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'Shale Capacity' Key In Shale Modeling

By Ahmed Ouenes

HOUSTON–After more than a decade of successful shale development, many of the preconceived ideas about unconventional reservoirs can be revisited, now that a wide range of data and experience are available. One of these preconceived ideas was that shale reservoirs were uniform and homogeneous, and could be "mined" with the proper number of horizontal wells through manufacturing-type processes.

As expected, the geology of any reservoir is more complex than initially thought, and the reality is that shale well performance has turned out to be highly variable, even among similarly designed offsetting wells within close proximity. The extensive data available in the first modern shale resource play–the Barnett Shale in the Fort Worth Basin–illustrate the significant variability in well performance.

Based on the 2009 well data shown in Figure 1, in the worst-case scenario, a Barnett gas well could have initial production of less than 1.0 million cubic feet a day. On the other hand, a well could be an average performer producing 1.0 MMcf/d-2.0 MMcf/d. Or, in the best-case scenario, it could come on line at an IP greater than 5.0 MMcf/d. These large variations obviously have drastic consequences on the economics of shale wells and on a lease overall.

For a Barnett gas well, the P50 "break-even" price (the price at which the producer achieves a 10 percent internal rate of return) requires a 30-day average initial production rate of 1.610 MMcf/d. A Marcellus gas well requires 3.500 MMcf/d in 30-day average initial production. Based on these observations, it can be concluded that all the Barnett wells with IPs less than 1.000 MMcf/d shown in the red box in Figure 1 are uneconomical, those in the yellow box between 1.000 MMcf and 2.000 MMcf/d are either uneconomical or barely break even. The only wells worth drilling are the highest producers in the green box, which unfortunately also have the lowest probability.

Shale operators could adjust their well performance by selecting more optimal completion and fracturing strategies. Service companies have a complete menu to choose from for any basin and budget. However, fracturing technologies are not able to explain the wide variations in shale well performance. In other words, this variability is not caused by changes in fracturing designs. It is the result of something that is independent of any fracturing technology applied to a specific well.

Productivity Distribution

The focus of this article is on the Barnett, Marcellus, Eagle Ford, Bakken and Niobrara reservoirs. The data mined are not as rich as those used for the Barnett,

