

# EMPIRICAL VULNERABILITY ANALYSIS OF RAILWAY BRIDGE SEISMIC DAMAGE BASED ON 2022 MENYUAN EARTHQUAKE

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## ABSTRACT

A 6.9 magnitude earthquake at a depth of 10 km struck Menyuan County, Haibei Prefecture, Qinghai Province, China, on January 8, 2022. This earthquake damaged some railway bridges on the Lanzhou-Xinjiang Passenger Dedicated Line. This study combines relevant historical earthquake damage experience, considers the effects of earthquake intensity, site soil classification, superstructure type, foundation failure factor, number of spans, and total bridge length, and develops empirical formulas for seismic damage prediction of railway bridges using ordinal logistic regression model in SPSS software. Since the accuracy of both predictions for seismic damage is practically the same, using this regression to predict seismic damage to railway bridges is considered valid. The predicted seismic damage matrix, as were the anticipated multi-intensity mean damage index and the empirical vulnerability curve based on the two-parameter lognormal distribution function, were generated on this basis. We get a risk assessment of future seismic damage for regional bridges when they experience different intensities or peak ground acceleration. According to the conclusions, although the suggested particular equations and vulnerability curves do not apply to the remainder of the region owing to geographical uniqueness, the technical approach is valid. It may be used as a reference for seismic damage prediction and vulnerability evaluation in other regions. The earthquake damage prediction matrix derived from the regression analysis can provide reasonable and fast forecasts before the next earthquake.

## KEYWORDS

Railway bridges, Empirical vulnerability, Seismic damage prediction, Ordinal logistic regression

## INTRODUCTION

As a lifeline project, it is necessary to strengthen and improve the seismic capacity of bridges before earthquakes and to enable them to meet the needs of traffic and emergency resource deployment after earthquakes during their service phase. The seismic damage prediction and vulnerability study of railway bridges in the region is an effective and realistic technique to achieve these criteria. The predicted damage and vulnerability curves allow for a general estimation of which bridges in the region require targeted strengthening to improve seismic capacity. Bridge damage prediction methods are classified into four types: Empirical Statistical Methods, Code Calibration Methods, Pushover, and Integrated Qualitative and Quantitative Evaluation Approaches for big-span bridges. The empirical-statistical method is a seismic safety evaluation method that selects the main factors affecting bridge damage based on historical seismic experience, bridge seismic knowledge, and information provided by bridge samples and then performs statistical regression of the influence mode and weights of each influencing factor based on a large number of samples to establish an empirical bridge damage prediction formula [1].

In 1956, Keisaburo Kubo [2] defined the vulnerability index and counted thirty highway bridges based on ten influencing parameters, such as seismic intensity, site characteristics, and liquefaction. In 1986, Japan [1] proposed an updated method for vulnerability analysis of highway bridges by analyzing 124 earthquake-damaged bridges, considering 15 influencing factors such as design codes, superstructure type, and bridge axis slope, and using an empirical formula obtained by statistical methods. In 1994, Zhu Meizhen [3] developed an empirical formula for predicting nonlinear seismic damage to highway bridges based on the seismic damage of more than 100 bridges in China's Tangshan, Haicheng, and Tonghai earthquakes using statistical methods. In 1994, Wang Tianwei [4] published an empirical method for forecasting earthquake damage to railway bridges using linear regression analysis and the principle of least squares to construct a prediction formula. In 2003, Longjun Xu [5] provided a straightforward approach to forecast earthquake damage for railway bridges and illustrated the cumulative damage probability curves of railway bridges under various earthquake intensities. In 2013, Yang Fan [6] proposed a hierarchical weighted synthesis method based on the hierarchical analysis method applicable to assessing earthquake damage to railway bridges. In 2021, Y.J. Xu et al. [7] proposed a real-time regional seismic damage assessment framework based on Long Short-Term Memory neural network architecture. In 2022, Li WS et al. [8] established a probabilistic seismic demand model for a typical regular continuous-girder bridge and provided suggestions for seismic damage prediction and seismic insurance risk evaluation. Although railway and highway bridges' seismic damage phenomena differ, the forecast methodologies are identical. These approaches give a theoretical foundation for employing regression analysis to anticipate earthquakes. Still, they are no longer relevant to today's railway bridges due to changes in building technology and seismic design.

