Parking Demand Prediction Framework

Subjects: Transportation Science & Technology

Contributor: Tao Wang , Sixuan Li , Wenyong Li , Quan Yuan , Jun Chen , Xiang Tang

With the development of smart cities and smart transportation, cities can gradually provide people with more information to facilitate their life and travel, and parking is also inseparable from both of them. Accurate on-street parking demand prediction can improve parking resource utilization and parking management efficiency, as well as potentially improve urban traffic conditions.

parking demand prediction spatial-temporal feature analysis graph convolutional neural network

1. Introduction

With the continuous development of cities, social progress, and population increase, traveling by car has become a normal part of people's life, and cars have entered thousands of households, becoming consumer goods and necessities for ordinary families. However, the increasing number of motor vehicles does not match the capacity of urban parking facilities. According to the latest data released by the Ministry of Public Security of China on 8 December 2022, by the end of November 2022, the number of motor vehicles in the country reached 415 million, of which the number of cars reached 318 million. The number of motor vehicle drivers exceeded 500 million, of which the number of car drivers reached 463 million. At present, the total number of motor vehicles and drivers are the highest in the world. In recent years, the average annual increment of car ownership exceeds 20 million, the number of cars per 1000 people has reached 225, and the average number of cars per 100 households has reached 60 [1]. Most of the public parking lots in cities are business paid parking lots, or traffic or commercial parking lots attached to shopping malls, hospitals, transportation hubs, etc. Therefore, on-street parking is usually the choice of people [2]. When the number of on-street parking spaces cannot keep up with the large demand caused by the rapid increase of motor vehicles, it will easily cause traffic congestion [3], road safety and other problems, and there will be social problems in terms of environment and energy [4]. The prediction results of on-street parking demand can provide drivers with helpful information, thus improving the utilization of urban parking facilities. It is also one of the foundations of urban traffic control and guidance, and is one of the main functions of intelligent transportation systems (ITS) [2].

Predictions of parking demand generally require the use of large amounts of historical data. Generally, on-street parking information needs to be captured by various facilities. In the past, parking information was not available accurately due to technical, equipment, and economic constraints. Now, with advances in technology, some cities have been or are being equipped with advanced equipment to obtain accurate parking information. These facilities provide access to a large and accurate amount of historical on-street parking data, such as underground geomagnetic sensors, high-level video surveillance [5][6], etc. However, while such a facility can collect very accurate and valuable parking data, it also entails high installation and maintenance costs. For the time being, many places in China do not have all these facilities installed due to restrictions related to urban construction. Some areas are currently using handheld entry devices for parking information entry. Although the cost of such equipment is low, it requires the employment of certain human resources, and in many cases there will be errors in the vehicle parking and driving out time.

In the construction of smart cities, the managers expect that the parking lot is not only in a simple location that provides parking and that they can charge for it, but also that it will assist the city in the coordination of traffic aspects. Therefore, it will be helpful if the parking demand information can be used to analyze the changes of urban parking demand at the temporal and spatial levels, to grasp its global state, or even to combine multiple sources of data around parking resources, such as considering the surrounding traffic network [7], urban points of interest [8], weather, holidays, etc., or considering the relevant attributes of parking lots [9]. A more scientific parking allocation or inducement strategy can help the management of parking resources in the city, or even can provide reference to the construction planning of parking facilities resources from a higher level, at least from the regional level. Therefore, not only short-term parking demand prediction has been receiving attention, but also grasping the changes of parking demand from a higher level for effective management is the goal of much research.

2. Parking Demand Prediction Based on Static Traffic

Earlier, instead of using a large amount of micro-level historical parking data as the main basis for prediction, many studies on parking demand prediction have widely used static traffic demand prediction models. These mainly include prediction models based on land use, traveling, and socio-economic activity characteristics that mostly focus on some inherent characteristic values, such as parking generation rate models based on the relationship between land use properties and parking demand generation rates, trip attraction models that consider the amount of regional motor vehicle trips attracted, and parking demand–supply prediction models based on parking service levels, etc. [10][11][12][13]. For example, Hyeonsup et al. proposed an allocation model using a generalized cost approach through a sensitivity analysis of parking generation rate, walking speed, and space finding time, which enabled a more detailed prediction of the number of parking spaces [10]. Swanson et al. analyzed and explained the interrelationships obtained among employment, parking demand, and parking generation rate by studying the factors affecting the parking generation rate in the central business district, and obtained a prediction model for parking generation rate eventually [13]. Ho et al. studied the factors influencing parking demand in terms of population, car parking, new car registrations, and rail passenger capacity, and predicted future parking demand using linear regression [11]. However, the models used in such work are mostly unsophisticated and also rely more on traditional theoretical analysis and models for parking prediction, all of which may suffer from problems such as long-range applicability and credibility.

