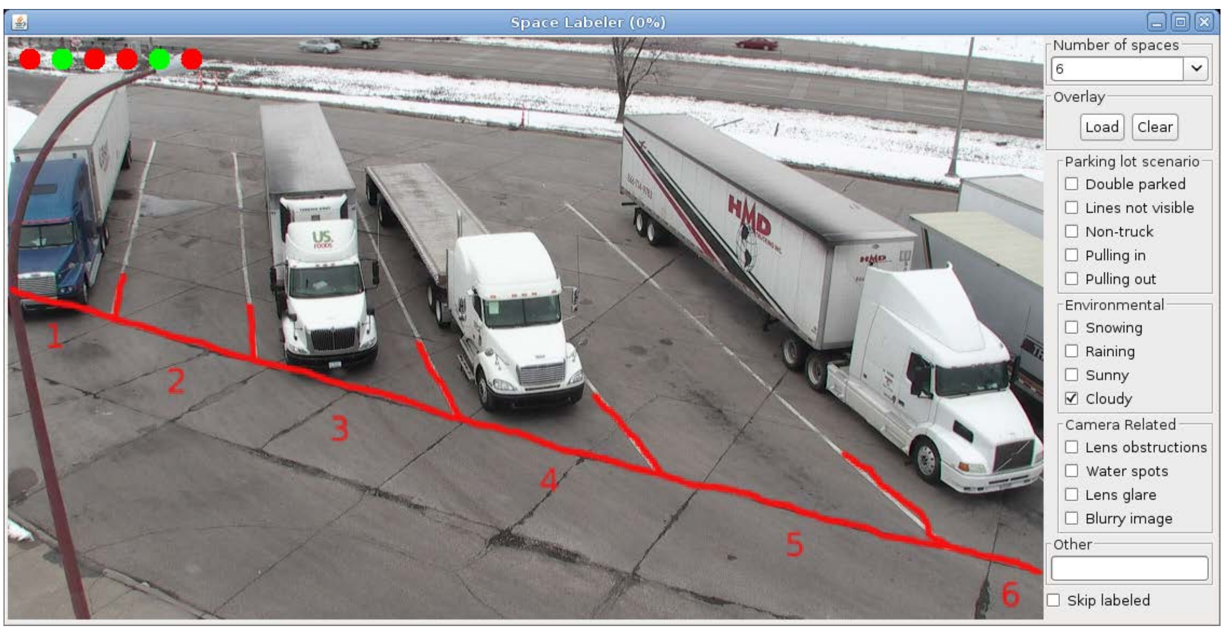


Figure 6.1. Observed ground-truth labeling interface.

Detection accuracy was evaluated based on 1) Per space accuracy, and 2) Total 'count' accuracy. To evaluate per-space accuracy, each parking status state (Occupied vs. Vacant) is compared to the manually observed parking status, at each moment of time. Then the accuracy is defined from the aggregate measure over all such comparisons by:

$$accuracy = \left(1 - \frac{FN + FP}{(FN + FP + TP + TN)}\right) \cdot 100\% \tag{6.1}$$

Where *FP* = number of false positive (occupied) detections, and *FN* = number of false negative (vacant) detections, and *TP* and *TN* represent the correct parking status detections. Furthermore, the detection *sensitivity* vs. *specificity* can also be calculated to provide insight into contributions for each of the two per-space false detection parking states on the overall accuracy in terms of detection sensitivity and specificity:

$$sensitivity = \left(\frac{TP}{TP + FN}\right) \cdot 100\%, \qquad specificity = \left(\frac{TN}{TN + FP}\right) \cdot 100\% \tag{6.2}$$

Thus sensitivity indicates the ability of the detection algorithm to correctly classify a space as occupied, while the parking detection specificity indicates the level of miss-detection of vacant parking spaces.

The second detection accuracy measurement compared the total occupancy count by summing all spaces over a given sample point in time. This performance measure was relevant from a system usability perspective (refer to Chapter CHAPTER 4:) since it duplicated the truck parking notifications disseminated to the operator or driver during the field operational tests.

6.2 PARKING SPACE DETECTION VALIDATION DATA SET

In order to access the detection algorithm to adequately subtract ‘foreground’ vehicle objects from the ‘background’, initial datasets were harvested from the first operational site, Elm Creek. The process entailed determining a boundary threshold to classify the parking space status as either vacant or occupied over diverse weather and lighting conditions (Table 6.1). Six parking spots were simultaneously detected by three camera view images on a single pole acquired at a point in time. The dataset samples for each such point in time were harvested between every five to ten minutes. The detection classification threshold was then adjusted according to the minimum detection error (*FP* + *FN*) using the Golden Section Search algorithm in MATLAB.

Table 6.1. Validation Data Set

Data Collection Period	Parking Events Ground-Truthed	Time Samples Collected	Snow Event Time Samples	Rain Event Time Samples
04/10/2013 – 04/12/2013	3,834	639	190 (29.7%)	
06/07/2013 – 06/10/2013	2,052	342		61 (17.8%)
02/21/2013 – 02/28/2013	10,956	1,826		
02/08/2013 – 02/11/2013	1,716	286	18 (6.2%)	
03/03/2013 – 03/05/2013	3,030	505	169 (33.4%)	1 (0.2%)
Total	**21,588**	**3,598**	**382**	**67**

The resulting detection accuracy truth table for the dataset is summarized in Table 6.2. The Left half presents the confusion matrix of miss-detections for occupied and vacant parking events. The overall accuracy was 98.0 percent. The accuracy during heavy snowing and raining events were reduced to 95.4 percent, which suggests that the weather events effected detection accuracy ($p < 0.01$). Other miss-detections arose from observed lane-encroachment from double-parking, catching dynamic maneuvers of a vehicle entering or exiting a parking space, or very dark/low-contrasting vehicles at night (Figure 6.2). In any case, the initial validation dataset indicated persistent vehicle 'foreground' detection could be achieved from the 3D reconstruction and alignment methodology.

Table 6.2. Validation Data Set Detection Results: All Samples

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	12,621 (TP)	98 (FP)	97.42%	98.86%	98.00%
GT-Observed Vacant	334 (FN)	8,535 (TN)			

Table 6.3. Validation Data Set Detection Results: Weather Event Samples Removed

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	10,797	53	97.67%	99.33%	98.36%
GT-Observed Vacant	256	7,852			

Table 6.4. Validation Data Set Detection Results: Weather Event Samples

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	1,824	45	96.00%	93.82%	95.40%
GT-Observed Vacant	76	683			

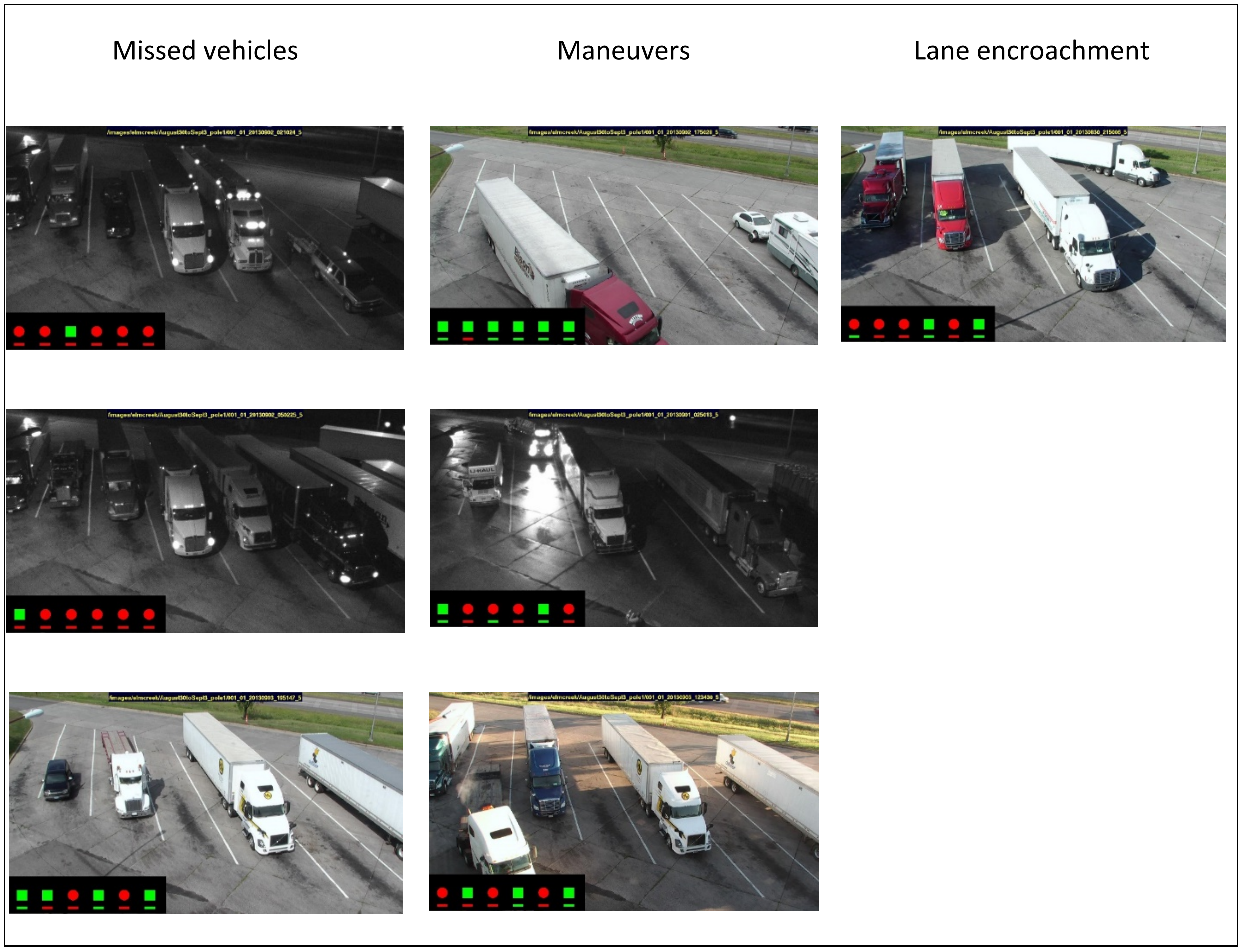


Figure 6.2. Conditions that resulted in parking detection errors.

6.3 DETECTION PERFORMANCE RESULTS

Additional detection datasets were harvested from local data storage at the sites (Table 6.5). The data sets consisted of around-the-clock continuous periods of time spanning between 3 and up to 9 days, each of which are several days, or weeks apart from one another. The periods of time were selected at random although they intentionally included mid-week periods (between Tuesday and Thursday) Historically at these rest areas mid-week periods tended to have higher truck parking volume activity than on weekends. The sampling period of ground-truth labeled examples ranged between one minute and five minutes, as a practical compromise between the manual ground-truth labeling process and observing variability in parking scenes across different time periods (the last dataset, encompassing several weeks, was sampled on the hour). The target detection update rate during operation was set to one minute intervals. During the operation of TPAS, parking status target update rate for a group of spaces was set to one minute.

