# A Neuro-Physical Inverter for Magnetotelluric Data of Geothermal Systems

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## SUMMARY

The magnetotelluric (MT) method is often used to image and characterize geothermal systems as MT data are sensitive to the presence of hot fluids and may help delineate thermally enhanced zones. The interpretation of MT data typically relies on inversion methods, where a subsurface electrical resistivity model is inferred and progressively updated by minimizing the discrepancies between the measured data and the forward simulated data from the resistivity model. However, geophysical inverse problems are notoriously non-unique and the interpretation of inverted models requires substantial amounts of hypothesis testing to arrive at reasonable conclusions. This motivates the use of machine learning to improve the analysis and inversion methods of MT data. Here, we propose the use of physics-coupled machine learning to invert for resistivity from MT data and use it for direct interpretation, bypassing the need for a fully numerical inversion. We use physical forward models to generate synthetic data from subsurface resistivity models and then use deep learning to reconstruct the resistivity model from the MT data. We rely on a self-supervised framework based on an autoencoder architecture, where one half is fixed by physics (i.e., Maxwell's equations) and the other half is neural. This allows us to train physically consistent "inverters", which capture both the physics of EM induction and the complexities of real-world data. We call this type of neural network "Neuro-Physical Inverters" (NPI). We apply our NPI to MT data and models from Gabbs Valley, Nevada, USA and compare with our baseline from Gauss-Newton inversions and ensemble-approximated Gaussian Processes.

**Keywords:** magnetotellurics, geothermal, machine learning

## INTRODUCTION

The magnetotelluric (MT) method is often used for imaging and characterizing geothermal systems (Kana et al. 2015) as it is particularly sensitive to variations in subsurface electrical resistivity, which can indicate the presence of hot fluids and thermally enhanced zones (Muñoz 2014). Traditional interpretation of MT data relies on inversion techniques (Parker 1994), where a subsurface resistivity model is iteratively updated to minimize the discrepancy between observed data and data simulated from the model. However, MT inversion is susceptible to ambiguities caused by the non-uniqueness of the geophysical inverse problem, necessitating extensive hypothesis testing to derive plausible subsurface models. This study addresses these challenges by introducing a novel approach that integrates physics-based machine learning to improve the interpretation and inversion of MT data.

### Objectives

The primary objective of this research is to develop a physics-coupled machine learning framework to invert MT data for subsurface resistivity and to evaluate its performance in comparison to traditional inversion methods. This approach aims to enhance the reliability and efficiency of MT data interpretation, particularly in the context of geothermal exploration.

### Methods

The study focuses on the Gabbs Valley geothermal area in Nevada, USA. Initially, a 3D resistivity model of the region (Craig et al. 2021; Faulds et al. 2021) is used to generate random 1D resistivity profiles through a PCA-based random sampling method. These 1D models serve as the basis for forward simulation of MT apparent resistivity and phase data.

To predict resistivity models from the simulated MT data, we employed a neural network framework. Specifically, we utilized a framework reminiscent of an autoencoder architecture. When learning from synthetic data, the architecture functions as an autoencoder where the encoder is fixed by the physics of electromagnetic induction (representing the forward problem) and the decoder is a neural network (representing the inverse problem). When applying to real data, the architecture is reversed, with the encoder being a neural network and the decoder fixed by physics (Figure 1). This hybrid model, termed "Neuro-Physical Inverter" (NPI), ensures the generated resistivity models adhere to physical laws while capturing the complexities of real-world data. The neural network component of the architecture is flexible and can be implemented using various types of neural networks, such as convolutional neural networks or even another autoencoder.

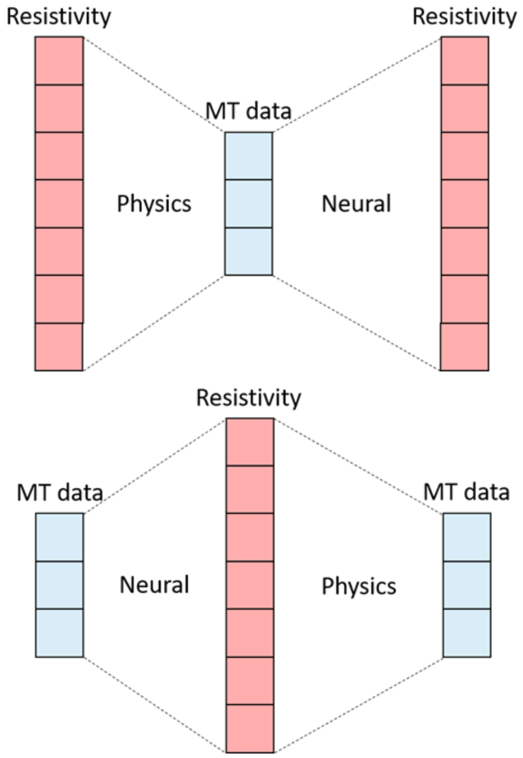

**Figure 1.** Schematic diagram of ML architecture we used for our study.

## Results

The Neuro-Physical Inverter (NPI) was trained on the synthetic MT datasets derived from the random 1D resistivity models. The NPI demonstrated robust performance in reconstructing the resistivity profiles, showing high consistency with the forward simulated data. Initial comparisons suggest that the NPI accelerates the inversion process and improves the interpretability of the results by effectively capturing the complex relationships in the MT data. The performance of the NPI was benchmarked against conventional Gauss-Newton inversion and ensemble-approximated Gaussian Processes (GP), showing promising advancements.

