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Fragility analysis of small- and medium-span bridges under region-specific traffic load characteristics

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Abstract: Overloaded traffic loads can increase the risk of bridge damage and reduce the service life of bridges. To further refine the research on the fragility analysis of different small and medium span bridges to traffic loads by considering the regional characteristics of traffic loads. This article systematically conducts a traffic load fragility analysis of bridges, taking into account the structural characteristics of small- and medium-span bridges and vehicle load characteristics within the region. First, statistical analysis is conducted on the collected measured traffic load data within a certain area, and the Metropolis-Hasting sampling algorithm and Copula function are used to consider the correlation of traffic load parameters to simulate random traffic flow. Then, the calculation method for the resistance level corresponding to the three states of bridge cracking, yielding, and failure is given. Finally, eight types bridges with a high proportion within a certain route is selected, and their fragility to traffic loads has been analyzed. The analysis indicates that the failure probability corresponding to cracking conditions exceeds the serviceability limit state target for all hollow slab bridges, even when the vehicle load limit is set at 15 t. Similarly, T-beam bridges are also relatively easy to enter a state of working with cracks. Furthermore, hollow slab bridges exhibit a higher failure probability than T-beam bridges under identical traffic loading conditions. This indicates that T-beam bridges are more suitable for the current traffic load conditions. In hollow slab bridges, the failure probability of 13m span and 16m is relatively high. In T-beam bridges, the probability of failure is relatively high for 30m span. These bridges should receive more attention in operation and maintenance work. The proposed fragility analysis method for traffic loads can facilitate bridge operation and maintenance, while also guiding the formulation of vehicle load limit policies.

Keywords: bridge engineering; traffic load fragility; resistance level calculation; load simulation; vehicle-bridge coupling; small- and medium-span; operation and maintenance

1 Introduction

With the continuous increase in freight demand, the level of traffic load continues to rise. The frequent passage of overweight vehicles can exacerbate the aging of bridges and even lead to their sudden collapse. Therefore, by analogy with the concept of seismic fragility assessment [1], analyzing the traffic-load fragility, that is, exploring the failure probability corresponding to a certain structural resistance under different traffic load levels, is very important for the safe operation of bridges.

Traffic load is the most important live load that a bridge bears, characterized by typical regional and random features. Currently, there are two main methods for obtaining actual vehicle load information on highway bridges: (i) directly measuring vehicle speed, axle number, wheelbase, and axle weight by installing a Weigh-in-Motion (WIM) system [2]; (ii) using the response generated by vehicle passage over the bridge to calculate the vehicle load information, which is called bridge WIM algorithm [3-4]. By utilizing the obtained real vehicle load information to statistically analyze its distribution characteristics, the random traffic flow model reflecting these characteristics can be further established using sampling algorithms [5-7]. Lin et al. [8] modeled the arrival sequence

of vehicles as a Markov process. The study by Li et al. [9] utilized a copula joint function to account for the interdependence of vehicle axle weights, showing that this approach yields a random traffic flow effect closer to the actual load effect. However, the above studies only consider the correlation between single variables. The correlation between multiple variables can also be comprehensively considered to simulate random traffic flow more refined [10].

Based on different random traffic flow models, scholars have analyzed their impact on bridges. Kwon et al. [11] considered the differences in traffic volume, vehicle weight, and bridge structure in various regions of the United States, recalibrated the live load factor in the AASHTO code [12]. A series of studies by Li [13-15], based on the traffic load effect parameters and distributions provided in the Chinese code JTG 2 120—2020, involved the development of bridge load limit analysis models and an evaluation of the safety implications of different load limit levels on highway bridges. O'Brien et al. [16] summarized the historical development process of highway systems in different countries. Based on the data measured by WIM, they loaded it onto the influence lines of different bridges, analyzed the impacts on different bridges, and suggested that scholars conduct research on the impacts of highway vehicle gross weight limits on infrastructure safety, economy,

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and other aspects. Subsequently, O'Brien et al. [17] used the MC method to simulate different random traffic flows, studied the characteristics for shear force and bending moment under the long-term action of traffic load, and compared them with the designed traffic load effects. Yuan et al. [18] started from the traffic load data actually measured by WIM, and gave suggestions on load limit values for small and medium-span bridges. Employing a self-developed random traffic flow-bridge coupling simulation tool and empirical traffic data, the work by Han et al. [19] assessed the impact of measured traffic conditions on conventional T-beam bridges. Collectively, the existing literature demonstrates substantial research into the influence of traffic loading on bridge structures. However, the refinement of traffic load models requires the comprehensive consideration of regional traffic characteristics and the statistical properties of load parameters. Furthermore, conducting a traffic load fragility analysis for different bridge types within a regional road network is crucial for informing targeted operation and maintenance strategies.

Hence, this paper proposes a traffic-load fragility assessment method of medium and small span bridges considering regional traffic load characteristics. The arrangement of the article is as follows. First, the overall process of the traffic-load fragility assessment is given. Then, utilizing traffic load data collected by the WIM system and incorporating the correlation between axle

weights and wheelbases, the random traffic flow simulation is conducted. Next, the resistance level of the structure under different states and the failure probability calculation method for the structure are determined. Finally, the traffic-load fragility of eight base bridges is analyzed based on considering the characteristics of regional traffic loads.

2 Framework of fragility assessment

The overall framework of traffic load fragility of bridges considering characteristics of regional traffic loads is as shown in Fig. 1. By conducting a statistical analysis of the on-site collected WIM data, the inherent characteristics of traffic loads can be systematically characterized. Subsequently, the interrelationships among traffic load parameters are explored, and traffic flow simulation is accomplished through advanced simulation algorithms. Based on this, random traffic flows with different load limit levels can be generated. The calculation of the resistance of prestressed concrete structures needs to consider the material and geometric uncertainties of the actual structure, and analyze it from three stages: concrete cracking, steel yield, and structural failure. Using the theory of vehicle bridge coupling calculation to obtain bridge responses under different random traffic flows, and combining extreme value extrapolation theory to analyze vehicle load effects.

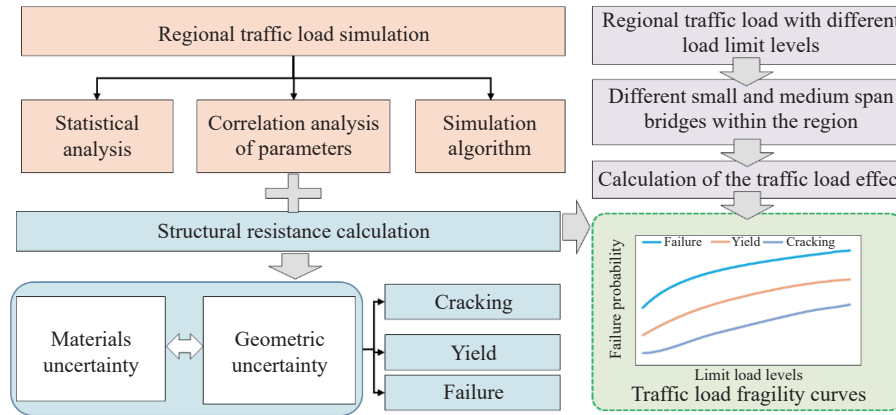


Fig. 1 The overall process of traffic-load fragility.

3 Regional traffic flow simulation

3.1 Statistical characterization of traffic loads

A dataset of WIM-recorded traffic loads from a two-way six-lane bridge, spanning four consecutive months, was employed as the foundational data. While this study utilizes high-quality data from a representative single site to demonstrate the proposed framework, the methodology is designed to be intrinsically compatible with multi-site datasets. Recent studies have highlighted the feasibility and advantages of integrating multiple traffic datasets across highway networks to capture broader regional characteristics [20–21]. The on-site layout of the WIM system is shown in Fig. 2. The data were preliminarily processed to obtain 724,834 sets of effective vehicle load data. Fig. 3 presents the distribution of vehicles by axle count. Two-axle vehicles dominate the traffic flow on this road section at 67.33%, followed by 6-axle vehicles (19.95%) and 4-axle vehicles (6.08%). In contrast, 3-axle and 5-axle vehicles are the least common, making up only 2.73% and 3.91% of the total, respectively.

Statistical analysis of the total weight distribution by vehicle axle count. The total weight of vehicles sharing the same axle count can vary due to differences in vehicle type and loading level, leading to a multi-modal distribution. A multi-modal normal distribution

model was proposed, benchmarked against the normal distribution, to describe this pattern, given as:

$$f(x) = \sum_{i=1}^n p_i f_i(x) \quad (1)$$

where, n is the number of normal distributions included; p_i is the weighting factor with the sum of all p_i equal to 1; $f_i(x)$ is the probability density function (PDF) for the i -th normal distribution. The equation for $f_i(x)$ can be expressed as:

$$f_i(x) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left(-\frac{(x-\mu_i)^2}{2\sigma_i^2}\right) \quad (2)$$

where, μ_i and σ_i are the mean and variance of the i -th normal distribution, respectively.

