Seismic AVO attributes and machine learning techniques characterise a distributed carbonate build-up deposit system in the Salawati Basin, eastern Indonesia

Yudistira Effendi[1]* and Lilik T. Hardanto[2] demonstrate that seismic volume-based unsupervised facies classification associated with advanced visualisation and detection helps delineate the prospect's potential.

Abstract

There are several undeveloped discoveries and drill-ready prospects in the Salawati Basin, Eastern Indonesia, especially offshore. These offer significant growth potential, particularly the challenging Miocene hydrocarbon-producing reservoirs. The seismic data suggests that this play extends to the north of the producing area, but this has not been confirmed by a successful well. The combination of standard seismic attributes with seismic Amplitude Variation with Offset (AVO) attributes is key to revealing the reservoir in the exploration phase.

In this project, poststack attributes from an AVO inversion were used as input for an unsupervised clustering technique based on a Growing Neural Gas algorithm, to generate the most probable facies distribution as well as the probability per facies, in order to better characterise a complex regional channel deposition system.

The classification of AVO-related seismic attributes as direct hydrocarbon indicators is used to extrapolate reservoir information from the seismic data that correlates with well data from surrounding fields.

The study demonstrates that seismic volume-based unsupervised facies classification associated with advanced visualisation and detection helps delineate the prospect's potential. In this example, the workflow identified a reservoir within the Kais interval of the Miocene Carbonate. The model also shows lateral variations in other reservoir intervals and contributes to the exploration hydrocarbon strategy.

Introduction

The acreage is located in the Salawati Basin, Eastern Indonesia on the western periphery of the island of Papua Barat. The fields are situated within the Kepala Burung or Birds Head region, at the westernmost extremity of Papua (Figure 1). The area is structurally complex, situated on the northern margin of the Australian Plate and near the junction of the Australian, Pacific and Asian Plates. The basin has a well-developed structural and stratigraphic feature with 15,000 feet of Tertiary marine sediments deposited within the basin depocentre (Redmond and Koesoemadinata, 1976). Development was initiated during the early Miocene period with local down warping, associated with movement along the Sorong Fault Zone, which bounds the basin to the north. The Sorong fault zone dominates the structure of this area and is interpreted by most authors as a major left-lateral strike-slip fault. However, Hamilton proposes that the fault system may be a suture zone and that the type strand of the system has been misidentified (Harry et al., 1992).

The Miocene Kais carbonates, one of the most challenging reservoirs in the Salawati Basin, have been in production since the 1930s. More than 160 exploration wells have been drilled targeting the carbonates. Due to the extensive exploration, a large amount of data is available on Kais carbonates. The analysis of the seismic data suggests the extension of this play

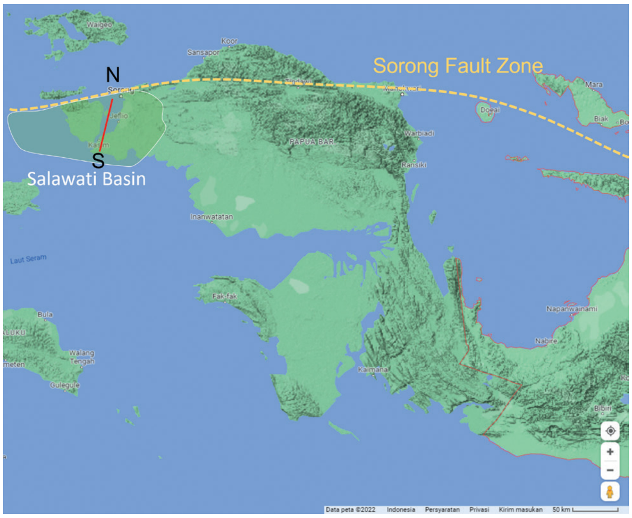

Figure 1 Salawati basin at the Sorong Fault Zone deformation in the Bird's Head region, Indonesia.

