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ANALYSIS OF THE INFLUENCE OF EXPRESSWAY EMERGENCIES ON TRANSMISSION SPEEDS AND TRAVEL DELAYS

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Abstract:

Expressway emergencies tend to cause traffic congestion, and understanding the travel time delays of on-road vehicles under different combinations of event scenarios and road traffic conditions is valuable for guiding the accurate emergency dispatch services. Most existing studies used methods that combine the Lighthill–Whitham–Richards (LWR) theory and basic traffic diagrams to solve this problem, but the discrete traffic flow characteristics caused by the presence of heavy vehicles have not been considered, thus affecting the applicability of those results to road traffic characteristics in China. Moreover, there is a lack of systematic research on multiple combinations of unexpected event scenarios and traffic conditions, and the guidance value of the previously obtained results is limited. In order to improve the applicability of the prediction model and accurately predict the severity of emergencies, based on a logistic model that is applicable to emergencies, a velocity–density model is constructed to describe discrete traffic flow characteristics. Based on LWR theory, the internal driving force of expressway traffic state evolution under emergency conditions is explored. Combined with real-time traffic flow data, the parameters of the logistic model are calibrated, and a logistic velocity–density model is constructed using a goodness-of-fit test and a marching method, including the free-flow velocity, turning density and heavy vehicle mixing ratio. Thus, the problem that existing models lack applicability to road traffic characteristics in China is solved. Travel time delay is associated with the impact range of an emergency, and it is an effective index for evaluating the severity of emergency incidents. Thus, the travel time delays under different scenarios, different numbers of blocked lanes and different orthogonal combinations of approximate saturation conditions are explored, and the impacts of lane blockage on emergency incidents and travel time delays are obtained. The conclusions show that the presented logistic velocity–density model constructed based on discrete traffic flow characteristics can properly quantify the impact of the presence of heavy vehicles. Additionally, the results can provide theoretical support for handling emergencies and emergency rescues.

Keywords: *expressway, congestion propagation, travel time delay, logistic velocity–density model*

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1. Introduction

Expressway emergencies can often cause significant road capacity reductions and cause widespread traffic congestion, thus imposing great negative impacts on the efficiency of expressway networks. Accurately evaluating the travel time delays of on-road vehicles under multiple emergency scenarios and multiple traffic condition combinations can provide a theoretical basis and guidance for dispatching expressway emergency rescue vehicles and diverting traffic (Zhao et al., 2020); thus, relevant research has significant theoretical and practical value.

Most researchers have used original traffic flow data to evaluate congestion, and existing studies on traffic congestion predictions have focused on the road traffic volume (Shen et al., 2019), traffic flow velocity (Wang et al., 2016) and so on. However, describing traffic congestion using only a single parameter is inadequate; for example, when the traffic flow velocity is low, it may be because traffic is blocked by severe congestion on the road, or it may be due to a low traffic density with few vehicles driving on the road. To obtain more reliable and accurate prediction results, Zhang et al. (2016) collected information from the three traffic attributes of flow velocity, density and volume to determine congestion levels and proved that these multidimensional attributes provide higher-accuracy results following the clustering process. Lopez-Garcia et al. (2015) attempted to use genetic algorithms and cross entropy to predict short-term traffic congestion, and the results confirmed this approach to be a relatively highly accurate method. In many cases, the above methods and models are not suitable for assessing complex congestion-propagation patterns. Although Nagy et al. (2021) believed that the data collected using these methods could be applied as an external data source, a new traffic prediction model (the Congestion-based Traffic Prediction Model) was developed to foresee potential congestion situations, thus greatly improved the resulting accuracy. However, considering that there are nonlinear relationships between road congestion and traffic conditions, the problems associated with parameter changes in dynamic situations are still difficult to solve.

With the widespread popularity of sensors and machine learning methods, researchers have started to try to predict traffic congestion using more advanced methods based on improved existing algorithms. The K-nearest neighbour (KNN) method is one of the simplest models available and is often used to predict traffic flows when traffic congestion is unstable (Zhang et al., 2013). However, this algorithm considers only the processing of original historical incident data and had obvious deficiencies in its ability to predict future traffic congestion. Therefore, Li et al. (2020) considered traffic congestion features and determined current congestion conditions to construct a congestion-visualization framework based on machine learning algorithms and Spark parallelization technology. In this framework, a quadratic determination was made based on the traffic congestion level, thus greatly improving the prediction accuracy. Fatima et al. (2022) installed sensors over road networks to collect real-time traffic data and proposed a traffic congestion prediction method based on a long-short-term memory (LSTM) model and the Long-Range (LoRa) network, thus saving a great amount of time needed for the prediction calculations. Neural networks, some of the most effective tools available among machine learning algorithms, have excellent capabilities when learning complex situations, facing nonlinear relationships and handling large data quantities. Neural networks possess the ability to infer complex relationships between nonlinear variables in inputs and outputs. Sharma et al. (2018) used a backpropagation neural network to develop a short-term traffic-forecasting model on a two-lane highway with mixed traffic conditions. However, this large dataset required analysis with a relatively appropriate algorithm, such as a deep neural network, that was prepared for confronting large datasets. Therefore, Elleuch et al. (2019) used global positioning system (GPS) satellites to collect vehicle trace information and adopted a deep neural network that was suitable for processing large datasets to establish a road traffic congestion prediction model that could distinguish the dynamic traffic patterns of freeways and expressways. However, the major shortcoming of traffic prediction methods based on neural networks cannot be ignored (Huang et al., 2022): the results of these prediction models are presented in a complex way that is difficult to understand.