Table 6.5. Detection Performance Data Set

Site	Data Collection Period	Park Spaces Observed	Parking Events Ground-Truthed	Time Samples Collected
Elm Creek	08/30/2013 – 09/08/2013	15	114,521	23,653
Enfield	10/07/2014 – 10/10/2014	18	109,580	14,055
Enfield	10/20/2014 – 10/22/2014	18	110,686	14,207
Big Spunk	08/25/2014 – 08/29/2014	16	62,903	15,303
Big Spunk	10/07/2014 – 10/09/2014	16	51,364	12,646
Big Spunk	10/20/2014 – 10/22/2014	16	51,271	12,606
Elm Creek	08/29/2013 – 12/23/2013	6	16,692	2,782
Total			**517,017**	**95,252**

The following two sections quantify detection performance in terms of per-space detection accuracy, and then as an aggregate occupancy 'count' of all spaces. As mentioned previously, the aggregated occupancy count was germane to the parking availability notifications broadcasted to drivers and carriers.

6.3.1 Per Parking Space Detection Performance

Tables Table 6.6 through Table 6.12 summarize the overall space detection accuracy for the three public truck parking facilities. The detection capabilities were fairly consistent between the implemented sites, with per space detection accuracy rate between 96 percent and 99 percent. Table 6.12 summarizes a dataset to investigate a larger range of time a sample set of data by harvesting and ground-truth labeling one hour intervals over several weeks of time at Elm Creek. The supposition for doing so was that the data set would capture more sample-to-sample variability in parking behaviors and environmental conditions. The results from were from a period from August 29th 2013 through December 23rd 2013.

Table 6.6. Elm Creek, 08/30/2013 – 09/08/2013, Detection Results

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	69,026	195	98.94%	99.56%	99.18%
GT-Observed Vacant	739	44,561			

Table 6.7. Enfield, 10/07/2014 – 10/09/2014, Detection Results

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	34,546	252	96.15%	98.24%	98.52%
GT-Observed Vacant	688	27,922			

Table 6.8. Enfield, 10/20/2014 – 10/22/2014, Detection Results

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	24,983	878	96.69%	97.70%	97.29%
GT-Observed Vacant	854	37,218			

Table 6.9. Big Spunk, 08/25/2014 – 08/29/2014, Detection Results

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	29,367	271	98.90%	98.87%	98.88%
GT-Observed Vacant	328	23,632			

Table 6.10. Big Spunk, 10/07/2014 – 10/09/2014, Detection Results

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	29,209	283	99.60%	98.72%	99.22%
GT-Observed Vacant	118	21,889			

Table 6.11. Big Spunk, 10/20/2014 – 10/22/2014, Detection Results

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	25,859	822	99.05%	96.73%	97.91%
GT-Observed Vacant	248	24,342			

Table 6.12. Elm Creek, 08/29/2013 – 12/23/2013, Detection Results

	Occupancy Detection	Vacant Detection	Sensitivity	Specificity	Accuracy
GT-Observed Occupancy	10,697	174	96.2%	96.88%	96.42%
GT-Observed Vacant	423	5,398			

The space detection performance defined by (6.1) and (6.2) can also be characterized on a per-space basis over a given range of time, or aggregated over a group of spaces for specific periods of time, in order to further study accuracy through space and time.

Figure 6.3 represents the aggregation of all parking space detections between daytime (sunrise to sunset) and nighttime (sunset to sunrise) hours for each of the three sites[3]. Under all sites accuracy diminishes during night-time hours (Elm Creek, Z=-14.48, $p < 10^{-6}$, Enfield, $Z = -10.35$, $p < 10^{-6}$, $Z = -15.76$, $p < 10^{-6}$). The reason for diminished accuracy at night is due to the fact that darkness reduced the signal to noise ratio and ability of the cameras to sharply focus the scene in some instances. This in turn reduced either the 3D point density of the reconstructions, or the accuracy of the bundled intrinsic and extrinsic camera calibration parameter estimates, because fewer distinct matching features were extracted from the images. The result was that, for the facilities which were observed to fill up and reach capacity faster and more often during the weekday evenings, the false negative detections further reduced the detection accuracy even when the sensitivity (correct occupancy detection rate) is preserved. Such false vacancy (negative) detections were also typically associated with very dark colored vehicles (a typical observation is shown in Figure 6.2). At night, when the contrast is further reduced, this was especially true. On the other hand, denser but noisy reconstructions tended to result in more over counting and thus the specificity was therefore reduced.

[3] As calculated from the MATLAB Air Sea Toolbox, which computes sunrise and sunset using the expressions taken from Appendix E in the 1978 edition of Almanac for Computers, Nautical Almanac Office, U.S. Naval Observatory. The calculations are valid for the years 1800-2100, with a solar declination accuracy of 1 minute.

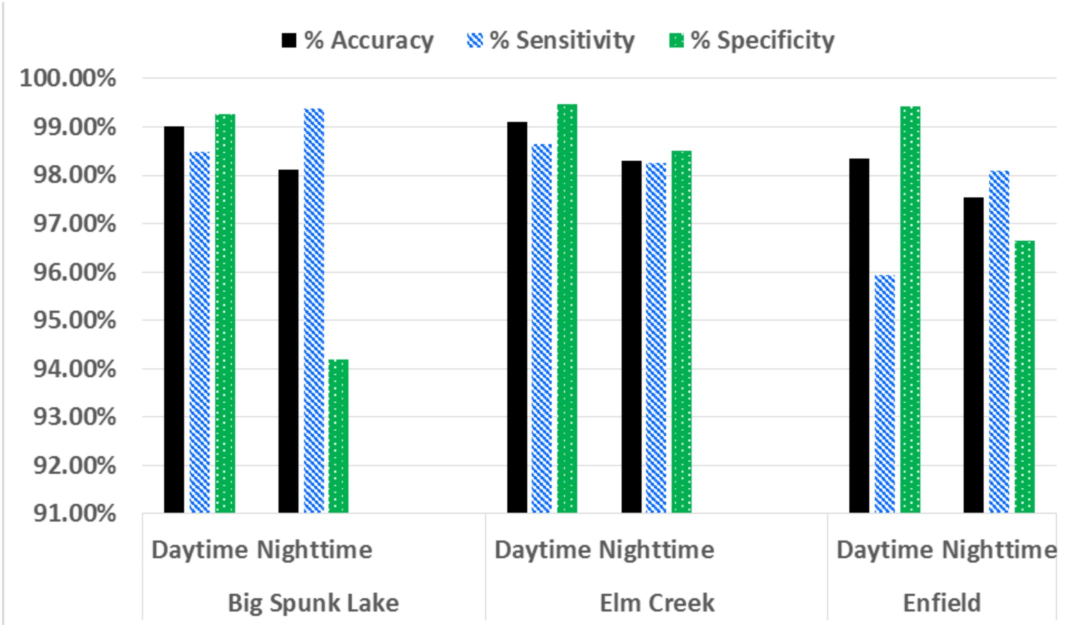


Figure 6.3. Daytime vs. nighttime truck parking space detection performance.

In addition to investigating the detection performance between night and day time hours, the aforementioned descriptive label categories in the ground-truth datasets can be used to further examine possible detection error causality. Tables Table 6.13 through Table 6.15 summarize the frequency of such observed and labeled phenomena, categorized by manual observations using the ground-truth derived labels for all the data collected at each site. Some aggregations of the ground-truth labeled observations were done to simplify the analysis. The observed separated vehicle enter and exit maneuvers were combined together. Human observed lens blur affects are considered as the anomalous camera observation, while lens obstructions – from any source was grouped as an anomalous lens condition. Both observed snowfall and rain fall conditions were grouped as a single weather condition. There was no attempt to categorize sunny vs. cloudy days. Double parked vehicles were categorized when any part of the vehicle was observed as being over the parking lane line. For the Lines Not Visible category, such instances typically can occur during or after snow fall which covered the parking lane lines (as shown in Figure 6.1 a visual template was overlaid on the image as a guide to help disambiguate the parking spaces). Note that more than one such observation label category could have been annotated for any given observed image sample. Lastly, there was no distinction between vehicle types (other than private vehicles), or the number of observed vehicles double parked or performing a maneuver.

Table 6.13. Elm Creek Detection Error Rate Associated with Labeled Data

	Daytime	Nighttime	All Day	Total Samples Categorized
Error-Maneuvers	18.92%	4.81%	10.06%	476
Error-Double Parked	39.37%	23.17%	29.19%	748
Error-Lines not vis.	43.92%	27.33%	33.50%	1088
Error-Weather	8.29%	8.56%	8.47%	792
Error-PV	21.69%	3.18%	10.06%	1334
Error-Lens obstruct	0.41%	0.25%	1.59%	65
Error-Camera	16.85%	4.16%	8.88%	602
No label	11.74%	60.52%	42.43%	

Table 6.14. Big Spunk Lake Detection Error Rate Associated with Labeled Data

	Daytime	Nighttime	All Day	Total Samples with Label
Error-Maneuvers	15.46%	3.37%	7.49%	431
Error-Double Parked	5.15%	0.00%	1.76%	61
Error-Lines not vis.	0.00%	0.00%	0.00%	0
Error-Weather	18.16%	16.33%	16.95%	2565

Error-PV	15.71%	3.11%	7.41%	2334
Error-Lens obstruct	0.00%	0.00%	0.00%	3
Error-Camera	0.37%	0.00%	0.13%	18
No label	50.80%	78.59%	69.11%	

Table 6.15. Enfield Detection Error Rate Associated with Labeled Data

	Daytime	**Nighttime**	**All Day**	**Total Samples with Label**
Error-Maneuvers	9.81%	3.00%	5.39%	314
Error-Double Parked	4.16%	0.69%	1.91%	61
Error-Lines not vis.	0.00%	0.00%	0.00%	0
Error-Weather	0.00%	0.00%	0.00%	0
Error-PV	10.34%	1.73%	4.75%	607
Error-Lens obstruct	0.00%	0.00%	0.75%	132
Error-Camera	0.00%	0.00%	0.00%	0
No label	77.08%	93.08%	87.46%	

Examining the tables Table 6.13 through Table 6.15, a majority detection errors were in general not associated with any of the observed label categories during the evening hours across all of the sites. In contrast a significantly greater proportion of the detection errors were associated with such labels during the day time hours. Other trends indicate detection errors occurred with observations of parked vehicles that encroached into other lanes, when vehicles were observed to be maneuvering into or out of a parking stall, and the largest proportions – when there was the inability to observe the parking lane lines from the camera image. Observed private vehicles also were associated with detection errors with a similar proportion to the aforementioned factors.

