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Predicting a Higher Heating Value for Torrefied Kesambi Leaf Biobriquettes through Ultimate Analysis

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ABSTRACT: The escalating global pursuit of sustainable energy solutions has led to the emergence of biomass-derived fuels, such as biobriquettes, as feasible substitutes for traditional fossil fuels. Kesambi leaves, which are abundant in Southeast Asia and boast a high calorific value, represent a promising prospect for the production of biobriquettes. In this investigation, a conclusive analytical method is employed to construct a predictive framework for estimating the Higher Heating Value (HHV) of torrefied kesambi leaf biobriquettes. By incorporating ash content (PS), volatile matter (BR), carbon (C), hydrogen (H), and oxygen (O) percentages, alongside experimental HHV data, through multiple linear regression and elemental composition data acquired from proximal analysis, the model aims to forecast HHV. The model's modest positive Mean Bias Error (MBE) and satisfactory Root Mean Square Error (RMSE) suggest a good fit. The substantial R-squared value indicates the model's capability to adeptly capture HHV variability. Ultimately, this approach grounded in fundamental principles contributes significantly to the sustainable exploitation of biomass resources by providing a pragmatic and effective technique for predicting HHV for kesambi leaf biobriquettes.

KEYWORDS: higher heating value, kesambi leaves, predictive model, sustainability, renewable energy, ultimate analysis.

INTRODUCTION

The global pursuit of sustainable energy solutions has intensified as concerns over climate change and environmental degradation escalate [1], [2], [3]. In this context, biomass-derived fuels have emerged as a promising alternative to fossil fuels, offering renewable and environmentally friendly energy sources [4]. Among the various biomass resources, kesambi leaves have garnered attention due to their abundance, low cost, and significant calorific value. Utilizing kesambi leaves for the production of biobriquettes presents an opportunity to address energy needs while simultaneously reducing waste and promoting sustainable practices.

Historically, conventional fossil fuels like coal, oil, and natural gas have been the primary sources of energy worldwide. However, their widespread use has led to detrimental environmental consequences, such as greenhouse gas emissions, air and water pollution, and the worsening of climate change. As a result, there is a growing urgency to transition towards cleaner and more sustainable energy alternatives.

Biomass, originating from organic sources like plants, agricultural leftovers, and forestry remnants, presents a renewable and carbon-neutral energy reservoir. [5], [6]. Biomass-based fuels, including biobriquettes, have gained prominence as they can be produced from a variety of biomass feedstocks, reducing reliance on finite fossil fuel resources. Biobriquettes are compacted biomass materials with high energy density, making them suitable for use in various heating and combustion applications.

Kesambi (Schleichera oleosa) is a tropical tree native to Southeast Asia, particularly prevalent in Indonesia. The leaves of the kesambi tree are abundant and often considered as waste material [7]. However, these leaves possess significant energy potential due to their high calorific value, making them suitable for conversion into biobriquettes. Employing kesambi leaves for biobriquette manufacturing not only aids in waste reduction but also enables the sustainable utilization of valuable energy assets [8]. The high heating value (HHV) or calorific value of a fuel denotes the heat liberated upon complete combustion. This parameter significantly impacts the efficacy and functionality of biomass-derived fuels such as biobriquettes. Precise estimation of HHV is indispensable for refining the production procedure, evaluating fuel quality, and gauging the energy capacity of biomass feedstocks.

Traditionally, determining the HHV involves expensive and time-intensive laboratory tests, which may not be viable for large-scale biomass projects. Hence, the development of predictive models based on biomass elemental composition presents a pragmatic and effective solution. These models facilitate swift screening of biomass feedstocks, aiding in material selection for biobriquette production and streamlining process optimization. The elemental composition, encompassing carbon (C), hydrogen (H), oxygen

(O), nitrogen (N), sulfur (S), and other elements, offers valuable insights into the energy content and combustion properties of biomass materials [8], [9].

One of the most important characteristics in biomass exploitation is its elemental composition. Although the ultimate analysis of biomass is an important factor in identifying its energy content and clean and efficient properties, a thorough investigation of the material requires highly skilled analysts and expensive equipment [10], [11], [12].

Predictive techniques for estimating HHV rely on ultimate analysis, which determines the elemental makeup of biomass samples. This study will use proximate data from earlier research [13] on kesambi leaf biobriquettes, with ultimate analysis based on the Nhuchhen model [14]. The following stage involves analyzing the HHV experimental data of torrefied kesambi leaf biobriquettes to create an HHV model based on final predictions.

In recent years, various statistical and machine learning techniques have been employed to develop predictive models for biomass HHV estimation [15], [16], [17], [18]. These models leverage the relationships between elemental composition and calorific value to establish robust prediction algorithms [19], [20], [21]. By utilizing large datasets comprising elemental analysis data and corresponding HHV measurements, predictive models can be trained and validated to accurately estimate the HHV of biomass samples [22], [23].

