Novel Multi Data Acquisition and Hybrid Neural Network for Pipe Inspection and Imaging

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Outline

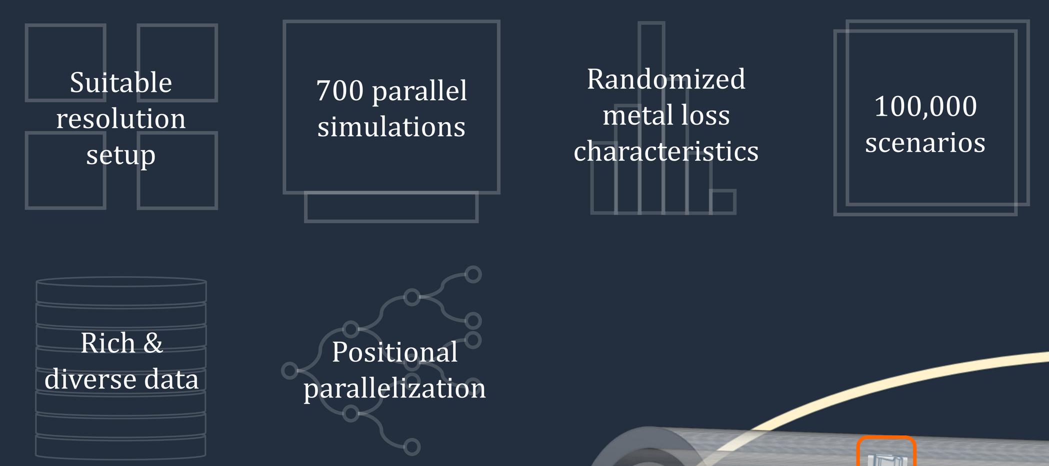
Over time, metal loss due to corrosion can occur. Some losses are small and difficult to detect, but may penetrate a casing, threatening its structural integrity. As such, it proves challenging for inversion algorithms to create reconstruction models using only inspection data. Large and diverse datasets are essential to correctly train artificial neural networks to generate casing cross-sectional images.

Metal losses may affect a large, shallow area (left), while others penetrate casings (middle). Yet others may be present in multiple regions (right)

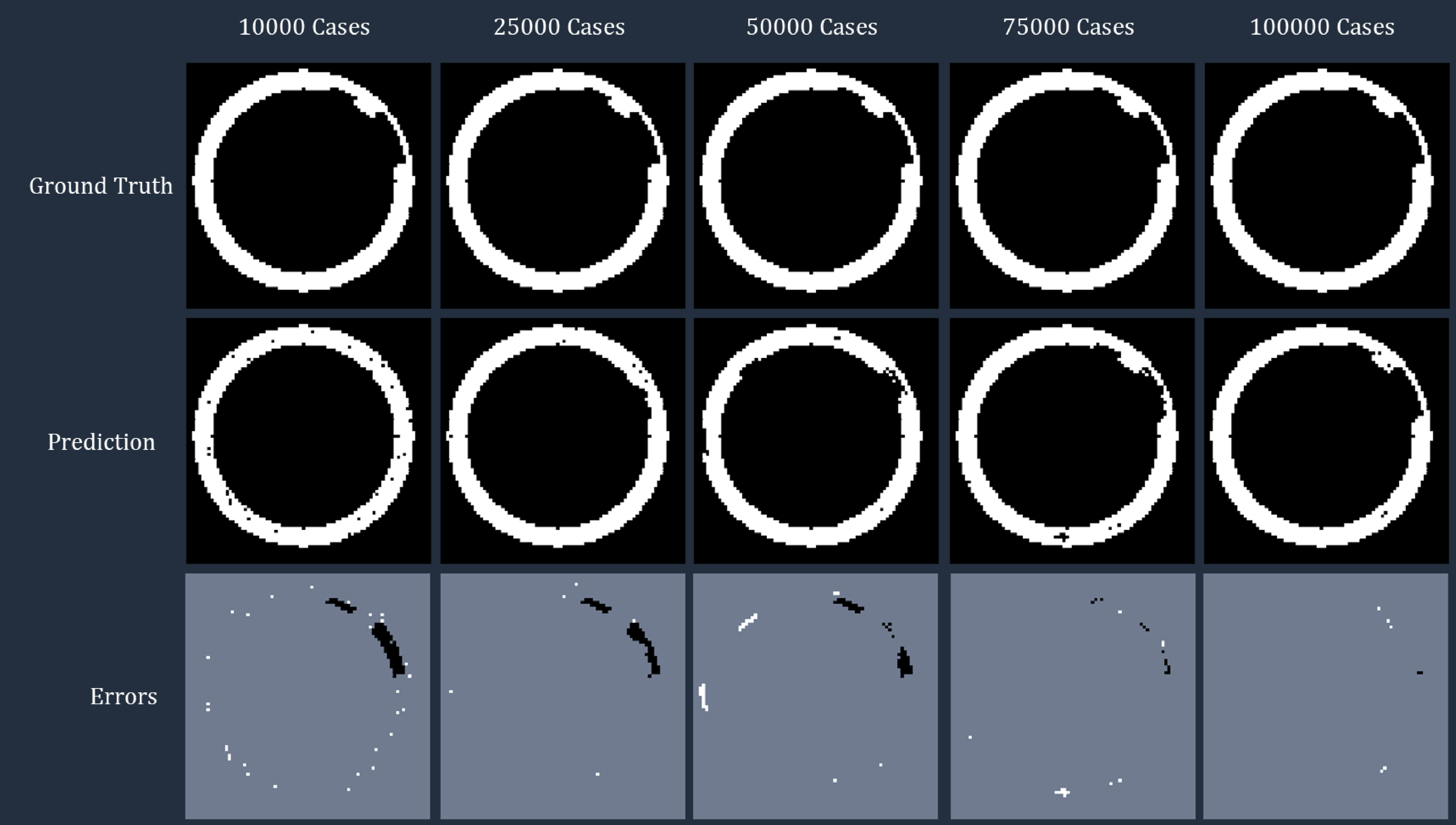
In this work, a massively-parallelized framework is developed in conjunction with a multi-frequency data acquisition model, coupled with a novel hybrid neural network (HNN) cluster, to fully visualize casings with defects. Large scale simulations are used to generate suitably effective datasets to the train, validate, and test the AI model.