A fitting procedure was conducted on the total weight distribution of vehicles by axle number using Eqs. (1) and (2). Fig. 4 shows the fitting results. The parameters corresponding to the bimodal normal distribution and the determination coefficients (R^2) between the fitted function curve and the actual sample were also shown in the figure. The vehicle gross weight distribution reflects the macroscopic level of vehicle loads, while axle weight and wheelbases determine the distribution of vehicle loads. Therefore, the probability distributions of vehicle axle weight and wheelbases were further statistically analyzed. The axle weight was represented

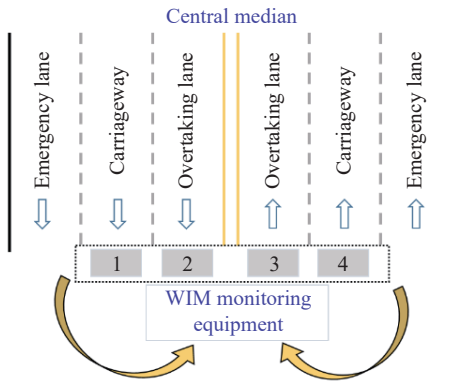


Fig. 2 The on-site layout of the WIM system.

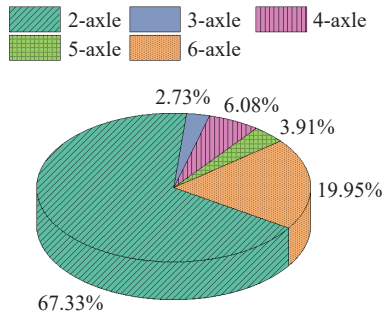


Fig. 3 The proportion of vehicles with different axle numbers.

ted by AW, and the wheelbase was represented by WB. The axle serial number increases one by one from the front of the vehicle to the rear, for example, AW61 represents the axle weight of the first axle for the 6-axle vehicle.

The 6-axle vehicles were taking as an example here. Table 1 presents the probability density distribution and its parameters of each axle weight. It can be seen that AW61 follows a normal distribution, while the rest of the axle weights all follow a bimodal normal distribution. At the same time, the probability distributions of AW62 and axle AW63 are similar, and the distributions of axle AW64, AW65, and AW66 are similar. This may be because axle 2 and axle 3 are controlled by the same coupling, and axle 4 to axle 6 are controlled by the same coupling. Table 2 summarizes the fitted probability distributions and their associated parameters for the wheelbase spacings of 6-axle vehicles. WB 61 and WB 62 follow a bimodal normal distribution, WB 63 follows a trimodal normal distribution, and WB64 and WB65 both follow a normal distribution. The probability distributions of WB64 and WB65 are similar. This is because the different distributions of WB61 to WB63 represent

different axle type combinations, and the last three axles are all group axles controlled by the same coupling, so the distributions of WB64 and WB65 are similar.

Vehicle speed is one of the significant factors governing the magnitude of the dynamic effect induced by traffic loads on bridges. Therefore, the statistical analysis of the driving speeds of vehicles with different axle numbers was carried out. Due to space limitations, only the statistical results of two vehicle models are listed in Fig. 5. The figure also presents the parameters of the bimodal normal distribution and the R^2 values indicating the goodness-of-fit. It can be observed that the speeds of both two- and six-axle vehicles conform to this distribution, with the peak value of the speed distribution progressively declining as the axle count increases.

The distance between vehicles is an important parameter for describing traffic flow. Since the WIM system records vehicle passage times and speeds but cannot measure inter-vehicle distances directly, these distances were deduced by assuming constant vehicle speed over short intervals, thereby converting the temporal data into spatial data. The PDF for the inter-vehicle distances, fitted with a log-normal distribution, is expressed as follows:

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right) \quad (3)$$

where, $f(x)$ is the PDF of a lognormal distribution; μ and σ are the distribution parameters. The mathematical expectation E and variance D are shown in the following equations, respectively:

$$E(x) = \exp(\mu + \sigma^2/2) \quad (4)$$

$$D = (\exp(\sigma^2) - 1)\exp(2\mu + \sigma^2) \quad (5)$$

As shown in the probability density distribution of vehicle spacing in Fig. 6, the log-normal distribution yields a better fitting effect for the inter-vehicle distances. Meanwhile, a significant disparity is observed between lanes, with spacings in the overtaking lane being markedly greater than those in the driving lane.

In addition, to further refine the classification of traffic load types, the k -means++ clustering algorithm [22] was used, combined with the Davies-Bouldin index [23], to divide vehicle types into 13 categories based on wheelbases of vehicles, as shown in Table 3.

3.2 Consideration of the correlation between traffic load parameters

The study incorporated the correlation of the vehicle arrival sequence as well as the correlation between vehicle axle weights and wheelbases. The correlation of vehicle arrival sequence can be explained as the following effect of vehicles, that is, vehicles do not randomly choose their own driving positions, but choose to follow according to the type of preceding vehicle and are independent of

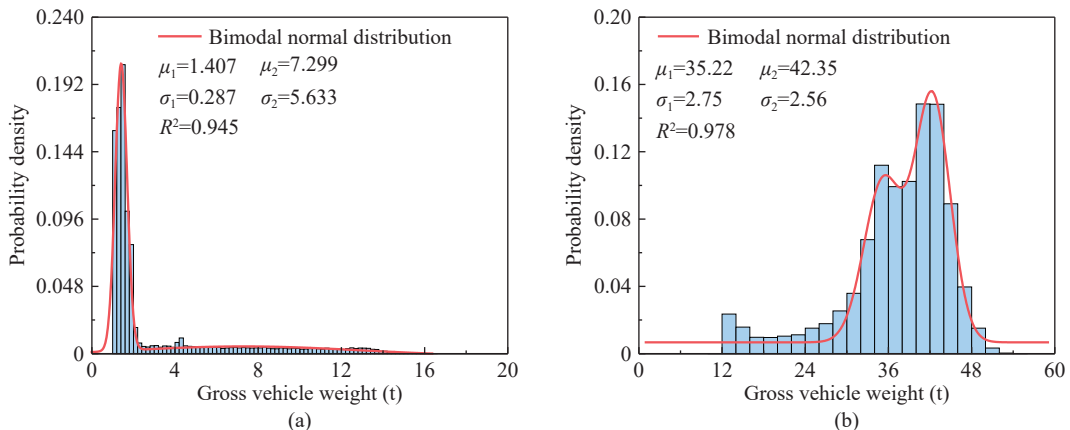


Fig. 4 The total weight distribution of 2-axle and 6-axle vehicles. (a) 2-axle; (b) 6-axle.

Table 1 Statistical characteristics and probability density distribution of axle weights.

The axle weight	Distribution	Parameters
AW ₆₁	Normal	$\mu=4.68, \sigma=0.69$
AW ₆₂	Bimodal normal	$\mu_1=3.02, \sigma_1=0.83$ $\mu_2=6.76, \sigma_2=1.20$
AW ₆₃	Bimodal normal	$\mu_1=5.66, \sigma_1=15.24$ $\mu_2=6.60, \sigma_2=0.99$
AW ₆₄	Bimodal normal	$\mu_1=2.27, \sigma_1=6.66$ $\mu_2=8.06, \sigma_2=1.48$
AW ₆₅	Bimodal normal	$\mu_1=1.73, \sigma_1=0.34$ $\mu_2=7.11, \sigma_2=1.17$
AW ₆₆	Bimodal normal	$\mu_1=1.74, \sigma_1=0.30$ $\mu_2=7.12, \sigma_2=1.54$

Table 2 Probability density distribution and parameters of each wheelbase of six-axle vehicle.

