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Research Article

AI-driven Predictive Analysis of Seismic Response in Mountainous Stepped Seismic Isolation Frame Structures

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ABSTRACT

In this paper, we propose a unique method for rapid prediction of seismic response of stepped seismic isolation frame structures in mountainous areas using artificial intelligence (AI), based on which the results of seismic response can be used to determine the damage level of stepped seismic isolation frames in mountainous areas under seismic action, and thus to make seismic damage prediction. This study fills the knowledge gap in earthquake damage prediction for stepped isolation frame structures in mountainous areas. In this study, a number of 7-story typical RC frame structures were designed using the structural design software Midas Gen. The dynamic time-history analyses of the structures were carried out using the control variable method, and based on the results of the analyses, five factors that have a greater impact on the seismic performance of mountainous step-isolated frame structures were obtained, which are: the arrangement of seismic isolation bearings, the degree of regularity of the structure, the intensity of defense, the type of the site, and the seismic intensity. based on the results of the dynamic time course analysis, a seismic sample library with a sample capacity of 384 is established by combining these influencing factors. Each influence factor is given a suitable domain and affiliation function, and fuzzy rules are established according to the seismic sample library, and a fuzzy inference model is established by using the fuzzy logic toolbox in MATLAB. The model can directly determine the damage state of the predicted structure. Random sampling confirms the stability and accuracy of the model for different times to build a framework. The results show that the method of analysis is correct, fast and efficient and the seismic related selected factors can predict and map the seismic damage prediction of the model structure. This method can also be applied to rapid seismic damage prediction for SSIFS (stepped seismic isolation frame structures) in rocky areas.

Keywords: Mountainous step-isolated Frame Structures, Seismic Response, Earthquake Prediction, Fuzzy Inference Modelling, Dynamic Time Course Analysis.

INTRODUCTION

Mountainous environments are inherently more susceptible to seismic activity due to their complex geological formations, steep inclines, and constant danger of landslips. There are promising mitigation strategies to overcome earthquake prone, this study develops SSIFS (Stepped Seismic Isolation Frame Structures) to resolve challenges (Dang, Liu, & Zhang, 2017; Huang, Li, Yi, Liu, & Wu, 2018; Zubovich et al., 2022). To reduce the seismic load to a high lever, efficient ground motion isolation has been provided by these designs. This is

proficient at different levels of integrating seismic isolation bearings. It is a big challenge to forecast SSIFS and how it can react seismically in hilly areas (Bao et al., 2022; Cody, Draebing, McColl, Cook, & Brideau, 2020). Old and traditional mechanisms in engineering have failed to deal with this relationship to these domains. However, vibration prediction patterns are a more challenging task in which different areas are involved at different levels. These create variations in exertion and checking properties in rock creations due to different areas' conditions (Frame, 2020).

To deal with these kinds of difficulties, a modern forecasting technique is needed to evaluate the complex seismic response of SSIFS in different rocky areas. This is basically non-linear behavior due to the variant relationships of different factors and structural response is problematic in traditional prediction models. FIM (Fuzzy Interference Modelling) and other AI methods are fruitful in these dynamic situations (Bao et al., 2022; Motosaka & Mitsuji, 2012).

There are a few benefits behind this FIM method. It is used to explore the different volumes of data regarding seismic by using data driven method to predict the complex connections between driving forces and structural responses. If this is compared with traditional or standard models which rely on linear prediction, FIM is more realistic in linking the non-linear associations intrinsically by using seismic loads (Koehler et al., 2021; Luco, Trifunac, & Wong, 1988). It is flexible and it can be enhanced continuously in response to new dataset, provide guaranteeing about the developing of seismic patterns and structural configuration shifting.

In the area of Stepped Seismic Isolation Frame Structures (SSIFS), the research interest has increased in rocky areas due to a useful earthquake mitigation method. However, there is a gap existed in predicting of building seismic reactions and this is a disadvantage in the technique (García, Pastén, Sepúlveda, & Montalva, 2018; Mishra et al., 2017; Kulariya & Saha, 2020). Firstly, the presentations of mountains lands have oversimplified the topography in recent models and ignored the complex variation geologically, vertical slopes and landslips related risks that are linked with these areas at ground level as well as the same surface (Ahmad et al., 2021; Ali et al., 2020; Maqsoom et al., 2021; Ji, Su, Qin, & Nawaz, 2021). This error to deal it is important due to topographical area consideration which affects the structure and its response during an earthquake. Additionally, the structure complexity is underestimated in hilly regions regarding buildings. The impact of rough seismic isolation and unique architectural features of this structure are sometimes skipped by traditional approaches which are typically treated as. Due to the simplicity of the traditional method, it is compromised in earthquake accurate prediction (Atalić, Uroš, Šavor Novak, Demšić, & Nastev, 2021; Cui & Ma, 2021; Kufner et al., 2018).

The non-linear effect which is ignored in the traditional model is also a significant gap by seismic forces (Dey, 2021; Branis, 2020; Zhang, Dai, Shen, & Gao, 2019). The oversight of seismic force-induced non-linear effects in seismic analysis shows a major deficiency in present approaches. Traditional linear models can't explain earthquakes' complicated, nonlinear behavior. This implies structures react unexpectedly. This limitation makes sophisticated approaches more significant and reduces the likelihood of incorrect results. Our options aren't data-driven either. Many models do not use seismic data because they prefer analytical methodologies and technological intuition. In hilly locations, this strategy makes it difficult to create models that can detect complex data patterns. We have several issues with how we calculate earthquake damage to SSIFS in steep places. Engineers and decision-makers struggle to prioritize disaster planning and retrofitting without data (Ballato et al., 2015; Morfidis & Kostinakis, 2018; Xie, Ebad Sichani, Padgett, & DesRoches, 2020).

This paper proposes an AI-driven fuzzy inference modeling method to address these issues. Non-linear effects, data-driven learning, and more complicated mountainous terrain models fill the gaps. This research aims to improve hilly SSIFS seismic response calculations. This novel idea should increase earthquake preparedness and structure safety. Because seismic reaction prediction is more accurate, engineers can adjust building designs to withstand earthquakes (Guidotti et al., 2016; Margerum, Zwickle, Bruce, & Thomas, 2022; Sinha, Feng, Yang, Wang, & Jeremic, 2017). This immediately secures SSIFS locations. The study improves earthquake prediction systems and data-driven earthquake preparation decision-making beyond its immediate applicability. They also encourage more robust design methods with wider ramifications for different building kinds and regions. Overall, this research advances earthquake engineering by empowering mountainous people to decrease seismic hazards and improve resilience.

The well-organized document explains the research technique. The introduction explains the study's goals, background, and restrictions, paving the way for subsequent research. The literature review summarizes key findings and places the current research in context. Data collection transparency and replicability tools are described in the study technique section. Data analysis critically assesses empirical findings and ties them to research goals. The study's relevance, general findings, and implications are discussed in the conclusions. This methodical approach offers a coherent narrative that guides readers through the work and shows its field

contribution.

LITERATURE REVIEW

SSIFS seismic response has been widely explored utilizing experimental testing and analytical models. Traditional investigations on level terrain and regular structures showed SSIFS seismic performance (Albano, Mancusi, Sole, & Adamowski, 2017; Farahan, Shojaeian, Behnam, & Roohi, 2023; Khatami et al., 2020). Topography and geology affect the seismic behavior of structures in hilly areas, thus overlooking them is difficult. The mountainous seismic response has been explored using geology and slope angles. In hilly terrains, SSIFS seismic performance has not been studied because most research focuses on certain construction types or lacks a robust seismic response prediction framework (Allen, Costello, Henning, Chamorro, & Echaveguren, 2023; Makris & Aghagholizadeh, 2019; Migoń, 2021; Oldfather & Ackerly, 2019; Roohi, van de Lindt, Rosenheim, Hu, & Cutler, 2020).

Machine learning and neural networks for earthquake forecasting are popular. AI structural reaction prediction, especially in mountainous topography, is less explored than short-term earthquake projections (Nawaz, Chen, Su, & Zahid Hassan, 2022; Nawaz, Chen, & Su, 2023a, 2023b; Nawaz & Guribie, 2022). This questions AI's ability to predict mountainous SSIFS seismic reactivity. Given these flaws, fuzzy inference modeling (FIM) seems promising. FIM has been used in structural engineering to assess damage and optimize design in various scenarios (Albano et al., 2017; Guidotti et al., 2016; Khatami et al., 2020). However, its use to evaluate the complex seismic response of SSIFS in mountainous terrain is novel and potentially transformative. This unique approach could improve mountainous terrain forecast, earthquake resilience, and structural safety(Sauti, Daud, Kaamin, & Sahat, 2021).

The earthquake response of Stepped Seismic Isolation Frame Structures (SSIFS) has been studied. The researchers tested SSIFS seismic performance using shaking table testing and analytical models (Dey, 2021; Frame, 2020). The seismic isolation bearing design and features were their attention. This research was beneficial, however, it only examined flat land and similar expansion, not hills. Another study examined supersymmetric folded iron slab earthquake constructions. According to Copilaş-Ciocianu and Petrusek, (2015), several isolation bearings were tested for structural response. The study's focus on single bearings and not mountainous formations was a major flaw. This hole emphasizes the need to examine SSIFS in various environments, particularly mountain terrain difficulties. Mountains are complex, thus more research is needed to understand how SSIFS respond to earthquakes. Look beyond isolation bearings and geography to understand how SSIFS constructions respond to earthquakes in different regions. These discoveries are crucial for making mountainous constructions safer and more resilient.

