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Research Article

Analysis of Traffic Volume and Travel-Time Relationship Using Continuous One-Hour Values on Urban Expressway

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To make more efficient use of the expanded freeway and urban expressway networks, various measures such as bottleneck management and wide-area congestion pricing based on traffic data obtained from traffic detectors, including traffic volume and travel time, have been considered. Generally, the congestion status of the data varies from day to day. This study proposes a method for analyzing a graph of traffic volume and travel time to visually and intuitively grasp the change in the daily traffic situation using continuous one-hour values. These values are continuously generated hourly values obtained by shifting data every minute. Twenty-four hours 1 minute data for 128 days on 32 segments with detectors in the Nagoya Expressway Network in Japan were used to draw a continuous one-hour value graph. A number of graphs showed loops of continuous one-hour values with congestion and a smooth variation characteristic of values over time. These graphs provide an accurate estimate of the daily maximum one-hour traffic volumes and facilitate a sequential understanding of the congestion pattern changes on successive route segments. Hourly travel-time prediction models were constructed to macroscopically examine congestion measures over a range of several hours. These models were fabricated with high accuracy using multiple regression analysis based on the characteristics of continuous one-hour values. Exploratory predictive analysis of hourly travel-time models has allowed us to study and discuss various congestion factors in road structures and traffic flows, and it has been found to be easy to grasp the phenomenon and ensure accuracy and operability.

1. Introduction

Traffic congestion is chronic on inter-city freeways and urban expressways in the Chukyo metropolitan area in Japan, where the network of radial and ring roads has expanded, especially on inner city expressways. Various measures such as congestion management at bottleneck points, congestion pricing, and traffic guidance have been considered to make more efficient use of the expanded network, by providing traffic information. The basic information for countermeasures is traffic status data such as traffic volume (volume later), travel time, and speed, which are obtained from traffic detectors installed on each segment of the expressway line and section. Although there is a certain regularity in expressway traffic in terms of congestion location and days of the week, congestion conditions generally vary widely from day to day, and the observed maximum volume and travel time also vary. The relationship between the volume and travel time also changes.

To understand the changing traffic visually and intuitively, we propose a continuous one-hour value graph analysis in this study that continuously generates plots of hourly volume and average travel time, shifting data every minute. In general discrete data analysis, if the time interval of aggregation is short (e.g., 5 min), the data plot variability will be large. Alternatively, if the time interval is large (e.g., 60 min), it becomes difficult to capture the traffic transition over time owing to the small amount of data. However, the continuous one-hour value graph proposed here shows that volume and travel time often increase when congestion occurs; after the maximum volume is observed, it decreases while travel time reaches its maximum value and then converges with a continuous smooth loop. By observing these time transitions, the causes of congestion changes in successive expressway sections can be understood intuitively and easily.

Besides, there are methods for evaluating freeway traffic such as analyzing the relationship between volume and speed or using speed contour maps. The volume-speed graph is easy to understand when analyzing traffic congestion owing to a decrease in speed. However, as the range of speed change becomes smaller the more severe the congestion, the volume-travel time graph can easily capture the extent of increase in heavy congestion. The speed contour map is a method used to determine the time-segment traffic for an entire route. Although it is easy to understand the change in speed over an entire route by section, it is necessary to synthesize other graphs when analyzing the relationship between the volume, maximum volume, and maximum travel time in a time transition. The continuous volume-travel time one-hour value graph provides a compact, single-slide view of daily traffic congestion changes as well as a daily maximum one-hour volume with high accuracy.

Congestion pricing and other measures have recently been explored to divert traffic from heavily congested urban expressways to wider freeway networks. These measures are expected to be applied uniformly or in phases over several hours in urban expressway networks. Hourly traffic analysis and prediction methods, that can capture major fluctuation trends are often more effective in examining the measures over several hours, because they are easier to grasp the phenomenon, ensure accuracy, and are more operable. Therefore, in this study, we conducted traffic congestion analysis by exploratively constructing hourly travel-time prediction models for expressway lines using continuous one-hour values. Note that the speed limit on the Nagoya expressway is 60–80 km/h on the mainline, whereas on the inter-city freeway it is 80–100 km/h.

2. Literature Review

Numerous studies on the relationship between traffic volume and travel time have analyzed the link performance function in macro-traffic assignments, congestion bottleneck analyses, and travel-time forecasting to provide traffic information to drivers. The link performance function is also known as the Volume Delay Function (VDF) like the BPR function. Horowitz [1] analyzed and constructed a delay-volume relation for travel forecasting, drawing several diagrams of these relations. Kucharski and Drabicki [2] studied the setting of the BPR function used in macroscopic traffic models, and drew a scatter plot of volume-travel-time on a general road; however, they pointed out that there was a large variation and proposed a transformation-based BPR function using quasi-density. Huntsinger and Rouphail [3] estimated the traffic demand above capacity while creating scatter plots of demand/capacity and travel times based on an analysis of freeway bottlenecks and queues. Lu et al. [4] estimated travel time functions for mixed traffic, including trucks, which have a significant impact on traffic flow in the transportation network analyses, by drawing volume and travel-time diagrams using various simulation scenarios. Pan et al. [5] modified VDF based on fundamental traffic diagrams (volume vs. delay/speed). However, the above-mentioned diagrams cover a monotonically increasing range, including congestion, and do not analyze the continuous transition of the hourly volume and travel time.

Das and Chilukuri [6] analyzed the varying capacity/volume versus travel-time relationships in a mixed traffic network at signalized intersections. Huo et al. [7] calibrated a link performance function using neural network analysis. Neuhold and Fellendorf [8] presented traffic capacity as a probability distribution, previously given as a constant in VDF. Zhang et al. [9] analyzed a travel-time function with simultaneous network capacity and traffic demand. van der Gun et al. [10] compared link travel-time formulations, including horizontal queuing, in quasi-dynamic traffic assignments. Barka and Politis [11] compared VDFs such as BPR and Conical. Cottrell [12] developed a queuing duration model using the AADT/C. These studies also analyzed the volume-travel time relationship, but they did not analyze continuous one-hour values on freeways, and there were no volume versus travel-time graphs from the data.

This study also deals with hourly travel-time predictions. Many travel-time prediction studies have been performed in the field of transportation. Paterson and Rose [13] proposed a model for predicting freeway travel time that overcomes the limitations of operational "instantaneous" speed models by using queuing theory. Yildirimoglu and Geroliminis [14] constructed travel-time prediction models such as stochastic congestion maps and bottleneck identification using historical real-time traffic information. They also showed instantaneous and experienced travel-time calculation methods to produce contour maps and travel-time diagrams based on the departure time. Bustillos and Chiu [15] and Soriguera and Martinez-Diaz [16] increased the accuracy of freeway travel-time predictions using a cumulative vehicle count curve. Kwon et al. [17], Zhang and Rice [18], and Rice and van Zwet [19] proposed freeway travel-time prediction methods that mainly used linear models based on the speed and occupancy data. Kuchipudi and Chien [20], Zou et al. [21], and Chen and Chien [22] derived prediction models by integrating path- and link-based models or merging spatial and temporal travel-time information. Kwak and Geroliminis [23] proposed using dynamic linear models to approximate nonlinear traffic states. Qiao et al. [24] and Caceres et al. [25] predicted freeway travel-time considering the time of day, inclement weather, and traffic accidents, as well as historical and real-time data. Pant et al. [26] introduced a travel-time prediction system for a freeway work zone. Miao et al. [27], Li et al. [28], and Tang et al. [29] estimated and compared freeway travel times using fuzzy logic and machine learning. These studies proposed travel-time prediction methods that were mainly based on time, location speed, and occupancy data. However, they did not show diagrams of volume and travel-time, nor did they clearly analyze their relationship. Furthermore, most of these studies are short-term travel-time predictions and do not statistically provide hourly average travel-time prediction and congestion analysis, as addressed in this study.