Simulated Data Generation

- Parallelization on the Ibex Cluster [1] of KAUST
- Metal losses of varying dimensions and locations
- Simulate EM field interactions and record readings
- Jobs are automatically allocated to available processors
- Automatically process data from completed simulations
- Re-initiation of new batches with randomized parameters
- Data processing and curation with suitably diverse variety
- Datasets are injected into HNN cluster for training AI model

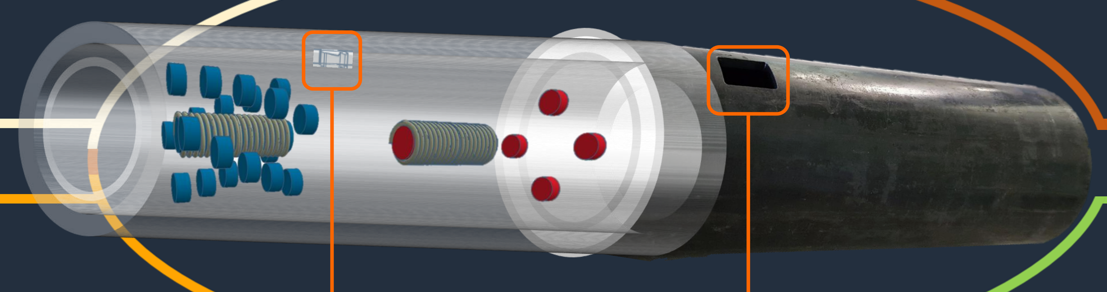


Observations & Results



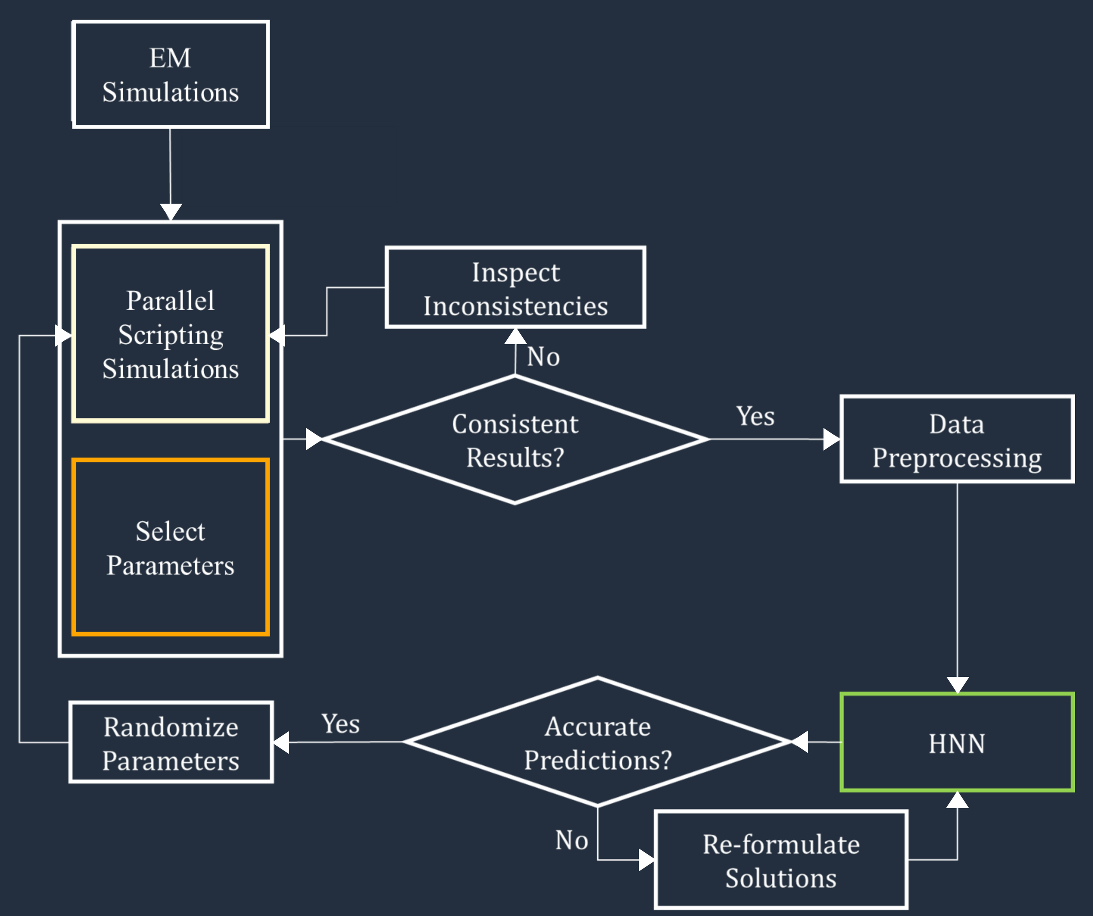
- The parallel execution framework completed 100,000 scenarios, with an impressive 43x speedup against a sequential run, using an i9-9980, 2.40 GHz processor and 64 GB RAM.
