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Formation vs. Completion: Determining the Main Drivers behind Production from Shale; a Case Study Using Data-Driven Analytics

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Summary

Is it the quality of the formation or the quality of the completion that determines or controls the productivity of a shale well? In this paper we attempt to address this important question. We present a case study using a fit-for-purpose approach with no attempt to generalize the final conclusions. The analysis presented in this article is based on measured data. No assumptions are made regarding the physics of the storage and/or the transport phenomena in shale. We let the data speak for itself.

The case study includes a large number of wells in a shale asset in the northeast of the United States. Characteristics such as net thickness, porosity, water saturation, and TOC are used to qualitatively classify the formations that each well is producing from. Furthermore, wells are classified based on their productivity. We examine the hypothesis that reservoir quality has a positive correlation with well productivity (wells completed in shale with better reservoir quality will demonstrate better productivity). The data from the field will either confirm or dispute this hypothesis.

If confirmed, then it may be concluded that completion practices have not harm the productivity and are, in general, in harmony with the reservoir characteristics. The next step in the analysis is to determine the dominant trends in completion and judge them as best practices. However, if and when the hypothesis is disproved (wells completed in shale with better reservoir quality will ***NOT*** demonstrate better productivity), one can and should conclude that completion practices are the main culprit for the lack of better production from better quality shale. In this case, analysis of the dominant trends in the completion practices should be regarded as identifying the practices that need to be modified.

Results of this study show that production from shale challenges many of our preconceived notions. It shows that the impact of completion practices in low quality shale are quite different from those of higher quality shale. In other words, completion practices that results in good production in low quality shale are not necessarily just as good for higher quality shale. Results of this study will clearly demonstrate that when it comes to completion practices in shale, “One-Size-fit-All” is a poor prescription.

Introduction

The conventional wisdom developed over several decades in the oil and gas industry states that better quality rocks produce more hydrocarbon. In other words there is a positive correlation between reservoir characteristics and production as depicted by the blue line in Figure 1. Since production from shale wells has become possible due to a significant amount of human intervention (in the form of long laterals with a large number of hydraulic fractures), many operators started asking a question that used not to be asked often and was always taken as the ground truth. The question was directed toward the impact of reservoir characteristics (rock quality) and its relationship with completion practices.

At the first glance it may seem that such question should be easy to answer. If the answer is not quite obvious from the operations (which one will quickly realize that it is not – please see Figure 16 and Figure 17 at the end of this

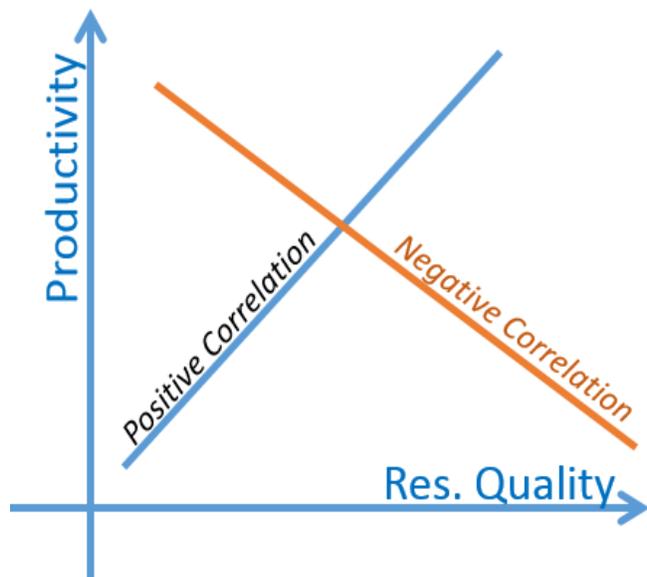


Figure 1. Conventional Wisdom: Productivity in a well increases with reservoir quality.

article as examples), then we can refer to our models for the answer. The procedure should not be very complicated. In our models, we can keep the completion and hydraulic fracturing characteristics constant and change the reservoir characteristics and observe its impact on production and then answer the above question. It sounds pretty simple and straight forward, until one realizes that such models (capable of realistically addressing questions such as this) do not exist.

In other words, the formulations that are currently used to model fluid flow (and therefore production) in shale¹, does not really represent what is happening, and therefore, scientists and engineers cannot fully trust the results generated by these models. This is true at multiple levels, including the modeling of the storage, the transport of the fluids, and the induced fractures.

A comprehensive and critical review of the state of reservoir modeling in shale has already been published (Mohaghegh, 2013) and therefore, it will not be repeated here.

In this article, to answer the question posed earlier for a given asset (there is no claim that the results shown in this article are general in nature. We recommend similar study be applied to each field), we will only refer to actual field measurements, or as we call them “Hard Data”. Hard data is defined as field measurements such as inclination, azimuth, well logs (gamma ray, density, sonic, etc.), lateral and stage lengths, fluid type and amount, proppant type and amount, ISIP, breakdown and closure pressures, and corresponding injection rates, etc. As far as the reservoir characteristics are concerned, we use measurements such as net pay thickness, porosity, gas saturation and TOC to define rock quality. Furthermore, we use pressure corrected production as indicator of productivity. Furthermore, as part of our Advanced Data Driven Analytics technology, we introduce Supervised Fuzzy Cluster Analysis (SFCA) that is used to perform and to reach the conclusions in this study.

Methodology

To explain how we carried out this analysis we first need to briefly introduce two very simple ideas. The first idea is called Supervised Fuzzy Cluster Analysis (SFCA), and the second idea is the use of SFCA to classify shale qualities, in a straight forward and non-controversial manner. Fuzzy Cluster Analysis (Bezdek, 1984) that is an implementation of Fuzzy Set Theory (Zadeh, 1965) in cluster analysis was introduced several years ago. In this study we modify the original algorithm such that engineers and geo-scientists with domain expertise can define the location of the cluster centers (shale quality). This is a simple but very important modification to the Fuzzy Cluster Analysis algorithm² in order to accommodate the type of analysis that is presented here. Again, the objective of this analysis is to answer a specific question regarding the importance and the influence of reservoir quality on production in shale basins. As you will note, this study would not have been possible without making this modification to the Fuzzy Cluster Analysis algorithm.

Cluster analysis, by nature is an unsupervised process. It aims at discovering order and patterns in seemingly chaotic, hyper-dimensional data. The modification to this algorithm is based on a simple observation that allows us

¹ This includes analytical or numerical solutions to the fluid flow equations that need to take into account the propagation of induced fracture in shale, its interaction with the natural fracture system, and many other intricacies that are inherent in production from shale.

² New, advanced data driven analytics algorithm developed by Intelligent Solutions, Inc. (Intelligent Solutions, 2015).

to impose certain domain expertise into our purely data driven analysis³. In other words, we attempt to address a common observation by engineers and geoscientist when they are exposed to the data-driven analytics. Since we do know certain underlying physics regarding the shale quality, we will guide (supervise) our analysis of the data in such a way so that it can identify to what degree reservoir characteristics of shale in a given well is similar to the known physics. For example, if I can distinguish between “Good” and “Poor” rock qualities, I would like to learn to what degree the formation encompassing each of my wells are represented by each of these semantics.

