Unlocking geothermal reservoir seismic characterization with physics-guided deep neural networks

JL. Formento[1], F. Allo[1], JP. Coulon[1], R. Reboul[1], L. Capar[2], M. Darnet[2], S. Marc[2], B. Issautier[2], A. Stopin[2]

[1] CGG
[2] BRGM

Summary

The use of seismic inversion for reservoir characterization, widely developed in the oil and gas industry, remains a challenge for geothermal quantitative interpretation due to a lack of reliable well and seismic data stemming from limited budgets and restrictions when operating in populated areas. Yet, the benefits of seismic data to de-risk geothermal activity have been demonstrated in the past (Mougenot, 1999). The recent development of advanced deep neural networks (DNNs) has opened the door to a new viable approach for directly estimating reservoir properties from seismic data. Although this kind of neural networks requires a large amount of labelled data to be trained, only a limited amount of real well data is required as synthetic data can be used to augment the training set. Recently introduced theory-guided techniques based on rock physics models can help generate catalogues of pseudo-logs representative of geologic variations. DNNs trained with synthetic data only are applied to a geothermal carbonate reservoir located in the Dogger formation north-east of Paris, France. The goal of the study is to characterize the extent of porous and permeable layers encountered at existing geothermal wells and ultimately guide the location and design of future geothermal wells in the area.

Introduction

The Dogger formation is the main geothermal reservoir for heat supply in the Paris Basin where forty or so low-enthalpy geothermal plants are currently in operation. Although it has been intensively studied for decades, the available information for geothermal reservoir characterization is limited to wireline logs and cores at the well locations, outcrops usually far away from the zone of interest, and series of old 2D seismic lines. While future 3D seismic acquisitions will provide much higher-quality data with better lateral coverage, several techniques already offer ways to retrieve more information from the existing 2D lines. The most popular one to get quantitative information of the reservoir properties is seismic inversion which is extensively used in the oil and gas sector. Inverting old seismic data requires particular care including amplitude preserving seismic processing and dedicated post processing prior to inversion. An acoustic inversion was run over five 2D seismic reflection lines totalling about 75 kilometres and using 34 wells drilled through the Dogger of the Paris Basin. In complement to this seismic inversion approach, the benefits of applying deep neural networks to estimate elastic and rock properties from seismic data were evaluated. Although such state-of-the-art networks require a very large amount of data to be trained, synthetic data can be used to augment the training set (Balz et al., 1999). To increase the robustness of the estimation, realistic synthetic data needs to be generated that represents possible geological variations away from the existing wells. Downton et al. (2020) introduced a hybrid theory-guided approach to the generation of such realistic synthetic data which combines the use of theoretical rock physics models (RPMs) and statistical simulations. This novel methodology is applied in parallel to the inversion study to generate hundreds of pseudo-wells to train DNNs for deriving P-wave impedance, total porosity and volume of clays in the Dogger formation from the same 2D seismic lines. These rock properties are in turn used to compute the effective porosity from which an absolute permeability is derived based on laboratory measurements on core data. Results have highlighted a set of relatively continuous porous and permeable layers that will be considered in the design of future geothermal wells in the area.

Data review and applied methodology

Out of the 34 wells located in the study area, only four, used for hydrocarbon exploration, have a suite of logs (gamma ray, neutron porosity, density, resistivity and sonic) suitable for quantitative reservoir characterization. A detailed joint petrophysical and rock physics analysis has been performed on all wells to estimate statistical mineral volumes and porosity logs displayed in Figure 1. To help control the quality of those volumes, a rock physics-based approach is used. Elastic logs predicted by theoretical RPMs from the mineral volumes and porosity are compared with available measured logs as shown on the 2 right tracks of Figure 1. The match achieved between predicted and measured elastic logs underlines the importance of running a joint analysis to produce a consistent set of rock and elastic properties and reinforce the role of rock physics in general as a quality control tool for petrophysical analysis.
The methodology proposed by Downton et al. (2020) is designed to reproduce in the synthetic data the geological variability observed in the measured log data. Each original well is broken down into intervals of homogeneous rock properties within which statistics are considered stationary and follow a defined background trend. Variations in rock properties can be simulated by shifting or scaling the trend in each interval as well as varying the thickness of each interval. These background trend modifications are based on the observed geological variability of the Dogger carbonate formation. A vertical variogram is used to estimate how quickly the rock property varies with depth. High-frequency variations are statistically simulated based on the variogram and added to the modified background trends to generate realistic pseudo-logs.

