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Enhancing Seismic Resilience of Bridge Infrastructure Using Bayesian Belief Network Approach †

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Abstract: The deteriorating state of North America's bridge infrastructure is a pressing issue, necessitating innovative risk management strategies. This study aims to enhance the seismic resilience of bridge infrastructure using a Bayesian belief network (BBN) model. The research uses literature review, expert opinions, and a Bayesian analysis framework to quantify bridge resilience, despite the scarcity of detailed historical data. The model, supported by conditional probability tables (CPTs), captures the complex interdependencies among parameters and uncertainties in seismic resilience assessment. Preliminary findings show that integrating expert judgment with BBN provides a robust methodology for assessing and enhancing bridge resilience to seismic hazards. This approach contributes to measuring bridge infrastructure resilience and offers practical guidance for policymakers, engineers, and stakeholders in sustainable transportation network development.

Keywords: seismic resilience; bridge infrastructure; Bayesian belief networks; sustainable transportation network

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1. Introduction

Amid growing concerns about the condition of North America's bridges, there is a pressing need for innovative and efficient risk management approaches. The 2019 Canadian Infrastructure Report Card highlights the deteriorating condition of bridge infrastructure in Canada, indicating that 39% of bridges and tunnels are in fair, poor, or very poor condition. This assessment emphasizes the urgent requirement for proactive actions to ensure the longevity of these crucial assets, as the financial consequences of replacement surpass CAD 21 billion. In the United States, the 2021 Infrastructure Report Card by the American Society of Civil Engineers (ASCE) gave bridges a 'C' grade, highlighting a significant need for enhancement. Approximately 231,000 bridges are in urgent need of repair, with an estimated cost of around $125 billion [1].

Therefore, assessing the resilience of bridge infrastructure to seismic hazards provides a thorough view of the difficulties and approaches required. Quantifying resilience in the bridge infrastructure is challenging due to the limited availability of well-organized historical data on damage and recovery, as pointed out by [2].

Although there have been advancements, there is still a notable research gap in the area of bridge infrastructure resilience to seismic hazards. Khan et al. [3] performed an extensive literature review on the resilience of bridge infrastructure, with a specific focus on seismic hazards. They conducted a bibliometric analysis using VOSviewer to investigate

the current literature, which highlighted a scarcity of thorough studies on the resilience of bridge infrastructure to seismic hazards.

The resilience of bridge infrastructure against seismic hazards is evaluated in this study using Bayesian belief networks (BBNs). BBNs are chosen for their remarkable ability to handle intricate connections between multiple parameters. The study requires an analytical methodology that encompasses both the reliability and recovery aspects of bridges, where each parameter is interconnected and significantly influences the overall assessment of resilience. BBN exhibits exceptional proficiency in incorporating complex connections within a network-oriented framework, accommodating both numerical data and qualitative inputs, such as expert assessments.

This research contributes to academic discussions and offers practical implications for policymakers, engineers, and stakeholders interested in the resilience and sustainability of transportation infrastructures through thorough literature reviews and the creation of a hierarchical model.

Based on the discussion above, the primary goal of this research can be summarized as follows:

- Determining the parameters for the seismic resilience of bridge infrastructure through a review of existing literature and insights from experts.
- Constructing a Bayesian belief network (BBN) model through a survey of ten experts in bridge engineering to gather critical data.
- Assessing the seismic resilience of bridge infrastructure and identifying the crucial parameters through a sensitivity analysis.

2. Bayesian Belief Network (BBN)

This section has been divided into two subsections: (i) parameter selection, and (ii) the BBN approach.

(i) Parameter Selections

Khan et al. [4] underlined that the resilience of bridge infrastructure depends on two main factors: reliability and recovery. Khan et al. [4] identified 15 parameters within these two factors of seismic resilience of bridge infrastructure. Improvements were made by replacing some parameters and adding new ones to enhance the model's sensitivity and comprehensiveness. This research has identified 18 parameters, with 11 categorized as independent (parent nodes) and 7 as dependent (child nodes), primarily addressing reliability and recovery factors, as shown in Table 1.

