

HIGH-RATE STATE ESTIMATION OF A PRINTED CIRCUIT BOARD UNDER SHOCK USING AN FPGA-DEPLOYED NEURAL NETWORK

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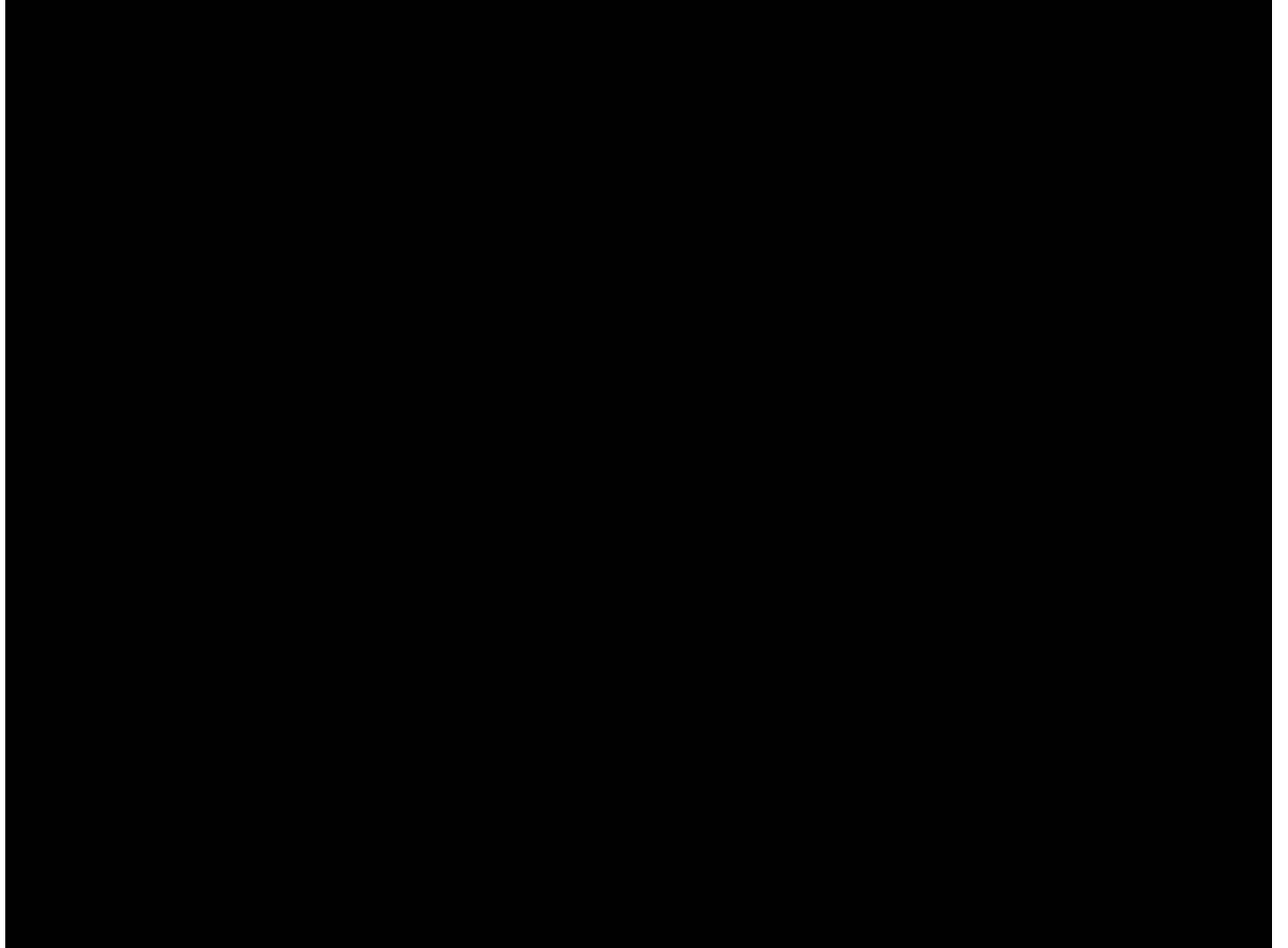


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OVERVIEW

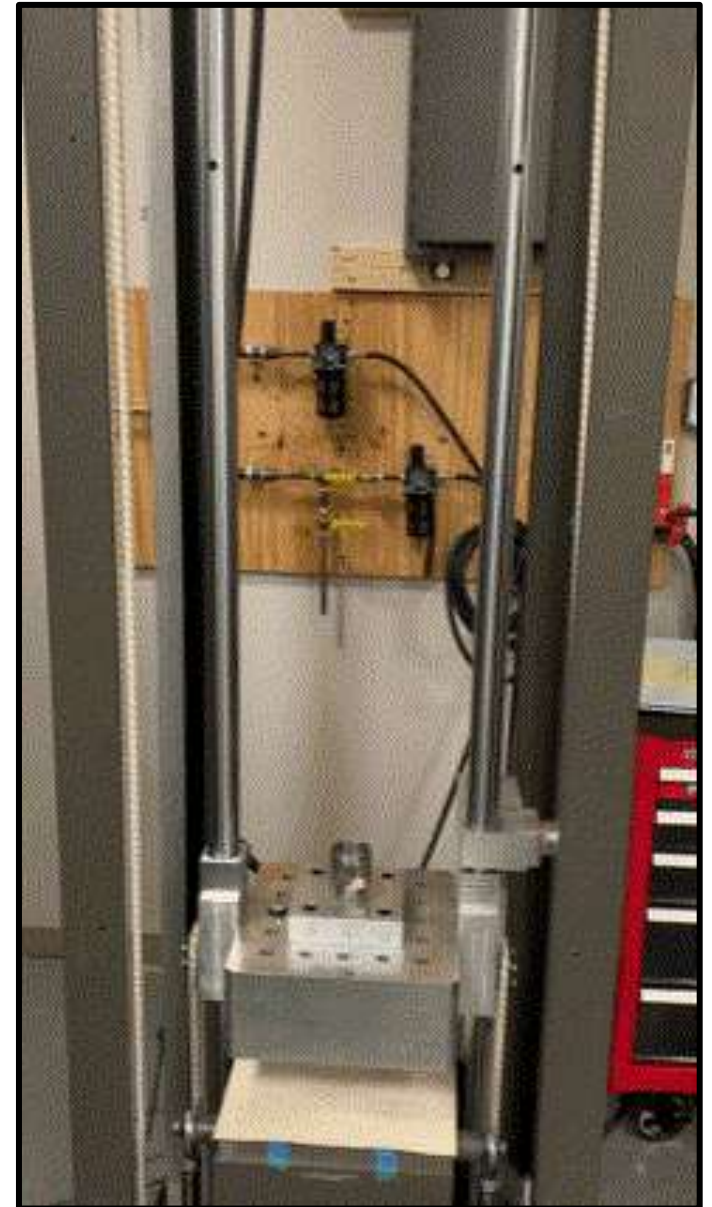
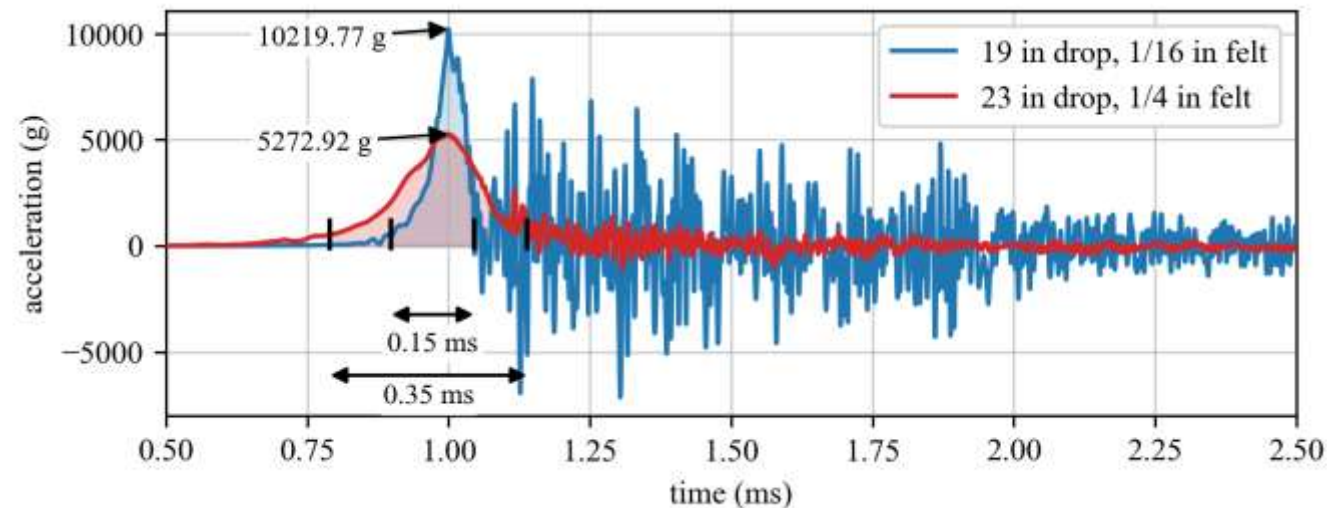
- Introduction
- Ongoing Work
- Focused Study
 - Objective
 - Experimental Dataset
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 - Model Training
 - FPGA Implementation
 - Performance
- Future Work