FIGURE 1

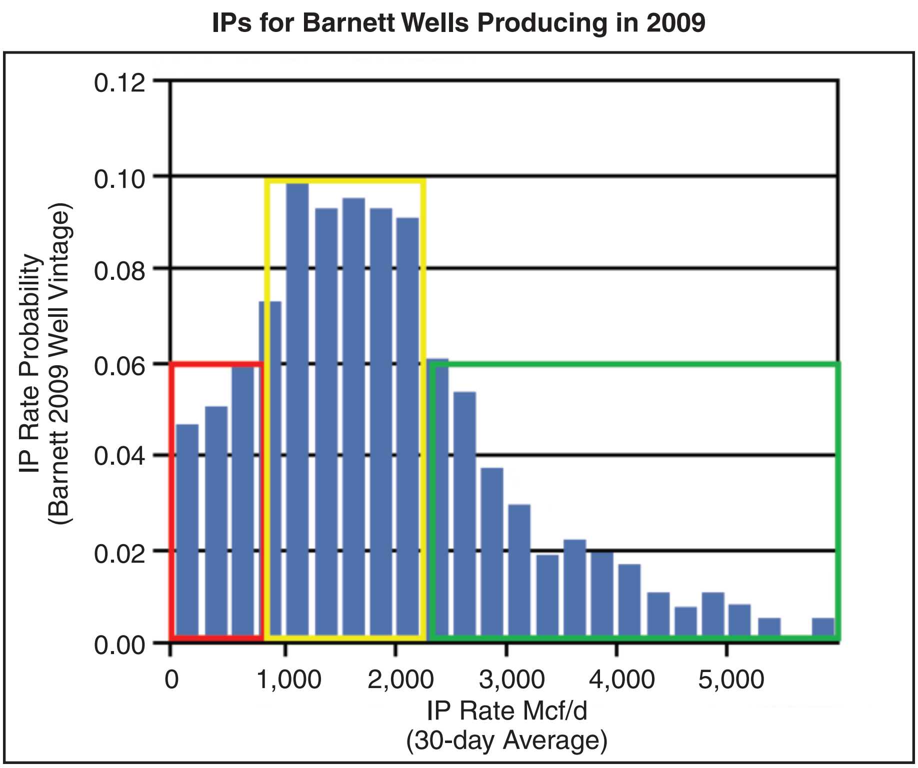


FIGURE 2A

IPs for 26 Marcellus Wells Producing For 300+ Days

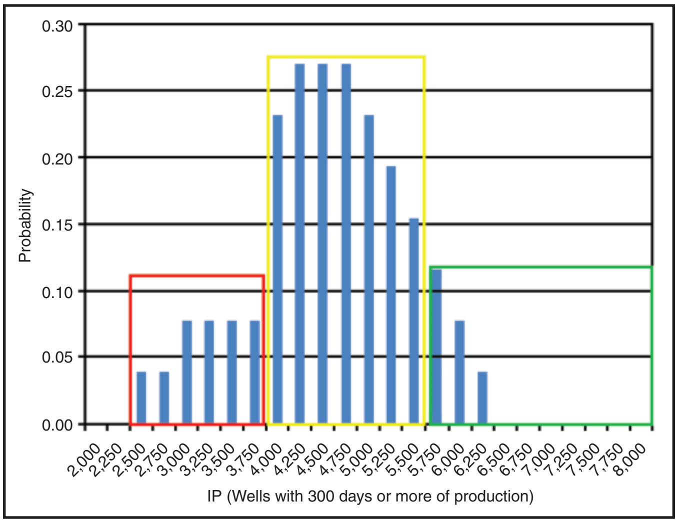
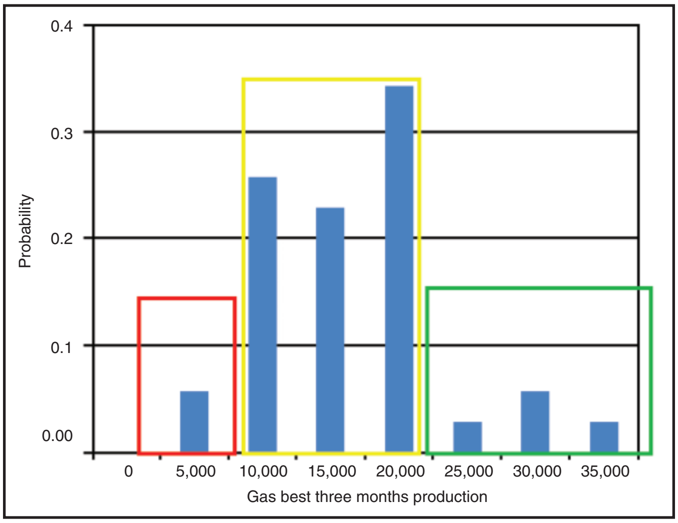


FIGURE 2B

Best Three Months of Production For 36 Eagle Ford Gas Wells



but they could be sufficient to start a discussion. The hypothesis is that the distribution of shale well productivity in any basin follows a typical distribution that can be seen over any geographical scale, given a sufficient distribution of wells.

The characteristics of this typical distribution remain the same for a 30 square-mile area, a bigger 100 square-mile area, or over an entire basin. Of course, the larger the area, the larger the number of wells and the longer the production times. That means the better the quantitative distributions of performance that can be made for the wells.

Furthermore, the hypothesis states that the distribution of well productivity depends mainly on the shale reservoir itself, while other factors such as fracturing design and lateral length do not dramatically alter these distributions.

