Artificial Intelligence-Powered Non-Destructive Testing for Pipelines Transporting Energy

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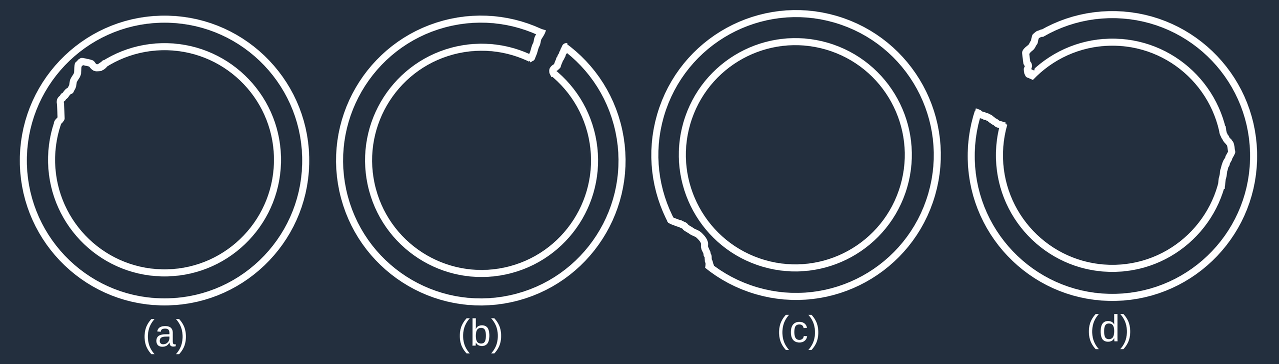
INTRODUCTION

Metal loss due to corrosion inevitably occur on metallic energy pipelines. Some losses are small and difficult to detect, but may penetrate a pipeline, threatening its structural integrity. As such, it proves challenging for inversion algorithms to create pipeline reconstruction models using only electromagnetic (EM) inspection data. Large and diverse datasets are essential to correctly train artificial neural networks to generate digital models of pipelines, showing the exact location, shape, and size of metal losses.