INTRODUCTION

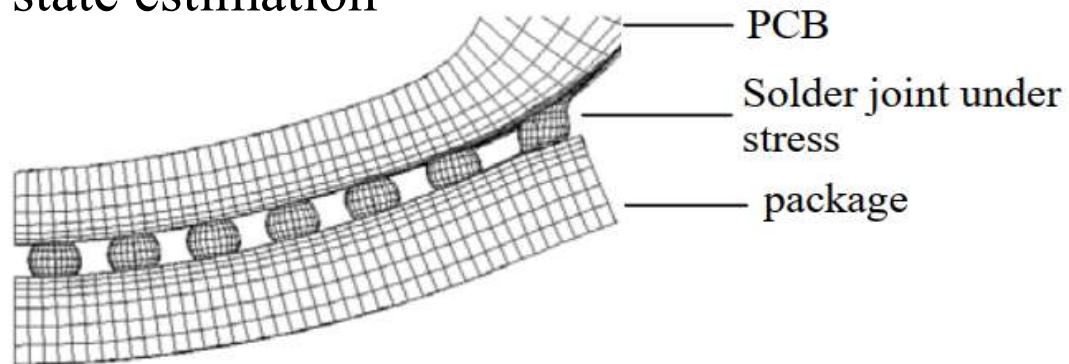
HIGH-RATE SHOCK

- Sudden, high-amplitude acceleration impulse (μs – ms duration)
- Broadband excitation with significant high-frequency content
- Generates extreme stress gradients and localized damage mechanisms
- Highly non-stationary and sensitive to boundary conditions
- Difficult to model and predict



ELECTRONIC ASSEMBLIES UNDER SHOCK

- PCBs are the structural and electrical backbone of nearly all modern electronic systems
- Board bending concentrates stress at package interconnects
- Solder joints, traces, and pads are susceptible to progressive damage
- High-rate response data can support earlier state estimation



WHY AN FPGA?

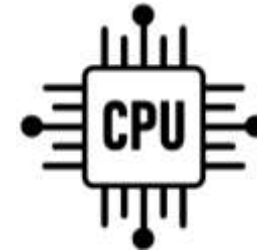
Field programmable gate arrays (FPGA) map a fixed model into dedicated hardware for predictable embedded inference.

- CPU/GPU execution is flexible, but timing can vary
- ASICs are efficient, but fixed-function and costly to redesign
- FPGAs provide reconfigurable hardware with bounded latency
- On-chip memory keeps model parameters close to computation
- Hardware parallelism can be tailored to the model architecture

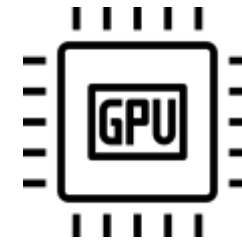


Kintex-7 K70T-2C

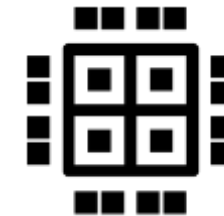
CPU



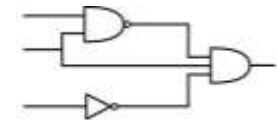
GPU



FPGA



ASIC



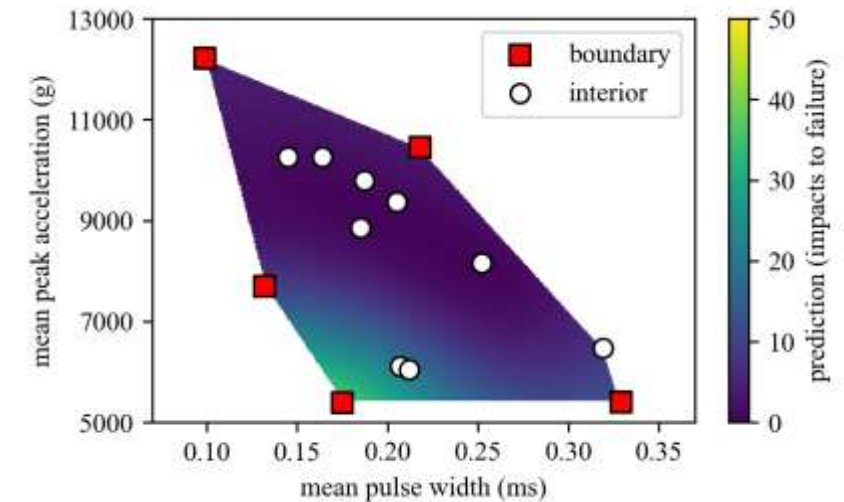
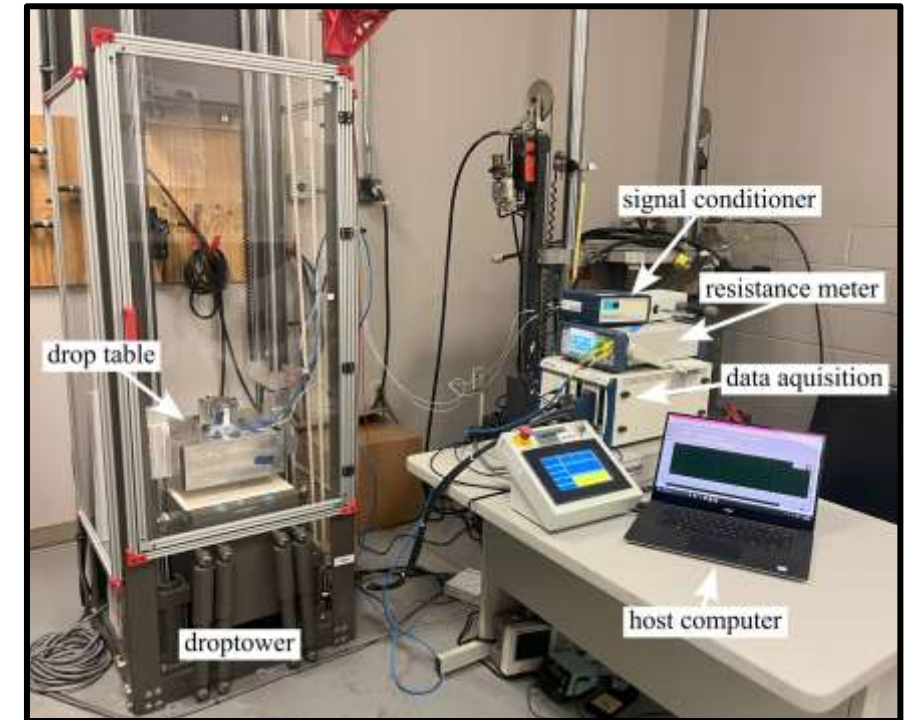
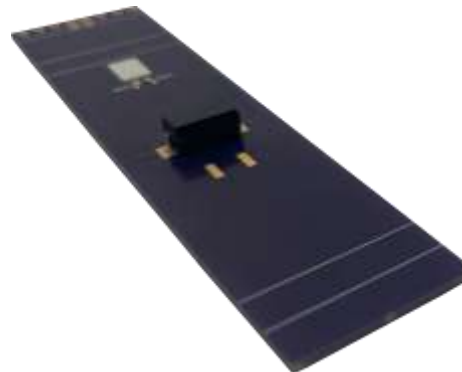
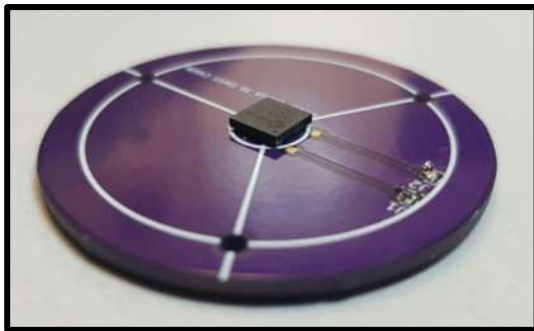
Flexibility

