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Rock typing and facies identification using fractal theory and conventional petrophysical logs

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Abstract. Rock typing or subdivision of a reservoir either vertically or laterally is an important task in reservoir characterisation and production prediction. Different depositional environments and diagenetic effects create rocks with different grain size distribution and grain sorting. Rock typing and zonation is usually made by analysing log data and core data (mercury injection capillary pressure and permeability measurement). In this paper, we introduce a new technique (approach) for rock typing using fractal theory in which resistivity logs are the only required data.

Since resistivity logs are sensitive to rock texture, in this study, deep conventional resistivity logs are used from eight different wells. Fractal theory is applied to our log data to seek any meaningful relationship between the variability of resistivity logs and complexity of rock fabric. Fractal theory has been previously used in many stochastic processes which have common features on multiple scales. The fractal property of a system is usually characterised by a fractal dimension. Therefore, the fractal dimension of all the resistivity logs is obtained.

The results of our case studies in the Cooper Basin of Australia show that the fractal dimension of resistivity logs increases from 1.14 to 1.29 for clean to shaly sand respectively, indicating that the fractal dimension increases with complexity of rock texture. The fractal dimension of resistivity logs is indicative of the complexity of pore fabric, and therefore can be used to define rock types.

Keywords: Cooper Basin, fractal geometry, Higuchi's fractal dimension method, resistivity well logs, rock typing.

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Introduction

Flow prediction of reservoirs requires identification and modelling of rock types. This results in finding the optimum location of well placement for production from the field. Rock typing is an integral part of reservoir characterisation which identifies different flow units (Gupta *et al*. 2017). The first step in trying to predict the behaviour of a reservoir system is characterisation of reservoir rock types to form a static reservoir model. Rock, fluid and rock–fluid properties are then attributed to up-scaled static model cells.

More accurate prediction of flow requires detailed knowledge of the heterogeneity of the reservoirs. The performance of a reservoir is controlled by intrinsic properties of fluids and the geometry of the pore system. The effective description of the reservoir requires an adequate understanding of petrophysical properties of the rock, such as porosity, permeability, capillary pressure, heterogeneity and fluid content (Porras *et al*. 1999).

Knowledge of these properties facilitates the subdivision of the reservoir into layers with similar properties according to flow point. This subdivision enhances flow behaviour modelling and reduces uncertainty in predicting production. This process is referred to as rock typing. There are many different definitions for 'rock type' in the literature; the most adopted definition is by Gunter *et al*. (1997): 'Rock typing is a method of classifying reservoir rocks into distinct units, each of which was deposited under similar geological conditions and has undergone similar diagenetic alterations'.

This definition includes depositional features along with diagenetic effects in defining a rock type. This implicitly suggests that the pore structure of a rock – i.e. pore and pore throat dimensions, geometry, size, distribution and capillary pressures – should be similar within a rock type. It has been long established in the oil and gas literature that these parameters are the main drivers of fluid flow in porous media.

In conventional reservoirs, flow unit rock typing is usually done based on porosity–permeability relations. There are numerous rock typing studies in the literature. The common evaluation techniques are:

- Physical core description of large- and small-scale features, along with core measurements of porosity and permeability; dominant pore throat diameter from mercury injection capillary pressure (MICP) data.
- Texture, composition and lithology of the rock, along with considering the deposition environment of the reservoir.
- Identification of lithofacies from log analysis complemented with core-based measurements.

Other methods include use of R35 measurements from mercury injection, proposed by Pittman (1992), in which average pore throat radius is measured from the 35% injection level of mercury. The concept of rock quality index and flow zone indicators was introduced by Amaefule *et al*. (1993). In tight sands, however, use of all the above techniques needed to be complemented with rock texture and fabric descriptions to achieve more accurate results (Rushing *et al*. 2008).

One way to infer rock types is by use of well logs. In this method, statistical features are defined for the trend of the corresponding well log, and these features are used to identify the same rock type in other wells. However, since conventional interpretations of logs do not provide any direct information on complex pore geometries, it is difficult to consider pore structure in rock typing methods using well logs.

