# Convolutional Neural Networks for Frequency Response Predictions

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# Convolutional Neural Networks for Frequency Response Predictions

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*Presented by:*

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AMRDEC – Aviation Engineering Directorate

3 May 2017 – ASME V&V Symposium

# Background and Objectives

# Background



IMAGENET

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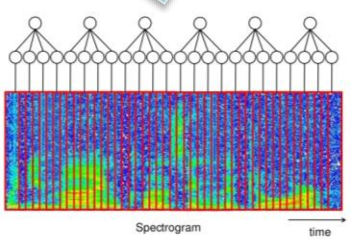
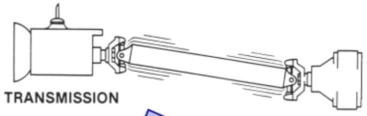
Microsoft CNTK

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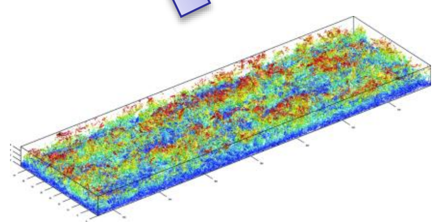
Sandia/AED Collaboration: Applying CNNs to frequency-response modeling

KDD



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# Test Problem Background



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- **Turbulent Boundary Layer Wall PSD**
  - LES is relatively cheap but misses near-wall dynamics
  - DNS is very expensive but high fidelity
  - Can CNNs use free-stream PSDs to predict wall PSDs?

- **Axial/Vertical Sensor Redundancy**
  - Two accelerometers fielded to all aircraft in perpendicular axes
  - Sensors + wiring costly (lbs on aircraft)
  - Years of collected operational spectra
  - Can CNNs use axial axis spectrum to predict vertical axis spectrum?

# CNNs for Frequency Response: Project Goals



- Can CNNs or other machine learning models be trained on spectral data sets to a satisfactory degree of accuracy?

- Do Convolutional Neural Networks provide any advantage over simpler methods?

- How can CNNs be validated for use as surrogate models to physical systems or high fidelity simulations?

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# Model Architectures



1. No model; use the input spectrum.

2. Random Forest Regressor
   – scikit-learn; 500 trees
3. Multilayer Perceptron (MLP)
   – 3 hidden layers; leaky ReLU
   – Optimized hyper parameters
   – 200-600 neurons per hidden layer
4. Convolutional Neural Network (CNN)
   – Conv → MaxPool → Dense
5. Convolutional-Deconvolutional NN (CDNN)
   – Conv → MaxPool → Dense → Dense → UnPool → Deconvolution

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1. No model; use the input spectrum
2. Linear Ridge Regression
3. Random Forest Regressor
   – scikit-learn; various params
4. Multilayer Perceptron (MLP)
   – 3 hidden layers; leaky ReLU
   – Optimized hyper parameters
   – Up to 512 neurons per hidden layer
5. Convolutional Neural Network (CNN)
   – Conv → MaxPool → Dense
6. Convolutional-Deconvolutional NN (CDNN)
   – Conv→ Dense → Dense→ Deconvolution

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# Sandia: Results

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# DNS Data Set

1. Mach 2.0 compressible flat plate turbulent boundary layer
2. Low-dissipation 5th order upwind biased flux-reconstruction scheme
3. Fourth order explicit Runge Kutta time integration
4. 100.7 M mesh cells
5. Near wall resolution: $\Delta x^+ < 5$, $\Delta y^+ < 0.2$, $\Delta z^+ < 4$
6. $1075 < Re_\Theta < 1310$
7. Run for > 1200$\tau$ (where $\tau = \delta_0 / U_\infty$)

