

SEISMIC SIGNAL PREDICTION USING ACCELEROMETER ARRAYS FOR ONLINE NEWTONIAN-NOISE MITIGATION ON FPGA

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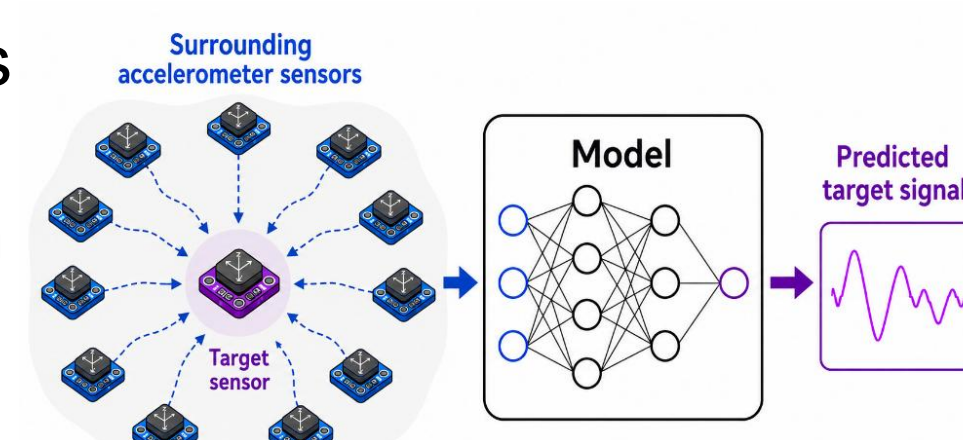
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1. NEWTONIAN NOISE PREDICTION

Newtonian noise is gravitationally coupled into interferometer mirrors and caused by various seismic activity. Accelerometer arrays can monitor the surrounding seismic field and provide input data for predicting this noise. Currently, this is done offline on recorded data [1]. Our goal is to predict it in real-time (online).

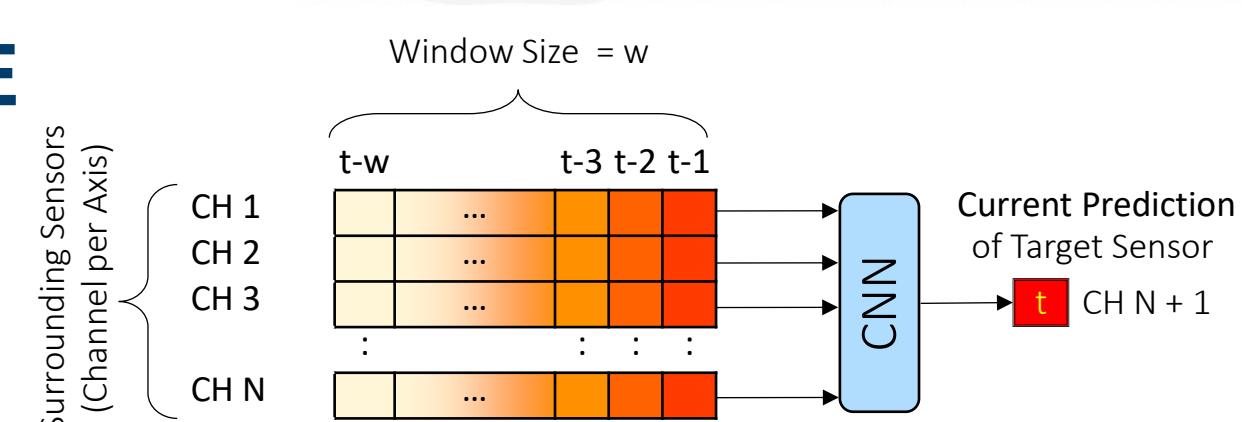
1.1 MOTIVATION FOR ONLINE PREDICTION

- Multi-messenger observation triggering requires online noise mitigation and signal analysis
- Low-latency input for **active mirror stabilization**
- Our **proxy**: prediction of the target sensor from the others



