Evaporite characterization with non-conventional seismic inversion using genetic algorithms.

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Abstract

One of the main challenges in drilling evaporitic basins is underground geology prediction. Identification of the different kind of lithologies and its properties allows a better geomechanic well planning. Evaporites have a different mechanical behavior when compared to other sedimentary rocks, with the tendency of moving from regions of thicker adjacent sediments to regions where thickness of overlaid sediments is lower. Using well logs and reflection seismic data, a non-linear multi-trace non-conventional seismic inversion was applied with the purpose of performing geological characterization of the salt, identifying the depths with lowest values of velocity, relating to carnallite and tachyhydrite that show greater values of fluence.

Introduction

The discovery of oil and gas fields in evaporitic sedimentary basins demanded a better understanding of the different kind of salts by the oil industry. According to Warren (1989), about 70% of the giant oil fields in carbonate rocks of the world have a relation with evaporites, considered excellent seals in oil systems due to its low porosity. The evaporitic deposits are found in environments where evaporation is greater than water precipitation or greater than the water entering on the basin. The controlled influx of water to the basin and the evaporation elevated rates due to the hot climate of the period favor the concentration of salts in these seas and the formation of these kinds of rocks. The saline evaporite rocks can be classified as sulfates or chlorides. The sulfates are gypsum and anhyhdrite while chlorides are halite, sylvite, carnallite and tachyhydrite.

Several studies broadly address the characterization of ultra-deep water evaporites present in the Brazilian east margin. Falcao *et al* (2017), Dias *et al* (2019) show the importance of inserting salt stratification when building seismic velocity models and the improvement in quality when generating seismic image of the reservoirs located below the salt. From the operational standpoint, Falcao *et al.* (2007) highlights that drilling of saline rocks is associated to several well stability and coating integrity problems, like well closure during drilling and/or coating collapse due to closure. The closure results from salt deformation when subjected to a constant deviating tension, also known as fluence or creep.

According to Li *et al*. (2012), the high viscosity and high-density contrasts between the several kinds of salts result in the movement of the evaporite layers, depending on mechanical properties, layer geometry, tension and temperature. The biggest fluency rates found on the salt are related to lithologies that have water in its chemical composition, like carnallites and tachyhydrite. When drilled, these lithologies move inside the well as soon as the cylindric cavity is established, (Falcao *et al.* (2007)).

To distinguish the different kind of salts, as seen above, is important in several areas of oil exploration and production and, allowing both improvements in the process of seismic image generation (construction of velocity models, data reprocessing, etc.) and supporting drilling engineering in well project planning. Thus, this study aims to characterize the different kind of salts, regarding lithology and compressional wave velocity, applying a non-conventional seismic inversion (genetic seismic inversion) that uses neural networks and genetic algorithms concepts.

Seismic Inversion

Seismic inversion can be defined as a technique applied to create an Earth model using seismic amplitude data as input. This technique is different than direct seismic modelling that generates synthetic seismic amplitude based on an Earth model or using well logs, Russel (1991). Mathematically, direct modelling of seismic data amplitude construction is defined as a convolutional model that represents the interaction between seismic waves propagation and the Earth, as seen in Equation 1 and represented in Figure 1.

$$S(t) = W(t) * r(t) \qquad (1)$$

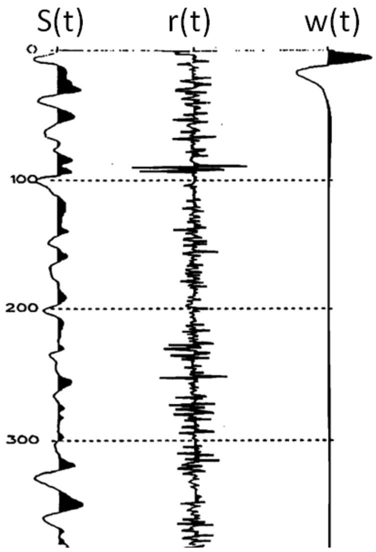


Figure 1 – Example of seismic trace S(t) generation from convolution of reflectivity coefficient and seismic wavelet. Adapted from Russel (1991).

