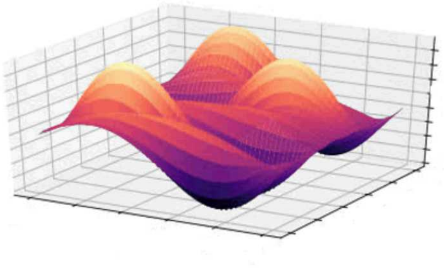
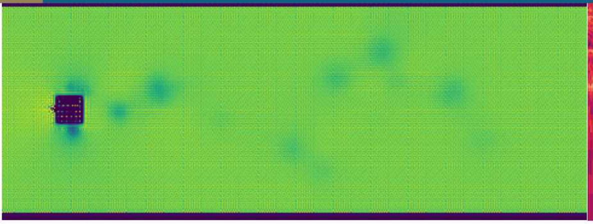
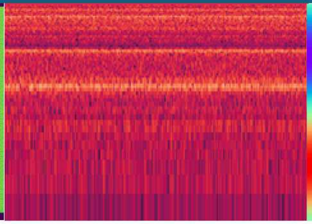
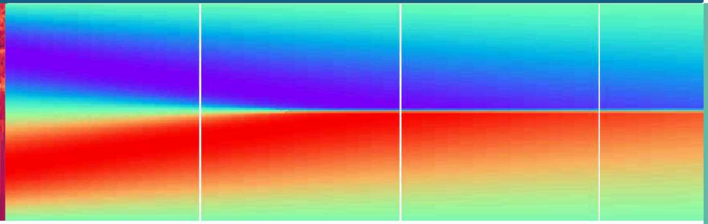
SAND2019-5886C

Machine Learning to Replicate Launch Vibration Conditions with Ground Testing









Spacecraft and Launch Vehicle Dynamic Environments Workshop 2019

PRESENTED BY

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Team: Adam Brink (Sandia National Labs)

Carianne Martinez (Sandia National Labs)

Kevin Potter (Sandia National Labs)

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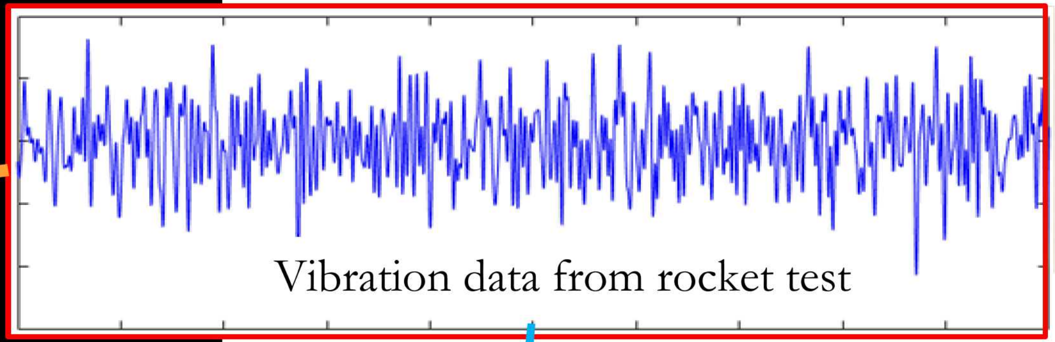
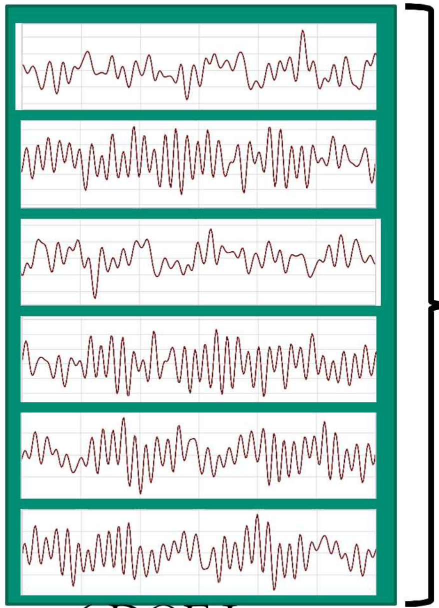
Can we replicate exact flight conditions during ground testing without a structural model?

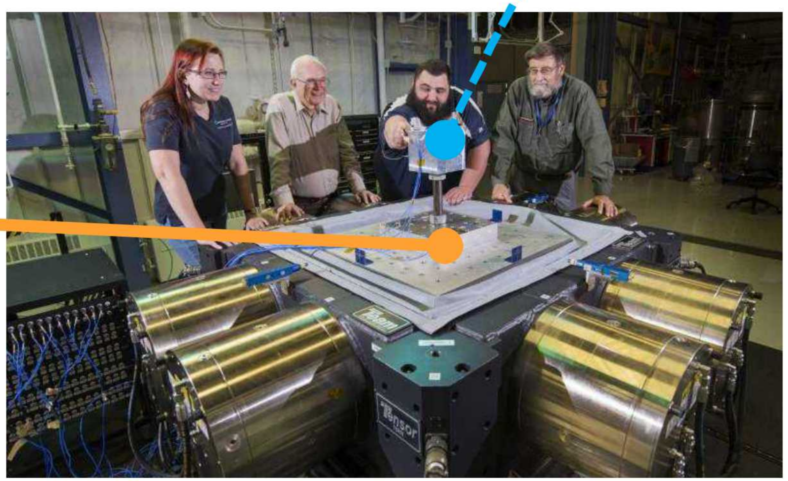


Vibration data from rocket test

Image credit: NASA



6 DOF Input



System on 6 DOF shaker

Objective: To replicate the exact flight environment during ground testing **without having to build a model** by reconstructing excitation force.

The typical approach for determining a shaker input relies on a finite element model to compute a transfer function between DOFs