(ii) BBN Approach

The BBN is depicted as a diagrammatic representation showcasing the fundamental causal relationships within the studied system, as described by [4]. This model delineates the qualitative aspects of BNs through directed associations, where nodes and links represent parameters and their dependencies or conditional relationships, respectively [4,5]. The model's quantitative aspects are articulated through the probabilities and conditional probabilities assigned to each node, defining their interrelations within the network. Nodes are assigned discrete states along with corresponding probability values, highlighting the dependencies between child and parent nodes through a conditional probability table (CPT). The derivation of CPT values can be achieved through expert evaluations and data training. One of the principal benefits of BN models lies in their ability to derive probabilistic inferences and update beliefs based on new data or expert opinions by leveraging Bayes' theorem [5–7]. Moreover, BN models are adept at providing insightful assessments even in scenarios characterized by imprecise or incomplete data [8,9].

The formula presented by [10] quantifies the revised probability of a set of mutually exclusive parameters, given the evidence Z, as follows:

$$\mathrm{p}\left(F_j|Z\right) = \frac{\mathrm{p}\left(Z|F_j\right) \times \mathrm{p}\left(F_j\right)}{\sum_{i=1}^{n} \mathrm{p}\left(Z|F_i\right) \times \mathrm{p}\left(F_i\right)} \quad (1)$$

Here, $\mathrm{p}\left(F_j|Z\right)$ represents the updated likelihood of F upon considering the evidence Z, $\mathrm{p}\left(F_j\right)$ signifies the initial probability of F_j, $\mathrm{p}\left(F_j|Z\right)$ denotes the likelihood given is accurate, and the denominator is the cumulative probability, serving as a normalization constant.

Table 1. Seismic resilience parameters for bridge infrastructure.

		Parameters	Reference	Scale	States
Reliability	Parent Node (Independent Parameters)	Age of Structure	[11]	<25 years 20–50 years >50 years	New Moderate Old
		Earthquake Return Period	[12]	2475 years 975 years 475 years	High Medium Low
		Soil Type (Site Class)	[13,14]	Hard rock or rock Very dense or stiff soil Soft soil or other soil	Type A or B Type C or D Type E or F
		Environmental Factor Exposure	[15,16]	Exposed to corrosive materials Structural elements not exposed	Marine Other than Marine
		Skilled Labourers	[17]	Experienced workers Non-experienced workers	Skilled Un-skilled
		Seismic Performance Category	[18]	No seismic analysis Performance-based or force-based design Mostly performance-based designed	Category 1 Category 2 Category 3
		Structure Configuration	[19,20]	The bridge has skewed foundation Bridge is curved Bridge is straight	Skewed Curved Straight
	Child Node (dependent parameters)	Construction Quality	[21]	Construction did not follow the design specification Construction partially followed design specification Construction fully followed design specification	Poor Moderate Excellent
		Material Property	[22]	Construction materials failed to meet design specification Materials partially met the design specification All the materials met the design specification	Poor Moderate Excellent
		Earthquake Resistant Design	[23]	Design prioritizes structural integrity and safety, adhering to conservative codes and standards Design aims to achieve desired performance levels through the use of materials' inherent properties, providing flexibility and innovation in design.	FBD PBD
		Seismic Hazard	Combination of EQ Return Period, Soil Type, and Seismic Performance parameters	2475 years EQ return period, soil type E or F, seismic performance category 1 975 years EQ return period, soil type C or D, seismic performance category 2 475 years EQ return period, soil type A or B, seismic performance category 3	High Moderate Low
		Strength Degradation	Combination of Construction quality, Seismic Hazard. Age of Structure parameters	Poor construction quality, high seismic hazard, >50 years old bridge Moderate construction quality, moderate seismic hazard, 25–50 years old bridge High construction quality, low seismic hazard, <25-year-old bridge	High Moderate Low

