

# Hysteresis-Based Modeling and Control of Piezoelectric Actuators for Precision Manipulation

**Gerardo Flores, Ph.D.**

Director, RAPTOR Lab  
Associate Professor of Systems Engineering  
Texas A&M International University

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## **Part I — The Problem** (10 min)

Why piezo actuators? The hysteresis barrier.  
Measurement constraints.

## **Part II — Modeling Hysteresis** (30 min)

Classical & Generalized Bouc–Wen. Dahl model.

## **Part III — Output Feedback Control** (30 min)

Observers, robust control, separation principle.

## **Part IV — Advanced Topics** (5 min)

Asymmetric hysteresis. Finite-time stabilization.  
MPC.

## **Part V — Applications** (5 min)

Distributed-parameter effects. Force control.

## **Part VI — Wrap-up** (10 min)

Takeaways. Lessons. Open problems.

## PART I

# The Problem

*Why should I care?*

~10 minutes

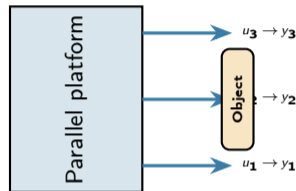
# Precision Manipulation: Where Piezo Actuators Shine

## Applications:

- Scanning probe microscopy & AFM
- Medical micro-robotics and micro-surgery
- Diesel injectors
- **Robotic hands** for manipulating fragile/deformable objects

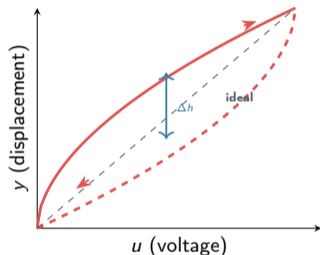
## Why piezoelectric?

- Resolution down to **nanometers**
- Bandwidth: **hundreds of Hz to kHz**
- No mechanical play (solid-state)
- Direct electrical supply  $\Rightarrow$  easy integration



Piezoelectric robotic hand

# Hysteresis: Not a Small Annoyance



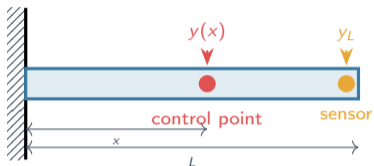
## Impact on performance

- 1 **Path-dependent output:** same voltage  $\Rightarrow$  different position depending on direction
- 2 **Up to 60% amplitude error** in open loop
- 3 **Can destabilize feedback** if not modeled

## Key point

Ignoring hysteresis is **not an option** for precision tasks.

# Measurement Reality Check



## Available:

- Position  $y$  at tip (sensor)
- Voltage  $u$

## Not available:

- Hysteresis state  $h$
- Velocity  $\dot{y}$
- Interaction force  $F$
- Position at arbitrary point  $y(x)$

## Implication

We must **estimate what we cannot measure**. This motivates the entire **output-feedback framework**: nonlinear observers to reconstruct  $h$ ,  $F$ , and hidden dynamics from  $y$  alone.

## PART I — KEY MESSAGE

The difficulty is not control —  
it's what you don't measure.

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- ▶ Piezoelectric actuators offer unmatched precision, but hysteresis is the price
- ▶ Ignoring hysteresis: up to 60% error or instability
- ▶ Only position is measured — everything else must be estimated

## PART II

# Modeling Hysteresis

*Without killing yourself*

~30 minutes

# How People Usually Deal with Hysteresis

## Approach 1: Feedforward inversion

- Model hysteresis precisely
- Compute inverse  $\mathcal{H}^{-1}[\cdot]$  and place in cascade
- ✗ No robustness vs. disturbances
- ✗ Model uncertainties accumulate

## Approach 2: Treat as disturbance

- Use linear model + robust controller
- ✗ Fails when hysteresis is strong
- ✗ No formal stability guarantee

## Approach 3: Direct model-based feedback

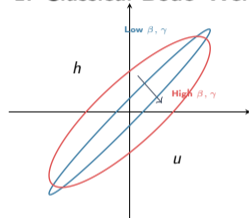
- ✓ Use explicit hysteresis model in control design
- ✓ Formal stability proofs
- ✓ Robust to disturbances
  - This is our approach

## Our philosophy

**Model just enough** hysteresis to make control possible.

# Hysteresis Models: Parameter Influence

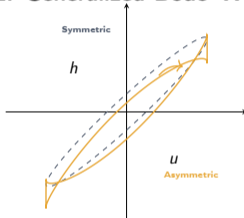
## 1. Classical Bouc–Wen



Parameters:  $\alpha, \beta, \gamma$

Controls amplitude and loop width (dissipation). Always symmetric.