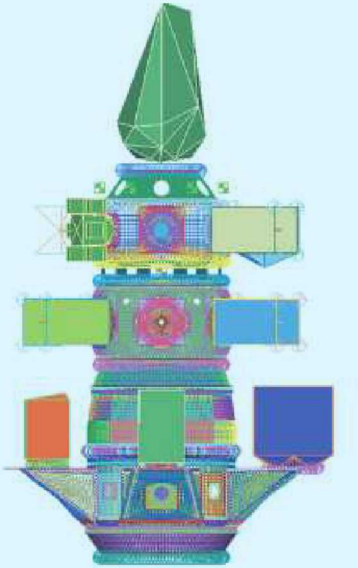
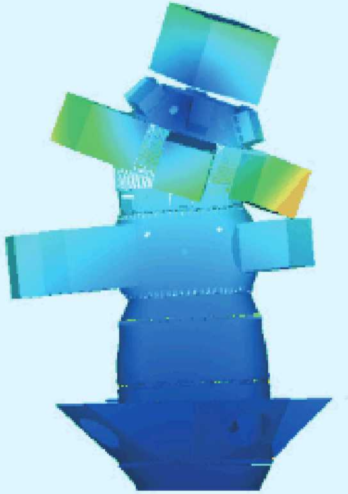
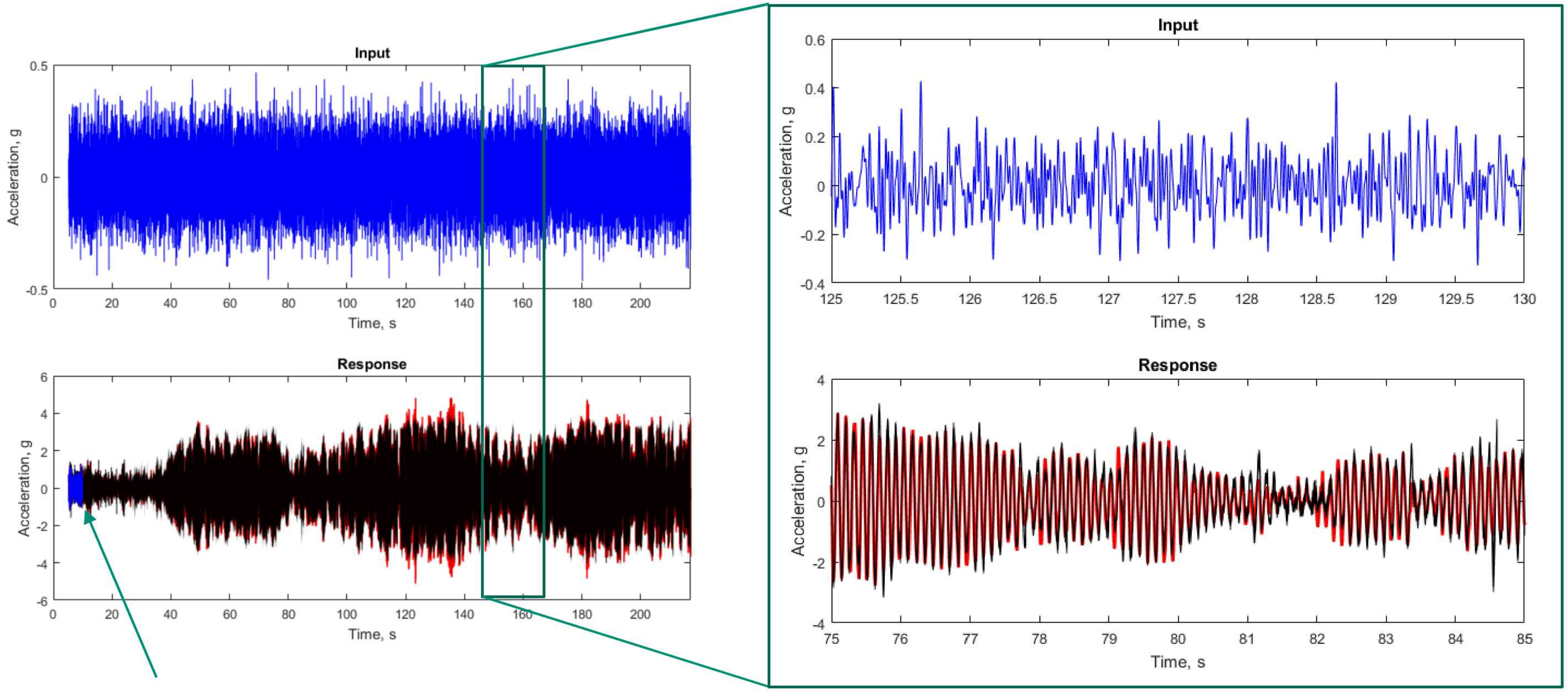
Build FEM and perform modal correlation to test data	Obtain mode shapes and mode frequencies	Force Reconstruction
 		Sandia's ***Sum Weighted Accelerations Technique*** (SWAT): Assumes linearity and relies on mode shapes ATA's ***Least Squares Force Reconstruction***: Assumes linearity and operates in the frequency domain

Image credit: ATA

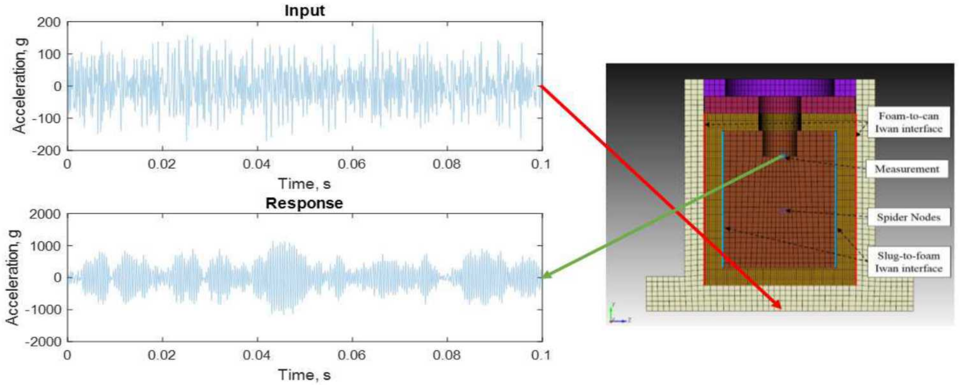
Can we develop a pure data-driven approach that does not rely on a finite element model AND does not assume linearity?

Recurrent neural networks were recently used to predict random vibration response of nonlinear systems



Actual
Prediction

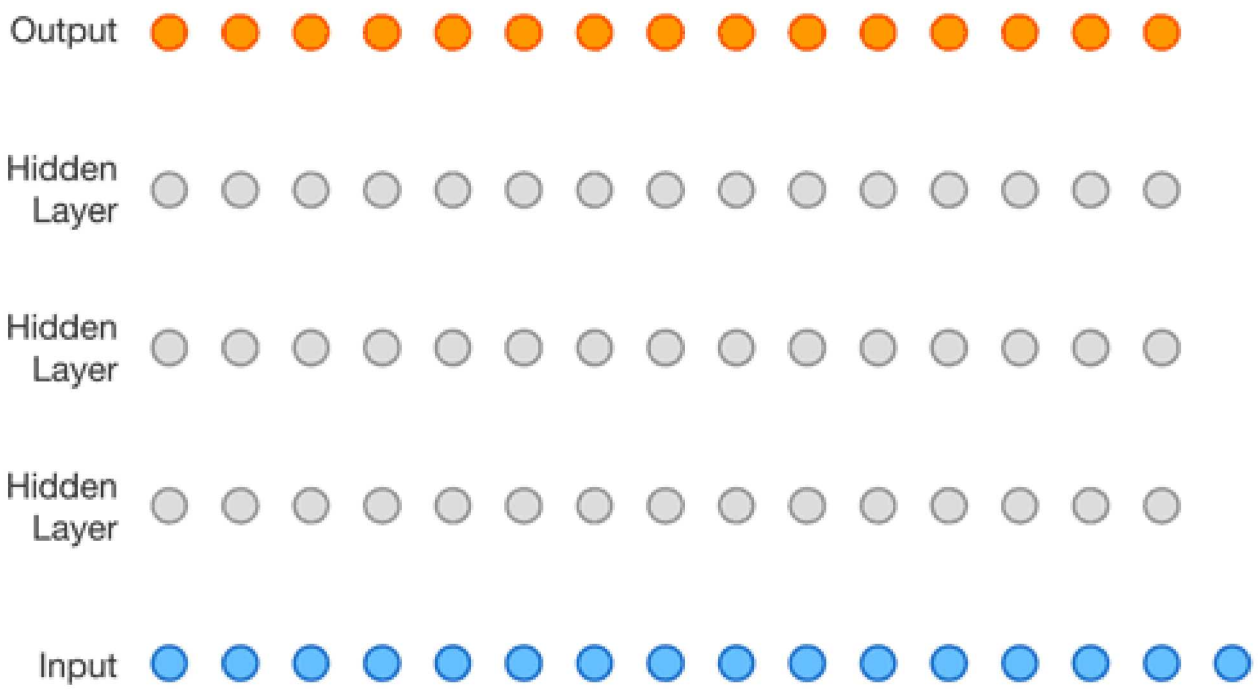
Portion of output that had to be fed to neural network



Najera-Flores, D.A., and A.R. Brink, "Efficient Random Vibration Analysis of Nonlinear Systems with Long Short-Term Memory Networks for Uncertainty Quantification." Proceedings of ISMA 2018 International Conference on Noise and Vibration Engineering and USD2018 International Conference on Uncertainty in Structural Dynamics, 2018.

