Truck Parking Pattern Aggregation and Availability Prediction by Deep Learning

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***Abstract*— With the significant increase of e-commerce, freight transportation demand has surged significantly over the past decade. Most of the demand has been served by trucks in the United States. One major problem commonly identified across the country is the worsening truck parking availability because the increase of truck parking facilities has lagged behind the growth of trucking activities. The lack of parking spaces and real-time parking availability information greatly exacerbate the uncertainty of trips, and often results in illegal and potentially dangerous parking or overtime driving. This paper elaborates on pilot research on improving truck parking facilities cooperated with the Washington State Department of Trans- portation (WSDOT), building and testing the advanced Truck Parking Information and Management System (TPIMS) with the real-time user visualization and prediction function empowered by artificial intelligence. Furthermore, by analyzing the activities of truck drivers, the researchers aggregated the regularity of truck parking patterns by a customized sequential similarity methodology. A Truck Parking Occupancy Prediction (TPOP) neural network for time-variant occupancy prediction by deep learning and attributes embedding is proposed and integrated into the TPIMS. The TPOP achieves 5.82%, 5.07%, 4.84%, and 4.19% mean average percentage error (MAPE) for 16, 8, 4, and 2 minutes ahead of occupancy prediction respectively, significantly outperforms other state-of-the-art methods. Clearly, the proposed solutions can benefit both the truck drivers and government agencies by a more efficient and smart TPIMS.**

***Index Terms*— Truck parking, parking information system, parking prediction, deep learning, pattern aggregation.**

I. Introduction

TRUCK-BORNE freight is a core component of modern logistics systems. With the huge increasing numbers of commercial trucks on the road, there is a rising apprehension about truck parking. Out-dated facilities and limited spaces always result in drivers' anxiety about finding a parking space. However, with the pressure of delivery due and hours-of-service-regulations [1], limited time is allowed on searching available parking slots. Under the situation of either continuing driving in fatigue or parking illegally on roadway shoulders and ramps, substantial safety concerns are raised for both drivers and operators. Based on the report from Federal Motor Carrier Safety Administration (FMCSA), the number of total fatalities in large truck crashes increased 46.90% from 2009 to 2018 across the U.S. [2]–[4]. Meanwhile, a strong correlation has been found between the hours of driving and fatigue-related crashes [4], [5]. In the eleventh hour, the potential risk related to crashes is about 36% higher than that in the first hour [5]. So, reliable real-time parking availability information and parking pattern prediction will significantly help truck drivers schedule their stops at parking facilities and avoid unnecessary slowdown.

Detailed pattern analysis and prediction for truck parking require a large amount of high-quality data, which need both huge investments on the parking infrastructures and the breakthrough of data collection techniques. Recently, with the rapid development of traffic sensing technologies and Truck Parking Information Management System (TPIMS), space level real-time truck parking occupancy status detec- tors are applied to practice in several states of the USA (including Washington, Florida, Minnesota and etc.). Gener- ally, there are two kinds of in-pavement parking sensors tested for TPIMS: radar-based detectors [6] (i.e., parking sensor manufactured by Sensys Networks, Inc.) and magnetic-based detectors [7] (i.e., parking sensor manufactured by SEN- SIT Technologies, LLC.). Both of them are installed below the surface of truck parking spaces and periodically report the occupancy status to the server. Previous research shows that the detection accuracies of both the radar-based and magnetic-based detectors are above 95% [8]. Thus, with the detailed parking activity data, advanced pattern analysis and availability prediction algorithms for trucks can be further developed.

Clearly, by summarizing the truck parking patterns with various impact factors, commercial vehicle (CV) operators and agency managers can further improve and optimize their strategies. In general, the spatio-temporal factors (i.e., parking utility with the truck parking lot location, time-of-day) are critical for finding truck parking patterns, which can help people find out when and where the imbalance of supply and demand occurs [9], [10]. Attributes factors (i.e., weather impact, parking lot supporting facilities like restrooms and food stores) are useful for people to understand how the exter- nal attributes influence the freight activities and how to provide truck drivers with better services [11]. The pattern aggregation,

Manuscript received 19 August 2020; revised 25 February 2021 and 16 July 2021; accepted 27 August 2021. Date of publication 20 October 2021; date of current version 9 August 2022. This work was supported in part by the Washington State Department of Transportation under Grant T1461- 73 MOD02 and in part by The Pacific Northwest Transportation Consortium (PacTrans). The Associate Editor for this article was M. Zhou. *(Corresponding author: Yinhai Wang.)*

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Digital Object Identifier 10.1109/TITS.2021.3117290

including distribution correlation and similarity analysis, can help managers set up different management schemes, thereby achieving dynamic control strategies. Furthermore, the parking availability prediction is a more straightforward way to help the CV operators better plan schedule and provide valuable parking utility reference in advance [12], [13]. However, to build an innovative and efficient TPIMS, several challenges are still need to overcome from both theoretical and practical perspectives:

- *Lack of Quantitative Aggregations for the Truck Parking Pattern:* Currently, the analysis and calculation of truck parking patterns still focused on primary analysis, which lacks of mathematical approach for the systematical pattern distribution aggregation [7], [8]. In gen- eral, the parking pattern is closely related two types of features: spatial-temporal features (including parking lot location, time of day, day of week, etc.) and attributes fac- tors (weather conditions, facilities quality of the parking lot, etc.). The quantitative pattern analysis, i.e., similarity calculation, can help researchers aggregate the truck drivers activities [14] and obtain more straightforward conclusions of parking utilities.
- *Poor Accuracy and Flexibility of Prediction Algorithms:* Generally, the truck parking availability prediction methods can be divided into two categories [14], [15], the traditional approaches and machine learning based approaches. The traditional approaches are always borrowed from statistical modeling regression, whose performances are not desirable for supporting real-time truck parking occupancy prediction. Meanwhile, even several researchers did investigations based on machine learning approaches and obtained encouraging results; the neural network architecture is generally born from sequential prediction modeling. Under the circumstances, the prediction scale is a fixed time step, which significantly reduce the flexibility and practical value of the proposed methods.
- *Limited Integration of Multi-Source Features Representations:* Nowadays, most of the previous truck parking prediction neural networks are based on temporal learning architecture, which is mainly designed for capturing the hidden pattern from the historical input sequence to the output [8], [15]. However, to infer the future truck parking occupancy, the historical sequential learning approaches need to be further improved by integrating other useful information sources, which are always in various data formats. The attributes and categories representations, including time of day, day of week, weather conditions and driver characteristics need to be fully involved into the prediction scheme.

