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A programming method to estimate proximate parameters of coal beds from well-logging data using a sequential solving of linear equation systems

A. Yusefi and H.R. Ramazi*

Department of Mining and Metallurgy Engineering, Amirkabir University of Technology (Tehran Polytechnic), Tehran, Iran

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Abstract

This paper presents an innovative solution for estimating the proximate parameters of coal beds from the well-logs. To implement the solution, the C# programming language was used. The data from four exploratory boreholes was used in a case study to express the method and determine its accuracy. Then two boreholes were selected as the reference, namely the boreholes with available well-logging results and the proximate analysis data. The values of three well-logs were selected to be implemented in a system of equations that was solved, and the effect of each well-log on the estimated values of the proximate parameter was expressed as a coefficient called the effect factor. The coefficients were incorporated in an empirical relationship between the parameter and the three well-logs. To calculate the coefficients used for the most accurate estimation, a total of 22960 systems of equations were defined and solved for every three logs. As there was the possibility of 560 combinations for selecting three logs from all the available 16 logs, the three equation-three variable systems were solved more than 12 million times. The programming methods were utilized to achieve the final results. The results of each system were tested for deviation of the estimated values of volatile matter, ash, and moisture, and the coefficients of the lowest deviation were accepted to be applied in the relation. Implementing this method for estimating the volatile matter resulted in an average deviation of 10.5%. The corresponding estimated values of the ash and moisture contents were 22% and 14%, respectively.

1. Introduction

In general, well-logging is the application of geophysical methods for exploratory boreholes. Although these methods are more common in oil and gas reservoir exploration, the utilization of some well-logging methods are common in mineral exploration, especially coal exploration. Coal beds, in comparison with other surrounding layers, are lower in gamma radiation and density. Therefore, the well-logging methods are widely used in coal exploration, and are based upon gamma radiation and density measurement, like gamma-gamma method along with the resistivity, sonic, and porosity measurement methods.

Of course, the characteristics of coal beds vary from seam to seam. Even the parameters like moisture, ash content, and volatile matter may vary along a single coal layer extension. These parameters are often reported as the proximate or ultimate analysis. Proximate analysis is a broad one that determines the amount of moisture, volatile matter, fixed carbon, and ash. This analysis is the most fundamental one among all coal analyses, and is of great importance in the practical use of coal [1].

While a difference is expected between the values of well-logs for the coal beds and other layers, a steady and unchangeable log for the coal beds could not be expected. Surely, well-logs vary in coal beds according to the bed characteristics. Therefore, a conclusion for the coal characteristics could be drawn from the coal exploration well-logs. In other words, the proximate parameters of

Corresponding author: ramazi@aut.ac.ir (H.R. Ramazi).

coal beds can be estimated from the geophysical well logs.

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

1. 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 well-logs could demonstrate the sample depth.
2. The results are instantaneous [2].
3. It could sample a much larger volume of the material surrounding the borehole than the core sample, and therefore, provides better sampling statistics [2].
4. The cost of drilling open holes is less than that of the cored holes [2].

The idea of determining the characteristics of coal-beds according to the geophysical well-logs is not a new one. The relationship between the geophysical well-logs and coal-bed characteristics was examined in 1975 [3]. In 1981, a relationship between the two sets of well-logging and analysing data was tried to find [4]. The error factor in determining the coal-bed quality parameters according to the logs has been noticed as well [5]. 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 [6]. During the last decade of the previous century, several related studies have been conducted by the researchers [7-9]. In another research work via ACARP (Australian Coal Industry's Research Program) in 2007 [10], the effective tools and equipment for an accurate estimation of coal parameters according to the well-logs were reviewed. In 2007, the researchers attempted to characterize the moisture and gas contents of coal according to low-field NMR logs [11]. Souza *et al*. considered only the gamma and resistivity logs as the criteria for determining the coal quality parameters [12]. Density logs were applied to coal gas reservoir modelling thorough a case study [13]. Using geophysical well-logs for evaluation of the coal bed methane reservoirs has been studied [14, 15]. Accordingly, a study addressed a plug-in developed for correlation of coal beds based on identification of key beds using the well-logging data [16]. Moreover, the researchers have detected the coal beds and then examined their proximate parameters by a negative exponential function based on the gamma ray log [17]. In another work aimed at estimation of the proximate parameters using the logs, the coal beds were initially separated by the cluster analysis [18]. The petro-physical data in combination with the geochemical one have been used as the entry data of a fuzzy cluster algorithm with the output of rock mass classification [19]. During a recent study, a combination of advanced numerical and statistical methods has been used for interpreting coal lithotypes from geophysical wire-line logs. The study particularly aimed to discriminate between the bright and dull coals at similar densities [20]. Applying the multivariate regression method with implementing neural-fuzzy algorithms for estimating proximate parameters was significantly studied [21]. Finally, determining the rock strength from well-logging measurements is another solution for detecting layers' conjunction and estimating coal layers' characteristics [22, 23], since the mechanical rock properties could be modelled from rock features such as ash content, density, and acoustic velocities based on the well-logging tools [24].

2. Statement of problem

The researchers have focused on the issue of proximate parameter estimation since the last decades of the past century. Although the value and importance of such estimations have always been identified, the errors related to the equipment, limited access to the exploratory information, and lack of advanced software for statistical analysis and modelling were the main restricting factors in the development of research works. From the beginning years of the present decade, and along with developments in methods and equipment of well-logging [25], information technology, more applicable software, and access to large databases via the web, further advanced research works have become possible.

Deviation in the estimated values has often been an important issue for researchers. Also most of the studies were developed using estimations based on a single well-log, whereas considering the impact of the parameters on several logs together would be much more helpful [22, 26, 27]. For example, neutron well-logs are affected by volatile matter, and such logs could be used for the volatile matter value estimation. However, other logs such as the density and sonic logs might be affected by the volatile matter as well [1]. Therefore, using a combination of these logs could result in a more acceptable estimation.

In this paper, with the aim of applying three different logs in estimating the proximate parameters of coal beds and reducing the deviation, the impact of three well-logs on the estimation is presented. In other words, here, we have three well-logs, combined in the form of an empirical relationship. Estimating the parameters using the relationship leads to more accurate results.

3. Methodology

The main purpose of this article is to summarize the impact of three well-logs in estimating the proximate parameters in the form of an empirical relationship. For example, the impacts of the three logs density, neutron, and sonic on the estimation could be represented as follows:

$$P = X_N . N + X_D . D + X_T . T + c \tag{1}$$

where P is the value of the parameters, N is the recorded value in neutron log, D is the recorded value in density log, T is the recorded value of sonic log, and X_N, X_D, and X_T are the coefficients representing the impacts of the neutron, density, and sonic logs on the estimated value of the parameter, respectively. These coefficients are called the effect factors in this paper, where c is a constant, P is commonly expressed in percent, and the unit for log value, depending on the type of log, may be expressed in API units or a conversion to SI units. For calculating the effect factors, a system of equations was formed and solved, as follows:

