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Enhancing the Prediction of Production by Incorporating Near-Wellbore Seismic Volumes

David Gray, Renjun Wen, Rongfeng Zhang
Geomodeling Technology Corp.

Summary

Producing oil and gas by leveraging their land positions is what keeps E&P companies profitable. Today, Tier 1 acreage becoming harder and harder to come by e.g., "…producers in the Permian's two main zones are pumping less oil per foot drilled in each new well, not more. Output guidance from Exxon Mobil Corp., Chevron Corp. and Devon Energy Corp. has shown that US shale growth is coming in at the low end of expectations." (BNN Bloomberg, Dec. 12, 2022). In order to make up for this, we need to improve production in Tier 2 and Tier 3 acreages. Even in Tier 1 acreage, there is often more variability in production than expected, especially along the horizontal. Additionally, any project requiring hydraulic fracturing comes under extreme scrutiny. Therefore, acquiring the best leases, putting as few wells as possible in the best locations and drilling them as safely as possible to optimal lengths to maximize production and minimize costs and surface disturbances is now key. As an industry, we have a lot of data, and especially so in more difficult areas. Data science is a tool that allows us to efficiently distil all this data into useful information. Since hydrocarbon production is what we are ultimately after, we have developed a method to predict the production of wells, including horizontal wells, away from existing well control, when predictors, such as seismic attributes, geologic models etc., are available in the vicinity the current and future wells. We have found that seismic attributes can make good predictors of the production of future horizontal wells. Oftentimes this requires multiple attributes, which may have non-linear relationships to production. This paper shows a case study where we use existing production to predict production elsewhere by carefully selecting attributes to put into a Neural Network (NN). The results show that there are significant areas of Tier 1, Tier 2 and Tier 3 acreage in this field. The NN results show that there are opportunities to optimize production even within the Tier 1 acreage.

Method

The method estimates production from existing producing wells that can be extrapolated to in future well locations. The production of horizontal wells is sampled to a stratigraphic grid (strata-grid), to which seismic attributes like inversion, curvature, and AVO volumes, etc., and/or properties of a geomodel, like porosity, facies, etc., can be sampled. All attributes are examined by the asset team for their ability to predict production and their correlations to each other. Relevant attributes are extracted to smaller, Near-Wellbore Volumes (NWVs). The advantage of the NWVs is that rock properties in some area around the wellbore, say the SRV (Stimulated Reservoir Volume), not just immediately adjacent to the well, have an influence on well production. These NWVs are used for training of a deep learning neural network (NN) to predict a metric of production observed to date, such as total production, EUR (Estimated Ultimate Recoverable hydrocarbons), or initial production. Because the NN has the ability find relationships between any of the input variables, any available metric can be used. Although, if there are multiple metrics, there will likely be one that can be predicted more accurately than the others. Therefore, it is important for the asset team to examine all useful metrics. Additional considerations are the review of the predictor attributes to ensure that they make physical sense and that they are not highly correlated to other predictors. Here is where we see a key role for the geoscientists and engineers on the asset team. In order to get the best NN results it is critical to incorporate their expert knowledge at this stage. Their role is to ensure the best predictors are used in the neural network, especially in cases where predictors are correlated. For QC, some proportion of the training data is used for validation and blind tests. We typically use 10% for each. The validation samples are used to avoid over training and the blind test samples are used to ensure the final trained NN works on data not used in training. The NN results are reviewed using SHAP (Lundberg and Lee, 2017) plots to understand the contribution of individual input attributes (Shapley, 1953) and training wells to the NN and to ensure that the trained NN model makes sense. For example, it is often the case that porosity has influence on production, with higher porosity usually correlated to greater production. Asset team geoscientists and engineers will know some of the attributes that are correlated to production in their field, and they should expect to see these effects when reviewing the attributes highlighted as most important by the NN. However, the inputs to the NN should not be restricted to just what the experts expect, as oftentimes there are surprising influences on production, that after technical examination make sense. Finding these surprises is one of the key benefits of using NNs over traditional workflows. Such influences should be observed in and explained by the SHAP plot. If the expected influence is not seen, or if a surprise occurs, then these technical experts are equipped with the knowledge and quality tools to answer the question “Why?” Often an unexpected influence can occur when one of the other attributes also correlates to the expected influencer. For example, density, Vp, or acoustic impedance have been shown in the past to be related to porosity. The geoscientists will be able to assess which one of these likely correlated attributes (Gardner et al., 1974) should be kept and which should be removed from the NN through their knowledge of the play and their science.

