# Collapse Simulation of Building Structures Under Earthquakes

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## Abstract

Reliable structural modeling requires analytical tools that can accurately predict strength and stiffness deterioration of structural elements in response to earthquake conditions. Computer simulations allow engineers to test different structural ideas and concepts to find a balance between a cost-effective design and structural integrity. To improve the accuracy of our simulation, we used the Particle Swarm Optimization (PSO) for its simplicity and effectiveness in optimization problems with real-world applications. In our approach, we used OpenSees to create structural models and assess their response to earthquake conditions through dynamic analysis. We ran Particle Swarm Optimization in MATLAB to optimize the Ibarra-Medina-Krawinkler (IMK) parameters to improve the accuracy of our computational simulations in relation to real-world observations. Using optimized parameters as a benchmark, we ran dynamic analysis on a single-column structure in OpenSees and used the Markov Chain Monte Carlo (MCMC) simulation to produce uncertainty quantifications for structural collapse. The MCMC allowed us to run simulations for models where we lacked analytical expressions for our problem simulations. From preliminary literature reviews and data analysis, we can model uncertainty quantifications for structural collapse when comparing individual IMK parameters to structural responses to earthquake conditions. The goal of this research project is to explore the application of Particle Swarm Optimization to calibrate the modified IMK deterioration model parameters and the corresponding uncertainty quantifications of structural models through computational simulations of building collapse under earthquake conditions.

## 1.0 Introduction

Earthquakes are one of the most destructive natural disasters known to plague urban structures in seismically active regions. Between 12,000 and 14,000 earthquakes occur annually worldwide ranging between a magnitude of less than 2.0, causing a glass to slightly shake on a table, and in excess of 8.0, causing structural damages and even total collapse [4]. The vast majority of annually recorded earthquakes are below 2.0 magnitude and the few making the news are of magnitudes surpassing 5.0 on the Richter Scale. While the low frequency of high magnitude earthquakes may lull the general public into relative indifference to the importance of improving the understanding of structures and their individual components in reaction to earthquakes. The social upheaval associated with deaths and injuries along with economic costs associated with rebuilding and repairing should stand as great motivators to mitigate impacts of earthquakes on modern buildings.

Over the past several decades, as research institutions have gained a greater understanding of earthquake behavior, the field of civil engineering has grown to encompass earthquake engineering. This specialized subfield concentrates on limiting the seismic risk to the man-made environment in response to an array of disasters. To encourage students to study the field, these institutions offer internship opportunities to the next generation of engineers, introducing them to some of the more common projects they will work on in the professional setting. San Francisco State University offers a 10-week summer research internship for California community college students majoring in STEM fields to explore cutting edge research. This paper relates the scientific studies conducted by four community college Civil Engineering student interns in designing a simulation of building structures under earthquake conditions.

## 2.0 Background

Aging infrastructure in the United States has served as a catalyst to the civil engineering community to begin implementing innovative design concepts to mitigate structural damages associated with earthquakes and related catastrophes.

There are two common research approaches to study building response to earthquake conditions. The first method is physically modeling the system with miniature representations of specific structures and using shake tables to gauge the building's response. The second, more cost-effective and time-efficient method, is using computational simulations. There are a wide range of simulation packages for earthquake engineering simulations including OpenSees. OpenSees is an object-oriented software framework where users create finite element applications for simulating structural response to earthquake conditions [11]. To produce building models, researchers use the Lignos database, a database for general strength and stiffness deterioration of structural elements, to generate Ibarra-Medina-Krawinkler parameters modeling deterioration for elements within a structure. To improve the accuracy of element deterioration within specific simulations, engineers use two subprograms in conjunction with OpenSees to optimize the deterioration characteristics. The first program is Particle Swarm Optimization (PSO), a computational method that optimizes problems through iteration of possible candidate solutions to produce the optimal solution set [2]. The second program is the Metropolis-Hastings (MH) Algorithm, a popular algorithm for the Markov Chain Monte Carlo (MCMC) simulations. The algorithm generates random new parameter sets by comparison with the general parameter set to minimize error and converge to better fit the experimental data [10]. Thus we were able to produce uncertainty quantification for structural collapse based on the distributions of IMK parameters [5]. Engineers use a combination of these two programs to produce precise simulations and uncertainty quantifications for structural collapse under earthquake conditions [3]. To test structural response to earthquake conditions, we used two earthquake ground motions from the PEER Ground Motion Database, the Northridge Earthquake (7.6 magnitude) (Appendix 1) and the Chi-Chi Earthquake (6.7 magnitude) (Appendix 2) [8].

## 3.0 Methodology

### 3.1 Structural Design

Simple structural models produced in OpenSees give engineers a greater understanding how individual components and subsections of structures will respond to earthquake perturbations. IMK modeling looks at the individual connective points between elements within a structure and models the strength and stiffness deterioration of the connections. In this study, we selected the Particle Swarm Optimization for the Ibarra-Medina Krawinkler model coefficient optimization to better match real world structural response.

### 3.1.1 Single-Story Structural Model

A deep understanding and analysis of the single-story structural model, one of the most common basic building structures, allows for a higher degree of comprehension on how simulated lateral loading affects building structures and allows for further extrapolation for the behavior of more complex structures.