In addition, hourly traffic assignment models were developed to forecast the hourly average travel time and volume for mid-to long-term traffic measures. (Shao et al. [30], Nakayama and Connors [31], and Fujita et al. [32]) are highly relevant to this study as examples of hourly traffic assignment research that uses the BPR function and applies it to a real-scale road network. An overview of the changes in continuous one-hour values based on actual data from a real-scale network will be very effective in studying their directions for improvement. We believe that a comprehensive understanding of the continuous one-hour value changes would have many implications for improving the above models and other traffic analyses.

The objectives and main contributions are summarized next.

As seen above, previous studies have neither defined nor comprehensively analyzed continuous one-hour values of travel time and volume. Therefore, this paper clarifies the characteristics of continuous one-hour values and examines their various use possibilities. The objective of this study was to develop an exploratory factor analysis method of traffic congestion based on hypotheses derived from continuous one-hour values for countermeasures in a multi-hour scale. Specifically, the following aspects of continuous one-hour values are addressed in this paper:

(1) Continuous one-hour values are first defined, and their following basic characteristics are then analyzed: difference between discrete time values and continuous one-hour values and effectiveness of observing the transition of continuous one-hour values over time; changes in continuous one-hour values over five weekdays on the same section of expressway; comparison of the maximum volume of continuous one-hour values with maximum one-hour volume aggregated every 5 and 15 minutes; changes in continuous and discrete one-hour maximum volumes, which decrease as the number of observation days increases; understanding of congestion factors based on the changes in continuous one-hour values over five weekdays on consecutive road segments, including JCTs and on/off-ramps; and changes in continuous one-hour values and understanding of congestion factors, in particular those affected by increases in downstream on-ramp traffic.

(2) Setting of continuous one-hour values for a road section consisting of many segments and development of multiple regression models for predicting hourly travel times and a predictive congestion factor examination method on this road section. Congestion factors are exploratively examined by deriving various hypotheses from roadway structural conditions and prediction model statistics, along with time transitions of continuous one-hour values.

(3) The advantages of hourly travel-time prediction analysis are as follows. The hourly prediction makes it easier to understand changes in variables and statistics, to generate hypotheses and inferences exploratively, and to identify congestion factors with high accuracy as shown in Chapter 5. This is because: the hourly prediction can greatly reduce the total number of variables and improve operability since there are only 1-2 time periods used in the analysis; and the objective variable is the one-hour average travel time, which has few minor variations; and time transitions along consecutive segments and hours are easy to understand from the basic analysis above.

This paper is structured as follows: Chapter 3 summarizes the definition and characteristics of the continuous one-hour values of volume-travel-time. Chapter 4 compares the transition graphs of the continuous one-hour values according to the aggregation methods and analyzes the differences in maximum one-hour volumes and spatial changes on expressway lines. The hourly travel-time prediction models using regression analysis is constructed in Chapter 5, taking into account the characteristics of the continuous one-hour values, and the congestion factors are exploratively analyzed. Section 6 presents the discussion.

3. Methodology

3.1. Basic Data. The Nagoya Expressway is an urban expressway with a total route length of 81.2 km through Nagoya City and its surrounding areas.

As shown in Figure 1, this study focuses on two lines of the Nagoya Expressway Network, the Toshin Loop Line clockwise one-way (25 segments) and the Odaka Line downhill (7 segments) which branches off the Toshin Loop Line to the south. These lines are separated into many segments that are 0.4~0.5 km apart, with the vehicle detector as the center of a segment. This study used the average speed and volume data of each lane on a 1-minute basis (for 128 weekdays from November 25, 2019, to March 31, 2020), which were obtained from the vehicle detectors in each segment. The volume data were the sum of all lanes and the speed data was the 1-minute average obtained by load-averaging speed of each lane with its corresponding volume. Assuming that the point speed obtained from the detector was constant within a segment (approximately 0.5 km); the unit travel time per kilometer (min/km) was calculated by taking the speed data reciprocal and adjusting the unit for ease of comparison. These 1-minute data were summed for 5 min to obtain a 5-minute discrete volume, for the discrete value analysis. The 1-minute data average over 5 min was calculated to obtain the 5-minute discrete average travel time.

3.2. Calculation of Continuous One-Hour Values. To understand the continuous changes in the one-hour volume and travel-time data, the one-minute values were continuously aggregated into one-hour values. The continuous one-hour values of volume Q_{jk} and average travel time T_{jk} are obtained as in equations (1) and (2), using 1440 one-minute

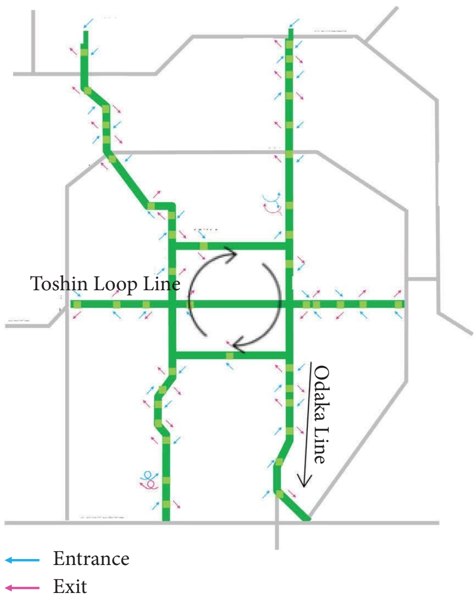


Figure 1: Nagoya Expressway Network and two subject lines.

data for the time period 0:00–23:59 per day for each traffic segment.

That is, i (=0:00–23:59) is the time in 1-minute increments and the time period k (k = 0:00–23:00) in 1-minute increments is the 60-minute time period from start time $i = k$ to end time $i = k + 59$. For example, $k = 420$ at 7:00 am and $k = 480$ at 8:00 am. Volume Q_{jk} is the sum of 60 1-minute volumes starting at time period k for segment j. T_{jk} is the average of 60 1-minute travel-time at time period k for segment j.

$$Q_{\mathrm{jk}} = \sum_{i=k}^{k+59} q_j(i), \tag{1}$$

$$T_{\mathrm{jk}} = \frac{\sum_{i=k}^{k+59} t_j(i)}{n_{\mathrm{jk}}}, \tag{2}$$

$q_j(i)$ is the volume provided per minute at time i on segment j (veh/min). $t_j(i)$ is the travel time provided per minute at time i on segment j (min/km). n_{jk} is the number of one-minute travel time data in period k in segment j.