As in the Barnett Shale in Figure 1, it appears that three boxes for poor (red), average (yellow), and good (green) wells are present in many other shale basins. For example, in the Marcellus, an intensely drilled area about 50 square miles was analyzed. Out of the wells in that area, only 26 extracted had been on production for more than 300 days. The distribution of the IP for those Marcellus gas wells is shown in Figure 2A.

With the P50 break-even price requiring a 30-day average IP of 3.500 MMcf/d for a Marcellus gas well, all wells in the red box are in the category of uneconomical or barely break even. The average wells in the yellow box (4.000 MMcf-5.500 MMcf/d) seem frequent in the Marcellus play, but very high rates (5.500 MMcf-8.000 MMcf/d) have been reported by few Marcellus operators in this study area and other parts of the basin. The well performance distribution in the Marcellus seems to indicate that most operators are successful in avoiding uneconomical wells.

Moving to the dry gas window in the Eagle Ford Shale, Figure 2B shows the distribution of well performance based on 36 wells over a 60 square-mile area. In this case, the performance is measured with the sum of the three best months of gas production. The worst wells have IPs less than 10.000 MMcf for three months, and the best wells have production for the best three months that could be as high as 35.000 MMcf.

For the Barnett, Marcellus and Eagle Ford gas shales, the three intervals for poor (red), average (yellow) and good (green) well productivity seem to follow the same characteristics, despite the differences in well numbers and covered areas. The reduced number of wells considered for the Marcellus and Eagle Ford does impact mainly the distribution of good wells in the green box. Unlike the Barnett case, where large numbers of wells were used, the log normal distribution of the good wells is not obvious in the Marcellus and Eagle Ford. It is very

FIGURE 3A

365 Days of Average Cumulative Oil From 870 Bakken Wells

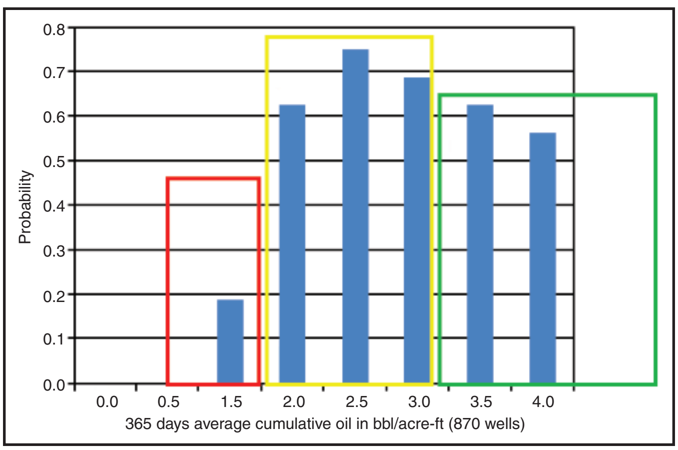


FIGURE 3B

IPs from 19 Niobrara Wells (Including 10 Highest-IP Wells)

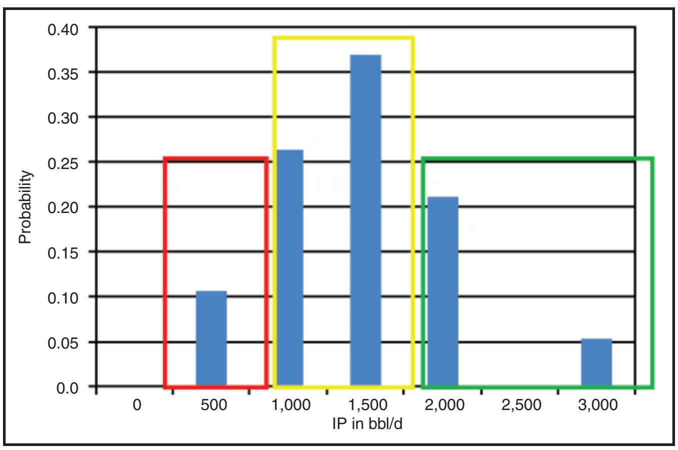


FIGURE 4

Cross-Section Along Poor Marcellus Well (IP = 1.314 MMcf/d)