A recurrent neural network used for speech generation was adapted to map random vibration response between DOFs

The Temporal Convolutional Network (TCN)



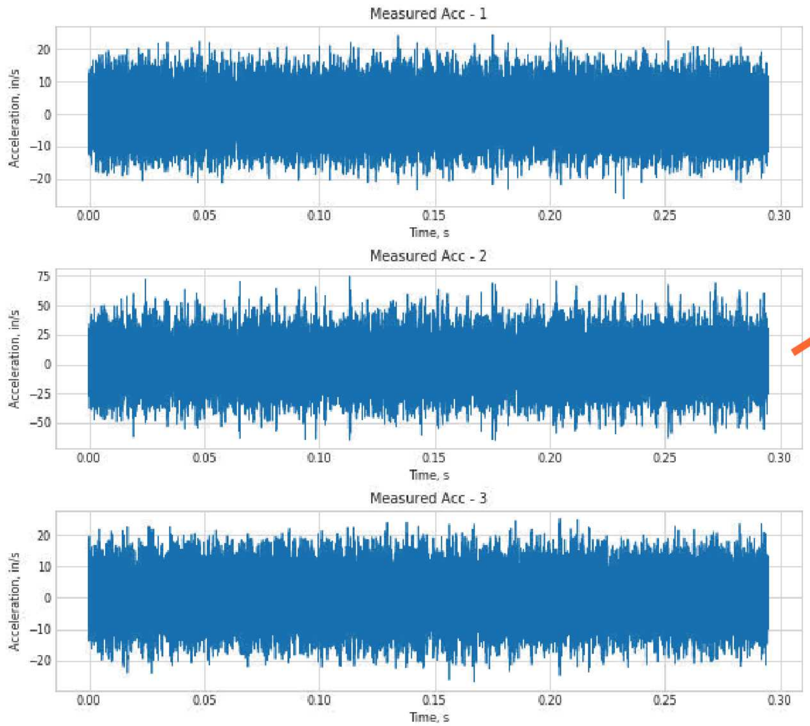
https://deepmind.com/blog/wavenet-generative-model-raw-audio/

The WaveNet was developed for text-to-speech generation.

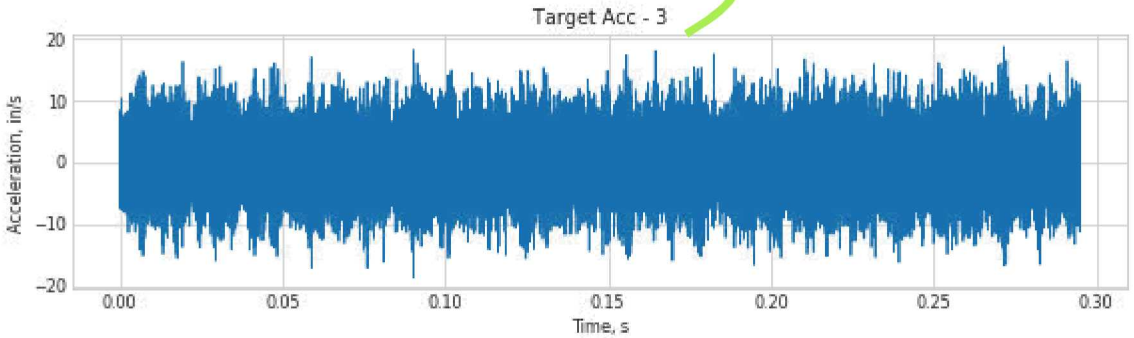
It is an autoregressive model that predicts one timestep at a time based on the knowledge of the previous states and inputs/outputs.

Instead of text and speech, the inputs and outputs were accelerations measured at different locations on a structure.

Source of training data would come from component response during ground test excitation to white noise



