

Advances in Machine Learning at the Edge for Enhanced Structural Health Monitoring and Control in SWaP-Constrained Environments

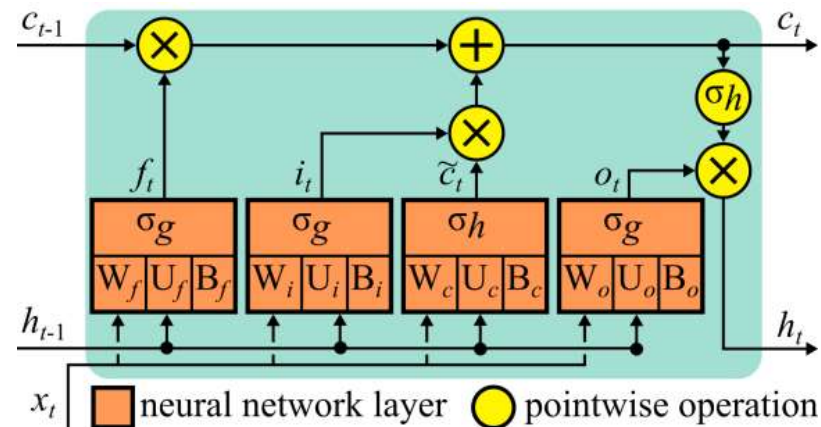
Adaptive Real-Time Systems Laboratory (ARTS-Lab)
An Interdisciplinary Controls Lab at USC

Austin R.J. Downey
Associate Professor
Mechanical Engineering
Civil and Environmental Engineering



Introduction

- **Part 1:** Overview of the ARTS-Lab
- **Part 2:** High-rate ML at the Edge
- **Part 3:** Signal Processing for UAV-deployed Sensors



About the ARTS-Lab

- **An Interdisciplinary Controls Lab** at the University of South Carolina.
- **Slogan:** “Hardware Keeps the Engineer Honest”—we focus on real-world validation of our research.
- **Aspirations:** Develop cutting-edge innovations and enable unparalleled student success.



University of South Carolina Campus

Mentorship & Student Growth

- **8 current Ph.D. students:** 2 graduated, 1 in academia.
- **7 current M.S. students:** 7 graduated.
- **23 current undergraduates:** 71 graduated, 2 NSF GFRP, 1 DoD SMART.
- **A growing alumni network:** past students have gone on to Government Labs and top graduate programs.
- **Undergraduates take part in real research:** leading conference and journal publications, and hardware development.
- **Commitment to Open Source:** We believe in democratizing knowledge through open-source software and hardware.

How We See Ourselves

We use

foundational
science



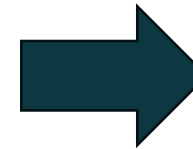
Day School



to develop
essential tools



Dan Thompson



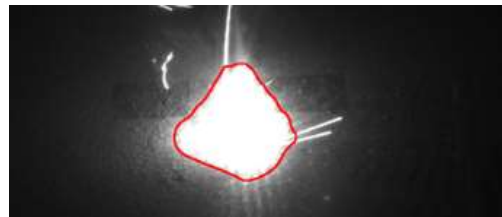
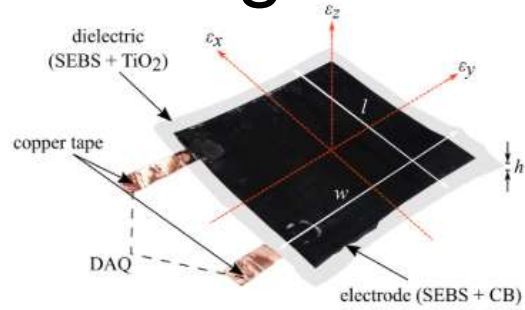
to solve real-world
problems



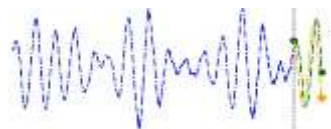
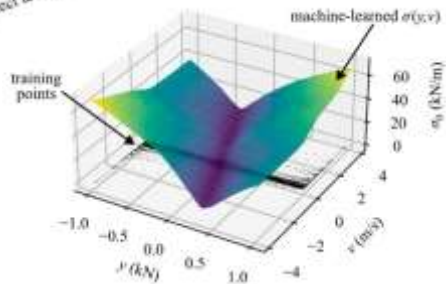
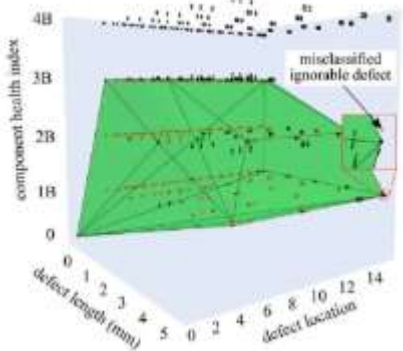
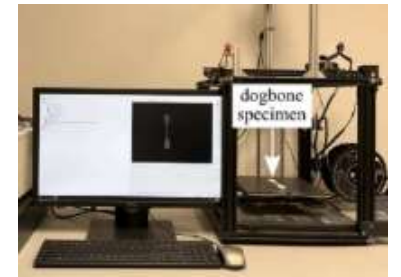
public domain

**We are Engineers
(mostly)**

Sensing



Data Assimilation

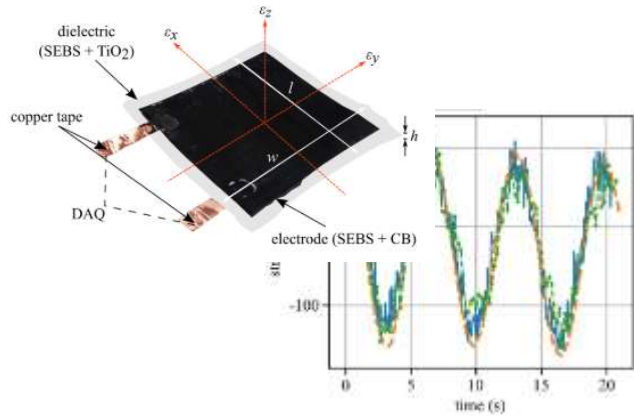


AI/ML

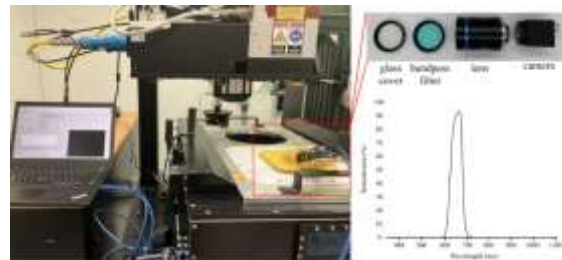


Embedded Systems

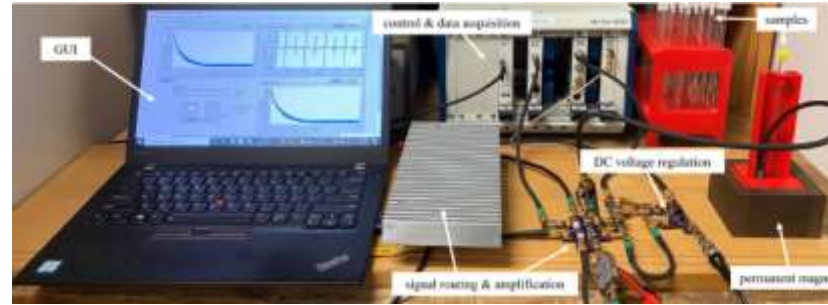
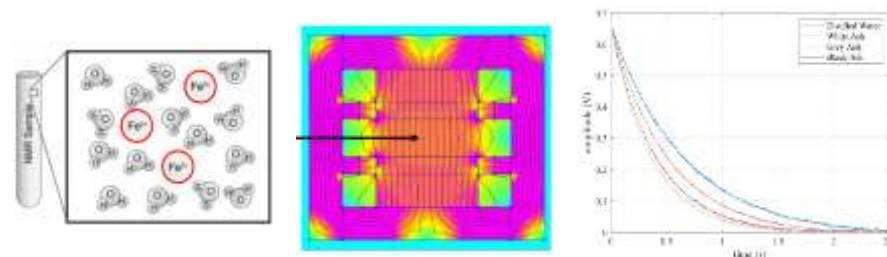
Sensing



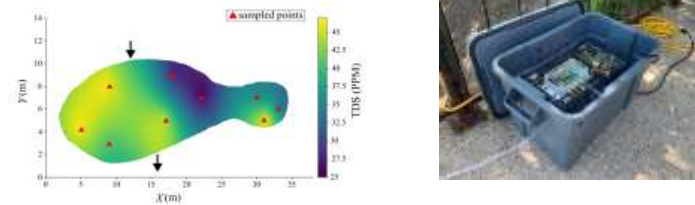
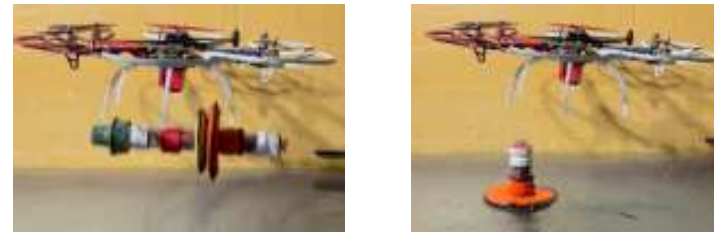
Flexible Electronics



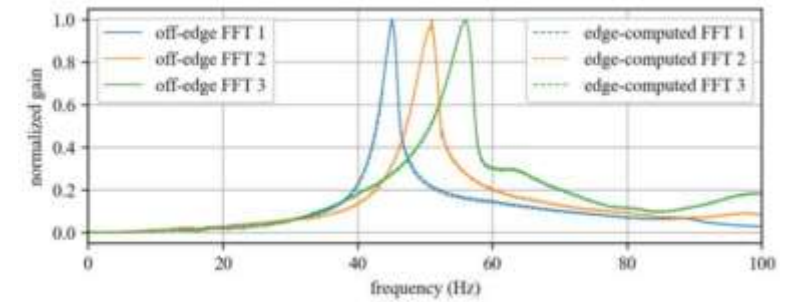
In Situ Monitoring of AM



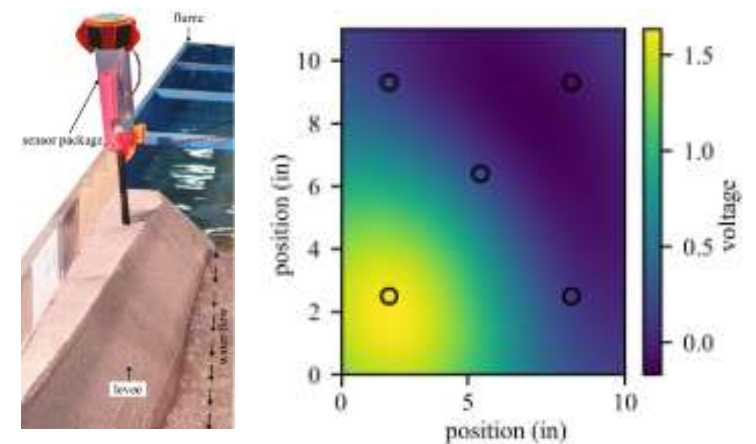
Nuclear Magnetic Resonance



Water Quality Sensors

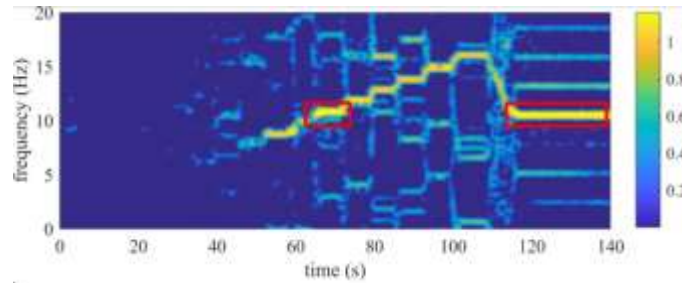


Vibration Sensors

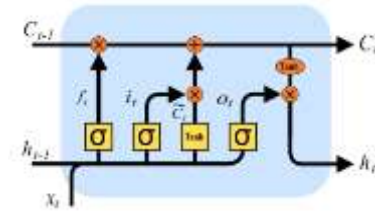


Geo Technical Sensors

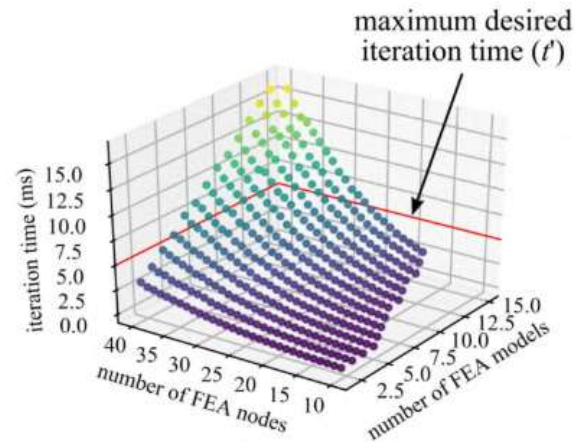
Data Assimilation



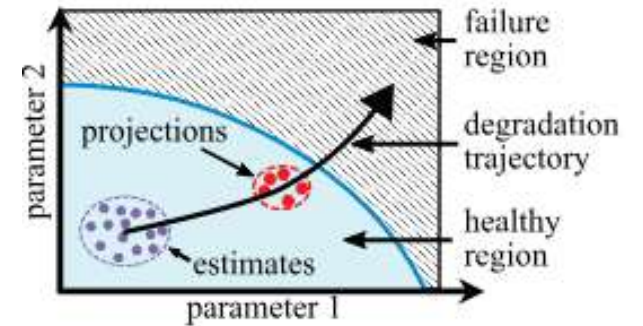
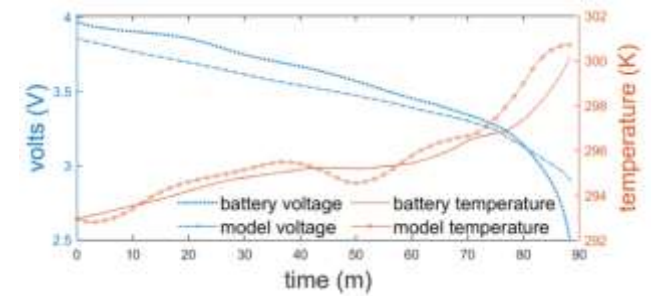
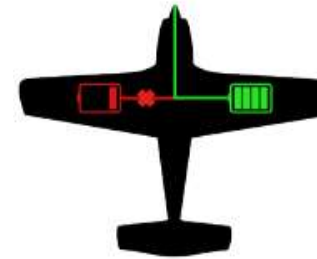
Civil Structures



$$\frac{-1}{\alpha} = \sum_{r=1}^m \frac{v_r^2}{\omega_r^2 - \Omega_r^2}$$

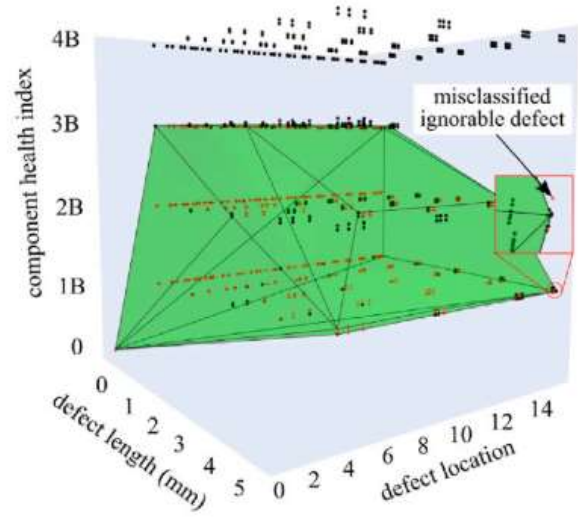
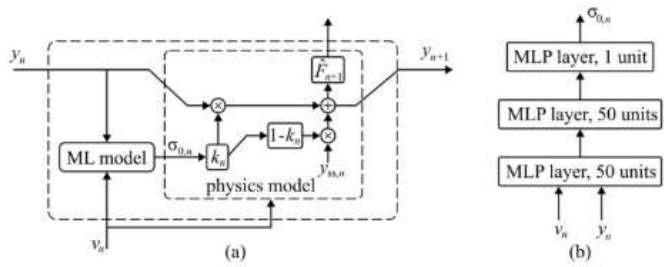


