Seismic Characterization of Carbonate Stringers using Machine Learning techniques: an example from the Western Flank of South Oman Salt Basin

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Abstract

Carbonate stringers are defined as a slab of carbonate bodies encased inside salt. In Oman, the intra-salt carbonate stringers are a very common target, especially in South Oman Salt Basin (SOSB). These stringers contain a large amount of hydrocarbon resources. In this study, the behavior of carbonate stringer bodies hosted in Ara salt structures from the SOSB is investigated. Both synthetic and real seismic data are use. A geological model is created from the structural interpretation of a newly acquired and processed seismic data from the area. The synthetic model is used to generate different seismic and elastic quantities such as P-wave, S-wave, density, synthetic gathers, and stack seismic data. Different attributes are computed from the synthetic gathers before inverting them to acoustic impedance, shear impedance, and density. In order to help us detect carbonate stringers and predict their distribution, Machine Learning, namely, Artificial Neural Network (ANN), is deployed to combine all the computed attributes into one probability cube. The cube highlights only stringers detected by the trained ANN. The ANN demonstrated a promising capability of detection of the targeted stringers. The above experiment is repeated on real prestack data after converting them to impedances using prestack seismic inversion. Likewise, the ANN was able to delineate the stringers and predict the distribution in the 3-D data. After several tests, a final 3-D distribution model of the stringers was obtained.

The cube has allowed us to find new potential zones that might be good prospects in any future drilling in the area.

Key words: Machine Learning, Carbonate stringers, seismic attributes, seismic inversion

1. Introduction

Carbonate stringers are defined as self-charging reservoirs. They are a very common target in the south Oman Salt Basin. Stringers are well known for their complicated characterization due to their heterogeneity, depositional setting, diagenetic alteration (Grotzinger and Al-Rawahi, 2014). Seismic characterization of stringer reservoirs is crucial for understanding their geometry, distribution, storage capacity, and fluid content. Seismic attributes are defined as any measurable or computed information extracted directly from processed seismic data or from impedances. Although numerous published studies discussed the use of seismic attributes in both clastic and carbonate reservoirs, there is a lack of research papers addressing carbonate stringers, which is the primary focus of this study. The abundance of seismic attributes that can be extracted from seismic data makes the interpretation a challenging and confusing task (Farfour et al. 2012b, Robles et al 2018, Farfour and Foster, 2022). To solve this issue, interpreters utilize various mathematical and statistical approaches to reduce the number of attributes to manageable independent quantities or combine attributes into one or a small set of output attributes.

The rapid integration of Machine Learning techniques into geoscience has revolutionized the way researchers analyze and overcome geological challenges. Machine Learning, a branch of Artificial Intelligence, involves algorithms and statistical models that enable computers to learn from data. Machine Learning methods enable machines (computers) to learn from data to accomplish specific tasks without explicit programming. These tasks may include dimension reduction, pattern recognition, classification, and anomaly detection. The learning can be supervised if the target (label) is defined or unsupervised if not.

Artificial Neural Networks are a sort of Machine Learning models that learn the relationship between data input and data outputs in a way that simulates human brain neurons. The input to ANN are represented as a set of attributes or features that are extracted from the data such as frequencies, amplitudes, etc. Over the past decades, ANN demonstrated a good capability in resolving challenging problems related to reservoir characterization (Farfour et al. 2012a). A large number of papers from different parts of the world reported the success of ANN in combining seismic attributes to detect fluids, delineate facies, and to predict quality and distribution of reservoirs. For example, Wrona et al. (2017) described the application of supervised Machine Learning to seismic facies analysis using 3D broadband seismic reflection data of the northern North Sea. Liu et al (2017) used unsupervised Machine Learning to reveal geological features from seismic attributes and quantitative interpretation.

This study aims to deploy Machine Learning techniques, namely Artificial Neural networks, to detect and characterize carbonate stringers from their surrounding salt and clastic rock. Elastic properties, namely, P-wave, S-wave, and density, are created from a geological model created from newly processed seismic data. The created elastic models are used to create stacked seismic data, and synthetic angle gathers. The gathers are inverted to generate P and S-wave impedances and density models. The latter quantities are utilized to train ANN to detect carbonate stringers and distinguish them from their background. The same experiment is then conducted on real gathers.

2. AVO attributes and inversion

Amplitude Variation with Offset (AVO) methods can be divided into amplitude-based methods and impedance-based methods (Russell, 2014). Amplitude-based methods deliver amplitude-related attributes such as the intercept, gradient, Scaled Poisson ratio, fluid factor, etc. After converting prestack gathers to impedances using AVO inversion, impedance-based methods produce attributes such as P-impedance, S-impedance, their ratio (Vp/Vs), Poisson ratio, bulk modulus and shear modulus combined with density ($K\rho$ and $\mu\rho$, respectively), etc. AVO attributes have many applications in clastic as well as in carbonate reservoir characterization such as fluid identification, lithology discrimination, facies classification (Farfour, 2020; Farfour and Foster, 2021; Farfour and Russell, 2024). Durrani et al. (2020) investigated the lithofacies and reservoir properties identification for mature carbonate field in Pakistan using AVO and Pre-stack inversion and found that two lithofacies (tight limestone and shale) can be identified from Pre-stack inversion and reservoir properties such as clay volume and porosity. In addition, Mohammed et al (2008) conducted a feasibility study to investigate the possibility of fluid discrimination in highly porous carbonate reservoir using AVO. The authors used P-wave and S-wave velocity, and density logs to discriminate hydrocarbon saturated facies from water-saturated facies

3. Geological setting

The study area is located on the western flank of the South Oman Salt Basin. The area is structurally complex and resides on the flank of a symmetric basin. The area is bounded from the west by an old high known as “Ghudun Khasfa High” and is affected by a major thrusting event known as the “Western deformation front.” The structural complexity of the area is evidenced by thin-skinned tectonics associated witha late pre-Cambrian, Pan-African orogenic event (550-520 MY). Stratigraphically, in SOSB above the basement, there is a Huqf supergroup representing a superub record of Ediacaran to early Cambrian earth history. The Huqf super-group started with the Abu-Mhara group, which consists of glacial clastic sediment. The latter is followed by the Nafun group, which can be classified as post-rift sediment. It has Hadash formation "cap carbonate" followed by Masirah Bay formation "shelf clastic sediment," Khufai carbonate "restricted prograding ramp," Shurum formation "storm dominated shelf clastic and carbonates" and Buah " storm dominated prograding carbonate ramp" Above Nafun there is Ara group which has four formations "Birba, Alnoor, Atheel, and Dahban." This study focuses on the lowermost three formations of the Ara group. Figure 1 represents the location of the study area and Ara group stratigraphic chart. It also shows the survey area where the seismic data of the study was acquired (Al-Obaidani,and Farfour, 2024).

