IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received January 16, 2020, accepted February 19, 2020, date of publication February 27, 2020, date of current version April 7, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2976433

Short-Term Parking Demand Prediction Method Based on Variable Prediction Interval

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This work was supported by the Basic Scientific Research Project of Liaoning Education Department under Grant LQ2017002.

ABSTRACT With the rapid economic development, parking problems have become increasingly prominent due to the city's development model and the emergence of a large number of private cars. Parking management departments around the world focus on intelligent parking system in order to solve parking problems, but most of them are limited to upgrading the parking infrastructure. There is no effective solution from a perspective of the fundamental cause to solve the parking problem. At present, it is generally believed that parking guidance systems can effectively alleviate parking problems and provide drivers and traffic managers with real-time and accurate parking information. As one of the prerequisites of the parking guidance system, the accuracy of the short-term parking demand prediction method determines whether the implementation of the parking guidance scheme can effectively solve the parking problem in a certain area. Based on this, we have studied a short-term parking demand prediction in this paper. First, focusing on the distribution of typical parking arrivals and departures regular pattern, a parking demand prediction model was constructed utilizing the Markov birth and death process, and model parameters were calibrated utilizing curve fitting method and undetermined coefficients method. The simulation environment was set up utilizing the Markov process to verify the accuracy of the availability of parameter estimation method. Secondly, a method for determining the prediction interval based on the parking trend was given for different situations with the parking rush hours and ordinary hours which parking arrival and departure parameters were different. In order to verify the effectiveness of the model in practical applications, parking arrival and departure data from June 17 to June 23, 2019 in Jilin University of Nanling Campus was used to verify the short-term parking demand prediction method proposed in this paper. The results show that the parking demand prediction model proposed in this paper can accurately calibrate model parameters, predict parking demand quickly and effectively and provide theoretical reference and technical support for parking planning and management.

INDEX TERMS Short-term parking demand prediction, parking arrival patterns, parking departure patterns, queuing model.

I. INTRODUCTION

In recent years, the urban economy has developed rapidly and the number of urban vehicles has increased significantly. The parking information has become one of the most primary factors affecting urban resident trip. According to "2017 China Intelligent Parking Industry Big Data Report," 30% of the traffic congestion problems in metropolis were caused by parking difficulties, and 48% of vehicles must be queued outside the parking lot on a daily routine [1]. In 2007, Scholar Shoup studied that vehicles to be parked on the road network account for 30% of the city's total traffic [2], [3], which not only increase road traffic flow, but also further aggravate a series of traffic problems such as urban traffic congestion and other problems [4], [5]. Practice has proved that an accurate and effective parking demand prediction methods to provide drivers with real-time or future parking information was the most effective way to alleviate the hard-to-park problem [6], [7]. At present, there were many studies in parking demand prediction around the world, which could be roughly divided into statistical learning and machine learning methods.

Statistical learning aims to find out the patterns of parking arrival and departure processes, and further quantify that pattern into a formula that can predict parking demand.

The associate editor coordinating the review of this manuscript and approving it for publication was Ran Cheng.

In 2012, Caicedo assumed that the process of parking arrival and departure followed the Gamma distribution and used that as a basis to conduct a parking simulation experiment, which included three sub-processes, including simulating and allocating parking requests based on the simulated driver's parking preferences and the availability of parking spaces, estimating the possible future number of leaving vehicles and parking space availability [8]. In 2018, Xiao proposed a prediction framework based on the Markov model. The Poisson distribution was used to simulate the vehicle arrival process and the negative exponential distribution was used to simulate the vehicle departure process. When the parking lot was not saturated, the arrival and departure parameters could be estimated simultaneously [9]. The patterns of parking arrival and departure were varied in different time periods. The above model lacks a clear method of dividing parking trends.

Machine learning mainly refers to the use of improved neural networks for parking demand prediction. The purpose was to improve the accuracy of prediction [10], [11]. In 2018, Shin proposed a parking guidance system based on neural network predictive control. The four most important influencing factors affecting parking selection behavior were used as neural network model inputs, and the parking lot was allocated to drivers with the goal of global optimization of the whole urban parking system [12]. In 2015, Zhang Jun *et al.* proposed a wavelet neural network model based on particle swarm optimization algorithm for low-precision short-term prediction of available parking spaces in parking lots [13]. In 2016, Ji Yanjie *et al.* proposed a wavelet transform and particle swarm wavelet neural network combined prediction method. The wavelet function was used to multi-scale decompose and reconstruct the effective parking space time series, and the reconstructed time series were predicted using wavelet neural networks respectively [14]. In 2017, Haipeng Chen *et al.* carried out wavelet decomposition and reconstruction of the effective parking space time series by wavelet function and used the extreme learning machine ELM to predict each time series obtained after the decomposition, and finally synthesized the prediction results of each neural network as the final prediction results [15]. Chen Qun *et al.* used El-man neural network to train the model in 2007 [16].

