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Natural Hazards Engineering Research Infrastructure

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

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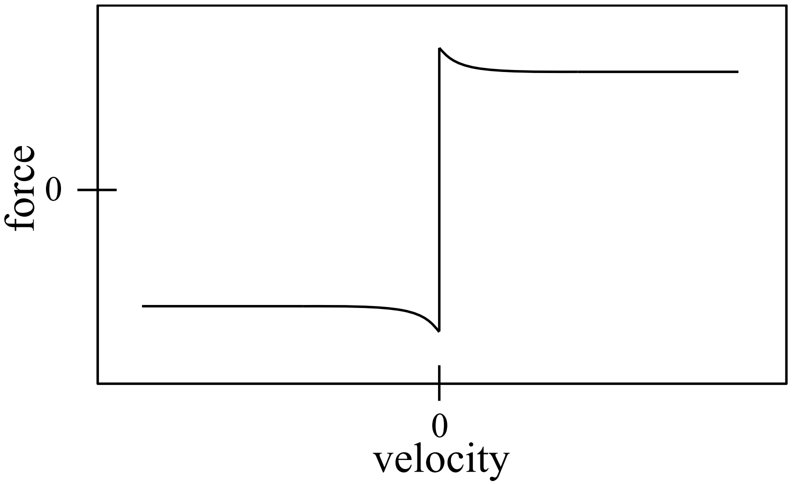
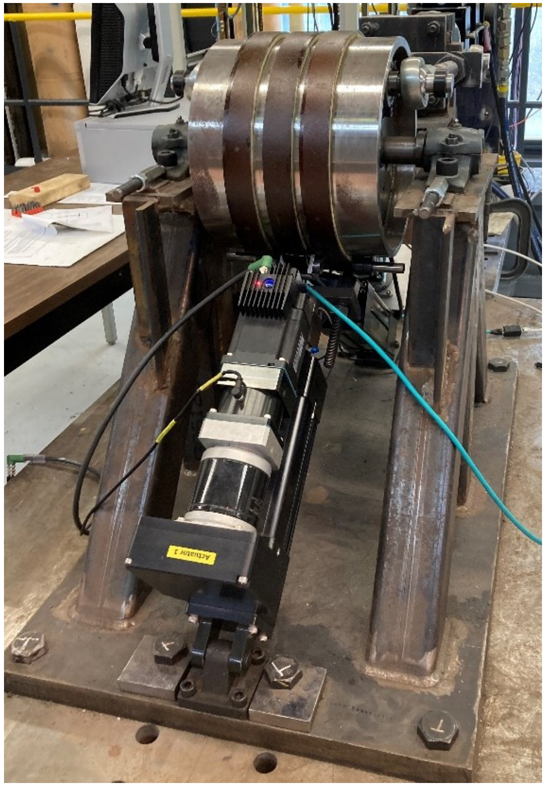
Why model friction?

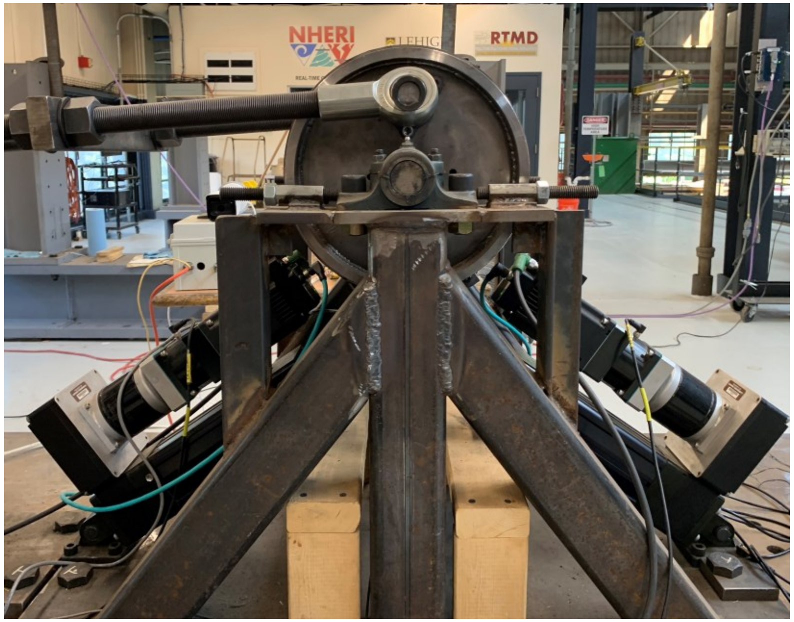
- Rate-dependent properties.
- Hysteretic behavior.
- Stribeck effect: static friction is greater than kinetic friction.
- Backlash: loss of friction during reversal of travel.