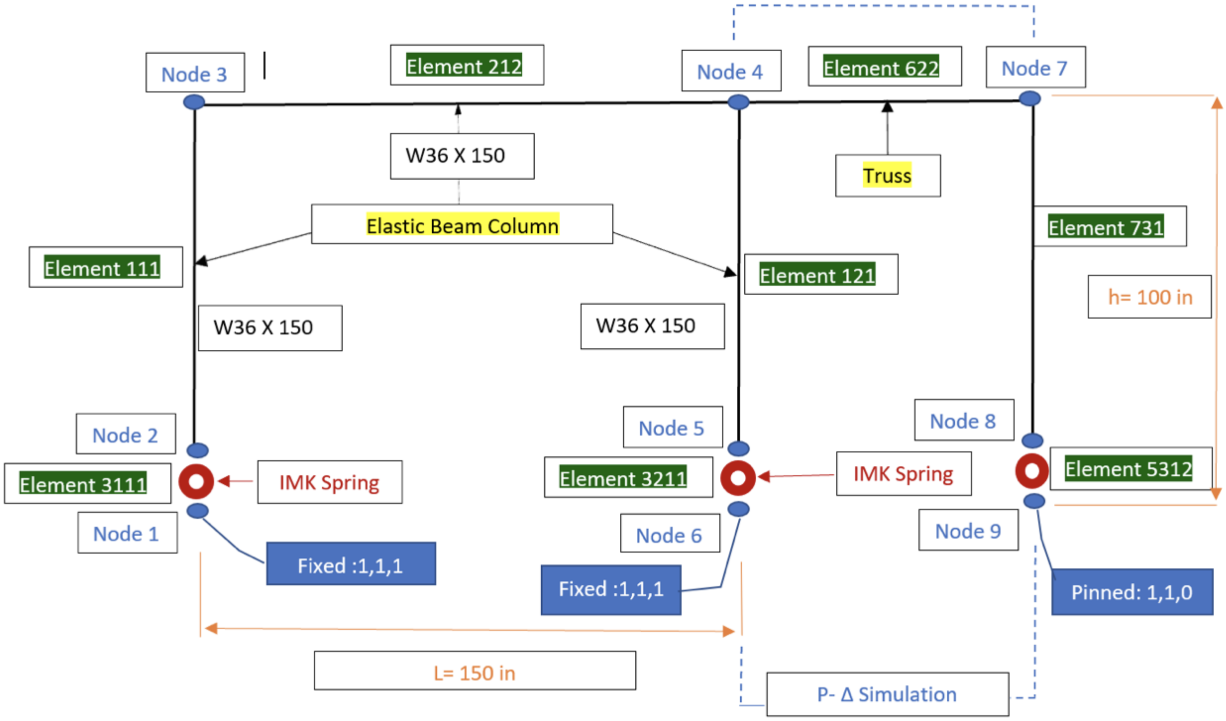

Figure 1. Single story steel frame model with p-delta column. Structural Geometry: Nodes 1 and 6 fixed in all degrees of freedom. Node 9 fixed in the x and y directions and has freedom of rotation. Elements 3111 and 3211 are IMK springs, elements with defined deteriorative properties. Element 5312 is a spring with minimal damping coefficients.

To replicate the single-story structural model shown in OpenSees (Figure 1), we began by defining the nodes, connecting points between each of the elements. Node pairs 1 and 2, 6 and 5, and 9 and 8 share the same location and simulate the springs, zero length elements, connecting them. For zero length elements 3111 and 3211, we applied Bilinear material to simulate the IMK model. Afterwards we defined the element characteristics of the beams and columns. The Elastic Beam elements are designed to readily deform and respond to earthquake conditions.

The frame modeled with P-Delta column was designed specifically for computational simulations to quantify lateral displacement and structural responses to earthquakes in real life. To model the P-Delta effect, the equilibrium and compatibility relationships of structural systems are taken into account and simulated by creating a single column and connecting it to the overall frame model with a truss. The truss is designed to be less deteriorative than the elastic beam columns so that we can easily measure the lateral displacement of our P-Delta column. The spring, element 5312, is designed to freely rotate, causing minimal damping. This enabled us to measure structural deformation and response to earthquake conditions while minimizing the error in our measured lateral displacements.

### 3.1.2 Single Column Structural Model

Figure 2 illustrates the scheme for the single column model. The PSO and MCMC simulations require comparison between the OpenSees outputs and the experiment measurements from Richel Spec II. In this study, we used the moment-rotation relationship. Therefore, Element 111 is made of rigid material, and the rotation at Element 3111 is controlled by the displacement control at Node 3.

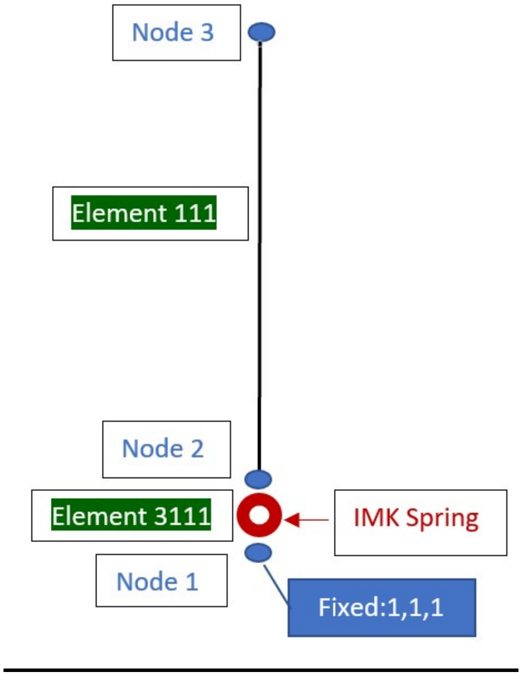

Figure 2. Singular column with IMK spring. Structural Geometry: Node 1 fixed in all degrees of freedom. Element 3111 is an IMK spring.

## 3.2 Ibarra-Medina Krawinkler Modeling and Particle Swarm Optimization

### 3.2.1 Ibarra-Medina Krawinkler Model

The IMK model captures the structural deterioration with the selection of its parameters based on calibration through comparisons with experiment data. It is crucial to understand how each variable affects the results since it is constructed of a tri-linear monotonic backbone curve that incorporates strength deterioration and cyclic deterioration of strength and stiffness. To model structural responses to earthquake conditions, we used the following strength and stiffness deterioration parameters: effective yield strength ($M_y$), which represent where permanent deformation occurs in the material. Post capping strength and post capping loading ($M_c$ and $\square_c$); effective stiffness ($K_{pc}$), which controls the rigidity of the material and how it resists deformation in response to applied loading; residual strength ($M_r$), which is the strength that the material can withstand without failure after being damaged; ultimate rotation capacity ($\square_u$). Each of these parameters will affect the way the building deteriorates and will change the results when graphing them on the strength-vs-stiffness deterioration graph [5].

The Single-Story Moment Frame (Figure 1) and Single Column with IMK Spring (Figure 2) are built with steel structural components, affecting the structural deterioration of our models to applied lateral loads. The experimental model for steel beam deterioration (Figure 3) relates the true strength-vs-stiffness deterioration of a steel beam in laboratory conditions. The steel strength deterioration model is the baseline from which we can quantify the accuracy of the Particle Swarm Optimization for IMK parameters and obtain error quantifications.