At present, these two prediction methods have not been widely used. Because parking patterns in a day change with time, it is difficult to accurately describe the arrival and departure patterns of parking with a single distribution over a long time range [8], [17]–[19]. Neural networks require a large number of parking label data. Publicly available parking data is generally lacking, and parking demand prediction method lacked a scientific method for determining the prediction time step in existing research [20]. In addition, the neural network algorithm fails to reflect other factors affecting parking demand such as traffic flow. The network can only learn the patterns of historical parking space data and cannot explain the essence of parking demand changes [21]–[25].

In view of the importance of parking available information for parking guidance system in real time and in the future, a parking demand prediction method based on the arrival and departure patterns of vehicles was proposed in this paper. Based on a small amount of historical data, the parking patterns of the day were classified by time. According to the parking patterns, the parking prediction interval was determined, which not only avoided wasting computing resources, but also accurately sensed the change in the number of parking occupancy and provided scientific and effective theoretical support for parking guidance.

II. SHORT-TERM PARKING DEMAND PREDICTION MODEL

A. PARKING DEMAND PREDICTION MODEL BASED ON ARRIVAL AND DEPARTURE DISTRIBUTION OF VEHICLES

The arrival and departure process of the vehicles in the parking lot is random. This process can be regarded as a queuing model. Poisson distribution and Binomial distribution are the most used. If the arrival process follows a Poisson distribution and then the departure time interval follows a Negative exponential distribution [26], [27]. Firstly, the parking process was analyzed to verify the regularity of the vehicle arrival and departure process over time. Based on this, a parking demand prediction method based on the parking arrival and departure pattern was proposed.

1) POISSON DISTRIBUTION ARRIVING AND BINOMIAL DISTRIBUTION LEAVING

It is assumed that the time interval for changing the parking state is small enough that the parking state at the same time can only be transferred to the neighboring state. The process of arriving and leaving of vehicles can be regarded as the Markov birth and death process, and the parking state is transferred only in the homogeneous Markov chain. There are only three possible ways to transfer between parking spaces at the same time: increasing one parking space, decreasing one parking space, or remaining the same [28]–[30]. Let h be an infinitesimal time interval, and the Markov birth and death process transition probability equations are shown in (1)-(4).

$$P\left(N_{t+h}=N_t+1\right)=\lambda h+o\left(h\right) \tag{1}$$

$$P\left(\mathrm{N}_{t+h}=\mathrm{N_T}-1\right)=\theta\cdot(1-\theta)^{\mathrm{N_T}-1}\,\mathrm{N_T}+o\left(\mathrm{H}\right) \tag{2}$$

$$P\left(N_{t+h}=N_t\right)=1-\lambda h-\theta N_t h+o\left(h\right) \tag{3}$$

$$P\left(N_{t+h}=l\right)=0,\quad \forall l\in I,\ l\neq N_t+1, N_t-1, N_t \tag{4}$$

$o\left(h\right)$ is a higher-order infinitesimal quantity of time interval h. $P\left(N_{t+h}=N_t+1\right)$, $P\left(N_{t+h}=N_t-1\right)$, $P\left(N_{t+h}=N_t\right)$ and $P\left(N_{t+h}=l\right)$ respectively represent the probability of N_t+1 parking space, N_t-1, N_t and l at $(t+h)$ moment; N_t, N_{t+h} respectively represent the number of parking space at t and $t+h$ moment; λ is the number of vehicles arriving per unit time i.e., parking arrival rate; θ is the probability of each car leaving per unit time i.e., parking departure rate.

Based on (1), (2), (3) and (4), the number of parking occupancy that change over time is as shown in (5). E_0 is the parking occupancy at moment $t = 0$.

$$E_t = \left(E_0 - \frac{\lambda}{\theta}\right) \times (1-\theta)^t + \frac{\lambda}{\theta} \tag{5}$$

In order to increase the applicability of the proposed model, adding the correction term α in (5) to increase the reliability of the model. The final expression is as shown in (6).

$$E_t = \left(E_0 - \frac{\lambda}{\theta}\right) \times (1-\theta)^t + \frac{\lambda}{\theta} + \alpha \tag{6}$$

Equation (6) is the changing model of parking state over time. E_t is the number of vehicles in the parking lot at moment t. When the parking lot has not reached the saturation state, it is expected that it will converge to λ/θ after a sufficient time.

2) POISSON DISTRIBUTION ARRIVING AND NEGATIVE EXPONENTIAL DISTRIBUTION LEAVING

Based on the above research approach, when the number of parking arrival pattern follows the Poisson distribution and average parking time pattern follows negative exponential distribution, the number of parking occupancy changes over time is as shown in (7).

$$E_t = \left(E_0 - \frac{\lambda_1}{\lambda_2}\right) \times e^{\lambda_2 t} + \frac{\lambda_1}{\lambda_2} \tag{7}$$

where λ_1 represents the number of vehicles arriving per unit time i.e., parking arrival rate; λ_2 is the average parking time of per vehicles i.e., parking departure rate; E_0 is the parking occupancy at moment $t = 0$.

In order to increase the applicability of the proposed model, adding the correction term α to increase the reliability of the model, and the final expression is as shown in (8).

$$E_t = \left(E_0 - \frac{\lambda_1}{\lambda_2}\right) \times e^{\lambda_2 t} + \frac{\lambda_1}{\lambda_2} + \alpha \tag{8}$$

Calculating the average parking occupancy of historical parking time series, utilizing curve fitting method or undetermined coefficient method to estimate parking arrival rate and departure rate, and utilizing the obtained parking arrival rate and departure rate parameters in formulas to predict parking demand.

