Real-Time Parking Information Integration, Visualization, and Prediction

WA-RD 904.1

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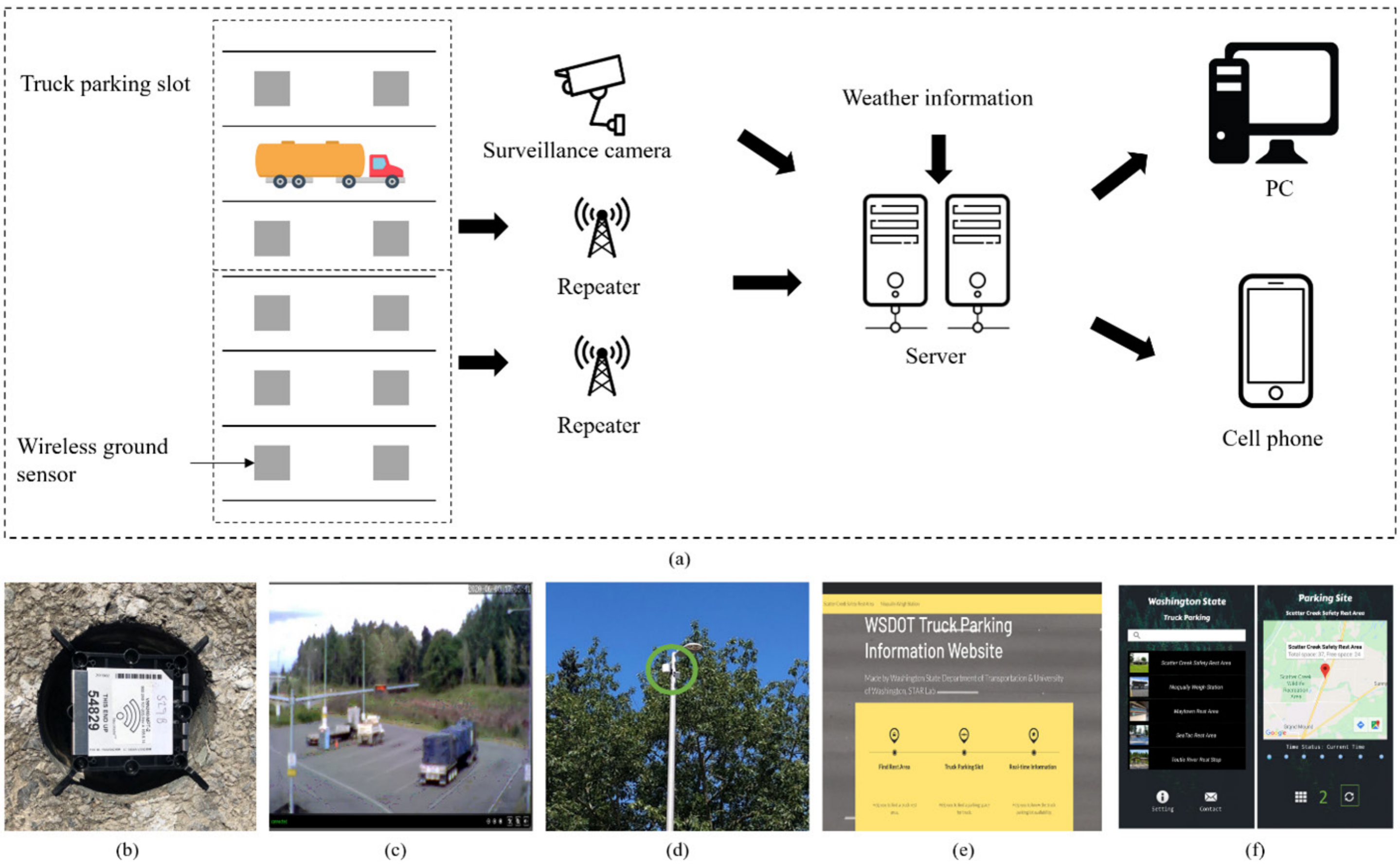
January 2023



Components of the Intelligent Truck Parking Information Management and Prediction System

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16. Abstract

The trucking industry plays a critical role in freight transportation in the United States. One major problem commonly recognized across the country is inadequate truck parking supply because existing truck parking facilities are struggling to meet the demand of increasing numbers of trucks on the road. Lack of parking spaces and real-time parking availability information greatly exacerbates the uncertainty of trips and often results in illegal parking and/or overtime driving.

In this project, WSDOT worked with the research team at the University of Washington (UW) Smart Transportation Applications and Research Laboratory (STAR Lab) to conduct a truck parking pilot study on advanced truck parking management systems. Specifically, this project developed a comprehensive solution in which a parking detection system collects and processes robust, real-time parking data, a predication algorithm estimates future parking availability information, and an online parking availability information platform accessible from smart phones and other personal electronic devices provides real-time and predicted parking information. Empowered by artificial intelligence and a deep learning prediction algorithm, the pilot Truck Parking Information Management System (TPIMS) achieved an error rate of less than 12 percent in predicting parking availability from 10 minutes to four hours ahead. Both the real-time and multi-timescale prediction occupancy information is successfully disseminated via a customized website and user applications in real time. This real-time truck facility monitoring information and truck parking availability prediction will provide information to truck drivers for trip routing and scheduling arrangements.

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1. INTRODUCTION AND BACKGROUND

Existing truck parking facilities, such as freeway rest areas, welcome centers, and weigh stations, are struggling to meet the demand of increasing numbers of trucks on the road, causing challenges for truck drivers to find appropriate parking spaces. Because inadequate parking can lead to many safety concerns, such as illegal parking and fatigued driving, it is highly desirable to offer truck drivers real-time information about the availability of parking spaces so that truck drivers can make informed decisions on when and where to park to avoid potential problems. Since current truck parking resources are insufficient for meeting the increasing demand of truck drivers in the U.S., the American Transportation Research Institute lists truck parking as a priority research topic (Boris and Johnson, 2015). The Washington State Department of Transportation (WSDOT) is fully aware of the growing challenges of the truck parking shortage and seeks cost-effective solutions to enhance the usage efficiency of existing truck parking facilities (Washington State Truck Parking Study, 2016).

The system that collects and conveys real-time parking information to truck drivers is called the Truck Parking Information Management System (TPIMS). A TPIMS normally functions in three steps: parking detection, data processing and parking availability prediction, and information dissemination. First, real-time truck parking data are collected by parking sensors. Then, the sensor data are processed to determine the current truck parking status and to predict future parking availability based on historical data and other relevant factors. Finally, the truck parking availability information is disseminated to truck drivers via dynamic message signs, websites, mobile apps, etc. In recent years, many states have installed and implemented such systems at their parking facilities, such as welcome centers, weigh stations, and safety rest areas (Federal Highway Administration, 2018).

While choices of parking detection approaches and technologies vary among states, studies have shown that the implemented approaches and technologies have a relatively high accuracy. The Minnesota Department of Transportation implemented a multi-view camera system to monitor truck parking availability with an accuracy of 95 percent or more (Morris et al, 2017). The Florida Department of Transportation implemented the Truck Parking Availability Systems (TPAS), which applied wireless in-ground sensor technology. The University of Florida Transportation Institute found that it had an accuracy of over 95 percent (Sun, 2018). With the development of truck parking detection technologies, more research is needed to study their pros and cons given factors such as installation, operations, maintenance, detection accuracy, reliability, and lifecycle cost for better guidance to inform the technology implemented for TPIMS.

Besides providing real-time parking availability information, a TPIMS would be of great help to truck drivers if it could provide a reasonably accurate prediction of parking availability for certain truck parking facilities. Being aware of predicted parking availability information could help guide truck drivers to better schedule their stops at parking facilities. There have been studies and applications of truck parking availability prediction based on real-time and historical truck parking data. Bayraktar et al. (2014) developed a truck parking management system that applied the Kalman filter approach to forecast parking lot occupancy. Sadek, Martin, and Shaheen (2018) proposed a Fourier method to predict truck parking occupancy for any specified time within the present day. Ioannou and Almeida (2018) studied several methods for truck parking availability prediction: a nonhomogeneous Poisson model, multivariate spatiotemporal model, curve similarity model, historical average model, and decision model. The results, however, indicated that none of the studied prediction methods based on traditional statical models performed significantly better than others, especially considering the impact of environmental factors. With more flexible architectures and the strong capacity for non-linear relationship modeling, neural networks are an encouraging choice for parking occupancy forecasting. This research detailed through this report evaluated application of these cutting-edge machine learning technologies to the prediction of truck parking availability.

2. RESEARCH OBJECTIVES

To address the truck parking challenges, WSDOT launched this research project with the University of Washington (UW) Smart Transportation Applications and Research Laboratory (STAR Lab). This project aimed to provide real-time truck parking information and predicted short-term truck parking space availability to truck drivers via a web service and a mobile application. Parking availability information can be predicted by using a novel artificial intelligence model based on historical truck parking space occupancy data as well as other contributing factors. To achieve this goal, the following three research objectives were accomplished in this project:

1. Assessed truck detection accuracy and parking pattern prediction accuracy. Leveraging the research team's expertise in vehicle detection research and prior experience in developing vehicle detection devices, truck parking detection technologies were assessed through published research materials. The most promising technology was selected for field evaluation in this project.
2. Provided real-time visualization of truck parking space information to assist truck drivers in obtaining available parking spots. The truck parking space availability information of multiple parking lots was collected by truck detection devices embedded in pavement and transmitted to a truck parking information center. A mobile application needed to be developed to receive the parking availability information from the center and to efficiently offer visual, real-time availability information.
3. Predicted short-term parking availability to support truck drivers in choosing available safety rest areas or parking lots and plan their driving routes. Studies have shown that vehicle operators spend a lot of time searching for parking spots, and availability may change when drivers arrive at parking lots (Washington State Truck Parking Study, 2016). Because truck detection devices continuously collect parking spot occupancy data, truck parking patterns can be measured and predicted on the basis of historical parking data, as well as other observed factors. Proper parking availability prediction algorithms were needed the predicted results and shared to truck drivers via a website as well as a mobile application.

The deliverables of this research include the following:

1) a comprehensive research report that documents the state-of-the-practice of parking sensors and parking availability predication algorithms; the results of the evaluation of the parking sensor selected for field experiment, design, and implementation of the TPIMS using data collected from the study sites; and a machine-learning algorithm developed for future truck parking availability;
2) a TPIMS website;
3) a mobile application that shows the real-time and predicted truck parking information at the study sites.

The results from this work provide a better understanding of the advantages, disadvantages, and retrofitting feasibility of the existing truck parking detection products and the current technologies used for TPIMS implementations. The mobile application and website serve as channels to disseminate both real-time and predicted truck parking availability information to truck drivers. Feedback on the TPIMS can also be collected from website and application users. These research products are expected to help improve the TPIMS and enhance the efficiency of truck parking infrastructure usage, thereby increasing the robustness of the entire freight operations network.

3. LITERATURE REVIEW

3.1 LITERATURE REVIEW SUMMARY

To accomplish the research goals, the researchers conducted a comprehensive literature review focused on three critical topics. The first topic was existing truck parking detection devices or systems. A comprehensive understanding of existing sensing technologies and products would help in finding a proper way to assess the truck parking detection sensors adopted in this project and would further enhance overall truck parking detection accuracy. The second topic of the literature review was web and mobile applications to provide truck parking availability information to truck drivers. Being aware of related or similar applications would be critical to developing a well-designed and ready-to-use mobile application. The third topic was existing algorithms for truck parking prediction or truck mobility patterns measurement, especially those focusing on historical data-based and online-learning algorithms.

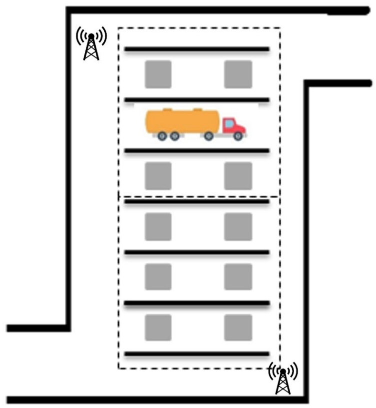
3.2 TRUCK PARKING INFORMATION MANAGEMENT SYSTEM

In general, a TPIMS includes three components: parking detection, data processing, and information dissemination. For occupancy detection, two major types of sensor approaches have been applied in TPIMS: the space-by-space approach and the entrance/exit count approach. Detailed information and summarization can be found in Table 3–1. The space-by-space approach involves the installation of parking detection sensors in each parking space and monitoring of the slot occupancy status. The entrance/exit count approach involves the installation of sensors at the entrance and exit of the parking facility to count trucks as they enter and exit the facility. Recently, many technologies and products have been developed and implemented for truck parking detection. These include closed-circuit television, camera vision systems, in-ground sensors, and side laser scanners (Federal Highway Administration, 2018).

Table 3–1. Function Summarization of Current Approaches to TPIMS by MAASTO - Adapted from MAASTO Annual Report (Luley, D., et al., 2018)

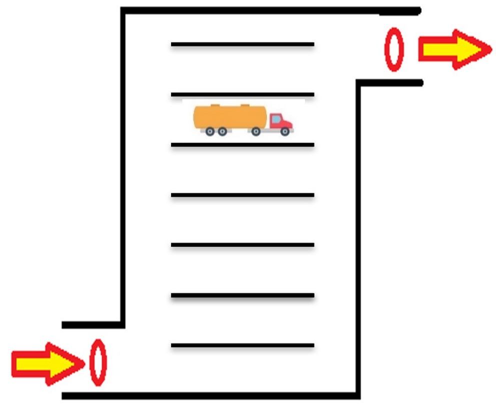
Functions	Michigan	Kentucky	Wisconsin	Indiana	Kansas	Minnesota
Data Collection Method	In/Out	In/Out	In/Out	In/Out	Space-by-Space	Space-by-Space
Data Collection Technology	Video	Radar	Magnetometer	Magnetometer	Video Rendering	Magnetometer
	N/A	Video	N/A	N/A	N/A	N/A
Operations & Maintenance	MDOT	KYTC	3rd Party	INDOT	3rd Party	MNDOT
	N/A		N/A	N/A	N/A	N/A
Information Dissemination	Roadside Signs, State Traveler Information site; 3rd party data feed	Roadside Signs, State Traveler Information site; 3rd party data feed	Roadside Signs, State Traveler Information site; 3rd party data feed	Roadside Signs, State Traveler Information site; 3rd party data feed	Roadside Signs, State Traveler Information site; 3rd party data feed	Roadside Signs, State Traveler Information site; 3rd party data feed

3.2.1 Data Collection Architecture Summary



(a)

Illustration of space-by-space sensing architecture

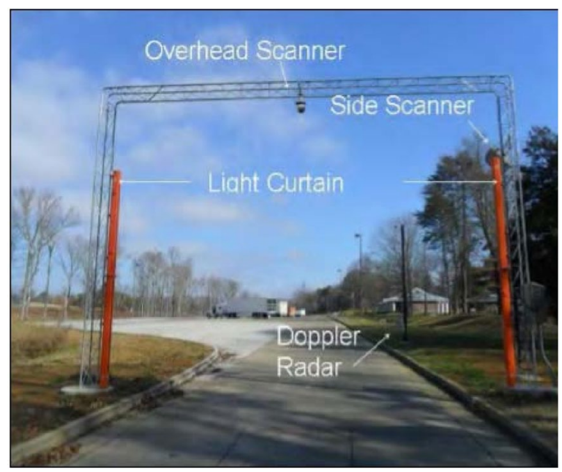


(b)

Illustration of in/out sensing architecture

(c)

Space-by-space sensing system in Washington



(d)

In/out detector configuration in Tennessee (Golias, et al., 2018)

Figure 3–1. Parking Sensing Facilities Illustrations and Examples, Including Space-by-Space and In/Out System

Current truck parking sensing systems can be divided into two approaches: space-by-space (decentralized) sensing or entry/exit (centralized) sensing (Luley, D., et al., 2018). Examples can be found in Figure 3–1. Parking Sensing Facilities Illustrations and Examples, Including Space-by-Space and In/Out System The decentralized system always relies on the sensors installed in each parking slot to monitor each parking slot status. Under normal circumstances, the decentralized system is more accurate and reliable, but it is usually more costly and requires a complex installation process. The centralized system installs sensors at the parking lot entrance/exit to count the number of vehicles entering and exiting the facility. In comparison with the slot-based approach, the entry/exit system is cheaper and easier to deploy. However, if the sensing technology is not very reliable, then such systems require personnel to provide frequent manual checks to prevent the accumulation of detection errors.

