The Implementation of Neural Networks for Phaseless Parametric Inversion

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Presentation overview

Introduction to the problem

- Grain bin imaging
- Measurement challenges

Neural network

Datasets

- Training data
- Testing data

Results

- Network performance
- Computational cost

Conclusion

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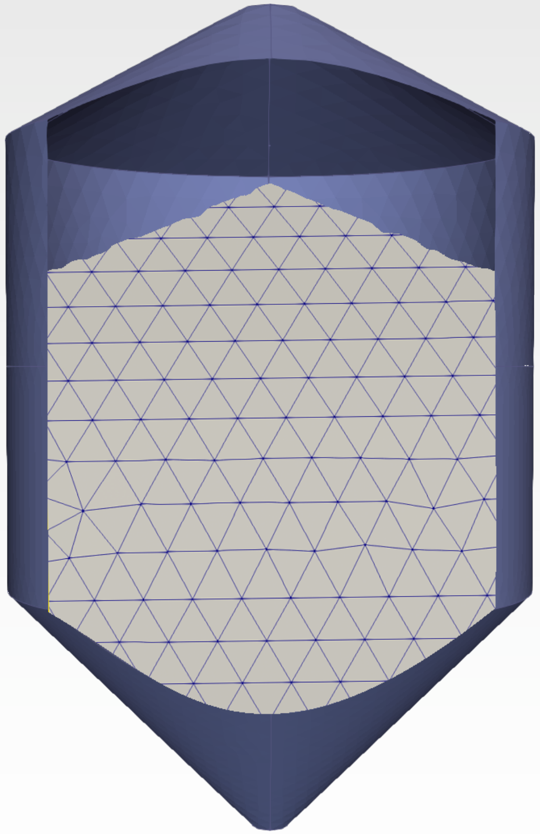
Grain bin imaging

- Microwave imaging of the interior of a grain bin
- Voxel-wise reconstruction of permittivities using contrast source inversion requires calibration and a good initial guess
- Bulk parameters can be used to calibrate experimental data to synthetic models



Grain bin (with grain) is modeled in 3D using a finite element mesh, an example tetrahedral mesh on the grain is shown.

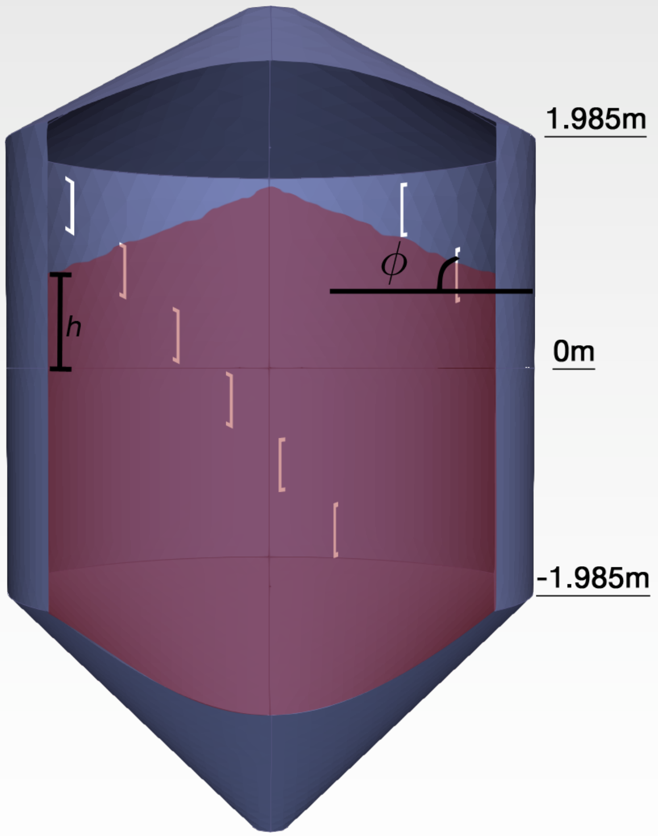
Measurement challenges

- Physical limitations prevent measurement on known calibration targets
- Bin measurements for inventory require climbing in the bin and are dangerous and impractical
    - **i.e. we cannot obtain a large dataset to be used for neural network training.**

Hopper-style bin at the University of Manitoba campus.

