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

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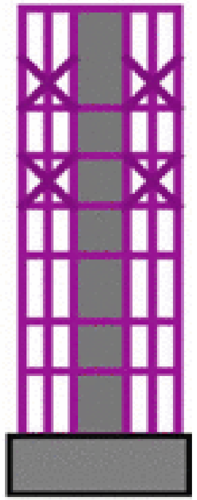
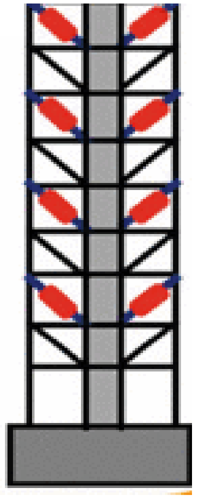
Natural Hazard Mitigation Solutions on Structures

- **Structural System Modification**
  - Obstacle:
    - Uneconomical
    - Difficult in implementation for existing building



- **Passive Damping System**
  - Obstacle:
    - Limited bandwidth for multi-level winds

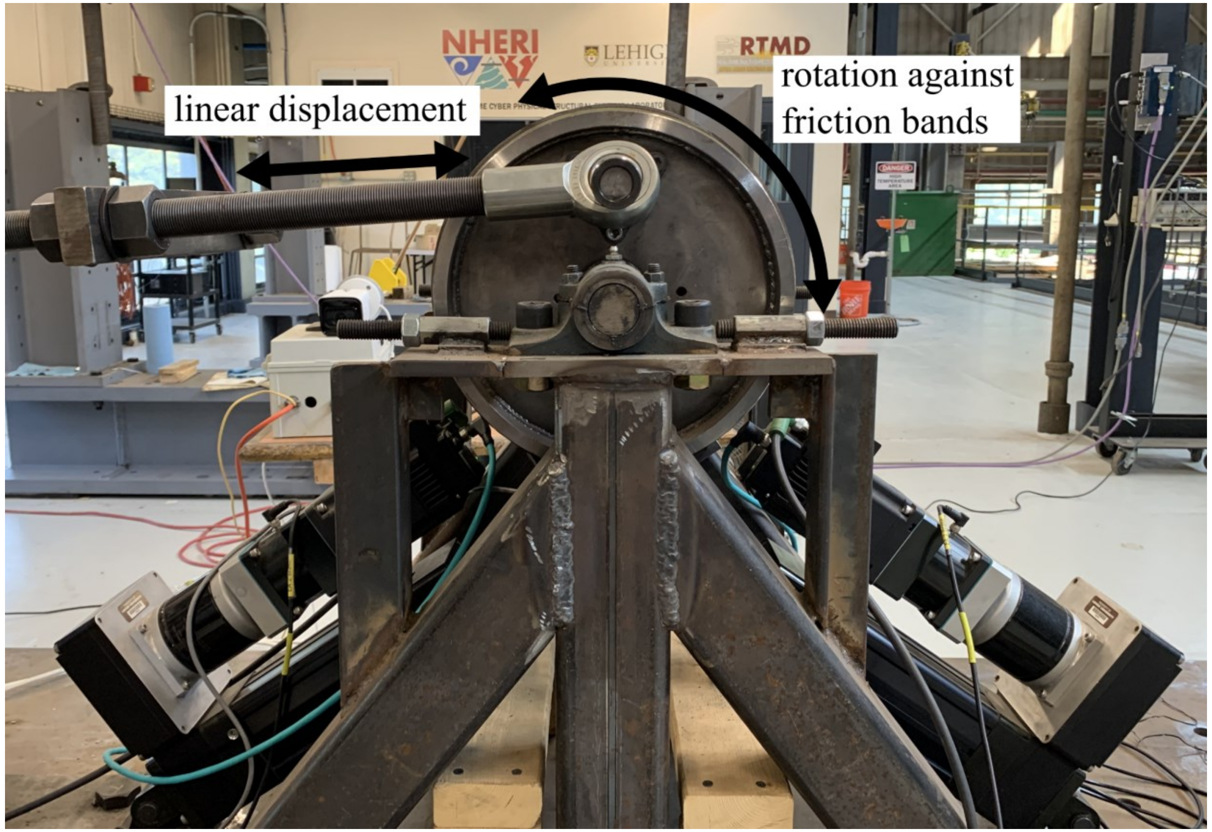


- **Semi-active Damping System**
  - Advantage:
    - Applicable to board range of excitations, ideal for multi-hazards
    - Low energy input for large energy dissipation

The Banded Rotary Friction Device

- A friction-based structural damper designed for high performance and mechanical simplicity located at Lehigh University ATLSS facility.
- An internal drum rotates against stationary friction bands.
- Self-energizing effect: energy from damping displacement increases damper force.
- Semi-active control possible with actuators connected to both ends of the band.