Ismail and Khattak (2015) examined mountain earthquakes. Higher mountain slopes may increase ground motion and earthquake reactivity theoretically (Ovsyuchenko et al., 2017). SSIFS was not explicitly addressed and no accurate prediction methodology was used (Cheddadi et al., 2017; Rumson & Hallett, 2019; Schulz, 2015). Numerical analysis of an earthquake's influence on frame buildings on sloping terrain showed the importance of ground-structure interaction in hills. The study didn't emphasize SSIFS or AI. Current research concentrated on generic earthquake prediction, not mountainous terrain or structural reaction estimations. Real-time sensor data and neural networks enhanced earthquake prediction. This program predicts earthquakes, not hills. Increased SSIFS issues.

Researchers studied multi-tower SSIFC seismic performance and bearing spatial dispersion. This investigation indicated seismic and structural optimal bearings. The research examined how seismic isolation bearing spatial distributions affect multi-tower SSIFC seismic behavior (Ismail & Khattak, 2015). Atkins, Makridis, Alterovitz, Ramoni, and Clancy (2022) explored isolation bearing viscoelasticity numerically and experimentally. This study found that these materials affect super-sensitive integrated filters' energy dissipation and dynamic responsiveness (Ovsyuchenko et al., 2017). For earthquake performance, Atkins et al. (2022) stressed isolation bearing viscoelasticity. The unique mountainous earthquake response analysis approach included topographic irregularity and soil-structure interaction. These features are crucial for earthquake forecasting in challenging terrains, according to this study. According to Atkins et al (2022), computer simulation, landslides and topographic amplification could damage mountainous concrete gravity dams. These findings demonstrate that mountainous locations' complex geological-structural linkages must be considered in seismic risk estimates.

Mei et al. (2019) projected earthquake damage using satellite images, demonstrating AI's seismic research potential. AI-enhanced damage assessment using a mixed machine learning model for real-time seismic hazard assessment from huge datasets. Combining AI algorithms improves forecast accuracy by including all hazards. The seismic response of hilly Stepped Seismic Isolation Frame Structures (SSIFS) remains poorly known despite

seismic research progress. Research suggests this topic is unclear. Current research focuses on flat terrain or mountain frame buildings, but SSIFS faces unique challenges (Ardebili & Padoano, 2020; Mahmood, Afrin, Huang, & Yodo, 2023; Mei et al., 2019). Current forecasting methods struggle to account for complex variable interactions and seismic reactions in mountainous places due to difficult geological conditions, steep slopes, uneven structures, and non-linear behaviors using basic analytical models or engineering intuition. AI-driven Fuzzy Inference Modeling (FIM) may close this gap (Soleimani-Babakamali & Zaker Esteghamati, 2022; Turch, Lumino, Gambardella, & Leone, 2023).

FIM manages complex data linkages and patterns, making mountainous SSIFS seismic response analysis more data-driven. We want to improve damage prediction, a vital mitigation tool and understand SSIFS seismic behavior across regions. It addresses insufficient data, limiting application, accuracy and dependability difficulties, real-time applicability, and explainability in current approaches. Improve disaster preparedness, structural safety, informed decision support, and seismic engineering AI by closing this gap.

METHODOLOGY

A number of 7-storey typical RC frame structures were designed using the structural design software Midas Gen. According to the needs of this study, a number of seismic waves were selected from the database of the Pacific Earthquake Engineering Research Centre (PEERC), and the designed structures were subjected to dynamic time-course analyses by the control variable method. The analyses obtained a number of influence factors that have a large impact on the seismic performance of mountainous step-isolated frame structures. Relying on the data from the dynamic time-course analysis, the seismic damage sample database is established by combining the multiple influence factors. A suitable artificial intelligence model is selected to process the data.

Selection of Artificial Intelligence Models

Seismic Damage Prediction Method based on BP Neural Network

BP (Back Propagation) neural network is the most successful neural network learning algorithm so far, which is widely used in engineering work to solve all kinds of practical problems. The BP neural network framework contains the input layer, hidden layer and output layer, and the algorithm belongs to supervised learning. BP neural network consists of a large number of neurons as the nodes of the network that are connected to each other, and after being processed by the excitation function, each neuron will get the calculation result as the strength connection signal of its network weights. The BP neural network consists of a large number of neurons as network nodes connected to each other, and through the processing of the excitation function, each neuron will get the result of the calculation of the strength of the connection signal as the weight value of the network, and then by adjusting the size of the strength value of these connections, the pattern information contained in the input data can be mapped to the output layer. The method of rapid earthquake damage prediction using the BP neural network is as follows: taking several frame buildings as the research object, the number of floors, floor height, building height, column area ratio and other easily accessible and highly correlated key data as the earthquake damage influence factors, and making full use of MATLAB's good visual modelling characteristics to train a BP neural network earthquake damage prediction model. Multiple sets of data tests are used to compare the data of single simulation results, and the accuracy and stability of the model are verified by randomly selecting data samples several times to build the model. The neural network model framework diagram is shown in **Figure 1**.

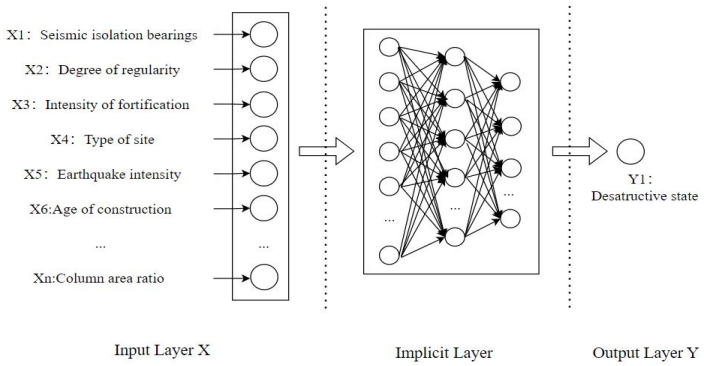


Figure 1. Neural Network Model Framework Diagram

Support Vector Machine (SVM)-based Earthquake Damage Prediction Methods

SVM is a method of machine learning, the basic idea is to build a support vector machine model based on the nonlinear relationship between the feature vectors and the categories in the given training samples and use the model to classify or regress the unknown samples. Cortes & Vapnik formally proposed the concept of a support vector machine in 1995. Its theoretical basis is the statistical learning theory that aims to solve the machine learning problem in the case of small samples. The most basic theory of SVM is the binary classification theory, and its basic idea is to build a classification function according to the principle of structural risk minimization to distinguish two different types of samples as much as possible. For different samples, the classification function can be roughly divided into two categories: linear classification function and nonlinear classification function. The basic idea of the SVM-based seismic damage prediction method for masonry structures is to extract the data from the seismic damage examples and input them into SVM to establish a nonlinear relationship model between various seismic damage influencing factors and the seismic damage level, and then analyse the existing data of the building to be evaluated according to the model, so as to predict the seismic damage level of the building under the effect of earthquakes of different intensities.

Fuzzy Inference-based Earthquake Damage Prediction Methods

L.A. Zadeh, an American automatic control expert, proposed the concept of fuzzy subsets in 1965. Since then, the theory of fuzzy systems has been developed. The fuzzy system, a system that defines input, output and state variables on fuzzy sets, is a promotion of a deterministic system. A fuzzy system starts from the macroscopic point of view, captures the fuzzy characteristics of human brain thinking, and has its strengths in describing high-level knowledge, which can imitate the comprehensive inference of human beings to deal with the fuzzy information processing problems that are difficult to be solved by the conventional mathematical methods, so that the computer application can be expanded to the fields of humanities, social sciences, and complex systems. It can better solve nonlinear problems and is now widely used in automatic control, pattern recognition, decision analysis, time series signal processing, as well as human-computer dialogue systems, economic information systems, medical diagnostic systems, seismic prediction systems, weather forecasting systems and other aspects. The earthquake damage prediction method based on fuzzy inference is as follows: analyse the typical earthquake damage of RC frame structures, summarize the main factors affecting the seismic performance of frame structures, and set up the analysis working conditions for different influencing factors. Using the finite element analysis method, the models of different influencing factors are analysed, and the maximum inter-storey displacement angle parameter of the structure under different intensities is used as the seismic performance index to analyse the influence of each factor on the overall seismic performance of the structure. A fuzzy inference model for the damage degree of RC frame structure is established, so as to achieve the purpose of quickly predicting the damage degree of the structure.

The above three methods have their own advantages and disadvantages, among which the BP neural network has strong nonlinear modelling ability and can be used to solve complex problems, but it is easy to fall into the local minima, the training process requires a large amount of data, and it is sensitive to the initial weights; SVM performs well in high-dimensional space and can deal with nonlinear relationships, but it has a large amount of computation in the training of large-scale datasets, and it is sensitive to the hyper-parameters; fuzzy system can deal with uncertainty and complex relationships, with good interpretability, but the performance is relatively poor when dealing with a large amount of data, and the design of fuzzy rules relies on the experience of experts. Due to the small sample capacity of this study, the vertical irregularity of the stepped seismic isolation frame structure in mountainous areas causes the degree of rules to be fuzzy, so this study adopts the fuzzy system in the artificial intelligence model for earthquake damage prediction.

