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Coal quality from geophysical logs for enhanced resource estimation

Final Report for ACARP Project C23015

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Abstract

Coal quality parameters such as ash content, density, volatile matter and specific energy are important to the coal mining industry from mine planning, design, extraction and beneficiation through to utilisation. These parameters are traditionally obtained through laboratory analysis conducted on drill-core samples. Currently, obtaining coal quality information requires the collection of bore cores, which are then subjected to pre-treatment to simulate the size reduction and liberation that can be expected during the mining process. This process is expensive and time consuming. In addition to this, most boreholes are drilled with limited or with no coring due to costs. Therefore, only a limited number of coal samples can be tested and analysed and this largely limits the ability to appropriately map the spatial variability of the coal quality in both horizontal and vertical directions. Obtaining estimates of these coal quality parameters from non-cored holes would complement this information and thus provide a better estimate of the resource.

The objectives of this project are to:

- Develop new methods for enhanced estimation of routinely measured coal quality parameters (i.e. proximate analysis properties, specific energy and relative density) from routinely acquired geophysical logs such as density, gamma and sonic, thus significantly improving the spatial definition of coal deposits.
- Establish whether the use of the multiple geophysical logs significantly enhances the reliability of the predicted coal quality parameters.

In this project, we reviewed the coal quality estimation from geophysical logs. It was found that the commonly-used approach for determining coal quality from the geophysical logs is mainly based on simple cross-plots. However, the relationships between coal quality parameters and geophysical logs are not always represented by simple linear trends and may instead be curved trends generated by complex equations. This suggests that instead of using a simple two-variable correlation approach, a multi-variable data analysis approach has a better chance of dealing with the complexity of coal quality parameters and thus improve the estimation accuracy of the these parameters. To perform coal quality parameter estimations using multiple geophysical logs, we proposed and implemented a multi-variable data analysis algorithm based on the use of a particular type of neural network known as Radial Basis Functions (RBF). We chose this approach because of its two important advantages: 1) it estimates coal quality parameters from parameters and relationships derived within the data set without a need for pre-existing assumptions or models; 2) it can easily accommodate the coal rank variations by simply adding the representative samples into the control data base. We also developed data pre-processing algorithms to extract the geophysical logging data corresponding to the coal samples.

The RBF-based coal quality parameter estimation algorithms were tested by using the data sets provided by Anglo American and BMA. In both cases, routinely-acquired geophysical logs such as density, gamma ray and sonic logs have been used to estimate the coal quality parameters such as relative density, ash content, fixed carbon and volatile matters. This has been demonstrated on both self-controlled training data sets and an independent data set. It is observed that the density logs play a key role in coal parameter estimation. However, the use of multiple types of geophysical logs, including logs with different resolutions, such as short spaced density log DENB and long spaced density log DENL, improves the estimation accuracy. It is therefore expected that more accurate coal quality parameters can be estimated if more geophysical logs such as photo-electric factor (PEF), SIROLOG and PGNAA which provide geochemical constituents are acquired.

The geophysical logs have also been used here to estimate the coal brightness profiles and lithotypes using the LogTrans software. The estimated lithotypes do not matched well with the original lithotypes provided by the mine for which there are two possible reasons: 1) the lithotypes may have been logged ‘by eye’ by different geologists; and 2) variability of the non-bright components within each band. Our limited tests suggest that the subjectivity of visually-logged lithotypes is the main cause for the poor reconciliation with LogTrans results. Therefore, it is highly recommended that careful reconciliation of the lithotypes should be carried out before conducting any automatic interpretation of lithotypes using geophysical logs.

Executive summary

Project objectives

The objectives of this project are to:

- Develop new methods for enhanced estimation of routinely measured coal quality parameters (i.e. proximate analysis properties, specific energy and relative density) from routinely acquired geophysical logs such as density, gamma and sonic, thus significantly improving the spatial definition of coal deposits.
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Work program

A comprehensive literature review was first undertaken to identify approaches which had been used in Australia, Canada, United States of America, the United Kingdom, China and other countries to obtain different coal quality information from different geophysical logging data. The feasibility of estimating the different coal quality parameters from geophysical logs was then tested using data sets provided by Anglo American and BMA. The Anglo American data set consisted of geophysical logging data, and laboratory coal quality proximate analysis data for 144 coal samples from 19 boreholes. All the coal samples are from the same coal seam with an average thickness of 6.95m. The second data set provided by BMA consisted of geophysical logging data and coal quality data for 1,012 coal samples from 26 boreholes, in which 23 boreholes were logged by the same logging service provider. The 23 boreholes were divided into two natural groups: Area-1 and Area-2 which are separated by about 9km. The coal samples are from different coal seams.

Estimates of the different coal quality parameters were then made using the individual geophysical logs and various combinations of multiple logs. This approach used only the logs which are routinely collected in Australian coal mines. This required an assessment of data quality so that wild data points could be eliminated.

The BMA data set had lithotype data provided for 23 of the boreholes, which enabled us to test the feasibility of extracting the lithotype/brightness information from the geophysical logs by using the LogTrans software.

Key achievements and deliverables

The key findings from this project:

- A review of coal quality estimation from geophysical logs was conducted. This review found that although the commonly-used approach for determining coal quality from the geophysical logs is based on simple cross-plots, the relationships between coal quality parameters and geophysical logs are not always best represented by simple linear trends but rather by curved trends generated by complex equations. We conclude from this that instead of using a simple correlation approach, a multi-variable data analysis approach would better deal with the complexity of coal quality parameters and thus improve the estimation accuracy.
- To test this hypothesis we performed multi-variable analysis with successful results.
- To enable coal quality parameter estimations from multiple geophysical logs, we
    - Developed data pre-processing algorithms to extract the geophysical logging data corresponding to the coal samples.

- Implemented a new multi-variable data analysis algorithm, namely a neural network based on Radial Basis Function, into a prototype software ***ParamEstimate***. The program in its current form is available free to ACARP members. It is attached to this report as part of the ACARP report materials.

- We demonstrated that the feasibility of the coal quality parameter estimations from geophysical logs using data provided by Anglo American and BMA, using both self-controlled training data sets and independent data sets. The results suggest that
  - Better coal quality parameters can be derived from interpreting data from multiple geophysical logs rather than an individual log such as the density log.
  - The accuracy of the estimation of these coal parameters increases with the number of geophysical logs used.
  - All geophysical logs irrelevant to their inherent depth resolutions, such as short spaced density log DENB and long spaced density log DENL, will positively contribute to the accuracy improvement of coal quality estimation.
  - It is therefore expected that more accurate coal quality parameter estimates can be made if additional geophysical logs, such as photoelectric factor (PEF), SIROLOG and PGNAA[1] which provide geochemical constituents, are acquired.
  - Density has a strong correlation with the coal parameters of ash content, fixed carbon and specific energy and therefore plays an important role in the estimation of these parameters.
  - Whilst the approach of using a large number of logs acquired over a relatively broad area enabled good predictions to be made against the coal quality parameters of relative density, ash value and specific energy, which correlate largely with the amount of coal and mineral in the sample, it did not work as well for the coal quality parameters which are affected by other factors such as coal rank and type changes (volatile matter content and crucible swelling number), depositional environment (total sulphur) or mineralogy (phosphorous).
- LogTrans has been used to estimate/interpret coal lithotype or brightness using geophysical logs. Our tests indicate that geophysical logs can be used for lithotype interpretation providing the training coal lithotypes are appropriately reconciled to eliminate any potential inconsistency or subjectivity in the logged lithotypes.

[1] Prompt Gamma Neutron Activation Analysis

Recommendations

Based on the observation that the accuracy of a broad range of coal quality parameter estimations, in general, increased with the number of different geophysical logs used, it is recommended that, in addition to those commonly used geophysical logs such as density, gamma ray and sonic logs, additional geophysical logging parameters such as neutron, resistivity, PEF, CSIRO's SIROLOG and PGNAA logs should be collected and used in multi-variable analysis for improved coal quality parameter estimation. The SIROLOG, which provides spectrometric natural gamma spectra measurements, allows various parameters to be derived, such as the natural (total) gamma, density, components of total natural gamma, thorium (Th), potassium (K) and uranium (U). The PGNAA log data can provide information such as the coal ash content, density and the major constituents of ash: Fe, Si, Ca, Al and S. Therefore, the SIROLOG and PGNAA logs provide important inputs for coal quality parameter estimation. CSIRO's newly-developed borehole logging technique, PFTNA (Pulsed Fast and Thermal Neutron Activation), uses a switchable electronically-controlled neutron generator instead of an active isotopic source, which makes PFTNA technique inherently safer and significantly circumvents the on-site occupational safety concern for the routine adaptation of this technology.

However, it should be noted that the use of additional geophysical logs will incur additional exploration costs. Exercises on effects of coal quality estimation accuracy with different geophysical log combination and their cost benefit analysis should be undertaken on a case by case basis to establish whether the improved resource evaluation obtained from having improved coal quality predictions is justified.

Subjectivity of the geologist who is logging the core may lead to lithotype inconsistency and poor correlation with geophysical logs. It is highly recommended that careful reconciliation of the lithotypes should be performed before carrying out automatic interpretation of lithotypes using geophysical logs. We recommend that a fully controlled reconciliation case study should be conducted to further confirm the observations from this project.

1 Introduction

Coal quality parameters such as ash content, density, volatile matter and in-situ moisture are important to the coal mining industry from mine planning, design, extraction and beneficiation through to utilisation. These parameters are traditionally obtained through laboratory analysis conducted on drill-core samples. Currently, obtaining coal quality information requires the collection of bore cores, which are then subjected to pre-treatment to simulate the size reduction and liberation that can be expected during the mining process (Swanson et al, 1998). To ensure there is a sufficient mass of sample to undertake the washability testing, individual plies often need to be amalgamated, but this process often limits the vertical variability in grade and coal quality information which can be obtained from slim core samples. The sample's washability characteristics are used to predict expected yield. The coal quality attributes such as volatile matter, sulphur content and coking and thermal attributes are used to predict the desired target ash value. This process is expensive and time consuming. In addition to this, most boreholes are drilled with limited or no coring due to costs. Therefore, only a limited number of coal samples can be tested and analysed and this largely limits the ability to appropriately map the spatial variability of the coal quality in both horizontal and vertical directions. Estimates of these coal quality parameters from non-cored holes would complement this information and thus provide a better estimate of the resource.

Geophysical logs are routinely acquired by coal mines. A significant improvement of coal quality based geological models to enhance estimates of the insitu resource may be possible by combining estimated coal quality parameters (such as ash content, volatile matter, in-situ moisture, brightness profile and lithotype) from geophysical logging with information from treated bore cores. It is well known that coal quality parameters have strong relationships with coal type and hence geophysical logging parameters. For example, Fallon et al. (2000) demonstrated that geophysical logs can be used to automatically interpret coal plies. Although deriving some coal quality attributes from geophysical logs is not a new topic, it is rarely used in the coal industry. A reliable link between geophysical attributes and industry standard measurements of coal quality has not yet been established. To date, this link has been limited to correlations between coal density and ash content, and, to a lesser extent, SIROLOG data with coal ash content and chemistry (Nicols, 2000).

In addition to the standard way of estimating the ash content from density measurements, the objective of this project is to investigate whether estimates of other industry standard coal quality parameters can be developed and improved through advanced computational analysis (such as Radial Basis Functions (RBF) and Self-Organizing Maps (SOM)) of multiple routinely acquired borehole logging data. We will also evaluate the degree of precision that can be obtained using these logs and discuss which additional logs could be used to enhance these estimates. The proposed approach builds upon previous ACARP work such as in Hatherly et al. (2004) (C11037) for geotechnical assessment, Fullagar et al. (2005) (C13016) for logging quality control checking, and Zhou et al. (2007) (C15036) on improving the reliability of density and grade estimation from geophysical logs.

The project deliverable will be a new methodology and prototype software for deriving coal quality parameters through analysis of routinely acquired wireline data and documented trials of conventional and advanced statistical methods for improved parameter correlation and estimation.

This project will provide the Australian coal mining industry with the ability to maximise the value obtained from routine geophysical logging, thus significantly improving the spatial definition of coal deposits. Information on the individual coal plies as well as the entire seam will enable better and more accurately determined quality and quantity of the coal resource/reserve and enable the integration of coal quality data into mine site modelling packages. This approach is designed to complement the routine testing programs commonly undertaken on cored boreholes by providing increased spatial coverage of the seam and ply-by-ply information.

2 Coal quality estimation from geophysical logs: an overview

Coal has distinctive physical properties compared with other sedimentary host rocks (e.g., sandstones, shales, mudstones, and siltstones) to which it may be found juxtaposed. Properties include (Figure 1):

- low density,
- low seismic velocity,
- low magnetic susceptibility,
- low natural radioactivity, and
- high electrical resistivity.

Such contrasts make geophysical logs a good tool for identifying coal seams, and to correlate them between boreholes to build coal seam models. Figure 1 also shows that different types of coals often have different geophysical log responses and therefore they can be explored for derivation of coal properties. Due to its potential cost saving, many attempts have been made around the world in the past to predict the coal quality from geophysical logs. This can be evidenced by the published papers on this subject as shown in Table 1. This section will provide a brief review of the development in coal quality parameter estimation from geophysical borehole logging data. Part of the materials are adopted from the similar review from a CSIRO internal report by Kahraman (1998).

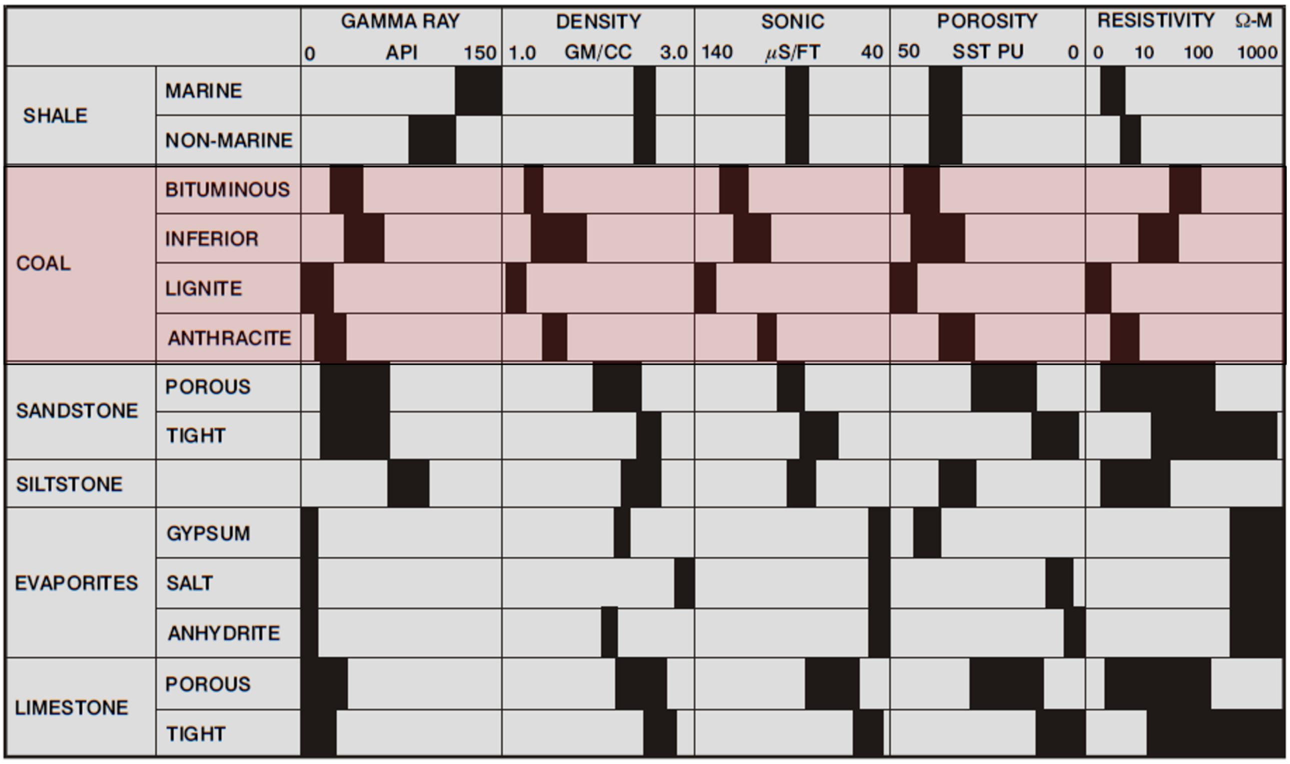


Figure 1 A summary of geophysical log responses to various lithologies. Geophysical log responses to different coal types (ranks) are highlighted in pink. From Firth (1999).

Table 1 A summary of papers related to coal quality estimation from geophysical logs in different countries

Country	References
Australia	Agostini (1977), McCracken and Mathew (1980), Renwick (1980), Groves and Bowen (1980), Borsaru et al. (1983, 1985, 1988, 1992, 1993, 2001, 2004a&b), Till (1985, 1987), Biggs (1991), Preston and Sanders (1993), Borsaru and Ceravolo (1994), Fallon et al. (2000), Nichols (2000), Charbucinski & Nichols (2003), Fletcher and Sanders (2003), Meyers et al. (2004), Mutton and Turner (2005), Preston (2005), Saghafi and Carras (2005), Zhou and Esterle (2008)
Canada	Kowalski and Holter (1976), Kowalski and Fertl (1977), Smith et al. (1977), Nargolwalla and Seigel (1977), Edward (1978), Edwards and Banks (1978), Hoffman and Wilson (1989), Lawton and Lyatsky (1991)
China	Li (1989), Pan and Huang (1991), Dong et al. (2001), Fu et al. (2009 a&b), Li et al. (2011), Mao et al. (2011, 2014), Meng et al. (2011), Yao et al. (2011), Huang et al. (2012), Jing et al. (2013)
UK	Reeves (1971, 1979 & 1981), Kowalski and Holter (1976), Kowalski and Fertl (1977), Smith et al. (1977), Nargolwalla and Seigel (1977), Edward (1978), Edwards and Banks (1978), Hoffman and Wilson (1989)
US	Bond et al. (1971) , Fasset and Hinds (1971), Davis (1976) , Abshier et al. (1979), Fishel and Mayer (1979) , Hallenburg (1979) , Norris and Thomas (1980) , Daniels et al. (1983) , Nations et al. (1984), Alcock et al. (1986), Mullen (1988, 1989), Herron et al. (1988, 1992), Johnston (1990), Mayor et al. (1990, 1994), Ahmed et al. (1991), Ayoub et al. (1991), Johnston and Scholes (1991) , Herron (1991) , Colson (1991), Karacan and Olea (2014)
Others	Weltz (1976), Lavers and Smits (1976), Kayal (1979) Brom and Driedonks (1981), Kayal and Das (1981), Csokas et al. (1986), Kayal and Christoffel (1982, 1989), Chatfield et al. (2009), Souza et al. (2010), Tercan and Sohrabian (2013), Webber et al. (2013), Ghosh et al. (2014), Srinaiah et al. (2014)

2.1 Australia

Research activity in Australia to derive coal quality data from geophysical logs was concentrated in the early to mid-eighties. A coal borehole-core analyser developed by McCracken and Mathew (1980) was based on measurements of the Compton linear attenuation coefficient and the photoelectric mass-absorption coefficient of the material. Their laboratory tests and measurements of 23 coal samples collected from a single colliery near Wollongong showed an accuracy of 1% ash and 0.01 g/cm^3 density for coal, while the accuracy of ash determinations decreased to 2.7% ash for 41 coal samples from nine different seams and locations in New South Wales due to variations in the mineral content. The regression equations derived from these two data sets have different coefficients but in the same linear form based on the ratio between the logarithm of the high-energy beam intensity and the logarithm of the low-energy beam intensity. These beam intensities were normalised by the intensities of the incident intensities of the corresponding energy beams.

In order to establish the possible relationship between log responses and laboratory core measurements, Renwick (1980) suggested that at least three log calibration core holes should be drilled. He reported that the resultant analytical data, particularly ash content, could be plotted against depth to produce a core ash log, which is then correlated with the long spacing density at the same scale. Once the basic correlations are made, the information is entered into a statistical package and the trends in data set could be established through cross-plots of the data. Based on this approach, a linear correlation between the core density in g/cm^3 and logarithm of LSD (long-spaced density) in CPS for Shell holdings in the Surat Basin, was established. In addition, Renwick demonstrated that it is possible to relate the density with the ash content and also the specific energy.

Using regression analysis, the third order polynomial nominal relationship was suggested by Groves and Bowen (1980) to produce optimum correlation coefficients. They calculated an ash content from the density log with an absolute accuracy of ±4% for the Boggabri area of New South Wales whilst they calculated an absolute accuracy of ±8% for an area near Toowoomba of Queensland. They also mentioned the use of neutron logging to estimate the content of volatile matter content in raw coal with an accuracy of ±5% for any one coal-bed. They concluded that no accurate log calibrations could be achieved for the inherent moisture content of raw coal because of the relatively high neutron moderation of the current neutron-neutron logging method in water-rich coal seam intervals. The factors that could influence the ash determination as a function of the density were also outlined. These are the degree of coalification or rank of the coal, the type of mineral matter associated with the coal (whether it is clay, quartz, pyrite, carbonate), the maceral composition of coal and the moisture content associated with either mineral matter or the coal substance. The relative degree of influence that the typical and chemical factors have on ash estimates was investigated by separating the direct raw density counts to ash conversion into two steps. The influence of inherent moisture and differing maceral densities is apparently responsible for the scatter in the ash against relative density cross plot suggesting that the chemical factors do not introduce significant errors seen in the density counts against ash cross plots. However, when the raw density count is plotted against the relative density, a significant scatter occurs due to physical factors. The importance of relative density was discussed in great detail by Preston and Sanders (1993).

In recognition of the importance of coal density in coal quality correlation and estimation, Zhou and Esterle (2007, 2008) investigated various factors affecting coal density from geophysical logging and demonstrated that the density wireline log, supported by other geophysical logs, provides a reliable direct measurement of in-situ coal density. They produced a consistent and reliable correlation of geophysical log density with a laboratory-derived density to within an accuracy of ±3%. This was achieved through careful constraints such as compensating for lost pore spaces and moisture to bring the laboratory relative density closer to in-situ environmental conditions, matching the laboratory sample depths with geophysical logs, excluding thin, boundary, and stone-band samples from the dataset, and calibrating the geophysical density with laboratory testing data and other geophysical logs through multiple variable simulation.

Till (1985, 1987) investigated the qualitative similarity between density, sonic and resistivity logs related to complementary coal properties. He concluded that the relationship between the density and ash percentage is better than the sonic velocity and resistivity, but this relation is not simple as the constituent minerals react differently to produce varying ash values for the same density. If the minerals in coal are assumed to be quartz, kaolinite and calcite (the major minerals, excluding pyrite), the total mineral matter content at a specific density would be nearly independent of the content of the relative minerals but that the ash value at that density will be influenced by mineralogy. Till showed that coal with any density and a mineral contaminant of either quartz, kaolinite or calcite will have essentially similar total mineral content. Pyrite being the densest would have less material to attain the same coal density. However, when the effect of weight loss upon ashing is taken into account the results are more complex. For example, for a coal with a density of 1.4 g/cm^3 the mineral matter content on weight basis is about 26% quartz, kaolinite and calcite or 20% pyrite. However upon combustion the ash is 13% for pyrite, 14% for calcite, 19% to 23% for kaolinite and 26% for quartz. For combinations of these minerals the theoretical range of ash is from 13 to 26%. In reality it is uncommon for the mineral matter in coal to be composed entirely of any one of these minerals especially pyrite, but the predominance of one mineral recorded (Ward, 1978) and fortunately for the majority of Australian coals, pyrite is a minor component.

The resistivity of coal samples in the laboratory showed no simple relationship between the ash percent and porosity, although anisotropy and the physical state of the coal such as fracturing affected the data (Till, 1985). The sonic response of coal did not show a consistent relationship to ash percentage. However, the sonic velocity appeared to relate to either the porosity or rank of coal with the sonic velocity decreasing as the porosity increased or increasing as the rank increased. Till also concluded that density response of coal can only be related to coal quality over a limited area because several factors such as maceral composition and the minerals content affect the density. He found that density and gamma logs were the most useful contributors in first-order multivariate regression analysis involving the density, gamma, neutron, sonic and focussed electric logs. Single log prediction of coal ash using the gamma or long spaced density log was accurate but the error decreased if a second or third polynomial regression equation was used.

Borsaru et al. (1985) achieved an accuracy of 2.2% ash for ash contents between 7% and 28% for coal in dry boreholes by using spectrometric gamma-gamma methods. Later Charbucinski et al. (1986) and Borsaru et al. (1988) used the neutron capture technique at Curragh Mine in Queensland and at Drayton Mine in the Hunter Valley of New South Wales. The data from both the tool and the laboratory analysis showed good correlation (1.6% deviation for the seams ranging 8% to 46% in ash content at Curragh Mine and 1.5% deviation for the seams ranging 5% to 26% in ash content at Drayton Mine).

The neutron-gamma and gamma-gamma techniques for ash prediction were compared at the Callide Mine by Borsaru et al. (1992). It was concluded that both gamma-gamma and neutron-gamma measurements could predict the ash content in coal seams and delineate the seams and inter-seam sediments. It was also found that the neutron-gamma technique gave slightly better prediction results and was less sensitive to variations in the borehole condition and to the borehole diameter. The other advantage of the neutron-gamma tool was that it could be calibrated against the iron content in order to predict the iron percentage in coal. This was further illustrated by Biggs (1991), Borsaru et al. (1993) using the neutron-gamma technique (SIROLOG tool) at the Callide Coalfields.

Later, Borsaru and Ceravolo (1994) used a low activity spectrometric gamma-gamma borehole logging tool in the Callide Coalfields, which does not require any special shielding for the radioactivity because the activities of the gamma ray sources used with the tool were very low. The tool employed both Cs and Ba with a 37x75 mm NaI (Tl) scintillation detector. The ash prediction obtained from this tool was also similar to commercially used SIROLOG tool.

Borsaru et al. (2001, 2004a) and Charbucinski and Nichols (2003) further developed and demonstrated CSIRO's spectrometric borehole logging tools SIROG and PGNAA (prompt gamma neutron activation analysis) techniques for estimation of density, ash content and some ash continents (such as Fe, Si, Al and sulphur) of coal with sufficient accuracy to be used as points of observation in calculation of reserves.

2.2 Canada

Kowalski and Holter (1976) and Kowalski and Fertl (1977) used cross plotting techniques for three different wells from Canada, England and Europe. In the interpretation, the density log is plotted on the y-axis and second device is plotted on x-axis of a graph. The locations of the carbon, ash and moisture points are determined from this plot and the amount and quality of the coal was also estimated. The method calculates percentages of carbon, ash and moisture by solving three simultaneous linear equations of volumetric analysis based on known densities, sonic travel times, conductivities and neutron porosities for carbon, ash and moisture.

A gamma ray log was used to evaluate the thermal coal deposit at Coal Valley, Alberta, by Smith et al. (1977). The linear regression analysis showed a mean value range of ±1.33% and ±4.82% at 95% confidence limits for the values between 10 and 40 API readings. The single gamma ray values between 10 and 40 API had a range of ±9.04% and ±10.20% at 95% confidence limits.

The prompt gamma ray analysis technique (Metalog) was applied to coal seam analysis to determine sulphur content (Nargolwalla and Seigel, 1977). It was stated that the 5.42 MeV prompt gamma emission from sulphur in the coal matrix would be prominent in an almost interference-free state and if the ash content is reasonably high in terms of the sensitivities for silicon and aluminium, their determination could be possible. A correlation coefficient of 0.95 and an average relative error of <8% of the actual grade over the sulphur concentration range examined was obtained from this study.

Edwards (1978) and Edwards and Banks (1978) concluded that the proper evaluation of a coal property requires accurate information on the in-situ water and ash content of the coal. The researchers divided the coal seam into three components; coal, water, and wet ash. Coal was defined as fixed carbon and coal volatiles (dry mineral matter free coal), whilst the wet ash was defined as the dry ash residue after burning, plus the water and volatiles associated with the ash when in-situ. The resistivity and density tool responses from samples falling within a narrow band of resistivity from 2000 to 2500 ohm - m were plotted to find the effect of ash and water content. This exercise showed that deviation of the ash content against density within this small range was significantly reduced. A series of formulae was developed to find the coal ash content.

Lawton and Lyatsky (1991) showed that density logs are indispensable for seismic modelling in a coal field in central Alberta, whereas sonic logs are less important because the seismic velocity in the coal seams does not appear to be significantly different from that of the host sediments. Sonic logs are often assumed to be suitable for constructing synthetic seismograms, and density logs are usually ignored. Although it is uncommon for the magnitude of velocity variations to exceed the magnitude of velocity variations in the subsurface, it was proved that the errors could be introduced into interpretation of seismic data if density information is not included in the generation of synthetic seismograms.

Hoffman and Wilson (1989) concluded that using the geophysical logs to determine the coal parameters leads to site-specific relationships and if a high degree of accuracy is required the constants for the equations must be carefully determined using the local data. Difficulties included data handling problems, identifications of bad data, the fundamental differences between in-situ geophysical measurements and laboratory analyses and the quality and calibration of the geophysical logs.

