Improved Permeability Estimates in Carbonate Reservoirs Using Electrofacies Characterization: A Case Study of Mumbai High South*

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Abstract

Electrofacies Characterization is a simple and cost-effective approach to obtaining permeability estimates in heterogeneous carbonate reservoirs using commonly available well logs. Permeability is one of the most important characteristics of hydrocarbon bearing formations in a reservoir. Formation permeability is often measured directly from core samples in the laboratory or evaluated from the well test data. The first method is very expensive. Moreover, the well test data or core data are not available in every wells in a field, however majority of wells are logged. Permeability determination is an active research area in petroleum industry as there is no direct formula for calculation of permeability from logs.

In this paper, we proposed a two-step approach. First, we classify the well-log data into electrofacies types. This classification does not require any artificial subdivision of the data population but follows naturally based on the unique characteristics of well-log measurements, reflecting minerals and lithofacies within the logged interval. A combination of principal component analysis (PCA), model-based cluster analysis (MCA), and discriminant analysis is used to identify and characterize electrofacies types. Second, we apply nonparametric regression techniques, the Alternating Conditional Expectation (ACE) algorithm, to predict permeability using well logs within each electrofacies. Such techniques are completely data-driven and do not require a priori assumptions regarding functional forms for correlating permeability and well logs. We applied the proposed technique to a highly heterogeneous carbonate reservoir in the Mumbai High South for generation of permeability transform. Such developed permeability transform by the aforementioned technique can solve problems for estimating continuous permeability profiles more accurately in uncored wells.

This approach appears to result in better permeability predictions, leading to an enhanced reservoir characterization based on flow, permeability (rather than storage), or porosity in Mumbai High South. This can have potential benefits both in daily operations and in reservoir simulation efforts. This application also envisages the power and versatility of electrofacies characterization in improving reservoir descriptions in complex carbonate reservoirs.

Introduction

Carbonate reservoirs throw challenges to geologists to characterize due to their heterogeneous tendency for depositional and diagenetic processes. The petrophysical heterogeneity of carbonate reservoirs is demonstrated by the wide variability observed in porosity-permeability cross-plots. Knowledge of permeability is significant for developing an effective reservoir description and quality. Formation permeability controls the requirements in involving well completions, stimulations and reservoir characterization. Since not all the wells are cored, permeability also can be obtained from well tests and well logs. The well logs, where one can use porosities, are generally utilized for predictions.

Characterization of carbonate reservoirs into flow units is a practical way of reservoir zonation. The presence of distinct units with particular petrophysical characteristics such as porosity, permeability, water saturation, pore radius, storage and flow capacities help to establish strong reservoir characterization. A quality and the future performance of a reservoir are controlled by hydrocarbon storage and flow capacity.

The purpose of present study is to develop a methodology for the permeability prediction of an oil field using conventional logs. In this study the Efacies and Grace Softwares are used for electrofacies determination and permeability prediction respectively from well log responses in consistent with depth. The Alternating Conditional Expectation (ACE) algorithm for data correlation and integration is use in the GRACE software. In present paper describes a two-step approach for permeability prediction that utilizes non-parametric regression with multivariate statistical analysis.

Methods of Applications

A. Data Correlation and Integration

We propose a two-step approach to permeability prediction that utilizes non-parametric regression in conjunction with multivariate statistical analysis. At First, we classify the well logs into electrofacies types. A combination of principal component analysis and model-based cluster analysis is used to characterize and identify electrofacies types. Secondly, we apply non-parametric regression techniques to predict permeability using well logs within each electrofacies.

B. Electrofacies Determination

The method used to perform the electrofacies classification is based on attempts to identify clusters of well log responses with similar characteristics. This classification of electrofacies in our study is done by Efacies Software discussed below:

Efacies is a Windows-based software for electrofacies characterization based on the multivariate analysis from well logs. Generally, a suite of well logs can provide valuable but indirect information about mineralogy, texture, sedimentary structure, fluid content and hydraulic properties of a reservoir. The distinct log responses in the formation represent electrofacies that very often can be correlated with actual lithofacies identified from cores, based on depositional and diagenetic characteristics. The importance of electrofacies characterization is reservoir description and management has been widely recognized. In this software, the calculation is done by Fortran 77 and the graphical interface is done by C++. There are three types of analysis are done by this software:

Step 1: Principal Component Analysis

Principal component analysis (PCA) is used to summarize the data effectively and to reduce the dimensionality of the data without a loss of significant information. First, to minimize the effects of scales and units of log variables, logs are standardized by subtracting from each reading the mean and dividing by the Standard deviation.

Step 2: Cluster Analysis

Cluster analysis is done for classify a data set into groups that are internally homogeneous and externally isolated based on a measure of similarity and dissimilarity between groups. In this study, model-based clustering technique is used. This approach can give much better performance than traditional procedures of clustering techniques, which are often fail to identify groups that are either overlapping or of varying sizes and shapes. Another advantage of model-based approach is that there is an associated Bayesian criterion for assessing the model. This provides a means of selecting not only the parameterization of the model, but also the number of the clusters without the subjective judgments.

The key idea of model-based clustering is that the data are generated by a mixture of underlying probability distribution. The identified clusters can be viewed as distinct electrofacies groups that reflect the hydrologic, lithologic, and diagenetic characteristics. If we have sufficient extra information viz. core observations or geological insight, the identified electrofacies groups could be calibrated to ensure their interpretable geological meaning.

Step 3: Discriminant Analysis

Discriminant Analysis is a multivariate method for assigning an individual observation vector to two or more predefined groups based on measurements. This method is actually termed linear discriminant analysis. The discriminant analysis requires prior classification of the data into relatively homogenous subgroups whose characteristics can be described by the statistical distributions of the grouping variables associated with each subgroup. Typically, the classification is performed by defining the distinct groups based on the unique characteristics of well log measurements or by applying known external geologic criteria such as core-derived lithofacies information. However, because in many situations a training dataset with absolutely known classifications is not easily obtained, a method like model-based cluster analysis is commonly used. In our analysis, group-specific probability density functions were determined by the distinct electrofacies groups defined in the model-based cluster analysis using a training dataset.

The Ace Algorithm

Once the electrofacies are identified, the next step is to develop correlations between permeability and well log responses for each electrofacies. We use non-parametric regression techniques that do not require a priori assumptions regarding functional forms to model the data. Thus, it provides a powerful tool for exploratory data analysis and correlation. In present study, specifically we utilize the ACE technique to examine our data by GRACE software for permeability prediction from different well logs.

Results and Discussions

In present paper, the proposed technique has been considered to a highly heterogeneous carbonate reservoir in the Bombay high basin of Bombay offshore field, western India. Figure 1 shows the location of Mumbai High. In this study, we are focusing on the Southern part of the Bombay High area with the data of three wells. Stratigraphically the field can be subdivided into several vertical zones based on paleontological and wireline data correlations. The sedimentary section of Bombay High can be classified into three major units (1) the basal sand, lignite and clays (2) the middle limestone and intercalated shale and (3) the upper shale and claystone.The L-III limestone of Early Miocene age occurs at an average depth of about 1300 m. It is the main pay zone and has a thick gas cap over the crestal part of the field. The GOC occurs at two different subsea depths in the northern and southern blocks of Mumbai High structure.

