Hardware-Software Design for Temporal Forecasting in Structural Health Monitoring

Dissertation Defense

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10/21/2024

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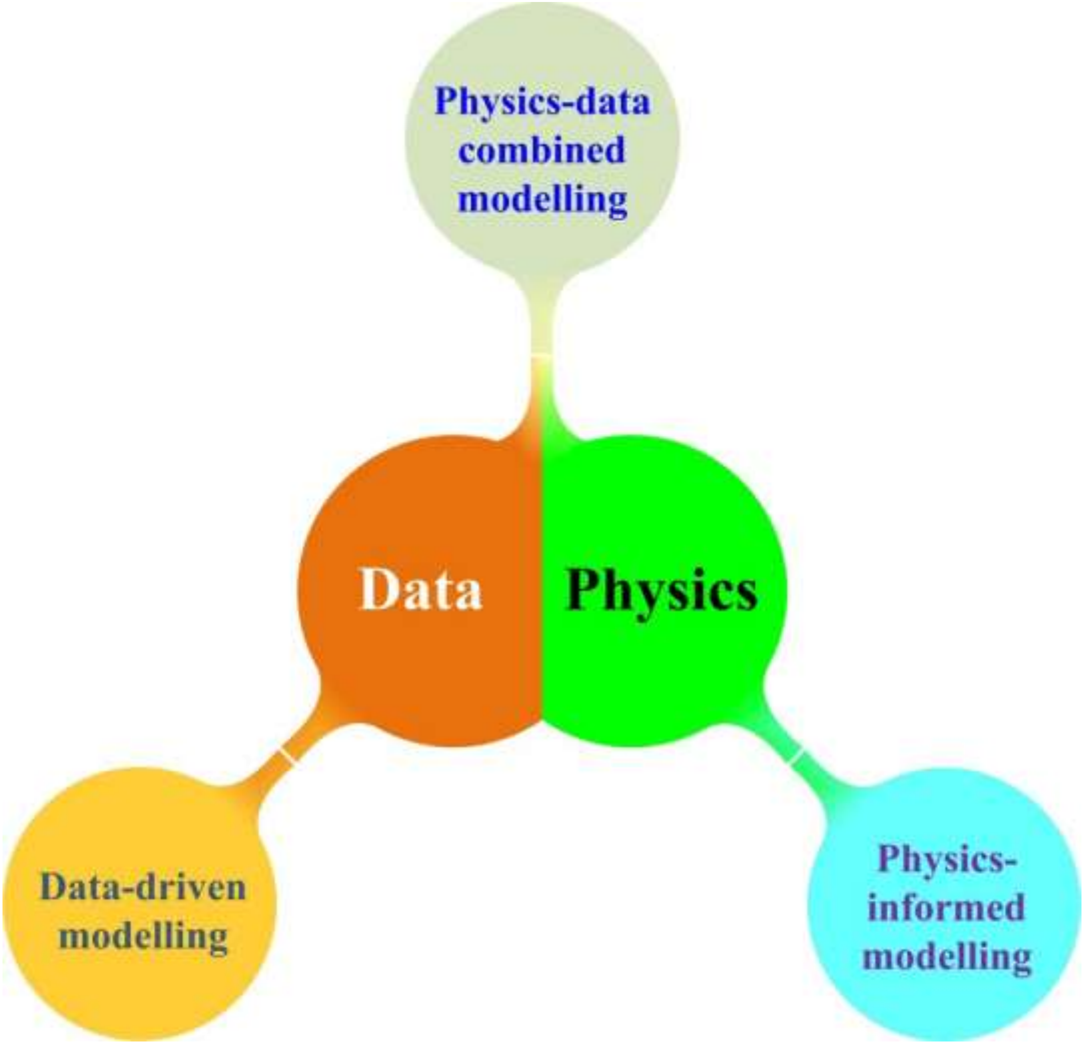
UNIVERSITY OF South Carolina

ARTS-Lab
Adaptive Real-Time Systems Laboratory

Outline

- Research Overview
- Research Areas
  - Research Area 1: Development
  - Research Area 2: Adding Physics
- Conclusions



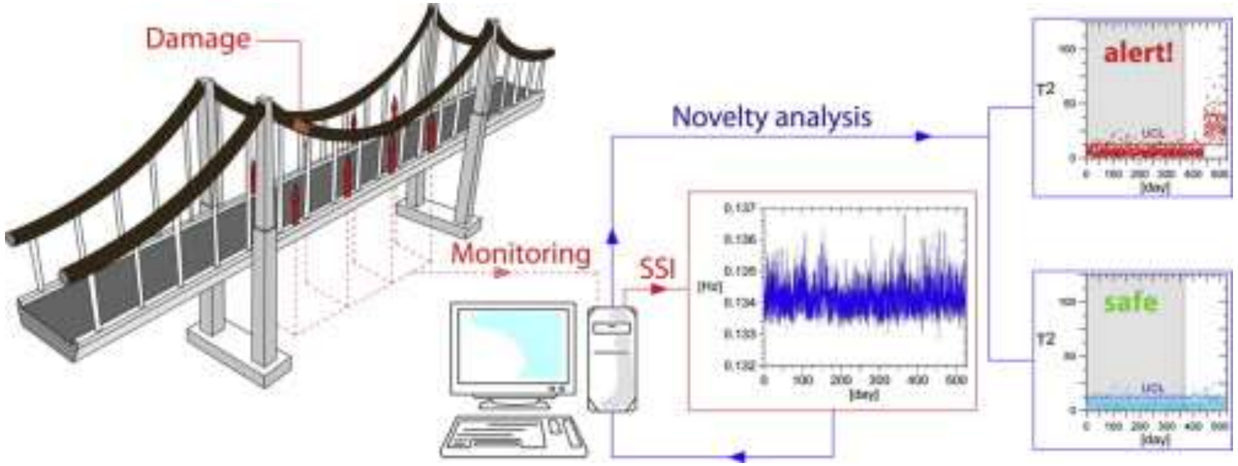
Fu, Jinlong, Dunhui Xiao, Rui Fu, Chenfeng Li, Chuanhua Zhu, Rossella Arcucci, and Ionel M. Navon. "Physics-data combined machine learning for parametric reduced-order modelling of nonlinear dynamical systems in small-data regimes." *Computer Methods in Applied Mechanics and Engineering* 404 (2023): 115771.

Research Overview

- Background
  - Structural Health Monitoring (SHM)
    - Case Study: High-Rate Dynamics (HRD)
  - Time Series Prediction
- Research Questions
  - How to design hardware and software for real-time forecasting for SHM?
  - How to synergize between data-driven and rule-based system?
- Relationship of Research
- Key Contributions
- Publications

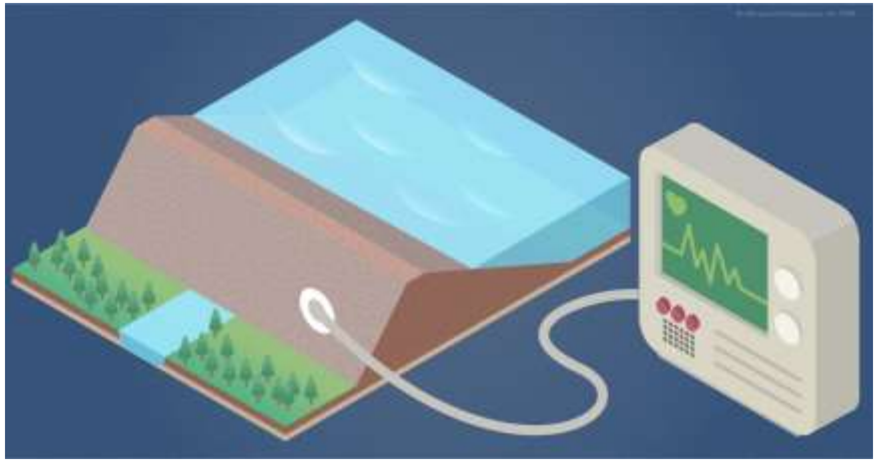
Structural Health Monitoring (SHM) System

- SHM system is a method of evaluating and monitoring structural health.



Source: https://www.sciencedirect.com/science/article/abs/pii/S0167610515000501

Figure: Bridge Monitoring and Evaluation



Source: https://www.agiusa.com/sites/default/files/field/image/Dam%20Monitoring_Header.png

Figure: Levee Monitoring

Case Study: High-Rate Dynamics (HRD)

- Description of High-rate dynamics:
  - high-rate (< 100 ms)
  - high-amplitude (acceleration > 100 g)
  - such as a blast or an impact
- The high-rate dynamics are subjected to
  - large uncertainties in external loads
  - high levels of nonstationarities and heavy disturbances
  - generation of unmodeled dynamics from changes in system configuration

Hypersonic vehicles

Space launch system

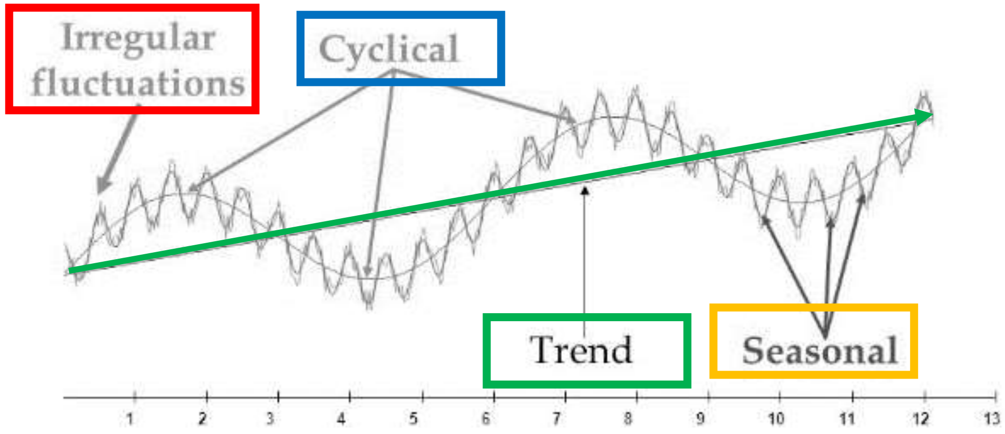
Vehicle collision

Ballistics packages

- Jacob Dodson, Austin Downey, Simon Laflamme, Michael Todd, Adriane G. Moura, Yang Wang, Zhu Mao, Peter Avitabile, and Erik Blasch "High-Rate Structural Health Monitoring and Prognostics: An Overview." Data Science in Engineering, Volume 9, Proceedings of the 39th IMAC, A Conference and Exposition on Structural Dynamics 2021, Springer International Publishing, p. 213-217, Oct 2021. doi:10.1007/978-3-030-76004-5_23
- Hong, J., S. Laflamme, J. Dodson, and B. Joyce. 2018. "Introduction to State Estimation of High-Rate System Dynamics," Sensors, 18(2):217, doi:10.3390/s18010217.

Time Series Prediction

- Time Series: A time-series is a set of observations, Y on a quantitative variable collected over time, t.
- In time series analysis, we analyze the **past behavior** of a variable in order to predict its **future behavior**.
- Component of Time Series:
  - Long Term Trend (T): Growth/Decline/Constant
  - Seasonal Variation (S): Upward or Downward movement repeat at the same time each year.
  - Cyclical Variation (C): Similar to seasonal variations except that there is likely not a relationship to the time of the year
  - Random Effects (I) : Unexplained variations which we usually treat as randomness.
- Time-Series Model:
  - Additive Model: $Y_t = T_t + S_t + C_t + I_t$
  - Multiplicative Model: $Y_t = T_t * S_t * C_t * I_t$



Time Series Prediction (Continued)

Time series prediction

Statistical models

- Autoregressive Integrated Moving average (ARIMA)
- Seasonal ARIMA (SARIMA)
- Least Absolute Shrinkage and Selection Operator (LASSO)

Machine learning models

- Artificial neural network (ANN)
- Decision Tree
- Gradient Boosting Decision Tree

Deep learning models

- Multilayer Perceptron (MLP)
- Convolutional Neural Network (CNN)
- Recurrent Neural Network (RNN)

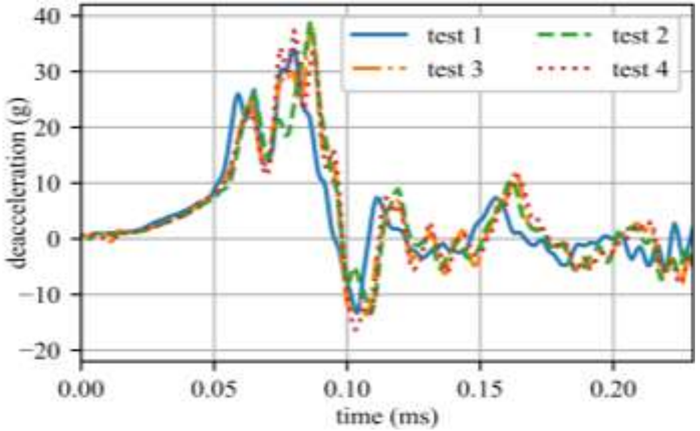
Physics-informed models

- Physics-Constrained ML
- **Data Augmentation**
- **Transfer Learning**
- Delta Learning (Missing Physics)
- Delta Learning (ML Prediction)
- ML Assisted Prediction

- Xuan, Ang, et al. A Comprehensive Evaluation of Statistical, Machine Learning and Deep Learning Models for Time Series Prediction. No. 6716. EasyChair, 2021.
- Thelen, Adam, et al. "A comprehensive review of digital twin—part 1: modeling and twinning enabling technologies." Structural and Multidisciplinary Optimization 65.12 (2022): 354.

Event Forecasting in HRD System

- Goal: Temporal Forecasting
  - Application: Real-time decision-making of structures
  - Required Technologies:
    - Low-latency model updating
    - System state prognostics in real-time
- Challenges:
  - Computation power is limited
    - Memory, available energy, processors
  - Unknown sources of the inputs (forces, location)
  - Inability to calculate fault scenarios in advance
  - Rare and extreme situations



Research Question 1: How to design hardware and software for real-time forecasting for SHM?

Hardware and Software Design for SHM

- Goal for RQ1:
  - Data generation in experimental environment.
  - Model development for temporal forecasting.
  - Hardware implementation in FPGA.
- Contribution:
  - Using co-design approaches
  - Developing Faster system
  - Real time implementation
- Cons:
  - Only used data driven approaches.
  - Memory problem.
  - Computational time.

Time series prediction:
Data Generation
Model Development
HW Implementation
Co-design

FFT, MLP

HW-SW Design

Research Question 1: How to design hardware and software for real-time forecasting for SHM?

Forecasting Approaches in HRD System

Data-driven

Evidence -> Hypothesis -> Decision

- Advantages
  - Self-learning systems
  - Handling more complex problems
  - Performing better with less human interaction than rule-based systems
  - Adapting over time (via continuous learning) to changes in data and environment.
- Disadvantages:
  - Needs to see a large number of input
  - Only learn from data
  - Not intelligence in the sense that humans are.

Rule-based

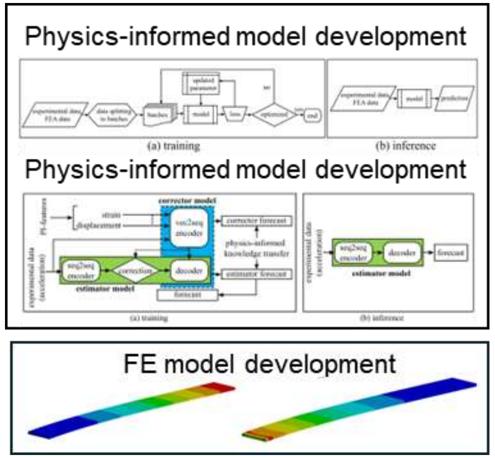
Hypothesis-> Decision

- Advantage
  - Easy to understand and interpret
  - Quick implementation
  - Easy modification
  - Durable in nature
  - Compatible with ML/AI
- Disadvantages:
  - Problems with a vast number of variables
  - Problems with many constraints
  - Limited intelligence

Research Question 2: How to synergize between data-driven and rule-based system?

