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 display highly non-linear damping phenomena such as the stick-slip phenomena and damper backlash during reversal of travel. In this work, we develop a new physics-informed friction model to represent a 40 kN rotary friction damper designed for high damping performance and mechanical simplicity. Specifically, the LuGre dry friction model is augmented with the use of online parameter estimation from two long short-term memory models. It is shown that the physics-informed model preserves a state-boundedness property similar to the LuGre model. A methodology for model training is given which uses direct training for static parameters and back-propagation to produce an indirect training method for the dynamic parameter σ_0 in the LuGre model. Results from training datasets are then compared against LuGre models found with the least-squares method. The model is validated with data from a hybrid simulation of the damper installed in a structure under wind loading.

KEYWORDS: *NHERI Lehigh; natural hazards; friction dampers; friction modeling; physics-informed machine learning; LuGre model.*

INTRODUCTION

Damping systems are now in widespread use in structural controls and are used to mitigate damage from wind and earthquake events (Saaed et al. 2015). Of interest to this paper is the class of friction dampers, which can produce larger damping forces than other damping systems, while maintaining mechanical simplicity and low costs (Cao et al. 2016). One problem preventing the implementation of friction dampers is their nonlinear dynamics. An accurate dynamical understanding of a damper is imperative, as an untuned damper may have either negligible or detrimental effects on a structure's performance (Nabid et al. 2018). However, modeling is complicated by the nonlinear stick-slip phenomenon present in dry friction interfaces. Furthermore, friction dampers exhibit loss of friction during reversal of travel termed backlash.

Most research in friction modeling is within servo and pneumatic controls, where model-based compensation allows for greater precision movement. A common choice for modeling dry friction systems is the LuGre model, which was developed as a modification of the Dahl model to account for the Stribeck effect (Canudas de Wit et al. 1995). The LuGre model calculates force as a function of velocity and a state variable, interpreted as average bristle deflection. However, fitting the dynamic parameters of 'rate and state' models to a friction system has been observed to be a difficult problem.

Various methodologies have been proposed for parameter identification of the LuGre model. Madi et al. (2004) proposed a methodology using set inversion to bound model parameters and validated by modeling an electro-pneumatic actuator. Liu (2006) applied a genetic algorithm to identify the system properties of a mechanical servo. Wenjing (2007) identified LuGre model parameters in a similar system using a particle swarm optimizing algorithm. These methods avoid the local minimum problem but suffer from inefficient computation time. In the realm of online training, adaptive controllers have been used to identify parameters for friction compensation of a pneumatic actuator (Khayati et al. 2009), while Wei et al. (2014) used a recursive least-squares method to fit piezoelectric actuation to a Bouc-Wen model.

A simple alternative to parameter identification in physical models is the use of data-driven models. Although given sufficient data, machine learning (ML) models are adequately able to describe a physical process, stakeholders are often wary to implement ML models because of their "black box" nature, which gives no certain model properties. Compare this to the LuGre model, which has known properties such as state-boundedness, and, under certain conditions, passivity (Canudas de Wit et al. 1995), (Barabanov 2000). Recently, researchers have become interested in a combined approach, termed physics-informed machine learning, which offers the advantages of both ML and physics-based modeling (Vadyala et al. 2022). Most physics-informed machine learning approaches have focused on constraining neural networks to behave under known physical rules, such as time or spatial invariance. Other work, more relevant to this paper, combines ML components into a larger physics-driven architecture in a method termed hybrid physics-ML modeling (Willard). Hybrid physics-ML models may be more accurate than pure physics models; while retaining certain advantageous properties.

In this paper, the authors create a physics-informed machine learning model to describe the friction effects of a 40 kN rotary friction damper. This model uses a modified LuGre model online parameter prediction from two long short-term memory (LSTM) models. The rest of this paper is organized as follows. First, the rotary friction damper and test setup are presented. The LuGre dry friction model and long short-term memory are then explained before a modified LuGre model used for online parameter updating is given. A training process for parameter prediction is given. Results are shown on characterization and validation datasets. The performance, reliability, and accuracy of the model are discussed.

THE BANDED ROTARY FRICTION DEVICE

The banded rotary friction device (BRFD) is a semi-active friction damper proposed for use in structural control by Downey et al. (2016). The system is based on a double wrap band brake system designed to produce a high amplification of the applied force. Fig. 1 shows a profile view of the BRFD. The device consists of three steel bands lined with a friction surface wrapped around a steel drum. Linear displacement, such as from interstory drift, is transduced to an angular displacement in the drum. Energy is dissipated from the friction contact between the friction material and the drum's surface.

