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Estimation of Proximate Parameters of Coal Seams by Well Logs through Kriging Interpolation

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Abstract

In this paper, a new method is implemented based on the Kriging interpolation to estimate the proximate parameters of coal seams using the well logs. For this purpose, the data of seven boreholes were employed through a case study to explain the method and reliability of the results. According to this method we assume the data of two or more well logs as Cartesian coordinate axes and a proximate parameter as the variable distributed in this coordinate system. At first, the values of each log corresponding to the coal seams are extracted from the reference borehole data, and the coordinate axes are determined based on the type of logs. In the present case study, given the integrity of gamma ray logs, sonic logs and porosity logs in all the boreholes of the region, three coordinate axes were defined and the distribution of proximate parameters was modelled in the coordinate system. Given the number of existing logs, it was possible to model all scenarios by a triple combination of logs, and the best cross correlated model was selected as the parameter distribution model. Using this model, the proximate parameters were eventually estimated in the borehole for which only well logging data were available. The estimation of proximate parameters based on the Kriging interpolation leads to improved results, especially for estimation of the ash content, compared with the conventional method which incorporates logs for estimation of the parameters based on the correlation between the log and the proximate parameter.

Keywords: Coal; Proximate Parameters; Well Logging; Geostatistics; Kriging.

Introduction

In general, well-logging is the application of geophysical methods in exploratory boreholes. Although these methods are more common in oil and gas reservoir exploration, but utilization of some the well-logging methods are common in mineral exploration, especially coal exploration. Coal as a lithology responds well to most geophysical methods because its properties contrast with those of others lithologies commonly found in coal bearing sequences [1]. Coal beds, in comparison with other surrounding layers, are lower in gamma radiation and density. Therefore, well-logging methods which are based on gamma radiation and density measurement; like gamma-gamma method, along with resistivity, sonic and porosity measurement methods are widely utilized in coal exploration.

Characteristics of the coal beds vary from seam to seam. Even parameters like moisture, ash content, and volatile-matters could vary along a single coal layer extension. The parameters are often reported as the proximate or the ultimate analysis. Proximate analysis is a broad analysis that determines the amounts of moisture, volatile-matters, fixed carbon and ash. This is the most fundamental of all coal analyses and is of great importance in the practical use of coal [2].

While a difference is expected in the values of well-logs between the coal beds and the other layers, a steady and unchangeable log cannot be expected for the coal beds. As well-log values are affected by the characteristics of coal beds, the proximate parameters of coal seams can be estimated from the values of coal geophysical well-logs. In other words, the characteristics of coal beds can be estimated from the well-logs.

It should be noted that the most accurate method for approximating coal-beds' parameters is through sampling and laboratory analysis. Although, there are some advantages in application of well-logs for coal-beds' parameter estimation, such as:

Consistency in the results of well-logging operations; unlike inevitable problems associated with core samples due to core washing off and losing the sample, the well73 logs could demonstrate the sample depth.

The results are instantaneous [3].

It could sample a much larger volume of the material surrounding the borehole than. The core sample and therefore provides better sampling statistics [3].

The cost of drilling open holes is less than that of the cored holes [3].

The idea of determining characteristics of coal-beds based on the geophysical well-logs is not a new idea. The relationship between geophysical well-logs and coal-beds characteristics was examined in 1975 [4]. In 1981 a relationship between the two sets of well-logging and analysing data was tried [5]. The error factor in determining coal-beds' quality parameters according to the logs has been noticed too [6]. While the correlation between the density logs and coal ash was confirmed, the effect of well-logging tools on the error of estimated amount of ash according to the values of gamma-gamma logs was examined [7]. During last decade of previous century, several related studies were conducted by researchers [8-10]. In another research via the ACARP (Australian Coal Association Research Program) in 2007 the effective tools and equipment for an accurate estimation of coal's parameters according to the well-logs were reviewed [11]. In 2007, researchers attempted to characterize the moisture and gas contents of coal according to low-field nuclear magnetic resonance (NMR) logs [12]. In 2010, Souza et al., considered only the gamma and resistivity logs as the criteria for determining coal quality parameters [13]. Density logs were applied in coal gas reservoir modelling, thorough a case study [14]. Webber et al. assayed the borehole geophysical data as soft information in the Indicator Kriging for the estimation of coal quality [15]. Two research developed aiming to estimate the coal parameters from the well logs were recently conducted by Ghosh el al.

[16] and Ghosh el al. [17]. They attempted to examine statistical analysis and Neural Network Modelling for estimating proximate parameters. Polynomial regression equations were used to improve coal quality estimation through multiple log analysis [18]. During a recent study, a combination of advanced numerical and statistical methods is used for interpreting coal lithotypes from geophysical wire-line logs. The study particularly aimed to discriminate between bright and dull coal at similar densities [19]. In addition, determining rock strength from well logging measurements is another solution for estimating coal layers' characteristics [20,21], since mechanical rock properties could be modeled from rock features such as ash content, density and acoustic velocities based on well logging tools [22].

