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Computer-aided energy prediction for selected and blended wood biomass using ultimate and proximate analysis

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ABSTRACT

This study evaluates the energy potential of wood biomass (sawdust) by employing computer-aided techniques to predict the higher heating value (HHV) through ultimate and proximate analyses. The ultimate analysis focuses on elemental properties, while the proximate analysis examines physical properties. The developed regression model demonstrates a high coefficient of determination (R^2) of 99.69% for ultimate analysis, indicating a strong predictive capability. In contrast, the proximate analysis reveals individual correlation coefficients of 85.80% for moisture content, 79.18% for fixed carbon, and 28.10% for volatile matter. To assess the significance of each independent variable in the model, the p-values associated with the coefficients were examined. For the ultimate analysis, all input variables except for sulfur (%S) ($p \approx 0.22$) had p-values less than 0.05 at a 95% significance level, indicating their statistical significance. However, in the proximate analysis, only volatile matter exhibited a relatively high p-value ($p \approx 0.12$), rendering it statistically insignificant in the model. The elevated p-values for sulfur and volatile matter suggest their minimal impact on HHV predictions in their respective models. The computer program developed for this study automates the prediction process, achieving an accuracy within ±5 MJ/kg between predicted and experimental values across the dataset and is uniformly applicable to all individual models or biomass type, significantly reducing analysis time. The findings of this study contribute to optimizing biomass energy systems, enhancing energy recovery efficiency, and advancing sustainable energy practices.

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1. INTRODUCTION

Energy is a crucial asset for human survival, primarily derived from the sun, earth, and moon [1]. It exists in primary forms such as hydro, coal, natural gas, wind, solar, and biomass, and in secondary forms like electricity, hydrogen, and gasoline [1]. Energy drives national wealth and economic growth, making it essential for industrialization and development across all sectors [2]. Consequently, societies are compelled to seek energy sources that are cost-effective, plentiful, and have minimal environmental impact due to the rising need for energy. However, fossil fuels fall significantly short in meeting these objectives. This has led to biomass being considered a plentiful, readily available, renewable, and environmentally sustainable energy source [3], [4].

Biomass has garnered considerable interest as a renewable energy source because it can provide charcoal, bio-oil, and biofuel. These products help address energy shortages and reduce the environmental risks associated with using fossil fuels for power production [5], [6]. Biomass is also classified as a CO_2 balanced or neutral fuel since it does not contribute to the overall rise in CO_2 emissions in the atmosphere [7]. Essentially, the quantity of CO_2 produced when biomass is burned is roughly equivalent to the amount of CO_2 absorbed from the atmosphere during photosynthesis in green biomass [8]. Due to its ability to reduce greenhouse gas emissions and decrease reliance on fossil fuels, biomass is highly regarded in renewable energy initiatives worldwide [7].

Biomass consists of a heterogeneous mixture of organic compounds, including proteins, lignin, lipids, and carbohydrates such as starch, hemicellulose, and cellulose, all of which influence its conversion into biofuels [9], [10]. The conversion of biomass into bio-oil, biochar, and syngas is facilitated by various thermochemical processes, including pyrolysis, liquefaction, gasification, torrefaction, and carbonization. Accurate assessment of elemental composition (C, H, N, O, S), proximate analyses (fixed carbon, volatile matter, moisture content, ash), and structural components (cellulose, hemicellulose, lignin, and ether extractives) plays a crucial role in optimizing these conversion yields [9], [11]. The ultimate analysis (UA) offers a detailed breakdown of the elemental composition of biomass, specifically carbon, hydrogen, nitrogen, sulphur, and oxygen content, which is essential for understanding the combustion characteristics and energy potential of the material [6], [12]. Meanwhile, proximate analysis (PA) determines the moisture content, volatile matter, fixed carbon, and ash content of biomass [12]. Together, these analyses provide a comprehensive profile of biomass, facilitating more accurate energy predictions [13], [14], [15], [16].

The growing global focus on sustainable energy has driven extensive research into alternative fuels. Biomass, particularly wood biomass such as sawdust, is recognized as a promising renewable energy source due to its abundant availability and carbon-neutral properties [17], [18]. Efficient utilization of wood biomass necessitates precise prediction of its energy potential, which is crucial for optimizing combustion processes, enhancing energy recovery, and minimizing environmental impacts [19], [20]. Integrating these analytical parameters (ultimate and proximate analyses) into a computer-aided model allows for the easy and quick prediction of the calorific value (CV) or higher heating value (HHV) of biomass [21]. This approach not only enhances the precision of energy assessments but also facilitates the optimization of biomass blending strategies to achieve desired energy outputs. Moreover, it supports the development of standardized protocols for biomass evaluation, which are essential for the broader adoption of biomass energy technologies [21], [22], [23]. Therefore, many authors have worked on the estimation or prediction of HHV for different biomasses based on multiple regression models from their proximate and ultimate analyses. The study by Ayúe and Serdar [24] applied the Adaptive Neuro-Fuzzy Inference system to predict the CV of biomass using proximate analysis. The study evaluates empirical models to predict biomass calorific value from proximate analysis, achieving reasonable accuracy ($r^2 \approx 0.812$-0.837). However, it struggles with low-calorific biomass and requires subclass-specific analysis for better predictions. Munshi et al. [25] predicted the gross calorific value (GCV) of coal using advanced decision tree-based ensemble techniques, such as bagging, boosting, and extra trees. The article evaluates machine learning models for predicting coal's GCV, highlighting XGBoost's good accuracy but noting on limitations in data generalizability, model complexity, and practical industrial application. Erol et al. [26] developed 13 empirical equations to estimate biomass calorific value from proximate analysis, achieving moderate accuracy ($r^2 \approx 0.829$-0.898). However, the limitations include variable accuracy across biomass types and higher prediction errors for simpler models.

