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## State-Of-The-Art in Permeability Determination From Well Log Data: Part 1- A Comparative Study, Model Development

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### Abstract

This study discusses and compares, from a practical point of view, three different approaches for permeability determination from logs. These are empirical, statistical, and the recently introduced “virtual measurement” methods. They respectively make use of empirically determined models, multiple variable regression, and artificial neural networks. All three methods are applied to well log data from a heterogeneous formation and the results are compared with core permeability, which is considered to be the standard.

In this first part of the paper we present only the model development phase in which we are testing the capability of each method to match the presented data. Based on this, the best two methods are to be analyzed in terms of prediction performance in the second part of this paper.

### Introduction

Reservoir characterization is a very important domain of petroleum engineering. An effective management strategy can be applied only after obtaining a detailed and close-to-reality “image” of spatial distribution of rock properties. Among these, the most difficult to determine and predict is permeability.

A great amount of work was done by several investigators<sup>1-10</sup> in the attempt to grasp the complexity of permeability function into a model with general applicability (Table 1). All these studies give a better understanding of the factors controlling permeability, but they also show that it is an illusion to look for a “universal” relation between permeability and other variables.

The regression approach, using statistical instead of “stiff” deterministic formalism, tries to predict a conditional average, or expectation of permeability, corresponding to a given set of

parameters<sup>12-14</sup>. However, the previous empirical studies give the guidelines for selecting the dependent variables which are to be used in the predictor development. A different predictive equation must be established for each new area or new field. The main drawback of this method is that the distribution of the predicted values is more narrow than that of the original data set.

The newest method, called “virtual measurement<sup>18,19</sup>,” makes use of the artificial neural networks, that are model-free function estimators. Because of this characteristic, they are very flexible tools. A back propagation neural network is trained with all the available data, including the measured permeability from cores. This is the “learning” process, during which the network recognizes the pattern of permeability distribution and “adapts” itself in order to be able to predict that pattern.

All three methods mentioned above are applied to log data from a heterogeneous oil-bearing formation and the results are compared with core-determined permeability, which is considered to be not the reality, but the standard.

### 1. Empirical Models

Empirical models are based on the correlation between permeability, porosity, and irreducible water saturation.

Kozeny, 1927. The first equation relating measurable rock properties with permeability was proposed in 1927 by Kozeny:

$$K = A_1 \frac{\phi}{S^2} \quad (1)$$

or

$$K = A_1 \frac{\phi}{S_p^2} \quad (2)$$

and modified by Carman:

$$K = A_1 \frac{\phi^3}{S_o^2 (1-\phi)^2} \quad (3)$$

where:

$A_1$ -empirical constant, known as the Kozeny constant

S -surface area per unit bulk volume  
 $S_p$  -surface area per unit volume of pore space  
 $S_o$  -surface area per unit volume of solid material.

The porosity function  $\phi^3/(1-\phi)^2$  is that measure of rock texture which relates permeability to average grain diameter. These formulations are valid for packs of uniformly sized spheres. Another major drawback is that surface area can be determined only by core analysis, and only with special equipment.

*Archie, 1941.* In his classical paper<sup>1</sup>, though he did not provide a permeability formula, Archie set the basis for quantitative log interpretation. Analyzing the laboratory-determined resistivities of a large number of brine-saturated cores from various sand formations, Archie introduced the concept of “formation resistivity factor” in the form:

$$F = \frac{R_o}{R_w} \quad (4)$$

where  $R_o$  is the 100% water-saturated formation resistivity (ohm-m), and  $R_w$  is the resistivity of the brine (ohm-m). He established that the formation factor, F, is a function of the type and character of the formation, and varies, among other properties, with the porosity and permeability of the reservoir rock:

$$F = \frac{a}{\phi^m} \quad (5)$$

where a is the formation factor coefficient, and m, the “cementation factor,” is the slope of the line representing the correlation under discussion ( $1.8 < m < 2.0$  for consolidated sands). For water saturations down to 0.15 or 0.20, the following approximate equation has been found:

$$S_w^n = \frac{F R_w}{R_t} \quad (6)$$

where  $R_t$  is the resistivity of the formation, and n is the saturation exponent ( $n \cong 2$ ). The cementation factor, m, and the saturation exponent, n, are the biggest sources of uncertainty in permeability determination<sup>3</sup>. They can be obtained by laboratory measurements, which is seldom the case, or approximated according to some general guidelines and/or experience. Methods for deducting the cementation factor have had a long history. We will present here only one method based on the establishment of a “water line” in a zone that is 100% water saturated<sup>15</sup>. In this case, equation 6 becomes:

$$\frac{R_t}{R_w} = \frac{a}{\phi^m} \quad (7)$$

which can be linearized to:

$$\text{Log} R_t = \text{Log}(a R_w) - m \text{Log} \phi \quad (8)$$

or

$$\text{Log} \phi = \left( \frac{1}{m} \right) \text{Log} R_w - \left( \frac{1}{m} \right) \text{Log} R_t \quad (9)$$

if  $a=1$ . Equation 9 describe a line with negative slope  $-1/m$  and the intercept  $(1/m)\text{Log}R_w$ . The line estimates of cementation factor and formation-water resistivity will then be used in the equation 5 for calculation of formation factor and then water saturation in productive zones.

