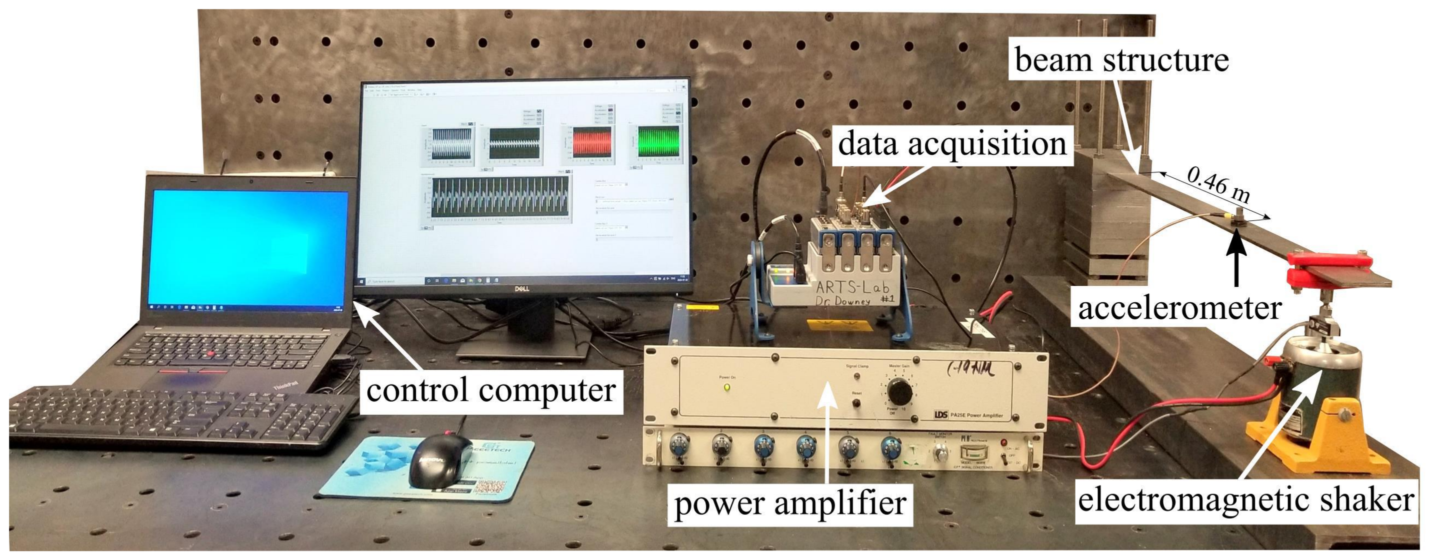
Deterministic and low-latency time-series forecasting of nonstationary signals

Puja Chowdhury*[a], Vahid Barzegar*[b], Joud Satme[a], Austin R.J. Downey[a, d,] Simon Laflamme[b, e,] Jason D. Bakos[c], and Chao Hu[b]
[a]Department of Mechanical Engineering, University of South Carolina Columbia, Columbia, SC, USA
[b]Department of Structural Engineering, Iowa State University,Ames, IA, USA
[c]Department of Computer Science and Engineering, University of South Carolina Columbia, Columbia, SC, USA
[d]Department of Civil and Environmental Engineering, University of South Carolina Columbia, Columbia, SC, USA
[e]Department of Electrical Engineering, Iowa State University,Ames, IA, USA

INTRODUCTION

- ❑ A software-hardware system for online structural vibration time-series forecasting
  - ❑ recognizing nonstationary events
  - ❑ alter the anticipated signal in response to the nonstationary events.
- ❑ Using an ensemble of multi-layer perceptron
  - ❑ trained offline on experimental and simulated data
- ❑ The key focus for the current hardware implementation
  - ❑ Deterministic timing of the proposed algorithm in FPGA implementation
  - ❑ time consumption for various components (code, device, etc.)



Setup for an experimental cantilever beam including main components and data acquisition.

