Geophysical Corner

Using Shale Capacity to Predict Well Performance Variability: Part 2

As discussed in part 1 of this article, when it comes to the attributes used in equation 1 for seismically determining shale capacity, it is difficult to make a manual choice for the cut off values. To alleviate such a problem, application of machine learning techniques could be useful and thus worth exploring.

There are different categories of machine learning techniques that may be used for our purpose, but we begin our discussion with unsupervised and supervised techniques. While supervised learning techniques are preferred over unsupervised, it is always challenging to collect adequate data for the former and abundance of data are required for training and validation purposes. For example, if we wish to predict shale capacity using one of the supervised machine learning techniques, say, based on neural networks, it is necessary to have enough training data points for SC. On the other hand, unsupervised machine learning techniques do not carry such requirements and hence have immense potential for use in the geophysical domain, where the lack of appropriate data is quite common. Therefore, an attempt has been made here to extract SC information with the help of unsupervised machine learning techniques. The prerequisite to follow any of the unsupervised techniques is that the production data associated with different wells must be available. As the well production data are easily available in the public domain in Canada, a dataset from the Western Canadian Sedimentary Basin is considered for application of machine learning computation for estimating shale capacity volume.

Preferred Properties

An ideal shale well would be drilled in a formation that has the following properties:

- It is organically rich and porous, and thus can produce enough quantity of hydrocarbons.
- It is brittle/frac'able enough to get fractured easily.
- The induced fractures resulting from hydraulic fracturing intercept the existing natural fracture system in the formation.
- The induced fractures are compatible with the type of fracture network pattern for the development.

Knowing the limitations of seismic data in measuring these properties directly, their proxies are derived from seismic data. For example, porosity variations may give rise to changes in impedance, density, velocity ratio, etc. Similarly, high quartz or carbonate content may impact on Young's modulus and Poisson's ratio in addition to other rock properties. Consequently, it should be possible to detect changes in different properties required for shale capacity volume from surface seismic response. However, coupling of reservoir properties with seismically-derived attributes are complex and not easy to understand. Therefore, different seismic attributes should be analyzed simultaneously to derive the individual components of shale capacity volume. For example, organic richness and porosity have prominent impact on P-impedance, density, V_P/V_S, and Lambda-rho and thus these attributes can be treated as their proxies. Furthermore, strain energy density,

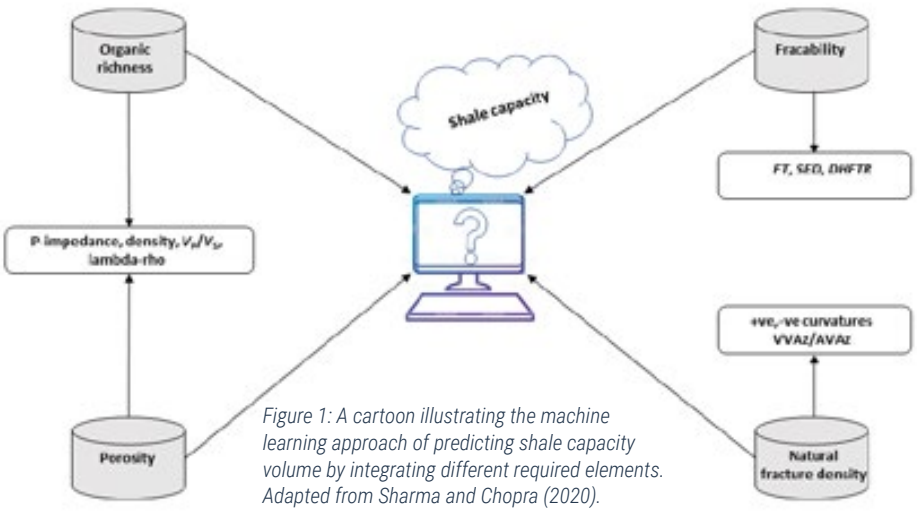

Figure 1: A cartoon illustrating the machine learning approach of predicting shale capacity volume by integrating different required elements. Adapted from Sharma and Chopra (2020).

and fracture intensity computed using velocity variation of azimuth (VVAz) and fracture toughness (FT) approach can be considered as a proxy for frac'ability and fracture/stress induced anisotropy in addition to curvature attributes. Next, all these attributes should be integrated using machine learning techniques to predict the shale capacity volume as illustrated in the cartoon shown in figure 1.