Physics-Informed Machine Learning

Integrating Physics-Informed ML for SHM



- Goal for RQ2:
  - Data generation in the experimental environment.
  - Physics data generation via Finite Element Model
  - Model development for temporal forecasting.
- Contribution:
  - Integrating Physics data
  - Transfer learning to reduce
  - Problem-specific customized model development
- Cons:
  - ~~Only used data-driven approaches~~
  - ~~Memory problem~~
  - ~~Computational time~~

Physics-informed Time series prediction:

Experiment Data Generation

Physics Data Generation

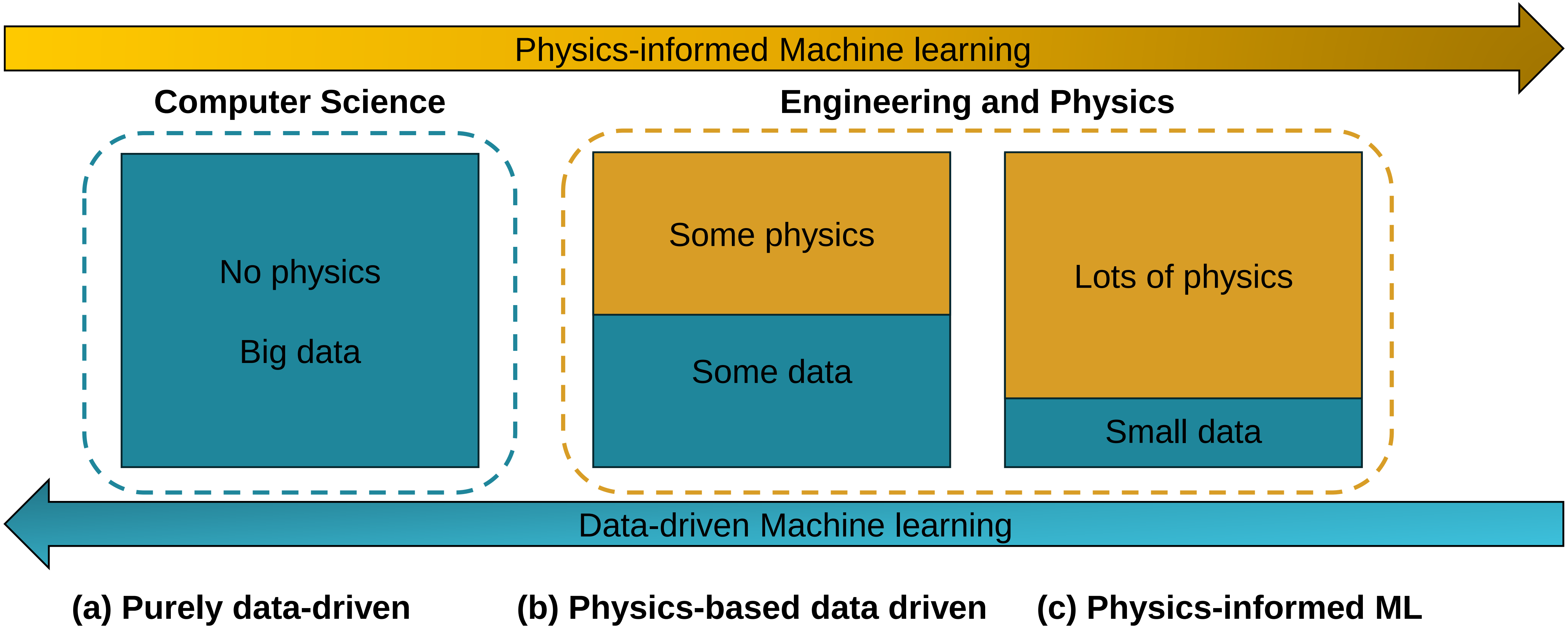
Customized Model Development

PISP, PIMENTO

Physics-Informed HSM

Research Question 2: How to synergize between data-driven and rule-based system?

Physics-informed Machine Learning (ML)



Jin, Hanxun, Enrui Zhang, and Horacio D. Espinosa. "Recent Advances and Applications of Machine Learning in Experimental Solid Mechanics: A Review." *arXiv preprint arXiv:2303.07647* (2023).

Relationship of Research

Final Dissertation

HW-SW Design for Temporal Forecasting in SHM

2 Research Question

How to synergize between data-driven and rule-based system?

Research Question 1

How to design SW-HW for SHM?

Overall Dissertation

RQ 2: How to add physics?

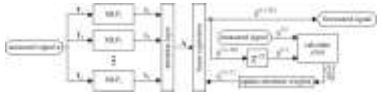
HW-SW Development

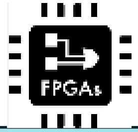
High-rate dynamics

Data generation

model development

model development





Data-driven ML

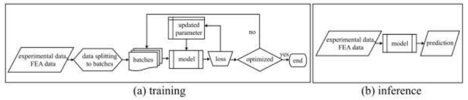
FFT based Time series prediction
Data Generation
Model Development
HW Implementation

MLP based Time series prediction:
Model Development
HW Implementation
Comparison

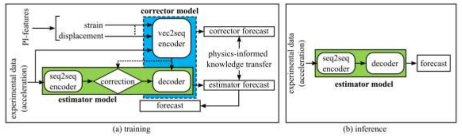
RQ1: How to design?

Adding Physics in SHM System

Physics-informed model development



Physics-informed model development



FE model development

Physics-informed ML

Physics data enhance Time series prediction
FE model development
Physics data generation
Integrate Physics data with experimental data

Physics knowledge transfer-based Time series prediction
FE model development
Physics data generation
Transfer Learning-based Model Development

HW-SW Design for Temporal Forecasting in SHM system

Key Contributions

- Data Generation
  - Experimental data generation: Developed solutions to overcome the lack of available data for HRD system research
  - Physics-informed Data Generation: Utilized physics principles to generate realistic data for HRD systems.
- Data-driven model development
  - Mathematical algorithm-based models: Employed mathematical algorithms, such as FFT in a windowed fashion, to develop models.
  - Deep learning-based models: Leveraged deep learning techniques, including ensembled MLPs, to create models.
- Physics-informed model development
  - Data augmentation:
    - Enhanced model performance by augmenting existing data.
    - Problem-specific customized model (PISP): Designed a tailored model to address specific HRD system challenges.
  - Transfer learning:
    - Applied transfer learning techniques, such as teacher-student models and BiLSTMs, to improve model efficiency.
    - Customized model (PIMENTO): Developed a unique model architecture for HRD system applications.
- Hardware implementation
  - Time deterministic hardware implantation of FFT model in FPGA.
  - Time deterministic hardware implantation of ensemble MLP model in FPGA.
- Application:
  - High-Rate Dynamic System:
    - Non-stationary time series prediction: Accurately predicted non-stationary time series in HRD systems.
    - Single impact prediction: Successfully predicted the impact of single events in HRD systems.
  - Others (Not included in the dissertation)
    - Data-driven fragility framework: Developed a framework for risk assessment of levee breaches.

Publications

Dissertation

Design

FFT SW

1. Chowdhury, Puja, Philip Conrad, Jason D. Bakos, and Austin Downey. "Time Series Forecasting for Structures Subjected to Nonstationary Inputs." In Smart Materials, Adaptive Structures and Intelligent Systems, vol. 85499, p. V001T03A008. American Society of Mechanical Engineers, 2021.

RA1-D1

RA1-D1

FFT HW

2. Chowdhury, Puja, Austin RJ Downey, Jason D. Bakos, Simon Laflamme, and Chao Hu. " Hardware implementation of nonstationary structural dynamics forecasting." In Active and Passive Smart Structures and Integrated Systems XVII, SPIE, 2023

MLP SW HW

3. Singh, Ishrat, Philip Conrad, Puja Chowdhury, Jason D. Bakos, and Austin Downey. "Real-Time Forecasting of Vibrations with Non-stationarities." In Data Science in Engineering, Volume 9: Proceedings of the 39th IMAC, A Conference and Exposition on Structural Dynamics 2021, pp. 21-29. Springer International Publishing, 2022.
4. Chowdhury, Puja, Vahid Barzegar, Joud Satme, Austin RJ Downey, Simon Laflamme, Jason D. Bakos, and Chao Hu. "Deterministic and low-latency time-series forecasting of nonstationary signals." In Active and Passive Smart Structures and Integrated Systems XVI, vol. 12043, pp. 466-472. SPIE, 2022.

RA1-D2

RA1-D2

FFT vs MLP

- FPGA-deployed Adaptive Ensemble of Neural Networks for Forecasting of Temporal Structural Dynamics. (Development Stage)

PI Review

5. Eleonora Maria Tronci, Austin R.J. Downey, Azin Mehrjoo, Puja Chowdhury, and Daniel Coble. "Physics informed machine learning part I: Different strategies to incorporate physics into engineering problems. In Conference Proceedings of the Society for Experimental Mechanics Series". Springer Nature Switzerland, 2024.
6. Austin R.J. Downey, Eleonora Maria Tronci, Puja Chowdhury, and Daniel Coble. "Physics informed machine learning part II: Applications in structural response forecasting". In Conference Proceedings of the Society for Experimental Mechanics Series. Springer Nature Switzerland, 2024.

RA2

RA2-D1

Data Augmentation

1. Predicting Structural Responses in Impact Scenarios with Physics-Guided Machine Learning. (Submission Stage)

Improvement

Transfer Learning

2. Online Structural Responses Forecasting Using a Physics-informed Knowledge Transfer Model. (Submission Stage)

RA2-D2

Risk Assessment of Levee Breaches

7. Chowdhury, Puja, Joud Satme, Ryan Yount, Austin R.J. Downey, Mohammad Sadik Khan, and Jasim Imran. "Spatial mapping of soil saturation levels using UAV deployable smart penetrometers". ASCE Geo-Institute 7th Annual Live Streaming Web Conference, 2022.
8. Chowdhury, Puja, Joud N. Satme, Malichi Flemming, Austin R. J. Downey, Mohamed Elkholy, Jasim Imran, and Mohammad Sadik Khan. " Stand-alone geophone monitoring system for earthen levees." In Active and Passive Smart Structures and Integrated Systems XVII, SPIE, 2023.
9. Chowdhury, Puja, Joud N. Satme, Ryan Yount, Austin RJ Downey, Sadik Khan, Jasim Imran, and Laura Micheli. "Classifying Soil Saturation Levels Using a Network of UAV-Deployed Smart Penetrometers." In Smart Materials, Adaptive Structures and Intelligent Systems, vol. 87523, p. V001T05A002. American Society of Mechanical Engineers, 2023.
10. Chowdhury, P., Crews, J., Mokhtar, A., Oruganti, S. D. R., Van Wyk, R., Downey, A. R., Flemming, M., Bakos, J. D., Imran, J., & Khan, S. "Distributed real-time soil saturation assessment in levees using a network of wireless sensor packages with conductivity probes". Proceedings of the ASME 2024 International Mechanical Engineering Congress and Exposition, IMECE2024-145950. (accepted)

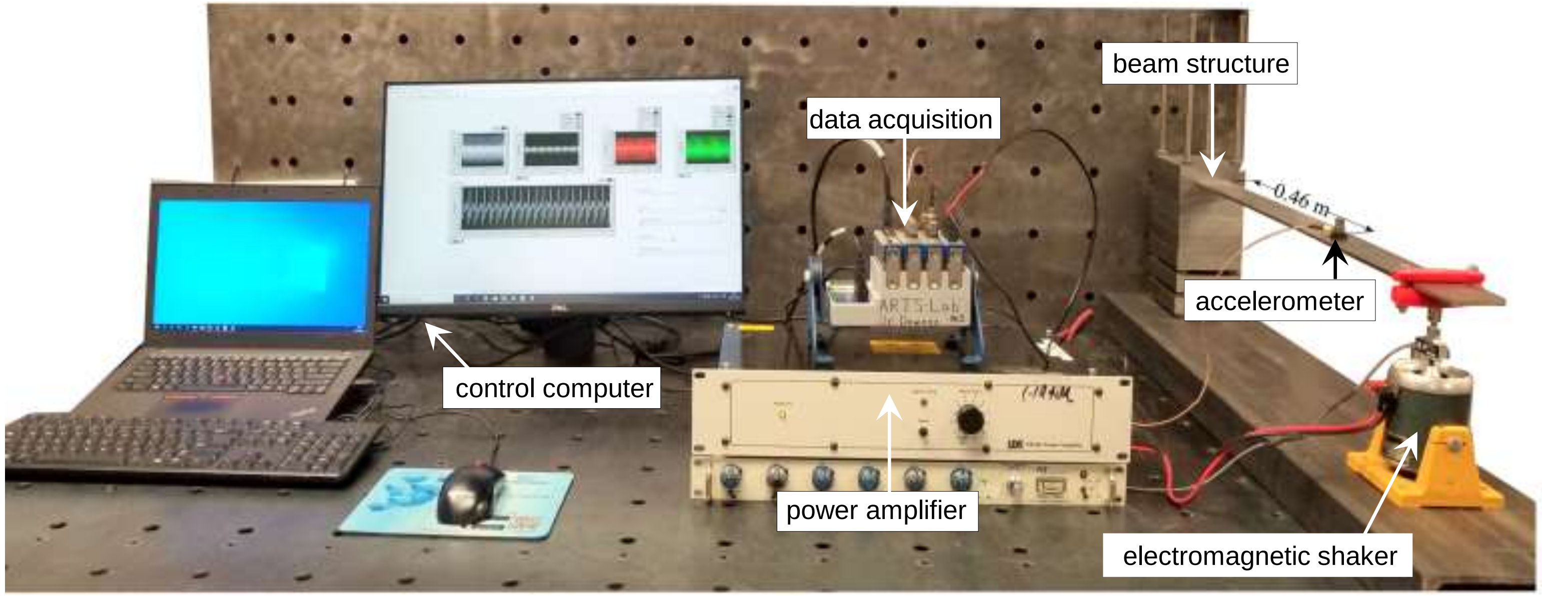
1. Nemnem, A.M., Chowdhury, P., Crews, C., Downey, A.R.J., Bakos, J., Khan, M.S., Chaudhry, M.H., & Imran, J. (2025). "Mapping Seepage Flow in Untreated and Biopolymer-Treated Soils Using Wireless Sensing Spikes". Submitted to the 2025 International Conference on Bio-mediated and Bio-inspired Geotechnics. (submitted)

3. Wireless Sensor Network for Distributed Real-Time Soil Saturation Monitoring in Levees. (submission stage)

Research Area 1: HW-SW Development

- Event Forecasting in HRD system (Discussed in previous slides)
    - Time series prediction
- Data Generation
- Implementation
    - Software
    - Hardware
- Key Takeaways of Research Area 1

Experimental Setup for Data Generation



- This data is available in a public repository [1]

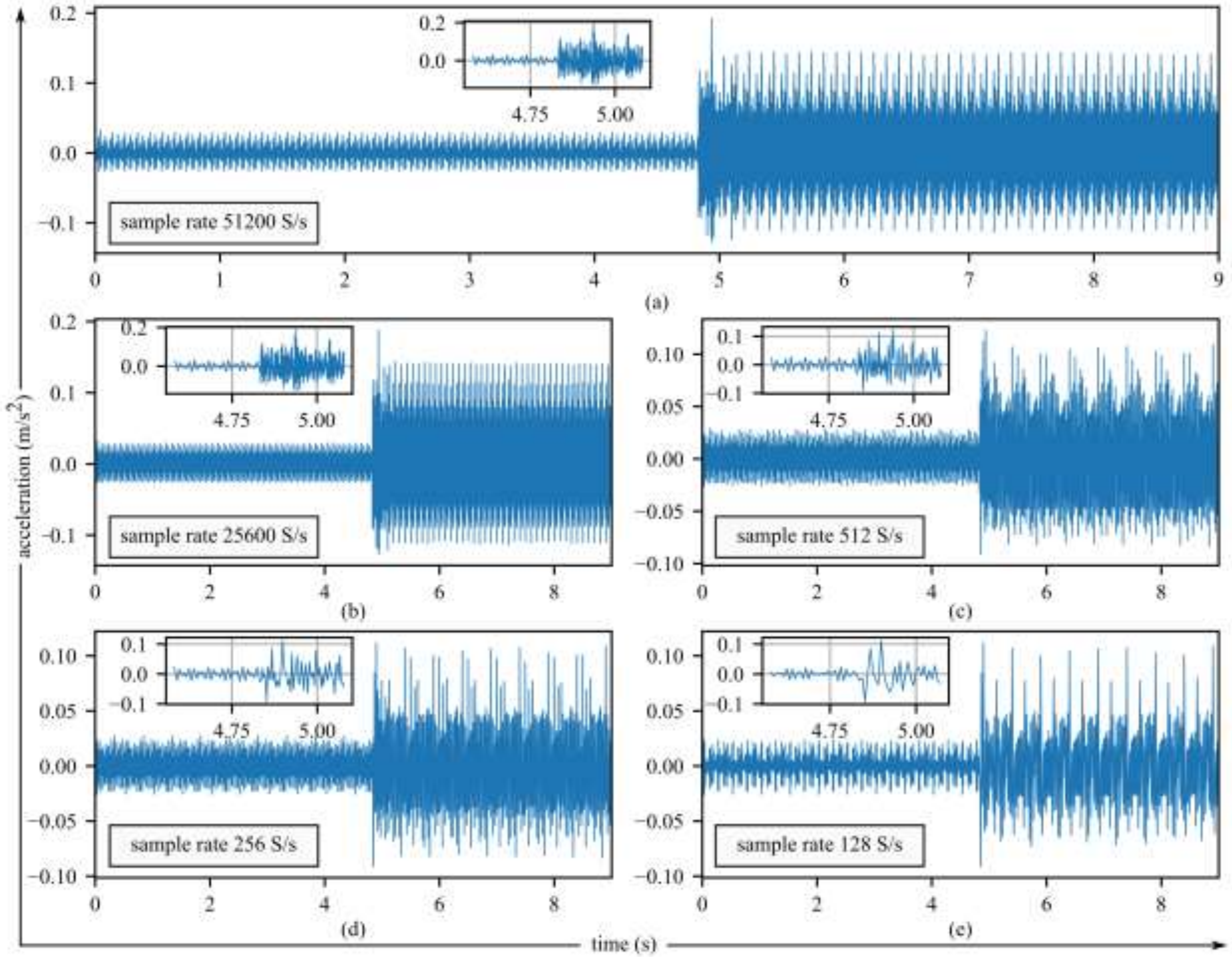
[1] High-Rate-SHM-Working-Group. Dataset-4 univariate signal with nonstationarity.
https://github.com/High-RateSHM-Working-Group/Dataset-4-Univariate-signal-withnon-stationarity