Recent studies have shown that highway delays are mostly caused by nonrecurrent events (Hu et al., 2011), such as vehicle breakdowns, vehicle crashes and other emergencies. Nonrecurrent congestion is caused by unpredictable incidents with complex characteristics and time-critical constraints (Dinh et al., 2022), thus resulting in temporarily reduced traffic road capacities. According to the accident statistics of the Dutch highway network (Adler et al., 2013), nonrecurrent events lead to relatively high-level congestion and severe vehicle loss hours (VLH); therefore, some researchers have tried to focus on assessing the durations of road emergencies to mitigate the impacts of these emergencies and, in turn, reduce drivers' time delays. In existing studies, the KNN model (Lee et al., 2017) has been shown to be equally applicable to the prediction of the durations of nonrecurrent emergencies and achieves reliable performance in modelling complex systems. Wang et al. (2018) identified six attributes as the main factors affecting duration predictions, 'day first shift', 'weekday', 'incident type', 'congestion', 'incident grade' and 'distance', and used a weighted distance metric based on a decision tree and weighted prediction algorithm to predict emergency durations on a two-lane highway. However, the accuracy of the prediction results was unreasonable for particular conditions, such as extremely short- or long-duration situations. In contrast, when the characteristics of the variables in the model are consistent, artificial neural networks have been shown to provide more accurate prediction results and to have wider prediction ranges, thus allowing the relationship between traffic emergency data and emergency durations to be more effectively developed. Vlahogiann et al. (2013) developed neural network models to predict durations with single and competing uncertainties and then identified the lane volume and number of blocked lanes as the critical factors for determining the incident duration.

The volume–velocity–density models described above are mainly applicable to situations with homogeneous conditions (Abhigna et al., 2016); however, more often, heavy vehicles are present on China's expressways, resulting in nonhomogeneous traffic flows. Heavy vehicles are of great importance in assessing traffic flows. First, the particular dimensions of heavy vehicles take up a large space. Moreover, the existence of heavy vehicles is believed to have a psychological impact on the drivers of nearby vehicles (Al-Kaisy et al., 2002). This heavy vehicle mixing ratio situation in China differs greatly from those in other countries, and these differences in the heavy vehicle mixing ratios lead to vehicle velocity differences (Jo et al., 2012), which are among the major causes of expressway traffic accidents; in addition, the domestic expressway vehicle speed limits in China are obviously different from those in other countries. The impacts of variations among heavy vehicle mixing ratios in different regions have not been sufficiently taken into account, so the existing models (Ghods et al., 2012) cannot be directly used to solve the road traffic situation in China. In addition, the main research scenes analysed in the studies mentioned above were urban roads and highways; these studies considered few expressway emergencies and included no combined scenarios involving multiple emergencies or multiple traffic conditions, and these shortcomings of the existing research could hinder the improvement of road service level and travel efficiency through information interaction (Hu et al., 2022). Therefore, this article aims to propose a prediction method that unifies the measurement standards of different types of emergencies, which can reduce the complexity of a system analysis. This method provides a unified evaluation standard for the severity of different types of emergencies, so that future researches do not need to consider the specific types of emergencies. Regardless of the type of emergencies, only the number of blocked lanes needs to change and calculate the remaining capacity. This evaluation standard is also applicable to the expressway situation in different countries.

Owing to its elegant mathematical form, adjustable parameters, conciseness and efficiency, the general logistic model is suitable for establishing the relationship in the velocity–density model. This model has higher fitting accuracy in practical application, and can describe the characteristics of traffic flow in a specific environment, which clearly shows the trend of the curve under parameter changes (Theodoulou et al., 2004). As a result of the above characteristics and existing research, it can be seen that this model is more suitable for modelling discrete traffic flow than the current fundamental diagram (FD) model. Based on the general logistic model and the influence of the heavy vehicle mixing ratio on the traffic flow parameters, a five-parameter logistic model suitable for simulating the discrete traffic flow conditions of expressways is proposed in this work to accurately describe the traffic states of typical nonhomogeneous expressways. Therefore, based on the proposed five-parameter logistic model, orthogonal scenarios of different closed-lane ratios and different traffic flow situations caused by emergencies are designed. The model explores the propagation speed and travel time delay impacts of emergency incidents under different orthogonal scenarios; the related findings are beneficial for obtaining increasingly accurate prediction results in the future.

2. Construction of the impact-spreading forecasting model under emergency incident scenarios

2.1. Impact of emergencies on transit traffic

There are many different types of emergencies, the characteristics of various emergencies are different, and the degree that emergencies impact expressway networks depends on the severity of the incident. Due to their limited propagation ability, small-scale emergencies generally cannot cause serious congestion. Severe emergencies lead to lane closures, forming point-scale traffic bottlenecks (Coifoman et al., 2011). Certain lanes are blocked by vehicles in single-point emergency incidents (Chen et al., 2018), resulting in reduced real-time traffic capacities of these road sections and promoting increased travel time delays and queue lengths in the incident sections. Therefore, to reduce the analysis complexity of point-scale emergencies, the remaining capacity after lane closures is used as a characterization indicator reflecting the severity of emergencies; with this indicator, the temporal and spatial traffic flow evolution processes in emergency incident sections are analysed (Kušić et al., 2021), and the measurement criteria for different types of emergencies are unified. According to the U.S. Highway Capacity Manual (National Research Council, 2010), the remaining capacities of road sections under emergency conditions are shown in Table 1.

2.2. A method for solving the propagation speed of emergency impacts in heterogeneous traffic conditions

There are many forms of traffic waves, and the impact of an emergency can occur in the form of blocking a road that directly interrupts or partially interrupts the traffic flow, thus forming a high-density, low-volume, low-velocity traffic flow situation at the bottleneck location of the emergency incident (Tanaka et al., 2011); when this region meets the low-density, high-volume, high-speed traffic flow, it generates a shock wave that spreads upstream. The formation of these shock waves (Li et al., 2020) thus leads to upstream-expanding road congestion. The essence of the propagation of emergency impacts is the propagation of shock waves. Therefore, shock waves have become the crucial medium used to study the propagation regularity of emergency impacts.