In recent decades, research combining regression modelling and computer-aided techniques for predicting the HHV of sawdust biomass based on proximate or ultimate analyses has been limited. Most studies have primarily focused on empirical models with only a few utilizing advanced computational methods. The integration of computer-aided techniques offers significant advantages for energy prediction by enabling the analysis of complex datasets, improving accuracy, and reducing manual computation errors. These methods enhance the efficiency and sustainability of biomass energy systems by simplifying and automating the HHV prediction process. [21], [27], [28].

Based on the aforementioned points, this study aims to develop and evaluate computer-aided prediction models that utilize proximate and ultimate analysis data to estimate the energy content of selected and blended biomass samples. This will serve as a fast and cost-effective tool for energy assessment. Specifically, the research seeks to demonstrate the effectiveness of computer-aided techniques in improving the predictability and reliability of biomass energy evaluations.

A key objective is to establish a strong correlation between HHV and the ultimate and proximate characteristics of biomass. The accuracy and robustness of these correlations are assessed through statistical indicators such as the coefficient of determination (R^2) and p-values. Furthermore, the study developed a predictive software application based on the established relationships, enabling reliable HHV estimation for various wood biomass types.

2. MATERIALS AND METHODS

2.1 Materials

Five sawdust samples were considered in this research for energy assessment and prediction. Four of the sawdust samples were collected from known parent woods, while the fifth sample was obtained from a sawmill dump site. These samples were sourced from local sawmills in Ede, Osun State, Nigeria during the dry season between September to November 2023 to minimize variations due

to moisture content and seasonal changes. Additional information of the sawdust samples used in this study are shown in Table 1.

The following equipment was used during this research: a 2000 cm³ graduated cylinder made of transparent glass, an electronic mass balance, a crucible, a Fisher Scientific Furnace (Model 186A), a Fisher Scientific Isotemp® oven (Model 665F), a thermometer, and a bomb calorimeter (Model D5865). These instruments were utilized at the Central Laboratory, Federal University of Technology, Akure, Ondo State, Nigeria. All equipment used is of analytical grade, and the testing methods conform to the appropriate ASTM standards.

Table 1 – *Information on the sawdust samples.*

S/N	Name	Sample Name	Scientific Name	Collection Sawmill
1	ORUNMODO	WBMS1	Ricinodendron heudelotii	Atidade Sawmill, Ede
2	URE	WBMS2	Dialium guineense	Atidade Sawmill, Ede
3	AYERE	WBMS3	Albizia glaberrima	Oke Gada, Ede
4	ARABA	WBMS4	Ceiba pentandra	Ededimeji Sawmill, Ede
5	MIX	MWBMS	-	All the three sawmills

2.2 Methods

2.2.1 Experimental procedure

The experimental procedure involved performing both ultimate and proximate analyses on the sawdust biomass samples to comprehensively characterize their chemical and physical properties. The UA was conducted to determine the elemental composition of the samples, specifically the percentages of carbon (C), hydrogen (H), nitrogen (N), sulfur (S), and oxygen (O) [6]. In contrast, PA provides insights into the physical and thermal properties of biomass, which are critical for evaluating its fuel quality, handling characteristics, and suitability for different energy conversion technologies [8], [26], [29]. The PA includes measurements of moisture content, volatile matter, fixed carbon, and ash content, each of which influences biomass combustion efficiency, emissions, and residual waste. Both UA and PA are fundamental for biomass characterization, as they enable a systematic evaluation of the feedstock and facilitate the optimization of biomass-based energy systems. The test methods used for conducting UA and PA are detailed in Tables 2 and 3, respectively. The selected ASTM methods were chosen for their standardization, reproducibility, and widespread acceptance in biomass characterization, ensuring consistency and comparability of the data with other studies.