2.3 China

Due to China's relatively late development and the introduction of advanced digital borehole logging technologies, published work in coal quality estimation from geophysical logs was reported mainly in Chinese in the late 1980s and early 1990s. Li (1989) reported on coal ash content estimation, through regression analysis, from geophysical logs from nearly one hundred boreholes from three different major coalfields in China: Heche coalfield of Shanxi Province, Yongcheng coalfield of Henan Province and Huainan coalfield of Anhui Province. They concluded that the correlations between coal quality parameters and geophysical logs are different even in the same coalfield. In general, ash content and specific energy correlate well with density logs but poorly with gamma rays. They also pointed out that although results of regression analysis provide a good prospect to estimate coal quality parameters from geophysical logs, the accuracy of the estimation was still not good enough for general use. The reasons were: coal sampling errors due to the mixing of coal and stone bands, log value error due to stone bands, coal samples contamination by drilling mud, computational errors due to manual regression calculation based on large number of data points (computers were not common at that time in China), and measuring errors of logging equipment.

The investigation of coal quality estimation/evaluation using geophysical logging data is mainly carried out as part of coalbed methane (CBM) exploration in China. Dong et al. (2001) reported on a method of evaluation using geophysical logging data for estimation of coal quality and CBM gas and successfully applied the method to the data from the eastern depression in Liaohe Oilfield. Fu et al. (2009a, b) used geophysical logs to evaluate the permeability and gas content of CBM reservoirs in Huainan and Huaibei coalfields of Anhui Province. The measured permeabilities and coalbed gas contents of coal seam samples are well correlated with the corresponding geophysical log responses. This largely improves prediction of the coalbed gas content from geophysical logs (mainly resistivity and sonic logs) and provides better understanding of the coal reservoir for CBM exploration in the studied coalfields. Similarly, Li et al. (2011) estimated permeability from dual lateral log and density logging data in Southern Qingshui Coalfield of Shandong Province. They found that the geophysically-estimated permeability is slightly higher than those from injection/falloff well tests. The reason for this is that the permeability model used did not include the influence of coal anisotropy.

Mao et al. (2011, 2014) described a crossplot approach for identification of coal ranks from geophysical logs such as density and neutron logs. An accuracy of 95% for rank identification was achieved from application to the real data from the CBM fields such as Qinshui Basin and Enhong Basin.

2.4 United Kingdom

Reeves (1971) was one of the earliest pioneers in geophysical responses of coal. He investigated four boreholes from the Yorkshire and Nottinghamshire areas using a universal chart to find the ash content from the gamma-gamma count rate. The chart employed the mud weight density, hole diameter, count rate and calculated ash percentage. However, he indicated that controlled borehole conditions do not exist and there is a difficulty in using a single chart for all conditions. He proposed several alternative steps to construct a chart for each borehole. The steps included selecting a coal seam having both the lowest gamma ray reading and the highest long space density (LSD), finding the lowest LSD deflection and corresponding the gamma ray reading, setting out the corresponding values on a logarithmic paper and plotting the count rates and joining the plots. He calculated similar or slightly higher ash content for the coals examined. He also proposed an alternative method that determines the total aluminium silicate content by running, at least theoretically, a spectral type of log, which is adjusted to read only radiations caused in the aluminium silicate region as a result of neutron bombardment. He commented that the techniques developed by the oil industry to determine the moisture content is directly applicable to coal seams. However, the conventional gamma ray/neutron logs are much more sensitive to small moisture content in calcareous and arenaceous rocks, and where there is relatively high moisture content or neutron moderation media the response is less pronounced. He also suggested a method to determine the type of coal. He explained that the simplest way to proceed would be to plot the gamma-ray deflection against the density measurement of a type coal and depending where the points fall, the variety of coal can then be identified.

Later, Reeves (1979) outlined the latest developments in coal wireline logging techniques and he gave an example to show the differences between two different ranked coals by using a sonic tool. A coal interpretation manual based on geophysical logs was developed for use within BPB to provide service to the coal industry (Reeves, 1981).

MacCallum (1992) reported that within a single site, over distances of up to about 1000 m, many seams maintain their gamma and density signatures and could be readily correlated in terms of seam fingerprint and quality. However, the differences in geophysical responses from the same coal seam could occur in distances as little as 3 m apart. This could be the result of local tectonics where the seam and closely associated strata had been subject to movement along closely spaced thrust planes at an angle close to that of the bedding. However, the remnants of the geophysical fingerprints from the seams in tectonically disturbed areas still remain to be of vital use in the elucidation of complex geological structures and identification of good quality coals from the inferior coals.

2.5 United States of America

As one of the major coal producers, USA also is the major country that conducted much research in coal quality estimations from geophysical logs. Bond et al. (1971) report that in the Illinois Basin an experimental program using computer processed data from logs of coal exploratory drill holes produced an excellent determination of moisture and ash in coal, based on volumetric analysis of the sonic and density logs. However, attempts to quantify coal composition using geophysical logs from wells in the Northern Great Plains using the same method had erratic results.

Davis (1976) and Abshier et al. (1979) outlined the importance of geophysical tools to determine coal quality parameters.

Norris and Thomas (1980) used density logs to determine ash and moisture content and the calorific value. The averages for the log intervals corresponding to the core report intervals were calculated and used with the core information in linear regression analysis to generate a set of three slopes and intercepts, which allowed estimation of in-situ quality parameters. One of the main problems encountered by using this technique was the mismatch between the geophysical log and core interval since the driller’s depths usually differ somewhat from the log depths, a depth shift was necessary to fit the core interval to the log interval. Another problem occurred when partings were removed and not noted on the core report. In this case the in-situ analysis showed a higher ash value than the core. A test case proved that initial correlation of log and core parameters allowed reasonable calculations of moisture, ash and heat content in-situ for a USA lignite deposit.

Daniels et al. (1983) also used geophysical logs to estimate ash content through cross plots of core sample measurements of ash and density along with solutions of a system of simultaneous equations involving two (or more) different types of geophysical well logs. They noticed that the variability of the neutron-neutron, sonic, and resistivity measurements makes them unacceptable for estimating coal quality parameters except for coals of the same age deposited in similar and uniform geologic environments. Based on analysis of Wyoming-Colorado core and well log data, they concluded that the best approach to determining coal quality parameters from geophysical well logs involves the primary use of density logs, with the secondary use of the gamma ray logs as a qualitative aid. Errors in estimating the ash content from the density log occur as a result of core sampling problems (where core is used for calibration), and the inherent inaccuracies of most slim hole gamma-gamma density measurements. If gamma-gamma density measurements are not available, then the total count gamma ray log can provide a rough estimate of ash content within an individual coal seam. They recommended that gamma ray measurements must be calibrated with results from core sample analyses for each coal seam to be useful for estimating ash content.

The solution proposed by Edwards and Banks (1978) to calculate the moisture content was criticised by the authors on the basis that the solution involves a number of approximations and assumptions that produce at least as much uncertainty in the final results. They also indicated that there is some correlation between the total sulphur content in coal and the induced polarisation response, which is a measure of the electrical polarisability of the mineral components in a rock. In sedimentary rocks, pyrite and high cation-exchange capacity clays are the primary minerals that produce a high induced polarisation response. If the clay content of coal is constant, then the induced polarisation response should be principally a function of the amount of pyrite contained in the coal.

Fishel and Mayer (1979) made correlations between the extremely high resolution (EHD) density tool curves and ash content. The correlation coefficient was 0.92.

Hallenburg (1979) showed an example of how a computerised on-line analysis using conductivity and density values would be a useful tool to identify the ash content and calorific value.

Alcock et al. (1986) used an interdisciplinary approach to model a lignite deposit in Texas. The depositional area was interpreted as an upper-delta plain, freshwater hardwood swamp between two regional distributary channels. Sulphur content was less than 0.8% and sediment supply was from the north so the overall ash content decreased southwards, although it increases in near small channels. The overall energy level increased through time with four recognisable higher energy pulses. These pulses were traced by density logs to predict ash distribution when designing a selective mine plan for part of the prospect. The plan increases the mined calorific value by 350-600 Btu/lb and reduces the ash content by 3-5% whilst losing only 8% of the original tonnage and increasing the strip ratio from 12.4 to 13.4. Resistivity log signatures can trace vertical maceral zoning, partly correlatable with depositional cycles.

Mullen (1988) employed the geophysical log analysis algorithms to calculate the main coal quality parameters such as ash, moisture, volatile matter and fixed carbon in the San Juan Basin of Colorado. The algorithms were modelled using basin-wide data after Fasset and Hinds (1971). Later, Mullen (1989) established some localised algorithms using one borehole, which was completely cored, to determine the resource potential Fruitland coal-beds. These algorithms were also applied to the other wells in the area and the log-calculated values were very close to results measured from the cores. The minimum gas content was calculated by using the previously published algorithm and the calculated results were quite comparable to the core measured values.

Mayor et al. (1990, 1994) used coal quality parameters to calculate the gas content from coal seams and concluded that log analyses could be performed much more rapidly and inexpensively than the core analyses. The major difficulty was found to be depth control when comparing coal seam reservoir open hole data to core data. To overcome this problem, a computerised axial tomography (CAT) scan was used. The relation between the ash content of the bore cores to gas content was established.

To determine the use of wireline-log and core data, the depth-shifted proximate, ultimate and gas content core data and the log data were investigated statistically. The most significant correlation was obtained between the log density and the coal ash content and the gamma ray log was found to be of limited use for quantitative evaluation of ash content. It was noted that the gamma ray does not have a regression coefficient exceeding 0.7 for any of the available core properties. The physical explanation for the lack of quantitative utility was thought to be due to the vertical resolution of the conventional gamma ray tool which is approximately 2 feet. Statistical evaluation of the relation between the log-derived bulk density and the measured ash content is derived. The authors indicated that although the correlations may be accurate for the data from which they were developed, they are not likely to be applicable beyond the original well locations.

Ayoub et al. (1991) summarised the link between the coal parameters and CBM production and the historical activity in this field in the USA and the rest of the world. Herron et al. (1988) and Herron (1991) briefly reviewed the logging properties of organic matter and presented a variety of wireline approaches that have been taken to evaluate the potential source rocks. Later, Herron et al. (1992) examined the impact of statistical uncertainties of elemental concentrations on geochemical log interpretation by using a fixed interpretation model and a synthetic data set. The results showed that for minerals the absolute error is generally <5wt% and the errors in petrophysical parameters generally fall within tolerable limits.

Colson (1991) used a computer package of Schlumberger (ELAN) to predict the gas content of Black Warrior Basin. Inputs used in ELAN processing are potassium, thorium, the photoelectric measurement, the enhanced vertical resolution bulk density and enhanced vertical resolution neutron porosity. The ELAN program is a mathematical engine solving a set of “x” equations for the “y” unknowns where x is greater than y. In addition to wireline measurements, log responses for each of the unknown volumes must be defined to obtain a solution. Published information on the constituents of coal was used (i.e. proximate and ultimate analysis) along with the SNUPAR (Schlumberger Nuclear Parameters code) to derive the appropriate log responses for modelled volumes. The actual computation of the volumetric constituent of the rock from wireline data on a ‘foot by foot’ basis is performed through the controlled combination of three different models solved simultaneously in the ELAN program. The first model solves for constituents in rocks surrounding the coals, the second model is used to solve for major constituents in coal when the well-bore is in good condition and the third model solves for coal constituents when the bore hole is not in good condition. The rank and the maceral content of the seams were also determined from the geochemical tool response.

Schlumberger’s geochemical logging tool (SNUPAR) was also used by Johnston (1990) and Johnston and Scholes (1991) to determine the cleats, cleat porosity, the mineral and maceral contents and the rank of the seams in a CBM study in San Juan Basin. The geochemical tool provides two modes of measuring data. In capturing mode, the elements that are resolved are aluminium, silicon, calcium, iron, sulphur, hydrogen, potassium, thorium, uranium, gadolinium and chlorine. Carbon and oxygen are obtained in the inelastic mode. The log data first is corrected for environmental effects. The next step is to determine log responses for each mineral. In addition the type of coal encountered in the bore hole must be known before log responses for that coal can be determined. When all log responses are determined, the data are input to a computer program that simultaneously solves for mineral-matter content and coal volume in one model and for the mineralogy and fluids in a second model.

2.6 Elsewhere

Simultaneous equations to predict the coal quality parameters were also used by Weltz (1976) for Pecket Zone in Brunswick Peninsula in Chile. First he described the lithologies such as clay, shale, sub-bituminous coal in density-sonic and density-gamma ray cross-plots using a criterion of geometrical centre, “mass” centre or location estimated by the log analyst that corresponds to element associated to the studied formation. He also successfully calculated the moisture content and heating value of the coals studied. In his calculations, the volatile matter and fixed carbon was calculated as total carbon.

Lavers and Smits (1976) noted that it was possible to establish a relationship between the bulk density and ash content in a geological province in South Africa. Although coal rank, coal and ash type did not cause any calibration problem for the researchers in South Africa and Australia, these parameters showed difficulty in the interpretation of Indonesian coals. However, some relations were still obtained between calorific value and neutron logs; volatile matter and single-electrode resistivity log.

The correlation of ash content with the HRD response was given in two different coal fields without any reference to their geographical location by Brom and Driedonks (1981). It was noted that establishing a separate relationship for each seam could improve the accuracy of prediction. Also, the use of a short spaced neutron-neutron tool showed the changes in H-content over the IH range and depicted variations were found to be caused by differences in the maceral content. The hydrogen rich intervals were thought to be vitrinite rich, whilst low-hydrogen parts represented inertinite rich horizons. Another finding was that the neutron log reading clearly differentiated three different coal seams on the basis of their maceral composition. The devolatilisation phenomena as well as maceral content was also thought to cause volatile matter differences in neutron reading cross plots. The calorific value was also obtained from the available logs. The washability was determined from density log. The bed resolution density was calibrated against the HRD to obtain reference BRD count rate levels corresponding to specific gravities of 1.45 and 1.6. The cumulative float at specific gravity 1.45 was then determined by summation of all intervals with log deflections indicating specific gravity lower than 1.45. To calculate the weight yield, the figure obtained divided by the total interval thickness and multiplied by a weighting factor corresponding to the ratio of average float density to average coal density (1.4/1.5) and a similar procedure was followed for the sinks. The results showed a reasonable comparison with the actual washability data (within about 5% absolute). The sulphur content was also successfully predicted from the neutron-capture gamma ray spectra with an accuracy of about 1% absolute.

The work done by Kayal and Christoffel (1989) in New Zealand is worth to mention. In New Zealand, systematic geophysical logging for coal exploration was conducted in 1980 and six lignite- coal deposit areas in the Southland lignite region. Kayal and Christoffel used geophysical logs not only for identification and location of coal seams, but also for estimation of coal quality parameters. They correlated ash, moisture, volatile matter, and fixed carbon measured from cored coal samples with the corresponding geophysical log data. They found that ash had strong positive correlation with the density and gamma ray logs; moisture had strong negative correlation with the density and positive correlation with the sonic log; and volatile matter and fixed carbon showed negative correlations with the gamma ray, density, and sonic logs. They developed empirical relationship between coal quality and geophysical logs through a stepwise multiple-regression method. The prediction accuracy of coal quality using these relationships were very good (mostly within 1%).

2.7 Summary

Based the literature review, it appears that a series of simple cross-plots are the most popular way of determining the coal quality from the geophysical logs. Coal quality to log relationship is not always represented by simple equations (straight lines) but also by curved lines generated by complex equations. Once the cross-plot has been prepared and the regression equation has been established, it is easy to predict the expected values from each additional drill hole. Available cross-plots include density versus percent ash, density versus heating value, gamma ray versus ash content, neutron density versus heating value, focussed dual point resistivity versus volatile matter and neutron density versus fixed carbon. These relationships will remain the same for each coalfield or basin as long as the depositional and geological conditions remain the same.

Although the prediction of ash content from the density logs is simple, the accuracy of ash determination from the geophysical logs could be affected by a number of factors such as inaccurate measurement of the borehole cavity, effective resolution of the density tools, coal's inherent moisture and maceral composition. Two samples with identical ash content may have different density log responses, suggesting that the macerals in the coal may account for part of the difference. Other problems in quality predictions are inaccurate determination of the core sample depth, a core sample that is not representative of the effective interval measured by logging probe and variations in borehole conditions that cannot be corrected by density compensation equations.

Similarly, gamma ray measurements can be used to predict coal quality although a small variation in clay content and the reducing geochemical environment adjacent to a coal seam might give a high gamma ray response. Problems associated with variations in ash composition are also present in the resistivity log response and there is little correlation between the resistivity and ash and other coal quality parameters.

3 Improving coal quality estimation from multi-geophysical logs

3.1 Parameter estimation using multi-geophysical logs

As we reviewed in the previous chapter, coal quality parameters such as ash content, density and volatile matter can be estimated by using model based regression approaches (exponential relationship or second order polynomial models) from geophysical logs. The outcomes of these methods largely depend on the model in use, and they cannot easily accommodate rock data variations not included in the “assumed” models. Apart from actual laboratory measurements, which are expensive, there are few methods available to accurately derive coal quality parameters. In this project, we propose to directly estimate the laboratory coal quality measurements from geophysical logs. This can be illustrated using parameter estimation from multi-geophysical logs in Figure 2. The reason for this is that each geophysical log reflects the petrophysical property variations of the rock. The basis of geophysical log interpretation exploits the contrasts in petrophysical signatures between different types of coals and rocks. We propose that increasing the number of geophysical log parameters should increase the chance of correct estimation of the coal parameter variations.

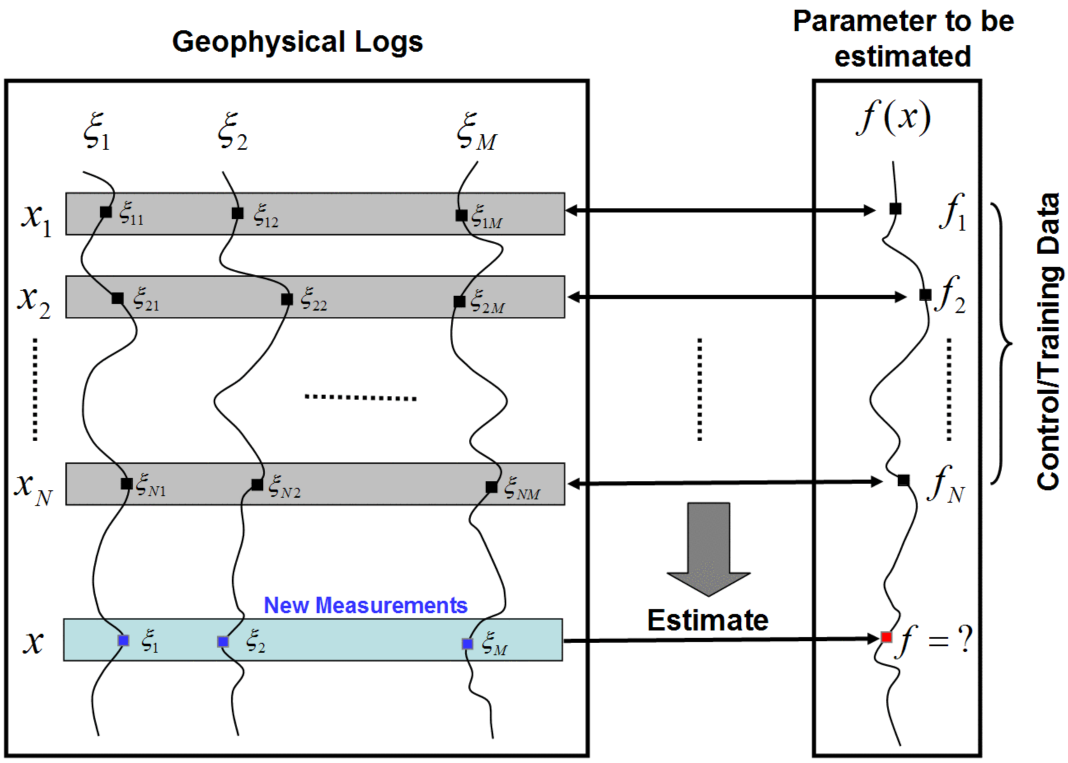


Figure 2 Illustration of parameter estimation using multiple geophysical logs. The discrete control data are used to train the parameter estimation algorithm and the trained algorithm is then used to estimate the target parameters with new measurements.

As with the regression approach of coal ash content using density data, the coal parameter estimation from multiple geophysical logs can be considered as a data modelling or interpolation problem from discrete known data points in multi-dimensional space. There are many ways to tackle this problem, such as model regression and neural networks, and a general review of these methods is beyond the scope of this report. In this section, we will describe a multi-parameter data analysis method using the radial basis function (RBF) algorithm for coal parameter estimation from multiple geophysical logs. Two of the most important advantages of such an approach are 1) it estimates coal quality parameters from parameters and relationships derived within the data set without a need for pre-existing assumptions or models; 2) it can easily accommodate the coal rank variations by simply adding the representative samples into the control data base.

3.2 Radial basis function (RBF) network

Method review

The Radial Basis Function (RBF) method is a type of artificial neural network method for application to problems of supervised learning such as regression, classification and time series prediction (Sarle, 1994; Orr, 1996; Haykin, 1999). During the last few decades, RBFs have had increasingly widespread use for functional approximation of scattered data in numerical analysis and statistics. Its applications includes the numerical solution of PDEs, data mining, machine learning, and kriging methods in statistics (Buhmann, 2003; Mongillo, 2011). RBF applications in geophysics include geophysical data interpolation (Billings et al., 2002a, b), and prediction of log properties from seismic attributes (Ronen et al., 1994; Russell et al., 2003). In this project, we use the RBF method to estimate coal quality parameters from geophysical logs by establishing a relationship between the geophysical logs and the laboratory coal quality parameter measurements.

RBF algorithm description

The RBF approach is a supervised learning method (Orr, 1996). The function is 'learned' from the examples that a teacher or training data set supplies. The set of examples or training data set, contains elements that consist of paired values of the independent (input) variable and the dependent (output) variable. Let $x = \{\xi_1, \xi_2, ..., \xi_M\}$ to be an M-dimension variable. Given training data set at nodes x_1, …, x_N in M-dimensions, the basic form for RBF approximations can be expressed as

$$s(x) = \sum_{k=1}^{N} \lambda_k \phi(\|x - x_k\|) \tag{1}$$

where $\|\cdot\|$ denotes the Euclidean distance between two points, and $\phi(r)$ is a kernel function defined for $r \geq 0$. This can be understood as a synthesis of the function $s(x)$ using the basis function $\phi(r)$. In this regard, the RBF method is very similar to the discrete inverse Fourier transform. Given scalar function values $f_i = f(x_i)$, the expansion coefficients λ_k can be obtained by solving the linear system

$$\begin{bmatrix} A_{1,1} & A_{1,2} & \cdots & A_{1,N} \\ . & . & \cdots & . \\ . & . & \cdots & . \\ . & . & \cdots & . \\ A_{N,1} & A_{N,2} & \cdots & A_{N,N} \end{bmatrix} \begin{bmatrix} \lambda_1 \\ . \\ . \\ . \\ \lambda_N \end{bmatrix} = \begin{bmatrix} f_1 \\ . \\ . \\ . \\ f_N \end{bmatrix} \quad \text{or} \quad A\lambda = f \, , \tag{2}$$

where $A_{i,j} = \phi(\|x_i - x_j\|)$. In our case, the function value f_i is one of the measured coal quality parameters from the selected core sample in the laboratory while $x_i = \{\xi_{i1}, \xi_{i2}, ..., \xi_{iM}\}$ is a suite of the geophysical logs such as gamma ray, sonic, neutron and resistivity measured at the corresponding depth of the coal sample in the borehole. The pairs (x_i, f_i) for $i=1, 2, … N$ form the training data set. The coefficients λ_k derived from equation (2) ensure equation (1) interpolates $f(x)$ exactly at x_1, …, x_N. Therefore, the RBF method is an exact interpolator and it attempts to honour the data. The common choices of the radial basis function $\phi(r)$ are (Golden Software Inc., 2014).

1) Inverse Multiquadric: $\phi(r) = 1 / \sqrt{r^2 + R^2}$;
2) Multi-logarithm: $\phi(r) = \log(r^2 + R^2)$;
3) Multiquadratics: $\phi(r) = \sqrt{r^2 + R^2}$;
4) Natural Cubic Spline: $\phi(r) = (r^2 + R^2)^{3/2}$;
5) Thin Plate Spline: $\phi(r) = (r^2 + R^2)\log(r^2 + R^2)$;
6) Gaussians: $\phi(r) = e^{-(r/\sigma)^2}$, where σ is a smoothness parameter and can be interpreted as the variance of a Gaussian distribution centred on *r*;

where *r* is a normalised relative distance from the point to the node while R is a smoothing factor in an attempt to produce a smoother surface.

The RBF method is schematically illustrated in Figure 3. It is a feed-forward network consisting of three layers (Haykin, 1999): an input layer, a hidden layer of radial kernels and an output layer of linear neurons. The input layer is made up of the sources nodes - in our case the geophysical logs. The hidden layer performs a non-linear transformation from the input space to the hidden space while the output layer acts as a linear regression to predict the desired targets – the coal quality parameters in this case. Each hidden neuron in an RBF is tuned to respond to a local region of feature space by means of a radially symmetric function $\varphi(r)$. The activation of a hidden unit $\varphi(r)$ is determined by the distance *r* between the new geophysical log measurement vector *x* and the prototype geophysical log measurement x_i in the training data set while the output unit is determined by the dot-product between the hidden activation vector $\boldsymbol{\varphi}$ and the weight vector $\boldsymbol{\lambda}$ or a weighted summation of the hidden units using the λ_k s as weights.

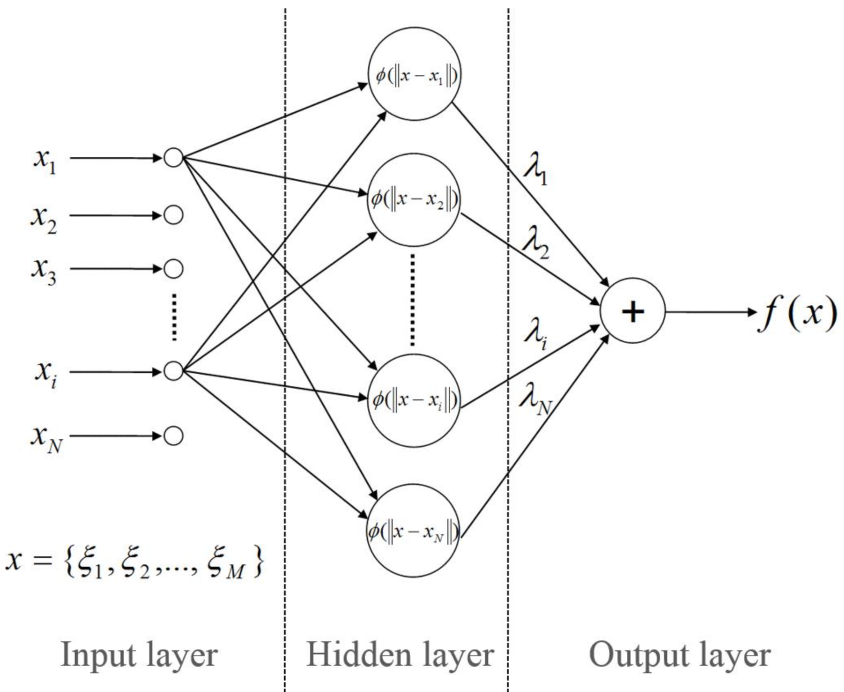


Figure 3 Schematic illustration of the RBF algorithm expressed by equations (1) and (2). It can be considered as a single layer neural network.

In real applications, the independent variables in the training data set are often also affected by noise. In our case, both geophysical logs and coal quality parameters are field and laboratory measurements with inherent measurement noise. This type of noise is more difficult to model and we shall not attempt it. In any case, as

Orr (1996) pointed out, not taking account of noise in the input data is approximately equivalent to assuming noiseless inputs but an increased amount of noise in the outputs.

3.3 Implementation of RBF method

The RBF algorithm described above was implemented for coal quality parameter estimation from multiple geophysical logs. Figure 4 shows the user interface of this prototype software ***ParamEstimate***. The details of the parameters on this user interface are discussed in Appendix A.

