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An Empirical Model to Estimate a Critical Stimulation Design Parameter Using Drilling Data

Amin Atashnezhad, Alexandra E. Cedola, and Geir Hareland, Oklahoma State University

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Abstract

Hydraulic fracturing is the stimulation process during which fractures are created by pumping mostly water and sand into the formations. Hydraulic fracturing is done on almost 90% of gas wells in the United States. Selectively determining the fracturing intervals along the borehole is one of the most critical factors for optimizing stimulation and maximizing the net present value (NPV) of the well. In this study, an empirical model was developed to predict the formation porosity using surface drilling data and gamma ray (GR) at the bit without needing log data.

In this study, data from three wells were used to develop an empirical model for porosity prediction through the use of drilling data. To find the best model, a differential evolution algorithm (DE) was applied to the space of solutions. The DE algorithm is a metaheuristic method that works by having a population of solutions, and it iteratively try to improve the quality of answers by using a simple mathematical equation. The developed model uses the unconfined compressive strength (UCS) obtained from an inverted rate of penetration (ROP) model and gamma ray (GR) at the bit to estimate the formation porosity.

Data from three offset wells in Alberta, Canada were evaluated to find a porosity estimation model. The DE algorithm was used to search the infinite space of solutions to find the best model. The models reliability and accuracy were studied by conducting a sensitivity analysis then comparing the results to offset well data. There is good agreement between the models estimated porosity and porosity from the well log data. This paper presents results from individual well sections that compare the neutron porosity from logs in the field to the calculated porosity obtained from the newly developed correlation. The results show accurate quantitative matching as well as trends. The model presented can be applied to horizontal wells where the porosity can be mapped in addition to the UCS value from the drilling data at no additional cost. Based on this formation mapping log, optimum fracturing interval locations can be selected by taking the UCS and porosity of a formation into account. The suggested approach can also be used to determine the porosity in real-time.

The novelty of this model is in the ability to estimate porosity using typically collected drilling data potentially in real time. By applying this model, there is no need for well services such as well logging to find hydraulic fracturing points, which significantly reduces the cost and time associated with the well completion operation.

Introduction

Hydraulic fracturing is an important process in the petroleum industry, more particularly, in well stimulation. The purpose of the hydraulic fracturing process is to increase formation permeability which in turn increases overall production. Hydraulic fracturing was implemented for the first time in 1947, and has since been used in thousands of wells worldwide (Charlez, Ph A, 1997). As of 2012 over one million hydraulic fracturing jobs have been performed in the United States.

One of the most important parameters used in determining zones to hydraulically frac is porosity. There are several common ways to determine porosity including but not limited to core analysis, well logging, and seismic surveys. Retrieving core samples is one method to determine different formation properties like porosity and permeability, but it can have several disadvantages. Taking core samples can be extremely time-consuming and expensive, and because the cores are taken from selective points within a well may not be representative of an entire formation. Core samples may also be affected by changes in pressure and temperature and are likely to degrade throughout the process. Well logging is another method used in determining important formation properties; while this method is more common than coring, measurements can be adversely effected by drilling fluid and result over/underestimations. Another issue with logging is that in highly deviated well or horizontal wells, the tools tend to lay on the low side of the wellbore and not take accurate measurements. The seismic method for determining porosity is a complex and expensive process. This method may also require log data analysis to determine if seismic modeling is accurate for determining reservoir characteristics (Marion et al. 1994). Seismic analysis can also be effected by tunneling effects (Alam et al. 1995).

Finding a way to determine formation properties that is less expensive, more accurate and can be done in real time would be highly useful. In rock mechanic domains, empirical models have been helpful in eliminating not only the costs of such expensive formation evaluation jobs but also the cost of conducting laboratory tests.

In this study, two lab data sets have been used to establish correlations between unconfined compressive strength (UCS) and porosity for sandstone and shale samples. These correlations have then been used in conjunction with data from three wells in Western Canada to develop and verify a porosity estimation model. This model estimates the formation porosity using drilling data and the gamma ray at the bit without the need for well logging operations. The comparison between model estimated porosity and neutron porosity data was also performed.

Methodology

Drilling rate of penetration (ROP) is a function of drilling operational parameters such as weight on bit (WOB), revolutions per minute (RPM), bit geometry, drilling hydraulic and formation rock strength. The Kerkar et al. (2014) equation incorporates the above parameters to develop an ROP model for PDC bits. In this paper, the ROP model was used to determine unconfined rock strength (UCS). The model is shown in Eq. 1.

$$ROP = \left[\frac{K1WOB^{a1}RPM^{b1}COS(SR)}{CCS^{c1}D_{Bit}TAN(BR)}\right]W_f h(x)b(x), \tag{1}$$

By inverting the ROP equation, rock confined compressive strength (CCS) can be found. The UCS is calculated from CCS using Eq. 2.

$$CCS = UCS(1 + a_s {P_e}^{b_s}) \tag{2}$$

a_s and b_s are rock strength lithology coefficients and P_e is the difference between mud hydrostatic pressure and formation pore pressure (Rampersad et al. 1994).