The northern and southern pools are separated by an E-W trending permeability barrier. Generalized stratigraphy of MH field is shown in Figure 2. The present study has been performed by using four-step procedure as discussed below:

Step 1: Data Preparation

The well log data considered in this analysis has been gathered from three wells (Well A, Well B and well C). In this field, we use seven well logs of 847 sample data along with there corresponding depth for characterizing the electrofacies groups. The used well logs are: Gamma ray (GR), resistivity (LLD), neutron (NPHI), density (RHOB), water saturation (SUWI), volume of clay (VCL) and log derived effective porosity (PIGN).

Step 2: PCA

PCA is applied to obtain the principal components PCj (j=1,…,7) from the well log data after normalization. In principal component analysis, there are three methods for analysis (Viz. sum of squares and cross products matrix method, covariance matrix method and correlation matrix method). After applying these three methods, the covariance and the correlation matrix methods give satisfactory results. In our work, we use the covariance matrix method, by which the principal components are based on the covariance matrix. Table- 1 shows the Eigen vectors and Eigen values developed from the covariance matrix with the help of the Efacies Software. Figure 3 shows the Scree plot, a bar plot of the variance of the principal components, which gives convenient visual information for identifying the important components. Only five principal components explain around 96% variation of the whole data set, which shows these are the most important components in the data set. We ignore the other two principal components except these most important five principal components in further data analysis processes. In the scatter plot (Figure 4), we can explore the relationship between reservoir properties and the two major principal components generated from seven well logs.

First principal component (PC1) appears to indicate porosity (NPHI) of the formation while second principal component (PC2) shows a stronger correlation with density (RHOB) readings. The eigenvectors of the covariance matrix (Σ) provides coefficients of the principal components transformation (Table 1). For example, PC1 and PC2 are given by,

PC1 = 0.268GR - 0.1097LLD + 0.5226NPHI - 0.2810RHOB - 0.5153SUWI + 0.5056VCL + 0.207PIGN

PC2 = 0.3229GR - 0.6248LLD - 0.0009NPHI + 0.5527RHOB + 0.2943SUWI + 0.1866VCL + 0.28PIGN

Step 3: MCA

Model based Cluster Analysis (MCA) is used to define some distinct groups based on the unique characteristics of the well log measurements. The first five most important principal components data set is used for this analysis as the input data. In Figure 5, there are four cluster groups shown along with numbers (1, 2, 3 and 4) and with varying colors. These clusters can be treated as an electrofacies that reflects the hydrologic, lithologic, and diagenetic characteristics. Qualitatively speaking, the first electrofacies group (1) indicates dense media with varying porosity values, the second group (2) indicates porous and low dense media, third group (3) indicates tight media and the last group (4) indicates low porous media with density value low.

Well-A shows electrofacies groups 1, 2 and 3; Well-B only shows two electrofacies groups (group 3 and 4); while Well-C shows facies groups 1, 2 and a zone of 3rd facies. The distribution of the four electrofacies groups of the three well is shown in Figure 6. Among the three Well data, the C well represents 82 sample data. In this dataset, the 72 data are shown in electrofacies facies group.

Step 4: Data Correlation

After partitioning of well log responses into electrofacies groups, statistical regression techniques are applied to model the correlation between permeability and well log responses within the partitioned groups. In this study, a non-parametric techniques are used viz. Alternating Conditional Expectation (ACE), also with there predictive performance. Here we used the 72-sample data set of well no. C for the electrofacies group 1, where there are the optimal numbers of nodes in the hidden layer. In this data set, the log variables are GR (Gamma Ray log), LLD (Resistivity log), NPHI (Neutron Porosity log), RHOB (Density log) and SUWI (Water saturation log) - used as independent variables while ln(k) used as dependent variable in training purpose, which gives some equations derived by the ACE algorithm.

Permeability model has been established for well no C. For developing permeability model the sample data set was divided into two subsets for training and supervising purposes. The supervising data set is used for testing purpose for validation of model. Initially a composite correlation between k and log variables was attempted combining core and well logs data of Well-C of Bombay High. Thus, a model is produced, where five log variables are selected for k prediction based on ACE.

For effective integration of core data and log data for the well necessary depth shift in indicated core depth has been considered to eliminate depth mismatching between the depths of well logs and coring depth. To obtain optimal solution for permeability prediction problem few core data were not used. Here we used 35 sample data for training purpose and the remaining 37 sample data for testing purposes among the total 72 sample data of electrofacies group-1 of Well C. Initially, the 35 sample data are used as input in this model. Then we obtained the predicted permeability from these data up to a certain depth in one network. The ACE algorithm method gives some valuable transformed equations of each log variables along with predicted k values in training process. Then for testing purpose, the depths data are related to the rest 37 sample log data, added to input in the produced algorithm earlier by the 35 sample data in an another network model, which also gives predicted permeability of that depth range.

The optimal transformations for permeability and selected log variables were obtained and the sum of transformed well log variables is constructed. Finally, permeability is predicted from well log data for uncored well using following equation derived by the ACE algorithm:

$$(GR)_{Tr} = -1.6673E\text{-}03\ GR^2 + 2.1833E\text{-}01\ GR - 6.6821E{+}00$$

$$(LLD)_{Tr} = -9.0571E\text{-}02\ LLD^2 + 9.2772E\text{-}01\ LLD - 1.6731E{+}00$$

$$(NPHI)_{Tr} = 1.9260E{+}02\ NPHI^2 - 1.0058E{+}02\ NPHI + 1.2762E{+}01$$

$$(RHOB)_{Tr} = 1.1506E{+}01\ RHOB^2 - 5.8005E{+}01\ RHOB + 7.2882E{+}01$$

$$(SUWI)_{Tr} = 3.0400E{+}00\ SUWI^2 - 4.8383E{+}00\ SUWI + 1.8041E{+}00$$

$$Sum_{Tr} = (GR)_{Tr} + (LLD)_{Tr} + (NPHI)_{Tr} + (RHOB)_{Tr} + (SUWI)_{Tr}$$

$$\ln (k) = -2.0935E\text{-}01\ Sum_{Tr2} + 1.7444E{+}00\ Sum_{Tr} - 8.3286E\text{-}01 \quad \ldots\ldots\ (6)$$

Above permeability model based on core and well log data of Well C. From the above equation (Equation 6) we calculate the value of k. Figure 7 and Figure 8 show the Optimal Regression transformations of sum of the log data and ln k and fitted with standard deviation respectively for prediction of permeability based on core and well log data of Well C. Despite some minor discrepancies, the general matching between core measured k - values and k – values predicted by ACE dose indicate that the ACE is able to reveal the average characteristics of the reservoir and provide a reliable basis for reservoir study.

From our study, the ACE method gives very satisfactory results. Figure 9 shows the core permeability and predicted permeability curve inconsistent with depth during training and Figure 11 shows linear trendline, between the core permeability and predicted permeability data, shows almost 77 % matching.

Figure 10 shows the core permeability and predicted permeability curve inconsistent with depth during testing and Figure 12 shows linear trendline, between the core permeability and predicted permeability data, shows almost 80 % matching.

The continuous permeable curves reveal detailed vertical variations. It may be due to not routinely sampling shaly interval or vertical intra-reservoir flow barriers at well locations. For example, in Figure 9 the reservoir unit from 1,393 – 1,400 m depth range, the permeability values less than 0.01 mD, would act as a vertical intra-reservoir flow barrier in Well C.

