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Modelling Travel Time After Incidents on Freeway Segments in China

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ABSTRACT The reduction in incident-induced delays on freeways is a main objective of transportation management. The use of travel time estimation model for freeway segments is an important method for estimating delays resulting from incidents on freeways. In this study, freeways with temporary partial lane closures were considered to simulate traffic accidents occupying lanes. Travel time, traffic volumes, and speeds under various traffic conditions on a few typical Chinese freeway segments under regular and simulated accident conditions were investigated through field experiments. The collected traffic data collected were used to establish travel time models based on the Bureau of Public Roads (BPR) function for basic freeway segments under both regular and accident conditions, and to obtain the model parameters. The results demonstrate that the calibrated BPR models established in this study fit the data well. In addition, this study proposes an application method for the established travel time models by which variations in travel time can be estimated rapidly and easily. The results of this study can be used to reduce travel time for road users and contribute to decision making of transportation management systems to improve traffic efficiency after incidents.

INDEX TERMS Traffic engineering, incidents, travel time, BPR functions, freeway segments, v/C ratio.

I. INTRODUCTION

Travel time is widely recognized as an important performance measure of highway operating conditions and is also one of the key factors for road users in arranging travel plans and choosing travel routes [1]. The estimation and forecasting of travel time is even more important for traffic operators and emergency response services. Recently, the prediction of traffic information as a critical step to achieve the performance of intelligent transportation systems has attracted significant attention. Tang developed a new travel speed prediction method based on an evolving fuzzy neural network in 2017 [2]. In 2019, he proposed an improved traffic flow prediction model based on artificial neural networks and a traffic flow prediction method combining denoising schemes and the support vector machine model [3], [4]. In addition, many researchers have focused on predicting travel time using various methodologies, such as theoretical model analysis, regression model analysis, machine learning methods and software simulation. Theoretical models, such as Greenshield's model and Greenberg's models, as well as Logistic models [5], are basic models for studying the macroscopic characteristics of traffic flow. Based on these models, Karchroo presented a method to estimate travel time on highways based on macroscopic models in 2001 [6] and used the modified Beckman formulation to derive the relationship between density and travel time in 2016 [7]. Zhang proposed a method to predict freeway travel time using linear regression [8]. Wu applied support vector regression for travel time prediction in 2013 [9], while Innamaa and Khosravi have each focused on predicting short-term travel time using neural networks [10], [11]. Lu developed a microscopic traffic simulation procedure to estimate the travel time functions of heterogeneous traffic flows on a freeway [12].

However, travel time is affected by various factors, such as traffic characteristics, roadway physical characteristics, weather conditions, and incidents [13]. Traffic characteristics include traffic compositions and traffic flow conditions. The physical characteristics of roads include their widths, geometric features, and traffic control features. Travel time models that use only traffic volume or density as an independent variable do not fully reflect the state of highway traffic

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flow for all conditions. Many researchers have attempted to develop models that can work well for all conditions. Yeon developed a model to estimate travel time on a freeway under congested conditions using discrete-time Markov chains [1]. Krishna focused on the travel time attributes of traffic flow and composition to develop a corridor travel time estimation model using a multiple linear regression approach [14]. Wang verified the existence of significant differences in travel time among different traffic streams using the Friedman test and showed that lane width and the number of lanes also influence travel time [15]. The impact of the number of lanes on travel time was also examined by He and Muhammad in their studies on travel time prediction in Dalian and Indonesia, respectively [16], [17]. Travel time can also be influenced by other variables and by unpredictable events such as repair work, traffic accidents, and weather conditions. Kwon conducted a thorough analysis of the relationship between macroscopic traffic parameters and inclement winter weather factors and established a free-flow speed percent reduction model to describe the relationship [18]. Chitturi proposed a real-time application for forecasting user delays in work zones and providing information to motorists upstream of the work zone [19]. Tan proposed an algorithm for evaluating the speeds of vehicles in incidents from videos [20]. Sun developed a traffic model for partial road closures caused by traffic accidents using the Nagel–Schreckenberg (NS) cellular automaton model, updated using mean field theory [21].

The phenomenon of traffic congestion on freeways as a result of the significant growth in vehicle population has become a ubiquitous problem in China. Congestion delays reduce productivity by significantly increasing travel time and decreasing travel time reliability [22]. In China, incident-related traffic delay is estimated to constitute the largest proportion of total congestion delay [23]. Sudden traffic accidents may cause traffic congestion upstream and increase traffic delays and travel time. In comparison with other traffic parameters, such as vehicle speed, delay rate, and buffer index, travel time is a parameter that is easier to understand and can be used directly as a travel reference for road users. Therefore, choosing travel time as a dependent variable can make research results more intuitive and practical, especially for accident conditions.

The best-known model for road link travel time is the standard Bureau of Public Roads (BPR) function; it is critical in the calculation of the travel time of vehicles on road links [24]. To make the BPR model more applicable and truly reflect the actual traffic condition, a number of calibrated versions of the BPR model was developed by researchers. In research done by Skabardonis, the BPR function was fitted against real field data by searching for the best parameters values [25]. Hansen developed a modified BPR function using real-time freeway flow and speed data for Highway 217 in Portland, Oregon [26]. To differentiate travel time according to vehicle types, Noriega proposed a BPR-type function by introducing a time factor for each vehicle type [27], and Lu proposed a piecewise continuous BPR-type functions to estimate travel time for each type of vehicle [12]. Despite the significant research focus on developing travel time models, limited research has been conducted on modelling travel time after incidents.

In the present study, traffic data were collected under various traffic conditions on a two-lane freeway (G5), a three-lane freeway (G65), and a four-lane freeway (G30) under regular and simulated accident conditions. Travel time estimation models for basic freeway segments under both regular and accident conditions were established based on the US BPR function.

