

Research Article

Analysis on Link Travel Time Estimation considering Time Headway Based on Urban Road RFID Data

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In this paper, the calculation method of the link travel time is firstly analysed in the continuous traffic flow by using the detection data collected when vehicles pass through urban links, and a theoretical derivation formula for estimating link travel time is proposed by considering the typical vehicle travel time and the time headway deviation upstream and downstream of the links as the main parameters. A typical vehicle analysis method based on link travel time similarity is proposed, and the theoretical formula is optimized, respectively. Then, an estimation formula based on maximum travel time similarity and an estimation formula based on maximum travel time confidence interval similarity are proposed, respectively. Finally, when analysing the fitting conditions, the collected data from urban roads in Nanjing are used to verify the proposed travel time estimation method based on the radio frequency identification devices. The results show that time headway deviation converges to zero when the hourly vehicle volume is more than 20 veh/h in the certain flow direction, and there are more positive and negative fluctuations when the hourly vehicle volume is less than 10 veh/h in the certain flow direction. The accuracy of the proposed improved method based on typical vehicle travel time estimation is significantly improved by considering the typical vehicle travel time, and typical vehicles on the road segment mainly exist at the tail of the traffic platoon in the corresponding period.

1. Introduction

The travel time is always one kind of quantitative indicators to analyse traffic network performance based on link travel time or route travel time. Even in the near future with the emergence of autonomous vehicles in urban traffic networks and the mixed flow, travel time plays an important role on solving autonomous traffic control problem such as the blue phase design [1]. In addition, travel time is one of the crucial factors affecting drivers' behaviour when they lead or follow vehicle platoon in the mixed flow with autonomous vehicles and human driven vehicles, and some works on the dedicated lane management consider the vehicle time factors

such as headway to improve lane capacity [2]. However, the estimation methods of travel time are mainly considered as mathematical laws and mathematical skills, and travel time is treated as a time series for analysis and prediction considering correlation road segments, which enriches and improves the algorithm. In addition, how the traffic platoon passing through road sections should be considered to estimating the urban link travel time (LTT stands for link travel time), and the proper analysis and research on the generation of travel time should be considered, with the support of fundamental traffic flow theory. In terms of traffic flow theory, the parameters describing the road traffic flow temporal characteristics mainly include the travel time in the

macroaspect and the time headway (TH stands for time headway) in the microaspect, etc., based on which, the relationship between the LTT and the TH can be established theoretically.

In the aspect of traffic data collection methods, there are many technologies on traffic flow data collection, such as microwave and video. Microwave vehicle detection technology can collect data such as traffic flow volume, road or link occupancy, and average speed of each lane, but it is difficult to collect basic data of vehicles. Video recognition is mainly used as the main method for the continuous monitoring of the traffic flow time data of adjacent sections on the road section, video data are susceptible to weather, light, etc., vehicle travel time data cannot be collected in a long term, and the accuracy and reliability of the collected data are affected due to the limitations of weather and climate change. These approaches cannot easily identify a vehicle's basic data, and some comparisons among the traffic data collection characteristics had been done in Gan's work [3]. With the application of radio frequency identification (RFID stands for radio frequency identification) technology and the widely application of automotive electronic identification technology, the use of RFID technology can not only collect all-weather information such as traffic flow volume and average speed but also collect information on the identification of vehicles [4, 5]; thus, vehicle's sequence can be located in the platoon.

In addition, for different data collection methods and data analysis purposes, the data collected by continuous movement methods such as floating car data (taxi) or GPS data [6, 7] can be used to extract travel patterns, such as the floating car or typical vehicle travel time, the waiting time at the node to detect the incident [8], and the OD travel path in the network, but the sample data come from the special vehicles; for fixed collection methods such as video and microwave collection, and the use of radio frequency technology to collect the identity information of the vehicle, the data of the full sample on the road can be obtained, and the objects of collection and analysis can focus on the road operation characteristics, such as the traffic flow volume, speed, headway of the collection node, or the link travel time. Of course, specific methods such as convolution can be used to obtain the travel time of any combination of links as one route in the network. In other words, the diversity and usability of the analysis purposes such as critical nodes and links identification [9, 10] in the traffic network, and traffic data acquired by the fixed traffic data collection method in road nodes, links, and networks level are more suitable than the floating car data collection method.

In this paper, we intend to use electronic vehicle license plate data from continuously collection between road segments and extract the license plate information to obtain road travel time information and time headway information. Then, the related traffic flow theories are combined, the theoretical model between link section travel time and link adjacent time headway is built, and the electronic license plate data are used to verify the theoretical model. Combined with the characteristics of traffic flow, a corresponding improved model is composed, that is, a method for road

travel time estimation based on typical vehicle's travel time based on the vehicle's sequence, and urban road radio frequency identification data are used to analyse the improved model and the improved method is compared with the theoretical model on the fitting effect.

2. Literature Review

It is important to discuss and study LTT or route travel time (RTT stands for route travel time). To analyse travel time reliability for traffic management, control, and network design, travel time distribution should be firstly discussed. Zheng et al. [11] proposed a network travel time distribution model based on the Johnson curve system. Under the mixed traffic flow with connected autonomous vehicles and human-driven vehicles, Wang et al. [12] discussed the travel time reliability based on the multilogistic regression method. Chen et al. [13] explored travel time distribution and variability patterns to provide more detailed analysis for each specific road type by using probe vehicle data.

As one of time dimension parameters describing the characteristics of traffic flow and vehicle operation, due to various traffic factors, there are plenty study results for the research object of travel time considering various traffic factors. Among them, scholars have made many research achievements in terms of modelling methods, data collection application, and special vehicles' travel time focused on the estimation method around travel time. For example, Chen et al. [14] proposed a method considering spatial correlation when studying the road travel time estimation method of urban road signal intersections, and the Gaussian copula model was used to describe the road association degree. Fu et al. [15] applied the license plate recognition data to estimate the travel time of urban roads, and Hopkins statistics method was used to describe the clustering trend when judging the relevance of the travel time of adjacent road sections. Tang et al. [6] used RFID data to analyse the statistical characteristics of urban road travel time, and a Gaussian mixture model was proposed, which was compared with the commonly used single-peak distribution method. Jenelius and Koutsopoulos [16] used a multivariate probabilistic statistical principal component analysis model to predict the travel time of urban roads based on floating car data. From the perspective of energy/emission estimation, Yang et al. [17] proposed an improved Gaussian mixture model to fit urban road travel time distribution characteristics, and the actual collected data were analysed and studied. Ma et al. [18] used the Markov process to estimate the probability distribution of travel time based on the correlation between time and space. Westgate et al. [19] analysed the travel time characteristics of ambulances by using regression estimation methods with explanatory variables such as path and time. Rahmani et al. [20] used the nonparametric model combined with floating car data to estimate the travel time distribution of the route instead of the link under the premise of analysing the potential deviation caused by the sparse distribution of floating cars. Ramezani and Geroliminis [21] discussed the correlation analysis of continuous road sections and travel time,

combined with Markov chain to analyse the travel time distribution characteristics, and obtained the travel time distribution characteristics by calculating the transition probability and road travel time. Tang et al. [22, 23] estimated route travel time distribution by aggregating weighted link travel time distribution based on convolution theory and evolving the fuzzy neural model.

There are many contributions on the travel time distribution and its application, and for each road type or data collection accuracy, there might be various distribution results, especially in the bus or transit scheduling, and the basic relationship between bus time head way and travel time is the main factor to optimize the public transport system-based online data [24, 25]. Based on the basic relationship, the mechanism or the relationship between LTT and operation condition seems to be extended and discussed under the traffic system.

In terms of microtraffic flow analysis, many scholars have carried out a lot of research work on the mining of time headway parameters to analyse the operating characteristics of traffic flow systems. The time headway is an important parameter which describes the car following behaviour, characterizes the operating characteristics of traffic flow, identifies vehicle safety, and quantifies traffic conditions. Adams [26] used Poisson distribution to study the arrival rules of vehicles and found that the statistical characteristics of the time headway accorded with the negative exponential distribution. Then, the statistical analysis method is applied to conduct more studies and research on the time headway. Based on the conclusion of time headway analysis results, Chen et al. [27] proposed a car-following model considering the time headway distribution and comprehensively considered parameters such as car position, speed, and time headway, and the Markov process was used to update the vehicle status. There are many data collection methods for time headway, such as manual, video, and other technical means. Gunay [28] used the number of vehicle identifications collected by the automatic license plate recognition technology and analysed the data of the time headway and other data from the perspective of the safety following time, and the distribution of the time headway in the regional road was discussed. Weng et al. [29] investigated work zone vehicle headway distribution by disaggregating the vehicle headways into four types, and a useful methodology was proposed to determine the best-fitted headway distribution model for each vehicle type. Pueboobpaphan et al. [30] analysed the time headway distribution of probe vehicles under highway condition and found that a shift negative exponential distribution had the closest fit which depended on vehicle volume, lanes, and market penetration of probe vehicles. Wang et al. [31] applied the time headway variation tendency (HVT) to analysis the traffic flow stability and found that the HVT could improve the stability.

Methods such as chi-square test and coefficient of variation were used to analyse the characteristics of the time headway by the vehicle data collected twice from the adjacent collectors, and the analysis results were used to identify unsafe driving vehicles. As a typical microscopic traffic flow characteristic parameter, the time headway can

be useful to describe the traffic operation characteristics from the microscopic perspective of traffic flow and the vehicle based on statistical analysis methods and measured data of various collection methods; thus, the details between link time headway (LTH stands for link time headway) and LTT should be discussed.

When studying link travel time, it is mainly regarded as a random variable, and the statistical analysis method is used for research. However, the discrete and random characteristics of road traffic flow itself make the statistical characteristics of road travel time highly complicated, and for each link's travel time distribution, there are also obvious difference, which makes it difficult to grasp the statistical law of travel time of all links at the city level. This paper attempts to establish the relationship between the two types of temporal dimension parameters of road traffic LTT and vehicle time headway by discussing the calculation rule of link traffic travel time, in which the statistical analysis methods were combined with actual data to verify the established model.

The content of this paper is arranged as follows. The regularity of LTT is firstly analysed, and then the derivation of the theoretical model of travel time estimation is proposed by considering the characteristics of traffic flow. The characteristics of urban road RFID data and the characteristics of case links, travel time, and time headway are discussed. The factor of similarity is used to select the typical car travel time information to improve the theoretical model, and both the theoretical model and the improved model are verified with the RFID data. At last, the conclusions are summarized.

