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State-Of-The-Art in Permeability Determination From Well Log Data: Part 2- Verifiable, Accurate Permeability Predictions, the Touch-Stone of All Models

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Abstract

The ultimate test for any technique that bears the claim of permeability prediction from well log data, is accurate and verifiable prediction of permeability for wells from which only the well log data is available. So far all the available models and techniques have been tried on data that includes both well logs and the corresponding permeability values. This approach at best is nothing more than linear or nonlinear curve fitting. The objective of this paper is to test the capability of the most promising of these techniques in independent (where corresponding permeability values are not available or have not been used in development of the model) prediction of permeability in a heterogeneous formation.

Since the empirical approaches for permeability prediction are mostly directed toward developing mathematical models from given data in particular formations, it has been shown that they lack the required generalization capability for the purposes of this study. These approaches have concentrated on modeling formation permeability as a function of porosity and irreducible water saturation. These models will be briefly discussed. The main focus of this paper will be on two techniques that show potentials in achieving the goal that was mentioned above. These techniques are "Multiple Regression" and "Virtual Measurements using Artificial Neural Networks." For the purposes of this study several wells from a heterogeneous formation in West Virginia were selected. Well log data and corresponding permeability values for these wells were available. In separate tests all data from an entire well were designated and put aside.

The techniques were applied to the remaining data and a permeability model for the field was developed. The model was then applied to the well that was separated from the rest of the data earlier and the results were compared. This approach will test the generalization power of each technique. After all, this is the way that these techniques are used in the real life situations.

The result will show that although Multiple Regression provides acceptable results for wells that were used during model development, (good curve fitting,) it lacks a consistent generalization capability, meaning that it does not perform as well with data it has not been exposed to (the data from well that has been put aside). On the other hand, Virtual Measurement technique provides a steady generalization power. This technique is able to perform the permeability prediction task even for the entire wells with no prior exposure to their permeability profile.

Introduction

In the first part of this paper[1], different methodologies that are available for permeability prediction were thoroughly reviewed. These methodologies can be divided into three categories: empirical, statistical, and neural modeling. In empirical modeling, the approach usually can be summarized by measuring porosity and irreducible water saturation of the cores and developing mathematical models relating porosity and irreducible water saturations to permeability. Next step in this approach is to get the best estimate of porosity and irreducible water saturation from logs and then use them to predict permeability. One of the most important contributions that different investigators[2-7] employing this method have made is the establishment of a relationship between porosity, irreducible water saturation, and permeability. Short comings of this approach can be summarized as follows: to get permeability one needs to know porosity (actually effective porosity, which is the portion of the porosity that is not isolated and is connected to the pore network and is therefore contributing to the flow) and irreducible water saturation. These parameters are most accurately measured in the laboratory using core samples. However, the point is if core samples are available to measure the effective porosity and irreducible water saturation, why not measure permeability instead of predicting it. To overcome this problem, effective porosity and irreducible water saturation is then estimated (calculated) with a certain degree of accuracy from well logs to be used in the empirically developed model. It should be noted that porosity calculated from logs is not necessarily effective porosity and calculating irreducible water saturation from well log responses is not a well-established method. Empirical models developed for certain formation perform poorly when used in other fields[1]. Another problem with this methodology is the fact that almost all investigators, when developing their methods, used all the available data. Once the empirical model was developed, the only measure of it's validity was the goodness of the fit between the empirical model and the data that was used to develop it. In other words, there is no generalization involved with these models.

Statistical models that use multiple regression approach to develop a relationship between log responses and permeability have been around since 1986[8-9]. They perform better on new data than empirical models, and are the subject of investigation in this part of the study. Virtual Measurement technique, which incorporates artificial neural networks to predict permeability values from well log responses have recently been introduced[10-12]. This methodology seems to be the most promising one in the literature. It should be noted that during the literature review authors came across two papers[13-14] that have used neural networks to predict permeability. Techniques implemented in these papers are not being considered as virtual measurement of permeability using geophysical well log responses simply because in both papers it is clearly mentioned that some information from cores have been used in the development process. As it was mentioned before this type of approach defeats the whole purpose of permeability predictions, since it is desired to predict permeability solely by information provided from logs.

In this paper, after preparing the ground rules for comparison, the last two methods, namely multiple regression and virtual measurement, will be compared and the results will be presented and discussed and some conclusions will be made at the end.

