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A New Method to Classification of Total Organic Carbon by Petrophysical Logs in Australia

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Abstract

Total Organic Carbon (TOC) is an importance parameter in the assessment of rock sources. By evaluating this parameter, we can estimate the total amount of hydrocarbons in the rocks. The most common method for measuring TOC is the use of cores obtained from drilled wells. This is a costly and time-consuming process and, in addition to the expenditure of coring, will cost a lot of maintenance. Over the past few years, extensive studies have been carried out to estimate TOC using less costly methods, which will be discussed in more details in the introduction. Modern and low-cost methods help to inspect reservoirs with high exploratory risk like gas shale reservoirs. In this paper, it was tried to make a correlation between conventional Petrophysical logs and TOC using the neural network in one well in western Australia. By encoding the initial data and categorizing them in the neural network, we finally conclude that it is possible to obtain a good accuracy of classification of hydrocarbon content.

Keywords: Neural Network; Petrophysical Logs; Total organic carbon; Western Australia

Abbreviations

ANN	:	Artificial Neural Network
Cal	:	Caliper Log
DT	:	Sonic
GR	:	Gamma Ray
LLD	:	Deep Laterolog
LLS	:	Short Laterolog
MLPNN	:	Multi-Layer Perceptron Neural Network
MSFL	:	Micro Spherical Logging Tool
NPHI	:	Neutron porosity
PCA	:	Principle Component Analysis
PCs	:	Principle Components
PCn	:	Principle Component Number
RHOB	:	Bulk Density
SP	:	Spontaneous Potential Log
TOC	:	Total Organic Carbon

Introduction

The total organic carbon is one of the vital information in shale oil reservoirs, whereas it has the ability to report oil approximation the quality of the reservoir rock and the ingredient of hydraulic fracturing [1]. Laboratory estimation of TOC is exact but immoderate and time assimilating. On the other hand, conjecture of TOC from experimental correlation enlarged based on well-logs data is fast but not exact enough. Accordingly, researchers have been attempting to invent methods for prognostication of TOC over the years. Predominantly, log-based methods to predicted TOC have been involved in the literature. Most of these methods accredit through system of cores to logs gradation [2]. Derived TOC estimation compares very well with cores results. The expected differences, due to the different amount of organic substance down-hole (kerogen and oil) and samples (kerogen only), lies on various maturity conditions. (Herron, 2011) [3] Has been concluded it is possible to distinguish the amount of organic matter by disparate logging techniques inclusive of multi tool petro physical assessment, elemental catch spectroscopy and nuclear magnetic resonance [4]. A number of core data for calibration with resistivity logs have been used to evaluate the TOC in organic rich reservoirs [5]. Several logs have been computed on the cores data on Jiaoshiba gas field, and eventually, bulk density method was opted for divination of TOC [6]. Juxtaposed different methods quantifying TOC from logs to calibrate with cores data for Niobrara formation and resulted The Schmoker and the Delta Log R methods are effective methods in deriving TOC from well logs in formations where the log respond are influenced by organic content and maturity [7].

In La Luna formation shown the differentiation between 62 wells with cores, inferred that La Luna formation is naturally fractured, it can produce hydrocarbons equal conventional reservoirs. Jorge Gonzalez et al, (2013) [8] exploited a new neutron induced gamma ray spectroscopy mensuration to appraise TOC in organic shale rocks. They have been assessed TOC without the necessity for local correlations and prohibitively expensive logs exegesis [9]. Propounded about well log anomalies caused by TOC as observed on various wire line measurements, including resistivity, acoustic, pulsed neutron, natural gamma ray spectroscopy, gamma ray, and nuclear. Field examples are in open or closed wellbores from several countries. Eventually, they ensued three issues: 1 - TOC content can be approximated from several types of geophysical well logs. 2 - TOC content can be distinguished in open and cased wellbores. 3 - Field case parables decorated factual correlations between TOC content and combinations or single of wire line logging parameters.