Semi-active control is accomplished with two electric actuators which connect to either end of the band. When an actuator is activated, the band tightens around the drum, increasing the pressure between the band and drum and increasing the friction force.

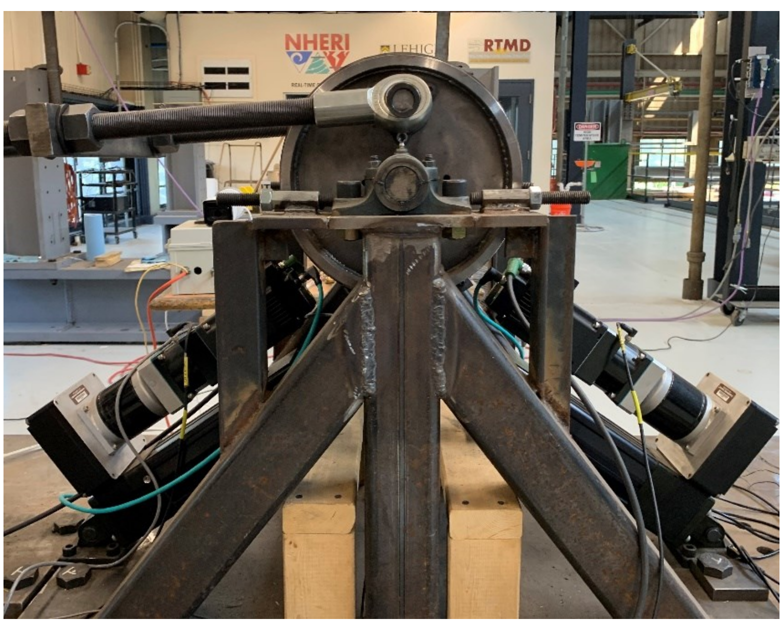


Fig. 1. Front view of the banded rotary friction device (Coble 2022).

As the drum rotates, the bands grip more tightly around the drum and increasing the friction force in what is known as the self-energizing effect. When angular velocity changes sign, the friction force drops as slack in the bands is introduced. The damping force is amplified again as the band rotates in the opposite direction, taking up the slack in the bands and again benefiting from the self-energizing effect. In the region where the self-energizing effect is not active in either direction, termed the backlash region, the damper behaves with different friction properties (Cao et al. 2016).

Fig. 2 shows the BRFD on a structural testbed. A displacement profile is given by a hydraulic actuator and a load cell connected to the actuator measures the responding force. Electric actuators are connected to each end of the bands and are used for semi-active control. Load cells are placed between the friction bands and electric actuators to obtain the generated tension force.

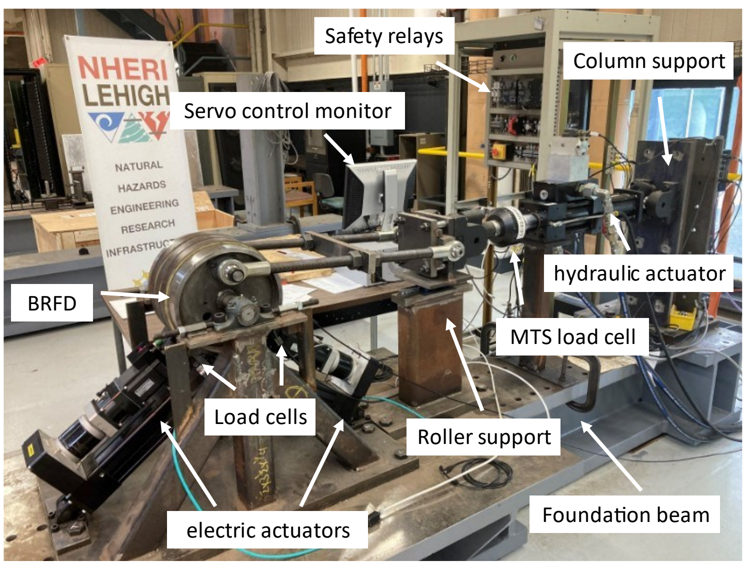


Fig. 2. Banded rotary friction device test set-up.