As was mentioned in the beginning of this section, the second simple idea has to do with judging the quality of the rock (shale), based on measured parameters. Since calculation of reserves in shale still is an ongoing topic of research, in order to be on the safe side and make the results of this study acceptable by engineers and scientists of all persuasions, we will not use any formulation to calculate reserves (as a proxy for reservoir quality) in shale. Instead, we will try to identify characteristics that is acceptable by almost anyone that has any background in reserve calculation of any type of formation, including shale. The rules of distinction between “Good” and “Poor” rock qualities will be based on simple observations, such as the following (everything else being equal):

1. Formations with higher values of Net Pay Thickness should have more hydrocarbon reserves than formations with lower values of Net Pay Thickness.
2. Formations with higher values of Porosity should have more hydrocarbon reserves than formations with lower values of Porosity.
3. Formations with higher values of Hydrocarbon Saturation should have more hydrocarbon reserves than formations with lower values of Hydrocarbon Saturation.
4. Formations with higher values of TOC should have more hydrocarbon reserves than formations with lower values of TOC.

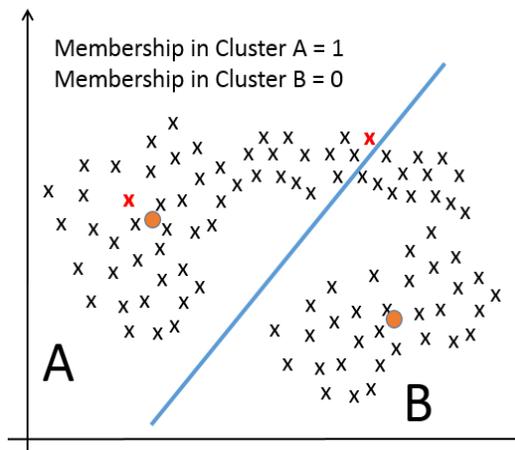


Figure 2. Hard cluster analysis. Clusters are separated via crisp lines and two-valued logic is used for clustering.

Supervised Fuzzy Cluster Analysis (SFCA)

In conventional cluster analysis as shown in Figure 2 clusters are separated by crisp boundaries. In this figure the two data points that are identified by red crosses belong to cluster “A”, and do not have membership in cluster “B”. In this figure cluster centers are identified by brown circles. In Figure 2 both identified data points have a membership of “1” in cluster “A” and a membership of “0” in cluster “B”.

If Figure 2 was not observable (for example instead of two, it was part of a hyper-dimensional data) and you would only be exposed to the algorithm output, then you would assume that these two points are quite similar. For example, if the cluster centers were representative of rock qualities (A=Good Shale and B=Poor Shale), both these wells were completed in “Good” quality shale. However, the reality, as presented in Figure 2 is quite different from this interpretation.

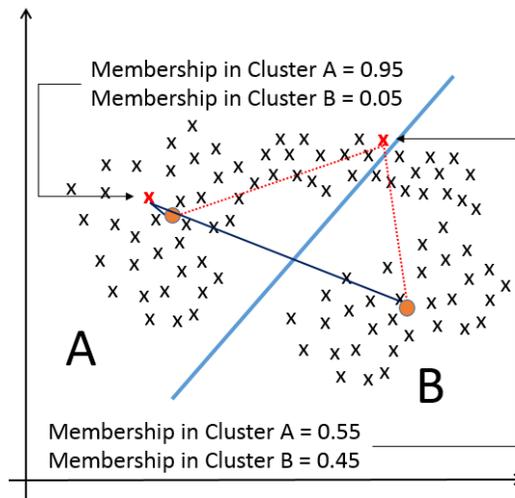


Figure 3. Fuzzy cluster analysis. Clusters are no longer separated via crisp lines and are identified with multi-valued logic (Fuzzy Logic) in order to discover order in the data.

³ As you will notice, the domain expertise we refer to here, is far from being bias, or based on assumptions, or interpretation of the data.

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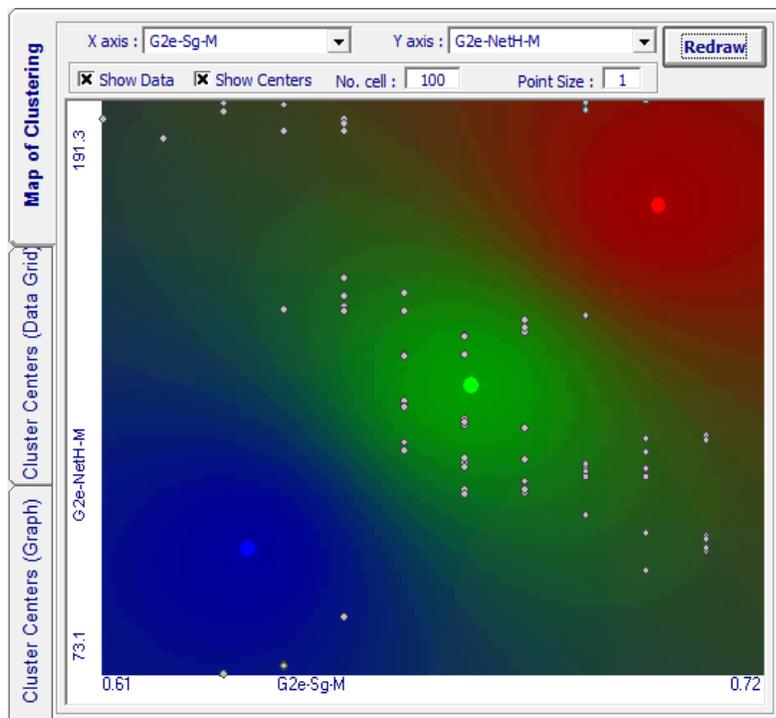


Figure 4. Plot of Net Pay Thickness versus Gas Saturation. The smaller white circles identify the location of measurements for each well. The location of colored larger circles identify our definition of "good", "Average" and "Poor" rock qualities.

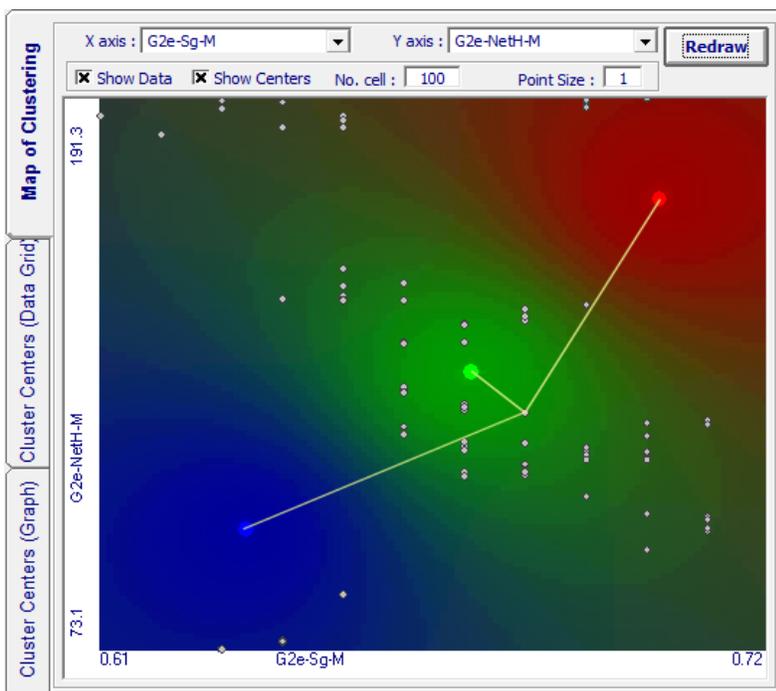


Figure 5. Each well has membership in all three fuzzy sets.

When the idea of Fuzzy Sets are introduced and Fuzzy Cluster Analysis are used to identify order in this data, as shown in Figure 3, the first data point (the well represented with the red cross on the left) has a membership of "0.95" in cluster "A" and a membership of "0.05" in cluster "B", while the second data point (the well represented with the red cross on the right) has a membership of "0.55" in cluster "A" (A=Good Shale) a membership of "0.45" in cluster "B" (B=Poor Shale).

