Optimal statistical method to predict subsurface formation permeability depending on open hole wireline logging data: A comparative study

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Abstract

One crucial parameter related to subsurface formations fluid flowing is the rock permeability. Generally, rock permeability reflects the formation capability to transmit fluid. Its significance reflected through several methods existing utilized to predict it, including rock core measurements, empirical correlation, statistical techniques, and other methods. The best and more exact permeability findings are acquired in the laboratory from core plug cored from a subsurface formation. Unfortunately, these experiments are expensive and tedious in comparison to the electrical and electronic survey techniques as wireline well logging methods, for example, not exclusively. The current study compares and discusses different methods and approaches for predicting permeability via wireline logs data. These approaches include empirical correlations, non-parametric statistical approaches, flow zone indicator FZI approach. In this research, we introduced a comparatively new process to predict permeability by the combination of FZI method and the artificial neural networks method. All these approaches are performed using well logs data to the non-homogenous formation, and findings are placed in comparison with permeability from laboratory experiments, which is regarded to be standard. Several statistical criteria, such as ANOVA test and regression analysis, were used to determine the reliability of calculated permeability results.

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1. Introduction

Formation permeability represents a formation property that reflects the capability of fluids (gas or liquid) flowing through the formation. Where high permeability value will allow liquids to flow quickly through rocks. Permeability represents significant [1] formation property and most complex to predict and determine all petrophysical characteristics [2]. An exact permeability estimation is substantial since it is an important parameter that controls the direction of liquids flowing and the rate of liquids flow through formation. Laboratory experiments of permeability estimations are traditionally utilized for evaluating permeability. Kozeny (1927) [3] and Archie (1941) [4] were among the first scientists who calculated permeability based upon electrical measurements applied on core samples. Often, these experiments are costly and tedious, or they are rare either because of the high cost of these types of investigations. Therefore, different attempts were made over the years to predict permeability utilizing various methods. One of the relatively reasonable and readily available sources for estimation permeability was wireline well logging techniques. Several models and correlations were developed to achieve this objective, such as Leverett, Tixier, Wyllie - Rose, Timur, and Coates - Dumanoir [5-9]. Using statistical methods to predict permeability depending on well log data was developed in the nineties of the last century, such as Lin et al. work, Balan et al. work, and Zhang et al., work [10-12]. The flexibility of statistical approaches is that it predicts an expected permeability value depending on to set of data resulted from well logs and analytical parameters.

In models with general practical application, several researchers [4-9] have attempted to capture the complexities of permeability behaviour. As this research leading to better explaining the permeability influence variables, they indicate that it is a misconception to consider a "general" association between permeability and wireline log variables. However, core permeability data exists in many cases for research; statistical models

have now become a more dependable option for estimating formation permeability. Thus, regression is commonly utilized for the analytical method in the search for relations between permeability determined from core and well log. This parametric method requires multinomial action and linearity to be assumed and satisfied. It is also a model-based approach and must, therefore, be implemented with care [13-14]. In addition to parametric statics, we use nonparametric regression techniques, called the algorithm of Alternating Conditional Expectation (ACE), for estimating permeability using well logs. These techniques are entirely data-driven and do not need preliminary assumptions regarding functional modes to correlate permeability and well logs data. Additionally, to statistical methods, a relatively modern nonlinear and non-parametric technique becomes progressively general in the geosciences and petroleum industry, namely Artificial Neural Networks (or merely neural networks) [15]. In the current study, all the above techniques and methods are applied for estimating formation permeability from the information of well logs variables. Core permeability and well logs data from a heterogeneous formation of one Iraqi oil field have been used to establish a predictive permeability model, and the findings are matched with core-determined permeability, which is assumed to be standard. In this study, different methods and approaches for predicting permeability from wireline logs data are discussed. We introduced a comparatively new process to predict permeability by the combination of FZI method and the artificial neural networks method. Several statistical criteria, such as ANOVA test and regression analysis, were used to determine the reliability of calculated permeability results.

2. Methodology

In this study, different methods and approaches for predicting permeability using wireline logs data are discussed. These approaches include; empirical correlations, non-parametric statistical approaches, flow zone indicator FZI approach and relatively FZI-Neural Network combination method. These methods and approaches are discussed below.

2.1. Permeability estimation from empirical correlations

Permeability prediction most released work and studies show there is no direct method for estimation permeability using well logs data. The literature survey shows that the well logging- determined permeability derives using properties of rock, which are associated with the permeability. These characteristics include saturation of water, porosity, capillary pressure, and resistivity of formation factor. Thus, we can say that most empirical predictions models are based upon the correlation between permeability, porosity, and connate water saturation. As a preliminary work before we start for estimating permeability from empirical correlation, we should calculate some rock properties using available well logs data. The rock porosity which represents the per cent of pores volume to total rock volume can be estimated from Schlumberger's (1974) equation from Neutron – Density combination derived porosities [16];

$$\Phi t = \frac{\Phi n + \Phi d}{2} \qquad (1)$$

Where; Φt is total porosity (interconnected and isolated pores), Φd is porosity derivative from the FDC density log, and Φn is porosity derivative from the neutron log. The effective porosity (Φe) which represent interconnected pores calculate using Schlumberger's (1998) [17];

$$\Phi e = \Phi t(1 - V_{sh}) \qquad (2)$$

and;

$$Vcl = 0.083(2^{3.7*GRI} - 1) \qquad (3)$$

with;

$$GRI = \frac{GR_{log} - GR_{min}}{GR_{max} - GR_{min}} \qquad (4)$$

Where; (Vcl) is clay volume content, (GRI) is the gamma-ray index, (GR_{log}) is gamma-ray log reading of formation, (GR_{min}) is gamma-ray of the non-clay zone (API) and (GR_{max}) is gamma-ray of clay zone (i.e., 100% clay zone (API)). The water saturation is determined by Archie's equation for clean formation using [18]:

$$S_w = \left(\frac{a \ R_w}{R_t \ \varphi^m}\right)^{\frac{1}{n}} \tag{5}$$

Where: (a) is tortuosity (assumed $a = 1$) ; (m) is cementation factor (assumed $m = 2$) ; (n) is saturation exponent (assumed $n = 2$) ; (Rw) is formation water resistivity ($Rw = 0.065 \ \Omega$ m), (Rsh) is resistivity value at shale formation ; (Rt) is rock resistivity ; (Sw) is water saturation, and φ is formation porosity.