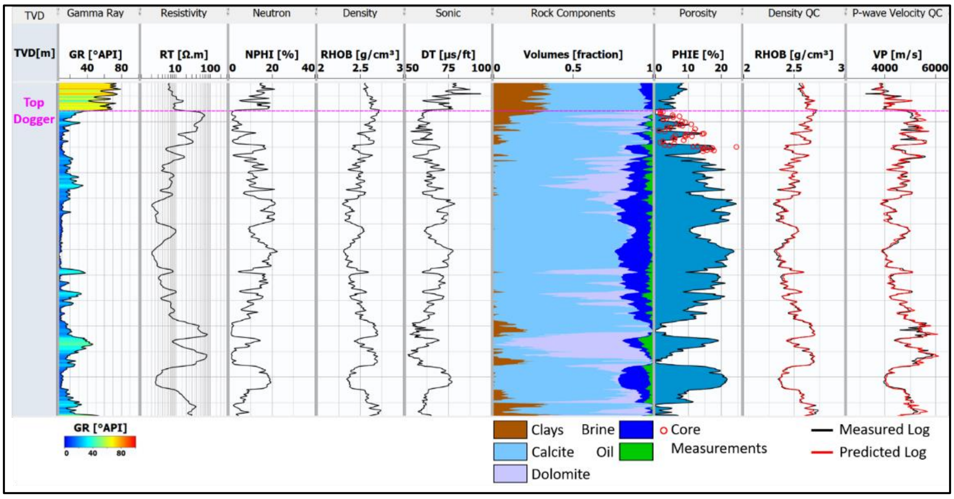

Figure 1 *Petrophysical analysis at one of the oil wells. Mineral volumes (track 6) and porosity (track 7) are computed from petrophysical logs (tracks 1 to 5) using multi-linear regressions. Quality controls include core measurements (red dots in track 7) and elastic log predictions from rock physics models (red curves in tracks 8 and 9).*

Altogether 324 pseudo-wells were created from the combination of all simulated scenarios (change of thickness of the overburden and reservoirs layers, change of porosity and volume of clays in the reservoir layers). The simulated petrophysical curves are input into the calibrated RPMs to calculate synthetic density and P-wave velocity curves. Synthetic zero-offset seismic traces are in turn obtained by convolving the reflectivity series extracted from the synthetic elastic logs with a statistical zero-phase wavelet derived from the spectral analysis of the seismic lines. The set of synthetic petrophysical logs and seismic traces is used to train the DNNs. None of the original well logs were included in the training set.

Validation of the methodology on synthetic dataset

Prior to applying the DNNs to the real seismic lines, tests were run to evaluate their performance in controlled conditions. Synthetic seismic data is derived from an existing 3D model (Issautier, 2015) of the subsurface populated with porosity and volume of clays and taken as ground truth to which the DNN results are compared. The calibrated RPMs are first applied to compute the acoustic impedance in the 3D model. A zero-offset synthetic 3D seismic cube shown on Figure 2a is then generated by convolving the impedance contrasts with the statistical zero-phase wavelet.
A first test consists in applying the DNNs to this 3D synthetic seismic cube and is designed to evaluate the ultimate accuracy of the methodology in perfect conditions with no noise. Figure 2 shows that the DNN manages to qualitatively recover the main variations in total porosity and also achieves a reasonable quantitative match with a mean average percentage error (MAPE) of around 24% in the reservoir interval over the entire 3D volume. While this first result is encouraging, its relevance is questionable as it does not account for the signal-to-noise ratio observed in the old 2D lines.

