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Development of Correlation Between GCV and Proximate Analysis of Indigenous Coals

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Abstract

Higher heating value (HHV) is very important for quality of coal when used as a fuel. It is often used for estimating the efficiency of treatment and other beneficiation methods and for research purpose Although it is a costly process and requires special equipment and experts to operate. Whereas proximate analysis data can be obtained easily using an ordinary muffle furnace Therefore, to simplify the task and to reduce the cost of analysis many correlations were developed for determining HHV from proximate analysis of coal. In the present work, an effort has been made to develop a correlation based on proximate analyses data for calculating HHV of coal (air-dried basis). The models presented here is established using analyses of 50 samples of indigenous coal and its importance lies in role of all the major variables affecting the HHV. The developed models appear to be better than the existing models. Heating values of basic types of indigenous coal samples were measured and calculated using empirical formulae and results were compared. Remarkable differences were observed in heating value of fifty samples of indigenous coal analyzed. It is determined that further study of these other types is merited for better and more economical utilization of the coal. A significant correlation was also observed between the Heating values proximate contents of the coal.

***Keywords**: Heating Value, Coal, Correlation.*

1 Introduction:

Coal is a dark brown to black graphite like material which is present naturally and it can be used as fuel, formed from the fossilized plants and composed of unstructured carbon forms with different organic and some inorganic compounds during coalification The first coal age which spanned 290 million to 360 million years ago, the formation of coal began during the Carboniferous Period There are different ranks of coal according to the age and the process of formation of coal, including anthracite, bituminous, sub bituminous, and lignite. Anthracite is types of coal which contain the highest carbon contents. Its carbon content varies between 86 to 98 percent. This type of coal which is used domestically produces nearly 15,000 Btu's per pound (a Btu, or British thermal unit, is the amount of heat needed to raise the temperature of one pound of water one degree Fahrenheit). The very type of coal is used in steel industry and power generation. Carbon contents in Bituminous coal ranges from 45 to 86 percent and a heat value of 10,500 to 15,500 Btu's per pound. Sub bituminous coal in which carbon contents ranges from 35 to 45 percent ranks just

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below bituminous coal. The heating value of sub bituminous coal is between 8,300 and 13,000 Btu's per pound. Lignite contains 25 to 35 percent carbon content. Lignite is also used to generate electricity. Sometimes lignite is known as brown coal because of its brown color. The heating value of lignite ranges between 4,000 and 8,300 Btu's per pound

Pakistan is moving towards the large scale use of coal today because huge coal deposits have been found in Pakistan. The Thar coal deposit in Sindh is one of the largest in the world. It contains of 175 billion tons of coal in four sections. Punjab has about 600 million tons of coal deposits. The Salt Range alone has about 500 million tons of coal that can be exploited and used as an energy resource economically. Beside Thar, there are seven other coal fields in Sindh; two of them are developed while the others are un-developed including Thar. KPK (Hangu and Cherat) and Azad Kashmir (Kotli) are also among the developed coal fields. Balochistan has more than ten developed coal fields contributing a major part of coal production in Pakistan. Germany has been developed a process for the up gradation of the Kalabagh iron ore, using indigenous coal of Makarwal. Coal is the best future energy resource for Pakistan. The most important uses of coal are in steel production, cement manufacturing, electricity generation and production of different chemicals and manufacture of gaseous and liquid fuels. Coking coal also known as metallurgical coal is mainly used in steel

2. Production:

2.1 Heating Value

Heating value of coal is the heat produced by combustion of a unit quantity of coal in a bomb calorimeter with oxygen under a specified set of conditions prescribed by standard test like (ASTM D-121; ASTM D-2015; ASTM D-3286; ISO 1928) [1-7]. The heating value of coal is neither the part of proximate analysis nor part of ultimate analysis it is one of many physical properties of coal. It is often found in the various sections that deal with the physical properties. The heating Value varies on the coalification, geographical age, ranking and location of the coal mines. The heating value is expressed in two different ways on account of moisture present in the coal. Heating value usually expressed as higher heating value (HHV) or gross calorific value (GCV) and lower heating value (LHV) or net calorific value (NCV). Coal contains moisture as an essential component so; difference between both these heating values is the latent heat of condensation of water vapors produced during combustion process. When coal burns the moisture in coal evaporates taking away some heat of combustion which is not available for our use. The higher calorific value presumes that all the vapors produced during combustion process are fully condensed and the lower heating value presumes that the water is removed with the combustion products without being fully condensed. When we say Higher Heating Value or Gross Calorific Value it is the total heat released when burning the coal. When we say Lower Heating Value or Net Calorific Value it is the heat energy available after reducing the loss due to moisture. Coal with greater percentage of volatile matter and fix carbon produces more heating value on combustion as they are the combustible constituents of coal and greater percentage of non-combustibles (moisture and mineral matter) contents lowers the heating value. In bomb calorimeter, the heating value of coal is either determined by an adiabatic process or by static method (isothermal) with the correction made if net heating value is of interest for analysis of coal. The unit is calories per gram, which may be converted to the alternate units. Heating value is the direct indication of heat content (energy value) of coal. The heating value represents the combined heats of combustion of carbon, hydrogen, nitrogen and Sulphur in organic matter and of Sulphur in pyrite and the higher heating value with correction applied if the lower heating value is of interest The significance of the correlation of heating value with composition in ordinary fuel usage is shown by the development, as early in 1940's 9 different formulas for calculating heating value of coal from the ultimate analysis and 11 formulas for calculating it from the proximate analysis. Formulas have been proposed within the last three years. The correlation is perhaps of even greater importance for the rationalization and modeling of conversion processes now being developed much work has been done on measurements of heating value of indigenous coal samples, where the calorific value was found to vary with percentages of fixed carbon, volatile matter, moisture and ash contents. These parameters can be used to estimate the calorific value coal. Some of the models proposed originally for correlation of heating value of coal with its proximate analysis.

