

"Bridges At Risk: Multi-Hazard Fragility Analysis Using Time History Analysis And Artificial Intelligence Models"

Ashwini Satyanarayana^{1,2*}, Dushyanth V Babu R¹, Sheethal H M²

¹Department of Civil Engineering, JAIN (Deemed to be University), Bengaluru, India

²Department of Civil Engineering, Dayananda Sagar College of Engineering, Bengaluru -560111

*Corresponding Author. E-Mail: ashsatya@gmail.com

ABSTRACT

Bridges are crucial for facilitating efficient commerce and transportation between cities and across the country, making them a key component of highway transportation networks. The substantial financial losses caused by recent earthquakes have highlighted the susceptibility of essential bridge components and the necessity for precise evaluation of their seismic performance. In addition to earthquakes, flooding is another significant force that can greatly harm bridge structures. Consequently, there has been an increased focus on multi-hazard vulnerability assessments over the past few decades. Many older bridges constructed prior to 1970 are displaying signs of wear that are exacerbated by factors such as climate change. When these bridges were originally built, seismic design standards did not provide the comprehensive guidelines needed to ensure their strength and resilience. As a result, many existing bridges often do not satisfy the criteria for structural integrity and load capacity, highlighting the critical need for enhancements to extend their lifespan and ensure safety in today's dynamic environmental conditions. If seismic forces are not sufficiently mitigated, bridges may undergo significant lateral shifts and ground movements that can lead to structural damage, disruptions in service, and potentially disastrous outcomes. The response dynamics of a structure during intense seismic events are heavily influenced by the properties and behavior of the surrounding soil, in addition to the structure's superstructure. Dynamic analyses, such as Time History Analysis, are performed to evaluate the bridge. Fragility analysis assesses the likelihood that a structure or its components will reach a certain level of damage based on a specific ground motion intensity measure. In this study, artificial neural networks (ANNs) are utilized to address uncertainties surrounding influencing factors. The input and output of the ANN models have been identified as the significant characteristics and fragility parameters of key components, respectively.

Keywords: Seismic Performance, Bridge Structure, Ground Movements, Time History Analysis, Regression Plot.

1. INTRODUCTION

Bridges play an essential role in infrastructure, enabling the movement of people and goods. Nevertheless, there are numerous risks tied to compromised bridges [1]. It is essential to verify a bridge's operational status, especially after a natural disaster, because a non-functional bridge hinders movement and leads to losses across various sectors[2]. Consequently, bridges are considered vital components of the transportation network [3]. They need to function effectively in both structural and non-structural aspects (e.g., their safety) to ensure adequate recovery from significant catastrophic incidents (resilience), like those caused by intense ground shaking during earthquakes [4]. The main goal of designing earthquake-resistant bridges is to maintain communication channels at an acceptable level during seismic events[5]. Apart from earthquakes, flooding poses a major threat to bridges. Most of the sediment found in riverbeds and river basins consists of a mix of gravel and sand, heightening the risk of scouring [6]. Scour reduces the strength of bridge foundations by washing away the soil that surrounds them as a result of water flow. The safety of the public could be compromised by damage to bridges caused by scour incidents[7]. The seismic vulnerability of bridges rises as the depth of scour increases,

based on a multi-hazard fragility assessment of these structures. To effectively depict the seismic risk faced by bridges, it is crucial to consider both earthquake and flooding scenarios simultaneously [8]. The seismic vulnerability of bridges can be assessed through fragility analysis, which determines the likelihood that a structure or its components will experience damage that meets or exceeds a defined threshold level in relation to ground motion intensity[9].

The term "fragility" describes a structure's sensitivity or weakness, which makes it more likely to fail or sustain damage quickly. The Latin word "fragile," which denotes the capacity to breakdown or deteriorate quickly[5]. The conditional chance of structural demands above a certain damage level for a given earthquake intensity is actually displayed by the fragility function[10]. Fragility function is expressed in Fragility = $P [D \geq C | IM = y]$ (1 as,

$$\text{Fragility} = P [D \geq C | IM = y] \dots\dots\dots (1)$$

Where,

IM is the intensity measure of input ground motions, such as peak ground acceleration (PGA), and y is the specified value of IM. D and C stand for structural demand and damage limit state capacity, respectively.

Fragility curves may be derived analytically by simulations. The curves that are produced by graphing intensity measures against damage measures are known as fragility curves. There is growing demand for the use of fragility curves, which are relationships between the intensity of ground shaking and the likelihood of reaching or surpassing a specific response level, for the assessment of seismic losses in both pre-earthquake disaster planning and post-earthquake recovery and retrofitting initiatives[11]. **Figure 1** represents the damage states for bridges.

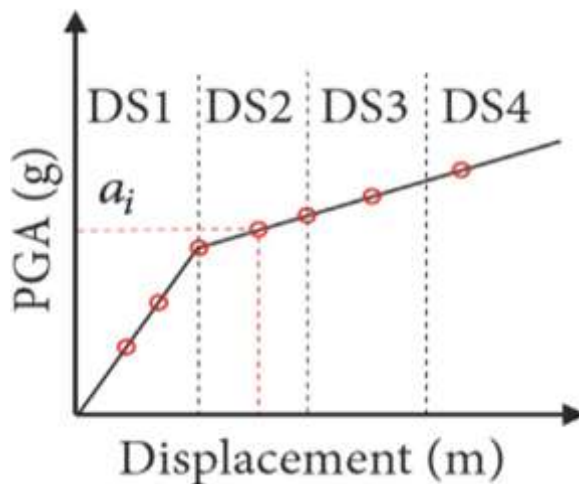


Figure 1: Representation of damage states for bridges [5]

Due to the limitations of the Capacity Spectrum method and Response Spectrum Analysis, the third method, combined with Incremental Dynamic Analysis (IDA), is preferred for fitting fragility functions. This approach provides a more accurate assessment of structural performance and helps in establishing detailed fragility curves based on specific damage indices[12]. The Incremental Dynamic Analysis (IDA) method entails performing nonlinear analyses on a prototype structural system with a variety of ground

motion records, each adjusted to different levels of Intensity Measures (IM) to provoke considerable global dynamic instability or critical failure in the structure[13]. From the obtained IDA curves, limit states are recognized, and the likelihood of surpassing a certain limit state at a specific IM (such as Peak Ground Acceleration (PGA) or Peak Ground Velocity (PGV)) can be determined [14]. The coefficients of the fragility function are then estimated by examining the logarithmic values of the IM associated with the initiation of these limit states and calculating their mean and standard deviation[15]. Linear modal time history analysis is a method in which the reaction of the structure is assessed by utilizing its modal characteristics (such as mode shapes and frequencies). It is presumed that the structural behavior stays elastic during the entire analysis. A sequence of ground motion is applied, and the structural response is determined by employing the superposition of individual modes.

Artificial Neural Network (ANN)

An artificial neural network (ANN) is a category of computational model often utilized in machine learning and artificial intelligence[16]. They possess a high level of nonlinear learning ability, especially in contexts such as reliability assessment and structural optimization challenges where a computational solution is unavailable or overly complex [17]. It draws inspiration from biological neural networks, like those found in the brain, in an effort to replicate complex input-output linkages[18]. Through modeling and learning on a large number of microscopic processing units, or neurons, it seeks to resolve difficult problems [19]. Each neuron is thought of as a node in an artificial neural network (ANN) that is connected to other neurons. After passing through the hidden levels and processing data from external sources, the input layer outputs the findings in the output layer. Following the use of a non-linear activation function to process inputs from other connected neurons, each neuron in the network communicates with other neurons [20]. The strength of the effect between neurons is determined by the weight of their connections. These weights are adjusted during the learning phase to optimize the network's performance. An ANN-based method was developed for the seismic fragility assessment of regular bridges as an alternative to the traditional NLTHA-based and statistical fragility methodologies [21]. The development of the ANN model involves a detailed analysis of finite element (FE) models of regular bridges [22]. Based on these, the ANN inputs and outputs are identified as the important components' influencing characteristics and fragility parameters, respectively [17]. The number of hidden layers, the number of neurons in the hidden layers, and the learning rate are the three main hyperparameters that the ANN technique depends on. It should be mentioned that adding more hidden layers to the ANN model does not significantly increase its performance [23].