Fortunately, the booming of sequential modeling approaches shed a new light on addressing the aforementioned difficulties. To quantify the relationship of parking pattern, sequence similarity comparison calculation method is introduced and improved in the research. In general, similarity estimation is a significant research topic with a long history in the transportation research community [16]–[19]. Through evaluating the similarity among objects, it is easy to do the classification and group feature extraction [20]. The main goal of similarity calculation is to estimate the given input's mathematical distance and classify data to match the real application with the pre-defined scenarios [21]. And then, different groups will be treated by customized rules according to the restrictions in the scene. In truck parking scenario, when discovering and clustering the parking pattern characteristics of a parking lot for various days within one week, the managers can obtain a straightforward idea for the weekly parking distribution and then make a periodic management plan for various days of week. Furthermore, in parking lot management and planning of dynamic charging strategy, similarity analysis of parking occupancy rate and parking pattern in different locations and different periods is carried out to set up different management schemes, thereby achieving dynamic control and optimizing benefits.

Furthermore, inspired by previous successful demonstrations of sequence learning approach for traffic prediction, including traffic network perceptions and parameters foresting [22]–[24], parking occupancy predicting [25]–[27], a more flexible and adaptable truck parking prediction algorithm can be achieved by the merging of state-of-the-art deep learning and representations embedding. Through sequence-to-sequence encoder and decoder architecture, reliable and precise multi-timescale prediction can be accomplished. With the help of attributes embedding and attention mechanism, the category information, including time of day, day of week, weather conditions and the drivers characteristics can be better integrated into the prediction framework to improve forecasting accuracy effectively. Also, through the customized the algorithm by a modular design structure, the whole truck parking prediction framework can be more flexible and adaptable.

In summary, the whole team claims the **technical innovations** below:

- Successfully implemented a pilot TPIMS for public agencies and CV operators with the Washington State Department of Transportation (WSDOT). The proposed system includes space-by-space parking status data collection, real-time data processing, multi-timescale occupancy availability prediction and information dissemination (via a website and a mobile app).
- Investigated and aggregated the truck parking pat- tern by long-term slot-level parking data in the USA. A novel sequence-based pattern similarity analy- sis method, Advanced Sequence Alignment Method (ASAM), was proposed to quantify sequential parking records similarity under various conditions, including time of day, day of week and various weather conditions. Through ASAM, unambiguous periodical parking pattern can be summarized and quantified.
- An attributes-aware sequence-to-sequence deep learning architecture – Truck Parking Occupancy Prediction (TPOP) neural network, was proposed for the availability prediction. TPOP models the interrelation of the input metadata sequence and the attributes information, conducts multi-timescale predictions for future parking availability simultaneously. It achieves 5.82%, 5.07%, 4.84%, and 4.19% mean average

percentage error (MAPE) for 16, 8, 4, and 2 minutes ahead occupancy prediction, respectively, outperforming other cutting-edge methods.

II. Literature Review

A. Parking Occupancy Pattern Analysis

Occupancy pattern is one of the most essential characteristics for a truck parking lot. A farseeing research was proposed by [28] in early 2015, using wireless ground sensors and cameras to investigate the parking lot utilization distribution in Florida State. However, with the limited data sources and computational power, slot-level parking pattern analysis was not feasible. An urban parking survey [29] systematically summarized the advanced parking system development all over the world in 2017. Additionally, the research also reflected the backwardness of truck parking infrastructure at the information perception and dissemination. Also, in 2017, the GPS-based truck parking utilization analysis was proposed by [30]. The result shows that "parking utilization was found to vary considerably throughout the day", which makes researchers release the importance of investigating truck parking behaviors.

With the development of sensor technologies, researchers from the University of Florida first proposed a detailed slot-level parking event and utilization analysis [8] in 2018. However, the research focused on comparing and evaluating three types of parking sensors, rather than discussing the truck parking pattern in detail. It is inspiring that the slot-level truck parking detectors' accuracies were above 95% (the best one was more than 97%), which can support precise truck parking pattern analysis. Simultaneously, a group of researchers also tried to extract the truck parking information from the truck travel diary log in 2018 [31]. The research was lasted for 2053 days and included 148 truck drivers. They found that the peak period for truck parking often happened during the nighttime, which is very different from public urban parking pattern. However, the inherent limitations of data collection approach made this study difficult to quantify the general pattern of the truck parking behavior. In 2020, a truck parking intelligent system survey [14] summarized the previous research on truck parking by pioneers. This paper analyzed different types of TPIMS sensors, including video-based sensors, laser-based sensors, radar-based sensors, magnetic-based sensors, etc. Furthermore, the survey also included the parking pattern modeling discussion with highly related factors, especially the spatial-temporal features and attributions, including parking lot location, time of day, week- day or weekend and weather conditions. To be continued, in this research, the authors establish a novel TPIMS system in Washington State and analyze the detailed truck parking pattern. Based on a quantified pattern aggregation, the internal correlation and distinction are further analyzed.

B. Review on the Parking Availability Prediction Models

Generally, the recent parking prediction research (summarized in Table I) can be classified into two categories, the traditional statistical approaches and machine learning approaches. The classical models were implemented for the truck parking prediction including Linear Regression [36], AutoRegressive Integrated Moving Average (ARIMA) [36], Non-Homogeneous Poisson model [14], [15], Trend switching model [15], Trend shifting model [15] and etc. These traditional prediction algorithms are usually derived from statistical regression models, whose key idea is to fit the occupancy pattern according to the metadata and variables. The advantages of these classical methods are: 1) high computing efficiency and easy deployment; 2) not relying on large amounts of data to fit and calibrate. Therefore, the traditional models have also been deployed in some actual parking prediction systems and accumulated some application experience for managers. However, in real life, many parking related factors affect the prediction result directly or indirectly such as parking lot location, time of day, day of week, weather conditions, etc. To better integrate the related features, the applicability of traditional models is far from enough.

With the booming of the machine learning methodologies in the transportation research community, neural networks also play significant roles in parking prediction. Several well-known architectures were successfully implemented on the parking occupancy prediction tasks, including recurrent neural network (RNN) [15], [37], Long short-term mem- ory (LSTM) neural network [27], [32], Graph Convolu- tional Network (GCN) [25], [26], and surpassed most of the traditional models. In detail, [25] proposed a Hierarchical Recurrent Graph Convolutional Network (HRGCN) for the city-wide urban parking utility prediction and achieved the mean absolute error (MAE) less than 10.63 and 9.23 in two world-famous megalopolises. The model successfully integrates the spatio-temporal features, phone app information, and the trajectory records by the graph attention component. Also it inspires the researchers to design a special module to fuse the heterogeneous features in the truck parking prediction. The group from Carnegie Mellon University proposed a customized deep neural network based on GCN and LSTM [26], which can incorporate the traffic speed and weather conditions. The model achieves a testing mean absolute percentage error (MAPE) of 10.6% when predicting block-level parking occupancy for 30 minutes advanced periods. A team from Google Research proposed a parking difficulty estimator through a feed-forward neural network [33]. Even the variables and strategies of urban parking and truck parking prediction are very distinct, the research motivation and features extraction methods can be referred by the truck parking prediction.