Efficiency

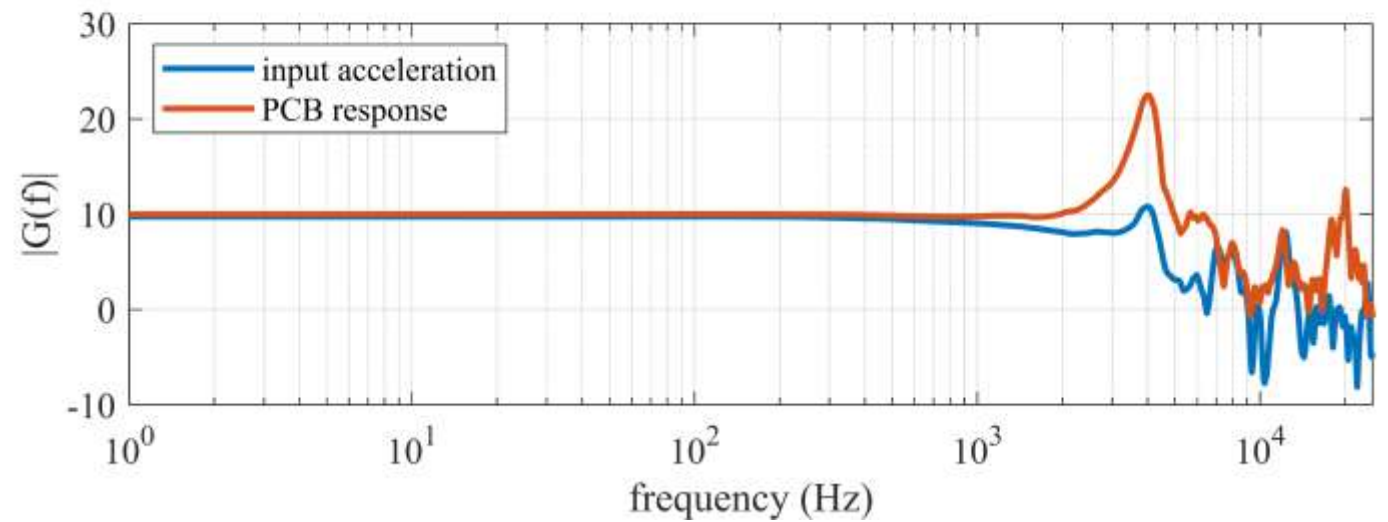
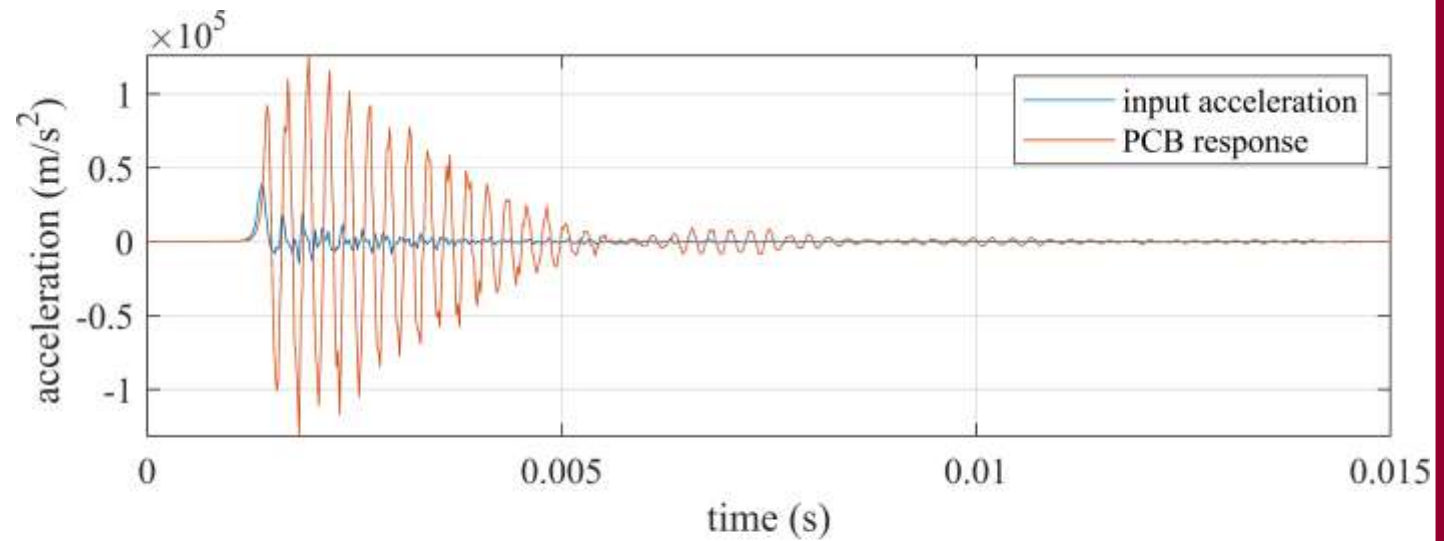
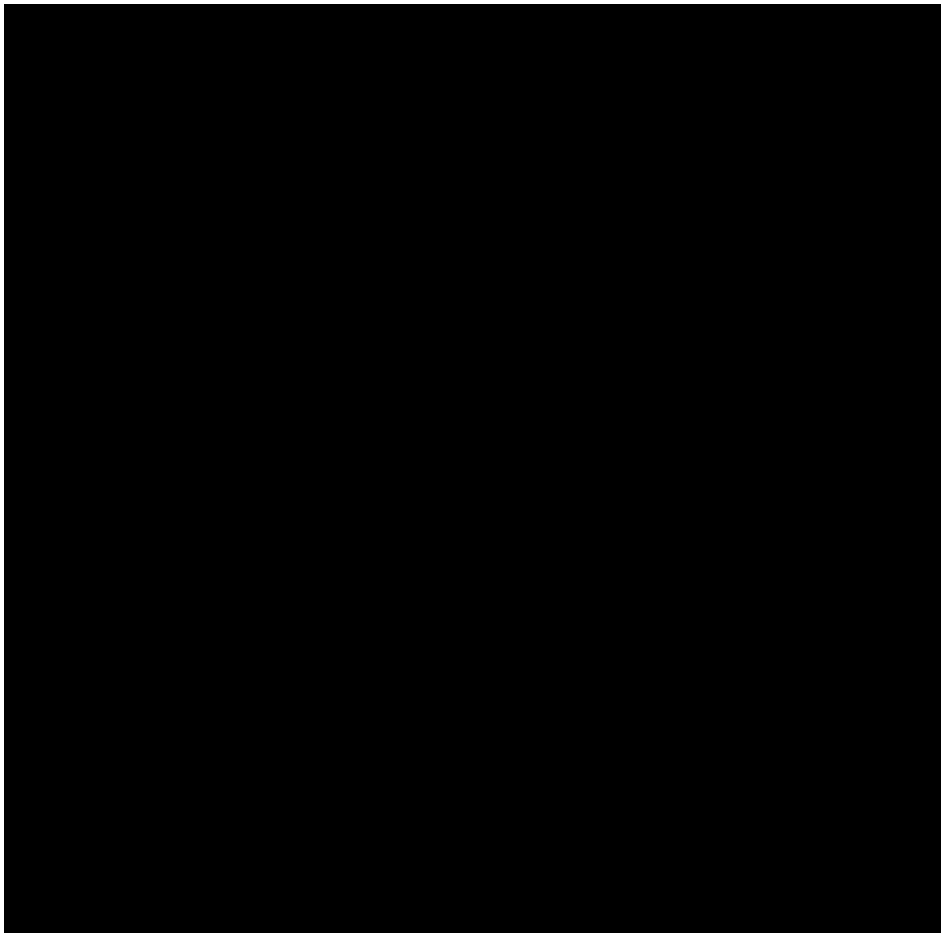
ONGOING WORK