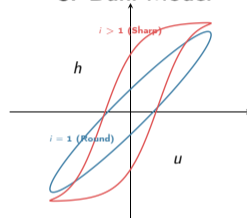
## 2. Generalized Bouc–Wen



Parameters:  $\dots, \psi, \delta_\nu$

Adds shape factors for asymmetry. Useful for specific piezo materials.

## 3. Dahl Model



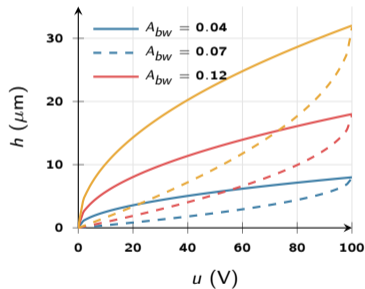
Parameters:  $\sigma, i$

Shape factor  $i$  controls transition sharpness ("elasto-plastic" behavior).

# Classical Bouc–Wen: Effect of Parameters

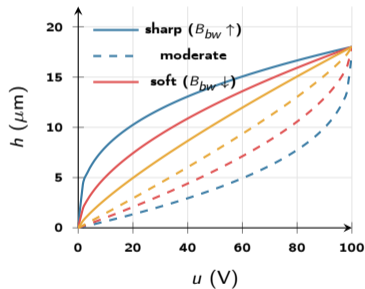
$$\dot{h} = A_{bw}\dot{u} - B_{bw}|\dot{u}|h - G_{bw}\dot{u}|h| \quad \text{— Symmetric loops, shape controlled by } A_{bw}, B_{bw}, G_{bw}$$

Varying  $A_{bw}$  (amplitude)



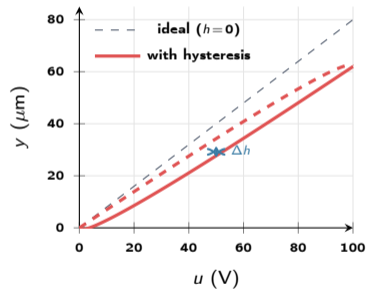
$A_{bw}$  controls the **width** of the hysteresis loop (amplitude)

Varying  $B_{bw}, G_{bw}$  (shape)



$B_{bw}, G_{bw}$  control the **shape**: sharp vs. gradual saturation

Full  $(u, y)$  map



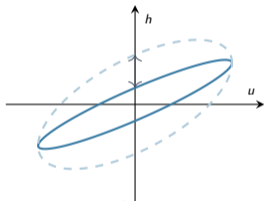
The output  $y$  deviates from the ideal line by the hysteresis  $h$

# Hysteresis Models: Visualizing the Parameters

## 1. Classical Bouc–Wen

$$\dot{h} = A_{bw}\dot{u} - B_{bw}|\dot{u}|h - G_{bw}\dot{u}|h|$$

Symmetric Variation

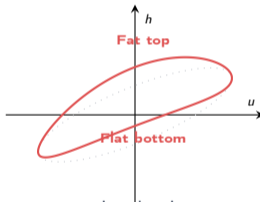


Parameters  $B_{bw}$ ,  $G_{bw}$  control the **width** (dissipation). The loop remains perfectly **symmetric**.

## 2. Generalized Bouc–Wen

$$\dot{h} = \alpha[A_{bw} - (B_{bw} \operatorname{sgn}(\dot{u}) + G_{bw})|h|^n]$$

Asymmetric Shape ( $\alpha$ )

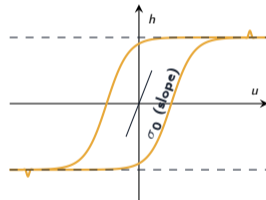


Parameter  $\alpha$  breaks the symmetry. Note different curvatures for loading vs. unloading phases.

## 3. Dahl Model

$$\dot{h} = \sigma_0 \dot{u} (1 - \frac{h}{h_c} \operatorname{sgn}(\dot{u}))^i$$

Stiffness & Saturation



$\sigma_0$  sets the initial stiffness (slope).  $h_c$  sets the saturation force. Inherently asymmetric.