B. A PREDICTION INTERVAL DETERMINATION METHOD BASED ON PARKING TREND

According to the change of parking trend during the day, the parking change trend is roughly divided into several similar stages, and the historical parking data was classified by time series.

Assuming that there are M days of historical data and calculating the average value of that. In order to distinguish the different parking trends in the time period, selecting the time point m corresponding to the turning point of the curve in the diagram of parking occupancy (the sign of the first derivative around this point is opposite). Let E=m, the initial time is denoted as t_0, and the number of parking occupancy within $[t_0, \text{m}]$ is fitted with a negative exponential function or a linear function. The function with greater goodness of fit R^2 is selected as the final fitting function. If $R^2 \geq 0.85$, the function is considered to be able to describe the characteristics of the curve, which means the parking trend in this period is consistent with the curve. Let E $=$ E $+$ 1, update m, iterate forward until $R^2 < 0.85$, output m. If $R^2 < 0.85$, set E $=$ E$-$1, update m, and output m until $R^2 \geq 0.85$. The above process is repeated to obtain the time interval with different stopping trends. The specific process is shown in Fig.1.

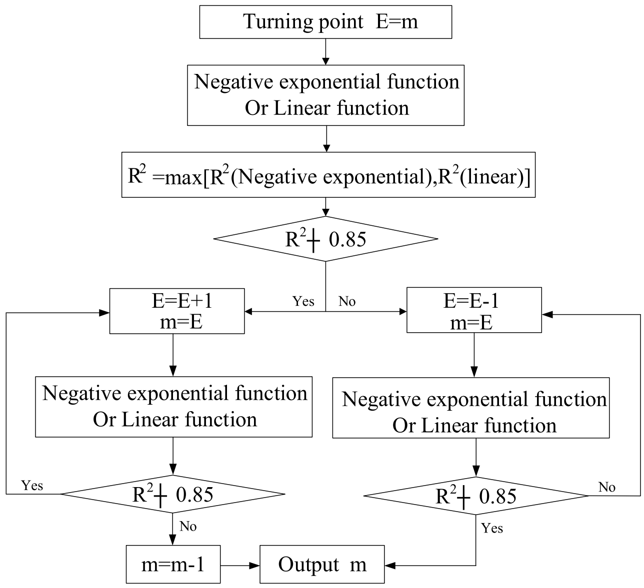

FIGURE 1. Iterative flow chart based on stop trend prediction interval.

The prediction interval is determined according to the above method, and a Chi-square test is used for the obtained prediction intervals to verify the appropriate distribution of each time period [31].

C. MODEL PARAMETER ESTIMATING

1) CURVE FITTING METHOD

Fitting the average of the historical parking occupancy and estimating the parking arrival rate and departure rate through the parking calculation (6) and (8), assuming that the arrival and departure parameters are constant during the period $[t_s, t_e]$, $t_e = t_s + i\Delta t\ (\forall i = 0, 1, 2\ldots\text{m})$, m represents the number of unit time intervals during the period of $[t_s, t_e]$, and $\bar{n}_{t_s+i\Delta t}$ is the average value of the historical parking occupancy at the time $t_s + i\Delta t$ in M day, and $\bar{n}_{t_s+i\Delta t} = \sum_{i=1}^{\text{M}} n_{t_s+i\Delta t}/\text{M}$.

The curve fitting optimization goal is to minimize the error between the predicted parking occupancy and the actual parking occupancy. The expression is as shown in (9).

$$min_{\lambda,\theta} \sum\nolimits_{i=1}^{m} \left(E_{t_s+i\Delta t} - E\left(t_s + i\Delta t\right)\right)^2 \tag{9}$$

$E_{t_s+i\Delta t}$ is the predicted occupancy at $t_s + i\Delta t$. When the departure pattern follows the binomial distribution,

$$E_{t_s+i\Delta t} = (1-\theta)^{i\Delta T}\left(\bar{n}_{t_s} - \frac{\lambda}{\theta}\right) + \frac{\lambda}{\theta} + \alpha(\text{I} = 1, 2, \cdots, \text{M});$$

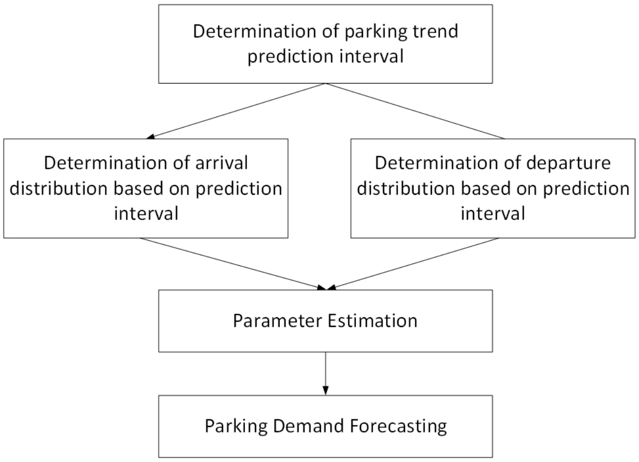

FIGURE 2. Flow of parking demand forecast.

when departure pattern follows negative exponential distribution, $E_{t_s+i\Delta t} = \left(E_0 - \frac{\lambda_1}{\lambda_2}\right) \times \mathrm{E}^{\lambda_2 t} + \frac{\lambda_1}{\lambda_2} + \alpha$. $E_{t_s+i\Delta t}$ is the average value of the actual occupancy calculated from historical data, $E(t_s + i\Delta t) = \bar{n}_{t_s+i\Delta t}$.

