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PREDICTION OF BEARING FAILURE WITH SURROGATE MODELING

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Abstract

Isolation, which comes at an increased design and construction cost, is sold as a return on investment due to the decreased damage to both the structure and its contents under typical earthquakes. Given this, and due to the higher upfront cost of isolated structures, building owners would assume an increased level of safety under large earthquakes. Worrisomely, recent studies have shown that code-permitted isolation designs do not outperform typical buildings in terms of collapse probabilities. Researchers have used the FEMA P695 methodology to ascertain these poor collapse probabilities. Furthermore, isolated buildings are used primarily for their high-performance, and designers should be able to adjust the targeted collapse probability based on their clients' needs. However, running detailed structural models to collapse is extremely computationally inefficient and achieving a specific collapse probability requires iterative analysis. This study looks at the ability of surrogate models to predict the performance of double friction pendulum bearings (DFPs) under large events. The data on which the surrogate model is built is derived from in-plane analysis of the DFP modeled with a rigid body model including inertia for each of the bearing components and a non-linear viscoelastic impact element to simulate the impact between bearing components. This model can simulate bearing component impact and uplift and thus, is capable of simulating bearing failure. As isolation systems are particularly vulnerable to long period excitations, analytical pulses are used as input excitations. The pulse parameters and design parameters of the DFP are used as input parameters for the surrogate model. Discrete outcomes of no-impact (building most likely functional), impact (large forces imparted to structure), and failure (significant damage or failure of structure expected) are predicted given a new bearing design and input. This is a first step in facilitating rapid initial design of bearings considering desired collapse margins.

Keywords: sliding bearings, friction pendulum, failure, extreme events, surrogate modeling

1. Introduction

Earthquakes are a significant threat to our society, and to mitigate seismic hazard, many innovative technologies have been used in practice, and base isolation has proven to be one of the most effective ways to improve the seismic performance. The FEMA P695 (2009) framework has been used to set design specifications for most building systems; however, it has not been systematically used to influence the guidelines for seismically isolated buildings. Isolation, which comes at an increased design and construction cost, is sold as a return on investment because of the decreased damage to both the structure and its contents under typical earthquakes. Given this, and due to the higher upfront cost of isolated structures, building owners would assume an increased level of safety under large earthquakes. However, recent studies [1],[2],[3] have shown this to be untrue. Not only do isolated buildings designed to the current code not have lower probabilities of collapse than conventional structures, some code-permitted isolation designs do not meet the target of 10% probability in an MCE event.

Researchers have used the FEMA P695 methodology to ascertain this poor collapse probability. However, running detailed structural models to collapse is extremely computationally inefficient. For example, in Bao and Becker [2], which only ran 2D analyses, a three-story, three-bay building with a moment frame and triple friction pendulum isolation bearings took two hours to run a single analysis, while the building using a concentrically braced frame as the structural system took ten hours to run. Each model was run under 28 different ground motions, each at a minimum of six intensities, to define the collapse fragility curve. Thus, it is a highly burdensome process to iterate and tune building design requirements.

Isolated buildings are used primarily for their high-performance, and designers should be able to adjust the targeted collapse probability based on their clients' needs. For example, isolation is being increasingly adopted for hospitals. As hospitals are critical for community resilience, the United States building code targets a collapse probability of 2.5% [4]. However, there has been no research to ensure that the prescriptions in the code satisfy this performance. New tools are needed that can help designers go more easily from desired collapse probabilities to initial design parameters. As a first step, in this paper, Gaussian process surrogate models are used to predict if a friction pendulum bearing remains stable under a large pulse. The results are used to explore important parameters that influence failure. This study lays the ground work for extending failure predictions to earthquake records and full isoalted buildings.

2. Training data for the surrogate model

2.1 Bearing parameters and model

The training data for the surrogate model is generated from a Matlab model of a relatively simple configured friction pendulum bearing, i.e. double friction pendulum bearing (DFP) is used in this study. The basic configuration of DFP is shown in Fig. 1. The DFP is made up of two concave plates, i.e. the top plate and bottom plate and a rigid slider. Along the perimeter of the concave plate there is a restraining rim to prevent the rigid slider from moving out of place when it reaches its maximum displacement. Even with a relatively simple bearing, there are many basic design parameters including: the radius of curvature R, the friction ocefficient μ, the diameter of the sliding surface D_{out}, the diameter of the slider D_{sl}, the height of the slider h_{sl}, and the height of the restraining rim h_{rim}. While the behavior of friction pendulum bearings is pressure independent if the friction coefficient is assumed constant, under extreme motions when there is impact and uplift the pressure on the bearing, p, may come into play.