The memberships of these points represent the quality of the rocks associated with these wells much more realistically, by identifying that the first well is completed in a location with much better rock quality than the well in the second location, and that they are not both the same rock quality as the crisp cluster analysis would make you believe.

It can be easily observed that the technique in Figure 3 is superior in describing the realities about the data points when it is compared to Figure 2. In other words, Fuzzy Cluster Analysis, is a better tool when we are trying to discover order in the seemingly chaotic behavior observed in the complex, multi-dimensional data sets, of which, data from shale is a good representative.

Furthermore, as was mentioned in the previous section, cluster analysis, in general, is an unsupervised technique. Here, since we have certain understanding of the physics of the problem, we can insert this knowledge of the physics into our analysis and "supervise" (to a certain degree) the process of the Fuzzy Cluster Analysis. We incorporate this knowledge by imposing the locations of the cluster centers in our analysis, developing the idea of Supervised Fuzzy Cluster Analysis (SFCA) (Intelligent Solutions, 2015). But first we have to formulate this knowledge in a fashion that is appropriate for this particular analysis.

Determination of Reservoir Quality

As was mentioned earlier we are going to use the four rules mentioned in the previous page in order to define reservoir quality in shale. The measured data will be the foundation for classifications. It is important to note that as

long as we are committed to work with actual field measurements, then we can only work with the “data we have” rather than the “data we wished we had”. In this particular field, there were four reservoir characteristics available: Net Pay Thickness, Porosity, Gas Saturation, and TOC. Referring to the rules identified in page 3, we define and impose (supervise) the locations of three cluster centers as “Good” (larger red circle), “Average” (larger green circle), and “Poor” (larger blue circle) shale reservoir qualities and identified them on the plots shown in Figure 4 and Figure 5. In this way, each well with its given value for these four parameters will acquire a membership in all three clusters. In other words, each well in this field is assigned a set of three memberships. The formation surrounding each well is “Good”, “Average” and “Poor”, each to a degree.

Using this technique we have achieved two important objectives. Figure 4 and Figure 5 both are the cross plots of Net Pay Thickness and Gas Saturation. Similar cross plots are generated for all the combinations of these four reservoir characteristics and the cluster centers for rock qualities “Good”, “Average”, and “Poor” are defined. It should be noted that based on these definitions, we now have a clear, and non-controversial, definition for “Good”, “Average”, and “Poor” shale reservoir qualities. Furthermore, thanks to the Fuzzy Cluster Analysis algorithm we know to what degree (fuzzy membership function) each well is completed in which of these reservoir qualities.

For example the well identified in Figure 5 (each small white circle represents reservoir characteristics measurements for a single well) has membership in all three fuzzy sets of “Good”, “Average”, and “Poor”, but each to a degree. As it is shown in this figure this particular well is represented by “Average” reservoir quality far more than by the other two clusters.

Figure 7 and Figure 6 provide graphical as well as statistical information regarding the results of the Supervised Fuzzy Cluster Analysis. Figure 7 shows that cluster of wells with “Good” reservoir quality end up having a higher value of Net Pay Thickness, Porosity, Gas Saturation, and TOC than the wells completed in areas of the reservoir identified as “Average”, and “Poor” reservoir characteristics. Furthermore, Figure 6 shows that the statistics of reservoir characteristics for each of the clusters support our original intent of classifying wells based on the quality of the reservoir that they are completed in.

Figure 6 shows that there are 39 wells that have been completed in parts of the reservoir with membership (each well to a degree) in the cluster of “Poor” reservoir quality, 127 wells have been completed in parts of the reservoir with membership (each well to a degree) in the cluster of “Average” reservoir quality, and 55 wells have been completed in parts of the reservoir with membership (each well to a degree) in the cluster of “Good” reservoir quality. Now that we have identified the degree of membership of each well in the relevant clusters we continue our analysis by trying

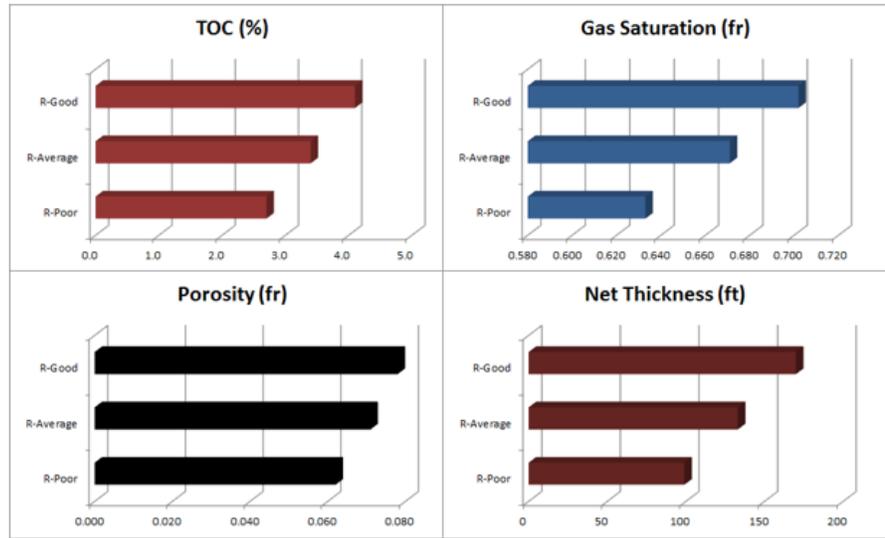


Figure 7. Results of the imposition of the rules mentioned in this section on the field data in classification of the shale reservoir quality.

Cluster Statistics			
Clusters	1	2	3
Well Quality	<i>R-Poor</i>	<i>R-Average</i>	<i>R-Good</i>
No. of Wells	39	127	55
Avg. Entropy	0.45	0.31	0.47
Avg. Membership	0.61	0.73	0.58

Cluster Centers			
TOC (%)	2.7	3.4	4.1
Porosity (fr)	0.062	0.071	0.078
Net Thickness (ft)	99	133	170
Gas Saturation (fr)	0.633	0.671	0.702

Figure 6. Statistics about each of the defined fuzzy clusters of reservoir qualities.

to first identify and compare (to one another) the production behavior of wells in these categories and then we will try to identify the completion parameters that are dominating a certain behavior in each categories of the wells.

Before continuing, let's introduce the production indicator as the last parameter that needs to be calculated for each well in this analysis. The production indicator is the pressure-corrected, three months cumulative production of each well. In this section of the analysis, we explore the production behavior of the wells that belong to each of the categories (clusters). The interest is to learn if the wells that were classified as "Poor" wells, based on reservoir characteristics (considering their degree of membership in that cluster) have lower production than wells that have been identified as "Average" wells, and "Good" wells? Also do wells that have been identified as "Average" wells based on reservoir characteristics (considering their degree of membership in that cluster) have lower production than wells that have been identified as "Good", and higher production than wells that have been identified as "Poor"? This is "conventional wisdom". When the productivity of wells positively correlate with their reservoir characteristics. In other words, does "conventional wisdom" apply to "unconventional resources"? We hope that the results of the analysis presented in the next section can shed some light on this question.

Granularity

One last item needs to be clarified before the results are presented and that is granularity. Granularity is defined as the scale or level of detail present in a set of data or other phenomenon. When discovering or analyzing patterns in a data set, the idea of granularity becomes important. It is hypothesized that a trend or a pattern is valid once it can tolerate (remain consistent) a certain level of granularity. In other words, a trend and/or a pattern would be acceptable if it can hold (remain the same) as the granularity increases, at least one level. Furthermore, classes, clusters or groups that form trends and patterns need a certain level of population to be judged as acceptable. For example it is not reasonable to expect a single well to represent a class. This would be more anecdotal evidence than trend or pattern.