The porosity found from well logs, the UCS calculated from an inverted ROP model, and gamma-ray data taken from the drill bit have been used to develop a porosity estimation model. Porosity and UCS data for a variety of sandstone and shale reservoirs have been plotted and have been used to find two porosity correlations. These correlations, which are called sandstone and shale corrolations hereafter, give an estimation of porosity at a given UCS for pure sandstone and shale lithologies. The plots and correlations are shown in Figs. 1 and 2. These sandstone and shale correlations were used to filter the neutron porosity data for three offset wells in Western Canada. The new proposed porosity model can be seen in Eq. 3.

$$\Phi = \frac{a}{GR^{b} \cdot UCS^{c}}, \tag{3}$$

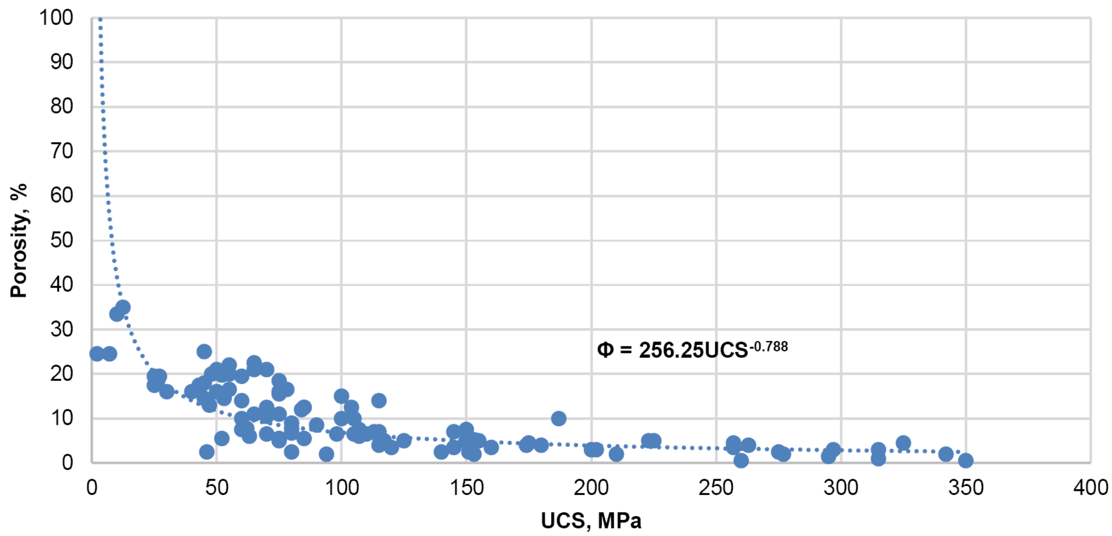

Figure 1—Porosity versus UCS for collected sandstone data

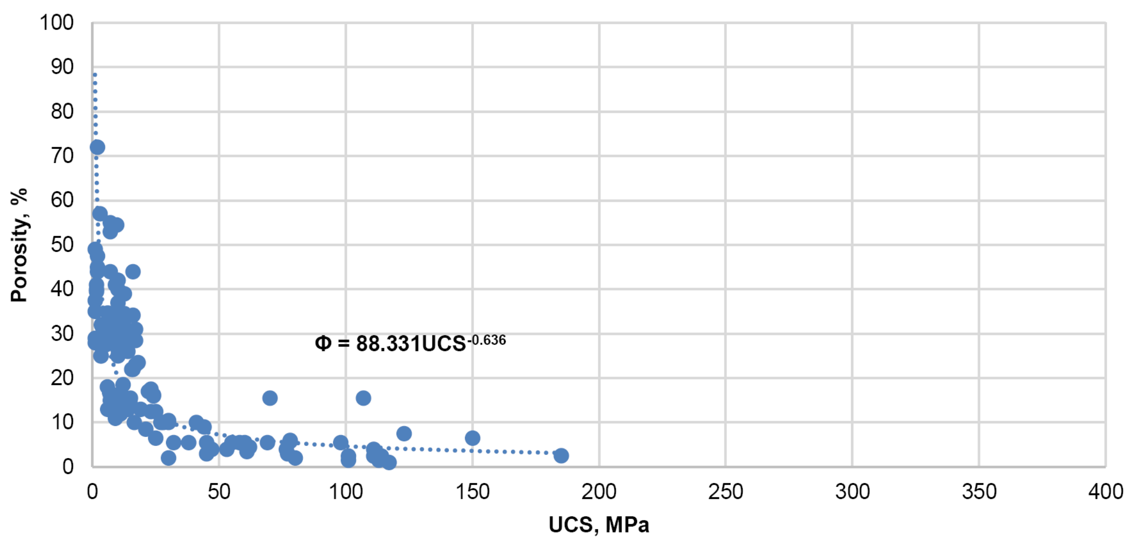

Figure 2—Porosity versus UCS for collected shale data

A differential evolution (DE) algorithm has been used to find the a, b and c coefficients in Eq. 3. The DE algorithm is a branch of evolutionary methods developed by Storn and Price (1997) and it is used to find the optimum solution for extensive, continuous domains. The DE algorithm begins with a population of random candidates and it recombines them to improve the fitness of each one iteratively using a simple equation.

Each random pair vectors (X_1,X_2) give a differential vector ($X_3 = X_2 - X_1$). The weighted difference vector, $X_4 = F \times X_3$, is used to perturb the third random vector, X_5 using Eq. 4 to achieve the noisy random vector, X_6.

$$X_6 = X_5 + X_4, \tag{4}$$

The "F" term is called weighting or scaling factor and it is primarily within the range of 0.5 to 2. The weighting factor determines the amplification of differential variation among candidates. A crossover (CR) factor regulates the amount of recombinations between candidates. The CR is applied to the noisy random vector by taking the target vector into account to achieve the trial vector. The fitness of the trial vector is then compared to the target vector and it is replaced if it is a better fit. The DE algorithm repeats the mutation (weighting factor), recombination (crossover factor) and selection steps until a predetermined criteria is achieved. The four major steps for evolutionary methods are provided in Fig. 3. The DE algorithm, like any other metaheuristic algorithm, doesn't guarantee that an optimal solution is ever found.