*Tixier<sup>2</sup>, 1949.* Using empirical relationships between resistivity and water saturation, water saturation and capillary pressure, and capillary pressure and permeability, Tixier established a method for determining permeability from resistivity gradients.

$$K = C \left( a \frac{2.3}{\rho_w - \rho_o} \right)^2 \quad (10)$$

$$a = \frac{\Delta R}{\Delta D} \frac{1}{R_o} \quad (11)$$

where:

C is a constant, normally about 20,

$\Delta R$  is the change in resistivity (ohm-m),  $\Delta D$  is the change in depth (ft), corresponding to  $\Delta R$

$\rho_w$  is formation water density ( $\text{g/cm}^3$ ),

$\rho_o$  is hydrocarbon density ( $\text{g/cm}^3$ ).

Equation 10 and 11 can be rewritten as:

$$\left( \frac{K}{20} \right)^{\frac{1}{2}} = \frac{2.3}{R_o (d_w - d_o)} \frac{\Delta R}{\Delta D} \quad (12)$$

The resistivity gradient is determined from a deep investigation tool, lateral or focused logs, and corrected for borehole effects. This method assumes that saturation exponent, n, is equal to 2.0, and that at any water saturation, capillary pressure is related to permeability in the manner:  $P_c = f/(K)^{1/2}$ . The model is physically limited in scope by the relative paucity of logs exhibiting valid oil-water contacts and the necessity for estimating the hydrocarbon density as it exists in the reservoir. Also, the calculated permeability is an average for the zone corresponding to the resistivity gradient.

Following the work of Wyllie and Rose<sup>3</sup>, Tixier developed a simpler model that is used more often than equation 12:

$$K^{\frac{1}{2}} = 250 \frac{\phi^3}{S_{wi}} \quad (13)$$

In this study we have used this equation as Tixier model.

*Wyllie & Rose<sup>3</sup>, 1950.* In their thorough analysis of the theoretical basis of quantitative log interpretation, Wyllie & Rose expanded the empirical relationship proposed by Tixier, based on the following assumptions:

-tortuosity, T, applicable to fluid flow of the wetting phase in a porous media is the same as the tortuosity affecting electrical conductivity through the fluid in the same media.

-irreducible water saturation  $S_{wi}$  is a straight line function of grain surface area.

-minimum water saturation computed in a reservoir is equal to the irreducible water saturation  $S_{wi}$ .

Their model is:

$$K = \text{Constant} \left[ \frac{1}{P_c^2 F^{(2-\frac{1}{m})} S_w} \right] \quad (14)$$

where the constant is equal to  $(21.2)d^2/t_s$ , for K in millidarcies, capillary pressure,  $P_c$ , in psi, and interfacial tension,  $d$ , in dynes/cm. The pore shape factor,  $t_s$ , lies between 2.0 and 2.5 and may be taken 2.25. When  $P_c$  is unobtainable (i.e., in the absence of an oil-water contact in the reservoir), they suggested the following correlation:

$$S_{wi} = C \left[ \frac{1}{K^{1/2} F^{0.67}} \right] + C' \quad (15)$$

where:

C-textural constant with dimension of a length (which is of the form  $\phi^3/(1-\phi)^2$ ).

C'-dimensionless constant which is related to percent of bound water due to clay content of the reservoir rock. For clean sand  $C'=0$ .

Wyllie & Rose pointed out that "the value of K deduced from these equations cannot, however, be expected to have more than an order of magnitude significance."

Sheffield<sup>4</sup>, 1956. Based on Kozeny's equation and following the establishment of a correlation coefficient for some well-known water-wet sands, Sheffield proposed the following correlation for permeability:

$$K = \frac{1}{2F} \left( \frac{\phi}{1-\phi} \right)^2 \frac{1}{S_{wi}^2} \quad (16)$$

He suggested that this model is valid only for clean sands.

Pirson<sup>4</sup>, 1963. The permeability formula proposed by Pirson is:

$$K = \left( \frac{850,000}{API Gravity} - 3.5 \text{depth, ft} \right) \frac{R_w^2}{FR_o R_{ti}} \quad (17)$$

where K is obtained directly in darcies. This empirical relationship was determined by multiple correlation from relatively few data. The formula should not be used for high gravity crudes (API > 40°) and for depths greater than 6500 ft.