The remainder of this manuscript is organized as follows. Section 2 introduces the methodology employed in this study. In Section 3, the results obtained from the analysis of the collected field data are presented and discussed in detail, and travel time models based on the BPR functions for both normal and accident conditions are presented. The key findings of the study are summarized in Section 4.

II. METHODS

The objective of this research was to develop a method for estimating travel time on basic freeway segments in China under traffic accident conditions. The effect of a traffic accident on the normal operation of a freeway depends on the number of lanes closed near the accident point [28], [29]. When an accident occurs on a roadway, all or part of lane is typically blocked by the vehicles involved in the crash. Often, additional lanes are blocked by police, emergency medical vehicles, and other equipment. When drivers drive through the accident area, they either must slow down for safety reasons or may choose to slow down out of curiosity. In either case, decreased vehicle speeds greatly reduce the freeway capacity and increase travel time, leading to traffic congestion. As real-time traffic flow data under actual traffic accident conditions can be difficult to obtain, an experiment was designed to simulate a traffic accident spot resulting in partially closed lanes.

A. FIELD TEST

Software such as VISSIM and TranStar can model complex traffic operations on freeways, and traffic volume, traffic flow density, and traffic speed can be calculated. However, differences in vehicle type and driver behavior in different countries render the default parameter values of models such as VISSIM, which was developed by German researchers, inapplicable to China. The differences mentioned can result in errors between simulation results and actual situations. Consequently, in this study, a field test was conducted to measure traffic volumes, speeds, and travel time under different traffic conditions on some typical basic freeway segments in China before and after incidents. As it is difficult to obtain real-time traffic flow data under actual traffic accident conditions, freeway segments with temporary partial lane closures were used to simulate traffic accident locations. To estimate the effect of incidents on travel time for basic freeway segments, traffic data were also collected on freeway segments with the same geometric alignments and lengths as the freeway segments with temporarily closed lanes.

1) TEST INSTRUMENT

For the purpose of this study, a large amount of data was required on average travel time under different traffic conditions on basic freeway segments before and after traffic accidents that occupy lanes. An AxleLight Roadside Laser vehicle classification device was used to collect traffic flow data (traffic volumes, instantaneous speeds, etc.) in the field. A Bluetooth-based travel time detector was used to automatically collect Bluetooth MAC addresses and corresponding time stamps and then save the data on a local storage device [30]. The hardware used in this study is shown in Figure 1.

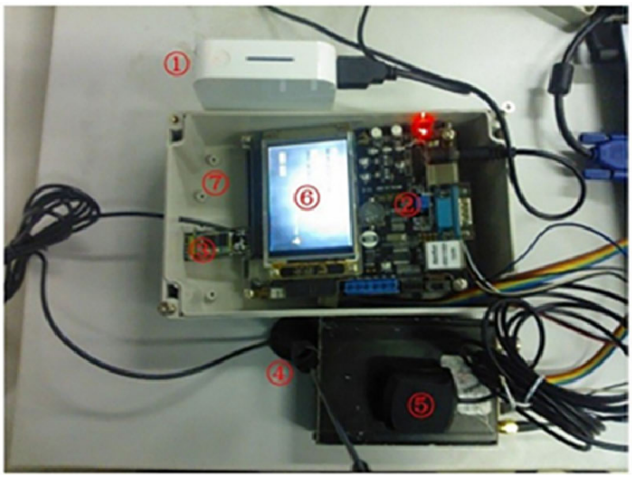


FIGURE 1. Bluetooth-based road travel time detector: ň Portable power source, ARM Single chip, ő Bluetooth, ŕ Omni-directional antenna, ř GSM module, ś LED touch panel, š Plastic casing.

As the data source for the whole system, the Bluetooth-based road travel time detector needs not only real-time interconnection with vehicles traveling on the road but also real-time data interaction with a central computer. The data interaction process is shown in Figure 2.

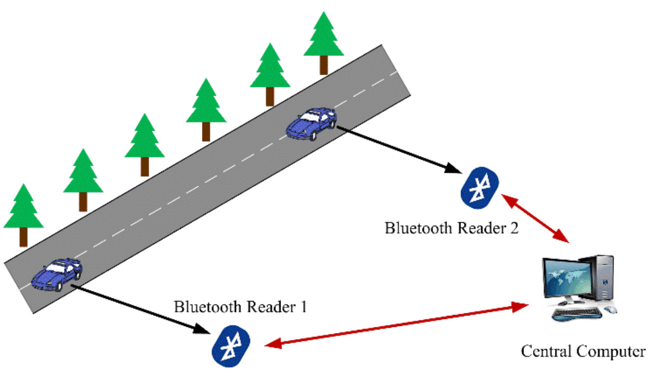


FIGURE 2. Bluetooth terminal data interaction mode diagram.

As Figure 2 shows, the working mode of the Bluetooth terminal is paired work. The Bluetooth Terminal 1 and Terminal 2 are time synchronized, and the data are sent synchronously so that the time taken by the vehicle to pass through the road segment can be calculated accurately. The data interaction can be divided into three steps:

i Collecting MAC addresses from a Bluetooth-based road travel time detector under a full spectrum of environmental and traffic conditions.

ii Adding time stamps to the MAC addresses collected so that travel time samples can be calculated and storing a large quantity of partial time-stamped MAC addresses in the memory of the Bluetooth terminal.

iii Sending real-time data from the two Bluetooth terminals simultaneously to the central computer, every 5 min, so that the central computer system can calculate the average travel time.

