Deep Learning-based Friction Modeling of Dry Interfaces for Structural Dampers

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ABSTRACT
Friction-based dampers have gained attention as a cost-effective way to provide structural control during natural hazards. However, the dry friction interfaces in these systems result in a highly non-linear damping response during the reversal of damper travel, termed damper backlash. Moreover, the stick-slip phenomena intrinsic to the sliding response of dry friction interfaces make the accurate modeling of friction-based structural dampers challenging. Dynamic friction modeling for structural dampers currently relies on analytical models to approximate the damper's response at a current location given the damper's state, and average out the complex system responses during travel reversal or stick-slip movement to obtain a model of the system's performance. In this work, we propose the use of a deep learning model to capture the temporal dynamics of the system that when combined with the LuGre friction model provides a physics-informed machine learning approach for inferring the damping force of a dry friction interface given the state of the model. Specifically, this work uses a long short-term memory model to infer the LuGre friction model's parameters. A methodology for parameter identification using truncated backpropagation through time is given which allows for real-time updating. Model validation is performed using a 9 kip rotary friction damper designed for high damping performance and mechanical simplicity. The model is validated with data from real natural hazard events and used in a real-time hybrid simulation. The performance, reliability, and accuracy of the deep learning-based friction model are discussed.

Keywords: friction modeling, physics-informed machine learning, LuGre model, structural control, damper

INTRODUCTION

Damping systems such as viscous dampers and tuned mass dampers are commonly used to mitigate damage from earthquake and wind events [1]. Friction dampers have the potential to be implemented as cost effective and mechanically reliable systems capable of producing large damping forces [2]. However, modeling the nonlinear dynamics of friction dampers is challenging. Such modeling is complicated by various nonlinear phenomena present in dry friction interfaces; such as hysteresis and the stick-slip phenomenon. Furthermore, due to the nature of their mechanical linkages; friction dampers exhibit a phenomenon termed backlash, where friction is momentarily drops during reversal of travel.

Physics-based models that describe simplified friction systems and have the ability to account for properties such as hysteresis and stick-slip phenomena [3]. However there is concern that physics-based models cannot accurately represent the complexities of real systems. Physics models typically ignore the backlash effect or use state-based modeling schemes which can be difficult

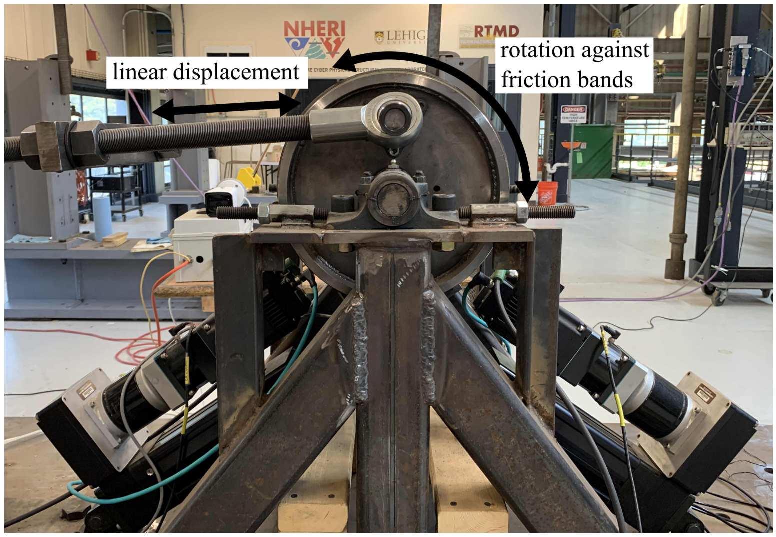

Figure 1: The banded rotary friction device [7].

implement and manage. Alternatively, data-driven models such as machine learning (ML) may capture system dynamics, but lack the informed structure of a physics-based model. Of particular concern is (1) the ability of the model to produce physically consistent results, and (2) how models generalize to data dissimilar to the training set. In general, physics-informed machine learning uses ML techniques within the informed structure of a physics model, with the goal of more accurately representing physical systems while conforming to the two problems given above [4]. Relevant to this work, with parameter prediction, ML is used to produce intermediate parameter values which are used by the physics model.