$$C = \left(e^{\mu\phi} - 1\right)\left(\frac{r}{r_b}\right) \approx 150$$



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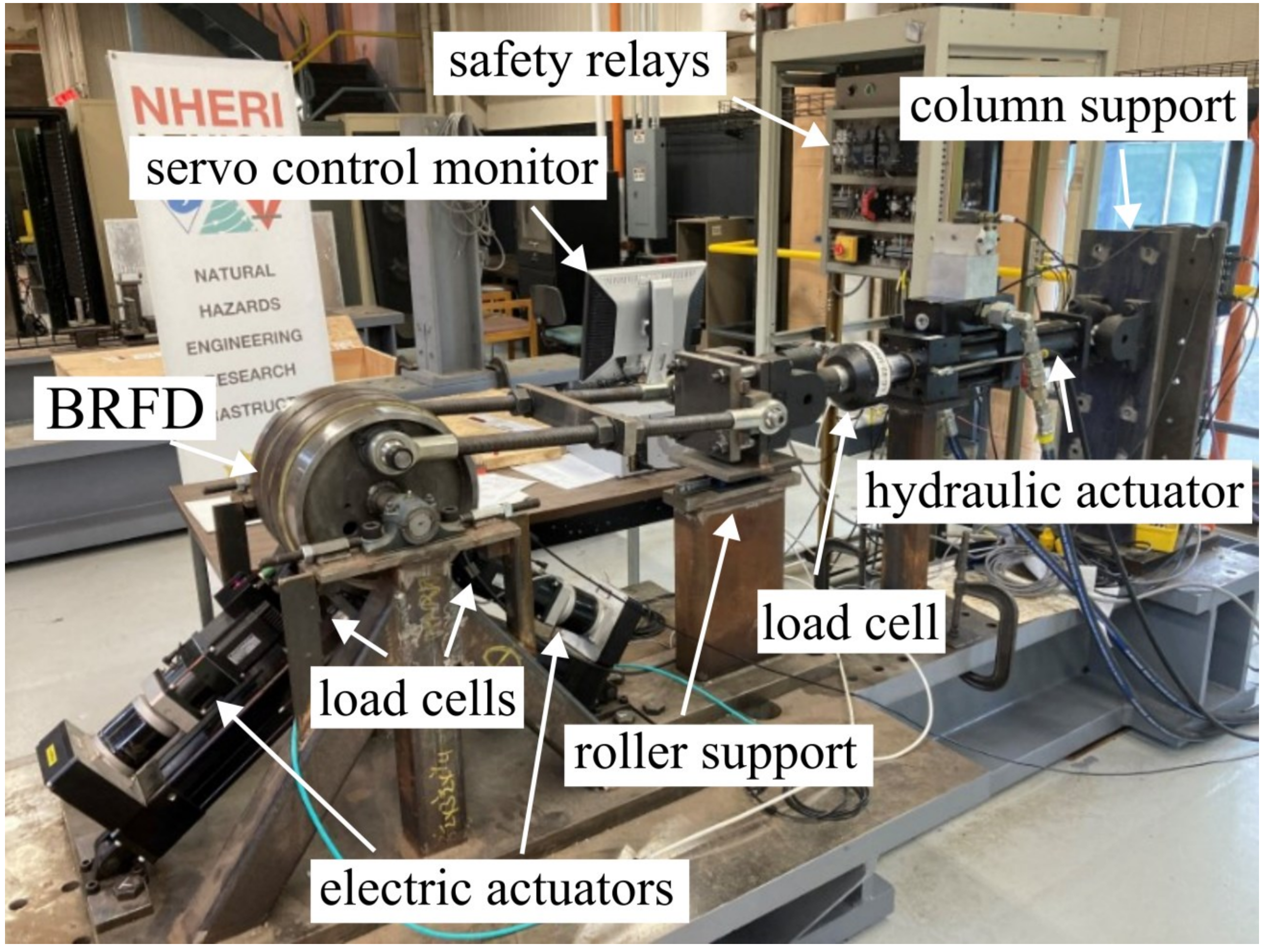

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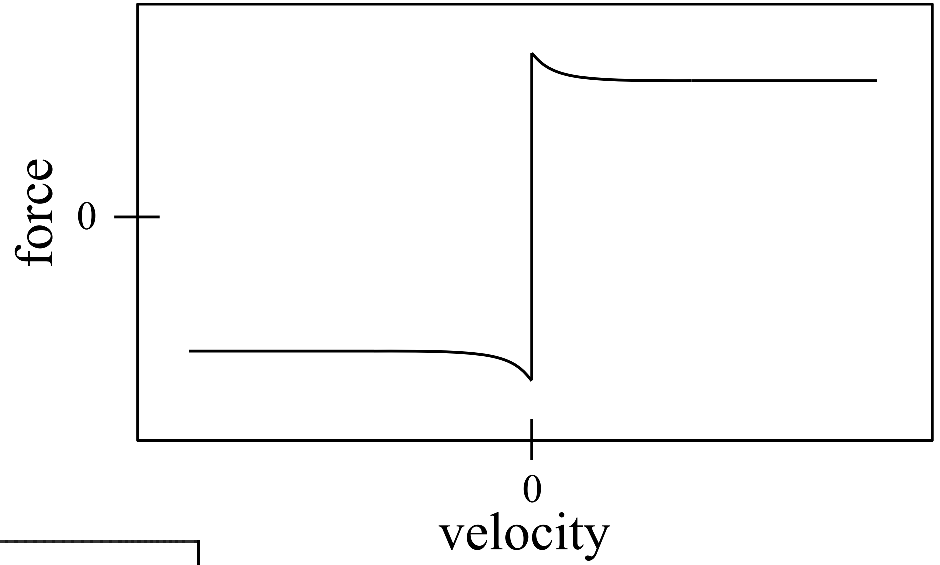
Problems in modeling friction