Conclusions

The present study is very useful to pre classify the well logs into several distinct clusters, electrofacies and finding the optimum permeability correlation model for each class, more accurate permeability predictions can be obtained.

- In electrofacies determination by EFacies Software, the PCA analysis gives convenient visual information for identifying the important components. The first five principal components explain around 96 % variation of the whole sample data set. The first principal component (PC1) appears to indicate porosity (NPHI) of the formation while second principal component (PC2) shows a stronger correlation with density (RHOB) readings.
- These first five most important components are used in (MCA) model-based cluster analysis. The whole data set divided into four cluster groups by the MCA. These each clusters can be treated as an individual electrofacies groups.
- The sample data of electrofacies group 1 are used for training and testing purposes in ACE method by GRACE software. The present study has been used the ACE modelling approach to achieve efficient and reliable quantitative integration of measured (core) permeability and well logs that are mainly indicators of lithology and porosity for developing a quantitative model to predict permeability.
- Initially, gamma ray (GR), resistivity (LLD), porosity (NPHI), density (RHOB) and water saturation (SUWI) logs have been used as the input for permeability prediction. After that, predicted permeability and core-derived permeability have been compared. This comparison gives satisfactory results with good accuracy.
- In spite of some minor discrepancies, the general agreement between permeability values estimated by the ACE and measured k-values for well C, does indicate that the ACE has satisfactory generalized relation between permeability and well logs.
- Continuous ACE derived permeability curves provide detailed vertical variations in important reservoir intervals of the individual wells. These curves allow evaluation of reservoir quality and facilitate detailed examination of vertical variations of permeable and less permeable units.
- Predicted permeability data can be utilized in simulation studies for more realistic performance prediction and consequent improvement in oil recovery factor. It also provides valuable information in context of further field development, profile modification, water shut-off, and reinterpretation of well test data and stimulation jobs of Mumbai High South.

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Lim, Jong-Se, J.M. Kang, and J. Kim, Multivariate Statistical Analysis for Automatic Electrofacies Determination from Well Log Measurements: SPE 38028, 5 p., doi:10.2118/38028-MS.

Figure 1. Location map Bombay Offshore Basin.

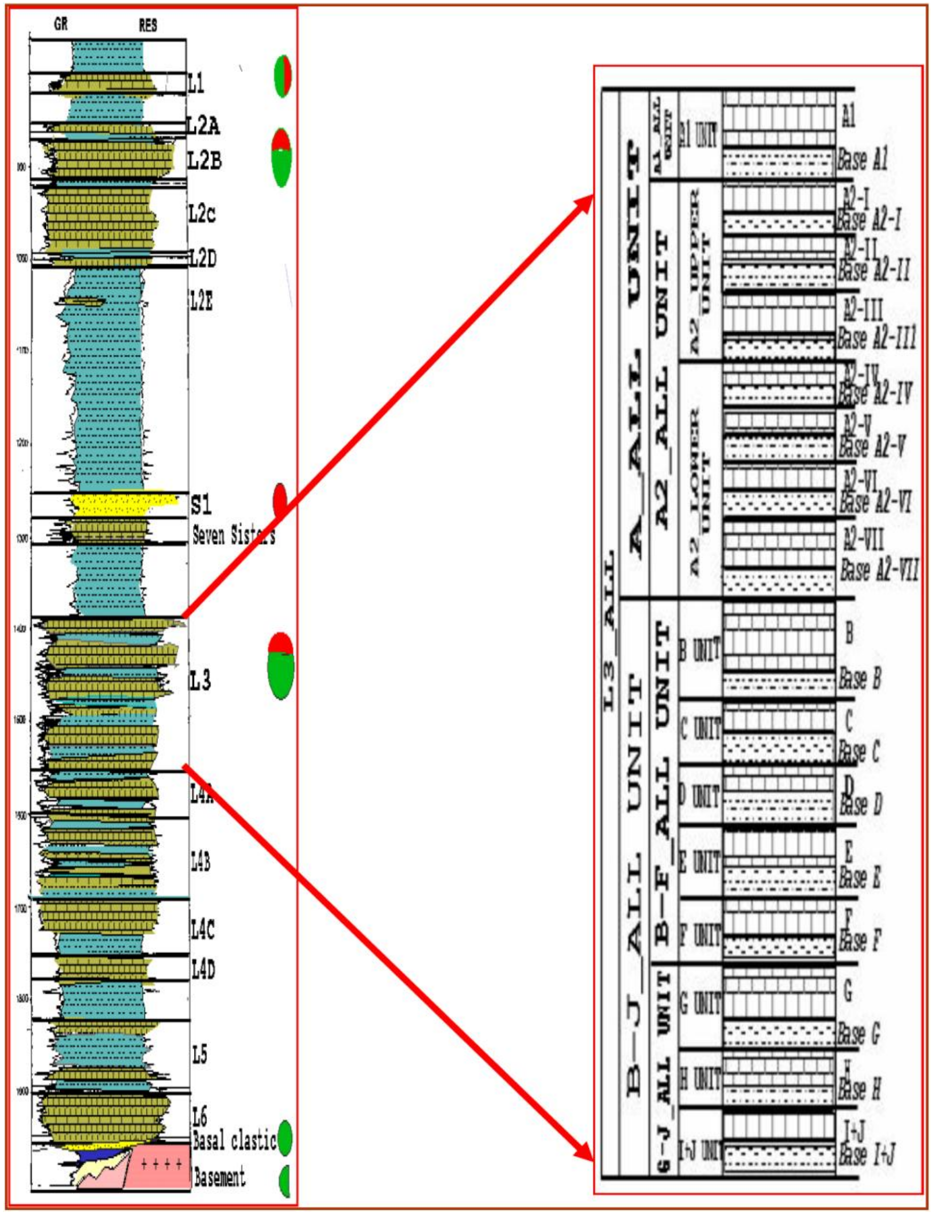

Figure 2. General stratigraphy Mumbai High Field.

