Enhancing coal quality estimation through multiple geophysical log analysis

Binzhong Zhou*
CSIRO Energy
PO Box 883, Kenmore, QLD 4069
Binzhong.Zhou@csiro.au

Graham O'Brien
CSIRO Energy
PO Box 883, Kenmore, QLD 4069
Graham.Obrien@csiro.au

SUMMARY

Coal quality information such as ash content, density, volatile matter and specific energy are important to the coal mining industry for mine planning, design, extraction, beneficiation and utilisation. These parameters are traditionally obtained through laboratory analyses conducted on drill-core samples from exploration drill holes. This process is expensive and time consuming. In this paper, we use a multi-variable data analysis algorithm based on the Radial Basis Function (RBF) neural network methods to estimate coal quality parameters from routinely-acquired multiple geophysical logs such as density, gamma ray and sonic logs. The performance of this RBF-based approach was demonstrated using both self-controlled training data sets and an independent data set from a mine. It was observed that although the density logs play a key role in coal parameter estimation, 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 the use of additional geophysical logs such as photoelectric factor (PEF), SIROLOG and PGNAA, which provide data of geochemical constituents, should improve estimates of coal quality parameters.

Key words: Coal quality; ash content; geophysical logs, Radial Basis Function (RBF).

INTRODUCTION

Coal quality parameters such as ash content, density, volatile matter and in-situ moisture are important to the coal mining industry for mine planning, design, extraction, beneficiation and utilisation. These parameters are traditionally obtained through laboratory analyses conducted on drill-core samples. Currently, obtaining coal quality information requires the collection of borecores, which are then subjected to pre-treatment to simulate the size reduction and liberation that can be expected during the mining process. 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 slimcore 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 establish the market value of coal products. The collection and laboratory analysis of borecore samples is expensive and time consuming. Most boreholes drilled for the acquisition of geophysical information have limited or no coring due to high costs. Therefore, only a limited number of coal samples are 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 in-situ 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 borecores. The derivation of coal quality parameters from geophysical logging data is not a new concept (Edwards and Banks, 1978; Fishel and Mayer, 1979; McCracken and Mathew, 1980; Renwick, 1980; Groves and Bowen, 1981; Daniels et al., 1983; Till, 1985 & 1987; Mullen, 1988 & 1989; Borsaru et al., 1992; Nicols, 2000; Zhou and Esterle, 2008). It is mainly based on the simple regression relationship of coal quality parameters with a single geophysical log such as the density log. Once the cross-plot of a coal quality parameters with a geophysical log is prepared and the regression equation is 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 approximately the same for each coalfield or basin as long as the depositional and geological conditions remain the same.

However, coal quality parameters are often complex and cannot be represented by simple correlation curves. As demonstrated by Till (1985 & 1987), the prediction of a coal quality parameter using a single gamma or long spaced density log was less accurate but the error decreased when a second or third polynomial regression equation was used. In this paper, we use a multi-variable data analysis algorithm based on the Radial Basis Function (RBF) neural network method to estimate coal quality parameters from routinely-acquired multiple geophysical logs such as density, gamma ray and sonic logs. The performance of this RBF-based approach will be demonstrated using both self-controlled training data sets and an independent data set from a mine.

COAL QUALITY ESTIMATION FROM MULTIPLE GEOPHYSICAL LOGS

Coal quality parameters such as ash content, density and volatile matter are commonly estimated by using model based regression approaches (exponential relationship or second order polynomial models derived from cross-plots) from a single geophysical log such as density. However, the coal quality parameter to log relationship is not always represented by simple equations (straight lines) as they can also be represented by curved lines generated by complex equations. The outcomes largely depend on the model in use, and cannot easily accommodate rock data variations that are not included in the "assumed" models. Apart from laboratory measurements, which are expensive to obtain, there are few methods available to accurately derive coal quality parameters. However, the estimation accuracy of the laboratory coal quality measurements can be improved through analysis of multiple geophysical logs, illustrated in Figure 1, where 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. Increasing the number of geophysical logs could increase the chance of correct estimation of the coal parameter variations.

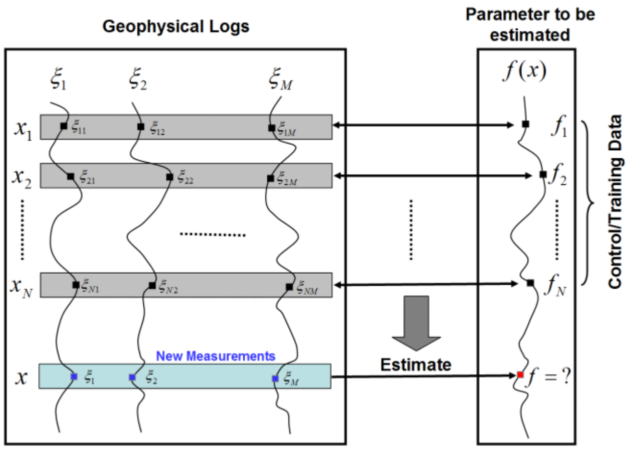

Figure 1 Illustration of parameter estimation using multiple geophysical logs. The discrete control data are used to train the parameter estimation algorithm and the trained algorithm is then used to estimate the target parameters with new measurements.