Table 2 – *Ultimate analysis of the samples.*

S/N	Element	Amount of Sample Tested	Testing Method/Reference
1	Carbon (%C)	2 g	ASTM E 777 [30]
2	Hydrogen (%H)	2 g	ASTM E 777 [30]
3	Nitrogen (%N)	2 g	ASTM E 778 [31]
4	Oxygen (%O)	-	Akinola and Fapetu [32]; James et al. [33]
5	Sulphur (%S)	1 g	ASTM E 775 [34]

Table 3 – *Proximate analysis of the samples.*

S/N	Property	Amount of Sample Tested	Testing Method/Reference
1	Moisture Content (%MC)	0.1 g	ASTM D 2974-8 [35] ASTM E870-82 [36]
2	Volatile Matter Content (%VM)	2 g	ASTM E870-82 [36]
3	Fixed Carbon (%FC)	2 g	Akinola and Fapetu [32]; James et al. [33]
4	High Heating Value (HHV) or Calorific Value (CV)	0.25 g	ASTM E870-82 [36]; Erol et al. [26]; Giuseppe and Ester, [37]; Nishiguchi and Tabata [38]

2.2.2 Data analysis

The data obtained from both PA and UA were used to establish a relationship between the energy content (HHV) of the wood biomass, the ultimate input parameters (UIP), and proximate input parameters (PIP) through regression analysis. Regression analysis is a statistical technique employed to identify the relationship between one or more variables, either through simple regression or multiple regression [39], [40]. When conducting linear regression, the focus lies on determining the statistical significance of the connection between the predictor variable and the response variable [39]. This approach considers the interactions among the explanatory variables and the response variable. In this study, multiple regression analysis (MRA) was adopted to establish the relationship between the independent variables (UIP and PIP) and the dependent variable CV or HHV (energy). Additionally, tests were conducted on every regression coefficient in the analysis to ascertain their significances in predicting any model. This test follows the approach of null and alternative hypotheses. The response model of the energy content of the biomass with UIP or PIP is defined by Equations 1 [41], [42].

Equation 1 presents a linear regression model where the dependent variable (HHV) is predicted as a sum of the weighted contributions from multiple independent variables (x_i) [40], [43], [44].

$$E = \sum_{i=1}^{i=n} \beta_i x_i + C \quad (1)$$

In this study, UIP and PIP are classified as independent variables, each associated with a coefficient (β_i). These coefficients (β_i) reflect the strength and direction of the relationship between each predictor (x_i) and the outcome (HHV), with positive values indicating a direct relationship and negative values indicating an inverse one. The constant term C serves as an intercept, accounting for the baseline value of HHV when all predictors are zero.

Furthermore, the summation notation in Equation 1 encapsulates the combined effect of all *n* predictors on the dependent variable, demonstrating a linear relationship where changes in HHV are proportional to changes in the independent variables. The extension of the Equation 1 to UIP and PIP are presented in Equations 2 and 3 respectively.

$$E_{UIP} = \sum_{i=1}^{i=n} \beta_i x_i + C_a \quad (2)$$
$$= \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + C_a$$

$$E_{PIP} = \sum_{i=1}^{i=n} \gamma_1 x_i + C_b \quad (3)$$
$$= \gamma_1 x_1 + \gamma_2 x_2 + \gamma_3 x_3 + \gamma_4 x_4 + \gamma_5 x_5 + \gamma_6 x_6 + C_b$$

Where E_{UIP} and E_{PIP} represent the predicted energy contents (HHV) from UIP or PIP, respectively. β_i and γ_1 are their corresponding regression coefficients or slopes of each term in the models, which indicate the degree of dependence of the predicted energy in each case. "C_a *and* C_b" are constants called correction factors.

2.2.2.1 Method for fitting a model

The ordinary least squares (OLS) approach was used to estimate the coefficients of the linear regression model. The OLS method aims to minimize the total sum of squared deviations between the observed dependent variable (HHV) and the predicted values generated by the model. The primary goal was to determine the set of coefficients β_i that would minimize the residual sum of squares (RSS), which is estimated by Equation 4:

$$RSS = \sum_{i=1}^{i=n} HHV_O + HHV_P \quad (4)$$

Where HHV_O represents the observed values of the variable and HHV_P represents the predicted values of the variable.

The model fitting process was conducted using regression software tool package on Microsoft Excel, Version 2021. This software provided estimates for the coefficients β_i and the intercept C. Model diagnostics, such as R-squared, adjusted R-squared, and mean squared error (MSE), were computed to evaluate the quality of the fit. These metrics offer insights into the extent to which the independent variables explain the variation in the dependent variable, as well as the overall accuracy of the model. The software also assessed the accuracy of the model, applied cross-validation methods, and prevent overfitting.