Currently, there are three broad groups of systems for quick seismic damage assessment assumptions based on historical earthquake damage data, information from earthquake intensity records, and fundamental structural features of bridges. The first one is the system formed by the seismic damage presumption process for highway bridges proposed by Kuan Kobayashi et al. [9], which has been widely used in Japan [10] and modified after the Kumamoto earthquake [11]. The second one is Murano Gallon et al. [12] proposed a software system [13] for forming a presumptive design chart for seismic damage with the ratio of the predominant period of ground motion to the intrinsic period of the structure as the horizontal coordinate and the ratio of the maximum acceleration of ground motion to the yield seismicity of the structure as the vertical coordinate, which has been used in the Japanese railway sector. The third one is the vulnerability curve approach, represented by the HAZUS earthquake damage assessment system in the United States [14]. These approaches, however, need a large and diverse sample of seismic data, and are computationally demanding. Among these three methods, the design codes of Chinese and Japanese bridges differ, so the seismic factors differ, and their evaluation systems cannot be used. In the Menyuan earthquake, the lack of specific ground motion data at the bridge site made it challenging to get the predominant period quickly. The HAZUS evaluation system used in the United States collects seismic hazard data of bridges in the United States, and the geological conditions and construction methods at the bridge site are so different that it does not apply to China.

This work aims to apply ordinal logistic regression to forecast seismic damage on the northeast edge of Qinghai, derive empirical vulnerability curves, and validate the method's broad applicability.

## THEORETICAL FOUNDATION

The analysis data of vulnerability that can be obtained is of utmost importance, and the methods used are subject to specific restrictions depending on the data information. The prediction of bridge damage has seismic uncertainty, structural insecurity, and regional character. Bridge vulnerability is the probability distribution of all limit states, and the degree of seismic damage to bridge structures is defined in terms of a number of limit states using probability distribution theory. This assessment is frequently based on ground shaking parameters or macroscopic fuzzy physical

quantities, takes structural strength stochasticity into account, and uses arbitrary resistance or limit state strength assessment of bridge structures [15].

While the seismic vulnerability of bridge structures is an important component of the probabilistic theory of seismic hazard analysis, which can effectively quantify a reasonable estimate of the seismic capacity of bridge structures, the northeastern edge of the Qinghai-Tibet Plateau is seismically prone. It has significant railways and infrastructure passing through it. As a result, it is important to study the risk assessment of railway bridges in this region. The seismic hazard matrix for the area can be obtained using the empirical equation for earthquake hazard prediction, and the vulnerability curve can be fitted using the seismic hazard matrix. Though Menyuan has experienced numerous earthquakes throughout its history, only the 6.9 in 2022 caused serious seismic damage to the railway system. The seismic vulnerability analysis of a few railway bridges on the Lanzhou-Xinjiang Passenger Dedicated Line for the magnitude 6.9 Menyuan earthquake in 2022 is significant for the future seismic risk assessment of the railway system in the northeastern margin of the Qinghai-Tibet Plateau due to the regional nature of seismic vulnerability assessment. Meanwhile, while high-speed railway bridge bearings were damaged by the Luzhou earthquake in 2021, the seismic damage of the Lanzhou-Xinjiang Passenger Dedicated Line bridge caused by the Menyuan earthquake was the first time that a high-speed railway bridge on China's mainland was subjected to a real earthquake assessment. The analysis of its seismic damage pattern characteristics is critical for the seismic design of future high-speed railway bridges.

This paper considers the effects of seismic intensity, site soil classification, superstructure type, foundation failure coefficient, number of spans, and total bridge length on bridge damage. The ordinal logistic regression model is used. The specific technical route is first establishing the empirical formula for predicting the earthquake damage to railway bridges, getting the damage matrix, and drawing the empirical vulnerability curve to achieve the empirical vulnerability analysis of the earthquake damage to railway bridges in the Menyuan earthquake. The technical flowchart is shown in Figure 1.

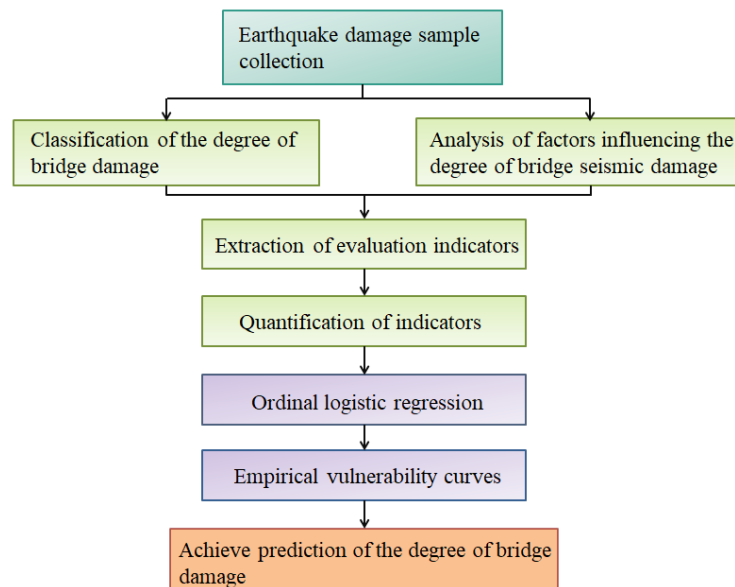


Fig.1 – Technical flowchart

## RAILWAY BRIDGE SEISMIC DAMAGE

On January 8, 2022, a 6.9 magnitude earthquake occurred in Menyuan County, Haibei Prefecture, Qinghai Province, China, with a depth of 10 km. The left-slip type earthquake occurred in the Lenglongling fault zone with a maximum intensity of IX degrees. In the IX degree zone, the girders were significantly displaced and slanted, the tracks were severely twisted and partially