III. The Proposed Pilot TPIMS System and Data Collection

In the research, the pilot TPIMS is implemented on truck parking rest areas in Washington State, showing in Fig. 1. Each parking lot is monitored by the TPIMS and the surveillance camera system. The TPIMS sensors are manufactured by the Sensys Networks, Inc. and the Smart Transportation Application and Research Lab (STAR Lab), University of Washington. Four different parts are integrated into the TPIMS:

TABLE I

Review on the Parking Occupancy Prediction Algorithms

Category	Features/Model	Performence Evaluation	Venue	Year	Ref
Urban parking	Long Short-Term Memory (LSTM) neural network for stochastic prediction	MAE/MAPE/RMSE/RRSE	International Conference on GCP	2018	[27]
Urban parking	Customized deep neural network based on Graph Convolutional Networks (GNN) and LSTM	MAE/MAPE	Transportation Research Part C	2019	[26]
Urban parking	LSTM neural network	Customized evaluation method (α value)	Neural Computing and Applications	2019	[32]
City-Wide parking	Parking difficulty estimation, feed forward deep neural network	Balanced normalized rewards	SIGKDD Conference	2019	[33]
Truck parking (Survey)	Non-homogeneous Poisson model, multivariate spatio-temporal model, classification model and etc.	Sensitivity and specificity	IEEE ITS Magazine	2020	[14]
City-Wide parking	Hierarchical recurrent graph neural network	MAE/RMSE	AAAI Conference	2020	[25]
Short-term urban parking	Poisson distribution model based on arriving and leaving distribution, classification Model and etc.	Occupancy accuracy evaluation	IEEE Access	2020	[34]
Urban parking	Periodic attributes-aware LSTM neural network	MAPE	IJCAI	2020	[35]
Truck parking	Static regular model, trend switching model, trend shifting model, hybrid model	MAPE/RMSE	J. Transp. Eng.	2020	[15]
Urban parking	Linear regression, ARIMA, SVM, back-propagation neural network	MAE/RMSE	J. Adv. Transp.	2020	[36]

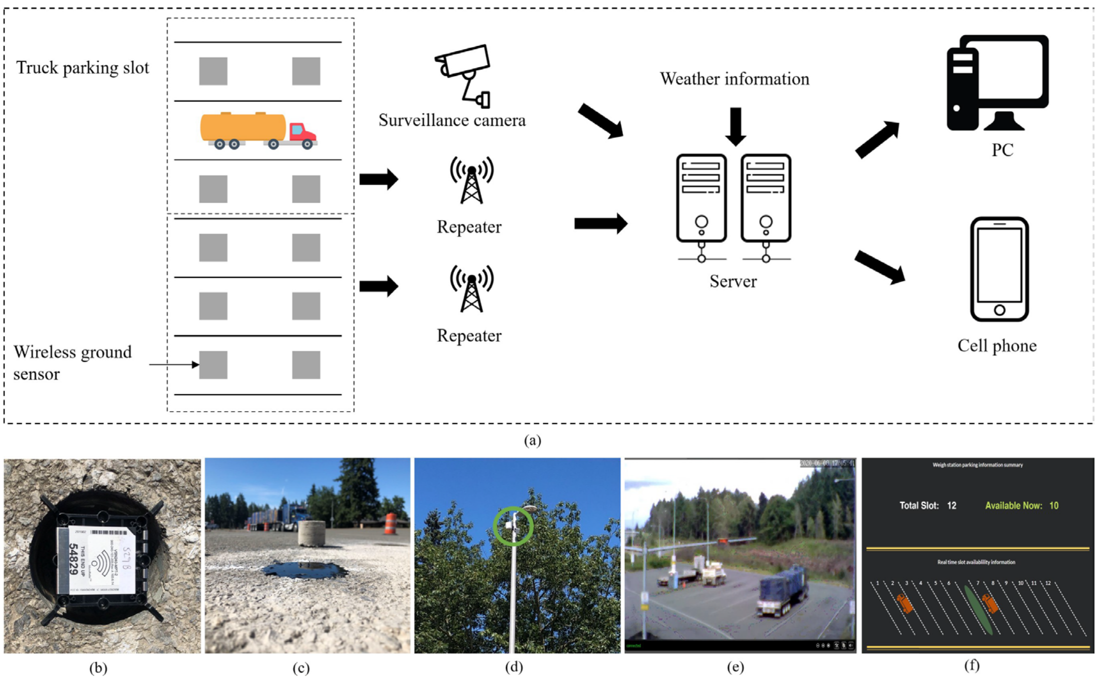

Fig. 1. The architecture of the proposed TPIMS in the pilot project. Six different parts are included in the system as follows: (a) illustration of the pilot TPIMS architecture; (b) radar-based wireless in-ground sensor made by the Sensys network; (c) the finished installation illustration of the in-ground radar sensor; (d) the finished installation of the wireless repeaters' on the light pole; (e) the real-time surveillance video stream; (f) the real-time slot level parking status visualization website.

- *Radar-Based Wireless Ground Sensor:* In each parking slot, two radar-based parking detectors are installed and sealed with industrial sealants.
- *Wireless Signal Repeater:* The repeater was installed on the top of the street light pole and used to transmit the sensor signal to the server.
- *The Server System:* The server is used to process and manage the real-time parking slot status. Databases are built in the server to store different kinds of data, including real-time weather information, the occupancy rate of parking lots, etc. In this research, the server is also used for collecting surveillance video data.
- *The User Interaction Application:* In the pilot TPIMS system, the research team builds a website and a cell phone app to show the real-time parking availability and the future utility information on slot level.

For truck parking pattern analysis and prediction model development, the team collected 49 truck parking spaces data in two truck rest areas adjacent to the I-5 freeway from Jan 05^{st} to Mar 15^{th} of 2020. The data were summarized into parking lot occupancy by every minute. The team also collected the real-time weather information from the closest weather station[1] and recorded per minute. Eight categories of weather conditions were summarized: cloudy, light rain, light snow, rain, snow, wintry mix, fair and fog.