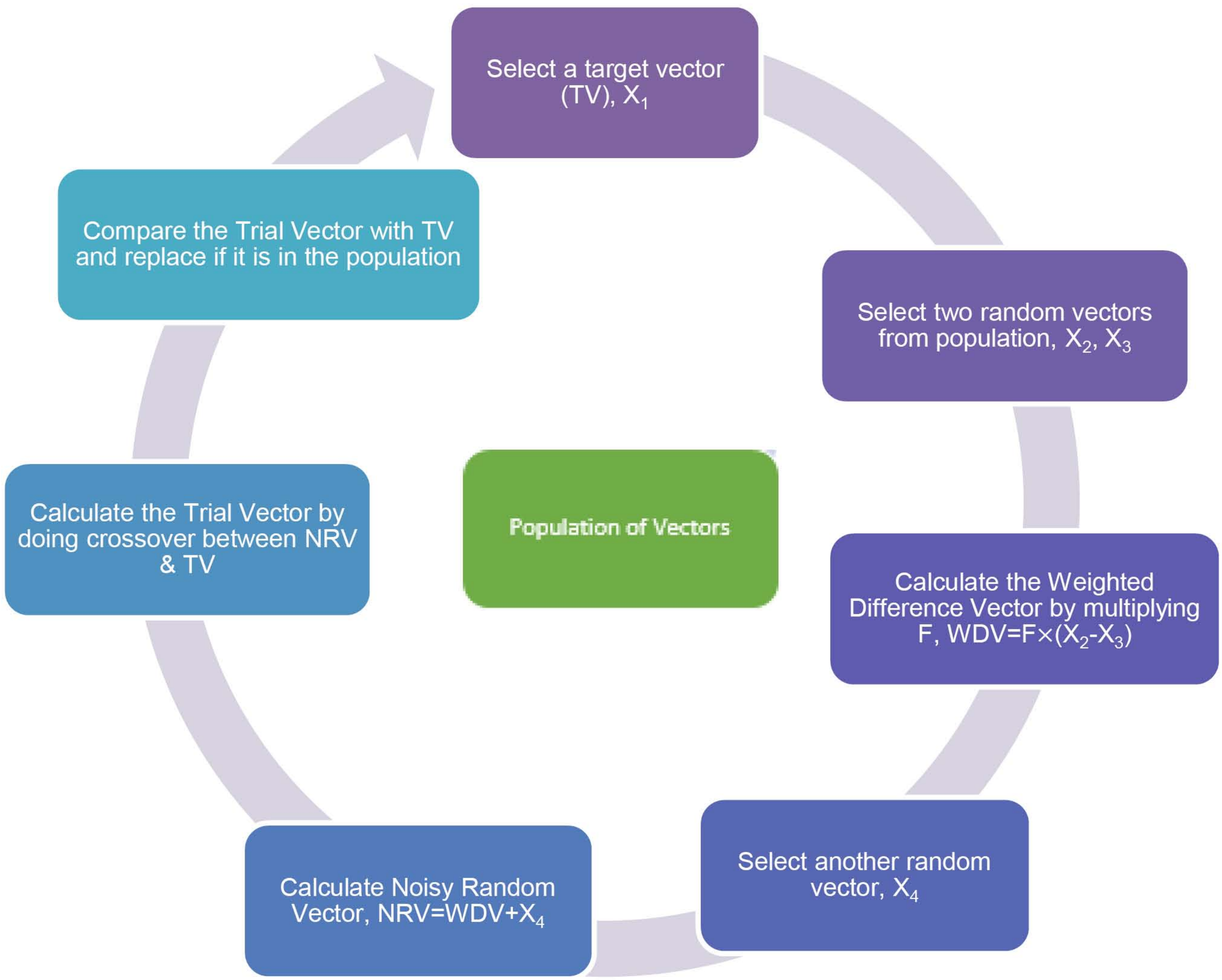

Figure 3—The Differential Evolution (DE) algorithm procedure

Results and Discussion

The coefficients in Eq. 3 were found using a DE algorithm for two of the three well datasets in Alberta, Canada. The porosity estimation model with ideal coefficients is provided in Eq. 5.

$$\Phi = \frac{1.75}{GR^{0.25} \cdot UCS^{0.47}}, \tag{5}$$

The UCS, GR, neutron porosity data and the model estimated porosity for the third well were plotted in Figs. 4 and 5. In Fig. 4, it is seen that the model estimated porosity is in good agreement with well log data and has a good sensitivity with the gamma ray. As the gamma ray decreases, the formation shale fraction increases and the model yields lower porosity values. Also, by increasing the UCS, the model estimates lower porosity values. This is also in agreement with lab data in Figs. 1 and 2. The bar plot in Fig. 4 shows the percentage difference between the neutron prosity and model estimated porosity for each data point. In Fig. 5, a comparison between model porosity and data porosity has been done for a different interval.