The above equations represent a continuous one-hour value which is calculated every minute. To avoid a large amount of output continuous one-hour data values, they can be calculated by shifting every 5 min or every 10 min. However, the temporal transition characteristics may differ with increased shifting time interval, as opposed to a 1-minute shift. In this study, the continuous one-hour value analysis was conducted every minute.

4. Analysis of Continuous One-Hour Values

4.1. Basic Characteristics. The relationships between volume and travel-time were compared between different aggregation methods using data for the entire time period (0:00~23:00). Figure 2 shows the relationship between the discrete 5-minute volume (veh/5 min) and average travel-time (min/km) for segment 0R01 of the Toshin Loop Line, aggregated separately every five minutes. Figure 3 shows the relationship between the discrete hourly volume (veh/h) and average travel time, aggregated separately by hour. Figure 4 shows the relationship between the hourly volume (veh/h) and average travel time using continuous one-hour values in equations (1) and (2).

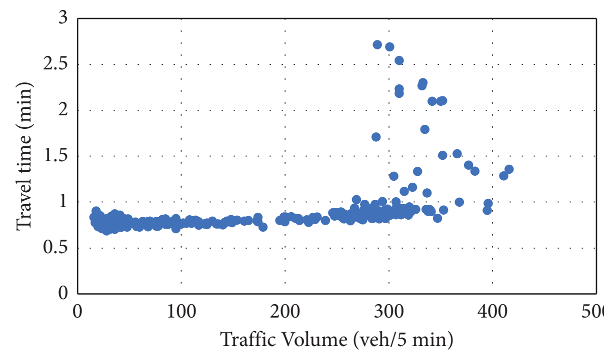


Figure 2: Discrete 5-minute values of traffic volume and travel time (0R01).

Figure 2 shows that the discrete 5-minute data has a large data variance and cannot accurately capture the time series of the traffic flow. Figure 3 shows that the number of points in the discrete hourly data is small and the changes during this data-free period were diverse, as described below. Therefore, it was difficult to complement and understand time transitions using discrete hourly data. However, in Figure 4, the continuous one-hour values show that the points are continuously connected, creating a loop from the occurrence of congestion to its elimination, thereby providing a concrete picture of the temporal transition of the traffic. Similarly, Figure 5 shows the discrete hourly graph and continuous one-hour graph of segment 302 of the Odaka line with two lanes at different locations. The scatter plots of discrete hourly values in Figure 5(a) show little time transition during traffic congestion, but the continuous one-hour values in Figure 5(b) allow us to understand the transition of traffic congestion. Furthermore, the discrete values in Figure 5(a) show that the maximum volume, which is a candidate for hourly traffic capacity, is 1398 (veh/lane/h), whereas the continuous one-hour values in Figure 5(b) show that it is 1502 (veh/lane/h). The discrete hourly data may underestimate the maximum hourly volume when only one day is considered. In practice, for maximum volume calculations, this difference is reduced by obtaining data over several months or more, even for discrete hourly volumes. This will be analyzed further in the next section. Figure 6 shows the continuous one-hour values for five weekdays (12/16-12/20, 2021) on segment 306 of the Odaka Line. The maximum volumes and travel time varied daily, even at the same location. However, the travel time during the congested period show time-series loops after the maximum volumes are observed, and the maximum travel times are observed while the volumes decrease. Therefore, continuous one-hour volume and travel-time graphs capture traffic flow transitions more clearly than discrete graphs.

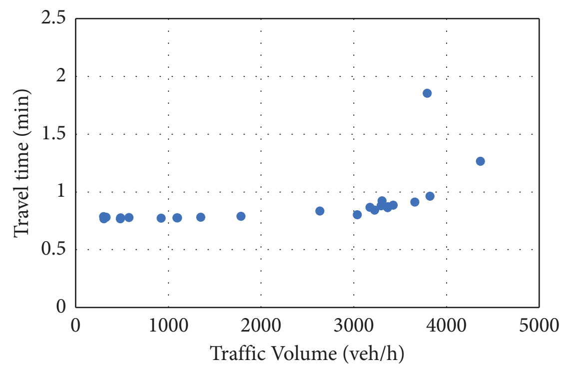


Figure 3: Discrete one-hour values of traffic volume and travel time (0R01).

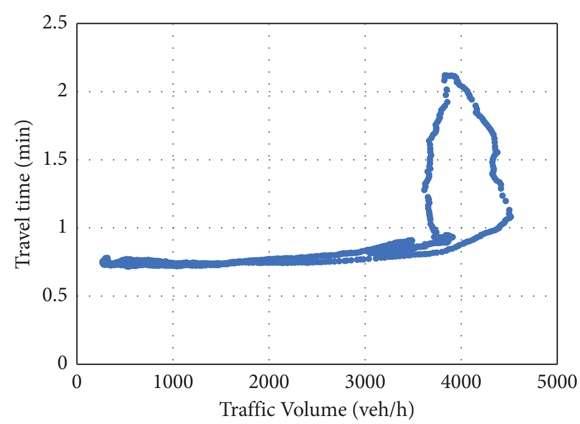
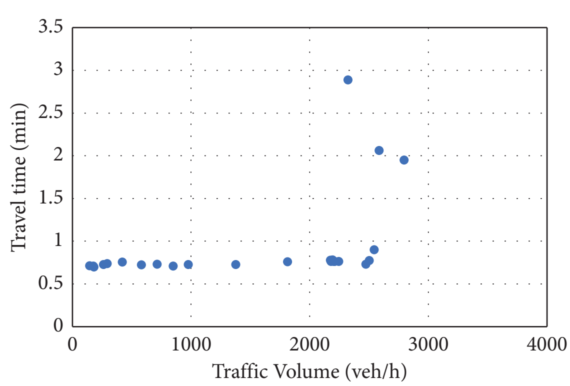
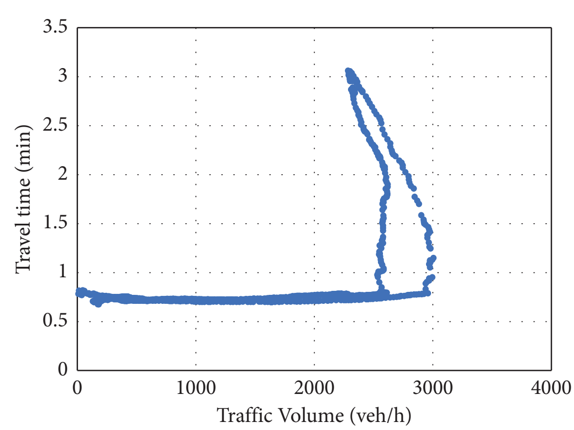


Figure 4: Continuous one-hour values of traffic volume and travel time (0R01).



(a)



(b)

Figure 5: Comparison of traffic volume and travel-time graphs (segment 302). (a) Discrete one-hour values. (b) Continuous one-hour values.