High-Rate Systems

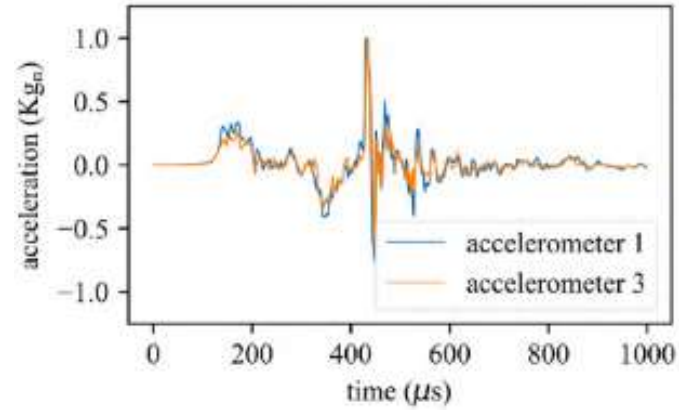


Battery Systems

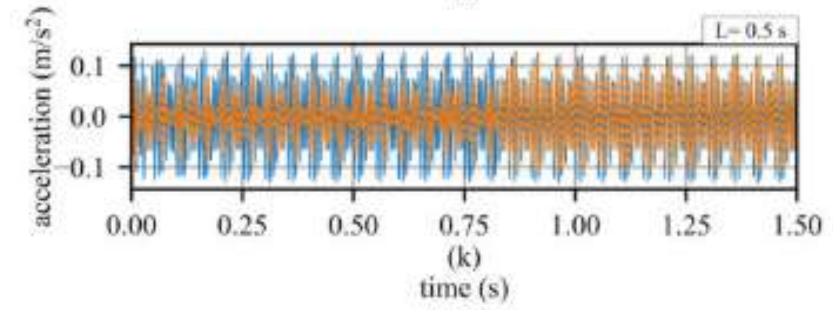
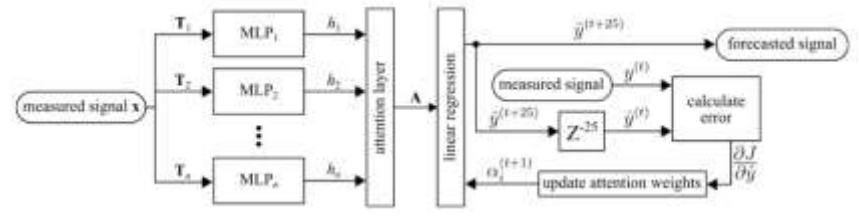
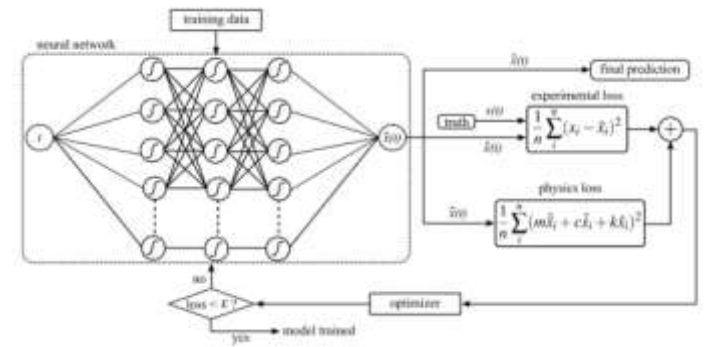
AI/ML



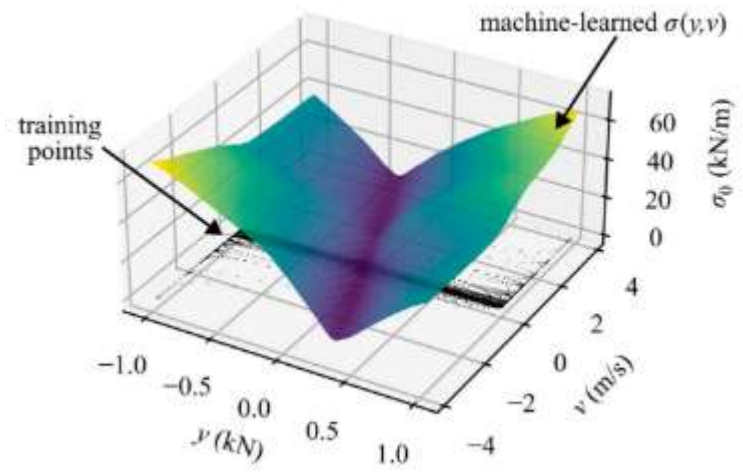
Decision-making



Generative

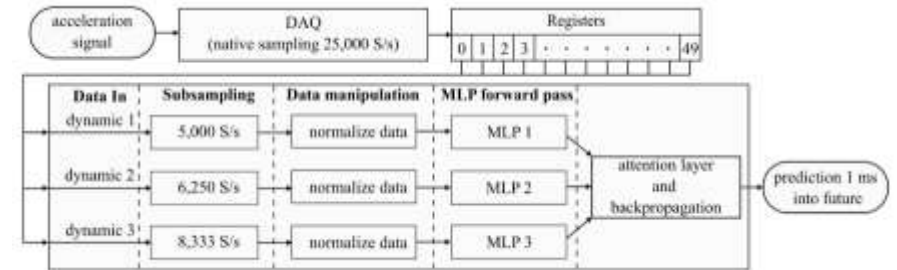
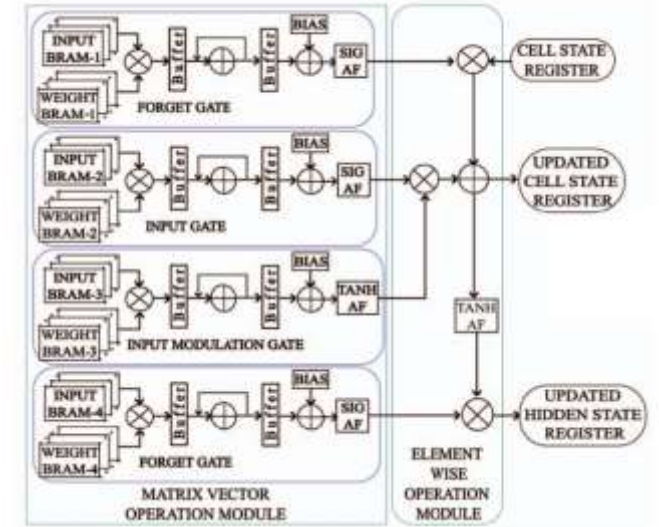
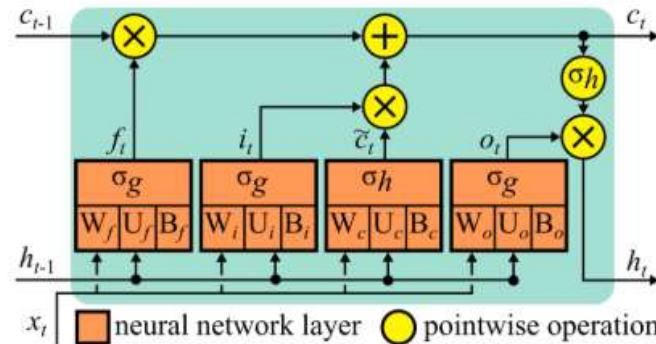
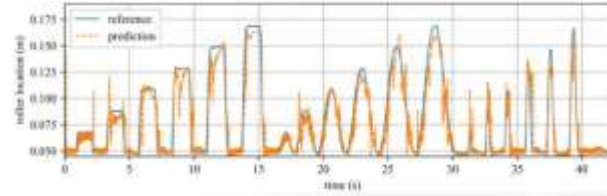
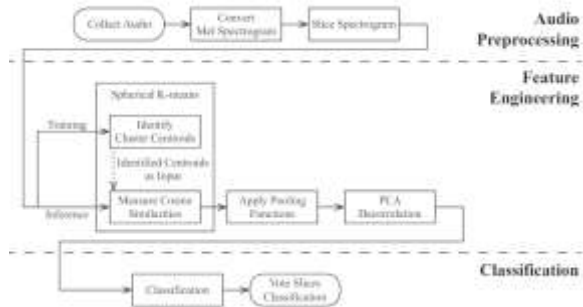


Forecasting



Explainability

Embedded Systems

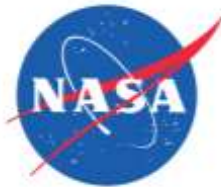


10 Microcontroller/
microprocessor

Real-Time OS

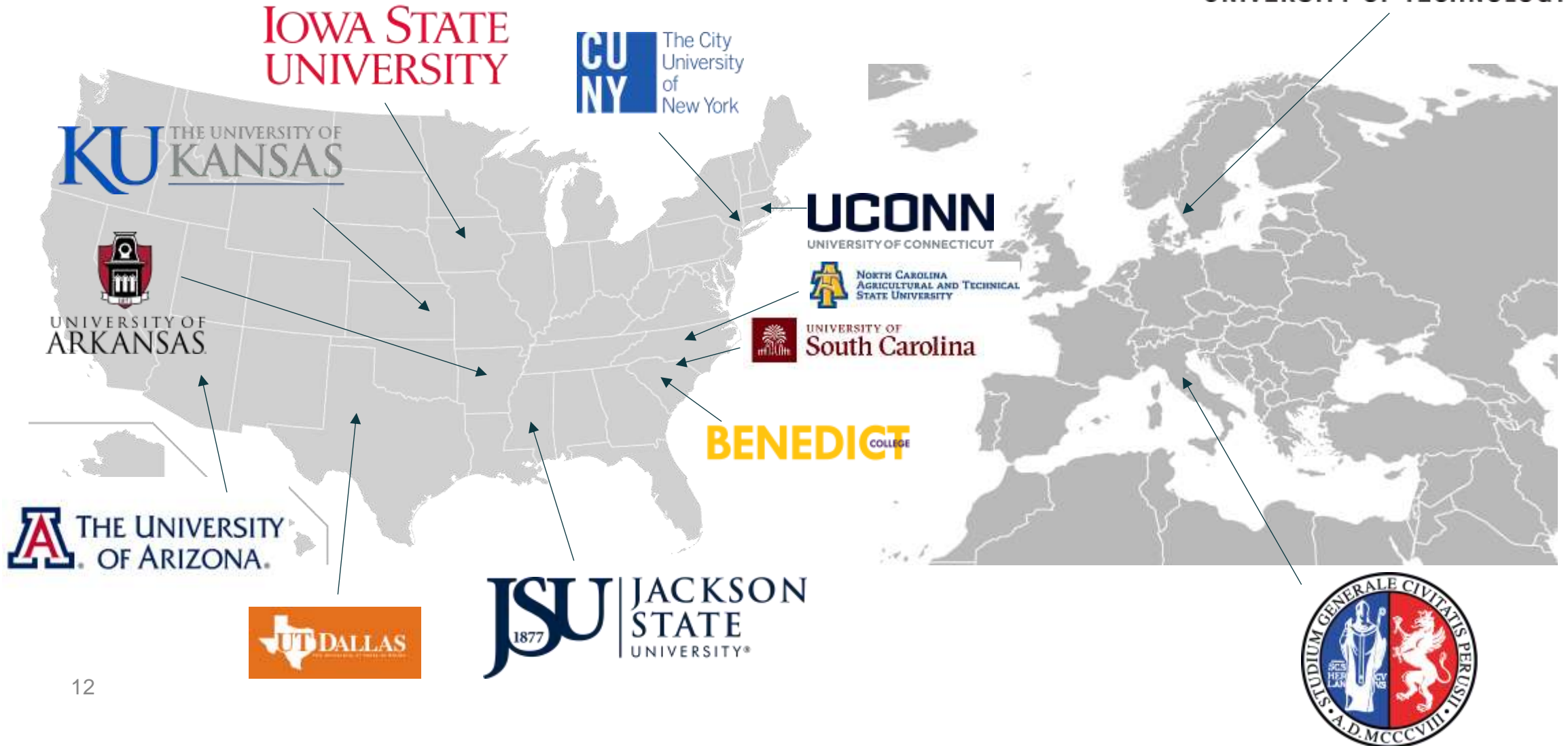
FPGA

Supporting Agencies, Companies, and Partners



Out Academic Partners

CHALMERS
UNIVERSITY OF TECHNOLOGY



Part 2: High-rate ML at the Edge

Description of High-rate Dynamics

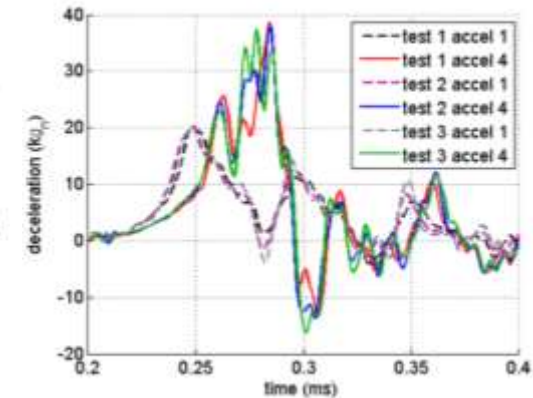
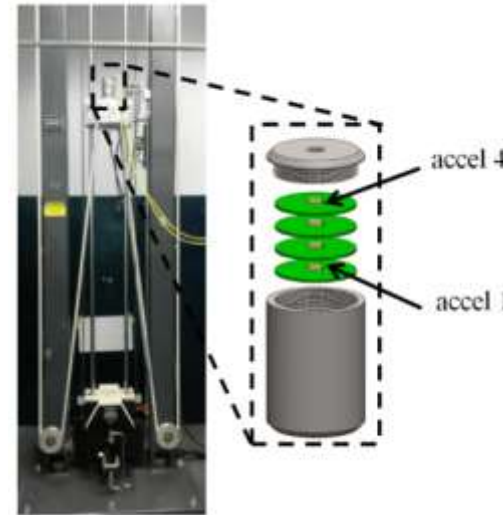
High-rate (<100ms)



High-amplitude (acceleration > 100 g)



The deceleration event in drop tower tests typically lasts for 0.5ms



- Large uncertainties in the external loads.
- High levels of nonstationarity and heavy disturbance.
- Generations of unmodeled dynamics from changes in mechanical configuration.