2.1.1 Permeability prediction from permeability – porosity correlation

Permeability-porosity correlation is made from core analysis and transformed into the corresponding well log data. This correlation can be performed by plotting core porosity as x-axis on linear scale versus core permeability as y-axis on a log scale and generating a best fit line equation as;

$$log \ K = a + b \ \varphi \tag{6}$$

Or;

$$K = a \ e^{b \ \varphi} \tag{7}$$

Where; K is the permeability (MD), φ: is the porosity (fraction), and $'a,'$ $'b'$ are constants. The optimal results of parameters ('a' and 'b') are determined graphically by plotting permeability and porosity on a semi-logarithmic scale. The statistical correlation coefficient (R^2) has been used as a guideline to choose the best correlation from the established equation between the measured values. A statistical package, "STATISTICA Software," was used to determine the values of empirical parameters.

2.1.2 Permeability prediction from permeability – porosity-connate water saturation correlation

A general correlation between rock permeability, porosity, and water saturation is established by Rose and Bruce (1949) [19] for a specific reservoir for estimating rock permeability from the combination of porosity and connate-water saturation determination. They developed a correlation between porosity, permeability and water saturation as follows;

$$[1] \quad k = a \frac{\cdot}{S_{wib}} \quad [2] \tag{8}$$

Where; 'K' is the permeability (MD), 'φ' is the porosity (fraction), 'Swi' is the irreducible water saturation (fraction), and 'a', 'b' and 'c' are parameters of the model statistically defined for each case study using regression analysis. This approach required to get the best estimation of irreducible water saturation 'Swi' from well logs or core samples in the laboratory. Nonlinear estimation analyses were made for estimating the values of parameters 'a', 'b', and 'c' by using a statistical package "STATISTICA Software."

2.2. Permeability prediction from non-parametric regression analysis

The nonparametric statistical method called Alternating Conditional Expectation (ACE) algorithm is performed for estimating permeability using wireline logs. The ACE algorithm is utilized to generate an optimal non-parametric correlation between a dependent variable (permeability) and independent variables using well log data (sonic, gamma-ray, neutron, density, and resistivity log). In this algorithm, we can create an optimal best correlation between a dependent variable and several independent variables, more than (30) independent variables.
This correlation will be performed by (non-parametric transformations) of independent and dependent inputs. Non-parametric means that no functional form is presumed between independent and dependent used inputs. A set of data is used to derive independent and dependent transformations. Finally, the last correlation is established through plotting the transformed-dependent variable opposite the summation transformed independent parameters. The outputting correlation can be shown to be optimal. [20-22].

2.3. Permeability estimation from FZI method

The flow units and Flow Zone Indicator (FZI) concept is introduced by Amaefule et al. in 1993[23]. They established a method for classifying and describing formation having the same (hydraulic flow units), founded on microscopic core samples measurements. Their approach was primarily based upon a modified Kozeny-Carmen equation [23]:

$$k = \left(\frac{1}{K_T * S_{vgr}^2}\right)\left(\frac{\varphi_{eff}^3}{(1 - \varphi_{eff})^2}\right) \quad (15)$$

Where; 'k' is permeability, md., 'φ_{eff}' is effective porosity, 'S_{Vgr}' is a specific surface area per unit grain volume, and 'K_T' is an effective zoning factor. Dividing porosity on the left-hand and right-hand side of equation (15) with using the square root of two sides will yield;

$$\sqrt{\frac{k}{\varphi eff}} = \left(\frac{\varphi eff}{1 - \varphi eff}\right) * \frac{1}{Svgr * \sqrt{K_T}} \quad (16)$$

If the porosity is expressed in fraction and permeability as a millidarcy, the left-hand side of equation (16) turn into;

$$RQI = 0.0314 \sqrt{\frac{k}{\varphi eff}} \quad (17)$$

Where 'RQI' is Reservoir Quality Index, and it is expressed in micrometres or μm (1 μm = 1x10^{-6}m), and it is presented by Amaefule et al. in 1993[23]. The flow zone indicator (FZI) is defined from equation (16) as;

$$FZI = \frac{1}{Svgr * \sqrt{K_T}} \quad (18)$$

and;

$$\varphi_z = \left(\frac{\varphi eff}{1 - \varphi eff}\right) \quad (19)$$

Where 'φz' is a normalized porosity and it is represented pore volume to grain volume ratio; thus equation (16) can be written as;

$$RQI = FZI * \varphi z \quad (20)$$

Solve equation (20) using the logarithm on both sides will yield;

$$Log\ RQI = Log\ FZI + Log\ \varphi z \quad (21)$$

Equation (21) presents straight-line has unit-slope on log-RQI against the log-φz plot. The FZI is the intercept of this straight-line at $\varphi z = 1$. Additional parallel lines will be used for samples with different FZI values. Points within identical straight-line have similar flow appearance, thus reflect a unit of flow. In clean sandstone formations, slopes straight lines are equal to unity should be predictable mainly. Slopes larger than one show a shaly formation.

The primary variable in this sorting method is the (*RQI*), which is a calculation of (average hydraulic radius) in a formation rock [24]. The technique of multiple regression was used to establish an association between log data with Flow Zone Indicator (FZI) for estimating permeability of formation under study. The permeability can be determined from straight-line created using log-*RQI* against log-*φz* plot from equation [22]:

$$k = 1014 * FZI^2 * \left(\frac{\Phi eff^3}{(1 - \Phi eff)^2} \right) \tag{22}$$

