Application of artificial neural network to predict permeability value of the reservoir rock

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Abstract. Permeability is an important reservoir property but it is difficult to predict. An accurate measurement of permeability values can be obtained from core data analysis. However, this analysis is not possible to do at all interval wells in the field, so that permeability information becomes incomplete. Then, the use of artificial neural network method can be an alternative to predict the incomplete permeability values. This study used 191 of sandstone core samples from Upper Cibulakan Formation in the North West Java Basin. These core data were used to determine hydraulic flow unit (HFU) from the reservoir, and to obtain a relationship between porosity and permeability for each HFU. The application of artificial neural network method is done by building a database of flow zone indicator (FZI) based on its relationship with log data. From this FZI value, the HFU class can be known. Afterward, the permeability value can be obtained according to the equation of the relationship between porosity and permeability at each HFU that had been generated. Artificial neural network was applied on G-19 and G-11 Well that had 51 of core data. Based on this study, the result of permeability value is not much different from core data at the same depth, so that this method can be applied to obtain the permeability in uncored intervals.

1. Introduction

Permeability is one of the important of reservoir properties because it is related to the ability of a rock to flow the reservoir fluid. An accurate measurement of permeability values can be obtained from core data analysis. However, not all well intervals in the field can be analyzed of core data so that the permeability information becomes incomplete. Then, the probabilistic method becomes an alternative that can be used for the process of calculating permeability values [1-3]. This probabilistic method is used to predict parameters at uncored intervals. The selection of this method is based on the unavailable secondary data which is log data that explicitly shows a direct relationship with the pore attributes [4,5].

The purpose of this study is to predict the permeability value of uncored intervals by applying artificial neural network method using software. The application of artificial neural network is done by building a database of Flow Zone Indicator (FZI) based on its relationships with the log data. From this FZI value, the Hydraulic Flow Unit (HFU) can be known for all depth interval of the well. Afterward, the permeability value can be determined based on the equation of the relationship between porosity and permeability that has been generated for each HFU.

2 Methodology

This study used 191 of sandstone core samples from Upper Cibulakan Formation in the North West Java Basin. These core samples had had porosity and permeability value from core analysis in the laboratory. These core data were used to determine hydraulic flow unit (HFU) [4,6,7], from the reservoir using Kozeny-Carman's approach [8,9]. In general, the Kozeny-Carman equation can be written as:

$$k = \frac{\emptyset_e^3}{(1 - \emptyset_e)^2}\left[\frac{1}{F_s\tau^2 S_{gv}^2}\right] \tag{1}$$

Then, new parameter is generated that expressed in the following equation:

$$RQI = \sqrt{\frac{k}{\emptyset_e}} \tag{2}$$

$$\emptyset_z = \left(\frac{\emptyset_e}{1 - \emptyset_e}\right) \tag{3}$$

From Equations (2) and (3) then a new parameter is generated, namely FZI (Flow Zone Indicator) which can be expressed in the following equation:

$$FZI = \left[\frac{1}{\sqrt{F_s}\tau S_{gv}}\right] = \frac{RQI}{\emptyset_z} \tag{4}$$

Then, to grouping the data based on the flow unit, the following equation is used:

$$FZI_{discrete} = ROUND\ (2\ x\ \ln(FZI) + 10,6) \tag{5}$$

After determining HFU class using Kozeny-Carman's approach, the relationship between porosity and permeability was obtained for each HFU. Afterward, the application of artificial neural network is used by building a database of FZI models based on its relationships with the log data. Artificial neural network was applied on G-19 and G-11 Well that had 51 of core data. After obtaining FZI value for all depth interval of the well, the class of HFU can be determined. Then, the permeability value can be obtained according to the equation of the relationship between porosity and permeability for each HFU class that had been generated.

