Improving the probability of success in resource plays

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Abstract

The role of the geophysicist in resource plays has been hard to define. There is obvious benefit to seismic structural interpretation for hazard avoidance and model building for geosteering applications, but when it comes to predicting optimal well placement, much of the industry still is struggling. Common applications of seismic attributes search for deterministic predictions using attributes such as rock strength and anisotropy. However, even with many claims of success and a rich base of literature, the value and use of these approaches are lacking in practice. A simple case study shows the value added by using a single seismic attribute, curvature, in the Barnett Shale. The key to understanding this value is the use of Bayesian statistics. For this case, controlling for just one seismic attribute is seen to increase the probability of a successful well by 10% or more, also leading to substantial increases in rate of return of 10 percentage points or more.

Introduction

Unconventional plays, or “resource plays,” have changed the interaction and processes used by geologists, engineers, and geophysicists in E&P field development. This has led to a paradigm shift in the way geophysical data are used. Whereas the value of seismic data as a tool for avoiding drilling and completion hazards has been clear since the early days of the Barnett Shale, geophysicists have struggled to extend the value beyond simple structural visualization. There are continuing attempts to use high-end seismic-derived rock properties, such as lambda-rho and mu-rho analysis or exploitation of azimuthal or orthorhombic anisotropy signatures for advanced fracture and stress characterization. Unfortunately, the practical day-to-day application of seismic still struggles to integrate these attributes into the workflow.

Some of the problem is related to communication barriers among geoscientists, engineers, and management, but a bigger part of the problem is how to convincingly demonstrate the efficacy of these attributes and their effect on the “bottom line.” Very often, we use a single attribute or even multiple attributes through statistical or neural-network analysis in an attempt to develop a deterministic model for predicting productivity. Typically, these results are either tenuous or difficult to sell to engineers who are asked to take a great leap of faith in implementing the recommendations. Yet we still face problems with enhancing production. In many cases, operators see themselves failing to meet type curves developed from early production, let alone improving production in later wells.

We present a simple case study from the Barnett Shale in which a single seismic attribute is used to optimize production, illustrate why we commonly overpredict type curves, and show how to maximize our probability of success in current and future resource plays using a Bayesian interpretation.

Case study in the Barnett Shale

Observations relating microseismic response to both anisotropy and curvature were made early in the development of the Barnett Shale play, with observations that the fast azimuthal velocity direction tends to follow ridges and run parallel to valley axes. It also was observed that microseismic events tend to disperse into “flatter” areas and away from ridges. Rich and Ammerman (2010) show a strong example of this behavior (Figure 1).

Structure has long been one of the most important factors in drilling success, from targeting traps to associated fractures. It is a simple but important variable in conventional reservoirs. Curvature as an attribute is simply a way to quantify the structure. Curvature measurements contain information on the magnitude and orientation of deformation. Structural interpretation of 3D seismic and volumetric curvature extraction allow for a much higher resolution of the curvature than otherwise would be possible with well tops and standard geologic maps.

Because curvature at any given point varies with azimuth, some confusion arises when choosing what value to represent on a map. Typically, values are chosen that represent the maximum or minimum magnitude of curvature, whose azimuth will vary from point to point. This is similar to an attribute such as azimuthal variation in amplitude or velocity in which only the maximum magnitude and its associated direction might be considered. However, it becomes more complicated because curvature can take on negative values based on whether the surface is warped upwardly or downwardly.

Sometimes maximum is used to refer to the maximum magnitude, and sometimes it refers to the maximum numerical value. In the past, the terms most positive curvature and most negative curvature have been used to signify the second derivatives, which are equivalent to curvature only in the case of zero dip (Rich, 2010).

Figure 1. Microseismic events for a horizontal well in the Barnett Shale. Background color indicates magnitude of $k_1$ curvature, and the lines are the orientation of $k_1$ curvature. After Rich and Ammerman (2010), Figure 3. Used by permission.

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2008). To avoid confusion, we will refer to the $k_1$ curvature, which is defined as the most positive numerical value of curvature, and $k_2$, which is the corresponding most negative numerical value (Guo et al., 2012). Hence, if the value of $k_1$ is negative, we are in a depression because all other directions of curvature at that point also must be negative.