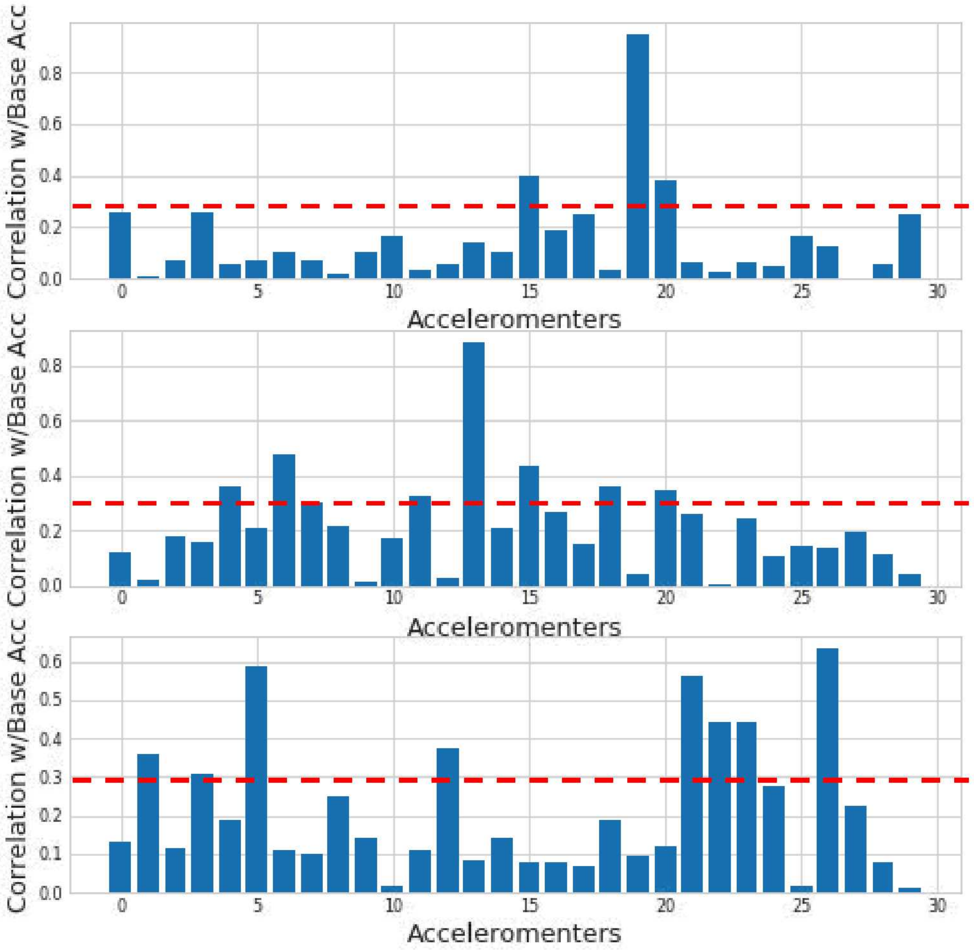
Response at gauges

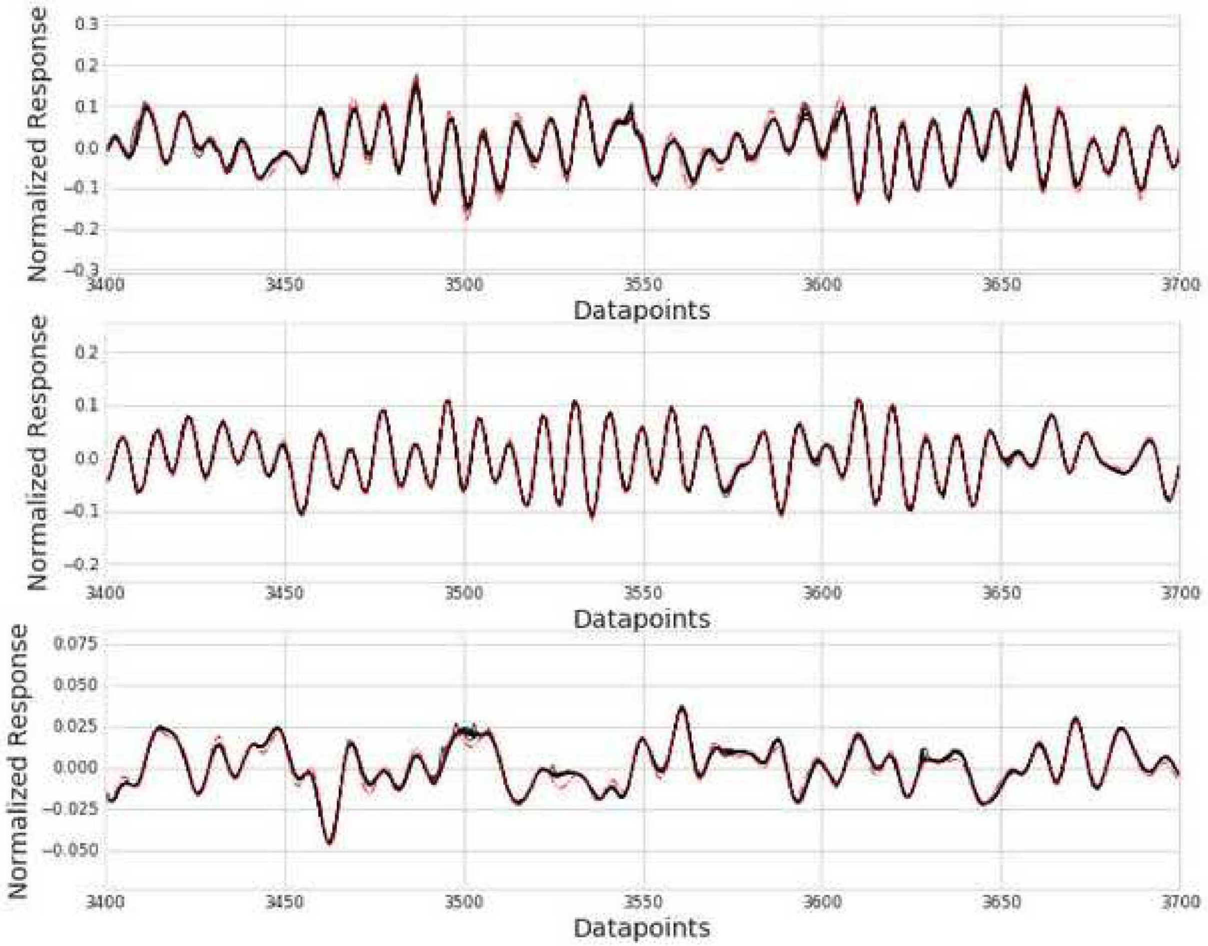


Input excitation

How many gauges are enough to find an exact mapping?

Idea: Pick the accelerometers with highest correlation to base acceleration





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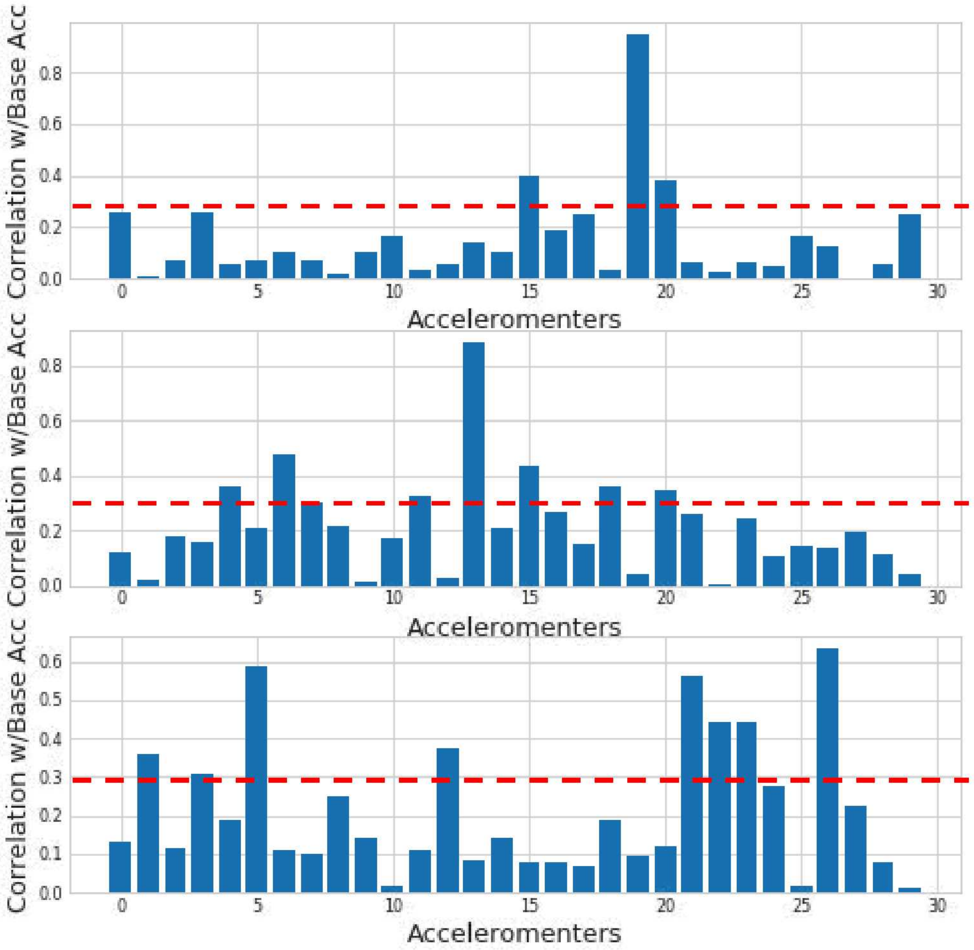
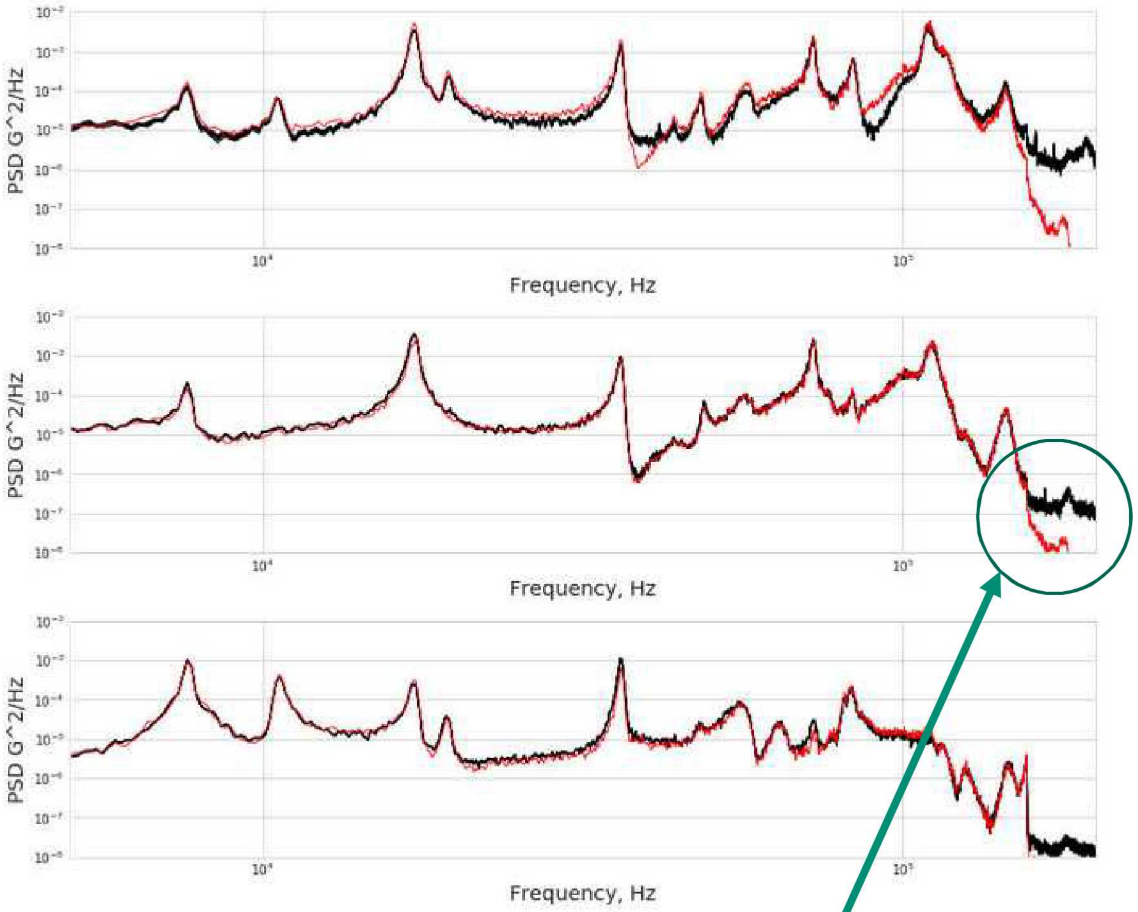
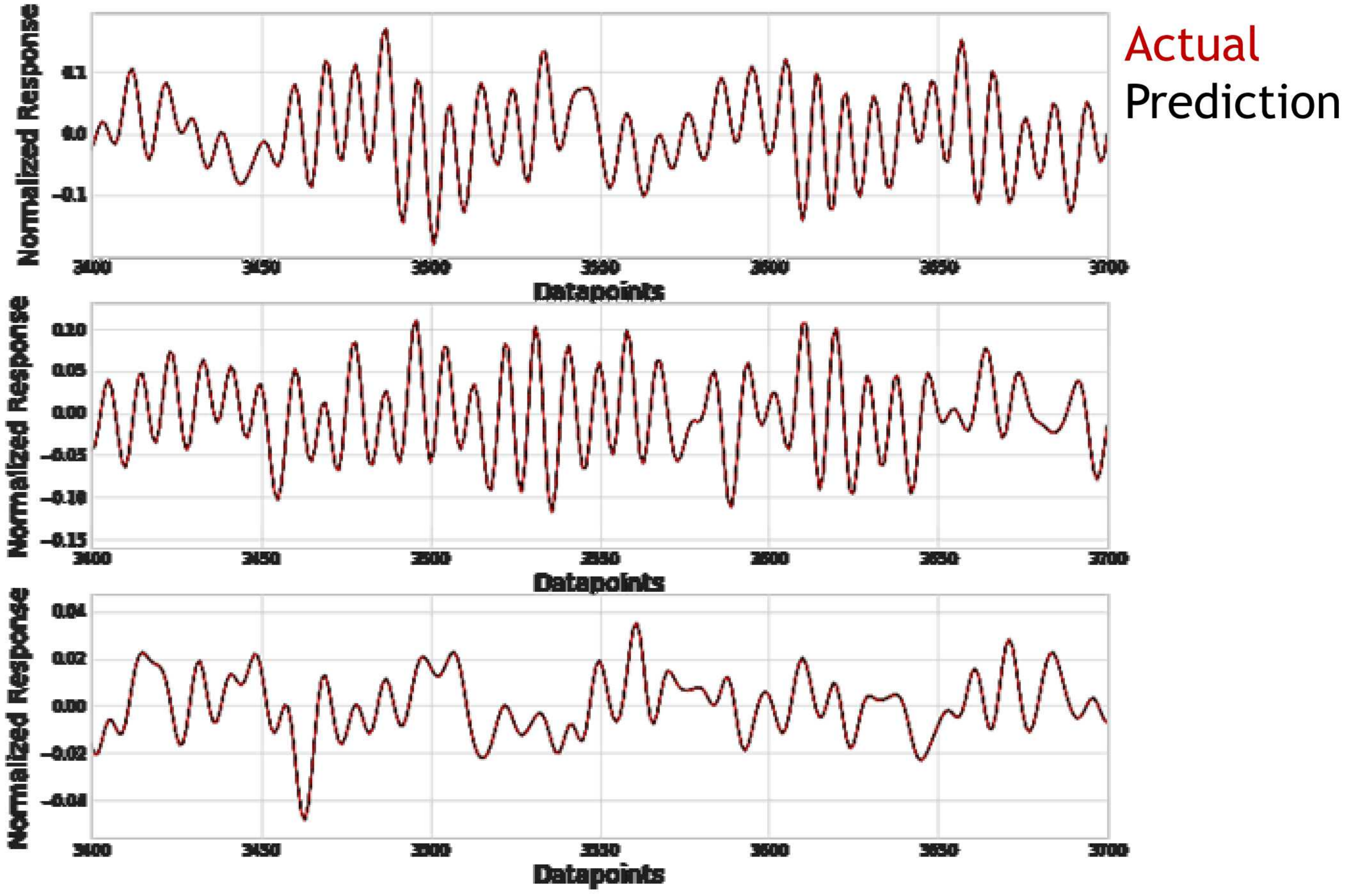




