ARCHIVES OF TRANSPORT
Volume 69, Issue 1, 2024

ISSN (print): *0866-9546*
e-ISSN (online): *2300-8830*
DOI: *10.61089/aot2024.b2h1zb09*

INFLUENCE OF TRAFFIC FLOW OF ON-RAMPS ON THE MAINLINE SPEED ON FREEWAYS

Han RU[1], Jian LUAN[2], Qingtao DING[3], Jinliang XU[4]

[1, 2, 3] *College of Water Resources and Architectural Engineering, Northwest A&F University, Yangling, China*

[4] *School of Highway, Chang'an University, Xi'an, China*

Abstract:

Vehicles entering from on-ramps can increase the speed dispersion of the mainline and induce frequent changing lanes or acceleration and deceleration behaviors. These complex traffic behaviors interfere with traffic on the mainline and thus result in congestion and safety issues. Reasonable management and control of ramps, especially on-ramps, has been proven to be an effective solution for traffic congestion caused by ramp traffic flow. Understanding the influence of traffic flow of on-ramps on the average speed of the freeway mainline is useful for creating effective ramp management strategies. In this study, field tests were employed to gather traffic flow data on some typical basic freeway interchanges in China. As it is difficult to obtain the required traffic conditions only through field tests, the VISSIM traffic simulation model was also utilized. The same set of field data was used in VISSIM and the driver behavior model parameters CC0 (standstill distance between vehicles) and CC1 (time headway) were calibrated based on the sensitivity analysis to truly reflect the actual traffic conditions. The simulation program was executed with the calibrated parameters and various on-ramp traffic volumes to supplement the traffic data. The gathered traffic data sets from field tests and simulations were classified into four groups based on the various on-ramp traffic flow patterns (free-flow, reasonably free-flow, unstable flow, and congested flow condition). The influence of on-ramp traffic flow on the mainline average speed is discussed for each group. The results showed that the average travel speed of the mainline is significantly affected by the v/C ratio of the on-ramp, as the v/C ratio of the entrance ramp increases, the average travel speed of the mainline significantly decreases. Additionally, the four-parameter logistic model was developed to model the mainline average speed changes with different mainline v/C ratios under various on-ramp traffic flow patterns. The results demonstrate that the model fits the data well. The findings of this study can provide reference information for the implementation of ramp management strategies.

Keywords: *freeway safety, on-ramp influence, travel average speed, VISSIM simulation, logistic model*

To cite this article:

Ru, H., Luan, J., Ding, Q., Xu, J., (2024). Influence of Traffic Flow of On-Ramps on the Mainline Speed on Freeways. Archives of Transport, 69(1), 59-73. https://doi.org/10.61089/aot2024.b2h1zb09.

Contact:
1) hanru@nwafu.edu.cn [https://orcid.org/0000-0003-0426-4778] – corresponding author; 2) jane-l@nwsuaf.edu.cn [https://orcid.org/0009-0005-2377-4126]; 3) dingqingtao98@nwafu.edu.cn [https://orcid.org/0009-0005-8895-4785]; 4) xujinliang@chd.edu.cn [https://orcid.org/0000-0002-5229-9468]

1. Introduction

The phenomenon of frequent traffic congestion and accidents on freeways has become a ubiquitous problem around the world. As an indispensable part of a freeway system, the ramp is a short segment of the freeway connecting two traffic facilities and providing vehicles of two roads with direct conversion. However, a growing body of evidence has shown that compared with other sections of freeways, freeway ramp influence segments contribute to more traffic crashes and traffic jams (Qi et al. 2020, Lyu et al. 2022). All the existing studies acknowledge that slow-speed vehicles entering from on-ramps and deceleration vehicles exiting off-ramps can increase the speed dispersion of the mainline and induce frequent changing lanes or acceleration and deceleration behaviors. These complex traffic behaviors interfere with the traffic on the mainline and thus result in congestion and safety issues (Sun et al. 2014, Cheng et al. 2022). Thus, reasonable management and control of ramps, especially on-ramps, is of critical importance in reducing vehicle crashes and relieving traffic jams. These management strategies can help existing road systems dynamically adapt to increasing demand.

To create effective operational strategies for freeway ramp management, it is essential to understand the influence of ramps on the traffic operation characteristics of freeway mainlines. Interactions are dynamic in freeway ramp influence segments, the operating conditions on the on-ramp can have an impact on the operating conditions on the freeway. Currently, most existing studies on the impact of freeway ramps have primarily focused on traffic flow behavior (Li et al. 2019, Zhang et al. 2023). The traffic flow operation analysis methods can be mainly summarized into regression analysis, theoretical analysis, and traffic simulation (Xu et al. 2020, Bhatt et al. 2022, Wang et al. 2023). The traffic speed of vehicles entering from on-ramps can be much lower than that of the mainline, which could cause drastic speed changes. That hinders the traffic on the highway, and affects the operating conditions on the freeway. Thus, understanding the influence of traffic flow of on-ramps on the operating characteristics of the freeway mainline can provide reference information for the implementation of effective ramp management strategies to relieve traffic congestion and reduce traffic crashes related to ramps.

Therefore, this study aimed to verify the impact of traffic flow of on-ramps on the average travel speed of the mainline on freeways. On a few typical basic freeway interchanges in Chin, field tests were carried out to collect the traffic flow data, including traffic volume, speeds, and vehicle type under various traffic flow patterns. As it is difficult to obtain the required traffic flow patterns only through field testing, the VISSIM traffic simulation model was also utilized to gather the data. The gathered data sets were divided into four groups according to the on-ramp traffic flow patterns (free-flow, reasonably free-flow, unstable flow, and congested flow condition). For each group, the influence of traffic flow of the on-ramp on the average speed of the mainline is discussed. In addition, a four-parameter logistic model was built to model how on-ramp traffic flow affects the average speed of the mainline.

The remaining sections of this manuscript are structured as follows. Section 2 provides a literature review of the existing studies. Section 3 introduces the traffic data collecting methodology used in this study. Section 4, analyzes the results obtained from the field data and simulation data in detail, and develops a four-parameter logistic prediction model. Section 5 summarizes the findings of this study.

