MePark: Using Meters as Sensors for Citywide On-Street Parking Availability Prediction.

Mr. Ghayatadak Jaibhimrao Eknath
Mr. Tathe Sachin G, Mrs. Mandhare V.V
Student of Dept. of Computer Engineering.
Vishwabharati Academy's college of Engineering, Ahmednagar, Maharashtra, 414201, India.
jaighayatadak14@gmail.com

ABSTRACT: **Real-time parking availability prediction is of great value to optimize the on-street parking resource utilization and improve traffic conditions, while the expensive costs of the existing parking availability sensing systems have limited their large-scale applications in more cities and areas. This paper presents the MePark system to predict real-time citywide on-street parking availability at fine-grained temporal level based on the readily accessible parking meter transactions data and other context data, together with the parking events data reported from a limited number of specially deployed sensors. We design an iterative mechanism to effectively integrate the aggregated inflow prediction and individual parking duration prediction for adequately exploiting the transactions data. Meanwhile, we extract discriminative features from the multi-source data, and combine the multiple-graph convolutional neural network (MGCN) and the long short-term memory (LSTM) network for capturing complex spatio-temporal correlations. The extensive experimental results based on a four-month real-world on-street parking dataset in Shenzhen, China demonstrate the advantages of our approach over various baselines.**

KEYWORDS: Parking availability prediction, spatial-temporal data, graph convolutional neural network, long short-term memory network.

I. INTRODUCTION

WITH the continuous increase of urban population and vehicles, many cities are suffering from intractable parking issues. Most of densely populated areas have insufficient parking spaces, especially for on-street parking, often causing various social issues such as traffic congestion, road safety, energy waste, and carbon emissions. A latest survey shows that, on average, drivers in New York spend 107 hours per year searching for a parking spot at a cost $2,243 per driver in wasted time, fuel and emissions [1]. If we can predict real-time on-street parking availability, many useful services will be enabled, such as helping people to select proper transportation modes in advance [2], [3], offering parking recommendations and navigation to en-route drivers via smartphones or driving assistance systems [4], [5], and assisting parking management authorities in dynamically adjusting parking rate for improving the efficiency of parking resource utilization [6]. It is often needed to deploy very dense sensors to obtain the real-time on-street parking occupancy information. For example, 8,200 in-ground geomagnetic sensors were installed for monitoring on-street parking spots in pilot areas of San Francisco [7]. For another, 13,800 on-street parking spots were monitored by cameras deployed about every 200 meters in Beijing [8]. Although these sensors can collect valuable parking data, the excessively high installation and maintenance costs have limited their large-scale applications in more cities and areas. Besides, crowd sensing based solutions have been developed to monitor on-street parking availability using smartphone sensors [9], [10] and on-vehicle sensors [11], [12], but they still impose extra cost (e.g., monetary incentive for recruiting participants) and dependencies on the existing parking systems.

This paper aims to investigate *whether* we can predict real-time citywide on-street parking availability with the already-deployed infrastructures and readily accessible data rather than fully relying on specially deployed sensors. With similar purposes, Rong *et al.* used mobility trace and navigation data from Baidu maps to infer real-time parking availability [2], while Arora *et al.* utilized crowd-sourced data by surveying Google Maps users to estimate parking difficulty [3]. Although they have achieved excellent performance in tested areas, their success relies heavily on data from sufficient map users. On the contrast, we consider another important data source, parking transactions data, since over 95% of on-street paid parking spots have been managed by meters [5], [13]. Moreover, various mobile payment methods are popularly used for parking management, and they could be treated as "virtual meters".

In fact, parking transactions data contains rich information such as when and how long a parker pays for parking on which spot. However, it is not trivial to effectively utilize the transactions data for parking availability prediction. A major issue lies in the difficulty of accurately obtaining the actual parking duration. The prepayment rule is commonly adopted for on-street parking, while the accurate departure time is always unavailable. For example, a parker pays one-hour parking fee, but she/he possibly uses the spot for only 30 minutes. The survey shows that drivers in New York add the extra time of averaging 96 hours per year or an extra $896 in parking payments to avoid tickets [1]. However, most of the existing studies simply consider that a parker does not depart from a spot until her/his purchased parking session expires, and use the aggregated occupancy of a street block at time *t* (i.e., the aggregated number of transactions among all the meters in the block that start before *t* and expire after *t*) for parking availability prediction, leading to a large error [5]. A few studies try to estimate the parking duration distribution, but the models are difficult to achieve robust generalization ability due to lack of sufficient and accurate data (e.g., only two-day data is collected from three streets at 10-min granularity by manual counts in [13]). Fortunately, the recent advances of sensing and communication technologies, such as low-power geomagnetic sensors with Narrowband Internet of Things (NB-IoT) modules, make sufficient and accurate parking occupancy data available. In the Chinese city Shenzhen, geomagnetic sensors have been deployed to monitor 34,259 parking spots in real time, and any parking occupancy change can be reported to the cloud at once with over 99.5% detection precision [14]. Moreover, the parking availability has been integrated in an App *Yitingche* [15], which has become a product with the largest number (over 3 million) of registered users for on-street parking in China. Nevertheless, there are still a large proportion (over 90% in Shenzhen) of streets uncovered by sensors due to expensive costs. It is of great value to predict real-time citywide on-street parking availability by combining the historical parking data reported by a limited number of sensors, the readily accessible parking transactions data in more streets without sensors, and other urban context data, such as the road network, POIs, weather and holiday events. In summary, our main contributions are as follows:

- We present the MePark system to enable the parking meters work as sensors for predicting the real-time citywide on-street parking availability at per-block spatial level (averaging 23 parking spots per block in Shenzhen) and fine-grained temporal level (per 10-min interval in the next 30 minutes), based on the readily accessible parking transactions data and other context data, together with the parking events data reported from a limited number of specially deployed sensors.

- We design an iterative parking availability prediction mechanism, which effectively integrates an inflow predictor and an outflow predictor. The inflow predictor outputs the per-block aggregated inflow in the next interval, while the outflow predictor considers each individual parker's arrival time independently and predicts her/his departure time based on a parking duration prediction model. In this way, the parking transactions data can be adequately exploited for improving the prediction performance.

- We extract discriminative features from the multisource data. Meanwhile, we combine the multiple-graph convolutional neural network (MGCN) and the Long short-term memory (LSTM) network to capture complex spatio-temporal data correlations for inflow prediction, and design a deep-learning-based probabilistic prediction model for parking duration prediction

- We evaluate the performance of MePark with a four-month dataset from 624,464 parking event records of 1735 sensors in Shenzhen. The results show that our approach achieves more than 43% relative error reduction over state-of-the-art baselines. Moreover, our solution is easy to be applied in more cities and areas due to its low cost. Also, it won a Data Creativity Award in the Shenzhen Open Data Innovation Contest 2019 [16].

II. RELATED WORK

Parking Availability Sensing

Extensive work has been conducted on detecting the parking occupancy state. One line of work utilizes specially deployed sensors in parking lots or garages [17], [18]. In recent years, some work uses NB-IoT based sensors [19] and video systems [20]–[23] for monitoring on-street parking spots. To reduce cost and increase the scalability of sensing on-street parking availability, another line of work leverages crowd sensing based solutions using in-built smartphone sensors [9], [10] and on-vehicle sensors [11], [12]. Gkolias and Vlahogianni [24] even adopt on-vehicle cameras to detect on-street parking spots. However, It still imposes extra cost and dependencies on the existing parking systems. By contrast, this paper explores the third line of work on leveraging the already-deployed infrastructures and readily accessible data rather than fully relying on specially deployed sensors for on-street parking availability sensing. Along this line, Rong *et al.* exploit the map mobility trace and navigation data from Baidu maps [2], while Arora *et al.* leverage historical geo location data and anonymized surveys from Google Maps users [3]. However , their success relies heavily on data from sufficient map users. Differently, we make use of the readily accessible parking transactions data and other urban context data at almost zero cost.

III. PROBLEM STATEMENT

Difficulty in locating available spaces in a multilevel parking garage is highly problematic, especially during weekends or public holidays. For around two-thirds of visitors, finding parking spaces during weekends or public holidays can take more than 10 minutes . During peak hours, stadiums and retail centers are heavily crowded, and customers may have significant difficulties finding available spaces at these locations. Insufficient car parking spots lead to congestion and frustration among drivers [8].The objective of the study is to develop and execute an intelligent system that will be utilized in intelligent parking garages to facilitate the identification of available parking spots.

IV. PROPOSED DESIGN

The project is essentially divided into two components: hardware architecture and software android program. The circuit design was implemented in the hardware architecture, and a prototype of the project was developed. Throughout the software development process, the entire prototype was controlled exclusively through programming code.

IV.I. Hardware Requirements

For this project various hardware components have been used which are illustrate below.