The Banded Rotary Friction Device

- A friction-based structural damper designed for high performance and mechanical simplicity.
- An internal drum rotates against stationary friction bands.
- Semi-active control possible with actuators connected to both ends of the band.





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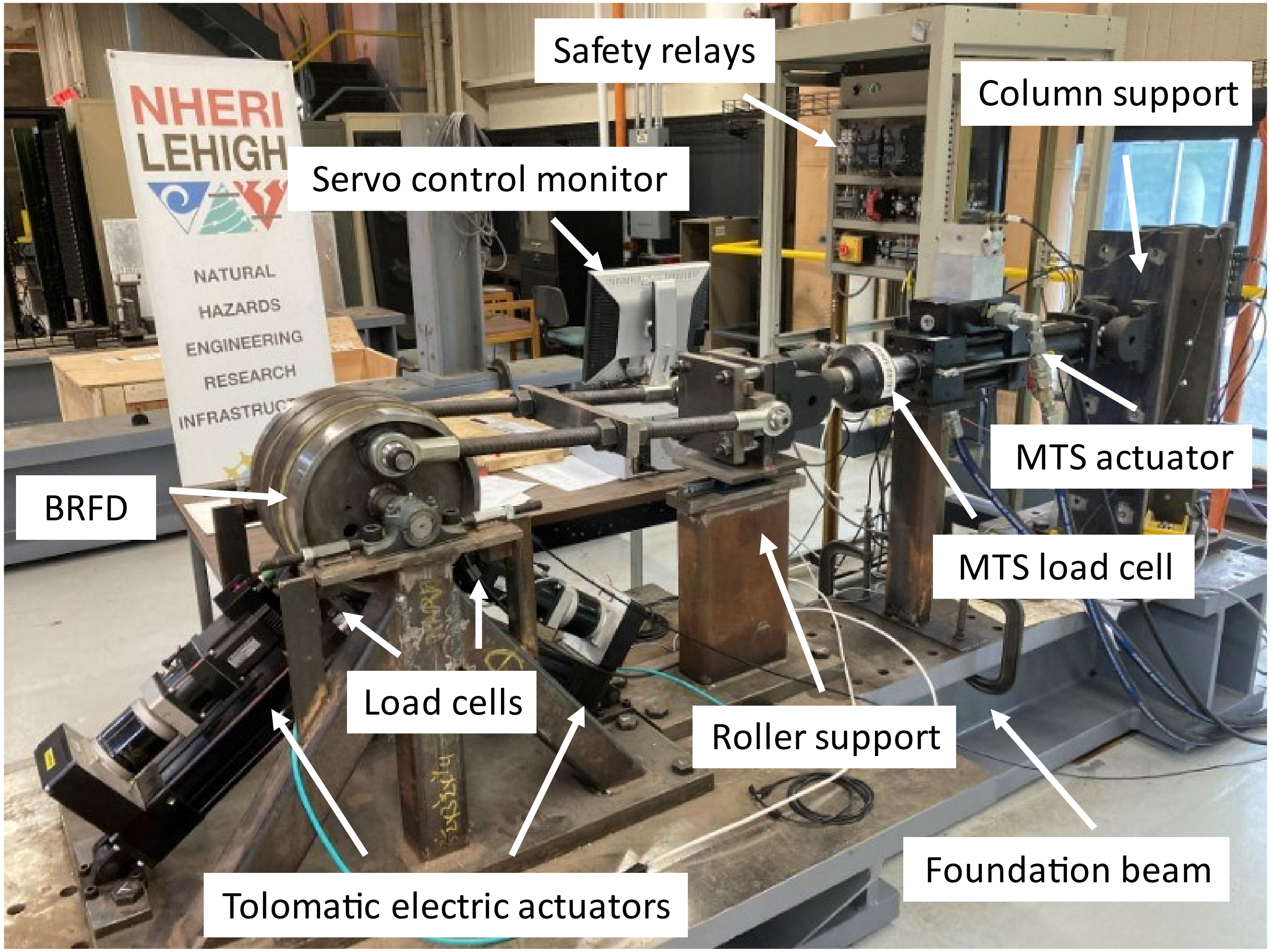
The Banded Rotary Friction Device