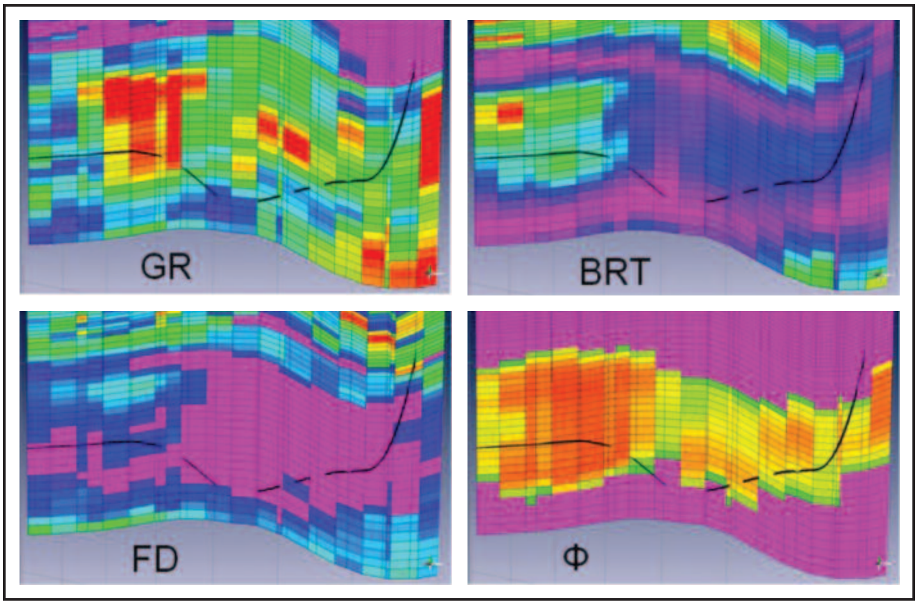


FIGURE 5

Cross-Section Along Good Marcellus Well (IP = 4.389 MMcf/d)

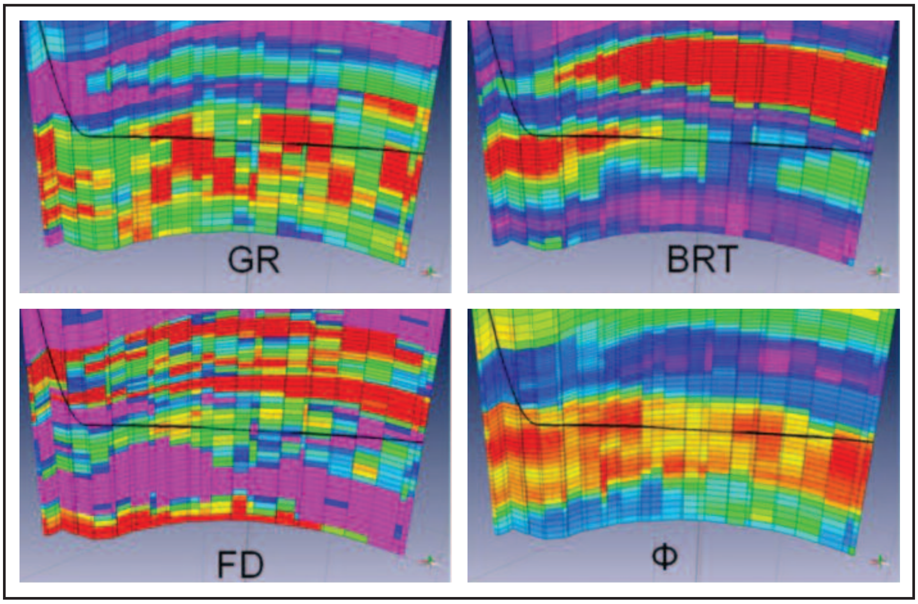
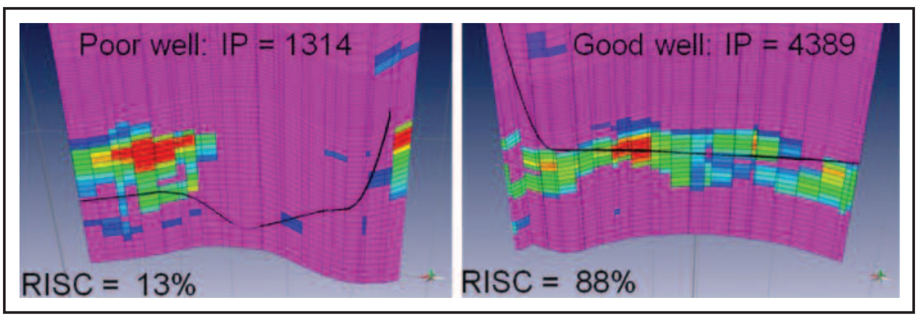


