

# Collaborations through REUs – A Lehigh Facility User Experience

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**Research Group, Spring 2023**



UNIVERSITY OF  
**SOUTH CAROLINA**

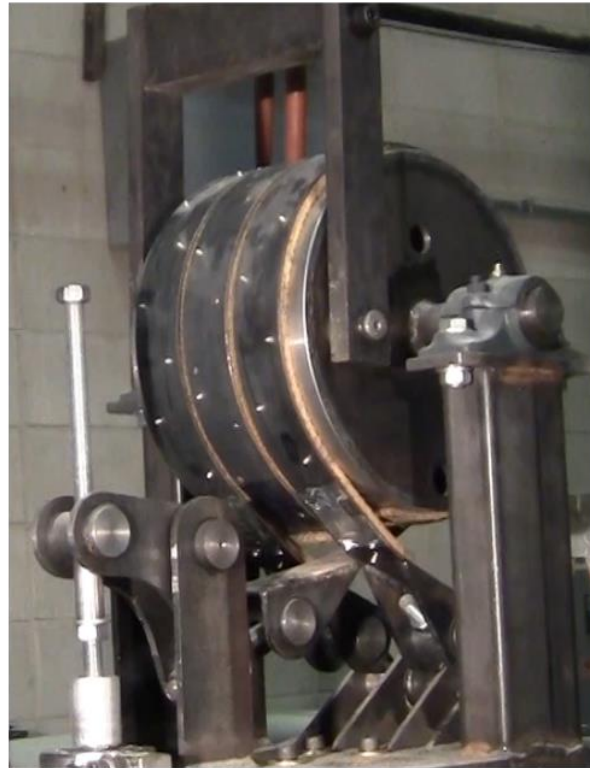
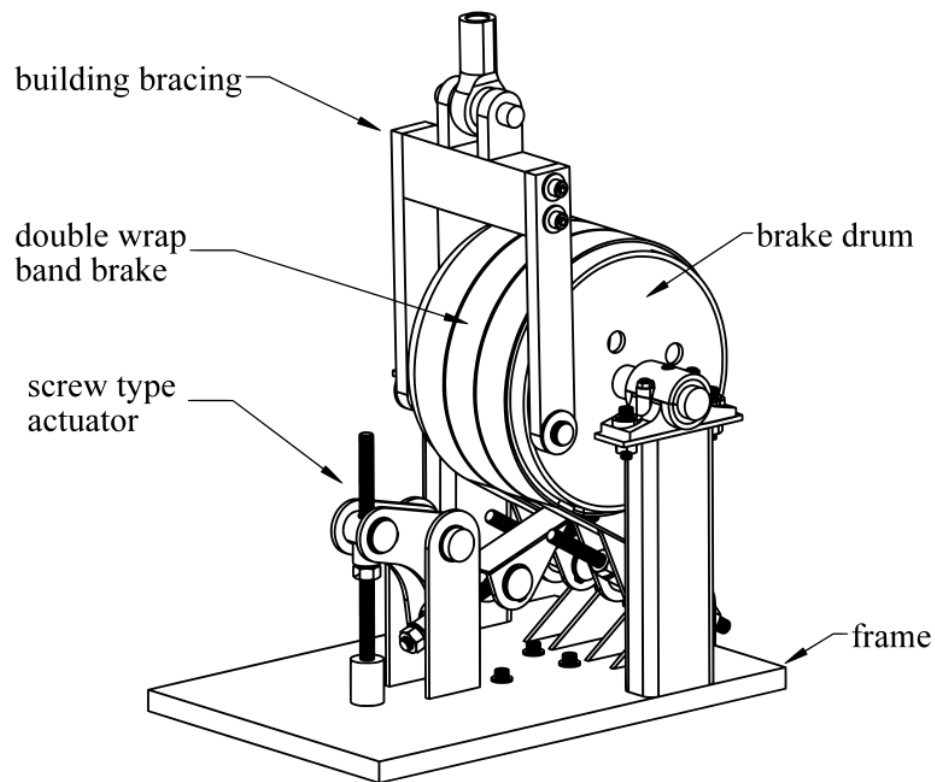
# Undergraduate Research

The lab has a large group of undergraduates doing active research. Currently about 25 undergraduate students.

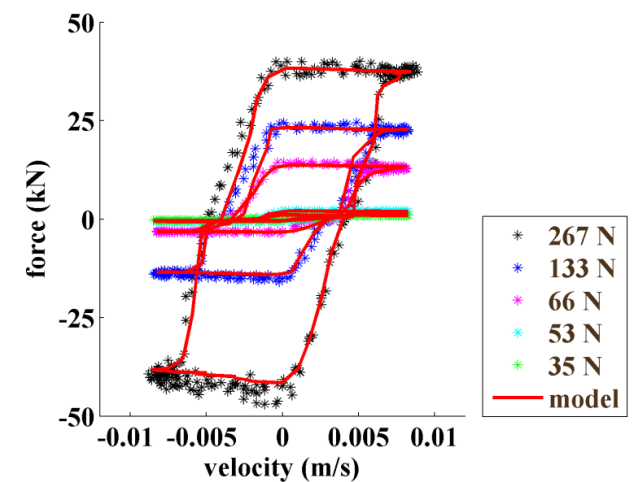
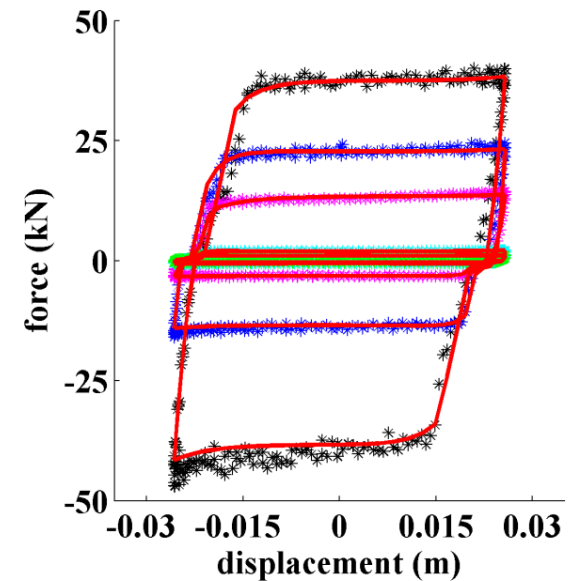


↓ Undergraduate

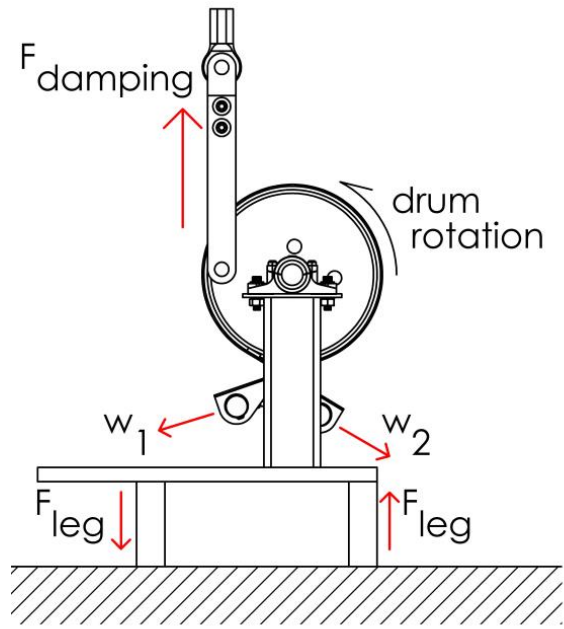
# Banded Rotary Friction Device (BRFD)



mechanical advantage of 142



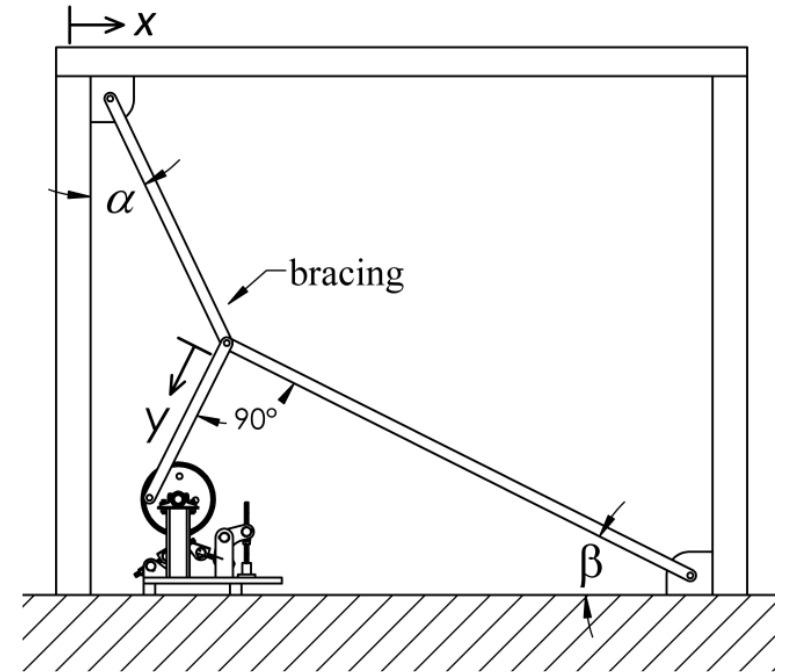
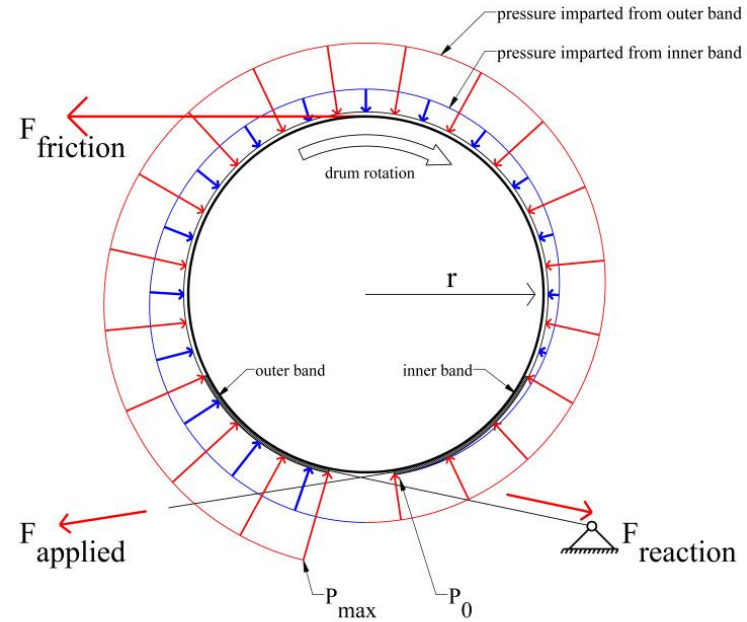
# Banded Rotary Friction Device (BRFD)



