Deep learning for instantaneous inversion of SkyTEM data

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ABSTRACT

The widespread application of Airborne Time-domain electromagnetic (ATEM) data, including the SkyTEM system (Sorensen and Auken 2004), to imaging shallow geothermal fluid pathways, is limited by the computational expense of inverting these large datasets. We present an approach using a physics-informed neural network to invert SkyTEM data in 1D and show early results of the application of the method to survey datasets. Neural network model predictions are several orders of magnitude faster than traditional inversion and produce very similar results. Future work will expand the neural networks to higher dimensionality, providing opportunities for large-scale 2D inversion, which is currently not computationally feasible yet is required for improved management of complex geothermal and hydrothermal systems.

1. INTRODUCTION

Airborne electromagnetic (ATEM) data is increasingly being applied to geothermal fields and hydrothermal systems to image the geometry of structures in the upper 200-500 m, at high lateral resolution, to determine connections between near-surface water and the geothermal reservoir (Finn et al. 2022, Gribenko et al. 2022, Reeves and Pederson 2023). The SkyTEM system (Sorensen and Auken 2004) is a type of ATEM system that has been deployed widely across New Zealand for these problems. The ATEM method uses a coil towed by a helicopter or plane which induces an electric field in the Earth. The measured signal is the rate of change in the magnetic field (dB/dT) as a function of time after the transmitted electric field is turned off. These dB/dT data can be inverted to produce high resolution models of subsurface electrical resistivity. However, the size of these datasets and consequently, computational expense of inverting them, limits the widespread application of ATEM data.

In recent years, deep learning approaches have been applied to inversion of geophysical data with impressive results (e.g., Li et al. 2020, Wu et al. 2022, Kang et al. 2023, Wu et al. 2024). Instead of the traditional inversion process, which computes multiple forward models, iteratively updating a subsurface property model, deep learning approaches train a model to learn the relationship between a geophysical response and the associated subsurface model. Once the model is trained, it is extremely fast (< 1 second) to produce a subsurface model from geophysical data. Deep learning approaches include physics-informed neural networks where physical property models and their computed geophysical response are used to train the model (e.g., Li et al. 2020, Wu et al. 2021, Wu et al. 2022), and physics-guided neural networks (Kang et al. 2023, Wu et al. 2024) where forward modelling is also incorporated in model training, to improve the fit of the final model with the data.

In this paper we present a physics-informed neural network approach to inverting SkyTEM data in 1D. We demonstrate the ability of the inversion to predict models from SkyTEM data and compare the results to a traditional (laterally constrained) inversion.

2. METHODS

We created a 1-D convolutional neural network similar to the design of Wu et al. (2021). A population of 100,000 training models was generated by creating smooth conductivity models with a random number of layers between 1 and 7, with random thickness normalized such that the total model depth is 600 m. Each layer was given a random conductivity between 0.001 and 1 S/m and piecewise cubic interpolation was used to interpolate between each layer.

The forward response (i.e., dB/dT as a function of time) of each training model was computed using SimPEG (Cockett et al. 2015, Heagy et al. 2017) incorporating the system geometry from the SkyTEM 312 dual moment system. The training dataset was split into training and validation sets with an 80:20 split, i.e., 80,000 training points and 20,000 validation points. Thus, 80,000 model and forward response pairs were used to train the model, and the remaining 20,000 models were used to assess the performance of the model. Neural network training was run using a root-mean-square error loss term, which quantifies the difference between the true and predicted model at each training epoch, and then updates the neural network model parameters. The network training was run for 250 epochs, by which time stable loss values were achieved. Generating the training dataset and training the neural network takes around 8 hours on a GPU equipped laptop and is a one-off procedure. Utilization of High Performance Computing would speed up this process.

3. RESULTS

The neural network predictions from four models in the validation data set are shown with the true models in Figure 1. The SkyTEM response, forward modelled from the predicted models is shown in Figure 2. These show a close match between the model and data at depths where the data has high sensitivity (Christiansen and Auken 2012). Correspondingly, the dB/dT response of the model predictions match well with the dB/dT responses of the true model, with an overall Root Mean Square Percentage Error (RMSPE) equal to 12.5 %. We quantify the model misfit in terms of median RMSPE, i.e., RMSPE is calculated per sounding, and then the median taken across the 20,000 training samples, returning a value 59 %. This higher value is likely skewed upward by sections of the model below the Depth of Investigation (DOI), or at a depth above which the SkyTEM data is sensitive, that generally display high misfits as indicated in Figure 1.