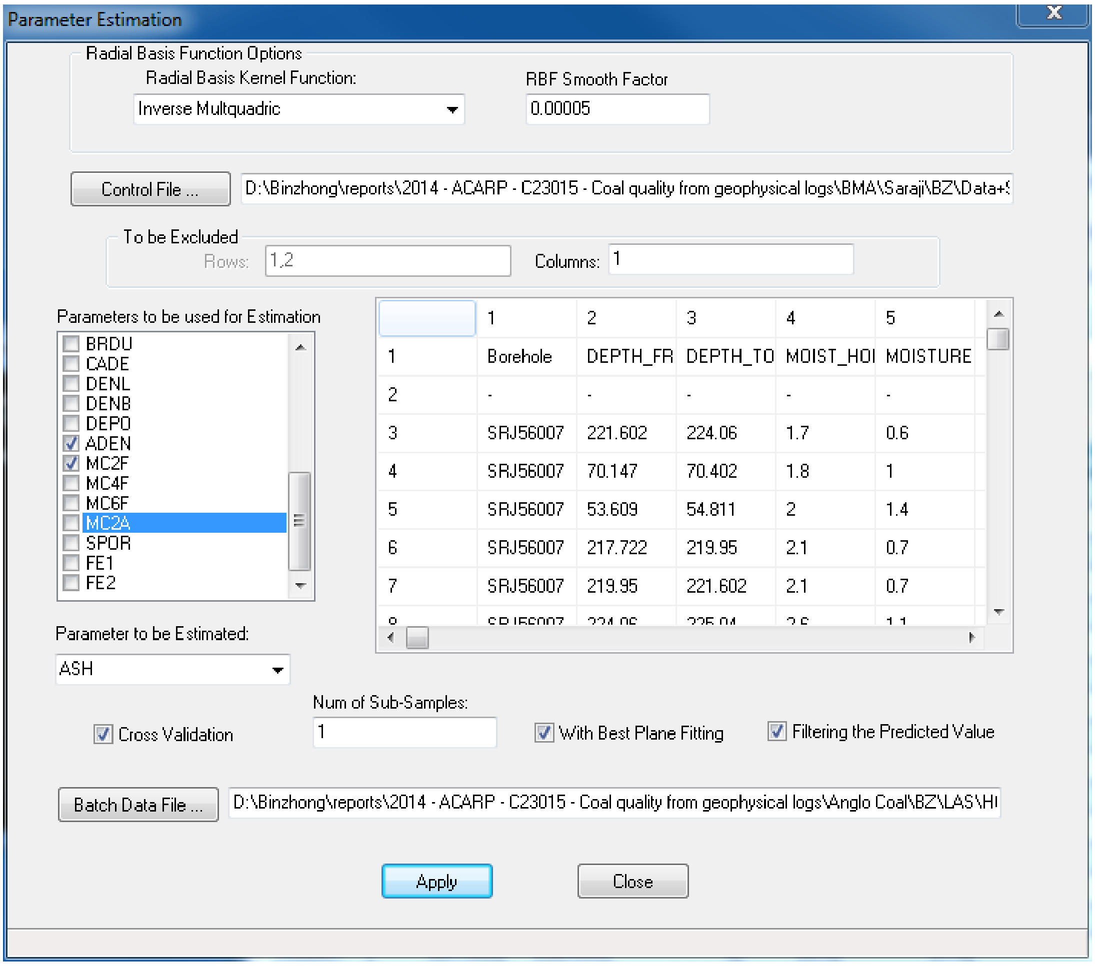


Figure 4 User interface of new RBF-based algorithm developed for coal quality parameter estimation from geophysical logs.

3.4 Summary

This Chapter provides a brief description of the RBF-based multiple variable analysis method. The RBF algorithm was implemented into a prototype software ***ParamEstimate*** for coal quality parameter estimation from multiple geophysical logs.

4 Examples of coal quality estimation from multi-geophysical logs

In this chapter, we will apply the RBF-based coal quality parameter estimation from multiple geophysical logs two data sets to demonstrate its feasibility and advantages over the conventional single-log analysis.

4.1 Example 1 – Data from Anglo American

Data description

The first data set that we analysed is from Anglo American. Along with the geophysical logging data, it was also provided with laboratory coal quality proximate analysis data of a total of 144 coal samples from 19 boreholes. All the coal samples are from the same coal seam that had with an average thickness of 6.95m. The 19 boreholes are well distributed from an area of about 2.6km x 8.4km (as shown in Figure 5). The coal quality and geophysical logging parameters provided are listed in Table 2 and Table 3, respectively. The geophysical logs were collected by Weatherford who is the major geophysical logging service provider to Australian coal mines.

Table 2 The key coal quality parameters provided by Anglo American.

Coal quality Parameters	**Description**
Imad	Inherent moisture on an air-dry basis
ASHad	Ash on an air-dry basis
ASHDry	Ash on a dry basis
Vmad	Volatile matters on air-dry basis
Vmdaf	Volatile matters on a dry, ash-free basis
Fcad	Fixed carbon on an air-dry basis
Tsad	Total sulphide on an air-dry basis
Tsdry	Total sulphide on an air-dry basis
CSN	Crucible swelling number
Rdad	Relative density on an air-dry basis
Rddry	Relative density on a dry basis
SE	Specific energy

Table 3 Geophysical logging parameters provided by Anglo American.

Logging Parameters	**Description**
GRDE (GAPI)	Gamma ray from density tool
CODE (G/C3)	Compensated density
CRCR (G/C3)	Density correction
LSDU (SDU)	Long spaced density
BRDU (SDU)	Bed resolution density
CADE (MM)	Calliper from density tool
DENL (G/C3)	Density from long spaced density tool
DENB (G/C3)	Density from short spaced density tool
DEPO (PERC)	Porosity from the sandstone-calibrated density
ADEN (G/C3)	VECTAR processed density
MC2F (US/M)	20 cm sonic transit time from receivers R1 and R2
MC4F (US/M)	40 cm sonic transit time from receivers R2 and R4
MC6F (US/M)	60 cm sonic transit time from receivers R1 and R4
MC2A (US/M)	20 cm sonic transit time from receivers R3 and R4
SPOR (PERC)	Porosity from the sandstone-calibrated sonic log
MC2U (US/M)	20 cm sonic transit time (raw data)
UCSM (MPa)	UCS – derived from sonic
GRNP (GAPI)	Gamma ray from neutron tool
LSN (SNU)	Neutron counts from long spaced neutron tool
SSN (SNU)	Neutron counts from short spaced neutron tool
RPOR (PERC)	Porosity from the sandstone-calibrated neutron

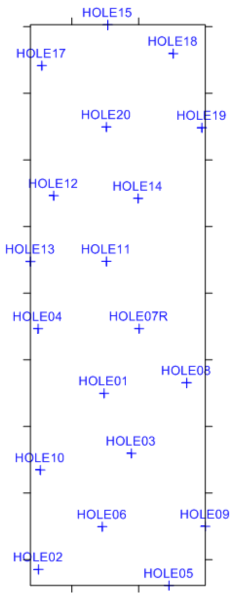


Figure 5 The borehole distribution of coal quality and geophysical logging data from Anglo American.

Data quality assessment

In the geophysical logging data provided, there is no density log ADEN provided for the deep part of the boreholes 04, 05, 11, 13 and 17. Therefore, this parameter will not be included in the coal quality data analysis so that the original 144 data samples can be maintained. To verify the quality of the provided data, we first plot the crossplot between laboratory-measured coal quality parameters with the relative density as shown in Figure 6. The cross plots exhibits the normal trends with a high-degree of correlation especially for ash contents, fix carbon and specific energies, which suggests the lab measurements are of good quality.

To check the quality of geophysical logging data, we first plot the geophysical density log DENB against the laboratory measured air-dry relative density RDad as shown in Figure 7. The red line is the fitted curve while the green line is the expected fitting line for the data. It is noted that most of the RDad data are above the green line, which is consistent with the expectation as the laboratory measured RDs are normally higher than the true density values due to the porosity reduction by the crushing process of the coal samples as discussed by Preston and Sanders (1993). In addition, there is one wild data point as indicated by a red arrow. The RD value is much smaller than the DENB value for this point. This point corresponds to sample QP06 from Borehole 10 as shown by Table 4 and Figure 8. Figure 8 indicates that this sample should be from a thin stone band, suggesting that the lab testing RD value is too low for a stone band and this sample should be excluded from analysis. After excluding this sample, the cross-correlation coefficient R^2 is increased from 0.9173 in Figure 7 to 0.9435 in Figure 9. This suggests that the density logs are of good quality. This can be further confirmed by Figure 10, which shows that the correlations of laboratory coal quality parameters (ash, fixed carbon, specific energy, inherent moisture, crucible swelling number and volatile matter) with geophysical density log DENB are comparable to the correlations of coal quality parameters with laboratory relative density RDad in Figure 6.

The quality of the geophysical logging data can be further evaluated by the statistics of the data such as average values, spreads and histograms, which can be easily generated by the prototype software LogQA developed through ACARP Project C13016 on quality appraisal for geophysical borehole logs (Fullagar et al., 2005). Figure 11 shows the averages and standard deviations of geophysical logs for calliper CADE, natural gamma GRDE, short spaced density DENB and sonic MC2F from different boreholes. Figure 12 and Figure 13 present the histograms of geophysical gamma ray log GRDE and density log DENB, respectively, for boreholes 01, 05, 12 and 20. Except for the hole size of Hole 05, which is slightly bigger than the boreholes, all other data shows correct data ranges and distribution. Therefore, we can conclude that the provided geophysical logging data are consistent between boreholes and of good quality.

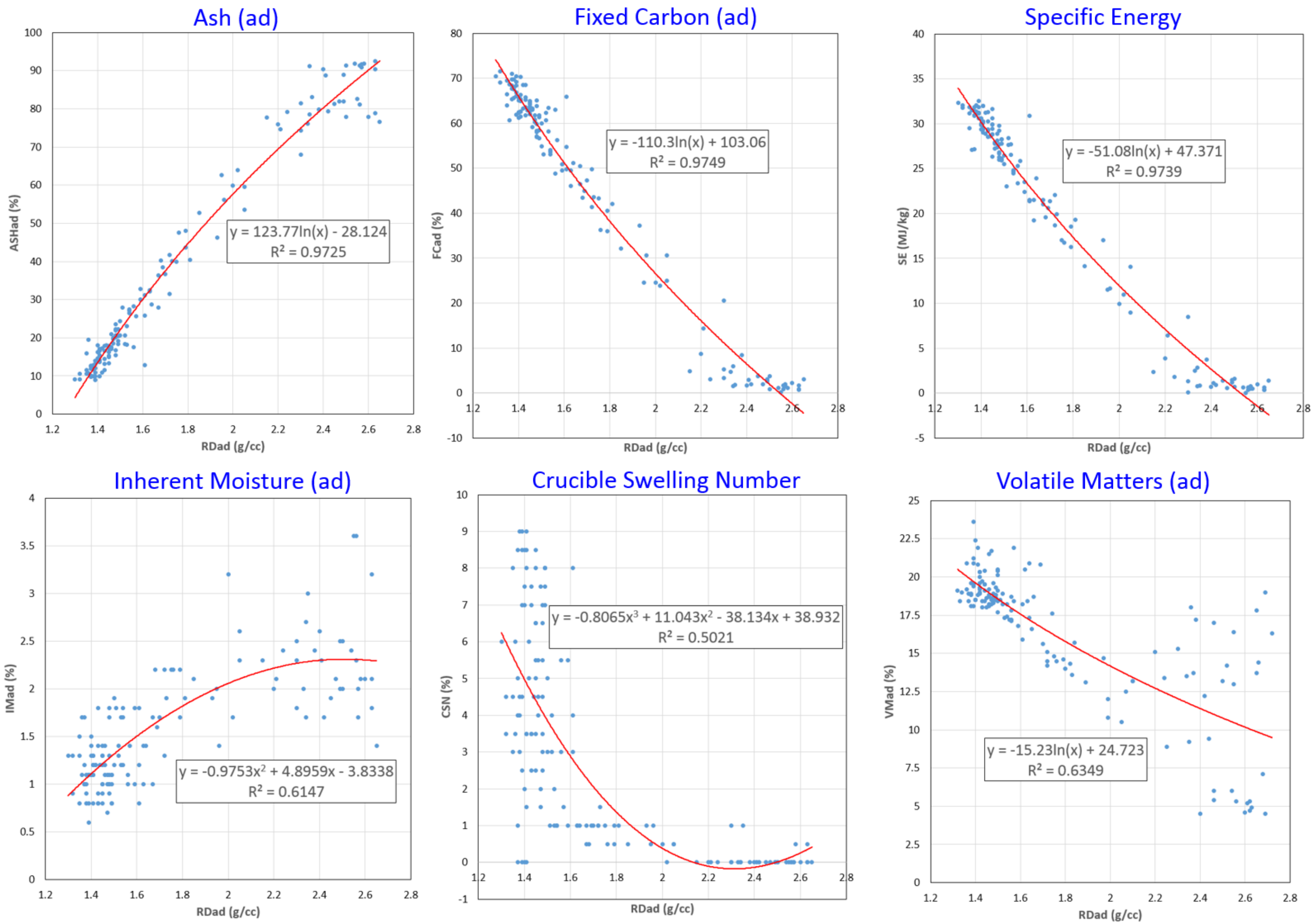


Figure 6 Correlations of laboratory coal quality parameters with relative density (air-dry basis). The regressions are in trends observed normally, suggesting the measured ash coal quality parameters and relative densities are in good quality. There are some degrees of scattering.

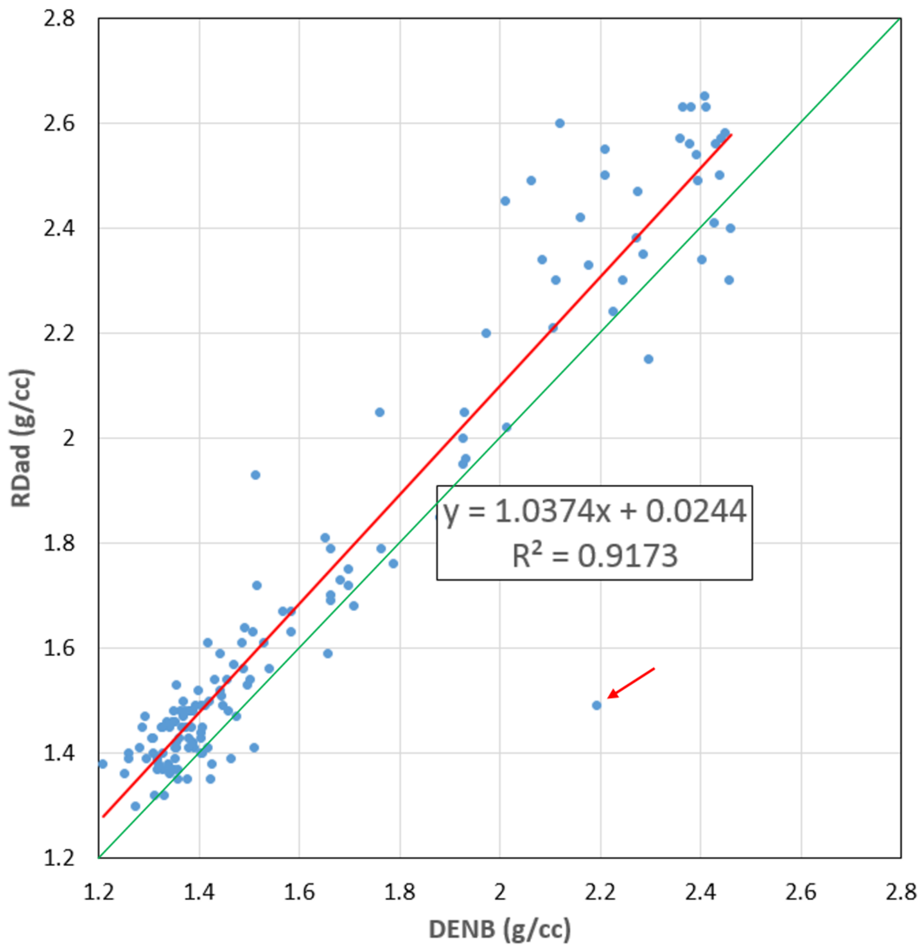


Figure 7 The crossplot of the laboratory measured relative density (RDad) and the geophysical density log (DENB). The red line is the fitted curve while the green line shows the expected fitting curve.

Table 4 Comparison of the laboratory measured relative density and the geophysical density log ADEN for the coal samples from borehole HOLE10.

Borehole ID	Sample ID	Depth_From (m)	Depth_To (m)	RDad (g/c3)	ADEN (g/c3)	RDad-ADEN (g/c3)	Error (%)
HOLE10	QP01	456.01	456.37	2.05	1.9889	0.0611	2.98
HOLE10	QP02	456.37	456.96	1.63	1.5007	0.1293	7.93
HOLE10	QP03	456.96	458.40	1.43	1.3609	0.0691	4.83
HOLE10	QP04	458.40	459.18	1.38	1.3318	0.0482	3.49
HOLE10	QP05	459.18	460.88	1.49	1.4121	0.0779	5.23
HOLE10	QP06	460.88	461.00	1.49	2.1723	-0.6823	-45.79
HOLE10	QP07	461.00	462.40	1.39	1.3765	0.0135	0.97
HOLE10	QP08	462.40	462.70	2.58	2.4916	0.0884	3.43

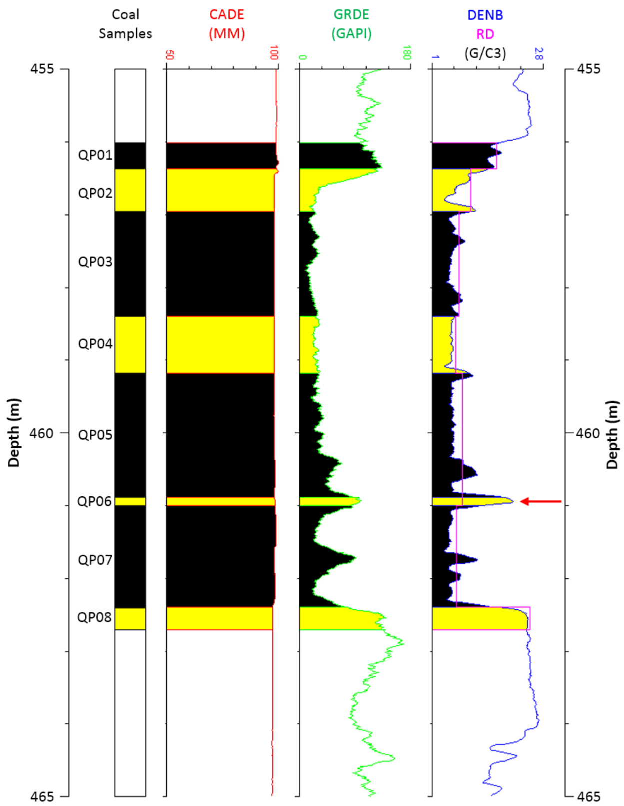


Figure 8 Coal samples and geophysical logs for borehole Hole10 from Anglo American. The magenta curve on the 4th column shows the relative density (RD) measured in laboratory. The RD of sample QP06 is much smaller than the geophysical density log value for the sample.

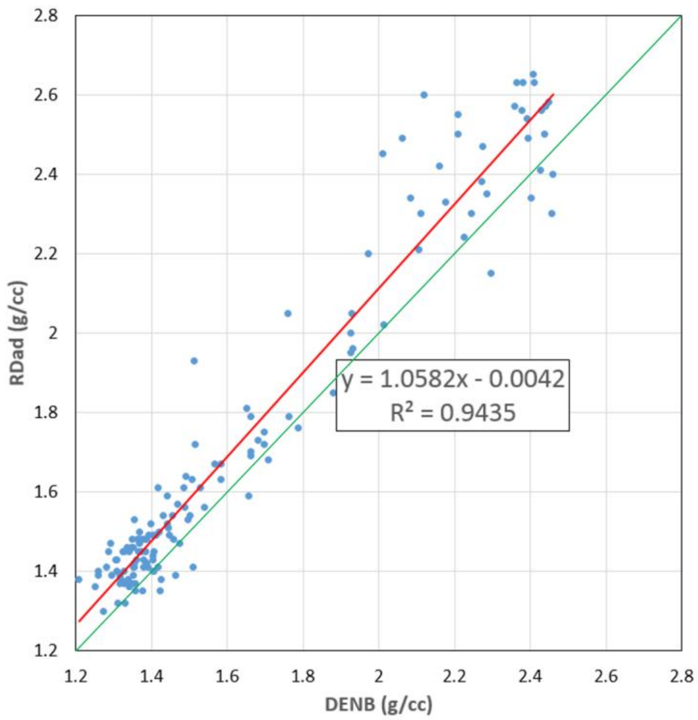


Figure 9 The correlation of the laboratory measured relative density RD and the geophysical density log DENB. The red line is the fitted curve while the green line shows the expected fitting curve.

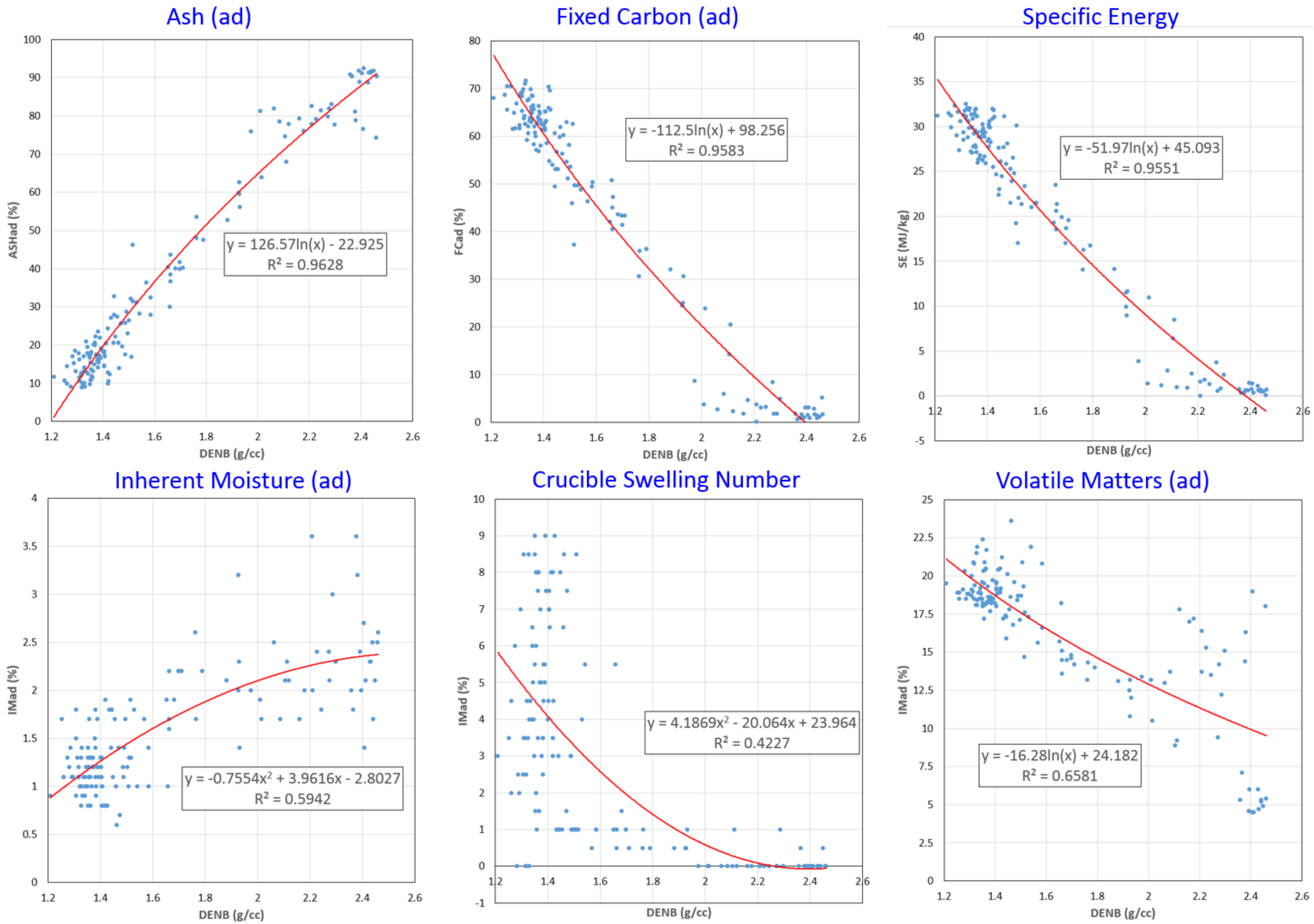


Figure 10 Correlations of laboratory coal quality parameters with the geophysical density log DENB: ash, fixed carbon, specific energy, inherent moisture, crucible number and volatile matters.

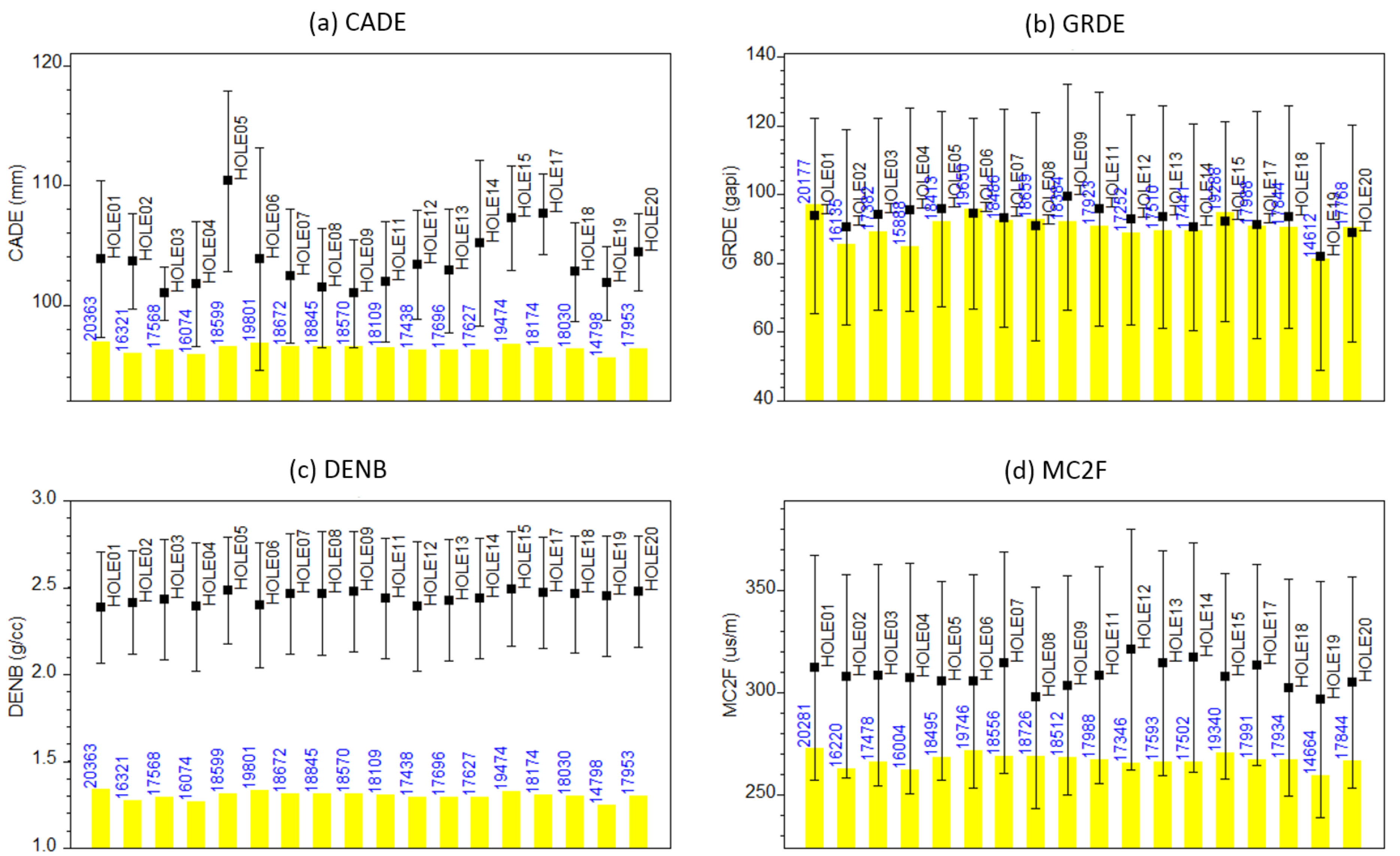


Figure 11 Averages and standard deviations of geophysical logs from Anglo American: (a) calliper CADE, (b) natural gamma GRDE, (c) short spaced density DENB, and (d) sonic MC2F from different boreholes. The yellow bars with blue numbers indicate the sample counts for the statistical computations.

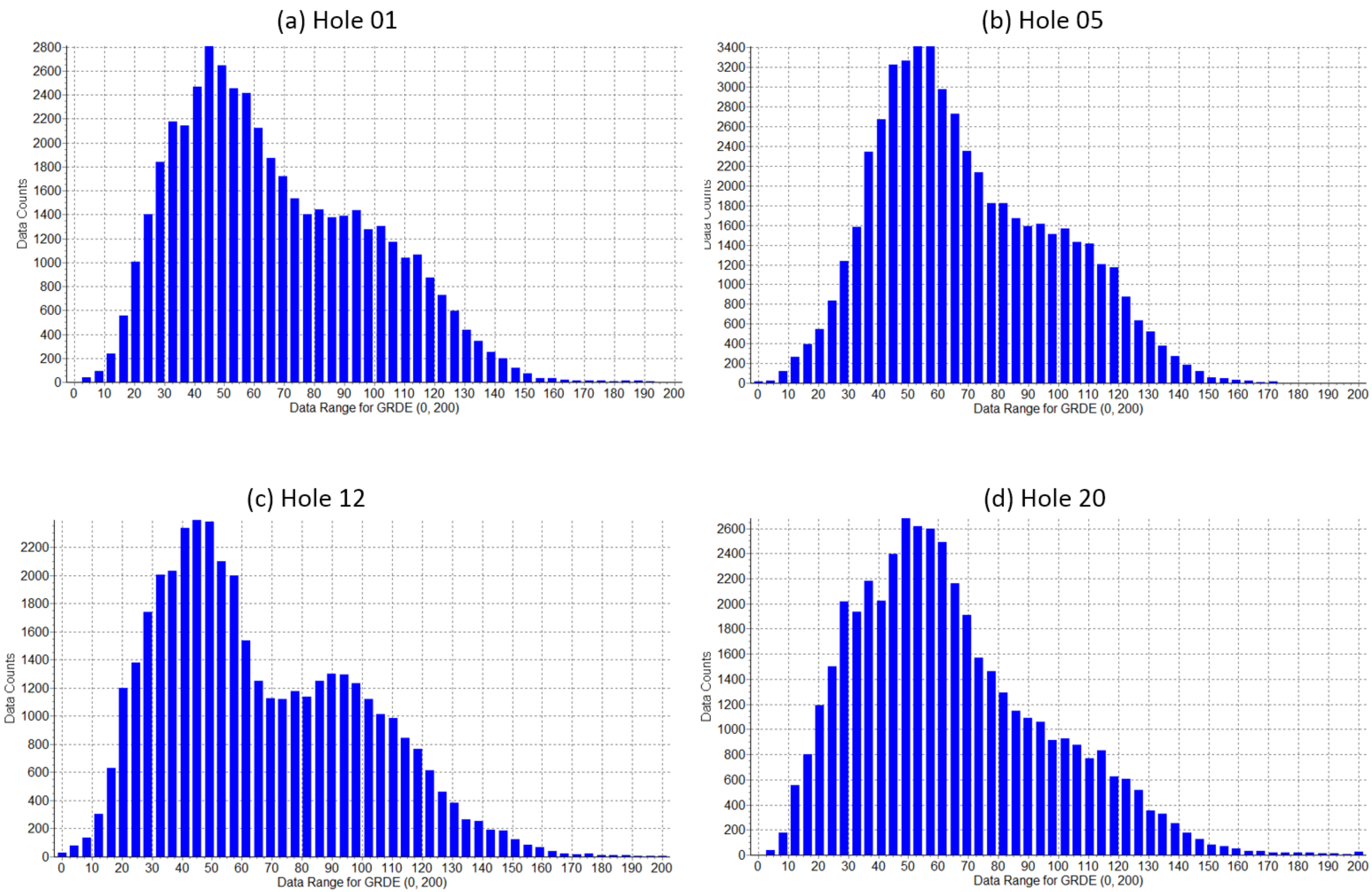


Figure 12 The histograms of geophysical gamma ray log GRDE for boreholes: (a) Hole 01; (b) Hole 05; (c) Hole 12; (d) Hole 20.