Many researchers focused on the feature classification by pattern methods in the earth science [10-13]. In this paper, it was used 138 samples from Laurel and Clan Meyer formations. The first has been investigated data in single dimensional space and significant results weren't achieved. In two dimensional space they were observed data aggregation in part of diagram and in three dimensional space results were the same and these haven't been clarified on diagrams. Then, it was tried to correlate between TOC and Principle Components (PCs) of logs. At the end, it is used Artificial Neural Network (ANN) as a classifier.

Data and Geology

In this paper, it was used a full dataset of an exploratory oil well, which is located in the Western Australia. The section penetrated in a well in age from Lower Permian to Upper Devonian. A detailed penetrated stratigraphic section is shown in (Figure 1). Formation Tops and ages are based upon lithologic and paleontologic studies of drill cutting, sidewall cores, and electric logs. One conformable and three unconformable formational contacts were found. Age date for the non-marine Permian, Permo-Carboniferous and part of the Lower Carboniferous are based entirely on palynological data. The marine Lower Carboniferous and Upper Devonian were dated by palynological and Ostra code data.

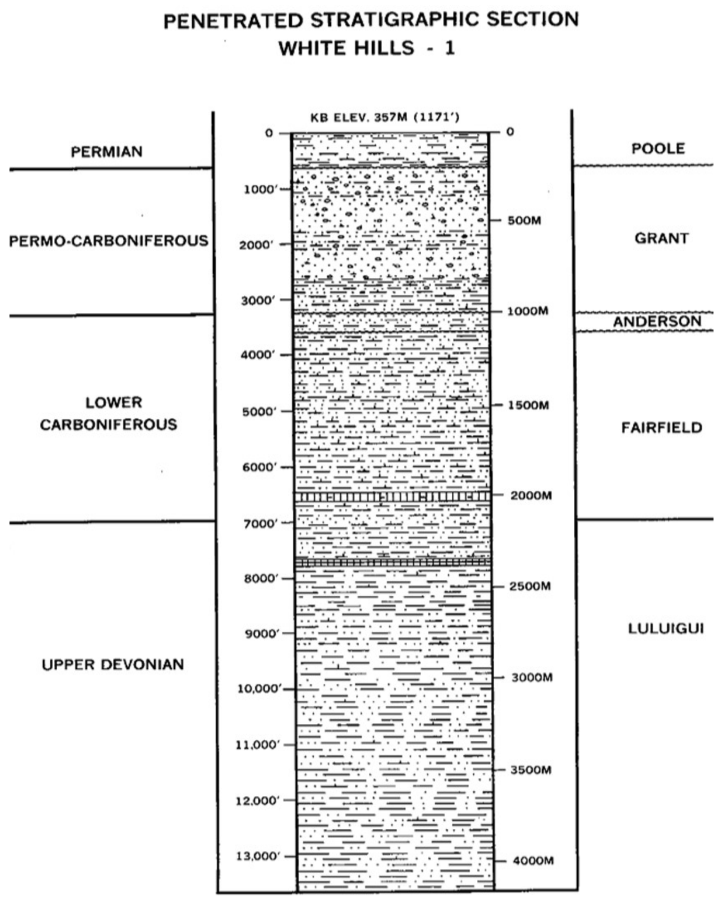

Figure 1: Penetrated stratigraphic section [14].

The studied oil field has embedded in Luluigui and Laurel Carboniferous Formations for which geological and Formation properties are available (Figure 2). The Tournaisian-Visean Laurel Formation is a lagoonal to marine section, which can subdivide into two units:

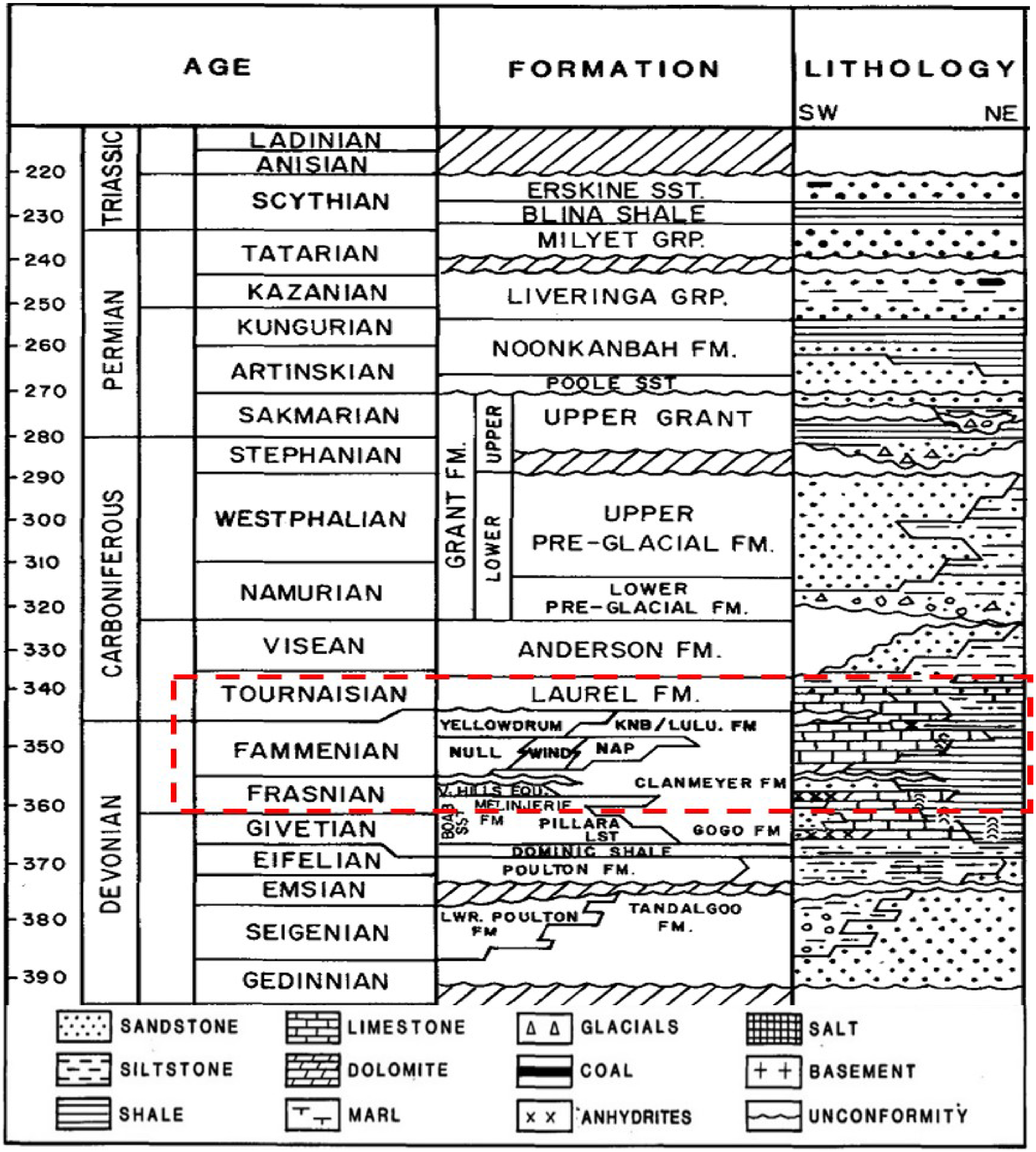

Figure 2: Stratigraphy of Laurel and Luluigui Formations [14].

Upper Laurel Clastic Formation

Lower Laurel Carbonate Formation

The Luluigui Formation may be divided into 3 zones based on lithology and electric log responses (mudstone and siltstone; thin inter beds of mudstone, siltstone and sandstone; very thin inter beds of sandstone, siltstone and mudstone) [14]. Available digitized well logs, geochemical parameters and geological interpretations have shown in Table 1. The available data include geochemical analysis of 137 samples (Table 1) and 3500 point for Petrophysical logs of this well.

Well No.	Depth (m)	Utilized Loges	Organic Geochemical data
Well. 1	1240-3500	GR, DT, SP, CAL , NPHI, LLD, LLS, RHOB, MSFL	TOC

Table 1: Data Available.