Low correlation gauges include useful high frequency information

The Temporal Convolutional Network (TCN) Predicted Response Matched the Actual Test Data Well - Time Domain

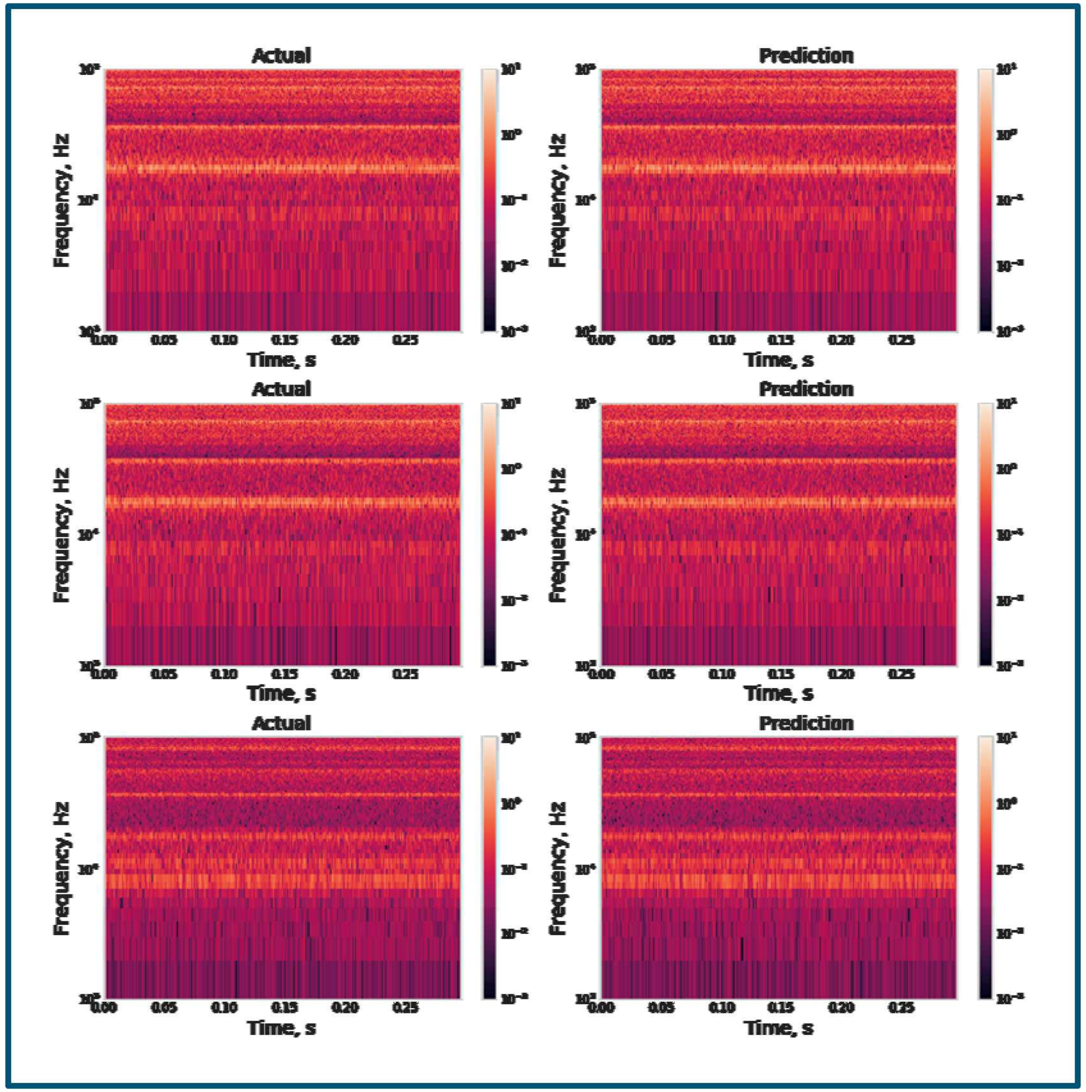
Including all 30 gauges results in exact match with target data