$$F_{\text{reaction}} / F_{\text{applied}} = e^{\mu\phi}$$

$$F_{\text{applied}} = \frac{F_{\text{friction}}}{(e^{\mu\phi} - 1)}$$

$$F_{\text{damping}} = \frac{T}{r_b} = \frac{F_{\text{friction}} \cdot r}{r_b}$$

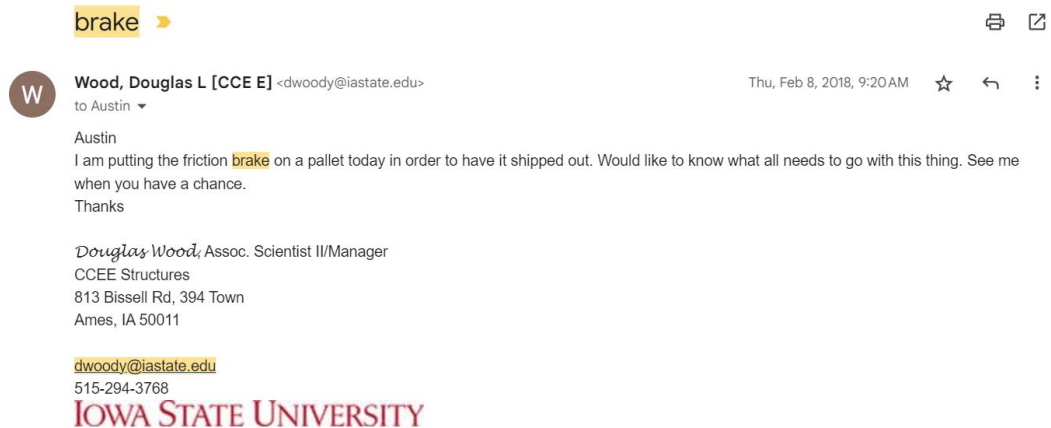


# BRFD Timeline

The BRFD was:

- Built in my home shop in 2014
- Journal paper published in 2015
- Iowa State Shop Manager pressed us to trash it in Fall 2017; Jim Ricles asked us to ship it Lehigh.

Iowa State lab manager happy to see it go!

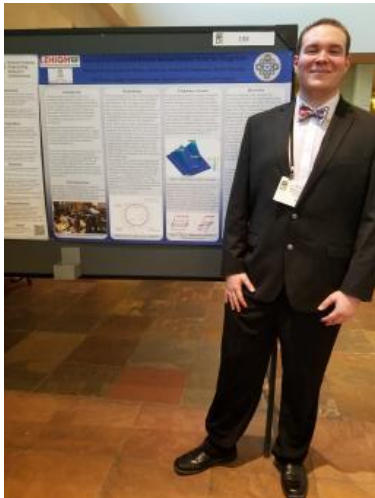
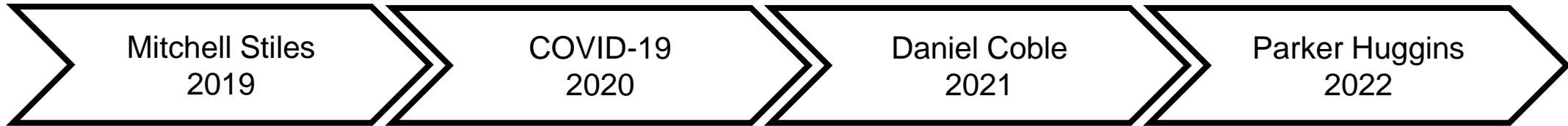


BRFD in 2019 with new bands



# BRFD Further Developed over three summers

REU students participating in summer REUs have continued the project since 2019

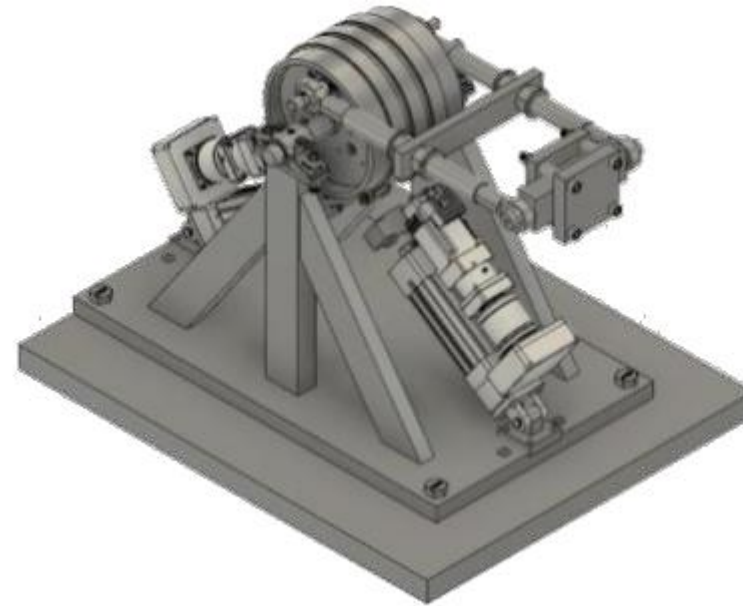


# Mitchell Stiles – System Hardware Improvement

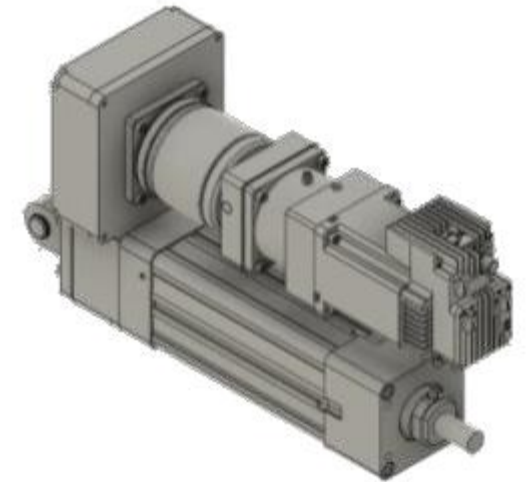


# Expanding to Semi-active Device

New device is being engineered to create a stiffer design and incorporate electric actuators to create a semi-actively controlled friction damping device.



Rendering new Design

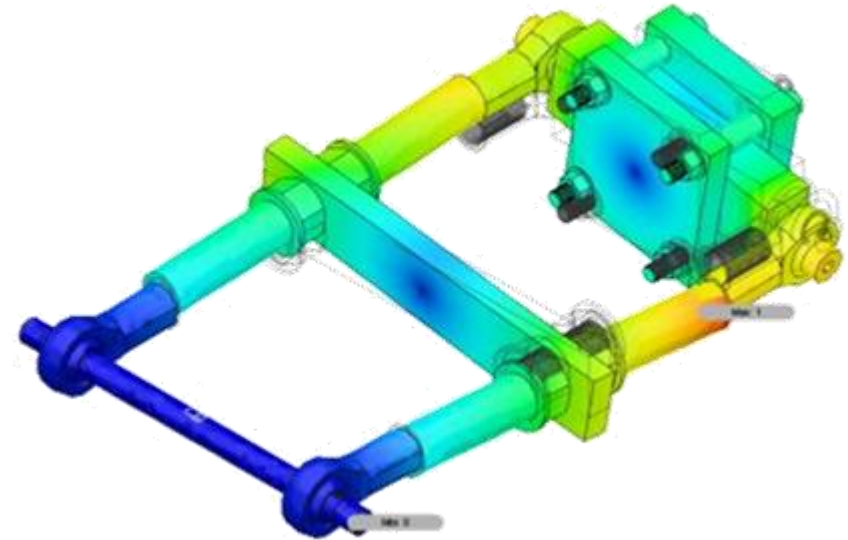




# New Structure to Drum Connection



Old drum with previous connection

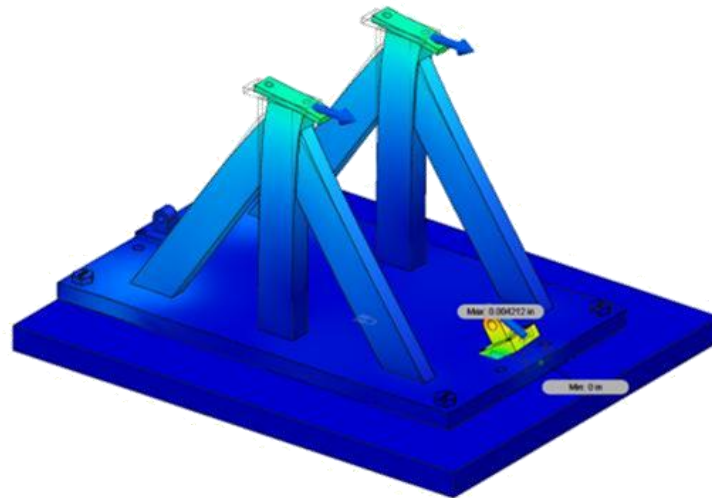


Mode Number	Frequency (Hz)
1	60.64
2	71.9
3	275.6
4	285.6
5	367.6

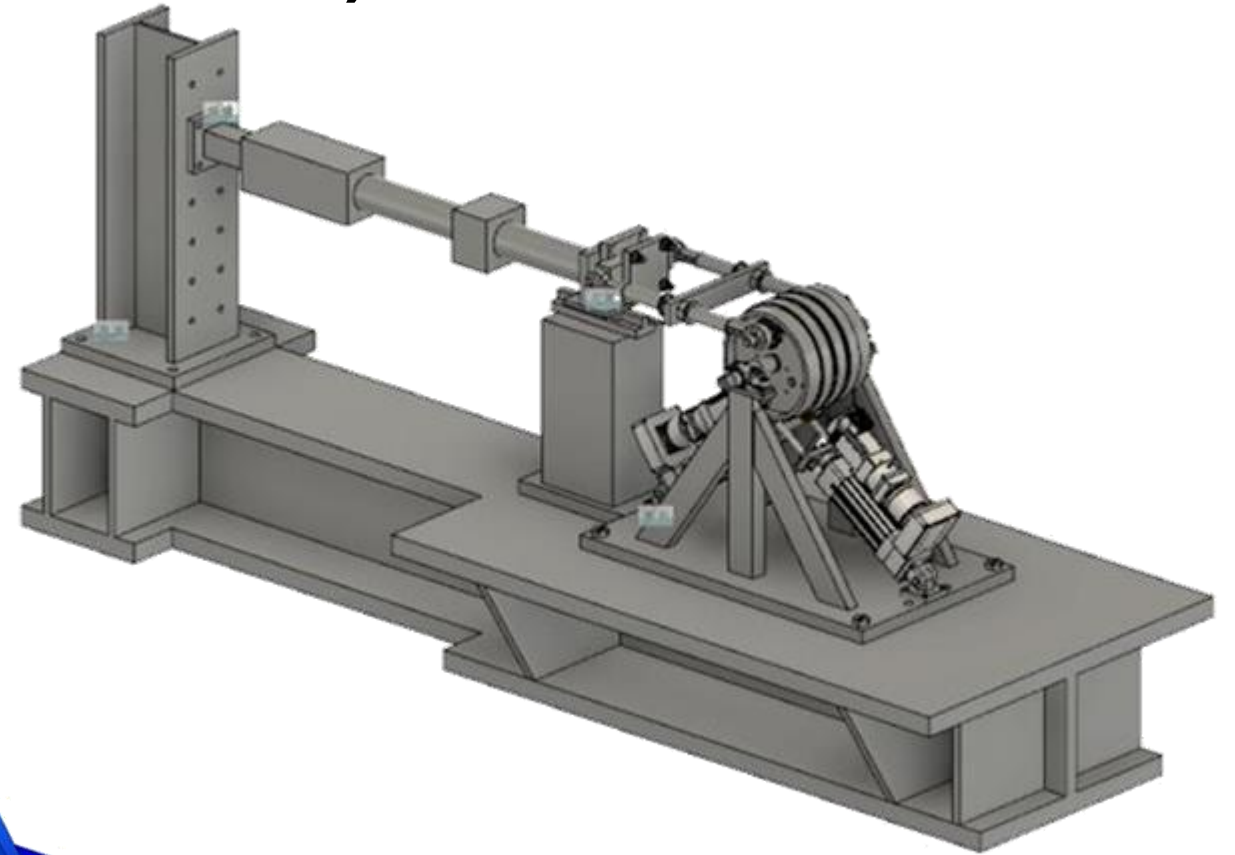
# Methodology (Drawings and Simulation)