2) UNDETERMINED COEFFICIENT METHOD

In an actual parking lot scene, it is easy to obtain the vehicle arrival number by short-term surveys or detector data and then arrival rate per unit time can be calculated by that, but parking time data is not easily available through short-term surveys or other method in the absence of detector data. In view of the availability of vehicle data, the parking arrival rate can be determined first based on acquired data, and departure rate can be estimated utilizing the undetermined coefficient method through (6) and (8). The prediction flow chart is shown in Fig.2.

III. NUMERICAL EXPERIMENT

In order to verify the effectiveness of the proposed model of parameter estimation method, numerical experiments were performed. Given the arrival and departure rates of parking process, the Markov state transition probability was calculated, and the number of parking occupancy was obtained. The method proposed in this paper was used to estimate the model parameters, and the set value and the estimated value were compared and analyzed to verify the accuracy of the proposed method.

A. MARKOV PROCESS

When the initial parking state $O(0)$ of the parking lot is known, and the parking arrival rate and departure rate parameters are unchanged, the prediction parking occupancy can also be obtained according to the Markov backward equation and the discrete random variable mean formula, which is as shown in (10).

$$E_t = O(0) * P(t) * \mathrm{C}^T \tag{10}$$

E_t is the number of parking occupancy in the parking lot at moment t; $P(t)$ is the Markov probability transition matrix with the given arrival and departure parameters; $\mathrm{C}^{\mathrm{T}} = [0, 1, 2 \cdots \mathrm{C}]^{\mathrm{T}}$ is the parking status column vector in certain parking lot.

B. SIMULATION PARAMETER SETTING

Based on the Markov process proposed above, a numerical experimental background was set up. The poisson distribution arrival process and binomial distribution departure process were taken as examples to verify the effectiveness of the proposed model. The parking lot capacity C was set to 20, and the simulation lasted a total of 80 units times. The simulation was divided into two parts. Let parking arrival rate $\lambda = 1$ and a departure rate $\theta = 0.05$ during the period of $\{1, 40\}$; when $t \in \{41, 80\}$ parking arrival rate $\lambda = 1.5$ and departure rate $\theta = 0.1$; initial parking state $O(0)$ was set in (11).

$$O(0) = \left(0, \frac{1}{10}, \frac{1}{5}, \frac{1}{10}, \frac{3}{10}, \frac{3}{10}, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\right) \tag{11}$$

$O(t)$ is the probability of parking number at moment t. According to the Markov backward equation $O(t) = O(0) * P(t)$, the Markov probability transition matrix $P(t)$ can be visualized in (12).

$$P(t) = \begin{pmatrix} p_{00} & p_{01} & p_{02} & \cdots & p_{0C} \\ p_{10} & p_{11} & p_{12} & \cdots & p_{1c} \\ p_{20} & p_{21} & p_{22} & \cdots & p_{2C} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ p_{C0} & p_{C1} & p_{C2} & \cdots & p_{CC} \end{pmatrix} \tag{12}$$

The general term p_{ij} represents the probability of changing from initial state i to final state j per unit time. The calculation formula is as shown in (13).

$$p_{ij} = \sum\nolimits_{k=0}^{i} P_d(k, \theta) \times P_a(j + k - i, \lambda) \tag{13}$$

Equation (14) indicates that under the condition that the change absolute value of parking spaces |j-i| is constant and the maximum value is smaller than the parking capacity C. The p_{ij} expression is as shown in (14).

$$p_{ij} = \begin{cases} \sum\nolimits_{k=0}^{i} \dfrac{i! \cdot \lambda^{(j+k-i)} \cdot e^{-\lambda}}{(j+k-i)! \cdot (i-k) \cdot k!} \; (i \le j) \\ \sum\nolimits_{k=i-j}^{i} \dfrac{i! \cdot \lambda^{(j+k-i)} \cdot e^{-\lambda}}{(j+k-i)! \cdot (i-k) \cdot k!} \; (i > j) \\ \qquad i, j = 0, 1, 2, \cdots C - 1 \end{cases} \tag{14}$$

Equation (15) indicates that the transition probability when the final state is equal to C is as shown in (15).

$$P_{i,C} = 1 - \sum\nolimits_{k=0}^{C-1} P_{i,k} \quad i = 0, 1, \cdots, C; \; j = C \tag{15}$$

According to (10)-(15), Markov probability transfer diagram was obtained, as shown in Fig.3, and parking expectation was shown in Fig.4, providing a basis for the following division of parking time interval. Utilizing the method shown in Fig.1, the whole simulation period was divided into {1,50} and {51,80}. The fitting curve in the simulation