The external manifestation of congestion propagation is the propagation of traffic waves, and the essence of congestion propagation is the spatial and temporal evolution of traffic conditions (Do et al., 2019). Traffic factors are the direct characteristics of traffic conditions, such as traffic volume, speed and mixed rate of heavy vehicles. Therefore, to explore the travel time delays associated with emergencies, the propagation speed of emergencies on expressways should be determined. Learning from Lighthill–Whitham–Richards (LWR) theory, the wave velocity in a hydrodynamic wave can be characterized as the propagation speed of an emergency incident. When a traffic flow (with a volume of q_1 and a density of k_1) meets another traffic flow (with a volume of q_2 and a density of q_1), a shock wave is generated, and the wave velocity is found as U, as shown in Figure 1.

Table 1. Remaining capacity loss ratios of road sections under emergency conditions

Number of one-way expressway lanes	One lane is closed	Two lanes are closed	Three lanes are closed
2	0.35	0.00	N/A
3	0.49	0.17	0.00
4	0.58	0.25	0.13
5	0.65	0.40	0.20
6	0.71	0.50	0.26
7	0.75	0.57	0.36
8	0.78	0.63	0.41

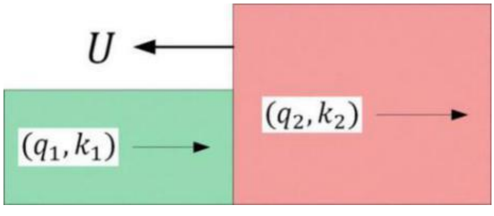


Fig. 1. Formation diagram of a shock wave

It is known that the formula used to relate the traffic volume and density is $q = k \cdot v$, and the emergency impact propagation position on a road is coincident with the position of the shock wave front. Using the shock wave velocity as the medium to assess the propagation speed of the emergency impact, the shock wave speed formula can be combined with the shock wave velocity formula as follows:

$$U = \frac{q_2 - q_1}{k_2 - k_1} = \frac{k_2 v_2 - k_1 v_1}{k_2 - k_1} \quad (1)$$

The velocity–density model can be used to describe the traffic flow parameters. In China's traffic environment, the mixing ratio of heavy vehicles has a great impact on the traffic flow conditions. Both single-stage and multistage models do not consider the influence of the heavy vehicle mixing ratio, and there are defects associated with the resulting insufficient fitting accuracy. Therefore, it is necessary to propose a velocity–density model with a high accuracy that conforms to the influence of the heavy vehicle mixing ratio in China's traffic environment. In view of the general logistic model proposed by Paul G. Gottschalk in 2005 (Gottschalk et al., 2005), this model was selected as the basis for establishing the following basic velocity–density relationship model:

$$y = f(x;p) = f(x; v_f, b, k_t, v_b, g) = \\ = v_b + \frac{(v_f - v_b)}{(1+\exp\left(\frac{x-k_t}{b}\right))^g} \quad (2)$$

where v_f represents the free-flow velocity, k_t represents the turning density of free flow to non-free flow, v_b represents the average speed of bumper-to-bumper flow, and b and g represent uncalibrated parameters.

By collecting the real-time traffic flow data of the Lianhuo Expressway and Baomao Expressway in Xi'an, the influence of heavy vehicles under free-flow conditions is analysed. Using the shock wave velocity as the medium to study the propagation formula of emergency impacts, the values of various parameters are determined under different heavy vehicle mixing ratios by means of a goodness-of-fit test and a marching method; finally, the improved velocity–density model is obtained as follows:

$$v = f(k,r) = \frac{v_f}{(1+\exp\left(\frac{k-k_t}{f_2(r)}\right))^{f_1(k_m)}} \quad (3)$$

where v_f represents the free-flow velocity, k_t represents the turning density of free flow to non-free flow, k_m represents the traffic block density, $f_1(k_m)$ represents a function related to k_m, r represents the mixing ratio of heavy vehicles, and $f_2(r)$ represents a function related to r.

By combining the improved velocity–density model and fundamental diagram, the volume–density model is established; this model considers different heavy vehicle mixing ratios:

$$Q = f(k,r) = \frac{k \times v_f}{(1+\exp\left(\frac{k-k_t}{-4.332 \times r + 5.402}\right))^{0.0025 \times k_m - 0.1538}} \quad (4)$$

where v_f represents the free-flow velocity, k_t represents the turning density of free flow to non-free flow, k_m represents the traffic block density, and r represents the heavy vehicle mixing ratio.

Based on the above model and parameter values derived under different heavy vehicle mixing ratios, volume–density curves are obtained, as shown in the figure 2.

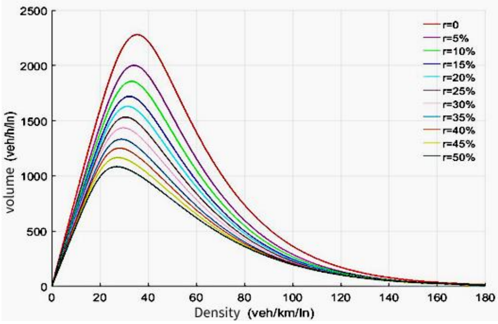


Fig. 2. Volume–density curves derived under different heavy vehicle ratios

It can be seen from the above conclusions that the propagation speed of an emergency impact can be expressed by the shock wave velocity. From the velocity–density model based on the logistic approach, the relationships among the traffic volume, velocity, and density are analysed. Combined with the speed formula of the shock wave, the propagation speed of the emergency impact in the relevant expressway section can be found using Equation (5):

$$\begin{cases} Q = f(k,r) = \dfrac{k \times v_f}{(1+\exp\left(\dfrac{k-k_t}{-4.332\times r+5.402}\right))^{0.0025\times k_m - 0.1538}} \\ U = \dfrac{Q_2 - Q_1}{k_2 - k_1} = \dfrac{k_2 v_2 - k_1 v_1}{k_2 - k_1} \end{cases} \tag{5}$$

where v_f represents the free-flow velocity, k_t represents the free-flow density, k_m represents the traffic block density, and r represents the heavy vehicle mixing ratio.