3. Methodology

3.1. Basic Travel Time Function. To solve the problem of LTT estimation, the stop line of the intersection or the detector cross section could be treated as the observation node, and the characteristics of vehicle travel speed and data collection point layout should be considered, and the TH should be used as the key parameter to analyse the road travel time. Then, the relationship between the LTT and TH could be quantified to a recursive model.

It is supposed that on a link, there is only one lane and the length of the link is L , and the vehicles run in sequence based on the rule of first in first out. A total of n vehicles are detected at the upstream point u and the downstream point d , and the detection time stamp of the first vehicle is (t_{u1}, t_{d1}) . The detection time record of the n th car is (t_{un}, t_{dn}) , and the travel time of any car v_i is T_i . It is assumed that the average speed of the vehicle is \bar{V} , the travel distance of any car on the road segment is S_j , and the density on the road segment is K . Then, the average travel time of the link is \bar{T} and the time headway of the vehicle at the upstream and downstream detection points is (τ_{ui}, τ_{di}) , and the relationship between which can be deduced according to the vehicle detection sequence.

As shown in Figure 1, the detection time of the first vehicle and the time interval between the first vehicle and the subsequent vehicle n are taken as the analysis parameters, and the recursive formula is obtained as shown in equation

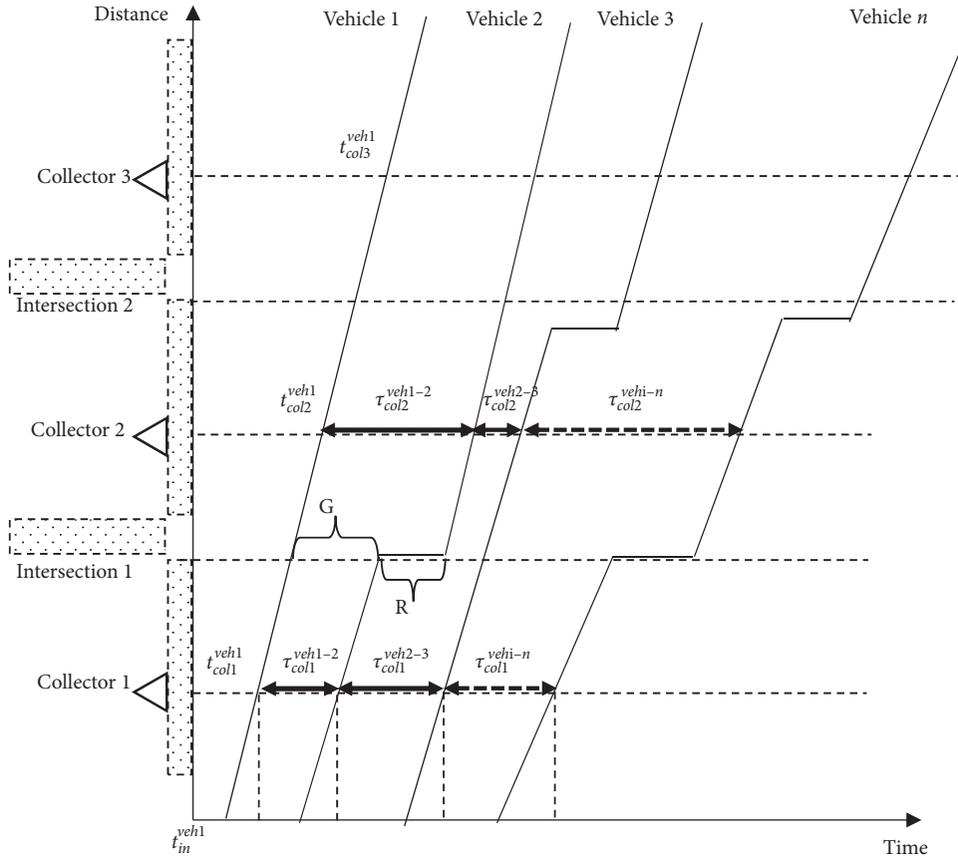


FIGURE 1: Vehicle travel time running through multi-intersections and collectors.

(1). The vehicle detection time, the time interval between vehicles, and the number of vehicles constitute the main

influencing variables for analysing the accuracy of vehicle link travel time estimation:

$$\begin{aligned}
 v_1: T_1 &= t_{d1} - t_{u1}, \\
 v_2: T_2 &= t_{d2} - t_{u2} = (t_{d1} + \tau_{d12}) - (t_{u1} + \tau_{u12}) = (t_{d1} - t_{u1}) + (\tau_{d12} - \tau_{u12}) = T_1 + (\tau_{d12} - \tau_{u12}), \\
 &\vdots \\
 v_n: T_n &= t_{dn} - t_{un} = (t_{d1} + \tau_{d1n}) - (t_{u1} + \tau_{u1n}) = (t_{d1} - t_{u1}) + (\tau_{d1n} - \tau_{u1n}) = T_1 + (\tau_{d1n} - \tau_{u1n}).
 \end{aligned} \tag{1}$$

The situation is further considered when the time interval of vehicle sequence fluctuates in the traffic flow, and three parameters of the vehicle arrival time, the vehicle time

interval corresponding to the upstream and downstream, and the travel time are treated as the main factors. The recursive formula obtained is shown as follows:

$$\begin{aligned}
 v_1: T_1 &= t_{d1} - t_{u1}, \\
 v_2: T_2 &= t_{d2} - t_{u2} = (t_{d1} + \tau_{d12}) - (t_{u1} + \tau_{u12}) = (t_{d1} - t_{u1}) + (\tau_{d12} - \tau_{u12}) = T_1 + (\tau_{d12} - \tau_{u12}), \\
 v_3: T_3 &= t_{d3} - t_{u3} = (t_{d1} + \tau_{d12} + \tau_{d23}) - (t_{u1} + \tau_{u12} + \tau_{u23}) = (t_{d1} - t_{u1}) + (\tau_{d12} + \tau_{d23}) - (\tau_{u12} + \tau_{u23}) = T_1 + (\tau_{d13} - \tau_{u13}), \\
 &\vdots \\
 v_n: T_n &= t_{dn} - t_{un} = (t_{d1} + \tau_{d1n}) - (t_{u1} + \tau_{u1n}) = (t_{d1} - t_{u1}) + (\tau_{d1n} - \tau_{u1n}) = T_1 + (\tau_{d1n} - \tau_{u1n}).
 \end{aligned} \tag{2}$$

According to equation (2) and Figure 1, the time interval decomposition matrix among vehicles is shown as follows:

$$\begin{pmatrix} s_u & veh_1 & veh_2 & veh_3 & \cdots & veh_n & s_d \\ s_u & - & t_1 & t_2 & t_3 & \cdots & t_n & \bar{T} \\ veh_1 & - & - & t_1 + \tau_{12} & t_1 + \tau_{13} & \cdots & t_1 + \tau_{1n} & \bar{T}_1 \\ veh_2 & - & - & - & t_2 + \tau_{23} & \cdots & t_2 + \tau_{2n} & \bar{T}_2 \\ veh_3 & - & - & - & - & \cdots & t_3 + \tau_{3n} & \bar{T}_3 \\ \vdots & \vdots \\ veh_n & - & - & - & - & \cdots & t_n & \bar{T}_n \\ s_d & \bar{T} & - & - & - & - & - & - \end{pmatrix}. \quad (3)$$

According to the analysis of recursive formulation (2) and (3), it is found that the LTT between upstream and downstream can be related to the three parameters of the travel time of the first vehicle and the time interval between the first car and other vehicles when they reach the upstream and downstream detection points. Therefore, the expression of the travel time of the link between nodes is shown as equation (4), with n collected vehicles during a period. The link upstream time headway and downstream time headway both have the statistical distribution as $LTH_u \sim (\bar{\tau}_u, D(LTH_u))$ and $LTH_d \sim (\bar{\tau}_d, D(LTH_d))$, respectively:

$$\begin{aligned} \bar{T} &= \frac{1}{n} \sum_{i=1}^n T_i = \frac{1}{n} \sum_{i=1}^n [(t_{d1} - t_{u1}) + (t_{d2} - t_{u2}) + \cdots + (t_{dn} - t_{un})] = \frac{1}{n} \sum_{i=1}^n [T_1 + T_1 + (\tau_{d12} - \tau_{u12}) + \cdots + T_1 + (\tau_{d1n} - \tau_{u1n})], \\ &= T_1 + \frac{1}{n} \sum_{i=2}^n (\tau_{d1i}) - \frac{1}{n} \sum_{i=2}^n (\tau_{u1i}) \approx T_1 + \bar{\tau}_{d1} - \bar{\tau}_{u1}. \end{aligned} \quad (4)$$

The expectation of the LTT between collectors can be rewritten as equation (5), and the variance of the LTT is shown as equation (5). LTT could be decomposed into two

parts, including head vehicle travel time and deviation between link adjacent upstream and downstream time headway:

$$\begin{aligned} \bar{T} &= T_1 + \frac{1}{n} \sum_{i=2}^n (\tau_{d1i}) - \frac{1}{n} \sum_{i=2}^n (\tau_{u1i}), \\ D(T) &= \frac{1}{n} \sum_{i=1}^n (\bar{T} - T_i)^2 = \frac{1}{n} \sum_{i=1}^n \left(T_1 + \frac{1}{n} \sum_{i=2}^n \tau_{d1i} - \frac{1}{n} \sum_{i=2}^n \tau_{u1i} - T_1 - (\tau_{d1i} - \tau_{u1i}) \right)^2 \\ &= \frac{1}{n} \sum_{i=1}^n \left(\left(\frac{1}{n} \sum_{i=2}^n \tau_{d1i} - \tau_{d1i} \right) - \left(\frac{1}{n} \sum_{i=2}^n \tau_{u1i} - \tau_{u1i} \right) \right)^2 \\ &= \frac{1}{n} \sum_{i=1}^n \left[\left(\frac{1}{n} \sum_{i=2}^n \tau_{d1i} - \tau_{d1i} \right)^2 + \left(\frac{1}{n} \sum_{i=2}^n \tau_{u1i} - \tau_{u1i} \right)^2 - 2 \left(\frac{1}{n} \sum_{i=2}^n \tau_{d1i} - \tau_{d1i} \right) \cdot \left(\frac{1}{n} \sum_{i=2}^n \tau_{u1i} - \tau_{u1i} \right) \right] \\ &= D(\tau_{d1}) + D(\tau_{u1}) - 2\text{cov}(\tau_{d1}, \tau_{u1}). \end{aligned} \quad (5)$$

