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RAPID SEISMIC RISK SCREENING OF SIMPLY SUPPORTED GIRDER BRIDGES USING A SIMPLIFIED ML-BASED APPROACH: A CASE STUDY IN SICILY

Ignazio Casiraro[1*], Gianluca Quinci[2], Francesco Castelli[3], Marinella Fossetti[3], Fabrizio Paolacci[2]

[1]Department of Civil Engineering and Architecture, University of Catania, Via Santa Sofia 64, 95125, Catania, Italy
*ignaziocasiraro@gmail.com

[2]Department of Civil, Computer Science and Aeronautical Technologies Engineering, Roma Tre University
Via Vito Volterra 62, 00146, Rome, Italy

[3]Department of Engineering and Architecture, Kore University of Enna, Cittadella Universitaria, 94100, Enna, Italy

Abstract

Ensuring the seismic resilience of bridge networks is a critical priority for infrastructure managers, particularly in seismically active regions where structural integrity and public safety are paramount. This paper presents a streamlined methodology based ON Machine Learning (ML) to facilitate a rapid, preliminary seismic risk assessment specifically for simply supported girder bridges. The proposed approach enables infrastructure managers to perform an efficient screening across extensive bridge inventories, producing a prioritized ranking of structures according to their seismic vulnerability. By systematically identifying high-risk bridges, this method supports targeted resource allocation and allows for detailed follow-up evaluations on prioritized structures, thereby optimizing inspection and reinforcement planning.

The methodology is applied to a case study within the Sicilian Region, an area characterized by significant seismic activity, to validate the model's effectiveness and illustrate its practical implications. Through the use of key parameters such as structural typology, material properties, and seismic zone classification, the ML model is trained to provide reliable and swift fragility estimates, bypassing the extensive computational requirements of traditional assessment methods. Results indicate that the ML-based approach can accurately highlight critical structures, offering a robust, time-efficient tool for preliminary seismic risk assessment. This novel application demonstrates the potential of ML methodologies to enhance proactive risk

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management strategies, ultimately contributing to the resilience and safety of bridge networks on a regional scale

Keywords: Bridges, Machine learning, Fragility Assessment, Fragility Curve.

1 INTRODUCTION

The assessment of infrastructure's health status currently represents one of the main challenges for the safety and sustainability of the Italian infrastructure system. The national territory is characterized by an extensive and complex network of bridges and viaducts, many of which were built between the 1950s and 1980s, a period when seismic regulations were either absent or poorly developed, and design load requirements significantly differed from those of today. Age-related deterioration, increased heavy traffic, exposure to seismic events and the frequent lack of continuous structural monitoring make the development of effective strategies for risk assessment and management increasingly urgent [1,2].

In this context, the traditional approach, based on targeted inspections and detailed numerical modeling, proves difficult to apply on a large scale. The high number of structures to be assessed across the entire country, would require substantial efforts in terms of time and technical and financial resources, effectively making impractical a widespread analysis using conventional methods [3]. Consequently, there is a growing need for tools capable of supporting an initial rapid screening phase to identify potentially more vulnerable structures and help define intervention priorities.

In this scenario, the adoption of Artificial Intelligence (AI)-based technologies, and in particular Machine Learning (ML), represents a promising opportunity to innovate infrastructure management practices. ML models, properly trained on meaningful datasets, can efficiently process large volumes of heterogeneous information, such as structural geometry, materials used, and seismic conditions of the territory. Integrating these parameters enables a preliminary estimation of the seismic vulnerability of structures, without requiring complex numerical simulations for each individual asset. In the field of earthquake engineering, several successful applications of Machine Learning have been proposed to support seismic risk assessments, with the aim of significantly reducing computational time while maintaining acceptable levels of accuracy. These studies have demonstrated the effectiveness and reliability of ML-based approaches as efficient alternatives to traditional numerical methods [4,5,6].