In this paper, a physics-informed deep learning approach is further developed to model non-linear dynamics of the dry friction interface present in structural dampers [5]. The LuGre dry friction model [6] provides the structure for the physics-based modeling where the LuGre model's parameter that considers the rising rate of friction is augmented with a deep learning model trained on experimental time-series data to capture the backlash effect. Parameter estimation comes from a long short-term memory (LSTM) model and a methodology for the indirect training of the LSTM model is presented. The characterization data comes from a 9 kip rotary friction damper which displays the backlash effect [7]. The experimental dataset used in this work is made available through a public repository [8]. The contribution of this work are twofold: (1) a deep learning-based friction modeling approach for dry interface modeling is presented and (2) the intermediate value calculation from the deep learning model is investigated to measurement of the estimated parameter before, during, and after the backlash region.

BACKGROUND

The banded rotary friction device (BRFD), shown in figure 1, is a rotary friction damper in which the friction force is produced as an internal steel drum rotates against a static double wrap band. In a proposed implementation of the BRFD, linear displacement from interstory drift is transduced into angular displacement. During semi-active control, the electric actuators connected to either end of the band alter band tension to control the dominant damping force. Both ends of the band are connected to electric actuators. During semi-active control, the electric actuators alter band tension to alter the dominant damping force. Figure 2 shows the BRFD test set-up at NHERI Lehigh Experimental Facility used to capture the experimental data used in this work where a hydraulic actuator produces the displacement profile. Characterization tests consisted of a sinusoidal displacement profile with a period varying between 1 and 20 seconds. The initial band tension was set to be constant and the band actuators did not activate during the tests. Band tension is measured by load cells attach on either side of the band and the damping force is measured by an internal load cell from the hydraulic actuator.

The BRFD benefits from a phenomenon known as the self-energizing, or positive servo effect. As the drum rotates, the grip pressure between the drum and band increases, consequently increasing the normal force on the friction interface. As the self-energizing effect is dependent on the direction of velocity, during reversal of travel the effect depletes before being reactivated in the other direction. When the friction band is not energized in either direction, termed the backlash region, the force momentarily reduces to zero. The backlash effect can be seen in the S-shaped deflection in the hysteresis curve shown in

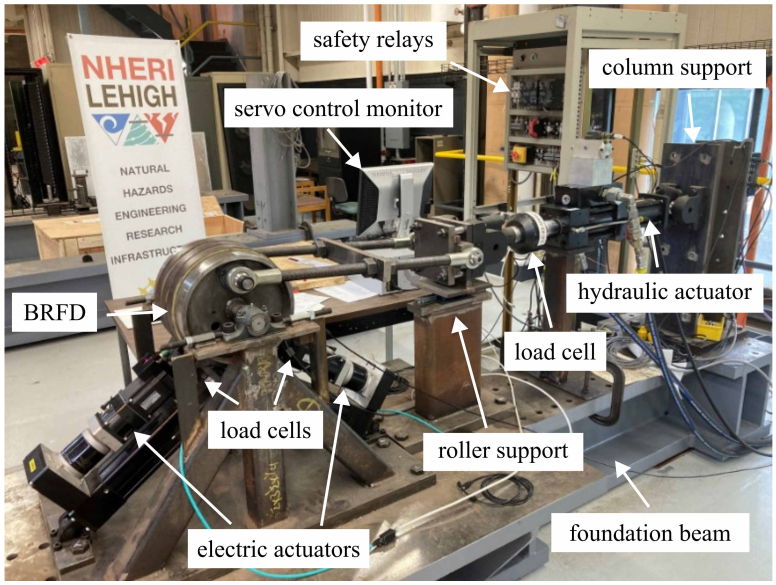

Figure 2: BRFD test setup at NHERI Lehigh Experimental Facility [9] that was used to create the open-source experimental dataset [8] used in this work.