3.2.2 Sensor Technology Summary

(a)

BOSCH magnetic Sensor (Mutiara et al, 2017)

(b)

NWAVE magnetic sensor (NWAVE, 2021)

(c)

Sensys radar sensor (Sensys Network, 2021)

Figure 3–2. Parking Space-by-Space Sensor Facilities

(a) <u>Magnetic Sensors</u>

Magnetic sensors can be used to detect the presence of vehicles, and a data acquisition system based on magnetic detectors can play an important role in the parking system. The basic principle of the sensor is to measure the resistance change triggered by environmental magnetic field fluctuations. Specifically, the magnetic sensor detects motor vehicles through analysis of changes in the Earth's original magnetic field. When there are no motor vehicles on the local magnetic sensor, the Earth's magnetic field is in a relatively stable state, and the system defaults to no car. In general, the magnetic parking space detection sensor is embedded in the ground and powered by a battery. When the vehicle occupies the parking space, the magnetic sensor detects the change in the external magnetic field caused by the truck and triggers the state change. Bosch (Bosch 2021, Mutiara et al. 2017, Linares 2018) and NWAVE (NWAVE, 2021) have developed magnetic-based parking detection technologies that can sense slot occupancy status. The vehicle information (existence, occupancy rate, and other traffic parameters) detected by the sensor is sent to the cloud through wireless communication technology and then transmitted to the vehicle management system, toll system, or other application systems (Williams, 2019).

(b) Radar Sensors

The radar detector is a new type of parking sensor. In general, the sensor transmitter shoots electromagnetic wave energy in a certain direction via an antenna, and an object in that direction reflects the electromagnetic wave encountered. The radar antenna receives the reflected wave, which is processed to extract certain information about the object (the distance from the target object to the radar, the rate of change of range or radial velocity, azimuth, altitude, etc.). The specific purpose and structure of various radars vary, but the basic components are the same: the transmitter, transmitting antenna, receiver, receiving antenna, processing part, etc. In comparison to traditional magnetic sensors, radar parking sensors have the advantages of smaller size, higher accuracy, and longer service life.

(c) Video Sensors

Sensors that use real-time video technology to detect the parking status of trucks have been tested and used in recent years (Vital FD, et al, 2020). With object detection and recognition technology, these video sensing devices automatically detect the entry/exit of vehicles parked on the road. Some sensors use deep learning embedded cameras as front-end parking management perception devices and use video analytics methods to achieve parking status detection, conduct vehicle parking motion detection and capture, and record the complete process of vehicle parking in detail. In general, the video-based solution greatly improves the efficiency of parking space management. Specifically, for truck parking monitoring, video-based detection is easy to install and provides rich information. However, its reliability is not sufficient for 24/7 accurate detection, since the detection result is highly affected by occlusions, weather, and lighting conditions (Vital, et al, 2020).

3.2.3 Information Dissemination Website and Applications Review

(a) Existing Website Services Review

In this study, the researchers first conducted a detailed review of the current websites for truck parking services on the market. These sites included the following:

- **Pilot Flying J (https://pilotflyingj.com/).** Pilot Flying J is a truck rest stop operator, with 750 stations in the United States and Canada and operations in 44 states. It provides refueling services, retail services, truck roadside assistance services, etc.
- **Truck Parking Europe (https://app.truckparkingeurope.com/).** Truck Parking Europe is an online platform that helps truck drivers plan their European parking locations by showing truck drivers safe parking spaces available along their route and allowing them to book locations online.
- **Trucker Path (https://truckerpath.com/).** Trucker Path is an itinerary planning product that helps truck drivers, enabling drivers in the huge truck driver community to assist each other by updating and sharing relevant key points of information on the road in real time (Hernández and Anderson, 2017).
- **American Truck Parking™** (**https://www.americantruckparking.com/**). American Truck Parking™ is an information platform that aims to serve truck drivers who transport goods across the United States by providing them with information on the availability of truck parking lots and parking spaces (Sadek et al., 2020).

(d) Website Function Summary and Comparison

A review of the current popular truck parking services websites revealed that their functions can be summarized into five categories:

- **Parking Lot and Amenities Information**. The parking lot and amenities features include general parking-related information, such as the number of total available spaces, restroom information, convenience store status, parking lot spatial visualization, etc.

- **Real-time Slot Information Availability.** Real-time truck parking information represents the real-time utility of the truck parking lot. In general, the information is updated frequently, e.g., every five minutes, based on the parking sensor inputs.
- **Occupancy Prediction.** Besides real-time utility status, predictions of future parking occupancy levels is also useful for truck drivers. Occupancy prediction is predicting future parking availability and providing such information to truck drivers.
- **Security Information.** Security information represents parking lot safety-related features and facilities, such as the surveillance monitoring system, illuminating status, emergency call station information, etc.
- **Location and Navigation.** The integration of detailed address and navigation information, i.e., links, interfaces, and APIs, that can help CV operators find the parking lot by using navigation applications.

Table 3–2 shows a function summary of current truck parking services websites. From Table 3–2, it is obvious that most websites provide static parking lot information, including lot features, amenities, location, and security information, whereas only Pilot Flying J provides necessary dynamic parking occupancy information and prediction services. However, Pilot Flying J does not have future slot status estimation for truck drivers. So, one of key goals of this research was to combine the five kinds of information into a website/mobile app and provide reliable and timely information services to both truck drivers and traffic managers.

Table 3–2. Function Summary of Current Truck Parking Services Websites (N (No), Y (Yes))

Name/Function	Parking Lot and Amenities Information	Real-time Slot Information	Occupancy Prediction	Security Information	Location and Navigation
Truck Parking Europe	Y	N	N	Y	Y
Trucker Path	Y	N	N	Y	Y
American Truck Parking	Y	N	N	Y	Y
Pilot Flying J	N	Some	N	Y	Y
Ours Pilot TPIMS	**Y**	**Y**	**Y**	**Y**	**Y**

3.3 TRUCK PARKING PATTERN ANALYSIS METHODOLOGY

3.3.1 Truck Parking Pattern Analysis

Detailed pattern analysis for truck parking requires a large amount of high-quality truck parking data. With the rapid development of traffic sensing technologies in recent years, many states (including California, Florida, and Minnesota) have implemented TPIMSs at public parking facilities that require the installation of highly accurate detection systems. With accurate and reliable parking data becoming more available, further research on the detailed truck parking pattern analysis and aggregation can be conducted.

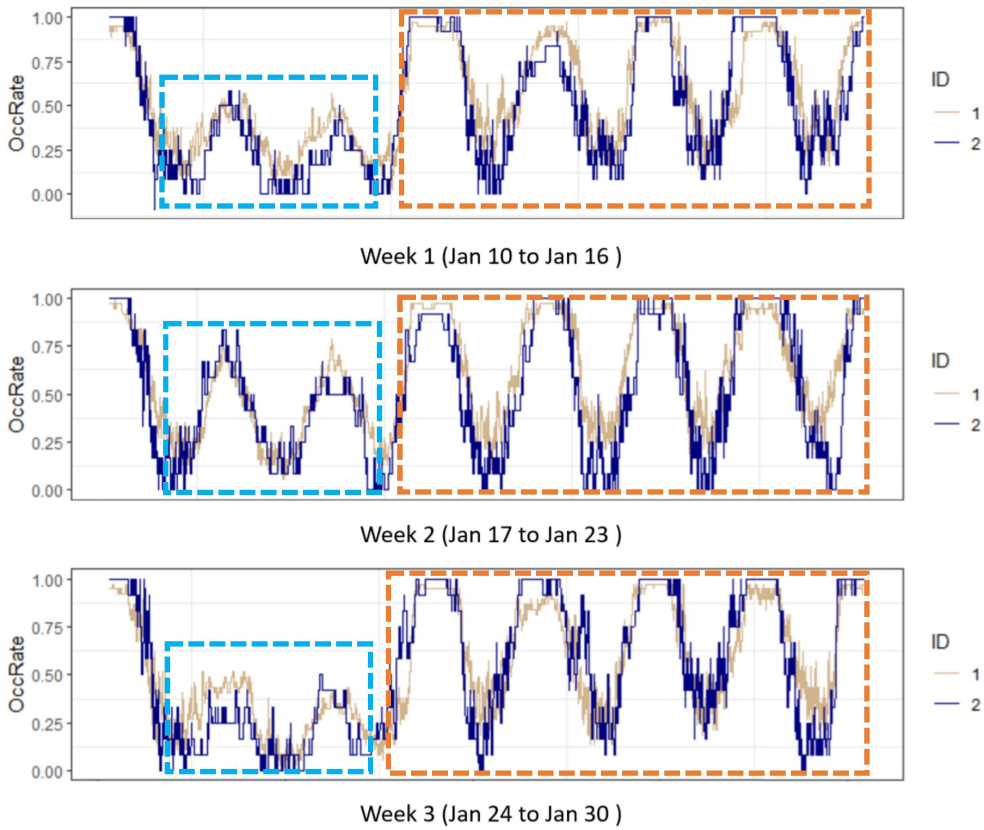
With the TPIMS, detailed pattern analysis can be divided into several perspectives. First, spatial-temporal information (i.e., the location of the truck parking lot, hour of day, and day of week) is critical for availability analysis (Sadek, et al. 2020, Mahmud, et al. 2020). Second, attribute information (i.e., weather, parking lot support facilities such as restrooms and food stores) is useful to help people understand how external attributes influence freight activities and how to provide truck drivers with better services. Last but not least, quantitative truck parking pattern analysis, including distribution correlation and similarity analysis, can help researchers understand the hidden internal relationships among truck parking activities.

3.3.2 Pattern Similarity Analysis

In traffic data analysis, the main goal of similarity calculation is to estimate the mathematical distance of the given input sequences and classify data to match the real application with pre-defined scenarios. Then, different categories are treated by customized rules according to restrictions in the scene. For example, as shown in Figure 3–3. Weekly Truck Parking Occupancy Sequence Similarity Visualization.

In the project, two truck parking lots were selected as the testing set, and the IDs represent the two truck parking lots used for data collection. The x-axis is time, and the y-axis is the occupancy rate. The sequence in the blue rectangle represents the parking patterns during weekend days (Saturday and Sunday), and the weekday's patterns are in the red rectangle. A high sequence similarity can be found for the same parking lot on different weekdays and weekend. So when the parking pattern characteristics of the parking lot are easily clustered for various days of the week, a manager can obtain an idea of the weekly parking distribution and then can make a period management plan for weekdays and weekends.

Furthermore, in parking lot management, similarity analysis of parking occupancy rates and parking patterns in different locations and different periods can be conducted to set up different management schemes, thereby achieving dynamic control and optimizing benefits. Also, in dynamic traffic control, some classic scenarios and corresponding solutions can be prepared. When the actual traffic situation is similar to the preset mode, then the system can automatically intervene according to the original control mode. Then, when information recommendations are provided for drivers and vehicles, their similarity can be calculated on the basis of target features and then combined with the subject that needs to be matched to give as many suitable alternatives as possible (Jiang, S. et al, 2015, Doyle, P.K. et al, 2020).



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Due to the significance of similarity analysis, several similarity methods, including the traditional Euclidean Distance, the Levenshtein Distance, the Cosine Similarity, and the Pearson Correlation Coefficient have been proposed in the last decades for use in various fields of study (Danielsson, 1980, Li and Liu, 2007, Najim et al., 2010, Jacob et al., 2009). The measurement of similarity in traffic mobility patterns has been studied for its critical role in numerous applications: (1) to form the basis for classifying individuals; (2) to quantify the goodness-of-fit in assessing how well observed activity-based patterns are predicted; and (3) to properly capture the sequential relationships embedded in activity-based patterns. However, unlike in other research fields, most similarity measures used in transportation science should be able to depict the sequential relationships along both temporal and spatial scales. For example, Hamming Distance (Waggener et al., 1995 and Qian et al., 2004) and Manhattan Distance (Qian et al., 2004, Stabili et al., 2017, and Li et al., 2017) are most used for traffic flow data similarity analysis.

For parking data analysis, the similarity is difficult to define and calculate because of its reliability on spatial and temporal features. For example, if parking slot A is occupied from 8:00 AM to 6:00 PM every day, while slot B is occupied from 9:00 AM to 7:00 PM every day, it is not easy to calculate the similarity between the two parking slots. With the traditional similarity calculation method, the two slots are totally different, whereas it is easy to see that the two slots have a similar pattern but a one-hour gap. The similarity between the two slots could be 0, or 23/24, or something else. This example indicates temporal dependency. Therefore, in the transportation field, there is still a long way to go in solving similarity and classification problems.

All the methods mentioned above can only deal with the distances between points or vectors and cannot handle the directional sequences similarity calculation. Furthermore, the variance in length of the two sequences generates more challenges. The sequence alignment method (SAM) is a sequence comparison method, that can address these challenges where the smallest number of changes (mutations) required to equalize the sequential order of letters between two strings is assumed to be an indicator of the true (dis)similarity (Joh et al., 2002). Since Wilson introduced SAM in the transportation field in 1998 (Wilson, C., 1998), it has been used in many studies on human mobility, travel route choice, and traffic safety. Nevertheless, SAM could only calculate the similarity between two uni-dimensional sequences until Joh introduced the multi-dimensional sequence alignment method (MSAM) in 2002. However, for the truck parking scenario, none of the similarity methods mentioned above will work well for the following three reasons: 1) none of the methods can handle temporal sequences; 2) they can only handle sequences with equal lengths; and 3) they cannot handle numeric elements.

3.3.3 Customized Advanced Sequence Alignment Method (ASAM)

Therefore, the Advanced Sequence Alignment Method (ASAM) was proposed, based on the traditional Sequence Alignment Method (SAM), to address the problem. Since Wilson first used SAM in the transportation field in 1998 (Wilson, C., 1998), many studies using the method have achieved satisfying results in studying human mobility, travel route choice, and traffic safety. In comparison to traditional SAM, the ASAM has the following advantages: 1) it can handle temporal/spatial dependency; 2) it can handle sequences with numerical elements; and 3) it can handle sequences with various lengths. The smallest number of changes (mutations) required to equalize the sequential order of letters between two strings is assumed to be an indicator of true (dis)similarity.

A simple example to illustrate ASAM is shown in Figure 3–4. Source sequence S = {3, 2, 0, 9}, and the target sequence T = {1, 2, 3, 4}. We assume Set 4 is the threshold in the case. Figure 3–4 (b) shows the result, and the minimum effort required is 4.5. The value in the matrix indicates the minimum effort needed to reach the position through the four operations: "Insert," "Delete," "Identify," and "Subtract." For example, the minimum effort required to reach (3,3) is 2.5. Similarly, in the graph, the horizontal arrows (i.e., the arrows pointing from *(i, j)* to *(i, j+1))* indicate the insert operation; the vertical arrows (i.e., the arrows pointing from *(i, j)* to *(i+1, j))* indicate the delete operation; and the oblique arrows (i.e., the arrows pointing from *(i, j)* to *(i+1, j+1))* represent the identify and subtract operations. If the values in *(i, j)* and *(i+1, j+1)* are the same, then the arrow denotes the "Identify" operation; otherwise, it denotes the "Subtract" operation.

Target

Source		Null	1	2	3	4
	Null	0	1	2	3	4
	3	1	1	1.5	2	3
	2	2	1.5	1	2	3
	0	3	2.5	2	2.5	3.5
	9	4	3.5	3	3.5	4.5

(a) Sequence Alignments cost matrix

NO	Explanation	Result	Operation Cost	Accumulated efforts
0	No operation	{3, 2, 0, 9}	0	0
1	Subtract "3" to "1" at position 1 of source sequence	{1, 2, 0, 9}	(3-1)/4*2=1	1
2	Identify the element on position 2 are the same (both "2")	{1, 2, 0, 9}	0	1
3	Subtract "0" to "3" at position 3 of source sequence	{1, 2, 3, 9}	(3-0)/4*2=1.5	2.5
4	Insert "4" to the position 4 of source sequence	{1, 2, 3, 4, 9}	1	3.5
5	Delete "9" from the position 5 of source sequence	{1, 2, 3, 4}	1	4.5

(b) Sequence Alignments operations explanation

Figure 3–4. Illustration of the ASAM Similarity Calculation Process

To apply the operation "Subtract" in the similarity calculation, a threshold must be determined based on the range and the importance of the value. If the difference between the two values exceeds the threshold, then the ASAM regards the difference as the sum costs of the "Delete" and "Insert" operations. If the difference is under the threshold, then the cost of "Subtract" should be calculated based on the threshold.