Timur<sup>5</sup>, 1968. Based on the work of Kozeny and Wyllie & Rose, Timur proposed a generalized equation in the form:

$$K = A \frac{\phi^B}{S_{wi}^C} \quad (18)$$

that can be evaluated in terms of the statistically determined parameters A, B, and C. He applied a reduced major axis (RMA) method of analysis to data obtained by laboratory measurements conducted on 155 sandstone samples from three different oil fields from North America. Based both on the highest correlation coefficient and on the lowest standard deviation, Timur has chosen from five alternative relationships the following formula for permeability.

$$K = 0.136 \frac{\phi^{4.4}}{S_{wi}^2} \quad (19)$$

and for residual water saturation:

$$S_{wi} = 3.5 \frac{\phi^{1.26}}{K^{0.35}} - 1 \quad (20)$$

with a standard error of 13% pore volume.

This model is applicable where condition of residual water saturation exists. Timur also assumed that a value of 1.5 for the cementation factor,  $m$ , holds in all cases.

Coates & Dumanoir<sup>6</sup>, 1974. An improved empirical permeability technique has been proposed by Coates & Dumanoir:

$$K^{1/2} = \frac{C}{w^4} \frac{\phi^{2w}}{R_w/R_{ti}} \quad (21)$$

where:

$$C = 23 + 465\rho_h - 188\rho_h^2 \quad (22)$$

and:

$$w^2 = (3.75 - \phi) + \frac{1}{2.0} \left[ \log_{10} \left( \frac{R_w}{R_{ti}} \right) + 2.2 \right]^2 \quad (23)$$

With the support of core and log studies, they adopted a common exponent,  $w$ , for both the saturation exponent,  $n$ , and cementation exponent,  $m$ .

$$m = n = w \quad (24)$$

Equations 21, 22, and 23 are valid for clean, oil-bearing formations, with oil density equal to 0.8. When the hydrocarbon has a density appreciably different from 0.8, the log readings of  $R_{ti}$  are multiplied, before entering equation 23, by the correction factor given by:

$$\frac{R_{tcorr}}{R_{tlog}} = 0.077 + 1.55\rho_h - 0.627\rho_h^2 \quad (25)$$

Coates & Dumanoir also presented a methodology for testing if the formation is at irreducible water saturation. However, they note that if the reservoir is heterogeneous, it may fail that test and still be at irreducible water saturation. If a formation is not at irreducible water saturation the assumed value of  $R_i$  from the log is less than  $R_{ti}$ , and the resulting  $w$  from equation 23 is in error. To overcome this, they classified the formation rocks in three lithological classes (table 1 of their paper). An empirical relation was then established between the clean matrix density ( $\rho_{gcn}$ ), rock classification, and  $R_i$ :

$$(R_w/R_t)_{cn} = (\phi S_{wirr})_{cn}^w = \frac{10^{-6}}{G(\rho_{gcn} - 2.6)^3} \quad (26)$$

where  $G$  is a coefficient involving the matrix classification. The corrected value of  $(R_w/R_t)_{cn}$  derived from equation 26 for a clean formation is used in place of  $R_w/R_{ti}$  in equation 23 to determine  $w$  when the formation is not at irreducible water saturation.

Another correction that Coates & Dumanoir provided is for shaly formations:

$$\frac{R_w}{R_{ti}} = \frac{R_w V_{sh}}{\phi R_{sh}} (\phi S_{wirr})_{cn} + \frac{(\phi S_{wirr})_{cn}^w}{(1 - V_{sh})^{w-1}} \quad (27)$$

This value of  $R_w/R_{ti}$  is entered in equation 23 to obtain  $w$ .

The method of Coates & Dumanoir is the first that satisfies the condition of zero permeability at zero porosity and when  $S_{wirr} = 100\%$ . Because of the corrections provided, this method can be applied to formations that are not at irreducible water saturation, and to shaly formations. Values for the exponents  $m$  and  $n$  are not needed because they are found as a result of the computation.

*Coates<sup>7</sup>, 1981.* Coates and Denoo proposed the following formula for permeability determination:

$$K^{1/2} = 100 \frac{\phi^2 (1 - S_{wirr})}{S_{wirr}} \quad (28)$$

where  $K$  is in millidarcies.

This formula also satisfies the condition of zero permeability at zero porosity and when  $S_{wirr} = 100\%$ . The formation must be at irreducible water saturation.

## 2. Multiple Variable Regression

Multiple regression is an extension of the regression analysis that incorporates additional independent variables in the predictive equation. Here, the model to be fitted is:

$$Y = B_0 + B_1 X_1 + B_2 X_2 + \dots + B_p X_p + e \quad (29)$$

where  $Y$  is the dependent variable,  $X_1, X_2, \dots, X_p$  are the independent random variables and  $e$  is a random error (or residual) which is the amount of variation in  $Y$  not accounted for by the linear relationship. The parameters  $B_1, B_2, \dots, B_p$ , called regression coefficients, are unknown and are to be estimated.

