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Production Metric Analytics in the Wolfcamp Formation

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Abstract

Successfully discriminating future lateral well locations with above average production from those with below average production is important for financial planning and field development with unconventional resource assets. To address this, a predictive analytics approach is utilized that will maximize an asset's value through infill drilling prioritization, as well as drilling and completion design by creating a production metric model.

As with most unconventional resource plays there is an abundance of production data from numerous lateral wells in various landing zones. A predictive analytic production metric model can be constructed for each landing zone using a supervised neural network- training 3D depth migrated seismic attributes with this statistically-rich production information. The production metric model indicates where the best rock (above average production) is, where strata with below average production is, and where completion or well paths might be optimized to improve production.

Introduction

While most lateral wells drilled into unconventional shale reservoirs or benches in the Permian Basin will be economical, some wells will have higher yields or better performance than others due to variations in shale mineralogy (Dopkin, et al, 2017). With modern high-fidelity seismic data, we can systematically identify variations in silica content, effective porosity and total organic carbon content either directly or by proxy. However, determining the best combination of these interdependent rock properties in terms of higher yields can be problematic, since the variability of shale reservoirs can demonstrate significant mineralogy changes across the extent of the asset (Bashore and Grant, 2018). The complexity and high variability of unconventional reservoirs (Dopkin, et al, 2108; Singleton, 2018) require a more generalized solution to classify asset areas with higher production potential beyond simple cross-plotting of wells with one or two seismic attributes and or simultaneous prestack inversions (with subsequent geo-mechanical or litho-porosity transforms). To that end, a predictive analytic production model is constructed using multi-attribute seismic data and normalized production metrics from lateral wells.

Methodology

Conceptually, a data science approach is employed instead of a geoscientific deterministic one. In lieu of computing individual calibrated seismic rock properties (e.g. seismic TOC, porosity and brittleness) and then combining these in some manner, the predictive analytic methodology assumes that the best combinations of rock properties occur where the best production is observed, and lower production yields indicate areas where suboptimal combinations of rock properties are present. The predictive analytic approach does not explicitly solve for any or each rock property; instead it incorporates constituent components of seismic rock property attributes while solving explicitly to classify the production performance into above, average and below average production.

The production metric model is computed with a multi-layer perceptron (MLP) neural network, training the multi-attribute seismic data with the asset's normalized production metric data. [See Ross and Cole (2017) for more information on classification MLPs.] This is a target specific process, and stochastic sampling of the geology and stationarity of the seismic data (bandwidth and signal-to-noise ratios) is required for reliable results. To that end, a relatively small stratigraphic window of 500-1000 feet is suggested. The production metric is normalized for a given production period and lateral length, and the multi-attribute seismic data may consist of simultaneous prestack inversion volumes such as acoustic and shear impedance, bulk density and compressional-to-shear velocity ratios, in addition to other attributes derived from these inversion answers. Ancillary prestack and post-stack seismic attributes that reflect lithology, pore fluid and depositional environments are included in the attribute set. A generalized solution is sought by minimizing the error between the production data at each lateral well used for training and the multi-attribute seismic vectors by weighting the input seismic attributes to match the production metric data used for training at each lateral well. A production classified seismic volume is computed (above average, average and below average production) in addition to a relative probability of each class. Out-of-sample or validation production metric data from lateral wells not used in the neural network training determines the robustness of the production metric model.

Training and testing the predictive analytics approach

Contemporary scales of unconventional assets or fields range from tens to 100s of square miles. Within these assets one typically observes significant variability in mineralogy and hence production yield or performance. This implies that seismic derived rock properties for TOC, porosity, brittleness, etc. will vary, and intra-attribute seismic variations may or may not be correlated (Singleton, 2018). In that regard, having a production metric model that can address these variations over tens of square miles has its advantages. For this Delaware Basin example, the seismic data presented covers approximately 55 square miles and includes 20 lateral wells within the Wolfcamp Formation's Ford West stratigraphic unit. The seismic data was acquired nearly 20 years ago with legacy acquisition parameters and has been reprocessed with contemporary depth-imaging (PSDM) techniques. The production metric for this example is MBOE cumulative production for a six-month interval normalized to 4800 ft lateral length. Above average production averaged just under 175 MBOE, average production is approximately 125 MBOE and below average production averaged 75 MBOE for the initial 6 month period with normalized lateral length. These values can be treated as production metric class centers for all intents and purposes. Note that there is 100 MBOE difference between the above average and below average production for the first six months and normalized lateral length, which is significant. The wells were sub-divided into training and validation sets. Half of the wells were used as out-of-sample wells and were hidden from the predictive analytic training; the remaining ten wells were used for training the seismic attributes with production metric data. The training and validation lateral well sets have roughly an equal number of above, average and below average production laterals, and the data points are spatially distributed across the 55 square mile 3D survey.