Fractal geometry offers a new approach for interpreting well logs. Use of fractal theory in oil and gas has a significant history. In 1986, Hewett proved that porosity logs were fractal (Hewett 1986). Using the fractal character, Hewett generated porosity distributions and used them to enhance fluid flow simulation. There were other similar studies (Crane and Tubman 1990; Emanuel *et al*. 1990; Hewett and Behrens 1990; Aasum and Kelkar 1991; Hardy 1992; Hardy and Beier 1994; Perez and Chopra 1997; Lozada-Zumaeta *et al*. 2012). Some authors found that the pore structure of rocks was a fractal property (Avnir *et al*. 1985). Others investigated different sandstones and confirmed their fractal character (Katz and Thompson 1985; Krohn and Thompson 1986). These workers also suggested methods to determine the fractal dimension of these structures. Pang and North (1996) suggested that the fractal dimension of well logs is related to stratigraphic heterogeneity; more heterogeneous rock produced well logs with a larger fractal dimension. Shen *et al*. (1998) suggested that the fractal dimension of pore structure can be used to classify rock type. They investigated 22 cores and concluded that the fractal dimension can be related to oil recovery at water breakthrough and irreducible water. Wang and Mou (2014) measured the fractal dimension of various wireline log data, including compensated neutron, density, gamma ray and acoustic logs for 108 wells, and found corresponding relationships between fractal dimension of logs and texture of volcanic rocks.

In most studies, the fractal dimension of the pore structure is derived from microscopic core images and images of thin sections using image processing techniques. Furthermore, no study has considered the fractal dimension of resistivity well logs and its relationship to rock texture. Considering the effect of rock texture on the resistivity of the rock, along with the fact that pore structure of rocks is fractal, makes it logical to expect that the fractal dimension of resistivity logs is related to rock texture.

The objective of this study is to show that fractal dimension of resistivity logs can be related to rock texture, and thus can be used as a new method to identify rock types. First, a background of fractal theory and resistivity of porous media is presented, followed by details of our proposed method. Then, data and results are interpreted and discussed.

Theory background

In this section, a background in fractal theory and some facts on resistivity in porous media are presented.

Fractal theory background

A fractal is a geometric pattern that shows similarity to itself at any level of magnification (scale). The pattern that causes the self-similarity can be repeated at multiple scales to produce irregular shapes and surfaces that cannot be modelled by conventional geometry. This is the main feature that differentiates fractal geometry from Euclidian geometry. The concept of fractals was introduced by Mandelbrot and has been shown to be capable of mathematically modelling irregular natural patterns.

Before the introduction of fractal geometry, mathematicians had come across many patterns and shapes that could not be modelled by Euclidian geometry. A turning point came when Benoit Mandelbrot introduced a more comprehensive definition of dimension. He stated that the dimension of a fractal must be used as an exponent when measuring its size (Mandelbrot 1983). As a result, fractals cannot be described with integer dimensions but require fractional dimension, hence the name fractal geometry.

Mandelbrot defined fractal as ‘a shape made of parts that are similar to, or repeat the whole in some way’ (Mandelbrot 1983). This is a definition of self-similar fractals. This type of fractal is too regular to model natural phenomena. Self-affine fractals, however, are defined as objects that are statistically similar to themselves. For example, a fern leaf would look similar to itself at different scales but would not be identical. Self-affine fractals are mainly used to model time–depth sequences and spatial distributions. This property that objects can look statistically self-similar while also exhibiting some variability in detail at different length scales is the central feature of fractals in nature (Feder 1988). Fractals have been used in many areas of natural sciences, e.g. river networks, fault lines, mountain ranges, coastlines, thickness of tree trunks, heart rates and earthquakes.

The scale invariance of fractals is mathematically described by a power law. A power law distribution is the only statistical distribution that is scale invariant.

One of the best methods for mathematical modelling of self-affine fractals is fractional Brownian motion (fBm). In terms of a function of time, fBm is defined as:

$$B_H(t) = B_H(0) + \frac{1}{\Gamma(H+\frac{1}{2})} \left\{ \int_{-\infty}^{0} \left[(t-s)^{H-\frac{1}{2}} - (-s)^{H-\frac{1}{2}}\right] dB(s) + \int_{0}^{t} (t-s)^{H-\frac{1}{2}} dB(s) \right\} \tag{1}$$

The fBm is a self-similar, stationary process with long range interdependence, and has a covariance in the form of:

$$E\{B_H(t)B_H(\tau)\} = 0.5\sigma^2\left(|t|^{2H} + |\tau|^{2H} - |t-\tau|^{2H}\right) \tag{2}$$

where $b_H(t)$ is an fBm as a function of time, σ is the standard deviation and H is commonly known as the Hurst exponent and characterises the scaling behaviour of the series; H ranges between 0 and 1. When H is close to zero the time series are rough with strong variation, and when H is close to 1 they are smooth with less variation.

The H is related to the fractal dimension of a one-dimensional time series by:

$$D = 2 - H \tag{3}$$

where D is the fractal dimension.

The H also quantifies the persistence and anti-persistence trend in the time series. Persistence ($H > 0.5$) means that an increasing trend is likely to be followed by an increasing trend; and anti-persistence ($H < 0.5$) means that an increasing trend is likely to be followed by a decreasing trend. Fractal statistics provide a simple way of relating variations at larger scales to those at smaller scales and vice versa (Gray *et al*. 1993).