2. Literature review

In previous studies, it has been proved that traffic jams and crashes are more likely to occur on ramp-influence segments. Golob et al. (2004) analyzed the accident characteristics of weaving sections using accident data for Orange County in Southern California. Wang et al. (2013) analyzed 2026 traffic crashes in Texas and developed a relationship between crash rates and influencing factors for on-ramp junctions. Qu et al. (2014) assessed the potential crash risks impacted of ramps in various types of locations (before on-ramps, between on-ramps and off-ramps, and after off-ramps) across different traffic lanes. Yang et al. (2019) explored the crash types and factors contributing to crashes on different ramp-influence segments of freeways. Many scholars have finished much valuable work on the safety assessment of the freeway ramp influence segments. Budzynski et al. (2021) used the accident data and data on interchanges on expressways in Poland to build a database to develop a safety evaluation system for interchanges. Owing to insufficient traffic accident data, traffic conflict technology was also

used in safety evaluation models. Qi et al. (2020) analyzed traffic characteristics as well as forecast traffic safety of the merging area using the modified post-encroachment time model. Despite significant progress in accident prevention, traffic safety issues in developing countries continue to be complicated.
Freeway congestion and crashes are mostly attributed to the merging or diverging around on-ramps and off-ramps, where travel speed can be much lower than that on the mainline. Thus, in addition to excessive lane changing or acceleration and deceleration, significant speed fluctuations may result. That impedes the movement of vehicles on the mainline and results in congestion and safety issues. Therefore, reasonable management and control of ramps has been accepted as an effective solution to relieve traffic jams and crashes caused by ramp traffic flow. These management strategies can help existing road systems dynamically adapt to increasing demand. Currently, most studies mainly focus on various control algorithms based on mathematical models for traffic flow (Yu et al. 2015). Many researchers have attempted to apply new techniques to realize more effective management and control of ramps. They include neural network control (Shi et al. 2013), fuzzy control (Liang et al. 2016), and reinforcement learning (Belletti et al. 2018). However, in addition to the abovementioned control algorithms based on mathematical models, understanding the influence of ramps on the traffic operation characteristics of freeway mainlines is essential to create effective operational strategies for freeway ramp management.
In recent, the operation analysis methods of freeway ramp influence segments can be mainly summarized into regression analysis, theoretical analysis, and traffic simulation. Regression analysis relies on field traffic data to conduct statistical analysis and establish the relationships between geometric design factors and performance measures (Xu et al. 2020). Lertworawanich et al. (2003) proposed a method for estimating the capacity for weaving sections based on gap acceptance theory and linear programming technique, while Evans et al. (2001) developed an analytical model for the prediction of breakdown at freeway merges using Markov chains. Mohamed et al. (2020) and Wang et al. (2023) use traffic simulation software, such as VISSIM and AIMSUN to simulate and analyze the operation status of interchanges. In addition, several studies suggest that traffic conditions affect the traffic operation characteristics of freeway ramp influence segments. Daamen et al. (2010) indicated that merging behavior varied under different traffic conditions. It was found that different merge locations were used during free-flow and congestion through analysis of 3459 vehicle trajectories. Shen et al. (2015) demonstrated different types of traffic flows influence the capacity of freeway merge areas. Li et al. (2019) analyzed the merging behavior on the freeway under different traffic densities and concluded that merging location, and merging speed are significantly influenced by traffic densities.
Interactions are dynamic in freeway ramp influence segments, and so the operating conditions on the ramp can have an impact on the operation of the freeway mainline. A variety of research on the influence of ramps is also ongoing. Diedrich et al. (2000) measured the effects of ramps on traffic dynamics in a cellular automaton for traffic flow. Mhirech et al. (2011) analyzed the effect of ramp positions on the traffic flow behavior of a one-dimensional cellular automaton. Tang et al. (2015) used the car-following model to explore the effects of ramps on the fuel consumption of vehicles on the mainline road. Through the analysis of the relationship between the status of traffic operation and traffic safety, Hu et al. (2017) analyzed the impact of on- and off-ramps on the security of the freeway. Despite many researchers having focused on the influence of ramps on the traffic flow behavior of freeways, little research has been carried out on the impact of ramps under various traffic conditions on the travel speed of the freeway mainline.
The traffic speed of vehicles entering from on-ramps can be much lower than that of the mainline, which could cause drastic speed changes. That hinders the traffic on the freeway, and affects the operating conditions on the freeway. According to a study in Northern Virginia, speed is the primary contributor of ramp-related vehicle crashes and traffic jams (Mccartt et al. 2004). Therefore, understanding the influence of traffic flow of on-ramps on the travel speed of the freeway mainline can provide reference information for the implementation of effective ramp management strategies to relieve traffic congestion and reduce traffic crashes related to ramps.

3. Method

As stated above, the objective of this research was to verify the influence of traffic flow of on-ramps on the average speed of the mainline on freeways. According to the actual road traffic, the influence of the entrance ramp under different traffic flow patterns on the speed of the mainstream differs. Therefore, an analysis of the change in the mainline speed with different on-ramp traffic flow patterns is required. Firstly, field tests were designed to collect the raw traffic data at the freeway observation points under different traffic conditions. Secondly, as it is difficult to obtain the required different traffic flow patterns only using field experiments, the VISSIM traffic simulation model was also employed to collect traffic data. There are some basic data about highway geometry, driver behavior, and traffic flow parameters that need to be entered into VISSIM. Figure 1 illustrates the flowchart of field tests and simulations.

3.1. Data collection

3.1.1. Field test

For this study, a large amount of traffic flow data under different traffic flow patterns around the freeway interchange is required. Therefore, field tests were used to collect the raw traffic data of the freeway under different traffic conditions. To make the results general and representative, the study sections should be the typical freeway segments in China. To eliminate the effect of road alignment on the traffic flow speed, the study area should not have mountainous areas, and routes with straight alignments or flat large-radius curves should be selected. In accordance with all the above requirements, road sections K449+100-K451+900 of a four-lane freeway G5 and K1029+800-K1031+900 of a four-lane freeway G30 were chosen as the study areas, as shown in Figure 2. The road section K449+100-K451+900 is a mainline section near the entrance ramp of Baqiao Interchange on the freeway G5. The road section K1029+800-K1031+900 is a mainline section near the entrance ramp of Hechizhai Interchange on the freeway G30.

The selected two road segments (G5 and G30) are both typical four-lane freeway segments in China, and there is a two-lane on-ramp on both selected road segments. The lane width of both the mainline and ramp is 3.75 meters. On the mainline sections of G5 and G30, the design speed is 120 km/h, and on the on-ramp sections of G5 and G30, the design speed is 60 km/h. The greatest longitudinal slope in the two study sections is between -1.5% and 1.5%. Based on the statistical data from nearby toll stations, it was found that the proportion of trucks during the experiment period was roughly 14%, with a variable range of no more than 2% in the two study sections.
The Traffic Engineering Handbook in China has shown that the operational effect of merging vehicles is heaviest in segments for a distance extending from the physical merge point to 760 m downstream and 150 m upstream. The study sites on the mainline were set outside the merge influence area. There are two study sites and one study site on each main road and each ramp, respectively. Figure 3 shows the details of the study areas. During the experiment, traffic flow data such as traffic volumes, instantaneous speed, and vehicle type were collected by using the AXLELIGHT Roadside Laser Vehicle Classification System. The device can automatically gather traffic flow data to assess traffic characteristics. Additionally, this instrument can be positioned on the farthest edge of the hard shoulder, where the driver generally does not pay attention, minimizing its impact on the driving behavior.

