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Seismically Derived Porosity Prediction for Field Development- An Onshore Abu Dhabi Jurassic Carbonate Reservoir Case Study

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Abstract

A high quality broadband impedance solution by inverting seismic amplitudes is one of the most common industrial standards to integrate geophysical inputs into geological models during field development studies and planning. The use of accurately quantified petrophysical volumes derived from seismic data during geological model building can help improve the understanding of the reservoir and in maximizing the value of seismic data.

During this case study for two sour gas carbonate reservoirs- reservoir units C & D, in an onshore Abu Dhabi field, the acoustic impedance volume from seismic inversion and the seismic data itself were further converted into a porosity volume by a probabilistic neural network (PNN) approach. This non-linear transform approach establishes the link between seismically-derived impedance and porosity through an optimized training correlation and error method approach at each well location. A combination of the following factors pertaining to training dataset, established a successful neural network based porosity prediction workflow for the reservoirs:

- Amplitude preservation of seismic data (target-reservoir specific re-processing)
- Many calibration wells with good quality calculated log porosity
- High quality inverted seismic impedance.

A high correlation of predicted porosity to measured well porosity was achieved at all the well locations. In addition, reservoir unit C porosity grades from a very high but thinner porosity at the top to medium-high thicker porosity at the base, which was well resolved within the available seismic bandwidth and the PNN method of porosity prediction matched this variation of the log porosity. High cross-validation scores achieved during PNN training for porosity prediction, in effect provided the confidence in prediction away from the wells. Furthermore, a close match of predicted and measured porosity at blind test wells drilled in the field extended the confidence in the porosity prediction results. The porosity prediction successfully delineated regionally known non-porous lineaments and faults (encountered while drilling wells) on mean porosity maps of the two reservoirs.

The main objective of reservoir-focused reprocessing was to minimize the amplitude damaging effects of the near-surface, mainly due to presence of large sand dunes, and adequately prepare the data for seismic inversion. Successfully estimating seismically derived porosity was an important tool for well planning, geosteering long reach horizontals and also a key input for reservoir characterization to

improve our understanding and distribution of reservoir properties in our geologic model.

INTRODUCTION

The primary objective of any seismic reservoir characterization study is to extend the understanding of the reservoir beyond the wells. This particular case study is aimed at predicting the porosity of the two reservoirs of interest using the fullstack seismic as well as other seismic attributes such as the acoustic impedance result from the seismic inversion. These gas-bearing grainstone dominated target reservoirs show varying quality of **highly porous unit C (10-25%) grading into medium (5-10%) porous unit D** at the base. The reservoir intervals form a large scale shallowing-upward cycle capped by the widespread anhydrite topseal. The lower reservoir unit consists of wackestones to mudstones of mid ramp to basinal setting (reservoir unit D) overlain by foreshoal and oolitic grainstone shoal deposit of the reservoir unit C (Lawrence et. al, 2015). The main reservoir unit C (25-30m thick) is mainly comprised of oolitic grainstone facies with only a meter of wackestones/packstones at the base. The two reservoir units of the same formation are treated separately while estimating their porosities and later merged to create a single 3-D porosity volume. Although, these two very prolific reservoir units are the proven targets for this field, the overlying thinner units A and B (restricted lagoon to backshoal and sabkha/salina origin) are hydrocarbon bearing but fall below the seismic resolution so they will not be discussed here.

It is common industrial practice for field development projects to integrate all available data and within this scope lie the ability to maximize the value from acquired seismic dataset. Seismic data plays a significant role, by not only providing a structural framework of fault, fracture and geologic horizons but also helps in deducing the lateral distribution of reservoir properties. During seismic inversion, the wavelet effect from the seismic is removed, and the initial model built from well data is updated to derive absolute acoustic impedance. The dependency of acoustic impedance and porosity amongst carbonate reservoirs is well known. This forms the very basis of deriving petrophysical properties from seismic derived impedance. However, as most geologic truths, this well-established relationship between acoustic impedance and porosity is of a non-linear nature. Hence, a probabilistic neural network method is employed by means of complex statistical analysis to solve for porosity from the seismic and acoustic impedance.