Fuzzy Inference Modelling Approach

The basic concept of fuzzy reasoning is the process of using a set of fuzzy sets to reason out fuzzy conclusions through fuzzy rules. The basic concepts involved in the theory of fuzzy reasoning are described below:

Theory

Domain refers to the range when discussing a fuzzy concept, e.g., the domain U=[0, 100] indicates that a person's age is in the range of 0 to 100 years.

Fuzzy Sets

The symbol A is generally used to denote a fuzzy set, while A(x) denotes the element x affiliation degree for the fuzzy set A. Mathematically, the representation of fuzzy set A can be written as:

$$A = \{(x, \mu_A(x)) | x \in U\}$$

Where U is the thesis domain and x is an element in the thesis, and $\mu_A(x)$ is the element x affiliation degree

for the fuzzy set A.

Affiliation Function

Reasonable choice of affiliation function is the key to achieving fuzzy inference, affiliation function is generally based on the nature of the domain and fuzzy set combined with practical engineering experience to choose, it can make a quantitative description of the concept of fuzzy, commonly used affiliation function including Gaussian, trigonometric function, bell function and trapezoidal function and so on.

Fuzzy Rules

Fuzzy rules are the preconditions for fuzzy reasoning, which represent the mapping relationship between input and output fuzzy linguistic variables, and usually consist of two parts: premise and conclusion, and the common form is "IF (premise)..., THEN (conclusion)...".

Example:

Rule 1	If x is A_1	Then x is B_1
.....	.....	.....
Rule m	If x is A_m	Then x is B_m
New input	x is A^*	
Output		y is B^*

Among them, x, y belongs to the thesis domain U, V; i = 1, ...m; A_i, B_i the set consisting of all fuzzy sets belonging to U, V.

The fuzzy inference modelling process is as follows (**Figure 2**):

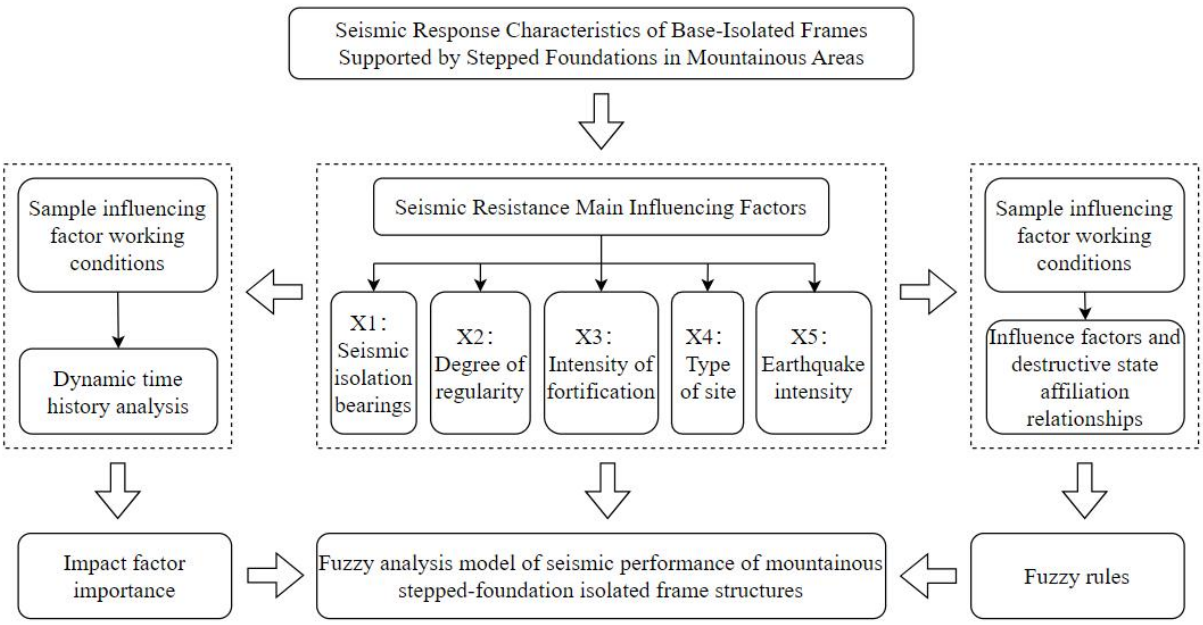


Figure 2. Fuzzy Inference Model Building Process

ESTABLISHMENT OF SEISMIC DATABASE

In actual earthquakes, the seismic damage of frame structures is the result of the combined effect of multiple factors, so it is important to study the degree of influence of different factors on the seismic performance of the structure, in order to build a seismic performance evaluation system. When studying the importance of each factor on the overall seismic performance of the structure, the factor can be used as a variable to explore the importance of each factor by comparing the seismic effects of different factors on the structure. In this paper, a mountainous terraced foundation frame structure N1 and an ordinary flat structure N2 are designed using the

structural design software Midas Gen. The relevant information of the model is shown in **Table 1**, and the three-dimensional drawings of the model are shown in **Figures 3** and **4**. Seismic isolation bearings are arranged at the bottom ends of the columns of the above structures to obtain N3 and N4, and the dimensional information of N3 and N4 is the same as that of N1 and N2, the relevant calculations are carried out for the designed structures using Midas Gen, and the seismic effect of each factor is selected. Midas Gen is used to calculate the designed structure and select the appropriate rubber isolation bearings, the relevant parameters of the rubber isolation bearings are shown in **Table 2**, and then Midas Gen is used to carry out the dynamic time-history analysis of the working conditions set by different influencing factors to obtain the maximum inter-story displacement angle of the structure under the action of earthquakes of different intensities, and the maximum inter-story displacement angle is used as the evaluation of the overall seismic performance of the structure θmax The maximum storey displacement angle is used as the evaluation index of the overall seismic performance of the structure, and the evaluation index of the damage state of the structure is shown in **Table 3**. Finally, the five influencing factors, namely, seismic isolation arrangement, degree of structural regularity, fortification intensity, site category and seismic intensity, are analysed based on the calculation results to provide an objective basis for the seismic damage sample database.

Table 1. Model Information Sheet

Model Number	N1	N2
Beam section size/mm	300 × 600	300 × 600
Column section size/mm	600 × 600	600 × 600
Concrete strength grade	C30	C30
Reinforcement type	HRB400	HRB400
Structure height/m	23.1	23.1
Drop layer height/m	6.6	0
Drop layer span/m	12	0

Table 2. Main Performance Parameters of Isolation Bearings

Type	Effective diameter (mm)	Total thickness of rubber (mm)	Stiffness before yield (kN/m)	Equivalent stiffness (kN/m)	Vertical stiffness (kN/mm)	Yield force (kN)
LRB500	500	92	10910	1270	2400	40

