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Total organic carbon prediction for Turonian source rock determination using probabilistic neural networks in the Sergipe-Alagoas basin

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Abstract Summary

The total organic carbon (TOC) is a critical parameter for evaluating source rocks. Although there is a known correlation between TOC and elastic properties, determining it from seismic data is challenging. Linear regression can predict TOC from impedance, but it overlooks seismic attributes that could enhance the prediction. Neural networks can utilize seismic inversion data and seismic attributes as features, although they require extensive training datasets and feature selection is time-consuming. In this study, we predict the TOC volume of the Turonian source rock in the Sergipe-Alagoas basin using probabilistic neural networks (PNN). The dataset includes TOC logs from seven wells tied to a seismic volume, and sample-based attributes calculated from full and angle stack volumes. The chosen subset of attributes is identified with stepwise regression and the reliability of the selected attributes is defined through cross-validation. A convolutional operator addresses frequency differences between target logs and seismic data. A PNN is trained and validated using the selected attributes. This procedure yielded a PNN model with a training correlation of 0.94 and validation correlation of 0.82. The resulting TOC property volume is consistent with the geological characteristics of the source rock.

Introduction

The petroleum system considers the source rock as the primary and essential component of the geological system needed to generate a petroleum play (Løseth et al., 2011). Total organic carbon (TOC), the critical source rock parameter, can be determined through geochemical analysis of core data or empirically calculated using well-log data (Steiner et al., 2016; Xu et al., 2017).

The determination of TOC from seismic data can be difficult due to the coupling of multiple effects such as overburden, overpressure, maturation, composition and TOC itself (Lacerda et al., 2023). For this reason, different methods have been used to predict TOC outside the range of wells: for instance, Løseth et al. (2011) established a relationship between acoustic impedance and TOC from wells and extrapolated to volumes, Refunjol et al. (2016) used neural networks, Xu et al. (2017) used block cokriging with multiple secondary attributes, Convers et al. (2017) used probabilistic neural networks, del Monte et al. (2018) analyzed acoustic impedance, AVO and attributes, Reis et al. (2023) used NGBoost and Wang et al. (2024) used multiple attributes.

In this work, we apply a workflow originally proposed to predict reservoir properties (Hampson et al., 2001) to the prediction of TOC from Turonian source rock found in the Sergipe-Alagoas Basin. The TOC log is defined as the target log to be predicted. Seismic data is used as input to generate attributes that will be evaluated in a multiple linear regression. Elastic volumes from deterministic inversion are also inputs for this process. Then, cross-validation is used to select a subset of the attributes in the multiple linear regression. These attributes are used as input data to train a Probabilistic Neural Network. The trained model is used to predict the TOC property volume from seismic and is found to be geologically consistent to define the source rock.

Method

This work follows the methodology proposed by Hampson et al. (2001): 1) Define the log curve to be predicted, the target log; 2) Computed attributes from the full and angle stack data and extract a trace of each volume in the well positions; 3) Apply non-linear transformations to the target log, attributes and seismic data; 4) Determine single variable regressions between each of the attributes and the target logs; 5) based on the regression, shift the target log to improve the correlation; 6) Compute stepwise multiple linear regressions to seek for the best number of attributes and convolutional operator length based on the lowest prediction training and leave-one-out validation error curves; 7) A Probabilistic Neural Networks (PNN) model is trained based on the selected number of attributes and convolutional operator length; 8) Cross-validation is employed to assess the reliability of the multiple attribute transformation derived. In this process, each well is systematically excluded from the training set, and the transformation is recalculated using the remaining wells; 9) After the model is trained and validated at the well positions, it is applied to the whole volume and the target property volume is generated.

Results

We applied our workflow to the Segipe-Alagoas basin. The 44370 km^2 of the Sergipe-Alagoas basin are distributed along three states of the northeast of Brazil, with 31750 km^2 located offshore (ANP, 2015). The source rock, deposited during drift phase, is divided into the albian-cenomanian shales from Riachuelo Formation and the cenomanian-turonian shales from Cotinguiba Formation (ANP, 2015). The Turonian shales of Cotinguiba Formation are the case of study in this work.

The dataset is composed of TOC logs and seismic volumes. Previously calculated TOC logs from seven wells covering the zone of interest were used as target logs in the calibration procedure. Time domain full stack, four angle stacks and volumes of P-impedance and S-impedance obtained from deterministic elastic inversion were used as seismic volumes. The Vp/Vs ratio computed from the impedance volumes was also considered in the analysis.

After the single correlation, the wells were shifted based on the Vp/Vs ratio volume to improve the correlation between the target log and the attributes. To avoid artificial correlation between TOC and the attributes in geologically uncorrelated regions the shift was limited to 10ms. The multiple linear regression was trained in the shifted target log with the minimum error found with $\sqrt{TOC}$ as target variable. The posterior error analysis indicated that the best prediction is achieved with six attributes and an operator of length five. The selected attributes in order of importance are P-Impedance^{-1}, Amplitude Weighted Frequency (Mid Stack), S-Impedance^2, Amplitude Weighted Frequency (Far Stack), Filter 15/20-25/30 (Ultra Far Stack), and $\sqrt{Mid\ Stack}$. After the sixth attribute the prediction error increases, and this is the indicative that the maximum number of attributes has been reached to prevent overfitting.

