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MODELLING THE ENERGY CONTENT OF MUNICIPAL SOLID WASTE AND DETERMINATION OF ITS PHYSICOCHEMICAL CORRELATION, USING MULTIPLE REGRESSION ANALYSIS

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ABSTRACT

Municipal solid waste (MSW) is an aggregate of unwanted and discarded materials that are generated, as man interact with the environment, in his daily activities. The agglomeration of MSW in the environment is huge and its inefficient management could result in land degradation and pollution, unsightly scenes, ecological contamination and global warming. The energy content of its individual components varies from $0 \leq 46.169\ \mathrm{kJ/kg}$ *while that of overall composition remains a function of mix; physicochemical and thermochemical characteristics of the components. Therefore, this paper presents a waste-to-energy method for MSW management and energy recovery for heating or electricity generation. A multiple regression analysis was used to develop a predictive model for the energy content of MSW, while the effect of physicochemical* *characteristic of the mix on the overall MSW energy values was established. Waste samples were collected from Lasojo dumpsite in Ilorin Metropolis of Kwara State, Nigeria. The wastes streams were identified and characterized to determine the properties of the various fractions that were available for energy generation (kg). Three regression models were therefore developed and fitted to variables derived from proximate analysis, ultimate analysis and the physical compositions of MSW. A diagnostic check on the models show that model 1 and 2 suffer the problem of multicollinearity. This necessitate the use of ridge regression estimator. The models developed in this study can therefore, accurately predict the energy content of municipal solid waste and correlate it with its physicochemical characteristics.*

Keywords: Municipal solid waste, Energy content, Regression analysis

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1. INTRODUCTION

The growth of municipal solid waste (MSW) on a daily basis, result in environmental problems which include pollution, land degradation and others (Shi *et al*., 2006; Akkaya and Demir, 2009). This research study was primarily induced by the MSW management problems of Ilorin metropolis in Kwara state, Nigeria. The predicted waste generation in the metropolis, amounts to 302,000 tons/year at a rate of 0.78 kg/capita/day. Presently, the MSW generated in Ilorin metropolis is disposed of, at Lasoju-Eyenkorin (along Ibadan-Ilorin express way), which is the only functional dumpsite at the period of this study. The dumpsite is already filled with waste to about 2/3 of its maximum capacity; moreover the collection system is inefficient as evident by the uncollected wastes blocking of the water ways during raining seasons and indiscriminate disposal of MSW into open fields and water ways by the general public. Efficient and appropriate waste management system is therefore critically required, to sustain clean and friendly environment. Landfilling is recognized as a renowned method for municipal solid waste disposal across the globe. The method has the capacity to accommodate large quantity of MSW, particularly where large area of land to be designated for waste disposal is available. Nevertheless the system has its disadvantages which include: production of some noxious odour, emission of greenhouse gas, and leachate production (Akkaya and Demir, 2009). In addition, scarcity of a sufficiently large area of land that could be sacrificed for landfilling. These reasons are sufficient enough to consider an alternative method of municipal solid waste management. The recent development in WTE technology makes it possible to consider the municipal solid wastes generated continuously in cities, as an essential renewable energy resources; notwithstanding, Ilorin still face crisis of power outage. Energy recovery from municipal solid waste is possible through processes which include: gasification, aerobic digestion, combustion and pyrolysis (Cynthia, 2013). The design of municipal solid waste fired power plant which will doubly serve as an efficient waste management method as well as energy recovery device. The design and operation of any energy recovery systems using MSW as energy resource depend on the heating value of the considered municipal solid waste fractions. Therefore, it is very important to determine the heating value of the waste fractions, in the metropolis to be able to perform the efficient design and operation of the waste to energy conversion based technologies. The heating value was experimentally determined by using (e 2k combustion calorimeter) electronic bomb calorimeter. The heating value obtained from the bomb calorimeter, is the high heating value

(HHV); the required low heating value is obtained by the summation of the product of each waste fraction's percentage weight and its corresponding high heating value (Islam, 2006). In this study, three models were developed based on: the proximate analysis, ultimate analysis and the physical compositions of MSW. The aim of this study, is to develop empirical models that could be used in the estimation of energy content, represented by the heating value of municipal solid waste(MSW) fractions, using their physical and elemental characteristics viz moisture content, volatile matter, fixed carbon, carbon, hydrogen, nitrogen, oxygen, and sulfur. The equation coefficients of the developed model equations, were obtained from multiple regression analysis (Juin, *et al*., 2012), using ordinary least square estimator and ridge regression estimator. The prediction performances of the developed models have been evaluated by means of regression and error analyses.