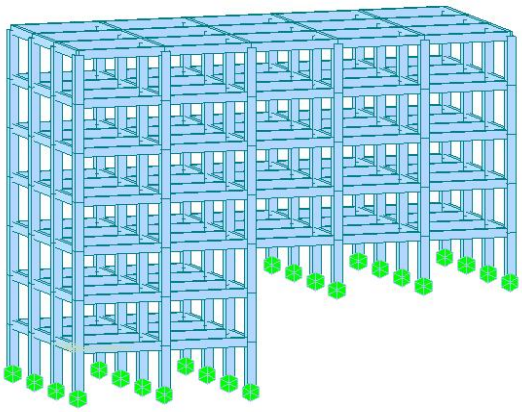


Figure 3. N1 3D Model

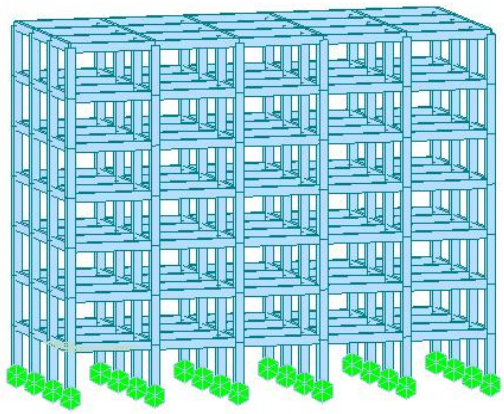


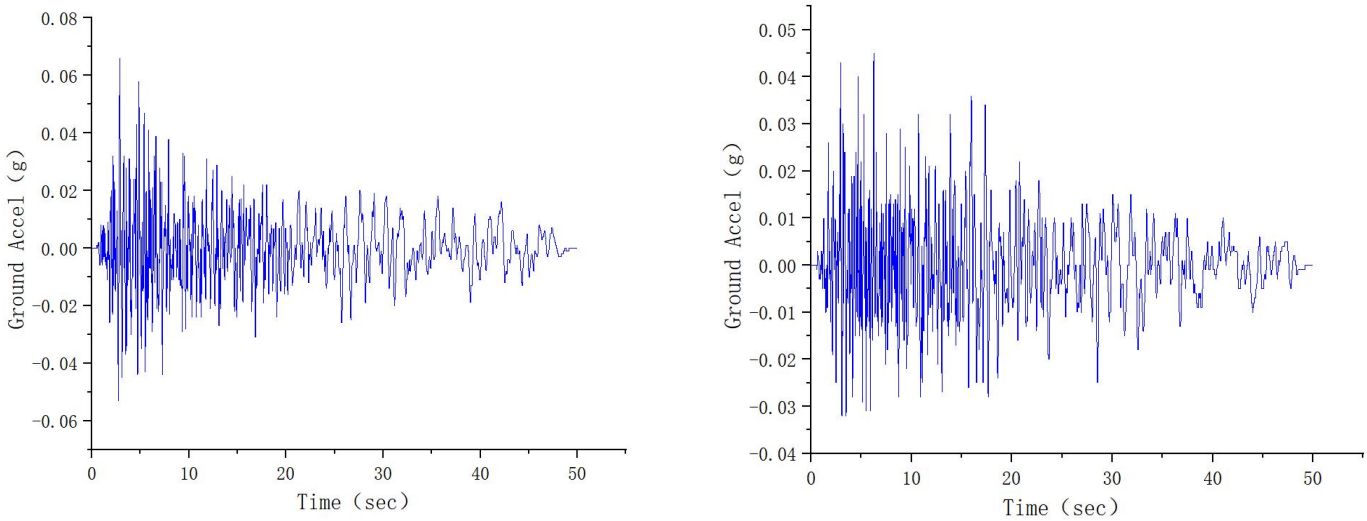
Figure 4. N2 3D Model

Table 3. Maximum Interlayer Displacement Angle under Different Damage States

Damage status description	Damage status	θmax
Basically intact	DS_1	$\theta \le 1/550$
Minor damage	DS_2	$1/550 < \theta \le 1/250$
Moderate damage	DS_3	$1/250 < \theta \le 1/120$
Serious damage	DS_4	$1/120 < \theta \le 1/60$
Collapse	DS_5	$\theta > 1/60$

Example of Judgement of Damage State of Single Building

According to the needs of this study, several seismic waves were selected from the Pacific Earthquake Engineering Research Centre (PEERC) database for dynamic time course analysis of the designed structure. One of the RSN9 seismic waveforms is shown in **Figure 5**.



RSN9-X Direction RSN9-Y Direction

Figure 5. RSN9 Seismic Wave Acceleration Time History Curve

The RSN9 seismic wave is amplitude modulated according to the code and then input into N1, N2, N3 and N4 which are designed according to the 7 degree defence, class II site, and power time analysis is carried out to obtain the maximum interstorey displacement angle of the four models, the maximum interstorey displacement angle and the damage state of the structure as shown in **Table 4**.

Table 4. Model Damage State under RSN9 Seismic

Model number	N1	N2	N3	N4
θmax	1/196	1/341	1/395	1/554
Destruction state	DS_3	DS_2	DS_2	DS_1

According to **Table 4**, the four models of N1, N2, N3 and N4, which are designed according to the 7-degree defence and Class II site, are in the states of Moderate damage, Minor damage, Basically intact, and Minor damage, respectively, under the RSN9 earthquake. "Moderate damage", "Minor damage", "Minor damage", "Basically intact".

The dynamic time course analysis of the structure was carried out, and according to the analysis results, the five factors that have a greater influence on the seismic performance of the mountainous step-isolated frame structure were obtained, which are the five influencing factors of the seismic isolation bearing, the structural regularity, the fortification intensity, the site category, and the seismic intensity, and combined with the floor plan of N1 and N2, the working conditions of the two types of typical frame structures were set up by using the design software Midas Gen, and the analysis of the structure was carried out by adopting the method of controlling variables.

Main Seismic Factors of Stepped Seismically Isolated Frame Structures in Mountainous Areas

Seismic Isolation Bearing (X1), Degree of Structural Regularity (X2)

This study focuses on the seismic performance of mountainous stepped-foundation seismically isolated frame structures, and the arrangement of seismic isolation bearings and the degree of regularity of the structure are taken as two important influencing factors because they have a greater impact on the seismic performance of the structure.

The four models N1, N2, N3 and N4 designed in this study have considered the two influencing factors of the

arrangement of seismic isolation bearings and the degree of structural regularity at the time of structural design. The only variable between N1 and N3, N2 and N4 is the presence or absence of seismic isolation bearings, when the bottom of the structure is not provided with seismic isolation bearings, the influencing factor is $X1 = 0$ When there is no seismic isolation at the base of the structure, the influence factor is determined as follows $X1 = 1$ The only variable between N1 and N2, N3 and N4 is the degree of specification of the structure. In this paper, parameters are proposed for the degree of structural regularity (X2)β. The meaning of the parameter is shown in **Figure 6** and β whose meanings are shown in **Figure 6** and Equation 1.

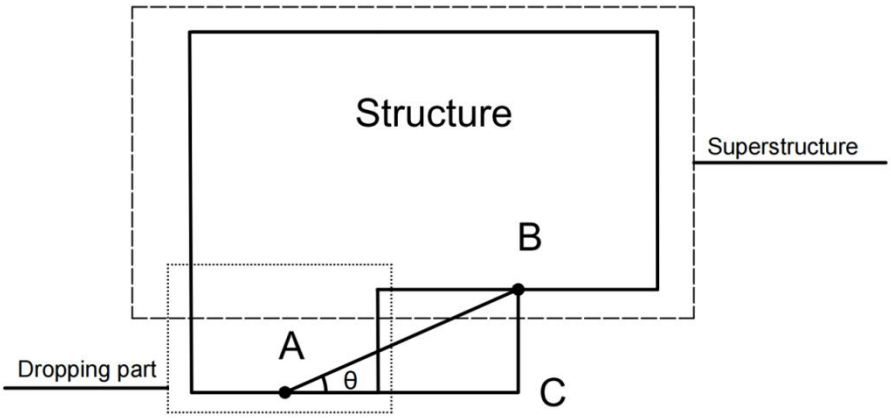


Figure 6. Simplified Drawing of Structural Elevation

In **Figure 6**, A is the centre of gravity at the base of the dropped floor portion of the structure and B is the centre of gravity at the base of the superstructure of the structure, creating a right triangle ABC with AB as the hypotenuse. D_{BC} denotes the distance between B and C, D_{AC} denotes the distance between A and C, and θ is the angle of inclination of the straight line AB, and the parameterβ of the triangle is expressed as follows:

$$\beta = \arctan\theta \tag{1}$$

When the structure is an ordinary level-foundation frame structure $\theta = 0$, that $\beta = 0$, when the structure is a hilly terraced foundation frame structure β. The values are taken according to Equation 1. This paper mainly introduces the earthquake damage prediction method based on fuzzy inference, the sample capacity is relatively small, and only two cases of structural rules and irregularities are considered in this study, so when the value ofβ is not 0, it represents that the structure is a mountainous stepped frame structure and an irregular structure, at this time, let $\beta = 1$

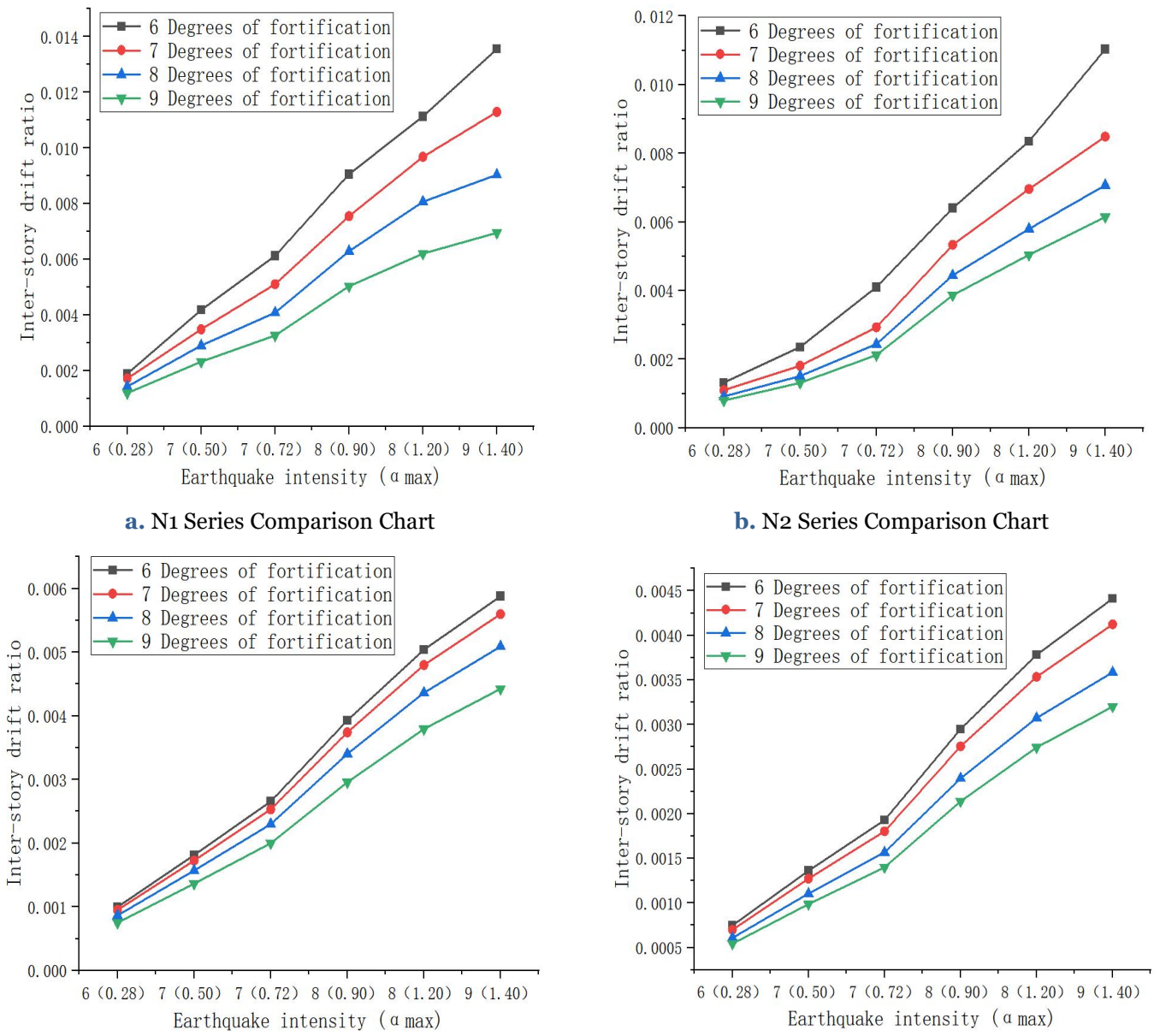
Intensity of Defence (X3)

