Facies prediction using Democratic Neural Network Association: Case study in an onshore portion of the Sergipe-Alagoas basin

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Abstract

The detailed knowledge about vertical and lateral facies distribution is essential for the characterization of reservoir properties, playing a fundamental role for the efficiency of the development and production of oil fields. Data integration is required for this purpose, however the variety of data resolution makes this task difficult by conventional methods. In this regard, alternative approaches, such as artificial intelligence, have been widely applied in the oil industry in recent years towards reduce uncertainties and exploratory risks related to the correct prediction of facies distribution. This work aimed to apply a neural network-based methodology called Democratic Neural Network Association (DNNA) from which electrofacies and poststack seismic attributes were used to train a neural network that established the relationships between these data in order to predict the facies distribution in the studied area, whose target was one of the most relevant onshore reservoirs in Brazil, the Carmópolis Member in the context of the Siririzinho and Castanhal fields. The results of this unprecedent study in the Sergipe-Alagoas basin, although preliminary, demonstrated that the methodology is a useful tool to deal with geological uncertainties, which was able to predict the reservoir facies distribution with good accuracy. Furthermore, the results showed a high degree of similarity with previous depositional models of the Carmópolis Member, which reveals the reliability of the method.

Introduction

The application of new methods and technologies to reduce risks and operational costs, as well as to increase the recovery factor in onshore and offshore fields, is a permanent issue in the oil and gas industry, which often involves large investments, where improving the knowledge of subsurface conditions is critical to achieving these goals.

The correct prediction of facies distribution and fluid content throughout the reservoir is one of the leading challenges in hydrocarbon recovery due to the uncertainties related to the determination of the rock properties in modeling studies, which require the integration of different types of data (well logs, cuttings, cores, pre and poststack seismic attributes) with different resolutions. Consequently, manual integration is a time-consuming and sometimes even impractical job (Hami-Eddine et al., 2015).

On the other hand, the use of artificial intelligence has been widely discussed in the oil industry, such as the machine learning approach as a tool for the automatic identification and classification of geological faults in seismic data (Li et al., 2019; Wu et al., 2018), salt bodies (Zeng et al., 2018) and facies (Hall, 2016). This is due to the efficient and fast integration of multidimensional data from several types of algorithms that are trained based on specific data and thus learn to recognize hidden and complex patterns in the subsurface (Anifowose, 2011).

In order to exemplify and evaluate the use of this method, the purpose of this study was to predict the reservoirs facies distribution of Carmópolis Member in the context of the Siririzinho and Castanhal oil fields (**Figure 1**), located at Aracaju Structural High, onshore of Sergipe-Alagoas basin, using a supervised machine learning approach that aimed to combine seismic attributes and electrofacies to be able to make the prediction of specific lithofacies in regions far away from the wells.

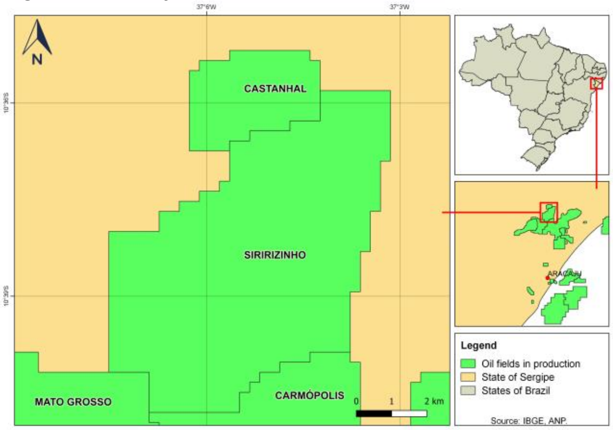

Figure 1. Location of Siririzinho and Castanhal fields in Sergipe-Alagoas basin.

Method

The workflow applied here was divided into four stages, according to the flowchart in **Figure 2**: data loading and quality control (QC), well to seismic tie, seismic interpretation and attributes generation and facies prediction.

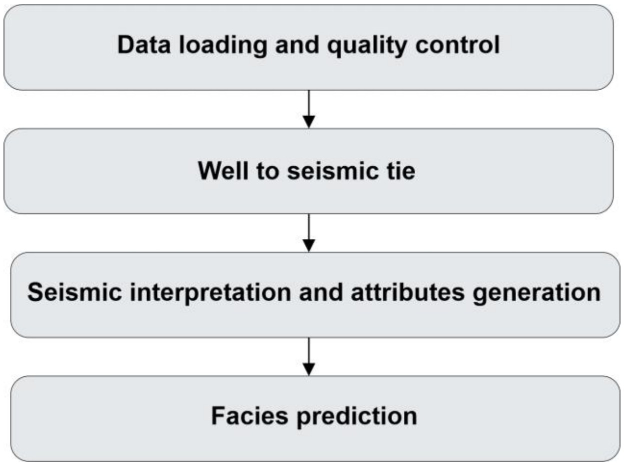

Figure 2. Flowchart summarizing the steps of the adopted methodology.