As with the regression approach for deriving coal ash content using density data, 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 artificial neural networks. In this study, we will use a multi-parameter data analysis method using the radial basis function (RBF) algorithm for coal parameter estimation from multiple geophysical logs. The 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). 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 (Mongillo, 2011). RBF applications in geophysics include geophysical data interpolation (Billings et al., 2002a, b), and prediction of log properties from seismic attributes (Russell et al., 2003). 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.

RESULTS

Data description

A real data set from a mine in central Queensland is used to test the feasibility of the RBF-based coal quality parameter estimation from multiple geophysical logs and demonstrate its advantages over the conventional single-log analysis. The data set consisted of 1012 samples with laboratory coal quality proximate analysis data from 23 boreholes and corresponding geophysical logging data from the same boreholes. 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 2. The coal samples are from different coal seams. The key coal quality parameters provided are air-dry basis relative density RDad, ash content ASHad, fixed carbon FCad and volatile matters VMad. The key geophysical logging parameters include caliper CADE, gamma ray GRDE, short-spaced density DENB, long-spaced density DENL, VECTAR processed density ADEN, compensated density CODE, 20 cm sonic transit time MC2F, 40 cm sonic transit time MC4F, 60 cm sonic transit time MC6F, Laterolog shallow resistivity FE1 and Laterolog deep resistivity FE2. Not all boreholes have the full suite of the geophysical logs. All the data are of good quality based on our examination.

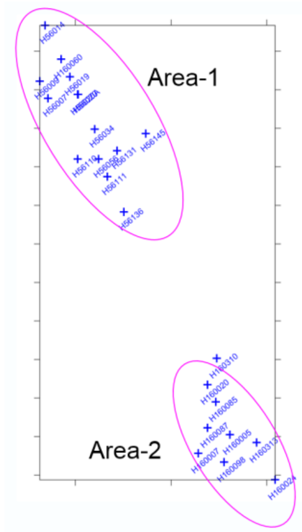

Figure 2: The borehole distribution of coal quality and geophysical logging data from a mine site in Central Queensland.

Coal quality estimations from geophysical logs – controlled training data set

Figure 3 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 3, we can use the density log ADEN to estimate the coal quality parameters as presented at the top row in Figure 4. In addition to this, 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 4. 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 suggests that multi-log estimation is more accurate than the single estimation.

As mentioned, 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 of coal samples with all the geophysical logs. The total number of samples for this reduced data set is 578. We use different combinations of the geophysical logs and the multi-logarithm RBF method to estimate the ash contents. Table 1 lists the statistics of the resulting ash estimations 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 decrease with an increasing number of geophysical logs used, while the correlations of the estimations are increased with the increasing number of geophysical logs used.

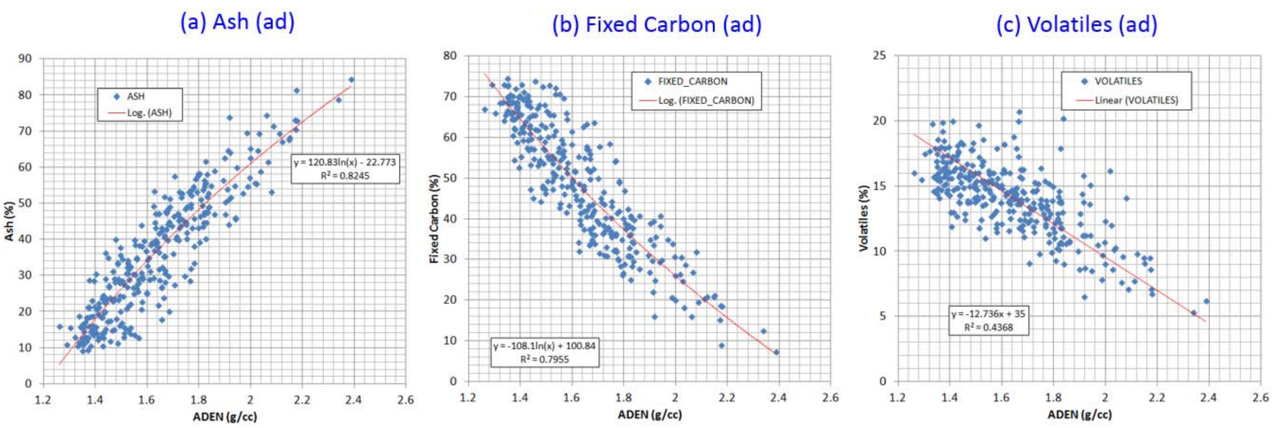

Figure 3 Cross-correlations of coal quality parameters with the geophysical log ADEN: (a) Ash content; (b) Fixed carbon; (c) Volatile matter.