A rigid body model developed by Sarlis and Constantinou [2] and modified by Bao et al. [6] is used in to simulate the failure of the DFP. The model was validated through experimental testing under extreme loading resulting in impact and uplift [7]. This model is based on the theory of rigid body kinematics, rigid body dynamics, and contact mechanics. Impact between components and posible uplift can be modeled. This feature makes this model the ideal candidate for this research. In this model, the motion of each component is measured at its centroid, and for this study the top plate is assumed only to have horizontal and vertical translational degrees of freedom while the slider has an additional rotational degree of freedom. All of the forces (i.e. normal forces, frictional forces and potential impact forces) are concentrated at the four vertices of the slider and the corresponding projection points on both plates. Due to the presence of the restraining rim, a couple will develop when DFP reaches its displacement limit, depending on the amplitude of the impact, these forces will either cause the restraining rim to yield or even fracture or they may cause the rigid slider to rotate and uplift. While both scenarios can lead to the failure of the DFP, the rigid body model can model only the uplift failure.

To concider energy dissipation during rim impact, the Hertz's contact law in parallel with a non-linear damper is used to explicitly consider the energy dissipation. In this formulation, to develop normal force and impact force in this model, small penetrations between the components are allowed and these forces are related to the penetration depth through the penalty stiffness, *k*. Energy dissipation is incorporated in the approaching phase of an impact through viscous damping; the damping coefficient is related to the coefficient of restitution, which directly reflects how much energy is dissipated during one impact, in this study the coefficient of resitution is kept constant at 0.65, where 0 is a fully plastic impact and 1 is a fully elastic impact.

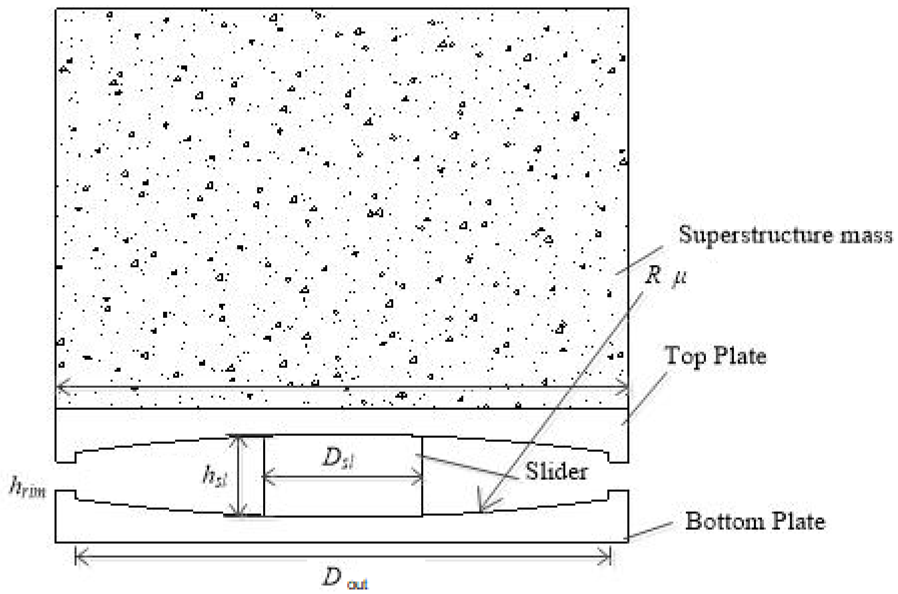

Fig. 1 - Basic configuration of double friction pendulum bearing

2.2 Excitation parameters and model

Because of the stochastic characteristics of ground motions, it is simpler to investigate the response of the DFP under analytical pulse excitations. Here, antisymmetric Ricker pulses [8] are used as input excitations. The analytical Ricker pulse are selected as input excitations for two reasons. The first is that the mathematical expression is relatively simple, only two parameters (period T_p and amplitude A_p) govern its expression. The antisymmetric Ricker pulse as

$$\ddot{u}_g = \frac{A_p}{1.38}\left(\frac{4\pi^2 t^2}{3T_p^2} - 3\right)\frac{2\pi t}{\sqrt{3}T_p} e^{-\frac{2\pi^2 t^2}{3T_p^2}} \tag{1}$$

Many pulse-type ground motions can be approximated by Ricker pulses, Fig. 2 below shows a record from the 2004 Niigata earthquake, with the assocaited antisymmetric Ricker pulse.

