THE DEVELOPMENT OF EQUATIONS FOR ESTIMATING HIGH HEATING VALUES FROM PROXIMATE AND ULTIMATE ANALYSIS FOR SOME SELECTED INDIGENOUS FUEL WOODS

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ABSTRACT

In this study, the development of equations for estimating higher heating values (HHV) using proximate and ultimate analysis for some selected indigenous fuel woods such as Daniella (Copaiba) oliveri, Vitellaria paradoxa, Prosopis Africana and Hymenocardia, was carried out. The HHV otherwise known as calorific value of the five fuel wood species which is the heat liberated when a unit quantity of the fuel wood is completely burnt was determined according to ASTM D 2015-85 using bomb calorimeter model Parr 6400. The proximate and ultimate analyses of the five wood samples were determined by reducing the samples to powder form using hammer mill and sieved to obtain up to 250 µm grain size according to ASTM D2013-86 standard. The equation for calculating HHV from proximate analysis used for the correlation was assumed to be a function of fixed carbon (FC), volatile matter (VM), moisture content (MC) and ash content (AC). While that equation for calculating HHV from ultimate analysis used for the correlation was assumed to be a function hydrogen, oxygen, carbon, sulphur, and nitrogen. The constant and coefficients of multiple regression equations were evaluated using reglin function in SCILAB environment. The models formulated for the estimation of HHV were validated using percentage (%) bias error. The obtained results indicated that the calculated values of HHV from the developed equations from proximate and ultimate analyses were in good agreement with the experimental HHVs. This was confirmed by lower positive bias errors of 0.030365, 0.171, 0.209, 0.499, and 1.137 % used for validation; thus confirming the validity and applicability of the equation for estimating HHVs for biomass.

Keywords: Ultimate analysis, proximate analysis, high heating value, fuelwood.

INTRODUCTION

The higher heating value (or calorific value) of wood is the amount of heat released when a given mass of wood is burnt. The most important parameter to characterize a substance as combustible is the calorific value or higher heating value. The number of units of energy produced by the combustion of a unit mass of a fuel is termed calorific value. The higher heating value is the absolute value of the specific energy combustion, in joules for unit mass of a solid biofuel burned in oxygen in a calorimetric bomb under specified conditions [1]. Calorific value can be defined as the amount of energy per unit mass or volume released on complete combustion of a wood and further stated that the moisture content of wood changes the calorific value of the latter by lowering it. Part of the energy released during the combustion process is spent evaporating water and is consequently not available for any desired thermal use; and that water evaporation involves the consumption of 2.44 MJ per kilogramme of water.

According to Lam and Sokhansanj (2014) calorific value of biomass is crucial to determine its energy that can be recovered during thermo-conversion. From recent studies, it was found that thermally treated biomass with increased calorific value could be a suitable candidate to blend and co-fire with coal for power generation with reduced greenhouse gas emissions. The most common methods currently being practiced to evaluate the heating of biomass are by using derived equation, or experimentally, by using the bomb calorimeter. There are numerous mathematical equations, which were created based on the data from physical composition, proximate or elemental analysis of biomass for computation of higher heating values (Telmo and Lousade, 2011). The energy content which also known as calorific value is the most essential parameter, which reflects effectiveness and efficiency of any fuel by determining the amount of heat generated from a unit mass (MJ/kg). Factors affecting the amount of heat produced by fuel refers to its quantitative conversion of carbon and hydrogen present in the fuel; to water and carbon dioxide is a function of chemical-elemental composition of fuel (Razak, 2016). The more the hydrogen and carbon content of the residue of the tree, the greater the heating value (Adikiigbe, 2012).