FIGURE 6

Shale Capacity from Four Shale Drivers for Poor and Good Wells



likely that using more wells and larger sample areas would show a green box behavior (log normal distribution) similar to the Barnett.

How about tight oil plays? One study of Bakken Shale well performance used 870 wells completed since January 2009 to evaluate the performance of the play. The authors compared 18 operators and normalized the 365-day average oil production by acre-feet. In this case, the most noticeable feature is the high probability of good wells in the green box (Figure 3A). This is not the case for the Niobrara data (Figure 3B), where 19 wells were used, including the 10 highest IPs recorded in the past four years. In the Niobrara, the good wells in the green box have not been easy to find to date.

Natural Fractures

Various observations could be made from the distribution of well productivity in these five oil and gas resource plays. First, the distribution of good wells in the green boxes seems to be highly dependent on the importance of the natural fracture system. In the Bakken, where fractures are "abundant," wells in the green box are highly probable, unlike in the Niobrara, where natural fractures are difficult to delineate without drill-bit-tested 3-D natural fracture modeling technologies. The Barnett green box shows a typical log normal distribution of a naturally fractured reservoir (the Marcellus and Eagle Ford distributions do not have enough wells to capture the same log normal distribution, but it very likely would be apparent with a larger number of wells).

Second, the widths of the red, yellow and green boxes in the distributions of well performance seem to follow some given ratios that are consistent from one basin to another. These observations are purely empirical and have been seen in many datasets from different shale basins. If confirmed, they could provide useful information and multiple uses for many shale operators.

However, the most striking observation made from the distribution of shale productivity is the relationship with the shale reservoir. One of the preconceived ideas in shale well productivity was that a 5,000-foot horizontal well should produce more hydrocarbons than a 4,000-foot lateral, based on the volume of reservoir exposed to fracturing. Data from different shale basins show that this is not the case, and in many instances, shorter laterals outperform longer ones.

Another preconceived idea was that bigger fracs and longer perforated lengths would yield higher recovery. This also has proven incorrect in the Eagle Ford and other basins. In other words, shale well performance seems to be controlled mainly by the reservoir and its characteristics, and not necessarily by the length of the wellbore or number of perforated intervals. To better understand shale characteristics and their impact on well productivity, a new reservoir property needs to be defined: shale capacity.

Shale Capacity

Shale capacity refers to the ability of a shale to produce hydrocarbons when properly stimulated. In unconventional reservoirs, the hydraulic fracturing process creates the pay (the stimulated reservoir volume, SRV), which is not limited to the rock properties determined by deposition and diagenesis. This involves shale brittleness. Since brittleness is a function of shale properties resulting from deposition, compaction and diagenesis, it is highly dependent on other rock properties.

Shale capacity could be defined as the normalized product of four shale drivers defined above a certain cut-off value: total organic content, natural fracture density, brittleness, and porosity (φ). Shale capacity exists only if all four drivers are above their respective cut-off values. For example, if a shale is too ductile, then brittleness will fall below the cut-off value, making the shale capacity equal to zero independently of the values of the three other drivers.