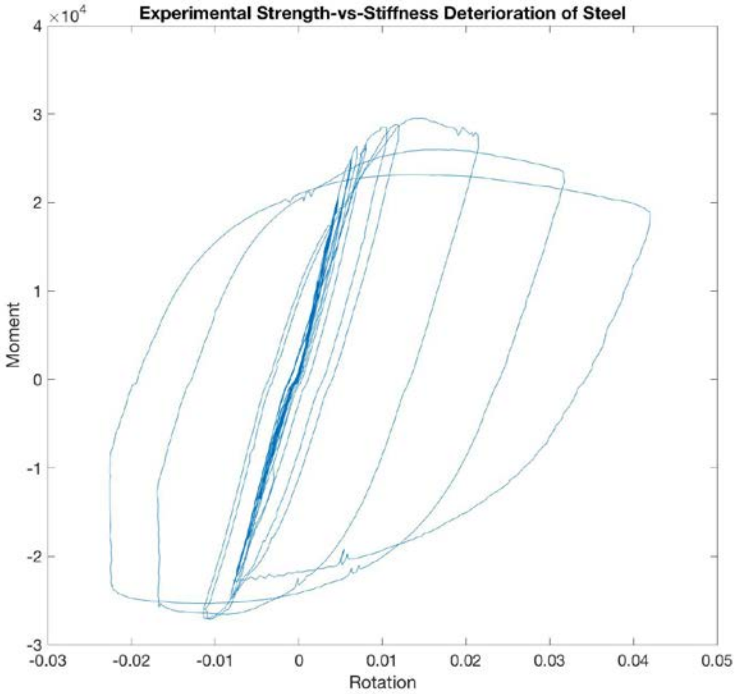

Figure 3. Experimental plot for steel strength-vs-stiffness deterioration from Lignos Database. [9]

Initially, we modeled the strength-vs-stiffness deterioration of our steel structure with the general IMK parameters taken from the Lignos Database (Figure 4). Figure 4 compares the experimental data for steel deterioration in blue with the IMK model with the general IMK parameters in orange. While the two models share a likeness in shape, the IMK model does not accurately portray the true steel deterioration for our structural model.

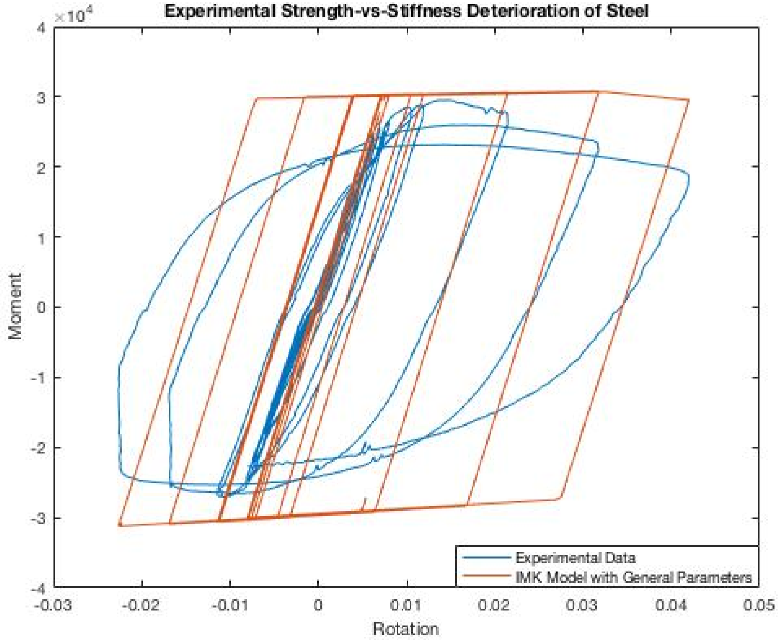

Figure 4. Comparison plot between experimental steel deterioration (blue) and IMK model with general parameters (orange). The old parameters are the general deteriorative properties for steel elements.

Table 1. PEER Database recommended parameter values for strength and stiffness deterioration of steel elements.

| Element Characteristics | Recommended Parameter |
|---|---|
| McMyP | 1.15 |
| McMyN | 1.05 |
| MyP | 30350 |
| MyN | -30350 |
| K | 4e6 |
| th_p | 0.025 |
| th_pc | 0.25 |
| LS | 10 |
| ResP | 0.4 |
| th_u | 0.4 |

The similarity in shape between the experimental data from the Lignos database and our IMK model with the general parameters is a result of the model representing steel material behavior under applied loads. As denoted by the strength-vs-stiffness graphs, the general parameter values characterize the same deterioration as those from the experimental data with significant error. To minimize the difference between the results of the two models, we employed the Particle Swarm Optimization.

### 3.2.2 Particle Swarm Optimization

The Particle Swarm Optimization (PSO) is a computational method that optimizes the solution set for a problem by iteratively trying to improve candidate solutions (particles) with regards to a given measure of quality. The PSO method optimizes parameter sets by manipulating a population of candidate solutions in the search-space according to simple mathematical equations, guiding the particles to their best known position within the search space and updated as better positions are found. Overtime, this is expected to move the particle to the best solution as the particles converge to the global best known position within the search-space, hus optimizing the solution set with respect to the actual data.