Thus, link travel time T could have a statistical distribution as $LTT \sim (\bar{T}, D(T))$ based on link adjacent time headway. Furthermore, route travel time (RTT) average value probability density could be written as multi-LTT

convolution equation, as equation (6). And in this paper, LTT would be mainly discussed, and RTT could be analysed based on the LTT distribution density function and convolution theory:

$$f(\bar{T}_r) = f\left(\sum_{i=1, i \in r}^n \bar{T}_i\right) = \int_{-\infty}^{\infty} f_{\bar{T}_{l1}}(\bar{T}_{l1}) f_{\bar{T}_{l1}}(\bar{T}_r - \bar{T}_{l1}) d\bar{T}_{l1}. \quad (6)$$

3.2. Model Improvements. Based on the theoretical analysis, if a typical vehicle can be found in the traffic platoon, whose travel time passing through the link is a key factor for estimation. In the other side, the volatility of the traffic flow through the link is introduced at the same time; that is, the improved form of the average travel time estimation formula for the link is shown as follows:

$$\hat{T} = T_k + T_e. \quad (7)$$

In equation (7), T_k represents the travel time of the link represented by the typical vehicle k in the traffic platoon. T_e represents link time headway deviation, namely, the volatility of the traffic flow in and out of the link, which is determined by the average characterization of the time headway of the vehicle entering the link and the time headway of the vehicle driving out the link.

Then, how to find out the typical vehicle is the problem. A method of travel time similarity index is proposed. The deviation between the link average travel time of the vehicle flow and the travel time of each vehicle is found based on the analysis of historical data. The similarity index T_s of travel time is introduced and calculated as equation (8) shown. Based on the similarity index, the typical vehicle could be found, and at the same time, the location and position of the vehicle in the traffic platoon could be determined:

$$T_s = \min\{|\bar{T} - t_i|\}. \quad (8)$$

3.3. Calculation Process. The average LTT calculation process based on typical vehicles considering the similarity of continuous traffic flow is shown in Figure 2(a).

In this paper, an analysis method is proposed by using travel time similar intervals in a certain analysis period. Based on the statistical analysis processing, the statistical rule of travel time in a certain analysis period is obtained, and the confidence interval of travel time is further obtained as the travel time similar interval. The method of road travel time extraction based on the typical vehicle selected in a similar interval in continuous traffic flow is shown in Figure 2(b).

In addition, the actual data are used for analysis and processing by considering the slow speed characteristics generated by the randomness of travel demand, which affects the travel time of the link. Therefore, the travel time extracted from the upstream and downstream detectors should be screened by a threshold value, which can be an extrapolation by combining the actual length of the link with the speed limit and the historical data distribution to determine the screening threshold value. For vehicle records processed by the threshold value, the hour is used as the analysis period to extract the number of vehicles that pass through the detection section, the time headway, and the

travel time of the link, particularly including the number of vehicles arriving at the upstream detection of the link during the analysis hour and the average time headway between the front and rear vehicles passing through the detector, the number of vehicles collected by the downstream detector of the link, and the average time headway between the front and rear vehicles passing through the detector. According to the vehicle license plate data, the average travel time could be obtained corresponding to the traffic flow passing through the upstream and downstream detectors of the link, and the travel time of the first vehicle driving through the link in the analysis hour. Then, the processed data should be applied to verifying the theoretical analysis formula and the improved model.

The head vehicle in the analysis hour has a certain degree of representative effect on the travel time of the traffic flow in this hour. When the traffic flow is congested or the traffic volume is close to the saturated flow, the traffic flow can be considered homogeneous. The travel time of the certain vehicle is the same as the travel time of the traffic flow. When the traffic flow has not reached the saturation condition, there is more spaces for vehicle passing, and the vehicle is unevenly distributed on the link, and when there is an opportunity to overtake slower cars, it can be considered that there is a weak representation between the travel time on the head car and the travel time of the traffic flow of the link. This conclusion can also be obtained through actual numerical analysis. At this time, the vehicle flow can be considered a discrete flow, and when it is close to the saturated flow, the vehicle flow can be considered a continuous flow.

4. Model Application and Data Analysis

4.1. Data Sets. The data used in this paper are collected from the actual road condition of the local road network in December 2015 in the city of Nanjing in China. The RFID collection equipment deployed on urban roads is built to collect the vehicle data, and vehicle identification data in the electronic tags are collected, such as license plates, passing time, speed, and lanes when the vehicle passes through the RFID base station, and the vehicle plate data are extracted to obtain the vehicle travel time information used between adjacent detection sections. The upstream and downstream adjacent base station collected data are further used by combined with license plate information and the travel time information of the link traffic between adjacent base stations, and the time headway information is obtained separately when the vehicle passes through the detection section.

In the small traffic zone, there are 43 RFID collection base points, and there are more than 20 million vehicle collection records in December, 2015. The sample traffic flow direction and base station layout used in this paper are shown in Figure 3. The data collection records of the two base stations numbered 6289 and 6430 are used as data example, where the traffic flow turns right at the base station at 6430 after straight leaving the base station of 6430, and then the vehicle data passing through the base station are analysed and extracted based on the plate. For one day, there are more than 10 thousand records in the 6289 (15873

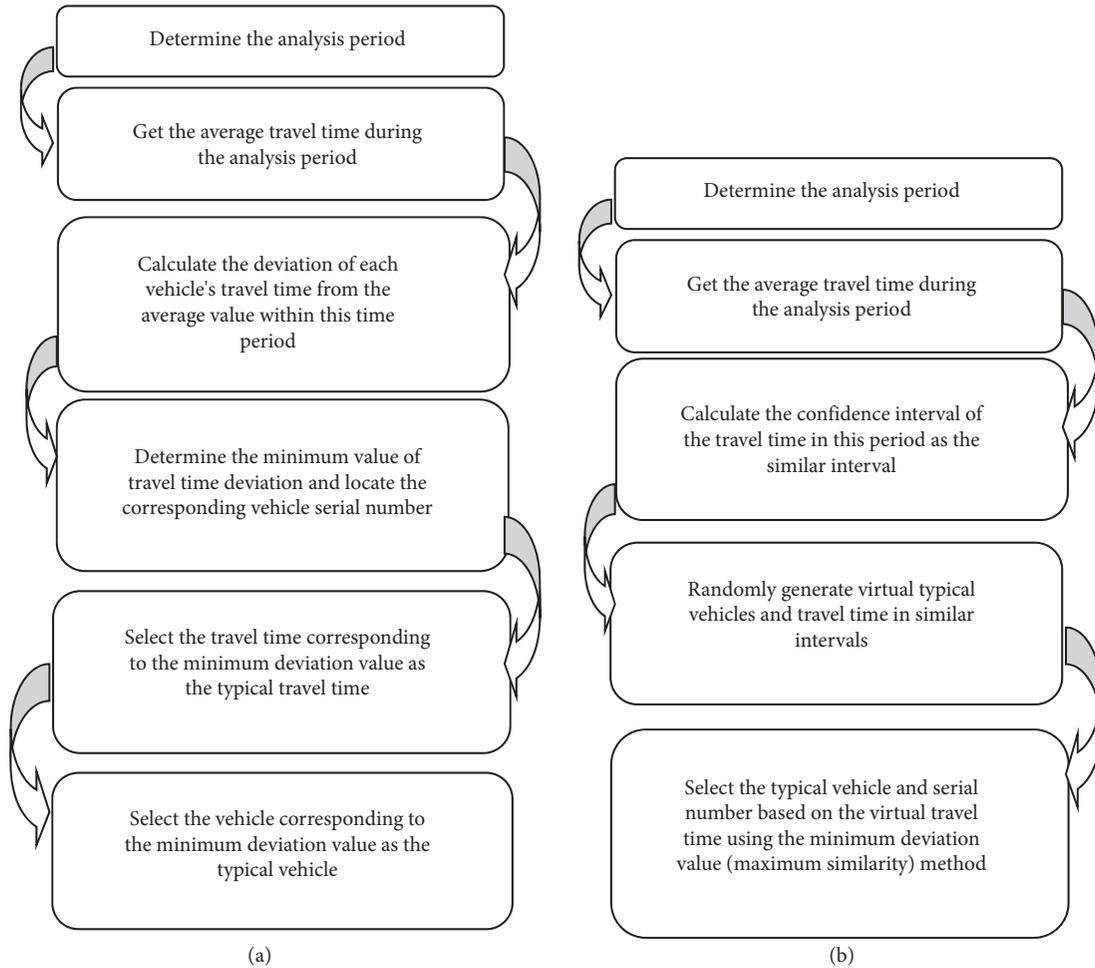


FIGURE 2: Two methods of link travel time data extraction: (a) method based on average travel time of typical vehicle; (b) method based on confidence interval of virtual typical vehicle travel time.

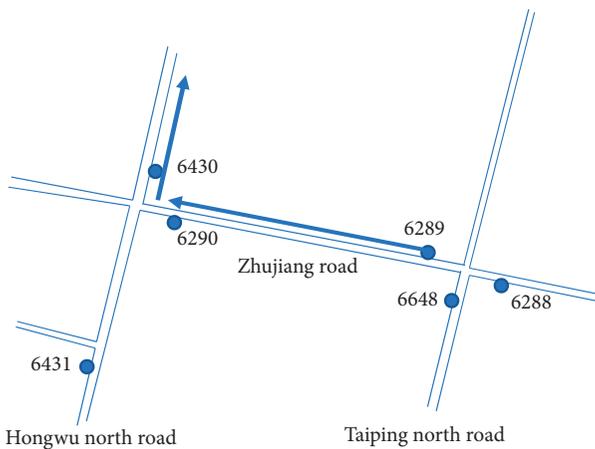


FIGURE 3: Layout of RFID points and traffic flow direction.

records on December 9, 2015) and 6430 (10972 records on December 9, 2015) base station, and only near 900 records can be used to analyse the link travel time and time headway based on the data screen process such as redundant data processing and invalid record deletion.