S(t) represents the seismic amplitude trace, W(t) or wavelet is the information of the pulse emitted by the source, r(t) is the information of geological reflections, "t" represents time domain and the symbol "*" represents the convolution operation. The simplified equation considers the noise component equals zero and wave incidence as normal, i.e., the seismic wave hits the geological reflective interfaces perpendicularly.

Ideally, a single seismic trace peak must refer to an acoustic impedance interface (or to a reflection coefficient), even though it is common for the seismic response to represent the overlap of more than one interface (tunning effect), making it difficult to discriminate seismic effects of each interface. Seismic inversion is one of the techniques used to undo these overlap effects, Veeken et al. (2002).

Rosa (2004) define o termo inversão sísmica como um processo global que remove e atenua simultaneamente as distorções presentes no dado de reflexão sísmica, resultando nas propriedades elásticas (velocidade, densidade e razão de Poisson, por exemplo) que são comumente representadas em escala de profundidade.

Rosa (2004) defines seismic inversion as a global process that simultaneously attenuates and removes the present distortions in the seismic reflection data, resulting in elastic properties (velocity, density and Poisson ratio, for example) that are commonly represented in depth scale.

The types of seismic inversion can be classified as conventional and non-conventional methods. According to Priezzhev (2009), the steps of conventional inversions consist of seismic trace modelling, extraction of a wavelet from seismic amplitude, convolution of the modeled trace with the wavelet chosen, and comparison of the result with the real seismic response. When the expected criteria are reached, the seismic data is inverted. Due to the absence of the low frequencies of the seismic data, these inversions and its results depend on an initial model. These low frequency models are commonly generated from the interpolation of the low frequency values of the wells.

Applications of conventional inversions on evaporite packages characterization using pos-stack reflection seismic can be seen in the works of Yamamoto (2019) and Teixeira and Lupinacci (2019), where the linear inversion algorithm Constrained Sparse Spike (CSSI) described by Russel (1991) is used to obtain the acoustic impedances of the different kind of salts.

According to Hampson (2001), the non-conventional approaches of seismic inversion can be thought as an extension of the conventional seismic inversion since both processes use the same input data (seismic data and well logs) and try to predict log properties. The main advantages of these methods are the possibility of predicting other properties besides acoustic impedance and the alternative of using seismic attributes as input data, without the need for prior knowledge of the seismic wavelet or the existence of a previous model. The most found non-conventional techniques consist of successive linear regressions (*stepwize*) and applications of neural networks (Todorov *et al*., 1997; Balz *et al*. (1999); Hampson (2001), Russel *et al*. (2002)).

Genetic seismic inversion

Genetic seismic inversion is used in reservoir characterization (Priezzhev *et al*., (2009); Veeken *et al*., (2009); Ampilov *et al*., (2009); Priezzhev & Stanislav (2018). It is a non-conventional seismic inversion method that uses a non-linear multi-trace operator to obtain the desired properties. The operator is the result of the training performed by neural networks over seismic sub volume and well profile data. According to Veeken *et al*. (2009), genetic inversion can be considered as a combination of a conventional inversion method (based on *wavelet*) with a neural network. The operator generated during a 3D genetic inversion will be applied on the complete seismic data in order to transform it on the desired property, similarly to a medium *wavelet* (on conventional inversion) that transforms the modelled well seismic trace on a resulting seismic signal.

According to Priezzhev *et al*. (2009), the genetic inversion process has two main steps: training and operator application. The first one consists of using genetic algorithms to update unknown weights on neural networks to match the properties found on the wells. The second phase consists of applying the operator found after the neural network training over the whole seismic volume. It is a robust and intelligent method that uses as input only seismic amplitudes and well profiles of the desired properties, which must be related to seismic reflection. The operator that will transform the seismic data into the desired property is determined in a minicube formed by seismic trace that exists around the well and a defined vertical window, defining the vertical and horizontal components.

Veeken *et al.* (2009) clearly show the genetic inversion performance on Figure 2.