1.2 FPGA-BASED ARCHITECTURE

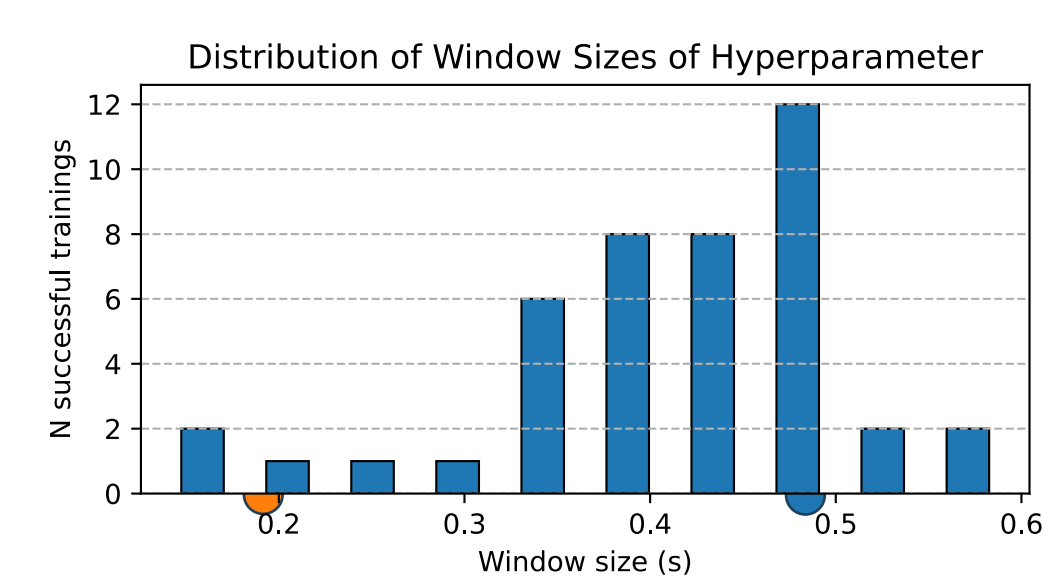
- Neural-network interface on FPGA
- Deterministic low-latency
- Streaming sensor input



2. MODEL SEARCH

Fixed parameters

- Epoch 1000
- Early stopping patience 10



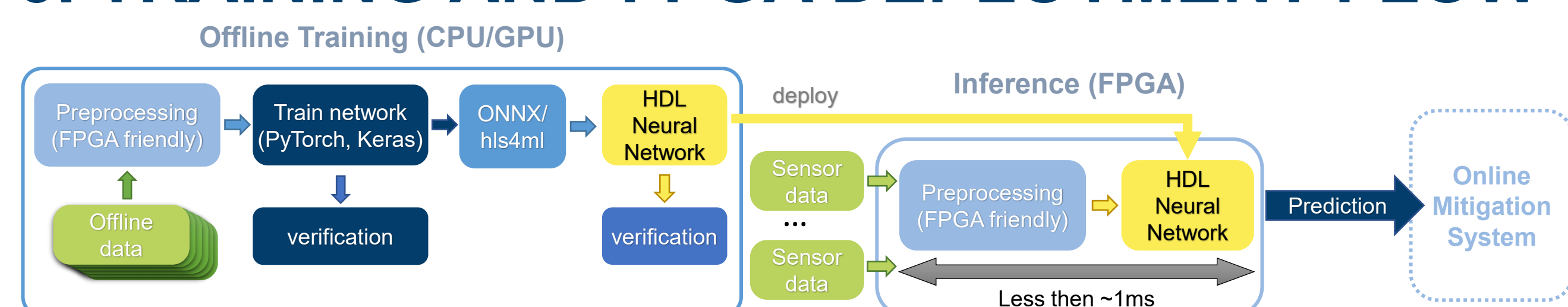
Data set Recorded at ETPathfinder Lab

- Size: 30 hours at 500 Hz/sample
- 13x **vertical** (Innoseis GRAVITON 0-20) sensors
- Data set from [2]: not shown but its Hyperparameter optimization yields Model B

Selected Model Hyperparameters [3]			
Hyperparameter	Model A	Model B	Search space
Window size	240	87	64–300 samples*
Learning Rate	6.37×10^{-4}	1.00×10^{-4}	$5 \times 10^{-5} - 10^{-3}$
Batch	64	16	1 – 128
Optimizer	Adam	RMSprop	—
Dropout	0.283	0.067	0.0 – 0.6
Conv. Layers	1	2	1 – 4
Channel L0	256	64	4 – 256
Kernel size L0	32	2	1 – 128
ReLU L0	False	True	—
Channel L1	—	16	4 – 256
Kernel size L1	—	2	1 – 128
ReLU L1	—	False	True/False
Hidden L2	16	32	4 – 256

*sampling rate: 500 Hz

3. TRAINING AND FPGA DEPLOYMENT FLOW



Resource Utilization for Model B (Model A pending due to ONNX issues)				
Input channels	BRAM (18K)	DSP	FF (K)	LUT (K)
1	402	71	91	73
4	409	70	95	73
8	417	70	101	76
11	422	71	105	77
13	426	71	108	78
22	444	73	119	82
ZCU216	2160	4272	850	425

- Offline Training:** PyTorch model optimization
- Conversion:** PyTorch → ONNX → HLS4ML → HDL
- Target:** sub-ms FPGA inference
- Driver for Search:**
 - prediction quality,
 - model size / FPGA deployment ability