4.2. *Data Process Based on Threshold Value of 300s.* According to the road map, the length of the link between 6289 and 6430 is 490 meters, and the speed limit is 60 km/h; then, a threshold value of 300 seconds is designed. The data of December 2, December 9, December 16, December 23, and December 30 are extracted from the basic data set as model training data. The actual collected data include lane information, so the collected data of the link can be further divided according to the lane situation. There are 3 lanes on the link at the position of the upstream detector 6289, and the leftmost side of the driving direction is lane 1, followed by the lane numbers, lane 2 and lane 3, to the rightmost side of the driving direction, and then the lane numbers of the 6289 detection section are 1, 2, and 3, respectively. There are 2 lanes on the link at the position of the downstream detector 6430, and the lane numbers are 1 and 2, respectively, and there would be a total of 6 consecutive link cases, particularly as “11,” “12,” “21,” “22,” “31,” and “32” corresponding to the lane combination conditions. Considering that the link is the research object, then an analysis case can be added, that is, the travel time of the traffic flow on the link and the time headway characteristics of the vehicles entering and exiting the link. According to equation (5), the sample data set is

divided according to the collection point, including the upstream time headway, the travel time of the link, and the downstream time headway, and the sample data set is processed according to the time segment and 7 analysis cases, respectively, including the upstream average time headway data set, link average travel time data set, and downstream average time headway data set.

4.2.1. Vehicle Volume and Average Time Headway from Upstream. In the data set, the number of vehicles and the average value of the time headway of the corresponding analysis period are, respectively, counted according to the direction of traffic flow, date, analysis period, and lane case. The processing flow is shown in Figure 4(a). Taking the data on December 2, 2015, as an example, the number of vehicles and the average value of time headway in the analysis hour are obtained from the upstream detector in the direction of traffic flow, and the results are shown in Table 1, where “H” stands for hour, “S” stands for the link case, “11” stands for the link 11 case, “Q” stands for the vehicle numbers based on the threshold value 300 s, and “T” stands for the average time headway.

4.2.2. Head Vehicle Travel Time and Average Travel Time. In the data set, the number of vehicles and the average travel time of the corresponding analysis hour and the travel time of the head vehicle in the analysis period are counted according to the traffic flow direction, date, time period, and lane case. The processing flow is shown in Figure 4(c). Taking the data on December 2, 2015, as an example, average travel time T_1 and the travel time \bar{T} of the head vehicle in the time period are obtained in the traffic flow direction by combined with the upstream and downstream detector data. The results are shown in Table 2.

4.2.3. Vehicle Volume and Average Time Headway from Downstream. In the data set, the number of vehicles and the average value of the time headway of the corresponding time period are, respectively, counted according to the direction of traffic flow, date, period, and lane case. The processing flow is shown in Figure 4(b). Taking the data on December 2, 2015, as an example, the number of vehicles and the average value of time headway in the analysis hour are obtained from the downstream detector in the direction of traffic flow, and the results are shown in Table 3.

According to Tables 1–3 data, in terms of traffic flow, although the number of vehicles in each analysis hour is not large, the traffic flow condition in the direction shows a more obvious characteristic of morning and evening peaks.

In terms of traffic flow lane distribution, the proportion of vehicles choosing link 11 is between 28% and 73%, the proportion of choosing link 12 is within 27%, the proportion of choosing link 21 is within 21%, and the proportion of choosing link 22 is within 14%, the ratio of selecting link 31 is within 47%, and the ratio of selecting link 32 is within 21%. It can be seen that the vehicle mainly selects the left-most driving direction of the link, which is because the right-side

driving direction is vulnerable to slow speed bus, frequent buses entering and leaving the station, mixed with nonmotor vehicles, pedestrian crossing, and vehicles entering and exiting at the roadside exit, etc. In terms of travel time, it can also be seen that the travel time of the right lane is shorter than other cases, even if the vehicle needs to change lanes near the intersection; however, it is more obvious that the vehicle chooses to drive on the leftmost lane. Correspondingly, the number of vehicles traveling in the selected lane 31 is also large, but the number of vehicles selected in lane 21 and lane 22 is small.

In terms of time headway, from the case data, it is found that the average time headway from the entrance section of the road section is not much different from the average time headway from the exit position under various lane selection scenarios. The ratio between them is fluctuated around 1 in a small range, as shown in Figure 5.

In terms of LTT, based on the analysis of the case data, it is found that the average travel time of the link is significantly different from the travel time of the head vehicle in the analysis hour. The ratio between them jumps up and down in the range of 1, as shown in Figure 6. It can be seen that when the average travel time of the single vehicle and the average time headway of the analysis hour are used to estimate the travel time of the link, there is less fluctuation for the average time headway of the upstream and downstream of the link, where the travel time of the head vehicle or typical vehicle is the main parameter in the condition of applying equation (5) to estimate the travel time, and there will be a large deviation. Thus, the main factor of the model needs to be improved, that is, to identify the typical vehicle based on the similarity method and improve the travel time estimation model.

5. Analysis and Results

In this part, time headway condition is firstly discussed based on equation (5), and then the data are applied to equation (5) evaluation, and two kinds of improved method are discussed, respectively, based on the average travel time of typical vehicle and the random travel time in confidence interval of typical vehicle, and the typical vehicle sequence is analysed and located. Comparison of fitting effects and method applications are discussed.

5.1. Time Headway Deviation (THD). According to equation (5), LTT could be decomposed into two parts, according to Figure 6, it can be illustrated that though there is less deviation between time headway upstream and downstream, link time headway deviation should be discussed as one factor due to that single collection time headway is mainly used to describe vehicle flow at the stop line and link travel time needs two-point time headway as a factor pair. In addition, according to equation (5), variance of LTT is $D(T)$ which mainly is defined by the link time headway and influenced the deviation degree around the link average travel time. From equation (5), it can be theoretically included that the correlation coefficient is equal to 1 when the vehicles pass lanes in the same direction, and the data results based on hour vehicle volume on Dec. 2, 2015, are shown in Figure 7.

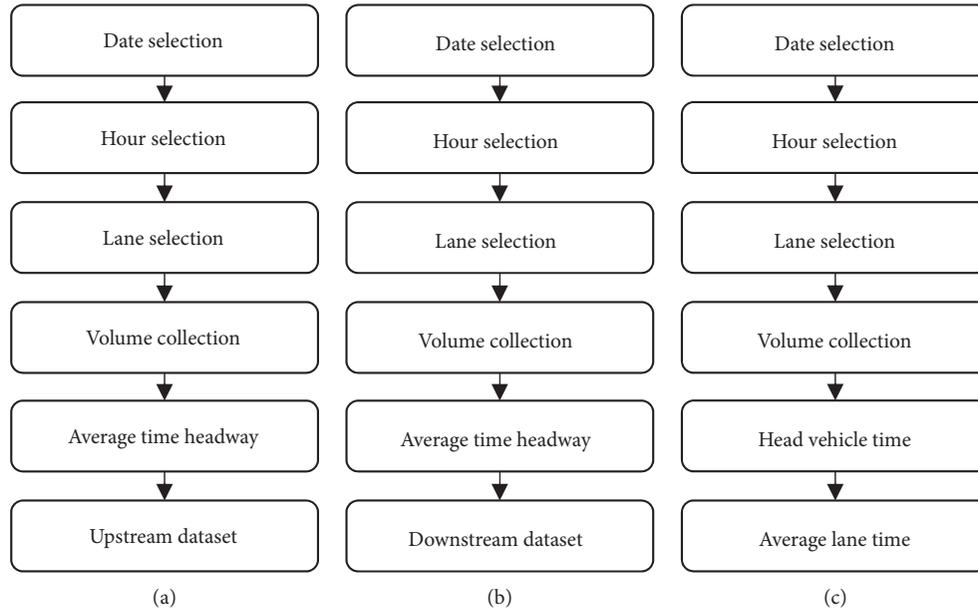


FIGURE 4: Data processing flow: (a) upstream data, (b) downstream data, and (c) lane data.

TABLE 1: Vehicle volume and average time headway from upstream on December 2, 2015.

H	S		11		12		21		22		31		32	
	Q	T	Q	T	Q	T	Q	T	Q	T	Q	T	Q	T
6	15	194	5	483	1	—	1	—	0	—	7	386	1	—
7	69	48	39	74	6	457	8	313	1	—	11	206	4	804
8	51	65	28	120	11	270	3	1002	2	1077	5	555	2	1022
9	54	65	26	133	7	526	9	397	3	617	8	392	1	—
10	63	57	29	126	5	520	8	363	7	482	5	507	9	250
11	46	76	26	136	7	546	5	737	1	—	5	452	2	1578
12	18	192	10	362	4	440	2	1119	0	—	1	—	1	—
13	26	137	15	244	2	1436	5	713	1	—	1	—	2	117
14	50	72	28	117	9	430	4	1033	2	25	6	565	1	—
15	35	98	16	196	3	1006	4	627	5	447	4	1021	3	1096
16	49	71	36	98	2	1417	4	492	1	—	2	380	4	537
17	51	69	31	114	6	546	7	415	2	131	4	1082	1	—
18	42	69	16	173	4	309	9	199	4	484	8	396	1	—
19	26	140	10	309	7	399	1	—	1	0	4	1156	3	939
20	43	84	12	319	11	284	3	932	2	653	10	359	5	679
21	26	134	8	350	0	—	2	378	0	—	11	334	5	603
22	28	128	12	292	4	122	0	—	0	—	6	494	6	519

The relationship could be built considering the vehicle volume and time headway deviation during the analysis hour shown in Figure 8 with sample data sets including all lane conditions. It can be illustrated that the deviation converges to zero when the hourly vehicle volume is more than 20 veh/h in the certain flow direction, and there are more positive and negative fluctuations when the hourly vehicle volume is less than 10 veh/h in the certain flow direction. For the details of the time headway distribution, the normal distribution is selected to describe and the result is shown as Figures 9(a) and 9(b), and time headway deviation has a distribution as $TH D \sim N(-1.39, 56.61)$ based on the sample data sets. From Figure 9(b), it can be found that more than 60% deviation is near to zero and it can be

concluded that the time headway deviation might have less influence on link travel time estimation equation (5) when there are more vehicles in the certain traffic flow direction.