[1]By Traveler Information API: https://www.wsdot.com/traffic/api/

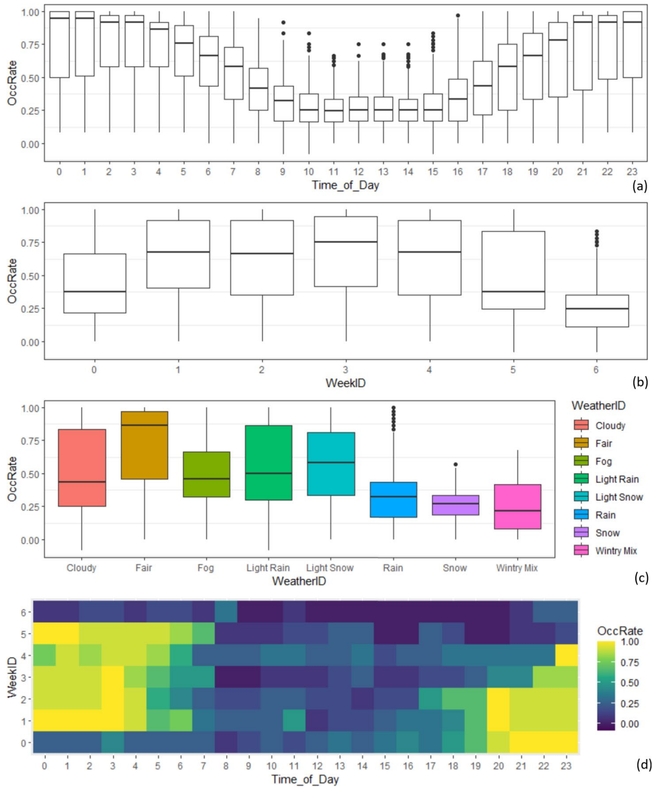

Fig. 2. The primary analysis of the truck parking occupancy distribution, including time of day (a), day of week (b, 0 represent Sunday), weather conditions (c) and combination of day of week and hour of day (d).

IV. Truck Parking Occupancy Pattern Analysis

A. Primary Analysis

In this research, the truck parking pattern investigation is conducted by two steps: primary analysis and pattern aggregation. Both parts contain the parking pattern exploration with the general concerned factors: time of day, day of week and weather conditions. First and foremost, primary statistical analysis of is finished and visualized in Fig. 2. It can be seen that the truck parking occupancy rate fluctuates significantly throughout a day. In Fig. 2 (a), by calculating the average occupancy rate for each hour, the occupancy rate from 21 o'clock to 4 o'clock the next day is above 90%. Among the 24 hours of a day, the occupancy rate from one to two in the early morning was the highest (97.74%). During the daytime (from 8 AM to 6 PM), truck drivers can find parking spaces easily, and the average occupancy rate of the parking lot is less than 60%. Similarly, each week's overall analysis shows a clear pattern distinction between working days and weekends, showing in Fig. 2 (b). The average parking lot occupancy rate on Friday night, Saturday and Sunday are less than 40%, and drivers can easily find parking spaces almost anytime. However, the average parking lot occupancy rate from Monday to Thursday is higher (all above 67%). Unfortunately, we did not find a clear relationship between weather conditions and parking occupancy (in Fig. 2 (c)). The next section will conduct a more detailed similarity measurement analysis and explain the potential reasons.

To investigate the distributions of time of day as well as day of week on truck parking activities in detail, we combine

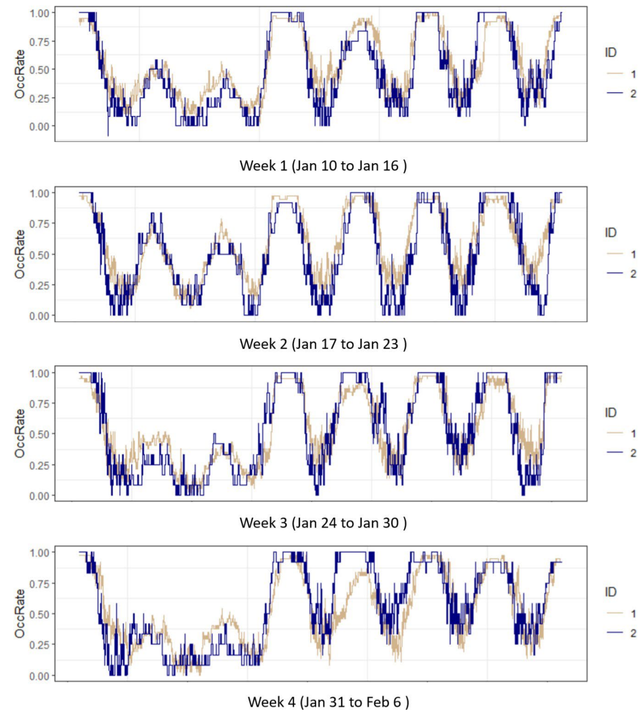

Fig. 3. Visualization of the periodical weekly pattern for truck parking.

these two variables together as shown in Fig. 2 (d). Through a more detailed analysis, the team found that no matter which day is, the parking lot occupancy rate is generally low (below 50%) during the daytime (9 AM to 5 PM). However, in the evening and nighttime (from 8 PM to 6 AM the next day), the occupancy pattern is closely linked to the day of week. The statistical result shows that the truck parking lot utility is very high in the evening and night time from Sunday to Thursday (above 95%). However, the occupancy rate from Friday to Saturday and Saturday to Sunday is very low (less than 40%). Such a considerable difference represents the different behavior of truck drivers in workdays and weekends.

After the statistical analysis was performed, the research team performed a rough quantification on the truck parking occupancy sequence pattern. We recorded the occupancy data by each minute summarized a total of 4 weeks of occupancy sequence for two parking lots. The details are shown in Fig. 3. There is no doubt that the distribution pattern of the different weeks is related and repeatable. The occupancy distribution of different parking lots also shows a similar pattern. Such findings encouraged us to carry a quantified sequence-based similarity analysis and cluster the pattern. Based on the result, a convinced pattern aggregation will help both the parking lot managers and the truck drivers.

B. Pattern Aggregation

1) ASAM Introduction: Before formally beginning to define ASAM, the traditional Sequence Alignment Method (SAM) [38] needs to be briefly introduced. In general, the SAM is proposed for the DNA sequence matching. SAM evaluates the workloads required to equalize the source sequence and the target sequence and treat the minimum efforts as the measurement of the difference between them. The equalization efforts are calculated by the basic operation accumulation. In SAM, there are three kinds of operations: “Insert”, “Delete”, “Identify”. The principle of SAM is to find out the set(s) of operations which can minimize the sum of operation efforts to equalize the two sequences. In a mathematical manner, we assume the source sequence of SAM is $S = \{S_i\}$, $i = \{1, 2, \ldots, m\}$, and target sequence is $T = \{T_j\}$, $j = \{1, 2, \ldots, n\}$. Therefore, the “insert” operation $IN(j)$ indicates the insertion of the an element of target sequence into the j^{th} position of the source sequence; the “delete” operation $DE(i)$ indicates the deletion of the i^{th} element of source sequence; the “identify” operation $ID(i)$ indicates the identification of the i^{th} element of both source and target sequences. As a result, the operation sets O_{SAM} from the source sequence S to target sequence T can be represented in Equation (1):

$$O_{SAM} = \{IN(j) \cup ID(i) \cup DE(i)\} \tag{1}$$

And the distance δ_{SAM} between the source sequence S and target sequence T can be calculated as the sum of the efforts EF of all three kinds of operations IN, ID, and DE:

$$\delta_{SAM} = \sum_{IN(j)\in O} EF_{IN} + \sum_{ID(i)\in O} EF_{ID} + \sum_{DE(i)\in O} EF_{DE} \tag{2}$$

