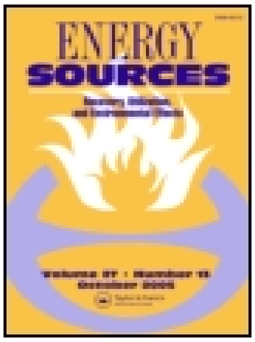

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Modeling and robust prediction of high heating values of municipal solid waste based on ultimate analysis

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ABSTRACT

The heating/calorific value of municipal solid waste (MSW) is essential in selecting or designing the appropriate waste to energy (WTE) systems. Experimental evaluation of the heating value of solid fuels is labor intensive, costly, and subject to experimental errors. Different models have been established to predict the high heating values of MSW and other solid fuels, from the ultimate analysis. However, the reliability of OLS estimator used in the linear regression model depends on the non-violation of assumptions that include independency of the predictor variables and normality of the error term. In this study, a new technique of robust estimators is employed to solve the problem of non-normality and dependency of the predictor variables in the linear regression model. The Robust ridge, robust Liu and robust K-L estimators were applied to mitigate the problems of multicollinearity and non-normality in the linear regression model. Eight (8) models were developed, and the adequacies were evaluated using the coefficient of determination (R^2), adjusted R^2, Akaike criterion (AIC), the mean squared error and the Schwarz criterion (SBIC). The eighth model is considered as the best because it has the highest adjusted R^2 (0.9710), the least mean squared error (1.9564), minimum AIC (133.2755) and SBIC (145.9437). The selected model with the robust K-L estimator is finally used to predict the high heating/calorific value of the ultimate analysis.

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Municipal solid waste; high heating value; ultimate analysis; linear regression models; robust estimators

Introduction

Solid municipal waste is the accumulation of undesirable matters/substances that are disposed on a day-to-day basis from human beings' endeavors when they interrelate with materials and their surroundings. Environmental problems that encompass air and water pollution, blockage of drainages and degradation of land occur due to irrepressible growth in MSW generation that lacks efficient management (Ibikunle et al. 2019; Shi et al. 2016). The waste produced in Ilorin (Nigeria) is a huge one that the customary waste disposal technique, could not sufficiently manage it, which resulted in uncollected wastes left at the collection points and consequently indiscriminate disposal of wastes to undesignated sites (Ibikunle et al. 2019, 2020). The MSW produced in Ilorin (Nigeria) includes wastes from households, public centers, markets, parks, and institutions; wastes from industries and hospitals are excluded. According to Ibikunle et al. (2019), the constituents of MSW generated in Ilorin comprise nylon, packaging box (carton), plastic bottle, polypropylene sack, wood, cow-dung, Excrement, bones, sand/ash, others, tins/metals, grass/trimmings, paper, leather, rubber, glass/ceramics, textiles (rag) and toiletries (spent pampers, sanitary tissues and pads).

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In 2000, facts from global data on MSW generation revealed 680 million tons per year; in 2010 it presented 1300 million tons per year, while the prediction for the years 2025 and 2055 was 2200 million and 4200 million tons per year discretely (Hoornweg and Bhada 2012). The World Bank reported the MSW generation in 2016 by the world city to be 2,010 million tons; with 0.74 kg per capita per day rate of generation. EPA (2017), presented the waste generated in 2005 by the U.S., to be 262.4 million tons at 2.03 kg per capita per day. The MSW rate of generation is considered as the major environmental indicator for the evaluation of wastes degree of production, to design an efficient waste management method. It is also helpful in comparing the degree of waste generation between one nation and others. According to IRENA (2018), the waste generated by United States of America in 2004, was rated at 942 kg per capita per year and it generated 8461000 MWh of electrical power; U. K. was able to generate 482 kg/person/annum of MSW to produce 1422000 MWh of electrical power; In Switzerland, MSW was generated at 730 kg per capita per day to initiate 1102000 MWh of electricity. India's rate of production was 385 kg per capita per person, to generate power of 1090000 MWh; while at 624 kg per capita per year rate of waste production, Japan produced power of 6574 GWh from MSW; Canada initiated power of about 89000 MWh from waste produced at 850 kg per person per year; France with MSW rate of generation 511 kg/capita/annum produced (IRENA, 2018). Increase in the generation rate of MSW poses a great concern because of the management processes (disposal and recycling) required. In 2003, about 12000 tons of MSW were generated in the city of Mexico (Baghban and Shamshirband 2019).

Despite power challenges in the developing nations particularly Nigeria, Africa as a continent, is still very dawdle in the area of waste to energy (WTE) systems of management, Africa's WTE power plant, built in Addis Ababa the capital of Ethiopia was commissioned in 2018. The plant can incinerate 1,400 tons of MSW, which is about 80% of the waste generated in the city to produce 185000 MWh/year using two of 25 MW steam turbines. Ghana is projecting for 60 MW thermal energy plant and the capacity of the WTE plants in South Africa (SA), exceeds 6.327 GW (UNEP, 2017). Nigeria has an average power rating of 0.107 MWh, at 12 W/capita/annum, which is comparably very low to power availability in other growing nations. Malaysia has 3.31 MWh with 337 W, SA has 4.347 MWh and 496 W (Hoornweg and Bhada 2012). According to Ibikunle et al. (2019), 196 million people in Nigeria produced 32 million tons of MSW annually, with about 70–80% of the waste left uncollected. In Onitsha, above 730412 people produced 370706 MSW tons/year; In Lagos, the commercial capital city of Nigeria, about 21 million populace produced more than 10,000,000 kg of MSW/day at 0.5 kg/person/day rate of generation (Maxwell 2010). Ibikunle et al. (2019), predicted the aggregate MSW generated in Ilorin metropolis to be 302,000 tons per year with 0.78 kg per person per day rate of generation. The waste produced in Ilorin increases tremendously daily due to rural-urban migration, industrialization, and demographic growth. Nearly all the designated dumpsites were exhausted, and many were already closed, thereby contributing more challenges for the traditional waste disposal system, that is practiced in Ilorin (Nigeria). The waste management system in Ilorin is relatively inefficient and not sufficient, thereby making the wastes to constitute a nuisance in the city. There is a need to incorporate other methods of waste management into the existing one, to engender efficient waste management and waste to wealth practices.