WELL DATA AVAILABILITY

A total of 15 wells were used during the study, covering the suite of logs required to perform the seismic inversion and porosity estimation analysis. Most of the well logs are considered of good quality for the purpose of the inversion, and for few wells some log correction was performed in the non-reservoir portion of the logs.

SEISMIC RE-PROCESSING & INVERSION

The target Jurassic reservoirs are located in a field to the south east of onshore Abu Dhabi. The field studied is an anticlinal structure and the porosity development lays mainly over the crest of the structure where most wells of the field are located. Much of the structural closure displays relatively high seismic amplitude corresponding with good porosity in the reservoirs while deeper on the flanks the seismic amplitude decreases markedly due to porosity reduction associated with secondary cementation (Buijs et al. 2011).

The seismic processing for this onshore field was challenging due to the surface topography consisting of sand dunes and inter-dune areas with elevations ranging between 93 to 193m amsl. A reservoir focused seismic re-processing workflow included a cascaded approach to surface consistently balance the amplitudes and integration of well based reflectivity trends. The re-processing workflow has been discussed in more details in *Burreson et al., 2015*. Figure 1 shows the comparison of rms amplitude map extracted around the reservoir of interest after different processing efforts from 2009 to 2015.

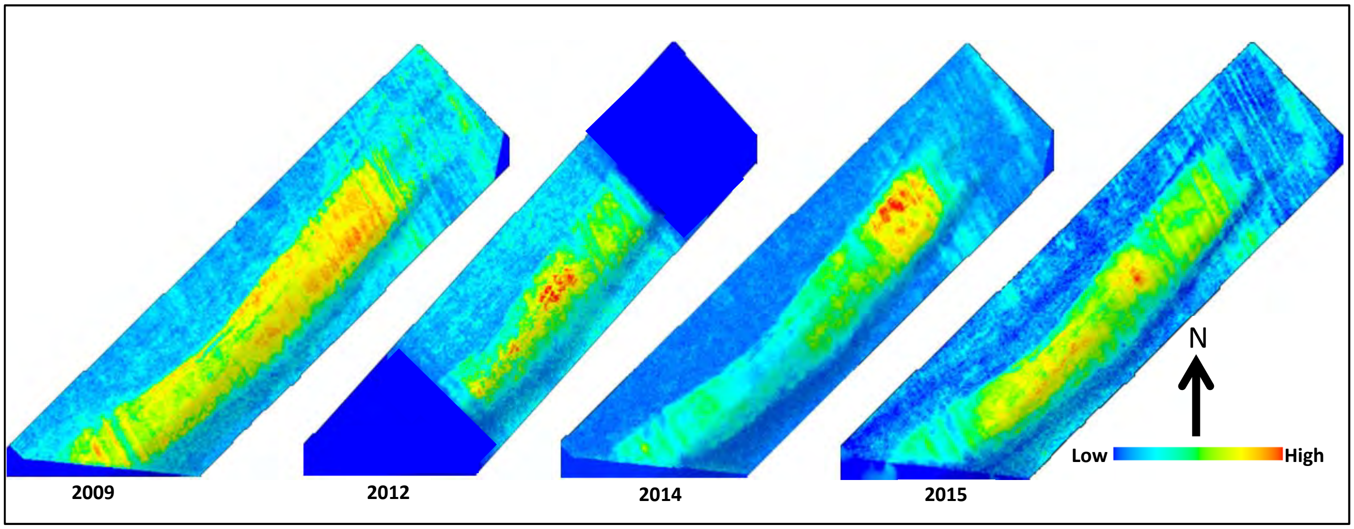
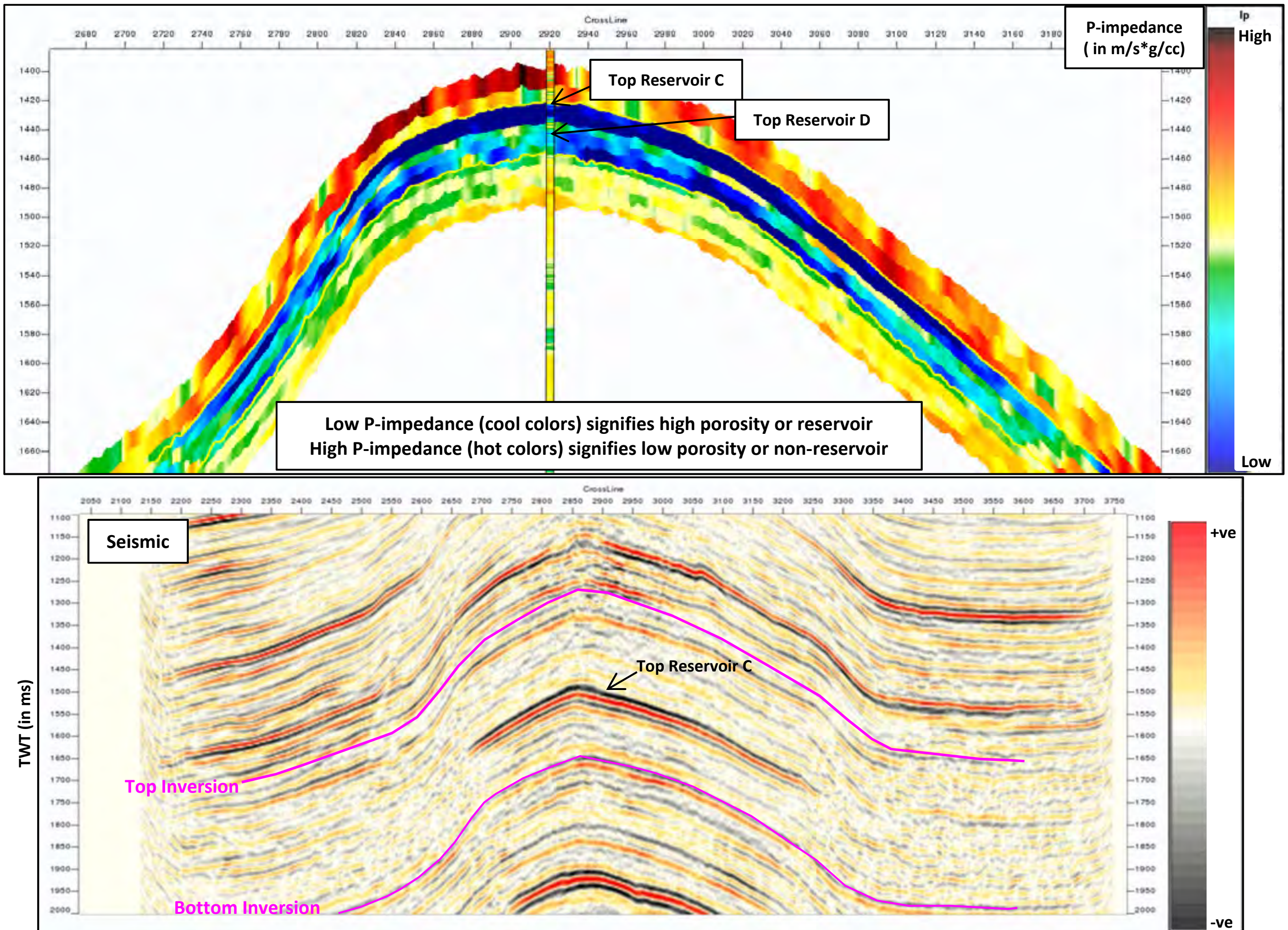


Figure 1: Rms amplitude map extraction around reservoir of interest for different reprocessing efforts from 2009 to 2015. The 2015 seismic reprocessing on the right is the reservoir focused reprocessing that was used in this study

The proposed 3D seismic inversion algorithm works within a stratigraphic grid. This stratigraphic framework constitutes a micro-layer system within each horizon interval conformable to the depositional sequence. After the well to seismic tie, the deterministic multi-well seismic wavelet is extracted from the seismic data (closed to zero phase) via a cross-coherency spectral matching filter between the synthetic trace derived from the log P-impedance and the seismic trace at the well location. Then, an initial model is constructed propagating the low frequency trend of log impedance in the previously mentioned stratigraphic grid built with the interpreted seismic horizons. An iterative algorithm, based on simulated annealing techniques (Duboz et. al, 1998), is used to obtain the optimized acoustic impedance and the layer thickness (in time) maximising the correlation between measured and synthetic seismics. Figure 2 and 3 shows the result of the acoustic inversion through an inline section.