Direct experimental determination of the heating value of carbon based materials can be accomplished by means of an adiabatic calorimeter. However, there are number of equations found in literature for an estimation of heating values of different carbo-based materials such as coal and lignocellulosics. The majority of these equations is based on elemental analysis and have been derived for coals and liquid fuels (Cordero et Al., 2001). According to Elneel et al. (2013) the heating value can be experimentally or numerically determined and the determination of heating value experimentally using bomb calorimeter involves laborious measurements while an ultimate analysis can be performed using automatic equipment. The authors further stated that there were many attempts to estimate the heating value of biomass based fuels on chemical analysis, proximate analysis and ultimate analysis. Proximate analysis data of solid fuel comprises of moisture content, volatile matter, ash, and fixed carbon. The HHV and proximate analysis data are usually used to generate multiple linear regression correlations and these correlations showed the influence of proximate analysis data on the HHV. Some possible combinations of dependent variables (proximate analysis data) that contribute to the energy content were developed and evaluated to produce the mathematical models (Gunamantha, 2016). Other researchers such as Parikh et al. (2005), Cordero et al (2001) and Gunamantha, (2016) carried out an investigation for the development of equations for calculating HHV from proximate analysis of some biomass.

Ultimate analysis correlations take into account the elemental composition of fuels, that is the mass fraction of carbon (C), oxygen (O), and hydrogen (H), and sometimes addition of nitrogen (N) and sulphur (S). The ultimate analysis based models by Dunlong (1880) as reported by Elneel et al. (2013), was the first model developed for calculation of heating values which was intended for prediction of heating values for coal samples. Many researchers thereafter proposed the variations of Dunlong's model, including new coefficients and sometimes new expressions. In 1997, Tillman as cited in Elneel *et al.* (2013) developed two new equations (the second derived from the first) to estimate he heating value from the ultimate analysis for biomass fuels and suggested that the biomass heating value has a very strong function in its carbon content. The estimation of HHVs from ultimate analysis were also investigated by other researchers such as Demirbas *et al.* (1977), and Elneel *et al.* (2016). Hence, this research studied the development of equations for estimating higher heating values from proximate and ultimate analyses of some fuel woods such as *Daniella (Copaiba) oliveri, Vitellaria paradoxa, Prosopis Africana* and *Hymenocardia.*

MATERIALS AND METHODS

Materials

The materials used for the research include the following: Five fuel wood species, 2 aluminium pot lids, digital balance (Metriz 235), oven (carbolite), bomb calorimeter (Parr 6400), infrared thermometer (EUROLAB 8811A), hammer mill, platinum crucibles.

Preparation of wood samples

The fuel wood samples were identified, collected around University of Agriculture, Makurdi road and dried for one month according to standard practices in order to reduce the moisture content shown in (Adekiigbe, 2012)

Determination of Higher Heating Value (HHV)

The Higher Heating Value (HHV) otherwise known as calorific value of the 5 fuel wood species which is the heat liberated when a unit quantity of the fuel wood is completely burnt was determined according to ASTM D 2015-85 using bomb calorimeter model Parr 6400. It consists of a small cup that contain the sample, oxygen, stainless steel bomb, water, stirrer, thermometer, ignition circuit connected to the bomb and printer.

The 5 wood samples were ground into powder form using hammer mill and sieved using 250 µm sieve size. One gram of the powder of sample A (*Copaiba oliveri*) was placed inside the small cup of the calorimeter, pressurized with pure oxygen at about 30 atm and small amount of water added to saturate the internal atmosphere. The whole bomb was submerged in water and electrically ignited. Energy was released by the combustion and the heat generated flowed across the stainless steel wall, thus raising the temperature in the steel bomb, its contents and the surrounding water jacket. The HHV was obtained from temperature observations made before, during and after combustion, making proper allowances for heat contributed by other processes, and for the thermometer and thermochemical corrections (ASTM D-85). The result of HHV was calculated by the software installed on the machine with the HHV result displayed on the touch screen and printed out. These procedures were repeated for samples B (*Prosopis Africana*), C (*Quassia undulata*), D (*Vitellaria paradoxa*) and E (*Hymenocardia*) to obtain the Higher Heating value

Determination of proximate and ultimate analyses

The samples were collected with due care in order to obtain the most representative samples. The samples were reduced to powder form using Hammer mill and sieved to obtain up to 250 μ m grain size according to ASTM D2013-86 Standard method.