The wheelbase	Distribution type	Distributed parameter
WB ₆₁	Bimodal normal	$\mu_1=2.05, \sigma_1=0.07$ $\mu_2=3.39, \sigma_2=0.14$
WB ₆₂	Bimodal normal	$\mu_1=1.39, \sigma_1=0.03$ $\mu_2=2.77, \sigma_2=0.05$
WB ₆₃	Bimodal normal	$\mu_1=5.87, \sigma_1=0.53$ $\mu_2=9.57, \sigma_2=0.26$
WB ₆₄	Normal	$\mu_1=1.33, \sigma_1=0.03$
WB ₆₅	Normal	$\mu_1=1.34, \sigma_1=0.03$

the type of vehicle before that. This behavior can be represented by a Markov chain. Based on the above considerations, to improve the accuracy of vehicle arrival sequence simulation, the Metropolis-Hasting (M-H) sampling algorithm [24] was adopted here. Fig. 7 shows the transition matrices of vehicle types CV1, CV2, CV6,

CV12, and CV13 with relatively high proportions of the total vehicles. As shown in the figure, on the overtaking lane, the following proportion of the CV1 vehicle type is relatively high, which is also in line with normal driving habits.

In addition to the correlation between vehicle arrival sequences, there is also a correlation between the axle weight of vehicles or wheelbase of vehicles. In this paper, the Spearman rank correlation coefficient was selected to analyze the correlation between the axle weight of vehicles or the wheelbase of vehicles. Fig. 8 presents the Spearman rank correlation coefficient matrix of axle weight or wheelbase for vehicle type CV12. As can be seen from the figure, there is a certain correlation between different axle weight or different wheelbases. The correlation between axle loads is stronger than the similarity between wheelbases.

To consider the correlation between different axle weight or wheelbases of the same vehicle. Here, the Copula function, a connection function acting on multivariate distribution functions and marginal distribution functions, was used. The joint distribution functions of the N -variate normal Copula and the N -variate t -Copula are expressed as follows:

$$C(u_1, u_2, \dots, u_N; \rho) = \Phi_\rho[\Phi^{-1}(u_1), \Phi^{-1}(u_2), \dots, \Phi^{-1}(u_N)] \quad (6)$$

$$C(u_1, u_2, \dots, u_N; \rho, k) = t_{\rho, k}[t_k^{-1}(u_1), t_k^{-1}(u_2), \dots, t_k^{-1}(u_N)] \quad (7)$$

where, ρ is a positive definite matrix of order N with unit diagonal elements; Φ_ρ is the standard normal Copula function, parameterized by the correlation matrix ρ ; $t_{\rho, k}$ is defined as the standard t -Copula function, where k denotes the degrees of freedom. Here, the correlation between axle weight was considered using the t -Copula function, while the correlation between wheelbases was con-

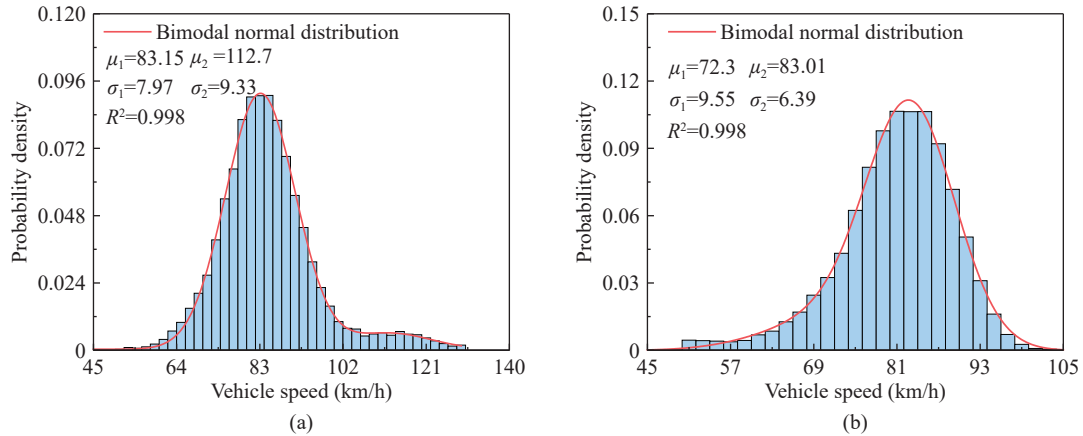


Fig. 5 The vehicle speed distribution of two-axle and six-axle vehicles. (a) 2-axle; (b) 6-axle.

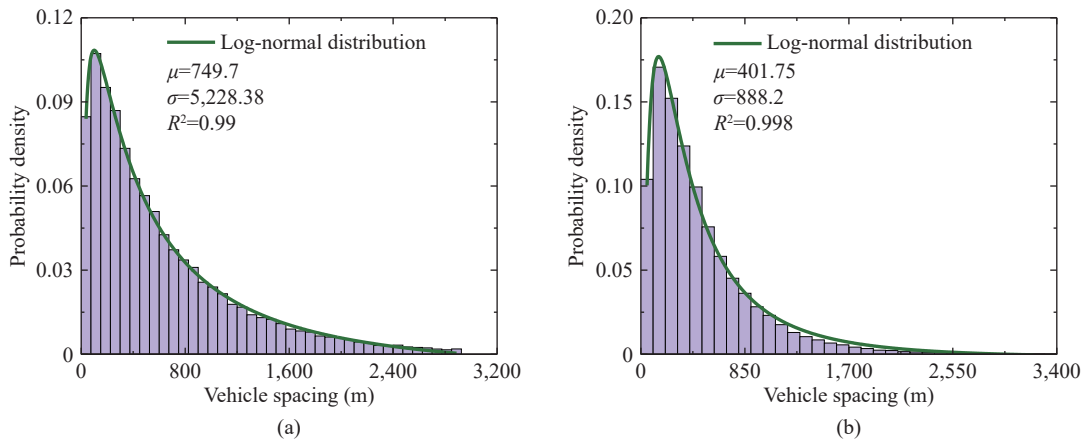


Fig. 6 Probability density distribution function of vehicle spacing. (a) Overtaking lane; (b) Carriageway.

Table 3 Different vehicle type information.

Type number	Axle number	Proportion (%)	Wheelbases (m)				
			WB ₁	WB ₂	WB ₃	WB ₄	WB ₅
CV1	2	60.03	2.89				
CV2	2	5.58	5.18				
CV3	2	2.05	7.28				
CV4	3	0.57	5.28	1.34			
CV5	3	2.13	2.31	5.52			
CV6	4	3.24	2.01	4.69	1.56		
CV7	4	2.77	4.16	9.34	1.34		
CV8	5	2.11	2.95	5.00	1.34	1.34	
CV9	5	0.57	3.34	1.45	8.76	1.33	
CV10	5	0.97	3.94	8.60	1.33	1.34	
CV11	5	0.22	1.94	5.02	8.89	1.34	
CV12	6	13.88	3.30	1.44	5.72	1.33	1.34
CV13	6	5.86	3.30	1.49	9.22	1.32	1.33

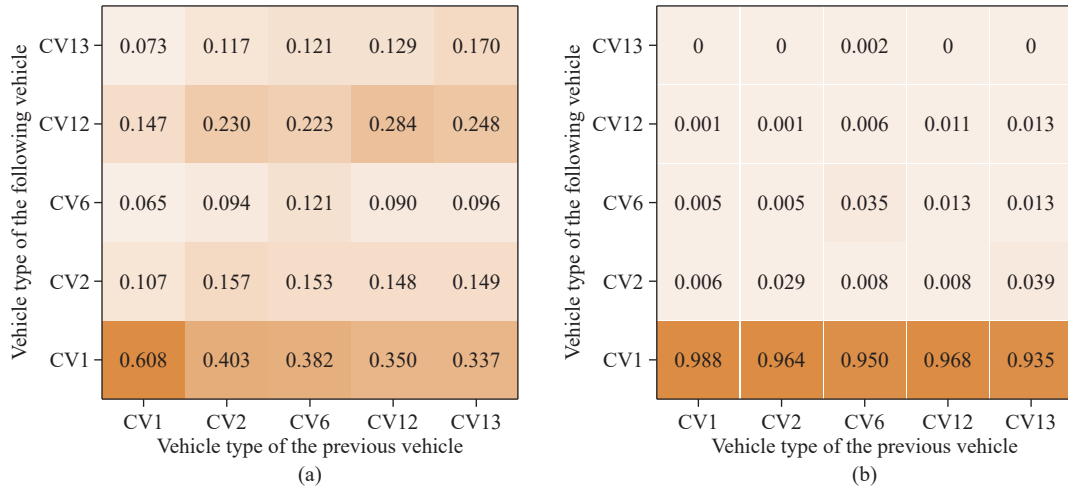


Fig. 7 Transition matrix between vehicle types. (a) The carriageway; (b) The overtaking lane.