Because anisotropy has been observed casually to correlate with structure, it makes sense to ask if there is a quantifiable correlation with curvature. The azimuthal anisotropies used here are derived from azimuthal variations in P-wave moveout velocities.

Figure 2 shows a strong correlation between the azimuth of the $k_2$ curvature and the fast velocity direction within a particular 3D survey in the Barnett Shale. This corresponds to the observation that the fast velocity tends to run parallel to ridges and normal to valleys. The simple conclusion would be that the azimuthal variations in velocity are being influenced directly by fractures, and the curvature is an indirect reflection of those same fractures. The fractures in the Barnett Shale generally are filled with calcite. However, the heterogeneity in tensile strength with the presence of fractures might influence how the rock responds when stimulated, depending on the orientation of those fractures.

Figure 1 shows microseismic along a well where there is a dramatic shift in magnitude of the $k_2$ curvature and azimuth of the $k_1$ curvature. Not shown here is the fast velocity azimuth, but as shown in Figure 2, the azimuthal directions would be similar using the velocity anisotropy. Stages 1 and 2 show narrow fracture pathways running parallel to both the horizontal regional stress (northeast-southwest) and the azimuth of most negative curvature. A dramatic difference in behavior is observed in stages 3 and 4. The microseismic events show significantly more dispersion and overlap in these two stages. This corresponds with both a negative value of the $k_1$ curvature and a flip of the azimuth of the $k_1$ curvature so that it is now perpendicular to the maximum horizontal stress.

If we assume that the correlation between azimuthal velocity anisotropy and curvature azimuth is the result of both of them acting as indicators of preferred natural fracture orientation, then a simple explanation can be proposed. Where the most positive curvature is larger, we expect a higher probability of preexisting fractures, and where it is negative, we expect a lower probability. Similarly, where the azimuth of fast velocity and $k_2$ curvature is parallel to the maximum horizontal stress, we expect those fractures to reactivate and grow in a linear manner in that direction. Where the fractures are not present or are perpendicular to the regional stress direction, we would expect a more complex behavior. This behavior is clearly evident in the microseismic response.

Moving from deterministic to probabilistic

Based on the correlation seen in the previous section, it is reasonable to expect a correlation with curvature and production. Clearly, the formation is responding differently in areas of low $k_1$ curvature than it is in areas of higher $k_1$ curvature. Because more rock appears to be stimulated in the lower $k_1$ curvature areas, it would be reasonable to expect wells in those areas to exhibit better production.

Figure 3 shows estimated ultimate recoveries (EUR) for vertical wells from within a single 3D survey in the Barnett Shale. What is immediately clear is the lack of a strong or even decent correlation. However, this does not mean there is not a benefit from targeting low $k_1$ curvature areas. A closer examination of Figure 3 reveals that there is a bound to well productivity, with the largest EUR wells occurring only in the low $k_1$ curvature areas and the high $k_1$ values never corresponding with the highest EURs.

In the previous section, we proposed an explanation for the difference in microseismic response with a change in curvature. If it is accurate, then a better understanding could help in the design of better completions, but even if this explanation is inaccurate, there still might be significant value in the observation. To quantify this value, it is necessary to move away from a deterministic approach and look at probabilities from a Bayesian perspective.

Figure 2. Histogram of azimuthal difference between $k_2$ curvature azimuth and azimuthal velocity anisotropy. The majority of the azimuthal differences fall within 15° of each other, indicating a strong correlation. The inset shows the CDF for the azimuthal difference compared with random azimuths.

Figure 3. Scatter plot of $k_1$ curvature versus normalized EUR values for vertical wells from one 3D survey in the Barnett Shale. The correlation is poor, but a clear upper trend to EURs is evident as a function of the $k_1$ curvature.
We will consider a simple example for understanding Bayes’ theorem. Envision a situation in which you are tasked with choosing the fastest car from a large population based on its acceleration time of 0 to 100 km/h. With enough information, we could find a deterministic solution and predict exactly what the 0–100-km/h time is for every car. However, practically, there are too many variables to write a deterministic solution. Even lacking one or two pieces of key information can have a dramatic effect on the accuracy of a deterministic solution. You might consider a vehicle with a large engine, but if it turns out to be a bus, it will clearly have a low 0–100-km/h time.