In some shale basins, one or more of the four drivers could show reduced variability and give the impression that it is not an important driver. This brings up the issue of how to estimate these four shale capacity drivers in a 3-D reservoir model.

Reservoir properties could be estimated robustly in 3-D by using various modeling techniques. The most reliable methods are those that use seismic data to provide the missing information between wells. However, the way seismic attributes are used seems to have taken two diverging paths.

On one hand, there is an artificial intelligence approach where neural networks are used to correlate various seismic attributes with rock properties, such as the ones needed to compute shale capacity. Another approach uses conventional statistics and associated linear multiregression analysis tools. The merits of one method over the other could be debated at length without resolution.

The reality is that these artificial intelligence algorithms are the only mathematical tools at the industry's disposal to model the complex geology that is characterized by the strong interdependency of the four shale capacity drivers. Using linear multivariate regression analysis violates a geological fact: These four drivers are not independent.

For example, the brittleness of the Marcellus depends mostly on the amount of quartz present in the shale. But higher quartz content requires that clay content be lower, which translates to lower TOC. Therefore, the interdependency between brittleness and TOC can be explained by the deposition of the Marcellus and the unique characteristics it has near the maximum flooding surfaces during transgressive-regressive cycles.

The same interdependence exists between the quartz content that controls brittleness and porosity that is critical to the reserves. Higher quartz content in the Marcellus translates to higher porosity. Finally, the natural fractures are highly dependent on quartz content also, making every shale driver interdependent on the others.

The shale drivers, and the multiple seismic attributes used to model them, are dependent variables that require mathematical tools that follow a set of rules designed to solve the problem. It is this geologic reality that makes artificial intelligence neural networks specifically designed to model interdependent variables and the coupled nonlinear relation that exist between them the appropriate modeling tool for predicting these properties.

3-D Modeling Workflow

To better illustrate the process that turns shale drivers into shale capacity, consider a Marcellus example where narrow-azimuth post- and prestack seismic data were available along with five wells that had reasonably complete sets of logs, including a well with an image log. The workflow that turns these raw data into useful 3-D models showing the distribution of the shale drivers has multiple steps.

The first step is to enhance the resolution of the seismic data using broadband

FIGURE 7A

**Correlation Between RISC and IPs
Of Six Marcellus Wells Producing in 2010-11**

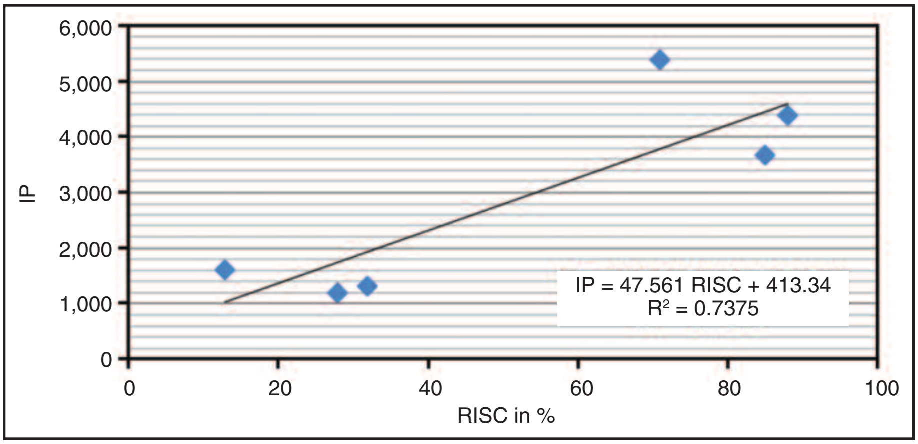
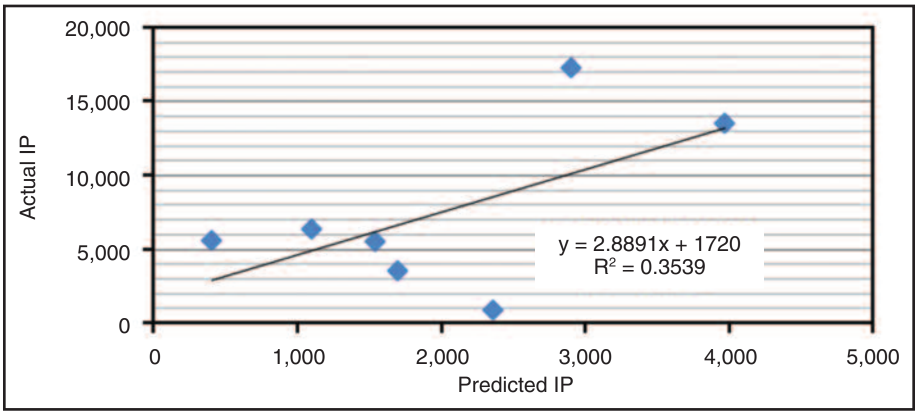