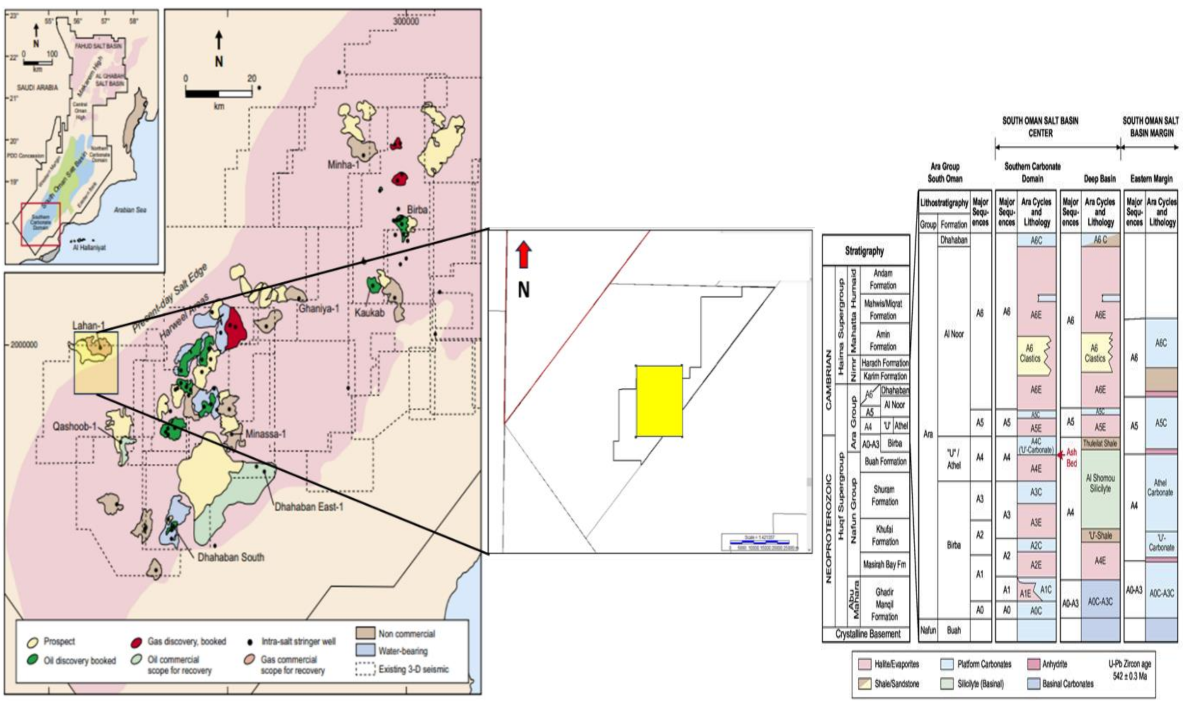

Figure 1: A map showing the study area's location (modified after Al Siyabi, 2005 and from Al-Obaidani and Farfour, 2024) and associated stratigraphic chart.

4. Methods

Initially, we conducted a thorough structural interpretation of the newly acquired seismic data. The results from the interpretation allowed us to create a seismic model for the area. The model includes different elastic modules (P-wave, S-wave, and density). Figure 3 shows the Vp/Vs model from the data interpretation. The models of P-wave, S-wave, and density are utilized to generate synthetic gathers using "Zoeppritz approximation from which a list of AVO attributes have been extracted. This includes intercept, gradient, scaled Poisson ratio, and scaled S-wave reflectivity using the three terms Aki-Richard equation. Afterward, the created synthetic gathers are inverted to generate several impedance-based attributes such as acoustic impedance, shear impedance, Vp/Vs, bulk modules, shear modules, K-ρho & Mu-ρho. Figure 4 shows the workflow used to create AVO reflectivity and impedance-based attributes from geophysical modeling. The extracted attributes are all incorporated to train ANN. The next step was to use real seismic data acquired recently in the western flank of the South Oman Salt Basin for a similar experiment. We started by evaluating and quality checking both "stacked seismic data & Pre-stack angle gather." After applying the median and band-pass filters to the real seismic data, several AVO attributes such as Intercept x Gradient, Scaled Poisson ratio, and Scaled S-wave reflectivity were created and used for the ANN process.

In order to conduct prestack inversion, we built low frequency impedance model from the available well logs and the picked horizons from structural interpretation.

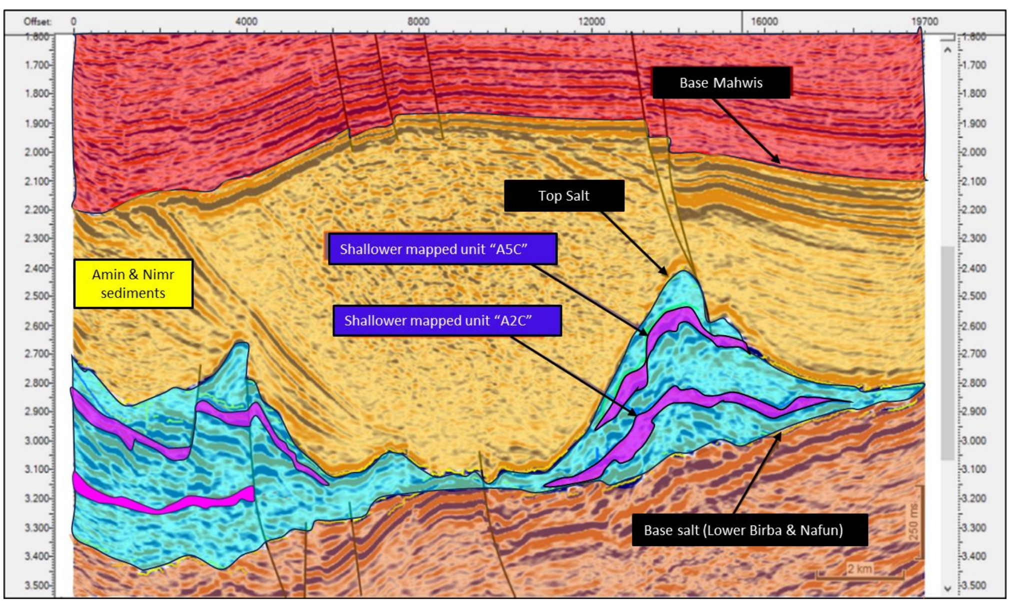

Figure 2: An interpreted seismic section from the data showing possible stringers.