IV.I.I. Arduino UNO

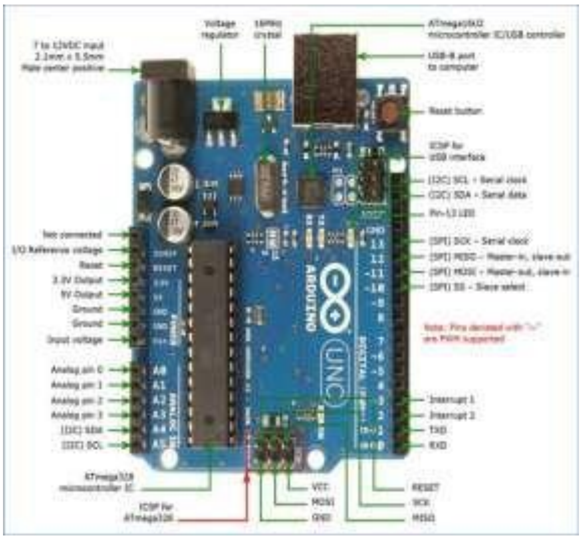

Fig. 1: Layout of Arduino Uno

The Arduino Uno is a series of open-source microcontroller board based on a diverse range of microcontrollers (MCU). It was initially developed and released by Arduino Company in 2010.The microcontroller board is equipped with sets of digital and analog input/output (I/O) pins that may be interfaced to various expansion boards (shields) and other circuits. The board has 14 digital I/O pins (six capable of PWM output), 6 analog I/O pins, and is programmable with the Arduino IDE (Integrated Development Environment), via a type B USB cable. It can be powered by a USB cable or a barrel connector that accepts voltages between 7 and 20 volts, such as a rectangular 9-volt battery. It has the same microcontroller as the Arduino Nano board, and the same headers as the Leonardo board. The hardware reference design is distributed under a Creative Commons Attribution Share-Alike 2.5 license and is available on the Arduino website. Layout and production files for some versions of the hardware are also available.

The word "uno" means "one" in Italian and was chosen to mark a major redesign of the Arduino hardware and software. The Uno board was the successor of the Duemilanove release and was the 9th version in a series of USB-based Arduino boards. Version 1.0 of the Arduino IDE for the Arduino Uno board has now evolved to newer releases. The ATmega328 on the board comes preprogrammed with a boot loader that allows uploading new code to it without the use of an external hardware programmer.

IV.I.II. IR Sensor

An infrared sensor, often known as an IR sensor, is an optoelectronic component that detects and responds to radiation in the infrared wavelength range of 780 nm to 50 µm. In contemporary applications, infrared sensors have become extensively employed in motion detectors. These detectors are used in building services to activate lighting systems and in alarm systems to identify intruders. The sensor components detect variations in heat radiation, specifically infrared radiation, brought about by people's movement in both time and space within a given range of angles. Infrared sensors of this kind merely need to fulfill modest specifications and are inexpensive, mass-produced commodities.

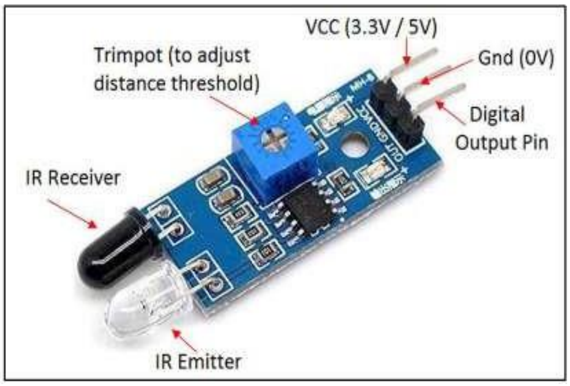

Fig. 2: IR Sensor

IV.I.III. Servo Motor

A servo motor is a motor with great precision that rotates at particular angles or distances. The device has a gear system that enables the production of potent rotational force in small,
lightweight units, and it can run on either a direct current (DC) or alternating current (AC) power source. These motors are used in a multitude of applications, including toy automobiles, RC helicopters, planes, and robotics. The system employs two servo motors as entry and exit gates, which autonomously
rotate from 45° to 140° upon detection of an automobile by an IR sensor. After a period of time, the motor reverts back to its original position. Servo motors can be classified into different categories depending on their gear arrangement and operational characteristics.

Fig. 3: Servo Motor

IV.I.IV. 12C Display

Fig. 4: 12C display

An I2C LCD (I2C Liquid Crystal Display) is a type of LCD display module that uses the I2C (Inter-Integrated Circuit) communication protocol to interface with a microcontroller. It simplifies the process of displaying text or graphics on an LCD by using just two wires (SDA and SCL) for communication, compared to the multiple wires required by standard LCDs.

IV.I.V. Jumper Wires

Jumper wires are connector pins used to connect two points without soldering, commonly used with breadboards and prototyping tools. They come in male-to-male and male-to- female types, with square and round head shapes. Male ends have a pin for plugging, while female ends do not.