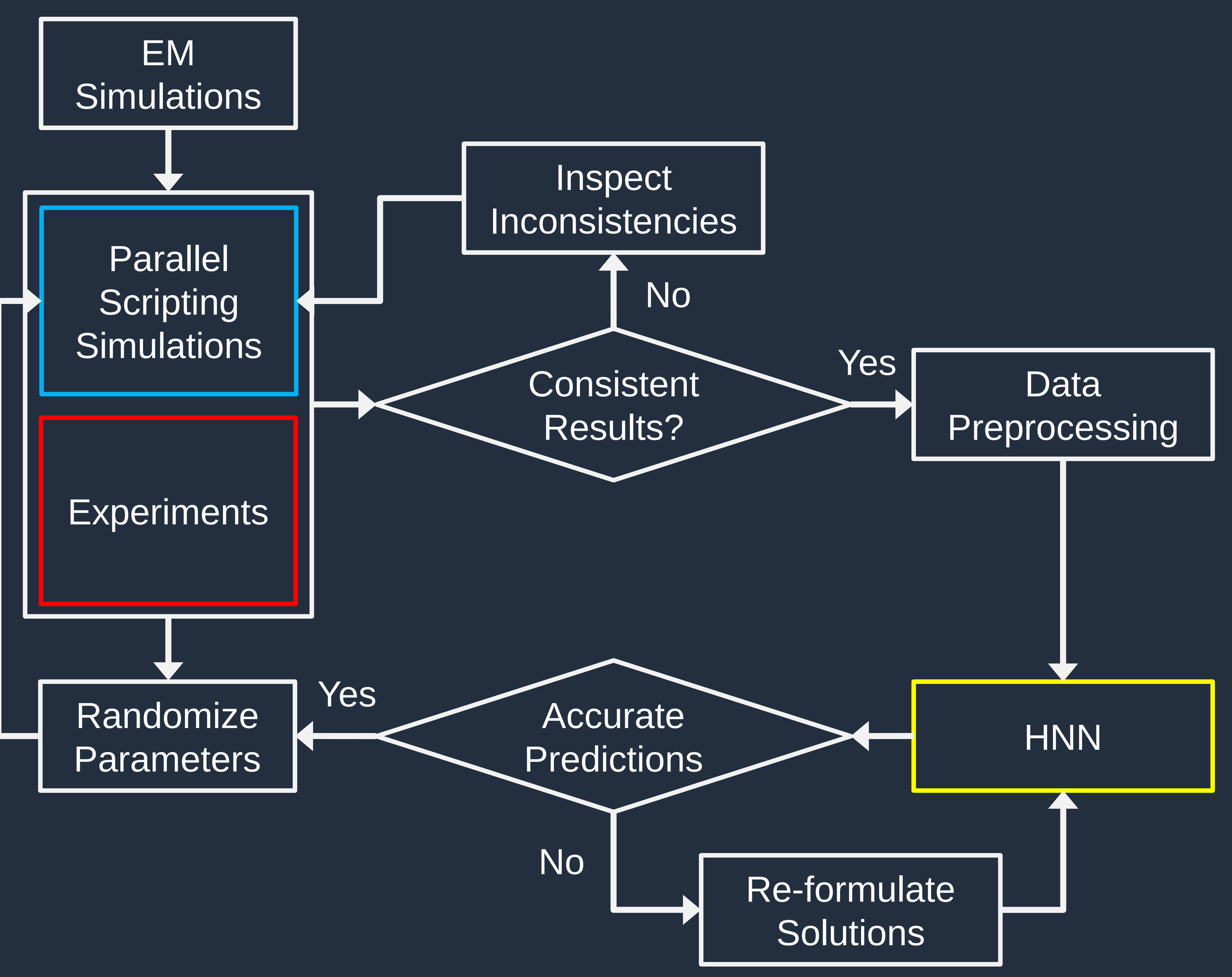


Metal losses may affect a large, shallow area (a), while others penetrate the pipelines (b). Yet others may be present on the outer surface (c) or in multiple regions (d).

In this work, a multi-frequency data acquisition model, coupled with a novel convolutional recurrent hybrid neural network (HNN), is developed to fully visualize metallic pipelines. Massively parallelized simulations are used to create training data, which is verified by an experimental setup.

METHODOLOGY AND FRAMEWORK

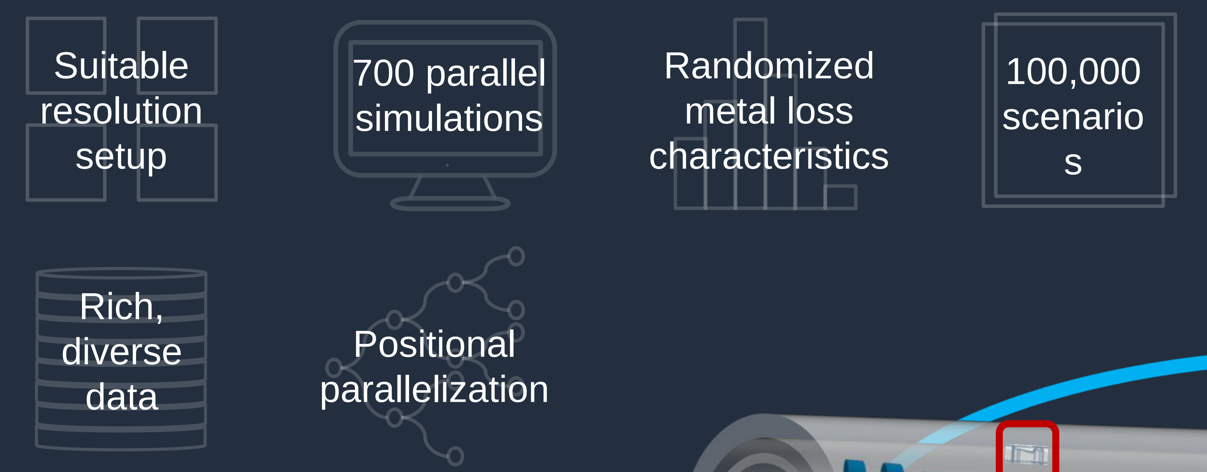
- Large-scale EM simulations for data generation
- Each batch consists of 700 simulations concurrently executed
- A diverse variety of 145 batches are executed