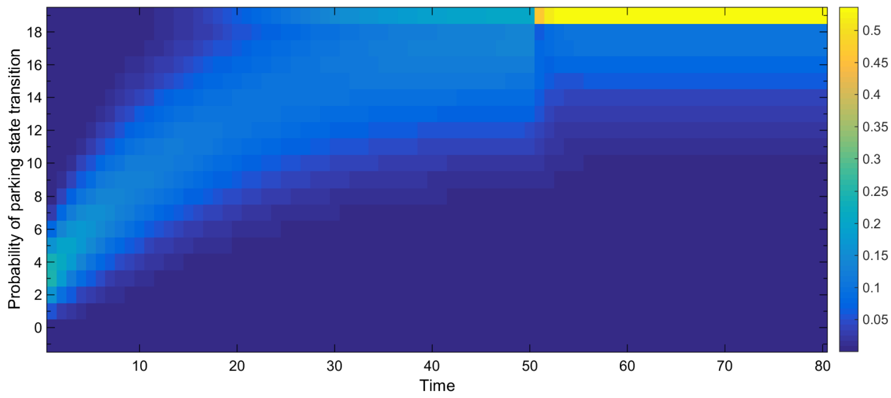

FIGURE 3. Probability of parking state transition.

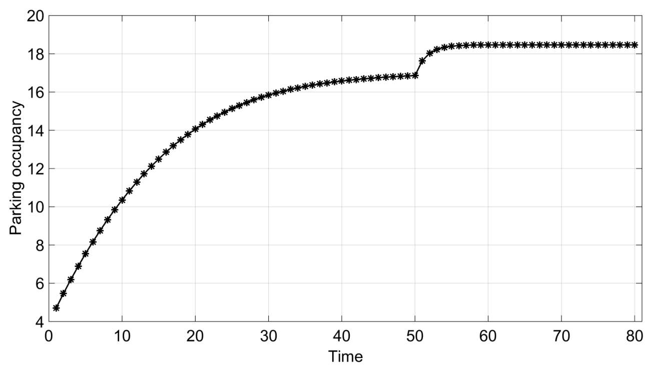

FIGURE 4. The number of occupancy calculated by the Markov process.

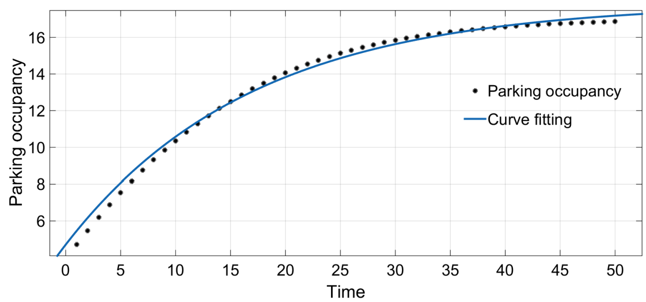

FIGURE 5. Simulation time $t \in \{1, 50\}$ parking expectation fitting curve.

time t ∈ {1, 50} was presented in Fig.5, and the fitting curve during time t ∈ {51, 80} was presented in Fig.6.

C. ACCURACY ANALYSIS OF CURVE FITTING METHOD OF ESTIMATING PARAMETERS

During the simulation time $t \in \{1, 50\}$, the number of simulated parking occupancy monotonically increased, and the parking lot was in unsaturated state. As time passed, its probability transition matrix followed conditions of Markov's detailed balance, for which the growth trend became more and more slowly, and the final state always converges to a fixed value. Applying the parking demand prediction model proposed and method of estimating parameters, calibrating model parameters $(\lambda, \theta) = (1.038, 0.058)$ and the correction term $\alpha = -0.072$, which were close to the parameter values $(\lambda, \theta) = (1, 0.05)$ set before simulation, the average estimation error of the parameters was 10%, and the mean square error RMSE = 0.279.

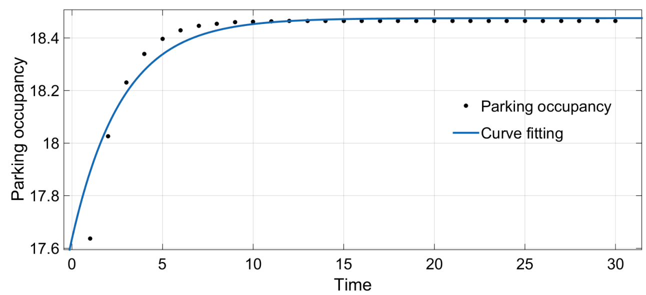

FIGURE 6. Simulation time $t \in \{51, 80\}$ parking expectation fitting curve.

TABLE 1. Estimating parameters with undetermined coefficient method.

Prediction interval	θ (fixed$\lambda = 1.5$)	error	λ (fixed$\theta = 0.1$)	error
1-50	0.097	3%	1.764	18%
51-55	0.086	14%	1.781	19%
56-80	0.083	17%	1.453	3%

In the simulation process, two sets of parameter values were set. From Fig.4, the point of discontinuity of curve is the turning point of the probability transition matrix. Applying the approach proposed in this paper, the calibration parameters $(\lambda, \theta) = (3.313, 0.1834)$ are far from the simulation set values during the time of {51,80}.