4.2. Maximum One-Hour Volume Analysis. In this section, the maximum volumes of the one-hour values, aggregated every 60, 30, and 15 min (mvex, $x = 60$, 30, and 15 min), are compared with the continuous one-hour values (mvc). This analysis uses vehicle detector data for 128 days in the abovementioned segment 302, where traffic congestion is chronic on the Odaka line. The analysis results are shown in Figure 7. The horizontal axis in the figure is mvc, and the vertical axis is the ratio of mvex to mvc. Rmxc is obtained using the following equation:

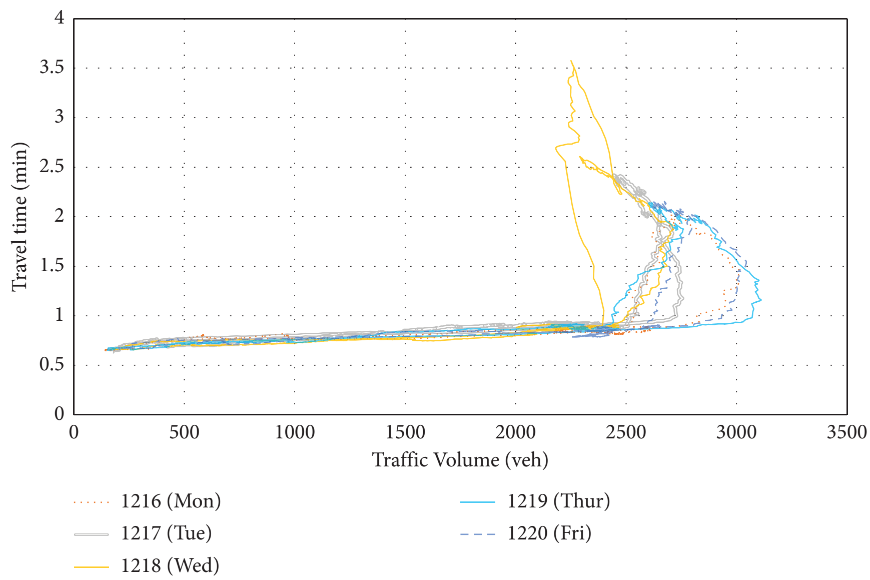


Figure 6: Variation of continuous one-hour values for five weekdays on the Odaka Line (segment 306).

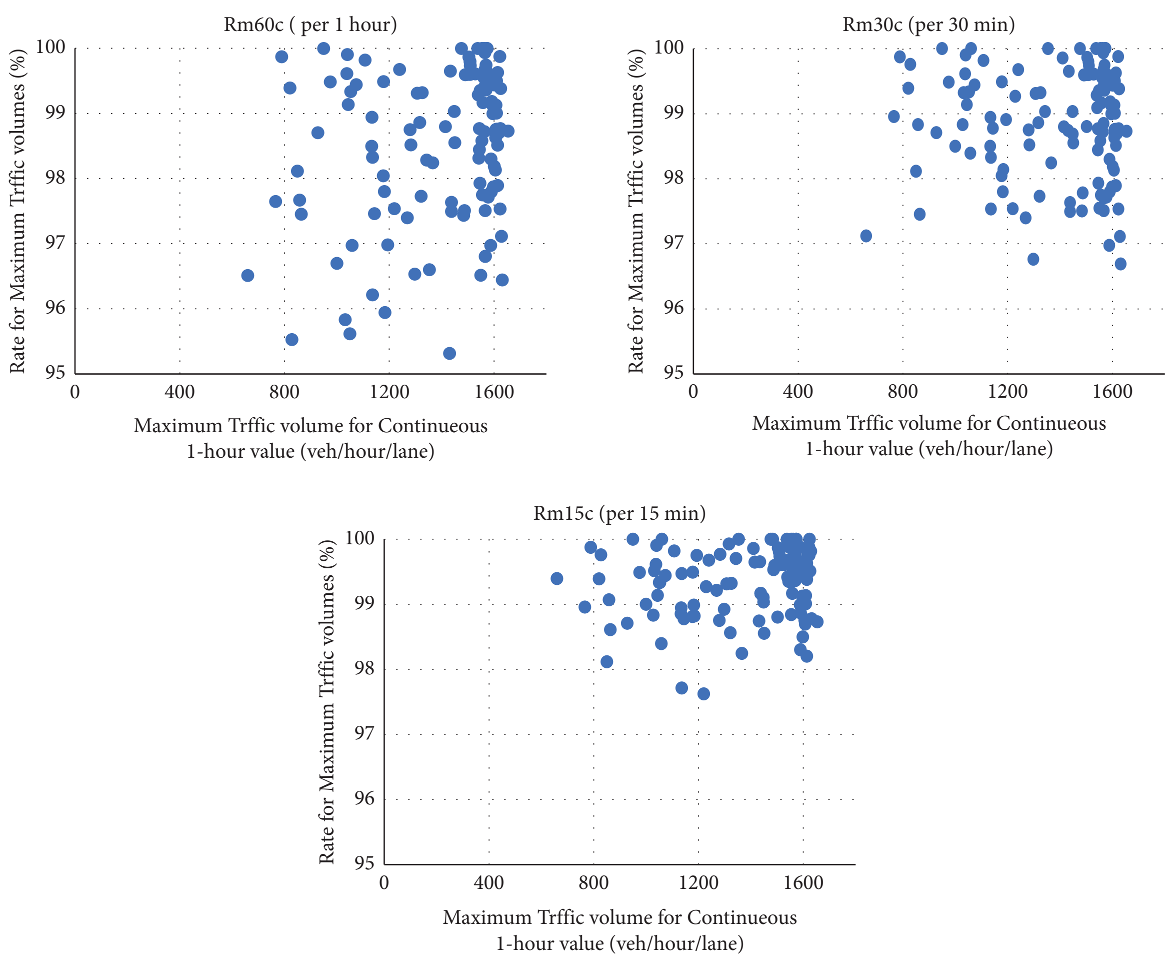


Figure 7: Ratio of the maximum 1-hour volume (Rmxc (%): $x =$ every 60, 30, and 15-minute values) to the maximum continuous one-hour volume (segment 302).

$$\mathrm{Rmxc} = \frac{\mathrm{mvex}}{\mathrm{mvc}} \times 100, \quad (3)$$

where mvex is the maximum one-hour volume (veh/h/lane) aggregated every x minutes; $x = 60$, 30, and 15. mvc is the maximum volume (veh/h/lane) of continuous one-hour values, aggregated every 1 minute. Rmxc is the ratio of mvex to mvc (%); $x = 60$, 30, and 15.

Looking at Rm60c in Figure 7, the distribution extends to 96%-97%, with an average of 98.3%. Therefore, if we consider discrete values every 60 min, it may be 3-4% less than the maximum one-hour volume in each day. If the number of observation days were increased, the error would be reduced. However, if the data is aggregated every 30 or 15 min, in Rm30c and Rm15c of the figure, the average values are 98.9% and 99.3%, respectively. Every 15 min value was almost the same as the continuous one-hour values. Therefore, in case of daily maximum volume, it is better to check the hourly values every 15 min or less. This tendency was also observed in other segments.

