Coal Velocity and Proximate Analysis Relationship Using Multiple Linear Regression

S Erfani¹, FM Siregar¹, A Zaenudin¹, Rustadi¹, IBS Yogi¹ and RC Wibowo¹*

¹ Department of Geophysical Engineering, Faculty of Engineering, Universitas Lampung, Jalan Prof. Dr. Soemantri Brodjonegoro No. 1 Bandar Lampung 35145, Indonesia

*Email: rahmat.caturwibowo@eng.unila.ac.id

Abstract. Coal properties such a velocity (Vp) is important to build a lateral distribution of coal seam using seismic data. The experimental determination of velocity analysis is sophisticated, long time consumed, and expensive, on the contrary, statistical approach such as linear regression can be run rapidly. The two main objectives of the study were to develop models for coal velocity using well log data variables (density and natural Gamma-Ray) and found the relationship between velocity with proximate analysis results. Multiple linear regression (MLR) methods were applied to estimate relationship between Vp estimated and proximate analysis. By conducting cross-validation, the prediction analysis of the models has been tested by using R^2 . The result showed that between Vp estimated versus Vp log have R^2 0.80 and Vp estimated versus proximate analysis that reflected have R^2 of 0.52. The main merit of the correlations is the ability to estimate the relationship between Vp and proximate analysis, then applied that correlation to distributed in seismic volume to obtained coal seam characteristic.

Keywords: velocity, coal, multiple linear regression, proximate, prediction

1. Introduction

The use of geophysical parameters for exploration of coal basins and in delineating coal seams and geological structures that affect coal deposits is now widely practiced. Since the 1973 oil crisis, the use of geophysical methods to identify coal deposits has increased by estimating coal targets that have economic value [1]. Several techniques have been used in oil and gas exploration and adapted for coal exploration purposes. This study uses an application of the geophysical method, namely geophysical logging to determine the relationship between its characteristics and the proximate value of the coal seam. Coal as a lithology responds well to most geophysical method in that its physical properties contrast with those of other lithologies commonly found in coal-bearing sequences. Coal has in general a lower density, a lower seismic velocity, a lower magnetic susceptibility, a higher electrical resistivity, and low radioactivity compared with surrounding rocks in typical coal-bearing sequences [1]. Density measurements of rocks are not usually measured in situ, but in the laboratory on some small outcrop or drill core samples. Previous research was conducted by Singh and Dubey (2000) [2] where the value of the P wave (P wave) was used to determine the effect of minerals from sandstones where the higher the P-wave, the values of uniaxial compressive strength (UCS), Young's Modulus (E) and density as well. high. However, the value of P-wave velocity (Vp) is inversely proportional. In the

research that has been carried out, taking one of the equations is looking for the Vp value to be used in estimating the relationship with proximate analyses. This research is expected to make an approach to predict the quality of the distribution of coal seams in a coal field.

Geophysical logging is the measurement of the variation with depth of particular physical properties of surrounding rocks with geophysical measuring tools (sondes) located in boreholes. Measurements are made by lowering a sonde attached to the end of a cable to the bottom of the borehole, and then raising the sonde back out of the borehole at a constant rate to record the geology. In coal exploration, density logs are useful in principle to identify coal, because coal has a lower density value compared to other lithologies such as shale and sandstones [3].

2. Method

One of the methods that can be applied in predicting the distribution of coal quality is statistical approaches. This approach has been carried out by many researchers, one of them is Singh and Dubey (2000)[2], where they conducted experiments by calculating the value of the P wave which is used to determine the effect of minerals from sandstones where the higher the P-wave, the uniaxial strength values. compressive (UCS), Young's modulus (E). From some of the resulting equations, this study refers to the research that has been done by taking one of the equations, namely looking for the value of Vp. Where the empirical equation given is:

$$Vp = 0,0009d^{1,0104}$$
(1)

The Vp value of the density log data is based on the results of the well log measurement to find the Vp value from the sonic log based on multiple regressions and will be correlated with the sonic log of the well log results. Vp values are correlated with proximate data to determine the relationship between these values and existing concepts. So that the empirical formula given can be used to determine the quality distribution of the wells that have been measured (table 1).

In the regression calculations carried out sequentially is to find the correlation value between the Sonic logs calculated from the empirical formula with the Sonic well log (Sonic vs Sonic) to validate the Sonic logs calculated, then do the correlation between the Sonic logs calculated from the proximate data, namely Sonic. vs Ash, Sonic vs Inherent Moisture, Sonic vs Volatile Matter and Sonic vs Fixed Carbon.

2.1. Calculated Vp estimate vs Vp well log

Based on the calculation, it is obtained a very good relationship between the two regressed variables, which indicates that the two variables have a directly proportional relationship. This means that the sonic calculation results are as good as the well log results with a correlation degree of 80%.