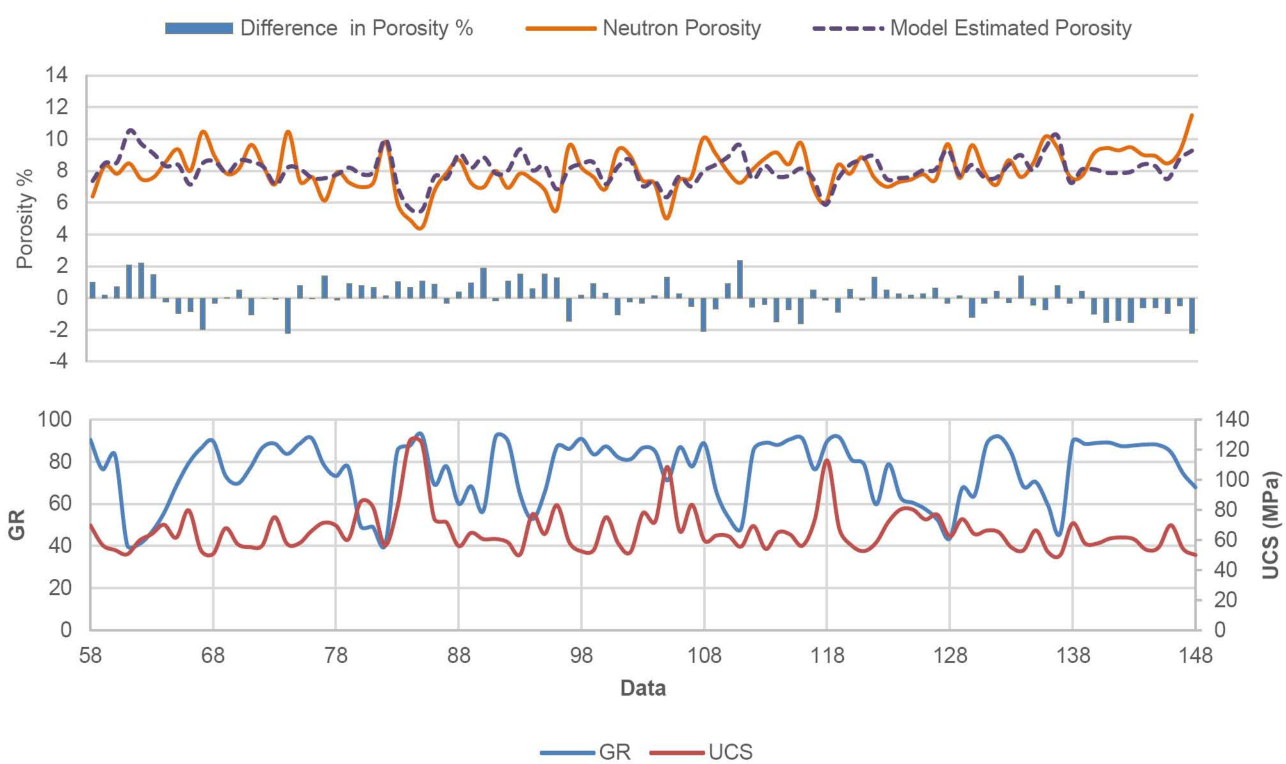

Figure 4—A comparison between model estimated porosity and neutron porosity for third offset wells

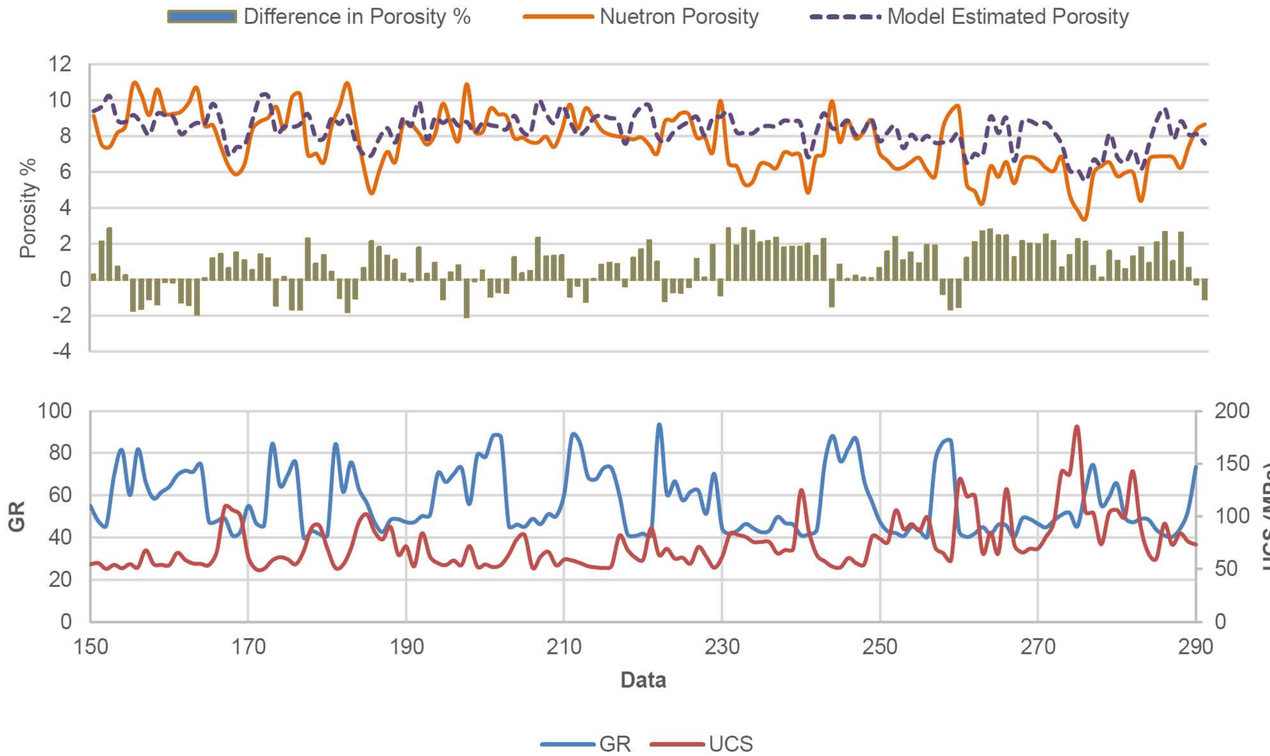

Figure 5—A comparison between model estimated porosity and neutron porosity for third offset wells

In Fig. 6, the UCS from the inverted ROP model and gamma ray from the bit were used to calculate the porosity. The porosity was plotted against neutron log porosity and a comparison was then performed. It can be seen that the estimated model porosity is in a reasonable range and the model gives a good estimation for formation porosity.