2. LITERATURE REVIEW

This study examines the development of research on bridge fragility using bibliographic analysis. Analysis of publication trends, citation patterns, and keyword co-occurrences is done with the goal of discovering important study areas and new trends. A search was performed using a number of terms, such as "bridges," "seismic performance," "fragility analysis," "fragility curves," "seismic vulnerability," and "Incremental dynamic analysis". Only articles from peer-reviewed journals were included in the search. VOS viewer was used to create a co-citation network that illustrates the field's intellectual structure. Three different clusters of study were identified by the network analysis, indicating three main research themes in the discipline, as shown in the **Figure 2**. Additionally, the study uses

density maps to pinpoint areas with a high frequency of seismic fragility analysis research output.

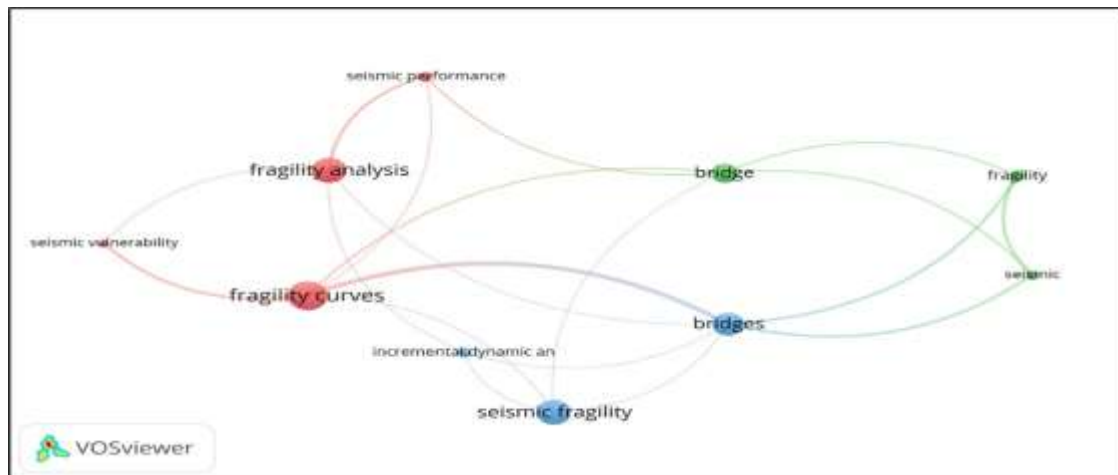


Figure 2: Keywords elicited from major scientific journals

In today's transportation network, bridges provide quick and convenient access to a number of sites. The study of how bridges respond to earthquakes and the analytical methods used to assess their effectiveness are examined in this research. The study's objective is to offer a theoretical framework for choosing appropriate methods for bridge structure analysis, loss measurement instrument rating, retrofitting strategies, and pre-earthquake planning [24]. The chance of a bridge failing under different earthquake intensities is evaluated using fragility analysis. Prioritizing retrofitting, pre-earthquake planning, and loss estimation are done using fragility curves. Emphasizing the importance of bridges in today's transportation system and the weaknesses of older bridges, particularly those built before 1970, as a result of the insufficient seismic design rules in place at the time[5]. All significant elements should be taken into consideration when determining bridge fragility curves. A total uncertainty value appropriate for the specific structural system should then be calculated after each component and limit state has been independently assessed for capacity, demand, and limit state definition uncertainty. In addition to the elements discussed here (piers, abutments, and bearings), one might additionally include foundation elements that could be important in specific bridge designs (for example, the failure of the piles supporting the abutments) [25].

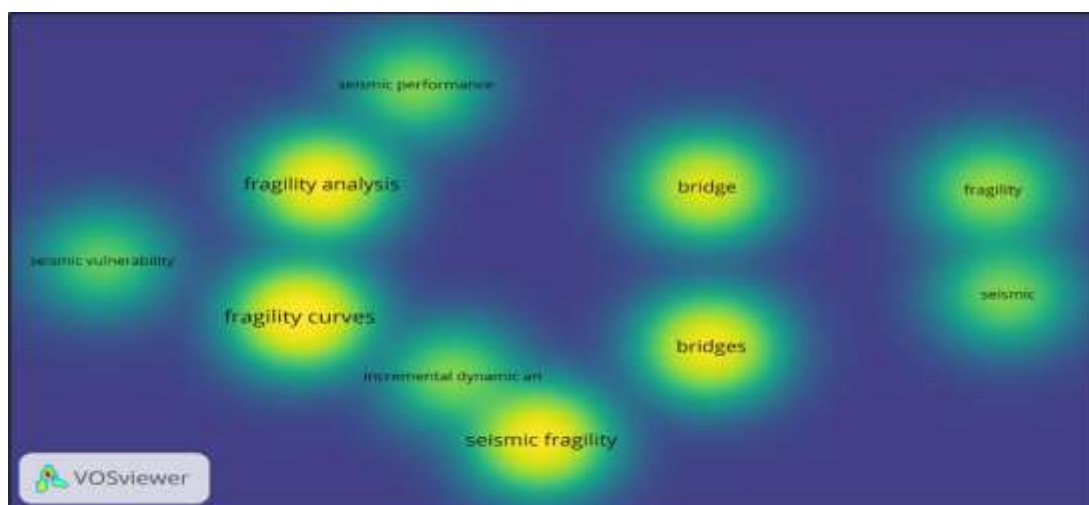


Figure 3: Major domain of research area

The fragility curves presented are first-order estimates of the actual bridge fragility curves' direction. More information about the individual reactions of the various bridge components in both longitudinal and transverse orientations may lead to improvements in these curves [26]. Several mainshock-aftershock sequences from different fault types (i.e., near-fault and far-fault) with different intensities were applied to analytical models of the bridge that was being studied. The potential for a seismic collapse of the mainshock-damaged bridge was investigated[27]. Pier drift was considered an engineering demand parameter (EDP), and the pier was considered the most crucial component. According to the research, the bridge can become more susceptible if aftershocks are included[28]. Accurate risk assessment and the use of mitigation procedures are two effective tactics for reducing the impact of an earthquake disaster on structures and infrastructure. Frailty curves can thus be used to assess damage and loss, which is an important tool in earthquake disaster management. Building fragility curves can be a valuable tool for predicting the degree of damage to structures of the same kind[29]. The effects of the unique relationship between ground motion and earthquakes on the behavior of seismically isolated bridges. Seismologically isolated earthquake response of typical bridges, taking into account the link between soil and water structures[30]. **Figure 3** represents major domain of research area.