Equation 3 is one method of calculating the fractal dimension, where H can be derived using the rescaled range method, considering the time series is best modelled as fBm. Other popular techniques are used to test for fractal scaling and determination of fractal dimension of wireline logs (or any time series): variogram and spectral techniques, box-counting method, Katz, Sevcik and Higuchi methods.

The three commonly used techniques for estimating fractal dimension (i.e. rescaled range, variogram and spectral techniques) are not reliable when the underlying signal is either limited, non-Gaussian or non-stationary (Gray *et al*. 1993). These methods are severely affected by small number of samples and non-stationarity, therefore they are not suitable for analysing logging data. This is especially true for fluvial facies of the Cooper Basin where production intervals are relatively small. The box-counting method is highly sensitive to sampling frequency. In addition, in the case of wireline logs the data axes are incompatible, in other words the x (resistivity) and y (depth) axes cannot be compared with each other. Raghavendra and Dutt (2010) developed a variation of the box-counting method called the Multiresolution Box-counting Method (MBCM) that resolved this issue, but the MBCM requires a high sampling rate, making it unsuitable for analysing well logs. The same study showed that the Katz and Sevcik methods yielded poor results compared with MBCM and the Higuchi method.

Among the mentioned methods, Higuchi's algorithm is least affected by the sample number of the signal and is most suitable for analysing the fractal dimension of short-interval signals. For this reason, we used Higuchi's method to calculate the fractal dimension of resistivity logs.

Higuchi's method

Higuchi's algorithm for calculating the fractal dimension of a one-dimensional signal is described below (Higuchi 1988):

Consider a finite, discrete set of samples taken at regular interval:

$$x(1), x(2), x(3), \ldots, x(N) \tag{4}$$

where N is the total number of samples. From this given time-series new subseries denoted by x_m^k are generated.

$$x_m^k = \left\{ x(m), x(m+k), x(m+2k), \ldots, x(m + \left[\frac{N-m}{k}\right].k \right\} \quad (m = 1, 2, \ldots, k) \tag{5}$$

where k is the scaling factor usually chosen based on the total number of samples. Both k and m are integer values, and [a] denotes the closest integer to a. For example, for $k=3$, and total sample number of $N=100$, the subseries are:

$$x_3^1; x(1), x(4), x(7), x(10), \ldots, x(97), x(100)$$

$$x_3^2; x(2), x(5), x(8), x(11), \ldots, x(95), x(98)$$

$$x_3^3; x(3), x(6), x(9), x(12), \ldots, x(96), x(99)$$

For each subseries x_m^k a corresponding length is defined as:

$$L_m(k) = \frac{1}{k}\left\{ \frac{N-1}{\left[\frac{N-m}{k}\right].k} \left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} |x(m+ik) - x(m+(i-1).k)| \right) \right\} \tag{6}$$

where $\frac{N-1}{\left[\frac{N-m}{k}\right].k}$, is a normalisation factor for the x_m^k subseries. The above formula will result in k number of lengths for each x_m^k subseries. The length for k is defined as $L(k)$ and is computed as the average value of the k sets of $L_m(k)$. That is:

$$L(k) = \sum_{m=1}^{k} L_m(k) \tag{7}$$

If $L(k)$ is proportional to k^{-D}, then the initial time series is fractal with dimension D.

If $L(k)$ is plotted against k on a double logarithmic plot, the points will fall on a straight line, the slope of which is fractaldimension (D) of the time series.

Resistivity of porous media

Resistivity logs are among the very first logs to be recorded. The principal use of resistivity logs is to locate hydrocarbons; however, they can also provide information on lithology, texture, facies overpressure and source rock aspects (Rider 1986).

The resistivity of the rock matrix is usually assumed to be infinite, thus the resistivity is presumed to be a function of the pore fluid alone. This is not entirely true as the matrix plays a passive role in resistivity of the rock. This passive role is dependent on the geometry of the pores, pore connections, tortuosity and pore size distribution. Studies have shown that resistivity of fluid-filled sedimentary rocks is mostly controlled by pore structure (Archie 1942; Bigalke 2000). Wettability, saturation history and temperature also play important roles (Swanson 1985; Kumar *et al*. 2010). Pore-structure characteristics can be estimated from electrical resistivity logs and used for a better estimation of permeability (Verwer *et al*. 2011).

Any clays present play an active role in conduction of the rock. Clays conduct electricity in two ways: through pore water and through clay itself (Rider 1986). The resistivity of reservoir rocks depends on numerous factors which can collectively be described as rock fabric. Rock fabric describes the spatial and geometric configuration of the rock, and can be represented by numerical engineering values complemented with geological descriptions of the rock.