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



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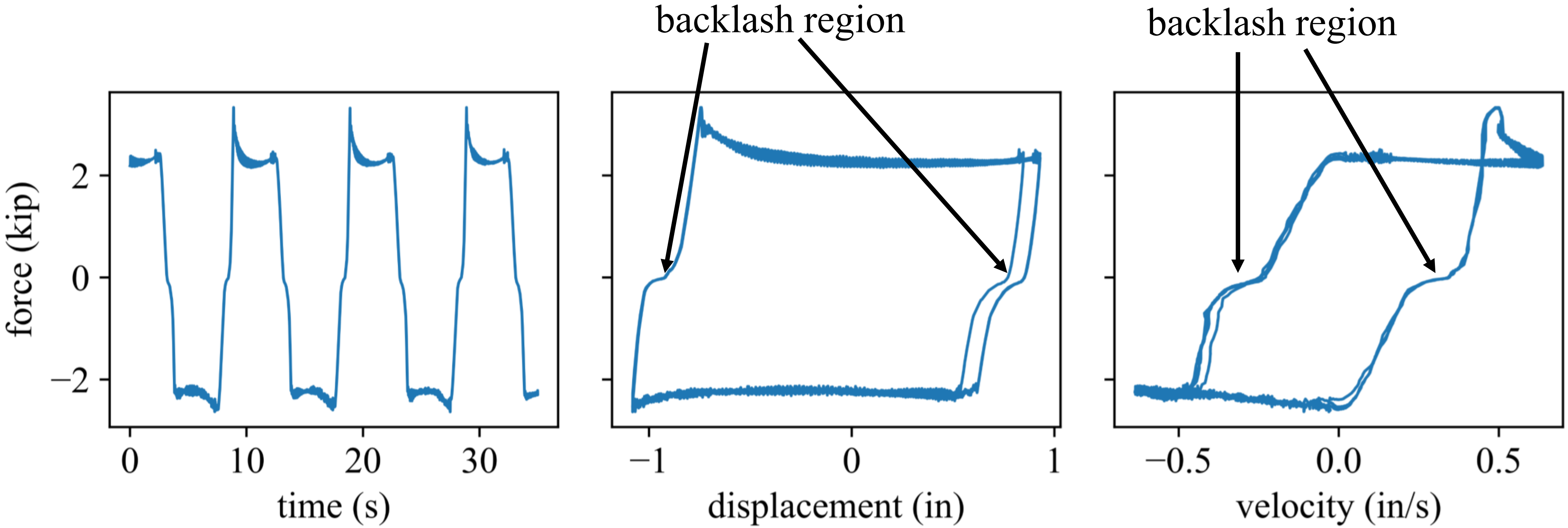
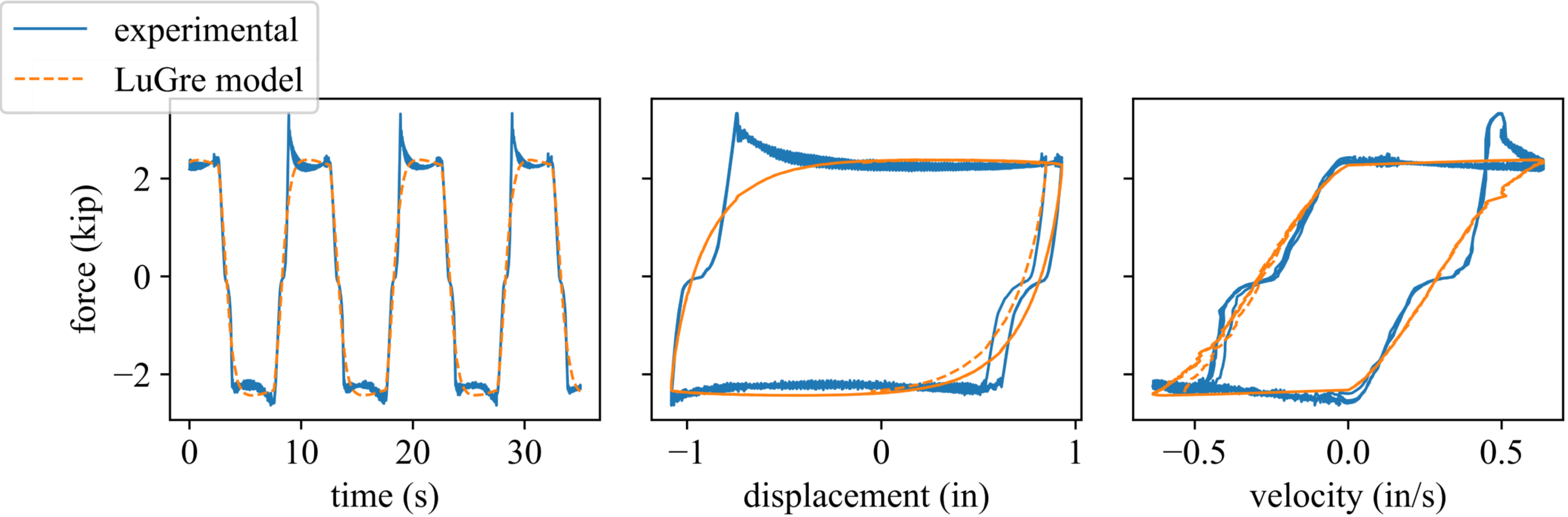
Device Characterization

- The device was characterized with four sinusoidal displacement tests with frequencies between 0.05 Hz and 1.0 Hz.
- The backlash effect: self-energizing effect depletes during reversal of travel.