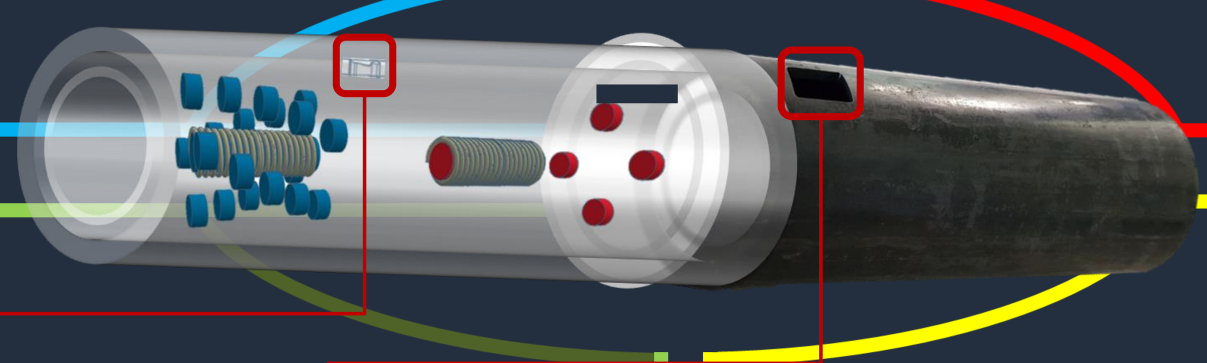


- Scripts orchestrate a highly parallelized simulation workflow
- HNN generates pipeline images with metal losses
- The overall AI performance is evaluated on predictions of pipelines with metal losses, with pixel-level accuracy

SIMULATED DATA GENERATION

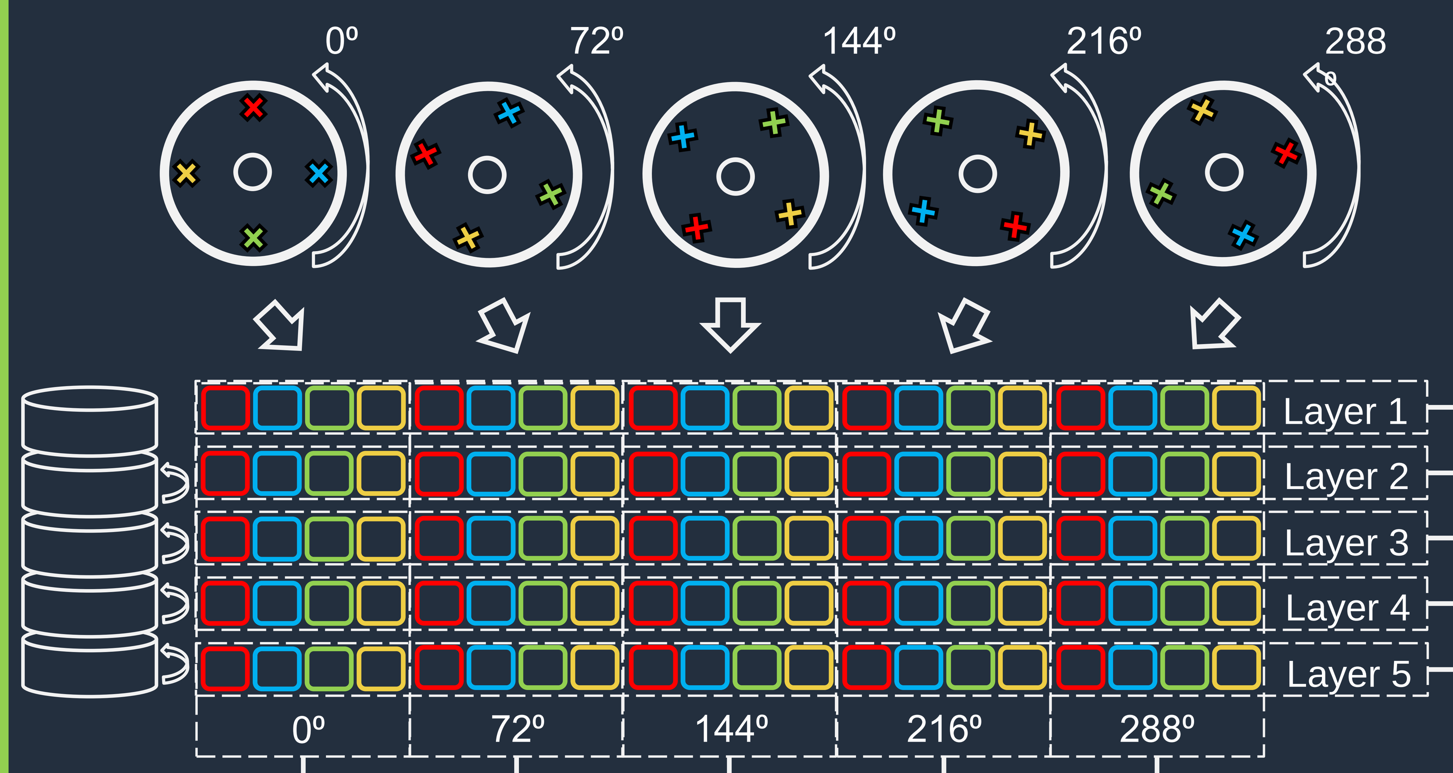
- Parallelization on the Ibex Cluster [1] of KAUST
- Metal losses of varying dimensions and locations
- Simulate EM field interactions and record readings
- Automatically process data from completed simulations
- Re-initiation of new batches with randomized parameters
- Data processing and curation with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