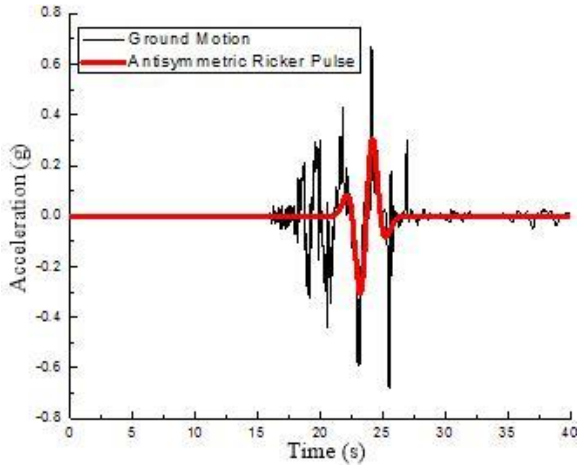

Fig. 2 - Antisymmetric Ricker pulse extracted from a Niigata ground motion record

2.1 Training points

The bearing and input formulation results in the following variables for the model: R, μ, D_{out}, D_{sl}, h_{rim}, p, k, T_p, and A_p. These variables are slightly manipulated. These variable R is related to the period of the bearing T_b by

$$T_b = 2\pi\sqrt{2R/g} \quad (2)$$

Additionally, instead of designing explicitly for D_{out} and D_{sl}, the total bearing displacement D_{tot} approximated by D_{out} - D_{sl} is used. As slider heigh is dependent on the width the ratio h_{sl}/D_{sl} is used. The ratio of the rim heigh to the sldier height h_{rim}/D_{sl} is also used. Two hundred and fifty training points are selected using latin hypercube sampling from standard design ranges given in Table 1. The output of each run is if the bearing impacts, if the bearing impacts but does not fail, and if the bearing fails.

Table 1 – Model input ranges

Bearing parameters	**Range**
T_b (s)	2.5 to 5.5
μ	0.02 to 0.12
D_{tot} (m)	0.450 to 0.850
h_{sl}/D_{sl}	0.33 to 1.3
h_{rim}/D_{sl}	0.05 to 0.2
p (MPa)	30 to 60
k (N/m$^{1.5}$)	2.5*10^8 to 50*10^8
Excitation parameters	**Range**
T_p (s)	0.25 to 5
A_p (g)	0.1 to 0.8

3. Surrogate model

3.1 Input parameters

While the training points focused on physical parameter limits of the bearings, it is helpful to understand how the the relation of these parameters, particularly the excitation to the design parameters, influences performance in extreme events. The following nondimentional variables are used for input, D_{ratio}, T_b/T_p, μ/A_p, h_{sl}/D_{sl}, h_{rim}/D_{sl}, and k_{norm}, where

$$D_{ratio} = \frac{D_{pulse}}{D_{tot}} = \frac{A_p g\left(\frac{T_p}{2\pi}\right)^2}{D_{tot}} \text{ and } k_{norm} = \frac{k}{p\sqrt{D_{pulse}}}$$

The resulting range of input parameters is given in Table 2.

To initial explore the data, logistic regressions were conducted using the above inputs, once to predict impact, and once to predict bearing failure. The resulting models resulted in 98% accuracy for predicting impact and 92% accuracy for predicting bearing failure. The p-values from the regressions are shown in Table 2. For prediction of impact (which of course can be estimated through response spectrum analysis) only D_{ratio}, and μ/A_p were significant parameters. While it is surprising that T_b/T_p was not significant, the lack of incluence for the aspecto ratio of the slider, height of the rim, and impact stiffness and pressure is unsurprising as they do not influence pre-impact behavior. For prediction of the failure only D_{ratio}, T_b/T_p, and μ/A_p. Surprisingly these other terms still are not significant on the prediction. This is perhaps because the firt three terms control the velocity at impact which has strong influence over whether a bearing fails [2].