For this production metric model, seismic texture, colored inversion, compressional impedance from the simultaneous inversion and dip/shape attributes ranked higher in contributions than other attributes such as lambda-mu, rho-mu, and frequency (instantaneous and average). The attribute selection is determined through error minimization approaches based on the production metric, the data quality, training interval and the geology. Other unconventional assets may have a different selection and ranking of attributes or features. Interpretation of the predictive analytic production metric model is performed in the following manner: interpretation of horizon-based extractions of landing zones with the classified production metric volume and relative probability of class volumes, and the plotting of class and relative probability statistics of extracted data at and in the vicinity of the lateral well bores. While the former is more in line with typical geoscientific interpretation, the latter yields a more quantitative measure using histograms and actual sample-by-sample measurements. Training and out-of-sample wells are reviewed to assess the robustness of the production metric model, and if the out-of-sample production metrics indicate a consistent and effective answer, future drilling locations, leases, and acquisitions and divestitures can be evaluated in a comparable way to better manage the asset and improve business intelligence.

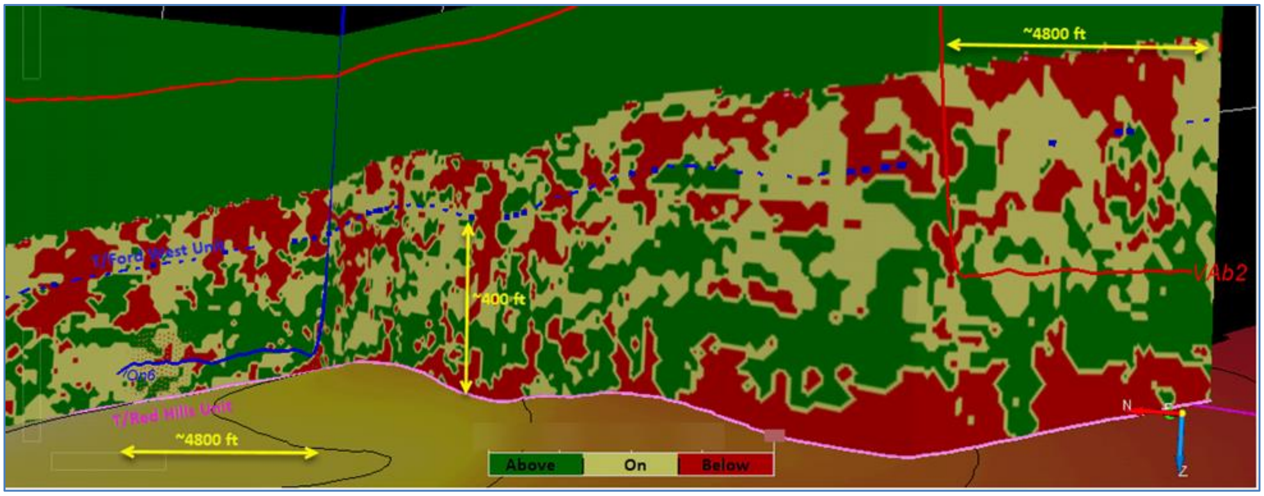

Figure 1- Arbitrary line through production metric class volume through two "blind" wells. The red well bore has a production metric of 139 MBOE/6 month cum/4800 ft lateral, and the blue well bore has a production metric of 103 MBOE.

Figures 1 and 2 are an arbitrary line traverse through two out-of-sample wells to demonstrate the effectiveness of the predictive analytic technique. Production metric class is presented in Figure 1 and the relative probability of above average production is shown in Figure 2. (The PSDM seismic data has been accurately depth-registered to facilitate MLP neural network training and evaluation.) There are two other outputs not shown in this abstract from the predictive analytic process- relative probability of average production and relative probability of below average production that can be used in a similar manner. The computed production metric volumes (class and probability) indicate that both lateral well paths drilled through above average and average production intervals, with the blue well path skirting an interval of below average production. In Figure 1, the above average, average (on) and below average production intervals correspond to green, gold and red, respectively, while the above average production relative probability display highlights the higher probability intervals in the brighter colors. One can visually correlate the above average production intervals in Figure 1 to the high relative probability intervals in Figure 2. These displays go hand-in-hand and can be used for interpretation and various measurements together or independently.