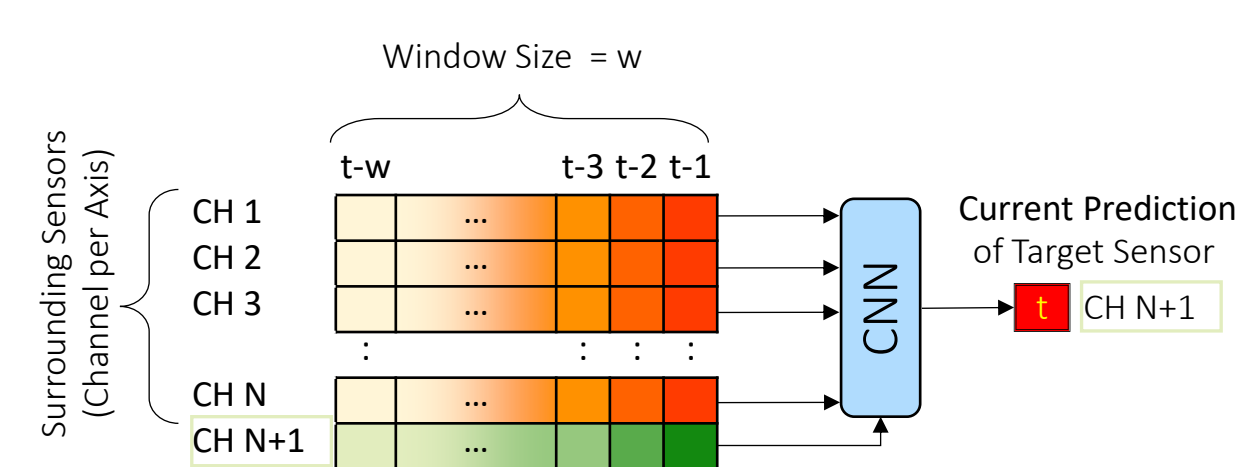
4. IDEALIZED BASELINE STUDY

Injected ground truth (GT), i.e. target sensor data, among the input channels for model testing (upper bound baseline). Analysis done in python, respecting FPGA limits.