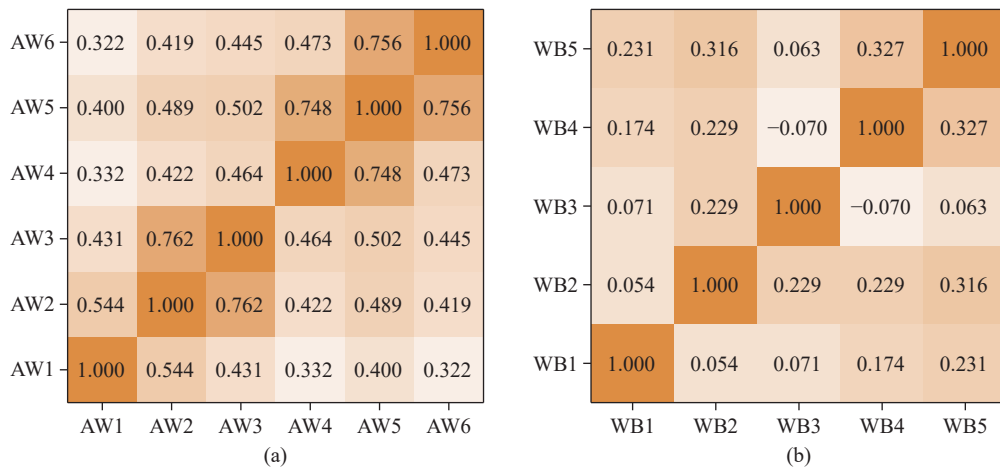


Fig. 8 The Spearman rank correlation matrix for axle weight and wheelbase of CV12 vehicle type. (a) The axle weight; (b) The wheelbase.

sidered using normal Copula. The corresponding correlation coefficient matrices of the CV12 vehicle type are presented in Fig. 9 and Fig. 10.

3.3 Simulation result of random traffic flow

Random traffic flow was simulated using the statistical parameters and correlation analysis of the traffic load data. Among them, the vehicle type arrival sequence was produced through the application of the M-H sampling algorithm; the Copula function was used to consider the correlation between axle weight of vehicles or the wheelbase of vehicles; and for total vehicle weight and the vehicle spacing, the sampling method from the cumulative distribu-

tion function was adopted. The sampling methodology for total vehicle weight should incorporate the applicable vehicle load limit levels. If the load limit requirement is not met, the total vehicle weight is resampled. The overall process is shown in Fig. 11. For specific details, refer to the author's previous research in reference [10]. Following the procedure described above, the simulation for a stochastic traffic flow on the driving lane at a specific time was performed, with the result presented in Fig. 12.

4 Determination of structural resistance level

Once the bending moment on a bridge exceeds its cracking mo-

AW6	0.351	0.527	0.540	0.488	0.763	1.000
AW5	0.429	0.600	0.602	0.749	1.000	0.763
AW4	0.368	0.540	0.544	1.000	0.749	0.488
AW3	0.512	0.919	1.000	0.544	0.602	0.540
AW2	0.546	1.000	0.919	0.540	0.600	0.527
AW1	1.000	0.546	0.512	0.368	0.429	0.351
	AW1	AW2	AW3	AW4	AW5	AW6

Fig. 9 The ρ of the t -Copula function between the axle weight of the CV12 vehicle type ($k=4.3279$).

WB5	0.226	0.288	0.026	0.297	1.000
WB4	0.168	0.193	-0.101	1.000	0.297
WB3	0.066	0.205	1.000	-0.101	0.026
WB2	0.029	1.000	0.205	0.193	0.288
WB1	1.000	0.029	0.066	0.168	0.226
	WB1	WB2	WB3	WB4	WB5

Fig. 10 The ρ of the normal Copula between the wheelbases of the CV12 vehicle type.

ment, concrete cracking occurs, which compromises the structure's durability and load-bearing capacity. When the bending moment exceeds its ultimate bending moment, the bridge will be damaged. When the bending moment reaches the yield bending moment, it means that the bearing capacity of the bridge has reached a critical turning point. Beyond this point, the deformation of the bridge will increase rapidly. Therefore, starting from the above information, taking the three limit values of bridge cracking moment, yield moment, and failure moment as the marker values for the bridge to enter three states [21].

(1) The cracking moment

As the beam nears its cracking state, the concrete in the tensile zone reaches its ultimate tensile strain, followed by cracking, upon which its tensile resistance becomes negligible. At this point, the bending moment borne by the beam is the cracking moment M_{cr} , and the calculation equation is as follows:

$$M_{cr} = (\sigma_{pc} + \gamma f_{tk}) W_0 \quad (8)$$

where, W_0 is defined as the elastic resistance moment for the tensile side of the converted cross-section; σ_{pc} is the concrete prestress generated at the tensile edge after deducting all prestress losses; γ is defined as the plasticity coefficient influencing the section modulus of the member; f_{tk} represents the axial concrete tensile strength.

(2) The failure moment

When the bending moment acting on the beam reaches the ultimate bending moment, the compressive strain at the compressed upper edge for the section attains the ultimate value. Once the concrete compressive strength is depleted, longitudinal horizontal cracks develop, leading to the crushing of concrete and the eventual failure of the beam. The bending moment at this failure stage is defined as the failure bending moment, which could be calculated using the following equations:

$$M_u = f_c b x \left(h_0 - \frac{x}{2} \right) + f'_s A'_s (h_0 - a'_s) \quad (9)$$

$$f_s A_s + f_p A_p = f_c b x + f'_s A'_s \quad (10)$$

where, h_0 and b are the beam effective height and width; x is the compression zone height, calculated by Eq. (10); f_c is the concrete axial compressive strength; f_s and f_p are the tensile strength for the longitudinal tensile reinforcement and the prestressed reinforcement in the tensile zone; A_s and A_p are the cross-sectional area for the longitudinal tensile reinforcement and the prestressed reinforcement in the tensile zone; a'_s represents the distance from the resultant force point of the reinforcement in the compression zone to the edge of the compression zone; A'_s and f'_s are the cross-sectional area and compressive strength of longitudinal compression reinforcement.

(3) The yield moment

When the bending moment on the beam reaches the yield bending moment, the reinforcement reaches the yield strength. Before this, the beam has experienced the decompression state. It follows that, at this juncture, the prestressed concrete beam is under the same stress conditions as an ordinary reinforced concrete beam. The calculation method for yield bending moment is similar to that of ultimate bending moment and will not be repeated here.

Due to the inevitable deviations in material processing, component fabrication, and installation, this will affect the structural resistance results to a certain extent and further affect the results of structural reliability analysis. Therefore, when calculating the resistance, the uncertainties of material and geometric parameters need to be considered simultaneously. The statistical information of those parameters is given in Table 4. On this basis, the probability distribution of resistance can be obtained through multi-dimensional integration. However, this will cause great difficulties in mathematics. Therefore, the MC sampling simulation method can also be used to obtain the resistance distribution.

5 Calculation of structural failure probability

For different load limit levels, the above-mentioned random

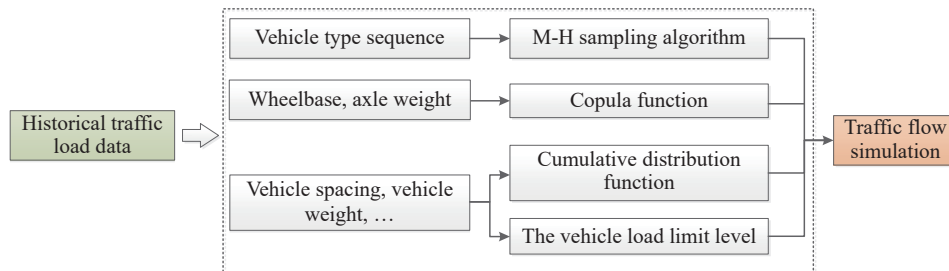


Fig. 11 The process of simulating random traffic flow.

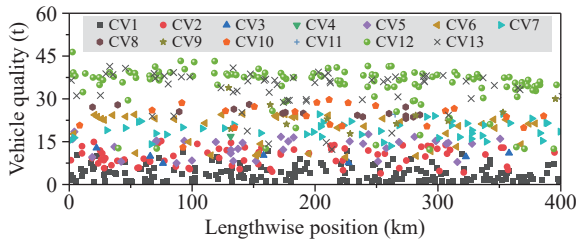


Fig. 12 The simulation result of random traffic flow.

traffic flow simulation method can be used to form random traffic flows with different load levels. For different limit states of the structure, it also has corresponding resistance levels. The objective of vehicle-induced fragility analysis is to determine the failure probability of a bridge under varying levels of vehicle load, relative to a specific resistance threshold. The performance function characterizing this analysis is given by:

$$Z = g(R, S_G, S_Q) = R - S_G - S_Q \quad (11)$$

where, R is the structural resistance; S_G is the structural static load effect; S_Q is the vehicle load effect. In practical engineering, R , S_G , and S_Q are all random variables. If the statistical parameters of each variable are known, the corresponding PDF can be uniquely determined. For the vehicle load effect S_Q , a stationary random process model is generally used to describe it.