However, in the truck parking scenario, the spatio-temporal sequences of occupancy rate are numerical values. In the traditional SAM method, only “Insert”, “Delete”, and “Identify” are considered; therefore, the difference between “0” and “9” is the same as the difference between “0” and “1” (i.e., both of them need two operations: Delete and Insert), which is not reasonable. Therefore, the paper introduces a new operation, “Subtract” into the traditional SAM, which is designed for the numerical values in the sequences when calculating similarities. We name the new method as Advanced Sequence Alignment Method (ASAM). To apply the operation “Subtract” in the similarity calculation, a threshold must be determined based on the range and the importance of the value. The paper assumes the operation “Insert” and “Delete” are equal-weighted, and sets their costs are both 1. Moreover, the cost of “Identify” is 0 because the operation does not change each sequence. If the difference between the two values exceeds the threshold, ASAM regards the difference as the sum costs of a “Delete” and an “Insert” operations. If the difference is under the threshold, the cost of the “Subtract” should be calculated based on the threshold. In the condition, the effort of operation “Subtract”, EF_{SU} can be represented as the following Equation (3), where φ denotes the threshold.

$$EF_{SU} = \begin{cases} 2(A-B)/\varphi, & if\,(A-B) < \varphi \\ 2, & if\,(A-B) \geq \varphi \end{cases} \tag{3}$$

The “Subtract” operation $SU(i, j)$ indicates the operation that replaces the i^{th} element of the source sequence by the j

As a result, the distance δ_{ASAM} between the source sequence S and target sequence T can be calculated as the sum of the efforts EF of all four kinds of operations IN, ID, DE, and SU:

$$\delta_{ASAM} = \sum_{IN(j)\in O} EF_{IN} + \sum_{ID(i)\in O} EF_{ID} + \sum_{DE(i)\in O} EF_{DE} + \sum_{SU(i,j)\in O} EF_{SU} \tag{5}$$

Based on the process mentioned in the previous paragraphs, we can get the distance δ between the two sequences S an T. Then, for the convenience for further comparison, the paper normalizes the similarity by a customized Sigmoid function, where “ξ ” denotes similarity, “δ” denotes the distance calculated after normalized by Gaussian function, and the L_{si} represents the total length of the two sequences.

$$\xi = 1 - \frac{1}{1 + e^{\frac{(2\delta - L_{si})*n}{L_{si}-1}}} \tag{6}$$

Obviously, from Equation (6) the larger distance indicates low similarity and the small distance indicates the 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 close to 0. Contrarily, the smallest distance is close to 0 (i.e., the two sequences are the same and there is no operation has been done); therefore, the similarity approaches to 1. In the truck parking scenario, usually, sequences with 0.4 to 0.8 similarity can be thought to have a similar pattern; sequences with 0.8 and higher similarity are highly related and dependent; the sequences with 0.4 and lower similarity are thought to have different even unrelated patterns. By comparing the aggregation result with metadata, the research team believes that the ASAM can be well used for the truck parking occupancy sequence pattern aggregation for the three reasons: 1) The added operation “Subtract” enables the method on numerical sequences analysis. 2) ASAM can process the sequences with various length to deal with the missing data situations.
3) ASAM can estimate the hidden correlations among the temporal sequence elements.

2) Occupancy Pattern Aggregation: Through the ASAM, the research team calculated the sequences of time of day, day of week and weather conditions from the two parking lots. Several conclusions can be summarized and the regular periodical pattern can be quantified into daily and weekly pattern.[2] Fig. 4 shows the results of pattern aggregation in detail.

For daily occupancy sequences, the similarity result shows an obvious “cross X” pattern. There are two high parallelism clusters aggregated by ASAM through daily truck parking pattern. In general, “daily off-peak hour” starts from 8 o’clock to 16 o’clock. In this time period, the truck parking lot’s occu-

th element of the target sequence. Therefore, the operation set of ASAM can be shown below in Equation (4):

$$O_{ASAM} = \{IN(j) \cup ID(i) \cup DE(i) \cup SU(i, j)\} \quad (4)$$

pancy rate is usually low (generally less than 40%), and the average parking time is relatively short (within 20 minutes). Meanwhile, during such a period, the occupancy sequence

[2]Due to drivers' habit difference, the pattern mainly reflect truck activities in North America including: United States, Canada, Mexico, etc.

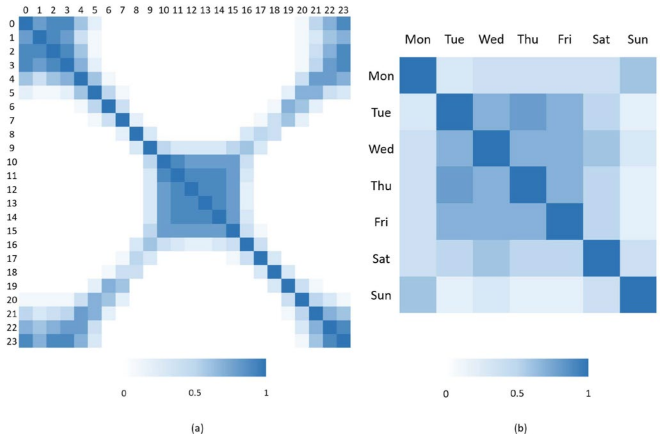

Fig. 4. Pattern aggregation result of the time of day (a) and day of week (b). The sequence similarity calculation result is showed by the color display (the higher the similarity, the bluer the display in the Figure 4).