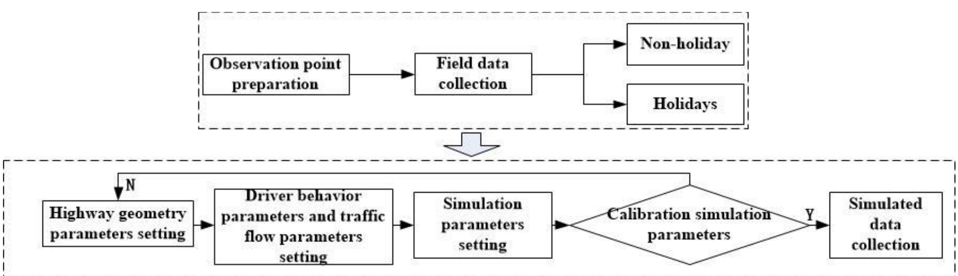


Fig. 1. Research flowchart

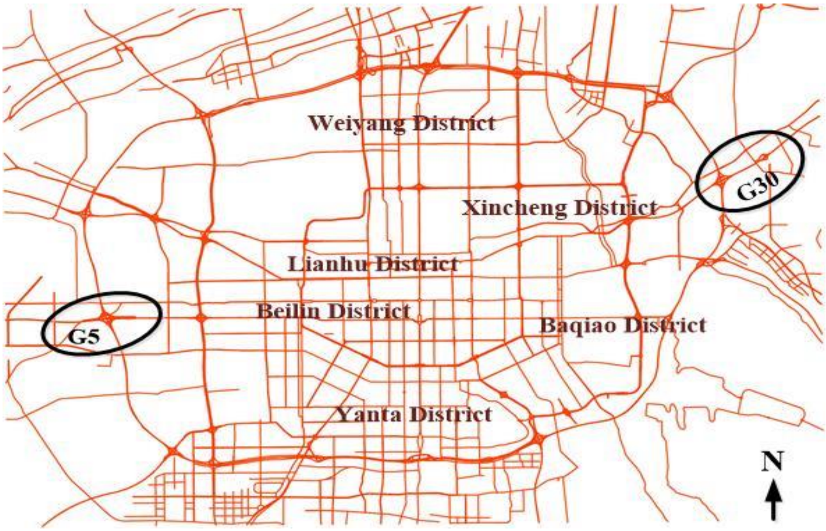


Fig. 2. Xi'an metropolitan area highway network and the study areas

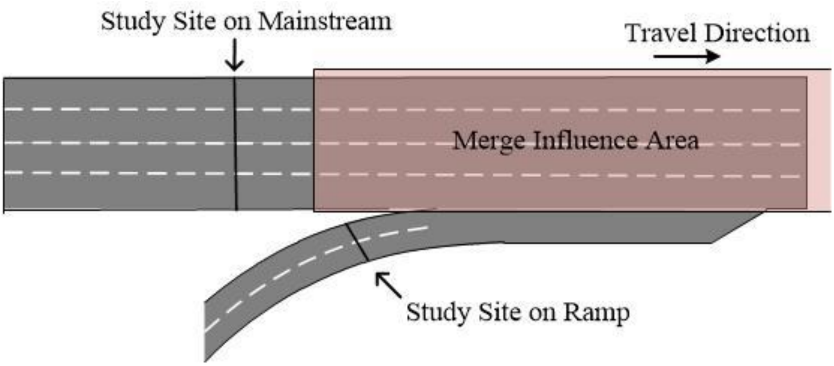


Fig. 3. Schematic map of study sites

The freeway does not have stable morning and evening peak periods, and there are obvious traffic fluctuations both on holidays and non-holidays. A non-holiday is usually a good time to observe traffic in low and medium-density conditions, whereas a holiday is a good observation time for high and congested traffic flows. To obtain a large amount of traffic data, the data were collected during a non-holiday period (April 4th to 7th, 2019) and during holidays (International Labor Day, May 1st to 4th, 2019, and Mid-Autumn Festival, September 13th to 15th, 2019). Sunny days without any rain or snow were chosen to remove variations in traffic flow data caused by adverse weather conditions. In this study, more than 60,000 raw data points were obtained.

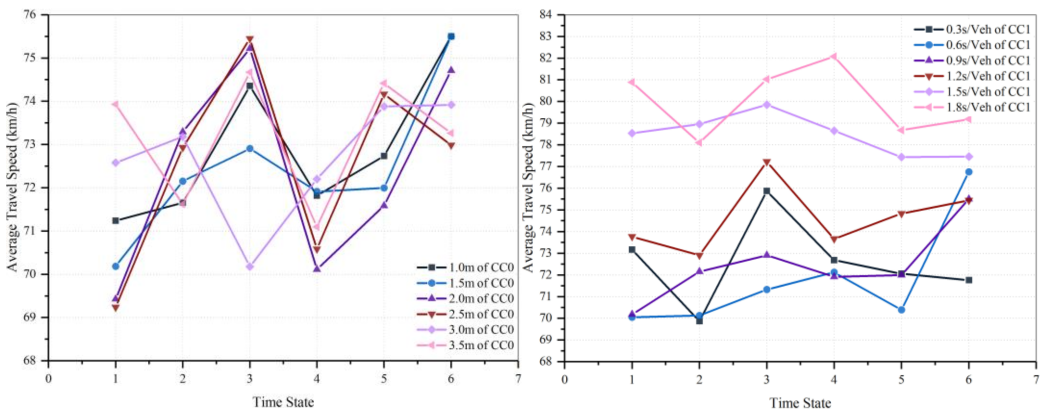
3.1.2.Simulation using VISSIM

As mentioned earlier, as it is difficult to obtain the required traffic flow patterns only through field experiments, the VISSIM traffic simulation model was also utilized. VISSIM is a microscopic simulation tool developed from an amount of real traffic flow data and is used to model complex traffic operations and estimate traffic parameters. The VISSIM simulation model was used in this study to simulate the traffic flow of the mainstream when the on-ramp is

under congestion flow conditions. To achieve realistic simulations and enable comparison, the VISSIM model was created using the results of the G30 freeway interchange field experiments. The basic data about highway geometry, traffic flow, traffic composition, and driver behavior models that need to be entered into VISSIM were developed, and the parameters of each model were reset and corrected.
The geographical map of the study area of the experimental freeway was imported into VISSIM, and the freeway geometry details, such as the number of lanes, lane width, adjacent exit, and entrance distance of the freeway interchange were assigned as observed in the field, as shown in Figure 4. Traffic volume and traffic composition were kept the same as observed in the field. The speed distribution diagram for passenger cars and heavy vehicles studied in the field was used as the basis for setting the desired vehicle speed in the model.

VISSIM performs trajectory-based network simulation that utilizes a psycho-physical driver behavior model developed by Wiedemann. As this study focused on the freeway interchange, the Wiedemann 99 model, which is a psychophysical driver behavior model of a freeway or suburban roadway, was used. Ten different parameters related to driver behavior are available in the Wiedemann 99 model, labeled from CC0 to CC9 with their default values. To check the sensitivity of these parameters on simulated results, the simulation was performed with varying values of these ten parameters in this study and the average travel speed of the section was evaluated. The results of the sensitivity analysis showed that two parameters, CC0 and CC1, had the most significant influence on driving speed. The effect of the two parameters on simulated driving speed is shown in Figure 5.