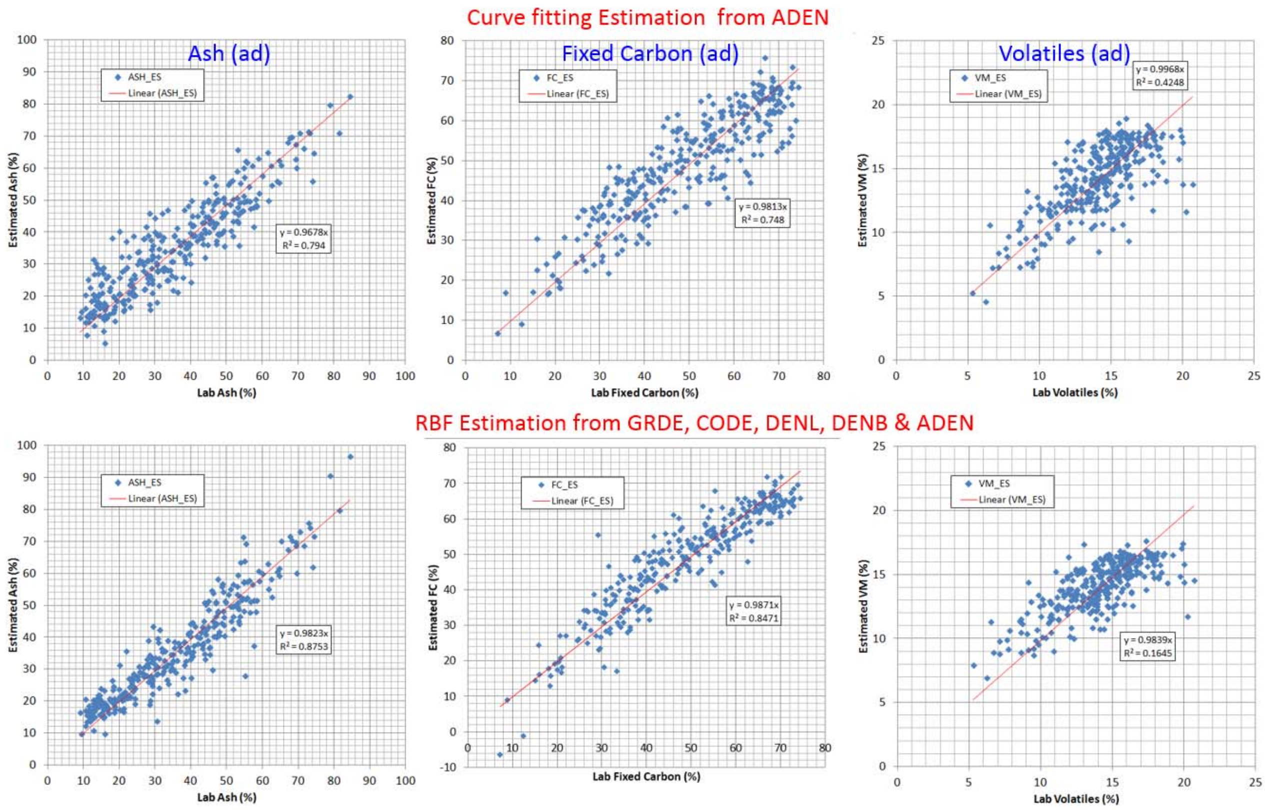

Figure 4 The estimated air-dry ash, fixed carbon and volatile matter from a single geophysical log ADEN (top row) and multiple geophysical logs (bottom row).

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

Table 1 Statistics of the estimated ash contents from multi-geophysical logs

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 method. 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 does 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 2). The whole data set (Sub-set 1 + Sub-set 2) is from the same data samples as those used in the previous controlled data set. 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 5 shows the estimated coal parameters RDs and ashes from geophysical logs GRDE, CODE, DENL, DEPO & ADEN for different data sets and Table 2 lists the statistics of the corresponding estimations. The resulting estimates for the whole data set and

Sub-set 1 (Figure 5(a), (b), (d) & (e)) are based on leave-one-out cross-validation, while the estimates for Sub-set 2 are results by applying the control Sub-set 1 to Sub-set 1. Figure 5 and Table 2 clearly demonstrate that we can use multi-geophysical logs to estimate coal quality parameters.