THE LUGRE MODEL

The LuGre dry friction model describes a simplified system where friction is generated from the contact and deflection of bristles coming from two surfaces. Fig. 3 shows a representation of two surfaces in a LuGre system. As one surface moves past the other, energy is absorbed in the deflection of the bristles.

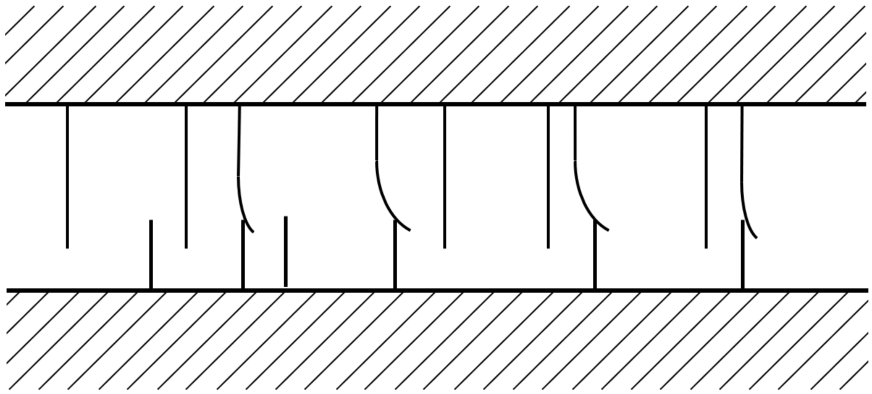


Fig. 3. A LuGre dry friction with contact between bristles on two surfaces. Adapted from Canudas de Wit 1995.

The LuGre model is described in Eqs. (1-3).

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

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

$$g(v) = F_{\mathrm{c}} + (F_{\mathrm{s}} - F_{\mathrm{c}}) e^{\left|\frac{v}{v_{\mathrm{s}}}\right|^2} \tag{3}$$

where z is a state variable representing bristle deflection. F_{s} and F_{c} are static and kinetic friction, and v_{s} is the Stribeck velocity. The dynamic parameters σ_0, σ_1, and σ_2 represent stiffness, the damping coefficient, and viscous friction respectively, are the hardest to determine experimentally.

A modified g can be used to capture effects that are not symmetric with the direction of force.

$$g(v, F) = \begin{cases} F_{\mathrm{c,neg}} + \left(F_{\mathrm{s,neg}} - F_{\mathrm{c,neg}}\right) e^{\left|\frac{v}{v_{\mathrm{s}}}\right|^2} & F \leq 0 \\ F_{\mathrm{c,pos}} + \left(F_{\mathrm{s,pos}} - F_{\mathrm{c,pos}}\right) e^{\left|\frac{v}{v_{\mathrm{s}}}\right|^2} & F > 0 \end{cases} \tag{4}$$

An important property of the LuGre model is state-boundedness. Given a general function g and a starting state $z_0 = 0$, state-boundedness gives

$$|z| \leq \frac{\max(g)}{\sigma_0} \tag{5}$$

where $\max(g)$ is the maximum value in the range of g.

LONG SHORT-TERM MEMORY

Recursive neural networks (RNNs) are designed for processing time-sequence data, where the desired output may have a history-dependance on the input data. While standard RNNs are able to represent history-dependence, in practice they suffer from an effect called the vanishing gradient problem, which limits learning from long sequences. Long short-term memory (LSTM) was proposed by Hochreiter and Schmidhuber in 1997 to overcome the vanishing gradient problem and has found success in areas such as machine translation and speech recognition. Eqs. (5-10) show the equation form of one LSTM timestep. W matrices are the weights for the current time step input and U matrices process the recurrent connection to the previous timestep output.

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \tag{6}$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \tag{7}$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \tag{8}$$

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \tag{9}$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \tag{10}$$

$$h_t = o_t \circ \tanh(c_t) \tag{11}$$

PHYSICS-INFORMED MODEL

The LuGre model is not capable of capturing the backlash effect or the changing normal force associated with semi-active control. To capture these effects, the authors present the modified LuGre model in eqs. (12-13), where the parameters F_c, F_s, and σ_0 are taken to be time-variable. Varying F_c and F_s captures changes in normal force, while σ_0, which is related to the rising-rate of force after the velocity changes sign and captures the backlash effect. Notice that with constant parameters, this model reduces to the standard LuGre model with the state parameter $y = \sigma_0 z$.

