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

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Purpose

The purpose of this research project is to investigate a physics-informed machine learning approach to dry friction modeling in a semi-active damper.

Introduction

Passive 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). Semi-active dampers, which provide active control by altering their mechanical properties, have the potential to be more effective and less costly. Among semi-active dampers, variable friction dampers can provide the highest reaction force but have highly nonlinear behavior that is difficult to model such as the stick-slip phenomenon (Downey et al. 2016). Furthermore, friction dampers exhibit highly nonlinear behavior during reversal of travel, termed backlash. Though multiple friction models have been proposed which account for most friction phenomena, thus far, backlash has not been well understood or modeled (Cao et al. 2016).

Background

- The banded rotary friction device (BRFD) is a semi-active friction damper based on a band brake system.
- As the internal drum rotates, energy is dissipated from the friction contact between the band and drum surface.
- Electric actuators connected to the band control the applied tension.

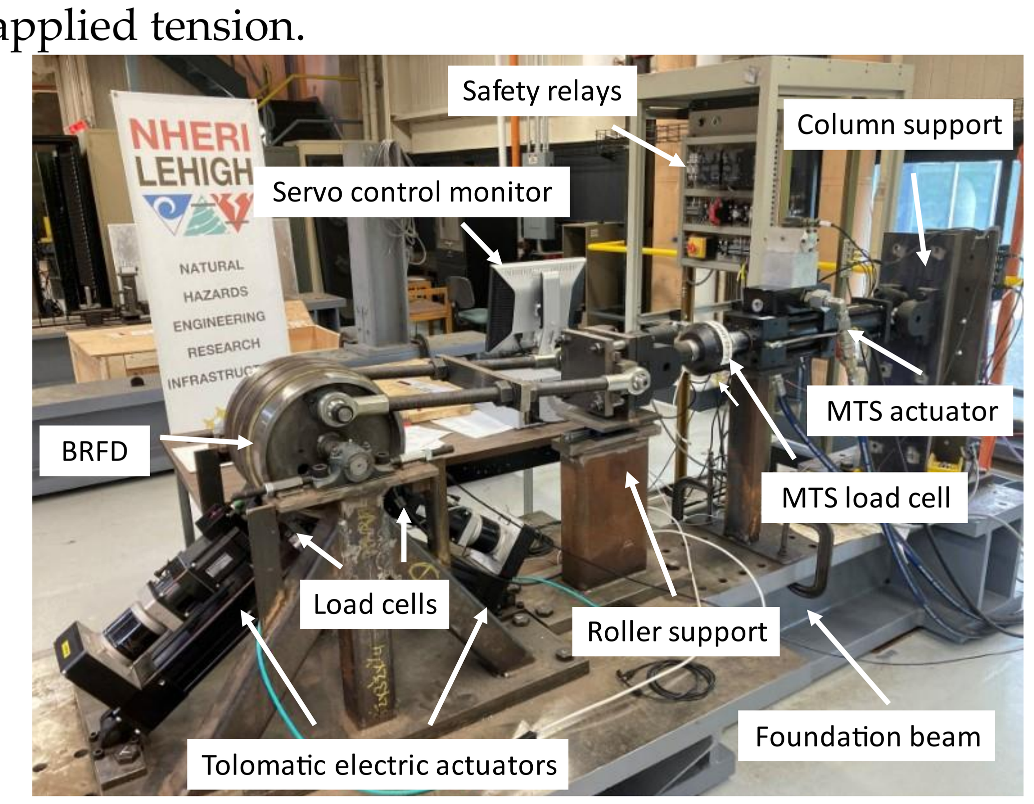

Fig. 1. BRFD test set-up.

- Long short-term memory (LSTM) is a type of recurrent neural network (RNN). RNNs are characterized by time series prediction and an internal state.