HHV=0.3536FC+0.1559VM-0.0078ASH (MJ/kg) [8-9].

$HHV=-0.03(A)-0.11(M)+0.33(V_M)+0.35(F_C)$ (MJ/kg) [10]

Many equations have been developed for the estimation of higher heating value or gross calorific value (GCV) based on proximate analysis and ultimate analysis. Regression analysis and data for 775 U.S. coal samples (with less than 30% dry ash) were used by Mason and Gandhi (1983) to develop an empirical equation that estimates the calorific value (CV) of coal based on C, H, S, and ash contents (all on dry basis). Their empirical equation, expressed in SI units, is (F. Rafezi 2005).

CV = 0.472C + 1.48H + 0.193S + 0.107A 12.29 (MJ/kg) [11]

Given et al. (1986) developed an equation to calculate the calorific value of U.S. coals from their elemental composition; expressed in SI units, their equation is:

CV = 0.3278C + 1.419H + 0.09257S 0.1379O + 0.637 (MJ/Kg) [12]

Empirical formulae are also available in the literature for the calculation of the heating value of coal based on ultimate and proximate analyses.

HHV=82F+ .V [13]

F= percentage fixed carbon

V= percentage volatile matter

= a constant depending upon the value of volatile matter expressed as dry ash free basis

This model assumes the coal consisting of volatile matter and fixed carbon, each contributing to heating value of coal. The fixed carbon of different coals is assumed of a fixed composition and hence of fixed heating value. The composition and heating value of the volatile matter differ from coal to coal and are assumed to depend upon the nature of coal as indicated by the volatile matter on dry as free basis. These assumptions limit the utility of the Goutal formula.

The following model have been developed by Central Fuel Research Institute, Dhanbad (CFRI), for the calculation of heating value of Indian coal form their proximate analysis.

For low moisture coals (M 2%)

HHV = 91.7F+75.6(V-0.1A)-60M

For high moisture coals (M 2%)

HHV=85.6[100-(1.1A+M)]-60M

Where M, A, V and F all in air-dried basis.

3. Proximate analysis:

Proximate analysis helps to determine the basic characteristics of coal which are important for user to make decision whether or not the coal under reference can be used according to his requirements including Moisture determined by using test method (ASTM D-3173), Volatile matter present in coal consist of certain gases like hydrocarbons, CO, CO_2, CH_4,H_2, N_2, O_2, etc. Which comes out on heating at specific temperature (950±20°C) measured by standard methods i.e., ASTM D-3175 under rigidly controlled conditions and Ash is the residue remaining after the coal combustion under specified conditions and temperature (700-750°C) according to ASTM D- 3174; it is mainly composed of unaltered minerals, oxides and sulfites. Chemical changes during the "*ashing process*" that occurs in the mineral matter produces ash and Fixed Carbon constituents in coal that left behind after the loss of ash, volatile matter and moisture, is referred to as fixed carbon content. The fixed carbon value is basically the value that is used for measuring efficiency of coal on burning[15-18].

4. Regression Analysis:

It is a statistical technique which is a multivariate function for examining the linear correlations between a single dependent variable(DV) and two or more independent (IV). This type of analysis is used for forecasting and prediction, and also used to determine the relationships between the dependent variable and independent variables. Many techniques have been developed in Regression analysis of which linear regression analysis and nonlinear regression analysis are vital for the current analysis. Multiple linear regression analysis was conducted in order to get predicted gross calorific value of coal by applying function on combustibles (fix carbon and volatile matter) and non-combustibles (moisture and ash contents) components of coal against calculated gross calorific value of coal respectively In this process dependent variable is illustrated as a function of different independent variables with corresponding coefficients, along with the constant term. Multiple regression analysis requires two or more predictor variables so it is known as multiple regressions

5. Methodology:

50 Representative gross samples weighing about 30 kg each were collected from different coal mines of Punjab, Sindh, KPK and Baluchistan for proximate analysis and GCV test. Samples for proximate analysis were prepared following the ASTM method (D 2013-04) (American Society for Testing and Materials 2008). Gross samples collected from the mines were first crused so that 95% of smaple passed from a four mesh sieve (-4.75 mm) one by one. Determined Air dried loss of each sample used for conducting GCV test and proximate analysis tests by placing weighed quantity of samples in an air drying oven maintained at 40°C for one hour. The air-dried samples were cooled in desiccators, weighted and again placed in the air-drying oven for one hour. The experiment was repeated until the loss in weight of total samples was not more than 0.1% per hour. Each sample was then thoroughly mixed and gradually reduced in size to -60, +80 mesh. The representative sample for proximate analysis and GCV were prepared Proximate analysis tests were carried out on samples using ASTM test methods and for heating value determination, the adiabatic bomb calorimeter method was used in which a weighed sample is burnt completely in oxygen under controlled conditions The calorific value is computed from temperature observations made before, during and after combustions by Heating value= m.Cp T

5.1 Determination of Pearson correlation (r)

Pearson's correlation was calculated by dividing the sum of the xy values (Σxy) (dependent variables and independent variables) by the square root of the product of the sum of the x^2 values (Σx^2) and the sum of the y^2 values (Σy^2) The resulting formula is:

$$r = \frac{xy}{\sqrt{x^2 \quad y^2}}$$

However, the correlation between these parameters was determined by using the software IBM SPSS statistics (version 16.0).