The above references show that various methods have been tested for estimation of the proximate parameters by the well logs, mainly using the simple, multivariate statistical methods, and advanced techniques such as the radial basis function (RBF) and the single- and multi-layered neural networks. In this paper, a different method is proposed for estimating the parameters using the logs based on the log Ordinary Kriging interpolation.

Methodology

Geostatistical interpolation techniques provides the best linear, unbiased prediction for the spatially dependent properties [23,24]. Among the most applied estimators for interpolation of the spatial data are Kriging techniques. They are considered as the interpolation methods for estimation of a regionalized variable at the selected grid points that predict values from interpolation without bias, and with minimum variance [25]. There are different types of Kriging techniques, such as Ordinary Kriging (abbr. OK); that is the most commonly used method, Universal Kriging (abbr. UK), Indicator Kriging, Co-Kriging and others. Selecting the appropriate Kriging method depends on the data characteristics. For a linear estimation, spatial inference, or estimation, of a quantity Z(x0), at an unobserved location x0, is calculated from a linear combination of the observed values zi = Z(xi) and Kriging weights of wi [26]:

$$\hat{Z}(x_0) = [w_1 \quad w_2 \quad \cdots \quad w_n].\begin{bmatrix} z_1 \\ z_2 \\ \\ z_n \end{bmatrix} = \sum_{i=1}^{n} w_i(x_0) \times Z_i(x_0) \qquad (1)$$

The Kriging weight factors of n observed point's values are found by solving the following system:

$$\begin{matrix} 0 & \gamma(\ _{1,2}) & & \gamma(\ _{1,n}) & 1 \\ \gamma(\ _{2,1}) & 0 & & \gamma(\ _{2,n}) & 1 \\ & & & & \\ \gamma(\ _{n,1}) & \gamma(\ _{n,2}) & & 0 & 1 \\ 1 & 1 & & 1 & 0 \end{matrix} \quad \begin{matrix} w_1 \\ w_2 \\ \\ w_n \\ \mu \end{matrix} = \begin{matrix} \gamma(\ _{x,1}) \\ \gamma(\ _{x,2}) \\ \\ \gamma(\ _{x,n}) \\ 1 \end{matrix} \qquad (2)$$

Where hi,j is the distance between input point i and input point j, hx,i is the distance between the output point of x and input point i, γ (hi,j) is the value of the semi-variogram model for the distance hi,j, wi is a Kriging weight factor for input point i, μ is a Lagrange multiplier, used to minimize possible estimation error.

The spatial variability was assessed using the semivariogram [24].

$$\gamma(\ ) = \frac{1}{2N(h)}\sum_{i=1}^{N(h)}(Z(x_i) \quad Z(x_i + \ ))^2 \qquad (3)$$

Where γ^* 134 (h) is the experimental semivariance, N(h) is the number of data pairs (Z (xi), Z (xi+h)) separated by the distance h. The experimental semivariograms were fitted by theoretical models.

In estimation of the parameters using logs to be used in Kriging technique, the log values are assumed as the local dimensions. In other words, two or more logs are assumed as coordinate axes X, Y, etc. The distribution of a parameter is then modelled in this two- or multi-dimensional space by Kriging. The distribution model would be created according to the reference borehole data, namely the boreholes with available well-logging results and the proximate analysis data. In the end, the ash content is extracted from the model for different log values. For instance, three well logs of Short-Space Density, Neutron Porosity, and Natural Gamma Ray are respectively applied as coordinates of X, Y, and Z. From reference borehole data, for every sampled coal layer, values of ash content, and three mentioned logs are available. Therefore a discrete distribution of analyzed ash content values is available in a 3D coordinate space with axes of Short-Space Density log, Neutron Porosity log, and Natural Gamma Ray log. The distribution of the ash content is modeled in the system using Kriging technique. In a blind borehole; or borehole with just the log values available, the ash content can be estimated by sampling from the Kriged model in the grid point with coordinates of well logs of Short-Space Density, Neutron Porosity, and Natural Gamma Ray.

The dimensions of modelling space or the number of logs used for modeling vary with the type of methods used for the well logging. For example, there may be 15 logs for a borehole, including a variety of density, sonic and porosity logs. Therefore, three logs of density, sonic, and porosity are selected and the modelling is performed in a three dimensional Cartesian coordinate system. Thus, several different models can be created by different triple combinations of each log and the most suitable model is selected by cross correlation. Figure 1 shows the possible coordinate systems for a set of well logs recorded for a borehole.

GAMMA LOGS (X)	SONIC LOGS (Y)	POROSITY LOGS (Z)	Possible combinations (X, Y, Z)
GRDE (.GAPI)	VL2F (.M/S)	SPOR (.PERC)	(GRDE, VL2F, SPOR)
CODE (.G/C3)	VL4F (.M/S)	LSN (.SNU)	(GRDE, VL2F, LSN)
LSDU (.SDU)	VL6F (.M/S)	SSN (.SNU)	(GRDE, VL2F, SSN)
BRDU (.SDU)	VL2A (.M/S)	RPOR (.PERC)	(GRDE, VL2F, RPOR)
DENL (.G/C3)			(GRDE, VL4F, SPOR)
DENB (.G/C3)			(GRDE, VL4F, LSN)
DEPO (.PERC)			(GRDE, VL4F, SSN)
ADEN (.G/C3)			...