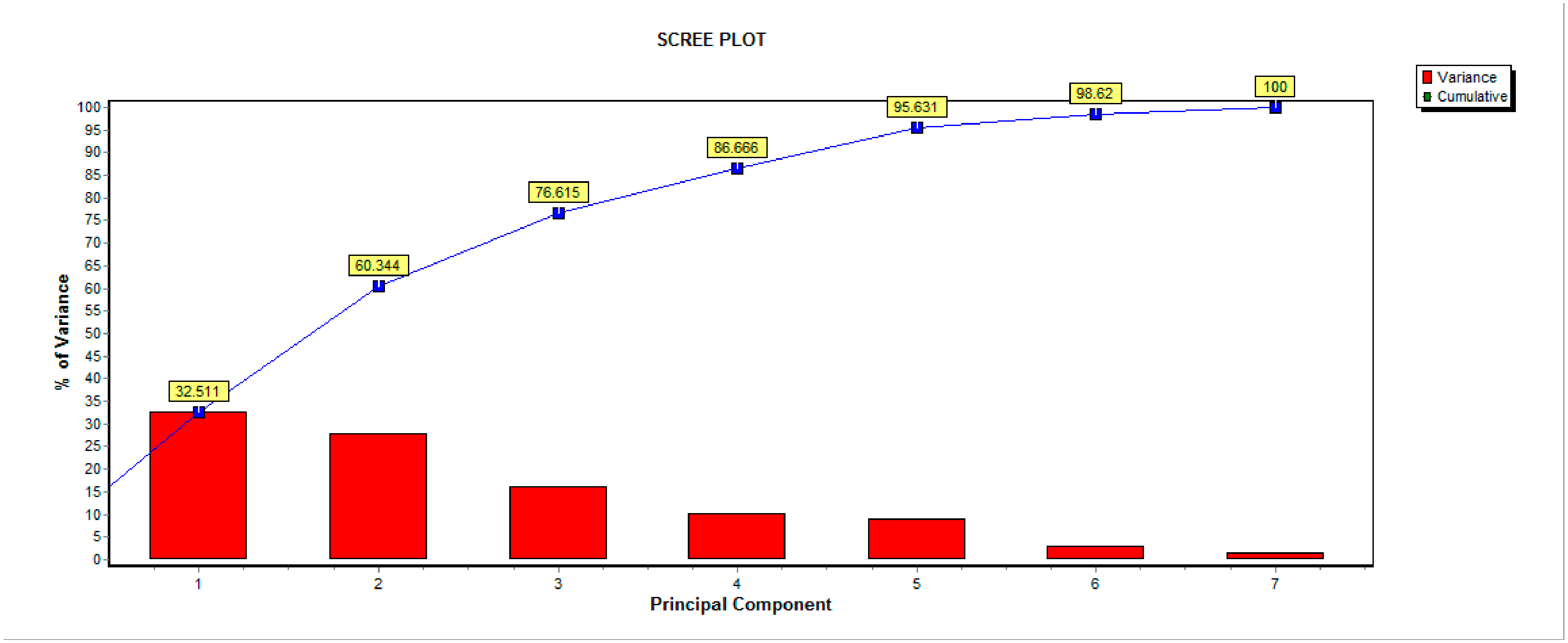

Figure 3. Scree plot of the sample data set from Wells A, B and C.

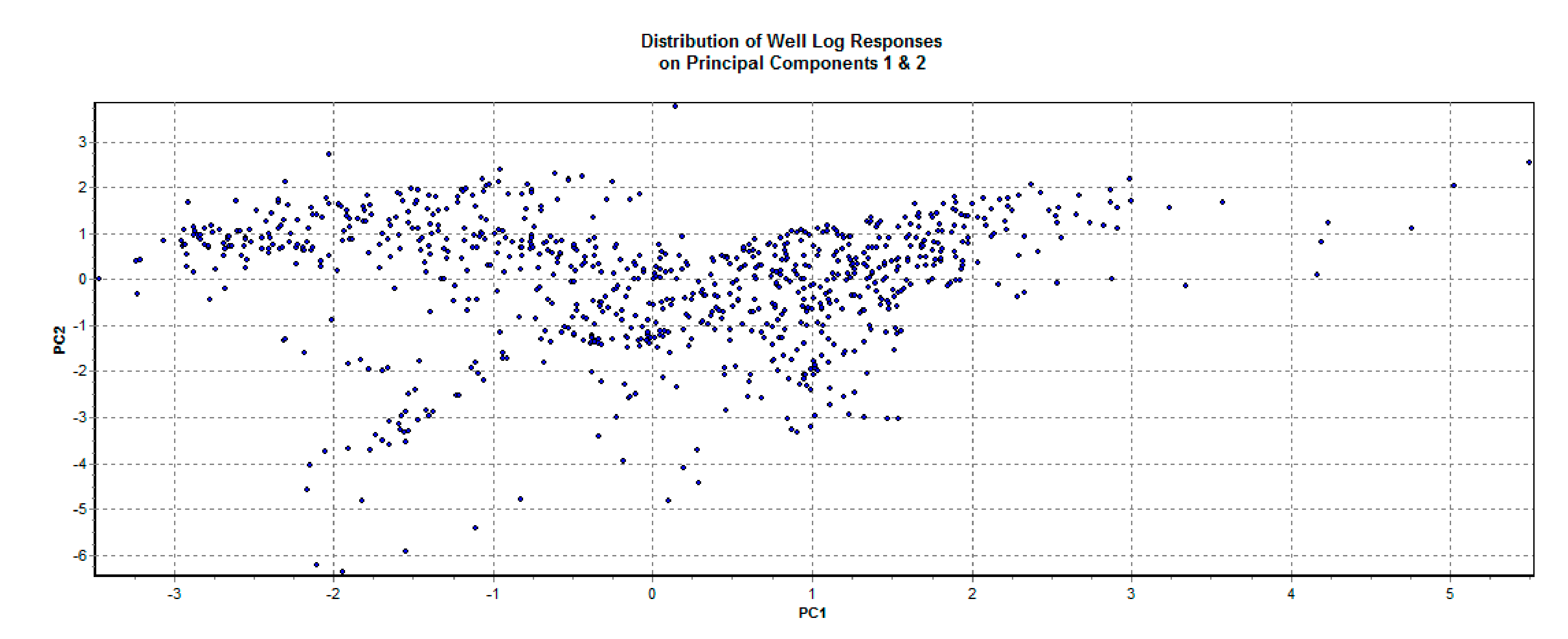

Figure 4. Scatter plot of the sample data set from Wells A, B and C.