Problems using current models

- Standard dry friction models like the LuGre model cannot capture backlash.



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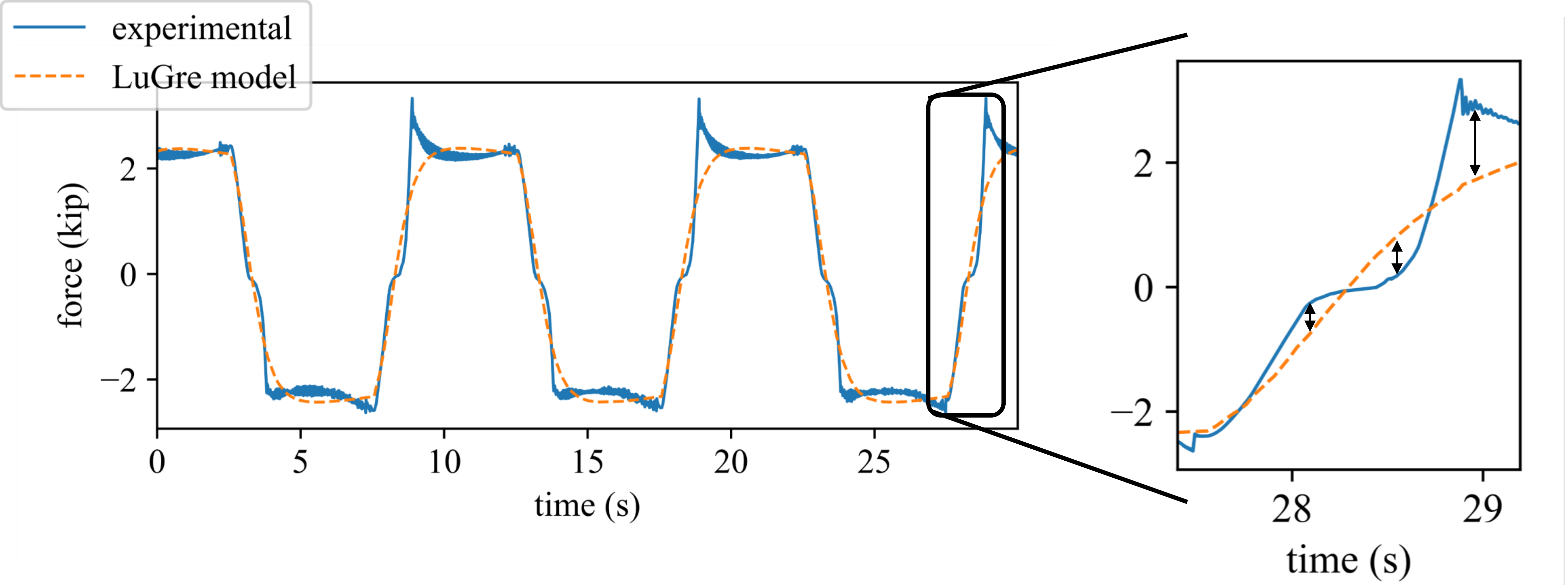

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Model Development

- Physics models:
  - Informed structure
  - Certain performance
- ML models:
  - Excellent data-driven performance
- Combined physics-ML approach:
  - Benefits of both approaches
  - Real-time parameter updating

Model Development

- Physics-informed component: the LuGre model.
- A ‘rate and state’ model with one state variable 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.
- σ_0 controls hysteresis rate of change–backlash effect.