Methodology

Principle Component Analysis

Principal Component Analysis (PCA) is a multivariate technique that analyzes a data table in which observations are described by several inter-correlated quantitative dependent variables. The goals of PCA are to (a) extract the most important information from the data table, (b) compress the size of the data set by keeping only this important information, (c) simplify the description of the data set, and (d) analyze the structure of the observations and the variables [15].

Multi-Layer Perceptron Neural Network (MLPNN)

While multilayer neural networks may appear to be somewhat ad hoc, we now show that when trained via backpropagation on a sum-squared error criterion they form a least squares to the Bayes discriminant functions [16]. It is generalized this result in two ways: to multiple categories and to nonlinear functions implemented by three layer neural networks. We use the network of Figure 3 and let gk (x; w) be the output of the k^{th} output unit "|" the discriminant function corresponding to category ωk. Recall first Bayes' formula,

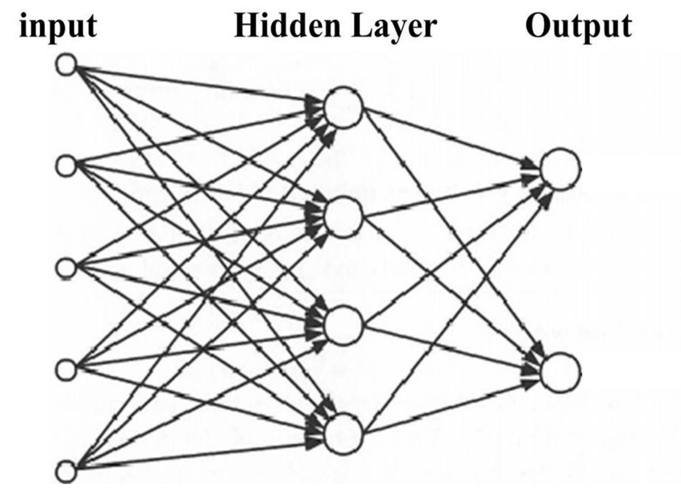

Figure 3: Architecture of a multilayer network.

$$P(\omega_k|x) = \frac{P(x|\omega_k)P(\omega_k)}{\sum_{i=1}^{c} P(x|\omega_i)P(\omega_i)} = \frac{P(x,\omega_k)}{P(x)} \qquad (1)$$

and the Bayes decision for any pattern: choose the category ωk having the largest discriminant function

$$g_k(x) = P(\omega_k|x) \qquad (2)$$

Suppose we train a network having c output units with a target signal according to (Duda, et al, 2012) [17]:

$$t_k(x) = \begin{cases} 1 & \text{if } x \in \omega_k \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

Process and Results

Classification for quality detection using Petrophysical Logs in 2D and 3D is illustrated in Figures 4 and 5, respectively. In these diagrams, it can be seen that types of quality zones have some overlaps in these cross-plots (Figures 4 and 5).