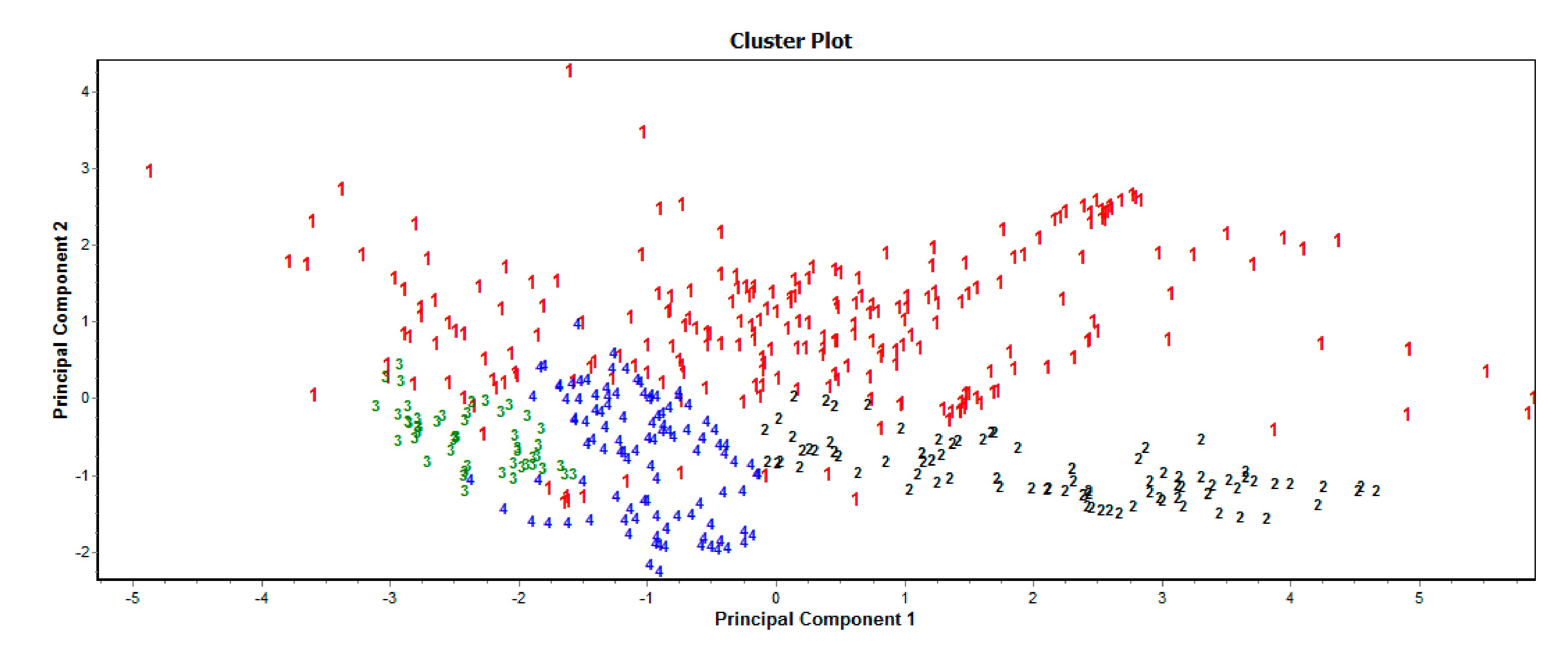

Figure 5. Cluster plot shows four cluster groups of the first two principal components after model based cluster analysis.

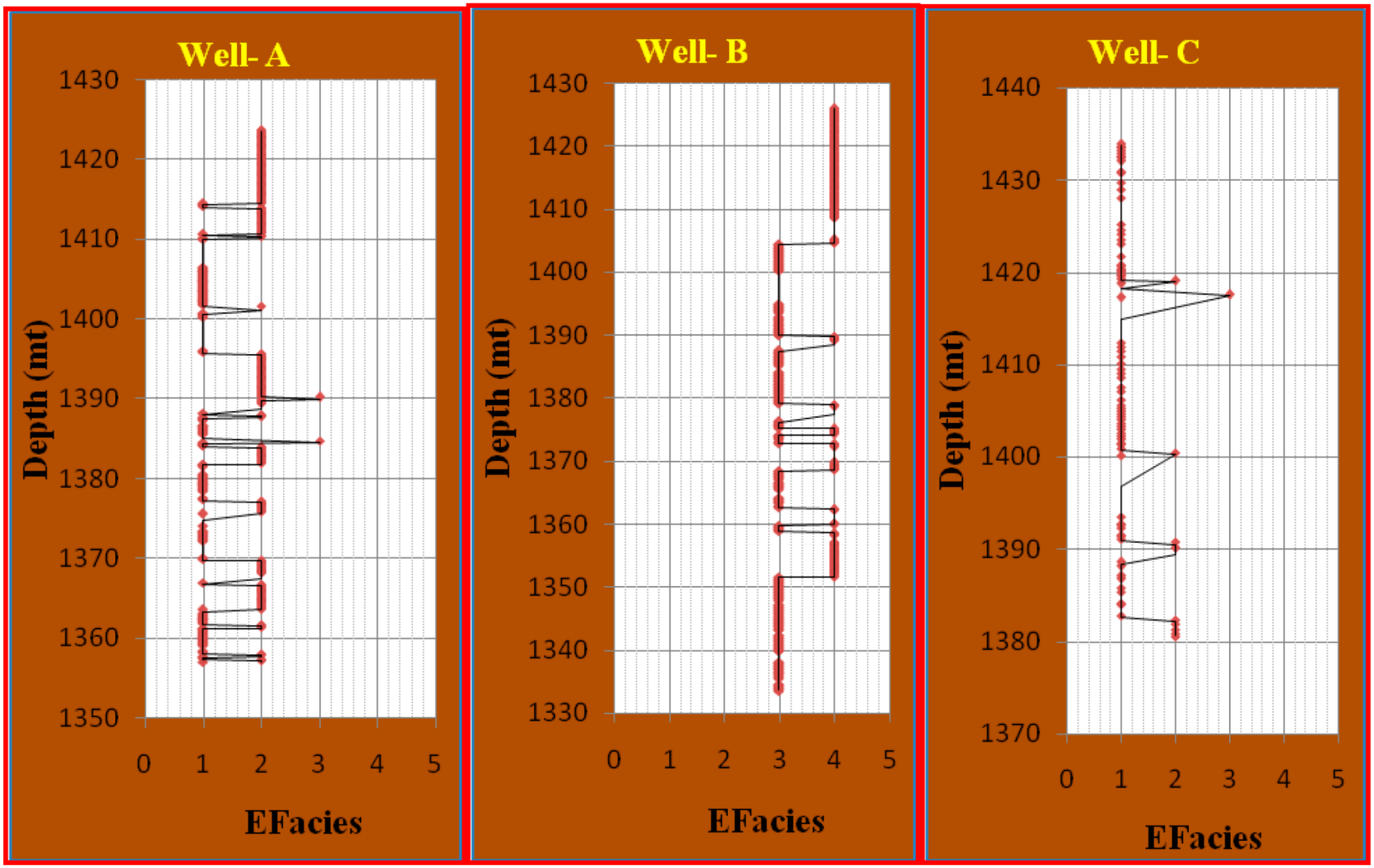

Figure 6. Distribution of the four electrofacies groups with respect to Depth of Well A, Well B and Well C.