2) STUDY LOCATION

As mentioned earlier, obtaining real-time traffic flow data under actual traffic accident conditions is complex. To analyze variations in the travel time on basic freeway segments before and after incidents, experiments were designed to simulate incidents sites resulting in partially closed lanes. In addition, given the dangers of performing simulation experiments, freeway segment with temporary partial lane closures for maintenance work was also used to simulate accident site.

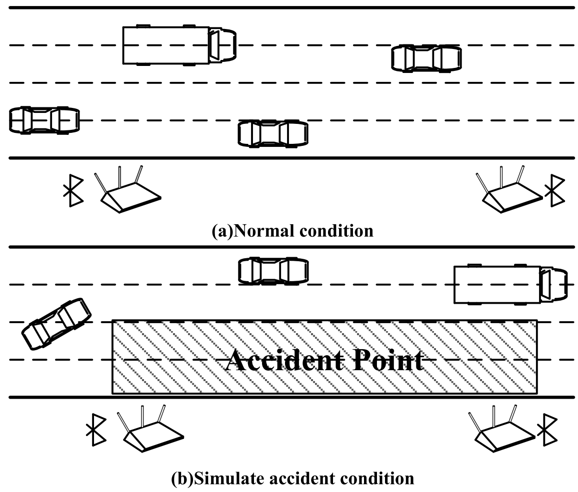
To eliminate variation in the collected traffic data due to adverse weather conditions, only sunny days with no rain or snow were selected. To eliminate the effect of differences in topography on travel time, sites that were not in mountainous areas and routes with straight alignments or flat large-radius curves were selected. In addition, only basic freeway segments (without features such as entrances, exits, tunnels, or bridges) were considered. Based on these criteria, three road sections, shown in Figure 3, were selected as the study areas: K33 + 130 to K38 + 700 on the two-lane freeway G5, K449 + 100 to K464 + 900 on the three-lane freeway G65, and K1029 + 800 to K1035 + 900 on the four-lane freeway G30.

FIGURE 3. Xi'an Metropolitan Area freeway network and the three selected study segments.

The three study sections have straight or nearly straight alignments (curve radii, if any, of 3000 to 5500 m), maximum longitudinal slopes of -1.5% to 1.5%, and lanes 3.75 m in width. On road sections G65 and G30, the design speed is 120 km/h, and on road section G5, the design speed is 100 km/h. Traffic flow data and vehicle type data for the study segments were examined before the field tests. Based on the results of the field tests and statistical data from nearby toll stations, the proportion of trucks was determined to be approximately 18%, with a variation range of no more than 2% on three study sections.

During the experiment, the Department of Transportation of Shaanxi Province was conducting pavement maintenance work on the study segment to improve the pavement condition of the freeway. This activity resulted in one of two lanes on G5 being occupied. Figure 4 (a) illustrates the condition of the study segment on G5. We designed experiments to simulate incidents that occupied one of three lanes and two of three lanes on G65, and two of four lanes on G30. The road condition for segment on G65 is shown in Figure 4 (b).

The objective of this research was to analyze the change in travel time on a freeway before and after incidents. As mentioned earlier, traffic data on freeways with the same geometric alignments and lengths as the segments with temporarily closed lanes were also collected in this study. Figure 5 illustrates the experiment implementation process on G30 under normal conditions and under simulated accident condition.



(a)Normal condition

(b)Simulate accident condition

FIGURE 5. **Experiment implementation process (on G30).**

(a) One of two lanes closed on freeway G5

(b) One of three lanes closed on freeway G65

FIGURE 4. **Lane closure conditions for two of the three study segments.**

B. DEFINITIONS OF TRAFFIC CONDITIONS

Excluding differences in road geometry, road surface conditions, and weather conditions, traffic conditions are perhaps the most important factors affecting average vehicle speed and travel time. As the average travel time varies with respect to traffic conditions, a large amount of travel time data corresponding to various traffic conditions are required to estimate vehicle travel time. Traffic conditions are typically categorized by service level [31]. The Highway Capacity Manual (HCM) developed in the US uses traffic density as an indicator of the service level of a freeway segment and defines six different service levels, represented by letters A to F [31]. Based on the ‘‘Technical Standard of Highway Engineering’’ in China, the ratio of traffic volume to freeway capacity (v/C ratio) was used in this study as an indicator of the degree of road congestion and of the road service level, as summarized in Table 1 [32]. There are six different service levels represented by the numbers 1 to 6 in the Chinese system, which correspond to US highway service levels A through F.

The ‘‘Technical Standard of Highway Engineering’’ provides a method for determining freeway capacity under normal conditions. In this study, the capacity of an experimental freeway segment was calculated based on this method, and then the v/C ratio was obtained. However, a traffic accident has a significant impact on the normal operation of a freeway. Road capacity decreases significantly when an accident occurs. The issue of capacity reduction due to traffic incidents is addressed in the HCM. The effect of an accident on capacity depends on the number of lanes on the roadway at

TABLE 1. Road service levels of freeway.

Level of Service	v/C ratio	Design Speed (km/h) 120	100	80
		Maximum Traffic [pcu/(h·ln)]		
1	$v/C \le 0.35$	750	730	700
2	$0.35 < v/C \le 0.55$	1200	1150	1100
3	$0.55 < v/C \le 0.75$	1650	1600	1500
4	$0.75 < v/C \le 0.90$	1980	1850	1800
5	$0.90 < v/C \le 1.00$	2200	2100	2000
6	$v/C > 1.00$	0-2200	0-2100	0-2000

Note: v/C is the ratio of the maximum service traffic volume to the basic traffic capacity. The basic traffic capacity is the maximum hourly traffic volume corresponding to level-of-service 5.

that point. Table 2 details the proportion of capacity available under traffic accident conditions, based on the number of lanes in the basic freeway segment and the severity of the incident (i.e., one, two, or three lanes blocked) [21]. In this study, v/C ratios under accident conditions were calculated based on the information in Table 2.