Although the information in the tables do offer insight into some of the possible conditions that may be associated with detection error, the significance of such conditions as it relates to detection error outcomes can be further corroborated. Note that because multiple labels were added for a given sample, and the number of each condition labels vary across each condition, the tables do not necessarily reflect the significance of the associations. Specifically, we wish to understand how each of the given observations influences the likelihood of observing a detection error, and the significance of such an influence. Such questions can be addressed using Logit Regression analysis, since the observed detection errors can be represented by a set of discrete outcomes [39]. With the Logit Regression analysis paradigm, one or more observed detection errors were generalized as a binary variable, with the response variable at sample *i*, Y_i=1 representing a detection error, otherwise for no observed detection errors, Y_i =0. The likelihood of a given detection error was then the probability $p(|Y_i = 1)$ of which the error occurred from one observation to the next. It therefore follows that the likelihood of that no detection error occurred is $1 - p(|Y_i = 1) = p(|Y_i = 0)$. Assuming such a detection error event outcome was independent and followed a Bernoulli distribution (e.g., a detection error did not depend on a previous outcome), the probability of observing a detection error for a given sample event *i* is commonly expressed using the following likelihood equation:

$$f(Y_i; p) = p(|Y_i = 1)^{Y_i} \cdot (1 - p(|Y_i = 1))^{Y_i - 1} \ ; \ Y_i = \{0,1\} \tag{6.3}$$

where $f(Y_i; p)$ is the probability mass function. In the Logit Regression formulation, a functional equation to relate $j = 1,2, \ldots m$ observations (or features) x_{ij} at sample *i*, to the probability $p(\boldsymbol{x}_i)$ can be expressed by:

$$p(\boldsymbol{x}_i) = \frac{e^{\beta_0 + \beta_1 \cdot x_{1,i} + \beta_2 \cdot x_{2,i} \cdots \beta_m \cdot x_{m,i}}}{1 + e^{\beta_0 + \beta_1 \cdot x_{1,i} + \beta_2 \cdot x_{2,i} \cdots \beta_m \cdot x_{m,i}}} \tag{6.4}$$

A useful representation is the summated log-likelihood, $L(\boldsymbol{\beta})$, derived by substituting (6.4) into (6.3) and taking the natural log, yielding:

$$L(\boldsymbol{\beta}) = \sum_{i=1}^{n} \left\{ Y_i ln\big(p(\boldsymbol{x}_i)\big) + (Y_i - 1) ln\big(1 - p(\boldsymbol{x}_i)\big) \right\} \tag{6.5}$$

Taking the natural log of both sides, of (6.4) provides the function to compute $p(x_i)$, e.g.

$$ln\left(\frac{p(\boldsymbol{x}_i)}{1-p(\boldsymbol{x}_i)}\right) = \beta_0 + \beta_1 \cdot x_{1,i} + \beta_2 \cdot x_{2,i} \cdots \beta_m \cdot x_{m,i} \tag{6.6}$$

Any attribute label j = 1,2,..m, at sample i, $x_{i\,j}$, is categorized with x_i = { 1,0}. For this analysis the very simple structural model of (6.6) was assumed.

The level of significance for each label in $\boldsymbol{x}_i$ can be obtained by straight forward analysis of variance for each of the resulting estimate of coefficients, $\hat{\beta}_0,\ \hat{\beta}_1,\ \hat{\beta}_2 \ldots \hat{\beta}_m$. Inspection of the model yields the following interpretation. For coefficients that are less than zero, the negative relationship in (6.6) effectively reduces the influence of the labeled observation on the log ratio of the detection error probability outcome, while a positive value will have the opposite effect. A value $\hat{\beta}_j = 0$, indicating no influence, can be thought of as a fair 'coin flip' probability—that is equation (6.4) would compute a probability of ½ = 0.5 (ignoring all other terms). Finding estimates of $\hat{\beta}_0,\ \hat{\beta}_1,\ \hat{\beta}_2 \ldots \hat{\beta}_m$ is done by taking the partial derivative with respect to each coefficient, β_j , of (6.6), and setting each of the partials equal to zero to find the maximum of the function. Such a maximum-log-likelihood solution for the set of equations is achieved numerically. Further details of the derivation and common solution strategies are described in [39]. The MATLAB statistical toolbox was used to solve the structural model using the aforementioned technique. Equation (6.6) is also used to infer the relative significance between any two models, which is computed by taking the difference between the two $L(\boldsymbol{\beta})$'s (equivalent of the log ratio), and multiplying this difference by 2. The result equates to a Chi-square cumulative probability $\chi(\nu)^2$ with $\nu = m$ degrees of freedom. The null hypothesis is that the covariates in question are not significant (i.e., the coefficient is zero). For example, the significance of the model itself can be calculated with the hypothesis that all the covariates (including the constant) are zero, and thus the second 'model' is based only on the overall expected probability value from a set of response variables – in this case the number of samples with at least one detection error divided by the number of samples associated with a label.

The observed events cannot be controlled through experimentation and thus processing data to provide an equal --and very large, sample number of such label occurrences across all sites under different control conditions representative of each type of labeled observation was not feasible. Although parking detection performances do vary somewhat from each site, all the sample data associated with one, or more, of the aforementioned categorical labels across the sites were aggregated together, resulting in 5,648 daytime samples, and 4,202 nighttime samples containing one or more ground-truth labeled categories, with 1,751 samples containing at least one False Positive (621) or False Negative (1,234) detection error. Lastly, in the analysis, an additional 'label' representing daytime vs. nighttime was added to the model to understand if such a factor may also be significant.

Table 6.16. Detection Error Response Logit Regression Results

Observable	Beta Coeff.	t-statistic	SE	p-value
(constant term)	-2.3888	-24.8964	0.0960	0
Error-Maneuvers	1.7407	16.4690	0.1057	0
Error-Double Parked	2.0757	19.6668	0.1055	0
Error-Lines not vis.	1.2494	13.2308	0.0944	0
Error-Weather	0.1136	1.1999	0.0946	0.2302
Error-PV.	0.1153	1.1787	0.0978	0.2385
Error-Lens obstruct	0.3126	1.3240	0.2361	0.1855
Error-Camera	-0.1853	-1.4528	0.1276	0.1463
$L(\boldsymbol{\beta})$= -3867.52				

Table 6.17. Detection Error Response Logit Regression Results, Day and Nighttime

Observable	Beta Coeff.	t-statistic	SE	p-value
(constant term)	-2.3652	-24.0504	0.0983	0
Error-Daytime	-0.0651	-1.0641	0.0612	0.2873
Error-Maneuvers	1.7365	16.4275	0.1057	0

Error-Double Parked	2.0689	19.5854	0.1056	0
Error-Lines not vis.	1.2639	13.248	0.0954	0
Error-Weather	0.1180	1.2460	0.0947	0.2128
Error-PV.	0.1179	1.2052	0.0978	0.2281
Error-Lens obstruct	0.3463	1.4533	0.2383	0.1461
Error-Camera	-0.1929	-1.5057	0.1281	0.1321
$L(\boldsymbol{\beta}) =$ -3868.08				

Table 6.16 displays the overall structural model results, while Table 6.17 added the daytime ($x_j = 0$), nighttime ($x_j = 1$) into the regression model as another covariate. The second column is the standard error normalized t-value statistic and an absolute value (two-tailed) greater than for example, $|t|$*=1.96* is indicative of committing a type I error at *p < 0.05* (rejecting that the label indeed has no effect). Note that the aforementioned Wald test indicates the level of significance of the variable and does not necessarily provide insight into its contribution to predicting a response (detection error). The standard errors of each coefficient are provided in the third column of the tables, and for most factors were relatively small and of similar values with exception of labels associated with lens obstruction and to some degree, camera-based anomalies. This implies a reasonable balance of information amongst the label variables for the structural model.

Apparently, only a very marginal association between daytime and nighttime detections with either False Positives (FP), False Negative (FN) detection errors was revealed ($\chi(1.12, \nu = 8)^2 = 0.0167 > 0.01$). The other logit regression coefficients were not affected too much by adding this factor to the model.

These findings support the earlier results that vehicle maneuvers, double-parked vehicles, and the inability to locate lines were associated with detection errors in general. Yet the structural model does not consider if in fact, there was a tendency to affect detection errors associated with FP or FN detections. To explore this relationship, the logit model was formulated with detection error response variable Y_i was categorized as a sample response containing strictly FP errors (Table 6.18), and then a second model whereby the response contains strictly FN errors (Table 6.19).

Table 6.18. False Positive Detection Response Logit Regression Results

Observable	Beta Coeff.	t-statistic	SE	p-value
(constant term)	-2.9075	-19.8487	0.1465	0
Error-Daytime	0.3380	3.8779	0.0872	0.0001
Error-Maneuvers	0.5171	3.1228	0.1656	0.0018
Error-Double Parked	0.0311	0.2121	0.1467	0.832
Error-Lines not vis.	1.1795	9.0907	0.1297	0
Error-Weather	0.4022	2.9212	0.1377	0.0035
Error-PV.	-1.5019	-8.5844	0.175	0
Error-Lens obstruct	-0.1665	-0.5307	0.3137	0.5956
Error-Camera	-0.6660	-3.8351	0.1737	0.0001
$L(\boldsymbol{\beta}) =$ -2079.1244				

Table 6.19. False Negative Detection Response Logit Regression Results

Observable	Beta Coeff.	t-statistic	SE	p-value
(constant term)	-3.3623	-27.6253	0.1217	0
Error-Daytime	-0.2571	-3.4705	0.0741	0.0005
Error-Maneuvers	2.3854	19.0636	0.1251	0

Error-Double Parked	2.8590	22.3739	0.1278	0
Error-Lines not vis.	1.0629	9.0767	0.1171	0
Error-Weather	-0.4715	-3.7928	0.1243	0.0001
Error-PV.	1.0436	8.6766	0.1203	0
Error-Lens obstruct	1.0533	3.5507	0.2967	0.0004
Error-Camera	0.3253	2.0093	0.1619	0.0445
$L(\boldsymbol{\beta})$ = -2891.5886				

With the detection responses separated, the influences between each of the covariates was much different. In this case, weather and daytime vs. nighttime were significant, as well factors related to private vehicle observations. Lens obstructions and double parked vehicle observations had no significant associations with FP type detection errors. On the other hand, all the covariates (labeled conditions) for the FN detections were significant, with exception of the Camera anomaly being the weakest, fall below the $p < 0.01$ level.

6.3.2 Space Detection Performance Summary

Some general concluding comments are in order. All the Logit Regression models were highly significant, with respect to random chance predictions using the overall mean probability of the response variable (All Logit Regression model cumulative probabilities were associated with $\chi(\cdot, \nu = 8)^2 < 10^{-5}$). The trends were what should be expected for future implementations and suggest where detection performance can be improved for future deployments. However, one should not assume that the associations will be quantitatively similar. There could be other endogenous variables that affect detection performance that have not been revealed in this study. In addition, there were large variations in the total number of each of the labeled events recorded. For example, if the camera image was labeled as blurry does not infer other camera images were blurry as well. Of course the opposite can be true: one image was clear and yet one or more of the multi-camera views which were not observed may in fact be blurry. In some sense, this exemplifies the robustness of the multi-view approach in that detection recovery was achieved by using information from the other cameras (e.g. the features and resulting 3D reconstructions) as evident from generally weak associations with detection errors. A similar circumstance may be associated with a lens obstruction, which could also have been associated with identified weather events as well.

6.3.3 Space Occupancy Count Performance Analysis

A parking status for all the spaces was imputed from within the Data Distribution Server by aggregating the latest detection output in time for each group of spaces. The same procedure was emulated within this analysis for the detection and the ground-truth data and then taking the difference between the two accumulated occupancy status values to examine under and over counting. Figure 6.4 illustrates the time series plot for Elm Creek, which shows that this rest area frequently reached parking space capacity primarily during evening hours. Similar trends were also observed for Big Spunk Lake and Enfield rest areas (Figure 6.5 and Figure 6.6).