Data structure

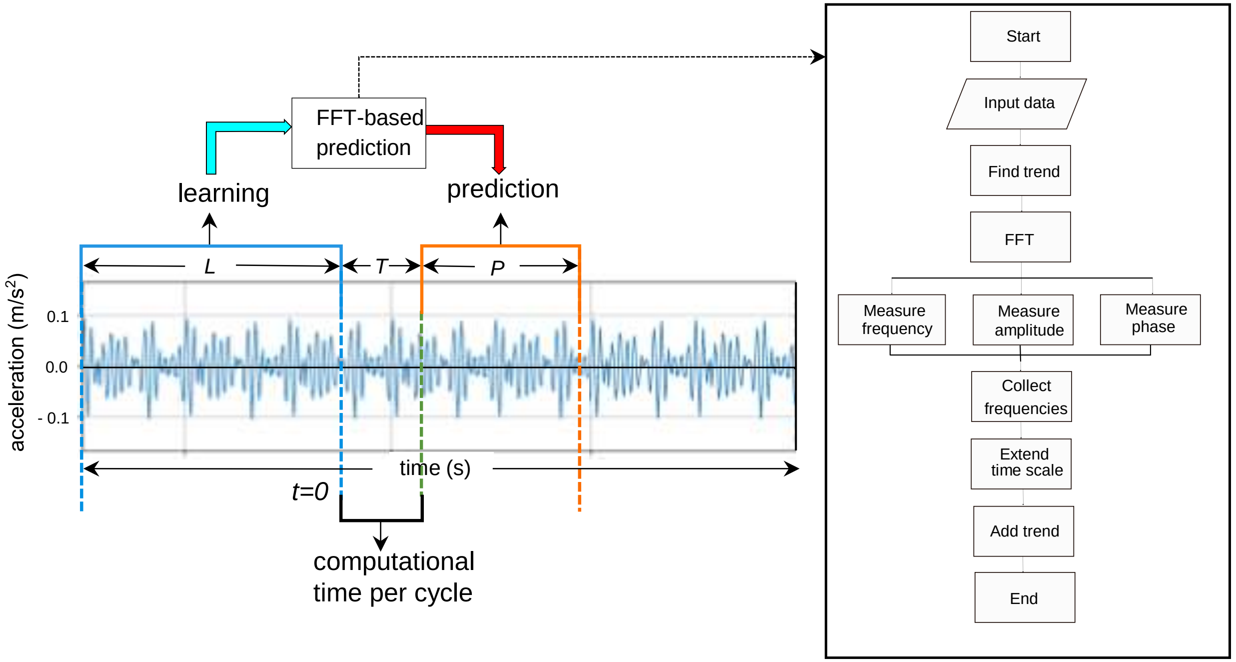
- Two sine wave signals are concatenated together
- Concatenated at t = 5
  - A nonstationary is present due to a change of frequency

First Half Frequencies (Hz)	Second Half Frequencies (Hz)
50, 70, 100	50, 100

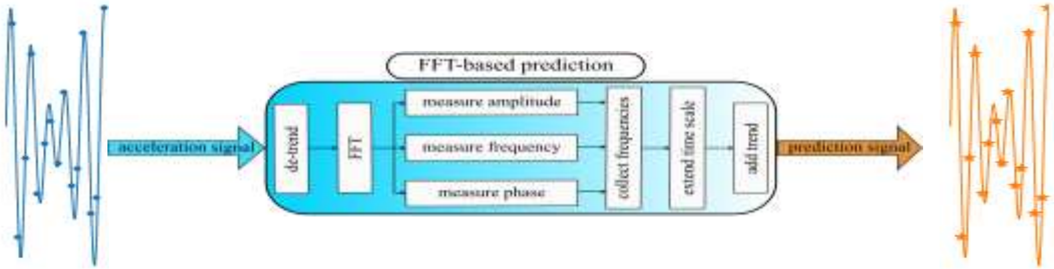
- Four different sampled data were created



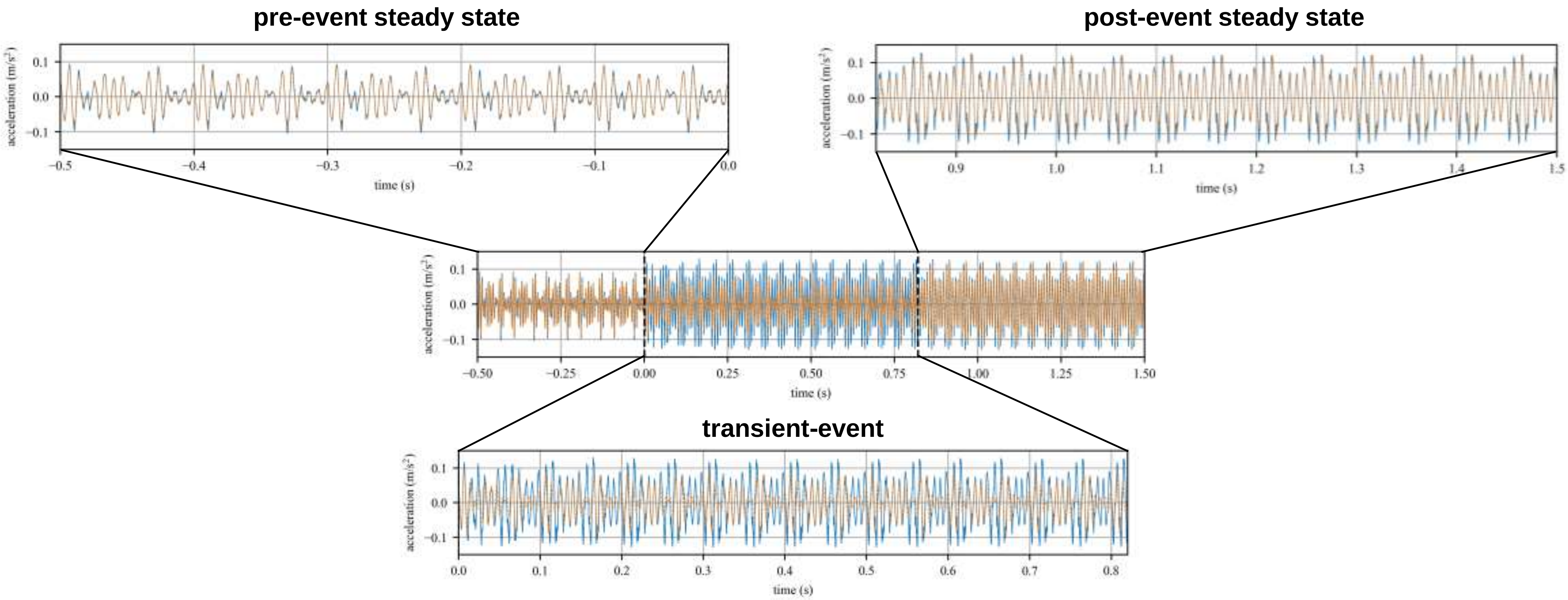
SW Implementation Direction 1: FFT Based Prediction



FFT-based prediction



Results

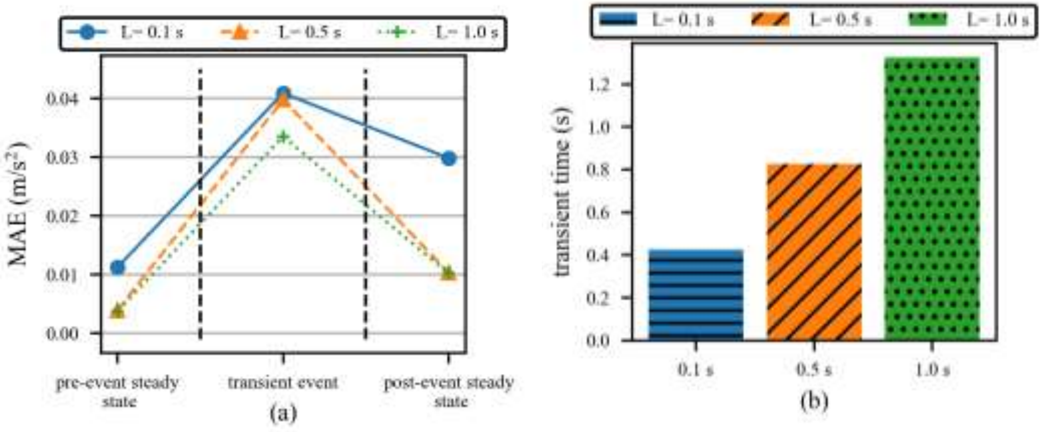


Time series prediction for 0.5 s learning window length in different states

Results

Learning Window Effect

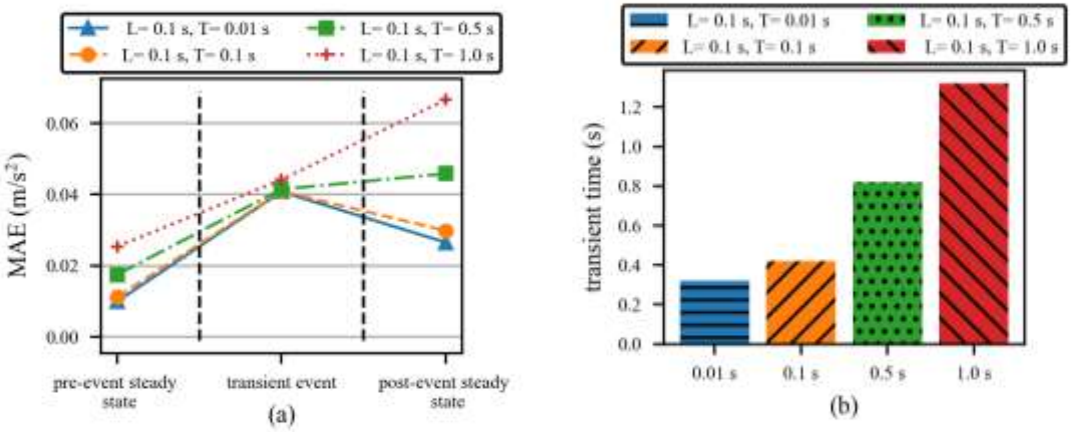
- $e_{mean} \propto \frac{1}{L_{window}}$
- $t_{transient} \propto L_{window}$



Effect of various learning window lengths (L) showing: (a) MAE in different states, and; (b) transient time.

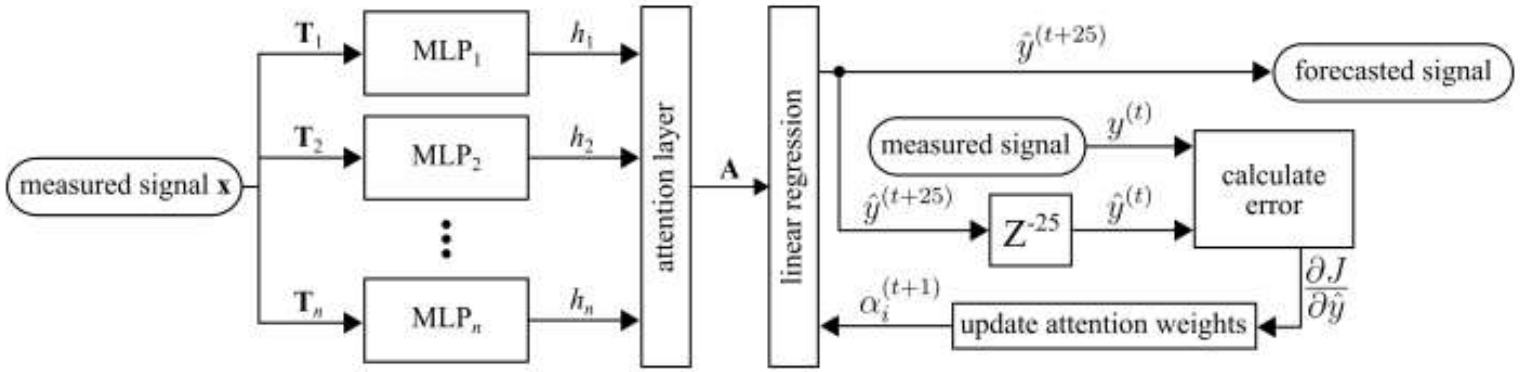
Computational Time

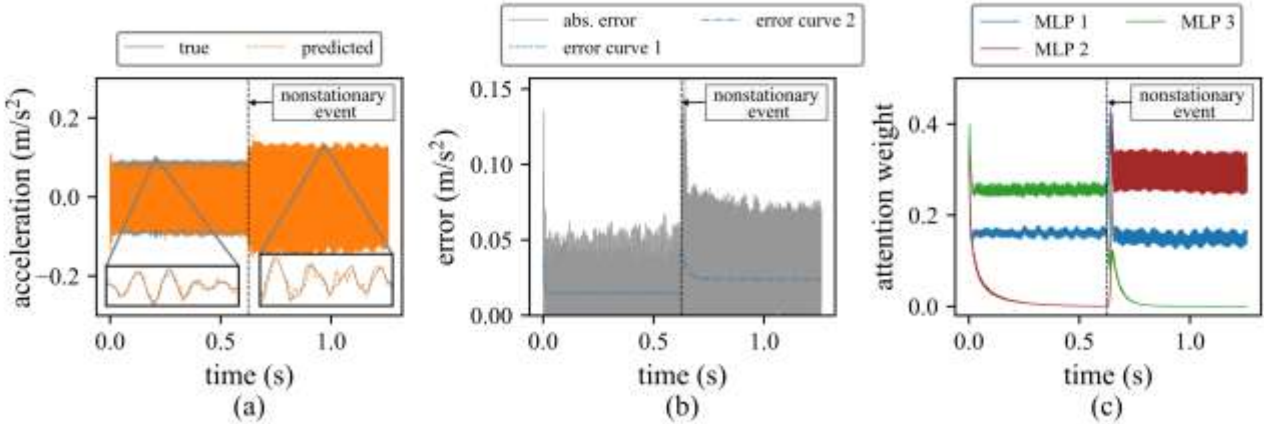
- $e_{mean} \propto T_{computational}$
- $t_{transient} \propto T_{computational}$



Effect of various computational time (T) in a specific learning window length (L) showing: (a) MAE in different states, and;(b) transient time.

SW Implementation Direction 2: Ensembled MLPs





	RMSE (m/s²)	SNR	Convergence (ms)
before nonstationary event	0.019	6.09	18.5
after nonstationary event	0.031	5.63	71.6

South Carolina

HW Implantation Workflow on FPGA

LabVIEW FPGA

- Module for designing and translating them directly to hardware.