- Performance of the MF-HNN on the same test scenario, opposite, with significant improvements observed in the cross-sectional inversion image of a pipe as the amount of data used is increased, left to right.

Cross-sectional inversion image of a pipe with the same defect, i.e. one record from the test dataset. Significant improvements in quality of prediction, middle column, in comparison to ground truth, top, as the amount of training data is increased, left to right. The difference errors plotted in the bottom panel



Methodology and Framework

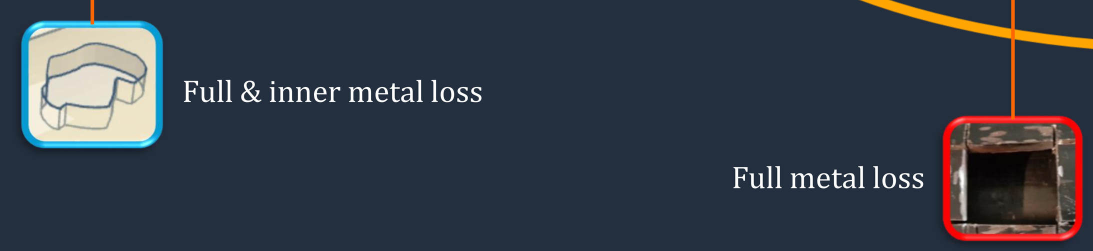
- Large-scale electromagnetic (EM) simulations for data generation
- A batch of 700 simulations are concurrently executed
- A diverse variety of a total of 145 batches are used