Objectives

- Obtain bulk parameters:
  - Height, cone angle, complex-valued bulk permittivity of grain
- Use supervised machine learning
  - Train only on **synthetic** data
  - Demonstrate performance on **experimental** data



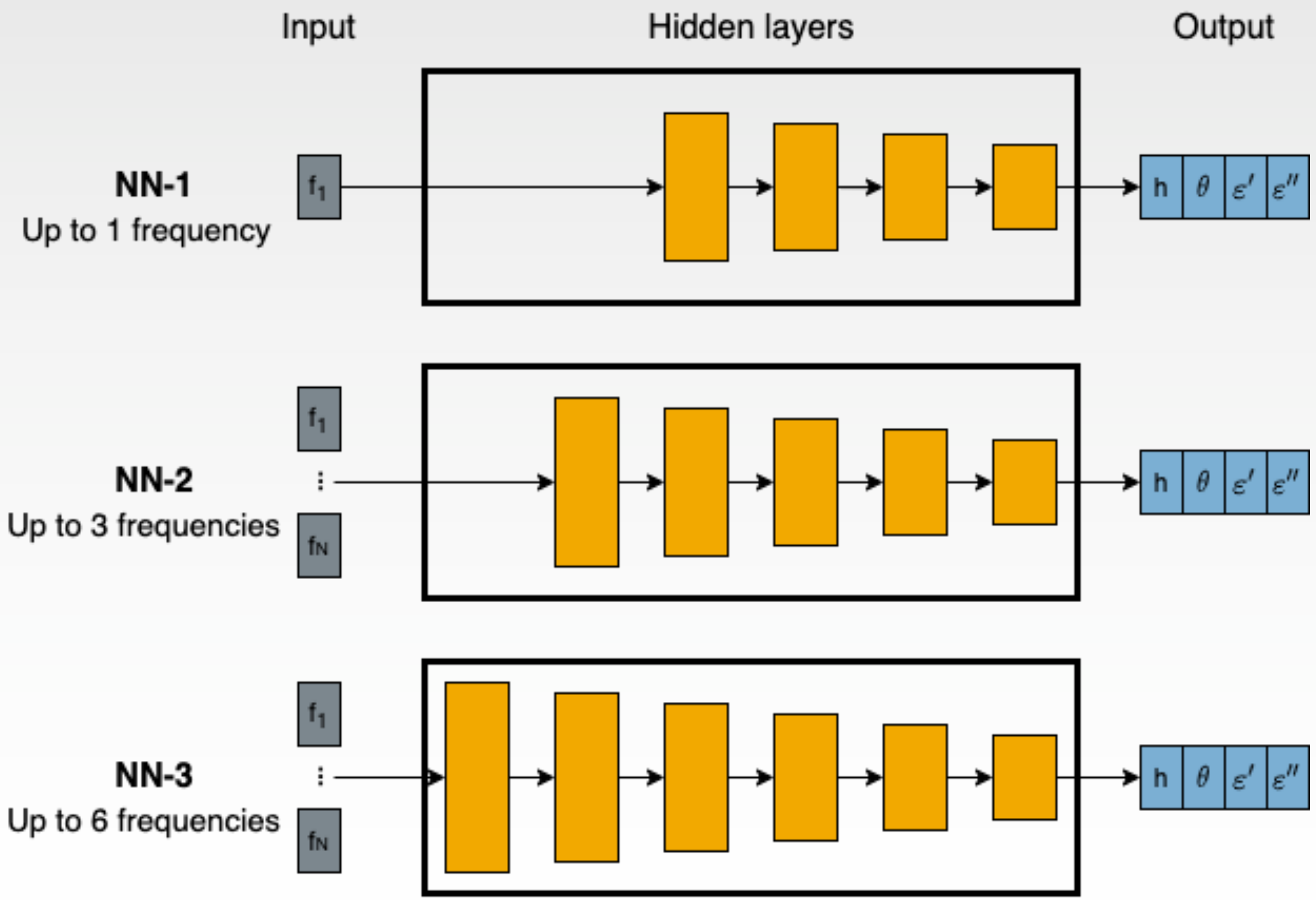
Grain in bin (red) is characterized by bulk parameters.

Neural networks

- Three fully connected networks
  - Differ in number of hidden layers, and maximum number of accepted frequencies
- Trained solely on **synthetic** data

- Input shape: 552Nx1 column vector
  where N is the number of frequencies
- Output shape: 4 parameters
  bulk parameters: [height, cone angle, permittivity (real part), permittivity (imaginary part)]

Neural networks



*All activations are ReLU

Training data

- Building an experimental training set is not practical:
  - Filling a grain bin with a known and controlled amount of grain is difficult
- Supervised learning requires **synthetic** training data
- Frequencies: 80MHz, 85MHz, 90MHz, 95MHz, 100MHz, 105MHz

- Synthetic data set:
  - Each dataset consists of 552 data points: Synthetic electromagnetic field estimate at each receiver point
  - 50,000+ datasets at each frequency
  - Generated by a finite element method forward solver

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Testing (experimental) data

- Frequencies: 80MHz, 85MHz, 90MHz, 95MHz, 100MHz, 105MHz
- Experimental data set:
  - 14 labelled data sets at various heights and cone angles (no permittivity labels)
  - Measurements taken from Hopper-style bin on University of Manitoba campus
  - Each dataset at each frequency consists 552 data points: S-parameter data at each transceiver (proportional to phi component of magnetic field)
  - Raw, uncalibrated experimental data