Figure 2 illustrates the results from the NPI models. The left panels depict the true resistivity models, the middle panels show the predicted resistivity models, and the right panels present the root mean squared error (RMSE) over the number of samples. Notably, the RMSE decreases significantly near the surface in the NPI model, indicating improved accuracy in the shallow subsurface.

## Discussion/Conclusion

This study introduces a novel physics-coupled machine learning approach for MT data inversion, leveraging the strengths of both physical modeling and neural networks. The Neuro-Physical Inverter (NPI) framework offers a promising alternative to traditional inversion techniques by providing physically consistent and computationally efficient solutions. Although the current work focuses on synthetic data, the next step involves applying the NPI framework to real MT data from Gabbs Valley to validate its effectiveness in practical scenarios.

Future work will focus on further refining the NPI framework, exploring its applicability to more complex 2D and 3D MT inversion problems, and validating its performance across different geothermal settings. The integration of physics-based machine learning models in geophysical exploration represents a significant step towards more effective and interpretable subsurface imaging.

## REFERENCES

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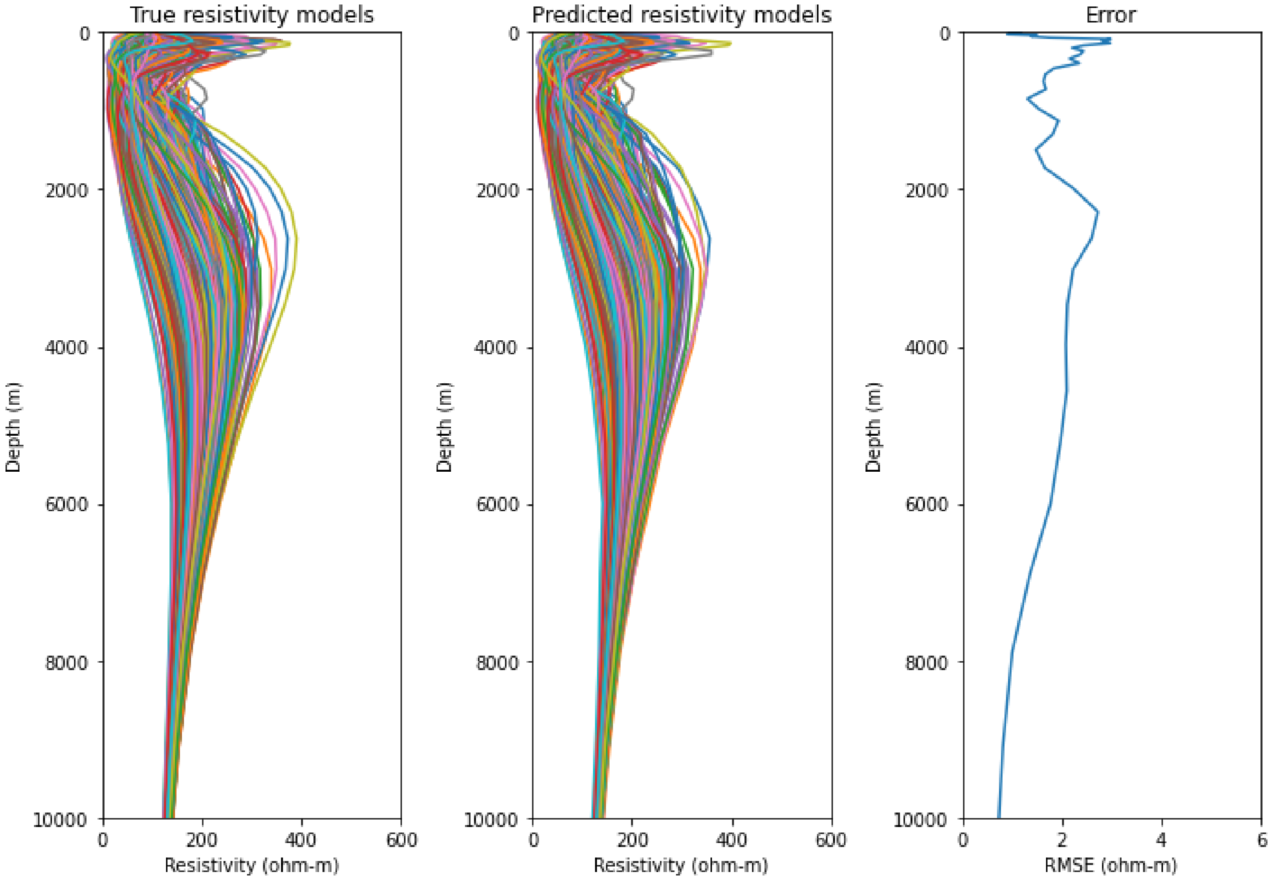

**Figure 2.** Preliminary results from the 1D synthetic problem: (left) true synthetic resistivity models, (middle) predicted synthetic resistivity models, (right) root-mean squared error over the number of samples.