Table 2 – Input parameter ranges

Input parameter	Range	Median	*p*-values in impact logistic regression	*p*-values in failure logistic regression
D_{ratio}	0.0004 to 1.112	0.14	0.012	0.011
T_b/T_p	0.5 to 22	1.50	0.792	0.004
μ/A_p	0.025 to 1.2	0.12	0.028	$7*10^{-7}$
h_{sl}/D_{sl}	0.33 to 1.3	0.68	0.689	0.20
h_{rim}/D_{sl}	0.05 to 0.2	0.13	0.204	0.52
k_{norm}	0.30 to 102.05	6.32	0.755	0.24

3.2 Model details

To generate the surrogate classification model, the Gaussian process toolbox by Rasmussen and Nickish [9] is used. The model is based on the discriminative approach in which the conditional proability of the classification (i.e. failure or no failure) given the input parameters is directly modeled. Because classification is non-Gaussian, an approximation must be used for inference of the posterior. Here the Laplace approximation is used. While this approximation is known to sometimes give poor shapes to the posterior distribution, for the given dataset, the Laplace approximation resulted in the same accuracy as using the expected propogration method when paired with probit regression. The probit regression forces the regression results into the cumulative distribution of a standard normal distribution with bounds of 0 and 1, so that the results of the regression are the proability of classification as failure.

A constant mean and squared exponential covariance function is used in the model. The length scales of the covariance function are optimized, and unsurprising length scales for the variables which were shown to have large p-values with logistic regression also had length scale an order of magnitude more that the significant variables relative to the variable ranges.

3.3 Model results

Using the parameters described, a surrogate model is generated using 75% of the data. With the other 25% of the data to validate, the model has 97% accuracy. The model classification predictions are shown in Fig.3, 4, and 5 top, with contour lines showing the proability of the model classifying the point to failure. The contour graphs are shown for constant median values of hsl/Dsl, hrim/Dsl, and knorm as these variables have less influence on the predictions. Then each figure gives the contour at constant values of a one of the remaining variables (μ/Ap, Tb/Tp, Dratio respectively). The data marked on the graph are the training points close to the specified parameter values; for example for Fig.3 the points shown under μ/Ap = 0.11, are within a range of μ/Ap equal to 0.09 to 0.13.