Taking the expectation of both sides of equation 29, we have:

$$E(Y | X_1, \dots, X_p) = B_0 + B_1 X_1 + B_2 X_2 + \dots + B_p X_p \quad (30)$$

where the expected value of the errors is zero. In this representation  $E(Y | X_1, \dots, X_p)$  is the conditional mean, or expected value of  $Y$ , given  $X_1, X_2, \dots, X_p$ . We can write the assumed relationship between  $Y$  and  $X_1, X_2, \dots, X_p$  as:

$$Y = E(Y | X_1, \dots, X_p) + e \quad (31)$$

where by  $Y$  on the left-hand side of equation 31 is meant  $Y$  given  $X_1, X_2, \dots, X_p$ .

The aim here is to estimate regression coefficients and thus  $E(Y | X_1, \dots, X_p)$  or  $Y$  in terms of the  $N$  observations. There are many accessible software packages that can solve this problem. In this study, the dependent variable  $Y$  is the logarithm of permeability - since permeability seems to be lognormal- and the independent variables  $X_1, \dots, X_p$  are well log variables. In their paper<sup>4</sup>, Wendt and Sakurai established a general procedure for permeability prediction by multiple variable regression. They also pointed out the shortcomings of using this technique. When the regression method is used for prediction, the distribution of predicted values is more narrow than that of the original data set. Kendall and Stuart<sup>15</sup> explained this, stating that the regression model "does not purport to represent a functional relation between mathematical variables or a structural relation between random variables; it either exhibits a property of a bivariate distribution or, when the regressor variables are not subject to error, gives the relation between the mean of the dependent variable and the value of the regressor variables." That is, the regression provides the best estimate on the average. The ability of a regression model to predict the permeability extremes is enhanced through a weighting scheme of the high and low values. But because of this, the predictor can become unstable and also statistically biased. The assumption that the error is related only to the dependent variable (permeability measurements) and not to the independent variables (log variables), can be verified by comparing repeat runs of properly calibrated instruments with the main runs of the logs, provided that there is no bias in the measurement. Logs of acceptable quality have errors with a relatively small unbiased scatter that is a function of the physics of the tool, its response characteristics, and the borehole environment. If the deviations are indeed random, then they would be expected to be normally distributed with a mean value of zero.

In the analysis of real logging data several initial remedial steps should be taken in order to maximize the validity and value of the analysis results<sup>15</sup>:

-the data should be environmentally corrected for systematic borehole effects;

- the logs should be shifted wherever necessary to ensure common depth registration;
- the logs should have a common vertical resolution, a compatibility requirement that may involve smoothing of finer resolution measurement;
- preferably, the logs should be zoned, with data sampled from peak and through extremes, to reduce extraneous errors introduced by transitional curve features.

After these steps are completed, the correlation matrix of all independent and dependent variables should be analyzed, to establish if there is a dominant X-variable, or if the X's are essentially uncorrelated with each other. This gives to the analyst some guidelines for selecting the variables and the order in which they should enter the model. However, sensible judgment is still required in the initial selection of variables, and also in the critical examination of the model through analysis of residuals.

### 3. Virtual Measurement Technique

There are many examples of neural network applications in the petroleum industry<sup>16</sup>, from exploration, reservoir and production engineering, drilling operations, to neural network-based models of chemical plants. These systems are in various stages of development, from prototypes to production systems.

Neural networks, unlike conventional programs, are general purpose systems that attempt to achieve good performance by dense interconnection of simple computational elements. For this reason they are also called connectionist models. The solution to a problem is not explicitly encoded in the program, but is "learned" by supplying examples of previously solved problems to the network. After the network has learned how to solve the example problems, it is said to be "trained." This is called "supervised training." New data from the same knowledge domain can then be input to the trained neural network that then outputs a solution. There are also neural networks that "learn" unsupervised, like Kohonen's self-organizing map network.

Virtual measurement technique was applied successfully in determination of permeability from well log data<sup>17-20</sup>. In this study we are applying this technique to a real data set and compare the results with those obtained by means of previously discussed methods.

The major advantage of neural network solution for this problem is that it does not need all the parameters and the relationship between these parameters to be explicitly specified. Since the neural networks "learn" to solve problems through examples, they are especially suited for subjective and interpretative processes that humans can easily perform intuitively, but which we cannot describe in terms of an algorithm or set of equations.

### Application to Heterogeneous Formation

To apply all three previously discussed methods we have chosen core and log data from eight wells in Granny Creek Field in West

Virginia. Figure 1 shows the Granny Creek Field and the location of the eight wells (1107, 1108, 1109, 1110, 1126, 1128, 1130 and 1134) that have been used in this study. This field is a well documented<sup>21-23</sup>, highly heterogeneous reservoir that has produced from the Big Injun sandstone since early the 1900's. Only Gamma Ray, Deep Induction, and Density logs were available for all the eight cored wells. Because of space considerations, we will present the data and the results for only one well, 1107. Data and results for the other seven wells are available upon request. Figure 2 shows the log and core data for this well. All the well logs are compatible in terms of depth and resolution and are corrected for different effects.