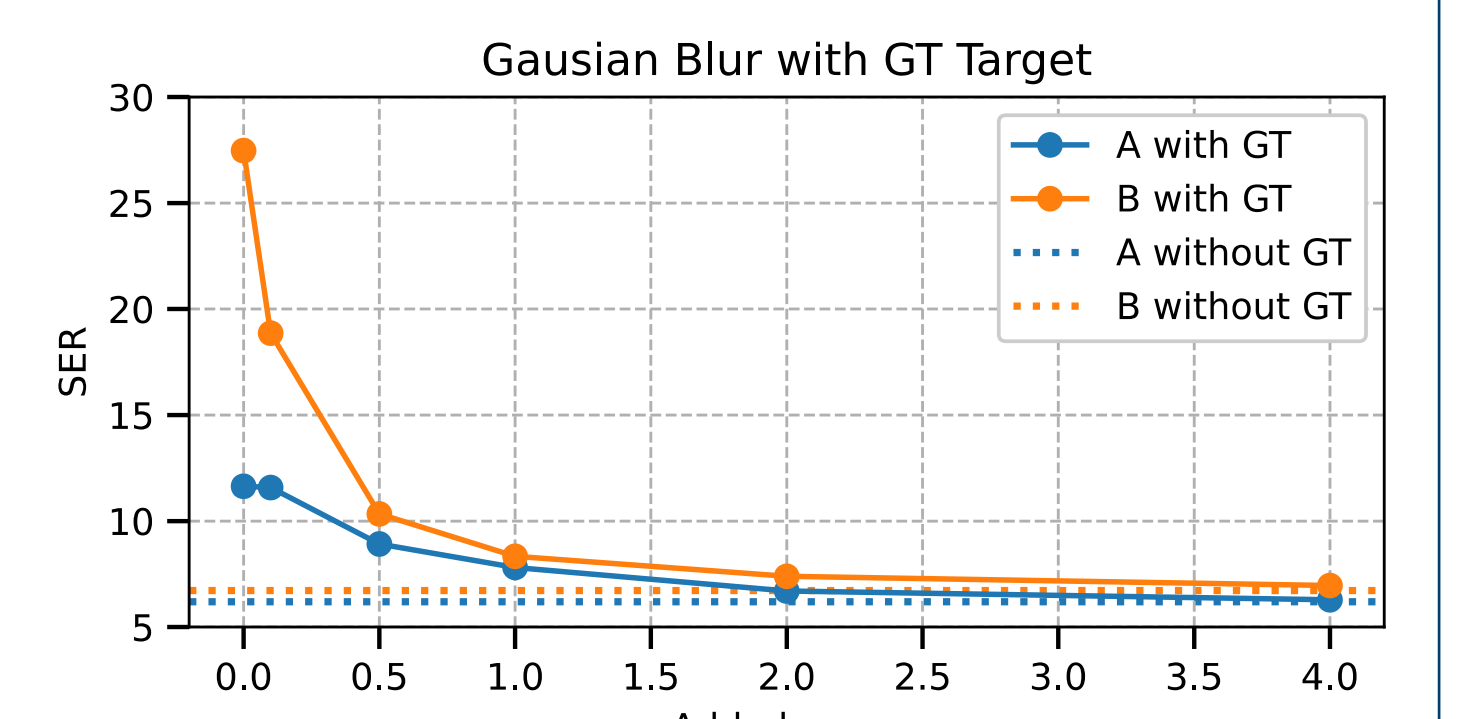
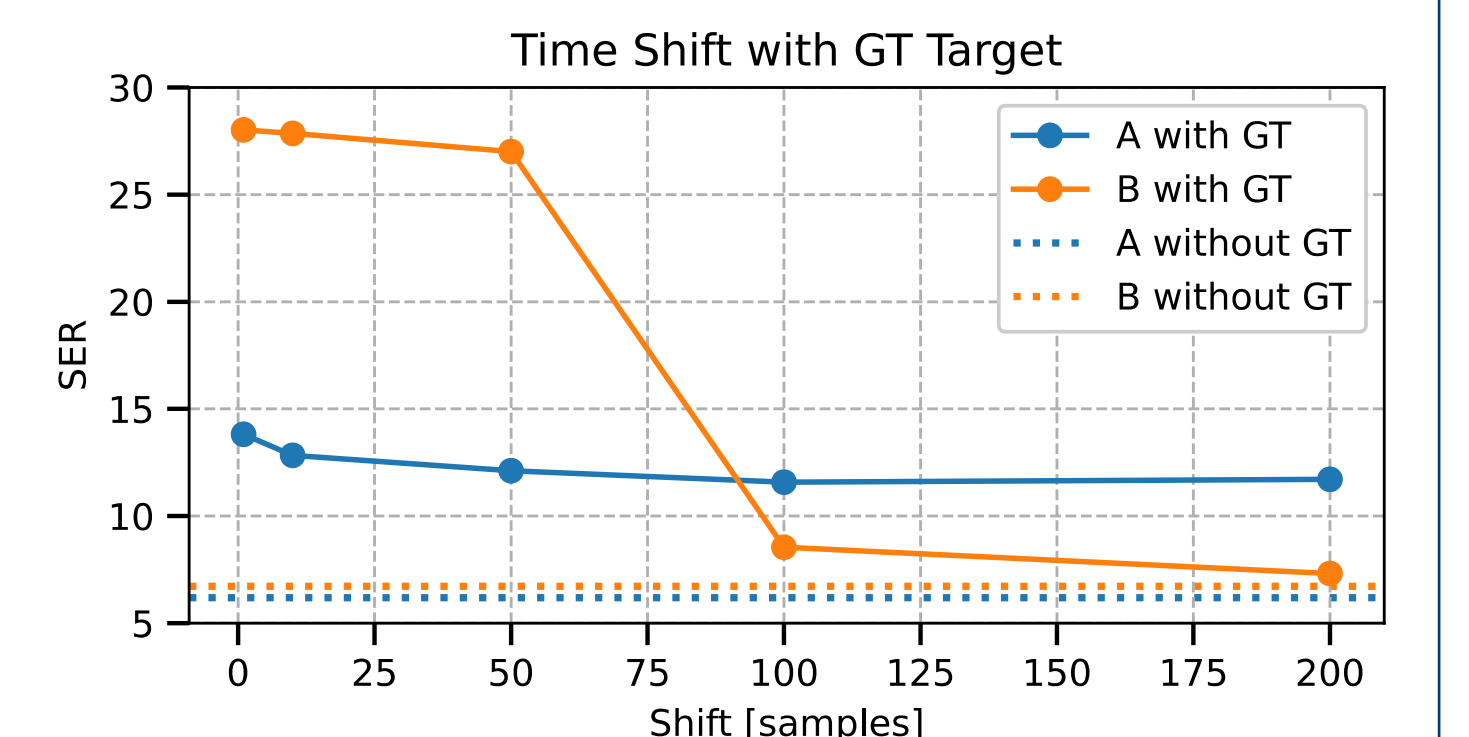