Moisture Content: One gram of the sieved sample A (*Copaiba oliveri*) was introduced into pre weighed platinum crucibles and passed to the drying oven at 105° C for a period of one hour, the weight was recorded after cooling in the dessicator. The moisture content was calculated using equation (1) (Mitchual *et al*, 2014).

$$MC = \left(\frac{P_i - P_s}{P_i} \ge 100\right)$$

Where,

MC is the moisture content

P_i, is the initial weight,

(1)

 P_{s} , is the weight of the charcoal after subjecting to $105^{\circ}C$

This procedure was repeated for samples B (*Prosopis Africana*), C (*Quassia undulata*), D (*Vitellaria paradoxa*) and E (*Hymenocardia*) to obtain their moisture contents.

Volatile Matter: One gram of sieved sample A (*Copaiba oliveri*) was introduced into pre weighed platinum crucible, covered with lid and placed into the furnace at 105 °C in order to determine the weight of charcoal and 950 °C according to ASTM D 2013 standard procedures and maintained at that temperature for about seven (7) minutes. The weight was recorded after cooling in the dessicator and the volatile matter was calculated using equation (2) (Marqueze-Mantesino *et al*, 2001).

$$VM = \left(\frac{P_S - P_V}{P_S}\right) \times 100$$
⁽²⁾

Where,

VM is the volatile matter

P_s is the weight of charcoal after subjecting to 105 °C,

 P_V is the weight of the charcoal after subjecting to 950 $^{\circ}C$

The same procedure was repeated for samples B (*Prosopis Africana*), C (*Quassia undulata*), D (*Vitellaria paradoxa*) and E (*Hymenocardia*) to obtain the volatile matter.

Ash Content: One gram of the sieved sample A (*Copaiba oliveri*) was introduced into a pre weighed platinum crucible, placed into the furnace at 950 °C and was allowed to burn completely to a constant weight. The loss in weight was recorded and the ash content was calculated using equation (3) (Marqueze-Mantesino *et al*, 2001);

$$AC = \left(\frac{P_a}{P_v}\right) \times 100 \tag{3}$$

AC is the ash content

P_a, the weight of the ashes

 P_V the weight of the charcoal after subjecting to 950 °C

Fixed Carbon: Percentage of fixed carbon (FC) was determined by the difference between 100 % and the sum of the percentages of moisture content, ash content and volatile matter, using equation (4) (Jigisha *et al*, 2006).

$$FC = 100 - (MC + VM + AC)$$

Where,

FC is the fixed carbon

MC is the volatile matter, AC is the ash content

Ultimate analysis: A correlation for calculating elemental composition from proximate analysis of the test samples was used to generate ultimate analysis result using relations in equations 5-8 (Jigisha *et al*, 2006).

(4)

The analysis of variance (ANOVA) was carried out at 5 % significant level in order to determine whether there is significant difference among the five wood samples in terms of proximate analysis.

C = 0.637FC + 0.455VM	(5)
H = 0.052FC + 062VM	(6)
O = 0.304FC + 0.476VM	(7)

Where;

C is carbon;

H is hydrogen; and

O is oxygen.

Sulphur S was obtained using the relation in equation (8)

$$S = H + C + O - 100$$

(8)

The N content was determined from Kjedahi method using ASTM- D3179 standard. Exactly 2 g of sample was weighed into a Kjeldahi digestion flask. 20 ml sulphuric acid and 1 g each of copper sulphate and potassium sulphate as catalysts were added into the flask. The flask was heated gently until boiling; the mixture was then diluted with 100 ml of distilled water and allowed to cool. The flask was then connected to the Kjeldahi distillation apparatus and sodium hydroxide solution was added to the mixture and then heated to boiling. The ammonia gas was condensed into the receiving flask containing 2% boric acid. Bromocresol green and methyl red indicators were added dropwise and alkaline distillate was titrated against 0.1 M hydrochloric acid. The procedure was repeated for the 13 samples and the percentage of nitrogen was calculated as shown in equation (9) (Adekunle *et al.* 2015):

% of
$$N = \left[\frac{(VH_2SO_4 \times NH_2SO_4) - (VBK \times NNaoH) - VNaoH \times NNaoH)}{1.4007 \times W}\right]$$
 (9)

where:

 $VH_2SO_4 = mL$ standard H_2SO_4 pipetted into flask for sample, VNaOH = mL standard NaOH used to titrate sample, $NH_2SO_4 = Normality$ of H_2SO_4 , NNaOH = Normality of NaOH, VBK = mL standard NaOH used to titrate 1ml standard H_2SO_4 minus B, B = mL standard NaOH used to titrate reagent blank distilled into H_2SO_4

1.4007 = milliequivalent weight of nitrogen x100, and W = sample weight.