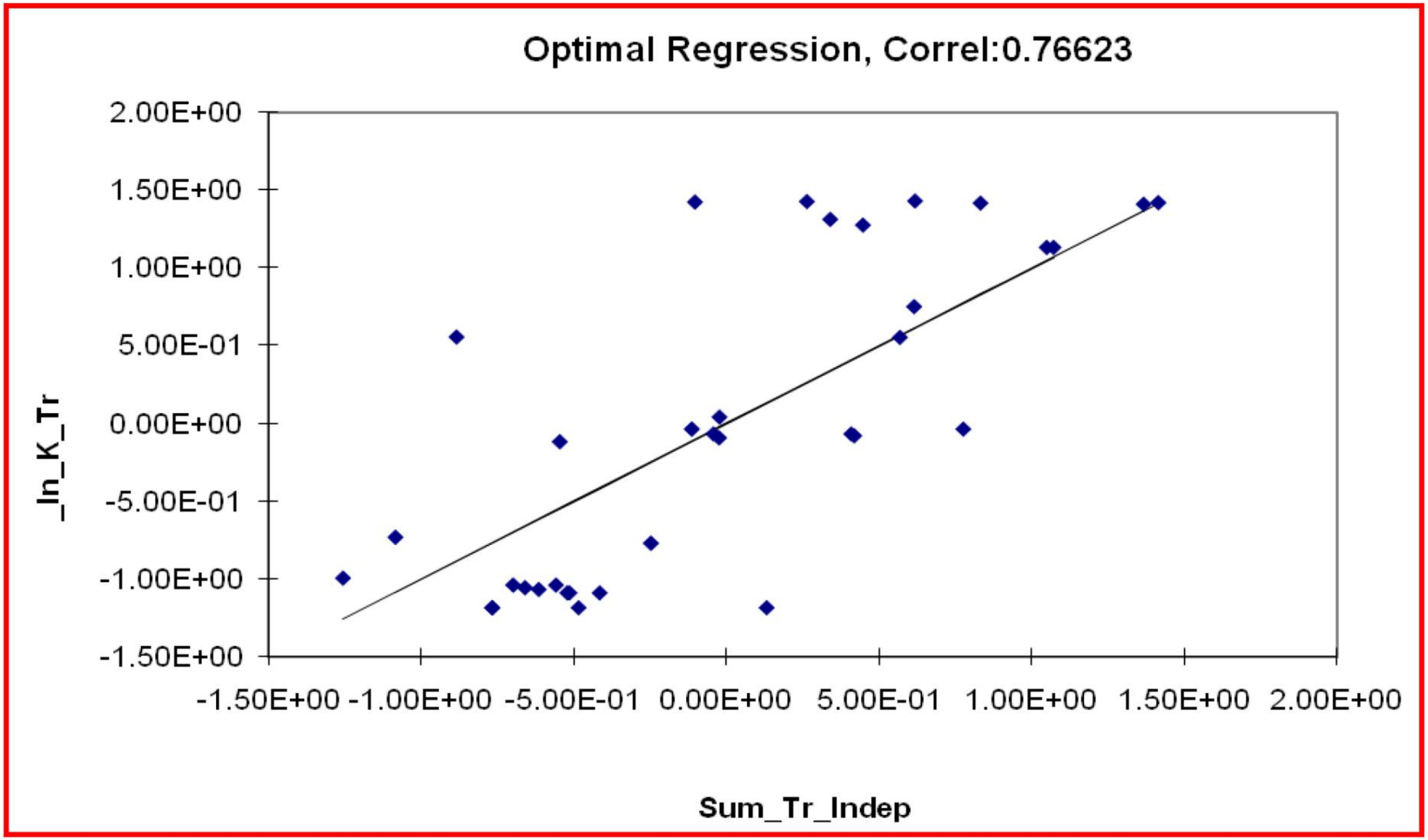

Figure 7. Optimal Regression transformation of sum of the log data and ln k.

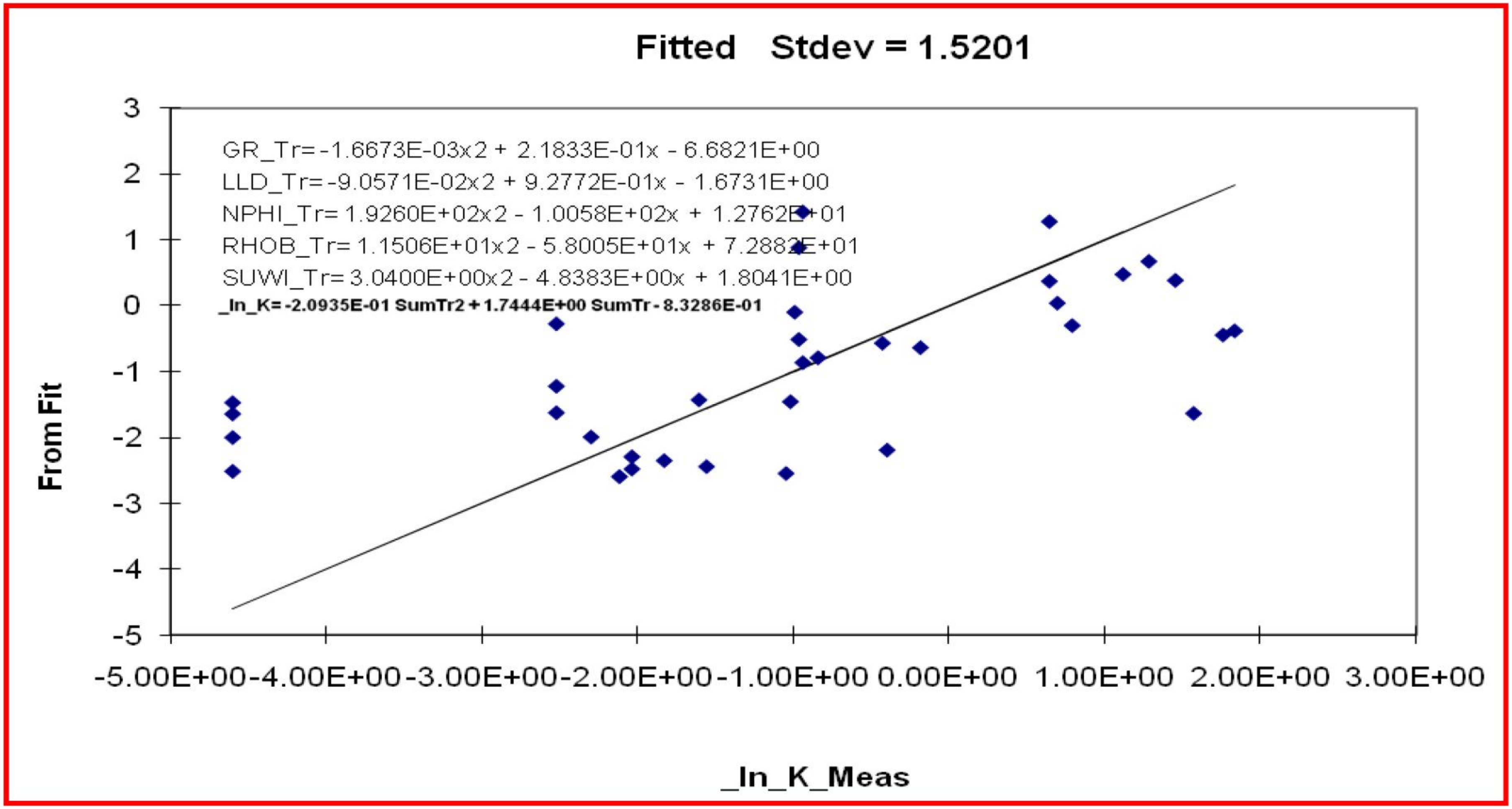

Figure 8. Fitted Standard Deviation.