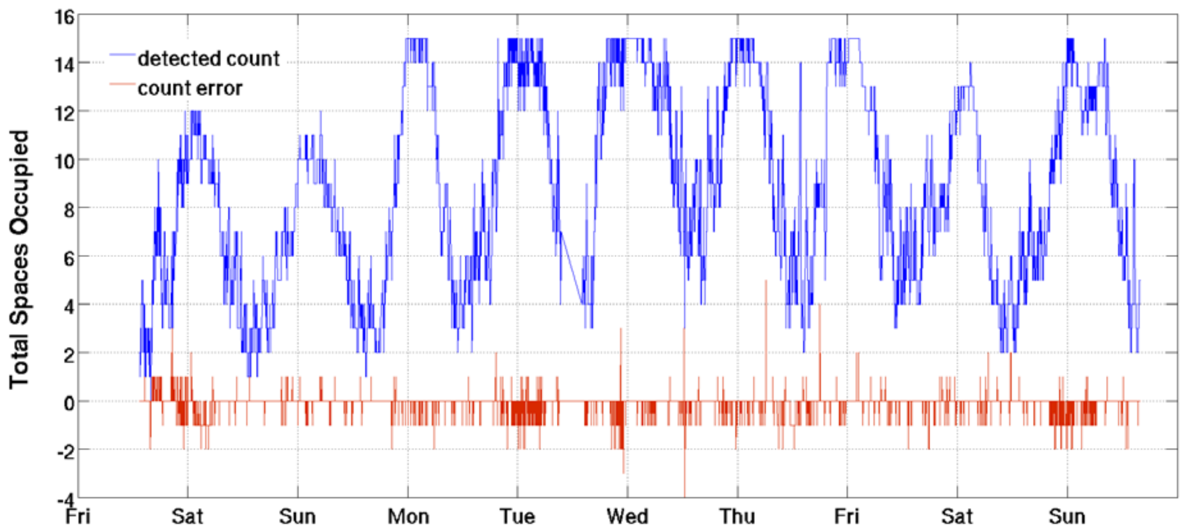


Figure 6.4. Elm Creek rest area truck parking space total occupancy counts over period 08/30/2013-09/08/2013.

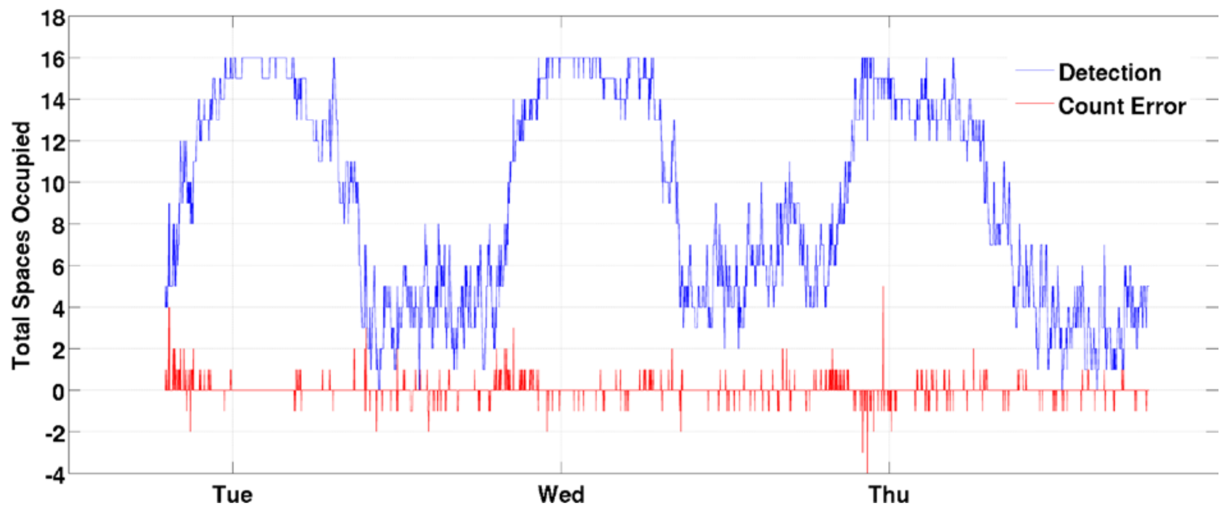


Figure 6.5. Big Spunk Lake rest area truck parking space total occupancy counts over period 10/07/2015 – 10/07/2015.

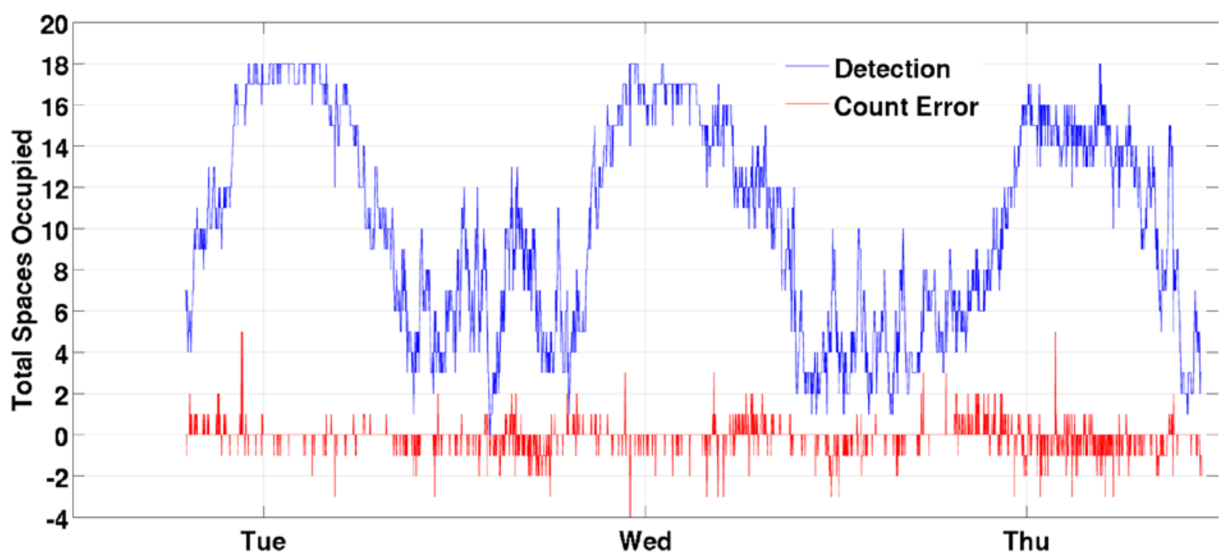


Figure 6.6. Enfield rest area truck parking space total occupancy counts over period 10/07/2015 – 10/09/2015.

Total count accuracies were assessed by accumulating the occupancy count errors across 6,409 time samples for Elm Creek, 9,436 time samples for the Big Spunk Lake, and 8,044 time samples for Enfield. The space count occupancy accuracy for the Elm Creek, the highest accuracy out of the three rest areas, was within ±1 count 99.1 percent of the time and within ±2 counts 99.9 percent of the time. Matching counts between the ground-truth observations and detections occurred 88.3 percent of the time. For Big Spunk Lake, the overall count was within ±1 count 96.5 percent of the time, within ±2 counts 98.8 percent of the time, and within ±3 counts 99.7 percent of the time. Matching counts between the ground-truth observations and detections occurred 83.7 percent of the time. The overall accuracy for Enfield had similar total space occupancy count errors as Big Spunk Lake sans the matching count proportion; the accuracy was within ±1 count 95.6 percent of the time, within ±2 counts 98.9 percent of the time, within ±3 counts 99.7 percent of the time, and matched the ground-truth labeled occupancy counts 73.5 percent of the time.

6.3.4 Parking Detection Communication Performance

During the initial phases of online testing and evaluation, the parking detection sampling period was set to two minutes apart, and subsequently reduced to the current desired sampling period range of one to one and a half minutes at the beginning of the concept of operations testing. An average ± standard deviation time of 33.0±12.0 seconds (*N*=16,216) was required for image data acquisition, processing, and uploading the data for 6 spaces at a time. The time variability was primarily due to the 'richness' of features in the scene; for example, the 3D reconstruction of an empty parking lot reduced the processing time, while generally, occupied spaces with vehicles, increased the processing time. Communication internet time-out gaps to the Data Distribution Server (DDS) from the cellular internet service operating at each site also contributed to the variability of the total processing time. The identification of such time-out gaps are explained below.

Monitoring and diagnostic tools developed by the team poled the system every 10 minutes to flag and sent notification of internet connection time-out failures lasting at least 10 seconds at a given site. Other monitoring tools flagged power outages (from messages sent by the UPS), and communication outages of the Data Distribution Server which aggregates and disseminates the parking information. Table 6.20 summarizes electrical and communication connectivity failures between 04/17/2014 and 09/26/2015. Generally, all sites had connectivity time-out problems less than 0.2 percent of the time regardless of the site location and its detection data collection characteristics ($p < 0.01$). A 'worse-case' scenario of such connectivity outages indicated an expected daily outage time for a given site of 0.0178 x 24 x 60 = 2.56 minutes per day.

Table 6.20. Site Communication Performance

		Internet comm. failure rate site comparison, *N*=75,942	
	Internet comm. failure rate %	**Elm Creek**	**Big Spunk Lake**
Elm Creek	0.1712		

Big Spunk Lake	0.1830	p=0.4044	
Enfield	0.1448	p=0.0550	p=0.0330
DDS	0.0290		

6.4 TRUCK PARKING SPACE DETECTION AND SYSTEM PERFORMANCE CONCLUSIONS

To conclude, it is evident that persistent parking detection over a variety of time periods and environmental conditions was achieved during continuous operation of TPAS. Per-space parking detection performance was investigated in some detail through analysis of 538,605 observed parking events that occurred in 98,850 samples (images), across different periods and scales of time, camera views, and facilities. Per space detection accuracy was no worse than 95 percent for the data collected. With the remaining detection error data (1 to 5 percent) between 25 to 50 percent was associated with private vehicles, maneuvering into and out of parking spaces, and occasional double parking. Such errors were generally transient in nature and the detections tended to be corrected in a subsequent sample or a short period of time after the event. Furthermore, there was some degree of subjectivity in the manual ground-truthing annotation process. For example, and in particular, judging vehicle encroachment in some instances did not actually inhibit parking in the adjacent parking stall; however, parking status was conformant with a binary state since ultimately, the information passed as notifications to drivers and operators follow such a representation. Nighttime detection performance was somewhat less than daytime performance. Actually, this was not completely surprising as the parking facilities operated generally under low-light conditions of design targets at or less than 0.5 lux [35].

The system detection performance for imputing a total occupancy count in section 6.3.3 indicated a 'count' error of no more than ±2 about 99 percent of the time. Perhaps some improvements could be achieved by adding non-intrusive, low-energy lighting such as eye-safe infrared lighting which should enhance nighttime illumination without distracting drivers and creating safety hazards. Other improvements can be tested to enhance contrast ranges of the images that do not tax computational resources should be investigated to also improve detection performance.

Total occupancy count data were typically within ±1 count 95 percent of the time, and within ±2 counts 99 percent time. It should be noted that many space detection errors which can affect the total count errors were very transient in nature – such as sampling a vehicle pulling into or out of a parking space—and was recovered with subsequent detections. A similar occurrence occurred for varied degrees of encroachment for a vehicle which was labeled to be double-parked. As previously mentioned, the parking state was strictly assigned a binary state. In this regard, it should be noted that there was some degree of subjectivity in ground-truth process under such conditions and thus some variance in the detection error can be attributed to the ground-truth labeling process itself.

CHAPTER 7: OPERATIONAL FIELD TEST AND EVALUATION

Once the three sites were installed, a concept of operations field test evaluated system performance and usability by drivers along the corridor. A description of the field test implementation, system reliability performance data, and a system user evaluation of the parking notification modalities are presented below. The aforementioned user evaluation was carried out by ATRI team members.