Correlation for Calculating Higher Heating Value (HHV) from Proximate and Ultimate Analyses

Proximate analysis: The following equation was formulated for computation of HHV from proximate analysis; as HHV was found to be proportional to carbon content and hydrogen content (Parikh *et al*, 2005). The result of proximate analysis used for the correlation of equation for estimating HHV is presented Table 1. Hence the HHV was assumed to be a function of fixed carbon (FC), volatile matter (VM), moisture content (MC) and ash content (AC) as shown in equation (10);

$$HHV = \alpha + \gamma_1 FC + \gamma_2 VM + \gamma_3 AC + \gamma_4 MC \tag{10}$$

where α is a constant, γ_1 , γ_2 , γ_3 , and γ_4 are coefficients of the multiple regression equation to be determined by the experimental results of proximate analysis. The development of equation for estimating HHV was also done graphically by plotting HHV against the proximate analysis results.

Ultimate Analyses: Two equations were formulated for calculation of HHV from ultimate analysis. Firstly to capture hydrogen (H), oxygen (O), and carbon (C) and secondly to capture hydrogen (H), oxygen (O), carbon (C), nitrogen (N), and sulphur (S); the equations were (equations 11-12);

$$HHV = \alpha + \gamma_1 H + \gamma_2 0 + \gamma_3 C \tag{11}$$

$$HHV = \alpha + \gamma_1 H + \gamma_2 O + \gamma_3 C + \gamma_4 N + \gamma_5 S$$
(12)

The equations were formed on the assumption that HHV is a linear function of ultimate analyses (Parikh *et al*, 2005). The multiple regression equations (10)-(12) were solved using Sample codes (shown in Appendix 1, 2 and 3) using the **reglin** function in the SCILAB environment evaluate the coefficients α , γ_1 , γ_2 , γ_3 , γ_4 , and γ_5 . These coefficients were then substituted into equations (10), (11) and (12) for each equation to give the estimated HHV.

The models formulated for the estimation of HHV were validated using percentage (%) bias error as given in equation (13) (Gunamantha, 2016);

$$HHV = \frac{1}{n} \sum_{i=1}^{n} \frac{HHV_e - HHV_m}{HHV_m} \times 100$$
(13)

Where, subscripts e and m indicate the estimated value from model (calculation) and from the result of measurement respectively and n, the number of samples. The development of equation for estimating HHV was also done graphically by plotting HHV against ultimate results (oxygen, and hydrogen) and fitting the trend lines to obtain the equations

Table 1: H	HV, Pro	ximate and	ultimate a	analyses i	results of	wood	Samples	investig	gated
	/			•					,

		Α	В	С	D	E
Proximate analysis (%)	roximate analysis (%) Moisture		5.63	3.01	4.74	4.97
	content					
	Fixed carbon	16.58	21.30	9.45	20.81	16.49
	Volatiles	64.23	66.25	39.27	66.64	65.05
	matter					
	Ash content	14.79	6.79	4.82	7.77	13.43
	Sulphur	0.05	0.03	0.029	0.04	0.06
	content					
Ultimate analysis (%, dry ash	С	41.7654	46.2735	25.2571	45.7339	42.3632
free)						
	Η	5.1141	5.5642	3.1128	5.5077	5.1987
	Ο	37.6844	40.6901	22.9981	40.3031	38.3425
	Ν	0.5961	0.6522	0.3630	0.6453	0.6056
HHV(Kcal/k g)		3935.620	4461.933	2282.14	4400.13	3974.1641

RESULTS AND DISCUSSION

Correlation for calculating HHV using proximate analysis

The constant and coefficients of multiple regression evaluated using **reglin** function in SCILAB environment were substituted into equation (10) to form equation (14), for

estimation of HHV from proximate analysis (fixed carbon, volatile matter, moisture content and ash content).