EXPERIMENTAL PLATFORMS

- Shock testing across multiple PCB geometries (circular, cantilever, fixed-fixed)
- Component-level fatigue studies (resistors, BGA dummy components)
- Controlled variation of impact energy and boundary conditions
- Creation of labeled, high-rate degradation datasets
- Kriging-based models guide adaptive test selection and predict failure boundaries



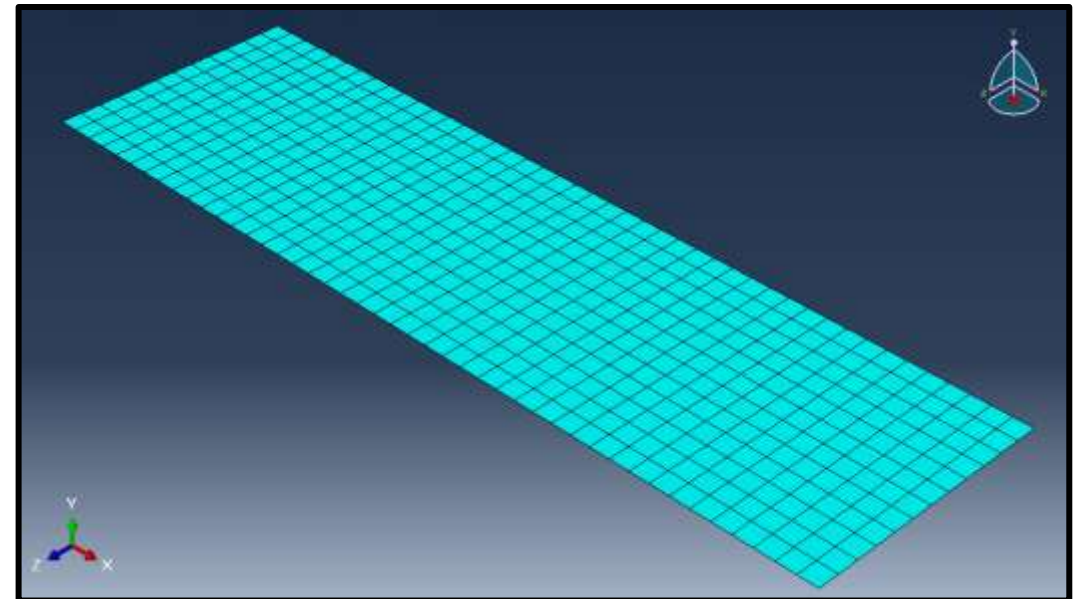
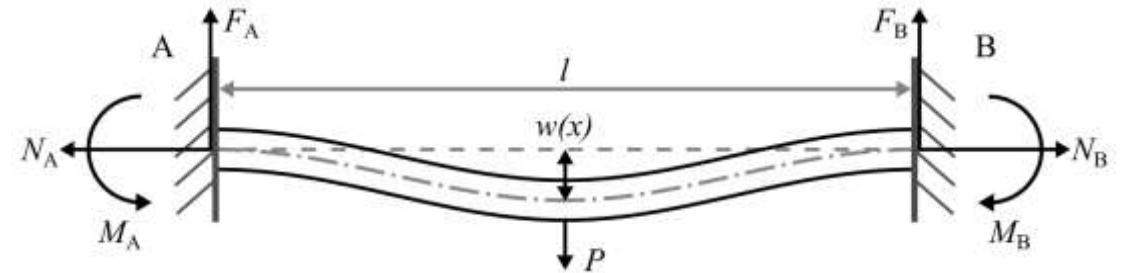
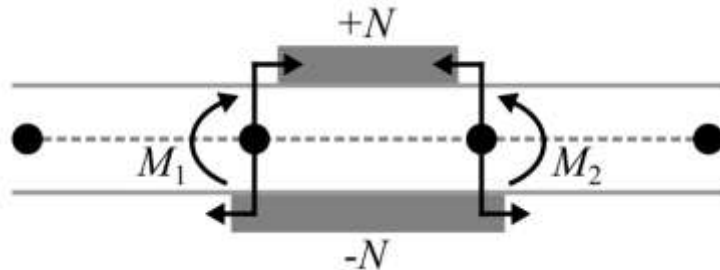
DATASET COLLECTION



REDUCED-ORDER MODELING OF SHOCKED PCBs

Fast models capture the dominant dynamics needed for control design.