For a coal bed, with well-logging data and available analysis of the proximate parameters, it was undoubtedly possible to initialize the relationship (1) as an equation with three variables (if c was assumed to be 0) or four variables (where c was not 0). The effect factors were assumed as the variables. If the data was available for at least three coal beds, three of these equations could be expanded, and a system of linear equations with three variables could be summarized. The effect factors could be obtained by solving the system. However, each borehole drilling often crosses several coal beds. Therefore, in a coalfield, if information concerning the proximate parameter analysis and well-logging for a single (or more) borehole(s) was available, the borehole data could be considered as the initial reference for estimation, and for every parameter, some three- or four-variable system of equations would be formed. These boreholes are assumed as the reference boreholes. Thus there would be a system of equations containing three or four variables and a few equations, which are equal to the coal beds in number. A general system of equations for *m* coal beds with 3 well-logs could be written as:

$$\begin{aligned} N_1 x_N + D_1 x_D + T_1 x_T + c_1 &= P_1 \\ N_2 x_N + D_2 x_D + T_2 x_T + c_2 &= P_2 \\ . \quad . \quad . \quad . \quad & . \\ . \quad . \quad . \quad . \quad & . \\ . \quad . \quad . \quad . \quad & . \\ N_m x_N + D_m x_D + T_m x_T + c_m &= P_m \end{aligned} \tag{2}$$

where x_N, x_D, and x_T are the unknowns, and, here, they are the effect factors; N_i, D_i, and T_i are the coefficients of the system, which, here, are the log values for coal beds; and P_1, P_2, …, P_m are the constant terms, where, here, they are the proximate analysed values of a parameter. It is usually expected that the number of equations is much greater than the number of unknowns. Therefore, a definite result for the variables is not expected, although the best-optimized result could be obtained.

The best-optimized results were obtained by sequentially solving the combinations of Equation 1 in the two different cases of c=0 and c≠0. The number of system of equations solved for the best results would be equal to C(n, r):

$$C(n, r) = \frac{n!}{r!(n-r)!} \tag{3}$$

where C(n,r) that is the number of different combinations of r equations can be chosen from a group of n. In this case, the variable r is the number of well-logs contributing in equation (2), and n would be the number of coal layers observed by well-logging.

For the first case, the constant value in the equations is assumed to be zero (c=0) and *r=3*. Then three of the *n* equations would be selected to be solved in a three equation-three unknown system. The system was solved and the results obtained were tested, calculating P_i in the equations, which are different from the three selected ones. Certainly, there are some deviations in the calculated P_i values, in comparison with the main values for P_i. The deviation was recorded as the selected combination deviation. The process of selecting, solving, and deviation recording was repeated, while all the *C(n,3)* combinations of equations were solved against each other in a three equation-three unknown system. Ultimately, the final answer for the equation would be the answer with the least recorded deviation. Thus the best optimized effect factors would be calculated.

The second case was performed in a similar manner but the constant value was entered in the calculations ($c \neq 0$). Therefore, the combinations of four equation-four unknown systems would be solved. The number of combinations to be solved would be $C(n,4)$.

By solving the system of equations and finding the best-optimized results, the effect factors are found to be embedded in relationship (1). An empirical relationship between a parameter and well-logs was then obtained. It is worth mentioning that in the case of the presence of more than three well-logs, a combination of 3 from number of logs would be available, and ultimately, Equation (2) could be created in $C(n_l,3)$ combinations, where n_l is the number of available well-logs.

The relationship could be used for estimating the parameter of coal beds in boreholes, where the core sampling analysis results were not available but well-logging was conducted. Figure 1 shows a flowchart of the above steps.

Also utilizing the relationship for estimation is more accurate than the common estimation methods, which are based upon a correlation equation between the proximate parameters and a specific well-log.

The explained method was programmatically performed and applied in the following case study. Application of the method and also its validation, in addition to deviations in the results, are discussed in the case study as well.

4. Case study

To apply the method, the exploratory data from Hunter Coalfield, near Manobolai area, New South Wales, Australia, was downloaded from the Geological Survey of NSW' database. The Hunter Coalfield shown in Figure 2 lies west of the Newcastle Coalfield and east of the Western Coalfield, with the northern and southern boundaries defined by the geographic features and the western margin by the adjoining Western Coalfield. It occupies an area of 21 km^2 towards the north-eastern margin of the Sydney Basin, and is cantered nominally over the catchment of the Hunter River. The coalfield extends for approximately 50 km north-west from Cessnock to Muswellbrook and a further 120 km north to Murrurundi [28].

There were 15 boreholes that were drilled at the area (Figure 3) in 2003. The proximate parameter analysis of core samples and well-logging data of four boreholes were elicited, and the boreholes numbers 7 and 1 were selected as the reference boreholes. The well-logging methods utilized in these boreholes were Natural Gamma, Long Spaced Density, Short Spaced, Density, Caliper, Multi-Channel Sonic, Neutron, Resistivity, Dip meter, Deviation, and ALT Scanner [29]. The data for all well-logs are available in the Wireline log format (LAS) files. Also the proximate analysis of the core samples from the boreholes including ash content, moisture, and volatile-matter, on air-dried bases is thoroughly provided in the related reports. It is noteworthy to mention that the coal samples could be analysed on the basis of '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 [29], 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 that carbon found in the residue remaining after the volatile matter 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, which are moisture, ash, and volatile matter, and 100% [1].

The depth of the reference boreholes is 410.86 m for borehole number 7 (DDH7) and 212.68 m for borehole number 1 (DHH1). In DDH7, core sampling was started from the depth of 9.20 downwards. The depth for core sampling was 74.20 for the next reference borehole. In summary, there were 42 coal beds crossed by the core sampling path. Coal beds' depth and proximate parameters were retrieved from the corresponding reports [29] and summarized in Table 1.