Similarly, a common approach for exploiting 3D seismic is attempting to find a deterministic solution to productivity with limited information, in which many unknown but significant factors are unable to be accounted for. Hence, our ultimate ability to build a deterministic model even with the latest and greatest approaches to nonlinear or neural-network machine-learning algorithms will remain poor.

It is better to recognize that we do not have enough information for a deterministic solution and instead ask a simpler question: “Can using the information I do have increase the probability that I will improve my success rate?” This might seem like semantics, but the effect on how we use and interpret our results can be dramatic.

Let us consider our large population of cars. Selecting cars at random, we would expect a certain distribution of 0–100-km/h times. We will refer to the median 0–100-km/h time as the P50. Selecting at random, 50% of the vehicles will be faster and 50% will be slower than this rate. Perhaps this value is 8 s.

Now let us say I know engine size. Instead of choosing vehicles at random, I choose only vehicles with an engine larger than 3.5 L. Even if the correlation between engine size and 0–100 km/h is weak because of all the other factors (e.g., weight), it is still valuable to ask, “With this new condition, what is the probability of choosing a vehicle that exceeds my previous P50 of 8 s?” This is answered with Bayesian statistics, which states that the probability of choosing an 8-s or faster car given a 3.5-L or larger engine is equal to the probability of a 3.5-L or larger engine given a faster than 8-s car times the probability of an 8-s car (50% in this case) divided by the probability of an engine larger than 3.5 L. Let us say this equals 0.7. This would mean that if you select only cars with an engine larger than 3.5 L, you have a 70% chance of being less than 8 s. Another way to look at this is that the P70 of the distribution of cars with engines greater than 3.5 L is 8 s.

Clearly, it would be much smarter to choose only cars from the population of the larger engines if you have this information, but there will always be exceptions (for instance, a bus with a big engine but also big weight, which we know nothing about). As a statistical sample, using this information, we will do better than if we did not use the information.

We will look at geophysical information in the same manner. We will not search for a deterministic solution because there always will be variables that we cannot account for. Instead, we search for variables that have an effect on our success and include them in our model so as not to predict success but to improve the probability of success. The example of curvature in the Barnett Shale is used here for its simplicity.

Considering the cumulative density function (CDF) for scaled EUR data from Figure 4, the P50-scaled EUR is 0.2992. The CDF is the probability that a value will be equal to or less than the given value. This means, selected by random, that our well would have a 50% probability of being equal to or less than 0.2992. If we consider the P75 of 0.3930, there is a 75% chance that a random sample is equal to or less than 0.3930. We will consider 1-CDF such that we have the probability of exceeding the given value (the probability of exceeding the P75 is 25%). We wish to use Bayes’ theorem to compute the probability that we will meet or exceed the original P50 given a maximum value of curvature.

Let us first consider the probability given a curvature cutoff equal to the median value of curvature. We exclude all wells with a k1 value greater than the median k value such that our probability of exceeding the original P50 given a cutoff equal to the median of k1, curvature is

\[
P(P50|k1) = \frac{P(k1|P50)P(P50)}{P(k1)}.
\]

The first term is found by considering the CDF of curvatures for the subset of wells with EURs from P50 through P100 and then finding the probability of the median curvature value in the reduced distribution. This is the probability of the median curvature given that the EUR meets or exceeds the P50 of the complete EUR distribution. The probability of the original P50 is 0.5 by definition, and the probability of the original curvature is also 0.5 by choice (we selected the median, or P50, k1 value for the cutoff).

In this case, if we would drill on a curvature value of k = .1611 or smaller, our chance of meeting or exceeding our original P50 is 60.4%, given as

Figure 4. 1-CDF for normalized EUR for vertical wells in a Barnett Shale 3D survey for the entire population of drilled wells and for only the wells with k1 less than the median k value. Note that the original P50 EUR has a 60% probability of being exceeded by considering only the smaller k1 values.
This is significantly greater than if we drilled without the a priori curvature information.