To formally specify the ASAM, we assume that the source sequence is a pattern that can be found. In the ASAM, there are two sequences, including the source sequence $S = \{S_i\}$, $i = \{1, 2, ..., m\}$ and the target sequence $T = \{T_j\}$; the 24 hours of a day and the elements in the matrix are $j = \{1, 2, ..., n\}$. Therefore, the total operation (O) indicates the similarity between the source and target truck parking sequences. Specifically, the "*insert(j)*" indicates the insertion of the j^{th} element into the j^{th} position of the source sequence. The "Delete" operation *delete*(i) indicates the deletion of the i^{th} element of the source sequence; the "Identify" operation *identify*(i) indicates the identification of the i^{th} element of both the source and target sequences. The "Subtract" operation *Subtract*(i,j) indicates the operation that replaces the i^{th} element of the source sequence by the j^{th} element of the target sequence. As a result, the operation sets can be represented as follows:

$$O = \{Insert(j) \cup Identify(i) \cup Delete(i) \cup Subtract(i,j)\} \tag{3-1}$$

Based on the process mentioned in the previous paragraphs, we can get the distance between the two sequences. Given the distance between the two sequences, a normalization approach is used to obtain the similarity level between 0 and 1.0 via the Sigmoid functions, where "ξ" denotes similarity and "δ" denotes the distance calculated before:

$$\xi = 1 - \frac{1}{1+e^{\left(\frac{2*\delta}{length_1+length_2}-1\right)*\frac{\pi}{2}}} \tag{3-2}$$

From the formula, the larger distance indicates low similarity, and the smaller distance indicates high similarity. The largest distance is the sum of the length of the two sequences (i.e., there is an operation on every position); therefore, the similarity is 0. In contrast, the smallest distance is 0 (i.e., the two sequences are the same and no operation has been done); therefore, the similarity is 1.

3.4 TRUCK PARKING PREDICTION METHODOLOGY

For the truck parking occupancy prediction algorithm, the main goal is to estimate the future truck parking lot occupancy status and availability. For specific truck parking lots, truck parking patterns can be well characterized from historical parking space occupancy data. According to parking availability prediction algorithms proposed by previous researchers (Boris, C., and R. Brewster, 2018, Sadek, et al. 2020, Mahmud, et al. 2020), the methodologies can be divided into two categories: the traditional model and the machine learning based model. In this section, several well-known methods are summarized. For the truck parking occupancy prediction task, the research team reviewed papers related not only to truck parking but also to urban parking, a deep learning framework for traffic pattern analysis and prediction, and even data mining methodologies to support the research.

3.4.1 Statistical Models

Referencing average occupancy for each parking lot is the most traditional method for occupancy prediction. Vythoulkas P. et al., (1993) argued that "traffic patterns observed in traffic networks are randomly varying with respect to time and space, and to be efficient and accurate short-term traffic forecasting, its procedures must need to be flexible and easily adaptive to current conditions." Therefore, in the last century, AVG (average) and the linear statistical models have been popular methods in transportation analysis to describe varying parking patterns, covering microscopic to macroscopic transportation models. Taking advantage of the development of graph theory and regression models, many studies contributed to parking prediction. Szczuraszek and Krystek (1994) proposed a nonlinear model to describe the regulation of traffic patterns on a two-lane road segment. Bennett et al., (1994) applied the logistic regression model in highway scenarios and got around 70 percent accuracy in traffic speed prediction. Following this, with the assistance of computing technology, more complicated transportation models have been developed. D'Angelo et al. (1999) applied a nonlinear regression model to a highway corridor to do travel time prediction. Olszewski et al. (1995) developed a simulation method for area-wide traffic speed-flow prediction in the Singapore central business district. The study greatly contributed to the development of transportation because people began to realize the power of computers. Since then, many of studies have been done on network-scale traffic pattern prediction (Sen et al., 1997 and You J, Kim TJ, 2000). In summary, the AVG and linear statistical methods are the most used methods in transportation analysis when computing technologies are not available. In most cases, the model or the simulation based on the method has been limited. Therefore, the conclusions and regulations summarized by the method can only be applied to limited applications, without generalizability.

3.4.2 Neural Network – RNN

The recurrent neural network (RNN) is one of the popular neural networks in the transportation field. In comparison to the normal neural network, RNN can perform the same task for every element of a sequence, with the output influenced by previous computations. In other words, RNN can use internal memory units to process arbitrary sequences of inputs, and this grants the RNN the capability of learning a temporal sequence, whereas a traditional neural network assumes that all the neural nodes are independent. Figure 3–5 shows the structure of a traditional RNN.

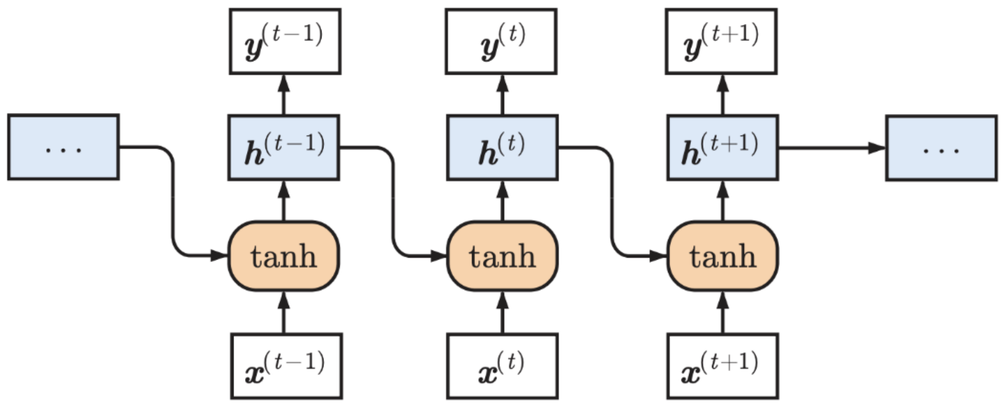


Figure 3–5. Basic Structure of a Recurrent Neural Network (RNN) (Ming et al., 2017)

As shown in Figure 3–5. Basic Structure of a Recurrent Neural Network (RNN) (Ming et al., 2017), a general RNN deals with the inputs and outputs in a sequential format. Given the input sequence as $\{x^{(0)}, \ldots, x^{(t-1)}, x^{(t)}\}$, the RNN can generate a time-variant hidden state vector sequence $\{h^{(0)}, \ldots, h^{(t-1)}, h^{(t)}\}$ and in same length output sequence $\{y^{(0)}, \ldots, y^{(t-1)}, y^{(t)}\}$. At each time step, the model takes new input, i.e., $x^{(t+1)}$, and updates the hidden state $h^{(t-1)}$ to $h^{(t)}$ and the output sequence ($y^{(t)}$) by the following equations, where the ***u***, ***v***, ***w*** are the trainable weights. The f and g are nonlinear activation function of the neural network, and $tanh$ is one of the most common choices activation functions for the vanilla RNN.

$$h^{(t)} = f(\boldsymbol{u} \cdot x^{(t)} + \boldsymbol{w} \cdot h^{(t-1)}) \tag{3-3}$$

$$y^{(t)} = g(\boldsymbol{v} \cdot h^{(t)}) \tag{3-4}$$

Traffic information, including traffic flow, density, speed, and parking pattern, is sequential information that considers both temporal scale and spatial scale. As a result, RNN performs much better in predicting traffic information than traditional neural networks. Previous studies have focused on using RNN models for traffic pattern prediction and have obtained satisfying results. For example, Lingras et al. (2002) built a time-delay model based on RNN to investigate time dependency in traffic patterns for travel time prediction. The model had more than 90 percent accuracy for travel time prediction. Van Lint et al. (2002) applied the RNN to a freeway scenario to study spatial dependency in traffic information for travel time prediction. Even at a large scale, the model still achieved more than 90 percent accuracy. Though RNN performs better than normal NN, it still has limitations. First, in theory, simple RNNs can make use of information in arbitrarily long sequences. However, in practice, they are limited to looking back only a few steps because simple RNNs lack the ability to deal with long sequences. Second, because of the vanishing and exploding gradient problem, simple RNN training is difficult and time-consuming. Therefore, various RNN variants have been proposed by researchers in recent years. For example, the long short-term memory (LSTM) neural network was created to deal with the above-mentioned limitations and has been applied in many fields to replace the traditional RNN approach. Gated recurrent units (GRU) are a gate mechanism in RNN like LSTM, but GRU has fewer parameters than LSTM because it lacks output gates.

3.4.3 Neural Network – LSTM and Bi-LSTM

The long short-term memory (LSTM) network is a special kind of RNN that was designed to learn long-term dependencies. LSTM was first proposed by Hochreiter and Schmidhuber (1997) and was refined by many researchers in the following decades. At present, various LSTM models have been designed for multiple purposes. In the transportation field, LSTM has become the most popular model for traffic pattern prediction. Figure 3–6. Single Cell of a Long Short-Term Memory Neural Network (Ma et al. 2015), shows the structure of a single LSTM cell. The detailed math operation for a single LSTM neuron can be found in the section Temporal Learning Component.

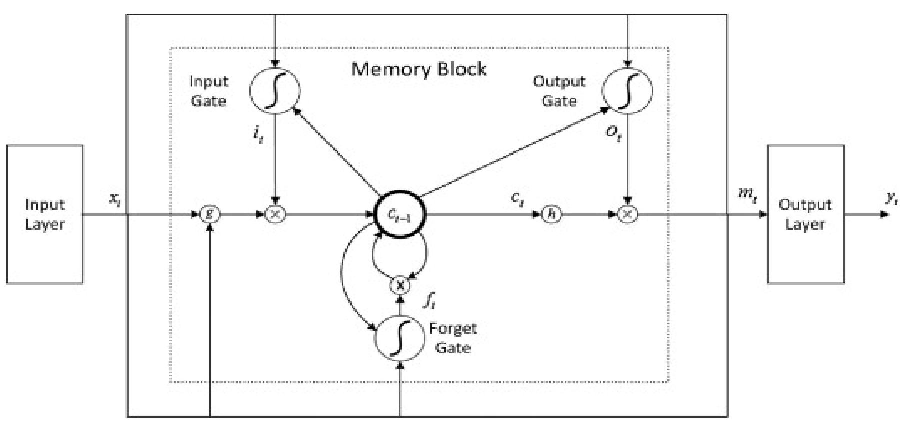


Figure 3–6. Single Cell of a Long Short-Term Memory Neural Network (Ma et al. 2015)

Ma et al. (2015) introduced LSTM to the transportation field for travel speed prediction and obtained great results. In the following years, more studies (Song et al., 2017; Zhao et al., 2017; Yu et al., 2017; and Fu et al., 2016) have been conducted, and their results have demonstrated the performance of LSTM for travel speed prediction. Shao et al (2018) and Anagnostopoulos et al (2019) successfully applied the LSTM method to sequence-based parking occupancy prediction and obtained impressive results. With its long sequence processing ability, LSTM can study long-term dependencies, which leads to better accuracy than simple RNN. However, a critical limitation of LSTM is that the dependencies are normally learned from chronologically arranged input data. As a result, only forward, instead of backward, dependencies are considered in the process (Cui et al., 2018). In the transportation field, both forward and backward dependencies are important for prediction, because traffic information is not only temporally dependent but also spatially dependent. Studies focused on LSTM limit their application to a road segment or corridor scale, rather than a network scale, because of its inability to learn the backward dependency.

To consider both the forward dependency and backward dependency of traffic information, bi-directional LSTM (Bi-LSTM) has been introduced in the transportation field for travel pattern prediction. The structure of Bi-LSTM is shown in Figure 3–7. As the figure shows, the input sequence $\{x_0, \ldots x_{t-1}, x_t\}$ for the Bi-LSTM can generate a time-variant hidden state vector sequence $\{h_0, \ldots h_{t-1}, h_t\}$ and the same length output sequence $\{y_0, \ldots y_{t-1}, y_{t}\}$. The key difference with traditional LSTM is that when the neural network generates the h_{t-1}, it not only takes into consideration the previous hidden state h_{t-2}, but the future status h_{t+1} is also used to capture the dependency. So, the Bi-LSTM neural network can generate two directional hidden sequences, one backward and one forward, for the output prediction sequence.

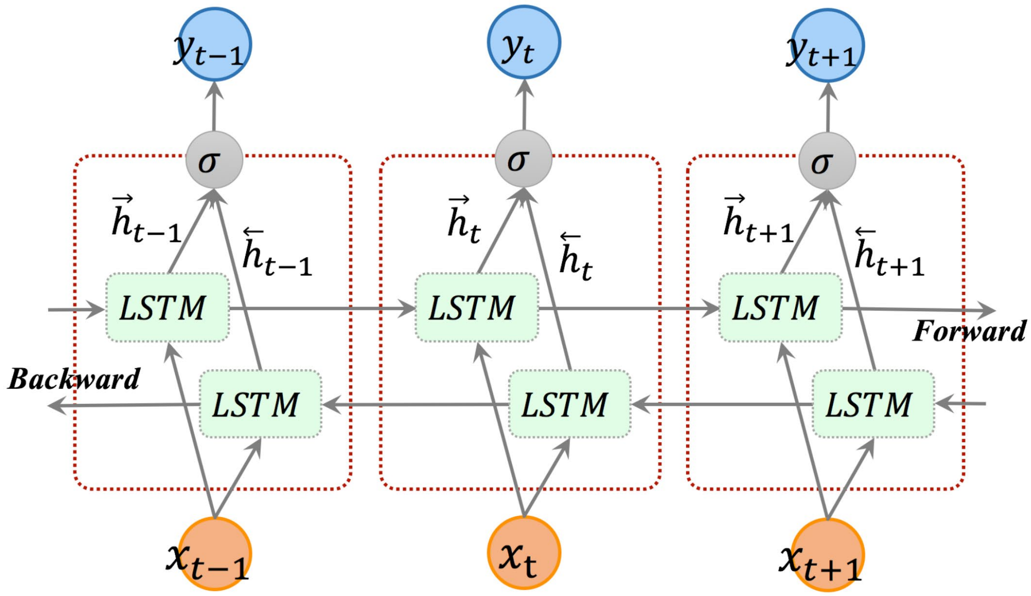


Figure 3–7. Structure of Bi-directional LSTM (Cui, Ke et al. (2018))

Siami et al. (2019) compared the performance of LSTM and Bi-LSTM in forecasting time series and concluded that the Bi-LSTM model performed better. In the transportation field, Wang et al. (2019) applied multiple Bi-LSTM models to future travel speed for a large traffic network, especially to critical paths. Cui, Ke et al. (2018) proposed a stacked bidirectional and unidirectional LSTM (SBU-LSTM) neural network, combining LSTM and BDLSTM, for network-wide traffic speed prediction. The proposed model was capable of handling input data with missing values and was validated on both large-scale freeway and urban traffic networks in the Seattle area.

3.5 LITERATURE REVIEW SUMMARY

In the literature review, the research team mainly investigated the following areas:

1) Current TPIMS sensing devices, systems, and related websites and mobile app services.
2) Parking pattern analysis procedures and methods.
3) Parking utility prediction methods, including both traditional and artificial intelligence approaches.

Truck parking occupancy detection technologies can be divided into entrance/exit and space-by-space categories. While the entrance/exit system is less costly, false positive or negative detections can accumulate and turn into unacceptable errors. The space-by-space system is reliable and accurate, but it has higher maintenance and life cycle costs.

The review of current truck parking service websites and mobile applications revealed that most website services include information about the parking lot and amenities, integrated well with the third-party navigation system. However, none of the reviewed website and mobile applications included prediction of future parking availability.

Research related to parking data analysis has mainly focused on the preliminary analysis and classification of parking-related attributes with occupancy rate, such as time of day and parking lot types, and has generally lacked quantitative analysis and comparison, such as sequence similarity, pattern recognition and evaluation, etc. Nevertheless, existing pattern analysis methodologies can partly help with truck parking pattern aggregation for primary analysis, and a novel quantitative analysis method for spatial-temporal truck parking sequence similarity needed to be proposed and improved.

In terms of parking prediction, the review indicated that methods based on artificial intelligence, especially deep learning, have greatly advanced the applicability and scalability of parking prediction models. Therefore, the combination of a temporal neural network with attribute representation learning is a promising approach for truck parking prediction.

4. TRUCK PARKING INFORMATION MANAGEMENT SYSTEM DESIGN AND IMPLEMENTATION

4.1 SYSTEM OVERVIEW

Following the specific needs of WSDOT and typical truck parking infrastructure users, the pilot TPIMS system architecture of this study was designed as shown in Figure 4–1.