Ground Rules

The purpose of this paper is to test the applicability of the two most promising methods for permeability prediction from well logs, namely, multiple regression and virtual measurement. A heterogeneous formation in West Virginia was designated for this test. Granny Creek field produces from Big Injun sand which is a highly heterogeneous formation. Located approximately 25 miles northeast of Charleston, West Virginia, Granny Creek field is structurally situated on the northwest flank of a syncline which strikes N 15-20 degrees east to S 15-10 degrees west. Upper Pocono Big Injun sandstone is the oil producing formation in the Granny Creek field. Development of this field started in 1916 and continued for 30 years. Production throughout the field has been continued until the present day. The crude produced in this field is a paraffin based Pennsylvania Grade oil. It has been estimated that this field has a total production of 6.5 to 6.75 million barrels of oil. A moderately successful water flooding operation was initiated during 1970's and early 1980's. A tertiary recovery CO2 pilot project was conducted beginning in 1976. The Pocono Big Injun sandstone is a well documented heterogeneous formation[15-16].

Eight wells that had both geophysical well log data and core analysis were chosen. Relative location of these wells are shown in Figure 1. The procedure of the test is as follows:

1. Seven of the eight wells are chosen to develop the regression and neural models.

2. The developed models will be applied to the eighth well. Using the eighth well's log data a permeability profile for the well will be predicted.

3. The predicted permeability profile will be compared with actual laboratory measurements of the permeability for this well. The technique that performs better under these circumstances should be the superior method.

4. Steps 1 through 3 will be repeated by substituting the eighth well with one of the seven wells. This is to ensure the robustness of the methods.

Results and Discussions

The eight wells that were used in this study were wells 1107, 1108, 1109, 1110, 1126, 1128, 1130, and 1134. Relative locations of these wells are shown in Figure 1. The approximate distance between wells 1110 and 1134 is about 2 miles. In the first trial, all wells except 1110 were used to develop the multiple regression and virtual measurement models. Variables used for this development were gamma ray, bulk density and deep induction log responses. Once the models were developed they were applied to well 1110. The multiple regression model had the following form:

$$K = 38.2542\ GR^{-0.5874}\ BD^{-40.9438}\ DI^{0.4066} \qquad (1)$$

The neural model developed by virtual measurement technique cannot be represented using mathematical equations. At the present time, the technology by which this type of model may be represented in mathematical equations does not exist. There are methods that enable scientists to extract fuzzy rules from the developed neural model. These rules can relate inputs (log responses) to output (permeability) by a series of fuzzy rules, by dividing the domain of each variable into fuzzy subsets. Implementation of this technique in reservoir characterization is currently under investigation.

The virtual measurement model was developed using a back propagation neural network with 18 hidden neurons in the mid layer, and logistic activation function in all hidden and output neurons. Figure 2 is a cross plot of both models performance against core measurements. Data in this figure are those used to develop the model. Figure 2 shows that in this case multiple regression tends to under-estimate the permeability values. Multiple regression’s coefficient of correlation in Figure 2 is 0.7329 while virtual measurement has a correlation coefficient of 0.9072, where 1.00 is a perfect match. Our experience with multiple regression technique points toward a consistent problem with independent variable’s domain coverage. There are occasions that multiple regression is not able to cover the entire domain of interest and it consistently under-estimate the target variable (Figure 2). In other occasions even when the entire domain of interest is covered during the model development (Figure 4), another problem surfaces during the application phase, where model is applied to new wells. In such cases the model is almost guaranteed to miss those dependent variables (permeability) in the new well that have values beyond the domain that was covered during the model development phase. Such problem can be avoided in virtual measurement technique. Adaptation of neural networks to the knowledge that has been presented to them in form of input-output pairs is one of their strong points. This characteristic sets virtual measurement technique apart from stiff and rigid statistical approaches.

The developed model is then applied to well 1110, keeping in mind that data from this well were not used during the model development. Figure 3 shows the prediction of both models with continuous lines while core measurements are shown using circles. Multiple regression clearly under-estimates higher permeability values, while virtual measurement shows better consistency in following the actual trend in permeability variation. In low permeability range, (from 1871' to 1895' and from 1933' to 1940') multiple regression predicts permeability with good accuracy. In most places in this range, virtual measurement predicts slightly higher permeability than multiple regression, which is closer to core measurements. Although in the bottom part of the interval both methods predict well. High permeability values occur in top of the formation in a thin section at 1870' and then later between 1903' and 1933'. In both cases, virtual measurement's predictions are far closer to core measurements than multiple regression. It is interesting to note the sharp changes in permeability at 1870' and 1903' and how closely virtual measurement's prediction detects the trend and follows it, while the tendency to under-estimate is clear in the multiple regression method.