Xilinx Vivado

- Compilation tools

Bitstream

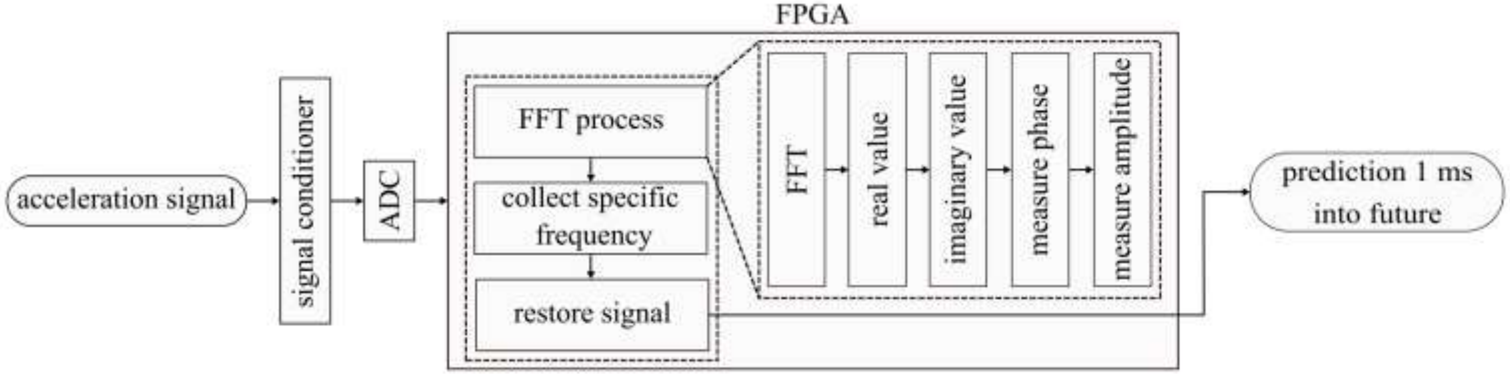
- BitFile generation Complete

Hardware

cRIO-9035
Kintex-7 70T FPGA

https://knowledge.ni.com/KnowledgeArticleDetails?id=kA03q000000YHVTCA4&l=en-US

Hardware validation (FFT)



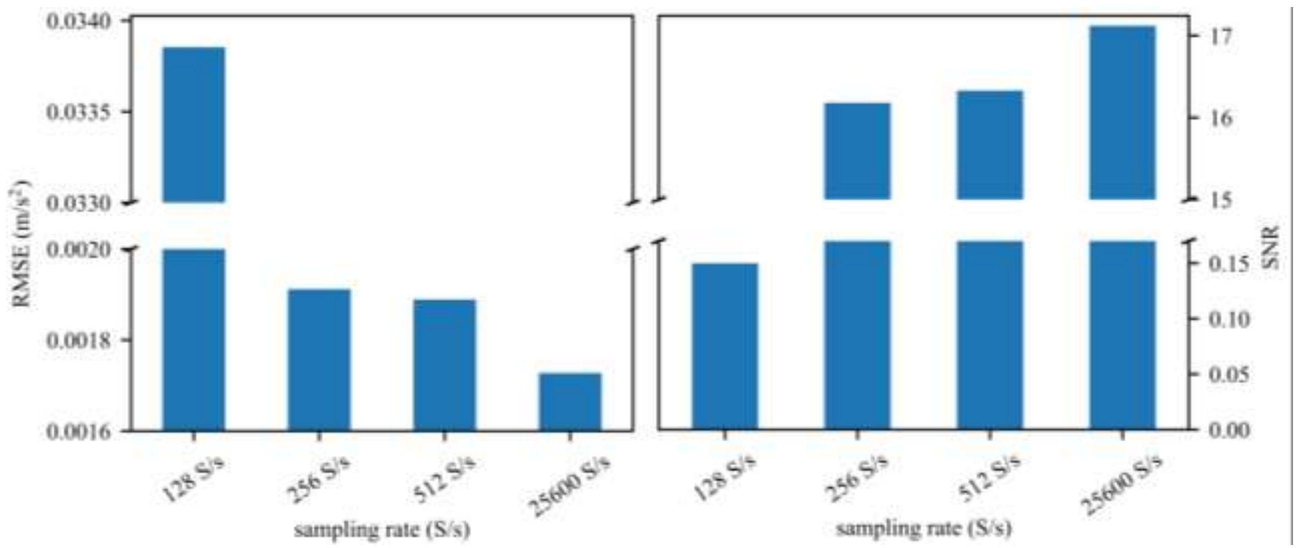
Flowchart for data collection and processing during FFT-based forecasting in case of hardware implementation.

- The built-in LabVIEW FPGA FFT function has a range of size limitations between 8 to 8192 samples.
- Each size of FFT has a latency of cycles from 16 to 16384.

sampling rate (S/s)	FFT size	input (samples)
25600	128	256
512	512	512
256	256	256
128	128	128

Simulation Results

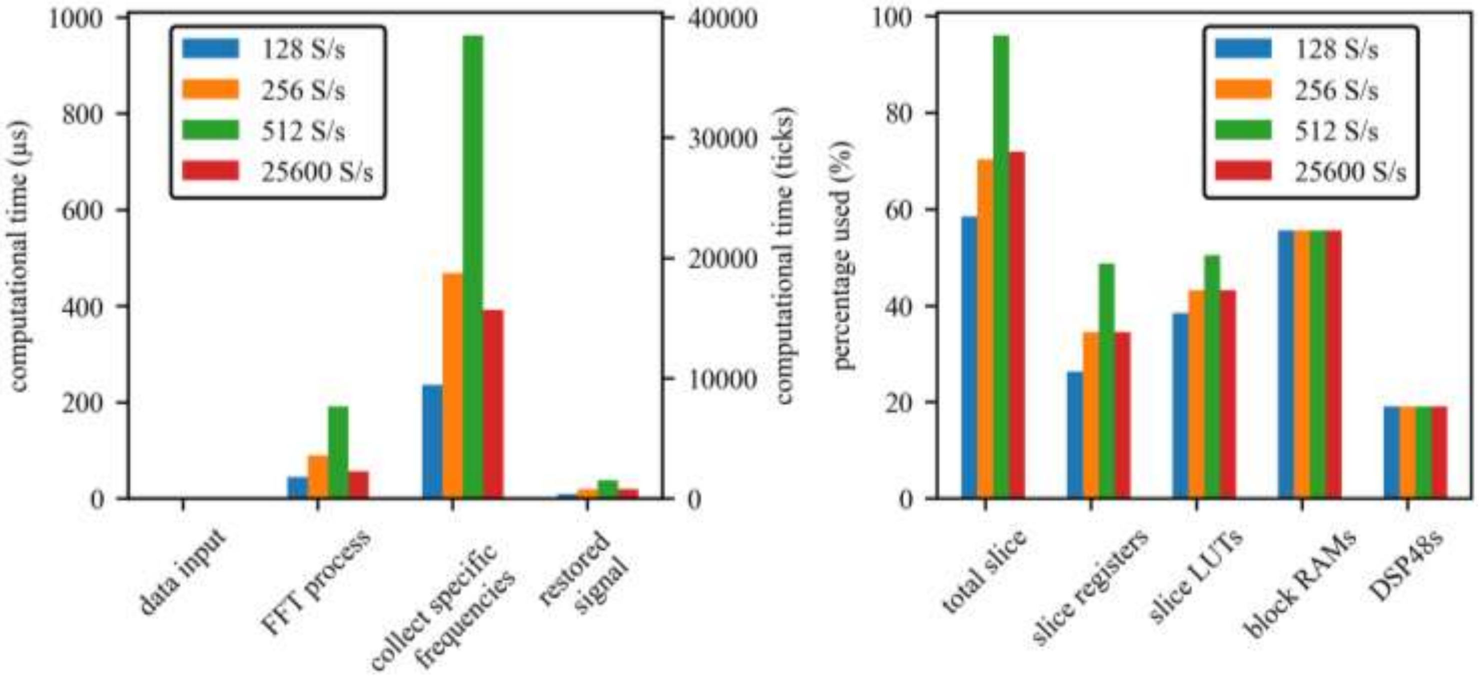
- The frequency list reveals that 25600 S/s utilized more frequencies.



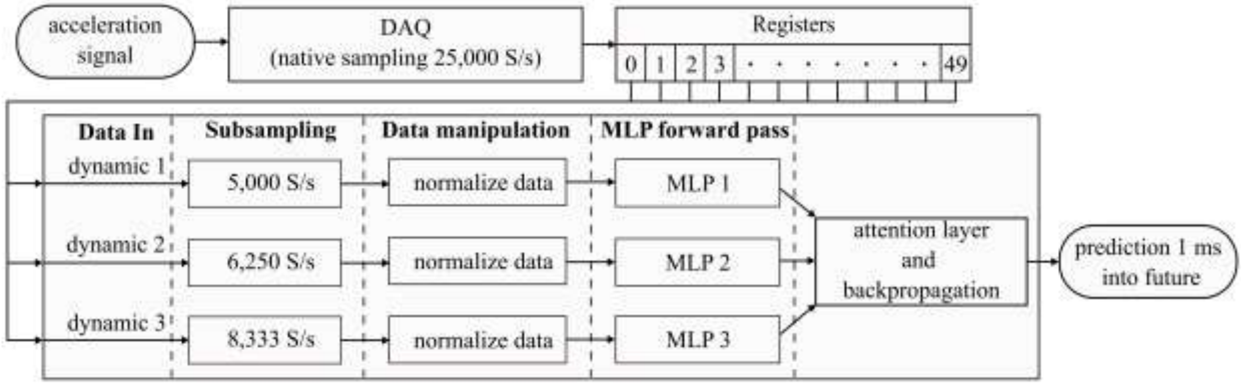
Sample rate (S/s)	RMSE	SNR	frequency list
25600	0.0017	17.12	50, 70, 100, 210, 220, 240, 260, 280, -50, -70, -100, -210,-220, -240, -260, -280
512	0.0019	16.33	50, 70, 100, -50, -70, -100
256	0.0019	16.18	50, 70, 100, -50, -70, -100
128	0.0338	0.15	50, 58, 22, 14, 20, 24, -50, -58, -22, -14, -20, -24

Hardware Validation Results

- The 512 S/s sampling rate takes greater computation time than other sampling rates.
- Device utilization, the signal sampled at 512 S/s uses 96% of the FPGA slices.
- The 25,600 S/s required its pairing with reduced FFT sizes to enable its deployment on the chosen FPGA hardware.



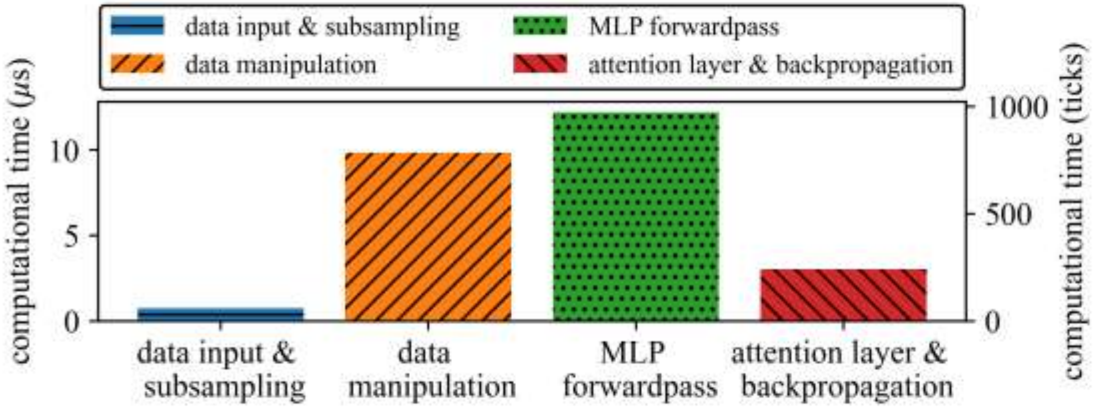
Hardware Validation (MLP)



	slices used	slices available	percentage used (%)
total slice	9895	10250	96.5
slice registers	36661	82000	44.7
slice LUTs	27917	41000	68.1
block RAMs	19	135	14.1
DSP48s	48	240	20.0

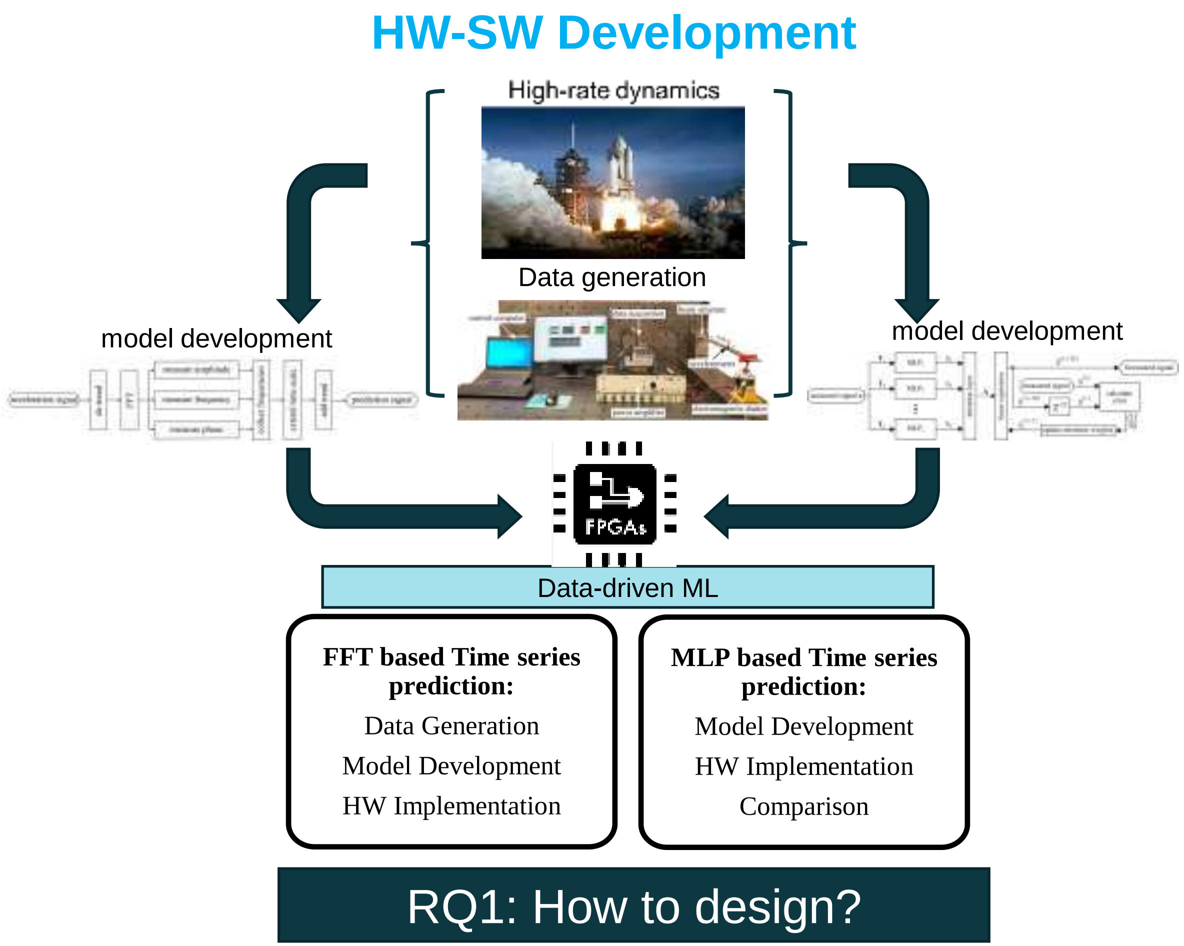
The FPGA elements are shown by the device utilization.

- Total system latency of 25.76 μs can be achieved on a Kintex-7 70T FPGA with sufficient accuracy for the considered system.



Time required for different aspects of the process.

Key Takeaways of Research Area 1



- RQ1: How to design the SW-HW for SHM System?
- Data Generation
- Showed the co-design approaches for HRD system
    - FFT based
    - MLP based
- Experimental Analysis

Overall Dissertation

RQ 2: How to add physics?