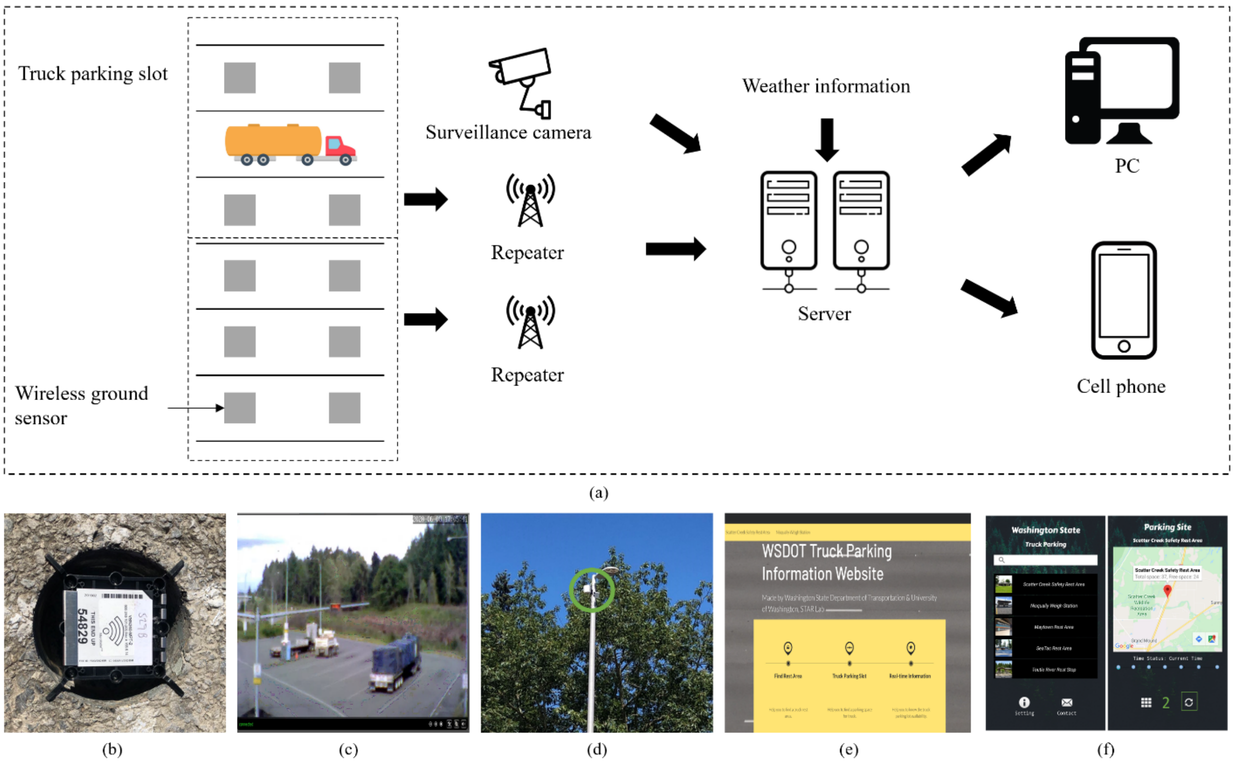


Figure 4–1. Architecture of the Intelligent Truck Parking Information Management and Prediction System (TPIMS) in the Pilot Testbed

The system includes six components, as shows in Figure 4-1:

(a) Algorithms and their software implementations for smart parking information management and prediction

(b) The radar-based wireless ground detector made by Sensys Networks, Inc.

(c) A real-time camera system for information collection

(d) A wireless repeater installed on a streetlight pole to transfer parking occupancy data from the sensors to the cloud

(e) The parking information visualization website

(f) A mobile application for real-time information visualization.

4.2 PILOT SITE ESTABLISHMENT

In this study, the pilot TPIMS was implemented at two truck parking rest areas in Washington state. The first parking lot was the Nisqually Weigh Station truck parking lot (NB I-5, MP ~116), with twelve truck parking slots available (Figure 4–2). The other site was the Scatter Creek Safety Rest Area (NB I-5, MP: ~93), with 37 truck parking slots available, shown in Figure 4–3. The Nisqually Weigh Station parking lot was monitored by the TPIMS and the surveillance camera system. The TPIMS parking slot status sensors were provided by Sensys Networks, Inc. In each truck parking slot, two FlexRadar sensors were installed in the pavement. The data analysis and visualization component were provided by the Smart Transportation Application and Research Lab (STAR Lab), University of Washington.

Figure 4–2. Nisqually Weigh Station Truck Parking Lot Overview

Figure 4–3. Scatter Creek Safety Rest Area Truck Parking Lot Overview

4.3 DATA COLLECTION AND MANAGEMENT SYSTEM

In the pilot TPIMS system, the data collection and management components included several parts. The captured data were summarized into two different utilities: 1) truck parking pattern analysis and prediction and 2) information visualization and dissemination through a website and mobile application. For the sequential data used for pattern analysis and occupancy prediction, a historical dataset was built to store the Sensys sensor inputs and the weather data in two separate text files. For each day, two different text files were stored in the database, one for truck parking occupancy record and another for weather information.

Meanwhile, for the data used for real-time visualization on the app and website, the necessary input was summarized into JSON files, and the files were renewed every 30 seconds. For each parking lot tested in the project, two JSON files were generated. The first was used for real-time occupancy visualization to show each truck parking slot's occupied/non-occupied status. Another JSON file contained the output predicted parking lot occupancy status with a confidence level. Detailed information can be found in Figure 4–4.

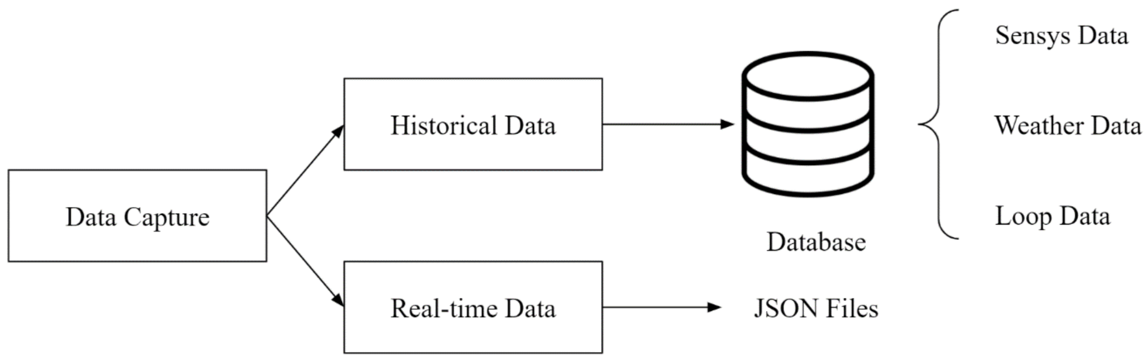


Figure 4–4. The Data Collection and Management System

4.4 WEBSITE DESIGN AND IMPLEMENTATION

For website design and implementation, the research team first conducted a panel discussion with WSDOT managers, researchers, and software developers and then developed the website architecture. Four different components are included on the website: the home page, service page, and two detailed parking lot information pages. The detailed structure of page links and relationships is shown in Figure 4–5.

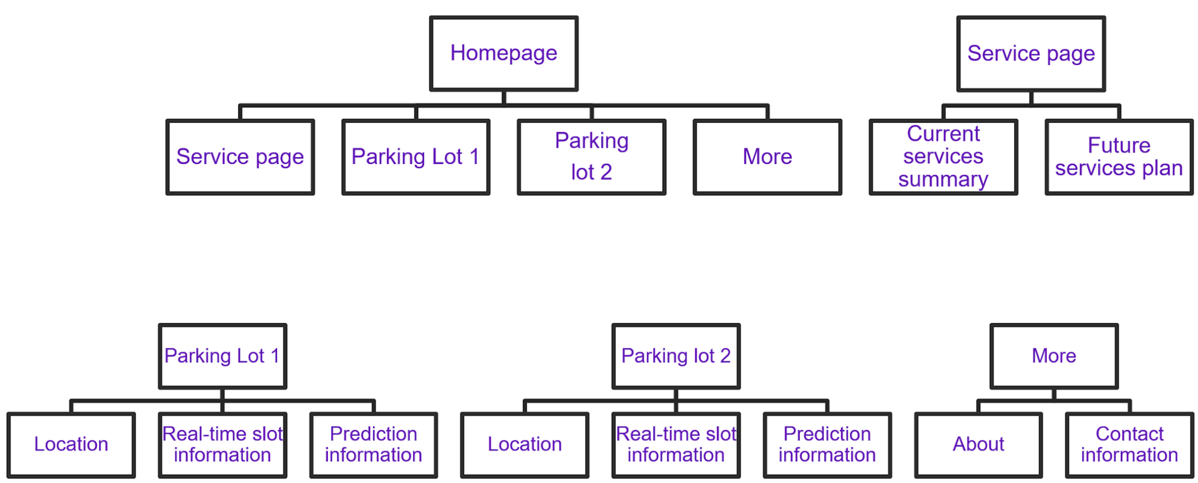


Figure 4–5. System Design of the Website

4.4.1 Home Page

The first page is the website homepage (Figure 4–6). Here, the general idea of the website is demonstrated, and it also includes the locations of connected parking lot services. At the bottom of the home page, a map displays each truck parking lot and its real-time occupancy status, detailed links, and Google Maps navigation directions. Users can click the icon or link and go directly to the target truck parking lot for more helpful information.

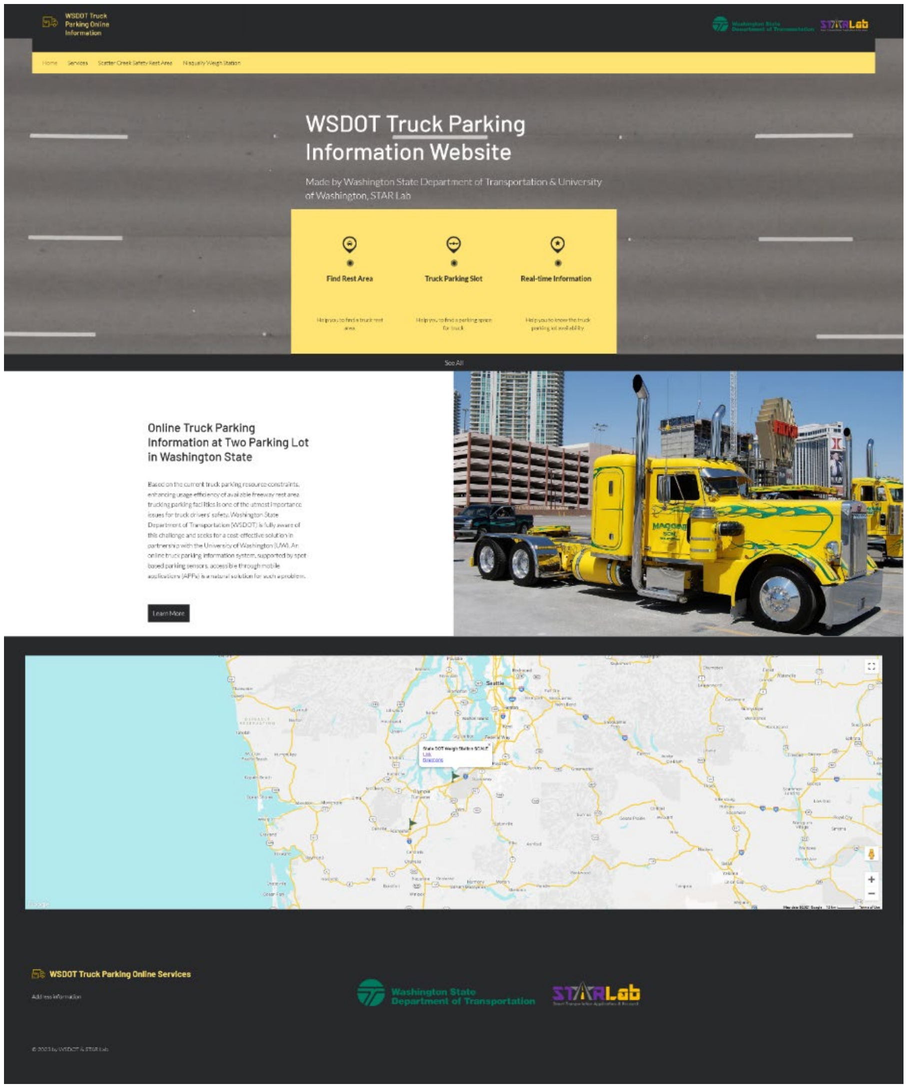


Figure 4–6. Home Page of the Truck Parking Website

4.4.2 Service Page

The second page is the services page (Figure 4–7), which shows the project's existing services. Currently, the website provides three types of services and information: the locations of target rest areas, real-time slot occupancy status information, and multi-timescale occupancy prediction. In the future it will also include more truck parking-related services.

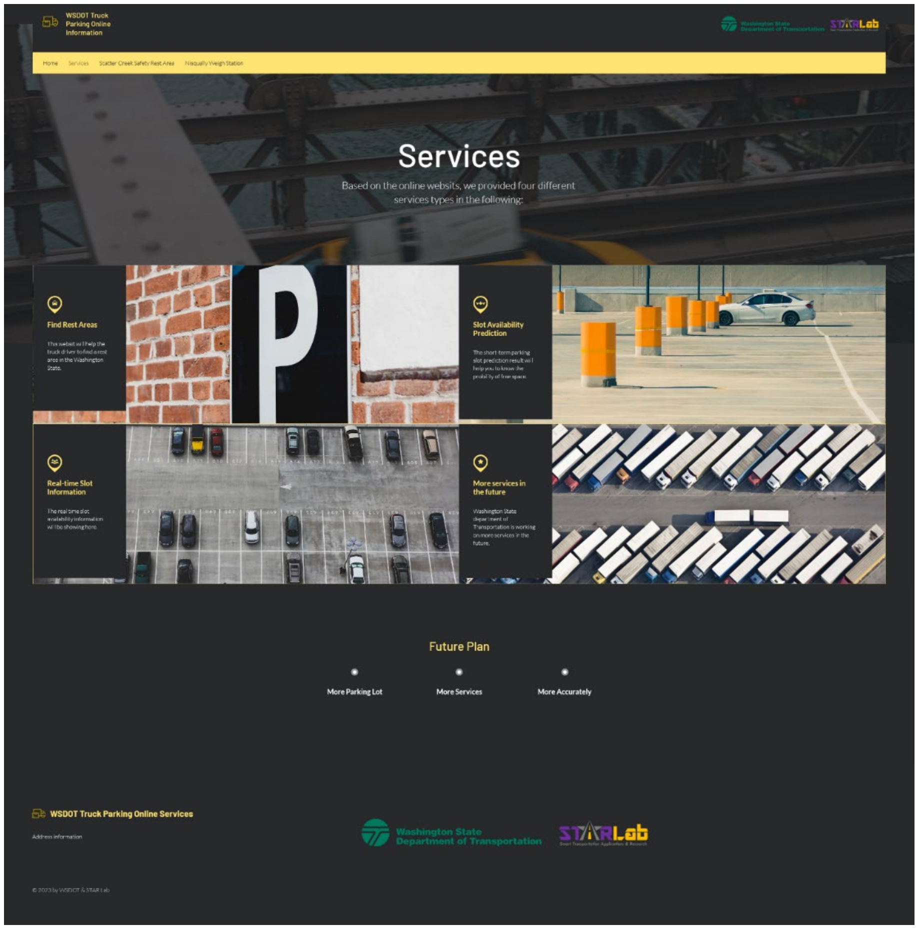


Figure 4–7. Services Page of the Truck Parking Website

4.4.3 Parking Lot Detail Page

On the parking lot detail page, four components are included for each truck parking lot: basic information; multi-time scale, real-time prediction results at various confidence levels; the real-time parking lot slot status visualization map; and the parking lot's retail location. The parking lot visualization page presents the date, time, total slots, and real-time availability of slots for the truck parking lot. The prediction visualization area shows future available parking slot numbers and the confidence levels for each prediction at different time intervals. The slot status visualization map shows the current truck parking occupancy status for each slot. This map can help truck drivers know precisely which parking spaces are available and their locations. For the location information, the truck parking lot is shown on Google Maps, and drivers can click to obtain navigation directions to the parking lot. Figure 4–8 and Figure 4–9 show pages for the two truck parking lots in the study: the Scatter Creek Safety Rest Area and the Nisqually Weigh Station truck parking lot.