Table 1. *Cont.*

		Parameters	Reference	Scale	States
Recovery	Parent Node	Structural Importance	[24]	Recovery probability high Recovery probability moderate Recovery probability low	Lifeline Major Route Other
		Community Preparedness	[25]	Small towns/villages Community of suburban area Major cities (urban area)	Poor Moderate Excellent
		Population Density	[26]	<150 people/km^2 150 to 1500 people/km^2 >1500 people/km^2	Low Moderate High
		Location and Accessibility	[27]	Rural area/hard to access Suburban area Urban area (easy access)	Poor Moderate Excellent
	Child Node	Resource Availability	[28]	Insufficient fund Moderate fund Adequate fund	Poor Moderate Excellent
		Repairing Maintenance Cost	[17]	Major structural damage Moderate structural damage Minor or no damage	High Moderate Low

3. Model Development

The BBN model for the seismic resilience assessment of bridge infrastructure against seismic hazards can be depicted as below in Figure 1.

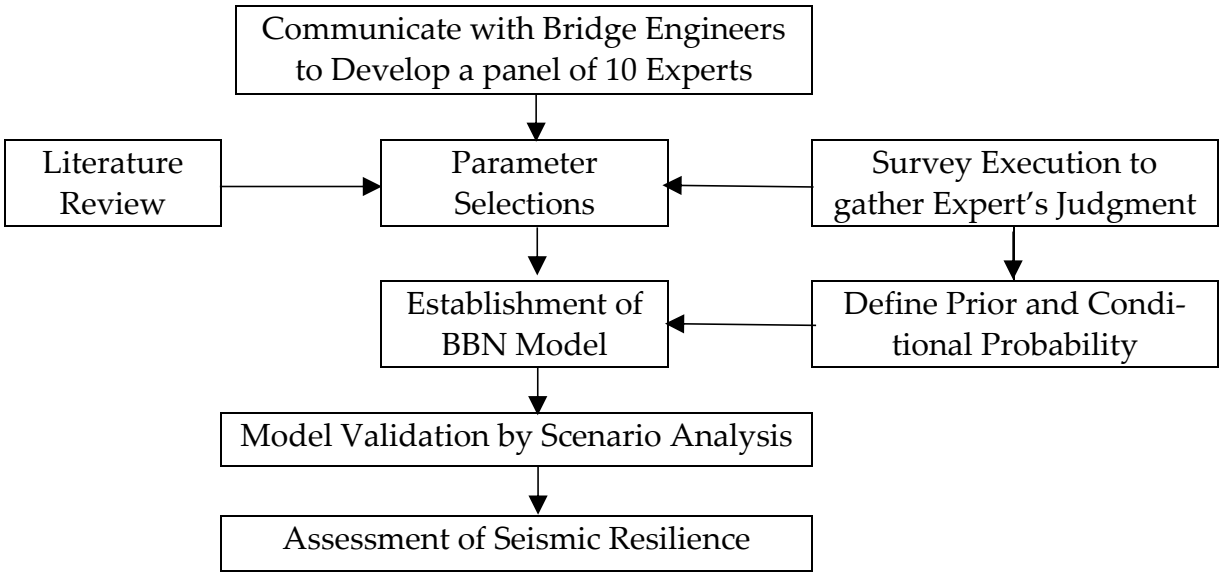


Figure 1. BBN model for seismic resilience assessment of bridge infrastructure.

In Table 1, the parent and child nodes within the 18 parameters related to the reliability and recovery aspects of bridge resilience are outlined. These nodes were derived from a comprehensive literature review as well as insights collected from ten experts through a survey distributed on the Qualtrics platform.

The BBN model was developed using the Netica version 605 software. The developed model is portrayed below in Figure 2.