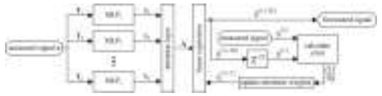
HW-SW Development

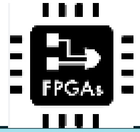
High-rate dynamics

Data generation

model development

model development





Data-driven ML

FFT based Time series prediction

Data Generation

Model Development

HW Implementation

MLP based Time series prediction:

Model Development

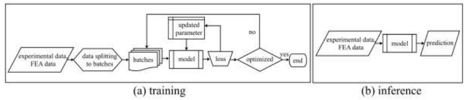
HW Implementation

Comparison

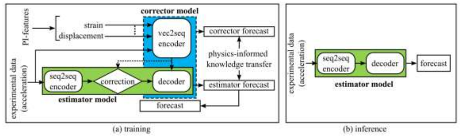
RQ1: How to design?

Adding Physics in SHM System

Physics-informed model development



Physics-informed model development



FE model development

Physics-informed ML

Physics data enhance Time series prediction

FE model development

Physics data generation

Integrate Physics data with experimental data

Physics knowledge transfer-based Time series prediction

FE model development

Physics data generation

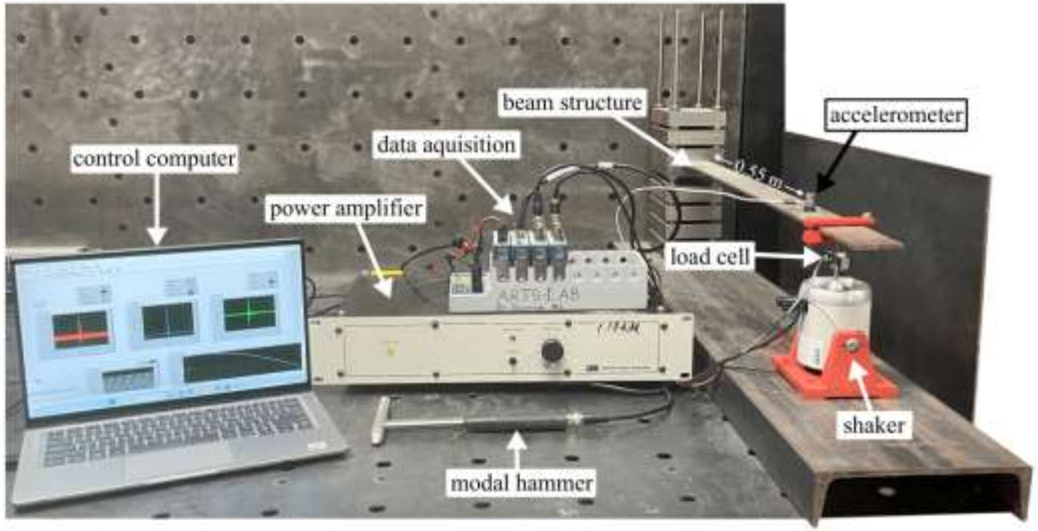
Transfer Learning-based Model Development

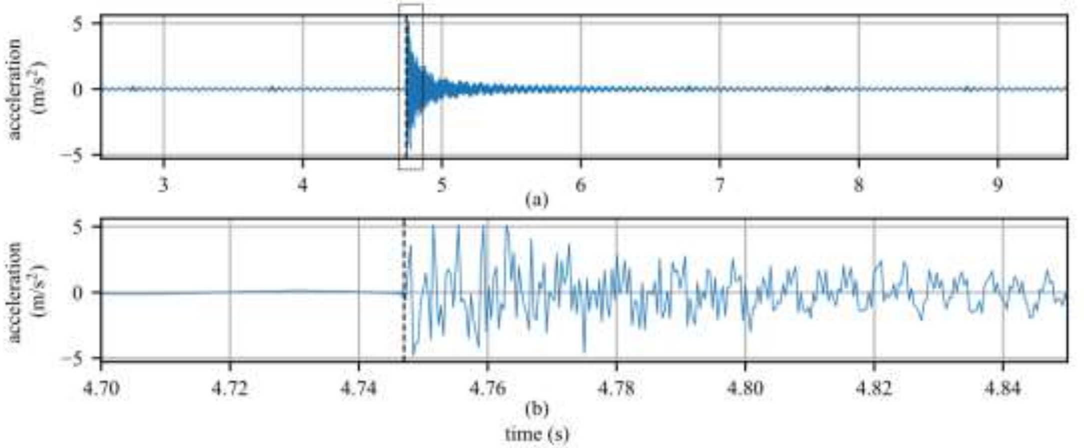
HW-SW Design for Temporal Forecasting in SHM system

Research Area 2: Adding Physics

- Background
- Problem Formulation
  - Beam Static Analysis
- Key Takeaways of Research Area 2

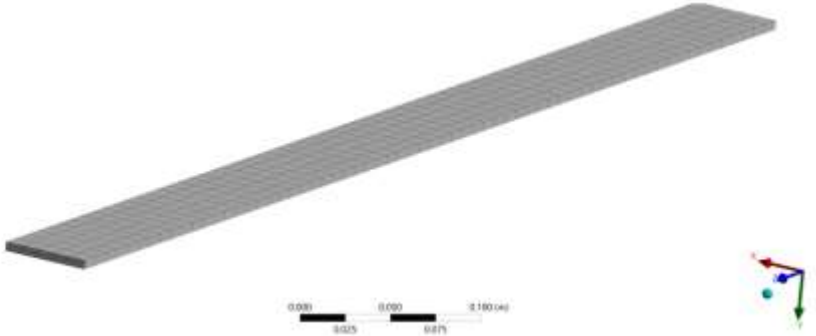
Single Impact Data Generation:

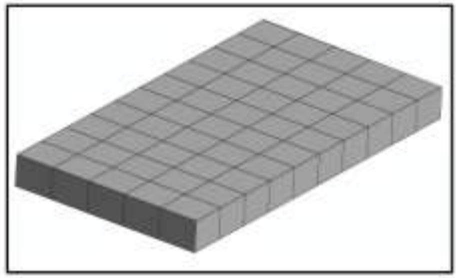




- Modal hammer is used to generate a single sudden impact

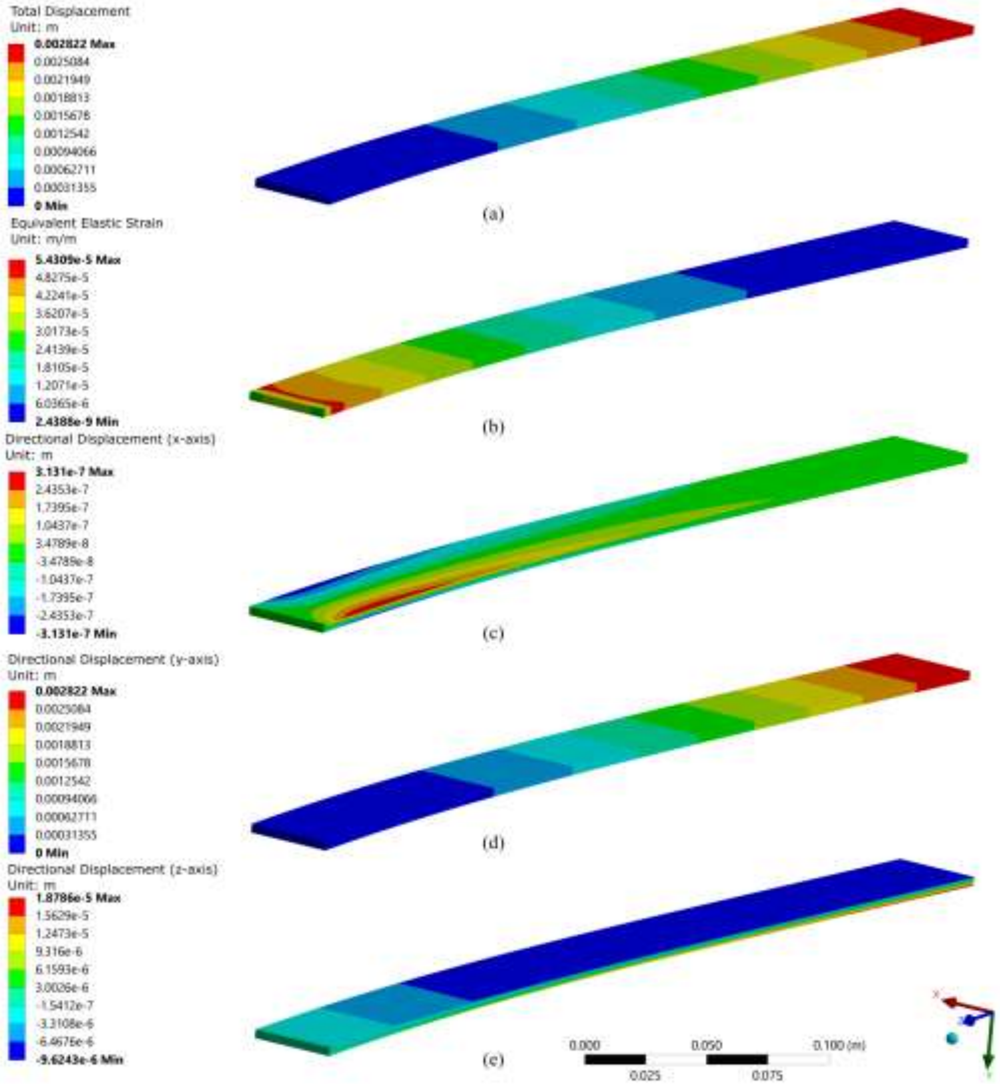
Physics Data Generation





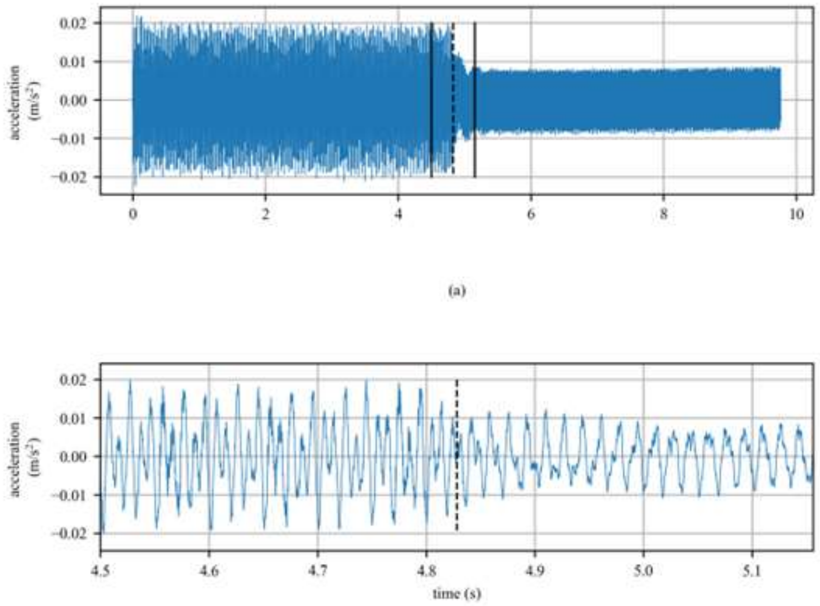
FEA model of a steel cantilever beam

- The fixed support cantilever beam is excited as an experimental excitation force through the free end.
- Total displacement, equivalent elastic strain, x, y, and z three displacement are generated.

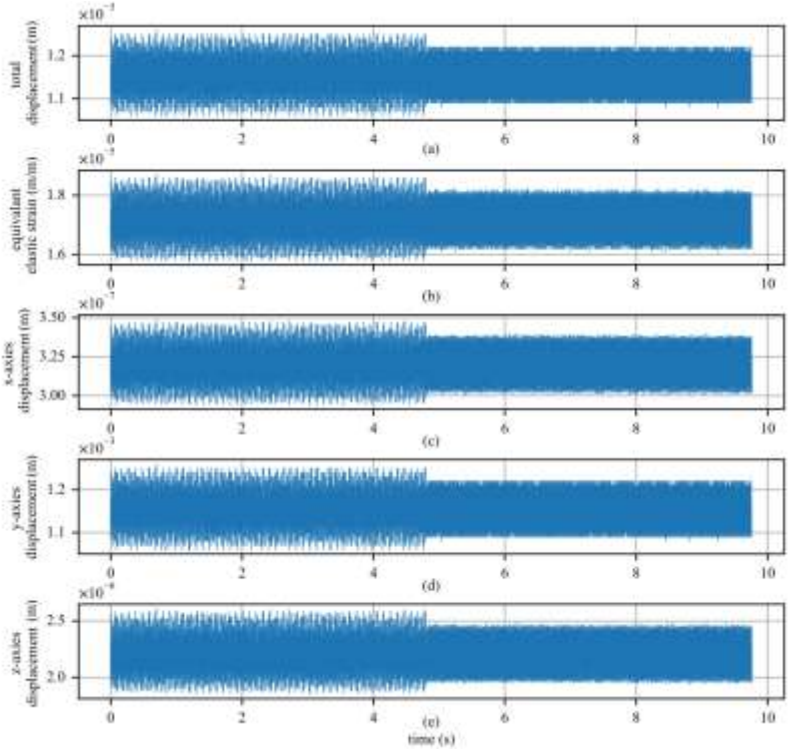


Physics Data Generation

- The overall physics-informed data from the FEA model have been generated for one of the single data here.



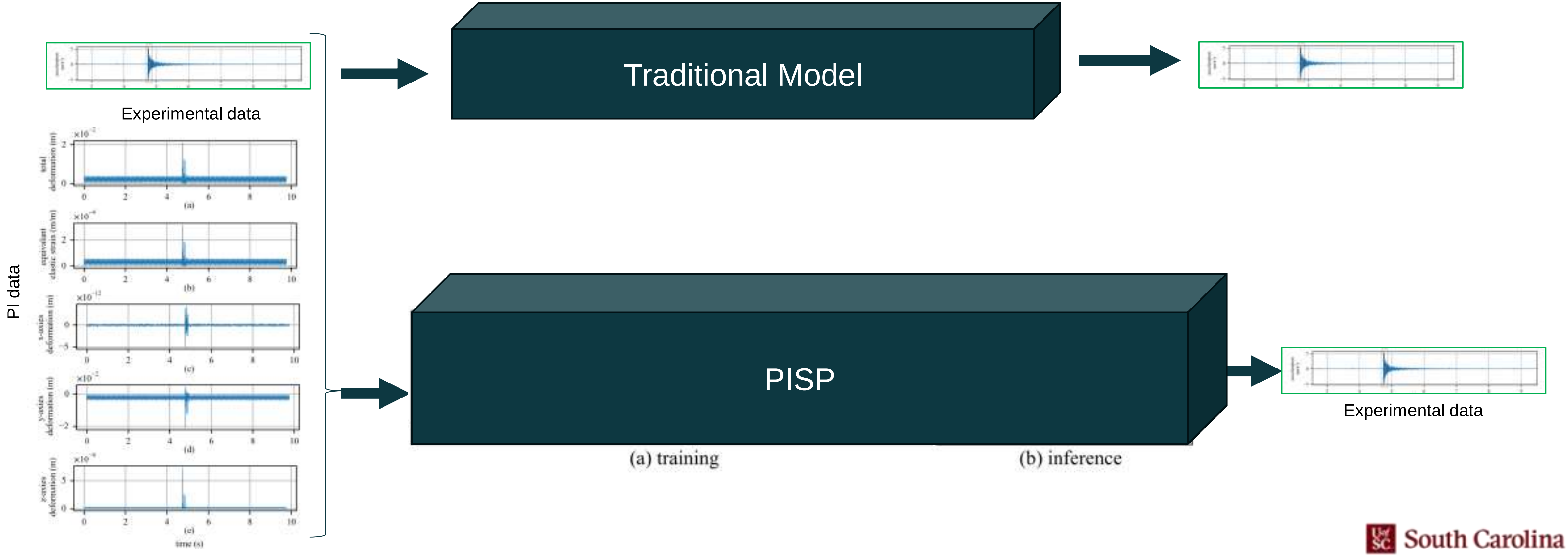
Experimental data



Physics informed data

Adding Physics Direction 1: Data Augmentation

- Problem-specific customized model: Designed a tailored model to address specific HRD system challenges
  - Physics Informed Series Prediction: PISP
- Physics data enhance time series prediction
- A model for series prediction from PI-augmented Data



Methodology:

- This study introduces the **PISP (Physics Informed Series Prediction)** model designed to enhance the accuracy of dynamic response forecasts for structural systems
- A physics-informed data-augmented machine learning model for time-series prediction.
- Improving the temporal forecasting in the case of univariate data with data augmented physics-informed model is the main contribution of this model.
- This model is a combination of Bidirectional Long Short-Term Memory (Bi-LSTM) representation learning to digest raw information; where the generation of latent features and fully connected layers-based regression for time series prediction is evolved eventually.