HHV = 0.6042FC + 0.4083VM + 0.2442AC + 0.4107MC - 25.204(14)

The HHVs of the samples estimated from the developed equation (14) range from 9.575 (C-Quassia undulate) to 18.714 MJ/kg B (Propdopis Africana) are shown in Table 1. The HHVs of the other samples were, 16.443, 18.515, and 16.610 MJ/kg for samples A (Daniella oliveri), D (Vitrllaria paradoxa) and E (Hymennocardia) respectively. The experimental values of HHV were 16.437, 18.682, 9.555, 18.423, and 16.423MJ/kg, for samples A (Daniella oliveri), B (Propdopis Africana), D (Vitrllaria paradoxa) and E (Hymennocardia) respectively are also shown in Table 1. It was observed that the calculated values of HHV were in good agreement with the HHV values developed from equation (14). This observation was confirmed by validation of the model using bias error. The error analysis confirmed the validity and applicability of the model to biomass. Positive bias errors of 0.0365, 0.171, 0.209, 0.499, and 1.137 % were obtained at values of 16.443, 18.714, 9.55, 18.423 and 16.423MJ/kg respectively. Elneel et al. (2013) stated that a positive value of average bias error implies estimation goes beyond measurement, while a negative value indicates an overall estimate below the measurement results. These results were in agreement with other researchers such as Elneel et al. (2013) and Gunanmantha (2016) where the bias errors were -16 - 4.5 %.

Samples	Measured HHV (MJ/kg)	HHV (MJ/kg) from New Equation (14)	Bias error
A (Daniella oliveri)	16.437	16.443	0.0365
B (Prosopis Africana)	18.682	18.714	0.171
C (Quassia undulata)	9.555	9.575	0.209
D (Vitellaria paradoxa)	18.423	18.515	0.499
E (Hymenocardia)	16.423	16.610	1.137

Table 2: Measured and computed HHV of wood samples from developed model and
otherothermodels using proximate analysis

The correlation of HHV with proximate analysis was also done graphically. The correlation of Higher Heating Values (HHVs) with ash content (AC) as presented in Figure 1 showed that, the HHVs of the wood samples decreased with increase in ash content. This confirmed earlier findings by Jenkins *et al.* (1998) who stated that wood with less than 1 % ash typically has heating value of 20 MJ/kg and increase in each 1 % ash translates roughly into a decrease of 0.2 MJ/kg. This is because ash does not contribute substantially to the overall heat released by combustion, although elements in the ash may be catalytic to the thermal decomposition (Kumar *et al.*2009). Montes *et al.* (2012) stated that ash content reduces HHV because ash is the non-combustible mineral residue in the wood as too much of it prevents the liberation of heat. Highly negative correlation was found between the HHV and ash content which gave the R² of 0.9944. This value of R² was higher than the value of R² = 0.79 presented by Nasser (2014) with the simple regression equation given as

HHV = 4748.1 - 51.599AC





Figure 1: Correlation for estimating Higher Heating Values with Ash Content.

Figure 2 presents the correlation of HHVs and fixed carbon content for five wood samples investigated and it shows that HHVs increased with increasing fixed carbon content. This confirms the findings reported by Nasser and Aref (2014). They stated that carbon is one of the main heat producing elements and therefore biomass with high fixed carbon tends to have higher HHV. Jenkins *et al.* (1998) also found correlations between the carbon and HHV; they found out that every 1 % increase in carbon raises the HHV by approximately 0.39 MJ/kg. The results obtained in this study indicate a high positive correlation of the HHV with fixed carbon content ($R^2 = 0.9571$) with simple regression analysis which showed that the trend of the data for all the sample studied was best described by

HHV = 661.44 + 187.34FC (R² = 0.9571) (17)

This relationship means that about 95.71 % of the total variability in the heating value was fixed carbon (FC). Montes *et al.* (2012) stated that fixed carbon (FC) is the solid combustible residue that is left after a wood particle is heated and volatile matter expelled; that a high FC content indicates that the wood will require a longer combustion time, thereby leading to increase in HHV (which is the heat release when 1 kg of wood is burnt). This result could mean that the wood samples are rich in lignin which is the heat producing element in woods rich in carbon and hydrogen.



Figure 2: Correlation for estimating Higher Heating Values with Fixed Carbon Content.