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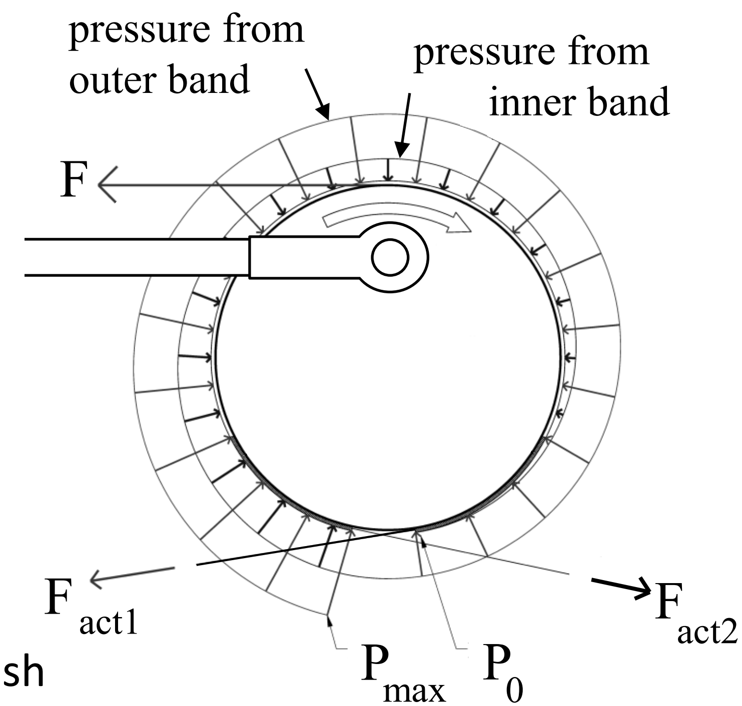
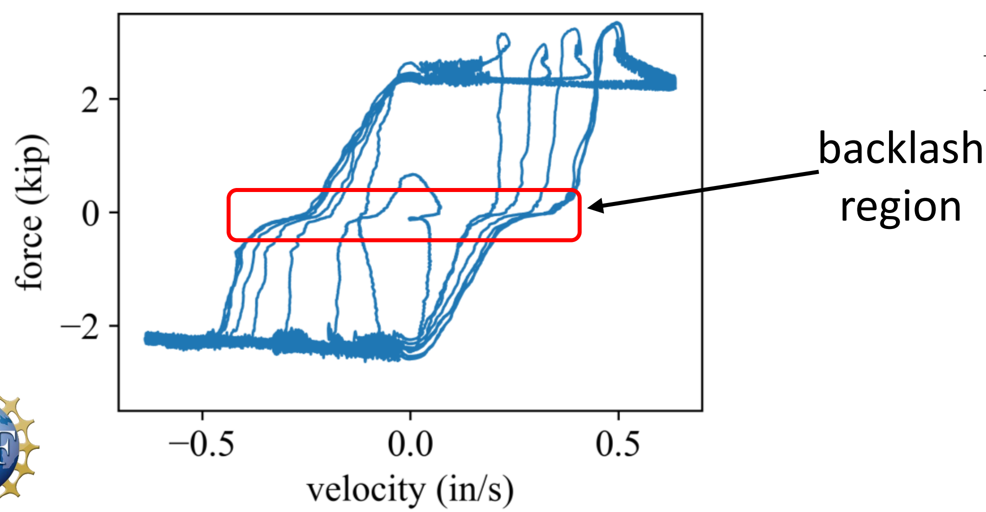
Device Characterization