2.4. Permeability from combination of FZI and neural network algorithm

An artificial neural network (*ANN*) model is a dynamic computational system capable of representing the complicated non-linear relationship between input and output data sets. A neural network consists of several processing materials, called 'neurons,' working in parallel—each neuron connected to other neurons via links of variable weights. The weights represent information being used by the network to solve a specific problem [27]. The most common (*ANN*) construction is Backpropagation (*BP*) algorithm with the multilayered perceptron (*MLP*) trained. The (*MLP*) network consisted mainly of input-layer, hidden layer, and output layer. Actual input-output variables numbers estimate the input- neuron and output-neuron numbers. The hidden layers numbers and the neurons are calculated using the trials and error method and depending on the situation complexity under evaluation. Every neuron in a layer gets weighted input from a preceding layer and sends its output towards the next layer of the neuron. The weighted input signal summation is calculated as follows:

$$y_{net} = \sum_{i=1}^{n} x_i w_i + w_b \tag{23}$$

Where: $'y_{net}'$ is weighted input summation; $'x_i'$ is input neuron; $'w_i'$ is a neuron input weight associated; $'w_b'$ is biased, and 'n' is examples number. Using the non-linear activation function, we can transform the findings of equation (22) by;

$$y_{out} = f_{(net)} = (1 + e^{-ynet})^{-1} \tag{24}$$

Where; $'y_{out}'$ is the neural network response system and. '$f_{(net)}$' is the function of the non-linear activation. Neural network system responses are compared to target values by a mean square error given by:

$$MSE = \frac{1}{2} \sum_{i=1}^{n} (y_i^{obs} - y_i^{out}) \tag{25}$$

where $'y_i^{obs}'$ and $'y_i^{out}'$ are values of observed and predicted, respectively. *ANNs* training (sometimes called learning) includes feeding samples through the built network as input vectors, measuring the output layer error, and then changing the network weight to minimize error. If the network error drops below a given threshold, training will stop. In the current study, a total of 241 core sample measurements and their corresponding nine sets of well logs data from a heterogenous formation were used to build the network model. Several well-logs are used in this method, such as gamma-ray log, porosity log, sonic log, resistivity log. Porosity is derived from the compensated formation density *FDC* log (*PHID*) and *CNL-FDC* log combination (*PHIE*). Because of the enormous distribution of permeability data, the logarithmic scale was used. The selection of input variables is a significant and critical step in permeability estimation from statistical methods. Gamma-

ray log responses offer additional indications of clay that effects on permeability. The neutron log, sonic log, and bulk density log are functions of porosity and clay volume; therefore, they related to the permeability of formation [24]. Resistivity log usually used for calculating water saturation information since water-saturation may or may not be an indication for water flowing in the rock so that it may have a contribution to permeability [25]. The *MATLAB R2017B* toolbox of neural networks utilized in this research. The first step in this method is to obtain an optimal (*FZI*) depending on well log data using the neural network algorithm. The neural network model for predicting (*FZI*) from logs has performed using two groups of data.

The first one is the input variables group, which are a set of well log data such as sonic, gamma-ray, deep resistivity, shallow resistivity, micro-spherical and neutron log. The other group is the target variable, which is (*FZI*) derived from core data using equations (17) through (20). The artificial neural network model was based upon a multilayered perceptron (*MLP*) algorithm with 100 hidden layers. The inputs and outputs information are processed in two steps: normalization of data and set the partition of data. Original input data usually consists of different parameters with different physical definitions and units, and their grades are therefore extremely variable. Data are typically rescaled to a specified interval to ensure that each variable is treated equally in a model such as [-1, 1] [0, 1] or other scaling criteria. The (mapminmax) scaling function was used to normalize the data set in the range [-1, 1]. After normalization, the data set was separated into two parts: 80% for training besides 20% for testing. The optimal hidden number nodes are 20, as determined by the trial and error method. The Backpropagation (*BP*) algorithm is used in training by the Levernberg-Marqurdrat implementation.

The hidden and output layer respectively uses the logistic sigmoid and linear activation functions. The quality of the network implemented was assessed using the correlation coefficient (*R*). The (*R*) coefficient measures the linear correlation between the observed and predicted values, and the optimum value is one. It will be computed using the following formula:

$$R = \frac{\sum_{i=1}^{n}(y_i^{obs} - \bar{y})(y_i^{out} - \breve{y})}{\sqrt{\sum_{i=1}^{n}(y_i^{obs} - \bar{y})^2(y_i^{out} - \breve{y})^2}} \tag{26}$$

where $'\bar{y}'$ and $'\breve{y}'$ are averages of observed and predicted permeability, respectively.

3. Results and discussions

3.1. Permeability estimation from empirical correlations

The permeability prediction from empirical models is based upon the correlation between permeability, porosity, and connate water saturation. Thus, two approaches were used to determine permeability in the current study; permeability-porosity correlation method and permeability-porosity-saturation correlation method. These approaches are discussed below.

3.1.1. Permeability prediction from permeability – porosity correlation

Permeability-porosity correlation is performed by plotting core porosity on linear scale versus core permeability on a log scale. The best fit line is plotted to find '*a*' and '*b*' parameters of equation (7). The optimal results of parameters ('*a*' and '*b*') are determined graphically by plotting permeability and porosity on a semi-logarithmic scale (Figure 1*a*). The statistical correlation coefficient (R^2) has been used as a guideline to choose the best correlation from the established equation between the measured values. A statistical package, "*STATISTICA*" software was used to determine the values of empirical parameters as (*a=0.52097*), and (*b=18.13129*) with (R^2=0.778) using (*241*) core samples used in this study. Accordingly, the predicted permeability was estimated using the parameters ('*a*' and '*b*') with log derivative porosity using equation (7). predicted permeability is plotted versus core permeability in Figure (1*b*), and the residual plot of predict permeability is plotted in Figure (2*a*), while Figure(2*b*) represented the normal probability plot. ANOVA analysis test is performed on predict permeability, and the correlation coefficient is found to be ($R^2 = 0.394$). Normal probability plot and residual plot indicate that the executed points cannot fit the line excellently, and curve away out of it in places, we might

get a non-normal distribution. From a quick look to the findings of this technique and comparing them with core results, it is clear that this method cannot satisfy the required task because of the existence of different types of rocks with multiple properties. Formations with comparable porosity and varying permeability are prevalent in subsurface formations. It can be clear from permeability-porosity semi-log plots that there is no clear relationship between them, so more than one variable required for accurate permeability estimation to improve the overall correlation.