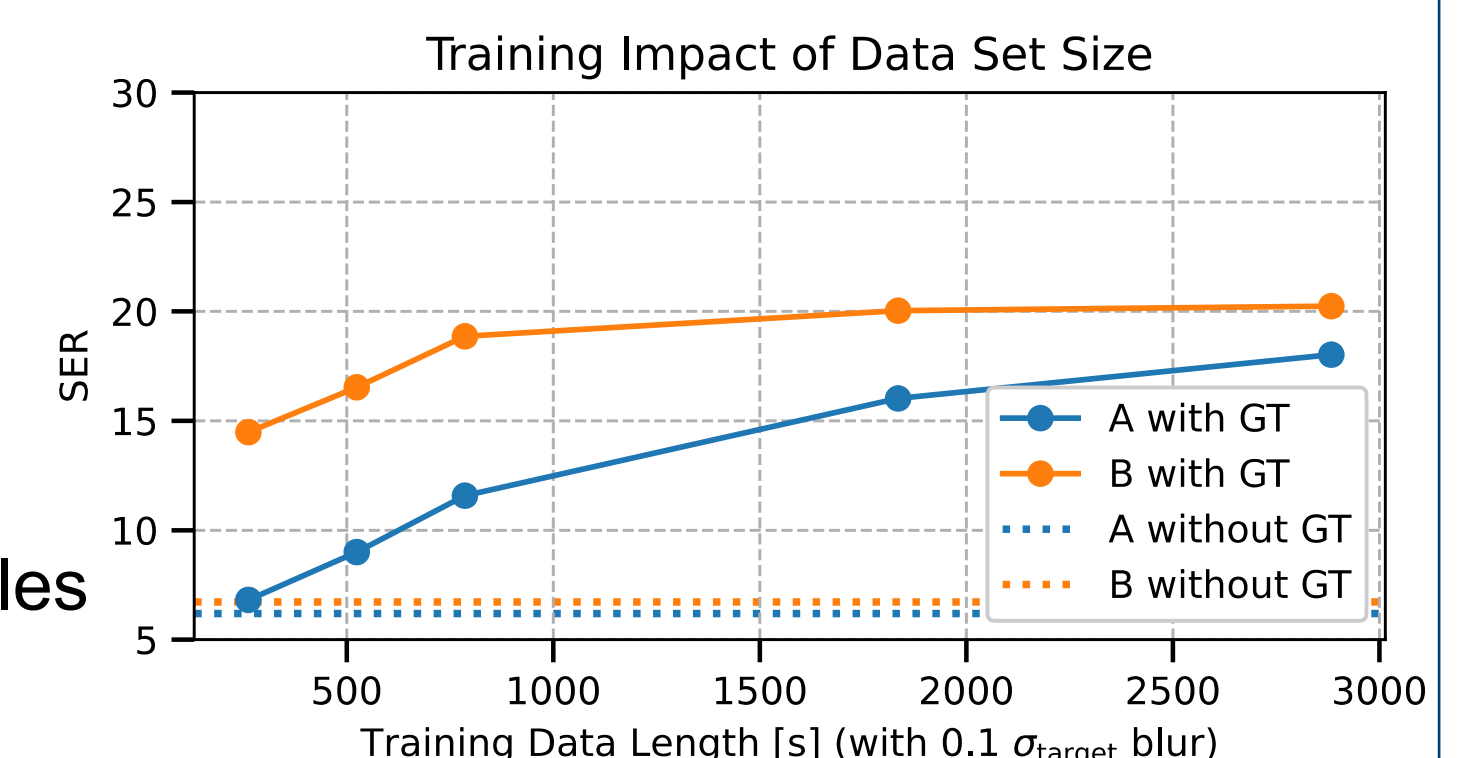
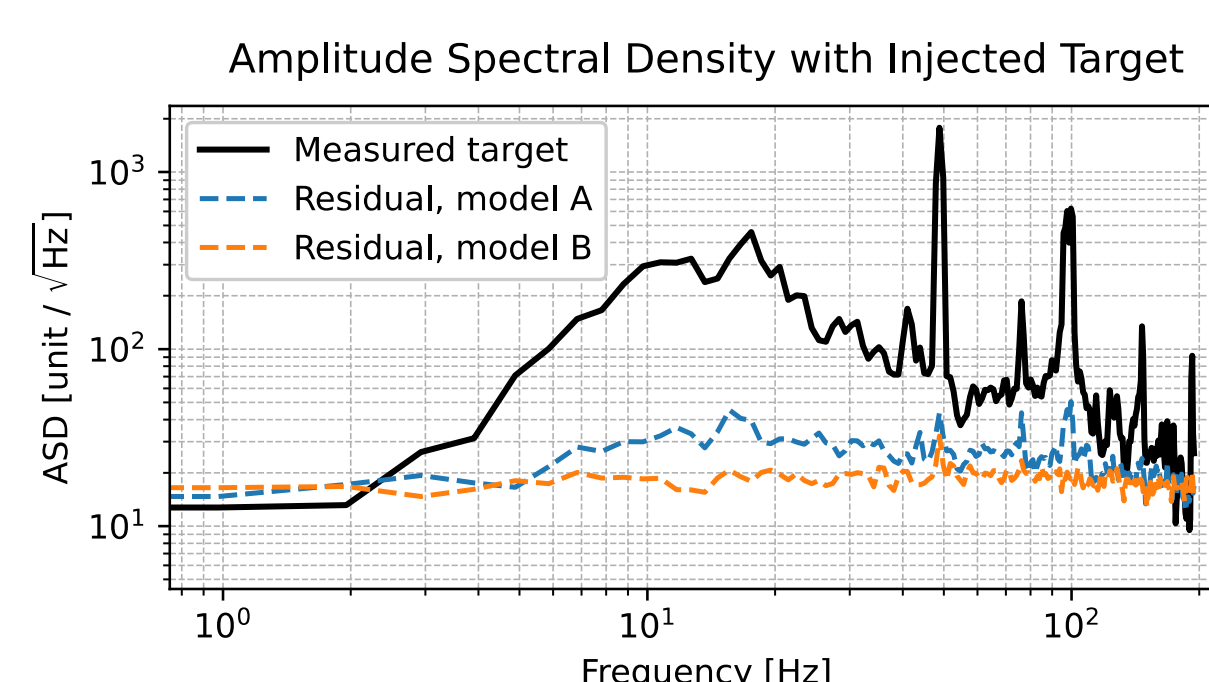