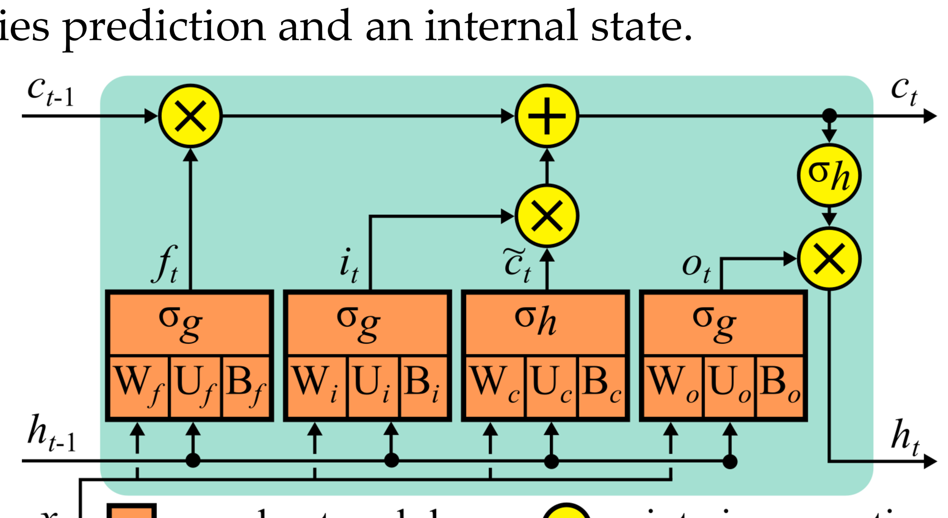

Fig. 2. Flow chart of LSTM forward pass.

Device Characterization

Dynamic properties

- The BRFD produces a large amplification of friction force compared to applied force.
- Self-energizing effect: contact pressure increases linearly across the contact surface of the drum.
- The backlash effect: self-energizing effect depletes during reversal of travel.

Testing procedure

- Characterization tests consisted of sinusoidal displacement profiles with varying frequency and tension force.
- Validation data collected from five hybrid simulations of the BRFD installed in a structure under wind loading.

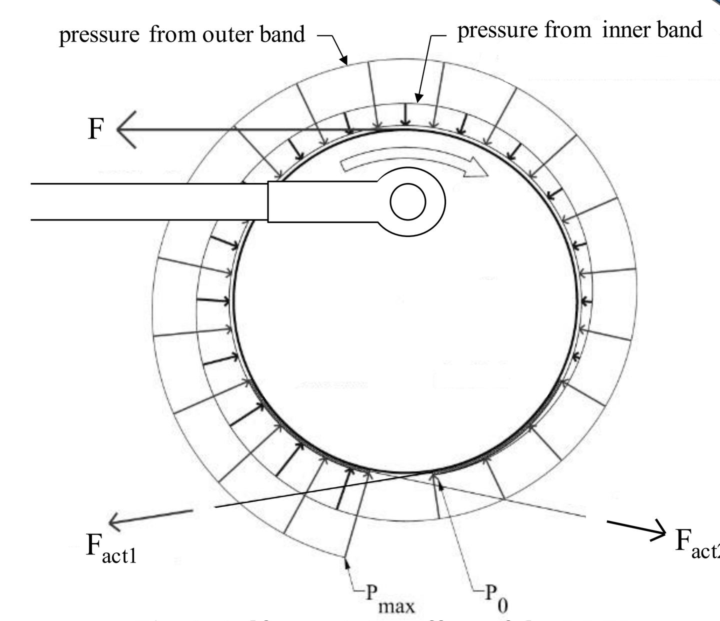

Fig. 3. Self-energizing effect of the BRFD.