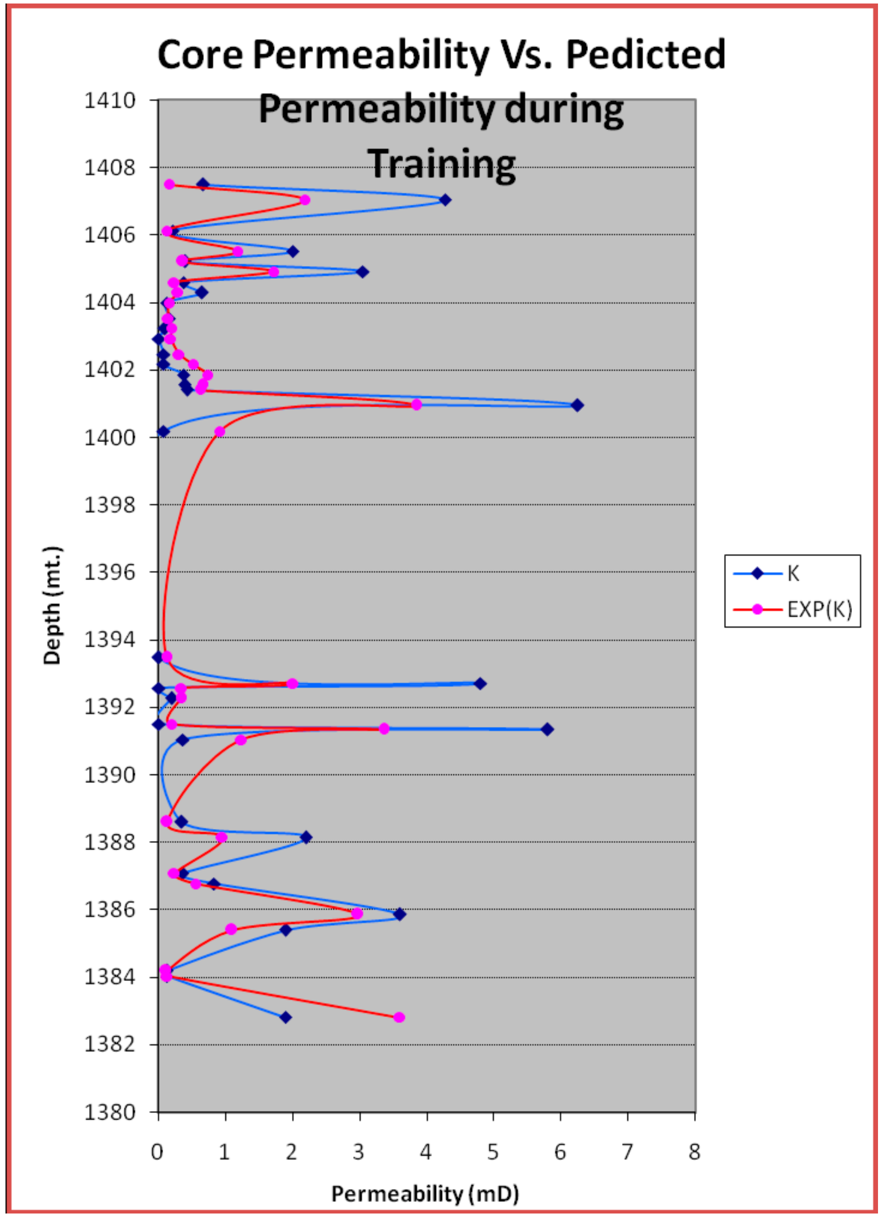

Figure 9. Core k and predicted k curve inconsistent with depth during training.

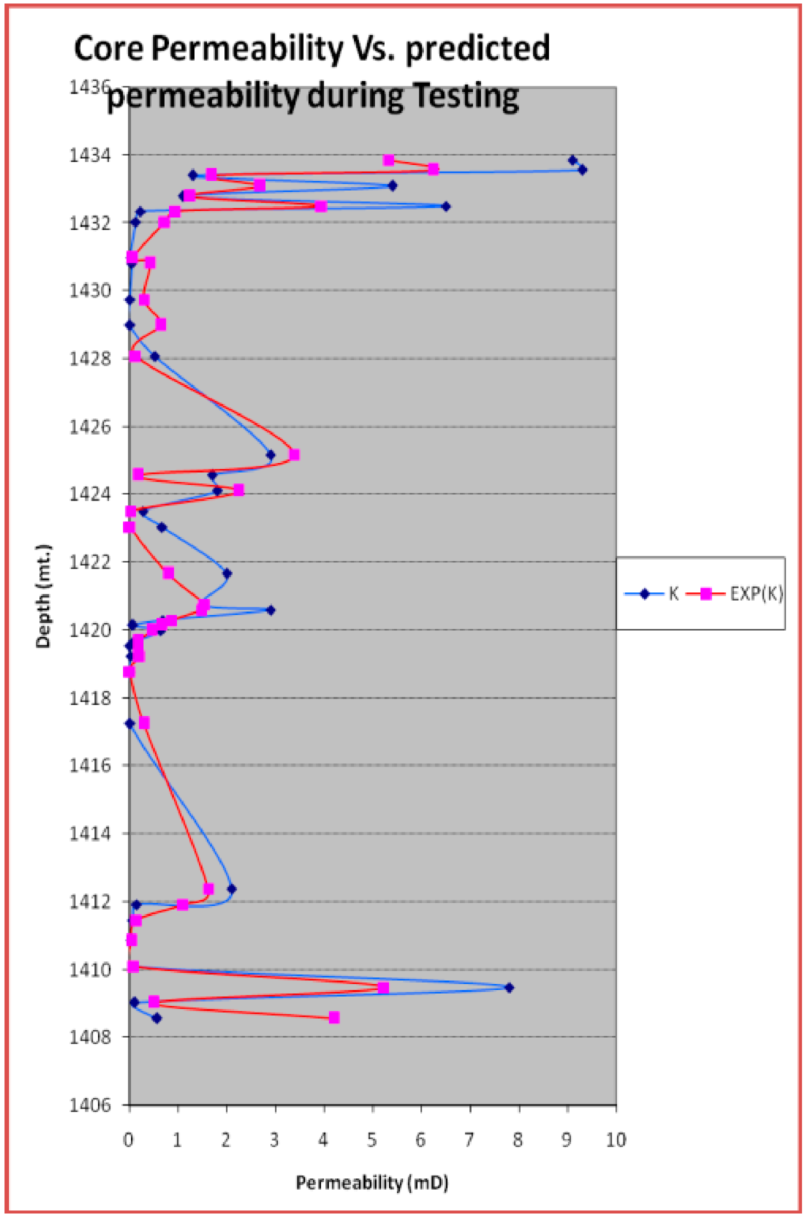

Figure 10. Core k and predicted k curve inconsistent with depth during testing.