The performance indicators obtained from these iterations were averaged to yield a more reliable assessment of model performance [39], [43]. The statistical tests and diagnostics were performed with a significance level of 0.05 to verify the statistical validity of the results [40], [45]. For the statistical tests, the significance of the regression coefficients was assessed using Equations 5 and 6, following the null and alternative hypotheses [45].

$$\text{Null Hypothesis } (H_o): \beta_i = 0$$
$$(\beta_{ith} \text{coefficient is equal to zero?}) \quad (5)$$

$$\text{Alternative Hypothesis } (H_A): \beta_i \neq 0$$
$$(\beta_{ith} \text{coefficient is not equal to zero}) \quad (6)$$

The p-value corresponding to the t-statistic was computed and used as a basis for decision-making. At a 95% confidence level, if the p-value for the t-statistic is less than or equal to 0.05 ($P \leq 0.05$), the null hypothesis (H_0) is rejected. Rejecting H_0 indicates acceptance of the alternative hypothesis (H_a), signifying a statistically significant relationship between the predictor variable (HHV) and the response variables in UIP or PIP. Conversely, if H_0 is not rejected for any independent variable from UIP or PIP, it suggests that the variable does not contribute significantly to the model's predictive capability [40], [45], [46]. Data analysis was conducted using Microsoft Excel, Version 2021 to generate the relationships and necessary charts, and a computer program was developed to predict future energy levels based on UIP and PIP.

2.2.3 Computer program development

Computer program development involves creating software, which is a collection of instructions or code written in a specific programming language that a computer executes to perform a defined task or set of tasks. This process aims to provide solutions or automate processes by manipulating data, controlling hardware components, or interacting with users [47]. The complexity of a computer program can vary significantly, ranging from a simple script or utility to a complex application or system software, depending on the requirements and objectives of the task [47]. As part of the methodology, a computer program was developed to facilitate HHV prediction using a set of validated models, as described earlier. This program, written in Visual Basic using Microsoft Visual

Studio, Version 2022, comprises a series of instructions designed to automate the process from data analysis to the simulation and prediction of the HHV of biomass upon inputting the relevant information. The development process involved writing and testing code that manipulates data, controls relevant hardware components, and interacts with users to achieve the desired outcomes. The program's complexity was tailored to meet the study specific requirements. The resulting software provided a seamless, efficient, and accurate solution for energy prediction based on UIP and PIP, significantly reducing errors associated with manual computations and playing a crucial role in the successful execution of the study's objectives.

3. RESULTS AND DISCUSSION

3.1 Ultimate analysis

The result of the ultimate analysis of the biomass samples is illustrated in Figures 1-3. The %C and %O contents in the biomass are presented in Figure 1. The percentage of oxygen (%O) in biomass significantly influences the available energy for combustion. While oxygen is essential, a higher %O decreases the net energy due to the energy consumed during combustion [48]. Among the samples, the MWBMS contains 35.89% oxygen, which is lower than WBMS-3 (38.98%) and WBMS-4 (52.14%), but higher than WBMS-1 (22.82%) and WBMS-2 (31.80%) (Figure 1). This moderate %O content suggests that MWBMS is optimized for energy release during combustion [48]. Figure 1 also shows the variation in carbon (%C) content among the samples. The %C is a primary determinant of energy content, and it varies across the samples [49]. MWBMS exhibits 61.28% carbon, which is higher than WBMS-3 (55.93%) and WBMS-4 (39.66%), but lower than WBMS-1 (68.06%) and WBMS-2 (63.12%). This balance ensures enhanced energy content while minimizing carbon emissions [49].

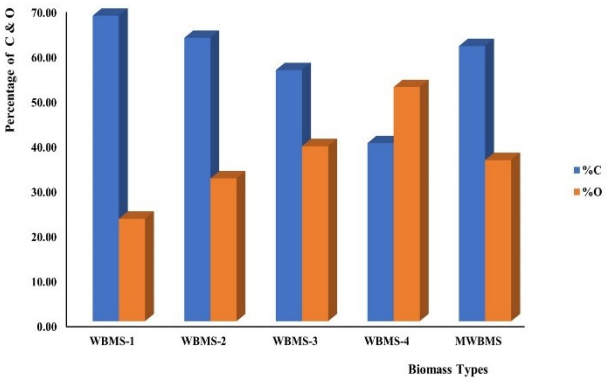

Fig. 1 Analysis of the carbon (C) and oxygen (O) percentages (%) in different biomass.

In terms of other elemental compositions, the hydrogen (%H) content in MWBMS is 5.25%, indicating a favorable energy yield, while the nitrogen (%N) content, which can reduce energy potential, is 1.28% (Figure 2). This is lower than in WBMS-2, WBMS-3, and WBMS-4, reducing energy loss. Sulfur (%S) content, critical for environmental considerations, is 0.006% in MWBMS, which is lower than in WBMS-1, WBMS-3, and WBMS-4, thereby minimizing harmful sulfur dioxide emissions during combustion (Figure 3). Ash content (%ASH), representing non-combustible materials, is 0.961% in MWBMS, higher than WBMS-2 (0.396%) but lower than WBMS-3 (1.160%) and WBMS-4 (2.290%). Lower ash content is desirable as it maximizes energy yield and reduces slagging during combustion. The moderate ash content in MWBMS suggests it is well-suited for efficient energy production without significant losses [50], [51], [52], [53], [54], [55].