3. Parking Demand Prediction Based on Machine Learning

The more common prediction models nowadays are based on a large amount of historical parking data and use more advanced methods such as machine learning neural network [2][7][14][15][16]. Various models have been proposed for accurate parking availability prediction. For example, Amini et al. proposed an electricity demand forecasting method considering the charging demand of electric vehicle parking lots using historical load data, which is based on an autoregressive integrated moving average (ARIMA) model for medium-term demand forecasting and has been shown to have high forecasting accuracy through its simulation results [14]. In addition, the more difficult and also more accurate method is also widely used. Xiao et al. proposed a parking availability forecasting model based on the spatio-temporal convolutional blocks constructed with graph convolutional networks, gated linear units, and one-dimensional convolutional neural networks to obtain instantaneous spatio-temporal correlation [2]. A wide range of techniques have been used to model parking prediction, in addition to the above-mentioned neural networks such as autoregressive integrated moving average, gated unit, and convolution, support vector regression (SVR) [17], multivariate autoregression [15], and clustering [18][19] are also used to predict parking demand. Another way of parking availability prediction is to analyze and predict parking demand based on the parking process [20][21][22]. For example, Zheng et al. constructed a parking demand prediction model using Markovian generation and extinction process, and gave a method to determine the forecasting interval based on the trend of the number of parking spaces according to the different parameters of the drivers' arrival and departure [21]. However, such kind of methods rely on a lot of assumptions and are less adaptable in the real environment. Demand forecasting using machine learning methods have achieved better performance, but they mainly analyze the characteristics of the historical data itself and do not take enough account of other influencing factors, so deep learning because of higher accuracy is also widely used in the analysis and prediction of parking demand.

In recent years, with the rapid development of artificial intelligence, deep learning has been widely used in various types of prediction, including traffic flow [23], passenger demand, electricity load [24], air pollution [25], etc., with its high adaptability and excellent performance. Its excellent performance in fields such as image recognition and natural language processing also proves the effectiveness of neural networks in dealing with multivariate, nonlinear, and nonstationary data, and implies the effectiveness in dealing with time series prediction problems as well. The proposition of neural network methods such as LSTM and GRU [26][27] not only enhance the model's ability to capture features in long sequences, but also effectively improve the accuracy of prediction results while avoiding the gradient explosion problem that tends to occur in RNNs. The U.S. technology company Uber has also designed a model with multiple LSTMs to predict the ride information of passengers in each city [28]. In addition, more and more optimization algorithms are being used to further improve the performance of these models [16][29][30][31], and more factors are being considered into the models, such as city points of interest (POIs) [32]. Xia et al. built a decision support model for parking space function substitution to share the burden of parking as much as possible through association patterns with other city points of interest (POIs) [33]. However, both the real-time parking availability prediction method named Du-Parking [34] proposed by Rong et al. and the multi-step LSTM prediction model [35] proposed by Fan et al., though their results proved to be superior to several classical benchmark models, including gated recursive units (GRU), stacked autoencoders (SAE), SVR models, and back propagation neural networks (BPNN), the inputs to the models are limited to 2D or 3D grid data in Euclidean space.

The proposition of GCN effectively extends convolution to non-Euclidean graph data [36] and is currently being widely used in various predictions presently. Yang et al. made multiple heterogeneous structured traffic data sources as input to extract the spatial relationships of traffic flows in a large-scale network using graph convolutional neural networks while incorporating LSTM to predict parking occupancy in a neighborhood in real time with excellent results [7]. Zhao et al. proposed a sensor for predicting real-time citywide on-street parking availability deployment at a fine-grained temporal level based on simple parking fee transaction data and other contextual data, while designing an iterative prediction mechanism that combines inflow prediction and parking duration prediction with a multi-graph convolutional neural network (MGCN) and LSTM to capture complex spatio-temporal correlations [37]. Graph convolution is similarly used to capture correlations from a variety of different graph structures, including physical adjacencies and semantically similar features.

Although parking demand prediction can alleviate many parking problems, however, considering it from another perspective, it may also cause other problems. For example, the prediction results of demand help drivers to make the selection of target parking sections in advance, but it may also cause the problem of multiple cars competing for parking spaces. Currently, there are a number of solutions to the parking resource allocation problem, such as parking space reservation [38]. However, on-street parking spaces are not available as a resource that can be reserved and made in advance, and such an approach is more suitable for off-street parking. An online real-time parking guidance system is more suitable, for example, on-street parking recommendations can be made in real time based on the prediction of available parking spaces [39], and although there is no research on parking guidance, reasonable guidance can effectively assist parking management and give greater play to the role of parking demand prediction to solve some problems in parking in practical scenarios.