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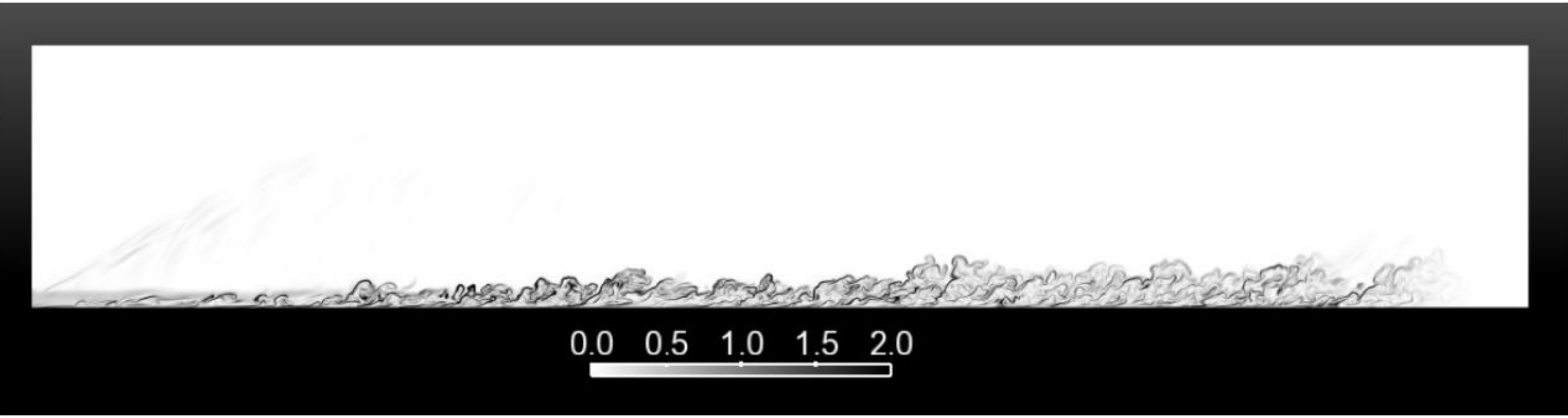
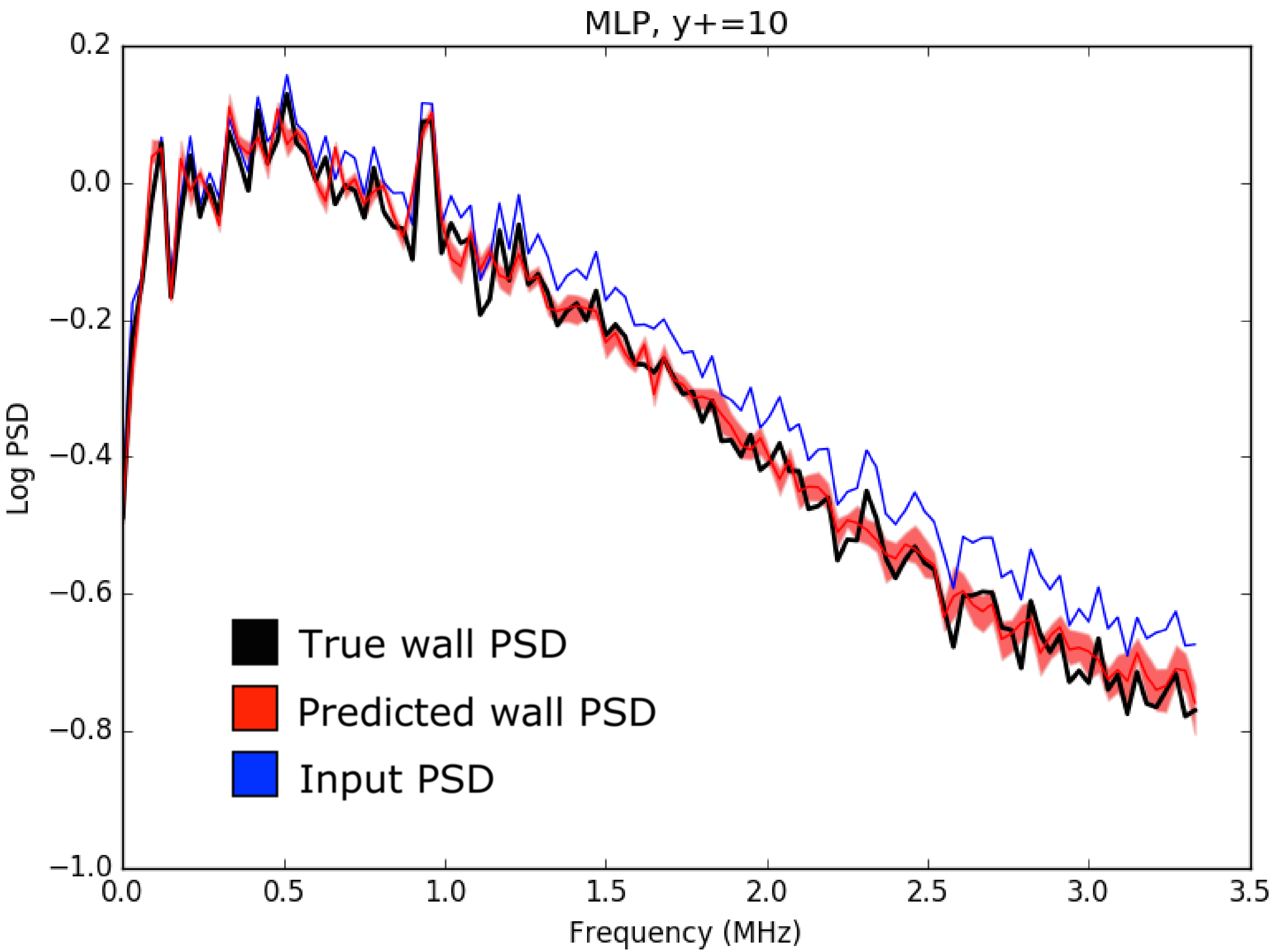