2. MATERIALS AND METHOD

2.1. Characteristics of municipal solid waste data

MSW samples of specific bin volume of 240 litres each were collected from dumpsite, and each is weighed, and hand sorted into different components in a screening table of size 1.5m x 3 m with 10 mm x 10mm mesh surface designed for heterogeneous solid waste (WHO, (1988) and Issam, *et al.,* 2010). The characterization study lasted for eight months, in which 62 samples were considered to avoid eventual error that may occur due to insufficient samples. Nineteen waste fractions were obtained and nine of them selected for energy generation, based on combustibility and availability. They are: food residue, paper, plastic bottles, textiles (rag), wood, grass/garden trimmings, nylon, packaging box (carton) and polythene-sac.

2.2. Determination of the heating value of the waste components

The high heating values (HHV) of the MSW fractions were determined with the aid of bomb calorimeter (*e 2k* combustion Calorimeter), based on standard ASTM D5468-02 (Shi *et al*., 2016). Waste sample of 0.5g, was burnt in a bomb in the atmosphere of oxygen at the pressure of about 2000 M Pa; and the result is displayed on the screen of the data logger. According to Islam (2006), low heating energy obtained from the waste fractions selected for power generation is presented

$$LHV = \sum_1^9 W_\mathrm{j} \times HV_\mathrm{j} \tag{1}$$

Where LHV is the lower heating value, HV_j typical heating values of MSW component- j and W_j is the weight fraction (%) of component- j.

2.3. Proximate analysis

The proximate analysis was carried out to determine the moisture content, volatile matter, fixed carbon content and the ash content of each of the nine selected waste fractions, for energy production based on ASTM D7582 – 12 Standard methods. Moisture content was determined by drying 1g of grinded air-dried sample, in an Electric oven (DHG 9053, 200 °C capacity), when maintained at about 110 °C for 1 h; it was later removed and cooled in a desiccator and weighed. The loss in weight is reported as moisture material according Vairam and Ramesh, (2013); Shi *et al*., (2016) to by using Equation 2.

$$M_w = \frac{(w-d)}{w} \times 100 \tag{2}$$

Where M_w is the wet moisture content %, *w* is the initial mass of sample as delivered (kg), and *d* is the mass of sample after oven drying (kg).

After the determination of their moisture contents, the residue of moisture analysis, was covered with a lid and placed inside an electric furnace (TDW, 1200 °C capacity) maintained at 950°C. It was removed after 7 min of heating and cooled in a desiccator; then it was weighed to determine the loss in weight; which is reported as volatile matter in percentage terms. (Adekunle *et al*., 2015 and Shi *et al*., 2016) using Equation 3.

$$V_d = \frac{A}{B} \times 100 \tag{3}$$

Where V_d is the percentage volatile matter, A is the mass loss of the sample, and B is the mass of the sample taken.

The residue left after determination of volatile matter was heated without the lid inside a furnace at 700 °c for 0.5 h. The crucible was taken out, cooled in the desiccator and later weighed; heating cooling and weighing was repeated until a constant weight is obtained. Ash content is the amount of residue obtained after ignition of solid waste which was obtained according to Vairam and Ramesh, (2013) and Kuleape *et al* (2014), using Equation 4.

$$Ash\ (\%) = \frac{w}{W} \times 100 \tag{4}$$

Where w, is the mass of ash and W is the mass of the sample taken.

The fixed amount of carbon left behind was calculated according to ASTM D3172-73 by deducting the percentage amount of ash, moisture, and volatile matter from 100, using Equation 5.

$$\text{Fixed carbon } (\%) = 100 - (\text{Moisture} + \text{Volatile matter} + \text{Ash}) \tag{5}$$

2.4. Ultimate Analysis

Ultimate analysis was performed to evaluate of the total carbon (C), hydrogen (H), nitrogen (N), sulphur (S), oxygen (O) percentages after the removal of volatile matters, the moisture and ash contents (Benjamin *et al*., 2014). Flash EA 1112 Elemental analyzer; was used based on the standard ASTM D5291. About **0.**5g of the powdered sample in put into a crucible with vanadium (v) oxide catalyst, dropped into the reactor in an environment of oxygen. The temperature then rises to about 1800°C, causing the sample to combust. The product of combustion was purified by a reactor, then flowed into the chromatographic column, where separation occurred. Oxides of Nitrogen and sulfur produced were reduced to elemental nitrogen and sulfur dioxide and excess oxygen retained. The gas blend containing N_2, CO_2, H_2O, and SO_2 gasses, which were sent to the TCD where electrical signs processed by 'Eager 300 software' gave percentages of nitrogen, carbon, hydrogen, and sulfur contained in the sample. The samples were replicated three times in the experiment, and the average values of the results considered as the typical values.