[1] RH Petrogas | [2] AspenTech
* Corresponding author, E-mail: yudistira.effendi@rhpetrogas.co.id
DOI: 10.3997/1365-2397.fb2023013

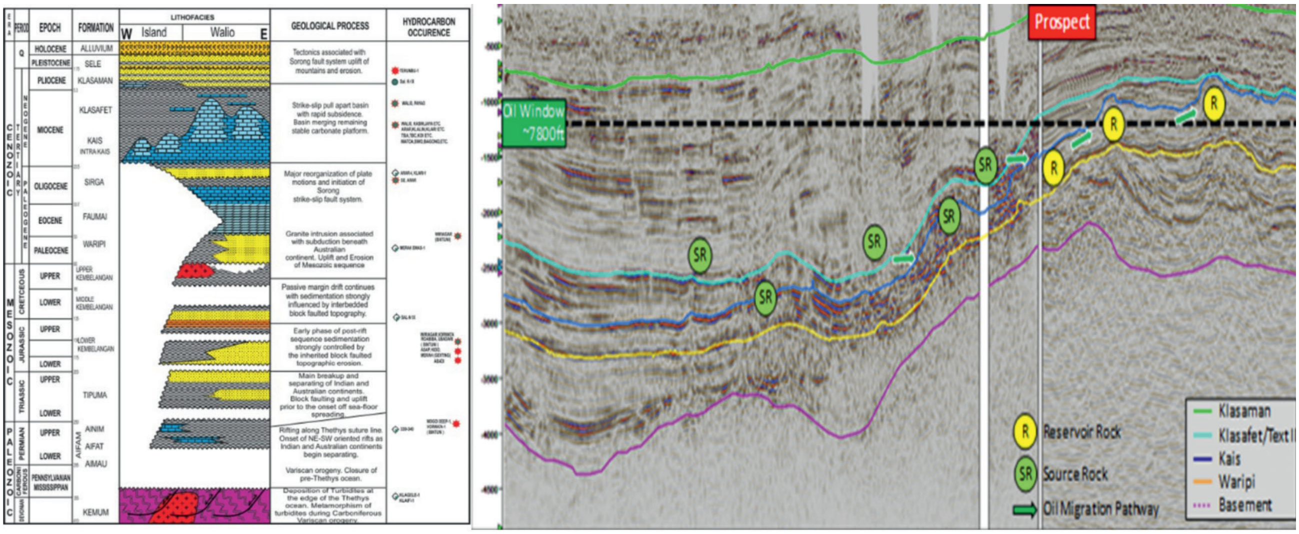

Figure 2 Stratigraphy column and seismic cross-section showing pliocene clastics overlying the Miocene Carbonate, from north to south in the Salawati Basin. (Images courtesy of RHPetrogas.)

to the north of the area, stratigraphically but currently without confirmation as no wells have been drilled yet (Figure 2).

Automatic seismic facies classification plays an essential role in integrated exploration and reservoir characterisation. It is a mappable, three-dimensional seismic unit composed of groups of reflections whose parameters differ from those of adjacent facies units, especially in Miocene Carbonates. It can help to describe and interpret seismic Amplitude Variation with Offset (AVO) attributes based on the attributes' reflection characteristics, such as configuration, continuity, amplitude and frequency, within the stratigraphic framework of a depositional sequence in the Salawati Basin. This study aims to determine all variations of seismic AVO attributes and their lateral lithofacies and fluid type changes in Miocene Carbonate reservoirs. The seismic reflection pattern geometries are perhaps most useful for calibration with lithofacies interpreted from wells. This study uses some seismic AVO attributes.

Seismic AVO analysis is identified as a key technique in the exploration phase. Geophysical characterisation of carbonates reservoirs is required because of the poor visualisation in the available seismic data, which usually reflects a low seismic resolution. Therefore, it is of considerable interest for creating a more realistic visualisation of the reservoirs where we do observe a high contrast of impedance between carbonates and siliciclastics. For this reason, a method which integrates the use of specific seismic attributes for mapping density changes between the carbonates reservoirs and the surrounding layers can be useful (Vincentelli et al., 2014; Artun, 2005).