# Run the Hysteresis Simulation Yourself

Open the interactive notebook:

[github.com/gfloresc/winter-school-2026-piezo-control](https://github.com/gfloresc/winter-school-2026-piezo-control)

Click: "Open in Google Colab/Jupyter Notebook/Binder"

No installation required

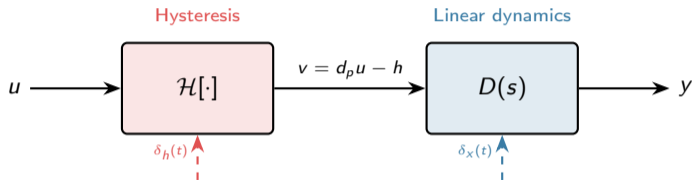
Runs in browser

Modify parameters live

Students can modify  $A_{bw}$ ,  $B_{bw}$ ,  $G_{bw}$  and visualize hysteresis in real time

# The Hammerstein Structure

All our models share this architecture:



- $u$ : driving voltage (control input)
- $h$ : hysteresis state (**not measured**)
- $v = d_p u - h$ : effective input to linear dynamics
- $y$ : output displacement (**measured**)
- $\delta_h, \delta_x$ : unknown disturbances / unmodeled terms

This structure is key: it separates the nonlinear hysteresis from the linear plant, enabling observer-based control.

# Classical Bouc–Wen (CBW) Model

The hysteresis dynamics:

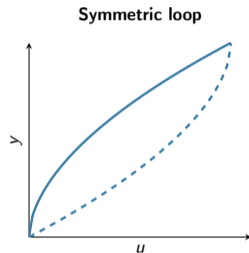
$$\dot{h} = A_{bw} \dot{u} - B_{bw} |\dot{u}| h - G_{bw} \dot{u} |h| + \delta_h(t) \quad (1)$$

The full system in state-space:

$$\begin{cases} \dot{h} = A_{bw} \dot{u} - B_{bw} |\dot{u}| h - G_{bw} \dot{u} |h| + \delta_h \\ \dot{x} = Ax + B(d_p u - h) + \delta_x \\ y = Cx \end{cases} \quad (2)$$

**Parameters:**

- $d_p$ : initial slope (piezo coefficient)
- $A_{bw}$ : hysteresis amplitude
- $B_{bw}, G_{bw}$ : shape parameters



## Limitation

CBW models **symmetric** hysteresis only.  
Real actuators are often asymmetric.

# Generalized Bouc–Wen (GBW) Model

To capture **asymmetric** hysteresis, we extend the model:

$$\dot{h} = \alpha \left[ \dot{u} (A_{bw} - (B_{bw} \operatorname{sgn}(\dot{u}) + G_{bw}) |h|^n) \right] + \delta_h(t) \quad (3)$$

where  $\alpha$  and  $n$  provide additional degrees of freedom for shaping the loop.

## What changes from CBW:

- Additional shape parameter  $\alpha$  controls asymmetry
- Exponent  $n$  controls sharpness of corners
- Nests the CBW as a special case ( $\alpha = 1$ ,  $n = 1$ )

## Used in:

- **Finite-time stabilization** [Flores & Rakotondrabe, L-CSS 2023a]
- **Model predictive control** [Flores, Aldana & Rakotondrabe, L-CSS 2022]

## Tradeoff

More accurate  $\Rightarrow$  more complex control design.  
Worth it when asymmetry is strong.

# The Dahl Model — An Alternative for Asymmetry

The Dahl hysteresis model:

$$\dot{h} = \sigma_0 \dot{u} \left( 1 - \frac{h}{h_c} \operatorname{sgn}(\dot{u}) \right)^i \quad (4)$$

where  $\sigma_0$  is the initial stiffness,  $h_c$  is the saturation value, and  $i$  controls the curve shape.

## Advantages:

- Naturally handles **non-symmetric** loops
- Bounded state:  $|h| \leq h_c$
- Simpler structure  $\Rightarrow$  simpler observer design

## When to use it:

- Strong asymmetry where CBW fails
- When boundedness simplifies stability analysis

## Full system:

$$\begin{aligned} \dot{h} &= \sigma_0 \dot{u} \left( 1 - \frac{h}{h_c} \operatorname{sgn}(\dot{u}) \right)^i \\ \ddot{y} &= -a_1 \dot{y} - a_2 y + b_0 (d_p u - h) \\ &\quad + \delta_y(t) \\ y_m &= y \end{aligned}$$

Used in: **ADRC position control** [Flores & Rakotondrabe, L-CSS 2023b]

## Key result

Global asymptotic stability using an extended observer + active disturbance rejection.