1. Data loading and quality control

The dataset available consisted in approximately 82 km² of 3D poststack seismic and 3 wells with their respective logs, markers and electrofacies (**Figure 3**).

Figure 3. Dataset used in this study.

The QC of wells was based on standardizing the names and units of the logs, removing spikes and checking missing data.

For the seismic data, after checking the loading parameters according to the header, in order to improve the data resolution and lateral continuity of the reflectors, the volume was preconditioned using the Dip Steered Enhancement (**Figure 4**), a structure-oriented filtering that extracts dip and azimuth information from each seismic trace and differentiates it between reflectors and random noises that are minimized, highlighting structural and stratigraphic features (Chopra & Marfurt, 2007).

2. Well to seismic tie

It is a fundamental step for seismic interpretation, whose function is to relate the subsurface data obtained from the wells, acquired in depth, with the seismic data, measured in time.

The procedure consisted of generating synthetic seismograms in each well, which were used to adjust the wells to the original seismic trace.

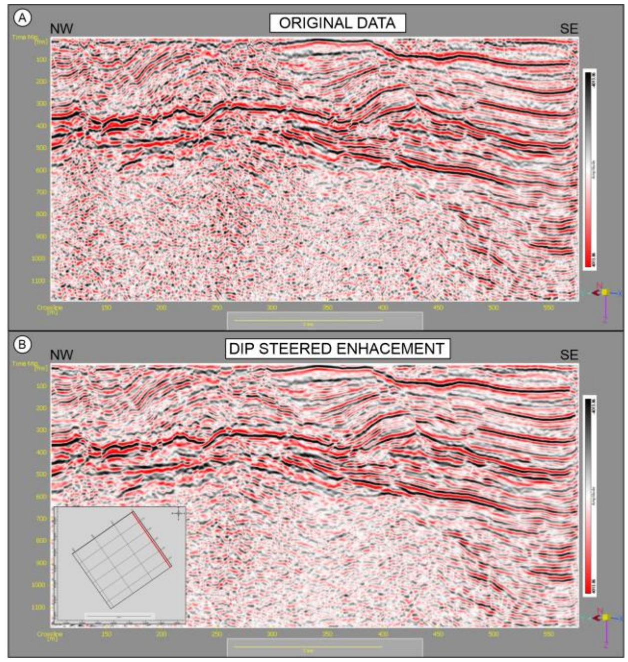

Figure 4. Inline 12 showing the noise and low quality of the original seismic data (A), the filtering and improvement of the lateral continuity of the reflectors after application of Dip Steered Enhancement (B).

3. Seismic interpretation and attributes generation

Seismic interpretation aimed to define the geometry of the facies prediction model. Due to the difficulty of defining a reflector that corresponds to the top of the Carmópolis Member, it was decided to map and define the top of Ibura Member as a reference marker to the model's upper boundary (**Figure 5**). As for the lower limit, a sampling window of 220 ms down was defined from the same reflector, which allowed to cover the entire reservoir thickness.

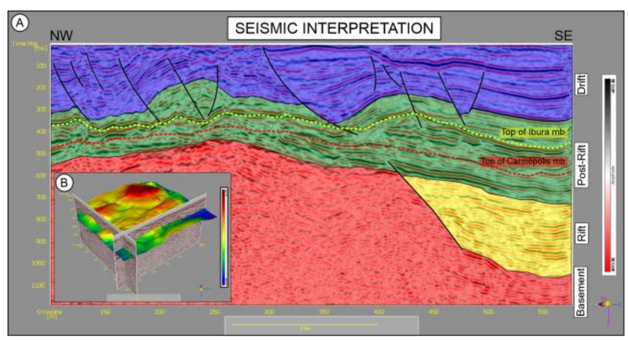

Figure 5. Understanding of local geology from the seismic interpretation of inline 12 (A), interpreted horizon referring to the top of the Ibura Member (B).