In order to determine the input attributes required for shale capacity, simultaneous impedance inversion was performed on 5-D PSTM pre-stack data by following proper data conditioning, robust low frequency models and accurate inversion parameters (discussed in the June 2015 Geophysical Corner). Such inversion yields P- and S-impedance volumes. Thereafter, other attributes such as Lambda-rho, Mu-rho, E-rho, Poisson's ratio, fracture toughness (see the April 2020 Geophysical Corner), and strain energy density (SED) were computed using impedance volumes. Next, simultaneous inversion was performed on the individual azimuth-sectored gathers to determine FT volumes for different azimuths. Having computed these volumes, the magnitude of seismic anisotropy was estimated from FT azimuthal variation via differential horizontal fracture toughness ratio (DHFTR). The analysis of variation of velocity with azimuth (VVAz) and the variation of amplitude with azimuth (AVAz) were also performed on the dataset used here. Volumetric curvature attributes are valuable in mapping subtle flexures and folds associated with fractures in deformed strata. There are many curvature measures that can be computed, but the principal most-positive and most-negative curvature measures are the most useful in that they tend to be most easily related to geologic structures.

Predicting Shale Capacity Volume Using Unsupervised Machine Learning

These attributes were generated for the dataset under investigation and put through the unsupervised machine learning

technique to predict the shale capacity volume. For the sake of simplicity, we began with principal component analysis (PCA), to figure out the patterns and relationships in them. Usually the first three principal components carry almost all the information contained in the input attributes, with PCA-1 containing a large part of that.

Consequently, PCA-1 can be treated as a proxy for the shale capacity volume. The lateral and temporal variation of it has been shown in part 1, where it was noticed that the productivity of a well increases from the greenish color to hot colors. It may therefore be concluded that hotter colors are preferable for the delineation of sweet spots. Consequently, we look for correlation of the variation in production for the different horizontal wells drilled from the same pad with the colours on the display. Figure 2 exhibits a zoom of the four wells

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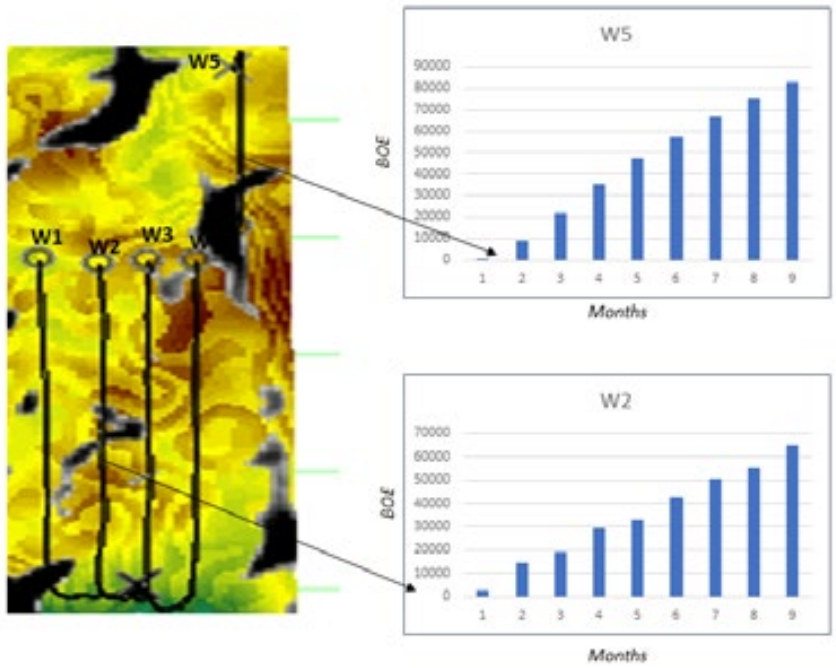
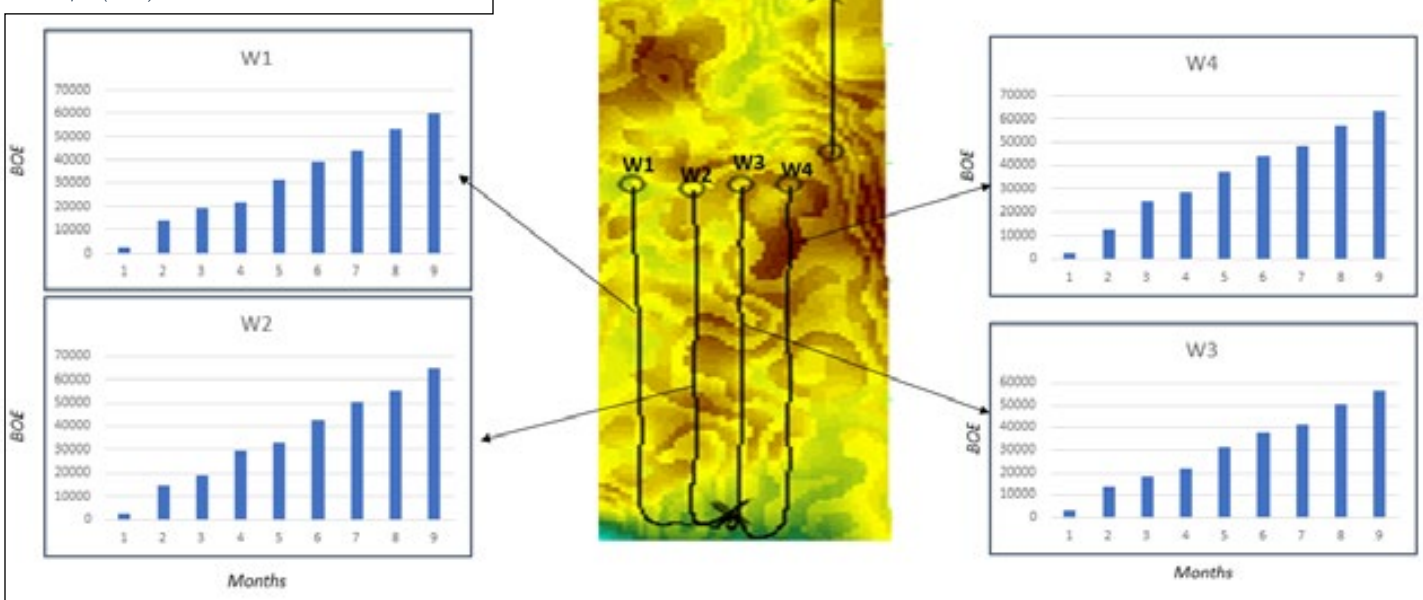