Figure 5 shows the probability of exceeding the original P50 for both EUR and first 90-day production for various cutoffs in the $k_1$ curvature. Note that lower values of curvature result in progressively higher probabilities of exceeding the original P50. As the $k_1$ curvature cutoff approaches the complete distribution, the probability approaches 0.5, as expected for the original P50.

Using Bayesian probabilities recognizes the difficulty in finding a deterministic solution when there is a large number of geophysical, geologic, and engineering parameters that all influence productivity. There will always be too many unknown variables, but we can substantially increase the probability of success by including geophysical attributes. This example showed a significant upside with the use of just a single attribute. Other plays might show sensitivity to other attributes. More complex, multiattribute approaches, including advanced analytics, might show substantially more upside. The important thing to remember is that you can never predict success, but you can influence the probability of success.

### Quantifying value

Tables 1 and 2 examine the effect of controlling for curvature on the economics for horizontal wells within the same 3D survey extents as the previous discussion. In this case, curvature values were extracted at perforation locations, and production (EUR) is normalized per 1000 ft of lateral length. This is a much smaller sample size than the vertical wells, and the observations suffer from smoothing of the production over the length of the lateral, but similar observations can be made (Table 1).

In this case, different cutoffs in curvature were considered, and the incremental increase in EUR by drilling in the reduced population was compared with the entire population without controlling for curvature. Table 2 illustrates the potential difference in rate of return that arises from the different populations. Drilling only on the smaller values of curvature would increase the mean rate of return by 10 percentage points or more. With dramatic differences such as these, using this information could change the decision of whether to drill a well, particularly in tight economic conditions.

### Discussion

Early in the development of an unconventional play, a deterministic understanding of what controls productivity is necessary. Based on experience from similar plays, the industry has become good at determining those parameters and quickly optimizing well development. This is not substantially different from conventional exploration. The difference arises when we move into “factory” mode and begin extensive development. To optimize this development and ensure that the best wells are drilled, we can exploit statistics and geophysical data. Bayes’ theorem provides a simple methodology for understanding which geophysical parameters can be used to optimize production through field maturity. The case study from the Barnett Shale using curvature is a simple but powerful example. Controlling for just one attribute allows for an increase in rate of return of 10 or more percentage points.

In other plays, multiattribute maps can be developed using traditional multivariate approaches and neural networks. In many cases, this can lead to even stronger predictors of success. These maps can be updated with every new well that is drilled, but it is important to remember that wells drilled with a priori information will correspondingly bias the probability distribution.

### Table 1. Mean EUR and gain in production by considering subsets of original horizontal wells for various $k_1$ curvature cutoffs.

<table>
<thead>
<tr>
<th>Mean most positive curvature along wellbore</th>
<th>Number of wells above cutoff</th>
<th>Number of wells below cutoff</th>
<th>Mean normalized EUR/1000′ (above cutoff)</th>
<th>Mean normalized EUR/1000′ (below cutoff)</th>
<th>Net gain per well normalized EUR/1000′</th>
</tr>
</thead>
<tbody>
<tr>
<td>None</td>
<td>0</td>
<td>58</td>
<td>N/A</td>
<td>.3717</td>
<td>N/A</td>
</tr>
<tr>
<td>0.015</td>
<td>16</td>
<td>42</td>
<td>.2723</td>
<td>.4097</td>
<td>.0379</td>
</tr>
<tr>
<td>0.01</td>
<td>30</td>
<td>28</td>
<td>.3278</td>
<td>.4186</td>
<td>.0469</td>
</tr>
<tr>
<td>0.005</td>
<td>41</td>
<td>17</td>
<td>.3427</td>
<td>.4416</td>
<td>.0698</td>
</tr>
<tr>
<td>0</td>
<td>50</td>
<td>8</td>
<td>.3494</td>
<td>.5104</td>
<td>.1387</td>
</tr>
</tbody>
</table>
Table 2. Example for effect on rate of return (ROR) by drilling wells with selected curvature cutoffs. ROR here is based on economics for the example area using 2009 figures. The increase in EUR is assumed to result from either a decrease in initial decline rate or a higher initial production rate.