Katz and Thompson (1985) proposed that the pore spaces of sandstones are fractal and presented several measurements to support their proposal. The electrical conductivity in porous media obeys a scaling law (Toledo *et al*. 1994), which suggests that resistivity well logs have fractal character:

$$\sigma_w \propto {S_w}^{\frac{1}{m(3-D)}} \tag{8}$$

where, σ_w is the electrical conductivity of the porous medium, S_w is water saturation and m is Archie's cementation factor.

We propose that the fabric of a rock type affects the variability of resistivity logs, and this can be uniquely characterised by the fractal dimension of the resistivity logs.

Data

The Cooper Basin is the most prospective onshore petroleum and natural gas province in Australia. It is a sedimentary basin that formed and developed from the late Carboniferous to middle Triassic geologic periods. It unconformably overlies the Warburton Basin and unconformably underlies the Cretaceous Eromanga Basin (Gravestock and Jensen-Schmidt 1998). The basin is located across the north-east of South Australia and the south-west of Queensland. The reservoir system comprises a multi-zone high-sinuosity fluvial sandstone ranging from tight (unconventional) to good-quality conventional reservoir rocks. There is a large range of porosity and permeability in the basin due to combination of facies and burial depth. The main gas reservoir is within the Patchawarra Formation with an average porosity of 10.5% and permeability up to 2500 mD, and the Toolachee Formation with an average porosity of 12.4% and permeability up to 1995 mD (Gravestock *et al*. 1998).

Oil is produced from the low-sinuosity fluvial sand within the Tirrawarra Sandstone with average porosity of 11.1% and permeability up to 329 mD (Gravestock *et al*. 1998).

In this paper, 59 core samples from different locations (laterally) in the Cooper Basin were chosen for analysis. The data was quality controlled and cores with missing or low-quality data such as noisy or low sample-rate logs, missing intervals or failed MICP tests were excluded. Eventually eight cores, with MICP data and a full suite of logs, were analysed. The pore size distribution of the core samples were derived using MICP. Porosity and permeability of the cores were derived using routine core analysis.

Work flow

In this study, we aimed to investigate the relationship between the rock texture and the fractal dimension of resistivity logs. For this purpose, core data and corresponding resistivity logs were analysed. The core data were used to classify the cores in rock types. Rock types were defined using porosity and permeability of the cores along with pore size distribution.

The collected data were primarily quality controlled. Any cores or intervals with missing or noisy data or failed MICP tests were excluded. Based on these properties, the cores were then divided into three different rock types.

The fractal dimension of the resistivity log corresponding to each core was calculated. To calculate fractal dimension, the data need to be unimodal and stationary without imposing any specific trend. This is a criterion of homogeneity required for a meaningful fractal dimension. Homogeneous datasets exhibit a unimodal distribution, and a visual inspection of the histogram is sufficient to ensure that just a single peak exists in the data density distribution. It should be noted that resistivity data are not Gaussian but log-normal. Thus, the logarithm of resistivity values should be taken before plotting the histogram. If the histogram is not unimodal, the log interval needs to be broken down into more homogenous sections. Also, before calculation of the fractal dimension, the data need to be normalised with zero mean and unit standard deviation. Given the type of data and common sampling rates of well logs, Higuchi's method was chosen for this study. Higuchi's algorithm was coded in Matlab software and used for calculating fractal dimensions.

Finally, the fractal dimensions were compared with the defined rock types.

Results and discussion

Cores from different locations in the Cooper Basin were analysed. The cores were classified into three rock types. The fractal dimension of the corresponding resistivity log to each core was then calculated using Higuchi's method as mentioned in the work flow.

Based on the porosity and permeability measurements of the cores, along with the pore size distribution from MICP tests, the cores were classified into three main rock types. Properties of the rock types are presented in Table 1. The pore size distributions of all cores are presented in Figs 1–3. The rock types were defined as follows:

Rock type I was characterised by porosities in the range of 13–20% and permeability range of 50–300 mD. The pore throat size distribution ranged within 1–100 µm throats. About 50% of the pore radiuses were in the range of 10–100 µm. This arrangement showed that the rock type consisted of large grain sizes and the high permeability suggested good interconnectivity in the structure.