High-Rate Systems

Hypersonic vehicles



Ballistic packages



Debris approaching space shuttle



Lightning strikes on aircraft



Civil Structures



Fighter jets



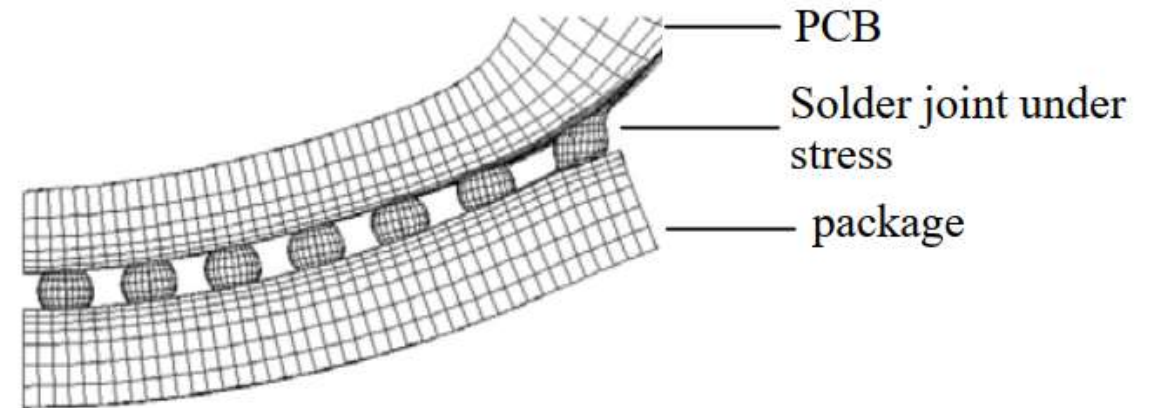
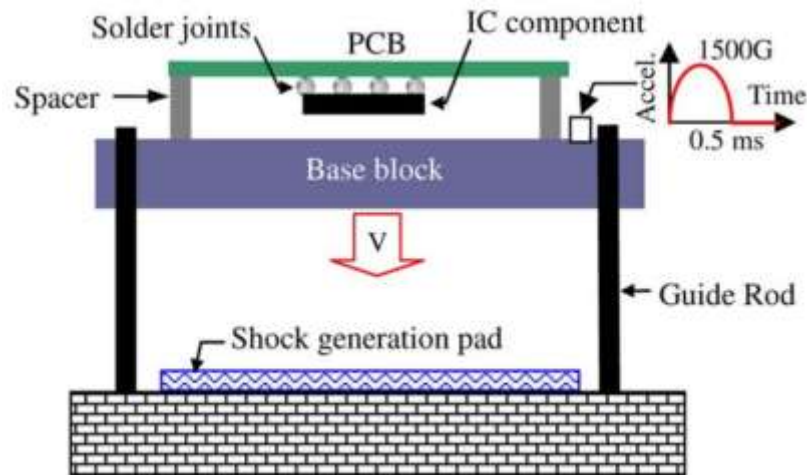
Active High-Rate Systems (Airbags)



Active High-Rate Systems (Electronics)

PCB failures under shock are caused by:

- Bending of the base PCB board, causing stresses to build up at the solder balls.
- Adhesion challenges of masses (components) accelerating away from the PCB.



Data Driven or Physics Based State Estimation



Data Driven or Physics Based State Estimation

- **Data-driven:**
 - Potential to be faster
 - Easier to implement
 - Students excited to work on it
 - AI/ML is moving quickly
- **Physics-based:**
 - Potential for prognostics
 - Potential for real-time control
 - Better suited for decision-making
 - Better suited for un-foreseen dynamics



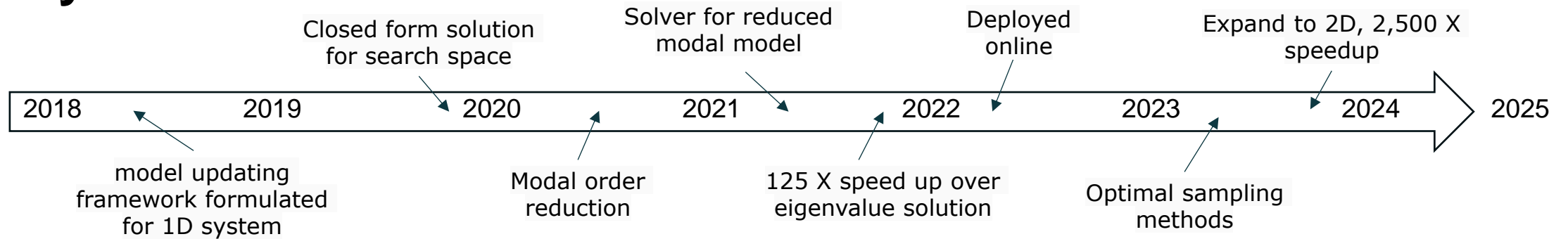
It was hard to decide,
so we did both

Timeline of Efforts on State Estimation

Physics-based - YIP



YIP

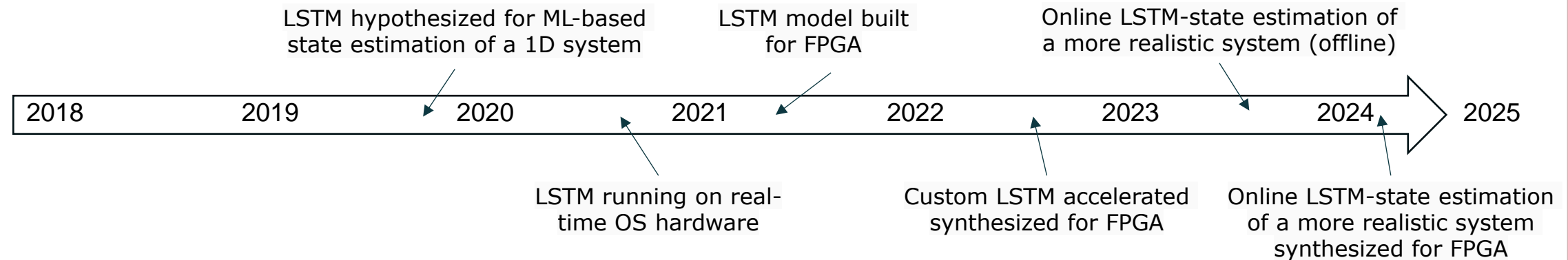


Data-driven



CRII/
CAREER

20



Data Driven Model Updating (Theory and Proof of Concept)

```
graph LR; A[Data Driven Model Updating  
(Theory and Proof of Concept)] --> B[Electronic Components  
Under Shock (Application)]; B --> C[FPGA Implementation  
(Timing Consideration)];
```

Data Driven Model Updating
(Theory and Proof of Concept)

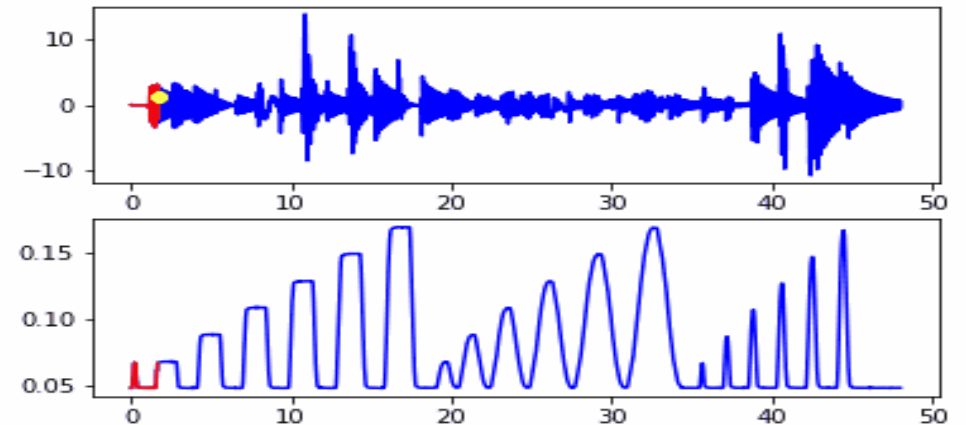
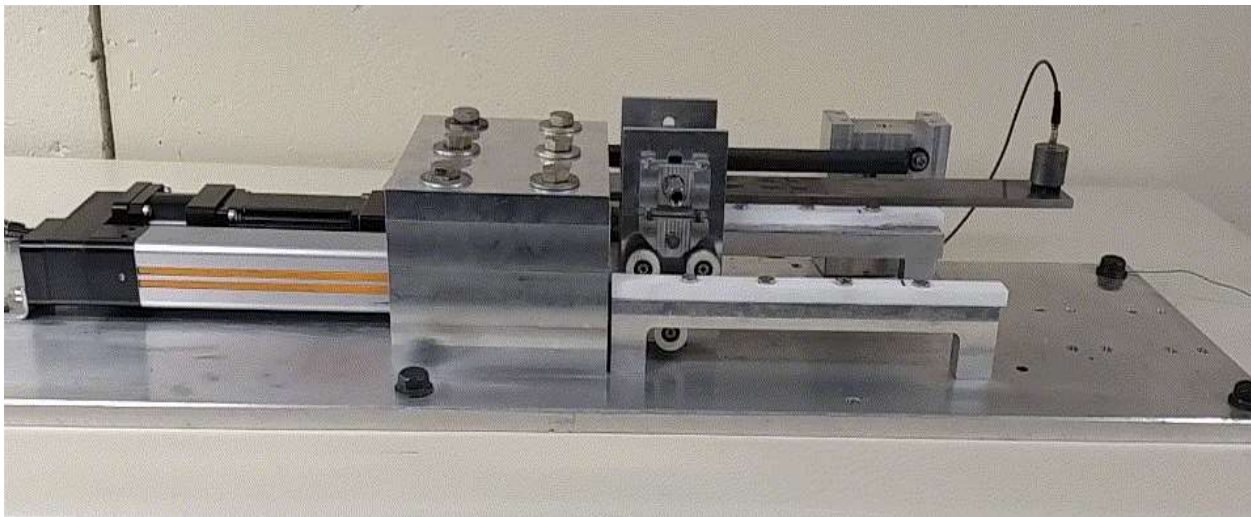
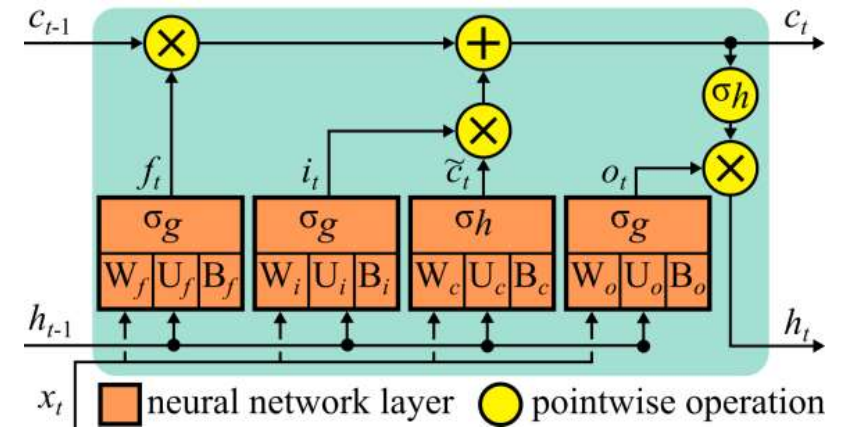
Electronic Components
Under Shock (Application)

FPGA Implementation
(Timing Consideration)

LSTM-based Real-time State Estimation

In this work:

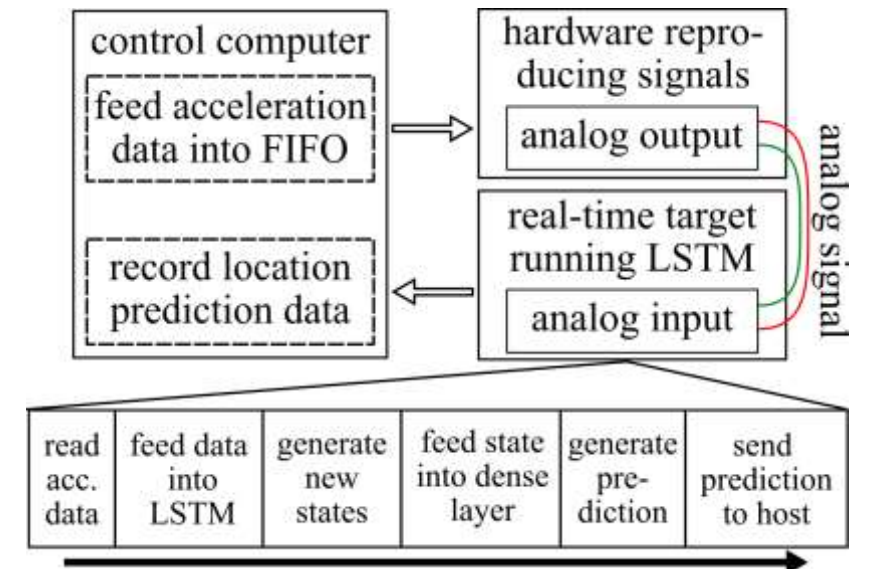
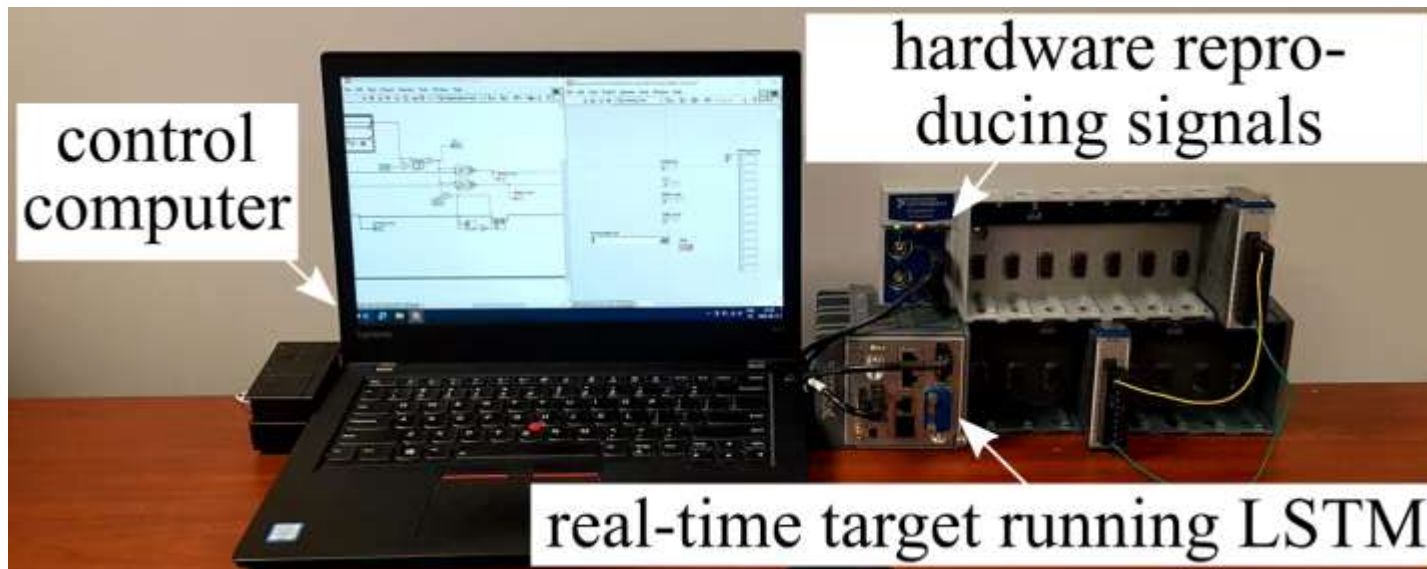
- Long short-term memory (LSTM) models are used for real-time state estimation.
- Experimentally validated on NI-Linux Real-Time.



Real-time Validation on Embedded Systems

Real-time validation performed on an embedded system running:

- **Hardware reproducing Signals** reproduces the DROPBEAR.
- **Real-time Target** digitizes the analog voltage and feeds the input LSTM.
- Data is sampled at 400 S/s, therefore, a prediction is made every 2.5 ms.