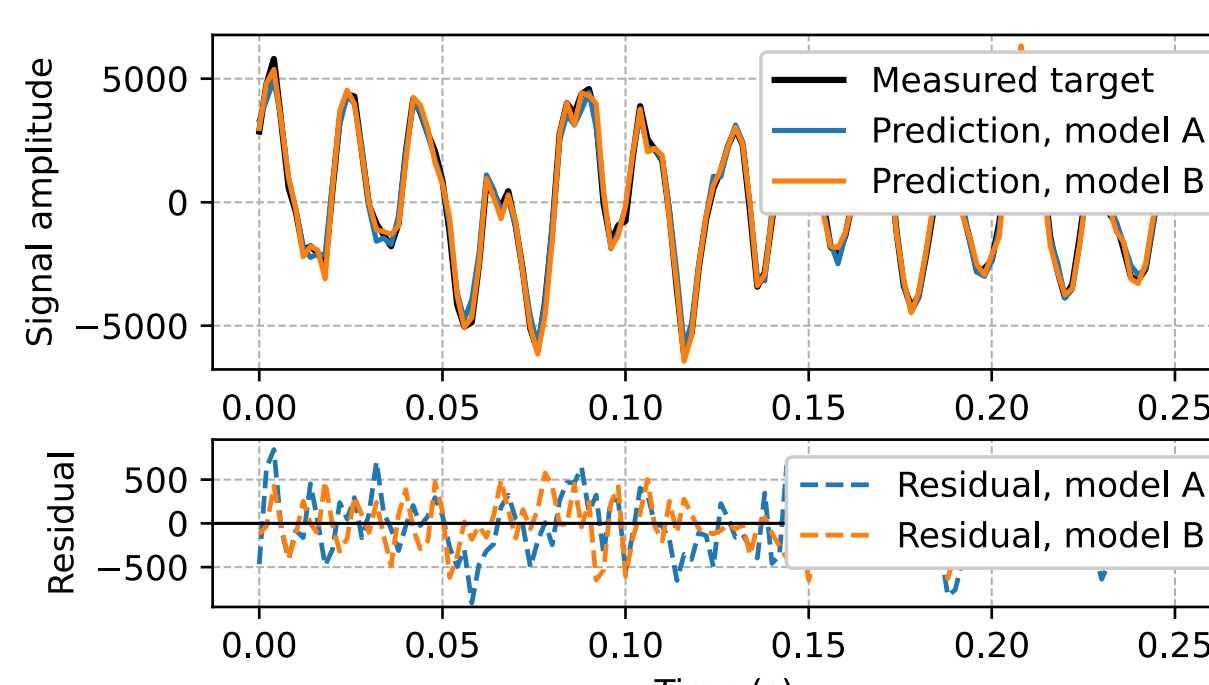
Signal to Error Ratio (higher is better)