According to the seismic classification of frame structures in the code, for frame structures with heights lower than 30 m, the corresponding frame seismic classifications for structural defence intensities of 6 degrees, 7 degrees, 8 degrees and 9 degrees are four, three, two and one, respectively. In this paper, 16 models are set up according to the structural defence level (**Table 5**). **Figure 7** shows the relationship between the maximum inter-storey displacement angle and the seismic intensity for N1, N2, N3 and N4 under different defence levels, respectively.

Table 5. Framework Intensity of Defence (X3) Working Condition Settings

Fortification intensity	9	8	7	6
N1 series	N1-3-1	N1-3-2	N1-3-3	N1-3-4
N2 series	N2-3-1	N2-3-2	N2-3-3	N2-3-4
N3 series	N3-3-1	N3-3-2	N3-3-3	N3-3-4
N4 series	N4-3-1	N4-3-2	N4-3-3	N4-3-4

Note: The design conditions for the N1, N2, N3 and N4 series are the same except for the difference in seismic intensity. Each case is designed in accordance with the Class II site and Seismic Group 2.



a. N1 Series Comparison Chart

b. N2 Series Comparison Chart

c. N3 Series Comparison Chart

d. N4 Series Comparison Chart

Figure 7. Maximum Inter-storey Displacement Angle Versus Seismic Intensity and Defence Intensity

Analysing the above graphs, the results show that the structural seismic performance improves with the increase of the structural defence intensity, in which the gap between the seismic performance of Grade III and Grade IV frames is smaller, while Grade I frames and Grade II frames have a significant effect on the improvement of the structural seismic performance; and the greater the intensity of the ground shaking is, the higher the intensity of the frame grade of the high intensity of the defence, the more obvious is the improvement of the seismic performance.

When the defence intensity of the structure is 6 degrees, X3 = 6; similarly, when the defence intensity is 7, 8 and 9 degrees, X3 takes the values of 7, 8 and 9 respectively.

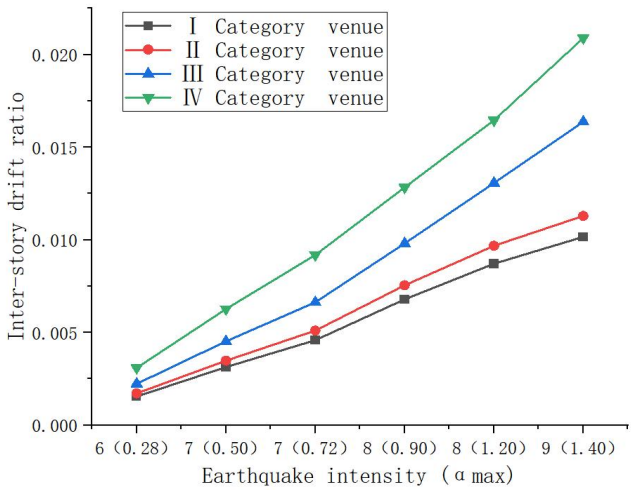
Site Conditions (X4)

The structural displacement responses of N1, N2, N3 and N4 in different site conditions corresponding to the seismic response spectra are calculated respectively, and 16 models are set up in this paper based on the structural site conditions, and the working conditions are shown in **Table 6**. **Figure 8** shows the relationship between the maximum interstorey displacement angle and the site conditions for N1, N2, N3 and N4 in different defence levels, respectively.

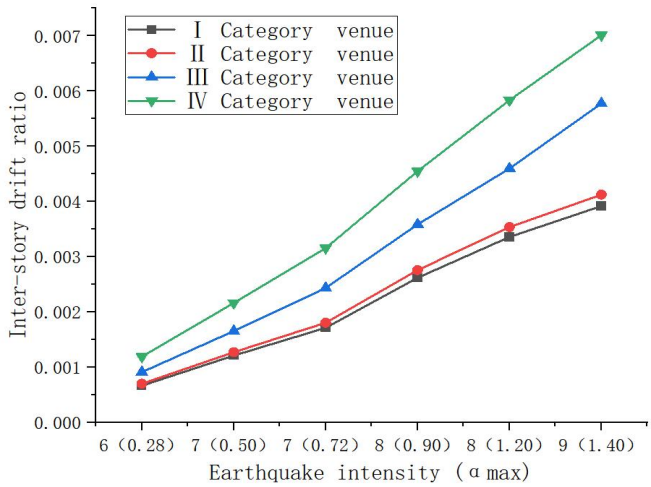
Table 6. Frame Site Conditions (X4) Working Condition Setting

Site conditions	Ⅰ Category	Ⅱ Category	Ⅲ Category	Ⅳ Category
N1 series	N1-4-1	N1-4-2	N1-4-3	N1-4-4
N2 series	N2-4-1	N2-4-2	N2-4-3	N2-4-4
N3 series	N3-4-1	N3-4-2	N3-4-3	N3-4-4
N4 series	N4-4-1	N4-4-2	N4-4-3	N4-4-4

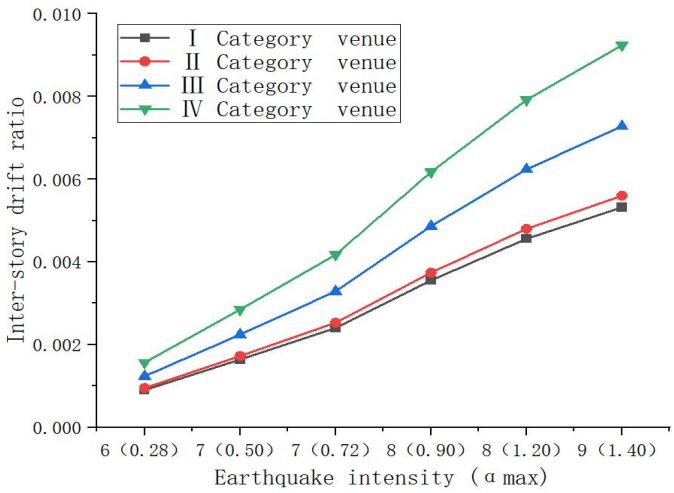
Note: The N1, N2, N3 and N4 series of conditions have the same design conditions except for differences in site types. Each case is designed in accordance with the 7th degree of defence and the 2nd design seismic group.



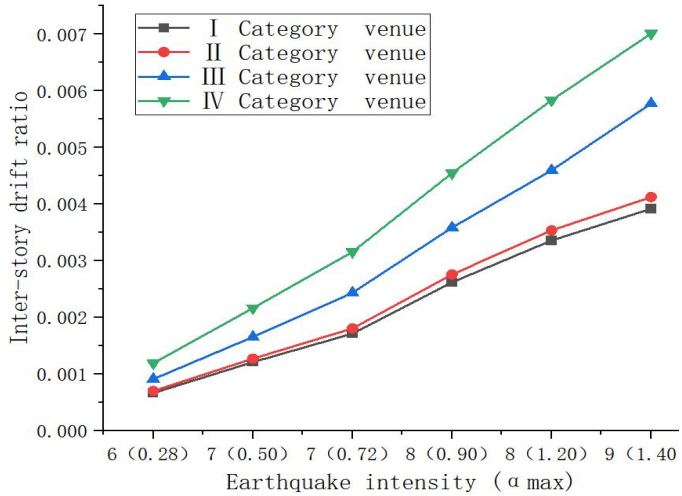
a. N1 Series Comparison Chart



b. N2 Series Comparison Chart



c. N3 Series Comparison Chart



d. N4 Series Comparison Chart

Figure 8. Maximum Interstorey Displacement Angle Versus Seismic Intensity and Site Category

Analyzing the above graphs, the trend of the influence of site conditions on seismic performance is consistent, under the same site conditions the seismic performance of N3 series is better than that of N1 series, and the seismic performance of N4 series is better than that of N2 series; when the site conditions are poorer, the rate of increase of the maximum structural interstorey displacement angle with the increase of the seismic intensity is improved. When the site conditions are the same, the maximum structural interstory displacement angle increases with the increase of seismic intensity, and the structural damage state is gradually aggravated; when the seismic intensity is the same, the worse the site conditions are, the larger the structural interstory displacement angle is, and the heavier the structural damage state is.