To determine the distribution for the maximum vehicle load effect over the design reference period, maximum value extrapolation theory can be used. This theory involves dividing the design reference period into l equal time periods, and the each time period is $\tau = T/l$. At the same time, the vehicle load data samples in each section satisfy the independent and identically distributed assumption. With the distribution function $F(x)$ given in Eq. (12), the distribution function $F_T(x)$ of the maximum vehicle load effect over the design reference period is derived as Eq. (13).

$$F(x) = P[Q(x) \leq x, t \in \tau] \quad (12)$$

$$F_T(x) = P[Q_T(x) \leq x] = \prod_{i=1}^l P[Q_i(x) \leq x] = [F(x)]^l \quad (13)$$

where i is the sub-time period sequence number.

For establishing extreme value samples, there are currently three main methods: (1) After determining the sub-time period, select the maximum value of load effect within this interval as the extreme value sample, that is called block maximum method (BM); (2) Sorting vehicle load effect samples to construct an order statistics model and taking the n largest values as extreme value samples,

that is called order statistics method (OS); (3) Determining the interval data threshold and selecting all samples over the threshold as extreme value samples, that is called peak over threshold method (POT). Among them, the OS and POT methods can make more use of the sample extremes of the sub-intervals, but the determination of their ordinals and thresholds is highly subjective. For this problem, the BM method can be solved by using the results of load probability characteristic analysis combined with the MC sampling method in the extreme value modeling process. In addition, all three methods involve the problem of choosing the interval length: first, the interval length should meet the assumption of independent and identically distributed among data samples as much as possible; second, the interval length should try to improve the utilization rate of sample data. Here, one day was selected as the interval length in this paper.

After the extreme value samples were established, a suitable probability distribution model needs to be selected to describe $F_T(x)$. Extreme value theory states that for independent and identically distributed random variables, the distribution of the sample maximum must converge to one of three types: the Gumbel (Type I), Fréchet (Type II), or Weibull (Type III) distributions. These three forms can be encompassed within a unified representation known as the generalized extreme value distribution, expressed as follows:

$$G(x) = \exp \left\{ - \left[1 + \zeta \left(\frac{x - \mu}{\sigma} \right) \right]^{-\frac{1}{\zeta}} \right\} \quad (14)$$

where ζ , μ and σ are the shape, location, and scale parameters, respectively. When $\zeta = 0$, it represents type I; $\zeta > 0$ for type II; $\zeta < 0$ for type III. According to the above method, the extreme value model for vehicle load effects can be established.

The MC sampling method was used to sample from the resistance model and the load effect model. Whether the structure is failed was judged according to whether Z in Eq. (11) is less than or equal to 0. If there are N samplings in total and n of them are failures, then the structural failure probability (P_f) is defined as the ratio of n to N . The overall calculation process of P_f is shown in the Fig. (13).

6 Case study

Statistical analysis of the typical small and medium span bridges along a selected route (Fig. 14) shows that prestressed concrete hollow slab (PC-H) and prestressed concrete T-beam (PC-T) bridges represent 54.95% and 17.99% of the total bridge count, respectively. In hollow slab bridges, the proportion of 20 m span is the highest. The proportion of 30 m span is the highest in T-beam bridges. The bridge information is listed in Table 5.

Table 4 Statistical information of the material and geometric parameters.

	Parameters	Distribution type	μ	σ
Materials	Concrete compressive strength	Normal distribution	1.221	0.110
	Yield strength of reinforcement	Normal distribution	1.280	0.102
	Yield strength of prestressed reinforcement	Normal distribution	1.140	0.130
	Width and height of the cross-section	Normal distribution	1.000	0.020
	The area of longitudinal reinforcement	Normal distribution	1.000	0.030
Geometry	Thickness of concrete cover	Normal distribution	1.000	0.300
	Distance from prestressed reinforcement to the near end of section.	Normal distribution	1.000	0.050
	Distance from reinforcement to the near end of section.	Normal distribution	1.000	0.030

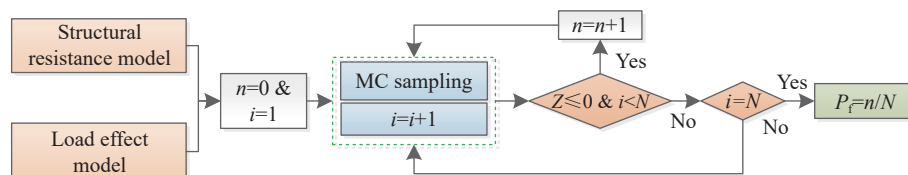


Fig. 13 Overall calculation process of P_f .

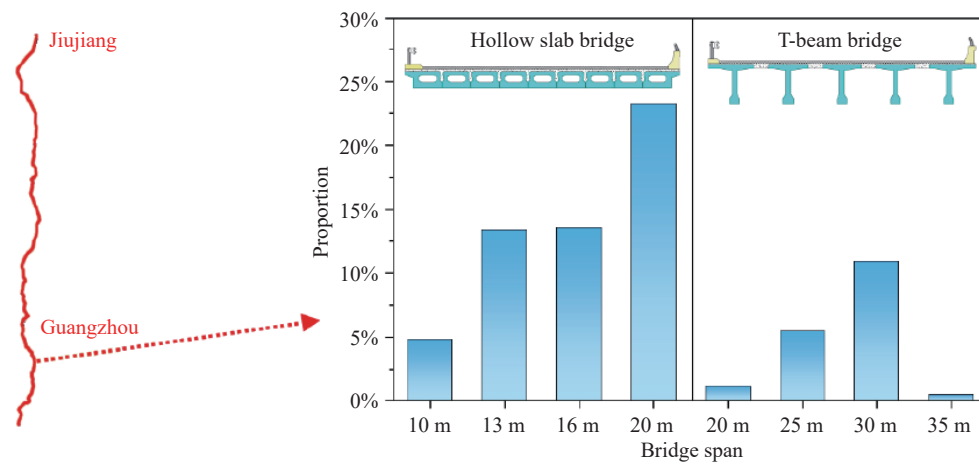


Fig. 14 Proportion of typical small-and medium-span bridges on a certain route. (a) Route alignment; (b) Proportion of small- and medium-span bridges.

Fig. 15 presents the typical cross-sections of the case bridges. The bridge deck is laid out with three lanes: overtaking lane, carriageway, and emergency lane. The girder numbers increase one by one from the overtaking lane to the emergency lane direction.

Combining the above calculation method and the standard data of each parameter, the cracking moment, yield moment and failure moment of eight case bridges were calculated. The standard values of the flexural capacity of each bridge are listed in Table 6.

The calculation and extrapolation of bridge response under random traffic flow were subsequently carried out. The finite element grillage models of PC-H and PC-T were established separately, in which virtual crossbeams were used to establish the transverse con-

nections of the bridge. The translational degrees of freedom of adjacent nodes at the crossbeam connections were coupled and the corresponding rotational degrees of freedom were released to simulate the hinge between adjacent slabs. At the same time, the prestress effect was simulated by applying initial stress. The corresponding finite element models are shown in the Fig. 16. Based on the finite element model, the response influence lines of specific points corresponding to different transverse bridge positions can be extracted, and the approximate influence surface can be obtained by connecting them laterally. Taking the 4th case bridge as an example, the mid-span bending moment influence surfaces of its 5th slab and 8th beam are plotted in Fig. 17. Based on the influence surface, the static response of each case bridge under random traffic flow was obtained, and then the top ten periods with the highest daily response were selected, each time period is 5 min. Furthermore, the bridge dynamic response under random traffic flow during these time periods should be calculated.

The bridge dynamic responses under traffic were obtained using a standard vehicle–bridge interaction (VBI) formulation, in which the vehicle and bridge are treated as two coupled dynamic subsystems linked through time-varying contact forces at the wheel–deck interfaces. The general derivation and commonly used solution

Table 5 Information of the case bridge.