More advanced seismic pattern recognition techniques in the area of rock type prediction are the association of seismic attributes and well data such as facies logs, to derive the most probable reservoir facies distribution associated with lithology and other reservoir properties. The selection of traditional seismic attributes for characterising a carbonate reservoir is a challenge because of the highly nonlinear relationship between heterogeneous reservoir features and seismic attribute responses. AVO attributes are prestack attributes that have as the basis for their computation the variation in amplitude of a seismic reflection with varying offset. These attributes include AVO intercept, AVO gradient, intercept multiplied by gradient, far minus near, fluid factor, etc. (Castagna and Bactus, 1993). The use of AVO as a direct hydrocarbon indicator in clastic/non-clastic rocks is based on changes to the P-wave velocity to S-wave velocity ratio of a reservoir rock when the hydrocarbon is introduced into the pore spaces (Allen and Paddy, 1993). AVO is used to search for a variation in the amplitude of a seismic reflection with offset on an NMO-corrected CMP gather. P-waves are sensitive to changes in pore fluid; the introduction of gas into the pore spaces of rocks greatly reduces the P-wave velocity. On the other hand, the pore space constituent does not affect the velocity of S-waves. The change in the ratio of P-wave velocity to S-wave velocity (characterised by Poisson's Ratio) causes the 'partitioning' of an incident wave (i.e., into its P-wave and S-wave reflected and refracted components) to differentiate the case of a gas-sand/shale or gas-sand/wet-sand reflector from that of most other reflectors. As a result, the reflections associated with some reservoirs for gas-bearing rocks increase in amplitude with an offset relative to other reflectors. This increase in amplitude is rare in seismic data; most reflections decrease in amplitude.

Lambda and Mu-Rho analysis aims to extract lithology and pore fluid information from seismic and well log data. The conversion of velocity measurements to Lamé's moduli parameters of rigidity and 'incompressibility' offers a new understanding of the original rock properties (Goodway et al., 1997). This study focuses on using AVO attributes as input data for a multi-attribute, unsupervised clustering method to gain more insight than through traditional approaches. Because the seismic data is suggesting a possible extension to the north of the carbonate reservoirs, a suite of adequate seismic interpretation and characterisation tools is needed, especially in the machine learning technology domain, to validate the assumption that attributes might make sense when combined rather than individually. Some previously published case studies use a similar approach to characterise carbonate reservoirs (Azadpour et al., 2020; de Ribet et al., 2018; Kuroda et al., 2016; Tran et al., 2020).

The calculation of a series of seismic attributes associated with unsupervised multi-attribute clustering is a key tool in the prospect delineation phase. The value of such a workflow is the ability to apply it in the case of lacking or non-existing wells in this area. In this project, we propose to associate a selection of AVO attributes with an unsupervised machine learning (ML) approach, based on a Growing Neural Gas algorithm (Fritzke, 1995) to create a volume of seismic facies related to our input dataset. This incremental neural network is learning the significant topological relations that exist in a given set of input vectors, and will continue learning, adding units and connections until a certain performance criterion has been reached. The global objective is to define a sub-space of lower dimension than the input vector space, keeping most or all input data through projection on to non-linear and discrete subspaces of a dimensionality, which has been defined a priori. The interpretation of the most probable seismic facies distribution is performed a postiori, through visual comparison with well data, in this case looking for the best correlation between electrofacies, if available, or logs.

Methodology

The dataset is composed of 3D seismic prestack and poststack attributes, structural interpretation and well data (including sonic, density, gamma ray and neutron logs) for validation. The AVO inversion is carried out to evaluate the vertical and lateral amplitude variations within the interval of interest, represented by a 100 to 200 ms temporal thickness window defined by the top and base structural interpretation of the Kais formation.

3D seismic attributes and advanced seismic-driven reservoir characterisation techniques are used for seismic reservoir characterisation to allow prospects to be defined and wells to be successfully developed in the Salawati Basin. Projects based on AVO inversion have helped the interpretation of stratigraphic features in this basin. This method delineates stratigraphic settings (such as channel and structural settings involving complex fault systems) in 3D seismic data. In our project, the seismic AVO attributes are computed to cover the Kais interval and are tuned by the rock physics properties within the analysis window.

The overall workflow consists of four main steps: project setup, data loading and QC, application of the core methods (AVO inversion, multi-attribute clustering and geobody detection) and generation of outputs for interpretation and characterisation. As mentioned above, the first step is collecting and preprocessing the seismic, well and interpretation data to create a suitable dataset for the method.

After applying careful preconditioning to the gathers through ray tracing based on the background velocity model to obtain the angles of incidence at all desired reflectors, the measured amplitude variations are analysed as a function of incident angle, and attribute sections are obtained for various elastic parameters.

These techniques are used to extract reservoir information from the seismic that correlates with well data from some of the surrounding oil fields. These techniques will be described briefly in the following section.