The fragility nephogram can display intuitively the changeable characteristics of the seismic damage probability with various PGA for each cross-section of the whole pier. It can also expose the damage diffusion and probability for the entire pier. In terms of the irregular bridge structure, there are considerable variances in seismic fragilities for different structural components in different damage stages [31]. A three-dimensional full-scale continuum model of a bridge system was created using the finite element approach to obtain the baseline data needed to evaluate the sub-structuring method. This included thorough modelling of the foundation, piling foundations, abutment construction, and overall bridge structure [32]. The orientation of the bridge axis relative to the fault trace has a considerable impact on the seismic response of bridges in fault zones . The biggest seismic reactions occur when the bridge is perpendicular to the fault track during the Chi-Chi earthquake. The bridge parallel to the fault zones exhibits the smallest responses. The records in the center region generate more seismic reactions than those in the forward and backward regions. As a result, bridges in the middle region are projected to face higher deformation and strength demands [33]. Spatially varying ground movements are developed to be compatible with the spatially varied ground motion components of incoherence, wave-passage, and site-response effects. The bridge models are tested for the specified spatially variable ground motion scenarios, accounting for and ignoring the impact of soil-structure interaction [34]. The primary purpose of the work was to calculate the fragility curves of a single circular cross-section pier of a simply supported RC bridge, which is a popular type of bridge. This was accomplished using two analytical methodologies. They achieved consistent outcomes by adjusting geometric and mechanical parameters, particularly the median fragility curve trend [35].

For the monolithic bridge under investigation, RC jackets were found to be more successful than FRP jackets for pier retrofit in the lower and intermediate limit states, whereas RC jackets were more effective in the higher limit state. The increase in stiffness, which increases seismic forces, is the main cause of RC jackets' decreased limit state efficiency [36]. The most sensitive metrics for evaluating fragility at minor damage limit states bearing are frequently the axial compressive ratio, column height, and concrete strength. The column's height, diameter, and longitudinal reinforcement ratio which

frequently occupy the top three positions, represents its most significant sensitivity [37]. The fragility functions of six different classes of bridges are computed when they are subjected to liquefaction-induced lateral spreading or seismic shaking. The study found a significant correlation between the fragility functions of bridges exposed to ground shaking or lateral spreading and their structural characteristics [38]. The unique characteristics of bridges must be taken into account when using incremental dynamic analysis (IDA) to create an analytical fragility curve. This technique's applications are especially made for bridges.

Poor bridge maintenance procedures and a lack of regular rehabilitation plans, aside from little repairs, are to blame for a bridge's capacity loss. Bridges are built in accordance with accepted standards, however because the soil next to a pile or well foundation offers lateral support, foundation scouring is frequently overlooked [8]. The scouring performance of highway bridges cannot be disregarded since lateral stiffness will be reduced if they are scoured, especially in an area with a high seismic activity where scouring is important. Damage caused by scouring can range from minor erosion to a bridge's collapse [7]. Running water-induced erosion, or scour, can be characterized as either local contraction, deterioration, or aggradation [3].

3. METHODOLOGY

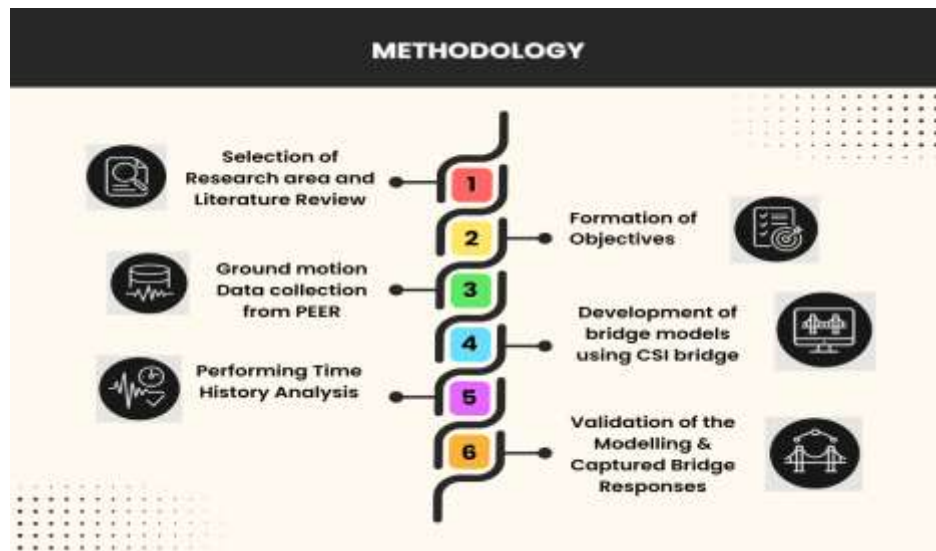


Figure 4: Flow chart of Methodology

The research's approach, which involves modelling RC T-beam bridges with the CSI BridgeV24 software, is depicted in the **Figure 4**.

Accordingly, the objectives of this study are as follows:

- To assess a bridge's performance using non-linear time history analysis under earthquake-induced stresses, presuming no scour.
- To evaluate a bridge's dynamic reaction through linear time history analysis.

Bridge Details for Validation:

Initially, the bridge was modelled in CSI bridge V24 software according to the details given in **Table 1** [3]. The bridge under consideration is situated in Nepal. The bridge is 225 meters long and features six simply supported spans over the pier cap, with edge spans of

38.5 meters and intermediate spans at 33 meters. The three longitudinal prestressed rectangular girders that measure 2500–750 mm, the five cross girders that measure 2200–400 mm and are evenly spaced at the end, and the intermediate span girders that measure 2200–300 mm make up the superstructure. The deck slab has dimensions of 200 mm in thickness and 11 meters in width. The main and cross girders provide monolithic support for the M35 grade concrete structure. **Figure 5** depicts the bridge's model. A time history study of the bridge is conducted using the ground motion record from the Imperial Valley earthquake.

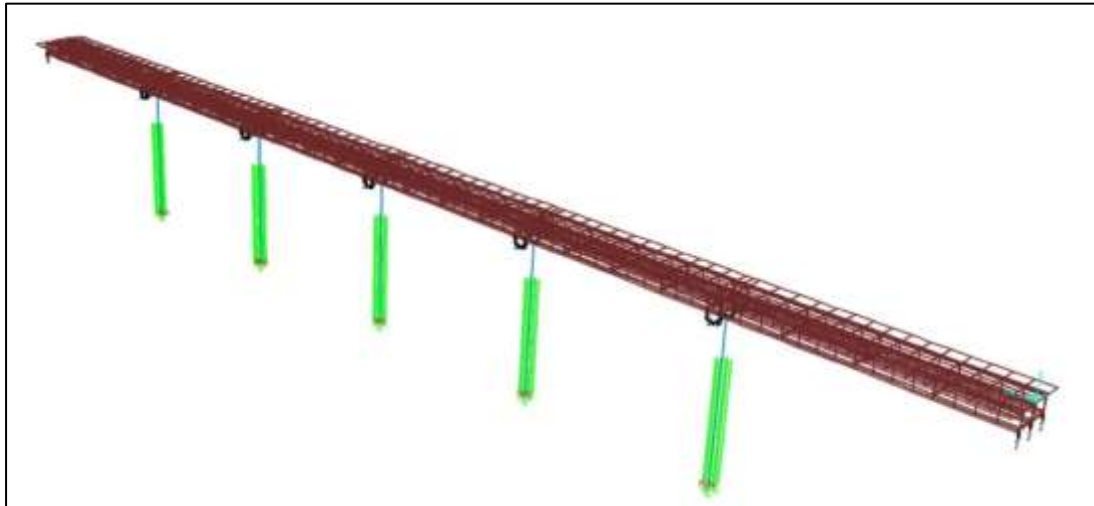


Figure 5: Three Dimensional model of Bridge

The soil spring characteristics and other parameters are used to create a 3D finite element model of the bridge as shown in **Figure 5**.