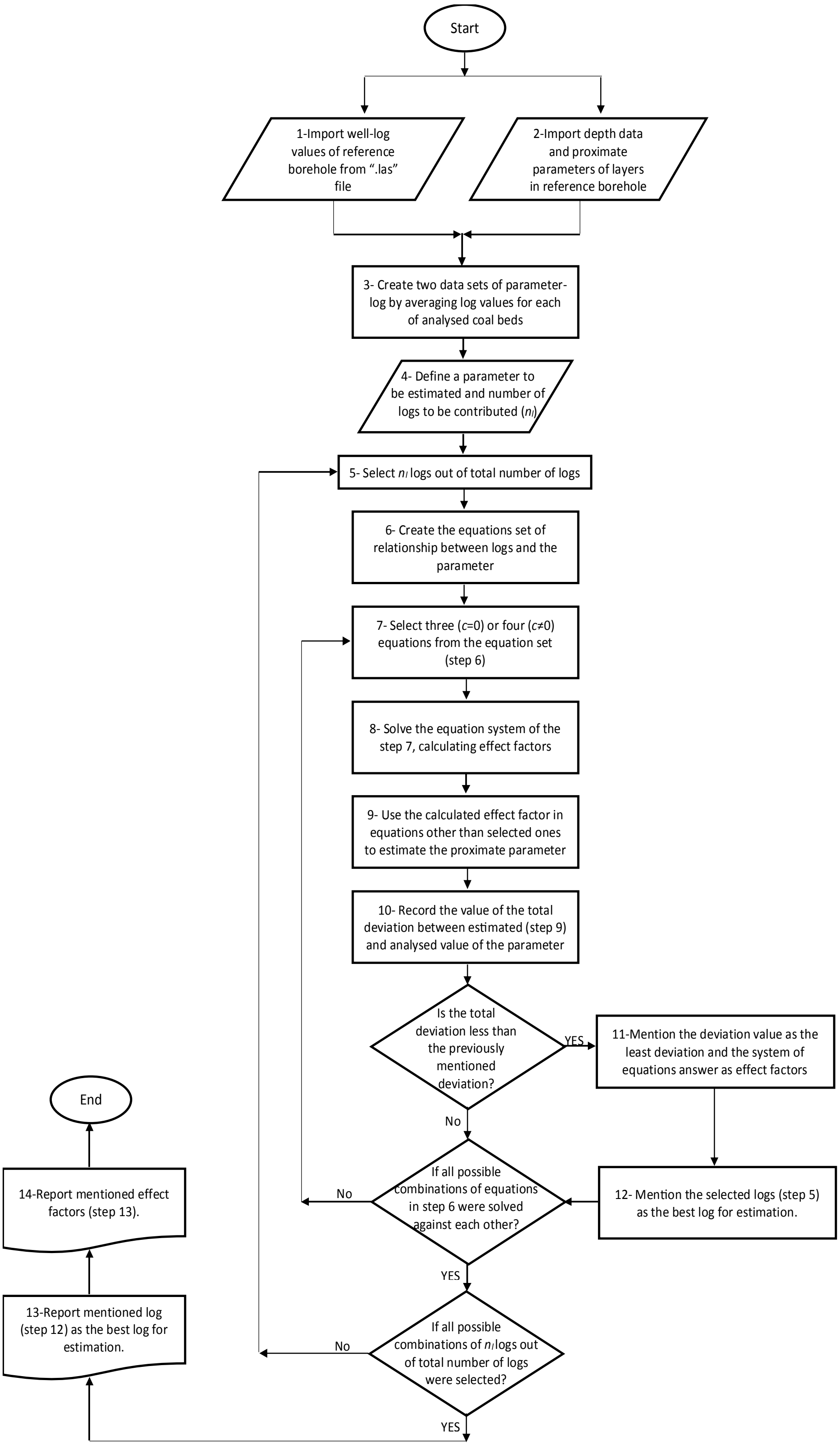

Figure 1. The process flowchart of calculating the effect factor including selecting equations, solving the system of equation, and deviation recording to find the least deviated results. As the effect factors were calculated, it would be possible to use the mentioned logs and the related effect factors for estimating the proximate parameter in a borehole with just the well-logging data available.

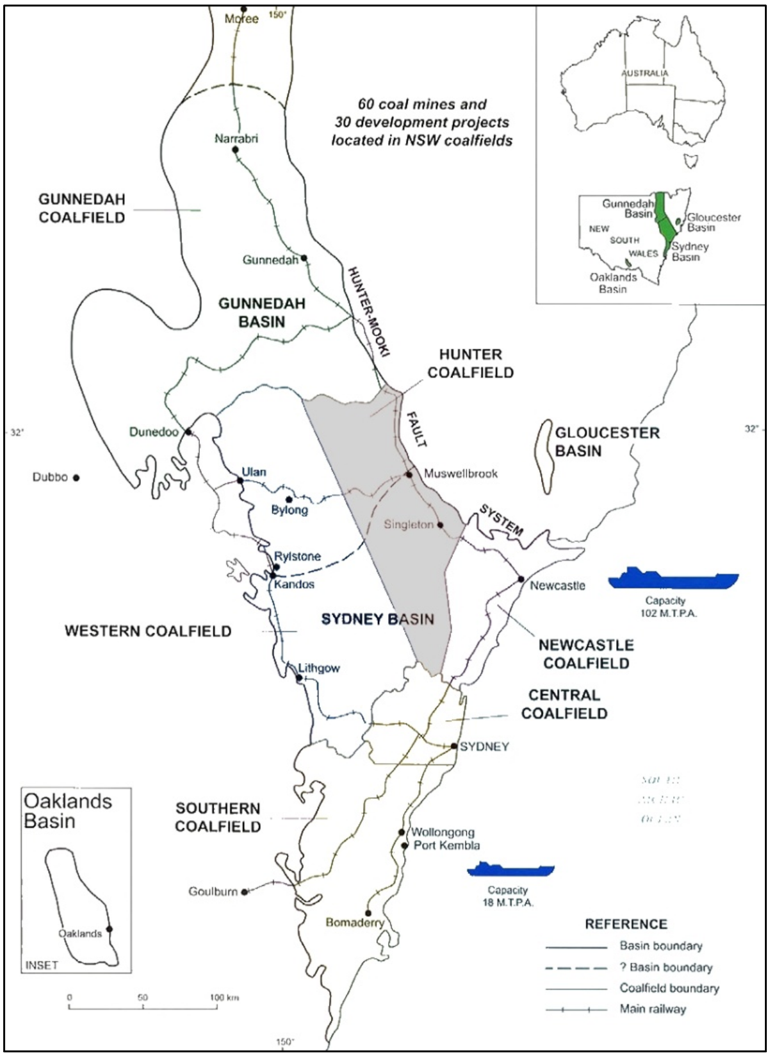

Figure 2. The Sydney-Gunnedah Basin and its recognized coalfields.

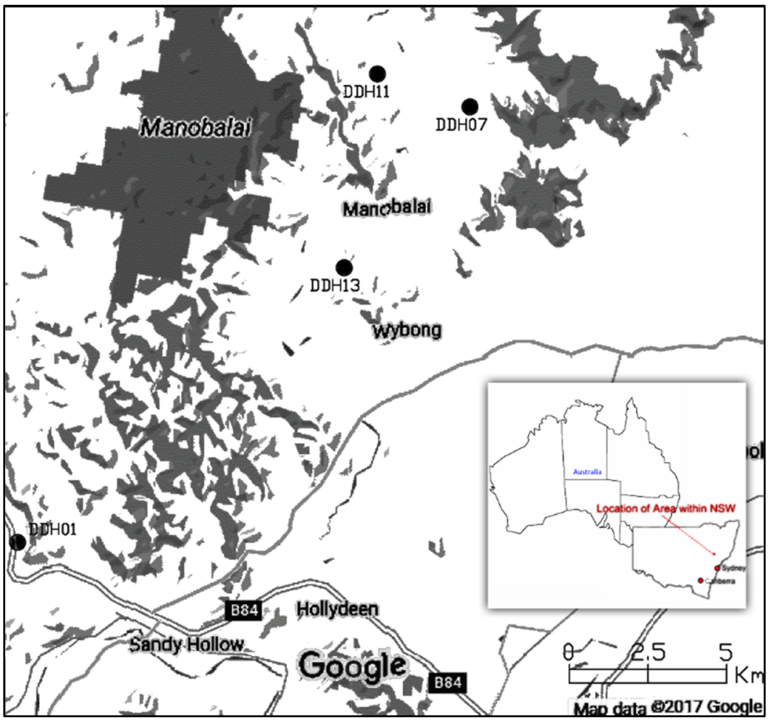

Figure 3. Location of the boreholes and studied area within NSW, Australia.

Table 1. Proximate analysis of core samples, boreholes number 1 and 7. Manobolai, Hunter Coalfield, NSW, where D is Relative Density in g/cm^3, and M, A, VM, FC are relatively moisture, ash content, volatile matter, and fixed carbon of coal bed, in percent [29].