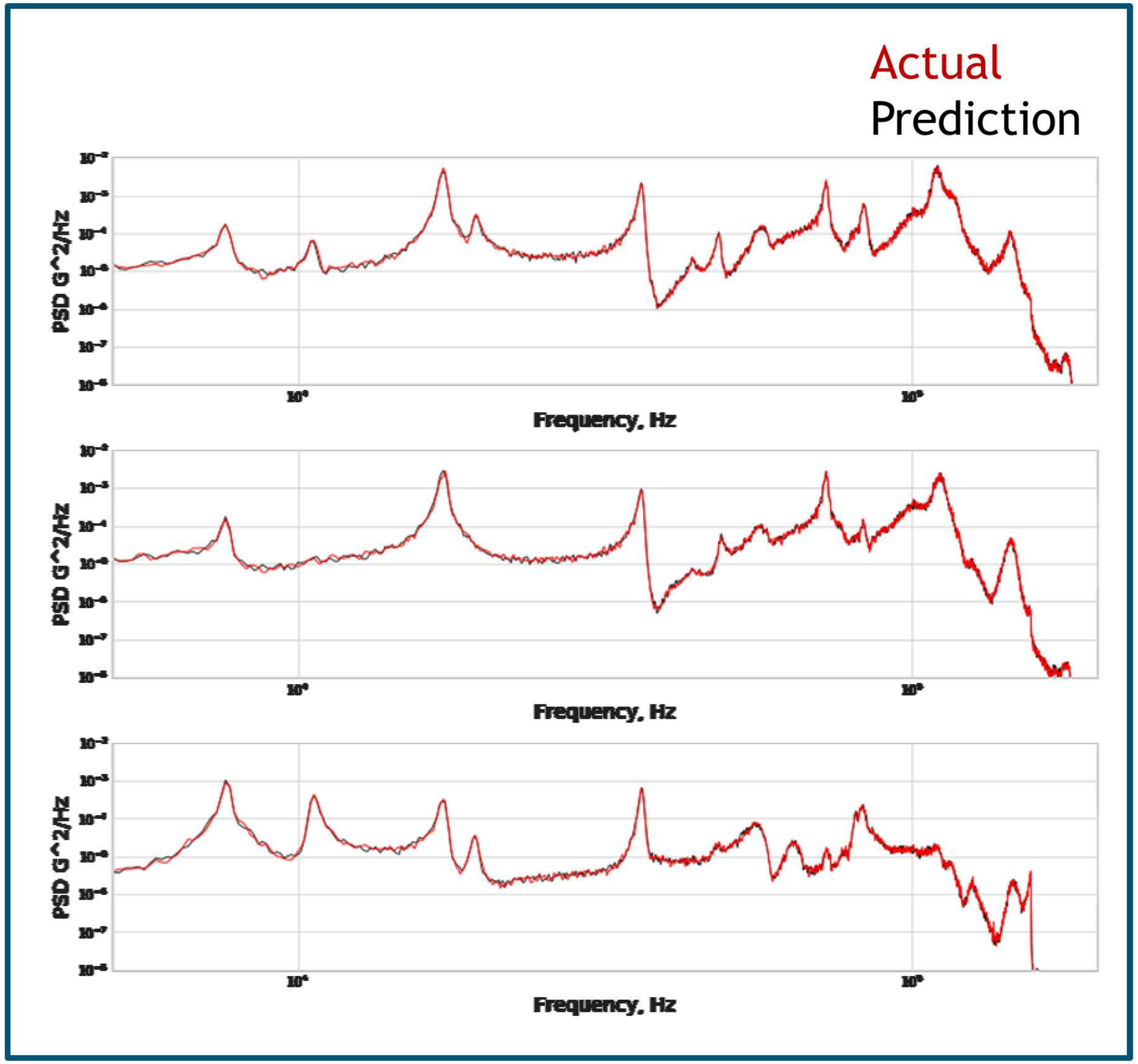
Training Data – Experimentation
Inputs – Response at Measure Locations
Outputs – Base Acceleration

The TCN was able to find a gauge-to-gauge force response function without explicit knowledge of the component.

The TCN Predicted Response Matched the Actual Test Data Well Frequency Domain

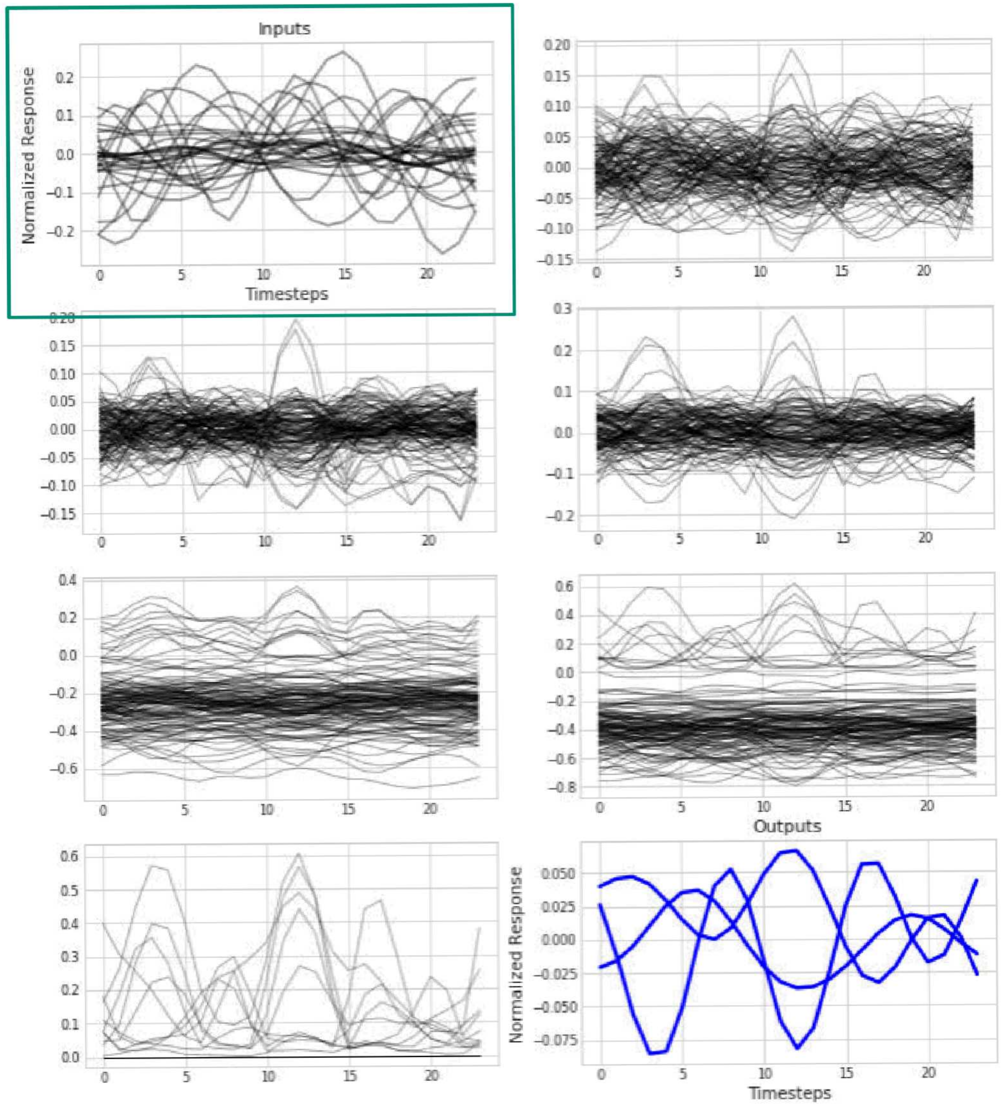


Spectrogram of response



Power Spectral Density of response

What is the TCN learning?