Table 1: Modelling parameters for steel and concrete

Material	Parameter	Value	Unit
Steel	Mass density	7850	Kg/m ³
	Poisson's ratio	0.3	-
	Ultimate tensile strength (f_u)	545	MPa
	Yield strength (F_y)	500	MPa
	Modulus of elasticity (E_s)	2×10^5	MPa
Concrete	Poisson's ratio	0.2	-
	Modulus of elasticity	33541.02 for (M35)	MPa
Unit weight		24	KN/m ³

A direct integration method is used to determine the displacement demand through non-linear time history analysis. Different PGA levels and frequency of recorded ground vibrations are applied as dynamic loading.

3.1 FRAILITY ANALYSIS

Vulnerability can be found with the help of fragility analysis. With respect to specific boundary states, it establishes a probabilistic characterization of demands by connecting capacity and demand. A limit condition's exceedance likelihood is shown by the fragility function under a particular intensity measure (IM) value. In mathematical terms, fragility is expressed in $P_f = P [S_d / S_c \geq 1]$ Equation 2 as,

$$P_f = P [S_d / S_c \geq 1] \text{ Equation 2} \quad [39]$$

Where,

- ☐ P_f represents the probability of failure,
- ☐ P is a reference probability,
- ☐ S_d denotes the structural demand parameter,
- ☐ S_c denotes the structural capacity parameter

This study uses the ductility ratio and pier displacement to identify the damage states.

The displacement ductility (μ_d) depicted in $\mu_d = \frac{\Delta D}{\Delta y}$ Equation 3 as,

$$\mu_d = \frac{\Delta D}{\Delta y} \text{ Equation 3} \quad [3]$$

where ΔD is the displacement of the pier top and Δy is the displacement that corresponds to the reinforcing steel's first yield[3] .

Regression analysis is used to determine displacement ductility for any arbitrary PGA input. The maximum displacement of the pier top is ascertained using time history analysis, and the yield displacement corresponding to the yield strain of the reinforcing bar is estimated. The capacity of bridge pier for different damage states for no scour condition taken for validation purpose is shown in **Table 2**.

Table 2: Capacity of bridge pier for different damage states for no scour condition
[3]

Damage states	Displacement (mm)	Displacement ductility (μ_c)	Mean displacement ductility
Slight	76.7	1.00	1.080
Moderate	88.9	1.16	1.883
Extensive	199.92	2.61	3.196
Collapse	290.4	3.79	3.786

Table 3: Capacity of bridge pier for different damage states for no scour condition

Damage states	Displacement (mm)	Displacement ductility (μ_c)	Mean displacement ductility
Slight	76.5	1.00	1.085
Moderate	88	1.17	1.915
Extensive	200	2.66	3.155
Collapse	289.2	3.65	3.65

The capacity of the bridge pier for different damage states for the '0' scour condition, as shown by time history analysis, is shown in **Table 3**. Fragility curves show the four levels of damage: mild, moderate, extensive, and collapse.

3.2 LINEAR DYNAMIC ANALYSIS

Linear Modal Time History Analysis

A ground motion database that accurately reflects the target region's seismic characteristics is chosen, and it is then filtered to provide ground motions with the right magnitude, distance, and soil conditions. The chosen ground motion is then scaled to the desired intensity levels. Initially, this study will analyze the bridge's time history using the ground motion record of the Gujarat Bhuj earthquake. The town of Bhuj, in the Kutch district, was the epicenter of a powerful earthquake that rocked the Indian state of Gujarat. This seismic event, which had a focal depth of roughly 16 kilometers and a Richter magnitude of 7.7, occurred at approximately 8:46 AM IST. Since the earthquake started inside the Indian tectonic plate and was not near any plate borders, it was categorized as an intraplate occurrence. The ground motion of Bhuj earthquake is represented in the form of function graph in **Figure 6**.

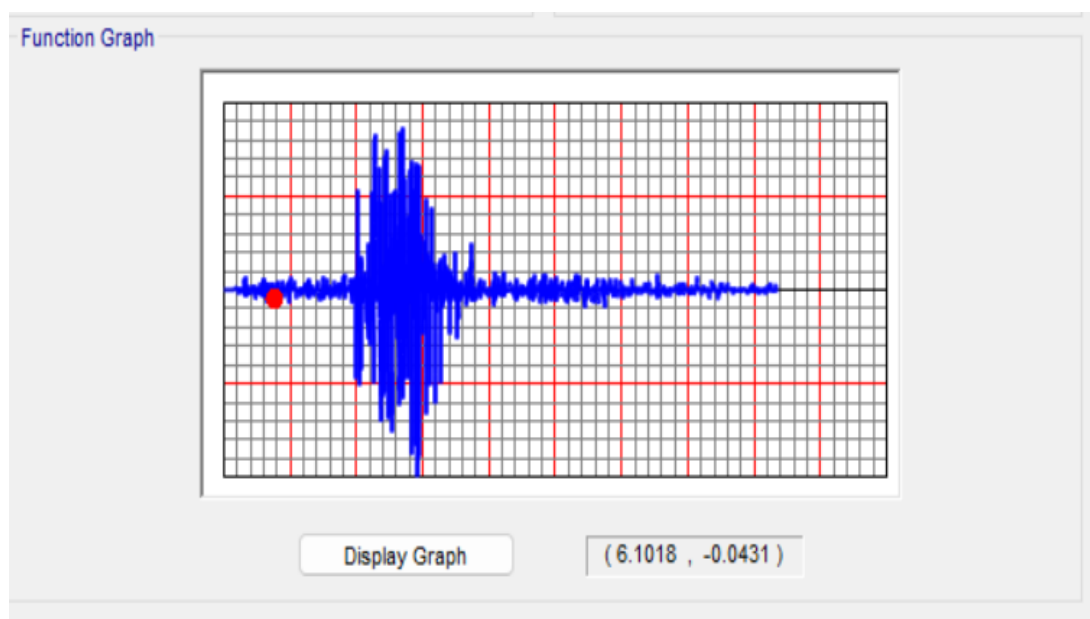


Figure 6: Bhuj earthquake - graph of ground motion

Bridge Model Details used for Linear Dynamic Analysis:

The modelled bridge is 100m long and 12m wide and consists of four span continuous reinforced concrete girders as shown in **Figure 7**. The superstructure is made up of four reinforced concrete girders that are 1040 mm deep and support a reinforced concrete deck slab that is 210 mm deep. Firm soil layers support sturdy piers that are 1.5 meters wide. The deck is modelled as a thin shell element in bridge modelling. The frame element is used to model girders and piers. Bridge is analyzed using the Time History Analysis Method. A 3D view of the 4-Span bridge in CSI Bridge is displayed in **Figure 8**.