Based on the potential for identifying different geological features some seismic attributes were generated to later be used as input for the workflow of facies prediction (**Figure 6**):

Coherence – which measures the trace-to-trace similarity of the seismic waveform within a small analysis window, very useful in identifying and visualizing faults and stratigraphic features (Herron, 2011);

RMS amplitude - defined as the square root of the average of the squared amplitudes (Sheriff, 2002), from which hydrocarbon indicators can be mapped directly by measure reflectivity in a zone of interest;

Relief – attribute that provides an aid to structural interpretation, highlighting high impedance contrasts;

Spectral Decomposition - reveals the seismic signal at its constituent frequencies, which allows the interpreter to see the amplitude and phase tuned at specific wavelengths (Othman et al., 2016);

Envelope - represents the instantaneous energy of the signal and is proportional in its magnitude to the reflection coefficient, which is useful in highlighting gas accumulation, discontinuities, faults, tuning effect and sequence boundaries (Latiff et al., 2001).

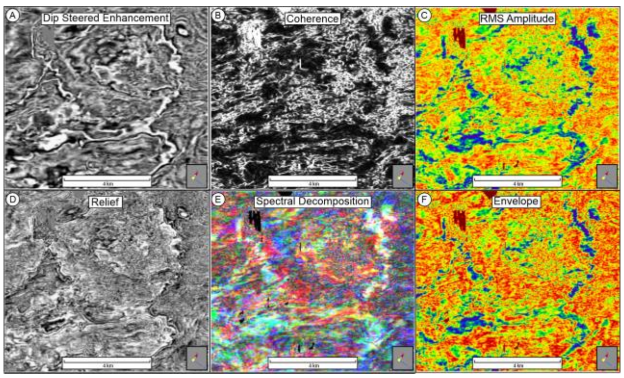

Figure 6. Timeslice 240 ms of the generated seismic attributes: DSE (A), Coherence (B), RMS Amplitude (C), Relief (D), Spectral Decomposition RBG blend (red = 10 Hz, green = 30 Hz, blue = 50 Hz) (E) and Envelope (F).

4. <u>Facies prediction</u>

The software used for doing the rock prediction was the Rock Type Classification, from Emerson/Paradigm. This application uses the method Democratic Neural Network Association (DNNA) (Hami-Eddine et al., 2015) to predict the facies.

DNNA is a methodology based on neural network that uses a probabilistic approach consisting of the training of well logs and pre or poststack seismic attributes in order to find seismic patterns that can predict lithofacies distribution and uncertainty, proven to be efficient for predicting lithology in the regions away the wells (Hami-Eddine et al., 2015).

Following the workflow shown in **Figure 7**, the definition of the training set was composed of the electrofacies identified in the 3 wells and 6 seismic attributes previously generated.

Then, the electrofacies were upscaled to remove thin layers that cannot be identified in the seismic due to the low resolution. A vertical sampling interval of 10 meters has been defined, the rate at which facies information and seismic attributes will be extracted throughout the well (in the zone of interest) to create the training set.

After processing, the neural network was trained, and the QC of its predictive capacity was done by evaluating the probability of facies being correctly predicted along the well, associated with the analysis of the reconstruction rate of each facies at the analyzed intervals.

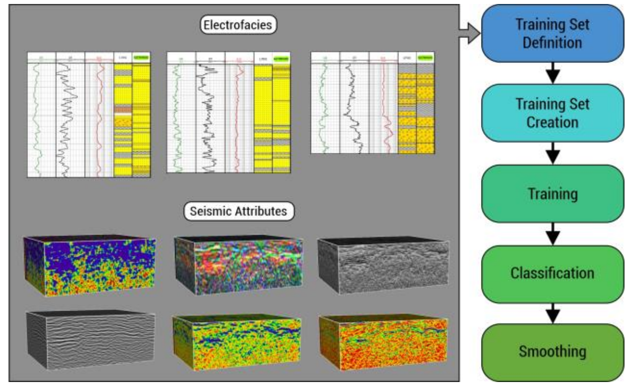

Figure 7. Workflow and data used to compose the training set.

Thus, the relationship established between the facies and attribute responses was defined and validated, and then the data from the study area could be classified by the trained neural network.

Results

The more scattered the network's neurons are in the range of attribute values, the greater their potential to distinguish each of the facies, which contributes positively to the learning process (Emerson, 2019). Despite the low density of neurons caused by the low sampling rate, their distribution is completely dispersed in most attributes, except for the “coherence”, which showed a concentration in its central range (**Figure 8**).

