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Response Surface Methodology Optimization of Sawdust in Water Boiling Test

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ABSTRACT

In the third world, the cutting down of trees for use as firewood is compounding to the environmental issues including global warming. Sawdust is considered as a solid waste, an environmental menace but could be used as means of domestic heating source since it is cheap, reduces deforestation, and can serve as a source of income. In this study, the one-at-a-time design of variables and the Response Surface Methodology (RSM) technique are used to optimize the influential independent variables in Water Boiling Test (WBT) with sawdust as the energy source. The best performing combination with the one-at-a-time design of variables are 0.45 kg, 85 min, and 1100 mL to attain the temperature of 92 ^{O}C while the optimization of the process conditions using the RSM software was conducted. The optimized values predicted from the model were 1100 mL reactor volume, with sawdust of 0.5 Kg at 55 minutes to attain a response of 96.648 ^{O}C and the developed model has fitted to describe the optimum conditions of the experimental data. These findings reflects resource management and solid waste utilization for environmental sustainability.

1. Introduction

In Nigeria, there are abundant biomass resources ranging from agroforestry residues, municipal solid waste, and sawdust [1]. Energy is a major factor that determines the socio-economic development of a nation however, it is preferred that the utilization should not be at the expense of the environment and the future generation however, the conventional energy source of cooking in developing countries is wood and agricultural residues [2]. Most of the poor households in developing countries over-relied on forest products (firewood, twigs, and charcoal) in household cooking thereby setting deforestation which has been detrimental to the ecosystem [3]. Therefore, a sustainable energy system is needed to curb the lurking menace, this can be achieved by the utilization of solid waste, disposed portions of wood (sawdust), and many other renewable and sustainable means. A large quantity of sawdust is produced on daily basis in most Nigerian cities and can be utilized for domestic heating [4]. Many studies focus on briquetting the sawdust before utilization [2,5,6] and blends with rice husk [6], cocoa pod husk [7], groundnut shell [8], rice husk/cocoanut shell [9]. Hence, there is a need of developing a simple sawdust cooking energy source and optimization the usage since briquetting requires technical knowledge of production.

The one-variable-at-a-time optimization is a parameter change of determining the optimal operating conditions of a system while keeping the others at a constant level [10]. A typical optimization by one-variable-at-a-time can be found elsewhere [11]. Response Surface Method (RSM) is a tool for function estimation that combines mathematical, statistics, and multiple quadratic regression to optimize influencing conditions and relate the response to the influential conditions [12] with good practical value, precision, and optimization effects. The effect of process conditions was optimized in briquette formation by many researchers using sawdust as briquette [8,13–15] however, these studies failed to present the effect of process conditions optimization of raw sawdust since the greater populace lacked the knowledge of briquetting.

As a way of reducing environmental pollution and degradation through deforestation, resulting from the burning of firewood, the potential of the raw sawdust biomass to serve as an alternative energy source in domestic cooking is explored in this work. Also, the Water Boiling Test (WBT) was carried out and optimized by the one-at-a-time design of variables and the RSM software to ascertain the optimum process conditions.

2. Results and Discussion

2.1. Results of the WBT

The one-variable-at-a-time optimization system result is shown in Table 1 for the WBT using variable quantities of sawdust, water, and variable volume of water till the 100 ^{O}C water boiling test was attained. The water boiling test is used to test the performance of the stove under variable conditions operating systems. Three variable reactors sizes were used in the WBT using variable quantities of sawdust and variable volume of water. Firstly, 0.3 kg was used to attain 78 ^{O}C within the time range of 61 mins before the sawdust burnt out. The quantity was increased to 0.3-0.35kg but it can be observed that the best performing combination is at 0.45 kg, 85 min, and 1100 mL to attain 98 ^{O}C.

Table 1. Water boiling test results.

S/No.	Volume of Water (mL)	Amount of Sawdust (Kg)	Time (Min)	Temperature (^{O}C)
1	900	0.3	61	78
2	900	0.35	66	92
3	1000	0.35	70	94
4	1000	0.4	87	95
5	1100	0.4	83	90
6	1100	0.45	85	98

2.2. Results of the RSM

Table 2 gives the results from the experiments carried out in obtaining the response which was fed to the software for optimization and statistical analysis.

Table 2. Responses results.

Run	Factor 1 A: Reactor Volume	Factor 2 B: Amount of Sawdust	Factor3 C: Time	Response Temperature
	mL	Kg	Min	^{O}C
1	1000	0.35	95	80
2	1000	0.35	75	88
3	1100	0.5	55	60
4	1000	0.35	75	82
5	1000	0.35	75	85
6	1100	0.5	95	100
7	900	0.35	75	100
8	900	0.2	95	54
9	900	0.5	55	81
10	900	0.2	55	46
11	1000	0.35	75	90
12	1100	0.2	55	40
13	1000	0.5	75	90
14	1000	0.35	75	88
15	1100	0.35	75	86
16	900	0.5	95	100
17	1100	0.2	95	52
18	1000	0.2	75	62
19	1000	0.35	75	92
20	1000	0.35	55	78

The quadratic model shows how the three factors (A, B, and C), affect the response (temperature). The values were obtained for the responses from experimental runs in accordance with the suggested experimental design. The result of the ANOVA is shown in Table 3.