Seismic amplitude variation with offset (AVO)

AVO is a well-known technique used as a direct hydrocarbon indicator in clastic gas fields. Carbonate reservoirs usually have a relatively rigid rock framework, making it more challenging to observe elastic parameter changes based on different fluid types and their saturation. Prior knowledge within the world of AVO suggests that zero-offset information is often insufficient to differentiate shale from carbonate porosity or discriminate gas-saturated from brine-saturated reservoirs. Significant efforts have been made to apply AVO analysis to carbonate reservoir characterisation in the last few years.

The AVO inversion provides two modes of inversion: using two parameters or three parameters. This study used three parameters:

- Angle Stacks: Angle stacks can be used for a qualitative indication of anomalous AVO behaviour. Angle stacks are normalised by the number of contributions to each sample of the angle stack. Therefore, the final amplitude of angle stacks is a normalised amplitude.
- Seismic AVO Attributes (with Linearized Zoeppritz Inversion): This inversion uses Aki and Richard's linearised approximation of the Zoeppritz equation to provide outputs such as P-wave Impedance Reflectivity (Fatti's equation), S-wave Impedance Reflectivity (Fatti's equation), P-wave Velocity Reflectivity, S-wave Velocity Reflectivity, Pseudo-Poisson's Reflectivity, Fluid Factor (Smith & Gidlow), Density Reflectivity.

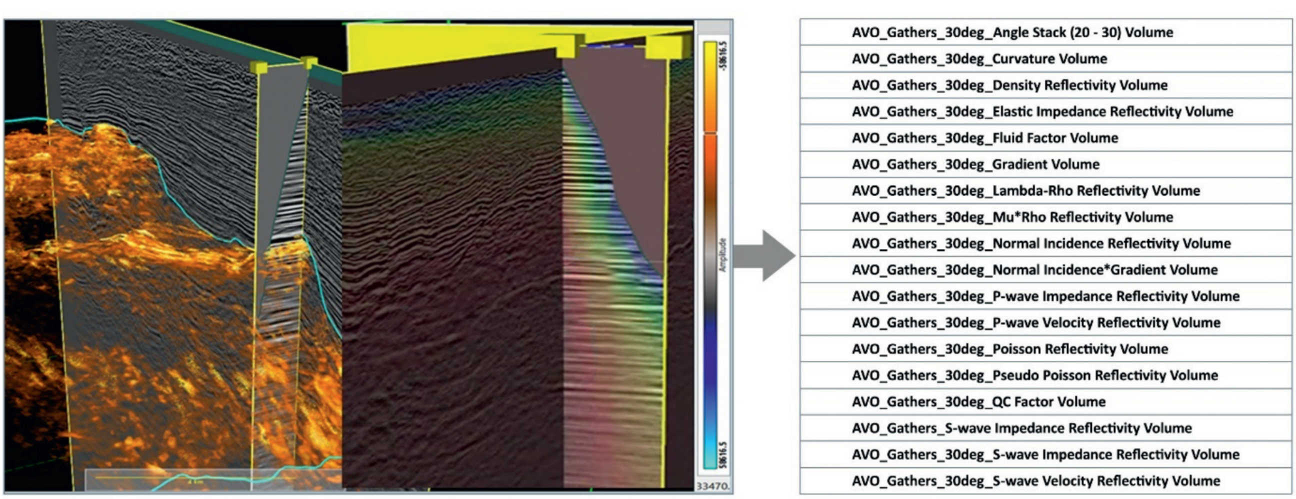

Figure 3 Seismic gathers and post-stack seismic data co-displayed in a 3D Viewer, used to generate AVO output.

AVO_Gathers_30deg_Angle Stack (20 - 30) Volume
AVO_Gathers_30deg_Curvature Volume
AVO_Gathers_30deg_Density Reflectivity Volume
AVO_Gathers_30deg_Elastic Impedance Reflectivity Volume
AVO_Gathers_30deg_Fluid Factor Volume
AVO_Gathers_30deg_Gradient Volume
AVO_Gathers_30deg_Lambda-Rho Reflectivity Volume
AVO_Gathers_30deg_Mu*Rho Reflectivity Volume
AVO_Gathers_30deg_Normal Incidence Reflectivity Volume
AVO_Gathers_30deg_Normal Incidence*Gradient Volume
AVO_Gathers_30deg_P-wave Impedance Reflectivity Volume
AVO_Gathers_30deg_P-wave Velocity Reflectivity Volume
AVO_Gathers_30deg_Poisson Reflectivity Volume
AVO_Gathers_30deg_Pseudo Poisson Reflectivity Volume
AVO_Gathers_30deg_QC Factor Volume
AVO_Gathers_S-wave Impedance Reflectivity Volume
AVO_Gathers_30deg_S-wave Impedance Reflectivity Volume
AVO_Gathers_30deg_S-wave Velocity Reflectivity Volume