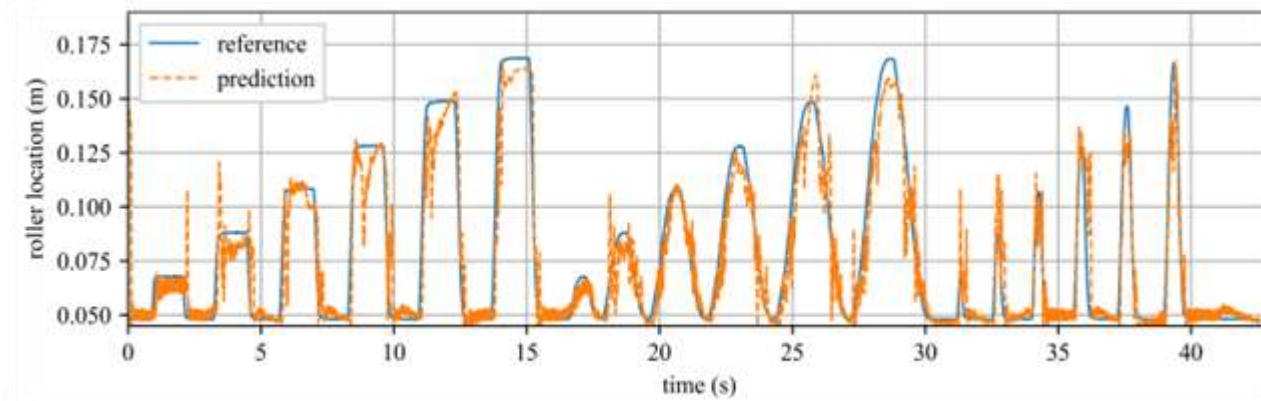
Real-time LSTM Modeling Results

LSTM model performance results:

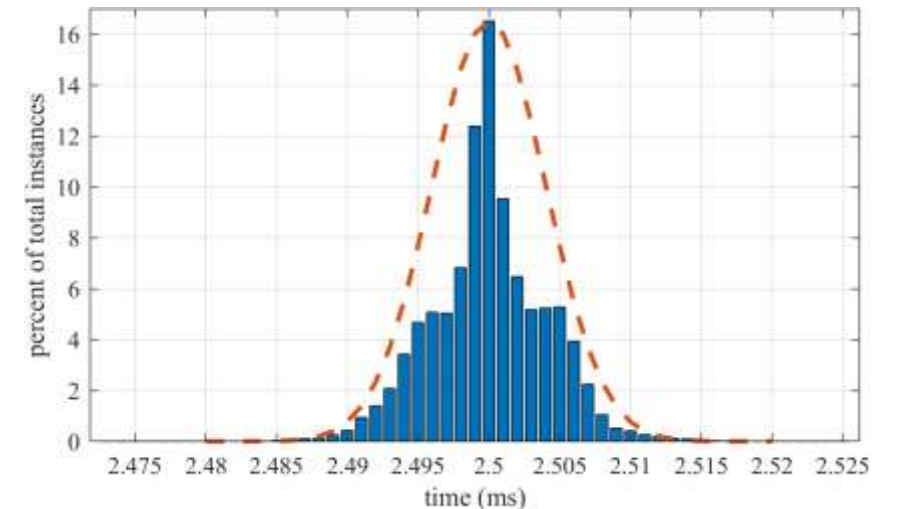
- SNR_{dB} of 43.2 dB.
- RMSE of 12.8 mm.
- LSTM traces reference pin location closely.

Timing accuracy results:

- Execution-time jitter is observed (expected).
- Timing follows a normal distribution.



Algorithm Timing



Mean	2.5 ms
Standard deviation	0.004 ms
Max overshoot	0.019 ms

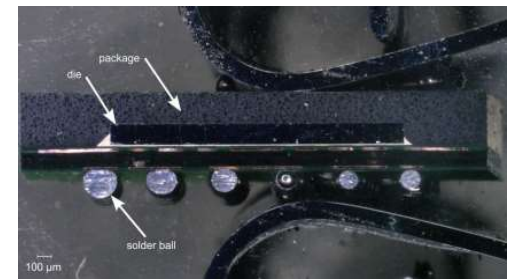
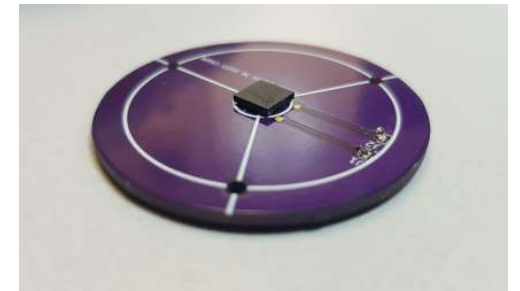
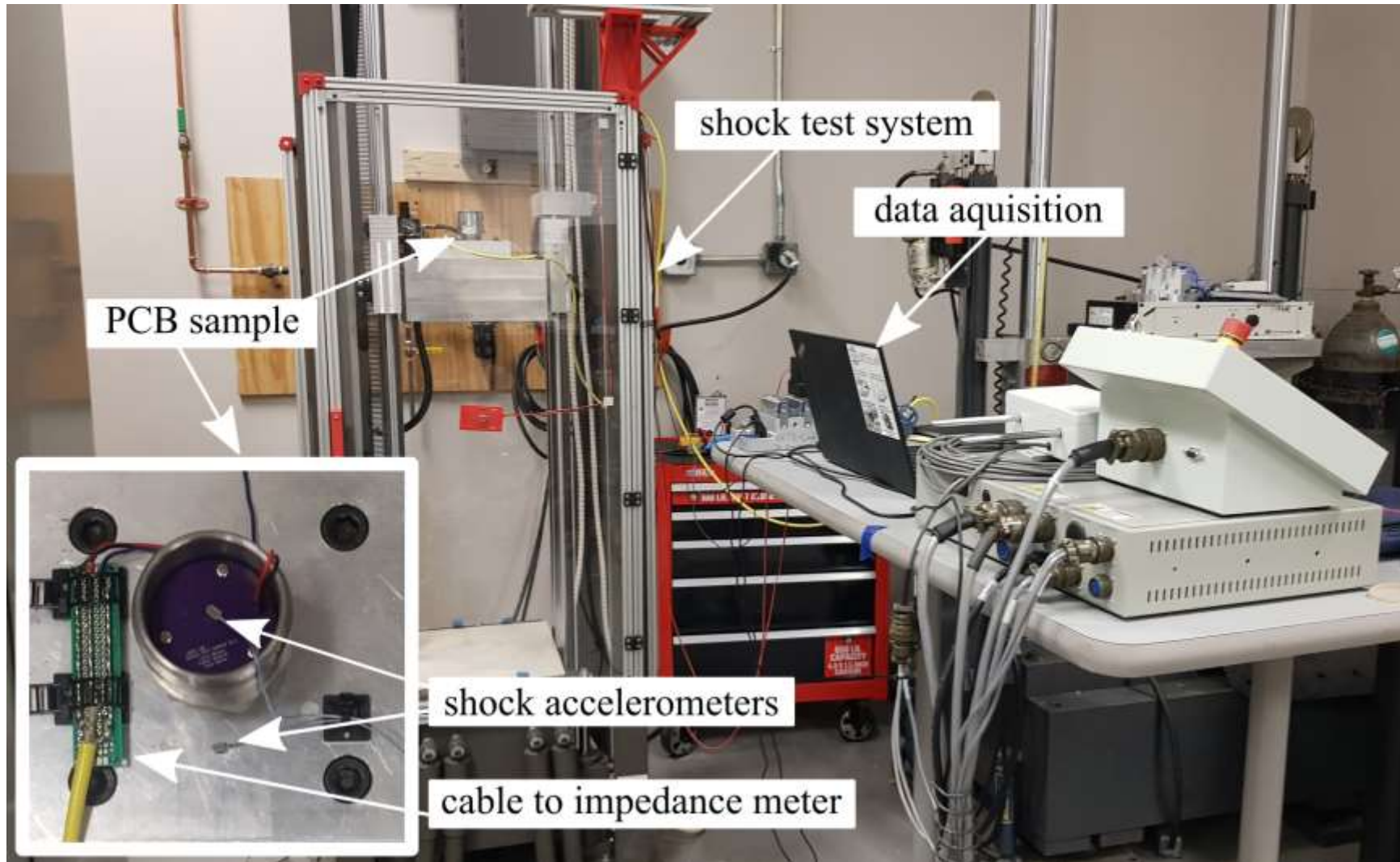
Electronic Components Under Shock (Application)

Data Driven Model Updating
(Theory and Proof of Concept)

Electronic Components
Under Shock (Application)

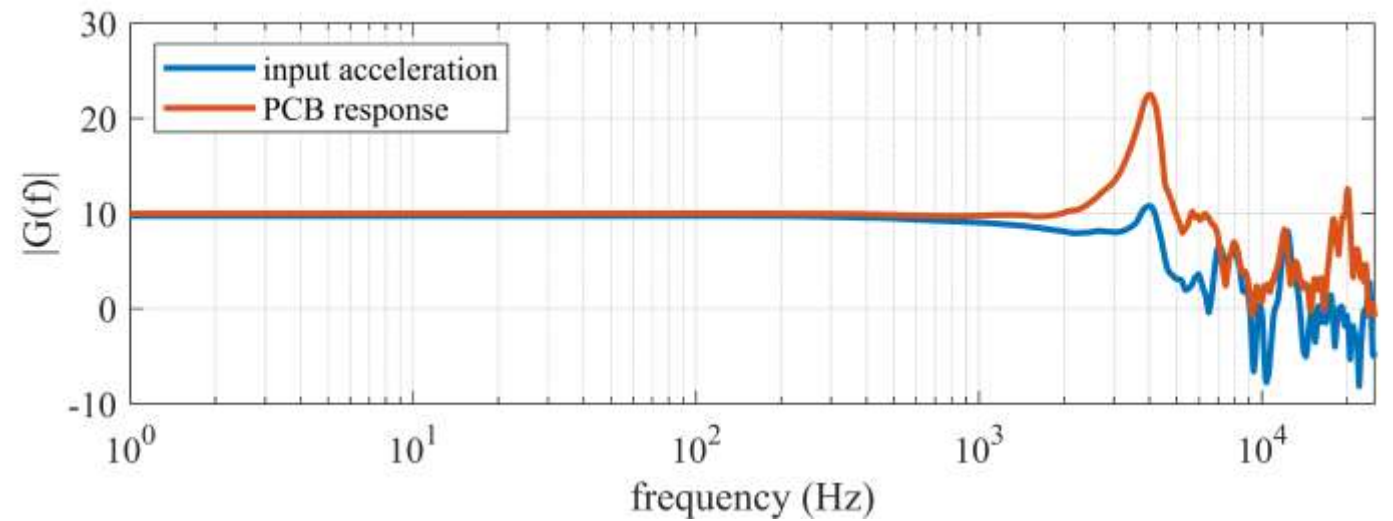
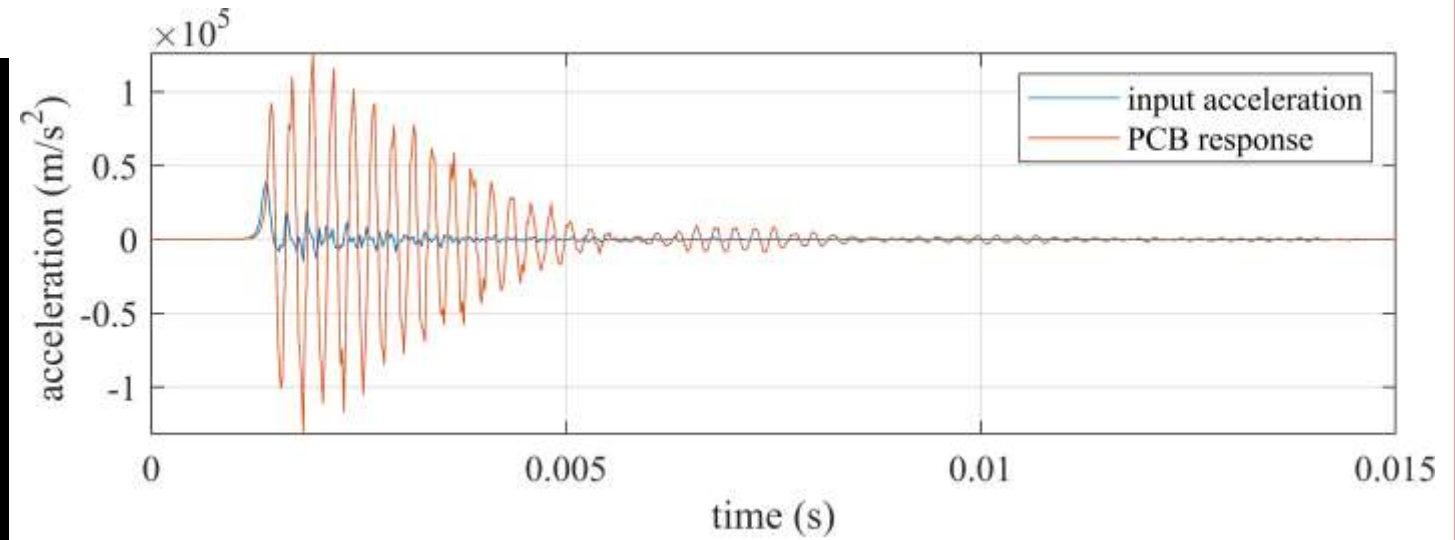
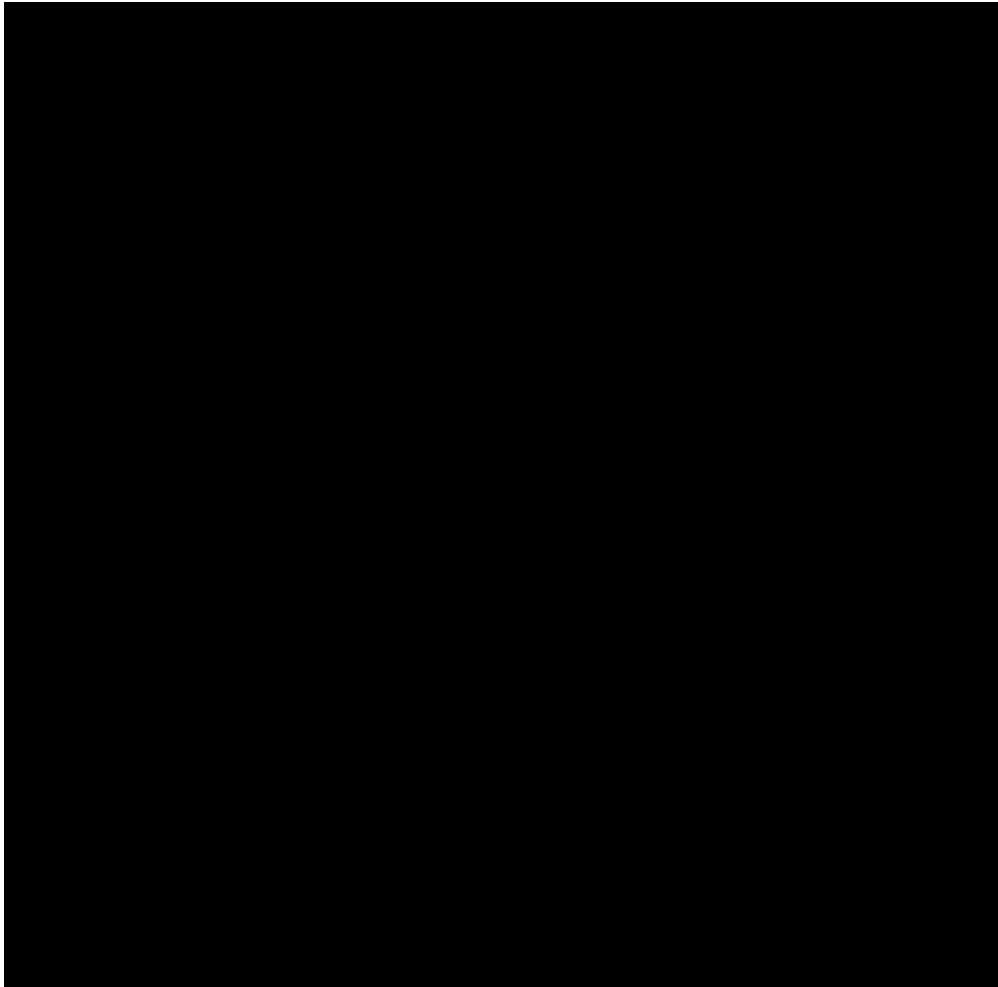
FPGA Implementation
(Timing Consideration)

Experimental System used for Validation

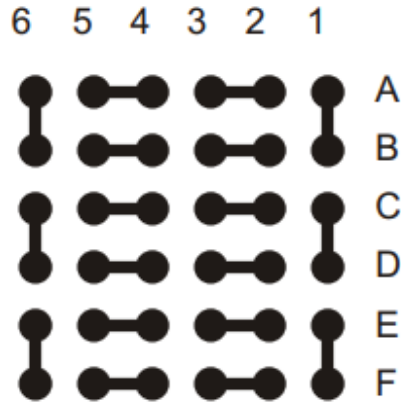


<https://github.com/High-Rate-SHM-Working-Group/Dataset-5-Extended-Impact-Testing>