Fig. 5: male to male & female to male wires

IV.II. Software Requirements

IV.II.I Arduino IDE

The Arduino IDE is a freely available piece of software used for authoring and compiling code for Arduino modules. It may be used on MAC, Windows, and Linux operating systems. The
software operates on the Java Platform and encompasses features for debugging, modifying, and compiling code. The Arduino modules consist of the Arduino Uno, Arduino Mega,
Arduino Leonardo, and Arduino Micro. The IDE environment comprises a text editor and a compiler that provide support for the C and C++ programming languages. It enables novices to acquire and enhance their proficiency in Arduino.

IV.II.II. Android Studio

Android Studio is the official Integrated Development Environment (IDE) for developing Android apps, designed and maintained by Google. It provides a comprehensive suite of tools to design, build, run, and test apps on the Android platform. Built upon JetBrains' IntelliJ IDEA, Android Studio offers specialized features for Android development, including a flexible build system, a fast and feature-rich emulator, and unified support for all Android devices.

V. DESIGN AND IMPLEMENTATION

The scheme illustrates the flow of inputs and outputs in the project's' work. For instance, when a car intends to park, the infrared (IR) sensor transmits a signal to the Arduino Uno, which in turn provides a signal to the servo motor. Additionally, the IR sensor for the output gate becomes operational. Additional infrared sensors are used to determine if a vehicle is positioned in a secure (parking slot) area. The outcomes are then showcased on mobile app and on 12C display. The following schematic represents the connection of the hardware components of the project, which is connection for programming, as the scheme shows the connection of each sensor and other piece with its respective ports.

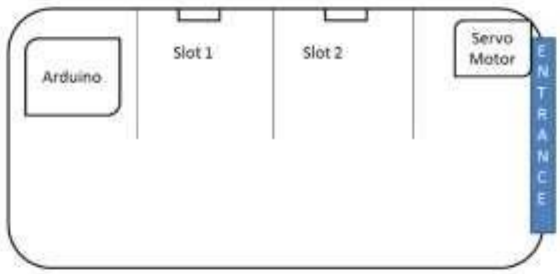

Fig. 6: Proposed System

The diagram illustrates the operational process of the programming code, wherein the initial IR sensors ascertain the presence of any vehicle at the input gate and determine whether the parking area is at maximum capacity or not. If the park reaches its maximum capacity, the entrance gate is closed and the park is marked as full in the Application.

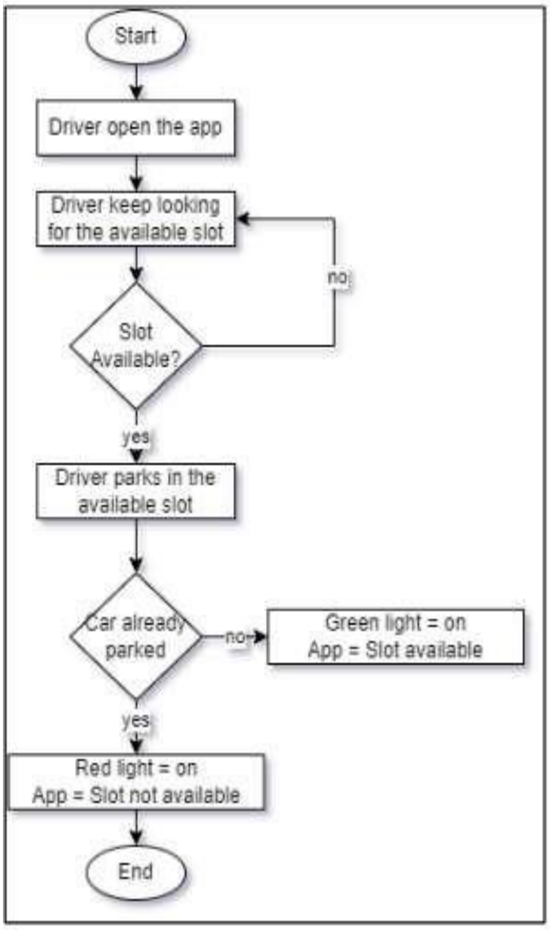

Fig. 7: Flowchart for the proposed algorithm

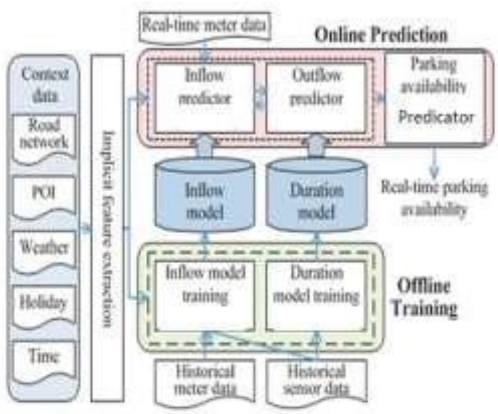

Fig. 8: Detail System Workflow.