To ensure that this is not an isolated incident, where virtual measurements method has outperformed multiple regression, the above exercise is repeated. This time, data from well 1110 is put back into data set that is used to develop the model and data from well 1126 is removed from that data set and put aside for testing the models.

Figure 4 shows a cross plot that shows the behavior of both models with respect to the development data set and Figure 5 is the predicted permeability in well 1126 using the developed model. Almost all of the above discussion holds true in this case. Virtual measurement consistently performs better than any other technique that is currently available for predicting permeability from well log responses.

The main reason for virtual measurement's superiority is its use of artificial neural networks. Neural networks, due to their ability to process data in a parallel and distributed fashion can discover highly complex relationships between input and output. Neural network's superior ability in pattern recognition is a known fact, and many disciplines in science and engineering take advantage of these abilities.

Conclusions

Verifiable and accurate permeability prediction from well logs in a well with no core measurement data is the bottom line for any technique that claims the permeability prediction capabilities. Many methods use certain core data such as effective porosity and water saturation to predict permeability.

Other methods use solely log data for this purpose, but do not perform adequately once new data are used. Virtual measurement technique uses neural networks to predict permeability from well log responses. As it was shown, virtual measurement can predict permeability values for entire wells without prior exposure to their log or core data and with accuracies that are unmatched by any other technique. The ability of neural networks to learn from experience and then generalize these learning to solve new problems sets it apart from all conventional methods.

It was shown in this paper that virtual measurement performs better than multiple regression method in predicting permeability from well logs in new wells. It was also shown that this characteristic of virtual measurement technique is not accidental and works for any combination of wells in model development and testing.

Nomenclature

GR = Gamma Ray, API
BD = Bulk Density, gr/cc
DI = Deep Induction, ohm-m^2/m

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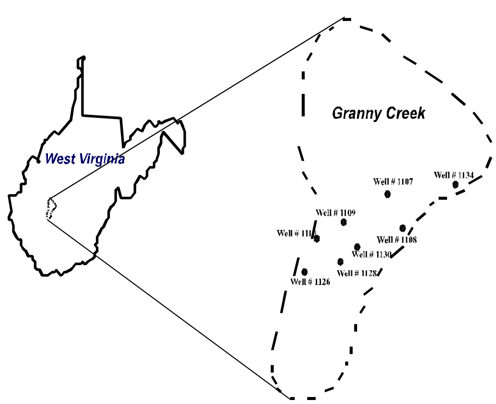

Figure 1. Granny Creek field in West Virginia.

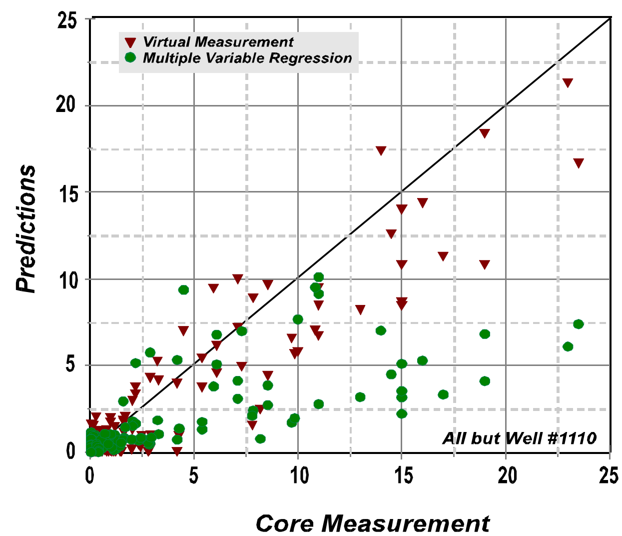

Figure 2. Prediction models permeability values vs. Core measurements. Models developed with all data but those of well #1110.