Sandia Wall PSD Results

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# Sandia Wall PSD Results

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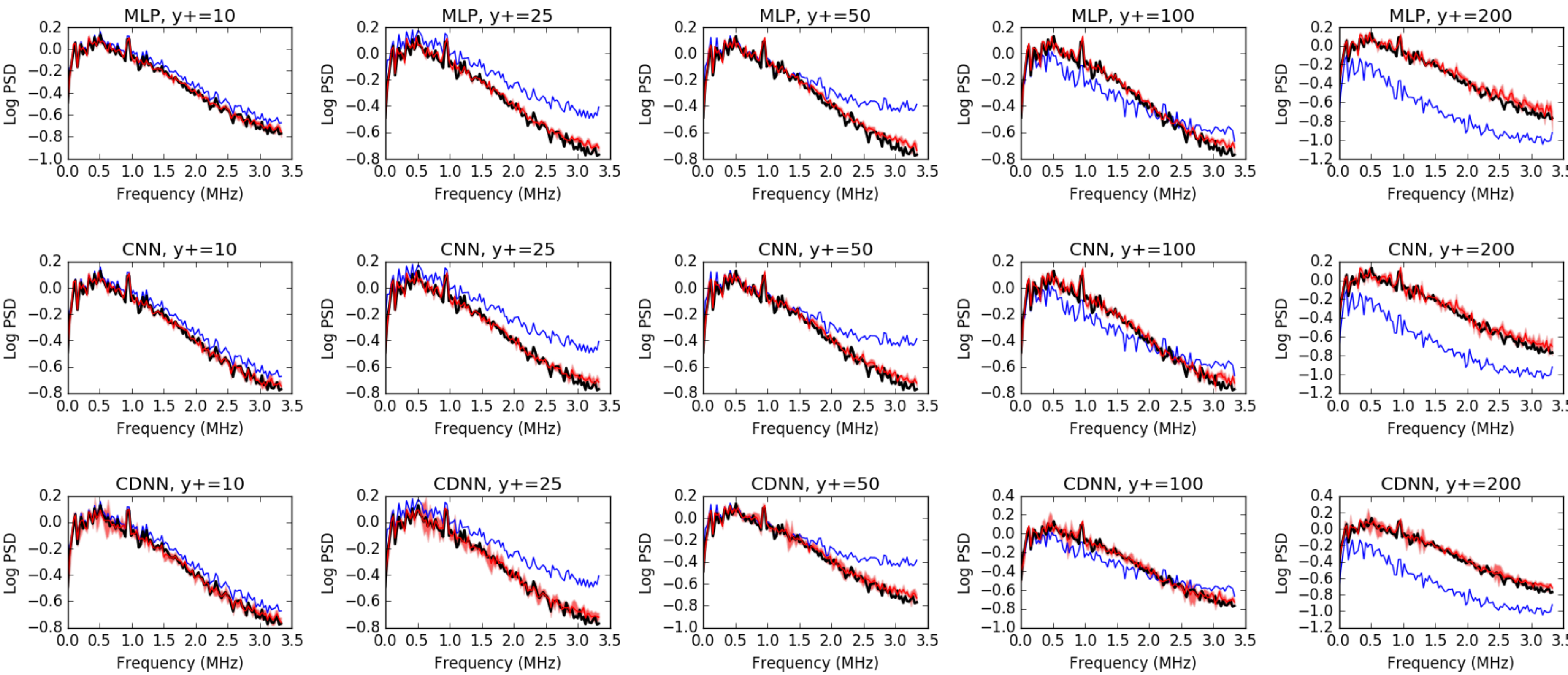
True wall PSD