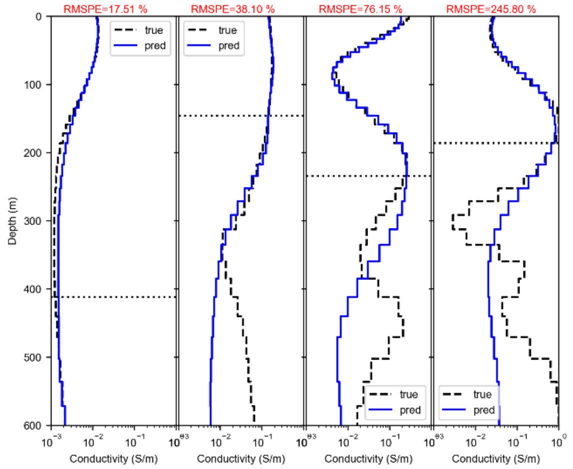

Figure 1. Conductivity models from the validation dataset (true; black dashed line) and predicted models from our deep learning model (blue line). Signal penetration depth estimated by the method of Christiansen and Auken (2012) using the true model, with a threshold of 0.8, shown in black dotted line.

We test the performance of the model on an independent dataset by applying the deep learning model to a SkyTEM survey collected for groundwater investigations in New Zealand (Kellett et al. 2024). We compare the results to those produced by spatially constrained inversion of the same dataset (Figure 3). In terms of inversion time, the spatially constrained inversion was run in two blocks to allow the >60,000 models to run to completion, with each block taking several hours to run. Predicting a model from a line of data using the deep learning method is much faster, taking approximately 2 s to return models for all 60,000 soundings. Thus, inversion using deep learning provides a rapid alternative to traditional inversion.

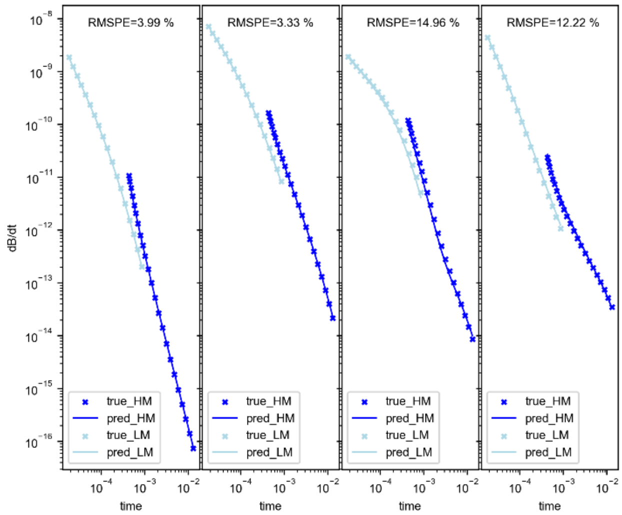

Figure 2. Forward modelled data (dB/dT (V/(A-m^4)) as a function of time) for the four models shown in Figure 1. Low moment (light blue) and High moment (dark blue) shown for both true and predicted models.

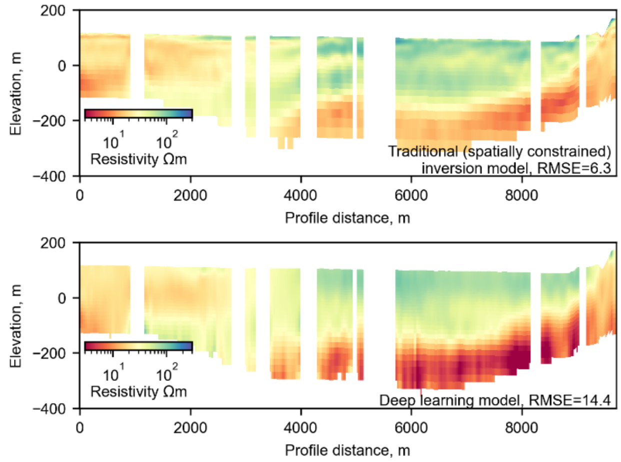

Figure 3. Comparison of predicted model from traditional (with spatial constraints) inversion model (top panel) compared to deep learning-based inversion (bottom panel). Data from Kellett et al. (2024).

There are small differences in the model resolved from deep learning compared to the traditional inversion, with a slight loss of detail in the deep learning model, however most of the main features are resolved by both methods at similar depth and resistivity values. Despite the deep learning model containing no spatial constraints, the model resolved using this method is relatively laterally smooth.