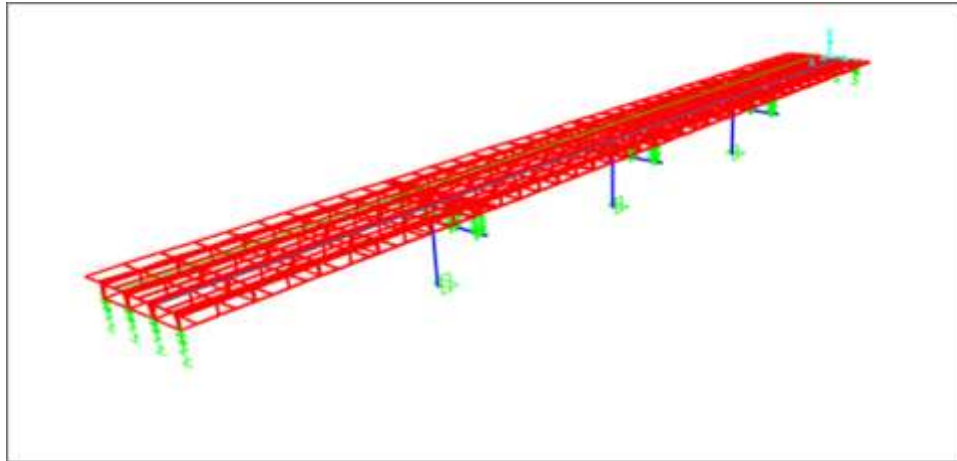


Figure 7: Lane view of 4-Span bridge model

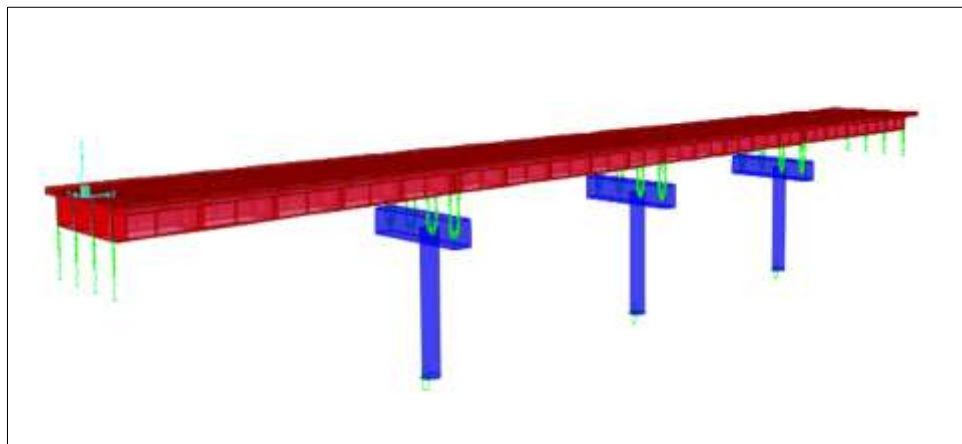


Figure 8: 3D view of 4-Span bridge in CSI Bridge

4. RESULTS AND DISCUSSION

Table 4: Base Reactions

Output Case	Case Type	Step Num	Global FX (KN)	Global FY (KN)	Global FZ (KN)	Global MX (KN-mm)	Global MY (KN-mm)	Global MZ (KN-mm)
MODAL	LinModal	1	0	0	0	0	0	0
MODAL	LinModal	2	0	0	0	0	0	0

MODAL	LinModal	3	0	0	0	0	0	0
MODAL	LinModal	4	2.239E-13	2.268E-13	1.223E-13	1.284E-10	-6.341E-09	1.14E-08
MODAL	LinModal	5	9.049E-15	7.148E-15	4.952E-15	2.693E-12	-2.31E-10	3.673E-10
MODAL	LinModal	6	-4.839E-15	-	-	-5.98E-12	1.588E-10	-3.441E-10
MODAL	LinModal	7	1.067E-14	6.523E-15	5.165E-15	-3.85E-12	-2.844E-10	3.415E-10
MODAL	LinModal	8	-1.637E-14	-	-	-7.945E-12	4.647E-10	-8.116E-10
MODAL	LinModal	9	2.801E-14	2.907E-14	1.514E-14	1.581E-11	-8.108E-10	1.457E-09
MODAL	LinModal	10	-7.887E-14	-	-	-3.879E-11	2.232E-09	-3.905E-09
MODAL	LinModal	11	8.943E-15	8.088E-15	4.719E-15	1.911E-12	-2.195E-10	3.554E-10
MODAL	LinModal	12	-2.505E-14	-	-	-1.589E-11	7.309E-10	-1.286E-09
MODAL	LinModal	13	1.939E-14	2.008E-14	1.08E-14	1.361E-11	-5.787E-10	1.019E-09
MODAL	LinModal	14	1.119E-15	1.257E-15	1.155E-15	2.535E-12	-6.452E-11	8.03E-11
MODAL	LinModal	15	-4.424E-14	-	-	-3.295E-11	1.329E-09	-2.342E-09
Time history	LinModHist		0.046	3.509E-17	1.9E-17	1.983E-14	523.33	45.91
Time history	LinModHist		-0.053	0	0	-3.122E-19	-451.63	-53.19

Modal Participation factors are shown in **Error! Not a valid bookmark self-reference.**, whereas Base Reactions are shown in Table 4.

The base reactions presented demonstrate minimal structural response under modal analysis, with the first three modes showing zero forces and moments, indicating rigid body motion. Subsequent modal steps yield base reaction values on the order of 10^{-13} to 10^{-15} kN or kN-mm, suggesting high stiffness and negligible dynamic contribution from higher modes.

In contrast, the time history analysis shows measurable but still small reactions: base shear (FX) peaking at ± 0.05 kN and moment (MZ) at ± 53.19 kN-mm. These values confirm that the bridge remains within the elastic range under the given seismic input, consistent with observations from displacement and fragility assessments. The results collectively

indicate structural adequacy under moderate loading, while also underscoring the need for further analysis under stronger or more complex seismic conditions.

Table 5: Modal Participation Factors

The modal analysis results reveal that the bridge exhibits negligible lateral displacements

Output Case	Step Num	Period (Sec)	UX (KN-mm)	UY (KN-mm)	UZ (KN-mm)	RX (KN-mm)	RY (KN-mm)	RZ (KN-mm)
MODAL	2	249445.1	0	0	- 0.082504	- 33.614914	- 1238.9835	0
MODAL	3	249445.1	0	0	- 0.168898	- 164.09776	-1086.693	0
MODAL	4	249445.1	-4.121E-09	-4.925E-12	- 0.268914	158.19069	854.26209	7.503E-07
MODAL	5	249445.1	-1.897E-10	-6.186E-12	- 0.013191	- 82.912476	726.90246	1.103E-07
MODAL	6	249445.1	7.037E-11	1.541E-12	0.013515	- 87.055981	- 1776.9222	5.102E-08
MODAL	7	249445.1	-2.042E-10	4.634E-11	0.004328	88.175186	- 700.51891	8.174E-08
MODAL	8	249445.1	2.987E-10	-9.486E-12	0.005705	61.681808	- 1605.5865	-4.949E-08
MODAL	9	249445.1	-4.979E-10	1.567E-11	- 0.029819	- 78.876957	- 139.21869	3.67E-08
MODAL	10	249445.1	1.447E-09	-3.646E-11	0.041177	41.684006	381.68112	-2.628E-07
MODAL	11	249445.1	-1.041E-12	2.127E-11	- 0.005554	169.74553	- 294.99338	9.113E-08
MODAL	12	249445.1	5.166E-10	1.346E-11	- 0.006838	-4.458442	- 477.65049	-6.947E-08
MODAL	13	249445.1	-4.14E-10	-2.909E-12	- 0.001182	131.77216	- 112.51312	-5.726E-08
MODAL	14	249445.1	-9.724E-12	1.362E-11	- 0.003498	- 185.47808	1137.2062	-3.555E-08
MODAL	15	249445.1	1.021E-09	6.92E-11	0.018858	344.29938	- 128.22556	1.374E-07

in the UX and UY directions, indicating significant stiffness in the horizontal plane. In contrast, vertical displacements (UZ) show greater activity in certain modes, highlighting the relevance of vertical vibration in the dynamic response. Rotational participation is most prominent about the Y-axis (RY), suggesting potential sensitivity to torsional effects.

Overall, the structure demonstrates strong lateral rigidity, with dominant modal contributions arising from vertical and torsional behavior.