New steel drum

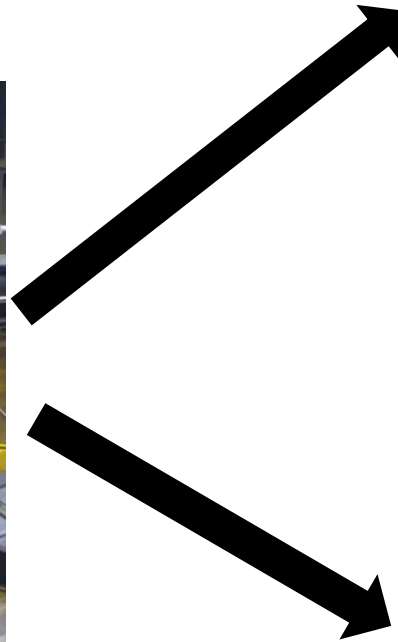
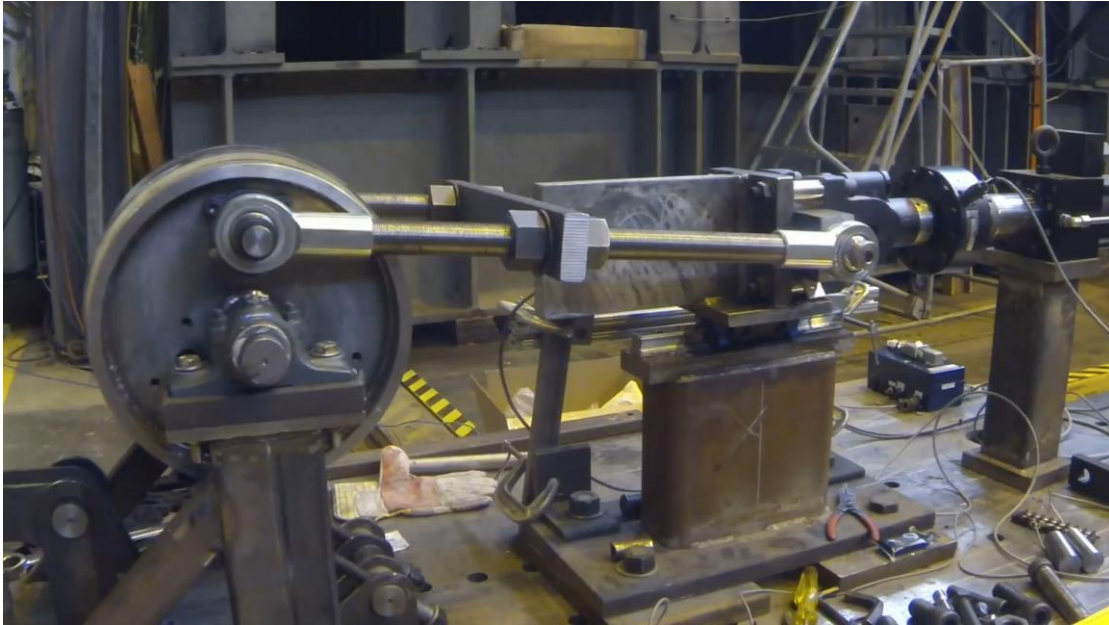


I-Beam Foundation with semi-active BRFD

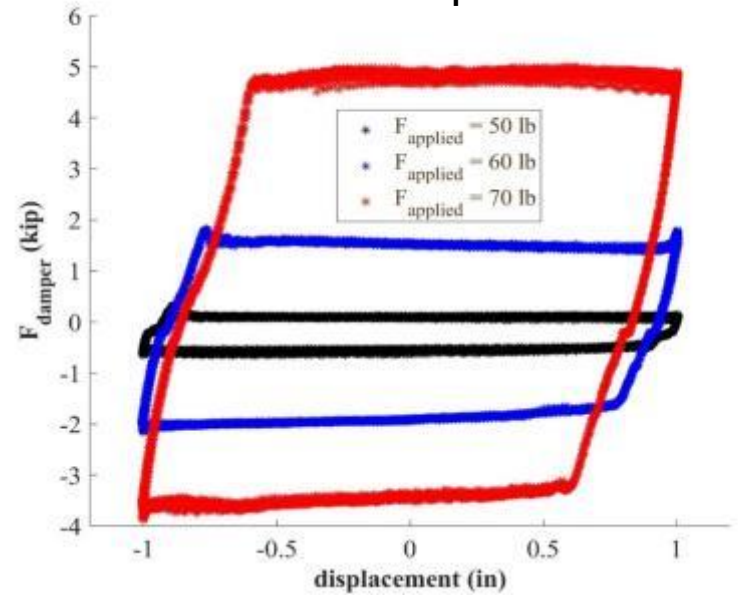


simulation is of the new frame and support struts

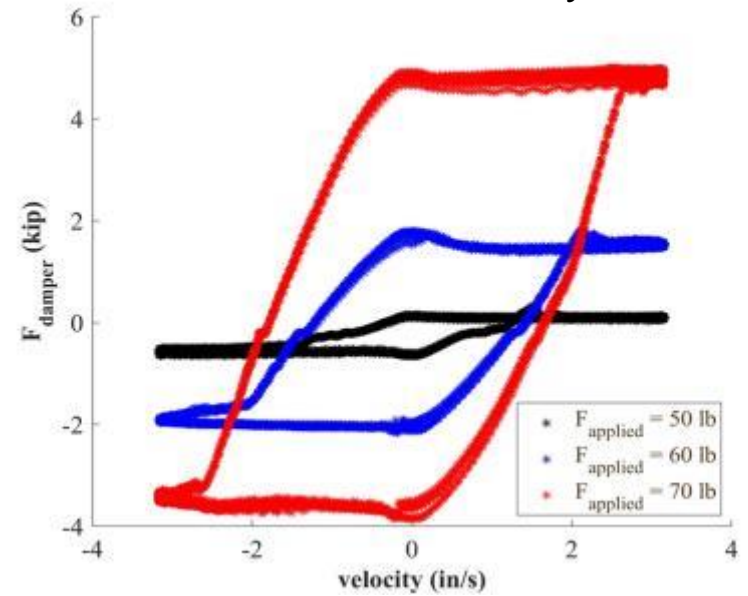
# Preliminary Results



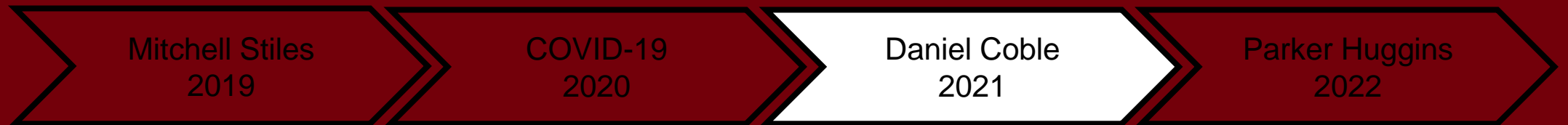
Force vs. displacement



Force vs. velocity

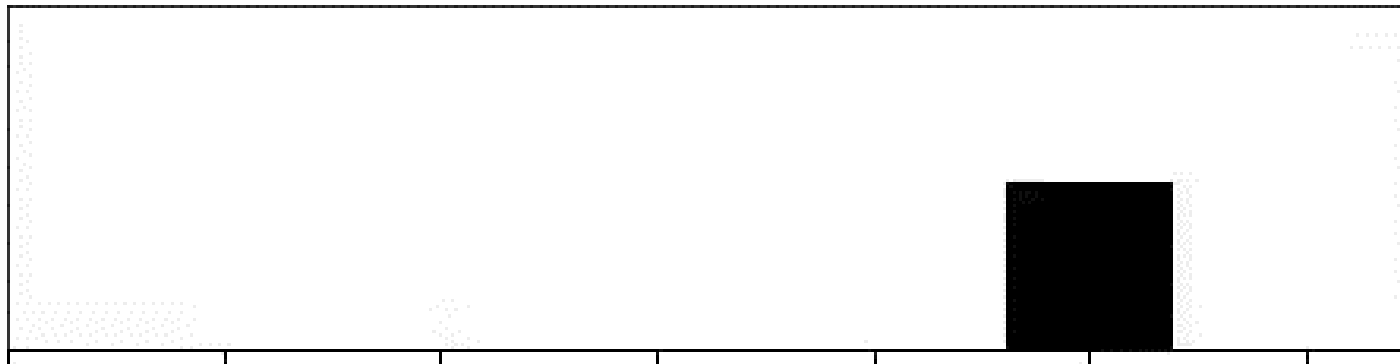
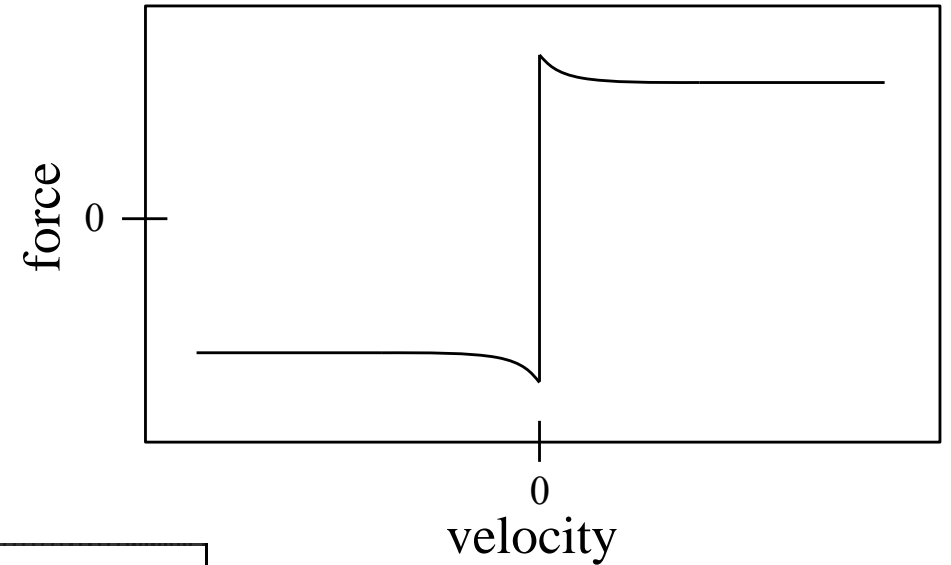