2.3. Method for solving travel time delays under emergency impacts

The occurrence of traffic incidents causes upstream traffic congestion and can even cause secondary accidents. A serious emergency causes a nonrecurrent bottleneck at the location the incident occurred, and blocked lanes make cars forcibly change lanes (Aiura et al., 2022), which can cause shock waves affecting subsequent vehicles and increase the congestion severity. The congestion bottleneck of an expressway network determines the location of traffic flow breakdown (Bakar et al., 2018). An emergency leads to a reduction in the traffic capacity at the location of the incident, and the propagation of congestion through the network results in the continuous gathering of blocked vehicles. The high-density and low-velocity traffic flow region then spread upstream, thus affecting the upstream traffic state. The travel time delay is related to the impact range of the emergency. On the basis of the wave speed, the travel time delay can be calculated to effectively evaluate the impact range caused by an emergency.
Assuming that the traffic velocity, traffic density and traffic volume at the location of the emergency incident are v_0, k_0 and q_0, respectively, and that the original upstream traffic velocity, traffic density and traffic volume are v_1, k_1 and q_1, respectively, when vehicles are evenly distributed in the road section, the headway can be calculated as $\Delta x = 1/k_0$, and the total number of vehicles in the road section can be calculated as $N = k_0 \cdot x$, as shown in Figure 3.
When the impact of an emergency incident spreads upstream, it causes congestion and changes the upstream traffic situation. Before an incident occurs, the normal travel time of the N$^{\text{th}}$ vehicle can be said to be $t = x/v_0$; this travel time becomes $t' = x/v_1$ after the occurrence of congestion. Therefore, the travel time delay of the N$^{\text{th}}$ upstream vehicle can be obtained as follows.

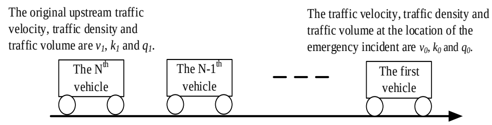


Fig. 3. Vehicle distribution in emergency road section

From the figure 3, it can be seen that the distance of the N-1$^{\text{th}}$ vehicle from the place of the emergency incident is . According to the same principle used to construct the above formula, the time delay of the N-1$^{\text{th}}$ vehicle can be obtained as follows:

$$t_N = \frac{x}{v_0} - \frac{x}{v_1} \tag{6}$$

From the figure 3, it can be seen that the distance of the N-1$^{\text{th}}$ vehicle from the place of the emergency incident is $L = x - \Delta x = x - 1/k_0$. According to the same principle used to construct the above formula, the time delay of the N-1$^{\text{th}}$ vehicle can be obtained as follows:

$$t_{N-1} = \frac{x - \dfrac{1}{k_0}}{v_0} - \frac{x - \dfrac{1}{k_0}}{v_1} \tag{7}$$

Similarly, the time delay of the first vehicle can be obtained as follows:

$$t_1 = \frac{x - \dfrac{N-1}{k_0}}{v_0} - \frac{x - \dfrac{N-2}{k_0}}{v_1} \tag{8}$$

By combining the above time delay formulas (6-8) with the propagation speed u_w and propagation time t of an emergency incident, the total time delay can be simplified as follows:

$$\begin{aligned} T &= \frac{x - \dfrac{N-1}{k_0}}{v_0} - \frac{x - \dfrac{N-1}{k_0}}{v_1} + \frac{x - \dfrac{N-2}{k_0}}{v_0} - \frac{x - \dfrac{N-2}{k_0}}{v_1} \cdots \frac{x}{v_0} - \frac{x}{v_1} \\ &= \frac{1}{2}\left(\frac{1}{v_0} - \frac{1}{v_1}\right)\left[k_0 \cdot (u_w \cdot t)^2 + u_w \cdot t\right] \end{aligned} \tag{9}$$

According to the total number of vehicles in the analysed road section, the average delay of each vehicle in the time period t can be obtained as follows:

$$t_s = \frac{T}{u_w \cdot t \cdot k_0} \tag{10}$$

3. Research results

By collecting traffic volume data measured on the Lianhuo Expressway and Baomao Expressway, the effectiveness of the velocity–density model constructed based on the logistic model is verified under the traffic volumes of different heavy vehicle mixing ratios. The results show that the relative error of this model is maintained at approximately 0.1; thus, this model has a higher reliability and accuracy than other classical models, such as the Greenshields model (Shlayan et al., 2017) and Underwood model. The heavy vehicle mixing ratio is considered in the proposed model, thus better aligning the simulations with the actual road traffic environment in China. Therefore, this emergency impact prediction model established based on a logistic model has a higher accuracy and applicability than other available models.

3.1. Propagation speed of emergency conditions in different saturation situations

Due to the influences of traffic conditions, road structures and other factors, the regularity and particularity of expressway emergencies are situation-specific (Chen et al., 2021). Major emergencies on expressways can cause parts of traffic lanes to be blocked or can even cause road sections to be completely closed, thus resulting in serious traffic capacity declines across the entire affected road section and causing large-scale congestion of the road network (Wang et al., 2018). The term   is the ratio of the road traffic volume and capacity; this term represents the service level of a road. Therefore, to explore the relationship between the propagation speed of the emergency impact and the road service level, it is necessary to first analyse the road capacity.