### Empirical models

The four latest methods, Tixier, Timur, Coates & Dumanoir, and Coates, were applied to log data from the eight chosen wells. Before that, several steps were performed:

1. Determination of porosity from the density log. Figure 3 shows a good agreement between log-determined and core-determined porosity for this well.
2. Estimation of formation factor. Knowing that permeability is very sensitive to the cementation factor,  $m$ , we have tried to find a consistent value for this parameter. This can be done by establishing a "water line" in a 100% water saturated zone (Figure 4b). The slope of this line is 0.504247, which yields  $m = 1.98316$ . The resulting formation factor is plotted against porosity in Figure 4c.
3. Determination of water saturation. We assumed a value of  $n = 2$  for the saturation exponent. Cross plot of porosity against water saturation for the well 1107 is presented in Figure 4d.

Having done these steps, now we can determine permeability as a function of computed porosity and water saturation. Figure 5 presents the computed permeability along with core-determined permeability versus depth. Figure 6 shows the cross plots of log and core permeability for each method. From these figures it is clear that permeability is overestimated by all empirical models. The best method seems to be Coates & Dumanoir (equation 17). This model provides a correction to account for formations that are not at irreducible water saturation. The presence of the G factor (which is related to lithological classification) in the denominator of equation 26 has a great influence on the values of permeability. This factor can subjectively be adjusted by the analyst. Thus, the bigger the G, the smaller the permeability.

The fact that permeability is log normal does not mean that if we obtain a good match in log scale we have achieved our objective. Figure 7 is an example. Looking at the graph with log scale one can be quite enthusiastic. Unfortunately, the distance D on this graph turns to be unacceptable (more than 70 md) when we look at the graph with normal scale. Therefore, logarithmic representation of the results (as it is done in many papers) can be deceiving.

### Multiple variable regression

Using the same data we developed several permeability models by means of multiple variable regression for each well. Based on the correlation matrix (Table 2, for well 1107), we have chosen the order in which the log variable enter the model: Bulk Density (BD), Deep Induction (DI), and Gamma Ray (GR). The best regression equation has been chosen by Forward Selection Procedure<sup>13</sup>. During this procedure new independent variables enter the equation. The following combination were tried: BD, DI; BD, GR; BD, DI, GR. The best results were obtained in the last case. The final permeability model for well 1107 is:

$$k = C_0^1 * BD^{C_1} * DI^{C_2} * GR^{C_3} \quad (32)$$

where  $C_0^1 = \exp(C_0)$ , and for well 1107,  $C_0=46.194$ ,  $C_1=-60.8094$ ,  $C_2=1.7972$ , and  $C_3=0.7615$ . These coefficients are determined by regression. The correlation coefficient for this well is 0.62. Figures 8 and 9 present the computed permeability and core permeability versus depth, and a crossplot of these variables, for well 1107. The fitting is much better than any of the empirical models. As we have already stated, the regression model gives the best results on the average. Table 3 shows the arithmetic and geometric means for all methods discussed in this paper, for well 1107.

### Virtual Measurement Technique

To achieve the aim of this study we have developed a three-layer back propagation neural network with 18 hidden neurons in the mid layer, and logistic activation function in all hidden and output neurons. The results are presented in Figures 10 and 11. As one can see, this method provides the best match between core permeability and log permeability. Because of its massive parallel computing characteristic and learning-by-example capability, the neural network can easily adapt to any new situations. While the regression tends to average the response, the neural network can match any peak in the permeability profile. There is no mathematical model to describe the trained network. It can be defined only by its topology (number of layers and neurons in each layer) that define the number of interconnections, and the strength of these interconnections.

### Conclusions

All three methods, empirical, multiple regression, and virtual measurement, were applied to log data from a heterogeneous formation. The results show that the last two techniques perform better than empirical models, which can be used only to obtain an order of magnitude for permeability. While multiple regression still has a few drawbacks that were previously mentioned, the virtual measurement technique seems to be an ideal tool, if used properly, for permeability determination from logs. A major advantage of both regression and neural network applications is that they do not require other parameters to be previously computed, as empirical models do (porosity and water saturation). They are also not affected by the uncertainty introduced by the cementation factor and saturation exponent. Because these two approaches were proved to be the best, they will be studied in terms of prediction capabilities in the second part of this paper.