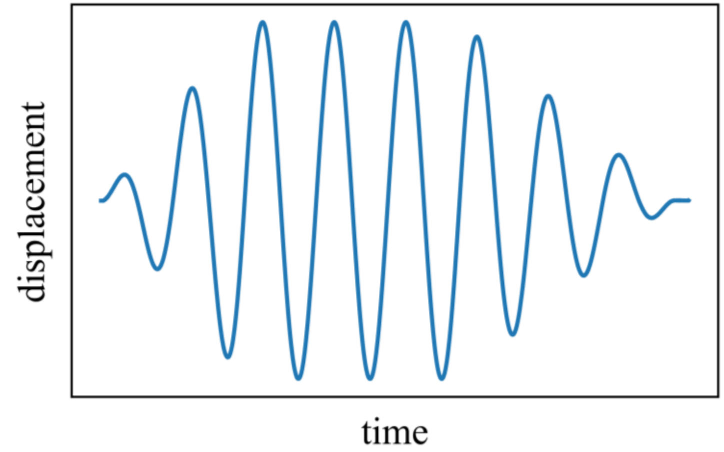
- The BRFD produces a large amplification of friction force compared to applied force.
- Self-energizing effect: contact pressure increases along the surface of the drum.
- The backlash effect: self-energizing effect depletes during reversal of travel.

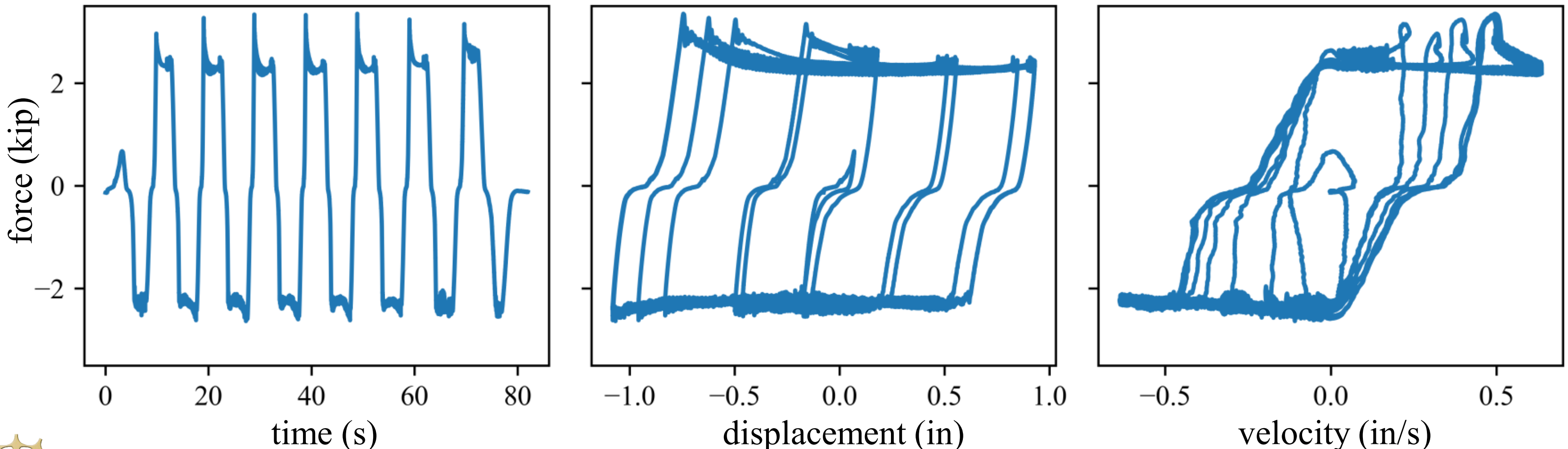




Device Characterization

- Characterization tests were run under a sinusoidal displacement profile.
- Frequency of sinusoid, tension of the friction band were altered to produce 24 datasets.
- Validation data collected from five hybrid simulations under wind loading.





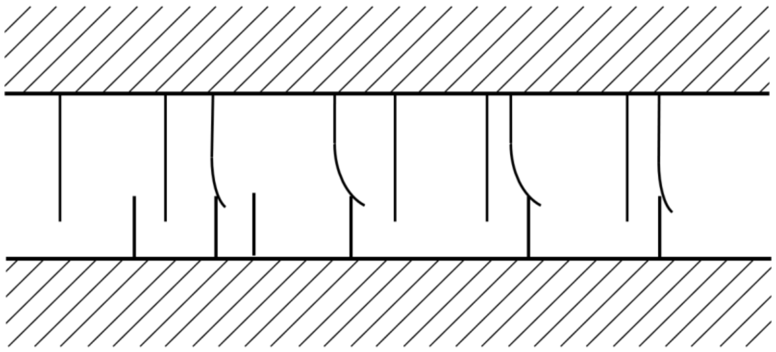
Model Development

- The LuGre model: a 'rate and state' model commonly used to describe dry friction systems.
- Physical interpretation of parameters.
  - Static parameters: F_c, F_s, v_s.
  - Dynamic parameters: σ_0, σ_1, σ_2.