Bridge type	Bridge number	Bridge span (m)	Number of main beams
PC-H	1	10	9
	2	13	9
	3	16	9
	4	20	9
PC-T	5	20	5
	6	25	5
	7	30	5
	8	35	5

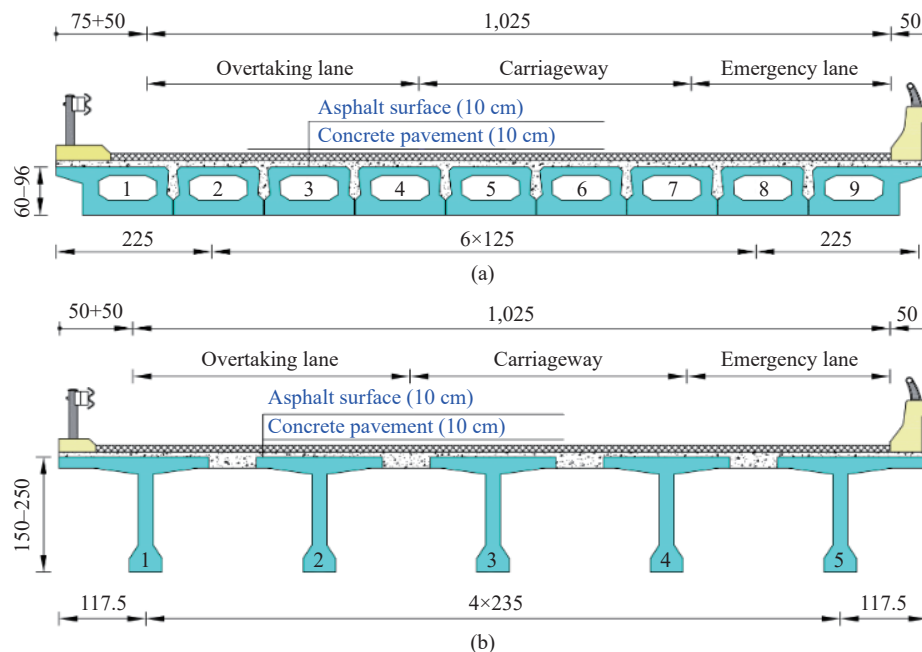


Fig. 15 Typical cross-section and main beam number of the case bridge (unit: cm). (a) PC-H; (b) PC-T.

Table 6 Standard value of flexural bearing capacity for case bridges.

Bridge type	Bridge number	Cracking moment (kN·m)	Yield moment (kN·m)	Failure moment (kN·m)
PC-H	1	714.66	1 166.72	1 264.91
	2	1 102.56	1 814.26	1 968.52
	3	1 528.07	2 740.06	2 905.29
	4	2 295.56	3 082.70	3 284.86
	5	4 801.23	7 745.76	7 999.46
PC-T	6	7 077.18	11 621.99	11 891.89
	7	8 259.61	13 939.94	14 374.61
	8	11 651.82	18 853.43	19 139.14

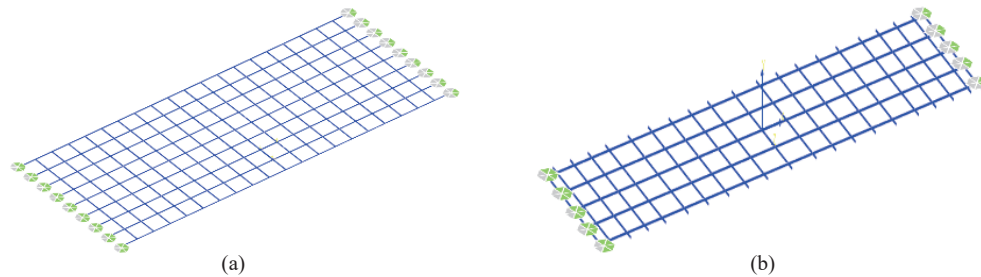


Fig. 16 Finite element models of bridges. (a) PC-H; (b) PC-T.

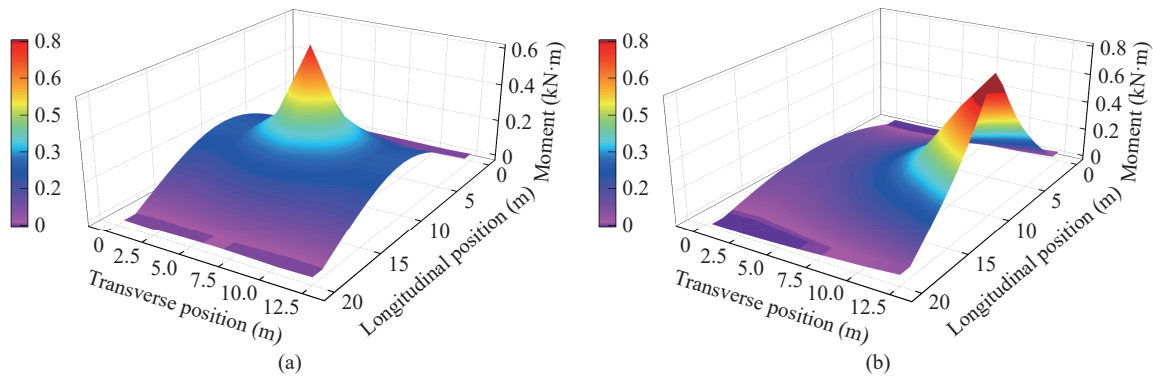


Fig. 17 The mid-span bending moment influence surfaces of the 4th case bridge. (a) The 5th slab; (b) The 8th slab.

strategies for VBI problems can be found in the literature [25–26]. Based on this established framework, the self-developed dynamic analysis system (BDANS) was employed to compute the bridge responses for the ten selected time periods, and the corresponding daily maximum response was extracted. The computational accuracy of the BDANS has been verified [27–28]. Fig. 18 shows the PDF and CDF of the daily maximum mid-span bending moment effect for traffic loads.

When using the MC sampling method to determine the P_f of a structure, too few sampling quantities will result in inaccurate calculation results, but too many will lead to excessive calculation time. Therefore, two working conditions, namely the vehicle load limit of 35 t for the 3rd case bridge and the vehicle load limit of 55 t for the 7th case bridge, were randomly selected. To ensure the numerical stability and robustness of the fragility results, a convergence analysis was conducted based on different sampling quantities. As illustrated in Fig. 19, when the sampling quantity reaches 10^7 , the failure probabilities corresponding to different structural states converge with minimal computational fluctuation. This high sampling frequency effectively minimizes the random error of the Monte Carlo simulation, ensuring the reliability of the mean fragility curves. Consequently, 10^7 samplings were adopted for each working condition in this study.

After determining the resistance level, load effect level, and P_f calculation method of the structure, the corresponding P_f of the structure can be calculated under different vehicle load limit levels, thereby forming a traffic load fragility curve. According to the

standard (JTG 2120—2020), the target reliability index was selected as 4.7, and the corresponding target P_f is 1.30×10^{-6} . It is worth noting that this target P_f corresponds to the ultimate state of the bearing capacity of the structure, i.e. ultimate limit state target P_f (ULST P_f). In addition, there is a target reliability index corresponding to the serviceability limit state of the structure, which is set as 2.90 [29] and the corresponding failure probability is 1.87×10^{-3} , i.e. serviceability limit state target (SLST P_f).

Fig. 20 plots the traffic-load fragility curves of the PC-H case bridges under different load-limit levels. Overall, the failure probabilities for the three limit states increase continuously with the load-limit level. This is because relaxing the load limit increases the likelihood that heavy vehicles enter the traffic flow and, consequently, increases the occurrence of extreme loading events. Combined with extreme-value extrapolation, the maximum traffic-load effect over the design reference period shifts toward higher values, making the mid-span bending moment more likely to approach or exceed the corresponding resistance threshold and thereby increasing P_f . The relative positions of the curves are mainly governed by the resistance thresholds of the different limit states. The cracking threshold is relatively low and is more sensitive to lane position and transverse load distribution. Therefore, even under a relatively low load-limit level, the load effect may exceed the cracking threshold, leading to an overall higher failure probability for the cracking state and indicating a high likelihood that the bridge works with cracks. In contrast, the yield and failure limit states have higher resistance thresholds, so their failure prob-