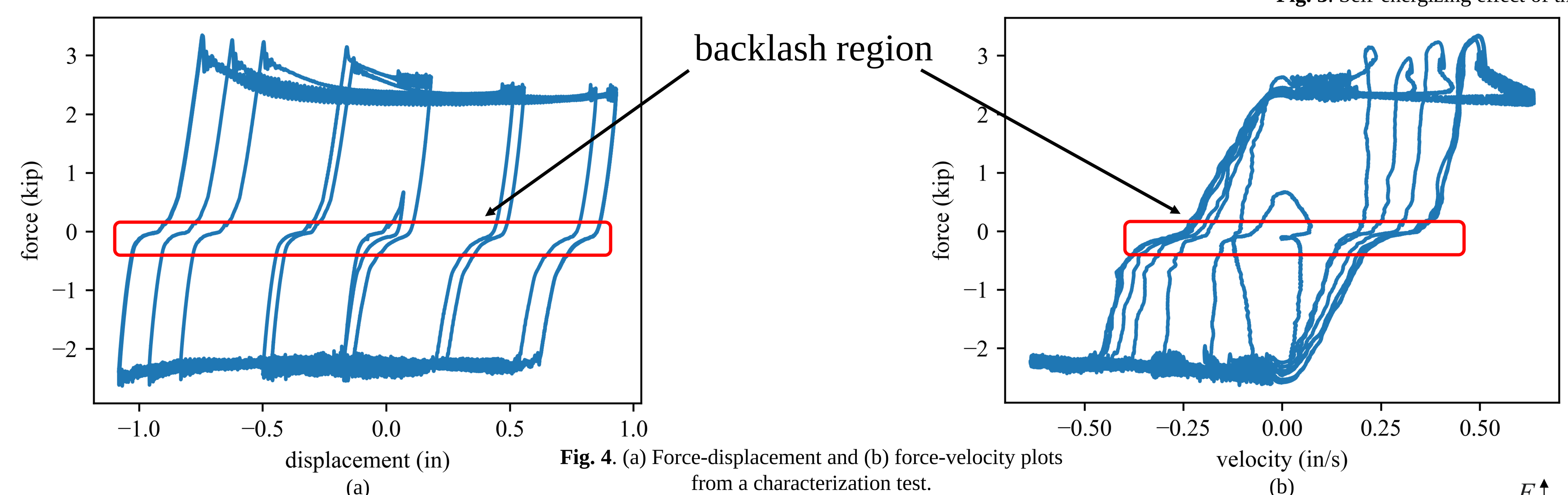

Fig. 4. (a) Force-displacement and (b) force-velocity plots from a characterization test.

Model Development

- The LuGre model is a widely used dry friction model but is not capable of modeling semi-active control or backlash effects.

$$g(v) = F_c + (F_s - F_c)e^{\left(\frac{v}{v_s}\right)^2} \quad \dot{z} = v - \sigma_0 \frac{|v|}{g(v)} z \quad F = \sigma_0 z + \sigma_1 \dot{z} + \sigma_2 v$$

- Two LSTM models produce time-series predictions of F_c, F_s, and σ_0.
- Input to LSTM models is band tension.
- Two training methodologies:
  - LSTM Training for F_c and F_s was performed using values identifiable in the characterization data.
  - The LSTM prediction for σ_0 was trained from error backpropagated from the LuGre prediction.

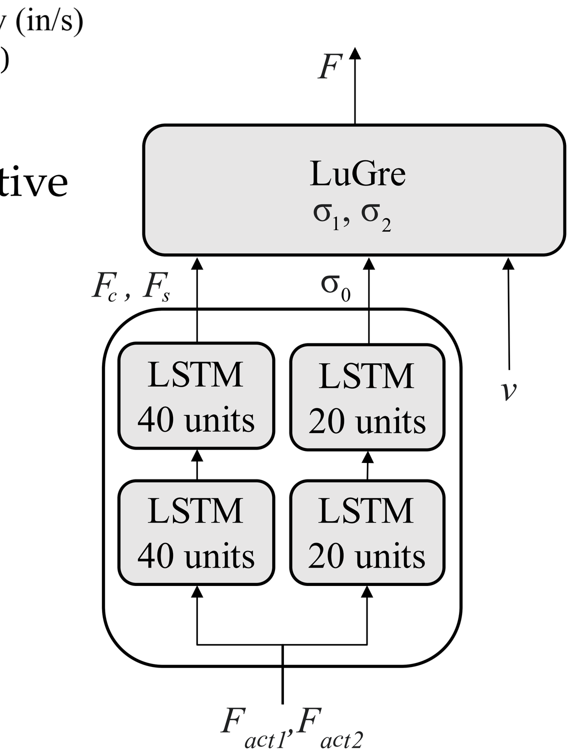

Fig. 4. Diagram of physics-informed ML model.