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

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

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

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Model Development

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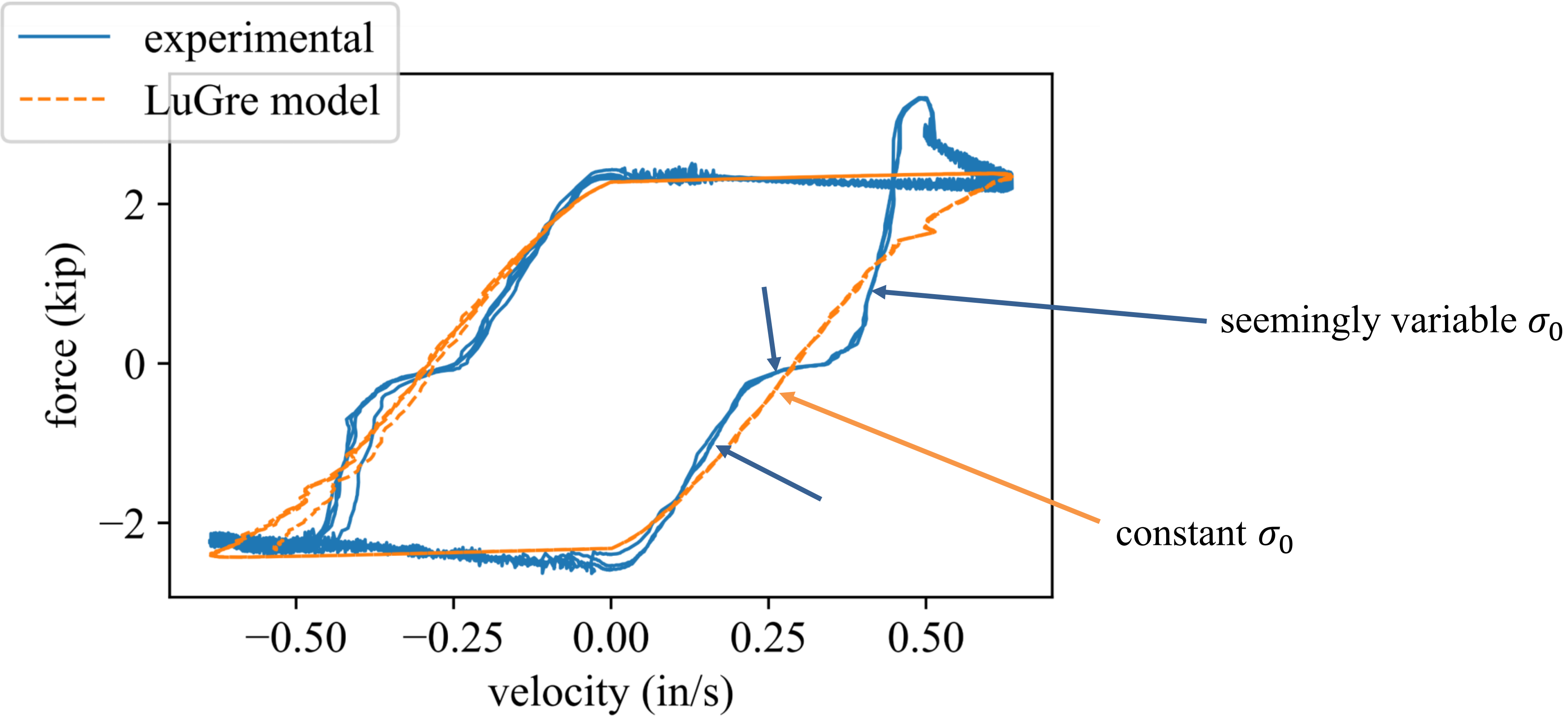

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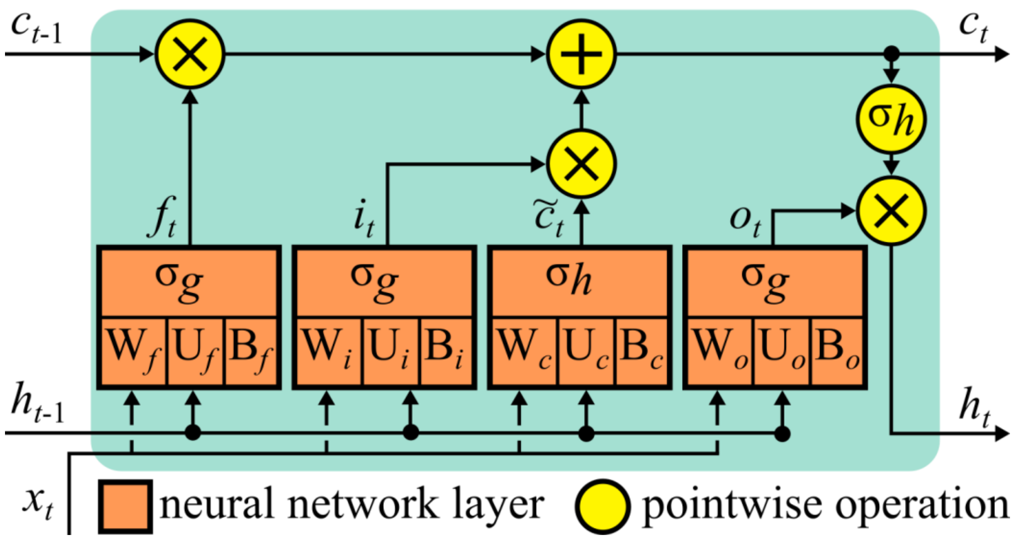
Model Development

- Machine-learning component: long short-term memory.
- A class of recurrent neural network designed to detect longer time-series patterns than standard RNNs.
- State vectors h_t and c_t maintain state information.

$$
\begin{aligned}
f_t &= \sigma_g\left(W_f x_t + U_f h_{t-1} + b_f\right)\\
i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i)\\
o_t &= \sigma_g(W_i x_t + U_o h_{t-1} + b_o)\\
\tilde{c}_t &= \sigma_h(W_c x_t + U_c h_{t-1} + b_c)\\
c_t &= f_t \circ c_{t-1} + i_t \circ \tilde{c}_t\\
h_t &= o_t \circ \sigma_h(c_t)
\end{aligned}
$$