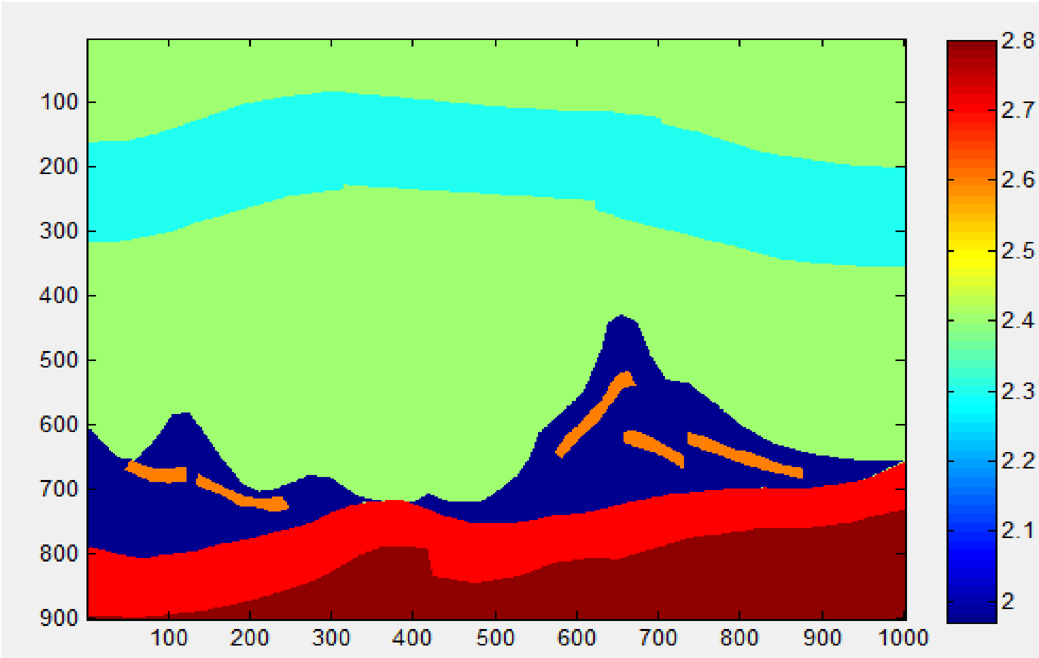

Figure 3: Vp/Vs model generated from the created geological model. Horizontal and vertical axes represent the horizontal and vertical number of samples of the model.

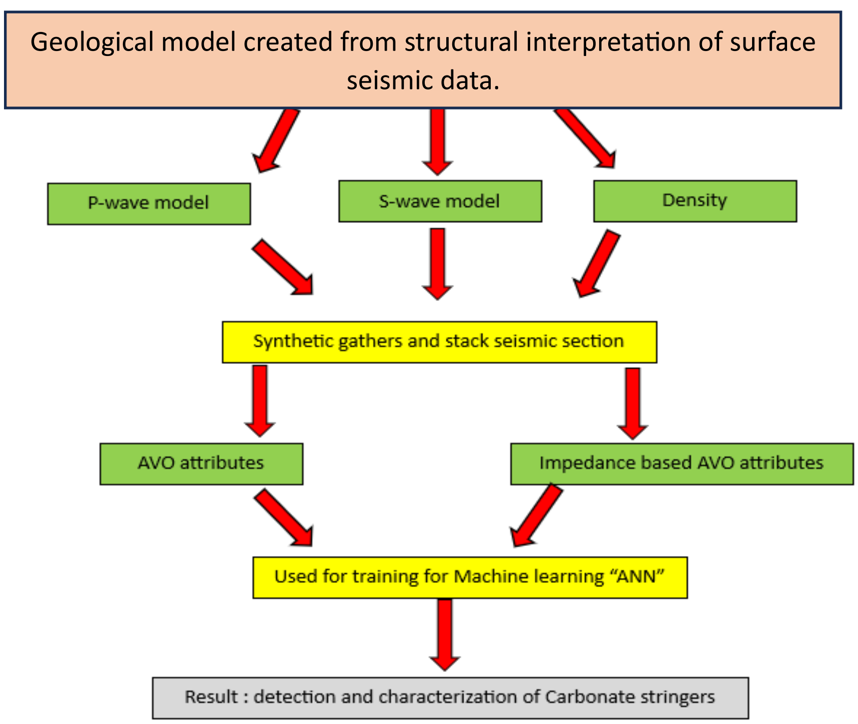

Figure 4: workflow used to create and analyze AVO attributes and impedance-based attributes from synthetic data.

5. Results and discussion

Several prestack and post-stack attributes have been created from the synthetic data. The inversion process was first run and evaluated at the well location (Figure 5). A very good match between the input gathers and the computed ones from the inversion is achieved. Figure 6 and 7 display the acoustic impedance and bulk modulus models obtained from pre-stack inversion. The two figures present some similarity which is due to the high compaction and consolidation which makes the impedance response dominated by the bulk modulus and appears somehow close to it (Farfour and Russell, 2024). The analysis of the results from the modeling and from the inversion allowed us to improve our understanding on carbonate stringers reservoirs, and their various elastic responses. In addition, the experiment demonstrated that if sufficient AVO attributes such as Scaled Poisson ratio, intercept, gradient, and fluid factor are integrated with impedance-based AVO attributes such as acoustic impedance, shear impedance, bulk modulus, shear modulus, Vp/Vs, Kρ and μρ, carbonate stringers can be detected and characterized with high level of confidence.

Next, Multi-layer Perceptron Artificial Neural Network (MLP ANN), has been used to go a step further in the detection task of carbonate stringers and produce a probability cube of stringers by combining all attributes discussed above. The ANN attribute highlights only stringers as displayed in Figure 8. The identified stringers are very consistent with the elastic models shown earlier which are used as ground-truth. It is clear that the selected attributes highlighted the key features of the stringers which make easy for the ANN to distinguish them. Those attributes have shown great success in differentiating facies, lithologies, and fluids in numerous publications (Qi et al. 2020; Pintea et al. 2021; Karakaya et al. 2024).

Next, the same experiment was applied to the real data. Initially because the real prestack gathers include noises that are not present in synthetic data, they were subject to a thorough pre-conditioning operation. This includes band-pass filtering, Radon transform to eliminate multiples and random noise, trim-static to improve the alignment of the reflectors (Figure 9). After, the preconditioning, AVO inversion was applied on the gathers at the well locations, achieving a minimum error with a high correlation rate (Figure 10).