BH	Basin	Depth from	Depth to	D	M	A	VM	FC
DDH1	Fassifern (lower)	135.93	136.025	1.49	5.0	19.1	25.6	50.3
DDH1	Fassifern (lower)	136.055	136.715	1.58	4.4	23.2	30.4	42.0
DDH1	Fassifern (lower)	136.825	137.15	1.44	5.2	15.9	25.4	53.5
DDH1	Fassifern (lower)	137.15	137.25	1.64	6.0	42.2	21.9	29.9
DDH1	Fassifern (lower)	137.31	137.47	1.60	6.1	33.2	25.0	35.7
DDH1	Fassifern (lower)	137.47	138.63	1.52	5.0	21.6	25.3	48.1
DDH1	Fassifern (lower)	138.685	138.935	1.62	4.8	36.8	21.4	37.0
DDH1	?Austra|asian	230.77	231.69	1.56	3.8	35.4	23.8	37.0
DDH1	?Austra|asian	231.825	232.625	1.58	4.0	35.0	24.6	36.4
DDH1	?Montrose	232.94	233.255	1.70	3.2	48.7	22.6	25.5
DDH1	?Montrose	233.325	233.56	1.47	3.9	28.2	30.2	37.7
DDH1	?Montrose	233.625	234.32	1.54	4.0	31.5	26.5	38.0
DDH1	?Montrose	234.32	234.585	1.54	4.5	32.8	27.0	35.7
DDH1	?Montrose	234.585	234.66	1.47	4.4	24.2	28.6	42.8
DDH1	?Montrose	234.66	234.88	1.56	4.4	33.4	26.0	36.2
DDH1	?Montrose	234.88	235.395	1.48	5.0	23.1	28.8	43.1
DDH1	?WaveHi||	235.77	236.035	1.55	4.2	31.4	26.5	37.9
DDH1	?WaveHill	236.035	236.315	1.73	3.6	47.2	21.2	28.0
DDH1	?WaveHi||	236.395	236.64	1.57	4.4	31.7	25.2	38.7
DDH1	?Dud|ey	278.055	278.49	1.51	4.8	24.8	29.6	40.8
DDH1	?Dud|ey	278.49	278.8	1.42	4.4	15.0	34.7	45.9
DDH1	Whybrow	335.71	336.615	1.49	4.2	23.2	30.4	42.2
DDH1	Whybrow	336.93	337.69	1.46	4.6	22.0	29.8	43.6
DDH1	?Wambo	357.405	357.63	1.83	3.4	49.9	19.0	27.7
DDH1	?Wambo	357.63	358.51	1.49	5.4	23.4	29.9	41.3
DDH1	?Wambo	358.6	358.67	1.40	6.0	15.6	29.2	49.2
DDH1	?Wambo	358.67	358.81	1.44	4.6	20.7	31.4	43.3
DDH1	?Whynot	392.985	393.52	1.45	4.0	21.1	31.8	43.1
DDH1	?Whynot	393.52	393.59	1.50	3.8	27.4	30.6	38.2
DDH1	?Whynot	393.59	393.89	1.77	3.8	46.2	24.8	25.2
DDH1	?Whynot	393.89	394.605	1.41	4.0	13.6	31.6	50.8
DDH1	?Whynot	394.605	394.62	1.47	3.8	27.2	31.4	37.6
DDH7	GreatNorthern	91.565	91.935	1.64	7.0	37.8	17.8	37.4
DDH7	GreatNorthern	91.935	92.55	1.41	7.6	11.4	25.6	55.4
DDH7	Fassifern	102.65	103.43	1.56	6.7	29.0	19.8	44.5
DDH7	Fassifern	103.62	104.195	1.50	7.2	24.7	22.8	45.3
DDH7	Fassifern	104.62	104.785	1.60	6.6	30.6	22.6	40.2
DDH7	Fassifern	104.785	105.77	1.45	6.9	17.0	25.0	51.1
DDH7	Fassifern	106.44	106.765	1.51	6.6	23.8	24.6	45.0
DDH7	Fassifern	106.78	107.03	1.50	7.2	22.5	25.3	45.0
DDH7	Fassifern	107.07	107.48	1.51	7.2	23.4	23.3	46.1
DDH7	Fassifern	107.61	108.49	1.78	5.8	48.7	17.8	27.7

Per each well-log, and depending on each coal bed thickness and the speed of well-logging probe, there are a few recorded numbers. To define a single number as the log value for each coal bed, the recorded values were averaged. For example, the values for Gamma from Density Tool log (GRDE), Compensated Density log (CODE), and Long Spaced Density log (LSDU) for each coal bed in DDH7 were averaged, as given in Table 2. The values for the other logs were averaged in a similar manner and defined for coal beds. Thus Table 2 was formed for all 16 well-logs of the reference boreholes and referring to the two tables 1 and 2, three different logs were selected to be implemented in the system of equations. To select the mentioned logs, the programming methods were used. All well-logs, with data recorded as LAS files, were loaded using the program code. The codeselected every three logs to create a three equation-three unknown system. For each created system, there were three unknowns that were the coefficient effects of the well-logs estimated from one of the parameters, for instance, volatile matter. The system coefficients are values of the selected logs, and the answers are the volatile matter values obtained from the proximate analysis results of core samples in the reference boreholes. The code continued running, while all the well-loges were involved with each other in the equations systems.

Table 2. Average of some well-log values, extracted from the LAS log file, borehole number 1. Manobolai, Hunter Coalfield, NSW [30]. GRDE is the values of Gamma from Density Tool log value (in API units), Code is Compensated Density log value (in g/cm^3), and LSDU is Long Spaced Density log value (in API units) for each coal bed in DDH7.

DEPT Min (.M)	DEPT Max (.M)	GRDE Ave (.GAPI)	CODE Ave (.G/C3)	LSDU Ave (.SDU)
135.93	136.02	156.765	2.215	1327.74
136.06	136.71	70.5753	1.63015	5438.213
136.83	137.15	43.85606	1.50364	6763.645
137.15	137.25	92.52455	1.49091	7311.663
137.31	137.47	171.9594	1.58824	5646.534
137.47	138.63	38.06103	1.51094	6837.867
138.69	138.93	104.3548	1.6252	5403.683
230.77	231.69	81.76419	1.66538	5431.884
231.83	232.62	67.511	1.64663	5349.477
232.94	233.25	123.6416	1.9275	3125.909
233.33	233.56	184.3642	1.68	4778.601
233.63	234.32	111.7504	1.55114	6271.732
234.32	234.58	121.9585	1.52222	6522.062
234.59	234.66	107.9088	1.5025	6755.774
234.66	234.88	99.54652	1.50348	6924.638
234.88	235.39	86.92673	1.46269	7523.061
235.77	236.03	169.7411	1.84481	3345.938
236.04	236.31	141.3543	1.65179	5187.326
236.4	236.64	179.3256	1.8244	3394.986
278.06	278.49	98.17205	1.75273	4575.223
278.49	278.8	42.24656	1.44062	7901.028
335.71	336.61	38.58967	1.61934	6080.744
336.93	337.69	82.42987	1.52377	7360.136
357.41	357.63	181.1483	1.82043	4408.986
357.63	358.51	74.01562	1.52225	6671.84
358.6	358.67	127.8175	1.62625	5011.136
358.67	358.81	134.4987	1.61867	5278.985
392.99	393.52	84.85981	1.69963	5151.874
393.52	393.59	49.08375	1.4075	8381.072
393.59	393.89	63.05258	1.52065	6549.265
393.89	394.6	31.43986	1.45931	7415.229
394.61	394.62	39.53	1.425	8412.617
91.57	91.93	97.16757	1.60703	5542.448
91.94	92.55	73.36258	1.49468	7575.163
102.65	103.43	82.24114	1.60937	5680.522
103.62	104.19	87.66138	1.58259	6045.902
104.62	104.78	170.2465	1.64118	5081.558
104.79	105.77	64.39586	1.45535	7802.444
106.44	106.76	60.90636	1.58576	5807.647
106.78	107.03	66.53385	1.49577	6797.174
107.07	107.48	69.43238	1.50167	6919.24
107.61	108.49	99.32067	1.74056	4220.318