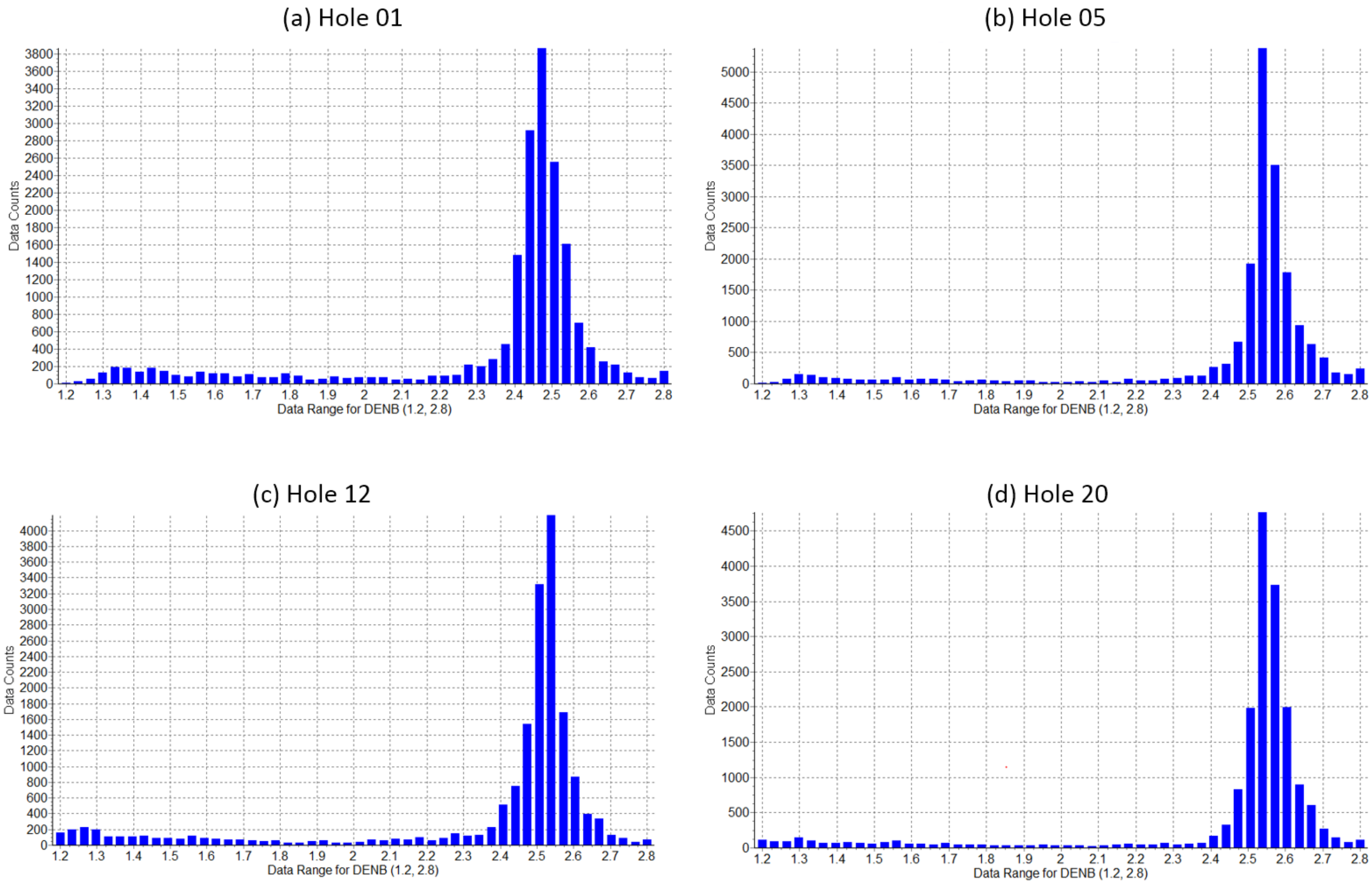


Figure 13 The histograms of geophysical density log DENB for boreholes: (a) Hole 01; (b) Hole 05; (c) Hole 12; (d) Hole 20.

Coal quality estimations from geophysical density log ADEN

As we have shown in Figure 9 and Figure 10, except for the crucible swelling number, the coal quality parameters such as relative density, ash, fixed carbon, specific energy, volatile matter and inherent moisture have good correlation with the geophysical density log DENB. The regression equations shown in these two plots can be used to estimate the corresponding coal quality parameters from density log DENB. The cross-plots of the estimated parameters with corresponding laboratory measured values are presented in Figure 14, while the statistics of the estimations are listed in Table 5. The average error in Table 5 is the average of the absolute errors of the estimations. The correlation coefficients (R in the table and R^2 in the plots) are relatively high and the average errors of the estimated parameters are relatively small in comparison with the average values of the parameters. This suggests that the density log plays an important role in coal quality parameter estimation, which is consistent with other people's observations. Please note that the estimation is considered as self-checking as all the data have been used for derivations of the regression equations.

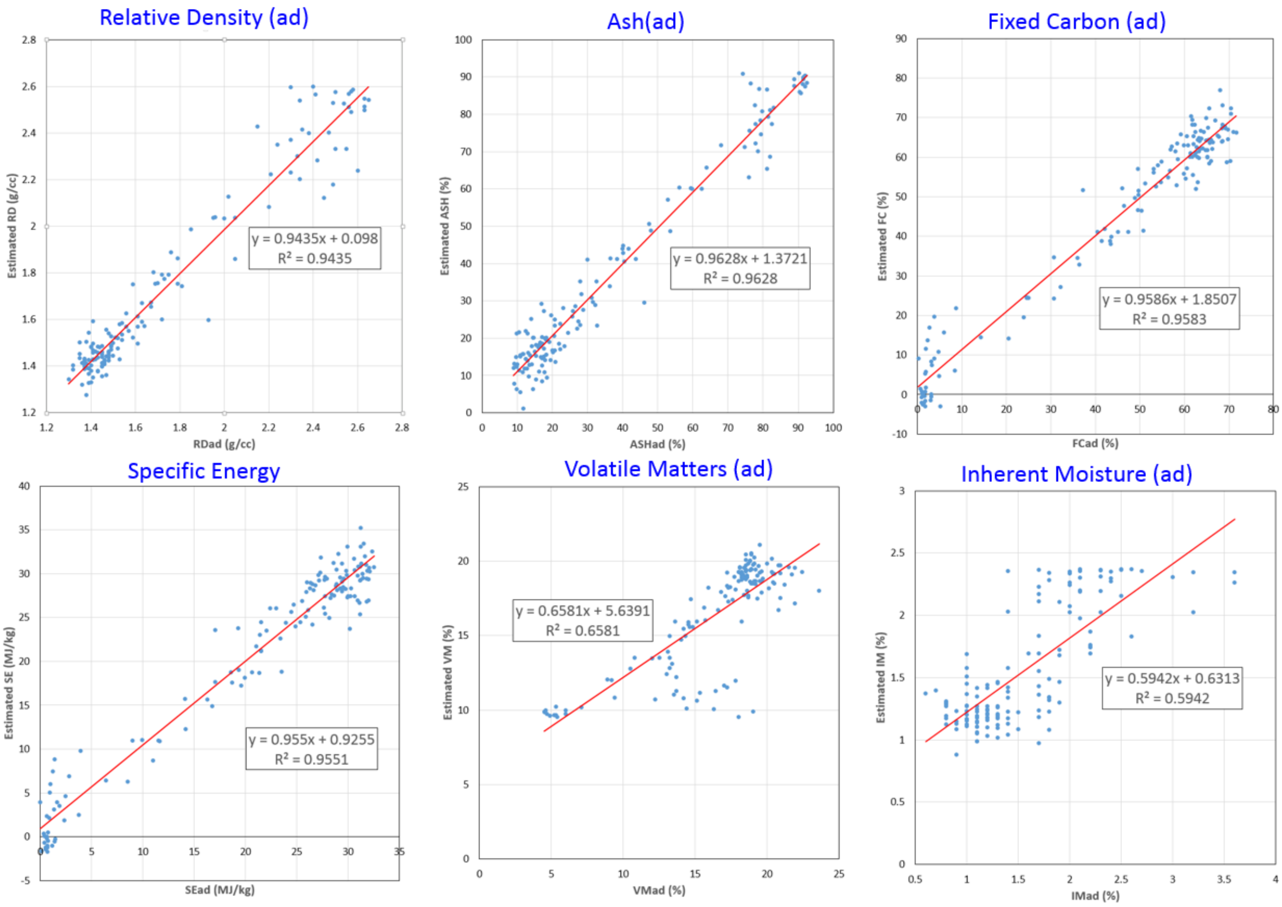


Figure 14 The cross-plots of the laboratory coal quality parameters with the corresponding coal quality parameters estimated from geophysical density log DENB.

Table 5 Statistics of the estimated coal quality parameters from geophysical density log DENB

	Average Value	Min. Error	Max. Error	Average Error	Average Error in %	Correlation R
RD (g/cc)	1.74	0.00	0.36	0.07	4.02	0.97
Ash (%)	36.86	0.14	16.64	4.10	11.12	0.98
Fixed carbon (%)	45.11	0.05	15.92	3.96	8.78	0.98
Specific Energy (MJ/kg)	20.54	0.01	7.41	1.93	9.40	0.98
Volatile Matter (%)	16.49	0.03	9.12	1.85	11.22	0.81
Inherent Moisture (%)	1.56	0.00	1.34	0.29	18.59	0.77

Coal quality estimations from multiple geophysical logs

Next we applied the RBF-based multiple variable analysis algorithm to the Anglo American data set to estimate the coal quality parameters from geophysical logs. As pointed out in the last chapter, the RBF method is an exact interpolator and it attempts to honour the data i.e. if you use the training data as the input, the output will be exactly the same as the input data. Therefore, we cannot use the whole training data set to test the performance of the RBF method like the curve fitting approaches used in the previous section. An alternative process is to use a technique called "cross-validation" (Hastie *et al*., 2001; Thore *et al.*, 2002). In k-fold cross-validation, the control data are divided into k subsets of (approximately) equal size. The interpolation method can then be trained k times, each time leaving out one of the subsets from training and using the omitted subset to compute whatever error criterion is of interest. If k equals the sample size, this is called "leave-one-out" cross-validation. When k equals 2, this is called the holdout method in which the control data set is separated into two sets: the training set and the testing set. For this Anglo American data set, we will use the leave-one-out cross-validation approach.

First we used different combination of the key geophysical logs to estimate ash content so that the best combination of the logs can be selected. The results are shown in Table 6. It is clear that the average error decreases while the correlation coefficient R increases with number of the geophysical logs used. This is consistent with our expectation in spite of the fact that incremental improvements are relatively small.

Based on the above results and other similar tests for other coal parameters, the optimum geophysical logs for coal quality parameter estimation for this data set are GRDE, DENB, DENL, DEPO, MC2F, MC4F, RPOR and GRNP. In these logs, GRDE and GRNP are gamma rays reflecting the lithology of the coal; DENB and DENL are short- and long-spaced density logs, which have strong correlation with coal ash content; DEPO and RPOR are sandstone-calibrated porosities derived from density and neutron logs; and MC2F and MC4F are 20cm-spaced and 40cm-spaced sonic logs, signifying the integrity and the strength of the coal samples. The estimated coal quality parameters from these geophysical logs using the leave-one-out cross-validation approach are shown in Figure 15 while the statistics of the estimations are listed in Table 7. Compared to the estimation results (see Figure 14 and Table 5) from the single density log DENB, the estimated parameters from multiple geophysical logs have smaller average errors in general with comparable correlation coefficients. Significant estimation improvement can be observed for the parameter volatile matters: the average error is decreased from 11.22% to 7.64% while the correlation coefficient is increased from 0.81 to 0.93.

Please note that the coal quality parameter estimations from the single log DENB use the whole data set as the input and output i.e. it is a self-validation approach, while the RBF-based estimation method uses the leave-one-out approach in which the estimated data sample is not in the training data set. Therefore, strictly speaking, the results from these two approaches are not compatible for comparison. It is not unexpected that the self-validation approach may produce better results. However, our tests suggest that the RBF-based multi-log analysis produces better results than the single log approach. All these indicate the importance of the multiple geophysical log analysis in coal quality estimation.

Table 6 Statistics of the estimated coal quality parameters from multi geophysical logs

Geophysical logs	Min. Error	Max. Error	Average Error	Correlation R
GRDE,DENB	0.03	38.28	6.90	0.9535
GRDE,DENB,DENL	0.04	31.92	6.61	0.9510
GRDE,DENB,DENL,DEPO	0.06	23.65	4.58	0.9738
GRDE,DENB,DENL,DEPO,MC2F	0.02	19.50	4.23	0.9809
GRDE,DENB,DENL,DEPO,MC2F,MC4F	0.09	17.86	4.10	0.9828
GRDE,DENB,DENL,DEPO,MC2F,MC4F,RPOR	0.03	14.86	3.98	0.9837
GRDE,DENB,DENL,DEPO,MC2F,MC4F,RPOR,GRNP	0.01	14.15	3.36	0.9845

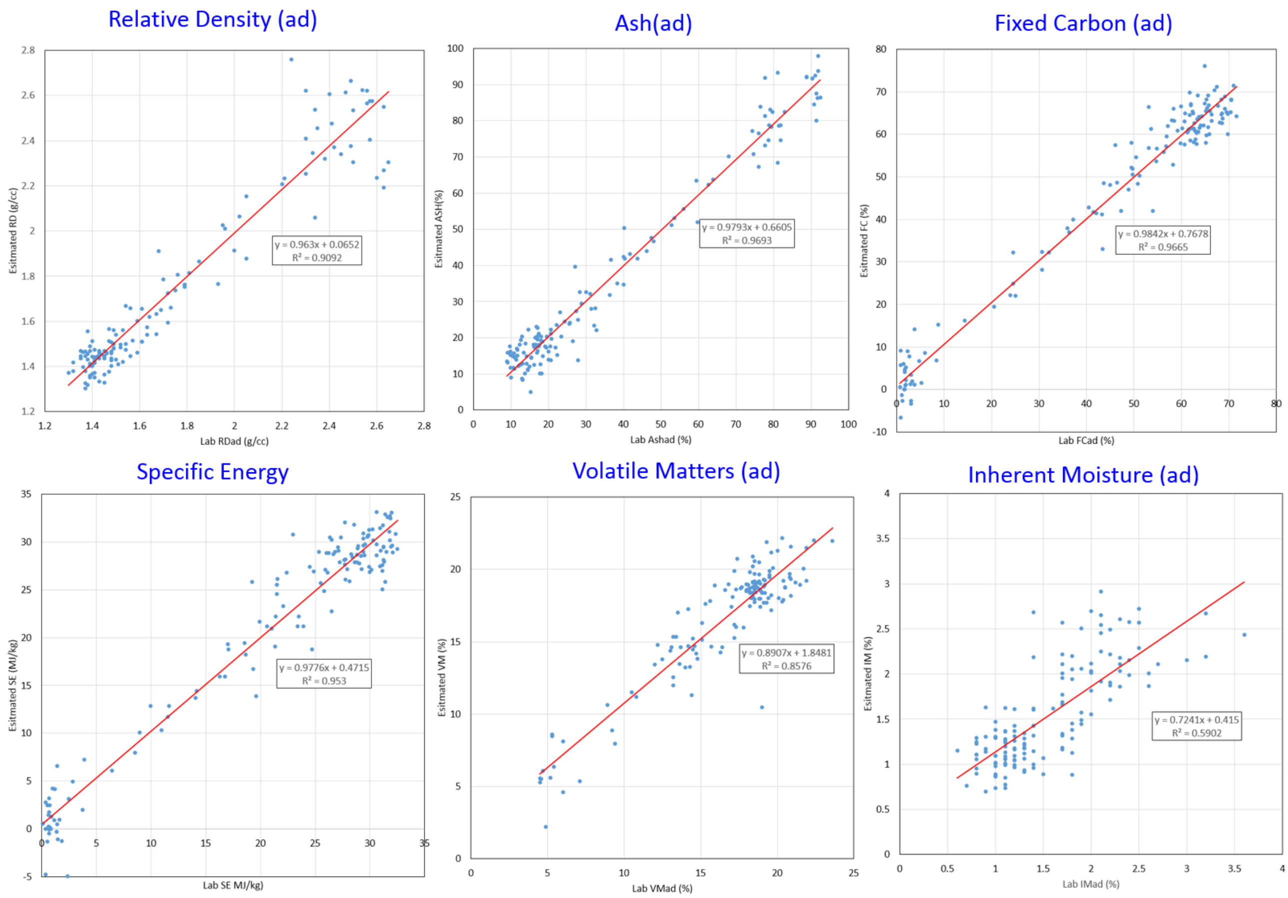


Figure 15 The cross-plots of the laboratory coal quality parameters with the corresponding coal quality parameters estimated from multi geophysical logs: GRDE DENL, DENB, DEPO, MC2F, MC4F, GRNP & RPOR.

Table 7 Statistics of the estimated coal quality parameters from multi geophysical logs: GRDE DENL, DENB, DEPO, MC2F, MC4F, GRNP & RPOR

	Average Value	Min. Error	Max. Error	Average Error	Average Error (%)	Correlation R
RD (g/cc)	1.74	0.00	0.67	0.08	4.60	0.95
Ash (%)	36.86	0.01	14.15	3.36	9.12	0.98
Fixed carbon (%)	45.11	0.02	15.18	3.48	7.71	0.98
Specific Energy (MJ/kg)	20.54	0.07	7.77	1.92	9.35	0.98
Volatile Matter (%)	16.49	0.01	8.53	1.26	7.64	0.93
Inherent Moisture (%)	1.56	0.01	1.27	0.30	19.23	0.77

4.2 Example 2 – Data from BMA

Data description

The second data set is from BM Alliance Coal Operations (BMA). BMA provided us with a relatively large data set in which there are 1012 samples with laboratory coal quality proximate analysis data from 26 boreholes and corresponding geophysical logging data from the same boreholes. There are only 23 usable boreholes as explained below. The 23 boreholes are distributed in the NW-SE direction in an area of 12.3km x 23.58km and can be divided into two natural groups: Area-1 and Area-2, which are separated by about 9km, as shown in Figure 16. The coal samples are from different coal seams as illustrated in Figure 17. The coal quality and geophysical logging parameters provided are listed in Table 8 and Table 9, respectively. As with the Anglo American data, the geophysical logs from BMA were mainly collected by Weatherford who is the major geophysical logging service provider to Australian coal mines.

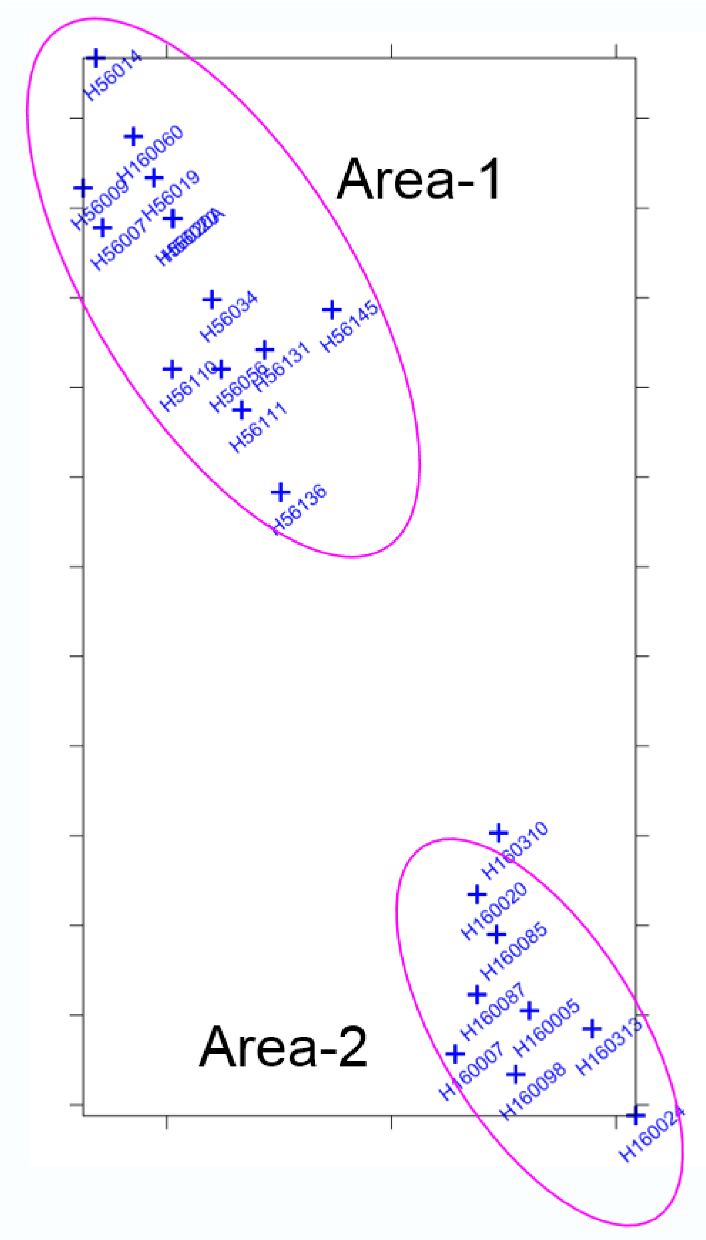


Figure 16 The borehole distribution of coal quality and geophysical logging data from BMA.

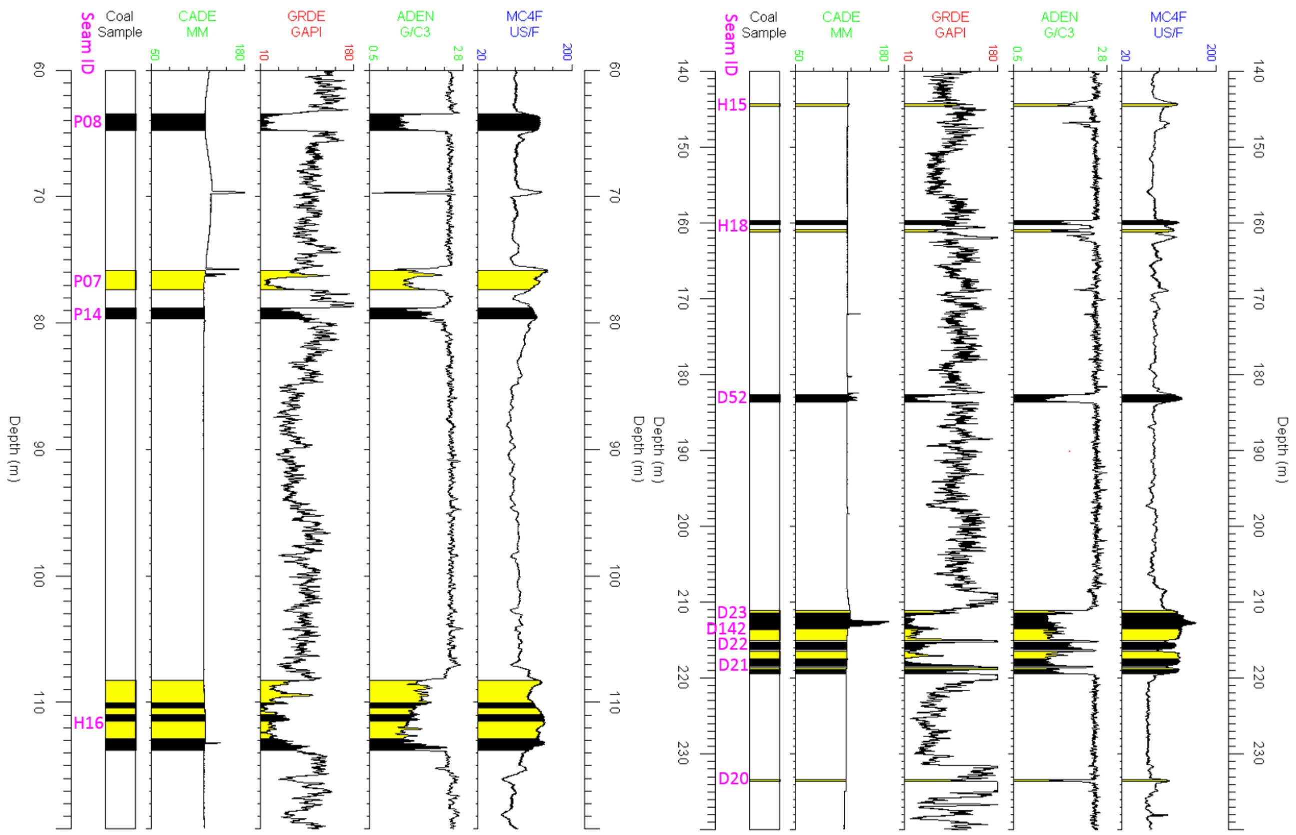


Figure 17 24 coal samples from 12 different seams for Borehole 56009.

Table 8 The key coal quality parameters provided by BMA.

Coal quality Parameters	Description
IM	Inherent moisture on an air-dry basis
MHC	Moisture holding capacity on an air-dry basis
ASH	Ash content on an air-dry basis
VM	Volatile matters on air-dry basis
FC	Fixed carbon on an air-dry basis
RD	Relative density on an air-dry basis
CSN	Crucible swelling number
PHS	Phosphorous

Table 9 Geophysical logging parameters provided by BMA.

Logging Parameters	Description
GRDE (GAPI)	Gamma ray from density tool
CODE (G/C3)	Compensated density
LSDU (SDU)	Long spaced density
BRDU (SDU)	Bed resolution density
CADE (MM)	Calliper from density tool
DENL (G/C3)	Density from long spaced density tool
DENB (G/C3)	Density from short spaced density tool
DEPO (PERC)	Porosity from the sandstone-calibrated density
ADEN (G/C3)	VECTAR processed density
MC2F (US/M)	20 cm sonic transit time from receivers R1 and R2
MC4F (US/M)	40 cm sonic transit time from receivers R2 and R4
MC6F (US/M)	60 cm sonic transit time from receivers R1 and R4
MC2A (US/M)	20 cm sonic transit time from receivers R3 and R4
SPOR (PERC)	Porosity from the sandstone-calibrated sonic log
FE1 (OHMM)	Laterolog shallow resistivity
FE2 (OHMM)	Laterolog deep resistivity

Data quality assessment

Although 1012 coal sample data points were provided by BMA, only 355 data samples were available with all coal proximate analysis data listed in Table 8 and also in consideration of the consistency of the geophysical borehole logging data as discussed below. Our analysis will concentrate on these 355 samples. To assess the coal quality data, we first cross-plotted the laboratory ash contents against the measured relative densities (RD) as shown in Figure 18. Figure 18(a) is the cross-plot for the raw ash and RD measurements. Although it shows a general logarithmic trend, there are many scattered wild data points as marked by the magenta ellipse. The cross-correlation R^2 is relatively low only 0.76 due to the data scattering. The data scattering does not necessarily suggest there are any issues with the measurements. The true reasons for this is not clear to us, but it could be due to the coked coal as these scattering samples are from the known coked coal intervals. These scatted samples will affect our data analysis. To reduce this effect, we excluded those scattering points from the data set and the data points are reduced from the original available 479 data points to 317 points. The cross-plot after excluding the wild data points is presented in Figure 18(b) with a significant increase of correlation coefficient R^2=0.96. The cross-plots for other coal quality parameters with the relative density are shown in Figure 19, which exhibits the normal trends with a high-degree of correlation especially for ash contents and fix carbons, which suggests the lab measurements for these two parameters are of good quality. Our coal quality analysis for this data set will be concentrated on relative density, ash, fixed carbon and volatile matters.

For the geophysical logging data, although they were mainly acquired by Weatherford, some logging data from three boreholes was collected by another logging contractor. Due to the incompatibility of these three borehole data with the rest of the data from Weatherford, these three boreholes were excluded from data analysis and are not presented in Figure 16. To evaluate the quality of the geophysical logs, we plotted the average values and spreads of the key geophysical logs calliper CADE, gamma ray GRDE, density ADEN and sonic log MC2F in Figure 20, which provides a good overview of the general variation of the measured geophysical logs from each borehole. From this plot, we can make the following observations:

1) The average diameters for boreholes 56007, 56014, 56056 and 56145 are about 100mm and smaller than other boreholes (~125mm).
2) It seems that the borehole diameter affects the logging data GRDE and ADEN:
    a. The average values of gamma ray GRDE from these four boreholes are generally lower than those from other boreholes.
    b. The average values of density log ADEN from these four boreholes are generally higher than those from other boreholes.