Figure 2 (below) shows a section through the deterministic acoustic inversion result of P-Impedance across one of the well locations.


P-impedance
(in m/s*g/cc)
High
Low
Top Reservoir C
Top Reservoir D
TWT (in ms)
Low P-impedance (cool colors) signifies high porosity or reservoir
High P-impedance (hot colors) signifies low porosity or non-reservoir
Seismic
Top Reservoir C
Top Inversion
Bottom Inversion
+ve
-ve

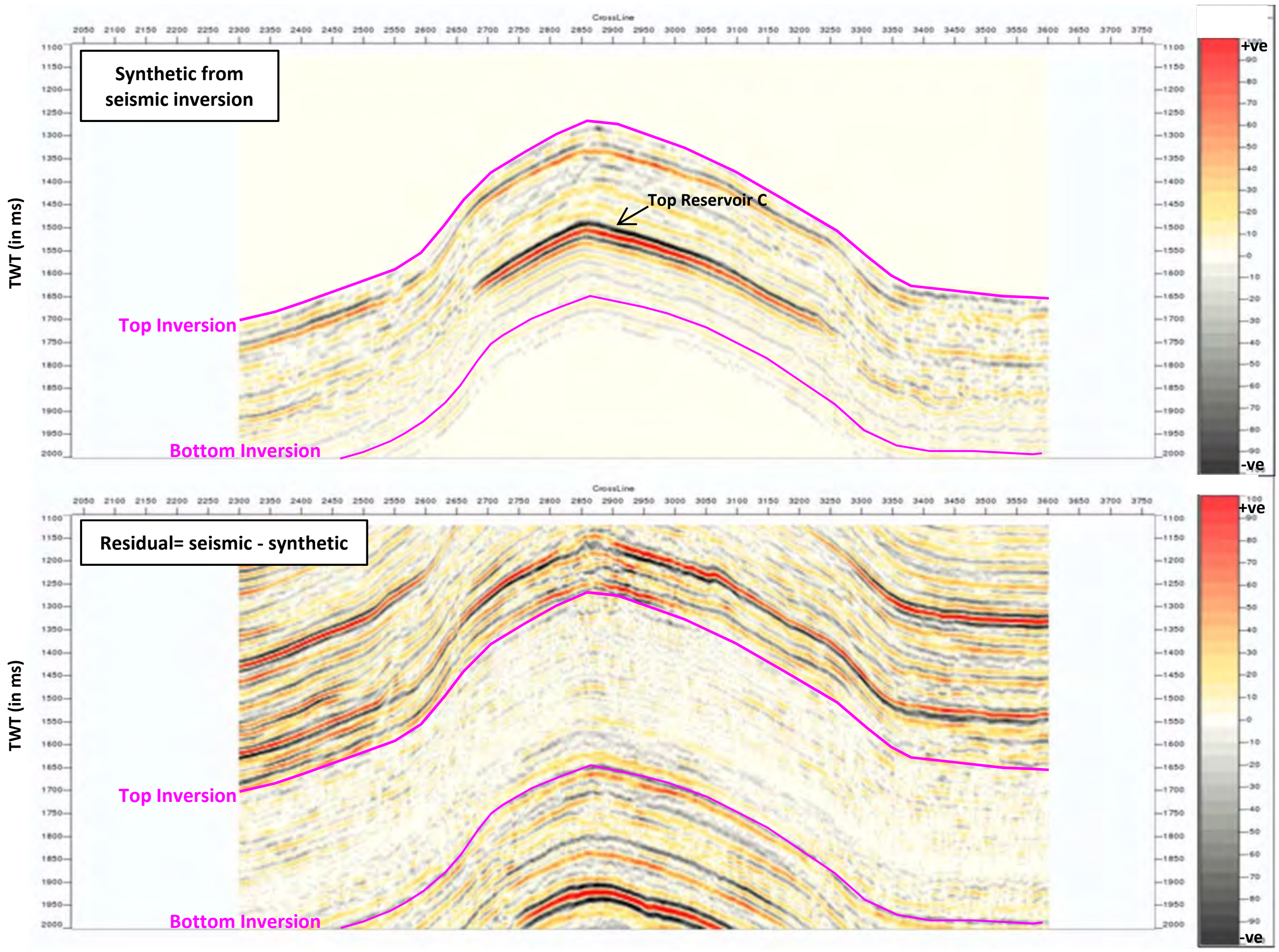


Figure 3: Section through residual (bottom) from seismic (top) minus synthetic (middle) indicative of a very reliable seismic inversion result.

The high well to seismic tie cross-correlations (CC>80%) observed across all wells and the stable deterministic multi-well wavelet extraction suggest the ability to achieve high quality P-impedance inversion product for the field. At this stage, the low P-impedance (or porous facies) could already be laterally traced out across the field from the P-impedance volume.

POROSITY ESTIMATION FROM SEISMIC

Prediction of reservoir petrophysical properties from seismic and derived seismic attributes such as acoustic impedance traditionally have been addressed through the application of multilinear multivariate statistics and, more recently, the Probabilistic Neural Network (PNN) methods, especially when it becomes necessary to extract nonlinear relationships between the input data and the target property. This paper describes below the PNN method of porosity prediction from seismic and inversion result, P-impedance.

A supervised PNN method is employed for the porosity prediction in this case where most of the available wells are used for the training. Together, Neural networks and the inversion can increase both the level of details and the degree of confidence in the results produced. As the PNN is a sample-to-sample prediction it honors the “best fit” prediction of reservoir properties at every seismic data sample. During the sample-to-sample prediction, a series of attributes are selected from seismic amplitude and attributes such as inversion derived P-impedance, to derive the porosity. Then, the best combination of “N” number of-attributes are used as inputs to the analysis.