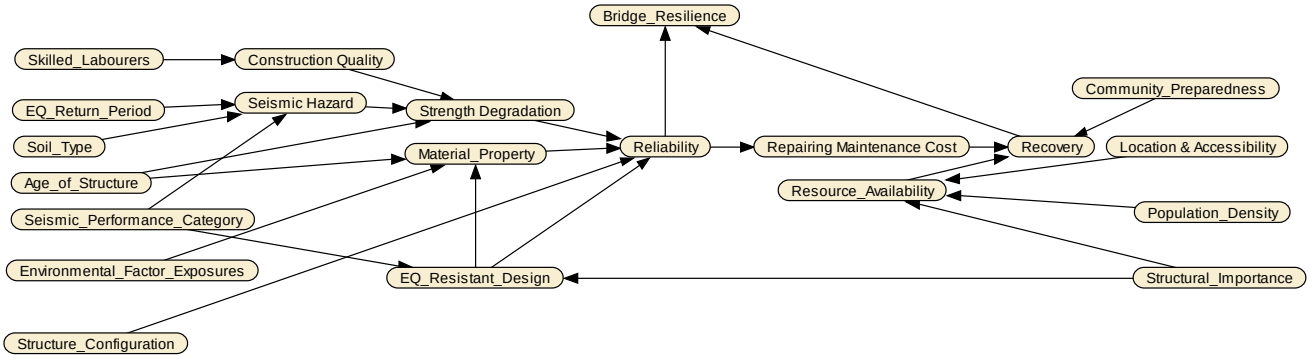


Figure 2. BBN model of seismic resilience for bridge infrastructure.

The interaction between child and parent nodes was measured using conditional probability tables (CPT). The computation of CPT values for the child nodes was based on expert opinions or the knowledge-gathering process. Table 2 provides an illustration focusing on the "Material Property" node to show how conditional probabilities are obtained through the process of knowledge gathering. The "Material Property" child node depends on the "Age of Structure", "Environmental Factor Exposure", and "Earthquake (EQ) Resistant Design" parent nodes. According to Table 2, for a new bridge with non-marine environmental factor exposure and a performance-based design (PBD) approach, the CPT values for "Material Property" are 0, 0, and 100. The data indicates that the likelihood of the "Material Property" being in poor, moderate, or excellent condition is 0%, 0%, and 100%, respectively. CPTs for additional child nodes were obtained using a similar approach. Netica uses uniform probabilities when there are missing entries or incomplete CPTs for specific nodes.

Table 2. Sample CPT for the "Material Property" child node.

Age of Structure	Environmental Factor Exposure	EQ Resistant Design	Poor	Moderate	Excellent
New	Marine	FBD	32	50	18
New	Marine	PBD	15.5	50	34.5
New	Other than Marine	FBD	16.5	50	33.5
New	Other than Marine	PBD	0	0	100
Moderate	Marine	FBD	64	36	0
Moderate	Marine	PBD	31	36	33
Moderate	Other than Marine	FBD	33	36	31
Moderate	Other than Marine	PBD	0	36	64
Old	Marine	FBD	100	0	0
Old	Marine	PBD	33.5	50	16.5
Old	Other than Marine	FBD	34.5	50	15.5
Old	Other than Marine	PBD	18	50	32

4. Results and Discussion

Both quantitative and qualitative validation methods could have been employed for validating the model. We performed a sensitivity analysis to identify the key parameters affecting the bridge infrastructure's seismic resilience and validate the model quantitatively. A sensitivity analysis shows how uncertain input parameters affect the model's results. We adopted variance reduction to evaluate the Bayesian belief network (BBN) model's sensitivity. In Table 3 and Figure 3, this sensitivity analysis shows how parent nodes affect child node resilience.

Table 3. Sensitivity analysis for the "Bridge Resilience" node.

Parent Node	Variance Reduction	Percent	Mutual Info	Percent	Variance of Beliefs
Seismic Performance Category	22.95	3.28	0.02846	1.85	0.0028164
Structural Importance	22.22	2.89	0.02435	1.58	0.0026004
Structure Configuration	14.88	2.13	0.01819	1.18	0.0020777
Community Preparedness	12.85	1.84	0.01556	1.01	0.001767
Age of Structure	8.034	1.15	0.00962	0.625	0.0010337
Environmental Factor Exposure	2.658	0.38	0.00317	0.206	0.0003342
Skilled Labourers	1.846	0.264	0.00222	0.144	0.0002297
Location and Accessibility	1.466	0.21	0.00175	0.114	0.0001886
Population Density	1.319	0.189	0.00157	0.102	0.0001693
Soil Type	0.151	0.0216	0.00018	0.0117	0.0000189
Earthquake Return Period	0.151	0.0216	0.00018	0.0117	0.0000189