$$\dot{y} = \sigma_0 \left(v - \frac{|v|}{g(v)} y \right) \tag{12}$$

$$F = y + \frac{\sigma_1}{\sigma_0} \dot{y} + \sigma_2 v \tag{13}$$

Preservation of the state-boundedness property was the main motivation for the substitution of the state variable in the modified model. In the modified model, state-boundedness is described by

$$|y| \leq \max\,(g) \tag{14}$$

The time-dependent parameter estimations come from two LSTM models which predict the static parameters F_c and F_s and the dynamic parameter σ_0 respectively. The inputs to these LSTM models are the actuator tension measured by load cells connected between the actuators and bands, $F_{\mathrm{act}-1}$ and $F_{\mathrm{act}-2}$. Actuator tension is expected to have a non-linear relationship to all three of the predicted parameters. Fig. 4 shows a flow chart representation of the model.

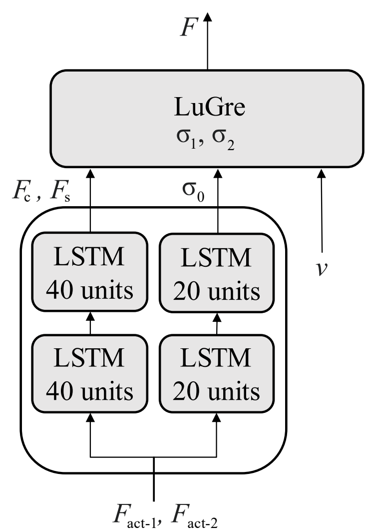


Fig. 4. Physics-informed machine learning model used in this work where the LSTM models are used to train select parameter.

TRAINING

In producing data for characterization, the BRFD was tested under a sinusoidal displacement profile. The profile was modified to vary the period of the sinusoid between 0.05 Hz and 1.0 Hz. To give data on the relationship between the tension force and friction force, tests were run varying initial tension between 20 lb and 80 lb. In total, 24 characterization datasets were produced. Validation data was collected from five hybrid simulations of the BRFD installed in a structure under wind loading. Displacement, velocity, friction force, and actuator tensions were recorded during these tests.

F_c and F_s may easily be found from the data by averaging friction force in the kinetic and static domains. As true values may be inferred from the data, an LSTM model can be trained which predicts F_c and F_s from the actuator force in a direct approach. This method would not work for predicting the dynamic parameter σ_0, which cannot be easily measured or inferred from the data. Therefore, an indirect approach was used where the LSTM prediction of σ_0 was trained with error from the LuGre prediction. Backpropagation produces an error gradient with respect to σ_0 which then propagates an error gradient to train the LSTM model. Fig. 5 shows the two-step process for training. Table 1. shows the sources of all parameters for the LuGre model.