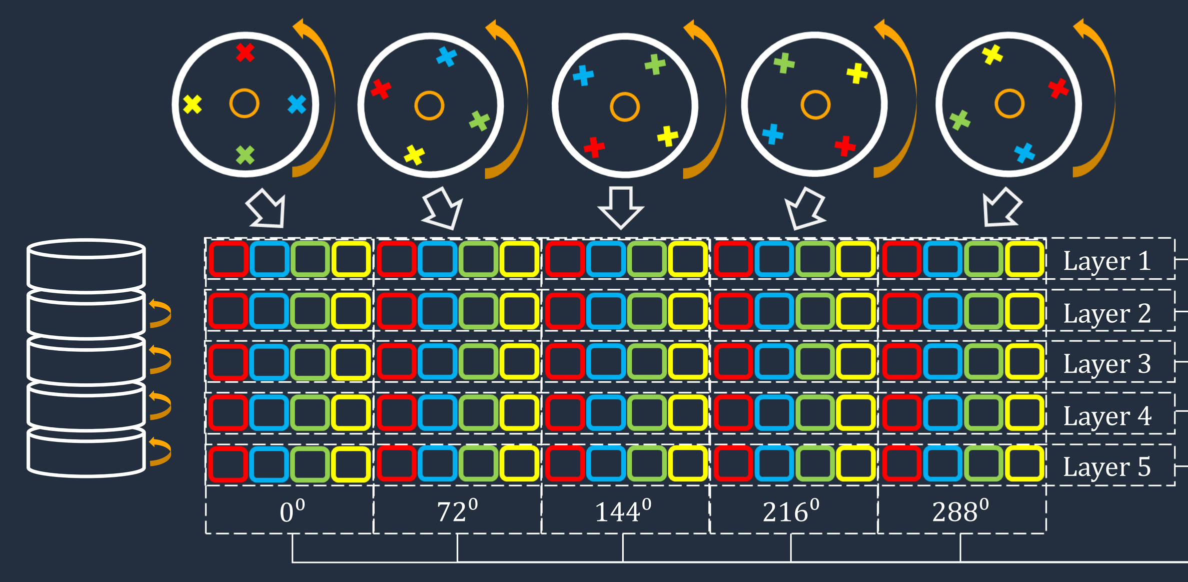
Flowchart of the overall data generation framework

- Scripts orchestrate a highly parallelized simulation workflow
- HNN cluster generates cross-sectional images with metal losses
- The overall AI performance is evaluated on predictions of casings with metal losses, with a highly reliable pixel-level accuracy

Data Acquisition



- Transmitter coils emit alternating EM fields in pipe
- Receivers azimuthally mounted measure the scattered EM fields
- Measurements across arbitrary distances with matching cross-sections are used as input-output pairs to train the HNN AI-model