However, comparing these two logs with the neighbouring borehole at the same coal seam level, the measured values show no significant difference (as shown by Figure 21), suggesting the logs are not affected by the variation of the borehole diameter. This is further confirmed by the density log ADEN from the borehole 56145 which is not affected by diameter variation as illustrated by the left plot in Figure 22.

3) The sonic log MC2F is not affected by the borehole diameter. However, the average value of the log MC2F for the borehole 56145 is higher than the rest of the boreholes with a very large spread, suggesting this log may have some problems. This is confirmed by the geophysical logs for this borehole presented in Figure 22, in which it clearly shows many cycle-skipping events in sonic logs MC2F, MC4F, MC6F and MC2A. Therefore, the sonic logs and their related derived parameters such SPOR should not be used in our subsequent analysis.
4) Some boreholes do not have sonic logs. The same can also be applied to lateral resistivity logs.

Based on the above observations, the most useable geophysical logs for all boreholes are gamma ray and density logs.

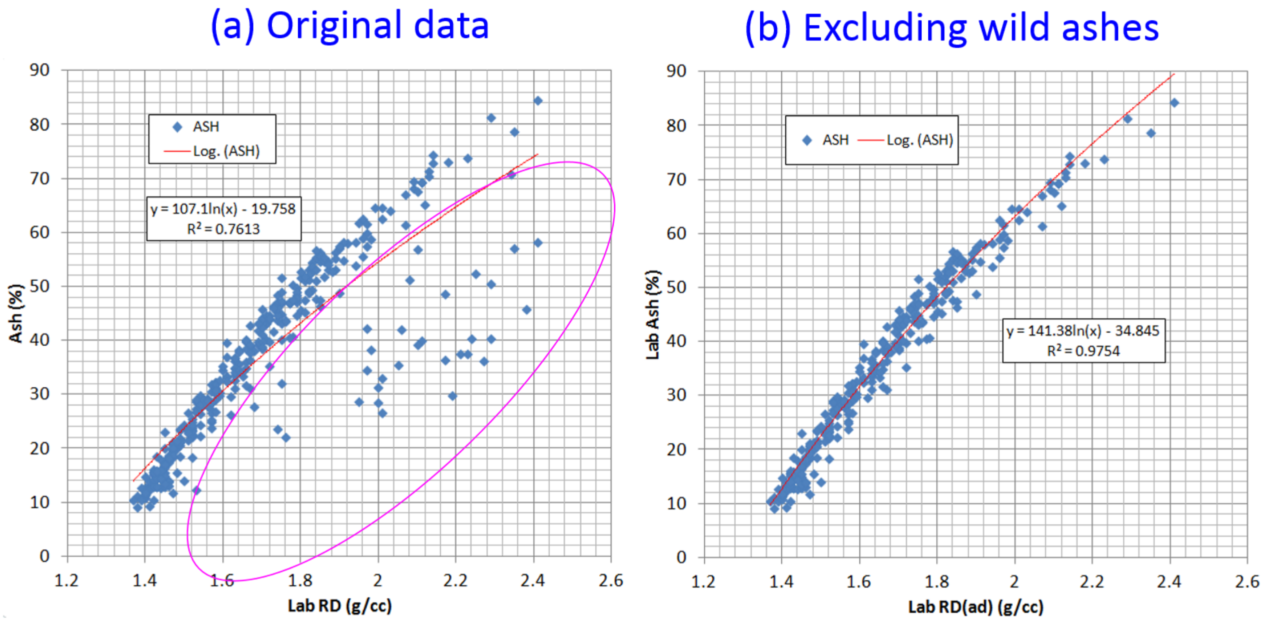


Figure 18 Cross correlation between laboratory ash contents and relative density measurements. (a) Raw data; (b) Data after the samples in the magenta ellipse in (a) are excluded.

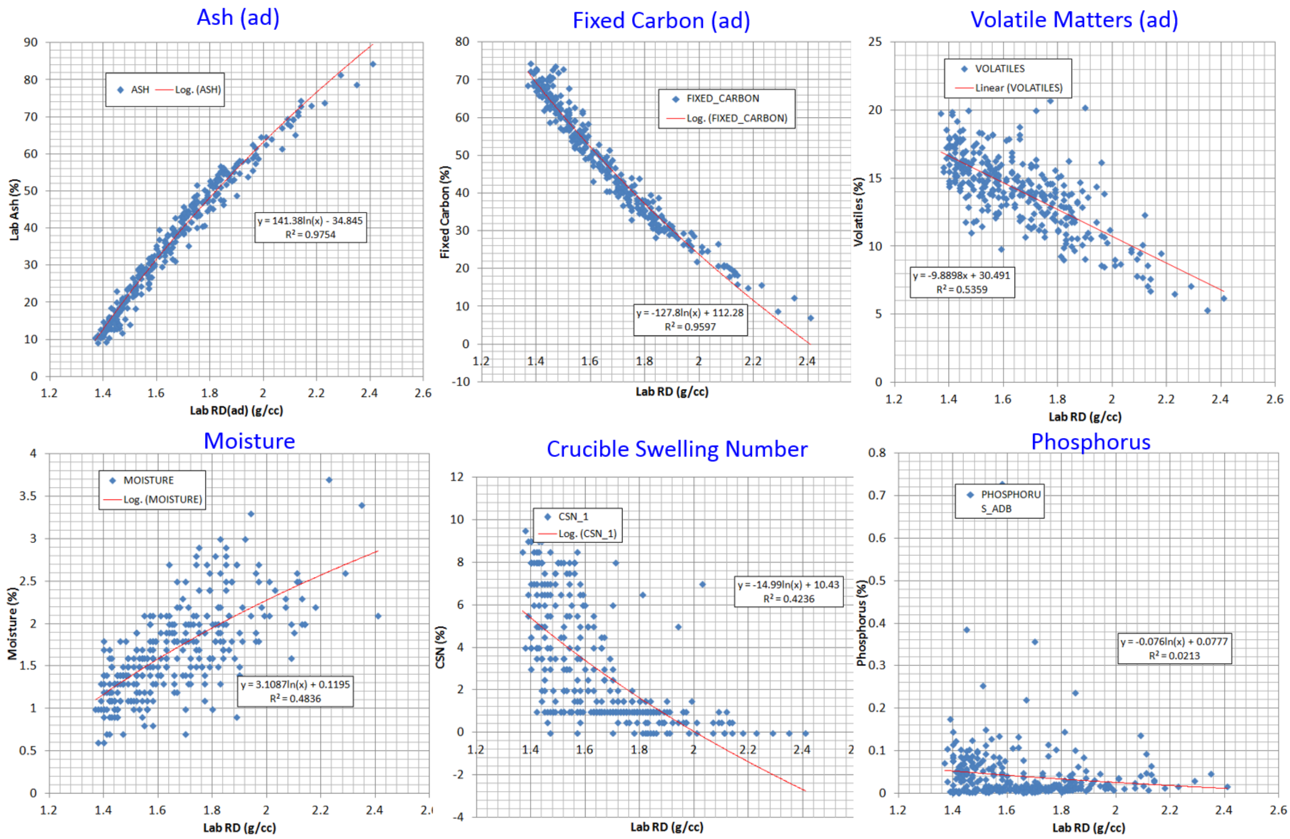


Figure 19 Correlations of laboratory coal quality parameters with relative density (after data samples with wild ash values are excluded). The regressions are in trends observed normally, suggesting the measured ash coal quality parameters and relative densities are in good quality. There are some degrees of scattering.

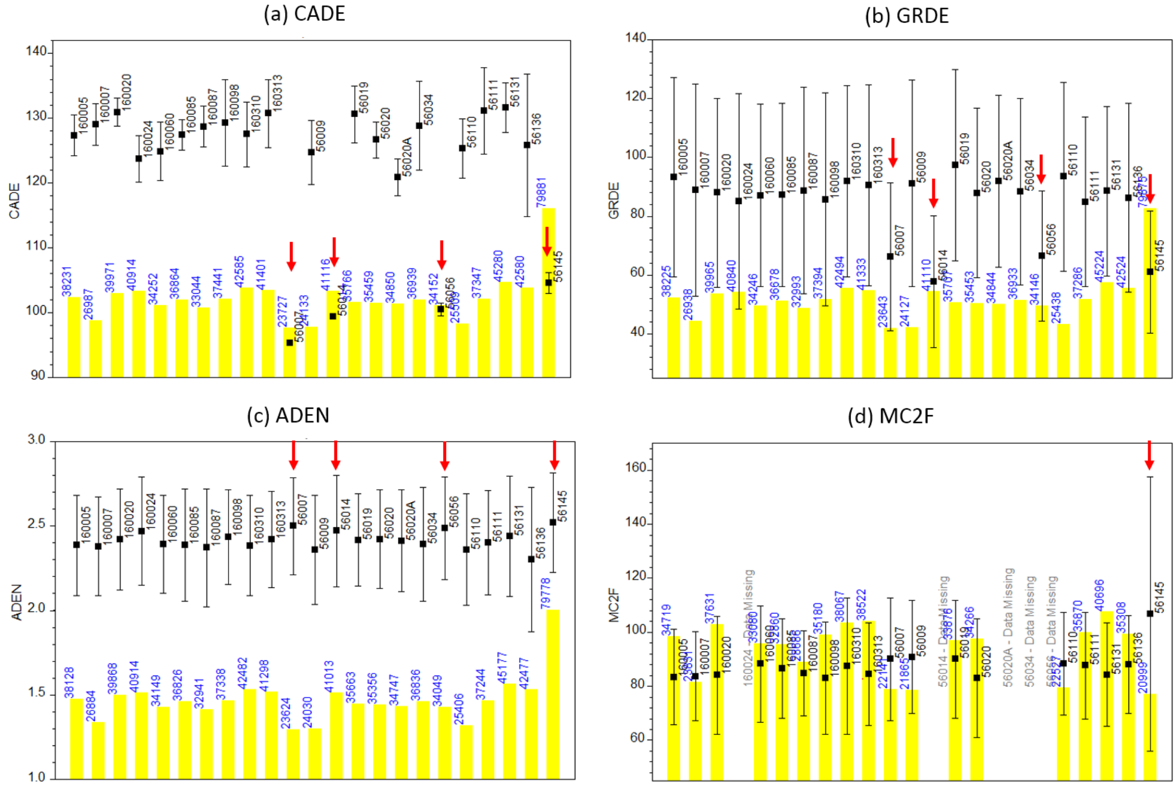


Figure 20 Averages and standard deviations of geophysical logs from BMA: (a) calliper CADE, (b) natural gamma GRDE, (c) short spaced density ADEN, and (d) sonic MC2F from different boreholes. The yellow bars with blue numbers indicate the sample counts for the statistical computations.

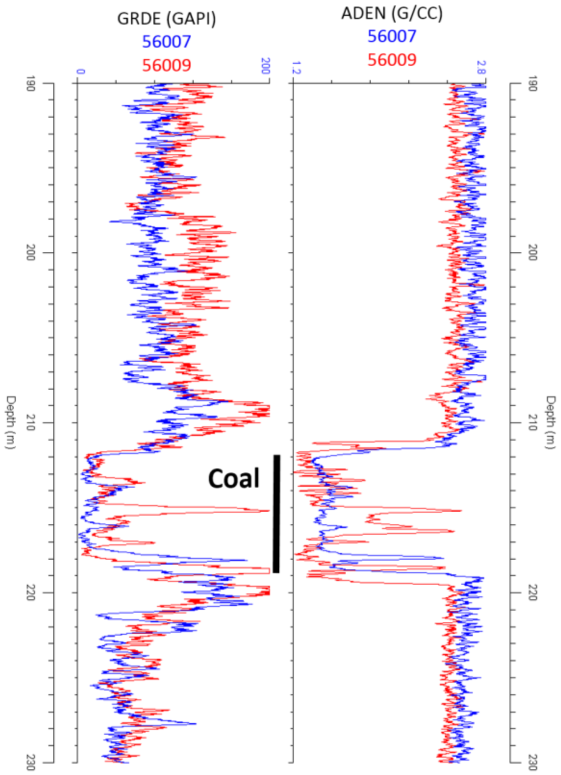


Figure 21 Comparison of the geophysical logs from borehole 56007 (blue) and 56009 (red). The log values of GRDE and ADEN from these two boreholes are very close at the coal seam level in spite of the slightly different values for surrounding rocks.

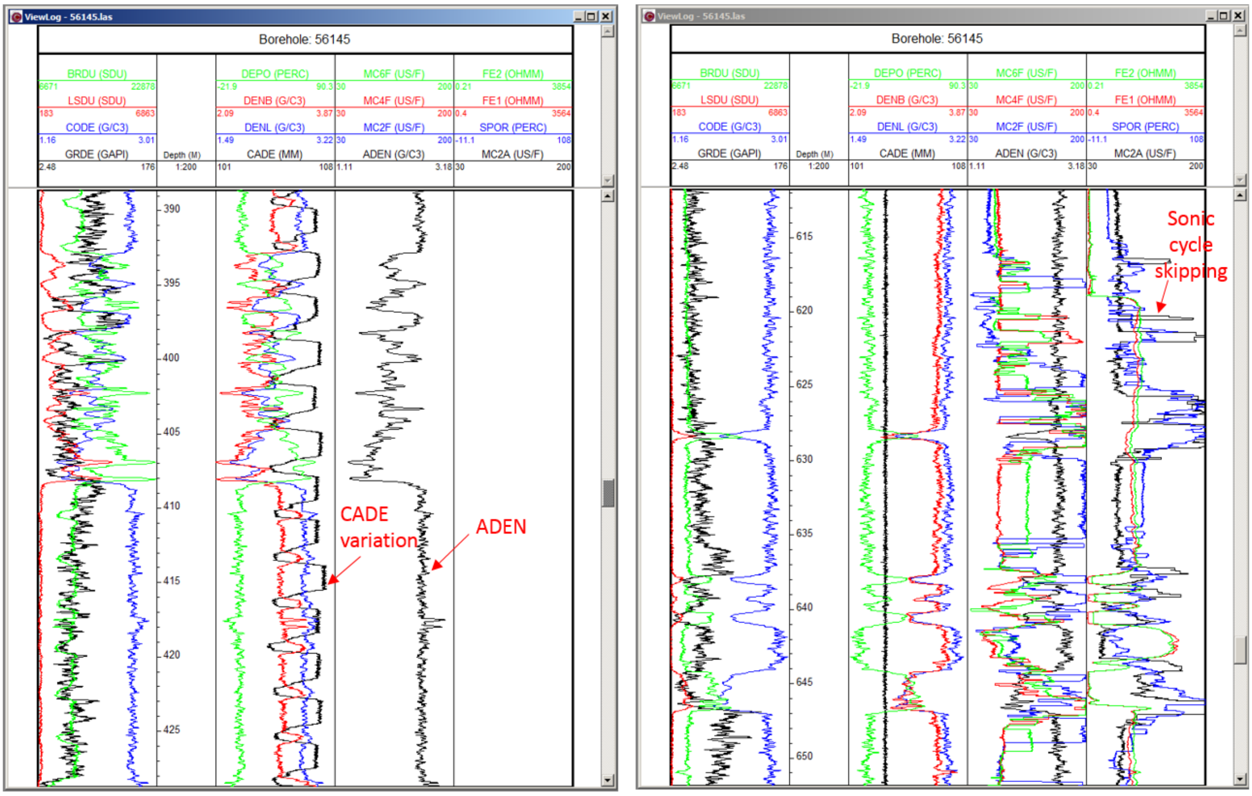


Figure 22 The geophysical logs from Borehole 56145. Left: The borehole diameter (CADE) variation has no significant effect on density log ADEN; Right: There are evident cycle skipping events with sonic logs MC2F, MC4F, MC6F and MC2A.

Relative density estimation from geophysical logs

Density is an important parameter in coal quality estimation. Although geophysical borehole logging provides density logs, they are often more scattered than laboratory measured relative densities as they are often influenced by the neighbouring strata, especially for those samples from thin beds (Zhou and Estlerle, 2007, 2008). The correlation between the measured laboratory RD and the corresponding geophysical density log ADEN is presented in Figure 23. The data are those after the samples in the magenta ellipse in Figure 18(a) are excluded. Overall, the data are well behaved. The correlation equation in Figure 23 is

$$RD = 0.8534 * ADEN + 0.2633.$$

This equation suggests that the laboratory measured relative density RD is higher than the geophysical log ADEN. We can use the density log ADEN to estimate the relative density RD as shown in Figure 24(a). In addition, we can also use multiple geophysical logs to estimate the RD. Based on our test, the best result can be achieved using the logs GRDE, CODE, DENL and ADEN with the inverse multi-quadratic RBF method. The result is shown in Figure 24(b). It is clear that the RD estimation from multiple geophysical logs are more concentrated around the desirable diagonal line than those estimated from the single density log ADEN. Therefore, multiple-geophysical-log-based estimation improves the data correlation and the estimation accuracy as shown by Figure 25 and Table 10. The estimation errors from multiple geophysical logs are more concentrated in the lower end than those from the single density log.

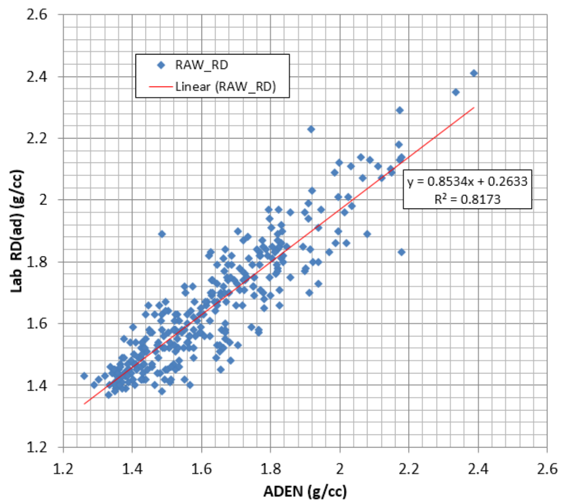


Figure 23 The cross-plot of the laboratory RD with the geophysical log ADEN.

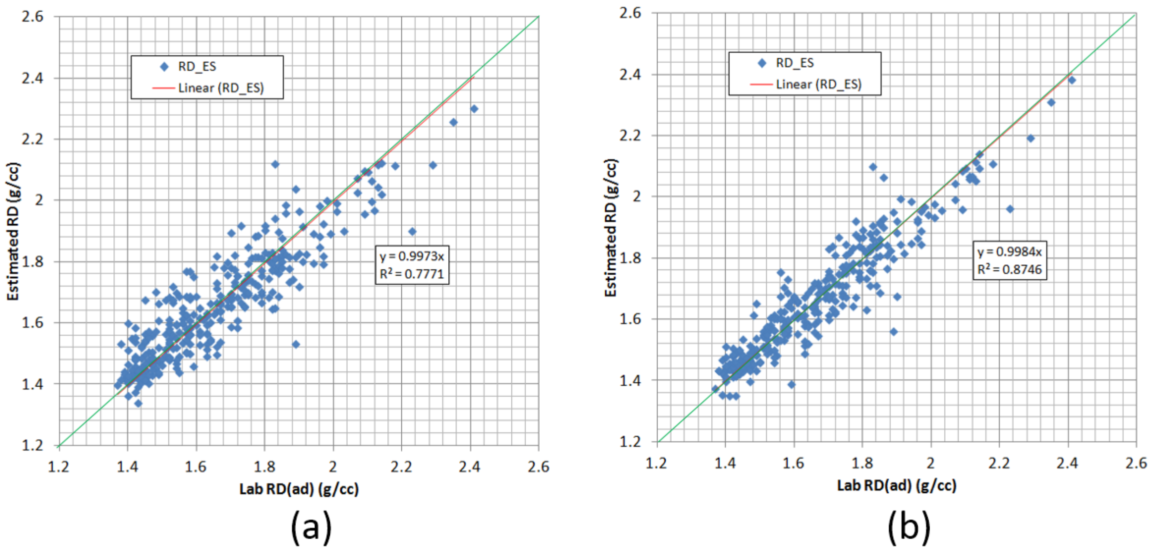


Figure 24 The cross plot of the estimated density RD with the laboratory RD: (a) Estimated from a single density log ADEN; (b) Estimated from multiple geophysical logs GRDE, CODE, DENL and ADEN. The red line is the linear-fitted curve while the green line shows the expected fitting curve.

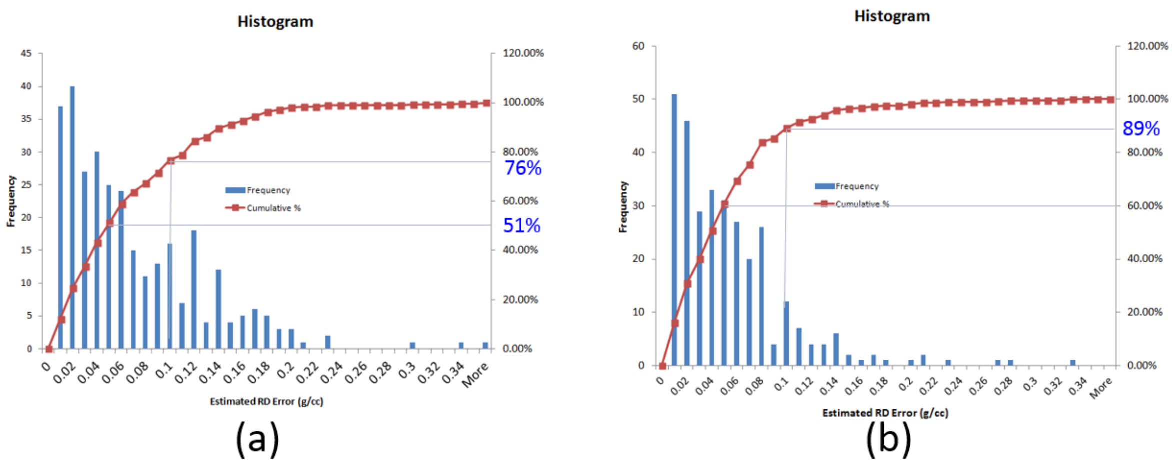


Figure 25 The error histograms for the estimated RDs from (a) the single density log ADEN; and (b) multiple geophysical logs. It is clear that the estimation errors from multiple geophysical logs are more concentrated in the lower end than those from the single density log.

Table 10 Statistics of the estimated RDs from the single density log ADEN and multiple geophysical logs

	From ADEN only	From 4 geophysical logs
Min. error (g/cc)	0.00	0.00
Max. error (g/cc)	0.36	0.33
Average (g/cc)	0.07	0.05
Correlation R	0.88	0.94

Coal quality estimations from geophysical logs – controlled training data set

We can also use geophysical logs to estimate coal quality parameters ash, fixed carbon and volatile matters based on the above edited BMA data set (samples with wild ash values are excluded). Figure 26 shows the cross-correlations of the coal quality parameters ash, fixed carbon and volatile matters with the geophysical density log ADEN. Based on the correlation relationships shown in Figure 26, we can use the density log ADEN to estimate the coal quality parameters as presented at the top row in Figure 27. In addition, we can also use multiple geophysical logs to estimate the coal quality parameters. In this case, we only have gamma ray and density logs available for the data analysis. The following logs GRDE, CODE, DENB, DENL and ADEN are used to estimate the coal quality parameters ash, fixed carbon and volatile matters as shown at the bottom row in Figure 27. Comparing the estimations of these two approaches, it is not difficult to see that the estimations from multiple geophysical logs are more concentrated around the desirable diagonal lines than those from the single log density ADEN, which again suggests that multi-log estimation is more accurate than the single estimation.

As mentioned before, there are 1012 coal sample data points in the BMA data set. These data samples have only ash content measured. To further test the advantage of multi-geophysical logging data, we used ash content as the coal quality parameter and compiled a data set with all the geophysical logs, in which the samples with wild ash values are excluded. The total number of samples for this edited data set is 578. Figure 28 shows the cross-correlations of laboratory ashes with the laboratory relative density RD and the geophysical density log ADEN. We use different combination of the geophysical logs and the multi-logarithm RBF method to estimate the ash contents. The statistics of the resulting ash estimations from different logs are listed in Table 11, while Figure 28 shows the estimated ashes using the conventional linear-fitting with the single geophysical density log ADEN and the multi-logarithm RBF method with the multi-geophysical logs of GRDE, DENB, DENL, CODE, ADEN, DEPO, MC2F, MC4F, FE1 and FE2. This further confirms that the overall estimation errors are decreased with the number of geophysical logs used while the correlations of the estimations are increased with the number of geophysical logs used.

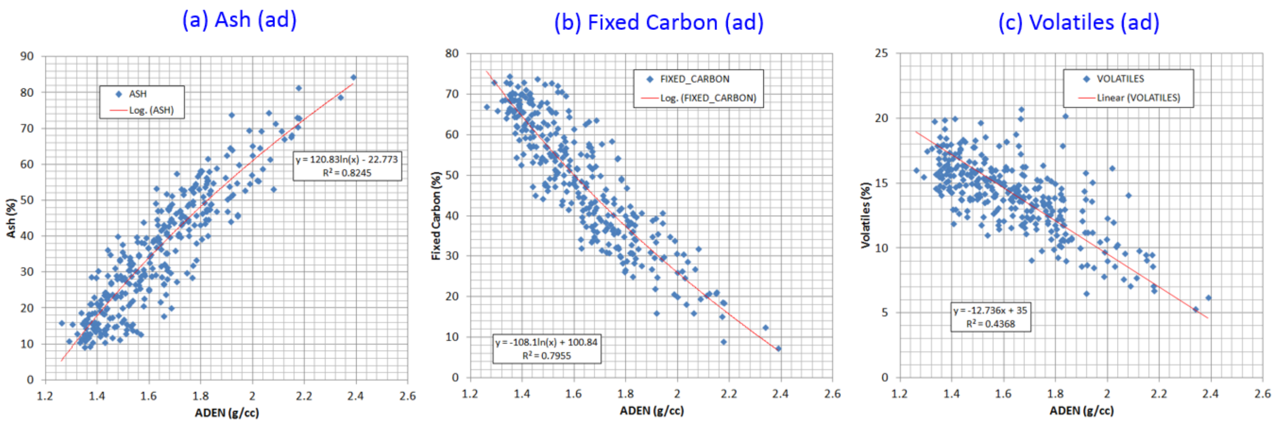


Figure 26 Cross-correlations of coal quality parameters with the geophysical log ADEN: (a) Ash content; (b) Fixed carbon; (c) Volatile matters.

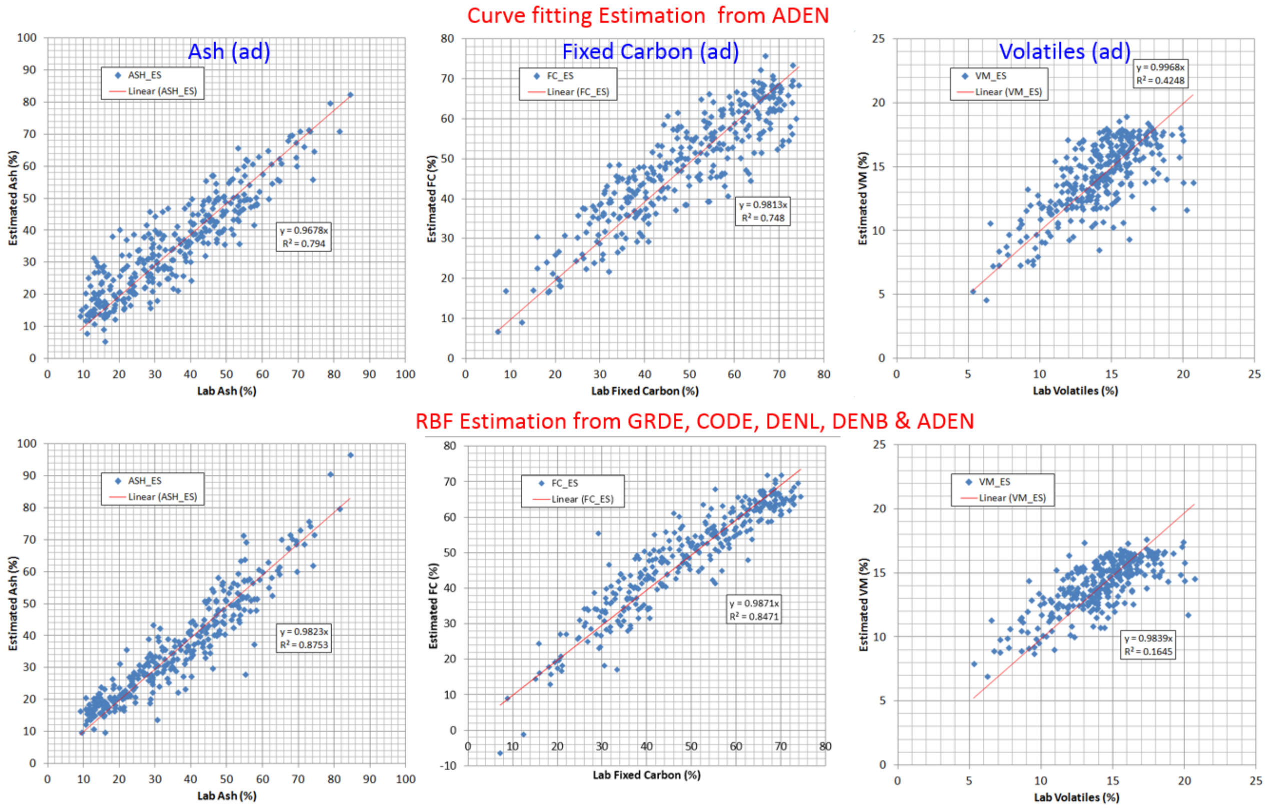


Figure 27 The estimated air-dry ash, fixed carbon and volatile matters from a single geophysical log ADEN (top row) and multiple geophysical logs (bottom row).