The outputs generated by these models can thus provide a first-level classification and prioritization of infrastructures based on their risk level. This offers concrete support for decision-makers, enabling targeted planning of maintenance, monitoring, or retrofitting interventions, focusing available resources on the most critical structures. In other words, Machine Learning does not replace traditional analysis methodologies but complements them, contributing to the optimization of time, costs, and resources, and fostering a more rational and proactive management strategy [7].

In summary, the main motivations driving this study are:

- Public safety: enhancing the ability to timely identify the most at-risk bridges, thereby reducing the likelihood of severe or catastrophic incidents during seismic events;
- Resource optimization: developing a tool to manage available funds for maintenance and retrofitting more effectively, directing them where they are most urgently needed;
- Technological innovation: promoting the integration of artificial intelligence techniques within a traditional engineering context, increasing the reliability and speed of assessments;

- Scalability: providing a streamlined methodology that can be easily applied to large infrastructure networks at both regional and national levels.

The objective of this work is therefore to explore and validate a Machine Learning-oriented approach for the preliminary assessment of bridges, with particular focus on seismic vulnerability. The method is applied to a case study in the Sicilian Region, a territory that is emblematic due to its seismic characteristics and high infrastructure density, in order to demonstrate its effectiveness and applicability in a real-world context.

2 AI METHOD FOR RAPID RISK ASSESSMENT OF BRIDGES

In seismic vulnerability assessment of bridge infrastructure, fragility curves play a key role in quantifying the probability of exceeding a specific performance limit state as a function of seismic intensity. When derived through rigorous numerical procedures, such as nonlinear time history analysis or pushover analysis coupled with cloud analysis techniques, fragility curves are typically represented by a lognormal cumulative distribution function [8]. This function is characterized by two main parameters:

- μ: the median structural capacity, representing the average response corresponding to a given seismic intensity (e.g., PGA),
- β: the logarithmic standard deviation, accounting for the dispersion in structural response due to seismic variability and modeling uncertainties.

For bridges, particularly those with regular geometries, the parameter μ can be expressed as a function of PGA using a power-law model of the form:

$$\mu = a \cdot PGA^{\beta}$$

where a and b are empirical coefficients that capture the sensitivity of the bridge's seismic demand, for example the max displacement of the pier d, to the ground motion intensity. In addition to μ and β, the ultimate displacement capacity of the pier, denoted as d_u is required to compute the probability of failure at each PGA level. Once these parameters are known, the fragility curve can be constructed by evaluating the exceedance probability as:

$$P(d > d_u|PGA) = 1 - \Phi\left(\frac{\ln\left(\frac{d_u}{\mu}\right)}{\beta}\right)$$

Where Φ is the standard normal cumulative distribution function.

The methodology proposed in this study aims to approximate the fragility curve parameters μ, β and d_u using supervised Machine Learning (ML) techniques. The idea is to train ML models capable of predicting these quantities directly from a reduced set of input features describing the bridge geometry, such as total mass, pier height, and longitudinal reinforcement area in the upper and lower portions of the pier section. A database of bridges is first created by performing time history analyses on a representative set of structures and extracting the corresponding fragility parameters through cloud analysis. This dataset is then used to train various regression-based ML algorithms, which learn the mapping between geometric features and fragility parameters.

Once trained, these ML models can be used to estimate fragility curves for new bridges without the need for computationally expensive simulations. While approximate in nature, this method provides a valuable tool for rapid seismic vulnerability screening of large bridge inventories. In particular, it supports the prioritization of interventions by ranking structures based on their predicted fragility, enabling infrastructure managers to make informed decisions under resource constraints.

The proposed methodology is applied in the following sections to a real case study involving a road network in the Italian region of Sicily. The case study is used both to evaluate the accuracy of the ML predictions and to calibrate the models for reliable use in large-scale vulnerability assessments.

3 DESCRIPTION OF THE CASE STUDY

The case study focused on a sample of 25 bridges located along the A19 Catania–Palermo motorway, one of Sicily's main transport corridors, which crosses areas characterized by high seismicity. All selected structures belong to the category of simply supported girder bridges, a structural solution widely adopted for viaducts built between the 1950s and 1980s. These bridges are composed of main beams—either precast or cast-in-place—resting on elastomeric or metallic bearings, and completed with a reinforced concrete deck slab, cross beams, bearing plinths, lateral curbs, and other secondary components.