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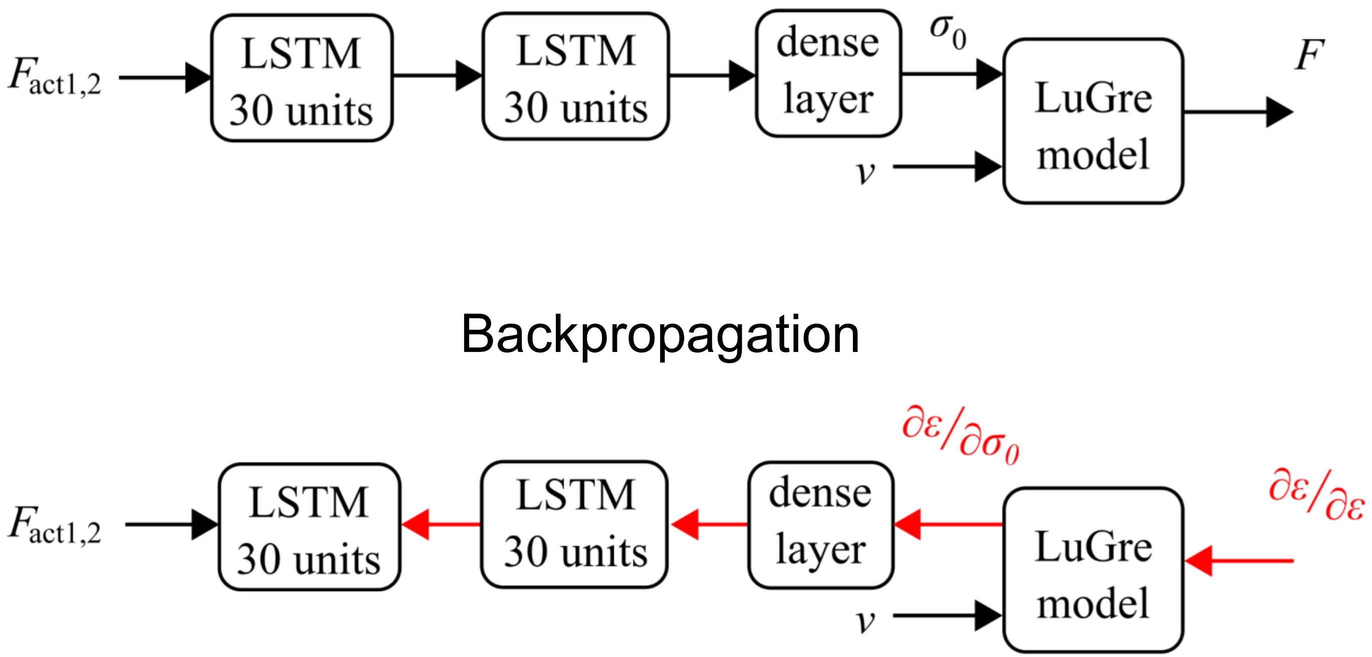
Model Training

- Static parameters F_c, F_s, and v_s found with a least-squares analysis.
- Supervised training procedure using damping force measured during characterization test.
- Backpropagation provides an error gradient ${}^{\partial\varepsilon}/_{\partial\sigma_0}$ as an intermediate value in updating weights.

Forward inference

Backpropagation



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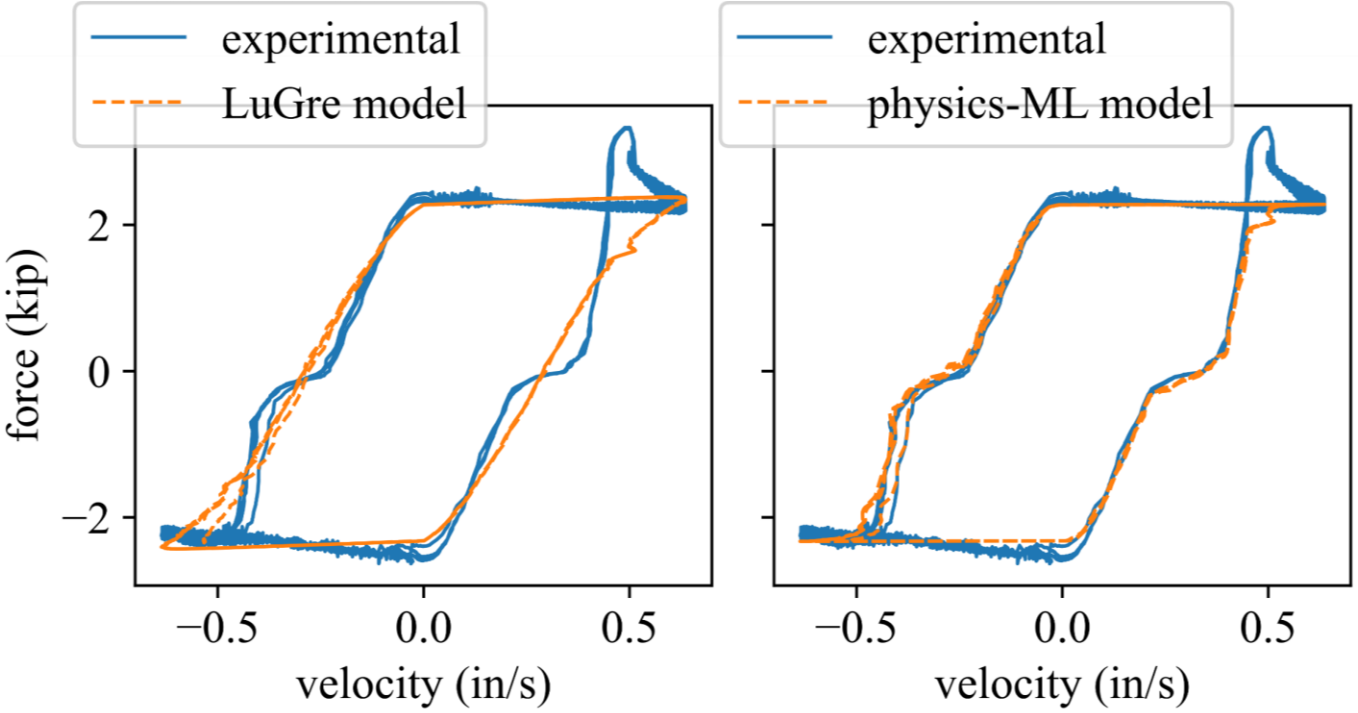
Results