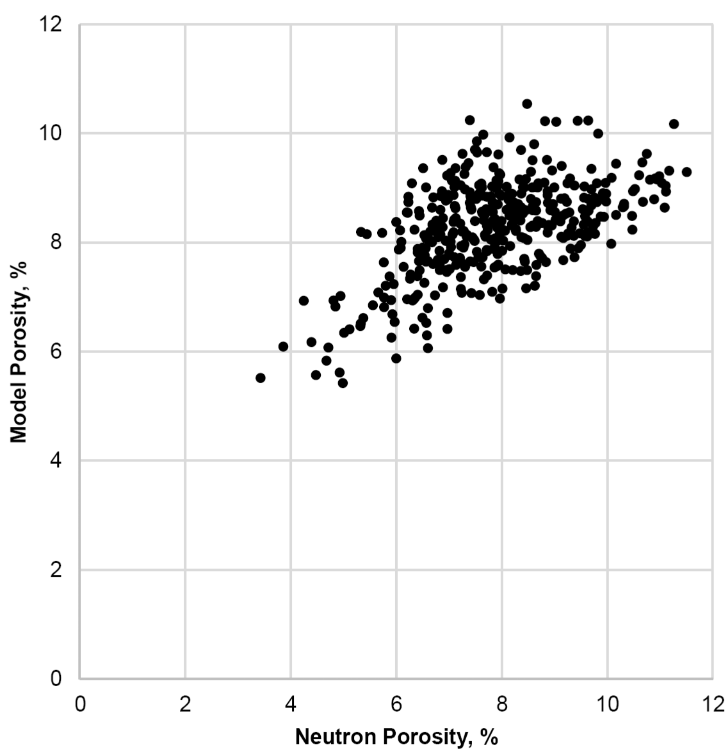

Figure 6—A comparison between model estimated porosity and neutron porosity for one of the offset wells

The model estimated porosity values for all the datapoints of the third well were compared with neutron porosity data in Fig. 7. In Fig. 8 the difference in the porosity values is shown. The average difference between model and neutron porosity log data was −0.41 percent and it is shown by the red line in Fig. 8.

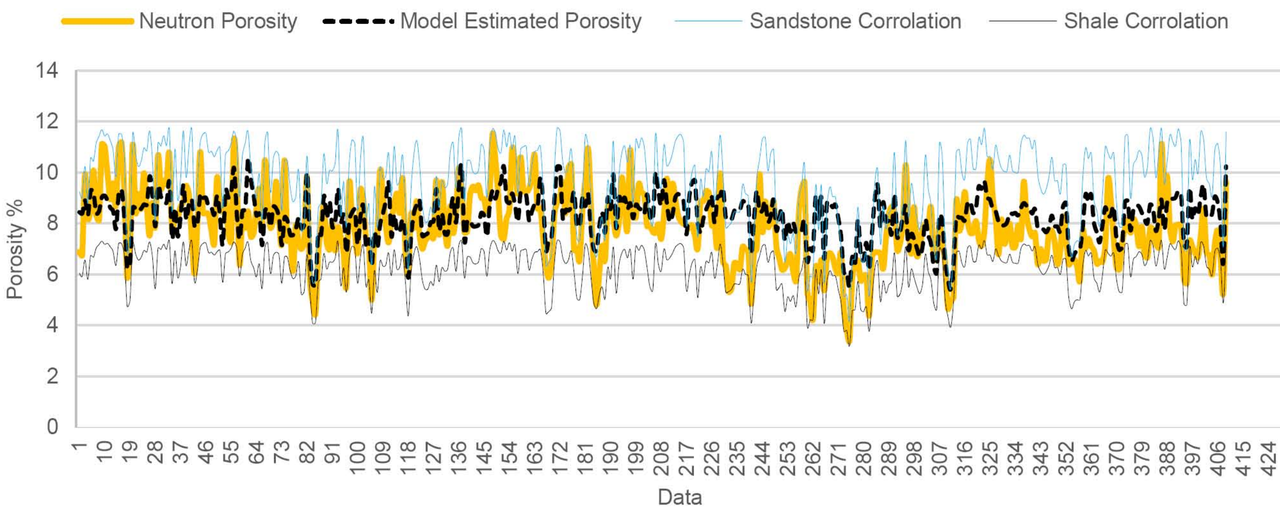

Figure 7—A comparison between model estimated porosity and the sandstone and shale correlations for one of the offset wells