broken, fractures formed on the road surface in several places, fissures and misalignments in the bedrock were evident, and the mountain fell. The severe earthquake damage to the bridges was mostly exhibited as lateral sliding of the major girders, damage to the bearings and retaining blocks, track system distortion, and tilting of the electric poles. Other bridges on the Lanzhou-Xin Passenger have earthquake damage, including pier fractures, bearing anchorages sliding off, and rail sleeper concrete cracking. The Liu Huanggou Bridge, for example, was the first true bridge of seismic damage in China's high-speed railway [16]. Figure 2 depicts typical railway bridge seismic damage.



Fig.2 – Typical railway bridge seismic damage

### Extraction and quantification of evaluation indicators

The seismic damage of railway bridges was divided into five degrees [3, 4] based on the collected seismic samples and associated experiences, as indicated in Table 1.

Tab. 1 - The defines of the degree of earthquake damage

degree of seismic damage	destruction phenomenon
Collapsed (D)	The bridge cannot be used.
Severely Damaged (C)	The main load-bearing structure is severely damaged and needs significant repair or reconstruction.
Moderately Damaged (B)	The main load-bearing structures suffer damage or local damage.
Slightly Damaged (A)	Non-load-bearing structures suffer damage.
No Damaged (A0)	No seismic damage.

The railway bridge damage sample was drawn from 135 railway bridges in the Menyuan earthquake area, which included 111 simply supported girder bridges, 23 continuous girder bridges and continuous rigid frame bridges, and one girder-arch combination bridge. According to the earthquake damage assessment in Table 1, there were no collapsed bridges, one severely damaged

bridge, seven moderately damaged bridges, four slightly damaged bridges, and 123 generally undamaged bridges, as indicated in Figure 3.

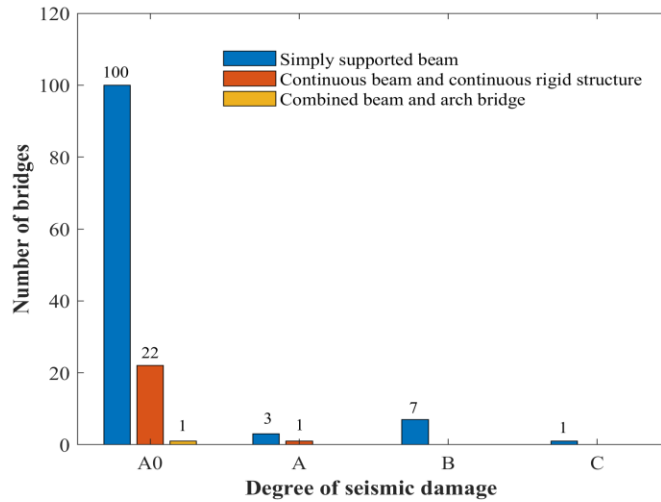


Fig. 3 – Earthquake damage statistics of railway bridges in Menyuan earthquake

Meizhen Zhu [3] believed that the coefficient values of each element are derived from mathematical statistics and offered the recommended coefficient values of the main influencing factors for highway bridges. Tianwei Wang [4] presented different coefficients for qualitative and quantitative factors for seismic damage prediction of railway bridges, and the connection between the coefficients is consistent with the general principles of seismic engineering. Based on the collected bridge seismic data and the relevant historical seismic experience, the following six factors are listed as the main factors affecting bridge seismic damage, as shown in Table 2.

Tab. 2 - Statistical value of impact coefficient of earthquake damage

No.	Main influencing factors	Categories	Statistical coefficient
1	Intensity	VI	1.0
		VII	1.1
		VIII	1.2
		IX	1.3
		X	1.4
		XI	1.5
2	Superstructure	girder-arch combination bridge	1.0
		continuous girder bridges and continuous rigid frame bridge	1.1
		simply supported girder bridge	1.4
3	Site soil classification	1	1.0
		2	1.1
		3	1.2
		4	1.3
4	Foundation failure	none	1.0
		slight	1.2
		heavy	1.6
5	Number of hole spans	=1	1.0
		1~6	1.1
		6<	1.2
6	Total length of bridge	<200m	1.0
		>200m	1.2



We discovered that the region's bridges have enormous spans during the statistical process. The overall length of bridges may approach 5200m, with varied superstructure shapes and site types, and the real seismic damage is dispersed in various intensity zones. These are connected to the bridges' location on the Qinghai-Tibet Plateau, which has a high concentration of permafrost, varied seismic protection for bridges, and various bridge spans owing to topography and geomorphological variations. As a result, this seismic damage index's division is irrelevant to the remainder of the plain area. It should be changed based on regional topography and bridge structural features.