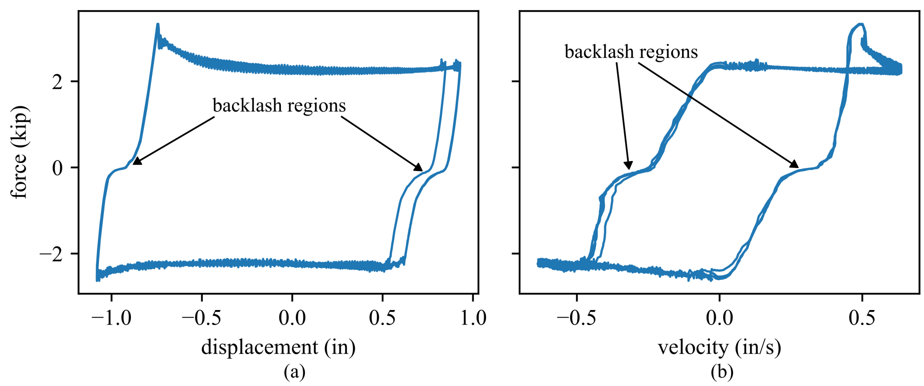

Figure 3: Friction force produced by the BRFD plotted against (a) displacement and (b) velocity with backlash regions labeled.

figure 3(b).

The LuGre dry friction model, shown in equations 1-3, is a commonly used dry friction model inspired by representing energy dissipation as the deflection of bristles in contact between two surfaces in relative motion.

$$\dot{z} = v - \sigma_0 \frac{|v|}{g(v)} z \tag{1}$$

$$F = \sigma_0 z + \sigma_1 \dot{z} + \sigma_2 v \tag{2}$$

$$g(v) = F_c + (F_s - F_c)\, e^{|\frac{v}{v_S}|^2} \tag{3}$$

with the state parameter z and velocity input v. Equation 1 is generally unsolvable, but a solution can be found that is locally true (i.e. $v \approx$ const) that motivates this analysis:

$$z(t+\varepsilon) = \frac{g(v)v}{\sigma_0 |v|} + \left(z(t) - \frac{g(v)v}{\sigma_0 |v|} \right) e^{-\sigma_0 \frac{|v|}{g(v)} \varepsilon} \tag{4}$$

Notably, σ_0 appears as the rate of change variable in the exponential decay function from $z(t)$ to the steady state value $z_{ss} = \frac{g(v)v}{\sigma_0 |v|}$.

Yet σ_0 also appears in the expression for the steady state value. The extreme values of z_{ss} are given when $g(v)$ is at its maximum and $v/|v| = \text{sgn}(v)$ is either positive or negative. As z is always approaching z_{ss}, these values also serve as extreme values for z. This is called the boundedness property and is given as

$$|z| \leq \frac{F_\text{s}}{\sigma_0} \tag{5}$$

The backlash effect could be captured by augmenting the LuGre model to allow a time dependent rate of change variable. However in the form above we see that σ_0 both controls the rate of change as well as the steady state value z_{ss}. When σ_0 is constant, this is inconsequential since z is multiplied by σ_0 to produce the steady state force $F_{ss} = g(v)\text{sgn}(v) + \sigma_2 v$. Such a derivation does not apply to a time dependent σ_0. In particular, there is potential for a 'slewing' effect, whereby force will change dramatically even though z changes only minorly, as σ_0 drives changes in F. In the most extreme case, F may become discontinuous or violate the boundedness property. A solution to this is to modify the model by defining the state variable as $y = \sigma_0 z$. The model given in equations 6-8 is equivalent to the standard LuGre model when σ_0 is constant, but does not produce a slewing effect when σ_0 is variable.