TABLE 2. Proportion of freeway capacity available under incident conditions.

Number of Freeway Lanes by Direction	Proportion of Freeway Segment Capacity Remaining: Shoulder Disablement	Shoulder Accident	Lanes blocked: 1	2	3
2	0.95	0.81	0.35	0.00	N/A
3	0.99	0.83	0.49	0.17	0.00
4	0.99	0.85	0.58	0.25	0.13
5	0.99	0.87	0.65	0.40	0.20
6	0.99	0.89	0.71	0.50	0.26
7	0.99	0.91	0.75	0.57	0.36
8	0.99	0.93	0.78	0.63	0.41

Note: N/A – not applicable.

III. ANALYSIS AND DISCUSSION OF FIELD TEST RESULTS

The data for normal conditions and simulated accident conditions (i.e., one of two lanes blocked, one of three lanes blocked, two of three lanes blocked, and two of four lanes blocked) for each study section consisted of the average travel time and 10-min-aggregated traffic volumes and speed. To understand the characteristics of travel time resulting from traffic accidents, this section analyzes and discusses the major findings that were obtained from the field test.

A. MEASURED FREE-FLOW SPEED

Based on HCM, the free-flow speed was measured by selecting the location of low and medium traffic flow rates, and the average travel speed of passenger cars was calculated as the free-flow speed of the freeway. Figure 6 shows box plots of the measured free-flow speed at the three test locations (G5, G65, and G30) under normal conditions. The horizontal axis represents the locations (lane 1 is the freeway lane adjacent to the hard shoulder, and lane 2, lane 3, and lane 4 are the freeway lanes adjacent to and to the left of lane 1, in sequence). The vertical axis represents the free-flow speed based on 10-min-aggregated data. As Figure 6 (a) shows, the measured median free-flow speed in lane 2 is 1 km/h higher than the measured median free-flow speed in lane 1.

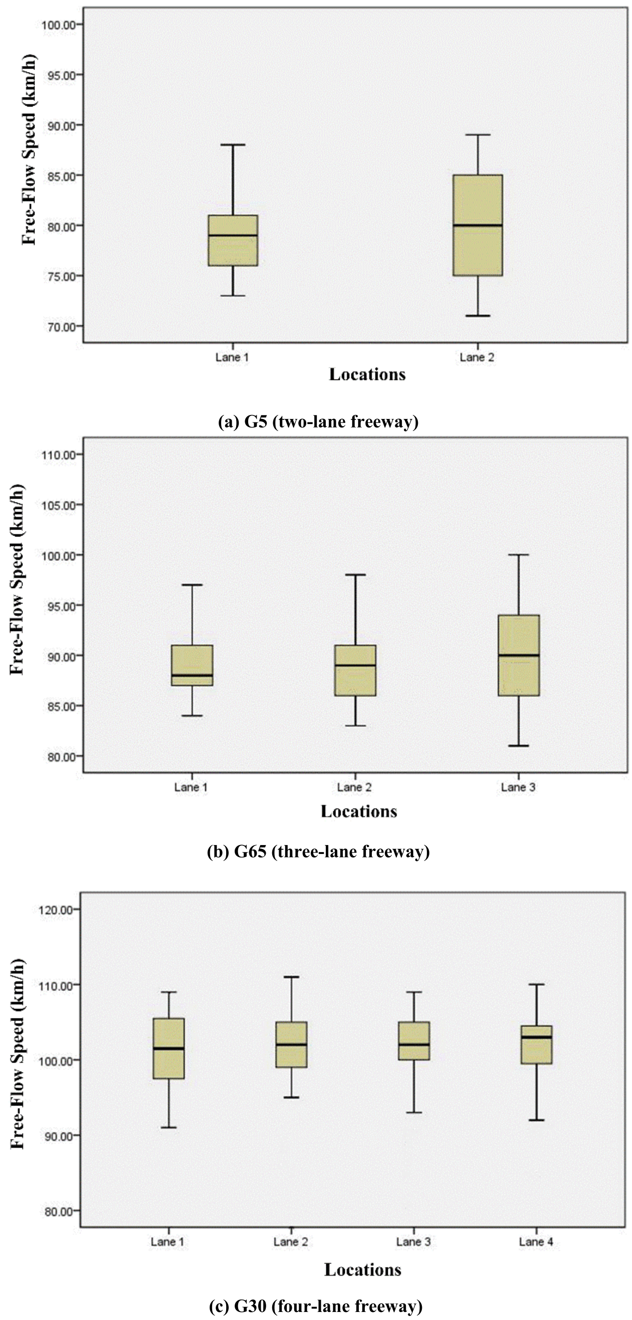


FIGURE 6. Box plots of free-flow speed under normal conditions.

As Figure 6 (b) shows, the measured median free-flow speed in lane 3 was the highest, and the measured median free-flow speed in lanes 2 and 1 were 1 km/h and 2 km/h lower, respectively, than that in lane 4. As Figure 6 (c) shows, the measured median free-flow speed in lane 2 was equal to that in lane 3. The measured median free-flow speed in lane 1 was 0.5 km/h lower than that in lane 2, and the measured median free-flow speed in lane 4 was 1 km/h higher than that in lane 2.

No differences were observed in the median free-flow speed among the lanes at any of the locations (G5, G65, and G30). Therefore, in this study, the lane characteristics were ignored. The free-flow speeds of the two-lane, three-lane, and four-lane freeways were 80 km/h, 90 km/h, and 103 km/h, respectively. The free-flow travel time per unit distance can be determined by inverting the reported free-flow speed, resulting in values of 45 s/km, 40 s/km, and 35 s/km, respectively.