## THE ORDINAL LOGISTIC REGRESSION MODEL

In order to represent the connection between the degree of bridge damage and its numerous influencing factors, this study on bridge damage prediction seeks a model of functional relationship class, describing this relationship either qualitatively or quantitatively. Regression analysis is a mathematical technique used to determine the law of interrelationship between dependent and independent variables from a large amount of data, as well as to perform factor analysis and determine the degree of prediction and influence by one or more variables on the value of the dependent variable. To analyze the factors influencing the degree of bridge damage and understand the law of bridge damage, an ordinal logistic regression model is established in this paper using each factor affecting bridge damage as the independent variable and the degree of individual bridge damage as the dependent variable. The projected outcomes are also contrasted with the actual harm to confirm that the regression model is accurate.

The logistic model belongs to nonlinear regression analysis, and its study is mainly aimed at a multiple regression method between the results of dichotomous or multi-categorical variables of the dependent variable and certain influencing factors. This study employs ordinal logistic regression since the different seismic levels are the dependent variable.

Let there be k classifications of the dependent variable and the probabilities of each classification denoted as P<sub>1</sub>, P<sub>2</sub>... P<sub>k</sub>, the following k-1 logistic regression equations can be fitted to the n independent variables [17]:

$$P_1 = \frac{\exp(\alpha_1 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}{1 + \exp(\alpha_1 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)} \quad (1)$$

$$P_2 = \frac{\exp(\alpha_2 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}{1 + \exp(\alpha_2 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)} - P_1; \quad (2)$$

...

$$P_{k-1} = \frac{\exp(\alpha_{k-1} + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}{1 + \exp(\alpha_{k-1} + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)} - P_1 - P_2 \dots - P_{k-2}; \quad (3)$$

The kth class is used as the reference class. Where:  $\alpha_1, \alpha_2 \dots \alpha_{k-1}$  are the constant terms of the regression equation;  $X_i$  ( $i=1, 2 \dots n$ ) is the influence factor;  $\beta_i$  represents the regression coefficient.

## Model building and results

This study employed the parameters affecting seismic intensity, site soil classification, superstructure type, foundation failure factor, number of spans, and overall bridge length as independent variables. The dependent variable was the seismic damage index of railway bridges. The data were imported into the statistical analysis program SPSS [18], and multiple logistic regression analysis was carried out with the help of the equation above to produce the regression model and coefficients for predicting the degree of bridge seismic damage, which are displayed in Table 3. As shown in Table 3, only these three components pass the significance test because their p-values for the intensity coefficient, site coefficient, and foundation failure coefficient are all less than 0.05.

Tab. 3 - Regression coefficients of each variable in Logistic regression

Model		Coefficient	Std. Error	Wald $\chi^2$	Significance P-value
Threshold	[A0]	181.820	89.872	4.093	0.043
	[A]	189.465	93.545	4.102	0.043
	[C]	190.480	93.694	4.133	0.042
Independent variables	1(Intensity)	89.939	42.416	4.496	0.034
	2(Superstructure)	28.250	23.263	1.475	0.225
	3(Site)	-108.005	47.073	5.264	0.022
	4(Foundation failure)	113.793	55.937	4.138	0.042
	5(Span)	88.912	58.658	2.298	0.130
	6(Bridge length)	-56.794	46.791	1.473	0.225

### Model Testing

The goodness-of-fit test shows that the significance p-values for both Pearson and Deviation tests are greater than 0.1, as shown in Table 4, and the model is considered to fit relatively well.

Tab. 4 - goodness-of-fit of Logistic regression

Model	Chi-Square	Degree of freedom	Significance P-value
Pearson	4.717	69	1.000
Deviation	5.239	69	1.000

The parallelism hypothesis test determines if the effect of each independent variable value level on the dependent variable is the same in each regression equation. Because the parallelism test's initial premise is that the model fulfils parallelism, if the P-value is larger than 0.05, the model accepts the original hypothesis, i.e., it passes the parallelism test. In contrast, if the P-value is less than 0.05, the model rejects the initial hypothesis and fails the parallelism test. As shown in Table 5, the findings reveal that  $P=1.0 > 0.1$ , which is compatible with proportionate dominance, i.e., the individual regression equations of the models are parallel.

Tab. 5 - Logistic regression parallel line test

Model	-2*Log Likelihood	Chi-Square	Degree of freedom	Significance P-value
Original hypothesis	0.000	-	-	-
Conventional	0.000	0.000	12	1.000

The model fit information test determines if the partial regression coefficients of all independent variables in the model are valid, as given in Table 6, with  $P < 0.05$  in the findings indicating that the model is valid.