Figure 1: Possible triple combinations as coordinate axes based on the number and type 161 of well logs.

Since various well log values have different ranges, it is necessary to normalize the values between 0 and 100. For example, the density log ranges between about 1 and 2.5 g/m³ in a coal seam, while the sonic log ranges from 2100 to 2500 m/s. Now the distribution of a proximate parameter in the Cartesian coordinate system is created by the coordinate axes using normalized values of several logs. The modeling method is then selected. If values of the parameter have a normal distribution, it is possible to apply ordinary Kriging. If the data distribution is normalized by applying a logarithmic function (the distribution function of log is normal), the log normal Kriging is used; otherwise the indicator Kriging is employed.

The method is implemented and verified as follows using an example.

Case Study

The well logs and core samples from Hunter Coalfield, Manobalai, are chosen to apply the method. The Hunter Coalfield shown in Figure 2 lies west of the Newcastle Coalfield and east of the Western Coalfield, with northern and southern boundaries defined by geographic features and the western margin by the adjacent Western Coalfield. It occupies an area of 21km2 towards the north-eastern margin of the Sydney Basin and is centred nominally over the catchment of the Hunter River. The coalfield extends for approximately50 km north-west from Cessnock to Muswellbrook and a further 120 km north to Murrurundi [27].

Preparation of data

In 2003, six boreholes were drilled within a distance of 10 km at the area (Figure 3) [28]. The proximate parameters analysis of core samples and well-logging data of boreholes were extracted and, the borehole number 10 (DDH10) was selected as the reference borehole. The well-logging methods that have been utilized in this borehole are summarized in Table 1. The data of all well-logs are available in Wire line log format (LAS1) files. Also, proximate analyses of the core samples from the boreholes, including ash content, moisture, and volatile-matters, on air-dried bases, have been thoroughly provided in the related reports.

In 1990, the Canadian Well Logging Society designed the LAS ASCII-type system for local Canadian markets to standardize the binary format used to digitize well logs. The simplicity and flexibility of the LAS ASCII-type encoding quickly led to its worldwide acceptance and use [29].

noteworthy to mention that the coal samples could be analysed on the 'as received' basis (a.r.), 'air-dried' basis (a.d.b.), 'dry' basis (dry), 'dry ash-free' basis (d.a.f.), and 'dry, mineral matter-free' basis (d.m.m.f.). According to the Borehole completion reports [30], the proximate parameters were analysed on an air-dried basis and that is why in this paper, we ignored the fixed carbon estimation.

The fixed carbon content of coal is the remaining carbon found in the residue, after the volatile-matters has been liberated. Fixed carbon is not determined directly, but is the difference, in an air-dried coal, between the total percentages of the other components including moisture, ash and volatile-matter, and 100%.

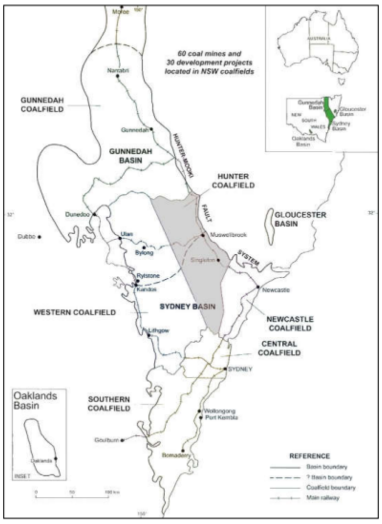

Figure 2: The Sydney-Gunnedah Basin and its recognized coalfields [27].

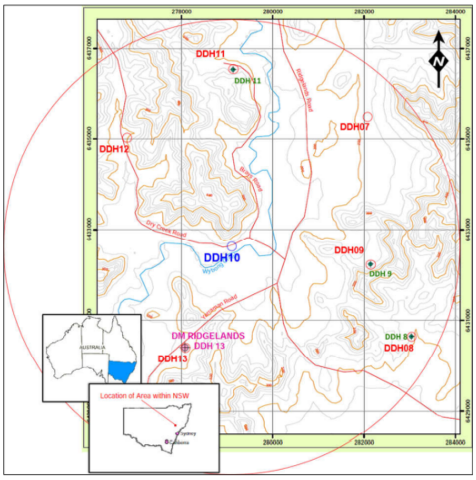

Figure 3: Location of the boreholes and study area within NSW, Australia [30].

The depth of the reference borehole was 383.5 meters. Core sampling has been started from the depth of 170.6 m downwards. There were 53 coal beds, crossed by the core sampling path. Coal beds' depth and the proximate parameters were retrieved from the corresponding reports and summarized in Table 2 [30].

