Enhancing Deep Geothermal Exploration with Multi-Physics Data Integration: A Neural Network-Based Approach

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Summary

Geophysical methods such as seismic reflection and electromagnetic (EM) surveys are indispensable tools for deep geothermal exploration, enabling the estimation of critical rock properties, including porosity and clay volume. When used independently, these methods face significant limitations in resolution and coverage. For example, bandlimited legacy seismic data may lack low-frequency components, resulting in poor well constraints on large-scale features such as porosity distribution and fault zones. Similarly, EM methods, while sensitive to resistivity variations, struggle to resolve fine-scale details. These shortcomings hinder the ability to create reliable reservoir models, particularly in complex geothermal systems characterized by multi-scale heterogeneity and structural complexity.

The goal of this work is to explore the potential of integrating multi-physics geophysical data (seismic and resistivity) to enhance predictions when there is a scarcity of well data to derive a reliable low-frequency model (LFM) for the rock properties of interest. By leveraging a network with a U-Net architecture trained on seismic data, we highlight the role EM-derived resistivity can play in the estimation of this LFM. The approach improves predictions of porosity (PHIT) in the absence of an explicit low-frequency model, paving the way to more reliable geothermal reservoir characterization while minimizing assumptions about local structural variations and petrophysical relationships. This study builds on previous work highlighting the use of neural networks, including the methodologies proposed by Allo et al. (2021), for geothermal reservoir characterization.

Method

We employ a supervised learning framework in which input data (seismic, resistivity) are processed through a U-Net-like (Ronneberger et al., 2015) network architecture to establish mappings between the input features and the target property (PHIT). The seismic, resistivity, and target data are preprocessed using a robust scaler to mitigate the influence of outliers. The network consists of a U-shaped architecture made up of multiple convolutional layers with 1D kernels that capture temporal patterns along seismic traces. The network is trained over 500 epochs employing the Mean Squared Error (MSE) loss function and the AdamW optimizer (Loshchilov and Hutter, 2017) with a learning rate of 0.001. The dataset is divided into training and testing sets with a random train-test split of 25%, and both the training and validation sets show consistent convergence throughout the training process. Upon completion, the network outputs scaled predictions of the total porosity, which are subsequently transformed back into absolute porosity values using inverse scaling. This workflow allows the model to effectively uncover non-linear relationships between multiple geophysical inputs and the underlying petrophysical laws governing the property of interest.

In a first test, seismic data serves as input while the residual of the porosity relative to its low-frequency model (PHIT LFM) is used as the target. After applying the trained network to the input data, the LFM is added back to the predictions to reconstruct the absolute values of porosity. To evaluate the impact of the LFM, a second network is trained with absolute values of porosity as target and the seismic data as sole input, bypassing the residual approach. In a third test, EM-derived resistivity is incorporated alongside seismic data to evaluate its impact on absolute porosity predictions. The fourth test involves training two separate networks and combining their outputs. The first network follows the residual porosity approach from the first test, using seismic data as input. The second network takes EM-derived resistivity as input and predicts PHIT LFM. Since resistivity exhibits a strong nonlinear anticorrelation with PHIT LFM, it is expected to serve as a reliable proxy for large-scale porosity variations. The output of this second network is then added to the residual porosity predicted by the first network to obtain the absolute porosity estimate.

Results

Figure 1 shows the target porosity, seismic amplitudes, resistivity obtained by inversion of EM data, and the predicted porosity for the 4 tests at a random trace in the dataset. The normalized percentage error (NPE) was selected as the primary evaluation metric due to its ability to account for the relative magnitude of predictions, ensuring that errors are scaled proportionally to the variability of the data. In Test 1, where seismic data served as input and the residual of porosity was used as the target, the network achieved a mean NPE of 1.33%. This result underscores the ability of the network to extract the link between porosity and seismic amplitudes when the training data is ideal. Test 1 is used as benchmark as it corresponds to the best result that can be achieved when the LFM is known. By comparison, subsequent tests will show increases in NPE as a result of error in the estimation of the LFM.

The second experiment involved training a U-Net network using the absolute PHIT values without incorporating any low-frequency model. The mean NPE increased to 18.56%. This is a notable reduction in accuracy directly attributable to the absence of low-frequency information in the training data that results in poor porosity estimates in the overburden and basement intervals. This result highlights the pivotal role of the LFM in constraining solutions and improving predictive precision when relying solely on seismic data.

In the third test, resistivity data was added in addition to the seismic data as inputs to predict absolute values of porosity without any PHIT LFM input. In this case the mean NPE is 3.25%, representing a notable improvement over test 2 but remaining less accurate than test 1, where the LFM was explicitly provided.

In the fourth test, two networks were trained separately. The first network estimated the porosity residual from seismic data, while the second predicted PHIT LFM from EM-derived resistivity. The absolute porosity is obtained by summing the output of both networks. This hybrid approach achieved a mean NPE of 2.15% that is even closer to Test 1. This hybrid approach performs better than test 3 because resistivity is better correlated to PHIT LFM than to the absolute porosity due to its relatively low vertical resolution.