Tab. 6 - Fitting information of Logistic regression mode

Model	-2*Log Likelihood	Chi-Square	Degree of freedom	Significance P-value
Intercept Only	99.075	-	-	-
Final	0.000	99.075	6	0.000

The anticipated values were compared to the actual statistical values, and the results are displayed in Table 7. The predicted earthquake damage rates are identical to the actual earthquake damage rates. The ordered logistic regression model has high discriminative performance and can forecast the bridge damage level more accurately.

Tab. 7 - Comparison of Logistic regression predicted earthquake damage rate and actual earthquake damage rate

Seismic damage	A0	A	B	C
Actual/%	91.11	2.96	5.19	0.74
Prediction/%	91.11	2.22	6.67	0
Error/%	0	25	27	100

### Example

Since the accuracy of both predictions for seismic damage is practically the same, using this regression to predict seismic damage to railway bridges is considered valid. Ordinal logistic regression can predict each bridge damage stage at a given intensity, and some of the findings are displayed in Table 8.

For example, the probability of A0 for bridge No. 69 is 0, the probability of A is 0.09, the probability of B is 0.79, and the probability of C is 0.12. As a result, the anticipated category is "B," indicating the greatest likelihood of injury.

Although the ordered logistic regression effectively predicts bridge seismic damage, some errors exist, such as bridge No. 67 in Table 8. The predicted object often cannot be entirely consistent with the background information of the bridge at the time of statistics, and sometimes even significant differences, which will affect the prediction accuracy to a certain extent [3]. In addition, some secondary factors will lead to a specific error in predicting seismic damage to bridges. However, this error will not make the seismic damage level show a significant difference, which can only be a difference of one neighbouring level.

Tab. 8 - Schematic table of ordered logistic regression calculation (part)

Bridge No.	Influence factor coefficient						Real		A0	A	B	C	Prediction
	1	2	3	4	5	6							
	.....												
67	1.2	1.4	1.0	1.0	1.2	1.2	A		0.00	0.09	0.79	0.12	B
68	1.2	1.4	1.2	1.2	1.2	1.2	B		0.00	0.03	0.92	0.05	B
69	1.2	1.4	1.0	1.0	1.2	1.2	B		0.00	0.09	0.79	0.12	B
	.....												
73	1.2	1.4	1.0	1.0	1.0	1.0	A		0.03	0.96	0.01	0.01	A
74	1.2	1.4	1.0	1.0	1.1	1.0	B		0.00	0.01	0.98	0.01	B
75	1.2	1.4	1.0	1.0	1.1	1.0	B		0.00	0.01	0.98	0.01	B
	.....												

### BRIDGE SEISMIC EMPIRICAL VULNERABILITY

Railway bridge seismic vulnerability can be expressed by vulnerability curves that reflect the conditional likelihood of the structural reaction surpassing the structural load-bearing capacity defined by the damage phase under varying intensities of seismic action. Empirical and analytical approaches can be used to calculate bridge vulnerability curves. The vulnerability curves obtained through empirical methods are generally based on damage reports from previous earthquakes [19].

The damage probability matrices of various types of bridges were calculated through statistical regression after collecting damage data from regions where earthquakes have occurred. These matrices are then used as the foundation for the empirical vulnerability curve. Yamazaki et al. proposed an empirical vulnerability model and used the least squares regression method to obtain the log-normal distribution parameters; Tanaka used a two-parameter normally distributed vulnerability function [20].



Bridges in different intensity zones will present different degrees of damage, and it is difficult to judge their vulnerability to earthquake damage in the region by only analyzing their damage at a particular intensity. This paper presents the prediction statistics of bridge structures in different intensity zones and establishes a damage prediction matrix based on multiple intensity zones, as shown in Table 9. The actual seismic damage in this Menyuan earthquake is shown in parentheses.

Tab. 9 - Seismic predicated matrix of railway bridges %

Intensity Damage	VI	VII	VIII	IX	X	XI
A0	100(100)	82.22(100)	0(8.34)	0(0)	0(0)	0(0)
A	0(0)	17.78(0)	91.85(33.33)	3.70(0)	0(0)	0(0)
B	0(0)	0(0)	8.15(58.33)	88.15(0)	3.70(0)	0(0)
C	0(0)	0(0)	0(0)	8.15(100)	96.30(0)	91.85(0)
D	0(0)	0(0)	0(0)	0(0)	0(0)	8.15(0)

The outcomes of the forecast demonstrate that the bridge damage's severity increases with the earthquake's magnitude. In the earthquake intensity zone of magnitude VI, all railway bridges exhibited basic intactness; in the earthquake intensity zone of magnitude VII, 17.78% of the bridges suffered minor damage; in the earthquake intensity zone of magnitude VIII, virtually no bridges were intact and showed minor and moderate damage; in the earthquake intensity zone of magnitude IX, 88.15% fewer bridges were slightly damaged; 80% more moderate damage; and 8.15% more severely damaged bridges; in the earthquake intensity zone of magnitude X, bridges essentially occurred Bridges in the X degree zone sustained 96.30% major damage, but there was no destruction; in the XI degree zone, 8.15% of bridges were destroyed.