VI. RESULTS

Based on the design schematic, the hardware level of the system has been introduced in this section.

Fig. 9: Detail System Workflow.

Fig. 10: Parking status on mobile app

DISCUSSION AND FUTURE WORK

The concept of incorporating wavelet [13] and multiwavelet [14, 15, 16and 17] transforms into the system described here is an interesting proposition. Here's how these transforms could potentially improve parking availability prediction. Feature Extraction from Sensor Data: using Wavelet and multiwavelet transforms [18] can be used to analyze the data collected from IoT sensors in parking spaces. This data might include ultrasonic sensors where signal variations can reveal presence/absence of a vehicle and potentially information about vehicle size. Magnetic sensors usually change in magnetic field can indicate vehicle presence. Cameras (if used) will include image analysis using wavelets could extract features related to occupancy or parking space condition (e.g., blocked by cones). Such techniques can lead in capturing temporal Variations since Wavelet transforms excel at analyzing signals over time [19]]. This allows for capturing how sensor readings change, potentially revealing patterns related to parking usage throughout the day. As well as such idea will improve feature representation by decomposing the sensor data into different frequency bands. Note that wavelets can potentially extract more informative features compared to using raw sensor readings alone. These features could then be used as inputs for the ensemble-based model. Multiwavelet transforms offer additional flexibility compared to single wavelets. Choosing appropriate wavelet bases could allow for better adaptation to the specific characteristics of the sensor data. Integration these transforms with Ensemble Model provide the following advantageous:

1- Feature Engineering: The features extracted using wavelets and multiwavelets can be combined with other relevant data points like time of day, weather, or upcoming events. This enriched feature set can then be fed into the ensemble model for training and prediction.

2- Potential for Improved Accuracy: By incorporating richer and more informative features, the ensemble model might learn more complex relationships between sensor data, parking availability, and other actors, potentially leading to improved prediction accuracy.

However, some challenges need to be addressed:

1- Increased Complexity: Introducing wavelet and multiwavelet transforms adds complexity to the system, requiring expertise in feature engineering and potentially increasing computational cost.

2- Data Volume: Wavelet transforms might generate a larger volume of features compared to raw sensor data. This can impact storage requirements and potentially training time for the ensemble model.

3- Hyper parameter Tuning: Selecting appropriate wavelet bases and parameters for the transforms requires careful optimization for optimal performance.

Overall, incorporating wavelets and multiwavelets holds potential for improving parking availability prediction by extracting more informative features from sensor data. However, the added complexity, potential increase in data volume, and need for careful hyper parameter tuning need to be weighed against the potential benefits.

VII. CONCLUSION

This paper presents a system to predict the real-time city- wide on-street parking availability based on the readily acces- sible parking transactions data and other urban context data instead of specially deployed sensors. We design an iterative deep-learning-based model to effectively integrate the aggre- gated inflow prediction and individual parking duration pre- diction for adequately exploiting the parking transactions data. Extensive experimental results based a four-month real-world dataset in Shenzhen show that our approach achieves more than 43% relative error reduction over state-of-the-art base- lines. Moreover, our solution is easy to be applied in more cities and areas due to its low cost. In addition, our iterative prediction framework has potential implications for other traffic prediction problems, especially for the problems that involve in mobility events associated with transactions data, such as the fine-grained traffic (i.e., check in and check out) prediction on a per-station basis in bike-sharing or car-sharing systems, and the fine-grained passenger flow prediction in bus transit systems.

VIII. REFERENCES

[1] (2017). Searching for Parking Costs Americans $73 Billion a Year. [Online]. Available: https://inrix.com/press-releases/parking-pain-us/

[2] Y. Rong, Z. Xu, R. Yan, and X. Ma, "Du-parking: Spatio-temporal big data tells you realtime parking availability," in Proc. ACM SIGKDD, 2018, pp. 646–654.

[3] N. Arora et al., "Hard to park: Estimating parking difficulty at scale," in Proc. 25th ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining, Jul. 2019, pp. 2296–2304.

[4] K. S. Liu, J. Gao, X. Wu, and S. Lin, "On-street parking guidance with real-time sensing data for smart cities," in Proc. 15th Annu. IEEE Int. Conf. Sens., Commun., Netw. (SECON), Jun. 2018, pp. 1–9.

[5] S. Yang, W. Ma, X. Pi, and S. Qian, "A deep learning approach to real-time parking occupancy prediction in transportation networks incorporating multiple spatio-temporal data sources," Transp. Res. C, Emerg. Technol., vol. 107, pp. 248–265, Oct. 2019.