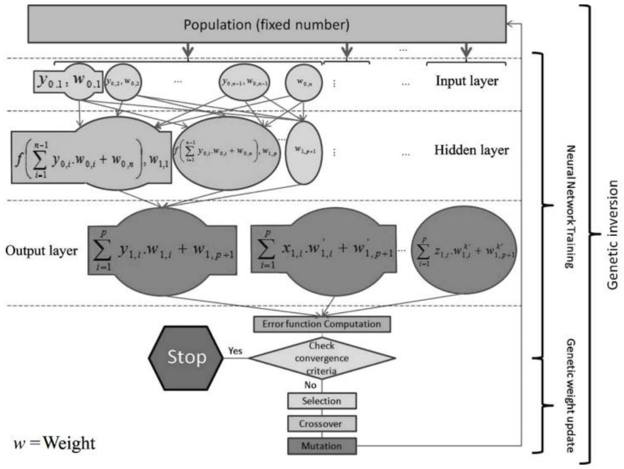


Figure 2: Working of genetic inversion, Veeken et al. (2009).

The neural network used in this paper is a multilayer (with a hidden layer) and presents a sigmoid activation function. Well logs and seismic data are used as inputs of the neural network that tries to find a classificatory relation (nonlinear) between them.

Initially, data are combined with randomly chosen weights and are activated by the sigmoid function of the hidden layer. The output activation function of the hidden layer is once again combined with new random weights in the output neuron and activated again. The result is compared with the expected value through an error function. If the error is acceptable, the inversion is done. Otherwise, the genetic algorithm (selection, crossing and mutation technique) is applied using the weight set that presents the best results to create a weight generation. This procedure is repeatedly updated until the minimum mean squared error reaches a threshold after a maximum number of iterations.

The solution found by the genetic algorithm to obtain the inversion operator has three steps: selection; crossing and mutation, Veeken *et al*. (2009). Initially, the error associated with the results given by the neural network application is calculated and the best results are selected. From this selection, other possible scenarios are calculated applying crossing and mutation. During crossing, there is a swap of weights between chosen scenarios to generate a new solution formed by parts given by each of the best scenarios, while during mutation, the weights are randomly swapped from one combination to the other to ensure that there is no convergence to a local minimum. Mutation happens with bigger probability when the error function approaches stabilization, i.e., reach its minimum.

The genetic algorithm application on the multilayer neural network learning phase replaces the backpropagation algorithm (by gradient descent), reducing the risk of finding an optimal solution in a local minimum, increasing the chances of finding a global minimum (ideal) solution. The operator defined by genetic algorithms has a variable form in space and time, more irregular than a seismic wavelet.

The quality and control step is performed determining the correlation between the real data and the inverted data and comparing the inverted cube with the real data of the wells of the training set and the ones that were not used in the inversion process, known as blind tests Veken *et al*. (2009). Just like the results pass by a quality control process, the wells used in training can also pass by this process. The results are not expected to exactly match the well data, although the low-frequency background trend can be seen in the results - Priezzhev *et al*., (2009).

One of the main advantages of genetic inversion over conventional inversion, asides from the simplicity of the input data, is the possibility of directly obtaining other rock properties besides acoustic impedance, since conventional techniques commonly use inverted impedance data to estimate other properties.

The application of genetic seismic inversion on salt can be seen in Ferreira *et al*. (2018). This paper is a broader and more detailed approach of that study.

Studied area

The studied area is located in the Brazilian east margin, in ultradeep waters with water depth over 2000m. The evaporites presented in these areas show cyclostratigraphy like the one found by Freitas (2006), with precipitation order starting with anhydrite deposition, then halite and K and Mg salts (carnallite and tachyhydrite), returning to halite and then anhydrite deposition, starting a new cycle. This cycle indicates a drying period with a progressive increase in salinity (*brining-upward*), with a minimum level in K and Mg salt deposition and then a salinity drop (*brining-downward*) due to the basin refill with external water. These cycles are correlated to the reflection seismic amplitude and were identified along the Brazilian east margin.

Rodrigues *et al.* (2018) identified the main intervals of salt deposition and its proportions, as well as its seismic facies. The acoustic transparent chaotic seismic facies are associated with bigger proportions of halite (>80%), while the highly reflective and high frequency continuous seismic facies represent lower proportions of halite (<80%) cyclically interbedded with high density anhydrite and low density carnallite. Furthermore, structural styles found internally in large thickness of the evaporitic package, for instance deformation and folding, richly discussed by Fiduk and Roman (2012), show the geological complexities that can be found.

Data and Methods

The data used in this study consists of information from 20 wells (interpreted lithology - Lito, compressional-wave slowness (Dtc) profile and 3D post-stack reflection of seismic amplitude data. The methodology followed can be seen in Figure 3 and was taken from Ferreira *et al*. (2018).