This study aims to contribute to the advancement of biomass energy technology and facilitate the sustainable utilization of kesambi leaves for biobriquette production. The development of an ultimate-based model for predicting the HHV of kesambi leaf biobriquettes holds significant implications for both research and practical applications. Firstly, it enhances our understanding of the factors influencing the energy content of biomass materials and provides valuable insights into their combustion behavior. Secondly, the predictive model offers a rapid and cost-effective means of estimating HHV, enabling efficient screening of biomass feedstocks and process optimization in biobriquette production.

MATERIALS AND METHODS

The experimental HHV values shown in Table 1 as well as Ash, VM, and FC data from earlier research [13] are used in this study.

Table 1. Previous research data from the Ash, VM, FC, and HHV experiments ([13]

Run	PS	BR	Ash	VM	FC	HHVExp
	mesh	[%]	[%]	[%]	[%]	[MJ/kg]
1	40	3	3.48	13.63	77.5	14.97
2	60	15	1.75	16.99	73.83	15.79
3	12	10	3.02	15.06	78.28	14.74
4	70	10	1.65	15.82	77.86	15.94
5	20	15	2.54	14.54	77.28	14.64
6	20	5	3.28	14.61	76.49	15
7	60	5	2.87	14.2	79.3	15.78
8	40	10	2.16	15.25	78.58	15.25
9	40	10	2.14	14.37	79.15	15.45
10	40	17	2.31	16.11	73.11	15.06
11	40	10	2.56	14.42	79.37	15.37
12	40	10	2.84	14.22	78.44	15
13	40	10	2.12	14.25	77.55	15.65

Based on biomass proximate studies, a new correlation for determining elemental composition is presented in this paper based on the Nhuchhen models [14]. Based on direct proximate analysis, this newly formed relationship can be utilized to precisely determine the elemental composition of biomass, especially for biomass with a high percentage of ash. The main benefit of this correlation is

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that it can be used to gasification and pyrolysis processes by calculating the elemental components of biomass materials using direct proximate analysis.

The correlation of ultimate analysis from proximate data offers valuable insights into the elemental composition of biomass materials, aiding in understanding their energy content and combustion characteristics [14]. By establishing relationships between variables such as ash content (PS), volatile matter (BR), carbon (C), hydrogen (H), and oxygen (O) percentages, this correlation provides a basis for predicting key parameters like Higher Heating Value (HHV) in biomass-derived fuels. Through statistical analysis and modeling techniques, this correlation facilitates the development of predictive models that enable efficient screening of biomass feedstocks and optimization of biobriquette production processes.:

$$C = -35.9972 + 0.7698VM + 1.3269FC + 0.3250ASH \quad (1)$$
$$H = 55.3678 - 0.4830VM - 0.5319FC - 0.5600ASH \quad (2)$$
$$O = 223.6805 - 1.7226VM - 2.2296FC - 2.2463ASH \quad (3)$$

Multiple linier regression is used in data analysis to build models (SPSS 20). The following equations are used to verify model predictions and experimental data in statistical analysis to determine the model's reliability: average bias error (Eq 4), root mean square error (Eq 5), and coefficient of determination (Eq 6):

$$\mathrm{MBE} = \frac{1}{n}\sum_{i=1}^{n} (y_{exp} - y_{pred}) \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{exp} - y_{pred})^2} \quad (5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_{exp} - y_{pred})^2}{\sum_{i=1}^{n}(y_{exp} - \bar{y}_{exp})^2} \quad (6)$$

Where:

$y_{exp} = HHV\ experiment$
$y_{pred} = HHV\ predicted$
$\bar{y}_i = average\ HHV experiment$

RESULT AND DISCUSSION

The results of data analysis using the Nhuchhen models to determine the elements C, H, and O using proximate analysis data from previous research are presented in Table 2.

Table 2. C, H, O Nhuchhen models [14]

Nhuchhen[14]			HHV Predicted
C	H		Parikh
55,57	4,88	5,94	30,04
54,76	4,89	7,65	30,53
56,72	5,00	6,64	30,96
56,79	5,03	7,12	31,20
55,84	4,92	6,45	30,41
55,37	4,88	6,41	30,20
56,97	5,00	6,26	30,86

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56,99	5,03	6,81	31,15
56,96	5,01	6,41	30,90
53,91	4,81	7,19	29,89
57,12	5,02	6,39	30,99
56,44	4,97	6,27	30,62
55,89	4,92	6,35	30,36

The resulting equation, which is a model for predicting HHV, is as follows (Eq 7):

$$HHV\ predicted\ = 7{,}605 + 0{,}019\ x\ PS - 0{,}017\ x\ BR - 0{,}748\ x\ C + 16{,}215\ x\ H - 1{,}018\ x\ O \quad (7)$$