Fig. 4. Simulation 3D rendering in VISSIM



(a) (b)

Fig. 5. Effect of parameters CC0 and CC1 on simulated driving speed

Parameter CC0 represents the standstill distance (m) between vehicles and CC1 is the time headway (s) that it is desirable for a driver should maintain at a certain traffic volume level. Therefore, the present study focused on the calibration of these two parameters, and the other parameters of the driver model were set to the system default values.
The value ranges for the selected two parameters were chosen and all possible combinations and speeds were obtained from the simulation program. To find a good solution for the combinational parametric optimization problem, an objective function was established based on the similarity between v_s (the speed from the simulation program) and v_m (the speed observed in the field).

$$s = \left|1 - \frac{v_s}{v_m}\right| \tag{1}$$

The results showed that the objective function s has the minimum value when the prepositional parameters combination of CC0 and CC1 is 1.5 (m) and 1.2 (s/veh), respectively. The VISSIM run for these values given as inputs to the driver behavior model could replicate the field traffic flow satisfactorily. Therefore, in this study, a value of 1.5 (m) was taken for CC0 and a corresponding value for CC1 of 1.2 (s/veh). VISSIM was run with these values given as input parameters, and the simulated speed and traffic volume of the study sections were compared with the observed data. The results of t-tests showed that the difference in the simulated data and the actual data was not significant at the 95% level. This indicated that the simulation model satisfied the calibration requirements.

3.2. Division of Traffic Flow Patterns

Traffic flow patterns affect the vehicle operating conditions of individual vehicles. Vehicle speeds are often highly reliant on traffic flow, excluding variations in road geometry, road surface conditions, and weather conditions (Wang et al. 2016). As the speed of the mainline varies to the entrance ramp and mainstream traffic flow patterns, a large amount of traffic flow data corresponding to various traffic flow patterns is required to ensure the integrity of the test data. Traffic flow patterns can be typically categorized by service level (Manual 2000). The traffic volume to freeway capacity (v/C ratio) was employed as an indicator of the service level of the road in accordance with the "Technical Standard of Highway Engineering" in China, as indicated in Table 1. There are several different service levels, from 1 ("free-flow") to 6 ("most congested"). The Highway Capacity Manual (HCM) published in the US uses traffic density as an indicator of the service level and defines six different service levels represented by letters A to F, which are equivalent to Chinese highway service levels 1 through 6.
According to the road service levels of freeways in China, with the v/C ratio as the evaluation index, four traffic flow patterns can be defined as illustrated in Table 2. The free-flow condition corresponds to the Grade-1 service level. The reasonably free-flow condition, where the consequences of slight disruption are easily absorbed, is represented by the Grade-2 service level. Grade-3 and grade-4 service levels relate to the unstable flow condition, where vehicles interfere with each other, and minor incidents can be expected to create queues. The congestion flow condition corresponds to the Grade-5 and grade-6 service levels. To acquire traffic flow data for this manuscript, tests were repeated under different traffic flow patterns (free-flow, reasonably free-flow, unstable flow, and congested flow condition) of the entrance ramp and mainline throughout both holiday and non-holiday times.

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	$v/C \leq 0.35$	750	730	700
2	$0.35 < v/C \leq 0.55$	1200	1150	1100
3	$0.55 < v/C \leq 0.75$	1650	1600	1500
4	$0.75 < v/C \leq 0.90$	1980	1850	1800
5	$0.90 < v/C \leq 1.00$	2200	2100	2000
6	$v/C > 1.00$	0-2200	0-2100	0-2000

Table 2. Correspondence between the v/C ratio and traffic flow patterns.

v/C ratio	Traffic Flow Patterns
$v/C \leq 0.35$	free-flow condition
$0.35 < v/C \leq 0.55$	reasonably free-flow condition
$0.55 < v/C \leq 0.9$	unstable flow condition
$v/C > 0.9$	congestion flow condition.

4. 4. Results

4.1. Statistical Results

As mentioned above, tests were repeated under different traffic flow patterns of the on-ramp and mainline to gather traffic flow data, and more than 60,000 raw data points were collected. Throughout the experiment period, the v/C ratios of the on-ramp ranged between 0.1 and 0.9, corresponding to free-flow, reasonably free-flow, and unstable flow conditions of the on-ramp. The v/C ratios of the mainline were mostly concentrated in the range of 0.1–1.1, corresponding to free-flow, reasonably free-flow, unstable flow, and congested flow conditions of the mainline.

Due to real-time traffic flow data of the entrance ramp under congestion conditions being difficult to obtain, the VISSIM microscopic simulation model was employed to collect the traffic flow data when the on-ramp is under congestion flow conditions. A simulation program of the four-lane freeway interchange G30 was executed with combinations of different on-ramp traffic volumes (from 3150 vph to 3850 vph) and different mainstream traffic volumes (from 700 vph to 7700 vph). The v/C ratios of the on-ramp ranged between 0.9 and 1.1, and the v/C ratios of the mainstream ranged between 0.1 and 1.1

This section analyzes and discusses the key statistical findings that were acquired from the field data and simulated data to understand the impact of the on-ramp traffic flow on the mainline speed. The data consisted of 10-minute aggregated data. By grouping the raw data, the traffic volume and average traffic speed were calculated. For each data set, the v/C ratios of the on-ramp and mainline, and the average speed of the mainstream were determined. The collected data were then used to analyze the change in mainline speed with different on-ramp and mainline traffic flow patterns for the purpose of this article. Figure 6 shows a scatter plot of the variations in the mainline average speed with different mainline v/C ratios under various on-ramp traffic flow patterns (free-flow, reasonably free-flow, unstable flow, and congested flow condition).

From Figure 6, in general, the data analysis showed some similarities in how changes in the mainline average travel speed with different v/C ratios of mainstream under different traffic flow patterns of the on-ramp. Regardless of the traffic flow patterns of the on-ramp, the average speed of the mainline first initially decreased gradually from an upper asymptote as v/C ratios values of the mainstream increased, sharply decreased in the middle, and then leveled off at a lower asymptote after a certain decrease.