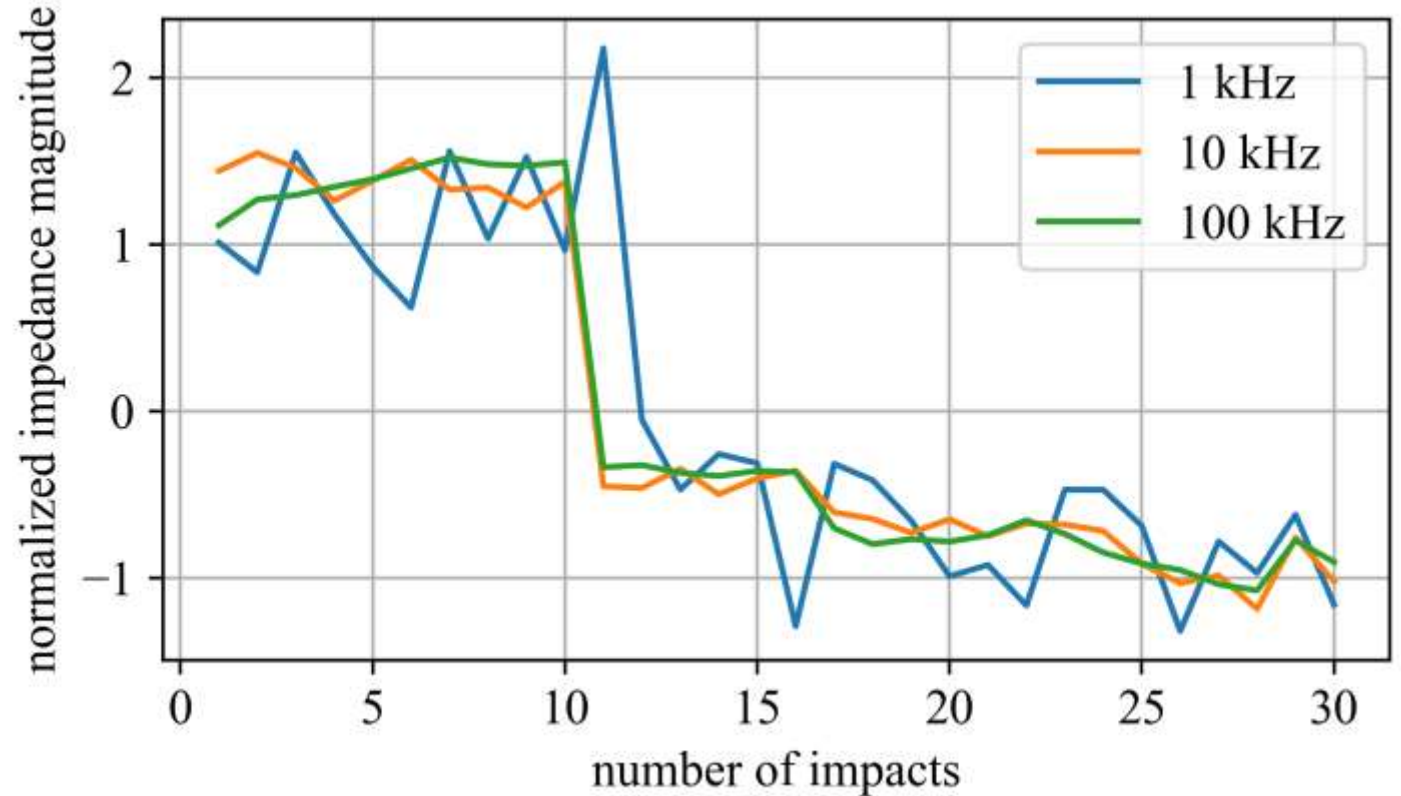
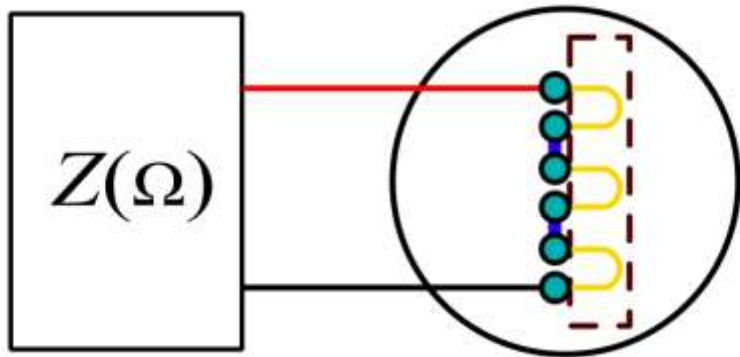
Experimental System used for Validation



Experimental System used for Validation



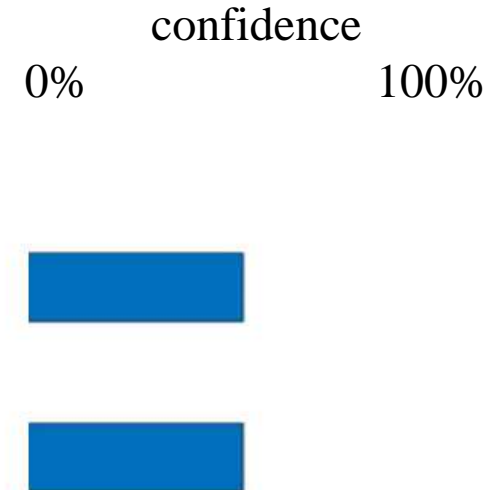
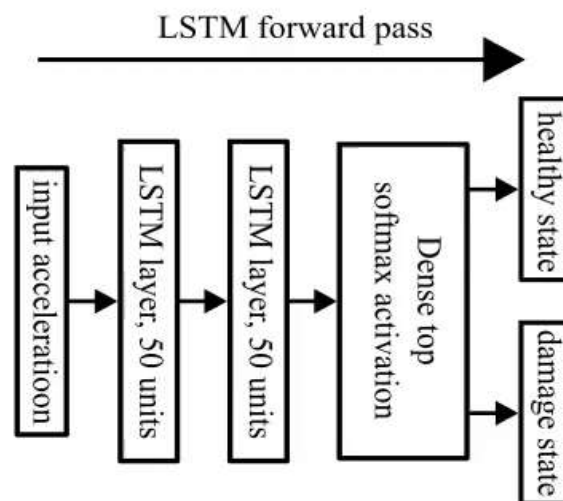
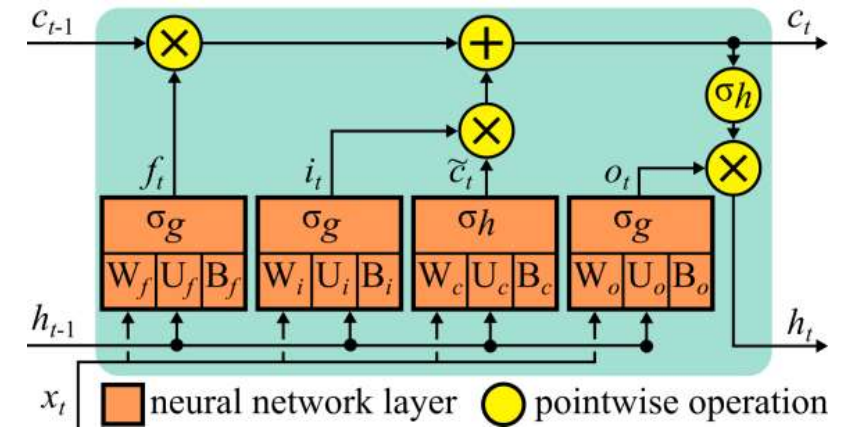
— PCB connection
— internal connections



LSTM-based Real-time State Estimation

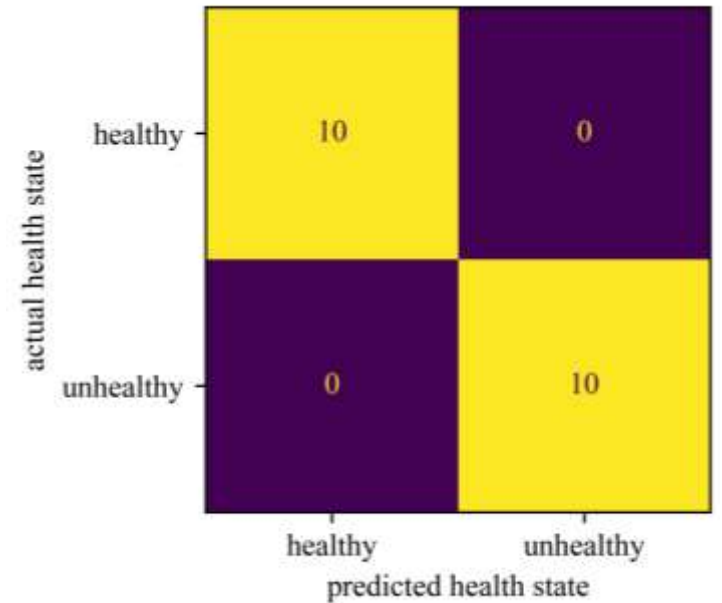
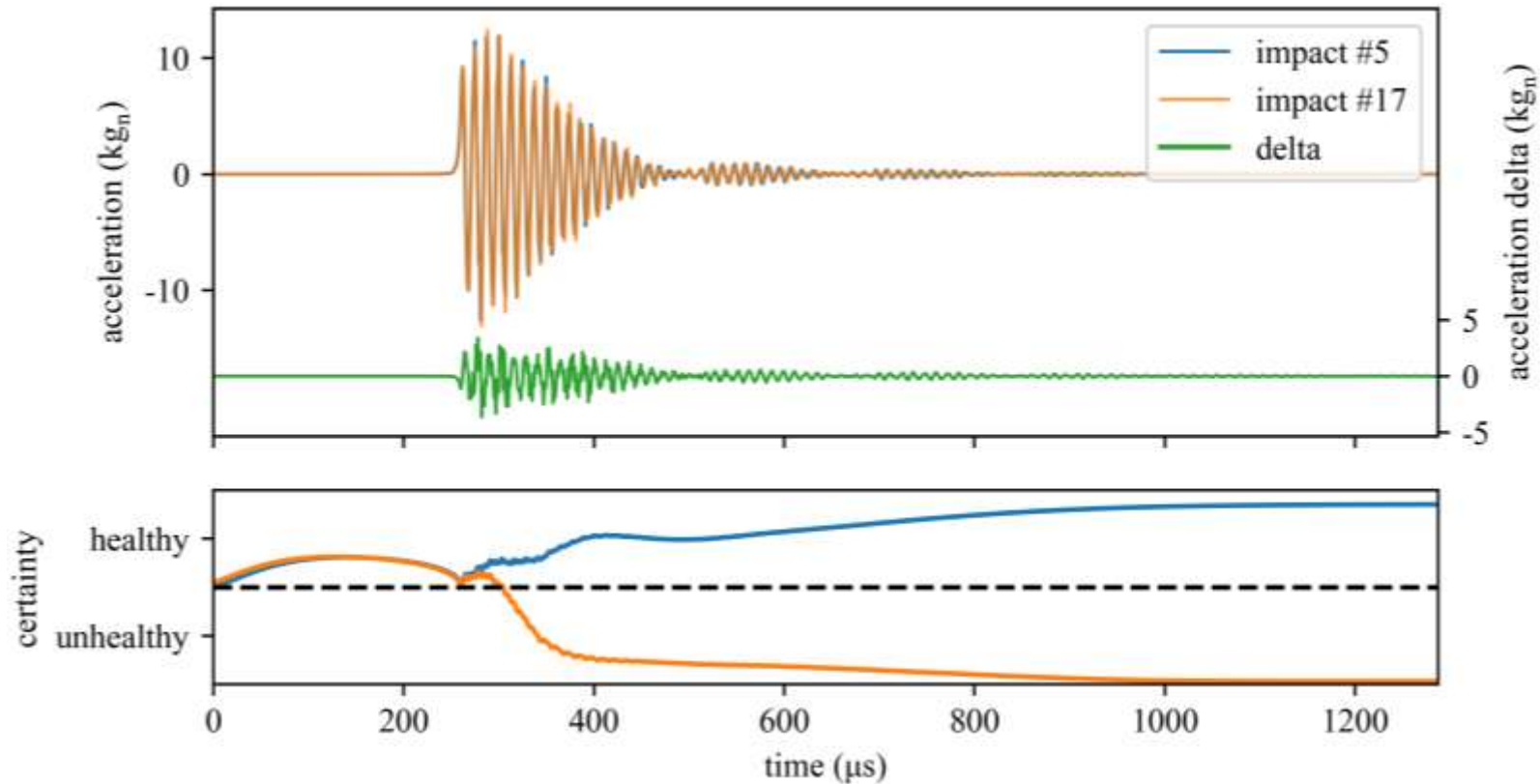
In this work:

- Long short-term memory (LSTM) models are used for real-time state estimation.
- Models are initially trained offline on pre-recorded data.
- LSTM architecture is (50, 50 units) with a dense layer at the output with SoftMax activation



Model Results

Prediction of survivability of PCB exposed to shock loads



FPGA Implementation (Timing Consideration)

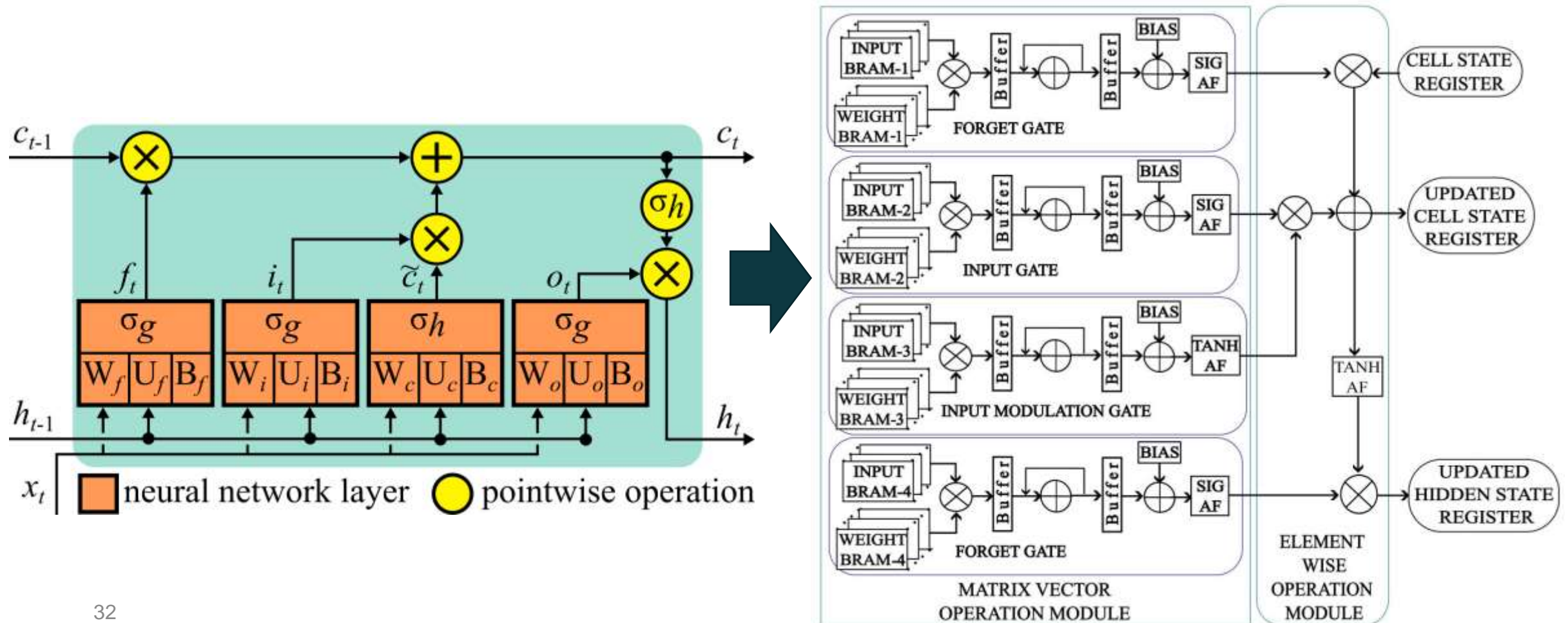
Data Driven Model Updating
(Theory and Proof of Concept)