Throughout this analysis, there is need to check for “overtraining” or false prediction. So, a cross-validation technique is used to find the statistically meaningful attributes. Once the attributes are selected, weights are assigned to each of them. The output based on these initial settings is compared with known wells to determine errors, which are then fed back through the network to determine a better weight for each attribute. This iterative training process is designed to minimize errors and produce the best estimate of each attribute across all samples in the seismic volume.

PNN training for porosity prediction at Reservoir Unit C: PNN training was carried out using porosity logs of 11 wells. Cross correlation of 92% during training and 88% during validation were achieved. The best ranked 3 attributes used for analysis are: Quadrature trace (seismic), Quadrature trace (P-Impedance) and Integrated absolute amplitude (seismic).

PNN training for porosity prediction at Reservoir Unit D: PNN training was carried out using porosity logs of 8 wells. Cross correlation of 84% during training and 76% during validation were reached. The best ranked 2 attributes used for analysis are: Quadrature trace (seismic) and P-Impedance.

For porosity predicted at reservoir unit C, very high average cross-correlation of 0.92 was obtained across the wells while for reservoir unit D, an average cross-correlation of 0.84 was obtained. These two volumes were combined later to produce one porosity volume.

Figure 4 shows the porosity result extracted at different well locations (in red) against the measured well log porosity (in black).