7.1 FIELD OPERATIONAL TEST DESCRIPTION

The SmartPark in-cab truck parking notification system consists of a custom application that automatically alerts drivers of upcoming parking availability automated parking notification alerts when the vehicle passes through pre-assigned geo-fences upstream of the parking facilities being monitored. The application runs on an embedded windows in-cab display. No interaction by the driver was necessary to receive the notifications. The notifications provide a brief description of the facilities—including its designed parking capacity, its mile post and relative location downstream of the vehicle for up to two facilities, and the most up-to-date parking status. The parking status displays both the detected number of spaces available, as well as a categorical representation using colors to denote parking availability as either “low”/Red, “medium”/Orange, or “high”/Green.

The upstream location criteria to place roadside CMS’s was initially guided by the survey results of the usability study conducted by ATRI, which had concluded that drivers preferred to receive parking status information within 5 and particularly 20 or more miles upstream from the parking facilities. As it turned out, deploying the signs at these distances upstream from the truck parking facilities interfered with other roadside traffic and information signs located nearby, or would have been place along unfavorable road geometry that could have limited readability of the sign by truck drivers (horizontal curve alignments). The parking information to be displayed was constrained by information complexity guidelines to between 2 and 4 bits per line (depending on the number of lines, where each word is at least 1 ‘bit’). The resulting MMUTCD compliant hybrid CMS designs, with truck vehicle approach design speeds of approximately 70 miles per hour (103 KPH) are presented appendix B.

Several unforeseen deployment issues associated with the lack of nearby electrification and communications, as well as conspicuity issues with other rest area information signs located just after the feasible CMS locations, resolved the team to investigate the usage portable large message boards. During the process MNDOT indicated that the existing rest area signs would need to be modified (or re-built), and then reinstalled in a location before the aforementioned CMS signs. There was a general concern that the first information any driver should see upon nearing a rest area location should not include the truck parking information.

Two portable changeable message trailers were integrated with the truck parking architecture and deployed. Right of Way Permits were submitted through the permitting offices of MnDOT for two feasible portable CMS locations — each between 2 to 3 miles upstream of the Enfield and Elm Creek truck parking rest areas, respectively. The signs were operational during a period between June 20th 2014, through October 17, 2014.

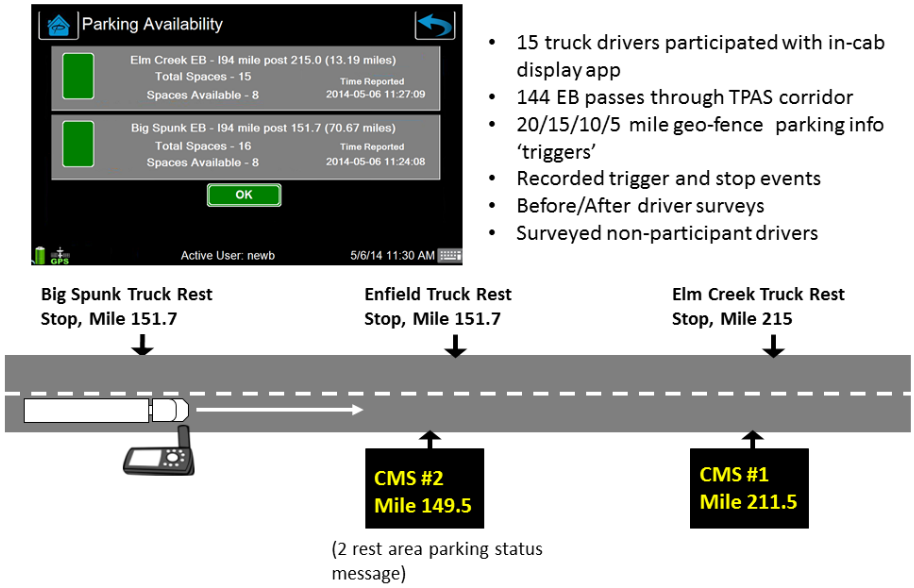
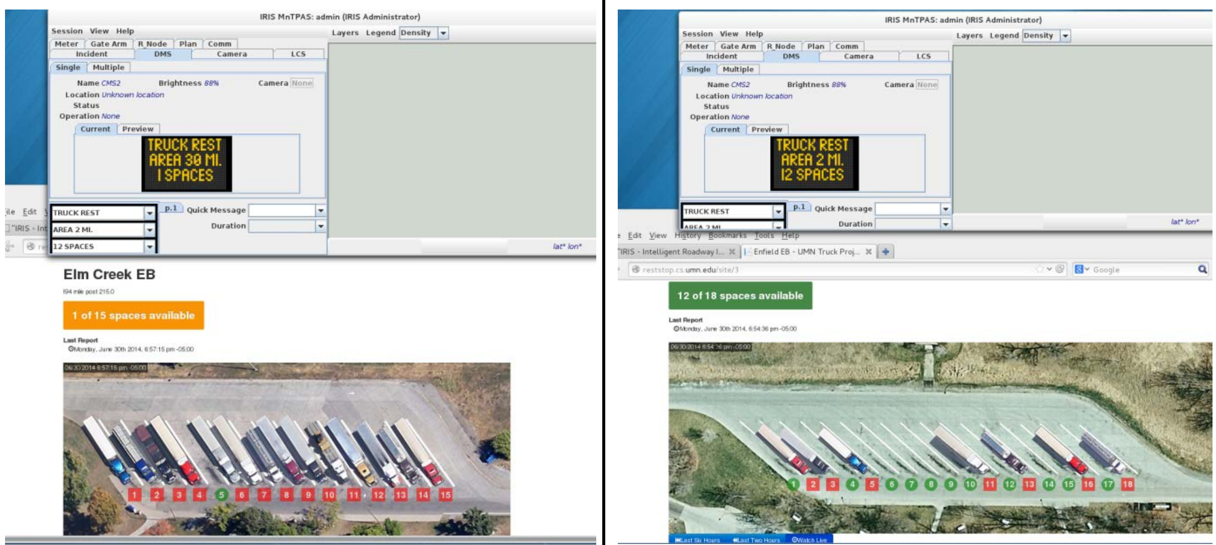


Figure 7.1. Configuration for TPAS concepts of operations field test.

The messages went 'live' June 20th 2014. The first eastbound portable roadside CMS was located 2.1 miles and 30 miles from Enfield and Elm Creek rest area exits respectively. The second CMS was placed 3.5 miles from the Elm Creek rest area exit. The first CMS indicated the number of available parking spaces at 1) Enfield, and 2) Elm Creek, with two separate alternating pages every 2 seconds. The second CMS displayed available parking space notifications for Elm Creek only. The CMS notifications were verified frequently through the IRIS client application and the TPAS DDS web interface (Figure 7.2). Several driving trips by the research team members were also performed during the testing period to validate their operation.



a. Elm Creek first EB CMS notification

b. Enfield first EB CMS notification

Figure 7.2. CMS verification of parking status shown through IRIS and TPAS DDS interfaces.

Initially, just before the start of the field operational testing, all three public rest areas were online. However, during first few weeks of the field testing, the Enfield site experienced hardware problems that required repairs of faulty communication and electrical wiring, as well as replacing a defective camera. The site was brought back online in mid-July but by this time it was too late to integrate it into the SmartPark in-cab truck parking notification system tests. Both Big Spunk Lake and Elm Creek were included over the entirety of the in-cab notification system evaluation.

7.2 SYSTEM USABILITY EVALUATION

The system usability evaluation is divided into two parts. The first part evaluated efficacy and potential scalability of SmartPark, the in-cab, geo-reference truck parking availability notification application. The second part determined if there were any before-and-after changes in driver attitudes toward utility of the real-time parking information, through on-site and follow up surveys. Note that on-site surveys also included drivers who only could obtain information from the Roadside Changeable Message Signs (CMS), although no distinction in the results was made between the participants who utilized the in-cab truck parking notification application.

7.3 IN-CAB REAL-TIME TRUCK PARKING NOTIFICATION METHODOLOGY

Two trucking companies participated in testing the SmartPark in-cab parking notification system. Each company outfitted five of their vehicles with the SmartPark system. During the test there were two active rest areas along the interstate 94 (I-94) corridor in Minnesota, Big Spunk Lake eastbound (EB) and Elm Creek EB (the facility near Maple Grove, MN). In the following analysis, an event is defined when a vehicle crosses through a specific geo-fence location. Once an event is established, a vehicle can record up to five such events for a given rest stop, one each for twenty, fifteen, ten, and five mile geo-fences and a fifth event for actually stopping to park. A vehicle may record less than four events if it departs the geo-fenced highway after initially crossing into a geo-fenced area. The collection of events for a given vehicle and a given rest stop at one period of time is considered a “pass”. Interestingly, one conclusion that was borne out from the data is that there were no instances of a driver stopping and parking at either of the rest stops registered with the application during the test.

In the field test study there were 594 distinct events spread across fifteen drivers. These events made up a total of 144 passes. Across the events, the average percentage of occupied spaces was 54.93 percent with the median value equal to 56.26 percent.

7.4 IN-CAB REAL-TIME TRUCK PARKING NOTIFICATION RESULTS

Several factors might influence a driver’s decision to stop at the rest area. One of these is the time of day during which the events occurred. However, while many events occurred during normal daylight hours, a significant number occurred between 10:00 PM and 5:00 AM in the morning, times when a driver might be expected to take a rest (Figure 7.3). Another contributing factor could be the remaining driving hours the driver has before going into violation. While the average number of hours available was 4.39 hours, there were instances in which the driver had less than an hour remaining, the smallest of which was 36 minutes. The number of miles a driver had covered from the start of his day at the time of an event might also be a factor in a driver’s decision to stop. The average number of miles that had been driven at an event was 347.96 miles. The least number of miles driven was less than ten miles while the largest was just under 950 miles.

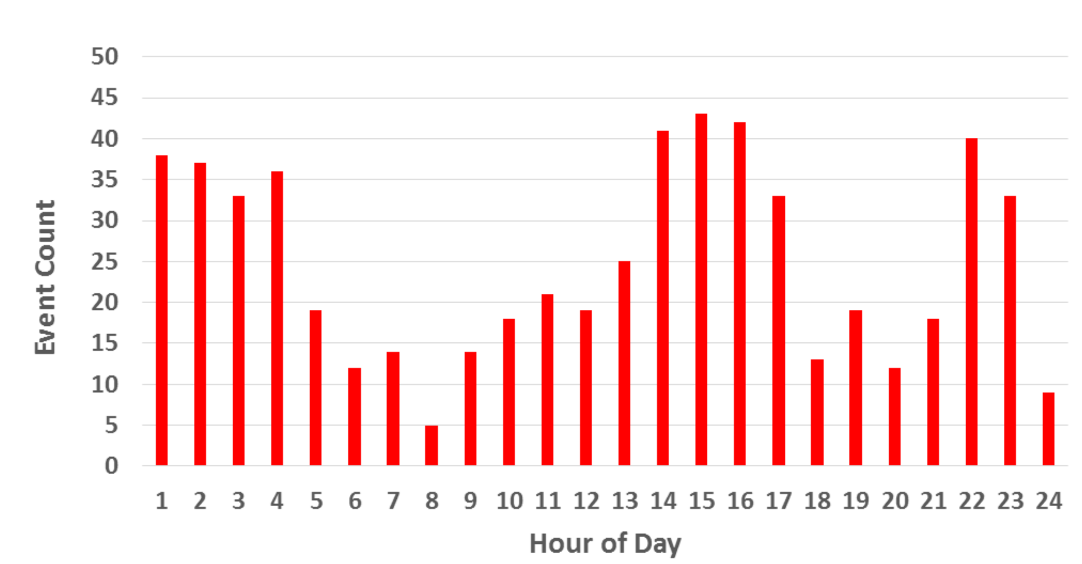


Figure 7.3. SmartPark events aggregated by hour of day.