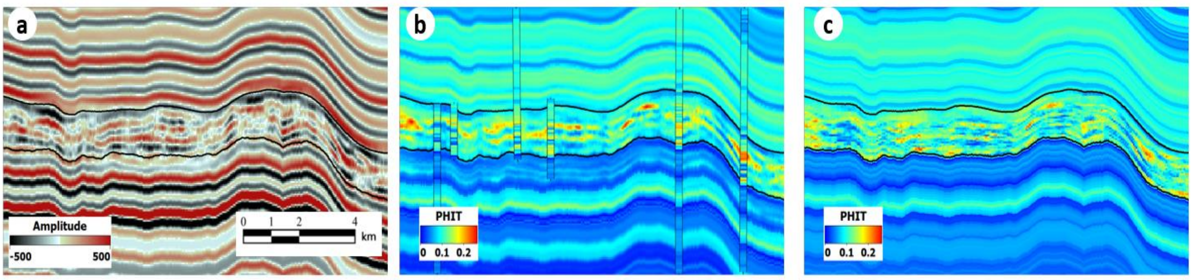

Figure 2 *Total porosity estimation from ideal seismic data. a: 3D synthetic seismic obtained by applying a rock physics model to a reference 3D porosity model (Issautier, 2015). b: Total porosity estimated by the DNN trained on synthetic data. The true porosity model is displayed at selected well locations c: Total porosity model taken as ground truth. The reservoir interval is delimited by the black horizons*

A second test is therefore designed to analyse the impact of the presence of noise in the input seismic data. It consists in applying the same neural network on noisy synthetic seismic data obtained by adding random noise with a signal-to-noise ratio of around 5 as observed on the real seismic sections. Figure 3b shows that the estimated total porosity contains a large portion of the added noise. The MAPE in the reservoir interval is around 41% in this case which indicates a rather unreliable estimation. Based on this observation, an additional test was performed by creating a new neural network trained on noisy synthetic traces obtained by adding the same level of noise to the synthetic seismic traces of the training set. This approach was conclusive as the MAPE decreased to almost 30% and a large portion of the noise present in the input seismic data did not end up in the estimated rock properties. It appears that the DNN was able to partly reproduce the observed noise when adding it in the synthetic training set. This third test gives a good idea of what can be achieved with this kind of neural network from old seismic lines.

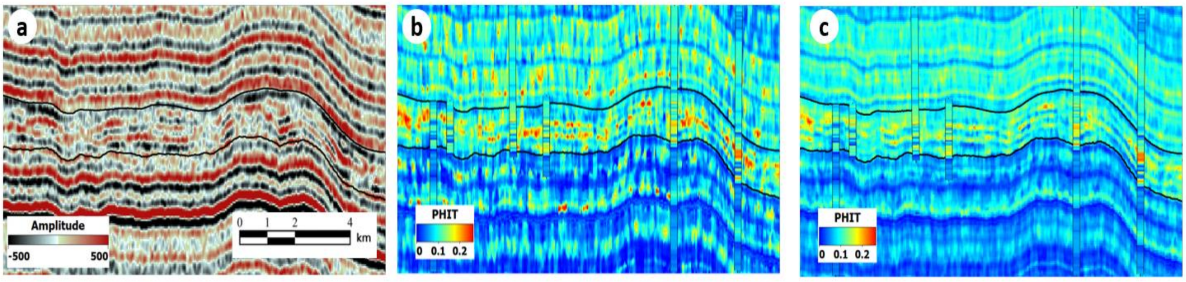

Figure 3 Total porosity estimation from noisy seismic data. a: Input noisy synthetic seismic obtained by adding random noise to the original synthetic seismic shown on Figure 2. b: Porosity estimated by the same DNN as the first test. c: Porosity estimated by a DNN trained on noisy synthetic seismic traces obtained from the pseudo-wells.

Application to real dataset

Before estimating the total porosity, P-wave impedance is predicted from five reprocessed seismic 2D lines from the 1980s using both acoustic inversion and DNN. Figure 4 shows very consistent results from the two methods which increase the degree of confidence in both. The residual energy between seismic and synthetic traces is very low with both methods. While this is expected with the inversion, it is a reassuring observation for the DNN as it is not set-up to minimize the residual energy but statistically reproduce the impedance traces from the seismic amplitude traces.