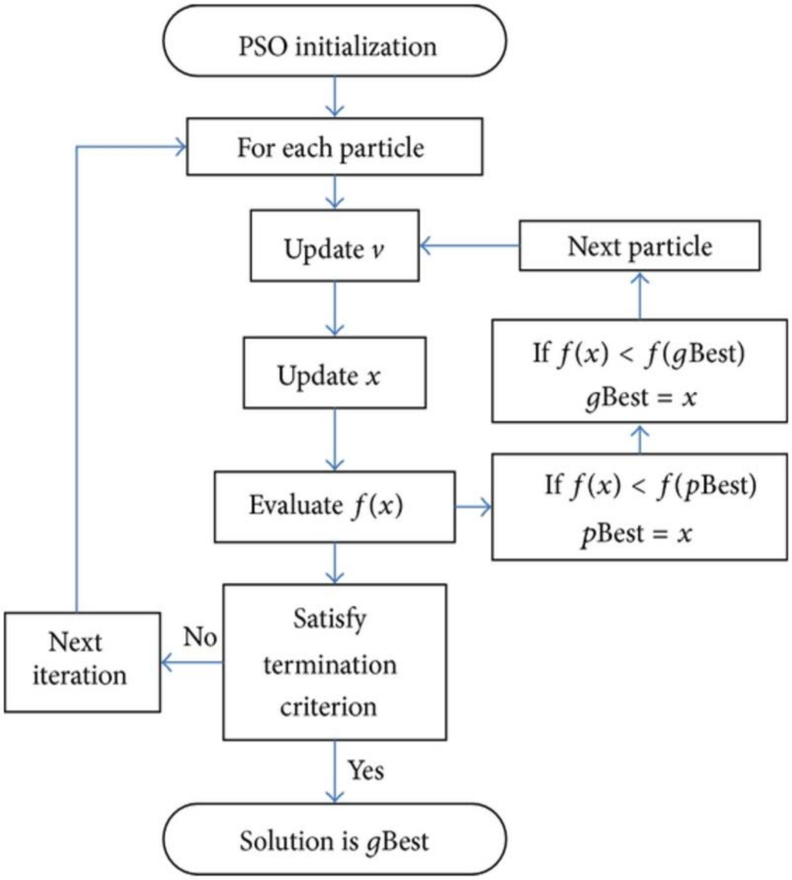

Figure 5: Flowchart illustrating implementation of Particle Swarm Optimization on population of particles to find the solution set that optimizes the IMK model to better fit the experimental data from Richel Spec II.

Once we created a general model for steel deterioration and applied it to our dynamic analysis for the single-story structural model, we ran PSO to optimize our IMK parameters so that our element characteristics would provide a more accurate representation of real world structural responses to earthquake conditions. Using the experimental data for steel deterioration from Lignos Database, we ran 40 particles through 50 iterations to minimize the error function between the experimental data and the IMK model. Using MATLAB we were able to optimize the IMK coefficients as depicted in Figure 5 [7].

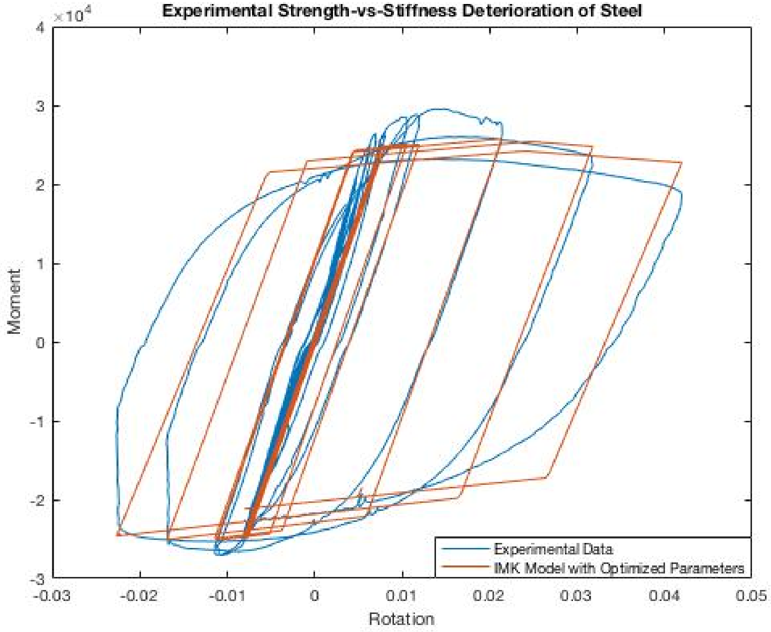

Figure 6. Comparison plot between experimental steel deterioration (blue) and IMK model with optimized parameters (orange). The new parameters represent the optimized deteriorative properties for steel elements, allowing the IMK model to better fit the experimental data from Richel Spec II.

Table 2. Optimized parameters for strength and stiffness deterioration of steel elements found from Particle Swarm Optimization.

| Element Characteristics | Recommended Parameter |
|---|---|

| | |
|---|---|
| McMyP | 1.73347 |
| McMyN | 1.28276 |
| MyP | 23377.6 |
| MyN | -23377.6 |
| K | 3.22736e6 |
| th_p | 0.0222353 |
| th_pc | 0.275686 |
| LS | 1.17218 |
| ResP | 0.571738 |
| th_u | 0.425687 |

After implementing the Particle Swarm Optimization, our IMK parameters better represented our deterioration model. Figure 6 summarizes the PSO results. The graphical representation illustrates that the IMK model with optimized parameters mimics the actual data for steel deterioration more precisely. Our optimized IMK model did not precisely fit the model due to our model only representing the strength-vs-stiffness deterioration of steel. Had we wanted to measure the ductility of our elements, our IMK model would be more curved and a closer visual fit to the experimental data from Richel Spec II.

### 3.3 Structural Analysis

After designing building structures and before buildings can be constructed, it is vital to run structural simulations under earthquake conditions to understand how structures will respond to different applied loads. The three primary analysis types are static analysis, cyclic analysis, and dynamic analysis. As a result of these analyses, the cause of structural failure and the evaluation of structural design can be recognized early in the design process.

Direct use of Ibarra-Medina Krawinkler calculated parameters, may lead to misrepresentation of structural response. Therefore, we used optimization techniques to modify the IMK coefficients. To compare the IMK parameters acquired in OpenSees with the experimental parameters obtained from Richel Spec II, we simulated a stiff single column prototype (Section 3.2) to control the rotation at the bottom of the model. By multiplying the rotation by the height of the column (100 in), we were able to control the displacement by applying loading protocols (Appendix C) at the top of the column, thus controlling the rotation of the IMK single column model at the bottom. Once we ensured that the rotation in OpenSees and Richel Spec II were identical (Appendix D), we were able to compare the moment. With the displacement control, the cyclic analysis was implemented on a point of interest of the single column structure to run our Particle Swarm Optimization for IMK parameter performance improvement.

The dynamic analysis was performed to gain valuable information on the structural response of our models when exposed to seismic motion. The results obtained from the Particle Swarm Optimization and the Markov Chain Monte Carlo simulations were implemented to run the dynamic analysis. We created individual probability distributions for each of the IMK parameters in relation to element deterioration. Applying the optimized IMK coefficients from the Particle Swarm Optimization improved the precision and real world applicability of our models to mitigate seismic induced damages to urbanized society.

## 3.4 Uncertainty Quantifications

Computational simulations provide professionals with the ability to model real world events and their consequences in the virtual world to be able to accurately produce models for testing purposes. To better represent the real world material characteristics, incorporating uncertainty quantifications for element characteristics enables engineers to account for variable structural properties without compromising structural integrity. Using uncertainty quantifications, we can produce a normal Gaussian distribution representing the probability of element characteristics in relation to structural integrity. These can then be compared to the maximum allowable deteriorative properties to minimize possible sources for element fatigue and collapse.