The contemporary development in WTE technology in the developed nations is enough to encourage the private organizations and the municipalities to venture into energy recovery processes. Recovery of energy from MSW is possible through processes that include aerobic digestion, gasification, incineration and pyrolysis (Cynthia, Keat, and Moses 2013). Abelha et al. (2003) and Li, Li, and Xu (2008), suggested that combustion is the method among the energy recovery technologies that are most economically prudent and ecologically friendly. Ibikunle et al. (2018), stated that about 74% of the total waste generated, can be consumed via energy recovery processes and Ibikunle et al. (2019), established that about 71% of the waste generated in Ilorin were combustible and could be used for energy recovery via incineration. To establish any WTE system, the design and the operation of the power plant, is dependent upon the heating value of the quantity of the MSW fractions considered. However, the heating value (HV) or the calorific value (CV) of the MSW components available in the city must be determined; to efficiently design the capacity of the WTE power plant required in such locality. The HV, is one of the paramount qualities, to determine the energy content of MSW as solid fuel. According to Reddy (2011), the HV is about an inverse proportional capacity of the WTE furnace/boiler and could be obtained by using a combustion calorimeter; or determined by a model obtained empirically. It is deprecatory to establish a heating value data that is reliable for the operation, maintenance, and design of a waste-to-energy plant. HV can be classified as high and Low heating Values (HHV and LHV). HV (or CV) defines the energy and the power potentials of MSW as a solid fuel, and it is one of the principal resources required in fuel to obtain a balance of energy, analysis in engineering, design modelings, and simulations of conversion systems for heat energy (Parikh, Channiwala, and Ghosal 2005). The HV is commonly classified as LHV or HHV. Gross calorific value (GCV) also known as HHV, is the heat released during thorough combustion of fuel, presuming the water contained in solid fuel before combustion process began and the one produced during combustion are present as condensed liquid (Ghugare et al. 2014; Parikh, Channiwala, and Ghosal 2005). Combustion of MSW is a reliable source of energy recovery since it has significant HHV that is required in use as a solid fuel (Alireza and Taghi, 2018). Energy recovery from MSW is possible via the combustion of waste components above a temperature of about 1123 K when sufficient air is available for the appropriate execution of the procedure (Baghban and Shamshirband 2019).

The HHV can be obtained experimentally, by combusting solid fuel in a high-pressure oxygen environment combustion calorimeter; it measures the change in enthalpy between the reactants and the products (Cordero et al. 2001; Parikh, Channiwala, and Ghosal 2005). LHV is the net HV, produced during combustion when the water present is assumed to be in vapor form when combustion is completed, and it is obtained by deducting the latent heat of vaporization of water from the HHV (Vargas-Moreno et al. 2012).

The HHV of MSW resource as a solid fuel, have been predicted using various mathematical models that include Dulong's and Steuer's models (Ibikunle et al. 2019). The models utilized the values obtained from ultimate analysis while other models used the values obtained from proximate analysis and physical composition. The fundamental characteristics of fuel that are used to project the HHV are revealed through the physicochemical analysis. Ultimate (chemical) analysis determines the principal chemical (elemental) components of the samples; these include oxygen (O), sulphur (S), hydrogen (H), nitrogen (N) and carbon (C) in weight proportion (wt. %) (Ibikunle et al. 2018; Yin 2011). Sheng and Azevedo (2005) established that the models developed from ultimate analysis values are more reliable compared to others. Yin (2011), also stated that models developed based on values from the ultimate (chemical) analysis exhibit better accuracy. Many prefer developing proximate analysis-based models, because, elemental analysis required in experimental procedures is very costly (Küçükbayrak et al. 1991). The proximate analysis determines, the percentage moisture (M), volatile matter (VM), fixed carbon (FC) and ash contents contained in every sample (Ibikunle et al. 2019; Yin 2011). Proximate analysis is faster, cheaper and easier; it can be performed by any competent researcher, scientist, or engineer that is acquainted with familiar laboratory equipment that includes digital Top-loading balance, electrical-oven (of $\leq$ 200 ° C) and electrical furnace (of $\leq 1200^{o}$ C) using standard test methods like European Committee for Standardization (CEN) and American Society for Testing and Materials (ASTM) (Demirbas 2003; Ibikunle et al. 2019; Küçükbayrak et al. 1991).

This study aims is to develop Ultimate-based models to predict the HHV of the combustible fractions of MSW using regression models. The proposed regression models are based on elemental components of MSW fractions (C, N, H, S and O) obtained from the ultimate analysis, to ensure a more accurate model that can be applied to other combustible biomass or biowaste components. We carry out regression diagnostics to assess the adequacy of each of the proposed models, and the best model will be employed to predict the HHV of the MSW in Ilorin Nigeria. The most suitable estimators will be adopted to estimate the parameters in the model. Previous studies have mostly adopted the conventional ordinary least squares estimator. However, in this study, we will consider some more robust estimators.