The data-model misfit from the deep learning model (14.4) is higher than in the traditional inversion (6.3), which may be expected given that the neural network used in our inversion does not compare dB/dT responses of predicted models to true dB/dT data during training (i.e. it is not a physics-guided neural network). Work to include this is underway, which will help to improve the data-model misfit in model predictions.

4. DISCUSSION AND CONCLUSION

We have implemented a simple 1-D convolutional neural network to invert SkyTEM data, which produces similar results to a traditional inversion of these data, but in several orders of magnitude less time. Work is ongoing to improve the model predictions by:

(1) Refining training data to encompass a full range of realistic resistivity structures
(2) Include physics in the training loss term (i.e. physics guided neural network) to improve the data-model misfit of the model predictions
(3) Improve the network architecture to reduce training and validation losses

In addition to the above points, this method will eventually be extended to include 2D and 3D geometries, making it more applicable to settings with strong lateral changes in conductivity (e.g., geothermal systems). This may require leveraging existing 2D or 3D geological models to expedite generating appropriate training data (e.g., Jessell et al. 2022). Ultimately, deep learning is a stepping-stone to advanced modelling of multiple geoscientific datasets, allowing us to process and model an abundance of geophysical data significantly faster and with improved accuracy. This will allow improved rapid decision making for the future management of geothermal resources.

REFERENCES

Christiansen, A. V. and E. Auken (2012). "A global measure for depth of investigation." Geophysics **77**(4): WB171-WB177.

Cockett, R., S. Kang, L. J. Heagy, A. Pidlisecky and D. W. Oldenburg (2015). "SimPEG: An open source framework for simulation and gradient based parameter estimation in geophysical applications." Computers & Geosciences **85**: 142-154.

Finn, C. A., P. A. Bedrosian, W. S. Holbrook, E. Auken, B. R. Bloss and J. Crosbie (2022). "Geophysical imaging of the Yellowstone hydrothermal plumbing system." Nature **603**(7902): 643-647.

Gribenko, A., L. Cox, M. Jorgensen and M. S. Zhdanov (2022). Integrated 3D inversion of magnetotelluric and HeliTEM data collected in the geothermal area of Japan. Second International Meeting for Applied Geoscience & Energy, Society of Exploration Geophysicists and the American Association of Petroleum Geologists.

Heagy, L. J., R. Cockett, S. Kang, G. K. Rosenkjaer and D. W. Oldenburg (2017). "A framework for simulation and inversion in electromagnetics." Computers & Geosciences **107**: 1-19.

Jessell, M., J. Guo, Y. Li, M. Lindsay, R. Scalzo, J. Giraud, G. Pirot, E. Cripps and V. Ogarko (2022). "Into the Noddyverse: a massive data store of 3D geological models for machine learning and inversion applications." Earth Syst. Sci. Data **14**(1): 381-392.

Kang, H., M. Bang, S. J. Seol and J. Byun (2023). "Deep-learning-based airborne transient electromagnetic inversion providing the depth of investigation." GEOPHYSICS **89**(2): E31-E45.

Kellett, R. L., A. Kirkby, B. Keats, F. Sanders, T. Brakenrig, D. T. Berhe, L. Coupe and M. Herpe (2024). Ruamāhanga Airborne Aquifer Mapping Project: SkyTEM data processing and resistivity models. GNS Science Consultancy Report. Avalon (NZ), GNS Science.

Li, J., Y. Liu, C. Yin, X. Ren and Y. Su (2020). "Fast imaging of time-domain airborne EM data using deep learning technology." GEOPHYSICS **85**(5): E163-E170.

Reeves, R. and J. B. Pederson (2023). Insights into the Waiotapu Geothermal Field using high resolutions SkyTEM data. New Zealand Geothermal Workshop. 2023.

Sorensen, K. I. and E. Auken (2004). "SkyTEM - a new high-resolution helicopter transient electromagnetic system." Exploration Geophysics **35**(3): 194-202.

Wu, S., Q. Huang and L. Zhao (2021). "Convolutional neural network inversion of airborne transient electromagnetic data." Geophysical Prospecting **69**(8-9): 1761-1772.

Wu, S., Q. Huang and L. Zhao (2022). "Instantaneous Inversion of Airborne Electromagnetic Data Based on Deep Learning." Geophysical Research Letters **49**(10): e2021GL097165.

Wu, S., Q. Huang and L. Zhao (2024). "Physics-guided deep learning-based inversion for airborne electromagnetic data." Geophysical Journal International **238**(3): 1774-1789.