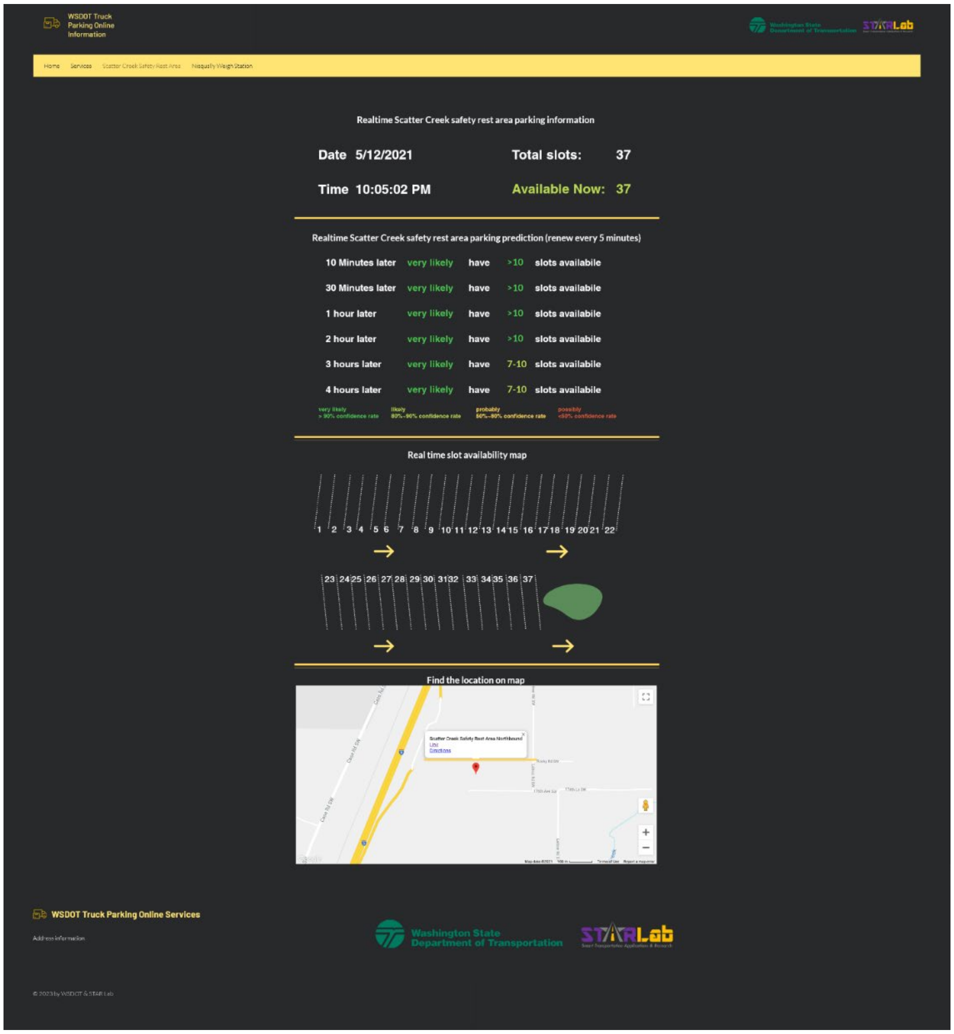


Figure 4–8. Scatter Creek Safety Rest Area Detail Information Page

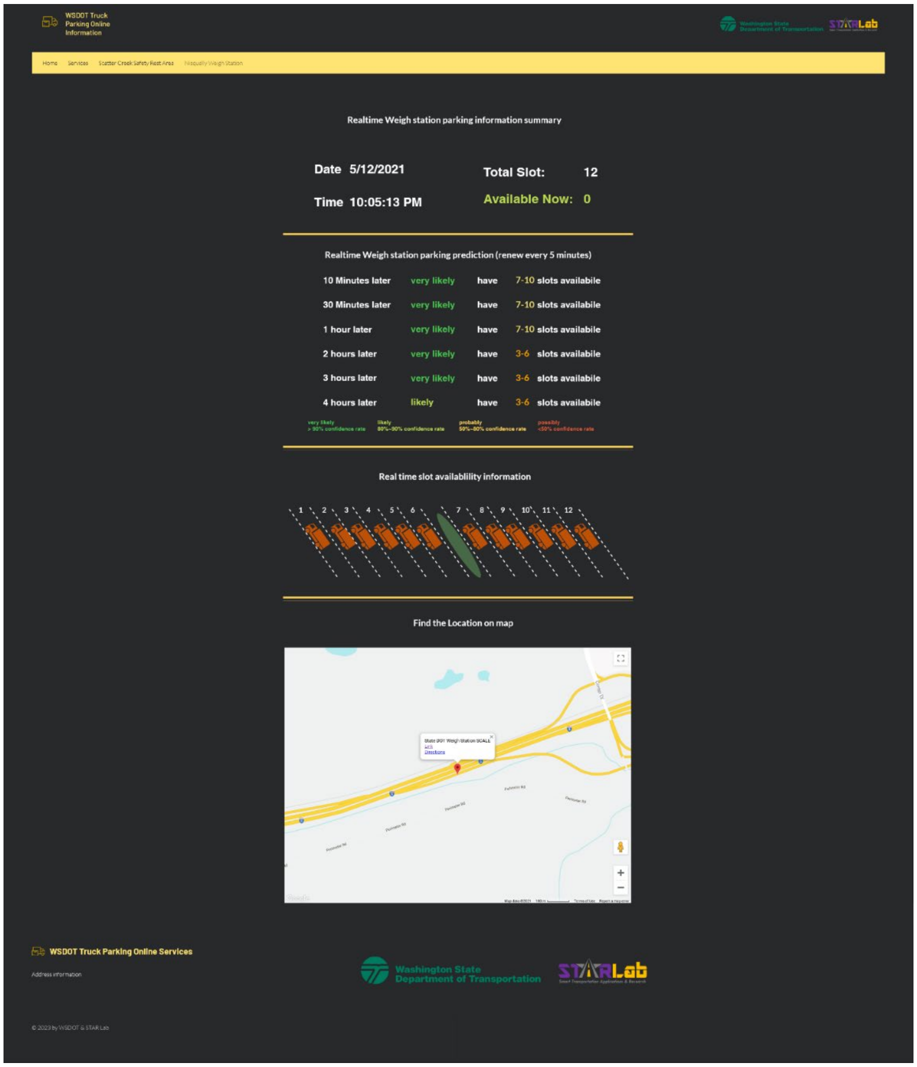


Figure 4–9. Nisqually Weigh Station Detail Information Page

4.5 APPLICATION DESIGN AND IMPLEMENTATION

To ensure that truck drivers can conveniently obtain parking-related information, a user application based on the Android system was designed to expand the traditional Web-based service to a phone-based service. The app includes four components: a welcome page, main page, parking lot data visualization page, and contact page. The welcome page is the first page users see when they open the app. The main page allows truck drivers to select the parking lot for which they want to obtain detailed information. After users click on the parking lot, the data page shows total spaces and spaces currently available. A drag bar integrated into the app allows truck drivers to obtain prediction information at different time intervals with a confidence level.

The last page is the contact page. If truck drivers need help, they can contact the listed developers to obtain more useful information. The pages of the app are shown in Figure 4–10, Figure 4–11, and Figure 4–12.

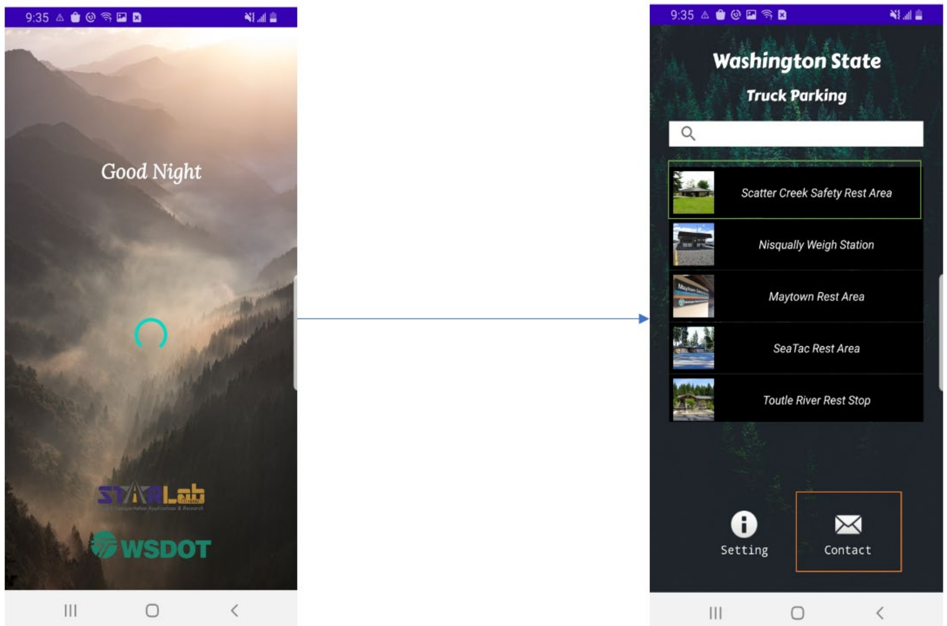


Figure 4–10. Welcome Page and Main Page of the Truck Parking App

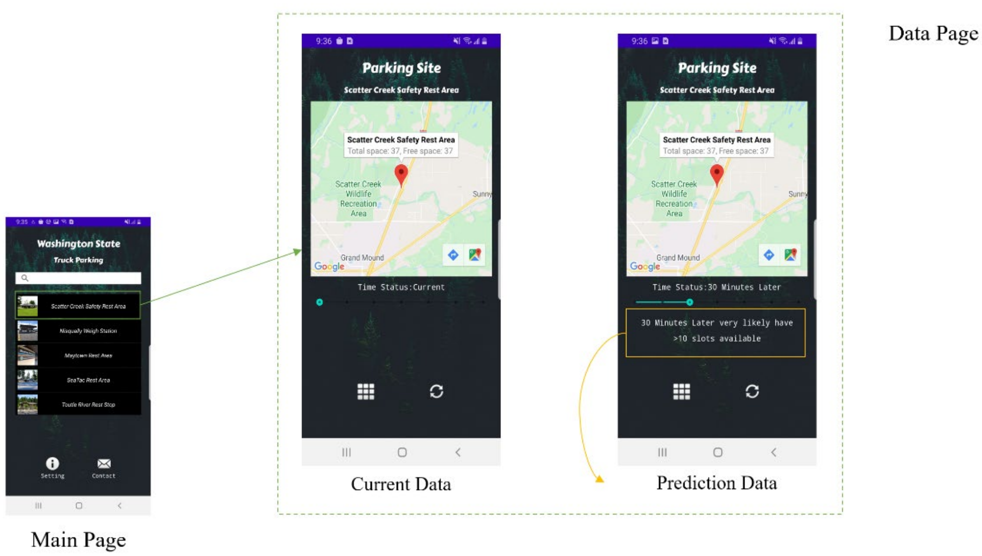
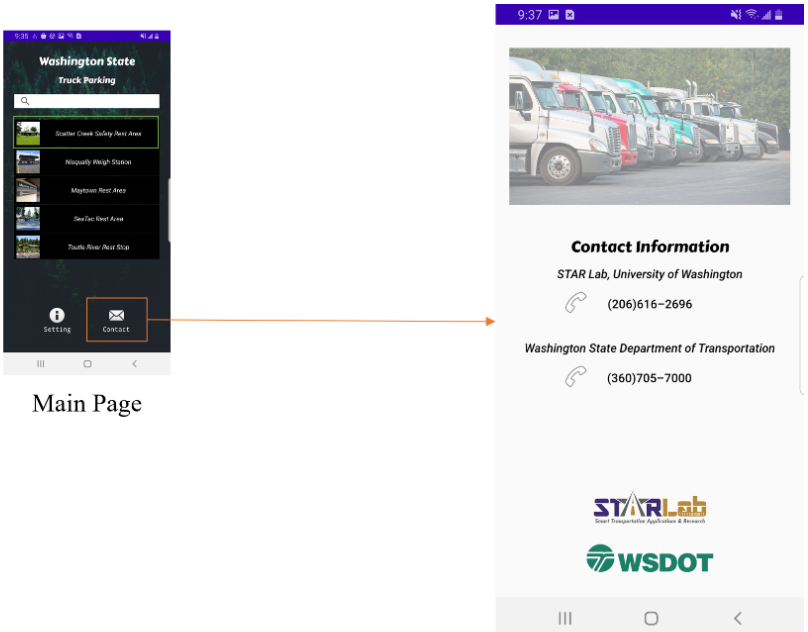


Figure 4–11. Data and Occupancy Status Page for a Truck Parking Lot, on Which Users Can Select a Parking Facility to See Additional Details



Main Page

Contact Page

Figure 4–12 Detailed Contact Information Page

5. DATA COLLECTION

5.1 TRUCK PARKING DETECTION ACCURACY EVALUATION

In this study, two independent systems were used to collect truck parking data simultaneously for the Nisqually Weigh Station truck parking lot (12 truck parking slots). The first system was a radar-based wireless ground sensor system provided by Sensys Networks, and the second one was a surveillance camera system. To evaluate the wireless ground sensor system's performance in accuracy and reliability, we chose to test in May and June, months that are usually rainy in Seattle. Finally, the research team collected up to 28 days of effective images and radar sensor records at the Nisqually Weigh Station for evaluation.

5.1.1 Evaluation Experiment

For the evaluation, data from CCTV camera footage were used as ground truth and then compared with real-time radar ground sensor records. For convenience, the radar-based ground sensor detection results for each parking slot are displayed in real time on the website (shown in Figure 5–2). Then, the team manually compared the ground truth data with the radar sensor records per minute. The team then summarized the error minute, slot id, and slot number in a new file. In this study, the research team compared 28 days of records, totaling 672 effective hours, with 40,320 effective figures and 483,840 radar-based wireless ground sensor records (examples are shown in Figure 5–3 and Figure 5–1). Among the 672 hours, 127 hours were rainy, 325 hours were cloudy, 214 hours were sunny, and six hours had heavy rain.

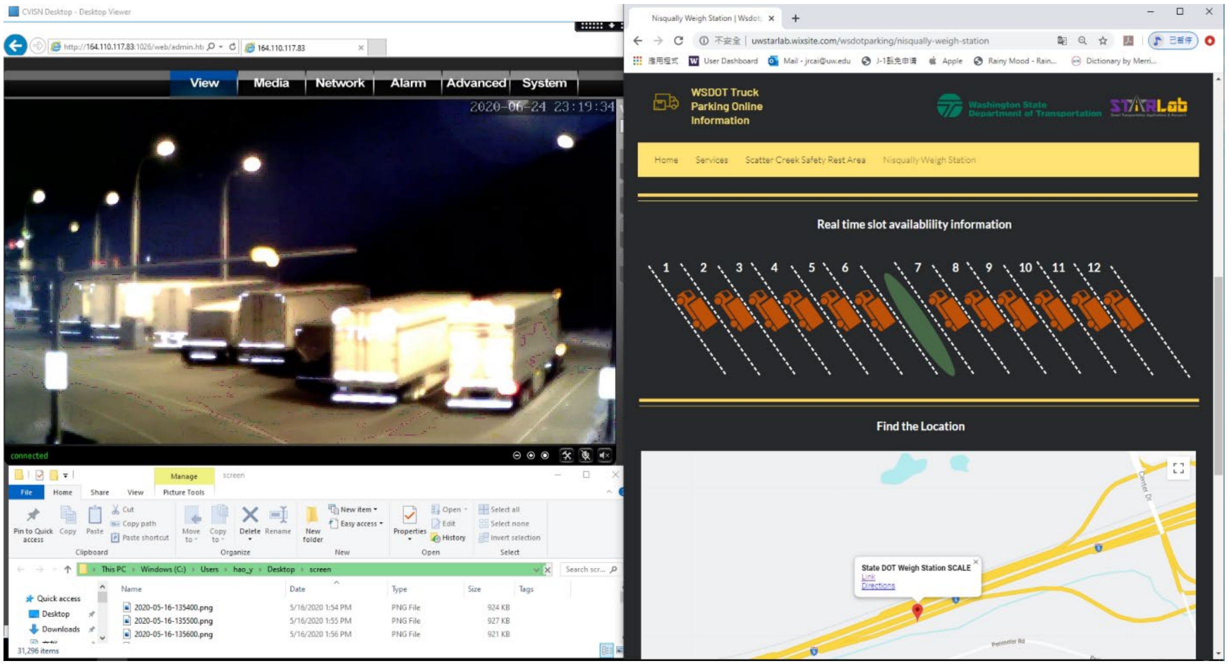


Figure 5–1. Example of Real-Time Comparison for Surveillance Camera Record and Radar Sensor Status (Parking lot #2, at 11:19 PM, 06/24, 2020)