As mentioned earlier, on road sections G65 and G30, the design speed was 120 km/h, and on road section G5, the design speed was 100 km/h. In China, the posted speed limits are set based on the design speed. On the road sections G65 and G30, the posted speed limit was 120km/h, and the free-flow speeds of G65 and G30 were 90 km/h and 103 km/h, respectively. When the other road conditions such as posted speed limit are same, as the number of freeway lanes decreases, the free-flow speed decreases. This is consistent with the HCM, which states: "the reduction in the number of lanes will result in a reduction in free-flow speed." To reflect the effect of the number of lanes on the free-flow speed, adjustments to the free-flow speed can be made, based on data collected on urban and suburban freeways in the US. It is estimated that, compared to the free-flow speed of a freeway segment with four lanes (in one direction), the free-flow speeds of freeway segments with three lanes and two lanes are 2.4 km/h and 4.9 km/h lower, respectively.

B. TRAVEL TIME ESTIMATION MODEL

The best-known model for road link travel time is a function proposed by the US Bureau of Public Roads (1964), known as the standard BPR function:

$$t_a = t_0 \left[1 + \alpha \left(\frac{v_a}{C_a} \right)^{\beta} \right] \tag{1}$$

where t_a is the average travel time per unit distance under normal conditions on link a (s/km); t_0 is the free-flow travel time (i.e., the travel time at zero flow) per unit distance under normal conditions on link a (s/km); v_a and C_a are the demand volume and capacity, respectively, on link a (pcu/h/l); parameter α determines the ratio of free-flow travel time to the travel time at capacity; and parameter β determines how rapidly travel time increases from the free-flow travel time. Dowling (et al. 1997) empirically evaluated the standard BPR function with $\alpha = 0.15$ and $\beta = 4$.

Vehicle characteristics and capabilities, as well as driver behavior, have changed considerably in the years since the BPR function was introduced. The standard BPR function is based on data that do not reflect today's traffic operating conditions in China. Therefore, firstly, it was considered important to investigate large sets of data that are representative of modern traffic characteristics under normal conditions in China to calibrate the parameters α and β in the BPR function in this study. Secondly, in the event of a traffic accident blocking a part of the lane, the traffic characteristics

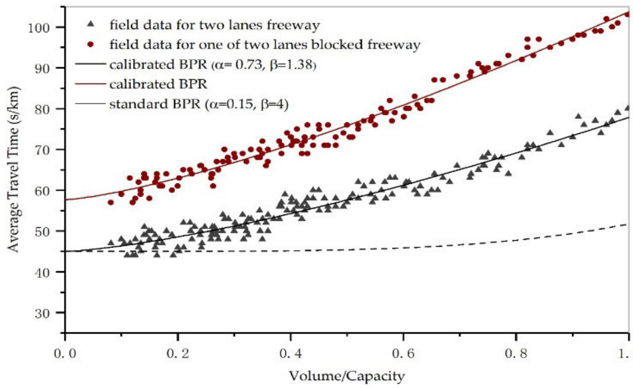
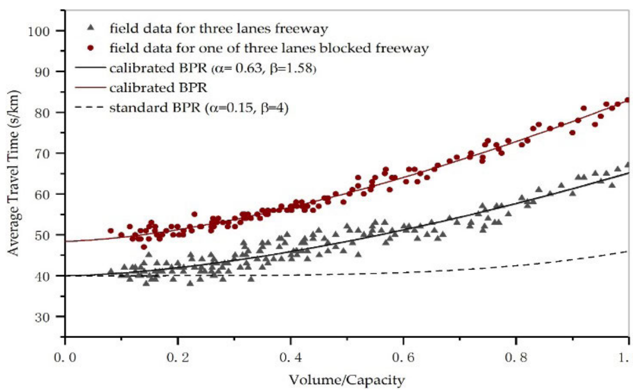
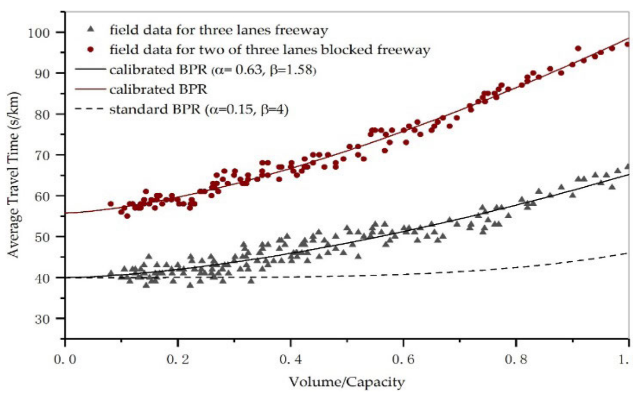


FIGURE 7. Comparison of the average travel time for v/C < 1 under normal and accident conditions on two-lane freeway (one of two lanes blocked).



(a) One of three lanes blocked



(b) Two of three lanes blocked

FIGURE 8. Comparison of the average travel time for v/C < 1 under normal and accident conditions on three-lane freeway.

and driving behaviors change. A large amount of field data reflecting the effect of incidents on travel time were collected to develop the revised impedance function models under incidents conditions.

Tests were repeated under various traffic conditions to collect vehicle travel time under normal conditions and simulated accident conditions on two-lane, three-

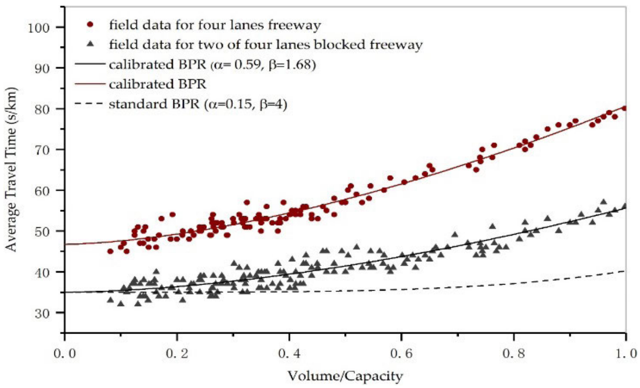


FIGURE 9. Comparison of the average travel time for v/C < 1 under normal and accident conditions on four-lane freeway (two of four lanes blocked).

lane, and four-lane freeway segments, as shown in Figures 7, 8 (a) and (b), and 9, respectively.