$$SER = 10 \times \log_{10} \frac{\sum_{i=1}^N y_i^2}{\sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

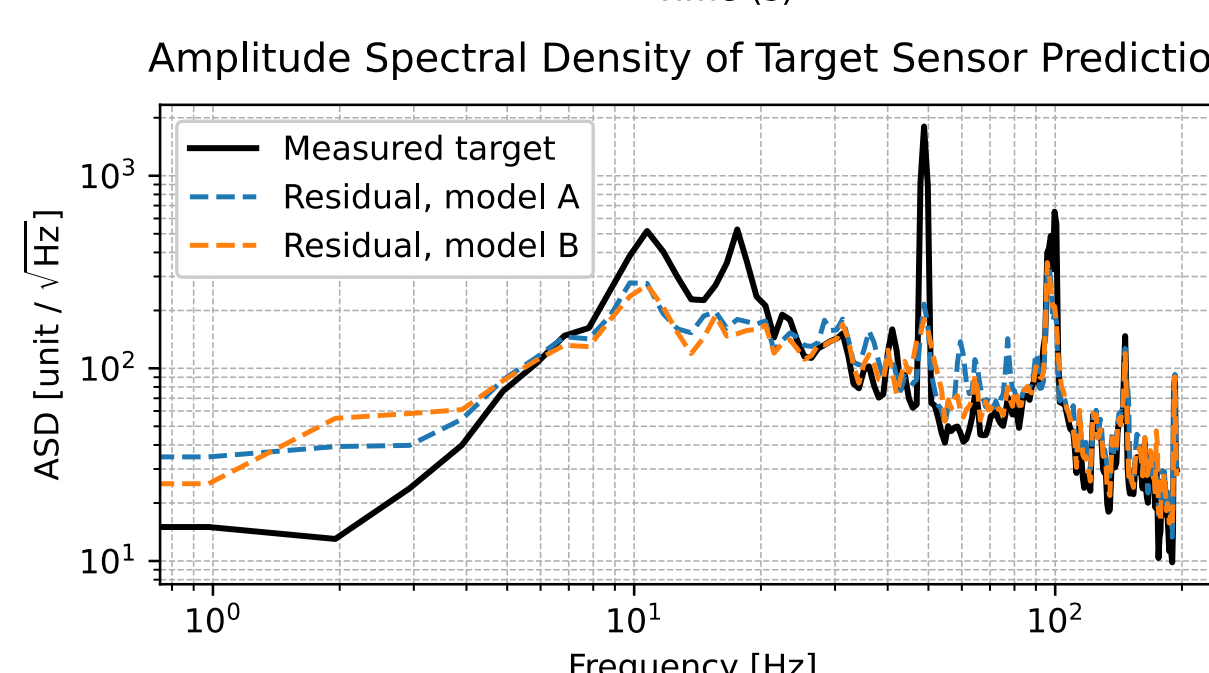
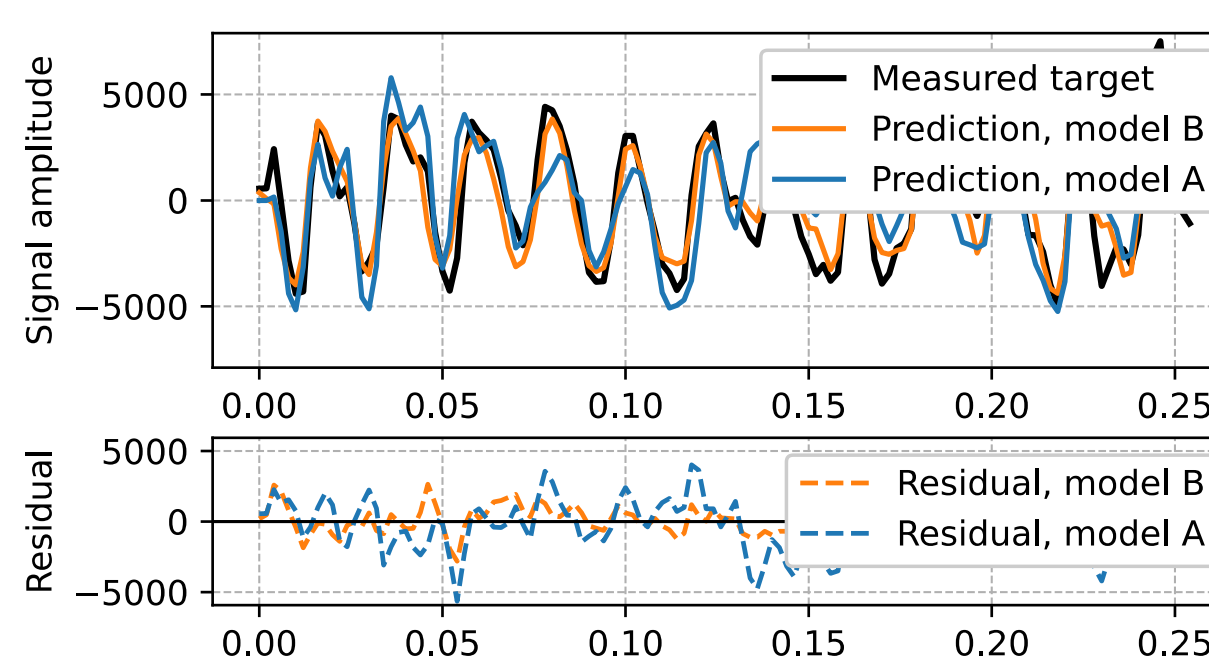
SER is the ratio between target-signal power and residual power, expressed in dB