These results highlight the potential of resistivity data to be used as proxy for porosity LFM. Density (from gravity data) and P-wave velocity (from full waveform imaging) are other potential proxies as both are directly linked to the absolute porosity of the rock unlike seismic amplitudes that vary according to impedance contrasts caused by differences in porosity among many other factors.

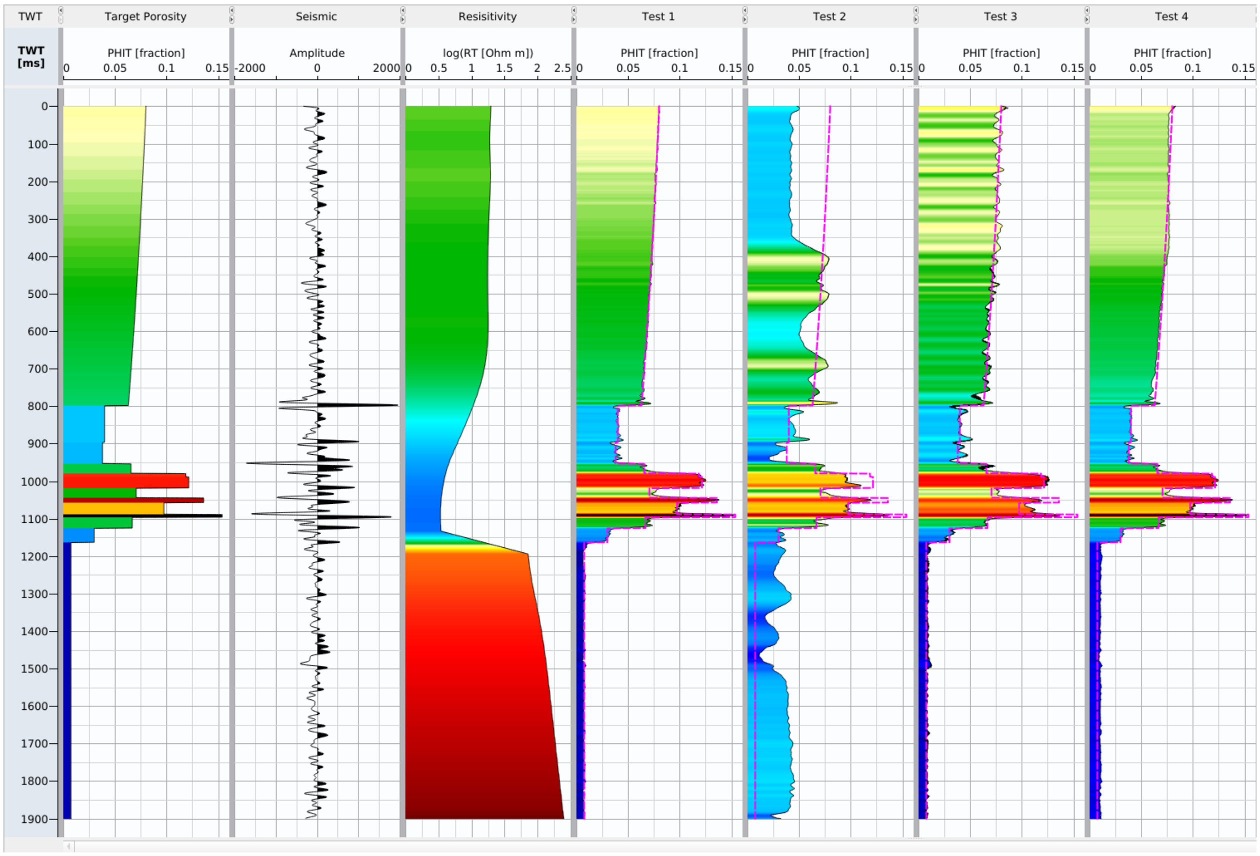

Figure 1: Random trace in the dataset showing from left to right, the target porosity, seismic amplitudes, resistivity, test 1, test 2, test 3 and test 4 porosity predictions. The dashed pink trace in the last four tracks corresponds to the target porosity shown in the first track.

Conclusions

This study demonstrates that integrating multi-physics data into neural network-based reservoir characterization workflows can benefit deep geothermal exploration. The use of EM-derived resistivity as LFM helps reduce the lack of low-frequency information in bandlimited seismic data. Nevertheless, inclusion of additional low-frequency information is only beneficial if this information is well correlated with the target to estimate (PHIT LFM in this study). A careful analysis of this correlation is therefore critical prior to feeding this additional information to the network.

By leveraging the complementary nature of seismic and resistivity data, the proposed workflow produces accurate estimates of total porosity. These advancements not only improve the understanding of subsurface geology but also contribute to the de-risking of geothermal projects, paving the way for more efficient and sustainable energy exploration.

Future work will aim to extend this methodology by incorporating additional geophysical datasets, such as gravity, magnetics and seismic velocities, while also testing its application on field data from ongoing geothermal projects. While this study focused on geothermal reservoir characterization, the approach can be adapted for other domains, such as mining (e.g., ore probability estimation) or oil and gas exploration. In the latter case, instead of using full stack data, partial stacks or gathers can be utilized to account for AVO effects that are linked to fluid saturations in the pore space.

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