It could be seen from Fig.6 that the parking trend changes around the simulation time $t = 55$. Using the method proposed in Fig.1, the time period {51,80} could be further divided into {51,55} and {56,80}. During the period of $t \in \{51, 55\}$, the calibration parameters $(\lambda, \theta) = (1.363, 0.0673)$ while the correction term $\alpha = -0.004$, and the average parameter estimation error was 21%, and the mean square error RMSE was 0.121.

D. ACCURACY ANALYSIS OF PARAMETER CALIBRATION OF UNDETERMINED COEFFICIENT METHOD

The model parameters were estimated according to the undetermined coefficient method proposed above. During the period of $t \in \{1, 80\}$, the number of simulated parking occupancy and estimated parameters were shown in Table 1.

Calibration parameters $(\lambda, \theta) = (1.498, 0.081)$, correction factor $\alpha = -0.072$, which was close to the parameter values

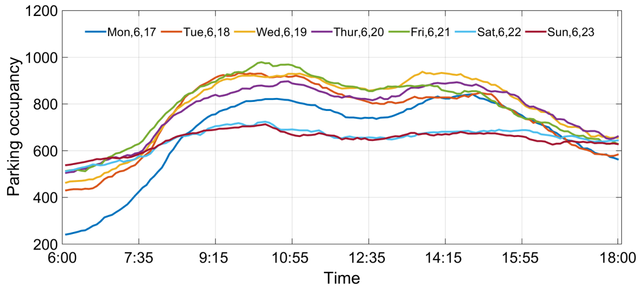

FIGURE 7. Number of parking occupancy in the parking lot from June 17 to June 23, 2019.

set during simulation period $(\lambda, \theta) = (1.5, 0.1)$, and the average parameter estimation error was 10% where the square error RMSE = 0.146.

IV. EXAMPLE VERIFICATION

In order to verify the accuracy and feasibility of the model proposed in this paper, a one-week parking data from June 17 to June 23, 2019 in Jilin University of Nanling Campus was selected as the model training set. In order not to lose the generality, June 25 (Tuesday) and June 29 (Saturday), 2019 were selected as the test set. The practical parking data was shown in Fig.7.

Jilin University of Nanling Campus is used for educational purposes. There is a total of 720 internal parking spaces. Parking demands are mainly occupied by faculty vehicles and supplemented by social vehicles. As can be seen from Fig.7, the parking rush hours on weekdays appeared between 7: 30-9: 30 in the morning, and the number of parking occupancy had remained basically stable during the period of 10: 00-15: 00 while departure began at 15:00 pm. The changing trend of non-workdays parking was relatively flat. It would grow at a lower growth rate within 6: 00-10: 30, and the number of parking would fluctuate within 600-700. It could be seen that the parking characteristics of educational land were similar to the general parking patterns. There were obvious differences between the parking patterns on workdays and non-workdays. In order to accurately excavate the parking patterns and predict the parking demand, the parking demand could be divided into workdays and non-workdays to predict respectively.

A. NON-WORKDAYS PARKING DEMAND PREDICTION ANALYSIS

1) DETERMINATION OF PREDICTION INTERVAL FOR NON-WORDAYS

According to the method for the prediction interval based on the parking trend, parking arrival and departure for non-workdays were classified as shown in Table 2. Let y, x respectively represents actual number of parking occupancy and corresponding time.

2) DISTRIBUTION OF CALIBRATION

In order to accurately describe the arrival and departure patterns of parking process, chi-square test was performed. Because the number of vehicles entering the parking lot

TABLE 2. Prediction interval based on parking trend for non-workdays.

Prediction interval	Equation	R^2
6:00-10:30	y=519.5e0.0067x	0.95
10:30-13:10	y=-1.4494x+688.17	0.87
13:10-15:35	y=-0.0447x2+1.9794x+657.38	0.91
15:35-18:00	y=-1.5153x+676.5	0.89

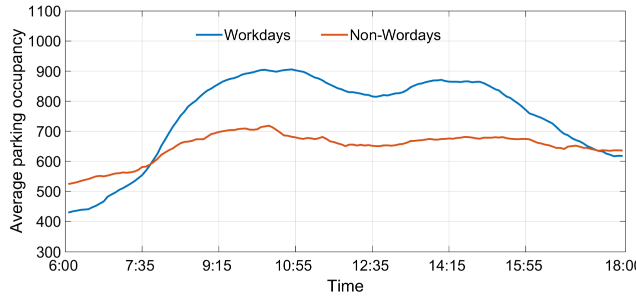

FIGURE 8. Number of average parking occupancy in the parking lot from June 17 to June 23, 2019.

TABLE 3. Chi-square test value of approaching vehicle.

Prediction interval	The value of X^2	
	Poisson distribution	Binomial distribution
6:00-10:30	11.458	95.399
10:30-13:10	10.410	91.389
13:10-15:35	11.458	95.378
15:35-18:00	11.458	95.399

roughly followed to the Gaussian distribution trend, according to statistical knowledge, the vehicles entering the parking lot regularly follow the Poisson distribution or binomial distribution. According to Fig.7 and Fig.8, it could be known that there was a big difference between the parking patterns of workdays and non-workdays, so the distribution of calibration and parking demand prediction were divided into workdays and non-workdays. The parking data during the period from June 17 to June 23, 2019 were applied to test the distribution of incoming traffic flow compliance. The calculation results were shown in Table 3.