5.2. Coefficient of Multiple Determination (R^2):

The determination coefficient of a multiple regression model is the result of division for variances of the fitted values and observed values of the dependent variablesIf y_i is denoted as the observed values of the dependent variable, ý as its mean, and y_i as the fitted value, then the coefficient of determination is:

$$= \frac{(\acute{y}_i - \acute{y})^2}{(y_i - \acute{y})^2} \quad \text{or} \quad R^2 \quad \frac{E\text{xlainedvariation}}{\text{Totalavariation}}$$

Average squared difference between the predictor and the resulted values,was measured by calculating mean squared error. It is somewhat reasonable measure of performance for predictors. In general, any increasing function of the absolute distance would serve to measure the goodness of a predictor

$$\text{MSE} = \frac{y \quad \acute{y}^{\;2}}{n \quad K}$$

Where,

n = numbers of total experiments performed.

K = number of predictors used in the model.

6. Results and Calculations:

In the development of linear regression model for prediction of higher heating value (HHV) of indigenous coal, percentage values of V.m (volatile matter), M (Moisture), F.c (fixed carbon) and ash contents on air dried basis were used as independent variables while HHVs MJ/kg (higher heating values in Mega Joules per kilo gram) were used to target the output dependent variable. The studies included two models; Model 1 contained all the proximate analysis components as predictors of HHV

$$(Y = \;\; + \; {}_1X_1 + \;\; X + \;\; X + \;\; X$$

While, the predictors of model 2 included fixed carbon, moisture and volatile matter. Ash contents were excluded.

$$(Y = \alpha + \; {}_1X_1 + \;\; X + \;\; X$$

As the proximate contents of coal (moisture, ash, fixed carbon and volatile matter) are directly related by their percentages as follows;

Moisture% + Ash% + Volatile matter% + Fixed carbon% = 100

So, according to above relation for the proximate components of coal, the Model 2 ultimately has ash% as predictor [19-24]. Descriptive statistics of the data set considered in the model development are presented in Table 1.

Table 1. Descriptive statistics of coal samples used

Parameters	N	Minimum	Maximum	Mean	Std. Deviation
Moisture%	50	2.170	9.940	4.07940	1.638883
Ash%	50	9.570	46.500	2.81722E1	10.293310
Fixed carbon%	50	13.720	66.440	3.50684E1	11.588341
Volatile matter%	50	13.980	48.540	3.26800E1	9.422630
GCV MJ/kg	50	17.300	26.400	2.20725E1	2.436373
(Fixed carbon %)	50	1.137	1.822	1.52159	0.146177
Valid N (list wise)	50				

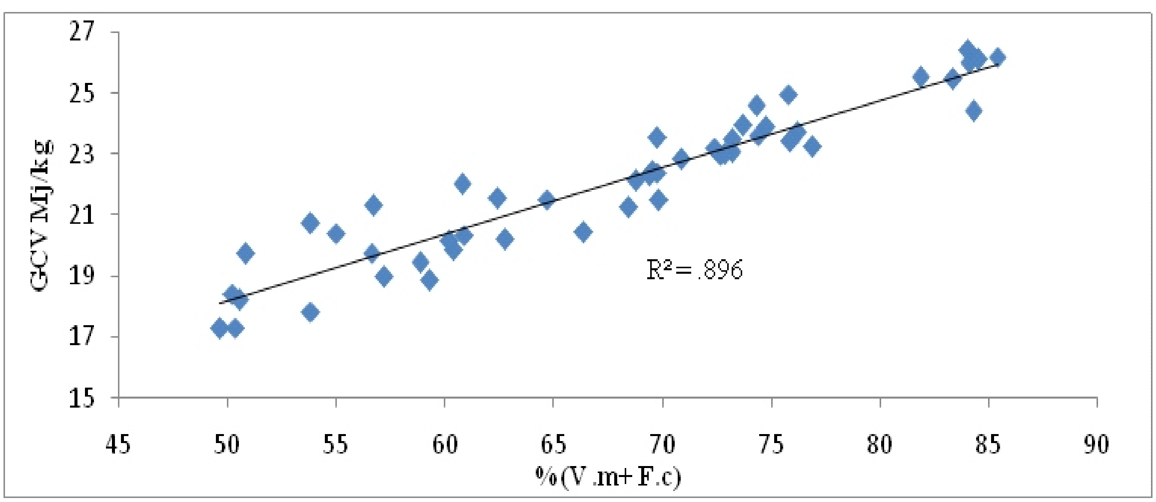


Figure 1: Effect of Volatile matter and Fixed carbon contents on HHV of coal

It was observed from the above figure that there is a positive linear relation between HHV, volatile matter content and fixed carbon content. Percentages of moisture and ash exhibits negative relation with HHV of coal samples as shown in figure. 2.