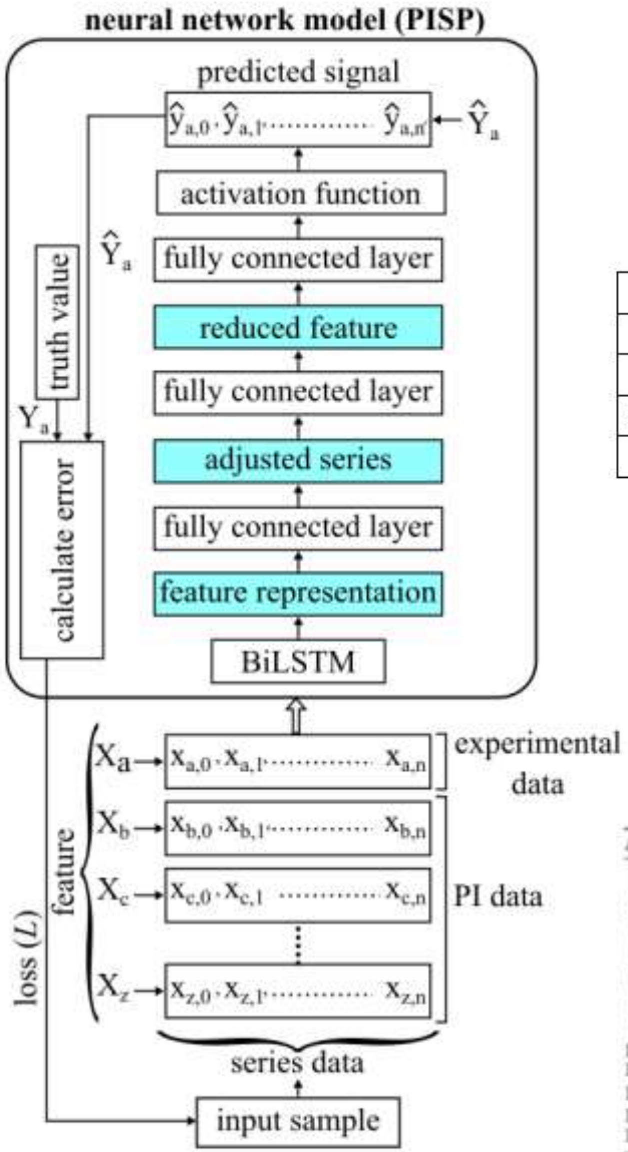


TABLE 1. Model Parameters used for PISP model.

hyper-parameters			
input window	hidden dimension	number of layers	output window
50	32	2	5
activation function	batch size	epoch	learning rate
'Selu'	2	100	5E-04

Algorithm 1 PISP workflow

```
X_a ← acceleration data                                  ▷ figure. 6.2(a)
X_b ← total displacement                                 ▷ figure. 7.19(a)
X_c ← equivalant elastic strain                          ▷ figure. 7.19(b)
X_d ← x-axies displacement                               ▷ figure. 7.19(c)
X_e ← y-axies displacement                               ▷ figure. 7.19(d)
X_f ← z-axies displacement                               ▷ figure. 7.19(e)
Y_a ← truth value
repeat
    H = get_BiLSTM_features ([X_a, X_b, X_c, X_d, X_e, X_f])   ▷ equation 7.27
    S = get_adjusted_series (H)                          ▷ equation 6.4, 6.5
    R = get_reduced_features (S)                         ▷ equation 6.6
    Ŷ_a =activation (get_final_features (R))             ▷ prediction, equation 6.7
    L =MSE (Y_a, Ŷ_a)                                    ▷ equation 6.8
until convergence
```

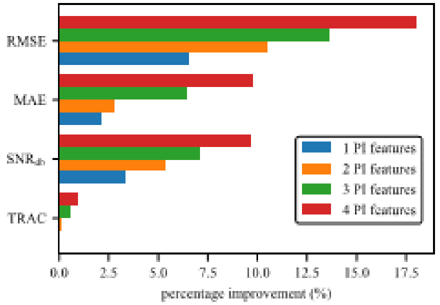
Results

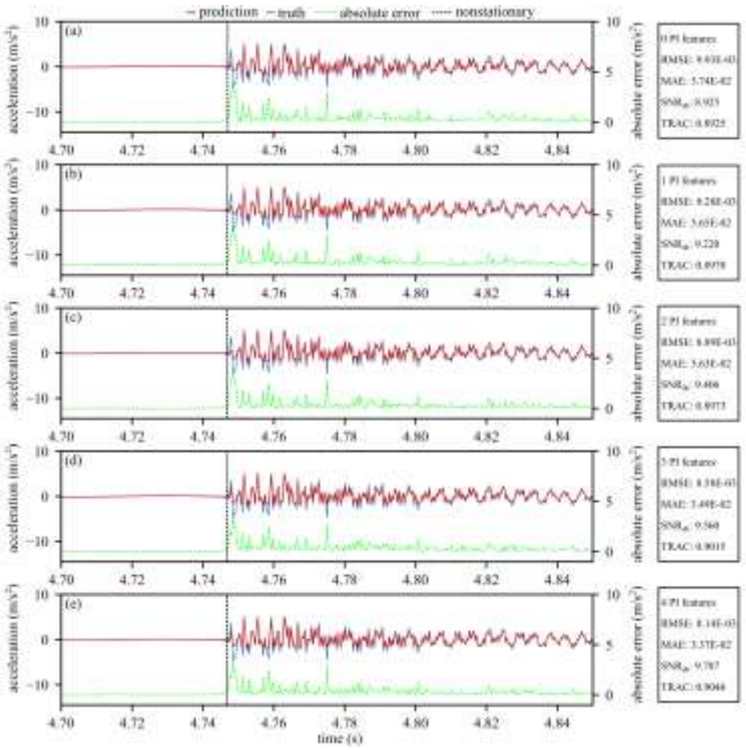
- A total of five PI features: total displacement, strain, x-axis displacement, y-axis displacement, and z-axis displacement; the data-augmented PISP model has been developed in four fashions with different PI feature combinations.
  - Displacement
  - Displacement + strain
  - Strain+ x-axis displacement+ y-axis displacement
  - Strain+ x-axis displacement+ y-axis displacement + z-axis displacement

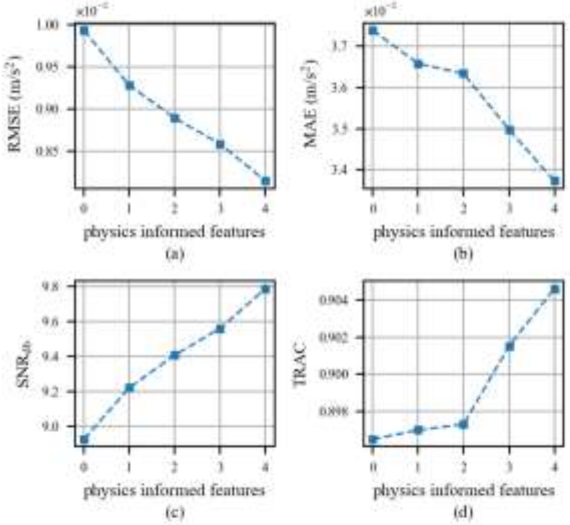
- Acceleration experimental data is included as well in the four configurations listed above. Only experimental data acceleration with no PI features is taken into consideration in the case of 0 PI feature configuration.

TABLE 2. Performance analysis with and without physics information in terms of percentage improvement.

metrics	without physics informed	physics informed	feature	percentage improvement
RMSE	9.93E-03	9.28E-03	1	6.57%
		8.89E-03	2	10.48%
		8.58E-03	3	13.60%
		8.14E-03	4	18.00%
MAE	3.74E-02	3.65E-02	1	2.17%
		3.63E-02	2	2.82%
		3.49E-03	3	6.46%
		3.37E-02	4	9.80%
SNR_{db}	8.925	9.220	1	3.30%
		9.406	2	5.39%
		9.560	3	7.11%
		9.787	4	9.65%
TRAC	0.8965	0.8970	1	0.06%
		0.8973	2	0.09%
		0.9015	3	0.55%
		0.9046	4	0.91%





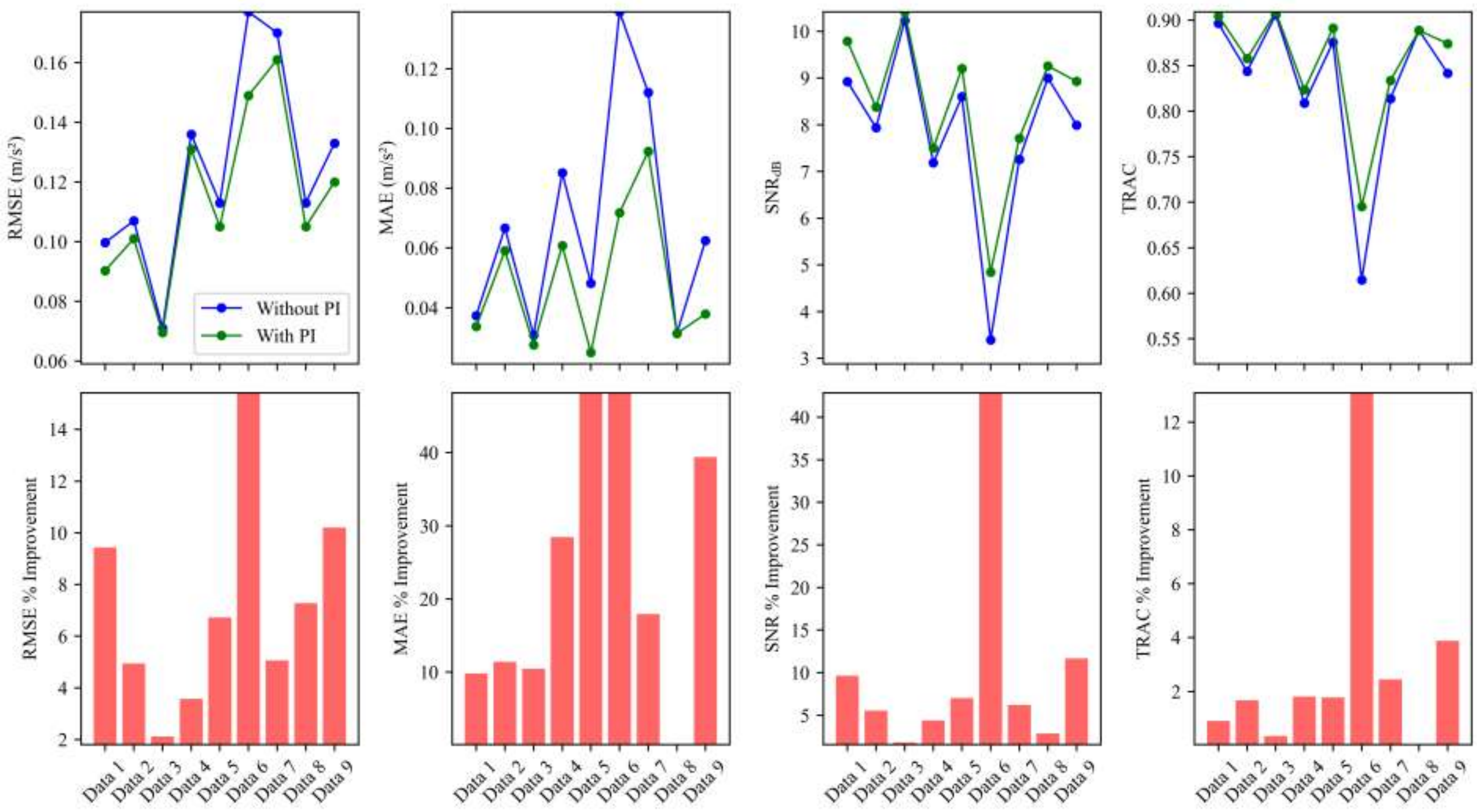


Results

- A comprehensive comparison of the performance with and without physics-informed features across multiple datasets. This broader analysis further highlights the significant impact of incorporating physics-informed features on the model's accuracy and effectiveness.

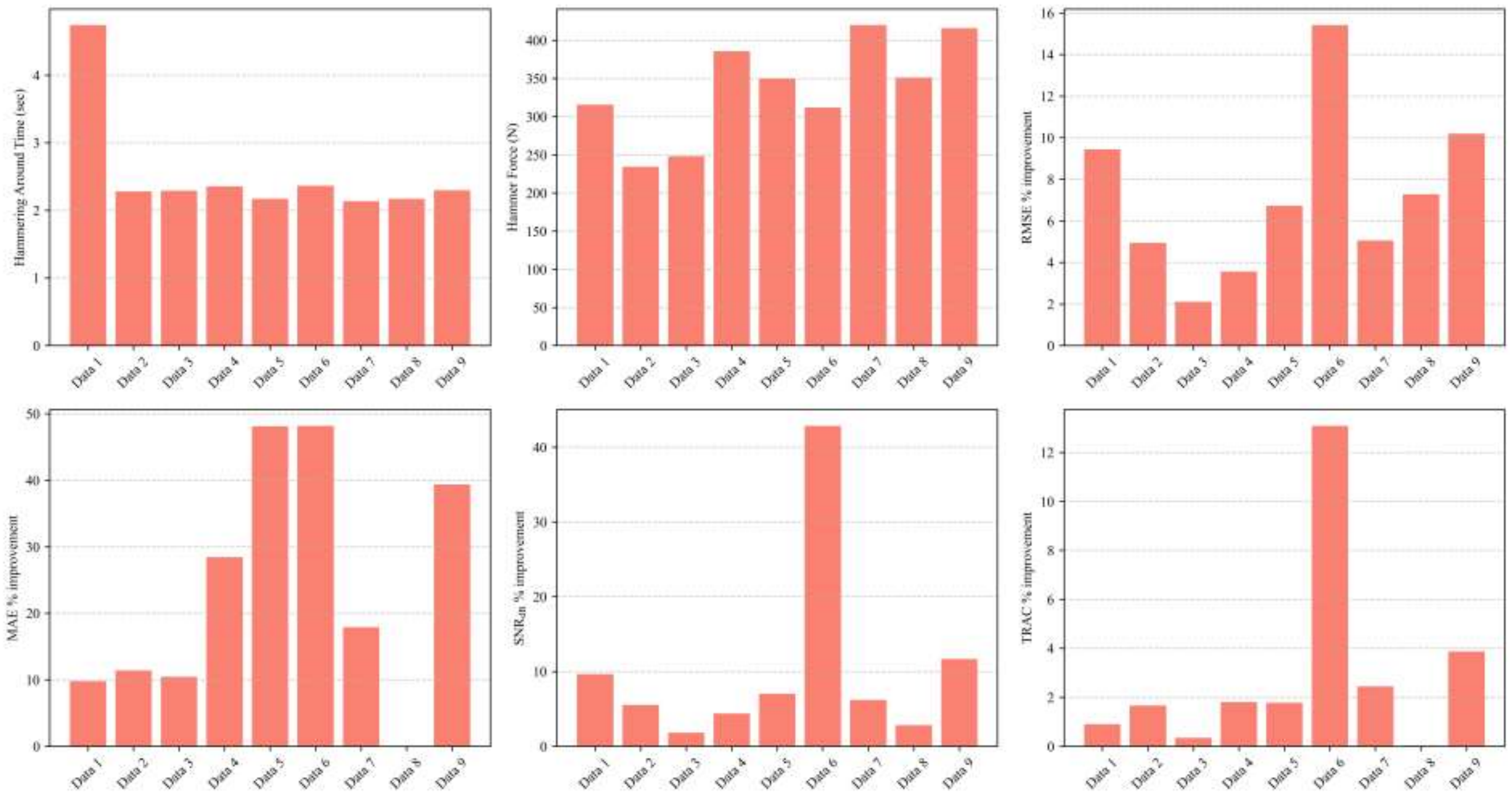
		data 1	data 2	data 3	data 4	data 5	data 6	data 7	data 8	data 9	Average
data configuration	**hammering around (sec)**	4.74	2.2809	2.294	2.356	2.173	2.365	2.137	2.173	2.2977	2.54
	sample rate (S/s)	2560	25600	25600	25600	25600	25600	25600	25600	25600	23040
	data duration (sec)	9.75	9.75	9.75	9.75	9.75	9.75	9.75	9.75	9.75	9.75
	hammer force (N)	315.73	234.5	248	386	350	312	420	351.5	416	337.0811111
without physics informed (0 PI features)	**RMSE**	9.97E-02	1.07E-01	7.10E-02	1.36E-01	1.13E-01	1.77E-01	1.70E-01	1.13E-01	1.33E-01	1.24E-01
	MAE	3.74E-02	6.67E-02	3.08E-02	8.51E-02	4.82E-02	1.39E-01	1.12E-01	3.14E-02	6.25E-02	6.81E-02
	SNR	8.925125	7.9368	10.22905	7.185807	8.601029	3.393895	7.259046	9.001195	7.993113	7.836117371
	TRAC	0.8965	0.8439	0.906	0.8088	0.8758	0.6148	0.8138	0.8889	0.8416	0.832233333
with physics informed (4 PI features)	**RMSE**	9.03E-02	1.01E-01	6.95E-02	1.31E-01	1.05E-01	1.49E-01	1.61E-01	1.05E-01	1.20E-01	1.15E-01
	MAE	3.37E-02	5.91E-02	2.76E-02	6.08E-02	2.50E-02	7.18E-02	9.23E-02	3.14E-02	3.79E-02	4.88E-02
	SNR	9.787	8.3776	10.4153	7.5018	9.2063	4.8486	7.7097	9.2574	8.9272	8.447877778
	TRAC	0.9046	0.858	0.9091	0.8235	0.8914	0.6952	0.8337	0.8886	0.8743	0.853155556
percentage improvement	**RMSE**	9.44%	4.95%	2.12%	3.57%	6.73%	15.42%	5.06%	7.28%	10.20%	7.20%
	MAE	9.80%	11.42%	10.47%	28.46%	48.12%	48.19%	17.92%	0.08%	39.39%	23.76%
	SNR	9.65%	5.55%	1.82%	4.40%	7.04%	42.86%	6.21%	2.85%	11.69%	10.23%
	TRAC	0.91%	1.67%	0.35%	1.81%	1.78%	13.09%	2.45%	0.03%	3.88%	2.89%