# Daniel Coble – Friction Modeling using Physics Informed Machine Learning



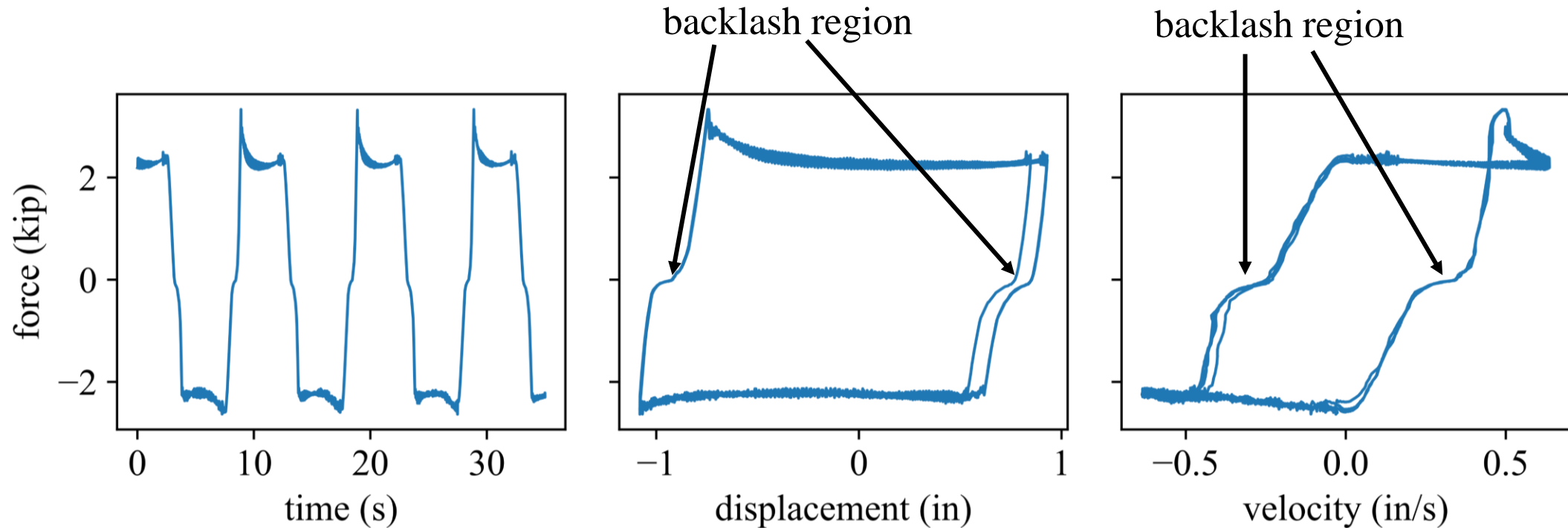
# Problems in modeling friction

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



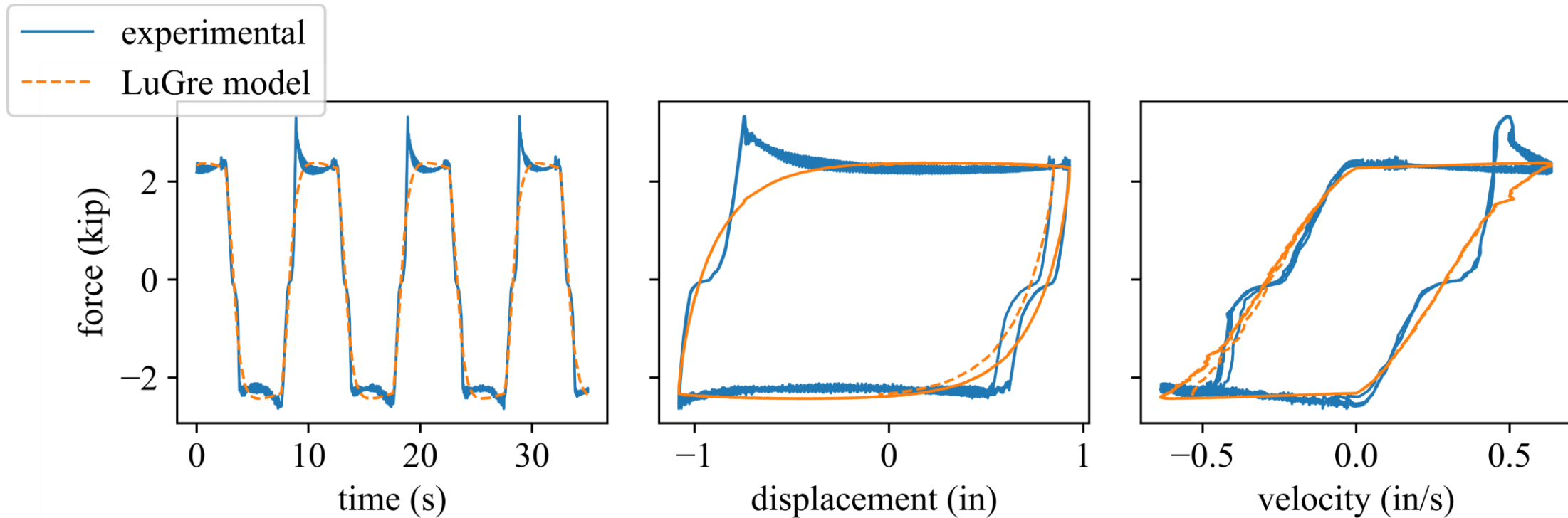
# Device Characterization

- The device was characterized with four sinusoidal displacement tests with frequencies between 0.1 Hz and 1.0 Hz.
- The backlash effect: self-energizing effect depletes during reversal of travel.



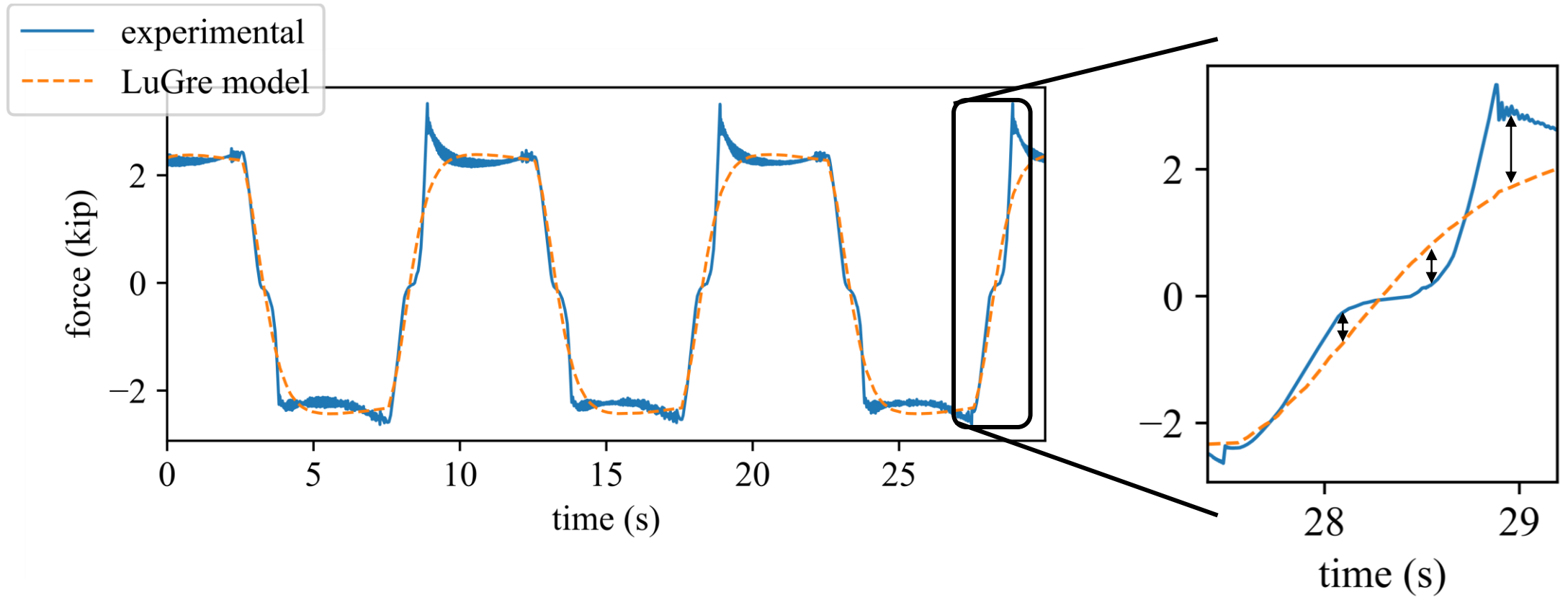
# Problems using current models

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



# Problems using current models

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





# 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:  $\sigma_0, \sigma_1, \sigma_2$ .
- $\sigma_0$  controls hysteresis rate of change–backlash effect.