2.5. Multiple regression analysis

Three models were developed on the heating value as dependent variable, using proximate products, ultimate products and physical components of the MSW as the independent variables. GRATEL statistical software with ordinary least square method. Diagnostic check was performed using Jarque-Bera test to determine the error distribution. The correlation of the regressors were examined by using variance inflation factor (VIF) for a diagnostic check of a problem of multicollinearity. The three models developed are specified in Equations 6-8.
Model for Ultimate Analysis is defined as:

$$HV = \beta_0 + \beta_1 C + \beta_2 H + \beta_3 N + \beta_4 S \tag{6}$$

Where β_0, β_1 ……... β_4 are the regression coefficients; and carbon (C), hydrogen (H), nitrogen (N), and Sulphur (S), are the selected independent variables.

Model for Proximate Analysis is defined as:

$$HV = \lambda_0 + \lambda_1 FC + \lambda_2 M + \lambda_3 VM \quad (7)$$

Where λ_0, λ_1 ……... λ_3 are the regression coefficients; and fixed carbon (FC), moisture (M), and volatile matter (VM), are the selected independent variables.

Model for physical composition is defined as:

$$HV = \gamma_0 + \gamma_1 G + \gamma_2 C^1 + \gamma_3 P \quad (8)$$

Where γ_0, γ_1 ……... γ_3 are the regression coefficients; and garbage (G) consists of food residue and grass, cellulose (C^1) consists of paper and packaging box, and polythene materials (P) consists of nylon, plastic and polythene sac, are the selected independent variables.

3. RESULTS AND DISCUSSION

In this section, the summary of the municipal solid wastes physical, chemical and thermochemical characteristics is provided, and also present the three regression models developed as well as the impact the increase of any of the characteristics will make on the net value of the waste stream's heating value.

3.1. Characteristics of MSW from Ilorin Metropolis

The characterization process was completed after the period of eight months. The result for the dry season sampling, sorting and characterization is presented in Table 1. The table shows the weight of each component in the waste stream per month, the total weight of components samples per month, the percentage weight of each component, the volume of each component available in the waste stream and the amount of waste generated per capita per day (kg/cap./day). It reveals that Nylon fraction of 19.42% has the highest proportion in the waste aggregate, followed by Others 11.98%, and the least is Leather of 0.06% proportion. The reason for having nylon as the highest is during dry season people are more thirsty, and they go for affordable table water in nylon sachets.

Table 1 The physical characterization of MSW for Dry season

S/N	MSW Fractions	Months				Total Wt (kg)	Wt %	Vol. m^3
		1	2	3	4			
		NOV. Wt. (kg)	DEC. Wt. (kg)	JAN. Wt. (kg)	FEB. Wt, (kg)			
1	Food residue	3.70	46.30	10.90	8.00	68.90	5.26	0.34
2	Wood	1.60	3.40	4.00	0.00	9.00	0.68	0.04
3	Paper	14.80	31.50	30.50	12.60	89.40	6.83	0.45
4	packaging box	10.40	49.60	12.50	7.80	80.30	6.13	0.40
5	Grass/trimmings	31.60	8.20	6.90	2.40	49.10	3.75	0.25
6	Texiles (rag)	27.20	46.00	42.40	27.30	142.90	10.92	0.71
7	Toiletries	18.40	14.10	29.10	31.10	92.70	7.08	0.46
8	Feaces	1.40	11.60	1.00	5.10	19.10	1.46	0.09
9	Cow dung	8.70	3.00	3.20	0.00	14.90	1.14	0.07
10	Nylon	59.00	70.40	72.20	52.50	254.10	19.42	1.27
11	poly (bagco sac)	23.20	11.30	24.20	8.20	66.90	5.11	0.33
12	Plastic bottle	7.00	64.20	18.40	18.30	107.90	8.24	0.54
13	Rubber	0.40	0.10	1.20	0.00	1.70	0.13	0.01

14	Leather	0.60	0.20	0.00	0.00	0.80	0.06	0.00
15	Glass/Ceramics	10.40	9.80	20.40	6.00	46.60	3.56	0.23
16	Bones	2.60	0.00	0.80	2.50	5.90	0.45	0.03
17	Tins/Metals	8.00	35.00	8.00	4.20	55.20	4.22	0.27
18	Sand/Ash	11.90	9.30	15.30	9.30	45.80	3.50	0.22
19	Others	20.00	50.60	59.40	26.80	156.80	11.98	0.78
	Grand Total	260.90	464.60	360.40	222.10	1308.00	100	6.54

The Wet season is considered as the combination of May, June, July and August shown in Table 2. The result of the physical characterization shows that the Food waste is 14.14 %, Packaging 12.32 %, followed by Nylon 12.11 %, Plastic bottle 10.92 % and the least is Leather 0.08 %. The reason for more food residue during the wet season could be new annual crops like maize, yams and others that are more available and affordable during the season.