Table 6: Joint Displacements

Output Case	Case Type	Step Num	U1 (mm)	U2 (mm)	U3 (mm)
MODAL	LinModal	1	0	0	0
MODAL	LinModal	2	0	0	0
MODAL	LinModal	3	0	0	0
MODAL	LinModal	4	4.26E-16	4.41E-17	-9.22E-17
MODAL	LinModal	5	1.454E-17	1.552E-18	-3.193E-18
MODAL	LinModal	6	-1.176E-17	-1.175E-18	2.442E-18
MODAL	LinModal	7	1.646E-17	1.759E-18	-4.091E-18
MODAL	LinModal	8	-3.089E-17	-3.2E-18	6.778E-18
MODAL	LinModal	9	5.467E-17	5.633E-18	-1.192E-17
MODAL	LinModal	10	-1.484E-16	-1.538E-17	3.25E-17
MODAL	LinModal	11	2.027E-17	1.954E-18	-5.011E-18
MODAL	LinModal	12	-4.763E-17	-4.841E-18	1.097E-17
MODAL	LinModal	13	3.721E-17	3.94E-18	-8.024E-18
MODAL	LinModal	14	2.413E-18	2.599E-19	-4.542E-19
MODAL	LinModal	15	-8.216E-17	-8.281E-18	1.577E-17
Time history	LinModHist		6.59E-20	0	0
Time history	LinModHist		0	0	-1.423E-20

The modal displacement results show that the first three modes exhibit zero displacement in all directions, indicating rigid body motion without dynamic deformation. In higher modes, displacements in U1, U2, and U3 remain extremely small, generally in the range of 10^{-17} mm, highlighting the very high stiffness of the bridge structure and minimal modal participation under elastic conditions.

The time history analysis confirms this trend, with displacements on the order of 10^{-20} mm, effectively indicating negligible dynamic deformation under the given ground motion input. These findings collectively demonstrate that the bridge remains well within the elastic range, and its dynamic response is minimal under both free vibration and moderate seismic excitation. This behavior is consistent with a stiff substructure and effective mass distribution, typical of seismically stable bridge configurations.

Figure 9 demonstrates that the structure remained well within its elastic limits with extremely minor displacements and negligible base shear forces in all directions, even in the face of input seismic loading (the Bhuj earthquake). In **Table 6**, the joint displacements are shown. This demonstrates that the bridge is not under any significant stress or potential harm, as per the current analysis.

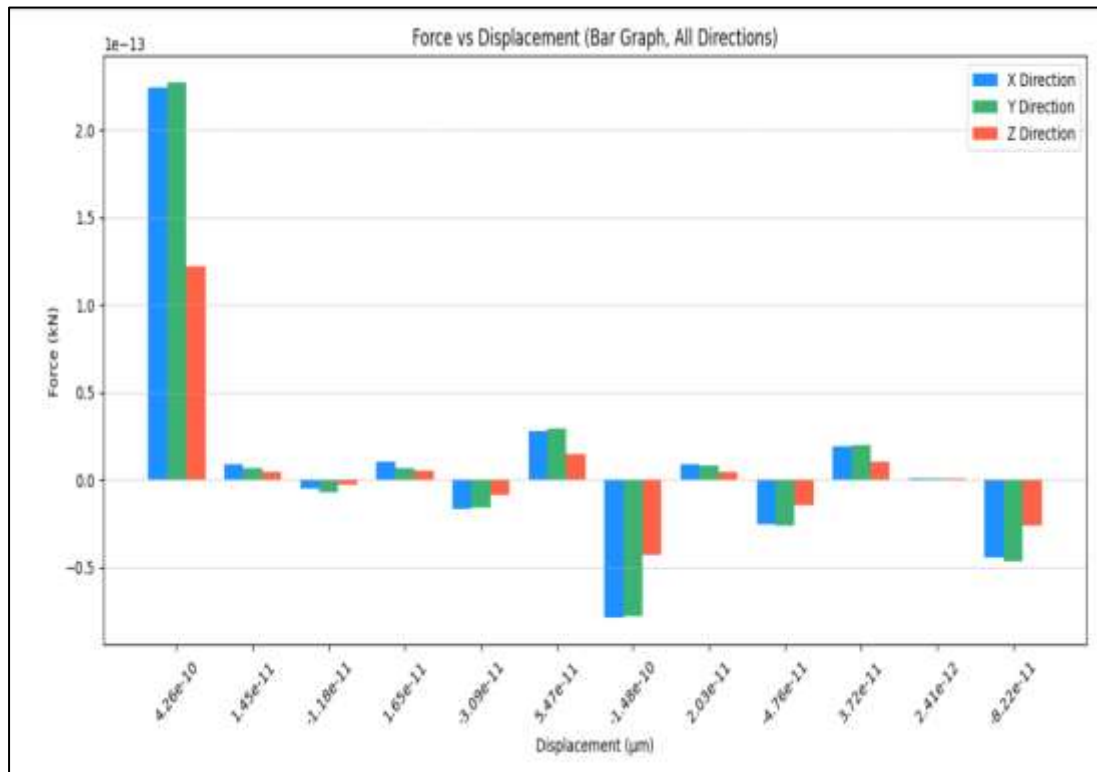


Figure 9: Force vs Displacement graph

The bar graph shown in Figure 9 illustrates the relationship between modal displacements and corresponding base forces in the X, Y, and Z directions. Displacements, though extremely small (in the range of 10^{-11} to 10^{-10} μm), result in base forces on the order of 10^{-13} kN, reaffirming the high stiffness and elastic response of the structure under modal excitation. The largest force components occur at the smallest displacements, indicating sensitivity in the early modes. The symmetry and consistency of force magnitudes across directions also suggest uniform structural behavior, with no

pronounced directional bias. This behavior aligns with expectations for a well-restrained and symmetrically configured bridge substructure.

Artificial Neural Network

Artificial neural networks (ANNs) are employed as a tool for quickly evaluating the seismic response of existing structures[40]. A typical ANN architecture includes three distinct types of layers: input, output, and one or more hidden layers. Neurons, which make up each layer, use an activation function to relay information to the subsequent layer after receiving input from the previous one. Each neuron is associated with specific weights and thresholds. When the output signal surpasses the threshold, the neuron activates and transmits the output value to a neuron in the lower layer. The input consists of acceleration values $A_1, A_2, A_3, A_4, A_5, A_6$, while the output comprises displacement values U_1, U_2, U_3 . **Figure 11** illustrates the visual representation of how closely the model's predictions match the actual target values for various inputs. **Figure 10** shows the ANN Basic Model.