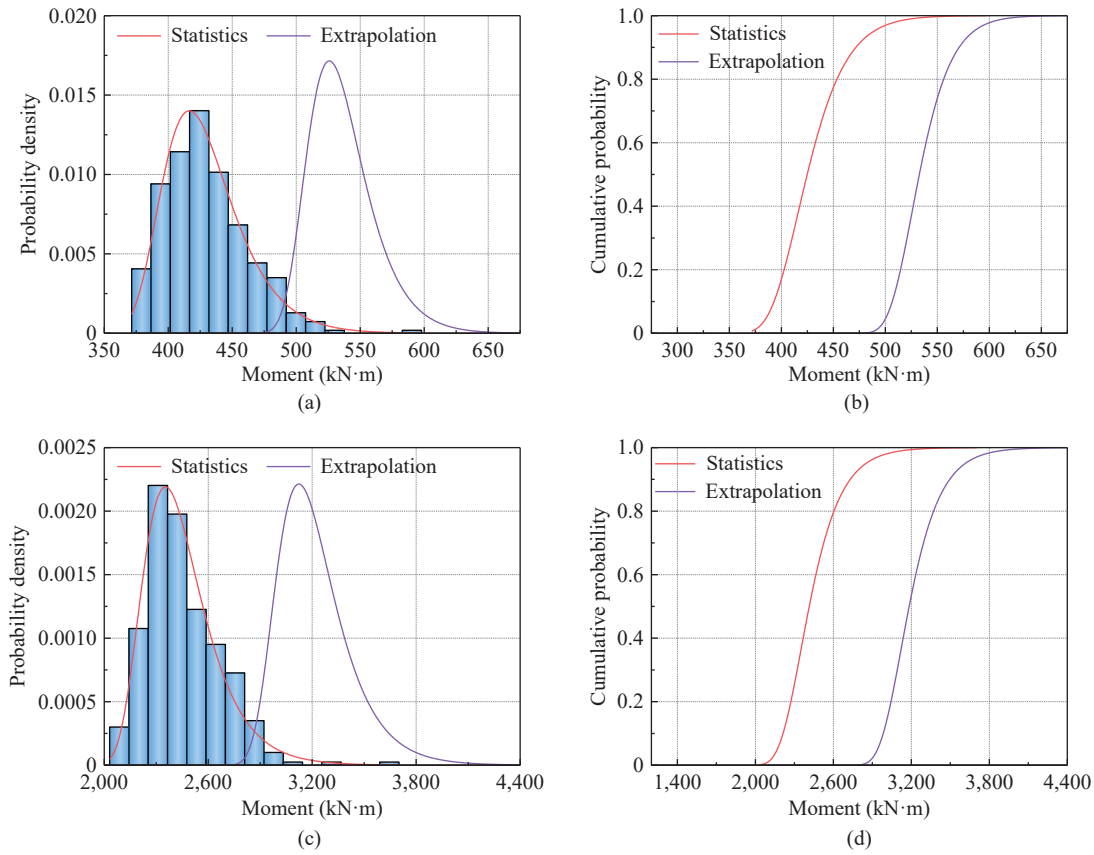


Fig. 18 Distribution of daily maximum bending moments for the 4th and 8th case bridges. (a) PDF of the effect for the 4th case bridge; (b) CDF of the effect for the 4th case bridge; (c) PDF of the effect for the 8th case bridge; (d) CDF of the effect for the 8th case bridge.

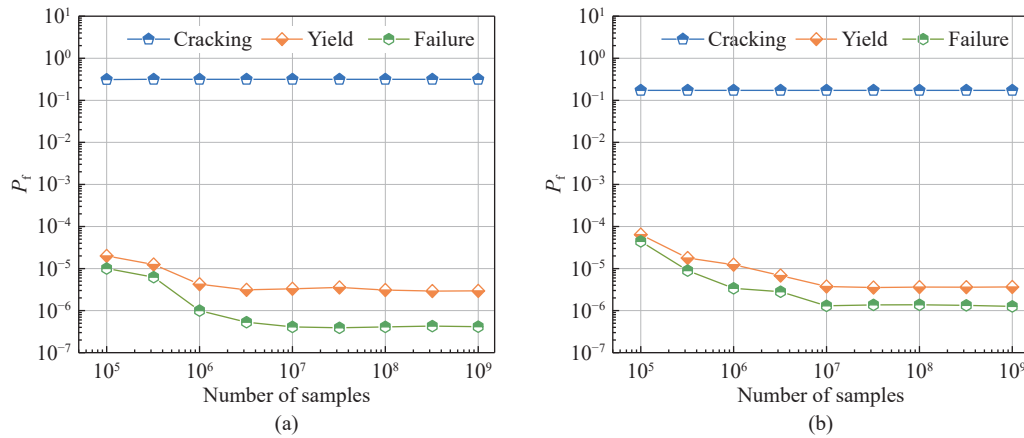


Fig. 19 P_f corresponding to different sampling quantities. (a) The 3rd case bridge with the vehicle load limit of 35 t; (b) The 7th case bridge with the vehicle load limit of 55 t.

abilities are at a lower level and increase gradually as the load-limit level rises. It can also be observed that some case bridges reach the ULST criterion earlier in the range of approximately 30–40 t. This is related to differences among the case bridges in section dimensions, reinforcement, and prestressing arrangements, which affect the resistance margin for the yield or failure limit state and also influence the growth of the mid-span effect under extreme traffic events. As a result, the fragility levels differ among bridges under the same load-limit level.

Fig. 21 shows the traffic-load fragility curves of the PC-T case bridges under different load-limit levels. Similar to the PC-H bridges, the increase in P_f with the load-limit level reflects the same mechanism of a higher probability of heavy-load events and

an elevated extreme load effect over the reference period. Compared with the PC-H bridges, the PC-T bridges generally exhibit lower failure probabilities and a slower increase for the yield and failure limit states. This is usually associated with their structural system and flexural resistance reserve, making the mid-span effect less likely to exceed the higher thresholds under the same traffic loading. Meanwhile, the cracking state may still maintain a non-negligible failure probability even when the load-limit level is high, indicating that cracking, as a low-threshold limit state, remains sensitive to relatively common traffic loading events and that the bridges may still work with cracks. Within the PC-T group, the differences among curves mainly arise from differences in span length and structural detailing, which lead to different mid-span effect

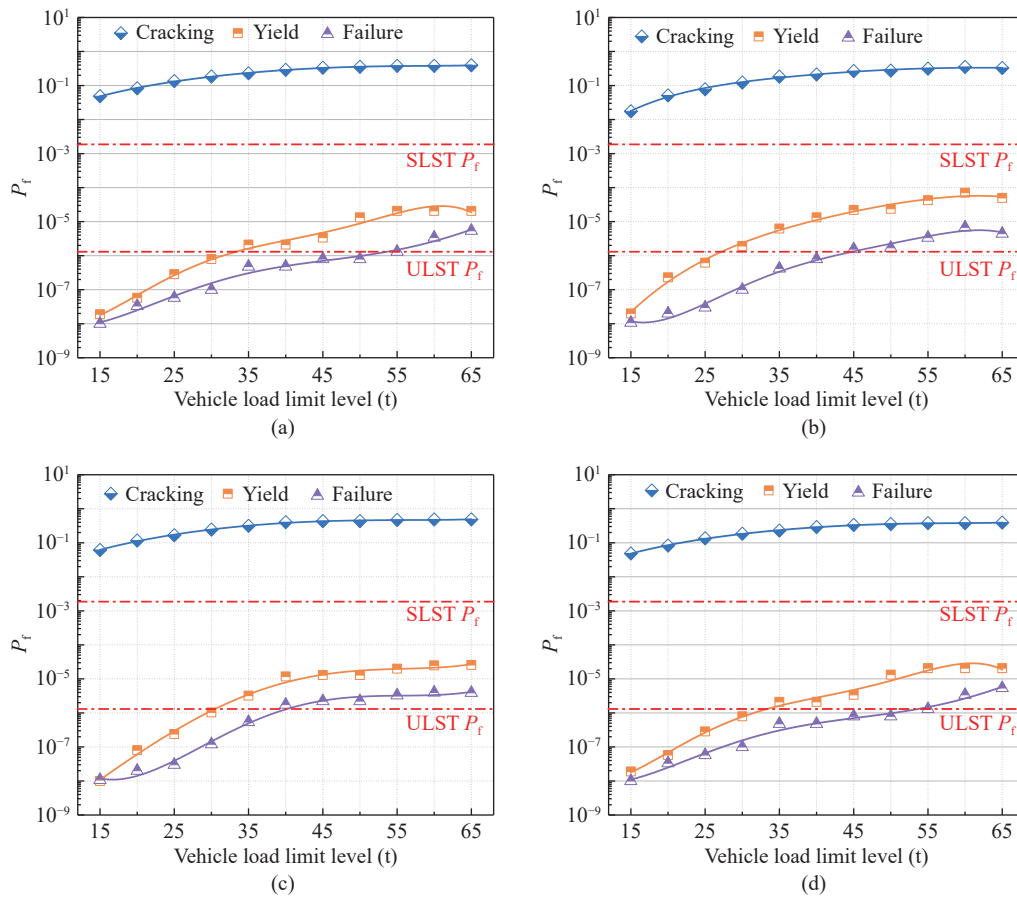


Fig. 20 Traffic load fragility curves of different PC-H case bridges. (a) The 1st case bridge; (b) The 2nd case bridge; (c) The 3rd case bridge; (d) The 4th case bridge.

levels and resistance margins. The 7th case bridge shows comparatively higher fragility under different load-limit levels, which can be attributed to a higher tendency to develop unfavorable bending-moment effects at the critical section or a relatively smaller resistance margin for the corresponding limit states, making P_f more sensitive to the load-limit level.