[6] A. O. Kotb, Y.-C. Shen, X. Zhu, and Y. Huang, "iParker—A new smart car-parking system based on dynamic resource allocation and pricing," IEEE Trans. Intell. Transp. Syst., vol. 17, no. 9, pp. 2637–2647, Sep. 2016.

[7] (2018). Parking Sensor Data Guide—SFMTA. [Online]. Available: https://www.sfmta.com/sites/default/files/reportsdocuments/2018/08/sfpark_dataguide_parkingsensordata.pdf

[8] (2019). On-Street Parking Fee Collection Goes Digital in Central Beijing. [Online]. Available: https://www.chinadaily.com.cn/a/201907/02/WS5d1af0b9a3105895c2e7b2bc.html

[9] S. Nawaz, C. Efstratiou, and C. Mascolo, "Parksense: A smartphone based sensing system for on-street parking," in Proc. ACM MobiCom, 2013, pp. 75–86.

[10] B. Xu, O. Wolfson, J. Yang, L. Stenneth, P. S. Yu, and P. C. Nelson,"Real-time street parking availability estimation," in Proc. IEEE MDM,Jun. 2013, pp. 16–25.

[11] S. Mathur et al., "ParkNet: Drive-by sensing of road-side parking statistics," in Proc. ACM MobiSys, 2010, pp. 123–136.

[12] F. Bock, S. Di Martino, and A. Origlia, "Smart parking: Using a crowd of taxis to sense on-street parking space availability," IEEE Trans. Intell. Transp. Syst., vol. 21, no. 2, pp. 496–508, Feb. 2020.

[13] S. Yang and Z. Qian, "Turning meter transactions data into occupancy and payment behavioral information for on-street parking," Transp. Res. Part C: Emerg. Technol., vol. 78, pp. 165–182, May 2017.

[14] Intelligent Road Parking Solving Solution. Accessed: 2021. [Online]. Available: http://www.cncadre.com/solution/detail-4.html

[15] Yitingche. Accessed: 2021. [Online]. Available: https://www.szrtc.cn

[16] (2019). Shenzhen Open Data Innovation Contest. [Online]. Available:https://opendata.sz.gov.cn/sodic2019/

[17] M. R. Schmid, S. Ates, J. Dickmann, F. von Hundelshausen, and H.-J. Wuensche, "Parking space detection with hierarchical dynamic occupancy grids," in Proc. IEEE IV, Jun. 2011, pp. 254–259.

[18] O. Zoeter, C. R. Dance, M. Grbovic, S. Guo, and G. Bouchard, "A general noise resolution model for parking occupancy sensors," in Proc.ITS World Congr., 2012, pp. 1–9.

[19] J. Shi, L. Jin, J. Li, and Z. Fang, "A smart parking system based on nb-IoT and third-party payment platform," in Proc. ISCIT, 2017, pp. 1–5.

[20] X. Sevillano, E. Màrmol, and V. Fernandez-Arguedas, "Towards smart traffic management systems: Vacant on-street parking spot detection based on video analytics," in Proc. 17th Int. Conf. Inf. Fusion (FUSION), 2014, pp. 1–8.

[21] C.-F. Yang, Y.-H. Ju, C.-Y. Hsieh, C.-Y. Lin, M.-H. Tsai, and H.-L. Chang, "IParking—A real-time parking space monitoring and guiding system," Veh. Commun., vol. 9, pp. 301–305, Jul. 2017.

[22] G. Amato, F. Carrara, F. Falchi, C. Gennaro, C. Meghini, and C. Vairo,"Deep learning for decentralized parking lot occupancy detection,"Expert Syst. Appl., vol. 72, pp. 327–334, Apr. 2017.

[23] B. Y. Cai, R. Alvarez, M. Sit, F. Duarte, and C. Ratti, "Deep learning-based video system for accurate and real-time parking measurement,"IEEE Internet Things J., vol. 6, no. 5, pp. 7693–7701, Oct. 2019.

[24] K. Gkolias and E. I. Vlahogianni, "Convolutional neural networks for on-street parking space detection in urban networks," IEEE Trans. Intell. Transp. Syst., vol. 20, no. 12, pp. 4318–4327, Dec. 2019.

25] F. Caicedo, C. Blazquez, and P. Miranda, "Prediction of parking space availability in real time," Expert Syst. Appl., vol. 39, no. 8,pp. 7281–7290, 2012.

[26] A. Klappenecker, H. Lee, and J. L. Welch, "Finding available parking spaces made easy," Ad Hoc Netw., vol. 12, pp. 243–249, Jan. 2014.