Depending on the coal bed thickness and the speed of well-logging probe, there would be a few values recorded for a single coal bed as the well-logging value. To define a single log value for each of coal beds, the recorded log values versus the layer were simply averaged. For example, the values of GRDE (Gamma from Density Tool) log, CODE (Compensated Density) log, and LSDU (Long Spaced Density) log for coal beds in DDH10, were averaged as given in Table 3. The values of other logs were averaged in a similar manner and defined for the coal beds. So, Table 3 was formed for all 17 well-logs of the reference boreholes.

GAMMA & DENSITY LOGS	GRDE (.GAPI): GAMMA FROM DENSITY TOOL
	CODE (.G/C3): COMPENSATED DENSITY
	LSDU (.SDU): LONG SPACED DENSITY
	BRDU (.SDU): BED RESOLUTION DENSITY
	DENL (.G/C3): DENSITY LONG SPACED
	DENB (.G/C3): DENSITY SHORT SPACED
	DEPO (.PERC): SANDST DENSITY POROSITY
	ADEN (.G/C3): VECTAR PROCESSED DENSITY
VELOCITY LOGS	VL2F (.M/S): 20 CM VELOCITY R1R2
	VL4F (.M/S): 40 CM VELOCITY R2R4
	VL6F (.M/S): 60 CM VELOCITY R1R4
	VL2A (.M/S): 20 CM VELOCITY R3R4
POROSITY LOGS	SPOR (.PERC): SANDST. SONIC POROSITY
	LSN (.SNU): LONG SPACED NEUTRON
	SSN (.SNU): SHORT SPACED NEUTRON
	RPOR (.PERC): SANDST NEUTRON POROSITY
RESISTIVITY LOGS	FE1 (.OHMM): FE RESISTIVITY SHALLOW
	FE2 (.OHMM): FE RESISTIVITY DEEP

Table 1: Well logging methods applied in the study area.

Basin	From	To	Recovery	Relative Density	M	A	VM	FC
Great	170.58	171.23	90.4	1.45	6.4	10	27	56
Great	171.23	172.035	88.9	1.46	6.4	9.7	26	58.3
Great	172.065	172.61	92	1.48	6.1	14	24	55.5
Great	172.695	173.33	95.3	1.46	5.8	16	27	50.8
Great	173.33	174.535	91.6	1.45	5.8	12	27	55.3
Great	174.535	175.415	93.9	1.45	5.8	15	28	51.7
Great	175.415	175.505	90.7	1.66	4.6	37	24	34.8
Great	175.525	175.995	92.6	1.65	4.6	34	20	41
Fassifern	177.07	177.36	90.7	1.91	2.6	57	13	27.1
Fassifern	177.41	178.465	92	1.5	5.8	19	26	49.8
Fassifern	178.585	179.1	90.7	1.54	5.2	25	26	44.7
Fassifern	179.1	179.44	92.8	1.45	6.1	17	29	48.5
Fassifern	179.495	179.71	95.5	1.42	6.2	14	32	48.4
Fassifern	179.71	179.75	92.6	1.83	4.4	50	23	23.4
Fassifern	179.75	180.41	92.4	1.4	6.2	8.8	31	54.4
Fassifern	180.41	181.17	92.2	1.39	6.6	8.7	30	54.7
Fassifern	181.22	181.93	92.7	1.41	6.1	11	29	53.5
Fassifern	181.96	182.6	91.1	1.46	5.8	15	28	51
Fassifern	182.6	182.695	95.4	1.82	4.2	50	22	23.6
Fassifern	182.765	182.97	91.3	1.49	5.8	22	30	43
Fassifern	182.97	183.91	93.3	1.42	5.8	13	28	53.5

Fassifern	183.91	184.26	89.8	1.43	5.7	14	29	50.6
Fassifern	184.26	184.455	95.9	1.52	4.8	26	26	43
Fassifern	184.54	184.78	92.4	1.69	3.6	40	20	36.4

Table 2: Proximate analysis of core samples of the reference borehole (DDH10). Manobolai, Hunter Coalfield, NSW [30].

		GRDE	CODE	LSDU	BRDU
From	To	Ave (.GAPI)	Ave (.G/C3)	Ave (.SDU)	Ave (.SDU)
170.58	171.23	57.45258	1.37545	8695.516	32957.47
171.23	172.035	60.66099	1.40617	8242.501	32472.89
172.065	172.61	124.65	1.55	6049.097	27376.64
172.695	173.33	113.8458	1.50164	6793.877	31466.26
173.33	174.535	196.8511	1.64222	4766.002	23992.7
174.535	175.415	108.8302	1.42797	7872.658	32414.96
175.415	175.505	55.01504	1.37306	8654.34	32630.76
175.525	175.995	54.74489	1.41216	8125.314	32593.23
177.07	177.36	119.6356	1.55667	5775.884	28165.39
177.41	178.465	115.14	1.56	5672.835	28519.96
178.585	179.1	94.45787	1.65319	5041.804	29634.85
179.1	179.44	222.4053	2.07579	1917.729	22776.51
179.495	179.71	124.9443	1.84233	3300.5	26003.03
179.71	179.75	132.9867	1.63833	4742.003	27400.09
179.75	180.41	82.48264	1.49292	6928.439	31550.6
180.41	181.17	227.8225	1.7825	3623.903	22603.02
181.22	181.93	76.22	1.52404	6728.989	31757.32
181.96	182.6	108.2874	1.48571	6964.015	31230.98
182.6	182.695	167.74	1.53667	6068.218	27041.06
182.765	182.97	102.3941	1.44864	7395.172	32710.63
182.97	183.91	70.22	1.36	8658.108	31098.51
183.91	184.26	36.95134	1.34716	9196.861	33125.28

Table 3: Average of some the well-log values, extracted from the LAS log file, borehole number 10, Manobolai, Hunter Coalfield, NSW.