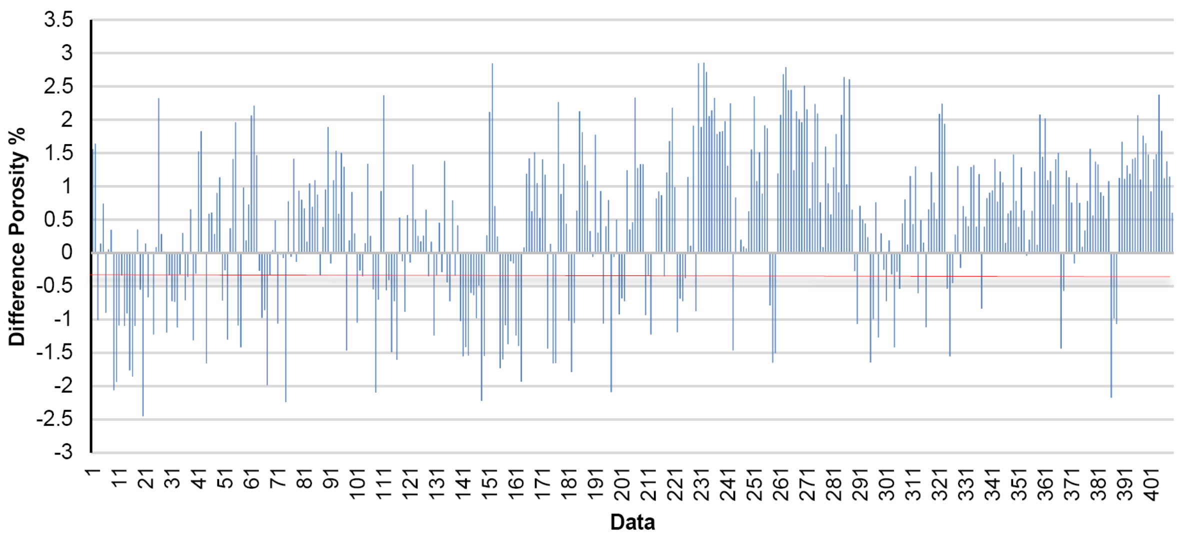

Figure 8—The difference in porosity between the model estimated porosity and the neutron log porosity for each data point for the third offset well

In Fig. 9, the sensitivity of the model is shown. It can be seen that increasing the UCS estimates lower porosity values for constant gamma-ray and is in agreement with the lab data in the Figs. 1 and 2. In addition, the model estimation for porosity increases with decreasing gamma-ray which is in agreement with the expectations. The formations that have lower gamma-ray reading have higher sandstone fractions.

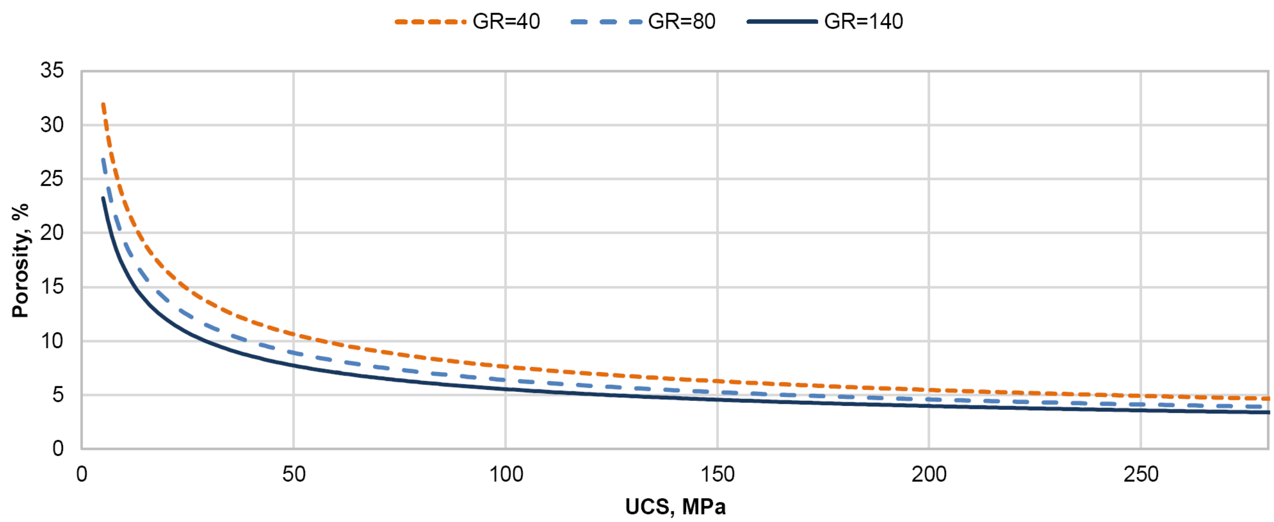

Figure 9—A sensitivity analysis for the model estimated porosity and the pure sandstone and shale porosities

In Fig. 10 the model shale and sandstone lines were compared with the sandstone and shale model correlations. The model gamma-ray was fixed to 40 and 140 for sandstone and shale, respectively. It is seen that the model shale line has a good agreement with the shale correlation, while the model sandstone line makes a good agreement for UCS higher than 60 MPa. In addition, the neutron porosity data from the third well has been plotted in Fig. 10. As it is shown on the plot, all the data are between model shale line and sandstone lines, and that the shandstone and shale correlations roughly satisfy the data. This is due to the fact that the model was developed based on the neutron porosity data, while the sandstone and shale corrolations were found using lab data.