### Average seismic damage model for multi-intensity areas

The damage to the bridge at each seismic level was calculated as shown in Table 9, with the corresponding damage indices within the different levels, as shown in Table 10, to analyze the overall damage of the bridge at different intensities. A weighted average was then performed to obtain the parameter known as the mean damage index (MSDI) % [21], as shown in equation (4):

$$[MSDI] = \sum_{i=1}^5 d_i \delta_i \quad (4)$$

Where:[MSDI] represents the average damage index of railway bridges in the region;  $d_i$  represents the normalization of the damage index to obtain a continuous value between 0 and 1, representing the damage degree of the structure from intact to destroyed;  $\delta_i$  damage level is the damage ratio of the bridge structure for  $i(=1,2,3,4,5)$ .

Tab. 10 - Earthquake damage index of different grades

Damage Value	A0	A	B	C	D
highest value (h)	0	1.6	2.4	3	4
mean value (m)	0.8	2	2.7	3.5	4.5
lowest value (l)	1.6	2.4	3	4	5

Equation (4) is matrixed with the existing seismic vulnerability matrix in order to obtain the damage of bridge structures in various intensity zones. Equations (5) through (7) then build a vulnerability matrix model based on the average seismic damage index.

$$[MSDI]\alpha = [d_i]^T [\delta_{ji}] \quad (5)$$

$$[\text{MSDI}]\alpha = \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_i \end{bmatrix}^T \begin{bmatrix} \delta_{61} & \dots & \delta_{6i} \\ \vdots & \dots & \vdots \\ \delta_{j1} & \dots & \delta_{ji} \end{bmatrix} \quad (6) \quad [\text{MSDI}]\alpha = \begin{bmatrix} \text{MSDI}_6 \\ \text{MSDI}_7 \\ \text{MSDI}_8 \\ \vdots \\ \text{MSDI}_j \end{bmatrix} \quad (7)$$

Where  $\delta_{ji}$  denotes the damage ratio (number of damage ratio) of the structure subjected to the  $i$ th seismic damage level in the  $j$  ( $j=6, 7, 8, 9, 10, 11$ ) intensity zone,  $[\text{MSDI}]\alpha$  indicates the average seismic damage index limit,  $\alpha$  indicates  $h, m, l$ .

The average seismic damage index matrix of the bridges in the region is obtained as shown in equations (8) - (10):

$$[\text{MSDI}]S_h = \begin{bmatrix} 0 \\ 5.69 \\ 33.30 \\ 48.39 \\ 59.56 \\ 61.63 \end{bmatrix} \quad (8) \quad [\text{MSDI}]S_m = \begin{bmatrix} 16.00 \\ 20.27 \\ 41.14 \\ 54.79 \\ 69.41 \\ 71.63 \end{bmatrix} \quad (9) \quad [\text{MSDI}]S_l = \begin{bmatrix} 32.00 \\ 34.84 \\ 48.98 \\ 61.19 \\ 79.26 \\ 81.63 \end{bmatrix} \quad (10)$$

Figure 4 depicts the vulnerability curve of the average seismic damage of bridges for multi-intensity areas. When the region suffered an earthquake of magnitude VII, the probability of bridge damage was 33% at the highest value, 19% at the mean value, and 4% at the lowest value. The predicted vulnerability curve of bridges under MSDI parameters can predict the minimum to maximum level of bridge seismic damage at different intensities. This is a very conservative approach.

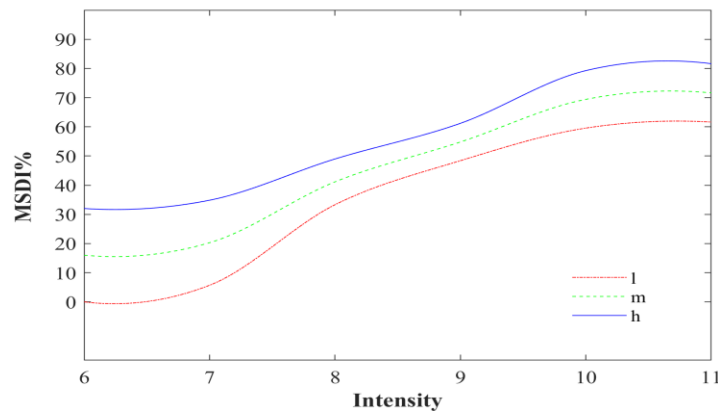


Fig. 4 –Predicted vulnerability curve of bridges under MSDI parameters

### Vulnerability curves based on two-parameter log-normal distribution functions

Each seismic damage class was assigned its own vulnerability curve. To guarantee precise prediction, C and D were classed as the same class in this earthquake due to the lack of damage in the destroyed condition.