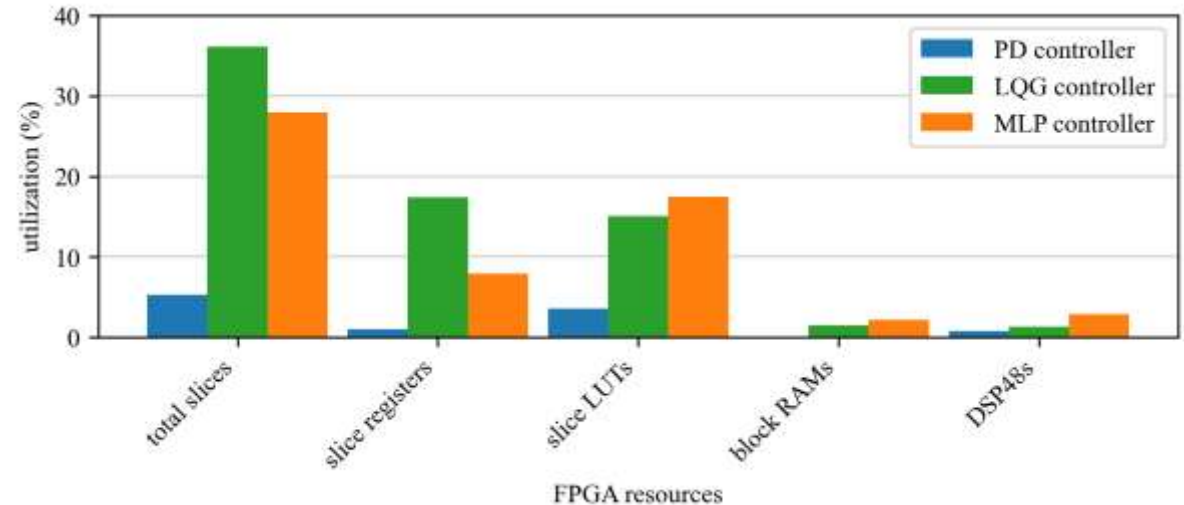
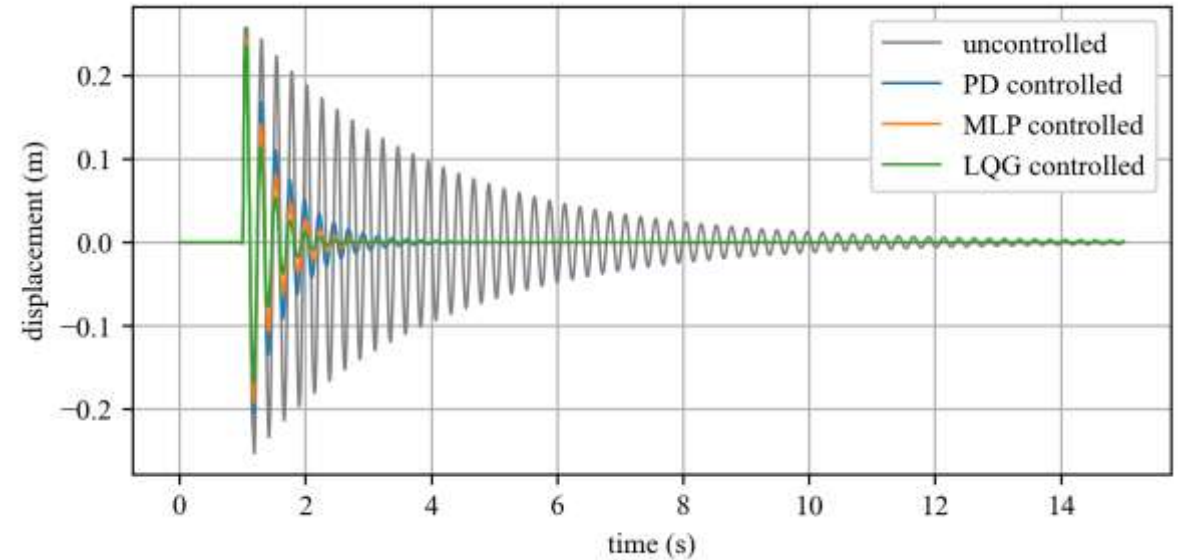
- Beam models represent the dominant PCB bending response
- Piezoelectric patches are represented as localized moment couples
- Predictions are validated against higher-fidelity shell models
- Reduced order enables rapid simulation and control development



FPGA-BASED ACTIVE CONTROL

Ongoing work compares embedded controllers for rapid vibration suppression.

- PD, LQG, and MLP controllers are deployed on FPGA hardware
- Controller performance and FPGA resource use are benchmarked
- Learning-based control can reduce hardware cost while maintaining damping performance
- Supports future low-latency active mitigation of shock response

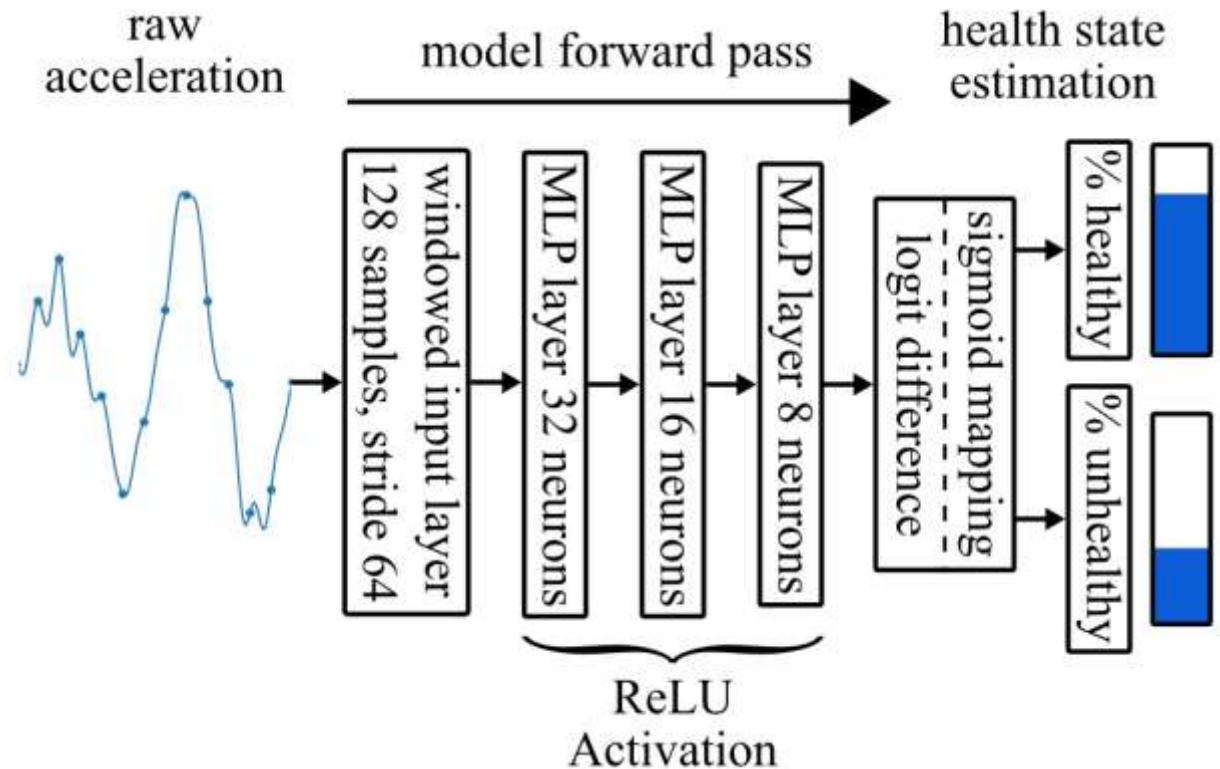


FOCUSED STUDY

OBJECTIVE

Develop and evaluate an FPGA-deployed MLP for high-rate PCB health-state estimation from shock-response acceleration. The model must provide:

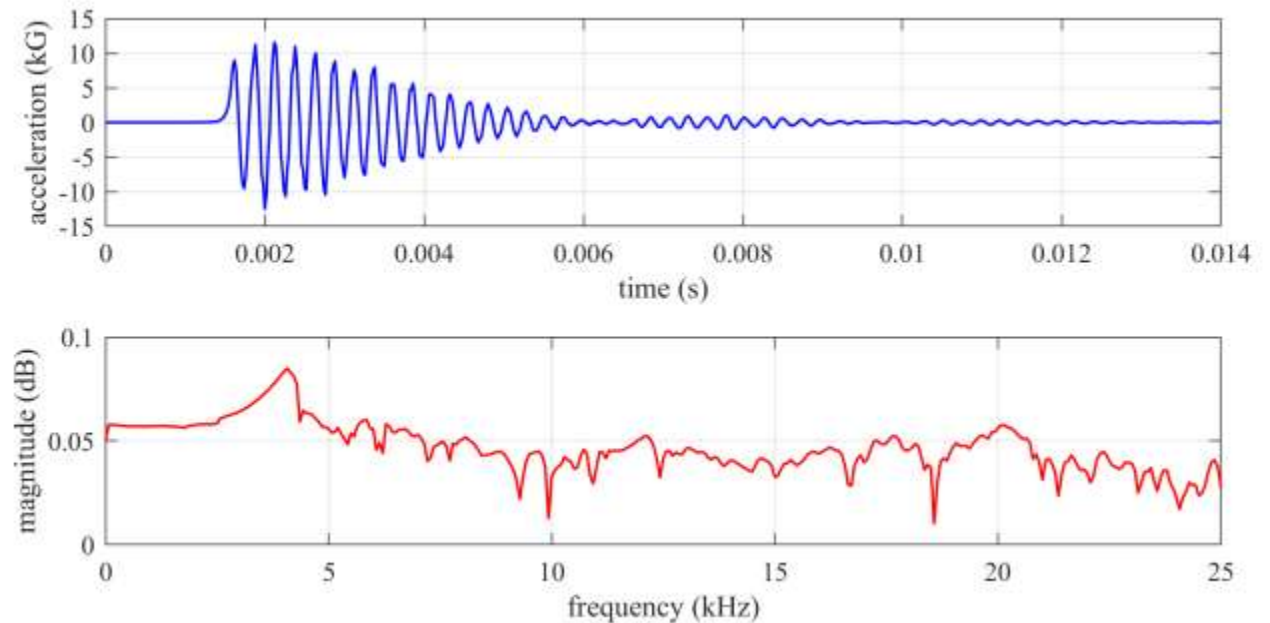
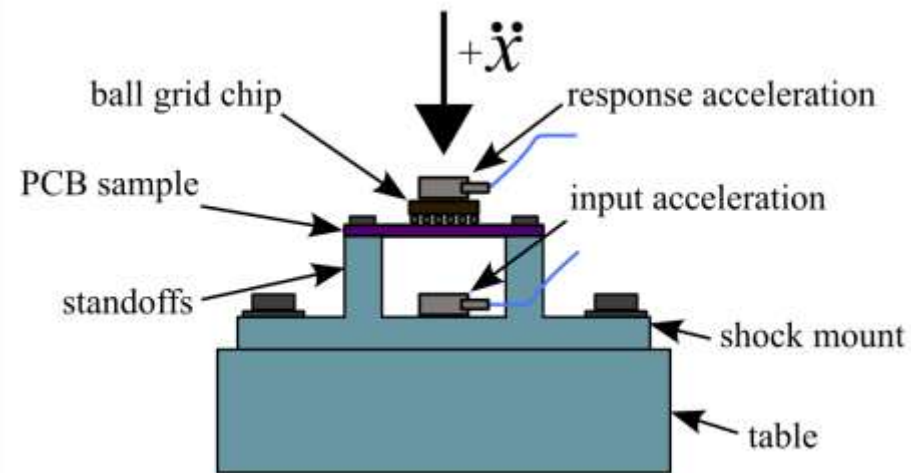
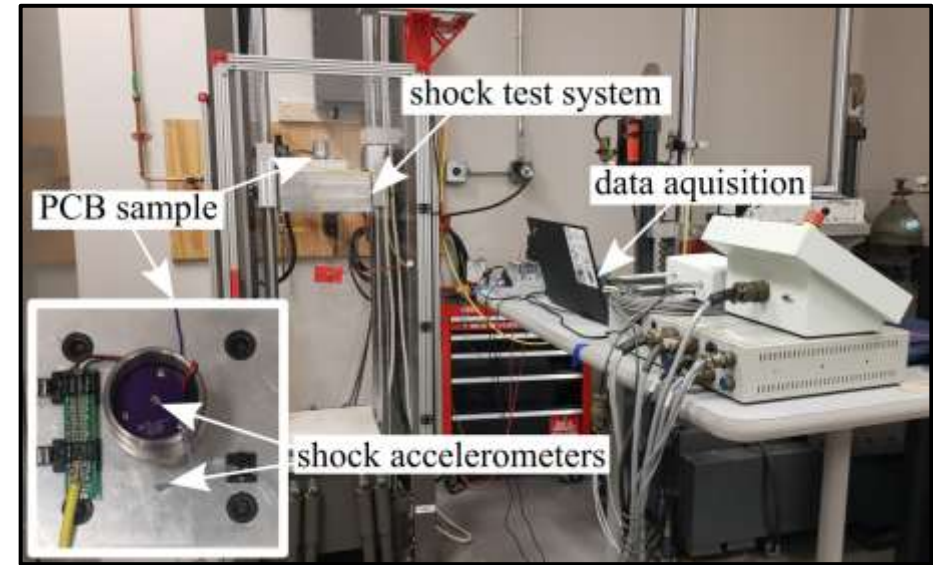
- Accurate impact-level classification
- Deterministic, sub millisecond inference
- Effective FPGA resource utilization



EXPERIMENTAL DATASET

PCB response acceleration was measured during controlled repeated-shock testing.

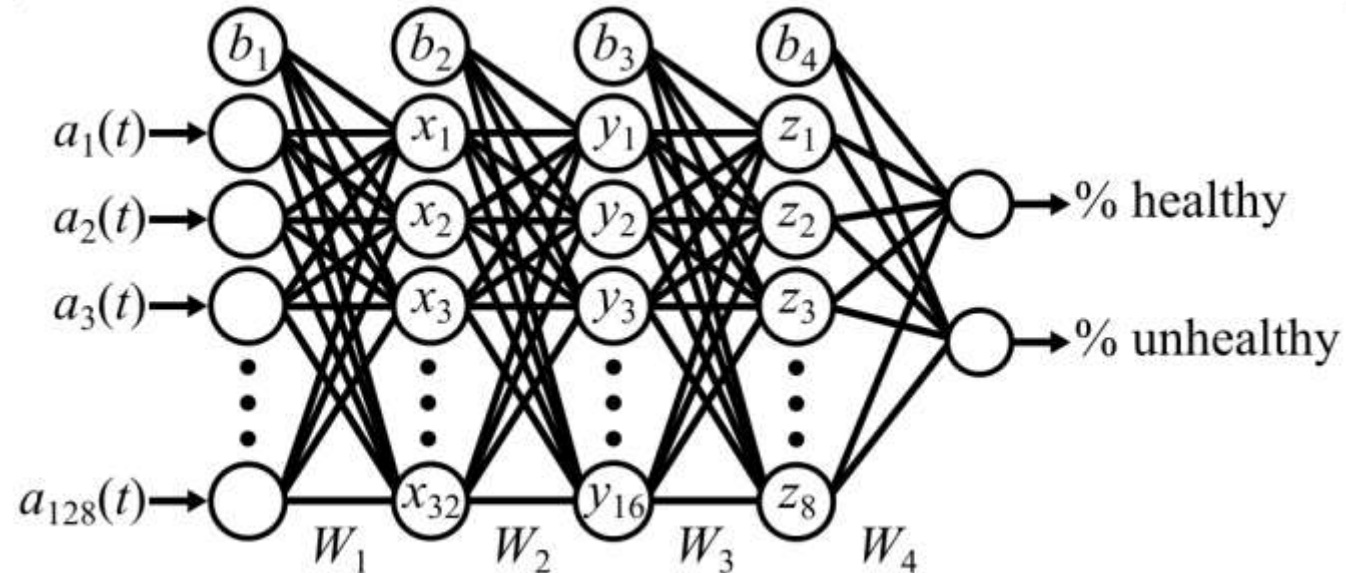
- 30 controlled impacts, sampled at 51.2 kS/s
- Average response: 10,000 g_n, 322 μs half-sine duration
- ≈ 4 kHz dominant PCB resonance



MODEL ARCHITECTURE

A compact MLP maps each acceleration window to a health-state estimate.