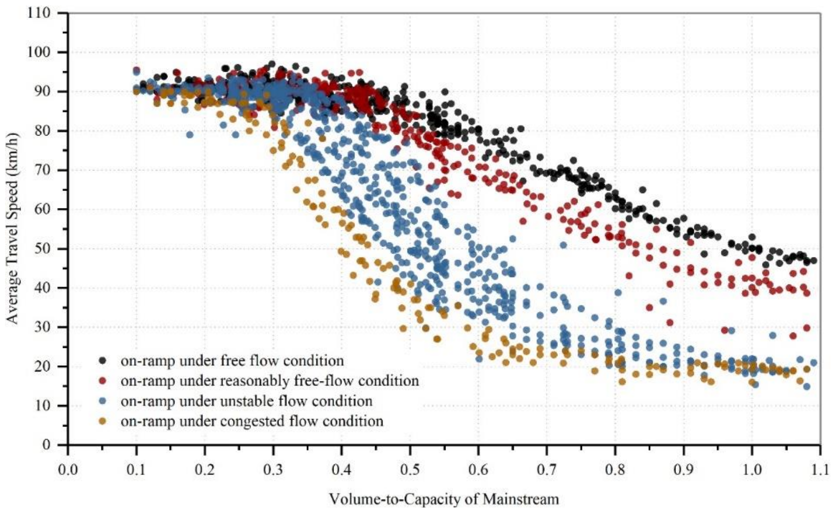


Fig. 6. Statistical results obtained from field test data and simulation data

On the whole, when the v/C ratio of the mainstream is less than 0.35, vehicle driving is not affected by other vehicles. In this case, as the v/C ratio of the mainstream increases, the average speed of the mainline decreases slowly. When the v/C ratio of the mainstream is in the range of 0.35-0.9, vehicles affect each other, and the speed of the vehicle is greatly affected by uncertainty. Under these circumstances, a slight fluctuation in the traffic volume of the mainstream will cause changes in the speed, so as the v/C ratio of the mainstream increases, the average speed of the mainline sharply decreases. When the v/C ratio of the mainstream is greater than 0.9, vehicle velocity has been reduced to a certain value and variations from "stop-and-go" waves, so as the v/C ratio of the mainstream increases, the average speed of the mainline decreases slowly.
In addition, it can be seen from Figure 6, that with a fixed mainstream volume-to-capacity ratio, the influence of different traffic flow patterns of the entrance ramp on the average travel speed of the mainstream also differs. When the traffic flow of the on-ramp is under congestion flow condition, the decrease in average travel speed is largest, and then followed by the decreases when the traffic flow of the entrance ramp is under unstable flow condition, reasonably free-flow condition, and free flow condition. Based on the observation, with a fixed mainstream v/C ratio, a high value for the on-ramp v/C ratio results in a low value for the average travel speed of the mainline. In other words, the speed of the mainline is significantly affected by the v/C ratio of the on-ramp, as the v/C ratio of the entrance ramp increases, the average travel speed of the mainline significantly decreases.

4.2. Data Model

The generalized logistic curve was first developed to model population growth (Marchetti et al. 1996). This function has been extensively employed in simulation studies of plant growth in agriculture (Proctor 2010), epidemic growth in biology (Chen et al. 2005), and market growth in economics (Qu et al. 2016). The logistic growth curve, which has been used to represent functions that initially increased gradually from an upper asymptote, then displayed rapid growth in the middle section, slowly increased at the end, and leveled off at a lower asymptote after a certain increase, is a "S-shaped" curve (sigmoidal shape curve).

Similar adjustments can be made to this curve to model a reversing trend. This reverse curve has a reversed 'S' shape that progressively declines from an upper asymptote at the beginning, decreases quickly in the middle, and then steadily decreases to a lower asymptote that levels off at a specific minimum value. Because of its graceful "S-shaped" mathematical form, adjustable parameters, and ability to adapt to various numerical fittings, this type of curve has been frequently applied. The four-parameter logistic is a very flexible model for data following a sigmoidal-shaped curve. The function of the four-parameter logistic model is as follows:

$$\mathrm{y(x)} = \mathrm{f}(\mathrm{x}; \mathbf{p}) = f(x; a, b, c, d) = d + \frac{(a-d)}{1+\left(\frac{x}{c}\right)^{b}} \qquad (2)$$

where, $\mathbf{p}$ = [a, b, c, d] is the parameter vector of the logistic model. The domain of the parameters is restriction c > 0. As observed in the equation, this logistic model has four parameters, and each parameter has a different impact on the function. Parameter a is the upper asymptote, which controls the position of the top asymptote. Parameter b controls the slope of the curve. Parameter c is the inflection point, which is defined as the point on the curve where the curvature changes direction. Parameter d is the lower asymptote and controls the position of the bottom asymptote.
As stated in Section 3.1, according to the results of the field test and simulation, regardless of the traffic flow patterns of the on-ramp, observation scatter plots of the average travel speed of the mainstream changes with different v/C ratios of mainstream exhibit a reversed 'S' shape. Moreover, with a fixed mainstream volume-to-capacity ratio, a high value of v/C ratio of on-ramp results in a low value of the average travel speed of the mainline. To find the exact relationship between the traffic flow of on-ramps and the mainline speed, the trend line must be fitted through the scatter plot. Therefore, it is important to choose a mathematical function that accurately approximates the underlying curve. This approximating function is called a curve model. The ideal curve model can possess the following qualities: (1) it statistically agrees with the trend line of the empirical observation, (2) it includes exact and obvious physical meaningful parameters, and (3) it has a straight-

forward functional structure. The four-parameter logistic model therefore effectively satisfies the specifications.
By observing traffic flow, some of the parameters in the logistic model can be given specific physical meanings, which have been applied in transportation to solve macroscopic traffic flow problems (Wang et al. 2011, Liu et al. 2019). The physical interpretation of some of the parameters is shown in Table 3.
As Table 3 summarizes, v_f and v_b are the upper and lower asymptotes respectively, and the values of v_f and v_b can be obtained from observation of traffic flow. Parameters b and c are typically represented as dimensionless constants to control the shape of the curve, and the values of these constants can be constrained using statistical data. Specific to this study, parameter c designates the point at which the average travel speed abruptly changes. According to the observation in Section 3.1, parameter c can be concluded to be directly related to the traffic conditions of the on-ramp, and this parameter could be given physical meaning as the v/C ratio of the on-ramp. Thus, c $=f_1$ (v/C_r) could be used to compute the parameter c. Then, the four-parameter logistic model can then be used to determine the average travel speed of the mainline as follows:

$$V_{up} = f\left(\mathrm{v}/\mathrm{C}; \mathrm{v}_f, b, f_1\ (v/C_r), \mathrm{v}_b\right) = \\ = \mathrm{v}_b + \frac{(\mathrm{v}_f - \mathrm{v}_b)}{1+\left(\frac{\mathrm{v}/\mathrm{C}}{f_1\,(v/C_r)}\right)^b} \tag{3}$$

where, v_{up} is the average travel speed of the mainline under a v/C_r condition. v/C is the volume-to-capacity ratio of the mainstream. v/C_r is the volume-to-capacity ratio of the entrance ramp. v_f is the free-flow speed of the mainstream. v_b is the average travel speed under congested conditions of the mainstream. Taking "Δ $v/C_r = 0.1$" as the step size, the statistical data were divided into 11 groups ($v/C_r = 0.1$, $v/C_r = 0.2$, $v/C_r = 0.3$, $v/C_r = 0.4$, $v/C_r = 0.5$, $v/C_r = 0.6$, $v/C_r = 0.7$, $v/C_r = 0.8$, $v/C_r = 0.9$, $v/C_r = 1.0$, $v/C_r = 1.1$). The above-mentioned four-parameter logistic model was selected as the fitting function, the statistical data and plot of the model are depicted in Figure 7.