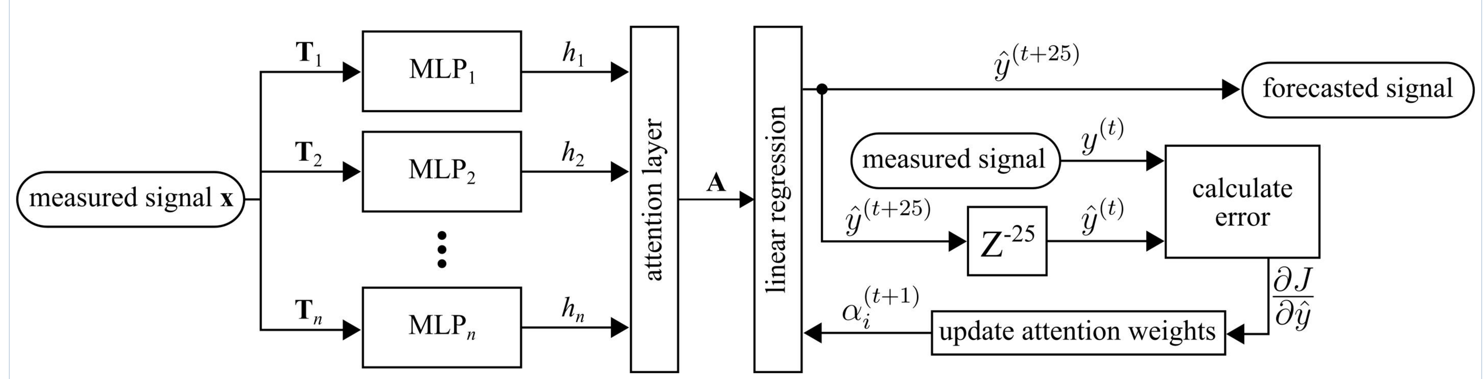
cRIO-9035
Kintex-7 70T FPGA

Hardware Configuration

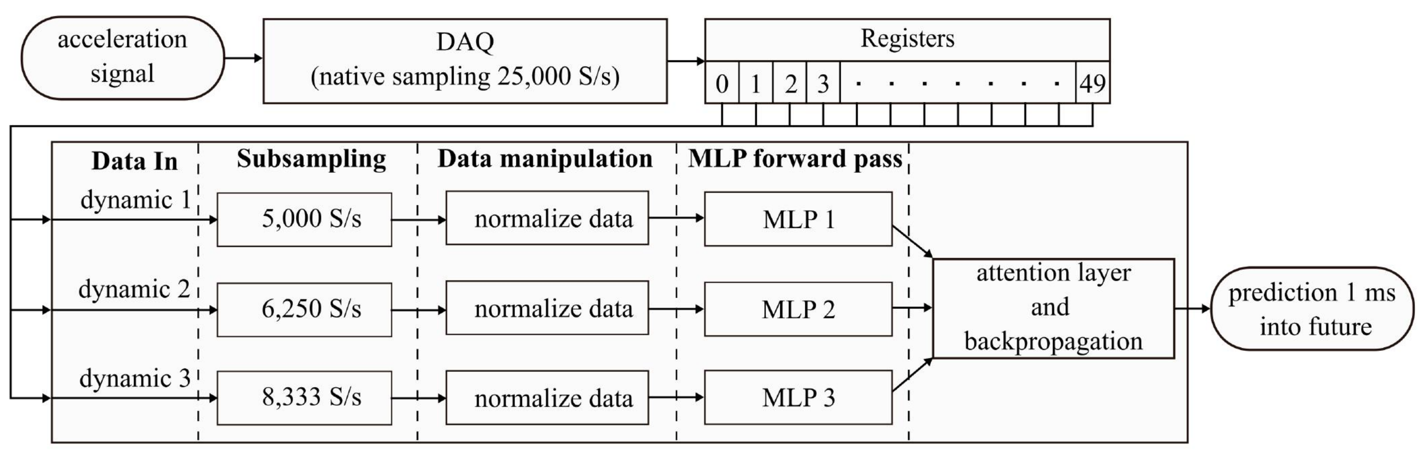
- ❑ A Kintex-7 70T FPGA housed in a NI cRIO-9035
- ❑ incorporates a CPU running NI Linux Real-Time
- ❑ 1.33 GHz Dual-Core CPU
- ❑ 1 GB DRAM
- ❑ 4 GB Storage
- ❑ 8-Slot CompactRIO Controller
- ❑ Internal clock of 24-bit ADC

METHODS

- ❑ The algorithm consists of an ensemble of MLPs running in parallel, each sampling the incoming observations at a different rate.
- ❑ The use of an ensemble empowers multi-rate sampling to capture multi-temporal features of the time series.
- ❑ In this work, hardware validation is done on a Kintex-7 70T FPGA housed in a NI cRIO-9035 that also incorporates a CPU running NI Linux Real-Time.