When the site conditions are class I, make X4 = 1; similarly, when the site conditions are class II, class III, and class IV, X4 take 2, 3, and 4 respectively.

Seismic Intensity (X_5)

Seismic intensity is a direct reflection of the amount of energy released by an earthquake. Larger seismic intensities usually result in greater seismic effects, such as the amplitude and frequency of seismic waves. These effects directly affect the stresses on the structure, thus seismic intensity is a key factor that directly affects the seismic hazard of the structure. By taking seismic intensity as an input, a fuzzy inference model can learn the complex relationship between seismic intensity and structural damage, thus providing a prediction of the degree of structural damage. In this paper, seismic intensity is used as an independent variable for comparative analysis when studying the influencing factors X_3 and X_4. When the seismic intensity is 6 degrees and the maximum value of the horizontal seismic influence coefficient is 0.05 g, let $X_5 = 6$; when the seismic intensity is 7 degrees and the maximum value of the horizontal seismic influence coefficient is 0.10 g, let $X_5 = 7$; when the seismic intensity is 7 degrees and the maximum value of horizontal seismic influence coefficient is 0.15 g, let $X_5 = 7.5$; when the seismic intensity is 8 degrees and the maximum value of horizontal seismic influence coefficient is 0.20 g ,let $X_5 = 8$; when the seismic intensity is 8 degrees and the maximum value of the horizontal seismic impact coefficient is 0.30g, $X_5 = 8.5$; when the seismic intensity is 9 degrees and the maximum value of the horizontal seismic impact coefficient is 0.40 g, $X_5 = 9$; and when the seismic intensity is n, $X_5 = n$ (n is the intensity of the specific earthquake).

Database of Seismic Samples

Combining the above five seismic factors, a seismic sample database is obtained based on the results of the dynamic time-range analyses, and the sample database is shown in **Table 7**.

Table 7. Database of Seismic Samples

Number	Influencing factors										Number	Influencing factors									
	X_1	X_2	X_3	X_4	X_5							X_1	X_2	X_3	X_4	X_5					
					6	7	7.5	8	8.5	9						6	7	7.5	8	8.5	9
1	0	1	6	1	DS1	DS2	DS3	DS3	DS4	DS4	33	0	1	6	3	DS2	DS3	DS3	DS4	DS4	DS5
2	0	0	6	1	DS1	DS2	DS2	DS3	DS3	DS4	34	0	0	6	3	DS1	DS2	DS3	DS4	DS4	DS4
3	1	1	6	1	DS1	DS1	DS2	DS2	DS3	DS3	35	1	1	6	3	DS1	DS2	DS2	DS3	DS3	DS3
4	1	0	6	1	DS1	DS1	DS2	DS2	DS2	DS3	36	1	0	6	3	DS1	DS1	DS2	DS2	DS3	DS3
5	0	1	7	1	DS1	DS2	DS3	DS3	DS4	DS4	37	0	1	7	3	DS2	DS3	DS3	DS4	DS4	DS4
6	0	0	7	1	DS1	DS1	DS2	DS3	DS3	DS3	38	0	0	7	3	DS1	DS2	DS2	DS3	DS4	DS4
7	1	1	7	1	DS1	DS1	DS2	DS2	DS3	DS3	39	1	1	7	3	DS1	DS2	DS2	DS3	DS3	DS3
8	1	0	7	1	DS1	DS1	DS1	DS2	DS2	DS2	40	1	0	7	3	DS1	DS1	DS2	DS2	DS3	DS3
9	0	1	8	1	DS1	DS2	DS2	DS3	DS3	DS3	41	0	1	8	3	DS2	DS2	DS3	DS3	DS4	DS4
10	0	0	8	1	DS1	DS1	DS2	DS2	DS3	DS3	42	0	0	8	3	DS1	DS2	DS2	DS3	DS3	DS4
11	1	1	8	1	DS1	DS1	DS2	DS2	DS3	DS3	43	1	1	8	3	DS1	DS2	DS2	DS3	DS3	DS3
12	1	0	8	1	DS1	DS1	DS1	DS2	DS2	DS2	44	1	0	8	3	DS1	DS1	DS2	DS2	DS2	DS3
13	0	1	9	1	DS1	DS2	DS2	DS3	DS3	DS3	45	0	1	9	3	DS1	DS2	DS3	DS3	DS3	DS4
14	0	0	9	1	DS1	DS1	DS2	DS2	DS3	DS3	46	0	0	9	3	DS1	DS1	DS2	DS3	DS3	DS3
15	1	1	9	1	DS1	DS1	DS2	DS2	DS2	DS3	47	1	1	9	3	DS1	DS1	DS2	DS2	DS3	DS3
16	1	0	9	1	DS1	DS1	DS1	DS2	DS2	DS2	48	1	0	9	3	DS1	DS1	DS2	DS2	DS2	DS3
17	0	1	6	2	DS2	DS3	DS3	DS4	DS4	DS4	49	0	1	6	4	DS2	DS3	DS4	DS4	DS5	DS5

Num	Influencing factors										Num	Influencing factors									
18	0	0	6	2	DS1	DS2	DS3	DS3	DS4	DS4	50	0	0	6	4	DS2	DS3	DS3	DS4	DS4	DS5
19	1	1	6	2	DS1	DS1	DS2	DS2	DS3	DS3	51	1	1	6	4	DS1	DS2	DS3	DS3	DS4	DS4
20	1	0	6	2	DS1	DS1	DS2	DS2	DS2	DS3	52	1	0	6	4	DS1	DS2	DS2	DS3	DS3	DS3
21	0	1	7	2	DS1	DS2	DS3	DS3	DS4	DS4	53	0	1	7	4	DS2	DS3	DS4	DS4	DS4	DS5
22	0	0	7	2	DS1	DS1	DS2	DS3	DS3	DS4	54	0	0	7	4	DS2	DS2	DS3	DS4	DS4	DS4
23	1	1	7	2	DS1	DS1	DS2	DS2	DS3	DS3	55	1	1	7	4	DS1	DS2	DS3	DS3	DS3	DS4
24	1	0	7	2	DS1	DS1	DS1	DS2	DS2	DS3	56	1	0	7	4	DS1	DS2	DS2	DS3	DS3	DS3
25	0	1	8	2	DS1	DS2	DS3	DS3	DS3	DS4	57	0	1	8	4	DS2	DS3	DS3	DS4	DS4	DS4
26	0	0	8	2	DS1	DS1	DS2	DS3	DS3	DS3	58	0	0	8	4	DS1	DS2	DS3	DS3	DS4	DS4
27	1	1	8	2	DS1	DS1	DS2	DS2	DS3	DS3	59	1	1	8	4	DS1	DS2	DS2	DS3	DS3	DS4
28	1	0	8	2	DS1	DS1	DS1	DS2	DS2	DS2	60	1	0	8	4	DS1	DS2	DS2	DS3	DS3	DS3
29	0	1	9	2	DS1	DS2	DS2	DS3	DS3	DS3	61	0	1	9	4	DS2	DS3	DS3	DS4	DS4	DS4
30	0	0	9	2	DS1	DS1	DS2	DS2	DS3	DS3	62	0	0	9	4	DS1	DS2	DS2	DS3	DS4	DS4
31	1	1	9	2	DS1	DS1	DS2	DS2	DS2	DS3	63	1	1	9	4	DS1	DS2	DS2	DS3	DS3	DS3
32	1	0	9	2	DS1	DS1	DS1	DS2	DS2	DS2	64	1	0	9	4	DS1	DS1	DS2	DS2	DS3	DS3

RESULTS AND DISCUSSION

Matlab-based Fuzzy Inference Model

In this paper, a fuzzy inference model is established based on the rules of a fuzzy system with the isolation bearing (X1), the degree of structural regularity (X2), the intensity of defence (X3), the site category (X4) and the seismic intensity (X5) as fuzzy inputs, and the damage state of the structure (Y1) as fuzzy outputs. In order to accurately express the relationship between the damage state and each seismic influence factor, a nonlinear regression equation is established, and the equation is as follows:

$$Y1=f(X1, X2, X3, X4, X5) + error$$

Determination of the Theory Domain and Affinity Function

Here, the seismic isolation bearing domain is [0, 1], the fuzzy linguistic variables are "Non-existence", "Existence", and its affiliation function selects trapezoidal; the structural regularity degree domain is [0, 1], the fuzzy linguistic variable is "Irregularly", "Regularly", and its affiliation function selects trapezoidal; the defense intensity domain is [6, 9], and the fuzzy linguistic variables are "6-degree ", "7-degree", "8-degree", "9-degree", and its affiliation function selects trapezoidal; the site category domain is [1, 4], and the fuzzy linguistic The site category domain is [1, 4], and the fuzzy language variables are "I class", "II class", "III class", "IV class", and its affiliation function selects triangle. The seismic intensity domain is [6, 9], and the fuzzy linguistic variables are "6 degree", "7 degree", "7.5 degree", "8 degree ", "8.5 degrees", "9 degrees" and its affiliation function is trapezoidal; the damage state domain is [0, 5] and the fuzzy linguistic variables are "Basically intact", "Minor damage", "Moderate damage", "Serious damage", "Collapse" and its affiliation function is chosen as trapezoidal.