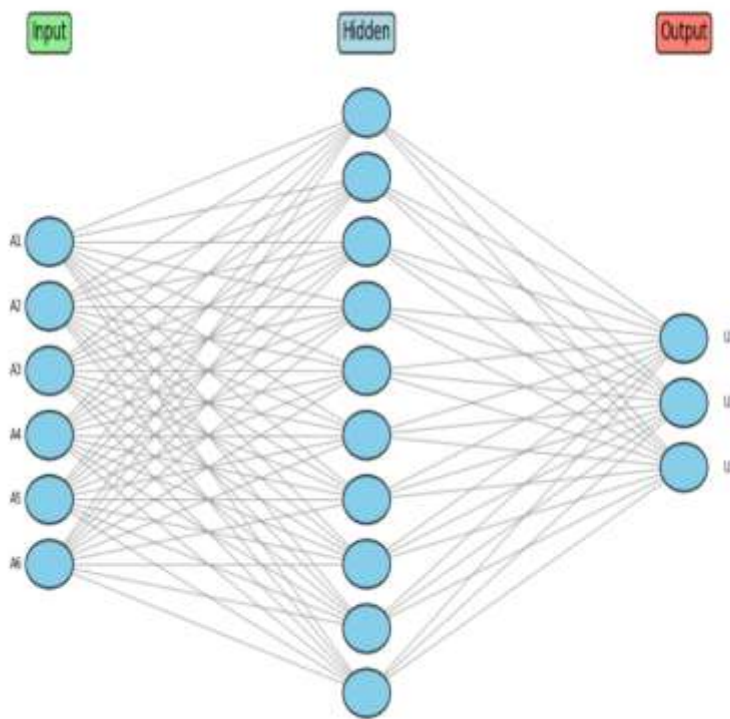


Figure 10: ANN Basic Model

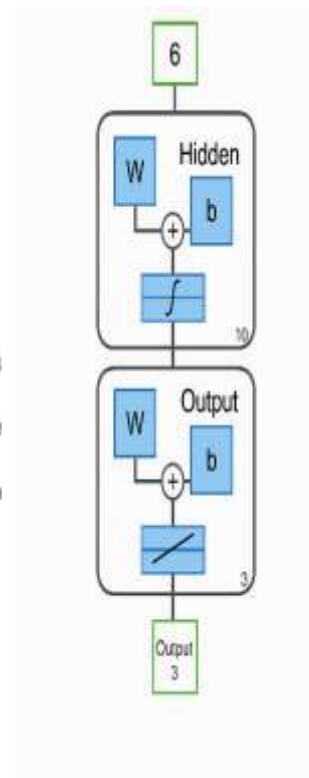


Figure 11: ANN Model with hidden layer

An error histogram serves as a statistical visual tool for analyzing the distribution of discrepancies between a model's predicted outputs and the corresponding true values. In neural networks and other regression models, error is commonly defined as the difference between the expected and actual results. To facilitate visualization, the error values are categorized into intervals by dividing the histogram into 20 bins, as depicted in **Figure 12**. Red bars represent errors from the test dataset, green bars denote errors from the validation dataset, and blue bars signify errors from the training dataset.

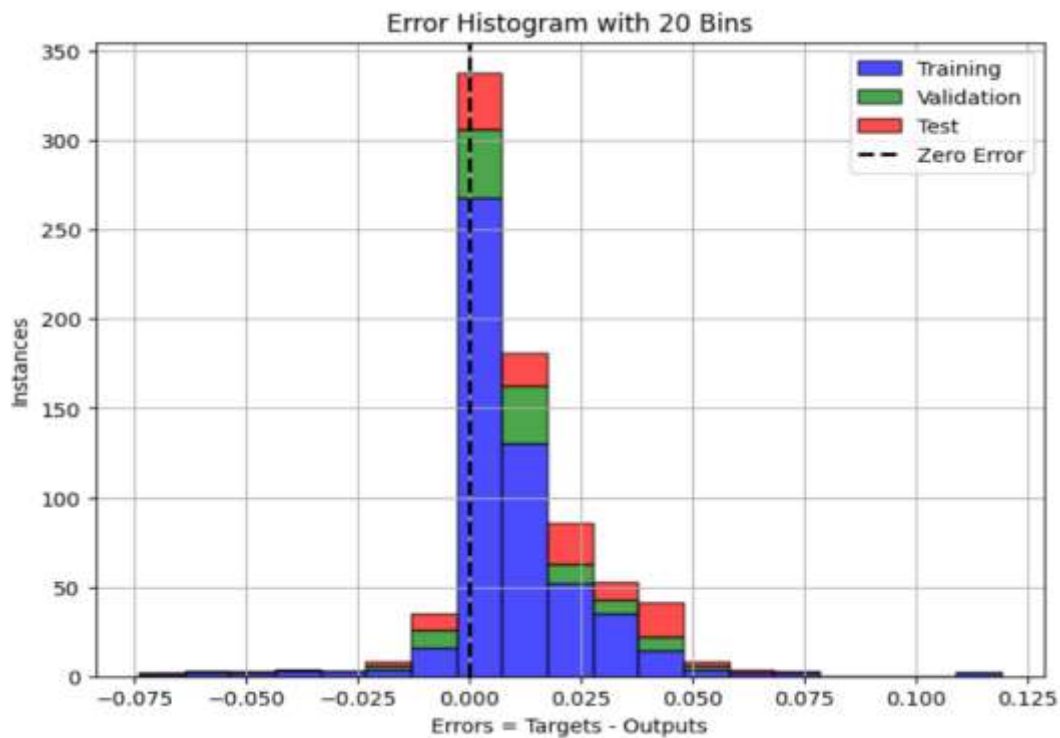


Figure 12: Error histogram for Bhuj Earthquake

A neural network's training process can be visually depicted using an epoch diagram, which charts the Mean Squared Error (MSE) on the vertical axis and the number of epochs on the horizontal axis. An epoch refers to a complete pass through the entire training dataset, and such diagrams typically feature separate curves for training, validation, and test errors, allowing us to monitor the model's learning and generalization capabilities. Consistent learning is shown by the green line (representing validation error), which indicates a realistic and continuous reduction. It seems that there is effective generalization since both training and validation errors initially decrease together before starting to separate. **Figure 13** maintains steady behavior by avoiding abrupt drops or strange flatlines.

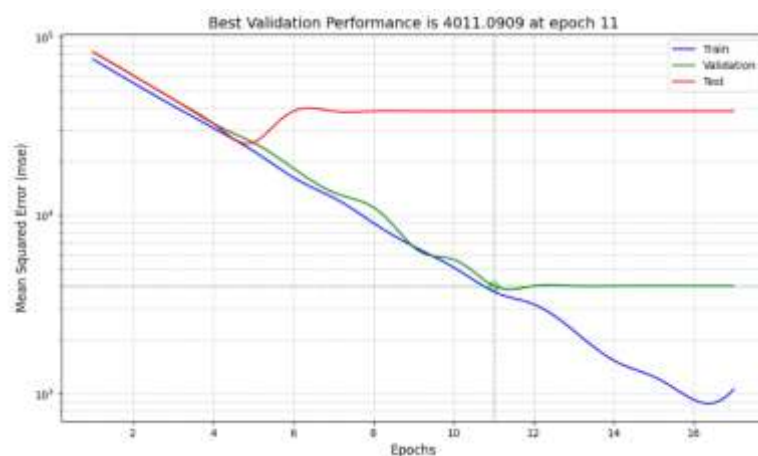


Figure 13: Best validation performance graph for Bhuj Earthquake

Development of Regression Plot using Artificial Neural Network

Regression plots play an essential role in illustrating the relationship between input variables and the expected output generated by artificial neural networks[41]. These visual representations indicate the degree to which the model's predictions align with the actual target values across various inputs. Typically, these plots display a collection of points, each representing a pair of actual and predicted values. **Figure 14** presents regression plots for the Bhuj earthquake, which are utilized in the latter stages of artificial neural networks (ANNs) to aid in comprehending the complex relationship between input data and anticipated outcomes in the field of artificial intelligence. In an effectively fitted regression plot, points that are closely clustered around a diagonal line suggest a strong capacity for prediction.

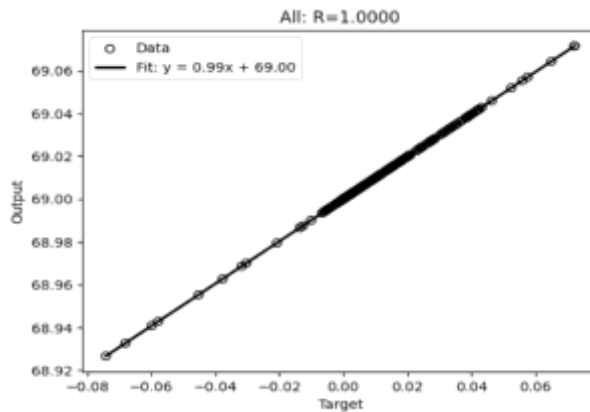


Figure 14: Regression Plots for all values

Discussion

The seismic performance of bridges remains a critical concern in infrastructure resilience, particularly in regions prone to both earthquakes and flooding. This study utilized nonlinear and linear time history analyses in conjunction with artificial neural networks (ANNs) to assess the fragility and displacement response of bridge piers under seismic excitation.