Results

- To provide comparison, a LuGre model was parameterized to each characterization dataset using a least squares method.

Table 1. NRMSE error of LuGre parameterization to characterization datasets

		displacement signal frequency			
		0.05 Hz	0.1 Hz	0.5 Hz	1 Hz
actuator tension	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 2. NRMSE error of physics-ML model to characterization datasets

		displacement signal frequency			
		0.05 Hz	0.1 Hz	0.5 Hz	1 Hz
actuator tension	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%

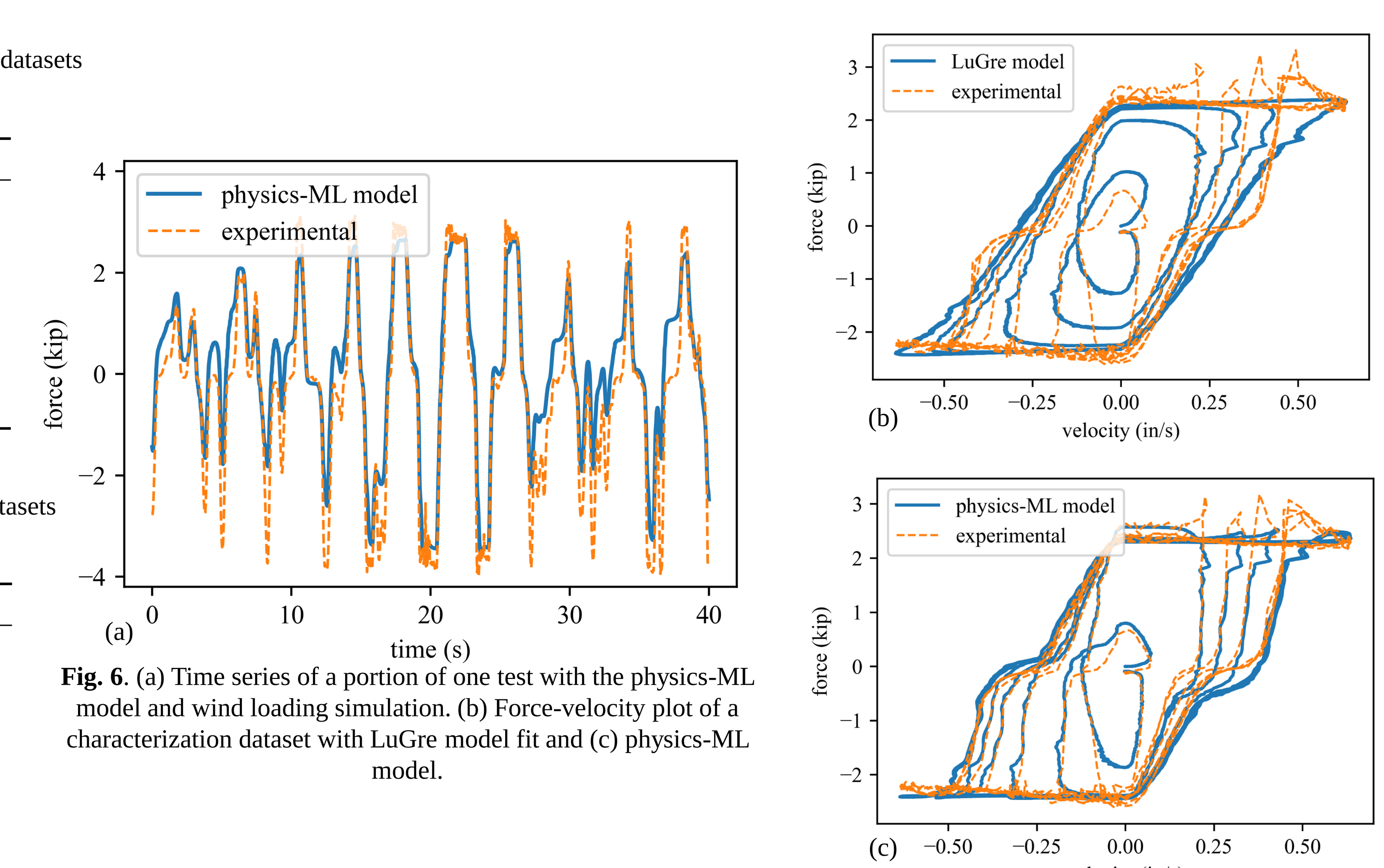

Fig. 6. (a) Time series of a portion of one test with the physics-ML model and wind loading simulation. (b) Force-velocity plot of a characterization dataset with LuGre model fit and (c) physics-ML model.

Discussion

- In the characterization dataset, the physics-informed ML model outperformed the LuGre model fits to each dataset. NRMSE decreased from 4.5% to 2.8%, a reduction of 37%.