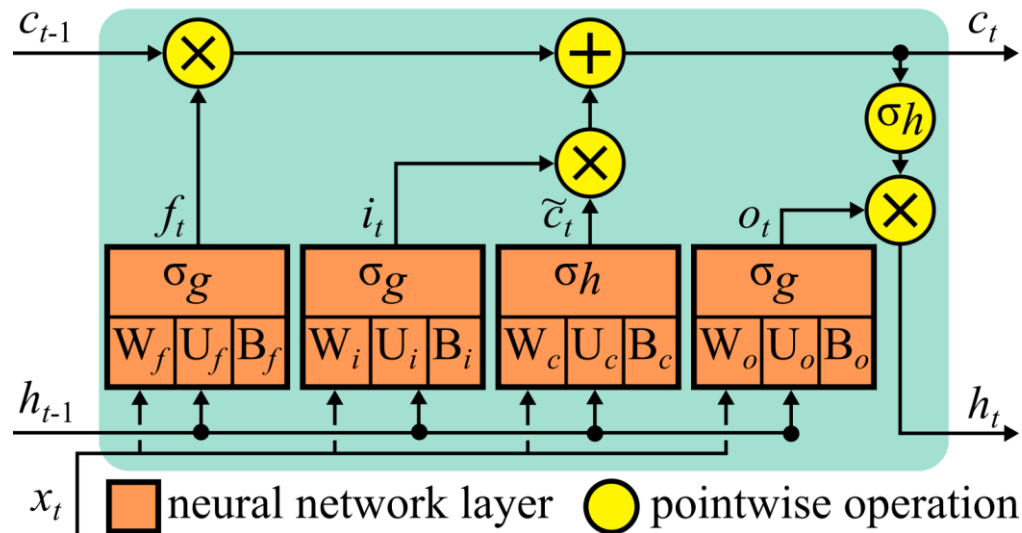
$$\dot{z} = v - \sigma_0 \frac{|v|}{g(v)} z$$

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

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

# 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.

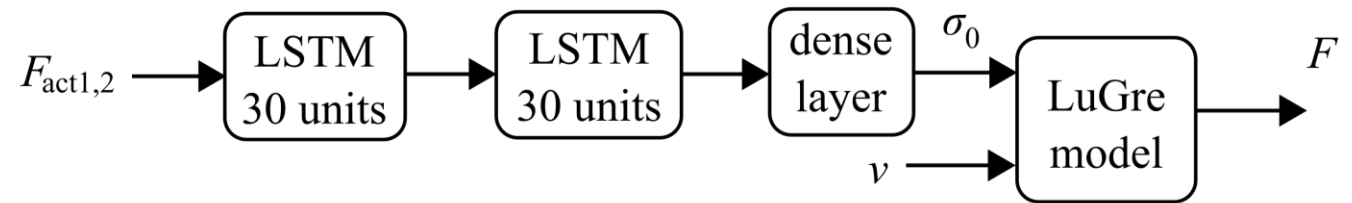


$$\begin{aligned}
 f_t &= \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\
 i_t &= \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\
 o_t &= \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\
 \tilde{c}_t &= \sigma_h(W_c x_t + U_c h_{t-1} + b_c) \\
 c_t &= f_t \circ c_{t-1} + i_t \circ \tilde{c}_t \\
 h_t &= o_t \circ \sigma_h(c_t)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

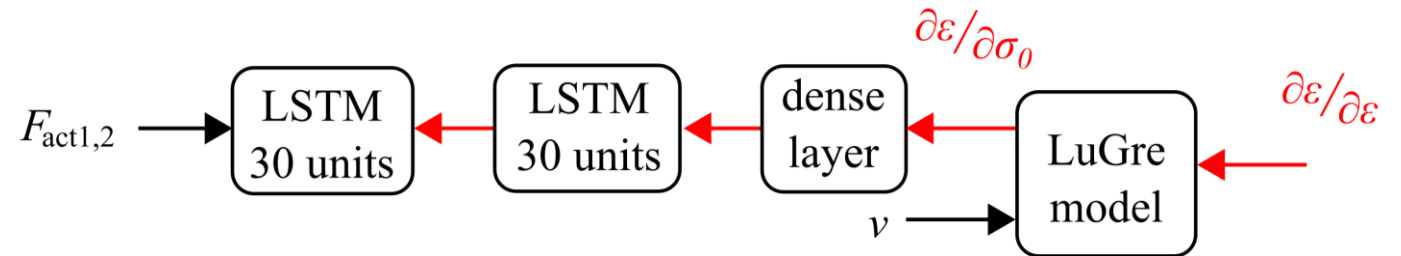
# Model Training

- 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

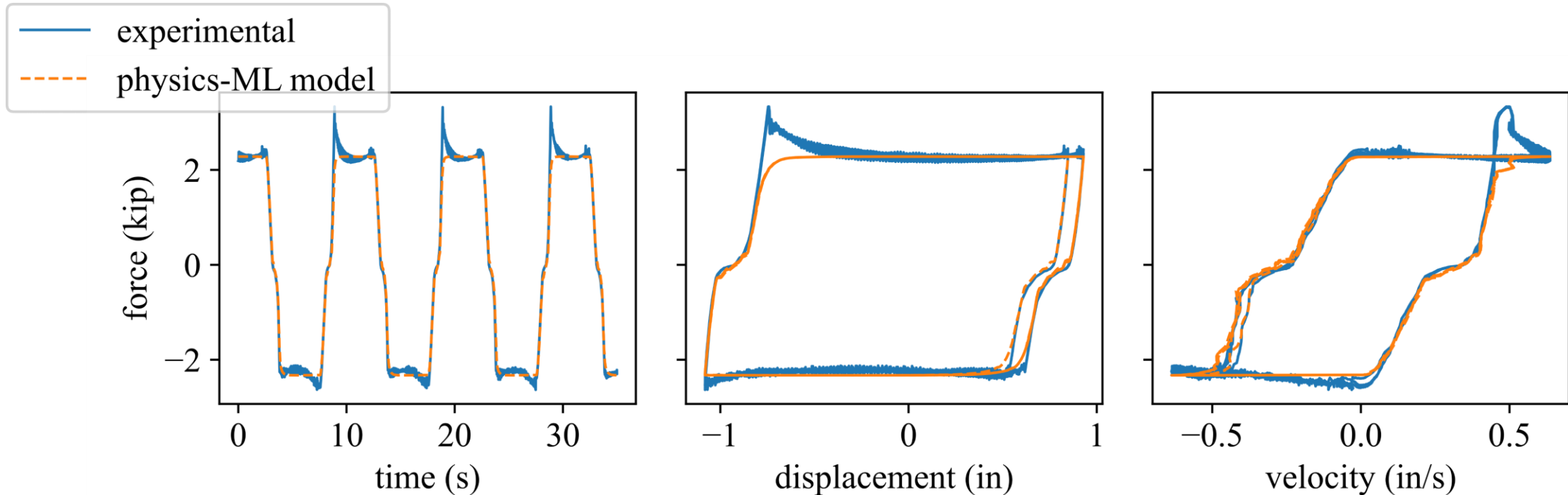


Backpropagation



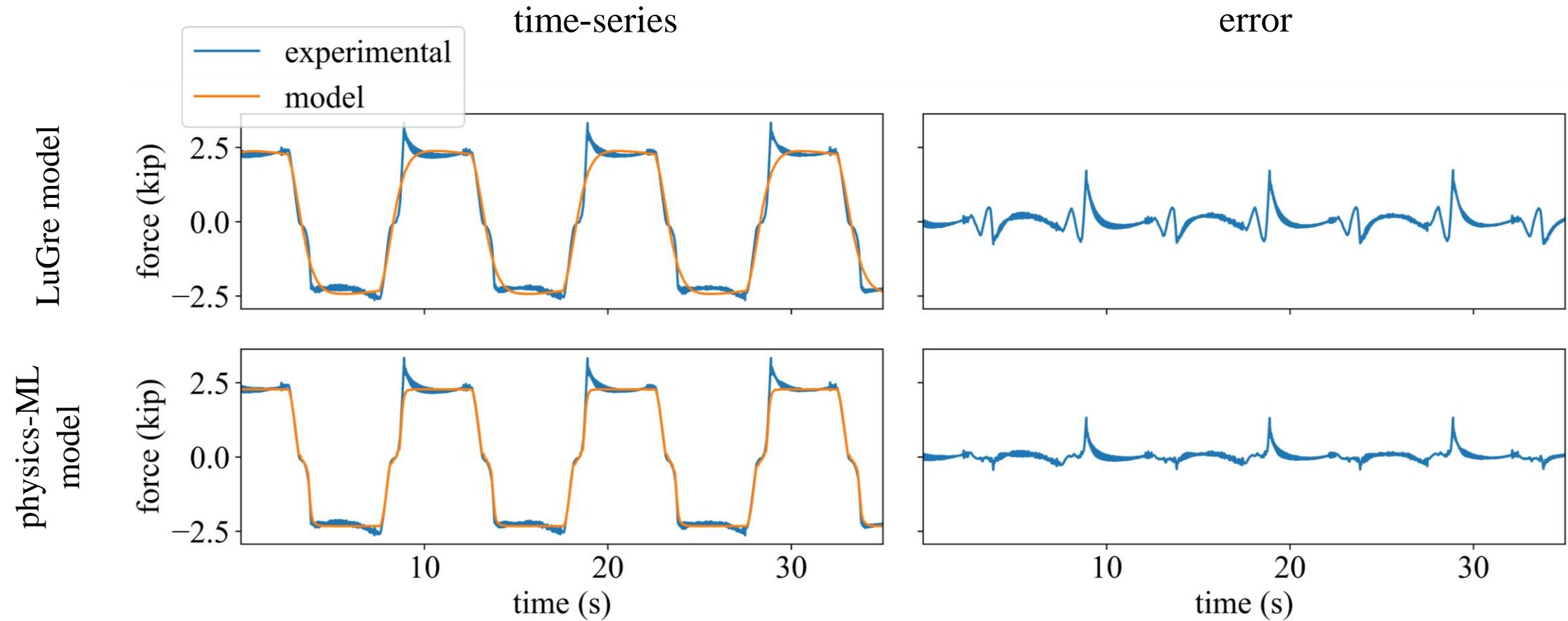
# Results

- 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.