In Figures 7, 8, and 9, the relationships between the estimated travel time and volume-capacity ratio for two-lane, three-lane, and four-lane freeways, respectively, are plotted based on the standard BPR function as dotted lines. As these figures show, the standard BPR function is a poor fit to the field data collected in this study. It was necessary to calibrate the BPR function to better replicate the traffic behavior, as represented by the field data collected in this study. Model calibration generally consists of changing the values of model input parameters to match field conditions as well as possible within some acceptable criteria. Calibration was performed for each freeway segment separately in this study. The curves for the estimated travel time according to the BPR equation calibrated with field data for v/C < 1 for each freeway segment are shown as solid black lines in Figures 7 to 9. As these figures show, the calibrated BPR curves describe the field data well.

The parameters of the calibrated BPR function are presented in Table 3. The calibrated BPR model provides a good fit (R^2) to the field data. In the BPR function, parameter α determines the ratio of the free-flow travel time to the travel time at capacity. The calibrated α of each of the three experimental freeway segments is larger than the α used in the standard BPR function. Parameter β determines how rapidly travel time increases with respect to the free-flow travel time. The calibrated β of each of the three experimental freeway segments is larger than the β used in the standard BPR function. Smaller values of β make estimated travel time more sensitive to the v/C ratio. This means that the average travel time in China is larger than that in the US.

As Table 3 summarizes, as the number of lanes increases, the value of parameter α decreases, while the value of parameter β increases. In other words, the travel time (i.e., the free-flow travel time and the average travel time) and road traffic impedance decrease as the number of lanes increases.

Calibrating parameters for different types of roads can make the BPR model more applicable. Table 3 presents the

TABLE 3. Parameters of the calibrated BPR function.

Number of Freeway Lanes by Direction	Posted Speed Limit (km/h)	Free-flow Speed (km/h)	Free-flow Travel Time (s/km)	α	β	R^2	Adj R^2
2	100	80	45	0.73	1.38	0.9415	0.9408
3	120	90	40	0.63	1.58	0.9070	0.9058
4	120	103	35	0.59	1.68	0.8646	0.8630

calibrated parameters of two-lane freeways with a posted speed limit of 100 km/h, and three-lane and four-lane freeways with a posted speed limit of 120 km/h. According to this table, travel time models can be obtained for freeways with different numbers of lanes under normal conditions.

The objective of this research was to estimate the travel time on basic freeway segments in China as a result of traffic accidents. In the event of a traffic accident blocking part of lane, the freeway capacity is decreased, free-flow travel time is increased, and driving behaviors change. The BPR function for normal conditions does not apply well to accident conditions. Based on the classic BPR function, a revised impedance function model that considers the influence of incidents can be expressed in the following general form:

$$t'_a = t_0 * \gamma \left[1 + \alpha * b \left(\frac{v_a}{C_a} \right)^{\beta * c} \right] \tag{2}$$

where t'_a is the average travel time per unit distance under accident conditions on link a (s/km), γ is a correction factor for the influence of free-flow travel time under accident conditions, and b and c are correction factors for the influence of capacity under accident conditions.

Field data collected under simulated accident conditions on two-lane, three-lane, and four-lane freeways were used to validate the correction factors. To achieve good fit (R^2) and prediction accuracy, the values of the correction factors were determined and are summarized in Table 4. Curves of estimated travel time based on the revised impedance function and field data for v/C < 1 on the simulated accident freeway segments (i.e., with one of two lanes blocked, one of three lanes blocked, two of three lanes blocked, and two of four lanes blocked) are shown in Figures 7 to 9.

TABLE 4. Values of correction factors.

Number of Freeway Lanes by Direction	Lanes blocked	γ	b	c	R^2	Adj R^2
2	1	1.2814	1.0951	0.9738	0.9742	0.9738
3	1	1.0764	1.0843	0.9839	0.9809	0.9806
	2	1.3943	1.2317	0.9441	0.9808	0.9805
4	2	1.3363	1.2269	0.9657	0.9663	0.9658

Given a known freeway segment length, the average travel time of a vehicle passing through the freeway segment can also be predicted, and the calculation method is as follows:

$$t_a^z = Lt_a \tag{3}$$

$$t_a^{\prime z} = L t\prime_a \tag{4}$$

where t_a^z is the average travel time under normal conditions on link a (s), $t_a^{\prime z}$ is the average travel time under accident conditions on link a (s), and L is the length of the freeway segment (km).

The number of available lanes has been shown to directly affect the travel time [16], [17]. Parameter γ reflects the influence of the free-flow travel time under accident conditions, and its value accounts for both the total number of lanes in the basic freeway segment and the severity of the incident (i.e., one or two lanes blocked), as summarized in Table 4. Traffic accidents blocking part of lanes can result in the increase in the free-flow travel time, and the increase varies in freeways with different lane amount and different accident conditions. Table 4 indicates the highest increase in free-flow travel time results when two of three lanes are blocked by accidents, followed by two of four lanes being blocked, then one of two lanes being blocked, and finally one of three lanes being blocked. Clearly, as the number of available freeway lanes decreases, the free-flow travel time increases nonlinearly.