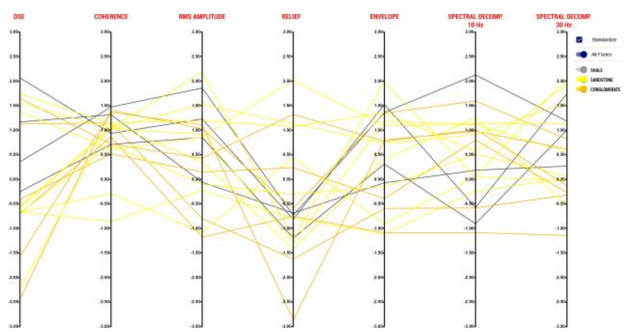

Figure 8. Distribution of neurons of the neural network in each attribute.

Regarding the network's predictive capacity, the maximum probability of facies identification (track 5) correlated almost entirely with the predicted facies (track 4). As for the probability of identifying each facies (track 6), it was observed that only well C had an interval with strong overlap of EFACs 1 (shale) and 2 (sandstone), where only 1 occurs according to the predicted facies (**Figure 9**).

Table 1 shows that the rate of facies reconstruction was 100% in all wells. This result is important because it ensures that the entire range of interest was fully represented in the training set.

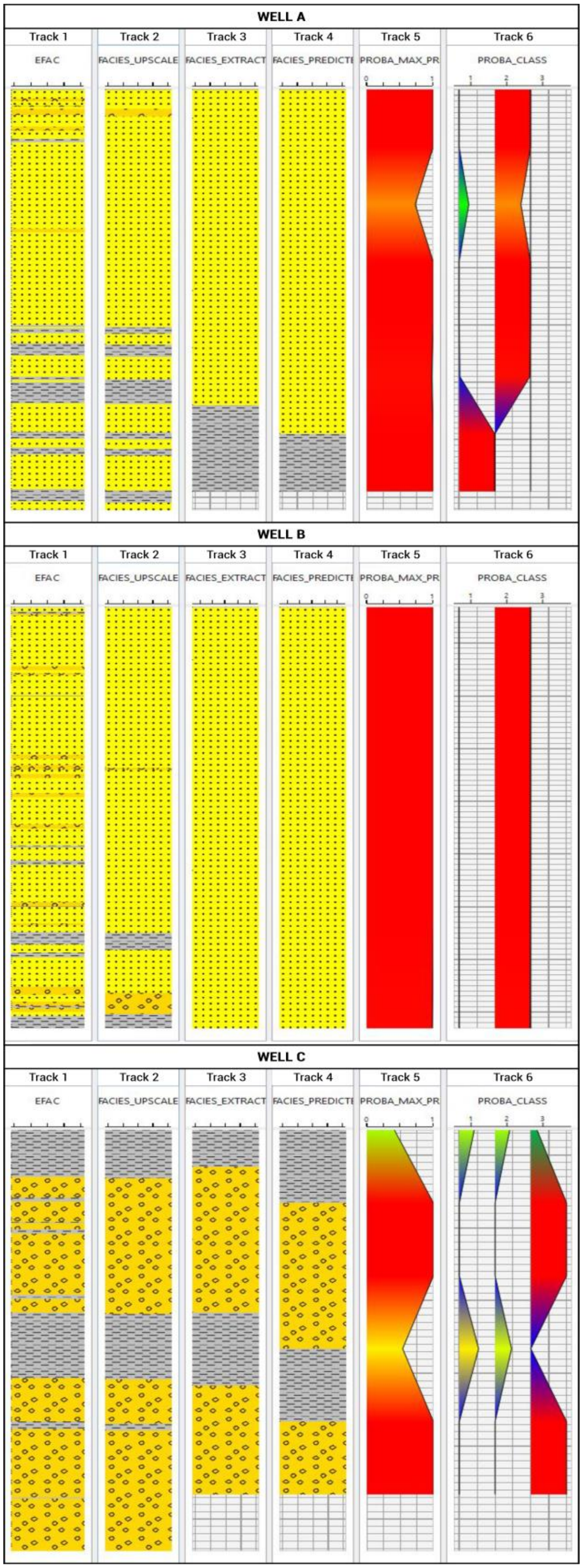

Figure 9. Probability of the input facies being correctly predicted along the interval (track 5) and distribution of this probability by facies (track 6).

Table 1. Reconstruction rates matrix of facies after training the algorithm.