3. Results and discussion

Determination of HFU was carried out by applying Kozeny-Carman's approach using 191 of sandstone core samples. From the results of this calculation, it is known that the analyzed reservoir consists of eight different HFUs. The relationship between porosity and permeability of each HFU can be seen in Figure 1.
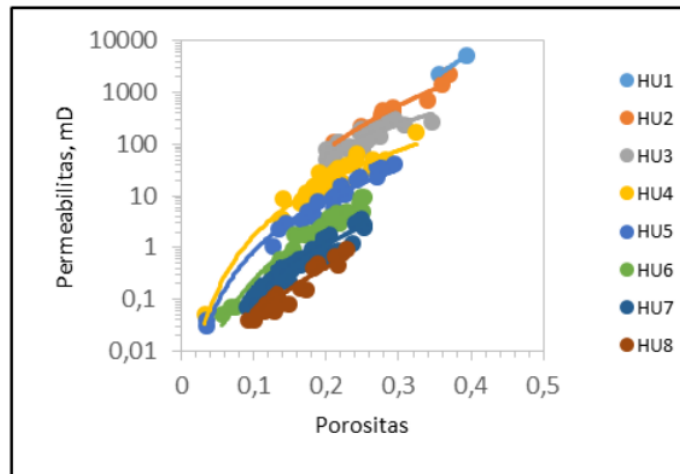
Figure 1. Porosity vs. permeability relationship for each HFU.

From the relationship of porosity and permeability, the empirical equations generated by each HFU can be seen in table 1, where x is porosity and y is permeability.

Table 1. Empirical equations of porosity and permeability relationship for each HFU.

HFU	Empirical Equation
1	$y = 1E{+}07x^{8.394}$
2	$y = 19,8170\ x^{4.879}$
3	$y = 15,918x^{3.481}$
4	$y = 5,064.7\ x^{3.479}$
5	$y = 1,759.9\ x^{3.316}$
6	$y = 840.51\ x^{3.552}$
7	$y = 450.54\ x^{3.718}$
8	$y = 87.244\ x^{3.325}$

Then, to estimate the permeability value of uncored intervals, the calculations was carried out by applying artificial neural network using software. The artificial neural network was applied on G-19 and G-11 Well, G Field that located in the North West Java Basin.

This method is obtained by building a database of FZI model based on its relationships with the existing log data, such as Vshale, SP log, and porosity using the software. After obtaining the FZI value, then the HFU class owned by the G-19 and G-11 Well can be determined.

After that, the permeability value can be calculated using the equations from the relationship between porosity and permeability in each HFU that listed in the table 1. The results of the calculations can be seen in figure 2 and 3.
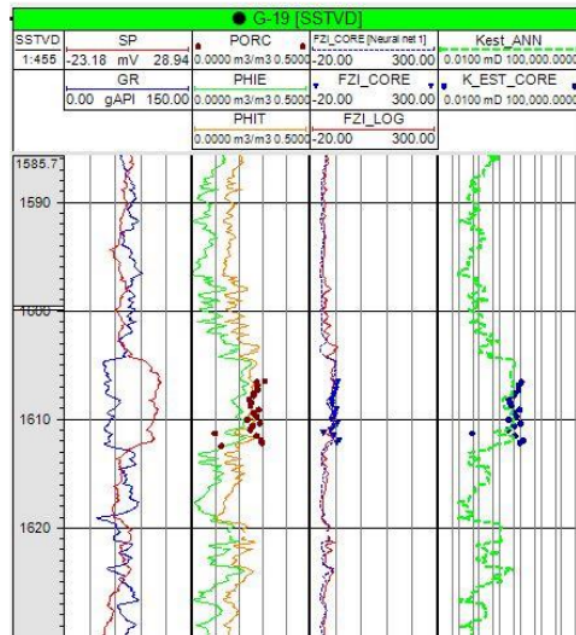
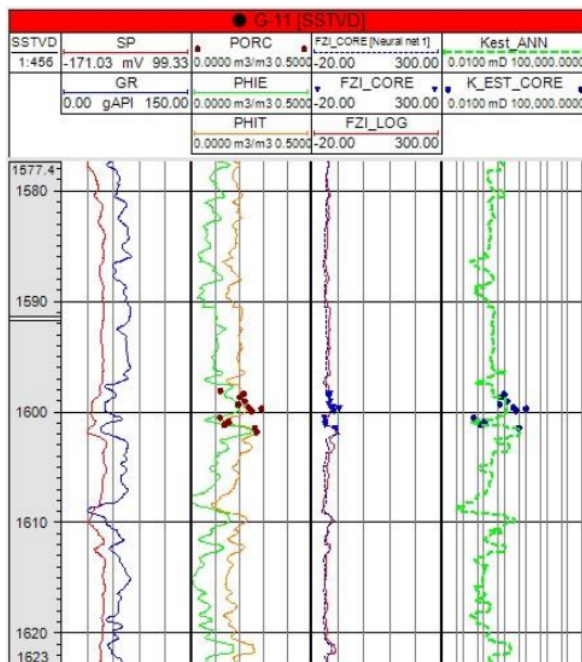**Figure 2.** Log section of permeability calculation using artificial neural network on G-19 well.