Taking the significance level $\alpha_4 = 0.01, X^2_{1-\alpha}(7-1) = X^2_{0.99}(6) = 16.812$ in this paper. The observed values of the Poisson distribution test statistics were all less than $X^2_{0.99}(6)$, and the observed values of the binomial distribution were much larger than $X^2_{0.99}(6)$, so it was considered that the approaching vehicle flow followed the Poisson distribution.

The observed values of the Poisson distribution test statistics were all less than $X^2_{0.99}(6)$, and the observed values of the binomial distribution were much larger than $X^2_{0.99}(6)$, so it was considered that the departing vehicle flow followed the Poisson distribution and parking time followed negative exponential distribution.

TABLE 4. Chi-square test value of leaving vehicle.

Prediction interval	The value of X^2	
	Poisson distribution	Binomial distribution
6:00-10:30	7.583	184.754
10:30-13:10	7.583	184.754
13:10-15:35	7.583	184.754
15:35-18:00	7.583	184.754

TABLE 5. Chi-square test value of leaving vehicle.

Prediction interval	λ	θ	α	R^2
6:00-10:30	2.021	-0.003	-0.104	0.95
10:30-13:10	39.76	0.0618	-2.46	0.91
13:10-15:35	93.16	0.1371	0	0.91
15:35-18:00	22.14	0.03627	1.015	0.89

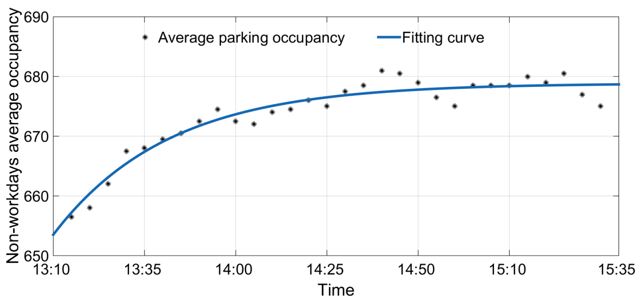

FIGURE 9. Non-workdays 13: 10-15: 35 fitting curve.

3) NON-WEEKDAYS PARKING ARRIVAL RATE AND DEPARTURE RATE ESTIMATING

According to Fig.1, the time intervals with different parking trends were obtained, including {6:00,10:30}, {10:30,13:10}, {13:10,15:35} and {15:35,18:00}. According to (6), (8) and Fig.1, arrival rate λ, departure rate θ, parameter α and goodness of fit parameter R^2 in different periods of non-workdays were solved by fitting, and the results were shown in Table 5.

Taking time period {13:10,15:35} as an example, the model proposed in this paper was using to fit the actual parking data, as shown in Fig.9. The maximum error value is not greater than 10%.

4) PARKING DEMAND PREDICTION ON NON-WEEKDAYS

Bringing the model parameters presented in Table 5 into (6) and (8) to obtain a non-workdays parking demand prediction model. The parking demand for the next Saturday was calculated to verify the validity of the model. The prediction results and error were shown in Fig.10.

As can be seen from Fig.10, in the prediction method based on the initial parking number, the maximum parking demand prediction error was 11%, and 97% of the prediction error was less than 5%; in the real-time prediction method based on the number of parking occupancy at the previous time, the maximum prediction error was 3%, and 97% of the prediction error was less than 1%.

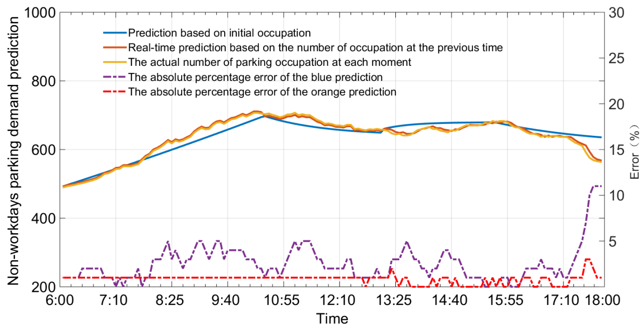

FIGURE 10. Non-workdays parking demand prediction and error.

TABLE 6. Prediction interval based on parking trend for workdays.

Prediction interval	Equation	R^2
6:00-10:10	y=10.378x+376.34	0.966
10:30-13:10	y=866.46e-0.004x	0.934
13:10-14:35	y=-0.2644x2+8.2683x+768.11	0.985
14:35-18:00	y=-6.2053x+856.13	0.989

TABLE 7. Chi-square test value of approaching vehicle.

Prediction interval	The value of X^2	
	Poisson distribution	Binomial distribution
6:00-10:10	10.631	812.072
10:30-13:10	8.087	7.950
13:10-14:35	8.087	7.950
14:35-18:00	8.087	7.950

B. WORKDAYS PARKING DEMAND PREDICTION ANALYSIS

1) DETERMINATION OF PREDICTION INTERVAL FOR WORKDAYS

According to the iterative method proposed in Fig.1, a preliminary arrival and departure classification of average parking occupancy was conducted, as shown in Table 6. During the period {6:00,10:10} and {14:35,18:00}, the parking trend showed a linear trend; during the period {10:30,13:10}, the trend generally showed a negative exponential development; during the period {13:10,14:35}, the trend generally developed as a quadratic function. The goodness of fit parameter R^2 were all greater than 0.9.