- Compared against LuGre models found with least-squares fit.
- Normalized root mean squared error from 6.71% to 3.16%, a reduction of 53%.
- Most of the error reduction comes from the ability to reproduce the backlash effect.



	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	6.10%	19.88	2.92%
0.5 Hz	9.74	8.20%	19.44	2.69%
1.0 Hz	8.97	9.06%	17.91	3.24%
overall	12.85	6.71%	19.39	3.16%

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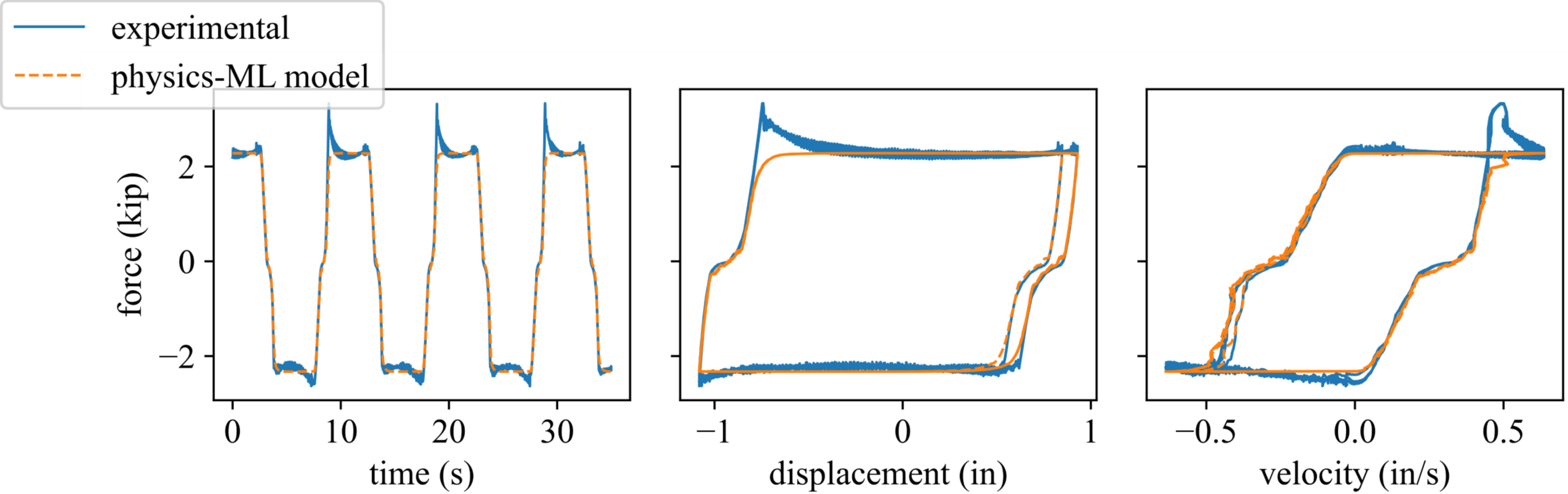
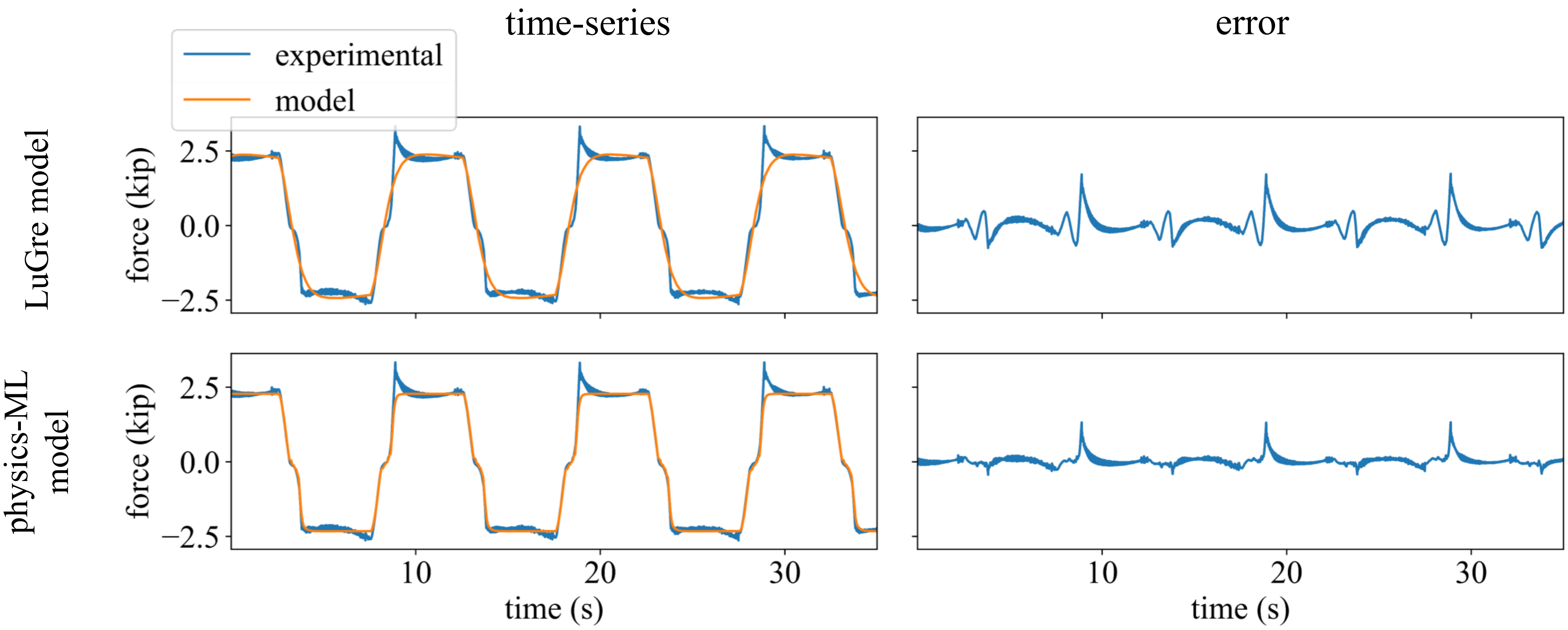