Table 1. Properties of the defined rock types

Rock type	Porosity (%)	Permeability (mD)	Fractal dimension	Description
I	13–20	50–300	1.145–1.158	Majority of pore throats in the range 10–100 µm
II	7–14	5–40	1.186–1.199	Majority of pore throats in the range 1–10 µm
III	5–14	0.096–3	1.221–1.286	Majority of pore throats in the range 0.1–1 µm

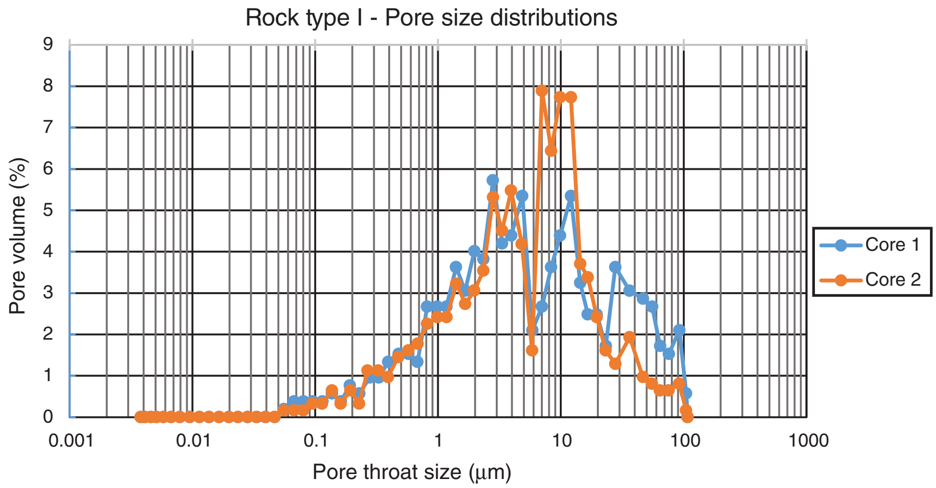

Fig. 1. Pore size distribution of the cores related to rock type I.

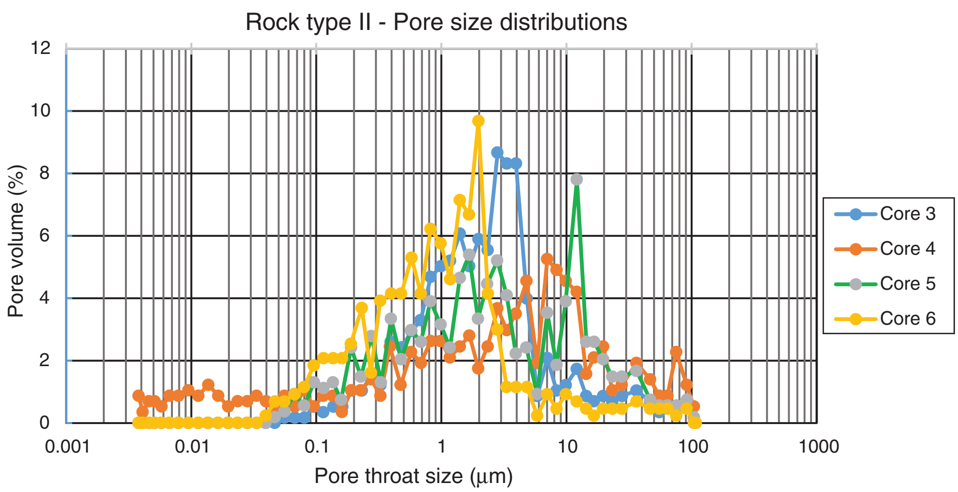

Fig. 2. Pore size distribution of the cores related to rock type II.

Rock type II featured porosities ranging within 7–14% and permeability within 5–40 mD. The majority of the pore throat sizes were within 1–10 µm, which was an order of magnitude smaller than that of type I. The pore size distribution suggested that the grain sizes in this type were smaller and reduction in permeability was due to increase in capillary pressures.

Rock type III was a tight sandstone reservoir with porosities ranging within 5–14% and permeability within 0.096–3 mD. The majority of the pore throats were 0.1–1 µm, which was an order of magnitude smaller than that of type II. Although the porosity was similar to type II, the permeability suggested that most of the porosity was ineffective. The grain sizes in this rock type were very fine and pore throats were filled with clay.

The fractal dimension of the resistivity well logs corresponding to each core was calculated using Higuchi's method. Some of the well log intervals are presented in Figs 7 and 8 as examples. In order to calculate fractal dimension of logs, the data needed to be stationary and Gaussian. To achieve this, homogenous intervals were chosen