5.2. *Data Fitting Based on Equation (5)*. According to equation (5), combined with the case data set, a variety of lane scenarios are calculated, and the estimated LTT is calculated according to the formula, and the error value between the real link travel time and the estimated value is obtained. The results are shown in Figure 10.

As shown in Figure 10(a), the maximum travel time in each case is 180 s, which appears at 9 am and in the case of lane 22. Correspondingly, the minimum travel time is 60 s

TABLE 2: Head vehicle travel time and average travel time on December 2, 2015.

H	S		11		12		21		22		31		32	
	T_1	\bar{T}												
6	75	83	75	68	87	87	73	73	0	0	2	95	76	76
7	159	103	97	94	75	104	54	125	100	100	159	124	82	97
8	61	90	61	92	96	81	115	114	77	96	72	88	110	89
9	70	108	61	97	111	111	70	106	153	184	86	120	59	59
10	49	116	44	97	49	93	130	141	118	136	1	150	141	133
11	112	117	112	112	97	112	163	146	92	92	60	141	72	75
12	54	93	54	87	95	93	99	111	0	0	112	112	101	101
13	122	118	122	114	100	95	102	141	86	86	128	128	86	123
14	77	121	127	126	56	102	118	152	94	117	77	109	121	121
15	105	126	113	128	56	102	88	96	174	140	144	135	132	158
16	81	108	81	105	105	95	151	111	101	101	98	106	145	128
17	121	107	121	103	133	106	120	131	114	124	112	103	69	69
18	138	106	138	96	84	106	134	115	114	109	102	105	159	159
19	92	93	81	101	128	109	92	92	97	97	72	85	112	90
20	109	101	98	121	112	88	65	90	112	109	109	98	104	95
21	121	90	62	75	143	86	121	114	0	0	110	97	63	88
22	109	86	111	95	0	0	0	0	0	0	109	78	186	93

TABLE 3: Vehicle volume and average time headway from downstream on December 2, 2015.

H	S		11		12		21		22		31		32	
	Q	T	Q	T	Q	T	Q	T	Q	T	Q	T	Q	T
6	15	194	5	475	1	0	1	—	0	—	7	359	1	—
7	69	47	39	74	6	468	8	320	1	0	11	211	4	820
8	51	66	28	123	11	265	3	996	2	1115	5	562	2	980
9	54	65	26	135	7	523	9	399	3	688	8	407	1	—
10	63	58	29	128	5	539	8	366	7	482	5	549	9	242
11	46	75	26	134	7	548	5	744	1	—	5	472	2	1583
12	18	193	10	364	4	431	2	1142	0	—	1	—	1	0
13	26	135	15	242	2	1425	5	715	1	—	1	—	2	191
14	50	75	28	119	9	454	4	1071	2	70	6	575	1	—
15	35	98	16	197	3	996	4	640	5	443	4	1023	3	1107
16	49	72	36	98	2	1363	4	478	1	0	2	396	4	529
17	51	69	31	112	6	551	7	410	2	151	4	1071	1	—
18	42	68	16	171	4	293	9	197	4	485	8	398	1	—
19	26	140	10	313	7	397	1	—	1	—	4	1167	3	923
20	43	83	12	320	11	277	3	950	2	646	10	354	5	681
21	26	131	8	352	0	—	2	363	0	—	11	329	5	606
22	28	127	12	289	4	131	0	—	0	—	6	483	6	495

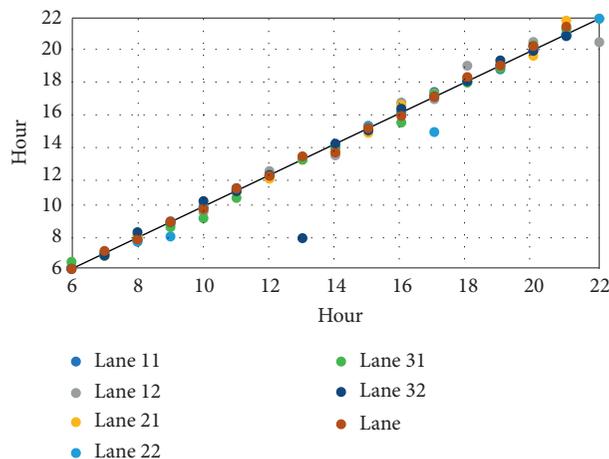


FIGURE 5: Average time headway of upstream and downstream.

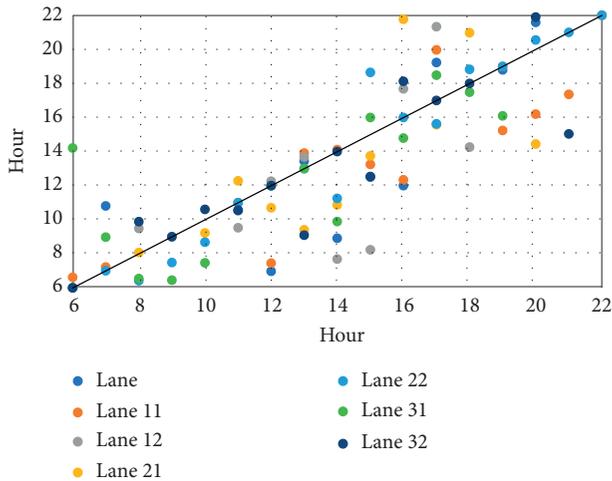


FIGURE 6: Head vehicle average travel time vs. average link travel time.

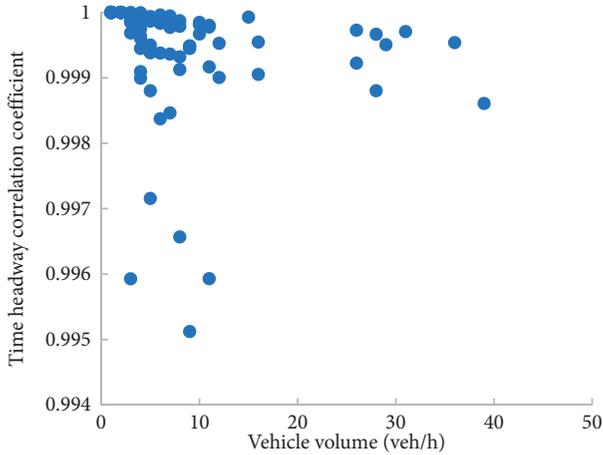


FIGURE 7: Time headway correlation coefficient vs. vehicle volume.

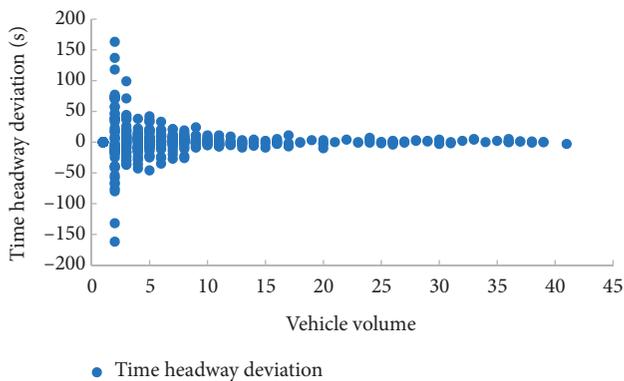


FIGURE 8: Time headway deviation with hourly vehicle volume.

(excluding no vehicle running in the road), and it also appears in 9 a.m., but in the case of lane 32. Since the direction of traffic is straight before turning right, so vehicles running in the case of lane 32 can complete the travel with turning right after going straight without frequent lane

changes, so in this scenario, the minimum travel time is reasonable; however, vehicles running in this scenario are easily affected by vehicles driving in adjacent lanes, non-motor vehicles, bus stations, and entrances and exits of the road segment, resulting in large fluctuations in travel time. Corresponding to the lane 11 case, since the link is in the leftmost lane in the driving direction, it is not easily affected by vehicles in the adjacent lanes, so the travel time fluctuation is small, which only floats up and down around 90 s.

As shown in Figures 10(b) and 10(c), according to equation (5), after the average travel time of the head vehicle and the upstream and downstream time headway of the analysis hour are extracted, the estimated results and accuracy of the average travel time of the analysis hour are obtained. The estimated result shows the change of travel time. However, the estimated result is affected by the travel time parameter of the head vehicle. The estimated result differs greatly from the real situation, the error is obvious, and the individual estimated value exceeds the minimum value in the real situation. The estimation model needs improvement.

For the conditions of different scenarios in each lane, the data fitting effect is shown in Figure 11. From the analysis of Figure 11, it is shown that theoretical equation (5) can be used to estimate the change of the real situation, but for the estimated value, there is a large accuracy shortage, the error value cannot float well above or below the value of 0, and there is a large jitter.

5.3. Improved Method Based on the Average Travel Time of Typical Vehicle. According to the processing procedures of equations (7) and (8), and Figure 2(a), equation (5) is improved. Thus, the travel time of the most similar vehicle in the corresponding period is selected as the key parameter to estimate the average link travel time in conjunction with the average travel time of the link in the historical analysis hour. The corresponding vehicle is the typical vehicle. The estimated value of the travel time of the lane and the error result are obtained. Taking the upstream lane 1 as an example, the result is shown in Figure 12. Compared with the theoretical derivation formula, the improved formula can better fit the data trend. For the error value, there is a small range fluctuates around the 0 value. Due to the difference in the number of vehicles in each lane, there are still large errors in the individual analysis hour. For example, the error corresponding to an analysis hour of 16 p.m. in the case of lane 12 is a little larger value compared with the other case.