There is no widely acceptable values or numbers for these (number of classes for granularity or population in a class) and we may judge them based on our experience in the field that we are applying them to. In this study acceptable trends and patterns are those that hold at least one level increase in granularity. Furthermore, we postulate the acceptable minimum number of wells (population) in a cluster or category is eight wells (almost one pad).

Results and Discussions

The results and discussions are divided into two sections. In the first section the strategy for performing the analysis and how this strategy is implemented, is covered. Furthermore, in this section detection of general trends in data that explains the interaction between reservoir quality and completion practices in different rock qualities are explained. In the second section of the results and discussions the focus will switch on completion parameters. In this section influence of different completion parameters are examined.

Results of Pattern Recognition Analysis

The question that was asked in the title of this article was "Formation or Completion; which one is controlling the production in shale basins?" To answer this question we designed the following strategy:

- A. We develop qualitative definitions for the reservoir characteristics.
- B. Each well is assigned a membership to each of the clusters of reservoir qualities (Good, Average, and Poor).
- C. Productivity of each well is calculated and applied to the membership of its reservoir quality (cluster).
- D. Productivity of wells in each cluster (reservoir quality) is averaged to represent the productivity of the cluster.

To make this analysis as comprehensive as possible we implement the above strategy in several steps. In the first step, let's start the process by dividing the wells in this asset into only two categories of "Good" and "Poor" reservoir qualities. Figure 8 shows the results of this analysis. In this figure the horizontal bar charts on the bottom show that all the 221 wells in this field have been completed in regions that are divided into "Good" and "Poor"

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reservoir qualities and that “Good” reservoir quality is consisted of thicker shale with better porosity and gas saturation and higher values of TOC.

Furthermore, this figure shows (vertical bar chart on left of Figure 8) that, as expected, based on “conventional wisdom” wells completed in the “Good” parts of the formation have higher productivity than wells completed in the “Poor” parts of the formation. Based on this figure the 221 wells in this field are divided into 39 and 182 for “Poor” and “Good”, respectively. Now let’s see whether this conclusion will hold once we increase the granularity of the analysis from two categories (clusters) to three categories.

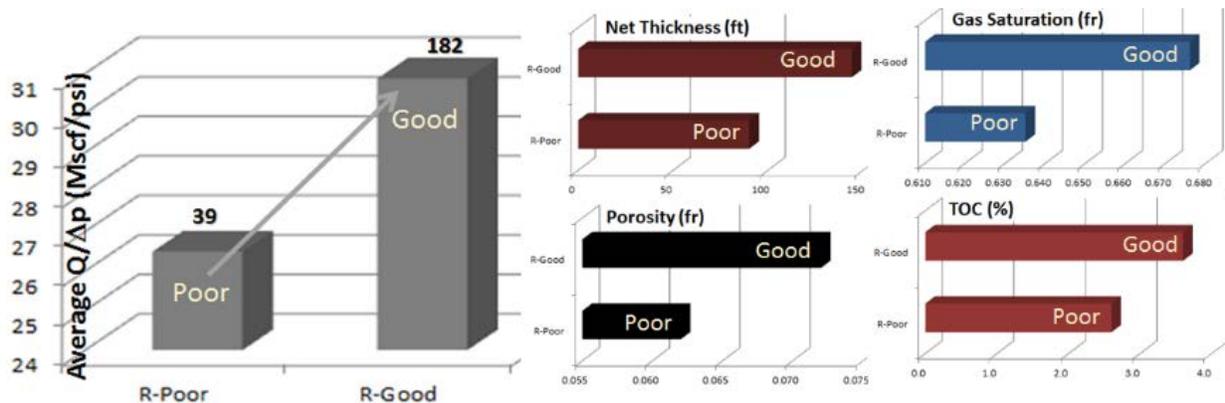


Figure 8. Wells completed in areas with "Poor" reservoir quality have lower productivity than well completed in areas with "Good" reservoir quality.

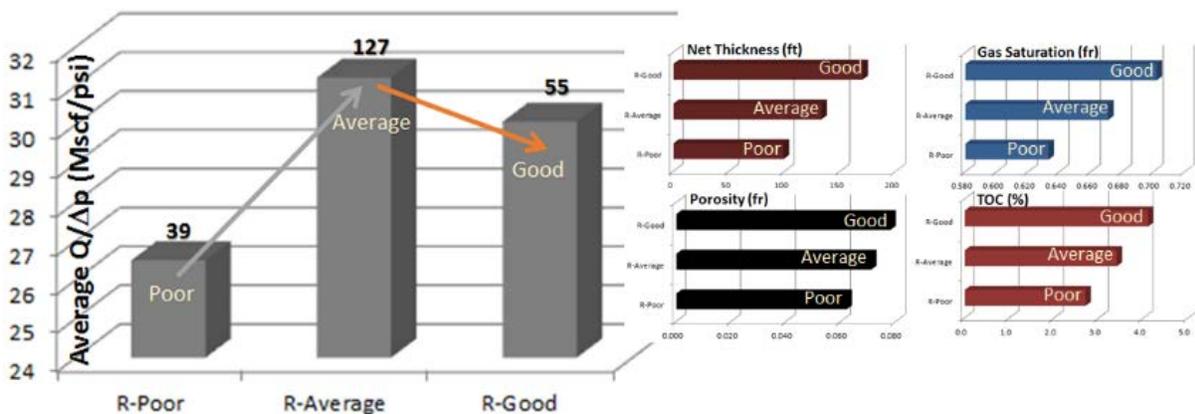


Figure 9. Wells completed in areas with "Poor" reservoir quality have lower productivity than well completed in areas with "Average" reservoir quality and these wells have higher productivity than well completed in areas with "Good" reservoir quality. An unexpected result.

Figure 9 shows the results of this analysis when the granularity is increased from two to three categories of reservoir quality. In this figure the horizontal bar charts on the bottom clearly show the values of reservoir characteristics representing the classifications of “Good”, “Average”, and “Poor”. Of the 221 wells in this field, the 39 wells in the “Poor” cluster remain in this category as before, while the remaining wells are divided into 127 and 55 wells in the clusters “Average”, and “Good”, respectively. The vertical bar chart on the left of Figure 9 shows that the productivity no longer follows the expected trend. In other words, the wells completed in areas with “Average” reservoir quality have produced better than the wells in the areas with “Good” reservoir qualities. This is an unexpected results. But before we make any conclusions, we first have to make sure that the trends that are observed in Figure 9 can withstand the scrutiny of increase in granularity.

To do this, the granularity of each section of the bar graphs shown in Figure 9 is increased from two to three categories. In other words, concentrating on the “Poor” to “Average” part of the field, we will increase the

granularity of this section from two to three clusters and then switching concentration to the “Average” to “Good” part of the field, we will increase the granularity of this section also from two to three clusters. Therefore in general, one can argue that we have increased the granularity of the analysis for the entire field from three to five or even six clusters (depending how one would look at this, since there will be an overlap of 34 wells between the wells in the best cluster of one classification and the wells in the worst cluster of the next classification, as will be explained in the next few paragraphs).