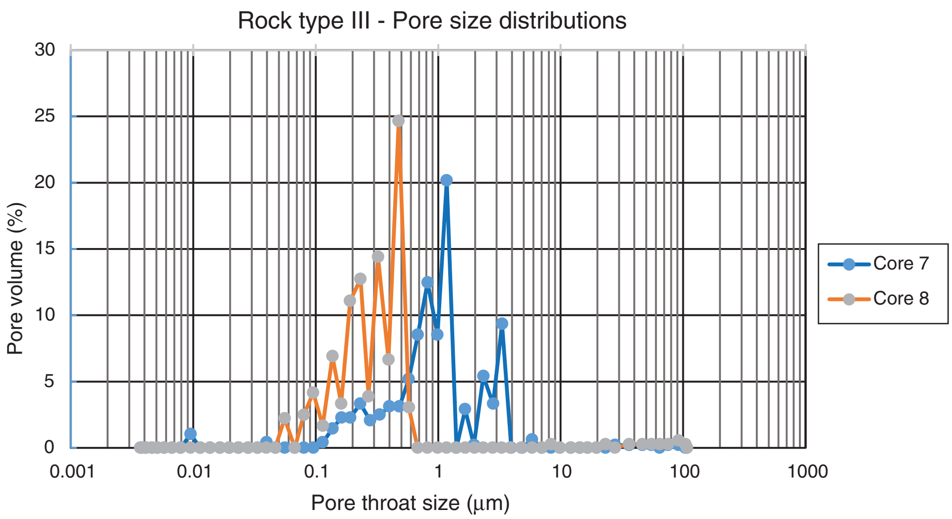

Fig. 3. Pore size distribution of the cores related to rock type III.

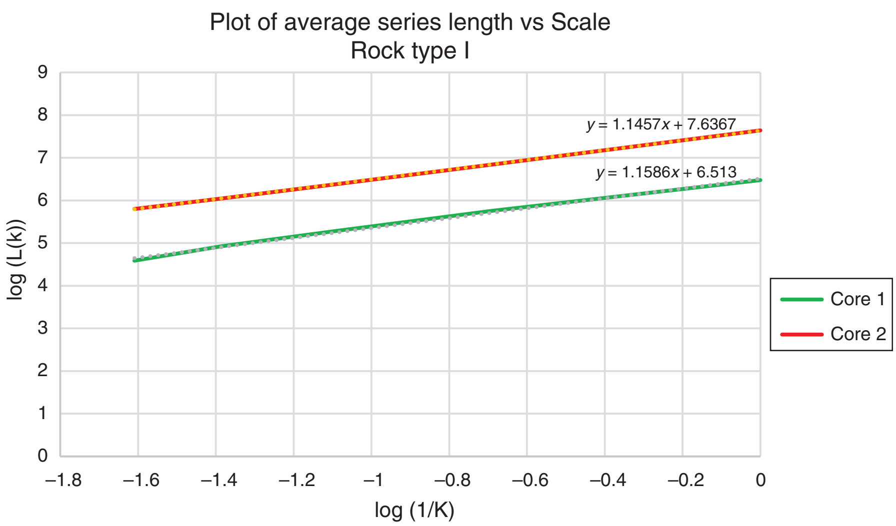

Fig. 4. Plot of scale vs length of series (well log) related to rock type I.

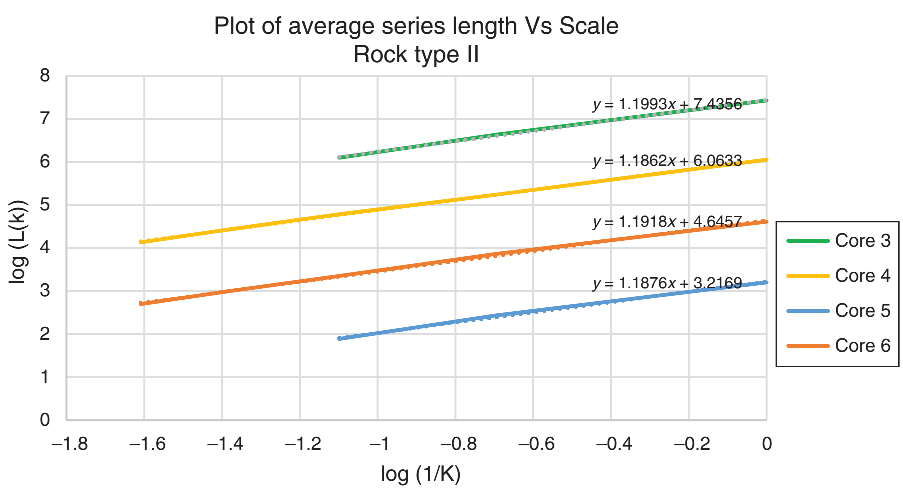

Fig. 5. Plot of scale vs length of series (well log) related to rock type II.

based on the gamma ray and sonic logs. The numerical values of resistivity curves were then extracted and normalised by subtracting the average and dividing by the standard deviation of the data.

As per Higuchi's method, series lengths were calculated for different scales k. The log of the average length of each series ($\log(L(k))$), was plotted against the log of the inverse of the scale ($1/k$). The result was a straight line, with slope equal to the fractal dimension of the resistivity log. The plots of k vs $\log(L(k)$ for every core are shown in Figs 4–6. The slope of the line was determined by a best linear fit to the points. The range of the fractal dimensions of each rock type is presented in Table 1.