The ability to resist the effects of expressway emergencies differ among different road service levels. When the road service level is relatively high, the ability of the expressway to resist the impacts of emergencies is strong; thus, the road service level of an expressway determines the propagation speed of the emergency impacts to a certain extent.

Most expressways with important national channels have been reconstructed according to the two-way six lane standard, and the proportion of two-way, six-lane expressways in the national road network is gradually increasing. However, few studies have explored the traffic performances of two-way, six-lane expressways (Singh et al., 2022), so it is critical to take two-way, six-lane expressways as the research object in this work and to popularize the research achievements. According to the collected data, a heavy vehicle mixing ratio of 15% on expressways is the most common and most-representative ratio; in normal road traffic situations, the heavy vehicle mixing ratios of expressways rarely exceed 15% (Guériau et al., 20200). Therefore, the 15% heavy vehicle mixing ratio on two-way, six-lane expressways is selected in this work, and an analysis framework of multi-emergency scenarios is designed by considering the road residual capacity values listed in Table 1. From the volume–density curves shown in Figure 2, the volume–density curve under the 15% heavy vehicle mixing ratio is obtained, as shown in Figure 4.

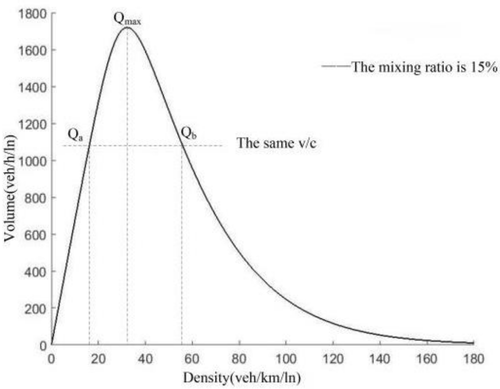


Fig. 4. Volume–density curve when the heavy vehicle mixing ratio is 15%

As shown in Figure 4, when the heavy vehicle mixing ratio is 15%, the maximum traffic volume of the road is 1727 *veh/h* ln and the block density is 148 *veh/h* ln.

3.1.1. One lane is closed

According to the remaining capacity loss values listed in Table 1, when the number of one-way lanes in an expressway is 3, the remaining capacity of the road after one lane is blocked is reduced to 0.49, and the maximum traffic volume of the remaining lanes is 2539 *veh/h* under ideal conditions.

Therefore, when the road flow is less than 2539 *veh/h* , *v/c* is less than 0.49, and an emergency incident will not cause congestion. When the road traffic volume is higher than 2539 *veh/h* , *v/c* is more than 0.49, and the traffic supply at the incident location is less than the upstream traffic demand, thus generating upstream-spreading congestion. Therefore, according to the actual situation, analysis is needed only for the situation in which *v/c* is higher than 0.5.

3.1.2. Two lanes are closed

According to the remaining capacity loss values listed in Table 1, when there are 3 one-way lanes in an expressway, the remaining capacity of the road after two lanes are blocked is reduced to 0.17, and the maximum traffic volume of the remaining lane is 881 *veh/h* under ideal conditions.

Therefore, when the road flow is less than 881 *veh/h* and *v/c* is less than 0.17, emergency incidents will not cause congestion. When the road traffic volume is higher than 881 *veh/h* and *v/c* is above 0.49, the traffic supply at the incident location cannot meet the upstream traffic demand, thus generating congestion that spreads upstream. Therefore, according to the actual situation, analysis is required only for the situation in which *v/c* is higher than 0.2.

3.1.3. All lanes are closed

According to the remaining capacity loss values listed in Table 1, when all three lanes are closed, the traffic capacity at the incident location will be reduced to 0. Regardless of the *v./c* value, the congestion caused by an emergency in this situation will always spread upstream.

Through the above calculations, the remaining traffic capacities under different lane closures are derived, as shown in Table 2.

Table 2. Remaining road capacities under different lane closure situations

	Proportion of remaining capacity	**Remaining capacity/(*veh/h*)**
One lane is closed	0.49	2539
Two lanes are closed	0.17	881
Three lanes are closed	0	0

According to the conclusions drawn above and using the propagation speed formula for emergency impacts in expressway sections, we can calculate the upstream propagation speed of traffic congestion under different conditions when one lane, two lanes and all lanes are closed, as shown in Figure 5.

According to Figure 5, when an emergency occupies one lane or two lanes, the propagation speed of the emergency impact is largest when the road service level is 0.9; when an emergency occupies all lanes, the propagation speed of the emergency impact is highest when the road service level is 1.0.

3.2. Travel time delay of emergency impact

From the above conclusions, it can be seen that the propagation speed of an emergency impact accelerates as the road service level increases; in addition, when the traffic volume is maximized, the propagation speed of the emergency impact is highest and the scope of impact is enlarged.

It can be seen from the volume–density curve in Figure 4 that when *v/c* is determined, two points can be seen on the curve: Q_1 is the volume in the free-flow state on the left side of the curve, while Q_2 is the volume in the non-free-flow state on the right side of the curve. Based on the volume–density curve, the traffic densities k_1 and k_2 of the corresponding traffic volumes Q_1 and Q_2, respectively, are obtained. When the road traffic volume coincides with the point on the right side of the curve, it indicates that the traffic flow at that time is in a congestion state with a high density and low velocity, resulting in the degree of freedom of vehicles declining. If an emergency occurred at this time, road congestion would be generated. Therefore, it is necessary to analyse the delay times under free-flow and non-free-flow conditions.