Study area

A case study of Ilorin (Nigeria) was considered for this investigation, due to its demographic development and the enormous MSW generated daily. Ibikunle et al. (2019), reported that the aggregate waste produced in the metropolis in 2016, was 302,000 tons per year at 0.78 kg per capita per day. The population accountable for the generation of waste in 2011 was projected to be 908,490 people, based on 2006 census (NPC, 2006; Ibikunle et al. 2019), projected the population of people responsible for waste generation in 2017 to be 1,087,660. The city comprises municipals that include Ilorin east, Ilorin south and Ilorin west. Ilorin is the capital of Kwara State (Nigeria) and is situated on latitude and longitude of 8^0 30′N and 4^0 35′E, respectively, on the territory of 100 km^2 area of land. It is located between the middle belt and South Western part of Nigeria. The principal towns in Ilorin metropolis are presented in the map shown in Figure 1(a). Ilorin is divided into zones that consist of the traditional settlement, as well as modern urban area. The city Center comprises the Emir's palace zone, the king's market (Oja-oba) and the Central mosque. The traditional zone encompasses area with deteriorating buildings and work man unrestrained zone, that comprises the second procreative movement to the city. Another zone accommodates categories of people that comprise, middle class, the professionals, and the businessmen. The last is the commuter zone which consists of small settlements and villages (Ajadi and Tunde, 2017). The waste management method practised in Ilorin is the disposal of MSW into the dumpsite which is insufficient to cater for the enormous waste produced; this thereby encourages people to indulge in indiscriminate dumping of garbage to wrong locations as shown in Figure 1(b). As at the time of this study, out of about ten dumpsites that were approved for MSW disposal, only Lasoju dumpsite of about 20 acres presented in Figure 1(c), was operational; the site is about 25 km away from the city, along Lagos – Ilorin express. This study will encourage sorting of waste fractions from source as well as an energy recovery system, which will provide an acceptable waste management method.

Materials and methods

This study was conducted on municipal solid waste (MSW) fractions from Ilorin metropolis in Nigeria. The MSW generated in Ilorin metropolis is a very huge one, comprising nylon, paper, carton, plastic bottle, Styrofoam, polypropylene sack, bones, sand/ash, grass/trimmings, food residue, glass/ceramics, textiles (rag), toiletries (pampers, sanitary tissues and pads), cow-dung, excrement, leather, rubber, and other biogenic waste. Thirty samples of MSW was characterized at Lasoju dumpsite, twelve (12) waste components that were considered combustible were prepared as test samples for Laboratory analysis. The high heating value (HHV) of each component was determined using *e 2 k* combustion calorimeter, and the Ultimate analysis was performed using Inductively Coupled Plasma – Optical Emission Spectrometer (ICP – OES Perkin Elmer 8000). The heating value was modeled with the chemical elements obtained from the ultimate (chemical) analysis to determine the thermochemical interrelationship between the HV and the composing chemical elements.

Sampling, sorting, and characterization of MSW components

On-site characterization of MSW fractions was performed at Lasoju dumpsite four months. Thirty (30) samples of wastes were randomly collected as suggested by Sharma and McBean (2007), from different locations of the dump heaps based on ASTM D5231 standard (Ibikunle et al. 2019), and were adequately mixed using a shovel to heap it into a cone shape. Later it was divided into four parts, as suggested by Abd Alqader and Hamad (2012) Two slices that were opposite in a crosswise direction were thrown away, and the remaining were again mixed to give a parent sample of 240 liters of bin volume; this process was replicated 30 times (EC Ibikunle et al. 2018; SWA-Tool 2004). Each of the samples was poured into the screening table suggested by WHO, made of mild steel of 1.5 by 3 m dimensions with sieving mesh of 10 by 10 mm holes as adopted by Ibikunle et al. (2018) and Issam

Figure 1. (a): Map Showing the Major Towns in Ilorin Metropolis (Google maps world "Google maps world Gazetteer–Ilorin Nigeria" 2020). (b): Indiscriminate disposal of MSW into water ways in Ilorin). Lasoju dumpsite along Lagos – Ilorin express way.

et al. (2010). Individual components were manually sorted into different containers, labeled, and later weighed. The20 MSW fractions characterized are paper, carton (packaging box), wood, plastic bottle, nylon, polypropylene sack, styrofoam, bones, tins and metals, food residue, grass/trimmings, glass/ceramics, textiles (rag), toiletries (pampers, sanitary tissues and pads), cow-dung, excrement, leather, rubber, sand/ash and unidentified biogenic matters. The wastes components were classified into combustible and others. Every component that can burn if classified under combustible category and the rest were classified as others.

Preparation of laboratory test samples

The available combustible waste components that encompass wood, packaging box, paper, polypropylene sack, nylon, plastic bottle, styrofoam, rags, bones, grass/garden trimmings and food residue and other biogenic were prepared for the laboratory analysis. Each sample was shredded and milled into smaller particles of less than 1 mm, other than plastic that is larger. Shredding and milling into smaller particles will encourage a larger surface area for effortless digestion of the test samples when mixed with reactants. The test samples prepared are presented in Figure 2(a – i).

Ultimate analysis of the combustible MSW fractions

The chemical elements are composed of carbon (C), hydrogen (H), nitrogen (N), sulphur (S) and oxygen (O) that are present in the MSW test samples. They were determined based on ASTM C1111-10 standard test method, with the aid of Inductively Coupled Plasma – Optical Emission Spectrometer

2 a. Polypyrene sack 2 b. Textile (rag) 2 c. Paper

(d) Packaging Box (Carton) (e) Food Residue (f) Grass / Garden Trimming

(g) Milled wood (h) Shredded Plastic Bottle (i) Nylon.

Figure 2. Three samples of milled MSW fractions prepared for laboratory tests.

(ICP – OES Perkin Elmer 8000) as suggested by Ibikunle et al. (2018). Step 1: The digestion process requires that 1 ml of the sample be digested in tubes and heated to a temperature of 150 ^{o} C, it is further heated in a Gerhardt – Kjeldatherm digestion machine until the samples become light brown. When the digests become a clear yellow-like color, and the temperature was raised to 240 ^{o} C until dryness; then the digestion tubes were taken out of the block to cool.

Step 2: Elemental analysis by ICP – Spectrometer. The aqueous solution of the sample preparation is injected to ICP. It was nebulized to a mist of fine droplets called aerosol, the ICP dissociates the sample into component ions by argon plasma, and was stirred to emit typical light wavelength. The emitted light wavelength was set into its constituent radiation (through diffracting grating) and evaluated using a photomultiplier tube at the specific wavelength for each element. The signal produced by the electron was juxtaposed with other intensities measured for related element concentration, and it was computed in the system's data analyzer. The components of mineral in every sample was investigated by ICP – Spec. using "WINLAB 32" software. The spectrometer data collection parameters were configured, viewed graphically, and the results of the analysis give the percentage constituents of the elements in the wastes test samples.