### 3.4.1 Markov Chain Monte Carlo

The Markov Chain Monte Carlo (MCMC) is a statistical simulation designed to produce uncertainty quantification based on random sampling from probability distributions. The Markov Chain method randomly generates values within the desired search space in the system or model based on previous data [6]. Monte Carlo is an idiomatic expression that denotes inferences about unknown values through simple averages and is modeled using histograms and kernel density estimates. The histograms and kernel estimates will produce uncertainty quantifications for actual realizations of parameter values. The MCMC begins by implementation of the Bayes Formula (Equation 1).

$$\square(\square|\square) = \frac{\square(\square|\square)\square(\square)}{\square(\square)} \qquad \text{[Eq 1]}$$

where $\square(\square|\square)$is the posterior (probability) distribution, which can also be described as our goal. $\square(\square|\square)$represents the likelihood function (Equation 2). $\square(\square)$is the past information given by the model. $\square(\square)$is a single value that normalizes the likelihood times prior portion.

$$\square(\square|\square, \square^2) = (2\square)^{-\frac{\square}{2}}\square^{-\square}\square\square\square\{\frac{-1}{2\square^2} \bullet (\sum_{\square=1}^{\square} (\square_\square - \square(\square_\square; \square))^2)\} \qquad \text{[Eq 2]}$$

where $\sigma^2$represents the unknown variance; $n$ stands for the amount of independent observations.

We implemented the Metropolis-Hastings (MH) algorithm to model the uncertainty from the IMK model parameter selection given experimental measurements. By post-processing the MCMC chain, the simulation produced probability distributions for each of our IMK parameters. Interpretation of these curves allowed us to estimate what set of IMK parameters would produce an IMK model best suited for evaluating the uncertainty in structural response.

## 4.0 Results

Once we designed the simple single-story single-frame structural model in OpenSees, we ran optimization and calibration programs, PSO and MCMC, to produce a precise simulation for the single-story structural model's response to simulated earthquake conditions.

The PSO produced an optimized set of IMK parameters so that the IMK model would best fit the experimental data (Figure 5) with minimized error. Due to the time and computational limits, we applied 40 particles and 50 iterations. We used these optimized parameters as the new set of parameters to ensure that our single-story frame model would be the best possible representation of deterioration under earthquake conditions.

Once the optimized parameters were applied to the IMK model for the single-story frame model, we were able to run the Markov Chain Monte Carlo simulation to produce uncertainty quantifications for IMK parameter sets representing the possible realizations for these parameter values under the given experimental data. We began by inputting our general IMK parameter set and then plotted the 10000 IMK parameter sets from the MCMC to produce uncertainty quantifications for our IMK parameter sets in relation to structural deterioration. After inputting the general IMK parameters, the MCMC simulation either adds new values to the chain of possible realizations under given experimental data or else rejects the new IMK values. In Figure 7, the perfectly horizontal lines illustrate the period when the new randomly generated parameters are rejected. Each time that the graph makes a jump represents the IMK model producing a more precise IMK model as the errors decrease.

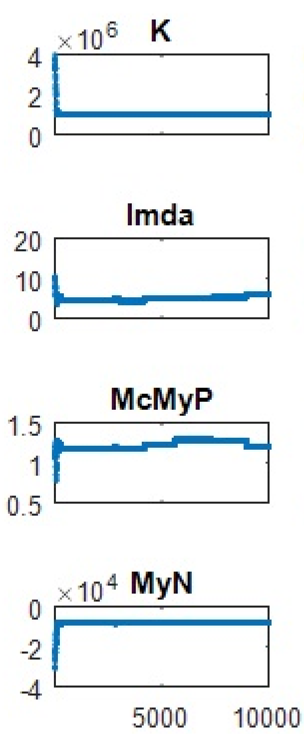

Figure 7: Metropolis-Hastings plot of IMK parameters as possible candidate solutions for IMK parameters under given experimental data are either accepted and added to the chain or else rejected.

Once we produced uncertainty quantifications for our IMK parameters in relation to structural collapse, we graphed histograms to more readily represent our MCMC conclusions.

For the distribution curves pictured in Figure 8, the narrower distributions of the K, MyP and MyN parameters (compared to theta_p, theta_pc, lmda, theta_u, k_res, McMyP, McMyN) equate to a greater confidence of IMK parameter values to optimize the IMK model to better represent actual structural responses to earthquake conditions.