Table 2. The physical characterization of MSW for Wet season

		Months						
		1	2	3	4			
S/N	MSW Fractions	MAY Wt (kg)	JUN. Wt (kg)	JUL. Wt (kg)	AUG. Wt (kg)	Total Wt (kg)	Wt %	Vol. m^3
1	Food residue	28.20	56.50	55.10	109.80	249.60	14.14	1.25
2	Wood	4.70	2.40	8.00	0.60	15.70	0.88	0.08
3	Paper	21.50	15.50	32.50	26.80	96.30	5.46	0.48
4	packaging box	56.80	47.50	50.00	63.00	217.30	12.32	1.09
5	Grass/trimmings	18.20	24.24	35.30	10.40	88.14	4.50	0.44
6	Texiles (rag)	21.60	27.40	21.50	60.40	130.90	7.42	0.65
7	Toiletries	33.70	22.80	25.60	15.60	97.70	5.54	0.49
8	Feaces	6.50	14.60	4.60	3.60	29.30	1.66	0.15
9	Cow dung	5.90	13.40	6.60	1.80	27.70	1.57	0.14
10	Nylon	58.40	66.80	41.10	47.40	213.70	12.11	1.07
11	poly (bagco sac)	19.80	17.50	25.92	33.40	96.62	5.48	0.48
12	Plastic bottle	80.50	48.40	26.50	37.40	192.80	10.92	0.96
13	Rubber	0.80	1.00	0.80	1.00	3.60	0.20	0.02
14	Leather	0.00	1.00	0.00	0.40	1.40	0.08	0.01
15	Glass/Ceramics	7.90	9.60	9.60	8.60	35.70	2.02	0.18
16	Bones	7.60	8.60	3.20	2.20	21.60	1.22	0.11
17	Tins/Metals	45.20	15.20	22.10	6.80	89.30	5.06	0.45
18	Sand/Ash	12.45	14.60	11.20	6.40	44.65	2.53	0.22
19	Others	29.30	37.50	25.00	20.40	112.20	6.36	0.56
	Grannd Total	459.05	444.54	404.62	456.00	1764.21	100	8.83

The components of the waste stream considered for energy estimation, their corresponding percentage in the total waste generated and the fraction predicted per day is given in Table 3.

Table 3 The waste components considered for Energy Generation

Waste fractions	Fractions predicted/day (tons)	Total fractions characterized for 8 months (kg)	Wt.%
Food residue	85.76	318.50	10.37
Wood	6.62	24.70	0.80
Paper	49.95	185.70	6.04
Packaging box	80.14	297.60	9.69
Grass/Trimmings	36.97	137.24	4.47
Textiles (rag)	73.69	273.80	8.91
Nylon	125.95	467.80	15.23
Poly-sac	43.99	163.52	5.32
Plastic bottle	80.96	360.70	9.79
	584.03	2169.56	70.62

3.2. Proximate Analysis results

Proximate analysis results given in Table 4. Show that the range of moisture content of the components analyzed is 6%-13% and the dispersion is 0.58%-1.16 %; the highest is wood 13 %, followed by grass/trimmings 10 % and the least is packaging box (carton) 6 %. Volatile matter's range is 2 %-67 % and the dispersion is 0.58 %-15.18 %; the highest is paper 68 %, wood 67 % and the least is plastic bottle 2 %. Ash content's range is 1 %-36 % with dispersion of 0.00 % - 4.04 %; the highest is grass 36 %, followed by Textile (rag) 23 % and the least is plastic 1.00 %.