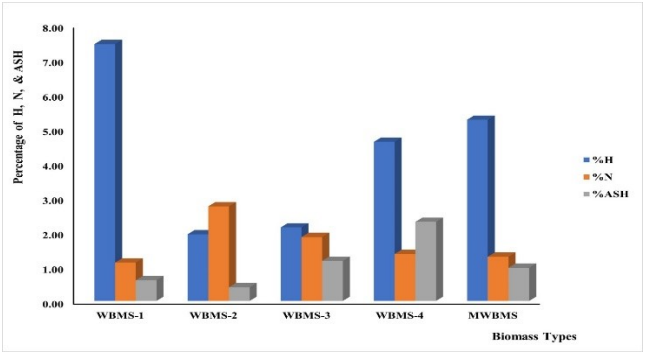

Fig. 2 Analysis of hydrogen (H), nitrogen (N), and Ash percentages (%) in different biomass.

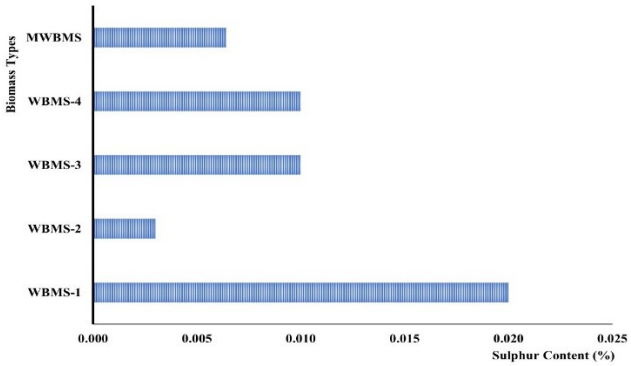

Fig. 3 Analysis of sulphur (S) percentage (%) in different biomass.

3.2 Proximate analysis

The proximate analysis further supports the energy potential of MWBMS in terms of HHV, %MC, %FC, and %VM. The MWBMS displayed the highest HHV at 21.83 MJ/kg, outperforming the individual biomass samples by 6.60%, 9.90%, 10.60%, and 16.40% for WBMS-1, WBMS-2, WBMS-3, and WBMS-4, respectively (Figure 4). The %MC is lowest in MWBMS (15.41%), facilitating higher energy release [56]. Additionally, the %FC content in MWBMS is substantial at 59.22%, contributing to a strong energy output. The increased %FC content in MWBMS enhances energy output due to the greater availability of solid carbonaceous material for combustion [57]. The analysis of %VM in Figure 4 revealed that MWBMS exhibited the highest value among the various

biomass samples, except for WBMS-3. The %VM in MWBMS demonstrated remarkable increases of 28.90%, 47.30%, and 37.80% compared to WBMS-1, WBMS-2, and WBMS-4, respectively, and was only slightly lower than WBMS-3 by 1.50%. Volatile matter refers to the combustible gases and hydrocarbons released from biomass during combustion, contributing to the overall energy content [58]. The high %VM in MWBMS indicates a superior energy content, making it ideal for efficient energy utilization and enhanced combustibility [59]. Thus, the blend of biomass in MWBMS optimizes energy output by balancing elemental composition and proximate properties, making it a superior choice for efficient energy production.

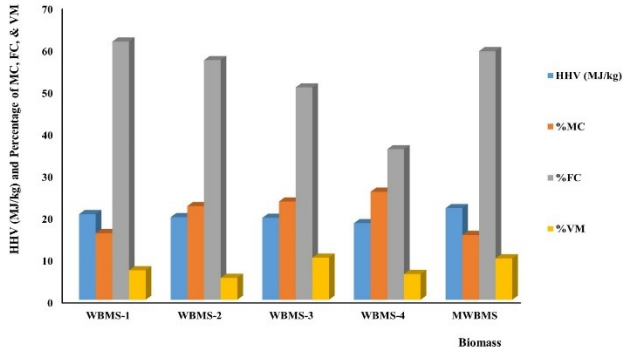

Fig. 4 Analysis of HHV, MC, FC and VC in different biomass.

3.3 Model prediction and validation from ultimate and proximate analysis

In this study, statistical regression analysis was employed to establish correlations between the energy content of biomass and its UIP and PIP. Table 4 shows the statistical regression analysis summary of the influence of UIP on the caloric value of the biomass.

Table 4 – *Statistical regression analysis summary for UIP and PIP.*

Correlation Type	UIP Values	%MC	%FC	%VM
Multiple R	0.99842	0.92629	0.88983	0.53014
R Square	0.99685	0.85801	0.79181	0.28105
Adjusted R Square	0.99292	0.84026	0.76578	0.19118
Standard Error	0.09508	0.45168	0.54693	1.01638
Observations	5			

The multiple regression (Multiple R) value obtained shows the correlation and strength of the relationship between the independent variables and the dependent variable. The new statistical regression analysis summary of each PIP, indicating a strong relationship between the energy content of the biomass and %MC, %FC, and %VM, accounting for 92.63%, 88.98%, and 53.01% (Table 4). The closer the Multiple R value is to +1 or -1, the stronger the relationship [39], [60]. The Multiple R value of 0.998 indicates a strong relationship between the UIP (%C, %H, %O, %N, %S, and %ASH) and the energy content of the biomass [61]. This suggests that 99.7% of the variation in energy (MJ/kg) of the biomass can be explained by the UIP [43], [62].