Figure 3. Log section of permeability calculation using artificial neural network on G-11 well.

To test the accuracy of the results of permeability value, it was also carried out the comparison between permeability values obtained from the artificial neural network process with the value of the core data at the same depth that can be seen in figure 3.
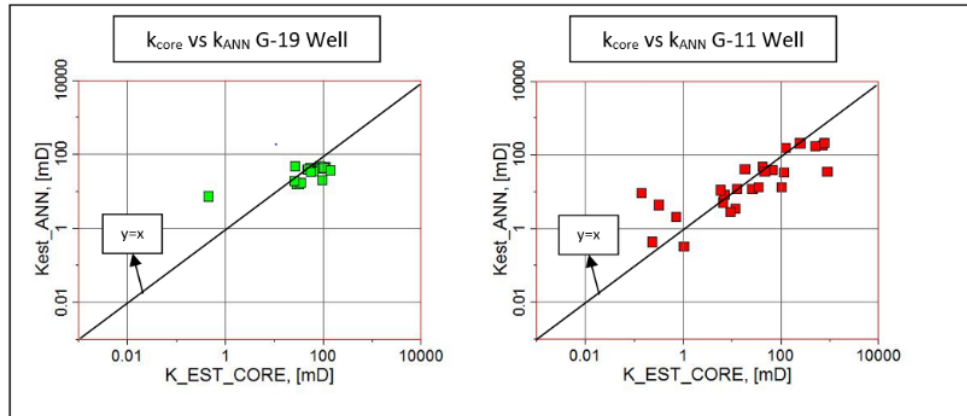

Figure 4. Validation of permeability calculation of G-19 and G-11 well.

Permeability values are on a logarithmic scale, therefore the deviation of resulting permeability from this study is obtained by looking at the cycle differences. The number of available core data in G-11 and G-19 Wells are 51, thus the deviation of permeability values from the artificial neural network and core data can be seen in table 2.

Table 2. The deviation of permeability values from artificial neural network and core data.

Cycle differences	Number of data	Percentage
Same Cycle	34	66.67%
1 Cycle	14	27.45%
>1 Cycle	3	5.88%

From these results, it can be seen that the deviation from artificial neural network is not much different, because most of the results are in the same cycle with the core data, and only a small portion of the data has a difference more than 1 cycle.

4. Conclusion

The results of this study show that artificial neural network can be used to predict permeability value of the reservoir rock, and the results of permeability calculations using artificial neural networks are not much different from core data, because most of the results are in the same cycle with core data. Permeability prediction at uncored intervals using artificial neural network method can provide benefits to the company because permeability values can be determined without coring and its analysis, so it can reduce the expenses of the company.

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