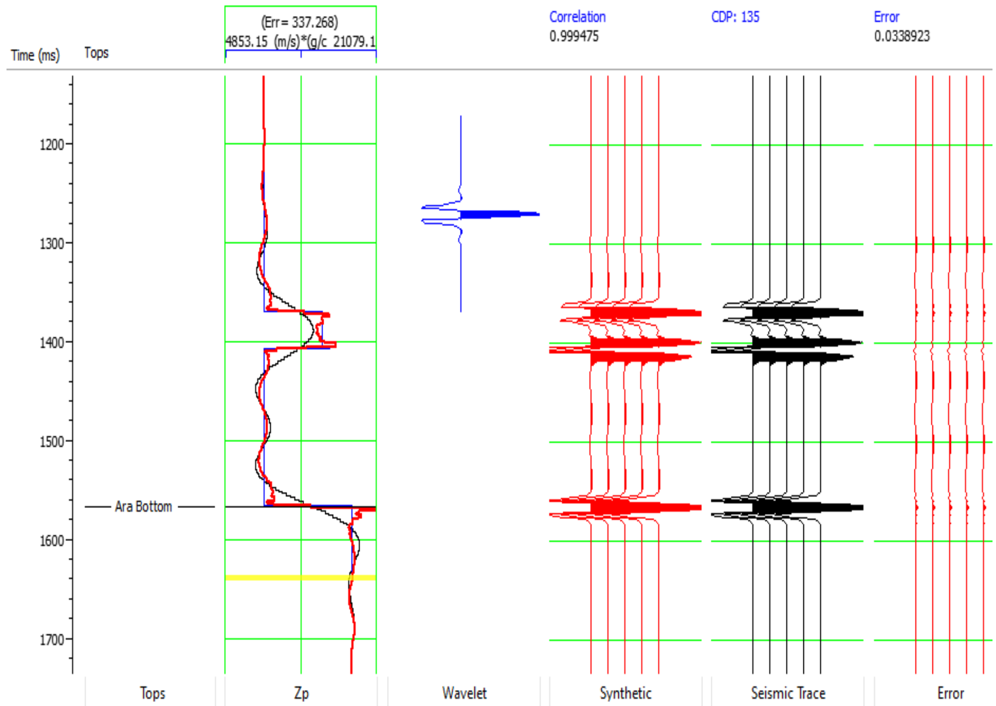

Figure 5: QC of performed inversion by comparison between computed inversion and modeled data

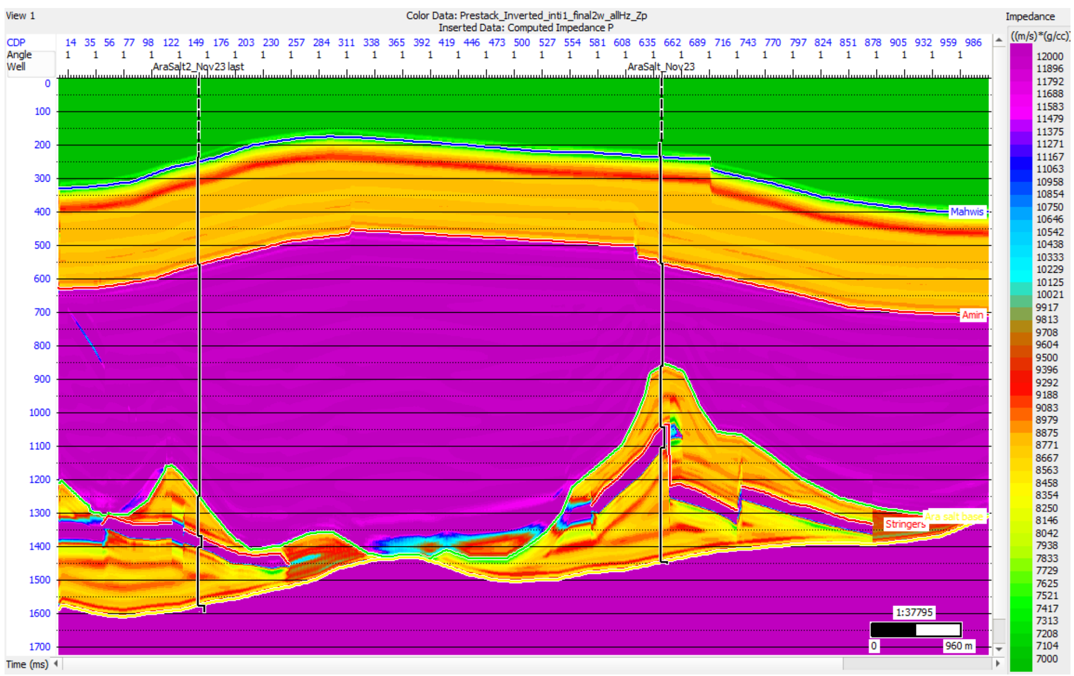

Figure 6: Inverted P-impedance from geophysical modeling data

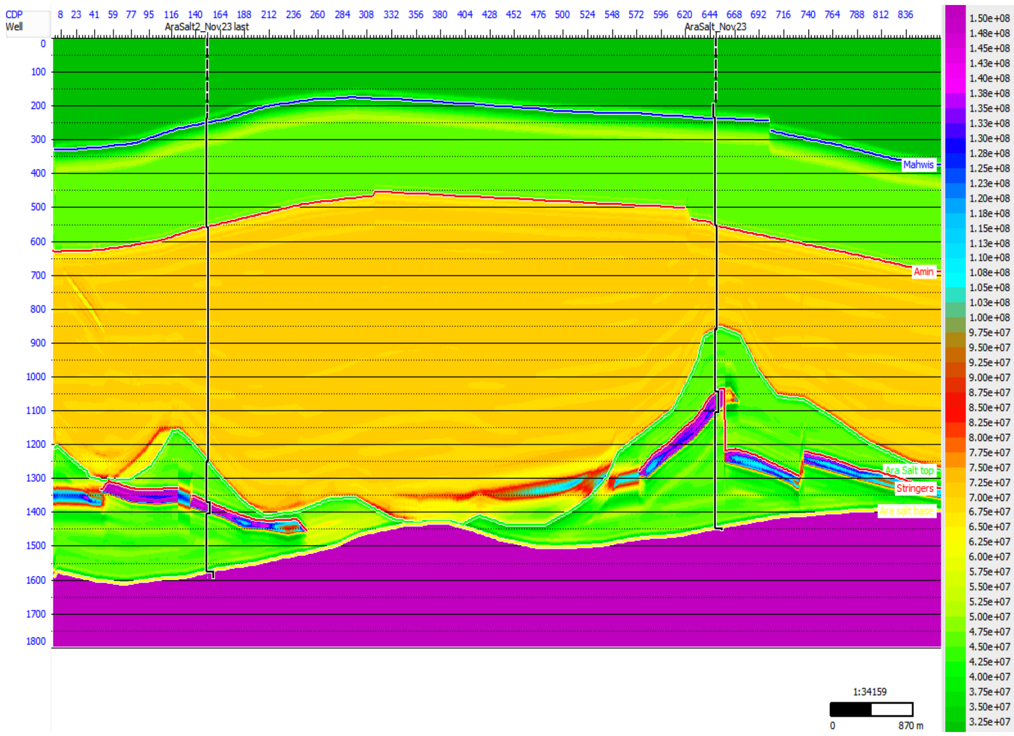

Figure 7: Bulk modules derived from Pre-stack inversion of geophysical modeled data