FIGURE 7B

**Predicted Relative IP Values
Of Seven Marcellus Wells Producing in 2012**



spectral inversion. The enhanced seismic data are used as input in the extended elastic inversion (EEI) to create the elastic properties needed to compute the brittleness, and are used as input in the geologic and fracture modeling effort that uses the neural network. The stochastic inversion was used in the EEI to create seismic attributes with a resolution of 1 millisecond, which allows the building of geologic and fracture models that have a vertical resolution on the scale of three to five meters (a necessary requirement for proper quantitative characterization of shale reservoirs).

The enhanced seismic also is used as in input for spectral imaging and volumetric curvature to create additional seismic attributes for the geologic and fracture modeling effort. A sequential geologic modeling approach is used to estimate the gamma ray model (GR), followed by density (RHOB), porosity, and finally resistivity (RT) and fracture density (FD). The entire modeling effort is done in a 3-D geocellular grid that takes into account the complex stratigraphic features of the shale reservoir.

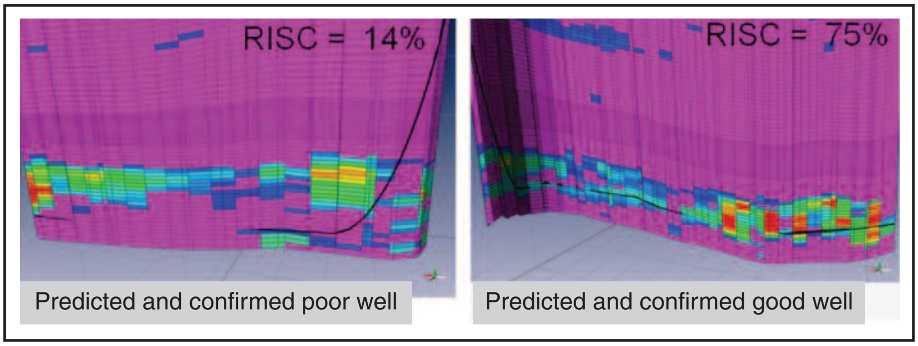
Six wells produced in 2010 and 2011 with different IPs and different numbers of days and productivities were retrieved from the Pennsylvania Department of Environmental Protection's oil and gas reporting website. The longest producing well had 344 days of production and the shortest had only 11 days of production. The highest IP of the six wells was 5.383 MMcf/d and the lowest was 1.314 MMcf/d.

Figure 4 shows the distribution of the four drivers (gamma ray as a proxy for TOC, brittleness, fracture density and porosity) used to compute the shale capacity at the poor well with the lowest IP over 63 days of production. Figure 5 shows the same four drivers for a good well that had an IP of 4.389 MMcf/d with 344 days of production data. In both figures, red cells correspond to high values, blue cells correspond to low values, and purple cells correspond to zero (the driver is below the cut-off value).