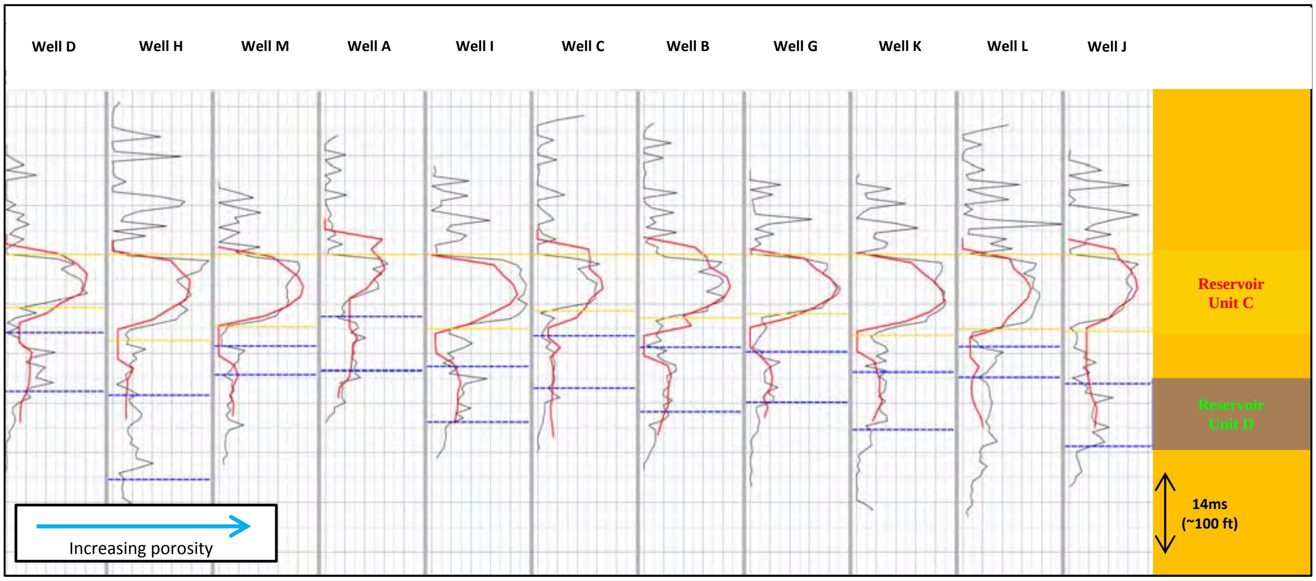


Figure 4: Porosity result extracted at well locations. Red curve is the porosity result against the black curve which is well log porosity.