Table 3. Physical meanings of two parameters

Original parameter	New notation	Physical meaning	Unit
a	v_f	Free-flow speed of mainstream	km/h
d	v_b	Average travel speed under congested conditions of mainstream	km/h

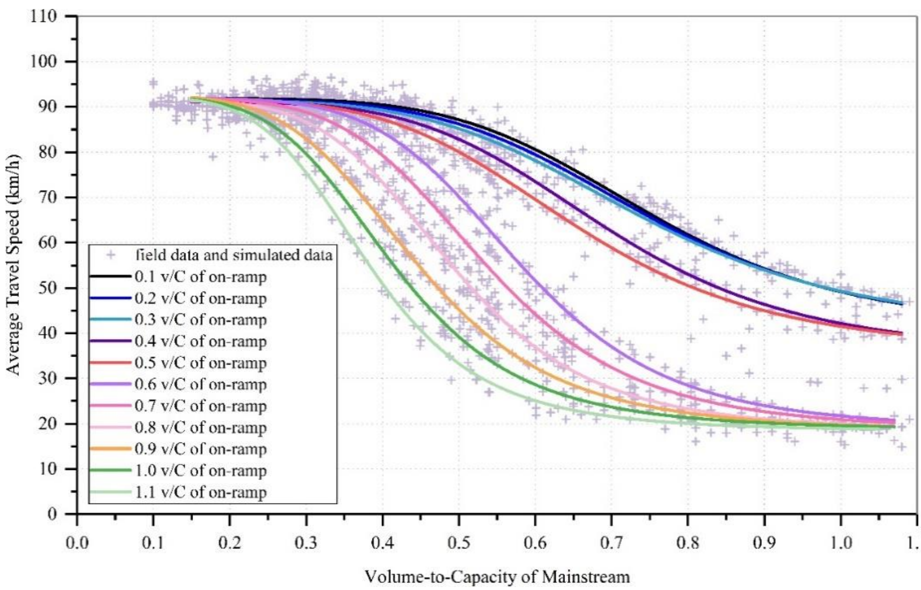


Fig. 7. Fitting results of different groups

As the figure shows the logistic model curve describes the data well. The values of v_f and v_b for the different groups were obtained by empirical observation, and the best values of b and c for the different groups were found by fitting method, they are given in Table 4.

Using the best values of the on-ramp volume-to-capacity ratio coefficient c =f_1 (v/C_r), the relationship between c and v/C_r could be determined using a linear model. The result of linear regression is presented in Figure 8. It provides a good fit (R^2) to the data (R^2 = 0.984 and adj R^2 = 0.982).

With the above results, the model of the impact of the on-ramp on the average travel speed of the mainstream could be developed, and the model equation is given below:

$$V_{up} = \mathrm{v}_b + \frac{(\mathrm{v}_f - \mathrm{v}_b)}{1+\left(\frac{v/C}{0.835-0.418*v/C_r}\right)^b} \tag{4}$$

The value of parameter b under different v/C_r conditions is summarized in Table 5.

Table 4. Values of parameters in the model

v/C_r (volume-to-capacity ratio of the on-ramp)	v_f (km/h)	v_b (km/h)	Best b	Best c
0.1	91	44	5.435	0.763
0.2	91	44	5.435	0.746
0.3	91	44	5.435	0.724
0.4	91	36	5.267	0.694
0.5	91	36	5.267	0.654
0.6	91	18	5.069	0.579
0.7	91	18	5.069	0.535
0.8	91	18	5.069	0.491
0.9	91	18	5.069	0.445
1.0	91	18	5.069	0.413
1.1	91	18	5.069	0.382

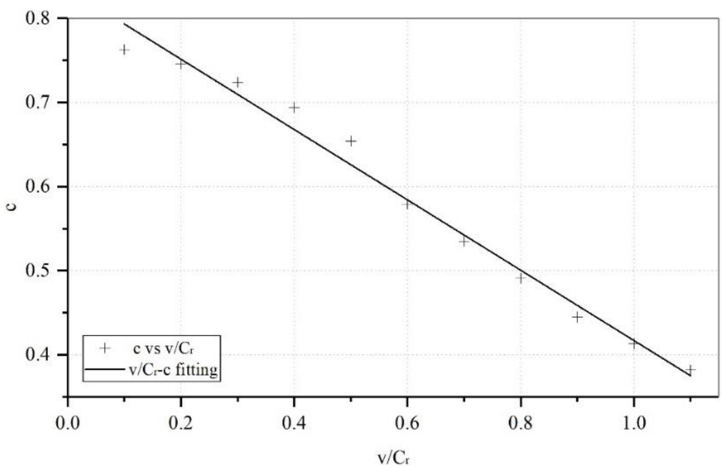


Fig. 8. Linear regression of c= f1 (v/C r)

Table 5. Values of the parameter b

Traffic Flow Patterns of the on-ramp	v/C_r ratio	b
free-flow condition	[0.1, 0.3]	5.435
reasonably free-flow condition	(0.3, 0.5]	5.267
unstable flow and congestion flow condition	(0.5, 1.1]	5.069

4.3. Model Verification

The model can be used to determine the average speed of the mainline under various on-ramp traffic flow patterns. However, the model was developed using statistical information obtained from the G5 and G30 freeways. Therefore, it is necessary to confirm the versatility and accuracy of the model. Furthermore, data from another freeway must be gathered to confirm the model's accuracy.

The data that were gathered from a part of the three-lane freeway G65 interchange with a one-lane on-ramp were utilized to validate the model. Throughout the experiment period, the traffic flow of the entrance ramp was under free-flow conditions, and the v/C ratios of the mainstream were mostly concentrated in the range of 0.1 and 1.0. The model is directly related to the traffic flow of the on-ramp, data with a volume-to-capacity ratio of the on-ramp of 0.2 were chosen to verify the mode (i.e., $v/C_r = 0.2$). According to the field observation, $v_f = 81$ km/h, $v_b = 40$ km/h. According to Table 5, b = 5.435. The field data and plot of the model are depicted in Figure 9.

As can be seen in Figure 9, the model fits the field data from the freeway G65 well. To evaluate the model accuracy, the mainstream speed values calculated by the model were compared with the field data, shown in Figure 10. The relative error of the model was below 10%, which suggested that the model accuracy achieved in this study met the requirements.