Table 5 presents the model coefficients, t-statistics, and P-Values for all the considered UIP variables in predicting energy. This analysis highlights the significance of each independent variable (UIP) in the regression model. A coefficient is deemed significant if its P-Value is ≤ 0.05 at a 95% confidence level [23], [39], [41], [44], [61], [62]. The initial data analysis showed that the P-Values of all UIP variables except %S were significant for energy prediction (P-Value ≤ 0.05).

However, the P-Value associated with sulfur content (%S) was relatively large (≈0.22), making it statistically insignificant in the model formulation (H_o is accepted in this case). Previous literatures have discussed that %S does not directly impact the energy content of biomass [63], [64], [65]. As a result, %S was excluded from the regression model, and the model was rerun to ensure accuracy. The final HHV (E_{UIP}) model based on the UIP is given by Equation 7.

$$E_{UIP} = 0.5083\ \%C + 0.3942\ \%H + 0.2592\ \%N + 0.4244\ \%O + 0.5802\ \%Ash - 27.5082 \quad (7)$$

In validating the predictive model for PIP, which considers energy and all PIP variables together, the model failed to demonstrate significant P-values for energy prediction. The P-values for %MC, %VM, and %FC were approximately 0.72, 0.907, and 0.990, indicating statistical insignificance ($p>0.05$), despite a strong combined Multiple R (0.929) and a significant Significance-F (0.00541). This suggests that linearity and multicollinearity issues among the PIP variables hinder effective energy prediction [40], [60], [66], [67]. Consequently, the PIP variables were separated, and energy content was regressed individually with each variable. Table 5 presents the new statistical regression analysis summary, revealing stronger individual relationships between energy content and %MC, %FC, and %VM, accounting for 92.63%, 88.98%, and 53.01% of the energy (MJ/kg) variations of the biomass types.

Table 5 – *The significant of the model coefficients for UIP.*

UIP	Model Coefficients	t-Statistics	P-value
Intercept (C_a)	-27.50821514	-11.59141453	0.000316489
%ASH	0.580199634	4.329380492	0.012355737
%C	0.508309132	21.52545124	0.0000275498
%H	0.394196871	9.055368003	0.000824172
%N	0.259173994	2.521125312	0.048652785
%O	0.424363258	17.03461501	0.0000696482
%S	15.11179753	1.547407628	0.2195076025

The results in Table 6 indicate that the P-values of all PIP variables, except for %VM, are statistically significant for energy prediction (P-value ≤ 0.05). The P-value associated with %VM is relatively large (≈0.12), making it statistically insignificant in the model formulation, thereby leading to the acceptance of the null hypothesis in this instance. The weaker correlation of VM in this model may be due to its indirect relation to fixed carbon and energy content, as well as its variability due to measurement conditions [40].

The model formulations for energy prediction based on each PIP variable are detailed in Equations 8 to 10:

$$E_{PIP} = 24.0418 - 0.1055\ \%MC\ [p < 0.05, \text{Significant}] \quad (8)$$

$$E_{PIP} = 14.4248 + 0.1030\ \%FC\ [p < 0.05, \text{Significant}] \quad (9)$$

$$E_{PIP} = 17.4374 + 0.2855\ \%VM\ [p > 0.05, \text{Not Significant}] \quad (10)$$

Table 6 – *The significant of the model coefficients for PIP*

PIP	**%MC**	**%FC**	**%VM**
Intercept (C_b)	24.0418	14.4248	17.4374
Model Coefficients (x_i)	-0.1055	0.1030	0.2855
P-Value	0.000118	0.00056	0.1150
t-Statistics	-6.9530	5.5160	1.7684

Equation 8 reveals that for every unit increase in %MC, the energy of the biomass decreases by 0.1055 MJ/kg. The negative coefficient suggests an inverse relationship between %MC and energy content, implying that as moisture content increases, the energy available for combustion decreases due to the energy required to evaporate the moisture [8], [24]. In Equation 9, for every unit increase in %FC, the energy of the biomass increases by 0.1030 MJ/kg [26]. This positive coefficient indicates a direct relationship between %FC and energy content, which has been also shown by different authors, highlighting that higher fixed carbon content contributes to more energy being released during combustion [8], [29], [68]. Finally, Equation 10 suggests that for every unit increase in %VM, the energy of the biomass increases by 0.2855 MJ/kg. However, the statistical insignificance ($p > 0.05$) of this result implies that the relationship between %VM and energy content is not robust enough to be predictive [69], [70].