For instance, in the step, the three logs LSDU, VL6F, and SPOR were selected by the program code for estimating the volatile matter. The equations of the first and second coal beds in DHH1 were formed as follow:

$$\begin{aligned} &25.6 = 1327.740\, X_{LSDU} + 3229.069\, X_{VL6F} + 30.152 X_{SPOR} + c \\ &30.4 = 5438.213 X_{LSDU} + 2712.780 X_{VL6F} + 44.920 X_{SPOR} + c \\ &\ldots \end{aligned} \tag{4}$$

The same equations were formed for all the 42 coal beds of the reference boreholes, and thus the system of equations with three unknowns and 42 equations (c=0) or four unknowns and 42 equations (c≠0) was formed. Because there were 16 well-logs, recorded as LAS files, it was possible to select three different logs in 560 combinations. In other words, 560 systems of equations could be combined with three variables and 42 equations. Surely, we had to use programming methods for solution of these systems. To solve the system, two cases were considered.

For the first case, the constant value in the equations was assumed to be zero (c=0). Then three of the 42 equations were selected to be solved in a three equation-three unknown system. The process of selecting, solving, and deviation recording was performed, while all the 42 equations were solved against each other in a three equation-three unknown system. The final answer of the equation was the answer with the least deviation. Thus the effect factors were calculated.

The second case was performed in a similar manner with c≠0. Therefore, the four equation-four unknown systems were charged to be solved by the program.

To implement the above-mentioned method, the C# language in Visual Studio was incorporated for writing the code. The Gaussian method was employed to solve the system of equations. While there were 11480 combinations of three equations in all the 42 equations, we solved the three equation-three unknown systems in 22960 iterations for each 560 combinations of the logs. In other words, 12.857.600 systems were solved to find the best estimation of the volatile matter according to the well-logging. This huge amount of calculations was performed using a window based tool, programmed by visual studio. The program completed the computations in approximately 180 s. The output of the program is given in Figure 4.

```
File:QualityDH1_AL.txt LOADED       File: QualityDH07_AL.txt ADDED
--------------------
Logs are used:         CODE Ave (.G/C3), VL6F Ave (.M/S), LSN Ave (.SNU),
To estimate:   VM
--------------------
Factors are:   -19.492299    0.024813        -0.035316        er: 86.006449
--------------------
Filters Applies on Quality Data File:
A < 50
FC > 10
--------------------
Applying factors in the reference borehole(s):
Estimated VM     Analysed VM     Deviation
25.6             25.6            %
30.428           30.4            0.09%
26.314           25.4            3.60%
23.442           21.9            7.04%
21.206           25              15.18%
24.945           25.3            1.40%
23.36            21.4            9.16%
25.096           23.8            5.44%
26.798           24.6            8.94%
19.985           22.6            11.57%
25.25            30.2            16.39%
26.925           26.5            1.60%
27.804           27              2.98%
28.898           28.6            1.04%
29.537           26              13.60%
29.661           28.8            2.99%
24.39            26.5            7.96%
28.29            21.2            33.44%
26.317           25.2            4.43%
26.859           29.6            9.26%
28.469           34.7            17.96%
29.086           30.4            4.32%
28.366           29.8            4.81%
20.816           19              9.56%
29.9             29.9            %
26.166           29.2            10.39%
26.593           31.4            15.31%
28.554           31.8            10.21%
30.46            30.6            0.46%
29.031           24.8            17.06%
29.14            31.6            7.79%
28.901           31.4            7.96%
21.563           17.8            21.14%
25.211           25.6            1.52%
21.218           19.8            7.16%
22.8             22.8            %
20.84            22.6            7.79%
25.029           25              0.11%
21.937           24.6            10.83%
23.203           25.3            8.29%
21.651           23.3            7.08%
20.192           17.8            13.44%
Average Deviation is: 8.08%
```

Figure 4. Output of the program, determining the best well-logs for estimating volatile matter of coal beds in reference boreholes.

The results and the related deviations, obtained by running the program, showed that for estimating the volatile matter, the minimum deviated estimation corresponded to the logs of Compensated Density (CODE), 60 cm Velocity (VL6F), and Long Spaced Neutron (LSN) when applied to the systems. In addition, when the constant value was set to zero (c=0), the results were more accurate. The effect factors of logs of CODE, VL6F, and LSN were calculated as follows:

$X_{CODE} = -19.492299,$

$X_{VL6F} = 0.024813,$

$X_{LSN} = -0.035316,$

$c = 0.0$

Embedding the effect factors in relation 1 resulted in a relation between the well-logs and estimated volatile matter.

$$V = -19.492299\ CODE - 0.024813\ VL6F - 0.035316\ LSN + 0.0 \quad (5)$$

where V is the estimated value of the volatile matter in percent, and the CODE, VL6F, and LSN were log values expressed in API units, which were read from Log ASCII Standard files.
Referring to Figure 4, the amounts of volatile matter of the coal beds in the reference boreholes were estimated using the relationship. Then the estimated values were compared with the values of the proximate analysis. For instance, the volatile matter of the first coal bed in DDH1 was estimated as follows:

$$-19.492299 \times 2.215 - 0.024813 \times 3229.069 - 0.035316 \times 321.267 + 0.0 = 25.601$$

This is an exact estimated value for the first coal bed with a deviation of less than 1% with respect to the analysed value. However, the corresponding estimations of all the other beds were not so accurate. The deviation value was calculated for all the coal beds in the reference boreholes, and the results obtained were summarized in Figure 4. The average deviation was 8.08%.
The above steps were implemented to derive the relationships between the well-logs and ash content as well for moisture of the coal beds.

According to the results obtained, the logs of Long Spaced Density Log (LSDU), Bed Resolution Density (BRDU), and Short Spaced Neutron (SSN) would be the most accurate logs to estimate the ash content. Therefore, the relationship between the ash content and the above three logs were defined as:

$$A = -0.009120\ LSDU - 0.003235\ BRDU - 0.009300\ SSN + 0.0 \quad (6)$$

Similarly, the relationship between moisture and well-logs were derived as follows:

$$M = -0.085245\ CADE + 0.212860\ SPOR + 0.021822\ SSN + 0.0 \quad (7)$$

In Equations 4 and 5, A is the estimated value for the ash content, M is the estimated value of moisture in precent, and LSDU, BRDU, SSN, CADE, and SPOR are the log values in API units, to be read from the Log ASCII Standard files.
The relationships were implemented in the boreholes other than the reference boreholes as well. The boreholes with IDs of DDH11 and DDH13 were selected. As shown in Figure 3, the borehole number 11 was drilled between the reference boreholes. However, borehole number 13 was located away from the reference boreholes. Although the proximate parameters of the coal beds in boreholes 11 and 13 were analysed and reported, to check the accuracy of relationships (6), (7), and (8), it was assumed that the parameters were not analysed. Then we estimated the proximate parameters using the relationship, and finally, the results obtained were compared against the analysed values. The results are summarized in Tables 3 and 4.
A comparison made between the estimated and proximate analysed values of volatile matter in the boreholes revealed an average 10.31% deviationin DDH11 and 10.52% deviationin DDH13. Also the average deviation of ash content estimated values obtained from the analysed values was 25.53% for DDH11 and 20.75% for DDH13. The figures for moisture estimations were 15.70 and 12.80 in boreholes numbers 11 and 13, respectively.