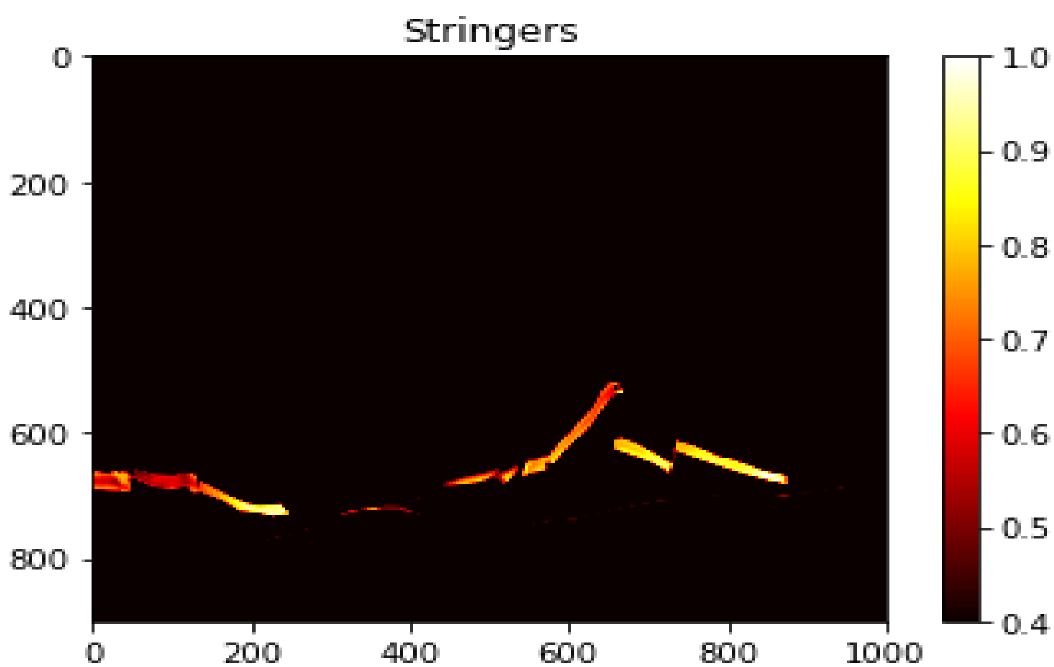

Figure 8: Carbonate stringers were identified using ANN, and the color bar represents the probability of their presence.

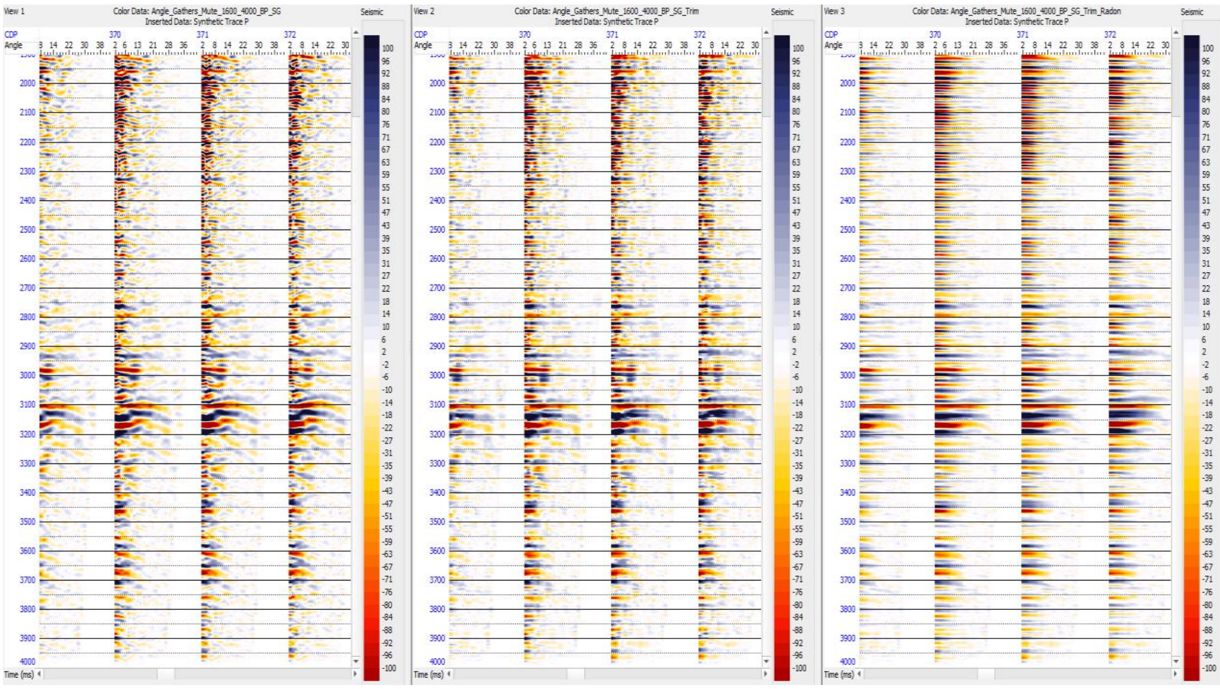

Figure 9: Prestack gathers improved after pre-conditioning.

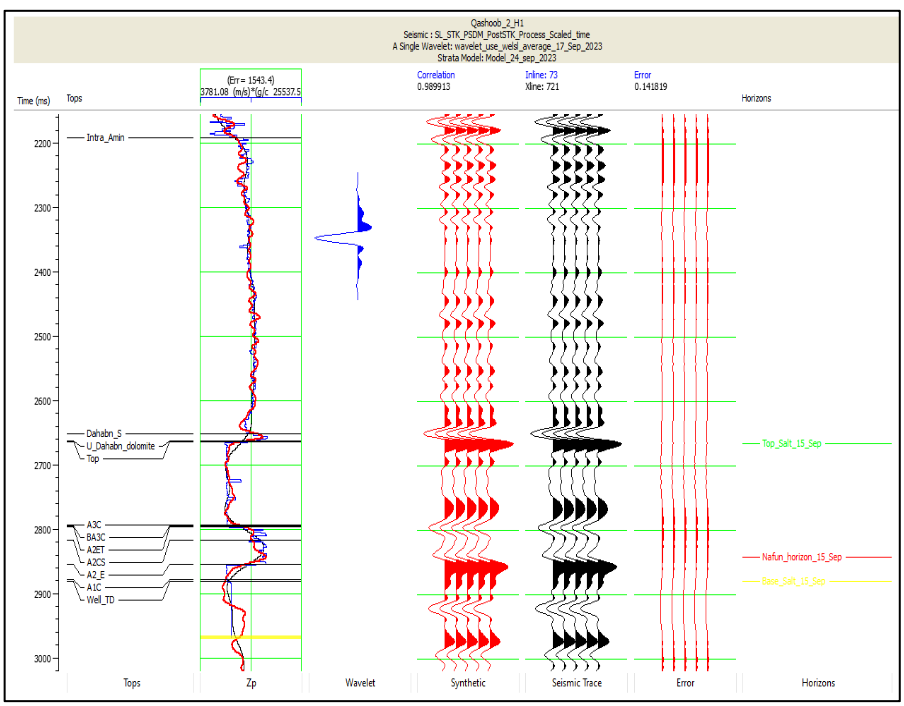

Figure 10: QC of performed inversion by comparison between computed inversion and real seismic data

Figure 11, 12 and Figure 13 show examples of P impedance, S impedance, and density models derived from the inversion. The inversion demonstrated that the stringers are characterized by their distinctive elastic properties, high compressional and shear impedances, and density, which is found consistent with the synthetic data example. This observation matches very well with the results from the inversion run on the synthetic data.