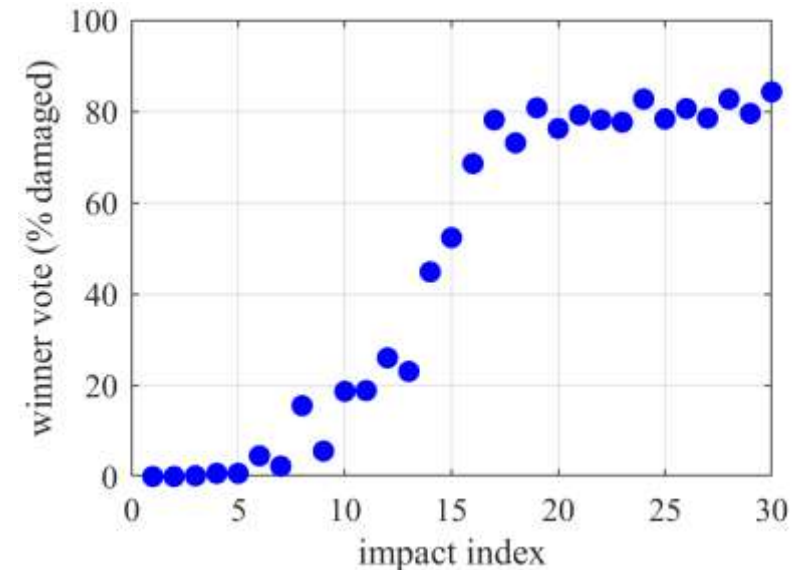
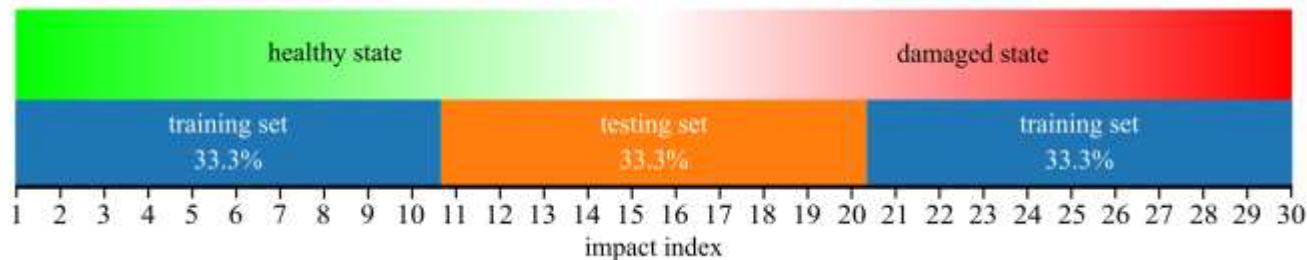
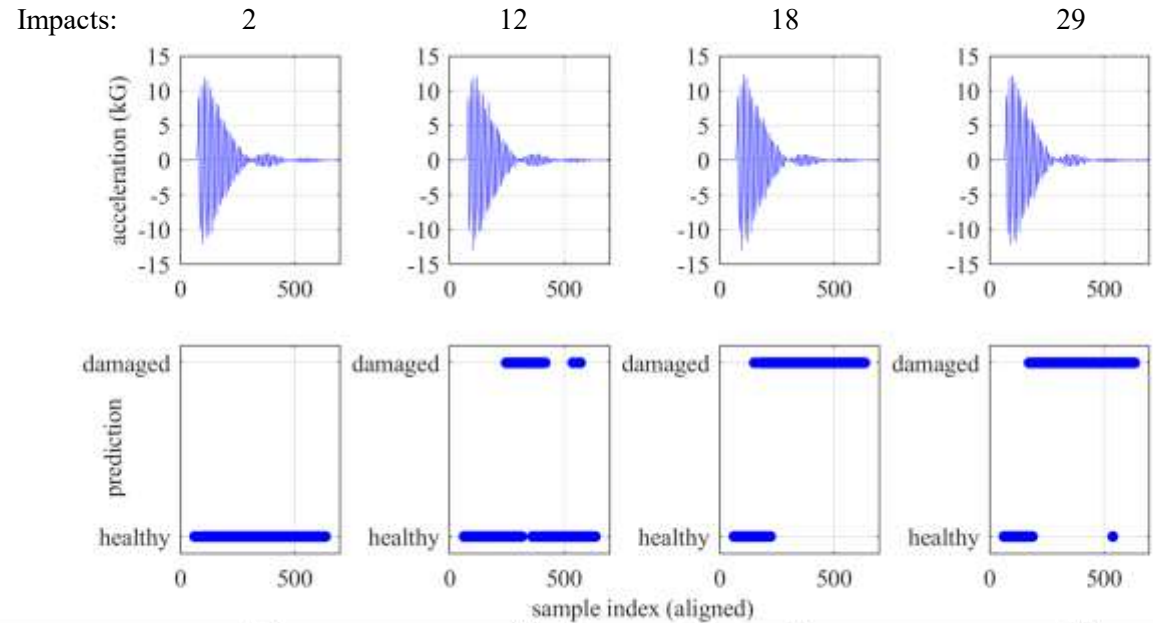
- 128-sample acceleration windows with a stride of 64 samples
- Three hidden layers with 32, 16, and 8 neurons; ReLU activation after each hidden layer
- The output-logit difference is mapped through a sigmoid to estimate unhealthy-state probability



MODEL TRAINING

The MLP was trained offline using chronologically separated impact events.

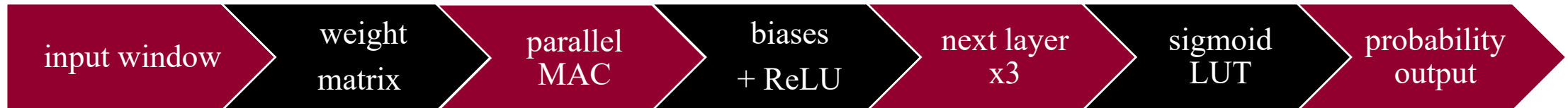
- Train: first 10 healthy + final 10 damaged impacts
- Validate: middle 10 impacts
- Acceleration traces were aligned to the PCB-response peak and trimmed to a fixed length
- Adam optimization with mini-batch updates and early stopping
- Dropout in the first two hidden layers during



FPGA IMPLEMENTATION

The FPGA executes one bounded MLP forward pass per input window.

- Transposed weights and biases are stored in on-chip BRAM
- Fully connected layers use parallel multiply-accumulate operations
- ReLU activations are stored and passed to the next layer
- A 512-entry sigmoid lookup table returns the unhealthy-state probability



Fixed arithmetic and memory-access sequences produce deterministic per-window execution.

PERFORMANCE

The deployed MLP achieved accurate classification with deterministic FPGA inference.