The modal analysis revealed negligible displacements, forces, and moments during the first few modes. This indicates that either rigid body movements are dominant or these modes do not significantly contribute to structural response. The joint displacement values in the order of 10^{-16} to 10^{-17} mm further suggest the bridge's stiffness is high under elastic loading conditions. While such stiffness implies favorable elastic behavior under moderate loads, it could also limit energy dissipation capacity during high-intensity seismic events. Furthermore, minimal modal participation in early modes suggests that higher-mode effects may be underrepresented—an aspect particularly relevant in cases involving high-frequency excitations or irregular geometries.

Under time history analysis using the Bhuj ground motion, the bridge exhibited small displacement and base reaction values ($FX \approx \pm 0.05$ kN, $MZ \approx \pm 50$ kN-mm), indicating acceptable performance under moderate seismic loading. However, the displacement ductility analysis revealed a narrow margin between the "extensive" and "collapse" damage states (3.155 to 3.65), implying that once major damage occurs, structural collapse may follow rapidly. This progression highlights the importance of early-stage

strengthening interventions, particularly for older bridges constructed without modern seismic design provisions.

When comparing these findings with studies such as Liu et al. (2022) and Pan et al. (2007), a similar trend is observed—older RC bridges tend to exhibit rapid transition from moderate to collapse-level damage once critical ductility thresholds are exceeded. However, this study differs in its application of ANN models, which provided rapid seismic response prediction with high accuracy. The ANN regression plot yielded an R^2 value of 1.0000, indicating excellent alignment between predicted and actual displacement values.

While the ANN model's accuracy is promising, such a high R^2 warrants caution. In real-world applications, perfect fits are rare and can indicate overfitting, especially in the absence of independent test datasets. To improve reliability, future work should involve cross-validation using alternative earthquake records, different bridge geometries, and soil conditions. Additional evaluation metrics like RMSE or MAE would further help quantify prediction robustness.

The error histogram showed a narrow, symmetric distribution of errors centered around zero for training, validation, and test sets, suggesting good generalization without signs of overfitting. Additionally, the Mean Squared Error (MSE) vs. epoch graph indicated smooth convergence, with the lowest validation error at epoch 11—evidence of stable and effective learning.

From a practical perspective, the results indicate that this specific RC bridge, with stiff foundations and moderate span lengths, performs well under moderate seismic loads. However, performance may vary significantly for structures in softer soil profiles or subjected to spatially varying ground motions. Notably, this study assumes uniform support excitation, which may not accurately reflect real-world conditions in bridges crossing valleys or fault zones. Incorporating multi-support excitation and soil-structure interaction would likely yield more realistic fragility estimates.

Taken together, the results reinforce the need for multi-hazard vulnerability assessment that integrates both simulation-based fragility modeling and AI-based predictive tools. While the ANN offers a fast and efficient alternative to traditional fragility analysis, its broader applicability should be tested under diverse structural and seismic scenarios. This dual-method approach—combining physical modeling with machine learning—represents a forward-looking strategy for enhancing seismic risk assessment and decision-making in bridge engineering.

5. CONCLUSION

- The essential function of bridges within contemporary transportation systems highlights the pressing necessity to tackle their weaknesses, particularly in areas susceptible to seismic activity.
- Numerical modal analysis conducted through a finite element model of the bridge aids in identifying its dynamic characteristics. By utilizing the software, the mode shapes and natural frequencies of the original model are evaluated against experimental data. The strong alignment between the model and experimental findings validates the precision of the finite element model, supporting its application for further analysis.
- The focus is on the seismic vulnerability of bridges, emphasizing the significance of precise fragility analysis for evaluating bridge performance during seismic and flood events. The fragility analysis indicates that as the displacement ductility ratio increases, the bridge transitions from minor deformations to severe damage and

ultimately failure. The very small gap between collapse (3.65) and major damage (3.155) indicates that the bridge has a limited timeframe before structural failure, highlighting the importance of early intervention strategies.

- The initial three modal steps show no displacements, forces, or moments, indicating that they could represent rigid body movements or do not significantly influence the structural response.
- Furthermore, the joint displacements fall between 10^{-16} and 10^{-17} mm, indicating minimal deformation. In the modal analysis, this suggests that the structure is either highly rigid or only marginally influenced by the applied stresses, leading to negligible dynamic effects.
- The force in the global x-direction (FX) is 0.046 KN, while the moment around the Z-axis (MZ) is 45.91 KN-mm. At a different time step, the global x-direction force (FX) measures -0.053 KN, and the moment around the Z-axis (MZ) is -53.19 KN-mm. All of these values indicate minimal displacements, suggesting that the structure exhibits exceptional rigidity even when the reaction forces and moments are relatively small.
- The ANN model showed a notable ability to predict outcomes after being trained using acceleration inputs (A1–A6) and output displacements (U1–U3). With an R-value of 1.0000 and a regression plot indicating excellent alignment between predicted and actual values, the ANN's skill in accurately understanding the input-output relationship was recognized.
- The error histogram divided into 20 bins indicated that the majority of errors fell within the ± 0.01 range and were mainly concentrated around zero. The model showcased strong generalization without signs of overfitting, which is reflected in the symmetrical and minimal distribution of errors for training (blue), validation (green), and testing (red).
- The Mean Squared Error (MSE) was graphed against the number of training epochs in the epoch graph. With an MSE of 4011.0909, the 11th epoch exhibited the best validation results, reflecting a consistent and successful learning process. The training and validation curves demonstrated reliable model performance, as they both decreased together and did not diverge significantly.
- Based on these values, the structure demonstrates stability and is unlikely to undergo substantial deformation under the given loading conditions.

Scope for further studies

- The bridge is likely to endure considerable damage if a stronger earthquake, exceeding magnitude 7.5, strikes the region. The piers and superstructure may undergo much larger rotations and horizontal displacements, while the bearings designed to absorb seismic energy could slide or deform beyond their intended capacity, leading to instability.
- The future durability and earthquake resilience of the bridge can be enhanced by adopting several proactive measures. The addition of energy dissipation devices will help absorb seismic forces and reduce stress on essential components, whereas base isolators and other advanced technologies can significantly minimize the transfer of ground motion to the superstructure when retrofitted.
- Existing columns can be reinforced through techniques such as fiber-reinforced polymer (FRP) or steel jacketing, which will enhance their ductility and load-bearing capacity.
- Nonlinear time history analysis outcomes would illustrate more authentic behaviors, such as residual displacements, cracking, and the formation of plastic hinges. Consequently, greater displacements and rotations are expected, especially in critical components like piers and bearings.

- Furthermore, nonlinear analysis facilitates the modeling of energy dissipation mechanisms and the accumulation of damage, resulting in a more accurate assessment of the structure's seismic fragility.

Author Contributions:

Ashwini Satyanarayana: Conceptualization, Methodology, Supervision, Writing – Original Draft Preparation.

Dushyanth V Babu R: Formal Analysis, Writing – Review & Editing.

Sheethal H M: Data Curation, Investigation, Validation.

All authors have reviewed and approved the final manuscript.

Competing Interests:

The authors declare that there are no competing interests associated with this study.

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