		EFAC			
		EFAC 1	**EFAC 2**	**EFAC 3**	**All EFACs**
WELL	**A**	100% (2/2)	100% (6/6)	*N/A*	**100% (8/8)**
	B	*N/A*	100% (5/5)	*N/A*	**100% (5/5)**
	C	100% (2/2)	*N/A*	100% (4/4)	**100% (6/6)**
	All Wells	**100% (4/4)**	**100% (11/11)**	**100% (4/4)**	**100% (19/19)**

The trained neural network was then used to classify the study area, resulting in a volume of facies (**Figure 10**) in which each value in a given (x, y and z) position corresponds to the most probable distribution of facies predicted by the DNNA, that is, each facies associated with its highest probability value.

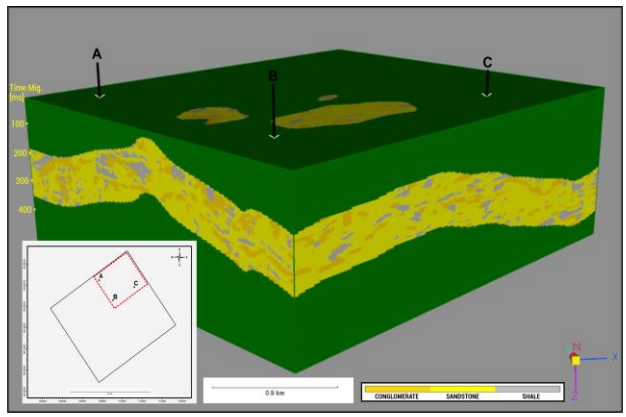

Figure 10. Volume of predicted facies by the DNNA.

By means of a composite section crosscutting the wells, intercalations between conglomeratic, sandstone and shale facies were observed with a great lateral continuity predicted by DNNA in the interval that comprises the Carmópolis Member (**Figure 11A**). In addition, other shale facies less distributed in area were interpreted, which resulted in a stratified pattern to the reservoirs. In general, the predicted facies around the wells showed a good correlation with those already identified on each well and used in the training of the algorithm (**Figure 11B**, **C** and **D**).

This observed pattern, although preliminary, is compatible with the large-scale geometry of the Sergipe-Alagoas basin contextualized in previous depositional models, which interpret the Carmópolis Member as the product of alluvial fans prograding lacustrine environment, and alluvial fans truncated by anastomosing fluvial systems (Azambuja Filho et al., 1980; Candido & Wardlaw, 1985; Sombra, 1987; Souza, 1989).

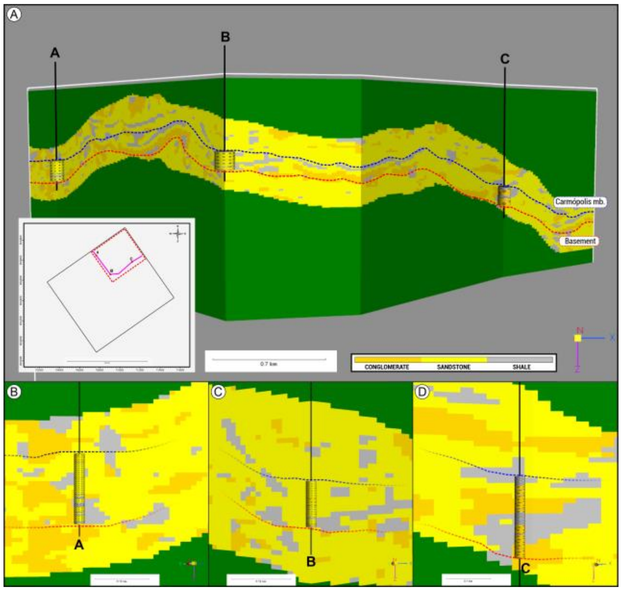

Figure 11. Composite section crossing the three wells in the study area (A); Predicted facies around well A (B), B (C) and C (D).

Conclusions

The DNNA method was useful for integrating seismic and well data. The algorithm enabled the training of a neural network that established the relationships between the seismic attributes extracted in a noisy data with very low vertical resolution and electrofacies from three wells that are on average 2.8 kilometers apart. By using the seismic data for the propagation of the relationship created, the method was able to classify and predict the occurrence of facies in the analyzed reservoir, information that was previously restricted only to the well. We assessed that the stratigraphic relationships and lateral variations of predicted facies by this methodology have a high degree of similarity when compared to previous depositional models of the Carmópolis Member. These results, although preliminary, are unprecedent in the Sergipe Alagoas Basin, and shows the confidence on DNNA to predict facies. Further works with drilling cores information and more wells should provide more reliable input data for the algorithm, improving the predictive capacity of the method.

Acknowledgments

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