3.3 Computer program development

A computer program for predicting energy generation from selected and blended wood biomass offers several key benefits. It enhances efficiency by automating and streamlining the assessment process, ensuring faster and more accurate results than manual methods [47]. The program reduces the risk of human error, supports scalability by handling large datasets, and allows for customization to meet specific needs [71]. It also serves as a decision support tool, providing valuable insights for planning and resource allocation in energy generation [72]. The flowchart outlining the program development process is presented in Figure 5.

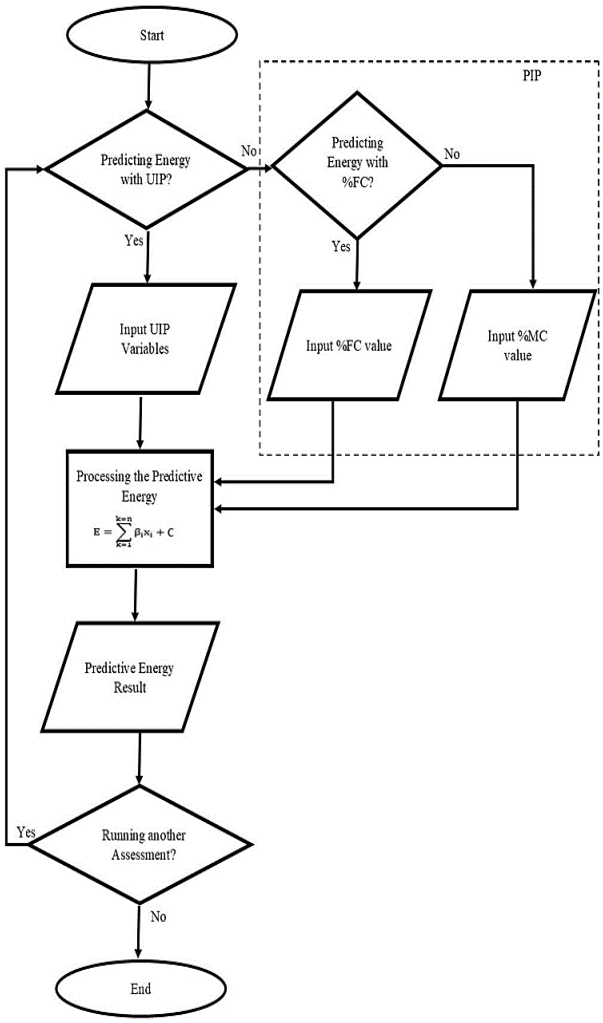

Fig. 5 Flowchart of the computer program development.

Additionally, the program ensures reproducibility, aiding in research, regulatory compliance, and quality control. Overall, it optimizes efficiency, accuracy, scalability, flexibility, decision-making, and reproducibility in the energy sector [71], [72]. The regression models discussed in Section 4.3 were used to develop a computer-based program for rapid energy content prediction in wood biomass. This program was created using Visual Basic (VB) within the Microsoft Visual Studio 2021 development environment. To run both the host application and the developed program successfully, the system must meet specific requirements, including a minimum of 2GB of RAM and .NET Framework version 4.0 or higher. The flowchart outlining the program development process is presented in Figure 5.

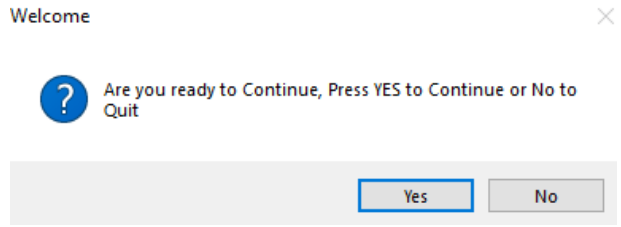

Fig. 6 Launching interface of the program.

Figures 6 to 10 illustrate various stages of the program's interface, showcasing its user interaction and functionality in detail. These stages include the initial launch screen, where users can access the main functions of the software, followed by prediction analysis using the UIP module, which relies on elemental composition data for estimating the HHV. The interface also displays prediction analysis based on %FC and %MC through the PIP module, allowing for alternative input pathways depending on data availability.

Finally, the sequence concludes with the program exit screen, indicating a completed session. This visual walkthrough highlights the intuitive structure and practical utility of the application in supporting energy prediction tasks.

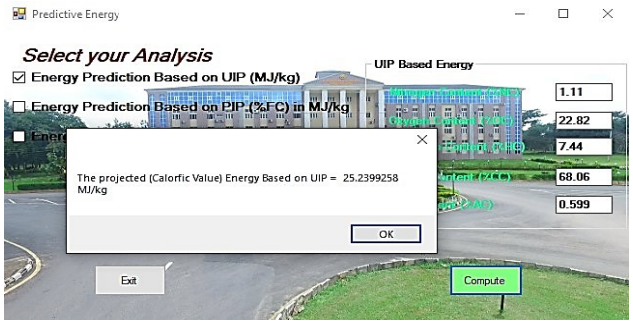

Fig. 7 Prediction analysis using UIP.