Overall, when the number of available lanes decreases, the value of parameter α decreases, while the value of parameter β increases, under all different accident conditions. In other words, incidents blocking a portion of lanes can increase travel time and road impedance. The correction factors b and c reflect the influence of capacity under accident conditions. The result shows that values of b and c varied in different accident conditions, which means that the increases in travel time and road traffic impedances are different on freeways with different numbers of lanes under different accident conditions.

As summarized in Table 4 and Figures 7 to 9, traffic accidents blocking part of a lane can result in an increase in road traffic impedance and travel time becoming more sensitive to the volume-to-capacity ratio. Compared with the travel time-vs.-v/C ratio curve under normal conditions, the curve under accident conditions increases more rapidly when the freeway is at a level of service of 2 to 5 ($0.35 < \mathrm{v/C} \leq 1$).

C. MODEL VERIFICATION

The travel time estimation models under normal and accident conditions can be developed from the results presented above. However, the models were developed based on the statistical data obtained from freeways G5, G65, and G30. Thus, the accuracy of the model needs to be further verified. Furthermore, the model needs to be validated, and the data to verify the model accuracy must be collected from another freeway.

The data that were used to validate the model were collected from a section of the two-lane freeway G70, for which the posted speed limit was 100km/h. An experiment to simulate an accident that occupied one of two lanes was designed. The road condition is depicted in Figure 10.

For the travel time model in the case where one of the two lanes is blocked, according to Figure 7 and Table 4, the values

FIGURE 10. Lane closure conditions for study segments on G70.

of the correction factors can be obtained ($\gamma = 1.2814$, $b = 1.0951$, and $c = 0.9738$). The model equation is given below:

$$t'_a = t_0 * 1.2814 \left[1 + \alpha * 1.0951 \left(\frac{v_a}{C_a} \right)^{\beta * 0.9738} \right] \tag{5}$$

The values of α and β for freeways with different numbers of lanes are presented in Table 3. For a two-lane freeway with a posted speed limit of 100 km/h, $\alpha = 0.73$ $and \beta = 1.38$. The field data and plot of the calibrated model under normal and accident conditions are illustrated in Figure 11.

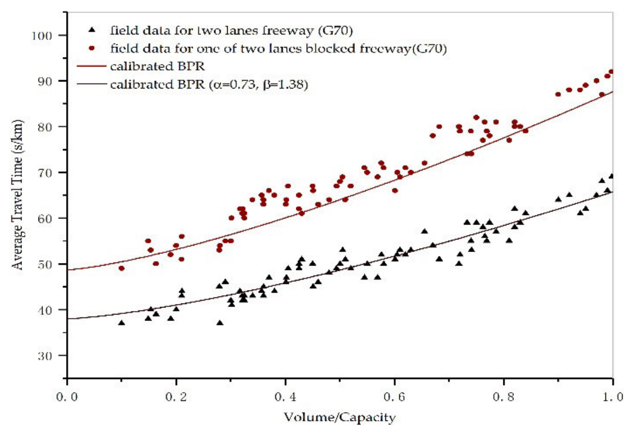


FIGURE 11. Field data and plot of the calibrated model on G70.

As can be seen in Figure 11, the curves of the calibrated models under normal and accident conditions fall closely into the cloud of the field data. To evaluate the model accuracy, the travel time values of the models under normal and accident conditions were compared with the field data in Figures 12 and 13, respectively. The relative error of the models under both conditions was below 10%, which suggested that the model accuracy achieved in this study met the requirements.

D. APPLICATION OF TRAVEL TIME ESTIMATION MODEL

To illustrate the influence on travel time of the v/C ratio of a basic freeway segment under normal conditions and accident conditions, the rates of change of average travel

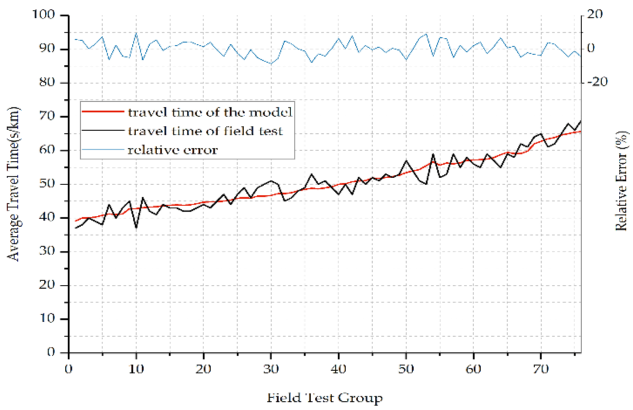


FIGURE 12. Comparison of the model and field data under normal conditions.

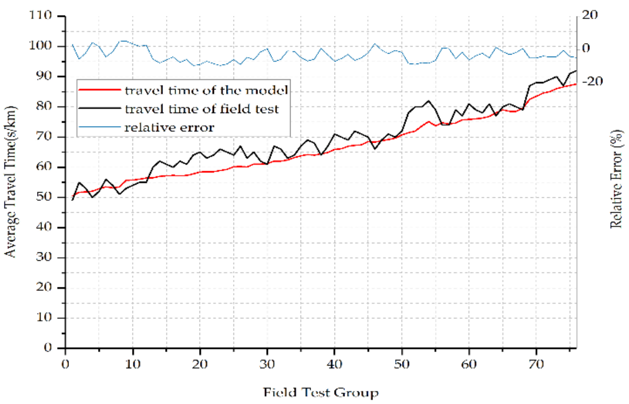


FIGURE 13. Comparison of the model and field data under accidents conditions.

time per unit distance of each experimental freeway segment with changes in the v/C ratio under normal conditions and under accident conditions were calculated and are summarized in Tables 5 and 6. As $|\Delta v/C|$ increases, the rate of change of the average travel time per unit distance increases. The rates of change of average travel time on all three experimental freeway segments under accident conditions were greater than those under normal conditions.