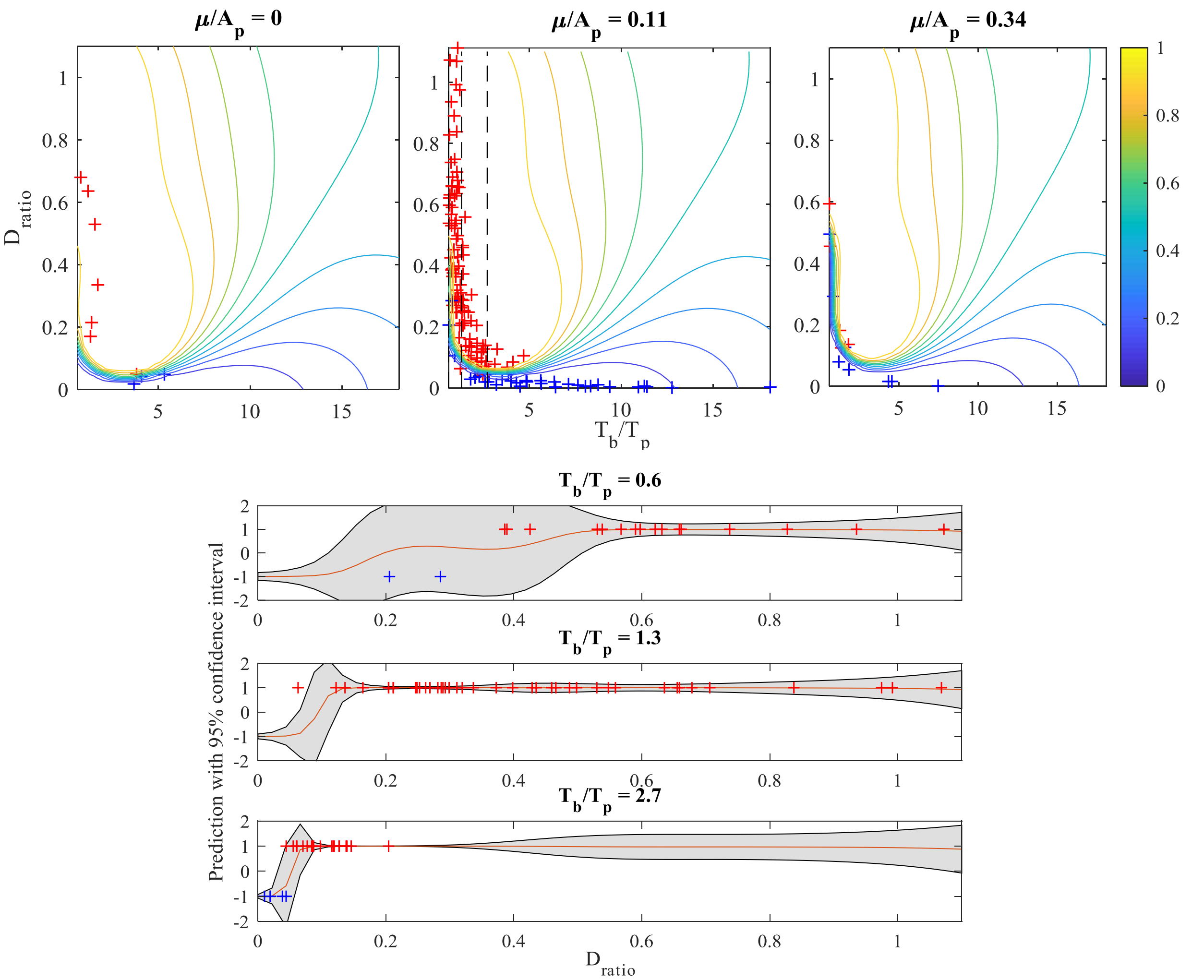

Fig. 3 – (Top) Plots for the equal proability lines given medin values for h_{sl}/D_{sl}, h_{rim}/D_{sl}, and k_{norm}. (Bottom) 95% confidence intervals of the prediction, -1 is no failure, 1 is failure, given constant T_b/T_p values shown in dotted lines on top graph. Local training data is shown with blue indicating no failure and red indicating failure.