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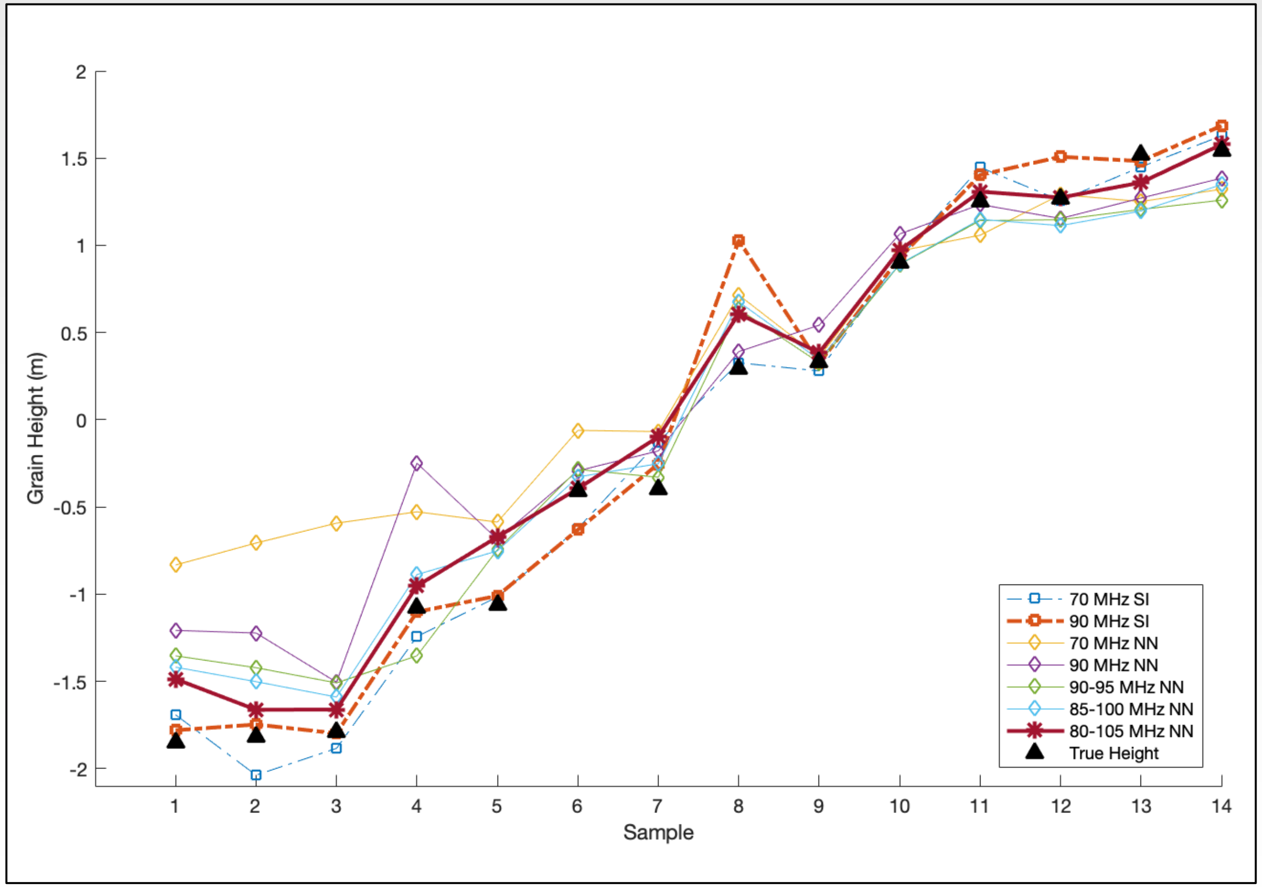
Simplex inversion performance

