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Case study

# Electrofacies analysis for coal lithotype profiling based on high-resolution wireline log data

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ABSTRACT

The traditional approach to coal lithotype analysis is based on a visual characterisation of coal in core, mine or outcrop exposures. As not all wells are fully cored, the petroleum and coal mining industries increasingly use geophysical wireline logs for lithology interpretation.This study demonstrates a method for interpreting coal lithotypes from geophysical wireline logs, and in particular discriminating between bright or banded, and dull coal at similar densities to a decimetre level. The study explores the optimum combination of geophysical log suites for training the coal electrofacies interpretation, using neural network conception, and then propagating the results to wells with fewer wireline data. This approach is objective and has a recordable reproducibility and rule set.In addition to conventional gamma ray and density logs, laterolog resistivity, microresistivity and PEF data were used in the study. Array resistivity data from a compact micro imager (CMI tool) were processed into a single microresistivity curve and integrated with the conventional resistivity data in the cluster analysis. Microresistivity data were tested in the analysis to test the hypothesis that the improved vertical resolution of microresistivity curve can enhance the accuracy of the clustering analysis. The addition of PEF log allowed discrimination between low density bright to banded coal electrofacies and low density inertinite-rich dull electrofacies.The results of clustering analysis were validated statistically and the results of the electrofacies results were compared to manually derived coal lithotype logs.


## 1. Introduction

Along with rank and grade, coal organic composition, defined megascopically by lithotype and microscopically by maceral analysis, will control the physical and chemical properties of coal that influence its utilisation and coal seam gas reservoir behaviour. Accordingly, geologists manually log core and use the distribution of lithotypes (Fig. 1) to characterise the coal seams for correlation and sampling for further laboratory analysis. Visual analysis of coal lithotypes can be subjective, and once the coal is sampled, crushed and analysed, its megascopic properties are destroyed. Core is also considered expensive, and as a result, geophysical wireline logs have become an alternative source of information for coal characterisation (Reeves and Muir, 1976; Johnston, 1991; Sutton, 2014). The impetus for this study was that the coal seams in the study area were not contiguously cored, so full seam characterisation was not possible unless we developed a characterisation method based on the wireline logs.

A common approach to coal characterisation using wireline data applies cut-off values on each wireline log measurement (Zhou and Esterle, 2007). Density is used for identification of coal, and gamma ray or sonic values (among others) for interburden lithology. Provided good correlation between sampled core properties and the selected wireline, the approach demonstrates quite good results. This method might produce significant errors if the wrong cut-off values were chosen, or if they vary between different coal seams or formations (Fullagar et al., 2004).

This paper describes a methodology that exploits geostatistical cluster analysis of wireline geophysical data and uses laboratory and visual core logging analysis data for initial control and subsequent validation of the results. It does not require any predefined cut-offs and assumptions about coal quality which potentially makes the method less prone to an interpreter bias and more robust and reproducible. In addition to identification of high or low density coal, the method is interpreted to discriminate inertinite-rich low density dull from mineral-rich dull from higher density or mineral matter rich dull coal and from banded or bright (high vitrinite) low density coal.

## 2. Methodology

### 2.1. Background

The application of cluster analysis, often referred to as electrofacies analysis, to identify different lithologies of facies in clastic

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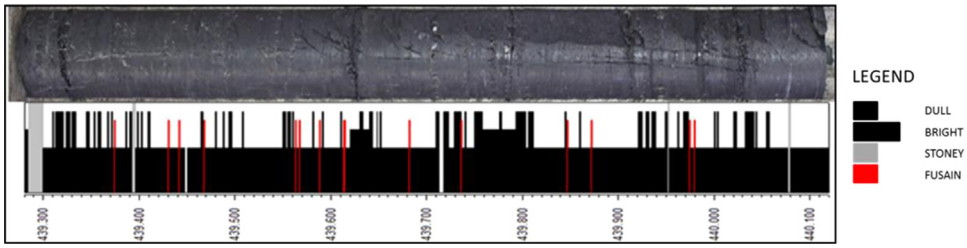


**Fig. 1.** An example of a manual coal lithotype profile plotted next to coal core for end member coal lithotypes. Core is 80 cm long (image provided by Natalya Taylor, University of Queensland).

sedimentary rocks is common (Ellis and Singer, 2007; Rider and Kennedy, 2013), so a similar approach could be applicable for coal lithologies. The term "electrofacies" refers to a cluster or group with common wireline log signatures or values that distinguishes it from other clusters. Ye and Rabiller (2005) define electrofacies as an element of the N-Dimensional (N being the number of wireline logs considered) data structure created by all petrophysical material available, whose ordering reveals the organised relationship imparted to petrophysical properties of interest by natural geologic systems ordering (Ye and Rabiller, 2005). Electrofacies, in contrast to geological facies, is an interval defined on wireline logs, with consistent or consistently changing wireline log responses and characteristics – sufficiently distinctive to separate it from other electrosequences (Rider and Kennedy, 2013). Electrofacies analysis involves partitioning a set of log data into electrofacies units and presenting them in a manner that is comparable to that used by geologists for interpretation purposes – each electrofacies is assigned a number, or index, which can be plotted against depth or used to control colour coding on displays (Ye and Rabiller, 2005).