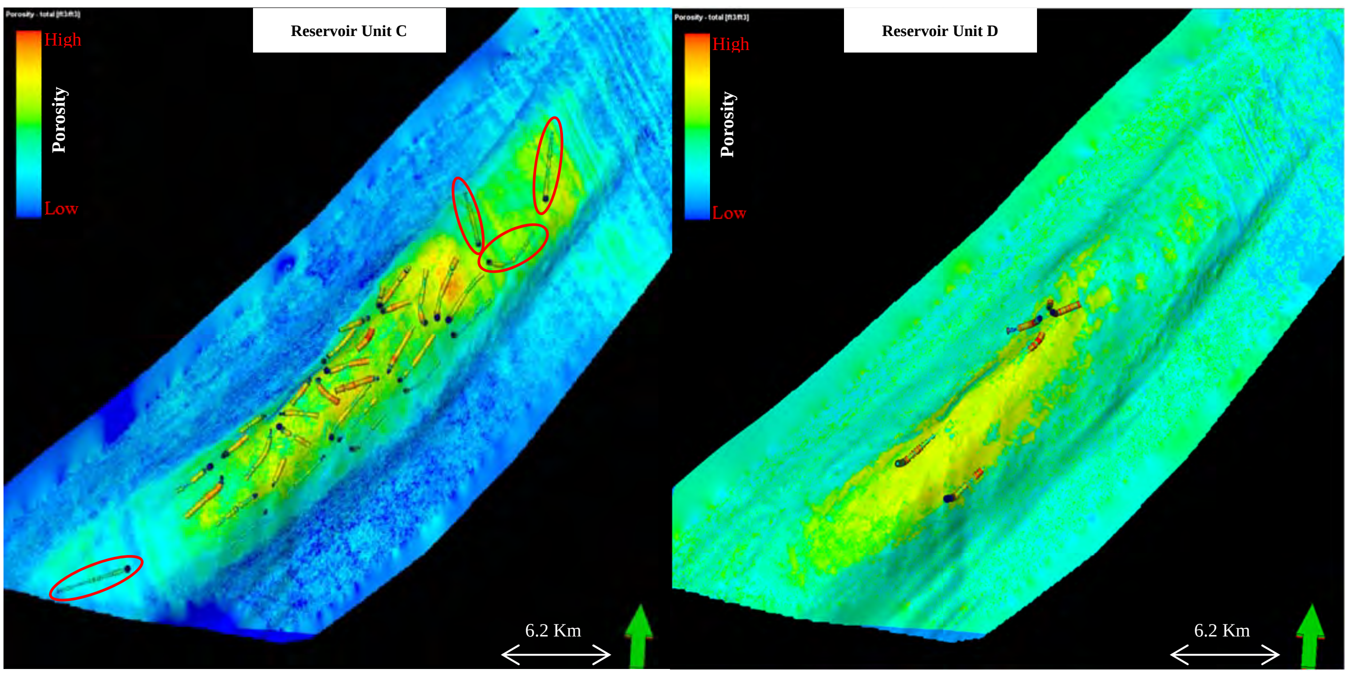
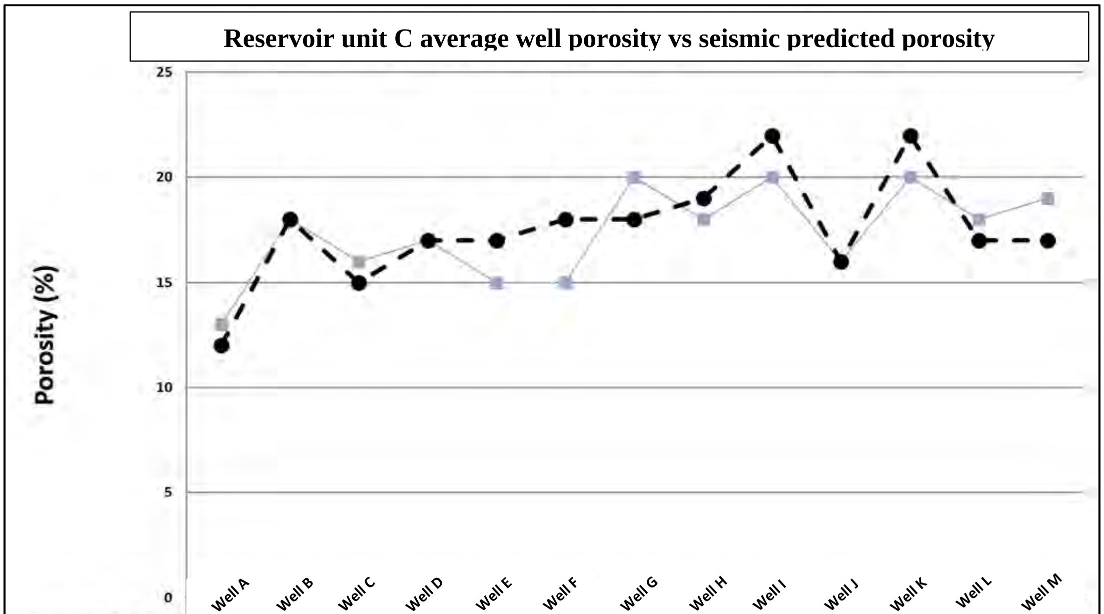


Figure 5: Mean porosity map result extracted around the two reservoirs of interest: reservoir unit C (left) and reservoir unit D (right) along with horizontal wells.