Prediction of the HHV of MSW using linear regression methods

Linear regression model has been employed by several authors to predict the HHV of some solid fuel, as presented in the following eaution:

$$y = X\beta + \varepsilon \tag{1}$$

where y is an $n \times 1$ vector of response variable, X is a known $n \times p$ full rank matrix of predictor or explanatory variables, β is an $p \times 1$ vector of unknown regression parameters, ε is an $n \times 1$vector of errors such that $E(\varepsilon) = 0$ and $V(\varepsilon) = \sigma^2 I_n$, I_n is an $n \times n$ identity matrix.

The HHV of solid fuels that encompass municipal solid waste, lignite coals, Biomass, Coal, greenhouse crop residues, Spanish biofuels and others, had been predicted by researchers that include Jiménez and González (1991), Küçükbayrak et al. (1991), Demirbas (2003), Cordero et al. (2001), Khuriati et al. (2017), Kathiravale et al. (2003), Sheng and Azevedo (2005), Parikh, Channiwala, and Ghosal (2005), García et al. (2014) Özyuguran and Yaman (2017), Nhuchhen and Afzal (2017), Qian et al. (2018), Baghban and Shamshirband (2019), and others using linear regression model. The authors have employed the ordinary least squares (OLS) estimator defined in equation (2) for their prediction, based on either proximate or the ultimate analysis.

$$\hat{\beta} = (X'X)^{-1}X'y \tag{2}$$

However, the authors did not take cognizance of the fact that the performance of the OLS estimator, is a function of the non-violation of certain assumptions. Lukman and Ayinde (2017), reported that the OLS estimator performs best, when there is no violation of assumptions which include none correlation of the predictors. The presence of multicollinearity in a linear regression model reduces the efficiency of the OLS estimator (Kibria and Banik 2016; Lukman et al. 2020). The regression estimates might exhibit a wrong sign using the OLS estimator when there is multicollinearity (Lukman et al. 2019a; Qasim, Amin, and Omer 2019; Saleh et al. 2019). The variance inflation factor and the condition index are popularly employed to test for the presence of multicollinearity (Gujarati 1995; Kibria and Lukman 2020). Alternative estimators have been suggested for parameter estimations in the linear regression model. Hoerl and Kennard (1970), developed the ridge regression estimator as presented in the folloiwng equation:

$$\hat{\beta}(k) = (X'X + kI_p)^{-1}X'y = (X'X + kI_p)^{-1}X'X\hat{\beta} \tag{3}$$

where $I_p$is the identity matrix, k is the shrinkage parameter.

In this study, shrinkage parameter (k), was estimated as presented inthe folloiwng equation :

$$\hat{k} = \frac{p\hat{\sigma}^2}{\sum_{i=1}^{p} \hat{\beta}_i^2} \tag{4}$$

where $\hat{\sigma}^2 = \frac{Y'Y - \beta' X' Y}{n-p}$ is the estimated mean squared error from the OLS estimator.

The Liu estimator developed by Liu (1993), to solve the problem of multicollinearity is as presented inthe folloiwng equation :

$$\hat{\beta}(d) = (X'X + I_p)^{-1}(X'y + d\hat{\beta}) = (X'X + I_p)^{-1}(X'X + dI_p)\hat{\beta} \tag{5}$$

where d is the shrinkage parameter and it was estimated in this study, by adopting the folloiwng equation:

$$\hat{d} = \min\left[\frac{\hat{\beta}_i^2}{\hat{\sigma}^2/\lambda_i + \hat{\beta}_i^2}\right] \tag{6}$$

where λ_i is the ith eigenvalue of $X'X$matrix. Recently, Kibria and Lukman (2020), developed the K-L estimator to also handle the problem of multicollinearity in the linear regression model. The estimator is defined inthe folloiwng equation, as $\hat{\beta}_{KL}$:

$$\hat{\beta}_{KL} = (X'X + k^* I_p)^{-1}(X'X - k^* I_p)\hat{\beta} \tag{7}$$

where k^* is the shrinkage parameter and is estimated in the following equation :

$$\hat{k}^* = \min\left[\frac{\hat{\sigma}^2}{2\hat{\beta}_i^2 + \hat{\sigma}^2/\lambda_i}\right] \tag{8}$$

The scalar mean squared error (SMSE) is adopted for the purpose of comparing the performance of these estimators. Estimator with the least mean square error has the best performance. The mean square error of the estimators are defined in equations (9–12):

$$SMSE\left(\hat{\beta}\right) = \hat{\sigma}^2 \sum_{i=1}^{p} \frac{1}{\lambda_i} \tag{9}$$

$$SMSE\left(\hat{\beta}(k)\right) = \hat{\sigma}^2 \sum_{i=1}^{p} \frac{\lambda_i + k^2\hat{\beta}_i^2}{(\lambda_i + k)^2} \tag{10}$$

$$SMSE\left(\hat{\beta}(d)\right) = \hat{\sigma}^2 \sum_{i=1}^{p} \left(\frac{(\lambda_i + d)^2}{\lambda_i(\lambda_i + 1)^2} + \frac{(d-1)^2\hat{\beta}_i^2}{(\lambda_i + 1)^2}\right) \tag{11}$$

$$SMSE\left(\hat{\beta}_{KL}\right) = \hat{\sigma}^2 \sum_{i=1}^{p} \left(\frac{(\lambda_i - k^*)^2}{\lambda_i(\lambda_i + k^*)^2} + 4k^{*2} \sum_{i=1}^{p} \frac{\hat{\beta}_i^2}{(\lambda_i + k)^2}\right) \tag{12}$$

Another assumption that is often violated in the linear regression model is the normality of the error term (Ayinde, Lukman, and Arowolo 2015; Kibria and Lukman 2020; Lukman, Osowole, and Ayinde 2015). The robust estimators are employed to solve the problem of non-normality in the linear regression model. These include the M-estimator, the MM-estimator, the least absolute deviation estimator, the least trimmed mean squared estimator and others (Huber 1973; Rousseeuw and Leroy 1987; Rousseeuw and Yohai 1984; Yohai 1987).