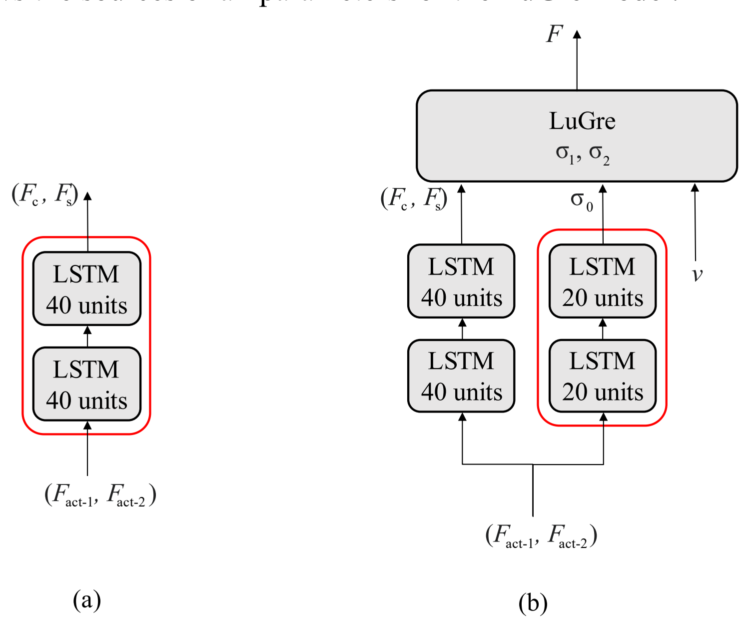


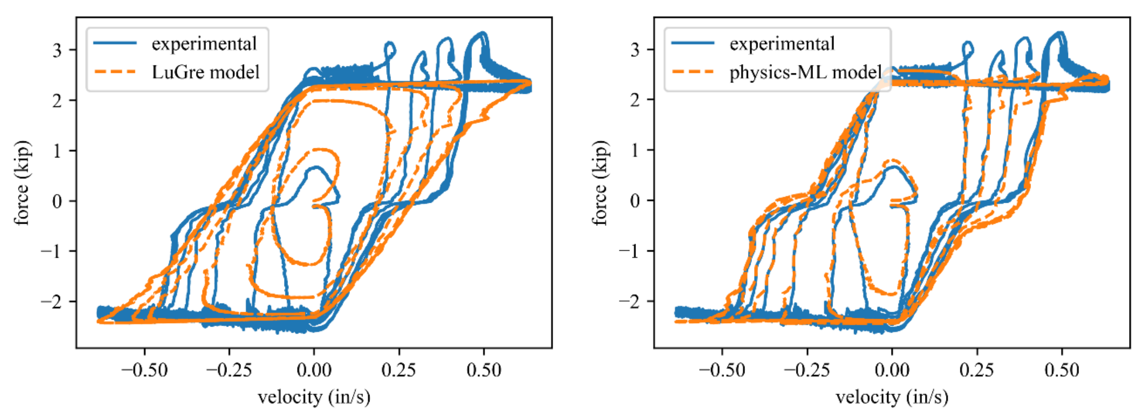
Fig. 5. Model training where the cells trained are boxed in red, showing: (a) the direct first step, and; (b) the indirect second step.

Table 1. Sources of LuGre model parameters.

Parameter	Source
σ_0	indirectly trained LSTM
σ_1	LuGre model
σ_2	LuGre model
F_c	directly trained LSTM cell
F_s	directly trained LSTM cell
v_s	manually selected

RESULTS

Results are reported in normalized root mean squared error (NRMSE). To provide comparison, a constant-parameter LuGre model was parameterized to each characterization dataset using a least squares method. Tables 2 and 3 give NRMSE for each dataset for both the LuGre and the physics-ML model. For the characterization datasets, the LuGre models produced a total NRMSE of 4.5%. In comparison, the physics-ML model reduced the NRMSE to 2.8%. Fig. 6 shows force-velocity plots for a test with 0.1 Hz frequency with initial band tension of 35 lb. The experimental data is plotted against the LuGre and physics-ML model predictions.



(a) (b)

Fig. 6. Force-velocity plots of (a) LuGre and (b) physics-ML prediction.

The physics-ML model was validated with data from five hybrid tests. The aggregate NRMSE for all tests was 14.7%. This shows a roughly five-fold increase in the error from the training and characterization dataset to the validation dataset. Fig. 7 shows a time-series plot of a portion of one test with the physics-ML model and experimental data.

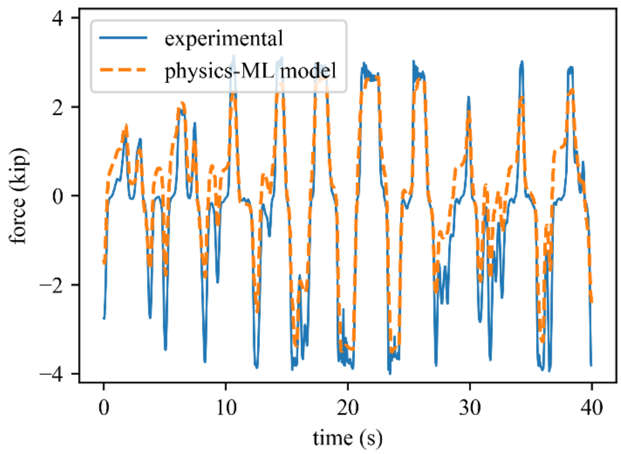


Fig. 7. Time series of a portion of one test with the physics-ML model and wind loading simulation.