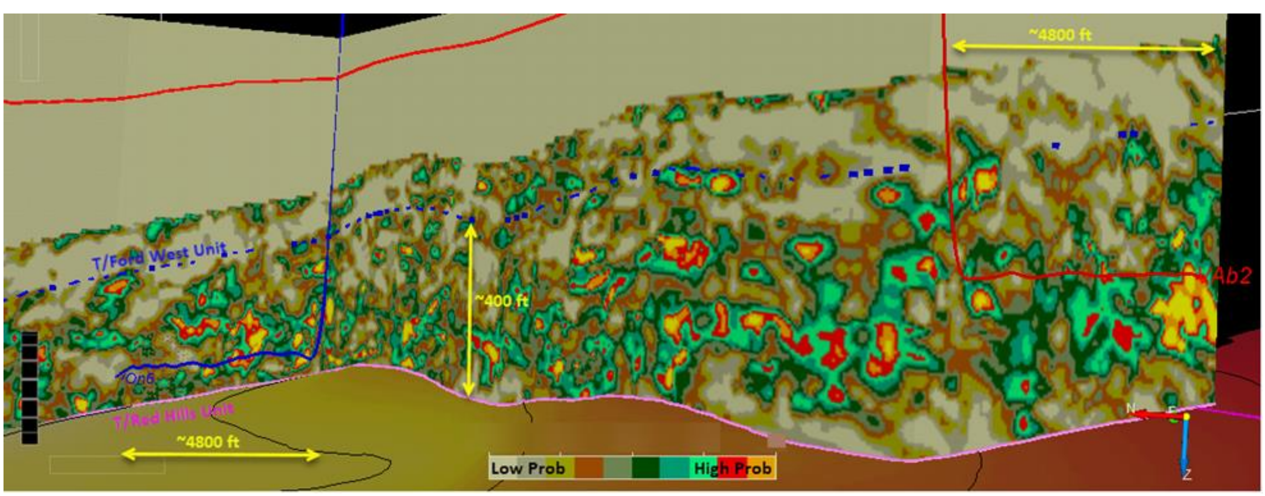

Figure 2 - The arbitrary line from Figure 1 through the relative probability of above average production volume. Intervals with brighter colors are more likely to have above average production while intervals in tan and brown colors are more likely to have average or below average production. Potential landing zones can be identified with the class or relative probability volumes.

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As mentioned previously, visually one can estimate which lateral wells might have higher production metric values by noting which laterals lie more within the above average production class or below average production class, and this can be done with vertical sections as presented here or using horizon slices through landing zones. Or, the data can be sampled in by some means at and adjacent to the lateral's position and more quantitative measures performed. A distribution of the relative probabilities (above average, average and below average) in the left portion of Figure 3 for the red well bore in Figures 1 and 2 indicates the well will be at or above average production since the above average production and average production relative probability distribution curves essentially overlay each other. This is also borne out in the histogram of classes (right pane in Figure 3)—the above average production and average production counts are nearly the same (with slightly more counts for the above average production). From these extracted samples, the estimated 6 month MBOE cumulative production for a 4800 ft normalized lateral is 135.2 MBOE, and the actual normalized value for this out-of-sample well is 139 MBOE. These measurements and comparisons are repeated using the out-of-sample wells and indicate that a fairly robust production metric model has been computed, which can be used for guide asset management. The ends (out-of-sample lateral wells) justify the means (explicitly solving for normalized production metrics).