For each bridge, a detailed geometric survey was carried out to acquire the essential structural information. The on-site surveys specifically included:

- total bridge length and span lengths;
- height, width, and cross-sectional dimensions of the piers;
- deck width;
- number, cross-section, and geometric dimensions of the main beams;
- number, cross-section, and geometric dimensions of the cross beams;
- geometry of bearing plinths and lateral curbs.

All collected data were systematically cataloged and digitized, creating a consistent database of geometric information, suitable for accurately describing the structural characteristics of the assets.

In parallel with field surveys, an extensive effort was made to retrieve and analyze the original design documents. These documents, dating back to the time of construction, provided key information regarding the mechanical properties of the materials used, including:

- compressive strength of concrete;
- elastic modulus of concrete;
- ultimate strain of concrete;
- yield strength of steel;
- tensile strength of steel;
- elastic modulus of steel;

- thickness and layout of the reinforcement.

The integration of design data with field measurements allowed for a more complete representation of the infrastructure's condition. This preparatory phase was essential for setting up the numerical analyses and evaluating seismic response, forming the basis for determining the critical structural parameters used in the fragility curve development.

To assess the seismic response of the 25 simply supported girder bridges along the A19 Catania–Palermo motorway, a methodology based on nonlinear static analyses (pushover analysis) was adopted, implemented according to the N2 method [9]. This approach enables the estimation of the ultimate deformation capacity of structures under seismic actions of varying intensity, overcoming the limitations of traditional linear dynamic analyses and offering a more realistic assessment of vulnerability.

To simplify the structural model and reduce computational complexity, each bridge was modeled as a single-degree-of-freedom (SDOF) oscillator. This was composed of an equivalent mass corresponding to the total deck mass within an influence area for one pier, calculated by considering all elements contributing to the superstructure. System stiffness was determined as the ratio of yield shear force to yield displacement, obtained from moment capacities, curvatures, and geometric parameters of the piers. For each bridge, moment-curvature diagrams were developed based on the mechanical properties of the concrete and steel, enabling the extraction of key parameters such as yield and ultimate shear forces and the corresponding displacements required to assess the deformation capacity of each structure.

The pushover analysis was carried out through the construction of the Acceleration-Displacement Spectrum Response (ADSR) and the bilinear capacity curve. For each bridge–spectrum combination, the fundamental period of the system was determined, and the corresponding spectral acceleration was derived from the demand spectrum. The comparison between the capacity curve (in force–displacement terms) and the spectral demand allowed the identification of the Performance Point, i.e., the equilibrium point representing the expected displacement of the deck under the given seismic action.

Based on this modeling, a total of 3750 nonlinear static analyses were performed (25 bridges × 150 response spectra), using 150 accelerograms representative of the local seismic hazard, selected based on the region's hazard curves. Each response spectrum was used to calibrate the seismic action in the N2 method, implemented via a custom MATLAB [10] code.

The MATLAB model was designed to systematically and automatically manage the large volume of required simulations, breaking the calculations into blocks and optimizing computational resource usage. The analyses yielded, for each bridge–spectrum combination, the displacement reached by the deck under the corresponding seismic event.

These displacements are key parameters for defining seismic fragility curves, which describe the probability of exceeding various limit states as a function of seismic intensity. The seismic fragility curves for the 25 bridges were developed using the Cloud Analysis method, based on the statistical processing of the results from the 150 nonlinear static analyses conducted per bridge. From each analysis, the peak ground acceleration (PGA) and the maximum top displacement of the pier "d" (EDP, Engineering Demand Parameter) were extracted. These

PGA–EDP pairs formed a “cloud” of data points representing the seismic response of the system over a wide intensity range.

Based on this dataset, a linear regression was performed in natural logarithmic scale, yielding the median relationship between the seismic intensity parameter (PGA) and the demand parameter (EDP). The dispersion of the data points around the median was quantified through the logarithmic standard deviation, assuming a lognormal probabilistic behavior—that is, assuming that the natural logarithm of displacement follows a normal distribution.