Table 3. The ANOVA results.

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F	Remark
Model	6280.37	9	697.82	23.59	< 0.0001	significant
A-Reactor volume	184.90	1	184.90	6.25	0.0314	
B-Amount of sawdust	3132.90	1	3132.90	105.90	< 0.0001	
C-Time	656.10	1	656.10	22.18	0.0008	
AB	21.13	1	21.13	0.71	0.4179	
AC	78.13	1	78.13	2.64	0.1352	
BC	190.13	1	190.13	6.43	0.0296	
A^2	27.84	1	27.84	0.94	0.3549	
B^2	525.09	1	525.09	17.75	0.0018	
C^2	321.84	1	321.84	10.88	0.0080	
Residual	295.83	10	29.58			
Lack of Fit	232.33	5	46.47	3.66	0.0904	not significant
Pure Error	63.50	5	12.70			
Cor Total	6576.20	19				

The CCD is performed in three steps: carrying out the designed test, prediction of coefficient(s) in a mathematical model, and validation of the model [16]. The statistical test yielded a high regression coefficient (R^2=0.9550) for validation of the model's appropriateness. The F-value of 23.59 indicates that the model is significant. For Prob> F (0.05),

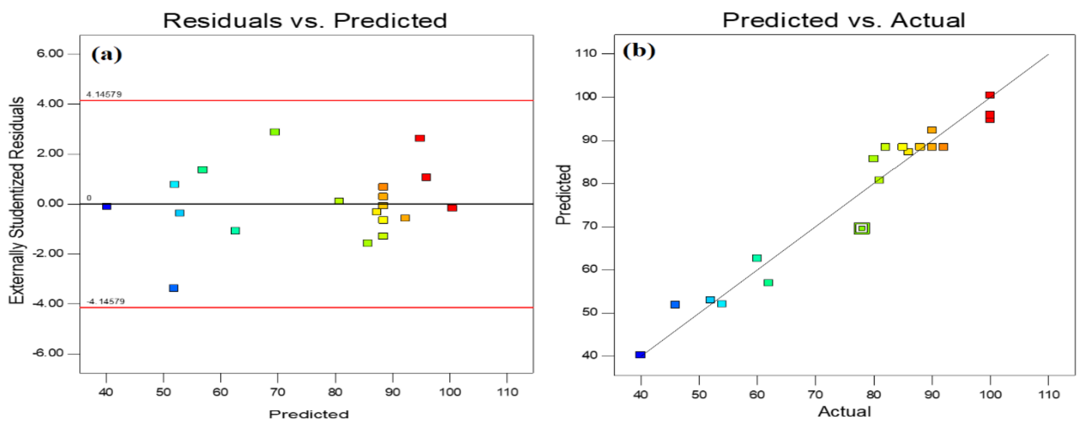

Figure 1: (a) Residuals versus Predicted (b) Predicted versus actual value

the model terms are significant; hence, A, B, C, BC, B^2, C^2 can be deemed significant model terms; also, for Prob> F greater than 0.1000, the model terms are not significant. model equation that relates the independent variables and the response: Temperature (^{0}C) = 88.43–4.30*A+17.70*B+8.10*C1.2*AB+3.13*AC+4.88*BC+ 3.18*A^2–13.82*B^2–10.82*C^2 (1)

By comparing the factor coefficients, the equation is useful for relating the impact of the factors on the response. The quadratic model shows how the three variables influence the response; it has one factor and multi-factor coefficients, which show the effect of a single factor as well as the combined effect of several factors. Positive and negative expressions are used to describe synergistic and antagonistic effects, respectively [17]. Fig. 1 shows the plot of the residuals vs. predicted and predicted vs. actual. The residual distribution helps in verifying the homogeneous variance assumption [18]. The residuals are on both sides of the straight line in Figure 1(a), indicating that errors are distributed normally. The equal scatter above and below the X-axis describes the goodness of the fit. When the predicted values are near to the actual values (in Figure 1b), it means that the developed model can represent the independent variables. It also means that the experimental results are close to the expected values as shown by the regression model and Chukwuneke et al [17] stated that it justifies the established quadratic model. This study depicts that the use of RSM for optimization is superior to one-at-a-time optimization since it gives a model equation.