# Model Comparison: Which One to Use?

Property	CBW	GBW	Dahl
Symmetric hysteresis	✓	✓	✓
Asymmetric hysteresis	✗	✓	✓
Bounded state	requires proof	requires proof	built-in
Number of parameters	4	5–6	3
Control design complexity	moderate	high	moderate
Observer design	HGO, NNO	nonlinear	extended
<b>Stability achieved</b>	local exp.	finite-time	global asympt.

## Part II — Meta-message

**Model just enough hysteresis to make control possible.**

The CBW is the workhorse; GBW when asymmetry matters; Dahl for simpler analysis.

# ~ Pause ~

Before we dive into control:

*Which model would you choose and why?*

## PART III

# Control with Almost No Measurements

*The heart of the contribution*

~30 minutes

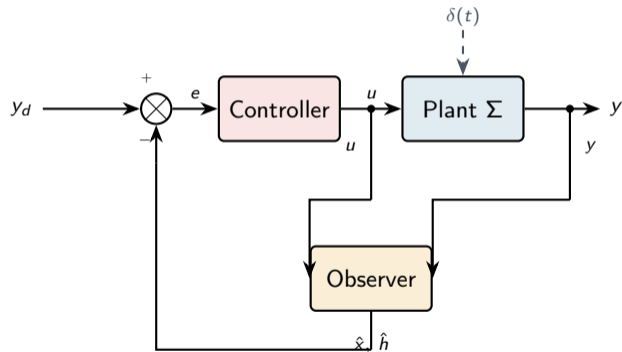
# Output Feedback: The Core Idea

## The situation:

- Only  $y$  (position) is measured
- $h$  (hysteresis state) is hidden
- $\dot{y}$  (velocity) is not available
- External forces  $F$  are unknown

## Our solution:

- 1 Design a **nonlinear observer** to estimate  $(x, h)$  from  $y$
- 2 Design a **control law** using the estimates  $(\hat{x}, \hat{h})$
- 3 Prove stability of the **interconnected** system via separation principle



# System Reformulation for Observer Design

Rewrite the system  $\Sigma$  in observer-canonical form. Setting  $z = [z_1, z_2]^\top = [x, h]^\top$ :

$$\begin{aligned} \dot{z} &= \underbrace{\begin{pmatrix} 0 & -B \\ 0 & 0 \end{pmatrix}}_{\Phi} z + \underbrace{g(z, \dot{u})}_{\text{known nonlinearity}} + \underbrace{\delta(t)}_{\text{disturbance}} \\ y &= \bar{C} z = \begin{pmatrix} 1 & 0 \end{pmatrix} z \end{aligned} \tag{5}$$

where  $g(z, \dot{u}) = \begin{pmatrix} Az_1 + Bd_p u \\ f(h, \dot{u}) \end{pmatrix}$ ,  $\delta(t) = \begin{pmatrix} \delta_x \\ \delta_h \end{pmatrix}$

**Observability:** Since  $\text{rank } \mathcal{O} = \text{rank} \begin{pmatrix} \bar{C} \\ \bar{C}\Phi \end{pmatrix} = 2$  when  $B \neq 0$ , the system is **observable**.

This reformulation is the foundation for all observer designs that follow.

# High-Gain Observer (HGO)

The observer:

$$\begin{aligned}\dot{\hat{z}}_1 &= A\hat{z}_1 + B(d_p u - \hat{z}_2) + \frac{k_1}{\varepsilon}(y - \hat{z}_1) \\ \dot{\hat{z}}_2 &= f(\hat{z}_2, \dot{u}) + \frac{k_2}{\varepsilon^2}(y - \hat{z}_1)\end{aligned}\tag{6}$$

where  $\varepsilon > 0$  is small, and  $k_1, k_2$  are chosen such that

$$s^2 + k_1 s + k_2 \text{ is Hurwitz.}$$

**Key assumption on disturbances:** The disturbance  $\delta(t) = [\delta_x, \delta_h]^\top$  satisfies  $\|\delta\| \leq \varrho \|\tilde{z}\|$ ,  $\varrho \in \mathbb{R}^+$  i.e., the perturbation is bounded by the observation error itself.

**Result:** Under this assumption, the observation error  $\tilde{z} = \hat{z} - z$  is **locally exponentially stable**.