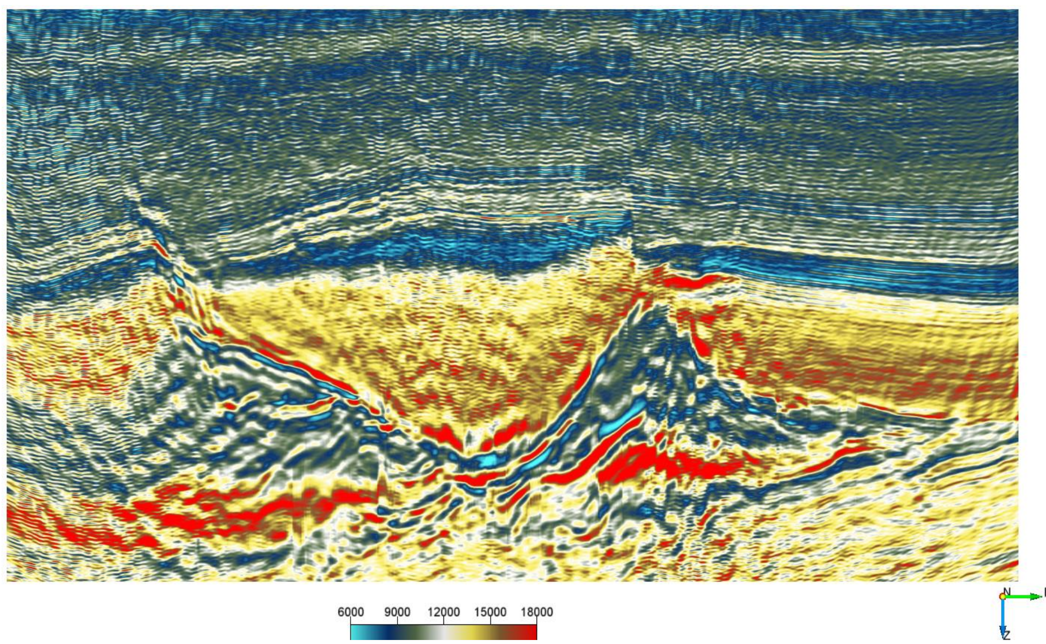

Figure 11: Inverted P-impedance from real seismic data. Stringers are showing large P-impedance.

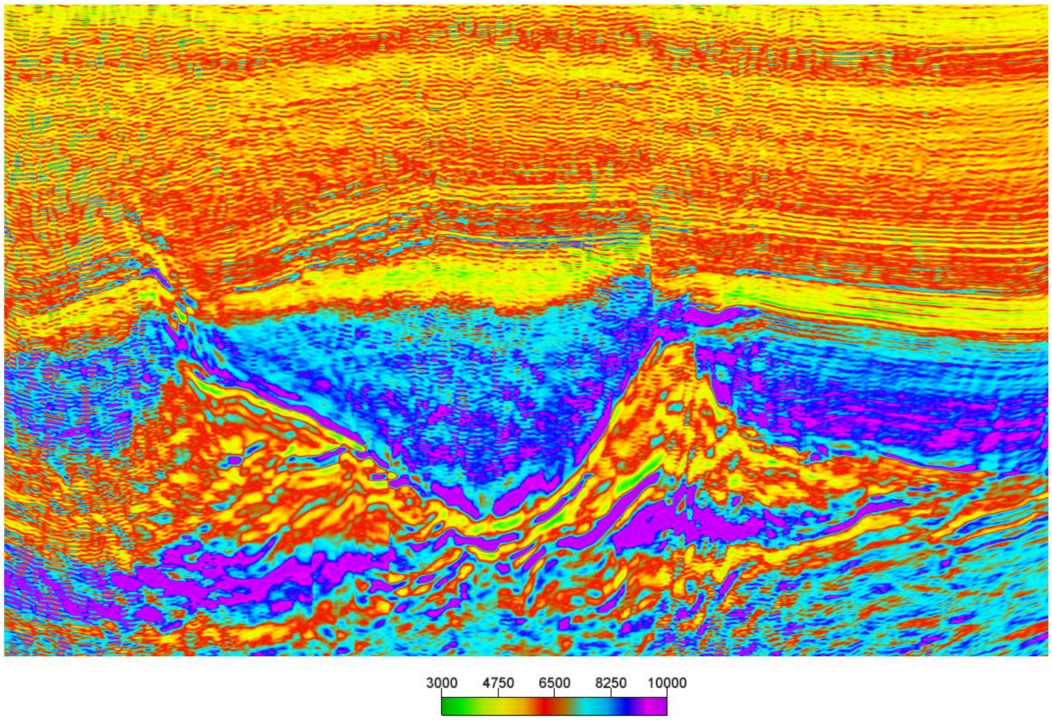

Figure 12: Inverted S-impedance from real seismic data. Stringers are showing large S-impedance.

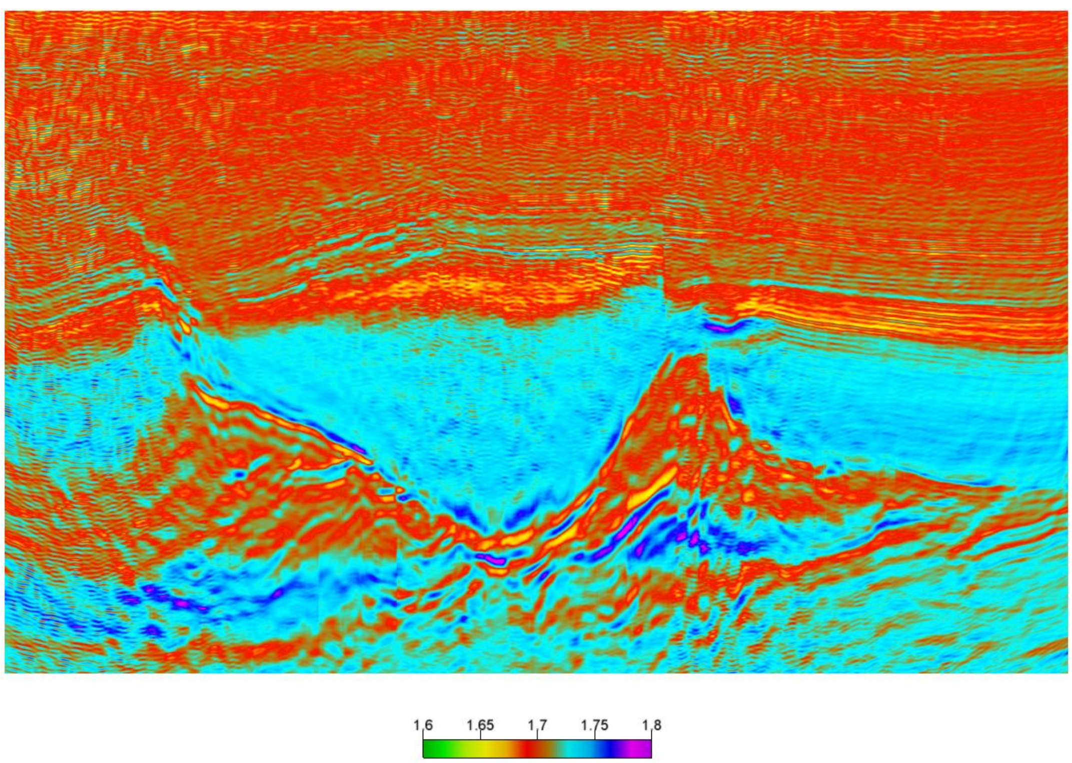

Figure 13: Vp/Vs obtained from real seismic data. Stringers are showing large density compared to their host rock.