Table 2. Normalized root mean squared error of LuGre parameterization to characterization datasets.

act. tension	0.05 Hz	0.1 Hz	0.5 Hz	1 Hz
20 lb	5.0%	5.2%	5.6%	6.6%
22 lb	5.6%	4.9%	5.0%	8.0%
25 lb	5.2%	5.5%	5.7%	5.8%
35 lb	5.0%	5.2%	5.1%	6.4%
70 lb	4.8%	4.9%	5.3%	5.9%
80 lb	4.2%	4.4%	5.0%	6.3%

Table 3. Normalized root mean squared error of physics-ML model to characterization datasets.

act. tension	0.05 Hz	0.1 Hz	0.5 Hz	1 Hz
20 lb	6.8%	6.7%	5.9%	7.2%
22 lb	3.6%	3.5%	4.9%	6.3%
25 lb	4.3%	3.5%	4.0%	4.5%
35 lb	4.4%	3.9%	3.1%	3.9%
70 lb	5.4%	4.5%	3.1%	3.5%
80 lb	4.5%	3.8%	3.3%	3.7%

DISCUSSION

Trained and tested in the characterization dataset, the physics-informed ML model was able to outperform LuGre model fits to each dataset. NRMSE decreased from 4.5% to 2.8%, a reduction of 37.3%. Most of the error reduction comes from the ability to reproduce the backlash effect. In the backlash region, the LSTM model produces smaller estimations of σ_0, which decreases the force's rising-rate. The LSTM model also accurately predicts static and kinetic friction parameters from the actuation tension. This is necessary for semi-active control, where changes in the actuation tension will drive higher or lower friction forces. LSTM prediction of static and kinetic friction also captured the asymmetric properties of the BRFD resulting from the friction band.

The model showed poor generalization to data from a hybrid simulation of a structure under wind loading. We observed that the largest source of error in the validation prediction came from the large force asymmetry seen in Fig. 8 (a) where experimental results on one side of the damper produced forces in excess of 6 kip. The source of the asymmetry comes from the nature of wind loading, where vibrations occur around an initial displacement. A frequency analysis of the hybrid tests, shown in Fig. 8 (b) showed that a significant portion of the dataset contained frequencies greater than the 1.0 Hz maximum that was used in characterization. Expanding the frequency sweep and applied force range could result in better fits to the wind profiles. Wind loading effects could also be replicated in the characterization tests by testing performing tests with an initial displacement.

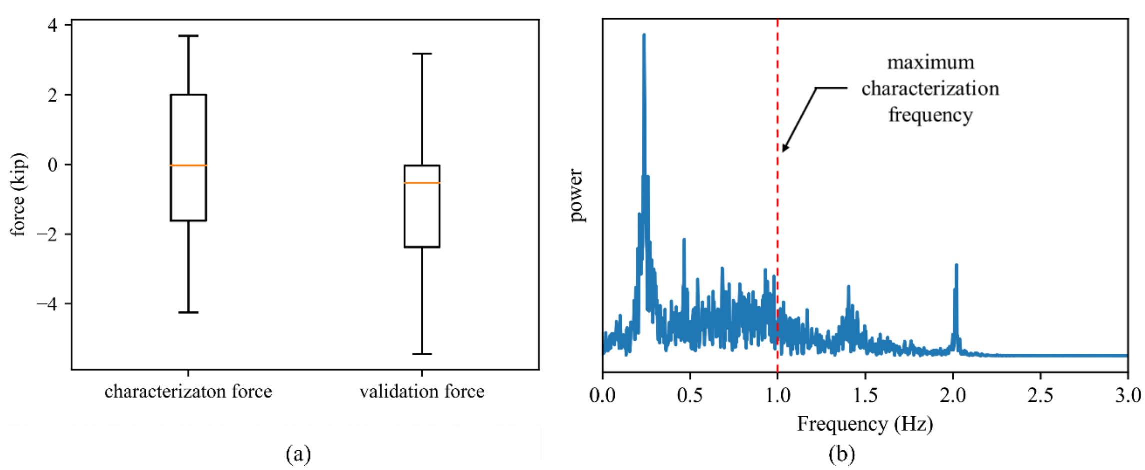


Fig. 8. Data for explaining the poor validation forces, showing: (a) box plot of force distribution in characterization and validation datasets, and; (b) frequency distribution of velocity in validation dataset.

SUMMARY AND CONCLUSION

The objective of this project was to develop a physics-informed ML model capable of capturing the backlash effect and semi-active control of a dry friction damper. To that end, a modified LuGre model was created which accepted time-dependent F_c, F_s, and σ_0 parameters. Two LSTM models were developed to predict these parameters from the actuator tension. Model training for F_c and F_s utilized a direct training method while model training for σ_0 utilized an indirect training method. This model improved prediction in the characterization dataset by capturing the backlash effect but poorly generalized when applied to a hybrid simulation of a wind event. Future work will look at improvements to combined physics and machine learning models, including improving generalization to tests of both wind and earthquake events.

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