The shale drivers used to compute the shale capacity include many areas that have a zero value. The resulting shale capacity, along with good and poor wells, are shown in Figure 6. Again, the purple cells indicate a shale capacity equal to zero. A wellbore crossing this zone cannot yield production no matter how it is fractured.

FIGURE 8

Cross-Section of Shale Capacity and RISC along Two Marcellus Wells Drilled in 2012



Higher values of shale capacity (red and yellow cells) indicate the best sweet spots that will yield the highest rates and reserves. Note that the wellbore of the poor well crosses a very small zone of useful positive shale capacity, while the good well intercepts a larger zone of high shale capacity. Could these empirical observations be translated to quantitative relationships that relate IP to shale capacity?

The RISC Factor

When examining the positive shale capacity intercepted by the wellbore, an anomaly appeared when comparing longer and shorter laterals and their relationship to IP. The same puzzling anomaly appeared when comparing wells with different frac stages all placed in the zone of high shale capacity. This anomaly indicates that the intuitive absolute length of the wellbore intercepting the high shale capacity would correlate very well with the IP of the well.

The relative well performance seems to be sensitive to the length of the wellbore crossing the zone of high shale capacity divided by the total length of the wellbore. This "factor" is defined as the relative intercepted shale capacity (RISC). When using the IP for the limited six wells producing in 2010-11, a strong correlation was found between RISC and IP. This relationship was used to predict the relative performance of wells drilled in 2012.

With Figure 6 showing that the good well did not intercept the very high values of shale capacity, the six IP values available at the end of 2011 may not provide the entire spectrum of possible well performance. Nevertheless, the derived correlation shown in Figure 7A can be used to predict the relative IP of the seven new wells drilled and produced in 2012. The absolute IP of the predicted wells will depend on the number of frac stages and their successful execution. The resulting absolute IP retrieved from the Pennsylvania DEP's oil and gas reporting website varied between 876 Mcf/d computed with 82 days of production and 17.250 MMcf/d computed with 57 days of production.

Despite this mix of IP values computed with different numbers of days, the pre-

AHMED OUENES

Ahmed Ouenes is global director of operations for natural fracture modeling at SIGMA3 Integrated Reservoir Solutions, focusing on developing new ways to integrate seismically driven geologic and geophysical models, fracturing data, and microseismic events in unconventional reservoirs. Before joining SIGMA3, Ouenes was founder and president of Prism Seismic, a software and consulting company that was sold in 2011 to the Symphony Technology Group. He had served previously as chief reservoir engineer at (RC)2, where he developed the first commercial software for continuous fracture modeling. Ouenes was executive vice president of an independent oil and gas producing company. He has successfully characterized and simulated more than 100 fractured reservoirs around the world. He is a graduate of Ecole Centrale de Paris and holds a Ph.D. in petroleum engineering from New Mexico Tech.

dicted relative IP was good in five of the seven wells (Figure 7B). In other words, the predicted relative high-IP wells turned out to have the absolute highest producing rates, while the predicted relative low-IP wells turned out to be the lowest absolute producers. None of these predictions involved using the number of frac stages, type of frac technology, or anything related to the completion of these wells.

Figure 8 shows the RISC at a good and a poor well drilled and produced in 2012. The RISC shown at the two Marcellus wells explains the difference in performance between the wells.

These empirical observations have been verified with multiple studies and seem to be robust from one area to another in the same basin and across different shale basins. The most striking of all these observations is the link between RISC and the distribution of the shale productivity described as red, yellow and green boxes.

After examining a considerable amount of data, it appears that a RISC less than 50 percent will put a well in the red box of uneconomical wells, while a RISC greater than 50 percent correlates to average and good wells in the yellow and green boxes. This shows that it does not take that much to get the best wells, if the shale operator has the shale capacity 3-D volume to compute RISC on future wells to adjust landing zones, azimuths and lengths, accordingly, to reduce drilling and fracturing costs while achieving the best return on investment and accelerating the time to payout. ❐