5.4. Improved Method Based on Random Travel Time in Confidence Interval of Typical Vehicle. According to the processing procedures of equations (7) and (8), and Figure 2(b), equation (5) is improved. Considering the randomness of the traffic flow, based on the statistical rule of the travel time of the link in the historical period, the statistical law of the travel time of the road segment is obtained, then the link travel time randomly generated based on the confidence interval is applied to select the most similar vehicle in the corresponding analysis hour, whose travel

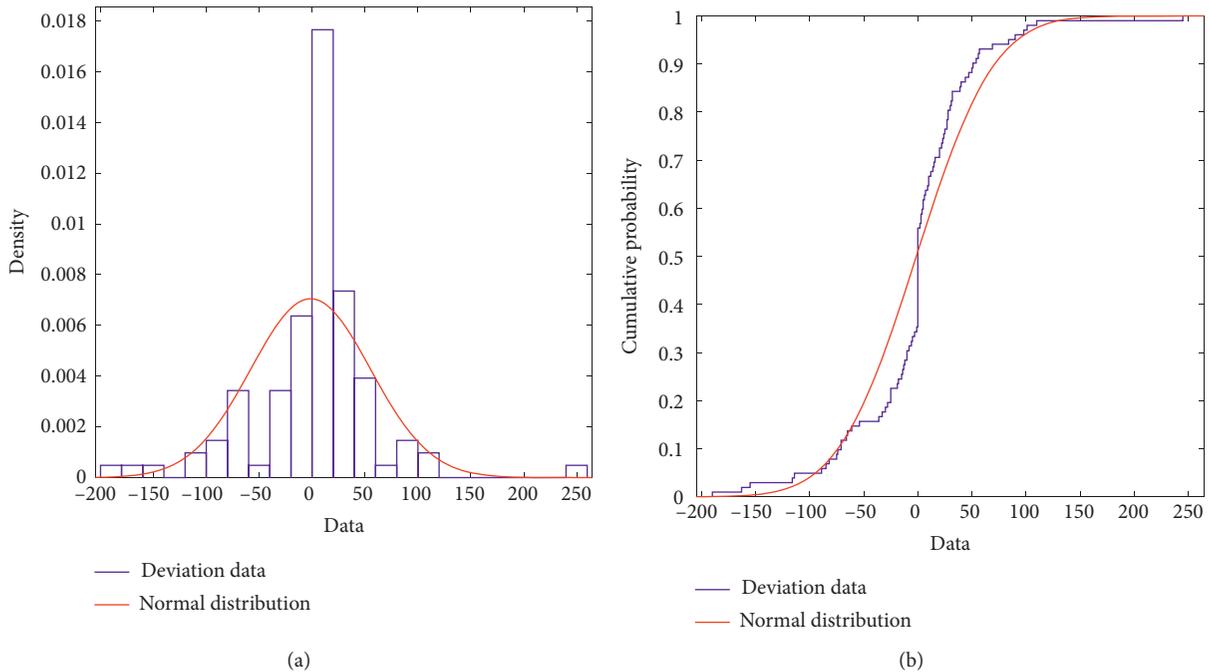


FIGURE 9: Time headway normal distribution: (a) density; (b) cumulative probability.

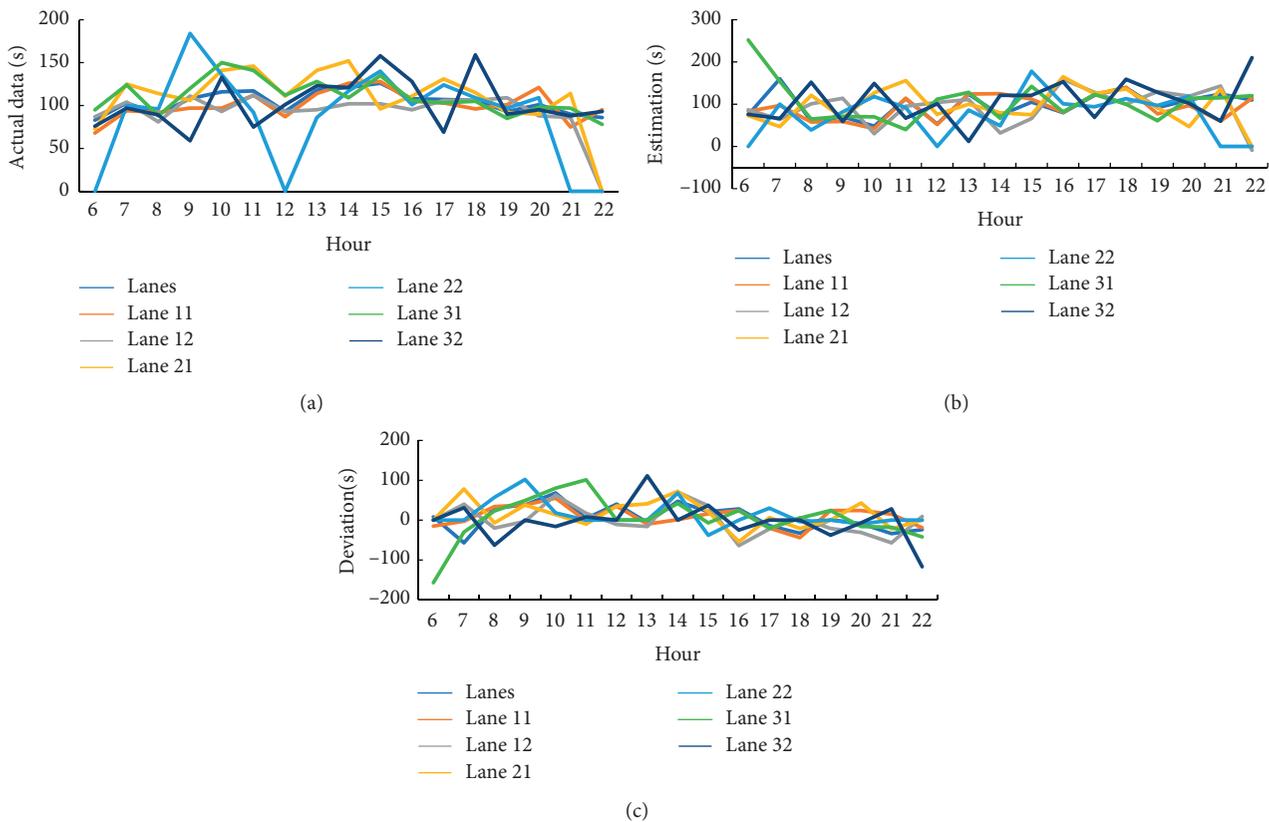
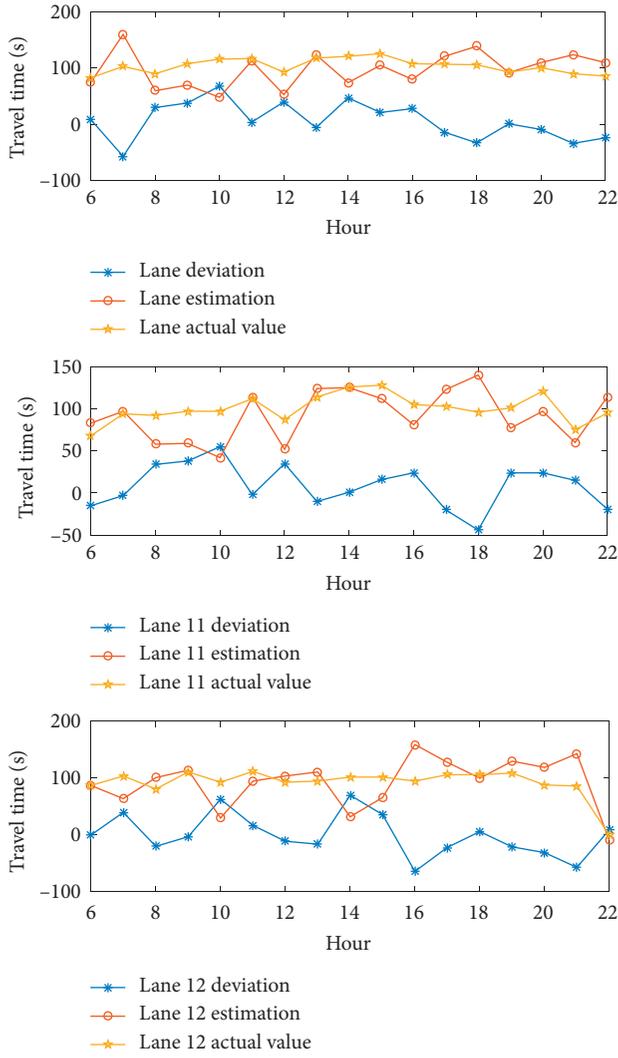


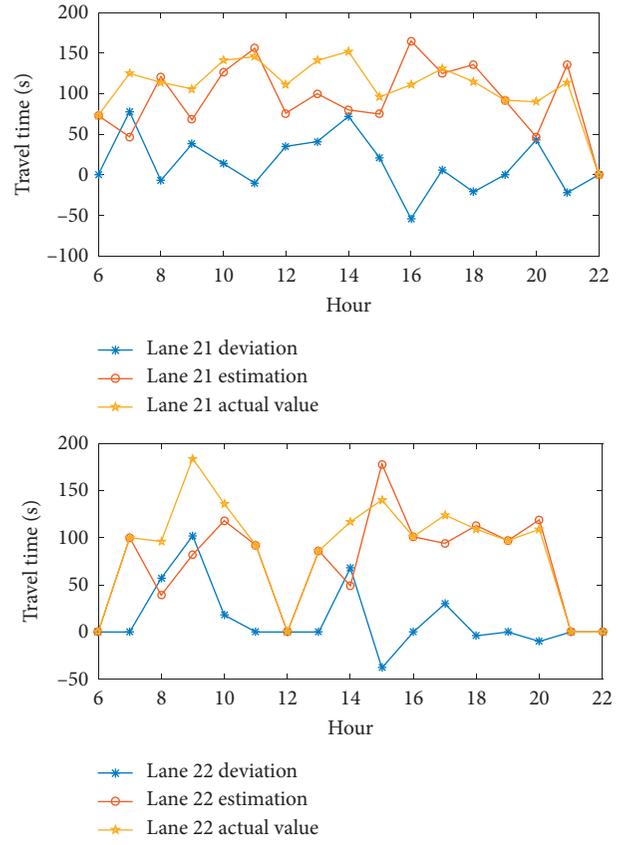
FIGURE 10: Actual value vs. estimated value vs. deviation: (a) actual value, (b) estimated value, and (c) deviation.

time is used as the key parameter to estimate the link travel time, and the estimation and error results are obtained. Taking the upstream lane 1 as an example, the results are

shown in Figure 13, compared with the theoretical derivation formula, the improved formula can better fit the data trend, the error value is fluctuated around 0, but the effect of



(a)



(b)

FIGURE 11: Continued.

