Prediction Model for Damage of Box-Girder Seat-Type Ordinary Bridge Structures

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Abstract

Earthquakes are a recurring phenomenon in California, with a significant impact on structural engineering practices. Accurate prediction of structural damage is crucial for designing resilient infrastructure. This project aims to enhance bridge engineering by producing an effective model for predicting the damage that bridge columns might sustain from earthquake-caused **ground motions** (**GM**s), under the key assumption that the behavior of a bridge is closely linked to the behavior of its columns. To achieve this, we have developed and tested LASSO regression, generalized additive models, and neural networks. Our findings indicate that these models produce highly accurate predictions with low error rates, providing valuable tools for engineers.

Background and Goals

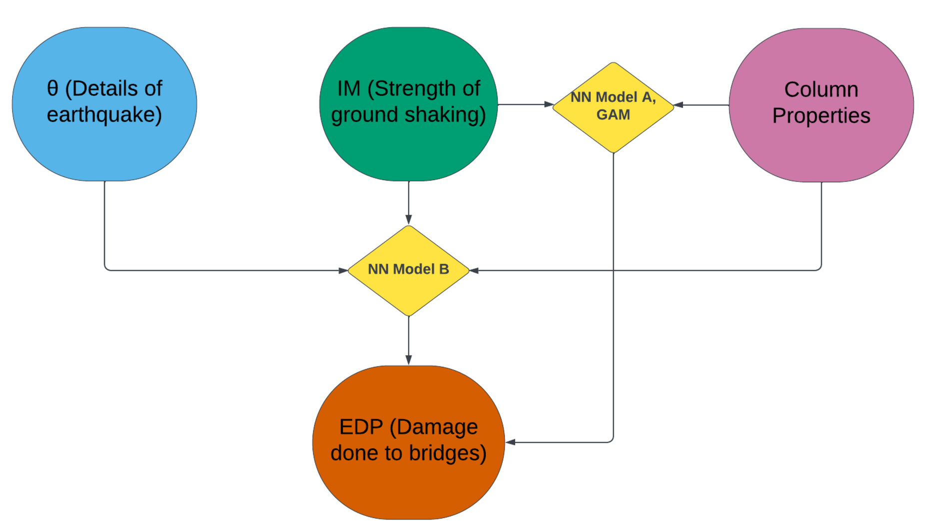

Figure 1. Flowchart of predictor variable types to response variable type

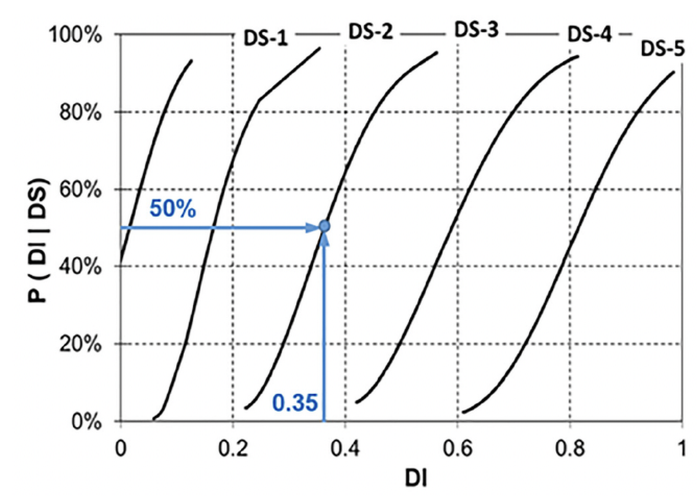

Figure 2. Plot of probability of getting a certain Damage State or greater given a certain Damage Index

Our data was provided by Principal Investigator Dr. Farzin Zareian. GM data was generated with a stochastic GM simulation model and bridge columns were modeled using OpenSees, a software framework for simulating the response of systems to earthquakes. These modeled bridge columns are not based on any existing columns, but are instead designed from a matrix of possible parameters, with the resulting column undergoing a preliminary check for basic feasibility at the location.

Our project follows the key assumption that the behavior of a bridge reflects the behavior of its bridge columns. Thus, rather than needing to analyze an entire bridge, we can focus on the column level. Our goal is to find a model to accurately predict the damage done to a column, based on relevant input parameters.

Variables are divided into several types: **Column Properties**, **Event Parameters** (θ) containing information about an earthquake event such as magnitude and location, **Intensity Measures** (**IM**s) measuring a GM in dimensions such as duration and ground acceleration, and **Engineering Demand Parameters** (**EDP**s) recording the resulting damage and displacement to the column.