Table 4. The result of proximate analysis of the waste sample

S/N	MSW Fractions	% FC	% VM	% Ash	% Moisture	HV (%)
1.	Packaging Box	65. 32.22	16.0 ± 2.7	14. 01.3	4.67±0.9	7.02
2.	Nylon	80. 06.67	18.3±7.11	1.67±0.89	0. 0 ± 0.0	20.4
3.	Textiles (rag)	43. 09.33	30.7±10.9	20. 02.0	6.33±0.4	6.96
4.	Wood	27.7±9.56	59. 0 ±10.0	1.67±0.44	11.67±1.1	8.14
5.	Grass/Trimmings	15.3±0.89	51.7±8.44	23.33±8.4	9.67±0.4	7.88
6.	Plastic Bottle	97.7±0.44	1.33±0.44	1. 00 ±0.0	0. 0 ± 0.0	16.50
7.	Paper Waste	24.3±4.89	58.7±5.56	10.33±0.4	5.67±0.9	7.53
8.	Food Waste	88.7±3.11	2.67±2.22	2.33±0.44	6.33±0.44	18.03
9.	Bagco-Bag	90.0±2.67	4.33±0.44	5.67±3.11	0.00±0.00	38.69

The chart showing the relationship between the heating value and the values obtained from proximate analysis is presented in Fig. 1.

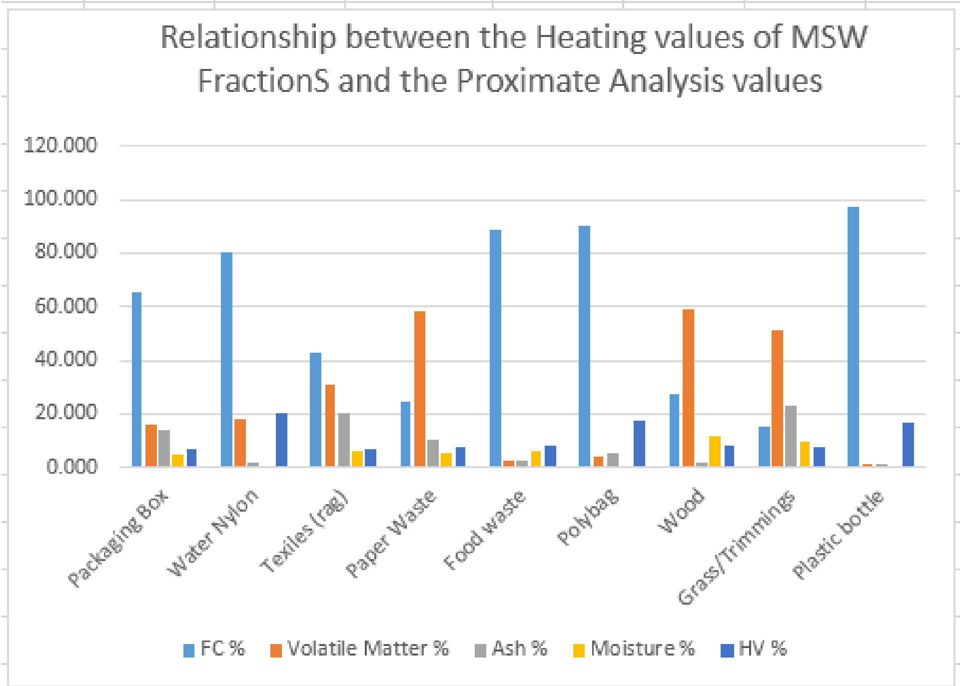

Figure 1 The heating values versus the proximate analysis of MSW.

3.3. Ultimate analysis results.

The ultimate analysis results in Table 5, show that the carbon range of the components analyzed is 21 %-38 % with dispersion of 0.04 %-0.85 %; the highest is food residue 38.08 %, followed by wood 37.45 % and polythene 21.07 %. Hydrogen range is 0.09 %-0.17 % with standard deviation of 0.001 %-0.031 %; the highest is food residue 0.17 %, Polythene bagco-sac is 0.15 % and the least is Textile (rag) 0.09 %. Nitrogen range is 2.12 %-5.10 with dispersion of 0.01 %-0.71 %; the highest is paper 5.10 % followed by food residue 5.01 % and the least is Polythene bagco-sac 2.12 %. Oxygen range is 0.065 %-0.085 with dispersion of 0.0006%-0.001%; the highest is nylon 0.085 %, followed by packaging box (carton) 0.083 % and grass/trimmings 0.065 %. Sulphur range is 0.05 % - 3.13 %. With dispersion of 0.002 %-0.039 %; the highest is food residue 3.13 %, followed by wood 0.13 % and the least is nylon 0.52 %.