### Nomenclature

$A_1$	-Kozeny constant
BD	-bulk density
DI	-deep induction
F	-formation factor
G	-coefficient related to matrix classification
GR	-gamma ray
K	-rock permeability
m	-cementation factor
n	-saturation exponent
$P_c$	-capillary pressure
$R_o$	-100% water-saturated formation resistivity
$R_{sh}$	-shale resistivity
$R_t$	-formation resistivity
$R_{ti}$	-formation resistivity at irreducible water saturation
$R_w$	-brine resistivity
S	-surface area per unit bulk volume
$S_p$	-surface area per unit volume of pore space
$S_o$	-surface area per unit volume of solid material
$S_w$	-water saturation
$S_{wi}$	-irreducible water saturation
$V_{sh}$	-volume of shale
w	-exponent, $w=m=n$
$\phi$	-rock porosity
$\rho_w$	-brine density
$\rho_o$	-hydrocarbon density
$\rho_{gcn}$	-clean matrix density

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**Table 1.**

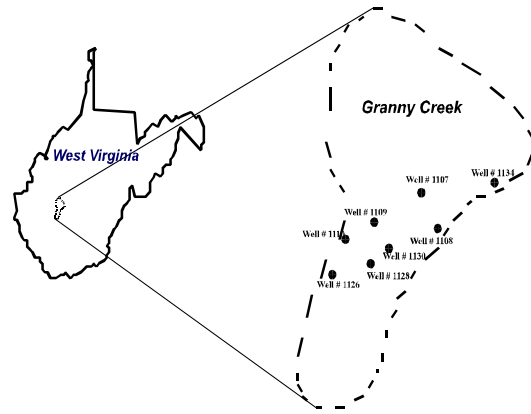
Author(s)	Year
KOZENY	1927
TIXIER	1949
WYLLIE & ROSE	1950
SHEFFIELD	1956
PIRSON	1963
TIMUR	1968
COATES & DUMANOIR	1974
COATES	1981

**Table 2.**

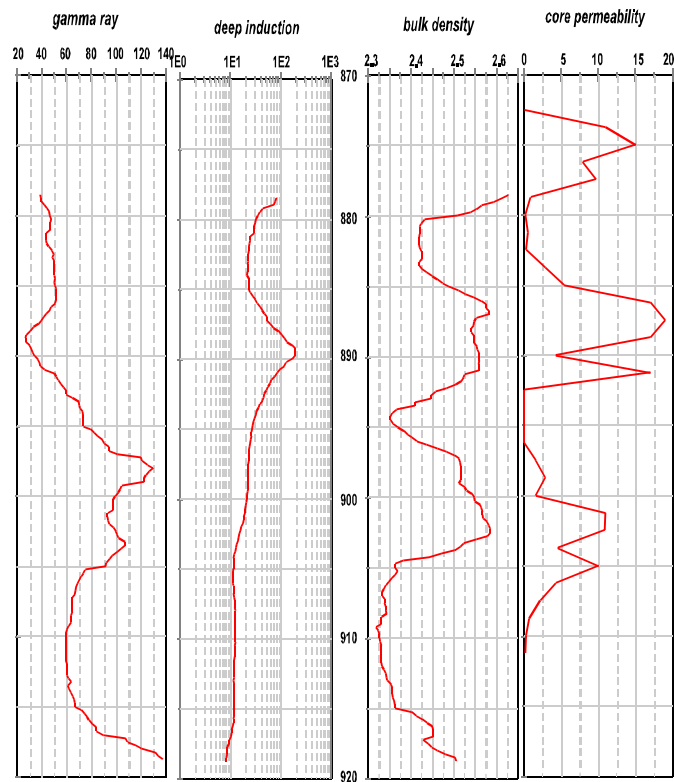
Correlation matrix	Gamma Ray	Bulk Density	Deep Induction	Core Permeability
Gamma Ray	1.00	0.03	-0.5418	-0.0714
Bulk Density	0.03	1.00	0.5556	-0.4615
Deep Induction	-0.5418	0.5556	1.00	-0.1902
Core Permeability	-0.0714	-0.4615	-0.1902	1.00

**Table 3.**

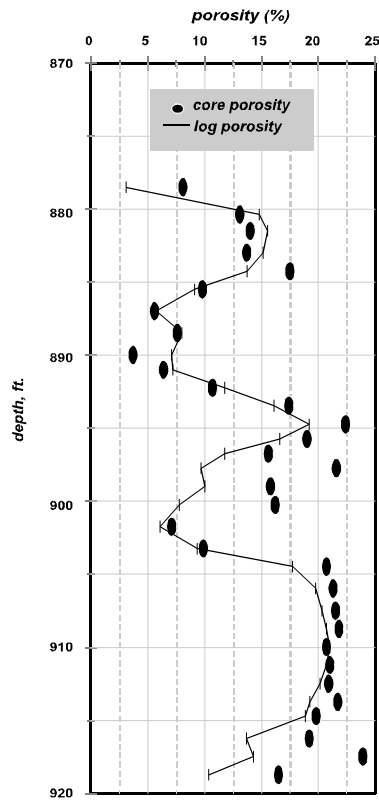
	Arithmetic Mean	Geometric Mean
Core	5.57	1.64
Tixier	15.67	1.62
Timur	30.4	5.94
Coats & Dumanoir	9.14	0.95
Coats	34.95	5.41
Multiple Regression	4.3	1.64
Virtual Measurement	6.13	3.0