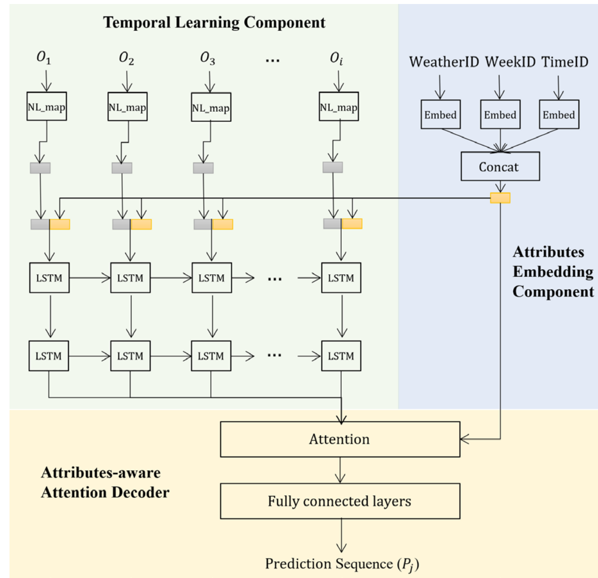

Fig. 5. The architecture of the TPOP neural network. Three components are integrated including attribute embedding component (blue), temporal-learning component (green), and attributes-aware attention decoder (yellow).

similarity is very high (above 56.05%), and the pattern is highly repetitive. The "daily peak hour", another high sim- ilarity cluster of the parking pattern, starts from 21:00 to 5:00 of the next day (especially from 22:00 to 4:00 of the next day). In the peak hour pattern, the parking lot occupancy rate is usually very high (more than 90%), and the average parking time is longer than two hours (with an average value of 145 minutes). For weekly pattern, in general, every week's truck parking pattern can be divided into two clusters: working mode and off-working mode. The working mode starts from Sunday night until Friday daytime. These days, the parking sequence similarity is very high (above 56%) and fits well with the daily peak-hour and off-peak hour pattern. The off-working mode, representing the relax time of truck drivers, usually starts on Friday night. On Saturday, Sunday or even sometimes Monday morning, the truck parking pattern similarity is low (less than 35%), and the random and personalized parking activities are more frequent than workdays.

After a careful sequence similarity investigation based on various weather conditions, the impact is negligible on the truck parking pattern. The possible reasons are: 1) the over- all weather in Washington State is relatively moderate, and extreme weather (heavy snow, dense fog) is not found in the research period. 2) the rich professional experience enables the truck drivers to eliminate the impacts of weather impacts.

V. Availability Prediction Based on Deep Learning

In this research, a sequence-to-sequence deep learning model – **T**ruck **P**arking **O**ccupancy **P**rediction (TPOP) neural network is developed to predict the truck parking occupancy statuses, and successfully integrated into the pilot TPIMS system. Based on the truck parking occupancy pattern analy- sis and aggregation result, the attributes information has a great influence on the availability. By Integrating attri- butions and temporal-features together, the TPOP achieves multi-timescale truck parking occupancy prediction precisely. In this section, researchers describe the architecture of our proposed TPOP.

A. TPOP Preliminary

The definitions and preliminaries are listed formally:

1) Definitions: Definition 1 (Historical Occupancy Sequence (O_i)): The historical occupancy sequence (O_i) is a sequence-based continuous temporal occupancy records obtained from a parking lot. The time gap (t^g_i) of the O_i is fixed. The length of the O_i is L_{O_i}. In this work, the O_i is used as the input of TPOP including the records of $o_1, o_2 \ldots O_i$.

Definition 2 (Prediction Sequence (P_j)): The prediction sequence (P_j) is a sequence of future occupancy data for a parking lot. The time gap of the P_j is customized (need to be n times of t^g_i and n is an integer ($n > 0$)). The length of the P_j is j. In this work, the P_j represents the output of the neural network and including the records of $p_1, p_2 \ldots p_j$.

Definition 3 (Attributes Sequence (A_i)): The attributes sequence (A_i) is a sequence-based attributes information that belongs to each occupancy status for a parking lot. In this work, the A_i includes the weather condition (weatherID), the day of week (WeekID) and time of day (timeID).

2) Prediction Objective: The overall target of this section can be divided into two parts. During the training phase, the researchers train the neural network in a supervised manner to fit the P_j based on the input O_i and the A_i. In the testing phase, we test our model based on the given O_i and A_i, and generate the P_j. Then, evaluate the prediction result based on the ground truth data.

B. TPOP Model Description

TPOP neural network (as shown in Fig. 5.) is con- sists of three subcontinents: attribute embedding component, temporal-learning component, and attributes-aware attention decoder. The attribute embedding component is used to process the category factors (e.g. day of week and weather conditions) and the time information of the given sequence (e.g. hourID). Its output is fed to the other two components as part of inputs. The temporal component is used to learn and memorize the temporal dependencies from O_i to P_j. Finally, the attributes-aware attention decoder is used to balance the trade-off between the historical dependency and the effectiveness of the attribute, and maps the previous two components outputs to the P_j.

1) Attribute Embedding Component: Based on the truck parking pattern analysis, the occupancy is highly affected by the attribute information, including hour of day, day of week and mode of working or off-working. To better use such information, the TPOP neural network includes and integrates the attributes set into the parking occupancy prediction process. Here, the set includes weatherID (rainy, snowy, sunny, etc.), weekID (from Monday to Sunday), and the timeID (hourID and MinuteID).

However, the attribute information format is always discrete categorical values, which cannot be fully used and under- stood by sequential-oriented neural networks [39]. Meanwhile, the impact of the attribute information on the output sequences is always complicated and multifaceted. Thus, a learnable procedure incorporated with the network is necessary. Inspired by feature learning techniques in using natural language processing (NLP), mapping the words or phrases from the vocabulary to vectors of real numbers, embedding becomes a bridge to connect these discrete values to a vector dimension. In the framework, we adopted the low dimension embedding method proposed by [40] to transform categorical factors into a neural network input sequence. Using A_i represents the attributes sequence after embedding. The overall output of the attribute component is:

$$A_i = E^{\alpha}(weather_i) \circ E^{\beta}(week_i) \circ E^{\gamma}(time_i) \tag{7}$$

2) Temporal Learning Component: Based on the literature review and the section of truck parking pattern analysis, the temporal dependency is the key factor to the prediction result. To better capture the temporal relationship among the input and output sequences, the researcher team firstly introduced a non linear mapping where map the i_{th} historical occupancy record into a R^{16} vector.

$$O_i^{nl} = tanh(W_{(O_i^{nl})} \cdot O_i) \tag{8}$$

In the Equation (8), the H_i^{nl} means the output of the non-linear mapping map result. The $W_{(O_i^{nl})}$ is the learnable weight matrix which is used to transform the input sequence records into the R^{16} dimension vector. The tanh is used here to normalize the input size of the original value.