When the number of observation days h, increased from the first day of observation to h (~128) days in segment 302, we examined the change in Rm60c using all observation data within h days. The results indicate that Rm60c was 96.9% at $h = 1$ day, 97% at 10 days, and 99.5% at 20 days. Subsequently, Rm60c was 98.7% for 128 days, and it fluctuated between 98.5% and 99.5% from 20 to 128 days. Therefore, as the number of observation days increased, the maximum one-hour volume also increased. Simultaneously, Rm60c increased or decreased, but the difference remained at approximately 1%. This result needs to be verified with more data, but it is expected that the difference between mve60 and mvc will almost disappear if there are sufficient observation days where the maximum 1-hour traffic volume does not change, such as in several months to year-round observations. Consequently, it was found that if the maximum one-hour volume should be accurately examined for each day, as shown in Figure 6, it is preferable to use continuous one-hour values. However, if the maximum one-hour volume is to be examined over a long period, such as a year, the maximum volume estimated by the discrete hourly values will be almost the same as the continuous one-hour values.

4.3. Congested Area Analysis for Multiple Segments. To analyze the traffic of multiple segments on the Nagoya Expressway using continuous one-hour values, volume versus travel-time graphs for each segment were prepared, as shown in Figures 8 and 9. Figure 8 shows the congestion on five weekdays at the end of November on the Toshin Loop Line (clockwise one-way traffic), which has a large change in time transition owing to the dense installation of JCTs and on/off-ramps. It is easy to understand the congestion situation in terms of segment relationships, particularly around JCTs, where travel times change significantly with volume fluctuations.

Figure 9 shows the congestion status on Sunday, November 28, 2019, on the Odaka Line from the Tsurumai-minami JCT (A) to the Horita off-ramp (C), which is connected to the southbound direction from the Tsurumai-minami JCT on the Toshin Loop Line. Focusing on volume versus travel-time graph for each section, the maximum volume and travel time significantly changes before and after the Takatsuji on-ramp (B), owing to the increase in volume at that point. The travel time started to increase at approximately 7:00 am and the congestion continued until 9:00 am.

5. Hourly Travel Time Prediction and Analysis

This section first describes the method for calculating the volume and travel times under a section containing multiple segments, and then describes the hourly travel-time prediction model and analysis on the section.

5.1. Section Travel Time Calculation. The section used for the hourly travel-time prediction is the two-lane, and 4.19 km section of the Odaka Line between Tsurumai-minami JCT and Horita off-ramp as shown in Figure 9, where the segment at Tsurumai-minami JCT of the Odaka Line is the start segment and the segment after Horita off-ramp is the end segment.

The travel time per minute for a vehicle to start, from the start segment to the end segment is the sum of travel-time of the eight segments along the trajectory and is calculated using the section travel-time calculation (STTC) below. The STTC, which is nearly equal to the experienced travel time [14], is expressed as follows: The travel time of the current segment was calculated from its arrival time and its detector data at that time. This is used to calculate the arrival time of the next segment. Again, the travel time for the next segment is calculated in the same manner as that of the current segment. This calculation is sequentially performed in all sections every minute for vehicles to start from the start segment during the period of interest. The volume in each segment was the sum of two lanes, and the travel-time data were the average of the two lanes weighted by the volume in each lane. Equations (4) and (5) show the section travel time for vehicles travelling between the start and end segments every minute. Similar to the section travel time, volume q_j for segment j along the trajectory and average volume q_i^s for the entire section were obtained using equation (6).

$$u_j(i) = \sum_{m=1}^{j-1} h_m\left(i + u_m(i)\right), \quad (4)$$

$$t_i^s = \sum_{j=1}^{n} h_j\left(i + u_j(i)\right), \quad (5)$$

$$q_i^s = \sum_{j=1}^{n} \frac{q_j\left(i + u_j(i)\right)}{n}, \quad (6)$$

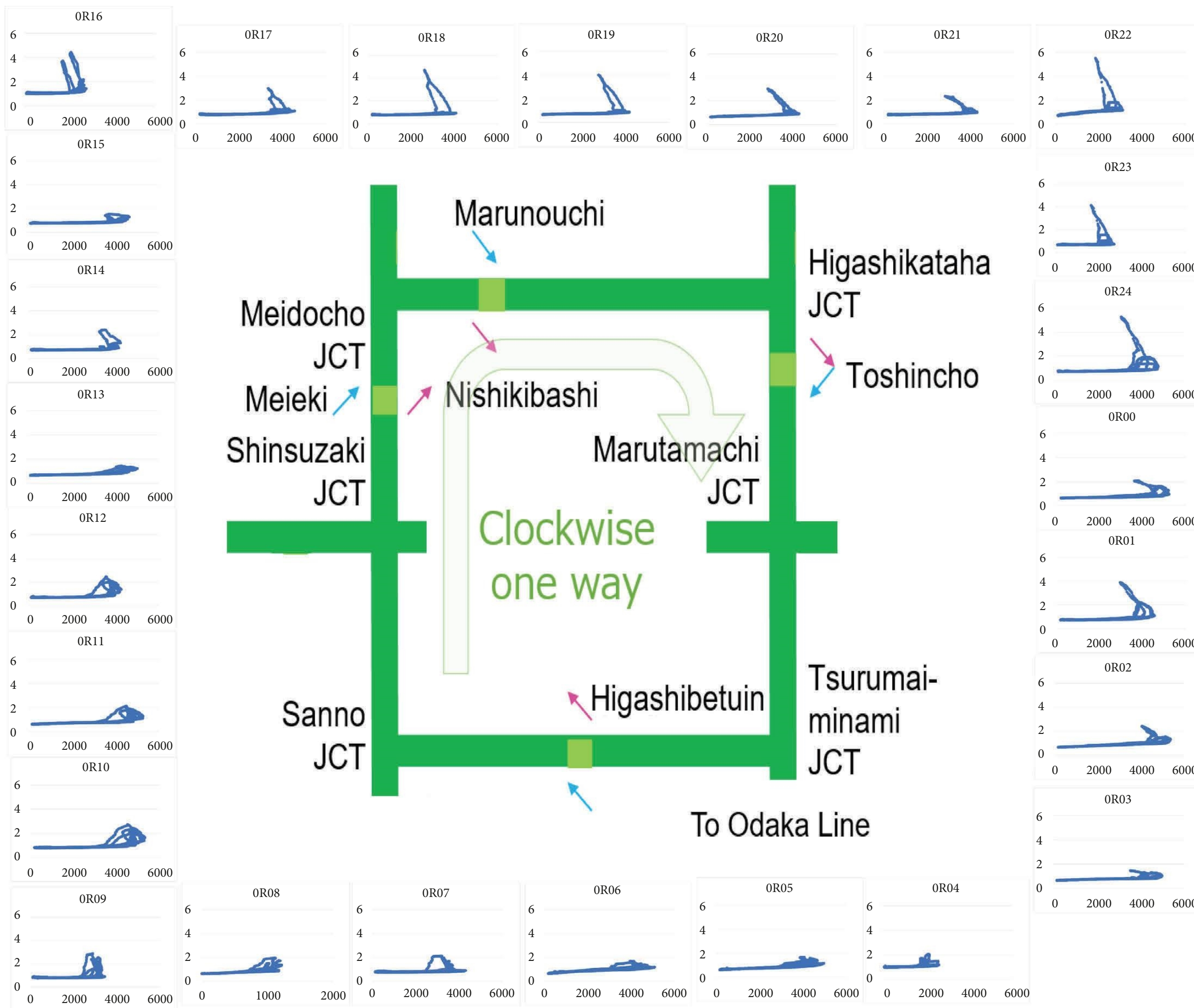


Figure 8: Continuous one-hour values for five weekdays on the Toshin Loop Line.