The M-estimator is employed in this study because, the estimator is generally preferred when there is outlier in the y-direction (Lukman, Arowolo, and Ayinde 2014; Samkar and Alpu 2010). Studies have shown that both problems can exist jointly in the linear regression model which is a threat to the performance of the OLS estimator (Kan, Ozlem, and Yazici 2013; Lukman et al. 2019b).

The robust ridge and the robust Liu were introduced in literature to jointly handle the problem of multicollinearity and non-normality in the linear regression model (Kan, Ozlem, and Yazici 2013; Lukman et al. 2019b). In this study, we employed the robust ridge, robust Liu and the robust K-L estimator to mitigate these problems. The robust ridge estimator is defined inthe folloiwng equation :

$$\hat{\beta}_k^M = (X'X + k_M I_p)^{-1} X'X \hat{\beta}_M \tag{13}$$

where k_M is the robust shrinkage parameter and it is estimated in this study using the folloiwng equation:

$$\hat{k}_M = \frac{p\Omega}{\sum_{i=1}^{p} \hat{\beta}_{i,M}^2} \tag{14}$$

where Ω is the scaled mean squared error of $\hat{\beta}_M$, $\hat{\beta}_M$is the regression estimate of the M-estimator. The robust Liu estimator is defined as

$$\hat{\beta}_d^M = (X'X + I_p)^{-1}(X'X + d_M I_p)\hat{\beta}_M \tag{15}$$

where d_M is the robust shrinkage parameter and it is estimated in this study using the following equation :

$$\hat{d}_M = \min\left[\frac{\hat{\beta}_{i,M}^2}{\Omega/\lambda_i + \hat{\beta}_{i,M}^2}\right] \tag{16}$$

where λ_i is the ith eigenvalue of $X'X$ matrix. The robust K-L estimator is defined in the following equation as $\hat{\beta}_{KL}^M$:

$$\hat{\beta}_{KL}^M = (S + k_M^* I_p)^{-1}(S - k_M^* I_p)\hat{\beta} \tag{17}$$

where k^*, the shrinkage parameter is estimated as follows:

$$k_M^* = \min\left[\frac{\Omega}{2\hat{\beta}_{i,M}^2 + \Omega/\lambda_i}\right] \tag{18}$$

Results and discussion

Characterization of MSW into components

The MSW fractions were characterized into 20 components as presented in Table 1. The quantity of MSW characterized during this study, was about 1670 kg, with bin volume of 8.312 m^3 at a production rate of 1.003 kg/capita per day. The characterization revealed that the waste component with highest proportion is nylon with 14.01% and production rate of 0.14 kg per capita per day, followed by food waste 9.54% with production rate of 0.096 kg per capita per day, plastic bottle 9.0% at rate of 0.090 kg per capita per day, and the least is leather with 0.007% at rate of 0.001 kg per capita per day.

Table 1. The waste components showing the quantity characterized and the generation rate.

Waste components	Wt. (kg)	Wt. %	Vol. (m^3)	kg/capita /day
Food residue	159.25	9.54	0.72	0.096
Wood	12.35	0.74	0.06	0.007
Paper	92.85	5.56	0.47	0.056
packaging box	148.80	8.91	0.69	0.089
Grass/trimmings	68.62	4.11	0.36	0.041
Textiles (rag)	136.90	8.20	0.71	0.082
Toiletries	95.20	5.70	0.53	0.057
Excrement	24.20	1.45	0.12	0.015
Cow dung	21.30	1.28	0.11	0.013
Nylon	233.90	14.01	1.24	0.140
Polypropylene-sac	81.76	4.90	0.42	0.049
Plastic bottle	150.35	9.00	0.71	0.090
Styrofoam	133.73	8.01	0.63	0.080
Rubber	2.65	0.16	0.01	0.002
Leather	1.10	0.07	0.00	0.001
Glass/Ceramics	41.15	2.46	0.22	0.025
Bones	13.75	0.82	0.07	0.008
Tins/Metals	72.25	4.33	0.34	0.043
Sand/Ash	45.23	2.71	0.24	0.027
Others	134.50	8.05	0.70	0.081
Grand Total	1669.83	100	8.312	1.003

Thermochemical analysis of MSW components

Thermochemical analysis of twelve (12) combustible components of the twenty (20) waste fractions characterized is presented in Table 2. The typical HHV of the combustible waste components is 21.3 MJ/kg. The waste fraction with the highest HHV proportion is plastic with 16.92%, followed by 11.10% of rubber, 10.94% of Styrofoam and the least is bone with 5.72%. The average proportion of the chemical elements in the combustible waste components reveals that carbon is 51.80%, oxygen is 33.82%, hydrogen is 7.49%, nitrogen is 1.14% and the least is sulphur with 0.42%. The carbon constituent in the waste fractions show that plastic has the highest with 80.22%, followed by rubber with 67.88% and the least is bone with 33.83%. Hydrogen constituent shows that plastic has 14.98%, followed by Styrofoam 8.05%, the least is high density plastic with 5.73%. In nitrogen constituent, bone has 4.89%, other biogenic fraction has 2.88% and the least is 0.03% plastic. The highest constituent of sulfur is rubber with 1.8%, followed by food residue 1.05% and the least is wood with 0.03% while paper has 44.95% oxygen, followed by 43.98% food residue ant the least is 4.18% plastic.

Table 2. Thermochemical characterization of waste components.