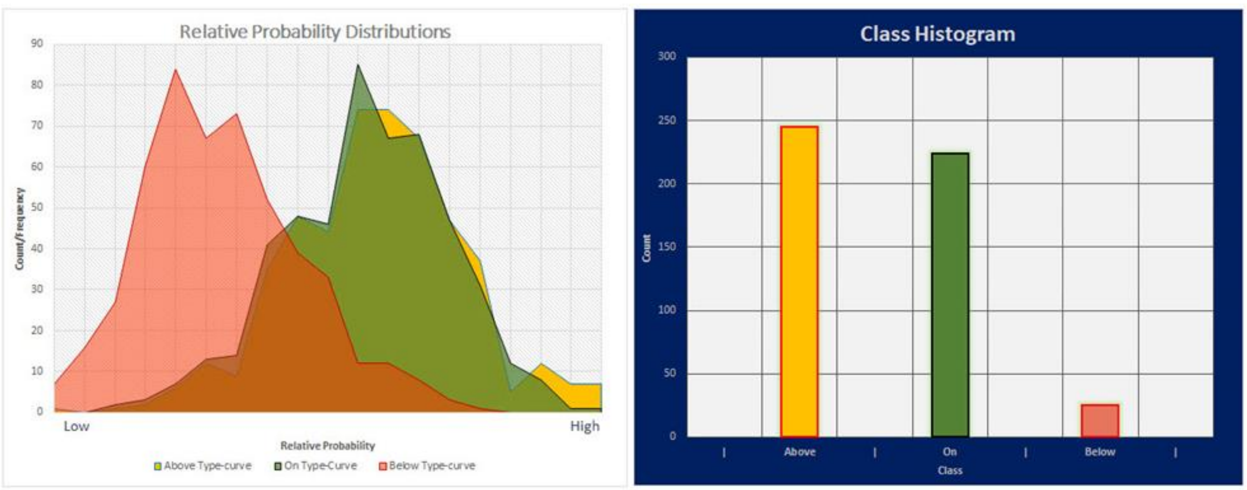

Figure 3 - Distribution of relative probabilities and histogram of classes sample along the VAb2 (red well) well path indicating above average production.

Discussion

One might contend that these results could be serendipitous or there is a spurious correlation between the predictive analytic production metric model and known normalized production. However, with an equal number of out-of-sample and training lateral wells, these claims become moot and further emphasize the importance of a larger number of blind wells to better evaluate the production models' effectiveness, as opposed to incorporating a larger number of wells for MLP training. Moreover, using a different, contemporary, richer azimuth, overlapping PSDM 3D, with a different production metric and training wells, a highly correlative production metric model was computed, indicating the approach is repeatable using different data inputs (well and seismic) and bears merit.

With regard to explicitly solving for a production metric instead of solving directly for a given well-calibrated seismic rock property, this predictive analytic approach does not preclude the search for the most important seismic-petrophysical or geo-mechanical rock property; rather it is a first order approximation to these deterministic solutions. Constituents of seismic TOC, seismic porosity and seismic brittleness (for example) are listed in the neural network attribute weighting table, and from these constituents the best rock properties can be "reverse-engineered." Note that the larger weighted constituents (seismic attributes) indirectly indicate the best rock properties. Furthermore, recent comparison of production metric class to drilling measurements indicate a strong correlation between reduced rates of penetration (ROP) in lateral wells with below average production classified intervals. The correlation of lower ROP with below average production class indicates that the production metric model does implicitly solve for rock properties and engineering information, which can effectively be used for future drilling and engineering decisions.

All production metric models need to be evaluated using validation techniques to avoid overtraining and to assess robustness and shortcomings. Once evaluated for effectiveness[1], the production metric model can be used to prioritize drilling schedules (drill above average production intervals first), modify planned laterals (avoid below average intervals with lower ROP if possible), improve completion plans (alter completion practices in wells with below average production intervals) and better assess the value of a potential acquisition or determine when to optimally divest an asset.

Conclusions

With improvements in seismic technologies such as prestack depth imaging, once the seismic data is depth registered correctly, time-depthing errors are mitigated and more meaningful seismic extractions at and along well paths can occur (Rauch-Davies, et. al., 2018). This permits more effective seismic attributes to be used with well and engineering data as demonstrated with this predictive analytic production metric model. Predictive analytics is a proactive and forward-looking methodology to better anticipate or prognosticate future outcomes (i.e. good, better and best lateral well locations as part of asset performance) using multiple weighted data sets on an asset scale encompassing tens of square miles. This predictive analytics approach incorporates multi-attribute 3D data with production monitoring of lateral wells to build a production metric model which objectively determines which intervals or benches will better perform or underperform within an unconventional shale reservoir. A production metric model can be updated over the lifetime of the asset to continually improve business intelligence.

As in most unconventional resource plays, production metric data is as abundant as there are lateral wells in the landing zone, and this information should be incorporated into all facets of decision making and general business intelligence for the asset. Integrated seismic answers can be improved by infusing this statistically-rich data into a predictive analytic production metric model. This model demonstrates where the best rock is within the asset, as opposed to traditional approaches that focus on determining the best rock property or properties. The effectiveness of the model is gauged by the plethora of lateral wells in the stratigraphic interval that were held out of the training or model-building process. These validation wells determine the value of the model for above, average and below average production areas within the asset, which directly contributes to asset development and financial planning.

References and suggested readings

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[1] Note that each class (above average, average and below average production) needs to be reviewed and evaluated as a function of spatial positioning within the 3D survey. Depending on the inputs to the MLP neural network production metric computation, different classes may have greater or lesser accuracy than each other. These differences (if any) need to be factored into any asset management decision.

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