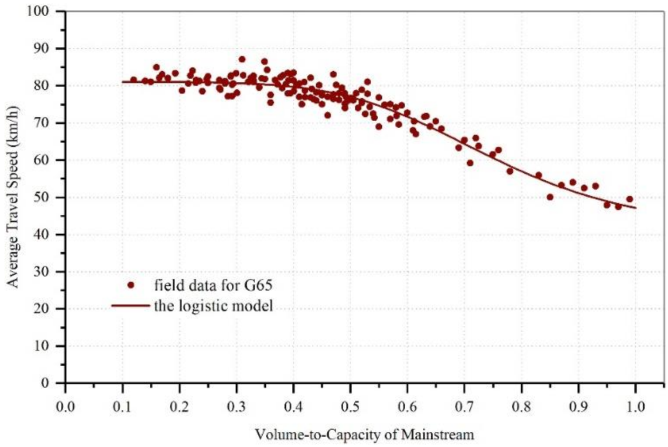


Fig. 9. Field data and plot of the model on G65

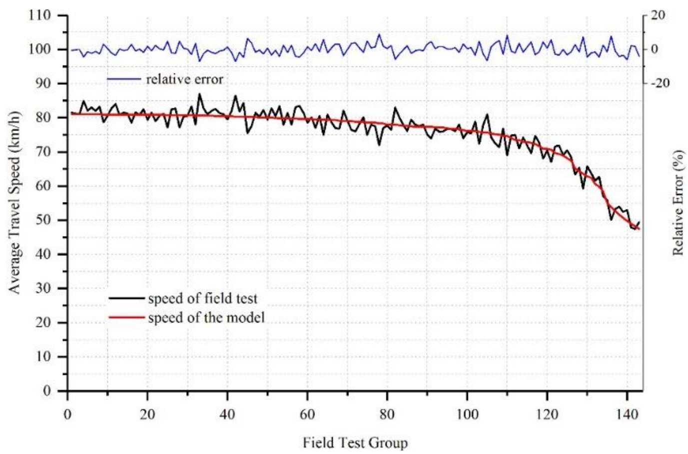


Fig. 10. Comparison of the model and field data

5. Discussion and Conclusions

Interactions are dynamic in freeway ramp influence segments, the operation of the on-ramp can have an impact on the operating conditions on the freeway (Hu et al. 2017, Li et al. 2019). This study was conducted to understand the impact of traffic flow of on-ramps on the speed of the mainline on freeways. Field experiments were conducted to collect traffic data under various traffic flow patterns on some typical Chinese basic freeway interchanges. The VISSIM simulation model was also used to generate traffic flow patterns that were difficult to obtain in the field. Driver behavior parameters CC0 to CC9 were tested by sensitivity analysis of the traffic data obtained from the VISSIM simulations, and the result showed that two parameters, CC0 and CC1, had the most significant influence on simulated results. This finding is consistent with earlier studies (Chandra et al. 2016, Srikanth et al. 2022). Therefore, parameters CC0 and CC1 were calibrated to truly reflect the Chinese actual traffic conditions in this study.

The traffic speed of vehicles entering from on-ramps can be much lower than that of the mainline, which could cause drastic speed changes (Cheng et al. 2022). The obtained data both from field tests and simulations were used to analyze the change of mainline speed with different mainline v/C ratios under various on-ramp traffic conditions. The results showed that observation scatter plots of the speed of the mainstream changes with different v/C ratios of mainstream exhibit a reversed 'S' shape. Moreover, with a fixed mainstream volume-to-capacity ratio, a high value of v/C ratio of on-ramp results in a low value of the average travel speed of the mainline. In other words, the speed of the mainline is significantly affected by the traffic flow of the on-ramp, as the traffic flow of the entrance ramp increases, the speed of the mainline significantly decreases.

The logistic model has been applied in transportation, and the parameters in the model can be given specific physical meanings by observing traffic flow (Wang et al. 2011, Liu et al. 2019). To find the exact relationship between the traffic flow of on-ramps and the mainline speed, the four-parameter logistic model was developed to model the impact of the traffic flow of on-ramps on the mainline speed under different traffic flow patterns. The physical meanings and values of all the parameters in the model were determined, and the versatility and accuracy were also proven using field data and relative errors. The model developed in this research can provide reference information for the implementation of ramp management strategies. If the v/C ratio of the on-ramp and mainstream can be determined, the model can be used to predict the mainstream average speed. However, considering that the traffic data were collected on some typical Chinese basic freeway interchanges, whether this model is suitable for other highway grades will need to be considered in future research.

Acknowledgements

The study funded by the Natural Science Basic Research Program of Shaanxi (Program No. 2023-JC-QN-0790), and the Chinese Universities Scientific Fund (No. 2452020238).

References

[1] Belletti, F., Haziza, D., Gomes, G., & Bayen, A. (2018). Expert Level Control of Ramp Metering Based on Multi-task Deep Reinforcement Learning. IEEE *Transactions on Intelligent Transportation Systems*, 19, 1198-1207. http://dx.doi.org/10.1109/TITS.2017.2725912.

[2] Bhatt, K., & Shah, J. (2022). An Impact of Gap Acceptance on Road Safety: A Critical Systematic Review. *Journal of Sustainable Development of Transport and Logistics*, 7(1), 6–22. https://doi.org/10.14254/jsdtl.2022.7-1.1.

[3] Budzynski, M., Tubis, A., & Rydlewski, M. (2021). Preliminary Safety Assessment of Polish Interchanges. *Archives of Transport*, 58(2), 99-113. https://doi.org/10.5604/01.3001.0014.8969.

[4] Chandra, S., Mehar, A., & Velmurugan, S. (2016). Effect of Traffic Composition on Capacity of Multilane Highways. *KSCE Journal of Civil Engineering*, 20, 2033-2040. https://doi.org/10.1007/s12205-015-0479-9.

[5] Chen, W., & Bokka, S. (2005) Stochastic Modeling of Nonlinear Epidemiology. *Journal of Theoretical Biology*, 234(4), 455-470. https://doi.org/10.1016/j.jtbi.2004.11.033.

[6] Cheng, M., Zhang, C., Jin, H., Wang, Z., & Yang, X. (2022). Adaptive Coordinated Variable Speed Limit between Highway Mainline and On-Ramp with Deep Reinforcement Learning. *Journal of Advanced Transportation*, 2022(2435643), 1-16. https://doi.org/10.1155/2022/2435643.

[7] Daamen, W., Loot, M., & Hoogendoorn, S. (2010). Empirical Analysis of Merging Behavior at Freeway On-ramp. *Transportation Research Record Journal of the Transportation Research Board*, 2188(2188), 108-118. https://doi.org/10.3141/2188-12.

[8] Diedrich, G., Santen, L., Schadschneider, A., & Zittartz, J. (2000). Effects of On- and Off-Ramps in Cellular Automata Models for Traffic Flow. *International Journal of Modern Physics C*, 11(02), 335-3450. https://doi.org/10.1142/S0129183100000316.

[9] Evans, L., Elefteriadou, L., & Gautam, N. (2001). Probability of Breakdown at Freeway Merges Using Markov Chains. *Transportation Research Part B: Methodological*, 35(3), 237-254. https://doi.org/10.1016/S0191-2615(99)00049-1.

[10] Golob, F., Recker, W., & Alvarez, M. (2004) Safety Aspects of Freeway Weaving Sections. *Transportation Research Part A Policy & Practice*, 38(1), 35-51. http://dx.doi.org/10.1016/j.tra.2003.08.001.

[11] Hu, J., Li, F., Han, B., & Yao, J. (2017). Analysis of the Influence on Expressway Safety of Ramps. *Archives of Transport*, 43(3), 43-51. https://doi.org/10.5604/01.3001.0010.4226.

[12] Lertworawanich, P., & Elefteriadou, L. (2003). A Methodology for Estimating Capacity at Ramp Weaves Based on Gap Acceptance and Linear Optimization. *Transportation Research Part B*, 37(5), 459-483. https://doi.org/10.1016/S0191-2615(02)00024-3.

[13] Li, G., & Cheng, J. (2019). Exploring the Effects of Traffic Density on Merging Behavior. *IEEE Access*, 7, 51608-51619. https://doi.org/10.1109/ACCESS.2019.2911302.

[14] Liang, X., Lu, Q., Lin, P., & Xu, J. (2016). Freeway Ramp Metering using Fuzzy Logic and Genetic Proportional Plus Integral Control. *International Journal of Control and Automation*, 9(11), 61-76. http://dx.doi.org/ 10.14257/ijca.2016.9.11.06.