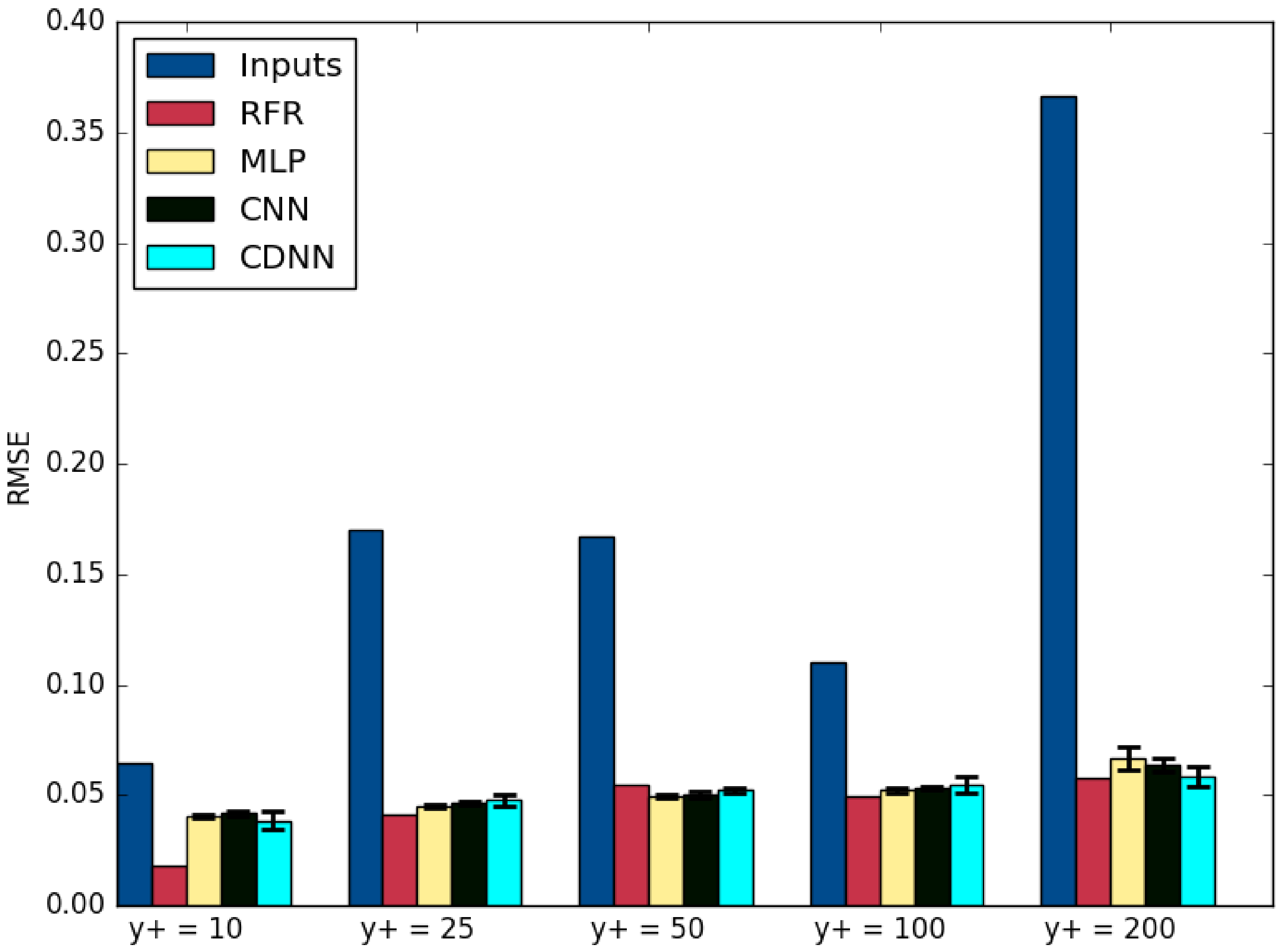
Predicted wall PSD

Input PSD



# Sandia Wall PSD Results