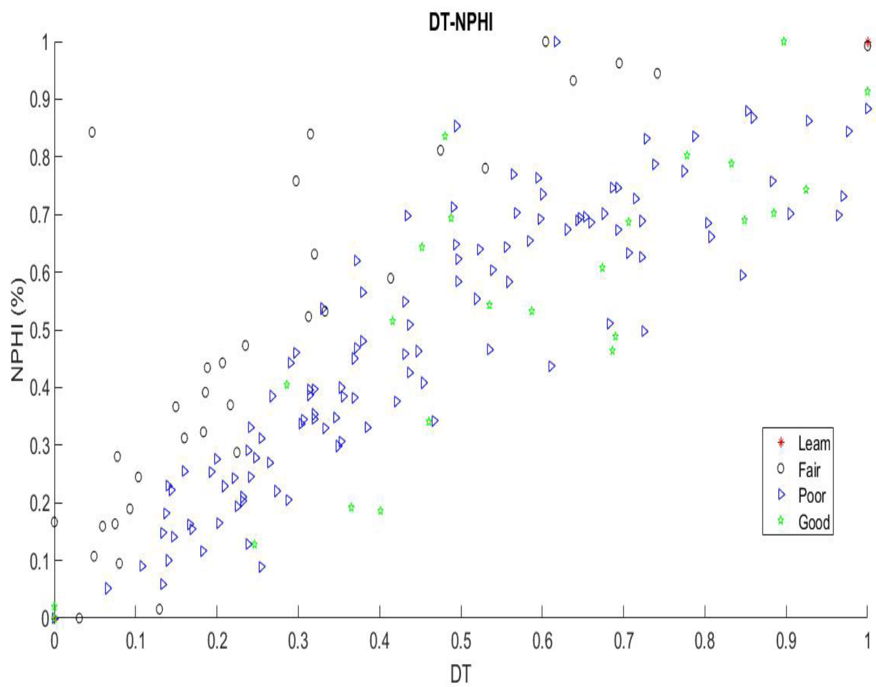

Figure 4: Graph DT according to NPHI based on code division.

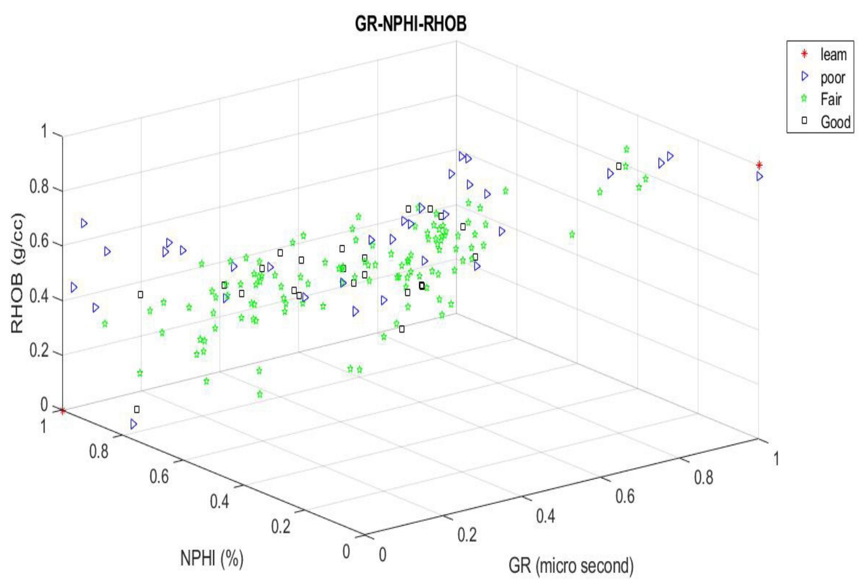

Figure 5: Graph GR-NPHI-RHOB based on code division.

Due to the lack of data resolution and their aggregation in a certain part of the graph, it seems not possible to interpret and verify the graph. Consequently, the data were reflected in 2D and 3D space. The data were again encoded and discriminated by color and then the graphs were plotted.

The result of the 3-D graph was presented as an example. The MATLAB software was used to plot the graphs in the 3D space, and the following result was obtained as an example for GR, NPHI, and RHOB data.

The data in the 3D space is better discriminated; however, it is still difficult to verify and comment on this graph. After that, it is tried to reduce space dimension by Principle Component Analysis (PCA). Correlation between geochemical parameters and logs and PCs are very low (Table 2). According to the available data from the core, the number of verified data was 137. Again, favorable results were not obtained. In the final step, we tried to carefully examine the data using the Neural Network (MLPNN). In this case, it is found that the incompatibility of the results represents a verification error.

	DT	SP	CAL	GR	RHOB	NPHI	FCNL	LLD	LLS	MSFL	PC1	PC2	PC3
TOC	0.16	0.17	-0.01	0.09	0.1	0.15	0.01	0.18	0.15	0.17	-0.29	0.01	-0.02

Table 2: Correlation between TOC and logs.

To discriminate between all of quality zones, a multi coding system is used. In this system, code 1 is used for poor, code 2 is used for fair and code 3 is used for good zones. This coding system is caught from TOC contents and maturity. Then Neural Network classifier is selected to detect types of quality zones. The PLs are used for classification. Comparing final results with core reveals that NN classification is a good approach to identifying between types of quality zones in gas shale resources.