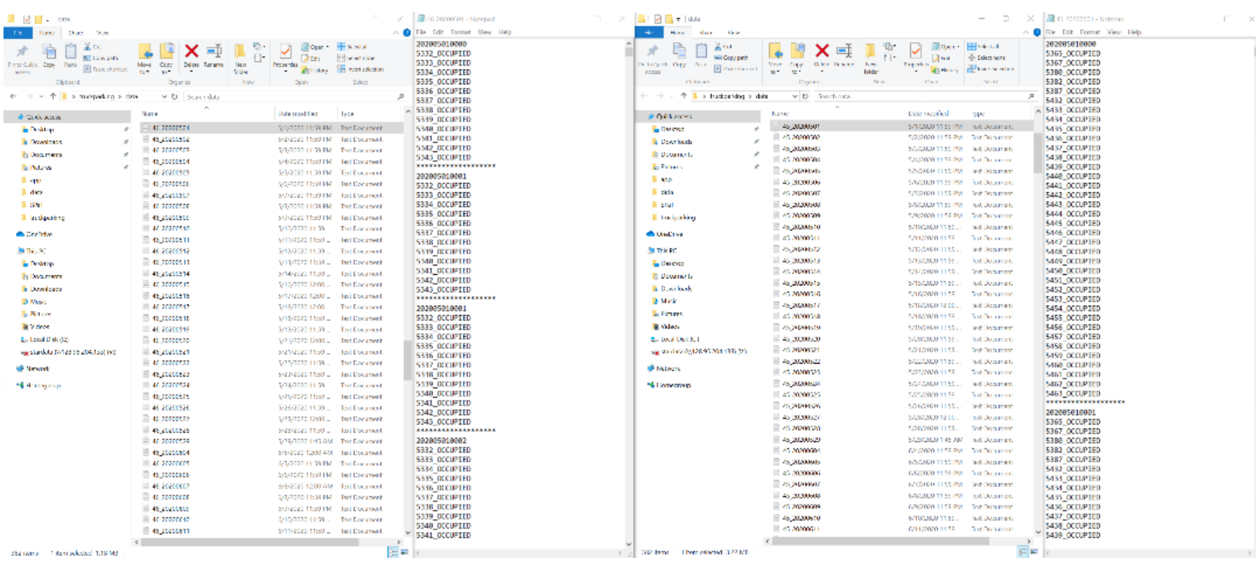


Figure 5–2. Radar-Based Wireless Ground Sensor Record Examples

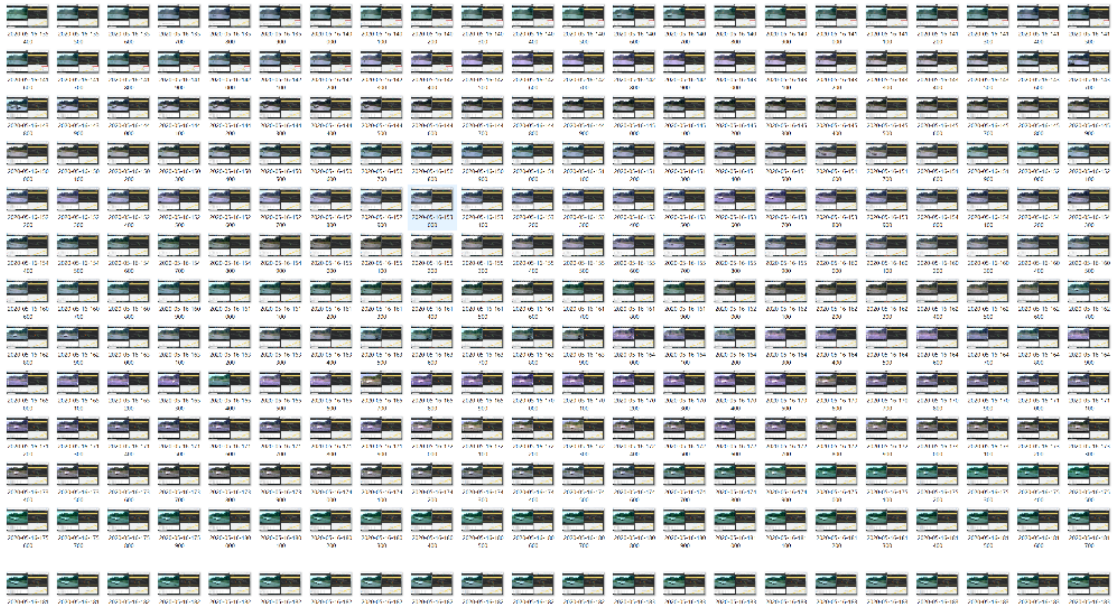


Figure 5–3. Surveillance Camera Record Examples

5.1.2 Result Summary

For the result summary and evaluation, the hourly accuracy level was estimated by the following equation (5-1):

$$Acc_{hourly} = \frac{F_{correct}}{F_{total}} \tag{5-1}$$

where, $F_{correct}$ means the minutes that the radar-based sensor showed the correct occupancy status in 49 slots. If the incorrect records continued for 10 minutes, then those 10 minutes were all treated as error values in the evaluation. The evaluation status was summarized into a table. An example of the evaluation records is shown in Figure 5–4. As seen in the figure, the error start minute shows the exact minute the error occurred, the slot id shows the parking slot with incorrect occupancy status, and the slide number represents the continuing error slides (we recorded the video one slide per minute). Then, the total accuracy per hour is summarized.

date	hour	error start minute	slot id	slide num	hourlyaccuracy
5/16/2020	14	28	1	2	0.966666667
5/16/2020	15	58	1	2	0.966666667
5/16/2020	16	53	2	1	0.983333333
5/16/2020	17				1
5/16/2020	18	21	1	1	0.983333333
5/16/2020	19	8	2	1	0.983333333
5/16/2020	20				1
5/16/2020	21				1
5/16/2020	22				1
5/16/2020	23				1
5/17/2020	0				1
5/17/2020	1				1
5/17/2020	2				1
5/17/2020	3	28	2	1	0.983333333
5/17/2020	4				1
5/17/2020	5				1
5/17/2020	6				1
5/17/2020	7				1
5/17/2020	8				1
5/17/2020	9				1
5/17/2020	10				1
5/17/2020	11				1
5/17/2020	12				1
5/17/2020	13	20	1	1	0.983333333
5/17/2020	14				1
5/17/2020	15	28	4	4	0.933333333
5/17/2020	16				1
5/17/2020	17				1

Figure 5–4. Hourly Accuracy Summarization Records Example

The final hourly accuracy results are shown in Figure 5–5. Among the 672 hours, 622 (92.56 percent) hours did not have any incorrect records. Finally, the overall accuracy was calculated by a weighted arithmetic mean using the following equation (5-2):

$$Acc_{all\_hour} = \frac{\sum_{hour} Acc_{hourly} * hour\_num}{F_{total}} \tag{5-2}$$

The final accuracy level was 99.31 percent among all weather conditions and a time period of 28 days. In addition, the team did not find a significant difference in error (>0.1 percent) under different weather conditions (fair, rainy, and cloudy).

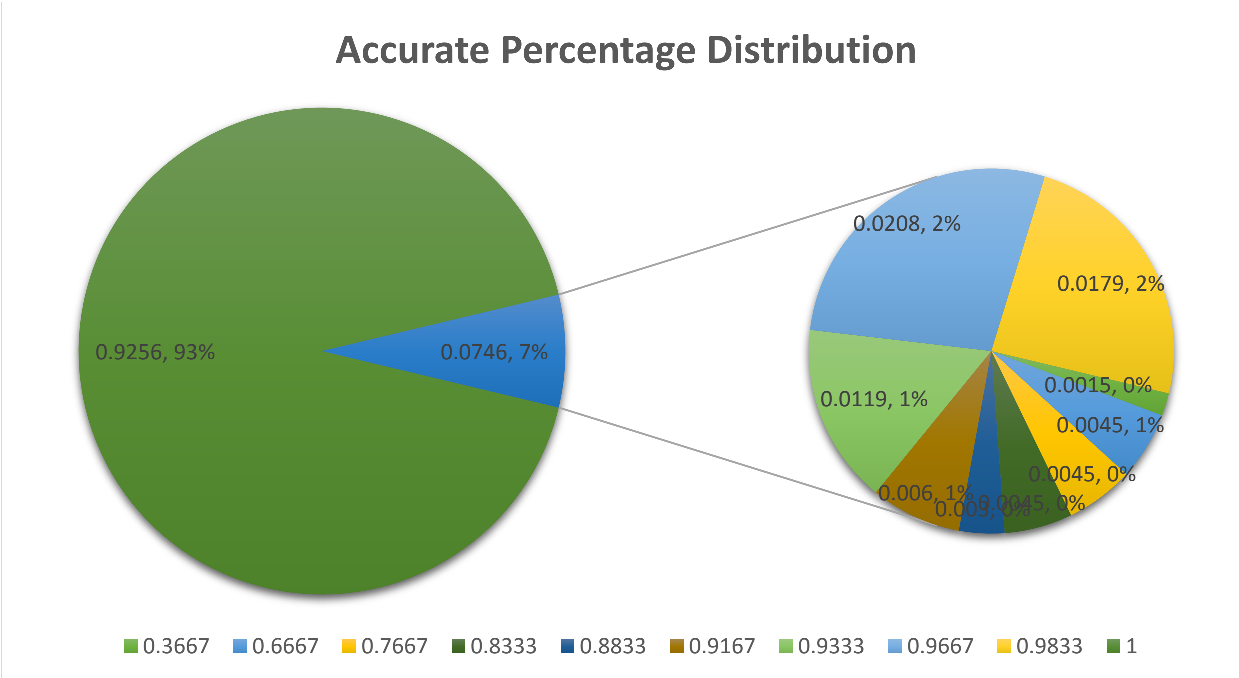


Figure 5–5. Hourly Accuracy Summarization Visualization. Based on the statistical result, most of the hourly accuracy results were 100 percent, and only a few hours had an error.

5.2 TRUCK PARKING OCCUPANCY DATA COLLECTION

The team collected the slot-based data for 49 truck parking spaces at the two described truck rest areas (the Nisqually Weigh Station truck parking lot, NB I-5, MP ~116, and the Scatter Creek Safety Rest Area, NB I-5, MP: ~93) from January 1 to March 10, 2020, and January 1 to March 1, 2021. Then, the truck parking data were used for parking pattern analysis and aggregation. For each parking space, the original slot record was classified as "occupied" or "unoccupied". Furthermore, the space-level truck parking status data were summarized into parking lot occupancy rate (from 0 percent to 100 percent) and recorded every minute.

OverID	Min_of_d	OccRate	AvSlot	YearID	MonthID	DateID	HourID	MinID	WeatherI	WeekID	ID
1	1	0.945946	2	2020	1	10	0	0	Cloudy	5	1
2	2	0.945946	2	2020	1	10	0	1	Cloudy	5	1
3	3	0.945946	2	2020	1	10	0	2	Cloudy	5	1
4	4	0.945946	2	2020	1	10	0	3	Cloudy	5	1
5	5	0.945946	2	2020	1	10	0	4	Cloudy	5	1
6	6	0.945946	2	2020	1	10	0	5	Cloudy	5	1
7	7	0.945946	2	2020	1	10	0	6	Cloudy	5	1
8	8	0.945946	2	2020	1	10	0	7	Cloudy	5	1
9	9	0.945946	2	2020	1	10	0	8	Cloudy	5	1
10	10	0.918919	3	2020	1	10	0	9	Cloudy	5	1
11	11	0.918919	3	2020	1	10	0	10	Cloudy	5	1
12	12	0.918919	3	2020	1	10	0	11	Cloudy	5	1
13	13	0.918919	3	2020	1	10	0	12	Cloudy	5	1
14	14	0.918919	3	2020	1	10	0	13	Cloudy	5	1
15	15	0.918919	3	2020	1	10	0	14	Cloudy	5	1
16	16	0.891892	4	2020	1	10	0	15	Cloudy	5	1
17	17	0.891892	4	2020	1	10	0	16	Cloudy	5	1
18	18	0.891892	4	2020	1	10	0	17	Cloudy	5	1
19	19	0.891892	4	2020	1	10	0	18	Cloudy	5	1
20	20	0.918919	3	2020	1	10	0	19	Cloudy	5	1
21	21	0.918919	3	2020	1	10	0	20	Cloudy	5	1
22	22	0.945946	2	2020	1	10	0	21	Cloudy	5	1
23	23	0.945946	2	2020	1	10	0	22	Cloudy	5	1
24	24	0.945946	2	2020	1	10	0	23	Cloudy	5	1
25	25	0.945946	2	2020	1	10	0	24	Cloudy	5	1
26	26	0.945946	2	2020	1	10	0	25	Cloudy	5	1
27	27	0.945946	2	2020	1	10	0	26	Cloudy	5	1
28	28	0.945946	2	2020	1	10	0	27	Cloudy	5	1
29	29	0.945946	2	2020	1	10	0	28	Cloudy	5	1
30	30	0.945946	2	2020	1	10	0	29	Cloudy	5	1
31	31	0.945946	2	2020	1	10	0	30	Cloudy	5	1
32	32	0.945946	2	2020	1	10	0	31	Cloudy	5	1
33	33	0.945946	2	2020	1	10	0	32	Cloudy	5	1
34	34	0.945946	2	2020	1	10	0	33	Cloudy	5	1
35	35	0.945946	2	2020	1	10	0	34	Cloudy	5	1
36	36	0.945946	2	2020	1	10	0	35	Cloudy	5	1
37	37	0.945946	2	2020	1	10	0	36	Cloudy	5	1
38	38	0.945946	2	2020	1	10	0	37	Cloudy	5	1

Figure 5–6. Full Data Records Visualization

5.3 WEATHER DATA COLLECTION

In addition to parking occupancy, real-time weather information from the closest weather station was collected to evaluate weather conditions during data collection. . For the Scatter Creek Safety Rest Area, the research team collected data from the WSDOT weather station near Grand Mound on I-5, at milepost 88.32. For the Nisqually Weigh Station, weather data were captured from the weather station near Nisqually on I-5, at milepost 114.29. The team summarized the weather conditions in eight classes for further analysis, including: sunny, cloudy, light rain, light snow, rain, snow, wintry mix, and fog. The weather information for both parking lots can be accessed through the WSDOT weather API connection (https://wsdot.wa.gov/traffic/api/WeatherInformation/rss.aspx).

6. TRUCK PARKING PATTERN ANALYSIS

6.1 PRIMARY ATTRIBUTES ANALYSIS

Truck parking occupancy patterns with attributes that included time of day, day of week, weather conditions, and their combinations were analyzed. As shown in Figure 6–1, some key findings of the truck parking occupancy patterns of the two parking lots were as follows:

- The parking lot occupancy rate from 9:00 PM to 4:00 AM the next morning was generally above 90 percent. The 1:00 AM to 2:00 AM period had the highest occupancy rate (average 97.74 percent occupancy rate).
- During the daytime (from 8:00 AM to 6:00 PM), truck drivers could find parking spaces easily, and the average occupancy rate was less than 60 percent.
- There was a clear distinction between working days (Monday to Friday afternoon) and off-working days for truck drivers' weekly patterns.
- The average parking lot occupancy rate on Friday, Saturday, and Sunday was less than 40 percent.
- However, the average parking lot occupancy rate from Monday to Thursday was high (all above 67 percent), especially at night.
- We did not find a clear relationship between weather conditions and parking occupancy (the sequence similarity score was less than 0.1); detail can be found in Section 6.2, Pattern Aggregation.