<table>
<thead>
<tr>
<th>Well case</th>
<th>After-tax rate of return</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gain from initial decline</td>
<td>Gain from initial rate</td>
<td></td>
</tr>
<tr>
<td>Base</td>
<td>21.9%</td>
<td>21.9%</td>
<td></td>
</tr>
<tr>
<td>Increase of .0379 EUR/1000'</td>
<td>29.5%</td>
<td>31.1%</td>
<td></td>
</tr>
<tr>
<td>Increase of .0698 EUR/1000'</td>
<td>35.1%</td>
<td>40.8%</td>
<td></td>
</tr>
<tr>
<td>Increase of .1224 EUR/1000'</td>
<td>43.1%</td>
<td>56.0%</td>
<td></td>
</tr>
</tbody>
</table>

A common issue in correlating attributes in horizontal wells is the unknown distribution of productivity along a wellbore. Production logs and the continuing development of fiber-optic sensing can aid in this. However, as shown in this case study (Table 1), even without horizontal logs, the influence was still observable over the catalog of horizontal wells, with probabilities from horizontal wells similar to those observed using only vertical wells.

Many operators find that production consistently underachieves relative to the type curve, particularly as a play matures. Bayes’ theorem can be used to understand this effect. Early wells typically are drilled with some a priori information. The issue might be as simple as depth or thickness. Then as we continue to drill wells, the remaining population has a reduced probability of these simple attributes. Therefore, a random well from the remaining population will have a lower probability of achieving results consistent with the P50 of the original population.

Stated simply, if we are good at drilling the best wells first, then obviously, we should expect results to decline with time. The best we can hope for is to use the drilled population to make observations (using geophysics, for instance) on parameters that can ensure the greatest probability of reaching or exceeding our original P50. Results still might underperform the original P50 but outperform the results that would have been achieved if the geophysical (or other) parameters were not controlled for. This decreasing performance can lead to questioning of deterministic predictions, even though they might be perfectly valid. By using a Bayesian approach, it is easier to quantify the benefit and understand why results might vary.

Conclusion

Whether the explanation and interpretation presented here for the difference in response of the microseismic with curvature is correct, it is undeniable that if the early wells had been drilled preferentially in the low most-positive-curvature areas, there would have been a substantial upside, with the best wells being drilled first. It is also clear that any wells drilled in the future will have an increased probability of success if they are drilled on the lower $k_1$ values. Unconventional plays are all about statistics and repeatability on large scales. By recognizing the geophysical parameters that relate to the probability of success, we can significantly improve how we optimize and high-grade locations.

Appendix A

Seismic curvature example

Seismic curvature is a simple but sometimes confusing seismic attribute. In two dimensions, curvature is easy to grasp as a quantification of how “curved” a line is at any point along its length. For surfaces in three dimensions, two complications arise which lead to confusion. Both relate to the specific “line” on the surface for which the curvature is measured.

In general, we consider the curvature of a line formed by the intersection of a plane with the surface. With respect to that plane, we must choose both its azimuth and inclination. In all cases discussing seismic curvature, the inclination is chosen such that the plane is normal to the surface at the point of interest. This is where the term normal curvature arises.

The second issue is the azimuth of the plane. Usually we are not concerned with the curvature at a particular azimuth but instead consider only the curvatures at the two azimuths where the extremes of the curvature measurements occur. For any given point on a surface, we refer to these extremes as the most positive curvature ($k_1$) and most negative curvature ($k_2$). Correspondingly, we also can consider the associated azimuths at which these extremes occur.

Figure A-1 illustrates curvature measurements on a small section of a horizon from the 3D seismic data example in this article. The horizon has been smoothed and is shown with a fairly extreme vertical exaggeration for illustration purposes. Note that in the depression, the $k_1$ curvature (most positive curvature) is negative, although it is still a larger value than the $k_2$ curvature. Similarly, there is an area along the ridge
where the $k_2$ curvature (most negative curvature) is positive. The azimuth of $k_2$ curvature can be seen to lie in the direction of the axis of that same ridge and perpendicular to the axis of the valleys.

For a more complete review of seismic curvature, readers are encouraged to refer to Roberts (2001) or to Chopra and Marfurt (2007). Detailed mathematical derivations of curvature can be found in texts on differential geometry such as Do Carmo (1976).

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