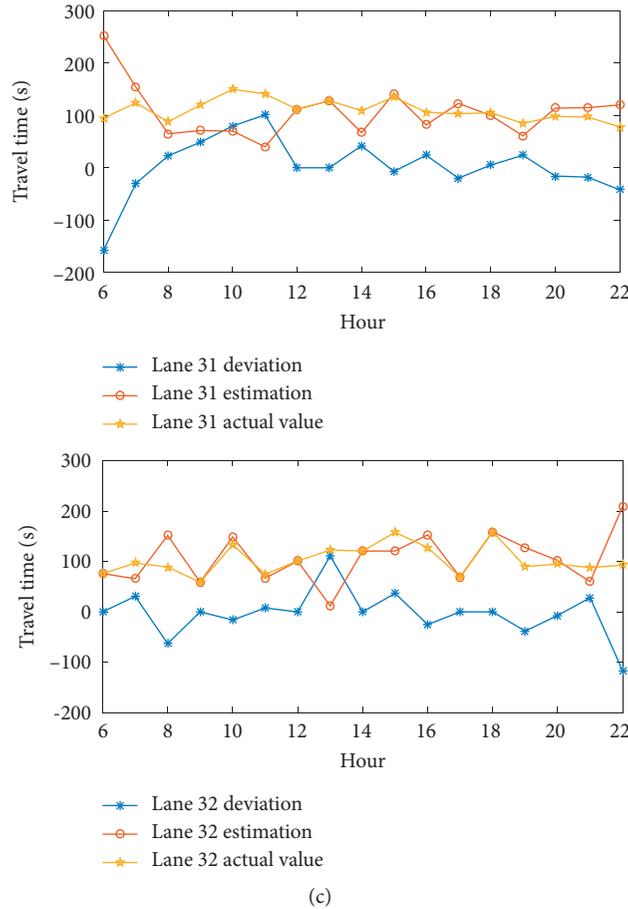


FIGURE 11: Data fitting accuracy at each lane condition: (a) lanes and lane 1 upstream conditions, (b) lane 2 upstream conditions, and (c) lane 3 upstream conditions.

converging to 0 is worse than the effect in Figure 13. Due to the difference in the number of vehicles in each lane, there are still large errors in the individual analysis hour. For example, the corresponding error in the case of lane 12 is a little larger error value than the other case.

5.5. Typical Vehicle Sequence Location. According to the processing flow of equations (5), (7), and (8), and Figure 2, a typical vehicle needs to be determined. This vehicle can be an actual physical vehicle or a virtual vehicle that conforms to the historical statistical law. This vehicle can be used as the key parameter to estimate the travel time of the link. Therefore, a comprehensive comparison is made by the number of vehicles in the analysis hour and the serial number of vehicles corresponding to the travel time determined by the two improved methods, and the results are shown in Figure 14.

It can be seen from the analysis of Figure 14 that the location of the vehicle with the highest similarity in each analysis hour is different, but the vehicle with the highest similarity will appear in the middle and rear of the corresponding vehicle platoon. This is similar to the driving characteristics of the vehicle. Earlier vehicles in the platoon are affected by the influence of the previous traffic flow, and

there are speed fluctuations. Because the interval value fluctuates around the average value, there is also a difference in the location of the vehicle with the largest confidence interval similarity, and the vehicle position fluctuates around the situation where the average similarity is maximum.

5.6. Comparison of Fitting Effects. To quantify the effects of fitting and estimation, two indexes, MAE and RMSE, as shown in equation (9), are selected for comparison. The results are shown in Table 4, and the corresponding scene is on December 2, 2015:

$$\begin{aligned}
 \text{MAE} &= \frac{1}{n} \sum |y_i - \hat{y}|, \\
 \text{RMSE} &= \sqrt{\frac{1}{n} \sum (y_i - \hat{y})^2}.
 \end{aligned}
 \tag{9}$$

5.7. Method Application. Using the same method, the data of the other 4 days are fitted and estimated. The results are shown in Tables 5–8.

It can be seen from the analysis of Tables 4–8 that the accuracy effect of the theoretical method is lower than the

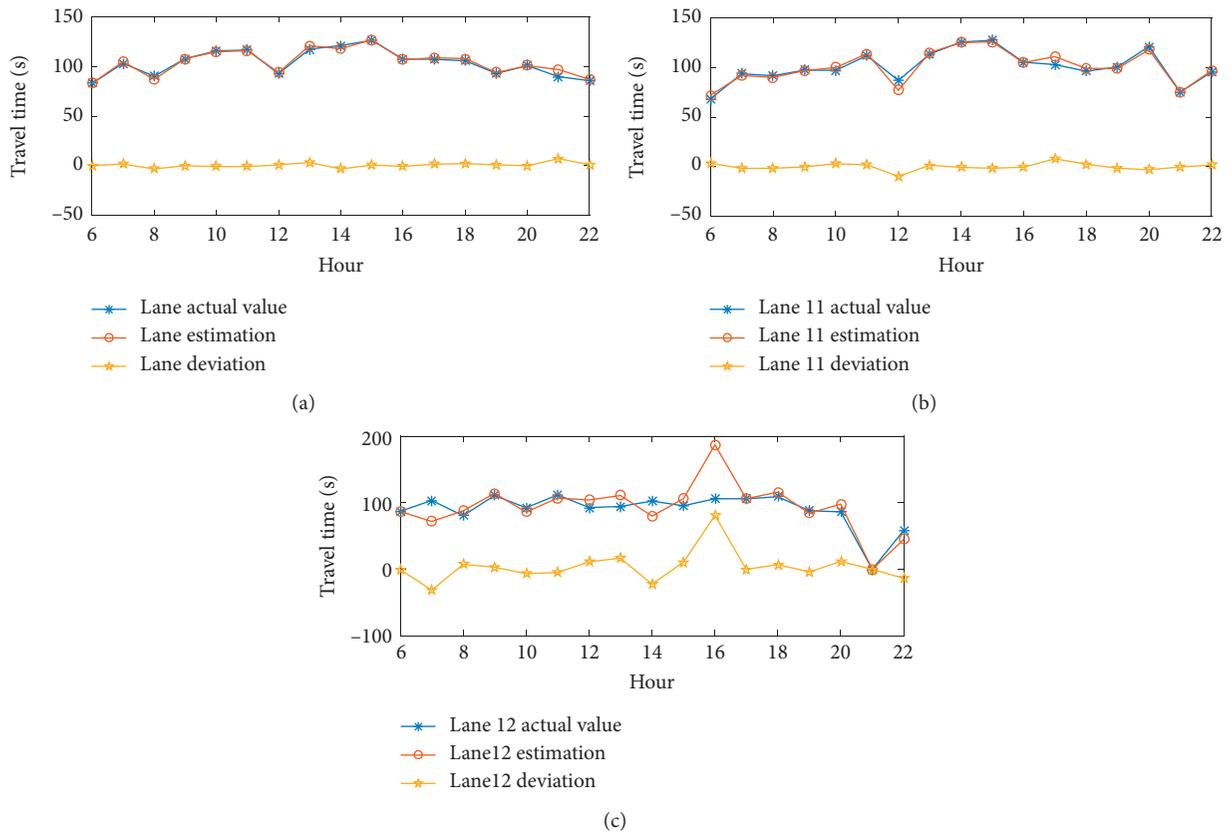


FIGURE 12: Lane travel time estimated based on typical vehicle average travel time on December 2, 2015.

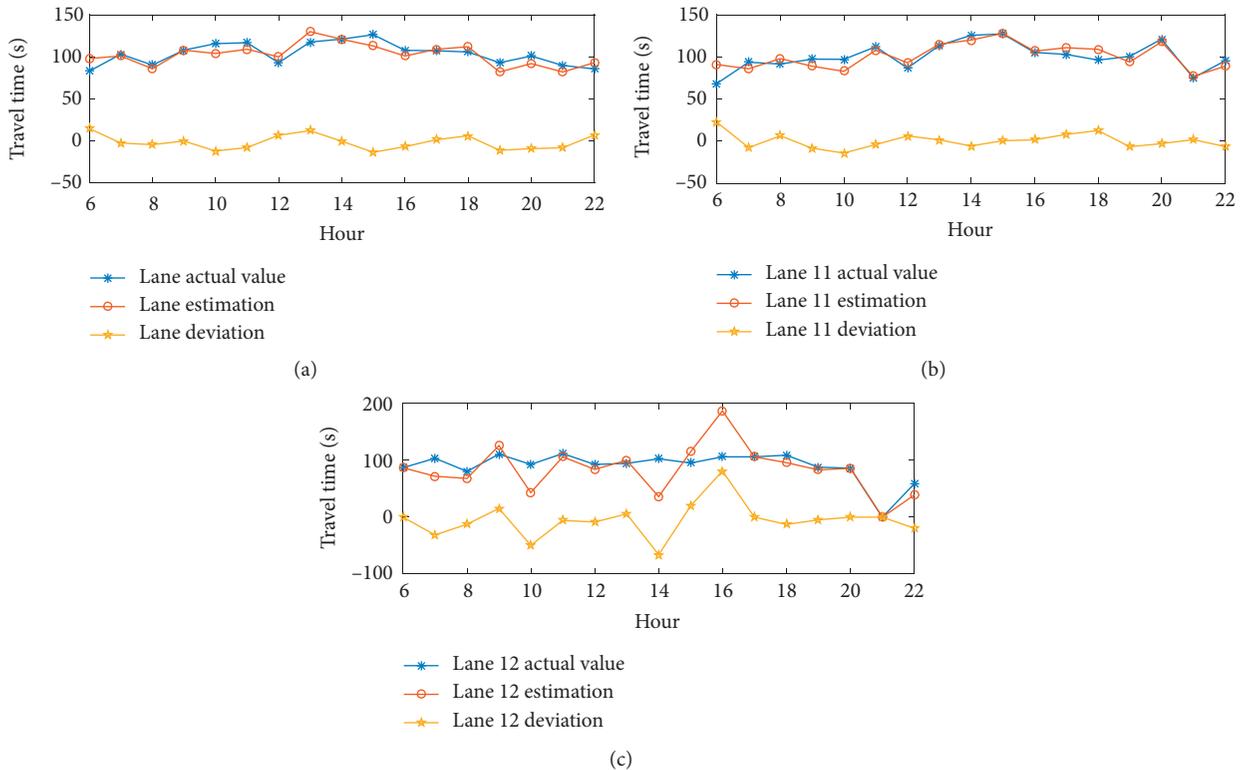


FIGURE 13: Lane travel time estimated based on typical vehicle random time of confidence interval on December 2, 2015.