3.1.2. Permeability prediction from permeability – porosity-connate water saturation correlation

The permeability, in this method, is determined from the combination of porosity and connate-water saturation determination using equation (8). This approach required to get the best estimation of irreducible water saturation Swi from well logs or core samples in the laboratory. In this study, the exact estimation of connate water saturation found from well log and core analysis to be (*Swi = 0.19*). Nonlinear estimation analyses (Figure *3a*) were made for estimating the values of parameters ('*a*', '*b*'), and ('*c*') by using a statistical package "*STATISTICA*" software. The best results for all parameters are found to be; (*a = 8.525018*), (*b = 5.892733*) and (*c = 5.884056*) with correlation coefficient ($R^2 = 0.787$) using (*241*) core samples used in this study.
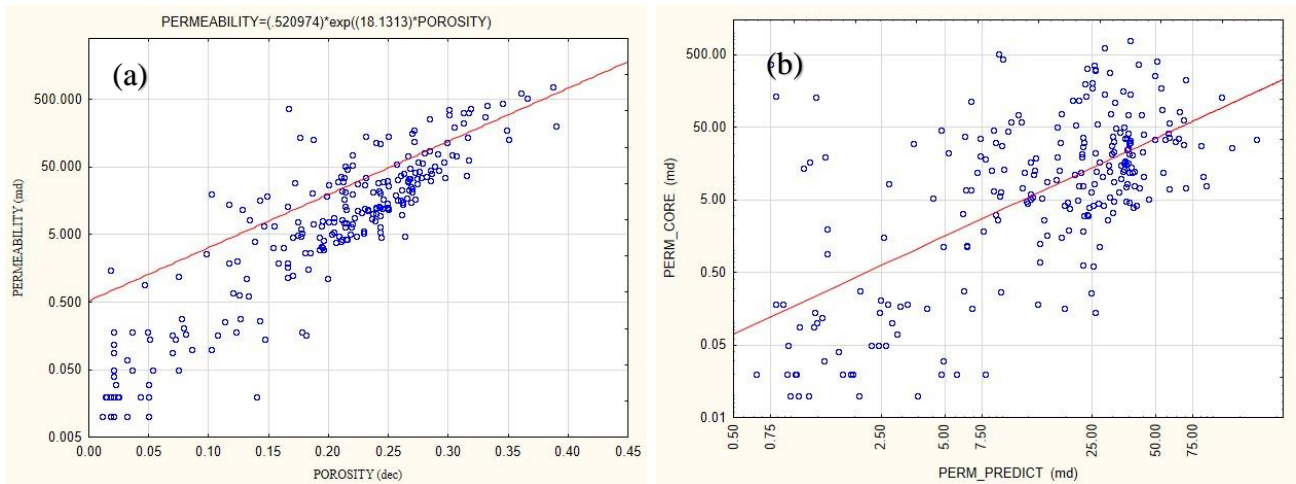

Figure 1. K-Phi correlation: (a) core permeability-core porosity plot, (b) core permeability vs predicted permeability plot
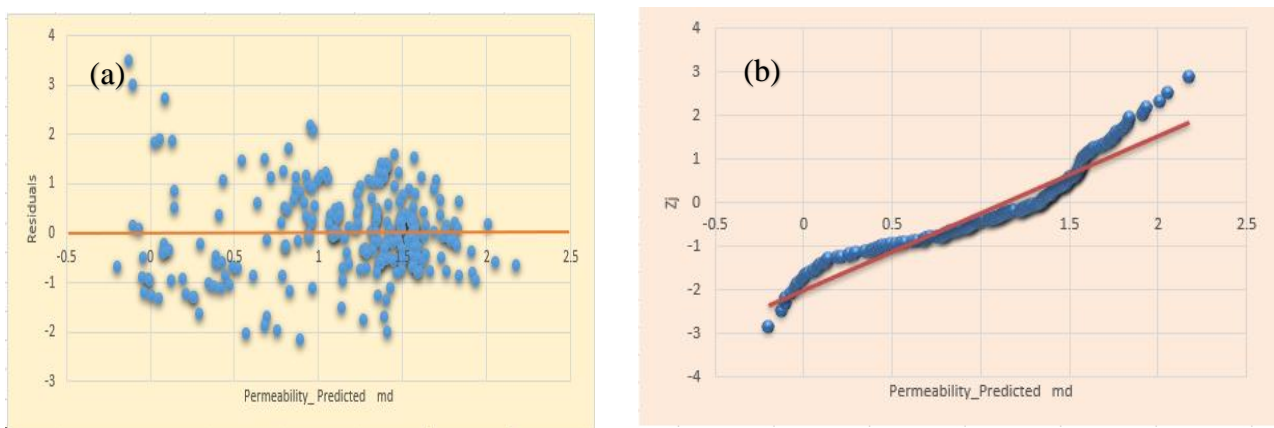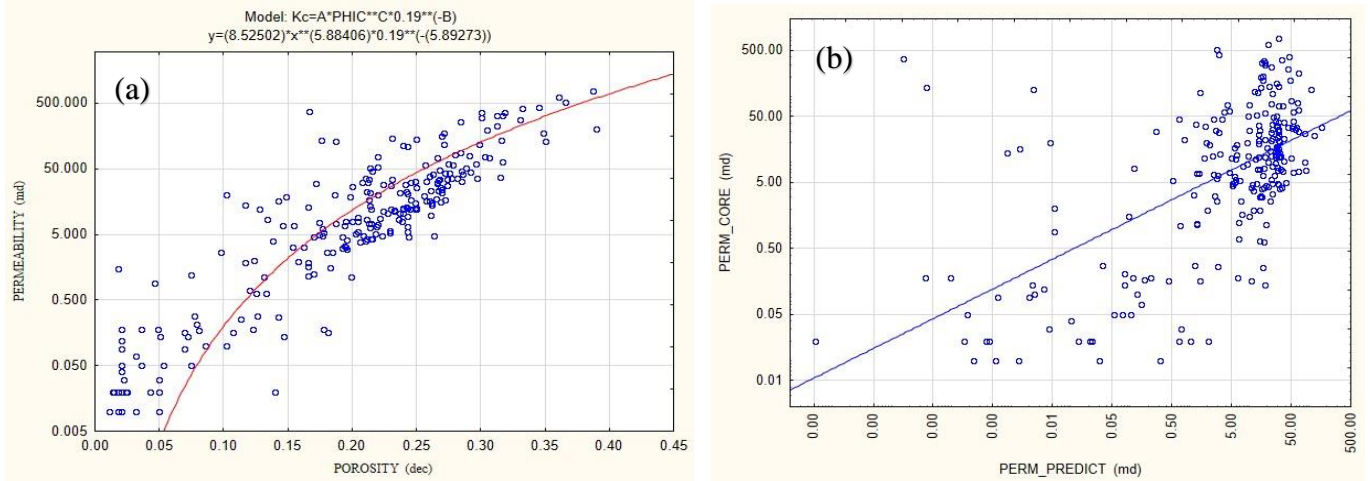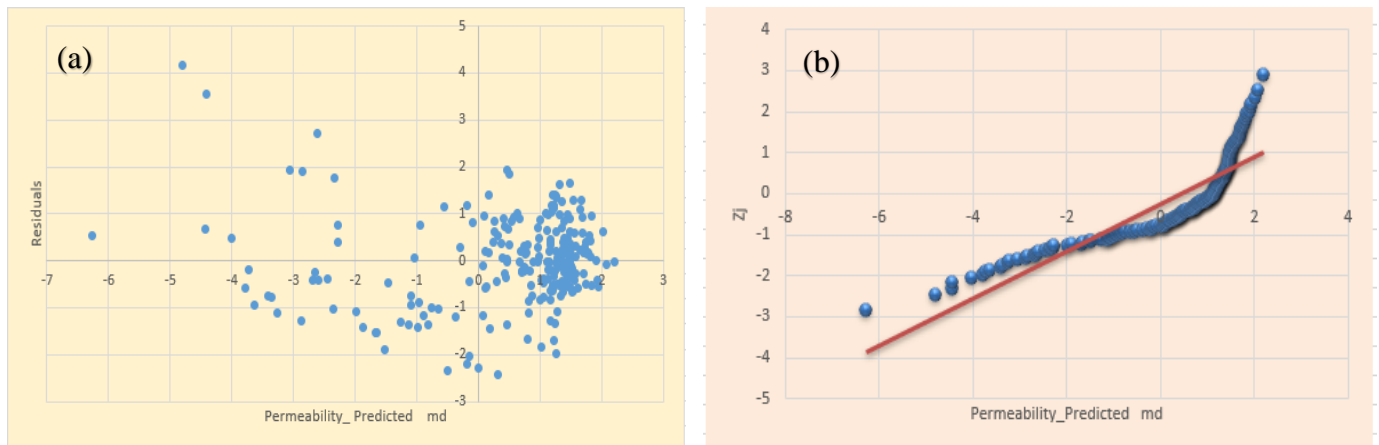