As the complexity of rock structure increased (due to smaller grain sizes and/or increased clay content) and fluid flow in the media became more difficult, the fractal dimension of the corresponding resistivity log increased (Table 1). This indicates that the complexity of the rock structure was reflected in the variability of the resistivity logs.

Rock type I featured large pore sizes and high porosity overall. Large pore size indicated large, well-sorted matrix grains and the high permeability indicated that pores were well connected. The pore size distributions of the cores of type I are plotted in Fig. 1. A considerable portion of the pore throat sizes ranged within 10–100 µm. The fractal dimension of the resistivity log

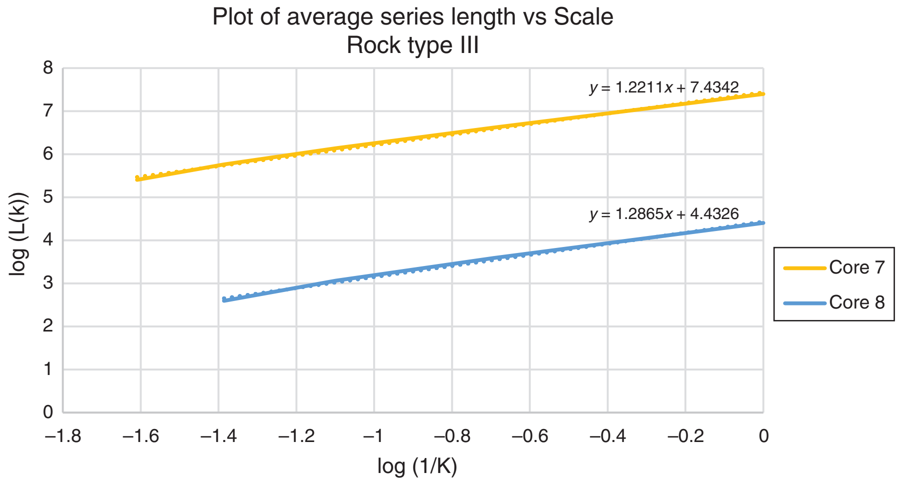

Fig. 6. Plot of scale vs length of series (well log) related to rock type III.

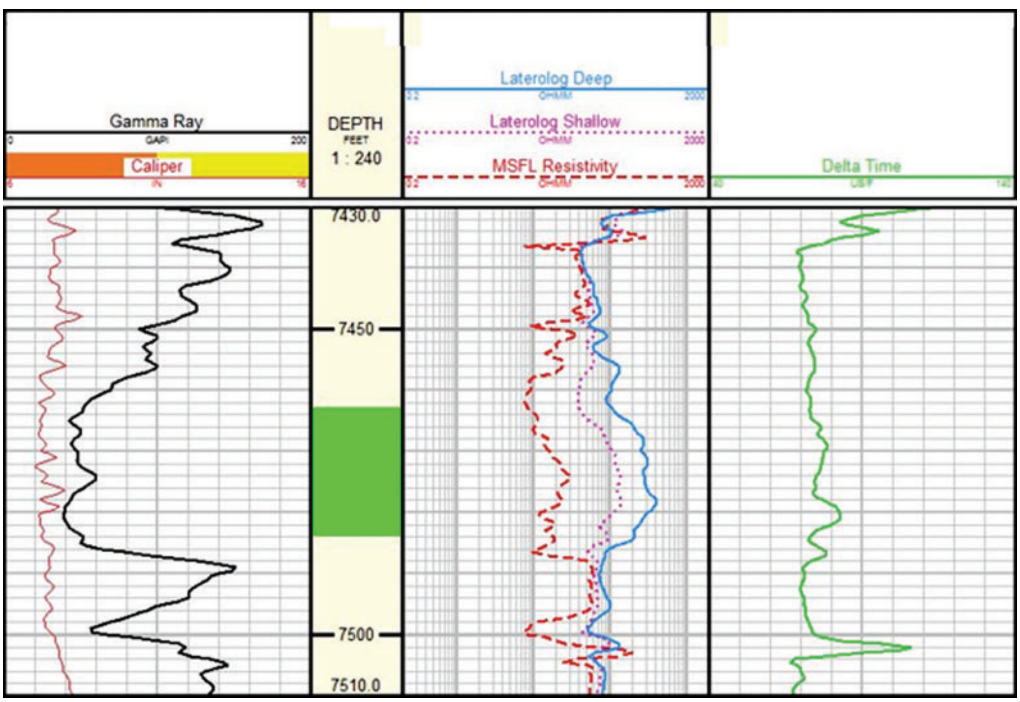

Fig. 7. Well logs corresponding to core 1.