The correlation between HHV and oxygen content (OC) as presented in Figure 3 clearly indicates that HHV increased with rising oxygen content thus contradicting the earlier findings by Ragland and Aerts (1991) that the effect of oxygen is to reduce the calorific value of the wood to about one half that of conventional fossil fuel. During combustion this oxygen is incorporated into the water and carbon dioxide in the combustion product gases. The results gave a high correlation of the HHV to oxygen content ($R^2 = 0.9887$) with simple regression analysis which showed that the trend of the data for all the sample studied was best described by equation (18)

HHV =
$$-494.27 + 119.50C (R^2 = 0.9887)$$
 (18)

Raglands and Aerts (1991) stated that char oxidation is the dominating reaction in a combustion environment. Since this is a surface reaction, the reaction rate depends on kinetics and diffusion of oxygen to the char surface. This is perhaps the reason for the discrepancy in the observation.

Correlation for calculating HHV using ultimate analysis

The models given in equations (11) and (12) for estimation of HHVs from ultimate analysis (H, C, O, N, and S) was fitted to the experimental data by regression analysis, in order to estimate the constant and coefficients. The constant and coefficients estimated using reglin function in SCILAB environment were substituted into equations (12) and (13) to form equations (19) and (20);

$$HHV = -0.37915H - 1.5863 \times 10^{-5}O + 0.8765C - 0.7811$$
(19)

 $HHV = -3.7623H - 4.3955 \times 10^{-5}O + 0.877C - 0.2794N - 0.0301S$ (20).

Equation (19) was developed to capture H, O, and C, while equation (20) captured H, O, C, N, and S.

The equations (19) and (20) developed were used to estimate the HHVs of the wood samples investigated as shown in Table 3. The HHVs of 33.886, 37.638, 20.177, 37.220 and 34.430 MJ/kg were obtained by equation (19) for A (*Daniella oliveri*), B (*Propdopis Africana*), D (*Vitrllaria paradoxa*) and E (*Hymennocardia*) respectively. This result clearly showed that the developed model did not estimate the HHVs correctly compared to the experimental values (16.437, 18.682, 9.555, 18.423 and 16.423 MJ/kg for A-Daniella oliveri), B-*Propdopis Africana*, D -*Vitrllaria paradoxa* and E - *Hymennocardia*, respectively) as

observed by higher bias errors. Bias errors were 21.230, 20.293, 22.223, 20.406, and 21 % were observed between the predicted and experimental values.



Figure 3: Correlation for estimating Higher Heating Values with Oxygen Content.

However, the HHVs estimated by equation (20) (Table 2) were 16.438, 18.682, 9.556, 18.423 and 16.640 MJ/kg for A (*Daniella oliveri*), B (*Propdopis Africana*), D (*Vitrllaria paradoxa*) and E (*Hymennocardia*) respectively. While the experimental values of HHV were 16.437, 18.682, 9.555, 18.423 and 16.423 MJ/kg for A-*Daniella oliveri*), B-*Propdopis Africana*, D - *Vitrllaria paradoxa* and E -*Hymennocardia* respectively. This observation clearly showed that the developed equation (20) estimated accurately the HHVs of the samples investigated. This was confirmed by lower values of bias errors of 0.484, 0.000, 0.0105, 0.000, and 0.264 % used for the validation of the model. This finding agreed with Thipkhunthod *et al.* (2006) who stated that bias errors should be or close to zero for effective performance of models. It was also observed that the estimated values of 18.682 and 18.423 MJ/kg using equation (20) were the same as the experimental values with 0.000 % bias errors.

 Table 3: Measured and computed HHV of wood samples from developed models models using ultimate analysis

Samples	Measured HHV (MJ/kg)	HHV New Equation (19) (2017) (MJ/kg)	Bias error (%)	HHV New Equation (20) (2017) (MJ/kg	Bias error (%)
A (Daniella oliveri)	16.437	33.886	21.230	16.438	0.484
B (Prosopis Africana)	18.682	37.638	20.293	18.682	0.000
C (Quassia undulata)	9.555	20.177	22.233	9.556	0.0105
D (Vitellaria paradoxa)	18.423	37.220	20.406	18.423	0.00
E (Hymenocardia)	16.423	34.430	21.929	16.640	0.264