Waste Fractions	C %	H %	N %	S %	O %	ASH %	HHV (MJ/kg)
Grass/trimmings	41.01	6.22	0.89	0.25	39.20	12.89	16.01
Styrofoam	57.95	8.05	0.80	0.09	31.35	2.201	27.96
Textile (rags)	48.95	5.95	0.31	0.24	42.98	2.160	17.89
Paper	43.28	6.83	0.16	0.09	44.95	4.990	16.75
Bone	33.83	6.17	4.89	0.24	24.86	30.00	14.61
Plastics	80.22	14.98	0.03	0.05	4.120	2.530	43.24
Other-biogenic	38.85	6.88	2.88	0.60	41.82	10.95	15.13
Rubber	67.88	7.76	0.45	1.81	11.89	14.59	28.37
High Density Plastic	63.00	5.73	0.09	0.13	33.87	0.156	22.99
Wood	46.95	6.77	0.16	0.03	43.55	1.120	17.96
Packaging box	52.10	7.89	0.55	0.45	43.23	6.650	16.49
Food residue	47.58	6.66	2.52	1.05	43.98	3.889	18.21
Typical value	51.80	7.49	1.14	0.42	33.82	7.680	21.30

Data description and modeling

The twelve (12) waste components that are combustible, were subjected to ultimate analysis. Each test sample was replicated, in other to get a reliable typical value for each component. The typical heating value of the combustible waste components considered as the dependent variable, was modeled against the chemical elements comprising Carbon, Hydrogen, Nitrogen, Sulphur, and Oxygen using the linear regression model. Also, we determine the thermochemical correlation between the HHV and the elements by adopting the correlation coefficient. The softwares adopted in this study include R and GRETL. Figure 3 shows the relationship among the variables using the scatter plot matrix. The scatter plot matrix reveals that a positive relationship exist between HHV and the chemical elements: C, H and S. A negative relationship exist between HHV and the following element: O and N.

Figure 3 is further supported with the estimation of the correlation coefficient using Pearson product moment method. In Table 3, it is established that relationship exist among the variables.

In this study, eight models were developed; the HHV of MSW was modeled using the linear regression analysis as presented in equations (19–24).

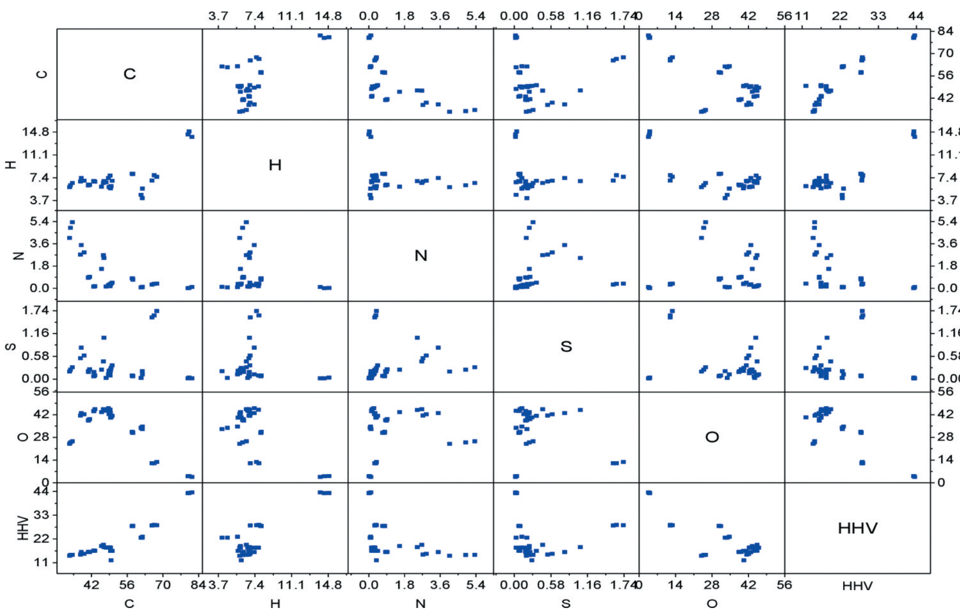

Figure 3. Scatter plot matrix of the variables.

Table 3. Correlation coefficient output.

		C	H	N	S	O	HHV
C	Pearson Correlation	1	.665**	−.611**	.115	−.720**	.926**
	Sig. (2-tailed)		.000	.000	.505	.000	.000
H	Pearson Correlation	.665**	1	−.194	−.091	−.683**	.838**
	Sig. (2-tailed)	.000		.257	.596	.000	.000
N	Pearson Correlation	−.611**	−.194	1	.125	.051	−.397*
	Sig. (2-tailed)	.000	.257		.466	.766	.016
S	Pearson Correlation	.115	−.091	.125	1	−.277	.044
	Sig. (2-tailed)	.505	.596	.466		.101	.798
O	Pearson Correlation	−.720**	−.683**	.051	−.277	1	−.817**
	Sig. (2-tailed)	.000	.000	.766	.101		.000
	Sig. (2-tailed)	.002	.310	.000	.081	.173	.051
HHV	Pearson Correlation	.926**	.838**	−.397*	.044	−.817**	1
	Sig. (2-tailed)	.000	.000	.016	.798	.000	