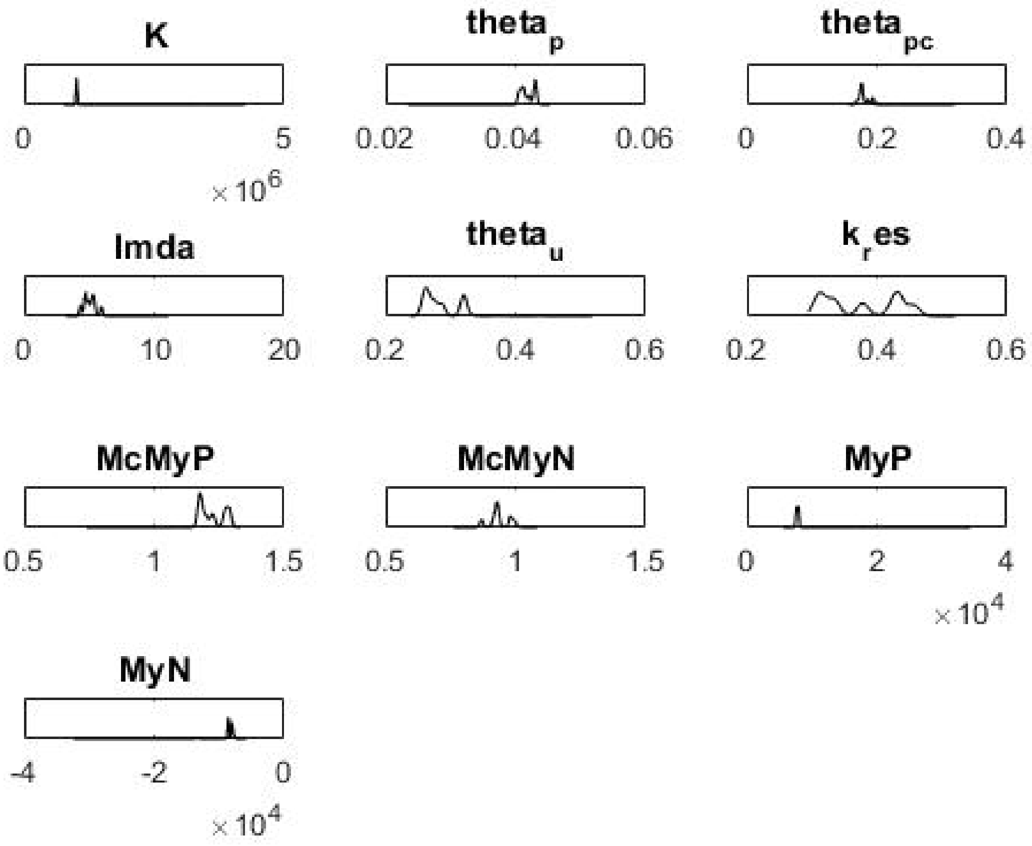

Figure 8: Metropolis-Hastings distribution plots of IMK parameters illustrating degrees of certainty for IMK parameters that will be possible realization under given experimental data to better represent the experimental data from Richel Spec II.

Once we produced the MCMC chains for the ten different IMK parameters, we input the chain of all possible IMK parameter sets into our dynamic analysis of the single-story frame model to produce a precise simulation for its structural response under earthquake conditions and quantify the drift ratio of the structural model under the Northridge Earthquake and Chi-Chi Earthquake ground motions. The drift ratio is a ratio of the lateral motion of the structure in relation to its overall height.

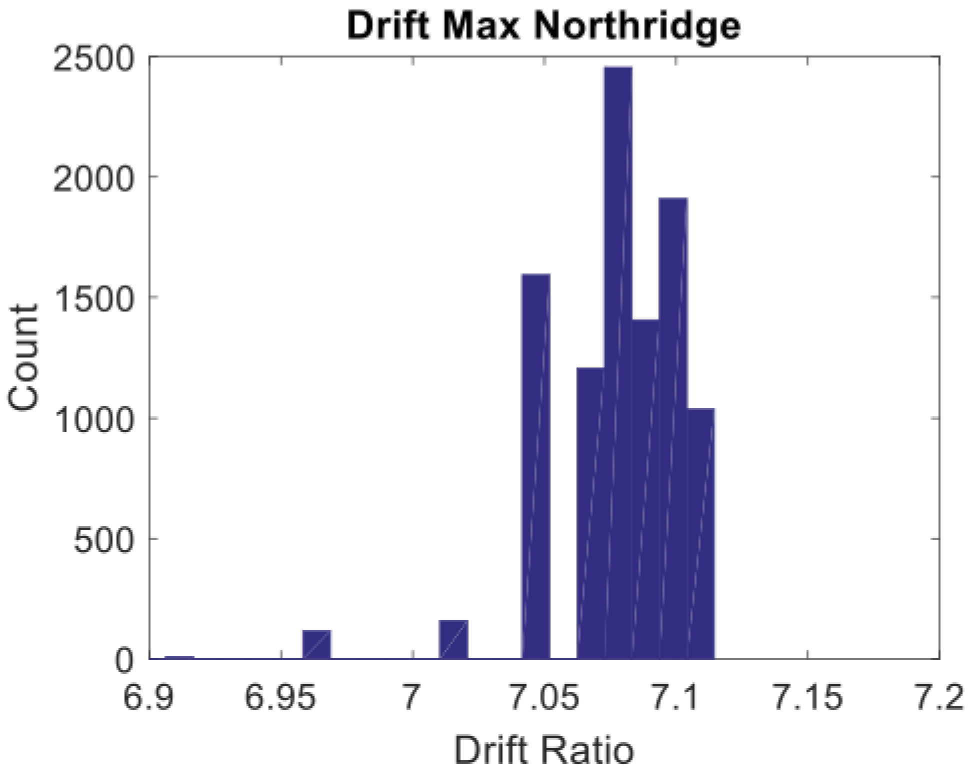

Figure 9. Drift ratio (in percent of structural height) for single story structural model given each set of IMK parameters from the Markov Chain Monte Carlo simulations (Figure 8) under the Northridge Earthquake ground motion.

Analysis of the histogram plot for the counts of lateral displacement of the single story frame model provided 10000 simulations allowed us to conclude that the lateral drift of the structure under simulated earthquakes will be approximately 7.75% of the height of the structural model.

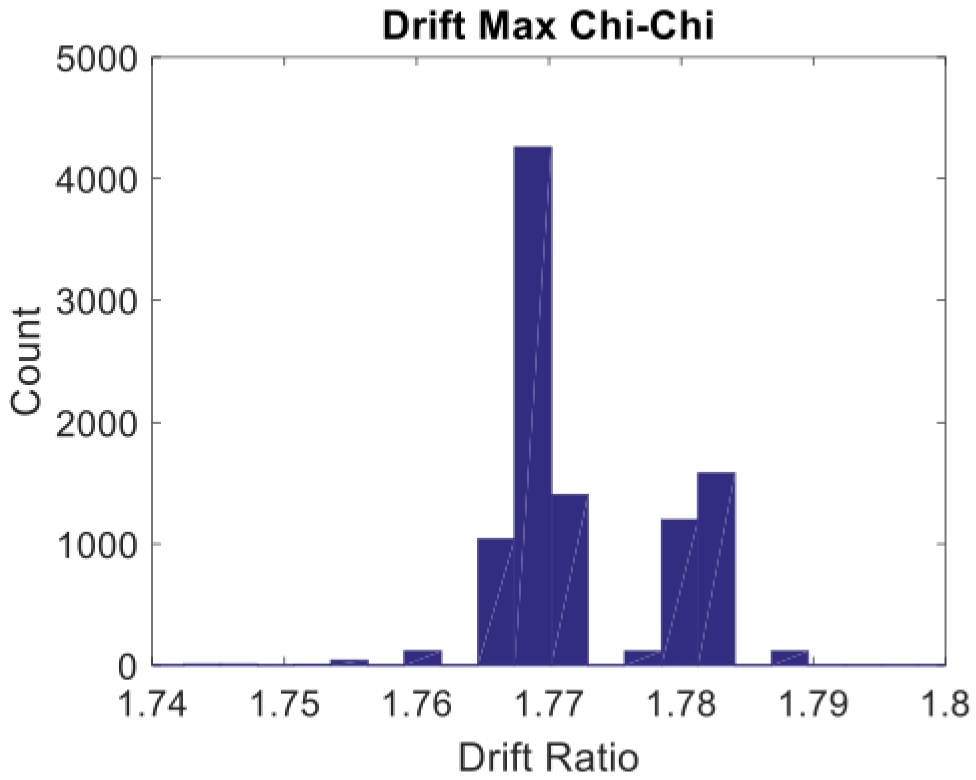

Figure 10. Drift ratio (in percent of structural height) for single story structural model given each set of IMK parameters from the Markov Chain Monte Carlo simulations (Figure 8) under the Chi-Chi ground motion.