Figure 2. K-Phi correlation: (a) predicted permeability residual plot, (b) normal probability plot of estimated permeability

Accordingly, the predicted permeability was estimated using the parameters (*a, b, and c*) with log-derived porosity using equation (8). predicted permeability is plotted versus core permeability in Figure(3b), and the residual plot of predict permeability is plotted in Figure(4a), while Figure(4b) represented the normal probability plot. ANOVA analysis test is performed on predict permeability, and the correlation coefficient is found to be ($R^2 = 0.35$). Normal probability plot and residual plot indicate that there is a "non-normal distribution" because of poor fitting between the plotted points and the drawing line, where the curve apart from the line in positions.

Figure 3. K-Phi-Swi correlation: (a) core permeability-core porosity plot, (b) core permeability vs predicted permeability plot

Figure 4. K-Phi-Swi correlation: (a. predicted permeability residual plot, (b) normal probability plot of estimated permeability

3.2. Permeability prediction from non-parametric regression analysis

The ACE algorithm is utilized to generate an optimal non-parametric correlation between a dependent variable (permeability) and independent variables using well log data. The optimum transformations for four selected log variables (*GR, LLD, NPHI, and RHOB*) and permeability were gotten, and summation transformed well log variables are created. Then, permeability is estimated using wireline log data by equations derivative from (*ACE*) algorithm:

$$GR\_Tr = 8.4738x10^{-04} \, GR^2 - 4.4730x10^{-02} \, GR + 4.8946x10^{-01} \tag{9}$$

$$LLD\_Tr = 2.0941x10^{-04} \, LLD^2 - 1.6146x10^{-02} \, LLD + 1.1798x10^{-01} \tag{10}$$

$$NPHI_{Tr} = -3.7588x10^{01} \, NPHI^2 + 2.0358x10^{01} \, NPHI - 2.2007 \tag{11}$$