Well logging data were normalized according to the equation below:

$$l_n = 100\,\frac{l-l_{min}}{l_{max}-l_{min}} \qquad (4)$$

Where lmax is the maximum log value in the reference borehole, lmin is the minimum log value in the reference borehole, l is the log value and ln is the normalized log value. Thus the log values are normalized between 0 and 100.

Investigation of data distribution

The probability distribution plot for the parameter was investigated with the aim of decision making for the interpolation method.

For example, the probability distribution plot, and the normalized probability distribution plot of ash content in the reference borehole are presented in figures 4 (a) and (b), respectively.

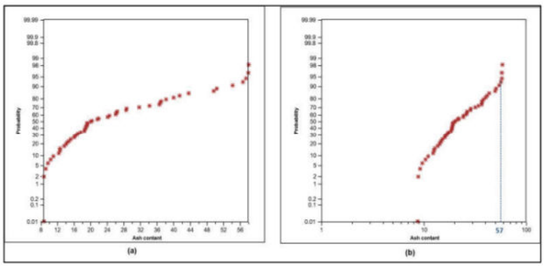

Figure 4: Probability distribution (a) and normalized probability distribution (b) plot for the ash contents obtained from analysis of the core sample taken from the reference borehole.

According to the plot, although two different statistical populations could be distinguished for the ash contents less than 57% (two statistical populations with the ash contents of less than 23% and more than 23%), they were assumed as a single statistical population with a normalized probability distribution due to the proximity of plot slopes corresponding to both statistical populations. So modeling was performed by log-Kriging. According to Figure 4, this assumption did not include ash contents higher than 57%. Therefore, the data of reference borehole used in the modeling were limited to samples with the ash contents of less than 57%.

Modelling

The well logging data that were available in all the boreholes of this case study were the log values listed in Table 1. Since a variety of gamma ray, sonic, and porosity logs were measured in all the boreholes, modeling was carried out in a three-dimensional system where the coordinate axes represented density, sonic, and porosity logs. Since resistivity logs were not recorded in some boreholes, the logs were not applied.

Given the number of logs, it was possible to create 128 triple combinations of gamma-sonic-porosity logs. The variogram and Kriging models were generated for all possible combinations and cross correlation was then performed to find the best model.

For example, in Figure 5, the variogram of ash content distributions is shown for a variety of selected logs as the coordinate axes. The spherical model is acceptable as the variogram model. Modelling was done only for the combinations where the variogram was bounded and it was possible to eliminate the local trend in their variogram by changing the search direction and the angle [31]. Variogram is the tool to study the structure of a regionalized variable and bounded variogram must be achieved for every triple combination, which is used in modelling. Because only stationary regionalized variables have bounded variograms [32,33]. It means the “hypothesis of second order-stationary”; that is a pre-requirement for application of geostatistical techniques, is valid for the models of Figure 6. The Figure 6 shows the log Kriging model for ash content distribution in the coordinate axes defined above. All models were produced in the three-dimensional system, but just the first layer of 3D models was displayed for simplicity. To estimate the ash content using three well logs that contribute to the modeling, the sampling from the model will be adequate. For instance, the model (a) in Figure 6 shows the distribution of ash content values in a 3D system with the axes of Density log (DENB), Sonic log (VL2F), and Porosity log (RPOR). In a borehole lacking the core sampling data, the value of ash content can be extracted from the model by three values of the mentioned logs.

For every Kriging model, the estimated ash content values were cross correlated versus the analysed values. Figure 7 shows the cross correlation results for models illustrated in Figure 6. The most accurate cross correlation was obtained for the model with coordinate axes of LSDU (Long Spaced Density), VL2F (20 Cm Velocity) and LSN (Long Spaced Neutron). Therefore, the model was selected as a criterion for estimating the ash contents using the well logs. The most accurate cross correlation selected based on the average deviation of estimated values from the sampled values. The least deviated estimates resulted from the model of Figure 6(b), as it concluded form the Figure 7(b) (Dev. = 5.5%).

In the boreholes except the reference borehole, the ash content can be extracted from distribution of ash values in the Kriging model with three log values of LSDU, VL2F and LSN axes.