As it can be seen, the accumulation of data in the initial part is quite evident. It can also be concluded that the highest frequency is considered for the code with mean = 2. Afterwards, the encoded geochemical data were verified with the well log data. This verification was conducted with graphs based on well log data. Examples of porosity and resistance graphs verification are presented below. Initially, the data were encoded in the same way as the first step. Due the lacking of number of data with code 4 (very good) dataset is abandoned. In order to apply this method, data were randomly divided into three data sets (training (70% of the data points), validation (15%) and testing (15%) data). After loading the data correctly, a MLP network of [10 10 1] architecture with Conjugate Gradient optimizing algorithm is a good ANN. Table 3 shows confusion matrix of MLP-ANN.

Stage	Confusion Matrix
Train	$\begin{bmatrix} 60 & 40 & 0 \\ 20 & 68 & 12 \\ 0 & 0 & 100 \end{bmatrix}$
Test	$\begin{bmatrix} NAN & NAN & NAN \\ 19 & 56 & 25 \\ 0 & 100 & 0 \end{bmatrix}$
Validation	$\begin{bmatrix} 100 & 0 & 0 \\ 8 & 75 & 17 \\ 0 & 0 & 100 \end{bmatrix}$

Table 3: Confusion Matrix.

The validation plot showed an error of 23.1% in the best condition. After verifying, it has been found that at some depths the encoding was erroneous and the quality was read completely wrong. But in some cases we face uncertainty that the network does not clearly indicate whether it is correct or not. The results were then improved by changing optimization function and distribution of data. In this case, the function (Levenberg-Marquardt) is used (Table 4).

Stage	Confusion Matrix
Train	$\begin{bmatrix} 100 & 0 & 0 \\ 20 & 65 & 15 \\ 0 & 0 & 100 \end{bmatrix}$
Test	$\begin{bmatrix} 100 & 0 & 0 \\ 22 & 63 & 15 \\ 0 & 0 & 100 \end{bmatrix}$
Validation	$\begin{bmatrix} 100 & 0 & 0 \\ 12 & 79 & 9 \\ 0 & 0 & 100 \end{bmatrix}$

Table 4: Confusion Matrix.

Finally, in Figure 6, we compared real data with multilayer perceptron neural network so that we can accurately measure the estimation rate.

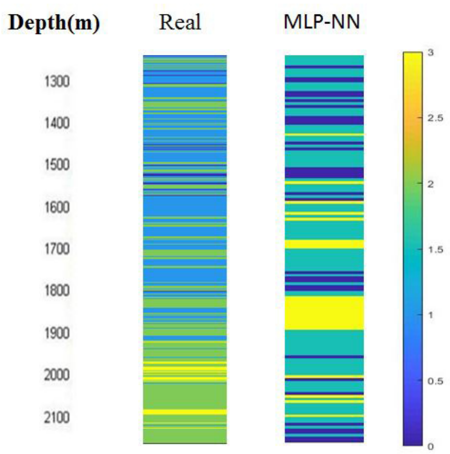

Figure 6: Comparison between real data and multilayer perceptron in NN.

Conclusion

The Total Organic Carbon Content (TOC) is a critical parameter in the geochemical evaluation of source rocks and their potential hydrocarbon deposits. However, due to the lack of cores and drilling cuts for old wells and the high cost of geochemical analysis, limited measurements are often available from the sample. Furthermore, Coring operations and core preservation are costly. Many methods have been developed to estimate this important parameter, regarding other available and affordable information. One of these methods is interpreting information obtained from some well logs that their variations are related to the total organic carbon. Different hybrid methods have been proposed to investigate the correlation between geochemical data and well logs data, which are described in detail in the introduction.

As brought up in the discussion section, by establishing the correlation between TOC and logs using the neural network, the results show that with this method, up to 76% accuracy can be checked for correlation that this method demonstrates the success of this procedure in examining data correlations.

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