[27] L. Peng and H. Li, "Searching parking spaces in urban environments based on non-stationary Poisson process analysis," in Proc. IEEE ITSC,Nov. 2016, pp. 1951–1956.
[28] F. Bock and M. Sester, "Improving parking availability maps using information from nearby roads," Transp. Res. Procedia, vol. 19, pp. 207–214,Jan. 2016.
[29] J. Xiao, Y. Lou, and J. Frisby, "How likely am I to find parking?A practical model-based framework for predicting parking availability,"
Transp. Res. B, Methodol., vol. 112, pp. 19–39, Jun. 2018.
[30] J. Fan, Q. Hu, Y. Xu, and Z. Tang, "Predicting the vacant parking space availability: An LSTM approach," IEEE Intell. Transp. Syst. Mag., early access, Oct. 1, 2020, doi: 10.1109/MITS.2020.3014131.
[31] A. Tamrazian, Z. Qian, and R. Rajagopal, "Where is my parking spot: Online and offline prediction of time-varying parking occupancy,"
Transp. Res. Rec. J. Transp. Res. Board, vol. 2489, no. 1, pp. 77–85,Jan. 2015.
[32] F. Yu, J. Guo, X. Zhu, and G. Shi, "Real time prediction of unoccupied parking space using time series model," in Proc. IEEE ICTIS, Jun. 2015,pp. 370–374.
[33] Y. Zheng, S. Rajasegarar, and C. Leckie, "Parking availability prediction for sensor-enabled car parks in smart cities," in Proc. IEEE ISSNIP,Apr. 2015, pp. 1–6.
[34] F. Bock, S. Di Martino, and A. Origlia, "A 2-step approach to improve data-driven parking availability predictions," in Proc. 10th ACM
SIGSPATIAL Workshop Comput. Transp. Sci., 2017, pp. 13–18.
[35] J. Fan, Q. Hu, and Z. Tang, "Predicting vacant parking space availability:An SVR method with fruit fly optimisation," IET Intell. Transp. Syst.,vol. 12, no. 10, pp. 1414–1420, Dec. 2018.
[36] T. Rajabioun and P. Ioannou, "On-street and off-street parking availability prediction using multivariate spatiotemporal models," IEEE Trans.Intell. Transp. Syst., vol. 16, no. 5, pp. 2913–2924, Oct. 2015.
[37] W. Alajali, S. Wen, and W. Zhou, "On-street car parking prediction in smart city: A multi-source data analysis in sensor-cloud environment," in Proc. SpaCCS, 2017, pp. 641652.
[38] Y. Ji, D. Tang, P. Blythe, W. Guo, and W. Wang, "Short-term forecasting of available parking space using wavelet neural network model," IET Intell. Transp. Syst., vol. 9, no. 2, pp. 202–209, Mar. 2015.
[39] E. I. Vlahogianni, K. Kepaptsoglou, V. Tsetsos, and M. G. Karlaftis,"A real-time parking prediction system for smart cities," J. Intell. Transp.
Syst., vol. 20, no. 2, pp. 192–204, Mar. 2016.
[40] X. Ma, Z. Tao, Y. Wang, H. Yu, and Y. Wang, "Long short-term memory neural network for traffic speed prediction using remote microwave sensor data," Transp. Res. C, Emerg. Technol., vol. 54, pp. 187–197,May 2015.
[41] J. Ke, H. Zheng, H. Yang, and X. M. Chen, "Short-term forecasting of passenger demand under on-demand ride services: A spatio-temporal deep learning approach," Transp. Res. C, Emerg. Technol., vol. 85, pp. 591–608, Dec. 2017.
[42] M. Chen, X. Yu, and Y. Liu, "PCNN: Deep convolutional networks for short-term traffic congestion prediction," IEEE Trans. Intell. Transp. Syst., vol. 19, no. 11, pp. 3550–3559, Nov. 2018.
[43] J. Zhang, Y. Zheng, D. Qi, R. Li, and X. Yi, "DNN-based prediction model for spatio-temporal data," in Proc. ACM SIGSPATIAL, 2016,pp. 1–4.
[44] J. Zhang, Y. Zheng, and D. Qi, "Deep spatio-temporal residual networks for citywide crowd flows prediction," in Proc. AAAI, 2017,
pp. 1655–1661.
[45] Y. Li, R. Yu, C. Shahabi, and Y. Liu, "Diffusion convolutional recurrent neural network: Data-driven traffic forecasting," 2017,
arXiv:1707.01926. [Online]. Available: http://arxiv.org/abs/1707.01926
[46] H. Yao et al., "Deep multi-view spatial-temporal network for taxi demand prediction," in Proc. AAAI, 2018, pp. 2588–2595.
[47] D. Luo et al., "Fine-grained service-level passenger flow prediction for bus transit systems based on multitask deep learning," IEEE Trans. Intell. Transp. Syst., early access, Jun. 25, 2020, doi: 10.1109/TITS.2020.3002772.
[48] B. Yu, H. Yin, and Z. Zhu, "Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting," in Proc.IJCAI, Jul. 2018, pp. 3634–3640.
[49] X. Geng et al., "Spatiotemporal multi-graph convolution network for ride-hailing demand forecasting," in Proc. AAAI, 2019, pp. 3656–3663.
[50] A. O. Kotb, Y.-C. Shen, and Y. Huang, "Smart parking guidance, monitoring and reservations: A review," IEEE Intell. Transp. Syst. Mag.,
vol. 9, no. 2, pp. 6–16, Apr. 2017.
[51] Y. F. Geng and C. G. Cassandras, "New 'smart parking' system based on
resource allocation and reservations," IEEE Trans. Intell. Transp. Syst.,
vol. 14, no. 3, pp. 1129–1139, Sep. 2013.
[52] E. H.-K. Wu, J. Sahoo, C.-Y. Liu, M.-H. Jin, and S.-H. Lin, "Agile
urban parking recommendation service for intelligent vehicular guiding
system," IEEE Intell. Transp. Syst. Mag., vol. 6, no. 1,