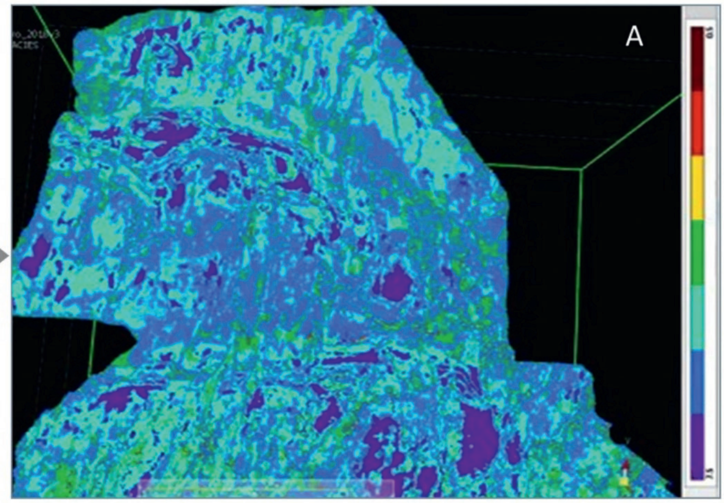

Figure 4 List of seismic attributes selected as input to generate a seismic facies volume using a Growing Neural Gas algorithm.

- Seismic AVO Attributes (Shuey's Approximation): This inversion uses the Shuey-Hilterman approximation of the Zoeppritz equation to provide outputs such as Normal Incidence Reflectivity, Gradient, Curvature (only for 3-parameter inversion), Sign, Poisson's Reflectivity, Elastic Impedance Reflectivity.

These seismic AVO attributes are used as input for unsupervised machine learning (Figure 3).

Growing neural gas network

The reason for using a machine learning algorithm resides in its ability to deal with a large amount of data, especially seismic, to learn from it, transform it and deliver an output which will be interpretable by the geoscientist. In the context of unsupervised learning from AVO attributes as related to be AVO anomalies, the Growing Neural Gas Network (Fritzke, 1995) appears to be the most flexible, as it matches the high dimensionality when referring to seismic attributes. It also enables an unlimited number of seismic attributes. Its main drawback is that all self-organising neural networks are attracted by data density, therefore the original algorithm needs to be adapted to consider the outliers as part of the data.

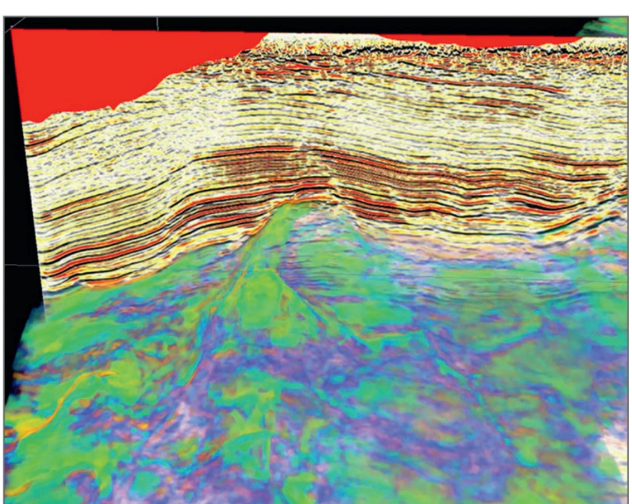

Figure 5 Seismic facies volume with opacity; original seismic data is displayed in the background.

In our project, outliers could be associated with AVO anomalies. To avoid such an issue, the training is performed on all points of the considered interval, then the outliers are detected and the training is run only on the outliers. Clustering is then applied using a topology approach, with an estimation of the probability of each point in the interval to be part of a specific cluster. Eighteen seismic AVO attributes were chosen for a final set of seven clusters or seismic facies (Figure 4).