The key metric used to represent damage was **Damage Index** (**DI**), an EDP used for finding the probability of a column sustaining certain damage states.

Data Structure

The data was contained within three sets:

1. GM Data - Contains detailed records of GM parameters from the simulated seismic events, namely θ from the event causing a GM and IMs about the GM itself.
2. Column Data - Contains structural characteristics of bridge columns, capturing various physical and mechanical properties, as well as EDPs of the column in response to a GM.
3. Location Data - Contains list of all locations, identified by location ID, and their geographic coordinates

Exploratory Data Analysis

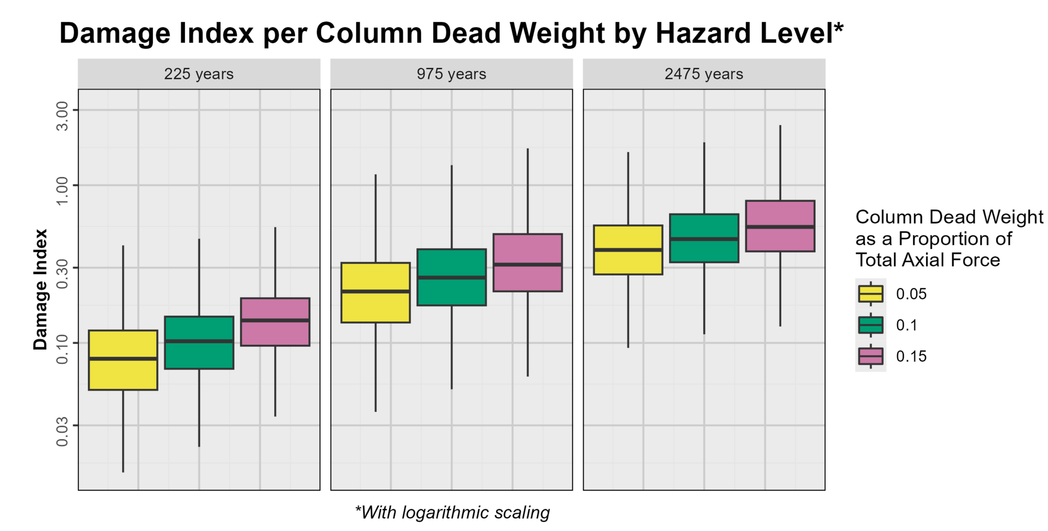

Figure 3. Boxplot of DI per Column Dead Weight

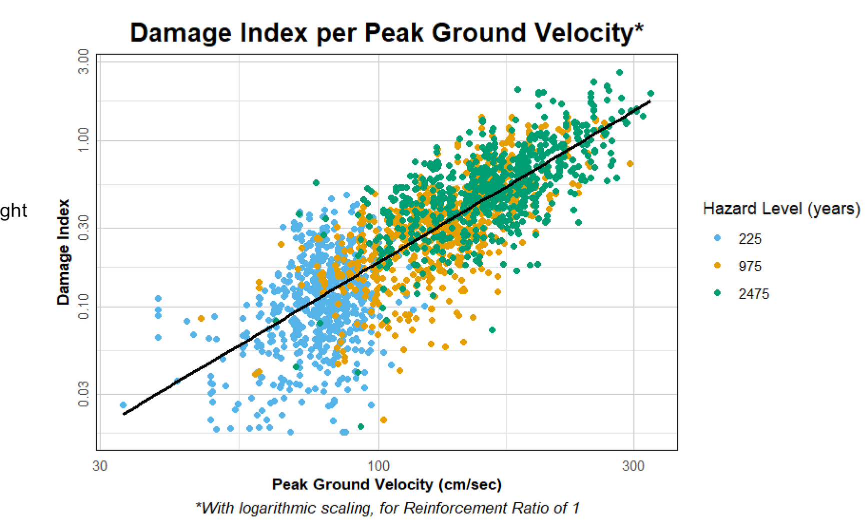

Figure 4. Scatterplot of DI per Peak Ground Velocity

1. **DI per Column Dead Weight:** The median DI values increase consistently with the relative Column Dead Weight, showing the importance of this value to column strength. Expectedly, DI also tends to increase with the Hazard Level.
2. **DI per Peak Ground Velocity:** As the Peak Ground Velocity (PGV) of a GM increases, so does the resulting DI of affected columns. PGV has a strong correlation with DI, and clusters in the scatterplot affirm DI tends to increase with Hazard Level.
3. **LASSO Variable Selection:** LASSO (Least Absolute Shrinkage and Selection Operator) is a regression method used for variable selection and regularization, enhancing model accuracy by setting less important coefficients to zero through use of a penalty term. In our study, we applied LASSO to identify key predictor variables. These selected variables, displayed in Table 1, were then used in later models where applicable to make those models more sparse and interpretable while maintaining good accuracy.