In Figure 10 the concentration is shifted only to the wells that have been completed in “Poor” to “Average” part of the field. We will call these parts of the reservoir the “Low Quality Shale – LQS”. In Figure 11 the concentration shifts to the wells that have been completed in “Average” to “Good” part of the field. We will call these parts of the reservoir the “High Quality Shale – HQS”. These figures show that as the granularity in each of these types of reservoirs increases from two to three categories, the trend that was first observed Figure 9 holds. Furthermore, in the LQS, Figure 10, the horizontal (reservoir quality) bar charts are in agreement with the vertical (productivity) bar chart, while in the HQS, Figure 11, the opposite is true. The trends in Figure 10 and Figure 11 mirror the trends shown in Figure 9 (the left vertical grey, bar chart) but at higher granularity.

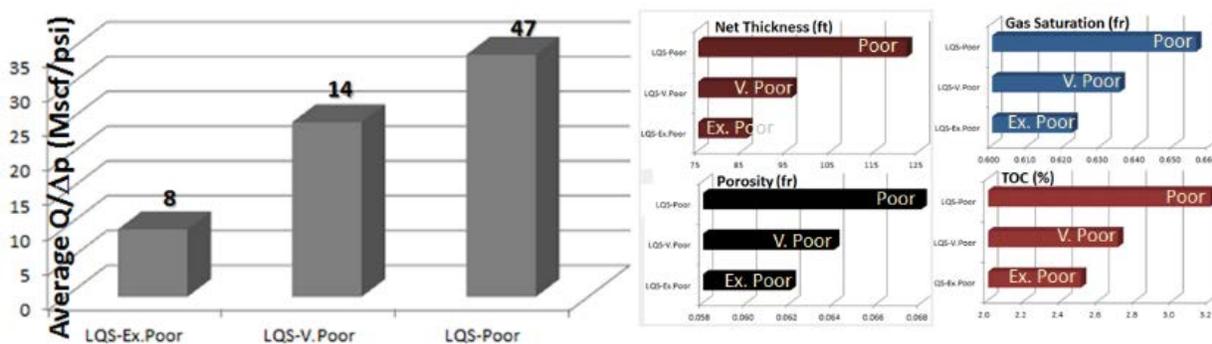


Figure 10. For Low Quality Shale (LQS) the productivity trend matches that of reservoir quality.

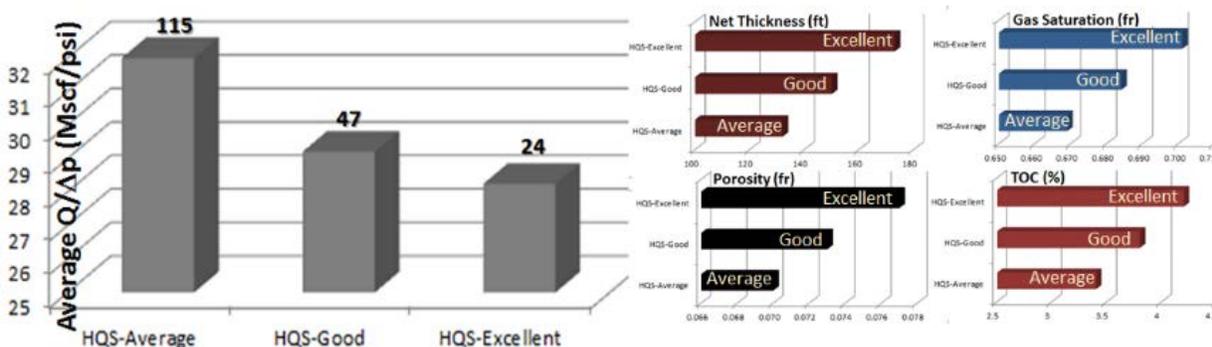


Figure 11. For High Quality Shale (HQS) the productivity trend does not match that of reservoir quality.

The only logical explanation of these patterns is that while “conventional wisdom” seem to hold for the Lower Quality Shale (LQS), it does not necessarily hold for the Higher Quality Shale (HQS). In other words, while reservoir quality seem to dominate production behavior in the LQS, it takes a back seat to other factors (such as completion practices) in the HQS. In the LQS, completion does not do much more than allowing the rock to behave in a matter that is expected of it and completion simply provides the means for the rock to express itself as it should. In the LQS operators get more production from wells located in the better parts of the reservoir, and as long as the completion practices are within acceptable industry range (nothing special) they should expect to get acceptable return on their completion investment.

However, in the HQS, the role and impact of the completion practice becomes much more pronounced. In the HQS if the completion practices are not carefully examined and designed based on sound engineering judgments and

detail scientific studies, they can actually hinder the capabilities of shale in producing all that it is capable of. Figure 11 provides the insight that is the source of this reasoning. This figure shows that as far as the reservoir characteristics are concerned, wells located in “Good”, to “Excellent” parts of the reservoir are less productive than those located in the “Average” parts of the reservoir. Therefore, if the reservoir quality is not driving the production, then what is? The only other potential culprits are completion and well construction practices.

Therefore, for the HQS they (completion and well construction practices) must be influencing the production such that they are overshadowing the influence of reservoir characteristics. Please note that these are not anecdotal observations about one or two wells. This is a pattern that includes 186 wells. Figure 11 suggest that this operator is not getting the type of productivity from its shale wells that it should, and therefore the completion practices and design can and should be improved. But How? Which completion parameters are actually controlling the productivity of these wells? And how should they be modified in order to improve productivity? These are the questions that will be addressed in the next section of this article, as we continue the implementation of these advanced data-driven analytics techniques.

Influence of Completion Parameters

Now that we have established that the influence of completion practices on production in shale wells is a function of reservoir quality, the focus will be switched to specific completion characteristics in order to determine their influence on the productivity of the shale wells. Following is a detail explanation of how this is accomplished. Each well is qualitatively classified based on the definitions of reservoir characteristics. Then the degree of membership of wells in each of the clusters is used as an indicator to calculate its production, as well as each of the completion variables and averaged for all the wells in that cluster. If the resulting productivity and completion variable show similar trends then the conclusions are made accordingly. Figure 12 through Figure 15 show this type of analyses.

Let’s examine Figure 12 to clarify this algorithm. This figure shows the analysis for the Low Quality Shale (LQS). The three reservoir characteristics have been identified as “Extremely Poor”, “Very Poor”, and “Poor” (this is the same bar chart better shown in Figure 10, right). These charts clearly show that the average Net Thickness, Porosity, Gas Saturation and TOC of the “Extremely Poor” shale is less than those of “Very Poor” shale and those of “Very Poor” are less than of those for “Poor” shale. In other words, the classification seem to be quite justified.

When the productivity of the wells that are classified as above, are plotted (top left vertical, grey bar chart in Figure 12), one can observe that as expected, productivity of the wells producing from “Poor” reservoir rock is higher than the wells producing from “Very Poor” reservoir rock, and so forth. When the membership of the wells based on their reservoir quality is used to calculate their share of the completion attribute and then plot them accordingly, one can see that for example in the case of “Total Number of Stages” (brown vertical bar chart on the middle right side of Figure 12) the trend is similar to that of production. In this case we make two conclusions for the LQS: **(a)** this particular attribute, “Total Number of Stages”, is a dominant (monotonic) attribute (since it has a dominant non-changing trend) and **(b)** based on the direction of the trend, higher values of “Total Number of Stages” cause better productivity. Similar conclusions can be made for attributes such as “Average Treatment Pressure” (the wells completed in the [relatively] better quality shale [within the LQS general category] should be treated at higher average injection pressure) and “Amount of Pad Volume” (wells completed in the better [relatively] quality shale [within the LQS general category] should be treated with larger amounts of pad volume) based on the two vertical bar charts at the bottom of Figure 12.