Fuzzy Rule Construction

The fuzzy rules for seismic isolation bearing, degree of structural regularity, intensity of defence, site category, seismic intensity and damage are constructed according to the sample library of seismic data in **Table 7**, and since the fuzzy rules in this study reached 384, the fuzzy rules correspond to the sample library, and only 12 of

them are shown in **Table 8**.

Table 8. Partial Fuzzy Rules

X1	X2	X3	X4	X5	Y
0	0	6	1	6	DS1
1	0	6	1	7	DS1
0	1	6	1	7.5	DS3
1	1	7	2	8	DS2
0	0	7	2	8.5	DS3
1	0	7	2	9	DS3
0	1	8	3	6	DS2
1	1	8	3	7	DS2
0	0	8	3	7.5	DS2
1	0	9	4	8	DS2
0	1	9	4	8.5	DS4
1	1	9	4	9	DS3

Fuzzy Inference Modelling

In this paper, the fuzzy inference model is implemented through the fuzzy logic toolbox in Matlab, and the fuzzy variables of the fuzzy inference model are set as shown in **Figure 9**. The argument domain, affiliation function is shown in **Figure 10**. The fuzzy rule setting process is shown in **Figure 11**.

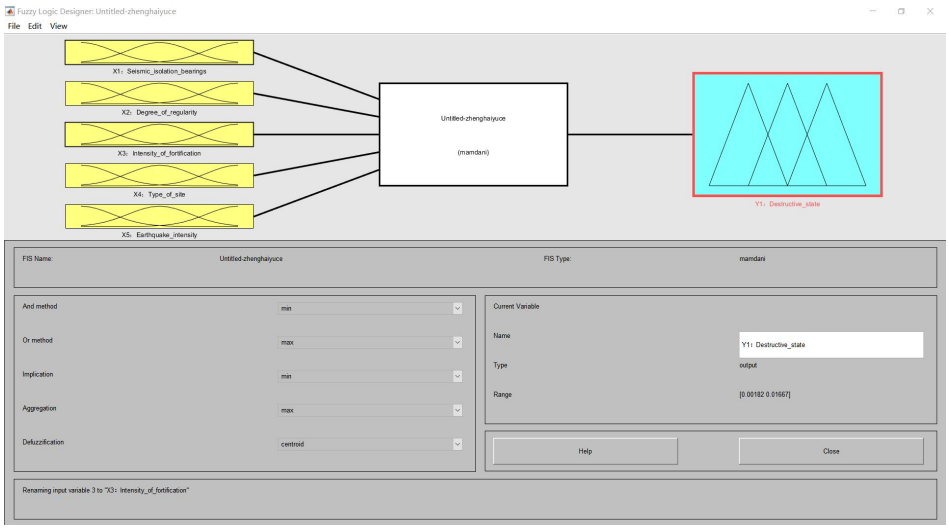


Figure 9. Fuzzy Variable Settings

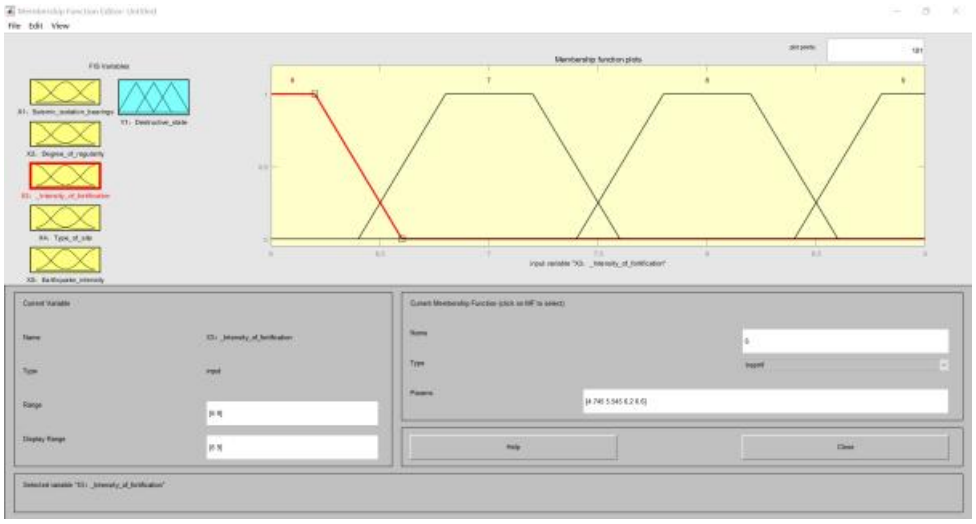


Figure 10. Thesis Domain, Affiliation Function

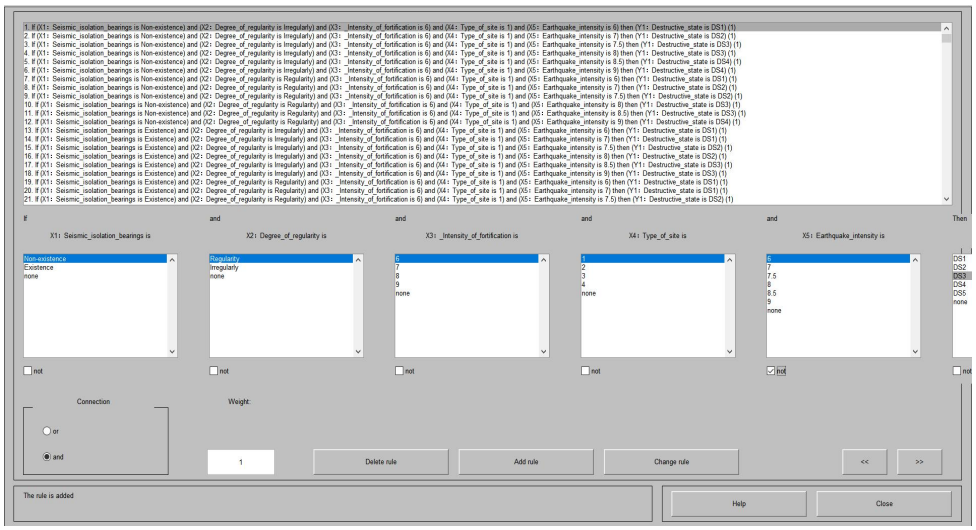


Figure 11. Fuzzy Rule Setup

The specific fuzzy rules are as follows:

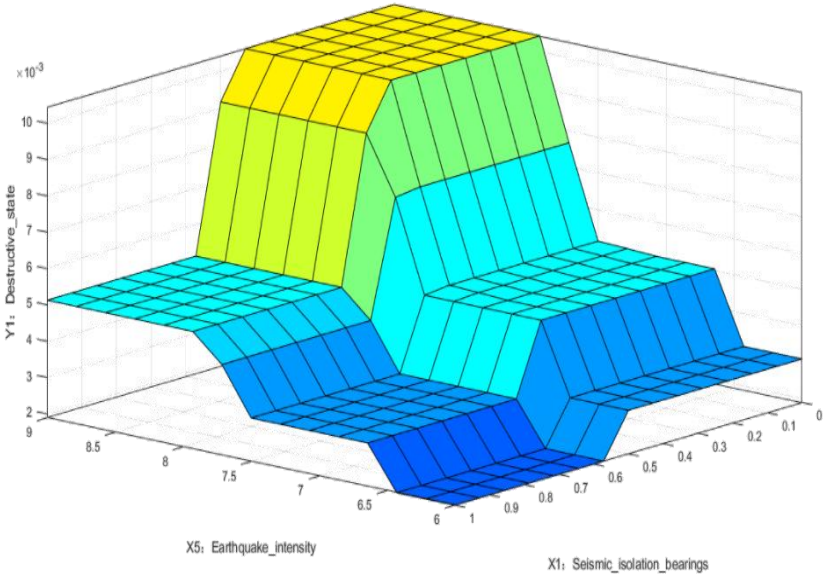
1. If X1 is 0 and X2 is 1 and X3 is 6 and X4 is 1 and X5 is 6 then Y1 is DS1;
2. If X1 is 0 and X2 is 1 and X3 is 6 and X4 is 1 and X5 is 7 then Y1 is DS2;
3. If X1 is 0 and X2 is 1 and X3 is 6 and X4 is 1 and X5 is 7.5 then Y1 is DS3;
……
197. If X1 is 0 and X2 is 1 and X3 is 6 and X4 is 3 and X5 is 8.5 then Y1 is DS4;
198. If X1 is 0 and X2 is 1 and X3 is 6 and X4 is 3 and X5 is 9 then Y1 is DS5;
199. if X1 is 0 and X2 is 0 and X3 is 6 and X4 is 3 and X5 is 6 then Y1 is DS1;
……
383.If X1 is 1 and X2 is 0 and X3 is 9 and X4 is 4 and X5 is 8.5 then Y1 is DS3;
384. If X1 is 1 and X2 is 0 and X3 is 9 and X4 is 4 and X5 is 9 then Y1 is DS3.