Figure 1. Relation of Vp estimated vs Vp well log.										
. Coal data (velocity, density, and proximate analysis) were used in this study										
Sample	Density	Density	Vp	Vp	Ash		VM	FC		
Number	core (g/cm^3)	(g/cm)	(m /s)	(m /s)	(%)	(%)	(%)	(%)		
1	1,2	1,30	0,00050	0,0012	2,6	14,4	39,4	45,		
2	1,2	1,40	0,00050	0,0013	2,6	14,8	39,8	46,		
3	1,17	1,29	0,00050	0,0012	1,3	13,8	39,4	42,		
4	1,23	1,33	0,00050	0,0012	5,0	13,4	41,9	43,		
5	1,25	1,28	0,00050	0,0012	9,8	12,3	40,6	36,		
6	1,18	1,27	0,00050	0,0011	2,9	12,6	40	46,		
7	1,18	1,25	0,00050	0,0011	3,2	13,0	42,6	43,		
8	1,21	1,33	0,00050	0,0012	3,8	11,8	41,2	43,		
9	1,21	1,31	0,00050	0,0012	3,4	10,2	38,8	32,		
10	1,26	1,30	0,00050	0,0012	6,6	11,6	39,8	43,		
11	1,24	1,29	0,00050	0,0012	6,6	7,7	41,1	41,		
12	1,29	1,28	0,00050	0,0012	14,3	8,2	43,6	41,		
13	1,21	1,27	0,00050	0,0011	2,3	10,8	43,6	38,		
14	1,27	1,24	0,00050	0,0011	2,1	11,4	40,7	37,		
15	1,24	1,24	0,00050	0,0011	3,8	11,5	41,6	42,		
16	1,3	1,25	0,00050	0,0011	9,3	9,0	42	41,		
17	1,28	1,50	0,00052	0,0014	7,7	15,48	39,2	33,9		
18	1,32	1,36	0,00050	0,0012	2,9	14,42	28,36	39,		
19	1,46	1,45	0,00051	0,0013	1,4	15,98	39,04	37,2		
20	1,28	1,43	0,00051	0,0013	3,4	16,34	39,18	39,		
21	1,3	1,35	0,00050	0,0012	4,6	16,4	38,74	41,4		

2.2. Ash vs Vp estimate

Ash is a residual material that remains during the coal combustion process with specific conditions where the main elements are oxides and sulphates. Based on the calculation results, the relationship between Ash vs Vp is inversely proportional, which means it explains that the higher the Ash content, the lower the velocity value and vice versa. This is not in accordance with the concept, the higher the value of ash content, the higher the Vp response. An example is lignite coal which has a high ash content value which tends to have a high sonic response as well when compared to the Vp value of anthracite coal.



2.3. Inherent Moisture vs Vp estimate

Inherent Moisture (IM) is the amount of water contained in coal micropores, in other words, the value of IM is not affected by the amount of external water such as formation water. IM values generally get lower as coal ranks rise. The IM value should be directly proportional to the Sonic value, namely the higher the IM value, the higher the Sonic value.



2.4. Volatile Matter Vs Vp estimate

Volatile matter, as determined by standard test methods (i.e., ASTM D-3175; ISO 562), is the percentage of volatile product / material, i.e. water vapor that is released during the coal heating process. The higher the Volatile value, the higher the product / material content in a coal sample. Sonic is directly proportional to the Volatile Matter value, the higher the Sonic response, the higher the VM value should be.



2.5. Fixed Carbon vs Vp estimate

Fixed carbon is the remaining material after determining the test results of measurements of moisture, volatile matter, and ash [4]. The higher the coal rank, the higher the Fixed Carbon value and the lower Sonic log response. The results of the calculations show conformity to the concept where the correlation is inversely proportional.

3. Results and Discussion

The results of multiple regression analysis with the sonic value input data as the dependent variable (y) with proximate values such as ash, inherent moisture, volatile matter and fixed carbon as the independent variable (x). The result of the correlation degree R^2 is 0.523 or 52.3%, where it can be said that the relationship between sonic responses to proximate values has a strong enough relationship and influences each other. The standard error of 0.00000062 indicates that the average data observed is very good, it is close to the regression line. The P-value obtained from the analysis shows that the sonic variable (intercept = 0.00) and ($x_2 = 0.00$) shows a variable that is statistically very significant. This variable is the content of Inherent Moisture (IM) which statistically has a significant relationship with sonic value. Meanwhile, the proximate variables ash content, volatile matter and fixed carbon have a p-value of $x_1 = 0.005$, $x_3 = 0.81$ and $x_4 = 0.17$ which indicates that these variables are not statistically significant.



Table 2. Multiple linear regression analysis result between velocity (Vp estimated) and proximate analysis.

	Coefficients	Standard error	P-value	\mathbf{R}^2
Intercept	0,001125903	0,000275068	0,00	
X 1	1,0494E-05	4,983E-06	0,05	
X 2	2,30685E-05	6,6799E-06	0,00	0,52
X 3	-1,25975E-06	5,17764E-06	0,81	
X 4	-5,408E-06	3,72869E-06	0,16	

4. Conclusions

The calculation results show that the empirical formula is sufficiently feasible to apply to coal seams. There are two correlation calculations in accordance with the concept of coal, namely the correlation between the Vp calculated from the empirical formula with the Vp log with a correlation degree of 0.80 indicates that Vp log computation with Vp log has almost no difference if applied especially if there is no log Vp data available, we can approach to calculate Vp by ourselves. The multiple linear regression analysis correlation is 0.52 (50%), that multiple regression analysis can be used as an alternative to log density in interpreting coal quality. It is hoped that the relationship between the results of this approach can be applied to other cases that have a lot of data, so as to estimate the distribution of coal quality. So it can be concluded that the log velocity value can be used for the distribution of quality properties in the coal seam.

5. References

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