TABLE 5. Rates of change of average travel time per unit distance according to $|\Delta v/C|$ under normal conditions.

|Δv/C|	Rates of Change of Average Travel Time Per Unit Distance / %					
	Two-lane freeway (one direction)		Three-lane freeway (one direction)		Four-lane freeway (one direction)	
	Δv/C > 0	Δv/C < 0	Δv/C > 0	Δv/C > 0	Δv/C < 0	Δv/C > 0
0.05	1.17	1.16	0.55	0.55	0.38	0.38
0.10	3.04	2.95	1.66	1.63	1.23	1.22
0.15	5.33	5.06	3.14	3.05	2.44	2.38
0.20	7.92	7.34	4.95	4.72	3.95	3.80
0.25	10.78	9.73	7.05	6.58	5.75	5.43
0.30	13.86	12.17	9.40	8.59	7.81	7.24
0.35	17.14	14.64	11.99	10.71	10.11	9.18
0.40	20.61	17.09	14.81	12.90	12.66	11.23
0.45	24.25	19.52	17.84	15.14	15.43	13.36
0.50	28.05	21.90	21.07	17.40	18.41	15.55

TABLE 6. Rates of change of average travel time per unit distance according to $|\Delta v/C|$ under accident conditions.

|Δv/C|	Rates of Change of Average Travel Time per unit Distance / %							
	One lane of two lanes blocked		One lane of three lanes blocked		Two lanes of three lanes blocked		Two lanes of four lanes blocked	
	Δv/C > 0	Δv/C < 0	Δv/C > 0	Δv/C < 0	Δv/C > 0	Δv/C < 0	Δv/C > 0	Δv/C < 0
0.05	1.43	1.41	0.65	0.64	0.89	0.88	0.56	0.56
0.10	3.62	3.49	1.91	1.87	2.50	2.44	1.73	1.70
0.15	6.24	5.88	3.58	3.45	4.58	4.38	3.33	3.23
0.20	9.19	8.42	5.60	5.30	7.04	6.57	5.32	5.05
0.25	12.41	11.04	7.92	7.34	9.81	8.94	7.64	7.10
0.30	15.85	13.68	10.51	9.51	12.88	11.41	10.27	9.31
0.35	19.50	16.32	13.36	11.78	16.21	13.95	13.18	11.65
0.40	23.33	18.92	16.44	14.12	19.78	16.52	16.37	14.07
0.45	27.33	21.47	19.74	16.49	23.58	19.08	19.82	16.54
0.50	31.49	23.95	23.26	18.87	27.60	21.63	23.51	19.04

From a practical point of view, if the v/C ratio can be accurately determined, the model developed in this study can be used to calculate the travel time of a specific freeway segment. In some cases, the value of the v/C ratio is not easy to obtain directly, but the magnitude of the change in the v/C ratio can be roughly estimated from historical data or similar road conditions. In this case, ranges of travel time can be estimated quickly and easily, based on the relevant information in Tables 5 and 6. This information can be provided to road users, so that they can adjust their travel arrangements and optimize their travel routes in a timely manner. For example, for a three-lane freeway, according to historical statistics, the v/C ratio during the peak period is 0.35 larger than that during the normal period. Based on Table 5, the average travel time during the peak period will increase by 11.99% compared to the normal period. If drivers plan to pass this freeway segment during the peak rush hour, to ensure their arrival at their destination on time, at least 11.99% more travel time normal period should be reserved. From the perspective of transportation management systems, the ability to predict the impact of road traffic efficiency when commuting and holiday peaks, or traffic accidents occur would be useful in controlling traffic to decrease traffic saturation of freeway segments.

IV. CONCLUSION

This research was conducted to obtain a travel time model, based on the BPR function, for basic freeway segments after incidents. Field testing was conducted to measure traffic volumes, speeds, and travel time under different traffic conditions on a few typical Chinese basic freeway segments under both normal and simulated accident conditions. These field data were used to develop the travel time estimation models under both normal and simulated accident conditions and to obtain the parameters for the models. The versatility and accuracy of the models were also proven using field data and relative errors. If the number of available lanes and v/C ratio can be determined after incidents, the model developed in this research can be used to calculate accurate travel times. Vehicle characteristics and driver behavior have changed considerably in the years since the standard BPR function was introduced; thus, the standard BPR function is based on data that do not reflect today's traffic operating conditions in China. The calibrated BPR function proposed in this research can reflect today's traffic operating conditions more accurately and has good versatility. In addition, this study demonstrates the application of the established travel time estimation model. The v/C ratio variation can be roughly estimated based on historical data and similar road conditions, such that variation within the ranges of travel time can be estimated quickly and easily to guide road users in arranging reasonable travel plans. The results presented here can also be used to support traffic assignment decisions made by a transportation management system.

The results of this study contribute substantially to the ability to estimate travel time on basic freeway segments under both normal and simulated accident conditions. These findings can assist both road users and decision makers in arranging and assigning travel. However, considering that the field experiments did not consider driver behaviors under real accident conditions, the results might represent an underestimation or overestimation within a certain range. Additionally, it should be noted that driving behavior characteristics in highway weaving areas and other special sections such as tunnels and bridges are different from those in basic freeway segments. The travel time estimation model established in this research only applies to basic freeway segments, and its applicability to other types of highways and special sections remains to be verified. Further research is planned to establish a model applicable to a wider range of conditions through field experiments and traffic simulations. However, in this era of big data and artificial intelligence, obtaining real data for these systems has become more feasible. In future work, we will try to obtain an appropriate amount of real incident and traffic flow data to better estimate travel time.

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