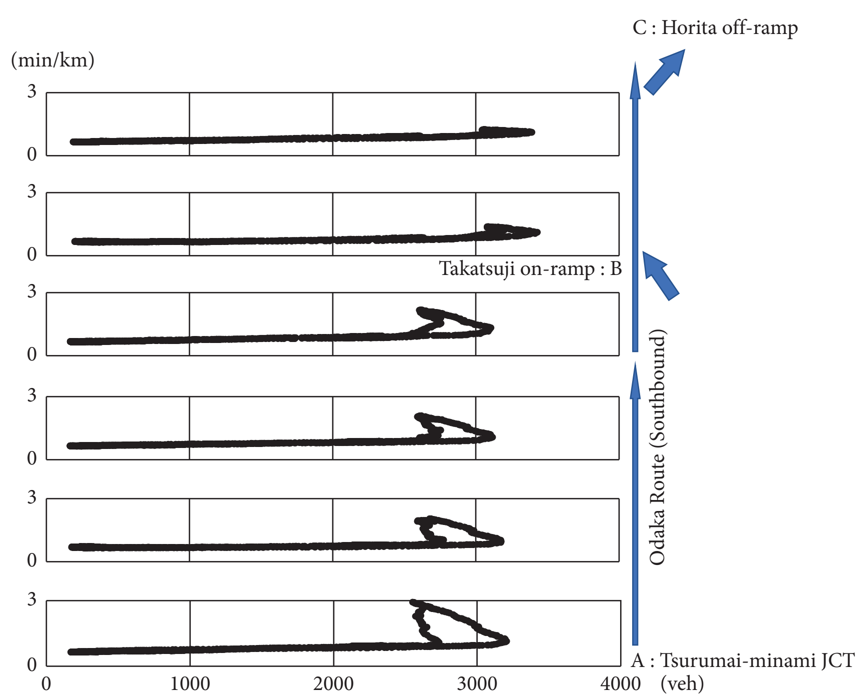


Figure 9: Continuous one-hour values for a weekday on the Odaka Line of each segment from the Tsurumai-minami JCT (A) to the Horita off-ramp (C).

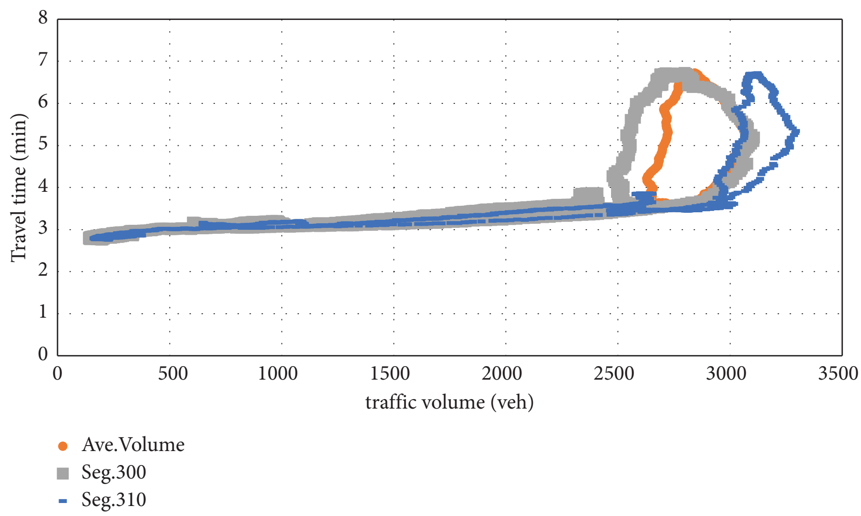


FIGURE 10: Continuous one-hour values of two types of volumes vs. section travel times through section (segments 300 to 310).

where $u_j(i)$ is the travel-time from the start segment to segment j at start time i (min) when $j \geqq 2$. If $j = 1$ then $u_1(i) = 0$. $h_j(i)$ is the travel-time in section j at time i (min). t_i^s is the section travel time for the entire section at departure time i (min). $q_j(i)$ is the volume of segment j at time i (vehs). q_i^s is the average volume for the entire section at departure time i (veh). n is the number of segments for the entire section.

Equations (5) and (6) are 1-minute values; therefore, substituted into equations (1) and (2) to obtain continuous one-hour values. Using the continuous one-hour values, a graph of the average volume (equations (6)) versus the section travel time for the section (segments 300–314) on December 16 is shown in Figure 10. It also shows the relationship between the single-segment volumes (300 and 310) and the section travel time. The single-segment volumes were aggregated when each vehicle left the start segment on the same trajectory as the section travel-time. These graphs follow a loop similar to that in Figure 9; however, the average volume versus section travel-time graph is averaged over the other single-segment volume graphs.

5.2. Hourly Travel-Time Prediction Models and Analysis. Considering the sequential and smooth transition of the continuous one-hour values in 300–314 sections as shown in Figure 9, the models were constructed using multiple regression to predict the average 1-hour travel time after one hour from the 7:00 am data, the maximum average 1-hour travel time during the morning peak period (7:00–9:00 am), and to exploratively examine the causes of traffic congestion as well as the prediction of travel time. The hourly travel-time prediction model uses the one-hour value of the section travel time at 8:00 am (T8) as the objective variable, which was obtained using the calculation method in the previous section. However, because this model considers a macroscopic future prediction of T8, the one-hour volume for each segment at 7:00 am in equation (1) is used as the explanatory variable.

The models constructed with the objective variable T8 are listed in Table 1. The mainline volumes for each of the eight segments at 7:00 am and the on/off-ramp volumes at the two locations were considered the initial explanatory variables. After trial and error, we consider the following two types of explanatory volume variables: one is the Takatsuji on-ramp volume taken to the power of 5, which is near the end of the section; the other is the composite variable of the volume taken to the power of 5, which is the sum of the volume at the Tsurumai-minami mainline segment and the Takatsuji on-ramp. The reason for using volume to the 5th power was that travel time tended to increase rapidly when the volume exceeded a certain threshold; therefore, the 5th power was the most appropriate. The most accurate model using only volume variable for this section is Model 1 in Table 1. It shows that the Takatsuji on-ramp traffic was the main cause of congestion along this section. The analysis was initially performed using only the volume variable at 7:00 am, but to improve the accuracy of the model, a variable "T7-Y7" was added to take into account the time transition characteristics of continuous one-hour values, in which T7 is the one-hour value of travel time at 7:00 am. Y7 is the uncongested section travel time obtained by inputting the 7:00 am volume (at segment 300) into the uncongested section travel-time function constructed by regression analysis as follows: The objective variable for the analysis below is the section travel time at 6:00 in equations (2) and (5) when there is no congestion, and the explanatory variable is the one-hour volume on segment 300 at 6:00 am in equation (1).

$$ut = 2.68 + 0.0003 \times \mathrm{Q}_{\mathrm{jk}}, \tag{7}$$

where ut is the uncongested section travel time (min) and Q_{jk} is the one-hour volume at period k in segment j (=300) (veh/h).