As this approach interacts simultaneously with several seismic attributes, a single seismic facies will more likely represent the same combination of responses from the initial set of seismic attributes. It also helps to investigate the distribution of a particular seismic facies using different techniques, such as isolating it through opacity in a 3D viewer, subvolume detection, or visual interpretation to analyse the potential connectivity with other seismic data – in our case, the extension of the carbonates reservoirs of the Kais formation to the north. Although the seismic attributes may be of high quality, it is a challenge to map the build-ups using conventional 3D seismic interpretation tools, due to the internal heterogeneity of the build-ups. This method helps to associate specific seismic facies and their distribution to the patterns identified in the amplitude data (Figure 5).

This method has allowed us to 3D map the carbonates (target facies) within the Kais formation (Figure 6). Available wells are now used as a blind test to validate the presence of the carbonate build-ups. A significant benefit of using such an approach is the option to focus on the reservoir itself, to avoid dispersion of the seismic facies classification when enlarging the zone of interest.

Geobody detection is then used to confirm the presence of the carbonate build-ups and evaluate the connectivity. Two approaches were selected: conservative and robust geobody detection. In conservative geobody detection, the connection of the geobody (target facies) uses six ways (faces) per voxet (Figure 7). The geobodies can be validated against existing wells near oil fields to find new opportunities for exploration and development.

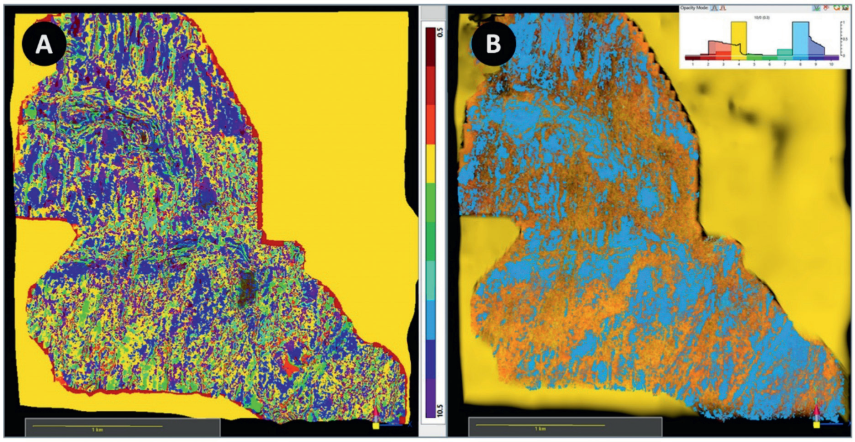

Figure 6 Visualization of the distribution of carbonate build-ups within the Kais formation, (A) without opacity (B) with opacity. In this example, 10 classes were used to improve the level of detail.

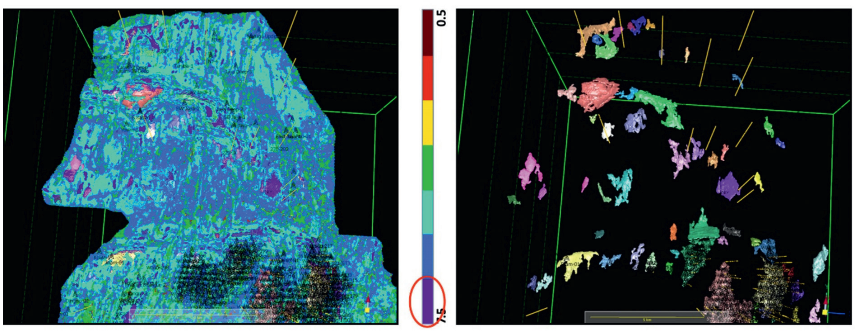

Figure 7 Seedless geobody detection using a conservative method. Note the correlation between well density and the detected geobodies identified as carbonate build-ups in the south section of the survey.

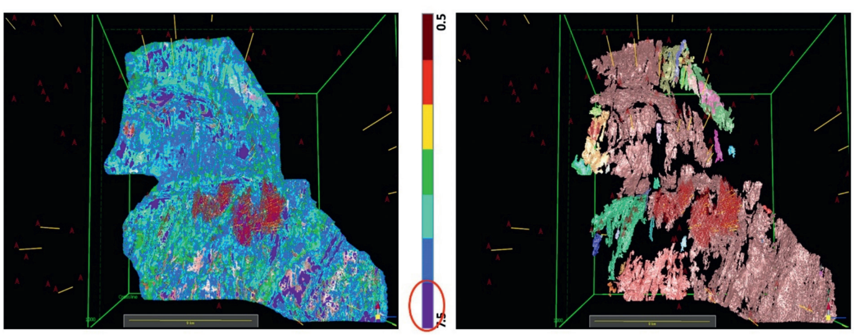

Figure 8 Seedless geobody detection using a robust method. Note the correlation between well density and the detected geobodies identified as carbonate build-ups. Wells are colored red in both images.