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

$$Model1: y = \beta_0 + \beta_1 C + \beta_2 H + \beta_3 N + \beta_4 S + \beta_5 O + \varepsilon_i \tag{19}$$

$$Model\ 2: y = \beta_0 + \beta_1 C + \beta_2 H + \beta_3 N + \beta_4 S + \varepsilon_i \tag{20}$$

$$Model3: y = \beta_0 + \beta_1 C + \beta_2 H + \beta_3 N + \varepsilon_i \tag{21}$$

$$Model4: y = \beta_0 + \beta_1 C + \beta_2 H + \varepsilon_i \tag{22}$$

$$Model5: y = \beta_0 + \beta_1 C + \varepsilon_i \tag{23}$$

$$Model6: y = \beta_0 + \beta_1 C + \beta_2\ C^2 + \beta_3 H + \beta_4 N + \beta_5 S + \beta_6 O + \varepsilon_i \tag{24}$$

$$\begin{aligned} Model7: y = \beta_0 + \beta_1 C + \beta_2\ C^2 + \beta_3 H + \beta_4 H^2 + \beta_5 N + \beta_6 N^2 + \\ \beta_7 S + \beta_8 S^2 + \beta_9 O + \beta_{10} O^2 + \varepsilon_i \end{aligned} \tag{25}$$

$$Model8: y = \beta_0 + \beta_1 C + \beta_2 H + \beta_3 N + \beta_4 N^2 + \beta_5 S + \beta_6 S^2 + \beta_7 O + \varepsilon_i \tag{26}$$

where $\beta_i,\ i = 0, 1, 2, 3, 4, 5, \ldots, 10$ denotes the regression coefficients, y represent the HV of the MSW, C denotes carbon content, H denotes Hydrogen content, N represents Nitrogen content, S represents Sulphur content, O represents Oxygen content and ε_i is the error term that is expected to be normally distributed with mean zero and variance, σ^2.

Table 4 provides the ordinary least square estimate of equations (1–26). We assess the model adequacy using the following criteria: coefficient of determination (R^2), adjusted R^2, Akaike criterion (AIC), the mean squared error and the Schwarz criterion. This was done for the purpose of selecting the best model for the ultimate analysis. Model 8 is the best because it possess the highest adjusted R^2, the least mean squared error, the least AIC and the least SBIC. Research has revealed that adjusted R^2 is better than the R^2 especially when you have to introduce new variables. The adjusted R^2 works on the limitation of the R^2 (Gujarati 1995). The carried out diagnostic check to examine if the assumptions in the linear regression model are satisfied. The results are also available in Table 3. Model (7) competes favorably with model (8). These shows that the quadratic model (8) fit well to the data. The R^2 and the adjusted R^2 are presented in Table 4, also the parameter estimation and diagnostic check of the best model is presented in Table 5.

The diagnostic check shows that there are certain violations in the assumption of the linear regression model which makes the OLS estimator not the most efficient estimator for this modeling. The Jarque-Bera (JB) test shows that the error term is not normally distributed. The test statistic value is 48.2133 with a corresponding p-value of 0.0000. Thus, since the p-value is less than the level of significance ($\alpha = 0.05$) then we conclude the error term is not normally distributed. The white test is employed to check if the error term has a constant variance. This shows there is no problem of heteroscedasticity. The white test value is 21.007 with a p-value of 0.7860. There is constant variance

Table 4. Model selection for MSW based on ultimate analysis.

Predictors	R^2	adj R^2	MSE	AIC	SBIC
Model 1	0.9635	0.9574	2.8789	145.6671	155.1682
model 2	0.9605	0.9554	3.0162	146.5249	154.4425
Model 3	0.9590	0.9551	3.0314	145.8484	152.1825
Model 4	0.9462	0.9429	3.8581	153.6376	158.3881
Model 5	0.8568	0.8526	9.9573	186.8451	190.012
Model 6	0.9655	0.9583	2.8115	145.5932	156.6778
Model 7	0.9771	0.9680	2.1615	138.7848	156.2035
Model 8	0.9768	0.9710	1.9564	133.2755	145.9437

Table 5. HHV Modeling based on the ultimate analysis using the OLS.

Predictors	Coeff.	SE	t-ratio	p-value	VIF
β_0	−7.9080	4.4692	−1.769	0.0877*	
β_1	0.4699	0.0519	9.058	0.0000***	7.938
β_2	0.9671	01703	5.678	0.0000***	2.918
β_3	3.8402	0.8588	4.472	0.0001***	28.178
β_4	−0.5763	0.1610	−3.578	0.0013***	21.902
β_5	−12.924	3.9207	−3.296	0.0027***	55.957
β_6	6.8369	2.4096	2.837	0.0084***	59.770
β_7	−0.0609	0.05315	−1.146	0.2617	8.796
R-squared	0.9768	F-test (p-value)	168.68 (0.0000)	Adjusted R-squared	0.9710
White test (p-value)	7.4937 (0.823)	JB-test (p-value)	58.244 (0.0000)		

since the p-value is greater than the level of significance. The other problem exhibited in this model is the challenge of multicollinearity since the variance inflation factors for some variables are greater than 10. According to Gujarati (1995), there is multicollinearity when the VIF exceeds 10. The diagnostic test revealed that the model suffers the problem of non-normality and multicollinearity. For the purpose of handling these problems simultaneously, we employed the robust-ridge estimator, robust-Liu and robust-KL estimator. The performance of the estimators is compared using the scalar mean squared error (SMSE). The results are presented in Table 6 and the estimator with the least SMSE is considered best. The robust-KL estimator possesses the least SMSE. Figures 4 and 5 shows the graph of the predicted value against the actual value using both the OLS and the robust-KL estimator.

Figures 4 and 5 also shows that model (8) fit well to the HHV data. Though both figures indicate that the actual heating values are not far from their corresponding predicted values. However, the

Table 6. OLS and Robust estimators' output.