After the mapping, the LSTM is introduced in this model to "memorize" the history in the processed sequence. Generally, each LSTM neural contains three gates [41], which are input gate $i^{(t)}$, output gate $o^{(t)}$ and forget gate $f^{(t)}$ inside a neural. Each gate is controlled by their own weight $W^{(t)}$ and the previous hidden neural output $h^{(t-1)}$. In the TPOP model, the input of the stacked LSTM layers can be divided into two parts. One is the historical occupancy sequence $O^{(nl)}$ and another is the attribute information sequence after embedding A_i. The matching records in both sequences are concatenated to a vector and then send into the stacked LSTM layers. The output of the LSTM layers can be shown in Equation (9). Where, the $W_i^{O_i^{nl}}$; W_i and W_i are all learnable parameter matrices used in the LSTM. The σ_{rnn} is the activation function. The h_i is the hidden state after processed the i_{th} records of the combination of O_i^{nl} sequence and A_i. After the temporal module, we obtained a sequence h_i to represent the association temporal features, which consists of $(h_1, h_2, \ldots, h_i)$.

$$h_i = \sigma_{rnn}(W_i^{O_i^{nl}} \cdot O_i^{nl} + W \cdot h_{i-1} + W_i^A \cdot A_i + \varepsilon^{(i)}) \tag{9}$$

3) Attributes-Aware Attention Decoder: The researchers finally introduce a sequential decoder component that combines the previously captured features and estimates the occupancy level for various time slots ahead. In this work, an attribute mechanism is incorporated with the sequential decoder architecture to improve the TPOP flexibility and accuracy for multi-timescale prediction. In our model, the TPOP has the ability to predict the parking lot occupancy status at eight different time intervals in the prediction sequence, from t_i^g, to $8t_i^g$. Here, We use $p_0, p_1, \ldots$ to p_7 to represent the eight occupancy status of eight different time gaps. The features set we used to represents P_j are F_{P_j}.

In fact, the actual challenge of occupancy prediction of different time intervals is caused by various critical time records. Even each record using in h_i are treated all equally while they are used as input; however, they are more like to contribute differently for the prediction result. For example, if the parking lot is fully occupied at late night, the neural network should pay more attention to the status since such a status might last for several hours. To achieve an effective feature fusion, we adopt the attention mechanism instead of the mean pooling. The attention mechanism is essentially the weighted sum of the sequence h_i, where the weights are parameters learned by the model. Formally, we have the attention-aware F_{P_j} calculated by Equation (10):

$$F_{P_j} = \sum_{i=1}^{L_{h_i}} \mu_i * h_i \tag{10}$$

where μ_i is the weight for the i_{th} input historical occupancy sequence record. To obtain μ_i, the team combined the attributes information and the historical occupancy information in the following Equations (11) and (12):

$$F_{Att_i} = (M(A_i) \; O_i) \tag{11}$$

$$\mu_i = \frac{e^{F_{Att_i}}}{\sum_i e^{F_{Att_i}}} \tag{12}$$

In Equation (11), the $M(A_i)$ is the non-linear mapping map the attributes record of A_i into the same dimension of the O_i. The $\langle , \rangle$ represents the inner product space operator. After the attention component, the team used fully connected layers mapping the O_i into a 2-dimension vector to represent the occupancy level in P_i.

4) Loss Function: The research team trained the TPOP end to end. During the training phase, we use MAPE (M) as our objective function and optimized using RMSprop. Furthermore, we used multiple standards to evaluate our

TABLE II

PERFORMANCE COMPARISON

Time Slot Ahead	2min			4min			8min			16min		
Method	**MAE**	**MAPE**	**RMSE**	**MAE**	**MAPE**	**RMSE**	**MAE**	**MAPE**	**RMSE**	**MAE**	**MAPE**	**RMSE**
AVG	7.43	16.59%	9.47	7.56	17.91 %	9.99	7.64	18.58%	10.36	10.33	20.88%	13.47
RNN	4.73	9.65%	5.87	4.88	9.96%	6.04	5.45	11.12%	6.74	5.74	11.71%	7.78
LSTM	4.22	8.61%	5.19	4.34	8.86%	5.52	4.79	9.78%	5.89	5.01	10.22%	6.39
LSTM (2-layer)	3.77	7.69%	4.65	4.14	8.23%	5.12	4.33	8.81%	5.41	4.72	9.32%	5.77
PewLSTM (2-layer)	2.45	5.73%	3.42	2.84	5.71%	4.01	4.92	6.34%	5.41	3.61	7.23%	4.82
TPOP	**2.02**	**4.19%**	**2.99**	**2.35**	**4.84%**	**3.26**	**2.48**	**5.07%**	**3.64**	**2.87**	**5.82%**	**3.99**

model, including the rooted mean squared error (RMSE) and the MAE. The mathematical equation of MAPE is in equation (13):

$$M_{P_j} = \frac{1}{N} \cdot \sum^{N} \left| \frac{P_j - \hat{P_j}}{\hat{P}_j - \varepsilon} \right| * 100\% \tag{13}$$

C. Experiment

1) Environment Description: The TPOP was implemented with PyTorch. The work station for training and testing is equipped with two GPUs (NVIDIA TITAN Xp) and the CPU is Intel Core i7 8700. The operation system is Linux Ubuntu 16.04.

2) Parameters: The parameters in the TPOP experiment are in the follows:

- For the input historical occupancy sequence in the definition 1, the length of L_{O_i} using as TPOP input sequence is fixed as 32. The time gap t^g_i of the two records in the O_i is 2 minutes.
- For the prediction occupancy sequence in definition 2, The length of the prediction sequence L_{P_i} is 8. The future records (p_0, p_1, ..., p_7) represent the occupancy information of 2 min, 4min, until 16 min later parking occupancy status.
- The size of the embedding vector for each attribute (in equation (7)) is settled as follows: weatherID mapping into R^3, weekID mapping into R^3 and time ID mapping into R^{10}. The total dimension size of A_i is R^{16}.
- In the temporal learning component, the number of hidden neural in the stacked LSTM is fixed as 32 and two hidden layers are used.
- The activation function in the equation (9) σ_{rnn} is *tanh* function. The mathematical expression of *tanh* is $tanh(x) = e^x - e^{-x}/e^x + e^{-x}$.
- In the attention-aware attention decoder, the number of fully connected layers for each prediction record is fixed as two. The layers downsample the 32 dimension vector to represent the predicted future occupancy level P_i.

D. Result and Comparison

In prediction evaluation, we trained our model based on two parking lot data and evaluated it separately. The final result is the weighted average value of two parking lots based on the slot numbers. For the evaluation of different time slots ahead, we trained the neural network based on the input sequence with the same time gap.