**Figure 1.** Granny Creek field in West Virginia.



**Figure 2.** Log and core data for well #1107



**Figure 3.** Log and core porosity for well #1107

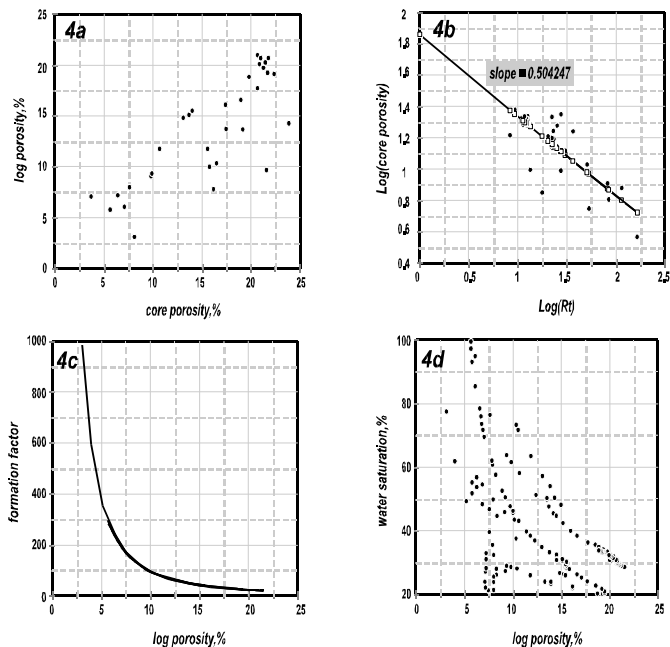


Figure 4. Characteristics of well #1107

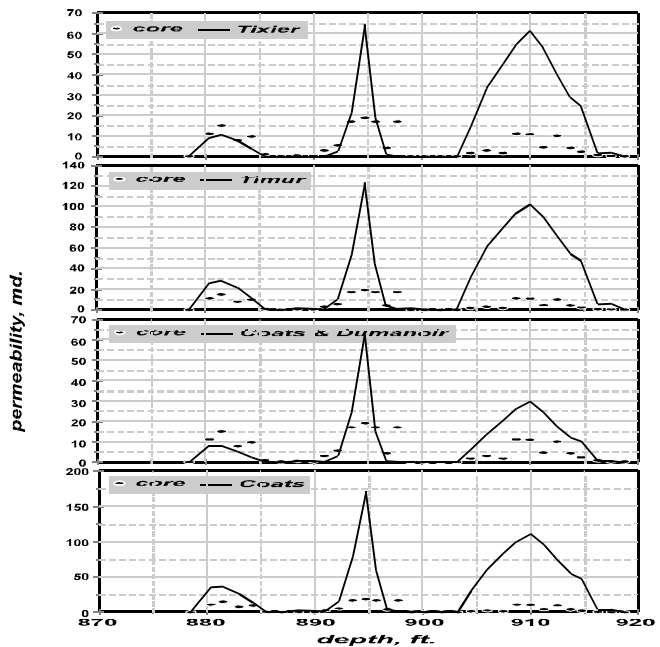


Figure 5. Core and computed permeability for well #1107

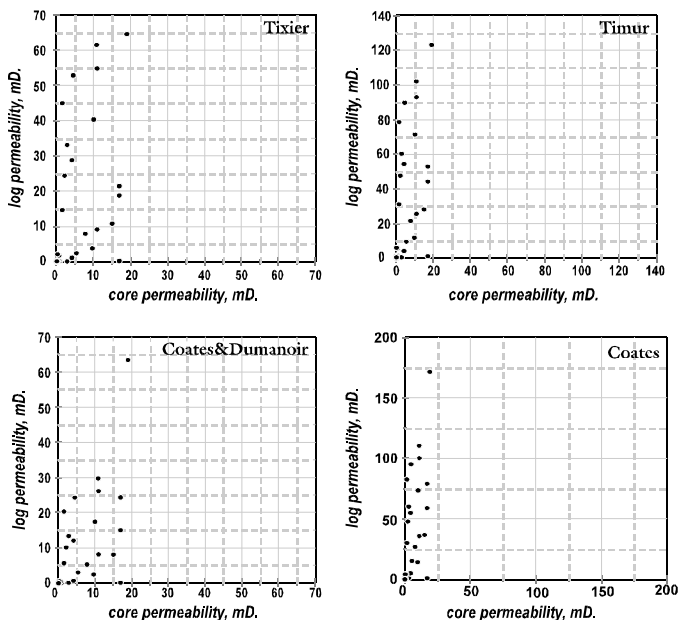


Figure 6. Computed Permeability versus core permeability for well #1107.