pp. 35–49,
Jan. 2014.
[53] D. Zhao, Z. Cao, C. Ju, D. Zhang, and H. Ma, "D2Park: Diversified
demand-aware on-street parking guidance," in Proc. ACM IMWUT,
2020, vol. 4, no. 4, pp. 1–25.
[54] W. Zou et al., "Limited sensing and deep data mining: A new
exploration of developing city-wide parking guidance systems,"
IEEE Intell. Transp. Syst. Mag., early access, Apr. 1, 2020, doi:
10.1109/MITS.2020.2970185.
[55] O. Zoeter, C. Dance, S. Clinchant, and J.-M. Andreoli, "New algorithms
for parking demand management and a city-scale deployment," in Proc.
ACM SIGKDD, 2014, pp. 1819–1828.
[56] A. Khaliq, P. V. der Waerden, D. Janssens, and G. Wets, "A conceptual
framework for forecasting car Driver's on-street parking decisions,"
Transp. Res. Procedia, vol. 37, pp. 131–138, Jan. 2019.
[57] N. Fulman, I. Benenson, and E. Ben-Elia, "Modeling parking search
behavior in the city center: A game-based approach," Transp. Res. C,
Emerg. Technol., vol. 120, Nov. 2020, Art. no. 102800.
[58] R. R. Weinberger, A. Millard-Ball, and R. C. Hampshire, "Parking
search caused congestion: Where's all the fuss?" Transp. Res. C, Emerg.
Technol., vol. 120, Nov. 2020, Art. no. 102781.
[59] G. D. Chiara, L. Cheah, C. L. Azevedo, and M. E. Ben-Akiva, "A policy-
sensitive model of parking choice for commercial vehicles in urban areas," Transp. Sci., vol. 54, no. 3, pp. 606–630, May 2020.
[60] D. K. Hammond, P. Vandergheynst, and R. Gribonval, "Wavelets on graphs via spectral graph theory," Appl. Comput. Harmon. Anal., vol. 30,no. 2, pp. 129–150, Mar. 2011.
[61] B. M. Williams and L. A. Hoel, "Modeling and forecasting vehicular traffic flow as a seasonal ARIMA process: Theoretical basis and empirical results," J. Transp. Eng., vol. 129, no. 6, pp. 664–672, Nov. 2003.
[62] W.-C. Hong, Y. Dong, F. Zheng, and S. Y. Wei, "Hybrid evolutionary algorithms in a SVR traffic flow forecasting model," Appl. Math.
Comput., vol. 217, no. 15, pp. 6733–6747, Apr. 2011.
[63] Y. Lv, Y. Duan, W. Kang, Z. Li, and F.-Y. Wang, "Traffic flow prediction with big data: A deep learning approach," IEEE Trans. Intell. Transp.Syst., vol. 16, no. 2, pp. 865–873, Apr. 2015.
[64] J. Chung, C. Gulcehre, K. Cho, and Y. Bengio, "Empirical evaluation of gated recurrent neural networks on sequence modeling," 2014,
arXiv:1412.3555. [Online]. Available: http://arxiv.org/abs/1412.3555
[65] S. Hochreiter and J. Schmidhuber, "Long short-term memory," Neural Comput., vol. 9, no. 8, pp. 1735–1780, 1997.
[66] H. Hersbach, "Decomposition of the continuous ranked probability score for ensemble prediction systems," Weather Forecasting, vol. 15, no. 5, pp. 559–570, Oct. 2000.