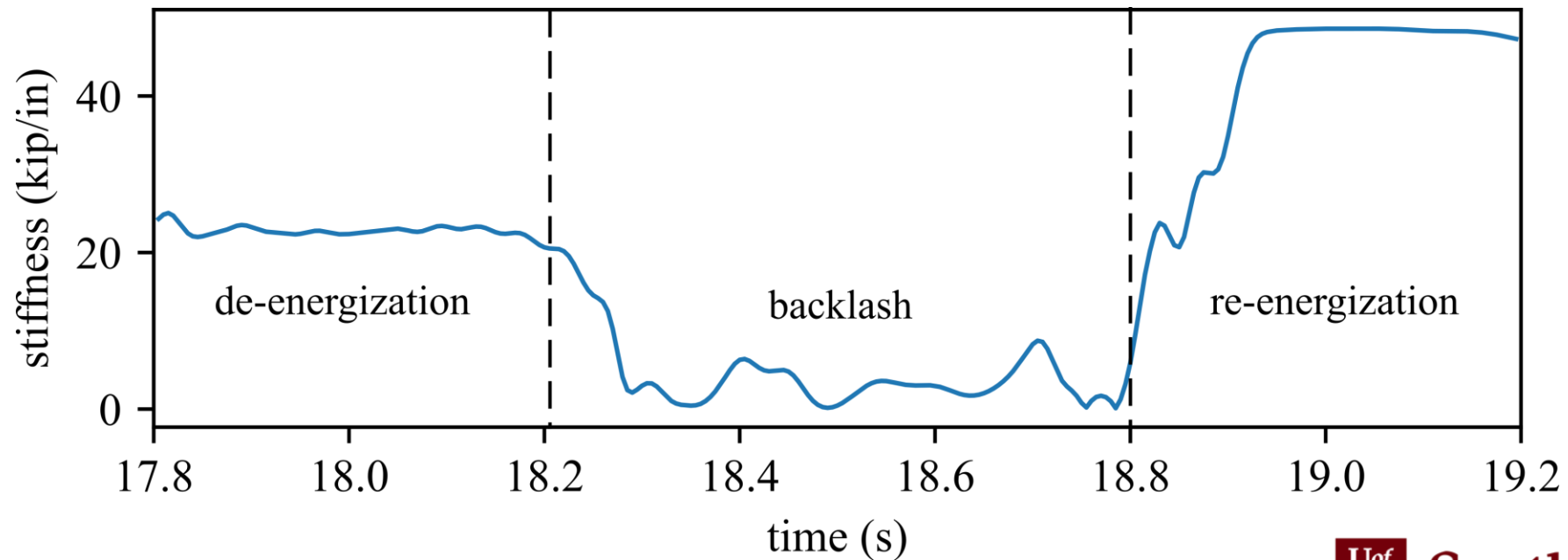
# Results

Comparison between standard LuGre model and physics-ML model



# Results

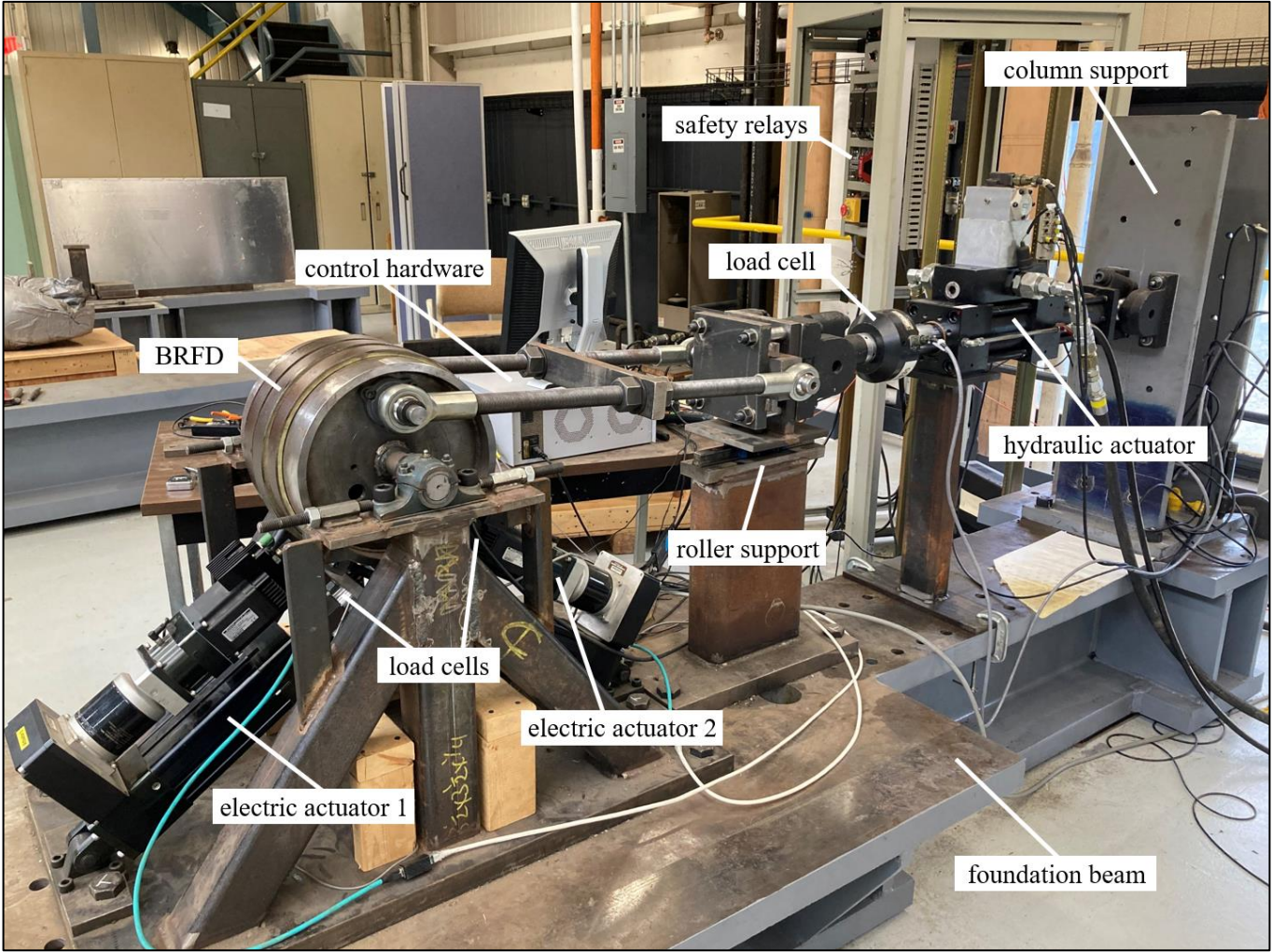
- The ML model produced a time-dependent function for  $\sigma_0$ —without any measurement of  $\sigma_0$ .
- Applications in ‘indirect measurement’ time-series characterization of physical systems.