2) DISTRIBUTION OF CALIBRATION

The calculated results of workdays distribution were shown in Table 7.

The observed values of the Poisson distribution test statistics were all less than $X^2_{0.99}$ (6) and the observed values of the binomial distribution are much less than $X^2_{0.99}$ (6) except for time interval {6:00,10:10}, so it was considered that the approaching vehicle flow follows the Poisson distribution.

According to the same idea to determine the distribution of departure traffic flow, the calculation results were shown in Table 8.

TABLE 8. Chi-square test value of leaving vehicle.

Prediction interval	The value of X^2	
	Poisson distribution	Binomial distribution
6:00-10:10	10.631	812.072
10:30-13:10	8.087	7.950
13:10-14:35	8.087	7.950
14:35-18:00	8.087	7.950

TABLE 9. Chi-square test value of leaving vehicle.

Prediction interval	λ_1	λ_2	α	R^2
6:00-10:10	-0.1541	-0.01601	4.81	0.93
Prediction interval	λ	θ	α	R^2
10:30-13:10	-22.1	-0.02372	0.17	0.9139
13:10-14:35	77.64	0.09119	-3.17	0.938
14:35-18:00	-18.14	-0.01679	1.39	0.9799

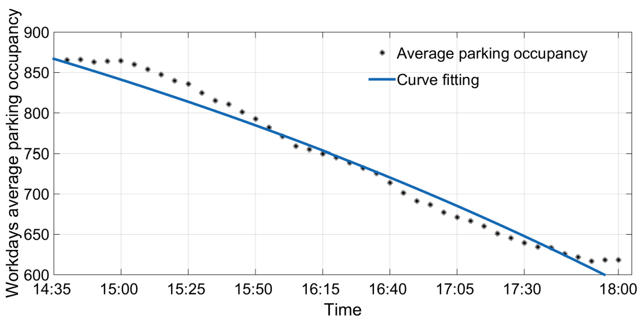

FIGURE 11. Workdays 14:30-18:00 fitting curve.

The observations of the Poisson distribution test statistics are all less than $X^2_{0.99}$ (6), and the observations of the binomial distribution are also less than $X^2_{0.99}$ (6) and less than Poisson in the period 10:30-18:00 Distribution test values, it is considered that the departure vehicle flow during the period of 6:00-10:30 obeys the Poisson distribution, the service time follows the negative exponential distribution, and the binomial distribution during the 10:30-18:00 period.

3) DISTRIBUTION OF CALIBRATION

According to (6) and (8), fitting and solving the parking arrival rate and departure rate at different time periods on workdays were shown in Table 9.

Taking the time period {14:35,18:00} as an example, and using the model proposed in this paper to fit the process of actual parking data, as shown in Fig.11. The maximum error value was not greater than 20, which was because the initial parking base was large, and the error value decreases with time while the fitting error was less than 10%.

4) PARKING DEMAND PREDICTION ON WEEKDAYS

Bringing the model parameters solved into (6) and (8) to obtain the parking demand prediction model on weekdays.

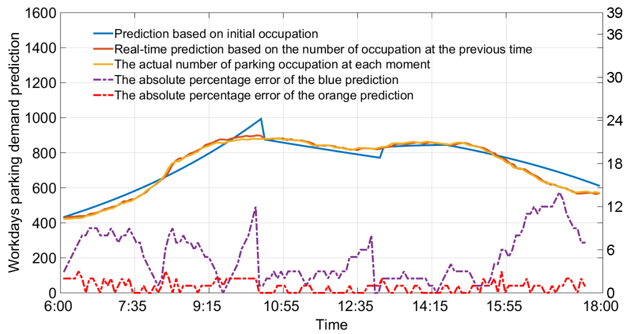

FIGURE 12. Workdays parking demand prediction and error.

Based on this, the parking demand on the following Tuesday was calculated to verify the validity of the model. The prediction results and error values were shown in Fig.12.

As can be seen from Fig.12, in the prediction method based on the initial parking number, the maximum parking demand prediction error was 14%, and 93% of the prediction error was less than 10%. In the real-time prediction method based on the number of parking occupancy at the previous time, the maximum prediction error was 3%, and 99% of the prediction error was less than or equal to 2%.

V. CONCLUSION

Based on the characteristics of parking demand in the parking lot, this paper explores the method for determining the parking prediction interval. Considering the arrival and departure patterns of vehicles in the parking lot, a parking demand prediction model based on the variable parking prediction interval was proposed, and numerical experiments were carried out under different conditions.

Due to the lack of parking data for different types of land, this article only verifies the accuracy and effectiveness of parking demand prediction of Jilin University of Nanling campus. In the future, we expect more types of parking lot data such as office land, storage land, and residential land to verify whether the model proposed in this paper has good prediction accuracy under different parking characteristic conditions.

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