[15] Liu, X., Xu, J., Li, M., Wei, L., & Ru, H. (2019). General-Logistic-Based Speed-Density Relationship Model Incorporating the Effect of Heavy Vehicles. Mathematical Problems in Engineering. 2019(6039846), 1-10. https://doi.org/10.1155/2019/6039846.

[16] Lyu, N., Wen, J., & Hao, W. (2022). Lane-Level Regional Risk Prediction of Mainline at Freeway Diverge Area. *International Journal of Environmental Research and Public Health*, 19(10), 5867. https://doi.org/10.3390/ijerph19105867.

[17] Manual, H.C., (2000). Highway Capacity Manual, Transportation Research Board, Washington, DC, fourth edition Edition, ISBN 0-309-06681-6.

[18] Marchetti, C., Meyer, P., & Ausubel, J. (1996). Human population dynamics revisited with the logistic model: how much can be modeled and predicted? Technological Forecasting & Social Change, 52(1), 1–30. https://doi.org/10.1007/BF02438865.

[19] Mccartt, A., Northrup, V., & Retting, R. (2004). Types and Characteristics of Ramp-Related Motor Vehicle Crashes on Urban Interstate Roadways in Northern Virginia. *Journal of Safety Research*, 35(1), 107-114. http://dx.doi.org/10.1016/j.jsr.2003.09.019.

[20] Mhirech, A., Ez-Zahraouy, H., & Ismaili, A. (2011). The Effect of On- and Off-Ramps Positions on the Traffic Flow Behavior, Canadian Journal of Physics, 87(2), 105-110. https://doi.org/10.48550/arXiv.physics/0612255.

[21] Mohamed, A., Ci, Y., & Tan, Y. (2020). A Novel Methodology for Estimating the Capacity and Level of Service for The New Mega Elliptical Roundabout Intersection. *Journal of Advanced Transportation*, 8467152, 1-18. https://doi.org/10.1155/2020/8467152.

[22] Proctor, M. (2010). Recovery Rates of Chlorophyll-Fluorescence Parameters in Desiccation-Tolerant Plants: Fitted Logistic Curves as A Versatile and Robust Source of Comparative Data. *Plant Growth Regulation*, 62(3):233-240. https://doi.org/10.1007/s10725-010-9456-y.

[23] Qi, W., Wang, W., Shen, B., & Wu, J. (2020). A Modified Post Encroachment Time Model of Urban Road Merging Area Based on Lane-change Characteristics. *IEEE Access*, 8, 72835-72846. https://doi.org/10.1109/ACCESS.2020.2987959.

[24] Qu, H., Chen, W., Niu, M., & Li, X. (2016). Forecasting Realized Volatility in Electricity Markets Using Logistic Smooth Transition Heterogeneous Autoregressive Models. *Energy Economics*, 54, 68-76. https://doi.org/10.1016/j.eneco.2015.12.001.
[25] Qu, X., Yang, Y., Liu, Z., & Jin, S. (2014) Potential Crash Risks of Expressway On-Ramps and Off-Ramps: A Case Study in Beijing, China. *Safety Science*, 70, 58-62. https://doi.org/10.1016/j.ssci.2014.04.016.
[26] Shen, J., Li, W., Qiu, F., & Zheng, S. (2015). Capacity of Freeway Merge Areas with Different On-Ramp Traffic Flow. *Promet-Traffic-Traffico*, 27(3), 227-35. https://doi.org/10.7307/ptt.v27i3.1566.
[27] Srikanth, S., & Mehar, A. (2022). Development of Lane Change Models Through Microscopic Simulation under Mixed Traffic. *Jurnal Teknologi*, 84(4), 21-27. https://doi.org/10.11113/jurnal-teknologi.v84.18074.
[28] Sun, J., Zhao, L., & Zhang, H. (2014). Mechanism of Early-onset Breakdown at Shanghai's Expressway On-ramp Bottlenecks. *Transportation Research Record Journal of the Transportation Research Board*, 2421, 64-73. https://doi.org10.3141/2421-08.
[29] Tang, T., Li, J., Yang, S., & Shang, H. (2015). Effects of On-Ramp on the Fuel Consumption of the Vehicles on the Main Road under Car-Following Model. *Physica A: Statistical Mechanics and its Applications,* 419, 293-300. http://dx.doi.org/10.1016/j.physa.2014.10.051.
[30] Wang, D., Fu, F., Luo, X., Jin, S., & Ma, D. (2016). Travel Time Estimation Method for Urban Road Based on Traffic Stream Directions. *Transportmetrica A: Transport Science*, 12, 479-503. https://doi.org/10.1080/23249935.2016.1151964.
[31] Wang, H., Li, J., Chen, Q., & Ni, D. (2011). Logistic Modeling of the Equilibrium Speed-Density Relationship. *Transportation Research Part A*, 45(6), 554–566. https://doi.org/10.1016/j.tra.2011.03.010.
[32] Wang, Y., & Cheu, R. (2013) Safety Impacts of Auxiliary Lanes at Isolated Freeway On-Ramp Junctions. *Journal of Transportation Safety & Security*, 5(4), 327-343. http://dx.doi.org/10.1080/19439962.2012.761661.
[33] Wang, Y., Wang, L., Yu, X., & Guo, J. (2023). Capacity Drop at Freeway Ramp Merges with Its Replication in Macroscopic and Microscopic Traffic Simulations: A Tutorial Report. *Sustainability,* 2023(15), 2050. https://doi.org/10.3390/su15032050.
[34] Xu, D., Rouphail, M., Aghdashi, B., Ahmed, I., & Elefteriadou, L. (2020) Modeling Framework for Capacity Analysis of Freeway Segments: Application to Ramp Weaves. *Transportation Research Record Journal of the Transportation Research Board*, 2674(1), 148-159. https://doi.org/10.1177/0361198119900157.
[35] Yang, B., Liu, P., Chan, C., Xu, C., & Guo, Y. (2019). Identifying the Crash Characteristics on Freeway Segments Based on Different Ramp Influence Areas. *Traffic Injury Prevention*, 20(4), 1-6. https://doi.org/ 10.1080/15389588.2019.1588965.
[36] Ye, Y., Liu, Y., Liang, X., & Dong, C. (2013). Freeway Ramp Metering Based on Cell Transmission Model and Single Neuron. *Applied Mechanics and Materials,* 423-426, 2877-2881. http://dx.doi.org/10.4028/www.scientific.net/AMM.423-426.2877.
[37] Yu, X., Xu, W., & Alam, F. (2015). Optimal Coordination of Ramp Metering via Iterative Dynamic Programming. *International Journal of Intelligent Transportation Systems Research*, 13(3), 203-218. http://dx.doi.org/10.1007/s13177-014-0096-x.
[38] Zhang, W., Wei, S., Wang, C., & Qiu, M. (2023). Asymmetric Behaviour and Traffic Flow Characteristics of Expressway Merging Area in China. *Promet - Traffic&Transportation*, 35(1), 12–26. https://doi.org/10.7307/ptt.v35i1.4200.