Analysis of the histogram plot for the counts of lateral displacement of the single story frame model provided 10000 simulations allowed us to conclude that the lateral drift of the structure under simulated earthquakes will be approximately 1.775% of the height of the structural model.

## 5.0 Conclusions

Aging infrastructure in seismically active regions of the United States has served as a catalyst for revolutionary structural designs that can better withstand earthquakes and other natural disasters. Reliable structural modeling requires analytical tools that can accurately predict strength and stiffness deterioration of structural elements in response to earthquake conditions. Computer simulations allow engineers to test different structural ideas and concepts to find a balance between a cost-effective design and structural integrity. During the course of the ten-week summer research into designing structural simulations under earthquake conditions, we student interns gained valuable experiences learning how to conduct scientific research and how to apply our classroom knowledge to real world applications. We learned how to code in tcl and MATLAB, in conjunction with OpenSees, to produce a precise simulation for the single-story single-bay model's structural response to simulated earthquake conditions.

Cañada College, in collaboration with San Francisco State University, developed a summer research internship opportunity for community college students to encourage students to pursue advanced academic work. The summer internship program has proven successful in recruiting students from underrepresented minority groups to pursue further education and potentially career opportunities in STEM.

## Acknowledgements

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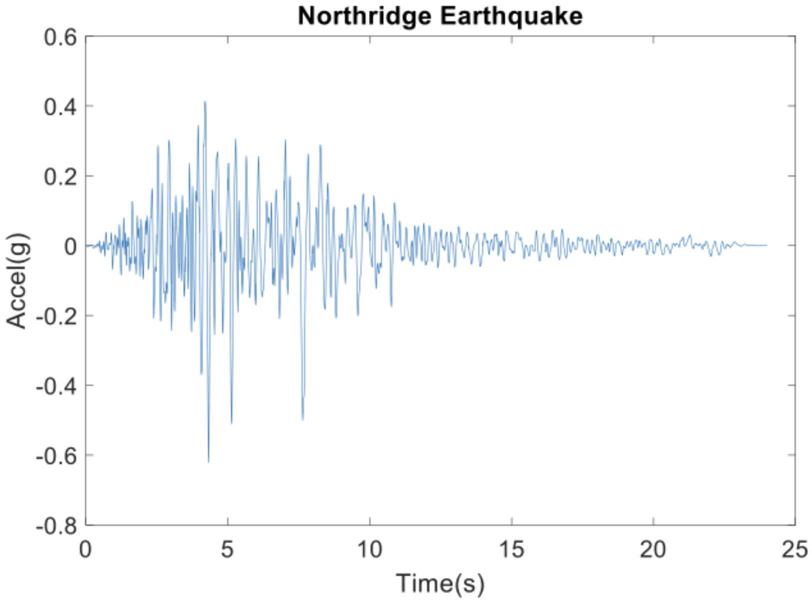
## References

1. Behnam, H. (n.d.). Seismic performance and failure mechanisms of reinforced concrete wide beam-column connections.

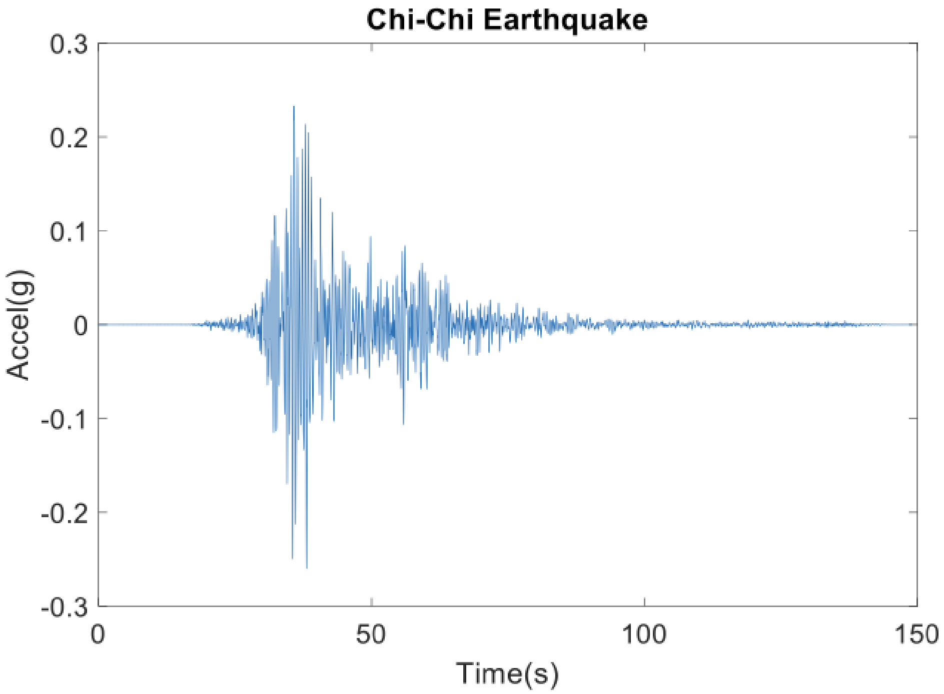
2. Brownlee, J. (2015). Particle Swarm Optimization. Retrieved from http://www.cleveralgorithms.com/nature-inspired/swarm/pso.html
3. Caicedo, J. M., Jiang, Z., & Baxter, S. C. (2017). Including Uncertainty in Modeling the Dynamic Response of a Large-Scale 200 kN Magneto-Rheological Damper. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 3*(2). doi:10.1061/ajrua6.0000873
4. (2011, June). *How Often Do Earthquakes Occur?* Retrieved July, 2016 from https://www.iris.edu/hq/files/publications/brochures_onepagers/doc/EN_OnePager3.pdf
5. Lignos, D. G., & Krawinkler, H. (2011). Deterioration Modeling of Steel Components in Support of Collapse Prediction of Steel Moment Frames under Earthquake Loading. *Journal of Structural Engineering*
6. Marko Laine, Yliopistopaino Helsinki (2008). *Adaptive MCMC Methods with Applications in Environmental Geophysical Models*
7. MATLAB & Simulink, Natick, MA: MathWorks, 2017.Computer software.
8. *PEER Ground Motion Database. (n.d.). Retrieved from PEER Ground Motion Database.*
9. (n.d.). Retrieved from http://dimitrios-lignos.research.mcgill.ca/databases/steel/
10. (n.d.) Retrieved from http://helios.fmi.fi/~lainema/mcmc/
11. (n.d). Retrieved from http://http://opensees.berkeley.edu/