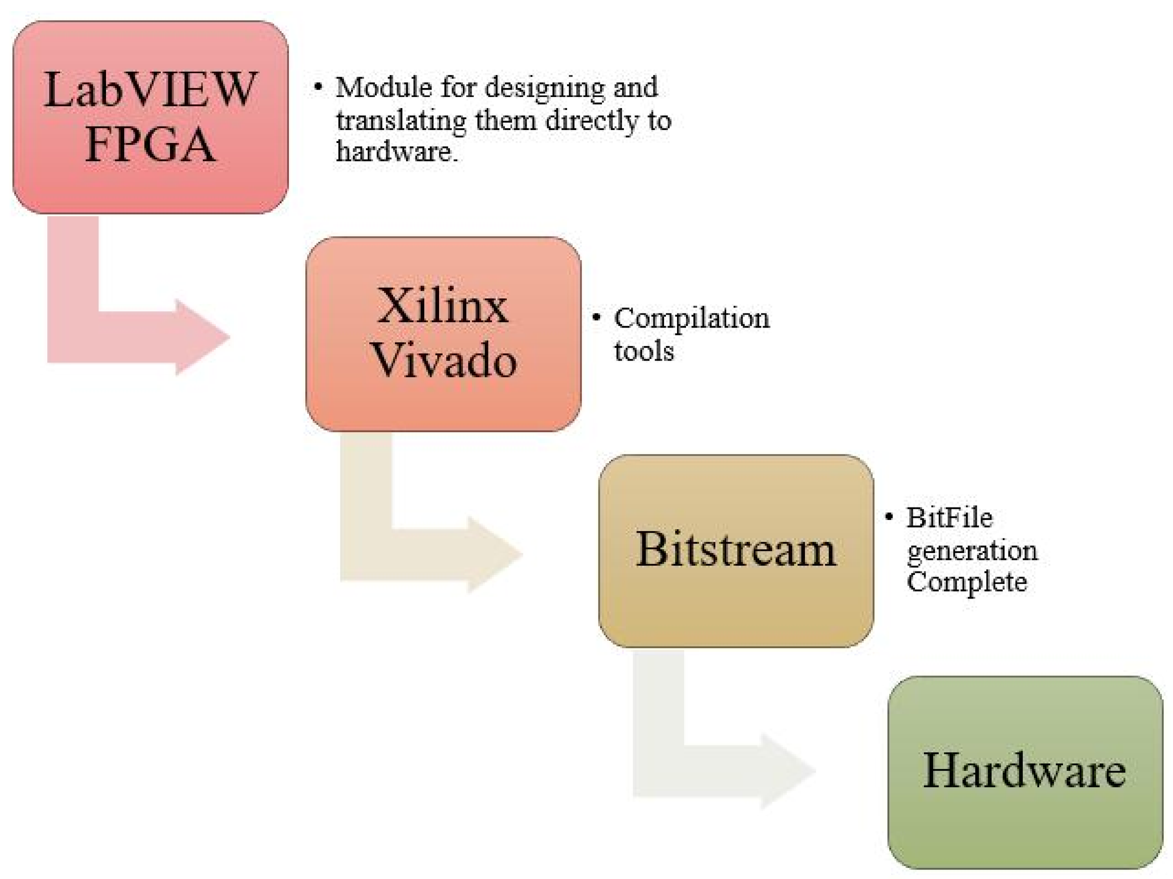


Schematic Algorithm diagram of an ensemble of MLPs using the 50 most recent data points and predicting 25 data points (1 ms) into the future**.**