## Intuition:

- Small  $\varepsilon \Rightarrow$  fast convergence
- But too small  $\Rightarrow$  noise amplification
- Practical tradeoff: choose  $\varepsilon$  based on noise level

## Physical meaning

$\hat{z}_1 \rightarrow x$ : estimated displacement state

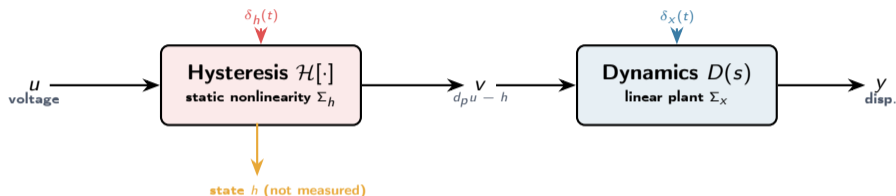
$\hat{z}_2 \rightarrow h$ : **estimated hysteresis** — the key unmeasured variable

## Why this assumption matters

It means the disturbance vanishes as the observer converges — this is what enables exponential stability rather than just bounded error.

# The Hammerstein Structure: How We Model the Actuator

A piezoelectric actuator has two physical parts: a **transduction stage** (electrical  $\rightarrow$  mechanical, contains hysteresis) followed by the **mechanical structure** (linear dynamics). This cascade is a **Hammerstein structure**.



In state-space form:

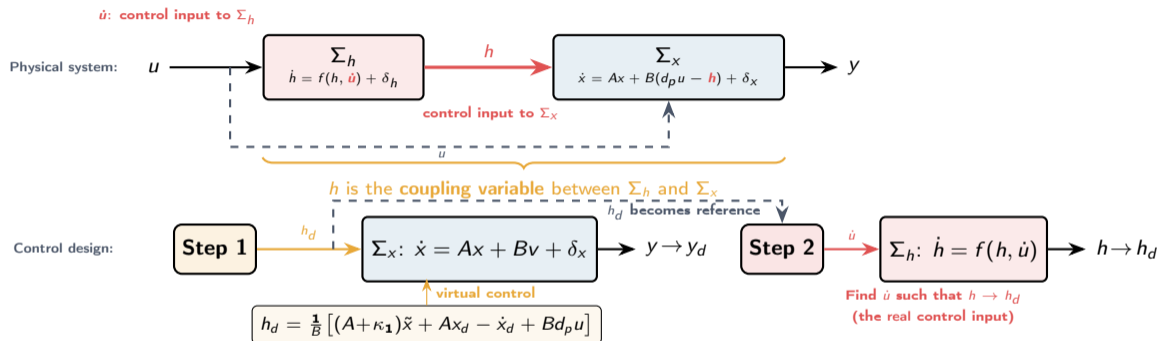
$$\Sigma : \begin{cases} \dot{h} = f(h, \dot{u}) + \delta_h(t) & \Sigma_h \\ \dot{x} = Ax + B \underbrace{(d_p u - h)}_v + \delta_x(t) & \Sigma_x \\ y = Cx & \text{output} \end{cases}$$

Why this structure matters:

- **Separates** the nonlinear hysteresis from the linear plant — each analyzed independently
- $v = d_p u - h$  is **not accessible** — we only measure  $y$
- Enables: observer design and *virtual control*
- ★ CBW, GBW, Dahl **all fit** this structure — only  $f(h, \dot{u})$  changes

# The Virtual Control Idea: Why $h$ Becomes a Design Variable

**Recall:** the hysteresis output  $h$  is the *only link* between  $\Sigma_h$  and  $\Sigma_x$  in the Hammerstein structure.



## The key insight

Treat  $h$  as if you could choose it (virtual control  $h_d$ ) to stabilize  $\Sigma_x$ . Then design the actual  $u$  to steer  $h \rightarrow h_d$  through  $\Sigma_h$ .

## Used across all papers

**CBW:**  $h_d$  stabilizes  $\tilde{x} \rightarrow 0$ ,  $\dot{u}$  drives  $h \rightarrow h_d$

**GBW+FTS:**  $h_d$  with saturation  $\sigma_1$

**Force:**  $h_d$  via barrier-Lyapunov

# Robust Nonlinear Control Law

**Step 1 — Virtual hysteresis control.** Define the desired hysteresis signal:

$$h_d = d_p u - \frac{1}{B} \left[ \dot{y}_d - (A + \lambda_1) \hat{z}_1 + \lambda_1 y_d \right] \quad (7)$$

where  $\lambda_1 > 0$  is a design parameter.