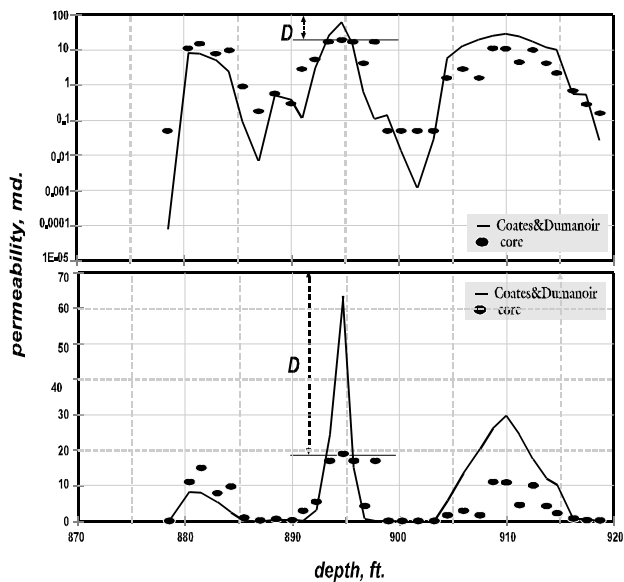


Figure 7. Logarithmic and normal scales for permeability representation.

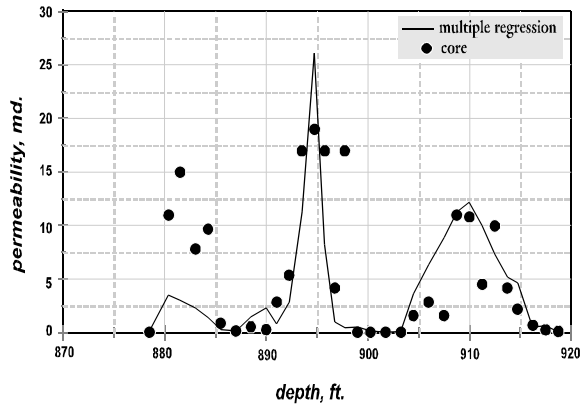


Figure 8. Core and computed permeability for well #1107.

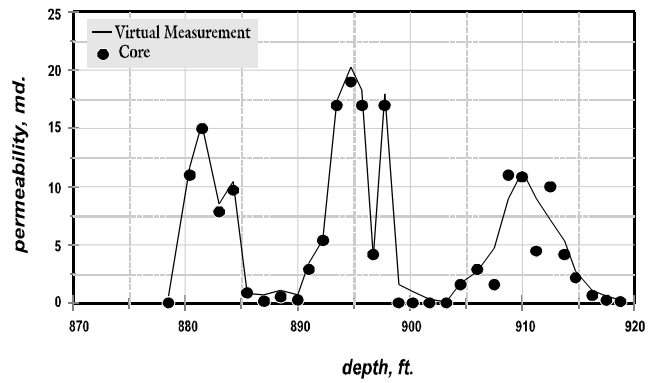


Figure 10. Core and computed permeability for well #1107.

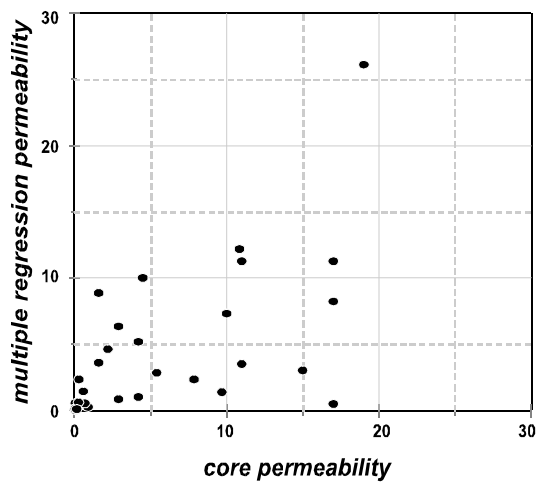


Figure 9. Core permeability versus computed permeability for well #1107.

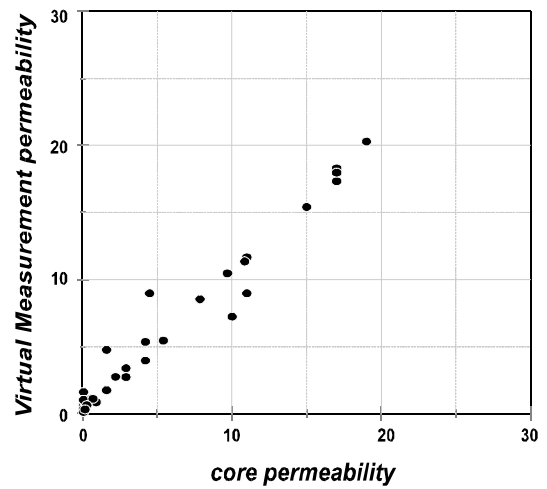


Figure 11. Core permeability versus computed permeability for well #1107.