The probability of exceeding the ultimate displacement threshold for each PGA value was then computed using the standard normal cumulative distribution. In this study, the reference threshold was the ultimate displacement (d_u) capacity obtained for each bridge through pushover analysis, representing a collapse limit state. The probabilities of exceeding this threshold were estimated for increasing PGA values, generating fragility curves specific to each structure. From the development of the fragility curves, the output parameters—specifically the median demand (μ) and the standard deviation (β)—were extracted and subsequently used as targets for training the neural network. The input parameters, on the other hand, consisted of the geometric and mechanical characteristics of the bridges described earlier. This way, the neural network learns to directly predict a bridge’s seismic fragility by estimating the parameters that define its fragility curve based on the structural configuration.

4 MACHINE LEARNING MODELS AND DISCUSSION OF RESULTS

Building upon the methodology outlined in the previous sections, a dataset was constructed based on 25 bridge configurations. Each configuration is described through a set of four geometric and mechanical features: total structural mass, pier height, and longitudinal reinforcement area in both the upper and lower portions of the pier section. These parameters were chosen to represent the most influential aspects of the bridge geometry affecting its seismic response. For each bridge, the seismic response was assessed via pushover analyses, and the corresponding fragility curve parameters were derived through cloud analysis, as described in Section 2.

Given the relatively small size of the dataset, particular care was devoted to selecting machine learning (ML) models that are known to be effective in low-data scenarios while still capturing non-linear and complex interactions among features. Five supervised regression models were investigated:

- Linear Regression, serving as a baseline model to capture potential linear trends [11];
- Decision Tree Regression, which is capable of modeling non-linear relationships through hierarchical data partitioning and is well-suited to small datasets [12];
- Support Vector Regression (SVR), known for its robustness in high-dimensional spaces and its ability to generalize well from limited training samples [13];
- Gaussian Process Regression (GPR), a probabilistic, non-parametric model that performs particularly well with sparse datasets and provides uncertainty quantification [14];
- Random Forest Regression, an ensemble learning method based on decision trees, offering improved accuracy and resistance to overfitting [15].

These models were trained separately to predict each of the parameters required to define the fragility curve: the ultimate displacement capacity d_u , the dispersion parameter β and, and the median demand μ.

To illustrate the process of model selection, the results obtained in predicting the dispersion parameter β are presented as a representative case. Figure 1 shows the performance of each model in terms of predicted vs. actual values. Among the tested algorithms, Gaussian Process Regression yielded the best results, achieving a coefficient of determination R^2=0.82, demonstrating its strong predictive capacity.

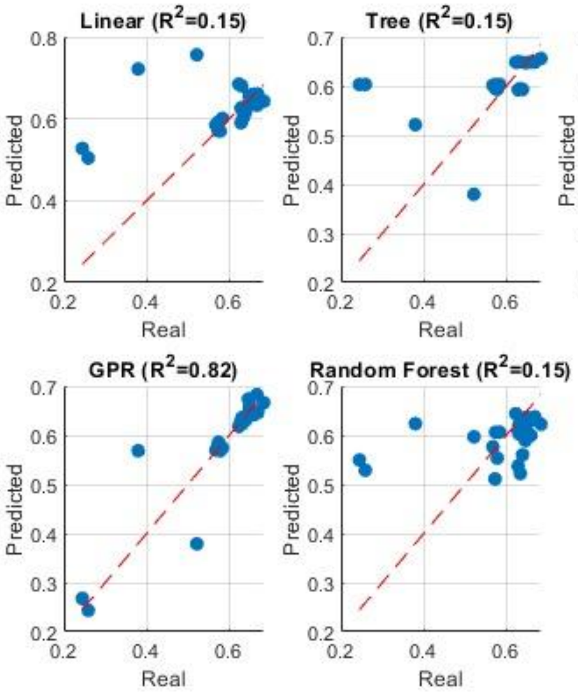

Figure 1: Comparison of trained ML models for deriving the β parameter

For the sake of conciseness, Table 1 summarizes, for each fragility parameter, the ML model that achieved the highest predictive performance. These models were then used to predict the fragility curve of a new bridge configuration that was not part of the training dataset.