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# AED: Results

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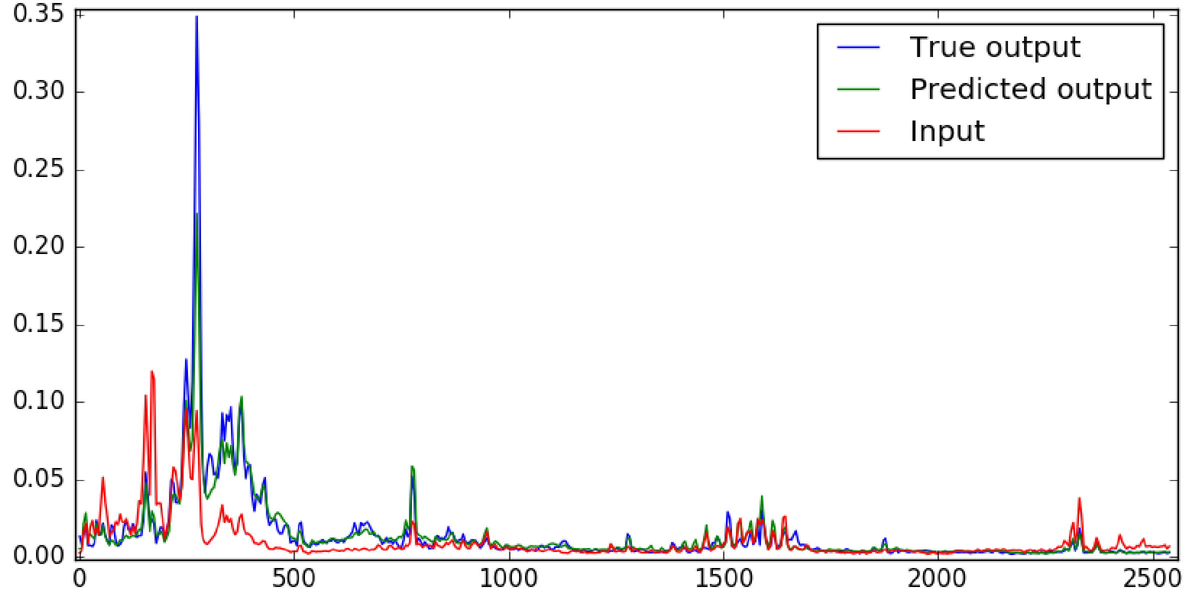