Reliability of method

Consequently, it was initially assumed that data of sampling analysis were not available for boreholes, except for the reference borehole. The well logging data were normalized for other boreholes using the LAS files in accordance with Equation (4) and the ash content was extracted from the model illustrated in Figure 6(b), based on the log values represented on LSDU, VL2F and LSN axes. These values were compared with actual values obtained from the proximate analysis. The average deviation of this estimation in the boreholes was as presented in Table 5. The average deviation of ash content estimation was 23.97% for the seams with the ash content equal or less than 57%. Similarly, Kriging model for distribution of volatile-matters and moisture values were performed. Comparing the estimated and analysed values, the average deviation from analysed values was 8.55% for volatile-matters estimation, and 25.06% for moisture estimation. The results are summarized in Table 4. On the other hand, it is possible to estimate each parameter through the regression equation between the parameter and the log with the highest regression coefficient. The best regressed well-log against ash content of the coal beds in the reference boreholes was DENB (Density Short Spaced) log. The regression equation was as follows:

$$A = 81.197\ DENB - 101.000 \quad (5)$$

The equations for the parameters of volatile-matters and moisture are presented as follows:

$$V = -0.030\ SSN + 84.974 \quad (6)$$

$$M = -5.824\ ADEN + 14.139 \quad (7)$$

Where SSN is the Short Space Neutron log value, and ADEN is the Vectar Processed Density log value. For instance, the ash content, volatile-matters, and moisture content of the first coal bed in DDH10 could be estimated using Equations (5), (6), and (7).

$$A = 81.197 \times 1.353 - 101.000 = 8.860$$

$$V = -0.030 \times 1942.452 + 84.974 = 26.700$$

$$M = -5.824 \times 1.345 + 14.139 = 6.306$$

Theses estimations were implemented for all the coal beds in the boreholes except for the reference bore hole. Comparing the estimated and the proximate analysed values of parameters, showed an average deviation of 20.24% for the volatile-matters, 34.51% for the ash content, and 51.03% for the moisture content. The results are summarized in Table 5. Comparing the contents of Table 4 and Table 5 exhibits an improvement in estimation when the geostatistical estimation method was applied. It means a more accurate estimation, especially for the ash content, has been achieved through application of the geostatistical estimation method.

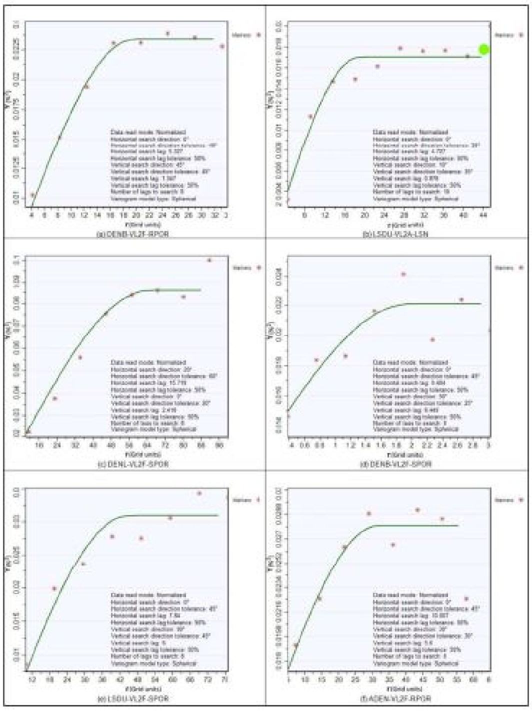

Figure 5: Variogram of ash content distributions for a variety of geophysical well logs, defined as the coordinate axes.

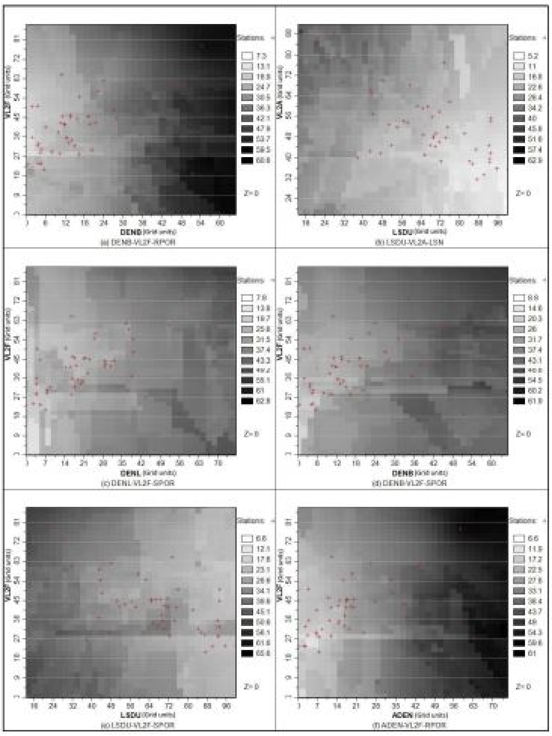

Figure 6: Log-Kriging distribution model for ash content in the coordinate system, with geophysical well logs as the axes.