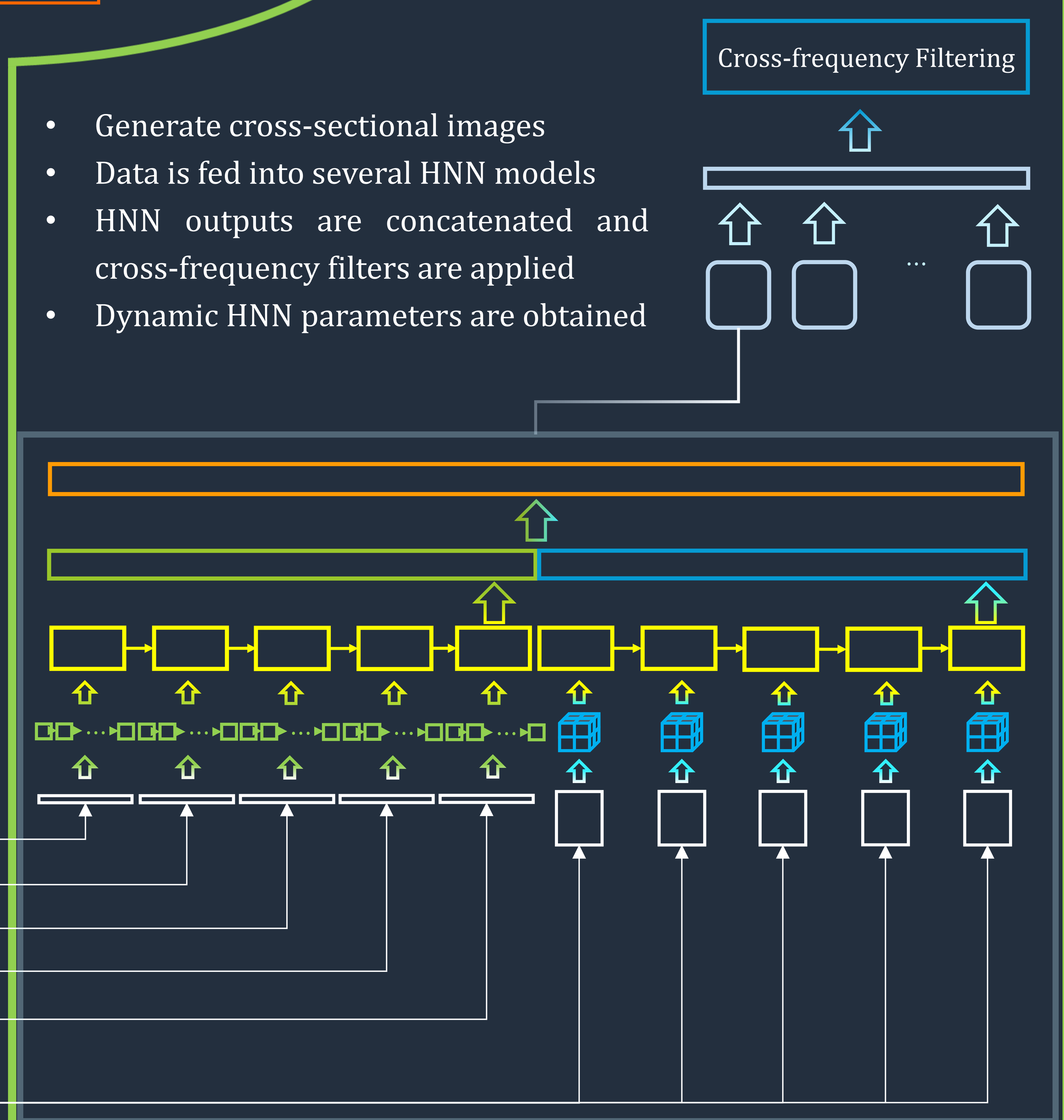


Example of a stack of five enclosures for a single frequency with five spatial orientations

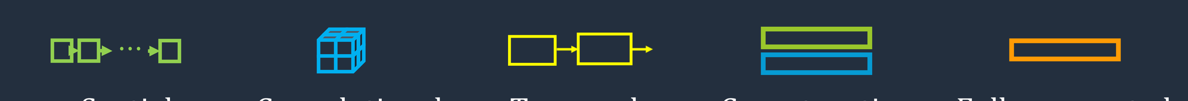
- Scalable data acquisition: requiring as few as four receivers to function, while accuracy is improved with increased data usage

Hybrid Neural Network

- Generate cross-sectional images
- Data is fed into several HNN models
- HNN outputs are concatenated and cross-frequency filters are applied
- Dynamic HNN parameters are obtained



HNN using five measurement layers as input, reshaping data into 1D and 2D arrays



Metrics & Conclusions

- To evaluate the performance of the models, the accuracy and specificity of the MF-HNN on the test datasets are calculated, from the correctly and falsely predicted metal and defect pixels. The resulting values are shown in the Table below.

Data Count	Accuracy	Specificity
10000	0.8322	0.0159
25000	0.8574	0.1053
50000	0.8618	0.2264
75000	0.9236	0.6345
100000	0.9790	0.9081

The increased improvements as a function on increased data points in MF-HNN performance demonstrate the importance of an effective data generation framework. A suitably diverse simulated data is used for the EM-based pipe inspection, within a feasible amount of time and significant speedups of 43x.

HPC Cluster

The authors would like to thank KAUST Supercomputing Laboratory, KSL, for the provision of the HPC resource of Ibex [1]. Ibex cluster hosts a combination of Skylake, Cascade Lake, and AMD Rome CPUs, as well as Nvidia GPUs.

[1] https://www.hpc.kaust.edu.sa/ibex