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

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

$$g(v) = F_c + (F_s - F_c) e^{\left(\frac{v}{v_s}\right)^2}$$



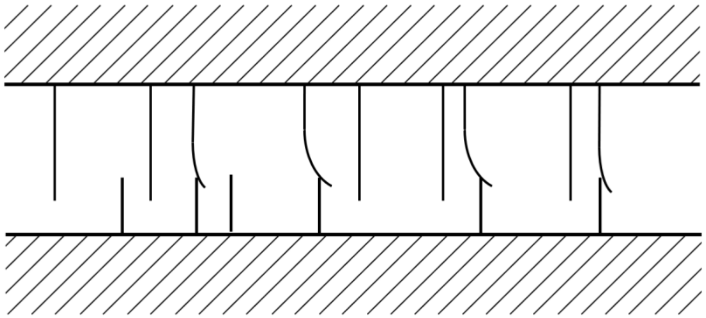
Model Development

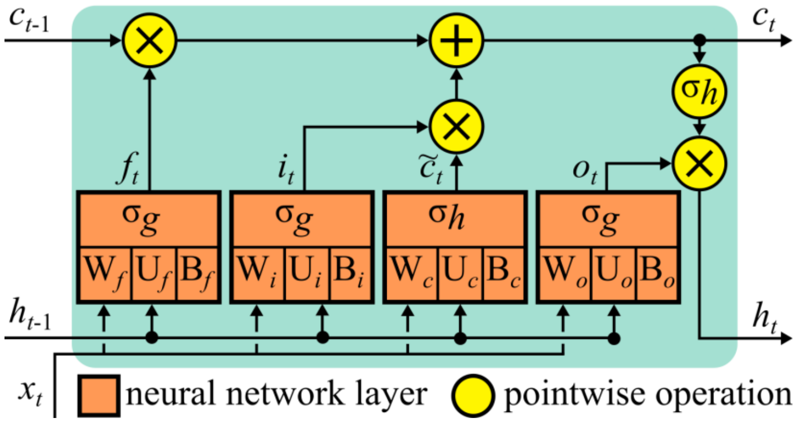
- The LuGre model cannot capture changing normal force or backlash effect.
- Real-time parameter updating for F_c, F_s, σ_0 using machine learning.
- Long short-term memory cells: RNNs propagate a cell state and produce time-series output.
- Input: band tension.