# Parker Huggins – Characterization of a Semi-active Model

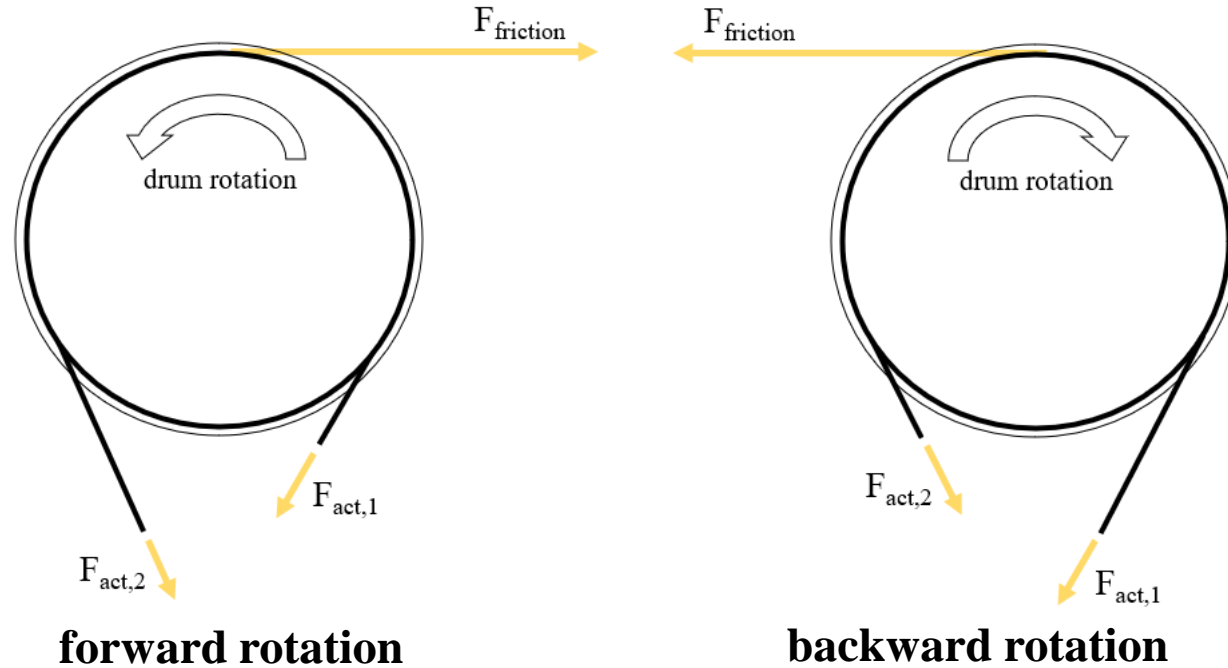


# Test Setup

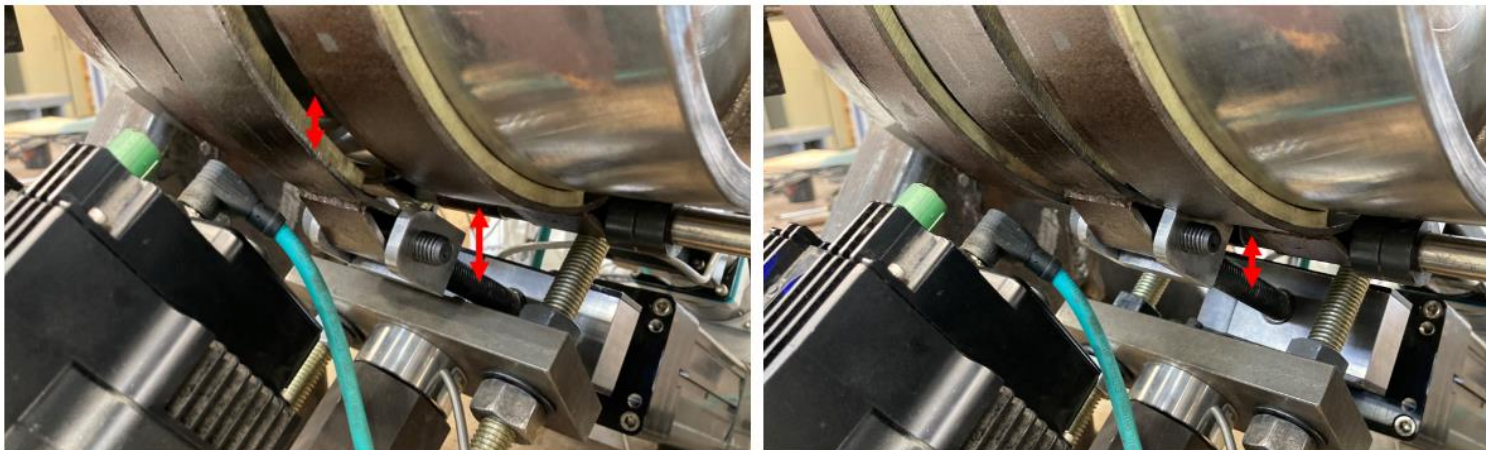




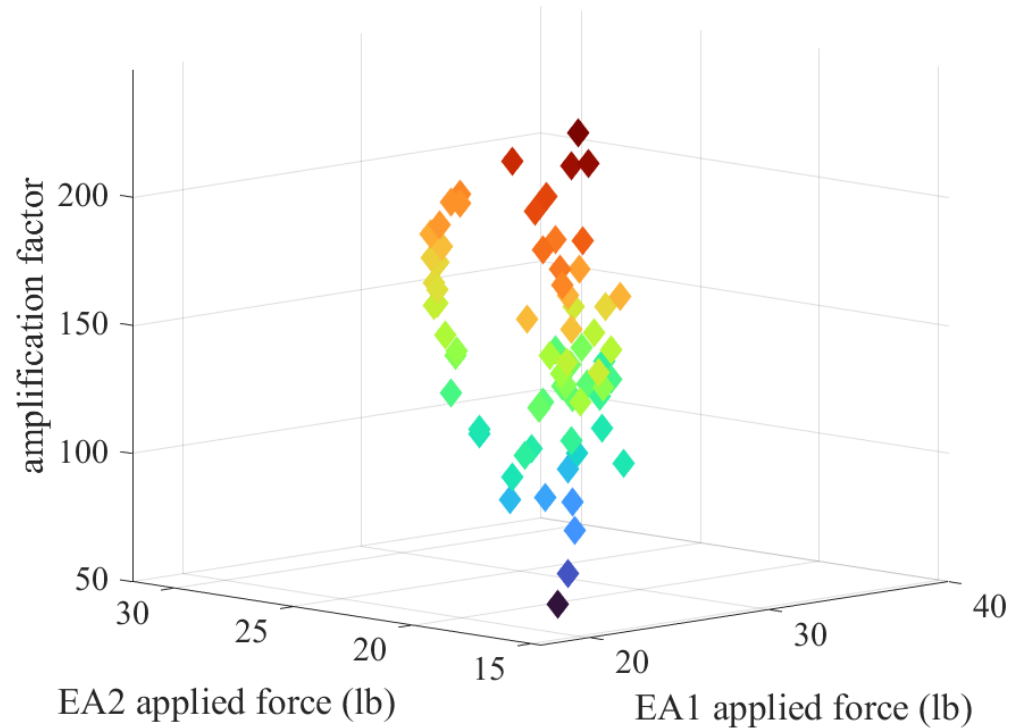
# BRFD Modeling Difficulties



- **Friction:** stiction, hysteresis, etc.
- **Deflections:** electric actuators/ friction bands
- **Sensitivity:** initial conditions



# Damper Force Amplification



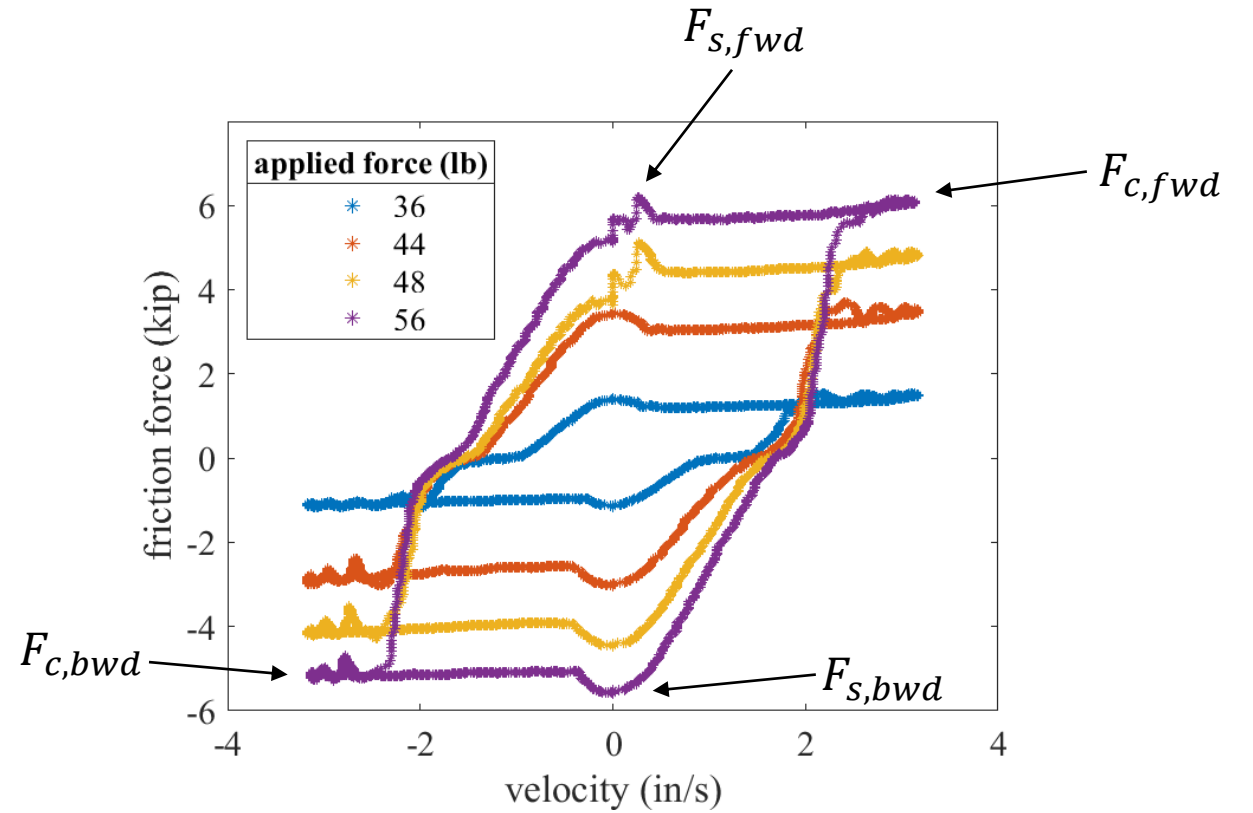
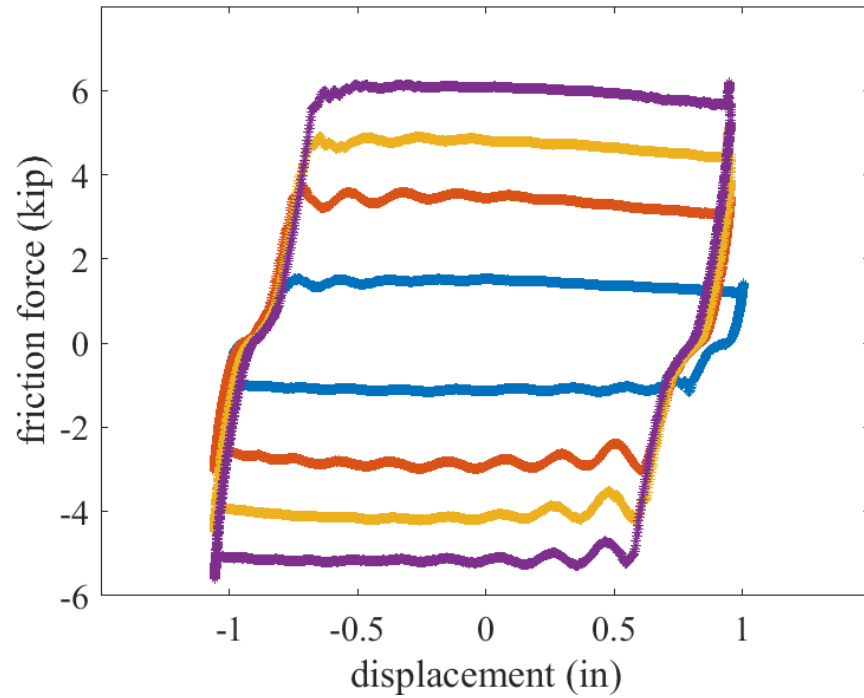
- Factor by which the BRFD amplifies its input
- Ratio of damping force to slack-actuator force

**Forward rotation:**  $C_{fwd} = \frac{F_{c,fwd}}{F_{act,1}}$

**Backward rotation:**  $C_{bwd} = \frac{F_{c,bwd}}{F_{act,2}}$

- BRFD capable of achieving amplification factors  $\gg 1$
- Amplification **increases** with pretension forces