A total of 128 datasets were used and the coefficient of determination for this equation (7) was 0.852, indicating high accuracy. Model 2 in Table 1 adds this "T7-Y7" to the volume variable in Model 1. Models 1 and 2 exhibited good accuracy and were excluded as insignificant variables. Model

Table 1: Hourly travel time prediction models.

No.	Hourly travel-time prediction models (T8)						Maximum travel-time model during peak hours	
	Model 1		Model 2		Model 3		Model 4	
Term	Estimates	t ratio	Estimates	t ratio	Estimates	t ratio	Estimates	t ratio
Intercept	3.23	22.8***	2.3	31.6***	2.87	26***	3.13	27.1***
T7-Y7 (min)	—	—	1.03	13.0***	1.19	16.61***	1.234	12.81***
Takatsuji on-ramp volume^5 in 7 am (veh/hour)	$5.71E-13$	13.1***	$2.74E-13$	7.5***	—	—	$2.92E-13$	6.57***
(Takatsuji on-ramp volume $^+$mainline volume)^5 in 7 am (veh/hour)	—	—	—	—	$2.1E-18$	6.61***	—	—
R square	0.578		0.821		0.807		0.804	
Number of data	128		128		128		128	

First 5 in the table means the fifth power of (Takatsuji on-ramp volume). The + in the table means the addition of (Takatsuji on-ramp volume) and (mainline volume). Next 5 in the table means the fifth power of (Takatsuji on-ramp volume plas mainline volume). *** means 1% significant.

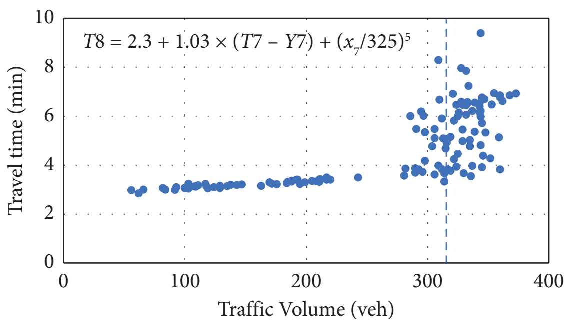


Figure 11: Relationship between Takatsuji on-ramp traffic volume and T8 (x_7 is Takatsuji on-ramp volume at 7:00 am.).

3 is the model with a "T7-Y7" and volume variable that is the sum of the mainline volume at section 300 and the Takatsuji on-ramp volume. Compared with Model 1, Model 2 had a much higher R squared value of 0.83, which greatly improved the accuracy. By using the "T7-Y7" variable, which considered the shape of continuous one-hour values in the graph, the prediction accuracy and explanatory power were improved.

A comparison of Models 3 and 2 shows that the impact of the on-ramp volume alone is higher than the total volume of mainline and on-ramp traffic. One reason for this is assumed to be because the on-ramp traffic merges into the second-lane side of the elevated mainline after climbing the grade from the surface street. The merging of vehicles is slower. This causes the traffic in the second lane of the mainline to slow. This is despite the fact that the second lane typically travels 60–80 mph faster than the first lane. Therefore, the impact of the increase in on-ramp traffic in Model 2 was higher. To understand the effect of the Takatsuji on-ramp volume in Model 2, Figure 11 shows the relationship between the Takatsuji on-ramp volume and T8. The vertical dotted line in this figure represents the value (325 vehicles) derived from the coefficient of the fifth power term of the Takatsuji on-ramp volume in Model 2, as shown in Figure 11. It can be observed that the travel time increases rapidly when the on-ramp volume exceeds a certain value.

Model 4 in Table 1 shows the most accurate model for the objective variable of the maximum average 1-hour travel time observed in this section during peak hours (7:00–9:00 am). It also has good accuracy in predicting the maximum travel time, and the statistical analyses of hourly travel time predictions with a view to the time transition of the continuous one-hour values have allowed us to examine and discuss various congestion factors in road structures and traffic flow, which was similar for the other sections as well.

6. Discussion

The continuous one-hour volume versus travel-time graph presented in this study provides a more accurate picture of the maximum one-hour volumes and traffic transitions than the discrete data. The graphs show that the maximum volumes and travel times varied widely daily, even at the same location on the expressway. Observing the graph loops reveal that when the maximum hourly travel time was particularly large, the maximum volume tended to be approximately 10% less than when it was not. Such shape change character of the continuous one-hour values is interesting.

Most of the continuous one-hour values show a smooth loop during congestion because they summarize, to some extent, the transition of fluctuations over a reasonably long period of time, which can absorb small fluctuations of 5–10 min and show a larger trend of traffic flow around the observation area. Although the characteristics of this effect are likely to be different for longer or shorter time periods than 1 h, the one-hour value was used in this study as the most tractable.

An hourly travel-time prediction models were statistically constructed with high accuracy. Looking at the coarse scatter plots in the graph of the discrete one-hour data, it was not easy to imagine a travel-time prediction 1-hour later. However, the smooth change in the continuous one-hour values provided an intuitive understanding of the predictability. The reason for predicting the 8:00 am travel time from the 7:00 am traffic data is that 8:00 am is the busiest time of the day on the network, and it makes sense to identify the causes of more severe congestion and lead countermeasures in earlier hours. In contrast, hourly traffic assignment models that predict hourly travel time and volume are often constructed using the volume-delay function. Because the graph of continuous one-hour values provides an overview of the volume-delay relationships across peak hours and routes, it may also be useful to verify the validity of these traffic assignment results. From the above results, it can be seen that the analysis method of continuous one-hour values does not compete with previous methods, such as traffic volume-speed relationships and travel-time prediction methods, but rather complements them to provide a more comprehensive understanding of hourly traffic phenomena from a macroscopic perspective.

The issues to be investigated in this study include analyzing the difference in effects using continuous 30-minute or 90-minute values instead of one-hour values, a logical verification of the shape of one-hour values, and proposing practical congestion analysis methods using one-hour values.

Data Availability

The Excel data used to support the findings of this study were supplied by Nagoya Expressway Public Corporation under license and so cannot be made freely. These data are only available upon request to the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] A. J. Horowitz, "Delay/volume relations for travel forecasting based upon the 1985 highway capacity manual," *The Federal Highway Administration U S Department of Transportation*, vol. 24, 1991.

[2] R. Kucharski and A. Drabicki, "Estimating macroscopic volume delay functions with the traffic density derived from measured speeds and flows," *Journal of Advanced Transportation*, vol. 2017, Article ID 4629792, 10 pages, 2017.