Electronic Components
Under Shock (Application)

FPGA Implementation
(Timing Consideration)

LSTM deployment on an FPGA

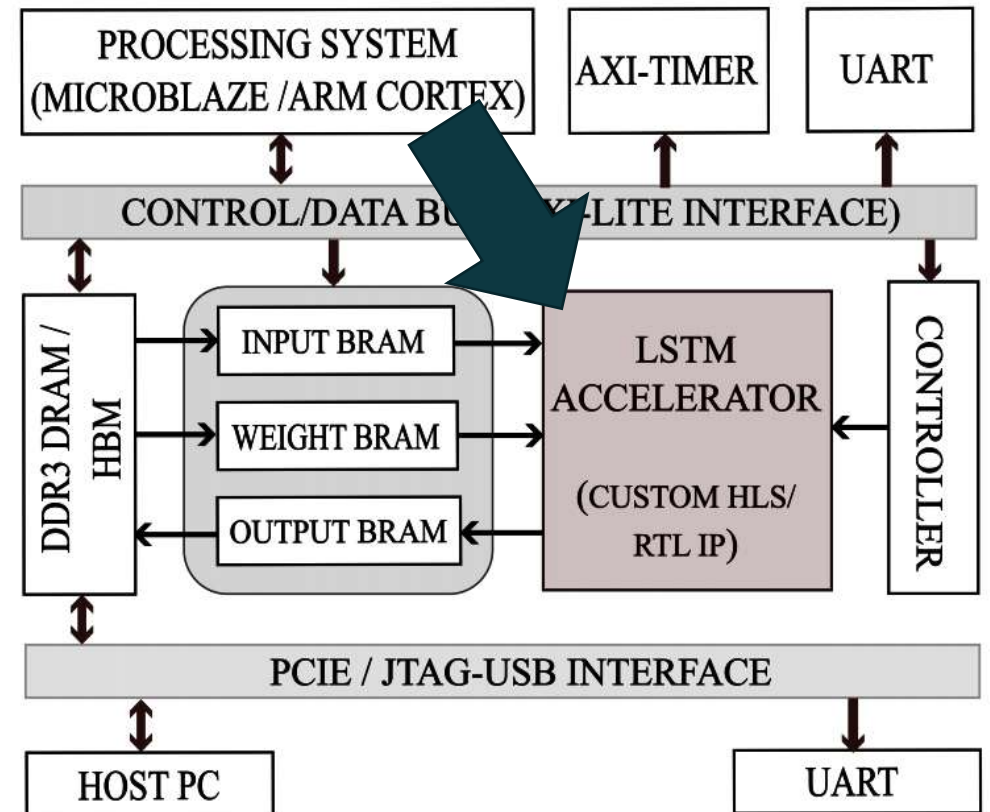
The developed hardware accelerator is split up into the LSTM's gates for deployment.



Custom LSTM Hardware Accelerator

Building a hardware accelerator for deploying LSTMs with a focus on low latency using High-Level Synthesis (HLS).

- Designed in C++ with Vitis HLS, then synthesized into Hardware Description Language (HDL).
- Two main units: Matrix-Vector Operations (MVO) and Element-Wise Operations (EVO).
- Partial or full array partitioning optimizes BRAM usage based on LSTM size.
- Loop pipelining improves parallelization, but BRAM port limits restrict full parallelism.



Parallelism study

Effect of Parallelism on HDL Design

- LSTM hardware accelerator replacement created in both Hardware Description Language (HDL) and High-Level Synthesis (HLS). HDL exposed more parallelism.
- Software baseline system developed on National Instruments testbed. State prediction output every 500 μs .

Platform	Bit Precision	LUT (%)	DSP (%)	Highest Level of Parallelism	Fmax (MHz)	Latency (μS)
Virtex 7	FP-32	28	69	4 Units	142	5.78
	FP-16	39	72	15 Units	166	2.06
U55C	FP-32	11	38	8 Units	150	2.38
	FP-16	9	22	15 Units	250	1.42

Takeaway

It is possible to use online data-driven models for micro-second tracking of structures during impact.



Part 3: Signal Processing for UAV-deployed Sensors

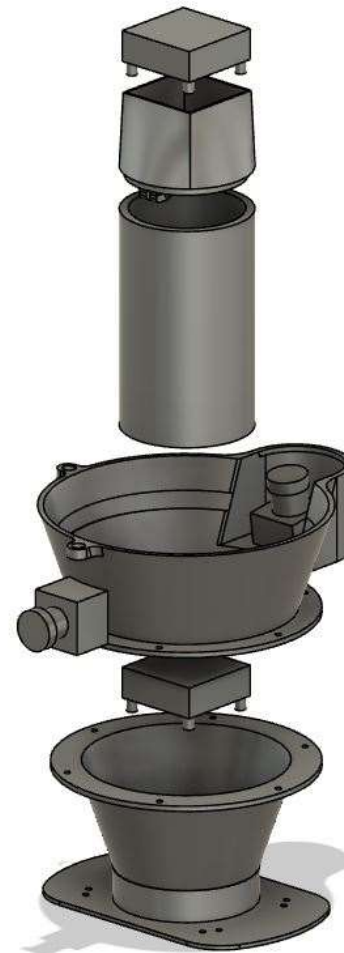
Challenges and Innovations in Structural Health Monitoring

- **Current Limitations:** SHM depends on specialized equipment and personnel, reducing speed and flexibility.
- **Deployment Challenges:** Hazardous or aging structures increase cost and safety risks.
- **Need for Rapid SHM:** Real-time insights, autonomous deployment, and wireless communication are essential for efficient monitoring.



Challenges and Innovations in Structural Health Monitoring

- **Autonomous Deployment:** Fast, precise sensor placement.
- **Real-Time Monitoring:** Continuous data for proactive assessment.
- **Cost & Time Efficient:** Reduces manual inspections.
- **Scalable Solution:** Works for bridges, levees, and more.
- **Enhanced Safety:** Minimizes human exposure.

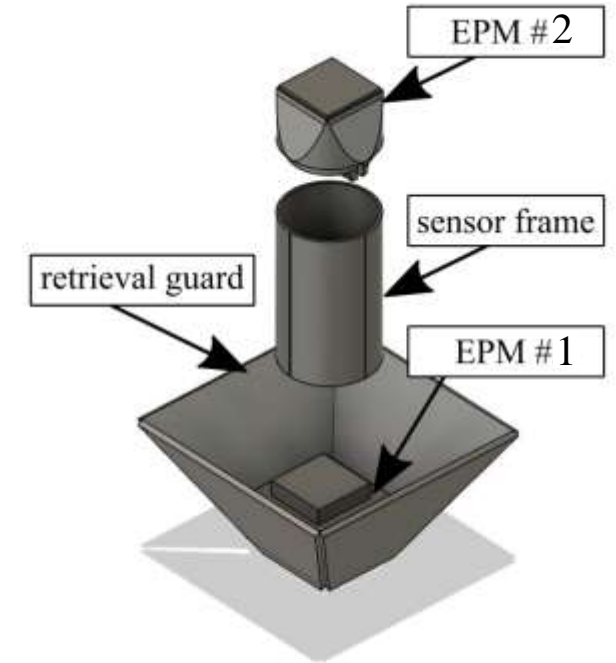
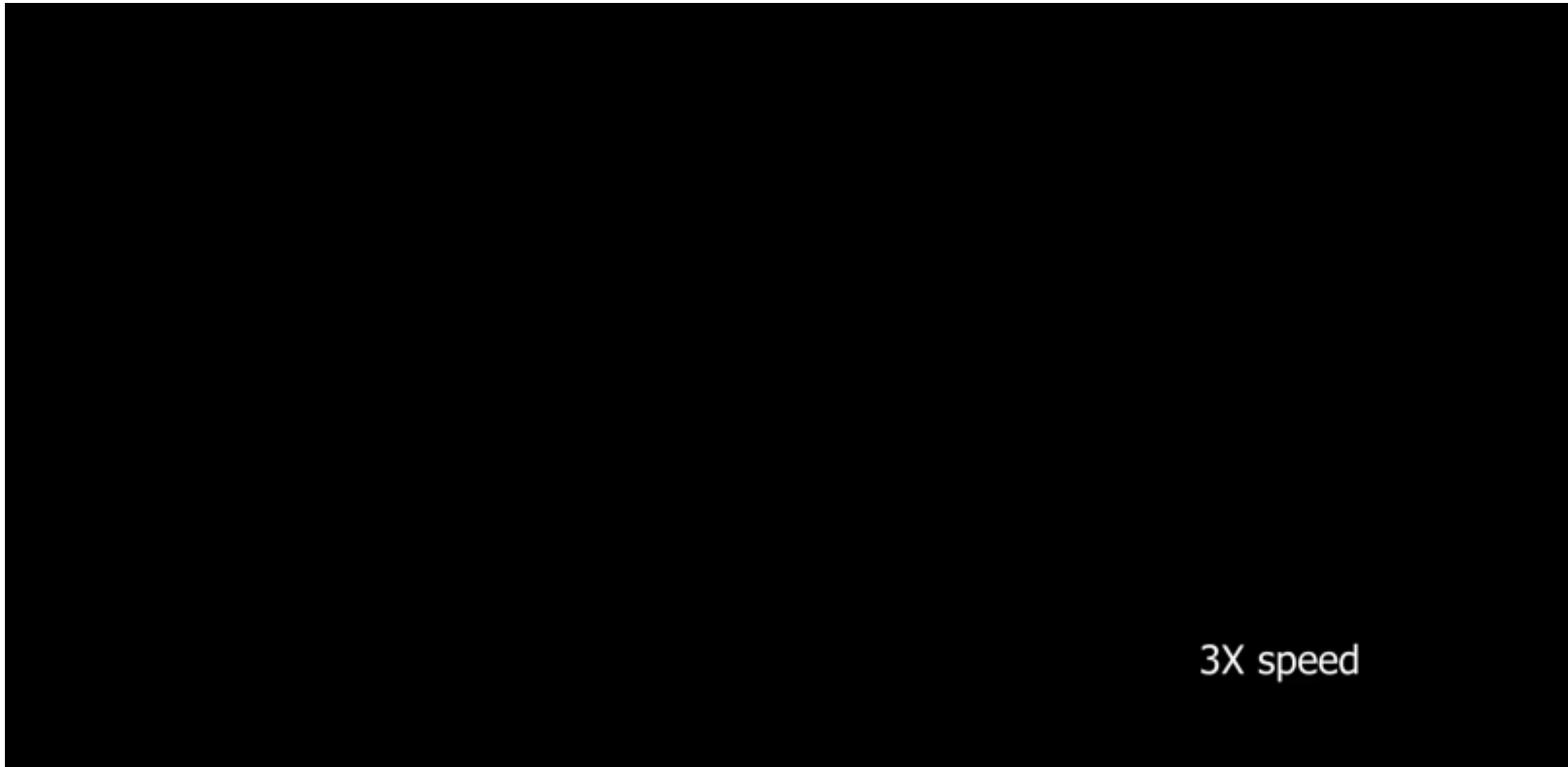


Sensor Package

- **Deployment System:** Uses a 3D-printed recovery cone for guided docking
- **Integrated Streaming:** Provides multiple camera views for precise navigation
- **Electropermanent Magnets:** Secure sensor placement and retrieval
- **Error Compensation:** Redundancy measures for safe, reliable operation in complex environments

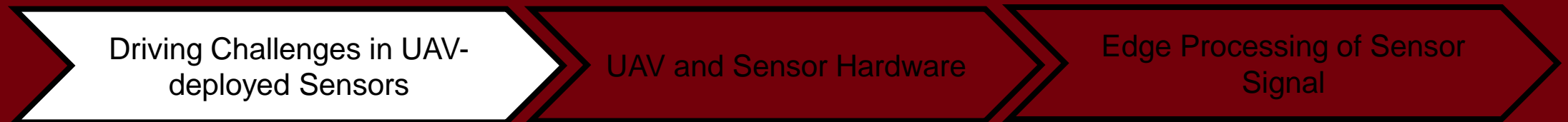


Deployment and Retrieval System



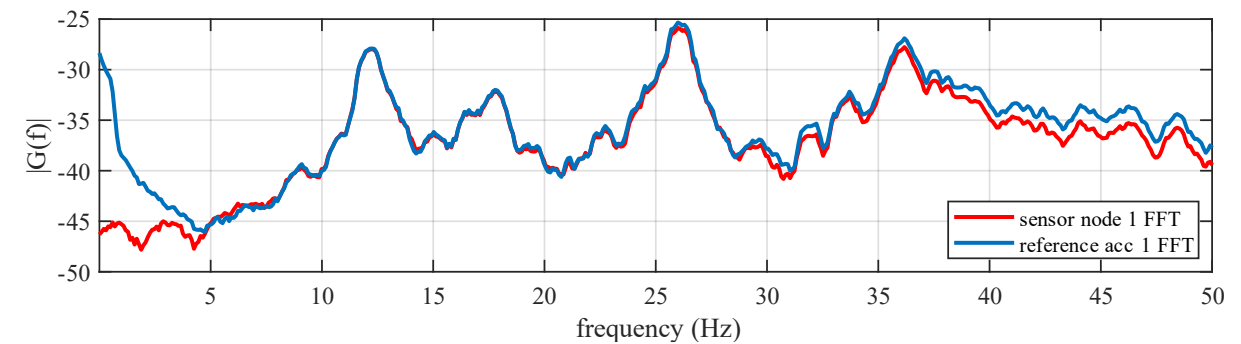
	EMP #1	EMP #2
Deployment	On	Off
Retrieval	Off	On

Driving Challenges in UAV-deployed Sensors



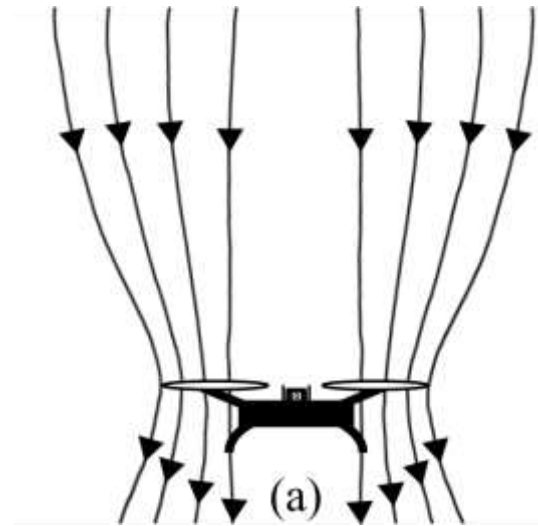
Our Solution – UAV-Deployable Sensor Package

- **Rapid Aerial Sensor Deployment:** Designed for quick, efficient sensor placement in SHM scenarios
- **Enhanced Spatial Awareness:** Multiple camera views for precise navigation, docking, and sensor deployment
- **Electropermanent Magnetic Docking:** Secure attachment with a recovery cone for guided docking
- **Built-in Redundancy:** Safety and reliability features to ensure successful deployments