Further, we deployed all the extracted attributes to train the ANN to detect the carbonate stringers and isolate them from their background. However, working with real data presents an additional challenge of noise including coherent and incoherent elements, such as multiples, random noise, etc. (Al Hooti et al. 2024, Farfour and Russell, 2024; Farfour et al. 2015; Qi et al. 2020). This noise can complicate the training task for the ANN and increase confusion. Different sets of attributes have been tested until a good training and test results were achieved. Once trained, the ANN successfully distinguished carbonate stringers from their surrounding salt and clastic bodies at the well location and away from it, as demonstrated in Figure 14. From the probability attribute created by the ANN, we generated a 3-D model of the stringers, as depicted in Figure 15. A number of potential stringers were identified. Some of them were selected as a potential target for future drilling plan.

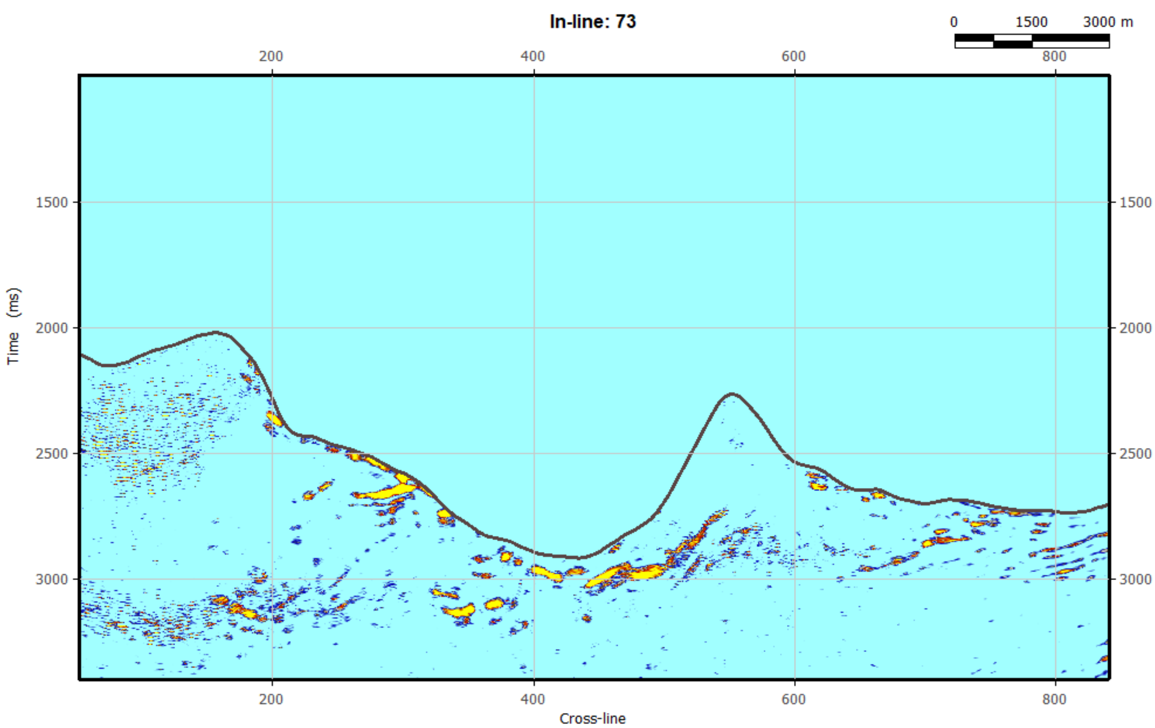

Figure 14: Carbonate stringers detection using ANN

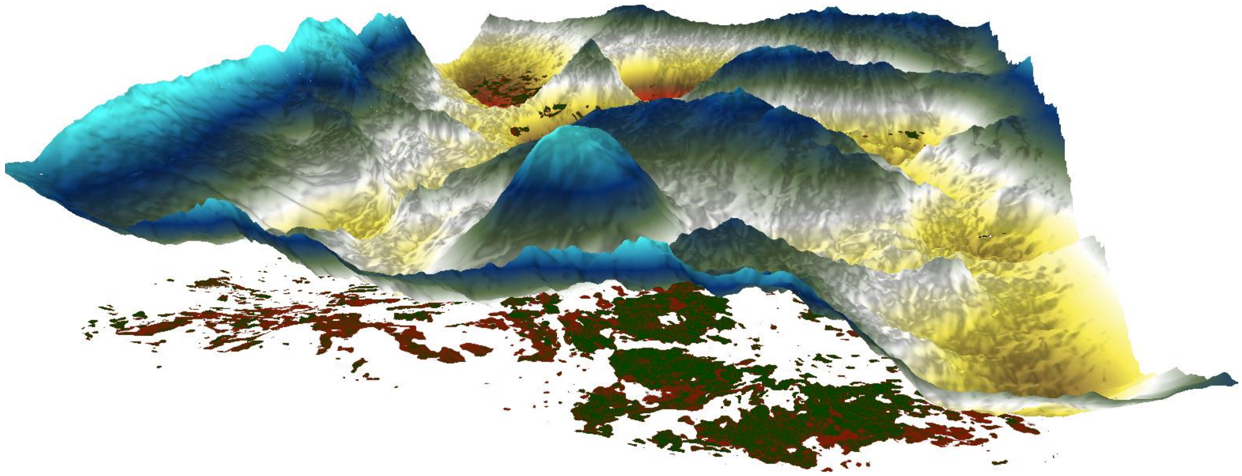

Figure 15: Carbonate stringers detection using ANN

It is important to note at this stage that different attributes yield different results, which makes the solution of the problem is not unique (Qi et al. 2020). To mitigate the non-uniqueness of the possible solution, one needs to integrate blind well test or incorporate the interpreter prior-knowledge about the area which was the case here. Our understanding of the stratigraphy, tectonic, lithology of the area helped us detect a number of false anomalies and exclude them.