**Step 2 — Actual control input.** From the hysteresis model, compute  $u$  to drive  $\hat{h} \rightarrow h_d$ :

$$u(t) = \int_0^t \frac{1}{A_{bw} - (B_{bw} \operatorname{sgn}(\dot{u}) + G_{bw}) |\hat{h}|} \left[ \dot{h}_d + \lambda_2 (\hat{h} - h_d) \right] d\tau \quad (8)$$

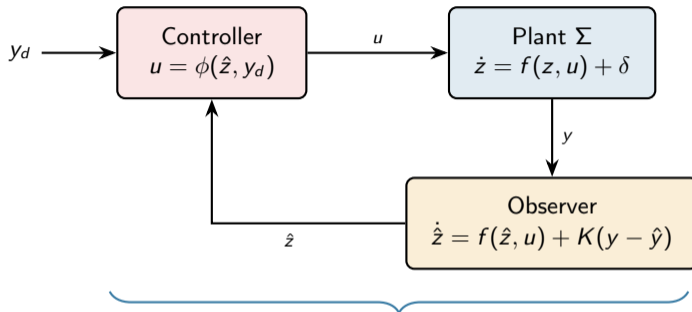
## Stability result

Under Assumptions 1–2, the closed-loop system with HGO is **locally exponentially stable**.

## Key feature

Only  $y$  is used for feedback. The control is an explicit function of Bouc–Wen parameters  $\Rightarrow$  **model-based robustness**.

# The Separation Principle



**Separation:** design observer and controller independently  $\Rightarrow$  stability of interconnection

- Observer error  $\tilde{z} \rightarrow 0$  at rate  $\mathcal{O}(1/\varepsilon)$
- Tracking error  $e = y - y_d \rightarrow 0$  once  $\tilde{z}$  is small
- The interconnection preserves stability properties

# Results: What Do We Get?

## Position tracking:

- Hysteresis **completely removed** in closed loop
- The  $(y_d, y)$  map becomes a straight line
- Tested with sinusoidal and multi-frequency references

## Disturbance rejection:

- Robust up to **37%** of output range
- External forces treated as bounded disturbances
- Multiple parameter sets tested

## Stability guarantees:

Paper	Guarantee
CBW + HGO	local exp. stable
GBW + FTS	finite-time conv.
GBW + MPC	tracking + robust
Dahl + ADRC	global asympt.
CBW + BLF	asympt. stable

### Key achievement

Formal stability from **position-only** measurements.

# Execute the Control System

Run the complete control implementation:

[github.com/gfloresc/winter-school-2026-piezo-control](https://github.com/gfloresc/winter-school-2026-piezo-control)

Click: "Open in Google Colab/Jupyter Notebook/Binder"

Load control model

Execute simulation

Visualize results

Students can run PID vs Robust control and observe tracking performance in real time

### PART III — KEY MESSAGE

A good model + a good observer =  
control with almost no sensors.

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The observer reconstructs the invisible hysteresis state.

The controller cancels it.

The separation principle glues them together with formal guarantees.

## PART IV

# When Things Get Serious

*Beyond the basic framework*

~5 minutes

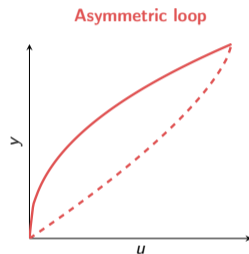
# Asymmetric Hysteresis: Why Classical Models Fail

## The problem:

- Real PZT actuators produce **asymmetric** loops
- CBW assumes symmetry  $\Rightarrow$  model mismatch
- Controller designed for CBW may **lose stability** on real hardware

## Solutions explored:

- 1 **GBW model** — additional parameters capture asymmetry at the cost of complexity
- 2 **Dahl model** — intrinsically handles asymmetry with fewer parameters



The ascending and descending branches have different curvatures — CBW cannot capture this.

## Why finite-time?

- Asymptotic:  $e(t) \rightarrow 0$  as  $t \rightarrow \infty$  (never quite reaches zero)
- **Finite-time:**  $\exists T^* < \infty$  such that  $e(t) = 0$  for all  $t \geq T^*$
- Critical for pick-and-place, precision assembly

## Our approach [Flores & Rakotondrabe, L-CSS 2023a]:

- 1 GBW model for asymmetric hysteresis
- 2 Three-part interconnected control:
  - Observer for  $(\hat{x}, \hat{h})$
  - Virtual hysteresis control  $h_d$
  - Actuator control  $u$  with finite-time terms

## Result:

### Theorem

Under bounded disturbances  $\delta(t)$  and partial knowledge of one hysteresis parameter, the closed-loop tracking error converges to zero in **finite time**  $T^*$ .

## Practical implication:

Exact zero error in finite time  $\Rightarrow$  well-defined task completion guarantees.