Results



RMSE (m/s²)
MAE (m/s²)
SNR_dB
TRAC
Without PI
With PI
RMSE % Improvement
MAE % Improvement
SNR % Improvement
TRAC % Improvement
Data 1
Data 2
Data 3
Data 4
Data 5
Data 6
Data 7
Data 8
Data 9

Results


Hammering Around Time (sec)
Hammer Force (N)
RMSE % improvement
MAE % improvement
SNR_{dB} % improvement
TRAC % improvement
Data 1
Data 2
Data 3
Data 4
Data 5
Data 6
Data 7
Data 8
Data 9

Key takeaways

PROS

- Can utilize physics data
- Achieves the data augmentation

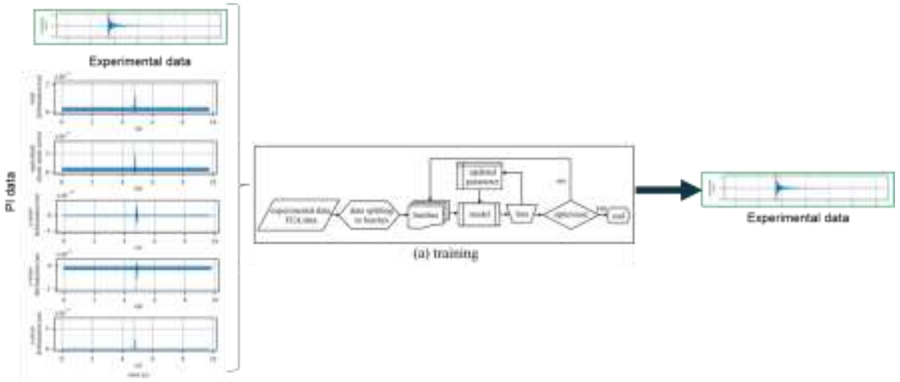
CONS

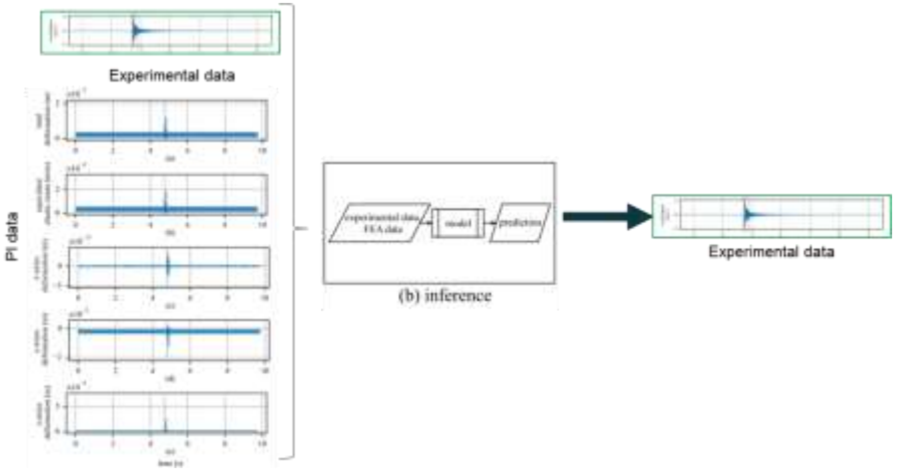
- Needs Physics data in the inference stage also

Solution: Transfer learning based model

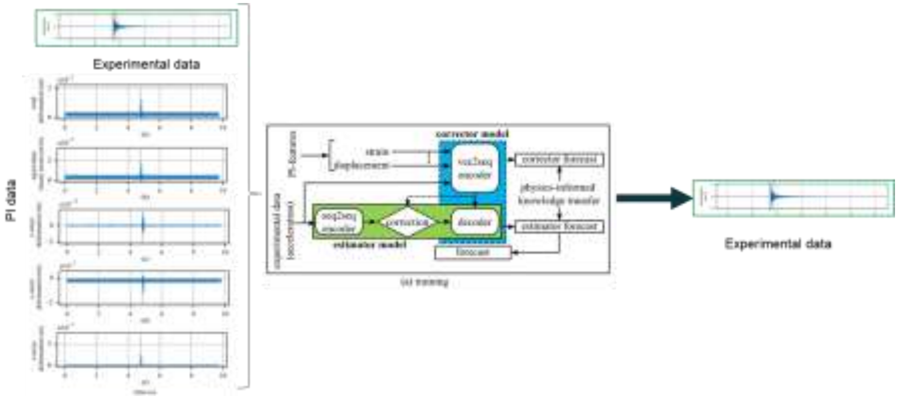
Data Augmentation vs Transfer Learning

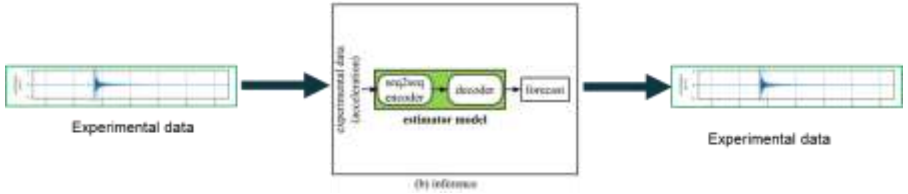
Data Augmentation



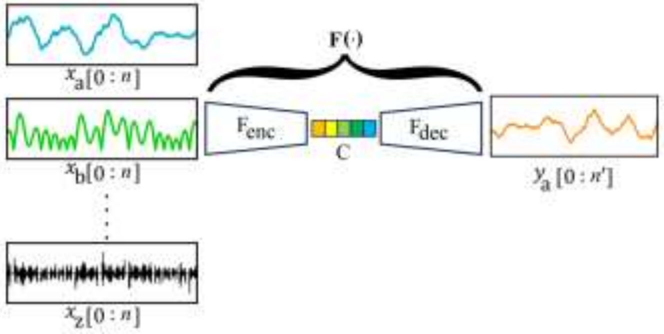


Transfer Learning

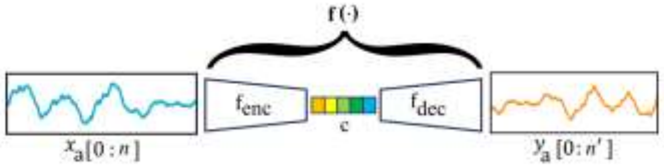




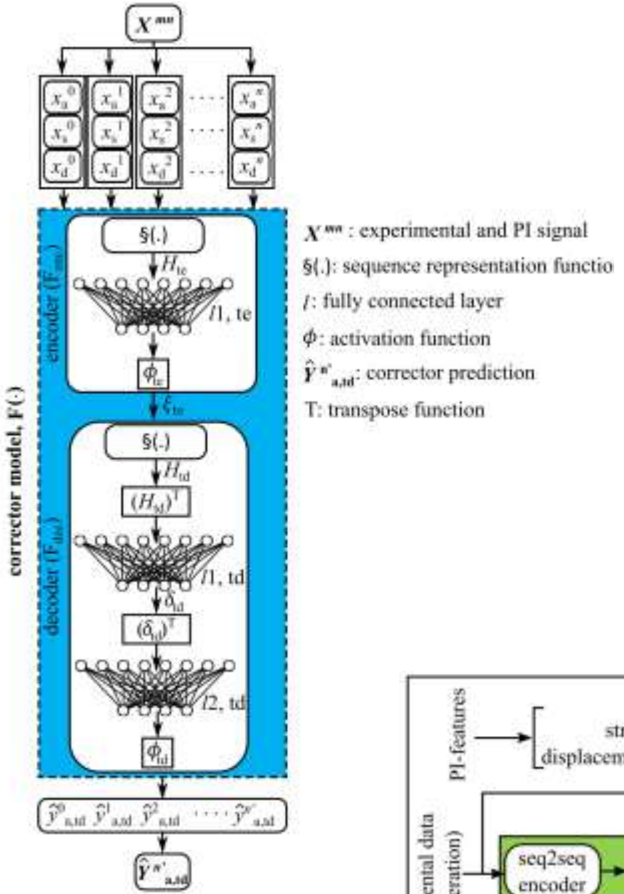
Adding Physics Direction 2: Transfer Learning

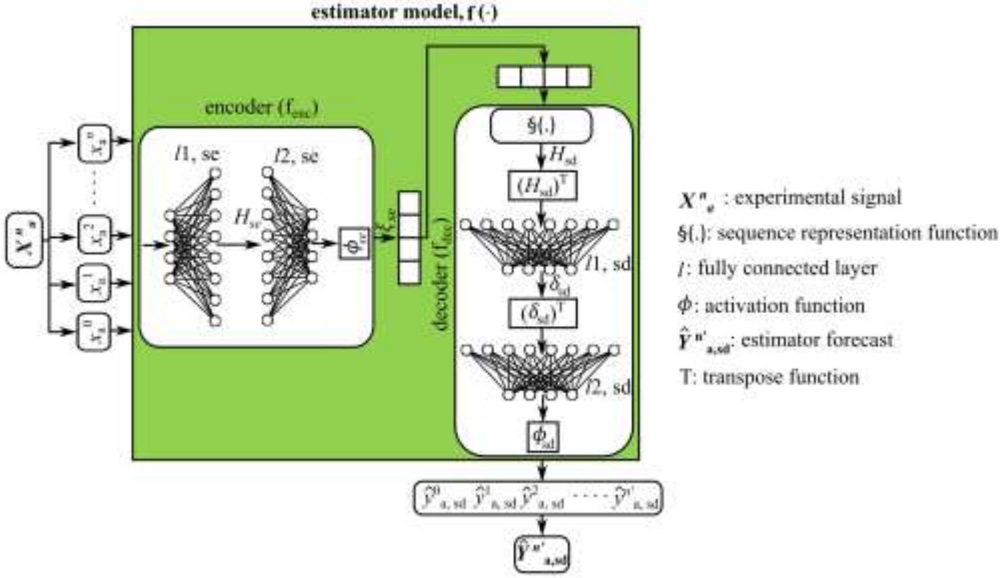


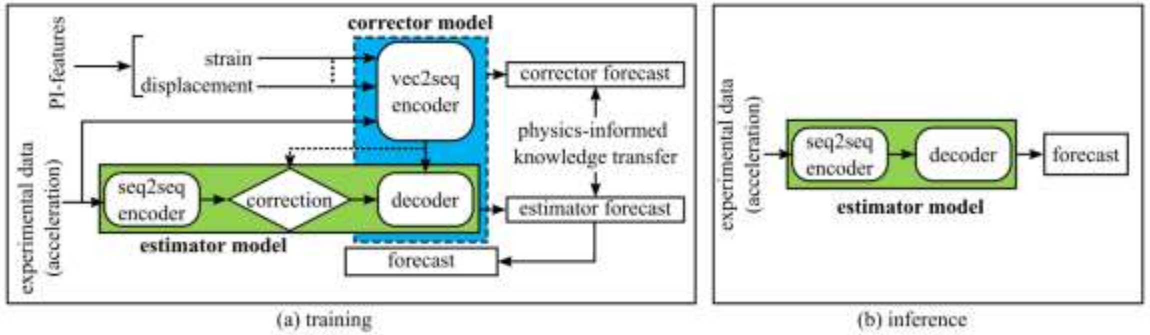
Corrector model



Estimator model



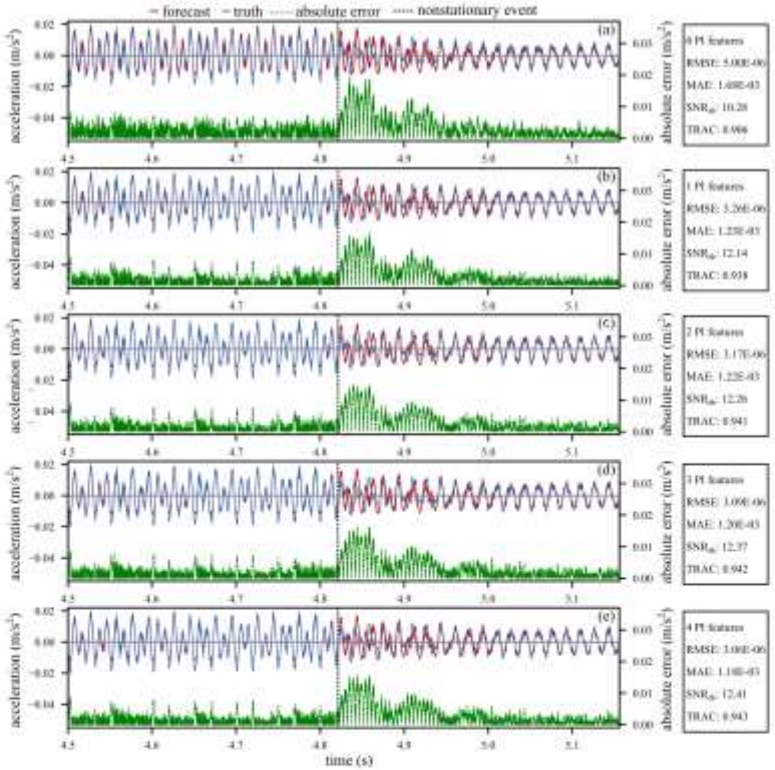


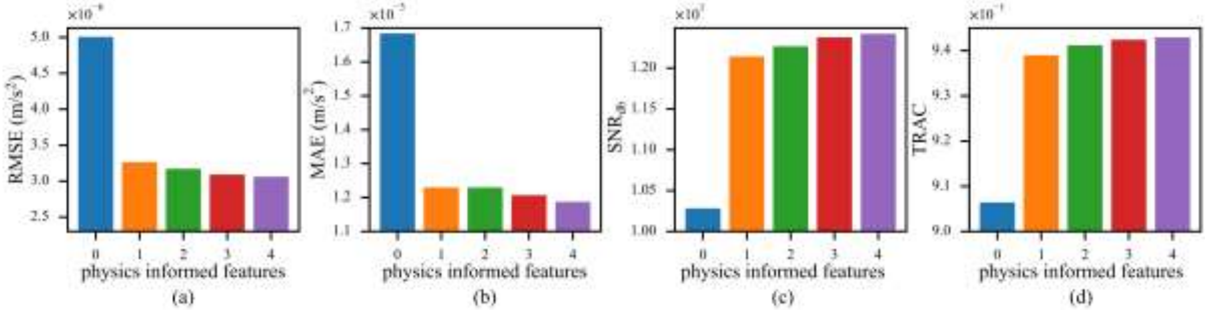


Results

- A total of five PI features: total displacement, strain, x-axis displacement, y-axis displacement, and z-axis displacement; the data-augmented PISP model has been developed in four fashions with different PI feature combinations.
  - strain
  - y-axis displacement + z-axis displacement
  - Strain+ x-axis displacement+ y-axis displacement
  - Strain+ x-axis displacement+ y-axis displacement + z-axis displacement

- Acceleration experimental data is included as well in the four configurations listed above. Only experimental data acceleration with no PI features is taken into consideration in the case of 0 PI feature configuration.