Based on the traffic load fragility curves provided for different bridges, the failure probabilities of various bridges under the same load limit level can be determined. According to the Chinese national standard GB 1589—2016, the maximum permissible total mass for vehicles is 49 t. However, under the earlier standard GB 1589-2004, this limit was specified as 55 t. Fig. 22 presents the failure probabilities of different bridges under 49 t or 55 t load limit scenarios. The results demonstrate that hollow slab bridges exhibit higher failure probabilities compared to T-beam bridges, indicating better safety performance of T-beam structures. Among hollow slab bridges, the 2nd and 3rd case bridges show relatively higher failure probabilities. For T-beam bridges, the 7th case bridge displays comparatively higher failure probabilities across different failure conditions. This indicates that under current traffic load characteristics, hollow slab bridges require greater attention than T-beam bridges regardless of whether the load limit is set at 49 t or 55 t. Furthermore, among hollow slab bridges, bridges of the No. 2 and No. 3 types deserve greater attention, while among T-beam bridges, bridges of the No. 7 type should receive more focus.

7 Conclusions

This study proposes a traffic-load fragility assessment framework for small- and medium-span bridges that incorporates regional traffic load characteristics. By integrating statistical analysis of WIM data, advanced simulation algorithms, and probabilistic struc-

tural resistance evaluation, the following key conclusions are drawn:

(1) There is a certain correlation between the axle loads of vehicles, as well as between the wheelbases of vehicles. The Copula function can be used to consider that correlations. In addition, the correlation of vehicle arrival sequences can be considered through the M-H sampling algorithm. Considering the correlation of these parameters will obtain a more realistic random traffic flow.

(2) In PC-H case bridges, when the load limit level is around 30 t, the failure probability of the 2nd case bridge corresponding to the yield condition of the reinforcement first exceeded ULST P_f . When the load limit level is around 40 t, the failure probability of the 3rd case bridge corresponding to the failure condition of the structure first exceeded ULST P_f . This shows that the P_f of hollow slab bridges of 13 m span and 16 m is relatively high. In PC-T case bridges, the probability of failure is relatively high for 30 m span.

(3) Under the same traffic load conditions, the failure probability of hollow slab bridges is higher than that of T-beam bridges. This indicates that T-beam bridges are more suitable for the current traffic load conditions.

(4) On the basis of considering the characteristics of regional traffic loads, by calculating the P_f of bridges corresponding to different states under different vehicle load limit levels, the fragility curve of bridges to current regional traffic loads can be formed, thereby gaining a more systematic understanding of the impact of different load limits on bridge structures. This can provide important support for the design of bridges and the formulation of vehicle load limit policies.

(5) In the fragility analysis of bridge traffic loads presented in this paper, neither the future degradation of bridge resistance nor the long-term evolution of traffic load characteristics is considered. These issues will be addressed in future work through model updat-

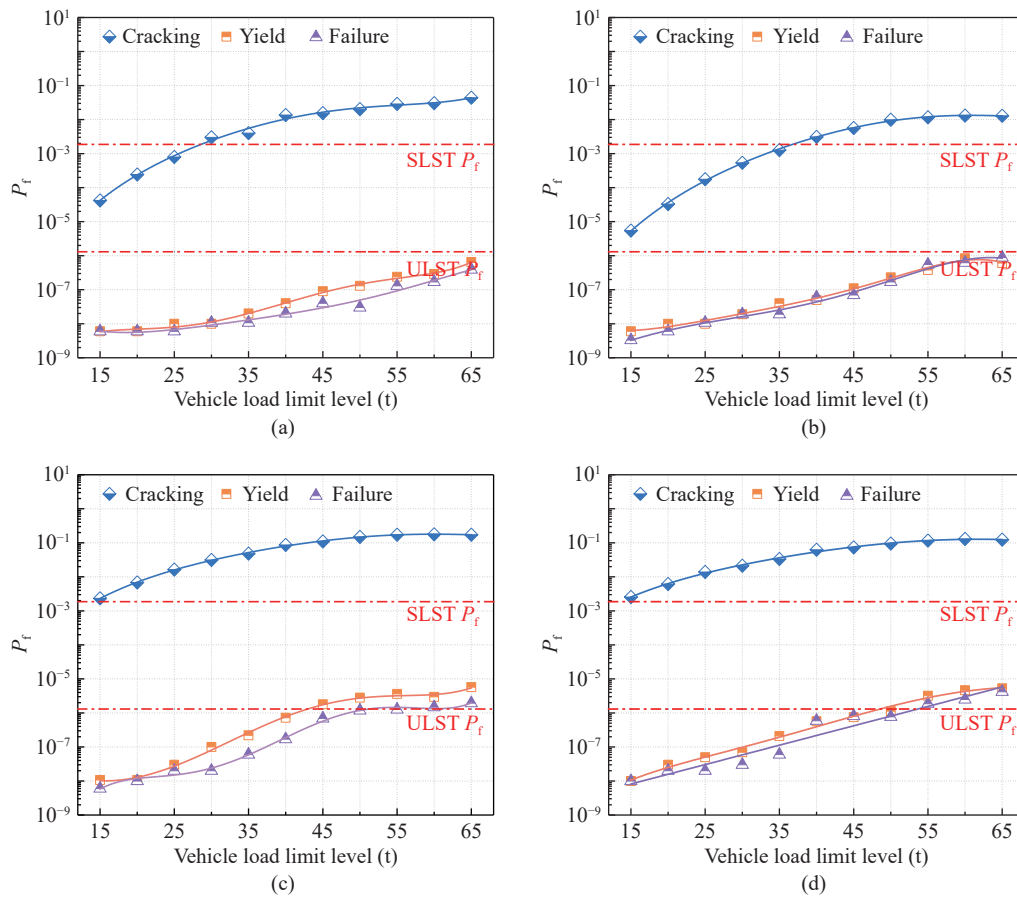


Fig. 21 Traffic load fragility curves of different PC-T case bridges. (a) The 5th case bridge; (b) The 6th case bridge; (c) The 7th case bridge; (d) The 8th case bridge.

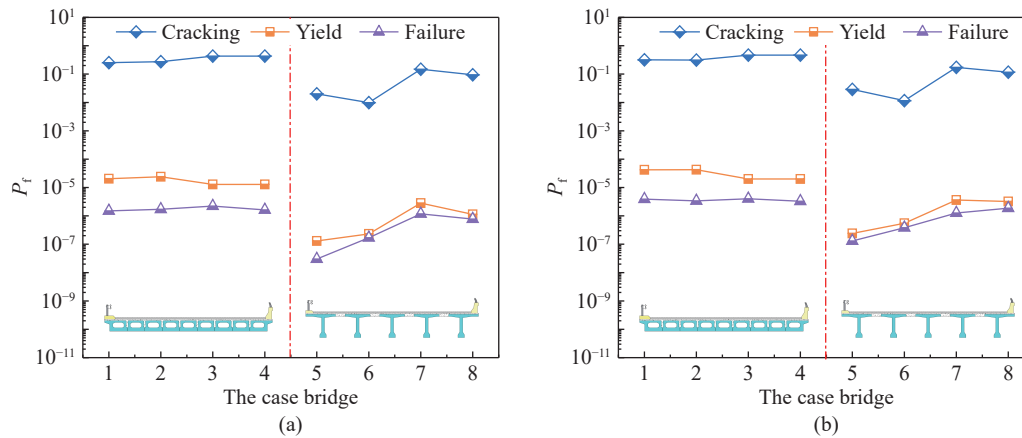


Fig. 22 The P_f of different medium and small span bridges under different load limiting levels. (a) The load limit level is 49 t; (b) The load limit level is 55 t.

ing and parameter calibration using inspection/monitoring data from in-service bridges, to enhance the engineering applicability of the fragility curves.

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The authors have no competing interests to declare that are relevant to the content of this article.

Author contribution statement

Yang Gan: Methodology, software, writing —original draft. Chen Shizhi: Conceptualization, data curation, methodology. Shuying Zhang: Data curation, methodology, investigation. Han-

Wanshui: Validation, investigation.

Data availability statement

Some or all Data, models, or code that support the findings of available from the corresponding author upon reasonable request.

Use of AI statement

No artificial intelligence tools were used in the research or preparation of this manuscript.

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