# Model Predictive Control with Hysteresis

**Idea:** Use GBW model as the **prediction model** inside an MPC framework.

[Flores, Aldana & Rakotondrabe, L-CSS 2022]:

## Architecture:

- 1 Nonlinear observer estimates  $(\hat{x}, \hat{h})$
- 2 NMPC solves at each step:

$$\min_{\{u_k\}} \sum_{k=0}^{N-1} \|y_{k+1} - y_{d,k+1}\|^2 + R\|u_k\|^2$$

subject to GBW dynamics

- 3 Hysteresis-aware prediction  $\Rightarrow$  **hysteresis removed in closed loop**

## Key results:

- Hysteresis **completely eliminated**
- Tested with  $\pm 20\%$  parameter variation
- Robust tracking maintained

### Why it works

Once you have a good model and a good observer, MPC becomes **viable**. The model does the heavy lifting.

## PART IV — KEY MESSAGE

Modeling enables advanced control —  
not the other way around.

## PART V

# Real Manipulation Scenarios

*Where applied people reconnect*

~5 minutes

# Distributed-Parameter Effects

## The problem:

The sensor measures at  $x = L$ , but the control objective may be at  $x \neq L$ .

[Trejo, Flores & Rakotondrabe, IFAC 2023]:

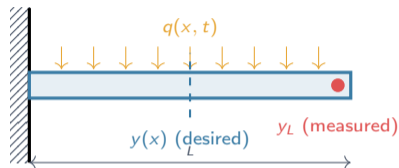
Extend CBW with Euler–Bernoulli beam theory:

$$EI \frac{\partial^4 y}{\partial x^4} + \rho A_s \frac{\partial^2 y}{\partial t^2} = q(x, t) \quad (9)$$

The hysteresis enters through the distributed load  $q(x, t)$  from the piezoelectric effect.

## Observers compared:

- High-Gain Observer (HGO)
- Neural Network Observer (NNO)
- NNO showed **better performance**



## Challenge

The sensor is **not** at the control point. The distributed-parameter model bridges this gap.

# Force Control with Deformable Objects

**Scenario:** Robotic hand manipulates a deformable object. Must control **force**, not just position.

[Flores & Rakotondrabe, L-CSS 2023c]:

## Combined model:

- Actuator: CBW hysteresis + linear dynamics
- Object: nonlinear deformation model  $\psi[y]$
- Interaction force:  $F = \psi[y]$

## Control approach:

- 1 Output feedback (only  $F$  measured)
- 2 **Barrier-Lyapunov function**  $\Rightarrow$  force error stays within prescribed bounds
- 3 **Saturation-based control**  $\Rightarrow$  bounded input

## Result:

### Theorem

The force-tracking error remains inside a **predefined set** for all  $t \geq 0$ , and the equilibrium is asymptotically stable.

## Significance:

- Aggressive disturbance rejection
- Bounded control  $\Rightarrow$  implementable
- Safe manipulation of fragile objects

# Object Characterization via Piezoelectric Manipulation

[Flores & Rakotondrabe, Nonlinear Dynamics 2025]:

**Idea:** Use the controlled actuator to **identify** the object's mechanical properties.

## Approach:

- 1 Control position precisely (CBW + output feedback)
- 2 Estimate interaction force  $F$  using observers **without** force sensor
- 3 Extract force–deformation curve  $F$  vs.  $y$
- 4 Identify object model parameters

## Key innovation:

No object model needed *a priori*. The actuator becomes a **sensing tool** for characterizing unknown objects.

## Validation:

- Nonlinear viscoelastic object
- Gaussian noise added to all channels
- Force estimation tracks ground truth
- Experimental validation included

## Implication

The hysteresis framework enables not just control, but also **perception** — estimating what the actuator touches.

## PART VI

# Wrap-up & Big Picture

~10 minutes

# Key Takeaways

## 1. Hysteresis must be modeled

Ignoring it  $\Rightarrow$  60% error or instability.  
CBW/GBW/Dahl provide control-friendly representations.

## 2. Output feedback is viable

Nonlinear observers reconstruct the hidden hysteresis state from position measurements alone.

## 3. Robustness is achievable

Formal stability guarantees (exponential, asymptotic, finite-time) with few sensors.

## 4. The framework extends

Force control, object characterization, distributed parameters — same core ideas.