Assuming a two-parameter log-normal distribution for the vulnerability curve:

$$F_j(a, c_j, \zeta_j) = \Phi \left[ \frac{\ln(a/\theta_j)}{\zeta_j} \right] \quad (11)$$

where  $F_j(a, \theta_j, \zeta_j)$  denotes the probability that the bridge reaches or exceeds the  $j$ th damage state;  $\Phi(\cdot)$  is the standard normal distribution function;  $a$  is the PGA value;  $\theta_j$  and  $\zeta_j$  are the median and

logarithmic standard deviation of the damage state corresponding to the vulnerability curve (j=1, 2, and 3 denote "A", "B", "C、D", respectively).

From the China Intensity Table [22], the relationship between intensity and PGA is shown in Table 11.

Tab. 11 - Correlation between intensity and PGA

Intensity	VI	VII	VIII	IX	X	XI
PGA(m/s <sup>2</sup> )	0.63	1.25	2.50	5.00	10.00	20.00
PGA(g)	0.064	0.128	0.255	0.510	1.020	2.041

With the seismic damage ratio matrix in Table 9, the corresponding transcendence probabilities can be obtained from equation (12) as shown in Table 12.

$$F_j(I_i) = \sum_{k=1}^j P_k(I_i) \quad (12)$$

Where,  $P_j(I_i)$  indicates the probability of being in the jth damage state under intensity i, that is, the damage ratio of being in the jth damage state under intensity i.

Tab. 12 - Exceedance probability F of bridges with different earthquake damage grades

Damage PGA(g)	A0	A	B	C、D
0.064	1	0	0	0
0.128	1	0.1778	0	0
0.255	1	1	0.0815	0
0.510	1	1	0.963	0.0815
1.020	1	1	1	0.963
2.041	1	1	1	1

The vulnerability curves corresponding to the damage states "A", "B", "C、D" obtained by using the cumulative function of the lognormal distribution is shown in Figure 5. When the PGA in the region is 0.5g, bridges are largely destroyed, more than 95% of the bridges are slightly damaged and 70% suffer moderate and severe damage. In addition, from this curve, we can know the possible magnitude of PGA in the region when 20% of the bridges exceed some damage state.

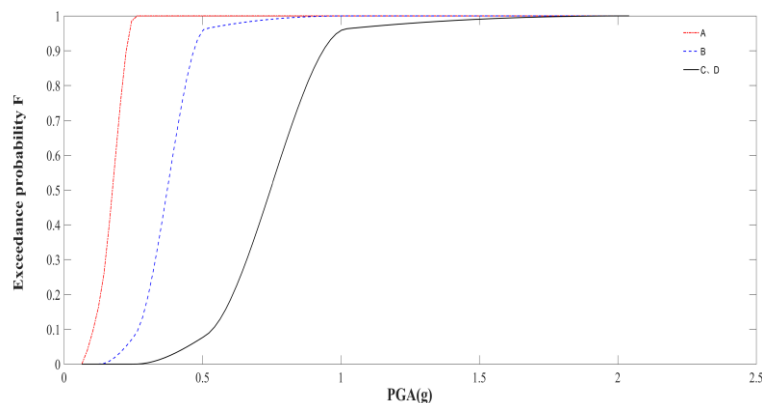


Fig.5 –Predicted vulnerability curve based on a two-parameter log-normal distribution function

## CONCLUSION

This study presents a seismic damage prediction formula based on ordinal logistic regression in SPSS. The method can predict the damage index of a single bridge and its likelihood of occurring in different damage states. On the base, the predicated empirical vulnerability curve may be used to quickly analyze the total damage of bridges in the region at various intensities and damage states.

The predicted vulnerability curve of bridges under MSDI parameters is a very conservative approach that can know the minimum to the maximum level of bridge seismic damage at different intensities. The predicted vulnerability curve based on a two-parameter log-normal distribution function can visualize the probability of damage for various seismic damage states of the bridge when the PGA is what and the possible PGA in the region when the bridge is damaged to a certain extent. Moreover, this method can serve as a reference for analyzing the risk assessment of railway bridges in the region and give some foundation for later prediction of bridge damage in the region with some reliability to make realistic forecasts before the next earthquake. It is important to note that the regression equation proposed in this paper does not apply to other regions because the defined damage index is based on a summary of the damaged bridges in the 2022 Menyuan earthquake, and the topography and climate of bridges in different regions vary greatly, as do their site classification and traditional structure types. The Lanzhou-Xinjiang Passenger Dedicated Line is located in the Qinghai-Tibet Plateau, with permafrost zones, a cold temperature, and more mountains, so there are some differences in the seismic design of bridges. As a result, when an earthquake happens, the seismic damage displayed is inconsistent. However, this work's technical line of study gives some pointers for other places to use when assessing vulnerability and risk. The findings of this study have substantial significance for the seismic risk assessment of bridges on Qinghai's northeastern border.