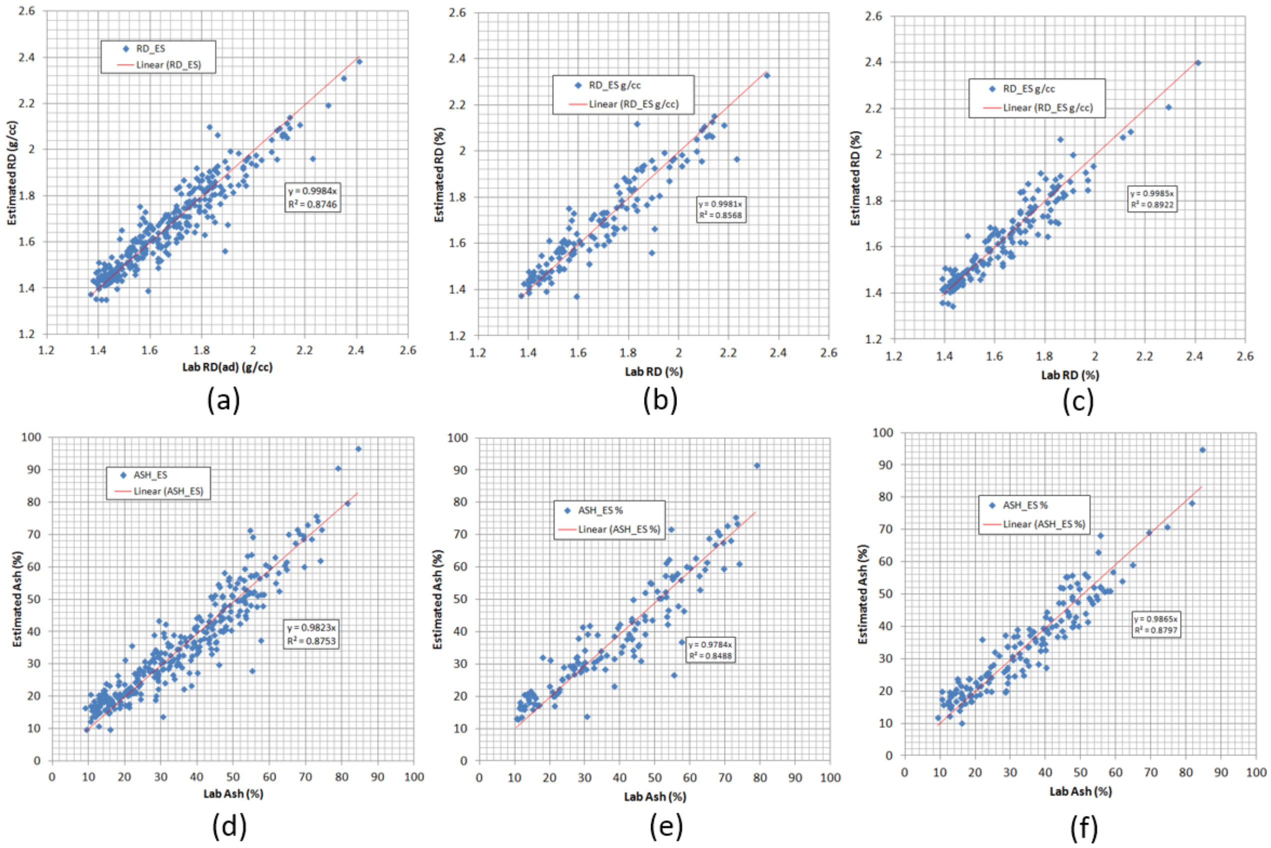

Figure 5 Estimated coal parameters from geophysical logs GRDE, CODE, DENL, DEPO & ADEN for different data sets: (a) Estimated RDs for whole data set; (b) Estimated RDs for Sub-set 1; (c) Estimated RDs for Sub-set 2 using Sub-set 1 as control data; (d) Estimated ash contents for whole data set; (e) Estimated ash contents for Sub-set 1; (f) Estimated ash contents for Sub-set 2 using Sub-set 1 as control data.

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

Table 2 The statistics of estimated RD and ashes for different data sets.

CONCLUSIONS

In this paper, instead of the commonly used simple correlation approach, we used a multi-variable data analysis approach based on Radial Basis Function (RBF) to perform coal quality parameter estimation using multiple geophysical logs. This approach has a better chance of dealing with the complexity of coal quality parameters and hence improve the estimation accuracy of these parameters. The feasibility of the method was demonstrated using a data set from a mine in Central Queensland. 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. Based on the current results, it reasonable to expect that further improvement will be made if more geophysical logs such as the geochemical logs from SIROLOG and PGNAA logging tools are acquired.

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