[3] L. F. Huntsinger and N. M. Rouphail, "Bottleneck and queuing analysis calibrating volume-delay functions of travel demand models," *Transportation Research Record*, vol. 2255, no. 1, pp. 117–124, 2011.

[4] Z. Y. Lu, Q. Meng, and G. Gomes, "Estimating link travel time functions for heterogeneous traffic flows on freeways," *Journal of Advanced Transportation*, vol. 50, no. 8, pp. 1683–1698, 2016.

[5] Y. Pan, H. Zheng, J. Guo, and Y. Chen, "Modified volume-delay function based on traffic fundamental diagram: a practical calibration framework for estimating congested and uncongested conditions," *Journal of Transportation Engineering, Part A: Systems*, vol. 149, no. 11, 2023.

[6] A. K. Das and B. R. Chilukuri, "Link cost function and link capacity for mixed traffic networks," *Transportation Research Record*, vol. 2674, no. 9, pp. 38–50, 2020.

[7] J. B. A. Huo, X. H. Wu, C. Lyu, W. B. Zhang, Z. Y. Liu, and L. Y. Xu, "Quantify the road link performance and capacity using deep learning models," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 10, pp. 18581–18591, 2022.

[8] R. Neuhold and M. Fellendorf, "Volume delay functions based on stochastic capacity," *Transportation Research Record*, vol. 2421, no. 1, pp. 93–102, 2014.

[9] J. J. Zhang, M. M. Liu, and B. Zhou, "Analytical model for travel time-based BPR function with demand fluctuation and capacity degradation," *Mathematical Problems in Engineering*, vol. 2019, Article ID 5916479, 13 pages, 2019.

[10] J. P. T. van der Gun, A. J. Pel, and B. van Arem, "Travel times in quasi-dynamic traffic assignment," *Transportmetrica A-Transport Science*, vol. 16, no. 3, pp. 865–891, 2020.

[11] R. E. Barka and I. Politis, "Fitting Volume Delay Functions under interrupted and uninterrupted flow conditions at Greek urban roads," *European Transport-Trasporti Europei*, vol. 127, no. 1, pp. 13–20, 2001.

[12] W. D. Cottrell, "Empirical freeway queuing duration model," *Journal of Transportation Engineering*, vol. 23, no. 10, 2022.

[13] D. Paterson and G. A. Rose, "A recursive, cell processing model for predicting freeway travel times," *Transportation Research Part C: Emerging Technologies*, vol. 16, no. 4, pp. 432–453, 2008.

[14] M. Yildirimoglu and N. Geroliminis, "Experienced travel time prediction for congested freeways," *Transportation Research Part B: Methodological*, vol. 53, pp. 45–63, 2013.

[15] B. I. Bustillos and Y. C. Chiu, "Real-time freeway-experienced travel time prediction using N-curve and k nearest neighbor methods," *Transportation Research Record*, vol. 2243, no. 1, pp. 127–137, 2011.

[16] F. Soriguera and M. Martinez-Diaz, "Freeway travel time information from input- output vehicle counts: a drift correction method based on avi data," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 9, pp. 5749–5761, 2021.

[17] J. Kwon, B. Coifman, and P. Bickel, "Day-to-day travel-time trends and travel-time prediction from loop-detector data," *Transportation Research Record*, vol. 1717, no. 1, pp. 120–129, 2000.

[18] X. Y. Zhang and J. A. Rice, "Short-term travel time prediction," *Transportation Research Part C: Emerging Technologies*, vol. 11, no. 3-4, pp. 187–210, 2003.

[19] J. Rice and E. van Zwet, "A simple and effective method for predicting travel times on freeways," *IEEE Transactions on Intelligent Transportation Systems*, vol. 5, no. 3, pp. 200–207, 2004.

[20] C. M. Kuchipudi and S. I. J. Chien, "Development of a hybrid model for dynamic travel-time prediction," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 1855, no. 1, pp. 22–31, 2003.

[21] Y. J. Zou, X. X. Zhu, Y. L. Zhang, and X. S. Zeng, "A space-time diurnal method for short-term freeway travel time prediction," *Transportation Research Part C: Emerging Technologies*, vol. 43, pp. 33–49, 2014.

[22] M. Chen and S. I. J. Chien, "Dynamic freeway travel-time prediction with probe vehicle data- link based versus path based," *Transportation Research Record*, vol. 1768, no. 1, pp. 157–161, 2001.

[23] S. Kwak and N. Geroliminis, "Travel time prediction for congested freeways with a dynamic linear model," *IEEE Transactions on Intelligent Transportation Systems*, vol. 22, no. 12, pp. 7667–7677, 2021.

[24] W. X. Qiao, A. Haghani, C. F. Shao, and J. Liu, "Freeway path travel time prediction based on heterogeneous traffic data through nonparametric model," *Journal Of Intelligent Transportation Systems*, vol. 20, no. 5, pp. 438–448, 2016.

[25] H. Caceres, H. Hwang, and Q. He, "Estimating freeway route travel time distributions with consideration to time-of-day, inclement weather, and traffic incidents," *Journal of Advanced Transportation*, vol. 50, no. 6, pp. 967–987, 2016.

[26] P. D. Pant, M. M. Polycarpou, P. Sankaranarayanan, B. Li, X. B. Hu, and A. B. Hossain, "Travel time prediction system (TIPS) for freeway work zones," in *Proceedings of the Conference on Traffic And Transportation Studies*, pp. 20–29, ICTTS, Beijing, China, 1998.

[27] X. Miao, B. Wu, Y. J. Zou, and L. T. Wu, "Examining the impact of different periodic functions on short-term freeway travel time prediction approaches," *Journal of Advanced Transportation*, vol. 2020, Article ID 3463287, 15 pages, 2020.

[28] Y. Y. Li, M. Zhang, Y. X. Ding, Z. H. Zhou, and L. Y. Xu, "Real-time travel time prediction based on evolving fuzzy participatory learning model," *Journal of Advanced Transportation*, vol. 2022, Article ID 2578480, 9 pages, 2022.

[29] J. J. Tang, Y. J. Zou, J. Ash, S. Zhang, F. Liu, and Y. H. Wang, "Travel time estimation using freeway point detector data based on evolving fuzzy neural inference system," *Public Library of Science One*, vol. 11, no. 2, Article ID e0147263, 2016.

[30] H. Shao, W. H. K. Lam, A. Sumalee, A. Chen, and M. L. Hazelton, "Estimation of mean and covariance of peak hour origin–destination demands from day-to-day traffic counts," *Transportation Research Part B: Methodological*, vol. 68, pp. 52–75, 2014.

[31] S. Nakayama and R. Connors, "A quasi-dynamic assignment model that guarantees unique network equilibrium," *Transportmetrica A-Transport Science*, vol. 10, no. 7, pp. 669–692, 2014.

[32] M. Fujita, S. Yamada, and S. Murakami, "Time coefficient estimation for hourly origin-destination demand from observed link flow based on semi-dynamic traffic assignment," *Journal of Advanced Transportation*, vol. 2017, Article ID 6495861, 14 pages, 2017.