The next step is to apply this NN to wells that have production data, but which were not used in the training. Once again, the expert knowledge of the engineers and geoscientists provide important feedback at this stage. If the prediction is unsatisfactory, then they will assess why and make changes to the training to compensate for any observed deficiencies. Then continue to iterate until satisfactory results are obtained.

Upon a satisfactory realization, the NN is applied using the rest of the selected attribute data to predict likely production away from existing well information. This production estimate is calibrated through the NN to the production already observed in the field, and so is likely the best estimate of production from future wells in this field at the time of the estimation.

Results

We were asked to find a way to understand the variability in production across a shale play. Many wells were good but too many were not, with the worst 1/4 of the wells producing less than 10% of the field’s production (top right of left graph in Figure 1). When examined in detail, similar production results are often observed in other fields. Conventional predictors of well performance, like horizontal length, are only marginally useful in this field (Figure 1, right). Therefore, a better way to understand how to optimize drilling and completions is needed here. Since ultimately production is what matters in any reservoir, we felt the prediction of expected production of blind test wells in this reservoir would lead to the ability to predict the production of future wells. We used the method described above to implement a deep NN on NWVs of seismic attributes to predict production from horizontal wells in this shale play. An example of an NWV used in this field is shown in Figure 2.

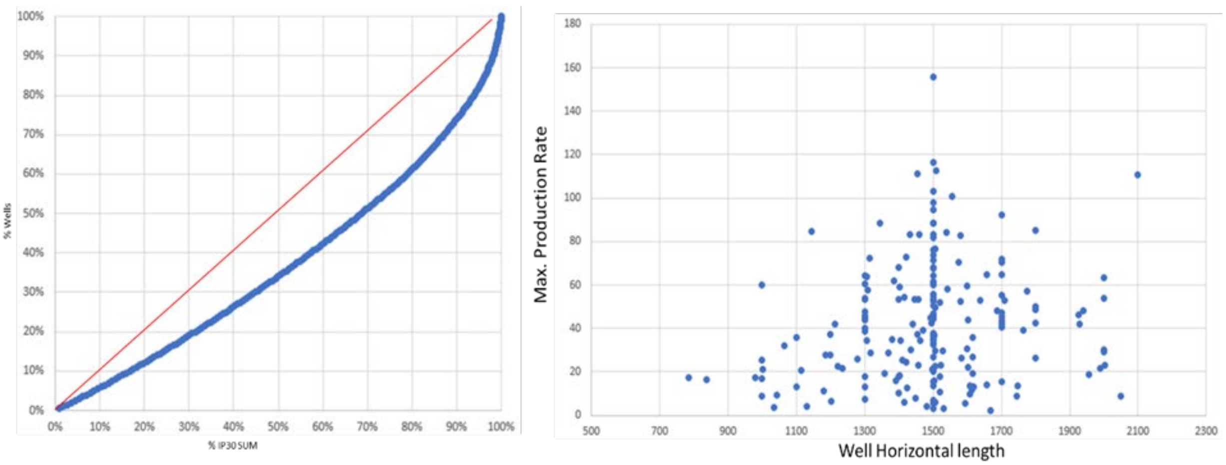

Figure 1 The worst 25% of the wells produce only 10% of the hydrocarbons (left), but conventional predictors like well length do not estimate well performance very well (right).