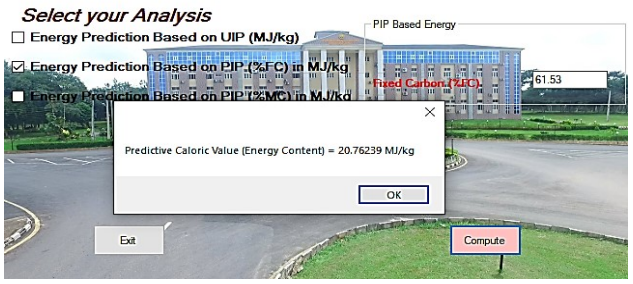

Fig. 8 Prediction analysis using %FC.

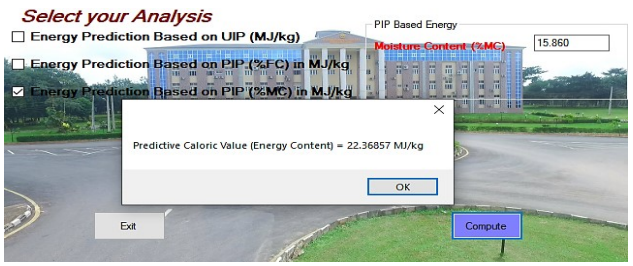

Fig. 9 Prediction analysis using %MC.

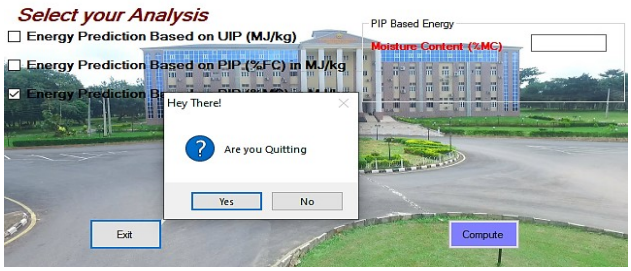

Fig. 10 Exiting interface of the program.

3.4.1 Performance evaluation of the program

The performance of the developed program was evaluated by comparing its predicted HHV outputs, using both UIP and PIP from various biomass samples, against the actual measured HHV values (Figure 11). The analysis revealed that the UIP-based predictions consistently overestimated the actual HHV values, while the PIP-based predictions, particularly those based on %FC and %MC, were closer to the actual values (Figure 11) [8], [24]. The energy prediction accuracies of both UIP and PIP are within ± 5 *MJ/kg* deviations between predicted and experimental values across the dataset and is uniformly applicable to all individual models or biomass types. Therefore, the findings suggest that while the program's UIP predictions require further refinement, the PIP-based models, especially %FC, offer a more reliable estimate of the biomass energy content [6]. This evaluation underscores the importance of accurate input selection in predictive modelling for biomass energy analysis. The program's performance was accessed by comparing its HHV outputs, predicted from UIP and PIP variables, against the actual energy values from the biomass [29].

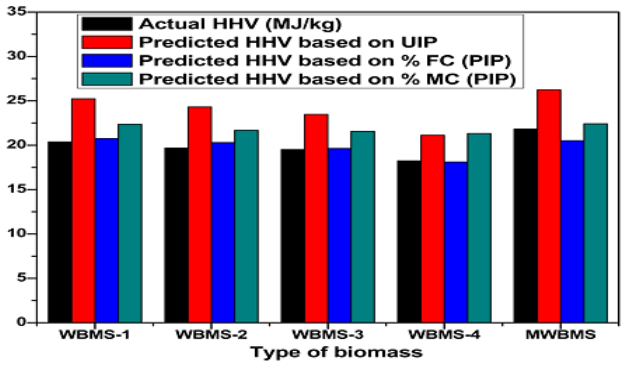

Fig. 11 Actual and predicted HHV values of the biomass.

4. CONCLUSION

The study concludes that computer-aided techniques, combined with comprehensive ultimate and proximate analyses, offer an approach for predicting the energy potential of wood biomass, particularly sawdust. By establishing a strong correlation between the HHV and the biomass's physical and chemical properties, the research demonstrates the viability of using regression models for accurate energy assessments. The developed computer

program effectively automates the prediction process, reducing the time and effort required for analysis while maintaining accuracy for all sample type are within ±5 MJ/kg. This not only enhances the efficiency of energy recovery from biomass but also supports the broader goal of sustainable energy development by enabling more precise optimization of biomass energy systems. The findings emphasize the importance of integrating advanced computational tools in biomass energy research, which can lead to improved resource utilization and reduced environmental impact. Future research should focus on expanding the model's applicability to other biomass types and refining the predictive algorithms for even greater precision. These include extending the model to other biomass categories (such as agricultural residues and aquatic biomass), increasing sample size for broader generalization, and integrating advanced techniques such as deep learning or ensemble machine learning methods for enhanced predictive performance.

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