Table 5 the result of Ultimate analysis of the waste sample

MSW Fractions	C %	H %	N %	S %	O %	HV %
Food residue	38.020 ± 0.44	0.165±0.00	4.938±0.05	3.100 ± 0.02	0.081 ± 0.00	18.624
Wood	36.523 ± 0.62	0.105±0.02	4.501 ± 0.04	0.101 ± 0.02	0.067±0.00	18.418
Paper	35.327±0.08	0.107±0.02	4.748±0.24	0.081 ± 0.00	0.069±0.00	17.038
Packaging box	20.987±0.06	0.111 ± 0.00	2.765±0.10	0.078 ± 0.03	0.082 ± 0.00	15.883
Grass/Trimmings	30.860 ± 0.11	0.098 ± 0.02	3.862 ± 0.06	0.071 ± 0.00	0.064 ± 0.00	17.838
Textiles (rag)	34.047±0.14	0.098 ± 0.00	4.373 ± 0.00	0.084 ± 0.00	0.075 ± 0.00	15.747
Nylon	22.057±0.08	0.110 ± 0.00	2.823±0.02	0.052 ± 0.00	0.076±0.00	46.160
Poly sac	20.950±0.11	0.111 ± 0.02	2.669±0.01	0.052 ± 0.00	0.078±0.00	39.352
Plastic bottle	23.050±0.03	0.105±0.00	2.925±0.00	0.078±0.02	0.078±0.02	37.282

The chart showing the relationship between the heating values of the municipal solid waste and the values from the ultimate analysis is presented in Fig.2.

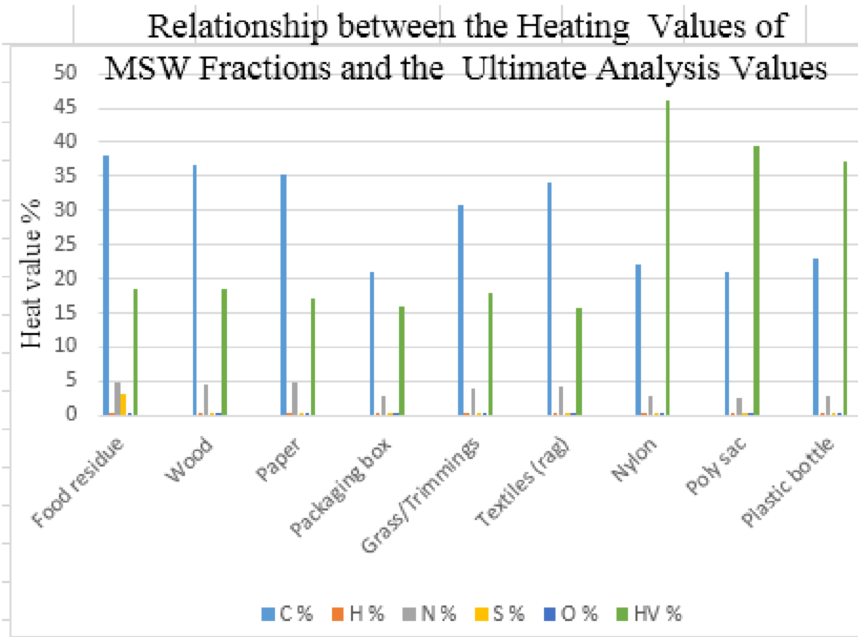

Figure 2 The heating values versus the ultimate analysis of the MSW.

3.4. The results of Heating value analysis

In Table 6, the net heating value of the waste components is determined to be about 20 MJ/kg. The heating value is about 44% of that of petrol, 46% of that of diesel, 49% of that of natural gas and 38% of that of methane (WNA, 2018). It is which is about 50 % of energy contained in coal and about 100 % of the energy contained in biomass. Nylon is the waste component that has the highest heating value of 20.4 %, Polythene bagco-sac 17.4 %, Plastic 16.5 % and the least is Textile (rag) 6.9 %.

Table 6 the thermo-chemical analysis of the waste components for energy Production.

S/N	Waste fractions	HHV(MJ/kg)	Mean	HHV%	Wt.%	HV=HHV*Wt.%
1	Food residue	18.624	18.624±0.545	8.23	10.37	1.9313
2	Wood	18.418	18.418±0.026	8.14	0.80	0.1473
3	Paper	17.038	17.038±0.920	7.53	6.04	1.0291
4	Packaging box	15.883	15.883±1.208	7.02	9.69	1.5391
5	Grass/Trimmings	17.838	17.838±0.251	7.88	4.47	0.7974
6	Nylon	46.160	46.160±0.246	20.4	15.23	7.0302
7	Textile (rag)	15.747	15.747±2.834	6.96	8.91	1.4031
8	Polythene sac	39.352	39.352±0.659	17.4	5.32	2.0935
9	Plastic bottle	37.282	37.282±0.734	16.5	9.79	3.6499
Total		226.324		100	70.62	19.6209

3.5. Multiple Regression analysis result.

3.5.1. Proximate analysis model

Multiple regression analysis result on the proximate analysis parameters (i.e. FC, M and VM) is given in Table 7.