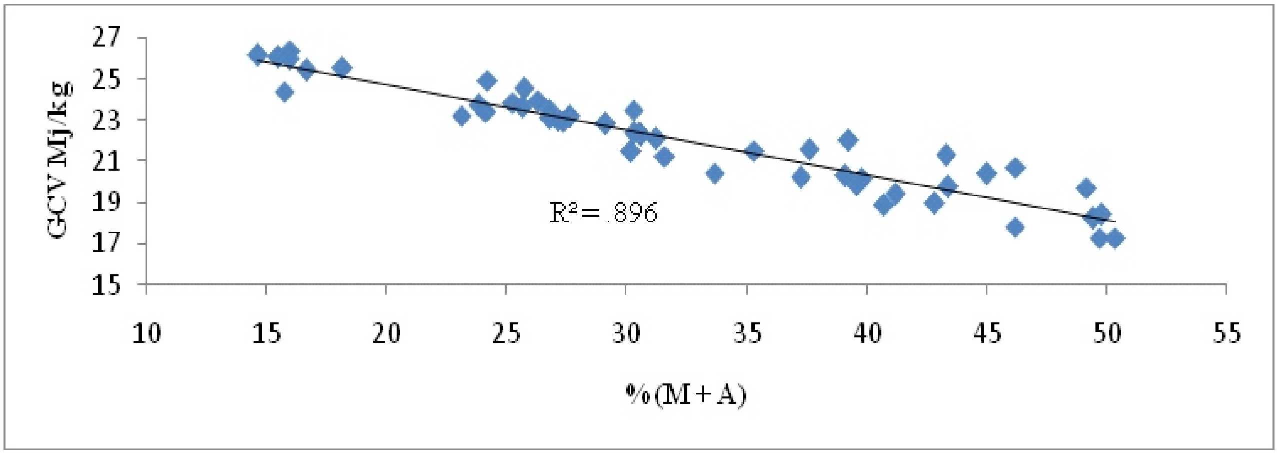


Figure 2. Effect of Moisture and Ash contents on HHV of coal

It means that it is necessary to use a linear model to make a better estimation models.

$$(Y= \ + {}_1X_1 + \ X + \ X + \ X$$

Therefore, on the basis of the considered model structures, multiple linear regression method based modeling was applied to estimate the higher heating values of the coals as the best fit models for the prediction of HHVs. Statistically; it was observed that there was a strong negative correlation between fixed carbon and ash. To see correlation between fixed carbon, ash and all other predictors for higher heating value of coal, Pearson correlation was employed. The results are presented in Table 2.

Table 2. Relationship among predictors and outcome

Predictors		M	A	V	F	GCV
M	Pearson Correlation	1	.031	-.014	-.158	-.224
	Sig. (2-tailed)		.833	.925	.274	.117
A	Pearson Correlation		1	-.329*	-.625**	-.928**
	Sig. (2-tailed)			.020	.000	.000
V	Pearson Correlation			1	-.519**	.153
	Sig. (2-tailed)				.000	.287
F	Pearson Correlation				1	.731**
	Sig. (2-tailed)					.000
GCV	Pearson Correlation					1
	Sig. (2-tailed)					

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Results show significant negative correlation between fixed carbon and ash contents of coal. However, the correlation between these parameters, fixed carbon and ash, which appeared to be strongly negative, thus showing that no more different information was obtained due to fixed carbon and ash for prediction of heating value of coal. It refers to a situation in which two or more explanatory variables in a multiple regression model are linearly related meaning that one can be linearly predicted from the others. So, model 2 does not contain percentage value of ash contents actually, but indirectly it contains percentage value of ash contents of coal because all proximate components of coal are directly related with each other by their percentage values as follows;

Moisture% + Ash% + Volatile matter% + Fixed carbon% = 100

In this situation the coefficient estimates of the multiple regression may change erratically in response to small changes in the model or the data.

Numbers of solutions are present in statistics to overcome multicolinearity problem for regression analysis. Two of these are proposed here as follows;

One is to change the original values by taking logarithm of one of the collinear predictors shown in Model 1.

Second is to exclude one of collinear predictors to evaluate the outcome shown in Model 2.

Model 1

Table 3. Significance Model fit through regression analyses

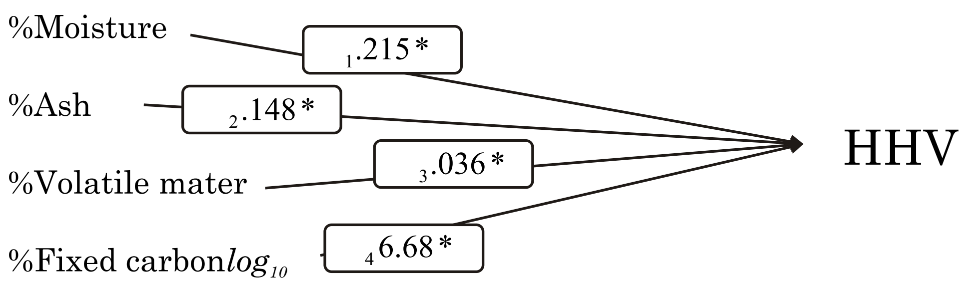
Model	Sum of Square	df	Mean Squares	F	P-value	R^2	Adj.R^2
Regression	271.667	4	67.917	159.243	.000	.934	.928
Residual	19.192	45	.426				
Total	290.860	49					

Table 4. Estimates of regression coefficients for multiple egression models and their significance

Predictors	B	Std. Error	β	t
(Constant)	15.78	6.25		2.52
Moisture	-.21	.06	-.145	-3.31
Ash	-.14	.03	-.624	-4.21
Volatile Matter	.03	.03	.138	1.05
F	6.68	2.69	.401	2.47

*P < .05. **P < .01. ***P < .001.

