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Machine learning assisted fast forward 3D modelling for time-domain electromagnetic induction data – lessons from a simplified case

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In (time-domain) Electromagnetic Induction (EMI) surveys, an image of the electrical conductivity of the subsurface is obtained non-invasively. An accurate interpretation of the data is computationally expensive as it requires a full (high fidelity) 3D simulation of the induced electric currents embedded within an iterative and ill-posed inverse problem. Therefore, this forward model is usually approximated with a 1D forward model (low fidelity model) which only considers horizontal layers and for which fast analytical forward models exist. Recent work [1] has shown that a multidimensional forward model can be relevant in time-domain Airborne EM inversion. To be more precise, we provided an appraisal tool for quasi/pseudo-2D inversion to indicate that fast forward 3D modelling for time-domain (Airborne) EM data is still worthwhile and, in fact, necessary, in some areas. Surrogate modelling and machine learning may replace 3D forward modelling on a mesh during a 3D inversion.

In this contribution, we first demonstrate the initial steps towards creating an efficient surrogate model for 3D modelling with only 5000 samples in the training dataset. Rather than predicting the high-fidelity or 3D data directly, we predict the relative error between the high and low fidelity data. The idea behind this approach is that predicting the difference with a relatively good low-fidelity model is easier and more robust than trying to find a surrogate for the full data set. The computation of low fidelity data via the 1D approximation is no longer a computational burden, yet it explains most of the variability in the observed data. The residual variability, originating from the non-1D nature of the subsurface, is predicted with a Gaussian process regression model. Combining the low-fidelity model with a trained correction term via Machine Learning saves significant computation times. We show encouraging results, currently limited to two layers, where the trained surrogate model proves to produce a significant 'learning gain' in 92,5% of the cases (see Figure 1), meaning that it can significantly reduce the residual multidimensional variability. The cases where the surrogate model makes the prediction of the high-fidelity data worse, occur at the limits of the training data space, indicating that those cases could be resolved by generating more training data in those areas.

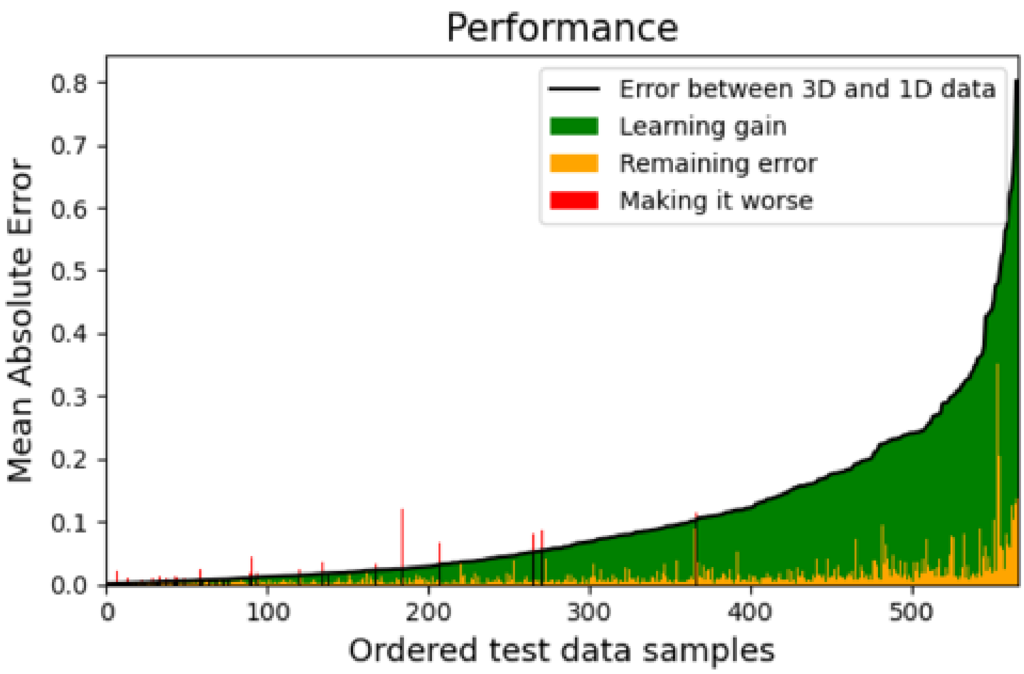

Figure 1 – The learning gain on the test dataset by using the trained surrogate model

References

[1] Deleersnyder, W., Dudal, D., & Hermans, T. (2022). Novel Airborne EM Image Appraisal Tool for Imperfect Forward Modeling. *Remote Sensing*, *14*(22), 5757. **https://doi.org/10.3390/rs14225757**