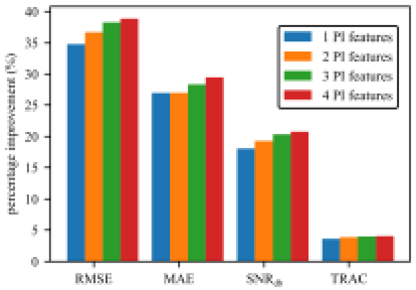


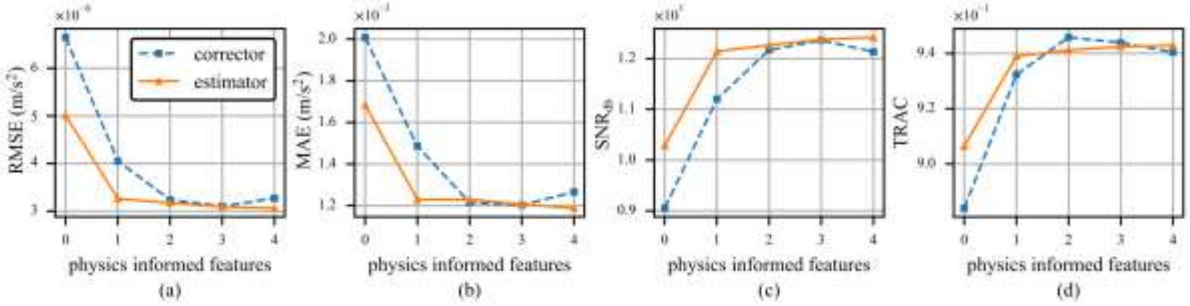
Table 7.4 Performance analysis with and without physics information in terms of percentage improvement.

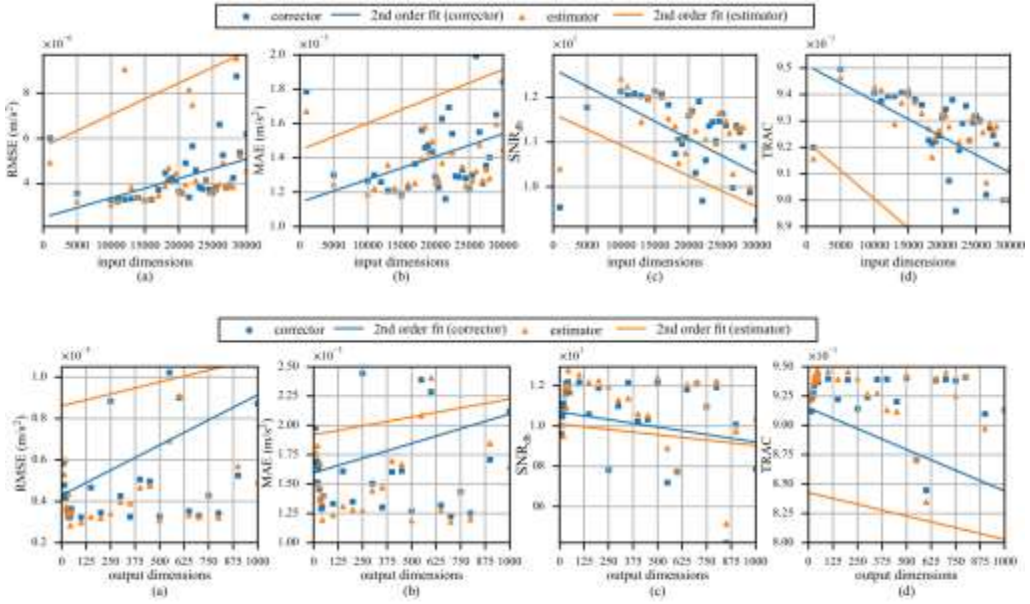
metrics	without physics informed	physics informed	feature	percentage improvement
RMSE	5.01E-06	3.26E-06	1	34.82%
		3.17E-06	2	36.66%
		3.09E-06	3	38.26%
		3.06E-06	4	38.86%
MAE	1.68E-03	1.23E-03	1	26.96%
		1.23E-03	2	26.97%
		1.21E-03	3	28.33%
		1.19E-03	4	29.48%
SNR$_{db}$	10.28	12.14	1	18.07%
		12.27	2	19.29%
		12.38	3	20.36%
		12.42	4	20.78%
TRAC	0.906	0.939	1	3.59%
		0.941	2	3.84%
		0.942	3	3.97%
		0.943	4	4.03%

South Carolina

Results

- Corrector and Estimator performance analysis with different features.
- Sensitivity analysis.
- For other data, detailed results are added in the supplemental document in the dissertation.





Overall Dissertation

RQ 2: How to add physics?

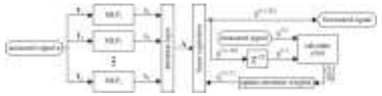
HW-SW Development

High-rate dynamics

Data generation

model development

model development



FPGAs

Data-driven ML

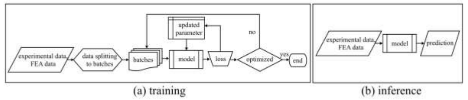
FFT based Time series prediction
Data Generation
Model Development
HW Implementation

MLP based Time series prediction:
Model Development
HW Implementation
Comparison

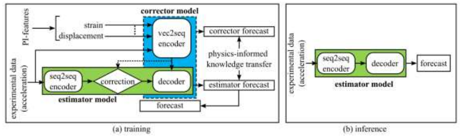
RQ1: How to design?

Adding Physics in SHM System

Physics-informed model development



Physics-informed model development



FE model development

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Integrate Physics data with experimental data

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Physics data generation
Transfer Learning-based Model Development

HW-SW Design for Temporal Forecasting in SHM system

Conclusions

- Key Takeaways
- Glimpse on RQ1
- Glimpse on RQ2
- Overall Proposal
- Progress and Schedule
- Publications

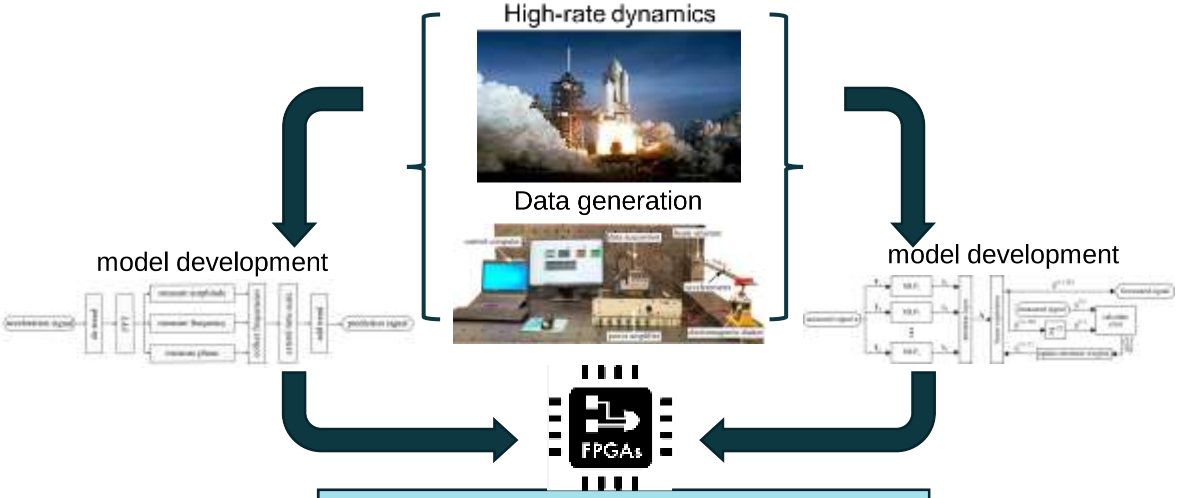
Key Takeaways

- Key Takeaways of Research Area 1:
  - RQ1: How to design the SW-HW for SHM System?
    - Data Generation
    - Showed the co-design approaches for HRD system
      - FFT based
      - MLP based
    - Experimental Analysis

- Key Takeaways of Research Area 2
  - RQ2: How to synergies between data-driven and rule-based system?
    - Physics data generation
    - Data augmentation based model
    - Transfer learning based model

Glimpse on RQ1

HW-SW Development



Data-driven ML

FFT based Time series prediction:
Data Generation
Model Development
HW Implementation

MLP based Time series prediction:
Model Development
HW Implementation
Comparison

RQ1: How to design?

HW-SW Design

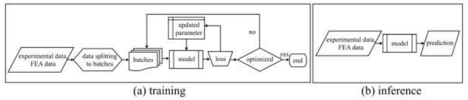
Overall Dissertation

RQ 2: How to add physics?

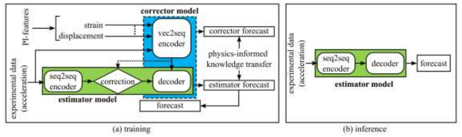
HW-SW Design

Adding Physics in SHM System

Physics-informed model development



Physics-informed model development



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Overall Dissertation

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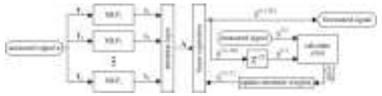
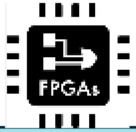




Data-driven ML

FFT based Time series prediction

Data Generation

Model Development

HW Implementation

MLP based Time series prediction:

Model Development

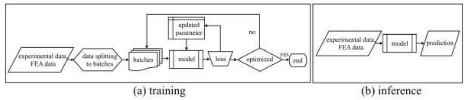
HW Implementation

Comparison

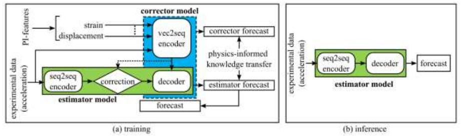
RQ1: How to design?

Adding Physics in SHM System

Physics-informed model development



Physics-informed model development



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Physics data generation

Transfer Learning-based Model Development

HW-SW Design for Temporal Forecasting in SHM system

Key Contributions

- Data Generation
  - Experimental data generation: Developed solutions to overcome the lack of available data for HRD system research
  - Physics-informed Data Generation: Utilized physics principles to generate realistic data for HRD systems.
- Data-driven model development
  - Mathematical algorithm-based models: Employed mathematical algorithms, such as FFT in a windowed fashion, to develop models.
  - Deep learning-based models: Leveraged deep learning techniques, including ensembled MLPs, to create models.
- Physics-informed model development
  - Data augmentation:
    - Enhanced model performance by augmenting existing data.
    - Problem-specific customized model (PISP): Designed a tailored model to address specific HRD system challenges.
  - Transfer learning:
    - Applied transfer learning techniques, such as teacher-student models and BiLSTMs, to improve model efficiency.
    - Customized model (PIMENTO): Developed a unique model architecture for HRD system applications.
- Hardware implementation
  - Time deterministic hardware implantation of FFT model in FPGA.
  - Time deterministic hardware implantation of ensemble MLP model in FPGA.
- Application:
  - High-Rate Dynamic System:
    - Non-stationary time series prediction: Accurately predicted non-stationary time series in HRD systems.
    - Single impact prediction: Successfully predicted the impact of single events in HRD systems.
  - Others (Not included in the dissertation)
    - Data-driven fragility framework: Developed a framework for risk assessment of levee breaches.

Publications

Dissertation

Design

FFT SW

1. Chowdhury, Puja, Philip Conrad, Jason D. Bakos, and Austin Downey. "Time Series Forecasting for Structures Subjected to Nonstationary Inputs." In Smart Materials, Adaptive Structures and Intelligent Systems, vol. 85499, p. V001T03A008. American Society of Mechanical Engineers, 2021.

MLP SW HW

3. Singh, Ishrat, Philip Conrad, Puja Chowdhury, Jason D. Bakos, and Austin Downey. "Real-Time Forecasting of Vibrations with Non-stationarities." In Data Science in Engineering, Volume 9: Proceedings of the 39th IMAC, A Conference and Exposition on Structural Dynamics 2021, pp. 21-29. Springer International Publishing, 2022.
4. Chowdhury, Puja, Vahid Barzegar, Joud Satme, Austin RJ Downey, Simon Laflamme, Jason D. Bakos, and Chao Hu. "Deterministic and low-latency time-series forecasting of nonstationary signals." In Active and Passive Smart Structures and Integrated Systems XVI, vol. 12043, pp. 466-472. SPIE, 2022.

RA1-D1 **RA1-D1** **RA1-D2** **RA1-D2**

2. Chowdhury, Puja, Austin RJ Downey, Jason D. Bakos, Simon Laflamme, and Chao Hu. " Hardware implementation of nonstationary structural dynamics forecasting." In Active and Passive Smart Structures and Integrated Systems XVII, SPIE, 2023

FFT HW

- FPGA-deployed Adaptive Ensemble of Neural Networks for Forecasting of Temporal Structural Dynamics. (Development Stage)

FFT vs MLP

PI Review

5. Eleonora Maria Tronci, Austin R.J. Downey, Azin Mehrjoo, Puja Chowdhury, and Daniel Coble. "Physics informed machine learning part I: Different strategies to incorporate physics into engineering problems. In Conference Proceedings of the Society for Experimental Mechanics Series". Springer Nature Switzerland, 2024.
6. Austin R.J. Downey, Eleonora Maria Tronci, Puja Chowdhury, and Daniel Coble. "Physics informed machine learning part II: Applications in structural response forecasting". In Conference Proceedings of the Society for Experimental Mechanics Series. Springer Nature Switzerland, 2024.

Improvement

Transfer Learning

2. Online Structural Responses Forecasting Using a Physics-informed Knowledge Transfer Model. (Submission Stage)

RA2 **RA2-D1** **RA2-D2**

1. Predicting Structural Responses in Impact Scenarios with Physics-Guided Machine Learning. (Submission Stage)

Data Augmentation

Risk Assessment of Levee Breaches

7. Chowdhury, Puja, Joud Satme, Ryan Yount, Austin R.J. Downey, Mohammad Sadik Khan, and Jasim Imran. “Spatial mapping of soil saturation levels using UAV deployable smart penetrometers”. ASCE Geo-Institute 7th Annual Live Streaming Web Conference, 2022.
8. Chowdhury, Puja, Joud N. Satme, Malichi Flemming, Austin R. J. Downey, Mohamed Elkholy, Jasim Imran, and Mohammad Sadik Khan. " Stand-alone geophone monitoring system for earthen levees." In Active and Passive Smart Structures and Integrated Systems XVII, SPIE, 2023.
9. Chowdhury, Puja, Joud N. Satme, Ryan Yount, Austin RJ Downey, Sadik Khan, Jasim Imran, and Laura Micheli. "Classifying Soil Saturation Levels Using a Network of UAV-Deployed Smart Penetrometers." In Smart Materials, Adaptive Structures and Intelligent Systems, vol. 87523, p. V001T05A002. American Society of Mechanical Engineers, 2023.
10. Chowdhury, P., Crews, J., Mokhtar, A., Oruganti, S. D. R., Van Wyk, R., Downey, A. R., Flemming, M., Bakos, J. D., Imran, J., & Khan, S. "Distributed real-time soil saturation assessment in levees using a network of wireless sensor packages with conductivity probes". Proceedings of the ASME 2024 International Mechanical Engineering Congress and Exposition, IMECE2024-145950. (accepted)

1\. Nemnem, A.M., Chowdhury, P., Crews, C., Downey, A.R.J., Bakos, J., Khan, M.S., Chaudhry, M.H., & Imran, J. (2025). "Mapping Seepage Flow in Untreated and Biopolymer-Treated Soils Using Wireless Sensing Spikes". Submitted to the 2025 International Conference on Bio-mediated and Bio-inspired Geotechnics. (submitted)

3\. Wireless Sensor Network for Distributed Real-Time Soil Saturation Monitoring in Levees. (submission stage)

Acknowledgement

- Dr. Jason D. Bakos
- Dr. Yi Wang
- Dr. Junsoo Lee
- Dr. Imran Jasim

- Collaborators
- Course Instructors
- School Staffs
- Relatives & Friends

My Advisor
Dr. Downey

Family

My Newborn

Devine Power

Thank You!

Questions or Comments?

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