To conclude, and in general, this aspect of the system usability study demonstrates that it is possible to geo-fence numerous parking facilities where available parking spaces can be determined using the TPAS parking space occupancy detection approach. Vehicles equipped with the SmartPark system running on telematics equipment can successfully retrieve the rest stop geo-fences each day and them to determine parking availability in a timely manner. The technology for informing the driver is functional and would be scalable to a much larger number of locations.

The fifteen drivers in the study recorded nearly 600 events. On average each driver experienced nearly forty alerting events for each of the two rest stops. One driver had over 120 events across the two stops and another recorded over 150 events. With the average driving hours remaining was above four, there were still events in which the driver had less than an hour of driving time remaining. The number of miles that had been driven by a driver at the time of an event was close to 350 miles. But some drivers had covered 700, 800 or 900 plus miles. As previously noted, many events occurred between 10:00 PM and 5:00 AM, a time when drivers might be expected to take their break.

7.5 REAL-TIME TRUCK PARKING INFORMATION SYSTEM EVALUATION METHODOLOGY

The ATRI team developed a survey which evaluated the perceptions and needs of truck drivers who utilized the real-time truck parking information system. The team received the contact information for drivers from the carriers participating in the testing of the aforementioned onboard real-time truck parking notification system. The ATRI team initially called each of these drivers to schedule a phone interview to complete the survey. In addition, ATRI researchers surveyed truck drivers at the Elm Creek rest stop who may encountered the Roadside CMS during the concept of operations field test, despite not having the onboard computer system.

7.6 REAL-TIME TRUCK PARKING INFORMATION SYSTEM EVALUATION RESULTS

7.6.1 Participant Demographics

Among the participants, 44.4 percent operate in the for-hire segment. Fifty percent of the for-hire drivers operate in the truckload sector, 25.0 percent operate in the less-than-truckload sector, and 25.0 percent operate in the express/parcel sector. Approximately 90 percent of participants identified as employee drivers, while 11.1 percent identified as an owner-operator ()-)) with own authority. The majority of drivers (66.6 percent), identified as long haul, hauling more than 1,000 miles per trip. Of the participants, 55.6 percent operate in fleets with 51 to 500 power units (PUs), followed by 22.2 percent operating in fleets with 21 to 50 PUs.

7.6.2 Truck Parking Information System Preferences

As done in the previous pre-implementation usability survey study in chapter CHAPTER 4: , the first set of questions addressed driver preferences for receiving real-time truck parking information. The first question of the survey asked drivers to rank order their preferred methods for receiving truck parking information, with 1 being the “most preferred” method and 4 being the “least preferred” method. As displayed in Figure 7.4, Sixty percent of drivers ranked onboard computers as the most preferred method for receiving truck parking availability information, followed by roadside CMS, a smart phone application, and a website.

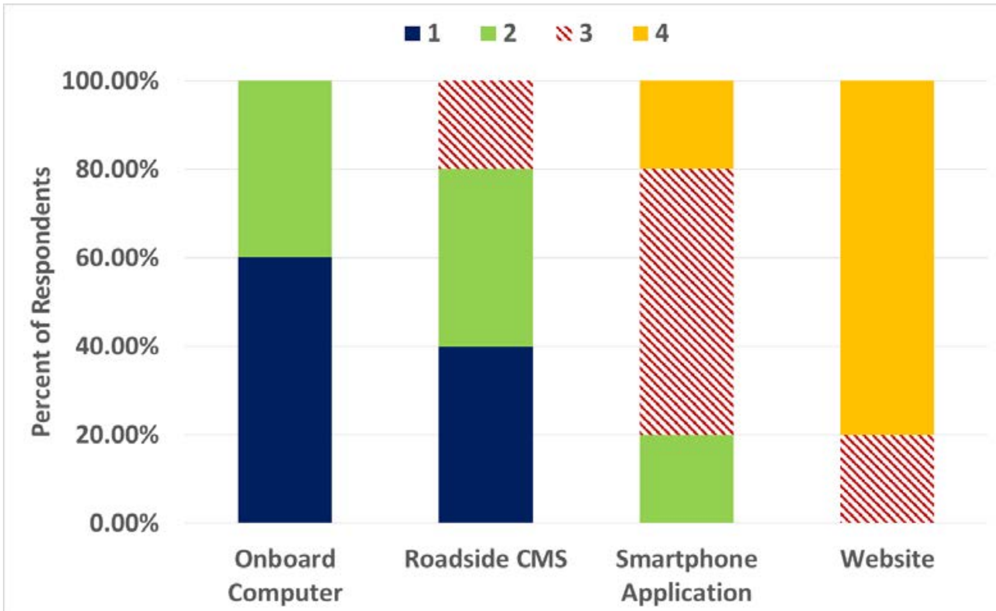


Figure 7.4. Preferred method for receiving truck parking availability information.

The next question asked the drivers, "How far ahead would you like to receive truck parking availability information?" As displayed in Figure 7.5, 44.4 percent would like to receive advance notification at twenty miles ahead of the rest stop. Of the 22.2 percent that selected "other", one driver indicated they would like to receive the advance notification fifty to 60 miles away, while another driver would like advance notifications 100 miles away.

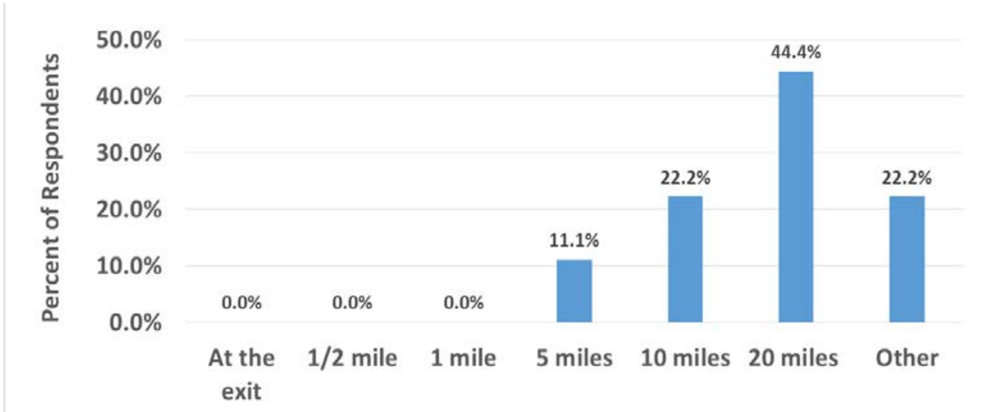


Figure 7.5. Preferred distance for advanced parking availability notification.

Next drivers were asked, "What factors are most important in selecting a truck parking location?" This was a multiple response question where drivers were instructed to select all applicable responses. As displayed in Table 7.1, 77.8 percent of drivers indicated "nearing their HOS daily driving limit" was an important factor in selecting a truck parking location, followed by 66.7 percent of respondents selecting "nearing HOS 30-minute rest break requirement". Note that regarding the response to "Nearing HOS 1am-5am requirement", at the time this survey was conducted, the Fiscal Year 2015 Omnibus Appropriations bill (which included language to suspend the "1:00 AM to 5:00 AM 2013 HOS provisions) had not been signed into law.

Table 7.1. Factors Influencing Selection of Truck Parking

Factor	Percent of Respondents
Changeable Message Sign	77.8%
Smartphone Application	66.7%
Internet/Website	55.6%
Onboard device	22.2%
Nearing HOS "1am-5am" requirement	11.1%
Staging for a pick up or drop-off	11.1%
Fueling	11.1%

The next question asked drivers, "If you were to receive advance notification of truck parking availability, which message would you prefer?" As displayed in Table 7.2, 37.5 percent of drivers would prefer a message that displayed the exact number of spaces available, while 50.0 percent indicated they would prefer either a categorical message, such as “low availability” or the exact number of spaces available.

Table 7.2. Preferred Message Display for Parking Availability

Parking Availability Message	Percent of Respondents
Exact number of spaces available	37.5%
Space availability: low, medium or high	12.5%
I would prefer either message	50.0%

7.6.3 Truck Parking Information System Impacts

The next set of questions addressed the impacts that the real-time truck parking information system has had on their operations. Drivers who participated in the concept of operations were asked, “What impact has the real-time truck parking information system had on your productivity?” Among the respondents, 66.6 percent indicated it has had a positive to very positive impact on their productivity (Figure 7.6).

To gauge the value of the experience from the study participant drivers, drivers who did not participate in the concept of operations were asked “What potential impact would a real-time truck parking information system have on your productivity?” Among these drivers, 66.7 percent indicated a positive to very positive impact on productivity.

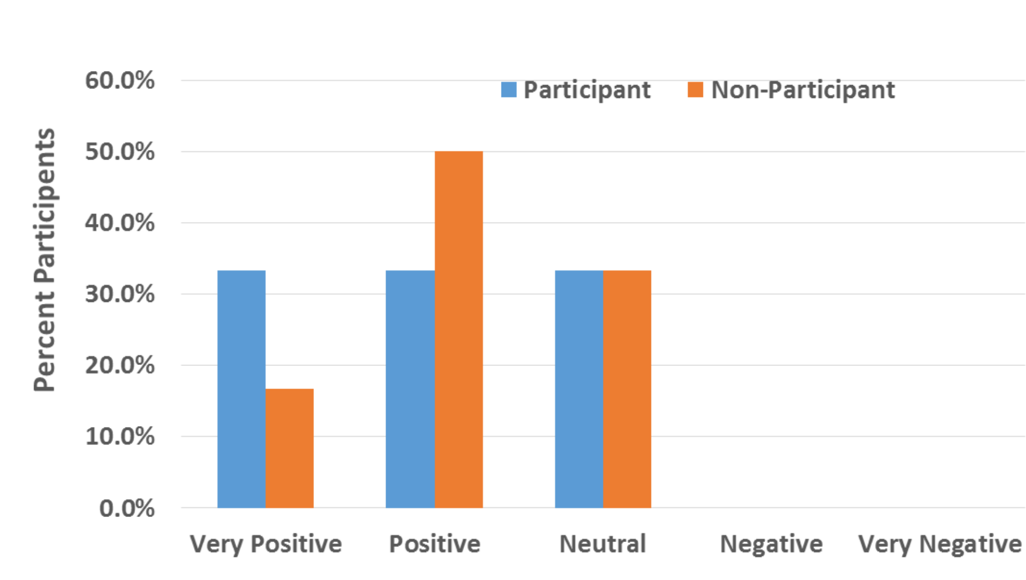


Figure 7.6. Impact of truck parking information system on productivity.

The next question addressed the impact that the real-time truck parking information system has had on a driver's ability to find available parking. As displayed in Figure 7.7, 66.7 percent of drivers that participated in the concept of operations indicated that the truck parking information system has had a significant impact on their ability to find available parking.

Drivers who did not participate in the concept of operations were asked "What potential impact would a real-time truck parking information system have on your ability to find available parking?" Among these drivers, 50 percent indicated a moderate impact.