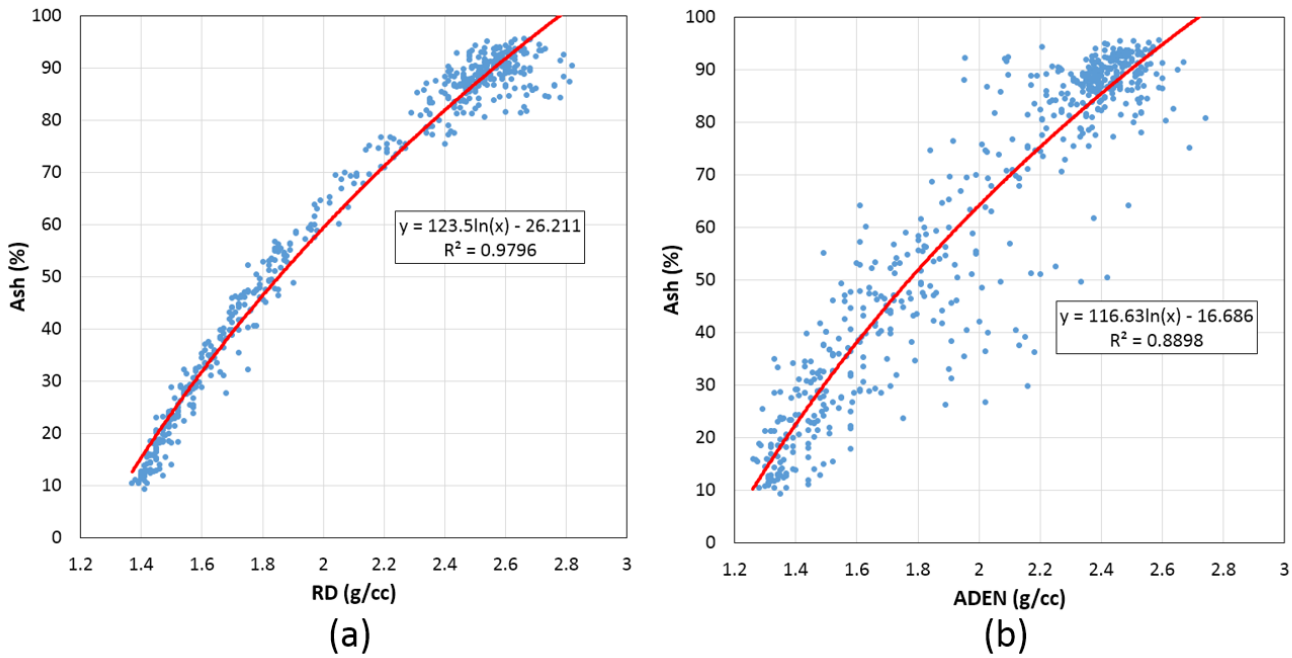


Figure 28 The cross-correlations of laboratory air-dried ashes with (a) the laboratory air-dried relative density RD and (b) the geophysical density log ADEN. Data samples with wild ash values are excluded from the data set. The cross-plot in (b) is more scattered than the one in (a), suggesting that the density log ADEN is more variable than the laboratory measured relative density RD.

Table 11 Statistics of the estimated ash contents from multi-geophysical logs

	Geophysical logs	Min. Error	Max. Error	Average Error	Correlation R
Linear Fitting	ADEN	0.02	43.23	6.67	0.9433
RBF	GRDE,DENB	0.02	55.91	8.12	0.9173
	GRDE,DENB,DENL	0.05	47.57	7.83	0.9313
	GRDE,DENB,DENL,CODE	0.05	32.14	5.60	0.9628
	GRDE,DENB,DENL,CODE, ADEN	0.03	31.60	5.58	0.9649
	GRDE,DENB,DENL,CODE, ADEN, DEPO	0.03	28.31	5.16	0.9696
	GRDE,DENB,DENL,CODE, ADEN, DEPO,MC2F	0.01	31.08	5.16	0.9694
	GRDE,DENB,DENL,CODE, ADEN, DEPO,MC2F,MC4F	0.00	30.57	5.04	0.9706
	GRDE,DENB,DENL,CODE, ADEN, DEPO,MC2F,MC4F,FE1	0.00	28.09	4.94	0.9725
	GRDE,DENB,DENL,CODE, ADEN, DEPO,MC2F,MC4F,FE1,FE2	0.00	27.88	4.94	0.9727

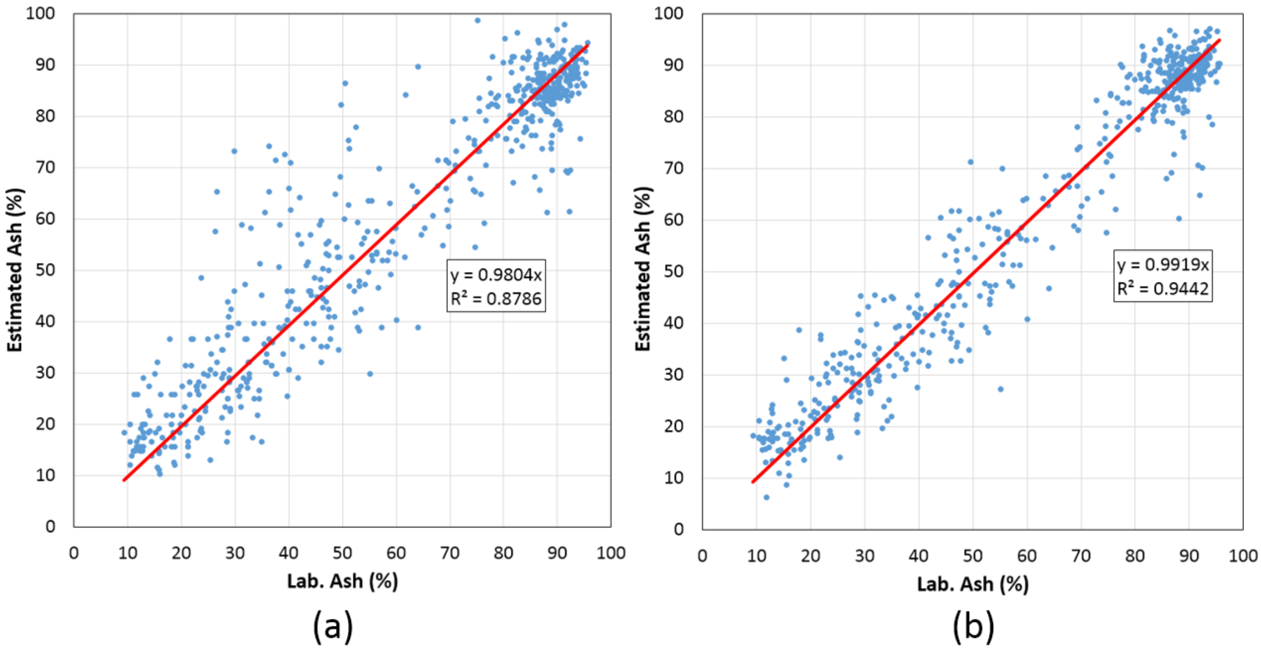


Figure 29 Cross-correlations of the laboratory measured ashes with the ashes estimated from: (a) the single geophysical density log ADEN; (b) the multi-geophysical logs of GRDE, DENB, DENL, CODE, ADEN, DEPO, MC2F, MC4F, FE1 and FE2.

Coal quality estimations from geophysical logs – independent data set

The previous examples demonstrate the feasibility of the RBF-based multi-log approach for coal quality parameter estimation through a self-controlled leave-one-out cross-validation. Correct estimation of coal quality parameters using geophysical logs through such a controlled training data set is a necessary condition for implementation of coal quality estimation. A stronger endorsement of the practical viability of such an approach is achieved if an independent data set, which do not belong to the control training data set, can be estimated correctly. To illustrate the application of the RBF method to a non-control data set, the BMA data set is divided into two sub-data sets: Sub-set 1 from the boreholes in Area 1 and Sub-set 2 from the borehole in Area 2 (Figure 16). The whole data set (Sub-set 1 + Sub-set 2) is from the same data samples as those shown in Figure 18(b). We use Sub-set 1 as the control training data set to derive the RBF-internal computational coefficients and apply these coefficients to the corresponding geophysical logs to estimate the coal quality parameters.

Figure 30 shows the estimated coal parameters RDs and ashes from geophysical logs GRDE, CODE, DENL, DEPO & ADEN for different data sets and Table 12 lists the statistics of the corresponding estimations. The estimations for the whole data set and Sub-set 1 (Figure 30(a), (b), (d) & (e) are based on leave-one-out cross-validation while the estimations for Sub-set 2 are results by applying the control Sub-set 1 to Sub-set 1. Figure 30 and Table 12 clearly demonstrate that we can use multi-geophysical logs to estimate coal quality parameters.

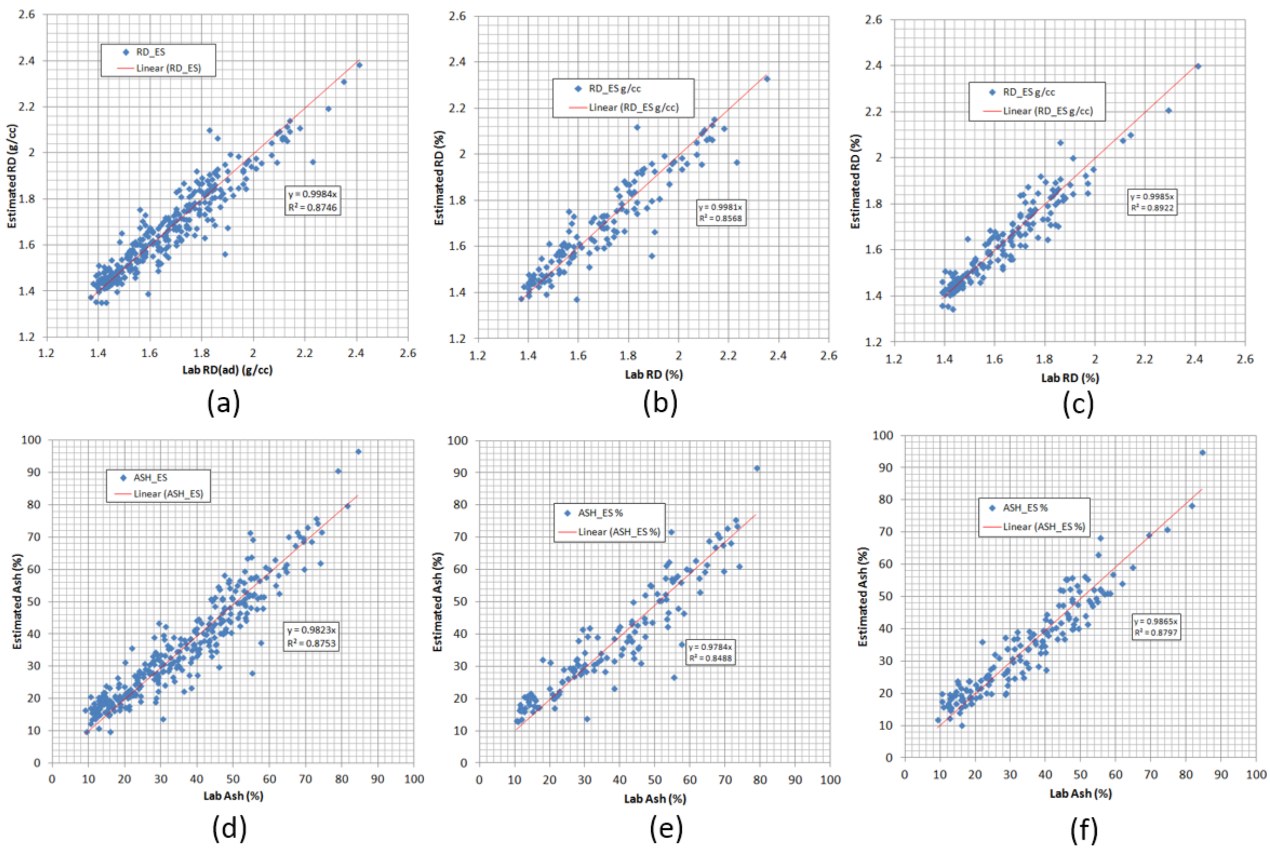


Figure 30 Estimated coal parameters from geophysical logs GRDE, CODE, DENL, DEPO & ADEN for different data sets: (a) Estimated RDs for whole data set; (b) Estimated RDs for Sub-set 1; (c) Estimated RDs for Sub-set 2 using Sub-set 1 as control data; (d) Estimated ash contents for whole data set; (e) Estimated ash contents for Sub-set 1; (f) Estimated ash contents for Sub-set 2 using Sub-set 1 as control data.

Table 12 The statistics of estimated RD and ashes for different data sets.

Coal Quality	Data Set	Min. Error	Max. Error	Average Error	Correlation R
RD (g/cc)	Whole set	0.00	0.33	0.05	0.9352
	Sub-set 1	0.00	0.33	0.06	0.9256
	Sub-set 2	0.00	0.21	0.04	0.9446
Ash (%)	Whole set	0.01	27.33	4.37	0.9356
	Sub-set 1	0.00	28.49	4.91	0.9213
	Sub-set 2	0.06	14.24	4.24	0.9379

4.3 Estimation of coal brightness

Interpretation of original lithotypes

Coal lithotype is a visual measure for characterising the compositional differences within and between coal seams as introduced by Stopes (1919). It is also called brightness profile which is a reflection of composition such as vitrinite content and texture in coal. By Australian standards, coal lithotypes are classified on a megascopic scale by the proportion of bright bands. The standard defines coal lithotypes as dull (< 1% bright), dull with minor bright bands (1-10% bright), banded dull coal (contains 10-40% bright), banded (40-60% bright), banded bright (60-90% bright) and bright (>90% bright). These lithotypes are normally logged through careful visual inspection of coal cores or outcrops by a competent geologist. This approach is time consuming and subject to the geologist's visual perception of coal brightness characteristics.

An alternative way for estimation/recognition of different coal lithotypes or brightness for the individual coal plies is through geophysical logs. Esterle and Le Blanc Smith (2005) illustrated the correlation of lithotypes with geophysical logs. Fallon et al (2000) and Roslin and Esterle (2014) demonstrated the feasibility to derive coal lithotype from geophysical logs. In addition to the conventional logs such as gamma ray and density logs, Roslin and Esterle (2014) also used the photoelectric factor (PEF), laterolog resistivity and micro-resistivity logs. They observed that PEF data can allow discrimination between low density bright to banded coal electrofacies and low density inertinite-rich dull electrofacies.

For this project, BMA also provided us with lithotype logs for the coal seams intersected by the 23 boreholes available. The key lithotypes from the BMA data set are listed in Table 13, in which the class ST is originally for siltstone but we will refer to it as any non-coal material or rock types. For ease of discussion, the legends in Figure 31 will represent these lithotypes. We will use this data set to test the feasibility of extracting the lithotype/brightness information from the geophysical logs by using the program LogTrans. LogTrans, as described in Appendix B, is a well-demonstrated program, which uses geophysical logging data for automated rock classification.

Again we divided the boreholes into the two natural areas: Area 1 and Area 2 as shown in Figure 16. We used the boreholes in Area 1 as control (training) boreholes for the calculation of statistics of geophysical logs for different lithotypes, while boreholes in Area 2 were used as independent boreholes for verification (i.e. based on the statistical data from Area 1 to interpret/estimate the lithotypes from the geophysical logs in Area 2). Figure 32 shows the computed means and spreads of the key geophysical logs ADEN, GRDE, FE2 and MC2F for the different lithotypes. From the plot, it is evident that there are clear trends: the means of ADEN and GRDE increase with the decrease of the brightness (from C1 to C7) while the means of FE2 and MC2F decrease with the increase of the brightness (from C7 to C1). In spite of the well-behaved trends, the separation between the neighbouring lithotypes is relatively small, especially for C1 – C3 and the spreads are relatively large especially for FE2. This makes it difficult to discriminate between the lithotypes.

Figure 33 and Figure 34 are the LogTrans test results of lithotype interpretation based on the statistics of geophysical logs in Figure 32 for both control boreholes in Area 1 and independent boreholes in Area 2, respectively. Based on the colours of the original lithotypes provided by the mine and the LogTrans interpreted lithotypes, it is not difficult to see that the LogTrans interpreted lithotypes are poorly matched with the original lithotypes. The overall success rates[2] for the control boreholes and the independent boreholes are very low, only 12% and 13%, respectively. Such results are consistent with the large spreads of the log statistics for different lithotypes shown in Figure 32.

[2] The success rate is calculated by the number of correctly interpreted rock samples divided by the total number of samples.

Table 13 The key coal lithotypes from BMA data set.

Litho-type	Description
C1	COAL, >90% BRIGHT
C2	COAL, 60-90% BRIGHT
C3	COAL, 40-60% BRIGHT
C4	COAL 10-40% BRIGHT
C5	COAL, <10% BRIGHT
C6	COAL, DULL <1% BRIGHT
C7	COAL, DULL, CONCHOIDAL
ST	Any non-coal materials/rocks

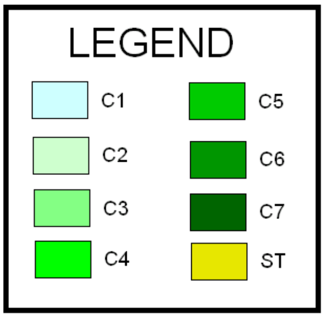


Figure 31 Legend of coals with different brightnesses.

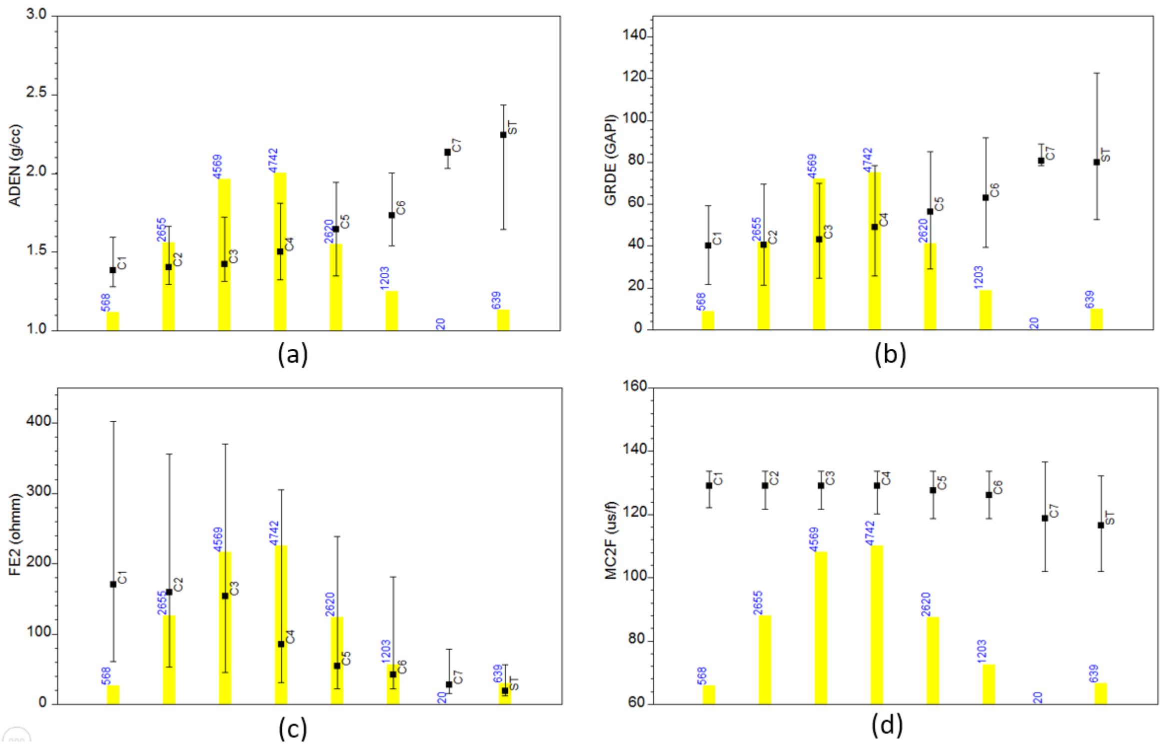


Figure 32 The medians and spreads of the geophysical logs for different lithotypes from the control boreholes in Area 1: (a) Density log ADEN; (b) Gamma ray GRDE; (c) Resistivity log FE2; and (d) Sonic log MC2F. The yellow bars indicate the number of samples used for computation of the statistics for each lithotype and log.

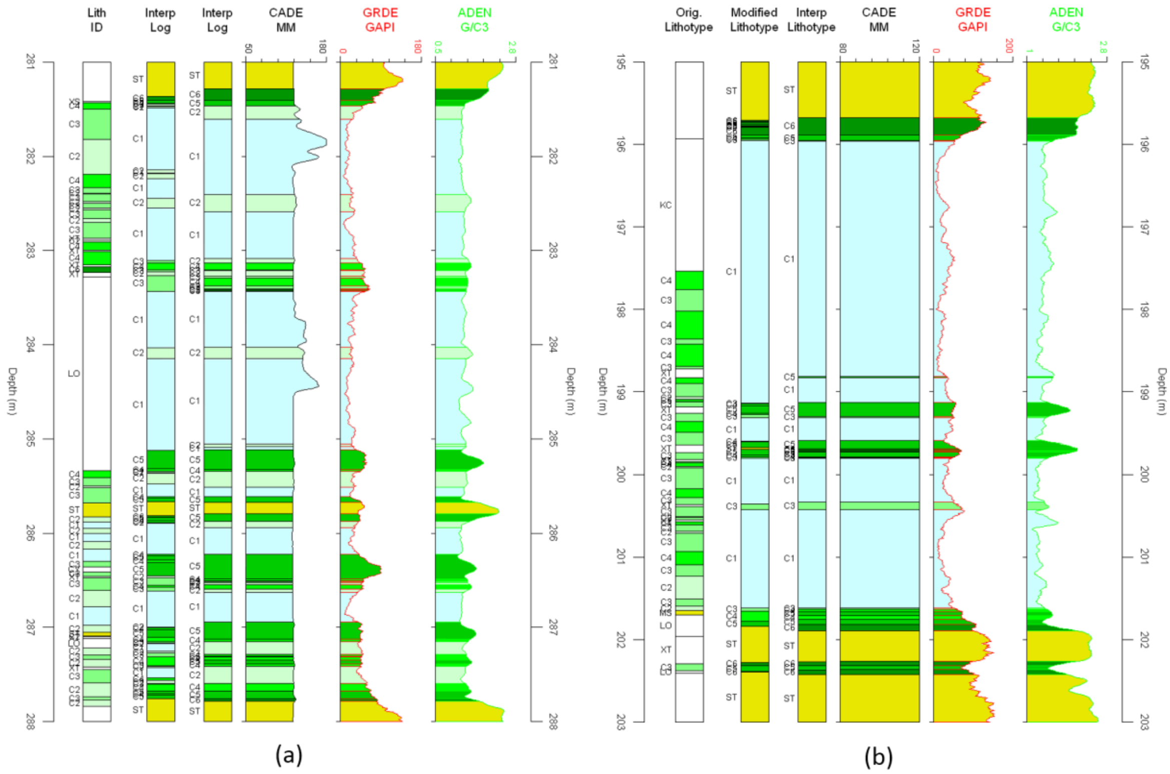


Figure 33 The LogTrans lithotype classification using density log ADEN, gamma ray GRDE, resistivity log FE2 and sonic log MC2F for the control holes in Area 1: (a) 16005 & (b) 160098. Shown from the left to the right: original lithotypes provided by the mine; interpreted lithotypes using LogTrans based on the training statistics in Figure 32; followed by logs calliper CADE, gamma ray GRDE and density log ADEN.

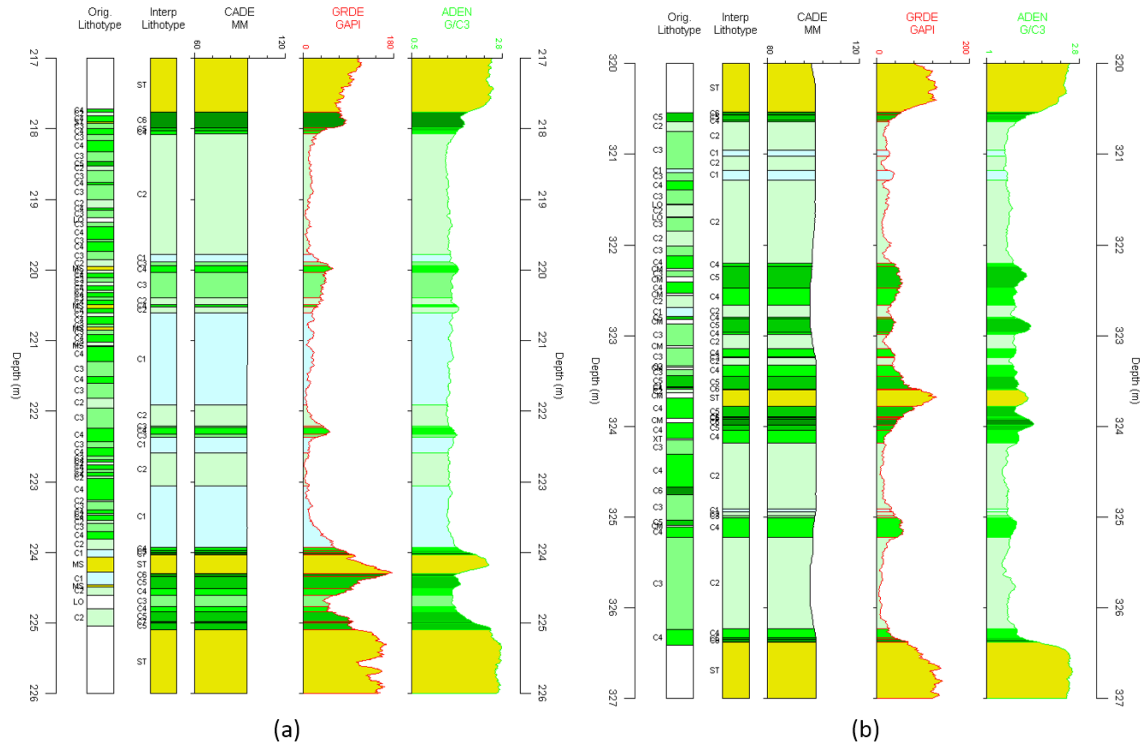


Figure 34 The LogTrans lithotype classification using density log ADEN, gamma ray GRDE, resistivity log FE2 and sonic log MC2F for independent holes in Area 2: (a) 56007 & (b) 56056. Shown from the left to the right: original lithotypes provided by the mine; interpreted lithotypes using LogTrans based on the training statistics in Figure 32; followed by logs calliper CADE, gamma ray GRDE and density log ADEN.

Interpretation of modified lithotypes

There are two possible reasons for the above behaviour of the poor interpretation of lithotypes. Firstly, correct rock/lithotype classification for the training boreholes is very important for the success of the LogTrans application. This requires the original input lithotype logs to be as accurate as possible to match the geophysical signatures for the corresponding lithotypes. In this case, lithotypes are subjective to the person doing the visual logging. Different individuals may log the same ply as different lithotypes if using visual means only. This subjectivity of lithotype logging may lead to the variability of the statistics of the geophysical logs for each lithotype as the lithotype logging is often done by different person for different boreholes. It is unlikely that the lithotype logging for the 23 boreholes in this data set was done by a single geologist.

In addition, we believe that the variability may also relate to the definition of the coal lithotype: each lithotype class covers a band of brightness. This band of brightness varies with the non-bright component in the lithotype. For example, it can be inertinite (coal maceral) or it can be a mineral. For example C1 may be 90% vitrinite and 10% inertinite (100% coal) or it may be 90% vitrinite and 10% mineral (90% coal). Similarly for C2, the extremes can still be 100% coal (60% vitrinite and 40% inertinite to 90% vitirinite and 10% inertinite) or 60% vitrinite and 40% mineral. This variability can be a reflection of the error bars associated with the graphs in Figure 32.

We can do little about the variations of the non-bright components in lithotypes. However, the inconsistency of the lithotypes logged by eye can be improved by reconciliation of geologists' logging with geophysical logs. This can be illustrated by the following approach. As we observed in Figure 33 and Figure 34, the interpreted lithotypes are generally consistent with the variations of the geophysical logs in spite of the mismatch with the original lithotypes. We use the interpreted lithotypes from the boreholes 16005 and 160098 in Figure 33 as reconciled lithotypes and recalculated the geophysical log statistics of these modified lithotypes as shown in Figure 35. Please note there is no lithotype C7 in these two boreholes. Compared with the statistics in Figure 32, the statistics of the geophysical logs for the lithotypes are largely improved: the trends remain and the spreads for the lithotypes are all reduced (except for C1 with FE2). This suggests that the modified lithotypes are much more consistent with geophysical logs, which is not surprising as they are from the lithotypes interpreted from geophysical logs.