Model 1 emerged from Multiple Regression



R^2 = 0.93

Model 1: HHV (Mj/kg) = 15.788 0.215M% 0.148A% + 0.036V.m% + 6.680F.c%

Model 2

Table 5. Significance Model fit through multiple regression analyses

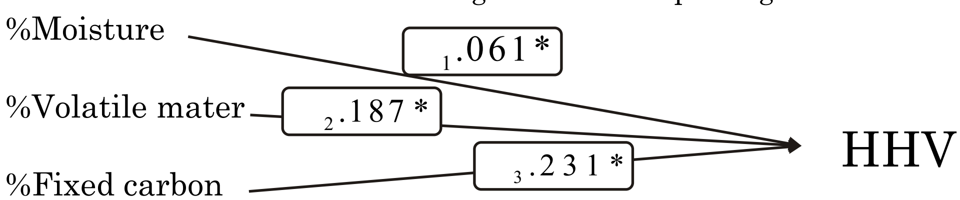
Model	Sum of Square	df	Mean Squares	F	P-value	R^2	Adj.R^2
Regression	269.046	3	89.682	189.120	.000^a	.925	.920
Residual	21.813	46	.474				
Total	290.860	49					

Table 6. Estimates of regression coefficients for multiple egression models and their significance

Predictors	B	Std. Error	β	t
Constant	8.084	.75		10.739
Moisture	-.061	.06	-.041*	-0.998
Volatile matter	.187	.01	.724***	15.236
Fixed Carbon	.231	.01	1.101	22.860

*P < .05. **P < .01. ***P < .001.

Model 2 emerged from Multiple Regression



R^2 = 0.925

Model 2: HHV (Mj/kg) = 8.804 0.061M% + 0.187V.m% + 0.231F.c%

Table 7. Resulted data after regression analysis

S.No	%Measured values				F.c $\log_{10}$	Measured	Predicted HHV MJ/kg	
	M	A	V.m	F.c		HHV / MJ/kg	Model 1	Model 2
1	3.400	12.560	17.600	66.440	1.822	26.400	25.999	26.549
2	4.840	38.540	27.860	28.760	1.459	19.763	19.785	19.663
3	7.000	32.600	35.650	24.750	1.394	19.872	20.040	20.063
4	5.800	18.010	34.380	41.810	1.621	23.722	23.930	23.846
5	3.460	22.850	38.920	34.770	1.541	23.962	23.346	23.210
6	2.660	46.500	18.240	32.600	1.513	19.730	19.100	18.883
7	4.080	20.130	13.980	61.810	1.791	24.972	24.396	24.758
8	3.600	23.730	34.920	37.750	1.577	22.983	23.282	23.142
9	2.450	23.260	46.290	28.000	1.447	24.580	23.136	23.086
10	3.920	22.840	35.080	38.160	1.582	23.470	23.381	23.247
11	6.200	20.600	18.130	55.070	1.741	23.083	23.682	23.846

14	3.320	25.800	36.190	34.690	1.540	22.832	22.836	22.689
15	7.000	42.670	17.600	32.730	1.515	17.310	18.720	18.528
16	4.220	35.000	17.200	43.580	1.639	22.014	21.268	21.134
17	2.230	28.240	35.660	33.870	1.530	22.424	22.622	22.466
18	4.200	21.060	48.540	26.200	1.418	23.874	22.972	22.984
19	5.240	18.840	43.250	32.670	1.514	23.510	23.528	23.427
20	2.340	21.780	15.350	60.530	1.782	23.440	24.514	24.825
21	3.420	12.290	46.380	37.910	1.579	24.422	25.431	25.337
22	2.210	14.430	30.320	53.040	1.725	25.460	25.778	25.904
23	6.350	9.570	47.090	36.990	1.568	25.983	25.156	25.078
24	5.350	10.140	41.380	43.130	1.635	26.110	25.530	25.490
25	2.930	24.210	39.200	33.660	1.527	23.013	23.174	23.038
26	2.540	12.070	27.910	57.480	1.760	26.193	26.203	26.459
27	5.450	40.750	15.630	38.170	1.582	20.723	19.713	19.513
28	9.940	21.630	40.200	28.230	1.451	21.250	21.572	21.541
29	3.040	34.200	33.820	28.940	1.461	20.200	21.045	20.931
30	2.800	27.360	34.380	35.460	1.550	21.490	22.717	22.560
31	3.150	19.940	45.150	31.760	1.502	23.250	23.801	23.700
32	2.870	36.940	36.440	23.750	1.376	20.130	20.196	20.231
33	4.670	22.960	33.120	39.250	1.594	23.220	23.214	23.087
34	6.560	43.790	33.540	16.110	1.207	17.300	17.160	17.695
35	3.410	39.860	22.230	34.500	1.538	21.322	20.226	20.024
36	2.680	42.320	19.250	35.750	1.553	20.422	20.017	19.800
37	2.860	27.400	32.820	36.920	1.567	23.530	22.759	22.602
38	3.600	35.500	24.530	36.370	1.561	20.345	21.064	20.876
39	2.850	37.840	45.590	13.720	1.137	18.850	18.801	19.626
40	3.270	30.380	46.230	20.120	1.304	20.456	20.947	21.201
41	4.020	27.180	38.840	29.960	1.477	22.130	22.150	22.048
42	2.480	40.320	36.800	20.400	1.310	18.983	19.352	19.547
43	2.970	43.200	34.280	19.550	1.291	17.834	18.608	18.849
44	2.170	23.470	35.200	39.160	1.593	23.632	23.744	23.608
45	5.800	29.490	32.460	32.250	1.509	21.530	21.412	21.274
46	6.670	34.500	33.830	25.000	1.398	19.443	19.795	19.800
47	2.640	27.620	37.280	32.460	1.511	22.400	22.559	22.418
48	5.430	44.350	33.290	16.930	1.229	18.423	17.456	17.907
49	3.340	34.250	29.890	32.520	1.512	21.552	21.171	21.005
50	3.220	27.370	33.710	35.700	1.553	22.310	22.620	22.464