When the *v/c* value of a road section is low, the propagation speed of the emergency impact is limited, and the trend is not significant; thus, this situation is not conducive to studying the time delay caused by emergency impacts under different road conditions, and *v/c* values of 0.7, 0.8, 0.9 and 1 are selected for analysis.

Taking the heavy vehicle mixing ratio of 15%, it can be seen from the above conclusions that when one lane is closed among the three lanes on one side in a two-way, six-lane road, the heavy vehicle mixing ratio of the road section is known to be 15%. According to the values of v_f and t_k and the table listing the congestion density values under different heavy vehicle mixing ratios reported in the literature, when the heavy vehicle mixing ratio is 15%, the free-flow velocity is 67.87 *km/h*, the turning density of the traffic flow from the free-flow state to the non-free-flow state is 29.0 *veh/km/* ln, and the congestion density is 148 *veh/km n*. By substituting the traffic flow densities k_1 and k_2 along with various parameter values into the formula used to calculate the propagation speed of an emergency impact, the propagation speed of emergency impacts under different free-flow and non-free-flow conditions could be obtained, as shown in Figure 6.

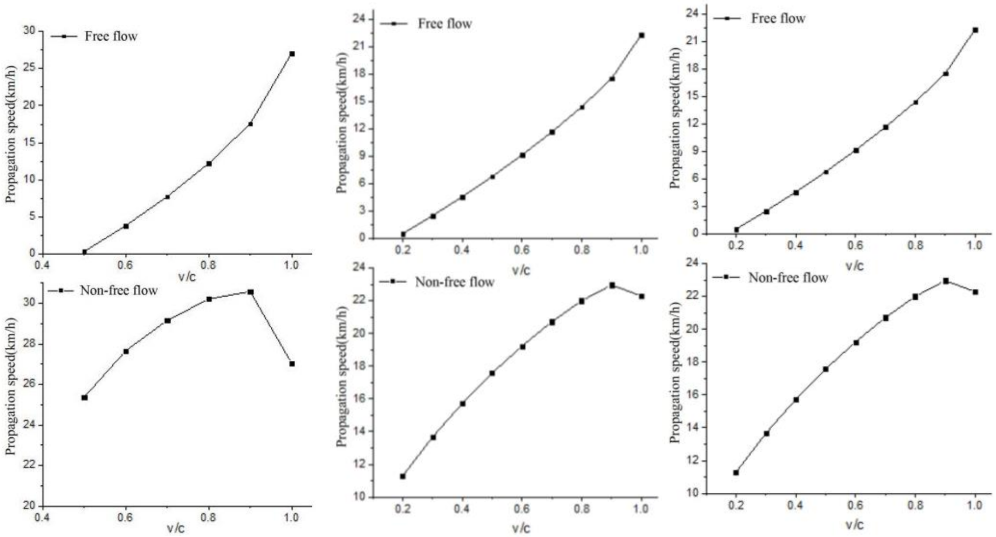


Fig. 5. Propagation speeds and ranges corresponding to the v/c values under different lane closure situations

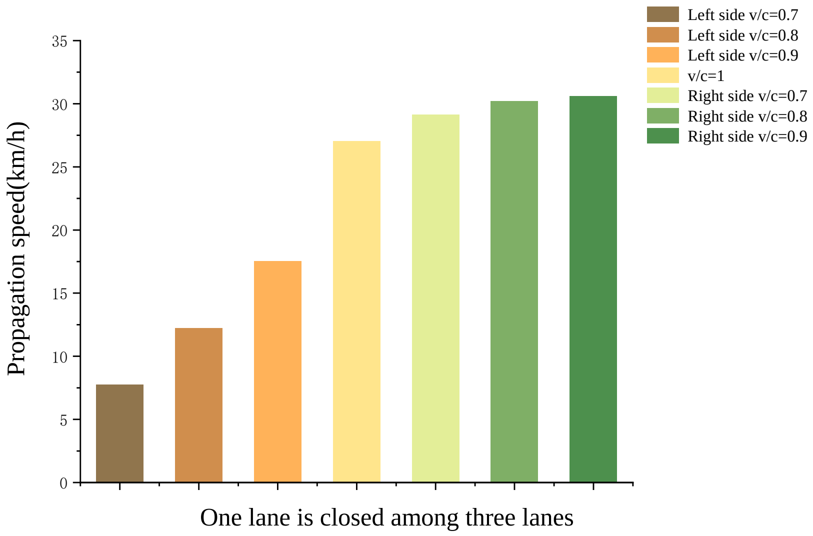


Fig. 6. Congestion propagation speeds with one lane closed

Similarly, the situations in which one lane is closed among two lanes; two lanes are closed among three lanes; one lane, two lanes, and three lanes are closed among four lanes; one lane, two lanes, and three lanes are closed among five lanes; and one lane, two lanes, and three lanes are closed among six lanes are assessed individually, and the results are shown in Figure 7.

Assuming that emergency impacts spread 1 km upstream, according to the method used to calculate the travel time delays caused by emergencies, the total delay time can be obtained by substituting v_0 and k_0 at the location of the emergency incident and the upstream value along with the propagation time t and propagation speed u_w of the emergency incident. Then, the average delay (t_s) of a single vehicle in this period can be obtained. The travel time delays are obtained under different conditions associated with various lane closures on various roads, as shown in Figure 8.

In summary, the propagation speed and single-vehicle average travel delay time thresholds derived under different values and different lane closure scenarios are summarized in Tables 3 and 4.