The model offered aims to estimate a substance's High Heat Value (HHV) based on multiple predictors, including PS, BR, C, H, and O. When any or all of the predictor variables—PS, BR, C, H, and O—are zero, the intercept reflects the expected HHV. In this case, the expected HHV is 7.61 in the case when all predictors are absent. The PS Coefficient (0.02) indicates a positive correlation between an increase in PS and a predicted HHV. This suggests that the HHV prediction is positively impacted by increasing PS content. BR Coefficient (-0.02): A negative coefficient means that the expected HHV will drop as BR rises. This implies that the HHV prediction is negatively impacted by higher BR content. The C Coefficient (-0.75) indicates a negative correlation between the expected HHV and an increase in carbon content. This suggests that the HHV prediction is negatively impacted by increasing carbon concentration. H Coefficient (16.21): A positive coefficient means that the expected HHV rises as the hydrogen level rises. This implies that the HHV forecast benefits with a higher hydrogen content. O Coefficient (-1.02): A negative coefficient indicates that the expected HHV decreases as the oxygen level rises. This suggests that the HHV prediction is negatively impacted by increasing oxygen content. The PS, BR, C, H, and O contents of a material are used by the model to forecast its HHV. While higher BR, C, and O concentrations have an adverse effect on the anticipated HHV, higher PS and H contents have a beneficial affect.

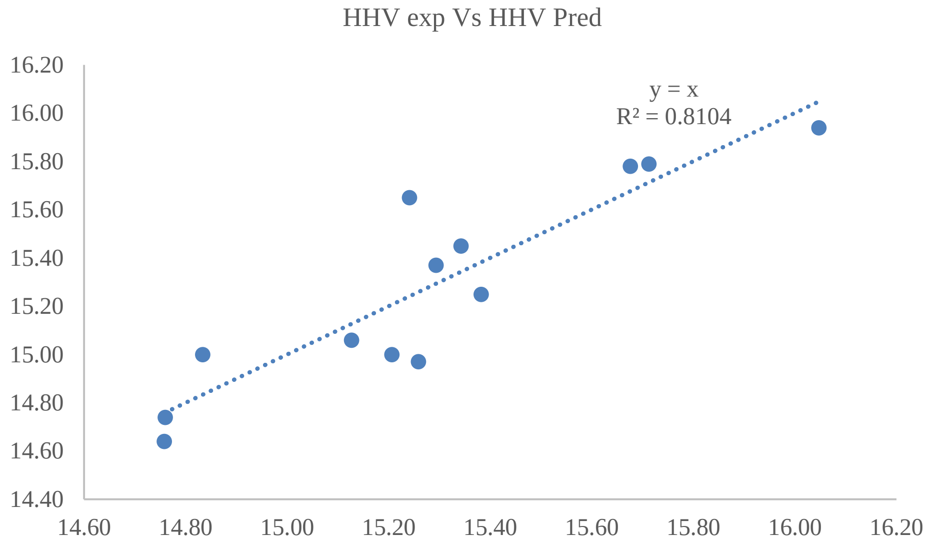

Figure 1.

MBE of 0.003: This suggests that, on average, the model tends to slightly overestimate the predicted values compared to the actual values. Since the MBE is positive and very close to zero, it indicates a minor tendency for overestimation. The RMSE measures the average magnitude of the errors between predicted and actual values. A value of 0.15 indicates that, on average, the difference between the predicted and actual values is relatively small. Therefore, the model's predictions are reasonably accurate overall.

The R-squared value represents the proportion of the variance in the dependent variable (actual values) that is explained by the independent variables (predicted values) in the model. An R-squared value of 0.81 indicates that approximately 81% of the variability in the actual values is accounted for by the model. This suggests that the model provides a good fit to the data, meaning it captures a significant portion of the variability in the dependent variable.

CONCLUSSION

Through the development of an ultimate-based model for predicting the Higher Heating Value (HHV) of torrefied kesambi leaf biobriquettes, this study represents a significant advancement in biomass energy technology. Utilizing elemental composition and experimental HHV data, the model incorporates key factors such as carbon, hydrogen, oxygen, volatile matter, and ash content.

The model's slight positive Mean Bias Error (MBE) and acceptable Root Mean Square Error (RMSE) demonstrate its effectiveness in estimating HHV accurately. Moreover, the robust R-squared value further validates the model's capability to precisely capture the variability in HHV. This predictive model facilitates efficient and accurate HHV estimation, expediting biobriquette production processes and enabling swift biomass feedstock screening.

By utilizing kesambi leaves for biobriquette production, this research promotes waste reduction and the sustainable utilization of valuable energy resources. It offers a clean and renewable alternative to traditional fossil fuels, ensuring the sustainable exploitation of biomass resources. Further validation and refinement of the model could enhance its applicability and encourage broader adoption in biomass energy systems, contributing to environmental sustainability and energy security.

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