DATA ACQUISITION

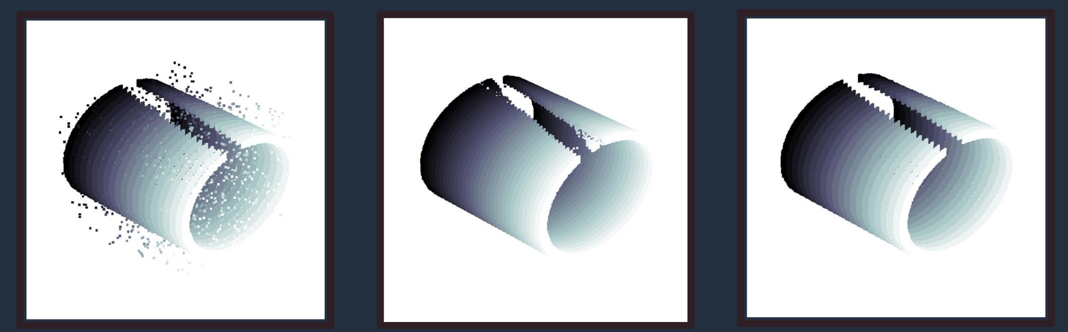
- Transmitter coils emit alternating EM fields in pipe
- Receivers azimuthally mounted measure the scattered EM fields
- Measurements across arbitrary distances with matching cross-sections are used as input-output pairs to train the HNN AI-model



- NFEC: middle enclosure is coplanar with the Tx coil
- RFEC: enclosure located at 1.5 - 3.5 times the inner diameter of the pipeline

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.