Figure 13 shows the trend analysis (LQS) for completion parameters that seem to have a dominant but opposite impact on productivity. Using the same logic presented in the previous paragraph, conclusions can be made on three other parameters. For amount of “Proppant per Stage”, it can be mentioned that based on the orange vertical bar chart on the bottom of Figure 13 (when compared with the trend of productivity) the data suggest that for the LQS, higher values of “Proppant per Stage” seem not to be an appropriate design consideration. This figure shows that shale wells completed in the “Extremely Poor” parts of the reservoir cannot produce better even when larger amounts of “Proppant per Stage” are used during their completion.

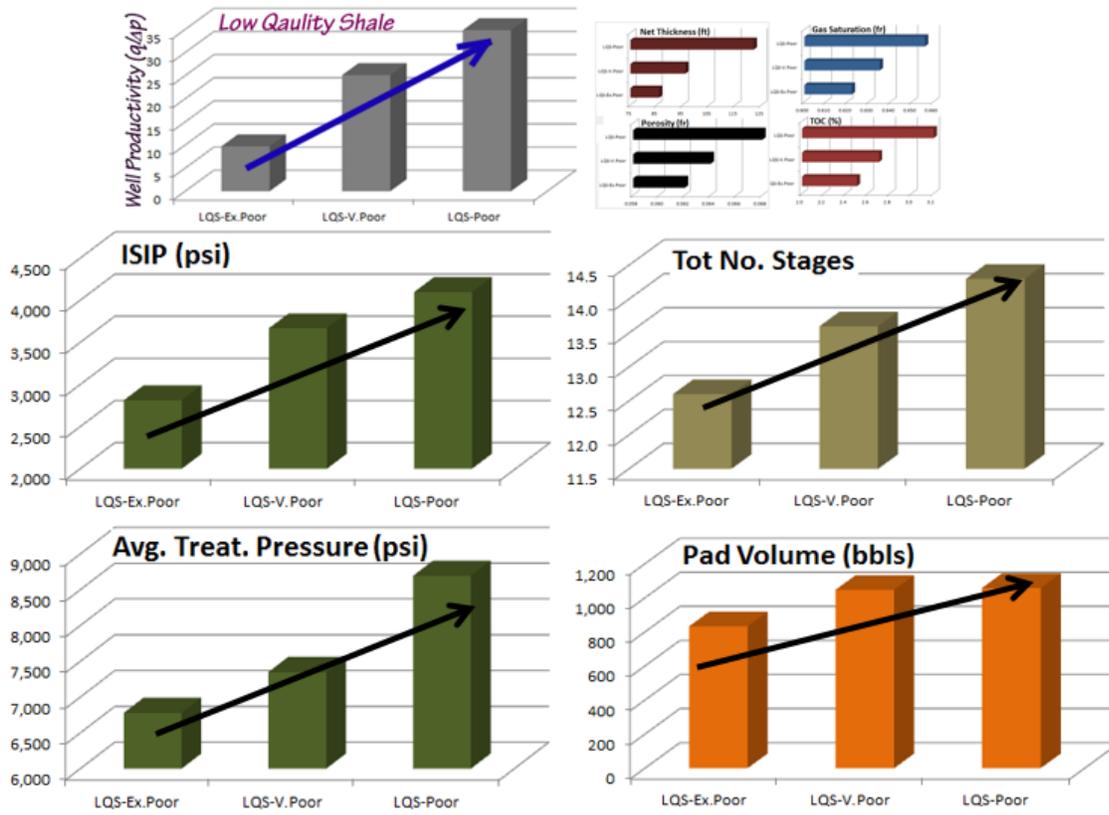


Figure 12. Impact of completion characteristics on production in Low Quality Shale; Trend similar to production.

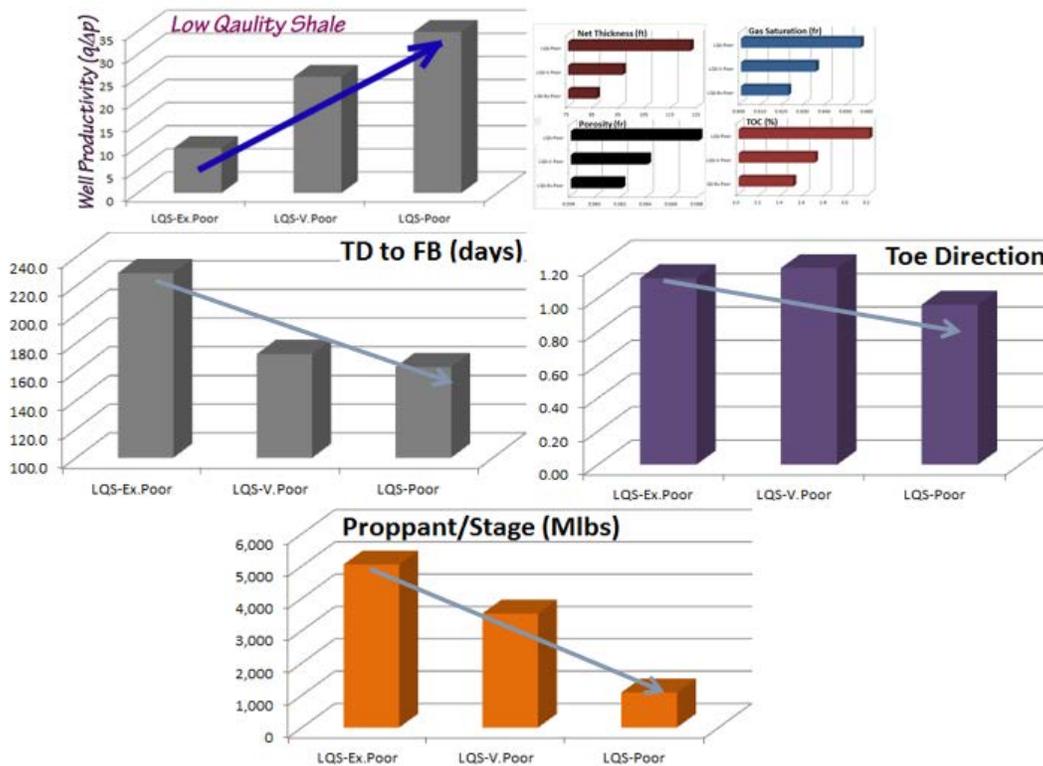


Figure 13. Impact of completion characteristics on production in Low Quality Shale; Trend opposite to production.