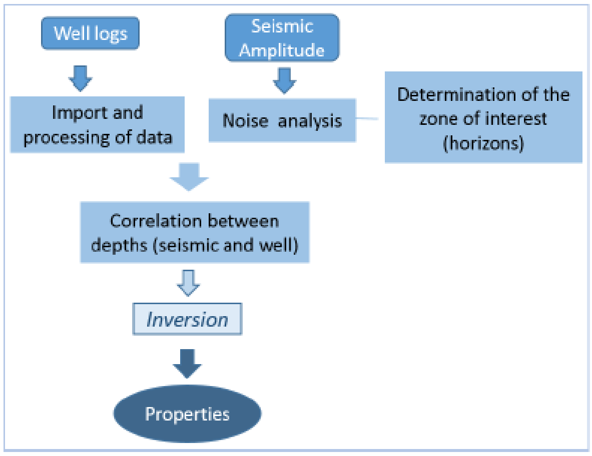


Figure 3: Flowchart by Ferreira et al. (2018).

The well data are imported inside the modeler, the profiles are analyzed and inconsistent values relating to reading errors are eliminated.

According to Nery (2013), the sonic profile of the well measures the slowness of a pulse between two fixed points on formation. The wave velocity (m/s) is given by the inverse of the transit time, given by Equation 2.

$$Vel=1/Dtc \qquad (2)$$

The velocity values derived from Dtc will be used in genetic inversion to obtain the velocity seismic cube. Due to differences in scale between well logs (kHz) and seismic data (Hz), it is necessary to smooth the data to get a better correlation between them.

Com as devidas posições correlatas entre o dado sísmico e de poço (etapa fundamental), os 4 principais horizontes que farão parte das limitações (topo e base) durante a aplicação da inversão são definidos utilizando o atributo sísmico Envelpe. O atributo Envelope descreve o fluxo de energia em subsuperfície através da amplitude da energia intantânea total de todo traço sísmico complexo em um determinado instante, Taner (1979).

With the correlated positions between well and seismic data (essential step), six horizons used on seismic inversion, were mapped. Two horizons (H1 and H6) represent respectively the top and bottom of salt and are identified by the high value of amplitudes (black peaks, on the white-grey-black scale). The other four horizons were identified using the seismic attribute Envelope, through their high values. The Envelope attribute describes the energy flow in a subsurface through the amplitude of the total instantaneous energy of every seismic trace in a given moment, Taner (1979).

After data treatment and zone definition by mapping of seismic horizons, the inversion can be applied. Of the 20 existing wells, 13 were used as training set, 6 were used for cross-validation (the results found during inversion are faced with the logs of these wells) and one in a blind test. The location can be seen in Figure 4.

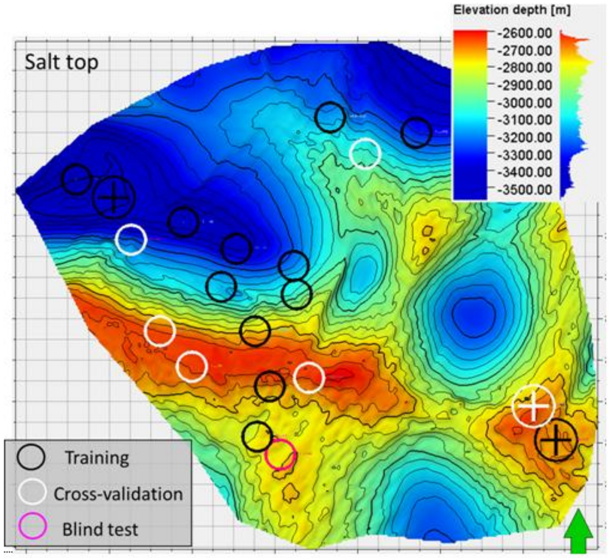


Figure 4: The image shows the location of the wells used in genetic inversion analysis.

The seismic inversion quality was obtained comparing the velocity values generated by the seismic inversion and the velocity values of the wells. This comparison was performed with the wells used as training set, as cross-validation and the well of the blind test that was not included in the inversion process. The mean absolute percentage error (MAPE) and were calculated.