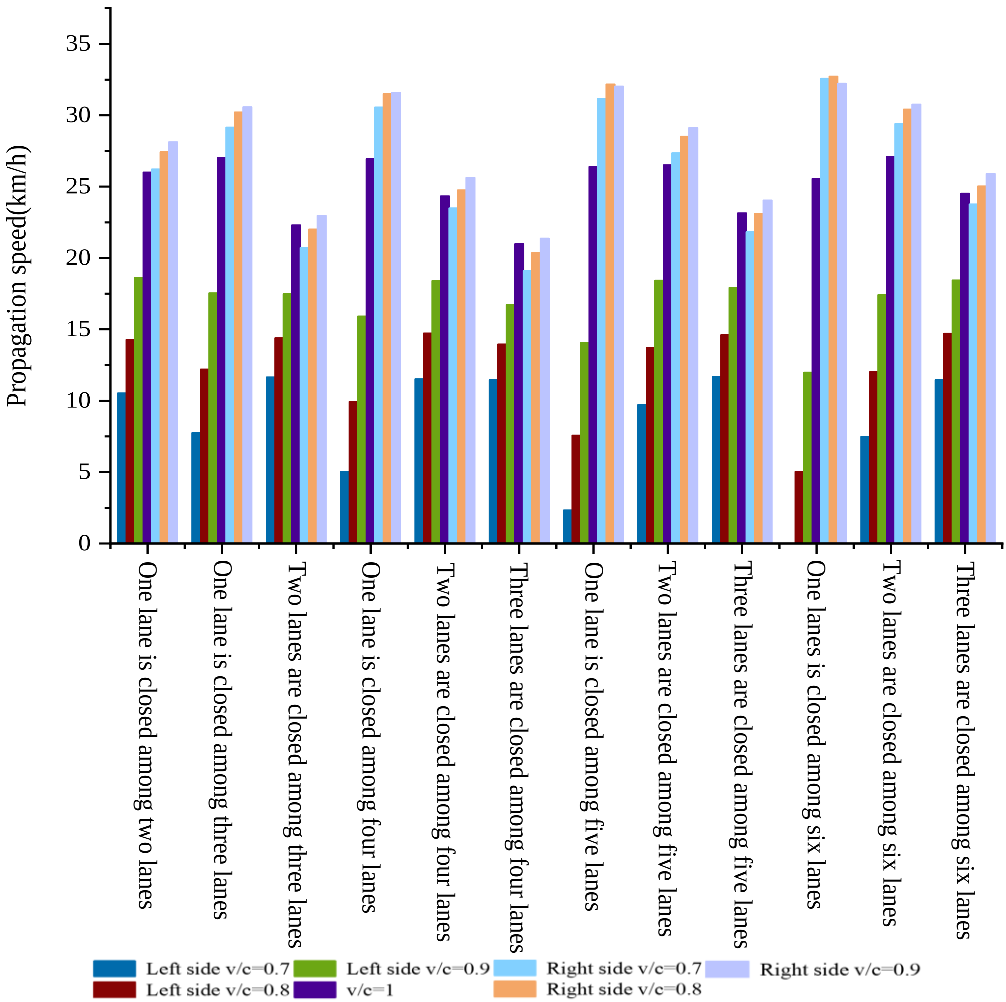
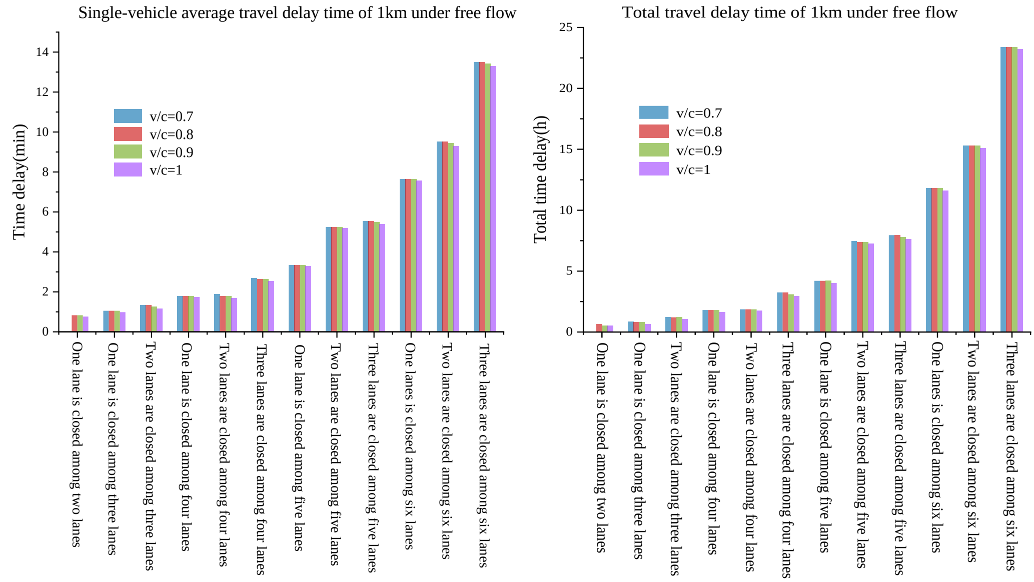
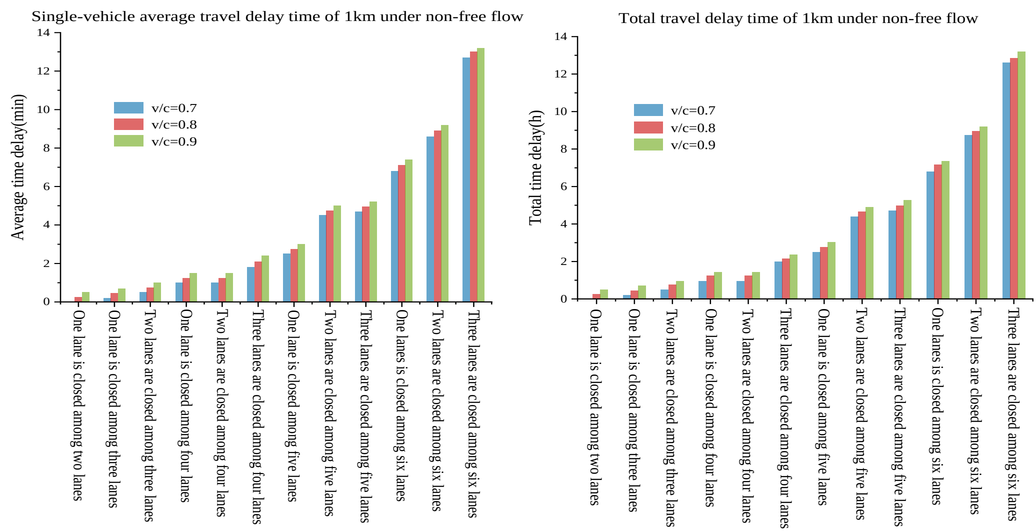