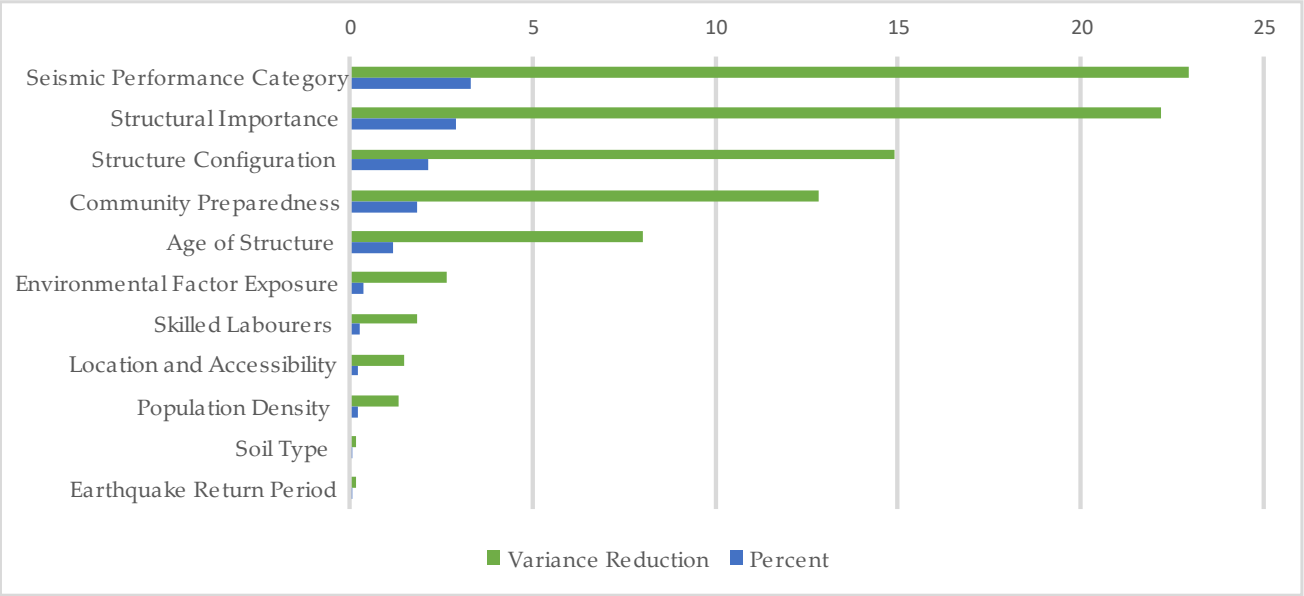


Figure 3. Sensitivity analysis of the BBN model.

Table 3 shows that the Seismic Performance Category accounts for the highest variance at 3.28%, followed closely by the Structural Importance type at 2.89%. The sensitivity of these parameters significantly influences the resilience outcome of the model. Other parameters such as Structure Configuration, Community Preparedness, and Age of Structure show sensitivities of 2.13%, 1.84%, and 1.15% respectively. Environmental Factor Exposure, Skilled Labourers, Location and Accessibility, Population Density, Soil Type, and Earthquake Return Period have lower sensitivities, ranging from 0.0216% to 0.38%.

5. Conclusions

This study has introduced a technique for assessing the resilience of bridge infrastructure to seismic hazards using the Bayesian belief network (BBN) approach. This analysis will help identify important elements by assessing the resilience of different bridge infrastructure parameters. This will allow authorities to quickly focus on and strengthen these crucial factors, ultimately enhancing the overall resilience of the bridges. The results of this study will greatly assist decision-makers in assessing the seismic resilience of bridge infrastructures. The research findings and data will assist management in effectively preparing for and recovering from seismic incidents. Management can enhance the resilience of less robust parameters against future seismic challenges by focusing on parameters with high resilience. This investigation did not include a qualitative assessment for validating the model. Future studies could include this assessment for validating the model. Furthermore,

utilizing real-time data from functioning bridges could offer a more thorough insight into the model's efficiency.

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