CONCLUSION

It was concluded that the three equations for estimating HHV from proximate and ultimate analysis were observed to predict HHV accurately as confirmed by low bias errors. It was observed that correlation for calculating HHV of the investigated fuelwood samples using ultimate analysis (equation 19) was more accurate than the proximate analysis equation (equation 14). This trend was supported by Parikh *et al.* (2005) and Sheng and Azevedo (2005). They reported that correlations based on ultimate analysis are most accurate and reliable. The reason for this was further explained by Elneel *et al.* (2013) that correlations based on proximate analysis had low accuracy because proximate analysis provides only an empirical composition of the biomass.

REFERENCES

- Adekunle, J.O., Ibrahim, J.S., & Kucha, E.I. (2015). Proximate and ultimate analyses of biocoa briquettes of Nigerian's Ogbotaga and Okada sub-bituminous coal. British Journal of Applied Science & Technology. Vol.7 (1), 114-123.
- Adekiigbe, A. (2012). Determination of heating value of five economic trees residue as a fuel for biomass heating system. Nature and science. Vol.10 (10). 26-29.
- Cordero, et al. (2001). Predicting values of lignocellulosics and carbonaceous materials from proximate analysis. *Fuel. Vol.* 80. 1567-1571.
- Demirbas, A., (1977). Sustainable cofiring of biomass with coal. *Energy conversion and management*. Vol.44 (9), 1465-1479.
- Elneel, R., Shaharin, A., & Ariwahjoedi, B. (2013). Prediction of heating values of oil palm fromds from ultimate analysis. *Journal of Applied Sciences. Vol.* 13(3), 491-496.
- Gunamantha, M. (2016). Prediction of higher heating value bioorganic friction of municipal solid waste from proximate analysis data. *International Journal of Engineering Research & Technology. Vol.* 5(02). 442-447.
- Lam, P.S., & Sokhansanj, S. (2014). Engineering properties of Biomass. Engineering and Science of Biomass Feddstock Production and Provision. Springer, http://www.springer.com/978-4899-8013-7, 1-35.
- Jenkins et al. (1998). Combustion properties of biomass. *Biomass Technology*. Vol. 54, 17-46.
- Jigisha, P., Channiwala, S.A., & Ghosal, G.K. (2006). A correlation for calculating HHV from proximate analysis of solid fuels. *Fuel. Vol.* 84, 487-494.
- Klanja, B., Orlovic, S., & Galic, Z. (2014) Comparison of different wood species as raw materials for bioenergy. *South East European Forestry. Vol.* \$ (2). 81-88.
- Marquez-Montesino, et al. (2001). Estudio del potencial energeticco de biomassa Pinus Caribea Morelet Var, caribea (Pc) y Pinus tropicalis orelert (Pt); Eucalyptus saligna smith (Es) Eucalyptus citridora Hook (Ec) y Eucaplytus pellis F. Revista Chapingo Cien-Cias Foreatale y dei ambient Vol. 7(1), 83-89.
- Mitchual, S.T. Mensah, F.K. & Darkwa, N.A. (2014). Evaluation of fuel properties of six tropical timber species for briquettes. *Journal of Sustainable Bioenergy Systems*. *Vol.*4 pp 1-9. http://www.scirp.org/jounal/jsbs
- Montes et al. (2012). Effect of region, soil, land use and terrain type on fuelwood properties of five tree/ shrub species in the sahelian and sudanian ecozones of Mali. *Annals of Forest*. Vol. 69. 747- 756.
- Nasser, R. A. & Aref, I. M. (2014). Fuelwood characterization of six acacia species growing wild in the southwest of Saudi Arabia as affected by geographical location. *BioResources. Vol.* 9(1). Pp 1212–1224.