Results and Discussions

The lithologies found in the studied area are anhydrite, halite, carnallite and tachyhydrite. The velocity of each of these lithologies, derived from the Dtc log obtained on the well, can be seen in Figure 5. It is possible to notice that carnallites and tachydrites show the lowest velocity values, anhydrites the biggest values and halites the intermediate values.

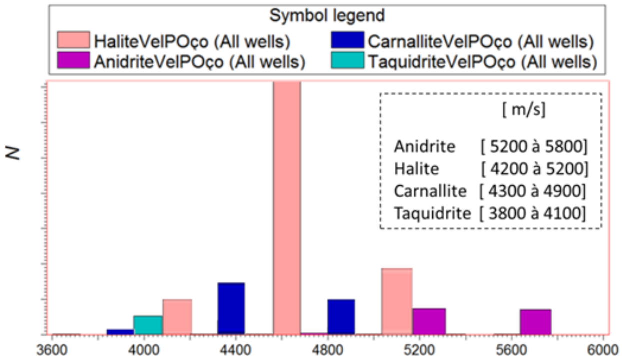
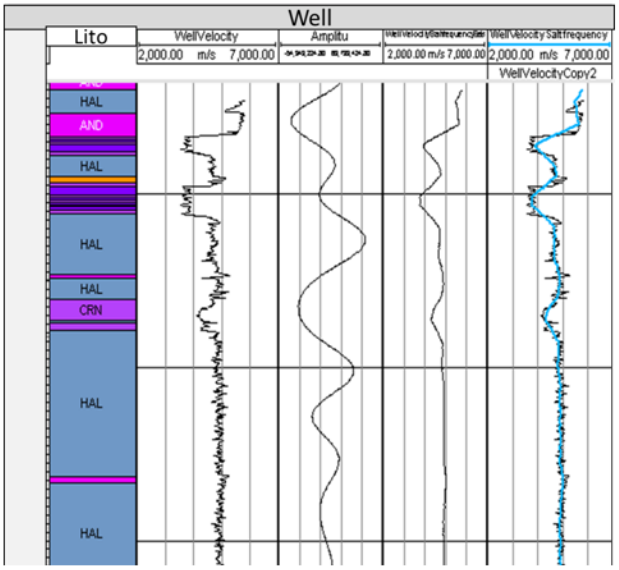


Figure 5: Distribution of the velocities found on the wells and its corresponding lithologies.

O escalonamento entre o *log* Dtc e o dado sísmico foi realizado utilizando a média aritmética e pode ser visto na Figure 6. É possível notar que a velocidade filtrada para a frequência sísmica (*log* em azul no último *track*) representa o comportamento de fundo das velocidades encontradas no sal. Esse perfil foi utilizado para a realização da inversão sísmica.

The scale change of the log data to seismic data scale was performed using arithmetic mean and can be seen in Figure 6. It can be noticed that the filtered velocity for the seismic frequency (blue log in the last track) represents the bottom behavior of the velocities found in the salt. This profile was used in order to perform the seismic inversion.



. Figure 6: Visualization of the well velocity profile resampled in the frequency of the seismic amplitude data. *Track 1:* lithology; *Track 2:* velocities found in the well; *Track 3:* Seismic amplitude; *Track 4:* velocity found in the resampled well; *Track 5:* Overlap of well velocity curve and resampled velocity.

The horizons mapped used at genetic seismic inversion can be seen at the well in Figure 7.

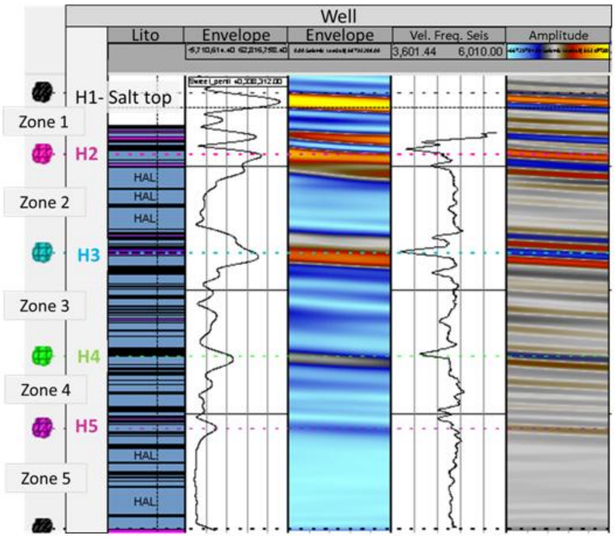


Figure 7: Visualization of the well Envelope attribute. Track 1: lithology; Track 2: profile of the Envelope attribute; Track 3: Envelope attribute; Track 4: velocity found in the resampled well; Track 5: seismic amplitude. The color scale of Envelope is the same used in seismic amplitude.