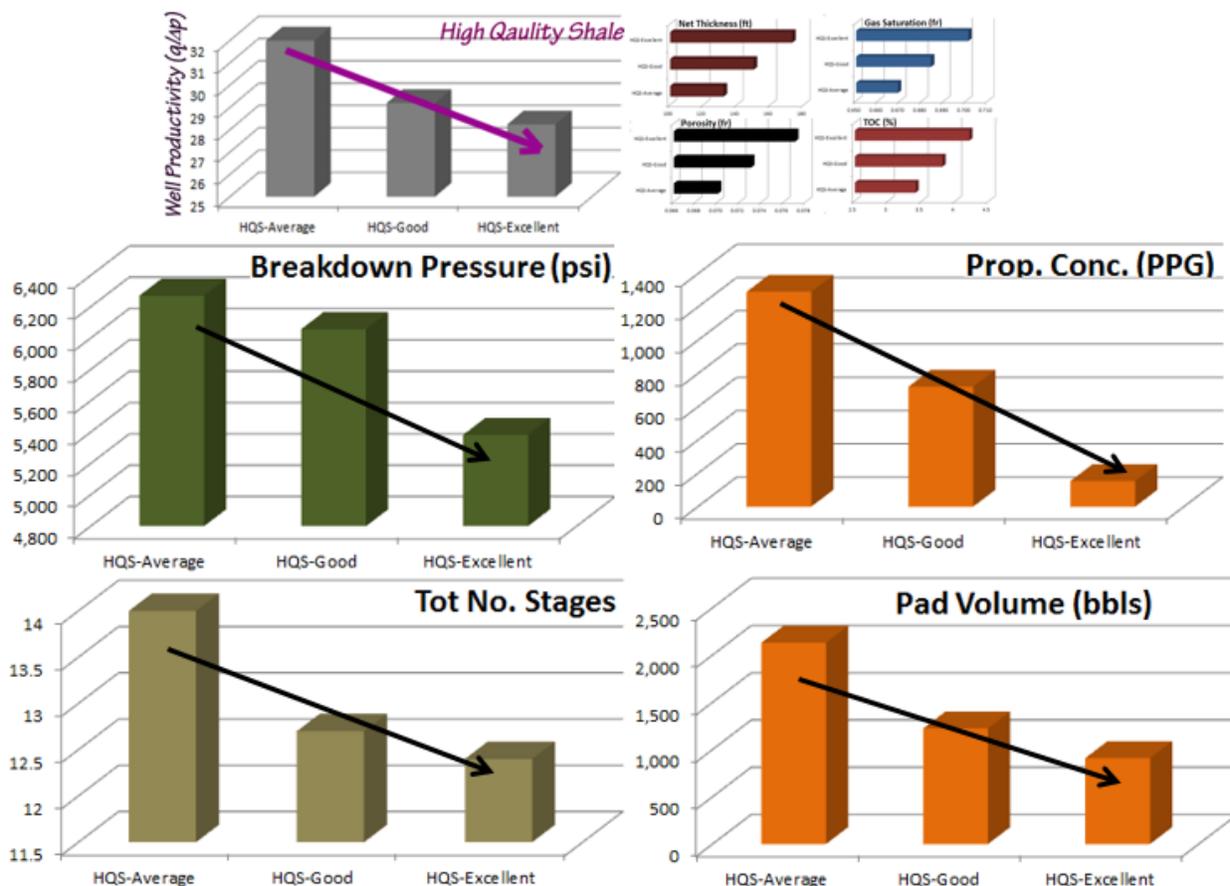


Figure 14. Impact of completion characteristics on production in High Quality Shale; Trend similar to production.

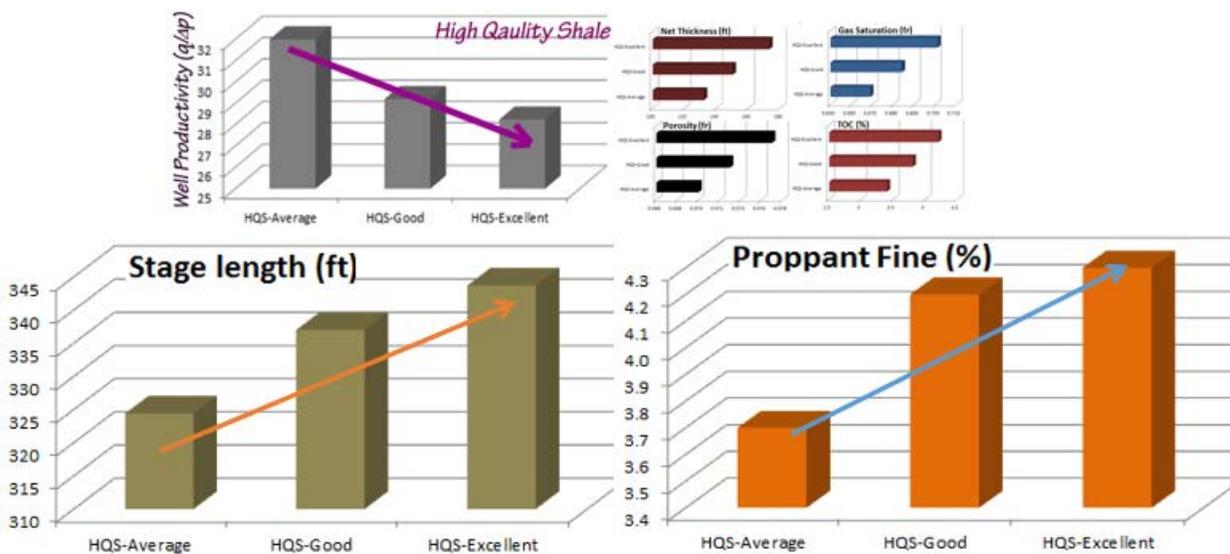


Figure 15. Impact of completion characteristics on production in High Quality Shale; Trend opposite to production.

Similar conclusions can be made regarding the “Soak Time“. The analysis show that in this particular field, shorter soak time (number of days between completing the well and flowing it back) seem to be beneficial (please note the soak time in this field is generally high).

To analyze the completion parameters in the High Quality Shale in this filed Figure 14 and Figure 15 are presented. The logic is similar to those presented for the LQS. The top left (vertical, grey) bar chart in this figure shows an unintuitive plot. Here it is seen that as the quality of the rock gets better (x axis) the productivity decreases (the bars). This is exactly the opposite of what is expected. So what is causing this? The bottom left, brown, vertical bar chart shows that in the wells that have been analyzed in this field the “Total Number of Stages” have become less as the quality of the rock gets better. A clear positive correlation exist between lower productivity (in the shale wells completed in better quality rock) and “Total Number of Stages”. This may explain (at least partially) the lower productivity of the wells that were supposed to produce better. Similar conclusions can be made for completion parameters such as “Proppant Concentration” and “Pad Volume”.

Completion parameters with opposite (negative) correlation for the HQS are “Length of Each Stage” and “Percent of Fine Proppant”. Figure 15 suggest that in the case of both of these parameters lower productivity is directly and positively correlated with higher values. In other words, in the shale wells that have been completed in the better parts of the reservoir, the productivity has suffered mainly because these wells have been completed with larger stage lengths and higher values of fine sized proppant.

Important Notes on the Results and Discussion

The reader may have noticed that throughout this article the author has avoided using numbers. When the LQS and the HQS are mentioned no numbers are presented (although one can read it on their own from the axes). There is a good reason for this. As engineers we have been conditioned to continuously deal with numbers and associate everything with a scale. That is fine and appropriate with many of the analyses that we perform day in and day out as engineers and geoscientists. However, when it comes to pattern analyses almost all of them are “fit-for-purpose”. Specifically, when it comes to shale, author would like to warn against using the results presented here and generalizing them in any shape or form to any other shale basin and/or even other fields in the same basin. If you have enough data, then we suggest to perform similar analyses and make the appropriate conclusions.

Conclusions and Closing Remarks

The technology presented in this paper provides the type of insight that is required in order to dig deeper into the completion practices in the shale basins. It was demonstrated that pattern recognition technology that is an integral part of Advanced Data-Driven Analytics can shed important light on the influence of design parameters in shale wells productivity and distinguish the impact of parameters that control rock quality and those that control completion practices. It was shown that general completion design is not as important in wells completed in Low Quality Shale (LQS) as they are in wells completed in High Quality Shale (HQS).

While “One-size-fit-all” design philosophy may be sufficient for LQS, it certainly is not (and short sells) the HQS. The author firmly believes that by changing and optimizing the design of the completion and hydraulic fracturing in shale much more can be expected from this prolific resource. The question that was asked in the title of this article was “Formation or Completion; which one is controlling the productivity?” It was demonstrated that this is not an easy question to answer and the answer is different for every field⁴. However, for the field that was the subject of this article, it was demonstrated that Advanced Data-Driven Analytics is capable of using facts (field measurements) in order to provide answers to help the operators in their quest to optimize production from shale.