Predictors	$\hat{\beta}$	$\hat{\beta}_k^M$	$\hat{\beta}_d^M$	$\hat{\beta}_{kl}^M$
β_0	−7.9080	−6.3178	−5.3458	−5.2716
β_1	0.4699	0.4588	0.4496	0.4489
β_2	0.9671	0.9240	0.9117	0.9107
β_3	3.8402	3.3389	3.1753	3.1648
β_4	−0.5763	−0.5219	−0.5095	−0.5088
β_5	−12.924	−9.8073	−8.6217	−8.5418
β_6	6.8369	4.8947	4.1551	4.1048
β_7	−0.0609	−0.0810	−0.0942	−0.0952
SMSE	41.950	23.3342	18.5338	18.2421

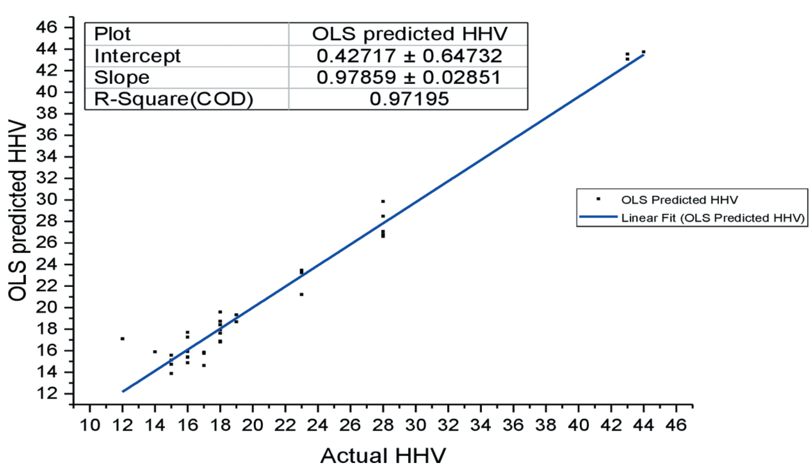

Figure 4. Graph of the predicted and experimental HHV using the OLS estimator.

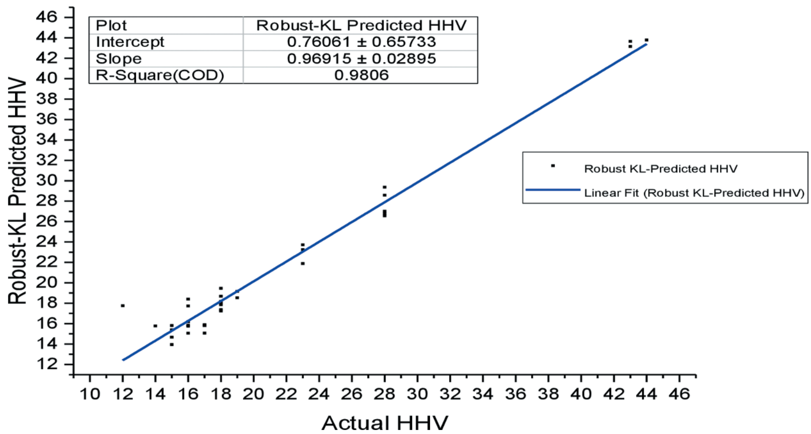

Figure 5. Graph of the predicted and experimental HHV using the robust-KL estimator.

formal estimation revealed that the robust-KL is generally preferred to estimate the parameters in the best model. In Table 7, the actual values were compared to the values predicted via OLS and Robust-KL discretely. Comparing the parameter estimation with some existing models, we observed the heating value increase with increases in Carbon, Hydrogen and Sulphur (quadratic term) while

Table 7. The actual values and the predicted values.

Actual values	Precited values using OLS	Predicted values based on Robust-KL
16	15.41	15.84
16	15.40	15.75
16	15.92	16.18
28	27.07	26.78
28	26.79	26.56
28	26.76	26.56
18	16.89	17.37
18	17.62	17.84
18	16.80	17.23
17	15.75	15.80
17	15.86	15.89
17	14.63	15.07
15	13.88	13.94
15	14.74	14.67
14	15.89	15.77
43	43.54	43.66
43	43.07	43.16
44	43.75	43.79
15	15.58	15.81
15	15.13	15.39
16	14.88	15.05
28	29.86	29.37
28	26.61	27.01
28	28.49	28.58
23	23.47	23.72
23	23.25	23.25
23	21.22	21.89
18	18.41	18.18
18	19.59	19.46
18	18.73	18.68
16	17.71	18.40
16	17.26	17.73
12	17.11	17.75
18	17.94	18.00
19	18.68	18.53
19	19.33	19.15

Oxygen and Nitrogen (quadratic term) shows a negative impact. This result agree with the Modified Duolong equation adopted by in the study of Tchobanoglous, Theisen, and Vigilintegrated (1993), Meraz et al. (2003) and Komilis et al. (2012).

Conclusion

In this study, we developed the linear regression models for the prediction of the high heating values based on the ultimate analysis of the municipal solid waste. The heating value of the combustible waste components was considered as the dependent variable, modeled against the chemical elements comprising Carbon, Hydrogen, Nitrogen, Sulphur, and Oxygen using the linear regression model. Eight different models were developed either in the linear or quadratic form. The adequacy of the models was evaluated using some criteria, and model (8) was eventually selected as the best, because it possesses the highest adjusted R^2 of 0.9710, the least mean squared error of 1.9564, the least AIC of 133.2755 and the least SBIC of 145.9437. The parameters of the selected model were estimated, using ordinary least square, the robust ridge, the robust Liu and robust KL estimators. Comparatively, the robust KL estimator performs best in terms of lower scalar mean squared error. Finally, the HHV of the MSW based on the ultimate analysis was predicted using the robust KL estimator. This study provides a more robust method of estimating the parameters in the ultimate based model of the HHV of Ilorin MSW as compared to previous studies. We robustly diagnosed the model and provided alternative estimators to the conventional OLS estimator. In future research, for more robust results, we will adopt other statistical tools such as the artificial neural network, support vector machine learning and some other machine learning tools.

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Nomenclature

Adjusted R^2:	Adjusted coefficient of determination
HHV:	High heating value
HV:	Heating value
ICP-spec:	Inductively Coupled Plasma – Optical Emission Spectrometer
JB:	Jarque-Bera Test
KLestimator:	Kibria-Lukman estimator
LHV:	Low heating value
MSE:	Mean Squared error
MSW:	Municipal solid waste
OLS:	Ordinary Least Squared
R^2:	Coefficient of determination
SBIC:	Schwarz information criterion
AIC:	Akaike criterion
SE:	Standard error
SMSE:	Scalar Mean Squared error
VIF:	variance inflation factor
WTE:	Waste to energy

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