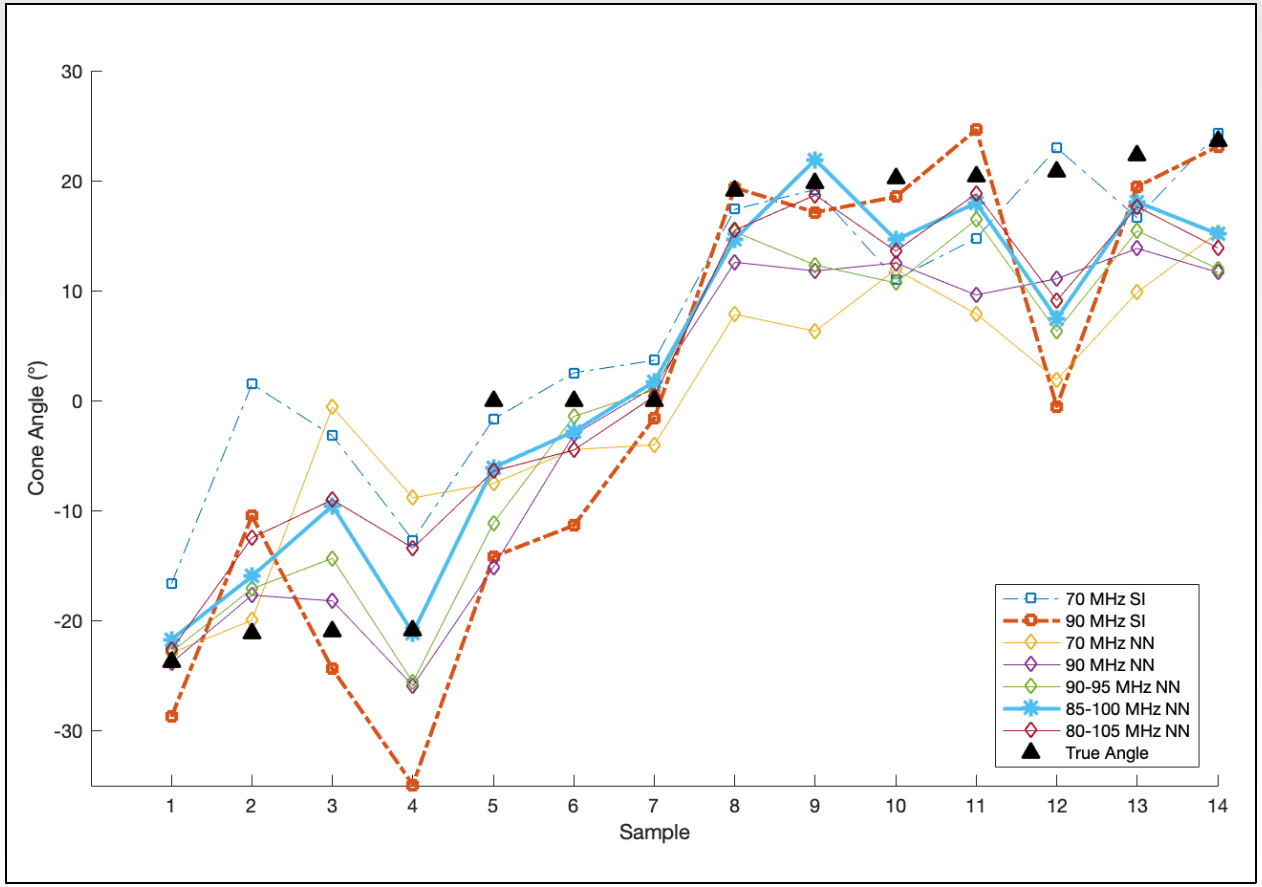
- Our previous work uses an optimization method (simplex method) for obtaining the bulk parameters
  - Simplex inversion is performed on data from a single frequency
- We use the results from this simplex inversion (at two separate frequencies) as a baseline for neural network performance

Height prediction



- Neural Network 3 (NN3) using all frequencies performed best on height predictions (bold dark red)
- Comparison to Simplex Inversion (SI) at 90 MHz (bold red dash)

Angle prediction



- NN3 for 85-100 MHz performed best on angle predictions (bold blue)
- Comparison to SI at 90 MHz (bold red dash)

Permittivity prediction

- Permittivity predictions are reasonably close to both Simplex Inversion (SI) predictions, and theoretical model predictions
- Bulk permittivity: $\varepsilon = \varepsilon' + j\varepsilon''$

Method	Avg. ε’	std.	Avg. ε”	std.
Neural Networks*	[4.17, 4.25]	0.219	[-0.502, -0.435]	0.0690
Simplex Inversion (70) Simplex Inversion (90)	4.11 4.07	0.233 0.141	-0.572 -0.657	0.303 0.421
Composite model[1]	[3.90, 4.13]	--	[-0.42, -0.38]	--

*Average permittivity values are given as a range of averages across all networks tested

[1] A. Kraszewski, *J. Agric. Engng Res.*, 1989

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Computational cost

- Simplex inversion:
  - Measurement analysis (per frequency): ~3 hours, *per measurement*
- Neural network:
  - Synthetic data generation: ~1 day per frequency, *one time cost*
  - Training data preparation and network training: < 30 minutes, *one time cost*
  - Measurement analysis: < 1 minute, *per measurement*
    - Analysis time is not significantly affected by additional frequencies once the synthetic training set is created.

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Conclusion

- Neural network trained solely on **synthetic** data can accurately obtain bulk parameters from **experimental** data
- Bulk parameters can be obtained from raw, uncalibrated data
- For continued field use, neural network method reduces computational cost of parametric inversion (as compared to optimization based simplex inversion)

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Thank you

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