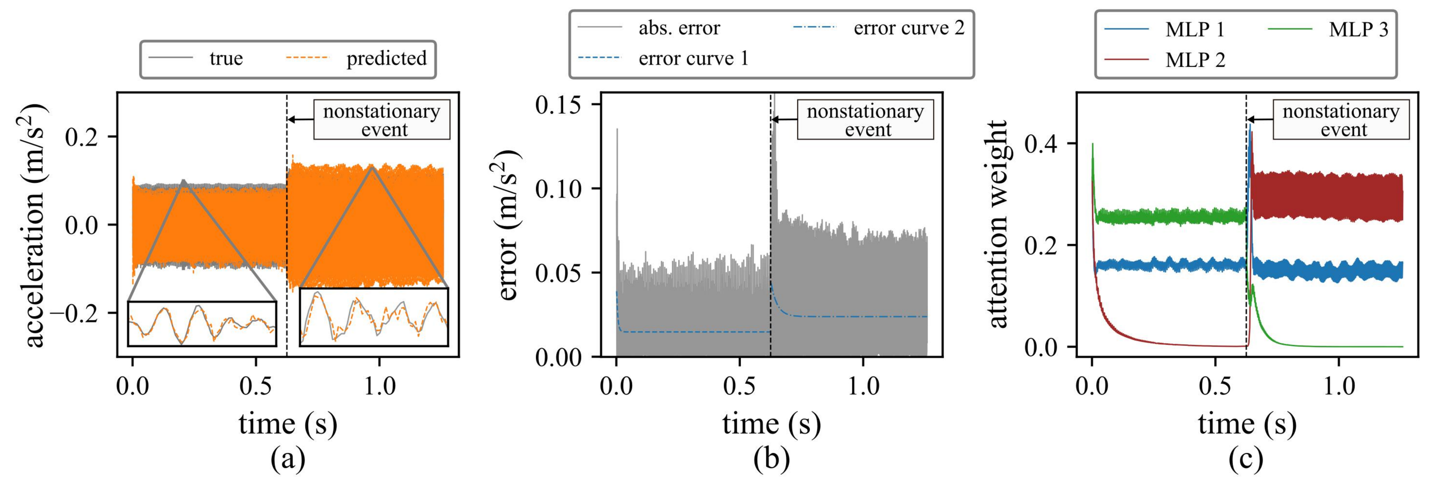


Flow chart of data collection and processing in parallel MLP tracks.

FPGA Workflow



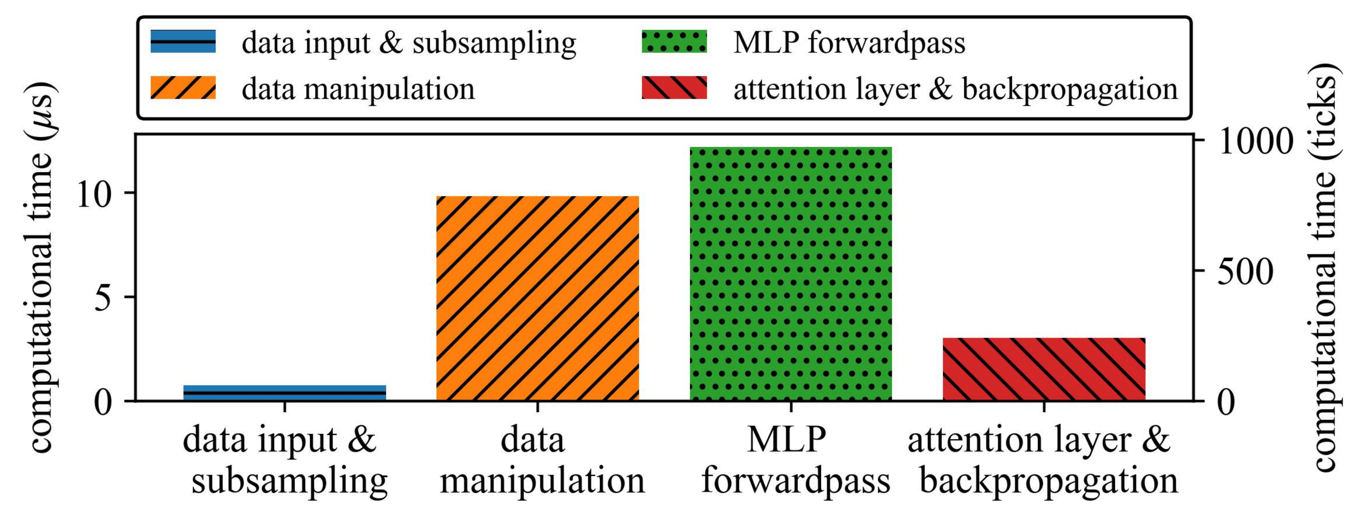
RESULTS



Algorithm results, showing: (a) the truth and prediction result of the ensemble; (b) the absolute error before and after the nonstationary event, and; (c) the evolution of the attention weights for different MLP's.

Performance metrics of the predicted results.

	RMSE (m/s²)	a (m/s²)	SNR	Convergence (ms)
before nonstationary event	0.019	0.015	6.09	18.5
after nonstationary event	0.031	0.024	5.63	71.6



Time required for different aspects of the process.

The FPGA elements are shown by the device utilization.

	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

CONCLUSIONS

1. This study outlines the development of a software-hardware system for online forecasting of structural vibration time-series that can learn over nonstationary occurrences and adjust the expected signal accordingly.
2. The results reveal that a total system latency of 25.76 μs can be achieved with sufficient precision for the high-rate systems under discussion.
3. The current implementation is largely limited by the amount of memory available in look-up tables at the cell level block

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