**Unified message:** Hysteresis-aware modeling  $\rightarrow$  observer  $\rightarrow$  control  $\rightarrow$  formal guarantees

Paper	Model	Control	Stability
L-CSS 2022a	CBW	HGO + nonlinear	local exp.
L-CSS 2022b	GBW	observer + NMPC	tracking
L-CSS 2023a	GBW	FTS (3-part)	finite-time
L-CSS 2023b	Dahl	ext. obs. + ADRC	global asympt.
L-CSS 2023c	CBW + object	BLF + saturation	asymptotic
IFAC 2023	CBW (distributed)	HGO vs NNO	separation
Nonlinear Dyn. 2025	CBW + force est.	obs. + identifica- tion	robust

## Don't overmodel

A model is a **tool**, not a goal. Model just enough to enable the control you need. CBW covers 80% of cases.

## Control $\neq$ tuning gains

If your “control design” is tuning PID gains until it works, you have no guarantees. A model-based approach gives you **provable** robustness.

## Don't ignore physics

The Hammerstein structure, boundedness of  $h$ , the separation principle — these come from **understanding the physics**, not from optimization.

## Write the proof first

If you can prove stability on paper, the simulation will confirm it. If you start with simulation, you may never prove anything.

# Open Problems & Future Directions

## Learning + Physics:

- Can neural networks learn the *residual* after Bouc–Wen?
- Physics-informed neural networks for hysteresis
- Online adaptation of model parameters

## Soft Robots:

- Piezo-driven soft actuators with distributed hysteresis
- Infinite-dimensional control challenges
- Model reduction strategies

## Hybrid Data-Driven Models:

- Combine Bouc–Wen structure with data-driven corrections
- Guarantees + adaptability
- Transfer learning across actuator families

## Multi-Actuator Coordination:

- Three-finger robotic hand: coupled hysteresis
- Cooperative manipulation with deformable objects
- Decentralized vs. centralized control

# Thank You

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**Gerardo Flores, Ph.D.**

RAPTOR Lab — Texas A&M International University

`gerardo.flores@tamiu.edu`

All papers available on IEEE Xplore and Springer

Slides prepared for Winter School 2026

# Backup Slides

## Backup: CBW Parameter Sets Used in Simulations

Parameter	Set 1	Set 2	Set 3	Units
$d_p$	0.16	0.16	0.16	$\mu\text{m}/\text{V}$
$A_{bw}$	0.07	0.09	0.05	$\mu\text{m}/\text{V}$
$B_{bw}$	0.02	0.03	0.015	$\mu\text{m}^{-1}$
$G_{bw}$	0.01	0.015	0.008	$\mu\text{m}^{-1}$
$A$	-86.28	-86.28	-86.28	$\text{s}^{-1}$
$B$	$7.95 \times 10^7$	$7.95 \times 10^7$	$7.95 \times 10^7$	$\text{s}^{-2}$

Multiple parameter sets demonstrate **robustness** of the control framework to model uncertainties.

## Backup: Extended Observer for Dahl Model

Extended state:

$$\bar{x} = \begin{pmatrix} y \\ \dot{y} \\ \Delta(t) \end{pmatrix}, \quad \Delta(t) = -a_1\dot{y} - a_2y + b_0(d_p u - h) + \delta_y$$

Observer:

$$\dot{\hat{x}} = \bar{A}\hat{x} + \bar{B}u + L(\varepsilon)(y - \hat{y}) \quad (10)$$

where  $L(\varepsilon) = \begin{pmatrix} k_1/\varepsilon \\ k_2/\varepsilon^2 \\ k_3/\varepsilon^3 \end{pmatrix}$  and the ADRC law:

$$u = \frac{1}{b_0 d_p} \left[ \ddot{y}_d + \lambda_1(\dot{y}_d - \hat{\dot{y}}) + \lambda_0(y_d - y) - \hat{\Delta} \right] \quad (11)$$

**Result: Global asymptotic stability** of tracking error.

# Backup: Barrier-Lyapunov Function for Force Control

To constrain the force error  $e_F = F - F_d$  within  $|e_F| < k_b$ :

**BLF candidate:**

$$V = \frac{1}{2} \ln \frac{k_b^2}{k_b^2 - e_F^2} \quad (12)$$

Properties:

- $V \rightarrow \infty$  as  $|e_F| \rightarrow k_b \Rightarrow$  error **never** leaves the set  $(-k_b, k_b)$
- Combined with saturation-based control  $\Rightarrow$  **bounded input**
- Asymptotic stability proven via Lyapunov analysis

This combines constrained control (BLF) with bounded actuation (saturation), a powerful combination for safe manipulation.