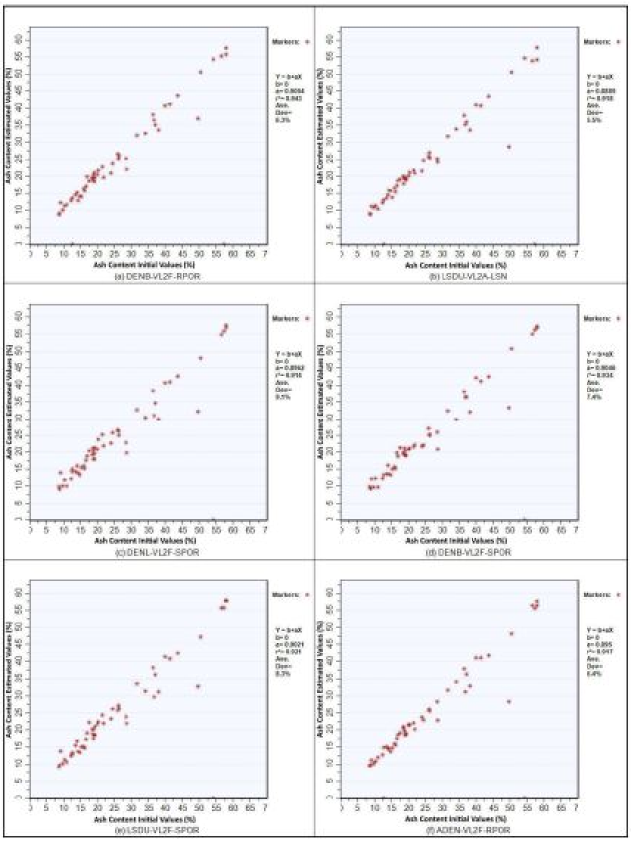

Figure 7: Cross correlation results for models illustrated in Figure6.

Contributed logs	Borehole ID	Deviation %
LSDU-VL2A-LSN	DDH07	24.36
LSDU-VL2A-LSN	DDH08	23.5
LSDU-VL2A-LSN	DDH09	28.8
LSDU-VL2A-LSN	DDH11	22.05
LSDU-VL2A-LSN	DDH12	29.18
LSDU-VL2A-LSN	DDH13	18.88
LSDU-VL2A-LSN	Ave. Deviation	23.97
(a) Average deviation form analysed ash content		
Contributed logs	Borehole ID	Deviation %
ADEN-VL2A-SPOR	DDH07	22.71
ADEN-VL2A-SPOR	DDH08	15.99
ADEN-VL2A-SPOR	DDH09	17.91
ADEN-VL2A-SPOR	DDH11	20.88
ADEN-VL2A-SPOR	DDH12	50.2
ADEN-VL2A-SPOR	DDH13	16.97
ADEN-VL2A-SPOR	Ave. Deviation	25.06
(b) Average deviation form analysed moisture values		
Contributed logs	Borehole ID	Deviation %
ADEN-VL6F-SSN	DDH07	11.67
ADEN-VL6F-SSN	DDH08	4.26
ADEN-VL6F-SSN	DDH09	8.09
ADEN-VL6F-SSN	DDH11	4.64
ADEN-VL6F-SSN	DDH12	9.05
ADEN.VL6F.SSN	DDH13	10.95
ADEN-VL6F-SSN	Ave. Deviation	8.55
(c) Average deviation form analysed volatile matter		

Table 4: Deviation of the estimated proximate parameters incorporating the geostatistical method from the analysed values.

Borehole ID	Deviation (%)
DDH07	25.15
DDH08	30.29
DDH09	51.73
DDH11	23.65
DDH12	47.37
DDH13	28.84
Ave. Deviation	34.51
(a) Average deviation form analysed ash content	
Borehole ID	Deviation (%)
DDH07	36.2
DDH08	24.97
DDH09	60.14

DDH11	27.8
DDH12	118.27
DDH13	38.79
Ave. Deviation	51.03
(b) Average deviation form analysed moisture values	
Borehole ID	Deviation (%)
DDH07	23.25
DDH08	6.61
DDH09	33.19
DDH11	13.17
DDH12	32.24
DDH13	13
Ave. Deviation	20.24
(c) Average deviation form analysed volatile matter	

Table 5: Deviation of the estimated proximate parameters incorporating the regression equation from the analysed values.

Conclusion

Estimating proximate parameters from well logs was performed based on the Kriging interpolation technique. By applying the method and creating the distribution model of the parameter in the defined coordinate system, the Kriging models obtained, and the most accurate model selected through the application of cross correlation. Then, for the logs used as the coordinate axis, the parameter value could be extracted from the distribution model.

In the performed case study, the estimated value of ash content deviation from the proximate analyzed values was up to 23.97% on average. The deviation was 8.55% for the volatile-matters and 25.06% for the moisture while the figures were 34.51%, 20.24%, and 51.03%, respectively for the ash content, volatile matter, and moisture estimated values using the regression equation. It means the Kriging estimated ash content, in compared against those obtained using the regression equations have 10.54% less deviated and it means an improvement in ash content estimation. The increase was 11.69% for volatile matter estimation and 25.97% for moisture estimation.