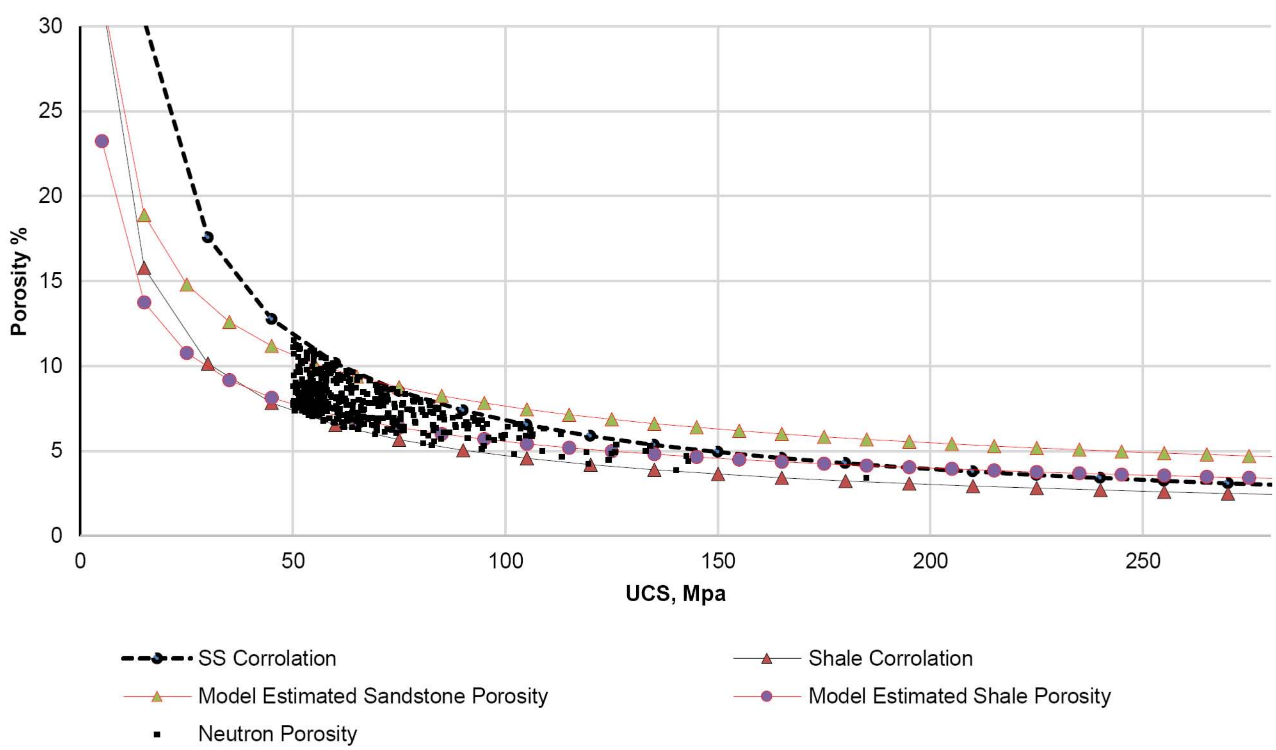

Figure 10—A comparison between model estimated porosity and the sandstone and shale correlations to the neutron porosity values taken from one of the offset wells

Conclusions

The model estimated porosity presented in this paper has many potential advantages. Comparisons between the model estimated porosity and neutron porosity as well as the model estimated porosity and the collected sandstone and shale porosity correlations. Having the ability to determine formation porosity from UCS and GR at the bit can allow for better stimulation design. Because the model porosity estimation uses GR at the bit and UCS found from an inverted ROP model, the potential for real-time application exsists. Compared to previous techniques for determining porosity, the model estimated porosity benefits include: no pressure or temperature effects, reduce the cost of logging or coring, remove time taken for well testing/laboratory testing, and that the measurements are not affected by mud invasion.

Nomenclature

ROP : Rate of Penetration
WOB : Weight on Bit
RPM : Revolution per Minute of the Bit
BR : Back Rake
SR : Side Rake
CCS : Confined Compressive Strength
UCS : Unconfined Compressive Strength
GR : Gamma Ray
SS : Sand Stone
Sh : Shale
F : Weighting factor or scaling factor
CR : Crossover factor
DE : Diffrential Evoluation
W_f : Wear function
h(x) : Hydraulic efficiency function
b(x) : function for the effect of Number of Blades
a_1,b_1,c_1 : Emperical Cofficients
a_s,b_s : Rock strength lithology coefficients
P_e : The difference between the mud hydrostatic pressure and formation pore pressure

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