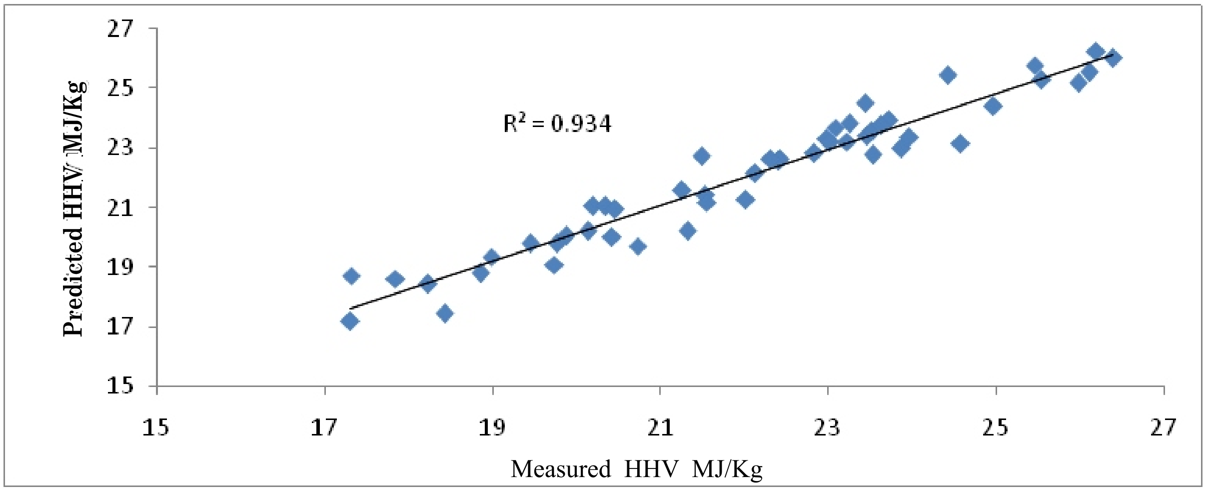


Figure 3: Correlation between the measured and the experimental values of HHV of indigenous coal

Table 8. Comparison of HHV (MJ/kg) by models derived from study, A.K Mjumdar and Goutal's Formula.

Sr.No.	Measured	(Model 1)	(Model 2)	A.K Mjumdar	Gaulat's formula	CFRI
1	26.400	25.999	26.549	28.311	35.655	28.917
2	19.763	19.785	19.663	17.571	39.557	17.758
3	19.872	20.040	20.063	18.679	43.682	18.786
4	23.722	23.930	23.846	24.801	40.969	25.293
5	23.962	23.346	23.210	23.947	42.706	24.810
6	19.730	19.100	18.883	15.742	31.856	15.942
7	24.972	24.396	24.758	25.194	31.771	25.506
8	22.983	23.282	23.142	23.628	39.964	24.376
9	24.580	23.136	23.086	24.108	44.171	25.265
10	23.470	23.381	23.247	23.816	39.354	24.532
11	23.083	23.682	23.846	23.957	32.354	24.023
12	18.234	18.440	18.372	15.293	34.920	15.252
13	25.540	25.274	25.296	27.110	38.271	27.925
14	22.832	22.836	22.689	22.945	38.474	23.728
15	17.310	18.720	18.528	15.213	29.199	14.802
16	22.014	21.268	21.134	19.415	29.323	19.538
17	22.424	22.622	22.466	22.530	37.245	23.430
18	23.874	22.972	22.984	24.094	40.964	25.065
19	23.510	23.528	23.427	24.565	38.875	25.307
20	23.440	24.514	24.825	25.340	30.522	25.918
21	24.422	25.431	25.337	27.829	38.976	29.012
22	25.460	25.778	25.904	27.894	35.153	28.905
23	25.983	25.156	25.078	27.501	38.346	28.295
24	26.110	25.530	25.490	27.858	36.904	28.682
25	23.013	23.174	23.038	23.668	35.446	24.596