Table 3. Deviation of the estimated proximate parameters using Equations (5), (6), and (7) from the analysed values in borehole number 11.

DDH11								
Volatile Matter%			Ash Content%			Moisture%		
Estimated	Analysed	Deviation	Estimated	Analysed	Deviation	Estimated	Analysed	Deviation
31.06	23.60	31.59%	33.27	15.40	116.04%	3.40	5.30	35.80%
25.43	24.40	4.20%	20.11	15.20	32.31%	5.47	5.60	2.31%
25.78	24.40	5.65%	16.65	17.80	6.48%	5.61	5.30	5.92%
25.96	23.20	11.89%	27.49	27.40	0.34%	4.75	5.00	4.94%
22.31	19.30	15.60%	38.51	41.60	7.43%	4.84	4.20	15.23%
27.45	25.20	8.91%	24.08	20.90	15.20%	4.95	4.80	3.14%
26.00	27.90	6.81%	15.66	14.80	5.79%	5.61	4.70	19.37%
25.92	28.40	8.75%	17.40	13.60	27.91%	5.52	4.80	15.07%
25.69	26.10	1.57%	19.71	15.60	26.36%	5.41	4.50	20.17%
22.61	24.30	6.95%	30.37	49.30	38.41%	5.53	3.40	62.71%
23.75	28.00	15.17%	31.50	24.20	30.16%	5.11	5.20	1.78%
27.37	27.20	0.63%	13.87	14.60	5.03%	5.20	5.20	2.00%
22.33	19.20	16.32%	35.04	44.00	20.36%	4.70	4.00	17.59%
Average Deviation:		**10.31%**	**Average Deviation:**		**25.53%**	**Average Deviation:**		**15.70%**

Table 4. Deviation of the estimated proximate parameters using Equations (5), (6), and (7) from the analysed values in borehole number 13.

DDH13								
Volatile Matter (%)			Ash Content (%)			Moisture (%)		
Estimated	Analysed	Deviation	Estimated	Analysed	Deviation	Estimated	Analysed	Deviation
27.58	24.40	13.01%	16.73	12.60	32.74%	5.19	6.20	16.36%
24.97	22.80	9.50%	26.97	17.40	55.00%	5.25	5.80	9.54%
26.83	26.20	2.40%	15.82	15.60	1.38%	5.50	5.80	5.13%
25.80	24.50	5.29%	10.83	14.00	22.66%	5.91	5.60	5.59%
26.43	26.60	0.65%	13.87	14.20	2.36%	5.57	5.40	3.18%
26.73	23.90	11.85%	24.52	28.60	14.26%	4.89	4.40	11.02%
26.98	20.40	32.24%	31.46	33.00	4.67%	4.30	4.40	2.18%
26.86	23.60	13.79%	24.69	24.90	0.85%	4.77	4.40	8.46%
28.08	22.90	22.61%	23.88	28.60	16.50%	4.41	4.10	7.59%
25.59	25.00	2.36%	20.01	21.00	4.72%	5.52	5.20	6.23%
26.41	28.50	7.33%	19.40	22.40	13.38%	5.37	5.20	3.19%
27.32	29.90	8.63%	9.51	12.00	20.74%	5.60	5.10	9.75%
27.21	29.60	8.08%	12.99	13.40	3.04%	5.36	4.60	16.49%
25.56	23.60	8.29%	17.49	46.70	62.55%	5.40	3.40	58.88%
25.64	27.00	5.04%	24.22	13.40	80.75%	5.26	4.80	9.59%
25.95	28.80	9.89%	32.34	21.30	51.83%	4.68	4.70	0.41%
27.06	27.00	0.22%	13.31	13.40	0.64%	5.38	5.20	3.53%
26.48	21.90	20.93%	26.11	34.00	23.20%	4.54	4.10	10.76%
25.00	21.10	18.46%	39.44	36.90	6.87%	3.84	3.40	12.91%
22.11	22.50	1.75%	42.45	45.00	5.67%	4.37	2.60	67.89%
28.68	32.80	12.56%	8.74	9.80	10.82%	5.09	5.30	3.89%
23.54	20.20	16.53%	35.17	45.00	21.85%	4.25	3.90	8.96%
Average Deviation:		**10.52%**	**Average Deviation:**		**20.75%**	**Average Deviation:**		**12.80%**

On the other hand, it was possible to estimate each parameter through the regression equation between the parameter and the log with the highest regression coefficient. For instance, the best regressed well-log against the volatile matter values of coal beds in the reference boreholes was Sonic Porosity log (SPOR). The regression equation was as follows:

$$V = -0.287\,SPOR + 40.890 \tag{8}$$

The equations for the parameters ash and moisture are as follow:

$$A = 0.091\,GRDE + 19.619 \tag{9}$$

$$M = 0.133\,SPOR - 1.813 \tag{10}$$

where V, A, and M are the estimated values for the volatile matter, ash content, and moisture, respectively. Log values are expressed in API standard units. Volatile matter, ash content, and moisture of the first coal bed in DDH11 could be estimated using Equations (8), (9), and (10).

$$V = -0.287 \times 43.477 + 40.890 = 28.412$$

$$A = 0.091 \times 138.034 + 19.619 = 32.180$$

$$M = 0.133 \times 43.477 - 1.813 = 3.969$$

Theses estimations were implemented for all coal beds in the boreholes numbers 11 and 13. Comparing the estimated and the proximate analysed values of parameters showed an average deviation of 12.34% and 14.33% for the volatile matter, 53.20% and 55.48% for the ash content, and 17.51% and 16.58% for the moisture, respectively, in the boreholes numbers 11 and 13. The results obtained are summarized in Tables 5 and 6. Comparing the contents of Tables 3, 4, 5, and 6 reflects an improvement in estimation when relationships (5), (6), and (7) are applied. When a direct estimation method was incorporated to estimate the proximate parameters of coal beds in borehole number 11, the average deviation from analysed values was 12.34% for volatile matter, 52.23% for ash content, and 17.51% for moisture estimated values, while, in case of using relationships (5), (6), and (7), the respected percentages were 10.31%, 25.53%, and 15.70%, respectively. A similar conclusion would be valid for borehole number 13. It means that a more accurate estimation, especially for ash content, has been achieved through the use of our innovative estimation method.

Table 5. Deviation of the estimated proximate parameters using Equations (8), (9), and (10) from the analysed values in boreholes number 11.