Input: 30 time signals

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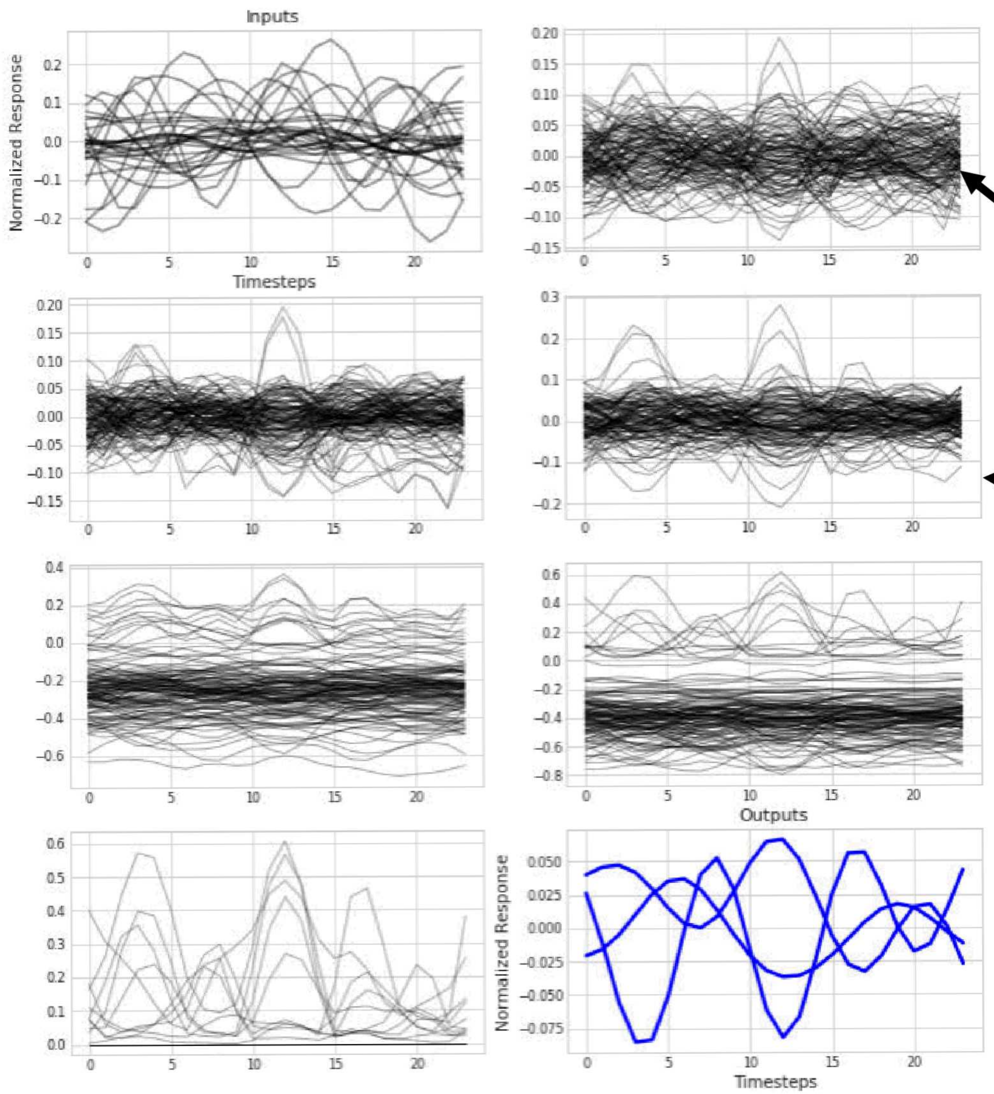

Input: 30 time signals

Network projects original time signals onto a new space with 128 dimensions

New signals undergo series of nonlinear transformations

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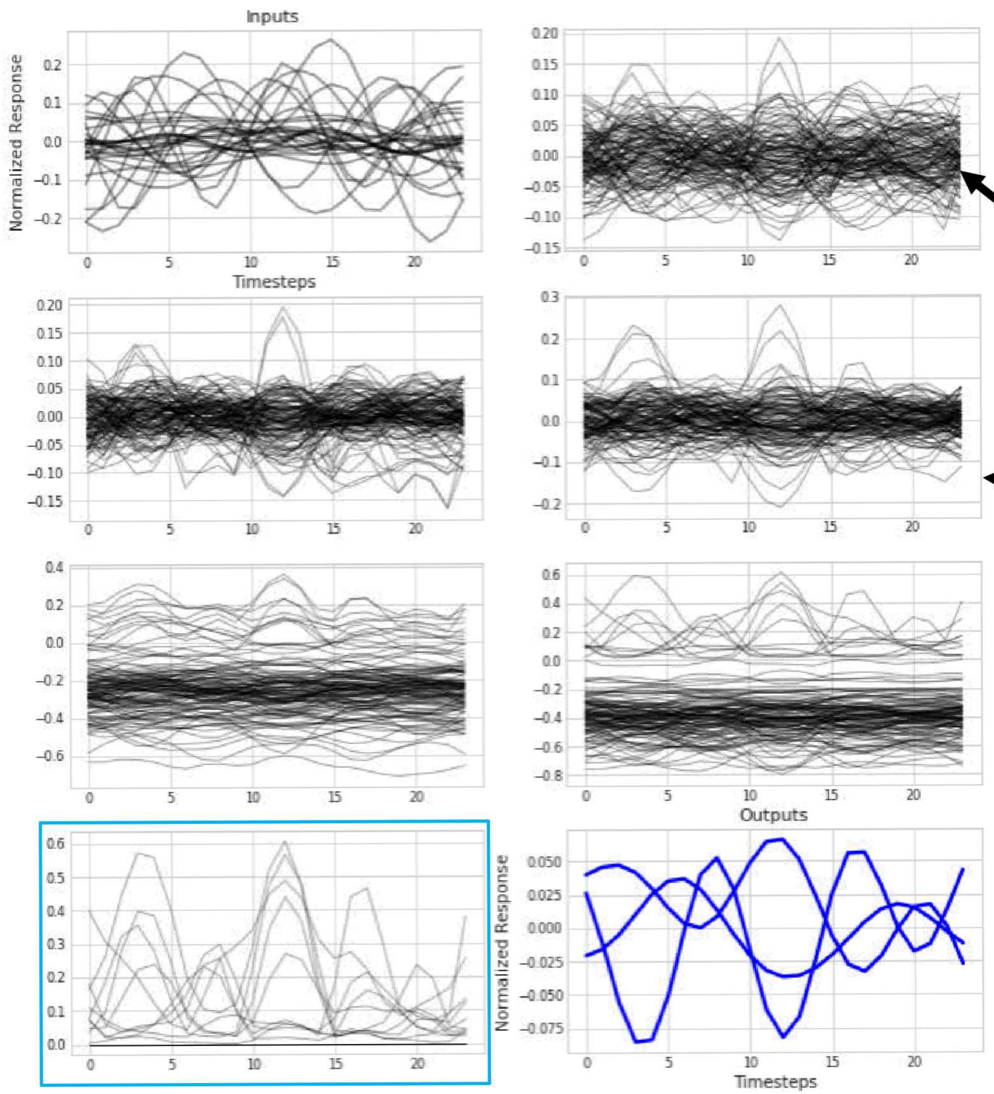