Figure 36 shows the LogTrans interpretation of the modified lithotypes by applying the statistics in Figure 35 to the control boreholes 16005 and 160098. The interpreted lithotypes are well matched with the modified lithotypes and the overall success rate of interpretation for these control holes is 87%, which is much higher than the overall success rate of 12% for the original lithotypes in Figure 33. The same statistics in Figure 35 were applied to the independent boreholes 56007 and 56056 and the results are shown in Figure 37. Although the interpreted lithotypes are not as well matched with the modified lithotypes as for the control boreholes in Figure 36, the overall success rate of interpretation for these independent boreholes is 50%, which is a significant improvement to the 13% success rate achieved for the original lithotypes in Figure 34. There are many misinterpretations of the major lithotypes C1 and C2 as they have very similar geophysical signatures (as shown in Figure 35). After modification of the lithotypes based on the initial geophysical interpretation using geophysical logs, the improved results indicate that there is scope to improve the consistency of lithotype logging. However, the lithotypes provided cannot be reconciled with geophysics as the cores are no longer available after they were used for laboratory testing.

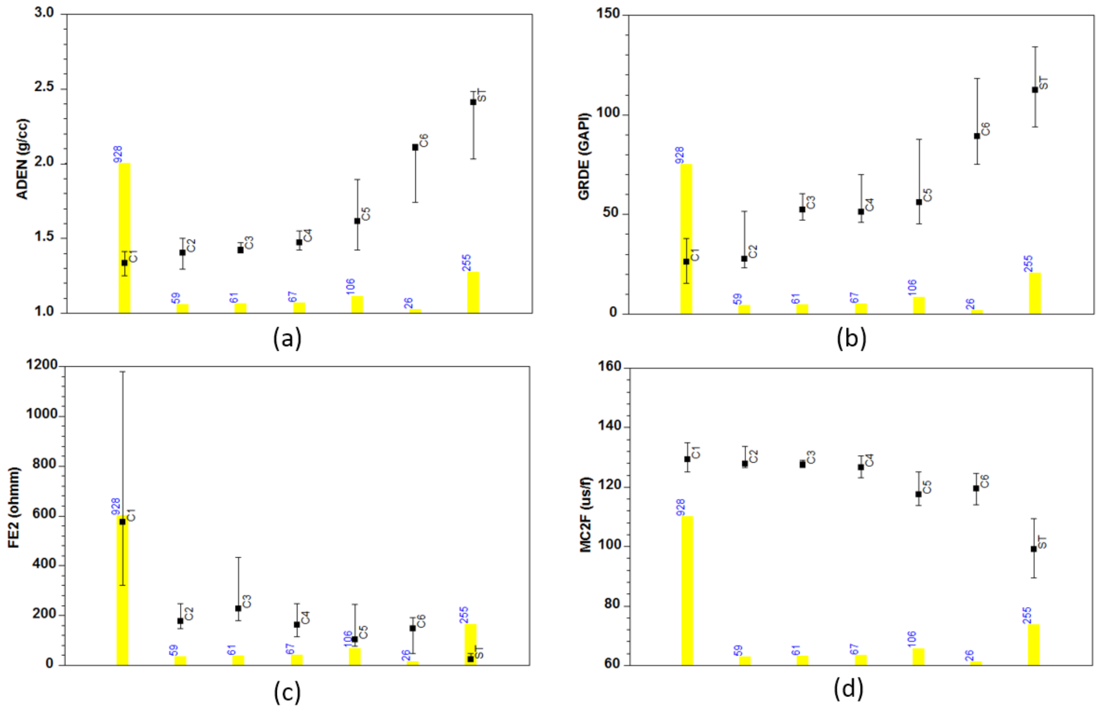


Figure 35 The medians and spreads of the geophysical logs for the modified lithotypes from the control boreholes 16005 & 160098 in Area 1: (a) Density log ADEN; (b) Gamma ray GRDE; (c) Resistivity log FE2; and (d) Sonic log MC2F. The yellow bars indicate the number of samples used for computation of the statistics for each lithotype and log.

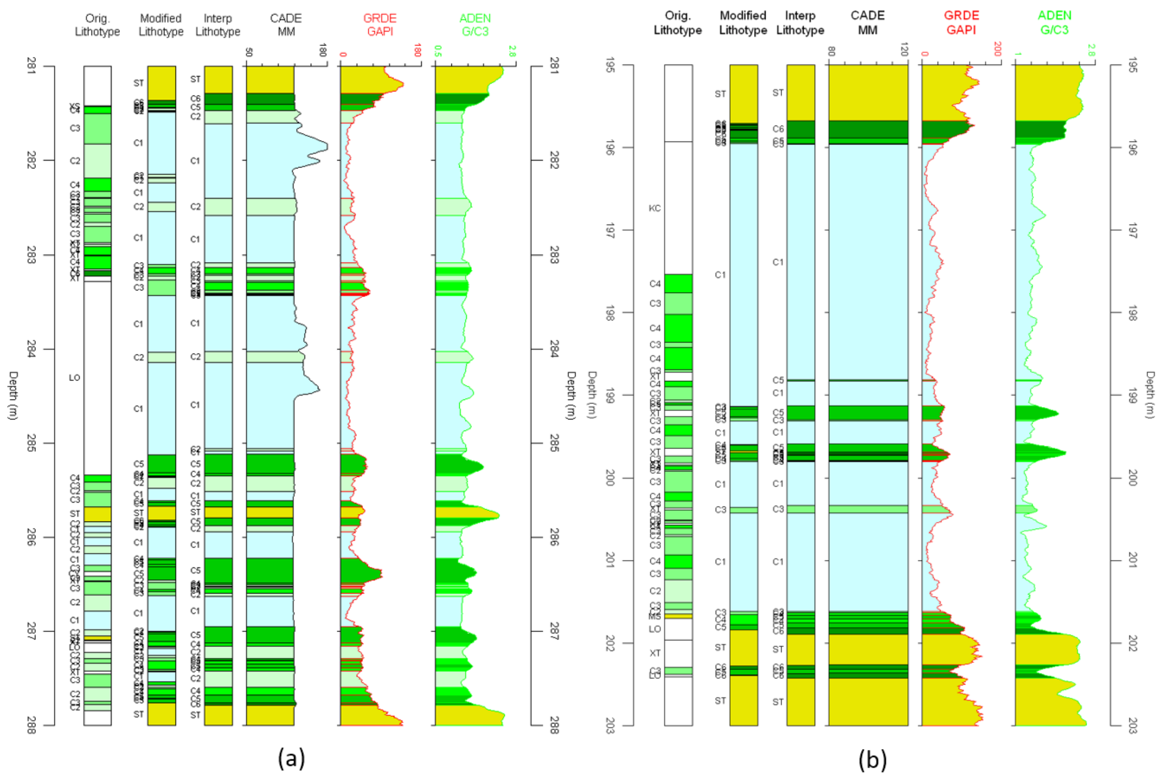
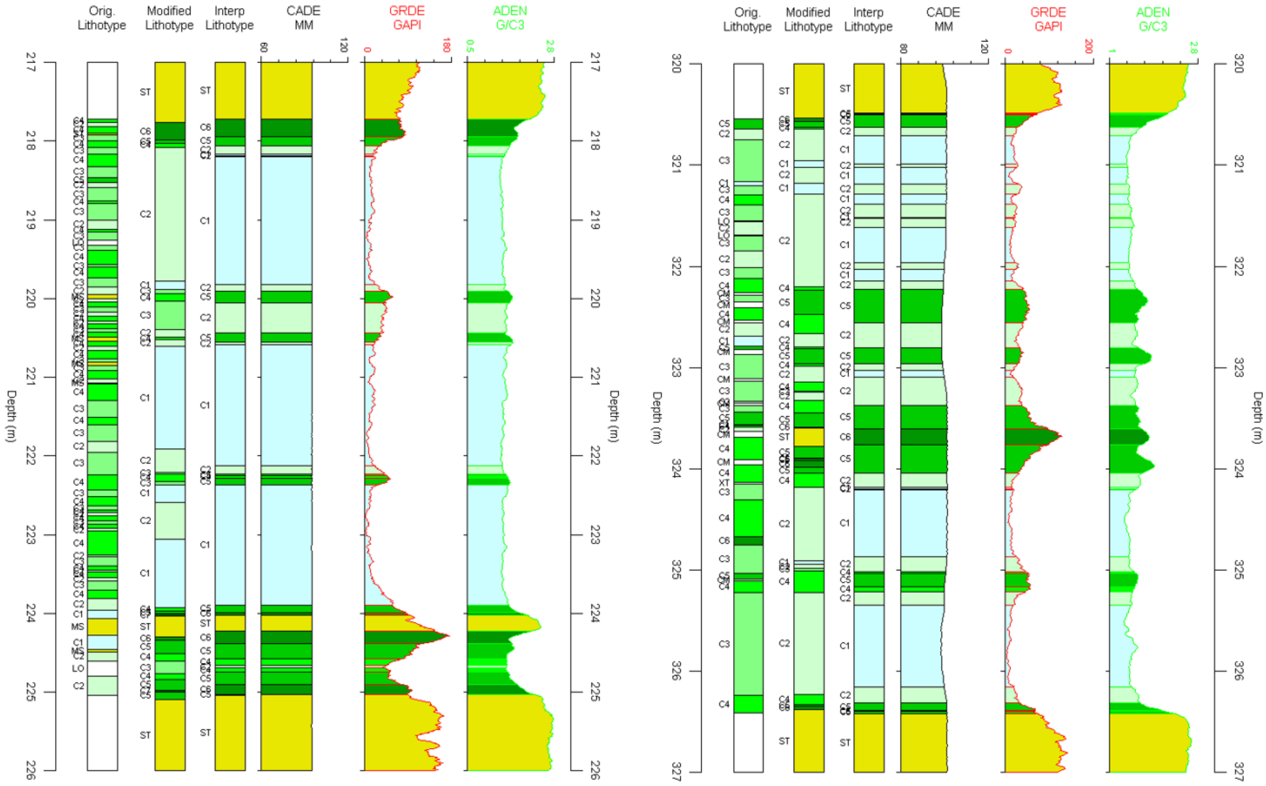


Figure 36 The LogTrans classification of the modified lithotypes using density log ADEN, gamma ray GRDE, resistivity log FE2 and sonic log MC2F for the control holes in Area 1: (a) 16005 & (b) 160098. Shown from the left to the right: original lithotypes provided by the mine; modified lithotypes; interpreted lithotypes using LogTrans based on the training statistics in Figure 32; followed by logs calliper CADE, gamma ray GRDE and density log ADEN.



(a) (b)

Figure 37 The LogTrans classification of the modified lithotypes using density log ADEN, gamma ray GRDE, resistivity log FE2 and sonic log MC2F for independent holes in Area 2: (a) 56007 & (b) 56056. Shown from the left to the right: original lithotypes provided by the mine; modified lithotypes; interpreted lithotypes using LogTrans based on the training statistics in Figure 32; followed by logs calliper CADE, gamma ray GRDE and density log ADEN.

4.4 Summary

The RBF-based coal quality parameter estimation algorithms are tested by using the data sets from Anglo American and BMA. In both cases, geophysical logs have been used to estimate the coal quality parameters such as relative density, ash content, fixed carbon and volatile matters. This has been demonstrated on both self-controlled training data sets and an independent data set. It is observed that the density logs play a key role in coal parameter estimation. However, the use of multiple types of geophysical logs, including logs with different resolutions, such as short spaced density log DENB and long spaced density log DENL, improves the estimation accuracy.

The geophysical logs have also been used here to estimate the coal brightness profiles and lithotypes. The estimated lithotypes poorly matched with the original lithotypes provided by the mine for which there are two possible reasons: 1) the lithotypes may have been logged using eye by different geologists; and 2) a variability of the non-bright components within each band. Our limited tests suggest that the subjectivity of the geologist is the main cause for the poor reconciliation with LogTrans results. Therefore, it is highly recommended that careful reconciliation of the lithotypes should be done before carrying out any automatic interpretation of lithotypes using geophysical logs.

5 Discussion and Conclusions

In this project, we reviewed the coal quality estimation from geophysical logs. It was found that the commonly-used approach for determining coal quality from the geophysical logs is mainly based on simple cross-plots. However, the relationships between coal quality parameters and geophysical logs are not always represented by simple linear trends and may instead be curved trends generated by complex equations. This suggests that instead of using a simple correlation approach, a multi-variable data analysis approach has a better chance of dealing with the complexity of coal quality parameters and hence improve the estimation accuracy of the these parameters. To perform coal quality parameter estimation using multiple geophysical logs, we proposed and implemented a multi-variable data analysis algorithm based on Radial Basis Function (RBF). We also developed data pre-processing algorithms to extract the geophysical logging data corresponding to the coal samples.

The feasibility of the coal quality parameter estimation from geophysical logs using the RBF-based algorithms was demonstrated using the data sets provided by Anglo American and BMA. The demonstrations were conducted on both self-controlled training data sets and an independent data set. It is observed that the density logs play a key role in coal parameter estimations as they have strong correlations with coal parameters such as ash content, fixed carbon and specific energy. However, with the use of more geophysical logs, including logs with different resolutions such as short spaced density log DENB and long spaced density log DENL, the estimation accuracy is improved. This result is consistent with our hypothesis. Although the results achieved are still under the accuracy expectation of the coal industry due to the limited routinely acquired geophysical logs available, it is fair to say that further improvement will be made if more geophysical logs such as the geochemical logs from SIROLOG and PGNAA tools are acquired. The SIROLOG and PGNAA are the well-demonstrated techniques for coal quality estimation (Biggs, 1991; Borsaru et al., 1992, 1993, 2014a, b; Nichols, 2001; Charbucinski and Nichols, 2003). They are not widely used by the industry probably due to safety concerns as active isotopic nuclear sources are used. However, CSIRO have developed a new borehole logging technique called PFTNA (Pulsed Fast and Thermal Neutron Activation) (Smith, 2015). This new technique uses a switchable electronically-controlled neutron generator which circumvents the requirement of an active source and overcomes the safety issue and other limitation associated with traditional permanent isotopic sources. This makes PFTNA technique inherently safer and significantly improves occupational safety on site.

The approach of using a large number of logs enabled good predictions to be made against the coal quality parameters of relative density, ash value and specific energy which correlate well with the amount of coal and mineral in the sample. However the approach was less successful for the coal quality parameters that are affected by other factors such a change in coal rank. Volatile content decreases with increasing coal rank (O'Brien et al, 2013) and therefore any lateral change in coal rank in the area from which the bore cores are collected will impact on the correlation obtained with geophysical logs.

As crucible swelling number is primarily related to coal rank and vitrinite content (O'Brien et al, 2013) so it was not surprising to see a wide scatter in the plots of crucible swelling number versus geophysical properties. Phosphorous has a strong correlation with minerals such as apatite but not with minerals such as quartz or pyrite, so the poor correlations between geophysical logs and total phosphorous values is also not unexpected.

Since the completion of our ACARP Project C13016 on quality appraisal for geophysical borehole logs, the quality of geophysical logs has largely improved as more attention is now paid to the acquisition of more reliable logging data by both the logging service providers and the mining companies. However, geophysical logs still have relatively large discrepancies compared with the laboratory measurements, despite attempts by Zhou and Esterle (2007) to accommodate for issues related to:

- the coal/rock interface/boundary;
- caved borehole walls;
- thin seams;
- those containing stone bands;

- a small depth shift between the sample and the geophysical log; and
- other measurements such as in-situ (logging) versus air-dried and crashed measurements (laboratory).

This can be observed by comparing the laboratory obtained relative density measurements with the geophysical density logs. The other factors are inherent within the resolution of the geophysical logging measurements and related borehole conditions and calibrations. For example, the highest resolution of the density logs is from the bed resolution density (BRD, 15 cm) sonde but it is more common to obtain a short-spaced density measurement (SSD, +20cm) (Chatfield, 2014). However, as we have demonstrated in this project, the resolutions of geophysical logging measurements may differ to the coal samples, all logging parameters will positively contribute to the improvements of coal quality estimation. This makes the improvement of coal quality estimation more feasible through collection of more geophysical logs.

Additionally, we have shown that the geophysical logs can also be used to estimate the coal brightness profile or lithotypes. Although the estimated lithotypes poorly match the original lithotypes provided by the mine, the reasons may be that they may have been logged by eye by different geologists in addition to there being various non-bright components within each band. The latter is a true variation due to the depositional environments, but the former is caused by subjectivity and can be improved by involving additional assessments and methods. One way to reduce the subjectivity is to use geophysical logs to reconcile the lithotypes logged by geologists. To illustrate this, the initial geophysically-interpreted lithotypes are used as the "reconciled" lithotypes for training and interpretation. It has demonstrated that the geophysical statistics for the "reconciled" lithotypes are largely improved with much smaller spreads. The application of these improved statistics to both the control and independent boreholes significantly improved the success rates of lithotype interpretation: the overall success rate of interpretation for these control holes is increased from 12% for the original lithotype interpretation to 87% for the "reconciled" lithotypes, while the corresponding success rate of interpretation for the boreholes increased from 13% to 50%. These results suggest that the variability of geophysical signatures are most likely caused by the subjectivity. It is strongly recommended that careful reconciliation of the lithotypes should be carried out prior to performing automatic interpretation using geophysical logs.

6 References

Abshier, J. F., McBride, G. E. and Beardsmore, S. F., 1979, Saving money with coal geophysics: Coal Age, September, 100-110.

Agostini, A., 1977, Correlation of high resolution density log counts and ash content of coal in the Goulburn Valley, N.S.W.: Bull. Austral. Soc. Explor. Geophys. 8, 26 – 31, 1977.

Ahmed, U., Johnston, D. and Colson, L., 1991, An advanced and integrated approach to coal formation evaluation: 66th Annual Technical Conference and Exhibition of the Society of Petroleum Engineers, Dallas, Texas, October 6-9, pp. 755-770

Alcock, J. B., Beckman, S. W., Juckett, D. A., Luppens, J. A, Moster, N. H., Schorno, K. S and Waldrop, M. A., 1986, An interdisciplinary geoscientific approach to modeling coal-quality variations in a Texas lignite deposit: implications for mine planning and use: U.S. Geological Survey Circular, Symposium proceedings; A national agenda for coal-quality research, Garbini, Susan (editor); Schweinfurth, Stanley P. (editor), pp. 216, Report Number: C 0979, Symposium Proceedings; A national agenda for coal-quality research, Reston, VA, United States, April 9-11, 1985

Ayoub, J., Colson, L., Hinkel, J., Johnston, D. and Levine, J., 1995, Learning to produce coalbed methane in Schlumberger Coalbed Methane: A Forum for the industry presenting Schlumberger Technologies, 13-14 December, 1995, Brisbane, Australia.

Biggs, M., 1991, The application of neutron-gamma sirolog to estimate iron content in coal and implications for estimating ash fusion characteristics: Queensland Coal Symposium, 29-30 August, 1991, Brisbane, Australia, pp. 187-198

Billings, S.D., Beatson, R.K., and Newsamn, G.N., 2002a, Interpolation of geophysical data using continuous global surfaces: Geophysics, 67, 1810-1822.

Billings, S.D., Newsamn, G.N., and Beatson, R.K., 2002b, Smooth fitting of geophysical data using continuous global surfaces: Geophysics, 67, 1823-1834.

Bond, L. O., Alger, R. P. and Schmidt, A. W., 1971, Well log applications in coal mining and rock mechanics: Transactions of SME, December, Vol. 250, pp. 355-362.

Borsaru, M., Biggs, M. S. and Nichols, W. J. F., 1993, Neutron-gamma logging for iron in coal and implications for estimating the ash fusion characteristics at Callide Mine: Nucl. Geophys., Vol. 7, No. 4, pp. 539-545.

Borsaru, M., Biggs, M. S. and Nichols, W. J. F., Bos, F., 2001, The application of Prompt Gamma Neutron Activation Analysis to borehole logging for coal: Appl. Rad. Isot, 54, 335-343.

Borsaru, M., Berry, M., Biggs, M., Rojc, A., 2004a, In-situ determination of sulphur in coal seams and overburden rock by PGNAA: Nucl Instr. Meth., B 213, 530-534.

Borsaru. M., Charbicinski. J., Rojc. A., Thanh. N.D. and Tuy. N.T., 2004b, Probe for determination of ash in coal stockpiles: Nuclear Instruments and Methods in Physics Research B 213, 422-425.

Borsaru, M. and Ceravolo, C., 1994, A low activity spectrometric gamma-gamma borehole logging tool for the coal industry: Nucl. Geophys., Vol. 8, No. 4, pp. 343-350.

Borsaru, M. and Ceravolo, C., Eisler, P. L. and Youl, S. F., 1983， Ash determination of black coal in exploration boreholes by the neutron-gamma method: Internat. Sympos. And Workshop on Borehole Geophysics, Toronto.

Borsaru, M., Charbucinski, J., Eisler, P. L. and Youl, S. F., 1985, Determination of ash content in coal by borehole logging in dry boreholes using gamma-gamma methods: Geoexploration, 23, 503-518

Borsaru, M., Charbucinski, J., Huppert, P., Youl, S. and Eisler, P., 1988, Coal ash determination in dry boreholes by the neutron capture technique: Nucl. Geophys., Vol. 2, No. 4, pp. 201-206.

Borsaru, M., Millitz, P. and Ceravolo, C., 1992, Comparison between the neutron-gamma and gamma-gamma techniques for ash prediction in 140 mm diameter quality control holes at the Callide Mine: Nucl. Geophys., Vol. 7, No. 1, pp. 125-132.

BPB Instruments Ltd, 1981, Coal Interpretation Manual, East Lake, Loughborough, England.

Brom, R. W. C. and Driedonks, F., 1981, Applications of petrophysical logging in the evaluation of coal deposits: Transactions of the 22nd SPWLA Annual Logging Symposium. Houston, Texas, June 23-26, 1981, pp. 1-29.

Buhmann, M.D., 2003, Radial Basis Functions: theory and implementations: Cambridge University Press.

Charbucinski, J. and Nichols, W., 2003, Application of spectrometric nuclear borehole logging for reserves estimation and mine planning at Callide coalfields open-cut mine: Applied Energy, 74, 313-322.

Charbucinski, J., Youl, S. F., Eisler, P. L. and Borsaru, M., 1986, Prompt neutron gamma logging for coal ash in waterfilled boreholes： Geophysics, 51, 1110-1118.

Chatfield, M., 2014, Wireline Workshop, Issue 3, January 2014.

Colson, J.L., 1991, Evaluating gas content of Black Warrior Basin Coalbeds from wireline log data: SPE Gas Technology Symposium, Houston, Texas, January 23-25, 1991.

Csokas, J., Dobroka, M. and Gyulai, A. 1986, Geolectric determination of quality changes and tectonic disturbances in coal deposits, Geophysical Prospecting 34, 1067-1081.

Daniels, J. J., Scott, J. H. and Liu, J., 1983, Estimation of coal quality parameters from geophysical well logs: Transactions of the SPWLA 24th Annual logging Symposium, Vol. 2, pp. 1-19.

Davis, D., 1976, Geophysical logging of coal: Symposium on the Geology of Rocky Mountain Coal, pp. 115-119.

Dong, H., Hou, J., Li, N., and Wang, H., 2001, The logging evaluation method for coal quality and methane: Geophysical & Geochemical Exploration, 25, 138–143.

Edwards, K. W., 1978, Coal analysis using geophysical log: Abstracts with Programs - Geological Society of America. Vol. 10, 395, Issue Number: 7, Date: August 1, 1978, The Geological Association of Canada, The Mineralogical Association of Canada, The Geological Society of America (91st annual meeting); 1978 Joint Annual Meeting, Toronto, Canada

Edwards, K. W. and Banks, K. M., 1978, A theoretical approach to the evaluation of in-situ coal: Can. Mining Metall. Bull., Vol. 71, No. 792, pp. 124-131.

Emilsson, J., 1993, Geophysical multi-parameter logging techniques applied to ore exploration in the Skellefte Field, MSc Thesis, Tekniska Hogskolan I Lulea, Sweden.

Esterle, J. and Le Blanc Smith, G., 2005, Petrophysical analysis of coal lithotypes: The 22nd Annual Meeting of The Society for Organic Petrology, Lexington, KY, USA, Sept. 11-14, 2005.

Fallon, G., Fullagar, P.K., and Zhou, B., 2000, Towards grade estimation via automated interpretation of geophysical borehole logs: Exploration Geophysics, 31, 236-242.

Fasset, J. and Hinds, J. S., 1971, Geology and fuel resources of the Fruitland Formation and Kirtland Shale of the San Juan Basin, New Mexico and Colorada: US Geological Survey Professional Paper, 676, p 76.

Fishel, K. W. and Mayer, R. 1979, Extremely high resolution density coal logging techniques: In Coal Exploration, Edited by George O. Argall, Jr., Proceedings of the 2nd International Coal Exploration Symposium, Denver, October 1978, pp. 490-504.

Firth, D., 1999, Log analysis for mining applications: Reeves Wireline Services, P. Elkington (Editor).

Fletcher, I.S., and Sanders, R.H., 2003, Estimation of in-situ moisture of coal seams and product total moisture: Final Report for ACARP Project C10041.

Fu, X., Qin, Y., Wang, G.G.X., and Rudolph, V., 2009, Evaluation of gas content of coalbed methane reservoirs with the aid of geophysical logging technology: Fuel, 88, 2269-2277.

Fu, X., Qin, Y., Wang, G.G.X., and Rudolph, V., 2009, Evaluation of coal structure and peameability with the aid of geophysical logging technology: Fuel, 88, 2278-2285.

Fullagar, P. K., Zhou, B. and Fallon, G. N., 1999, Automated interpretation of geophysical borehole logs for orebody delineation and grade estimation. Mineral Resources Engineering, 8, 269 – 284.

Fullagar, P., Zhou, B. and Biggs, M., 2002, Automated geotechnical interpretation of geophysical logs: Presented at KEGS/MGLS Symposium, Toronto, 21-23, August.

Fullagar, P.K., Zhou, B., and Turner, R., 2005, Quality appraisal for geophysical borehole logs: Final Report for ACARP Project C13016.

Ghosh, S., Chatterjee, R., Paul, S. and Shanker, P., 2014, Designing of plug-in for estimation of coal proximate parameters using statistical analysis and coal seam correlation: Fuel, Vo. 134, 63-73.

Golden Software Inc., 2014, Surfer 12 User's Guide.

Groves, B. and Bowen, E. 1981, The application of geophysical borehole logging to coal exploration: J. of Coal Geology Group of the Geological Society of Australia, Volume 3, Part 1, pp. 51-59

Hallenburg, J.K., 1979, On-site computer analysis of coal logs: In Coal Exploration, Edited by George O. Argall, Jr., Proceedings of the 2nd International Coal Exploration Symposium, Denver, October 1978, pp. 526-535.

Hastie, T, Tibshirani, R, and Friedman, J., 2001, The elements of statistical learning: data mining, inference, and prediction: Springer.

Hatherly, P., Sliwa, R., Turner, R. and Medhurst, T., 2004, Quantitative geophysical log interpretation for rock mass characterisation: ACARP Project C11037 Final Report.

Haykin, S., 1999, Neural networks: a comprehensive foundation: (2nd ed.) Upper Saddle Rever, New Jersey: Prentice Hall.

Herron, S., Letendre, L. and Dufour, M., 1988, Source rock evaluation using geochemical information from wireline logs and cores: AAPG Bulletin, Mediterranean Basins Conference and Exhibition, Vol. 72, 1007, Issue Number: 8, Date: August 1, 1988, Meeting Name: Mediterranean basins conference and exhibition, Sept. 25-28, 1988, Nice, France

Herron, S., 1991, In-situ evaluation of potential source rocks by wireline logs: In R. K. Merill "Source and Migration Proccesses in Evaluation Techniques" AAPG Publication, pp. 127-134.

Herron, S., Chiaramonte, J. M. and Grau, J., 1992, Impact of statistical uncertainties of elemental concentrations on geochemical log interpretation: Nucl. Geophys. Vol. 6, No. 3, pp. 351-358.

Hoffman, G. L. and Wilson, R. A., 1989, Determining coal quality parameters from downhole geophysical logs: Alberta Research Council, Information Series Advances in Western Canadian Coal Geoscience - Forum Proceedings April 24-25, 1989, No. 103, Published by Alberta Research Council Edmonton Alberta, Canada, pp. 361.

Huang, Z., Zou, C., Yang, Y., Zhang, G. and Wang, W., 2012, Coalbed methane reservoir evaluation from wireline logs in TS District, Southern Qinshui Basin: Geoscience, Vol.26, No.6, 1275-1282.

Jin, Z., Xue, H., Gao, H., Zhao, X., and Bai, G., 2013, Technology for evaluation of CBM reservoir logging and its application: Coal Geology & Exploration, Vol.41, No.2, 42-45.

Johnston, D., 1990, Geochemical logs thoroughly evaluate coalbeds: Oil Gas Journal, Dec 24, 45-51

Johnston D.J. and Scholes P. L. 1991. Predicting cleats in coal seams from mineral and maceral composition with wireline logs. Rocky Mountain Association of Geologists, pp. 123-136.

Kahraman, H., 1998, Literature survey on coal quality predicted from the geophysical logs: CSIRO internal report.

Karacan, C.O. and Olea, R.A., 2014, Inference of strata separation and gas emission paths in longwall overburden using continuous wavelet transform of well logs and geostatistical simulation: Journal of Applied Geophysics, 105, 147-158.

Kayal, J.R., 1979, Electrical and gamma-ray logging in Gondawana and Tertiary coalfields in India: Geoexploration, 17, 243-258.

Kayal, J.R. and Christoffel, D.A, 1982, Relationship between electrical and thermal resistivities for differing grades of coal: Geophysics, 47, 127-129.