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

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

$$g(v) = F_c + (F_s - F_c) e^{\left(\frac{v}{v_s}\right)^2}$$



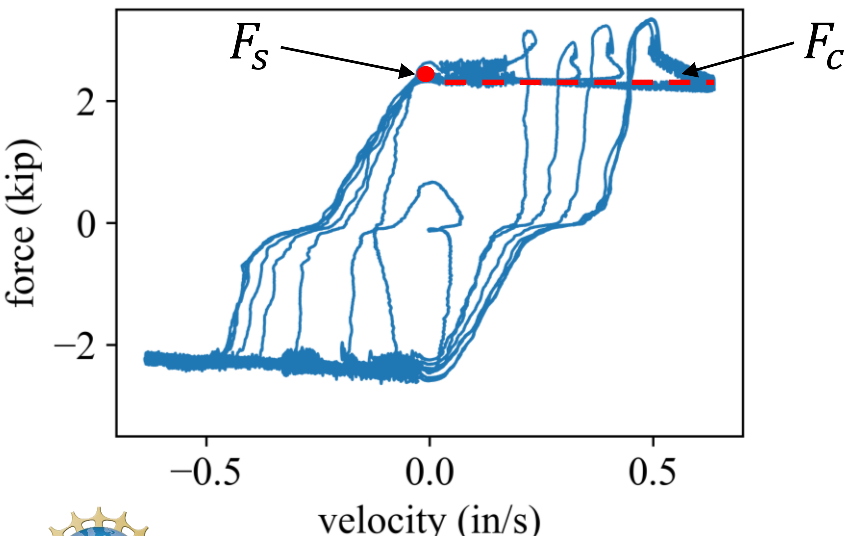


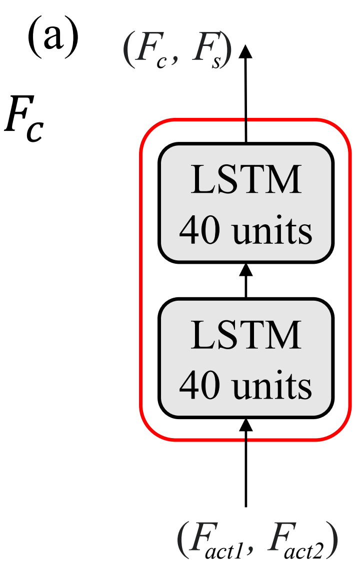
Model Training

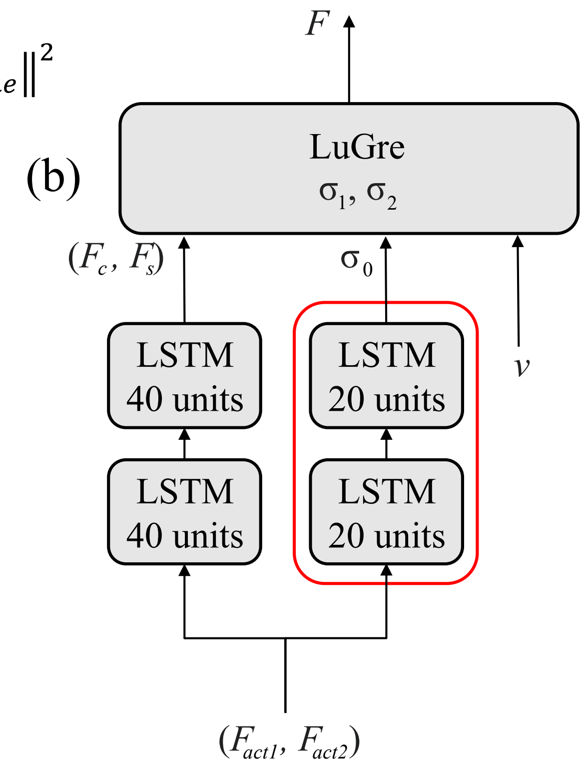
- F_c, F_s can be easily extracted from force data, but σ_0 cannot.
- Two-step training process for static and dynamic parameters.

$$\varepsilon = \left(F_{pred} - F_{true}\right)^2$$

$$\varepsilon = \left\|(F_c, F_s)_{pred} - (F_c, F_s)_{true}\right\|^2$$







Passive mode LuGre models

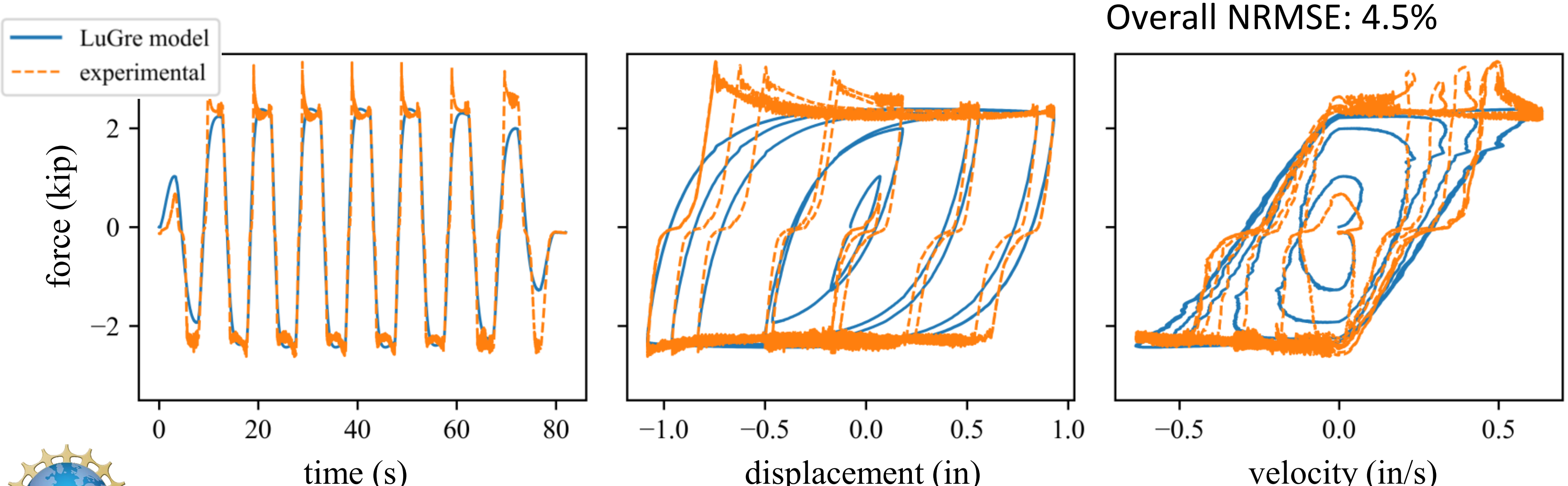
- To provide comparison, a LuGre model was parameterized to each characterization dataset.
- Loss of meaning for model parameters such as σ_0.