Electrofacies ordering can be performed by different algorithms such as genetic algorithms (Goldberg, 1989) and neural networks. Artificial neural networks are computational models inspired by biological neural networks and are used to approximate functions that are generally unknown. There are many types of artificial neural networks and more details can be found in Potvin (1993). The neural-network scheme, first developed by Angeniol et al. (1988) is derived from the Kohonen's Self-Organising Map (SOM). An advantage of the SOM is that the resulting map is automatically ordered in the data space. A self-organising map (SOM) or self-organising feature map (SOFM) is a type of artificial neural network (ANN) that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretised representation of the input space of the training samples, called a map. Self-organising maps are different from other artificial neural networks in the sense that they use a neighbourhood function to preserve the topological properties of the input space. An SOM performs an ordered mapping from a hyper-dimensional data space onto a lower (one- or two-) dimensional lattice of points (neurons). It can be considered as a non-linear regression of the reference vectors (neurons) through the input data (Ye and Rabiller, 2005).

The SOM network is made up of a specified number of neurons interconnected into a one- or two-dimensional array. This interconnection among neurons is called the lateral relationship. Neurons are initialised randomly. The input data are iteratively presented to the network for a given number of cycles. The convergence is controlled by two learning parameters: the width of the neighbourhood (Gaussian) function and the learning rate. In the neuron-splitting technique, all the input data are presented to the learning mechanism simultaneously instead of successively as in the SOM. Ye and Rabiller (2005) presented a simple and fully automated method based on the neuron-splitting technique using a 1D line-structured SOM. The input data are electrofacies kernels. These could be derived from any method. Multi-Resolution Graph-based Clustering (MRGC) method (Ye and Rabiller, 2000) available within software was used for this coal electrofacies research.

MRGC is a multi-dimensional dot-pattern-recognition method based on non-parametric K-nearest-neighbour and graph data representation (Ye and Rabiller, 2000). The underlying structure of the data is analysed, and natural data groups are formed that may have very different densities, sizes, shapes, and relative separation. MRGC automatically determines the optimum number of clusters, yet allows the geologist to control the level of detail actually needed to define the electrofacies. Some vector analysis programs let the user to decide how many clusters based on a "goodness of fit". In turn, software used for the research offers a number of probability tables to estimate and validate the clustering results. These probability tables were used in this research for validation of the clustering results.

The electrofacies ordering method which was presented by Ye and Rabiller (2005) performs a complete training of the SOM between each splitting process, whereby the newly split neurons are fully trained before being split again. This process was called a Coarse-to-Fine Self-Organising Map (CFSOM), because the electrofacies ordering is made from a low-resolution (coarse) map towards a high-resolution (fine) map. There are no concerns about how many cycles of input data presentation are necessary to split neurons and what the optimal parameters for SOM might be when the data configuration and the size of problem are changed. All that is needed is for the algorithm to add a reasonable number of neurons at each step and re-apply the ordinary SOM algorithm.

### 2.2. Dataset

The research was focused on the northern Bowen Basin (Fig. 2) and included geophysical wireline logs from wells intersecting three main Late Permian coal measures – Moranbah, Fort Cooper and Rangal. In general, the character of the coals changes stratigraphically up section, with a general increase in inertinite group macerals in the Rangal Coal Measures (Mutton, 2003). That area is also characterised by good collection of high-quality wellbore data and has previous research results that were exploited for validation of the current study.

The dataset included 26 wells which had been geophysically logged and cored. Wireline logs included caliper, gamma ray (GR), laterolog resistivity, density, photo-electric factor (PEF) and thermal neutron porosity; three wells contained sonic data (dt and dipole data). Borehole electrical images were available for 18 of the 26 wells. Of these 26 wells, not all coal seams were fully cored and analysed, making the validation against megascopic description a bit sporadic. The lack of contiguous coring was actually an impetus for this study, so that complete seams might be characterised within the measures. Coal proximate analysis data were available for samples from 23 wells. Visual lithotype logging (using an end member millimetre scale approach (Esterle et al., 2002)), maceral and reflectance analysis data were available for 182 sampled metres of core from 12 wells. The summary of data available for