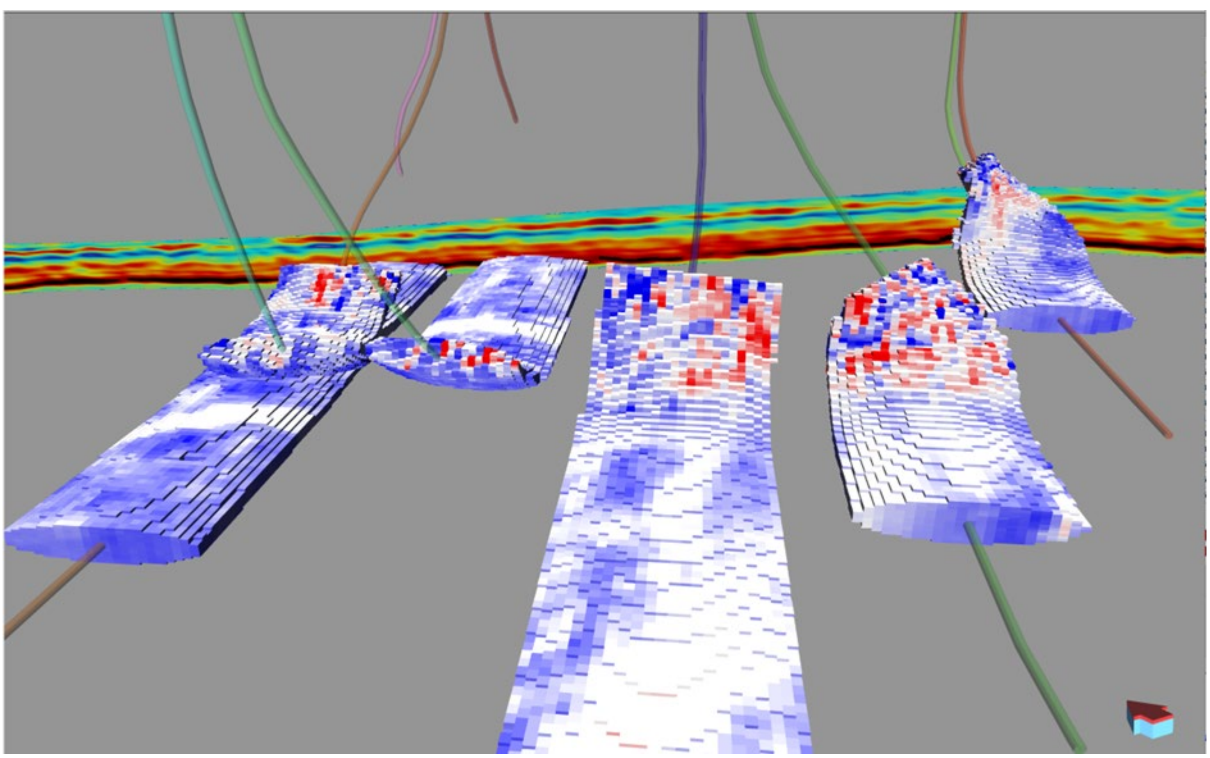

Figure 2 Near-Wellbore Volumes (NWV) in this case is the ellipse of a seismic attribute around the producing length of the wellbore track, in this case showing curvature along the wellbore with a brittleness section in the background.

All available attributes are extracted into the NWVs at the start of the production prediction. These included seismic inversion products, which are related to geomechanical properties, a brittleness estimate derived from the inversion products, spectral decompositions, which are related to thicknesses and faults, curvature, which is related to faults and fractures, and other attributes like distance to the well from points in the seismic survey and MD (measured depth). After analysis, curvature attributes and the inversion attributes of density, P-wave velocity, and Young's modulus were found to be the most important predictors of production for the producing wells in this field.