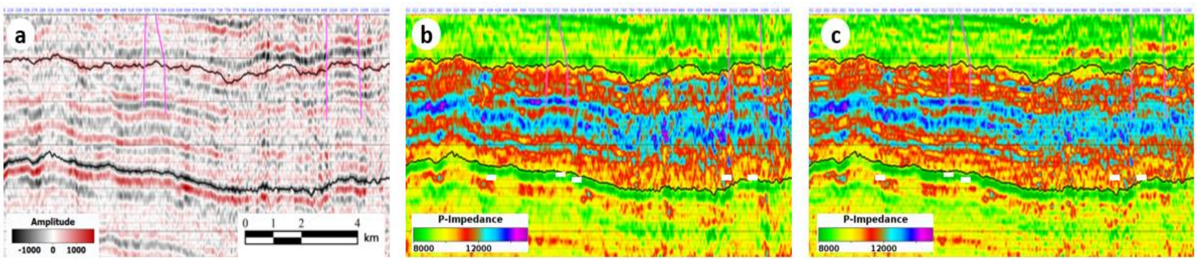

Figure 4 a: Input seismic section crossing the study area from west to east. The top horizon represents the top of the Dogger formation, the bottom horizon corresponds to the top of the marls with Ostrea acuminata (Middle Bajocian). b: P-impedance estimated by acoustic inversion. c: P-Impedance estimated by using the DNN trained on noisy synthetic seismic traces obtained from the pseudo-wells.

Two DNNs are then used to directly estimate the total porosity and volume of clays from the seismic amplitudes. An effective porosity is then derived from the total porosity and clay volume by application of Equation 1:

$$\phi_E = \phi_T(1 - V_{clay}) \tag{1}$$

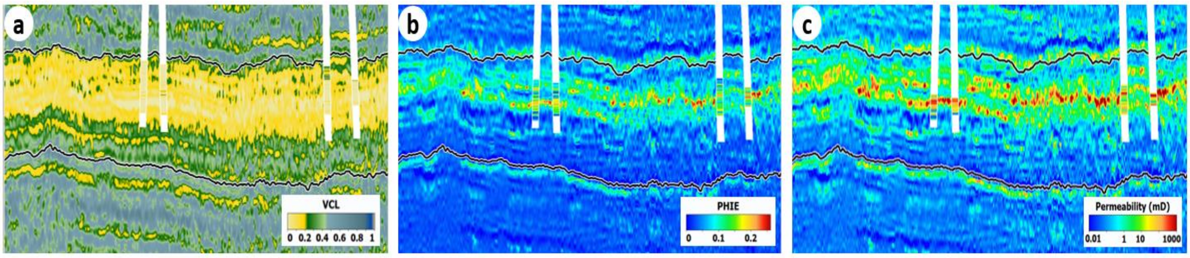

Figure 5 *a: Estimated clay volume section crossing the study area from west to east. b: Effective porosity section obtained by combining the estimated total porosity and clay volume highlighting the most porous layers. c: Absolute permeability section derived from the effective porosity*

Figure 5b shows the estimated effective porosity derived from the volume of clays (Figure 5a) and total porosity along one of the sections crossing the area from west to east. Absolute permeability is not estimated directly from the seismic amplitudes but rather computed from the effective porosity based on a statistical relationship obtained from core lab measurements. Figures 5b&5c confirm the presence of several highly porous and permeable layers in the upper part of the Dogger formation that represent a potential target to consider during the design of future geothermal wells in the area.
As with any quantitative interpretation from seismic data, a major pitfall is the strong dependence on the low-frequency model supplied to both the inversion model and neural network to fill the low-frequency range absent from the input seismic. The estimated rock properties are highly impacted by the input low-frequency model which represents a severe limitation when well data is very scarce or of poor quality. Acquiring broadband seismic data or any other mean to obtain a reliable geological input to control this low-frequency is key for a better quantitative interpretation of geothermal formations. To conclude, while generating synthetic pseudo-wells is an undeniable asset for studies with sparse data, the simulated scenarios need to rely on sound representative geological information to avoid biasing the rock property estimates.

Conclusion

The rock properties of the Dogger formation estimated from old 2D seismic lines from the 1980s using DNNs have complemented and validated the results obtained from acoustic inversion. The simulation of realistic pseudo-wells from rock physics models and the generation of synthetic seismic traces with a representative noise level have successfully helped overcome the lack of data needed to train such advanced neural networks. The effective porosity and permeability sections obtained from the DNN output, while uncertain quantitatively, brings valuable additional information to update the static reservoir model and support future geothermal wells in the area. Beyond this geothermal study, the ability to train neural networks on synthetic data makes them a practical alternative to seismic inversion when well log data is either limited or of poor quality and the geological knowledge of the target formation is relatively well known as is the case for the Dogger formation of the Paris Basin.

Acknowledgements

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