Fig. 7. Propagation speeds of emergency impacts under different lane closure conditions



(a) Free flow



(b) Non-free flow

Fig. 8. Travel time delays under different lane occupancy conditions

Table 3. Propagation speed and travel delay thresholds of emergencies under free-flow conditions

Road condition	v/c=0.7-0.8		v/c=0.9-1	
	Propagation speed/(km/h)	**Average travel delay time of vehicles/(min)**	**Propagation speed/(km/h)**	**Average travel delay time of vehicles/(min)**
One lane closed among two lanes	(10.5, 14)	3.35	(18.6, 26)	3.28
One lane closed among three lanes	(7.8, 12)	1.88	(17.5, 27)	1.8
Two lanes closed among three lanes	(12, 14)	9.52	(17, 22)	9.46
One lane closed among four lanes	(5, 10)	1.35	(16, 27)	1.27
Two lanes closed among four lanes	(11.5, 14.7)	5.55	(18.4, 24)	5.49
Three lanes closed among four lanes	(11.5, 14)	13.5	(16.7, 21)	13.43
One lane closed among five lanes	(2.3, 7.6)	1.05	(14, 26.4)	0.98
Two lanes closed among five lanes	(9.7, 14)	2.7	(18.4, 26.5)	2.63
Three lanes closed among five lanes	(11.7, 14.6)	7.64	(18, 23.2)	7.57
One lane closed among six lanes	(0, 5)	0.83	（12, 25.6）	0.76
Two lanes closed among six lanes	(7.5, 12)	1.8	(17.4, 27)	1.75
Three lanes closed among six lanes	(11.5, 15)	5.25	(18.5, 24.5)	5.19
All lanes closed	(5, 8)	-	(10.4, 15)	-

Table 4. Propagation speed and travel delay thresholds of emergencies under non-free-flow conditions

Road condition	v/c=0.7-1	
	Propagation speed/(km/h)	**Average travel delay time of vehicles/(min)**
One lane closed among two lanes	(26.2, 28.3)	(2.5, 3)
One lane closed among three lanes	(29, 30.7)	(1, 1.5)
Two lanes closed among three lanes	(20.5, 23)	(8.6, 9.2)
One lane closed among four lanes	(30, 31.7)	(0.5, 1)
Two lanes closed among four lanes	(23.3, 25.7)	(4.7, 5.2)
Three lanes closed among four lanes	(19, 21.5)	(12.7, 13.2)
One lane closed among five lanes	(31, 32.5)	(0.2, 0.7)
Two lanes closed among five lanes	(27.3, 29.3)	(1.8, 2.4)
Three lanes closed among five lanes	(21.8, 24.2)	(6.8, 7.4)
One lane closed among six lanes	(29.4, 30.8)	（0, 0.5）
Two lanes closed among six lanes	(29, 30.8)	(1, 1.5)
Three lanes closed among six lanes	(23.7, 26)	(4.5, 5)
All lanes closed	(12.7, 14.7)	-

4. Conclusions

In this research, we used an improved logistic velocity–density model and the shock wave speed formula to analyse the propagation speeds of emergency impacts on typical expressways. Based on real-time traffic flow data measured on expressways, combined with the calculated propagation speeds of emergency impacts, the travel time delays under different event conditions are discussed, and the following conclusions are obtained:

(1) The propagation speed of an emergency impact is related to both the road service level and the number of closed lanes. Regardless of whether the upstream traffic is in a state of free flow or non-free flow, when a road lane is closed, the spreading speed of the emergency impact will accelerate as the road service level increases and will be maximized when the road traffic volume is at its maximum. When not all lanes of a road where an incident has occurred are completely closed, the more closed lanes there are, the faster the congestion caused by the emergency spreads.

(2) The total travel delay times and average delay times of vehicles caused by emergency impacts are related to the road service level, the number of closed lanes and the propagation speed of the emergency impacts. The travel time delay is less affected by the road service level than by other factors. The faster the emergency impact spreads, the more severe the total travel time delay is and the longer the average delay time of vehicles is; in addition, the increase in the delay time is positively proportional to the number of lanes blocked by the emergency.

(3) Under the same lane-closure conditions, the total travel time delay and average delay time of vehicles under non-free-flow conditions are both lower than those under free-flow conditions because the original traffic velocity under non-free-flow conditions before an emergency occurs is lower and the travel time required to cover the same distance is longer; thus, the travel time delay caused by an emergency incident under non-free-flow conditions is relatively small.

By analysing the maximum remaining road capacity after an expressway emergency occurs, according to LWR theory and the improved logistic model, the upstream propagation speed of emergency congestion impacts under different scenarios can be predicted while considering heterogeneous traffic flow scenarios affected by the presence of heavy vehicles. The total travel time delay and the average delay time of vehicles after an emergency can be analysed to provide managers with an understanding of the development trend of emergencies and can establish a basis for formulating emergency and rescue plans.

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