Parameter	ML model	R^2
β	GPR	0.82
d_u	GPR	0.81
μ	GPR	0.79

Table 1: Top-performing ML models for parameter prediction

It is worth noting from Table 1 that for all the parameters to be determined, GPR is the best-performing model.

To evaluate the accuracy of the ML-based fragility prediction, the resulting curve was compared with the reference curve obtained via full nonlinear time history analysis. As shown in Figure 2, the two curves exhibit excellent agreement. The mean absolute error (MAE) between the two curves is found to be less than 2%. These results confirm that, despite its approximate nature, the ML-based method is sufficiently accurate for preliminary seismic screening purposes and can support large-scale vulnerability assessments by enabling rapid fragility curve generation for multiple structures.

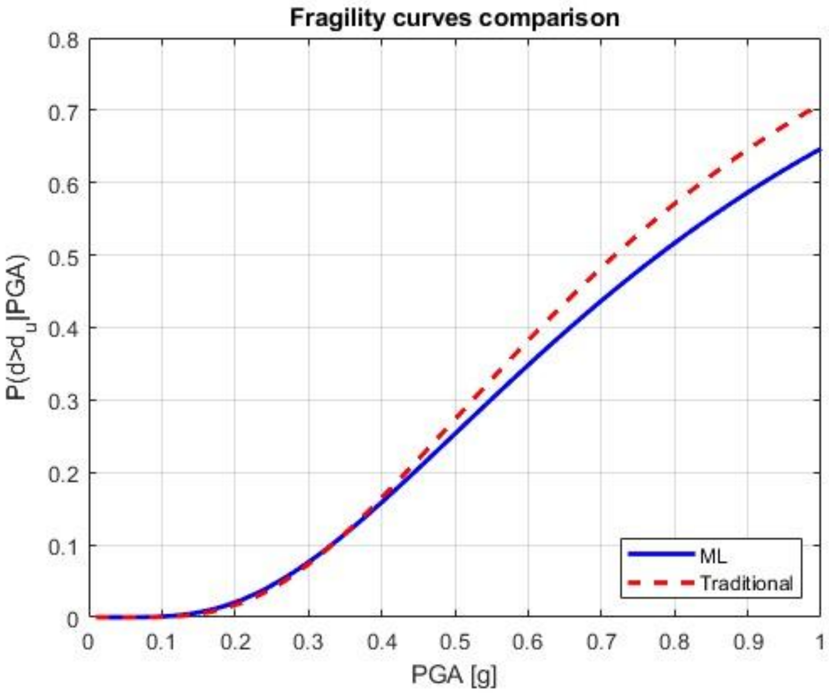

Figure 2: Comparison between the fragility curve obtained with the ML model and the one derived using the traditional method

5 CONCLUSIONS

This study presents a novel approach for deriving seismic fragility curves of bridges using Machine Learning (ML) techniques, based solely on a limited set of structural parameters. By training regression models to estimate the key parameters of the fragility function, namely, the median value (μ), the standard deviation (β) and the ultimate displacement (d_u) from input variables such as mass, pier height, and reinforcement details, the proposed method provides a computationally efficient alternative to traditional Cloud Analysis procedures.

Among the different ML algorithms tested, Gaussian Process Regression (GPR) consistently demonstrated the best performance in predicting all parameters, as confirmed by cross-validation metrics. Furthermore, the comparison between fragility curves derived through ML and those obtained via conventional methods shows a strong agreement, validating the reliability of the proposed approach.

This method enables rapid estimation of fragility curves for large inventories of bridges without the need for extensive numerical simulations, making it highly suitable for preliminary risk screening and prioritization of structural assessments in regional-scale studies. Future work will focus on extending the approach to other structural typologies and damage metrics, and on exploring the integration of epistemic uncertainties in the ML models.

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