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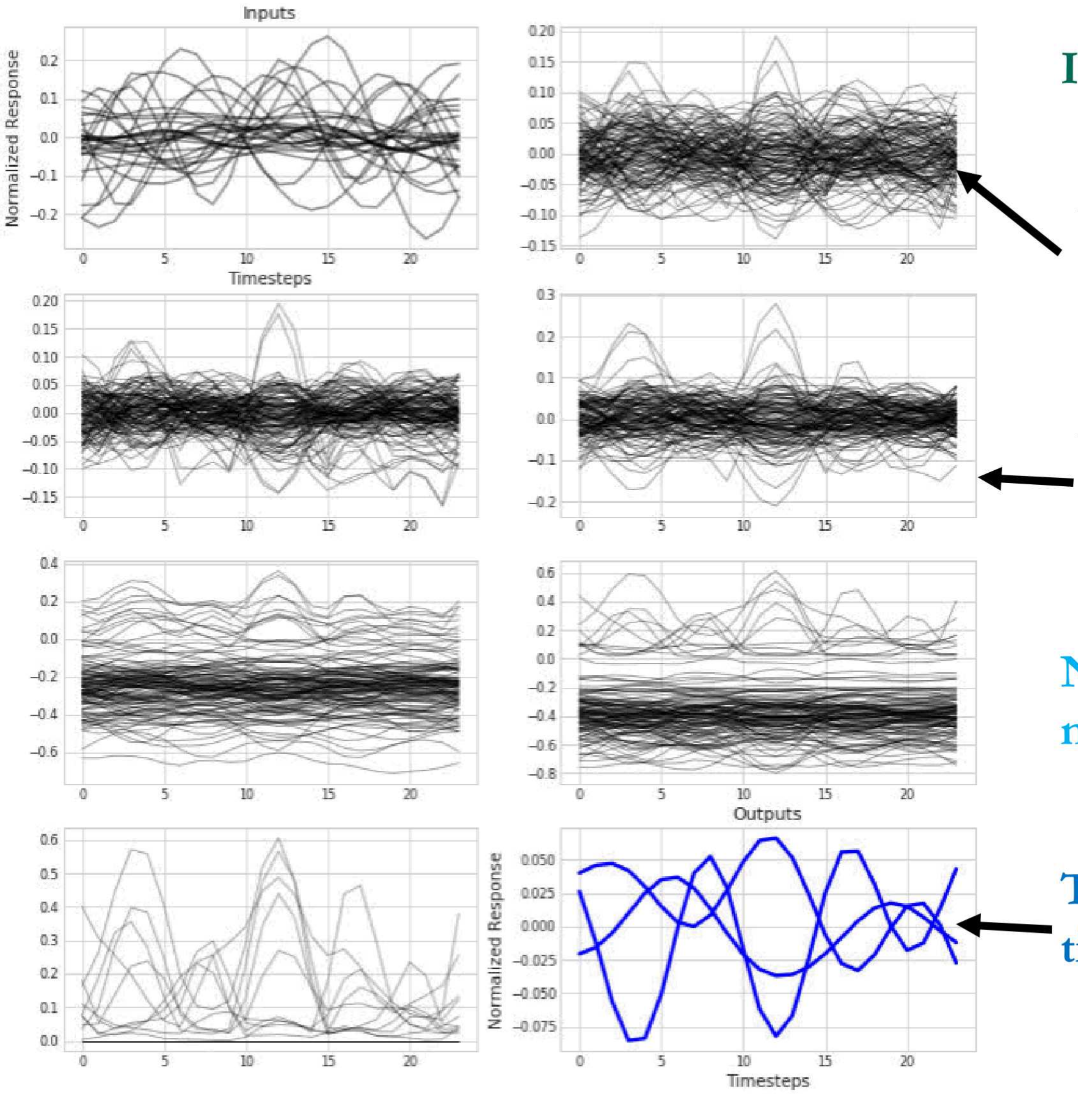
Network projects original time signals onto a new space with 128 dimensions

New signals undergo series of transformations

Network learns to discard most of the new signals, except for 10

What is the TCN learning?



Input: 30 time signals

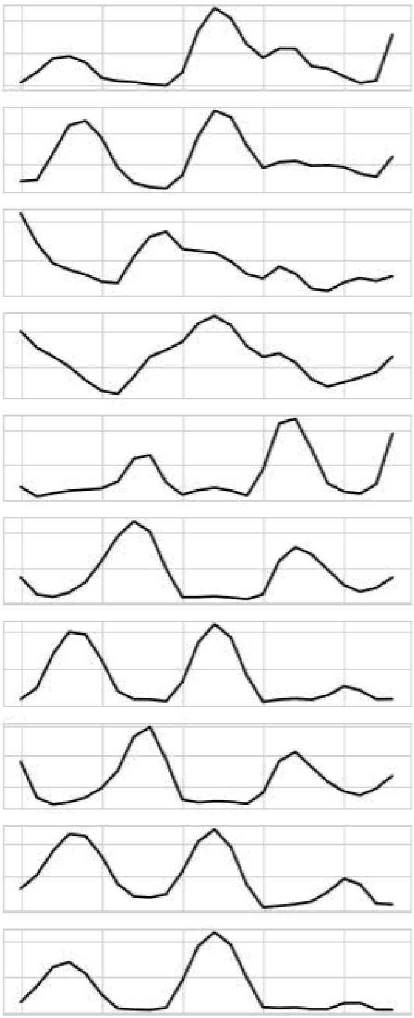
Network projects original time signals onto a new space with 128 dimensions

New signals undergo series of transformations

Network learns to discard most of the new signals, except for 10

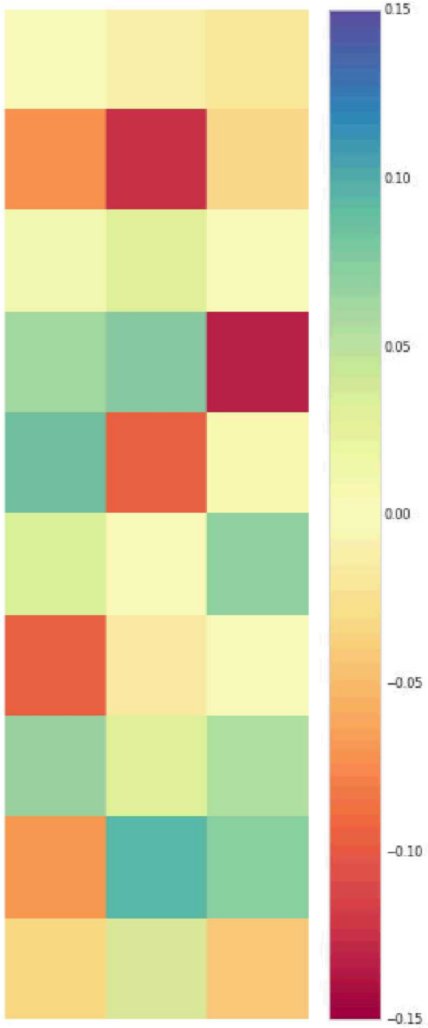
These 10 signals are combined into 3 final time signals that match target output

Final operation is just linear combination of the 10 non-zero signals that the TCN found



10 non-zero signals

*



Last layer weights

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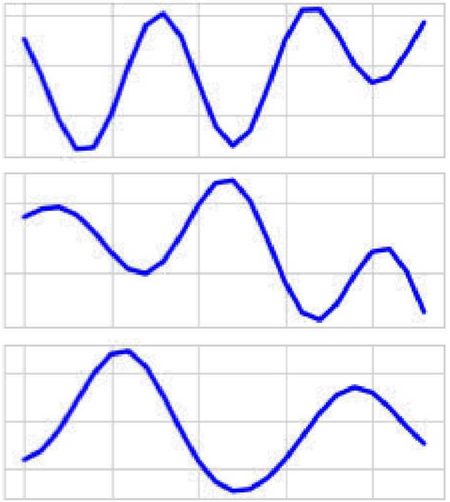

Predicted response

The transfer function was decomposed into a series of nonlinear transformations followed by linear superposition.

Conclusions

A new method was developed to solve the inverse problem of force reconstruction to replicate flight conditions in the time domain using neural networks.

No need for a finite element model or explicit computation of transfer functions or mode shapes

It can handle nonlinear response because it does not rely on linear superposition

No spatial representation is given. The location of the applied forces must be known or assumed.

Training requires sample data from ground test (could be white noise)

Any Questions?

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