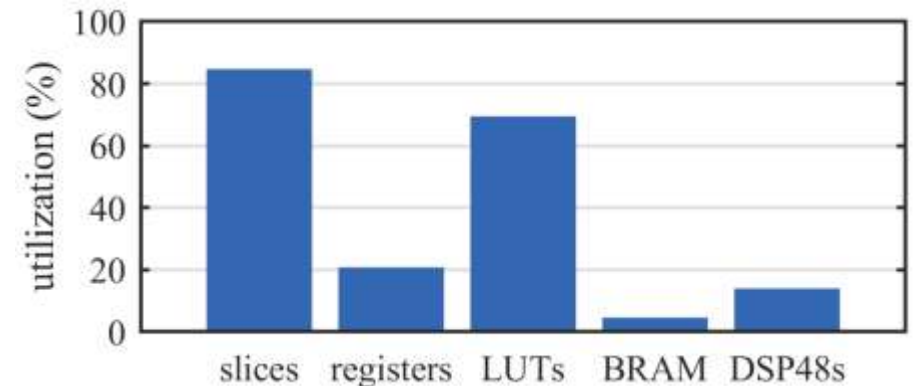
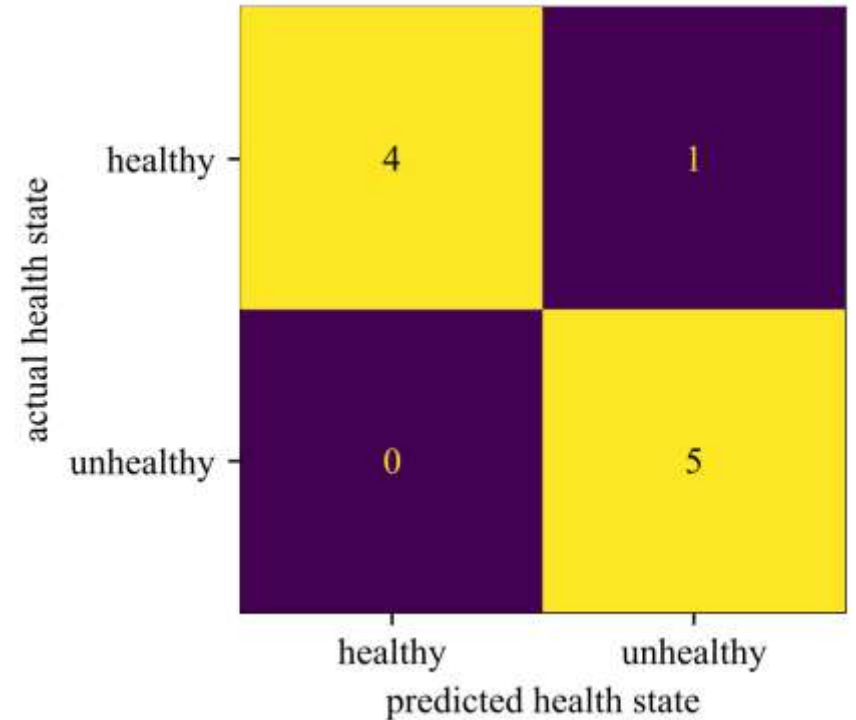
Model:

- **90%** impact-level validation accuracy

Hardware:

- **0.609 ms** per 128-sample window at 40 MHz
- Resource use is dominated by slices and LUTs

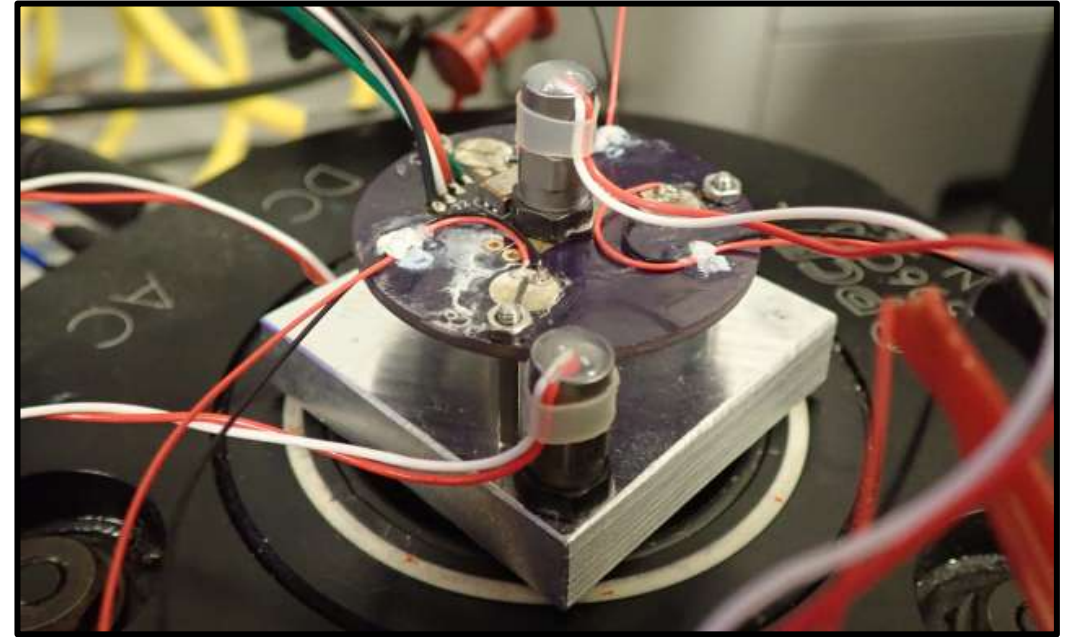
	slices	registers	LUTs	BRAM	DSP48s
utilized	21479	42230	70488	15	84
total	25350	202800	101400	325	600
percent	84.7%	20.8%	69.5%	4.6%	14.0%



FUTURE WORK

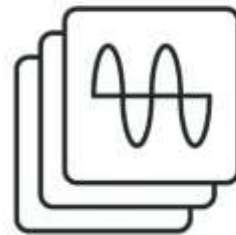
The long-term objective is to use state-aware control to reduce damaging PCB response.

- Measure high-rate structural response and damage progression
- Estimate state on embedded FPGA hardware
- Drive piezoelectric actuators to mitigate damaging vibration and shock response

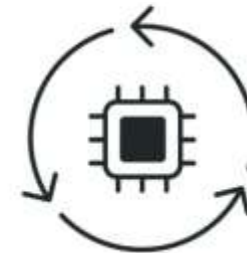


PZT Actuator Patches

High-rate
Sensing



FPGA State
Estimation



Piezoelectric
Actuation



QUESTIONS?

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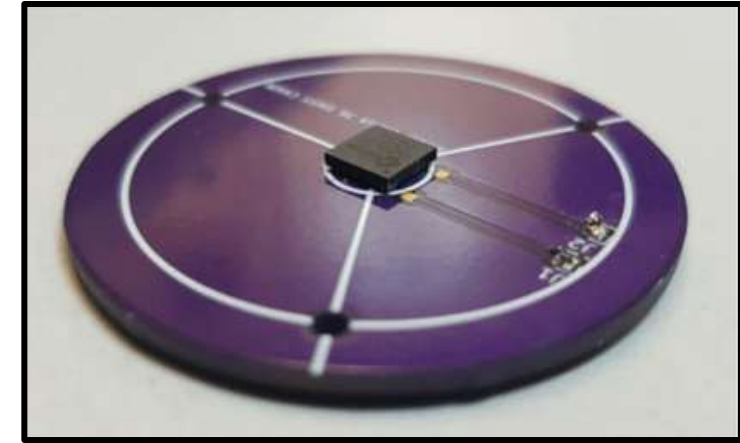
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EXTENDED WORK

- Extended dataset to 150 controlled impacts (more data to train/validate)
- Xilinx matrix multiply implementation ($15.9 \mu s$)




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ai <+/-,32,16>[32]
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cr <+/-,64,37>[1]
ci <+/-,64,37>[1]
operation overflow
a valid
b valid
ready for output
output valid
ready for a
ready for b