$$\dot{y} = \sigma_0 \left(v - \frac{|v|}{g(v)} y \right) \tag{6}$$

$$F = y + \frac{\sigma_1}{\sigma_0} \dot{y} + \sigma_2 v \tag{7}$$

$$g(v) = F_\text{c} + (F_\text{s} - F_\text{c})\, e^{|\frac{v}{v_s}|^2} \tag{8}$$

and boundedness is represented as

$$|y| \leq F_\text{s} \tag{9}$$

Recurrent neural networks (RNNs) are a type of neural network designed to process time-sequence data. A generic RNN contains weight matrices for the current timestep input and a recurrent weight matrix, which connects to a state vector from the previous timestep. Such a connection allows RNNs to produce inference based on all previous timesteps. Long short-term memory (LSTM) is a type of RNN designed to solve the vanishing gradient problem. LSTMs have become the most common form of RNN and have shown success in areas such as speech recognition and machine translation. Equations 10-15 show the calculations of an LSTM for one timestep.

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{10}$$

$$i_t = \sigma\left(W_i x_t + U_i h_{t-1} + b_i\right) \tag{11}$$

$$o_t = \sigma\left(W_o x_t + U_o h_{t-1} + b_o\right) \tag{12}$$

$$\tilde{c}_t = \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right) \tag{13}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \tag{14}$$

$$h_t = o_t \circ \tanh\left(c_t\right) \tag{15}$$

where σ is the sigmoid activation function. W and U are the current timestep and recurrent connection weight matrices respectively.

In a direct training approach, the parameter in question would be measured along with the training inputs to train the physics-ML model. However, direct measurement of the dynamic parameters of the LuGre model, including σ_0 is impossible. Therefore, training the LSTM model prediction of σ_0 proceeded using an indirect approach. In the indirect method, the error gradient from the model prediction is backpropagated through the LuGre model to produce an error gradient for the prediction of σ_0. Backpropagation is then used to train the LSTM prediction. Figure 4 shows forward inference and backpropagation in the model. The error gradient with respect to σ_0 is an intermediate value to the error gradient with respect to the model weights. Multiple model configurations were tested with the best results given by the model shown in figure 4, containing two stacked LSTM cells with 30 units and a dense layer. Band tension is used as the input to a LSTM model.

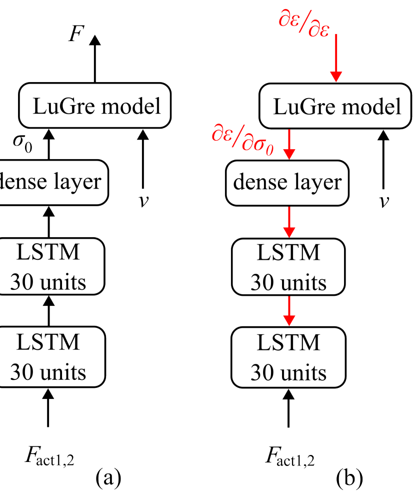

Figure 4: Dataflow through the model in (a) forward inference and (b) training through backpropagation.

ANALYSIS

Figure 5(a) shows a force-velocity plot of a characterization test fitted to a LuGre model with a least-squares approach. The model does not capture the dynamics of the backlash region, and model's rising rate is roughly an average of those in the three distinct regions before during and after backlash region. Figure 5(b) shows the same test plotted with the physics-ML model. The model fits the distinct regions of reversal travel, and produces a smaller error. Table 1 shows error in normalized root mean squared error (NRMSE) and signal to noise ratio (SNR) for the LuGre comparison models and the physics-ML model. Formulas for NRMSE and SNR are given in equations For each dataset, a separate LuGre comparison model was fitted. In contrast, the same physics-ML model is used across all datasets. Overall NRMSE error was reduced 53% from the LuGre model to the physics-ML model.

$$\mathrm{NRMSE} = \frac{\sqrt{\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}}{T\,(y_{\max} - y_{\min})} \tag{16}$$

$$\mathrm{SNR}_{\mathrm{dB}} = 10 \times \log\left(\frac{\sum_{t=1}^{T} y_t^2}{\sum_{t=1}^{T}(y_t - \hat{y}_t)^2}\right) \tag{17}$$