# Passive to Semi-active

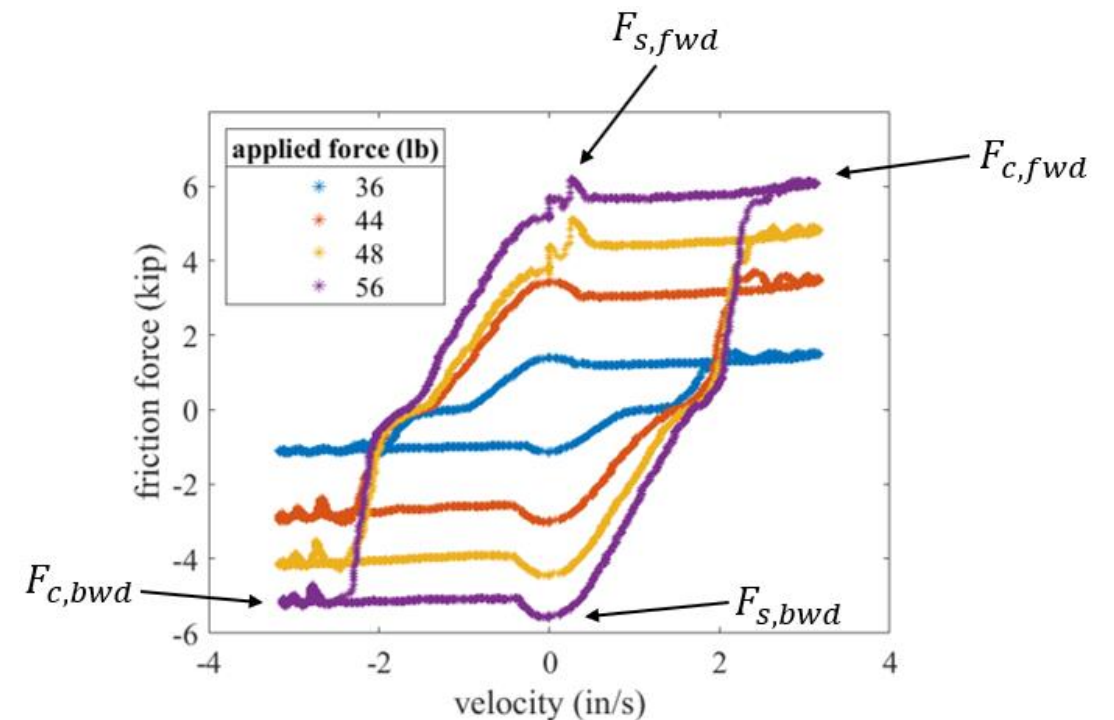


# Approach

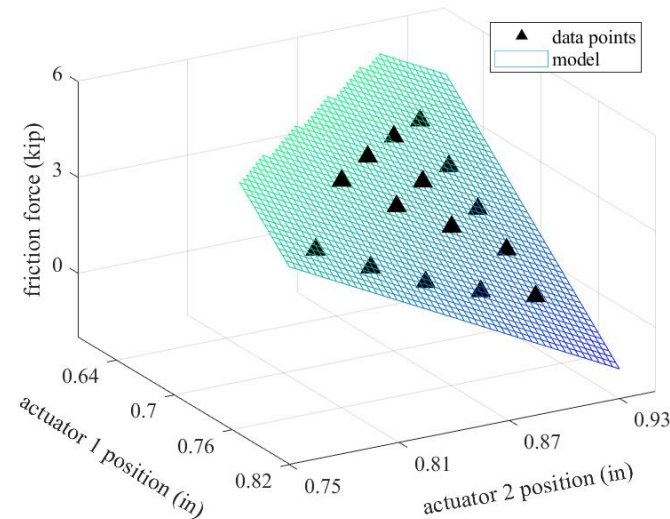
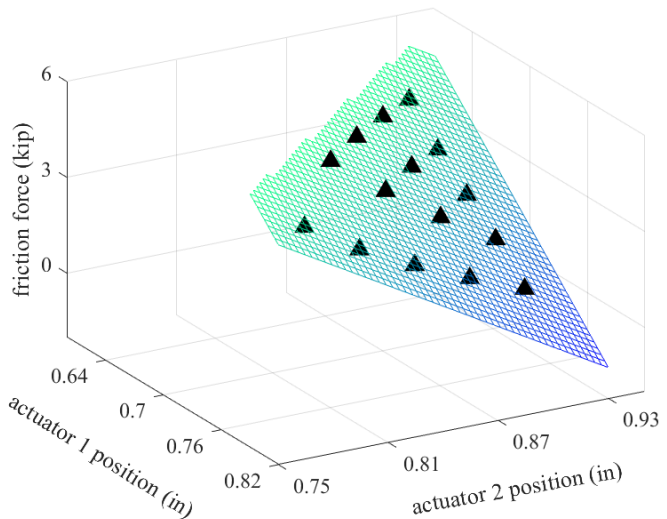
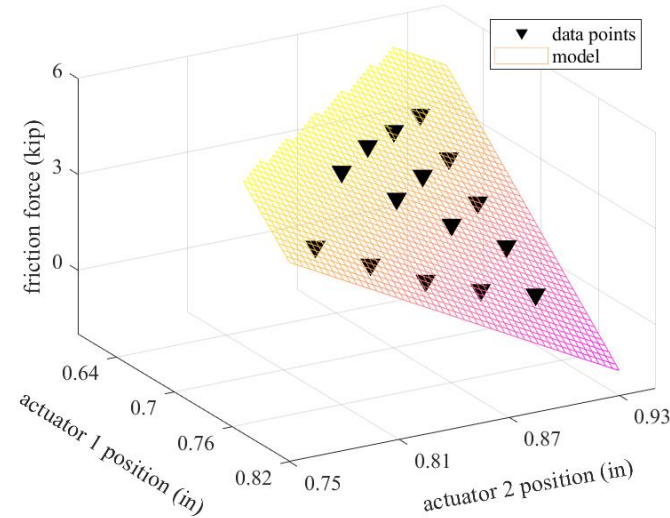
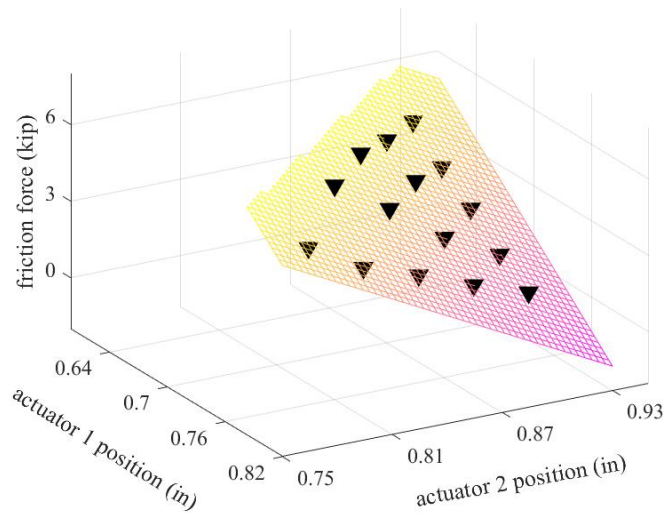
- Sets of passive characterization tests conducted for analysis
- Used sinusoidal input with amplitude **1 in** and frequency **0.5 Hz**
- Electric actuators incrementally retracted between tests
- Data from **90** tests collected in total

		Actuator 1 position (in)								
		0.715	0.73	0.745	0.76	0.775	0.79	0.805	0.82	0.835
Actuator 2 position (in)	0.81									
	0.825						x	x		
	0.84					x	x	x	x	
	0.855				x	x	x	x	x	
	0.87			x	x	x	x	x	x	
	0.885		x	x	x	x	x	x	x	
	0.9	x	x	x	x	x	x*	x	x	
	0.915		x	x	x	x	x	x	x	
	0.93		x	x	x	x	x	x	x	
	0.945									

Full Test
Safety Limit
*conducted twice



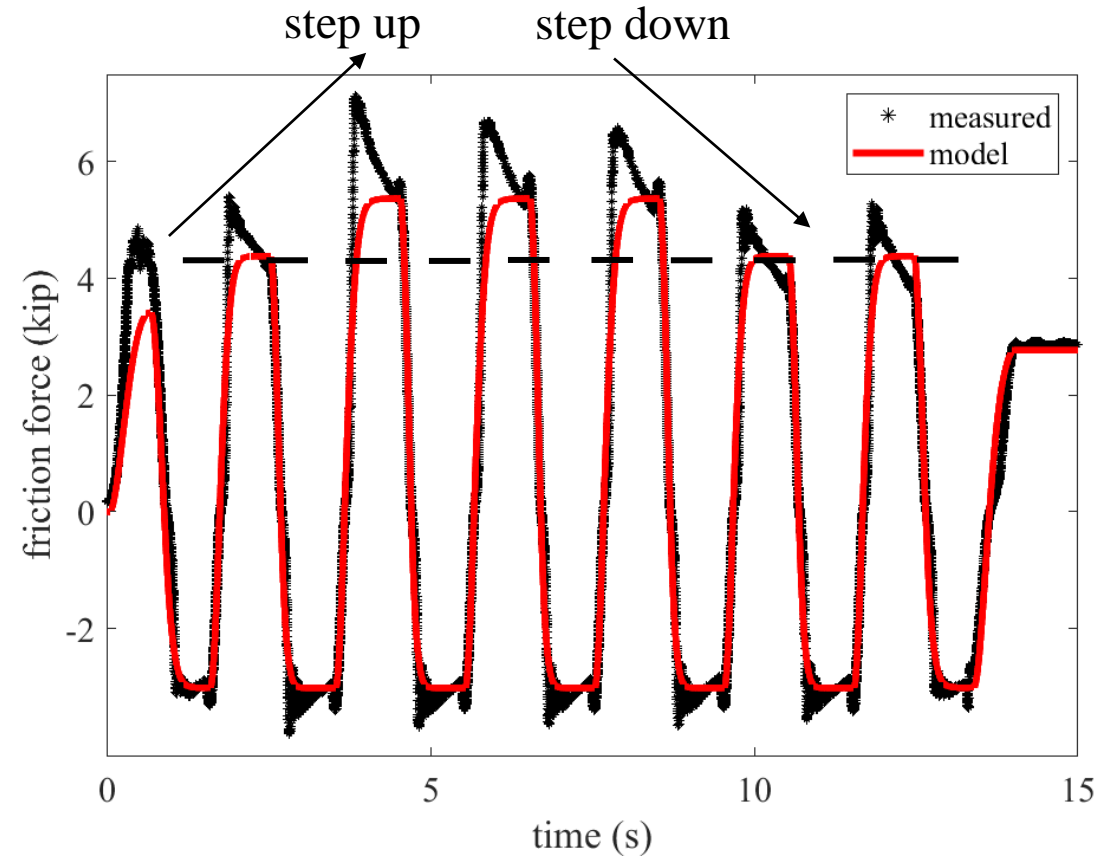
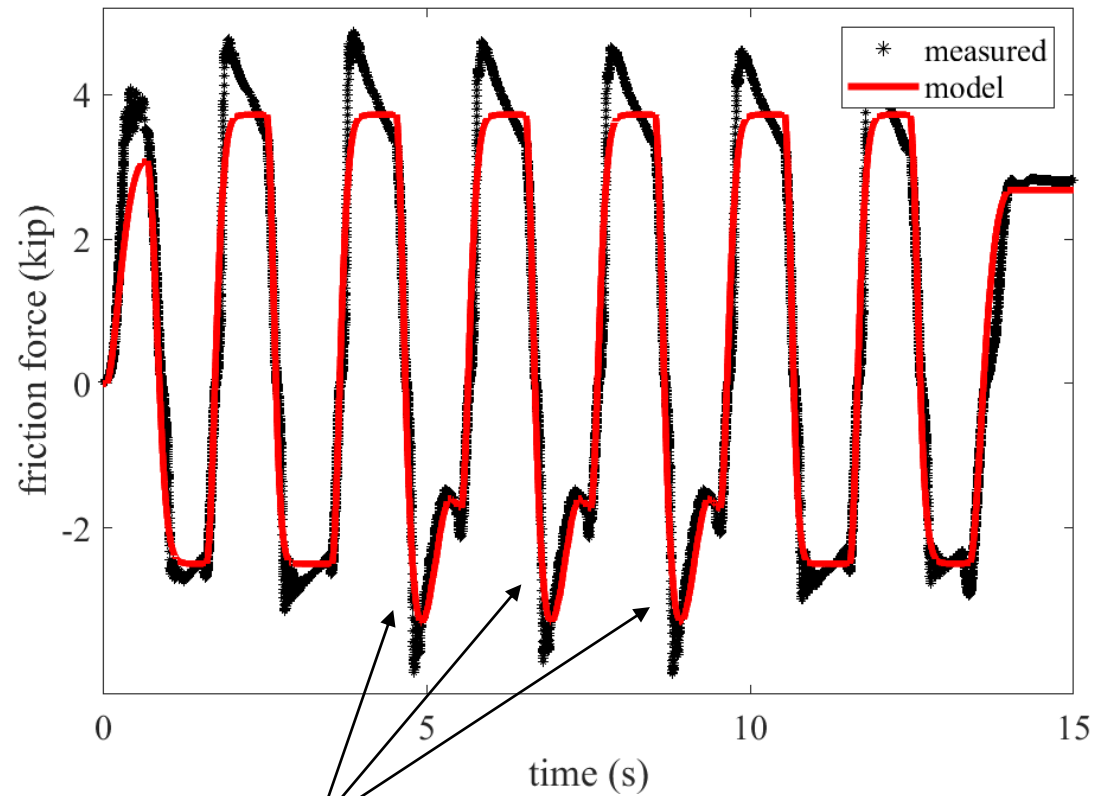
# Regression Analysis



- Actuator initial positions vs. static/kinetic friction
- Slopes  $\rightarrow$  rates at which damping changes with actuator **displacements**
- Linear models ignore potential for actuator coupling

# Results

- Model able to predict changes in damping induced by electric actuator displacements



dynamic  $F_S$  and  $F_C$

# THANK YOU!

## WANT THE DATA?

<https://github.com/ARTS-Laboratory/Dataset-Friction-Damper-with-Backlash>



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Github: <https://github.com/austindowney>  
Github-Lab: <https://github.com/Arts-laboratory/>