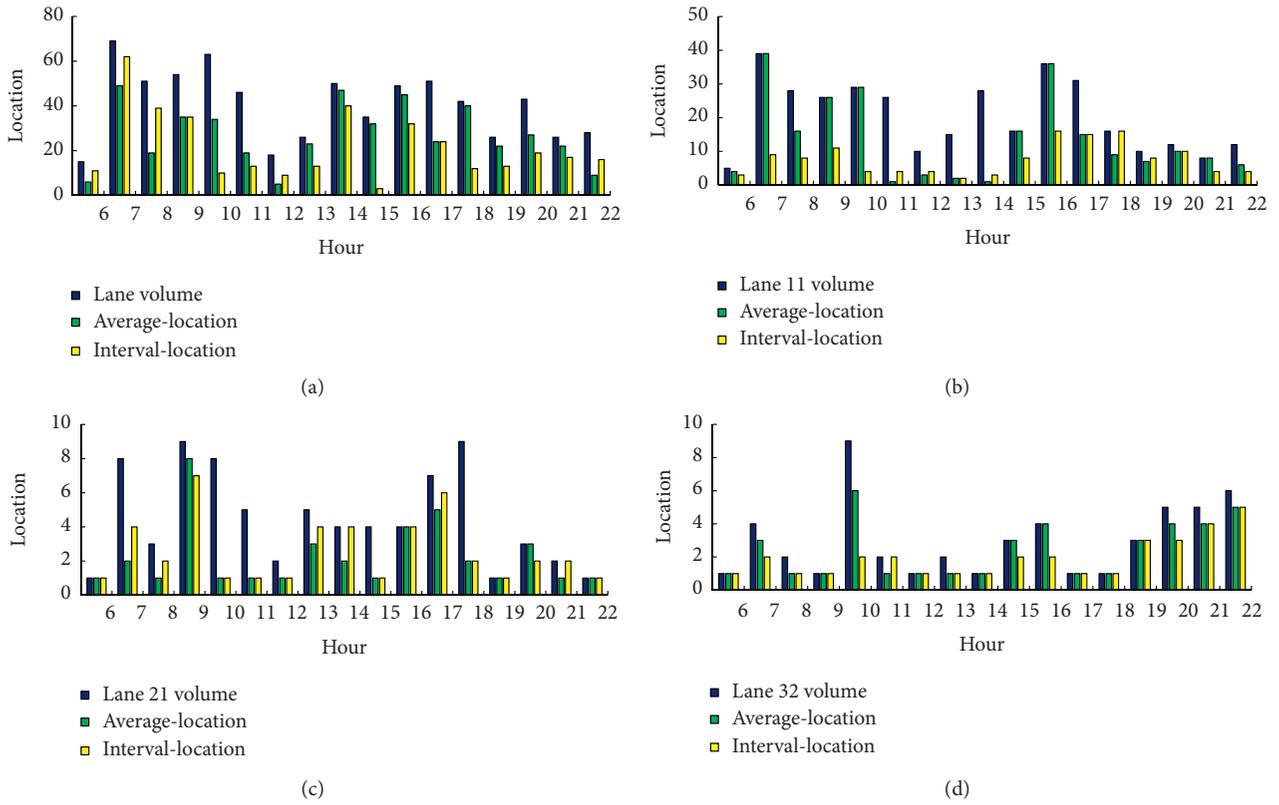


FIGURE 14: Typical vehicle location in the lane vehicle platoon on December 2, 2015: (a) lane condition, (b) lane 11 case, (c) lane 21 case, and (d) lane 32 case.

TABLE 4: Data fitting accuracy by MAE and RMSE on December 2, 2015.

1202	MAE			RMSE		
	Theoretical method	Average value method	Interval value model	Theoretical method	Average value method	Interval value model
Lanes	27.2	1.7	7.3	33	2.4	8.5
Lane 11	22.3	2.6	6.9	26.7	3.6	8.7
Lane 12	28.6	13.6	19.7	36.1	23.1	30.6
Lane 21	27.2	11.5	15.8	36.1	16.2	21.6
Lane 22	19.2	16.3	17.3	35.2	33.6	41.3
Lane 31	37.5	11.5	15.5	54.7	17.1	20.1
Lane 32	28.3	14.7	17.7	45.7	31.9	33.9

TABLE 5: Data fitting accuracy by MAE and RMSE on December 9, 2015.

1209	MAE			RMSE		
	Theoretical method	Average value method	Interval value model	Theoretical method	Average value method	Interval value model
Lanes	25.2	1	4.9	30.9	1.3	6.3
Lane 11	15.8	2.4	7.2	21.5	3.2	8.7
Lane 12	47	14.7	18.8	69.8	27.1	37.3
Lane 21	44.8	22.2	24.2	55.2	37.3	33.3
Lane 22	20.6	13.6	14.8	37.6	30.1	30.9
Lane 31	54.2	23	16.7	70	52	24.6
Lane 32	28.2	16.2	17.9	42	27.2	31.7

TABLE 6: Data fitting accuracy by MAE and RMSE on December 16, 2015.

1216	MAE			RMSE		
	Theoretical method	Average value method	Interval value model	Theoretical method	Average value method	Interval value model
Lanes	41.9	1.3	5.4	60	1.5	6.4
Lane 11	39.2	3.3	9.9	59.1	4.2	16.8
Lane 12	61.8	30	31.4	90.9	63	63.3
Lane 21	27.1	9.4	18	39.1	15.5	26.4
Lane 22	34.9	18.4	17.4	48.9	28.6	30.3
Lane 31	25.9	15.1	18.2	43.4	31.7	25.2
Lane 32	22.5	11.6	7	38.6	29	12.3

TABLE 7: Data fitting accuracy by MAE and RMSE on December 23, 2015.

1223	MAE			RMSE		
	Theoretical method	Average value method	Interval value model	Theoretical method	Average value method	Interval value model
Lanes	36.5	2.1	7.2	43.2	2.7	8.3
Lane 11	30.9	4.1	9.6	40.4	6	12.8
Lane 12	23.4	12.5	18.3	36.3	28.2	25.4
Lane 21	18.4	7.7	10.2	26.5	14.3	13.8
Lane 22	32.5	25.4	21.2	57.6	53.8	36.9
Lane 31	47.8	28.3	25.7	66.2	56.2	36.6
Lane 32	31.2	21.5	17.2	66	60.1	32.4

TABLE 8: Data fitting accuracy by MAE and RMSE on December 30, 2015.

1230	MAE			RMSE		
	Theoretical method	Average value method	Interval value model	Theoretical method	Average value method	Interval value model
Lanes	24.4	1.9	5.3	34.2	2.9	6.3
Lane 11	31.6	2.5	8.6	39	4	10.8
Lane 12	23.1	9.2	17.3	30.8	15.3	24.3
Lane 21	34.1	14.5	16.8	47.5	29.9	20.6
Lane 22	28.1	18	20.1	37.4	24.1	27.8
Lane 31	37.6	24.8	19.3	58.2	48.5	30.5
Lane 32	21.4	11.9	15.2	30.8	20.8	24.2

average method and the confidence interval method in each scenario, and the average method is superior to the other two methods. It is due to that the head vehicle in the theoretical method in the analysis hour is used as the representative vehicle, and the head vehicle in the time-segment statistics is influenced by the previous traffic flow speed fluctuations, resulting in the representative shortage of travel time in the theoretical model. In the other two methods, by introducing the maximum similarity of average travel time and the maximum similarity of random travel time in the confidence interval, the accuracy of the model is improved.

In each scenario, the accuracy effect on link condition is better than that on lane separation condition. Since the link is the analysis object, the vehicle travel time of each lane is comprehensively considered, and the sample size is more than the lane condition. In addition, due to lane-by-lane statistics, the sample size of vehicles decreases in each lane, and the variance statistical characteristics of travel time fluctuate greatly between link and lane condition which shows a large fluctuation in travel time.

6. Conclusions

In this paper, the calculation method of the LTT is analysed in the continuous traffic flow by using the detection data collected when vehicles pass through urban links from RFID collections, and a theoretical derivation formula for estimating link travel time is proposed by considering the typical vehicle's travel time and the fluctuation of the time headway upstream and downstream of the links as the main parameters, namely, LTT is decomposed into two parts including typical vehicle travel time and time headway deviation, and two parts have been discussed with actual data. Some contents could be concluded as follows from these two aspects.

When we analyse the factor of time headway deviation, we find that the deviation converges to zero when the hourly vehicle volume is more than 20 veh/h in the certain flow direction, and there are more positive and negative fluctuations when the hourly vehicle volume is less than 10 veh/h in the certain flow direction. Also, the time

headway deviation has a distribution as $THD \sim N(1.667, 22.58)$ based on the sample data sets and more than 90% deviation is near to zero, and it can be concluded that the time headway deviation might have less influence on the link travel time estimation equation (5) when there are more vehicles in the certain traffic flow direction.

When we discuss the other factor of typical vehicle travel time, the similarity relationship between the history travel time trend and the current traffic flow characteristics is considered, and a typical vehicle analysis method based on link travel time similarity is proposed, and the theoretical formula is optimized, respectively. Then, an estimation formula based on maximum travel time similarity and an estimation formula based on maximum travel time confidence interval similarity are proposed, respectively. To analyse and compare the fitting conditions, the collected data from urban roads in the city of Nanjing in China are used to verify the proposed travel time estimation method based on the RFID technology. And the results show that the accuracy of the proposed improved method based on typical vehicle travel time estimation is significantly improved by considering the typical vehicle travel time, and typical vehicles on the road segment mainly exist at the tail of the traffic platoon in the corresponding analysis hour, which is consistent with the theoretical formula. Thus, based on the vehicle identification data and sequence location, the method on guiding typical vehicle's speed in the certain flow direction may be useful to improve the traffic flow speed, and the details will be discussed in the future research.

In addition, to match the actual application demand, the confidence interval similarity method based on the statistical characteristics of links and lane level travel time can be recommended to estimate the average travel time under the premise of differences and fluctuations in the average travel time of links and lanes. Route travel time would be discussed in details based on the link travel time in the future work by considering convolution theory or other deep learning methods.

Data Availability

The data used to support the findings of this study have not been made publicly available because these data relate to third party privacy and there is a data confidentiality agreement with the data provider.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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