DDH11								
Volatile Matter (%)			Ash Content (%)			Moisture (%)		
Estimated	Analysed	Deviation	Estimated	Analysed	Deviation	Estimated	Analysed	Deviation
28.42	23.60	20.41%	32.15	15.40	108.75%	3.95	5.30	25.47%
24.97	24.40	2.34%	30.31	15.20	99.39%	5.54	5.60	1.04%
24.76	24.40	1.47%	26.10	17.80	46.63%	5.64	5.30	6.41%
25.99	23.20	12.03%	26.38	27.40	3.74%	5.07	5.00	1.40%
25.88	19.30	34.11%	34.37	41.60	17.38%	5.12	4.20	21.92%
25.71	25.20	2.00%	28.05	20.90	34.21%	5.20	4.80	8.40%
24.48	27.90	12.25%	25.36	14.80	71.38%	5.77	4.70	22.72%
24.68	28.40	13.10%	25.18	13.60	85.17%	5.68	4.80	18.25%
24.78	26.10	5.07%	25.76	15.60	65.10%	5.63	4.50	25.16%
25.09	24.30	3.23%	35.77	49.30	27.44%	5.49	3.40	61.44%
25.22	28.00	9.93%	34.77	24.20	43.68%	5.43	5.20	4.36%
24.98	27.20	8.15%	23.94	14.60	63.99%	5.54	5.20	6.46%
26.18	19.20	36.38%	33.13	44.00	24.70%	4.98	4.00	24.54%
Average Deviation		**12.34%**	**Average Deviation**		**53.20%**	**Average Deviation:**		**17.51%**

Table 6. Deviation of the estimated proximate parameters using Equations (8), (9), and (10) from the analysed values in boreholes number 13.

DDH13								
Volatile Matter (%)			Ash Content (%)			Moisture (%)		
Estimated	Analysed	Deviation	Estimated	Analysed	Deviation	Estimated	Analysed	Deviation
25.68	24.40	5.25%	25.99	12.60	106.24%	5.21	6.20	15.91%
25.66	22.80	12.53%	33.73	17.40	93.84%	5.23	5.80	9.91%
24.91	26.20	4.93%	30.52	15.60	95.62%	5.57	5.80	3.96%
24.26	24.50	0.97%	24.80	14.00	77.14%	5.87	5.60	4.80%
24.32	26.60	8.56%	24.18	14.20	70.28%	5.84	5.40	8.18%
25.88	23.90	8.28%	30.55	28.60	6.82%	5.12	4.40	16.41%
27.39	20.40	34.24%	27.29	33.00	17.29%	4.43	4.40	0.60%
26.34	23.60	11.59%	28.56	24.90	14.70%	4.91	4.40	11.63%
26.55	22.90	15.95%	26.62	28.60	6.91%	4.81	4.10	17.35%
25.09	25.00	0.36%	27.72	21.00	32.01%	5.49	5.20	5.52%
24.95	28.50	12.44%	28.68	22.40	28.05%	5.55	5.20	6.73%
24.55	29.90	17.89%	24.67	12.00	105.61%	5.74	5.10	12.48%
24.77	29.60	16.32%	24.62	13.40	83.76%	5.64	4.60	22.49%
24.72	23.60	4.75%	23.95	46.70	48.72%	5.66	3.40	66.38%
24.95	27.00	7.59%	27.37	13.40	104.22%	5.55	4.80	15.65%
25.63	28.80	11.00%	29.47	21.30	38.37%	5.24	4.70	11.42%
24.88	27.00	7.87%	23.73	13.40	77.08%	5.59	5.20	7.42%
26.46	21.90	20.81%	30.78	34.00	9.47%	4.86	4.10	18.42%
28.16	21.10	33.46%	31.43	36.90	14.82%	4.07	3.40	19.67%
26.95	22.50	19.76%	34.66	45.00	22.98%	4.63	2.60	78.05%
25.17	32.80	23.25%	23.17	9.80	136.46%	5.45	5.30	2.80%
27.76	20.20	37.42%	31.48	45.00	30.05%	4.25	3.90	9.07%
Average Deviation:		**14.33%**	**Average Deviation:**		**55.48%**	**Average Deviation:**		**16.58%**

The contents of Tables 3 to 6 are summarized in Figures 5, 6, and 7. A higher level of deviations in volatile matter estimation could be concluded from Figure 5. In this figure, the horizontal axis presents the analysed values for volatile matter of boreholes 11 and 13, and the vertical axis values are the deviations. The triangle markers represent deviation values of estimation of volatile matter using equations (8), (9), and (10), while the star markers are the representatives of the deviation for estimations using Equations (5), (6), and (7). The solid line and dotted line are an indicator of the average level of deviation. As it could be concluded from the figure, less deviations for estimation using Equations (5), (6), and (7) were achieved. The same conclusion can be drawn for Figures 6 and 7. Figure 6 shows deviation levels of the methods for ash content estimation and Figure 7 presents the deviations for moisture.

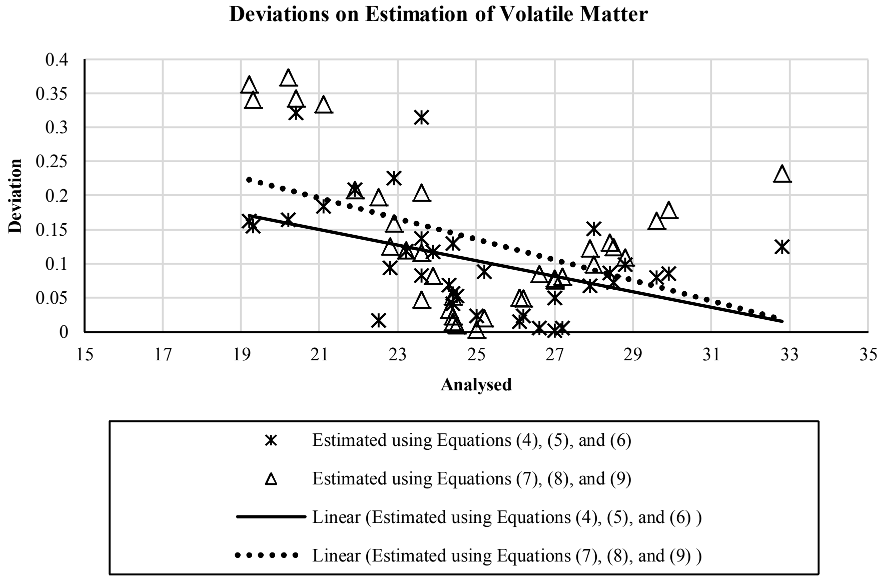

Figure 5. Deviation of the estimated volatile matter from the analysed values using Equations (5), (6), and (7) (star markers and solid line) *vs.* the deviations estimation using Equations (8), (9), and (10) (triangle marker and dotted line) in boreholes numbers 11 and 13.