Kayal, J.R. and Christoffel, D.A, 1989, Coal quality from geophysical logs: Southland lignite region, New Zealand: The Log Analysist, v30., pp 343-352.

Kayal, J.R. and Das, L.K., 1981, A method of estimating ash content of coal from combined resistivity and gamma ray logs: Geoexploration, 19, 193-200.

Kowalski, J. J. and Holter, M. E., 1976, Coal analysis from well logs: CIM Bulletin, June, pp. 99-103.

Kowalski, J. and Fertl, W. H., 1977, Application of geophysical well logging to coal mining operations: Energy Resources, Vol. 3, No. 2, 133-147.

Lavers, B. A and Smits, L. J. M., 1976, Recent developments in coal petrophysics: Transactions of the 17th SPWLA Annual Logging Symposium. Colorada, June 9-12, 1976, pp. 1-19.

Lawton, D. C. and Lyatsky, H. V., 1991, Density based reflectivity in seismic exploration for coal in Alberta, Canada: Geophysics, Vol. 56, No. 1, pp. 139-141.

Li, D., 1989, The prognosis of ash content in raw coal by means of regression analysis: Geophysical & Geochemical Exploration, Vol.13, No.2, 116-122.

Li, J., Liu, D., Yao, Y., Cai, Y., and Qiu, Y., 2011, Evaluation of the reservoir permeability of anthracite coals by geophysical logging data: International Journal of Coal Geology, 87, 121-127.

MacCallum, R., 1992, Geophysical logs and the search for opencast coal reserves: Geophysical logs and the search for opencast coal reserves, Geological Society Special Publications, Case histories and methods in mineral resources evaluation, Annels, Alwyn E. (editor), Vol. 63, 77-93.

Mao, Z.Q., Zhao, P.Q., Jin, D., Sun, B.D., Sun, W., and Pang, X., 2014, Investigation on log responses of bulk desnity and thermal neutron in coal bed with different ranks: 76th EAGE Conference & Exhibition, Amsterdam RAI, The Netherlands, 16-19 June 2014.

Mao, Z.Q., Zhao, Y., Sun, W., Cai, W.Y., Luo, A.Y., and Zhou, Y.C., 2011, Identification on the type of coal rank by using geophysical well logging data: Journal of Chia Coal Society, Vol. 36, No. 5, 766-771.

Mayor, M. J., Close, J. C. and McBane, R. A., 1990, Formation evaluation of exploration coalbed methane wells: Technical Meeting of Petroleum Society of CIM and the Society of Petroleum Engineers, Calgary, June 10-13, 1990.

Mayor, M. J., Close, J. C. and McBane, R. A., 1994, Formation evaluation of exploration coalbed methane wells: SPE Formation Evaluation, December 1994, pp. 285-294.

McCracken, K. G. and Mathew, P. J., 1981: Bolt-hole and borehole core logging instrumentation: J. of Coal Geology Group of the Geological Society of Australia, Volume 3, Part 1, pp. 31-36.

Meng, Z., Zhu, S., Jia, L. and Shen, H., 2011, Relationship between apprimate analysis of coal and log parameters and its models: Coal Geology and Exploration, Vol. 39, No.2, pp. 1-6.

Meyers, A., Clarkson, C., Wex, T., and Leach, B., 2004, Estimation of in-situ density of coal from apparent relative density and relative density analyses: Final Report for ACARP Project C10042.

Mongillo, M., 2011, Choosing basis functions and shape parameters for radial basis function methods: SIAM.

Mullen, M. J., 1988, Log evaluation in wells drilled for coalbed methane: Geology and Coalbed Methane Resources of the Northern San Juan Basin, Colorado and New Mexico Guidebook, Rocky Mountain Association of Geologists, pp. 113-124.

Mullen, M. J., 1989, Coalbed methane resource evaluation from wireline logs in the Northeastern San Juan Basin. A case study: Proc. SPE Joint Rocky Mountain Reg Low Permeability Reservoir Symposium and Exhibition Proceedings: SPE Joint Rocky Mountain Regional/Low Permeability Reservoirs Symposium and Exhibition, March 6-8, 1989, Denver, CO, USA.

Mutton, A.J. and Turner, R, 2002, Mt Pleasant Project, Hunt Valley, NSW: Estimation of coal quality from geophysical log data – Stage 1: A report to Coal & Allied Operations Pty Ltd.

Nargolwalla, S. and Seigel, H. O., 1977, In-situ mineral deposit evaluation with the Metalog system: Canadian Mining Journal, April, 75-89.

Nichols, W., 2000, Application of the SIROLOG downhole geophysical tool at Callide coalfields – Eastern Central Queensland: Proceedings of the 4th International Mining Geology Conference, 14-17 May 2000, Coolum, Queensland.

Norris, J.O. and Thomas, R., 1980, An in-situ coal quality prediction technique: 55th Annual Fall Technical Conference and Exhibition of the SPE of AIME, Dallas, Texas, September 21-2, 1980.

O'Brien, G., Firth, B., Warren, K. and Hapugoda, P., 2013, Improved understanding of coal exploration samples by coal grain analysis: ACARP Project C20040 Final Report, CSIRO Report EP1210575.

Orr, M.J.L., 1996, Introduction to Radial Basis Function Networks: Technical report, Institute for Adaptive and Neural Computation, Division of Informatics, Edinburgh University, www.cc.gatech.edu/~isbell/tutorials/rbf-intro.pdf accessed 15/08/2015.

Pan, H. and Huang, Z., 1991, Analysis of lithology and coal quality with optimized scale transformation method: Geophysical & Geochemical Exploration, Vol. 15, No. 3, 168 – 175.

Preston, K.B., 2005, Estimating the in-situ relative density of coal – old favourites and new developments: The Preceeding of Bowen Basin Symposium 2005, 13-20.

Preston, K.B. and Sanders, R.H., 1993, Estimating the in-situ relative density of coal: Australian Coal Geology, Vol. 9, pp. 22-26.

Reeves, D. R., 1971, In-situ analysis of coal by borehole logging techniques: CIM Bulletin, February, pp. 67-75.

Reeves, D. R, 1979, Some improvements and developments in coal wireline logging techniques: In Coal Exploration, Edited by George O. Argall, Jr., Proceedings of the 2nd International Coal Exploration Symposium, Denver, October 1978, pp. 468-489.

Reeves, D.R., 1981, Coal interpretation manual, London: BPB Inst. Ltd.

Renwick, R.I., 1980, The uses and benefits of down hole geophysical logging in coal exploration programs: J. of Coal Geology Group of the Geological Society of Australia, Volume 3, Part 1, pp. 37-50.

Ronen, S., Schultz, P.S., Hattori, M., and Corbett, C., 1994, Seismic-guided estimation of log properties, Part 1, 2, and 3: The Leading Edge, 13, 305-310, 674-678, and 770-776.

Roslin, A. and Esterle, J., 2014, Electrofacies analysis for coal lithotype profiling based on high-resolution wireline log data: Abstracts of the 31st Annual Meeting of the Society for Organic Petrology: 2014, Volume 31, Sydney, NSW, Australia, 27th September to 3rd October 2014

Russell, B.H., Lines, L.R., and Hampson, D.P., 2003, Application of the radial basis function neural network to the prediction of log properties from seismic attributes: Exploration Geophysics, 34, 15-23.

Saghafi, A. and Carras, J., 2005, Measurement of fugitive seam gas emissions from open cut operations: Final Report for ACARP Project C12027.

Sarle, W.S., 1994, Neural Networks and Statistical Models: In Proceedings of the Nineteenth Annual SAS Users Group International Conference, Cary, NC, 1538-1550.

Smith, C.P., Jeanneau, P., Maddever, R.A.M., Fraser, S.J., Rojc, A., Lofgren, M.K. and Flahaut, V., 2015, PFTNA logging tools and their contributions to in-situ elemental analysis of mineral boreholes: TOS Forum – wcsb7 proceedings, 5, 157-164.

Smith, W. K., Mulder, D. C. and Krueger, V. P., 1977, Geological procedures for a preproduction evaluation of the thermal coal deposit at Coal Valley, Alberta: CIM Bulletin, March, pp. 179-186.

Souza, V., Salvadoretti, P., Costa, J.F.C.L., Beretta, F., Koppe, J.C., Bastiani, G.A., Junior, J.A.C. and Grigorieff, A., 2010, Coal quality estimation using the geophysical logging of natural gamma and resistivity: R. Esc. Minas, Ouro Preto, 63(4): 653-660.

Srinaiah, J., Laxmi, G. U., and Ramadass, G., 2014, Well log data analysis for coal seams delineation and its proximity analysis in Mahuagarhi coal field, Jarkand, India: International Journal of Natural and Applied Science, Vol 3, No. 1, 1-5.

Stopes, M.C., 1919, On the four visible ingredients in banded bituminous coals: Proc. Royal Soc.

Swanson, A., Fletcher, I., Membrey, W. and Davis, R., 1998, Improve washability prediction through establishment of correct coal size distributions: ACARP Project C5053 Final Report.

Tercan, A.E., and Sohrabian, B., 2013, Multivariate geostatistical simulation of coal quality data by independent components: International Journal of Coal Geology, 112 (2013) 53–66.

Thore, P., Shtuka, A., Lecour, M., Ait-Ettajer, T., and Cognot, R., 2002, Structural uncertainties: Determination, management, and applications: Geophysics, 67, 840-852.

Till, V. S., 1985, Quantitative estimation of coal parameters from geophysical logs: End of Grant Report No. 529, Commonwealth of Australia National Energy Research, Development and Demonstration Program, NERDDP/EG/86/529, 106 pp.

Till, V.S., 1987, Coal quality from geophysical logs; methods and ideas: Proceedings of 21st Newcastle symposium on Advances in the study of the Sydney Basin, Engel, B. A. E. (convener). Vol. 21, 149-157, April 10-12, 1987.

Ward, C. R., 1978: Mineral matter in Australian bituminous coals: Proc. Australas. Inst. Min. Metall. 267, pp. 7-25.

Webber T, Costa JFCL, Salvadoretti P., 2013, Using borehole geophysical data as soft information in indicator kriging for coal quality estimation: Int J Coal Geol, 112:67–75.

Weltz, L. S., 1976, Log evaluation of sub-bituminous coals in Magallanes, Chile: Transactions of the 17th SPWLA Annual Logging Symposium. Colorado, June 9-12, 1976, pp. 1-33.

Yao, J., Sima, L. and Zhang, Y., 2011, Quantitative identification of deformed coals by geophysical logging: Journal of China Coal Society, Vol.36, Supp.1, 94-98.

Zhou, B. and Esterle, J., 2007, Improving the reliability of density and grade estimation from borehole geophysical log suites: Final Report for ACARP Project C15036, CSIRO Exploration and Mining Report P2007/62.

Zhou, B. and Esterle, J., 2008, Toward improved coal density estimation from geophysical logs: Exploration Geophysics, Vol. 39, No. 2, 124-132.

Appendix A. The prototype RBF-based software for parameter estimation

Overview

This appendix provides a detailed description of the user interface of the prototype RBF-based software ***ParamEstimate*** as shown in Figure 4 and Figure A - 1. The program was written specifically for coal quality parameter estimation from multiple geophysical logging data. The program in its current form is available free to ACARP members. It is attached to this report as part of the ACARP report materials.

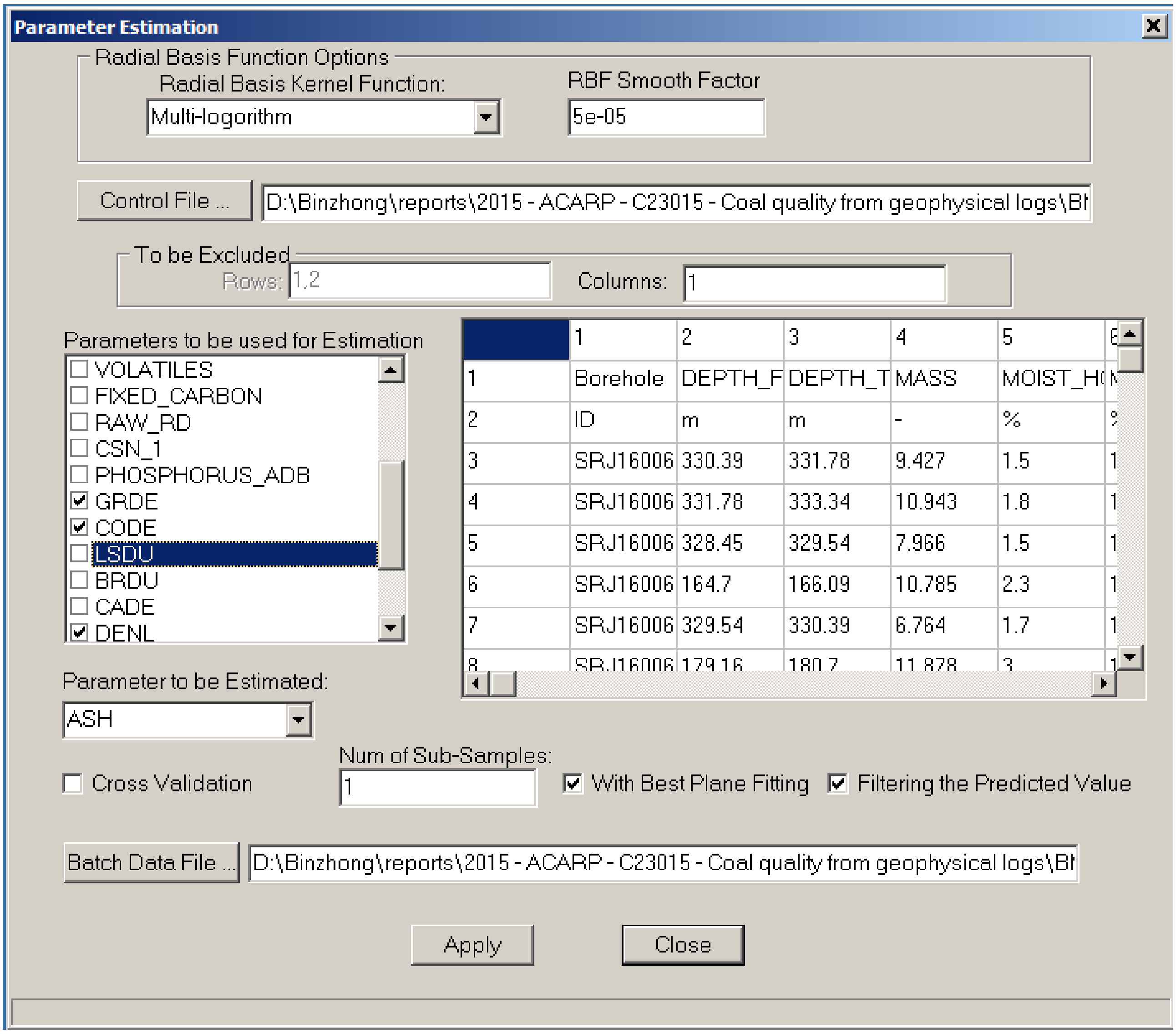


Figure A - 1 User interface of new RBF-based algorithm developed for coal quality parameter estimation from geophysical logs.

Input data files

Two input data files are required:

- The control data file is a CSV file containing both coal quality data from lab tests and corresponding borehole logs. A sample control data file is shown in Table A - 1. This file is established using a separate pre-processing program called “extract” to combine the coal quality data with the geophysical logging data from LAS files. It is not discussed in this report.

- The borehole log files are standard LAS files to be used for coal quality parameter estimation based on the control data. This is controlled by a batch data file as explained below.

Table A - 1 Input data format with borehole ID, coal sample depth range, coal qualities and corresponding geophysical log data.

Borehole	DEPTH_FROM	DEPTH_TO	MS	ASH	VM	FC	RD	GRDE	CODE	DENL	DENB	DEPO	ADEN
ID	m	m	%	%	%	%	g/cc	API	g/cc	g/cc	g/cc	%	g/cc
160005	281.421	282.326	1.1	16	16	66.9	1.43	20.8703	1.2884	1.2856	1.2532	82.4976	1.2617
160005	317.639	319.389	1.2	14.5	16	68.3	1.43	26.5082	1.3801	1.3853	1.3693	76.9507	1.3543
160005	359.959	360.353	0.9	15	18.6	65.5	1.45	49.0013	1.6745	1.6792	1.5372	59.0535	1.5262
160005	286.172	287.844	1.4	20.7	15.6	62.3	1.47	48.8092	1.4222	1.4378	1.4522	74.4111	1.4039
160005	319.389	320.374	1.7	39.8	14	44.5	1.69	69.4323	1.6491	1.6625	1.6698	60.6565	1.6307
160005	300.429	301.642	1.8	47.8	16.3	34.1	1.84	62.365	1.7064	1.7243	1.7236	57.1871	1.6697
160005	83.249	86.808	2	56.7	12.9	28.4	1.84	73.34	1.7945	1.8087	1.8297	51.8518	1.786
160005	228.109	229.754	1.6	52.8	14.7	30.9	1.88	57.1904	1.7141	1.7286	1.7778	56.7341	1.7333
160005	81.689	83.249	2.5	69.3	10.1	18.1	2.11	84.2436	2.0394	2.0554	2.0794	37.0156	2.0322
160007	204.875	206.701	0.9	12.3	17.9	68.9	1.4	20.9983	1.3858	1.3892	1.3652	76.6019	1.3576
160007	241.945	242.495	0.7	9.3	19.9	70.1	1.41	31.8639	1.4907	1.4825	1.3465	70.2756	1.3698
160007	257.855	258.565	1	18.1	17.8	63.1	1.44	70.8459	1.5649	1.5608	1.4677	65.7861	1.4801
160007	95.072	96.612	0.9	28.5	18	52.6	1.54	33.901	1.4232	1.4418	1.45	74.3285	1.3946
160007	222.625	224.375	1.4	28.1	16.1	54.4	1.54	49.1079	1.5066	1.5143	1.498	69.2886	1.475
160007	186.898	190.094	1.5	36.8	13.7	48	1.63	53.4038	1.6084	1.6109	1.6016	63.128	1.5947
160007	186.898	190.094	1.5	36.8	13.7	48	1.63	53.4038	1.6084	1.6109	1.6016	63.128	1.5947
160007	98.174	100.409	1.6	47.9	15.6	34.9	1.79	52.0119	1.7005	1.7032	1.6843	57.5439	1.6762
160007	206.701	207.769	1.9	51.3	12.9	33.9	1.82	67.9795	1.6912	1.7013	1.7157	58.0896	1.6867
160020	205.255	206.697	1	10.8	18.6	69.6	1.39	32.1733	1.3893	1.3983	1.3801	76.4101	1.352
160020	256.977	257.956	1.1	10.5	16.5	71.9	1.39	54.6551	1.4088	1.4135	1.3955	75.2219	1.3815
160020	325.019	325.519	1.2	14.2	15.7	68.9	1.42	42.5798	1.5226	1.5216	1.4282	68.2895	1.4332
160020	255.288	256.507	1.1	14.4	16	68.5	1.43	31.832	1.3793	1.3907	1.4159	77.0118	1.3815
160020	253.868	255.288	1	16.5	15.9	66.6	1.45	28.9328	1.3489	1.3641	1.3942	78.854	1.3489

The batch data file has an extension of *.DAT which is inherited from the batch processing file of the LogTrans program and includes all the LAS files to be processed and the corresponding lithological files (ALT files for the corresponding boreholes). The following is a sample batch data file:

```
#LASALT#   !File ID
"160005\160005.las"   "160005\160005.ALT"   "-999.25"  "-999.25"
"160007\160007.las"   "160007\160007.ALT"   "-999.25"  "-999.25"
"160020\160020.las"   "160020\160020.ALT"   "-999.25"  "-999.25"
!"160060\160060.las"  "160060\160060.ALT"   "-999.25"  "-999.25"
"160085\160085.las"   "160085\160085.ALT"   "-999.25"  "-999.25"
"160087\160087.las"   "160087\160087.ALT"   "-999.25"  "-999.25"
"160098\160098.las"   "160098\160098.ALT"   "-999.25"  "-999.25"
"160310\160310.las"   "160310\160310.ALT"   "-999.25"  "-999.25"
"160313\160313.las"   "160313\160313.ALT"   "-999.25"  "-999.25"
```

1st line is a file header line and must be “#lasalt# “

2nd and subsequent lines = path*.LAS path*.alt and depth controls]

The contents on each line are:

1st column is for the LAS file name and path

2nd column is for ALT file (if available). If missing, use double quotes “”.

3rd column is for the start depth to be processed. -999.25 indicates the processing start from the top of the borehole.

4th column is for the end depth to be processed. -999.25 indicates the processing will be to the end of the borehole.

The control file can be loaded into the program by clicking the “Control File …” button on the form while the batch data file can be loaded through the “Batch data …” button.

Batch data file is not mandatory for cross-validation of the control data performance if the “cross validation” checkbox is selected. This file is only needed when the control data are used to estimate coal qualities from independent boreholes.

Output data files

There are two different output files: one for cross-validation of the control data performance; one for application of the control data to independent boreholes to estimate the specific coal quality. For cross-validation of the control data performance, the output file is a CSV file as shown in Table A - 2.

Table A - 2 A sample cross-validation output of ash estimation from geophysical logs GRDE, DEPO and ADEN.

GRDE	DEPO	ADEN	ASH	ASH_ES
API	%	g/cc	%	%
20.8703	82.4976	1.2617	16	8.38
26.5082	76.9507	1.3543	14.5	15.01
49.0013	59.0535	1.5262	15	19.25
48.8092	74.4111	1.4039	20.7	21.87
35.5424	63.056	1.5308	28.9	22.81
29.4261	77.5805	1.376	28.7	19.15
50.5491	68.849	1.4868	29.1	26.64
57.7243	58.7046	1.6441	36.4	36.44
69.4323	60.6565	1.6307	39.8	38.77
57.5676	65.1122	1.5507	39.8	31.65
66.1372	60.6909	1.6287	44.7	38.05
76.7228	54.4143	1.6657	40.6	36.30
62.365	57.1871	1.6697	47.8	38.76
73.34	51.8518	1.786	56.7	49.36
57.1904	56.7341	1.7333	52.8	46.19
84.2436	37.0156	2.0322	69.3	66.21
20.9983	76.6019	1.3576	12.3	14.28
31.8639	70.2756	1.3698	9.3	9.29
70.8459	65.7861	1.4801	18.1	24.42
49.1079	69.2886	1.475	28.1	25.33

Table A - 3 presents a sample output of ash estimation for application of control data to independent boreholes. The first line identifies the title of the estimated coal quality and the second line is the unit for the quality parameter. The remaining lines are the depths and the corresponding parameters estimated.

Table A - 3 Sample output of ash estimation for application of control data to independent boreholes.

ASH	
%	
81.69	39.17
83.25	49.74
95.07	24.76
98.17	37.36
118.03	39.02
186.90	34.38
186.90	39.79
204.88	33.74
205.26	29.63
206.70	33.53
222.63	30.00
226.70	27.73
228.11	44.87
229.75	23.73
241.95	28.40
255.29	18.41
256.98	23.76
257.86	19.73
281.42	16.32
282.33	24.08

Operations of ***ParamEstimate***

The operation of ***ParamEstimate*** can be summarised as the following:

1) Load the control data file.
2) Select the columns and rows to be excluded from the control data file.
3) Select *only the geophysical logging parameters* to be used for estimation from the list box.
4) Select the coal quality parameter to be estimated from the dropdown list box.
5) Select the radial basis kernel function and corresponding smooth factor. You may experiment with different functions to choose one with the best performance for your data.
6) Select the coal quality estimation approach: Cross validation or application of the control data to independent boreholes by checking or unchecking the “Cross validation” checkbox.

Appendix B The LogTrans algorithm

In this project, the coal brightness classification/interpretation from geophysical logs was carried out using the automatic interpretation program LogTrans (Fullagar et al., 1999) developed jointly by CMTE (Now CRCMining) and CSIRO. The program exploits the contrasts between petrophysical signatures of different rock types and performs rapid analysis of multi-parameter logs. The rock types or interpretational classes differ by lithology, stratigraphy, grade, mechanical properties, or combination of these. LogTrans makes the assumption that the physical properties of a given rock type will be statistically invariant over a usefully large volume.

LogTrans processing entails three steps:

- *Statistical characterization* (with program GRSTAT), involving determination of the centroids (means or medians) and ranges (standard deviation or spreads) of the distributions of each petrophysical parameter for each class, based on a representative control data set;
- *Discrimination* (with program FLUSTER), in which data points are assigned to the nearest control class in multi-parameter space.
- *Stratigraphic correction* (with program STRAT) to impose an *a priori* stratigraphic order on the interpretation (This is optional and will not be discussed in this report. More details can be found in Fullagar et al, 2002).

Statistical characterization

In order to obtain the ‘petrophysical calibration’ for the automatic interpretation of geophysical logs, it is necessary to petrophysically characterize each rock type. For this, it is essential to have reliable data in the control holes based on geological logs, geochemical assays or geotechnical measurements. Unreliable control data will produce unreliable predictions. Also, care must be taken to reconcile the geophysical logging depths with drilling depths before the rock types are petrophysically characterized. In this analysis we have used the depths of coal seams as markers.

The LogTrans algorithm can be understood as an extension of the “domainal” interpretation of scatter plots from two to multiple dimensions (e.g., Emilsson, 1993). Each rock type populates a certain domain in multi dimensional space as shown schematically for a two dimensional case in Figure B - 1. For each rock class a centroid can be defined in the ‘parameter space’, representing the typical rock properties for that class. In LogTrans the centroids are the class medians or means derived from the control data set. The control data must be representative of the lithologies intersected in the boreholes. It is advisable to have the control holes drilled in the same deposit with the holes to be interpreted.

In reality, the domain boundaries, as shown in Figure B - 1 are not always sharply defined especially if the number of data points is small for a given rock class. This may be due to a gradational rather than discrete geological changes or natural scatter.

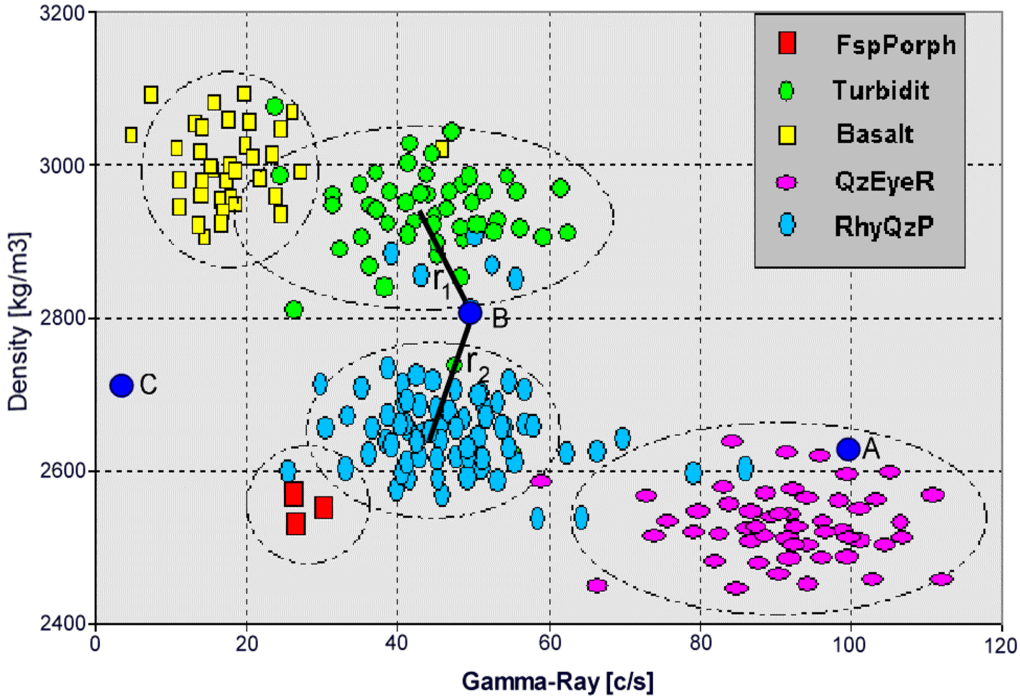


Figure B - 1 Hypothetical control data set, to illustrate the LogTrans algorithm (modified after Emilsson, 1993). Points A, B, C define (density, gamma) data pairs recorded in non-control holes. LogTrans interprets A, B, C as belonging to the nearest rock class domain on the control data scatterplot.

Discrimination

The concept of LogTrans discrimination is easily explained in two dimensions as shown by Figure B - 1. Assuming that the plot represents petrophysical log data from a set of control holes, a pair of natural gamma and density readings from a new hole is interpreted according to where it sits with respect to the control data domains. The data point is assigned to the rock type associated with the closest centroid in parameter space. Sometimes the data point is assigned to a rock formation unambiguously, e.g. point A assigned to quartz rhyolite (QzEveR) in Figure B - 1. However, more typically, there is a degree of ambiguity when a point is almost equidistant from two or more class centroids, e.g. point B in Figure B - 1. Other data points may lie outside any domain, indicating that the rock type to which it corresponds is not represented in the control holes, e.g. point C in Figure B - 1.

A detailed discussion regarding the statistical analysis of the data is given by Fullagar et al. (1999). In use, the discrimination algorithm is simple, intuitive, fast and flexible. However, it is not a black box. Its performance relies on the integrity of the control information: the geological, geochemical, and/or geotechnical data from the control holes, as well as the geophysical logs. Performance is enhanced when the parameter distributions are uni-modal and compact and when there is a large petrophysical contrast between classes. Critical assessment of control information may lead to the introduction of new classes by sub-division of existing classes or otherwise and the derivation of new parameters through mathematical combination of original parameters.

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