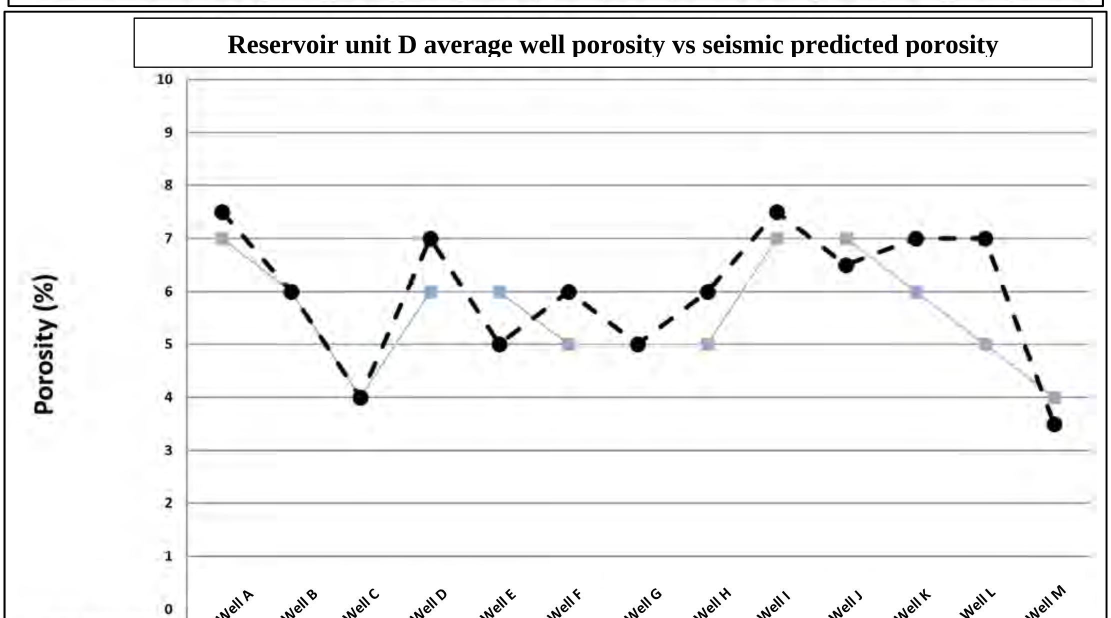
In addition to the high cross-validation scores during the neural network training, the porosity prediction away from the wells is consistent with the existing geological knowledge of the field, which gives more confidance in the results. The porosity prediction successfully delineated regionally known non-porous lineaments and faults (encountered while drilling wells) on mean porosity maps of the two reservoirs. Furthermore, a close match of predicted and measured porosity for blind-test wells drilled in the field extended the confidence in the porosity prediction results. The good fit between predicted and measured porosity across the field is shown along the horizontal wells in figure 5 where, encircled are the horizontal wells that relied most on porosity prediction result for planning and while drilling.

Figure 6 below shows match of predicted vs measured average porosity at various wells in reservoir unit

C and reservoir unit D on a graph.



	Well A	Well B	Well C	Well D	Well E	Well F	Well G	Well H	Well I	Well J	Well K	Well L	Well M
Porosity Prediction	13	18	16	17	15	15	20	18	20	16	20	18	19
Well Porosity	12	18	15	17	17	18	18	19	22	16	22	17	17



	Well A	Well B	Well C	Well D	Well E	Well F	Well G	Well H	Well I	Well J	Well K	Well L	Well M
Porosity Prediction	7	6	4	6	6	5	5	5	7	7	6	5	4
Well Porosity	7.5	6	4	7	5	6	5	6	7.5	6.5	7	7	3.5

Figure 6: Average well porosity vs predicted porosity plotted on a graph for reservoir unit C (top) and reservoir unit D (bottom)

CONCLUSION

Understanding the porosity distribution across a field is important for many facets of field development including well planning, decisions while drilling, and constraining the reservoir model. The goal of this study was to provide a high confidence porosity prediction that would improve the understanding of the reservoir. The seismic inversion took advantage of good well control and reservoir targeted seismic reprocessing that preserved true amplitude. The PNN porosity estimation utilized both the seismic amplitude and the P-impedance from the inversion and high correlation between predicted and measured porosity was achieved.

The seismically derived porosity prediction helped with the following:

- Planning horizontal production wells so as to target the highest porosity areas in the field.
- Deciding whether to drill past the planned TD of the well based on the predicted porosity in the reservoir ahead of the drill bit.
- Distributing properties in the reservoir model by co-kriging the seismic porosity prediction with log porosity to better guide the distribution of porosity

This study produced a high quality seismic based porosity prediction that improved the understanding of the field and provided higher confidence in the ability to predict reservoir quality.

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