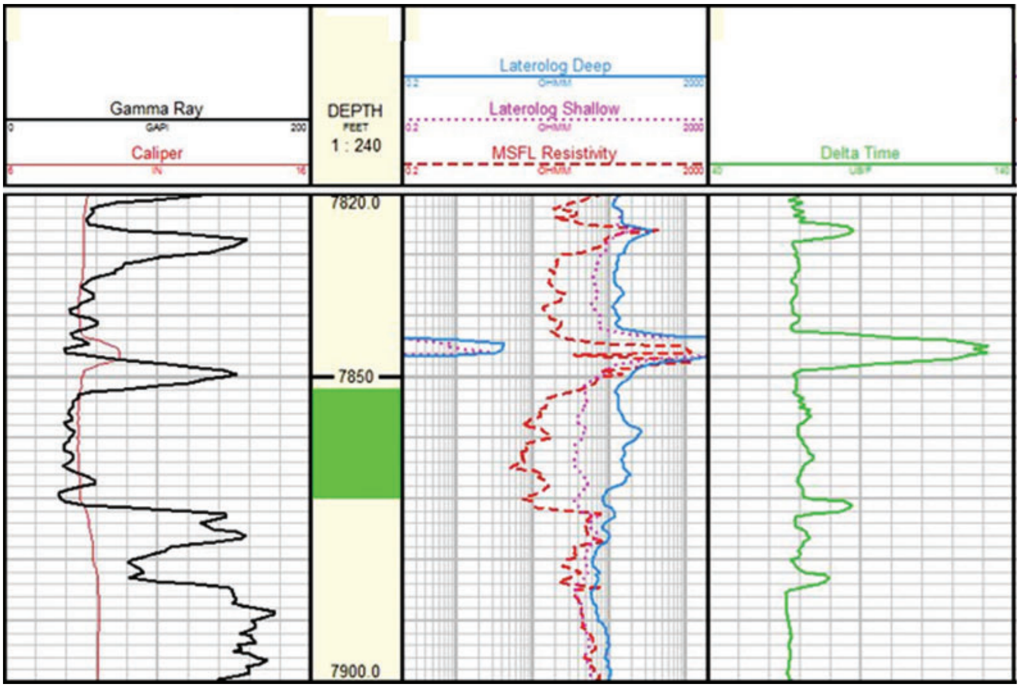

Fig. 8. Well logs corresponding to core 4.

corresponding to this rock type was in the range of 1.145–1.158, which is the lowest among the three rock types investigated.

For rock type II, pore sizes were an order of magnitude smaller than for type I. Smaller pores indicated a component of smaller grain sizes and this rock type also showed lower permeability. The pore size distribution of the cores of this rock type are shown in Fig. 2. A considerable fraction of the throat sizes were in the range of 1–10 µm. The fractal dimension of the resistivity log relating to this rock type ranged within 1.186–1.199, showing more complexity in the logs compared with type I.

Rock type III had very low permeability and the pore sizes are hypothesised to be much smaller than types I and II, as shown in the pore size distribution of the corresponding cores (Fig. 3). The gamma readings in this rock type were typically high, indicating the presence of clays, consistent with the very low permeability. Porosity in type III was similar to that of type II (ranging around 5–14%) but the majority of this porosity would be ineffective due to the clay content. The fractal dimension measured for the logs relating to type III ranged within 1.221–1.286, which was higher than both other rock types, although in this case electrical matrix surface conductivity would be an important component in the resistivity response.

The results of this study could be used to confirm chosen rock types, and also show that information could be hidden in the variability of logs which has so far been neglected.

Conclusions

In this study, core data from Cooper Basin were categorised into three rock types based on porosity, permeability, pore size distribution and core descriptions. The fractal dimension of the resistivity logs corresponding to each rock type was calculated using Higuchi's method.

The fractal dimension of resistivity logs related to rock type I, which was characterised by better sorting and bigger pore sizes, was 1.145–1.158. Rock type II was more resistant to fluid flow than type I but less than type III, and had fractal dimension range of 1.186–1.199. Finally, rock type III with the most complex pore structure showed the highest fractal dimension range of 1.221–1.286.

The results suggest that higher fractal dimensions corresponded to more complex rock fabric, i.e. as the pore structure became more resistant to fluid flow, with smaller pore sizes, more dead-end pore spaces and more tortuosity, the fractal dimension of the resistivity well logs increased. We conclude that fractal dimension of resistivity logs can be used to identify complexity of the electrical conductivity network fabric (often equivalent to the pore network fabric) and thus rock types.

This work was carried out using gas-saturated sandstone reservoir intervals. More research is needed to extend the findings to water- or oil-saturated zones and other lithologies.

Conflicts of interest

The authors declare no conflicts of interest.

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