Normalized root mean squared error

displacement signal frequency

actuator 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%

Overall NRMSE: 4.5%



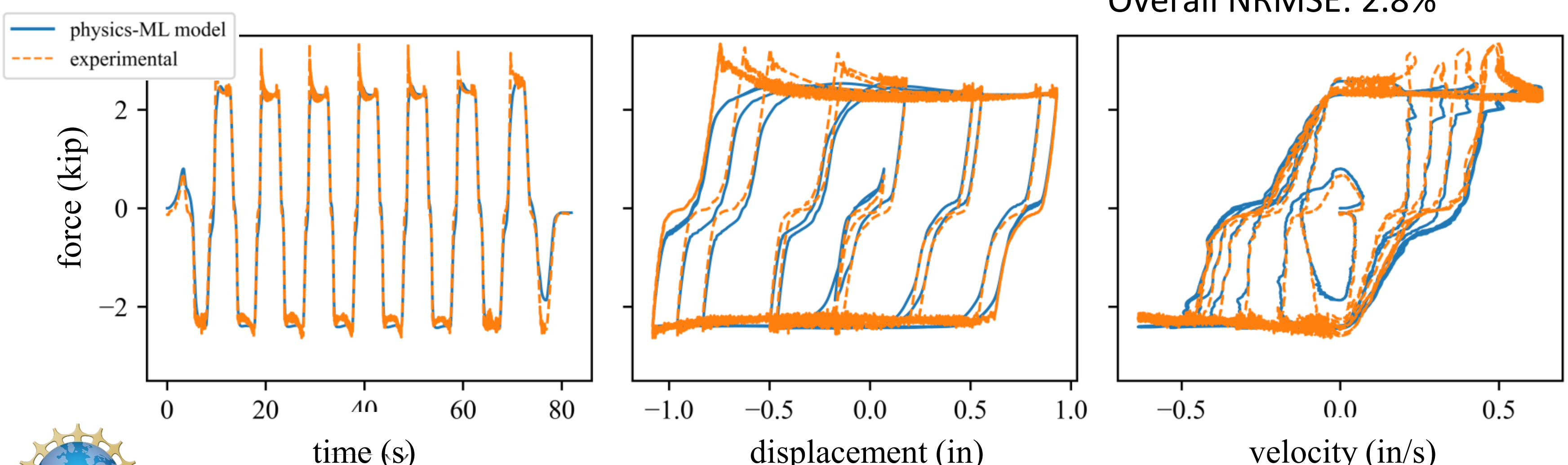
Deep learning-based model

- 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.
- Single model compared to 24 different models.