Conflict of interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. Zhou B, Esterle J (2008) Toward improved coal density estimation from geophysical logs. Explor Geophys 39:124-132.
2. https://raregeologybooks.files.wordpress.com/2014/11/coal-geology.pdf.
3. https://www.osti.gov/etdeweb/biblio/307527.
4. Kowalski JJ, Holter ME (1975) Coal analysis from well logs. Fall meeting of the society of petroleum engineers (AlME), Dallas, Texas.
5. Kayal JR, Das LK (1981) A method of estimating ash contant of coal from combained resisitivity and gamma-ray logs. Geoexploration 19: 193-200.
6. Daniels JJ, Scott JH, Liu J (1983) Estimation of coal quality parameters from geophysical well logs. 24th annual logging symposium, Calgary, Alberta, Canada.
7. Borsaru M, Charbucinski J, Eisler PL, Youl SF (1985) Determination of ash contant in coal by borehole logging in dry boreholes using gamma-gamma methods. Geoexploration 23: 503-518.
8. https://archives.datapages.com/data/meta/rmag/cbm_1988/prensky_op_firstpage.pdf
9. Kayal JR, Christoffel DA (1989) Coal Quality from geophysical logs: Southland lignite region, New Zealand. Petrophysics 30: 343-352.
10. Borsaru M, Jecny Z (1999) In-situ and off-belt bulk analysis for calorific value and partial elemental composition of coal. J Mine Environ 10: 633-647.
11. https://www.osti.gov/etdeweb/biblio/21240465
12. Guo R, Mannhardt K, Kantzas A (2007) Characterizing moisture and gas content of coal by low-field NMR. J Can Pet Technol 46: 49-54.
13. Souza Vd, Salvadoretti P, Costa JFCL, Beretta F, Koppe JC, et al. (2010) Coal quality estimation using the geophysical logging of natural gamma and resistivity. Rev Esc minas 63: 653-660.
14. Calvert S, Percy I, Pritchard T, Morgan N, Graham J, et al. (2011) Coal petrophysical properties for realistic coal gas reservior modelling. In: SPWLA 52nd annual logging symposium, Colorado Springs, Colorado.
15. Webber T, Costa JFCL, Salvadoretti P (2012) Using borehole geophysical data as sof information in indicator kriging for coal quality estimation. Int J Coal Geol 112: 67-75.
16. Ghosh S, Chatterjee R, Paul S, Shanker P (2014) Designing of plug-in for estimation of coal proximate parameters using statistical analysis and coal seam correlation. Fuel 134: 63-73
17. Ghosh S, Chatterjee R, Shanker P, Paul S (2016) Estimation of ash, moisture content and detection of coal lithofacies from well

logs using regression and artificial neural network modelling. Fuel 177: 279-287.

18. Whetton JA, Elkington PAS (2012) Weatherford processing and interpretation of density and neutron logs for the evaluation of coal bed methane reservoirs. SPE/EAGE European Unconventional Resources Conference and Exhibition, Vienna, Austria.
19. Roslin A, Esterle JS (2016) Electrofacies analysis for coal lithotype profiling based on high-resolution wireline log data. Comput Geosci 91: 1-10.
20. https://www.academia.edu/download/67087562/New_Approaches_for_Rock_Strength_Estimat20210505-16164-1lsbm1.pdf.
21. Oyler DC, Mark C, Molinda GM (2010) In situ estimation of roof rock strength using sonic logging. Int J Coal Geol 83:484-490.
22. Das B, Chatterjee R (2017) Wellbore stability analysis and prediction of minimum mud weight for few wells in Krishna-Godavari Basin, India. Int j rock mech min sci 93:30-37.
23. Journel AG, Huijbregts J (1978) Mining geostatistics. (1stedn), Academic Press, New York , San Francisco, London.
24. Ferreirol PJ, VazquezI EV, Vieira SR (2010) Geostatistical analysis of a geochemical dataset. Bragantia 96: 121-129.
25. Kis IM (2016) Comparison of ordinary and universal kriging interpolation techniques on a depth variable (a case of linear spatial trend), case study of the sandrovac field. Min Geol Petrol Col 31: 41-58.
26. https://en.wikipedia.org/wiki/Kriging.
27. https://ro.uow.edu.au/scipapers/733/.
28. https://digsopen.minerals.nsw.gov.au/digsopen/.
29. Robert D, Crangle J (2007) Log ASCII Standard (LAS) files for geophysical wire line well logs and their application to geologic cross sections through the central Appalachian basin. U.S. Geological Survey, Reston, Virginia.
30. https://pubs.usgs.gov/of/2007/1142/.
31. Baroth J, Breysse D, Schoefs F (2013) Construction Reliability: Safety, Variability and Sustainability. (2ndedn), Hardcover Wiley & Sons Ltd.
32. Armstrong M (1998) Basic Linear Geostatistics. (1stedn), Springer Berlin, Heidelberg.
33. Matheron G, Pawlowsky GV, Serra J (2019) Matheron's Theory of Regionalized Variables. (1stedn), Oxford University Press.