26	26.193	26.203	26.459	28.687	34.066	29.637
27	20.723	19.713	19.513	16.695	25.627	16.510
28	21.250	21.572	21.541	21.404	34.547	21.328
29	20.200	21.045	20.931	19.929	32.366	20.576
30	21.490	22.717	22.560	22.628	32.334	23.429
31	23.250	23.801	23.700	25.071	34.526	26.150
32	20.130	20.196	20.231	18.914	32.085	19.596
33	23.220	23.214	23.087	23.465	31.274	24.026
34	17.300	17.160	17.695	14.671	31.285	14.629
35	21.322	20.226	20.024	17.840	26.543	18.110
36	20.422	20.017	19.800	17.301	25.166	17.584
37	23.530	22.759	22.602	22.616	29.671	23.376
38	20.345	21.064	20.876	19.363	26.760	19.719
39	18.850	18.801	19.626	18.398	31.349	19.252
40	20.456	20.947	21.201	21.027	30.581	21.947
41	22.130	22.150	22.048	22.046	29.092	22.754
42	18.983	19.352	19.547	17.802	27.974	18.497
43	17.834	18.608	18.849	16.532	27.027	17.058
44	23.632	23.744	23.608	24.379	28.248	25.353
45	21.530	21.412	21.274	20.477	26.400	20.751
46	19.443	19.795	19.800	18.145	25.742	18.237
47	22.400	22.559	22.418	22.544	26.736	23.424
48	18.423	17.456	17.907	14.983	24.660	15.098
49	21.552	21.171	21.005	19.851	24.475	20.373
50	22.310	22.620	22.464	22.444	25.421	23.168

5. Discussion on Results:

A comparison of experimental results of higher heating value with those computed by using both equations developed in the present study, and the equations suggested by Majumdar, Gautal's and CFRI (Central Fuel Research Institute)[25-28] by making use of experimental results of proximate analysis of indigenous coals indicate much better fit in of the regression model developed herein compared to that of other models shown in figure 4.

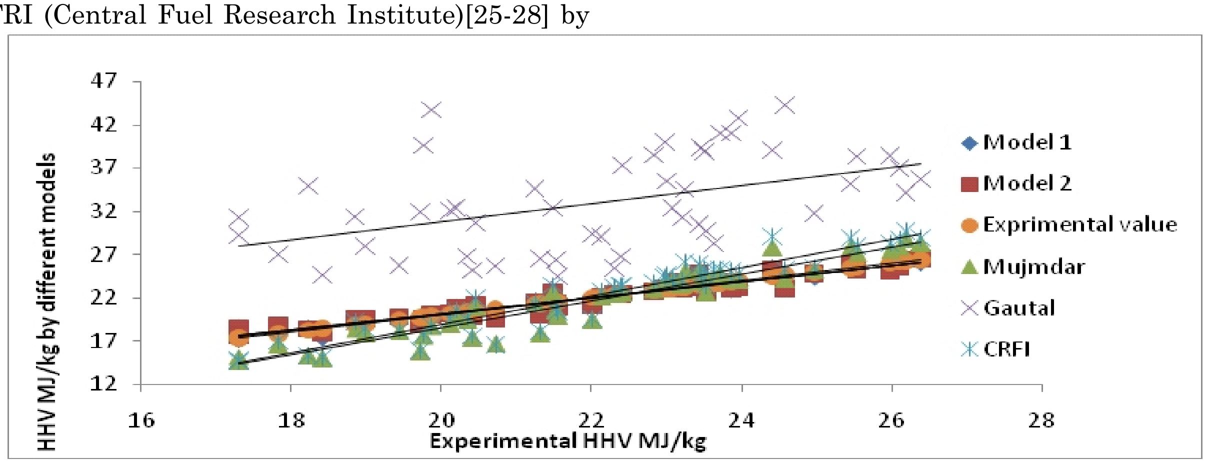


Figure 4: Comparison of HHV (MJ/kg) by models derived from study, A.K Mjumdar and Goutal's Formula.

The value of determination coefficient (R^2) for model I and mode II of the present study have been found to be 0.93 and 0.92 respectively, which are reasonably close to its maximum value 1.00. The models developed in the present study have also been tested by taking proximate analysis results of Indian, Indonesian, South African and Afghan coals from the published literature. The results for Indonesian and South African coals show reasonable agreement with their experimental values and those computed by model II of the present study shown in figure 5 And 6 Respectively.