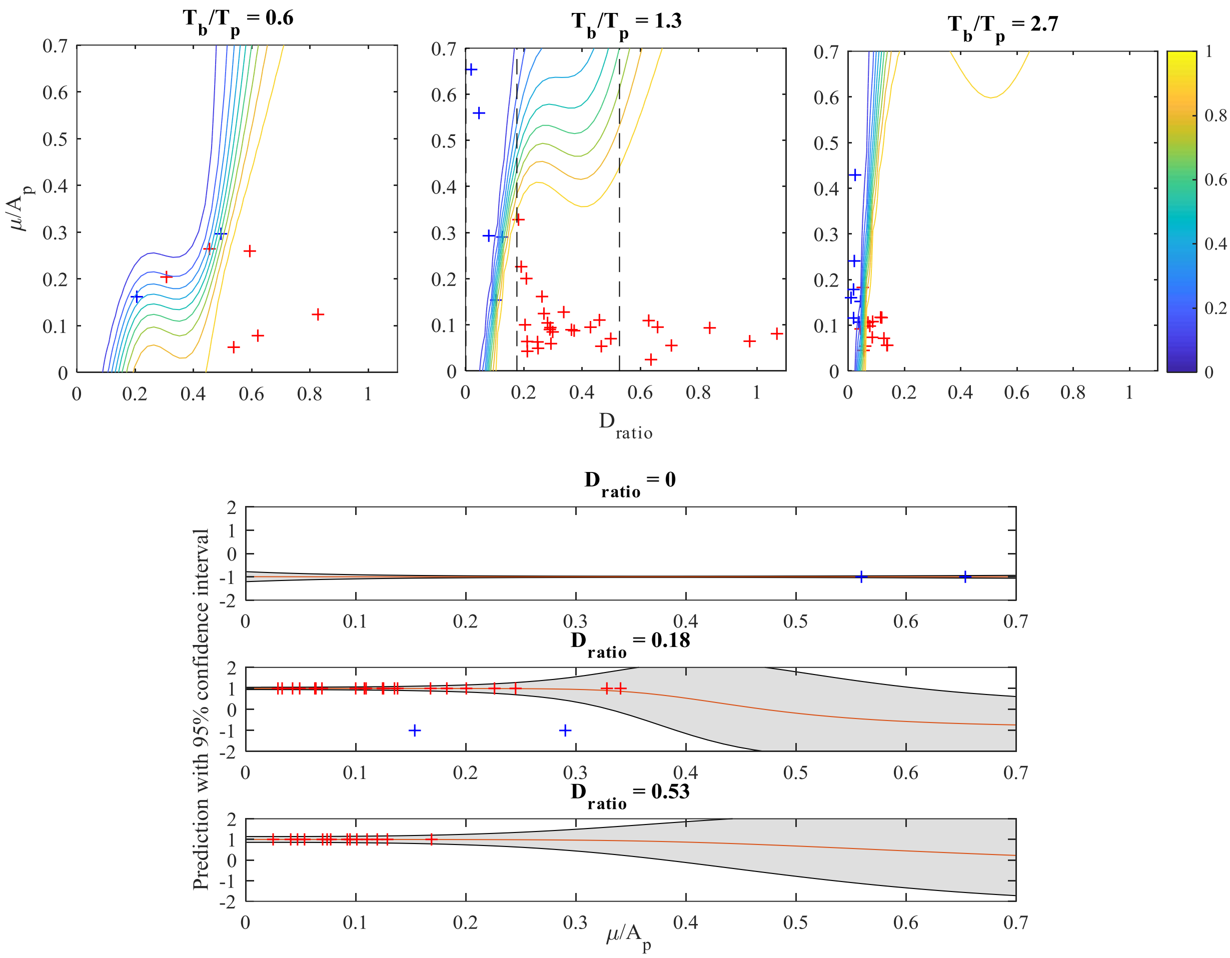

Fig. 4 – (Top) Plots for the equal proability lines given medin values for h_{sl}/D_{sl}, h_{rim}/D_{sl}, and k_{norm}. (Bottom) 95% confidence intervals of the prediction given constant μ/A_p values. Local training data is shown with blue indicating no failure and red indicating failure.

For the most part, the contour graphs show the ability of the surrogate model to seperate distinct regions of failure and non-failure data and capture nonlinear trends in the data (see Fig.3) that would not be posible to capture using a linear logistic regression. There are of course instances where the model still does not form a sharp boundary between the categories, such as in Fig. 4 on the left. This may be a result of not incorporating best posible input variables or may be due to the sensitive nature of the system under extreme behavior.

In Fig.3, 4, and 5 bottom, the model prediction, with -1 being no failure and 1 being failure, is given with the 95% confidence interval and local training data points. The graphs correspond only for the middle subplot of the top graph and are shown for constant x-values shown in the top plot with dotted lines. When the variables are in region were there is data of only failure or non failue, it is clear that the uncertainty is very small. However, in regions where the classification changes abruptly, where data is mixed, or where there is little data, the uncertainty increases considerably. This increase in uncertainty can help target future analyses to limit the amount of computational time necessary to achieve enhanced results.