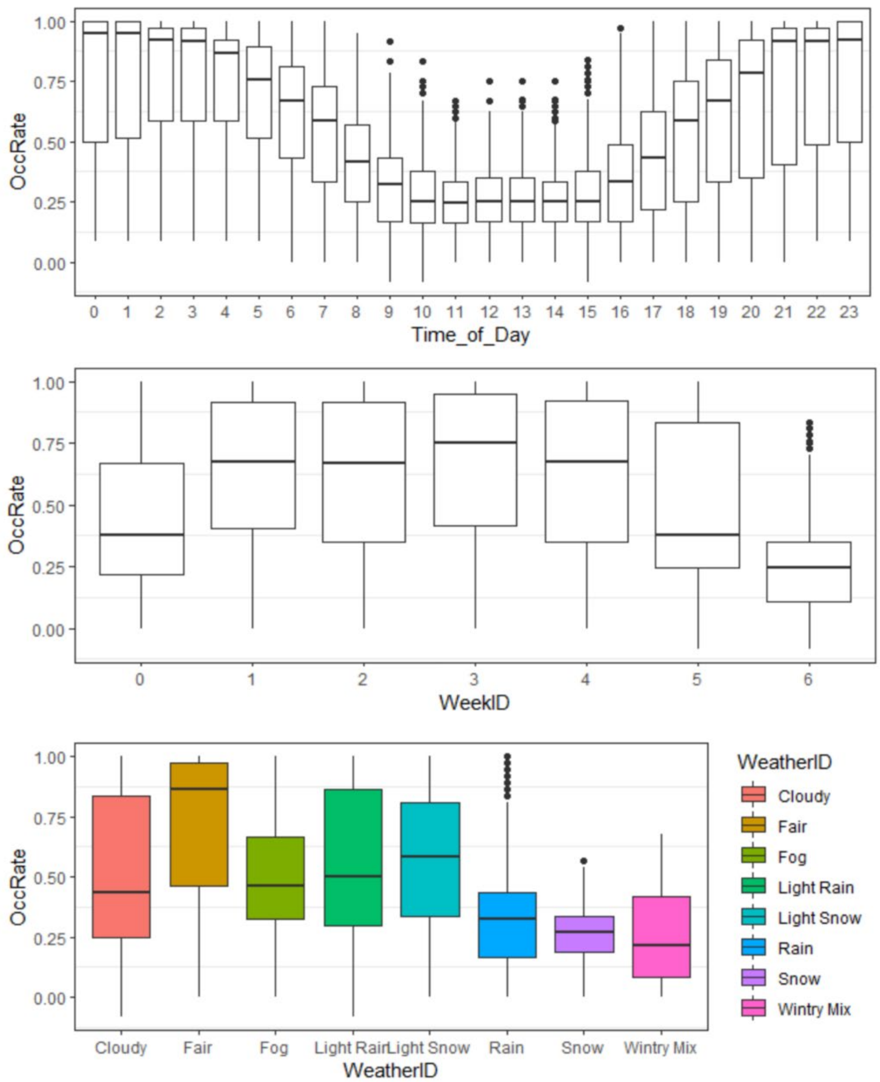


Figure 6–1. A Box Plot of Truck Parking Occupancy Rates for Time of Day, Day of Week, and Weather Conditions

6.2 PATTERN AGGREGATION

In traffic data analysis, similarity analysis is a very useful tool and can help solve many practical traffic challenges (Qian et al., 2004, Stabili et al., 2017). The main goal of similarity calculation is to classify data and match real application scenarios with sets of pre-defined constraints. Then, different categories can be treated with customized rules according to the restrictions in the scene. For example, when the parking pattern characteristics of a parking lot are determined and clustered for day of the week, the manager can obtain a straightforward idea of the weekly parking distribution and make management plans for weekdays and weekends.

Furthermore, for dynamic parking lot management, similarity analysis can help implement specialized parking lot management strategies based on various characteristics of the observed occupancy pattern (location, time of day, etc.). When the actual traffic situation is close to the pre-defined scheme, the system can automatically intervene according to the original control mode. Then, to provide recommendations for drivers and vehicles, we can calculate similarity based on candidate target features and then combine those with the subject that needs to be matched to give as many suitable alternatives as possible.

In the project, the customized ASAM method (demonstrated in section 3.3.3) is used to calculate the truck parking pattern sequential similarity. Specifically, the obtained pair similarity results of 0.4 to 0.8 was defined as pattern resemblance; a sequential pair similarity above 0.8 was regarded as closely related and dependent; and a sequential pair similarity below 0.4 was defined as less similar or different patterns. Through ASAM, several useful conclusions were made, and the periodical regular pattern was quantified into daily and weekly patterns.

6.2.1 Daily Patterns

The daily patterns are shown in Figure 6-3.

- The pattern similarity for a day was obvious, and a "cross-X" pattern was found. Two highly parallel clusters were aggregated for truck parking patterns.
- In the “daily off-peak hour” from 8:00 to 16:00 (see Figure 6-3), the occupancy rate of the truck parking lot was usually low (generally less than 40 percent), and the average parking duration was relatively short (within 20 minutes). Meanwhile, also during this period, the occupancy sequence similarity was very high (above 51.05 percent), and the patterns were highly repetitive.
- Another highly similar parking pattern was seen in the “daily peak hour,” starting from 20:00 to 5:00 of the next day (especially from 22:00 to 4:00 of the next day) (see Figure 6-3). In this cluster, the parking lot occupancy rate was usually very high (more than 95 percent), and the average parking duration was long (an average of more than 145 minutes).

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
0	1	0.8	0.9	0.9	0.6	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0.5	0.7	0.9
1	0.8	1	0.9	0.8	0.4	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0.3	0.6	0.7
2	0.9	0.9	1	0.9	0.6	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0.4	0.7	0.9
3	0.9	0.8	0.9	1	0.7	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0.5	0.8	0.9
4	0.6	0.4	0.6	0.7	1	0.6	0.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0.4	0.8	0.8	0.7
5	0.2	0.1	0.1	0.2	0.6	1	0.5	0.1	0	0	0	0	0	0	0	0	0	0	0	0.2	0.7	0.7	0.4	0.3
6	0	0	0	0	0.1	0.5	1	0.4	0	0	0	0	0	0	0	0	0	0	0.1	0.7	0.6	0.2	0	0
7	0	0	0	0	0	0.1	0.4	1	0.2	0	0	0	0	0	0	0	0	0.1	0.4	0.6	0.2	0	0	0
8	0	0	0	0	0	0	0	0.2	1	0.3	0	0	0	0	0	0	0.3	0.5	0.4	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0.3	1	0.5	0.3	0.3	0.3	0.3	0.5	0.6	0.3	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	0.5	1	0.9	0.8	0.8	0.8	0.8	0.4	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0.3	0.9	1	0.9	0.9	0.9	0.8	0.3	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0.3	0.8	0.9	1	0.9	0.9	0.8	0.2	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0.3	0.8	0.9	0.9	1	0.9	0.8	0.2	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0.3	0.8	0.9	0.9	0.9	1	0.8	0.3	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0.5	0.8	0.8	0.8	0.8	0.8	1	0.4	0.1	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0.3	0.6	0.4	0.3	0.2	0.2	0.3	0.4	1	0.4	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0.1	0.5	0.3	0	0	0	0	0	0.1	0.4	1	0.3	0	0	0	0	0
18	0	0	0	0	0	0	0.1	0.4	0.4	0	0	0	0	0	0	0	0	0.3	1	0.3	0	0	0	0
19	0	0	0	0	0	0.2	0.7	0.6	0	0	0	0	0	0	0	0	0	0	0.3	1	0.4	0.1	0	0
20	0.1	0.1	0.1	0.1	0.4	0.7	0.6	0.2	0	0	0	0	0	0	0	0	0	0	0	0.4	1	0.5	0.3	0.1
21	0.5	0.3	0.4	0.5	0.8	0.7	0.2	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0.5	1	0.7	0.6
22	0.7	0.6	0.7	0.8	0.8	0.4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.3	0.7	1	0.9
23	0.9	0.7	0.9	0.9	0.7	0.3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.1	0.6	0.9	1

Figure 6–2. Pattern Aggregation Results for Time of Day

6.2.2 Weekly Patterns

The weekly patterns are shown in Figure 6-4.

- The truck parking pattern of every week was divided into two clusters: working mode and off-working mode.
- For the "working mode," starting from Sunday night until Friday evening, the parking sequence similarity was very high (above 56 percent) and fit well with the daily peak-hour and off-peak hour patterns.
- The relaxation time for truck drivers, called "off-working mode," usually starts on Friday night. For Saturday, Sunday, and even sometimes Monday morning, the truck parking pattern similarity was low. Random and personalized parking events were relatively frequent.

	Sun	Mon	Tue	Wed	Thu	Fri	Sat
Sun	1	0.3	0.4	0.4	0.4	0.4	0.6
Mon	0.3	1	0.7	0.8	0.7	0.5	0.2
Tue	0.4	0.7	1	0.7	0.7	0.6	0.3
Wed	0.4	0.8	0.7	1	0.7	0.5	0.2
Thu	0.4	0.7	0.7	0.7	1	0.5	0.2
Fri	0.4	0.5	0.6	0.5	0.5	1	0.4
Sat	0.6	0.2	0.3	0.2	0.2	0.4	1

Figure 6–3. Pattern Aggregation Results for Day of Week

7. MULTI-TIMESCALE OCCUPANCY PREDICTION BY DEEP LEARNING

The comprehensive literature review showed that the use of neural networks and artificial intelligence to predict truck parking occupancy status is a current research topic (Song et al., 2017; Zhao et al., 2017; Yu et al., 2017; and Fu et al., 2016). In this project, through pattern similarity analysis and aggregation, the dependency of spatial-temporal factors in the truck parking distribution was observed. Attribute information was found to highly affect parking occupancy, including hour of day, day of week, and weekend/weekday. So, the prediction methodology development process worked well with the truck parking pattern analysis.

The goal of this project was to develop a neural network—the Truck Parking Occupancy Prediction (TPOP) neural network—to predict future occupancy levels of truck parking lots (see Figure 7–1). By adopting the low dimension embedding method to transform categorical factors into a neural network input sequence, the attribute features are integrated into the TPOP. The non-linear mapping and Recurrent Neural Network (RNN) are used in this model to “memorize” the history of the processed sequence. Then a two-layer stacked LSTM is implemented within the TPOP. An attention component is used to combine the previous two outputs.

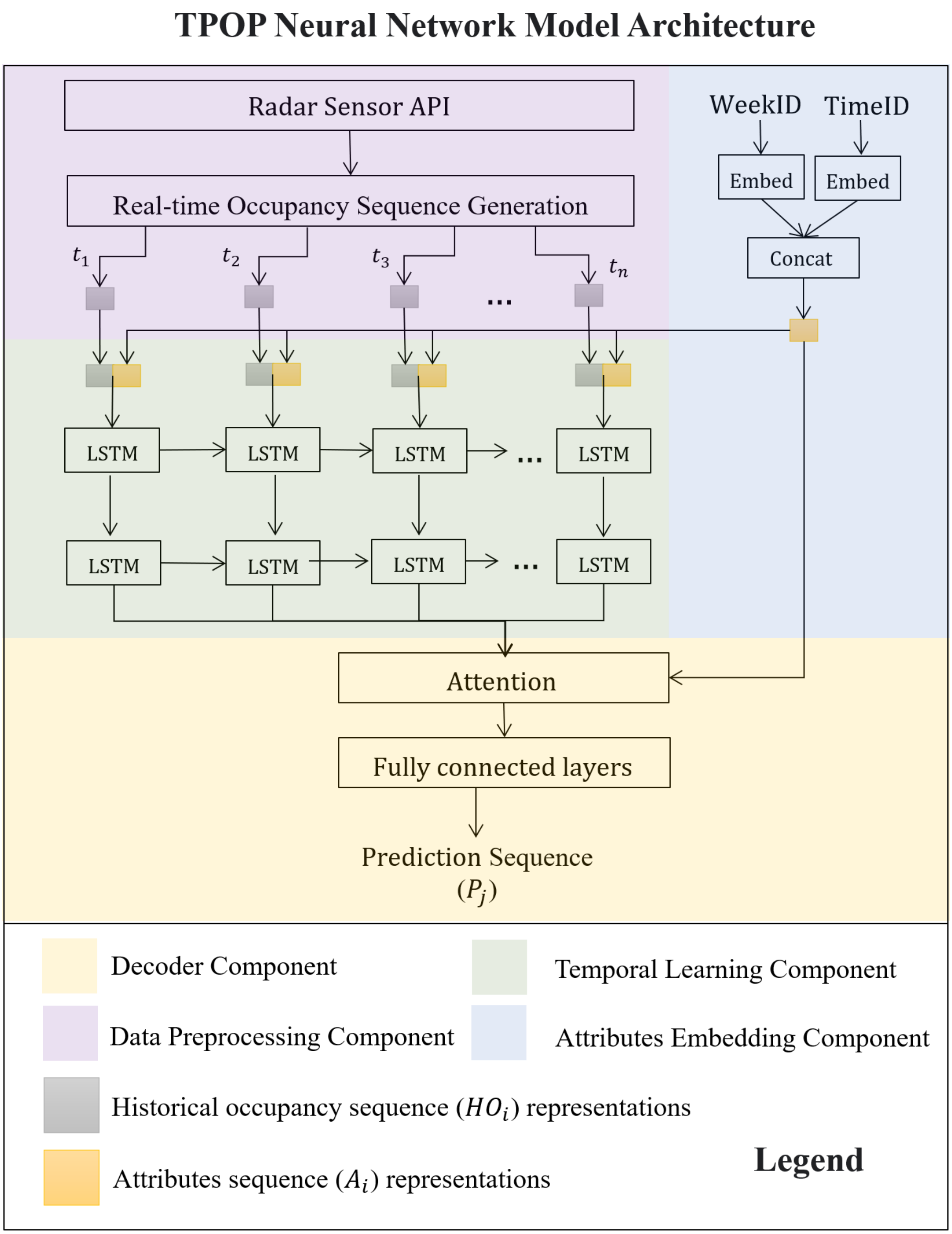


Figure 7–1. The Architecture of the TPOP Neural Network

7.1 THE PRELIMINARY TPOP MODEL

The neural network model designed for truck parking occupancy prediction included the following variables and components:

Definition 1, Historical occupancy sequence (HO_i). Occupancy records consisted of sequence-based, continuous, temporal occupancy data obtained from a parking lot. The time gap of the historical occupancy sequence was fixed. In this model, the historical occupancy sequence was used as the input for the TPOP.

Definition 2, Prediction sequence (P_j). The prediction sequence was a sequence of future occupancy data for a parking lot. The time gap was customized as an integer. In this model, P_j represented the output of the neural network and included multiple occupancy records.

Definition 3, Attributes sequence (A_i). The attributes sequence consisted of the sequence-based characteristics information that indicated the occupancy status of the parking lot. In this model, A_i included the weather conditions (weatherID), the day of the week (weekID), and the time of day (timeID).

The TPOP prediction task statement. The overall task comprised two parts. During the training phase, the researchers trained the neural network to predict P_j on the basis of the input HO_i and A_i. In the inference phase, we tested our model on the basis of a given HO_i and A_i and then generated P_j. Then, we evaluated the prediction results on the basis of multiple conditions.

7.2 TPOP NEURAL NETWORK

7.2.1 Attributes Integration Component

For truck parking prediction, the attributes were shown to have a significant effect on parking patterns. However, the attributes information was always formatted as discrete categorical values, which cannot be fully used and understood by a temporal-learning neural network (Yang et al, 2021). In addition, the impacts of the attributes information on the output sequences were always complicated and multifaceted. Because of the feature learning techniques used in natural language processing (NLP) to map words or phrases from a vocabulary to vectors of real numbers, a learnable attributes embedding component was integrated into the TPOP. In general, embedding becomes a bridge to connect those discrete values to a vector dimension (Cui et al, 2018). In the framework, we adopted the low dimension embedding method proposed by Press and Wolf (2017) to transform categorical factors into a neural network input sequence. We used $E(A_i)$ to represent the attributes sequence after embedding. The overall output of the attribute component consisted of the embedding results concatenated together and then sent to the temporal and attention component.

7.2.2 Temporal Learning Component

The long short-term memory (LSTM) network is a special RNN that is designed to learn relative long-term dependencies. LSTM was first proposed by Hochreiter and Schmidhuber (1997) and has since been refined by many researchers in the following decades. In the transportation field, LSTM is the most popular model for traffic pattern prediction. Figure 7–2 shows the structure of a single LSTM cell.

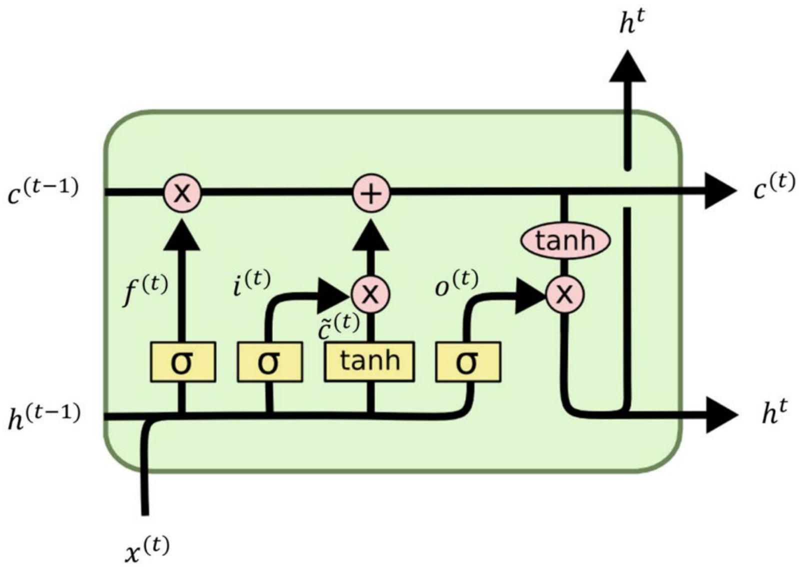


Figure 7–2. Single Cell of a Long Short-Term Memory Neural Network (Yang et al, 2021)

Generally, each LSTM neuron contains three gates: an input gate i_t, output gate o_t, and forget gate f_t. Each gate is controlled by its own weight W_t and the previous neural output h_{t-1}. The designed cascading process for passing the memory generated by the previous neuron to the next can be divided into two parts: new memory generation $\tilde{c}_t$ and final memory generation c_t. After the final memory has been generated, the new hidden state h_t is raised by control of the output gate o_t. The o_t makes the assessment regarding what parts of the memory need to be shown in the h_t. The detailed mathematical formulations of LSTM are shown in equations (7-1) through (7-6), which represent a single LSTM unit's working procedure (Hochreiter & Schmidhuber, 1997):

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \tag{7-1}$$

$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \tag{7-2}$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \tag{7-3}$$

$$\tilde{c}_t = \sigma_h(W_c x_t + U_c h_{t-1} + b_c) \tag{7-4}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \tag{7-5}$$

$$h_t = o_t \circ \sigma_h(c_t) \tag{7-6}$$

After mapping, the Recurrent Neural Network (RNN) is introduced into this model to "memorize" the history of the processed sequence. When processing the current time step in the sequence, the RNN uses internal memory units to process arbitrary sequences of inputs, thus granting the RNN the capability to learn temporal sequence. To better capture long-term dependency and solve vanishing and exploding gradient problems, in practice, we used two stacked LSTM layers instead of the traditional RNN layers. In comparison to the normal RNN layer, the LSTM introduces a forget gate and input gate to control the information interaction. Such gates enable the LSTM to forget some unimportant information and effectively alleviate the gradient vanishing/exploding problem.