Table 1: Error from LuGre and physics-ML models

	LuGre model		physics-ML model	
dataset	SNR (dB)	NRMSE	SNR (dB)	NRMSE
0.05 Hz	13.22	6.65%	19.26	3.32%
0.1 Hz	13.49	6.1%	19.88	2.92%
0.5 Hz	9.74	8.2%	19.44	2.69%
1.0 Hz	8.97	9.06%	17.91	3.24%
overall	12.85	6.71%	19.39	3.16%

Intermediate value calculation produces an indirect measurement of the estimated parameter. In the case of friction damping, this is useful as direct measurement of σ_0 is not possible. Figure 6 shows a time-series plot of the LSTM model's prediction of σ_0 during reversal of travel. The model produces three distinct values during the three phase of the backlash cycle. In the initial drop, the bands are de-energized and the average σ_0 value is 23 kip/in. During the backlash region σ_0 averages 3 kip/in. After the band is re-energized in the opposite direction, σ_0 prediction rises to 48 kip/in.

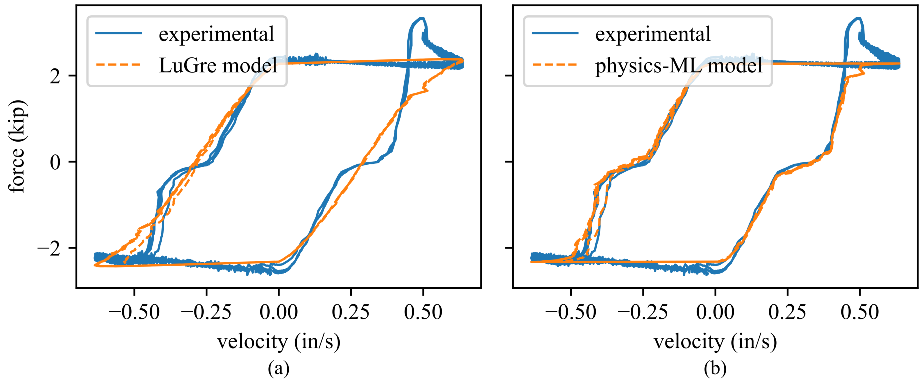

Figure 5: Force-velocity hysteresis plots for the 0.1 Hz dataset, showing the predictions obtained from the (a) LuGre model and (b) physics-ML model.

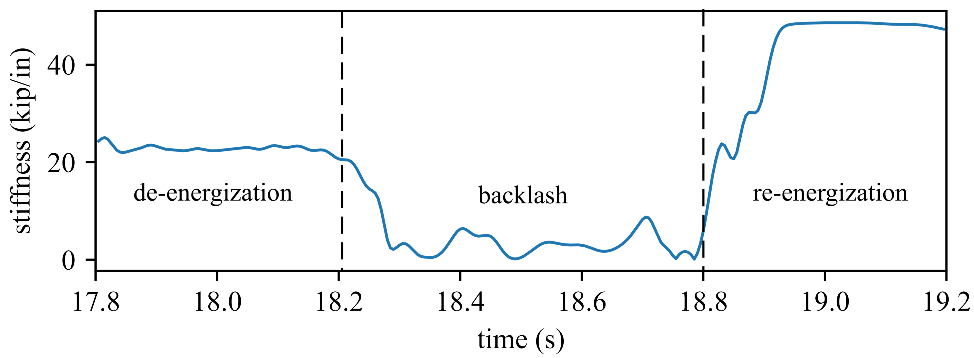

Figure 6: Model prediction of σ_0 during a reversal of travel with the three regions annotated.

CONCLUSION

The design of a model for dry friction systems was presented and applied to a 9 kip rotary friction damper. This new model augmented the LuGre friction model to accept a time-variable σ_0 parameter, and time series estimation of the parameter was produced by an LSTM model. An indirect methodology for training the LSTM model was demonstrated. The resulting model fitted the data with a SNR of 19.39 dB and an NRMSE of 3.16%. Such results reduced error by 53% compared to LuGre models fitted using a least-squares method. Finally, the use of the deep learning model as a way of indirect measurement of was investigated, and the ML model was shown to produce parameter predictions in three distinct regions during reversal of travel, matching the expected results of backlash behavior.

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