Table 7 Multiple Regression Analysis on Proximate Result using OLS

Ordinary Least Square Estimator and its Diagnostic check					Ridge Regression	
Regressors	coefficient	standard error	t-ratio	p-value	Regressors	coefficient
constant	-7.19477	7.27918	-0.9884	0.36834	constant	-3.5553
FC__	0.116768	0.07671	1.5221	0.18848	FC__	0.0786
Moisture__	-0.347287	0.20225	-1.7171	0.14661	Moisture__	-0.1065
Volatile_Matter	0.151701	0.09633	1.5748	0.17612	Volatile Matter	0.3684
R-squared	0.70493	Ftest	3.9817			
Adjusted R-squared	0.52789	Jarque-Bera test	1.7550 (0.4158)			
MAX(VIF)	27.581					

*** ** and * denote significant levels at 1%, 5% and 10% respectively. Value in parenthesis is the p-value

The multiple regression analysis results presented on proximate analysis parameters, was possible by using OLS estimator and ridge regression estimator. The regression model for the ultimate analysis is:

$$\hat{HV} = -7.19477 + 0.116768\hat{FC} - 0.34728\hat{M} + 0.151701\hat{VM} \quad (9)$$

Where: HV is the heating value, FC is the fixed carbon percentage content of the municipal solid waste, MC is the moisture content percentage, and VM is the volatile matter percentage content. Using Jarque-Bera test for a diagnostic check, it shows that the error term is normally distributed because the p-value, 0.42 is greater than 5% level of significance. Another diagnostic check was conducted using variance inflation factor (VIF) to examine if the regressors are correlated (which is referred to as problem of multicollinearity). The rule of thumb shows that, if the VIF is greater than 10 then there is multicollinearity which implies that the regressors are correlated. There is a need to correct this problem, this necessitate the adoption of Ridge regression as an alternative method to OLS to correctly estimate the regression model. From the ridge regression estimate in Table 3.6. Fixed carbon and volatile matter have positive effect on heating value while moisture has a negative effect. It implies 1 % increase in fixed carbon and volatile matter will increase heating value by 8 % and 37 % respectively; while 1 % increase in moisture content will reduce heating value by 11 %. The R-squared shows about 70 % of the variation in the response is explained by the regressors. The F test shows that the overall model fitted to the data is significant at 4 %.

3.5.1. Ultimate analysis model

The result of multiple regression analysis performed using ultimate analysis parameters (i.e. C, H, N, and S) is given in Table 8.

Table 8 Multiple Regression Analysis on Ultimate Result using OLS

Ordinary Least Square Estimator and its Diagnostic check					**Ridge Regression**	
Regressors	**coefficient**	**standard error**	**t-ratio**	**p-value**	**Regressors**	**coefficient**
constant	1.3849	9.46871	0.1463	0.89079	constant	1.53324
C__	85.0807	23.2496	3.6594	0.02159	C__	79.08237
H__	-28.9675	71.9485	-0.4026	0.70782	H__	-30.16026

N__	-666.125	182.261	-3.6548	0.02168	N__	-619.09869
S__	11.6296	3.60443	3.2265	0.03208	S__	10.83630
R-squared	0.837249	Ftest	5.144354**			
Adjusted R-squared	0.674498	Jarque-Bera test	0.471254 (0.790075)			
MAX(VIF)	161359.816					

*** ** and * denote significant levels at 1%, 5% and 10% respectively. Value in parenthesis is the p-value

The multiple regression analysis results presented in Table 7 on Ultimate analysis parameters, was possible by using OLS estimator and ridge regression estimator. The regression model for the ultimate analysis is:

$$H\hat{V} = 1.3849 + 85.0807\hat{C} - 28.9675\hat{H} - 666.125\hat{N} + 11.6296\hat{S} \tag{10}$$