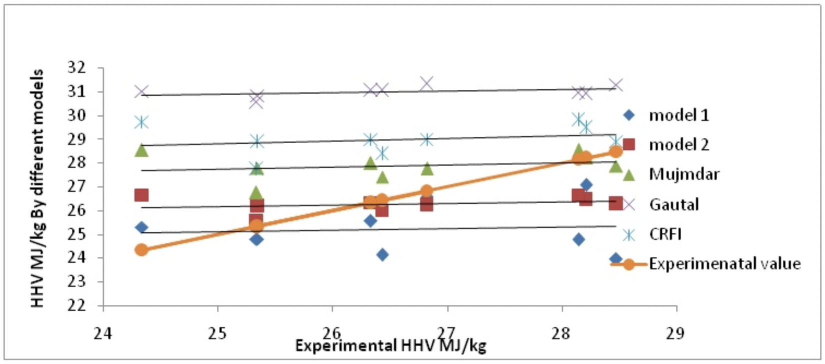


Figure 5: Comparison of Indonesian coal by different models

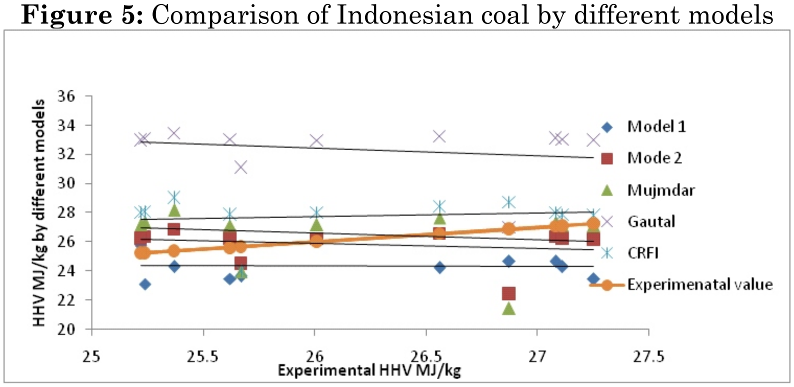


Figure 6: Comparison of S.A coal by different models

However, values computed by model I of the present study and those by models by Majumdar, Gautal's and CRFI (Central Fuel Research Institute) are significant by different than the experimental values. The results for experimental HHV (Higher Heating Value) of Afghan coals and those computed by model II of the present study and by CRFI (Central Fuel Research Institute) models are reasonably close while those computed by model I the present study and other models differ significantly as shown in figure 7.

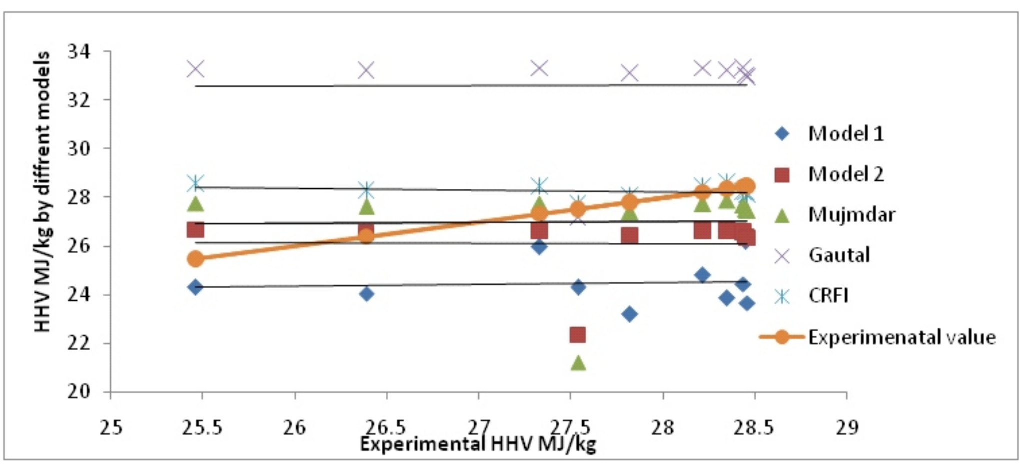


Figure 7: Comparison of Afghan coal by different models

The HHV computed by model II of this study and CRFI are close to the experimental HHV of Indian coals shown in figure 8.

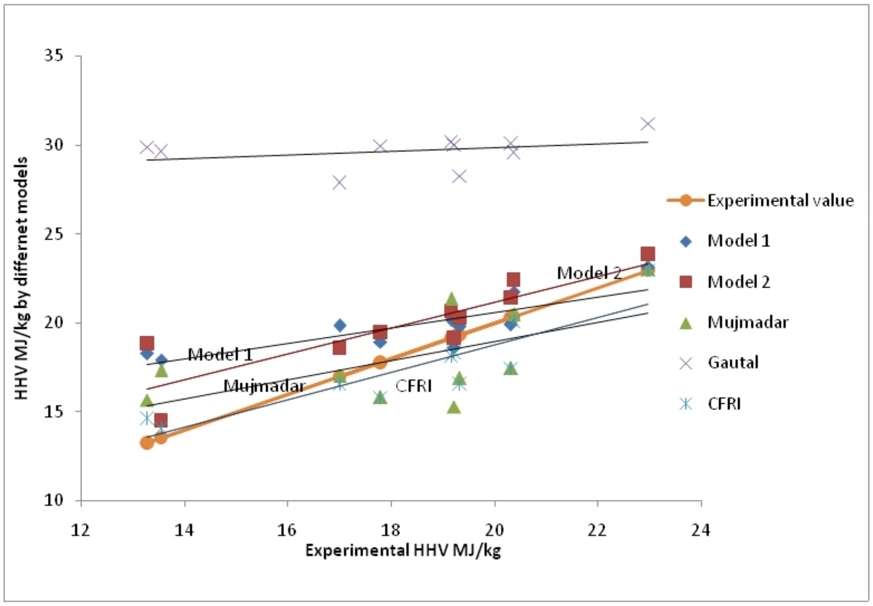


Figure 8: Comparison of Indian coal by different models

However, the values computed by model I of this study are not very different to the experimental values. The values calculated by Gautal model are far different compared to the experimental results.

5. Conclusions:

The results of present study have shown that computed values of Indigenous low rank coals (lignite and sub-bituminous) by model I model II fit well with their experimental values while these developed models can reasonably be applied to the higher rank coal compared to the other models available in literature

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