- Training data length at least 1800 s
- Arrival Δt shift ok if within window
 - e.g. Model B window = 87 samples
- Adding noise reduces accuracy
 - Nominal ~ 4 sigma blur

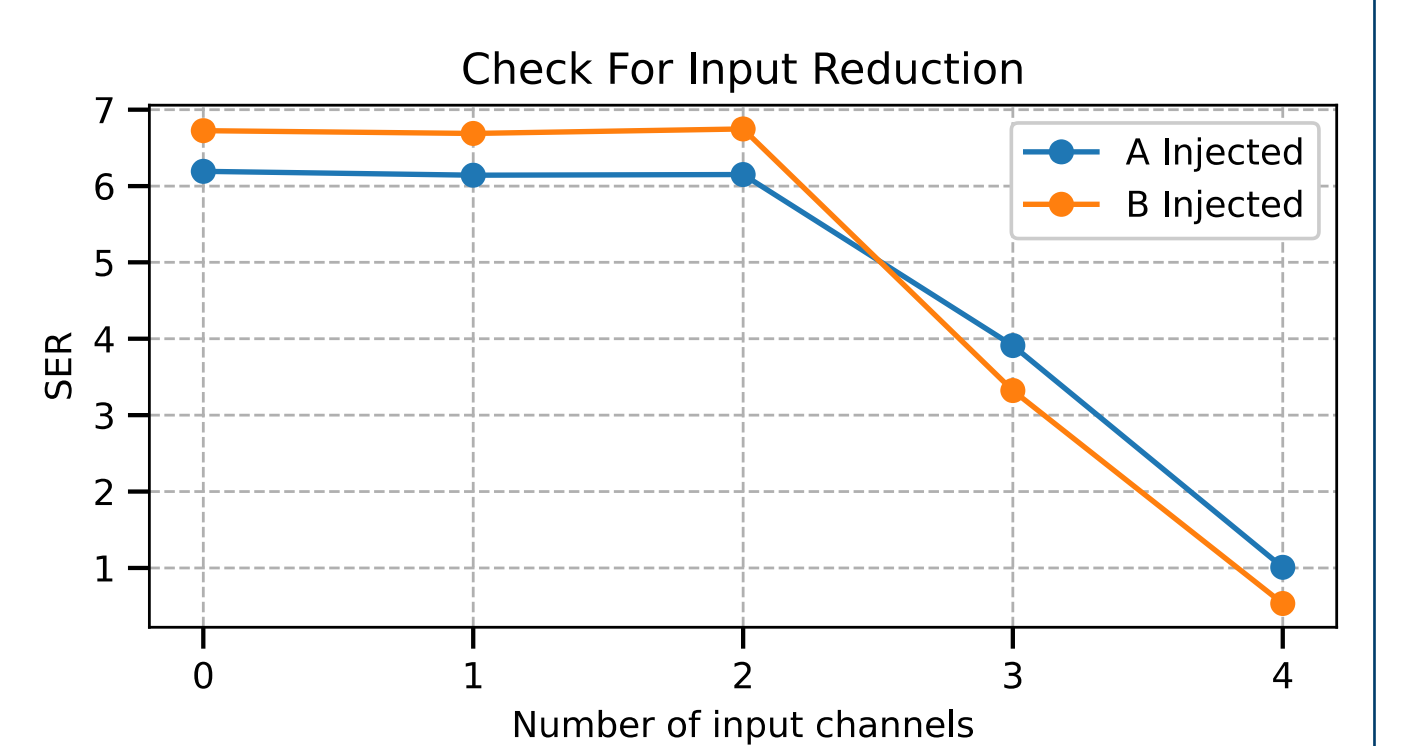


5. VALIDATION RESULTS



Model	RMS _{res}	Residual / measured
Model A	353.5	0.120
Model B	268.6	0.093

The performance of both models (A,B) is evaluated by comparing the predicted signal with the measured target sensor signal. The residual qualifies unpredicted seismic component.



Residual RMS Compared with Measured Signal

$$(2) \quad RMS = \sqrt{\int_1^{220} ASD^2(f) df}$$

- Reduction of ~90% of initial measured signal for target sensor
- Model deployable on ZCU216 evaluation board
- Model B hyperparameters suitable for Model A data, similar performance

CONCLUSION AND OUTLOOK

A pipeline for FPGA-based, low-latency prediction of ETPathfinder accelerometer data is developed. It is based on neural network models that are selected, trained, and validated for seismic target sensor prediction, achieving up to **90% amplitude mitigation** in a first implementation while staying under idealized potential.

Future work will focus on improving the prediction accuracy, estimating real-time latency, optimizing FPGA resource usage, and testing the complete online system.