References

1. Xinhua News Agency. 415 Million Vehicles, More Than 500 Million People! China Releases Latest Motor Vehicle and Driver Data. Available online: http://www.gov.cn/xinwen/2022-12/08/content_5730661.htm (accessed on 6 April 2023).
2. Xiao, X.; Jin, Z.; Hui, Y.; Xu, Y.; Shao, W. Hybrid Spatial–Temporal Graph Convolutional Networks for On-Street Parking Availability Prediction. Remote Sens. 2021, 13, 3338.
3. Tilahun, S.L.; Di Marzo Serugendo, G.; Angel, I.; Ibeas, A. Cooperative Multiagent System for Parking Availability Prediction Based on Time Varying Dynamic Markov Chains. J. Adv. Transp. 2017, 2017, 1760842.
4. Bock, F.; Di Martino, S.; Origlia, A. Smart Parking: Using a Crowd of Taxis to Sense On-Street Parking Space Availability. IEEE Trans. Intell. Transp. Syst. 2020, 21, 496–508.
5. On-Street Parking Fee Collection Goes Digital in Central Beijing. Available online: https://global.chinadaily.com.cn/a/201907/02/WS5d1af0b9a3105895c2e7b2bc.html (accessed on 2 July 2019).

6. Promote the Construction of Smart Cities to Break the Parking Difficulties in Large Cities. Available online: https://tech.chinadaily.com.cn/a/202103/11/WS604970c5a3101e7ce97436af.html (accessed on 11 March 2021).
7. Yang, S.; Ma, W.; Pi, X.; Qian, S. A deep learning approach to real-time parking occupancy prediction in transportation networks incorporating multiple spatio-temporal data sources. Transp. Res. Part C Emerg. Technol. 2019, 107, 248–265.
8. Balmer, M.; Weibel, R.; Huang, H. Value of incorporating geospatial information into the prediction of on-street parking occupancy—A case study. Geo-Spat. Inf. Sci. 2021, 24, 438–457.
9. Zhao, Z.; Zhang, Y.; Zhang, Y. A Comparative Study of Parking Occupancy Prediction Methods considering Parking Type and Parking Scale. J. Adv. Transp. 2020, 2020, 5624586.
10. Hyeonsup, L.; Grant, T.W.; Dua, A.; Joseph, A.; Ziwen, L.; Davis, W.P.; Christopher, R.C. Alternative Approach for Forecasting Parking Volumes. Transp. Res. Procedia 2017, 25, 4171–4184.
11. Ho, P.W.; Ghadiri, S.M.; Rajagopal, P.; Zainorizuan, M.J.; Yee Yong, L.; Alvin John Meng Siang, L.; Mohamad Hanifi, O.; Siti Nazahiyah, R.; Mohd Shalahuddin, A. Future Parking Demand at Rail Stations in Klang Valley. MATEC Web Conf. 2017, 103, 9001.
12. Junbin, X.; Zhiyong, Z.; Jian, R. The Forecasting Model of Bicycle Parking Demand on Campus Teaching and Office District. Procedia-Soc. Behav. Sci. 2012, 43, 550–557.
13. Swanson, H.A. The Influence of Central Business District Employment and Parking Supply on Parking Rates. ITE J. 2004, 74, 28–30.
14. Amini, M.H.; Karabasoglu, O.; Ilić, M.D.; Boroojeni, K.G.; Iyengar, S.S. ARIMA-based demand forecasting method considering probabilistic model of electric vehicles' parking lots. In Proceedings of the 2015 IEEE Power & Energy Society General Meeting, Denver, CO, USA, 26–30 July 2015; pp. 1–5.
15. Rajabioun, T.; Ioannou, P.A. On-Street and Off-Street Parking Availability Prediction Using Multivariate Spatiotemporal Models. IEEE Trans. Intell. Transp. Syst. 2015, 16, 2913–2924.
16. Ye, X.; Wang, J.; Wang, T.; Yan, X.; Ye, Q.; Chen, J. Short-Term Prediction of Available Parking Space Based on Machine Learning Approaches. IEEE Access 2020, 8, 174530–174541.
17. Fan, J.; Hu, Q.; Tang, Z. Predicting vacant parking space availability: An SVR method with fruit fly optimisation. IET Intell. Transp. Syst. 2018, 12, 1414–1420.
18. Li, T.; Wu, X.; Zhang, J. Time Series Clustering Model based on DTW for Classifying Car Parks. Algorithms 2020, 13, 57.