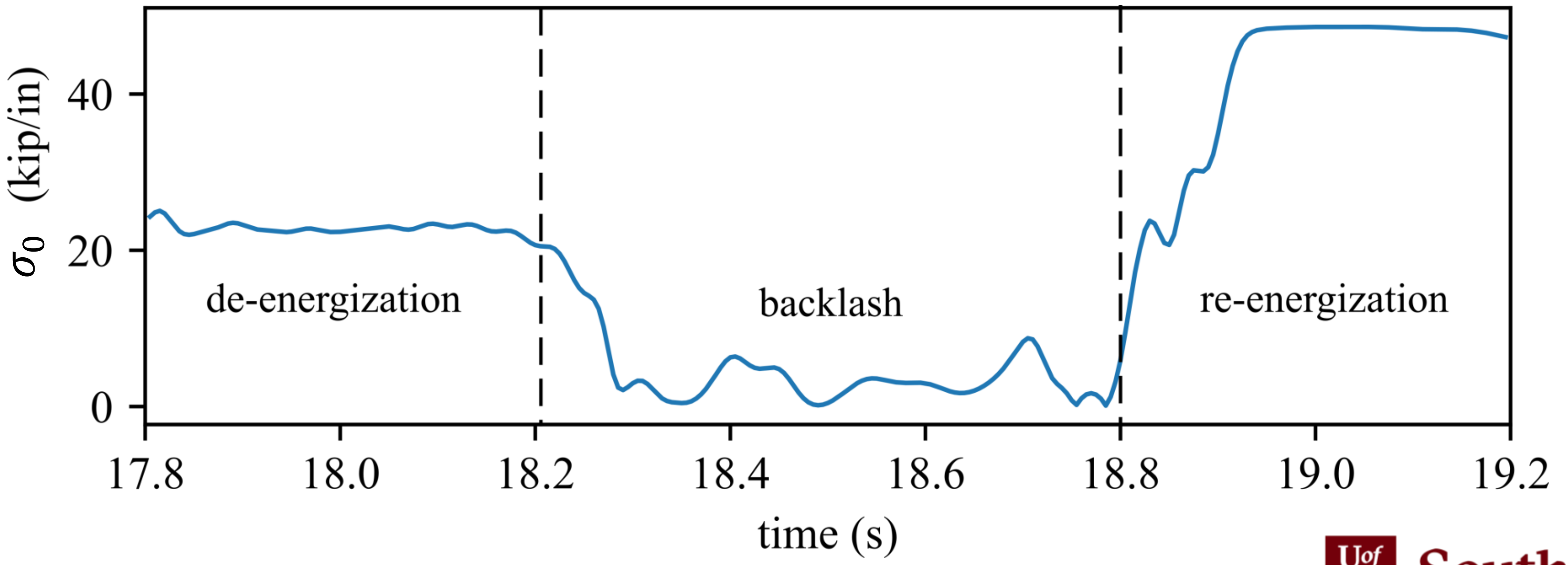
Results

Comparison between standard LuGre model and physics-ML model



Results

- The ML model produced a time-dependent function for σ_0—without any measurement of σ_0.
- Applications in ‘indirect measurement’ time-series characterization of physical systems.



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Conclusion

- Due to the backlash effect, characterization of friction dampers with standard models is difficult.
- A standard friction model was augmented with time-series parameter prediction supplied by an ML model and applied to a rotary friction damper.
- The combined physics-ML model was able to reduce error by 53% compared to a standard LuGre model.
- Physics-informed machine learning combines the benefits of informed structure and data-driven learning.

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THANKS!

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