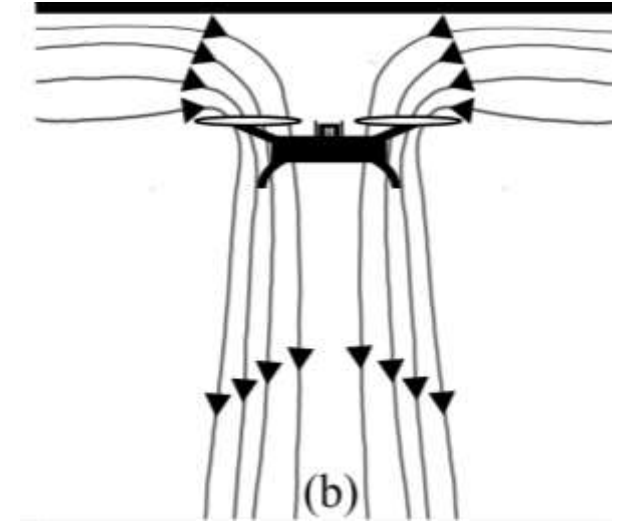
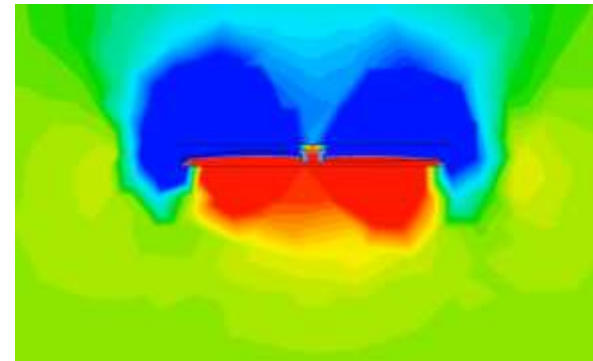


Understanding the Ceiling Effect in UAVs

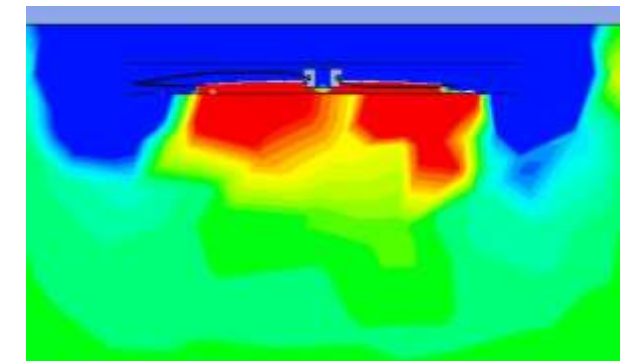
- **Definition:** The ceiling effect occurs when a propeller operates near a barrier, like a ceiling, altering the airflow and making lift more efficient.
- **Cause:** Impeded airflow above the propeller leads to a pressure drop, creating an increase in lift.
- **Impact on Control:** The UAV operator may notice sudden, unexpected lift or reduced control near the ceiling.



propeller in open air



propeller under ceiling effect



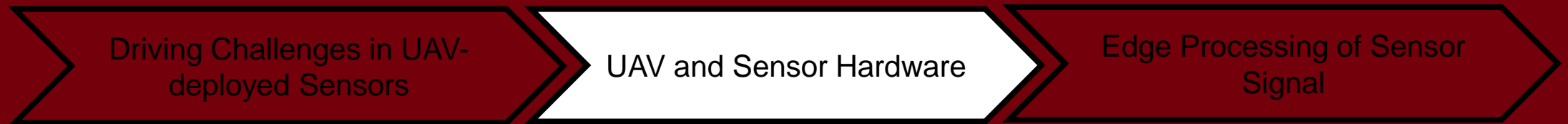
Challenges in Human-Operated Flight for Sensor Deployment in SHM

- **Ceiling Effect Variability:** Sudden lift changes near ceilings
- **Pilot-Induced Instability:** Oscillations from manual control
- **Signal Interference:** Issues near metal structures
- **Line of Sight Limitations:** Restricted visibility impacts precision

No researchers were harmed during this endeavor!

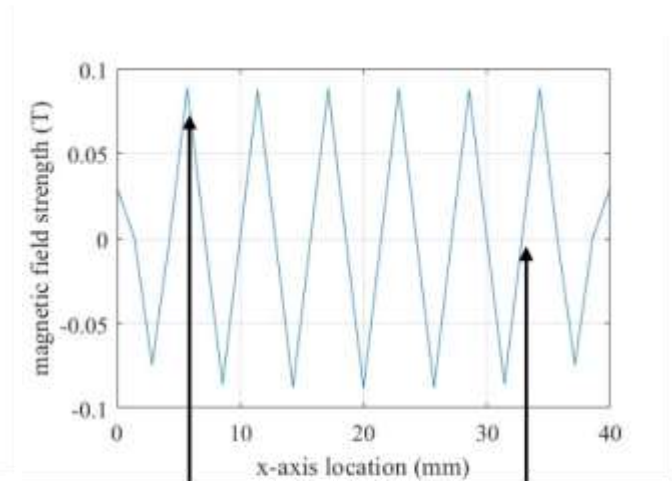
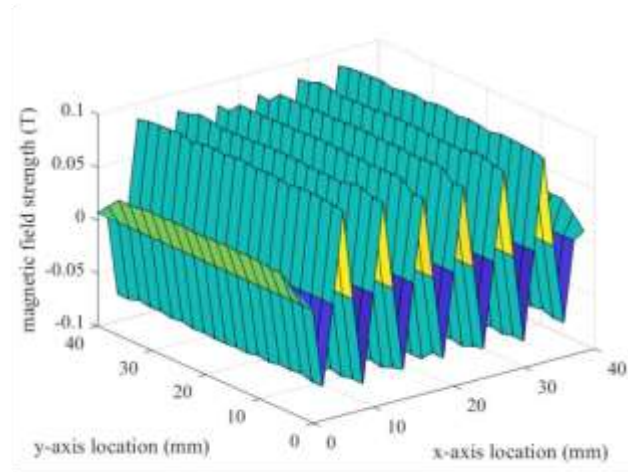


UAV and Sensor Hardware



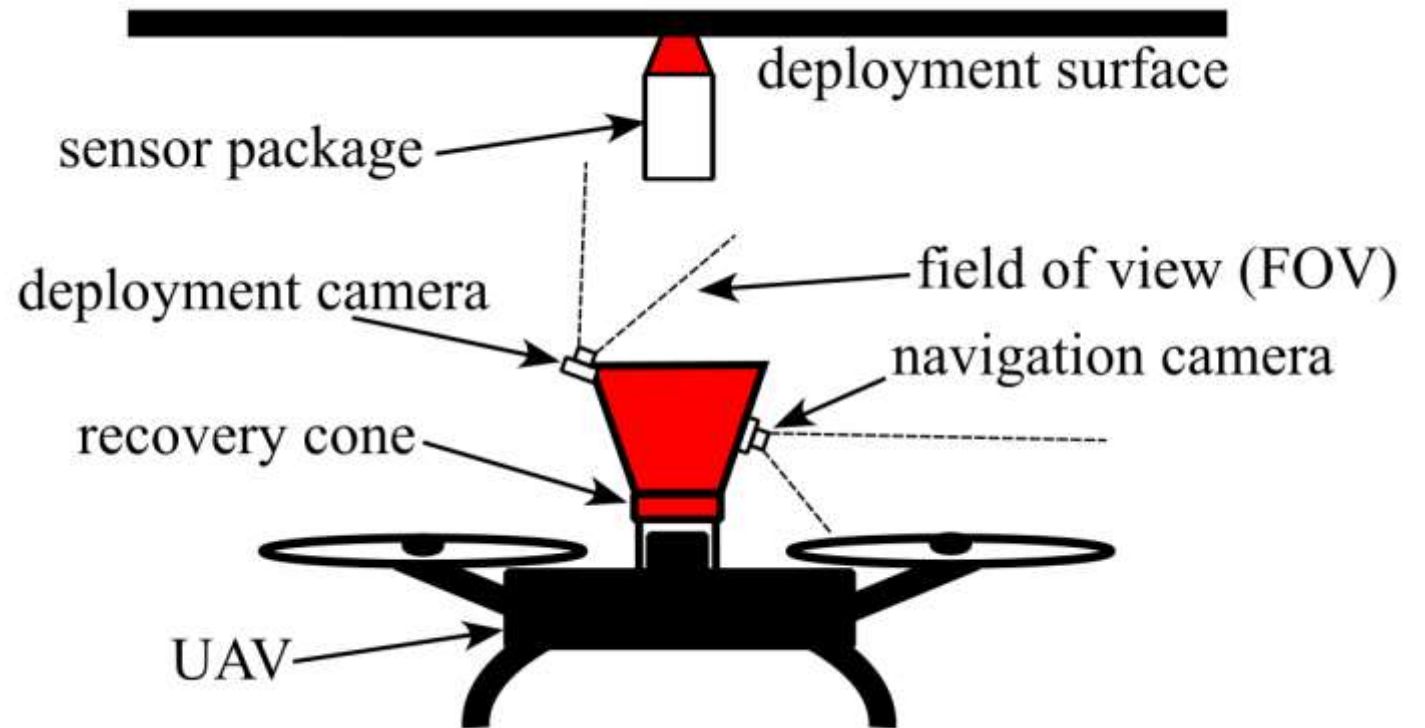
Deployment and Retrieval System

- **Electromagnetic Activation:** Pulse-activated magnetic polarity control
- **Energy-Efficient:** Holds magnetic state without continuous power
- **Versatile Applications:** Ideal for clamping, lifting, and sensor deployment
- **Stable Magnetic Configuration:** Maintains position securely using South-South or South-North fields



Camera-Assisted Deployment

- **Multi-Camera Setup:**
Provides real-time spatial awareness for precise navigation.
- **Target Identification:**
Assists in locating the sensor package with visual feedback.



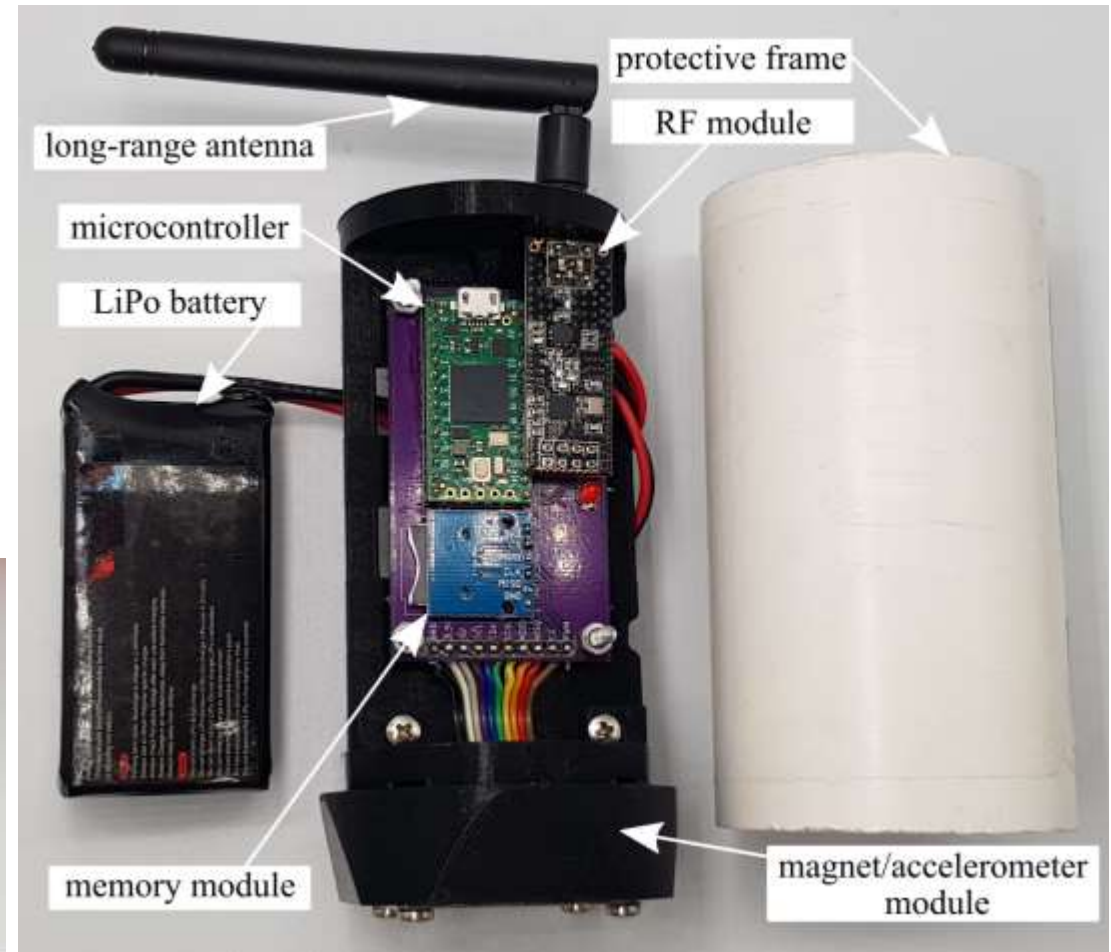
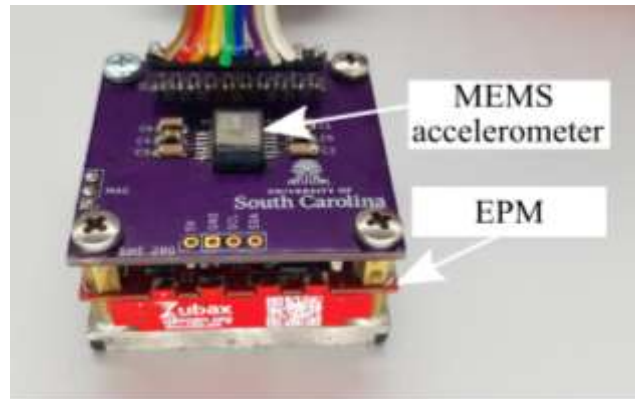
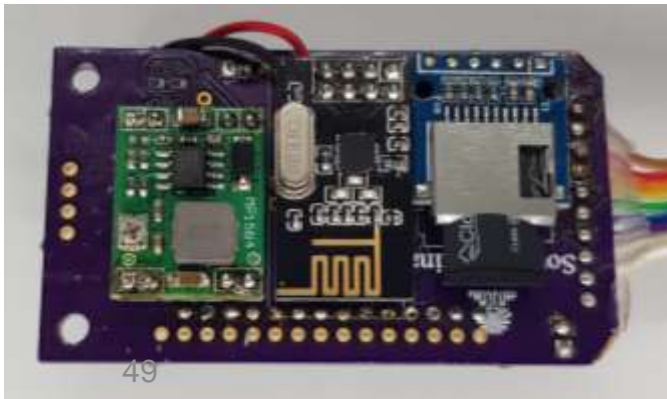
In-flight Data Collection

- **Accurate Alignment:** Guides the UAV to align the recovery cone with the sensor package.
- **Foundation for Autonomy:** Key step towards a fully autonomous UAV system.
- **End-to-end Machine Learning Control:** Currently developing end-to-end methods for the autonomous retrieval of sensor packages.