$$RHOB\_Tr = 6.6690x10^{-01}RHOB^2 - 3.2688\,RHOB + 4.0002 \qquad (12)$$

$$Sum\_Tr = GR\_Tr + LLD\_Tr + NPHI\_Tr + RHOB\_Tr \qquad (13)$$

$$ln\_KC = 5.6631x10^{-01}\,Sum\_Tr^2 + 3.3981\,Sum\_Tr + 1.2535 \qquad (14)$$

Where: '*GR*' is gamma-ray log; '*GR_Tr*' is transformed gamma-ray; '*LLD*' is deep resistivity log; '*LLD_Tr*' is transformed deep resistivity; '*NPHI*' is neutron log porosity; '*NPHI_Tr*' is transformed neutron log porosity; '*RHOB*' is density log; '*RHOB_Tr*' is transformed density log, and 'K_C' is core permeability. This permeability model is based upon the well log, and core data were using the above equation (Equation 14) we can estimate the value of permeability. Figure (5a) shows the transformation dependent variable (*ln_KC_Tr*) vs. summation transformation independent variables (*Sum_Tr_Indep*) with optimal regression transformations ($R^2 = 0.75514$) using (241) core samples used in this study. Figure (5b) shows the optimal transformations fitted with standard deviation for prediction of permeability based upon the well log and core data. It is seen that this method gives a high coefficient of correlation than previous methods, so it represents the best one compared with other discussed methods. In the current study, we found that the (*ACE*) technique gives very satisfactory results despite some minor discrepancies.
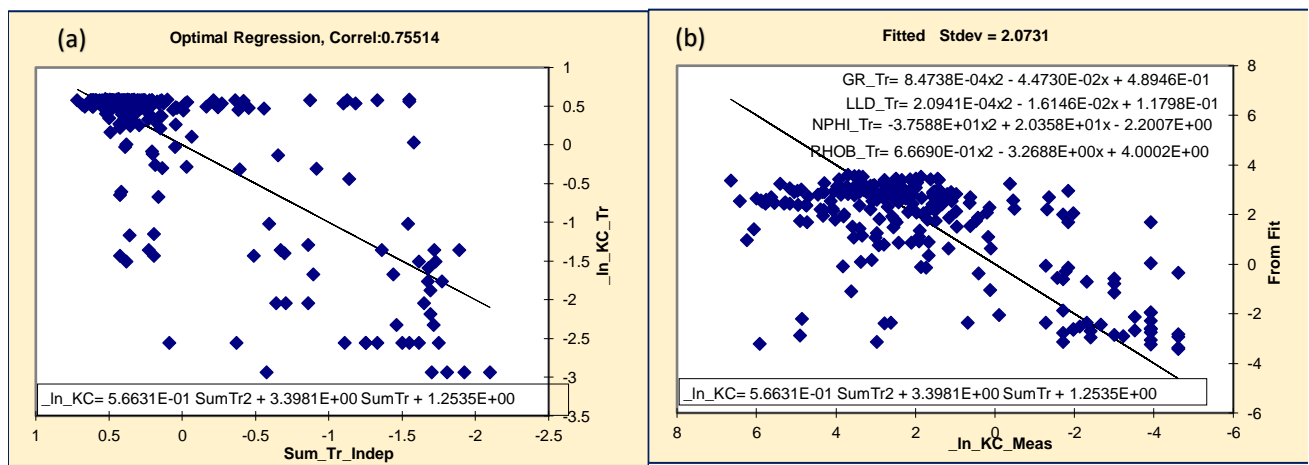

Figure 5. (a) Optimal regression transformation of summation log data and ln k, (b) fitted standard deviation

3.3. Permeability estimation from FZI method

The flow zone indicator (FZI) method used to classify and describe formation having the same (hydraulic flow units), founded on microscopic core samples measurements. The technique of multiple regression was used to establish an association between log data with Flow Zone Indicator (FZI) for estimating permeability of formation under study. Figure (6) shows a logarithm plot of porosity-permeability data obtained from core analyses. The extensive distribution in the size of the pore throat shows significant differences in particle size and sorting in each type of rock, which control the permeability. Figure (6) illustrations, there are many different groups of points, where some groups have low and medium porosity - permeability, while other groups have high porosity – permeability values. Table (1) gives the five regression formulas with their Correlation coefficient (R^2).

Table 1: Formulas and correlation coefficients From FZI Method

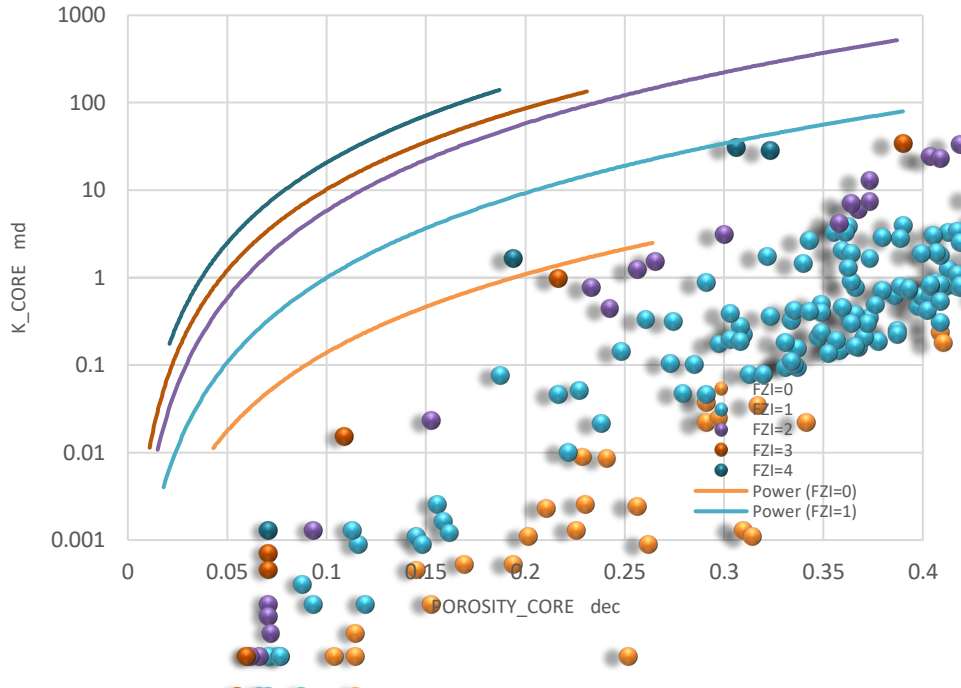| FZI	Correlation	R^2
"FZI-0"	K = 131.93 φ^2.9777	0.7342
"FZI-1"	K = 1647.3 φ^3.2175	0.8979
"FZI-2"	K = 12080 φ^3.3166	0.9903
"FZI-3"	K = 12281 φ^3.0804	0.997
"FZI-4"	K = 23555 φ^3.0561	0.9986