Where: HV is the heating value, C is the carbon percentage content of the municipal solid waste, H is the hydrogen content percentage, N is the nitrogen percentage content and S is the sulphur percentage content. The diagnostic check using Jarque-Bera test shows that the error term is normally distributed since the p-value, 0.79 is greater than 5% level of significance. The variance inflation factor (VIF) is another diagnostic check conducted to examine if the regressors are correlated which is referred to as problem of multicollinearity. The rule of thumb says if the VIF is greater than 10 then there is multicollinearity which implies that the regressors are correlated. There is a need to correct this problem, this necessitate the adoption of Ridge regression as an alternative method to OLS to correctly estimate the regression model. From the ridge regression estimate in Table 1, carbon and Sulphur both have a positive effect on heating value while hydrogen and nitrogen have a negative effect. A 1% increase in carbon and nitrogen will increase heating value by 79.08% and 10.83% respectively while a 1% increase in hydrogen and nitrogen decrease heating value by 30.2% and 619.1% respectively. The R-squared shows about 84% of the variation in the response is explained by the regressors. The F test shows that the overall model fitted to the data is significant at 5%.

3.5.3. Physical composition model

Multiple regression analysis result on the physical composition data (i.e. Garbage, Cellulose, and Polyethylene) is given in Table 9.

Table 9 Multiple Regression Analysis on Physical Compositions using OLS

Ordinary Least Square Estimator and its Diagnostic check				
Regressors	coefficient	standard error	t-ratio	p-value
constant	0.171002	0.273787	0.6246	0.56610
Garbage	0.010962	0.002906	3.7717	0.01958**
Cellulose_	0.008054	0.004783	1.6836	0.16755
Polyethylene	0.010242	0.003165	3.2363	0.03179 **
R-squared	0.976923	Ftest	56.4453	
Adjusted R-squared	0.959616	Jarque-Bera test	3.22706 (0.19918)	
MAX(VIF)	5.391			

*** **and*denote significant levels at 1%, 5% and 10% respectively.

The value in parenthesis is the p-value.

Multiple regression analysis on the physical composition data yielded the following model:

$$H\hat{V} = 0.171002 + 0.010962\hat{G} + 0.008054\hat{C} + 0.010242\hat{P} \quad (11)$$

Where: HV is the heating value, G is the garbage composition of the municipal solid waste, C is the cellulose components of the waste fractions and P the polyethylene fractions. Using Jarque-Bera test for a diagnostic check, it shows that the error term is normally distributed because the p-value, 0.20 is greater than 5% level of significance. Another diagnostic check was conducted using variance inflation factor (VIF) to examine whether the regressors are correlated (i.e. to check for multicollinearity problem). The variance inflation factor (VIF) is less than 10; this infers there is no multi-collinearity which implies that the regressors are not correlated. The results of p-value show that all the independent variables all have positive effect on the heating value. .It implies 1 % increase in Garbage, Cellulose and Polyethylene fractions, will cause heating value to increase by 2 %, 17 % and 3 % respectively. The R-squared shows about 98 % of the variation in the response is explained by the regressors. Moreover, Garbage and Polyethylene show that the model fitted to the data is significant at 5 %.

4. CONCLUSIONS

Energy content estimation of municipal solid waste is of practical interest in the design and operation of the related energy conversion systems. Model development is necessary for the accurate estimation of heating value in order to minimize cost in the design and operation of municipal solid waste based engineering application. In this research, three models have been developed based on multiple regression analysis, for the estimation of the high heating value of municipal solid waste; using their contents of fixed carbon, moisture, volatile matter, carbon, hydrogen, nitrogen, sulfur and the physical compositions. The multiple regression models obtained from the physical composition, proximate and ultimate analyses give an accurate prediction of the energy content of MSW from Ilorin metropolis. The results of this study show that the developed model equations give high estimation performance. The model based on ultimate analysis reveals that 1% increase in carbon and nitrogen will increase heating value by 79.08% and 10.83% respectively while a 1% increase in hydrogen and nitrogen decrease heating value by 30.2% and 619.1% respectively. The model based on proximate analysis implies that fixed carbon and volatile matter have positive effect on heating value while moisture has a negative effect. It shows that 1 % increase in fixed carbon and volatile matter will increase the heating value by 8 % and 37 % respectively; while 1 % increase in moisture content will reduce heating value by 11 %. Also the model based on physical composition implies 1 % increase in Garbage, Cellulose and Polyethylene fractions, will cause heating value to increase by 2 %, 17 % and 3 % respectively. This study reveals that the waste streams generated in Ilorin metropolis have substantial combustible volatile matters, constituent elements, and organic matters that could add to the heating values thereby making the MSW, suitable for energy generation. The heating values of the MSW are 226 MJ/kg and 20 MJ/kg, high heating and low heating values respectively. The regression model equations developed in this study constitute a reliable reference study, for the estimation of heating value of municipal solid waste (MSW) and also help the researchers that are working on MSW as an energy resource for power generation.

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