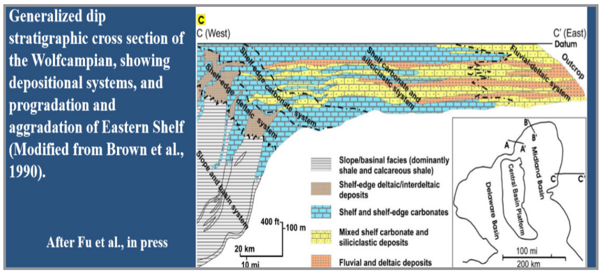
Using Artificial Intelligence to Increase Reservoir Productivity in the Permian Basin, Texas

RESULTS

- The 3D facies volumes and map provided geological intelligence that helped the oil and gas operator make better field development investment decisions.
- Results were obtained quickly from properly calibrated and conditioned electrofacies and seismic data. Project times for predicting the detailed facies model were accelerated 10X.
- Based on the results, a new drilling location was proposed and approved.



APPLICATION

Emerson Democratic Neural Network Association (DNNA)™ machine learning algorithm embedded in the SeisEarth™ interpretation system.

CUSTOMER

Halliburton Operating Company

CHALLENGE

The customer faced a daunting challenge: it had gone to considerable expense to acquire a high-resolution 3D seismic survey in the Eastern Shelf of the Permian Basin, but was unable to assemble its collection of seismic attributes into an interpretation which could explain the lithofacies being observed at the wells. Viewed individually, the seismic attributes did not seem to indicate lithofacies and fluid content. They also provided much lower vertical resolution than the mudlog and wireline logs. The company felt that its ability to decide where to drill next was hampered by this lack of concrete information.

> ***"The study results were accurate - after moving the rig from its original position, the well found a good pay facies at correct depth, with double the pay zone thickness and an increase in porosity from 10% to 17%."***
>
> **Monte Meers,** Project Manager

SOLUTION

In order to help the operator link lithology, fluid content, and seismic response, a proprietary Emerson Machine Learning algorithm called Democratic Neural Network Association (DNNA) was employed. DNNA consists of a set of single-layer neural networks, all possessing slightly different learning strategies. The neurons, supervised by lithofacies logs, learn how to identify patterns in seismic data that could indicate lithofacies and fluid content.

The initial round of learning and classification takes place at the well locations, but then the algorithm enriches the seismic training set by looking for blocks on seismic data away from the wells, where the neurons all agree on the classification prognosis. If they unanimously agree, that block of seismic data becomes part of the enriched training dataset, which is used for the second round of training and 3D volumetric classification. This second round involving data located away from the wells is done to combat overtraining at the wells.

	Class No	Class Name	Class Description	Pattern	Color
1	1	dm	Dolomite	dm	
2	2	ls	Limestone	ls	
3	3	sh lm	Shaly lime	lm	
4	4	lm sh	Limey shale	sh...	
5	5	pk oil	Packstone oil filled	o...	
6	6	ps	Packstone	ps	
7	7	sh	Shale	sh	
8	8	st	Siltstone	st	
9	9	ws	Wackestone	ws	

Figure 1 – Facies classification table. Facies 5 is pay (dark green).

The outputs from this process are not only the most probable facies volume, but also the probability volumes associated with every facies. Report spreadsheets describe the reconstruction success rates for wells, for facies classes, and globally. A "confusion matrix" table indicates which facies were wrongly misclassified as other facies. Seismic dip and azimuth-guided smoothing may optionally be applied to increase the usability of the facies and facies probability volumes. Finally, these volumes may be exported for use in any geocellular modeling or seismic interpretation package.

In this case, the algorithm searched through the available 3D seismic data simultaneously, and was able to build a model which reconstructed the nine lithofacies (Figure 1). No evidence was seen of false positive or false negative predictions at the wells for the oil-filled packstone.

RESULTS

The results provided a significant uplift from conventional seismic-driven reservoir characterization workflows (Figure 2). Lateral resolution was also improved. Additional drilling opportunities could be identified from the facies probability voxel clouds (Figure 3) or the net pay facies thickness map (Figure 4).