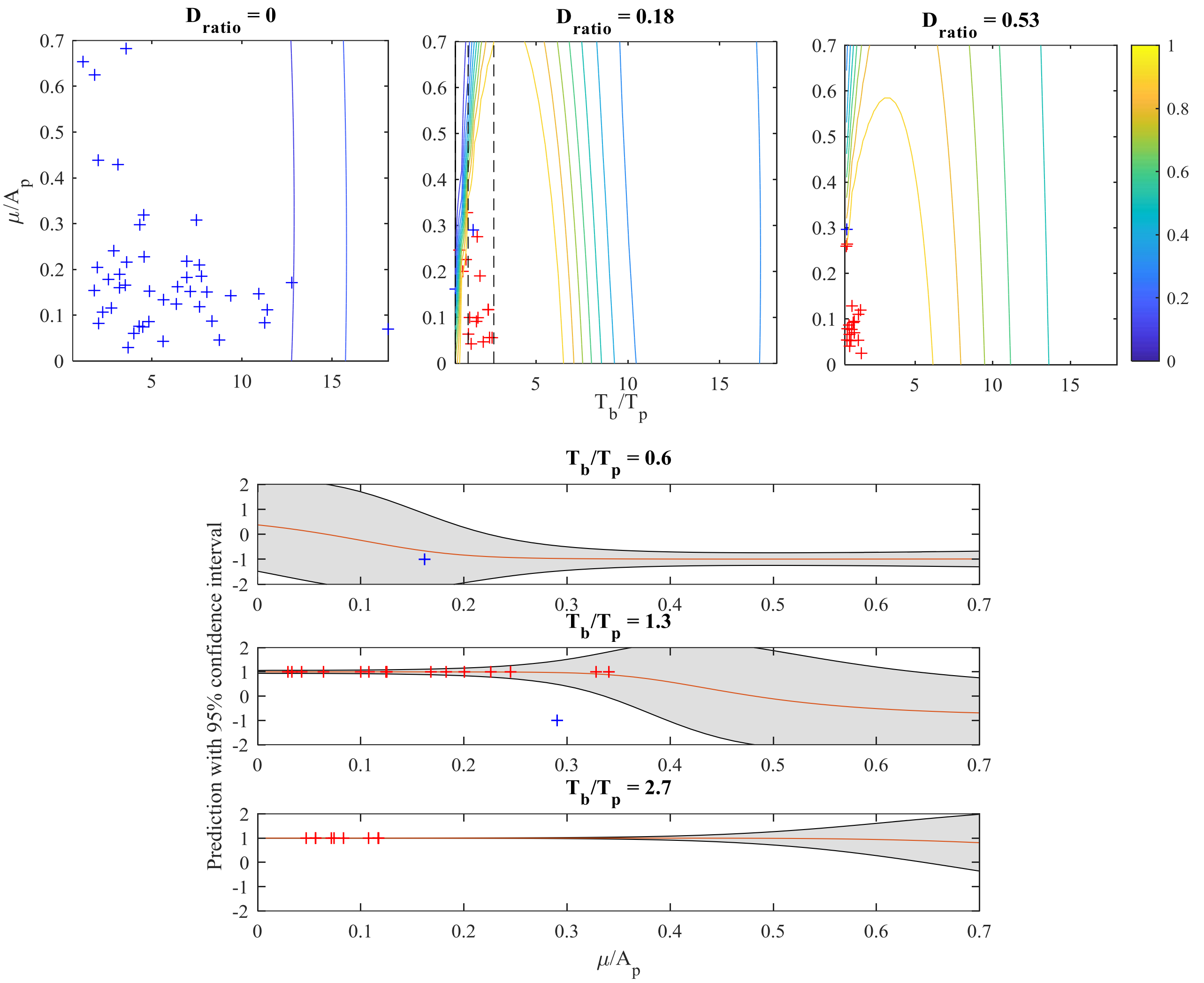

Fig. 5 – (Top) Plots for the equal proabability lines given medin values for h_{sl}/D_{sl}, h_{rim}/D_{sl}, and k_{norm}. (Bottom) 95% confidence intervals of the prediction given constant μ/A_p values. Local training data is shown with blue indicating no failure and red indicating failure.

4. Conclusions

As modeling failure of friction pendulum bearings is computationally expensive, the ability to predict failure using Gaussian process surrogate models was explored. To general training points, a rigid block model which cancapture failure was used with Ricker pulses as the inputs. Two hundred and fifty training points were generated using latin hypercube sampling to select over a range of feasible bearing design paramters and input parameters. The paramters were normalized when used to train the model as for more complex situations in future extensions, it is best to be able to relate bearing design paramters with input paramters.

First, simple linear logistic regression was used to explore th input paramters, finding that the paramters with most control over the failure were the ratio of bearing period to pulse period, ratio of pulse displacement to displacement capacity, and ratio of friction coefficient to pulse amplitude. This finding held when moving forward with the Gaussian surrogate model. While the linear logistic regression had very good accuracy in predicting failure (92%). The surrogate model imporved upon this accuracy, reaching 97%. Furthermore, the model gives enhanced information on uncertainty of predictions. This study forms an initial basis into predicting the behavior of these complex systems. In the future Gaussian process models can be used for building level performance to ensure robust desings, and help target designs for specific collapse probabilities.

6. References

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