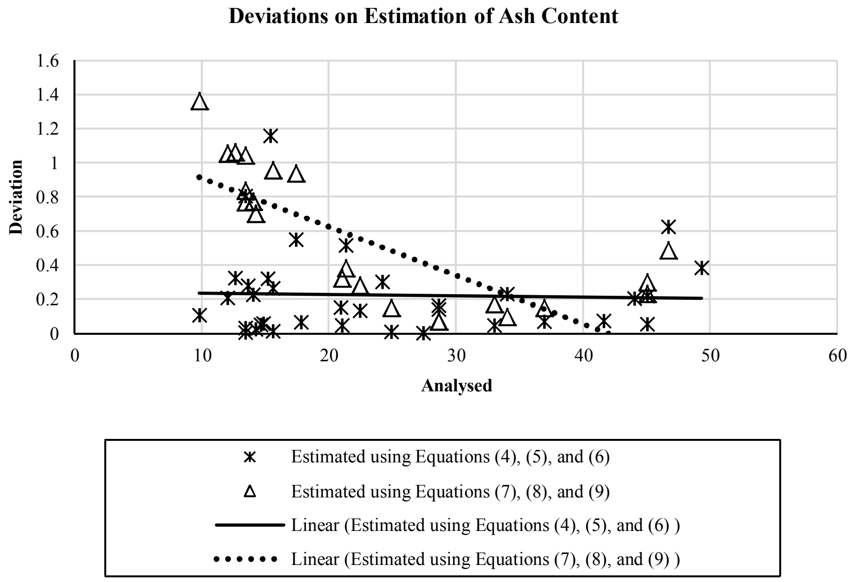

Figure 6. Deviation of the estimated ash content from the analysed values using Equations (5), (6), and (7) (star markers and solid line) *vs.* the deviation estimation using Equations (8), (9), and (10) (triangle marker and dotted line) in boreholes numbers 11 and 13.

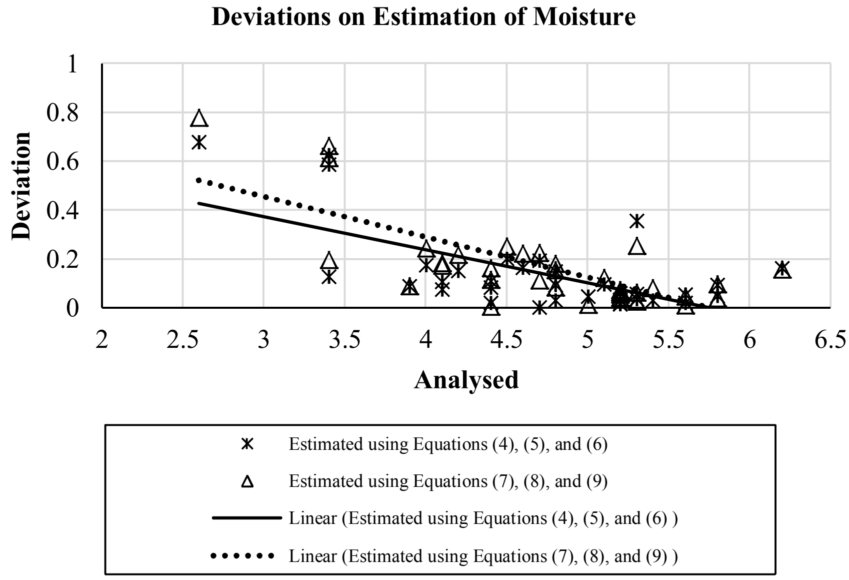

Figure 7. Deviation of the estimated moisture from the analysed values using Equations (5), (6), and (7) (star markers and solid line) *vs.* the deviations estimation using Equations (8), (9), and (10) (triangle marker and dotted line) in boreholes numbers 11 and 13.

5. Conclusions

What can be concluded from this work can be summarized as follows:

1. Estimating the proximate parameters was performed using a new method based on the sequential solution for the systems of equations. We performed a case study in this work to support our method.
2. For each one of the parameters, by applying the method through solving 12.857.600 systems of equations, the most accurate relationship was obtained to express the impact of each log on the estimated parameter.
3. Therefore, the empirical relationships were developed in the form of:

$$V = -19.492299\,CODE - 0.024813\,VL6F - 0.035316\,LSN,$$
$$A = -0.009120\,LSDU - 0.003235\,BRDU - 0.009300\,SSN,$$
$$M = -0.085245\,CADE + 0.212860\,SPOR + 0.021822\,SSN,$$

for estimating the volatile matter, ash content, and moisture, respectively.

4. In the performed case study, the estimated value of volatile matter deviated from the proximate analysis values up to 10.52% on average. This value was 25.55% for the ash content and 15.70% for the moisture. The results were more accurate than those obtained using the regression equations for the estimation.
5. From the case study, the improvement in estimating the deviations, especially for the ash estimation, was concluded.

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یک روش برنامه‌نویسی برای برآورد ویژگی‌های کیفی لایه‌های زغال‌سنگ با استفاده از داده‌های چاه پیمایی و حل متوالی دستگاه‌های معادلات خطی

امیر یوسفی و حمیدرضا رمضی*

دانشکده مهندسی معدن و متالورژی، دانشگاه صنعتی امیرکبیر، ایران

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* نویسنده مسئول مکاتبات: ramazi@aut.ac.ir

چکیده:

این پژوهش یک راه‌حل نوآورانه برای برآورد ویژگی‌های کیفی لایه‌های زغال‌سنگ از نمودارهای چاه پیمایی ارائه می‌دهد. برای اجرای این راه‌حل، زبان برنامه نویسی C# به کار گرفته شد و طی یک مطالعه موردی داده‌های چهار گمانه اکتشافی برای بیان روش و بررسی دقت آن مورد استفاده قرار گرفت. ابتدا دو گمانه به عنوان مرجع؛ یعنی گمانه‌هایی که داده‌های چاه پیمایی و نتایج آنالیز ویژگی‌های کیفی آن‌ها در دسترس است، انتخاب و مقادیر سه نمودار برای ایجاد یک دستگاه معادلات به کار گرفته شد. با حل دستگاه معادلات، اثر هر نمودار بر روی مقادیر برآوردی هر ویژگی کیفی با عنوان ضریب تأثیر بیان شد. این ضریب‌ها در کنار مقادیر سه نمودار چاه پیمایی یک رابطه تجربی برای برآورد هر ویژگی ایجاد کردند. برای محاسبه ضریب‌های تأثیر با دقیق‌ترین برآورد، در مجموع ۲۲۹۶۰ مورد دستگاه معادلات برای هر سه نمودار چاه پیمایی تعریف و حل شده است. از آنجایی که امکان انتخاب ۵۶۰ ترکیب سه‌تایی از مجموعاً ۱۶ نمودار چاه پیمایی وجود داشت، بیش از ۱۲ میلیون دستگاه سه معادله- سه مجهولی ایجاد و حل شد که روش‌های برنامه‌نویسی برای دست‌یابی به نتیجه نهایی استفاده شد. با حل هر دستگاه و برآورد هر ویژگی با استفاده از نتایج و سپس مقایسه مقدار آزمایشگاهی مواد فرار، خاکستر و رطوبت با مقادیر برآورد شده، نتایجی که برآوردی با کمترین انحراف از مقدار آزمایشگاهی را داشتند به عنوان ضریب‌های تأثیر پذیرفته شد. پیاده‌سازی این روش برای برآورد مواد فرار با انحراف ۱۰/۵٪ همراه بود. انحراف‌های مربوط به برآورد مقدار خاکستر و رطوبت به ترتیب ۲۲ و ۱۴ درصد بود.

کلمات کلیدی: زغال‌سنگ، چاه پیمایی، ویژگی‌های کیفی، ضریب تأثیر، دستگاه معادلات.