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## REFERENCES

- [1] Wang DS, Feng QM. Prediction Method of Bridge Earthquake Damage [J]. Journal of Natural Disasters, 2001(03): 113-118.
- [2] Keizaburo Kubo, Zhang SS. Earthquake Damage Prediction of Bridges [J]. World Earthquake Engineering, 1984(05): 8-11.
- [3] Zhu MZ. Practical Methods of Earthquake Damage Prediction for Highway Bridges [J]. Journal of Tongji University (Natural Science Edition), 1994(03): 279-283.
- [4] Wang TW, Yang CH. Earthquake Damage Prediction and Seismic Reinforcement of Railway Bridges [J]. Railway Construction, 1991(08): 4-9.
- [5] L. J. Xu, Q. Zhang. Prediction of earthquake damage of railway bridges [J]. Journal of Shandong College of Construction Engineering, 2003(01): 27-31.
- [6] F. Yang, M. B. Su. Techniques for earthquake damage assessment of railway bridges [J]. Journal of Natural Hazards, 2013(03): 213-220.
- [7] Y. J. Xu et al.. Real-time regional seismic damage assessment framework based on long short-term memory neural network [J]. Computer-Aided Civil and Infrastructure Engineering, 36(4) (2021)504-521.
- [8] W. S. Li, Y. Huang, Z. K. Xie. Machine Learning-Based Probabilistic Seismic Demand Model of Continuous Girder Bridges [J]. Advances in Civil Engineering, (2022).
- [9] Kobayashi HIROSHI, etc. The method of deducing the degree of disaster of the road and bridge in Okeo during the great earthquake [J]. Technical Information on Civil Engineering, 2005, 47(12): 48-53.
- [10] Kazuhiro NAGAYA, Shojiro KATAOKA, Takaaki KUSAKABE, etc. A Research on Immediate Damage Estimation Technology to Improve Crisis Management for MEGA-Earthquakes [J]. Journal of Japan Society of Civil Engineers, Ser. A1 (Structural Engineering & Earthquake Engineering), 2017, 72(4): 966-974.
- [11] Omichi KAZUHO, Shojiro KATAOKA, etc. Verification and Improvement of Structure Damage Estimation Method for Highway Bridges Based on Damage Data of the 2016 Kumamoto Earthquake [J]. Journal of Japan Society of Civil Engineers, Ser. A1 (Structural Engineering & Earthquake Engineering), 2020, 76(4): 765- 773.

- [12] Murano YOSHITAKA, NOGAMI YUTA, MIYAMOTO TAKEFUMI. Simple Method to Predict Outline of Seismic Damages of Railway Structures and Running Vehicles [J]. Journal of Japan Society of Civil Engineers, Ser. A, 2010, 66(3): 535-546.
- [13] Naoto Iwata, Tojun Sakai, Tojun Yamamoto, etc. Earthquake Countermeasures for Railway Stations in Railway Systems Development of a Railway Earthquake Damage Estimation Information Distribution System for Quick Resumption of Operations [J]. Railway Architecture News, 2020, 77(2): 30-33.
- [14] Zong L, Wang YQ, Yang SN et al. Research on Earthquake Damage Assessment Model of Highway and Bridge in China Based on HAZUS Platform [J]. Journal of Civil Engineering, 2014, 47(S1):263-268.
- [15] Hu Y. Earthquake Engineering [M]. Beijing: Seismological Press, 2006:354-400.
- [16] Cai LW, HUANG Yong, HE Jing et al. Transportation System Damage from the 2022 M6.9 Menyuan Earthquake in Qinghai Province and its implications[J]. Earthquake Engineering and Engineering Vibration, 2022. 42(04): 8-16.
- [17] Gao WD. Discrimination and Classification of Expansive Soil Based on Logistic Regression Model [J]. Journal of Yangtze River Scientific Research Institute, 2020. 37(06): 153-155.
- [18] Wang DH et al. Multivariate Statistical Analysis and SPSS Application [M]. Shanghai: East China University of Science and Technology Press Co., LTD, 2018:150-220.
- [19] H. Hwang, Liu JB. Vulnerability Analysis of Reinforced Concrete Bridge Structures under Earthquake [J]. Journal of Civil Engineering, 2004(06): 47-51.
- [20] Chen LB, Zhen KF et al. Vulnerability Analysis of Bridges in Wenchuan Earthquake [J]. Journal of Southwest-Jiao tong University, 2012. 47(04): 558-566.
- [21] Li SQ, Yu TL, Zhang M. Comparative analysis of vulnerability of typical structures in different intensities [J]. Journal of South China University of Technology (Natural Science Edition), 2020. 48(03): 67-75.
- [22] GB/T 17742-2008 China Intensity Table[S].Beijing: Standards Press of China, 2008.