Variable Type	Important Variables
Event Parameter	Hazard Level, Magnitude, Horizontal Distance
Intensity Measure	Peak Ground Velocity, Peak Ground Acceleration, Significant Duration, Arias Intensity
Column Properties	Period of Vibration, Ultimate Displacement, Dead Weight on Top, Spectral Acceleration, Demand DI, Reinforcement Ratio, Height, Demand Displacement, Diameter, Stiffness

Table 1. Important Variables by Type

Modeling

Computing the EDPs for a bridge's columns is critical for assessing a bridge's overall strength and forecasting its performance against future earthquakes. These parameters are usually calculated with Nonlinear Time History Analysis, a computationally intensive and time-consuming process.

Seeking a simpler method for finding EDPs, we fit one **Generalized Additive Model** (**GAM**) for each Hazard Level to predict DI using column properties and IMs. These GAMs allowed us to fit linear and nonlinear relationships using linear regression or thin-plate splines on each input variable.

We also built two **Neural Network** (**NN**) models with three hidden layers. NN Model A predicted DI using column properties and IMs, whereas NN Model B also used θ as predictors. NN models are adept at handling large amounts of data with many variables and finding the complex relationships in between them.

Results

Hazard Level	225	975	2475
Error	Cumulative Relative Frequency (%)		
0.01	14	8	5
0.02	29	16	10
0.04	59	31	19
0.05	70	38	23
0.06	78	45	28
0.08	87	56	36
0.10	92	65	44

Table 2. Relative Frequency of Absolute Errors for Predicted DI Values from each GAM

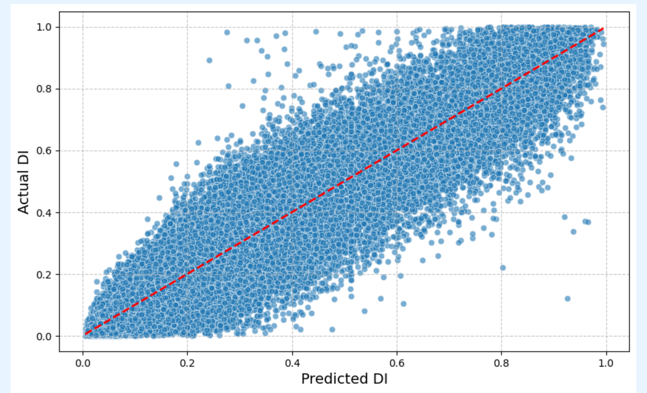

Figure 5. NN-A, Predicted vs. Actual (San Francisco)

	NN Model A			NN Model B		
	RMSE	Correlation	R-Squared	RMSE	Correlation	R-Squared
SF	0.078	0.94	0.88	0.085	0.93	0.85
LA	0.088	0.92	0.85	0.082	0.94	0.88
SD	0.083	0.88	0.68	0.079	0.92	0.86

Table 3. NN Comparison for San Francisco, Los Angeles, and San Diego

From Table 2 we observe that the GAM for the 225 Hazard Level is the most accurate of the three, with **70%** of its predictions achieving a small error of **0.05** or less and **92%** achieving a tolerable error of **0.1** or less. The accuracy of the remaining GAMs is considerably lower.

Practical Applications:

- **Risk Assessment:** The predictive models can be employed to assess bridge structures' risk and resilience, providing crucial insights for architects and civil engineers in the design and retrofitting processes.
- **Budget Allocation:** By estimating potential damage, the models assist in prioritizing funding for the most vulnerable structures, optimize resource use, and budget efficiently.
- **Safety Enhancements:** Accurate damage predictions help prepare for potential issues and reduce the risk of bridge collapse, protecting public infrastructure and ensuring safety.

Future Work

- Further models may be developed. These current models may be polished and improve, and other models could potentially be developed to go from column properties and θ to predicting IM, or to go directly from column properties and θ to predicting EDPs.
- We would like to include data from more locations to allow further exploration of the influence that geographic location has on IMs and EDPs.

Acknowledgements

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