Additionally, another factor contributing to the generation of false anomalies by ANN is their tendency to perform better in interpolation problems while exhibiting limited success in extrapolation problems (Singh et al., 2007; Zhang et al., 2019; Dixit & Mandal, 2020). In fact, in our study, the primary challenge arises from the lack of sufficient well data which restricted our ability to conduct more rigorous and detailed quantitative characterization.

The results of this study provide a clear insight on how stringers will manifest in seismic attributes and inversion attributes and how all attributes can be combined to characterize carbonate stringers and distinguish them from their hosting rock.

The study demonstrates a good example of the capability of Machine Learning and their growing role in reservoir understanding and characterization.

Conclusion

Seismic forward and reverse modeling (inversion) have been used to understand elastic properties of carbonate stringers from Southern part of Oman. Different attributes have been extracted from seismic and from impedance data. The extracted attributes have been combined and integrated using an artificial neural network to detect the stringers and to distinguish them from their surrounding salt body. The experiment is carried out on synthetic and on real data. ANN demonstrated a good capability to detect carbonate stringers, especially if a good set of AVO attributes and impedance-based AVO attributes are available. The result of this study can be used for the detection and characterization of carbonate stringers in another part of the South Oman salt basin or another part of the world

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References

1. Al-Barwani, B., & McClay, K. (2008). Salt tectonics in the Thumrait area, in the southern part of the South Oman Salt Basin: Implications for mini-basin evolution. *GeoArabia*, *13*(4), 77–108. https://doi.org/10.2113/geoarabia130477
2. Al-Obaidani, H.S., Farfour, M. Integration of seismic modeling and interpretation of real seismic data for the detection and characterization of carbonate stringers: example from Oman. *Sci Rep* **14**, 16853 (2024). https://doi.org/10.1038/s41598-024-67789-x
3. Al-Siyabi, H. A. (2005). Exploration history of the Ara intrasalt carbonate stringers in the South Oman Salt Basin. *GeoArabia*, *10*(4), 39–72. https://doi.org/10.2113/geoarabia100439
4. Dixit, A., & Mandal, A. (2020). Detection of gas chimney and its linkage with deep-seated reservoir in poseidon, NW shelf, Australia from 3D seismic data using multi-attribute analysis and artificial neural network approach. *Journal of Natural Gas Science and Engineering*, *83*, 103586. https://doi.org/10.1016/j.jngse.2020.103586

5. Farfour, M., & Russell, B. (2024). The old and new of fluid indicators: An overview and application. *Leading Edge*, *43*(5), 294–302. https://doi.org/10.1190/tle43050294.1
6. Farfour, M., Yoon, W. J., & Kim, J. (2015). Seismic attributes and acoustic impedance inversion in interpretation of complex hydrocarbon reservoirs. Journal of Applied Geophysics, 114, 68–80. https://doi.org/10.1016/j.jappgeo.2015.01.008.
7. Farfour, M., Yoon, W. J., Ferahtia, J., & Djarfour, N. (2012a). Seismic attributes combination to enhance detection of bright spot associated with hydrocarbons. *Geosystem Engineering/Geosystem Engineering*, *15*(3), 143–150. https://doi.org/10.1080/12269328.2012.702089
8. Farfour, M., Yoon, W.J., Jo, Y. (2012b). Spectral decomposition in illuminating thin sand channel reservoir, Alberta, Canada. Canadian Journal of Pure Applied Science, 6, 1981-1990.
9. Farfour, M., & Foster, D. (2022). Detection of hydrocarbon- saturated reservoirs in a challenging geological setting using AVO attributes: A case study from Poseidon field, Offshore Northwest region of Australia. Journal of Applied Geophysics, 203, 104687. https://doi.org/10.1016/j.jappgeo.2022.104687.
10. Farfour, M. (2020). Amplitude components analysis: Theory and application. The Leading Edge, 39(1), 62a1-62a6. https://doi.org/10.1190/tle39010062a1.1
11. Farfour, M. and Foster, D. (2021). New AVO expression and attribute based on scaled Poisson reflectivity. Journal of Applied Geophysics, 185, https://doi.org/10.1016/j.jappgeo.2021.104255.
12. Hashem, I., Helal, A. E., & Lala, A. M. S. (2022). Application of AVO and seismic attributes techniques for characterizing pliocene sand reservoirs in Darfeel Field, Eastern Mediterranean, Egypt. *International Journal of Geosciences*, *13*(10), 973–984. https://doi.org/10.4236/ijg.2022.1310049
13. Hooti, M. N, Glukstad, M. M., & Farfour, M. (2024). A New World Revealed With Amazing Detail: Using the Latest WAZ Seismic to Review Key Structural Elements of the Fahud Salt Basin, Oman. https://doi.org/10.2523/iptc-24292-ms Paper presented at the International Petroleum Technology Conference, Dhahran, Saudi Arabia, February 2024.
14. Karakaya, S., Ogiesoba, O. C., Olariu, C., & Bhattacharya, S. (2024). Generating 3D lithology probability volumes using poststack inversion, probabilistic neural networks, and Bayesian classification — A case study

from the mixed carbonate and siliciclastic deposits of the Cisco Group of the Eastern Shelf of the Permian Basin, north-central Texas. *Geophysics*, *89*(2), B131–B146. https://doi.org/10.1190/geo2023-0157.1.

15. Li, W., Yue, D., Colombera, L., Duan, D., Long, T., Wu, S., & Liu, Y. (2023). A novel method for seismic-attribute optimization driven by forward modeling and machine learning in prediction of fluvial reservoirs. *Geoenergy Science and Engineering*, *227*, 211952. https://doi.org/10.1016/j.geoen.2023.211952
16. Pintea, S. L., Sharma, S., Vossepoel, F. C., Van Gemert, J. C., Loog, M., & Verschuur, D. J. (2021). Seismic inversion with deep learning. Computational Geosciences, 26(2), 351–364. https://doi.org/10.1007/s10596-021-10118-2
17. Qi, J., Zhang, B., Lyu, B., & Marfurt, K. (2020). Seismic attribute selection for machine-learning-based facies analysis. *Geophysics*, *85*(2), O17–O35. https://doi.org/10.1190/geo2019-0223.1
18. Singh, V., Srivastava, A. K., Tiwary, D. N., Painuly, P. K., & Chandra, M. (2007). Neural networks and their applications in lithostratigraphic interpretation of seismic data for reservoir characterization. *Leading Edge*, *26*(10), 1244–1260. https://doi.org/10.1190/1.2794381
19. Wrona, T., Pan, I., Gawthorpe, R. L., & Fossen, H. (2018). Seismic facies analysis using machine learning. *Geophysics*, *83*(5), O83–O95. https://doi.org/10.1190/geo2017-0595.1
20. Zhang, J., Guo, X., Xu, B., Wang, X., Shen, P., & Chen, S. (2019). Application of pre-stack simultaneous inversion on the reservoir identification and fluid prediction: A case history of Es2 member reservoir in Shengli Oilfield. *IOP Conference Series. Earth and Environmental Science*, *227*, 062003. https://doi.org/10.1088/1755-1315/227/6/062003