19. Tamrazian, A.; Qian, Z.S.; Rajagopal, R. Where is My Parking Spot?: Online and Offline Prediction of Time-Varying Parking Occupancy. Transp. Res. Rec. 2015, 2489, 77–85.
20. Peng, L.; Li, H. Searching parking spaces in urban environments based on non-stationary Poisson process analysis. In Proceedings of the 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), Rio de Janeiro, Brazil, 1–4 November 2016; pp. 1951–1956.
21. Zheng, L.; Xiao, X.; Sun, B.; Mei, D.; Peng, B. Short-Term Parking Demand Prediction Method Based on Variable Prediction Interval. IEEE Access 2020, 8, 58594–58602.
22. Xiao, J.; Lou, Y.; Frisby, J. How likely am I to find parking?—A practical model-based framework for predicting parking availability. Transp. Res. Part B Methodol. 2018, 112, 19–39.
23. Li, M.; Li, M.; Liu, B.; Liu, J.; Liu, Z.; Luo, D. Spatio-Temporal Traffic Flow Prediction Based on Coordinated Attention. Sustainability 2022, 14, 7394.
24. Wang, J.; Gao, J.; Wei, D. Electric load prediction based on a novel combined interval forecasting system. Appl. Energ. 2022, 322, 119420.
25. Tao, Q.; Liu, F.; Li, Y.; Sidorov, D. Air Pollution Forecasting Using a Deep Learning Model Based on 1D Convnets and Bidirectional GRU. IEEE Access 2019, 7, 76690–76698.
26. Chung, J.; Gulcehre, C.; Cho, K.; Bengio, Y. Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling. arXiv 2014.
27. Cho, K.; van Merrienboer, B.; Gulcehre, C.; Bahdanau, D.; Bougares, F.; Schwenk, H.; Bengio, Y. Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation. arXiv 2014.
28. Zhu, L.; Laptev, N. Deep and Confident Prediction for Time Series at Uber. In Proceedings of the 2017 IEEE International Conference on Data Mining Workshops (ICDMW), New Orleans, LA, USA, 18–21 November 2017; IEEE: Ithaca, NY, USA, 2017; pp. 103–110.
29. Xue, J.; Shen, B. A novel swarm intelligence optimization approach: Sparrow search algorithm. Syst. Sci. Control Eng. 2020, 8, 22–34.
30. Bahdanau, D.; Cho, K.; Bengio, Y. Neural Machine Translation by Jointly Learning to Align and Translate. arXiv 2014.
31. An, G.; Jiang, Z.; Chen, L.; Cao, X.; Li, Z.; Zhao, Y.; Sun, H. Ultra Short-Term Wind Power Forecasting Based on Sparrow Search Algorithm Optimization Deep Extreme Learning Machine. Sustainability 2021, 13, 10453.
32. Nie, Y.; Yang, W.; Chen, Z.; Lu, N.; Huang, L.; Huang, H. Public Curb Parking Demand Estimation with POI Distribution. IEEE Trans. Intell. Transp. Syst. 2022, 23, 4614–4624.

33. Xia, B.; Ruan, Y. Function Replacement Decision-Making for Parking Space Renewal Based on Association Rules Mining. Land 2022, 11, 156.
34. Rong, Y.; Xu, Z.; Yan, R.; Ma, X. Du-Parking: Spatio-Temporal Big Data Tells You Realtime Parking Availability. In Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, London, UK, 19–23 August 2018; ACM: New York, NY, USA, 2018; pp. 646–654.
35. Fan, J.; Hu, Q.; Xu, Y.; Tang, Z. Predicting Vacant Parking Space Availability: A Long Short-Term Memory Approach. IEEE Intell. Transp. Syst. Mag. 2022, 14, 129–143.
36. Kipf, T.N.; Welling, M. Semi-Supervised Classification with Graph Convolutional Networks. arXiv 2016.
37. Zhao, D.; Ju, C.; Zhu, G.; Ning, J.; Luo, D.; Zhang, D.; Ma, H. MePark: Using Meters as Sensors for Citywide On-Street Parking Availability Prediction. IEEE Trans. Intell. Transp. Syst. 2022, 23, 7244–7257.
38. Kotb, A.O.; Shen, Y.; Zhu, X.; Huang, Y. iParker-A New Smart Car-Parking System Based on Dynamic Resource Allocation and Pricing. IEEE Trans. Intell. Transp. Syst. 2016, 17, 2637–2647.
39. Liu, K.S.; Gao, J.; Wu, X.; Lin, S. On-Street Parking Guidance with Real-Time Sensing Data for Smart Cities. In Proceedings of the 2018 15th Annual IEEE International Conference on Sensing, Communication, and Networking (SECON), Hong Kong, China, 11–13 June 2018; pp. 1–9.