In Figure 7, it is possible to notice that the high energy values, where the horizons (H2, H3, H4 e H5) were mapped, are related with the low velocity values found in the wells, aside from showing some periodicity. Zones 2, 3, and 4 present low-velocity values at the base and the top of their horizons. All the horizons mapped can be seen in Figure 8.

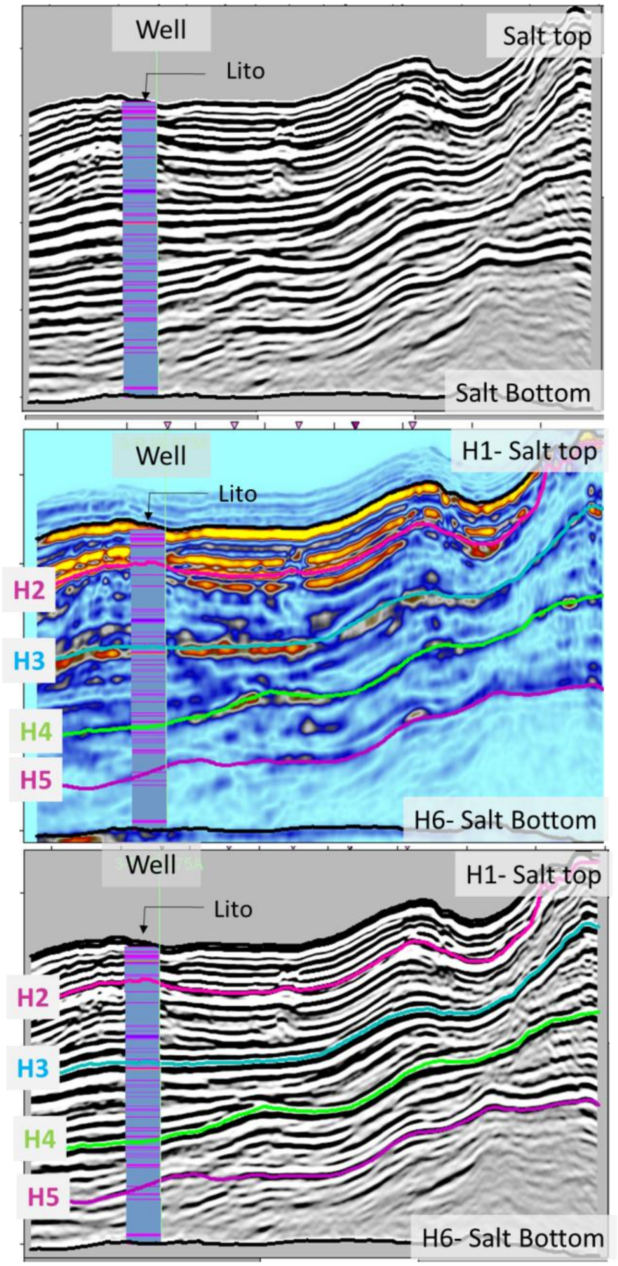


Figure 8: Visualization of a seismic section through a well. The first image represents the seismic amplitude. The second image represents the Envelope attribute applied in seismic amplitude and the mapped horizons. The third image represents the seismic amplitude and the mapped horizons.

The laterally continuous seismic reflectors in Figure 8 represent the salt stratification inside the evaporitic package. It is possible to see that zone 5, limited at the topo by horizon H5 and at the base by horizon H6, presents a more homogeneous seismic signal and it is more like A1 seismic faceis, identified by Rodriguez *et al*. (2018). These faceis are related to the presence of halite (>85%).

The velocity seismic cube obtained from the genetic inversion showed a correlation coefficient of 0.8, as can be seen in Figure 9.