Multifactor Fuzzy Surfaces

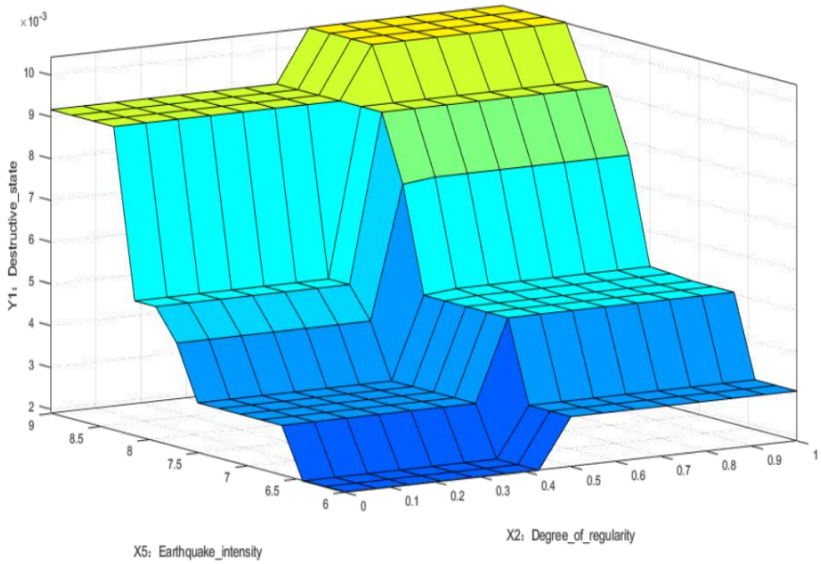
A fuzzy inference model has been established in Matlab, and the relationship between the inputs and outputs in the fuzzy inference model can be represented by the fuzzy surface in **Figure 12**, which represents the combined effects of seismic isolation bearing, degree of structural regularity, intensity of defence, site category, seismic intensity and damage level.

Figure 12-a is the damage degree of the structure with the seismic intensity, seismic isolation bearing fuzzy

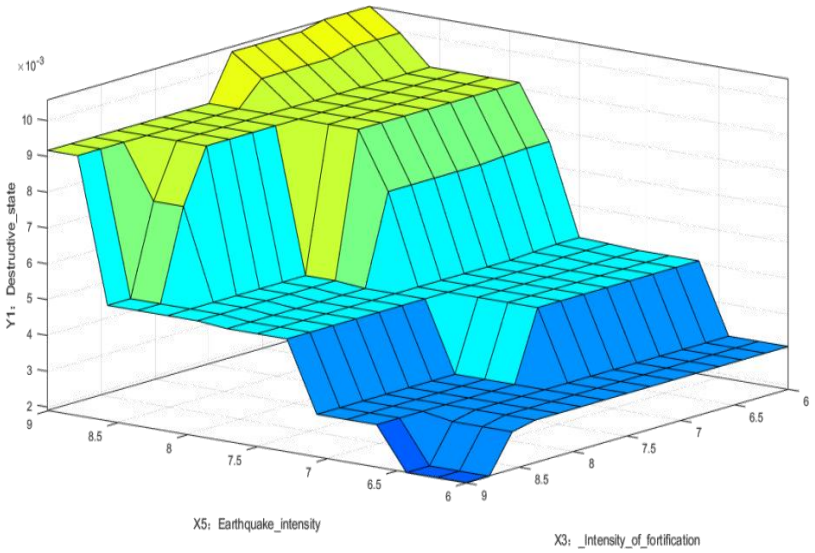
surface, according to the surface diagram can intuitively see the seismic isolation bearing on the seismic performance of the structure has a greater impact, intuitively reflecting the damage degree of seismic isolation structure and ordinary structure with the change rule of seismic intensity. **Figure 12-b** is the damage degree of the structure with the seismic intensity, the degree of regularity fuzzy surface, according to the surface map can intuitively see the degree of regularity on the seismic performance of the structure has a greater impact, intuitively reflects the damage degree of the mountainous terraced foundation frame structure and ordinary frame structure with the change rule of seismic intensity. **Figure 12-c** is the damage degree of the structure with the seismic intensity, defence intensity fuzzy surface, according to the surface map can intuitively see the defence intensity of the structure of the seismic performance has a greater impact, intuitively reflecting the damage degree of the structure of different defence intensity with the change rule of seismic intensity. **Figure 12-d** is the damage degree of structure and seismic intensity, site category fuzzy surface, according to the surface can intuitively see the site category of the structure of the seismic performance of the greater impact, can intuitively reflect the structure of the damage degree of different site categories with the change rule of seismic intensity.



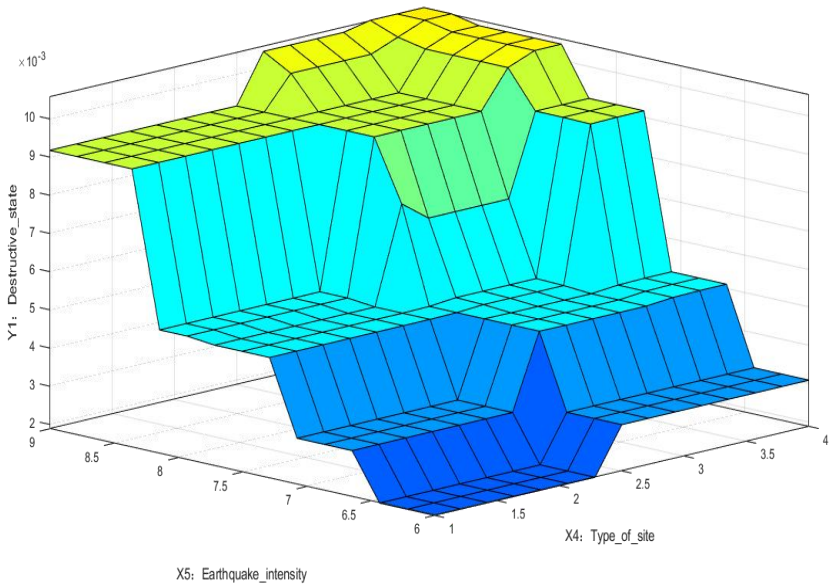
a. Damage Level and Seismic Intensity, Fuzzy Surfaces of Seismic Isolation Bearings



b. Fuzzy Surfaces of Damage and Seismic Intensity, Degree of Regularity



c. Fuzzy Surfaces of Damage and Seismic Intensity and Defence Intensity



d. Fuzzy Surfaces of Damage with Seismic Intensity and Site Type

Figure 12. Fuzzy Surface

The arrangement of seismic isolation bearings, regularity of building structure, defence intensity, site category and seismic intensity are inputted into the fuzzy inference model, for example, a structure is arranged with seismic isolation bearings for a mountainous stepped seismic isolation frame structure, and the defence intensity of the structure is 6 degrees, the site category is IV, and the seismic intensity is 6.5, and the input vector is i.e., [1, 1, 6, 4, 6.5] and the output vector is [0.00309], corresponding to the maximum inter-story displacement angle of the structure is 0.00309, and the damage state is DS2 (Minor damage).

Model Accuracy Test

The comparison of the results obtained by the fuzzy inference model with the actual results of the test set consisting of four randomly selected samples is shown in **Table 9**, which shows that most of the data can be correctly reflected, but there is also a small amount of deviation in some of the data, but on the whole, the model is well fitted, and the above errors in the model are acceptable.

Table 9. Comparison of Model Accuracy Results

Number	Input vector	Actual result	Damage status	Projected results	Damage status	Goodness of fit
1	[1, 0, 7, 3, 8]	0.00348	DS2	0.00359	DS2	91.09 %
2	[0, 0, 6, 2, 8]	0.00624	DS3	0.00690	DS3	89.42%
3	[1, 0, 7, 2, 7.5]	0.00162	DS1	0.00184	DS2	86.41 %
4	[0, 1, 6, 4, 7.5]	0.0110	DS4	0.0135	DS5	77.27 %

CONCLUSION AND OUTLOOK

This paper takes the mountainous stepped seismic isolation frame structure as the research object and introduces a method of rapid prediction of seismic response based on artificial intelligence technology. This study fills the knowledge gap in earthquake damage prediction for stepped seismically isolated frame structures in mountainous areas. A number of typical frame structures are designed by using finite element software, and the dynamic time-course analysis of the structures is carried out by the control variable method to obtain five factors that have a greater influence on the seismic performance of mountainous stepped seismic isolation frame structures, which are: the arrangement of isolation bearings, the degree of regularity of the structure, the intensity of defence, the site category and the seismic intensity. Based on the results of the dynamic time course analysis, a seismic sample library with a sample capacity of 384 is established by combining these influencing factors. Each influence factor is given a suitable domain and affiliation function, fuzzy rules are established according to the seismic sample library, and a fuzzy inference model is established by using the fuzzy logic toolbox in MATLAB. The model can directly determine the damage state of the predicted structure. The accuracy and stability of the model are verified by randomly selecting data samples several times to establish the model. The test results show that the seismic impact factors selected in this paper can accurately map the seismic damage prediction results of frame structures, and the method is accurate, fast and efficient, and can be applied to the rapid seismic damage prediction of stepped seismic isolation frame structures in mountainous areas.

The seismic impact factors selected in this paper are five, which cannot accurately simulate the seismic response of structures in real scenarios, and all the data are derived from finite element analysis, which lacks real seismic data. In future research, the types of influence factors and the number of samples in the database can be increased, which will further increase the accuracy of the model and give the model a wider application space in the actual earthquake damage prediction engineering. At the same time, we can also selectively replace some of the seismic impact factors on the basis of the model to do further research, and derive the degree of importance of the impact of each factor on the results of the earthquake damage by comparing the results, and the above ideas need to be further verified in practice.

CONFLICT OF INTEREST

No potential conflict of interest was reported by the authors.

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