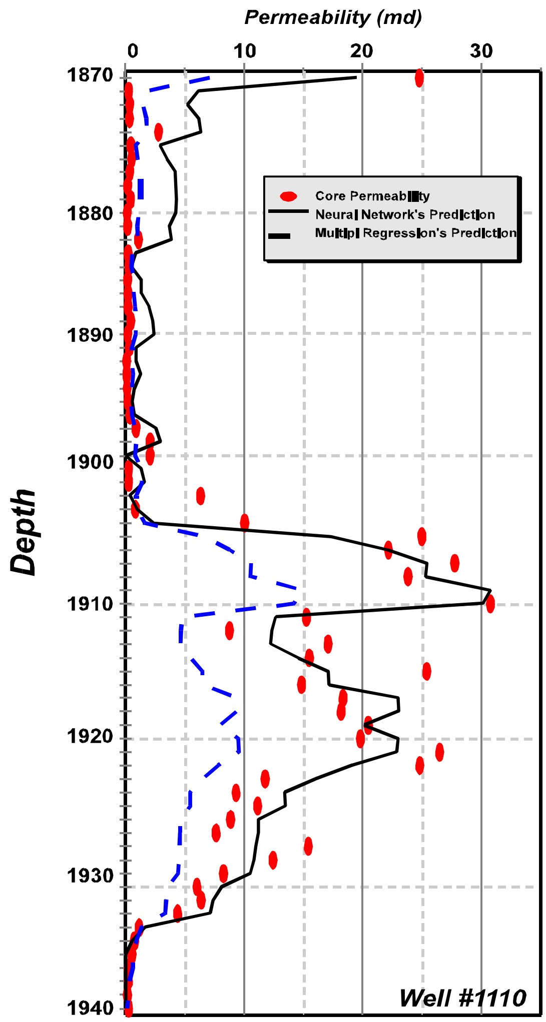

Figure 3. Prediction models permeability values vs. Core measurements for well #1110.

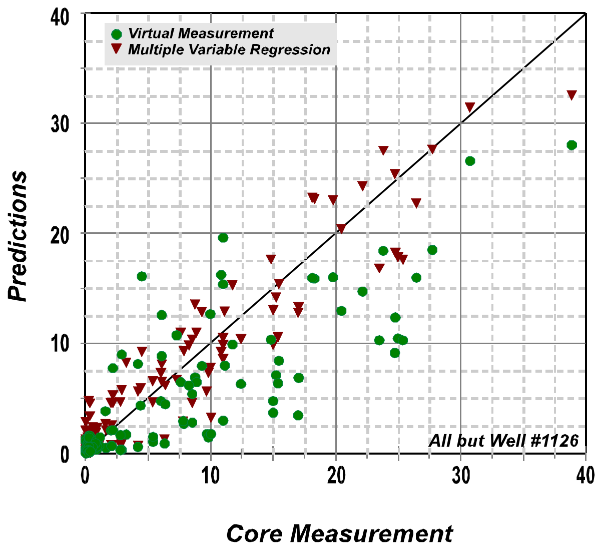

Figure 4. Prediction models permeability values vs. Core measurements. Models developed with all data but those of well #1126.

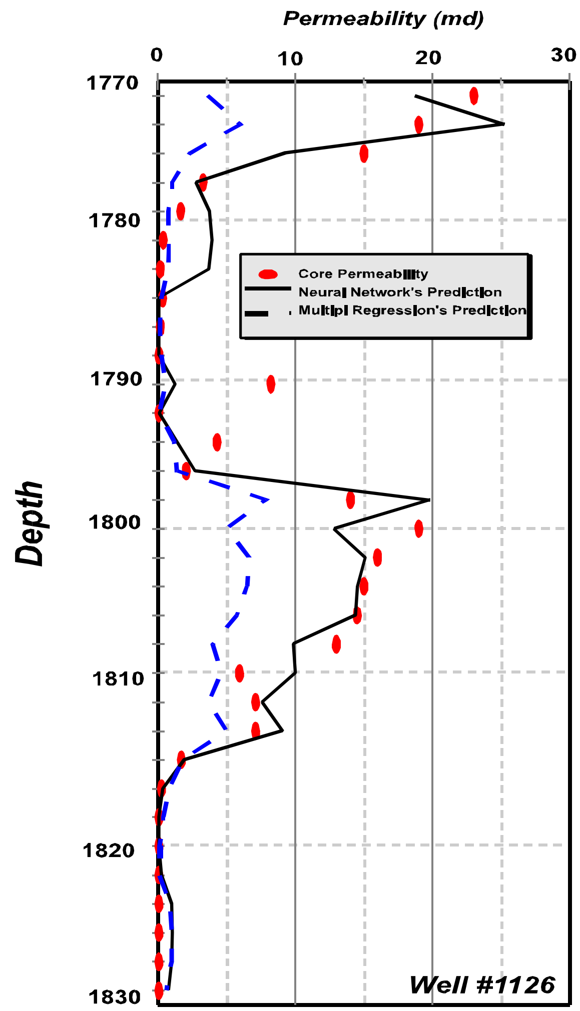

Figure 5. Prediction models permeability values vs. Core measurements for well #1126.