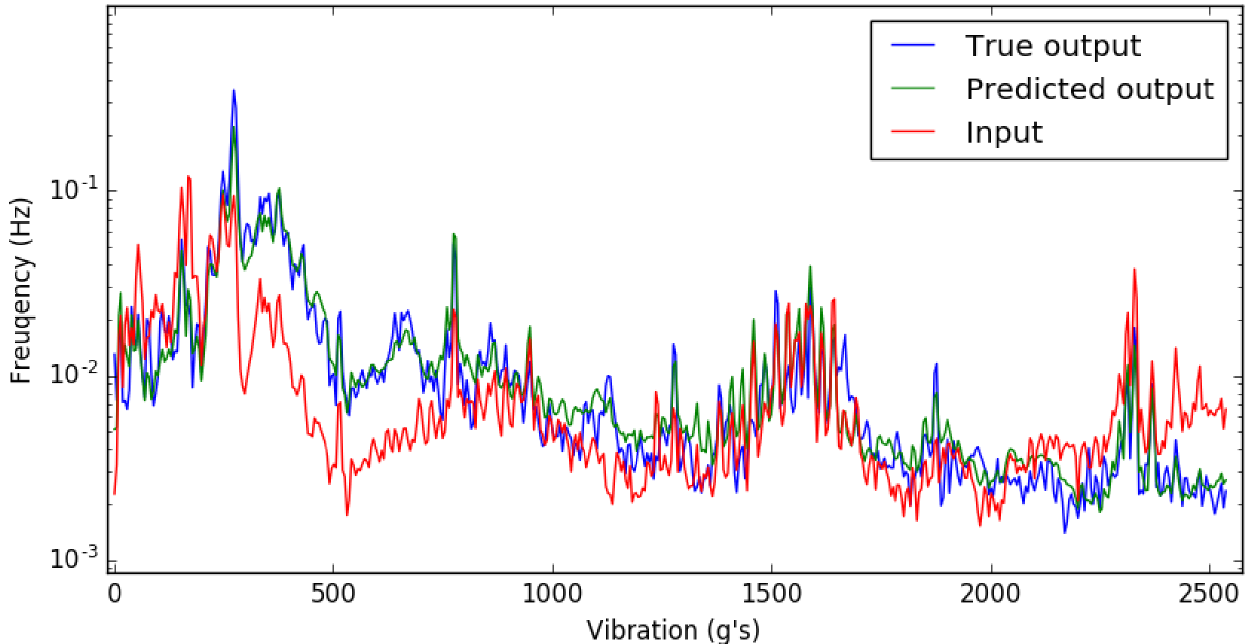
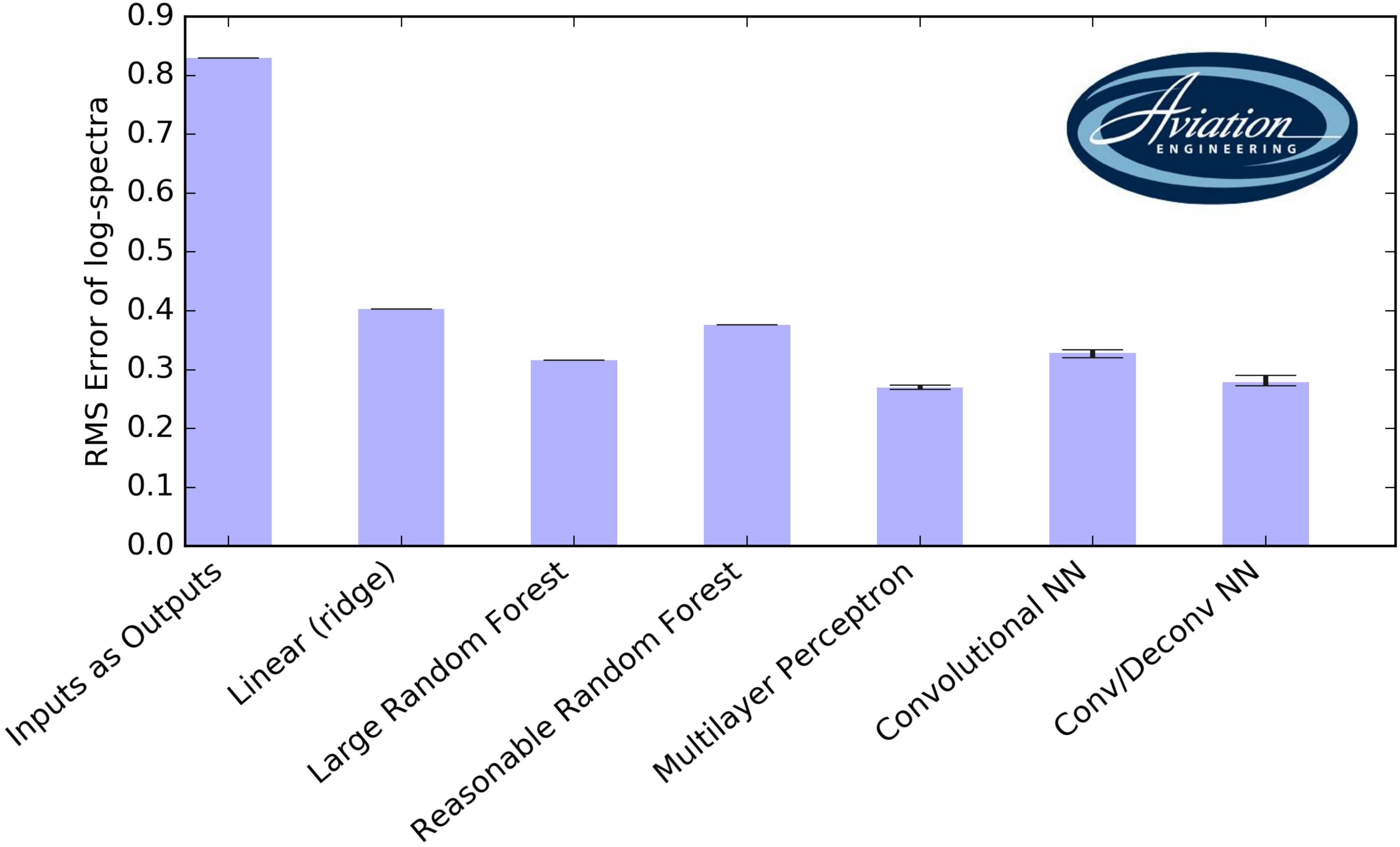
# AED Perpendicular Axis: Results