Figure 1 shows the original TOC logs (black) against the predicted TOC logs (red). The vertical time scale is centered in the source rock marker defined in each well. Figure 1a shows the multiple linear regression validation and Figure 1b shows the PNN validation. The models were trained in the interval around the source rock defined by the regions between the yellow bars. The statistics of the models were calculated in the same region and are displayed at the top of the figures. The multiple attribute training correlation is 0.87 and the training error is 0.35, not shown in the figure. The validation correlation is 0.77 and validation error is 0.44, top of Figure 1a. The PNN training correlation is 0.94 and the error is 0.24, not shown in the figure. Figure 1b shows that the PNN validation correlation is 0.82 and validation error is 0.39. The PNN increased the correlation, and thus the TOC prediction.

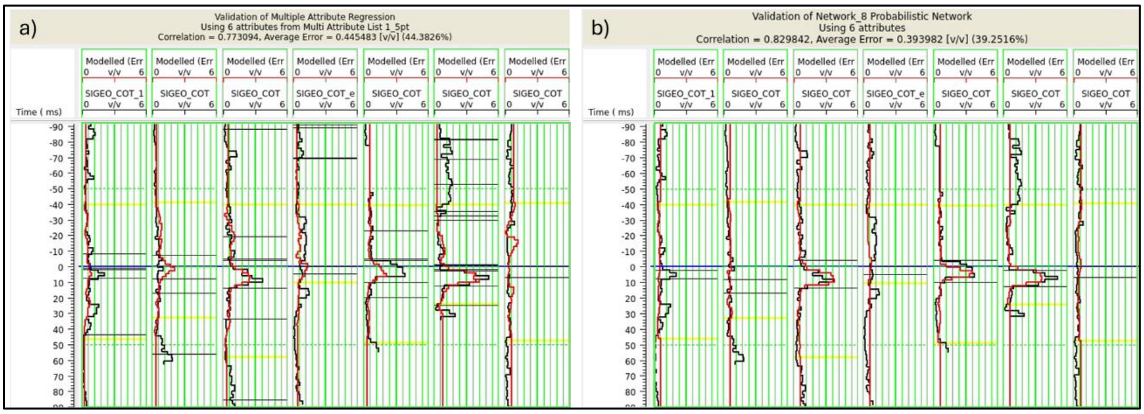

Figure 1: Model validation. a) Multiple Linear Regression and b) Probabilistic Neural Networks model validation. The target log is shown in black and the predicted log in red. The metrics that are computed between the yellow lines are shown at the top of the images.

Figure 2 shows the TOC predicted applying the PNN model to the complete seismic region. Figure 2a shows a cross section of the TOC volume passing through an arbitrary line. Three wells with TOC overlays the predicted TOC showed in the arbitrary line. Figure 2b shows a slice of the TOC property volume around the horizon of interest. The seven wells are shown in white circles and the arbitrary line displayed in Figure 2a is shown in white. High and low values of TOC are geologically consistent.

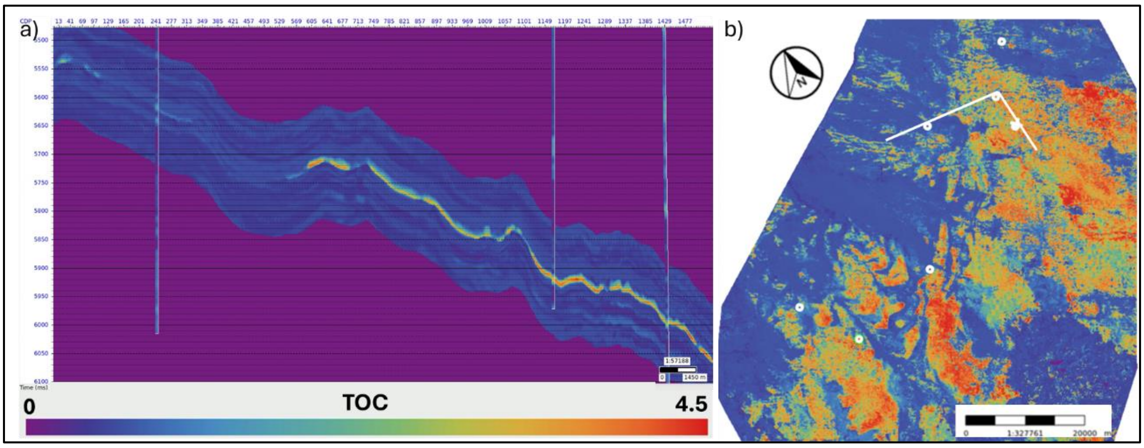

Figure 2: PNN TOC property volume estimates. a) Cross section of the TOC volume over an arbitrary line with three overlaying wells and b) slice of the maximum predicted TOC over the horizon of interest. The seven wells and the arbitrary line are indicated as white circles and white lines in b), respectively. The color scheme is the same for both images.

Conclusions

We estimated the Total Organic Content distribution in a basin in Brazil using probabilistic neural networks. The training data was computed from attributes and non-linear transformations of seismic data and elastic property volumes. Multiple linear regression prediction of the target log was used to select the sixth attributes used for the neural network model. The chosen subset of attributes is identified with stepwise regression and the reliability of the selected attributes is defined through cross-validation. The frequency differences between the TOC logs and the attributes data were addressed with a convolutional operator. The attribute with the higher correlation with the TOC log was the inverse of the P-impedance. The PNN prediction increased the correlation when compared to the Multiple Linear Regression prediction, and thus the TOC prediction was increased. The high correlation in the validation prediction of the neural network model demonstrated the effectiveness of this method. The first TOC predicted volume in a northeast Brazilian basin sounds geologically consistent with the characteristics of the source rock. These results encourage us to apply the methodology in other areas.

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