Figure 6. core permeability vs core porosity with FZI for Used 241 Core Sample

Figure (7) demonstrates a cross-plot of log (*RQI*) versus the log (*φz*) with several straight-line that representing flow zone indicator (FZI) values. All points are falling on the same straight-line regarded as having similar characteristics (i.e., they have identical flow zone indicator). Accordingly, these equations were applied to the formation under study; figure (8) shows the predicted and observed permeability profiles.
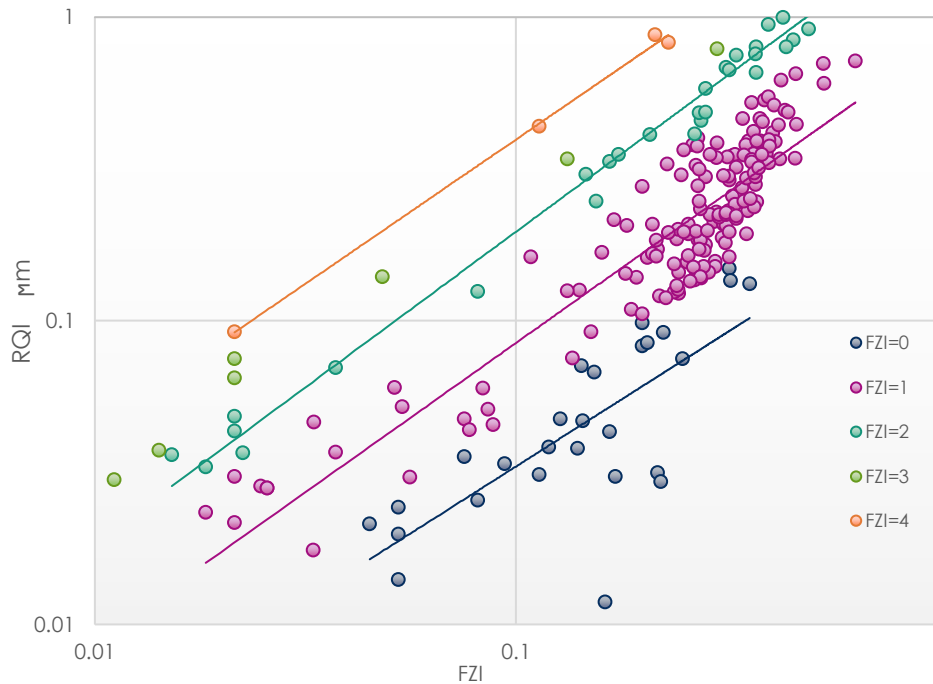

Figure 7. Cross plot of logarithm RQI versus logarithm *φz* with flow zone indicator (FZI) for 241 core sample under study
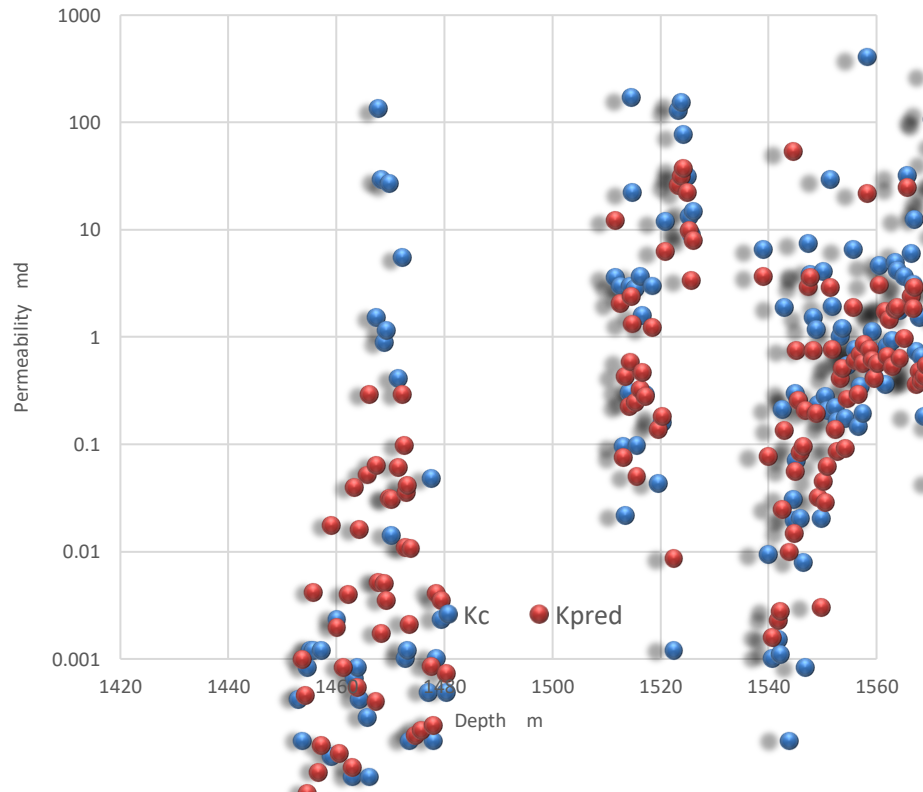
Figure 8. Core and predicted permeability versus depth

3.4. Permeability from FZI-ANN combination algorithm

Permeability estimation methodology using this relatively new approach was discussed in detail in section (2.4). A total of 241 core sample measurements and their corresponding nine sets of well logs data from a heterogenous formation were used to build the network model. Several well-logs are used in this method, such as gamma-ray log, porosity log, sonic log, resistivity log. Porosity is derived from the compensated formation density *FDC* log (*PHID*) and *CNL-FDC* log combination (*PHIE*). Because of the enormous distribution of permeability data, the logarithmic scale was used. The *MATLAB R2017B* toolbox of neural networks utilized in this research. The neural network model structure and the training correlation coefficient plots are shown in Figure (9) and Figure (10), respectively. The abscissa represents the FZI calculated from core sample data, and the ordinate represents the predicted FZI using wireline-log data. Finally, we can substitute predict FZI_log in equation (22) with porosity derived from a log to predict permeability. The measured permeability plot versus network prediction permeability is presented in Figure (11). Figure (12) show the predicted and observed permeability profiles. The high correlation coefficients, ($R^2 = 0.8343$), indicate that the *ANN* method established here can yield findings with a right level of accurateness, despite high grade of heterogeneity formation involved. In this study, the developed *ANN* can be used to predict permeability for new wells in the same field from wireline log data with no need for a very costly coring procedure.
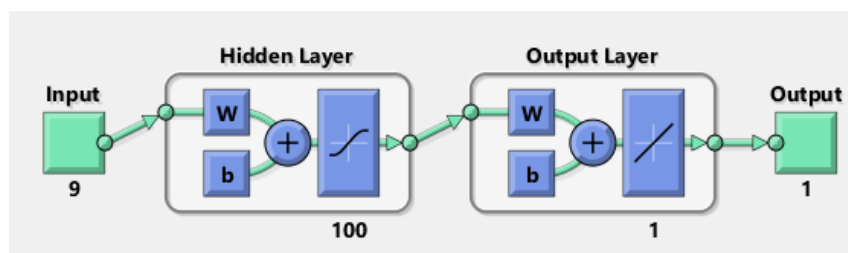