# AED Perpendicular Axis: Results

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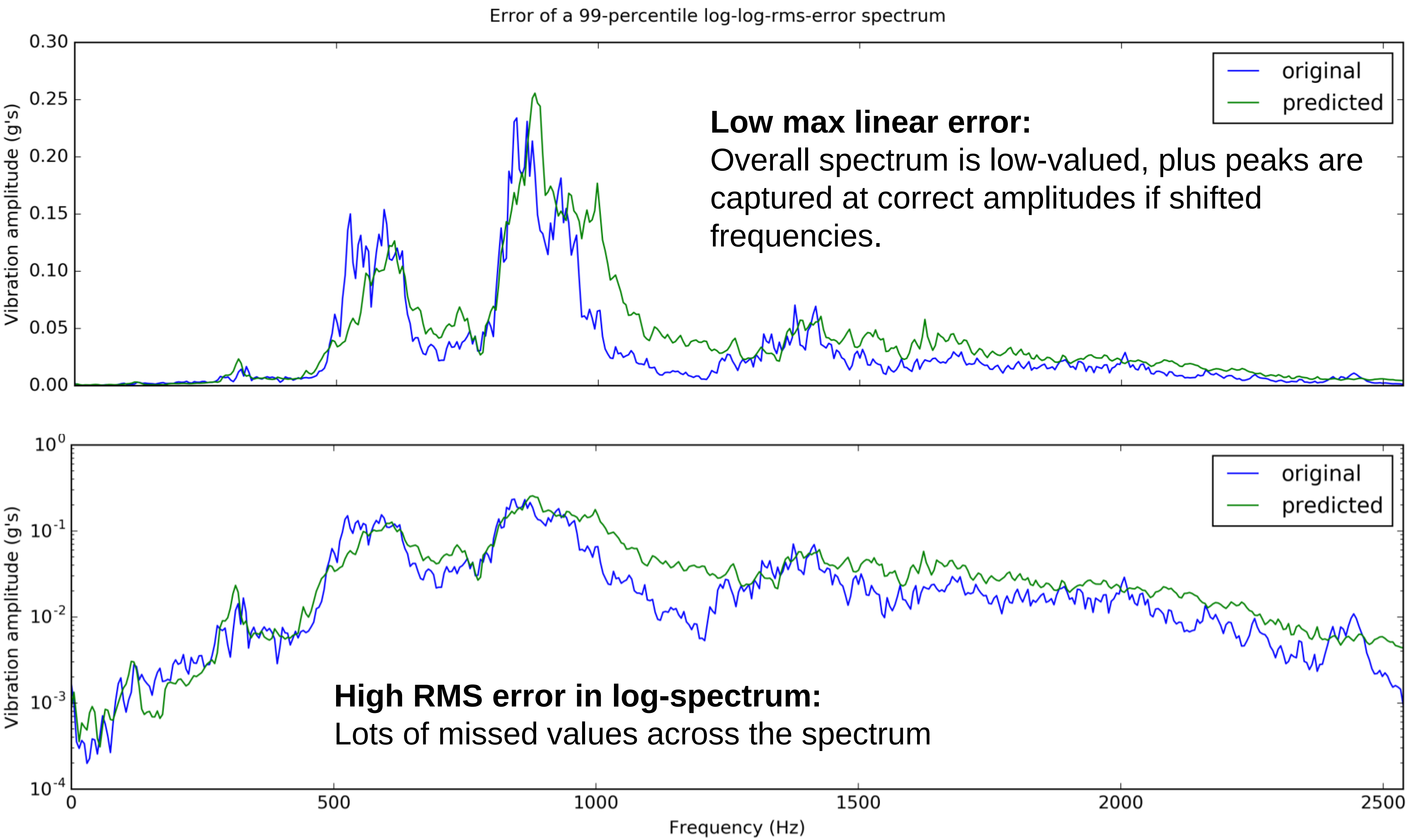
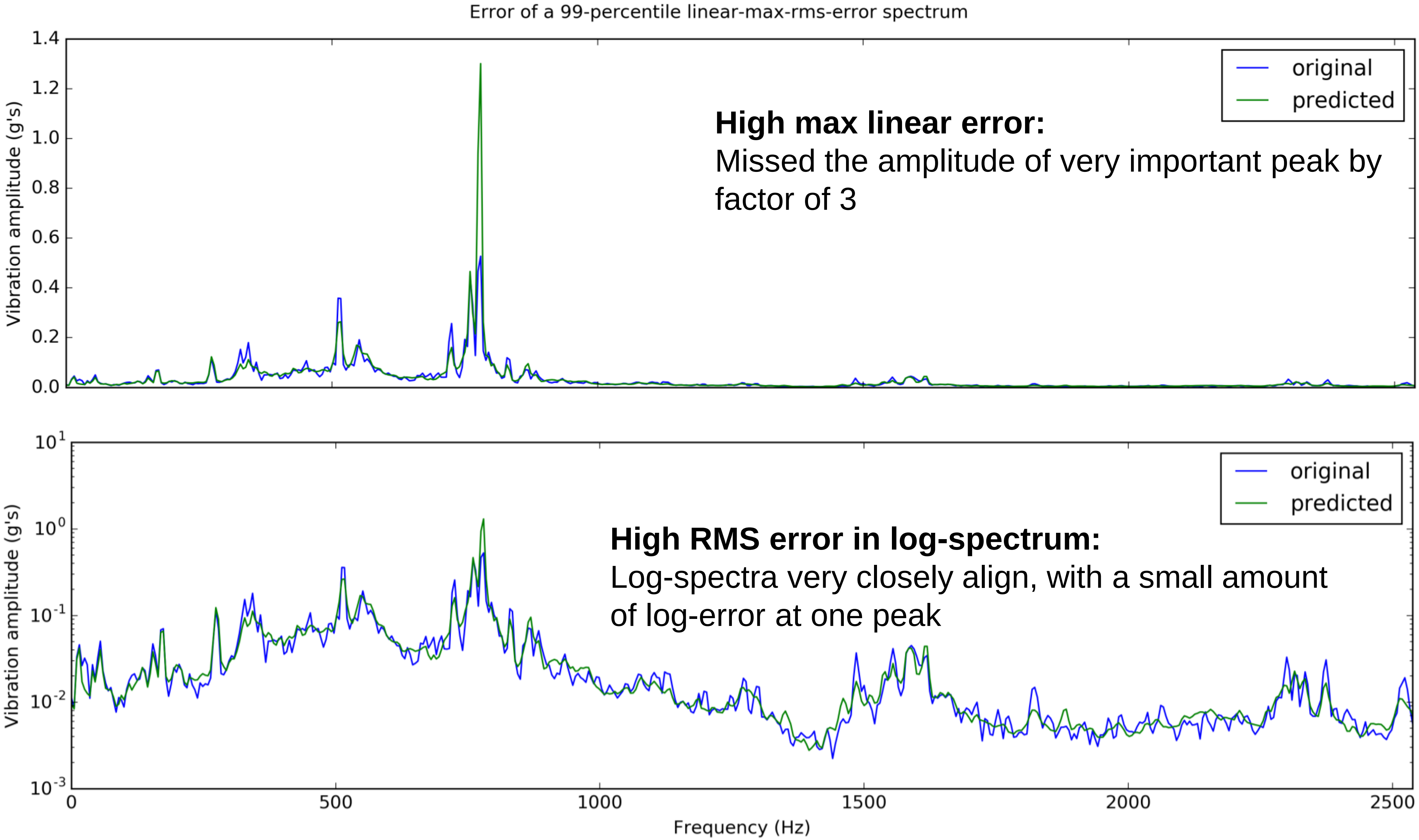
# Metrics and Validation; Conclusions


Error of a 99-percentile log-log-rms-error spectrum
Vibration amplitude (g's)
0.30
0.25
0.20
0.15
0.10
0.05
0.00
original
predicted
Low max linear error:
Overall spectrum is low-valued, plus peaks are captured at correct amplitudes if shifted frequencies.
Vibration amplitude (g's)
$10^{0}$
$10^{-1}$
$10^{-2}$
$10^{-3}$
$10^{-4}$
original
predicted
High RMS error in log-spectrum:
Lots of missed values across the spectrum
0
500
1000
1500
2000
2500
Frequency (Hz)

# RMS vs Max
# Linear vs Log




**High max linear error:**
Missed the amplitude of very important peak by factor of 3

**High RMS error in log-spectrum:**
Log-spectra very closely align, with a small amount of log-error at one peak

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# Conclusions and Future Work



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- Performance of all methods similar
- Can predict PSD at wall, even out to y+ = 200
- High frequency predictions require further work
- Data partitioning methodology

- Definite difference in performance
- Depth of NN important?
- Max-errors unacceptable in linear domain
- RMS errors very good

- Pursue max-error loss functions for NN training
- Need to further explore validation/evaluation criteria
- Powerful and promising methods

# Questions

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