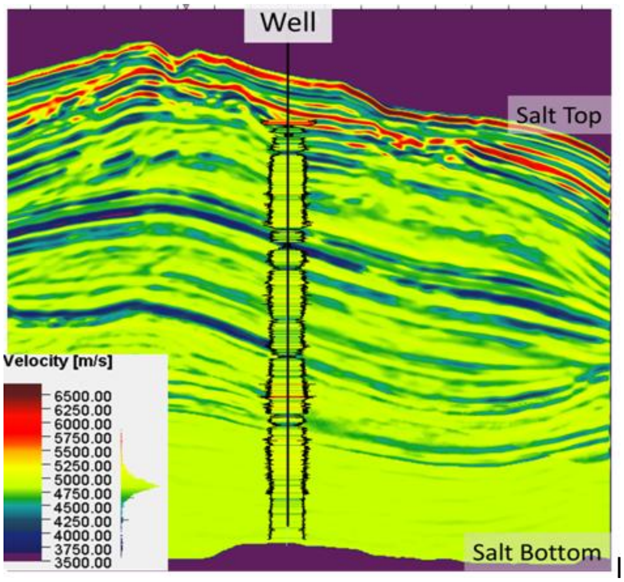


Figure 9: Visualization of a velocity cube section estimated by the inversion, passing through one the wells used in training.

The comparison between the profiles used by the inversion and the results can be seen in Figure 10.

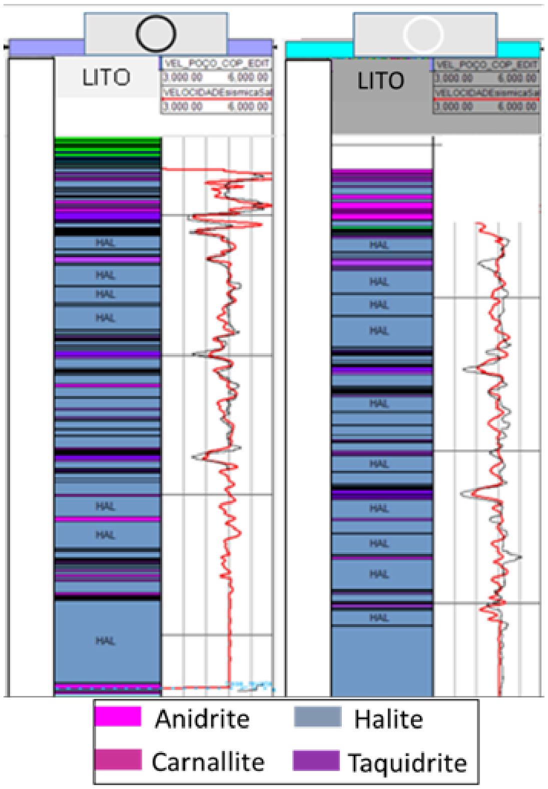


Figure 10: Visualization of the resulted inversion in one of the training wells (black circle) and in one of the cross-validation wells (white circle). *Track 1*: lithology; *Track 2:* velocities found in the resampled well (in black) and velocity estimated by the seismic inversion (in red).

The histogram generated from the calculated MAPE error values in all wells, except in the blind well, showed concentrated values below 5%. Figure 11 shows the inversion result and the calculated error in the well of the blind test.