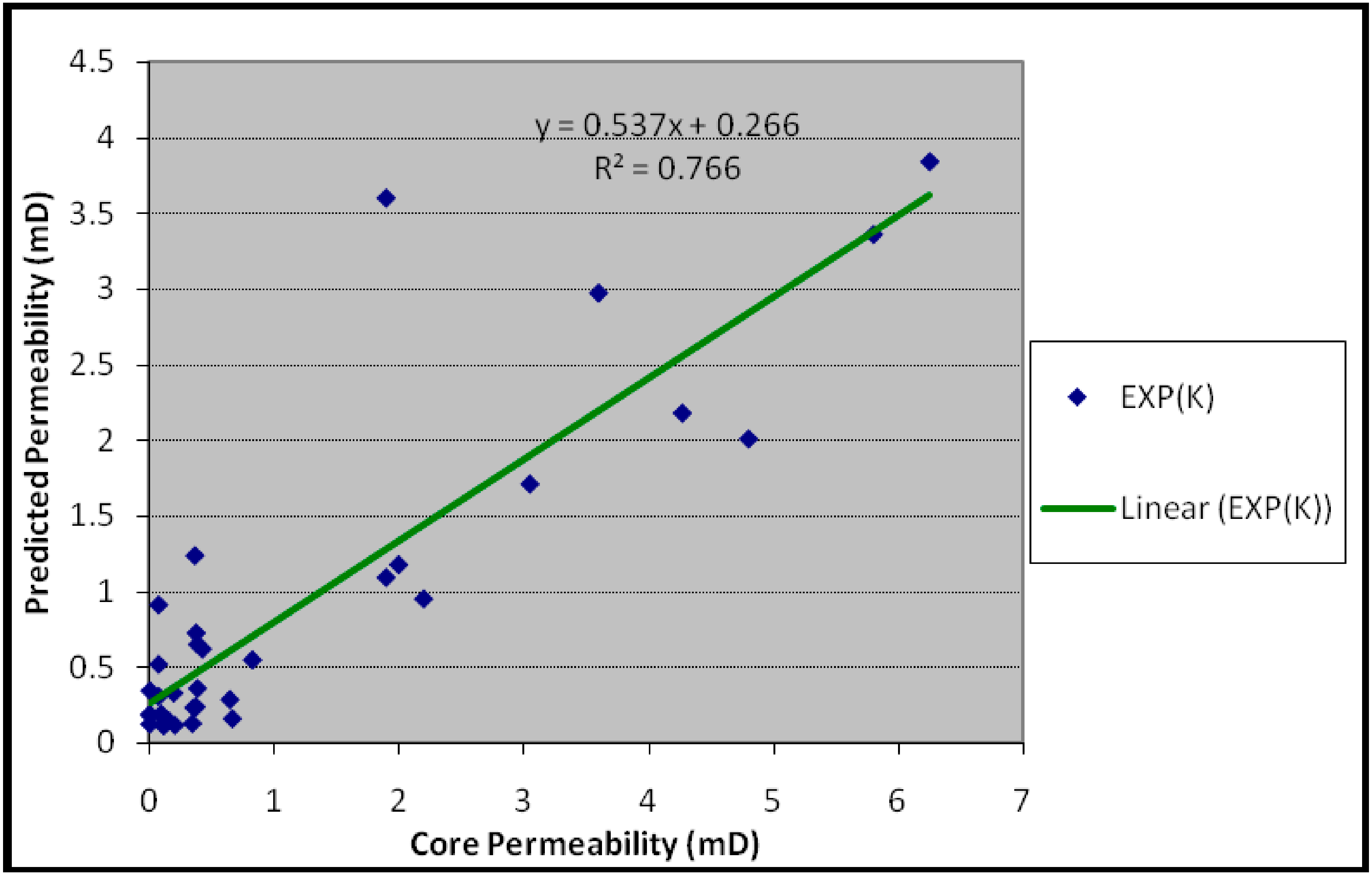

Figure 11. Linear trendline, between the core and predicted k data.

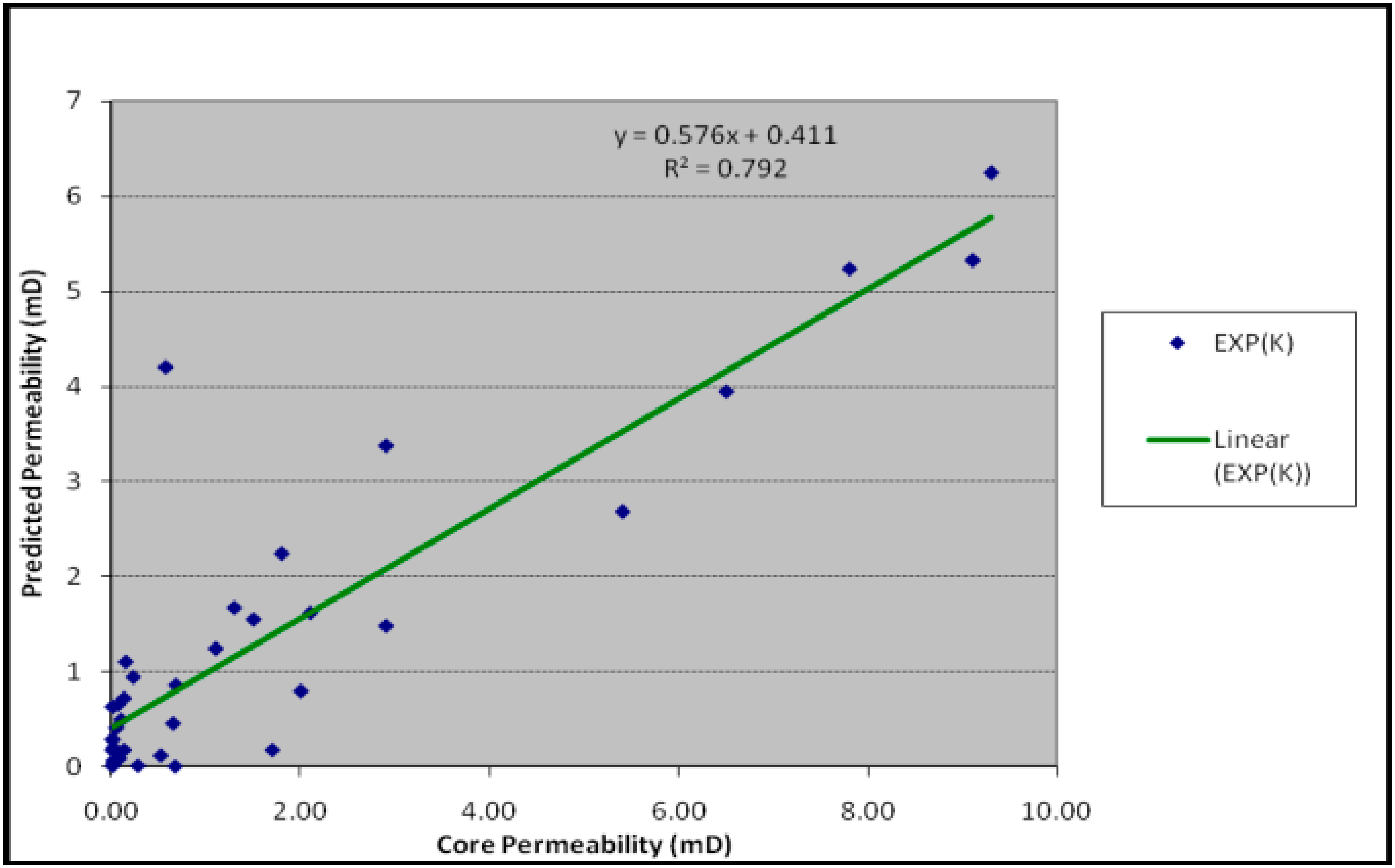

Figure 12. Linear trendline, between core k and predicted k data.

VARIABLES	PC1	PC2	PC3	PC4	PC5	PC6	PC7
GR	0.2680	0.3229	0.4269	0.5770	-0.5509	-0.0718	-0.0036
LLD	-0.1097	-0.6248	0.1985	-0.0603	-0.3927	0.5093	-0.3754
NPHI	0.5226	-0.0009	0.2229	0.2337	0.6053	0.5059	-0.0177
RHOB	-0.2810	0.5527	-0.2962	-0.0574	-0.1924	0.6834	0.1432
SUWI	-0.5153	0.2943	0.3009	0.1480	0.3246	-0.0793	-0.6510
VCL	0.5056	0.1866	-0.4971	-0.1334	-0.1550	-0.0784	-0.6438
PIGN	0.2071	0.2801	0.5508	-0.7522	-0.0971	0.0074	-0.0030
Eigen value	1927.5876	1650.2268	964.7438	595.8977	531.5630	177.2358	81.8048
Contribution (%)	32.5108	27.8329	16.2714	10.0505	8.9654	2.9893	1.3797
Cumulative Contribution (%)	**32.5108**	**60.3437**	**76.6152**	**86.6656**	**95.6310**	**98.6203**	**100.0000**

Table 1. Results of principal component analysis.