BENEFITS

The customer received 3D volumetric seismic products stated in terms of the actual lithofacies codes (1-9) observed at the wells, not seismic attributes with arbitrary units with no direct geological meaning. Furthermore, the vertical resolution obtained was significantly better than that obtained in the original seismic. The results were received quickly; the first predictions were produced soon after the data loading and QC were completed. It took only a few more days of work to analyze and deliver the final results.

The 3D volumes and map (Figures 2-4) all provided intelligence that helped the customer make more informed decisions regarding its upcoming investments.

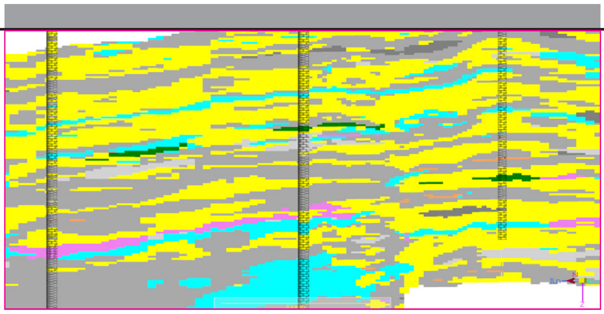


Figure 2 – An excellent tie between the facies logs at the three wells and the 3D seismic facies classification results. The common color scheme in Figure 1 is used, the pay is dark green Facies 5, oilfilled packstone.

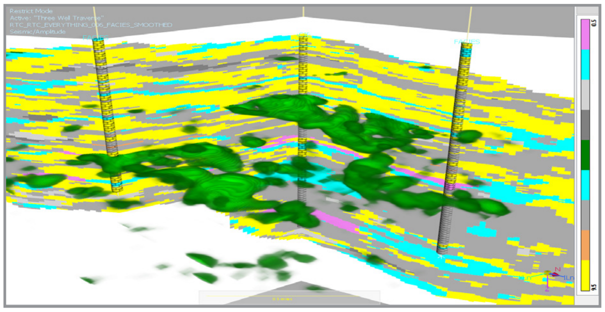


Figure 3 - 3D semi-opaque voxel cloud view of the oil-filled packstone probability cloud

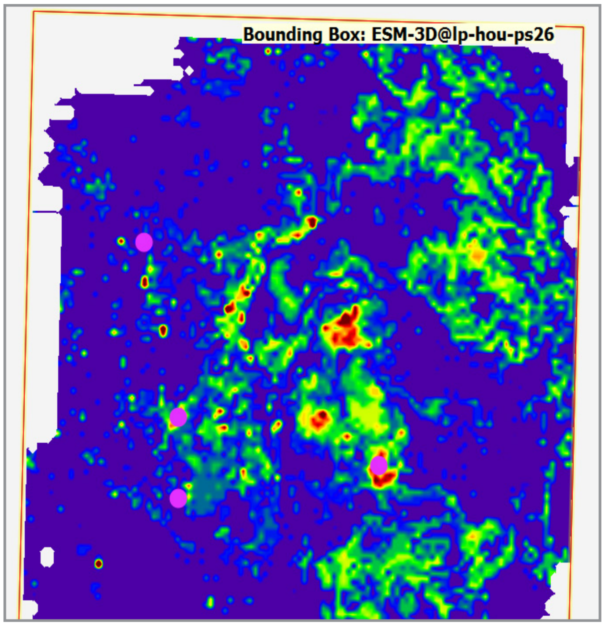


Figure 4 – Oil-filled packstone two-way time thickness map

RESOURCES

Recording: Exploring for Wolfcamp Reservoir in the Permian Basin, Using a Machine Learning Approach
http://www.pdgm.com/news-and-events/global-events/virtual-lectures/exploring-for-wolfcamp-reservoir-in-the-permian-ba/

Based on a presentation, "Exploring for Wolfcamp Reservoirs, Eastern Shelf of the Permian Basin, USA, Using a Machine Learning Approach", co-authored by Monte Meers, Howard Renick, Russ Creath, Ryan McKee, Peter Wang and Bruno de Ribet, presented at industry events, including ADIPEC 2018.

Data courtesy of Halliburton Operating Company.

Emerson E&P Software
Two Memorial Plaza
820 Gessner, Suite 400
Houston, TX 77024
T +1 713 393 4800