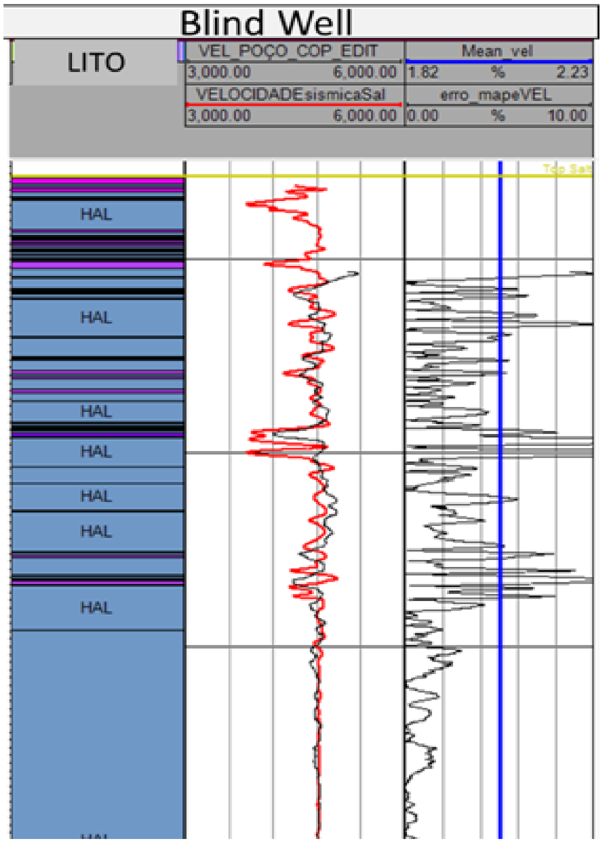


Figure 11: Velocity result obtained from genetic inversion in a blind test. *Track 1*: lithology; *Track 2:* velocities found in the resampled well (in black) and estimated values by the seismic inversion (in red); *Track 3*: MAPE error (in black) and MAPE error mean (in blue).

Figure 11 shows that the results present a great relation with the well, with velocity values matching the ones found in the wells. The errors found are low, with MAPE error below 10% and MAPE mean below 2.49%. A seismic section of the velocity model passing through the blind test well can be seen in Figure 12.

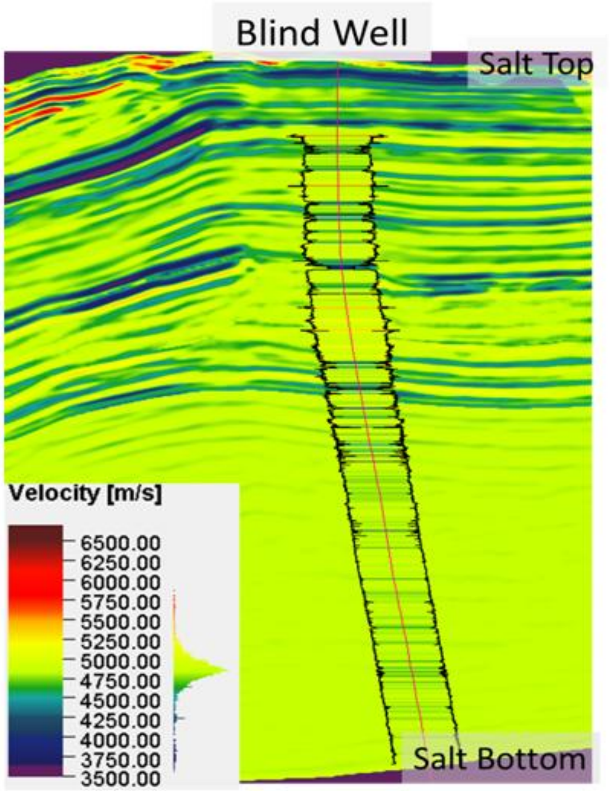


Figure 12: Visualization of a section of the velocity cube estimated by the inversion, passing through the well used as blind test.

Elastic inversion using pre-stack data and AVO analysis are the most recommended methods to obtain elastic properties of the seismic data, although the data availability limitation and the good results showed by the genetic inversion technique (Veeken *et al*. (2009); Priezzhev *et al*. (2009)) reinforce the application of this method in salt characterization. Furthermore, empirical equations related to acoustic impedance and velocity (derived from the sonic profile) are also shown by Teixeira e Lupinacci (2019) as a way to obtain elastic properties of the salt.

The seismic inversion quality is lowered when there is a large presence of great saline domes of type A1 faceis, where it is not possible to map the salt stratifications. The models generated by the genetic seismic inversion method can be used as secondary data in the well geostatistics distributions, providing spatial information between the wells.

Conclusions

Genetic inversion showed great efficiency in geological characterization of evaporites. Applying seismic inversion in thick layers of evaporitic salts, around 1500 meters, showed good results, being able to represent the velocity values of the found lithologies, especially the low velocity ones, which relate to carnallite and tachydrite presence. Predicting these lithologies is extremely important in well geomechanics projects since these salts present the higher rates of fluence, hence, prior knowledge of their existence and its respective depths allows a better operational planning of the well security. Also, the generated seismic velocity cube can be used to refine seismic velocity models that will be used to increase seismic image quality.

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