Normalized root mean squared error

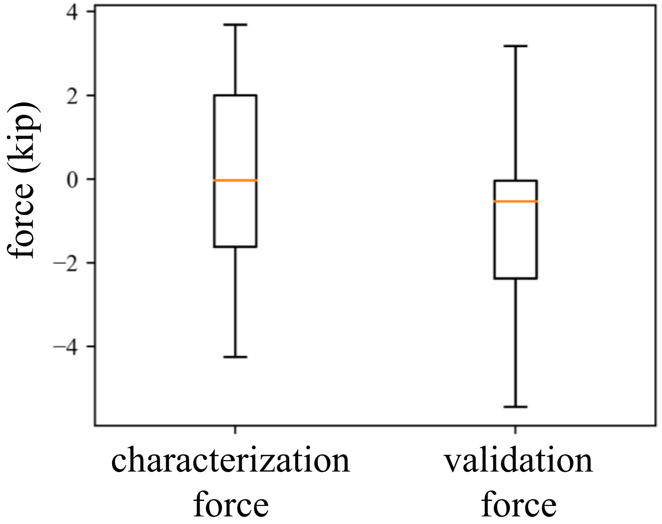
actuator tension	displacement signal frequency: 0.05 Hz	0.1 Hz	0.5 Hz	1 Hz
20 lb	6.8%	6.7%	5.9%	7.2%
22 lb	3.6%	3.5%	4.9%	6.3%
25 lb	4.3%	3.5%	4.0%	4.5%
35 lb	4.4%	3.9%	3.1%	3.9%
70 lb	5.4%	4.5%	3.1%	3.5%
80 lb	4.5%	3.8%	3.3%	3.7%

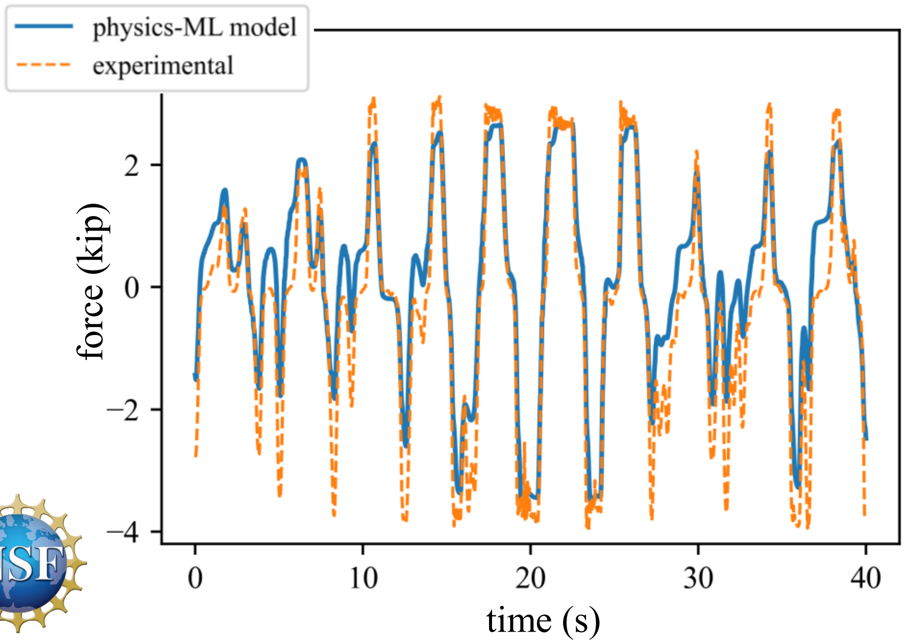
Overall NRMSE: 2.8%

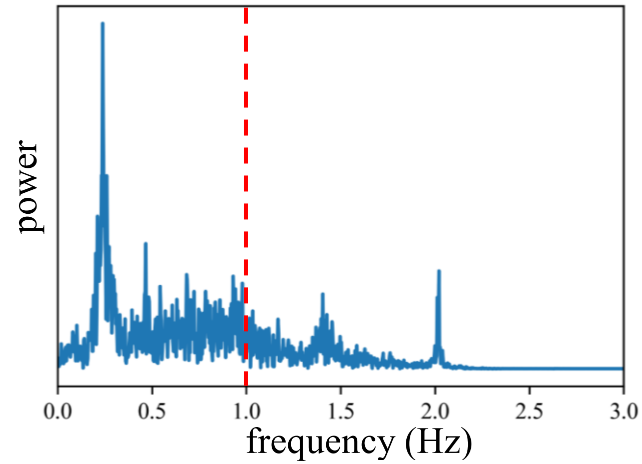


Validation on a wind event profile

- 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.







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