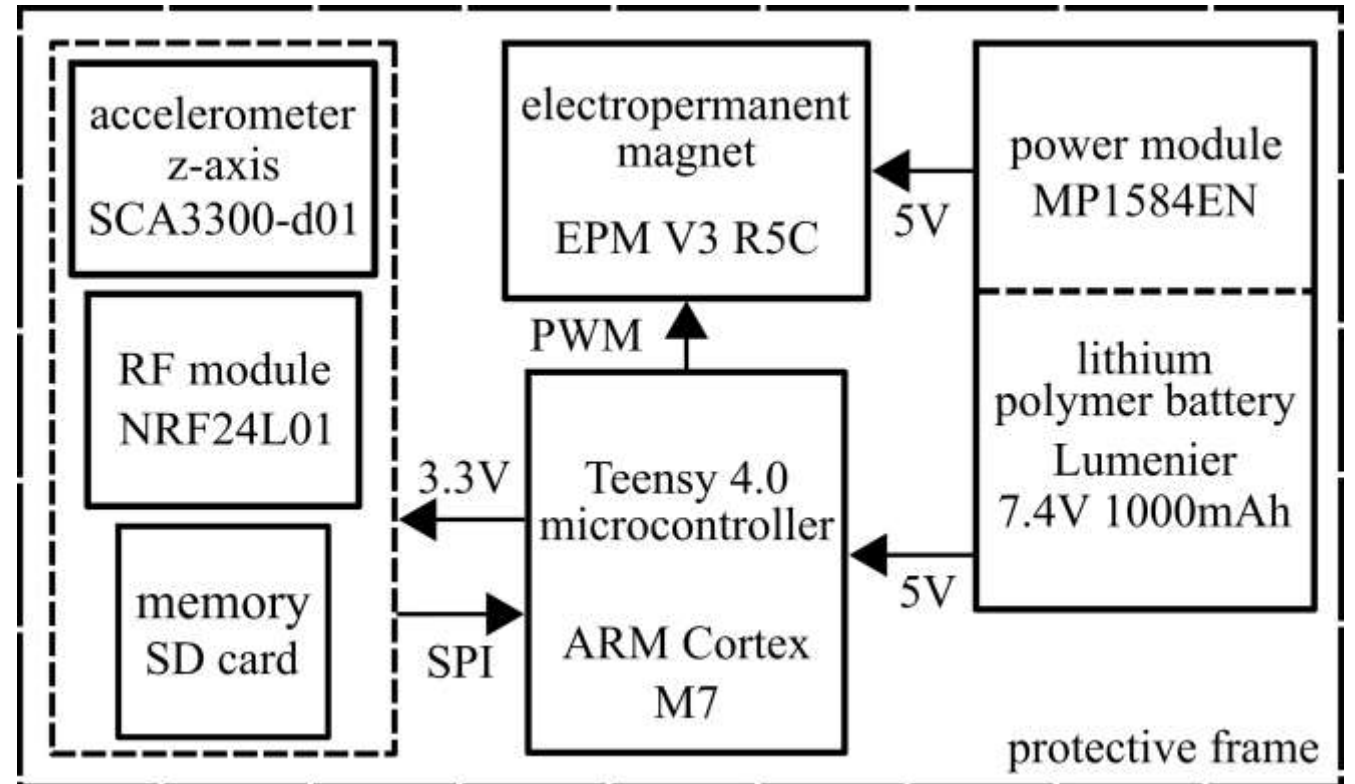
Sensor Hardware and Onboard Systems

- **Robust Design:** Aerially deployable with noninvasive EPM docking
- **Reliable Operation:** Power management, nonvolatile memory, and wireless communication
- **Sensing:** Accelerometer up to 28 kS/s; frame minimizes transmissibility loss



Sensor Package System Architecture

- **Core Processing:** Teensy 4.0 microcontroller (ARM Cortex M7) with SD card for data storage
- **Communication:** High-sensitivity accelerometer and RF module for real-time data and commands

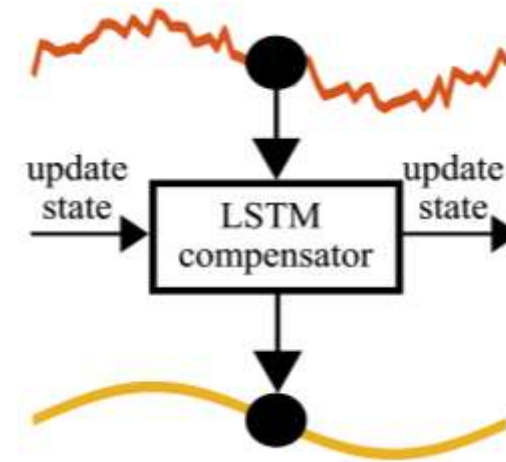


Edge Processing of Sensor Signal

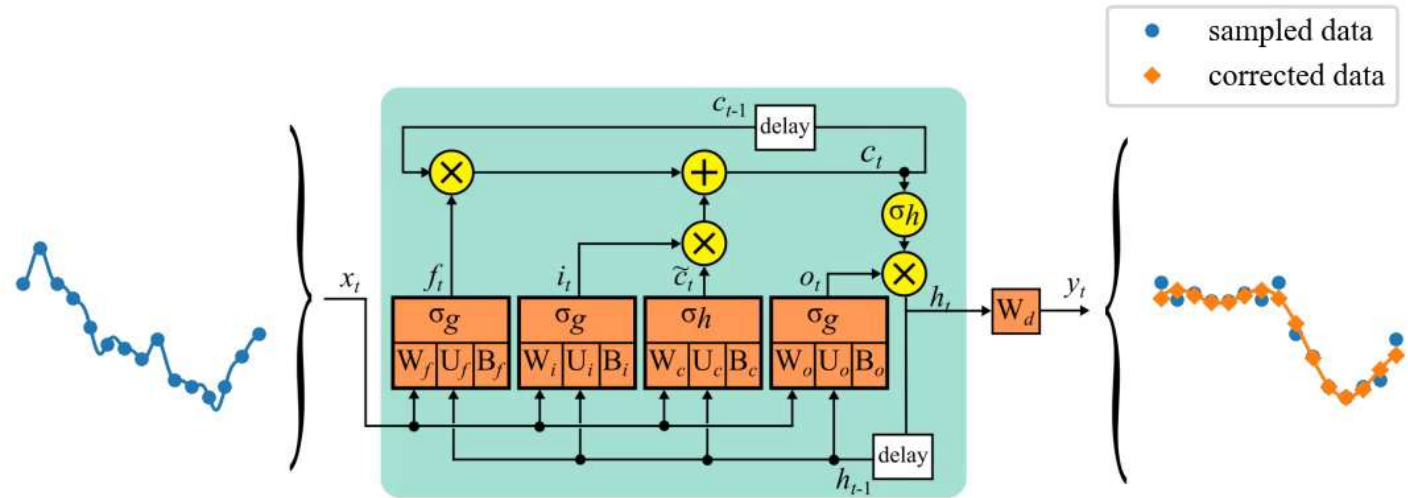


LSTM-Based Signal Compensation Process

- Model training procedure
- Supervised learning method
- Assumptions:
 - Sampling rates were set equal (400 S/s)
 - Zero phase between the two sensors
 - Bandwidth of interest to be < 10 Hz
- Model chosen is a single-layer 50-unit LSTM
- Backpropagation is done online every 400 datapoints (1 second)



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



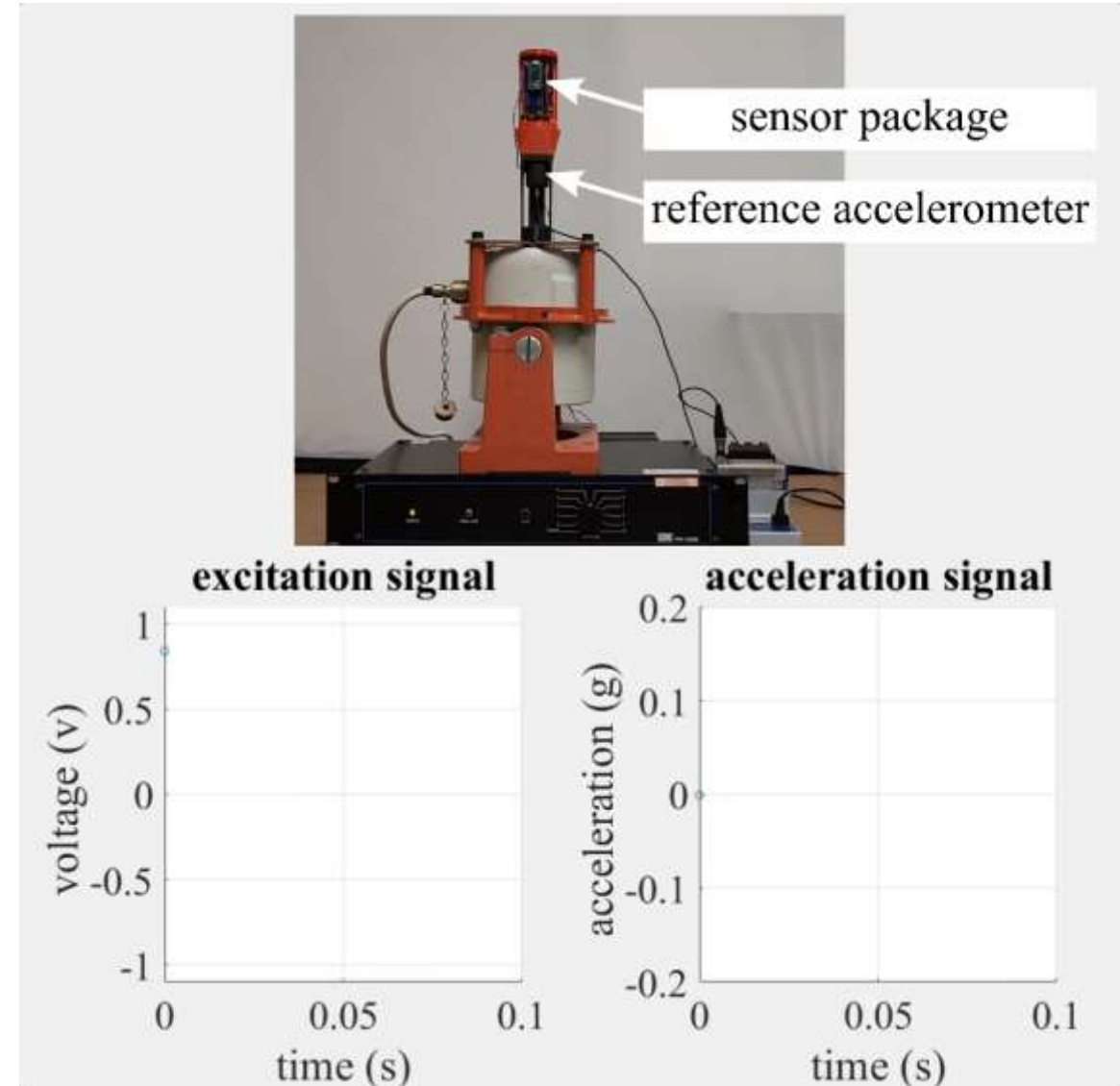
Signal Conditioning and Error Compensation

- Chirp excitation is fed into the electromagnetic shaker using an analog output module
- A data acquisition is used to record reference acceleration
- A digital trigger is set to synchronize both the reference accelerometer and sensor package
- Various dynamic ranges were used to expand the training range of the LSTM model

$$x(t) = \sin \left(2\pi \left(\frac{f_{\text{end}} - f_{\text{start}}}{2(\text{test time})} t^2 + f_{\text{start}} t \right) \right)$$

$$\text{SNR}_{\text{dB}} = 10 \log_{10} \left(\frac{\sum_{i=1}^{\text{data length}} (\text{signal}(i))^2}{\sum_{i=1}^{\text{data length}} (\text{noise}(i))^2} \right)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{\text{data length}} (\text{truth}(i) - \text{prediction}(i))^2}{\text{data length}}}$$

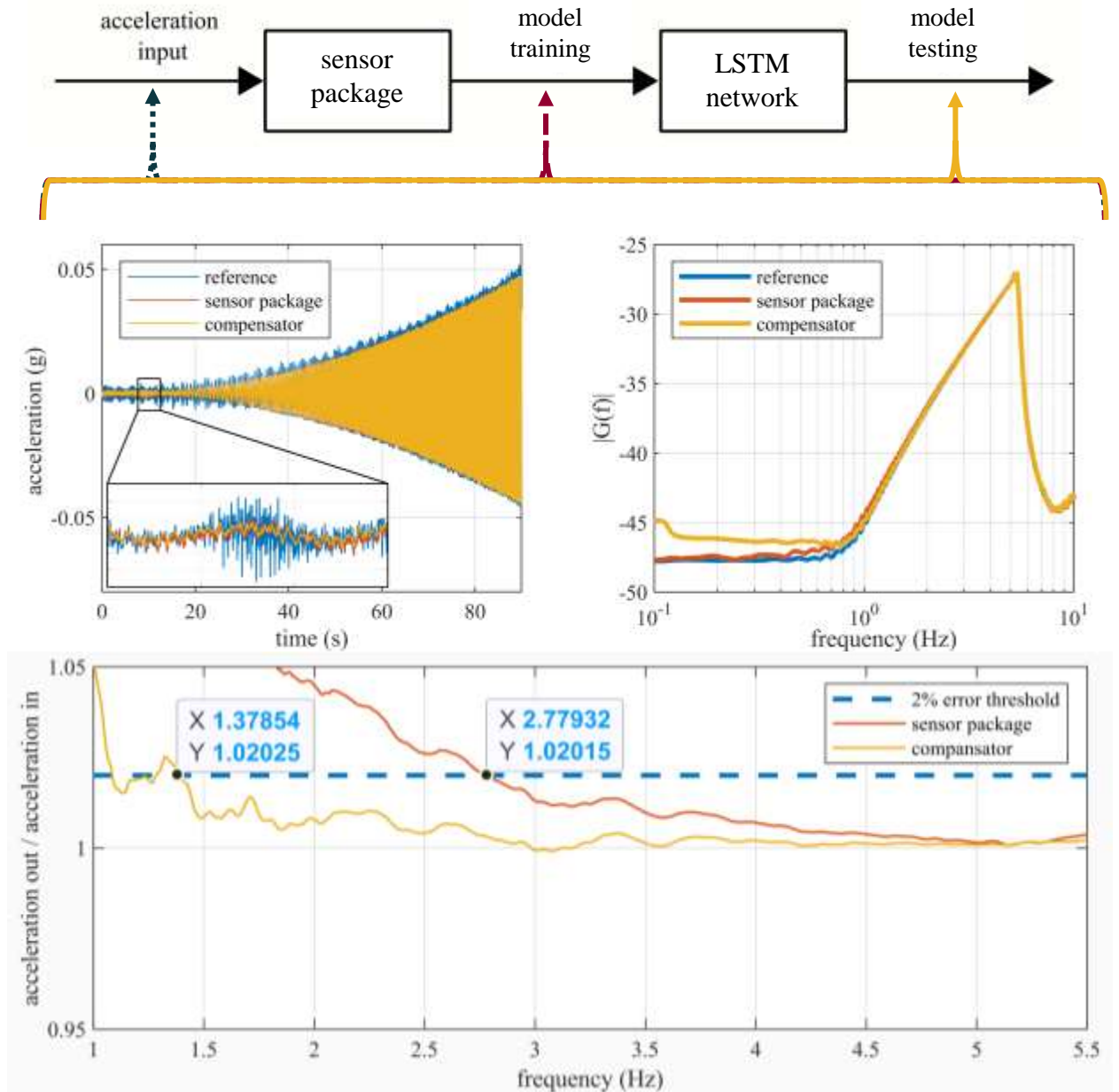


LSTM Performance

LSTM compensator performance

- For testing a chirp excitation in 0-5 Hz is used
- SNR_{dB} enhancement of 9.34%
- RMSE reduction of 19.66%
- Usable bandwidth (< ±2%) is shown to increase from 2.78 Hz to 1.34 Hz
- An overall increase in gain below 0.9 Hz due to training bias

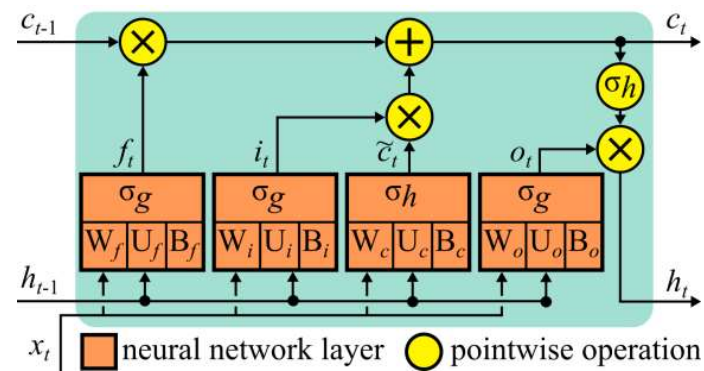
testing	SNR _{dB}	RMSE
sensor package	17.26 dB	1.795×10^{-3}
LSTM compensator	18.88 dB	1.442×10^{-3}
% improvement	9.34%	19.66%



Conclusion

The ARTS-Lab is a multidisciplinary research lab tackling challenges in control and edge computing.

- High-rate ML at the edge enables structural model updates in microseconds.
- Online signal compensation enhances data usability for UAV-deployed sensors in structural health monitoring.



Acknowledgement



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DISCUSSION

Hardware Keeps the Engineer Honest



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