The robust approach uses 26 ways (faces, edges, corners) (Figure 8). The seismic facies model shows lateral variations of high interest in the Kais reservoir interval and provides new insights into exploration and development of hydrocarbons in the Salawati Basin.

Conclusion

In the Salawati Basin, a self-organizing Growing Neural Network is applied to a suite of seismic AVO attribute data to help map the seismic facies of interest away from the well. This technique reduces drilling costs when developing a reservoir within the Kais interval of the Miocene Carbonate. In addition, the model helps to identify potential opportunities and reveals an updated 3D cartography of the carbonate build-ups, which will support a more effective delineation of the optimal location for new drilling targets, increase drilling success and reduce cost and risk.

Acknowledgments

The authors would like to thank RHP for its agreement to publish this article and AspenTech for use of its software.

References

Allen, J.L. and Peddy C.P. [1993]. *Amplitude Variation with Offset: Gulf Coast Case Studies*, SEG Library, Tulsa, Oklahoma.

Artun, F.E. [2005]. *Reservoir characterization using intelligent seismic inversion, Graduate Theses, Dissertations, and Problem Reports*. 1620. https://researchrepository.wvu.edu/etd/1620.

Azadpour, M., Saberi, M.R., Javaherian, A. and Shabani, M. [2020]. Rock physics model-based prediction of shear wave velocity utilizing machine learning technique for a carbonate reservoir, southwest Iran, *Journal of Petroleum Science and Engineering*, 195, 107864.

Castagna, J.P. and Backus, M.M. [1993]. *Offset Dependent Reflectivity – Theory and Practice of AVO Analysis*. Society of Exploration Geophysicists. ISBN 1-56080-059-3.

De Ribet, B., Jun, J., Kim, Y., Trowbridge, T. and Shin, K.S. [2018]. Machine Learning Provides Higher-Quality Insights into Facies Heterogeneities over Complex Carbonate Reservoirs in a Recently Developed Abu Dhabi Oilfield, Middle East, Abu Dhabi International Petroleum Exhibition & Conference.

Fritzke, B.A. [1995]. A Growing Neural Gas Network Learns Topologies, Neural Information Processing Systems 7, MIT Press, Cambridge MA, pp. 625-632.

Goodway et al. [1997]. Improved AVO fluid detection and lithology discrimination using Lamé petrophysical parameters, *CSEG Recorder*, 3-5.

Hami-Eddine, K., de Ribet, B., Durand, P. and Patxi. G. [2017]. A growing machine learning approach to optimize use of prestack and poststack seismic data. *2017* SEG International Exposition and Annual Meeting, Houston, Texas.

Kuroda, M.C., Vidal, A.C. and Papa, J.P. [2016]. Analysis of porosity, stratigraphy, and structural delineation of a Brazilian carbonate field by machine learning techniques: A case study, *Interpretation* **4**(3), T347-T358, 2016.

Livingstone, H.J., Sincock, B.W., Syarief, A.M., Sriwidadi and Wilson, J.N. [1992]. Comparison of Walio and Kasim Reefs, Salawati Basin Western Irian Jaya Indonesia, *IPA*, 1992.

Redmond, J.L. and Koesoemadinata, R.P. [1976]. Walio Oil Field and the Miocene Carbonates of Salawati Basin Irian Jaya Indonesia, Fifth Annual IPA Convention.

Tran H., Kasha, A., Sakhaee-Pour, A. and Hussein, I. [2020]. Predicting carbonate formation permeability using machine learning, *Journal of Petroleum Science and Engineering* 195, 107581.

Vincentelli, M.G.C., Contreras, S.A.C. and Chaves, M.U. [2014]. Geophysical characterisation of Albian carbonates reservoirs in Brazilian basins: the sweetness as a tool for carbonate reservoirs definition. *Brazilian Journal of Geophysics*, **32**(4), 695-705.