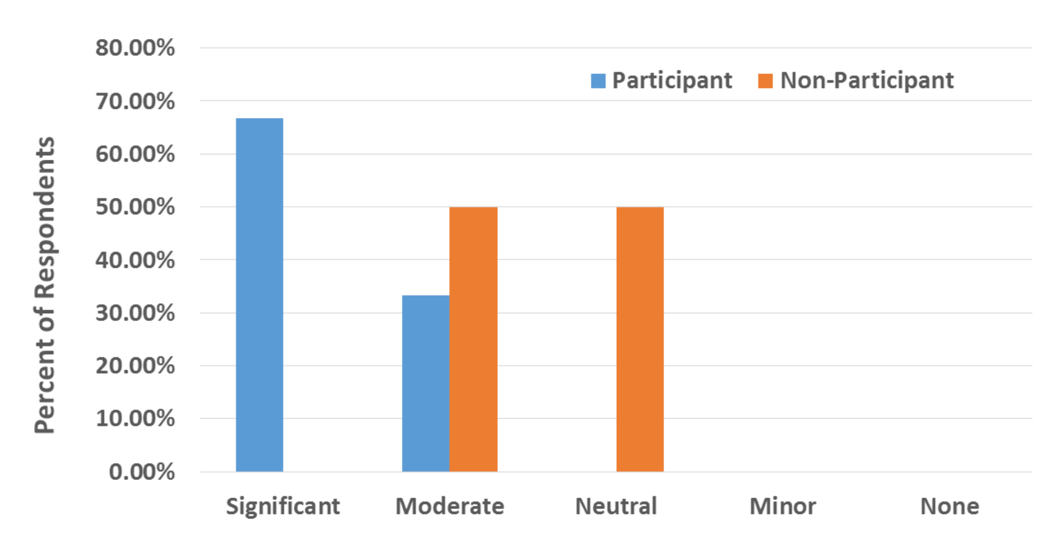


Figure 7.7. Impact of truck parking information system on the ability to find available parking.

Next drivers who participated in the concept of operations were asked, "What impact has the real-time truck parking information system had on your ability to comply with Hours-of-Service (HOS) regulations." Approximately 67 percent of drivers indicated that the truck parking information system has had a significant impact on their ability to comply with HOS regulations (Figure 7.7).

Drivers who did not participate in the concept of operations were asked "What potential impact would a real-time truck parking information system have on your ability to comply with HOS regulations?" Among these drivers, 33.3 percent indicated a significant impact.

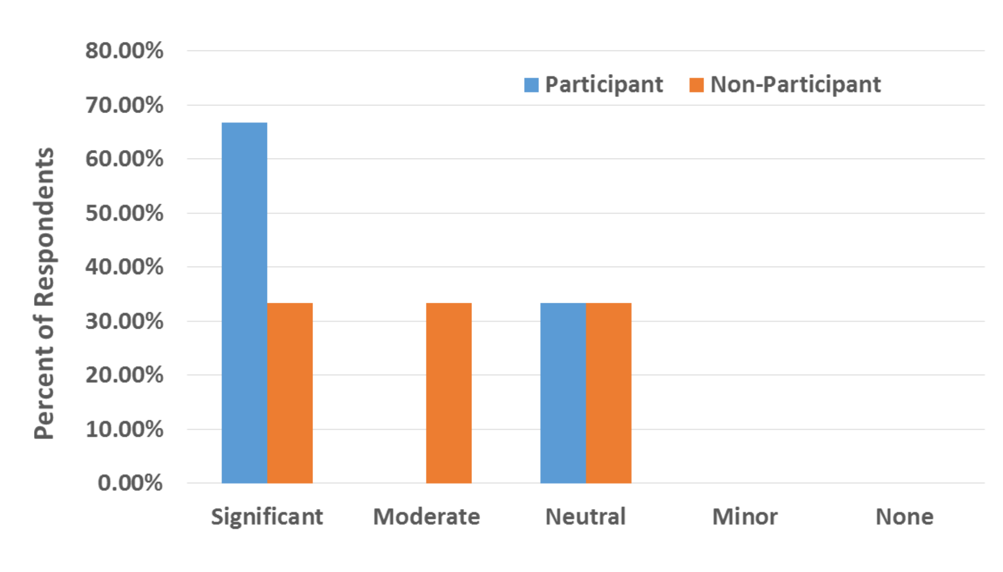


Figure 7.8. Impact of truck parking information system on ability to comply with HOS regulations.

7.6.4 Public Rest Stops and Private Truck Stops

The next set of questions queried drivers on their perceptions and use of public rest stops and private truck stops for parking. Drivers were asked, "Where is it more difficult to find available parking?" As displayed in Figure 7.9, 55.6 percent of drivers noted that finding available parking was equally difficult at public and private rest stops.

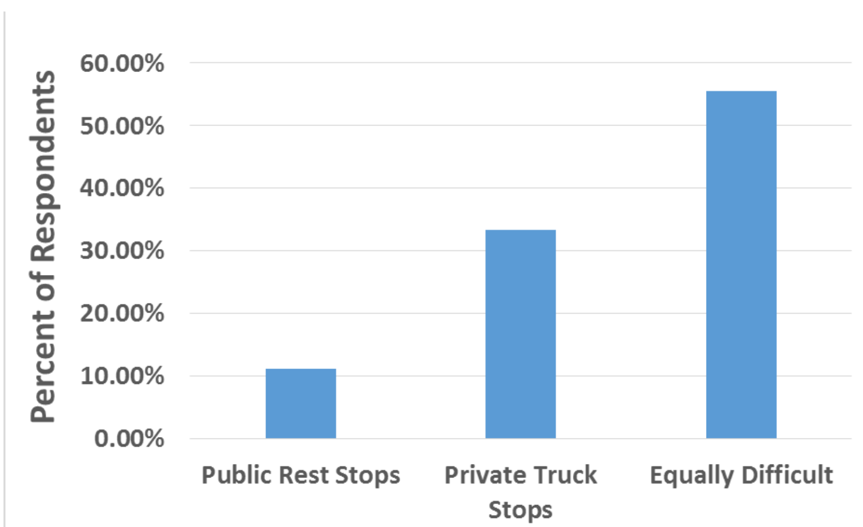


Figure 7.9. Where is it More Difficult to Find Available Parking?

Drivers were then asked, “For every 10 stops you make, how many are public rest stops and how many are private truck stops?” On average, drivers noted that 4.4 of their stops are at public rest stops and 5.6 of their stops are at private truck stops.

7.6.5 Addition Thoughts from Participants

The final set of questions were open-ended and asked drivers their overall perceptions and opinions of the real-time truck parking information system. The first question asked, “What do you like most about the real-time truck parking information system?” Among the responses to this question, drivers indicated they liked the advance parking availability notification that the in-cab telematics system provided. The drivers did not note any negatives or aspects they would like to change about the real-time truck parking information system.

Finally, drivers were asked, “Do you have any additional thoughts on the real-time truck parking information system’s impact on a driver’s ability to find available parking?” Among the responses, one driver indicated that the system would be especially useful for new routes where they would be less aware of available parking spots.

Another driver noted that integrating the real-time truck parking system with a GPS provider may be useful as the GPS systems provide traffic density information which is an important factor when selecting a parking spot. While the drivers found utility in the real-time truck parking information system, they noted they would not pay to reserve a parking space. Finally, drivers noted that this system would further increase truck driver efficiency and productivity if it was implemented across multiple states.

7.7 FIELD TEST CONCLUSIONS

The concept of operations field test provided valuable insights to where possible system wide improvements can be made, such as locating additional roadside message signs, and the value of real-time onboard parking availability notifications. The field testing period was carried out and monitored for about a four month period. Generally, the technology proved capable of reliably providing around-the-clock uninterrupted parking information to several information mechanisms; the available cellular communication infrastructure was generally very cost effective, albeit the system reliability would very likely be significantly better if system wide broadband were available.

Developing an advance notification, real-time truck parking information system could greatly assist drivers in productivity and compliance with federal regulations. Based on the responses to this concept of operation test, drivers would prefer to receive advance notification via onboard computers or Changeable Message Sign (CMS). In addition, the plurality of drivers (44.4 percent) would like to receive truck parking information at least 20 miles from the rest stop.

Among the top factors influencing the drivers’ parking decisions were if they were nearing their HOS maximum daily driving limit, nearing their 30-minute HOS rest break requirement or need to use the facilities. When surveyed on the CMS parking availability message, the majority of drivers (50.0 percent) indicated they would prefer either the exact number of spaces available or a categorical message (e.g., “space availability: low”).

Of the drivers that participated in the concept of operations test, 50 percent noted a positive impact of the real-time truck parking information system on their productivity. Likewise, 66.7 percent noted the system had a significant impact on their ability to find available truck parking and 66.7 percent noted a significant impact on their ability to comply with HOS regulations.

Overall drivers indicated they liked the advance notification feature of the onboard computer and CMS and that this information would be especially helpful if they were on unfamiliar routes. Furthermore, drivers indicated that if this system was implemented at a national or even multi-state level it would have an even greater impact on their productivity and efficiency.

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

The primary objective of this research project was to develop, test and demonstrate a comprehensive ITS approach to deliver truck parking information to drivers and carriers. In particular, a prerequisite of the approach was to avoid modifying pavement surfaces or underlying substructures since it would especially in seasonal climates such as the Midwest introduce excessive maintenance budgets while previous vehicle parking studies have proposed camera-based solutions, due to their ease of maintenance and wide availability, there were no non-intrusive systems to directly detect truck parking space availability. The team developed and deployed a multi-camera based per-stall truck parking detection system to allow around-the-clock, continuous parking detection at three state-sponsored truck parking facilities. The facilities have been in continuous operation, providing parking detection data for between 1.3 and 2.7 years, thus demonstrating overall operational efficacy across seasonal and weather variations in Minnesota. From the continuous operation of TPAS, it is evident that persistent parking detection over a variety of time periods and environmental conditions is achievable. Total occupancy count data are typically within ±1 count 95 percent of the time, and ±3 counts 99 to nearly 100 percent of the time. A per-space detection accuracy of 95 percent or better was achieved without any needed human intervention to re-calibrate the parking detections.

A concept of operations test evaluation indicated that drivers and operators who used the system during the test period could improve their productivity and better comply with federal HOS regulations for their long-haul trips. Results of comparative participant/non-participant usability assessments with in-cab notifications supported a clear impact in driver and carrier attitudes and perceptions for utilizing TPAS notifications to more efficiently plan and complete long-haul trips. Specifically, an increase of over 30 percent of drivers indicated significant impact for helping them comply with HOS regulations, and similarly an increase of 60 percent indicated it “significantly” helped them with their ability to find parking during their trips. More than half of all users traveling along the corridor (drivers and operators) indicated “positive” or “very positive” impacts of TPAS on their productivity.

The project evaluated detection performance in some detail through a variety of collected continuous operative datasets. There is a tendency for detection error to increase during nighttime vs daytime from reduced lighting and visibility. Some of the sources of detection errors were also correlated with driving and parking behaviors. Such parking scenarios, for example, vehicle maneuvers into and out of parking spaces are very transient in nature and generally the detections recover in subsequent time samples. For many cases of lane encroachment (double parking), part of a vehicle may be slightly over the parking stall lane and thus labeled by the observer as containing a double parking event when the detection indicated otherwise. Indeed, in some cases a truck pulled into the space at a later time. This does not necessarily infer that the detection was correct and the ground-truth observation was incorrect but rather there exists some degree of subjectivity in making this observation from one of the camera images. In short, the parking state was strictly assigned a binary state. We learned that there was some level of subjectivity in ground-truth process as a result and thus some variance in the detection error can be attributed to the ground-truth labeling process itself.