- Most of the error reduction comes from the ability to reproduce the backlash effect.
- Overall, NRMSE for the wind loading hybrid simulation was 14.7%, showing limited ability to generalize outside the dataset.
- Expanding the frequency sweep and tension range could result in better fits to the wind profiles.

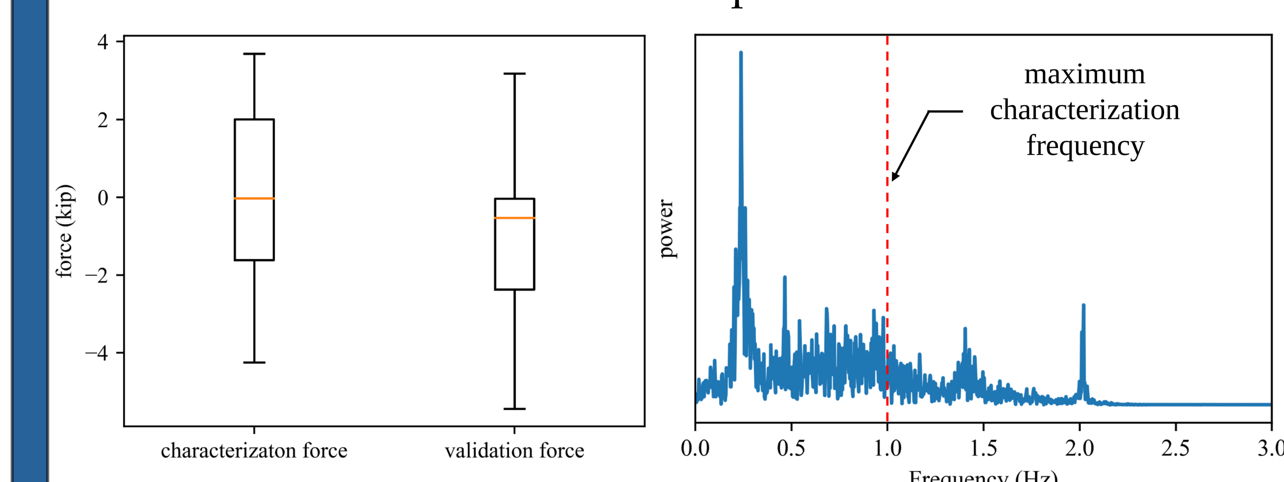

Fig. 7. (a) Box plot distribution of characterization and validation forces. (b) Frequency distribution of velocity in the validation dataset.

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. This model improved prediction in the characterization dataset 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. Future work will also investigate embedding models into real-time hybrid simulations to gauge model accuracy.

References

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