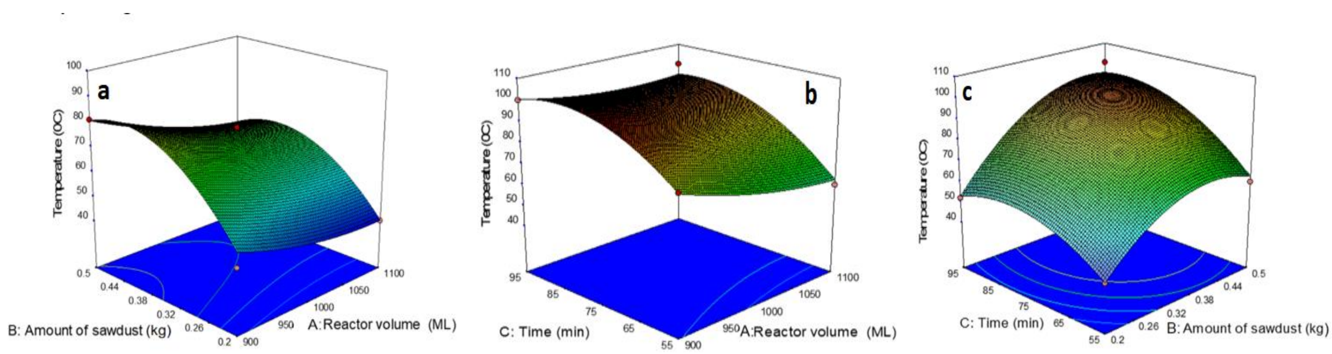

Figure 2: (a) Amount of sawdust and reactor volume surface plots interactions (b) Time and reactor volume interaction (c) Time and amount of sawdust surface plots interaction

2.3. Response Surface Analysis

Figure 2a shows the interactive effects of temperature with two independent variables. It can be deduced that the temperature increases when the amount of sawdust was increased. Furthermore, at the low level, the temperature was minimal and so also at the high levels of the reactor volume, however, the high temperature was realized at the middle levels. With the increase of sawdust, and abundant surface area for the reactor volume, the temperature is high corresponding to the reactor volume of 1100 mL, with a 0.5 Kg amount of sawdust and temperature of 62.648 ^{0}C in 55 min. The interaction between the amount of sawdust and the reactor volume is the perfect curvature of contour lines which also revealed that the effect of the amount of sawdust compared to the reactor volume was more relevant as far as the temperature is concerned. The interactions in Figure 2b followed a pattern that is like Figure 2a. There is a consistency of time effect on the reactor volume with a decrease observed at both the lowest and highest time level. Figure 2c further shows the interactive effects of temperature with two independent variables i.e time and amount of sawdust, when the amount of sawdust was uniform throughout and the period increased, there was an increase in temperature.

2.4. Optimization and Validation of the Model

The validation of the model is confirmed by carrying out an experiment to test for the optimum independent variables as predicted by the software. These optimum values were 1100 mL reactor volume, amount of sawdust was 0.5 Kg and 55 min to give a response of 96.648 ^{O}C. This result is predicted by the RSM software and was verified in the laboratory with only a reasonable slight difference of 2.648 ^{O}C observed. Therefore, the model can ultimately describe the experimental data under the predicted optimum conditions.

3. Experimental

3.1. Water Boiling Test (WBT)

The sawdust was collected and dried till the moisture content has drastically reduced, some quantity of sawdust was measured and charged into the combustion chamber, of the locally fabricated sawdust stove and a little amount of kerosene was added to the sawdust to aid the ignition speed while the switch of the blower was on, the flow rate was kept at a constant rate while the time for the sawdust to burnt was recorded. Also, the temperature was measured using a thermometer and this procedure was repeated with a variable amount of sawdust, time, and reactors until 100 ^{O}C was attained. Each experiment was conducted thrice, and average values are reported Table 4 gives the design experiment summary.

Table 4. Design summary.

Factor	Name	Units	Minimum	Maximum
A	Reactor volume	mL	900	1100
B	Amount of sawdust	Kg	0.2	0.5
C	Time	min	55	95

The RSM design was utilized to discover the best influential parameters related to maximizing water boiling using Central Composite Design (CCD) and Design-Expert Version 10.0 software (Stat-Ease, Inc.). The experimental design consisted of three independent variables one response, 20 runs, and six central points. In the present work, Analysis of Variance (ANOVA) was used in verifying the adequacy of the model, a similar study can be found in the literature [16].

4. Conclusion

An application of RSM and one-variable-at-a-time optimization of sawdust in WBT was performed. The statistics test gave a high regression coefficient of R^2=0.9550 therefore, the developed model equation can be considered a good fit to make predictions about the temperature for given levels of each independent variable. It can be concluded that sawdust as a source of heat made from sawdust is cheap for use, prevent or reduces deforestation, and can serve as a source of income if produced for commercial purposes.

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