An overall look at the analyses presented in this paper, and the results and discussions in the previous section may result in the conclusion that “we already knew many of the conclusions that have been presented in this article”. Why should one bother with all these details in order to reach the conclusions that are so intuitive (such as more stages are better)?

⁴ If similar analyses are performed on multiple fields in multiple assets, then we may be able to produce some general conclusions. At this point, it is safe to conclude these are field dependent analyses and should not be generalized.

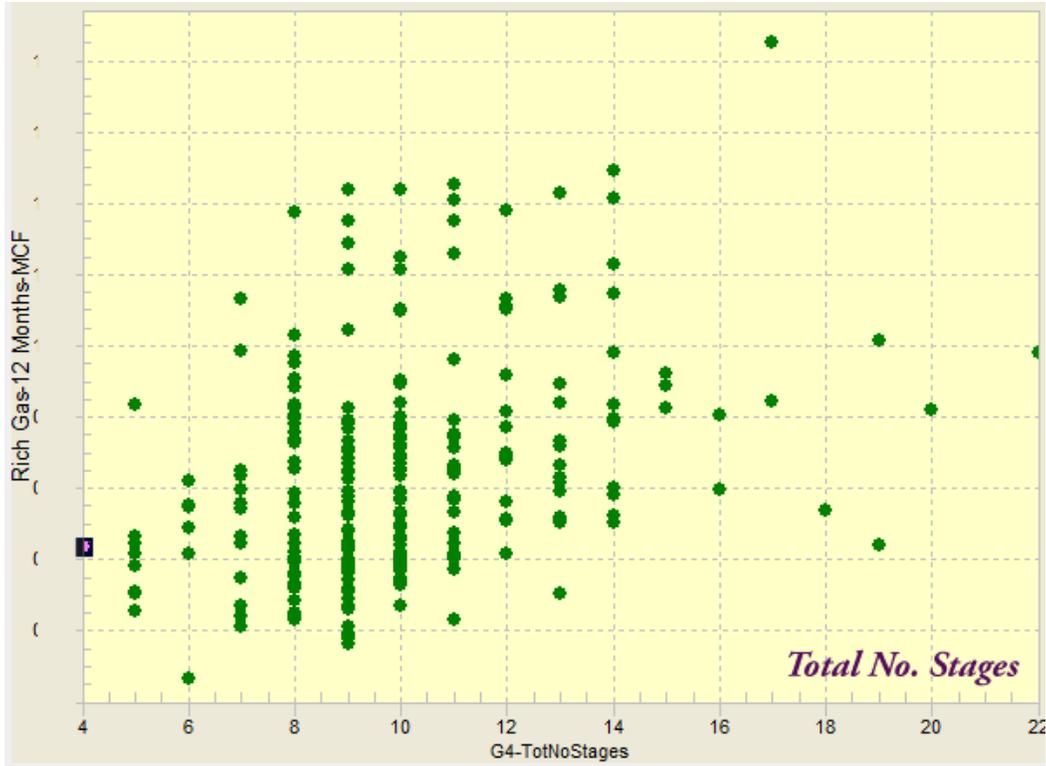


Figure 16. Cross plot of 12 months cumulative production versus total number of stages, on a per well basis.

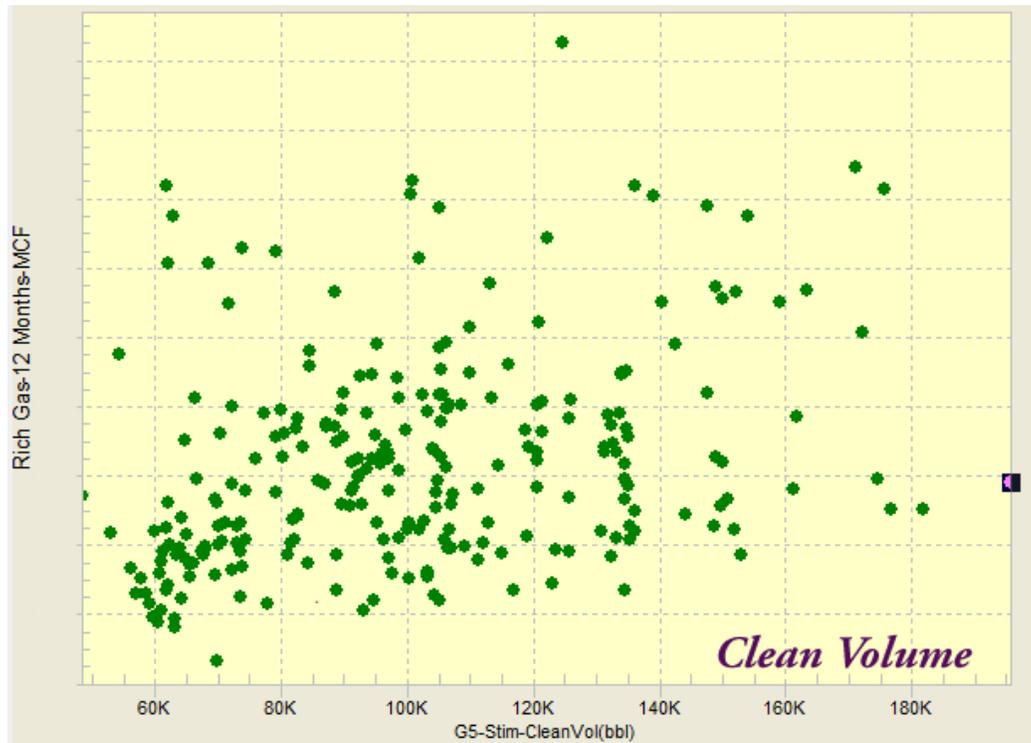


Figure 17. Cross plot of 12 months cumulative production versus total amount of clean (pad) volume, on a per well basis.

Well, the more important question should be “do we need to learn from the measured data (facts from the field)?” One of the main conclusions of this article was that in both low and high quality shale, it is better to have more number of stages. This is quite intuitive and most reservoir and production engineers will tell you that they already knew it. This holds true since in shale you only produce where you make contact with the rock, and although not all your hydraulic fractures are successful, by increasing the number of hydraulic fractures (stages) one increases the chances of success. This is indeed a true statement. However, the more important question is “can one make the same conclusion by looking at the actual data from the field?”

Figure 16 is the cross plot of best 12 months of cumulative production versus total number of stages that was used in the analyses. Can anyone make the conclusion that “in this field, for better productivity, regardless of the rock quality, it is better to have a higher number of stages” by looking at this plot? Once it is demonstrated (by the analysis presented in this article) that such a reasonably intuitive conclusion can indeed be made from the actual data, regardless of its seemingly chaotic behavior (as shown in Figure 16), then one may feel more confidence regarding other conclusions that are reached by these analyses (technology) that are not so intuitive.

Although note presented here in its entirety (for the confidentiality purposes), other conclusions were also made as a result of this study. For example “in this field, for better productivity, regardless of the rock quality, it is better to start the frac jobs with a higher amount of pad volume.” Figure 17 shows the cross plot of best 12 months of cumulative production versus total amount of pad volume that was used in the analyses provided in this article. This is an unintuitive but yet important conclusion that can serve the operator in optimizing their frac jobs.

Although analyses presented here provide only qualitative values in the form of adjectives such as “more” and “less”, a different version of these analyses (using advanced data driven analytics) can help in design of the new frac jobs using actual values and numbers, which is the subject of a separate article.

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