- Parikh, J. Channiwala, S.A., & Ghosal, G.K. (2005). A correlation for calculating HHV from proximate analysis of solid fuels. Fuel. Vol.84. 487- 494.
- Ragland, K.W., & Aerts, D.J. (1991). Properties of wood for combustion analysis. *Bio-Resources Technology. Vol.* 37, 161-168.
- Razak, et al. (2016). Preliminary study on properties of small diameter wild leucaena species as potential biomass. *Energy Sources. Vol.* 11 (9). 6128- 6137
- Sheng, C., & Azevedo, J.L.T. (2005). Estimating higher heating value of biomass fuels from basic analysis data. *Bioenrgy. Vol.* 28, 499-507.
- Telmo, C., & Lousada, J. (2011). Heating values of wood pellets from different species Biomass and bioenergy. Vol. 35. 2634-2639.
- Thipkhunthod, et al. (2006). Sewage sludge heating value prediction through proximate and ultimate analyses. *Asian Journal on Energy and Environment.* Vol. 7(2), 324-335.

APPENDICES

Appendix 1: Sample Code for Multiple Regressions using the Reglin Function for correlation calculating HHV from proximate analysis

x1=[16.58 21.30 9.45 20.81 16.49]

x2=[64.23 66.25 39.27 66.64 65.05]

x3=[14.79 6.79 48.24 7.77 13.43]

x4=[4.35 5.62 3.01 4.74 4.97]

y=[16.437 18.682 9.555 18.423 16.640]

X=[x1; x2; x3; x4;];// create matrix x from the four rows

[a, a0, sigma]=<u>reglin</u> (X,y);// perform a multiple regression analysis of y as a function of x1, x2, x3 and x4

ypred = a0 + a(1)*x1 + a(2)*x2 + a(3)*x3 + a(4)*x4 // fitted data

filename = myreglindir + basename(myfile) + "-plot.png":// *create filename from basename of file*

xs2png(wn, filename);// save graphic in PNG format

result = ["a0" "a(1)" "a(2)" "a(3)" "a(4)"];// first row of data

Appendix 2: Sample Code for Multiple Regressions using the Reglin Function for correlation calculating HHV from ultimate analysis using H,O and C

x1=[5.1141 5.5641 3.1128 5.5077 5.1987]x2=[37.6844 49.6901 22.9981 40.3031 38.3425]x3=[41.7654 46.2735 25.2571 45.7339 42.3632]y=[16.437 18.682 9.555 18.423 16.640]X=[x1; x2; x3;];// create matrix x from the three rows[a, a0, sigma]=reglin (X,y);// perform a multiple regression analysis of y as a function of x1,x2 and x3ypred = a0 + a(1)*x1 + a(2)*x2 + a(3)*x3 // fitted datafilename = myreglindir + basename(myfile) + "-plot.png";// create filename from basenameof filexs2png(wn, filename);// save graphic in PNG formatresult = ["a0" "a(1)" "a(2)" "a(3)"];// first row of data

Appendix 3: Sample Code for Multiple Regressions using the Reglin Function for correlation calculating HHV from ultimate analysis using H,O and C

 $x1=[5.1141 \ 5.5641 \ 3.1128 \ 5.5077 \ 5.1987]$ $x2=[37.6844 \ 49.6901 \ 22.9981 \ 40.3031 \ 38.3425]$ $x3=[41.7654 \ 46.2735 \ 25.2571 \ 45.7339 \ 42.3632]$ $x4=[0.5961 \ 0.6522 \ 0.3630 \ 0.6453 \ 0.6056]$ $x5=[0.05 \ 0.03 \ 0.029 \ 0.04 \ 0.06]$ $y=[16.437 \ 18.682 \ 9.555 \ 18.423 \ 16.640]$ $X=[x1; \ x2; \ x3; \ x4; \ x5;];// \ create \ matrix \ x \ from \ the \ four \ rows$ $[a, a0, sigma]=reglin \ (X,y);// \ perform \ a \ multiple \ regression \ analysis \ of \ y \ as \ a \ function \ of \ x1, \ x2, \ x3, \ x4 \ and \ x5$ $ypred = a0 + a(1)*x1 + a(2)*x2 + a(3)*x3 + a(4)*x4 + a(5)*x5 \ // \ fitted \ data$ filename = myreglindir + basename(myfile) + "-plot.png";// \ create \ filename \ from \ basename \ of \ file $xs2png(wn, \ filename);// \ save \ graphic \ in \ PNG \ format$

result = ["a0" "a(1)" "a(2)" "a(3)" "a(4)" "a(5)"];// first row of data