- *AVG [42]:* Calculating the average value for each input sequence and use as the output sequence is the most traditional method for parking availability prediction. Here, researchers calculated the average occupancy rate of the input sequence and used as outputs. Then estimate the errors based on real occupancy and the average value of the input sequence.
- *RNN [37]:* RNN can use internal memory units to process arbitrary sequences of inputs, and thus grants the RNN the capability of learning temporal sequence. In the comparing process, the authors used a basic RNN to predict the parking occupancy and compared with the real availability record. Here, we set the neural number of RNN as 32 and using one hidden layers.
- *LSTM [43]:* For comparing, the authors used LSTM neural network to predict the occupancy directly. We set the number of hidden units as 32 and in one hidden layer. Based on the LSTM output, then estimate the errors based on ground truth and the predicted sequence.
- *LSTM (2-Layer) [27]:* For comparing, the authors also used two layers stacked LSTM neural network to predict the occupancy directly. We set the number of LSTM hidden units as 32 in two hidden layers.
- *Periodic Weather-Aware LSTM (PewLSTM) [35]:* PewLSTM is proposed in 2020, which is a novel sequential model incorporating the weather conditions and periodic patterns for parking occupancy prediction. By integrating a weather-aware gating mechanism into traditional the LSTM neuron, the PewLSTM successfully surpass the LSTM models in various weather conditions and environments. Here, we set the number of PewLSTM hidden neural as 32 in one hidden layer.

From the comparison of Table II, we can see that the TPOP prediction accuracy is significantly better than other parking prediction methods. Comparing with the traditional temporal learning model like RNN and LSTM, the attribute feature extraction module do extract more useful attributes representations and show positively impact on the prediction sequence. To show the prediction result, the research team uses a week data and visualize the comparison between the prediction result with ground truth in Fig. 6. The general prediction result is auspicious and encouraging. Also, we found that the attributes-aware decoder does help the performs of different prediction time slots. A more detailed analysis of the TPOP components can be found in the next section.

E. Effect of Attributes Information Incorporation

In our pattern analysis, the attributes information fusion is crucial because the truck parking sequence is highly related to the factors. To thoroughly show the effectiveness of different

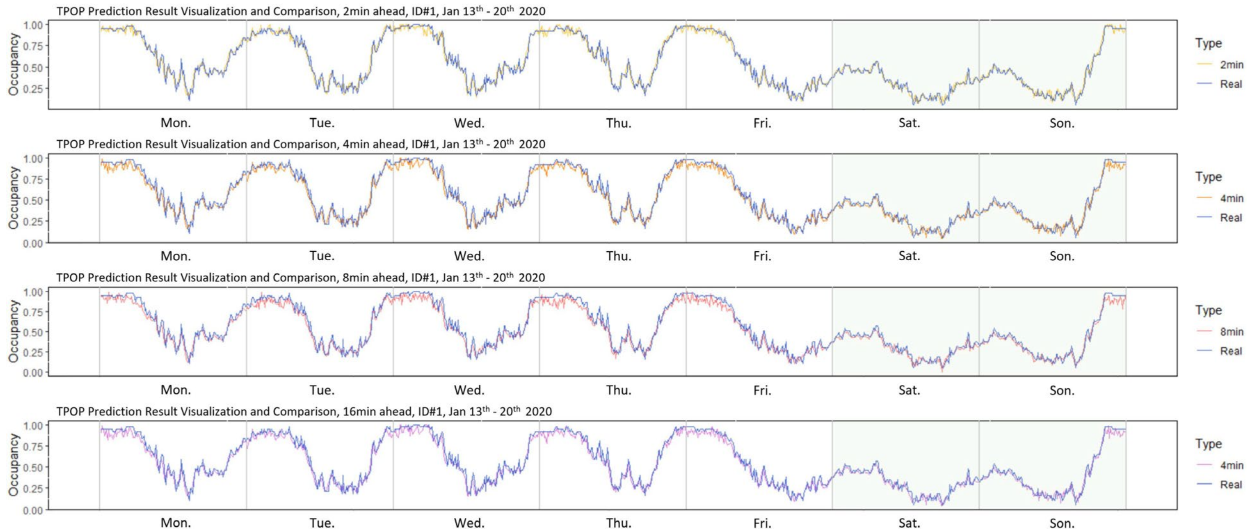

Fig. 6. Comparison of TPOP prediction result with metadata at 2min, 4min, 8min and 16min ahead.

TABLE III

ATTRIBUTES INTEGRATION COMPARISON

Time Slot Ahead	2min			4min			8min			16min		
Method	MAE	**MAPE**	**RMSE**	MAE	**MAPE**	**RMSE**	MAE	**MAPE**	**RMSE**	MAE	**MAPE**	**RMSE**
TPOP	**2.02**	**4.19%**	**2.99**	**2.35**	**4.84%**	**3.26**	**2.48**	**5.07%**	**3.64**	**2.87**	**5.82%**	**3.99**
TPOP (No weatherID)	2.21	4.42%	3.17	2.51	5.07%	3.43	2.61	5.28%	3.82	2.94	5.97%	4.16
TPOP (No timeID)	2.88	5.25%	4.11	2.96	5.99%	4.42	3.07	6.23%	4.73	3.72	7.04%	4.94
TPOP (No weekID)	3.09	6.02%	4.31	3.21	6.78%	4.57	3.44	7.04%	5.01	3.83	7.91%	5.28

attributes, including the weather condition, day of week and time of day, we devise a set of controlled experiments on our trucking parking dataset. The results are summarized in Table III.

We eliminate exactly one attribute with the same testing dataset and test our well-trained model for each experiment. Then, we summarize the before and after MAE, MAPE, and RMSE for the same week for comparison in Table III. From the experiment, it can be found that day of week and time of day affect the estimation significantly. Eliminating such two attributes causes an error growth of 1.94% and 1.12%, respectively. This also conforms to our intuitive sense, i.e., based on the pattern aggregation and similarity analysis, the time of day and day of the week shows an obvious impact on truck parking activity. The working mode and off working mode, daily peak hour and off-peak hour, are recognized and distinguished by the attributes embedding component and integrated into the final prediction result. Meanwhile, eliminating the weather information causes an error increment of 0.19% which seems not significant. However, we stress the data in the Washington state, most of the weather conditions are light rain and cloudy. For other states and countries, the weather information might be more helpful in estimating parking patterns. We leave it as an intriguing direction for the future work.

VI. Conclusion and Future Work

In this paper, comprehensive advanced truck parking research was conducted with WSDOT. A slot-based truck parking dataset was collected, and a novel method ASAM was proposed to aggregate the parking pattern. A path- breaking sequence-to-sequence learning neural network TPOP was trained and tested for real-time truck parking occupancy prediction for multi-timescales, which achieved state-of-the- art results. The achievements of this research are used to build the pilot TPIMS and served truck drivers in Washington State. This research can better help the CV operators transport shipments and schedule routes and contribute to the government agencies to improve the level of service for parking operation and management. In the future, more parking lots will be selected as the test site of the research. Also, more external attributes information and driver's preference will be considered as the input of the occupancy prediction task. Network-level parking occupancy patterns and predictions will be investigated.

Acknowledgment

The authors would like to thank WSDOT for participating and supporting this research. For more informa- tion on truck parking in Washington State, please visit https://wsdot.wa.gov/freight/trucking.

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