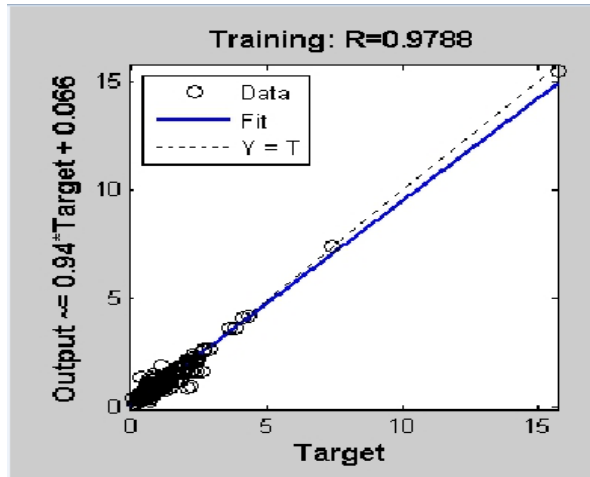Figure 9: The structure of used artificial neural network

Figure 10: Core vs predicted FZI performed using neural network algorithm in MATLAB environment
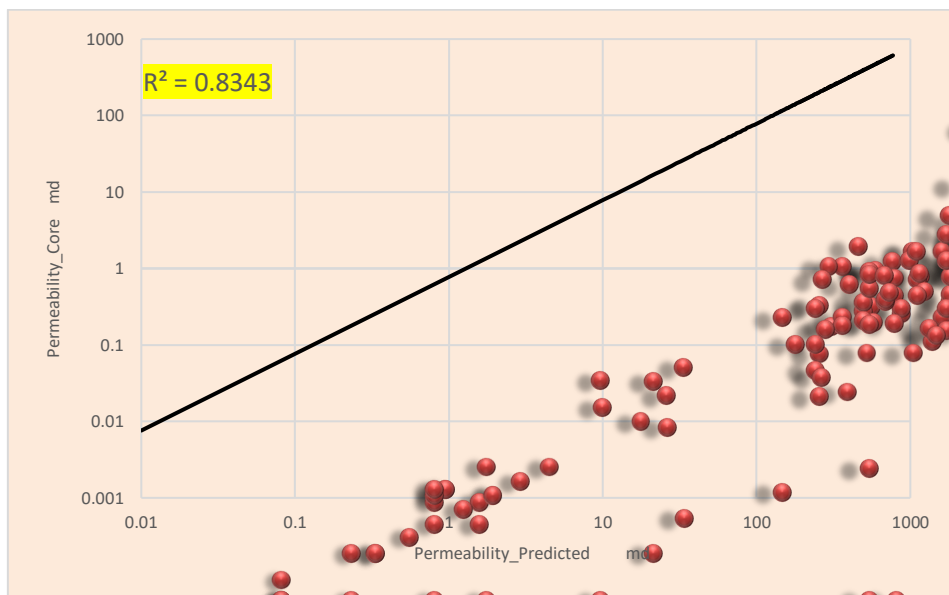

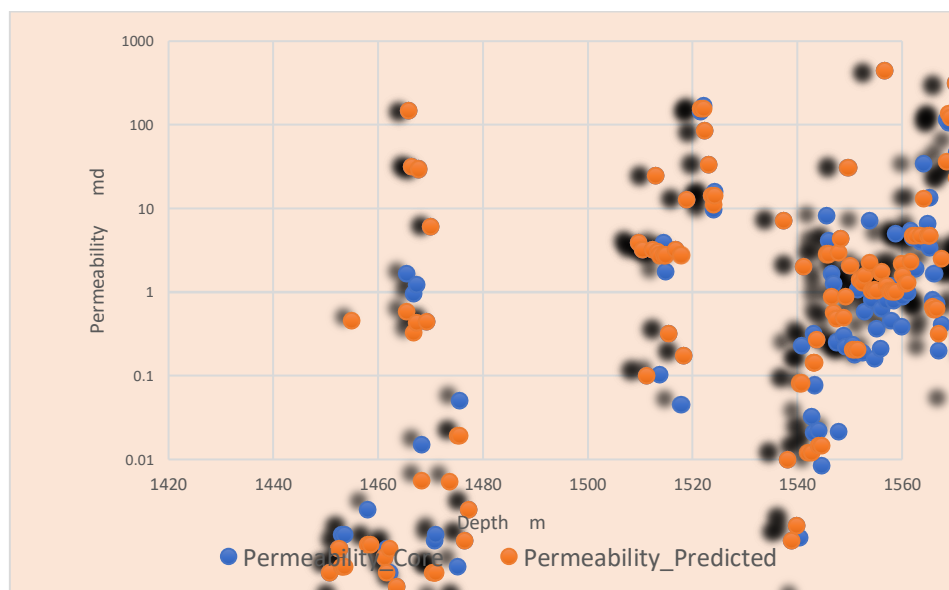Figure 11: Measured and predicted permeability comparison

Figure 12: Measured and predicted permeability comparison vs depth

4. Conclusion

All four methods, empirical, non-parametric multiple regression, FZI, and ANN-FZI combination methods was applied to heterogeneous formation using wireline-log data. All findings show that the last three techniques work better than empirical approaches used to determine the permeability. The non-parametric method of multiple regression still appears to be an ideal tool for evaluating permeability from logs, if used properly. The main advantage of non-parametric multiple regression and neural network implementations is that they do not allow previously measurement of other parameters, as do empirical models (porosity and water saturation). They are also not affected by the uncertainty introduced by the cementation factor and saturation exponent. The result of the FZI method is more accurate than empirical models to calculate the permeability using log records. The developed FZI-ANN model is capable of estimating formation permeability with high accuracy by using only well log data for nine conventional logs. By adding additional parameters to the FZI-ANN model, the input could increase the capability of the model, but it may constrain the extrapolation capability of it. Determination of permeability from other artificial-intelligence and machine-learning methods such as the neuro-fuzzy inference system and model trees by applying a single technique or a hybrid from one or more techniques is recommended for future work.

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