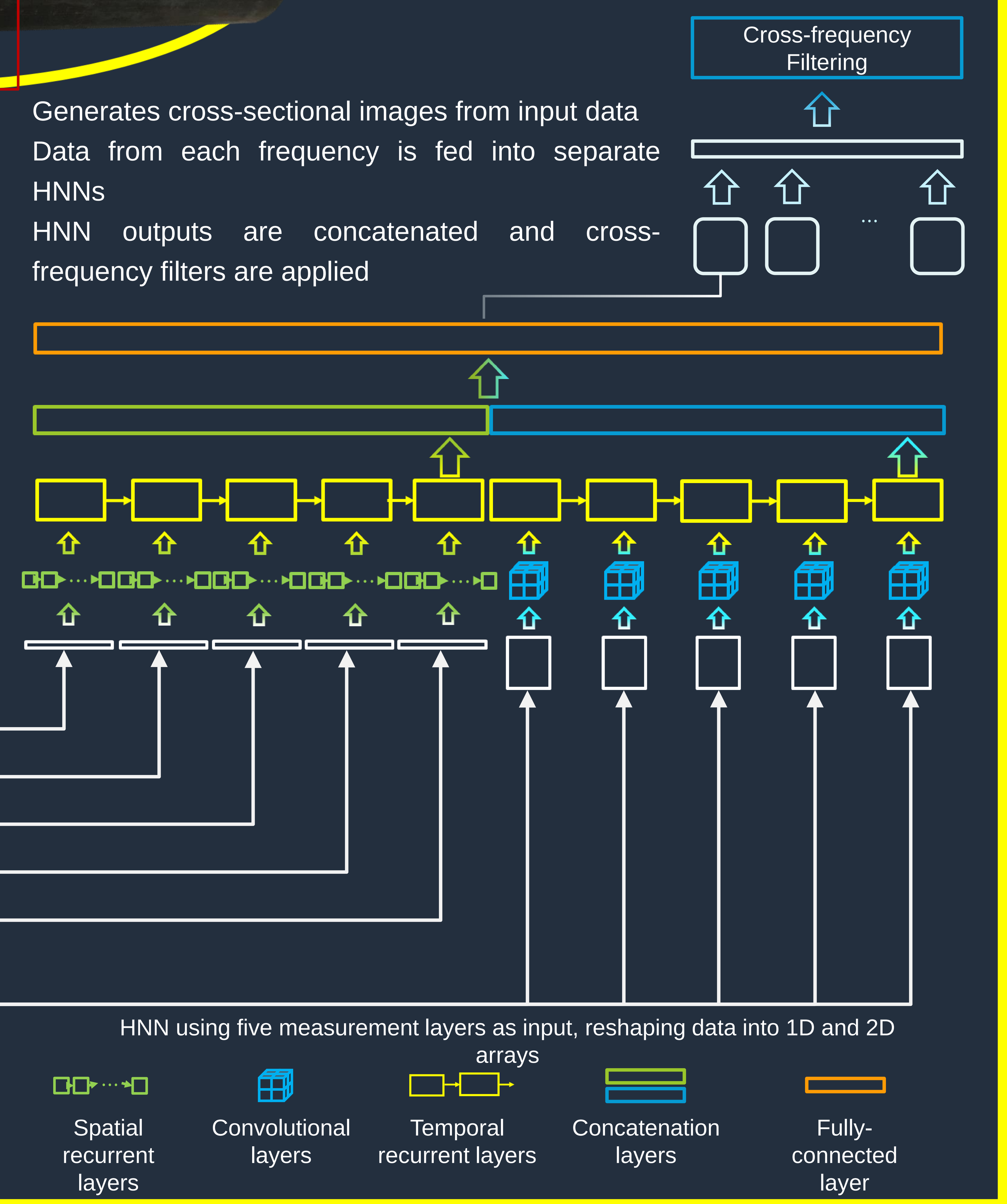


- Performance of the MF-HNN on the same test scenario, opposite, with significant improvements observed in the cross-sectional inversion image of a pipe as the amount of data used is increased, left to right.

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

HYBRID NEURAL NETWORK

- Generates cross-sectional images from input data
- Data from each frequency is fed into separate HNNs
- HNN outputs are concatenated and cross-frequency filters are applied



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

Metrics and 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 accuracy and specificity of the MF-HNN are 0.9790 and 0.9081, respectively.
- 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.

Test case predictions showing small degrees of uncertainty

- The MF-HNN remains capable of making generalizable predictions even after training with large amounts of scenarios.

KAUST 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