Figure 3 (right): Equivalent display to the one shown in figure 2 after overlaying the lineaments interpreted on the curvature attribute using transparency. Sharma and Chopra (2020).

Figure 2 (below): Zoom of south eastern part of horizon slice shown in figure 2 of part 1 of this article. Sharma and Chopra (2020).



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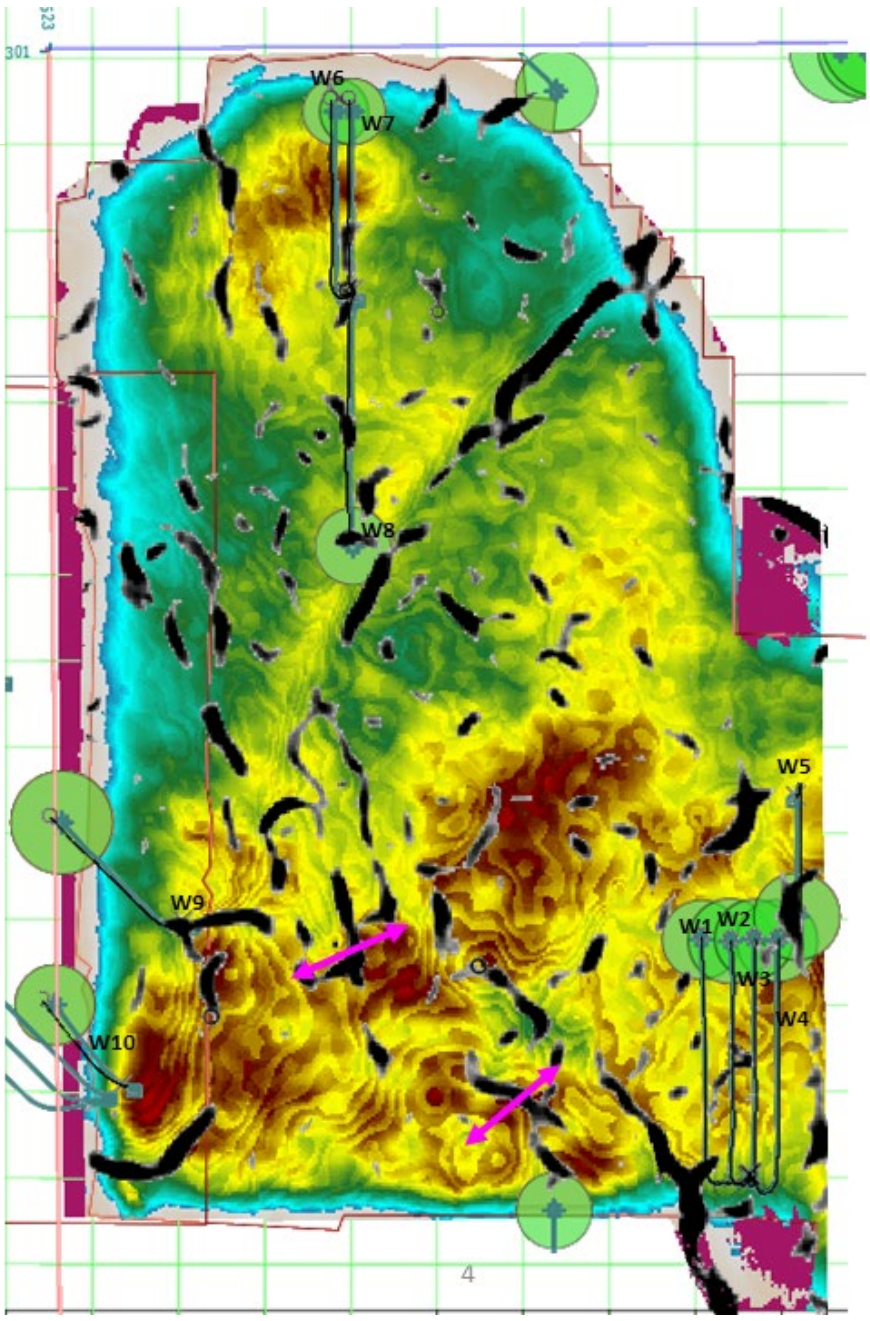
seen to the southeast part of the horizon slice in figure 2 (part 1), along with their none-month cumulative BOE production data. The general trend of increased