In the TPOP model, the input for the stacked LSTM layers were divided into two parts. One was the historical occupancy sequence HO_i and the other was the attribute information sequence after embedding $E(A_i)$. The matching records in both sequences were concatenated to a vector and then sent into the LSTM layers. The output h_i of the LSTM layers is shown in equation (7-7), where w_i^{HO} , w_i and w_i^A are learnable parameter matrices. The output of h_i is the hidden state generated by the i^{th} neuron. So, after an input sequence passes the LSTM module, a new sequence h_i is obtained to represent the combined temporal features; it consists of $h_1, h_2, \dots, h_i$.

$$h_i = f(w_i^{HO} \cdot HO_i + w_I \cdot h_{i-1} + w_i^A \cdot A_i + \varepsilon_{(i)}) \tag{7-7}$$

7.3 ATTENTION COMPONENT

The main challenge of truck parking occupancy prediction is to capture the various temporal dependencies. Even if all historical records are treated equally when they are used as input, they are very likely to contribute differently to the prediction result. To solve this problem, the attention mechanism was adopted in the prediction methodology instead of traditional mean pooling (a normal down sampling approach for connecting different neural network layers, Boureau et al, 2010). The attention mechanism is essentially the weighted sum of sequence h_i, where the weights are parameters learned by the model. In this study, linear attention was used in the component (Yang et al, 2021).

After the attention component, the project used multiple groups of fully connected layers, mapping the output of the attention layer into a two-dimensional vector to represent the occupancy level in P_j. Each record of P_j was passed through the fully connected layers to down-sample into a suitable dimension to represent the prediction value. These independent, fully connected layers were connected by the loss function of multi-task learning and were trained at the same time.

7.4 EXPERIMENTS

7.4.1 Experimental Environment

The TPOP was implemented with PyTorch 0.3.1. The workstation for training was equipped with a GPU (NVIDIA TITAN XP), and the CPU was an Intel Core i7 8700. The operation system was a Linux Ubuntu 16.04.

7.4.2 Training Data and Testing Data

The project collected data for 49 truck parking slots at two rest areas near Interstate 5 from January 1 to March 10, 2020, and January 1 to March 1, 2021. To avoid COVID-19 impacts on model training, data from the period of April to December 2020 were ignored. The data set was split into 70 percent for training, 10 percent for validation, and 20 percent for testing.

7.4.3 Model Training

Because the study needed to predict future occupancy from 10 minutes to 4 hours later, the input sequence was summarized into three time gaps: a 10-minute gap sequence, a 30-minute sequence, and a 60-minute sequence. The model trained on an input sequence of every 10 minutes to predict the future truck parking lot occupancy rate 10 minutes later and 30 minutes later. Similarly, the 30-minute sequence was used to predict occupancy information 60 minutes and 120 minutes later, and the 60-minute sequence was used to predict parking status 180 and 240 minutes later. Three models were trained separately with various parameter settings (learning rate, batch size, epoch numbers, etc.).

7.4.4 Loss Function

The TPOP was trained end to end. During the training phase, three well-known standards were used to evaluate the proposed model, including mean absolute percentage error (MAPE) and mean absolute error (MAE). L_{P_j} was used to represent the j^{th} result of the loss function in the sequence of P_j, where:

$$L_{P_j} = \sum \left| \frac{P_j - \widehat{P_j}}{\widehat{P_j} - \varepsilon} \right| * 100\% \tag{7-8}$$

where the ε represents the relative error and prevents the denominator from being zero.

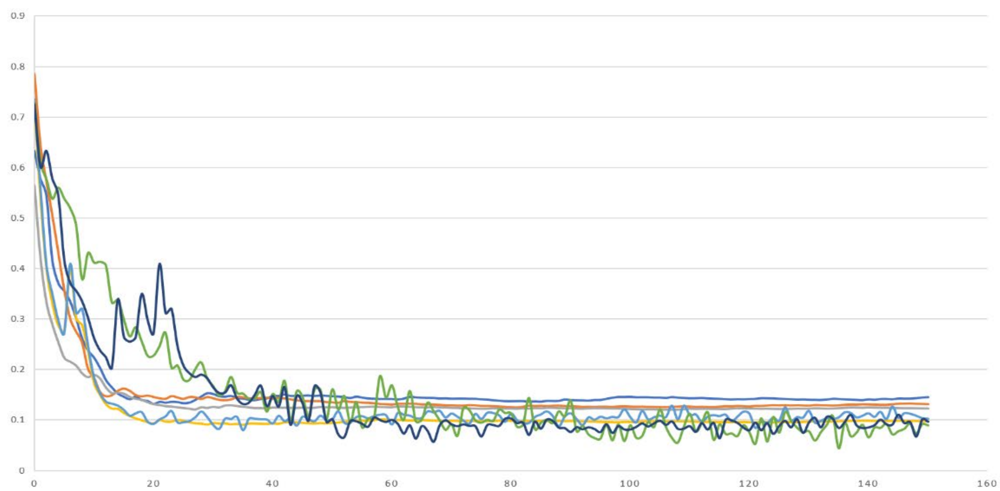


Figure 7–3. Training Loss Visualization

7.5 RESULTS SUMMARY AND ANALYSIS

In the prediction evaluation, the model was trained and evaluated based on data collected from two parking lots. The results were the weighted average values of the two parking lots based on their total number of slots. The best performance results of the three models are summarized in Table 7–1, and the results are shown in Figure 7–4.

Table 7–1. Prediction Accuracy Summary of the TPOP at Different Time Scales

	10min	30min	1h	2h	3h	4h
MAPE	8.79%	9.01%	9.16%	9.47%	10.27%	11.34%
MAE	4.31	4.41	4.49	4.64	5.03	5.56

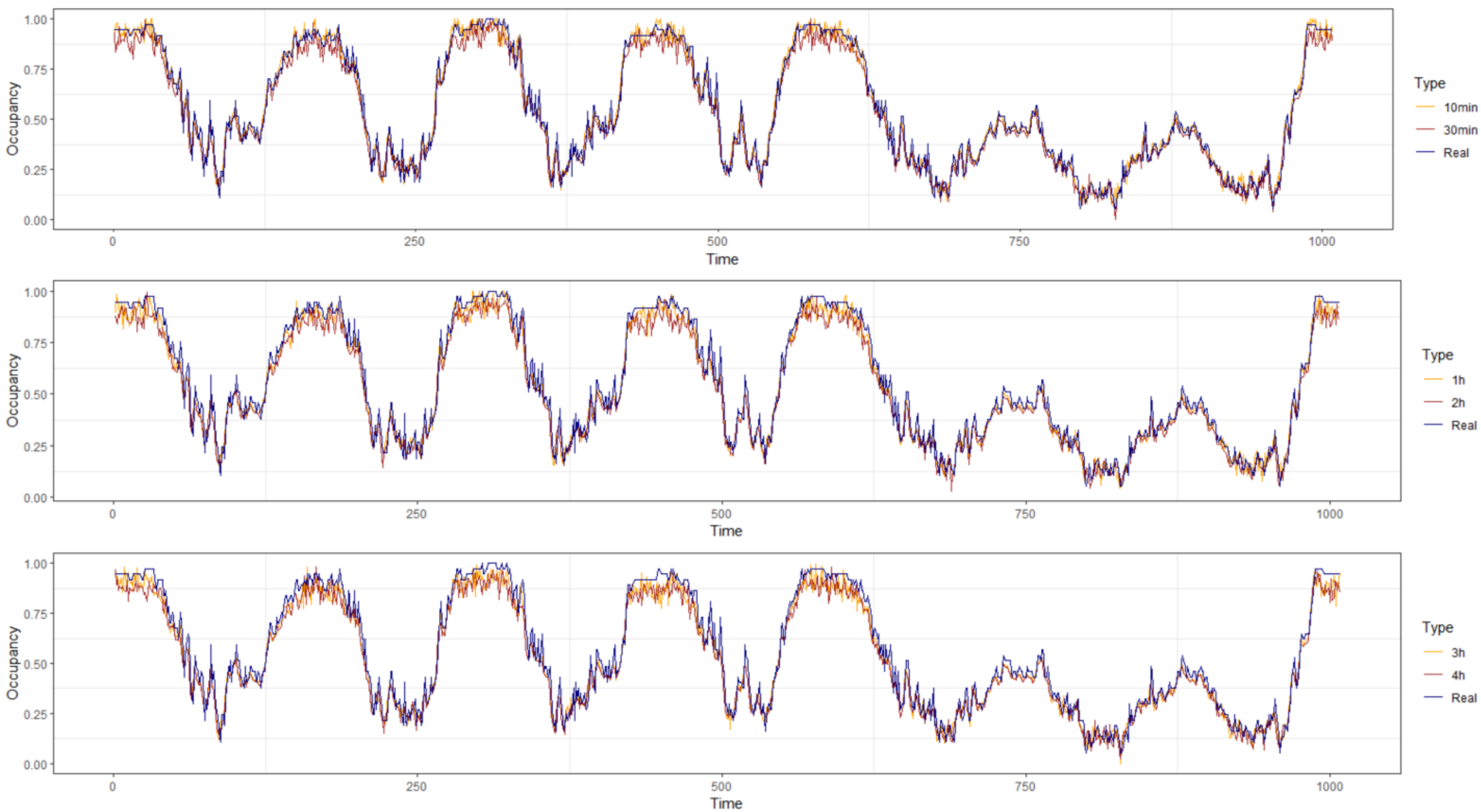


Figure 7–4. Prediction Results and Comparison with Ground Truth Data

Based on the results evaluation, the TPOP neural network achieved accurate occupancy prediction, with a MAPE of 8.79 percent for 10 minutes ahead, 9.01 percent for 30 minutes, 9.16 percent for 60 minutes, 9.47 percent for 2 hours, 10.27 percent for 3 hours, and 11.34 percent for 4 hours ahead. Among all times of day, the TPOP prediction error was relatively small for the afternoon daytime (between 12:00 PM and 4:00 PM) and evening hours (between 4:00 PM and 8:00 PM), with an average MAPE of 9.86 percent and 9.23 percent, respectively. While late night (between 12:00 AM and 4:00 AM) was the busiest period (occ rate% > 92 percent), the prediction error was relatively large (MAPE = 11.23 percent). The ground truth video suggested two possible reasons:

1) During these periods, the average parking duration was quite long (always more than 120 minutes). However, the temporal features in the prediction algorithm were mainly captured by the LSTM, which always performs worse than it does with short-term sequences (Zhou et al., 2021). Long-term dependency was not fully captured by the TPOP because of internal parking pattern differences.
2) Illegal parking (small vehicles, vehicles parked in multiple parking spaces) issues, convoy parking, and other external factors reduced the predictability of these periods.

Pattern analysis also suggested that the day of week attribute highly affected the utilization of the truck parking lots. For example, the TPOP performance on Tuesdays, Wednesdays, and Thursdays was better than on other days. Ground truth data extracted from the CCTV camera revealed that a potential reason for the TPOP performance difference may have been the more frequent random parking and short-term truck parking on the other days. The features of those random and short-term parking events were not well determined and deserve further research.

8. CONCLUSIONS AND FUTURE RESEARCH

8.1 CONCLUSIONS

This research developed a truck parking management system that can identify and predict vacant truck parking stalls at a future point in time, thereby addressing an immediate need for commercial drivers in Washington state to locate a safe place to rest. It also improves the management of truck parking facilities, such as highway rest areas, welcome centers, etc. Specifically, the development and testing of a pilot truck parking management system evaluated different system components to enhance truck parking facility management and the information provided to the travelling public. Empowered by artificial intelligence and deep learning for parking prediction, the pilot TPIMS system achieved an error rate of less than 12 percent in predicting parking availability from 10 minutes to four hours ahead. Finally, both the real-time and multi-timescale prediction occupancy information can be disseminated via a customized website and user mobile application in real time.

A comprehensive study on truck parking pattern aggregation and availability prediction was conducted by WSDOT and the University of Washington team. First, a reliable long-term truck parking occupancy data set was collected with occupancy sensors made by Sensys Networks (with an estimated accuracy of above 99 percent). Second, by aggregating the truck parking occupancy data sequence along various attributes, including time of day, day of week, and weather conditions though the ASAM, weekly parking patterns were clearly found and were divided into a truck working mode and off-work mode. Third, a novel deep learning neural network, TPOP, was trained and tested for real-time truck parking occupancy prediction for multiple time slots. It showed that future parking availability (between 10 minutes and four hours ahead) could be predicted with minimal error. The findings and outcomes of this project can be used to expand the pilot TPIMS system to other locations in Washington state.

8.2 FUTURE RESEARCH

Recommendations for future research include three aspects: 1) investigation of occupancy detection technology, 2) integration of new data sources and improving the prediction algorithm, and 3) scalability and public outreach.

8.2.1 Investigation of Occupancy Detection Technology

New sensing technologies, including entry/exit, video-based, and hybrid sensing systems should be investigated. Currently, most TPIMSs are based on in-ground sensors to detect parking space occupancy status. The pilot study suggested that they can offer accurate and reliable parking detection in most conditions. However, in-ground, sensor-based TPIMSs currently have two limitations:

- High cost. The need to install one or two sensors in the ground at each parking space creates significant expenses for installation, communication, and future maintenance.
- Damage to the pavement. Work crews must cut the parking lot pavement to install, maintain, and replace the sensors.

Therefore, new sensing solutions, including video detection, radar sensors, and loops at facility entrances/exits, should be further considered and investigated for their relatively low costs and easy scalability.

8.2.2 Integration of New Data Sources and Improving the Prediction Algorithm

The expansion of the prediction time interval and integration of new data sources will be critical to further improve the prediction algorithm. For prediction, more comprehensive algorithms are needed to further advance the embedded integration of other information, such as cargo information (type, size), driver information, and even truck features, as input variables. This will provide two potential benefits. First, the integration of information from multiple sources will allow further classification of the dataset that will benefit prediction accuracy. Through the novel embedding method, the network training process can better find and fit mapping from driver information (or other category information such as cargo type, vehicle type, trip characteristics) to a multi-dimensional vector space. This process will transform the factors (irregular combinations of numbers and characters) into a multi-dimensional space vector that the neural network can better understand and use in the prediction procedure. Furthermore, through such a customized multi-dimensional vector, the driving habits of different drivers and other characteristics of various trucks and drivers can be better distinguished. In the next step, our team will also work on a more detailed and powerful heterogeneous feature embedding methodology. In addition, expanding the current prediction scheme to a new, network-level parking occupancy prediction framework requires further investigations, especially regarding the integration of parking lot correlation features such as graph distances, similarity level, service types, etc. More data will be collected for training and evaluating the current prediction algorithm.

8.2.3 Scalability and Public Outreach

Continued scalability and public outreach are necessary to improve system performance for both agencies and public users. The methods and application developed in this project have been implemented at two state facilities. Both locations are located along northbound I-5, one a WSDOT rest area and the other a jointly operated Washington State Patrol/WSDOT weigh station. For future research on truck parking pattern analysis and parking availability prediction, more parking lots will be included. Also, more attribute information and drivers' preferences need to be considered for input into the prediction neural network. WSDOT is also working on additional opportunities to expand the TPIMS, including expansion to 400 parking stalls in 28 state-owned facilities. WSDOT also plans to develop strategies related to land use, policy, and technology to improve the state's truck parking strategies. For long-term sustainability, there is interest in sharing the data with third-party information providers to disseminate truck parking information through their application. There is also interest in sharing this technology and information with other bordering states to help drivers plan their routes and rest stops across state lines.

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