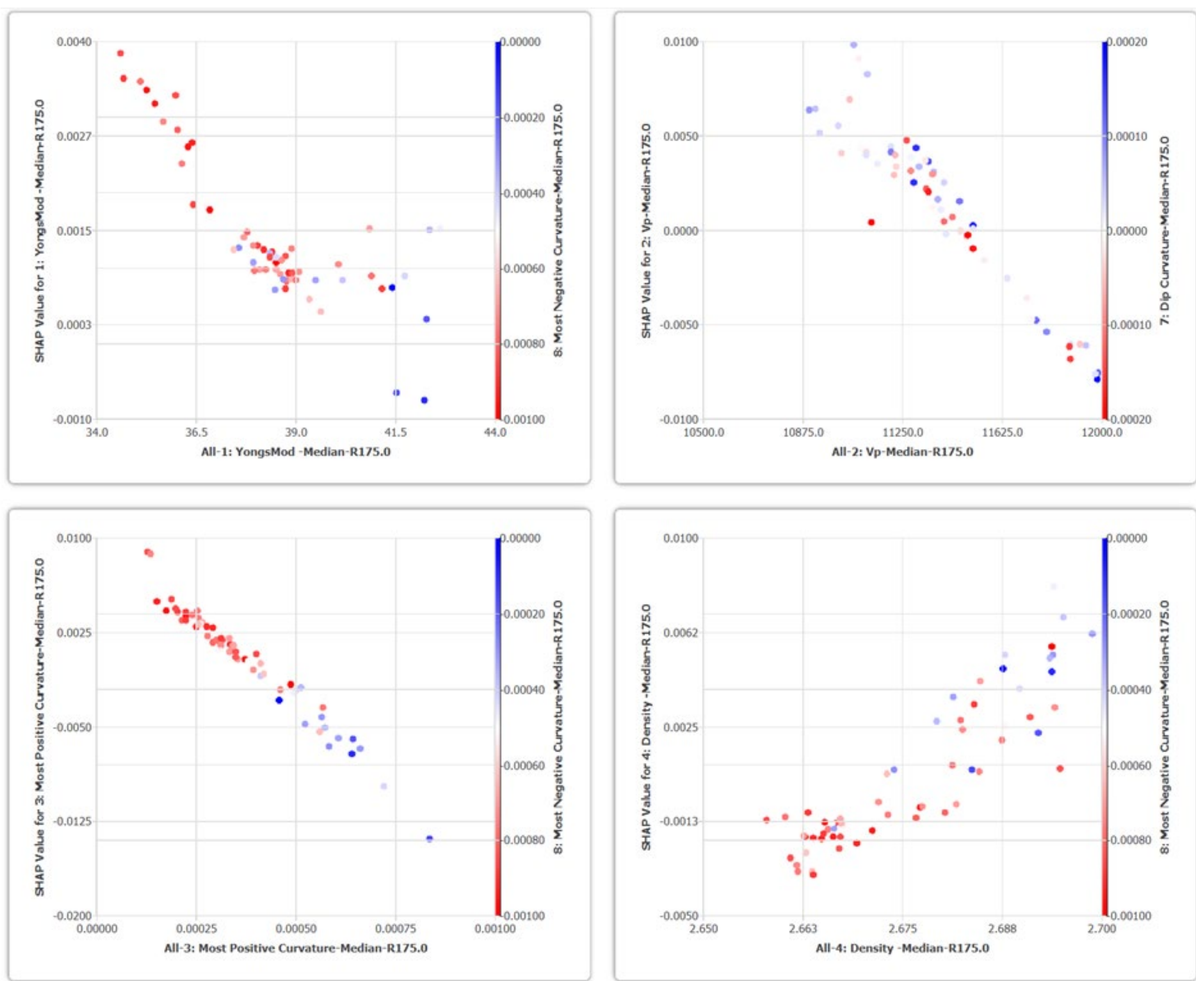

Figure 3 SHAP Plots (Lundberg and Lee, 2017) show how various attributes affect the NN result. For example, low values of Vp (top right) increase the production estimate and high values decrease the estimate. This is likely because Vp is related to porosity. Use of these SHAP plots reduce the "Black Box" view of neural networks.

The evaluation of these predictor variables, as above, is a key role that the asset team of engineers and geoscientists must play in the assessment of the NN to ensure its results are valid. The team dropped many attributes from this prediction, either because they were intercorrelated or because they did not significantly influence the production prediction. Also, for example, from the geophysicists' domain knowledge, it is known that local drops in instantaneous frequency may indicate the presence of gas or an increase in fracture density (Taner, 2001). Lower P-wave velocities have also been indictors of fractures (Castagna et al., 1985). Lower values of P-wave velocity and density can be associated with the presence of gas (Toksöz et al., 1976). So, from a geotechnical standpoint, the attributes that this deep learning NN found to be associated with production make sense. Domain knowledge of the whole asset team, the geologists, engineers, and petrophysicists provide additional insight and constraints on these results. This technical review, in conjunction with the QC of these attributes, seeing how their values relate to production, allows us to move forward with the results of the NN with confidence.

The resulting NN prediction of production, which will be shown in the presentation, shows an area of Tier 1 reservoir near the top of the structure where production is expected to be greater, although it is not uniform. There is another area of Tier 1 acreage downdip where production is expected to be as good as atop the structure, but it is more heterogeneous. There is a larger area of Tier 2 acreage downdip to the SW that is quite continuous where moderate production is expected. To the north, there appears to be an area of undrained Tier 1 acreage. Outside of these zones in what we now expect to be Tier 3 acreage, limited production is expected. In the Tier 3 acreage, individual wells (rather than pads) could effectively drain a few identified small compartments. Furthermore, these results suggest that wells drilled in an E-W orientation would have a better chance of encountering more productive reservoir along their length than wells that are drilled in the NE-SW direction, as most wells have been to date.

Conclusions

For future drilling, we now know where and in what direction to drill to maximize production and also avoid low production wells. These results will be scrutinized to see where E-W drilling might be preferable over the common practice of drilling in a NW-SE direction. Based on the above results, we expect future average well production to increase by ~50% with savings of more than 1/6 of the development costs, as we avoid drilling low producers in the future and maximize wells' contact with productive reservoir. This will also result in reduced HSE risk and environmental impact, as fewer wells are being drilled. We can differentiate Tier 1 acreage from Tier 2 and Tier 3 acreage, and therefore different drilling and completion plans can be made for these different reservoir qualities.

Novel/Additive Information

The ability to extract NWVs (Near-Wellbore Volumes) of attributes immediately around horizontal or, indeed, any well geometry is critically important in the ability of the NN to estimate production because production is influenced by the rock properties an area around the well, e.g. the SRV, not just immediately adjacent to the well.

The use of SHAP plots by the domain experts, the geoscientists and engineers of the asset team, to assess how individual predictors influence the outcome of the NN is an important new role for geoscientists where they are going to make key contributions.

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