productivity with the intensity of hot colors holds true if wells W1 and W4 are compared. However, it falls short of explaining the higher production associated with W2. In our attempts to find an answer here, PCA-2 and PCA-3 volumes are also examined, in the hope of extracting additional information. It was found that PCA-3 is dominated by the curvature attribute, which as a discontinuity attribute is different from the other input attributes. Although only ranking third in PCA, it is a key component in defining shale capacity volume.

Therefore, the different lineaments in the zone of interest are identified on the curvature attribute and then overlaid on the horizon slice from PCA-1 attribute using the transparency as shown in figure 3. The well W2 seems to have been drilled into a naturally fractured zone as it is passing through a lineament that could be the possible reason of exhibiting higher production. Similarly, the enhanced production from well W5 is seen to be associated with a zone exhibiting hot colors and crossing a large lineament that probably exhibits higher permeability. In a similar fashion, the variation of different wells from the northern side can be explained in terms of amplitude on PCA-1 being associated with lineaments interpreted on the curvature attribute. Well W7 seen on the display in figure 2 of part1 is associated with higher production than well W6, though they are both drilled from the same pad and exhibit similar amplitudes in terms of their colors. There are, however, curvature lineaments that well W7 traverses, but not well W6. In a similar vein, well W8 drilled from the same pad but in the southerly direction yields higher production than well W6, even though it is not associated with hot colors, but traverses more lineaments.

Figure 4: Composite horizon slice display from the PCA-1 volume averaged over a 30-millisecond window covering the Duvernay interval, overlaid with curvature lineaments using transparency and cumulative nine-month BOE production. Sharma and Chopra (2020).



Conclusions

Finally, in figure 4, besides overlaying the curvature lineaments using transparency, the production data has been posted on the horizon slice, with the higher producing wells having bubbles of a bigger radius. Based on the discussion mentioned above, the following are the takeaway points from this analysis:

- Production of a well is seen to increase with the intensity of colors.
- The presence of intersecting lineaments in the hot-colored zones leads to the higher production as noticed for the wells W5 and W9.
- As shown in figure 4, the location of double-sided magenta arrows could be considered as hot spots for future drilling.

Thus, in conclusion, considering the importance of shale capacity in defining the potential of a shale play, we have attempted to extract this information from seismic data using machine learning techniques. The different input attributes (namely, organic richness, porosity, natural fracture density and frac'ability) for shale capacity determination were derived from seismic data and integrated using principal component analysis. The variability in well performance was addressed by using the PCA-1 along with the curvature attribute (PCA-3). Such an analysis suggests that the combination can be used for identifying future drilling locations.

(Editors Note: The Geophysical Corner is a regular column in the EXPLORER, edited by edited by Satinder Chopra, Chief Geophysicist, Reservoir, for SamiGeo, Calgary, Canada, and a past AAPG-SEG Joint Distinguished Lecturer.)