# Appendices

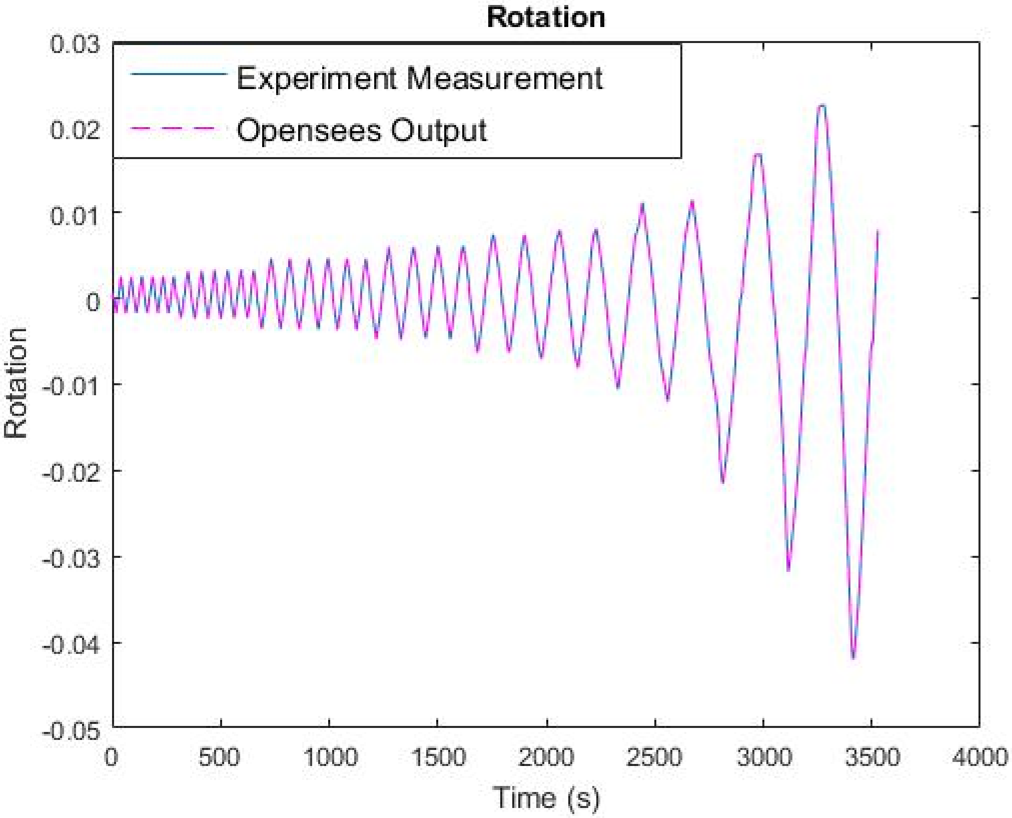
## Appendix A



# Appendix B



# Appendix C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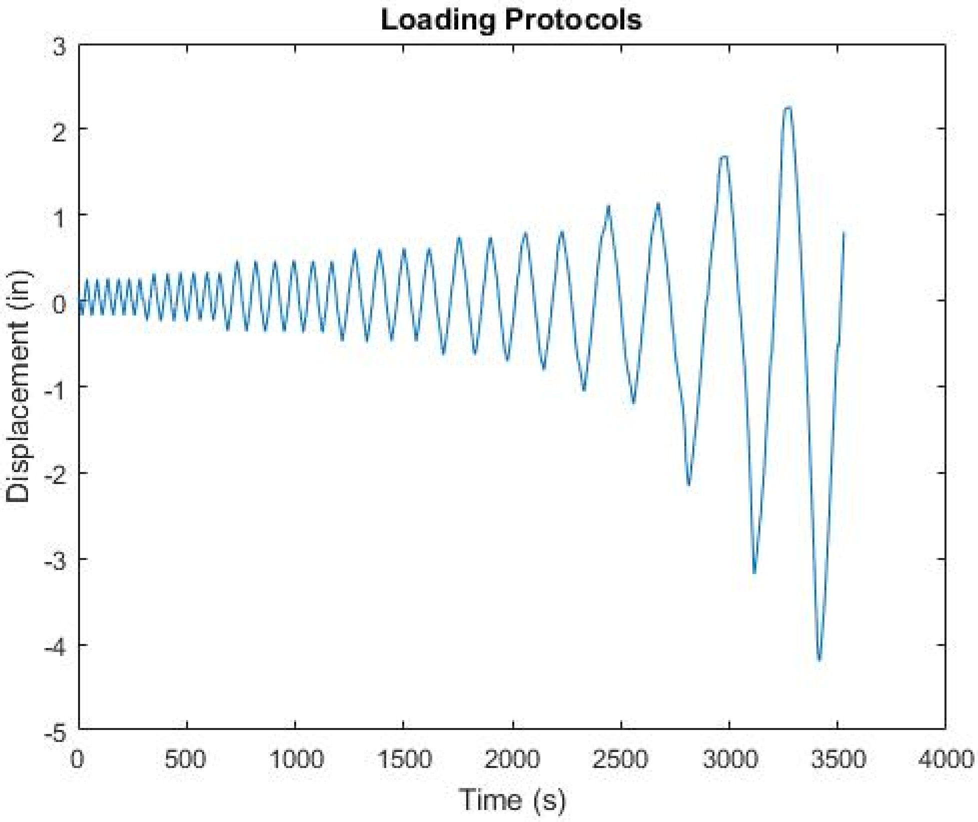
# Appendix D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