Second, an interesting parking behavior observation during the course of the project was the occurrence of one or more vacant parking spaces during periods where overcapacity was observed from the ground-truth camera views. That is, several vehicles were parked along overflow and near the ramp entrances, but there were designated truck parking spaces unoccupied. Actually, similar observations were noted in other parking studies [3]. A counting system under these scenarios would conclude that there were no parking spaces available because the facilities was 'over capacity' when in fact this was not the case, and therefore discouraged drivers from entering the facilities to utilize the vacant parking space. In short, regardless of the aforementioned detection errors and parking and environmental conditions that may have been associated with them, there was never the possibility for any of the aforementioned errors to continuously accumulate over time and require human interventions to correct before they rose to an unacceptable level.

Further improvements to detection performance should be possible with the current approach. Today's trends in professional commercial off-the-shelf surveillance camera sensors continue to improve lighting sensitivity and optics in order to improve signal-to-noise ratios during poorly lit scenes. In addition, non-invasive, low-power consumption outdoor illuminators in the Near Infrared range are widely available and might be a reasonable alternative to improve nighttime scene and vehicle illumination for very dark areas. In addition, image enhancements to improve contrast during low-visibility conditions should also be evaluated to further improve detection performance (with or without any lighting enhancements). Since it is clear that drivers and operators prefer truck parking notifications well ahead of downstream truck parking facilities, forecasting methods to predict parking availability at different time headways should be examined in light of the level of detection accuracy that can be achieved using this approach. Lastly, deployment cost reductions could be realized if existing infrastructure were to be used to mount cameras.

Generally, the cellular service communication links between instrumented truck parking facilities and the information retrieval and dissemination mechanisms were reliable; a service outage estimate of 2.5 minutes a day could be expected for any given site. The system gracefully recovers from the outages at the expense of delayed parking notifications. The operation of this system would benefit from higher speed broadband communication links to further improve the system reliability and remove the need to process and store any of the data on-site.

A more comprehensive study to understand the impact of truck parking availability information on truck parking behaviors along the corridor would further elucidate parking utilization and ultimately its costs and benefits. More instrumented parking facilities—at least along the same direction— would give drivers a more complete regional picture of truck parking. In this regard, such a study should include private truck stops since they represent a very significant portion of truck parking capacity along the corridor. It is possible to build in other information delivery protocols to fit other architectures suited for region-wide, interstate truck parking availability standards and delivery mechanisms. This should be part of a more wide-spread implementation of the system in future efforts. Second, with space-level detection capabilities, forecasting methodologies can be explored to predict parking availability at different headway time scales as drivers travel through the corridor to improve trip planning and logistics.

Lastly, the ensemble of individual parking behaviors through time and space being collected have not been exploited for this study. Facility usage performance metrics—such as where trucks tend to park, and the length of time such spaces were occupied, were not considered in this evaluation. Furthermore, the raw 3D point cloud data of occupied vehicles contain features that may be exploited to discriminate between different vehicle types to quantify facility space utilization trends by different user types [40] —for example, private vehicles vs. heavy commercial vehicles.

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APPENDIX A. TRUCK PARKING INFORMATION SYSTEM DRIVER SURVEY

TRUCK PARKING INFORMATION SYSTEM

DRIVER SURVEY

Supported by the Federal Highway Administration, the American Transportation Research Institute (ATRI) is working with several state departments of transportation to develop a real-time truck parking information system for truck drivers. ATRI is now documenting truck driver needs and suggestions for the system. Your input on the following questions is critical to ensuring that the truck parking system delivers value for truck drivers.

1. Gender

- Male
- Female

2. Age

- Younger than 25
- 25-44
- 45-64
- 65+

3. Employment Status (check one):

- Employee/Company Driver
- Owner-Operator/Independent Contractor

4. How many power units are operated by your employer (check one)?

- Less than 50
- 50-249
- 250-999
- 1,000+

6. What is your average length of haul (check one)?

- Local (less than 100 miles per trip)
- Regional (100-499 miles per trip)
- Long-Haul (500+ miles per trip)

7. What percent of your loads require travel on the I-94 corridor between North Dakota and Michigan, including Minnesota (check one)?

- 1 – 25%
- 26 – 50%
- 51 – 75%
- 76 – 100%
- None

8. Typically, how much advance notice do you have for your long-distance trips (check

one)?

- ▯ Less than 24 hours
- ▯ 1-4 days
- ▯ 5-9 days
- ▯ 10+ days

5. What is the primary vehicle configuration that you typically drive (check one)?

- ▯ 5-axle Dry Van
- ▯ 5-axle Flatbed
- ▯ 5-axle Tanker
- ▯ Straight Truck
- ▯ Longer Combination Vehicles (Doubles, Triples, etc.)
- ▯ Other (please specify)

9. How often do you personally experience the following issues (check one response for each row)?

Condition	Never	Rarely	Occasionally	Often	Always
Rest area time limit restrictions	❍	❍	❍	❍	❍
Parking only available on ramps or shoulders	❍	❍	❍	❍	❍
Parking only available in unsafe locations	❍	❍	❍	❍	❍
Truck vandalism	❍	❍	❍	❍	❍
Cargo theft	❍	❍	❍	❍	❍

10. Please rank order (1-11) the following reasons for seeking truck parking with 1 being the MOST important.

Truck Parking Reasons	Rank (1-11)
HOS Mandated Rest / Fatigue	
Awaiting Dispatch	
Avoiding Congestion	
Mechanical Issues/Failures	
Restaurant/Eating	
Showering/Restroom	
Staging/Waiting for Loads	
Obtaining Directions	
Safety Checks/Load Securement	
Personal Communication (e.g. cell, internet)	
Weather-related	

10. Please rank order (1-10) the following truck parking amenities with 1 being the MOST important.

Truck Parking Amenities	Rank (1-10)
Restrooms	
Fueling Services	
Restaurant	
Vending Machines	
Showers	
Retail Store	
Adequate Lighting	
Adequate Security	
Internet Access/Wi-Fi	
Access to the Interstate	
Other:	

12. How do you access the internet while on the road (check all that apply)?

- ▯ Truck Stop/Rest Area Kiosk
- ▯ Hotel/Motel Business Center
- ▯ Onboard Communication Device (e.g. PeopleNet, Qualcomm)
- ▯ Laptop in Vehicle
- ▯ Smartphone
- ▯ Other (please specify)

13. The I-94 truck parking information system will provide truck parking availability information through onboard communication/computer systems, internet and roadside message signs. Please rank order (1-5) your preferred method for receiving truck parking information, with 1 being the MOST preferred:

Method	Rank (1-5)
Onboard communications/computer system	
Internet/website information	
Roadside Changeable Message Signs	
Dispatcher Contact	
511 System	
Smartphone Application	
Other: ______________________________	

14. Please indicate how far away you would like to be notified of available truck parking (check all that apply):

Distance from Parking Location	
At the exit	❍
½ mile away	❍
1 mile away	❍
5 miles away	❍
10 miles away	❍
20 miles away	❍
Other:________________	❍

15. Would you like the ability to reserve a parking spot?

▯ Yes

▯ No

If yes, how much, if any, would you be willing to pay to have a guaranteed reservation?

____

16. Recognizing that the technology systems can be negatively impacted by power outages, system failures and other unintended consequences, please indicate the level of 'reliability' that you believe the system must provide to be useful to you (check one):

System Reliability	
Always 100% Reliable / Accurate	❍
85% or more Reliable / Accurate	❍
50% or more Reliable / Accurate	❍
25% or more Reliable / Accurate	❍
Other: ________________	❍

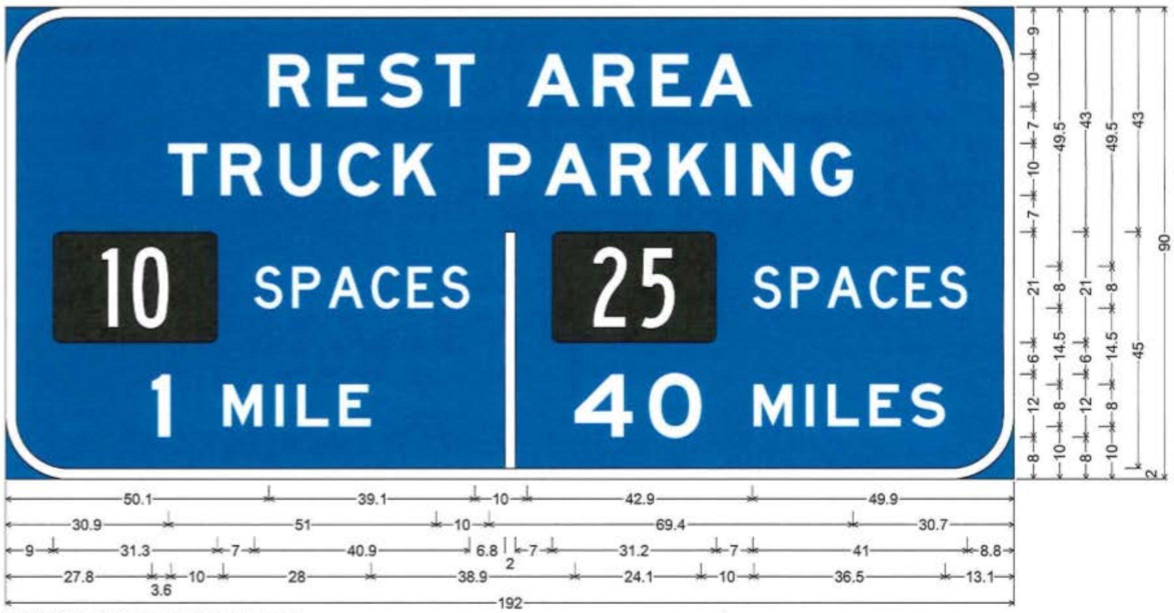
Thanks for your input!

APPENDIX B. MUTCD COMPLIANT HYBRID CMS DESIGN DETAILS

Both hybrid CMS designs were designed within SignCAD for MMUTCD compliant for with an approach design speed is 75 mph from 900 feet away, along a straight alignment road section, positioned 30 feet from clear zone.

12.0" Radius, 2.0" Border, White on Blue;
"REST AREA" E Mod; "TRUCK PARKING" E Mod; Rounded Rectangle 1.5" Radius Black;
"SPACES" D; "1 MILE" E Mod;

Figure B.1. Hybrid single rest area downstream truck parking information CMS design, with overall dimensions of 7.5 x 12.5 feet (2.3 x 3.8 m).



12.0" Radius, 2.0" Border, White on Blue;
"REST AREA" E Mod; "TRUCK PARKING" E Mod; Rounded Rectangle 1.5" Radius Black;
"SPACES" D; Rounded Rectangle 1.5" Radius Black;
"SPACES" D; "1 MILE" E Mod; "40 MILES" E Mod;

Figure B.2. Hybrid CMS design for displaying truck parking information for two downstream rest areas, with overall dimensions of 7.5 x 16 feet (2.3 x 4.9 m).